ASSESSMENT AND PREDICTION OF CLIMATE VARIABILITY IMPACT ON LAND USE LAND COVER CHANGE IN SIKASSO REGION, MALI

BY

SIDIBE, Mohamed
MTech/SPS/2015/6071

WEST AFRICAN SCIENCE SERVICE CENTRE ON CLIMATE CHANGE AND ADAPTED LAND USE
FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA

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THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL, FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF TECHNOLOGY (MTECH) IN CLIMATE CHANGE AND ADAPTED LAND USE

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DECLARATION

I hereby declare that this thesis titled: "**Assessment and Prediction of Climate Variability Impact on Land Use Land Cover Change in Sikasso Region, Mali**" is a collection of my original research work and it has not been presented for any other qualification anywhere. Information from other sources (published or unpublished) has been duly acknowledged.

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CERTIFICATION

This thesis titled: "**Assessment and Prediction of Climate Variability Impact on Land Use Land Cover Change in Sikasso Region, Mali**" by: SIDIBE Mohamed (MTech/SPS/2015/6071) meets the regulations governing the award of degree of Master of Technology in WASCAL (Climate Change and Adapted Land Use) of the Federal University of Technology, Minna and is approved for its contribution to scientific knowledge and literary presentation.

Dr. (Mrs) A. Abdulkadir ……………………
Major Supervisor Signature & Date

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Director, WASCAL, FUT-Minna Signature & Date

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Dean, Postgraduate School Signature & Date

To the good faith, uprightness, generosity and exemplarity of my dear and amiable uncles Amadou Sidibé and Modibo Sidibé.

They gave me all that which was needed.

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ABSTRACT

Climate change and variability are worldwide phenomena and their impact is different in nature from one region to the other. In that context, this study focused on the assessment and prediction of climate variability impact on Land Use Land Cover Change (LULCC) in Sikasso region, Mali with focus on agricultural lands. Three objectives were achieved in this study: (1) assess changes in LULC, (2) examine climate variability and its impact on agricultural LULC and (3) predict future changes in LULC by 2030 and 2050. The dataset composed of time series satellite images from Moderate Resolution Imaging Spectroradiometer (MODIS) Terra for the years 2000, 2008 and 2016, monthly rainfall and temperature from 1981 to 2016 for the four main meteorological stations across the study area and socioeconomic information. The Savitzky-Golay (SG) filtering process (smoothing) was performed on Normalised Difference Vegetation Index (NDVI) time series images with TimeSat software and an ISODATA classification scheme adopted for four main classes which are cropland, vegetation, water and others. Standardised anomaly, Coefficient of Variation (CV) and Modified Mann-Kendall (MMK) trend test were used to analyse rainfall and temperature data. Pearson's Chi-square test of association was performed on questionnaire data to determine whether climate variability has impact on LULCC and the prediction was carried out using Cellular Automata (CA)-Markov model. The LULCC analysis showed that agricultural lands increased by 4 % (129,665 ha) between the year 2000 and 2016 and the vegetation cover decreased by -1 % (30,000 ha) during the same period; water bodies increased and the class others decreased. The expansion of agricultural lands and decreases in vegetation cover are expected to continue. Furthermore, the mean temperature increased from 1981 to 2016 at the rate of 0.3 °C per decade and the minimum temperature recorded the highest rate of increase (0.44 °C per decade); on monthly basis, the highest deviations in the temperature were observed in the months of November (+1.24 °C), March (+0.69 °C) and October (+0.67 °C) while lowest was observed in the month of February (+0.15 °C). At 5 % significance level, an increasing trend was detected in the regional annual average rainfall and the amount of rainfall during the rainy season (for years after 2010) was considerably higher than the climatological mean-normal (1981-2016) except the years 2011 and 2013. The LULC model revealed that cropland will increase by 6.54 % (217,599 ha) between the period 2016-2030 and 18.58 % (618,179 ha) in 2016-2050. Vegetation will decrease by -11.14 % (-357,149 ha) between 2016-2030 and by -34.49 % (-1,105,814 ha) by 2050. Generally, the observed increment in annual and seasonal rainfall was not the primary factor for the expansion of agricultural lands as questionnaire analysis revealed that farmers' decisions to bring changes in their farms size was rather a function of market prices, changes in production systems, access to improved seeds and number of male workers. The intensification of LULCC as apparent from the model predictions and spatio-temporal climatic pattern signals the need for the development of mitigation and adaptation strategies that will minimize the sensitivity and exposure as well enhance the resilience of the Sikasso region to the anticipated changes. Further study should address rainfall variability in terms of its intra seasonal distribution and impact on agricultural production in the region.

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ABBREVIATIONS AND ACRONYMS

AVHRR	Advanced Very High Resolution Radiometer
CA-Markov	Cellular Automata Markov model
CGCM	Canadian Global Circulation Model
CV	Coefficient of Variation
DEM	Digital Elevation Model
DOY	Day Of Year
EOSD	Earth Observing System Data and Information System
ESTARFM	Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model
ETM	Enhanced Thematic Mapper
EVI	Enhanced Vegetation Index
FUT-Minna	Federal University of Technology, Minna, Niger State
GPS	Global Positioning System
HadCM	Hadley Coupled Model
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use Land Cover/Change
LULCC	Land Use Land Cover Change
MK	Mann-Kendall
MLC	Maximum Likelihood Classifier
MMK	Modified Mann-Kendall
MODIS	Moderate Resolution Imaging Spectroradiometer
MRT	MODIS Reprojection Tool
NASA	National Aeronautics and Space Administration
NDVI	Normalised Difference Vegetation Index
OLI	Operational Land Imager
PSA	Programme de Securite Alimentaire
SAI	Standardised Anomaly Index
SG	Savitzky-Golay
SPI	Standardised Precipitation Index
SPSS	Statistical Package for Social Science

TM	Thematic Mapper
UNFCCC	United Nations Framework Convention on Climate Change
USGS	United State Geological Survey
UTM	Universal Transverse Mercator
WASCAL	West African Science service on Climate Change and Adapted Land Use
WGS	World Geographic System

CHAPTER ONE

1.0. INTRODUCTION

1.1. Background to the Study

Mali is a landlocked country with an economy largely dependent on rural activities including farming and livestock productions. About 80 % of the Malian population are involved in rural activities whereas natural resources in general and land specifically are the major asset (Ministere de la Sante et de l'Environnemnt, 2011). However, climate change in combination with the rapidly growing population and expansion of urban cities are putting pressure on land resources in Mali. Consequently, the environmental degradation of agro-ecosystems and large-scale land-use change are becoming critical issues of farmers' vulnerability across the rural areas. The negative implications of the Land Use Land Cover Change (LULCC) for socio-ecological sustainability, changing land entitlement and other productive resources in agriculture-based economies like the one of Mali are emphasised in several literatures (Padgham *et al.*, 2015).

As in many other countries throughout the world, Mali has been experiencing an increase in temperature for a long time. The Ministere de la Sante et de l'Environnemnt (2008) has in fact reported that since 1960, the annual average temperature in Mali rose by 0.7 °C, corresponding to the rate of 0.15 °C per decade. It also documented that the temperature exhibits seasonal changes. Furthermore, Bodegom & Satijn (2015) stated that sahelian Mali is characterised by frequent droughts, annual rainfall variability and that local temperatures, rainfall variability and the extent of severe weather events are expected to increase due to climate change. By implication, the higher temperature values and positive changes in recent times will adversely impact on Land Use Land Cover (LULC) across the study area.

Changes related to climate are felt in Mali and have led to a substantial relocation of agricultural, fishing and livestock keeping activities in the southern part of the country where the density of population is much higher, that increases the conflicts amongst farmers, fishermen and pastoralists (Bodegom & Satijn, 2015). These weather induced migration will not only increase southern population but also impact on land resources in southern parts of the country particularly, the study area.

Climate variability and change are challenges that the Malian agriculture may have to face. It has been projected that climate will demonstrate decreases in precipitation and increases in temperature. Precisely, the Canadian Global Circulation Model (CGCM) and the 2030 projections of the Hadley Coupled Model (HadCM) indicate that the average temperature in Mali might rise by about 1° – 2.75 °C, with precipitation decreasing slightly (Butt *et al*., 2005). In addition, the following projections were made: 1) crop production to increase or decrease in the range from –17 % to +6 % at country level 2) yields of forage to decrease by between 5 % and 36 % (Butt *et al*., 2005; Butt *et al.*, 2011). Consequently, these challenges will affect LULCC in Mali and particularly in Sikasso which constitutes an important agricultural zone in the country.

1.2. Statement of the Problem

Deceasing trend of rainfall coupled with higher temperatures trend have been documented across Mali. The National Directory of Meteorology (2001) depicted decreases in the rainfall trend from 1961 to 2001. Bodegom & Satijn (2015) reported that in the 1950s', the annual precipitation used to vary within the range 500 and 1500 mm but in the course of the last 15-20 years the maximum has not been beyond 1300 mm. Moreover, Traore *et al*. (2013) reported that during the period 1965-1993, the number of dry days have increased during the rainy season in Sikasso region and identified variation as one of the most important characteristics of climate change in southern Mali. These trends necessitate proactive approaches which should be based on accurate and adequate information of anticipated future change.

Land resources are the key pillars for agricultural production which involves the large portion of rural population in Mali. However, the degradation of land resources as a result of climatic and non-climatic factors combined with the population growth and urbanisation are affecting the land cover change in Mali and most semi-arid countries. Land use dynamics, logging of trees for firewood, construction of houses and other social needs are taking away the vegetation cover thereby exposing the land to various agents of degradation. Furthermore, the intensification of human activities through continuous agriculture and animal grazing has continued to aggravate land degradation and shrinkage of productive lands and vegetation cover.

Fundamentally, climate change and variability in sahelian Mali is encroaching on marginal lands and thereby forcing people to migrate southwards. As reported by Bodegom & Satijn (2015), 'migration is likely to be caused by climate change' and concluded that the region of Sikasso will receive more migrant from northern regions. Despite the apparent features of climate variability and change, decreasing rainfall (erratic rainfall pattern), intensive degradation and southwards migration of people and livestock, few researches have been conducted to assess and predict climate change and variability impact on LULCC in Sikasso region as earlier efforts were concentrated on analyses of vegetation trends and changes. The combination of these elements makes it important to assess and predict the impact of climate variability on LULC changes in Sikasso region, with a view of documenting accurate and adequate information on the anticipated future changes as a pathway for the attainment of sustainable LULCC in rapidly changing environment and thereby enhancing socio-economic livelihood.

1.3. Justification for the Study

Assessing changes in agricultural LULC is of great importance for forests protection and the preservation of pasture lands. Massive agricultural LULCC may lead to different types of land degradation, landscape and ecosystem perturbations.

Agricultural intensification is a very slow process in most West African countries. This leads to increase in agricultural production through deforestation and expansion of agricultural lands instead of improved technologies, practices, fertiliser application and seed amelioration. This is a primary phenomenon leading to forests loss, shrinking of pasture lands and degradation of soils. Barbier (2004) stated that agricultural land is the most important source of natural wealth for developing countries not having oil and natural gas reserves and also mentioned that the agricultural land base is rapidly expanding through conversion of wetlands, forests and other natural habitat. This led to the question of continuity / sustainability of that scenario and ascertains the importance of this study. In such context, studies on monitoring LULCC with particular regards on agricultural lands and vegetation is of great interest for environmental protectionist and climate scientist for mitigation actions. Katana *et al*. (2013) reported that the identification, delineation and mapping of the types of land covers are regarded as important activities in support of sustainable natural resource management.

The fast growing population in West Africa leads to the need of growing more food to meet the increasing food demand of the escalating population and to expansion in croplands. This expansion has negative impact on the sub-region's ecosystem and repercussions on biodiversity, climate, water and soil quality. To monitor appropriately these changes in croplands and assess their impact on the ecosystem and other environmental processes, precise and up-to-date information on agricultural land use is essential (Knauer *et al*., 2017a). In this regard, Lambert *et al*. (2016) stated that it is very important to monitor land use change and develop thorough understanding of the detailed spatial patterns and the temporal dynamics of cropland. Relatively, this study aims at providing accurate and adequate information that is crucial for monitoring the Sikasso region, and the development of mitigation and adaptation approaches to the changing environment.

Sikasso is the most successful agricultural zone in Mali (Diallo, 2011). It is of primary importance when it comes to food security-related matters. It lodges most of the country’s forested area and natural reserves. However, most of the studies in agricultural sector in Mali focused on agricultural productivity and soil fertility loss. In addition, the very few studies related to LULC mapping were mostly based on the usage of Landsat single date images which are very limited in delineating agricultural lands from vegetation cover. Therefore, in this study, the Moderate Resolution Imaging Spectroradiometer (MODIS), Normalised Difference Vegetation Index (NDVI) time series images were used in addition to Landsat images for a better identification and classification of different LULC types. Furthermore, no study has addressed the issue of prediction of future changes in LULC and assessed climate variability and its impact on LULCC in Sikasso. Consequently, it becomes necessary to assess past changes for a better prediction, identification of strategies for the attainment of sustainable development through implementation of appropriate mitigation and adaptation practices.

1.4. Aim and Objectives

Aim

The study was aimed at assessing and predicting climate variability impact on LULC in order to have information that will be crucial for the development of LULC mitigation and adaptation strategies commensurate with the changing environment in Sikasso region, Mali.

Specific objectives

The following objectives were tackled in order to achieve the aim of the study:

1. Assess changes in agricultural LULC in Sikasso,
2. Examine climate variability and its impact on agricultural LULC,
3. Predict future changes in LULC by 2030 and 2050.

These specific objectives were achieved by answering these questions

1. What are the changes in agricultural LULC in Sikasso?
2. How is climate variable and what is the impact on agricultural LULC?
3. What is likely to be the nature of LULC change by 2030 and 2050?

1.5. Scope and Limitations of the Study

This study aimed at the assessment and prediction of climate variability impact on LULCC in the region of Sikasso, it looked at LULCC in general but with particular focus on agricultural LULC changes. It used MODIS Terra time series images to assess changes LULC from the year 2000 to 2016 and Cellular Automata (CA)-Markov model to predict changes by the years 2030 and 2050. Temperature and rainfall data were used to examine the climate variability and trend. Questionnaires were administered to farmers in order to understand their decision making process with regards to changes in LULC with particular interest on agricultural lands.

Mapping LULC using MODIS images can be challenging, for they are of coarse resolution. That makes it sometimes difficult to adequately identify some of the spatial features. Moreover, the basic assumption of the prediction is that the factors having influence on LULCC process will continue keeping their past trends. In real life, these factors can behave differently and therefore, one should be cautious holding too much on results from such predictions for they are subject to uncertainties.

1.6. Study Area

1.6.1. Location

The study was conducted in Sikasso region, located between longitude 4° 39' to 8° 68'W and latitude 10° 15' to 12° 82'N. Sikasso is one of the ten regions of Mali, composed of 7 *cercles*-second level administrative units (Bougouni, Kadiolo, Kolondieba, Koutiala, Yanfolila, Yorosso and Sikasso-*cerlce*), located in the southern part of the country and sharing border with Côte-d'Ivoire, Guinée Conakry and Burkina Faso. It has a total land mass of 70 280 km^2 (5.8 % of the national territory) and a population of 2 625 919 in 2009 (Ministere de l'Adiministration Territoriale, 2011). Figure 1.1 shows the map of Sikasso region in Mali.

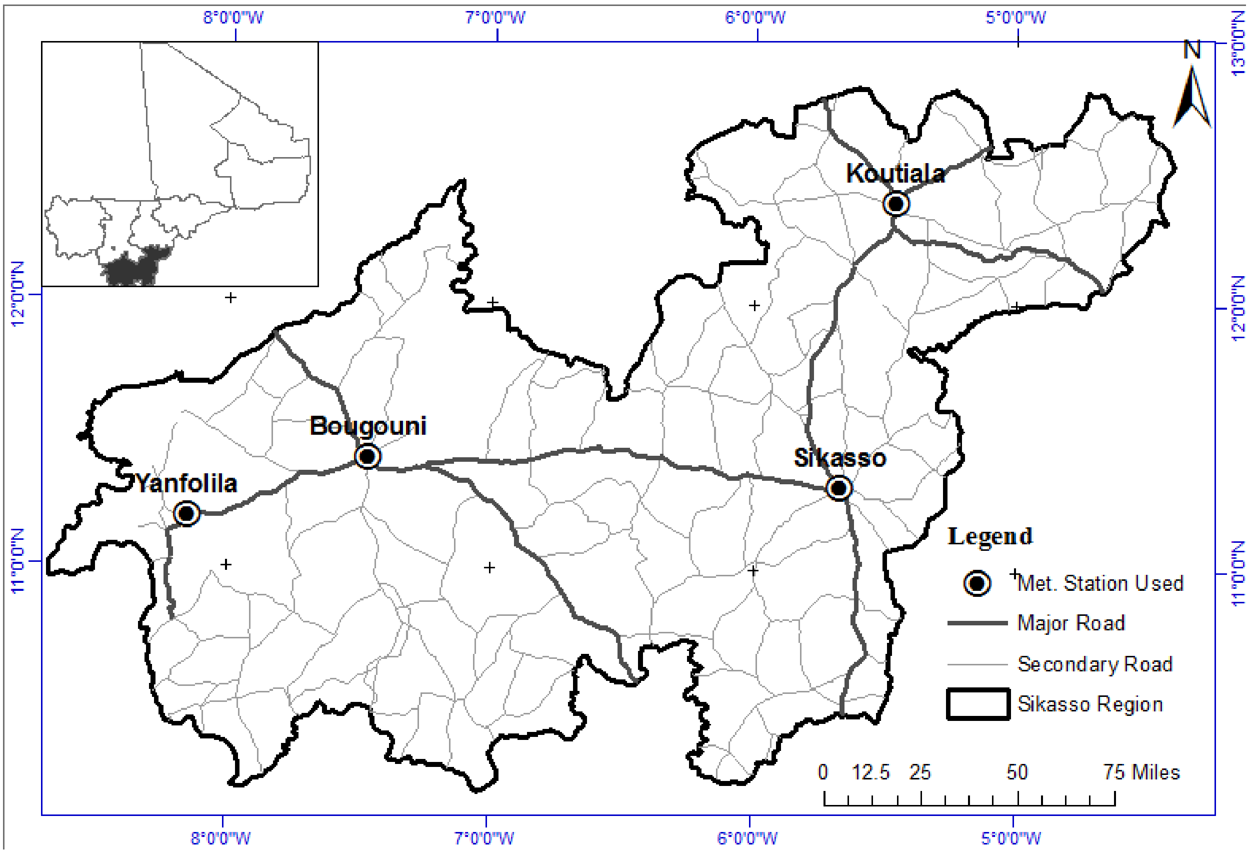


Figure 1.1 Study Area

1.6.2. Climate

In the entire Mali, the annual average temperature is 28 °C, the north is characterised by higher average temperatures while lower averages are observed in the south; the absolute maximum temperature is 51 °C, whereas the minimum temperature has not been lower than 10 °C which causes high rates of evapotranspiration (Ministere de la Sante et de l'Environment, 2008). However, Sikasso receives the highest amount of rainfall in comparison with the other regions of the country. The climate is of tropical Sudanian type, subdivided into two climatic zones, the Sudanian humid and the Guinean zone, which is the wettest region of Mali and receives the highest rainfall (700-1,500 mm / year) with an average annual temperature of 27 °C (PSA, 2011). Among others, continuous degradation of forest, lack of agricultural lands, soil erosion and loss of soil fertility have been identified as main problems of the region (PSA, 2011).

1.6.3. Economic activities

Agriculture is the main economic activity in the region of Sikasso, and it is in fact the most agricultural successful zone in the country. The main crops produced are maize, millet, sorghum, rice and cotton.

CHAPTER TWO

2.0. LITERATURE REVIEW

This section of the thesis defines the concepts used in the study and presents a review of related studies in accordance with the three different objectives which are: agricultural LULCC assessment, climate variability analysis and LULCC prediction.

2.1. Review of Concepts

2.1.1. Climate change

Climate change is differently defined by the Intergovernmental Panel on Climate Change (IPCC) and the United Nations Framework Convention on Climate Change (UNFCCC). While the IPCC makes inclusion of both natural and human factors as causes of changes in climate (mean and/or variability of its properties) for an extended period of time, the UNFCCC defines it by focusing on the human activity causing direct or indirect changes in climate over long periods of time added to natural climate variability (IPCC, 2007). The latter excludes the natural factors as causes of change. Though they differ in including natural variability, both of them agreed that it should be over a long period of time (a minimum of thirty years). That suggests that at least three decades of statistical data are required for studies aiming at showing evidence of climate variability/change. In this regard, Adhikari *et al*. (2011) mentioned that ‘It refers to a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period (typically decades or longer)’.

2.1.2. Climate variability

Climate variability refers to variations in the mean state and other climate statistics (standard deviations, the occurrence of extremes, etc.) on all temporal and spatial scales beyond those of individual weather events (Adhikari *et al*., 2011). Variability may result from natural internal processes within the climate system (internal variability) or from variations in natural or anthropogenic external forces (external variability).

Climate variability and changes and their consequences are worldwide (IPCC, 2007), and Mali is not an exception. In addition to seasonal changes, an increase of 0.7 °C in temperature over the period (1960-2001) has been reported by the *Ministere de la Sante et de l'Environment* (2008). Furthermore, future projections of climate in Mali are worrisome. Projected changes in mean annual rainfall range from -22 to +25 % by the 2090s, depending on 'wet' or 'dry' scenarios with the most likely change between 0 and -11 % (Bodegom & Satijn, 2015). These changes in temperature and rainfall though the latter not precise, establish the evidence of climate change and variability occurrence in Mali. Therefore, this study focused on climate variability and its impact on agricultural LULCC rather than climate change.

2.1.3. Land use land cover

Whereas land use refers to different activities which human put land to, land cover on the other hand is (are) the feature(s) on the surface of land and its immediate subsurface and the attributes of that part of the Earth's surface. Land cover includes biota, soil, topography, surface and groundwater, and human structures (Lambin *et al.,* 2000). In other words, land cover is all about Earth's surface observed physical and biological cover while land use refers to purposes for which humans exploit the land cover. The land use type in the centre of this study is agricultural lands.

Land-use and land-cover change is considered to be one of the main driving forces of global environmental change and very important for sustainability. Their changes have impacts on a wide range of environmental and landscape attributes including the quality of water, land and air resources, ecosystem processes and function, and the climate system itself through greenhouse gas fluxes and surface albedo effects (Lambin *et al*., 2000). The expansion of croplands for example may lead to changes in surface albedo, greenhouse house emissions, thereby, impacting on the environment.

Since humans have controlled fire and domesticated plants and animals, they have cleared forests to wring higher value from the land. About half of the ice-free land surface has been converted or substantially modified by human activities over the last 10,000 years' (Eric *et al.*, 2003).

2.1.4. Agricultural lands

Agricultural lands in a general sense refer to lands that are devoted to permanent crop production, pastures and arable lands ("OECD," n.d.). In this thesis, is meant by agricultural land, lands used for the production of food or industrial crop for at least once a year. Pasture and range lands not included.

2.1.5. Normalised difference vegetation index

The NDVI is a numerical indicator that uses the visible red and near-infrared bands of the electromagnetic spectrum. It is adopted to analyse remote sensing measurements and assess whether or not the target being observed contains live green vegetation. NDVI was first used in 1973 by Rouse *et al*. from the Remote Sensing Centre of Texas A&M University ("FSNAU," n.d.).

Generally, healthy vegetation will absorb most of the visible light that falls on it, and reflects a large portion of the near-infrared light; unhealthy or sparse vegetation reflects more visible light and less near-infrared light; bare soils on the other hand reflect moderately in both the red and infrared portion of the electromagnetic spectrum (Holme *et al*., 1987).

The NDVI algorithm subtracts the red reflectance values from the near-infrared and divides it by the sum of near-infrared and red bands. The formula is as follow:

NDVI= (NIR-RED) / (NIR+RED)

The higher the difference between the near-infrared and the red reflectance, the healthier the vegetation. The technique makes it easy to differentiate vegetative areas from non-vegetative areas.

The NDVI can be computed from different satellite images but, the commonest way to accede NDVI products directly is by downloading them from very high temporal resolution sensors. In that matter, the Moderate Resolution Spectroradiometer is a good supplier which, in addition to NDVI products provides the Enhanced Vegetation Index which is also used for vegetation dynamics studies. 'The MODIS NDVI complements NOAA's Advanced Very High Resolution Radiometer (AVHRR) NDVI products and provides continuity for time series historical applications. MODIS also includes a new Enhanced Vegetation Index (EVI) that minimizes canopy background variations and maintains sensitivity over dense vegetation conditions. The EVI also uses the blue band to remove residual atmosphere contamination caused by smoke and subpixel thin cloud clouds. The MODIS NDVI and EVI products are computed from atmospherically corrected bidirectional surface reflectance that have been masked for water, clouds, heavy aerosols, and cloud shadows. Global MOD13Q1 data are provided every 16 days at 250meter spatial resolution as a gridded level3 product in the Sinusoidal projection. Lacking a 250m blue band, the EVI algo=rithm uses the 500m blue band to correct for residual atmospheric effects, with negligible spatial artefacts', NASA Land Data Products and Services (NASA LP DAAC, 2014).

2.1.6. Smoothing of time series data

Despite the pre-processing of satellite time series data, some of the images issued are still affected by atmospheric disturbances that leads to the presence of extraordinary values in some time series data. To deal with such, a noise reduction process is then required in order to produce data series with normal behaviour (Smoothing). In this context, one of the smoothing techniques applied on satellite time series data that one can easily come across because of its applicability in recent years is Savitzky-Golay (SG) filtering (Chen *et al*., 2004).

2.2. Literature Review

2.2.1. Agricultural land use land cover change assessment

LULCC detection and monitoring is a subject of great importance to climate scientist and urbanist for better management of natural resources. Subedi and Thapa (2013), stated that 'understanding land use change has been a matter of interest and concern among landscape planners and environmentalist because of the influence land-use change has on the global environment'. Zoungrana *et al*. (2015) mentioned that accurate LULC classification and statistically sound change area estimates are essential for a better understanding of LULCC processes. Understanding these processes will generate information which may serve as decision tool for policy makers regarding LULCC planning.

Agricultural lands have been expanding in many places throughout the world and over time. The expansion happens to be at the expense of forests and other types of vegetation cover. In this regard, Barbier (2004) mentioned that the agricultural land is expanding rapidly through conversion of forests, wetlands, and other natural habitat. This leads to different types of land degradation such as deforestation and desertification.

However, several studies have been conducted aiming at the assessment of LULCC and cropland mapping. Butt *et al*. (2015) mapped and analysed land use and cover change over Simly watershed in Pakistan using Landsat and SPOT images for the years 1992 and 2012. They produced a map of five land use/cover types, agriculture, bare soil, settlements, vegetation and water using the supervised Maximum Likelihood Classification (MLC) method. The authors reported a significant shift from vegetation and water cover to agriculture, bare soil and settlements cover, which shrank by 38.2 % and 74.3 % respectively; they also stated that these transformations pose serious threats to watershed resources and require a proper management system (Butt *et al*., 2015). Zoungrana *et al*. (2015) investigated land use land change detection in the southwest of Burkina Faso using Landsat and ancillary data for the period 1999 to 2011; a random forest classification was performed to obtain five LULC classes which were, water, agricultural area, woodland, bare soil and mixed vegetation. That was followed by a post-classification change detection process comparing the maps of the two periods. The study revealed that agricultural area and bare surface have increased at the expense of woodland and mixed vegetation, which decreased over the years.

Knauer *et al*. (2017a) studied the expansion of agricultural land in Burkina Faso over a period of fourteen years (2001-2014); they used the Enhanced Spatial and Temporal

Adaptive Reflectance Fusion Model (ESTARFM) to generate Landsat-like time series images at eight-day interval from the MODIS time series dataset. SG filtering technique implemented TIMESAT software was applied on MODIS NDVI time series data for noise reduction and the Random Forest classifier was used for the classification of the images. The authors reported an increase of 91 % in agricultural area over the fourteen years.

Vintrou *et al*. (2009) mapped cultivated area in Senegal and Mali using MODIS time series data 16-Day L3 Global 250m for the years 2004 and 2005; they stratified Senegal into sixteen agro-ecological zones and Mali into ten zones. K-means classification technique was performed inside each agro-ecological zone, the initial classes generated were then regrouped into three classes: crops, crops mixed with vegetation and others. Landsat and Google Earth imageries were used for the interpretation and classification of MODIS time series images. The study concluded that the cultivated domain can be separated from other land-cover types on the basis of its NDVI temporal behaviour. The same author, in 2011 (Vintrou *et al*., 2011) conducted a similar study in Mali using the same MODIS product 16-Day L3 Global 250m for the year 2007. The ISODATA classification was performed inside each stratified zone; the initial classes generated were regrouped into two classes: crop and non-crop. The result of their classification was compared with four global products which are GLC2000 for Africa, GLOBCOVER, MODIS V05 (MCD12Q1) and ECOCLIMAP-II. They reported that their classification from MODIS 250m NDVI time series data performed better and can be used for cropland mapping in the study area.

Doraiswamy *et al*. (2006) used a three-year MODIS terra 250m resolution eight-day composite for mapping soybean area in four provinces in Brazil. SG technique for smoothing time series data was performed before proceeding to the classification with a decision tree-based algorithm. The authors mentioned that filtering improves the result of classification and concluded that MODIS imagery can be used for regional classification when screened for data anomalies and contaminations due to clouds and compositing procedures.

Kaishan *et al*. (2011) used MODIS 250m NDVI time series from 2001 to 2007 and Landsat data to map the LULC of Amur river basin in Russia. They compared the different maps and reported that MODIS time series dataset have high potential in mapping more features than Landsat products. Lambert *et al*. (2016b) mapped croplands in West African Sahelian and Sudanian agro systems (area of interest 17°W–23°E to 9°N–18°N) using PROBA-V times series at 100m resolution. For the discrimination of croplands, five temporal features were selected, the maximum of the red band, the minimum and maximum of the NDVI and the increasing and decreasing slopes of the NDVI profile (Lambert *et al*., 2016b).

Krishna *et al*. (2014) used MODIS 500m resolution NDVI products for mapping seasonal rice cropland extent and area in the high cropping intensity environment of Bangladesh for the year 2010. They used 46 composites dates (8 days interval) and applied unsupervised classification (ISODATA), based on NDVI, Monthly Maximum Composites Values (MVC) and Land Surface Water Index (LSWI). They were able to discriminate rice production area by the spectral signatures (Krishna *et al*., 2014). Similar methods were used by Traore *et al.* (2014) to assess long-term trends in vegetation productivity change over the Bani river basin in Mali using NDVI from Landsat imagery time series for the period 1982-2011.

However, the review of these literature revealed that the methods for monitoring and detecting changes in agricultural lands have been evolving from the massive usage of Landsat single date satellite images to very high temporal resolution satellite images like MODIS and NOAA AVHRR. Therefore, this study combined the usage of the two types of satellite images. In addition, the use of NDVI in these recent studies, ascertains its effectiveness in mapping croplands. Hence, there is need to take advantage of this effectiveness for cropland mapping and the assessment of the impact of climate variability of agricultural LULC dynamics in Sikasso region.

2.2.2. Climate variability assessment

2.2.2.1. Impact, perception and adaptation strategies

Agriculture in developing countries where the production system relies mainly on rainfall and temperature regimes is threatened by any variability in the pattern of these climatic variables. Knowing the pattern of these climate variables helps in adapting agricultural production systems in order to tackle food insecurity and malnutrition. Therefore, it is very important to analyse climate variability in order to determine trends and adapt the agriculture systems. That is even crucial in countries where agriculture constitute the soul of the economic system, amongst which is Mali.

According to Sivakumar *et al*. (2005), ‘climate variability has been, and continues to be, the principal source of fluctuations in global food production in the arid and semi-arid tropical countries of the developing world’. This includes some West African countries amongst which, Mali which is typically affected. In fact, several studies have been conducted throughout the world with regards to climate change, its variability and socio-economic sector. Traore *et al*. (2013) studied the effects of climate variability on crop production in southern Mali (Sikasso and N'Tarla), using weather data set from 1965 to 2005. They reported an increase of 0.05 °C per year in the minimum air temperature during the period (1965-2005) while the maximum remained the same; a significant decrease in rainfall at N'Tarla between 1965 and 1993 (N'Tarla is located within Sikasso region-the study area) was reported; large seasonal inter-annual variability of rainfall in its distribution which have negative impact on cotton production was also reported. To compensate for these changes in production, farmers in general resort to changes in cropping systems by changing land size which result in LULCC.

Agriculture and agricultural LULCC interact with the climate in both directions. On one hand, agricultural land use systems and cropland expansion through deforestation and others practices can contribute to more release of greenhouse gases into the atmosphere, contributing to climate change. In this regard, IPCC, (2014) reported that in 2010, 24 % of net greenhouse gas emissions were from agriculture, forestry and other land uses. On the other hand, changes in climate variables like rainfall and temperature have direct impact on agricultural land use and land cover practices. Moreover, Sivakumar *et al*. (2005) stated that inter- and intra-annual variability in rainfall is perhaps the key climatic element that determines the success of agriculture in the arid and semi-arid tropics in Africa, Asia and Latin America.

Moreover, IPCC (2014) reported that 'assessment of many studies covering a wide range of regions and crops shows that negative impacts of climate change on crop yields have been more common than positive impacts'. Given the fact that continuous changes in crop production induce changes in agricultural LULC, especially in developing countries, where intensification through new technologies, improved seeds and fertilizer is not well rooted, farmers rely on their land size to adjust their production. In context, this study was aimed at singling out the case of Sikasso region in Mali.

Scientific understanding of climate change and variability is different from farmers' understanding. While scientists make use of quantifiable evidences, farmers' take note of changes in their daily life and seasonable planning and activities. In this context, several studies have been conducted to investigate farmers' perception and adaptation strategies.

Akponikpè *et al*. (2010) investigated farmers' perception of climate change and adaptation strategies in five Sub-Saharan West-African countries (Benin, Burkina Faso, Ghana, Niger and Togo) using questionnaire to interview a total number of 234 farmers. The authors reported that, 98 % of farmers acknowledge climate change; though, depending on their climatic regions, they have different opinions of when it has started changing; 50 % of those in Guinean Ghana mentioned about less than 10 years while 55 % of farmers in sahelian Niger stated that it started about 20-30 years ago. The authors also reported that changing from late to early crop cultivars, soil water conservation strategies (for sahelian farmers' in Burkina and Niger Republic) and late onset have been widely mentioned by farmers'. Similar results were obtained by Toure *et al*. (2016) who studied farmers' perceptions on climate variability and adaptation strategies to climate change in Cinzana, (Mali) using also questionnaire and reported that all the farmers interviewed are aware of climate change and identified change in crop variety as major adaptation strategy.

Rao *et al*. (2011) examined farmers' perceptions of short- and long-term variability in climate, their ability to discern trends in climate and how the perceived trends converge with actual weather observations in five districts of Eastern Province in Kenya where the climate is semi-arid with high intra- and inter-annual variability in rainfall. They also conducted field surveys to elicit farmers' perceptions about climate variability and change in the districts. The authors analysed long-term rainfall records from five meteorological stations within a 10 km radius from the survey locations and compared the results with farmers' observations. It was reported that farmers are well aware of general climate, its variability and impacts on crop production but, farmers' perception of changing rainfall pattern was not supported by the observations from the meteorological data.

2.2.2.2. Climate variability assessment methods-trend analysis

Different techniques have been used in diverse studies in order to monitor climate variables like rainfall and temperature in order to establish whether or not there is variability. However, some of the most widely used are: anomalies, standardised anomalies, Coefficient of Variation (CV) and Mann-Kendall (MK) trend test.

Anomaly is generally defined as the departure or deviation from the mean value (normal), it explains an unexpected behaviour of the observed value in relation to the expected value. Kawale *et al*. (2000) explained that the central idea behind anomaly construction is to split the data into two parts, data with expected behaviour, and anomaly data that shows the variability from the expected value. It is generally used for understanding climate change phenomenon (Kawale *et al*., 2000)**.** The standardised anomaly is the anomaly divided by the standard deviation, it is also referred to as normalised anomalies. It generally provides more information about the magnitude of the anomalies because of the removal of dispersion influences and one of its advantages is that it does not require that dataset have a particular distribution before computation (Karavitis *et al*., 2011).

The CV is the ratio of the standard deviation to the mean over a determined period. It is expressed in percentage and in the form of the level of variability (Eshetu *et al*., 2016). MK test is said to be the most popularly used non-parametric test for detecting trend in the time series data. It is widely used for different climatic variables (Suryanarayana & Parekh, 2016). Pohlert (2016) defined it as a non-parametric test that is commonly employed to detect monotonic trends in series of environmental data, climate data or hydrological data. The null hypothesis, H_0, is that the data come from a population with independent realizations and are identically distributed while the alternative hypothesis, H_A, is that the data follow a monotonic trend (Pohlert, 2016). The purpose of the MK test (Mann 1945, Kendall 1975, Gilbert 1987) is to statistically assess if there is a monotonic upward or downward trend of the variable of interest over time. A monotonic upward or downward trend means that the variable consistently increases or decreases through time, but the trend may or may not be linear. The MK test can be used in place of a parametric linear regression analysis, which can be used to test if the slope of the estimated linear regression line is different from zero. The regression analysis requires that the residuals from the fitted regression line be normally distributed; an assumption not required by the MK test, that is, the MK test is a non-parametric (distribution-free) test (Suryanarayana & Parekh, 2016).

These methods have widely and sometimes simultaneously been used by researchers over space and time for trend analyses in climate and other time series datasets. Eshetu *et al*. (2016) used MK test for trend and variability analysis of daily rainfall data for two meteorological stations (Setema and Gatira) in Ethiopia and were able to identify decreasing trend in Setema and an increasing one in Gatira.

Ekpoh and Nsa (2011) used standard deviation method and the CV to investigate extreme climatic variability in north-western Nigeria by analysing rainfall trends and patterns over the period (1915-2008); the results showed substantial fluctuations in rainfall pattern and quantity over the period of concern and within the study area.

Jhajharia *et al*. (2013) analysed trends in temperature over Godavari River basin in Southern Peninsular (India) employing the non-parametric MK test to detect the trends in maximum temperature, minimum temperature and mean temperature at 35 stations in the basin and Theil Sen's slope to determine the magnitude of the trend. The result showed both upward and downward trends for maximum temperature at different stations. Gopal *et al*. (2015) also used MK test to analyse rainfall trend for 102 years (1901-2002) in Punjab (India); they reported increasing trend in all the seventeen districts of Punjab over the period of study. Ganguly *et al*. (2015) used MK and Sen's slope estimates to analyse trend of the precipitation data for three districts in India for the period (1950-2005). Suryanarayana *et al.* (2016) also used MK technique to detect trends in mean monthly maximum temperature, mean monthly minimum temperature, mean monthly precipitation, mean monthly wind speed and mean monthly relative humidity for the Vadodara district in the state of Gujarat in India. Therefore, all the above mentioned authors have confirmed the ability of these methods to detect trends in climate data. That ascertains our interest in adopting them in addition to standardised anomalies for analysing rainfall and temperature datasets in the study area.

2.2.3. Land use land cover change modelling and prediction

Several models have been developed and used for the prediction and modelling of LULCC; from statistical models to rule-based models. 'Statistical models make use of statistical techniques to model spatial change in land. The allocation of the land is considered to be the result of different forces, or driving factors (socio-economic, environmental, and other factors), assumed exogenous to the land-use system. In particular, a system of equations is used to represent the relation between land demand or supply, and its determinants. This relation, expressed by the coefficients in the system, is normally obtained implementing multiple or multivariate regression techniques. The empirical analysis is supported by some rules, which concur to control the land competition among different uses. These approaches, simple to apply and manage, lack an endogenous categorisation of land-use economics and normally do not foresee a role for feedback effects' (Melania, 2012). Some of them are CLUE model and ELPEN models. None of these addresses explicitly the interaction of land-use processes and driving factors, problem solved by Rule-based models (Melania, 2012).

Rule-based models try to replicate land-use processes addressing more explicitly the interactions between such processes and driving factors. They can capture the effects of new land-use policies and can incorporate different factors for future land prediction (Melania, 2012). Some of them are Cellular Automata Markov Chains Analysis (CA-Markov), SALU and KLUM. Amongst these models, CA-Markov model has been widely used for modelling and predicting LULCC in recent years. It is used for as well agricultural land use change studies as urban dynamic studies as states Yang *et al*. (2008): 'recently, Cellular Automata (CA) models have been applied in urban growth and land use change prediction'(Soffianian, 2011).

The Markov model can quantitatively predict the dynamic changes of landscape pattern, while it is not good at dealing with the spatial pattern of landscape change. On the other hand, Cellular Automata (CA) has the ability to predict any transition among any number of categories (Li et., 2015). 'Combining the advantages of Cellular Automata theory and the space layout forecast of Markov theory, CA-Markov model performs better in modelling land cover change in both time and spatial dimension. At present, IDRISI software is one of the best platforms to conduct CA-Markov model, which is developed by Clark Labs in the United States' (Li *et al*., 2015).

CA-Markov is a combination of two models, Cellular Automata and Markov Chain. It integrates multiple criteria and objectively allocates land in order to predict land cover change over time (Sang *et al*., 2011). Cellular Automata adds into Markov model the spatial contiguity and the probable spatial transitions occurring in a particular area over a time (Subedi *et al*., 2013). These authors (Subedi *et al*., 2013), in fact investigated the applicability of CA Markov model in predicting land use change in Saddle Creek drainage basin in Florida and concluded that inclusion of spatio-temporal land-use change dynamics in hybrid models such as CA-Markov, prove to be a valuable tool for better land use change prediction. Due to its quality of considering both spatial and temporal components of land cover dynamics, CA-Markov models have been regarded suitable by many authors for land cover change prediction and simulations as it has been reported in several studies (Katana *et al*., 2013).

Cheng and Jui (2006) used SPOT data of Jiou Jiou Mountain from four different periods (March 1999, October 1999 and November 2002 & 2005) to study vegetation cover in 2006. Finally, they used Markov chain analysis and Cellular automata to predict temporal and spatial changes of vegetation cover. The paper concluded that CA Markov model is a more suitable method than others for the simulation of vegetation cover changes (Soffianian, 2011).

Muhammad (2015) predicted land use changes in Cameron Highland (Malaysia) using CA-Markov model. It has also been used by Katana *et al*. (2013) for detection and prediction of land use/cover changes in upper Athi river catchment, Kenya. The change analysis over the period (1997-2005) revealed that forests and wetlands have decreased while agricultural lands, built up and open water areas have increased; the prediction for the year 2020 revealed that agriculture, open water and built up areas will know an increase.

Razavi (2014) used Markov chains model to detect LULCC in Kermanshah city (Iran) over the period (1987-2006) and predicted changes for the year 2025; a decreasing trend in range land, forest, garden and green space areas and increasing trend in residential and agricultural lands have been reported over the period (1987-2006). The result of the prediction based on the maps of years 1987 and 2006 have shown that 82 % of residential land, 58.51 % of agriculture, 34.47 % of water, 8.94 % of green space, 30.78 % of gardens, 23.93 % of waste land and 16.76 % of range lands will remain unchanged from 2006 to 2025.

Sang *et al*. (2011) analysed land use spatial pattern in Fangshan (Beijing, China) over the period (2001-2008) and simulated for the year 2015 using CA-Markov Model. The simulation result showed that the original rate of changes in trends will be constant from 2008 to 2015. These applications ascertain the ability of CA-Markov model to predict

LULCC. Consequently, it is evident that CA-Markov is a suitable model for land use/ cover prediction.

CHAPTER THREE

3.0. RESEARCH METHODOLOGY

This part contains all the materials, data, software and methodology that were required for the achievement of the stated research objectives. The Table 3.1 indicates the materials, data, software and models and their usages in this study.

Table 3.1 List of Materials and Software

Data / Material/ Model	Purpose / Usage
GPS	Collection of ground reference points for classification and accuracy assessment
MODIS NDVI products	Cropland land mapping
MRT	Reprojection and extraction of NDVI layer from MODIS
TIMESAT	SG filtering
Climate data (Rainfall and Temperature)	Climate variability assessment
CA-Markov Model	LULC prediction
IDRISI	Change Detection and CA-Markov model running
IDRISI, QGIS, ArcGIS, ENVI	Pre-processing, classification, output map production
R software, SPSS and XLSTAT	Statistical analyses on climate data and questionnaire
Questionnaire	Socio-economic information, farming practices and decision making process

Source: Author's, 2017

3.1. Data

This sub-section describes all the data collected, starting from satellite images, model input data, climate data to socio-economic information and the sampling method used for their collection.

3.1.1. MODIS data

The Moderate Resolution Imaging Spectroradiometer MODIS / Terra Surface Reflectance sixteen-day L3 Global 250 m SIN Grid v006 (MOD13Q1) NDVI time series for the 01-March-2000 to 28-February-2001, 01-March-2008 to 28-February-2009, 01-March-2016 to 28-February-2017 were downloaded. The numbers from 49 to 33 correspond to Julian calendar Day Of Year (DOY) with an interval of sixteen days starting from March 1 to February 28 of the next year in Gregorian Calendar. These correspond to 23 composites images (excluding the last images) of 16-day for each period for total of 69 composites for the three periods, spanning the rainy seasons of the years 2000, 2008 and 2016. All were downloaded from the National Aeronautic Space Administration (NASA)'s Earth Observing System Data and Information System EOSD website (https://reverb.echo.nasa.gov/reverb). The MODIS tile covering the study area is h17v07.

Table 3.2 MODIS Data Description

Product	Tile	period	Number of Images	Layer	Resolution (m)
MOD13Q1	h17v07	01/03/00 - 28/02/01	23	NDVI	250
MOD13Q1	h17v07	01/03/08 - 28/02/09	23	NDVI	250
MOD13Q1	h17v07	01/03/16 - 28/02/17	23	NDVI	250

Source: Author's compilation, 2017

The NDVI is said to be a well-established and frequently used vegetation index in studies that use remote sensing data because of its rough correlation with green plant biomass and vegetation cover (Yu *et al*., 2004).

3.1.2. Landsat data

Nine Landsat 5 Thematic Mapper (TM), 7 Enhanced Thematic Mapper (ETM+) and Landsat 8 Operational Land Imager (OLI) images were downloaded from the United States Geological Survey (USGS) Glovis website (http://glovis.usgs.gov/) for free. The downloaded images covered four districts within the study area. The dates of acquisition were October, November and December 2000, 2009 and 2016. These months were chosen because of the likelihood of having cloud free images and the easiness of differentiating cropland from other types of vegetation. Therefore, the images were free from cloud, geometrically corrected and in GeoTIFF format with the UTM WGS84 Zone 29N projection. The Landsat images for the year 2008 were not available and were replaced by the images of the following year 2009.

Table 3.3 Landsat Data Description

Sensor	Path/Row	Acquisition date	Bands	Resolution (m)
ETM+	198/51	04/10/2000	7	30*30
	198/52	04/10/2000		
	199/52	27/10/2000		
TM	198/51	05/10/2009	7	
	198/52	06/11/2009		
	199/52	12/10/2009		
OLI	198/51	20/10/2016	11	
	198/52	04/11/2016		
	199/52	06/12/2016		

Source: Author’s compilation, 2017

3.1.3. CA-Markov model input data

For the LULC prediction, the CA-Markov model requires basically two classified maps of earlier and later dates; the road layer, Digital Elevation Model (DEM), slope and aspect can also be added to the model as factors for a better prediction. Therefore, the classified maps of 2000, 2008 and 2016 along with the Road Network and DEM from which the slope and aspect maps were derived and used as input for the model. The DEM was downloaded from the United States Geological Survey (USGS) website (earthexplorer.usgs.gov/) at approximately thirty-meter resolution and the road network was downloaded from Open Street Map website (www.openstreetmap.org). It was then imported in Google Earth in order to check if the major roads were properly represented.

3.1.4. Sampling method

To collect the data needed for this study, a multistage sampling technique was applied. Two major criteria were established to identify the districts and villages for the selection of the respondents.

The two criteria were that:

(i) Three villages of the district should be located on one single Landsat scene;

(ii) The district must have a reliable meteorological station covering the area.

Based on these criteria, four districts were identified. From each district, three villages were selected, giving a total number of twelve villages. Twenty household heads with age not less than thirty-five years were then selected in each village making a total number of two hundred and forty (240) household heads interviewed. The criterion of using one Landsat scene was aimed at avoiding the effect of mosaicking images acquired on different dates which could affect the result of the classification. Furthermore, the availability of reliable meteorological stations was judged important for the access to reliable climate data (less missing observations). The number twenty household heads in each village was estimated reasonable and achievable with regards to the timeframe. The minimum age of thirty-five years was chosen because some of the questions related to the past could only be answered by people of this category.

3.1.5. Ground reference data

Global Positioning System (GPS) was used to obtain ground reference data from the twelve villages in the four selected districts within the study area. Google Earth High Resolution Images helped to increase the number of ground reference points (Son *et al.*, 2014).

3.1.6. Climate data

Monthly weather data, rainfall and temperature (Min-Max) for 36 years (1981-2016) for four stations (Yanfolila, Bougouni, Sikasso and Koutiala) within the study area were acquired from the national meteorological service Mali-Meteo. Additionally, the monthly rainfall and temperature data from the four stations were averaged to get regional data series which was also subject to analyses. A few number of missing data were observed in the dataset obtained from the station of Yanfolila and they were filled-in using the average of the values of the first previous and first next non missing observations.

3.1.7. Questionnaire

The questionnaire comprising three sections (i) socio-demographic information (ii) LULCC dynamic and impact (iii) climate variability perception, impact and adaptation was prepared and validated before being administered to the real respondents. The targeted people were household heads with age not less than thirty-five years. It is only people of that category that could answer some of the questions related to past situations. Based on that, two hundred and forty (240) household heads were interviewed in the twelve selected villages. The questionnaires were written in English, then translated into French and administered in local language *Bambara*. The questionnaire contained both closed and open questions. The data collected were coded and entered into the Statistical Package for Social Science (SPSS) for analysis.

3.2. Data Analysis

The methods for data analysis consisted of different approaches used to depict the processes of LULCC, the impact of climate variability on agricultural LULCC and prediction of the future change. The following methods were used for the attainment of the stated objectives and the research questions.

3.2.1. Land use land cover change assessment

This section explains the methodology used for the achievement of the first objective which is to assess changes in land use land cover with focus on agricultural lands.

3.2.1.1. Pre-processing of satellite images

Before classification of any satellite images, some preliminary operations are needed in order to prepare the images. In this regard, the Landsat images downloaded were re-projected from WGS UTM Zone 29N to UTM Zone 30N. An overlay action was executed to determine whether there is need for any geometric correction. There were no distortions identified. The shape files were also re-projected to the same UTM Zone 30N as Landsat images. They were used to clip the study area, and stacks of bands 1, 2, 3, 4, 5 (for Landsat 5 and 7) and bands 2, 3, 4, 5, 6 (for Landsat 8) were then produced. These bands correspond respectively to Blue, Green, Red, Near Infrared (NIR) and Shortwave Infrared (SWIR) which are generally used for a better visibility of different classes. These operations were performed using ENVI 5.1 and ArcGIS 10.3.1.

Images from MODIS were re-projected from their sinusoidal projection to WGS UTM Zone 30N and the NDVI layers were extracted. These two operations were performed using MODIS Reprojection Tool (MRT) which is a package developed for the pre-processing of MODIS images. After extraction, the NDVI layers were then rescaled with a scaling factor of 0.0001 as indicated in (NASA LP DAAC, 2014) from their original values ranging from (-10,000 to +10,000) to normal NDVI values ranging from -1 to +1 (using ENVI 5.1). The buffered shape file was used to extract the Whole of Sikasso Region. After these steps, a smoothing process was applied using SG filtering method in TimeSat software.

3.2.1.2. Savitzky-Golay (SG) filtering algorithm

'SG (1964) suggested a simplified least squares fit convolution to smooth and compute derivatives of a consecutive values set. The convolution is to be understood as a weighted moving average filter with weighting given as a polynomial of a certain degree. The weight coefficients, when applied to a signal, perform a polynomial least-squares fit within the filter window. This polynomial is designed to preserve higher moments within the data and to reduce the bias introduced by the filter' (Chen *et al*., 2004). Any data series with equal time interval can be subject to this filtering process. The formula is as follows:

$$Y_j^* = \frac{\sum_{i=-m}^{i=m} C_i \times Y_{j+i}}{N} \tag{3.1}$$

$$N=2*m+1$$

where

Yj* = filtered value at position j

Ci = filter coefficient at position i

Yj+I = data value at position j+i

m = filter interval

N = number of data points for calculation

(Chen *et al*., 2004)

3.2.1.3. Classification and validation

After pre-processing of the images, classification is the next step. Ground reference points were collected with the GPS, Google Earth Imagery (Knauer *et al*., 2017b; Hentze *et al*., 2016 and Traore *et al*., 2014) and Landsat images. Both Landsat images and those ground reference points combined with the NDVI profiles were used for the identification of different classes from MODIS images.

The frequently used unsupervised classification technique-ISODATA employing the so-called Iterative Self-Organizing Data Analysis Algorithm to partition n-dimensional imagery into a number of clusters according to a specified value (Eastman, 2012) was used for the classification of MODIS images. Forty initial classes were generated. As our interest was mainly on cropland and the fact that there is no much difference between bare surface and urban NDVI profiles, the initial classes generated from the ISODATA classification were then regrouped into four main classes: cropland, vegetation, water and others, the later one combines bare surfaces and built-up areas altogether. We finally ended up with those four classes and assume that any increase in the class (others) refers to urban area expansion and increase in bare surfaces or degraded lands. The producers, users and overall accuracy along with kappa coefficient techniques were used for the accuracy assessment of the classified maps. The MODIS classified map of the year 2008 was also compared with GlobCover map of 2009 for validation.

3.2.1.4. Change detection

In order to achieve the first objective, change detection was performed using Land Change Modeler module under IDRISI Selva 17.0 software. That module quantifies changes between different classes from one period to the another along with change maps. Therefore, three change maps were produced for three periods: 2000-08, 2008-16 and 2000-16. The year 2008 was chosen as intermediate point in order to look at specific details of the change pattern between 2000 and 2016. The results are presented in graphs, tables and change maps.

3.2.2. Examination of climate variability and its impact on agricultural lands

This section give details of the methodologies used to examine climate variability and to assess its impact on agricultural lands.

3.2.2.1. Analysis of rainfall and temperature data

Standardised anomalies and CV for variability analysis and MK test for trend analysis were performed on rainfall and temperature data in order to achieve the first part of the second objective. These were carried out using XLSTAT, Excel and R statistical software with MK package.

3.2.2.1.1. Standardised anomaly and coefficient of variation

The formula for computing the **standardised anomalies** is as follows:

$$Z = \frac{x - \mu}{\sigma} \quad (3.2)$$

Where

Z is the standardised anomaly;

x is the variable in concern;

μ is the mean of the dataset;

σ is the standard deviation of the dataset.

(Nicholson, 1985; Karavitis *et al*., 2011)

The formula for the **CV** is by dividing the standard deviation by the mean and multiplying the result by hundred and is given as:

$$CV = \frac{\delta}{\bar{x}} \times 100 \quad (3.3)$$

Where:

CV = coefficient of variation; x = mean; δ = standard deviation

(Ekpoh & Nsa, 2011)

For calculating the climatological means of rainfall and temperature, the period from 1981 to 2010 was considered, which correspond to thirty years. In this study, the climatological mean is referred to as normal or simply climatology.

3.2.2.1.2. Mann-Kendall (MK) test

The formula for the non-parametric MK **test** is expressed as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign(x_j - x_k)$$

$$\begin{aligned} sign(\boldsymbol{x_j} - \boldsymbol{x_k}) &= \mathbf{1}\ \boldsymbol{if}\ \boldsymbol{x_j} - \boldsymbol{x_k} > \mathbf{0} \\ &= \mathbf{0}\ \boldsymbol{if} \boldsymbol{x_j} - \boldsymbol{x_k} = \mathbf{0} \\ &= -\mathbf{1}\ \boldsymbol{if} \boldsymbol{x_j} - \boldsymbol{x_k} < \mathbf{0} \end{aligned}$$

(3.4)

Where: **n** is the number of data points

Assuming (x_j-x_k) = θ, positive values of θ indicate increasing trend while negatives ones are indicator of decreasing trend. If the θ = 0, that means the data has no trend. The MK test verifies the null hypothesis (H0) of no trend versus the alternative hypothesis (H1) for the existence of increasing or decreasing trend (Gopal *et al*., 2015; Pohlert, 2016). By implication, positive or negative trend will signal the nature of impact on LULC within the study area over the period of consideration. The modified MK method was adopted because it takes into account the effect of autocorrelation and corrects it using Hamed and Rao (1998) methods.

3.2.2.2. Climate variability impact on agricultural lands

This subsection addresses the analysis of climate variability impact on agricultural lands, which is the subsequent part of the second objective. Firstly, the Pearson’s correlation test was performed to investigate the relationship between changes in agricultural lands and rainfall trend and coefficient of variation. Sivakumar *et al*. (2005) affirmed that inter- and intra-annual variability in rainfall is perhaps the key climatic element that determines the success of agriculture in the arid and semi-arid tropics. Secondly, percentage, frequency and mean computations were carried out on questionnaire data in order to produce graphs and tables for explanation of farmers' perception of climate variability. Finally, the Pearson's Chi-square Test of association was also performed on questionnaire data to identify the factors which have influence on farmers' decision to make changes in their farm size.

3.2.2.3. Land use land cover change prediction

This third objective which is the prediction of LULCC by the 2030 and 2050 was achieved using CA-Markov model in IDRISI environment. The derived LULC maps, the DEM and roads networks were used as input for the development of the model, validation and prediction. The maps of the years 2000 and 2008 were used as base maps to predict for the year 2016 which was then compared with the reference map of 2016 for validation. After the validation of the model, the maps of 2008 and 2016 were then used to predict for the years 2030 and 2050. For both periods, all the transitions were considered. The DEM was used to derive the slope map and both were included for the development of the model. The distance to major roads was calculated using major roads layer which was extracted from the roads network.

CHAPTER FOUR

4.0. RESULTS AND DISCUSSION

This fourth chapter of the thesis presents the findings of the study using tables, graphs and figures.

4.1. Agricultural Land Use Land Cover Change

This section illustrates the role the smoothing process in the classification of images, presents LULC maps of the years 2000, 2008 and 2016 followed by change detection results and discussion.

4.1.1. NDVI profiles

This subsection demonstrates the role of the SG filtering process (smoothing) in the LULC classification of NDVI time series by comparing and presenting the raw and smoothed NDVI profiles of water and cropland and the smoothed profiles of the different LULC classes.

4.1.1.1. Water and cropland smoothed and raw NDVI profiles

The SG filtering was used to reduce noises from the NDVI profiles and improve the results of the classification. The comparison of smoothed and raw NDVI profiles for water and cropland is illustrated in Figure 4.1. It is apparent that clear pattern can be identified from the smoothed profiles compared to raw profiles. Abrupt variations in NDVI profiles due to the presence of unexpected values have been reduced by replacing those values with new ones that gave clear shape to the NDVI profiles over time which improved the classification result.

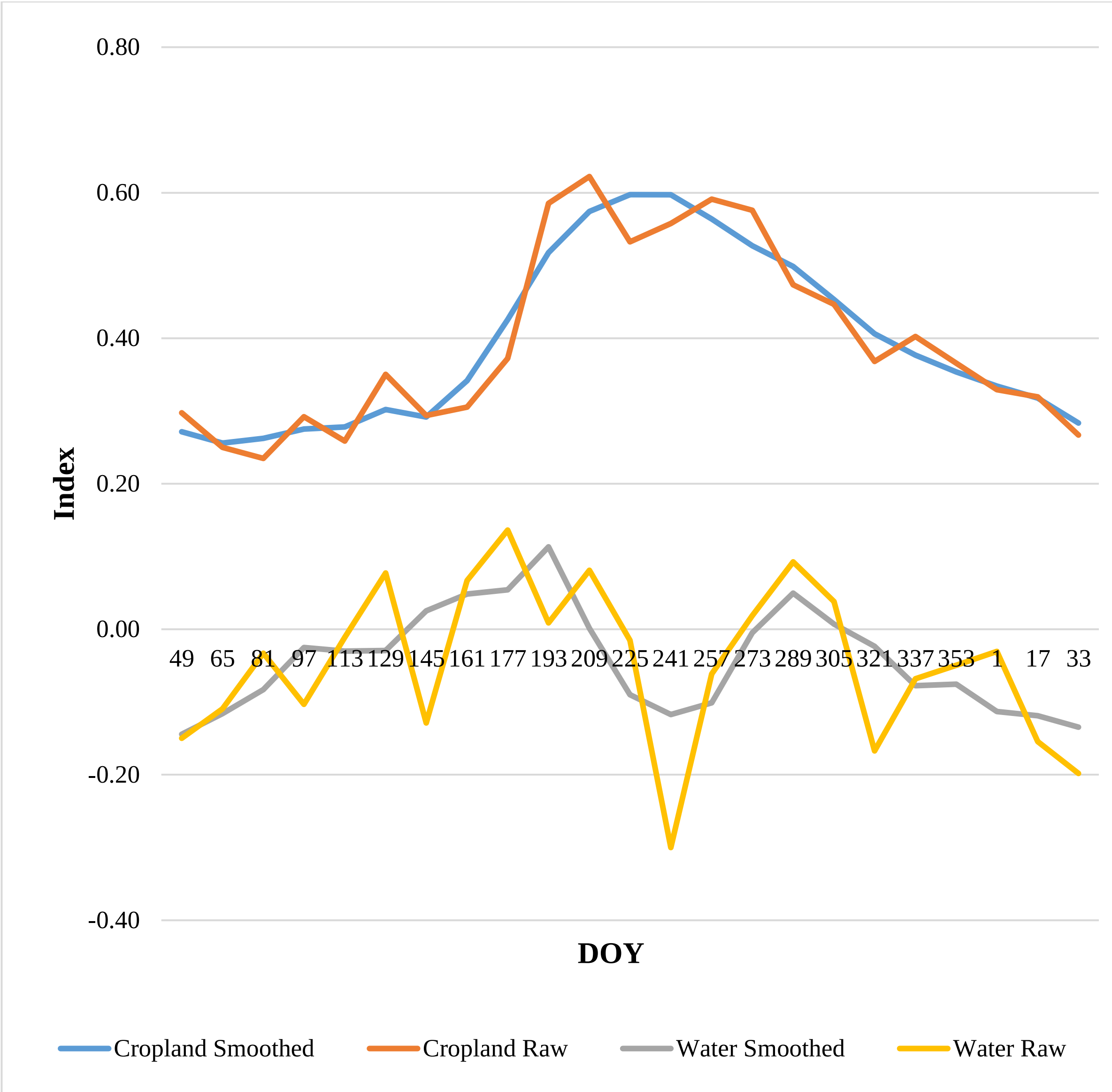


Figure 4.1 Effect of Smoothing

This SG filtering method revealed to be very important in generating high quality NDVI profiles and improved the result of the classification. Accordingly, many researchers have recommended this technique for the enhancement of classification accuracy. Kaishan *et al*. (2011) reported that the method was more effective for generating high-quality NDVI time series data for their classification. Furthermore, Kim *et al*. (2014) reported that the SG filtered NDVI time series was most suitable for classification and delineation of land cover types compared to the original NDVI data sets; the study also confirmed that 'phenological signature of an individual ecosystem class is an intrinsic advantage of using time-series data and yields better classification maps'.

4.1.1.2. NDVI profiles of the different land use land cover classes

From the smoothed NDVI profiles, six classes were identified: Water, Cropland, Bare Surface, Urban or Built-up, High vegetation and relative high vegetation were identified (Figure 4.2). These classes were later regrouped into four broad classes: cropland, vegetation, water and others as earlier explained in the methodology. The results showed that water bodies reflected lower NDVI values (-0.15 – 0.1), urban (0.2 – 0.38) and bare surfaces (0.15 – 0.3) were almost within the same range, cropland (0.25 – 0.6) was also differentiated by its specific profile; high vegetation (0.42 – 0.8) and relative high vegetation (0.35 – 0.7) reflected higher NDVI values.

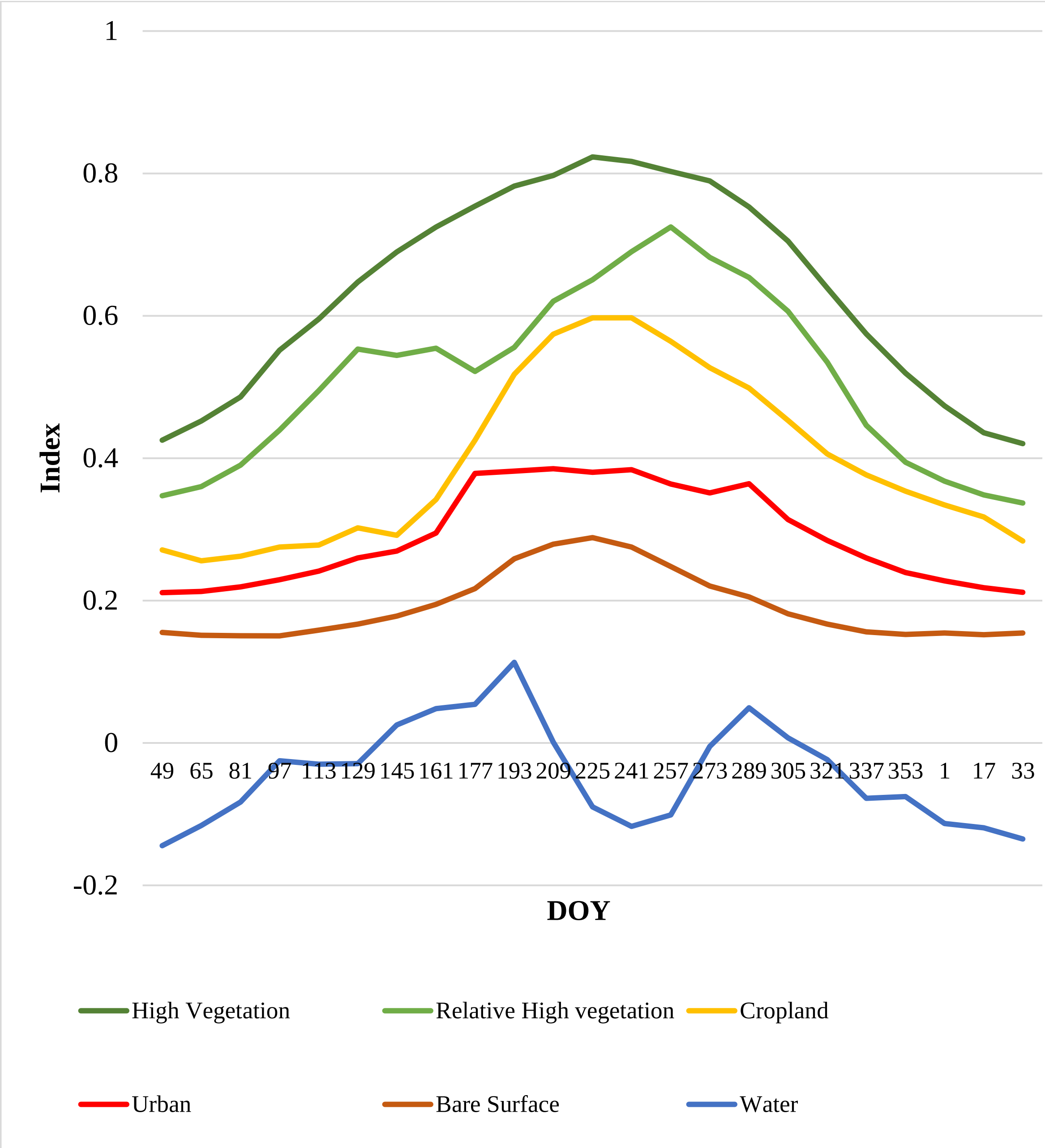


Figure 4.2 NDVI Profiles

From these NDVI values, it is apparent that the higher the vegetation the higher the NDVI values as mentioned by Holme *et al.* (1987). Similarly, Kim *et al*. (2014) found around (0.2 – 0.9) for cropland, urban (0.15 – 0.4) for urban area, (0.2 – 9.6) for broad leaf vegetation and (0.3 – 0.9) for needle leaf vegetation in South Korea. Furthermore, Doraiswamy *et al*. (2006) found NDVI values ranging from around 0.25 to 0.9 for soybean crop in four different provinces in Brazil. However, it is worth mentioning that the slight differences between these results could certainly be due to the duration, number of seasons and amount of rainfall received throughout the year in the different locations. The highest NDVI values were reached by around the 225th DOY (midst of August) which corresponds to the peak of the rainy season when highest rainfall is recorded and vegetation is always at its pick over the study area. By implications, croplands reached their highest NDVI positive values within the same period, water bodies reached their lowest values, which is certainly due to their depth in response to the rainfall recorded. Differences between land cover categories were also clearly shown based on the evolution of their NDVI profiles over time as illustrated in the Figure 4.2 where the profile of each land cover category could be observed.

4.1.2. Land use land cover in 2000

In the year 2000, the major land cover type was vegetation which occupied more than 45 % of the total area, followed by cropland with 3197845 hectares corresponding to 44.79 % of the total area. Water bodies occupied less than 1 % and the class others which combines built-up areas and bare surfaces (or degraded lands) occupied around 10 % of the area. The Table 4.1 presents the details of the area occupied by each land cover type along with proportions.

Table 4.1 LULC Area in 2000

LULC	2000 (ha)	Proportion (%)
Cropland	3197845	44.79
Vegetation	3236242	45.33
Water	38333	0.54
Others	666789	9.34
Total	7139208	100

Source: Author’s computation, 2017

In addition, Figure 4.3 visualizes the spatial distribution of each land cover category. It is apparent that most of the vegetation cover were distributed across the southern part of the region, croplands mostly in the central part and the class others in the northeast. This is explained by the rainfall regime which is of south-north gradient in the area (Brandt *et al*., 2014; Vintrou *et al*., 2009). The rainfall starts from south where the quantity is high and the duration is long to the north with low quantity and short duration.

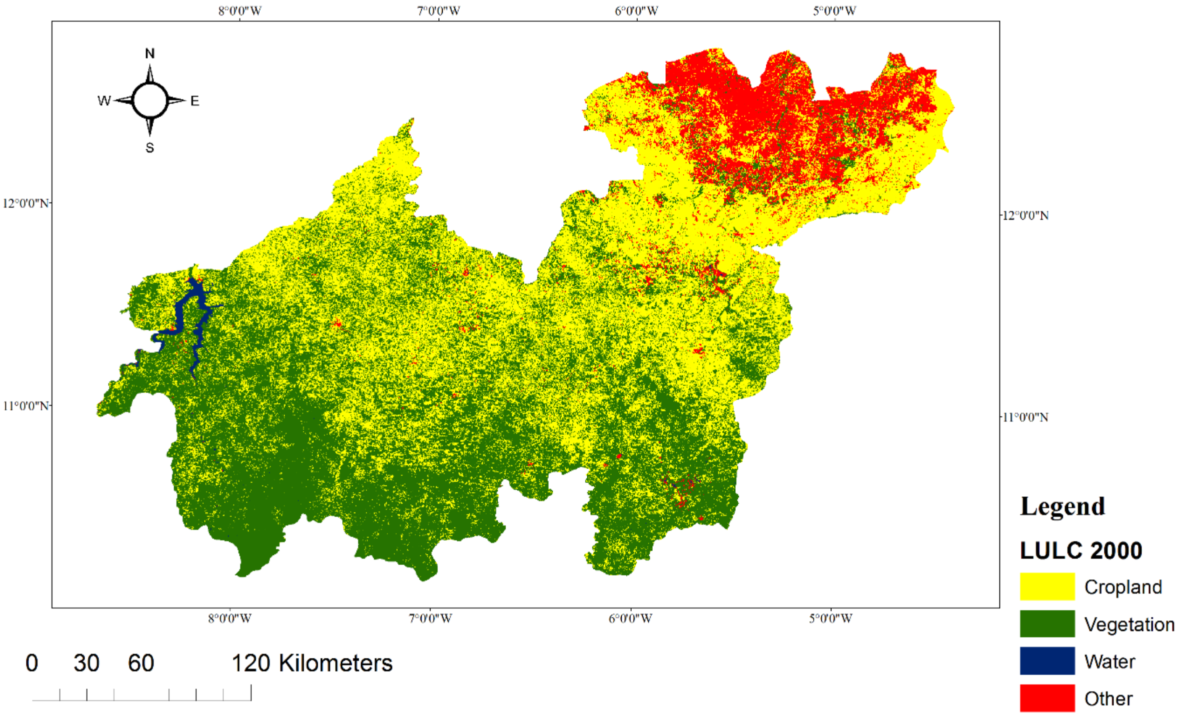


Figure 4.3 LULC Map of 2000

4.1.3. Land use land cover in 2008

In the year 2008, cropland occupied larger area than vegetation. It became the major land cover type and occupied around 46 % of the whole area while vegetation occupied 44 % of the area. Water bodies have slightly decreased and Built-up and bare surfaces have slightly increased. Table 4.2 gives details about areas and proportions of each land cover type.

Table 4.2 LULC Area in 2008

LULC	2008 (ha)	Proportion (%)
Cropland	3278464	45.93
Vegetation	3156824	44.22
Water	35805	0.50
Others	667414	9.35
Total	7138508	100

Source: Author’s computation, 2017

Additionally, Figure 4.4 shows the spatial distribution of the various features in 2008. Likewise, the map of the year 2000, as in 2008 it was depicted that most of the vegetation cover were dominant across the southern part of the region, croplands mostly in the central part and bare surfaces in the north. However, the presence of more cropland in north is apparent.

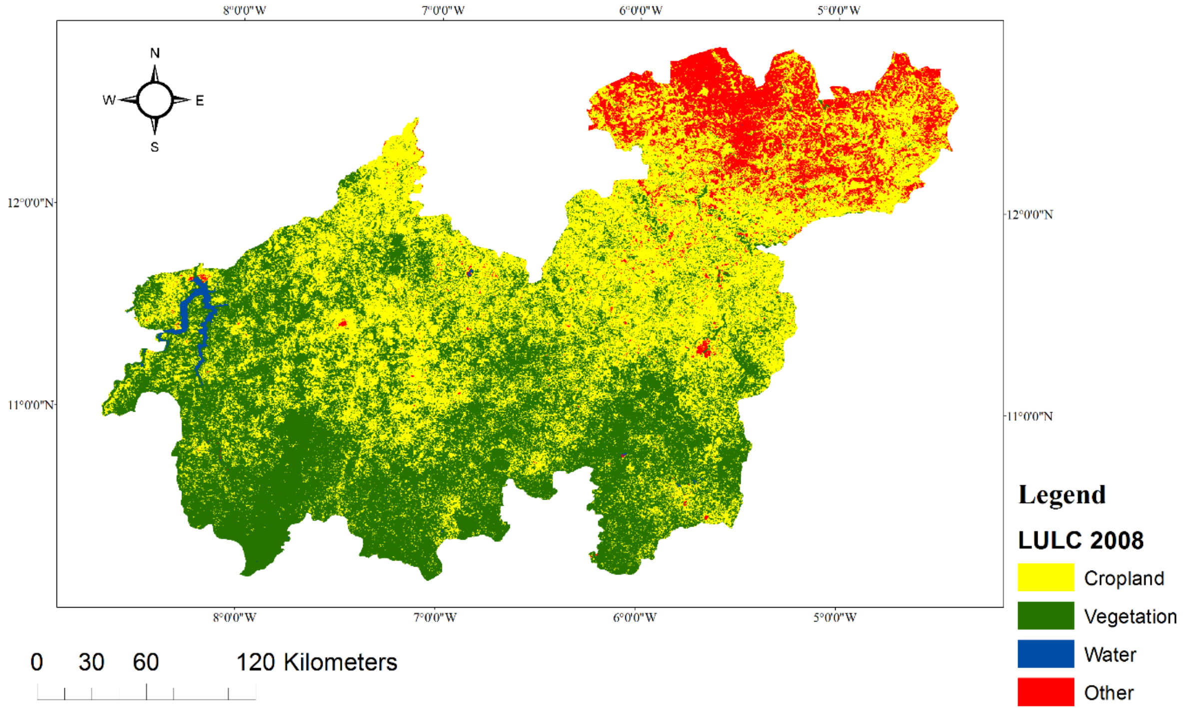


Figure 4.4 LULC Map of 2008

4.1.4. Land use land cover in 2016

In 2016, the area occupied by cropland was around 47 % of the total land mass of the region, vegetation occupied 45 % while water bodies-which have slightly increased still occupied less than 1 % and the class others occupied around 8 % of the total area. Table 4.3 presents the details about the areas and proportions of each land cover category.

Table 4.3 LULC Area in 2016

LULC	2016 (ha)	Proportion (%)
Cropland	3327509	46.61
Vegetation	3206270	44.91
Water	47815	0.67
Others	557613	7.81
Total	7139208	100

Source: Author’s computation, 2017

In addition, Figure 4.5 shows the spatial occupation of each land cover category for the year 2016. More presence of cropland northward intensified, the class others has increased in proportion in the central part of the area and vegetation was well distributed across the southern and central regions.

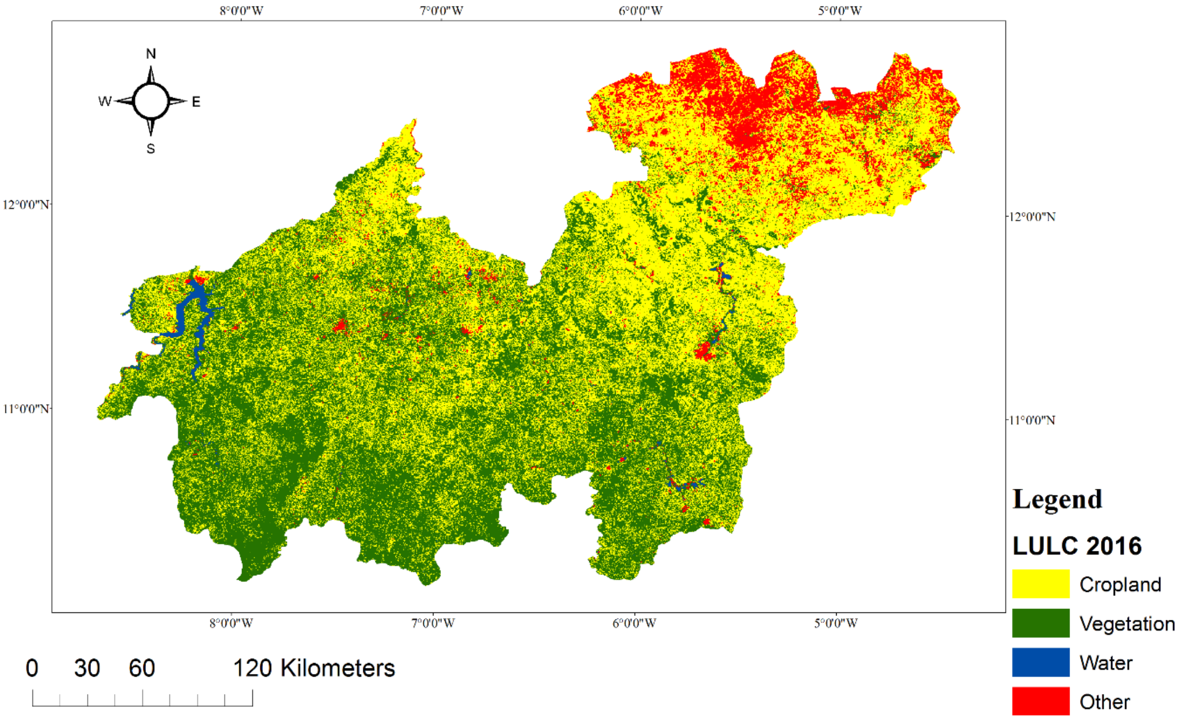


Figure 4.5 LULC Map of 2016

4.1.3. Accuracy and comparison with GlobCover map of 2009

An overall accuracy of 80, 88 and 83 percent were obtained from accuracy assessment of the years 2000, 2008 and 2016 respectively. The computed Kappa coefficient for all the three maps reached 0.99 which shows very strong agreement. Among all the classes, water was the most accurately classified, followed by vegetation, cropland and the class others but none of them had an accuracy less than 60 % for both user's and producer's accuracy. Table 4.4 presents different values of accuracy obtained for the three different maps.

Table 4.4: Confusion Matrix

	2000		**2008**		**2016**	
	Producers	**Users**	**Producers**	**Users**	**Producers**	**Users**
Cropland	0.66	0.62	0.80	0.63	0.75	0.63
Vegetation	0.79	0.70	0.97	0.89	0.84	0.94
Water	0.93	1	0.91	1	1	0.96
Others	0.62	0.71	0.52	1	0.87	0.71
Overall accuracy	0.8		0.88		0.83	
Kappa Coefficient	0.996		0.997		0.995	

Source: Author's computation, 2017

In addition to the usual way of map accuracy assessment using kappa coefficient, producer's and users' accuracy, the classification for the year 2008 was compared with Global Land Cover map of the year 2009. It was assumed that one year of difference between two LULC maps do not generally have great impact on their classification output (Vintrou *et al*., 2009). Therefore, in order to evaluate the performance of the classification scheme and the ability of MODIS 16-day NDVI (MOD13Q1) data in cropland mapping in the study area, the Glob Cover 2009 was considered as reference for comparison. It was observed that both maps have very close values for cropland, vegetation and water with a percentage of agreement in quantity of 89.1, 91.5 and 96.4 percent respectively but have different estimations for the class others (3.6) as shown in Figure 4.6.

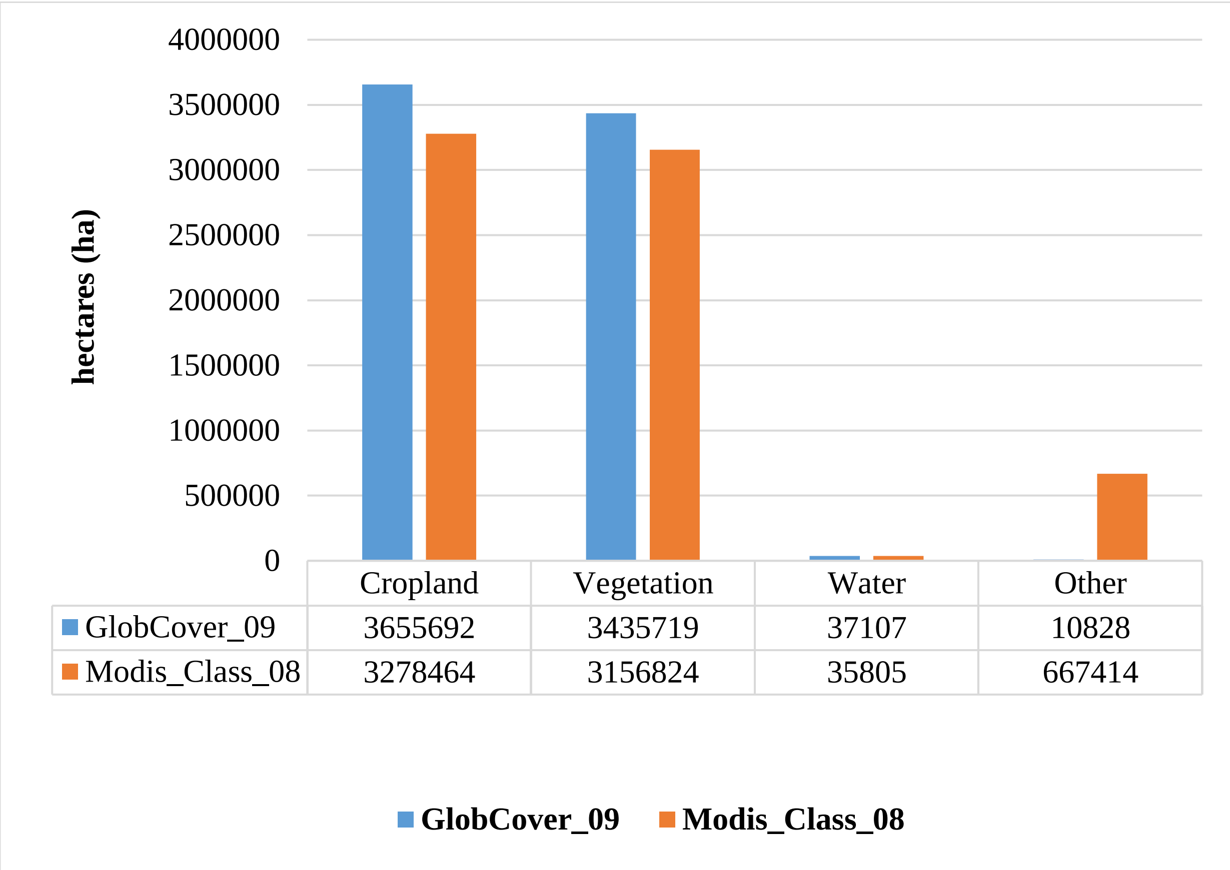


Figure 4.6 Comparison Glob Cover Vs MODIS Classification

The difference in estimation of the class others may be due to the relatively coarse resolution (300m) of Glob Cover which fails to estimate very well that class. Moreover, the slight over-estimation of cropland from Glob Cover is certainly attributed to the generalisation process in which the class 20 representing a mosaic of cropland (50-70 %) / vegetation (grassland/shrubland/forest) (20-50 %) was added to cropland. However, from these statistics it is obvious that these two maps are very similar to each other which strengthened the confidence in the classification scheme adopted in this study. Similarly, Vintrou *et al*. (2009) reported that their classification from MODIS time series data 16-Day L3 Global 250m (2004-2005) performed better after the comparison with GLC2000, MCD12Q1 and ECOCLIMAP-II. By implication, it is clear that the MODIS product (MOD13Q1) is more suitable for cropland mapping in the study area. Additionally, Figure 4.7 shows the abovementioned similarities between the classification from MODIS and GlobCover.

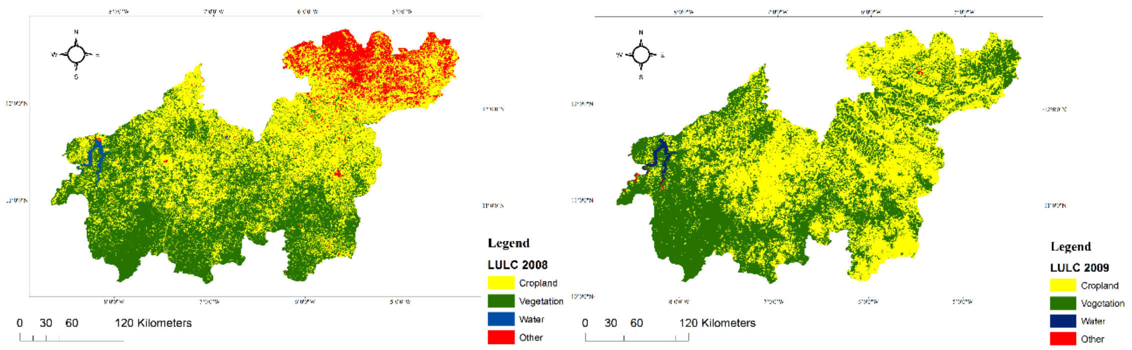


Figure 4.7 LULC from MODIS 2008 Vs GlobCover 2009

4.1.4. Change detection

The change detection was conducted in three different periods, from 2000 to 2008, 2008 to 2016 and 2000 to 2016.

4.1.4.1. Land use land cover change from 2000 to 2008

Within this period (2000-2008) vegetation cover has largely decreased with a net value of 79,563 ha while cropland has increased with almost a similar value (76,349 ha). Water bodies have decreased and the class others has also increased. The analysis of contributions to net change in cropland have shown that vegetation was the main land cover category that was converted to cropland whereas some cropped areas were also replaced by the class others. Figure 4.8 below shows contributions to net changes in cropland from 2000 to 2008. It is clear that vegetation was the main contributor to cropland expansion.

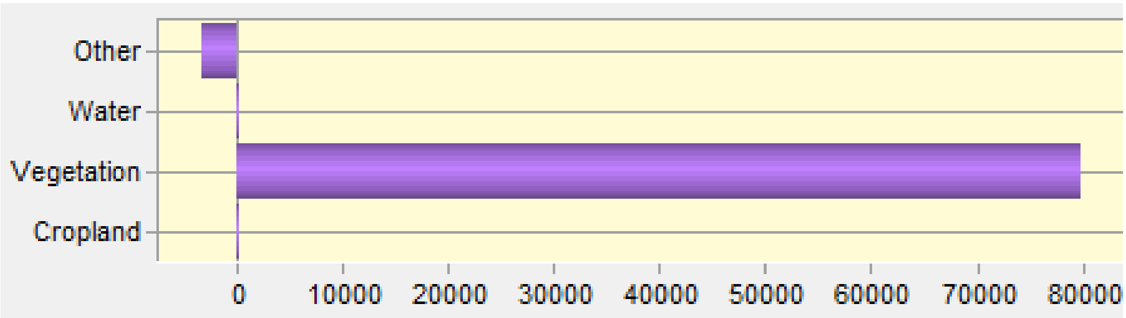


Figure 4.8 Contributions to Net Change in Cropland 2000-08

In addition, Figure 4.9 shows the spatial changes that have occurred from 2000 to 2008. The green colour represents areas that have been converted from vegetation to cropland from 2000 to 2008, red refers to conversion from the class others to cropland, blue represents water to cropland and other represents unchanged area. From this map, it was observed that the increase in cropland has taken place all across the study area.

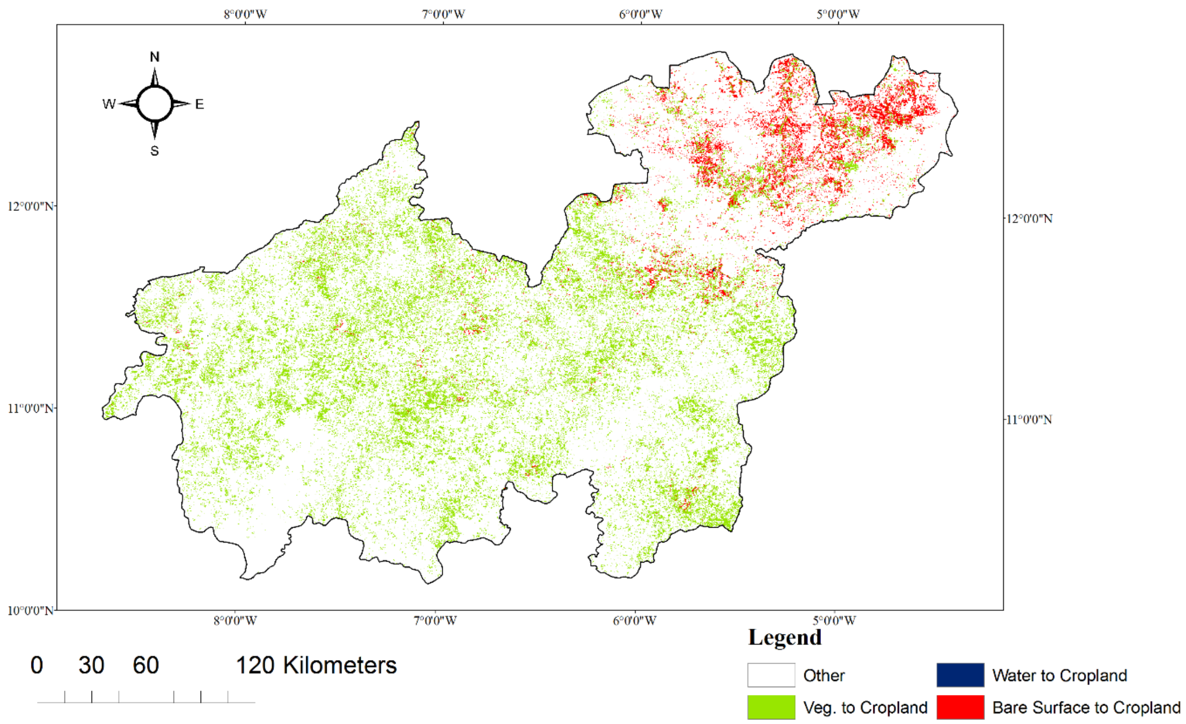


Figure 4.9 LULC Change Map from 2000 to 2008

4.1.4.2. Land use land cover change from 2008 to 2016

This period has recorded slight increase in vegetation cover, cropland and water bodies while the class others has considerably decreased. The net contributions analysis showed that the class others contributed most to the increases in cropland within this period; a regrowth of vegetation has also occurred unlike the period 2000-2008. This implies that new croplands were established on lands that were considered as marginal lands whereas vegetation regrew on fallow lands. This regrowth of vegetation was elsewhere ascertained by Brandt *et al*. (2014) who conducted a study in the Sahel of Mali and Senegal after which they reported significant greening trends from 1982 to 2010; the study also identified some factors like agroforestry practices, laws of protection and planting programmes, the widespread dispersion of robust species replacing diverse woody vegetation and increases in rainfall (recovery from droughts) to be responsible for the regrowth of vegetation during this period.

In addition, Figure 4.10 shows the contributions to net changes in cropland from 2008-2016. From this Figure, the regrowth of vegetation can clearly be observed by its negative contribution to increases in cropland.

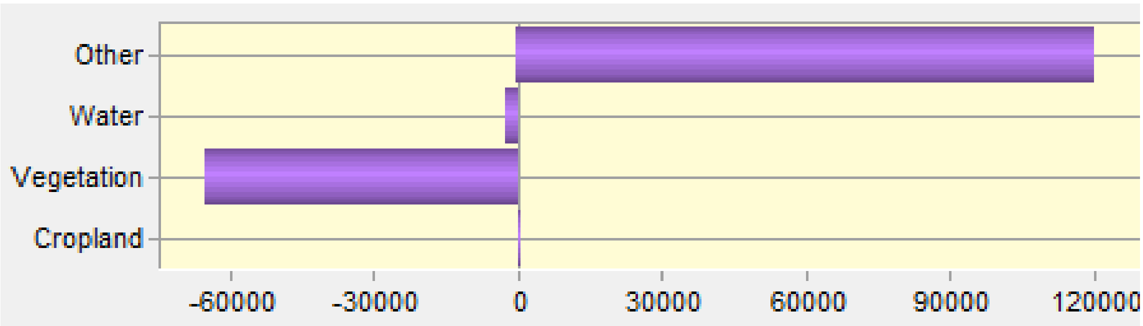


Figure 4.10 Contributions to Net Change in Cropland 2008-16

Furthermore, Figure 4.11 illustrates that spatial changes occurred from 2008 to 2016. The red colour represents areas that have been converted from the class others to cropland between 2008 and 2016, green refers to conversion from vegetation to cropland, blue represents water to cropland and Other represents unchanged places.

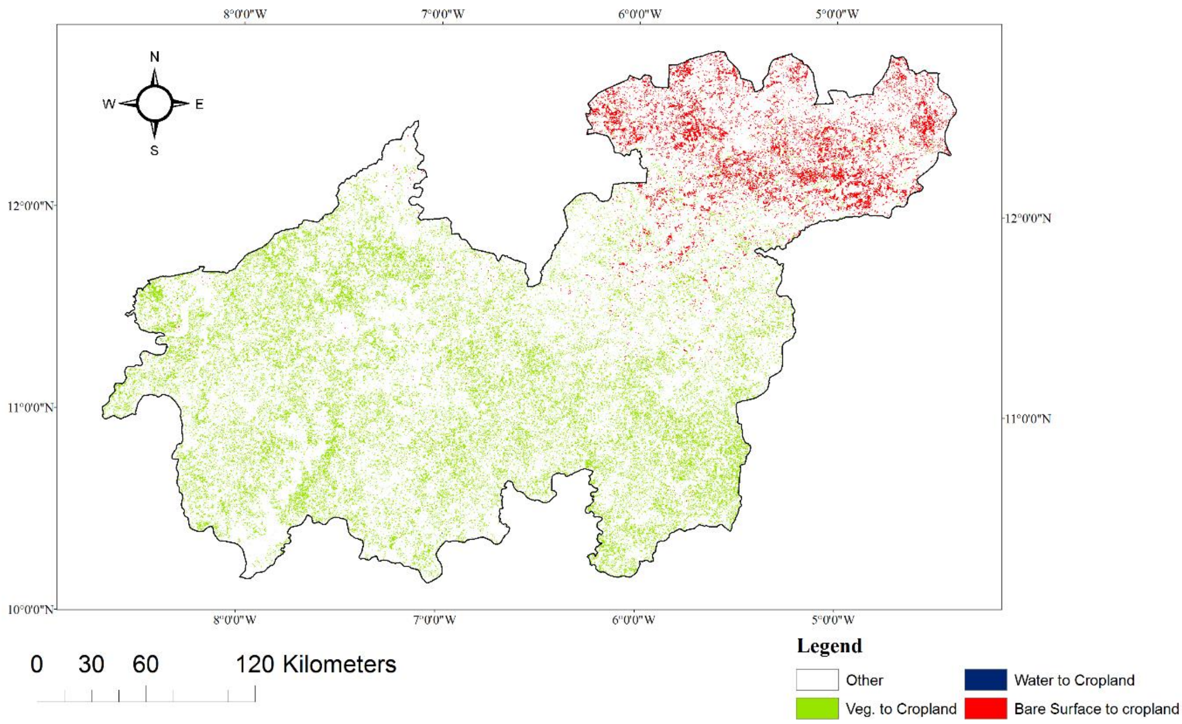


Figure 4.11 LULC Change Map from 2008 to 2016

4.1.4.3. Land use land cover change from 2000 to 2016

From 2000 to 2016 which is the main period of concern, it was observed that cropland has expanded with 129,665 ha which corresponds to an annual rate of increase of 0.25 % (4 % for the whole period), vegetation has decreased by 30,000 ha corresponding to -0.06 % per year (-1 % from 2000-16) and the class others with 109,175 ha, -1.12 % per year. The net changes between different land cover categories is shown in the Figure 4.12. This Figure shows clearly that cropland has largely expanded; water bodies has also increased but vegetation and the class others have decreased in contrast.

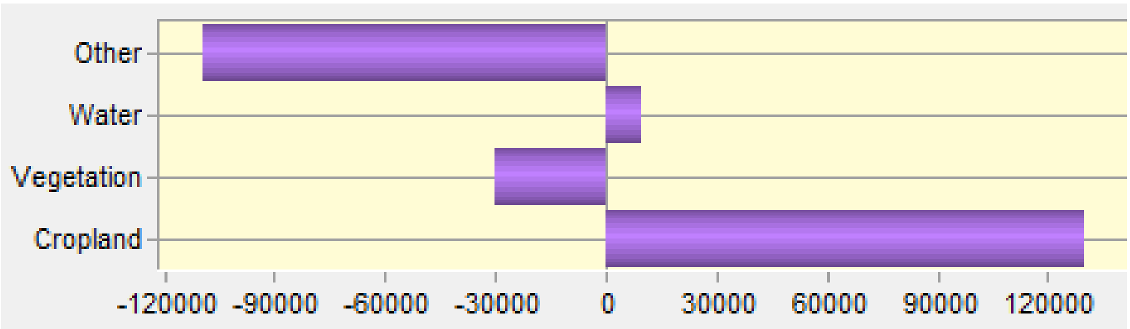


Figure 4.12 Net Change Between 2000 and 2016

This result shows that expansion of agricultural land is at the expense of vegetation cover and marginal lands. However, it is apparent that this expansion was rather a gradual process than drastic. Similar results were found by Knauer *et al*. (2017a) who studied the expansion of agricultural lands in Burkina-Faso over a period of 14 years (2001-2014) and reported an increase of 91 % at national scale. Zoungrana *et al*. (2015) also reported an increase in agricultural lands and bare surfaces at expenses of woodland and mixed vegetation from 1999 to 2011 in the southwest of Burkina-Faso. Moreover, Katana *et al*. (2013) reported increases in agricultural lands and built-up area and decreases in vegetation cover in the Upper Athi River Catchment (Kenya) during the period 1984-2010. Furthermore, a significant shift from water and vegetation to agricultural lands, bare soils and settlement was also reported by Butt *et al*. (2015) in their study of monitoring Simly watershed in Pakistan. From these results, it is clear that the vegetation cover in the study area is threatened by uncontrolled expansion of agricultural lands. Consequently, appropriate actions need to be taken to support the regrowth of vegetation and prevent desertification and land degradation.

Additionally, the change map (Figure. 4.13) shows that LULCC has occurred across the entire study area. The red colour represents areas that have been converted from the class others to cropland between 2000 and 2016, green refers to conversion from vegetation to cropland, blue represents water to cropland and Other represent unchanged places.

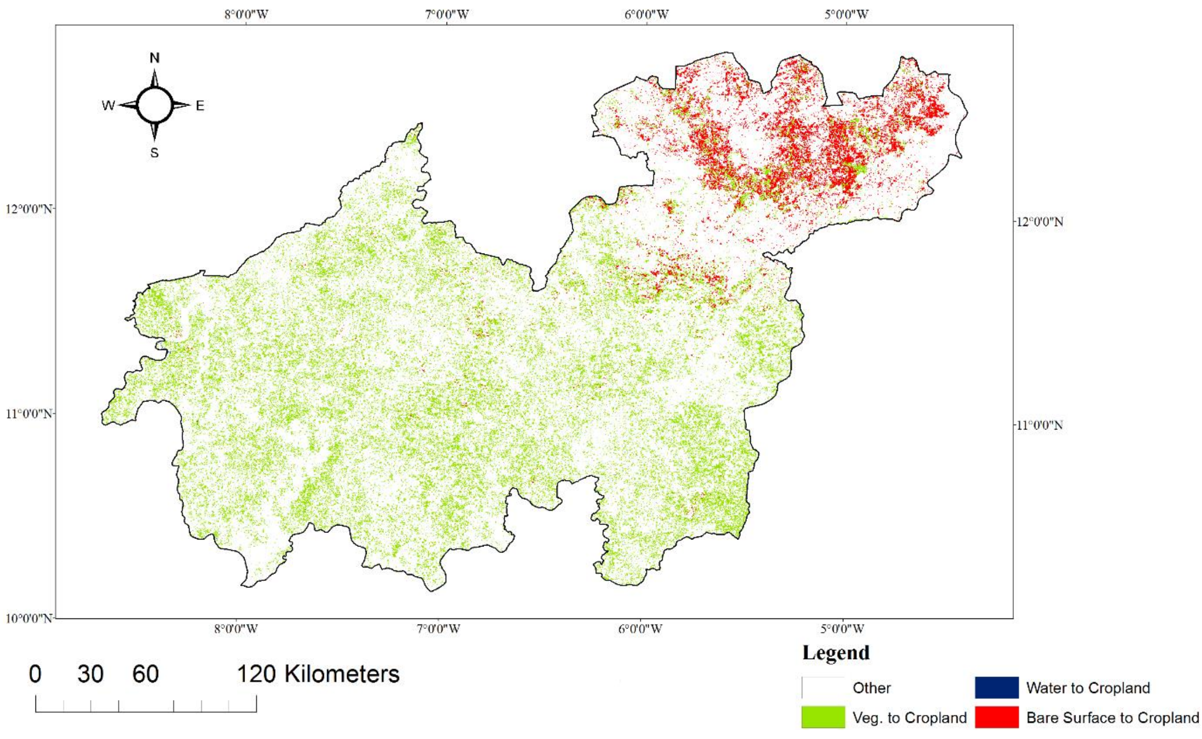
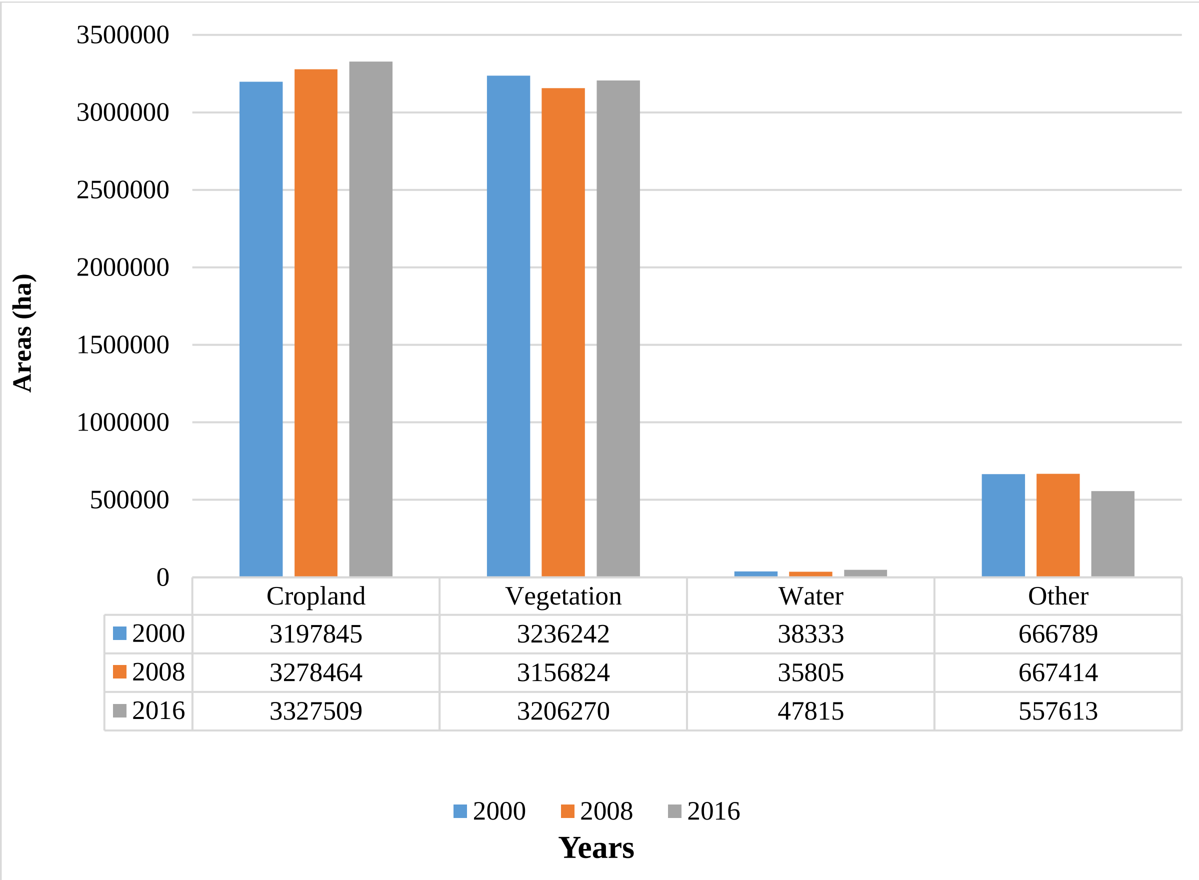


Figure 4.13 LULC Change Map from 2000 to 2016

Furthermore, the overall evolution of different land cover categories is illustrated by the Figure 4.14 where cropland expansion can easily be observed. The Figure shows the quantity (ha) of each LULC category for the three different years (2000, 2008 and 2016). The increase in cropland from 2000 to 2016 through 2008 is shown in statistics. The decrease of vegetation from 2000 to 2016 and the slight regrowth between 2008 and 2016 (Brandt *et al*., 2014) is also shown. Water bodies have slightly decreased between 2000 and 2008 and increased considerably after 2008. The class others increased from 2000 to 2008 but largely decreased after 2008. All these statistics are detailed in the Figure 4.14.



	Cropland	Vegetation	Water	Other
2000	3197845	3236242	38333	666789
2008	3278464	3156824	35805	667414
2016	3327509	3206270	47815	557613

Figure 4.14 LULC Evolution from 2000 to 2016 (ha)

4.2. Climate Variability and Trend

This section answers the second research question by presenting the results of the variability and trend detection analyses performed on rainfall and temperature data. The last part of the section presents the results from the analyses of the socio-economic statistics.

4.2.1. Rainfall

4.2.1.1. Rainfall pattern

The monthly evolution of rainfall from 1981 to 2010 which was considered as normal (climatological mean) compared to monthly average rainfall for the period 2011-2016 is illustrated in the Figure 4.15.

The results indicated that rainfall is received as early as in April and stop definitely in October in the study area. However, it was clear that the bulk of the rainfall was received between June and September which is officially considered as the rainy season given the fact that the amount and distribution of rainfall in April, May and October do not meet the requirements of the main cultivated crops in the area as ascertained by Funk (2012). Therefore, the distribution and amount of rainfall within that period determine the annual agricultural production. However, the comparison of the average for the period 2011-2016 with the climatological mean-normal (1981-2010) on monthly basis shows that some changes have occurred in the rainfall pattern in the study area. More rainfall has been received in the months of July, August and September in these recent years than it used to be, which depicts the monthly variability in rainfall pattern across the study area. Specifically, the average rainfall for the months of July, August, September and October (2011-2016) were more than normal (1981-2010) with 16, 37, 24 mm respectively. These results indicate an increase in the quantity of monthly rainfall during the rainy season in the study area.

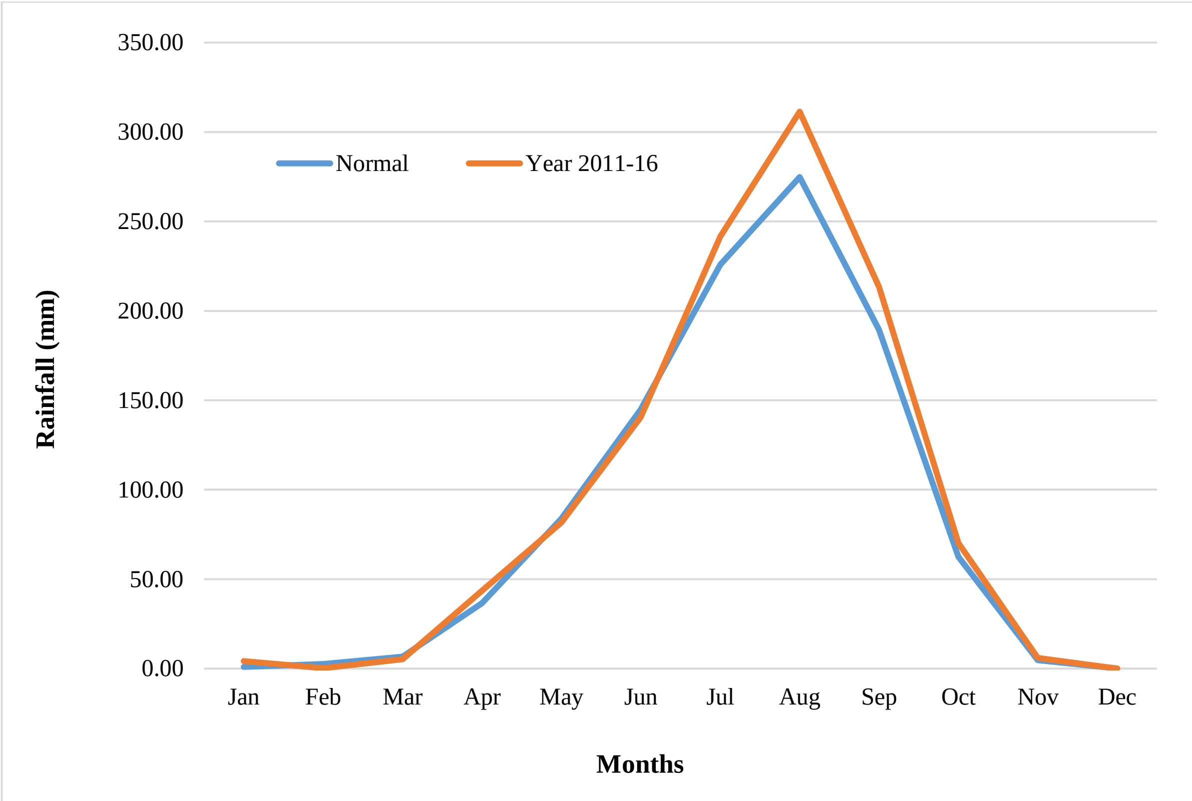


Figure 4.15 Comparison of the Normal (1981-2010) Vs Average Rainfall (2011-16)

4.2.1.2. Regional annual rainfall anomalies

The rainfall anomalies were interpreted according to the categorisation of McKee (1993) of Standardised Precipitation Index (SPI) in Table 4.5. The rainfall index values are divided into seven categoayries starting from extremely dry to extremely wet situations.

Table 4.5 Standardised Rainfall Index Categorisation

2.0 +	Extremely Wet
1.5 to 1.99	Very Wet
1 to 1.49	Moderate Wet
0.99 to -0.99	Near Normal
-1 to -1.49	Moderate Dry
-1.5 to -1.99	Severely Dry
-2 to less	Extremely Dry

Source: Adapted from Eshetu *et al*., 2016

In application of this categorisation scheme, it was found that the average regional rainfall recorded more wet than dry years. Specifically, the years 1994 and 2010 were extremely and very wet years respectively; 1991, 1998, 2007, 2012 and 2014 were moderate wet years and the year 1984 was the driest during the period (1981-2016), 1983, 1987 and 2002 were also severely dry years. All the other years were within the range of near normal years. Figure 4.16 shows the abovementioned details about the annual rainfall anomalies.

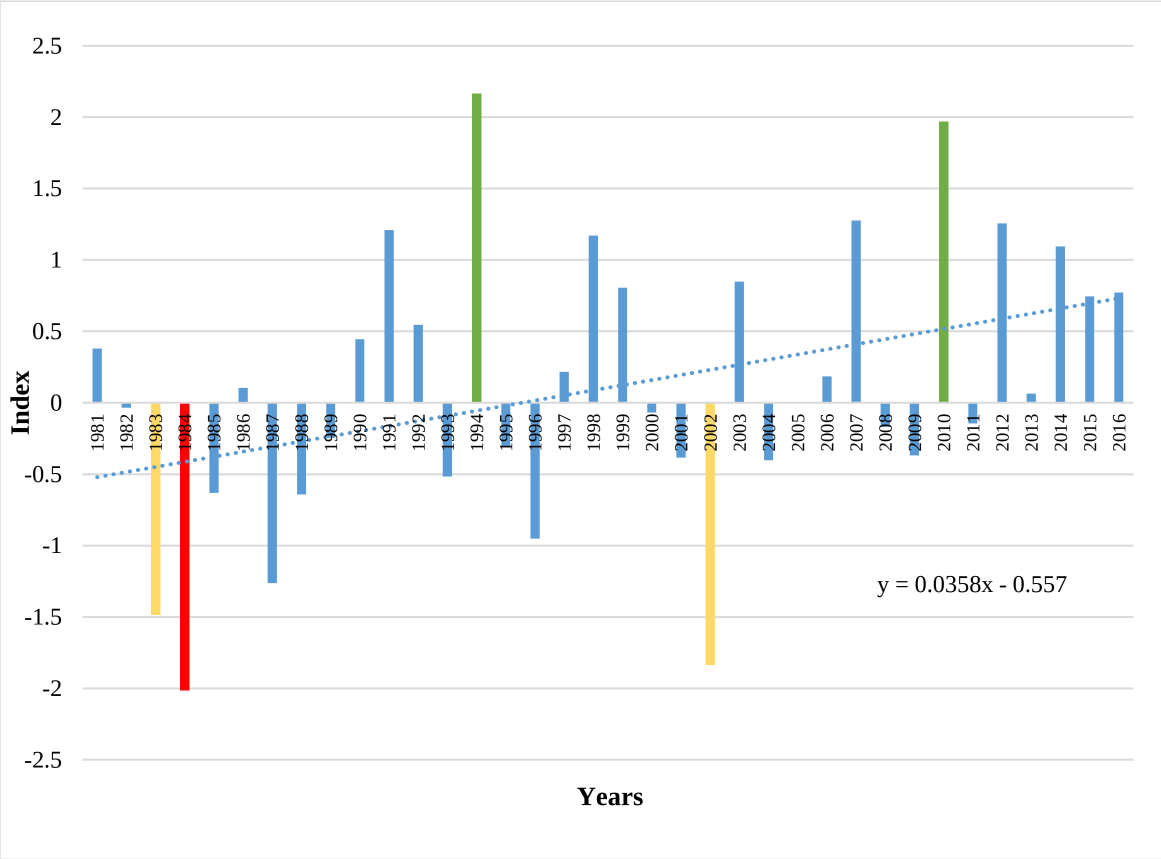


Figure 4.16 Annual Standardised Rainfall Anomaly Indices from 1981 to 2016

These results confirmed the occurrence in the study area of the severe droughts of the years 1983-1984 which was experienced in many locations across Africa as reported by Traore *et al*. (2013) for the case of Sikasso. Similarly, Eshetu *et al*. (2016) reported negative anomalies for the years 1983 and 1984 at the stations of Setema and Gatira in Ethiopia over the period 1983 to 2013 (for Gatira) and 1979 to 2011 (for Setema). However, it was clear that recent years (2012-2016) have received much more quantity of rainfall successively. This increase in rainfall was ascertained by Brandt *et al*. (2014)

who reported that rainfall is recovering in recent years compared to pre-drought period in two sites of Mali and Senegal. Thus, the cultivation of marginal area and vegetation recovery may be associated with this trend in rainfall.

4.2.1.3. Regional seasonal rainfall anomalies

The seasonal June-July-August-September (JJAS) standardised anomaly indices showed that the amount of rainfall during the rainy season (for years after 2010) was considerably higher than the normal except the years 2011 and 2013 (Figure 4.17).

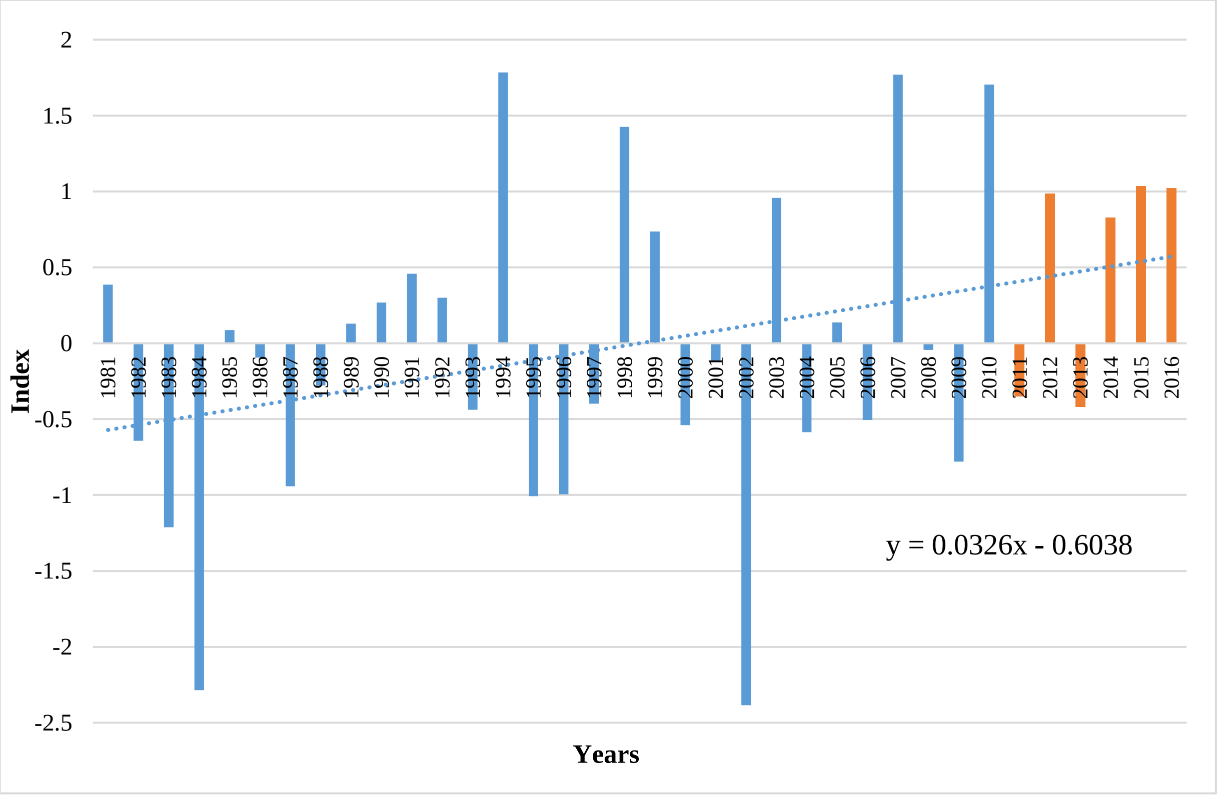


Figure 4.17 Seasonal Standardised Rainfall Anomaly Indices from 1981 to 2016

As shown by the annual anomalies, the seasonal rainfall for the years 1983 and 1984 were characterised by severe droughts. From 1982 to 1988 the only year that recorded a positive index value of rainfall was the year 1985. All the other years during that period were characterised by negative index values (Traore *et al*., 2013; Eshetu *et al*., 2016). These results indicate high similarities in seasonal and annual rainfall patterns. However, the seasonal rainfall variability was higher compared to annual variability.

4.2.1.4. Spatio-temporal rainfall variability

The rainfall variability was interpreted in the light of the classification of Hare (1983)- low variability (<20 %), moderate variability (21-30 %) and high variability (>30 %) (Thangamani & Raviraj, 2016). The four stations revealed different magnitudes of variability in rainfall (Table 4.6). The station of Koutiala exhibited moderate variability in both annual and seasonal rainfall; the three other stations displayed low variability in annual and seasonal rainfall. On annual basis, the station of Sikasso recorded the highest quantity of rainfall and the lowest was recorded at the station of Koutiala. The highest seasonal rainfall was recorded at the station of Bougouni, followed by Yanfolila, Sikasso and Koutiala.

Table 4.6 Coefficient of Variation of Rainfall

Station	Period	Mean (mm)	CV (%)	Classification
Regional average	Annual	1047	12	Low
	Seasonal	847	14	Low
Sikasso	Annual	1138	16	Low
	Seasonal	889	18	Low
Koutiala	Annual	867	21	Moderate
	Seasonal	734	21	Moderate
Bougouni	Annual	1136	14	Low
	Seasonal	917	17	Low
Yanfolila	Annual	1105	16	Low
	Seasonal	902	19	Low

Source: Author’s climate data analysis, 2017; Provided by *Agence Mali-Meteo*

It is apparent that the station of Koutiala was the less watered location from 1981 to 2016 which is certainly due to its northward position. The results also showed that the variability in rainfall is higher from one season to the other than on annual basis which may induce difficulties in seasonal rainfall prediction and therefore, impact on agricultural production and food security. Besides, the study area seems to experience increases in rainfall variability. Traore *et al*. (2013) reported a CV of 17 % in seasonal rainfall at the station of Sikasso from 1965 to 2005 while this study revealed 18 % from 1981 to 2016. That implies an increase in rainfall variability which affects negatively seasonal planning and agricultural production consequently.

4.2.1.5. Spatio-temporal rainfall trend

At 95 % confidence level, the stations of Sikasso (annual and seasonal) and Yanfolila (seasonal) exhibited increasing trends in rainfall (Table 4.7). The regional average rainfall exhibited also increasing trend in annual rainfall at five percent significance level and in seasonal rainfall at six percent (α= 0.06) but the null hypothesis was not rejected for the latter at five percent significance level (α= 0.05). This is due to the higher variability observed in seasonal rainfall (CV=14 %) compared to annual rainfall (CV=12 %). The null hypothesis (no trend) was not rejected at the other stations. However, all of them showed increasing linear trends as indicated by positive (S) statistic values but only those that are statistically significant according to the MK test technique are mentioned.

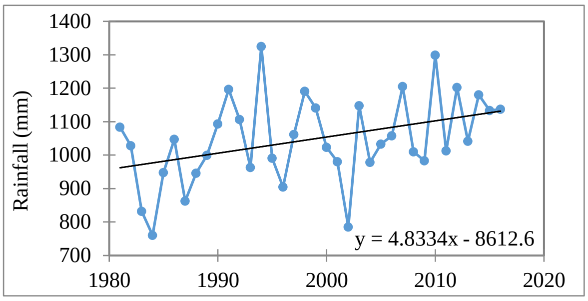
Table 4.7 Rainfall Trend

Stations	Period	MK (S) Statistic	MK trend test			
			P-value	Alpha	Hypothesis	Nature
Regional average	Annual	170	0.0213	0.05	H1	Increasing
	Seasonal	144	0.0514	0.05	H0	No trend
	Seasonal	144	0.0514	0.06	H1	Increasing
Sikasso	Annual	196	0.0079	0.05	H1	Increasing
	Seasonal	160	0.0303	0.05	H1	Increasing
Koutiala	Annual	106	0.1527	0.05	H0	No trend
	Seasonal	52	0.4873	0.05	H0	No trend
Bougouni	Annual	68	0.3615	0.05	H0	No trend
	Seasonal	66	0.3760	0.05	H0	No trend
Yanfolila	Annual	105	0.0917	0.05	H0	No trend
	Seasonal	147	0.0179	0.05	H1	Increasing

Source: Author's climate data analysis, 2017; Provided by *Agence Mali-Meteo*

These results show that rainfall has been increasing during the period 1981-2016 in the region of Sikasso. Indeed, increases in rainfall has been observed in many part of West Africa in recent years compared to pre-drought period (Nicholson, 2005). A report from the USGS (2012) stated that rainfall is recovering in Mali but the 2000–2009 rainfall is on average twelve percent lower than the average rainfall between 1920 and 1969. Similarly, Sanon & Vaksmann (2013) reported a recovering trend of rainfall since the end of the 1980s in Burkina Faso but the mean rainfall still remains lower than what it was during the wet period (1941-1970). Consequently, increases in rainfall in the study area will favour the recovery of vegetation (Brandt *et al*., 2014) and prevent land degradation.

In addition, Figures 4.18-4.22 show the increasing trends detected at different stations along with the slopes. These five figures represent areas where statistically significant increasing trends were detected using MK trend test. The highest slope (7.66mm) was found at the station of Yanfolila in the seasonal rainfall (fig. 4.22); the second highest slope was obtained at the station of Sikasso in annual rainfall (7.58mm) and seasonal (6.19mm), illustrated in the Figure. 4.20 and 4.21 respectively. Slopes of 4.83 and 3.79mm were obtained in the annual (Figure 4.18) and seasonal (4.19) average regional rainfall.



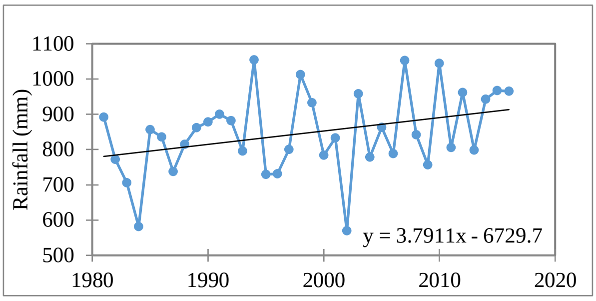
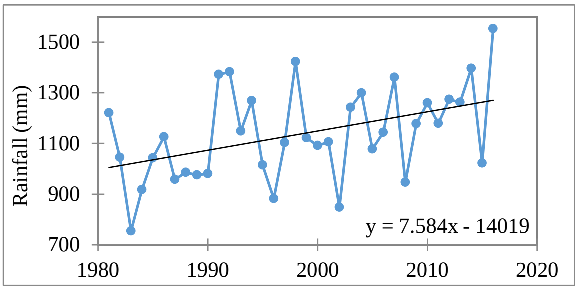


Figure 4.18 Rainfall Annual Trend Regional Average

Figure 4.19 Rainfall Seasonal Trend Regional Average



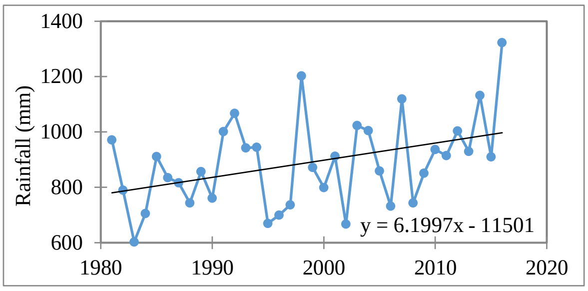


Figure 4.20 Rainfall Annual Trend Station of Sikasso

Figure 4.21 Rainfall Seasonal Trend Station of Sikasso

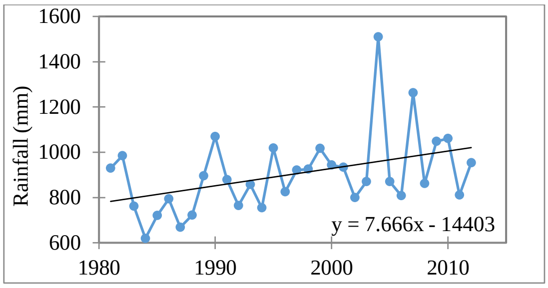


Figure 4.22 Rainfall Seasonal Trend Station of Yanfolila

4.2.2. Temperature

4.2.2.1. Evolution of the temperature

The monthly evolution of the minimum, maximum and mean regional average temperatures from 1981 to 2016 are illustrated in Figure 4.23. Highest temperatures were recorded in April before the rainy season and in October-ending of the rainy season while lowest were recorded in December and August-peak of the rainy season. The average minimum, maximum and mean temperatures were respectively 22, 34 and 28 °C from 1981 to 2016.

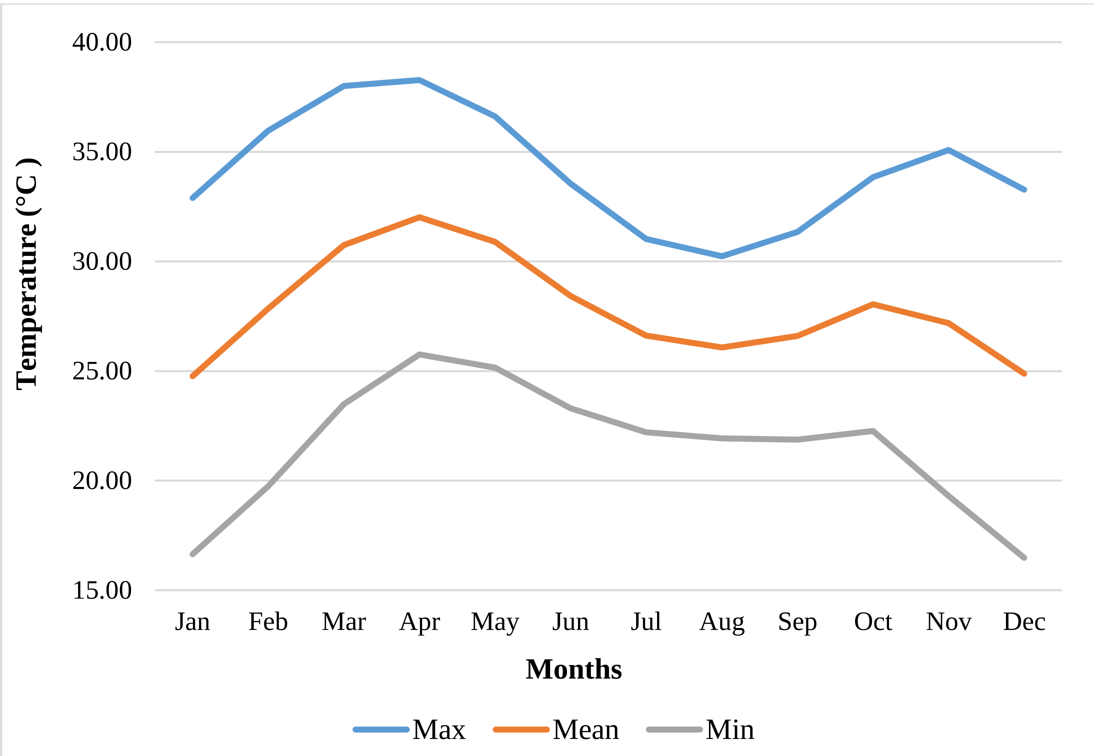


Figure 4.23 Monthly Temperature Averages from 1981 to 2016

Bodegom and Satijn (2015) confirmed that the average mean temperature in Mali is 28 °C. The same was obtained for the region of Sikasso and at all the stations considered separately. Additionally, an average seasonal minimum and maximum of 22 and 33 °C was reported by Traore *et al*. (2013) over the period 1965-2005 at the station of Sikasso which is very similar to the findings of this study. These previous studies confirmed the pattern of the evolution of temperature observed in this present study.

4.2.2.2. Annual temperature anomalies

The annual data revealed that hottest years have been recorded since the year 2001 till 2016 as shown by the Figure 4.24. The Figure shows clearly that from 2001 to 2016, only the years 2008 and 2012 recorded negative index values and the years 2002, 2004, 2010, 2013-2016 were very hot years with 2016 being the hottest. From 1981 to 2000 all the years recorded negative index values with the exception of the years 1987, 1993, 1996 and 1998.

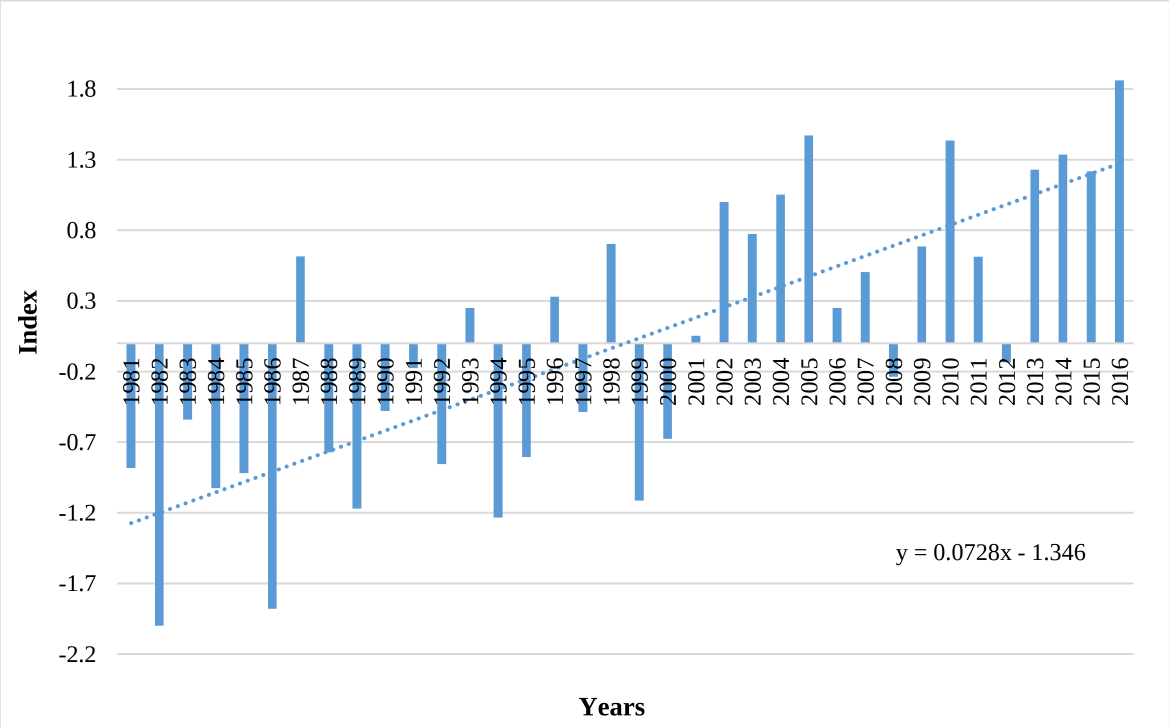


Figure 4.24 Standardised Regional Average Temperature Anomaly

The occurrence of more dry years in recent period indicates a clear warming trend in temperature in the region of Sikasso with 2016 being the warmest. Similar warming trend in temperature was observed in many other parts of Africa as reported in the IPCC Fifth Assessment Report (AR5). The report indicated that near surface air temperature anomalies in Africa were significantly higher for the period 1995–2010 compared to the period 1979–1994; West Africa and the Sahel near surface temperatures have increased over the last 50 years (Niang *et al.*, 2014). Furthermore, Traore *et al.* (2013) and Funk *et al.* (2012) respectively confirmed increase in temperature in Sikasso (1965-2005) and at national level (1975-2009). Increases in temperature lead to more evapotranspiration and reduction of soil water content which may increase stresses on plants and thus threaten agricultural production which in turn affects food security.

4.2.2.3. Spatio-temporal temperature variability

Different levels of variabilities were exhibited in minimum, maximum and mean temperatures at different stations. Table 4.8 shows in fact the max, min and mean temperatures for all the stations along with the CV obtained. The station of Koutiala recorded the highest mean temperature, followed by Bougouni and Sikasso-the lowest. The highest variability was observed in min temperature at the station of Sikasso and the lowest at both the stations of Koutiala.

Table 4.8 Variability of the Temperature

Stations	Measure	Mean (mm)	CV (%)
Regional average	Max	34.17	1.30
	Min	21.51	2.10
	Average	27.84	1.50
Sikasso	Max	33.68	1.30
	Min	21.47	2.70
	Mean	27.58	1.40
Koutiala	Max	34.41	1.30
	Min	21.74	2.50
	Mean	28.07	1.60
Bougouni	Max	34.44	1.93
	Min	21.31	1.90
	Mean	27.88	1.73

Source: Author's climate data analysis, 2017; Provided by *Agence Mali-Meteo*

These results indicated clearly that variabilities in temperature were not as high as in rainfall in the region of Sikasso. It is also apparent that higher variabilities were observed in minimum temperatures than maximum temperatures (Traore *et al*., 2013; Niang *et al*., 2014) and thus explained more variabilities in average temperatures as well and signalled warming of the Sikasso region.

4.2.2.4. Spatio-temporal temperature trend

The MMK test was performed on annual min, max and mean temperature series from 1981 to 2016 at 95 % confidence level. The results revealed statistically significant increasing trend in min, max and mean temperatures at the stations except the station of Sikasso where the max temperature showed no statistically significant trend (Table 4.9).

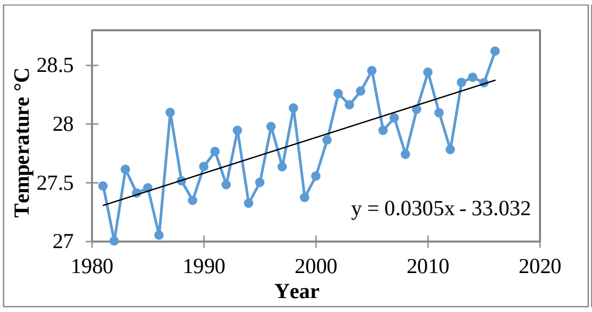
Table 4.9 Temperature trend

Stations	Measure	MK (S) Statistic	MK trend test			
			P-value	**Alpha**	**Hypothesis**	**Nature**
Regional average	Max	293	0.0001	0.05	H1	Increasing
	Min	376	0.0001		H1	Increasing
	Average	357	0.0001		H1	Increasing
Sikasso	Max	139	0.0601		H0	No trend
	Min	374	0.0001		H1	Increasing
	Mean	330	0.0001		H1	Increasing
Koutiala	Max	259	0.0004		H1	Increasing
	Min	351	0.0001		H1	Increasing
	Mean	353	0.0001		H1	Increasing
Bougouni	Max	338	0.0001		H1	Increasing
	Min	256	0.0005		H1	Increasing
	Mean	343	0.0001		H1	Increasing

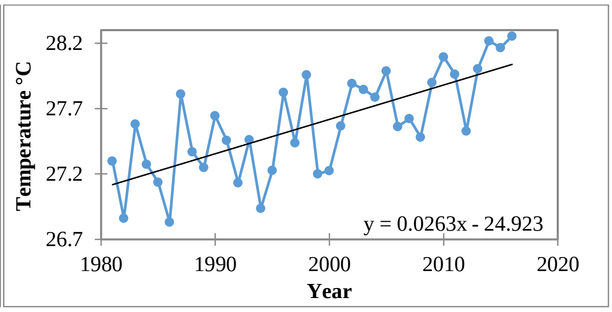
Source: Author's climate data analysis, 2017; Provided by *Agence Mali-Meteo*

The station of Koutiala showed the highest value in min temperature, followed by Sikasso and Bougouni (lowest) while the station of Bougouni showed the highest value in max temperature, followed by Koutiala and Sikasso (lowest). Moreover, on monthly basis a comparison of the climatological mean-normal (1981-2010) with the average of the period 2011-16 showed clearly that the average temperatures have increased for all the months. The highest deviations were observed in the months of November (+1.24 °C), March (+0.69 °C) and October (+0.67 °C) while lowest was observed in February (+0.15 °C).

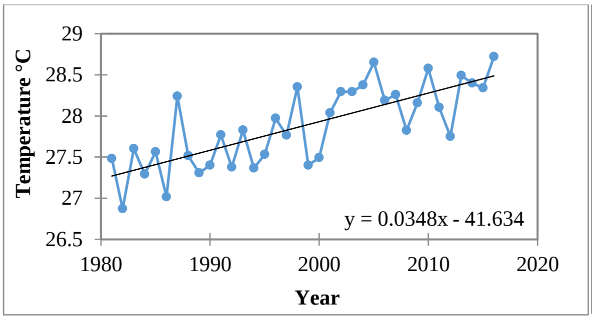
Additionally, Figure 4.25 illustrates the trends that were detected in mean temperatures at the regional level and at the three stations along with the slopes. The station of Bougouni showed the highest upward trend with a slope of 0.035 °C per year, followed by Koutiala (0.031 °C) and Sikasso (0.026 °C).



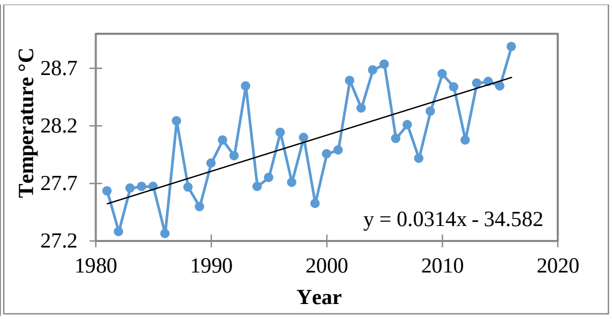
(a)



(b)



(c)



(d)

Figure 4.25 Annual Average Temperature Trend at the Station of (a) Regional, (b) Sikasso, (c) Bougouni and (d) Koutiala

These results strongly indicate that temperature has been increasing from 1981 to 2016 in Sikasso region, with an increase rate of 0.3 °C per decade. Similarly, Funk *et al*. (2012) reported an increase rate of more than 0.2 °C per decade over the period 1975-2009 at national scale in Mali. The highest rate of increase was detected in the minimum temperature with 0.44 °C per decade and the lowest in maximum temperature with 0.2 °C. Similar result was obtained by Traore *et al*. (2013) who reported an increase rate of 0.5 °C per decade in minimum temperature with the maximum being constant at the station of Sikasso over the period 1965-2005. This implies that the warming of the Sikasso region is mainly due to increase in minimum temperature. Moreover, this increasing trend detected in the study area confirmed the general trend exhibited over West Africa and the Sahel as a whole where near surface temperatures have increased over the last 50 years (Niang *et al*., 2014).

4.2.3. Climate variability in farmers' perspective

83 % of the farmers' interviewed mentioned that temperature has been increasing in recent years, 10 % said they have no idea about the trend, 4 % percent said it has decreased and 3 % mentioned that no changes have occurred. These results state clearly that the majority of the farmers are interestingly following the evolution of temperature and can identify its trend as well as statistical techniques applied on meteorological data. This is to say that this result is in agreement with the findings from the analysis of meteorological data which showed an increasing trend in temperatures from 1981 to 2016 in the study area. However, farmers were largely divided on the start of the rainy season. Whereas 46 % stated that rains have started earlier in recent years, 42 % mentioned a later start. The climate data available could not help to separate these two sides because it was monthly data. Only daily data can be used to clearly identify changes in the start of the rainy season

unless the shift is as high as more than one month. Moreover, 71 % stated that the rainy season is shorter against 13 % who stated that it is longer; 71 % also mentioned that the quantity of rain has decreased against 18 % who said it has increased. This is in total disagreement with the result from the rainfall data that were analysed which showed increasing trend. However, this may be due to the mind-set of farmers who generally associate the quantity of rain with agricultural production. Nevertheless, it is to be remembered that increases in rainfall quantity do not guarantee increases in production. The rainfall distribution is a very important parameter which should be taken into account. Additionally, 52 % reported more frequent floods and 72 % also mentioned longer dry spells. This is indicative of the occurrence of more intense rains followed by longer dry spells.

4.2.4. Climate variability impact on agricultural lands

The observed increment in monthly rainfall between July and September signals increased wetness in current decade. In addition, the average inter-annual regional rainfall showed that there is more increase in wet years than dry years. As it was confirmed that higher quantity of rainfall was recorded between 2012 and 2016 which by inference will impact on agricultural lands expansion. Furthermore, the low and moderate variability recorded in annual and seasonal spatio-temporal rainfall variability should have played a crucial role in agricultural lands expansion. The spatio-temporal trend analysis equally revealed an increasing trend in annual and seasonal rainfall averages (as ascertained by Brandt *et al*. 2014), because even in areas where the trend was not statistically significant, positive MK (S) values were obtained. Despite all these, the increasing trend in temperature affirms the impact of global warming in the Sikasso region which is more a function of increase in minimum temperature as confirmed by Traore *et al*. (2013) and Mohamed *et al*. (2014).

However, the Pearson's correlation test revealed that no statistically significant correlations exist between agricultural LULCC and rainfall trend and variability. Table 4.10 shows the correlation coefficient and probability values obtained from the analysis. The negative (positive) correlation coefficients show that there is a negative (positive) relationship between increases in agricultural lands and rainfall trend (variability). However, the higher probability values show that the relationship is not statistically significant.

Table 4.10 Pearson Correlations

		Annual Trend	**Seasonal Trend**	**Annual CV**	**Seasonal CV**
Agricultural LULCC	Pearson's r	-0.745	-0.575	0.737	0.504
	p-value	0.465	0.610	0.472	0.663

* p < .05, ** p < .01, *** p < .001, CV: Coefficient of Variability

Source: Author's data analysis, 2017

This result indicates that despite the increasing trend detected in rainfall, the expansion of agricultural lands is not to be associated with that. However, it could have impact on agricultural productivity, production and vegetation dynamics as well indicating that other factors could have played a fundamental role in agricultural lands expansion.

From farmers' perspective

Likewise, the Pearson's Chi-square test of independence conducted on different factors revealed that neither variability in rainfall nor in temperature has impact on farmers' decision making process to bring changes in their farm size. Variations in market prices, change of production systems, access to improved seeds and number of male workers were rather found to be associated with farmers' decision to either increase, decrease or keep unchanged the size of their farmland. Table 4.11 shows the Pearson's Chi-square values and p-values along with significance level.

Table 4.11 Pearson's Chi-square Test Results

Variables	Chi-square value	P-value	Alpha
Male Workers	40.90770998	0.031704	0.05
Production System	20.61777877	0.000377	0.05
Improved Seeds	7.331937799	0.025579	0.05
Market Prices	6.35637489	0.041661	0.05

Source: Author's computation from field survey data, 2017

Increases in markets prices encourage farmers to produce more for additional profits. More increases were also witnessed from farmers whose aim is to produce for both family consumption and commercial purposes. Farmers having access to improved seeds and those whom the number of male workers have increased have also been increasing their farm size. These results imply that despite the variabilities reported in temperature and rainfall, they do not affect farmers' decision on their farmland dynamics. However, they may have impact on natural vegetation cover and water bodies dynamics.

4.3. Land Use Land Cover Change Prediction by 2030 and 2050

This third section of the fourth chapter provides answers to the third research question. The section starts by introducing the model input data, model validation process followed by the presentation and discussions of the results from LULCC prediction by the years 2030 and 2050.

4.3.1. Model input data

The LULC maps of the years 2000, 2008 and 2016, DEM from which was derived the Slope map in addition to the Distance from Major Roads were used for the development of the model. The LULC maps are presented and discussed in the first section of this chapter. Figure 4.26 shows the DEM map of the study area.

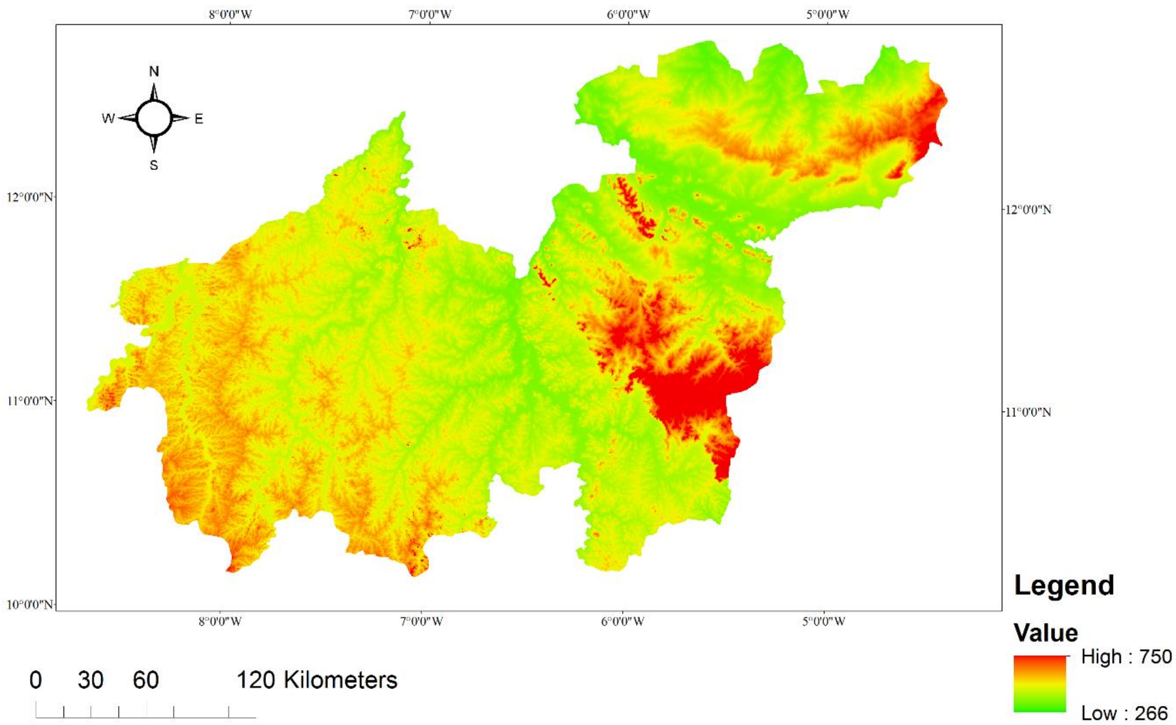


Figure 4.26 Digital Elevation Model Map

The DEM map shows that high elevations are located in the eastern part of the Sikasso region which are not suitable for agricultural production. Agricultural lands are generally located on lands that are neither considered high nor low, that makes the western and southern parts of the study area more suitable for agriculture.

Similarly, Figure 4.27 shows the slope map derived from the DEM.

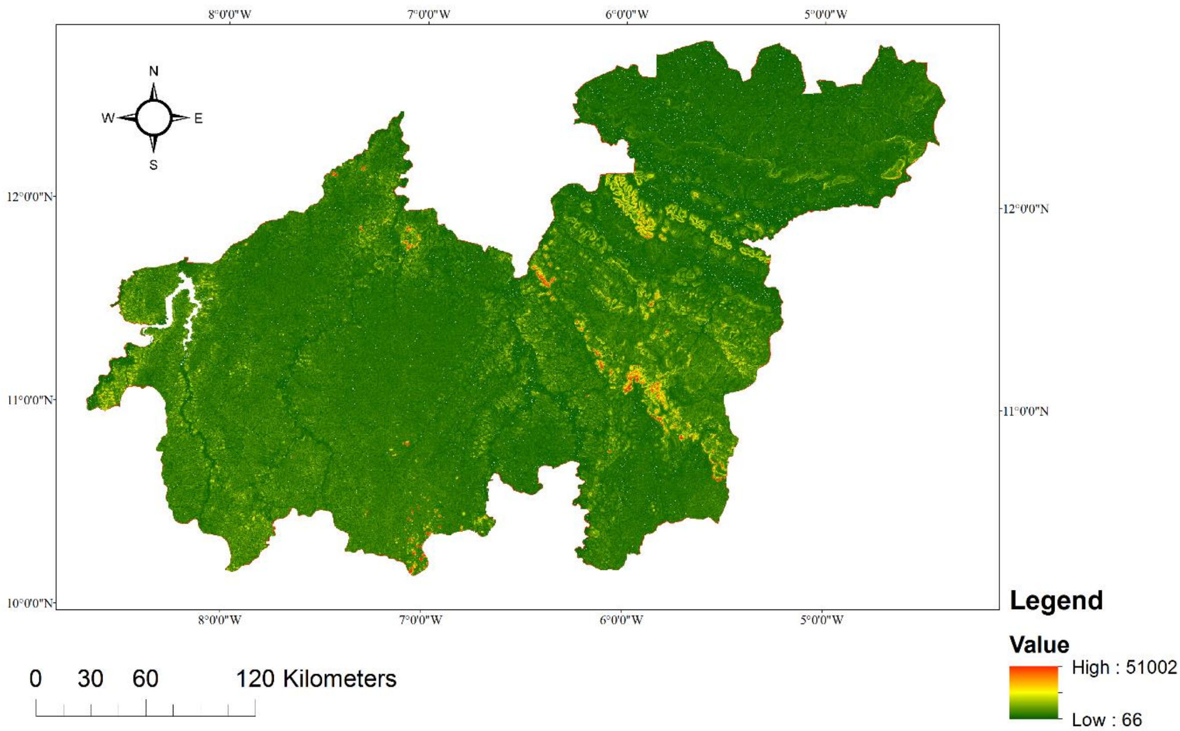


Figure 4.27 Slope Map

The slope map indicates areas suitable for cropping based on their exposure to runoff where locations with slope value are the most exposed. Therefore, this map shows that very few locations can be considered not suitable for agriculture based on their higher slope values which are marked by red colour.

Additionally, Figure 4.28 shows the distance to major roads which was derived from the major road basic layer.

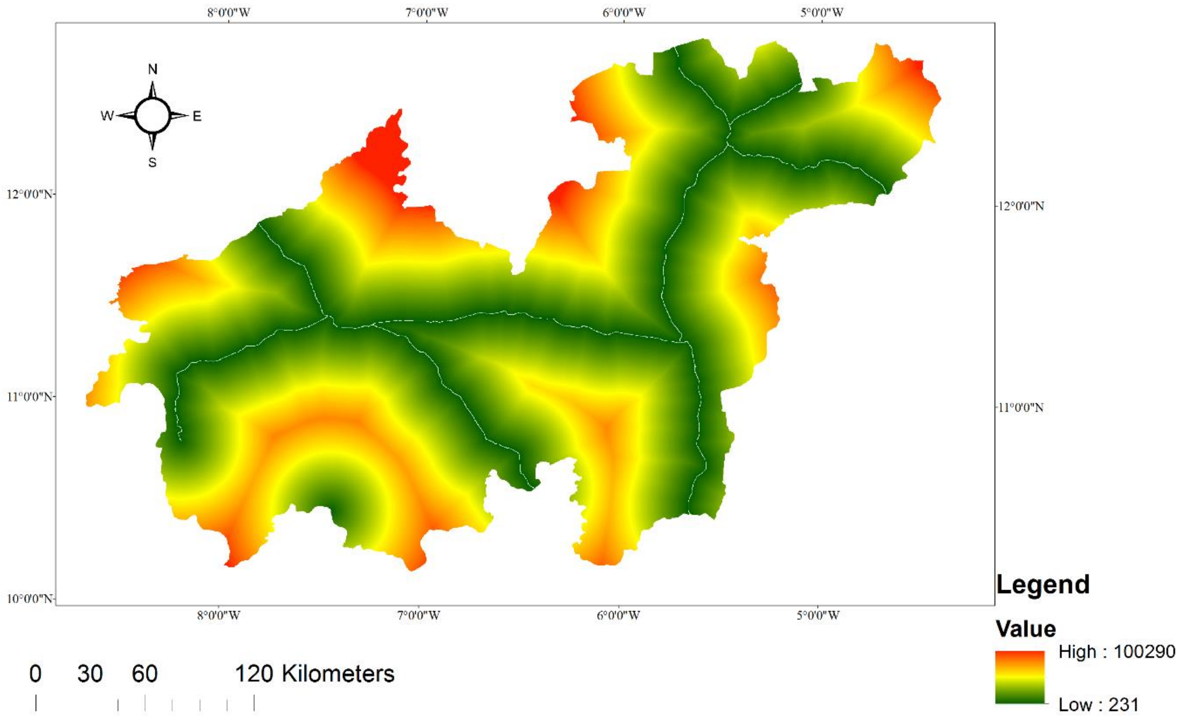


Figure 4.28 Distance to Major Roads

This map shows the degree of accessibility of different locations based on how distant they are from the major roads. Locations very far from roads are generally less suitable because of difficult accessibility. However, locations closer to major roads are preferred for urban development. Therefore, areas suitable for agriculture are located between the two extremes, marked by the colour yellow and light green.

4.3.2. Validation of the model

The developed model based on transitions from maps of 2000 and 2008 with an accuracy of 97 % predicted quite interestingly the LULC map of 2016. The comparison with the reference map of 2016 showed an overall Kappa Kstandard = 0.81, Kappa of no information Kno = 0.85, Klocation = 0.82 and Klocationstrata = 0.82. The perfect Kappa index of agreement is 1 while 0.80 is considered good. The Kappa values obtained were all above 0.8 which indicated the goodness of the model. Kappa indices of no information (Kno), location (Klocation), Location Strata (KlocationStrata) and overall Kappa (Kstandard) of 0.85, 0.87, 0.87 and 0.83 were respectively obtained by Mishra and Rai (2016) for the validation of their model for prediction, values which are very similar to the results of this study. These values indicate that both in terms of location and quantity the model has been able to perform well; the model was then validated and Table 4.12 shows the statistical estimation of different classes from the predicted and reference maps of 2016. The similarity can be observed from this table which shows areas by category in hectares for the predicted and reference for maps for 2016.

Table 4.12 LULC 2016 Areas Predicted Vs Reference

	Actual LULC 2016 (ha)	**Predicted LULC 2016 (ha)**
Cropland	3327509	3306827
Vegetation	3206270	3109523
Water	47815	37474
Others	557613	685383

Source: Author’s computation, 2017

In addition, Figures 4.29 and 4.30 show respectively the reference and predicted maps of 2016. High similarities can be visually observed between these two maps, high density of vegetation in the southern part, cropland in the central part and the class others in the northern part of the study area.

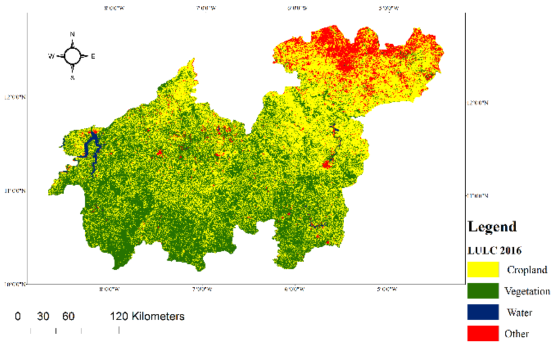


Figure 4.29 Reference Map of 2016

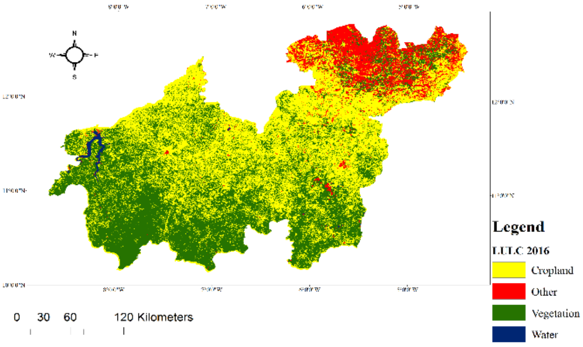


Figure 4.30 Predicted Map of 2016

4.3.3. Land use land cover in 2030

The predicted map of the year 2030 revealed that cropland, urban areas and bare surfaces (or degraded lands) will increase while vegetation and water bodies will decrease. Cropland will occupy half of the total area of the region by the year 2030, representing an increase rate of 6.54 % (0.45 % per year), vegetation will decrease by -11.14 % (-0.84 per year) occupying 40 % of the total area. Table 4.13 shows the area occupied by each land cover category, the proportion and rate of increase or decrease experienced in those categories.

Table 4.13 LULC Areas Predicted by 2030 Vs Reference 2016

	LULC 2016 (ha)	Portion (%)	LULC 2030 (ha)	Portion (%)	Increase Rate (%)
Cropland	3327509	46.61	3545108	49.66	6.54
Vegetation	3206270	44.91	2849121	39.91	-11.14
Water	47815	0.67	35896	0.50	-24.93
Others	557613	7.81	709082	9.93	27.16
Total	**7139208**	**100**	**7139208**	**100**	

Source: Author’s computation, 2017

Additionally, Figure 4.31 represents the predicted map for the year 2030. Like the previous land cover maps, the predicted map of the year 2030 will have much of the vegetation cover in the southern part of study area, cropland in the central and the class others in the northern parts.

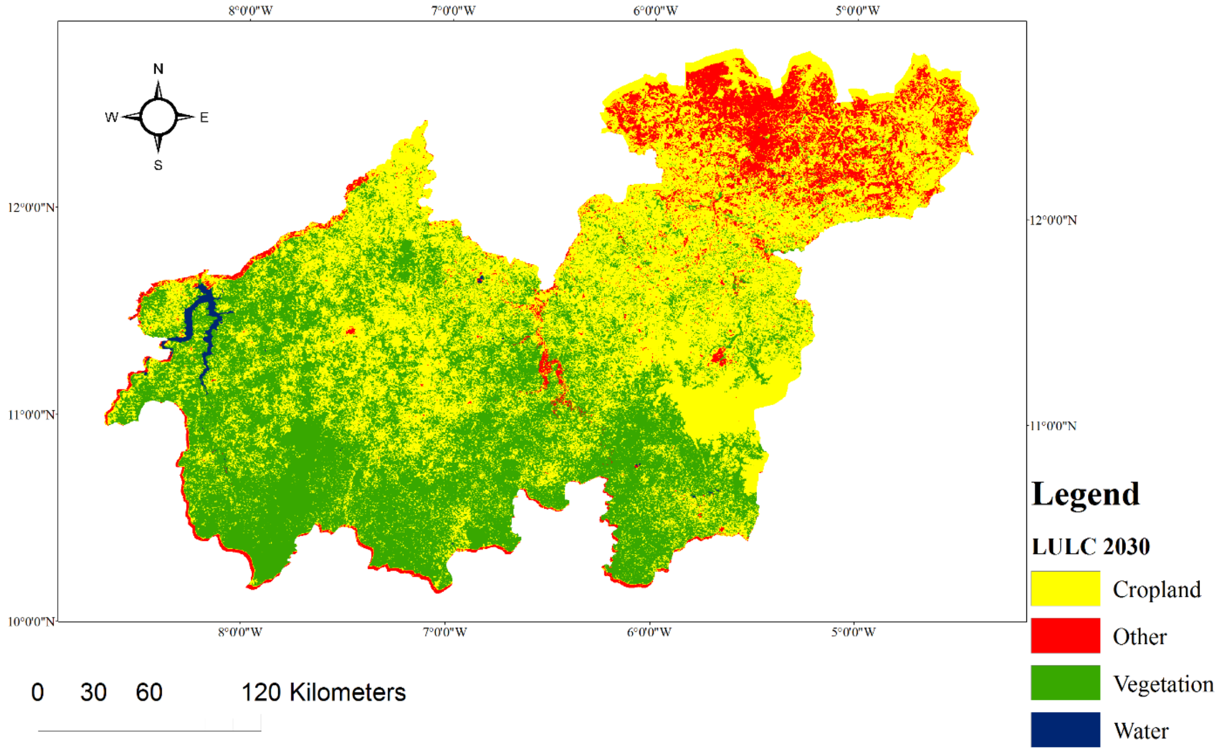


Figure 4.31 Predicted Map of 2030

4.3.4. Land use land cover change in 2050

The phenomenon of croplands expansion will still continue and in fact, occupy 55 % of total area of the region with a rate of increase of 18.58 % (1.22 % per year) while Vegetation will just represent 29 % of the whole, a decrease of -34.49 % from the year 2016. Built-up area and bare surfaces (the class others) will increase by about 90 % which is almost the double of the current proportion representing 15 % of the total area compared to 8 % in 2016. Table 4.14 presents the area occupied by each land cover category, the proportion and rate of increase or decrease experienced by those categories.

Table 4.14 LULC Areas Predicted by 2050 Vs Reference 2016

	LULC 2016 (ha)	Portion (%)	LULC 2050 (ha)	Portion (%)	Increase Rate (%)
Cropland	3327509	47	3945688	55	18.58
Vegetation	3206270	45	2100456	29	-34.49
Water	47815	1	35896	1	-24.93
Others	557613	8	1057167	15	89.59
Total	**7139208**	**100**	**7139208**	**100**	

Source: Author's computation, 2017

Similarly, Figure 4.32 represents the predicted map for the year 2050. Increases in cropland will occur in every part of the study area and the class others will occupy some areas in the southern part which was not the case in previous maps.

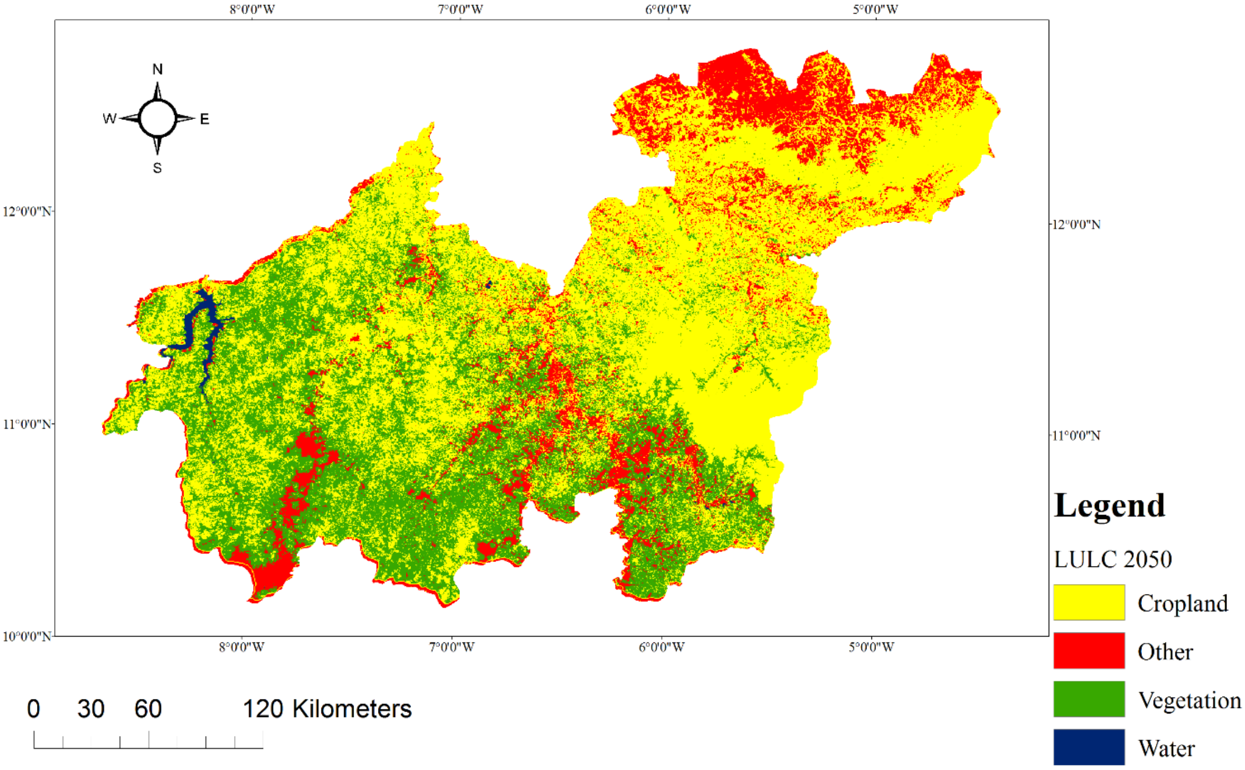


Figure 4.32 Predicted Map of 2050

These results state clearly that cropland will continue expanding considerably in the study area and vegetation decreasing. Similarly, increases in agricultural lands and built-up areas and decreases in vegetation cover were also predicted by (Mishra & Rai, 2016) in the Patna district (India) predicting LULC by the year 2038. Furthermore, similar trends were also reported by Katana *et al*. (2013), predicting land cover changes in the Upper Athi River Catchment (Kenya) by the year 2030. This uncontrolled and fast growing expansion of cropland and Built-up area will have serious consequence on vegetation cover (Mishra & Rai, 2016) and may certainly lead to the deforestation of the region of Sikasso. The vegetation cover being less than 30 % of the whole area will not only have impact on forest resources but on pasture as well and may intensify soils erosion and thus create more degraded lands. Consequently, to prevent deforestation and land degradation, appropriate actions are required to promote sustainable agriculture and protection of the forests.

CHAPTER FIVE

5.0. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

The identified increase in agricultural lands and warmer temperature will continue to impact negatively on the vegetation cover, water resources and land which are vital for enhanced livelihood, food security and attainment of socio-economic development of the major agrarian region in Mali. The intensification of these as apparent from the model predictions and spatio-temporal climatic pattern signals the need for the development of mitigation and adaptation strategies that will minimize the sensitivity and exposure as well enhance the resilience of the Sikasso region to the anticipated changes. Implementation of sustainability measures are crucial because global effort today is mainly proactive and not reactive. Thus, implementation of mitigation and adaptation measures such as adoption of conservation agriculture, improved land management practices and efficient management of water resources are necessary since yesterday's predictions become today's realities.

Besides, the increases in annual rainfall amount led to vegetation recovery in some areas during the period 2008-2016. However, the higher variability that characterised seasonal rainfall in recent years compared to previous years in a region where large proportions of agricultural production are rainfed is a threat to food security. This is an indication of the need for the development and breeding of improved/ early maturing seed species as pathway towards enhanced agricultural production under a changing climate. Finally, this study will provide the basis for the development of agricultural and environmental sustainability policies in the Sikasso region.

5.2. Recommendations

In the light of these findings, some measures and actions appear to be necessary. Hence, the following are recommended:

- The observed increases in temperature requires development and adoption of new varieties of crops which can grow under higher temperature values;
- Programmes of afforestation and reforestation should be promoted through bottom-up approaches to compensate for losses in forest cover and to tackle land degradation;
- Intensive agriculture should be encouraged by bringing in new technologies and more productive crop varieties in order to limit the uncontrolled expansion of agricultural land and forests loss;
- Conservation agriculture should also be promoted for the preservation of soils quality and fertility;
- Environmental policy makers should enhance forests protection laws to prevent losses through the predicted expansions in croplands;
- Further study should address rainfall variability in terms of its intra seasonal distribution and impact on agricultural production and land cover change. Because, the increasing trend in the amount may not be synonymous with good distribution within the rainy seasons.

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APPENDICES

APPENDIX A: Questionnaire

Date ………/………. / 2017

Questionnaire number:

District Name:

Village Name:

Respondent's name:

Phone number:

A. General Information

Question	Options	Answer
1. Gender	1= Male ; 2=Female	
2. Age		
3. Marital status	1=Single; 2=Married; 3=widowed; 4=Divorced	
4. Level of education	1=No formal education; 2=Primary school; 3=Secondary school; 4=Graduate 5=Other	
5. Number of person in the household	Number	
	Male	
	Female	

6. Major source of income	1=Farming 2=Livestock production 3=Fishing 4=Commerce 5=Forestry 6=Other (specify)		
7. Major source of income	1=Farming 2=Livestock production 3=Fishing 4=Commerce 5=Forestry 6=Other (specify)		
8. What is your production system ?	1=Commercial		
	2=Family consumption		
	3=Both		
	4=Others (to be specified)		
9. Average income (F CFA) ?	2000	2008	2016
10. Access Input (1=Yes ; 2=No)	2000	2008	2016
11. Access credit (1=Yes ; 2=No)	2000	2008	2016
12. Access to technical assistance (1=Yes ; 2=No)	2000	2008	2016

B. Land use change and impacts

<table>
<tr><th>Question</th><th colspan="2">Options</th><th colspan="2">Additional information</th></tr>
<tr><td>13. How long have you been farming ?</td><td colspan="2">1=less than 20 years ;
2=20-29 ; 3=30-39 ;
4=40 and more</td><td colspan="2"></td></tr>
<tr><td>14. Land ownership</td><td colspan="2">1=Owner;
2=Rent;
3=Borrow;
4= share-cropping;
5=Gift ;
5=Other (préciser)</td><td colspan="2"></td></tr>
<tr><td rowspan="3">15. Superficie de l’exploitation en ha ?</td><td colspan="2">2016</td><td colspan="2"></td></tr>
<tr><td colspan="2">2008</td><td colspan="2"></td></tr>
<tr><td colspan="2">2000</td><td colspan="2"></td></tr>
<tr><td rowspan="8">16. Farm size per crop type</td><td>Variety</td><td>2000</td><td>2008</td><td>2016</td></tr>
<tr><td>Maize</td><td></td><td></td><td></td></tr>
<tr><td>Millet</td><td></td><td></td><td></td></tr>
<tr><td>Sorghum</td><td></td><td></td><td></td></tr>
<tr><td>Rice</td><td></td><td></td><td></td></tr>
<tr><td>Groundnut</td><td></td><td></td><td></td></tr>
<tr><td>Cotton</td><td></td><td></td><td></td></tr>
<tr><td>Others(… ……..)</td><td></td><td></td><td></td></tr>
</table>

<table>
<tr><td>17. Which crop were you not growing before ?</td><td colspan="4">1=Maize; 2=Millet; 3=Sorghum ;4=Rice ;5=Groundnut; 6=Cotton; 7=Others(……………………………………)</td></tr>
<tr><td>18. Why did you start growing these crops ?</td><td colspan="4"></td></tr>
<tr><td>19. Why did you drop some crops?</td><td colspan="4"></td></tr>
<tr><td>20. Farm size evolution</td><td>1=Increasing
2=Decreasing
3=Unchanged
4=No ideas</td><td colspan="3"></td></tr>
<tr><td rowspan="6">21. Which land cover type has Increased or Decreased during the last 20 years?</td><td rowspan="6">1=Cropland
2=Forest
3=Bare soil
4=Water
5 = Pasture/grass land/shrub</td><td>Increased</td><td>Decreased</td><td>No change</td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td colspan="2">22. What is the impact of increase in farm size on forests and pasture ?</td><td colspan="3"></td></tr>
<tr><td>23. Soil fertility evolution</td><td>1=Increasing
2=Decreasing
3=Unchanged</td><td colspan="3"></td></tr>
<tr><td rowspan="2"></td><td>Chemical fertiliser</td><td>Yes</td><td>No</td><td rowspan="2"></td></tr>
<tr><td>Organic manure</td><td>Yes</td><td>No</td></tr>
</table>

24. Adaptation technique to soil fertility decline (Yes or No)	Composting	Yes	No	
	Fallowing	Yes	No	
	Crop rotation	Yes	No	
	Improved seeds	Yes	No	
	Others (…………………..)	Yes	No	
25. What are the major factors affecting your decision to increase or decrease your cultivated land ?	Household size	Yes	No	
	Technology availability	Yes	No	
	Market prices	Yes	No	
	Soil fertility loss	Yes	No	
	Decrease of yield	Yes	No	
	Climate variability	Yes	No	
	Other (To be specified)	Yes	No	

C. Climate Variability, perception and impacts

26. How has the temperature been evolving from the year 2000 to 2016 ?	1=Increasing 2=Decreasing 3=Unchanged 4=No ideas	
27. How is the starting of the rainy season ?	1=Earlier 2=Later 3=No change	

	4=No ideas	
28. How is the duration of the rainy season ?	1=Longer 2=Shorter 3=No change 4=No ideas	
29. How is the amount of rainfall ?	1=Increasing 2=Decreasing 3=Unchanged 4=No ideas	
How is the intensity of rainfall ?	1=More intense 2=Less intense 3=No change 4=No ideas	
31. What is the impact of rainfall duration change on your crop yield ?	1=Increased yield 2=Decreased yield 3=No impact 4=No ideas	
32. What is the impact of rainfall duration change on your farm size ?	1 = Increase of yield 2 = Decrease of yield 3 = No impact 4 = No ideas	
33. How is the occurrence of floods ?	1=Increased 2=Decreased 3=No change 4=No ideas	

34. How is the occurrence of droughts ?	1=Increased 2=Decreased 3=No change 4=No ideas	
35. How do you cope with a decreased yield ?	1=Increase farm size; 2=Increase fertilizer application; 3=Buy food; 4=Change crop type; 5=Change crop variety; 6=Selling animals; 7= Other	
36. Is there movement of pastoralists in your area ?	1= Yes; 2=No	
37. How can you compare their presence nowadays to years before ?	1=More present 2=Same as before 3=Less present 4=No ideas	
38. If more present, what do you think are causes ?		
39. How is the occurrence of conflicts between farmers and pastoralists ?	1=More conflicts 2=Same as before 3=Less conflicts 4=No ideas	

APPENDIX B: The leading author, collecting ground reference points

APPENDIX C: Conference paper presented at the Nigerian Meteorological Society (NMetS) 2017 International Conference and 31st Annual General Meeting (AGM), held at the Department of Geography and Meteorology, Enugu State University of Science and Technology (ESUT), Enugu, Nigeria, 20th to 24th November 2017.

Rainfall Variability and Trend Detection in four Districts of the Sikasso Region, Southern Mali

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Abstract

Climate change and variability are worldwide phenomena and their impact is different in nature from one region to the other. This study focused on seasonal and annual rainfall variability analysis and trend detection in the region of Sikasso, southern Mali. Monthly rainfall data from four meteorological stations in the districts of Bougouni, Koutiala, Sikasso-District (1981-2016) and Yanfolila (1981-2012) were collected. The Standardised Anomaly Index (SAI) and Coefficient of Variation (CV) methods were used to analyse the rainfall inter-annual and inter-seasonal variability; The modified Mann-Kendall (MK) test was performed for trend detection in the rainfall time series. The results showed that rainfall recorded more wet than dry years during the period (1981-2016) and that the quantity of rainfall during the rainy season (for years after 2010) was considerably higher than the normal except the years 2011 and 2013. The four stations revealed different magnitude of variability in rainfall. The station of Koutiala exhibited moderate variability in rainfall (CV=21%) while the other stations were characterised by lower variability. The inter-seasonal rainfall variability was higher than inter-annual variability at all the stations. Some stations showed statistical significant increasing trends while the null hypothesis (no trend) was accepted at some other stations. However, all the stations revealed linear increasing trends and positive MK(S) statistic values. The apparent annual and seasonal variability generally complicate its prediction and therefore, impact on agricultural production and food security.

Keywords: Rainfall Variability, Trend Detection, Standardised Anomaly, Modified Mann-Kendall Test, Sikasso Region (Mali).

1. Introduction

Mali is a landlocked country with an economy largely dependent on rural activities including farming and livestock productions. Rural activities in general and agriculture specifically constitute the major occupation of about 70% of the population (Sidibé et al., 2017). The agriculture in Mali as in many other African countries is characterised by low technological input, intensive labour, scarcity of capital and rainfall-based production system (Exenberger and Pondorfer, 2011). In Mali, most of the rain is received between June and September (Funk, 2012). The distribution and amount of rainfall within that period to a large extent determine the annual agricultural production. The first rains are received as earlier as in May and stop definitely in October in the southern part of the country.

Climate variability and change are challenges that the Malian agriculture faces. Since 1960, the annual average temperature rose by 0.7°C, corresponding to the rate of 0.15°C per decade (Ministère de la Santé et de l'environnement, 2008). The sahelian Mali is characterised by frequent droughts and annual rainfall variability (Bodegom and Satijn 2015). The Direction Nationale de la Meteorologie (2001) depicted decreases in rainfall trend from 1961 to 2001. In the 1950s, the annual precipitation used to vary within the range 500 and 1500 mm but in the course of the last 15-20 years the maximum has not been beyond 1300 mm and local temperatures, rainfall variability and the extent of severe weather events are expected to increase due to climate change (Bodegom and Satijn 2015). Traore et al. (2013) reported that during the period 1965-1993, the number of dry days have increased during the rainy season in Sikasso and identified variation as one of the most important characteristic of climate change in southern Mali. By implications, the higher temperature values and erratic rainfall in these recent years may adversely impact on agricultural production and food security consequently.

In addition to these current unfavourable climate trends, the future climate predictions are hampered with uncertainties. In fact, the Canadian Global Circulation Model (CGCM) and the 2030 projections of the Hadley Coupled Model (HadCM) indicated that the average temperature in Mali might rise by about 1° – 2.75°C, with precipitation decreasing slightly and crop produces to increase or decrease in the range from –17% to +6% at country level by 2030 (Butt et al. 2005). In such complexity where different trends and variability are observed throughout the country, it is necessary to investigate climate variability and trend at station-based level in Mali. Therefore, this study focused on rainfall variability and trend detection in four districts of the Sikasso region, southern Mali.

2. Material and Methods

2.1. Study area

This study was conducted in the region of Sikasso, located between longitude 4° 39’ to 8° 68’W and latitude 10° 15’ to 12° 82’N. It shares border with Ivory Coast, Guinea Conakry and Burkina Faso. Sikasso is one of the ten regions of Mali, composed of 7 “*cercles*”-second level administrative unit (hereby referred to as districts) which are Bougouni, Kadiolo, Kolondieba, Koutiala, Yanfolila, Yorosso and Sikasso-district. It has a total land mass of 70 280 km^2 (5.8% of the national territory) and a population of 2 625 919 in 2009 (Ministry of territorial Administration, 2011). The location of Sikasso Region is shown in the Figure 1.

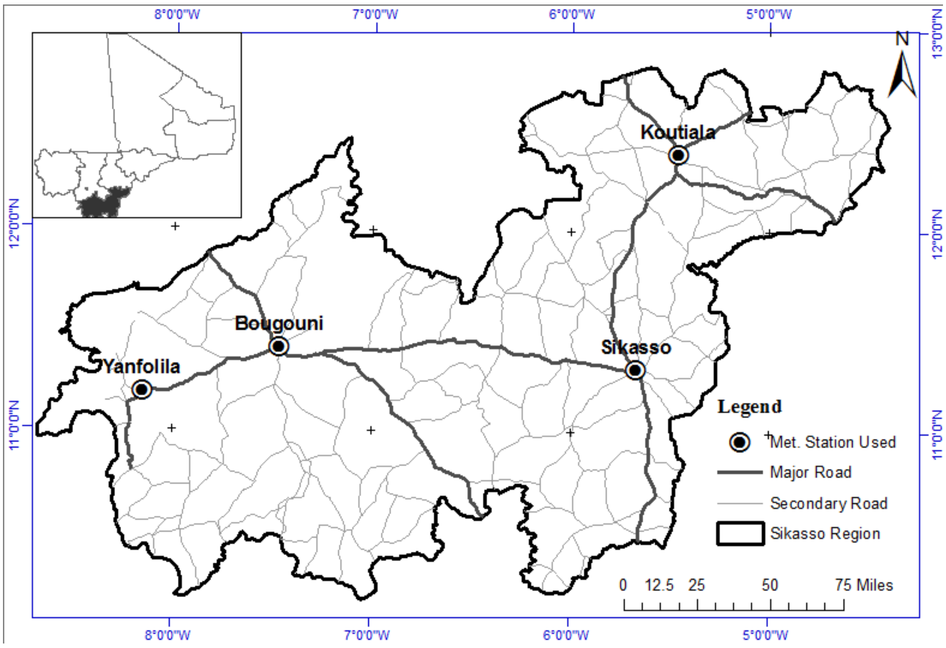

Figure 1. Study Area

In the entire Mali, the annual average temperature is 28°C; the north is characterised by higher average temperatures while lower averages are observed in the south; the absolute maximum temperature is 51°C, whereas the minimum temperature has not been lower than 10°C which causes high rates of evapotranspiration (Ministere de la Sante et de l'Environment, 2008). However, Sikasso receives the highest quantity of rainfall in comparison to the other regions of the country. The climate is of tropical Sudanian type, subdivided into two climatic zones, the humid Sudanian and the Guinean zone, which is the wettest region of Mali and receives the highest rainfall (700-1,500 mm / year) with an average annual temperature of 27 °C (PSA, 2011). Amongst others, continuous degradation of forest, lack of agricultural lands, soil erosion and loss of soil fertility have been identified as main problems of the region (PSA, 2011).

2.2. Data

Monthly rainfall data for four meteorological stations which are Bougouni, Koutiala, Sikasso and Yanfolila within the study area were acquired from the national meteorological service (Agence Mali- Metéo). The data covered the period from 1981 to 2016 and 1981 to 2012 for the latter. These four stations were selected based on data availability (more than thirty years) and data quality. The repartition of the stations is such that two are located in the north-eastern part of the study area and two in the south-western part for better representativeness of the whole area. The annual and seasonal June-July-August-September (JJAS) data were derived from the monthly data. Additionally, the monthly rainfall data from the four stations were averaged to get the region rainfall data which was also subject to analyses.

2.3. Methods

The Standardised Anomaly Index (SAI) and Coefficient of Variation (CV) methods were used to analyse rainfall variability and the Modified Mann-Kendall (MMK) test to detect monotonic trends in annual and seasonal rainfall. The standardised anomaly is the anomaly divided by the standard deviation; it is also referred to as normalised anomalies. It generally provides more information about the magnitude of the anomalies because of the removal of dispersion influences and one of its advantages is that it does not require the dataset to have a particular distribution before computation (Karavitis et al., 2011). The SAI is widely used (Kawale et al., 2000; Karavitis et al., 2011) and very popular for drought monitoring studies as it allows the determination of the dry and wet years in the record (WMO, 2012; Eshetu et al., 2016). The formula for computing the SAI is as follows:

$$Z = \frac{x - \mu}{\sigma}$$

Where: Z is the standardised anomaly; *x* is the variable of concern; μ is the mean of the dataset; σ is the standard deviation of the dataset. (Nicholson, 1985; Karavitis et al., 2011).

The CV is the ratio of the standard deviation to the mean over a determined period. It is expressed in percentage and inform of the level of variability (used by Belay, 2014, Ayelow et al., 2012, cited in Eshetu et al., 2016). The formula for the CV is obtained by dividing the standard deviation by the mean and multiplying the result by hundred and is given as:

$$CV = \frac{\delta}{\bar{x}} \times 100$$

Where: CV = coefficient of variation; x = mean; δ = standard deviation (Ekpoh and Nsa, 2011).

MK test is said to be the most popularly used non-parametric test for detecting trend in the time series data. It is widely used for different climatic variables (Suryanarayana and Parekh, 2016). Pohlert (2016) defined it as a non-parametric test that is commonly employed to detect monotonic trends in series of environmental data, climate data or hydrological data. The purpose of the MK test (Mann 1945, Kendall 1975, Gilbert 1987) is to statistically assess if there is a monotonic upward or downward trend in the variable of interest over time. The modified MK method takes into account the effect of autocorrelation and corrects it using Hamed and Rao (1998) methods. The formula for the non-parametric MK test is expressed as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign(x_j - x_k)$$

$$\begin{aligned} sign(\boldsymbol{x_j} - \boldsymbol{x_k}) &= \mathbf{1}\ \boldsymbol{if}\ \boldsymbol{x_j} - \boldsymbol{x_k} > \mathbf{0} \\ &= \mathbf{0}\ \boldsymbol{if} \boldsymbol{x_j} - \boldsymbol{x_k} = \mathbf{0} \\ &= -\mathbf{1}\ \boldsymbol{if} \boldsymbol{x_j} - \boldsymbol{x_k} < \mathbf{0} \end{aligned}$$

Where: n is the number of data points

Assuming (x_j-x_k) = θ, positive values of θ indicate increasing trend while negatives ones are indicator of decreasing trend. If the θ = 0, that means the variable has no trend. The MK test verifies the null hypothesis (H0) of no trend versus the alternative hypothesis (H1) for the existence of increasing or decreasing trend (Gopal et al., 2015; Pohlert, 2016). Positive (negative) values of (S) indicate increasing (decreasing) trends.

3. Results and Discussions

Standardised Anomaly Index (SAI)

The SAI was calculated using the region average data. The rainfall anomalies were interpreted according to the categorisation of McKee (1993) of Standardised Precipitation Index (SPI) as shown in Table 1, the rainfall index values are divided into seven categories starting from extremely dry to extremely wet situations as details below.

Table 1. Standardised Rainfall Index Categorisation

2.0 to greater	Extremely Wet
1.5 to 1.99	Very Wet
1 to 1.49	Moderate Wet
0.99 to -0.99	Near Normal
-1 to -1.49	Moderate Dry
-1.5 to -1.99	Severely Dry
-2 to less	Extremely Dry

McKee (1993), adapted from (Eshetu et al., 2016)

In application of this categorisation scheme, the analysis revealed that the average region rainfall recorded more wet than dry years, the year 1994, 2010 were respectively extremely and very wet years, 1991, 1998, 2007, 2012 and 2014 were moderate wet years and the year 1984 was the driest during the period (1981-2016), 1983, 1987 and 2002 were also severely dry years (Fig. 2). The period 1983-1984 was actually marked by severe droughts in many locations across Africa as reported by Traore et al., (2013) for the case of Sikasso. Eshetu et al., (2016) also reported negative anomalies for the years 1983 and 1984 at the stations of Setema and Gatira in Ethiopia over the period 1983 to 2013 (for Gatira) and 1979 to 2011 (for Setema). All the other years were within the range of near normal years. However, it is clear that recent years (2012-2016) have received much quantity of rainfall successively. Likewise, the seasonal (JJAS) SAI showed that the quantity of rainfall during the rainy season (for years after 2010) was considerably higher than the normal except the years 2011 and 2013, shown in Figure 2. The years 1983 and 1984 were characterised by severe droughts. From 1982 to 1988 the only year that recorded a positive SAI value of rainfall was the year 1985, all the other years during that period were characterised by negative index values as shown in the Figure 3.

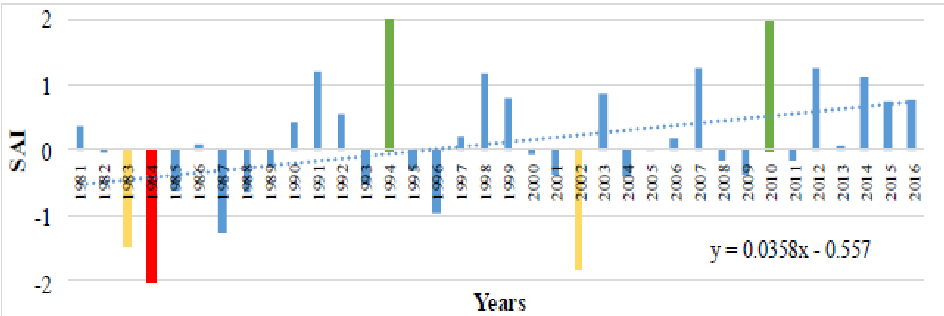

Figure 2. Annual Standardised Rainfall Anomaly Indices from 1981 to 2016

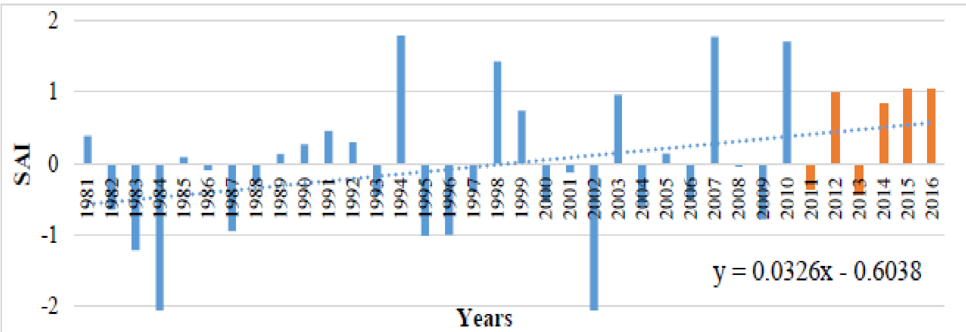

Figure 3. Seasonal Standardised Rainfall Anomaly Indices from 1981 to 2016

Coefficient of Variation (CV)

On annual basis, the station of Sikasso recorded the highest quantity of rainfall and the lowest was recorded at the station of Koutiala which is certainly due to its northward position. The highest seasonal rainfall was recorded at the station of Bougouni, followed by Yanfolila, Sikasso and Koutiala. It is apparent that the station of Koutiala was the least watered location from 1981 to 2016.

The rainfall variability was interpreted in light of the classification of Hare (1983)-low variability (<20%), moderate variability (20-30%) and high variability (>30%) (Thangamani and Raviraj, 2016). The four stations revealed different magnitude of variability in rainfall (Table 2). The station of Koutiala exhibited moderate variability on both annual and seasonal rainfall; the three other stations displayed low variability in annual and seasonal rainfall. The results also showed that the variability in rainfall is higher from one season to the other than on annual basis which may induce difficulties in seasonal rainfall prediction and therefore, impact on agricultural production and food security. Traore et al., (2013) reported a CV of 17% in seasonal rainfall at the station of Sikasso from 1965 to 2005 while this study revealed 18% from 1981 to 2016, that implies an increase in rainfall variability which affects negatively seasonal planning.

Table 2. Coefficient of Variation of Rainfall

Station	Period	Mean (mm)	CV (%)	Classification
Region average	Annual	1047	12	Low
	Seasonal	847	14	Low
Sikasso	Annual	1138	16	Low
	Seasonal	889	18	Low
Koutiala	Annual	867	21	Moderate
	Seasonal	734	21	Moderate
Bougouni	Annual	1136	14	Low
	Seasonal	917	17	Low
Yanfolila	Annual	1105	16	Low
	Seasonal	902	19	Low

Trend analysis

At 95% confidence level, the stations of Sikasso (annual and seasonal) and Yanfolila (seasonal) exhibited increasing trends in rainfall (Table 3). The region average rainfall exhibited also increasing trend in annual rainfall at five significance level and in seasonal rainfall at six percent (α= 0.06), but the null hypothesis was accepted for the latter at five percent significance level (α= 0.05). This is due to the higher variability observed in seasonal rainfall (CV=14%) compared to annual rainfall (CV=12%).The null hypothesis (no trend) was accepted at the other stations. However, all the stations showed increasing linear trends as indicated by positive (S) statistic values but only those that are statistically significant according to the MK test technique are mentioned. These results show that rainfall has been increasing during the period 1981-2016 in the region of Sikasso. Increases in rainfall has been observed in many part of West Africa in recent years compared to pre-drought period (Nicholson, 2005). A report from the United States Geological Survey (USGS) 2012 stated that rainfall is recovering in Mali but the 2000-2009 rainfall is on average twelve percent lower than the average rainfall between 1920 and 1969. Similarly, Sanon and Vaksmann (2013) reported a recovering trend in rainfall since the end of the 1980s in Burkina Faso but the mean rainfall still remains lower than what it was during the wet period (1941-1970).

Table 3. Rainfall Trends

Stations	**Period**	**MK (S) Statistic**	**MK trend test**			
			P-value	**Alpha**	**Hypo thesis**	**Nature**
Region average	Annual	170	0.0213	0.05	H1	Increasing
	Seasonal	144	0.0514	0.05	H0	No trend
	Seasonal	144	0.0514	0.06	H1	Increasing
Sikasso	Annual	196	0.0079	0.05	H1	Increasing
	Seasonal	160	0.0303	0.05	H1	Increasing
Koutiala	Annual	106	0.1527	0.05	H0	No trend
	Seasonal	52	0.4873	0.05	H0	No trend
Bougouni	Annual	68	0.3615	0.05	H0	No trend
	Seasonal	66	0.3760	0.05	H0	No trend
Yanfolila	Annual	105	0.0917	0.05	H0	No trend
	Seasonal	147	0.0179	0.05	H1	Increasing

In addition, the Figures (4-8) show the increasing trends detected at different stations along with the linear slopes. These five figures represent locations where statistically significant increasing trends were detected using MK trend test along with the region average trend.

The highest slope (7.66mm) was observed at the station of Yanfolila in the seasonal rainfall (Figure 8); the second highest slope was obtained at the station of Sikasso in annual rainfall (7.58 mm) and seasonal (6.19 mm), as illustrated in the Figures 6 and 7 respectively. Slopes of 4.83 and 3.79 mm were obtained in the annual (Figure 4) and seasonal (Figure 5) average region rainfall respectively.

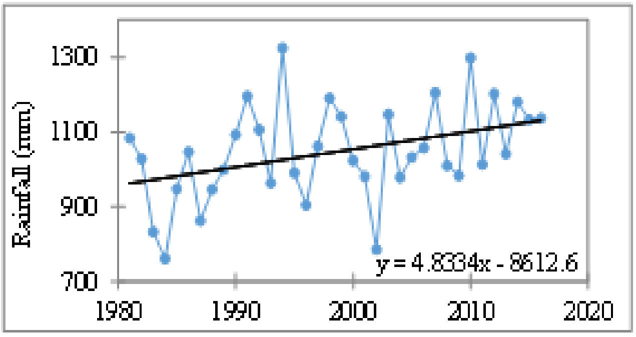

Fig. 4 Rainfall Annual Trend Region Average Average

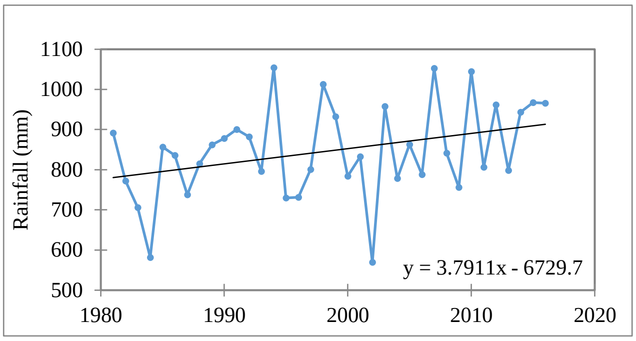

Fig. 5 Rainfall Seasonal Trend Region

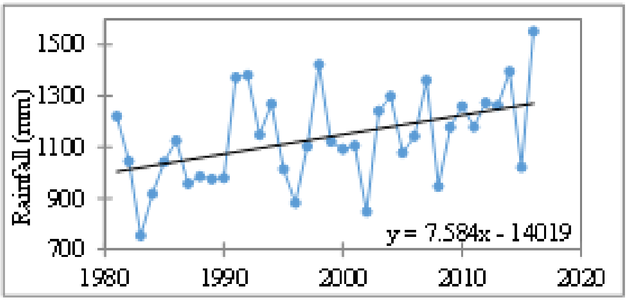

Fig.6 Rainfall Annual Trend Station of Sikasso

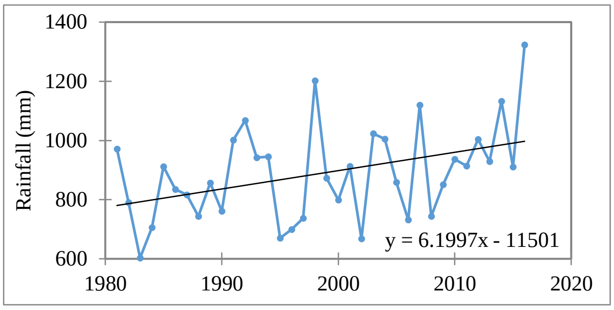

Fig. 7 Rainfall Seasonal Trend Station of Sikasso

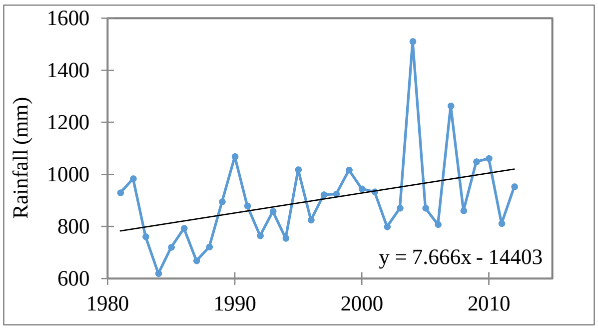

Fig. 8 Rainfall Seasonal Trend Station of Yanfolila

4. Conclusion

This study investigated the seasonal and annual rainfall variability analysis and trend detection in four districts of Sikasso region, southern Mali. The findings revealed that more positive values of SAI were observed in the study area from 1981 to 2016. Recent years were characterised by higher quantity of rainfall during the rainy seasons (for years after 2010 except 2011 and 2013). The CV exhibited lower and moderate (Koutiala) rainfall variability. However, the CV has increased in some locations compared to previous studies. All the four stations exhibited increasing linear trends and positive values of MK (S) statistic with the station of Sikasso (annual and seasonal) and the station of Yanfolila (seasonal) being statically significant. These results indicate that rainfall has been increasing during the period 1981-2016. However, these increases in rainfall should not be automatically considered as a positive phenomenon for if it is not accompanied with fair distribution, it may have negative impact on agricultural production and seasonal planning. Further studies should focus on the occurrence of extreme rain events, longer dry spells, shifts in onset and cessation dates for comprehensive understanding of the impact of these variabilities in rainfall quantity and trend on agricultural production.

Acknowledgments

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