Pan African University

Effects of Climate and Land Use Change on Hydrological Ecosystem Services in Pra River Basin, Ghana

Doctor of Philosophy in Environmental Management

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A dissertation submitted to the Institute of Life and Earth Sciences (including Health and Agriculture) in partial fulfilment of the requirements for the degree of Doctor of Philosophy (Ph.D.)

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Approval Sheet

EFFECTS OF CLIMATE AND LAND USE CHANGE ON HYDROLOGICAL ECOSYSTEM SERVICES IN PRA RIVER BASIN, GHANA

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Dedication

This work is dedicated to all Bessahs', especially, my wife, Matilda and son, Enoch. I also dedicate it to anyone working tirelessly on his or her present position to maintain a clean and safe environment.

Statement of the Author

By my signature below, I declare that this dissertation titled, “Effects of Climate and Land Use Change on Hydrological Ecosystem Services in Pra River Basin, Ghana”, is my work. I have followed all ethical principles of scholarship in the preparation, data collection, data analysis, and completion of this dissertation. I have given all scholarly matter recognition through accurate citations and references. I affirm that I have cited and referenced all sources used in this document. I have made every effort to avoid plagiarism.

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Abstract

Climate and land-use change influence ecosystem service types provided by hydrological processes of river basins. Previous studies used either different climate models with the same resolution or the same model at varying resolution to examine the impact of climate and land-use change on hydrological ecosystem services. The potential of reducing uncertainty in climate change impact studies with different climate models at different resolution is yet to be explored. This study, therefore, was designed to use climate models of varied resolutions to assess the combined impact of climate and land-use change on hydrological ecosystem services such as seasonal water yield, nutrient and sediment delivery ratios in the Pra River basin, Ghana.

The Statistical Mechanics and Dynamical Systems theories were adopted as framework and the Theory of Change for validation. Two Rossby Centre Regional Atmospheric Models, two Weather Research and Forecasting Models and one statistical downscaling model at 44km, 12km and 2m resolution respectively were purposively selected and used with generated land use/cover maps of 1986, 2002 and 2018 from satellite images to model seasonal water yield, nutrient and sediment delivery ratios. Using the reference data from 1981-2010, climate projection was conducted for 2020–2049 and using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model. The results from the model were evaluated based on farmer's perception of climate and land-use change within the basin. A multi-stage sampling technique was used to purposively select 10 districts and 344 farmers to whom a semi-structured questionnaire focusing on perception of climate and land-use changes was administered. Questionnaire data were analysed using descriptive statistics.

The ensemble of the five climate models projected rainfall to decrease by 1.77% and temperature increase by 1.25ºC in future. The variation in monthly rainfall could result in seasonal shift from a bi-modal to mono-modal rainfall pattern in future. Agricultural expansion and urbanization were the drivers of land cover change in the basin. Mean annual water yield at 0 - 335 mm in the control period was projected to decrease by 35% in future under the ensemble mean climate. The combined impact of climate and land-use change was adverse on nitrogen delivery and complimentary on phosphorus and sediment delivery when compared to their individual impact. Awareness of climate change was high (98.3%) among the farmers and they were extremely vulnerable to its impact. The use of improved crop varieties (97.1%), agrochemicals (96.2%) and on-farm tree planting (95.3%) were the major climate change adaptation strategies of farmers. Farmer's observation of temperature trends was consistent with gauge station records, however, rainfall trend was contrary. Farmers indicated that agriculture (79.4%) and small-scale mining (42.7%) were the major cause of deforestation driven by financial status (72.4%), climate change (64.5%) and market demand (63.7%).

Climate and land-use change will influence water availability and nitrogen export adversely and control erosion and phosphorus export in the Pra River Basin of Ghana between 2020 and 2049. Therefore, management practices that protect vegetation should be encouraged to control nutrient and sediment export and improve farmers' resilience through climate-smart agriculture.

Keywords: Climate change, Land-use change, Hydrological ecosystem services

Word counts: 500

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Abbreviations and Acronyms

ALOS	Advanced Land Observation Satellite
AOI	Area of Interest
ARIES	Artificial Intelligence for Ecosystem Services
AR4	The Fourth Assessment Report
AR5	The Fifth Assessment Report
ASD	Automated Statistical Downscaling
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BAU	Business as Usual
CanESM2	second generation Canadian Earth System Model
CBD	Convention on Biological Diversity
CCCma	Canadian Centre for Climate Modeling and Analysis
CCI	Climate Change Initiative
CCSM3	Community Climate System Model version 3
CICES	Common International Classification of Ecosystem Services
CM5A	first IPSL-Climate Model version 5 for CMIP5
CMIP	Couple Model Intercomparison Project
CN	Curve Number
CORDEX	Coordinated Regional Climate Downscaling Experiment
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DEM	Digital Elevation Model
ECHAM4	Fourth Generation of the Atmospheric General Circulation Model
ESA	European Space Agency

EU	European Union
ETo	Reference Evapotranspiration
ETM	Enhanced Thematic Mapper
FAO	United Nations Food and Agriculture Organization
GCMs	Global Climate Models
GCPs	Ground Control Points
GDEs	Groundwater Dependent Ecosystems
GFDL-ESM2M	General Fluid Dynamics Laboratory Earth System Model
GHG	Greenhouse gases
GIS	Geographical Information System
GLOVIS	Global Visualization Viewer
GMet	Ghana Meteorological Agency
GPS	Global Positioning System
HadGEM2	Hadley Global Environment Model
HEC-RAS	Hydrologic Engineering Center's River Analysis System
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
IPCC	Inter-Governmental Panel on Climate Change
IPSL	Institut Pierre Simon Laplace
ITPS	Intergovernmental Technical Panel on Soils
IWRM	Integrated Water Resource Management
Kc	Crop factor
KINEROS2	Kinematic Runoff and Erosion Model
LAM	Higher-resolution limited-area climate model

LANDSAT	Land Satellite
LARS	Long Ashton Research Station
LDD	Land Degradation and Deforestation
LOCI	Local Intensity Scaling
LRS	Length of Rainy Season
LULCC	Land Use and Land Cover Change
MAP	Mean Annual Precipitation
MEA	Millennium Ecosystem Assessment
MK3	Mark version 3
MM5	Meteorological Model version 5
MoFA	Ministry of Food and Agriculture
NASA	National Administration of Space and Aeronautics
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NDR	Nutrient Delivery Ratio
NSE	Nash-Sutcliffe Efficiency
R	Rainfall Erosivity Index
RCA4	Rossby Centre Regional Atmospheric Model
REDD	Reducing Emissions from Deforestation and forest Degradation
REMO	German Regional Climate Model
RCMs	Regional Climate Models
RCP	Representative Concentration Pathway
RH	Relative Humidity

RMSE	Root Mean Square Error
RUSLE	Revised Universal Soil Loss Equation
QC	Quality Control
QGIS	Quantum Geographic Infromation System
SAI	Standardised Anomaly Index
SCP	Semi-Automatic Classification Plugin
SDR	Sediment delivery ratio
SDSM-DC	Statistical Downscaling Model Decision Centric
SLC	Scan Line Corrector
SMHI	Swedish Meteorological and Hydrological Institute
SPSS	Statistical Package for Social Sciences
SRES	Special Report on Emissions Scenarios
SWAT	Soil and Water Assessment Tool
SWC	Southwestern and Coastal
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change
UPEI	University of Prince Edward Island
USGS	United States Geological Survey
USLE	Universal Soil Loss Equation
VIC	Variable Infiltration Capacity Model
VS	Variance Scaling
WASCAL	West African Science Service Centre on Climate Change and Adapted Land Use

WaSiM-ETH	Water Flow and Balance Simulation Model
WG	Weather Generator
WHO	World Health Organization
WRC	Water Resources Commission
WRF	Weather and Research Forecasting

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

Globally, available water quantity and quality are diminishing, making water a scarce commodity in this era of climate change. Degradation of a watershed is one of the direct causes (Murphy and Kapelle, 2014). Ecosystem's structure and its functions play a vital role in water sustainability (Enanga *et al*., 2011). Climate change threatens the sustainability of ecosystem services, especially in developing countries (Niang *et al*., 2014; Boon and Ahenkan, 2012) with the potential to cause negative trend in the changes that could happen (Bangash *et al*., 2013). Climate change is further projected to increase global temperature and change the patterns of rainfall, with more erratic changes in tropical regions (López-Moreno *et al*., 2011; Marcé *et al*., 2010). The projected changes could lead to environmental extremes like flooding and droughts, which may be less felt by the developed world because of better economic and political stability, and improved agricultural technology (Davis *et al*., 2015). However, the impact is quite great in Africa due to poverty and political instability amongst others (FAO, 2009; Bo *et al*., 2004; UNEP, 2002a).

Hydrological ecosystem services (freshwater, soil and nutrient regulation, and erosion control among others) and ecohydrological processes are directly affected by changes in terrestrial ecosystem components (Brauman *et al*., 2007). Forested areas contribute to groundwater recharge and maintaining surface water and consist of rich biological diversity. Sustainability of hydrological ecosystem services around the globe is currently a challenge due to unplanned use that resulted from population and economic growth, changes in land use and global dynamics (World Bank Group, 2016). Seasonal changes and water demand is a major risk especially now under climate change and consistent population growth (Allen *et al*., 2018; IPCC, 2014). The riverine ecosystem could be degraded as environmental flow reduces (Jujnovsky *et al*., 2010).

Water management systems, especially for agriculture, should be part of the forest conservation measures. Failure to protect ecosystem service directly linked with freshwater provision will affect livelihoods. This is because the production of these ecosystem services are fundamental to food security as well as the protection of human lives and properties (Duku *et al*., 2015; Jujnovsky *et al*., 2010). Ecosystem services are the benefits humans derive from intermediary productions via the relationship between ecological structures and processes (Brauman *et al*., 2007). Measures of valorising ecosystem services are necessary as part of an innovative mechanism to highlight positive outcomes capable of addressing the challenge of degradation in watersheds. A better understanding of the interactions between hydrological system and its impacting factors (climate and land use) on social and ecological systems are necessary for effective governance and formulation of adaptation and mitigation strategies.

1.2 Problem statement

Inter-Governmental Panel on Climate Change (IPCC, 2007) projected 10 – 30 % reduction in water availability in mid of the century at mid-latitudes and in the dry tropics. Water availability in major West African basins is projected to decrease by 10 – 40 % from mid to the end of the twenty-first century (Sylla *et al*., 2018). This is also the present scenario in the Pra River Basin, Ghana, due to current land use trends (Asare-Donkor and Adimado, 2016; Kusimi *et al*., 2015; Murphy and Kapelle, 2014; Oduro *et al*., 2012; Akrasi and Ansa-Asare, 2008). The main sources of pollution in the river basin are illegal artisanal small scale miners popularly referred to as "*galamsey*" (see Fig. 1.1), discharge of untreated liquid waste into water bodies and nutrient-laden run-off from commercial activities of residents in nearby villages (Ansa-Asare *et al*., 2014). The quality of majority of the river water in the basin is reported to be fairly good, few were poor and none in the class of good water quality (WRC, 2012). Groundwater as an alternative source of water for agricultural development has potential at only 24.5 % of the total land area of Ghana (Gumma and Pavelic, 2013). This calls for the regular assessment of surface water yield and quality in the basin threatened by uncertain climate and uncontrolled land use land cover (LULC) changes (Obuobie *et al*., 2012).

A rising world population, forecast to be 8.5 and 9.7 billion people by 2030 and 2050 respectively with Africa contributing about 20 % and 26 % in the respective projected years will result in increased wealth and changing dietary preferences (UN, 2015). Composition of food demand is projected to be 2960 and 3070 kcal/p/d in 2030 and 2050 respectively (Alexandratos and Bruinsma, 2012; Bruinsma, 2009). According to Steduto *et* *al*. (2012), a 70 % increase in food production at the global scale is required to meet the demand in 2050. Water scarcity is the major potential constraint to future food production (Davis *et al*., 2015; Steduto *et al*., 2012). Human activity, population growth, failure to implement policy and inadequate law enforcement have led to the degrading state of the Pra River Basin to the extent that although water is largely available, it is not in the form that could be readily utilised, thus resulting in water stress (Murphy and Kapelle, 2014). The population of the basin is made up of farmers majorly, who cultivate cocoa (the highest economic crop in Ghana) at large scale. Deforestation practices (timber extraction, fuelwood and charcoal production), crop production intensification through inorganic fertiliser usage and poor farming practices are changing the vegetative cover in the basin thereby augmenting or degrading the services it provides (Kusimi *et al*., 2015; Akrasi and Ansa-Asare, 2008; Brauman *et al*., 2007). According to Bentil (2011) a water treatment plant in Ghana stopped its operations due to intense sediment export as a result of *galamsey*. Sustainable management of river basins is critical challenges in Ghana due to intense human activities (Duncan *et al*., 2019).

According to Obuobie *et al*. (2012), the Pra River Basin is already water-stressed. The basin was projected to experience water scarcity (water supply less than 1000 m^3/capita/y) and absolute scarcity (water supply less than 500 m^3/capita/y) in 2020 and 2050 respectively (Obuobie *et al*., 2012). Climate change is expected to worsen the situation in the Pra River Basin since the projections were done without considering its impact (IPCC, 2014). Modelling how hydrological system will respond to a specific Representative Concentration Pathway (RCP) and land-use change gives an indication of what is likely to happen and help to prepare appropriate adaptation measures to reduce shocks. Therefore, to achieve the desired state (water quantity and quality being adequate for both environmental flows and human needs) of the Pra River Basin, further research is required to provide relevant information to all users for valorisation and understanding of the impacts of their activities (Murphy and Kapelle, 2014).

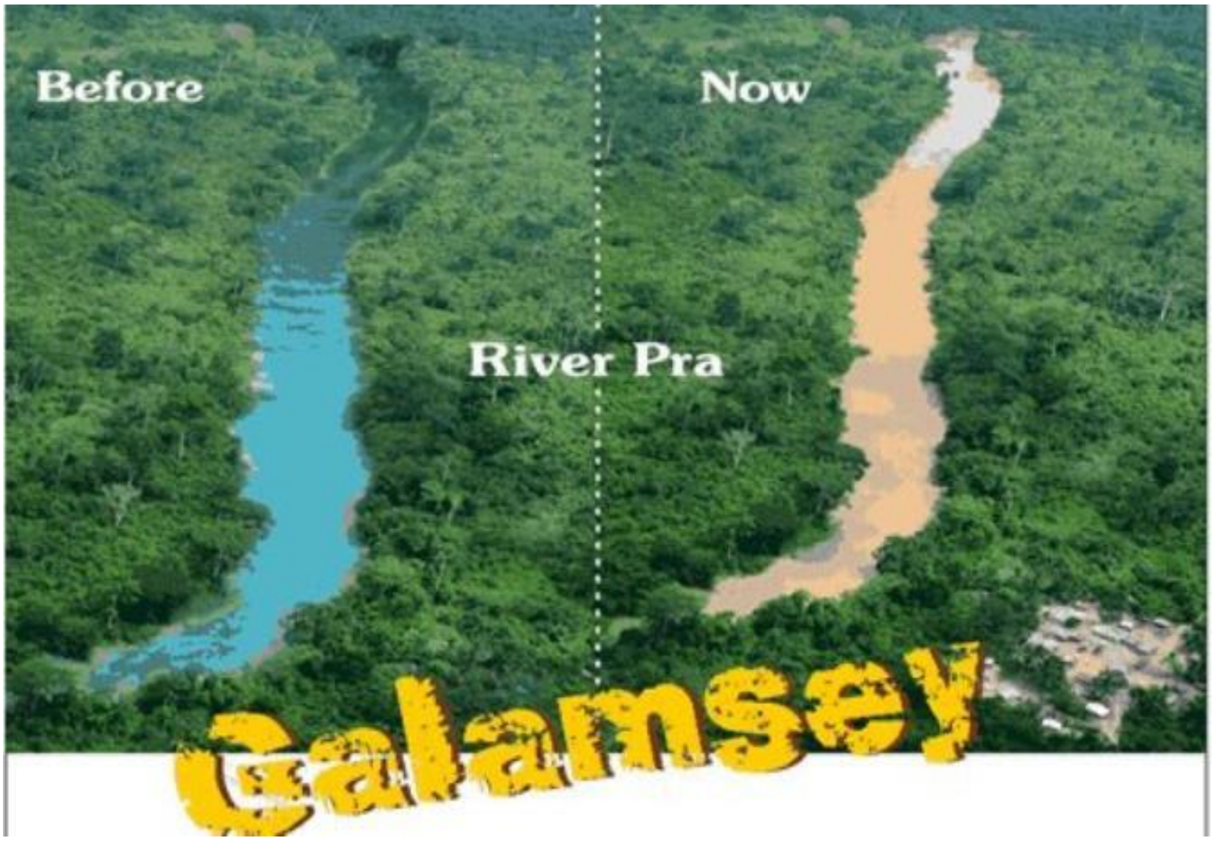

Fig. 1.1. State of the Pra River: (a) before and (b) after intense illegal mining "galamsey" activity.

Note: The later image described as "Now" was in 2016

(Source: Arthur-Mensah, 2016)

1.3 Justification of the study

Climate change impact studies either combine different spatial resolutions of the same climate model (Nikiema *et al*., 2017; Bossa *et al*., 2014) or different models of the same resolution (Okafor *et al*., 2019; Stanzel *et al*., 2018; Sylla *et al*., 2018; Amisigo *et al*., 2015; Aich *et al*., 2014; Jacob *et al*., 2007) in reducing uncertainty of projections. In Ghana, no climate impact study to the best of knowledge at the time of this work had employed a high spatial resolution climate model (in meters) to assess future water availability under climate change. This study combined different regional climate models with different spatial resolutions including a statistical downscaling model (resolution in meters) to compare model performance at a local scale and also to assess the impact of climate change from their ensemble mean on hydrological ecosystem services in the near future.

Mapping ecosystem services and their distribution at a local scale helps to identify areas under pressure for immediate interventions (Bangash *et al*., 2013). The capacity of a vegetation cover to offer hydrological ecosystem services like the reduction of runoff and nutrient regulation depends on the dynamics of changes in land use and land cover (Jujnovsky *et al*., 2010). The effect could be either adverse or complimentary. Therefore, this study sought to investigate the trend of the impact of changes in vegetation cover hereby referred to as land use/cover changes on hydrological ecosystem service delivery in order to determine the best adaptive management practices for the sustainable provision of these services. Furthermore, the study compared the standalone and combined impact of climate and land-use change on hydrological ecosystem services to identify the source of adverse impact on services for proper and specific interventions, especially in policy.

Hydrological ecosystem services are poorly monitored in Sub-Saharan Africa (SSA) for sustainable utilisation because of limited understanding of its importance to livelihood and poor availability of data. The Natural Capital Project (Sharp *et al*., 2016) has developed an ecosystem valuation model called the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST)[1] with minimum input data requirement which will serve the needs of Sub-Saharan Africa but it has not been adequately adopted yet. Testing and adopting the

[1] InVEST simplifies water movement by combining the movement of groundwater and surface water. It assumes that groundwater and surface water follows the same flow path to reach a stream. The model run on production function information in literature encoded within its deterministic sub-models (Sharp et al., 2016).

InVEST model which is capable of serving areas with scarce data (Volk, 2014) will facilitate a decision-making process, protect the degrading ecosystem and improve monitoring of ecosystem conservation (Sharp *et al*., 2016; Dimobe *et al*., 2015). This study was also with a view to providing frameworks for a broad range of policy and planning decisions relating to the environment and human well-being in the Pra River Basin.

1.4 Aim and objectives

The aim of this study was to assess climate and land-use change impact on the seasonal water yield, sediments and nutrients delivery ratios in the Pra River Basin of Ghana.

Specifically, the study sought to;

I. project climate variability and change of temperature and rainfall from four regional climate models and one statistical downscaling model for the period 2020 – 2049 (future) with reference to 1981 – 2010 (control).

II. analyse land use/cover changes from 1986 to 2018 in the basin.

III. model the changes in seasonal water yield, sediments and nutrients delivery ratios in the Pra River Basin for both historical and projected climate periods.

IV. assess the perception and adaptation strategies of farmers to climate change and the drivers of land use/cover change in the basin.

1.5 Research questions

i. What would be the future change and trend in temperature and rainfall distribution in the basin using a downscaled regional climate models and statistical downscaling model?
ii. Have the land use/cover changed significantly over time in the Pra River Basin?
iii. What are the impacts of climate and land use/cover changes on water yield, sediments and nutrient yield in the basin?
iv. How do farmers perceive and cope with climate change and what are the observed drivers of land-use change in the basin?

1.6 Hypothesis

i. Combined climate and land-use changes impact on seasonal water yield is in the same pattern as individual impact at the basin level.
ii. The amount of sediments and nutrient delivery ratios in a basin is a function of both climate and land-use changes.

1.7 Scope of the study

The climate analysis was limited to seven stations with available data of rainfall, maximum and minimum temperature between the period of 1981 – 2010. Future climate projections were between the period of 2020 – 2049 and analysis was carried out for the mean temperature at 2 m and rainfall. Two Coordinated Regional Climate Downscaling Experiment (CORDEX) on the African domain and two Weather Research and Forecasting (WRF) models focusing on the West African Region and one statistical downscaling model for station level modelling were used. Land use analysis was limited to two interval image analysis (1986 – 2002 and 2002 - 2018) due to lack of good freely available satellite images. Information available and reported in literature were used to gather biophysical data for the modelling of water yield, sediments and nutrient delivery ratios in the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) models. A total number of 344 respondents out of 399 sample size from 10 randomly sampled districts were interviewed.

CHAPTER TWO

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Conceptual Review

2.1.1 Hydrological ecosystem services

An ecosystem is a complex system of a plant, animal, fungal, and microorganism communities with their associated non-living environment such as water resources in the context of this study, all interacting as an ecological unit (CBD, 2009; Bond *et al*., 2008). Water resources provide numerous services to humans, which are sometimes termed as hydrological services. They encompass all the benefits humans get because of the terrestrial ecosystem effects on freshwater. Previous studies have divided ecosystem services into three categories; regulating, provisioning and cultural services (CICES, 2013; Kandziora *et al*., 2013; MEA, 2005). The services that define water resources in any category is further defined by their quantity, quality, location, and timing of flow (Brauman *et al*., 2007). The process of water flow in a landscape is impacted by its surrounding ecosystem. Therefore, water resources are directly influenced by terrestrial ecosystem services to either improve or degrade the supply of hydrologic services on its attributes.

The definition of hydrological ecosystem services has been evolving over the years (Schmalz *et al*., 2016; Martin-Ortega *et al*., 2015). Land cover/use is one of the immediate terrestrial ecosystems with direct impact on water resources. Its effect on these services differs from location to location due to the spatial and temporal scale and their inconsistencies with landscape hydrologic responses (Rodriguez-Iturbe, 2000). It is evident that those located upstream of a basin or watershed receive different benefits than those downstream. Land-use change might have positive or negative impact on water resource availability as well as the microclimate of the basin. Hydrological response varies with climate, geography and ecosystem type (Brauman *et al*., 2007). However, limited research has been conducted in the tropics compared to the temperate ecosystem to ascertain this fact. This has brought to the fore the need to assess hydrological ecosystem services in varying soil types, rainfall patterns and changing land uses.

Agriculture as a land-use practice can introduce pollutants into a stream at a faster rate via both surface and sub-surface lateral flow, whereas this might not be the case in a forest environment due to increased infiltration and reduced water yield by its canopies effects on precipitation. The geographic variability in the coupled impact of vegetation on hydrologic ecosystem services makes it difficult to predict the actual anthropogenic influence in the process (Martin-Ortega *et al*., 2015; Brauman *et al*., 2007).

2.1.1.1 Valorisation of ecosystem services

Valuing the attribute of ecosystem service is paramount to decision making. However, variation in the location of the services and land use being compared or contrasted influence the outcome of the value. An earlier study in the USA discovered that farmers in California have a net benefit from vegetated buffer strips, which improve the water quality available to them and at the same time reducing soil erosion (Rein, 1999). Also, the kind of ecosystem being delivered affects its value. The importance of watersheds and river basins to a community often determines the kind of community and traditional laws made to protect it. Although this has led to the evolution of models used to value hydrological ecosystem services (Guo *et al*., 2006), most African countries are yet to understand and plan based on drainage basin instead of the usual administrative boundaries. Another area of disparity is the spatial and economic disconnection between land users and beneficiaries of ecosystem services being derived (Brauman *et al*., 2007). A good policy mechanism is needed to harmonise these two sides to curtail the rate at which land-use changes occur, with or without the corresponding consequences on water delivery in a basin under consideration.

In the era of external drivers such as climate change, ecosystem service management must be prioritised for sustainability. Majority of the policies available to manage ecosystems are government-based. The policy mechanisms are usually voluntary payments, which allow non-government agencies to contribute to conservation, government control of land, government regulations and government incentive payments (Brauman *et al*., 2007). FAO (2002) in their bulletin and other studies such as Daily and Ellison (2002) expands on these mechanisms. The government can protect hydrologic ecosystem services by directly paying landowners to be able to control the changes that take place on them. Land use has been identified to play a major role in the characterisation of water resources and ecosystem services delivery in a basin or watershed. In some countries, landowners are paid specific amount for the services supplied from their land whereas in other countries services are valued before payment is made. Governments adopt different measures of conservation and protection based on the prevailing conditions on the land that supplies them with the needed services (Martin-Ortega *et al*., 2015). To assess feedback between hydrologic service delivery and land use, appropriate policy mechanisms must be in place to harmonise geographic, economic and cultural differences between landowners and those who benefit from services delivered by such ecosystems.

Brauman *et al*. (2007) identified that site-specific assessment information about the biophysical, social, economic and institutional dimension of ecosystem services are very important in the quest to understand and manage it. This is due to the variations in delivery based on landscape, vegetation and climate influence which are also geographically oriented. The information is vital to policymakers as they will be informed of the changes that are natural as well as those exacerbated by humans to help plan a specific conservation approach to them. The spatial nature of ecosystem services makes mapping an important tool in the assessment of the connections between delivery and beneficiaries. Mapping of ecosystem services is usually conducted by proxy-based maps (Terrado *et al*., 2014; Eigenbrod *et al*., 2010).

2.1.1.2 Attributes of hydrological ecosystem services

The attributes of water services are quantity, quality, location delivery and timing of delivery. Most people are informed about the first two, which are water quantity and quality because of their immediate impact on the environment and human activities. Water quantity is the amount of water available for drinking or for agricultural purposes. It also describes the volume of floodwater, whereas water quality is a measure of the levels of chemicals, pathogens, nutrients, salts, and sediments in surface and groundwater (Brauman *et al*., 2007). Ecosystem only modifies the water moving through it but does not create or add to its mass. However, an ecosystem contributes maximally to the quality of water passing through it by either adding or removing contamination from the flow. The quantity of water available at a particular time and location can be calculated with the water budget model in Equation 2.1.

$$Q = P - E - \partial W \qquad (2.1)$$

where;

Q = Water discharged from a watershed (surface + ground); P = Precipitation

E = Evapotranspiration (water use by plants + evaporation) and

∂W = Changes in water storage (surface + ground)

Ecosystem services such as transporting and redistribution of water affect the volume of water available to users in a watershed. The use of water by plants reduces water quantity available in a basin. Its location per time might be beneficial or harmful when found where it is not needed such as flooding near settlements. Both the location of water above or below ground levels are important for watershed management planning (Brauman *et al*., 2007). Downstream users might not have access to the volume delivered to the watershed from precipitation as compared to those upstream. Changes in an ecosystem (land use/cover changes) alter its delivery of water quality and can be measured with indicators such as changes in loads and concentration of chemical and physical properties and altered response to changes in extreme rainfall events.

Murphy and Kapelle (2014) recommends the assessment of land use/cover dynamics in the critical riparian areas in all river basins in Ghana due to the role played by aerodynamic characteristics of vegetation in the redistribution of water from vegetation to the atmosphere. There are limited studies done on the comparison of changes in surface and groundwater availability in a given LULC change. On the other hand, substantial research on surface flow in catchments has shown that streamflow is reduced by approximately 45 % when grassland is converted to forest land cover (Brauman *et al*., 2007). Taller trees, deep-rooted plants, smooth vegetation amongst other characteristics have their specific contribution to either the availability or scarcity of water in a watershed. Soils, slope, vegetation type and its age and management practice in a watershed are some of the drivers of water resources availability. These drivers vary spatially and in time, therefore, recommendations were made for site-specific and regional assessments for regular monitoring of their contribution to hydrological ecosystem services. Due to the daily and seasonal variations in contamination movements through a watershed which can span many years, assessments of these services must be done over an extended period. Therefore, models have been introduced for the assessment and monitoring of ecosystems effects on quality of water in a watershed (Bagstad *et al*., 2013a; Tallis *et al*., 2013). Ecosystem contributes to water quality of both surface and groundwater flows through various processes including physically trapping water and sediments, holding contaminants, enhancing infiltration via reduced water speed, transforming biochemical components of nutrients and contaminants, and nutrients uptake and regulation with its erosion control and water purification characteristics (Martin-Ortega *et al*., 2015).

Vegetative cover and tree heights influence the force with which raindrops hit the surface of the soil and further contributes to the reduction of rainfall impact by the amount of debris on the surface of the soil. It has been discovered that forests and other matured ecosystems improve the quality of water in a catchment. The protection of watersheds is mostly based on the ability of land covers to either improve or maintain water quality (Brauman *et al*., 2007). This affirms that land cover is a major driver in the delivery of ecosystem service, in relation to water quality. And changes in land cover over time in any basin calls for assessment so that site-specific planning and adaptation strategies can be developed. Murphy and Kapelle (2014) recommended that a critical assessment and identification of ecosystem services need to be carried out for the Pra River and Kakum River basins in Ghana. Precipitation is distributed seasonally across the globe and in an uneven quantity. Knowing when precipitation will occur is very important to farmers, construction workers and anyone who uses water for his/her activities. This is because water has a significant impact on their projects/occupation both directly and indirectly. The attribute of timing is defined as when water is or will be available (Brauman *et al*., 2007). The timing of precipitation determines how beneficial or harmful it will be per location. Information about the duration, seasons and predictable changes in stream flows and flood peaks are necessary for adaptation and management adjustment in a catchment. The timing of delivery is affected by land-use alterations which affect infiltration, groundwater recharge, subsurface lateral flow and rate of runoff (Guillemette *et al*., 2005).

2.1.2 Water footprint

Water covers about three-quarters of the earth's surface, however, 97.5 % of it is saline water (Shiklomanov and Rodda, 2003). Freshwater forms only 2.5 % of the global water stock. This is further distributed over the earth in the form of ice, snow and liquid. According to Hoekstra and Mekonnen (2011), accessible freshwater of the global water resources is less than 1 %. Freshwater as a renewable resource makes the accessible amount enough to meet human needs. However, the uneven spatial and temporal distribution of it often causes water scarcity (Savenije, 2000). The increasing demand for water also increases the pressure on accessible water resources especially in countries that are unfortunately located in water-scarce zones. To effectively manage and account for freshwater resources, the quantity and quality cannot be limited to the available or accessible amount in a country or river basin (Hoekstra, 2011).

The concept of water footprint is rooted in the earlier concept of virtual water introduced in the 1990s (Allan, 1998). Virtual water comprises of the total volume of water required to produce a good or service and it considers all inputs throughout the supply chain of production (Hoekstra and Chapagain, 2007). Water footprint is defined as an indicator of freshwater use that considers the direct and indirect water required to produce a product, measured over the full supply chain (Hoekstra *et al*., 2011). The concept also considers the origin of the water used, its quantity and quality impacts by grouping them into blue, green and grey water (Hastings and Pegram, 2012). Blue, green and grey water is one of the central concepts of water footprint that distinguishes its consumption. Other concepts are the direct and indirect water use and consumptive versus non-consumptive water withdrawals. The consumption concepts are defined as follows (Abdelkader *et al*., 2018; Hastings and Pegram, 2012):

- *Blue water footprint*: It refers to the amount of water used for the production of a good or service sourced from the surface or ground.
- *Green water footprint*: It refers to the amount of rainfall directly trapped by crops for the production of goods or services before the remaining runoff or infiltrate into the soil to recharge groundwater. Temporarily stored rainfall on top of soils for plant use is considered under green water footprint.
- *Grey water footprint*: It refers to the amount of fresh water needed to dilute pollutants in a water body to acceptable standard of water quality.

World Bank statistics indicate that 75 % of the world's poorest countries located in Sub-Saharan Africa rely on agriculture as the main source of livelihood (WFN, 2018). Enhancing agricultural performance is considered central to social and economic development in this region. A projection carried out by the Water Footprint Network in seven sub-Saharan African countries in 2016 revealed that agriculture contributes between

22 – 42 % of their GDP employing about 45 % of the total workforce in these nations. Moreover, the main use of the water footprint was for agriculture.

Ghana was reported to face blue water scarcity during dry seasons (November – February) in the year. Globally, blue water scarcity is estimated at 85 % per river basin analysis. When the annual average monthly blue water scarcity values per river basin are weighted according to population per basin it increases the global blue water scarcity to 133 % (Hoekstra and Mekonnen, 2011). Ghana was a net virtual importer of blue water and the largest green water exporter amongst the seven countries. It means that Ghana exports more products produced from rain-fed agriculture than it imports. The project recommended that farmers should be trained in sustainable agriculture practices that will increase their yield and reduce water footprint since their production is majorly rain-fed (WFN, 2018).

2.1.3 Climate Change

The Inter-governmental Panel on Climate Change (2007) defines climate as the average weather or the statistical mean and variance of relevant variables like temperature, precipitation, and wind over a long period. The World Meteorological Organization (WMO) defines the classical period of climate assessment to be a minimum of 30 years. IPCC (2007) further connected the definition of climate change to it cause whether natural variability or human activity. However, the United Nations Framework Convention on Climate Change (UNFCCC), attributed climate change to human activities either directly or indirectly. The climate is affected when changes in the atmosphere, land, ocean, biosphere and cryosphere resulting from both natural and anthropogenic activities can perturb the Earth's radiation budget, producing a radiative forcing (Cubasch *et al*., 2013). The drivers of change in climate may include, changes in the solar irradiance and changes in atmospheric trace gas and aerosol concentrations.

According to research, each of the last three decades has been successively warmer at the Earth's surface than any preceding decade since 1850. The global average combining land and ocean surface temperature data as calculated by a linear trend shows warming of 0.85°C (0.65-1.06°C) over the period 1880 to 2012 (IPCC, 2014). Anthropogenic greenhouse gas emissions (GHGs) have increased since the pre-industrial era, driven largely by economic and population growth, confirming UNFCCC's definition of climate change (IPCC, 2007). Global warming since the mid-twentieth century could be traced to the human-induced concentration of carbon dioxide, methane and nitrous oxide in the atmosphere. Between 1951–2010, findings show that GHGs contributed to a global mean surface warming between 0.5°C and 1.3°C (Bindoff *et al*., 2013). Anthropogenic forcings were reported to have a likely contribution between –0.6°C and 0.1°C and that from natural forcings likely to be between –0.1°C and 0.1°C. (Bindoff *et al*., 2013).

Climate change assessment in Africa recorded low to medium confidence in historical trends because of partial lack of data due to insufficient climate stations with consistent records, and also inconsistency in the reporting of available data. However, extreme temperature change was observed for areas with adequate data (Seneviratne *et al*., 2012). The future temperature under RCP 8.5 scenario for Africa projected an increase in the range of 3°C - 6°C in reference to 1986 – 2005 as base period for the 21st century which was observed to be rising faster compared the global rise in temperature (Niang *et al*., 2014).

2.1.3.1 Climate Representative Concentration Pathways (RCPs)

The terms climate scenarios and climate pathways have been used interchangeably due to the overlapping nature of the route or their definitions (Rosenbloom, 2017). According to IPCC (2000), a climate scenario entails the integrated description of likely future possibilities of the atmospheric system based on internally consistent narratives of both quantitative and qualitative trends. It is the conceptual framework behind the development of greenhouse gases emissions, climate change projections and climate change impact assessment (Allen *et al*., 2018). The concept of scenarios allowed the inclusion of socio-economic influence on energy and land-use change trends and its possible emissions into climate projection in biogeochemical models. Scenarios focus on climate policy. The Special Report on Emissions Scenarios (SRES) has been in use since the inception of the IPCC Assessment Reports (IPCC, 2000; Leggett *et al*., 1992). Climate pathway, on the other hand encompasses the periods of scenario evolution from the greenhouse gases emission scenarios to the socio-economic development and allows for the representation of scenarios as a standalone or in combination with others (Allen *et al*., 2018).

The trajectories of GHG concentration for climate projection are described under the Representative Concentration Pathways (RCPs) (van Vuuren *et al*., 2011). Due to the limitation of SRES to account for GHG emission reduction in future, the RCPs with a focus on human-induced climate change was developed into four trajectories of GHG concentrations to span the 21st century. The century was projected to start with a radiative forcing of 2.6 W/m^2 and run through two intermediary concentrations at 4.5 and 6.0 W/m^2 before ending the century at a maximum of 8.5 W/m^2 (van Vuuren *et al*., 2011). The IPCC Fifth Assessment Report (AR5) and the Coupled Model Intercomparison Project Phase 5 (CMIP5) assessed the RCPs (IPCC, 2014; Taylor *et al*., 2012).

2.1.3.2 Global Circulation Models (GCMs)

Global circulation models are based on computer programing of physical processes to replicate the functioning of the global climate system, as accurately as possible (Fenech *et al*., 2007). The complex interactions modelled are between the atmosphere, ocean, land surface, snow and ice, the global ecosystem and a variety of chemical and biological processes (Flato *et al*., 2013). It helps to understand how the climate system responds to increasing concentrations of greenhouse gases in the atmosphere. Global circulation models use mathematical equations to replicate the global climate system in three in three spatial dimensions and in time. However, due to the limitation of GCMs in capturing local climate variabilities, local climate simulations are needed for impact studies (Machenhauer *et al*., 1996). The development of downscaling models has provided an appreciable solution to this gap which was in climate change impact studies. Climate scenarios from GCMs can be used to assess the impact of climate change on agricultural and hydrological resources (Wigley *et al*., 1990).

2.1.3.3 Climate downscaling

Regional-scale climate information is important because global models are often too low in resolution to resolve regional features (Flato *et al*., 2013). Statistical and dynamical downscaling are used to generate region-specific climate information. Downscaling is a medium of closing the gap between climate models and observed records for the purpose of impact studies (Wilby and Wigley, 1997). Statistical downscaling (SD) involves deriving empirical relationships linking large-scale atmospheric variables (predictors) and local/regional climate variables (predictands). Interpolations are some of the statistical measures used for downscaling large scale atmospheric variables to local climate (Wigley *et al*., 1990). Statistical downscaling methods may also be applied to RCM output (Paeth, 2011; Van Vliet *et al*., 2011; Segui *et al*., 2010). The whole ideology of downscaling presupposes that, because of anthropogenic forcings, there will be significant (and predictable) changes in the stochastic simulation parameters (such as weather patterns), depending on the methodology adopted. All downscaling models have been found to be developed on one or more of the four methods namely; regression methods, weather pattern approaches, stochastic weather generators and limited area climate models (Wilby and Wigley, 1997).

2.1.3.4 Statistical downscaling model for climate projection

Statistical interpolation procedures adopted in statistical downscaling models are probably the most efficient method for obtaining details of local scenarios from GCMs and RCMs (Wigley *et al*., 1990). The three main classes of spatial downscaling are transfer functions, weather typing and stochastic weather generators (Fenech *et al*., 2007). There are numerous types of statistical downscaling climate model packages available for climate impact studies, namely the Statistical Downscaling Model (SDSM), the Long Ashton Research Station (LARS) Weather Generator (LARS-WG) and the Automated Statistical Downscaling (ASD) tool. Statistical Downscaling models have been used in assessing climate impacts with highly efficient predictions in terms of accuracy level. Downscaling in SDSM by two statistical processes, namely, stochastic weather generation and multiple linear regression algorithm.

2.1.3.5 Uncertainties in climate modelling

Parameterisation has been identified as a major error in climate models (Flato *et al*., 2013). It is due to the limited, though gradually increasing, understanding of very complex processes and the inherent challenges in mathematically representing the atmospheric process. Cloud processes, distribution of aerosols and simulation of sea ice remain major sources of uncertainty as well as the parameterisation of nitrogen and forest fires which pose as limitations in the biogeochemical components in Earth System Models. Parameterisation errors are the same in regional climate models (Evans *et al*., 2012; Boone *et al*., 2010; Pfeiffer and Zängl, 2010; Laprise *et al*., 2008; Wyser *et al*., 2008).

Resolution of a climate model, propagation of bias in the model association, palaeoclimate reconstructions, specified greenhouse gases scenarios in radiative forcings, and observational errors are also sources of uncertainty (Flato *et al*., 2013). Some phenomena or aspects of climate are found to be better simulated with models run at higher horizontal and/or vertical resolution. Besides the propagation of bias of one model affects others in the association. The root cause of biases resulting in the error of propagation is still unclear. The insufficient length or quality of observational data makes model evaluation challenging especially with the quality of data on arctic cloud properties, ocean heat content, heat and freshwater fluxes over the ocean and extreme precipitation. It has been found that newly observed data affect model evaluation conclusions in the current analysis (Flato *et al*., 2013).

2.1.4 Land use and land cover (LULC) change

Land use is defined differently by different disciplines and sectors. Whereas the natural scientists see land use as human induce change on natural vegetation, the social scientists and land managers define it in the context of socio-economic purposes (Ayivor and Gordon, 2012; Ellis and Pontius, 2007). It implies that land-use change may not be a physical alteration of land cover only.

2.1.4.1 Drivers of land-use change

Land-use changes have been found to be influenced by many factors globally. These drivers or factors may vary from location to location pertaining to the activities and environmental conditions of the place and triggered by interactions between biophysical and human activities (Geist *et al*., 2006). One of the major drivers of land-use change in the Pra River Basin is population growth. Very densely populated cities like Kumasi and Obuasi are located in the basin (GSS, 2014). This city is mostly termed the central part of Ghana, receiving migrants from mostly the northern part of the nation (Adaawen and Owusu, 2013). Population growth has been found to increase the demand of land for both settlement and agriculture to meet the food need of the people (Alexander *et al*., 2015; Foley *et al*., 2011; Wood *et al*., 2004; UNEP, 2002b). The demand of energy in terms of fuel resources also increases causing the trend in land-use patterns to change (Strapasson *et al*., 2016; Lambin and Meyfroidt, 2011; Schröter *et al*., 2005). A study by Addo *et al*. (2014) reported on the change of cropping in the northern region of Ghana to jatropha curcas to meet some bioenergy demand of the world. This was seen as a threat to food security as most of the arable lands were being used to produce Jatropha for biofuel production.

Mining was another major driver of land-use change in the basin (Ansa-Asare *et al*., 2014; Murphy and Kapelle, 2014; WRC, 2012). Both legal and illegal mining has attracted workers from the nation and around the world. The foreigners come with a variety of dietary needs which demand change in land use to meet the dietary needs (Strapasson *et al*., 2016; Alexander *et al*., 2015). Mining activities increase the economic capacity of dwellers and influence their dietary choices (Weinzettel *et al*., 2013; Tilman *et al*., 2011). Globally, population has been found to be the largest driver of agriculture land use change followed by dietary changes (Strapasson *et al*., 2016).

The international market and direct foreign investments are other drivers of land-use change (Alexander *et al*., 2015; Knickel, 2012). The Pra basin is dominated by cash crops especially cocoa. The demands of the foreign market directly affect what is being produced. A shift in international trade on these crops may definitely change the current land use (Strapasson *et al*., 2016). Knickel (2012) reported that between 2 % – 20 % of land in sub-Saharan Africa has been leased to produce food to meet the growing demand in Asia and some Arab countries. Policy interventions, especially in the area of development projects, are also drivers of change in land use (Knickel, 2012; Wood *et al*., 2004). An example is the proposed hydro-energy dam on the Pra River (Kabo-Bah *et al*., 2016; WRC, 2012). Policies changed the production pattern in Europe in the 1980s to early 1990s (Knickel, 2012).

Land tenure systems are also driving changes in land use in the Pra basin. Land systems have been found to be a major driver in West African countries (Wood *et al*., 2004). The land tenure systems in the Pra basin does not allow the leasing of farming lands due to the fear that inheritance might be lost along the line. This restricts the use of land according to the conditions of the owners since lands in the Pra basin are owned by families under the custodian of traditional rulers (Yeboah and Shaw, 2013). Climate change is another driver that cannot be ignored. The erratic patterns of rainfall in the tropics has a major impact on food production since agriculture in sub-Saharan Africa is majorly rainfed (WFN, 2018; Knickel, 2012; FAO, 2011). Nutrient absorption by crops will be affected by the limited availability of moisture in the soil resulting from changing rainfall patterns and increasing temperature trends (Amisigo *et al*., 2015; Obuobie *et al*., 2012). Climate change will impact crop yields, forcing the changes in types of crops to be cultivated and at which location to maximise yield (Strapasson *et al*., 2016).

Droughts, topography and bush fires are other biophysical factors that might drive changes in land use in the Pra River Basin (Gessesse and Bewket, 2014; Lambin, *et al*., 2003). Therefore, the dynamics of land use in the basin is a complex interaction of factors such as biophysical, economic, political and social with technology as a contemporary major player.

2.1.4.2 Land-use change assessment procedures

Mono-temporal classification is widely used in literature (Kadeba *et al*., 2015; Ouedraogo *et al*., 2014; Houessou *et al*., 2013; Schulz *et al*., 2010) for land use classification. Despite the fact that processing of single date image is faster as compared to multi-temporal classification, the vast area covered by basins in Ghana will mean that multi-temporal classification will be the most appropriate to use in this study (Zoungrana *et al*., 2015).

Ground control points (GCP) taken with a hand-held Global Positioning System (GPS) device for supervised classification of satellite images is scientifically accepted as an approach that reduces errors in land use classification. In addition to the in-situ collected points, high-resolution images (ALOS, ASTER, Quickbird and Google Earth) could be used to train and validate the image before going to the field. Similarly, LULC maps of the location may serve the same purpose if the accuracy is acceptable (Congalton and Green, 2008). Landsat images are preferred for land use assessment due to its spatial resolution (Braimoh and Vlek, 2005). Post-classification change detection algorithm is the most common approach used for monitoring land cover changes since it provides more useful information on the initial and final land cover types in a complete matrix of change direction (Shalaby and Tateishi, 2007; Fan *et al*., 2007; Campbell, 2002). In addition, it goes beyond simple change detection by quantifying the different magnitude and rates of changes described by Aldwaik and Pontius (2012) in terms of intensities. The concept of intensity analysis after the post-classification will unravel in detail the behaviour of each land class in the assessed period as required for future planning and recommendations in this study.

2.1.5 Hydrological ecosystem service modelling

The availability of accurate data is fundamental for developing efficient policies to improve water resources availability and accessibility (Nangia *et al*., 2010). The often expensive, complex and time-consuming nature of data collection makes modelling the best option to monitor and evaluate large scale assessment such as in watersheds and river basins (Kusimi *et al*., 2015). Application of models to areas that especially have inadequate data provides valuable information for adaptation and management planning (Khanchoul *et al*., 2010).

Vigerstol and Aukema (2011) report two types of tools for freshwater assessment. They are hydrologic tools (such as the Soil and Water Assessment Tool [SWAT]) and Ecosystem service tools (e.g. Integrated Valuation Ecosystem Services and Trade-offs [InVEST] model). Hydrological tools have been found to provide a higher degree of detail and mostly focus on ecosystem service drivers whereas the ecosystem service tools provide a more general picture of ecosystem services and are more accessible to non-experts. Ecosystem service tools, such as InVEST, are designed to be relatively easy to apply, to facilitate trade-off quantification between multiple services (Bagstad *et al*., 2013a). Lumping the quantification of these services together could reduce the efficiency, therefore, the use of specific models to assess specific services based on discipline is more appropriate and has proven to give good results. For instance, the Soil and Water Assessment Tool (SWAT model) by Arnold and Fohrer (2005), the Variable Infiltration Capacity Model (VIC model) by Nijssen *et al*. (1997) and the Hydrologic Engineering Center's River Analysis System (HEC-RAS model) by (Brunner, 2010) were developed for specific hydrological service assessment. Also, the development of the USGS Land Carbon project focused on carbon modelling (Zhu *et al*., 2010). These models are data-driven by their efficiency affected by inadequate data. However, ecosystem service tools/models are still efficient even with limited data. Simple deterministic models such as InVEST and ARIES are more appropriate in such areas where data availability is scarce (Vigerstol and Aukema, 2011). Both models predict changes resulting largely from reduced infiltration which is an undesirable change in the groundwater system. Understanding of how ecosystem service models operate will help its adoption in different locations across the globe (Bagstad *et al*., 2013b).

2.1.6 Conceptual overview of the InVEST models

The InVEST model simplifies water movement by combining the movement of groundwater and surface water. It is assumed that groundwater and surface water follows the same flow path to reach a stream where it is eventually discharged as baseflow.

Mendoza *et al*. (2011) used InVEST to test water yield in groundwater-dominated systems and the results were acceptable and can be calibrated to time-series streamflow data. Environmental problems, such as erosion, water quality depletion, declining aquatic habitat, and reduced groundwater recharge stern from faster runoff which is an undesirable effect of modelling these impacts. InVEST uses published production function information encoded within deterministic models to run its data. Although ecosystem service flows are accounted for in some models such as hydrology and viewsheds, service provisions such as use and flows are not systematically presented by the results (Bagstad *et al*., 2013a; Syrbe and Walz, 2012).

The current generation of InVEST models does not address uncertainty. Due to that, Kareiva *et al*. (2011) recommend the use of ecological coefficients ranged values to parameterise the InVEST models. Ideally, such sensitivity analyses would explore and account for potential parameter correlations (Elston, 1992). InVEST's Tier1 models are feasible for use by resource managers and gave adequate supporting data, GIS software licenses, and a moderate level of GIS expertise. Assembling the needed spatial data and parameterising the underlying data tables can be time-consuming and risks error if done poorly. However, when it is finally done for any area, it requires no more parameterisation for other works. Getting the underlying data is the largest obstacle to the widespread adoption of the InVEST model.

Although InVEST and ARIES simplified groundwater-system to such a degree that results are difficult to precisely interpret, Bagstad *et al*. (2013b) discovered groundwater flows from these two models were consistent with field studies and disciplinary hydrologic models verifying the efficiency of the model on ecosystems services.

2.1.6.1 Overview of Nutrient Delivery Ratio (NDR) model

The NDR model describes the transportation of nutrient on the basis of mass balance. It is based on the empirical relationship of nutrient uninterrupted flow for a long period in space (Sharp *et al*., 2016). Sources of nutrient across the landscape are known as nutrient loads in the model. Nutrients loads for the model is determined from the land use maps created for the specific study location. The model divides the nutrient flow into surface and subsurface. By design, the user is at liberty to model both surface and subsurface or only one of them. Secondly, the model computes delivery factors for each pixel based on that pixel's properties in the same generated flow path (Fig. 2.1). The slope and retention efficiency of the land use in question is usually used for the pixel characterisation. The output is the computed sum of the pixel-level contributions in the watershed or sub-watershed arriving at the outlet.

Limitations of NDR Model

The outputs of the model are invariably affected by the sensitivity of the limited inputs data. It implies that errors in the empirical load parameter values will largely affect the predictions. The averaged values used in empirical studies which are the basis for the determination of the retention efficiency affects the uncertainty of outputs (Sharp *et al*., 2016).

2.1.6.2 Overview of the Sediment Delivery Ratio (SDR) model

The SDR model works at the spatial resolution of the input digital elevation model (DEM) raster. The amount of eroded sediment is first computed, followed by the sediment delivery ratio, which is the proportion of actual soil loss reaching the catchment outlet (Fig. 2.2). The sediment delivery ratio (SDR) is calculated on the difference between upslope and downslope characteristics for each pixel on the flow path (Sharp *et al*., 2016). Borselli *et al*. (2008) were the first to work on this method of sediment delivery determination and later improved by Sougnez *et al*. (2011), Lopez-vicente *et al*. (2013) and Cavalli *et al*. (2013) to the current state used in this study.

Limitations of the SDR model

The SDR model was built on the Universal Soil Loss Equation (USLE) which can only capture rill or inter-rill erosion processes (Renard *et al*., 1997). Only gully erosion can be added by the user amongst other sediments sources not considered. Therefore, the errors in the USLE equations from its empirical parameters affect the estimation of SDR. The model allows for parameterization with site-specific information such as erositivity, erodibility, crop management and practices factors (Sougnez *et al*., 2011). Furthermore, the model does not differentiate the sources of sediments in the total delivery in the total sediment budget. Also, the explanation given by the literature on SDR model should be considered when users are interpreting model absolute values. Inputs parameters significantly influence the results generated by SDR due to its simplicity and the low number of parameters required to run it. Sensitivity analyses are recommended by developers of the model during adoption for appropriate conclusions (Sharp *et al*., 2016).

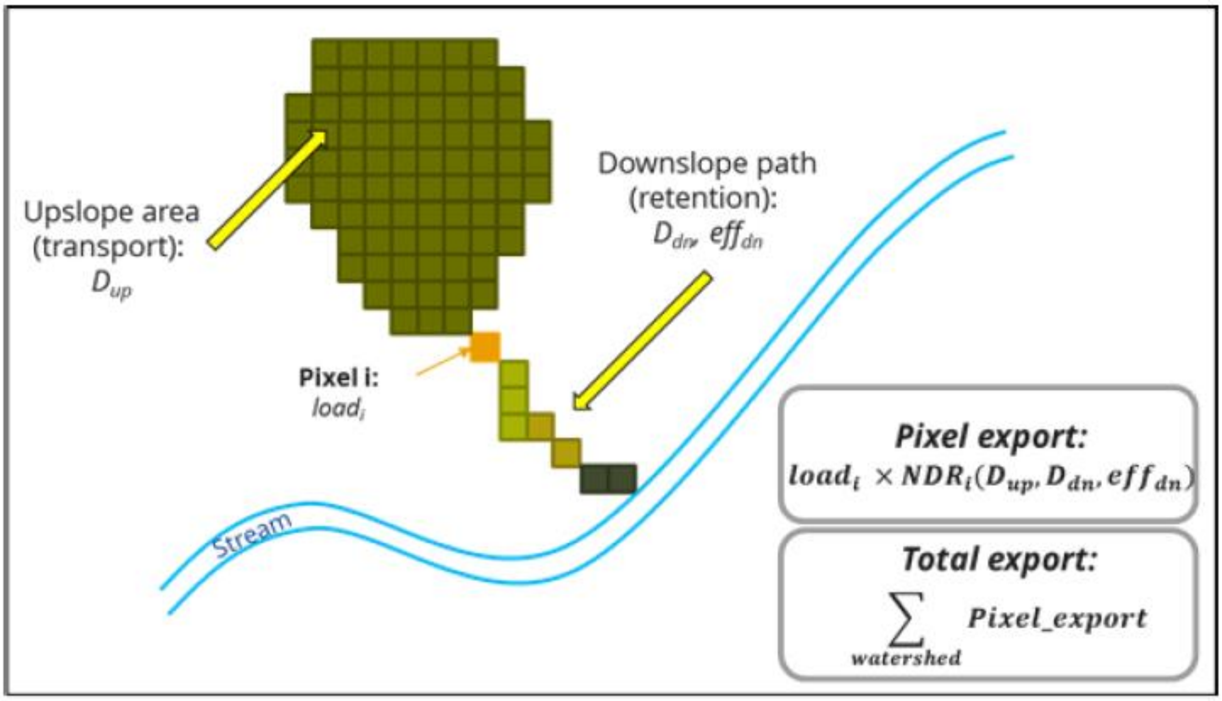

Fig. 2.1. Conceptual representation of the NDR model

(Source: Sharp *et al*., 2016)

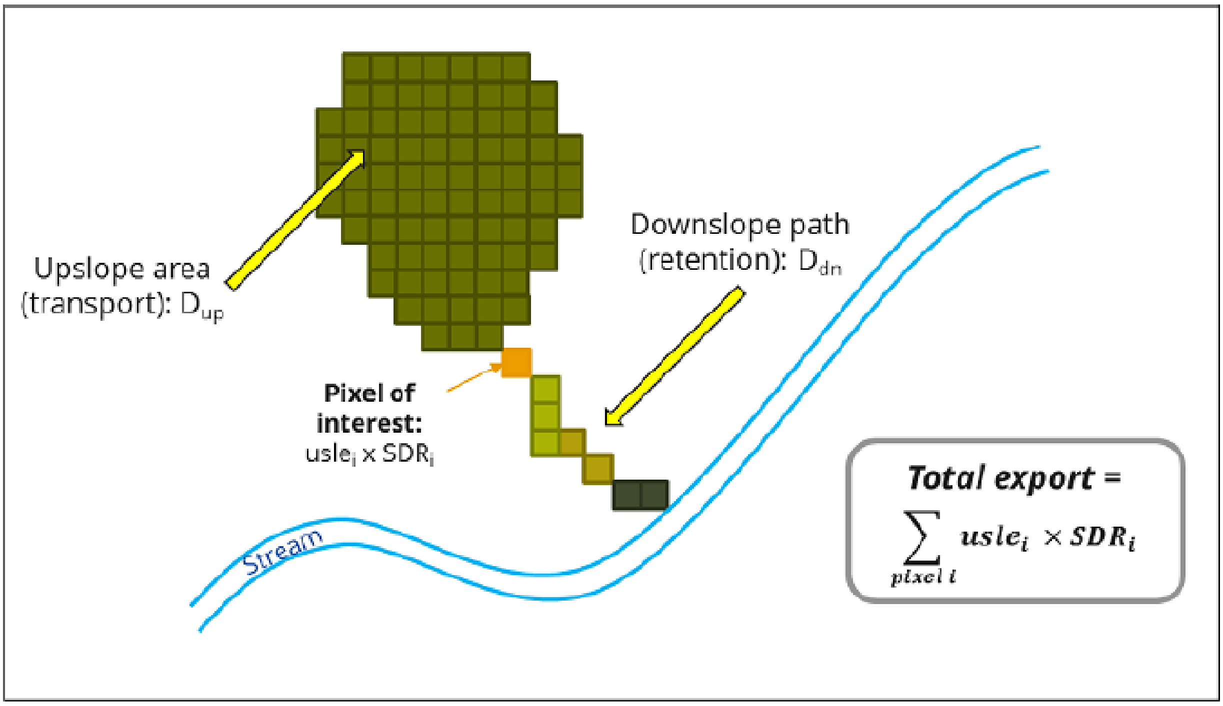

Fig. 2.2. Conceptual approach used in the SDR model

(Source: Sharp *et al*., 2016)

2.3.5.3 Seasonal water yield model

Understanding the effect of landscape management on seasonal water flow is of critical importance to watershed management. Environmental factors like climate, soil, vegetation, slope, and position along the flow path affect the contribution of a landscape to streamflow. Water flowing across the landscape is either evaporated, transpired, withdrawn by a well, or leaves the watershed as deep groundwater flow or streamflow. Two approaches are considered under water yield in an individual pixel. The first give credit to the net amount of water generated in a pixel to be equal to the incoming precipitation minus the losses to evapotranspiration in that pixel (Fig. 2.3). Actual evapotranspiration can be greater than precipitation in this scheme if the water is supplied to the site from upgradient. If that happens, the net generation in the watershed could be negative. Its limitation is that evaporated or withdrawn water along the flow path is not considered. Besides, it does not differentiate the water yield either as streamflow or from another source. The second approach gives credit to the water from a parcel that shows up as streamflow (Fig. 2.4). That is evaporated water is considered to be zero when generating flow for a parcel of land (Sharp *et al*., 2016).

The first approach of the seasonal water yield model emphasises the land-use and land-cover of a site since the focus is on net generation from that pixel or parcel of land (Fig. 2.4). The model accounts for the subsidy of water from upslope pixels but does not consider downgradient effects. It represents a potential to generate streamflow but not an actual generation of flow. The topographic position of a pixel is emphasised more in the second approach as that determines the potential for water generated on that pixel to be consumed before becoming streamflow (Fig. 2.4).

The generated water in the second approach represents the actual streamflow generated by a pixel. Since actual streamflow cannot be less than zero, this approach, unlike the first, will result in indices that are greater than or equal to zero. These concepts were used to develop a set of three indices, one for quick flow, one for recharge (which represents the ‘potential baseflow’), and one for actual baseflow. The baseflow was defined as the generation of streamflow with watershed residence times of months to years, while quick flow represents the generation of streamflow with watershed residence times of hours to days. Therefore, water yield is more of surface flow than accounted for sub-surface flow and deep percolation.

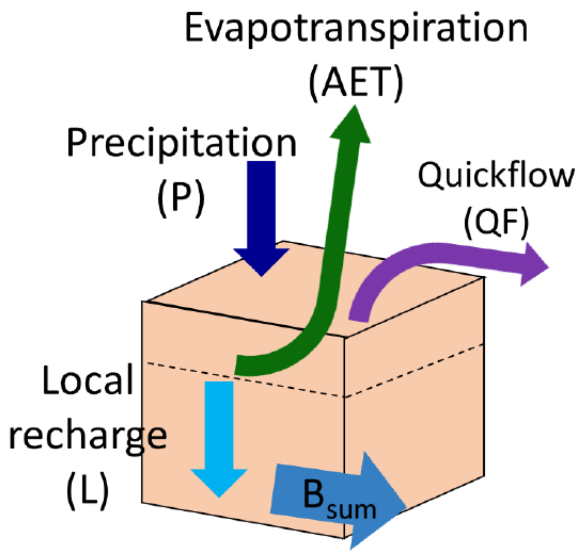

Fig. 2.3. Water balance at the pixel scale to compute the local recharge

(Source: Sharp *et al*., 2016)

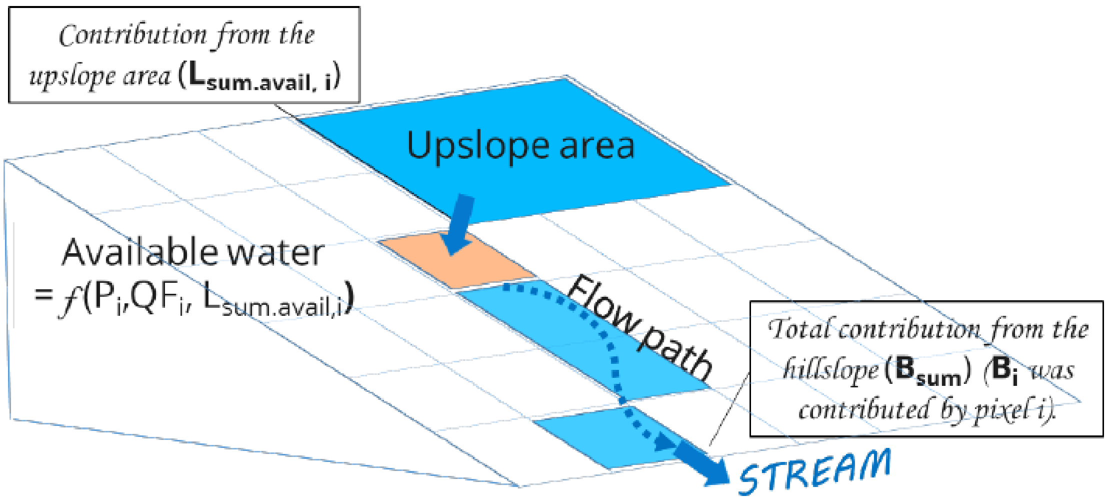

Fig. 2.4. Routing at the hillslope scale to compute actual evapotranspiration

Note: based on pixel's climate variables and the upslope contribution and baseflow (based on B: sub: 'sum', the flow actually reaching the stream)

(Source: Sharp *et al*., 2016).

2.1.7 Approach for a household survey

An informal interview has remained one of the effective methods to obtain information from targeted respondents before a survey questionnaire is designed. A checklist is another method from literature (Ikpa *et al*., 2009; Geist and Lambin, 2002) to know what information to concentrate on. Participatory Rural Approaches, namely: focus group discussions, semi-structured interviews and direct observations are methods for collecting qualitative data. A checklist is sometimes used to guide focused group discussions to obtain information from respondents. These informations are most at times the basis for questionnaires designed for further interviews (Dimobe *et al*., 2015; Damnyag *et al*., 2013). Both random and purposive sampling techniques are acceptable for climate and land-use change studies which could be driven by specific factors like age when assessing climate change. A respondent should be well knowledgeable and fully engaged in for example farming for 20 – 30 years to be able to give an accurate observation of climate impact on farming. The Statistical Package for Social Sciences (SPSSs), an IBM statistical software, is very useful in the analysis of data from the survey. Some analyses carried out are tests of normality, t-tests, ranking and Chi-square (Kruskal Wallis H) tests for validation of the significance of the association among data collected. Both logit and probit model of regression can be used on data to determine significant factors influencing decisions or conditions being assessed. Logit is mostly preferred to probit model since the logit model is more interpretable (Dimobe *et al*., 2015; Houessou *et al*., 2013; Long, 1997).

2.2 Theoretical Framework

The ensembling of both dynamical and statistical climate models in this study was based on the theory of statistical mechanics and the dynamical system theory. Statistical mechanics first reported by Jaynes (1957) combines physical laws on microscopic particles, statistical methods and probability theory to downscale atmospheric variables to a mean state of local relevance. Stochastic methods for downscaling is based on this theory because is able to capture errors of models, quantify uncertainties in predictions and ensemble simulations (Frankze *et al*., 2014). The limitation is that extremes conditions including atmospheric circulations (Shepherd, 2014) are not captured by stochastic methods under the statistical mechanics' theory which is accounted for in the dynamical system theory.

Dynamical system theory uses differential equations to represent complex systems. Small-scale processes are parameterized in dynamical models for even representation of the earth system (Dijkstra, 2016). Therefore, the combination of models from both theories in accessing future climate impact could complement the deficiencies in each of the theories thereby reducing model biases (Benjamin and Budescu, 2018; Baumberger *et al*., 2017; Frankze *et al*., 2014).

The Theory of Change was the bases of validating climate change from farmers' perception survey. The logic model and long-term outcomes elements of the theory based on the definition of Weiss (1995) applied in this study. The principle of how climate change is seen and why changes are being made by farmers to adapt to the impact of climate change. The theory of change has been used to investigate the social inclusion of resilience to climate change (Forsyth, 2018).

2.3 Literature Review

2.3.1 Climate change and water resources

Climate change is expected to result in erratic rainfall in the tropics (IPCC, 2007). Studies show that it has decreased rainfall, runoff and river flow in the Mediterranean area (López-Moreno *et al*., 2011; Milly *et al*., 2005). Previous studies on river basins show that climate change may impact ecosystem services delivery especially during dry conditions (Terrado *et al*., 2014). Hence, the application of future climate change prediction (rainfall and temperature) are essential to identify and determine the possible impacts on ecosystem services provision and regulation (Terrado *et al*., 2014; Bangash *et al*., 2013). The gap was the use of the same spatial resolution of different models or different spatial resolution of the same model in previous climate change impact studies. Boon and Ahenkan (2012) assessed the impact of climate change on livelihood in Sui Forest Reserve in Ghana and concluded that the principal livelihood sources affected by climate change impacts are agriculture, forest resources and water resources. Using different climate models at different spatial resolutions could reduce the uncertainty of climate projection and improve resilience through specific adaptation strategies.

Obuobie *et al*. (2012) analysed an ensemble of RCMs from Ghana Meteorological Agency (GMet) and reported that ECHAM4/CSIRO models jointly projected hotter and dryer climate conditions in 2020 and 2050 for the Volta and Pra basins in Ghana. The mean daily temperature in the White Volta and Pra basins are expected to increase by 0.6 and 0.5^{o}C, respectively, in 2020 relative to the baseline values from 1961 to 1990. There was also 1.9^{o}C increase projection for temperature in both basins for 2050. Precipitation was also projected to decrease in 2020 by 12.3 % and 17.8 % and in 2050 by 19.6 % and 25.9 % in the White Volta and Pra basins respectively. Currently, Ghana has more than 2000 m^3 of water available to a person (Amisigo *et al*., 2015). Similarly, the effect of these projections on the water is expected to worsen water stress conditions from 1,160 m^3/p/y to 529 m^3 by 2020 and 165 m^3 by 2050. Moreover, annual freshwater availability per capita may reduce to water scarcity (681 m^3 per capita per year) by 2020 and absolute scarcity (306 m^3/p/y) by 2050. Therefore, population growth and climate change threaten water availability in both 2020 and 2050. Amisigo *et al*. (2015) worked in the Pra basin of Ghana and projected −25.9 % and +60.9 % change in catchment runoff for Ghana dry and Ghana wet scenarios respectively whereas the global scenario simulations projected −12.2 % and −34.4 % for dry and wet conditions respectively for the period 2011 - 2050. These two studies used limited number of RCMs and all at spatial resolutions of about 50 km for their impact studies. There is the need to assess the impact of climate change with adequate climate data, using regional climate models to get more consistent scenarios at high resolutions to support decision making in the south-western coastal basins of Ghana.

2.3.2 Land use competition for water supply under changing climate

Boulton *et al*. (2014), for example, assessed the case of European settlements in Australia and found out that changes to land use and land cover in the area affected the ecological health of Australian freshwater ecosystems. Some of the impact of LULC change on freshwater ecosystems are changes in environmental flow and limited water supply for human consumption (Davis *et al*., 2015). Environmental flows are defined as “the quantity, quality and timing of water flow required to sustain freshwater and estuarine ecosystems including human livelihoods and well-being that depend on these ecosystems” (IRF, 2018). Knowledge on how water is distributed and the spatial arrangements of a possible modification to the pattern of water abstraction is necessary to receive enough flow in streams and rivers on a preferential basis. Timing as a service delivery determines how beneficial modest flow at the right time of the year affects ecological outcomes and protect individual species until when there is water stress (Bond *et al*., 2008). Conservation policies that support freshwater protection sometimes exclude social, economic and cultural values of water which are very essential to indigenous people. Therefore, indigenous knowledge needs to be incorporated in natural resources decision-making for a better understanding of the process to improve water management (Dale *et al.,* 2013; Ryder *et al*., 2010; Fazey *et al*., 2006). Changes in land-use also impact significantly on groundwater recharge (Crosbie *et al*., 2010). Land clearing for agriculture production diverts freshwater meant for immediate human needs. Meeting human needs, therefore, interfere with natural flows. An urgent response in land change management is required to avoid the multiple losses of ecosystem services (Davis *et al*., 2015).

In China, for example, Zhang *et al*. (2016) conducted research on the impact of land use and climate changes on hydrological ecosystem services (water supply) in the dryland area of the middle reaches of the Yellow River to identify innovative strategies for water-efficient land management to improve water quantity for secure water supply. The study showed that vegetation restoration efforts such as trees and grass planting are effective in controlling soil erosion on the Loess Plateau. Changes in land cover/use modify physical properties of the soil. However, the effect of vegetation restoration (land-use change) on hydraulic properties remains to be researched. He used streamflow, precipitation, potential evapotranspiration and climatic water balance as parameters for the investigation. Knowledge about base flow formation on catchment-scale was found to be inadequate and therefore needs further improvement. Ecosystem services including hydrological service in a water-scarce zone/environment, need to be balanced with minimum tradeoffs (Zhang *et al*., 2016). Soil erosion is a major factor of soil nutrient depletion via runoff leading to water quality degradation (Kusimi *et al*., 2015). Studies have shown that soil erosion has degraded about 38 % of the global agricultural land with high records of 45 %, 65 % and 74 % in South America, Africa and Central America respectively (Arekhi, 2008). Sedimentation impacts are mostly felt in reservoirs/dams where their water-holding capacities are reduced (Akuffo, 2003).

In Africa, carbon sequestration could be improved through the conservation of forest and its resource. However, human activities such as agricultural expansion and tree harvesting constrain this mitigation potential in Africa (Dimobe *et al*., 2015). Therefore, understanding the extent of vegetation cover change is important to support policies that focus on stopping or reducing the rate of deforestation. Bai *et al*. (2008) define land degradation as the long-term loss of ecosystem function and productivity caused by disturbances from which the land cannot recover unaided and it occurs slowly with cumulative long-lasting impacts (Muchena, 2008) on humans. Land use/cover changes have profound impacts on carbon storage, water cycle regulation and other ecosystem functions (MEA, 2005). It is therefore important to understand how these changes occur, and the underlying driving factors influencing the change. The global environment including climate from the local to the global scale and its biodiversity are affected by changes in LULC (Sala *et al*., 2000; Lambin, 1997) thereby resulting in a decline of ecosystem services and function as well as land degradation (Vitousek *et al*., 2008). Therefore, monitoring LULC change is relevant to sustainable landscape and environmental management. A regular map update is recommended for West Africa to aid the estimation of LULC change (Dimobe *et al*., 2015).

2.3.2.1 The role of a buffer in hydrological ecosystem service delivery

An integral part of water management at the basin scale is the maintenance of riparian buffer strips in the landscapes (Enanga *et al*., 2011; Sweeney and Blaine, 2007; Decker, 2003). However, the increased food production to meet the increasing human population makes it difficult to control the buffer zone encroachment, especially in peri-urban farming communities. Riparian buffer strips regulate nutrients from agriculture lands that runoff into streams (Kibichii *et al*., 2007). The size of a riparian buffer has been found to influence its capacity to control the intrusion of harmful chemicals from adjacent land uses into streams (Enanga *et al*., 2011; Cooper *et al*., 1995). There is, therefore, the need to determine or estimate the effective buffer strips for each watershed or basin since land-use activities and soil types vary across nations. It will also enrich policy with scientific evidence. Land use, therefore, impacts water resources both at the level of change in vegetation and the activities of humans in the soil.

2.3.2.2 Impact of land use/cover change

The widespread catchment erosion and subsequent river sedimentation, water shortage, pollution, and other physicochemical deterioration resulting from human activities impact both immediate and distant areas affected by deforestation. Ellis and Pontius (2007) reported that the impacts of land-use changes on river catchments could be very devastating, and could result in loss of biodiversity through habitat loss, habitat fragmentation, and edge effect irrespective of the causes of land-use change. Soil erosion negatively affects soil fertility. This makes the regular monitoring of land-use change and sediments yield in a catchment or basin key to the formulation of policies and strategies to protect hydrological ecosystem services. The effect of land-use change on freshwater ecosystem services in Ghana is not different from other nations (Martin-Ortega *et al*., 2015; Ayivor and Gordon, 2012).

2.3.3 Modelling water availability and quality under climate change

Ecosystem service valuation has been a subject of academic interest for a while. Currently, its evaluation informs policymaking at all levels (Daily *et al*., 2009; Ruhl *et al*., 2007). Various aspects of the service such as ecology, economics, and geography have been integrated into software as decision support tools for management and conservation (Vigerstol and Aukema, 2011). Ecosystem mapping tools support decision making by the provision of easy to interpret results and findings that can be easily related with in terms of value. Bagstad *et al*. (2013b) reported that landscape-scale urban growth scenarios were more closely aligned for the two models (InVEST and ARIES) whereas site-scale mesquite management scenarios were more divergent. They recommended follow-up studies, which could test the models in different geographic contexts to improve understanding of the strengths and weaknesses of the models and enhance their readiness as a day-to-day resource management-supporting tool.

Land use and land cover changes and their management affect both water flow and erosion regulation at the basin scale (Schmalz *et al*., 2016; Frank *et al*., 2014). A gap identified by Schmalz *et al.* (2016) was the relationship of land-use change impacts on human well-being which occurs on different spatial and temporal scales, which need to be understood when new management strategies are defined. Their study was a reasonable approach to provide spatiotemporal patterns of different river basins which can be used by stakeholders for further discussion and planning of sustainable land management. Kasei (2009) used the WaSiM-ETH (Water Balance Simulation model–ETH) hydrological model in the White Volta basin with Pwalugu as north of basin and Bui as south of basin. The findings showed that temperature and rainfall were projected to increase by a mean value of 1.2^{o}C and about 15 % respectively with the regional model MM5 (Meteorological Model version 5). However, the IPCC Scenarios A1B and B1 (Fenech *et al*., 2007) simulated in WaSiM by

German Regional Climate model (REMO) projected temperature to increase by 1ºC and 3 % – 6 % decrease in precipitation. The study was for the period 2001-2050 compared to 1961-2000 over the Volta basin. This reduced projected total mean discharge by 5 %.

The demand of water-dependent sectors in Ghana showed that the river basins across the nation in their current state were not capable of meeting the demands for agriculture, domestic and industrial, and hydropower generation (Amisigo *et al*., 2015). Calibration/validation of models is normally difficult in many SSA countries due to the lack of both quality climate data and runoff data (Sharp *et al*., 2016). Data for basin monitoring are very essential in this current advancement in spatial research and predictions.

2.3.5 Overview of Ghana and her watersheds and/or basins

Ghana is located in West Africa between latitude 4.67 to 11.23ºN and longitude 3.38ºW and 1.26ºE with a total land area of 238,533 km^2 (Fig. 2.1). The Gross Domestic Product (GDP) of the country is currently based on service and industry although agriculture employs the highest population of the labour force (Bessah and Addo, 2013). The country is covered by 27 basins (Fig. 2.1) grouped into three major surface water flows or resources, namely; the Volta river system, the Southwestern river system and the Coastal river system (GoG, 2007; AQUASTAT Survey, 2005). The total renewable water flows in Ghana is 53.2 trillion m^3/y. About 57 % of the renewable water resources are internal while 43 % are contributions from outside the country (Margat, 2001). The Volta river system, Southwestern river system and Coastal river system covers 70 %, 22 % and 8 % of land surface respectively (WRC, 2012).

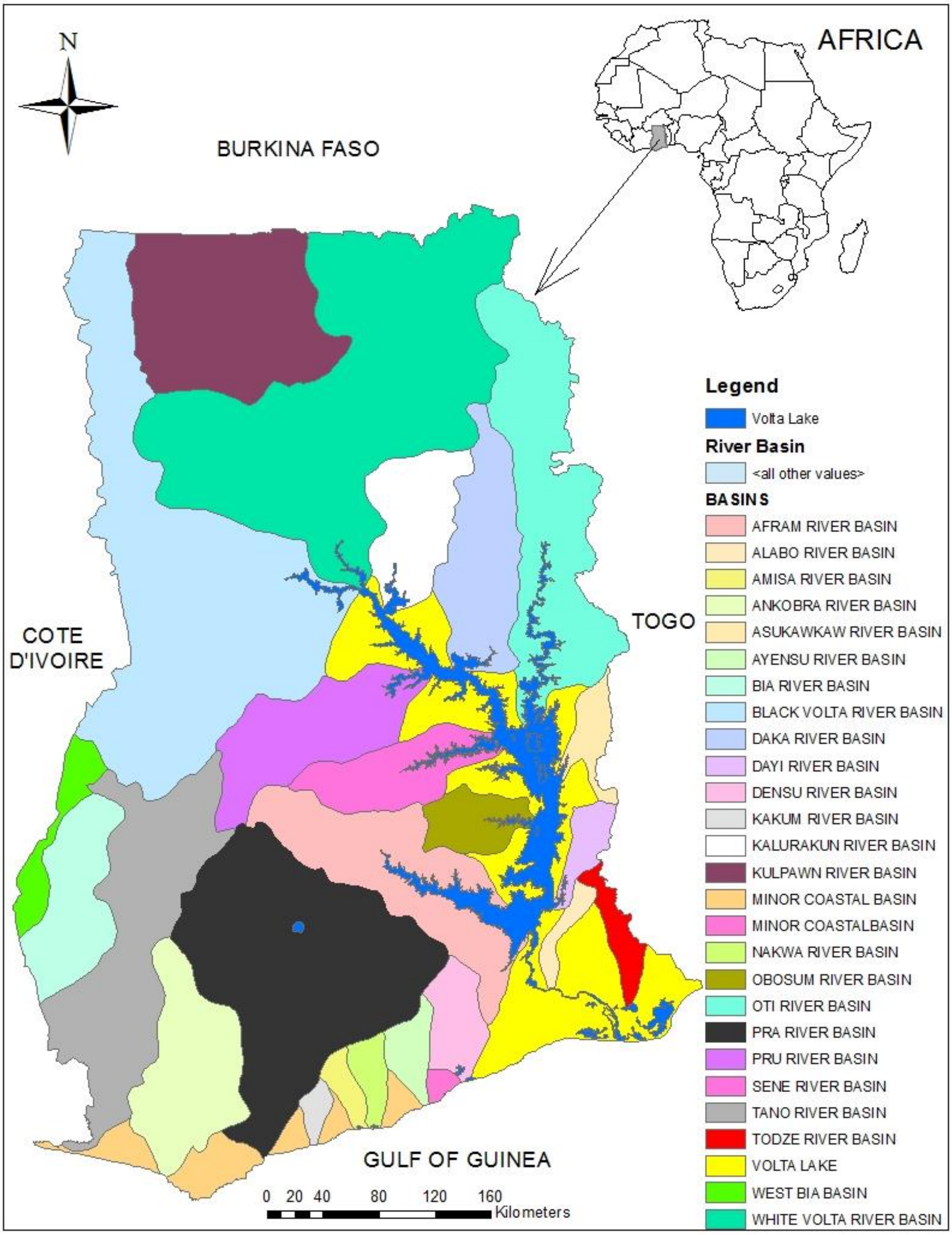

Fig. 2.5. River basins in Ghana

(Source: digital version of basin delineation prepared from the Geodatabase of the Department of Geological Survey, Ghana)

CHAPTER THREE

METHODOLOGY

3.1 Study area

3.1.1 Location and area

The Pra River Basin is located between latitudes 4°58' N and 7°11' N and longitudes 0°25' W and 2°13' W, covering an area of 23,321 km^2 crossing four regions in Ghana, namely; Ashanti, Eastern, Central and Western (Fig. 3.1). It is located south to the Volta River Basin in Ghana. The basin has the densest population in Ghana with more than 1300 towns located in it (WRC, 2012). Kumasi, the capital of the Ashanti region is the main place most of the migrants from Northern Ghana relocate to because of its position (central) to the southern part of Ghana. The mineral deposits spread across the basin has attracted both large scale and small-scale mining companies and activities. Majority of the small-scale mining, locally known as "*galamsey*" are operating illegally and has attracted migrants from all over the nation and from neighbouring nations into the area.

3.1.2 Climate

Pra River Basin experience two rainfall seasons (bi-modal: major and minor) annually under the wet semi-equatorial climatic belt. The major rainfall is normally from March to July and the minor starts in September and ends in October (Dickson and Benneh, 1995). The long dry season over the basin is between November and March. The basin is mainly under the semi-deciduous agro-ecological zone and therefore benefits from the moist south-west monsoon (Fig. 3.2). Annual rainfall amount ranges between 1250 and 2000 mm and with a relative humidity between 60 % and 95 % (Akrasi and Ansa-Asare, 2008). The annual mean minimum and maximum temperatures are 21°C and 32°C respectively.

3.1.3 Vegetation

The Pra Basin is habitat to most of the valuable timbers trees in Ghana within its moist-semi deciduous forest (Fig. 3.2). The climate is suitable for rapid vegetation development especially the bi-modal rainfall pattern that ensures moist in the soil in most part of the year. The mean height of timber trees ranges from 35 - 45 m (Dickson and Benneh, 1995). Most of Ghana's valuable timber trees like African mahogany (*Khaya ivorensis*), Ceiba (*Ceiba pentandra*) and Emeri (*Terminalia ivorensis*) can be found in the basin. The vegetation comprises of climbers, shrubs/bushes, lianas and trees which protect the soil and provide the service of erosion control

However, in the dry season, certain tree species shed their leaves during the long dry spell (Kusimi *et al*., 2015; WRC, 2012; Dickson and Benneh, 1995). Land use activities within the basin are very intense. Only a little of the original forest remains in the basin due to the rapid expansion of cocoa and cash crops industries (Kusimi *et al*., 2015; Dickson and Benneh, 1995). The basin contains most of the large cocoa growing areas in the Eastern, Ashanti, and Central Regions. Cocoa followed by oil palm are the major tree crops cultivated in the basin. Commercialised farming is gradually growing in the area and is currently the leading producer of tuber crops in Ghana (Kusimi *et al*., 2015; Nutsukpo *et al*., 2013).

3.1.4 Hydrology

The mean annual discharge rate of the Pra River was 214 m^3s^{-1} (Akrasi and Ansa-Asare, 2008) and flows to the Gulf of Guinea at Shama town in Western Region. Pra River Basin has the largest area coverage within the South Western drainage in the nation (Kusimi *et al*., 2015). Three regional capitals namely; Kumasi in the Ashanti region, Cape Coast in the Central region and Sekondi-Takoradi in the Western region (Fig. 3.1) source their municipal water from the basin for both domestic and commercial purposes (WRC, 2012).

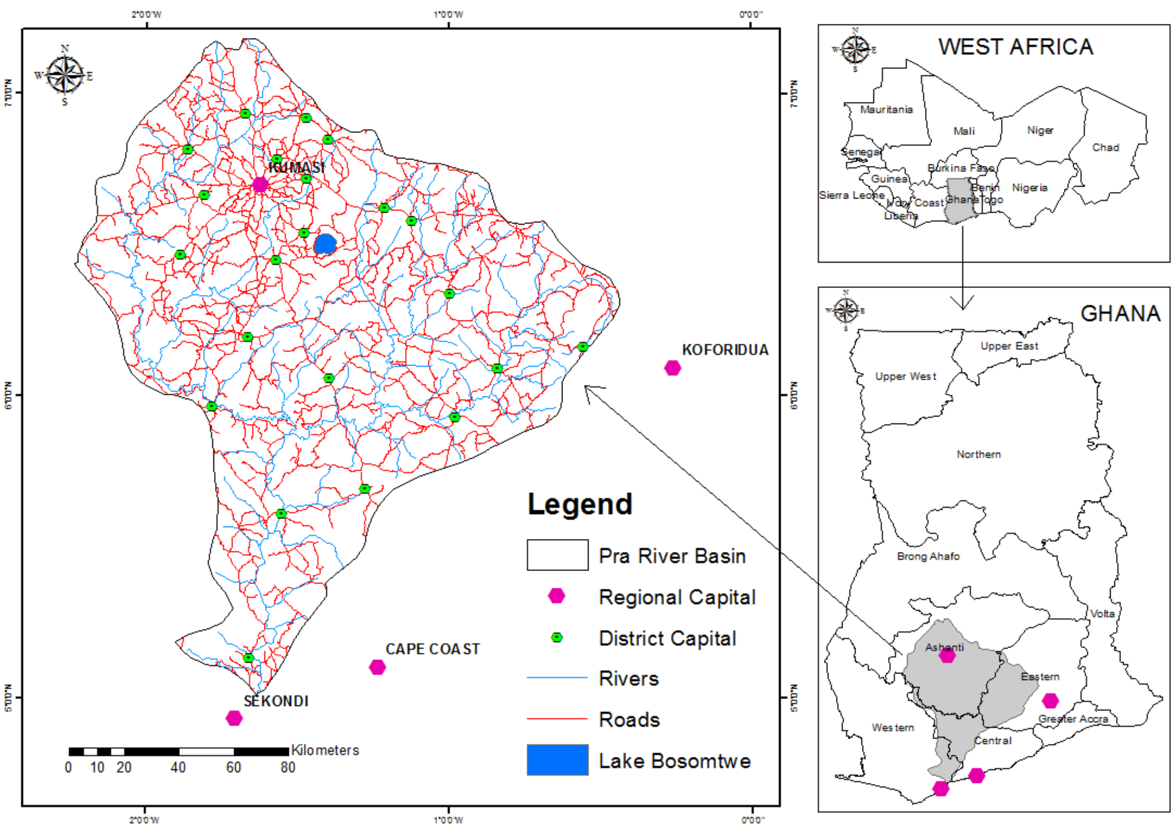

Fig. 3.1. A detailed map of the Pra River Basin

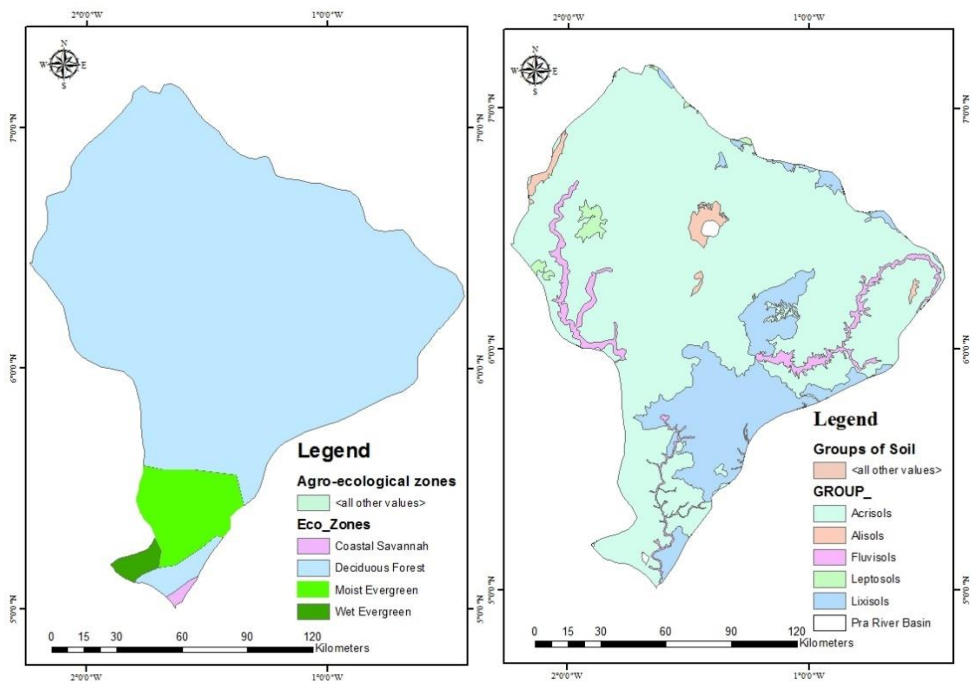

Fig. 3.2. (a) Agro-ecological map and (b) soil map of the Pra River Basin

3.2 Climate variability and change analysis

Variability and change were assessed within and between observed and future respectively.

3.2.1 Datasets for climate analysis

The dataset were the gauge stations and the model output temperature and rainfall data.

3.2.1.1 Meteorological data

Historical climate data from seven climate stations with most recent operation date in 1972 (Akim Oda) and earliest operation date in 1912 (Kibi) for the Pra River basin were acquired from the Ghana Meteorological Agency (GMet) (Fig. 3.3). The parameters considered were temperature (maximum, minimum and mean) and rainfall. Solar radiation, wind speed and relative humidity for the two synoptic stations (Akim Oda and Kumasi) were also acquired for the determination of evapotranspiration for the basin. The data period was between the years of 1975 and 2010. A thirty years' minimum reference period of 1980 – 2010 was used to evaluate the performance of the climate models (Arguez et al., 2012; Fenech et al., 2007) due to acceptable missing data range for rainfall and temperature. Climate stations that had missing data in rainfall for the reference period were Atieku (2.5 %), Konongo (0.8 %), Dunkwa (1.1 %), Kibi (14.2 %) and Twifo Praso (4.7 %). Kumasi and Akim Oda had no missing data on rainfall. Kumasi, Konongo and Akim Oda and Dunkwa had less than 5 % missing data for mean temperature whereas Twifo Praso, Kibi and Atieku stations were between 15 – 50 %. The historical analysis for the basin was done for the period 1981 – 2010 and projection was limited to near future from 2020 – 2049 (30 years as required in climate analysis).

3.2.1.2 Assessed Global Circulation Models and Regional Climate Models

Global circulation models outputs for the assessment of global climate change impact in the basin was done with the 43 GCMs of the fifth Assessment Report, AR5 (IPCC, 2014) from the climate database of the University of Prince Edward Island (UPEI) (UPEI, 2017). Four regional climate models (RCMs) were used in this study (Table 3.1). The two RCMs from the Rossby Centre Regional Atmospheric model (RCA4) from the Coordinated Regional Climate Downscaling Experiment (CORDEX) project at 44 km spatial resolution for this study were; the second generation Canadian Earth System Model (CanESM2) and the mid-resolution model Climate Model (CM5A-MR) (full description in Table 3.1).

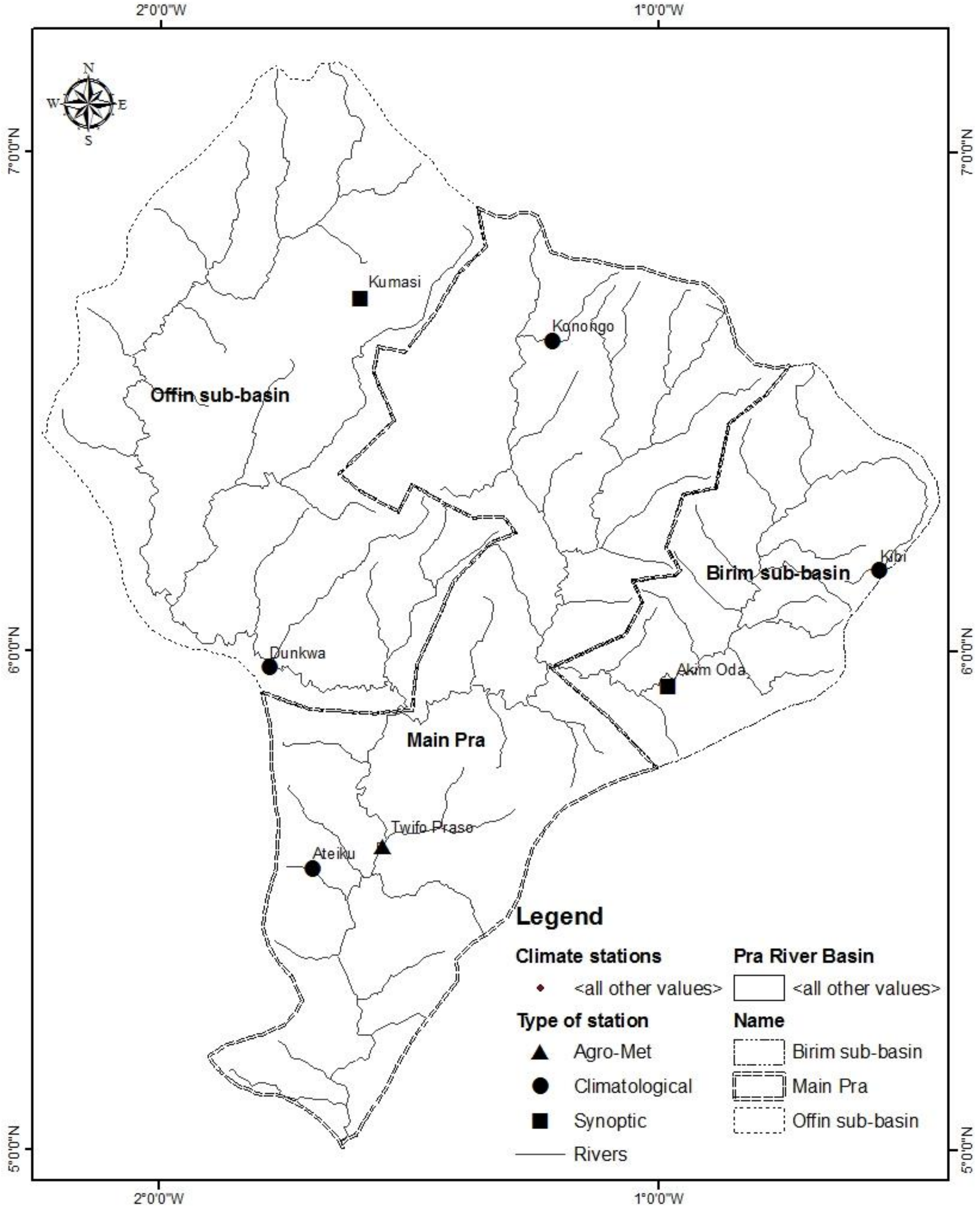

Fig. 3.3. Map of study area showing climate stations

Table 3.1. Description of the four regional climate models used

Model acronym	Model Name	Originating group	Country	Adopted Acronym	RCM	Resolution
GFDL-ESM2M	Second Generation Earth System Model	NOAA Geophysical Fluid Dynamics Laboratory	USA	GFDL	WRF	12 km
HadGEM2-ES	Second Generation Earth System Model	Hadley Centre for Climate Prediction and Research	UK	Hadgem	WRF	12 km
IPSL-CM5A-MR	Mid-resolution model (1.25° x 2.5°) Earth System Model	Institut Pierre Simon Laplace	France	IPSL	SMHI-RCA4	44 km
CCCma-CanESM2	Second Generation Canadian Earth System Model	Canadian Centre for Climate Modeling and Analysis	Canada	CanESM	SMHI-RCA4	44 km

The mean temperature (tas) and rainfall (pr) of the selected models for both historical simulation and projections were downloaded from the CORDEX website (IS-ENES, 2017). The Representative Concentration Pathways (RCP) 4.5 simulations from 2006 – 2010 was added to the historical simulation of the CORDEX RCMs dataset to complete the 30-year period from 1981 – 2010 (Dosio and Panitz, 2016).

The Weather Research and Forecasting (WRF) RCM at 12 km spatial resolution generated the two remaining regional climate models. They were the General Fluid Dynamics Laboratory Earth System Model (GFDL-ESM2M) and the Hadley Global Environment Model (HadGEM2-ES) (Table 3.1). Both were obtained from the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL) geoportal for the same parameters (mean temperature [tas] and rainfall [pr]). The historical simulation of the WRF data was from 1980 – 2009 and the future period was 2020 – 2049 (Heinzeller *et al*., 2016a, 2016b, 2016c, 2016d). The links to data sources of the models are presented in Appendix I. Due to the focus of this study, only the near future (2020 -2049) data were acquired. All analysis of the WRF model in the study were based on the reference period 1980 – 2009 for all stations. The historical simulation also ended in 2005, therefore 2006 – 2009 RCP4.5 projections were included (Dosio and Panitz, 2016).

The Representative Concentration Pathways (RCP) 4.5. was chosen for this study because it represents the mitigation option of the emission scenarios which United Nation Framework Convention on Climate Change (UNFCCC) through Kyoto protocol and Paris agreement are aiming to attain globally (Muthee *et al*., 2018; Lomborg, 2016 van Vuuren *et al*., 2011 Cubasch *et al*., 2013; Clarke *et al*., 2007).). The Sahel and tropical West Africa were also found to be hotspots of climate change under both RCP4.5 and RCP8.5 pathways projected to occur by late 2030s to early 2040s (Mora *et al*., 2013; Diffenbaugh and Giorgi, 2012).

The model names GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-MR, and CCCma-CanESM2 are referred to hereafter as GFDL, Hadgem, IPSL, and CanESM respectively.

3.2.2 Instruments for climate modelling

The statistical downscaling model was the main instruments used for the climate analysis in modelling the local climate of the basin.

3.2.2.1 Statistical downscaling model

The Statistical Downscaling Model – Decision Centric (SDSM-DC) version 5.2 developed by Wilby and Dawson in December 2015 with a spatial resolution of 2 m (Wilby *et al*., 2014; Wilby and Dawson, 2013; Wilby *et al*., 2002) was adopted for comparative climate projections. This was to reduce the uncertainty levels of future climate and increase the accuracy of risk and vulnerability assessment in the study area. The predictors for calibration and validation of the SDSM-DC were also acquired from the same source. The SDSM-DC 5.2 and predictor variables were downloaded freely from Loughborough University website hosting SDSM. Observed data from 1981 - 2010 obtained from Ghana Meteorological Agency (GMet) were used for calibration and validation of the models at the seven climate stations. Each climate variable was prepared in text file format for each station to fit into SDSM. Factors for the generation of future climate in SDSM were acquired from the ensemble mean of the 43 GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) on the climate database of the University of Prince Edward Island (UPEI, 2017). Mean of ensemble CMIP5 values for 2020s (2011 – 2040) and 2050s (2041 – 2070) were used since the near future period of this study was from 2020 – 2049. The model downscale climate variable of a location or station from the large atmospheric variables by combining stochastic weather generator and multiple linear regression (Wilby *et al*., 2002). SDSM-DC hereinafter was referred to as SDSM.

3.2.3 Climate data analysis

The analyses of the rainfall and mean temperature outputs of the five climate models namely CanESM, IPSL, GFDL, Hadgem and SDSM were carried out following the steps presented in Fig. 3.4. Amelia package in R software was used to fill gaps in data for the reference period 1981–2010 to enhance the performance assessment of the models at equal conditions of station data (Arguez *et al*., 2012). Rainfall data were subjected to quality control in RClimdex after filling the gaps to identify outliers and erroneous data such as negative rainfall values which were then removed (Aguilar *et al.*, 2009). The R software (Packages: ncdf.tools, ncdf and raster) was further used to extract RCMs daily rainfall using the geographical coordinates of the seven climate stations.

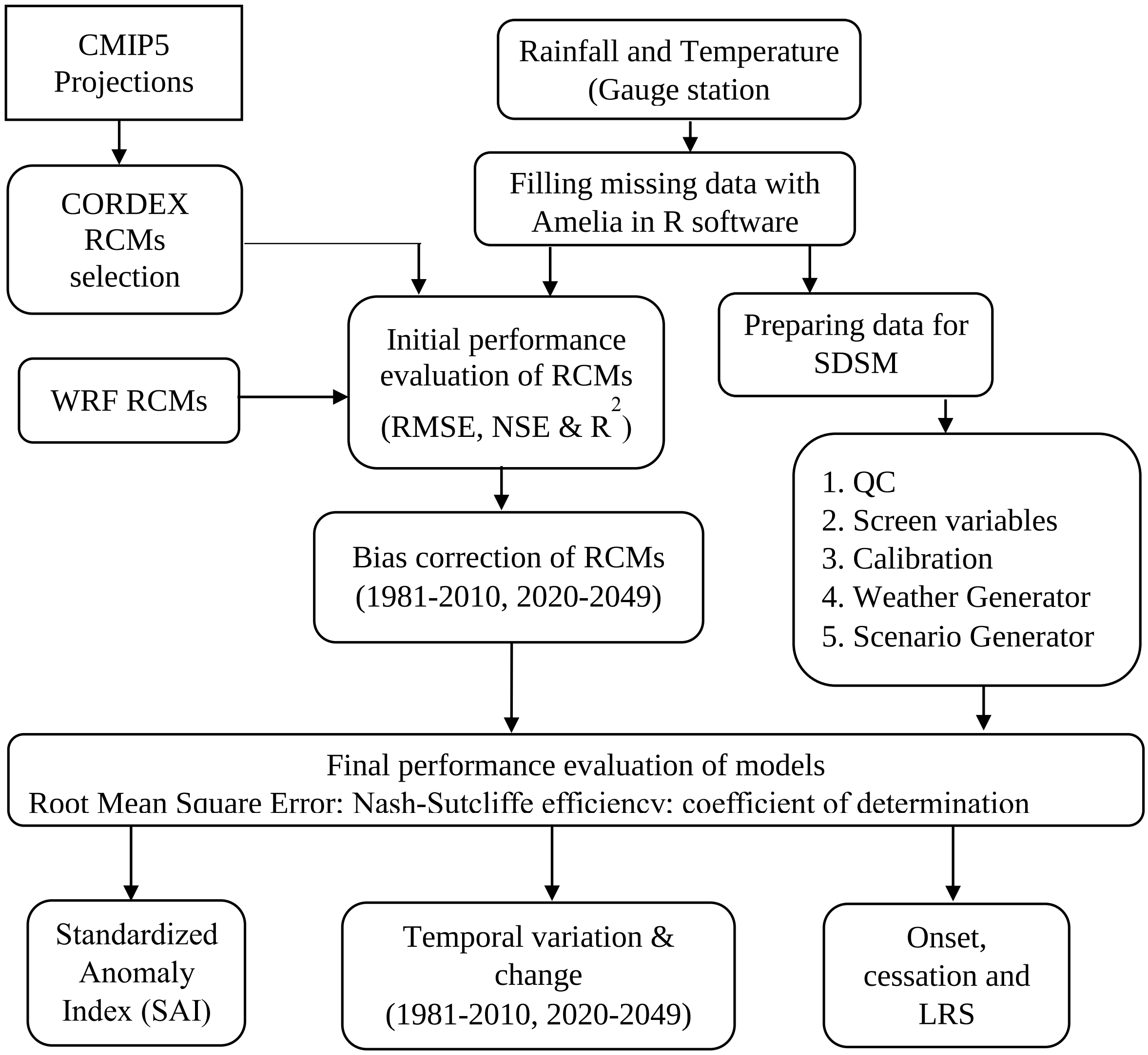

Fig. 3.4. Climate variation and change analysis

3.2.3.1 GCMs projections over the basin

An area assessment of temperature and rainfall from CMIP5 models in the Fifth Assessment Report (AR5) over the Pra River Basin was done by creating a rectangular boundary on the UPEI climate database. The boundary covered an area of 47, 192 km^2 (almost twice the actual area of Pra River Basin because this was a rectangular fit box) between latitude 4.94ºN and 7.20ºN and longitude 0.95ºW and 2.65ºW. The National Center for Environmental Prediction (NCEP) reanalysis data for the base period 1981 – 2010 was used to determine the change in the basin from 2011 – 2100 under global climate change from the AR5 43 GCMs. The method of validation of models using the 1xStdev and 2xStdev as zone of acceptable models (Fenech, 2016; Fenech *et al.*, 2007) was employed to determine GCMs with good skill of historical simulation of temperature and rainfall as the validated projection for the basin. Two of the GCMs with RCMs available on CORDEX earlier described (Table 3.1) were acquired from the African domain for this study.

3.2.3.2 Bias correction of RCMs

The bias-correction of simulated precipitation was performed using the linear scaling method and double-quantile mapping while temperature was bias-corrected using only variance scaling method (Teutschbein and Seibert, 2012; Leander *et al.*, 2008; Lenderink *et al.*, 2007). The linear scaling method aims to perfectly match the monthly mean of corrected values with that of observed ones (Teutschbein and Seibert, 2012). However, the variance in the data is not corrected by the linear scaling method. An effective approach to correct both the mean and the variance of temperature is the variance scaling method. The variance scaling method adjusts the RCM control run to have the same mean and standard deviation (i.e., variance) as the observed time series. The quantile-quantile or double quantile mapping ensures the reproduction of Cumulative Distribution Functions (CDFs) if the RCM period and the observation period are identical (Bárdossy and Pegram, 2011). The Q-Q transformation which creates identical distribution provides a purely statistical correction of the RCM results, independent of the weather type based on the test distribution created (Bogner *et al.*, 2012). It has been found that empirical estimation of CDFs and inverse CDFs from data, helps to illustrate the capacity of the algorithm using a quantile-quantile plot, which is the scatterplot between empirical quantiles of observed and modelled data (Ringard *et al*., 2017; Cannon *et al*., 2015; Sun *et al*., 2011). Since bias-correction was not an objective for this study, only RCMs output that was not within acceptable performances under the time-series-based metric were bias-corrected for the purpose of producing an ensemble climate output for the basin.

3.2.3.3 Calibration of rainfall and mean temperature in SDSM

The best predictors selected for rainfall calibration were direct shortwave radiation, surface lifted index, vorticity near the surface, vorticity at 850 hPa and vorticity at 500 hPa, surface divergence, precipitable water, total precipitation and relative humidity at 850 hPa and 500 hPa and near-surface relative humidity. Each station was calibrated with a minimum of four of the listed predictors at 95 % confidence level. Rainfall and temperature were calibrated as conditional and unconditional models respectively. At the screening stage of the variables for calibration, correlation at $p < 0.05$, followed by scatter plot was used at first and second stage to select the minimum number of atmospheric variables from NCEP. The predictors that best correlated with mean temperature were surface lifted index, mean sea level pressure, geopotential height at 850 hPa, potential temperature, relative humidity at 500 hPa height, near-surface specific humidity and mean temperature at 2 m. The simulated historical data from 1981 – 2010 from the model was used in measuring its capacity or skill to capture rainfall and mean temperature in the basin.

3.2.3.4 Performance evaluation of climate models

The performance evaluation of models is based on their abilities to reproduce precipitation and temperature of the study area. The performance was evaluated by comparing the rainfall and temperature of the models (bias-corrected or not) with observation datasets using the frequency-based indices and time-series-based metrics. Coefficient of determination, Nash-Sutcliffe efficiency and Root Mean Square Error were the time-series based metrics for the performance evaluation of the models, in addition, to mean, median and standard deviation frequency-based indices (Moriasi *et al*., 2007; Klein Tank and Können, 2003).

3.2.3.5 Standardised Anomaly Index (SAI)

Standardised Anomaly Index (SAI) was used to investigate annual rainfall anomalies. The SAI of rainfall was computed to determine the inter-annual variability of rainfall of both the baseline data and the projected rainfall data (Hadgu *et al*., 2013). The index is a descriptor of rainfall variability, and it indicates the deviation of a rainfall event from the mean value under consideration. It was further used to determine dry and wet years for both the baseline and projected data. Positive and negative values of SAI represent precipitation above average, and below-average respectively. The standard classification of rainfall anomaly index by van Rooy (1965) presented in Table 3.2 was used in this study. The Standardised Anomaly Index (SAI) by Hadgu *et al*. (2013) was calculated as:

$$SAI = \frac{(x-\mu)}{\sigma} \qquad (3.1)$$

Where;

x is the annual/seasonal precipitation;

μ is the long-term seasonal mean and

σ is its standard deviation

3.2.3.6 Onset, cessation and duration of rainfall

Daily observed and projected rainfall data were used to calculate the onset and cessation dates and duration of rainy season or length of the rainy season (LRS) in the study area. This was to predict to an extent what should be expected over the location by all who depend on rainfall for their activities. The length of the rainy season was the difference between the onset and cessation dates. The onset and cessation dates and LRS were determined by modifying the Walter-Olaniran method (Matthew *et al*., 2017) in Microsoft Excel 2016. Onset was calculated from the first month of effective rainfall where effective rainfall is defined by accumulated rainfall totals equal to or exceeding 50.8 mm (2 inches).

The formula is:

$$Onset\ Date\ (OD) = \frac{D(50.8-F)}{R} \qquad (3.2)$$

where;

D = number of days in the first month with effective rain.

F = accumulated rainfall total of the previous month;

R = total rainfall in the first month with effective rain.

Cessation dates were calculated with the same formula but in a backward format from December. The month that had accumulated rainfall totals, equal or exceeding 50.8 mm then becomes the end of the raining season (Matthew *et al*., 2017). The Walter-Olaniran method is said to perform poorly in the forest zone compared to the Savannah and Sudan-Sahel. According to Garbutt *et al*. (1981), the threshold value of rainfall amount required for a day to be counted as a rainy day in West Africa is 0.85 mm which might not be the same for the forest and coastal zones when considered separately. The modification involved a month being selected as onset when rainfall amount in the succeeding months is not less than 50.8 mm as developed by Walter-Olaniran method for the months in which onset is calculated (Matthew *et al*., 2017). The same modification was done for the determination of the cessation of rainfall.

Spatial analysis was done in ArcGIS 10.3. The ordinary kriging interpolation method using spherical semi-variogram was employed in generating the projected temperature and rate of change in rainfall and the graphical presentation of outputs in maps.

Table 3.2. Classification of rainfall anomaly index (RAI)

Rainfall anomaly index	**Class description**
≥ 3.00	Extremely wet
2.00 to 2.99	Very wet
1.00 to 1.99	Moderately wet
0.50 to 0.99	Slightly wet
0.49 to -0.49	Near Normal
-0.50 to -0.99	Slightly dry
-1.00 to -1.99	Moderately dry
-2.00 to -2.99	Very dry
≤ - 3.00	Extremely dry

(Source: van Rooy, 1965)

3.3 Trend of land use/cover changes

The analysis was done to address the second specific objective of this study.

3.3.1 Data sources for image processing

All data for image processing were secondary data except the ground control points.

3.3.1.1 Landsat Images

Satellite images that cover the Pra Basin for the years 1986, 2002 and 2018 were acquired freely from United States Geological Survey's (USGS) Global Visualisation Viewer (GLOVIS) based on cloud cover and quality. The spatial resolution of Landsat images used was 30 m with a cloud cover criterion of less than 10 %. Table 3.3 shows the dates and characteristics of the Landsat images used in this study. The three paths and rows of Landsat were taken at Datum WGS84 in Universal Transverse Mercator (UTM) zone 30 and were already geometrically corrected.

3.3.1.2 Ground truth and reference data

The 1986 images were classified with Google Earth historic image of the same year and the land cover shapefile database from the Geological Survey Department of Ghana. The globeland30 map for 2000 produced by the Chinese (global land cover map at a spatial resolution 30 m) was acquired (Chen *et al.*, 2014) and combined with the land cover shapefile database and Google Earth historic image of 2001-2003 to classify the 2002 Landsat combined images of the basin. The recently released 2016 European Space Agency (ESA) Climate Change Initiative (CCI) S2 prototype land cover map at 20 m for Africa was acquired from ESA and combined with 150 ground control points collected with handheld GPS and Google Earth image of 2018 to classify the 2018 Landsat images for the study (Braimoh and Vlek, 2005).

3.3.2 Image analysis for LULC change assessment

Image processing and analysis from the acquisition of the images from GLOVIS to the intensity analysis followed the chart in Fig. 3.5. Image pre-processing started with atmospheric corrections to merging under raster and extraction of the study area from image using clipper before the training of site for the classification in R software. Filtering and sieving were the main image post-processing carried out.

Table 3.3. Characteristics of Landsat images

Year	**Characteristics**	p193, r056	p194, r055	p194, r056
	Date Acquired	1986-12-22	1986-12-29	1986-12-29
1986	Spacecraft ID	Landsat 5	Landsat 5	Landsat 5
	Sensor ID	TM	TM	TM
	Date Acquired	2002-12-26	2004-02-06	2002-01-15
2002	Spacecraft ID	Landsat 7	Landsat 7	Landsat 7
	Sensor ID	ETM	ETM	ETM
	Date Acquired	2018-01-28	2018-01-29	2018-01-03
2018	Spacecraft ID	Landsat 8	Landsat 8	Landsat 8
	Sensor ID	OLI TIRS	OLI TIRS	OLI TIRS
Basin area coverage (%)		1.20 %	17.5 %	81.3 %

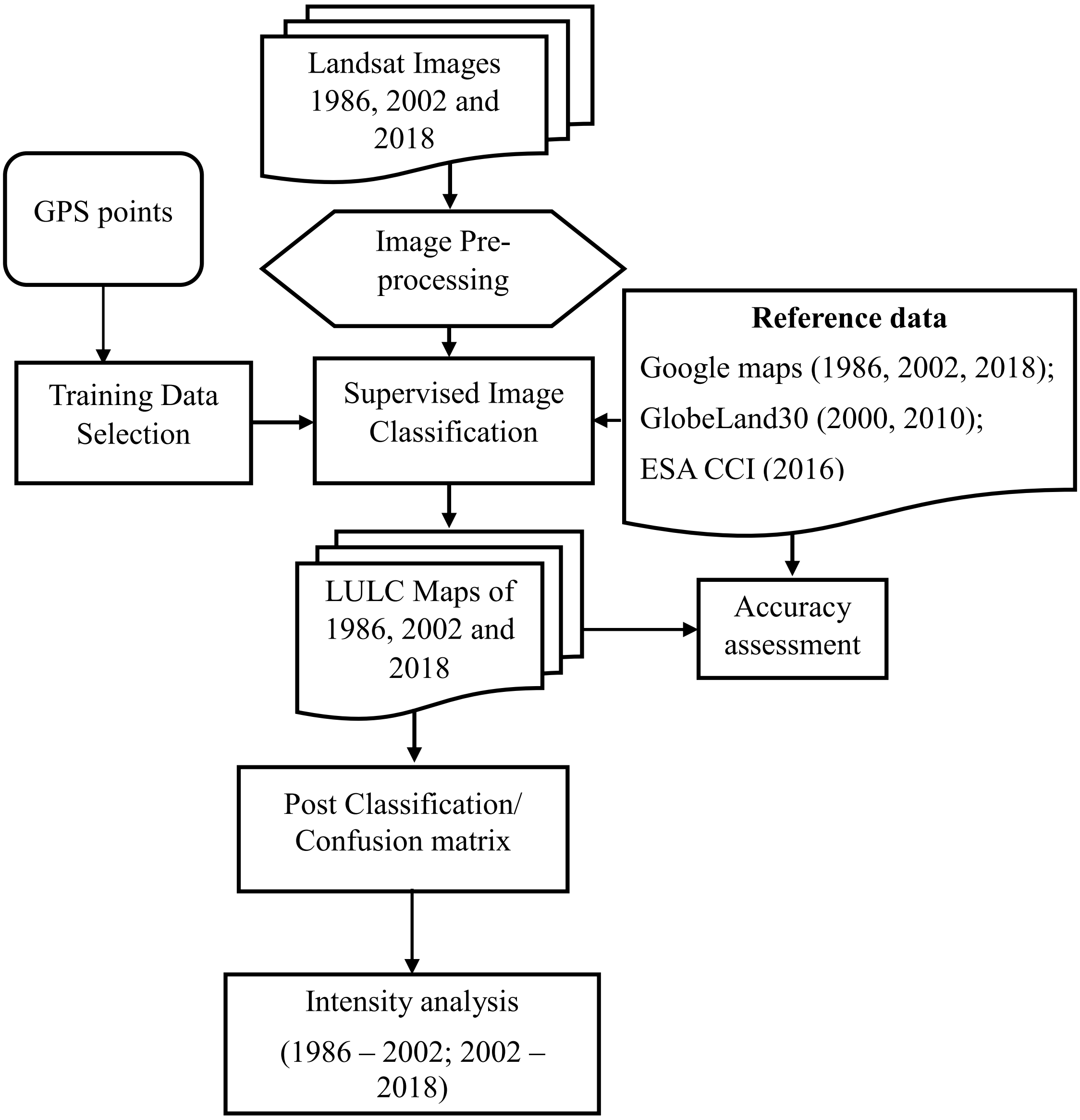

Fig. 3.5. Land-use change analysis

3.3.2.1 Landsat image classification and accuracy assessment

Atmospheric correction of all images for the purpose of the temporal analysis was done in QGIS 2.18 using the preprocessing tool under Semi-Automatic Classification Plugin (SCP). Bands combination 543 and 654 were used to differentiate the various land use classes for Landsat 5 & 7 and Landsat 8 satellite images respectively in QGIS (Ololade, 2012). Based on the pixel grouping and unsupervised classification records, the unit classification were Forest, Arable/Bare lands (cultivated, harvested areas, cleared fields, bare areas), Open vegetation (Grassland, shrubs, mixed vegetation), Water (water bodies) and Settlement (housings, roads, rural settlement, rock outcrops, etc) as detailed in Table 3.4 (Mahmoud, 2016).

Supervised classification was carried out in R software using the random forest algorithm. Training site for classification was created in QGIS from ground control points, reference maps and knowledge of the study area. Accuracy assessment indicating the level of correspondence of classified maps to reality were assessed based on the confusion matrix from the random forest algorithm which was set at a maximum of 100 samples for each class. The error matrix technique, which is one of the most widely used methods for accuracy assessment was adopted for this purpose (Forkuo and Frimpong, 2012; Braimoh and Vlek, 2005). Both the pixel-based and area-based error matrices were done (Olofsson *et al*., 2013). The error of commission (user's accuracy), errors of omission (producer's accuracy) and overall accuracy were determined.

3.3.2.2 Interval, categorical and transition intensity analysis

The intensity of change at each of the three levels was assessed with the intensity analysis software macros in Microsoft Excel 2016. The post-classification confusion matrix was transferred into the model at two intervals (1986 – 2002 and 2002 – 2018). The interval level determined the period with the highest annual total change in all classes whereas the categorical and transitional levels examined the change in each class in relation to the uniform annual change per interval and uniform rate of change per category respectively (Aldwaik and Pontius, 2012). All changes at interval, categorical and transitional levels with intensities higher than uniform rate are termed fast, active and targeted while values below uniform intensities are termed as slow, dormant and avoided respectively.

Table 3.4. Modified land use/cover classification scheme

Land use/cover	**Characteristics**
Forest	Trees usually over 5m tall with crowns interlocking (generally forming 50-100% cover or more than 150 trees per hectare)
Open vegetation	A complex mixture of grasses and shrubs with or without scattered trees with less than 10 trees per hectare. Open stands of trees usually over 5m tall with crowns not usually touching (generally forming 25-60% cover or with approximately 75-150 trees per hectare
Arable/Bare lands	Cultivated areas of diverse characteristics with field crops both food and cash crops such as maize, beans etcetera as well as harvested fields. Bare lands describe areas that do not have an artificial cover as a result of human activities including those areas with less than 4% vegetative cover (bare rock areas, sands and deserts).
Settlement	Areas of human settlements, commercial and industrial developments.
Water	Areas permanently covered with standing or moving water. This includes inland waters, streams, rivers, lagoon and reservoirs.

(Source: Mahmoud, 2016; FAO, 1995)

3.4 Modelling hydrological ecosystem services with InVEST

Hydrological modelling followed the framework in Fig. 3.6. Three sub-models of InVEST were calibrated based on the spatial parameters prepared in GIS. Digital elevation model (DEM) and shapefile of area of interest (watershed) were central to all sub-models. Rainfall maps on monthly and annual basis were used for the water yield and nutrient delivery ratio models respectively. Rainfall was converted into erosivity by a factor for use in the sediment delivery ratio model. Each model made use of both biophysical tables (containing physical and biological properties like coefficients of land classes for the delivery of a service) and spatially parameterized physical component to generate the needed outputs.

3.4.1 Sources of data used in InVEST models

Climate and land-use data were obtained from the results from objective one and two while other data, especially management practices were from literature and reports.

3.4.1.1 Required data to run the NDR model

The type of input data, sources and nature for the NDR model are tabulated in Table 3.5. All raster inputs were processed in ArcGIS 10.3. The biophysical table was filled with total phosphorus and nitrogen data from literature across Africa as provided by the model (Sharp *et al*., 2018). Details on settlement were taken from South Africa (Reckhow *et al*., 1980), open vegetation and water from Senegal (Lewis *et al*., 1999), forest from Ivory Coast (Bruijinzeel, 1991) and arable/bare lands from Nigeria, Mauritius and Burkina Faso (Lesschen *et al*., 2007; Kwong *et al*., 2002; Mackensen and Folster, 2000). Averages were determined across the land class to provide single values for the model. The biophysical data is presented in Table 3.6.

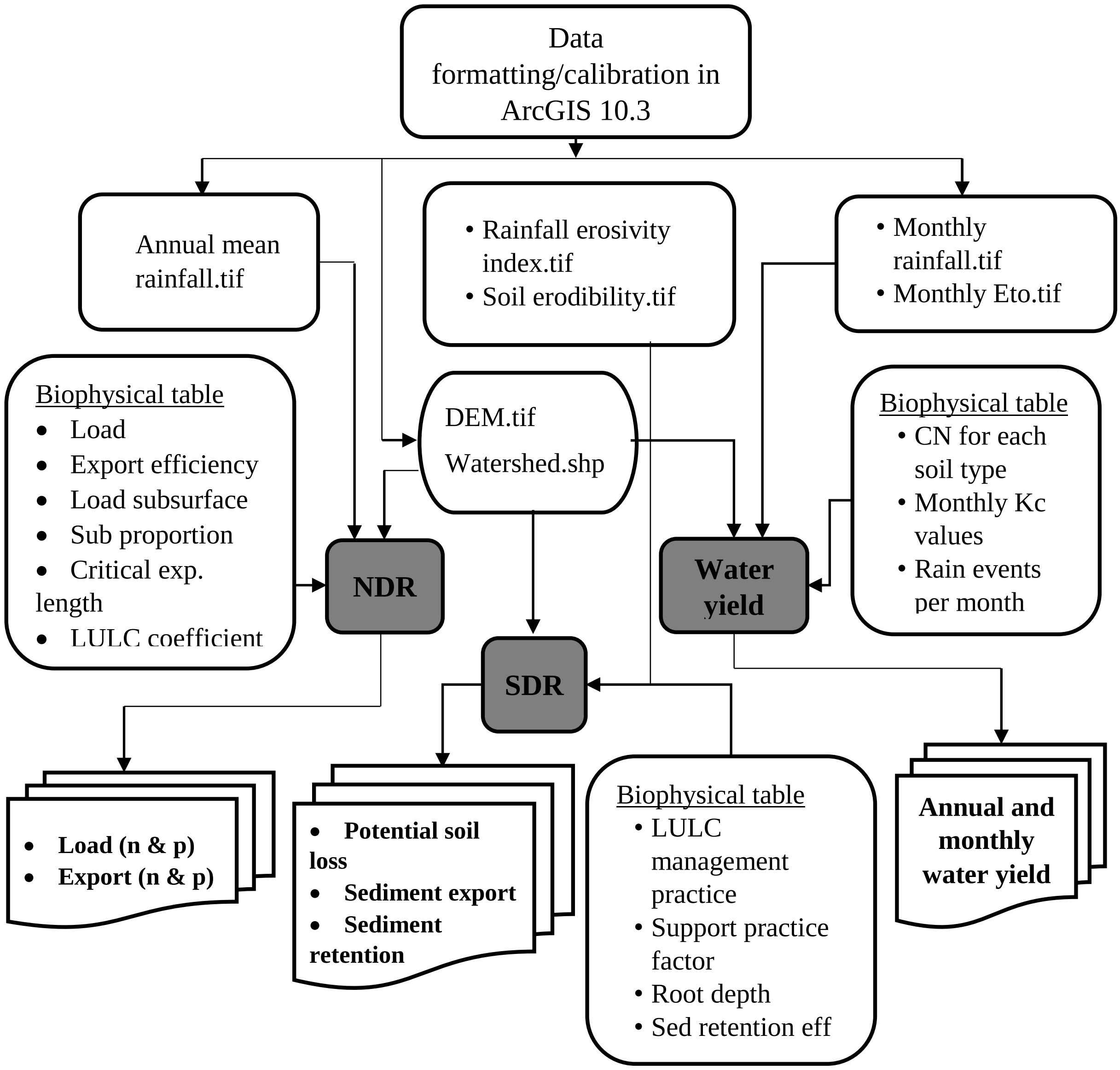

Fig. 3.6. Hydrological ecosystem service modelling in InVEST

Table 3.5. Data needs of the NDR model

Data	Nature/Function	Source
Digital elevation model (DEM) (required)	A GIS raster dataset. To ensure proper flow routing	https://urs.earthdata.nasa.gov/
Land use/land cover (required)	A GIS raster dataset. The LULC code was an integer.	Generated from Landsat images
Nutrient runoff proxy (required)	A GIS raster dataset. The annual precipitation for the basin was used.	Rainfall data from the study
Watersheds (required)	A shapefile of polygons	Ghana Geological Survey Department
Biophysical Table (required)	land use/land cover classes table in csv format, with water quality coefficient.	Land use maps and empirical literature
Threshold flow accumulation value	A stream layer from the DEM	Generate from DEM in ArcGIS 10.3
Borselli k parameter	The default value is 2.	Use default value

(Source: Prepared by author from Sharp *et al*., 2016)

Table 3.6. Nutrient and phosphorus requirement for NDR model

LULC Class	Load n	Eff n	Load p	Eff p	LULC veg	Crit len p	Crit len n	Load sub n	Load sub p	Prop sub n
Settlement	4.00	0.05	0.6	0.05	0	150	150	0.49	0.0001	0
Water	1.3	0.05	0.08	0.05	0	150	150	0.0001	0.0001	0
Forest	1.8	0.79	3.88	0.79	1	150	150	0.18	0.0011	0
Open vegetation	1.26	0.52	0.41	0.52	1	150	150	0.37	0.04	0.02
Arable/Bare lands	16	0.52	0.7	0.3	1	150	150	0.98	0.24	0.25

* n – Nitrogen; p - Phosphorus; Eff – Efficiency; veg – Vegetation; Crit – Critical; len – Length; sub – subsurface; Prop – Proportion

(Source: Sharp *et al*., 2018; Lesschen *et al*., 2007; Kwong *et al*., 2002; Mackensen and Folster, 2000; Lewis *et al*., 1999; Bruijinzeel, 1991; Reckhow *et al*., 1980)

3.4.1.2 Data requirement for the SDR model

The type of input data, sources and nature for the SDR model are presented in Table 3.7. All raster inputs were processed in ArcGIS 10.3. Rainfall erosivity values were determined based on the modified Fournier index (MFI) method because is suitable for the tropical region (Kusimi, 2014; Smithen and Schulze, 1982). Soil erodibility factor (K) were adopted from Ashiagbor *et al*. (2014) which was calculated from the alternative soil erodibility factor (ERFAC) from equation 3.3 (Table 3.8).

The range of the soil erodibility factors was comparable in a decreasing value to the findings of Teye-Mensah (1997) for four locations along the coast of Ghana and two in the semi-deciduous agro-ecological zone of Ghana. The estimated k-factor from nomograph was between 0.33 t/J and 0.48 t/J at Axim and Juaso respectively while the measured k-factor was between 0.36 t/J and 0.62 t/J at Ho and Juaso respectively (Teye-Mensah, 1997). However, the findings of Teye-Mensah (1997) was a mixture of soil types per the location while the k-factor from the alternative equation in this study was for specific soil type (Table 3.8).

$$K - factor = 0.32 \left[\frac{\%\, silt}{\%\, sand + \%\, clay}\right] \times 0.27 \qquad (3.3)$$

The support practice factor (usle_p) presented in Table 3.9 was assumed as 1 for all the five land-use classes because there was no provision for conservation support in the basin (Kusimi, 2014). Table 3.9 also present the sources of cover management factors (usle_c) averaged for this study. Rainfall erosivity (R) was determined using the interpolation table of rainfall (mm) and R factor reported by Elbasit *et al*. (2013) at a correspondence of 150 mm rainfall to 400 MJ mm ha^{-1} h^{-1} yr^{-1} erosivity. This was determined to be at r = 0.99 between Zimbabwe and Ethiopia and r = 0.81, 0.54 and 0.83 for Fournier index (FI), half-month rainfall erosivity (M_i) and monthly rainfall (P_i) formulas respectively. Earlier findings by van der Poel (1980) proposed 100 mm to 400 MJ mm ha^{-1} h^{-1} yr^{-1} change in R factor.

Table 3.7. Data needs of the SDR model

Data	Nature/Function	Source
Digital elevation model (required)	Raster dataset from a GIS platform.	https://urs.earthdata.nasa.gov/
Rainfall erosivity index (R) (required)	Raster dataset from a GIS platform.	Estimated from rainfall
Soil erodibility (K) (required)	Raster dataset from a GIS platform.	Calculated from ERFAC formular (equation 3.3)
LULC (required)	Raster dataset from a GIS platform. The LULC code was an integer.	Generated from Landsat images
Watersheds (required)	A shapefile of polygons	Ghana Geological Survey Department
Biophysical Table (required)	Land use land cover classes table in CSV format that contains corresponding factors for the modelling.	Land use maps and empirical literature
Threshold flow accumulation value (required)	Stream layer from the DEM	Generate from DEM in ArcGIS 10.3
kb and $IC0$	The default values were kb = 2 and $IC0$ = 0.5.	Use default value
SDRmax	Its default value was 0.8	-

(Source: Prepared by author from Sharp *et al*., 2016)

Table 3.8. Soil erodibility factor (K_factor)

Type of soil	**K_factor**	**Area (km^2)**
Acrisols	0.255	18,328
Alisols	0.245	318
Fluvisols	0.295	854
Leptosols	0.275	206
Lixisols	0.234	722

(Source: Ashiagbor *et al*., 2014)

Table 3.9. Cover management factor (ulse_c) and support practice factor (usle_p)

LULC Class	**Sources for usle_c estimation**	**usle_c**	**usle_p**
Settlement	Built up - 0.99 (Adediji *et al*., 2010)	0.99	1
Water	Kusimi, 2014	0.0000	1
Forest	0.001 (Roose, 1977)	0.0233	1
	0.02 (Adediji *et al*., 2010)		
	0.038 (El-Hassanin *et al*., 1993)		
	0.034 (El-Hassanin *et al*., 1993)		
Open vegetation	Woody savanna – 0.01 (Roose, 1977)	0.1119	1
	Woody savanna – 0.11 (Adediji *et al*., 2010)		
	Shrubs – 0.4 – 1.00 (Mati, 1999)		
	Grassland – 0.018 (El-Hassanin *et al*., 1993)		
	Grassland – 0.014 (El-Hassanin *et al*., 1993)		
	Grassland – 0.043 (El-Hassanin *et al*., 1993)		
Arable/Bare lands	Croplands – 0.314 (Angima *et al*., 2003)	0.4451	1
	Croplands – 0.122 (Angima *et al*., 2003)		
	Croplands/Natural – 0.415 (Angima *et al*., 2003)		
	Croplands - 0.01 – 0.1 (Roose, 1977)		
	Croplands – 0.16 (Adediji *et al*., 2010)		
	Croplands - 0.68 (Mati, 1999)		
	Croplands/Natural – 0.02 (Mati, 1999)		
	Croplands/Natural – 0.8 (Gobin *et al*., 1999)		
	Croplands/Natural – 0.33 (Gobin *et al*., 1999)		
	Baren/sparse – 1 (Adediji *et al*., 2010)		
	Baren/sparse – 1 (Roose, 1977)		

3.4.1.3 Data needs of the seasonal water yield model

Data characteristics and sources used to run the seasonal water yield model were described in Table 3.10. The Penman-Monteith evapotranspiration method in Instat v3.36 was used to calculate the reference evapotranspiration (ETo) inputs for the seasonal water yield model. Average insolation incident on a horizontal surface (MJ/m^2/day), relative humidity at 2 m above sea level (%), wind speed at 10 m above the surface of the earth (m/s) records, from 1983 – 2010 were downloaded from NASA Power database (NASA POWER, 2018) to calculate ETo of stations. Mean temperature input was from the observed data from each climate station. Wind speed was converted to 2 m above earth surface with factor 1.33. The ETo for 2020 – 2049 was calculated with SDSM-DC and Ensemble mean temperature of each climate station with downloaded average insolation incident on a horizontal surface (MJ/m^2/day), relative humidity at 2 m (%), wind speed at 10 m above the surface of the earth (m/s), from 2012 – 2017 from NASA Power database and replicated five times to cover 30 years' period. The study assumed that insolation, wind speed and relative humidity from 2020 – 2049 will not differ from the records of 2012 – 2017.

The estimated curve numbers are presented in Table 3.11 whereas crop factor sourced from Sharp *et al*. (2018) are presented in Table 3.12. All maps of monthly precipitation and reference evapotranspiration were created in ArcGIS 10.3 with ordinary kriging spatial analysis tool because of the distribution of the stations. Digital Elevation Model (DEM) downloaded from Earthdata NASA and hydrological soil groups acquired from International Soil Reference and Information Centre (ISRIC) are presented in Fig. 3.7.

Table 3.10. Data requirement of the seasonal water yield model

Name	Description and Type	Data Source
Pi,m	Maps of monthly precipitation (mm).	Observed and modelled data
ET0, m	Maps of monthly reference evapotranspiration (mm) using the Penman-Monteith Equation.	NASA POWER and climate data
DEM	Digital elevation model. Raster of decimals	https://urs.earthdata.nasa.gov/
LULC	Map of LULC. Raster of integers	LULC maps (Landsat images)
Soil group	Map of SCS soil hydrologic groups (A, B, C, or D), used in combination with the LULC map to compute the CN map.	International Soil Reference and Information Centre
AOI/ Watershed	Shapefile delineating the boundary of the basin.	Ghana Geological Survey Department
Biophysical table	Table comprising, each LULC type: • CN for each soil type • Monthly Kc values .csv file with column names: CN_A, CN_B, CN_C, CN_D, Kc_1, ….. Kc_12	Natural Resources Conservation Service (NRCS) and Agricultural Research Service (ARS); Washington State Department of Transportation
Rain events table	Table with 12 values of rain events per month. A rain event is defined as >0.1mm (USGS). .csv file with column names: month and events	Determined from observed and modelled rainfall data
Threshold flow accumulation	Generated stream layer.	Develop from DEM in ArcGIS 10.3
αm, βi, γ	Model parameters used for research purposes. Default values were: αm = 1/12, βi = 1, γ=1	Use default values

(Source: Prepared by author from Sharp *et al*., 2016)

Table 3.11. Estimated curve number (CN)

Description	CN_A	CN_B	CN_C	CN_D
Water	0	100	100	100
Forest	0	50	60	65
Settlement	0	75	83	86
Arable/Bare lands	0	68	76	80
Open vegetation	0	65	77	82

where A, B, C and D are soil hydrological groups

(Source: Natural Resources Conservation Service (NRCS) and Agricultural Research Service (ARS) [NRCS], 2017; Washington State Department of Transportation [WSDOT], 2014)

Table 3.12. Other LULC characteristics for SDR model

Description	Kc (1 – 12)	Root depth	sedret_eff
Water	1	800	0.43
Forest	1	7000	0.6
Settlement	0.3	350	0.05
Arable/Bare lands	0.56	1300	0.28
Open vegetation	0.74	4000	0.47

Kc = plant evapotranspiration coefficient; sedret_eff = sediment retention efficiency

(Source: Prepared by author from Sharp *et al*., 2018)

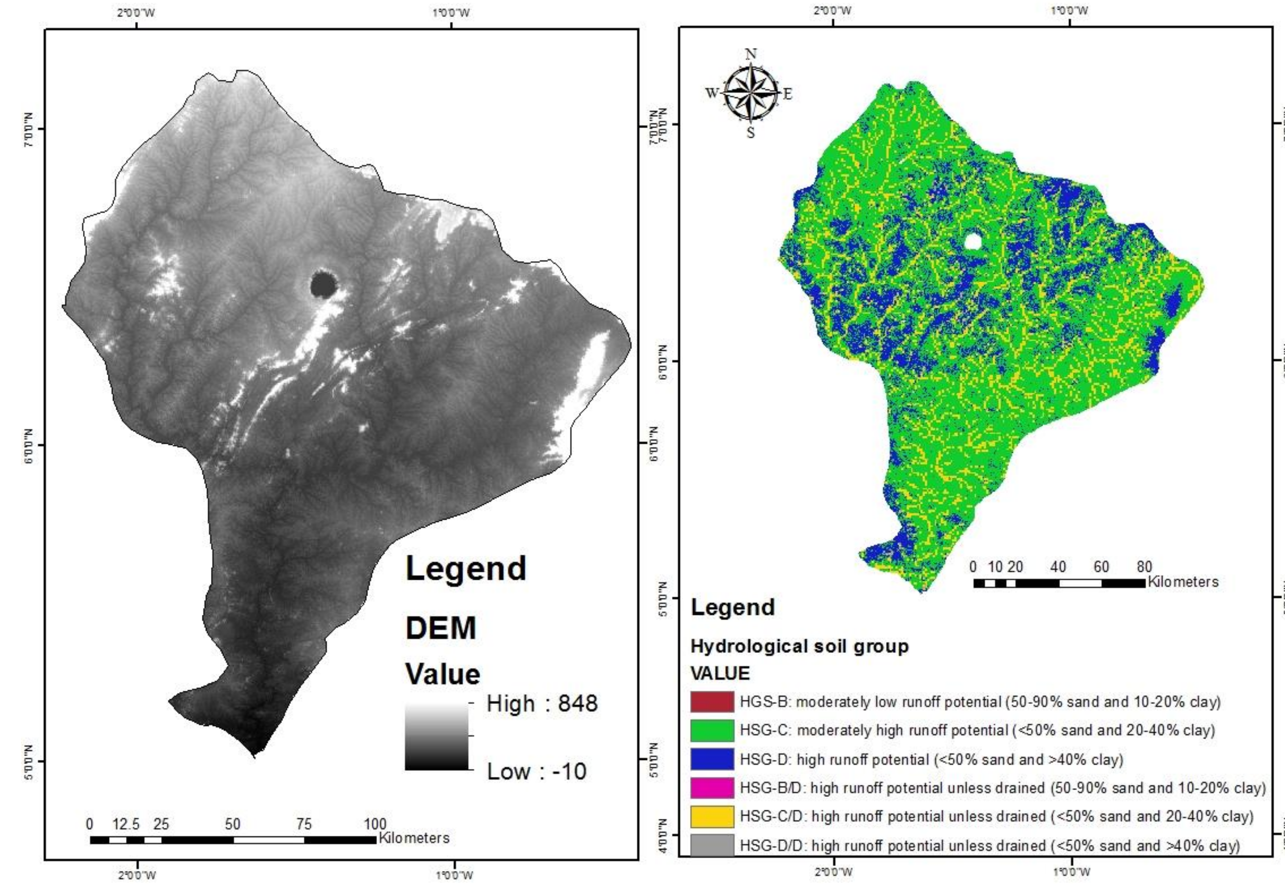

Fig. 3.7. DEM and Hydrological soil groups (250 m) in the Pra River Basin

(Source: Prepared by the author with data from NASA earthdata and Soilgrids)

3.4.4 Running of the InVEST models

Each of the selected sub-model of InVEST was run separately in the window mode.

3.4.4.1 Nutrient delivery ratio model

In the NDR model, land use land cover maps and digital elevation model were the physical components that determined the route of nutrient movement from each pixel. The retention coefficient of each land-use class in the biophysical data served as control of how many nutrients could be transported from the class through the stream path generated by the digital elevation model. The spatially prepared parameters (such as DEM, land use land cover, rainfall etc) were used to calibrate the model to account for the spatial distribution of the delivery (Sharp *et al*., 2016).

3.4.4.2 Sediment delivery ratio model

The InVEST SDR model was calibrated on the digital elevation model of the basin as the physical parameter to account for the sources of sediment generation and channel of export. It has also been designed to allow for user modification like representing complex processes to emulate local conditions (Sharp *et al*., 2018).

3.4.4.3 Seasonal water yield model

The InVEST seasonal water yield model estimated yield based on pixels accounting for both groundwater lateral flow and surface flow from the energy equation budget. A pixel was considered as the parcel of land from which flow is generated after a downpour. The current model used in this thesis does not estimate quantitative baseflow but only the relative contributions of pixels. This was a limitation that developers are working on to address in a separate tool in the next version of the InVEST model (Sharp *et al*., 2016). To estimate the impact of climate and LULC on water resources, LULC maps of 1986, 2002 and 2018 were run separately with the climate inputs of 1981 – 2010. This was done for all three models of InVEST used in this study to estimate the extent of LULC influence on water yield, sediments and nutrient delivery. LULC map of 2018 was used with climate inputs of SDSM (1^{st} best-skilled model) and ensemble mean of the five models to estimate the future water yield, sediment and nutrient delivery ratios in the Pra River Basin. All maps were prepared in ArcGIS 10.3.

3.5 Farmers' household survey

The survey was done to address the specific objective four of this study.

3.5.1 Sampling and data collection techniques

ArcGIS 10.3 was used to spatially sample 10 districts randomly over the Pra River Basin to prevent bias in sampling. This was done due to the limitation of funds and time to cover all the districts located in the Pra River Basin. Five of the districts fell within the Ashanti region (Amansie West, Atwima Mponua, Bosomtwe, Adansi North and Obuasi); three were within the Central region (Assin North, Twifo Ati Morkwa and Twifo Heman Lower Denkyira) and remaining two in the Eastern region (Atiwa and East Akim) of Ghana (Fig. 3.8).

The Yamane simplified formula for proportions at precision error of ±5 % was adopted to determine the number of respondents to interview (Singh and Masuku, 2014). The total crop farming household population from the 10 districts from the 2010 population census was 165,1985 (GSS, 2013). The determined sample size was 399 respondents which agreed with the 400 sample size proposed by Glenn (1992 cited in Singh and Masuku, 2014) from the published tables of sample size for populations above 100,000. Purposive sampling of minimum three major farming communities (lying close to a river course) under the extension area of the Ministry of Agriculture (MoFA) in Ghana was done to obtain the determined number of respondents within the ages of 35 – 60 years old per districts. Minimum of 14 respondents was targeted in each community, however, some communities were inaccessible because of bad roads due to flooding. Three communities, each located in the Twifo Ati-Morkwa, Twifo Heman Lower Denkyira and Abuakwa South District were not accessible due to bad roads resulting from flood while one community in the Bosomtwe district was located outside the extension zone of the district on ground. A total of 344 respondents were interviewed from the 10 districts in the months of April and May 2019.

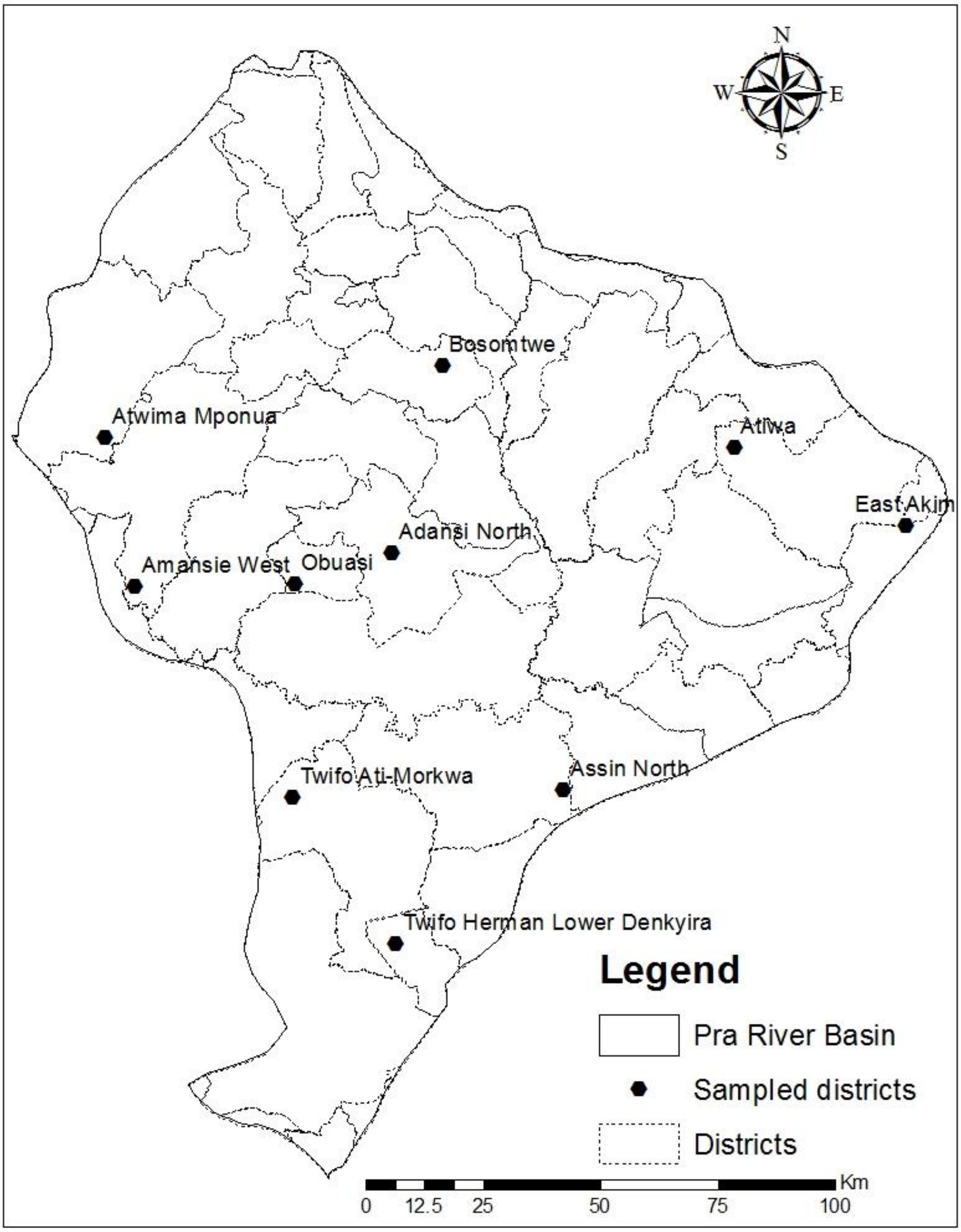

Fig. 3.8. Spatially random sampled district for questionnaire administration

3.5.2 Social data collection instrument

A supporting questionnaire (Appendix II), including both open and closed-ended questions, was designed to cover the socio-economic characteristics, land use and land-use change drivers, water quality and climate change and its adaptation strategies to gather perceptions and practices of farmers from the selected districts. The language used for the survey especially during the engagement with farmers was *Twi*[2]. A pretest of the questionnaire was carried out at Barekese, in the Atwima Nwabiagya District of Ashanti Region. A total of 12 households were interviewed during the pretest and outcome used to restructure the questionnaire to the current format used for this study (Appendix II).

3.5.3 Analysis of survey data

The questionnaire data were coded directly into IBM Statistical Package for Social Sciences (SPSS) version 21 after data cleaning and analyzed using quantitative methods involving descriptive statistics and rankings (Dimobe *et al*., 2015).

3.6 Uncertainties and limitations in the simulation of the models

The study has limitation and uncertainties especially in the modelling of climate and hydrological ecosystem services. All models have strengths and weaknesses. It is therefore important to know the limitations and assumptions made throughout this study. The uncertainties in the climate modelling aspect were:

i. The missing data in the observed records that required filling.
ii. The choice of predictors for the SDSM model to estimate the empirical relationship between predictors and predictands (observed data).
iii. The resolution complexities of the WRF, CORDEX and NCEP grids.
iv. The weather generator approach of using stochastic regression to downscale climate information from the NCEP data.

[2] Twi is the local language of most of the Akan ethnic group in Ghana. They are the major ethnic group covering most of the southern and central part of Ghana. There are different types of Twi depending on the specific tribe in the Akan ethnic group one belongs. The study used the Asante Twi for interviewing farmers.

Despite these modelling limitations, if the climate models could simulate past trends, means and variations then they are likely to provide useful insight about future trends, with consistent estimates in its results (Flato *et al*., 2013).

The InVEST model had more limitations based on the assumptions and computation of key parameters that were done from the literature of other locations because in-situ data were not available. The following limitations and assumption were made for seasonal water yield modelling:

i. In the determination of reference evapotranspiration (ETo) for the period 2020-2049, the study assumed that insolation, wind speed and relative humidity will not differ from the NASA observed records of 2012 – 2017. This was because the observed data for these parameters were available for only two stations and had gaps.
ii. Curve numbers and crop factors were estimated from the literature.
iii. The quick flow provides annual averages and not the extremes and neglect the interactions between surface and deep groundwater.

In the sediment delivery ratio model, the following were limitations to the work, including the accuracy of the assessed databases:

i. Rainfall erosivity were estimated based on interpolation relationship from a comparative study in tropical regions of Zimbabwe and Ethiopia.
ii. Soil erodibility were from an alternative method because soil structure codes and permeability values were not available to use nomograph.
iii. Biophysical factors were estimated from studies across sub-Saharan Africa.
iv. The model considers only sheet or rill erosion.
v. Extreme events are not computed by the model (only long-term annual averages are captured).

The limitation of the nutrient delivery ratio model was the computation of nitrogen and phosphorus loads and efficiency from literature.

The listed limitations and uncertainties are to guide users on the confidence level of the findings in this study and not to discredit the quality of the work.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Climate variability and change

The variability in climate was determined within the historical or observed period from 1981 – 2010 and future period from 2020 – 2049 while the change in climate was by subtracting the observed from the future. This section covers the results and discussion of the first specific objective of this study.

4.1.1 Gauge stations observed temperature from 1981-2010

The gauge stations were Atieku, Dunkwa, Kibi, Konongo, Kumasi, Akim Oda and Twifo Praso.

4.1.1.1 Historical monthly means of maximum and minimum temperature

The maximum temperature recorded lower readings about 29ºC – 30ºC during the peak of the rainy season between June and August (Table 4.1). The highest and lowest monthly observed maximum temperature of 34.51ºC at Akim Oda in February and 28.23ºC at the Kumasi station was in August. The highest monthly observed minimum temperature of 23.13ºC was at Twifo Praso in April while the lowest (18.61ºC) was at Kibi in January.

4.1.1.2 Historical mean annual temperature trend

The maximum annual temperature during the historical period was lowest at Konongo (29.80ºC) in 1999 and highest at Twifo Praso (33.00ºC) in 1997. The mean maximum temperature showed an increasing trend at $R^2 = 0.3757$ (Fig. 4.1). The mean increase was 1.11ºC. The years 1983, 1987, 1995 and 1998 showed the highest recorded maximum temperature in the basin. Konongo also recorded the lowest mean minimum temperature in the same year when the lowest maximum temperature was recorded (1999) while Twifo Praso also recorded the highest minimum temperature but this time in 2010. The mean minimum temperature showed an increasing trend which was faster than maximum temperature at $R^2 = 0.4664$ (Fig. 4.1). The results are in line with earlier reported maximum and minimum temperatures for the basin (Akrasi and Ansa-Asare, 2008).

Table 4.1. GMet observed monthly maximum and minimum temperature

	Climate stations						
	Atieku	*Dunkwa*	*Kibi*	*Konongo*	*Kumasi*	*Akim Oda*	*Twifo Praso*
Month	**MAXIMUM TEMPERATURE (ºC)**						
Jan	32.09	32.36	32.65	31.77	32.85	32.40	32.68
Feb	33.65	34.34	34.28	33.79	34.44	34.51	34.43
Mar	33.33	33.91	33.73	33.59	33.77	33.92	34.05
Apr	32.90	33.42	33.12	32.88	32.66	33.20	33.55
May	32.08	32.57	32.26	32.32	31.82	32.23	32.61
Jun	30.74	30.96	30.52	30.86	30.17	30.53	30.87
Jul	29.69	29.52	29.17	29.44	28.65	29.17	29.74
Aug	29.38	29.19	28.79	28.75	28.23	28.91	29.44
Sep	30.30	30.21	30.00	29.42	29.31	30.15	30.48
Oct	31.33	31.41	31.28	30.72	30.78	31.52	31.86
Nov	31.99	32.13	32.18	31.67	31.88	32.22	32.54
Dec	31.57	31.48	31.81	31.11	31.63	31.61	32.03
Mean	31.59	31.79	31.65	31.36	31.35	31.70	32.02
	MINIMUM TEMPERATURE (ºC)						
Jan	20.23	20.75	18.61	18.65	21.05	21.06	21.34
Feb	21.40	22.51	20.17	20.64	22.64	22.52	22.64
Mar	21.66	22.95	21.06	21.70	22.97	22.94	22.97
Apr	21.67	23.02	21.26	21.82	22.91	23.06	23.13
May	21.56	23.10	21.17	21.78	22.73	22.96	23.09
Jun	21.40	22.76	20.94	21.50	22.07	22.65	22.78
Jul	21.08	22.31	20.67	21.30	21.54	22.25	22.40
Aug	21.93	22.05	20.52	21.08	21.31	22.12	22.19
Sep	21.16	22.37	20.84	21.49	21.63	22.44	22.63
Oct	21.27	22.50	20.76	21.49	21.87	22.41	22.65
Nov	21.03	22.47	20.36	21.29	22.32	22.30	22.38
Dec	20.86	22.00	19.79	20.26	21.70	22.03	22.22
Mean	21.27	22.40	20.51	21.08	22.06	22.40	22.54

The increasing trend in mean maximum (+1.11ºC) and mean minimum (+1.47ºC) temperature indicates that night temperature was warmer than day temperature averagely from 1981 - 2010. Although both maximum ($R^2 = 0.3757$) and minimum ($R^2 = 0.4664$) temperature trend showed a weak prediction power, minimum temperature was stronger (Fig. 4.1). Kima *et al*. (2015) reported similar situation in the sub-humid zone of Burkina Faso where minimum (+0.89°C) temperatures increased faster than maximum (+0.66°C) from 1980 – 2012. Change in both maximum and minimum temperature in the sub-humid zone of Ghana reported in this study was higher than the same zone in Burkina Faso (Kima *et al*., 2015). Similar trends for maximum and minimum temperature has been observed over West Africa (Vose *et al*., 2005).

The mean temperature in the basin showed an increasing trend for the assessed period. Twifo Praso station recorded the highest mean temperature (27.30ºC) while Kibi station recorded the lowest mean temperature (26.10ºC). The change of station of the lowest temperature from Konongo (maximum and minimum) to Kibi could be due to the topography of Kibi that modulate temperature not to be too hot or cold although the station is located within mountains. The greenhouse effect phenomenon was behind the observed increasing trend of temperature due to the created atmospheric canopy by the Green-House Gases (GHGs) to capture emitted heat from the earth at night and distribute within the troposphere (Anderson *et al*., 2016; IPCC, 2007). It could be the main cause of increasing minimum temperature at a faster rate compared with maximum temperature during the day. Therefore, the daily increases insolation received on the earth creates a warm environment at night instead of the usual pattern of leaving the earth surface.

Moreover, albedo has a negative effect on global warming under climate change as cloudiness increases the reflectance of insolation (Held and Soden, 2000). Albedo effect during the day time could reduce the maximum temperature as volume of water vapour in the atmosphere turns to cool the earth by increasing reflection of irradiation. (Anderson *et al*., 2016; Oktyabrskiy, 2016; Karl *et al*., 1993). This phenomenon is not effective at night when the earth begins to release store energy into the atmosphere. Moreover, nighttime hours have been reported to show strong signals of urban heat island than day time (Karl *et al*., 1999; Karl *et al*., 1993). All these factors may be contributing to the faster rise of minimum temperature as migration into the basin is on the rise especially, migrants from the North to Kumasi and also migrants from within and outside the country engaged in small-scale (illegal or legal) mining (GSS, 2014; CONIWAS, 2011).

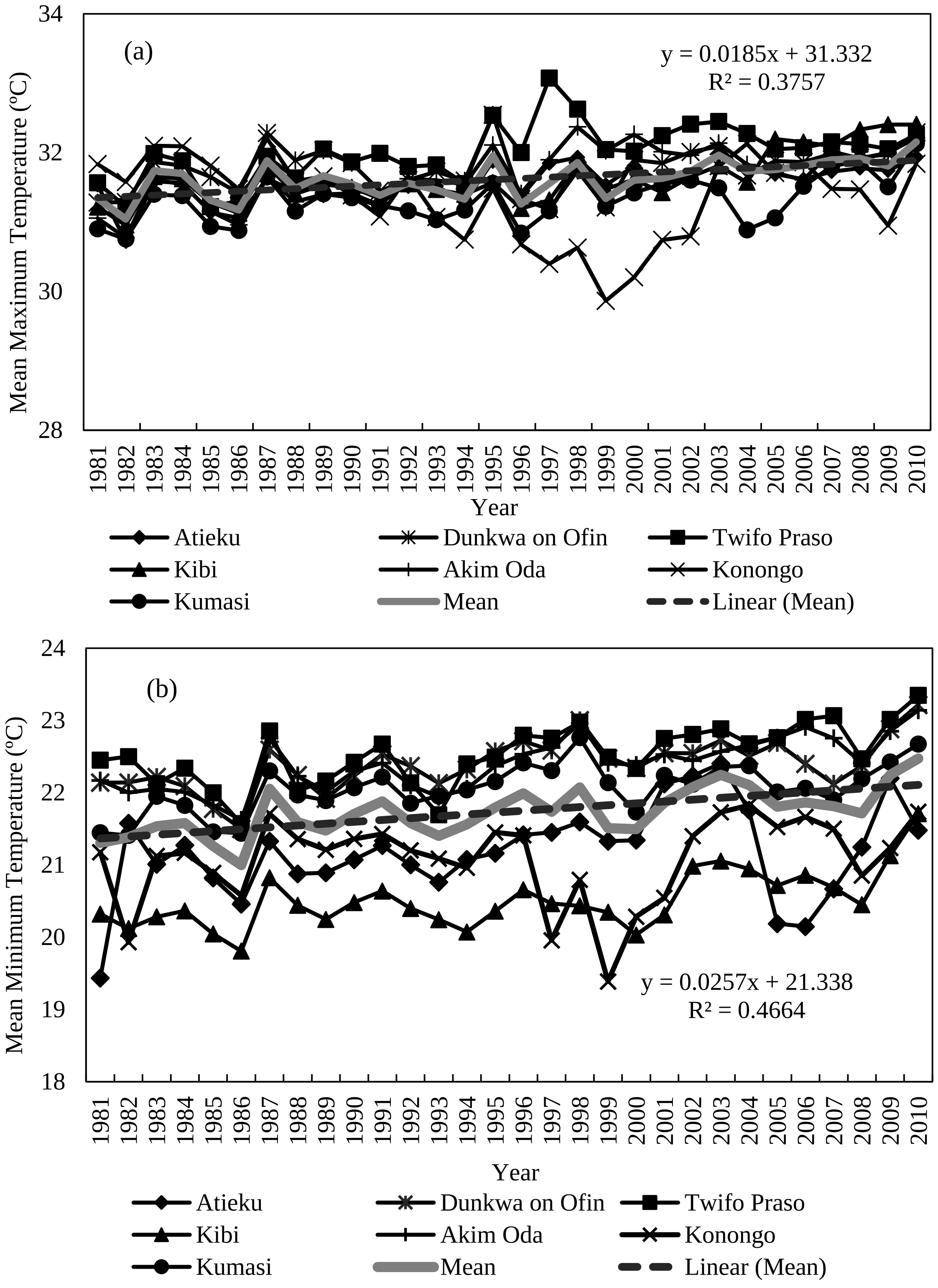

Fig. 4.1. Observed annual temperature trends in the Pra River Basin: (a) maximum and (b) minimum

4.1.2 Gauge stations observed rainfall

The analysis was limited to the period from 1981 – 2010.

4.1.2.1 Historical station monthly rainfall and standardized anomaly index

The mean monthly rainfall of the observed period is presented in Fig. 4.2 and 4.3. The GMet data for 1981 – 2010 at all the stations depicted the bi-modal rainfall pattern of the major season starting around April with mean daily rainfall ≥ 5 mm/d and peaking in June at about 7 mm/d. The minor season was from September, peaks in October and drops in November. The total annual rainfall in the basin was between 1300 – 1550 mm. The range fell within the annual rainfall amount reported for Ghana which varies between 710 mm and 2030 mm (Kabo-Bah *et al*., 2016).

The standardized anomaly index (SAI) of the observed period (1981 – 2010) is presented in Fig. 4.4 and 4.5. From the observed data, Twifo Praso, Akim Oda, Kibi and Kumasi were very wet (2.00 to 2.99) in 1999, 2002, 2007 and 2007 whereas Konongo recorded extreme wet period in 2006 and 2008. Only Atieku and Dunkwa stations recorded extremely dry (-2.00 to -2.99) years in 1983 and 2000 respectively. All stations except Dunkwa recorded a five drier than normal years, although, the years varied across stations. However, 1983 was drier than normal in all stations except Kibi which was at -0.30. Also, the year 2000, was drier than normal for all except Kibi recording -0.4 and Kumasi having a slightly wet year at 0.80. Dunkwa stations had seven years which were drier than normal (< -0.99). The drier than normal and extremely dry values in 1983 could be attributed to the West African drought within that period (Greene *et al*., 2009). The results showing a minimum of five years' drought (drier) in the basin is similar to the drought period reported for Tordzie watershed in the Volta Region of Ghana (Nyatuame and Agodzo, 2017). An average of five years was determined as wetter than normal across the seven stations.

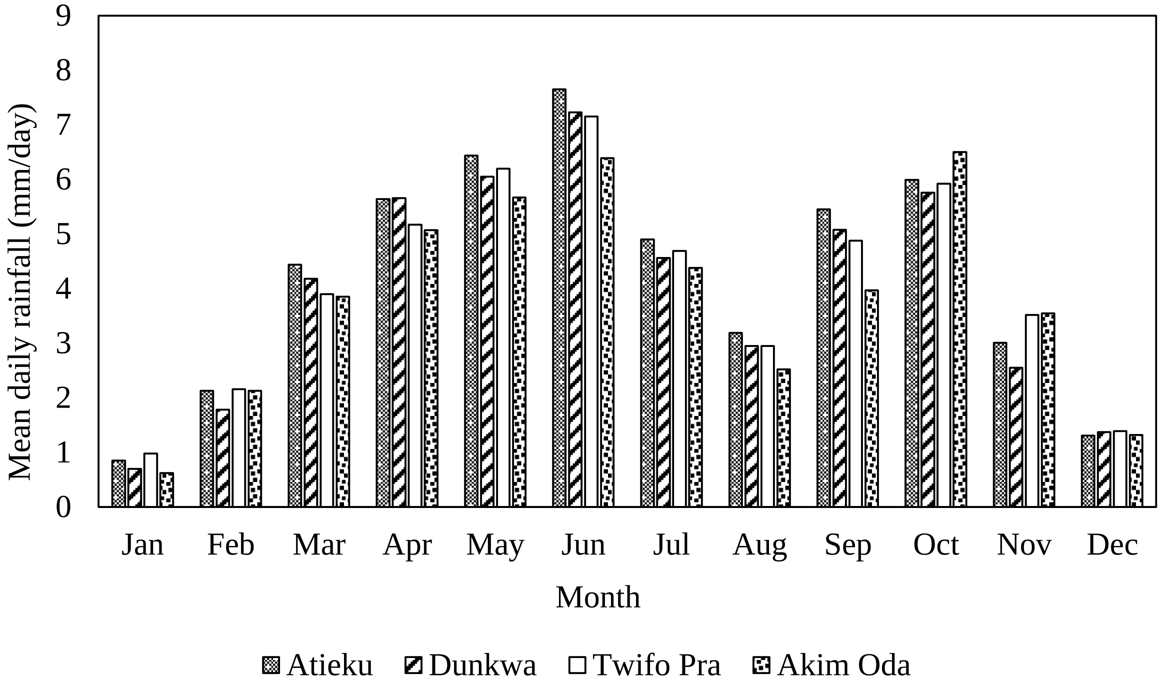

Fig. 4.2. Monthly mean rainfall amount of observed at four stations in the Pra River Basin

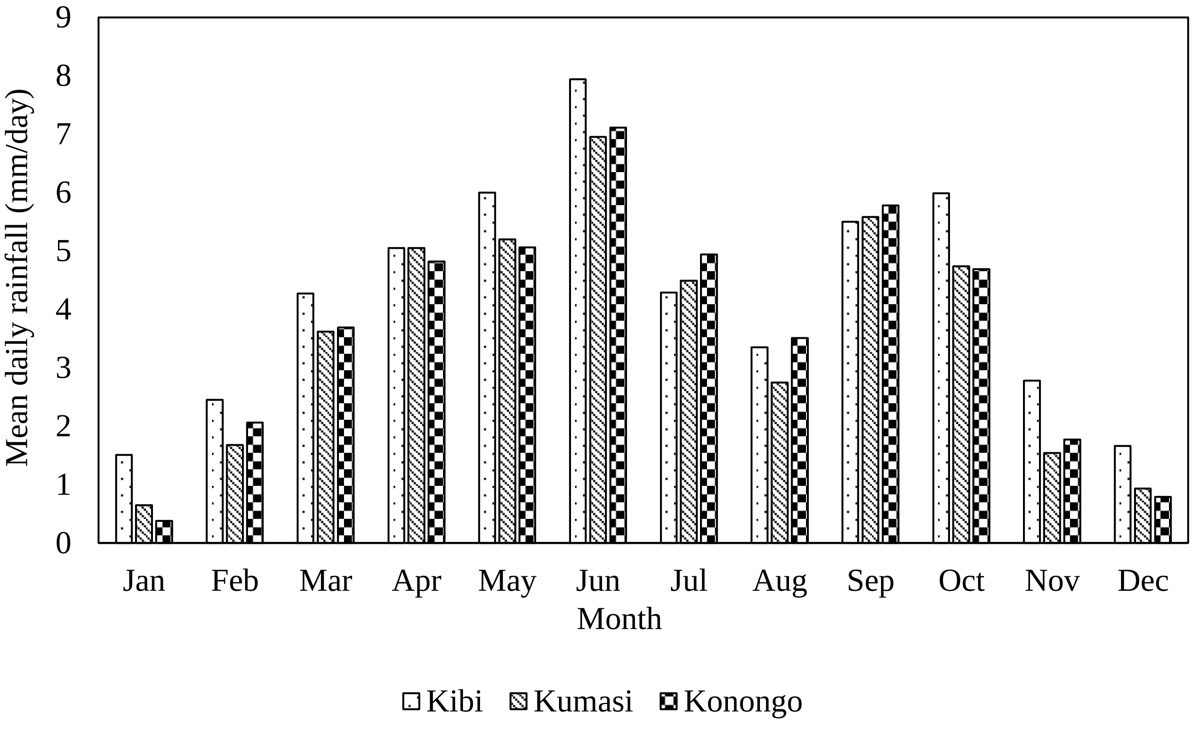

Fig. 4.3. Monthly mean rainfall amount of observed at three stations in the Pra River Basin

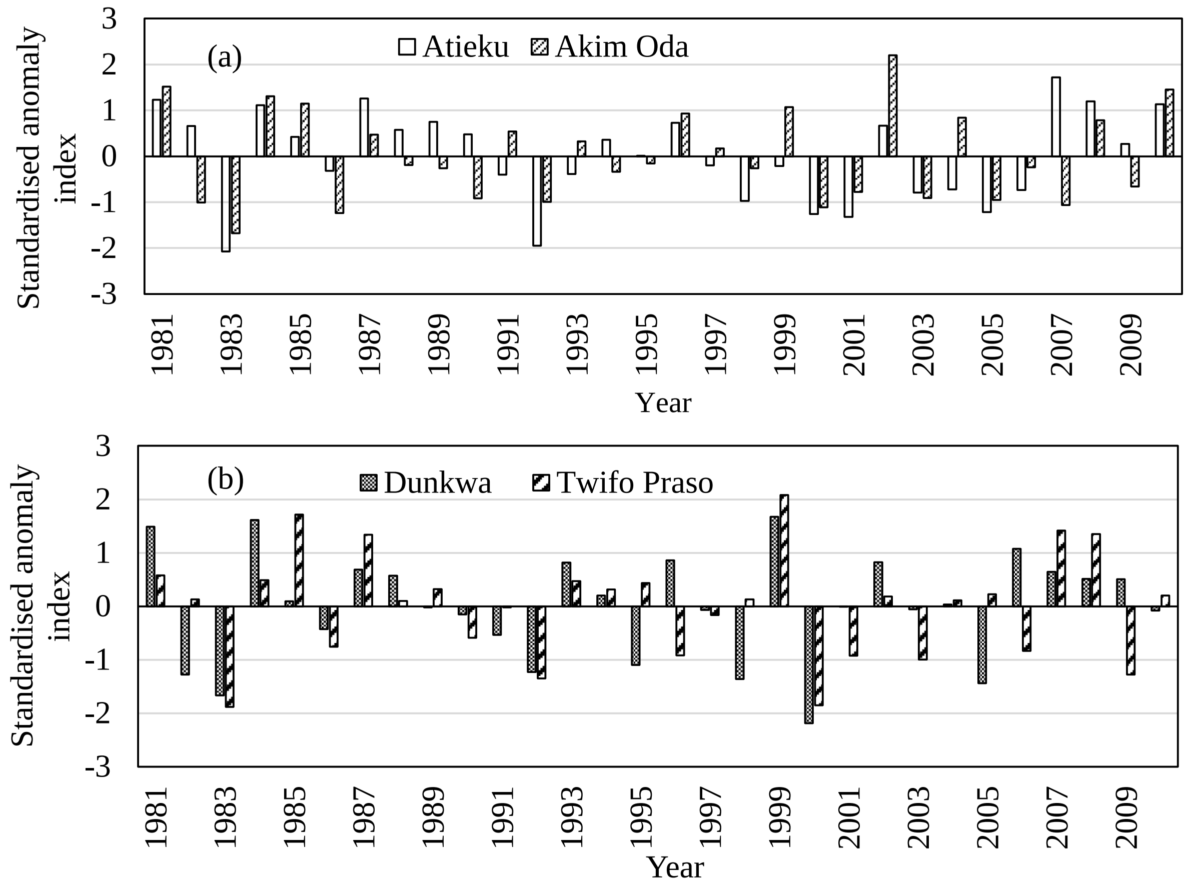

Fig. 4.4. Annual rainfall anomaly (SAI) of the observed period at (a) Atieku and Akim Oda and (b) Dunkwa and Twifo Praso climate stations in Pra River Basin

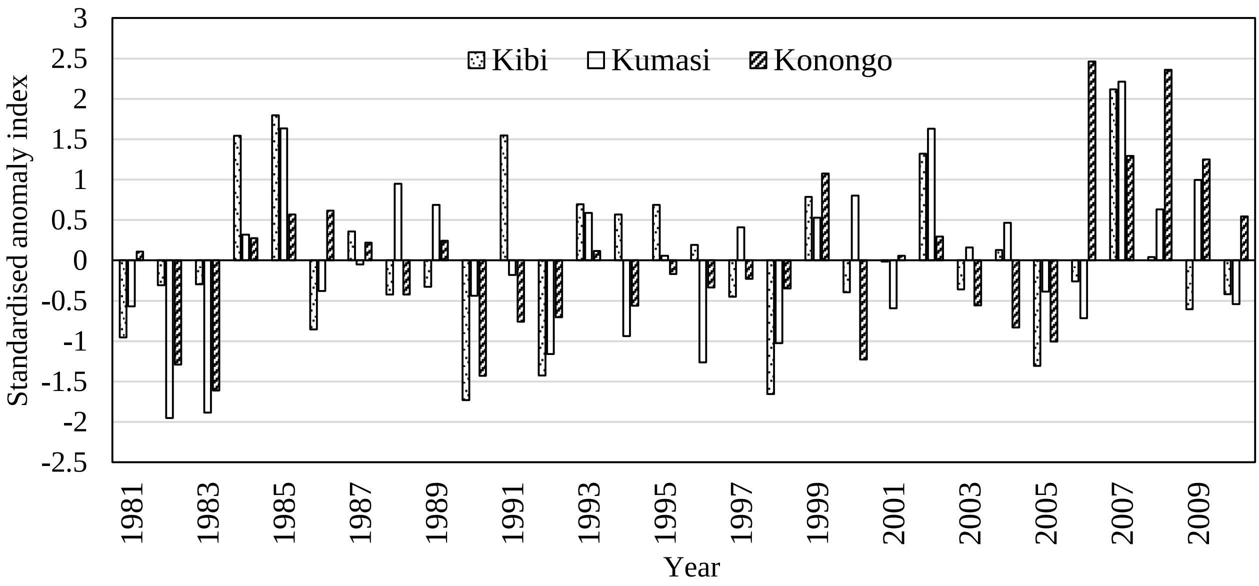

Fig. 4.5. Annual rainfall anomaly (SAI) of the observed period at three climate stations in Pra River Basin

4.1.2.2 Temporal rainfall variability during the historical period

Mean annual rainfall in the basin for the observed period shown in Fig. 4.6 was about 1446 mm (±226) with the lowest at Kumasi (1314.66 mm ±216.90) and highest at Atieku (1553.41 mm ±249.46) stations. The mean rainfall trend increased slightly at $R^2 = 0.0216$. There were seven years that recorded drier than normal (< -0.50) and wetter than normal (> +0.50) rainfall from 1981 to 2010 in the basin with variability indicated by the standardised anomaly index as high as -1.59 and +1.20 in 1983 and 2007 respectively as shown in Fig. 4.7.

4.1.3 Temperature and precipitation projections with 43 GCMs

Mean temperature from the Coupled Model Intercomparison Project Phase 5 (CMIP5) 43 global circulation models assessed in the IPCC's Fifth Assessment Report (AR5) for the Pra River Basin was 26.30ºC for the period 1981 – 2010. The highest and lowest temperature was 28.36ºC and 24.64ºC respectively. The result could be affected by the extra area covered by the grid set over the basin for the assessment. This resulted in the 0.37ºC difference between the mean of the seven stations and that of the grid area from the UPEI climate database (Table 4.2).

Mean rainfall rate for the period of 1981 - 2010 from the UPEI database using the 43 GCMs was 3.67 mm/d and minimum and maximum readings were between 1.81 – 7.09 mm/d. The mean rainfall rate calculated from the seven climate stations was 3.69 mm/d with a difference of 0.02 over that of the area analysis results (Table 4.3). The ensemble mean of the GCMs projected rainfall to increase by 0.81 %, 0.60 % and 1.62 % for the periods 2020s (2011 – 2040), 2050s (2041 – 2070) and 2080s (2071 – 2100) respectively from the base period (1981 – 2010) records in the basin. Taking the average results of the individual seven stations was similar to the results determined by considering a square area over the basin (Table 4.3). However, validated results from the selected stations projected rainfall decrease of 0.62 % and 1.62 % for the 2050s and 2080s periods respectively (Table 4.3). The variations in the results when comparing individual stations and the basin area could be due to the spatial variation of rainfall distribution over the Pra River Basin.

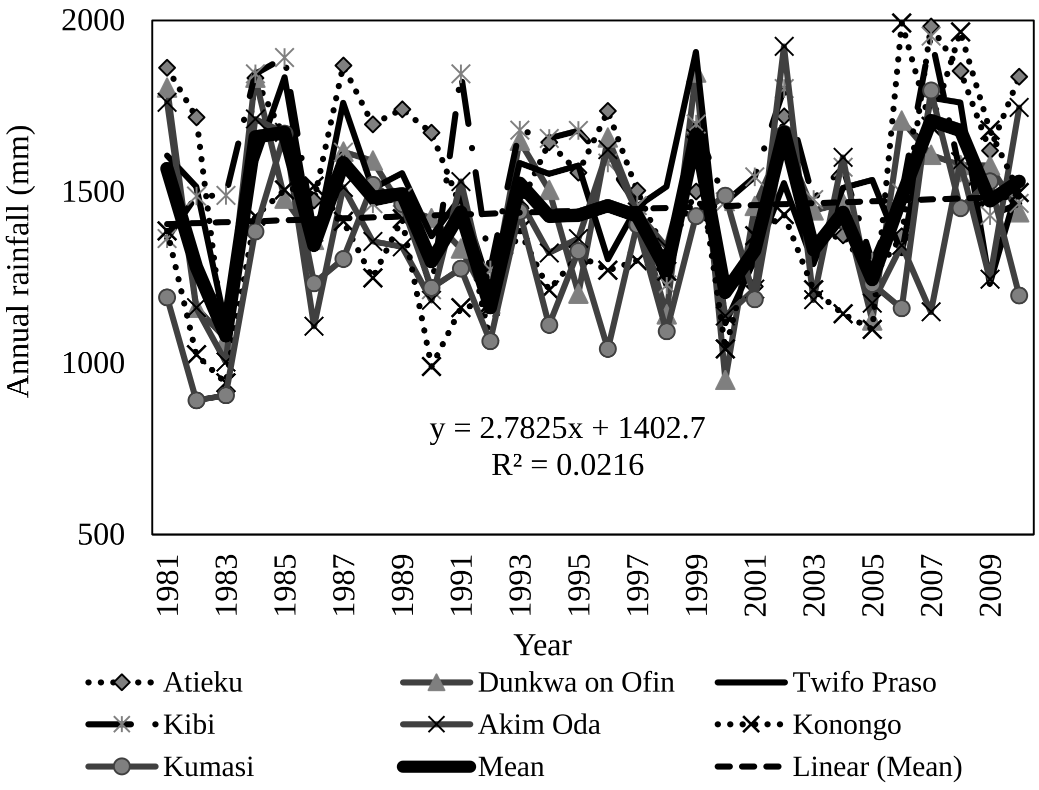

Fig. 4.6. Observed (1981 – 2010) annual rainfall (mm) in the Pra River Basin

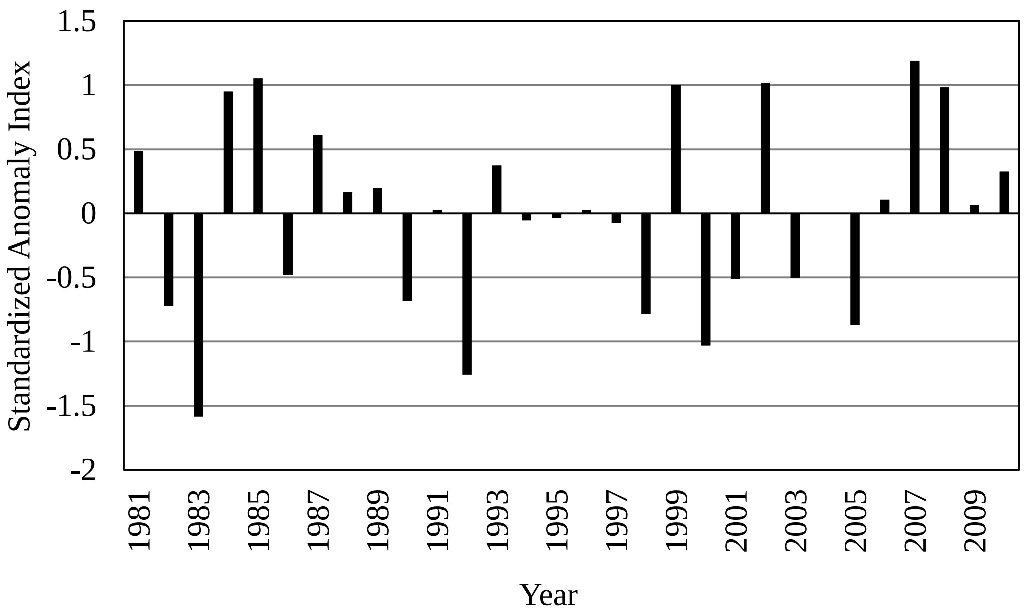

Fig. 4.7. Standardized anomaly index for the period 1981 – 2010

Table 4.2. CMIP5 temperature projections with AR5 models in the Pra River Basin

Climate Stations	Ensemble (Mean) in ºC				Validated Mean in ºC			
	Baseline	**2020s**	**2050s**	**2080s**	**Baseline)**	**2020s**	**2050s**	**2080s**
Akim Oda	26.25	0.83	1.76	2.68	25.98	0.91	1.91	2.88
Kumasi	25.94	0.84	1.79	2.74	25.31	0.95	1.95	2.98
Atieku	26.84	0.72	1.52	2.31	26.20	0.72	1.53	2.33
Dunkwa on Offin	26.18	0.84	1.77	2.69	25.58	0.91	1.83	2.79
Twifo Praso	26.72	0.78	1.65	2.51	25.88	0.79	1.67	2.54
Kibi	26.38	0.83	1.77	2.70	25.54	0.92	1.90	2.86
Konongo	26.00	0.84	1.79	2.73	25.46	0.93	1.96	3.02
Mean	**26.33**	**0.81**	**1.72**	**2.62**	**25.71**	**0.88**	**1.82**	**2.77**

**Ensemble - an average of all 43 AR5 GCMs; Validated – Models with acceptable performance over the study area*

Table 4.3. CMIP5 rainfall projections with AR5 models in the Pra River Basin

	Ensemble				Validated Mean			
Stations	**Baseline (mm/day)**	**2020s (%)**	**2050s (%)**	**2080s (%)**	**Baseline (mm/d)**	**2020s (%)**	**2050s (%)**	**2080s (%)**
Atieku	3.45	1.00	1.30	3.16	4.48	1.38	0.97	0.86
Akim Oda	3.60	1.64	2.63	4.40	3.73	2.01	1.96	0.47
Dunkwa on Offin	3.65	1.21	1.95	3.60	4.27	0.32	-0.61	-1.57
Konongo	3.89	0.91	0.76	1.53	4.43	-1.21	-3.47	-5.11
Kibi	3.92	1.00	0.83	1.43	3.87	-0.09	-1.57	-2.51
Kumasi	3.92	0.63	-0.04	0.40	4.07	-0.85	-3.32	-4.92
Twifo Praso	3.40	0.78	1.36	2.86	4.17	1.94	1.68	1.41
Mean	**3.69**	**1.02**	**1.26**	**2.48**	**4.15**	**0.5**	**-0.62**	**-1.62**

**Validated mean is the average of the good performing models out of the 43 AR5 models for the study area.*

The CMIP5 ensemble in this study projected a temperature change of +0.80°C, +1.68°C and +2.56°C for the 2020s, 2050s and 2080s respectively (Fig. 4.8). The results are comparable to the 2020s and 2050s projections of Laprise *et al*. (2013) over Southern Ghana. Two models namely; the Earth system version of the Max Planck-Institut fur Meteorologie (MPI-ESM-LR) and the Earth system version of the Canadian Centre for Climate Modelling and Analysis (CanESM2) showed an average increase in dry season temperature from January to March at about 0.75ºC for the 2020s (Laprise *et al*., 2013). For the 2050s period, MPI-ESM-LR projected a mean increase of 1.75ºC in temperature while CanESM2 projected a mean increase of 2.25ºC between January and March over the southern part of Ghana where the Pra River Basin is located. The minor dry season that starts at the ending of major rainfall in July to the beginning of the minor rainfall in September was projected to experience a temperature increase of about 1.5ºC and 0.75ºC for CanESM2 and MPI-ESM-LR respectively in the 2020s (Laprise *et al*., 2013). The maximum and minimum temperature change from CMIP5 in the basin could rise by about 5.00ºC by the year 2080 (Fig. 4.8).

The 0.80ºC projected increase in temperature and 1.02 % increase in daily rainfall amount, in the early century (2020s) could increase climate-related diseases as more warm nights could be experienced (Obuobie *et al*., 2012; Brahic, 2007). The 2050s mean projections (Fig. 4.8 and 4.9) of temperature and rainfall could reduce crop yield and water yield although there is a limited mean projected increase in rainfall (< 2.00 %) (Table 4.3). Floods could also affect the yield of crops and daily rainfall may increase under the ensemble maximum and mean of the models while the minimum change of rainfall, decrease in the range of 15 – 25 % (Fig. 4.9). The minimum rainfall projections suggest droughts. The findings may impact agriculture in the basin negatively under the extreme conditions of the projected temperature and rainfall changes (Fig. 4.8 and 4.9). The 2080s projection of +2.56ºC increase in mean temperature and 2.48 % increase in daily rainfall amount could create unfavourable conditions for sustainable development with significant impact on health, income, food security and resilience to climate disaster in the Pra River Basin (Gray and Brady, 2016; IPCC, 2014; Nutsukpo *et al*., 2013; Obuobie *et al*., 2012; Brahic, 2007).

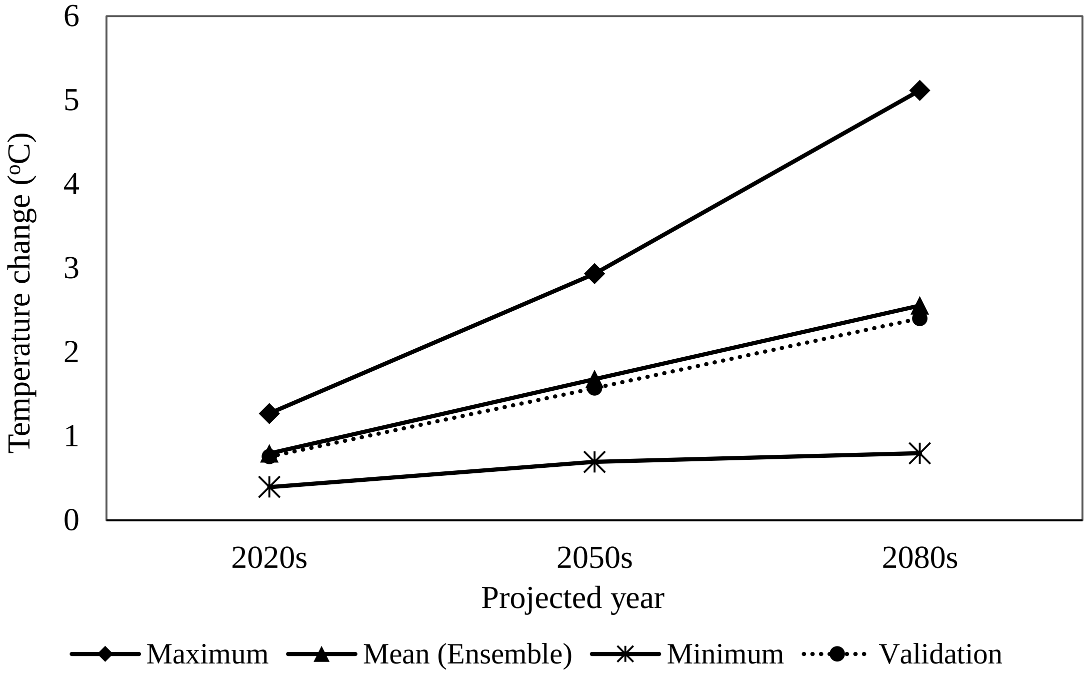

Fig. 4.8. CMIP5 future temperature over the basin

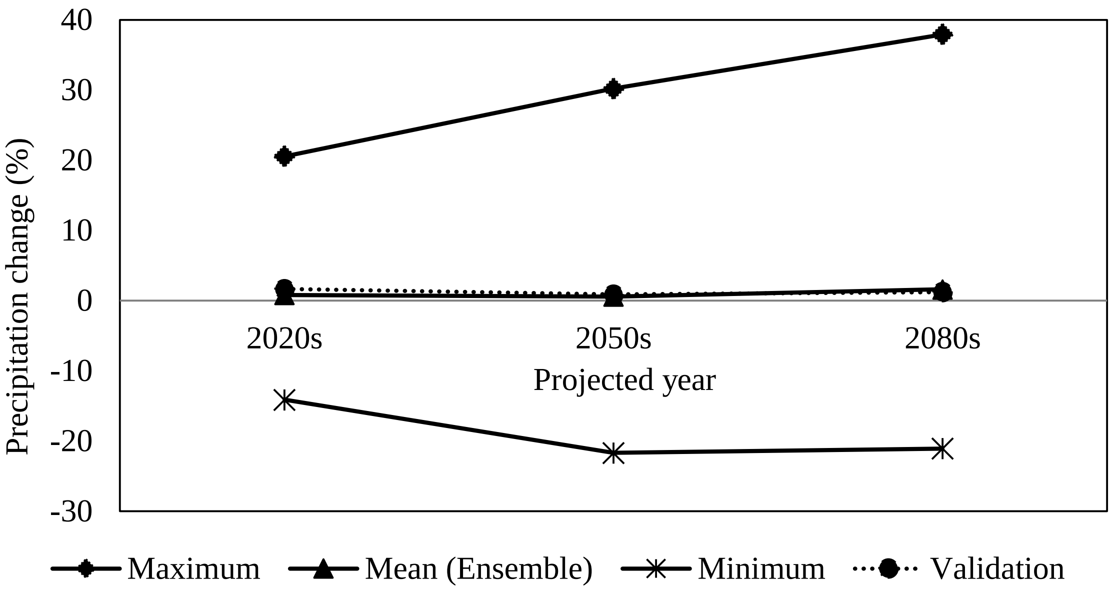

Fig. 4.9. CMIP5 change in rainfall in the basin

4.1.3.1 Selection of Regional Climate Models

The two CORDEX RCMs (CanESM and IPSL) were determined from the 43 GCMs of the fifth Assessment Report, AR5 (IPCC, 2014) using the method of validation of models (Fenech, 2016; Fenech *et al*., 2007). The output of the analysis in the form of a scatter plot of temperature and precipitation difference is shown in Fig. 4.10.

A total of ten GCMs fell within the validation zone as detailed in Table 4.4 depending on both the area and individual climate station analysis. The second-generation Canadian Earth System Model (CanESM2) and the mid-resolution model of Institut Pierre Simon Laplace (IPSL), were selected because they were available on the CORDEX platform for the African domain. The three resolution of IPSL model were all validated within the acceptable zone of the basin (Table 4.4). Two versions of the GFDL model were also part of the validated climate models for the area, however, its CORDEX version at 44 km spatial resolution was not used in this study because a higher spatial resolution version from WRF at 12 km was available through the West African Science Service Center on Climate Change and Adapted Land Use (WASCAL) project. The two WRF models (GFDL and Hadgem) were selected because model outputs were available for the West African Region through WASCAL.

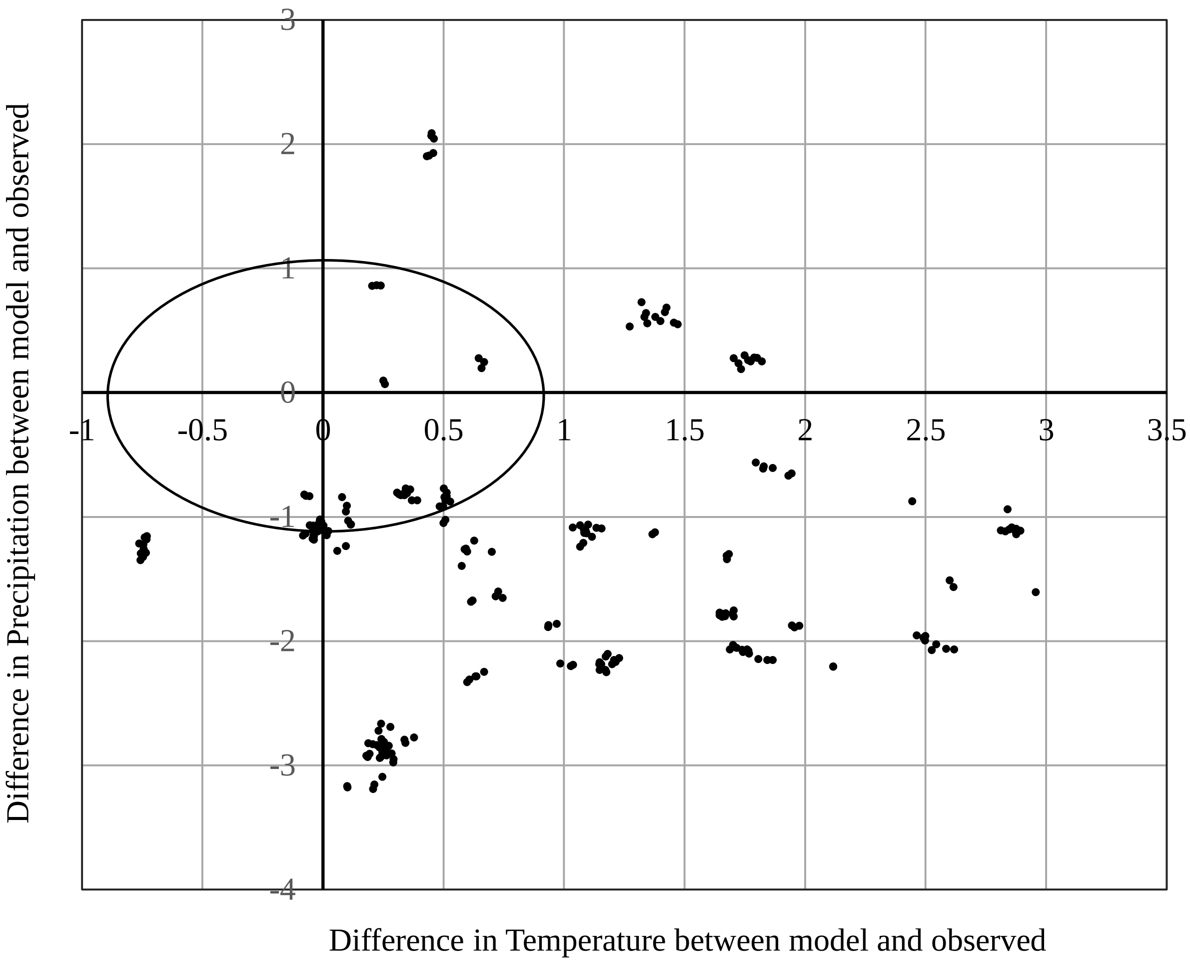

Fig. 4.10. Scatter plot of validating models

Table 4.4. CMIP5 GCMs within acceptable zones for Pra River Basin

GCMs	Atieku	Dunkwa	Kibi	Konongo	Kumasi	Akim Oda	Twifo Praso	Pra Basin	Total No. of YES
CCCma-CanESM2	No	Yes	Yes	Yes	Yes	Yes	Yes	No	6
CCSM4	No	Yes	No	Yes	Yes	No	No	Yes	4
GFDL-CM3	Yes	Yes	Yes	No	No	No	Yes	Yes	5
GFDL-ESM2M	Yes	Yes	No	No	No	Yes	Yes	Yes	5
IPSL-CM5A-LR	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	7
IPSL-CM5A-MR	No	No	Yes	Yes	Yes	Yes	No	No	4
IPSL-CM5B-LR	No	Yes	Yes	Yes	Yes	Yes	No	Yes	6
MPI-ESM-LR	Yes	No	Yes	No	No	Yes	Yes	Yes	5
MPI-ESM-MR	Yes	No	Yes	No	No	Yes	Yes	No	4
NorESM1-M	Yes	No	Yes	Yes	No	No	Yes	Yes	5

4.1.4 Rainfall and temperature calibration in SDSM

The analysis showed a very low partial correlation level between station rainfall data and predictors (Table 4.5). It implies that rainfall is very difficult to predict in this zone. Rainfall as a conditional model has an intermediary process between local weather and regional forcings that have a direct link with wet and/or dry day occurrence. The process further depends on parameters like atmospheric pressure and humidity (Gulacha and Mulungu, 2017; Wilby and Dawson, 2004). Therefore, rainfall downscaling has been found to be problematic and difficult compared to temperature (Hassan and Harun, 2011). The results are similar to the findings of Gulacha and Mulungu (2017). The cross-validation was two-fold, that is, data were divided into two equal 15 years' intervals for calibration and the remaining 15 years for validation. The mean of proportion accuracy (prop correct) for validation of the model was in the range of 61 - 71 % across the seven stations.

The predictors which showed good correlation with mean temperature were used for the calibration of SDSM (Table 4.5). The respective negative and positive coefficient of correlation (r) ranged between (-) 0.31 and 0.63, and (+) 0.38 and 0.70 respectively. According to Gulacha and Mulungu (2017), correlation within this range could be classified to be a medium to high for a temperature model. Mean temperature was better captured using the large atmospheric variables from NCEP compared to rainfall. This could be due to the vast spatial variation in rainfall with limited representation by the spatial resolution of the atmospheric variables and the conditioning of the rainfall process with a threshold (Okafor *et al*., 2019; Wilby *et al*., 2002). Relative humidity at a negative correlation with mean temperature was usable for calibration at two stations (Kibi and Dunkwa). These are mountainous areas and could be a major factor in the regulation of relative humidity with a minimal but relevant for calibration of mean temperature in the Pra River Basin (Table 4.5).

Table 4.5. Correlations of GMet rainfall and mean temperature to predictors for 1981 – 2010

Predictor		Climate Stations						
Code	**Description**	Akim Oda	Atieku	Twifo Praso	Kibi	Dunkwa on Ofin	Kumasi	Konongo
		Rainfall (Partial correlation)						
dswr	Direct shortwave radiation			-0.04				
lftx	Surface lifted index	-0.08		-0.08	-0.10	-0.09	-0.08	-0.09
p_z	Vorticity near the surface			-0.06				
p_zh	Surface divergence						0.06	
p5_z	Vorticity at 500 hPa				0.04			0.09
P8_z	Vorticity at 850 hPa					0.04		
pr_wtr	Precipitable water	0.08	0.09	0.06	0.08	0.04	0.04	0.09
prec	Precipitation total	0.04	0.08	0.05	0.06	0.06	0.06	0.06
r850	Relative humidity at 850 hPa height	-0.08	0.07	-0.04	-0.06	-0.06	-0.07	-0.08
r500	Relative humidity at 500 hPa height		0.06					
rhum	Near-surface relative humidity							0.05
		Mean Temperature (Pearson correlation)						
lftx	Surface lifted index	-0.49	-0.52	-0.50	-0.31		-0.51	-0.52
mslp	Mean sea level pressure	-0.48	-0.47	-0.49	-0.39	-0.63	-0.52	-0.51
p850	850 hPa geopotential height	-0.32	-0.33	-0.34		-0.39	-0.36	-0.34
pottmp	Potential temperature	0.50	0.50	0.50	0.38	0.69	0.54	0.53
r500	Relative humidity at 500 hPa height				-0.32	-0.31		
shum	Near-surface specific humidity	0.63	0.66	0.67			0.67	0.67
temp	Mean temperature at 2 m	0.54	0.54	0.54	0.49	0.70	0.58	0.57

4.1.5 Performance of climate models in simulating historical gauge station records

The evaluation was done with model outputs and station records from 1981 – 2010.

4.1.5.1 Simulation of mean temperature

Ranking the time-series-based metrics for model performance assessment showed that SDSM, followed by CanESM and IPSL were the top three models with good skill in simulating mean temperature in the Pra River Basin (Table 4.6). The Hadgem and GFDL were the last two in descending order of skill in simulating mean temperature. Although all bias-corrected models showed a perfect match for the Nash-Sutcliffe efficiency (NSE), they were ranked low in comparison with model outputs that required no bias-correction because the adjusted outputs were not fit to the monthly means of the observed records via bias-correction (Table 4.6). The NSE results were all within the acceptable range, however, IPSL and Hadgem results without bias-correction showed a very low skill of simulation (Moriasi *et al*., 2007). Similarly, bias-corrected stations had the smallest RMSE signifying a good model efficiency. The variation in mean temperature between station observed records and SDSM and CanESM were +0.01ºC, +0.02ºC respectively. The IPSL, Hadgem and GFDL varied by +0.09ºC, +0.10ºC and +0.11ºC respectively.

4.1.5.2 Rainfall simulations

Evaluating the performance of the models by the three selected time series-based metrics showed that SDSM performed best amongst the five models in simulating historical rainfall in the basin (Table 4.7). Acceptable models should have NSE values ranging between 0.0 and 1.0, lower RMSE and R^2 above 0.5 (Moriasi *et al*., 2007). Bias corrections were applied to two stations for CanESM and five for IPSL before the models fell within an acceptable range (Table 4.7). The Hadgem and GFDL at 12 km resolution did not need a bias-correction to perform well. Thus, higher resolution models (SDSM and WRF) have fewer variations from observed rainfall compared to the CORDEX over the basin. Therefore, the efficiency of the models in descending order of monthly means assessment was SDSM, Hadgem, GFDL, CanESM and IPSL. The performance evaluation was done on a monthly basis since it best depicts the characteristics of change in rainfall pattern (Gulacha and Mulungu, 2017). The high variations in the performance of the models emphasise the uncertainties in climate models (Karambiri *et al*., 2011; Paeth *et al*., 2011). This is either based on their computational process and dynamical structure and/or the greenhouse gas emission scenarios (Semenov and Stratonovitch, 2010; Covey *et al*., 2003).

Table 4.6. The skill of models in simulating mean temperature

	Ateiku	**Akim Oda**	**Dunkwa**	**Kibi**	**Konongo**	**Kumasi**	**Twifo Praso**
				Nash-Sutcliffe efficiency (NSE)			
SDSM	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CanESM	1*	1*	0.52	1*	1*	0.83	0.28
IPSL	1*	1*	0.04	1*	1*	0.44	1*
Hadgem	0.99*	1*	1*	1*	1*	0.12	1*
GFDL	0.99*	1*	1*	1*	1*	1*	1*
				Root mean square error (RMSE)			
SDSM	0.01	0.03	0.02	0.01	0.01	0.03	0.02
CanESM	0.0002*	0.0003*	0.55	0.0002*	0.0003*	0.37	0.63
IPSL	0.0003*	0.0003*	0.73	0.0003*	0.0005*	0.62	0.0004*
Hadgem	0.0004*	0.00011*	0.0009*	0.0006*	0.0008*	0.97	0.0006*
GFDL	0.014*	0.0009*	0.0009*	0.0005*	0.0005*	0.0009*	0.0008*
				Coefficient of determination (R^2)			
SDSM	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CanESM	1*	1*	0.91	1*	1*	0.91	0.89
IPSL	1*	1*	0.93	1*	1*	0.86	1*
Hadgem	0.99*	1*	1*	1*	1*	0.68	1*
GFDL	0.99*	1*	1*	1*	1*	1*	1*

* Bias-corrected with variance scaling method

Table 4.7. Performance of models' in simulating historical station rainfall data

Models	**Ateiku**	**Dunkwa**	**Twifo Praso**	**Kibi**	**Akim Oda**	**Konongo**	**Kumasi**
			Nash-Sutcliffe efficiency (NSE)				
CanESM	0.53	0.72	0.38	0.45[b]	0.63[b]	0.21	0.58
GFDL	0.37	0.30	0.22	0.15	0.01	0.50	0.02
Hadgem	0.53	0.75	0.51	0.418	0.71	0.70	0.50
IPSL	0.25[b]	0.06	0.35[b]	0.43[b]	0.63[b]	0.85[a]	0.02
SDSM	0.90	0.89	0.82	0.90	0.83	0.94	0.84
			Root mean square error (RMSE)				
CanESM	0.97	0.96	1.21	1.29[b]	1.01[b]	1.48	1.10
GFDL	1.28	1.37	1.28	1.57	1.42	1.14	1.45
Hadgem	1.09	0.83	1.04	1.11	0.83	0.93	1.06
IPSL	1.47[b]	1.51	1.37[b]	1.31[b]	1.03[b]	0.64[a]	1.53
SDSM	0.53	0.58	0.71	0.54	0.67	0.43	0.69
			Coefficient of determination (R^2)				
CanESM	0.72	0.85	0.66	0.98[b]	0.99[b]	0.82	0.86
GFDL	0.59	0.57	0.55	0.58	0.46	0.69	0.59
Hadgem	0.62	0.76	0.62	0.67	0.75	0.72	0.76
IPSL	0.78[b]	0.67	0.96[b]	0.96[b]	0.99[b]	0.92[a]	0.75
SDSM	0.99	0.99	0.99	0.99	0.99	0.99	0.99

[a]Linear scaling Bias-corrected, [b]linear scaling + double quantile mapping bias-corrected

4.1.5.3 Implication of climate models' performance

The skill of a model in simulating historical rainfall in the basin decreased as their spatial resolution increased. That is, SDSM at 2 m, had the best skill, followed by the Weather Research and Forecasting models (Hadgem and GFDL) at 12 km. The CORDEX models (CanESM and IPSL) at 44 km had the least skill for rainfall from 1981 – 2010 in the study area. It implies that coarse resolution models were limited in capturing the variations in rainfall distribution at the basin scale. On the contrary, CORDEX models had a better skill in simulating mean temperature than WRF models although the resolution of WRF was high than that of the CORDEX models. The statistical downscaling model (SDSM) was the best skilled for mean temperature as well. Therefore, temperature was not spatial resolution sensitive as compared to rainfall in the Pra River Basin. Furthermore, the parameterization of the GCMs for CORDEX may have a better representation of the tropical climate for mean temperature than Hadgem and GFDL. It implies that the resolution of the model could not be enough to conclude its skill for temperature simulation unless tested.

4.1.6 Future trends of mean temperature

The SDSM, CanESM, IPSL, Hadgem and GFDL modelled mean temperature to be 28.04ºC, 28.04ºC, 28.15ºC, 27.74ºC and 27.62ºC respectively from 2020 – 2049. The difference between the projections of the models was significant at $p < 0.05$. However, SDSM and the CORDEX models (CanESM and IPSL) showed no significant difference at $p < 0.05$. Similarly, the difference between Hadgem and GFDL was not significant.

All the five models projected temperature to increase (in the range of 1.05 – 1.51ºC) in the future period between 2020 and 2049 (Fig. 4.11). The highest mean temperature from SDSM was between 28.18ºC (2026) and 28.50ºC (2049). The temperature peaks from the CanESM model was between 28.14ºC (2021) and 28.59ºC (2041). The IPSL model projected peak mean temperature for 2025 at 28.35ºC and 2047 at 28.75ºC. All models projected more than two years in the future period to experience mean temperature above 28ºC except GFDL which was only in 2042 at 28.02ºC. Minimum of two models projected 2041, 2042 and 2047 to have peak mean temperature at 28.41ºC, 28.16ºC and 28.63ºC respectively. The projected increase in temperature will speed up the chemical reaction in the basin and may result in the fluvial erosion by the cohesion between chemicals and streambanks (Hoomehr *et al*., 2018).

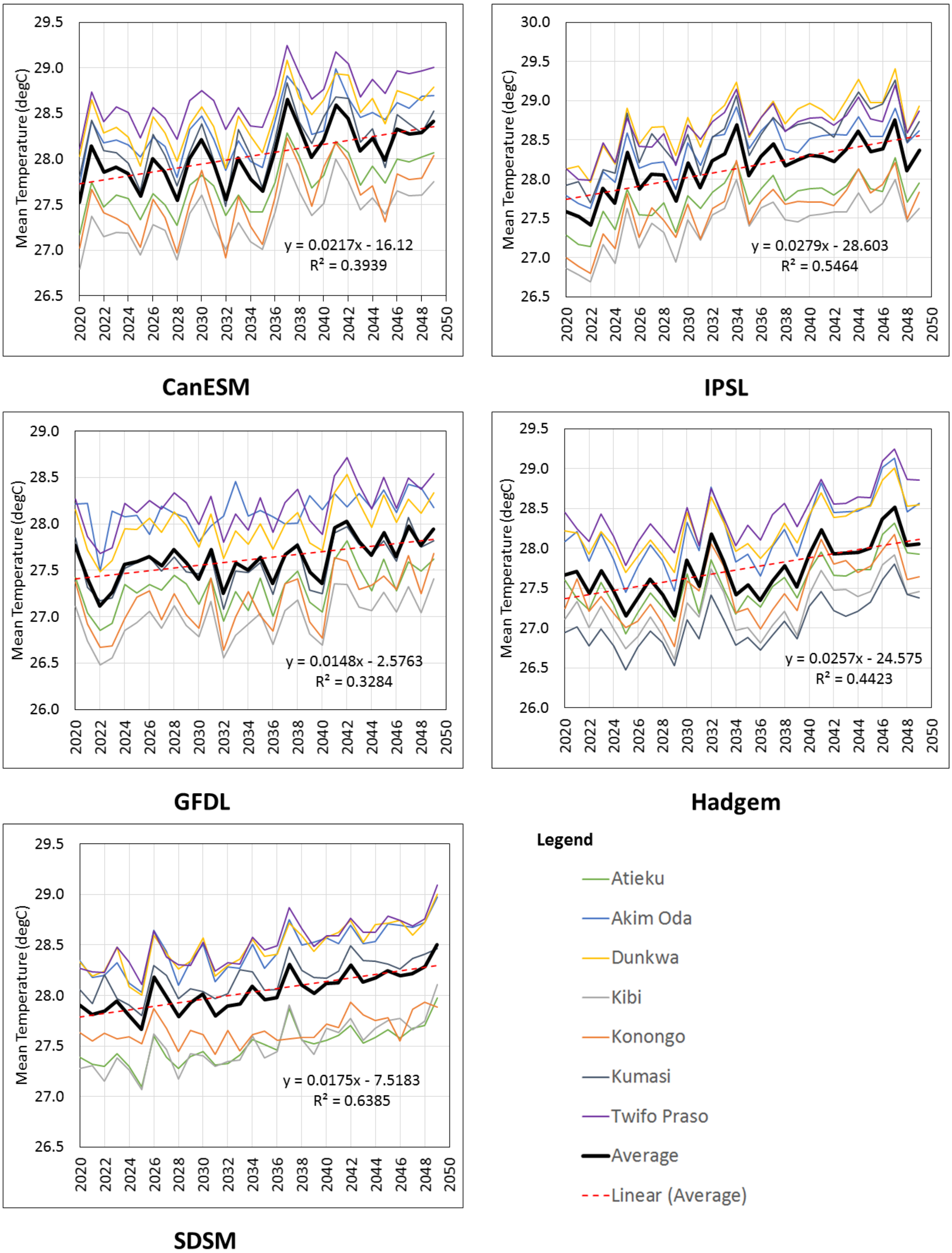

Fig. 4.11. Future mean temperature of the seven stations by the five models

The month of August and March recorded the lowest and highest mean temperature in the basin for the station observed records at about 25ºC and 28ºC respectively between 1981 and 2010 (Fig. 4.12). The mean temperature monthly distribution depicted the bi-modal seasonal rainfall pattern in the basin. Temperatures were lowest during the end of the major rainfall season in July through the minor dry period of August to the beginning of the minor rainfall season in September. This could be due to the cool environment created by the rains since its onset in March mostly in the basin. Also, rainfall increases atmospheric vapour which turns to act as an albedo to increase the reflection of irradiation on the earth (Held and Soden, 2000).

All models except SDSM captured the bi-modal pattern in temperature for the future period (2020 – 2049) (Fig. 4.12). The mean temperature changes in descending order as projected by the models; IPSL (1.47ºC), CanESM (1.37ºC), SDSM (1.36ºC), Hadgem (1.18ºC) and GFDL (1.06ºC). The ensemble of the five models showed that temperature could increase by almost 1.50ºC in the dry seasons (November to March). Moreover, the change was very high at the beginning of the year (January to March) and least from July to September (Fig. 4.12). The Northeast trade winds (harmattan) could contribute to the high change in temperature from January to April. Evaporation could negatively be influenced by the increased temperature projections with a major impact on water management for agriculture.

The future mean temperature was projected to increase between 0.40ºC and 1.49ºC (Fig. 4.13). The CMIP5 projected mean temperature over the basin for the 2020s and 2050s at 0.80ºC and 1.68ºC respectively are comparable to the mean ensemble result of the five models. The ensemble results further fall within the projection of the IPCC's AR4 temperature projection over West Africa in 2030 which was in the range of 1.10 – 1.30°C (WRC, 2012). Generally, IPSL (1.38ºC at Akim Oda to 1. 48ºC at Kumasi) projected the highest change over the basin whereas GFDL result was the lowest (0.92ºC at Kumasi to 1.14ºC at Akim Oda) (Fig. 4.13). The results from IPSL and GFDL shows a significant variation in climate modelling as the highest for one model is the lowest in another and vice versa. Therefore, the ensembling of multiple models is needed to build an acceptable roadmap for climate change adaptation planning. The change in mean temperature at the climate stations ranged between 1.15ºC – 1.48ºC, 1.31ºC – 1.46ºC and 0.41ºC – 1.28ºC for SDSM, CanESM and Hadgem respectively.

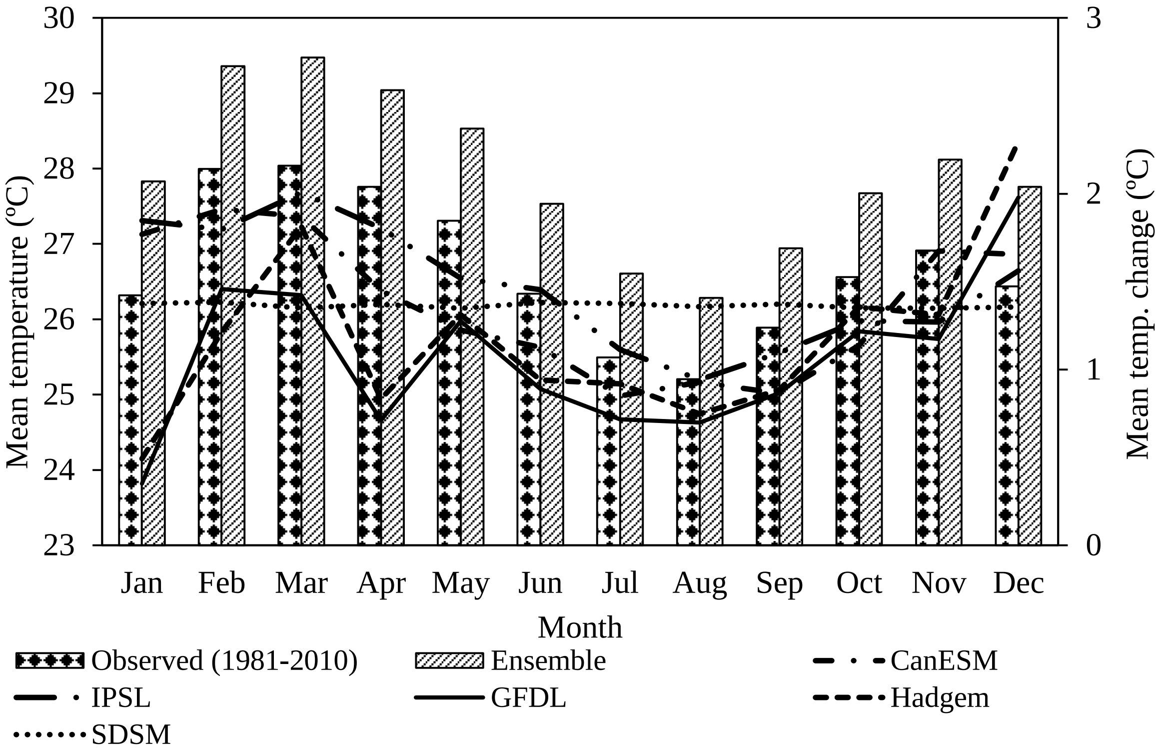

Fig. 4.12. Future changes in mean temperature by the ensemble of models

NB: Mean temperature is on the primary axis and mean temperature changes of the five models located on the secondary axis.

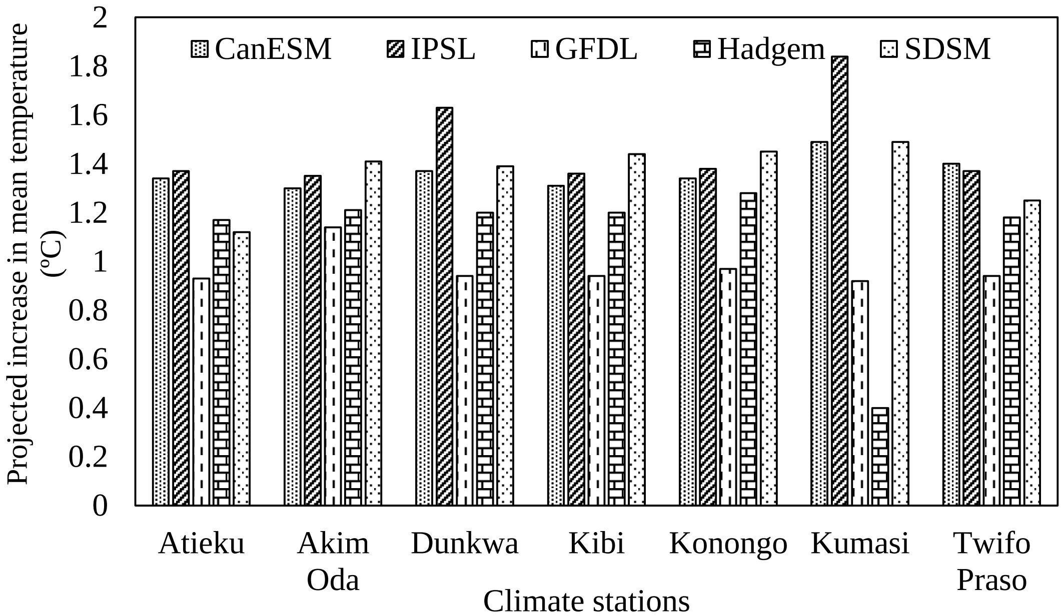

Fig. 4.13. Future climate station changes in mean temperature (ºC)

4.1.6.1 Spatial trend of future mean temperature

The spatial trend of temperature increase from the south to the north which was closely captured by the change projected by SDSM, CanESM and IPSL (Fig. 4.14). The change in mean temperature by SDSM increased from about 1.2ºC in the southern part of the basin to about 1.6ºC from the centre to the north. The CanESM mean temperature change was spatially increased from the east to the west at about 1.3ºC and a high change at the north at about 1.5ºC whereas IPSL showed a distributed change of 1.2ºC from east to the centre and increased from there to about 1.8ºC at the north (Fig. 4.14). The spatial change of GFDL was generally around 1.0ºC while Hadgem had a difficult spatial trend. The Hadgem model could not capture a uniform spatial distribution due to the significant difference in mean temperature projections at the climate stations.

The SDSM mapped the industrious cities like Kumasi, Akim Oda and Obuasi in the northern part of the basin to experience the highest change in mean temperature in future. The CanESM could capture only Kumasi in zone of highest change while IPSL covered Kumasi and Obuasi at the northwest part of the basin (Fig. 4.14). Due to industrialization and numerous economic activities that take place in urban centres, temperature change in these locations is higher compared to their surrounding neighbourhood. Furthermore, the high population of these centres contributes to urban heat island which might be a reason in the change in temperature projected by SDSM, CanESM and IPSL over the major cities in the Pra River Basin (Zeleňákováa *et al*., 2015; Zielinski, 2014; Sakakibara and Owa, 2005). Therefore, the spatial trend of change in mean temperature in future over the basin confirms the skill of SDSM and CORDEX models (CanESM and IPSL at 44 km) as good since the distribution is similar to the trend of temperature increase over Ghana (Nutsukpo *et al*., 2013).

The WRF models (GFDL and Hadgem) was not skilled enough to capture the urban impact on temperature increase since all urban centres were projected to have the least change in temperature compared to their surrounding communities (Fig. 4.14). Due to the variations in models, the ensemble showed a uniform change in temperature generally over the basin at about 1.25ºC.

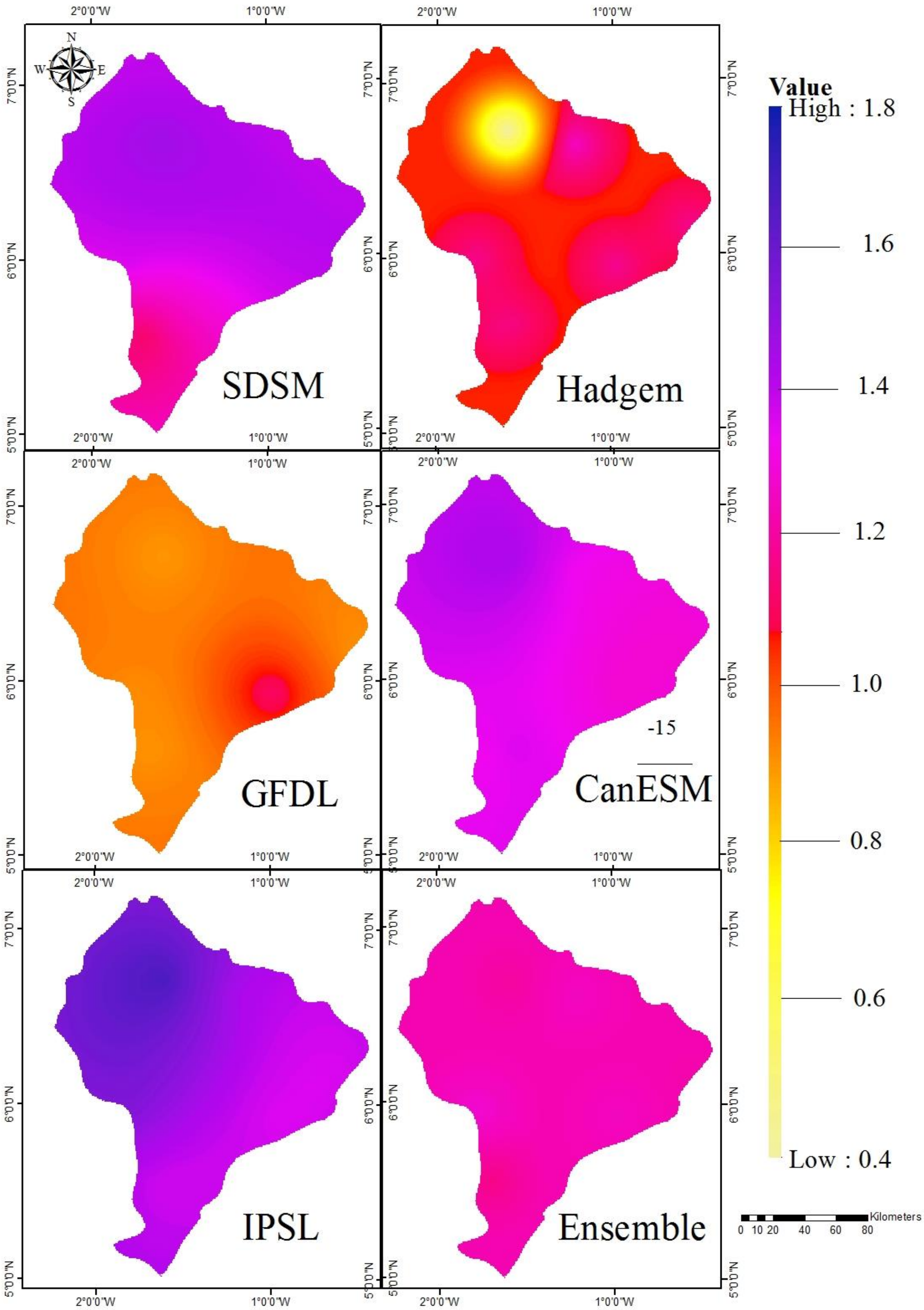

Fig. 4.14. Spatial distribution of changes in future mean temperature

4.1.7 Projected rainfall variability and change

The projected ensemble monthly mean rainfall in comparison with the observed records of 1981 – 2010 and the standardised anomaly index of the future period 2020 – 2049 are shown in Fig. 4.15 and 4.16. In the future period, the mean daily rainfall amount will decrease in January, February, March, June, October, November and December at about 32 %, 32 %, 8 %, 7 %, 6 %, 3 % and 20 %, respectively over the basin from the ensemble of the five models, whereas the remaining months will experience an increase in daily rainfall amounts (Table 4.8). All the models succeeded in depicting the bi-modal distribution of rainfall in the basin except for GFDL which showed a mono-modal rainfall pattern from April to October (Fig. 4.15).

The bi-modal distribution coincides with the onset of rainfall in February-March to the end of August and the minor rainfall season beginning in September to end in November-December. This was similar to the results obtained by Laprise *et al*. (2013), where ERA-driven fifth-generation Canadian Regional Climate Model (CRCM5) was successful in reproducing the minor raining season of the Guinea Coast region in September. The increase in rainfall amount in July and August might make it seems as if there was no break from the major season into the minor season in the future period.

The standardised anomaly index (SAI) in Fig. 4.16 shows that there could be more of drier than normal years (2021, 2023 & 2031) than wetter than normal years (2042 & 2049) in the future. However, 2020 (-0.38) and 2036 (-0.38) are closer to drier than normal years and should be considered in planning against drought with the three projected years of SAI < -0.5. The Hadgem and CanESM recorded the highest negative (-2.28) and positive (2.61) SAI in the year 2020 and 2033 respectively. The CanESM and IPSL projections from Table 4.8 of about 26 % and 18 % decrease in rainfall are similar to the findings of Obuobie *et al*. (2012) with ECHAM4/CSIRO joint model which had a decrease in rainfall of 17.8 % by 2020 and 25.9 % by 2050. This was because the models have about the same medium resolution (44 - 55 km). The SDSM and Hadgem projected rainfall increase of about 13 % and 27 % whereas GFDL being the third best-skilled model from the performance evaluation, projected a decrease of about 5 %. The spatial distribution of the projected rate of change (%) in mean annual rainfall amount in future varied amongst models as shown in Fig. 4.17. The SDSM and Hadgem had similar even spatial distribution of change in rainfall amount with spots of variations in Hadgem.

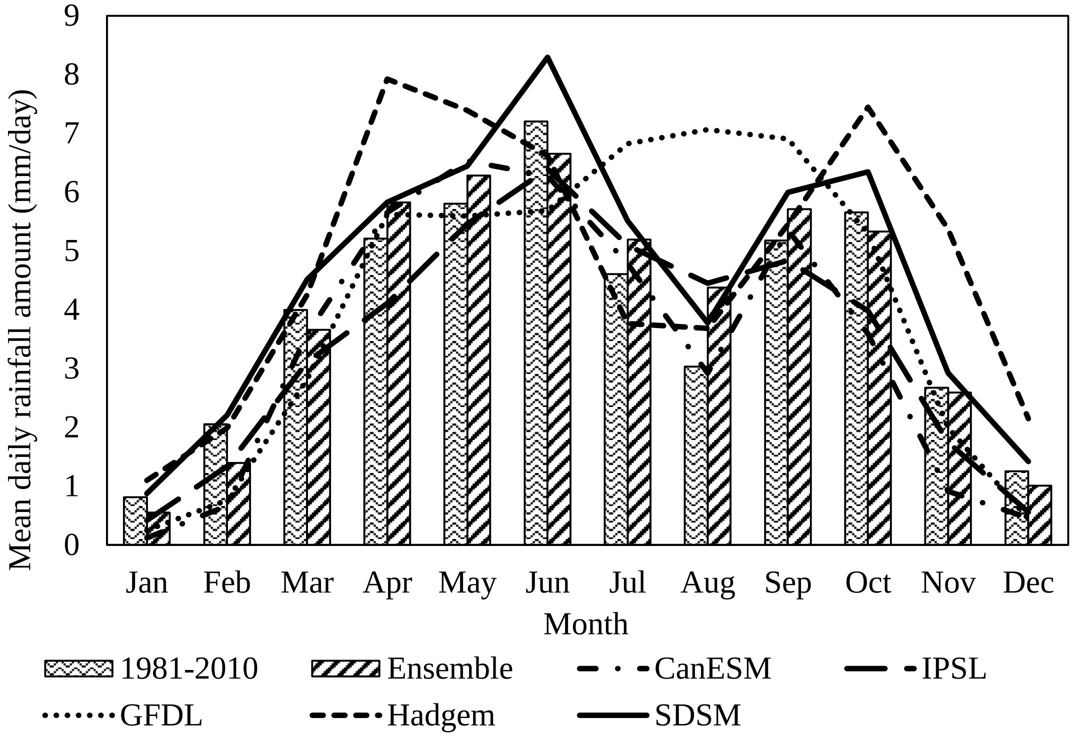

Fig. 4.15. Future mean daily rainfall amount

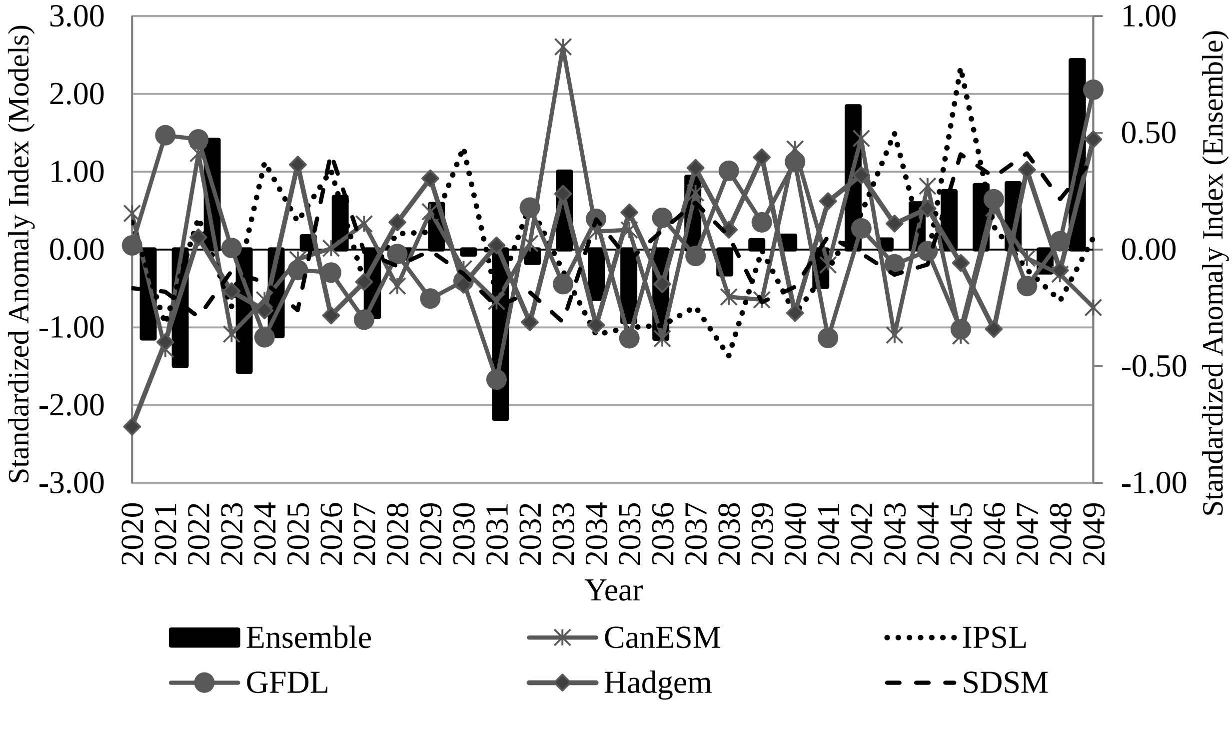

Fig. 4.16. Future standardised anomaly index

Table 4.8. Rainfall percentage (%) change over the Pra River Basin (2020 – 2049)

Month	CanESM	IPSL	GFDL	Hadgem	SDSM	Ensemble
Jan	-85.16	-48.77	-69.13	34.80	7.56	-32.14
Feb	-67.49	-35.05	-63.05	-3.12	7.48	-32.25
Mar	-10.10	-22.14	-29.48	6.53	13.08	-8.42
Apr	8.55	-21.13	7.94	52.13	11.88	11.87
May	12.58	-5.91	-3.59	27.35	11.09	8.30
Jun	-12.93	-11.29	-21.07	-8.17	15.12	-7.67
Jul	3.87	10.65	48.20	-18.23	19.72	12.84
Aug	-3.63	46.82	132.99	21.46	24.49	44.43
Sep	3.43	-6.64	33.31	5.26	15.78	10.23
Oct	-36.53	-29.57	-6.26	31.61	12.18	-5.72
Nov	-65.91	-34.80	-25.35	100.81	9.46	-3.16
Dec	-63.08	-55.47	-64.27	71.49	13.25	-19.62
Mean	**-26.37**	**-17.78**	**-4.98**	**26.83**	**13.43**	**-1.77**

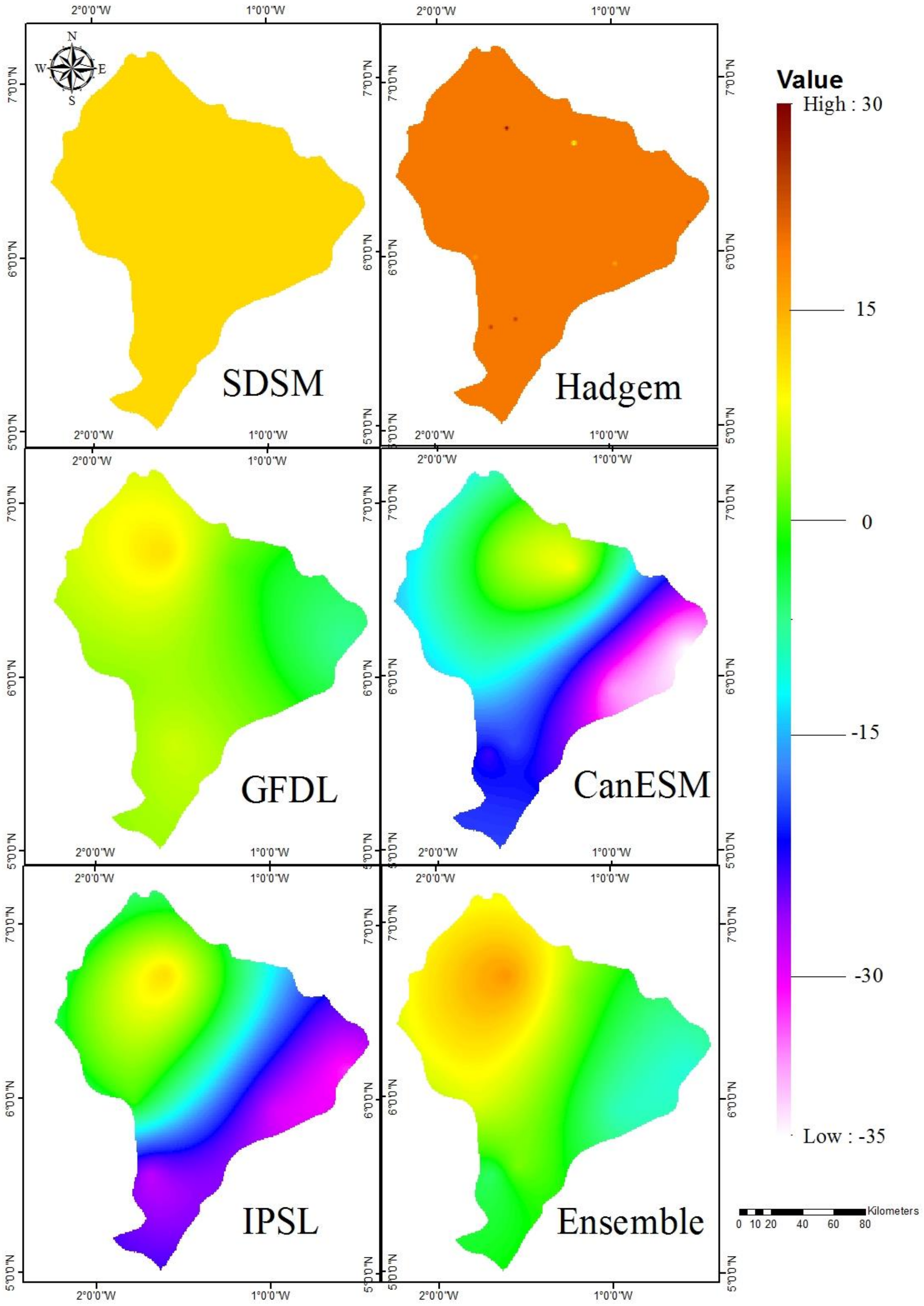

Fig. 4.17. The projected rate of change (%) in mean annual rainfall by models (2020 – 2049)

The projected rate of change of SDSM spatially was between 8% and 19 % whereas that of Hadgem was 0 – 29 % (Fig. 4.17). The GFDL model also projected an increasing trend at the southern part of the basin which is covered by the forest and coastal savanna zones at about 3 – 5 % and at the north from a central point of Kumasi in the range of 2 – 17 %. The rate of change by GFDL from the centre to the east of the basin was uniform (Fig. 4.17). Projections from CanESM and IPSL models was a spatial increase in rainfall northward, that is, increasing rainfall in the semi-deciduous zones whiles the forest and coastal savanna zones had a decreasing amount of rainfall between 1 % and 35 %. This might result in an increased runoff in the deciduous zones leading to flooding. The ensemble captured spatial increasing rate of change in mean annual rainfall amount from the east to the west in the range of 4 – 8 %. The ensemble suggests a decrease in rainfall at the east end of the basin. Adaptation measures should consider both potentials of increase and decrease in the amount of rainfall to prevent shocks from the projected changes.

4.1.8 Rainfall onset, cessation and duration in the basin

4.1.8.1 Climate station and models simulated onset, cessation and duration of rainfall

During the climate station observed period, early rainfall onset was on 4th February 2004 and late-onset was on 6th April 1983. Early and late cessation dates were 16th October 1987 and 15th December 1990 respectively with an average length of the rainy season at 255 days over the Pra River Basin. There was a drought in the year 1983 in Ghana which was captured by the early rainfall cessation on 26th October, resulting in the lowest length of rainy days of 218 during the 30-year observed period from 1981 to 2010. The rainfall onset had a decreasing trend, that is, onset was becoming early over the observed period and had an increasing trend with later cessation during this period. This implies that the length of the rainy season increased across the years over the basin in the observed period starting with 243 days in 1981 and increasing to 289 days in 2010 (Fig. 4.18). This was also seen in the onset and cessation trend over the basin in the assessed period (Fig. 4.18). The ensemble of the five model simulations for the period 1981 – 2010 followed the same trend for onset, cessation and length of the rainy season (Fig. 4.18). However, onset was late, cessation earlier and length of rainy season shorter compared to the station observed records.

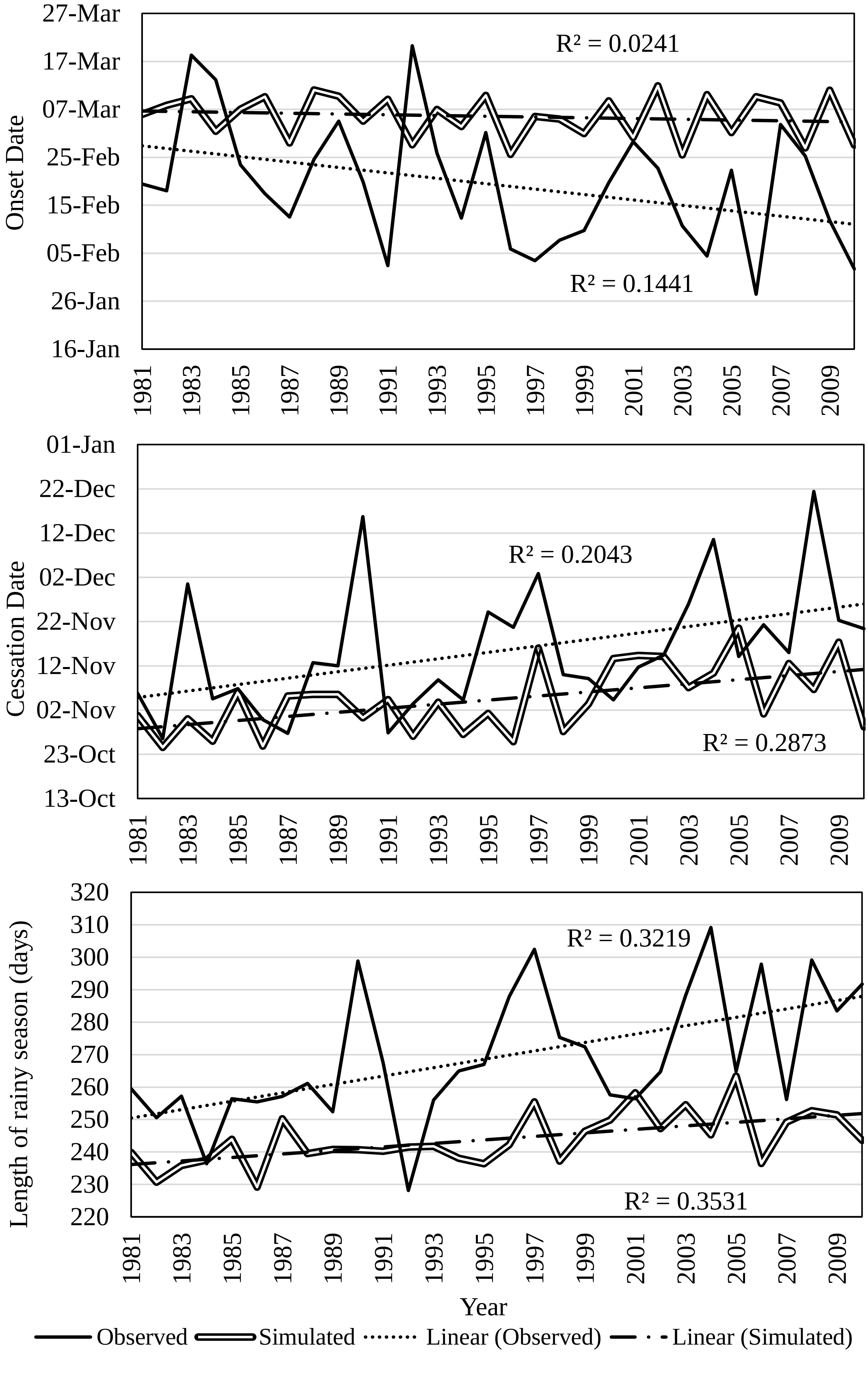

Fig. 4.18. Mean onset, cessation and length of the rainy season from station records in the Pra River Basin

Comparing the performance of the modified Onset, Cessation and LRS method adopted in this study

The onset date, cessation date and length of the rainy season at the seven stations considered in the study are presented in Table 4.9. Two synoptic stations; namely, Akim Oda and Kumasi were used as a reference based on findings from other studies. At Akim Oda station, early and late-onset of rainfall was 23^{rd} January and 4^{th} April respectively while early and late cessation of rainfall was on 3^{rd} October and 25^{th} December respectively. The mean onset and cessation dates for the observed period were 27^{th} February and 18^{th} November respectively. The average length of the raining season was 264 (±30). Mensah *et al*. (2016) used the fuzzy logic approach in Instat software to determine onset date, cessation date and length of rainy season for Akim Oda for the period 1998 - 2012. The mean onset and cessation dates were 15^{th} March and 10^{th} November respectively and the duration was 240 days.

Amekudzi *et al*. (2015) also used the percentage mean cumulative rainfall method to determine the onset, cessation dates and rainfall duration at 11^{th} March, 6^{th}/11^{th} November (rainfall amount/rainy days) and 245 days for the period 1970 – 2012. Comparatively, the study's modified Walter-Olaniran method (Matthew *et al*., 2017) results were 7 days and 19 days over that of cumulative curves method by Amekudzi *et al*. (2015) for cessation date and length of rainy season respectively and 8 days for cessation date and 24 days for length of rainy season above the results of Mensah *et al*. (2016). However, the mean onset date was earlier in this study at 12 and 16 days compared to the determined onset by Amekudzi *et al*. (2015) and Mensah *et al*. (2016) respectively.

At Kumasi station, early and late-onset of rainfall was 14^{th} January and 2^{nd} April respectively while early and late cessation of rainfall was on 1^{st} October and 21^{st} December respectively. The mean onset and cessation dates for the observed period were 27^{th} February and 22^{nd} October respectively. The average length of the rainy season was 237 (±32) days (Table 4.9). Amekudzi *et al*. (2015) determined onset, cessation and rainfall duration for Kumasi station to be 11^{th} March, 22^{nd}/27^{th} October (rainfall amount/rainy days) and 300 days respectively. Cessation date of this study was the same with the rainfall amount method used by Amekudzi *et al*. (2015) although the period of analysis was 30 and 43 years respectively. Onset was earlier in this study when compared to that of Amekudzi *et al*. (2015). Mensah *et al*. (2016) also determined 21^{st} March, 20^{th} November and 244 days as the onset, cessation and length of the rainy season for Kumasi station between 1998 – 2012. The difference in onset and cessation dates of the two methods compared with the method of this study was less than 15 days. A study with the same period is hereby recommended to test the modified method of this study with other available methods to determine its efficiency.

Onset, cessation and LRS from the historical simulations of the five models

The mean station observed onset at all stations in this study was in February except Konongo station which was in March (Table 4.9). November was the month for the mean station observed cessation date at all stations except at Kumasi and Konongo which was in October. Averagely at all stations, SDSM and Hadgem simulated mean onset date of the historical period (1981 – 2010) to be earlier than what was determined for the station observed period or same month except at Konongo and Kumasi where the mean onset of Hadgem was in March (late) (Table 4.9). The GFDL, CanESM and IPSL model on the other hand simulated onset to be late with reference to the station observed records. The SDSM simulation produced the same mean cessation months with the station observed records except for Kibi and Kumasi where the model was late. The Hadgem model cessation date were more late than being the same with the station observed cessation date for the historical period (Table 4.9). The GFDL, CanESM and IPSL simulations showed an early cessation which resulted in less length of rainy season for the historical period compared to the station observed length of rainy season in the basin. There were some notable variations in the length of rainy season between models and also between models and station obeserved records. However, SDSM and Hadgem had more close simulation of length of rainy season to the stations observed records compared to GFDL, CanESM and IPSL (Table 4.9).

Generally, the models were capable of simulating the onset of rainfall late, cessation to be early and length of the rainy season to be less compared to the station observed records in the basin (Fig. 4.18). The two extreme trends of SDSM and Hadgem (positive) and GFDL, CanESM and IPSL (negative) complimented in the ensemble to produce a favourable means relevant for decision making and acceptance of projections on onset, cessation and length of rainy season between 2020 and 2049. Ranking the mean deviation of onset, cessation and length of rainy season days of the models from observed showed that Hadgem was more reliable in determining onset, cessation and length of rainy days.

Table 4.9. Onset, cessation and length of the rainy season of observed station records and model simulations for 1981 – 2010

Data	**ONSET OF RAINFALL** Early	Late	Mean	SD (days)	**CESSATION OF RAINFALL** Early	Late	Mean	SD (days)	**LRS (days)**
				Akim Oda Station					
Observed	23 Jan	04 Apr	27 Feb	20	03 Oct	25 Dec	18 Nov	23	264 (±30)
SDSM	05 Feb	03 Mar	13 Feb	18	01 Nov	31 Dec	27 Nov	27	287 (±27)
Hadgem	14 Jan	02 Apr	28 Feb	15	01 Oct	30 Dec	25 Nov	25	271 (±24)
GFDL	21 Feb	14 Apr	18 Mar	14	01 Oct	24 Dec	17 Oct	22	213 (±28)
CanESM	13 Jan	09 May	08 Mar	31	02 Sept	26 Dec	31 Oct	31	237 (±39)
IPSL	17 Jan	10 Jun	20 Mar	37	01 Oct	27 Dec	08 Nov	25	233 (±46)
				Ateiku Station					
Observed	11 Jan	14 Apr	21 Feb	20	15 Sept	29 Dec	16 Nov	28	268 (±34)
SDSM	01 Feb	05 Mar	13 Feb	11	01 Nov	18 Dec	17 Nov	18	277 (±18)
Hadgem	02 Jan	10 Mar	18 Feb	19	01 Nov	29 Dec	07 Dec	19	292 (±22)
GFDL	12 Feb	01 May	08 Mar	18	01 Oct	25 Dec	28 Oct	25	234 (±31)
CanESM	12 Feb	24 Mar	06 Mar	11	01 Oct	27 Nov	24 Oct	18	231 (±23)
IPSL	08 Jan	27 Apr	08 Mar	27	01 Oct	28 Dec	29 Oct	26	234 (±38)
				Dunkwa on Ofin Station					
Observed	21 Jan	05 Apr	26 Feb	16	01 Oct	24 Dec	09 Nov	28	256 (±32)
SDSM	03 Feb	06 Mar	19 Feb	10	01 Nov	31 Dec	29 Nov	26	283 (±27)
Hadgem	11 Jan	01 Apr	26 Feb	15	01 Nov	30 Dec	01 Dec	23	278 (±23)
GFDL	21 Feb	13 Apr	18 Mar	14	01 Oct	26 Dec	20 Oct	24	216 (±27)
CanESM	13 Feb	23 Mar	07 Mar	10	02 Sept	29 Nov	17 Oct	20	224 (±23)
IPSL	03 Mar	10 Apr	23 Mar	12	01 Oct	29 Nov	20 Oct	24	211 (±26)
				Kibi Station					
Observed	11 Jan	20 Apr	21 Feb	20	01 Oct	30 Dec	17 Nov	29	269 (±35)
SDSM	23 Jan	01 Mar	29 Jan	06	01 Nov	30 Dec	11 Dec	22	316 (±22)
Hadgem	15 Jan	11 Mar	28 Feb	13	02 Oct	29 Dec	22 Nov	23	267 (±25)
GFDL	27 Feb	01 May	22 Mar	16	01 Oct	19 Dec	21 Oct	23	213 (±31)
CanESM	04 Jan	04 May	04 Mar	32	03 Sept	19 Dec	25 Oct	27	236 (±47)
IPSL	04 Jan	02 Jun	11 Mar	30	07 Sept	04 Dec	27 Oct	26	230 (±43)
				Konongo Station					
Observed	28 Jan	02 May	02 Mar	21	04 Sept	23 Dec	22 Oct	25	235 (±32)
SDSM	02 Feb	02 Apr	21 Feb	13	01 Oct	23 Nov	28 Oct	19	250 (±25)
Hadgem	10 Feb	05 Apr	10 Mar	10	01 Oct	30 Dec	05 Nov	30	240 (±35)
GFDL	06 Mar	01 May	28 Mar	15	01 Oct	21 Nov	13 Oct	13	199 (±16)
CanESM	17 Feb	05 Apr	14 Mar	13	02 Oct	28 Nov	20 Oct	16	220 (±17)
IPSL	17 Jan	06 Apr	09 Mar	21	01 Sept	18 Dec	29 Oct	27	234 (±36)
				Kumasi Station					
Observed	14 Jan	02 Apr	27 Feb	17	01 Oct	21 Dec	22 Oct	26	237 (±32)
SDSM	30 Jan	11 Mar	19 Feb	11	01 Oct	29 Dec	02 Nov	30	257 (±35)
Hadgem	07 Feb	04 Apr	07 Mar	10	01 Oct	30 Dec	12 Nov	26	250 (±27)
GFDL	05 Mar	20 Apr	26 Mar	14	01 Oct	28 Dec	13 Oct	19	201 (±23)
CanESM	17 Feb	02 Apr	12 Mar	11	01 Oct	27 Nov	18 Oct	16	219 (±19)
IPSL	03 Mar	10 Apr	25 Mar	11	01 Oct	29 Nov	12 Oct	15	201 (±18)
				Twifo Praso Station					
Observed	17 Jan	08 Apr	28 Feb	25	01 Oct	29 Dec	12 Nov	25	257 (±35)
SDSM	25 Jan	06 Mar	07 Feb	11	01 Nov	31 Dec	26 Nov	28	292 (±28)
Hadgem	10 Jan	10 Mar	20 Feb	18	01 Nov	27 Dec	07 Dec	19	290 (±21)
GFDL	11 Feb	19 Apr	07 Mar	16	01 Oct	22 Dec	27 Oct	25	235 (±29)
CanESM	12 Feb	01 Apr	07 Mar	12	05 Sept	27 Nov	21 Oct	20	228 (±24)
IPSL	10 Jan	01 May	12 Mar	28	01 Oct	29 Dec	06 Nov	26	239 (±40)

*LRS – Length of Rainy Season

4.1.8.2 Projected onset, cessation and rainfall duration

Rainfall onset, cessation dates and the length of rainy season projected by the ensemble mean of the five models for the future period are presented in Fig. 4.19. Early-onset was on 24th February 2025 and late-onset on 29th March 2036. Onset date showed a weak increasing trend at $R^2 = 0.0108$ (Fig. 4.19). Early and late cessation date for the ensemble mean was on 20th October 2021/2030 and 17th November 2037 respectively. Future cessation also should a weak increasing trend at $R^2 = 0.1155$. The slight increase and weak prediction power could be due to the high variations amongst the models (SDSM and Hadgem project increasing rainfall amount while GFDL, CanESM and IPSL project a decreasing amount of rainfall). The lowest and highest length of rainy season at 223 and 265 days were in 2036 and 2025 respectively (Fig. 4.19).

The onset and cessation date and length of rainy season projected by individual models are presented in Table 4.10. Averagely at all stations, SDSM and Hadgem projected mean onset date earlier than what was determined for the observed period or same month while GFDL, CanESM and IPSL projected late onset of rainfall with reference to the observed period. However, at Kibi, Konongo and Kumasi, the future onset date of Hadgem was about 5 days late in reference to the climate station observed records (Table 4.9). The trend was the same with projected cessation dates by the models. The SDSM and Hadgem models averagely projected late cessation date with reference to observed period whereas GFDL, CanESM and IPSL projected early cessation. The projected length of the rainy season by the models increased in SDSM and Hadgem whereas GFDL, CanESM and IPSL projected a decrease in the length of rainy days. The projected increased length of rainy days will facilitate crop growth since growth depends more on the number of rainy days in the season than the amount (Vischel and Lebel, 2007; Lebel and Le Barbe, 1997). Also, the hydrological cycle will be positively affected by the projection of SDSM and Hadgem (Modarres, 2010). However, the decreased length of the rainy season projected by GFDL, CanESM and IPSL might result in prolonged dry spells, seasonal drought and stunted crop growths.

The SDSM and Hadgem models projected an average length of the rainy season of 267 and 278 days respectively in the period 2020 - 2049. There was a projection of increased rainy days by 12 days and 23 days from the observed station climate records for 1981 - 2010 whereas GFDL, CanESM and IPSL projected a decrease in rainy days by 29 days, 40 days and 33 days respectively. Rainfall onset as projected by SDSM from 2020 – 2049 will be as early as 5th February in 2045 and a bit late on 13th March in 2039. Cessation was on 22nd October 2034 and 17th December 2026 for early and late cessation respectively (Table 4.10). The Hadgem, on the other hand, projected early onset on 31st January 2027 and late-onset on 28th March 2021 while early and late rainfall cessation was on 4th November 2028 and 20th December 2038 respectively. It implies that rainfall onset will be delayed by one month from the observed period into the future period while rainfall cessation will be maintained in same months with additional rainy days before ending according to the best performing models from this study. The GFDL model projected early and late onset of rainfall in the months of February and April and rainfall cessation to be October and November with 225 days as the length of the rainy season. The GFDL model projected increasing trends for both onset and cessation of rainfall, which implies that rainfall will be starting late and ending early in future. There was a slight difference between the projection of the GFDL and the CORDEX SHMI-RCA4 (CanESM and IPSL) models (Table 4.10).

The CORDEX models projected a decreasing trend in rainfall onset and cessation. It implies that rainfall onset is expected to be late and cessation to be early across the future period. The average length of the rainy season for CanESM and IPSL were 215 and 222 days. Early and late-onset for CORDEX models were in February and April respectively while early cessation was in September and October for CanESM and IPLS respectively (Table 4.10). Late rainfall cessation for CORDEX models was projected to be in November. The WRF models (GFDL and Hadgem) having the same spatial resolution performed differently in this study as shown in Table 4.10. This might be due to the varying boundary conditions under which the regional climate model was set in the GCMs or the parameterization of the GCMs from which WRF was run (Nikiema *et al*., 2017).

Based on the performance of Hadgem historical simulations in predicting on onset, cessation dates and length of rainy season (LRS) in the basin, future prediction of onset, cessation and LRS are more reliable compared to the other models. The second model after Hadgem was the SDSM, therefore, the models with good skill for rainfall simulation in the basin were also capable of predicting onset, cessation and LRS.

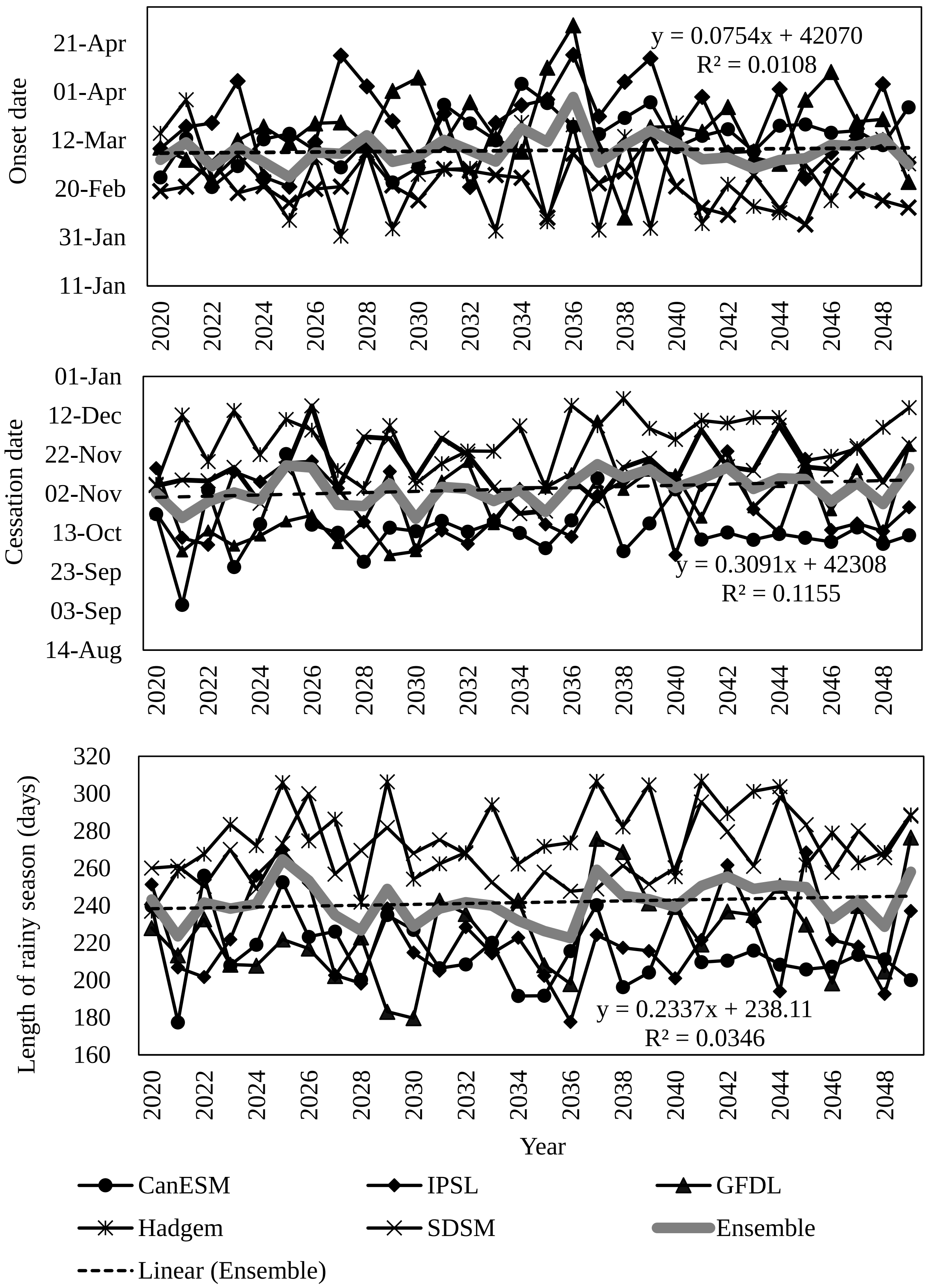

Fig. 4.19. Future annual trend of rainfall onset, rainfall cessation and length of raining season over the Pra River Basin

Table 4.10. Future onset, cessation and length of the rainy season at selected stations in the Pra River Basin

Data	ONSET OF RAINFALL Early	Late	Mean	SD (days)	CESSATION OF RAINFALL Early	Late	Mean	SD (days)	**LRS (days)**
				Akim Oda Station					
SDSM	21 Jan	16 Mar	20 Feb	14	03 Oct	31 Dec	24 Nov	26	277 (±30)
Hadgem	22 Jan	01 Apr	23 Feb	18	01 Nov	31 Dec	30 Nov	23	280 (±29)
GFDL	11 Feb	01 May	16 Mar	20	01 Oct	20 Dec	27 Oct	23	225 (±30)
CanESM	3 Feb	10 May	19 Mar	24	01 Sept	31 Dec	26 Oct	33	221 (±46)
IPSL	1 Feb	03 Jun	31 Mar	35	01 Oct	29 Dec	10 Nov	27	224 (±48)
				Ateiku Station					
SDSM	05 Feb	01 Apr	25 Feb	13	01 Oct	29 Dec	18 Nov	23	266 (±26)
Hadgem	13 Jan	04 Apr	09 Feb	22	01 Nov	30 Dec	09 Dec	17	303 (±29)
GFDL	19 Jan	10 Apr	08 Mar	22	01 Oct	30 Dec	10 Nov	28	248 (±38)
CanESM	02 Feb	05 Apr	10 Mar	12	04 Sept	22 Nov	12 Oct	19	215 (±22)
IPSL	18 Jan	17 Apr	06 Mar	21	01 Sept	23 Dec	06 Nov	28	246 (±35)
				Dunkwa on Ofin Station					
SDSM	23 Jan	05 Apr	26 Feb	17	01 Oct	28 Dec	22 Nov	26	268 (±31)
Hadgem	22 Jan	02 Apr	22 Feb	18	02 Nov	31 Dec	04 Dec	23	285 (±26)
GFDL	19 Jan	10 Apr	15 Mar	21	01 Oct	28 Dec	01 Nov	27	231 (±31)
CanESM	26 Feb	04 Apr	13 Mar	10	03 Sept	22 Nov	14 Oct	16	215 (±21)
IPSL	17 Feb	10 Apr	18 Mar	13	01 Oct	30 Nov	21 Oct	22	217 (±29)
				Kibi Station					
SDSM	15 Jan	05 Mar	03 Feb	13	01 Oct	27 Dec	29 Nov	30	299 (±35)
Hadgem	02 Feb	03 Apr	27 Feb	20	01 Nov	23 Dec	28 Nov	21	274 (±31)
GFDL	14 Feb	23 Apr	20 Mar	18	24 Aug	30 Dec	26 Oct	30	220 (±27)
CanESM	15 Jan	03 May	09 Mar	18	15 Sept	10 Dec	15 Oct	24	220 (±31)
IPSL	05 Jan	01 Jun	16 Mar	31	03 Sept	29 Dec	29 Oct	28	226 (±40)
				Konongo Station					
SDSM	02 Feb	06 Apr	22 Feb	21	01 Oct	28 Dec	25 Oct	29	241 (±39)
Hadgem	07 Feb	07 Apr	12 Mar	17	01 Oct	31 Dec	12 Nov	23	246 (±25)
GFDL	05 Mar	24 Apr	25 Mar	14	01 Oct	29 Nov	19 Oct	20	208 (±25)
CanESM	27 Feb	03 Apr	14 Mar	9	04 Sept	15 Nov	11 Oct	13	211 (±15)
IPSL	12 Jan	13 Apr	09 Mar	23	04 Oct	31 Dec	28 Oct	26	233 (±36)
				Kumasi Station					
SDSM	01 Feb	10 Mar	27 Feb	15	01 Oct	24 Dec	21 Oct	24	236 (±29)
Hadgem	04 Feb	05 Apr	09 Mar	17	01 Oct	31 Dec	21 Nov	24	257 (±31)
GFDL	26 Jan	20 Apr	02 Mar	19	01 Oct	23 Dec	20 Oct	22	211 (±32)
CanESM	25 Feb	04 Apr	13 Mar	09	02 Sept	15 Nov	11 Oct	14	212 (±15)
IPSL	22 Feb	09 Apr	19 Mar	12	01 Oct	21 Nov	12 Oct	14	207 (±21)
				Twifo Praso Station					
SDSM	23 Jan	01 Apr	18 Feb	17	01 Nov	30 Dec	28 Nov	25	283 (±28)
Hadgem	14 Jan	04 Apr	12 Feb	21	01 Nov	26 Dec	09 Dec	17	300 (±27)
GFDL	08 Feb	05 Apr	08 Mar	20	01 Oct	22 Dec	03 Nov	25	240 (±37)
CanESM	21 Feb	05 Apr	12 Mar	10	04 Sept	26 Nov	12 Oct	19	213 (±22)
IPSL	11 Mar	14 May	01 Apr	15	01 Sept	28 Nov	21 Oct	25	203 (±27)

*LRS – Length of Rainy Season

4.1.9 Implication of projected rainfall and temperature trends

The fast increasing minimum temperature increase the rate of night respiration and transpiration in crops. This reduces the yield of grains as the plants are stressed by the process. The impact is more severe during the reproductive stage in the life cycle of crops by impeding the physiological process (Rasel *et al*., 2011). According to Brahic (2007), a 2ºC increase in temperature could reduce crop yield in the range of 5 – 10 % in Africa. During warm temperatures, cereals such as maize experience stunt development at the reproductive stage and a consequent decrease in grain development (Hatfield and Prueger, 2015). Crops are very vulnerable to extreme temperatures, therefore, the projected increase in mean temperature could mean a rise in both minimum and maximum temperatures in the basin. This will put agriculture (both animals and crops) at risk (Barlow *et al*., 2015).

Water availability in some vulnerable regions, such as in several African nations has been estimated to decrease between 20 % and 30 % at the 2ºC rise in temperature (Brahic, 2007). The increasing and decreasing projected amount of rainfall by the models plus the increasing trends of temperature will negatively affect the water yield as evaporation increase with possibility of prolonged dry spells or droughts (Arias *et al*., 2014; Murphy and Charlton, 2006). The ensemble rainfall projection suggests a possible shift in the rainfall pattern in the basin as rainfall amount increase from April to September with a decrease in June (peak rainfall month). The usual bi-modal pattern that gave farmers two cropping season could be gradually shifted to a long monomodal rainfall for six months with possibilities of floods. The project long dry season may increase the frequency of bush fires in the basin. It will, however, favour crops that require regular availability of moisture to mature (Guan *et al*., 2015).

Increasing rainfall and temperature could imply the rise in vector-borne diseases (Thomson *et al*. 2018). At high temperatures, disease outbreak and transmission also rise in most part of the world especially the tropics (Elderd and Reilly, 2014; Choi *et al*., 2007). Emission of greenhouse gases (carbon and methane) from soils increase as temperature increases the process of decomposition and water transportation. According to Crowther *et al*. (2016), 30 petagrams of carbon are released from the soil anytime atmospheric temperature increases by 1ºC.

4.2 Temporal land use land cover (LULC) changes

Results in line with specific objective two were presented and discussed in this section.

4.2.1 Accuracy assessment based on error matrix

Both pixel-based and area-based error matrix was used to determine the overall, user's and producer's percentage accuracy for the three land use/cover maps of 1986, 2002 and 2018 as presented in appendix III. The overall percentage accuracy of 1986 for both pixel-based and area-based assessment was 96.65 % and 97.37 % respectively. Producer's accuracy of forest and open vegetation decreased from pixel-based to area-based assessment whereas settlement and arable/bare lands increased. The error in the sampling of forest and open vegetation affected their area-based matrix resulting in the decrease. Water was the same because classification samples were picked from the Lake Bosomtwe. Reference for this classification was the land cover shapefile from Geological Survey Department of Ghana and historic images of 1986 from Google Earth Pro.

In 2002, overall percentage accuracy was 89.11 % and 94.93 % for pixel-based and area-based error matrix respectively. The same trend of decrease and increase between pixel-based and area-based producer's accuracy for 1986 was observed (Appendix III). The overall accuracy was also lower than the accuracy of 1986 which could be attributed to the combination of images from different years due to availability and cloud cover requirements which must be less than 10 %. The reference data for this analysis included the 2000 globeland30 map from the Chinese government in addition to the mentioned reference for 1986. Producer's accuracy of settlement and arable/bare lands increased under the area-based error matrix and contributed to the increase in the overall percentage accuracy due to their percentage area for 2002 in the Pra River Basin.

A similar trend of increase of 0.32 % in the overall percentage accuracy between the pixel and area-based error matrix was produced in 2018. The reduced variation might be due to the combination of four reference data with the high resolution of the 2016 20 m land cover map of Africa created from sentinel and the 2018 ground control points picked with Handheld Garmin GPS. Producer's accuracy increased in arable/bare lands and open vegetation and decreased in forest and settlement between the pixel and area-based error matrix (Appendix III).

4.2.2 Pattern of LULC changes

The landscape dynamics over a period of 32 years in the Pra River Basin was assessed with Landsat images of 1986, 2002 and 2018. The land use/cover maps of the years analysed are presented in Fig. 4.20. Forest and open vegetation were the dominating land covers in 1986 with few dispersed arable/bare lands close to settlements in the basin. As the population increased and anthropogenic activities became prominent, land cover began to decrease at the expense of meeting human needs of food and settlements (Ayivor and Gordon, 2012; EPA, 2004). Sixteen years after 1986, more settlements became visible with expanded arable/bare lands which concentrated more in the central part of the basin. Major arable/bare lands in 1986 shifted position towards the southern part from the centre of the basin. Despite the implementation of afforestation and reforestation programs by the Forestry Commission and REDD+, deforestation was high (FC, 2017; CI 2014; Djagbletey and Adu-Bredu, 2007).

In addition, some of the towns expanded indicating urbanization possibly resulting from population growth (Fig. 4.20). In 2018, anthropogenic activities kept increasing, resulting in further expansion of settlement and arable/bare lands. For instance, legal and illegal mining activities at Obuasi and environs (south and south-west of Kumasi) were responsible for the vast arable/bare lands due to the selling of farms for illegal mining (Murphy and Kapelle, 2014; CONIWAS, 2011). The vast bare lands along the river channels were from the earthmoving equipment that small scale (legal or illegal) miners used to clear land cover and crops to channel water to their mining sites during their operations (CONIWAS, 2011). As forest decreased, settlement, arable and bare lands increased consistently in the two intervals from 1986 to 2018 (Ayivor and Gordon, 2012; Boon *et al*., 2007; Agyarko, 2001).

The land use/cover class sizes in percentage to total basin area and their changes during the two intervals are presented in Table 4.11. During the first interval (1986 to 2002, 16 years), water bodies increased by 19.33 % per annum. Because of the West African drought in 1983, most of the water bodies reduced in quantity including the Pra River Basin (Greene *et al*., 2009) during the image assessment year of 1986. After the drought, the basin recorded an increasing trend in rainfall amount (Refer to rainfall analysis in section 4.1). This increase might be the main reason for the increased volume of water in 2002.

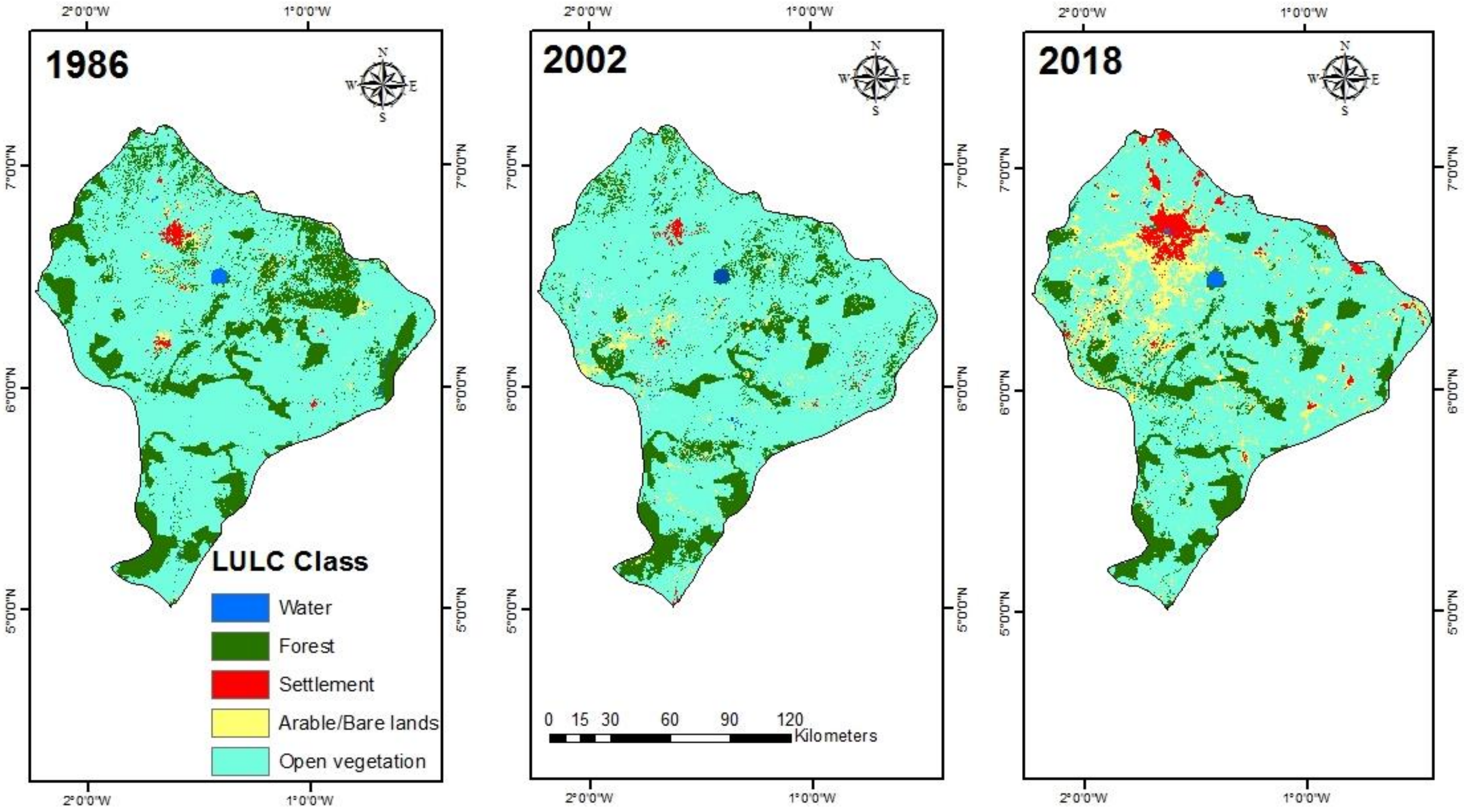

Fig. 4.20. Land use/cover maps of Pra River Basin for 1986, 2002 and 2018

Forest decreased by a margin of 19.89 % within the first interval. Open vegetation also decreased by 3.22 % while the two main classes influenced by human activities, that is, settlement and arable/bare lands increased by 107.42 % and 108.02 % respectively after the first 16 years (Table 4.11). Settlement, water and arable/ bare lands recorded the highest increase beyond 50 % in the first interval. The decrease in land cover (forest and open vegetation) in the Pra River Basin during the assessment period was influenced by socio-economic activities driven by local population growth, agricultural intensification, timber logging, increased small-scale mining activities, increased foreign direct investment in mining, timber and agricultural industries and forest fires (GSS, 2013; Kusimi, 2008; Asante, 2005).

Farmers dominate the population in the basin. Agriculture activities are intense including charcoal production, fuelwood business for both domestic use and selling, tree crops plantation (mainly cocoa and the now introduced rubber and palm oil) and vegetation intensification by the use of agrochemicals and fertilizers (Akrasi and Ansa-Asare, 2008). During the second interval (2002 to 2018, 16 years), settlement and arable/bare lands increased again by 35.05 % and 87.36 % respectively (Table 4.11). Mining has been reported to catalyse urbanisation (Kusimi, 2008). Obuasi, which is the largest gold mine city in Ghana is located in the heart of the basin which triggers population growth and settlements expansion by attracting people from all over the nation for their economic gains. Urbanisation will put pressure on surrounding rural areas to produce more food to meet the demand that will be created (Sage, 1994). This exacerbates the conversion of more forested lands into food and cash crop farms, thereby increasing the rates of deforestation (Bruinsma, 2003). It is evident in the results that more crop expansion took place in the second interval compared to settlement expansion.

Water, forest and open vegetation decreased by 75.32 %, 20.56 % and 0.69 % respectively in the second interval. The reduction of water in the second interval may be attributed to water quality loss resulting from illegal mining (makes surface water muddy) and not necessarily the loss of water quantity (CONIWAS, 2011). In a 32-year period of changes, it was seen that forest and open vegetation decreased annually by 2.27 % and 0.24 % respectively.

Table 4.11. Percentage of the mapped area of Land use and land cover changes between 1986 - 2002 and 2002 – 2018

	Land Use Land Cover (LULC)					
	Water (%)	Forest (%)	Settlement (%)	Arable/Bare lands (%)	Open vegetation (%)	Total (%)
1986	0.73	23.81	1.29	3.14	71.03	100.00
2002	2.98	19.07	2.67	6.53	68.75	100.00
2018	0.74	15.15	3.62	12.24	68.25	100.00
change 86-02	309.26	-19.89	107.42	108.02	-3.22	
change 02-18	-75.32	-20.56	35.05	87.36	-0.69	
change 86-18	1.01	-36.36	180.12	289.74	-3.88	
per annum 86-02	19.33	-1.24	6.71	6.75	-0.20	
per annum 02-18	-4.71	-1.28	2.19	5.46	-0.04	
per annum 86-18	0.06	-2.27	11.26	18.11	-0.24	

The trend of land cover change was similar to -27.7 % decline in forest reported by Koranteng and Zawila-Niedzwiecki (2015) for the Southern part of the Ashanti region within the basin. According to CI (2014), Ghana's deforestation was at per annum rate of 1.99 %, 1.97 % and 2.19 % for the period 1990 – 2000, 2000 – 2005 and 2005 – 2010 respectively and per annual rate of the deforested area for all three periods were between 100 ha and 1000 ha. EPA (2004) also, estimated deforestation rate of 2.8 % in 2000 for Ghana and attributed it to cumulative anthropogenic causes. Therefore, the per annum deforestation rate of 2.27 % from this study is within the range reported for the whole nation about the same period. The rate of forest and forest resources decline in Ghana has been found to be alarming (Boon *et al*., 2007; Agyarko, 2001) and has long-term impacts on local communities, especially on women and children livelihood (Boon *et al*., 2009). It could be seen that forest conversion was higher during the second interval (2002 – 2018) than the first interval (Table 4.11). Detected changes were due to anthropogenic activities considering 11.26 % and 18.11 % per annum rate of change or increase in settlement and arable/bare lands respectively from 1986 to 2018 (Kusimi *et al*., 2015; GSS, 2013; CONIWAS, 2011; Akrasi and Ansa-Asare, 2008).

The loss of natural vegetation could have also been exacerbated by climate variability, which acts as a catalyst to the anthropogenic pressure such as reduced crop yield and water scarcity (Brahic, 2007). The river system of the Pra River Basin comprises of river Ofin, Oda, Birim and Pra, which all drain into the Gulf of Guinea at Shama in the Western Region will be affected by these changes in land cover (Kusimi, 2014). Besides the impact of deforestation on the river system in the Pra River Basin, it will negatively impact climate change through the release of carbon emissions (IPCC, 2007). Open vegetation served as an intermediary land cover between the conversions from forest to arable/bare lands or settlement and vice versa and therefore recorded minimal change. Farmers do not convert forest at once for crop cultivation. Some trees are left within the farm to serve as shades and windbreaks which makes them to be classified under open vegetation. Fallow lands also come under open vegetation because of the presence of dispersed trees in them. Therefore, economic activities resulting from population growth is the major driver of the land-use changes in the Pra River Basin (Ayivor and Gordon, 2012). Similar findings on land-use change have been reported by Zoungrana *et al*. (2015) for Southwest of Burkina Faso; Aduah *et al*. (2015) in Ghana's Ankobra basin; Long *et al*. (2007) in China and others globally (FAO, 2010; Foley *et al*., 2005).

4.2.3 Two intervals of intensity analysis

At the interval level, the annual rate of LULC change in Pra River Basin was rapid between 1986 and 2002 and slow between 2002 and 2018 at a uniform intensity of 2.15. The annual LULC change was 2.25 and 2.06 for 1986 – 2002 and 2002 – 2018 respectively. It was observed that LULC changes were 35.95 km^2 and 32.93 km^2 for the periods 1986 – 2002 and 2002 – 2018 respectively. The rapid change in the first interval (1986 – 2002) could be attributed to an increase in anthropogenic land cover/use changes influenced by socio-economic drivers such as population growth, rural-urban migration, urbanisation and economic development from forest products that expanded within this period in the Pra River Basin (D'Orgeval and Polcher, 2008; Lambin *et al*., 2003).

The category level intensity analysis which examined the dormant or active LULC categories in their gain or loss of other LULC types was done for both time intervals as presented in Table 4.12. All LULC classes except open vegetation gained actively at a uniform intensity of 2.25 and 2.06 for first and second interval respectively. The active categories in the first interval were similar to the findings of Bessah *et al*. (2019) for same land classes for the Kintampo Municipality in Ghana for a similar period from 1986 - 2001. It could be a national driving force.

The same LULC classes that were active in gaining were also active in losing to other classes in both time intervals while open vegetation was dormant. Settlement and arable/bare land were dominant in all the changes and intervals for both gains and loss, implying the active role of anthropogenic drivers influencing LULC changes in the Pra River Basin. Settlement and arable/bare lands gained 34 km^2 and 92 km^2 and lost 14 km^2 and 43 km^2 respectively from 1986 – 2002 (Table 4.12). The change increased in the second interval where settlement gained 39 km^2 and lost 28 km^2 while arable/bare lands gained 142 km^2 and lost 71 km^2. There is more gain in this category of the class than loss and is comparable to the findings of Lambin *et al*. (2003). Forest, which was also active in gaining and losing in both intervals, recorded higher losses than gains. In the first interval, forest lost 200 km^2 and gained 131 km^2.

Table 4.12. Category intensity change between 1986 – 2002 and 2002 – 2018

Categories	Observed Gross Gain (km^2)	Intensity of Gains	Observed Gross Loss (km^2)	Intensity of Loss	Uniform change
			1986 - 2002		
Forest	131	**2.95**	200	**3.61**	
Open vegetation	226	1.41	260	1.57	
Settlement	34	**5.44**	14	**4.58**	2.25
Arable/Bare lands	92	**6.07**	43	**5.87**	
Water	40	**5.79**	7	**4.38**	
			2002 - 2018		
Forest	82	**2.73**	131	**3.45**	
Open vegetation	210	1.24	216	1.26	
Settlement	39	**5.46**	28	**5.18**	2.06
Arable/Bare lands	142	**5.81**	71	**5.42**	
Water	6	**4.33**	34	**5.78**	

*Bolded intensity values means active gain or loss

The deforestation of 69 km^2 in the first interval could account for the loss of major forest point at the west end of the basin comparing 1986 and 2002 LULC maps (Fig. 4.20). The forest loss in the second interval increased to 131 km^2 and had a gain of 82 km^2. It implies that deforestation is consistent and faster than reforestation in the basin. However, the second interval comparative saw reforestation of 20 km^2 over the first which could account for the reappearing of 2002 forest lost at the west end in 2018 LULC map (Fig. 4.20).

The land cover which experienced the highest but less intense change in both intervals was open vegetation. This could be due to its area coverage or size. Open vegetation covered about 71 %, 69 % and 68 % of the basin in the year 1986, 2002 and 2018 respectively (Table 4.11). Open vegetation lost 260 km^2 in the first interval and 216 km^2 in the second interval but was dormant due to the size of the lost area compared to the total coverage of the class (Table 4.12). Active gain by water decreased from 40 km^2 to 6 km^2 whereas active loss increased from 7 km^2 to 34 km^2 between the first and second interval. Therefore, the intense categorical conversion for both intervals took place in the forest, water, settlement and arable/bare lands.

The transition level of analysis from two land covers (forest and open vegetation) and to two land uses (settlement and arable/bare land) are shown in Fig. 4.21. It focuses on categories that contributed maximally to each particular LULC class, thus targeted classes for conversion and/or avoided class (transitions at intensity below the set threshold of uniformity). Forest transition to open vegetation was the only intense conversion in the first interval while settlement, water and arable/bare lands became intense during the second interval (Fig. 4.21a). The intense transition of forest to water bodies might be due to the clearing of riparian forest or buffer which exposed rivers/streams. Moreover, the clearing of forest and diversion of rivers for small scale mining (both legal and illegal) might be another reason (CONIWAS, 2011). Open vegetation targeted for forest transition may be explained by the kind of forest intrusion where big trees are left on the farm as windbreakers and shades. Fallowing or shifting cultivation causes this land use to grow quickly into shrubs due to the trees that were left on them during forest conversion.

Settlement, water and arable/bare lands were the targeted groups for the transition from open vegetation in both time intervals except water which was only targeted in the first interval (Fig. 4.21b).

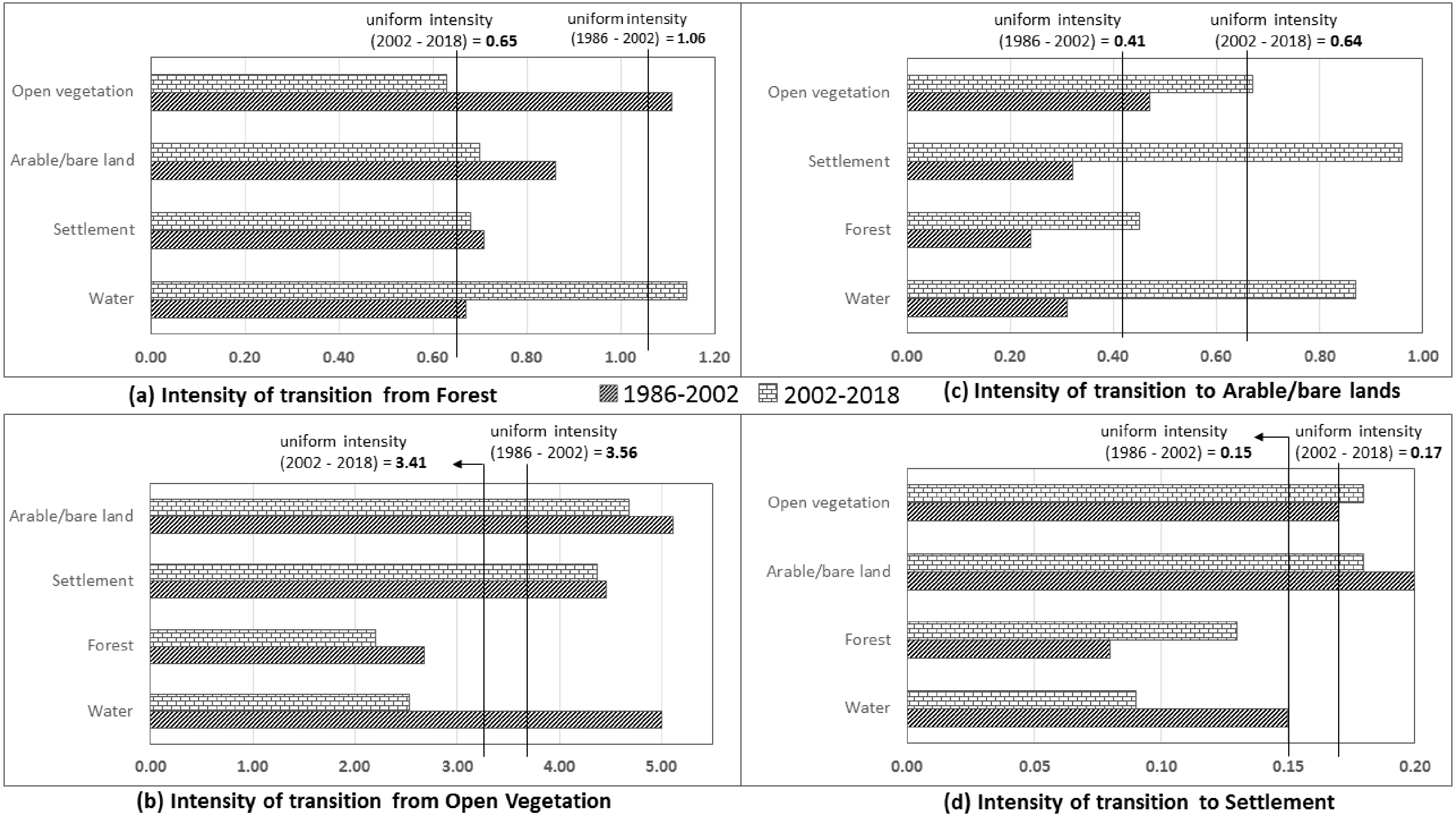

Fig. 4.21. Intensity of transition from (a) Forest (b) Open vegetation to (c) Arable/Bare lands (d) Settlement

This implies that forests were not the primary focus for land conversion for cropping in the Pra River Basin during the period of analysis. It is further confirmed by Fig. 4.21c, where open vegetation was targeted compared to the forest for the transition into arable/bare land in both time intervals. This was similar to the findings of Bessah *et al*. (2019) in the Kintampo Municipality in Ghana where savanna woodland, which in this current study, has the characteristics of open vegetation were the targeted land cover for the transition to cropland in both time intervals from 1986 – 2001 and 2001 – 2014. For the transition to the settlement, open vegetation, water and arable/bare land were the targets in both time intervals except the second interval where water was avoided for intense conversion to settlement (Fig. 4.21d). Settlements on farms (family farm) and operational centres for mining especially illegal mining might contribute to the gains in settlement from 2002 – 2018 when illegal mining increased rapidly in the nation (CONIWAS, 2011). In Ghana agricultural land is a major target for urbanization especially in the cities (Stow *et al*., 2014). Urbanisation in the study area focused on open vegetation and arable/bare lands for transitions (Fig. 4.21d). Since settlement and arable/bare lands did not target forest for conversion, it implies that another activity like logging could be a major contributing factor to the deforestation in the Pra River Basin (Fig. 4.20).

4.2.4 Implication of land use land cover change in the basin

Ghana, under the Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC), pledged a Nationally Determined Contribution (NDC) to lower its greenhouse gas emissions by 15.0 % relative to a business-as-usual (BAU) scenario emission of 73.95 $MtCO_2e$[2] by 2030 unconditionally (GoG, 2015). Sustainable land use and forest management are two activities out of the seven considered for this reduction policy. The mitigation action plan for the nation is to promote sustainable utilisation of forest resources through Reducing Emissions from Deforestation and Forest Degradation (REDD+) via reforestation and/or afforestation of degraded lands whereas the adaptation action plan in the area of sustainable land use is to build agriculture resilience in climate-vulnerable landscapes (GoG, 2015). Globally, LULC changes contributed to about 40.0 % of CO_2 emission into the atmosphere since 1970 (IPCC, 2014) whereas in European Union's 28 Member States, agriculture alone represented 10.0 % of total greenhouse gas emission in 2013 (Strapasson *et al*., 2016).

The observed trend of per annum deforestation at a rate of 2.27 % within 32 years (1986 – 2018) in the Pra River Basin indicate that forests are declining faster than the regeneration of vegetation through afforestation/ reforestation projects in Ghana such as REDD+. Urbanisation and competing economic activities such as small-scale mining over land resources and climate change must be considered under the sustainable land use policy. These drivers also influence food production and consumption patterns with a direct effect on land use (Strapasson *et al*., 2016). The trend of land-use change in the basin indicates that monitoring and evaluation of mitigation and action plan of the INDCs must be continuous and effective for the intended goals between 2020 and 2030 to be achievable. Agroforestry schemes which integrate woody vegetation, crops and/or livestock on the same farmland should be prioritized in promoting sustainable land use.

4.3 Modelling changes in hydrological ecosystem services

This section covered the results and discussion of specific objective three.

4.3.1 Seasonal Water Yield

The seasonal water yield was presented on annual and monthly basis (Appendix IV-VIII).

4.3.1.1 Rainfall and reference evapotranspiration

Rainfall and reference evapotranspiration (ETo) of the observed (1981 – 2010) and future (2020 – 2049) periods are presented in Tables 4.13 and 4.14 respectively. Highest monthly rainfall was recorded in June and Atieku station recorded the highest mean rainfall (5 out of 12 months) (Table 4.13). Reference evapotranspiration was highest at Dunkwa all through the twelve months. All stations depicted the bi-modal seasons in the ETo values except Dunkwa. This might be due to the remotely sensed insolation which was generally the same (NASA POWER, 2018). Projected rainfall and ETo varied between Ensemble and SDSM. The ensemble is the mean projections of the five climate models (CanESM, IPSL, Hadgem, GFDL and SDSM) used in this study whereas SDSM is the climate model that simulate observed climate well in the Pra River Basin. The SDSM projections were higher at all stations compared to Ensemble results (Table 4.14).

Rain events were lowest in January (2), December (3 except Ensemble which was 4) and February (4) for climate station observed period (1981 – 2010) and SDSM and Ensemble mean projections for the future (2020 – 2049). The rainfall event also depicted the bi-modal pattern of rainfall with Ensemble recording the highest events of 12, 18, 20, 20, 19, 16, 18, 17 and 10 from March to November in order. The observed climate station records and SDSM rainfall events were the same for March, April, July, August, September and November at 8, 9, 10, 9, 11 and 7 respectively. For the remaining months, SDSM projected rain events to be one day less compared to the observed climate station rain events. The events for the months of May, June and October for the observed station data were 11, 13 and 13 respectively. The high number of rain events from the Ensemble could be due to the variations in events days from the five models that were assembled. This could impact the intensity and distributed amount of rainfall in the basin. The high amount of rainfall in many rain events could be good for slow-maturing crops and have less intensity impact on young plant. It could also mean that rainfall amount would not be enough to give the required moisture in soil for plant growth.

Table 4.13. Observed (1981 – 2010) average monthly rainfall totals (mm) and reference evapotranspiration (mm)

Month	Atieku	Dunkwa	Twifo Praso	Kibi	Akim Oda	Konongo	Kumasi
				Rainfall (mm)			
Jan	26.36	16.59	24.52	24.46	19.24	11.75	20.12
Feb	60.24	50.13	55.42	53.90	60.27	58.14	47.45
Mar	137.67	129.69	108.41	109.31	119.39	114.53	112.13
Apr	161.65	169.82	147.52	128.70	152.15	144.73	151.49
May	192.49	181.83	182.57	164.40	175.69	156.99	161.10
Jun	229.50	216.98	207.73	218.00	191.83	213.39	208.54
Jul	151.70	141.30	144.55	116.58	135.67	146.05	139.11
Aug	90.07	91.44	89.60	85.98	78.23	108.68	85.36
Sep	154.88	147.40	142.61	144.95	119.20	173.48	167.47
Oct	177.72	178.42	181.62	161.26	201.62	145.29	146.83
Nov	86.43	76.42	100.76	73.29	106.63	49.18	46.34
Dec	37.76	42.37	39.29	38.82	41.01	21.51	28.70
				Reference evapotranspiration (mm)			
Jan	125.54	213.51	126.84	136.78	129.95	132.33	138.98
Feb	116.36	222.02	117.45	126.15	121.72	123.00	128.17
Mar	126.39	261.64	127.40	132.29	129.40	131.69	134.97
Apr	118.55	249.12	119.60	121.92	121.55	122.40	124.46
May	110.60	237.11	111.45	114.12	114.44	116.07	117.32
Jun	96.18	243.13	96.50	99.05	101.91	100.50	100.64
Jul	97.48	259.39	97.82	97.55	105.39	96.17	95.77
Aug	96.81	255.92	96.86	98.54	103.31	93.57	93.31
Sep	93.31	236.92	93.46	97.26	99.81	91.23	91.46
Oct	107.30	232.93	107.69	110.28	112.22	107.54	108.46
Nov	108.73	210.15	109.36	112.91	112.06	112.53	114.71
Dec	114.45	201.03	115.16	121.56	118.41	116.67	120.25

Table 4.14. Average monthly rainfall totals (mm) and monthly reference evapotranspiration (mm) from 2020 – 2049

Month	**Atieku**		**Dunkwa**		**Twifo Praso**		**Kibi**		**Akim Oda**		**Konongo**		**Kumasi**	
	SDSM	*Ensemble*	*SDSM*	*Ensemble*	*SDSM*	*Ensemble*	*SDSM*	*Ensemble*	*SDSM*	*Ensemble*	*SDSM*	*Ensemble*	*SDSM*	*Ensemble*
							Rainfall (mm)							
Jan	22.09	22.65	20.80	16.08	33.50	25.43	59.00	40.24	27.89	22.33	8.58	7.49	17.94	11.80
Feb	53.88	50.07	48.99	37.32	70.73	52.10	80.43	60.13	58.13	48.84	74.97	53.57	49.60	32.83
Mar	148.39	140.75	148.95	128.83	131.29	121.95	148.10	127.68	150.98	125.32	119.10	107.97	133.47	111.27
Apr	175.30	176.15	208.48	199.27	170.74	171.44	168.86	165.09	168.59	160.70	155.37	165.81	176.26	185.13
May	210.92	198.87	213.77	212.66	226.11	206.41	201.41	186.75	195.44	177.87	169.17	184.11	181.75	203.47
Jun	262.38	222.83	249.63	222.88	256.50	219.79	274.32	229.04	210.28	185.35	251.10	222.66	237.53	223.68
Jul	180.26	168.69	174.97	177.17	176.11	187.13	144.99	132.42	166.38	147.02	182.64	166.62	171.02	171.05
Aug	131.20	125.99	116.87	144.87	112.65	141.47	133.64	117.10	96.40	96.49	118.09	128.17	110.25	143.79
Sep	173.97	165.55	183.93	183.76	196.12	181.99	192.24	170.17	146.94	134.34	190.30	186.57	175.63	198.99
Oct	196.50	174.32	219.09	189.76	206.31	173.72	214.67	191.56	220.55	189.18	153.48	147.53	166.05	166.82
Nov	90.18	91.58	98.52	83.94	123.04	103.25	86.59	86.62	110.32	98.48	56.40	54.29	49.64	52.24
Dec	37.59	38.45	48.24	35.12	48.45	39.89	71.68	55.52	44.75	39.82	31.00	22.12	26.06	19.14
							Reference Evapotranspiration (mm)							
Jan	121.34	122.98	123.91	126.07	124.57	126.86	142.33	143.43	130.67	132.15	132.25	133.98	139.06	137.94
Feb	112.34	112.50	116.13	117.17	116.02	116.34	136.67	135.93	120.97	119.73	128.34	128.18	132.88	132.12
Mar	119.32	118.65	123.50	123.90	123.09	122.55	145.86	143.91	129.45	127.82	136.79	135.27	140.11	139.45
Apr	114.53	113.66	118.53	117.56	118.29	117.19	139.46	136.89	125.68	123.71	129.52	127.48	131.06	129.67
May	109.49	108.73	113.31	111.87	112.95	111.69	132.07	129.96	119.12	117.48	125.31	123.56	126.49	124.74
Jun	86.46	86.10	89.13	88.01	88.45	87.86	106.52	105.33	96.77	95.70	102.64	101.42	102.64	101.73
Jul	87.86	87.89	89.93	88.85	89.78	89.31	100.68	99.97	101.48	100.94	97.75	96.78	97.20	96.48
Aug	88.71	89.19	90.73	89.77	90.58	90.52	96.32	96.23	98.15	98.09	88.57	88.36	88.46	87.90
Sep	87.14	87.61	89.10	88.39	89.38	89.19	104.54	104.29	100.52	100.50	90.38	90.25	90.40	90.08
Oct	104.33	104.91	107.30	106.63	107.67	107.45	115.57	115.24	119.98	120.14	111.77	111.42	112.71	111.96
Nov	102.14	102.68	105.28	105.36	105.26	105.63	114.23	113.74	118.15	117.91	110.09	109.61	112.30	111.44
Dec	113.97	114.90	116.47	117.18	117.30	118.31	130.17	130.50	128.36	128.92	120.51	120.83	124.00	122.65

4.3.1.2 Water yield from the observed period

The mean annual water yield for the observed period for the years 1986, 2002 and 2018 are presented in Fig. 4.22. Water yield was very similar between the historical years of 1986, 2002 and 2018 at a mean ranges of 0 - 336 mm, 0 - 334 mm and 0 - 336 mm respectively. This implies that change in land use during the historical period had no significant impact on mean annual water yield in the Pra River Basin. However, the expansion of arable/bare lands and settlement showed that wide locations of the basin under these two classes had water yield between 100 mm – 240 mm (Fig. 4.22). Water yield was highest in settlement land-use class and least under forest. Settlement yielded water between 200 mm – 240 mm, forest yield was less than 40 mm and open vegetation was between about 41 – 160 mm (Fig. 4.22).

Land-use change influenced water yield specifically in its distribution (volume). When land-use changes from cover to use (settlement and agriculture), water yield increased. The mean annual yield was within the estimated runoff reported by Owusu *et al*. (2017) in the range of 200 mm – 450 mm/y for the Pra River Basin using rainfall records of 1990 – 2000 in the POLFLOW model. It further falls within the simulated areal runoff between 1999 and 2006 for 12 gauged stations in the Pra River Basin, which was in the range of 119 mm – 532 mm/y (WRC, 2012). The monthly variation in water yield for 1986, 2002 and 2018 are presented at Appendix IV, V and VI respectively. The major (April to June) and minor (September – October) rainfall season had an average seasonal yield of 52 mm and 43 mm respectively for the observed period. Water yield during the dry season (November – March) was at an average value of 17 mm (Appendixes IV - VI). This modelled dry season yield arouses concerns for the availability of water to run the proposed hydro dam on the Pra River Basin at that period of the season (Kabo-Bah *et al*., 2016).

4.3.1.3 Projected water yield

Mean annual water yield as projected from control climate period, increased by 148 mm and decrease by 117 mm under the SDSM and Ensemble mean climate scenarios respectively using the LULC of 2018 (Fig. 4.23). It shows that climate change has a great impact on the amount of water yield. Therefore, water yield is directly proportional to rainfall trend in the basin (refer to Table 4.8) and with a possible positive correlation which confirms rainfall as the major factor that causes flooding from runoff (Queensland

Government, 2011). The correlation between rainfall and runoff changes has been found to be at R = 0.49 for West Africa (Roudier *et al*., 2014). Sood *et al*. (2013) used COSMO-CLIM model in the Volta River Basin under A1B scenario and reported that annual rainfall and water yield showed a decreasing trend at R^2 = 0.2728 and R^2 = 0.1657 respectively from 1983 – 2097 similar to the Ensemble mean of this study but contrary to the projections of SDSM. Land use class with large soil exposure (arable/bare lands and settlement) were projected to have the highest mean annual yield at 219 mm and 484 mm by Ensemble and SDSM respectively (Fig. 4.20 and 4.23).

The projected change in mean annual water yield at -35 % and +44 % by Ensemble and SDSM respectively was similar to the findings of Amisigo *et al*. (2015). According to Amisigo *et al*. (2015), annual runoff in the Pra River Basin could change by -25.9 % and +60.9 % under the Ghana dry (IPSL_CM4 B1) and wet (NCAR_PCM1 A1b) scenario respectively from 2011 – 2050 in reference to 1950 - 2000. The decrease in projected yield by the Ensemble is comparable to streamflow projection for the period 2020 (2006 – 2035) and 2050 (2036 – 2065) in the basin at 22 % and 46 % respectively by Obuobie *et al*. (2012) in the basin.

Globally, climate impact on water yield has been found to be erratic just like rainfall pattern and distribution. The statistical downscaling model (SDSM) was used in China in the Wei River Basin and annual runoff was projected to increase by 12.4 % between 2046 and 2065 under the A2 and B1 emission scenarios (Zuo *et al*., 2015). Bagstad *et al*. (2013b) did not see much changes of projected water yield from the observed in their study because the constrained and open land-use scenarios projection for 2020 was with the same rainfall data in 2002. This further confirms rainfall being the major factor in water yield in a basin. The projected increase in rainfall for the period 2021 – 2050 in the Sabari sub-basin in India resulted in an estimated increase between 10 % – 25 % of runoff with RCM data from PRECIS model (Jeyakanthan *et al*., 2017). Therefore, water yield and runoff in the tropical regions will be erratic just like rainfall under climate change.

Monthly mean water yield for the major and minor rainfall season was projected to increase by 48 % and 30 % respectively under SDSM climate scenario and to decrease by 38 % and 30 % respectively under Ensemble mean climate scenario (Appendix VII–VIII). Similarly, change in dry season water yield was +35 % and -18 % by SDSM and Ensemble respectively.

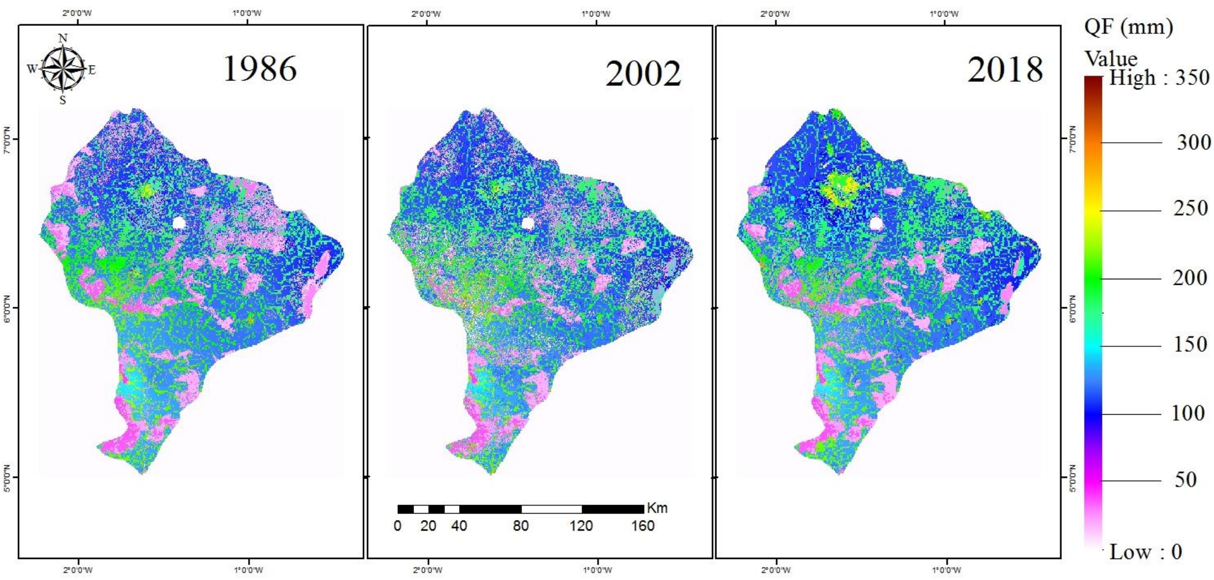

Fig. 4.22. Historical mean annual water yield

NB: Modelled with historical climate (1981 – 2010) and LULC of assessed years

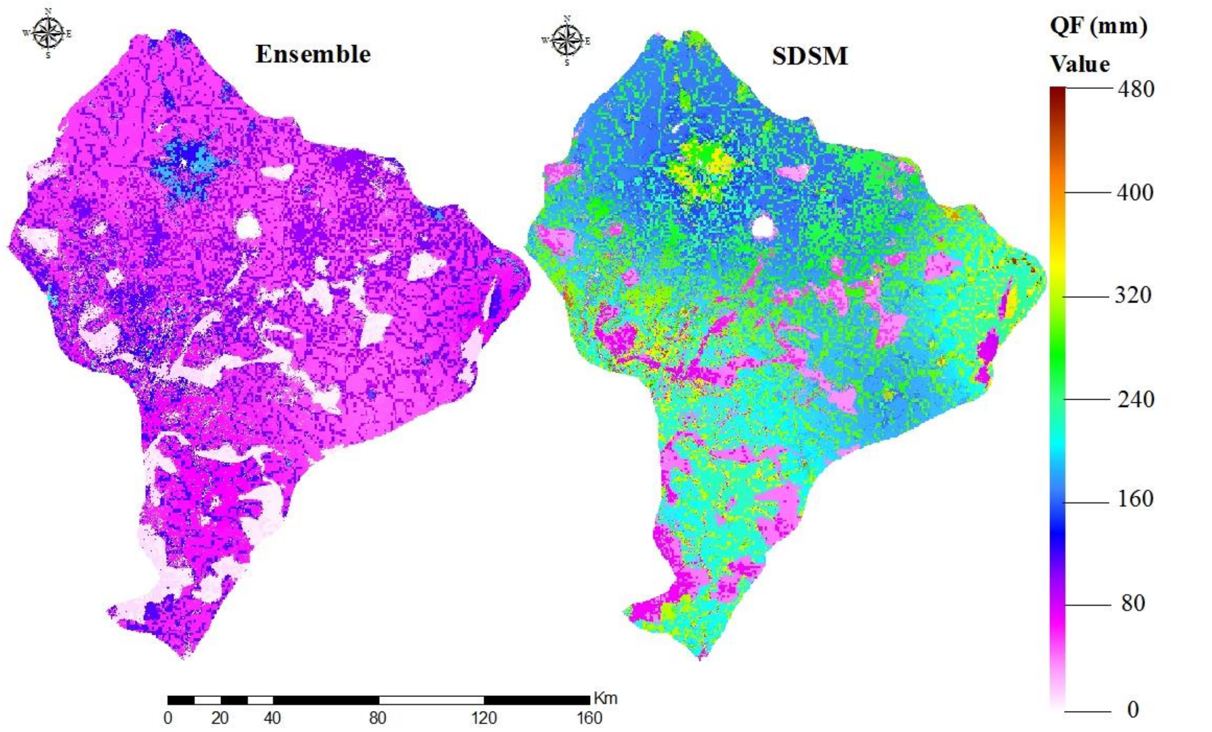

Fig. 4.23. Future mean annual water yield

NB: Modelled with climate period from 2020 – 2049 and 2018 LULC

4.3.2 Nutrient delivery ratio (NDR)

Nitrogen and phosphorus were the nutrients modelled in this study.

4.3.2.1 Mean annual total rainfall for NDR model

Nutrient runoff proxy was a required input data in running InVEST NDR model. It represents the capacity of transporting nutrient in the basin after a downpour (Sharp *et al*., 2018). Therefore, annual rainfall GIS raster dataset showing the spatial variability in transporting nutrients was used as the runoff proxy (Fig. 4.24). InVEST NDR normalized the annual rainfall raster to compute the runoff potential index (Sharp *et al*., 2018). Projected annual rainfall could not capture the spatial trend of low rainfall at the East end of the basin (Fig. 4.24). Projected (2020 – 2049) annual rainfall was 119 mm and 226 mm higher than the observed period by Ensemble of the five models and SDSM respectively.

4.3.2.2 Nutrient Loads and export at the basin scale

Modelled nitrogen delivery rates are presented in Table 4.15. Nitrogen loads increased by about 21 % from 1986 to 2002 with 1848 kg/y increase in nitrogen export in the basin. The load further increased by about 30 % from 2002 to 2018 under the same control period climatic conditions (Table 4.15). However, the increased load between 2002 and 2018 resulted in decreased nitrogen export of about 24 %. It implies that the location of land-use change (cover decline) can either increase or decrease nitrogen export in a river basin. With the same nitrogen loads in the projected year (that is, using the LULC of 2018), nitrogen export was modelled to increase by 95 kg/y under SDSM climate over the ensemble of models output (Table 4.15). Land use and climate change affect nitrogen export in the basin differently. When land covers are cleared for agriculture and settlement as observed for 1986 and 2002 land use maps (Fig. 4.20), nitrogen delivery increased.

Land cover (forest) and Land use (settlement and agriculture) have been found to have significant negative and positive influence respectively on nitrogen retention in a watershed (Hou *et al*., 2016). Although increasing rainfall is expected to increase the exportation of nitrogen, the results show that the specific location where LULC is altered has more influence on nitrogen export than the trend in total net change of LULC. The nitrogen load is within the range estimated by Akrasi and Ansa-Asare (2008) for the basin on nutrients loads to be between 1.98 t/d – 14.6 t/d (722,700 kg/y – 5,329,000 kg/y) (see Table 4.15). Nitrogen load in the basin is on the low side compared to 16,800 Mg/y reported for the Mediterranean basin (Terrado *et al*., 2014). It could be deduced that activities in the Mediterranean basin makes use of large quantities of nitrogen.

The phosphorus loads and export in the basin are presented in Table 4.16. Phosphorus load was modelled to decrease from 1986 to 2018 while export had no consistent pattern. Phosphorus export decreased from 1986 to 2002 and increased from 2002 to 2018 as well as under the future climatic conditions (Table 4.16). Phosphorus load was the same under future climate since the land use did not change (2018 LULC was used) while export increased by 100 kg/y between Ensemble and SDSM. It was observed that phosphorus export decreased under land-use change (increasing trend of land use and decline in land cover from 1986 to 2018) and increased under climate change (Table 4.16). Phosphorus loads for both observed years and the projected period was within the nutrient load range (722,700 kg/y – 5,329,000 kg/y) reported by Akrasi and Ansa-Asare (2008) for the Pra River Basin.

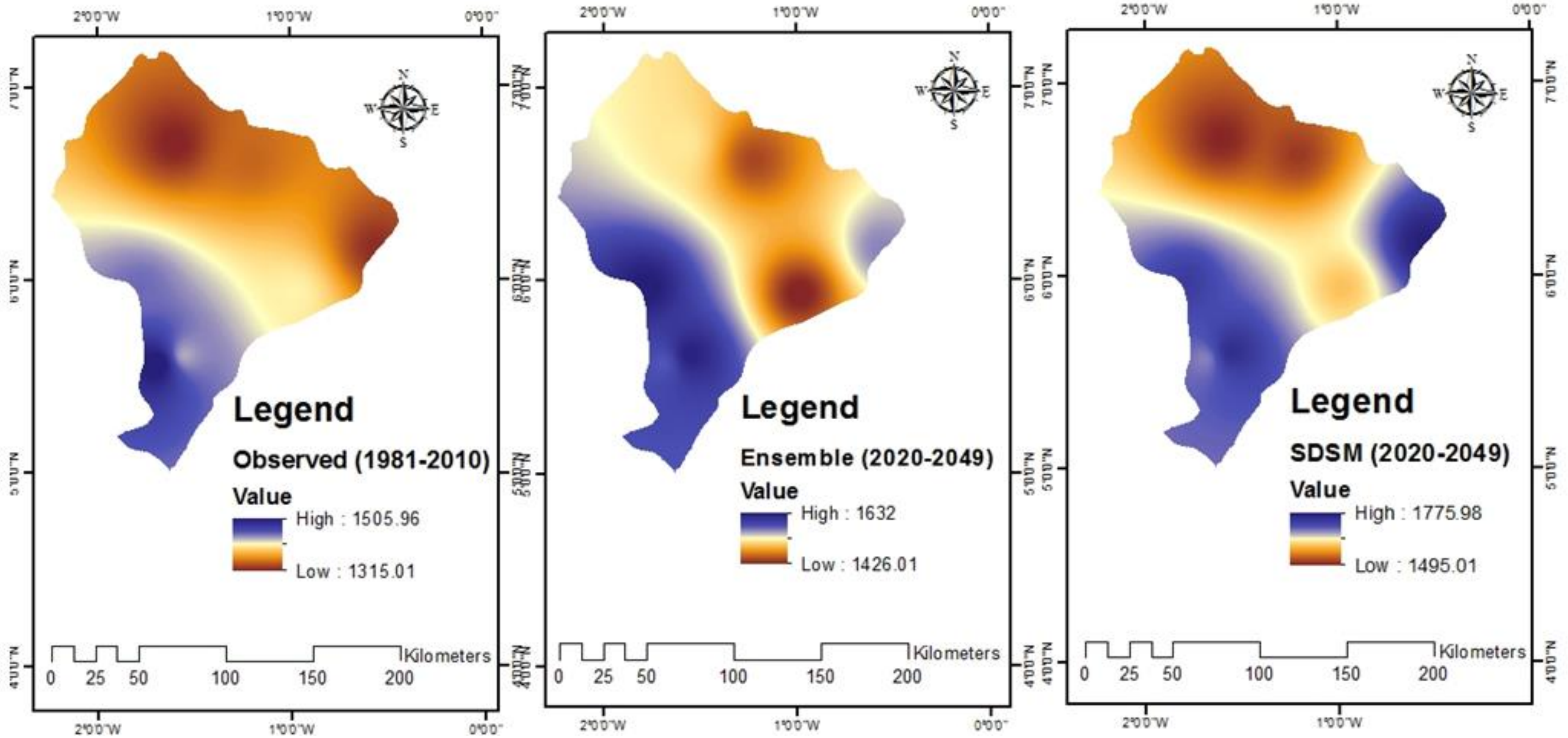

Fig. 4.24. Annual precipitation (mm) used in NDR model

Table 4.15. Total nitrogen loads (in the watershed) and export (from the watershed)

Year/model	Load (kg/y)	Export (kg/y)
1986	4088558	2562
2002	4977304	4410
2018	6459930	3338
Ensemble	6459930	3442
SDSM	6459930	3537

Table 4.16. Total phosphorus loads (in the watershed) and export (from the watershed)

Year/model	Load (kg/y)	Export (kg/y)
1986	2914697	3382
2002	2553860	2016
2018	2318530	2790
Ensemble	2318530	2873
SDSM	2318530	2973

4.3.2.3 Nitrogen delivery in the basin

Nitrogen export under land use and climate change are presented in Fig. 4.25 and 4.26 respectively. Climate has no impact on nitrogen load as observed for Ensemble and SDSM (Table 4.15). Maximum total nitrogen export was 856.13 kg/km^2, 862.93 kg/km^2 and 901.29 kg/km^2 for 1986, 2002 and 2018 respectively under the control climate (Fig. 4.25). It was projected to be about 915.97 kg/km^2 and 941.61 kg/km^2 for Ensemble and SDSM (climate change) respectively (Fig. 4.26). Therefore, nitrogen export increased under LULC change and climate change. High loads of nitrogen that were modelled to reach the stream were spatially located at the centre of the basin around Lake Bosomtwe and at the east end of the basin in the Atiwa, East and West Akim districts (Fig. 4.25). Other districts like KMA, Shama, Bosomtwe, Obuasi, Bosome Freho and Adansi North also showed the high coverage of nitrogen export in the ranges of 7 – 53 kg/km^2, 7 – 30 kg/km^2 and 11 – 88 kg/km^2 for the year 1986, 2002 and 2018 respectively under the control climatic conditions (Fig. 4.25). The range of high spatially visible nitrogen export for Ensemble and SDSM was similar to 2018 historical export (Fig. 4.26). This implies that major exportation activities of nitrogen are modulated by land use/cover while climate influences the maximum amount of nitrogen that could be exported per time.

4.3.2.4 Phosphorus delivery ratio in the basin

Exported total phosphorus to reach the stream in the basin ranged between 0 – 169 kg/km^2 in 1986 and 0 – 162 kg/km^2 in 2002 and 2018 (Fig. 4.27). Maximum projected phosphorus that could reach the stream under the future climate was 168.31 kg/km^2 and 179.94 kg/km^2 for Ensemble mean and SDSM respectively (Fig. 4.28). The highest point of phosphorus loads in the basin was more in the control climate period compared to future climate period (Fig. 4.27 & 4.28). Spatial distribution of phosphorus load was the same as described for nitrogen. Total phosphorus export increased by 6.9 % between Ensemble and SDSM (Fig. 4.28). The visible range of phosphorus export in 1986 and in future was in the range of 5 – 53 kg/km^2. LULC change between 2002 and 2018 had a negligible impact on phosphorus export (Fig. 4.27). The maximum export for both years was about 162 kg/km^2 and the highest distribution spatially was in the range of 3 – 48 kg/km^2. Therefore, the decline in vegetation cover (forest and open vegetation) and the increase in arable/bare land, an indication of increased fertilizer usage possibly had no significant contribution to phosphorus export.

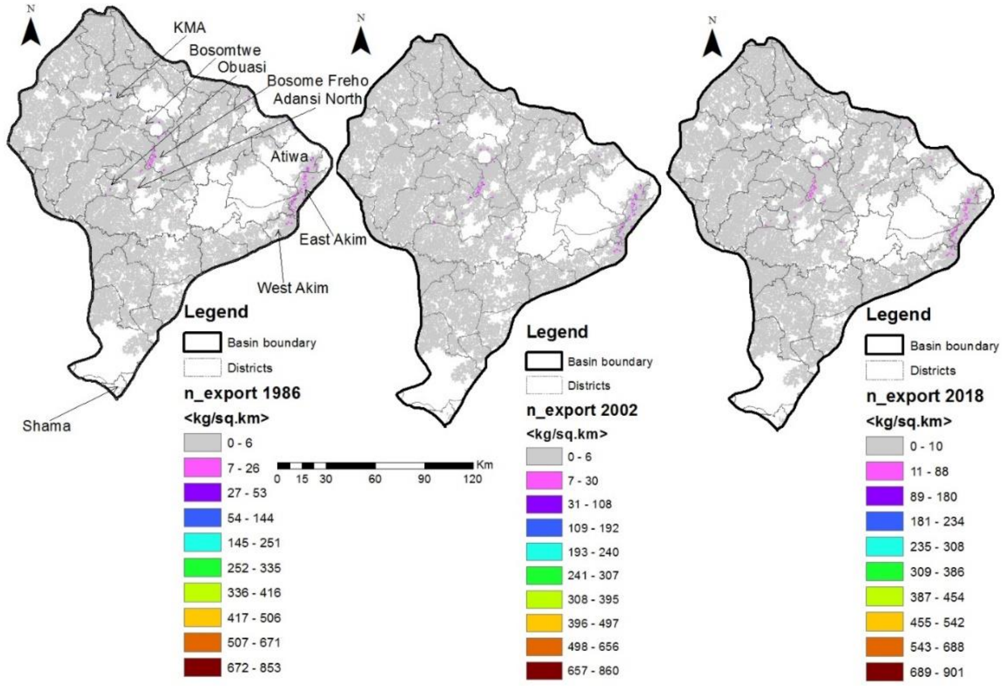

Fig. 4.25. Exported Total Nitrogen (TN) under control period climate period

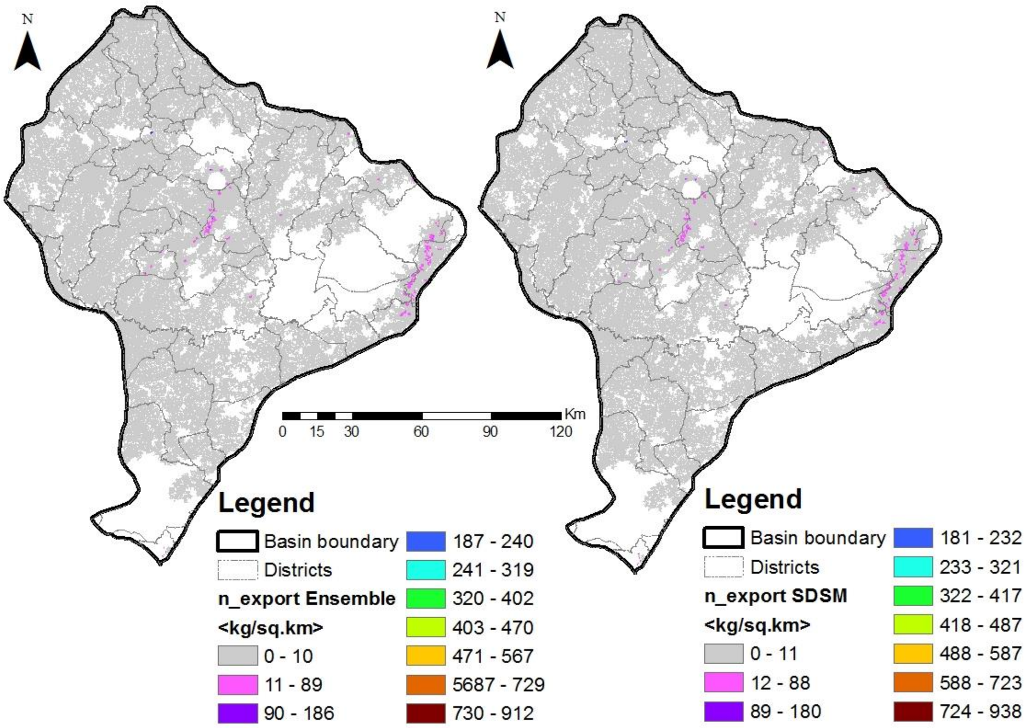

Fig. 4.26. Exported Total Nitrogen (TN) under future climate

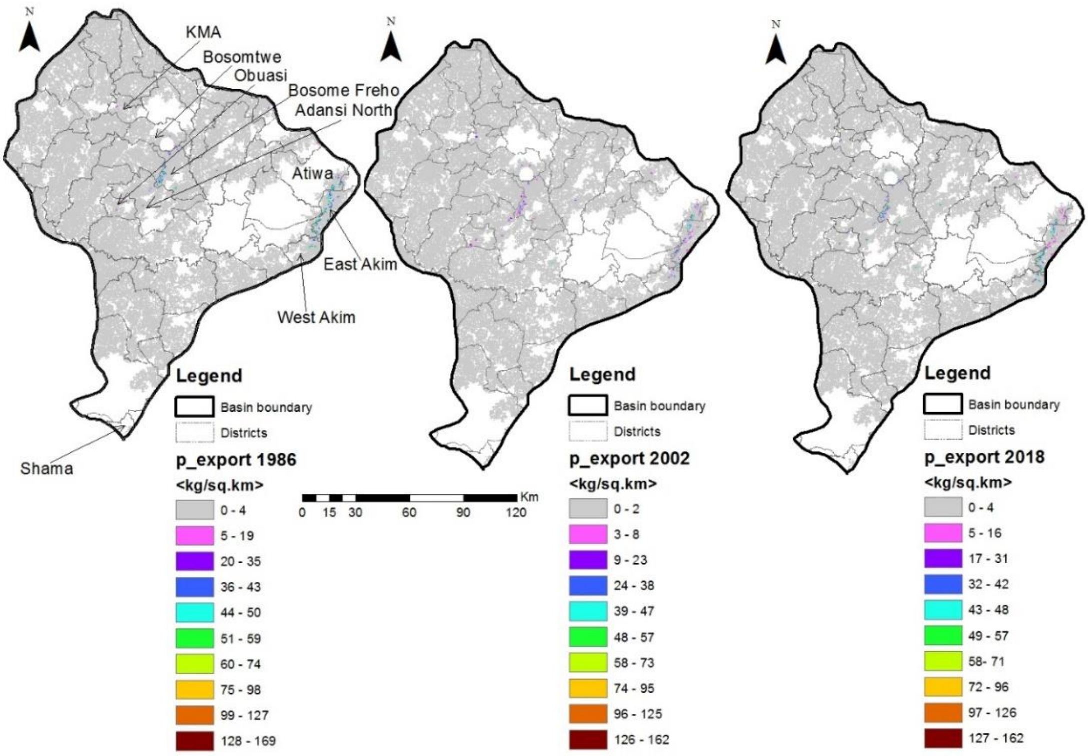

Fig. 4.27. Exported Total Phosphorus (TP) under control period climate

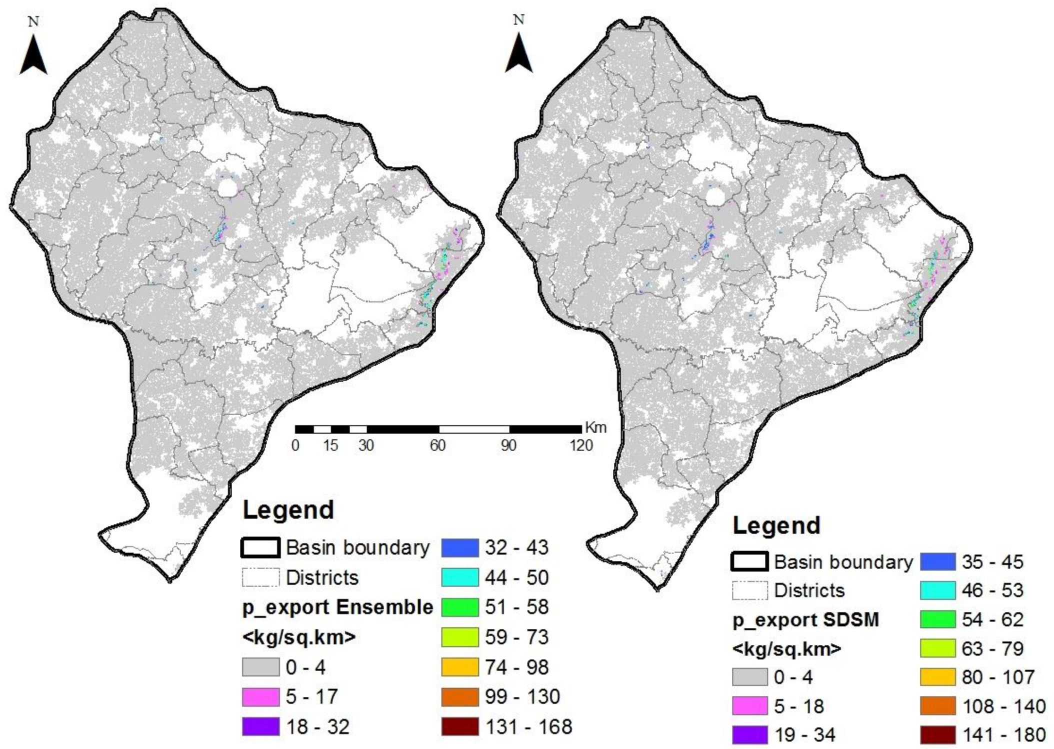

Fig. 4.28. Exported Total Phosphorus (TP) under future climate

4.3.3 Sediment delivery ratio (SDR)

The sediment delivery in this study comprised of sediment export, potential soil loss and sediment retention.

4.3.3.1 Erosivity and erodibility maps

GIS raster rainfall erosivity and soil erodibility maps are presented in Fig. 4.29 and 4.30 respectively. Erosivity (R factor) were averagely 3761 MJ mm ha^{-1} h^{-1} y^{-1}, 4078 MJ mm ha^{-1} h^{-1} y^{-1} and 4362 MJ mm ha^{-1} h^{-1} y^{-1} for the observed period, the ensemble mean of climate models and SDSM respectively (Fig. 4.29). The basin can be classified to have a medium erosivity based on the R classification of $2{,}452 < R \leq 4{,}905$ = medium erosivity (Kusimi *et al*., 2015). Soil erodibility was in the range of 0.234 ton·ha·hr $(MJ·ha·mm)^{-1}$ – 0.295 ton·ha·hr $(MJ·ha·mm)^{-1}$ (Fig. 4.30) from the alternative soil erodibility factor formula (Ashiagbor *et al*., 2014). The basin falls in the medium class of soil erodibility (Hagos, 2004) contrary to the very low-class erodibility adopted by Kusimi (2014).

4.3.3.2 Sediment export into the stream

The total sediments transported into the stream with threshold flow accumulation of 1000 m are presented in Fig. 4.31 and 4.32. Sediments export increased by 1.98 t/km^2 between 1986 and 2002 and decreased by 1.13 t/km^2 between 2002 and 2018 under the control climatic conditions (Fig. 4.31). The maximum export in 2002, modelled at 2.27 t/km^2 is comparable to the findings of Kusimi for the same study area for 2008 in a range of 0 $t/km^2/y$ – 1.94 $t/km^2/y$ by Kusimi (2014). The low levels of sediments export modelled might be due to the fact that the model accounts for only surface (sheet or rill) erosion and did not consider other erosions contributing to sediment export in the basin (Sharp *et al*., 2018). The large coverage of land cover (open vegetation) might be a contributing factor to the low values of sediment export in the basin. The findings indicate that a decrease in land cover increases the amount of sediments generated in a basin to be exported. Therefore, land management practices that protect the forest and open vegetation should be encouraged in the basin to control erosion (exported sediments). Furthermore, highest points of sediments exports were located in districts with records of high rate of urbanization (KMA, Asokore Mampong), agriculture expansion (Bosomtwe, Bosome Freho, Adansi South) and mining especially both legal and illegal (*galamsey*) small-scale mining in the Obuasi, Upper Denkyira East, West and East Akim, Atiwa, Atwima Mponua and Amansie West districts (CONIWAS, 2011).

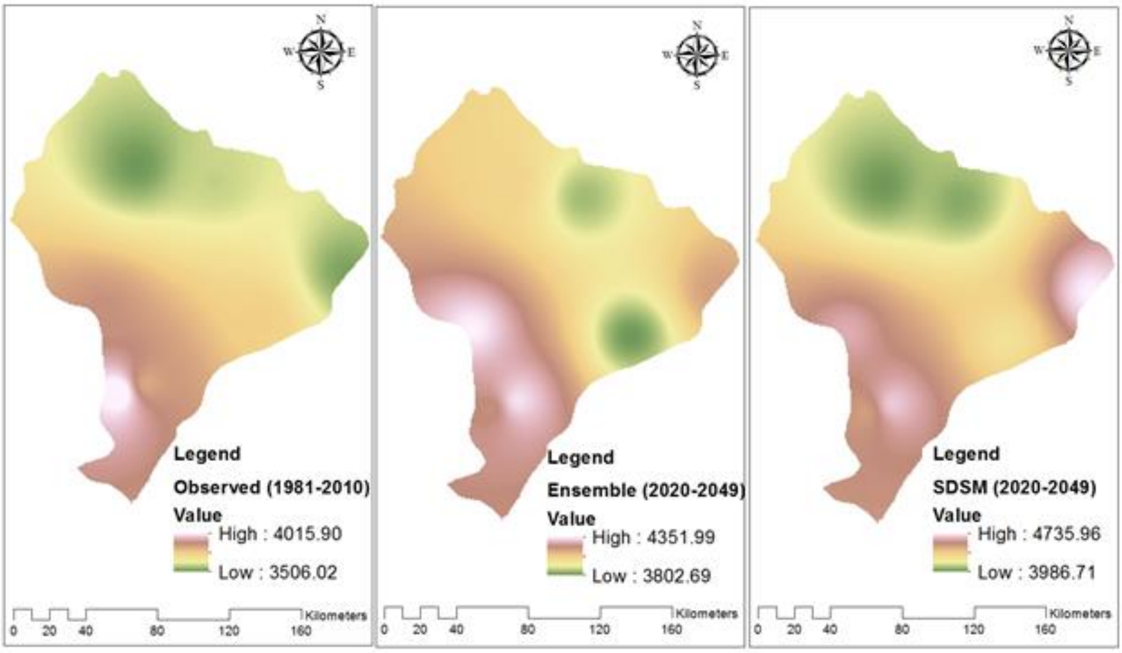

Fig. 4.29. Rainfall Erosivity (MJ mm ha^{-1} h^{-1} yr^{-1})

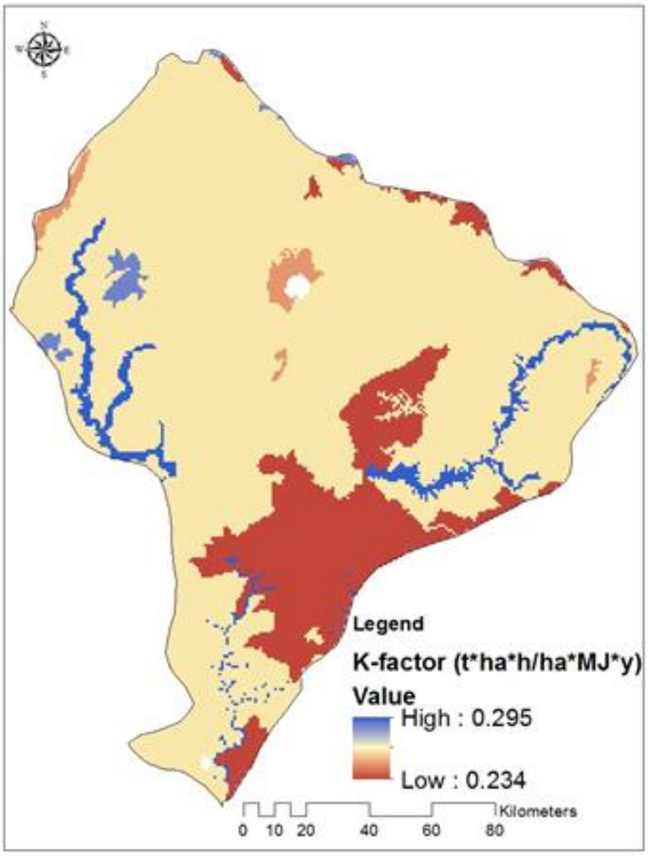

Fig. 4.30. Soil erodibility for the Pra River Basin

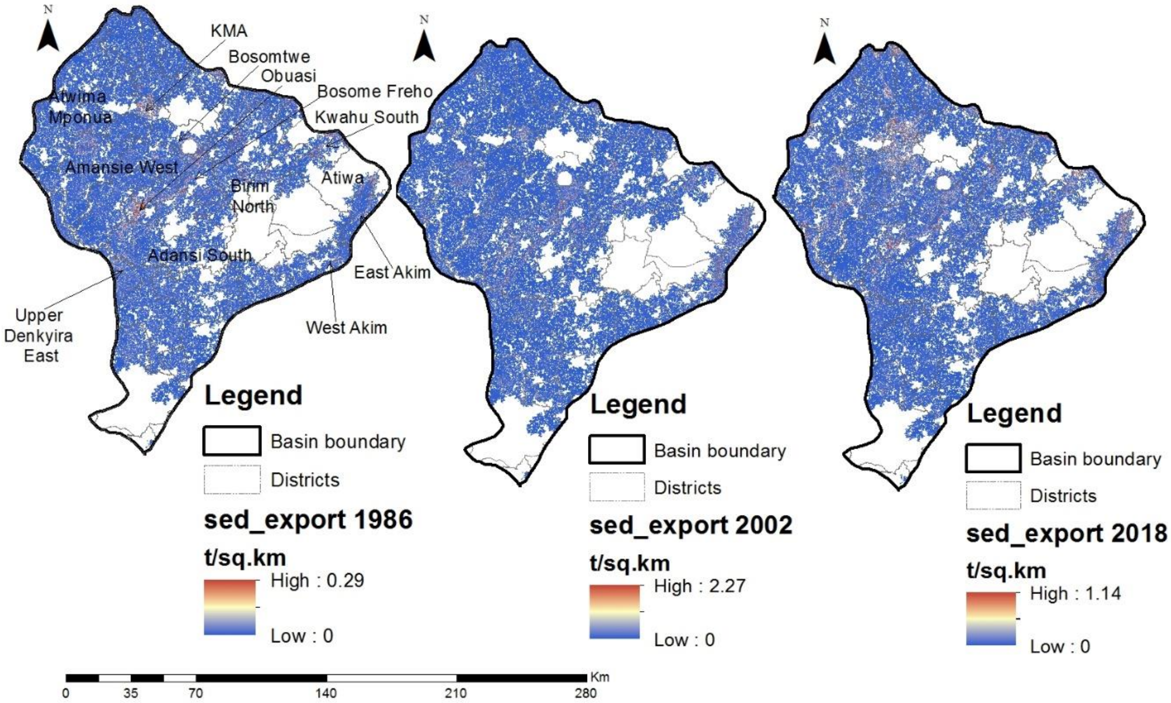

Fig. 4.31. Total amount of exported sediment under control period climate

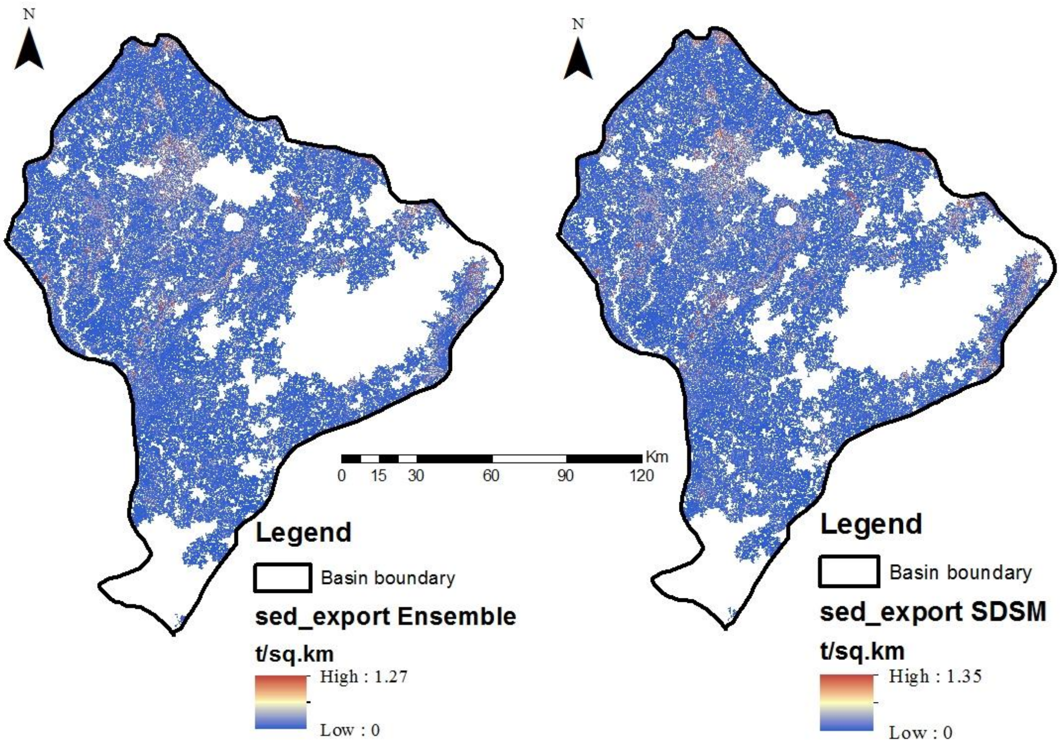

Fig. 4.32. Projected total amount of exported sediment

The increase in sediment export between Ensemble and SDSM confirms the findings of Akrasi (2011), that low sediment exports are due to the low energy conditions associated with sediment transport from catchment surface into the river channels (Fig. 4.31). According to Khalid (2017), high sediment yields are influenced by high slope, high rainfall, land-use and erodible soils. Increased rainfall between Ensemble and SDSM increased sediment export by 6.3 %. It implies that afforestation, reforestation and landcover conservation could further reduce the amount of sediment to be exported under the future climate (Fig. 4.32).

4.3.3.3 Potential soil loss

The potential of total soil loss by the Universal Soil Loss Equation (USLE) is illustrated in Fig. 4.33. Potential soil loss increased by 8.67 t/km^2 from 1986 to 2002 as landcover reduced thereby exposing more soils to be carried away by runoff. Contrary to the loss of land cover trend from 2002 to 2018 which was supposed to lead to increased potential soil loss, potential soil loss decreased rather by 5.7 t/km^2. This further confirms the findings of the study that the location of land use/cover change has a greater influence on sediments and nutrient yields than the total net change of LULC in a basin. Potential total soil loss was projected to be 5.22 t/km^2 and 5.54 t/km^2 by Ensemble and SDSM respectively (Fig. 4.34).

The 2002 potential soil loss range of 0 t/km^2 – 10.36 t/km^2 is higher than the estimated loss by Kusimi (2014) for the same basin at 0 t/km^2/y - 3.91 t/km^2/y and 0 t/km^2/y – 3.96 t/km^2/y for R factor events of 12 and 12.5 mm respectively using 2008 rainfall data. The variation could result from the difference in location change of land use/cover types used and the different C and K factors used for crop management and support practices in the basin. This study determined R factor from the climate period of 1981 – 2010 while Kusimi (2014) used only the year 2008 for his study. The basin falls under the low-risk soils class (Kusimi, 2014) comparable to findings in Brazil with similar tropical conditions and soil types (Silva *et al*., 2010; Silva *et al*., 2007). Also, fluvisols soil group has been reported to be susceptible to erosion which can be traced to their K factor at 0.295 (Ashiagbor *et al*., 2014) and its main ecosystem service is water runoff (FAO and ITPS, 2015).

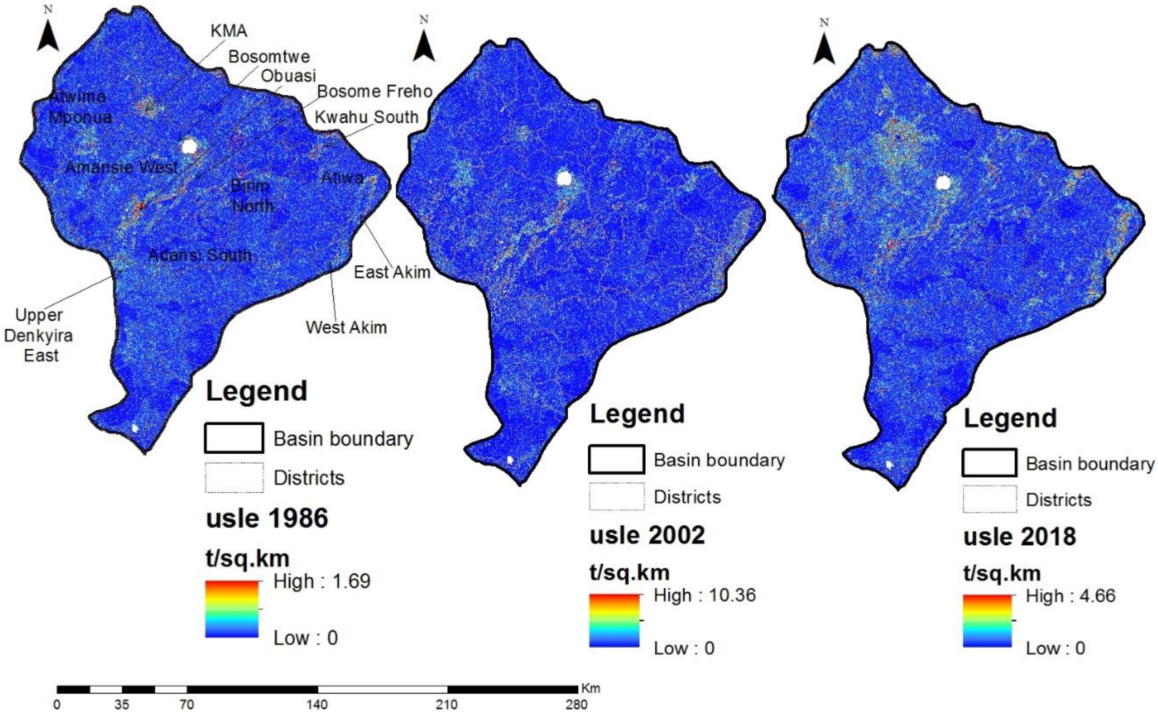

Fig. 4.33. Total amount of potential soil loss for the control climate period

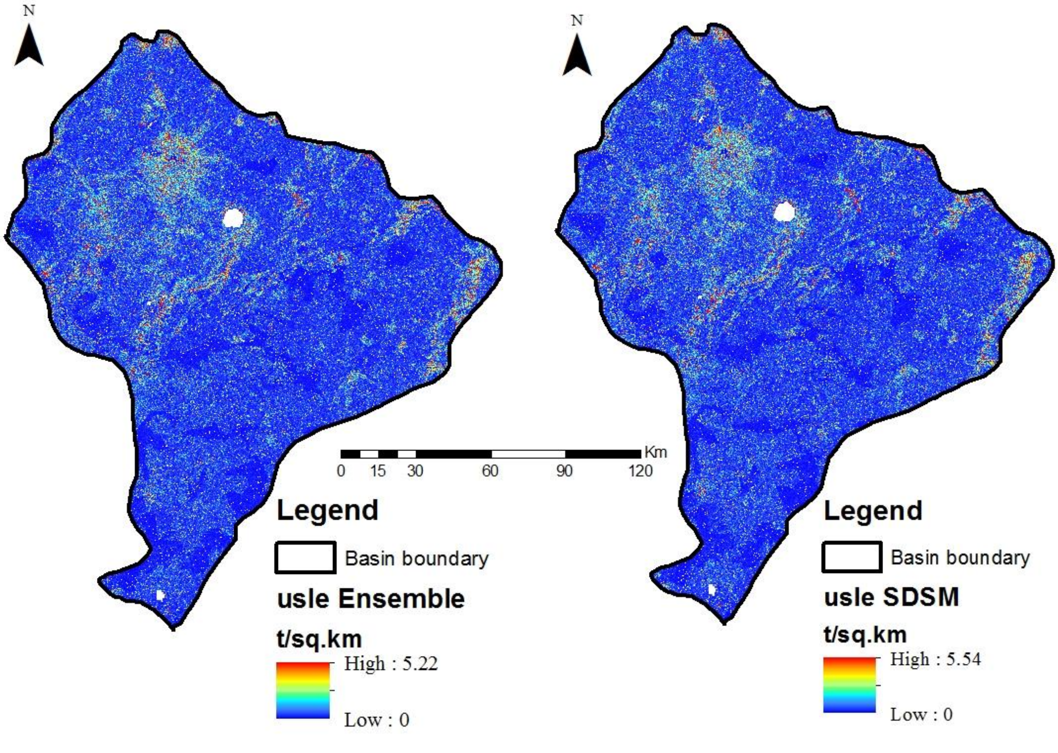

Fig. 4.34. Projected total amount of potential soil loss for the future climate period

Therefore, areas underlain by fluvisols recorded medium to high potential soil loss in the basin. Settlement and agriculture lands (including bare areas) showed the medium potential of soil loss. Potential soil loss increase had no specific trend nor pattern with land-use change between 1986 and 2018 under the climate of 1981 - 2018 but showed an increase of 6.13 % between Ensemble and SDSM for the climate period 2020 – 2049 under the LULC of 2018 (Fig. 4.34).

4.3.3.4 Sediment retention capacity

The basin's sediment retention capacity which may also be referred to as the sediment delivery ratio is presented in Fig. 4.35 and Fig. 4.36 under control and future climate respectively. Retention of sediments decreased between 1986 and 2002 by 1.62 t/km^2 as land cover with high retention capacity decreased. However, as the trend of land cover decline continued between 2002 and 2018, retention of sediments, on the contrary, increased from 2.06 t/km^2 to 2.57 t/km^2 (Fig. 4.35). The Ensemble and SDSM projected sediment retention at 2.88 t/km^2 and 3.06 t/km^2 respectively indicating that increased rainfall would also increase the capacity of the basin to retain sediments based on the spatial distribution of rainfall in relation to LULC (Fig. 4.36). Kusimi (2014) reported the retention capacity of the Pra River Basin to be in the range of 0 – 1 t/km^2 for 2008 which is about 100 % lower than the findings in this study for the year 2002. The low values of Kusimi (2014) can be attributed to the very low erodibility factors used in his studies.

4.3.4 Implication of hydrological ecosystem status in the basin

Water yield in the Pra River Basin for the observed period (1981 – 2010) was averagely in the range of 0 mm – 335 mm for the three land use/cover periods. It was evident that this annual yield varied extremely under the rainfall season and dry season. The amount of water yield in the dry season might not be enough to run the proposed hydro-dam on the basin and might lead to infrastructure installation losses (Kabo-Bah *et al*., 2016; WRC, 2012). Anthropogenic activities (settlement and agriculture expansion) increased the volume of water yield. However, its impact on nutrient and sediment delivery had no particular pattern. Nitrogen load increased with decline in land cover while phosphorus decreased with decline in land cover. Nitrogen and phosphorus export had no particular pattern under both climate change and land-use change.

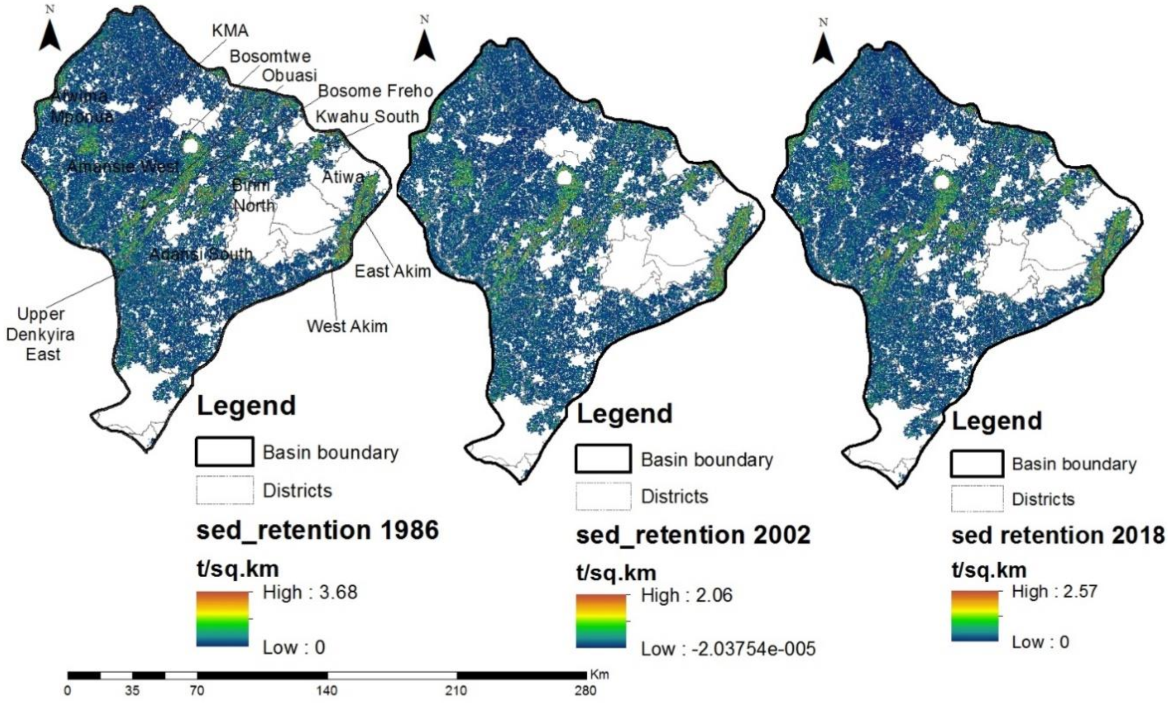

Fig. 4.35. Sediment retention of the basin under control climate conditions

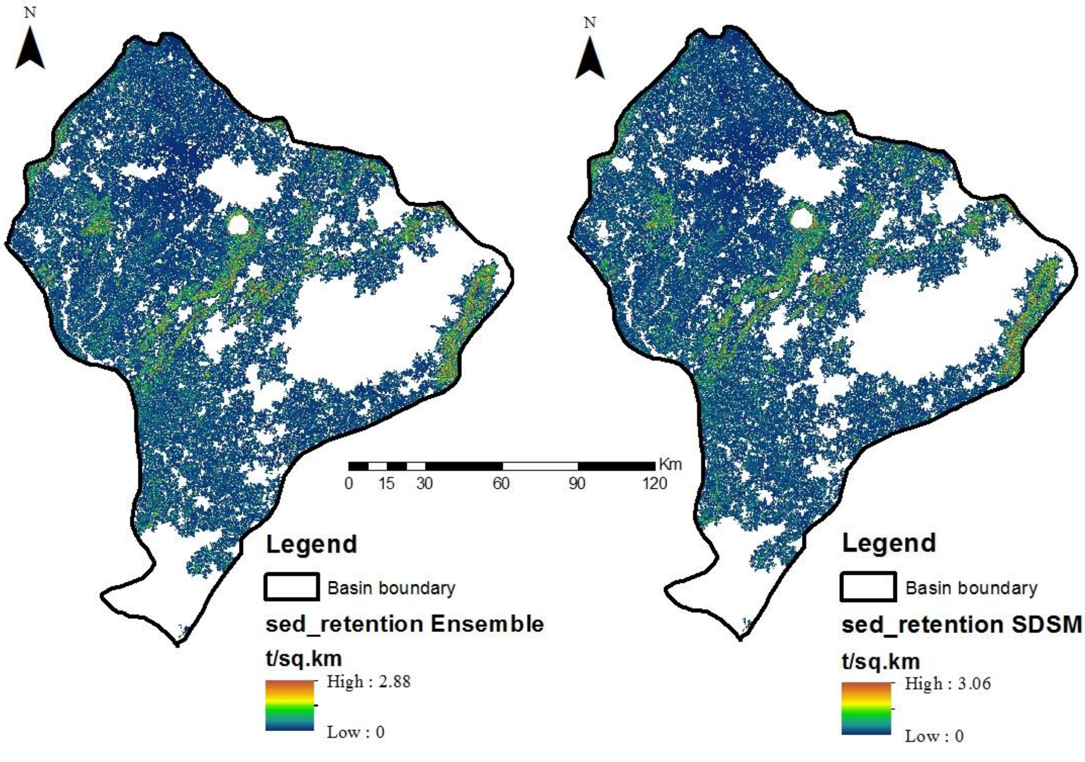

Fig. 4.36. Projected sediment retention of the basin under future climate conditions

Sediment export increased almost 7 times in 2002 via land-use change from 1986 and decreased by 50 % in 2018 from 2002. Therefore, the role of anthropogenic activities in driving hydrological ecosystem services in the Pra River Basin cannot be overemphasised. Awotwi *et al*. (2017) attributed 82.6 % and 17.4 % of the changes between 1987 – 2010 at the Lower Pra River Basin to human activities and precipitation variability respectively. Climate change showed a direct proportionality with water yield, nutrient and sediment delivery in the basin. The high rainfall amount projected by SDSM over the Ensemble mean of the climate models reproduced high water yield, nutrient and sediment deliveries in future.

The increased export of nitrogen in SDSM over Ensemble shows that the decreasing trend of phosphorus load was due to the land-use change and not the climate. The projected decrease and increase in annual water yield at 219.33 mm and 483.68 mm for Ensemble and SDSM might results in droughts and/or flood peaks respectively. Water yield change was higher under climate change than in land-use change because precipitation is the major determining factor of water yield. According to the models, nitrogen and phosphorus export increased under future climate projections by Ensemble and SDSM. Assessment of crop and land use management practices is required for sustainable management of nutrients in the basin. The increasing trend of sediments delivery in the basin both under climate and LULC changes raise concern about the successful operations of water treatment plants. The state of sedimentation in the basin at the Daboase water treatment plant intake point in the year 2013 in Fig. 4.37 is not different from the sedimentation shown by the muddy appearance of the rivers in the basin shown in Plate 4.1. This suggests the possibility of a worse water situation in the future as sediments and nutrients export might increase and water yield may also cause flood from SDSM projections. This has been found to be a direct impact of illegal mining in the basin (Agyei, 2016). Municipal waste also contributed to the increased nitrogen export in the basin as was observed in the Oda river (Plate 4.2).

Water treatment may be more expensive and treatment plants might shut down as was experienced in other basins in Ghana (Bentil, 2011). Mining being one of the activities in the basin is posing a threat to lives by the introduction of pollutants from their activities into the water resources (Awotwi *et al*., 2017; Asare-Donkor and Adimado, 2016; Ansa-Asare *et al*., 2014; Akrasi and Ansa-Asare, 2008). This was confirmed by farmers living around rivers like Birim, Offin and Pra. The projected increase in water yield implies that pollutants will be transported faster downstream where inhabitant use the water for domestic purposes without effective purification during the flow period with interactions with both the aquatic and terrestrial system. Hence, water treatment might be expensive due to the projected increase in sediment yield. Research in China showed that 100 % conversion of cropland (paddy lands) to drylands could reduce nitrogen export and increase water yield (Hu *et al*., 2018). This implies that reducing cropping systems that is agrochemical intensive and cultivating in wetlands like rice will help to improve the water quality in the basin. Implementation of the Integrated Water Resources Management Policy and Riparian Buffer Policy will help to minimize the impact of flood and reduce the influx of pollutants (sediments and nutrients) into the water resources (GoG, 2007). Aside from the impact of the projected climate on hydrological ecosystem services in the basin, it might also influence or directly change agriculture systems thereby changing land use in the Pra River Basin.

Fig. 4.37. Dredging Operations at Daboase Intake (February 2013)

(Source: Adombire *et al*., 2013)

Plate 4.1. State of (a) Pra, (b) Birim and (c) Offin rivers

Plate 4.2. Municipal waste from Kumasi Metro Assembly in Oda river

4.4 Farmers' perception of climate and land use change

This section covered the results and discussion of specific objective four.

4.4.1 Socio-economic characteristics of respondents

Out of the 344 respondents interviewed (Plate 4.3 and 4.4), the male gender was 70.1 % and the total respondents who were heads of their households were 74.7 %. Mean age of respondents was about 49 years with about 20 years' average experience in farming. Table 4.17 presents descriptive statistics of sampled households interviewed. The majority of the respondents (83.4 %) were married and the highest dominant educational level was Junior High School (JHS) including the form 4 educational system (57.6 %). The form 4 system was a four years JHS education. About 15.0 % of the respondents had no formal education and only 3.8 % had schooled to the tertiary level. Respondents with access to electricity, transportation to market, primary and JHS facilities were 88.7 %, 75.0 %, 82.0 % and 79.7 % respectively. Farming was the primary occupation of 95.9 % of the respondents followed by professional services (2.6 %). Trading was the most engaged activities of the respondents (24.7 %) as their secondary occupation.

4.4.2 Awareness of climate change

Respondents aware of climate change and its impact in the Pra River Basin were 98.3 %. The leading sources of awareness about climate change were through the radio (93.0 %) followed by observation based on respondents' experience at 89.0 % (Fig. 4.38). Internet (0.9 %) was the least source of awareness about climate change for farmers and this could be traced to their level of education (Table 4.17). Other sources of information on climate change at 0.3 % and 1.8 % of respondents were Farmline app and SMS from Ghana Meteorological Agency (GMet) respectively. Based on the findings of a survey by GMet, some farmers were registered for SMS alert on climate and weather information in the Assin North District of Central Region, specifically in Sekanbodua community. Respondents in the Pra River Basin by experience were very knowledgeable of their environments especially the climate which has a greater contribution to the output of their farming activities. Agricultural extension officers were among the least sources of information on climate for farmers. Respondents indicated that they have observed changes in both rainfall (82.8 %, n = 344) and temperature (95.9 %) (Fig. 4.39 and 4.40).

Plate 4.3. Questionnaire administration at Bunso (Abuakwa South Municipal)

Plate 4.4. Questionnaire administration at Tawiahkrom (Adansi Asokwa District)

Table 4.17. Socio-economic characteristics of respondents

Descriptive statistics of sampled households	**Range**
Age (years)	20 - 90
Household size	1 - 30
Number of children	0 - 18
Number of children under 18 years	0 - 12
Farm size (acres)	1 - 53
5 yrs change in farm size (acres)	0.2 - 15
Years in farming (years)	3 - 70
Years of stay in the community (years)	1 - 90
Highest Educational level	*(%), n = 344*
No formal education	15.4
Primary	15.1
Junior High School (JHS)	32.3
Form 4 (now converted to JHS)	25.3
Senior High School (SHS)/O or A level/Vocational/Technical	7.8
Tertiary (University/Training colleges)	3.8
Access to social amenities in farming communities	*(%), n = 344*
Electricity	88.7
Pipe borne-water	8.1
Tarred road	31.1
Transport to market	75.0
Health post	40.7
Primary	82
JHS	79.7
SHS	9.6

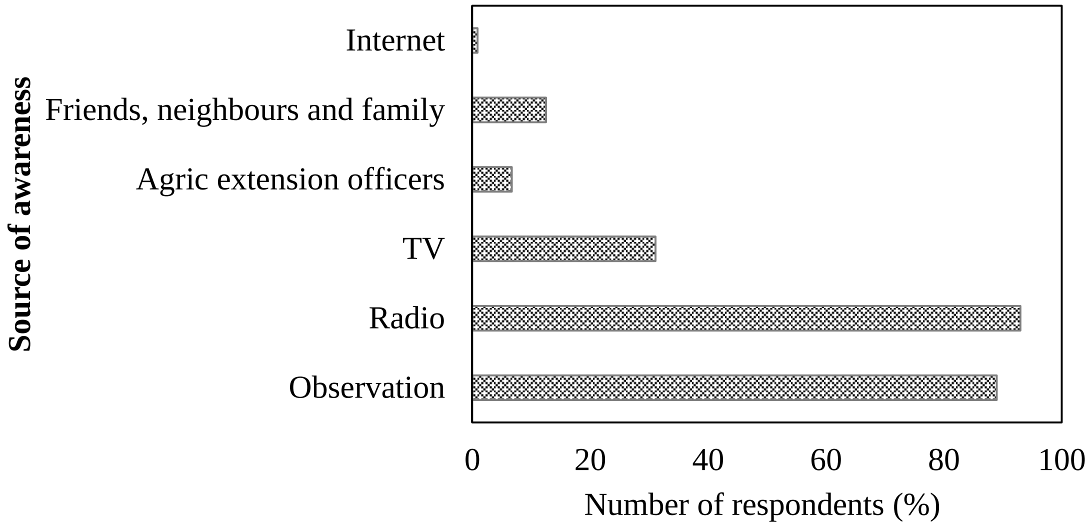

Fig. 4.38. Sources of awareness of climate change

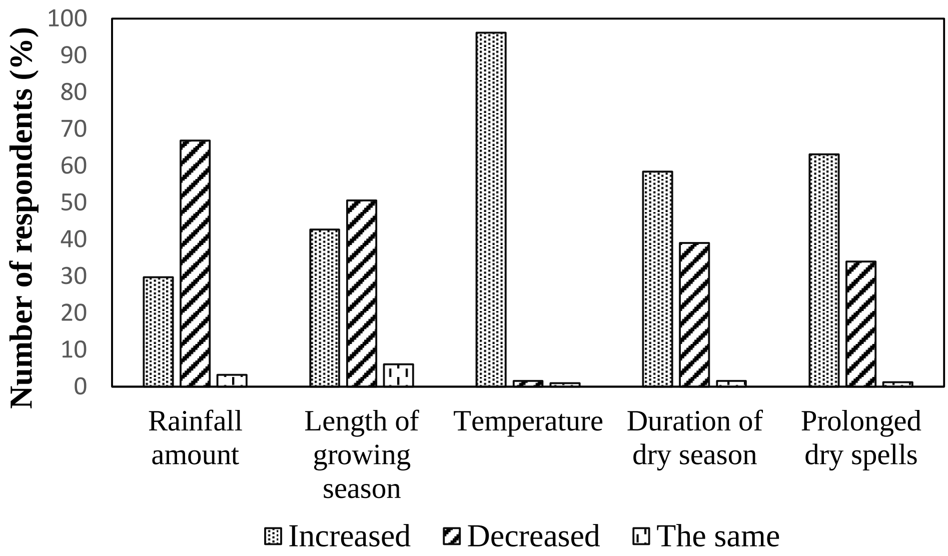

Fig. 4.39. Farmers' observed trends of climate parameters

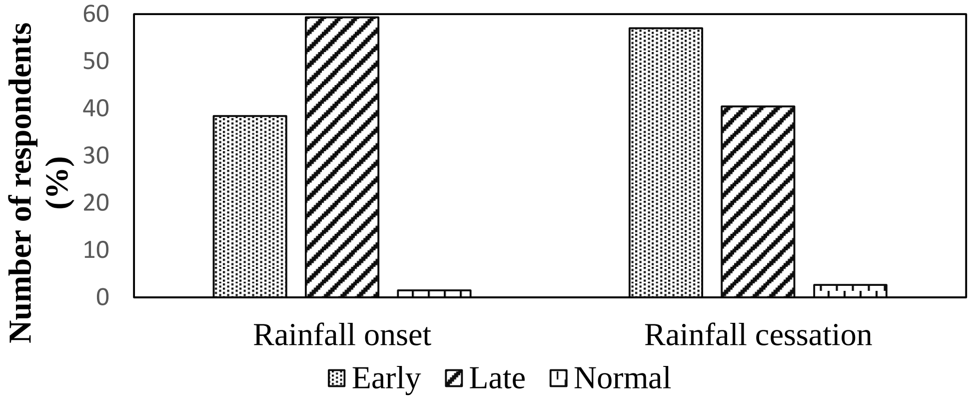

Fig. 4.40. Farmers' observed trend in rainfall onset and cessation

This result was in line with the determined increasing trend of maximum and minimum temperature in the basin from 1981 – 2010 (see Fig. 4.1). However, their perception of changes in rainfall was often contrary to gauge station records for the control period. Majority of the respondents perceived decrease rainfall amount (66.9 %) and length of the growing season (50.6 %) while duration of the dry season (58.4 %) and prolonged dry spells (63.1 %) were indicated to have increased (Fig. 4.39).

The findings from the perception survey could be due to the erratic spatial distribution of rainfall and the different agro-ecological zones within the basin. Therefore, a determined pattern of rainfall for the whole basin was often contrary to what was observed or perceived by farmers in their various communities. The length of the growing season was indicated to have decreased by most of the respondents and this was in line with the perception of rainfall onset and cessation (Fig. 4.40). Late-onset (59.3 %) and early cessation (57.0 %) of rainfall identified by respondents showed a decreasing growing season while about 40.0 % of respondents perceived early onset and late cessation of rainfall (Fig. 4.40).

The closeness of perception of when rainfall start and end shows the difficulty in rainfall forecasting and modelling. The perception of most of the respondents of late-onset and early cessation is contrary to the trend of rainfall onset and cessation determined for the basin for the period 1981 – 2010 (see Fig. 4.17). The variations could be due to the parameters used in the assessment. While onset and cessation were determined by the amount of rainfall in a month, farmers used the benefit of the rain to their production to select their response. For instance, if rainfall amount in February shows onset but farmers could not plant with it, then to them, the rains have not started. Similarly, rainfall in November and December that could not be used for crop production is not considered as profitable rainfall, therefore, the rains are perceived to cease early.

4.4.3 Impact of climate change on agriculture and related activities/resources

The impact of climate change was perceived to be extremely severe on changes in the onset and cessation of rainfall, increased frequencies of droughts and crop failure, the prevalence of pest invasion and the rising cost of farm inputs (such as fertilizers, pesticides and seeds) as indicated by more than 70.0 % of the respondents. Farmers perceived that the prevalence of crop diseases (66.3 %), deforestation (53.2 %) and abrupt changes in the growing season (59.5 %) were also impacts of climate change (Table 4.18). Loss of some traditional crop varieties (41.3 %) and siltation of water bodies (42.2 %) are some of the reported consequences of climate change. Although, migration has been found to be a major impact of climate change in other parts of the world (Rigaud *et al*., 2018; Baez *et al*., 2017) and currently reducing in the northern part of Ghana (Laube *et al*., 2012), rural-urban migration was perceived to be less severe in the Pra River Basin as an impact of climate change (Table 4.18).

Farmers in the Pra River Basin indicated that they were extremely vulnerable to the impact of climate change (Table 4.19). More than 60.0 % of the respondents perceived that their farming activities were extremely vulnerable to droughts during the cropping season, decreased rainfall and its poor distribution, changed duration of rainfall season and increased temperature. Less than 50.0 % of the respondents were either extremely vulnerable or vulnerable to floods in the study area (Table 4.19). During rainfall season, most of the farmers along rivers and on lowlands had their farms flooded for days and sometimes weeks. Due to the pollution of the rivers, crops are infested with unknown diseases after the flood water recedes according to the farmers. The yield of the crops has reduced due to the unknown impact of the polluted water from illegal small-scale mining (*galamsey*) that floods the farm for days (Sullivan *et al*., 2001). This was a common experience amongst farmers who had their farms near to river bodies in the study area. The farmers differentiated the climate impact from human activities affecting them by agreeing that siltation is the major cause of flooding and not due to increased rainfall amount. They also indicated the role of urbanization in the current floods experienced as waterways are being sold by community leaders such as chiefs and landowners for housing purposes. To scientifically differentiate the impact of climate and human activities in the ongoing flooding in the basin, all the observed activities must be accounted for in the modelling process.

Table 4.18. Severity of climate change impact on resources and events over the last 20 years

Resources and/or events impacted by climate change	Extremely severe (%)	Severe (%)	Less severe (%)
Changes in the onset and cessation of rainfall	74.1	20.1	4.7
Abrupt changes in the growing season	59.9	33.7	5.8
Increased frequencies of droughts and crop failure	70.6	25.3	3.2
Increased frequencies of floods and farms destructions	44.2	20.9	16.3
Prevalence of pest invasion (like armyworms)	78.2	6.1	5.2
Prevalence of crops diseases	66.3	14.5	10.5
Extinction of some crops and crop varieties	24.7	41.3	25.3
Deforestation	53.2	17.7	13.4
Erosions	14.5	28.8	37.8
Siltation of waterbodies	27.3	42.2	23.5
Extinction of fishes and aquatic life	4.9	13.4	34.9
Death of livestock	11.9	18.3	29.1
Rising cost of farming/fishing inputs	77.9	7.3	0.9
Rural-urban migration	5.2	29.1	30.8

Table 4.19. The vulnerability of farmers' activities to climate change

Climate events	Extremely vulnerable	Vulnerable
Increased temperature	92.2	6.7
Changed duration of rainfall season	73.3	22.4
Droughts (during cropping season)	66.3	26.5
Decreased rainfall and poor distribution during cropping season	64.8	26.7
Abrupt changes in onset of planting season	54.7	40.4
Floods	29.4	35.8

Moreover, the few farmers vulnerable to floods are experiencing financial loss as well as indirect income reduction to those who are not close to main rivers. Plate 4.5 shows a cocoa farm that floods every year due to its location close to river Birim in Abomosu community in the Atiwa West District of Ghana. The reason for farmers cultivating along the rivers was to have access to the water for irrigation during the dry season and also for farm management activities like mixing agrochemicals for pest and diseases control on their farms. These benefits are no longer feasible due to the impact of land-use change (*galamsey*) that has made the available water not useful for farming (Plate 4.5 and 4.6).

Some of the indirect impacts of flood is the inaccessibility of farms mostly during harvest periods according to the farmers. A break in farm visit due to flood for more than five days under the current climate change with the increased invasion of pest comes at a cost. The farmers' association in the Abomosu community have purchased a canoe (Plate 4.6) for crossing the river Birim daily to and from their farmers because majority of the farmers especially farm sizes above 2 hectares are beyond the river. The youth of the community volunteer in rotation to handle the canoe for easy crossing of the Birim river to the farm. These youths have no agreed payment plan, however, farmers out of free will give them a token to appreciate their good work and commitment to support farmers those who cannot swim to cross the river.

Despite the numerous negative impacts of climate change on the activities of farmers, a small portion of the respondents agreed that increased rainfall and floods have some opportunities that could improve farming. Flood water harvesting and improved groundwater yield were perceived by 38.1 % and 35.2 % of the respondents respectively to benefit from the changes in the climate causing flooding. The opportunity of flood increasing fish harvest was indicated by 2.3 % of the respondents who were involved in fish harvesting from the rivers in their communities. A respondent from Aduaben in the Bosomtwe districts attested to the fact that whenever the Oda river overflows its banks, it brings along fishes. The opportunities presented by flood made 55.6 % of the respondents envisaged irrigation farming in the future while 1.2 % may shift to fish farming. The frequent occurrence of floods in the basin makes floodwater harvesting an option that could be optimized for maximum benefit for crop production (Asumadu-Sarkodie *et al*., 2015).

Plate 4.5. Cocoa farm near river Birim at Abomosu community

Note: This river floods annually to deny access to farms

Plate 4.6. Community canoe for farmers' transport over Birim at Abomosu

4.4.4 Adaptation strategies adopted by farmers in response to climate change

All respondents (100 %) indicated that they had made one or more changes on their farm to improve their yield. Adopted strategies by more than 10.0 % of the respondents are presented in Fig. 4.41. The use of improved crop varieties was the highest adaptation strategy of farmers to climate change followed by the use of agrochemicals to control weeds and pest infestation on the farm. Farming near rivers and on lowlands was a strategy by 10.5 % of the respondents who could access farmlands in these locations. Most of the farmers were willing to move their farms near to a river to access the water for irrigation during the dry season but the availability of such farmlands was limited. It implies that farmers preferred their farms close to rivers despite the challenges it poses in rainy season. Their major reason was that crops produced during the dry season have high market value. Diesel pumps are used to transport water from the rivers to farms and manual watering cans used to irrigate the crops. Little farms who are well to do use sprinklers on their farms. Other measures adopted by respondents to cope with climate change were zero tillage farming, crop rotation, cover cropping, rainwater harvesting on-farm and reduction of shade on crops by cutting some trees to increase crop access to sunlight.

In future, respondents perceive that measures like early warning systems, education, irrigation facilities, organic farming, reducing farm size and reducing the number of crop types planted in mixed cropping will enhance their adaptation capacity to climate change and increase their productivity.

4.4.4.1 Constraints limiting adaptation capacity of farmers to climate change

Factors limiting the adaptation of farmers to climate change are presented in Fig. 4.42. Lack of access to credit was perceived as the highest constraint as indicated by 94.8 % of the respondents. This was followed by a lack of access to information on adaptation, no access to water for irrigation, educational level and fertility level of the soil (Fig. 4.42). Lack of extension services was perceived as a severe constraint to the adaptation of the respondents. The results imply that climate information services and knowledge or technical expertise on how to use adaptation information are very key besides access to credit for climate change adaptation. The severity of the lack of extension services further confirms the need to improve the availability of adaptation information and skills through training and workshops to farmers to enhance their coping capacity to the situation.

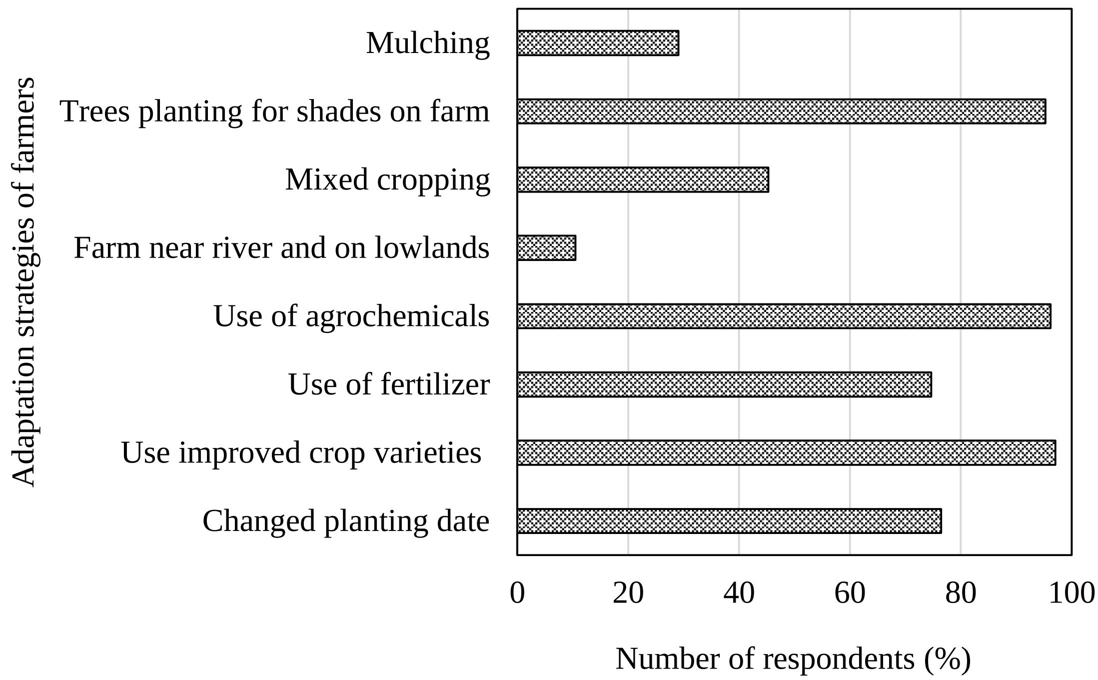

Fig. 4.41. Adaptation strategies of farmers to climate change

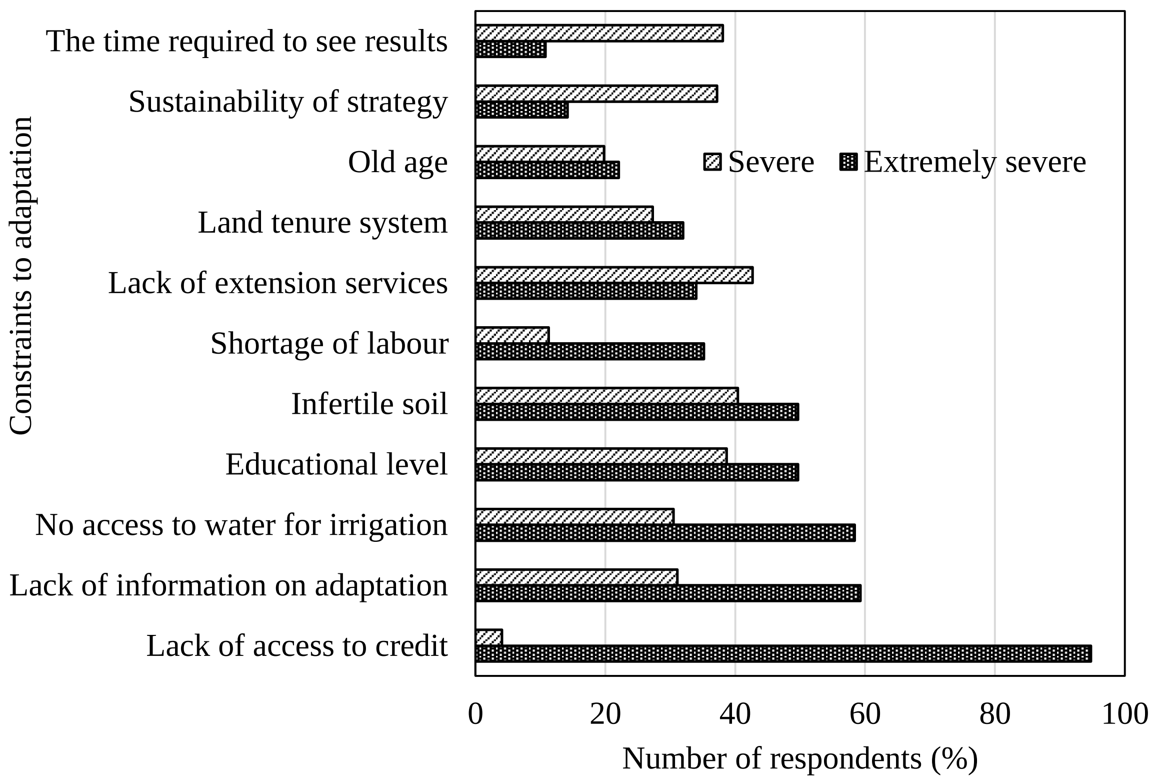

Fig. 4.42. The severity of constraints to the climate change adaptation

4.4.4.2 External Support for adaptation to climate change

The study showed that 87.8 % of the respondents receive one or more of financial, material, extension service, subsidized farm inputs, weather information, training and workshops support (Fig. 4.43). Extension service was the highest support received by 77.3 % of the respondents and financial support from farmers' cooperative received by 0.3 % was the least external support. The mean period of these support ranges between 2 – 7 years. The most recent support is the mass spraying of cocoa farms to prevent and treat pest and diseases. All support is free except the financial support that was to be paid back to the cooperative. Extension, subsidized farm inputs, training and workshops were provided by government agencies (Ministry of Food and Agriculture and Ghana Cocoa Board) as affirmed by 85.8 % of the respondents. However, subsidized inputs for non-cocoa farmers is of recent (less than 3 years) according to the respondents and the supply is not consistent. Sometimes, the inputs are available during off-seasons or after the crops are already matured. Apart from support from the government, agricultural research stations, NGO's and farmers' cooperatives offered support to 0.6 %, 4.4 % and 4.1 % of the respondents respectively. NGOs and cooperative unions offered material support, and training and workshops.

These supports were beneficial according to 79.4 % of the respondents while 8.4 % indicated that they do not benefit from the external support especially the subsidized farm inputs from the government. Inadequate farm inputs, irregular and late supply of inputs were the major reasons for it not being beneficial. Besides these limitations, the two main benefits from the external support were improved yield (78.8 %) and reduced postharvest losses (29.9 %). Other benefits enjoyed by less than 10.0 % of the respondents were an expansion of farms, reduced hunger, improved family living standard, reduced cost of production, buying of extra farm machinery and reduce pest and disease infestation on farms.

4.4.4.3 Needed services to improve the adaptation capacity of farmers

Despite the essential role of climate information in the climate change adaptation, only 26.5 % of the respondents receive information on rainfall and temperature from agriculture extension officers. An informal interview with the extension officers revealed that they have no special link or network with the Ghana Meteorological Agency (GMet) for information on climate to give to the farmers. They and the farmers get information from the same source, which is the radio and TV and sometimes when they attend workshops with officers from GMet and climate research organizations are present to give such information.

The main source of information that helps farmers in their adaptation to climate change was the radio. About 95.0 % of the respondents receive technical support on farming especially on climate information from the radio. Farmers who do not have radio sets or miss the information get assistance from their neighbours and relatives (43.0 %) (see Fig. 4.44). The internet and SMS alert were the least source of technical assistance due to the level of expertise required to operate them and the cost involved. However, this type of technology may be more accessible to local farmers over time. Some farmers may have growing access to more affordable devices, such as second-hand mobile phones and cheap equipment.

The five most needed services by farmers to help them cope with changes in climate are presented in Fig. 4.45. The cost of farm inputs, labour and sometimes land on lease for crop production was a major concern of the respondents, therefore, the service of credit providers was the topmost priority ranked by 55.5 % of the respondents. Farmers ascertain that all other services that could help them adapt to the current climate situation could be purchased or made available if they have the funds. Currently, farmers find it difficult to access credit for their activities due to the uncertainty of their production and lack of collateral to guarantee loans. They reported discrimination by banks and credit providers in granting loans for salary workers (such as nurses and teachers) and traders but refuse to grant loans for farmers to improve their work. This was a major concern by the respondents and indicated that it affected their adaptive capacity to climate change.

Availability of health services in the farming communities was the second needed service ranked by 25.6 % of the respondents. Farmers agree with the adage that your health is your wealth. Therefore, the lack of access to health services in a close distance in the communities or in nearby towns was a challenge to them. Access to climate information was the third needed service followed by agricultural mechanization and review of land tenure system (Fig. 4.45). Although land tenure was a major problem to settlers who are working on the basis lease arrangement, the first four most needed services were perceived to supersede the challenge of land tenure system.

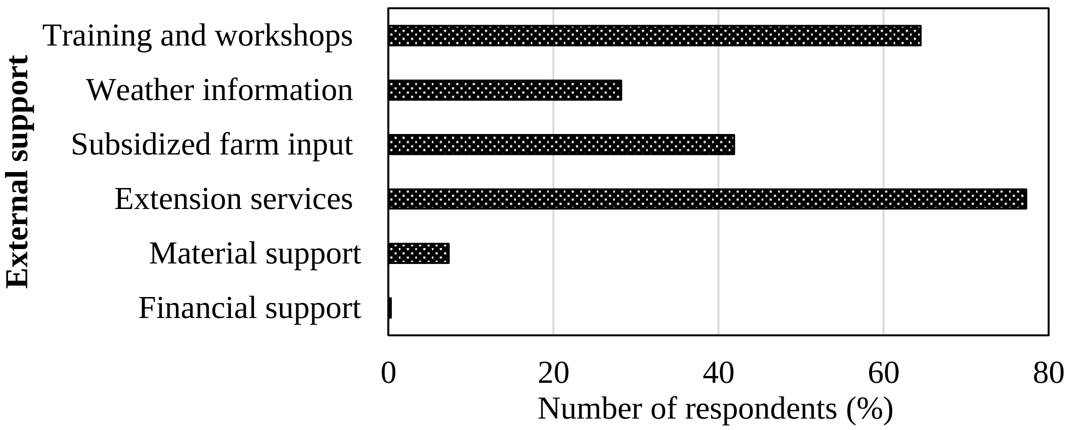

Fig. 4.43. Support for farmers' adaptation measure

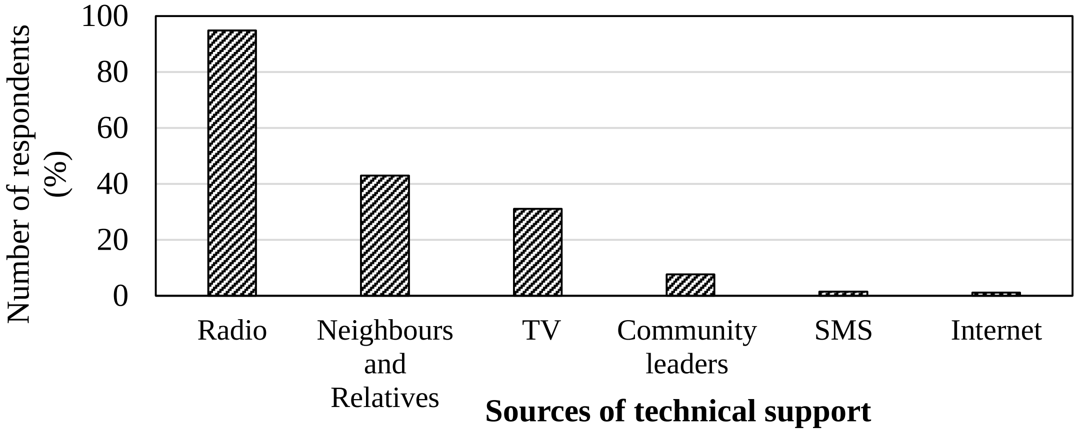

Fig. 4.44. Sources of technical assistance in adapting to climate change

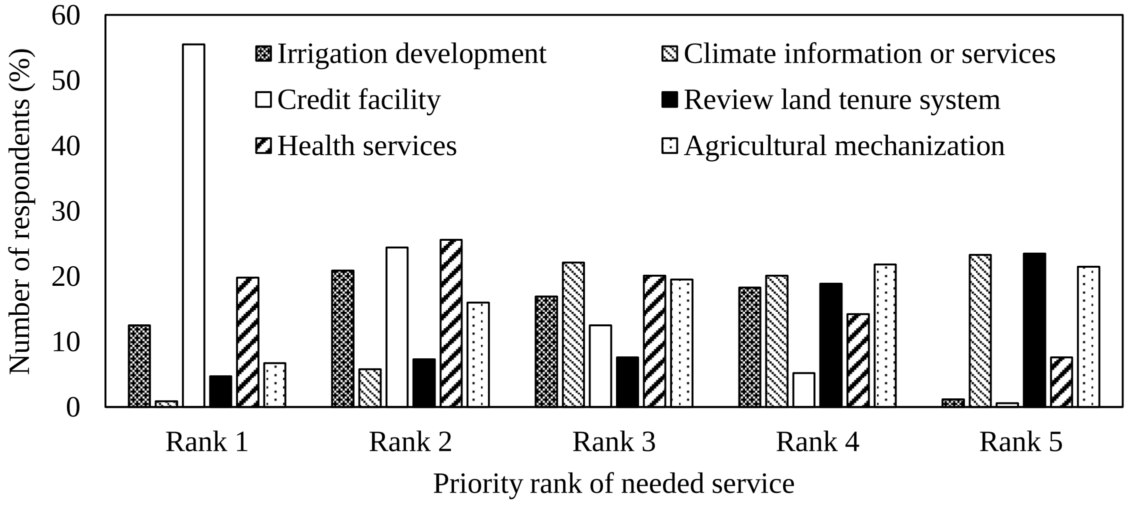

Fig. 4.45. The rank of the five most needed services to help adapt to climate change

Assessing the expectation of the respondents about the provision of the needed services revealed that 91.6 % ranked the government as the first, followed by the private sector (83.4 %) and the community (91.9 %) as the last option to provide the services needed. The challenge of individuals taking over community projects as personal properties and the cost of private sector services guided the decision of the respondents to select government as their first service provider.

4.4.5 Perception of trends and drivers of LULC change

The study showed that most of the respondents converted forest (41.3 %) and open vegetation (41.0 %) to farm. This gives a clue to the rate of deforestation and a decline in open vegetation in the second interval (2002 – 2008) in the basin. Fallow was the third most converted land cover type for agriculture in the study area. Furthermore, 7.6 % of the respondents had no new land to use for farming, therefore, they had to cut down an old cocoa plantation and replant. Mixed cropping was the farming type adopted by over 90.0 % of the respondents in both previous and current farms followed by tree plantation (cocoa). Mixed cropping helps to protect the tree crop (cocoa, cashew, palm tree and rubber) at the early stages and provide food and income to the family till the tree crop is matured to be harvested. This was a common practice in the study area for farmers that cultivate cocoa plantation. However, annual crops like cereals (maize) and tubers (cassava) are planted on different farmland either as a mono-cropping in a rotational system or mixed cropping. Crops planted by the respondents were tree crops (92.7 %), cereals (83.7 %), tuber (91.3 %), vegetables (46.5 %) and fruits (6.4 %). Farmers were satisfied with the type of farming system they practised. Therefore, only, 10.8 % have plans to change what they are currently cultivating to tree crops (7.0 %), agro-forestry (2.0 %), mixed cropping (2.0 %) and mono-cropping (0.9 %).

4.4.5.1 Farmers observed trend of LULC changes

Generally, 93.6 % of the respondents observed a decrease in forest area in their communities while 3.3% opined that forest size is the same. Only 0.3 % observed that forest area has increased in size in their community. Some of the reasons for the decreasing trend of land cover (forest and open vegetation popularly known as regenerated forest by farmers) were the expansion of farmland (79.4 %) and illegal mining (*galamsey)* activities (42.7 %). Therefore, the deforestation and crop expansion trend from the satellite image analysis is in line with the observation of the respondents (refer to Table 4.12). Respondents who have not expanded their farms in the past 5 – 10 years were constrained by one or more of the following: lack of farmland, funds and/or labour, old age, ill-health and inconsistency of benefits from farming. In future, 91.6 % of the respondents have plans to expand their current farmlands. This implies a great potential for change in land cover/use in the study area. The potential of converting or going into a particular land cover/use by the respondents in the future are presented in Table 4.20. Results show that more than 50 % of the respondents were most likely to target forest for expansion in the future and 45.3 % might go for open vegetation in future.

Reasons given for the interest in the forest was the fertility of the soil that gives them higher yield and early harvesting of tree crops like cocoa. However, most females interviewed preferred open vegetation for future expansion because the forest (unfarmed natural forest) was usually more difficult to farm compared to open vegetation. Furthermore, open vegetation was easy to prepare for vegetable production due to the limited stumps to be removed.

About 45 % of the respondent have plans of going into Agro-forestry in future (Table 4.20). This will be an afforestation and reforestation initiative to aid the conservation of forest and forest resources. Conversion of farmland into other non-farming land use such as settlement and *galamsey* (recent and common land use that target farmlands) was not a likely activity to happen in the future as 66.5 % of the respondents were not willing to sell current farmland. The only reason that will compel selling of farmland was when the community expands to meet the farm. In such situations, land-owners and farmers have little control over the decision to sell the land. Respondents that were willing to sell their farmlands when there is such an opportunity were mostly aged and there were no family or relatives in the community interested in farming.

However, majority of the respondents see land resources as an everlasting property that cannot be destroyed by either natural or artificial disaster that they know of and could be passed on to future generations as their forefathers did for them. Farmers preferred a continuous benefit from their land resource to a one-time payment which could be lost by an unfortunate situation.

Table 4.20. The targeted land cover by respondents for future expansion of farmlands

	LULC Types			
	Forest	**Open vegetation**	**Agro-forestry**	**Farmland**
Not likely (<10%)	18.6	26.5	20.3	66.5
May be (20 – 50%)	16.3	17.2	22.2	10.2
Likely (60 – 80%)	2.4	4.4	6.2	2.6
Most likely (>90%)	55.5	45.3	44.7	20.7

NB: The table present potential of expanding agriculture land into Forest or Open Vegetation, or going into agroforestry or selling current farmland for non-farming activities in future.

4.4.5.2 Drivers of land use/cover change

Seven drivers or factors of land-use change were assessed to determine the four most important factors driving the changes in the study area as presented in Fig. 4.46 and the severity of the factors in Fig. 4.47. Availability of funds or credit, climate change, market demand and pest/disease invasion were the four foremost drivers of land-use change. Long *et al*. (2007) reported industrialization, urbanization, population growth, and China's economic reform as the four major driving forces contributing to land-use change in Kunshan in China were comparable to the findings in the Pra River Basin. Population growth and urbanization contribute to the market demand while industrialization and economic reforms can be linked to the economic status of respondents (availability of funds or credit).

Market demand is directly linked to population and economic capacity of the populace (Alexander *et al*., 2015; Knickel, 2012). Therefore, change in the population growth and economic activities in the locality influence the demand for varieties and different quantity of food. Although the population (demography) is the ultimate driver of agriculture land-use change globally (Strapasson *et al*., 2016), the economic status or capacity of farmers in the Pra River Basin was their highest driver of land-use change. Finance was ranked by 95.6 % of the respondent as extremely important in determining their capacity to change land use or expand current land use.

Climate change which was the second driver was ranked by 59.0 % of the respondent as having a key role in their activities. Market demand was the third indicated driver of land-use change. Land tenure system which was reported to be a major driver in West Africa (Knickel, 2012) was fifth according to the respondents (34.3 %) with an indicated extreme severity by 39.5 % of them (Fig. 4.46).

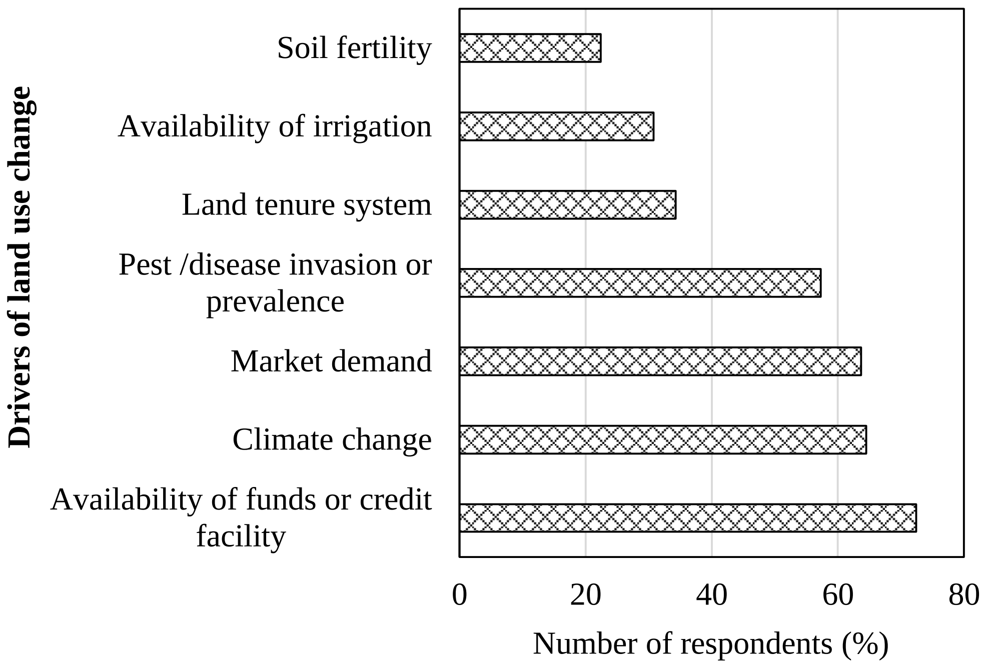

Fig. 4.46. Drivers of land use change in the Pra River Basin

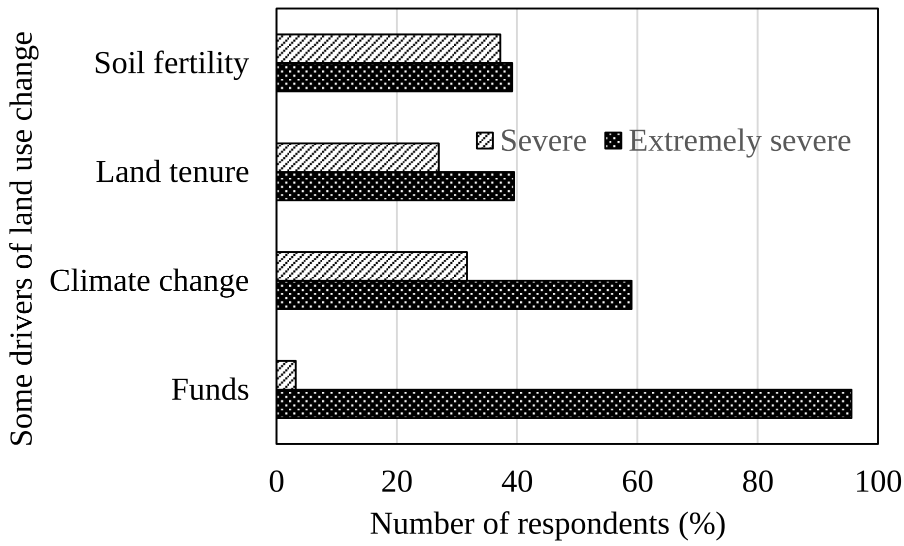

Fig. 4.47. Severity of some of the drivers of land use change

4.4.6 Implication of farmers' status and perceptions of climate and LULC change

Land availability for the practice of sustainable farming like shifting cultivation is now a challenge in the basin. This limit the adaptation options of farmers on the control of increased pest and diseases under climate change. It further implies that agriculture will be intensified by the use of agrochemicals and fertilizers rather than extensification. The negative outcome is the deterioration of soil nutrients by the excessive agrochemical usage and pollution of water bodies from exported nutrient in or on the soil. The planting of trees to enable working environment during sunny days and also to protect crops signifies that working hours on open fields will reduce. Therefore, crop productions that require no shades may be avoided in future as a social adaptation strategy since farmers have already changed their working hours to avoid heat stress from increased temperature and hot sunshine hours.

The readiness of farmers to access credit could make them willing to insure their crops in order to guarantee loans from financial service providers when crop insurance is promoted in the basin. However, awareness creation in this regard should commence now and be intense but slow in moving from one location to another for all farmers either educated or not to grasp the concept for easy adoption. Farmers recognize their vulnerability to climate change and that opens a market for climate information services. Co-production of these services by combining scientific and indigenous knowledge through citizen science will be welcomed. Reforestation, afforestation and modified community-based conservation agriculture are dynamics of land-use change that has the potential to achieve the Intended Nationally Determined Contributions (INDCs) of Ghana. Therefore, the potential for 44.7 % of the respondents in the basin going into agroforestry in the future is a positive signal for the nation towards the achievement of the intended nationally determined contributions to climate change. However, the 55.5 % of the respondents targeting native forest for future farm expansion calls for appropriate forest conservation policies and programmes if the INDCs will be attainable in the stipulated period.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

- The spatial resolution of the climate models impacted their skill in simulation of rainfall and temperature in the basin with a definite pattern for temperature and undefined trend for rainfall. The increasing temperature and decreased amount of rainfall from the ensemble mean of the five climate models will results in frequent occurrences of extreme climate events (drought and floods) between 2020 and 2049 in the Pra River Basin.
- Urbanization and agriculture were the drivers of deforestation or decline in vegetation in the basin from 1986 to 2018 with a faster rate of change from 1986 to 2002 compared to the latter interval. Therefore, remote sensing technique was cable of determining the drivers, intensity and location of land-use change in the study area.
- Both climate and land-use change influenced the delivery of hydrological ecosystem services in the basin. However, site-specific change in land-use determined the trend and size of change in hydrological ecosystem service delivered. Change in sediment and nutrients delivery was dependent more on the location of land-use change than the total net change while amount of water yield was dependent majorly on climate condition. Therefore, climate and land-use change will control erosion and phosphorus export and adversely impact water yield and nitrogen export from 2020 – 2049 in the Pra River Basin according to the ensemble mean climate of the five models.
- Farmers are currently vulnerable to climate change in the basin. Their lack of access to credit and information on adaptation suggests the limitation of external support they receive. Climate change was also a major driver of land-use change and the desire of farmers to convert native forests for farm expansion due to climate change impact implies that climate change benefits from the feedback loop of farmers' adaptation strategies in the basin. This is because, conversion of forest for agriculture expansion contributes to greenhouse gas emission.

5.2 Recommendations for research

The study recommends that high-resolution climate models such as SDSM be compared in climate change analysis in other sensitive locations like the Savannah zones of Ghana to ascertain the future possible realities to aid in site-specific adaptation planning and policy formulations. The modified formula for rainfall onset, cessation and duration should be tested in other locations in the semi-deciduous and rain forest zones to improve its accuracy and efficiency. The gap between the perceived rainfall onset and cessation by farmers and determined onset and cessation needs further investigation to improve the integration of scientific and indigenous forecast and adoption of scientific findings by farmers. Furthermore, the possibility of reducing the complexities in agent-based land-use modelling could be explored by integrating information from questionnaire interviews and historical land-use trends from biophysical land-use models. Analogous research should also be done for other African nations under similar conditions.

5.3 Recommendations for policy

Appropriate adaptation strategies such as climate-smart agriculture are recommended to improve the resilience of farmers to changes in rainfall patterns and increasing temperature in the basin. The provision of health post or services in or close to farming communities is necessary for minimizing the occurrence and consequences of climate-related diseases and protect farmers from climate-related disease mortality. Agro-ecological zoning, improved satellite and in-situ surveillance systems for land use, especially mining activities, and enforcement of environmental law, for example, the implementation of the Integrated Water Resources Management Policy and Riparian Buffer policy, could help reduce the impact of climate and land-use change on hydrological ecosystem services in the Pra River Basin. Technical support for farmers through a robust extension service, consistent training and workshops, regular and timely supply of subsidized input in adopting crop intensification, the use of agroforestry schemes and the zero-tillage system should be promoted. The extension services could be boosted by increasing the availability of well-qualified agronomical assistance to local farmers. This could be catalyzed through cooperatives, capacity building schemes and international collaborations, for example.

Further investments in Ghana's agricultural research institutions and universities are also encouraged in order to increase local knowledge about complex issues such as agricultural resilience, water and biodiversity conservation, climate change and local economic development with social inclusion. Farmers should be encouraged to adopt sustainable irrigation farming to enhance their adaptation to the projected paradoxical water yield under different climate scenarios since the basin contribute highly to the production of tree crops like cocoa and tuber crops with valuable economic gains to the nation.

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APPENDICES

Appendix I: Data and their sources

Data	Sources/Agency
Observed rainfall and temperature (1980 – 2010)	Ghana Meteorological Agency
National Centers for Environmental Prediction (NCEP) predictors	http://co-public.lboro.ac.uk/cocwd/SDSM/data.html
IPSL-CM5A-MR (tas and pr)	https://climate4impact.eu/impactportal/general/index.jsp
CCCma-CanESM2 (tas and pr)	https://climate4impact.eu/impactportal/general/index.jsp
GFDL-ESM2M (tas and pr)	https://wascal-dataportal.org/geonetwork/apps/search/
HadGEM2-ES (tas and pr)	https://wascal-dataportal.org/geonetwork/apps/search/
AR5 43 GCMs data	https://climate.upei.ca
Landsat images	https://glovis.usgs.gov/
Globeland30 2000 map	http://glc30.tianditu.com/
Land cover, soil and basin shapefile	Geological Survey Department of Ghana
Historic image (1986, 2002, 2018)	Google Earth Pro
Digital Elevation Model	https://urs.earthdata.nasa.gov/
2016 ESA-CCI S2 prototype land cover map	http://maps.elie.ucl.ac.be/CCI/viewer/index.php
RH, solar radiation and wind speed	https://power.larc.nasa.gov/common/php/
Nutrient runoff proxy	http://www.cru.uea.ac.uk
Rainfall erosivity index	http://www.fao.org/docrep/t1765e/t1765e0e.htm
Soil erodibility	http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/

Note: Websites mentioned within this table were last checked in February 2018.

Appendix II: Questionnaire used for field survey

INSTITUTE OF LIFE AND EARTH SCIENCES

PAN AFRICAN UNIVERISTY

UNIVERSITY OF IBADAN, NIGERIA

FARMERS' HOUSEHOLD SURVEY QUESTIONNAIRE

DRIVERS OF LAND USE CHANGES AND PERCEPTION OF FARMERS ON CLIMATE CHANGE AND ADAPTATION STRATEGIES

This questionnaire survey is part of a PhD research being carried out by Mr. Enoch Bessah working on Hydrological Ecosystem Services in the Pra River Basin and is purely for academic purposes. The objective is **"assessing the perception of farmers on the historical trend and drivers of land use/cover change and water quality and their adaptation capacity to climate change and fluctuating water availability in the basin".** You are assured of confidentiality of any view expressed in relation to this research. I therefore entreat you to provide information as accurate as possible to reflect the conditions on ground. Thank you for your kind and earnest cooperation.

Questionnaire Code…………………………….	District…………………………….
Village/Community……………………………..	Nearest Town……………………
Lat ……………Long…………….	Date of interview..…/…../……….
Code of the Interviewer………………………..…..	Time of Interview………………...

SECTION A: SOCIO-ECONOMIC CHARACTERISTICS OF THE RESPONDENTS

1a. **Age of respondent**………………

2a. **Gender**:

1. Male [ ] 2. Female [ ]

3a. **Marital status**:

1. Single [ ] 2. Married [ ] 3. Separated [ ] 4. Divorced [ ] 5. Widowed [ ] 6. Co - habitation [ ]

4a. **Highest Education Level**:

1. Primary [ ] 2. JHS [ ] 3. Form 4 [ ] 4. SHS/O Level/A Level/Voc/Tech [ ] 5. Tertiary (Uni/Col.) [ ] 6. Non formal [ ] 7. No formal edu. [ ]

5a. **Religion**:

1. Christianity [ ] 2. Islam [ ] 3. Traditional [ ] 4. Others (Specify)…………

6a. **Are you** a 1. Native [ ] or 2. Settler [ ]

7a. **How long have you lived in this community**? ………………………(years)

8a. **Household size**…………………………………………………………………

9a. **What is your relationship to the household head**?

1. Head [ ] 2. Wife [ ] 3. Son [ ] 4. Daughter [ ] 5. Nephew [ ] 6. Niece [ ] [ ] 7. Other (Specify): ………………………….

10a. **Total number of children in the household** …………

11a. **Number of children under 18 years in the household**……………

12a. **Do you have access to the following?** *Tick all that apply*

1. Electricity [ ] 2. Pipe borne water [ ] 3. Tarred road [ ] 3. Easy transport to Market [ ] 4. Health post/Clinic [ ] 5. Primary school [ ] 6. JHS [ ] 7. SHS [ ]

13a. **What is your main occupation**?

Farming [ ] Handiwork [ ] Trading [ ] Professional/service [ ] Others (specify) ………..

14a. **Select any other occupation you are engaged in apart from the main.** *Tick all that apply*

Farming [ ] Handiwork [ ] Trading [ ] Professional/service [ ] Others (specify) ………..

15a. **Type(s) of Farming occupation**: *Tick all that apply*

1. Crop farming [ ] 2. Fish farming [ ] 3. Livestock farming [ ] 4. Other (Specify):……………

16a. **How long have you been farming**? ……………(years)

17a. **Where is/are your farm(s) located**? *Tick all that apply*

1. Near river [ ] 2. On hill [ ] 3. Low land [ ] 4. Other specify……………

SECTION B: LANDUSE AND DRIVERS OF LANDUSE CHANGE

1b. **What type(s) of farming systems do you practice**? *Tick all that apply*

1. Shifting cultivation [ ] 2. Crop rotation on same land [ ] 3. Fallow system (leaves land for min 3 yrs before farming it again) [ ] 4. Perennial crops farming like cocoa, cashew [ ] 5. Other, specify ………..

2b. **What cover was on the land before you farmed on it for the first time**?

1. Forest [ ] 3. Open vegetation (shrubs and sparse trees) [ ] 3. Grass [ ] 4. Fallow (farmed before and left to regrow [ ] 5. Agro forestry [ ] 6. Tree Plantation [ ] 7. Cash crop (cocoa) [ ] 8. Other, Specify………

3b. **What type of farming (kind of crop cultivation) did you practice for the first time on the land**?

1. Mixed Cropping [ ] 2. Mono cropping [ ] 3. Tree plantation [ ] 4. Agro forestry [ ] 5. Other, specify…………………………..

4b. **What is your current farming practice (kind of crop cultivation)**?

1. Mixed Cropping [ ] 2. Mono cropping [ ] 3. Tree plantation [ ] 4. Agro forestry [ ] 5. Other, specify…………………………..

5b. **What kind(s) of crop(s) have you grown over the last 5 – 10 years**? *Tick all that apply*

1. Tree crops like cocoa [ ] 2. Cereal like maize [ ] 3. Tubers [ ] 4. Fruits [ ] 5. Vegetables [ ] 6. Other (specify)…………

6b. **What is your current farm size**: ……………………… acres

7b. **Has your farm size changed (increased or decreased) over the past 5 years**?

1. Yes [ ] 2. No [ ] ***If No Jump to 9b***

8b **If yes what is the average change (increase/decrease) in the past 5 year**?

……………. acres

9b**. If no, why**?

………………………………………………………………………………………..

10b. **Do you have plans to expand in future?**

1. Yes [ ] 2. No [ ] 3. Not Sure [ ] ***If No Jump to 14b***

11b. **On a scale of 1 – 10, what is the potential of clearing forest if you want to expand your farmland in the future**? ……………………….. [1 – not likely and 10 – most likely or very sure]

12b. **On a scale of 1 – 10, what is the potential of clearing open vegetation (includes shrubs, grassland) if you want to expand your farmland in the future**? ……………

13b. **On a scale of 1 – 10, what is the potential of going into Agroforestry (mixing trees and your crops on your farm) or leaving a minimum of 10 trees in an acre of farmland in the future**? …………………………

14b. **If no, why** ………………………………………………………………

15b. **Do you have plans to change what you are currently planting/cultivating**?

1. Yes [ ] 2. No [ ] ***If No Jump to 17b***

16b. **If yes to which type**?

1. Mixed cropping [ ] 2. Mono Cropping [ ] 3. Agro Forestry [ ] 4. Tree Plantation [ ]

5. Other, specify……………………………………

17b. **Select (by ticking) and rank (1, 2 …) the factors that will make you change what you are farming or leave farming to other jobs/occupation**

Factors	**Tick**	**Rank**	**Factor**	**Tick**	**Rank**
Climate change (rainfall, temp etc)			Pest/disease invasion or prevalence		
Market demand			Availability of irrigation facility		
Increased funds/credit			Soil fertility		
Land tenure issues			Other (specify)…………………………		

18b. **Rank (ticking) the severity of the following factors in limiting your capacity to expand your farm**

Constraint/Limiting factors	Extremely severe	Severe	Less severe	Not severe	I don't know
Funds					

Land tenure system					
Soil Fertility					
Climate change					
Labour					
Other, specify…………					

19b. **Have you observed changes in the size of forest in your farming locality over the last 5 - 10 years**?

1. Yes [ ] 2. No [ ] 3. Not sure [ ]

20b. **If yes, what have you noticed about the changes in the size of forest over the last 5 - 10 years**?

1. Decreased [ ] 2. Increased [ ] 3. Other (specify): ……………………..

21b. **On a scale of 1 – 10, what is the potential of selling any of your current farmlands for urban development (settlement, infrastructure development etc)**?

……………………… [1 – not likely and 10 – most likely or very sure of selling when asked to buy]

22b. **Is or was *galamsey* activities taking place in your community or nearby (2 or 3) communities away from here**?

1. Yes [ ] 2. No [ ]

23b. **If yes, in which year or period was it at its peak**? …………………………

SECTION C: PERCEPTION ON WATER QUALITY AND AVAILABILITY

1c. **What are the sources of drinking water in the community**? *Tick all that apply*

1. River [ ] 2. Bore well/ hand pump [ ] 3. Community well [ ] 4. Public tap [ ] 5. Household water supply (piped) [ ] 6. Household bore hole/well [ ] 7. Other(specify)…………

2c. **Which of the sources of drinking water does your household use**? *Tick all that apply*

1. River [ ] 2. Bore well/ hand pump [ ] 3. Community well [ ] 4. Public tap [ ] 5. Household water supply (piped) [ ] 6. Household bore hole/well [ ] 7. Other(specify)…………

3c. **Is the water clean for domestic use from source**?

1. Yes [ ] 2. No [ ] 3. I don't know [ ]

4c. **What is the reason for your answer in 3c**? ……………………………………………

………………………………………………………………………………………

5c. **Do you treat water from the source before domestic use**?

1. Yes [ ] 2. No [ ] 3. I don't know [ ]

6c. **If yes, what method of treatment do you use**?

1. Potash Alum [ ] 2. Chlorine [ ] 3. Sieving [ ] 4. Sedimentation [ ] 5. Boiling [ ] 6. Other (specify)…………………

7c. **What is/are your major source(s) of water for farming**?

1. Rainfed only [ ] 2. Irrigation only [ ] 3. Rainfed and irrigation [ ] 4. Other (specify):………

8c. **What are the sources of water for irrigation (watering crops) on your farm**? *Tick all that apply*

1. River [ ] 2. Harvest rainfall [ ] 3. Bore well/ hand pump [ ] 4. Community well [ ] 5. Public tap [ ] 6. Household water supply (piped) [ ] 7. Household borehole/well [ ] 8. None [ ] 8. Other(specify) …………………

9c. **Have you observed any pollution of water in the community**?

1. Yes [ ] 2. No [ ] 3. Not sure [ ]

10c. **What are some of the causes of water pollution in this community**? …………….

……………………………………………………………………………………………

11c. **Is the community doing anything to reduce water pollution**?

1. Yes [ ] 2. No [ ] 3. Not sure [ ]

12c. **If yes, what are some of the measures put in place by the community**?...

13c. **Has the community experienced water scarcity in the past**?

1. Yes [ ] 2. No [ ] 3. Not sure [ ]

14c. **Is the community currently experiencing water scarcity**?

1. Yes [ ] 2. No [ ] 3. Not sure [ ]

15c. **What has been the trend of water demand in the last 10 years**?

1. Increased [ ] 2. Decreased [ ] 3. Fluctuating [ ] 4. I don't know [ ] 5. Other (specify) ………………

16c. **Which of the following have you done to store enough water for domestic use and farming during water scarce periods**? *Tick all that apply*

Measures for water management	**Domestic use**	**Farming**	**None**
i. Rain water harvesting			
ii. Increased size water storage facility			

iii.	Water re-use			
iv.	Other (specify) ……………….			

17c. **Mention some factors that limit your capacity to store or access enough water for use during water scarcity periods**? ………………………………………………….
……………………………………………………………………………………………

18c. **What support will you need in order to access or store enough water for future uncertain conditions (scarcity)**? ………………………………………………………
……………………………………………………………………………………………

19c. **How much water does your household use averagely in a day**? ………… buckets (*standard*). *[You may find out how much buckets or basin of water fetched into the house daily]*

SECTION D: FARMERS' AWARENESS AND PERCEPTION OF CLIMATE CHANGE

1d. **Are you aware or heard that climate has changed or is changing**? [climate is weather conditions for min 30 yrs]

1. Yes [ ] 2. No [ ] 3. Not sure [ ]

2d. **If yes, from where did you hear about climate change**? *Tick all that apply*

1. own observation [ ] 2. radio [ ] 3. TV [ ] 4. NGO working in the area [ ] 5. Researchers [ ] 6. Informed by neighbours/friends/family [ ] 7. Others (specify)………

3d. **What are your observations about the following climatic parameters for the past 20 years**?

i Rainfall amount	Increased [ ]	Decreased [ ]	Same [ ]	Don't know [ ]
ii Onset (starting) of rainfall	Early onset [ ]	Late onset [ ]	Normal [ ]	Don't know [ ]
iii Cessation (end) of rainfall	Early [ ]	Late [ ]	Normal [ ]	Don't know [ ]
iv Length of growing season	Increased [ ]	Decreased [ ]	Same [ ]	Don't know [ ]
v Temperature	Increased [ ]	Decreased [ ]	Same [ ]	Don't know [ ]
vi Duration of dry season	Increased [ ]	Decreased [ ]	Normal [ ]	Don't know [ ]
vii Frequency of prolonged dry spells (no rains in some days during rainfall season)	Increased [ ]	Decreased [ ]	Normal [ ]	Don't know [ ]

4d. **To what extent are the observed changes in rainfall and temperature over the past 10 – 20 years**?

I. **Rainfall**: Extreme [ ] Somewhat [ ] Very little [ ] No change [ ] I don't know [ ]

II. **Temperature**: Extreme [ ] Somewhat [ ] Very little [ ] No change [ ] I don't know [ ]

5d. **What have you observed to be the consequences of changes in rainfall and temperature on the following resources and events over the last 10 - 20 years**?

Impact (Negative Effect)	*extremely severe*	*severe*	*less severe*	*not severe*	*I don't know*
i Changes in the starting and stopping of rains					
ii Abrupt changes in growing season (cultivation periods)					
iii Increased frequencies of drought and crop failure					
iv Increased frequencies of floods and farms destructions					
v Prevalence of pest invasion (like armyworm)					
vi Prevalence of disease					
vii Extinction of some crops and crop varieties					
viii Disappearance of vegetation cover (forest)					
ix Lack of potable water					
x Erosions					
xi Siltation of water bodies (Rivers are drying up)					
xii Extinction of fishes and aquatic life					
xv Death of livestock					
xiv Rising cost of farming/fishing inputs					
xv Destruction of farm roads and homes					
xvi Rural-urban migrations					

6d. **How vulnerable (likely to be negative impacted) is your farm activities to the incidence of the following climatic related factors**? *Vulnerability = livelihood exposure or state of being easily affected by these climates related incidences (lack of adaptive capacity)*

S/N	**Incidence**	*extremely vulnerable*	*vulnerable*	*less vulnerable*	*not vulnerable*	*I don't know*
1	Increased temperature					
2	Changed duration of rainfall season					
3	Abrupt changes in onset of planting season					

4	Decreased rainfall and poor distribution during cropping season					
5	Floods					
6	Droughts (during cropping season)					
7	Other (specify)……………					

7d. **What have you observed to be the main opportunities (positive effects) of climate change especially extreme rainfall**? *Tick all that apply*

1. Flood water harvested for irrigation, [ ] 2. Improved groundwater yields [ ] 3. Floods increase fish harvest [ ] 4. Dams for water storage [ ] 5. Other (specify): ……………………

8d. **How will you use these opportunities in the future for better farm productivity**? *Tick all that apply*

1. Adopt irrigation practice [ ] 2. Shift to fish farming [ ] 3. Other (specify): ………………

SECTION E: FARMERS' ADAPTATION OPTIONS

1e. **Have you made any changes in the way you farm in response to climate change over the past 10 – 20 years**? 1. Yes [ ] 2. No [ ]

2e. **What adjustments have you made due to changes in temperature and rainfall over the past 10 – 20 years**? *Tick all that apply*

1. Change planting dates [ ] 2. Use different varieties and crop types [ ] 3. Fertiliser application [ ] 3. Pesticides/herbicide application [ ] 4. Farm near rivers and in lowlands [ ] 5. Mixed cropping [ ] 6. Cover cropping [ ] 7. Plant/leaving trees for shades [ ] 8. Mulching [ ] 9. Crop rotation [ ] 10. Others (specify): …………

3e. **What additional measures would you consider in future in relation to climate changes**? ……………………………………………………………………………………..

4e. **Give reasons for USING or NOT USING the following the adaptation strategies**?

Why did you not use this or these strategies?	**Reasons (Key)**
i Use different variety and crop types	
ii Move to different sites (shifting cultivation)	
iii Implement soil conservation techniques	
iv Planting trees for shading	

v Build a water-harvesting scheme	
vi Irrigate more	
vii Change from crop to livestock	
viii Find off-farm job	
ix Migrate to urban area	
x Lease your land	
xi Buy insurance	

5e. **Rank how the following factors limit your capacity to cope with climate change**?

Constraint	*Extremely severe*	*Severe*	*Less severe*	*Not severe*	*I don't know*
i. Lack of money/credit facility (No loans for farmers)					
ii. Lack of weather and farming information					
iii. Shortage of labour in the community					
iv. Educational level limiting understanding of strategies to adopt					
v. Lack of extension services like MoFA					
vi. Incompatibility of adaptation strategy with societal norms and values (Eg. convenient fertilizer application day falling on a taboo day in the area)					
vii. Sustainability (consistency of practice to get results) of adopted coping strategy					
viii. Length of time required to see results of a strategy					
ix. Old age of farmer					
x. No access to water for irrigation as a strategy					
xi. Infertile soil					
xii. Topography of farmland (Eg. hill, lowland, etc)					
xiii. Land tenure system					
xiv. Other, ……………					

6e. **If you do apply fertiliser (NPK, Urea or Ammonia), how often do you practice this**?

1. Once a year [ ] 2. Twice a year [ ] 3. Once every two years [ ] 4. Once every three years [ ] 5. Other (specify): ……………………

7e. **If you do apply pesticide/herbicide, how often do you practice this**?

1. Once a year [ ] 2. Twice a year [ ] 3. Once every two years [ ] 4. Once every three years [ ] 5. Other (specify): ……………………

8e. **List the type of fertilizer(s) and/or pesticide(s) you have used or still use**

Used Fertilizer(s)	Used Pesticide(s)

SECTION F: SUPPORT FOR FARMERS' ADAPTATION MEASURES

1f. **Do you receive any of the following support for your farming activities**? *Tick all that apply*

1. Financial support [ ] 2. Material support [ ] 3. Extension services [ ] 4. Subsidized farm input [ ] 5. Weather information [ ] 6. Trainings and workshops [ ] 7. None [ ]

8. Other (specify) …………………………………………………………………..

2f. **How long has this support been in existence** (years)?

i. Financial support [yr] ii. Material support [yr] iii. Extension services [yr] iv. Subsidized farm input [yr] v. Weather information [yr] vi. Training and workshops [yr] vii. Others (specify):……………………………………

3f. **Is this support free**?

1. Yes [ ] 2. No [ ] 3. Other (specify): ……………

4f. **If no, what are the conditions attached**? *Tick all that apply*

1. Loan to be paid back [ ]

2. To buy farm machinery (tractor, spraying machine, harvester etc) on credit [ ]

3. To buy improved farm inputs (seeds/animals, fertilisers, pesticides) on subsidised prices [ ]

4. Provision of buffer stock (extra inputs on credit or for free in case of emergency) [ ]

5. Other (specify) ……………………..

5f. **How often do you receive this support**?

1. Once a year [ ] 2. Twice a year [ ] 3. Once every two years [ ] 4. Once every three years [ ] 5. Other (specify):………………………….

6f. **Which organisation offers this support**? *Tick all that apply*

1. Government agency e.g. MoFA [ ] 2. Agriculture research stations [ ] 3. NGOs [ ] 4. Farming groups in the community [ ] 5. Other (specify):…………………………….

7f. **Is this type of support beneficial**?

1. Yes [ ] 2. No [ ]

8f. **If yes, how has it benefited you**? *Tick all that apply*

1. I got capital to expand my farm [ ] 2. Reduced postharvest lost [ ] 3. Improved yield [ ] 4. Reduced hunger [ ] 5. Family living standard [ ] 6. Purchase additional farm machinery [ ] 7. Other (specify):…………

9f. **If No, why** ………………………………………………………………………..

10f. **Do extension officers provide regular information on expected rainfall and temperature**?

1. Yes [ ] 2. No [ ]

11f. **Apart from official extension workers, where else do you receive the necessary information and technical assistance for your farming activities**? *Tick all that apply*

1. Television [ ] 2. Radio [ ] 3. Neighbouring farmer [ ] 4. Community leaders [ ] 5. Relatives [ ] 7. None [ ] 8. Other (specify) …………………..

12f. **Rank the five most needed services, investments or developments you would want to be done for you in this community to help you cope with changes in temperature and rainfall**?

i. Irrigation development [ ]

ii. Climatic information services [ ]

iii. Provision of credit facilities [ ]

iv. Review of land tenure system [ ]

v. Health services [ ]

vi. Agriculture mechanization [ ]

13f. **Rank the institution you think should provide the services in 13f**?

i. Government [ ]

ii. Community [ ]

iii. Private sector [ ]

Comments and suggestions ……………………………………………………………….

………………………………………………………………………………………………

………………………………………………………………………………………………

Observations and Remarks ………………………………………………………………….

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Appendix III: Accuracy assessment of LULC maps for 1986, 2002 and 2018.

Table 1: **Pixel-based Error Matrix for 1986**

CLASSIFIED	Water	Forest	Settlement	Arable/Bare lands	Open Vegetation	Total Reference points	Total Area (pixels)	Total Area (hectares)	Stratum Weight (Wi)
Water	107	1	0	0	1	109	305482	27493.38	0.011783289
Forest	0	106	0	1	3	110	137791	12401.19	0.005314982
Settlement	0	0	102	0	1	103	5590623	503156.07	0.215645859
Arable/Bare lands	0	2	0	101	1	104	18871782	1698460.38	0.727937056
Open Vegetation	0	6	1	1	104	112	1019341	91740.69	0.039318814
Total Classified points	107	115	103	103	110	**538**	25925019	2333252	1
		Total Correct Reference Points	520			**Total True reference points**	538		
Overall Accuracy (%)		**96.65**							
	User's Accuracy	**Producer's Accuracy**							
Water	98.17	100.00							
Forest	96.36	92.17							
Settlement	99.03	99.03							
Arable/Bare lands	97.12	98.06							
Open Vegetation	92.86	94.55							

Table 2: **Area-based Error Matrix for 1986**

CLASSIFIED	Water	Forest	Settlement	Arable/Bare lands	Open Vegetation	Total Reference points	Total Area (pixels)	Total Area (hectares)	% of Total
Water	0.011567	0.000108	0.000000	0.000000	0.000108	0.011783	305482.00	27493.38	1.18
Forest	0.000000	0.005122	0.000000	0.000048	0.000145	0.005315	137791.00	12401.19	0.53
Settlement	0.000000	0.000000	0.213552	0.000000	0.002094	0.215646	5590623.00	503156.07	21.56
Arable/Bare lands	0.000000	0.013999	0.000000	0.706939	0.006999	0.727937	18871782.00	1698460.38	72.79

Open Vegetation	0.000000	0.002106	0.000351	0.000351	0.036510	0.039319	1019341.00	91740.69	3.93
Total Classified Area	0.011567	0.021335	0.213903	0.707338	0.045856	1.000000	25925019.00	2333251.71	100.00
Overall Percent Accuracy	**97.37**								
Unbiased Accuracy	**User's Accuracy**	**Producer's Accuracy**							
Water	98.17	100.00							
Forest	96.36	24.01							
Settlement	99.03	99.84							
Arable/Bare lands	97.12	99.94							
Open Vegetation	92.86	79.62							

Table 3: **Pixel-based Error Matrix for 2002**

CLASSIFIED	Water	Forest	Settlement	Arable/Bare lands	Open Vegetation	Total Reference points	Total Area (pixels)	Total Area (hectares)	Stratum Weight (Wi)
Water	100	1	0	1	1	103	1576670	141900.3	0.06081654
Forest	0	95	1	0	11	107	163428	14708.52	0.00630387
Settlement	0	0	102	1	1	104	5430892	488780.28	0.20948459
Arable/Bare lands	0	1	0	102	1	104	16165929	1454933.61	0.62356479
Open Vegetation	3	22	7	8	84	124	2588100	232929	0.09983021
Total Classified Points	103	119	110	112	98	**542**	25925019	2333252	1
Total Correct reference points		483		**Total True reference points**			542		
Overall Accuracy (%)	**89.11**								
	User's Accuracy	**Producer's Accuracy**							
Water	97.09	97.09							
Forest	88.79	79.83							
Settlement	98.08	92.73							
Arable/Bare lands	98.08	91.07							
Open Vegetation	67.74	85.71							

Table 4: **Area-based Error Matrix for 2002**

CLASSIFIED	Water	Forest	Settlement	Arable/Bare lands	Open Vegetation	Total Reference points	Total Area (pixels)	Total Area (hectares)	% of Total
Water	0.059045	0.000590	0.000000	0.000590	0.000590	0.060817	1576670.00	141900.30	6.08
Forest	0.000000	0.005597	0.000059	0.000000	0.000648	0.006304	163428.00	14708.52	0.63
Settlement	0.000000	0.000000	0.205456	0.002014	0.002014	0.209485	5430892.00	488780.28	20.95
Arable/Bare lands	0.000000	0.005996	0.000000	0.611573	0.005996	0.623565	16165929.00	1454933.61	62.36
Open Vegetation	0.002415	0.017712	0.005636	0.006441	0.067627	0.099830	2588100.00	232929.00	9.98
Total Classified Area	0.061460	0.029895	0.211151	0.620619	0.076876	1.000000	25925019.00	2333251.71	100.00
Overall Percent Accuracy	**94.93**								
Unbiased Accuracy	**User's Accuracy**	**Producer's Accuracy**							
Water	97.09	96.07							
Forest	88.79	18.72							
Settlement	98.08	97.30							
Arable/Bare lands	98.08	98.54							
Open Vegetation	67.74	87.97							

Table 5: **Pixel-based Error Matrix for 2018**

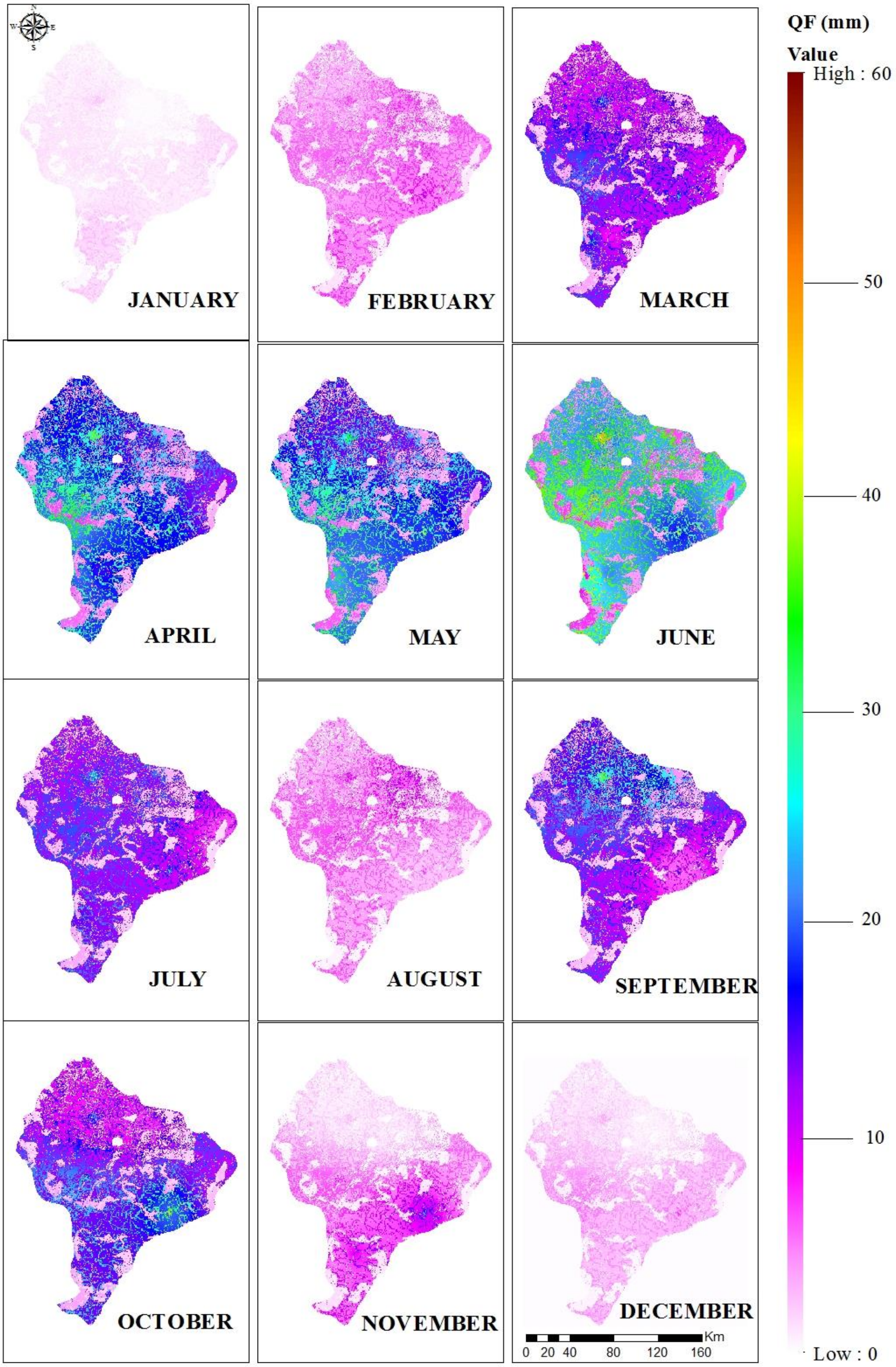
CLASSIFIED	Water	Forest	Settlement	Arable/Bare lands	Open Vegetation	Total Reference points	Total Area (pixels)	Total Area (hectares)	Stratum Weight (Wi)
Water	110	2	1	0	0	113	2566747	231007.23	0.09900656
Forest	0	107	0	0	0	107	88503	7965.27	0.00341381
Settlement	0	0	106	4	1	111	3109033	279812.97	0.11992404
Arable/Bare lands	0	0	1	113	0	114	15043950	1353955.5	0.58028694
Open Vegetation	0	1	1	2	107	111	5116786	460510.74	0.19736865
Total Classified points	110	110	109	119	108	556	25925019	2333252	1

Total Correct Reference Points	543	Total True reference points	556
Overall Accuracy (%)	**97.66**		
	User's Accuracy	**Producer's Accuracy**	
Water	97.35	100.00	
Forest	100.00	97.27	
Settlement	95.50	97.25	
Arable/Bare lands	99.12	94.96	
Open Vegetation	96.40	99.07	

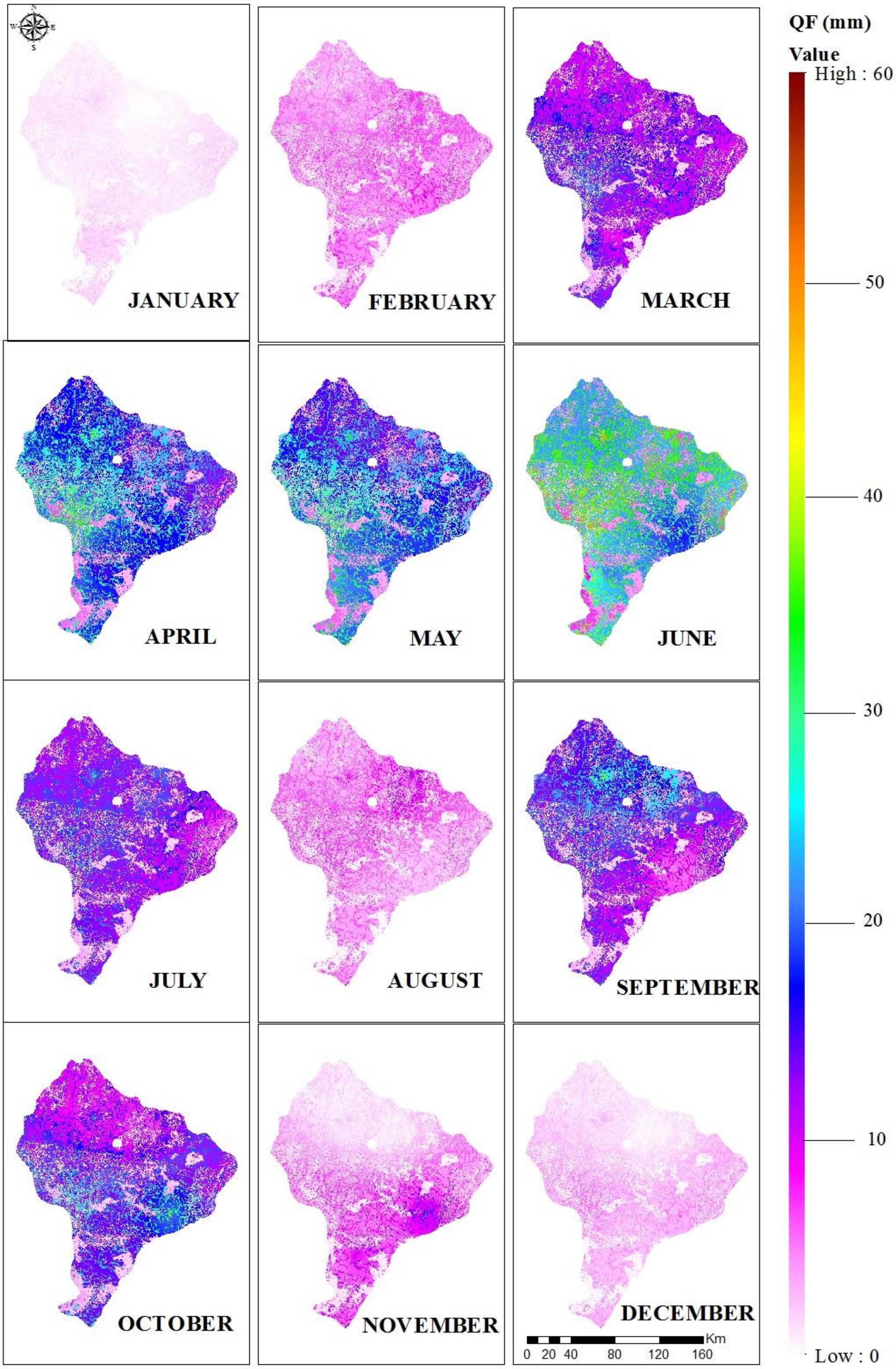
Table 6: **Area-based Error Matrix for 2018**

CLASSIFIED	Water	Forest	Settlement	Arable/Bare lands	Open Vegetation	Total Reference points	Total Area (pixels)	Total Area (hectares)	% of Total
Water	0.096378	0.001752	0.000876	0.000000	0.000000	0.099007	2566747.00	231007.23	9.90
Forest	0.000000	0.003414	0.000000	0.000000	0.000000	0.003414	88503.00	7965.27	0.34
Settlement	0.000000	0.000000	0.114522	0.004322	0.001080	0.119924	3109033.00	279812.97	11.99
Arable/Bare lands	0.000000	0.000000	0.005090	0.575197	0.000000	0.580287	15043950.00	1353955.50	58.03
Open Vegetation	0.000000	0.001778	0.001778	0.003556	0.190256	0.197369	5116786.00	460510.74	19.74
Total Classified Area	0.096378	0.006944	0.122267	0.583074	0.191337	1.000000	25925019.00	2333251.71	100.00
Overall Percent Accuracy	**97.98**								
Unbiased Accuracy	**User's Accuracy**	**Producer's Accuracy**							
Water	97.35	100.00							
Forest	100.00	49.16							
Settlement	95.50	93.67							
Arable/Bare lands	99.12	98.65							
Open Vegetation	96.40	99.44							

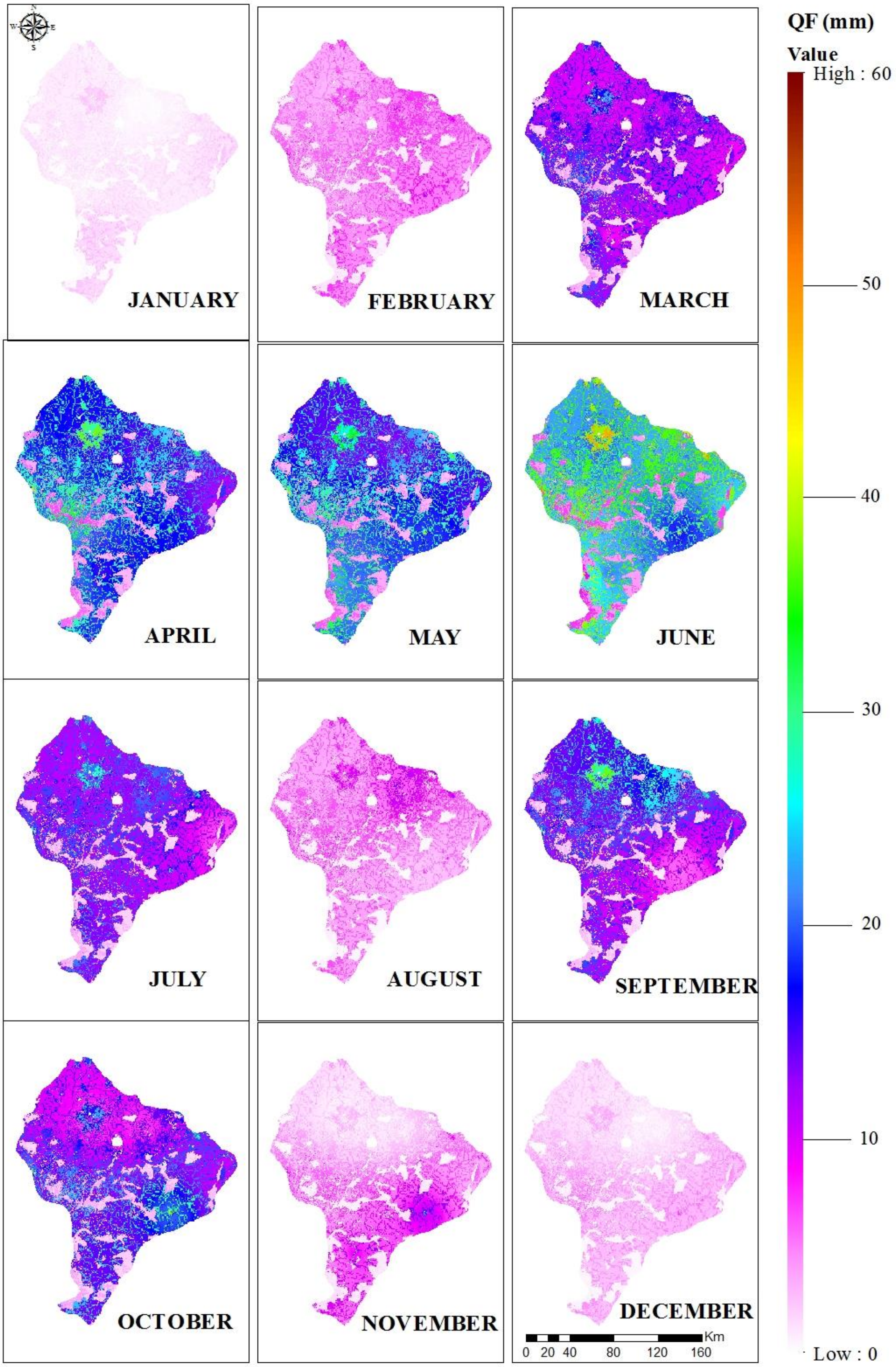
Appendix IV: Monthly water yield for 1986 under control climate



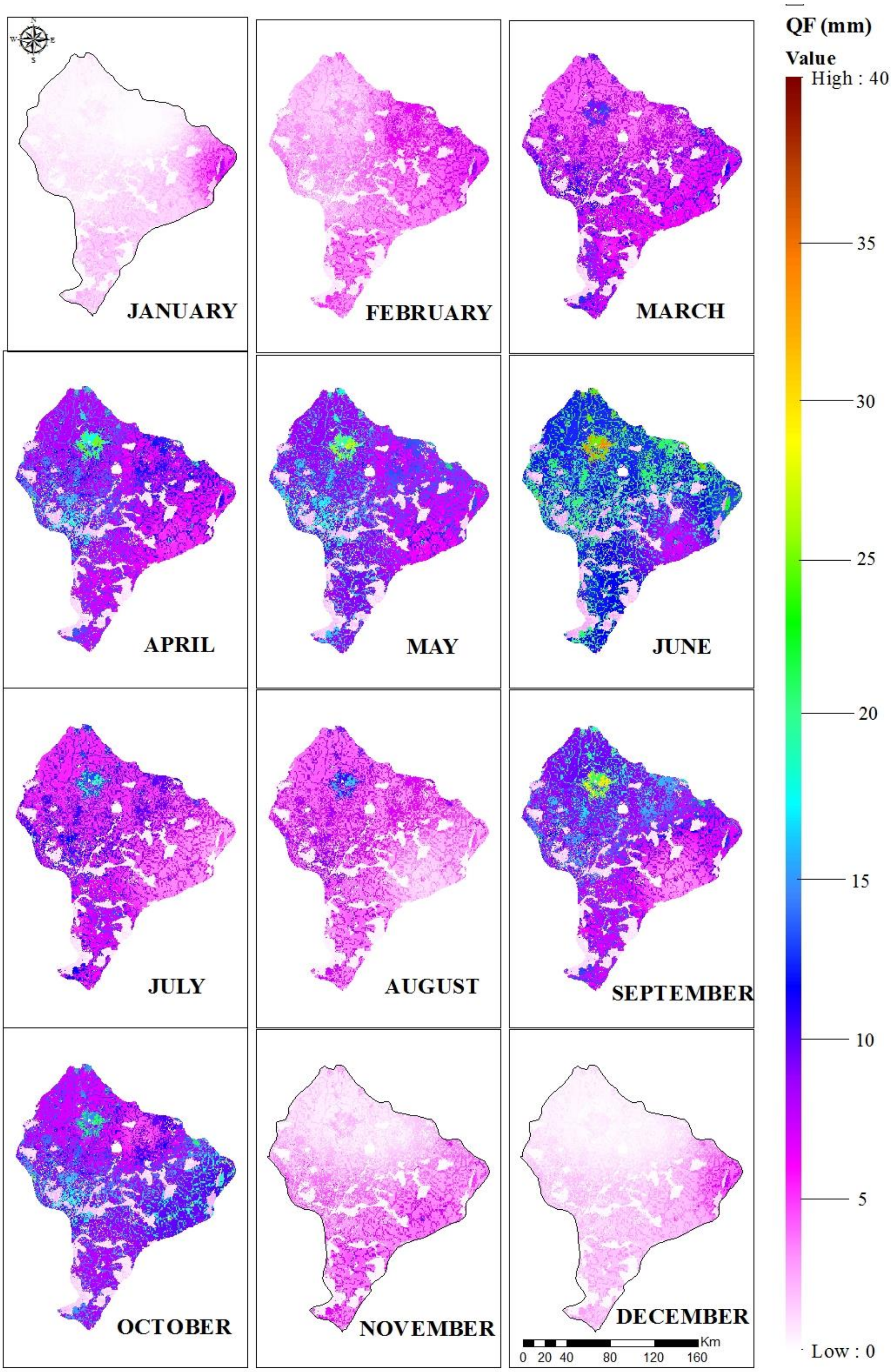
Appendix V: Monthly water yield for 2002 under control climate



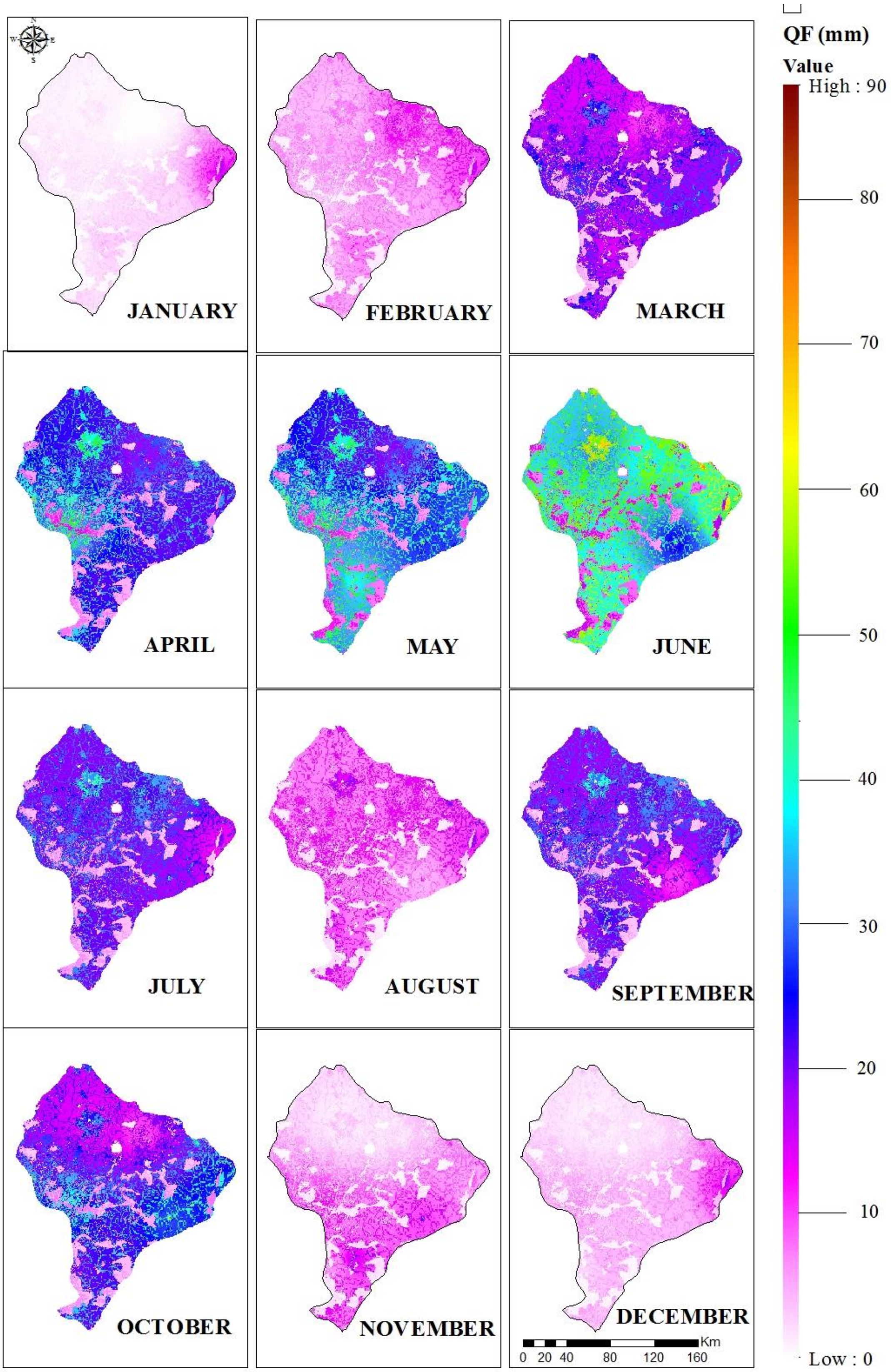
Appendix VI: Monthly water yield for 2018 under control climate



Appendix VII: Monthly water yield for 2018 under Ensemble future climate



Appendix VIII: Monthly water yield for 2018 under SDSM future climate



Appendix IX: Publications and manuscripts from thesis

1. **Bessah, E.,** Raji, A.O., Taiwo, O.J., Agodzo, S.K, Ololade, O.O. (2019). "The impact of varying spatial resolution of climate models on future rainfall simulations in the Pra River Basin (Ghana)". Journal of Water and Climate Change. doi:10.2166/wcc.2019.258

2. **Bessah, E.,** Raji, A.O., Taiwo, O.J., Agodzo, S.K, Ololade, O.O. (2018). "Variable resolution modelling of near future mean temperature changes in the dry sub-humid region of Ghana". Modeling Earth Systems and Environment, Vol. 4, No. 3, pp. 919 – 933. https://doi.org/10.1007/s40808-018-0479-0

3. Hydrological impacts of climate and land use changes: The paradox of regional and local climate effect in the Pra River Basin of Ghana (**Under Review**) – Journal of Hydrology: Regional Studies.

4. Gender and climate change adaptation services: Evidence from farmers in the Pra River Basin of Ghana. (**Under Review**) - Weather, Climate and Society.

5. Climate change influence on human-induced water ecosystem services dynamics in the Pra River Basin (**Ready for Submission**) – Science of the Total Environment