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Land Cover Land Use Change and Soil Organic Carbon Under Climate Variability in the Semi-Arid West African Sahel (1960-2050)

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LAND COVER LAND USE CHANGE AND SOIL ORGANIC CARBON UNDER CLIMATE VARIABILITY IN THE SEMI-ARID WEST AFRICAN SAHEL (1960-2050)

BY

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This dissertation is approved as a creditable and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this dissertation does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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ABSTRACT

LAND COVER LAND USE CHANGE AND SOIL ORGANIC CARBON UNDER CLIMATE VARIABILITY IN THE SEMI-ARID WEST AFRICAN SAHEL (1960-2050)

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Land Cover Land Use (LCLU) change affects land surface processes recognized to influence climate change at local, national and global levels. Soil organic carbon is a key component for the functioning of agro-ecosystems and has a direct effect on the physical, chemical and biological characteristics of the soil. The capacity to model and project LCLU change is of considerable interest for mitigation and adaptation measures in response to climate change. A combination of remote sensing analyses, qualitative social survey techniques, and biogeochemical modeling was used to study the relationships between climate change, LCLU change and soil organic carbon in the semi-arid rural zone of Senegal between 1960 and 2050. For this purpose, four research hypotheses were addressed.

This research aims to contribute to an understanding of future land cover land use change in the semi-arid West African Sahel with respect to climate variability and human activities. Its findings may provide insights to enable policy makers at local to national levels to formulate environmentally and economically adapted policy decisions. This dissertation research has to date resulted in two published and one submitted paper.

CHAPTER 1

INTRODUCTION

1.1 Conceptual Overview: Climate and Land Cover Land Use Change, Drylands and Soil Organic Carbon

It is thought that human activities since the industrial revolution, including fuel consumption and land cover and land use change, are the main cause of the increased concentration of greenhouse gases (GHG) such as carbon-dioxide (CO_2) in the atmosphere, and therefore of climate change (IPCC 2001, 2014). Global GHG emissions due to human activities have grown since pre-industrial times and the increase was estimated as 70% between 1970 and 2004 (IPCC, 2014). The resulting global warming is a global environmental concern. The natural greenhouse effect keeps the earth warmer than it would be otherwise (Adger and Brown, 1994). Land is critical to all aspects of human well-being and since prehistoric times has provided materials and resources for food, health, clothing, shelter and heat (Turner II and Meyer, 1994) and underlies most social and cultural systems (UNEP, 2009). The global land area is 13.2 billion ha; with 12% currently under agriculture, 28% under forest, and 35% comprising grasslands and woodland ecosystems (FAO, 2013). In Africa, land under agriculture represents 40% of the total area, supports the livelihoods of 80% of the population and provides employment for about 60% of the economically active population (FAO, 2013).

Land cover refers to the observed physical cover on the earth's terrestrial surface. Land use refers to the arrangements, activities and inputs people undertake in a certain land cover type, for example, to produce, change or maintain that land cover (FAO, 2013) and defines the purposes for which humans exploit a given land cover (Lambin et al., 2006). For example, “forest” is a land cover, whereas timber production is a forest land use. Land use establishes a direct link between land cover and the actions of people in their environment (FAO, 2000; Loveland et al., 2000). Land use decisions are taken at all levels, from household to national in both rural and urban areas (UNEP, 2009). Changes in land use occur as the direct and indirect consequence of human actions (Briassoulis, 2007; Ellis, 2013). Land cover land use change (LCLUC) is the general term used to reflect changes in land cover and/or land use, i.e., the impacts of human activities on the surface of the earth, including the clearing of land for cultivation and grazing, abandonment of agricultural lands, timber harvesting, reforestation, afforestation and shifting cultivation (Houghton, 2012; Lambin et al., 2006). It is thought that LCLUC started with the burning of land areas for hunting and accelerated dramatically with the start of agricultural activities around 10,000 BC (Vasey, 2002) with extensive clearing and land management practices that continue too today (Ellis, 2013). Industrialization since the 18th century has encouraged, on the one hand, the concentration of human populations within urban areas and, on the other hand, the intensification of agriculture in the most productive lands and the abandonment of some marginal lands (Turner II and Meyer, 1994; Briassoulis, 2007; Ellis, 2013).

One of the main challenges that policymakers and scientists generally face is the lack of comprehensive data on the types and rates of LCLU changes (Loveland, 2002). Practically, there are various approaches for establishing land cover land use and their changes. In the past, national planning and mapping agencies produced maps and information using ground surveys involving censuses, enumerations and observations (Anderson et al., 1976). Rates of LCLU change were generally obtained from agricultural and forestry statistics, historical accounts and national inventories. Nowadays, with the advent of remote sensing, satellite-based land cover data sets are developed based on the ability of satellite sensors to distinguish different land cover types by means of their spectral signatures (Prince et al., 1990; Loveland, 2000).

Remotely sensed data offers a unique opportunity for assessing at synoptic scale ecological systems and associated land cover and sometimes land use (Tucker et al., 1985; Townshend and Justice, 1988; Pickup et al., 1993; Lambin and Strahler, 1994). Land cover maps are derived from remotely sensed data using classification techniques based primarily on statistically defined rules that allow the categorization of the pixels of an image into a specific number of classes (Lillesand et al., 2004). Land cover mapping and change mapping techniques are evolving rapidly as attested by a number of review papers (Congalton, 1991; Lillesand et al., 2004; Foody et al., 2006; Hansen et al., 2008; Hansen and Loveland, 2012; Karlson and Otswald, 2016). Land use mapping using satellite data is more complex because different land use types are usually not unambiguously discernable from reflected or emitted remotely sensed surface radiation. Consequently, land use is usually deducted through a combination of remote sensing observation, and using contextual knowledge (including field observations) and ancillary information that links a given land cover in a region with a given land use (Lillesand et al., 2004; Lambin, 2006; Sohl and Sleeter, 2011).

Carbon exists in five distinct reservoirs or pools, namely the atmosphere, oceans, soils, geologic formations, and terrestrial biomass (i.e., plants and animals). These pools are interconnected, allowing a continual redistribution (cycling) of carbon among them (Watson et al. 1990). The term carbon *sink* refers to *a carbon pool that takes in stores (sequesters) more carbon than it releases* and the term carbon *source* refers to *a pool or component of the carbon cycle that releases more carbon than it absorbs* (FAO, 2002).

The redistribution of sources and sinks of carbon over the land surface is predominantly dominated by changes in land use (IPCC, 2001). In the tropics, current rates of deforestation are responsible for large sources of carbon; while in northern mid-latitudes past changes in land use explain much of the observed carbon sink (Houghton, 2002). Oceans play an important role in the global carbon cycle. The total amount of carbon in the oceans is about fifty times greater than the amount in the atmosphere; most of the carbon released from fossil fuels is absorbed in the oceans (Sarmiento, 1998; Bolin et al., 1979; Popkin, 2015).

The carbon cycle involves processes that take place over seconds, days, years and millennia (Bolin et al., 1979). Understanding of the carbon budget (i.e., the balance between sources and sinks) still hold numerous uncertainties and ongoing scientific questions. For example, is the amount of carbon moving from a given pool matched by an equal amount of carbon moving out, and is the global carbon cycle in a state of dynamic equilibrium? (Bolin et al., 1979; GEFSOC, 2006; Popkin, 2015). Presently, research findings suggest that the terrestrial carbon budget is not in a state of balance and scientists are still tracking down the gap between the amount of carbon emitted from human activities (i.e., from fossil fuels burning and land use changes) and the amount of carbon accumulated in the atmosphere and the oceans (Liu et al., 2003; Popkin, 2015; Liu et al., 2012a, 2012b).

The evaluation and monitoring of total terrestrial landscape carbon usually require measurement of carbon from several places, including the woody biomass, plant understory, crops, surface litter, roots, and soil. However, such measurements are not always achievable everywhere, or possible to collect systematically owing, for example, to technical and financial constraints, site inaccessibility, and lack of consistent national policy for systematic inventories (Woomer, 2004; Manlay, 2002; Liu et al., 2012a, 2012b; Popkin, 2015). During the last two to three decades a number of towers mounted with equipment were used to measure the exchange of CO_2, water vapor and energy between terrestrial ecosystems and the atmosphere (Baldochi et al., 2001). Named flux towers, these field instruments provide information specific to one ecosystem type or condition and their data have been applied in ecology, weather forecasting, and climate studies, especially for sites with several years of data that can be used to quantify inter-annual flux variations (Zhao and Li, 2015; Haszpra et al., 2015). At present over 650 tower sites are operated all over the world as part of national, regional, or global networks; however, flux tower sites are still spatially very sparse, only about 15 are located in Africa, mainly in Southern-Africa (Baldochi et al., 2001; Ramoelo et al., 2014).

To overcome the spatial scarcity of readily available *in situ* data, estimates of landscape total system carbon often rely on ecological models that allow simulation of carbon stocks and dynamics, using only fewer measurements to parameterize, calibrate and validate the models (Woomer et al., 2004; Liu et al., 2004; Tschakert et al., 2004; Mbow, 2014; Bellassen et al., 2010; Touré et al., 2013). In this regard, numerous carbon models, also named biogeochemical models, have been developed to simulate soil and vegetation carbon dynamics under different land cover land use and climate scenarios (Ardo and Olsson, 2003; Parton, 2004; Liu et al., 2004, Bellassen et al., 2010; Liu et al., 2012; Le Quéré et al., 2015;Wu et al., 2015).

This thesis focuses on soil organic carbon (SOC) and land cover land use change. Excluding geological formations, soils represent the largest terrestrial stock of carbon, about 1500 x 10^{15} g C (FAO, 2002); approximately twice the amount held in the atmosphere and three times the amount held in terrestrial biomass (Batjes, 1996). Soil carbon is present in inorganic and organic forms. Soil inorganic carbon consists of mineral forms of carbon and carbonate minerals are the dominant form of soil carbon in desert climates (Batjes, 1996). Organic carbon enters the soil as roots, litter, harvest residues, and animal manure; and is stored primarily as soil organic matter (FAO, 2002). In most soils (with the exception of calcareous soils) the majority of the carbon is held in the form of soil organic carbon (FAO, 2002; Milne et al., 2006). Soil organic carbon is composed of a range of materials with different biological, chemical and physical properties and degrees of decomposition, including individual simple molecules (amino acids, monomeric sugars, etc.), polymeric molecules (e.g., cellulose, protein, lignin, etc.), and pieces of plant and microbial residues (Batjes, 1996; Baldock, 2007; Bationo and Buerkert, 2001). Microorganisms, climate, irrigation and farming practices, land use and land cover determine whether the decomposition of organic matter results in carbon being stored in the soil in labile form (quick decomposition: years to decades) or recalcitrant form (resistant to decomposition: centuries to thousands of years) (Batjes, 1996).

Depending on the dynamics of the organic matter, the soil may act a sink or source of atmospheric carbon. If the carbon stocks increase with time, the soil becomes a carbon sink; conversely, with the decreasing of the carbon stock, the soil becomes a carbon source as carbon is moving from SOC compartments to the atmosphere (Woomer et al., 2001; Baldock, 2007). Knowledge of carbon sinks and sources is required to draw up strategies to reduce the risks related to climate change (Lal, 2001). The amount of SOC varies according to the soil texture, and also climate, vegetation and historical and current land use (Milne et al., 2006).

The amount of SOC is expressed as mass of carbon (C) per unit area. SOC outputs from GEMS model are expressed in **g C m^{-2}**, but for convenience can be converted to **Mg C ha^{-1}** as: **Mg ha^{-1} = 0.01 g m^{-2}** or conversely **g m^{-2} = 100 x Mg ha^{-1}**

To quantify SOC from the field, soil samples are collected and analyzed for soil C concentration and then soil C concentration is converted to C mass per unit area by multiplying it with bulk density (BD) to a fixed soil depth. BD is an indicator of soil compaction and is calculated as the dry weight of soil divided by its volume. Soil organic matter (SOM) contains approximately 58% C; therefore, a factor of 1.72 can be used to convert SOC to SOM (Lee et al., 2009; Woomer et al., 2004).

This thesis particularly focuses on soil organic carbon (SOC) in dryland systems. Drylands are classified as arid, semi-arid or dry sub-humid lands; usually where the average rainfall is less than the potential moisture losses through evaporation and transpiration, with typically the ratio of average annual precipitation to potential evapotranspiration ranging from 0.05 to 0.65 (UNEP, 1992). Approximately 40% of the global land area is considered as dryland and about 40% of the human population live on drylands (Van Boxel et al., 2004). Drylands are characterized by low productivity, sparse plant and animal life, and low soil fertility, even without consideration of human influences (FAO, 2011) and are vulnerable to land degradation (Van Boxel et al., 2004; Touré et al., 2013). The African Sahel is included among the world's drylands and is particularly affected by climate variability as rainfed agriculture accounts for the majority of cultivated land. This high dependency on climate has been amplified in the late 20th century due to the reduction of nearly 30% of rainfall over a period of forty years (Sultan et al., 2015). One approach for countering this decreasing agricultural production is seen through the enhancement of soil fertility, although irrigation may be required (Tieszen et al., 2004; Batjes et al., 2006).

Soil organic carbon and carbon inputs to the soil may improve soil properties such as nutrient uptake and water holding capacity, and consequently increase land productivity and crop yields and contribute to the restoration of degraded agro-ecosystems (Tschakert et al., 2004; Tieszen et al., 2004; Touré at al., 2013). Soil carbon contents and CO_2 fixing capacity are considered to be low in drylands (Batjes, 1996). It is estimated that SOC in arid environments amounts approximately to 4t C ha^{-1} in the 100 cm top layer compared to 7-24t C ha^{-1} in other regions (Batjes, 1996; Tschakert et al., 2004). Various dryland studies have indicated that poor land management practices have reduced SOC (Manlay et al., 2002; Tschakert et al., 2004; Bellassen et al., 2010). Conversely, despite the low carbon fixing capacity of soils in drylands, improved agricultural practices, such as crop rotation, livestock-crop integration, use of new crop types, water harvesting, and afforestation and reforestation, may increase SOC (Manlay et al., 2002; Lal, 2001; Tschakert et al., 2004; Touré et al., 2013). It is thought that if managed properly, dryland systems may not only enhance local land productivity but have the potential to function as a carbon sink (Tschakert et al., 2004; MEA, 2005; Bellassen et al., 2010; Plaza-Bonilla et al., 2015). On a per unit area basis, the carbon storage potential of dryland ecosystems is lower than for moist tropical systems, however, the large area of drylands means that globally they may have significant scope for carbon sequestration (Batjes, 1999; Liu et al., 2004; FAO, 2004; Touré et al., 2013).

1.2 The Intergovernmental Panel on Climate Change (IPCC), Development of Emission Scenarios and Climate Change Modelling

The Intergovernmental Panel on Climate Change (IPCC) is the leading international scientific body for documenting climate change. It was established in 1988 by the United Nations Environment Programme (UNEP) and the World Meteorological Organization (WMO) to provide the world with a clear scientific view on the current state of knowledge in climate change and its potential environmental and socio-economic impacts (IPCC, 2001, 2007). Since its establishment, the IPCC provides assessment reports, which are published materials composed of scientific and technical assessment of climate change (IPCC, 2001). Although it does not conduct any research or monitor climate related data or parameters, the IPCC reviews and assesses the most recent scientific, technical and socio-economic information produced worldwide relevant to the understanding of climate change (IPCC, 2007). So far, five Assessment Reports (AR) have been published in 1990, 1995, 2001, 2007 and 2014, termed AR1, AR2, AR3, AR4 and AR5 respectively.

Climate models are mathematical representations of the climate system components (atmosphere, land surface, ocean, and sea ice) and their interactions (Claussen et al., 2002). Climate models can be at large scales covering the entire globe (Global Climate Models) or downscaled to a specific region (Regional Climate Models). Given the number of climate system components they incorporate, climate models can be relatively simple, e.g. Atmospheric General Circulation Models (AGCM) or Ocean General Circulation Models (OGCM), more complex, e.g. by coupling atmospheric and ocean models together to form Atmosphere-Ocean Coupled General Circulation models (AOGCM), or models that integrate the atmosphere, ocean and land. According to the IPCC (2007) climate models are based on well-established physical principles and have been demonstrated to reproduce observed features of recent climate and past climate changes. For example, climate models are used to generate the information for modern day weather forecasts (Claussen et al., 2002). There is considerable confidence that Atmosphere-Ocean General Circulation Models (AOGCMs) provide credible quantitative estimates of future climate change, particularly at continental and larger scales. However, confidence on these estimates is higher for some climate parameters (e.g., temperature) than for others (e.g., precipitation) (IPCC, 2007).

It is agreed by scientists that climate projections are inherently uncertain. Climate models simulate climate system components based on a number of simplifying assumptions and integrate many physical processes (Randall et al., 2007). However, some of these processes, for example, those related to clouds, occur at scales that cannot be properly modelled. Thus, their known properties are averaged over larger scales; this process is thought to be a significant source of uncertainty in GCM-based simulations of future climate (Randall et al., 2007; Willems et al., 2012). Global climate models (GCM) produce data and variables related to each of the major climate system components at different spatial and temporal scales. Data from GCMs usually have a relatively coarse spatial resolution (in the range of few hundred kilometers or larger), while the temporal resolution may vary from few hours to months. GCMs may cover past or historical periods (called control periods or baseline periods, e.g. 1961-1990) or future periods (called scenario simulation periods, e.g. 2000-2050) (Claussen et al., 2002; Randall et al., 2012). Regional climate models (RCMs) are downscaled from GCMs and theoretically have much higher resolutions. However, RCMs are prone to error propagation from the GCMs; in addition RCMs are less available and comprehensible than GCMs (Willems et al., 2012).

The land surface is an important component of the global climate system and due to its location at the boundary between the atmosphere and the lithosphere, controls how energy received from the Sun is returned to the atmosphere (Baede, 2001; Claussen, 2002). Thus, by controlling the terrestrial surface energy balance, land surface processes influence climate change at local, regional and global levels (Baede, 2001; Zhao and Li, 2015). Key parameters generally considered within the land surface processes include the surface albedo, surface roughness, soil moisture, land surface temperature, and land cover. It is established that changes in these parameters may lead to variations in climate (Baede, 2001; Randall et al., 2007; Barnes and Roy, 2010; Pielke et al., 2002)

To project future climate change, emission scenarios unfolding plausible changes in anthropogenic factors, e.g. socio-economic development, population growth, technology, energy and land use, are required (van Vuuren et al., 2001). These factors are used with future scenarios of forcing agents (e.g., greenhouse gases and aerosols) to model a suite of projected future climate changes that illustrates the possibilities that could lie ahead (Randall et al., 2007). Until recently, the state of the art scenarios were the ones named Special Report on Emissions Scenarios (SRES) (IPCC, 2000; Nakicenovic et al., 2000). SRES made varying assumptions ("storylines") regarding future changes of the greenhouse gas emissions (Randal et al., 2007). The Third Assessment Report (AR3) and the Fourth Assessment Report (AR4) of the IPCC, published respectively in 2001 and 2007, were based on SRES scenarios. However, the SRES scenarios were criticized because they did not explicitly incorporate future policy driven by GHG emission controls (Taylor et al., 2012).

In preparation of the 2014 AR5, the IPCC advocated the development of new scenarios and the scientific community, through an initiative called Coupled Model Inter-comparison Project (CMIP5), and worked on new GHG emission scenarios that included possible policy intervention and mitigation measures (Taylor et al., 2012; Moss et al., 2010). The new scenarios, named 'Representative Concentration Pathways' (RCPs) specify a radiative imbalance at which the atmosphere will stabilize, rather than the greenhouse gas concentrations themselves: that imbalance is consistent with a range of social, technological and economic pathways (Moss et al. 2010; IPCC, 2014). The RCPs include mitigation scenarios that capture possible policy actions that could be taken to achieve certain GHG emission targets. Four RCPs were formulated based on a range of projections of future population growth, technological development, and societal responses: RCP8.5, RCP4.5, RCP6 and RCP2.6. The labeling of RCP reflects an approximate estimate of the radiative forcing in the year 2100 (relative to pre-industrial conditions). In this way, the "highest" (most pessimistic) scenario developed is RCP8.5 corresponding to a radiative forcing that increases throughout the twenty-first century before reaching a level of about 8.5 W m^{-2} at the end of the century. In the same manner, two intermediate scenarios, RCP4.5 and RCP6 were defined, and a low so-called peak-and-decay scenario, RCP2.6 that peaks at 3.0 W m^{-2} before declining to 2.6 W m^{-2} in 2100 (Taylor et al., 2012).

1.3 Modeling Future land cover land use

Land cover land use change plays a determinant role in shaping the environment and changing the global carbon cycle (Briassoulis, 2005; Houghton, 2012). In this regard, there is a growing interest in understanding LCLU change that includes not only past and present LCLU but also the possible future LCLU. Indeed, information on possible future LCLU is needed for effective management and planning of resources, and to understand and evaluate the consequences of such changes on both society and ecosystems (Lambin et al., 2006). Scenarios of future LCLU have been advocated to study alternative futures under different sets of assumptions given current understanding of the way that the drivers of LCLU interact and provide ‘‘descriptions of how the future may unfold based on ‘if-then’ propositions’’ (Alcamo et al., 2008; Sohl and Sleeter, 2011); in this regard, the major accepted driving forces of land change are biophysical and socioeconomic (Lambin et al., 2006).

Agarwal et al. (2002) reviewed different types of models and presented a framework to compare land-use change models with regard to their complexity, and how well they incorporate space, time, and human decision-making. More recently, the National Research Council (2014) classified the contemporary approaches for modeling LCLUC in six categories including machine learning and statistical models, cellular, spatially-disaggregated economic models, sector-based economic models, agent-based models and hybrid models that combine some of the previous approaches. Overall, the goals of the models are one or many of the following: i) improve our understanding of ecosystem and land use dynamics; ii) develop hypothesis that can be tested; iii) make predictions and/or evaluate scenarios.

Modeling and prediction of future LCLU is difficult, not least because statistical LCLU change trend data may not capture future changes in the LCLU driving forces, such as economic and policy modifications acting at varying scales, or a changing climate. In dryland systems LCLU is extensively soil moisture limited (Hiernaux and Justice, 1986), future LCLU scenarios can therefore only be meaningfully developed when coupled with future climate scenarios that consider precipitation (Hulme et al., 2001; Mbow et al., 2008, 2014).

Models of future LCLU should capture the complex ways in which humans and climate are modifying ecological systems and human societies (Batjes, 2005; IPCC, 2007). This can be done, for example, based on various plausible assumptions that allow developing land cover land use transition scenarios. The implications of this statement are that, given future regional climate predictions, future LCLU can be conceptualized in a simplified way based on perceived ecosystems and human responses vis-à-vis past climate patterns (Sohl and Sleeter, 2011; Liu et al., 2012; Karlson et al., 2016).

1.4 Modeling Soil Organic Carbon

Soil organic carbon is a key component for the functioning of agro-ecosystems and has a direct effect on the physical, chemical and biological characteristics of the soil (Lal, 2001).

As mentioned in the previous sections, soil organic carbon inventories are very sparse and in a number of countries, particularly in Africa, systematic soil carbon measurements remain challenging and have not yet been achieved (Manlay et al., 2002; Sambou, 2004; Mbow, 2014). Therefore, soil carbon stock dynamics are generally estimated using modeling approaches (Liu et al. 2004; Parton et al., 2004; Woomer et al., 2004; Lufafa et al., 2008; Touré et al., 2013; Loum et al., 2014). Well established carbon models, such as the CENTURY model (Ardo and Olsson, 2003; Parton, 2004) allow simulation of soil and vegetation carbon dynamics under different land management and climate scenarios.

Other carbon models widely used include the general ensemble biogeochemical modeling system (GEMS) (Liu et al., 2004), the Rothamsted carbon (RothC) model (Coleman and Jenkinson, 1999) and the denitrification-decomposition (DNDC) model (Giltrap et al., 2010). All of these models are generally spatially explicit. Typically the modelled information is related to geographical coordinates, and so are some of the model inputs including biophysical data (e.g., soil and vegetation characteristics), climate data (e.g., temperature and precipitation), land management data (e.g., crop composition and rotation), and the LCLU maps derived from remotely sensed data (Parton, 2004; Liu et al. 2004, 2012a, 2012b;).

1.5 Study area and wider Sahelian context of the research

The study area of this thesis research is located in the North-west of Senegal within the West African Sahel (Figure 1). It is bordered by the Senegal River to the North and the Atlantic Ocean to the West. It covers 1560 km^2 and lies between longitudes 15º24' and 17º00' W and latitudes 15º00' and 16º42' N. It is centered around the city of Louga, approximately 180 km north of Dakar, the capital of Senegal. The study area is predominantly in the Sahelian, semiarid, part of Senegal, with a climate characterized by a single yearly rainy season that lasts from June-July through September-October. Average rainfall decreased from 400-600 mm in the 1960s to 200-400mm in the 1990s (Fall et al., 2006). Mean monthly temperature varies from 24.5ºC in January to 31.9ºC in May (Fall et al., 2006).

The study area natural vegetation includes trees, shrubs and grasses across a diversity of ecosystems and land uses that include rainfed agriculture, irrigated agriculture, and pastoral activities. The study area encompasses four ecoregions (ecological zones) (Omernik, 1995), namely the *Senegal River valley*, the *Niaye*s, the *Peanut basin* and the *Sylvo-pas*toral zones (Tappan et al., 2004). Rainfed agriculture is mainly undertaken during the rainy season in the *Peanut basin*. Flood recession farming is practiced in the *Senegal River v*alley. Irrigated crop production, largely dominated by vegetable production, is practiced where groundwater is available in the *Niayes* (Photo 1). The *Sylvo-pastoral* zone is typical to a Sahelian environment, where livestock, alongside with rainfed agricultural production, is among the most important economic sectors (Photo 2).

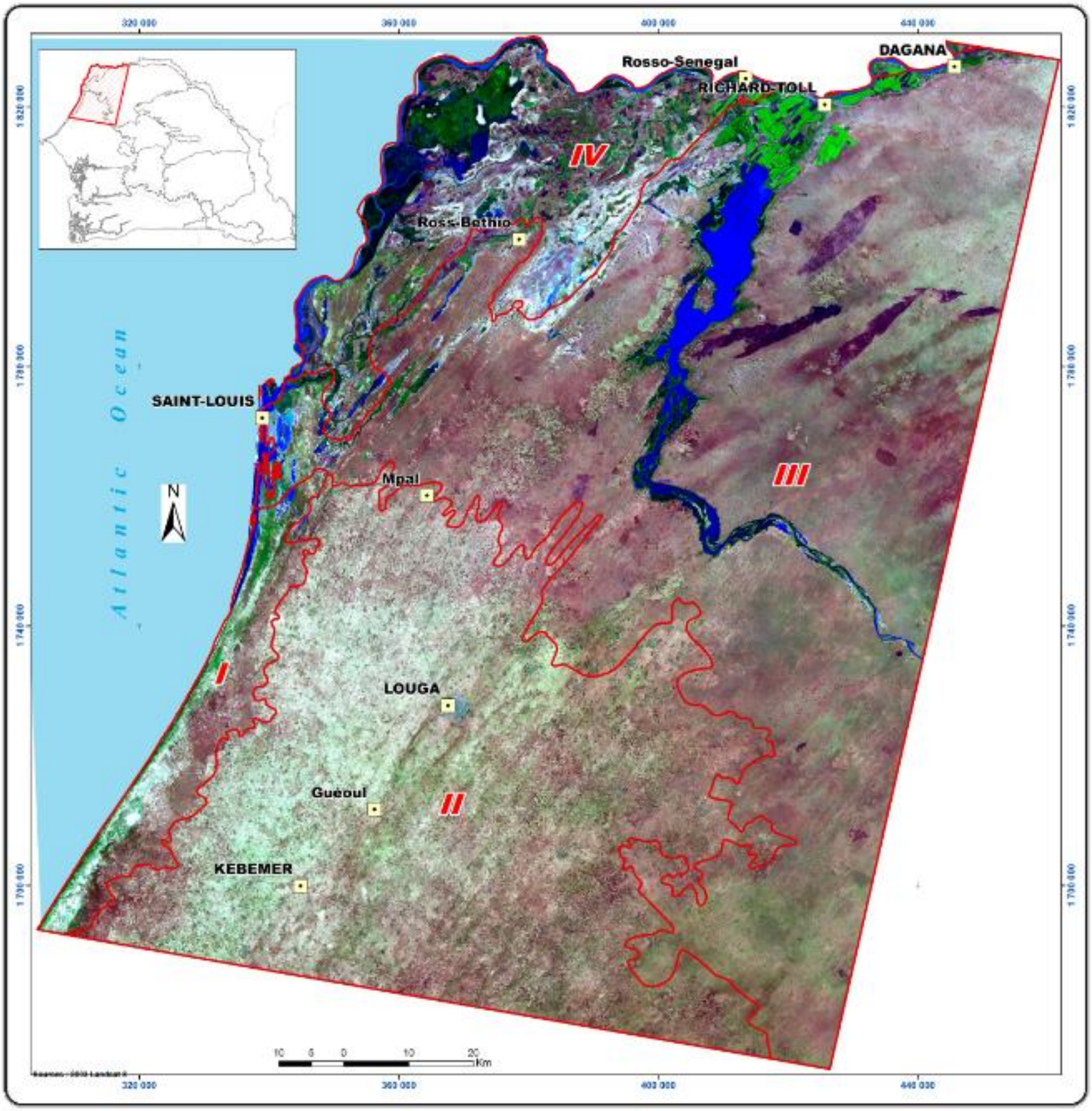

Figure 1 Illustration of the thesis study area. Landsat 28.5m image in north-western Senegal, covering 1560 km^2, lying 15º24' - 17º00' W and 15º00' - 16º42' N. The boundaries of the four main agro-ecological zones (I: Niayes; II: Peanut Basin; III: Sandy Ferlo; and IV: Senegal River Valley) are shown as red vectors. The small box (top left) illustrates the map of Senegal with limits of the agro-ecological zones in grey and limits of the study area in red.

Photo 1. View of the *Niayes* eco-region, characterized by longitudinal depressions and a shallow water table. Artisanal wells are dug and used for market gardening. Production includes carrots, onions and cabbage sold in Dakar, the Capital city. Photo: D. Roy.

Photo 2. View of the *Sylvo-pastoral* eco-region showing a herd of cattle arriving at a watering place, near the village of Amali. The background shows trees and shrubs typical of the area. Photo: A. Dieye.

The Sahel was the cradle of the desertification debate, however, desertification, land degradation and LCLU change are supposed due not only to climatic factors but are also influenced by human activities (Geist and Lambin, 2004; Herrman and Hutchinson, 2005; Nicholson, 2005, 2013; Brandt et al., 2015; Kaptué et al., 2015; Karlson and Ostwald, 2016). In the region, sufficient and timely rainfall is particularly an issue for arable and pastoral land uses (Hulme, 2003; Kaptué et al., 2015). During the 1970s and early 1980s, regional rainfall was erratic and droughts were common (Hulme, 2003; Tottrup and Rasmussen, 2004); although, since mid-1980s rainfall is believed to be increasing again (Nicholson, 2005; Lebel and Ali, 2009; Kaptué et al., 2015; Karlson and Ostwald, 2016). Consequently, speculation concerning a regional shift to a wetter climate started to emerge in the literature (Brooks, 2004; Boko et al., 2007; Lebel and Ali, 2009). It is unknown if recent observations imply a climatic shift that will continue throughout the coming decades (Nicholson, 2013).

Climate change predictions for West Africa suggest increased temperatures in the next 100 years (2-6 °C warmer) with uncertain but most likely decreasing rainfall (Hulme et al., 2001; Boko et al., 2007; Christensen et al., 2007, IPCC, 2007). Given that the region is expected in the future to become warmer one important consequence of rising temperatures will be higher evaporative stress on cereal crops (Blanc, 2012). As discussed in Sections 1.2 and 1.3 global climate predictions based on recently developed RCPs are available to establish a range of future climate scenarios. The dynamics driving LCLU changes in the region are complex; firstly, the forces driving land use changes operate at various levels, and encompass drivers and constraints including globalization and international trade, international and national policies, population growth, agricultural expansion, land tenure and local customary rights; and secondly, the driving forces interact and affect each other. A number of studies have attested that West Africa LCLU, including rural livelihoods, will probably continue to be strongly influenced by the climate, i.e., precipitation (Lambin et al., 2003; Tieszen et al., 2004; FAO, 2004). LCLU changes may have serious consequences on natural resources, for example through their impact on soil organic carbon, water quality, and biodiversity and so livelihoods (Bationo et al., 2001; Bellassen et al., 2010). In addition, LCLU practices such as fire, grazing, and agriculture may affect the ecosystem composition, cycling of nutrients and distribution of organic matter including loss of soil carbon due to land conversion, and play a role in increasing greenhouse gases in the atmosphere (Ojima et al., 1994). Soil carbon is particularly important in West African drylands for soil fertility and agricultural sustainability (Tieszen et al., 2004).

1.6 Research Hypotheses

The goal of this research is to investigate the relationships between climate change, land cover land use change (LCLUC) and soil organic carbon (SOC) in the North-west part of Senegal, within the West African Sahel (Figure 1). This will be undertaken using a combination of remote sensing analysis, qualitative social survey techniques, and biogeochemical modeling. The research will address the following four hypotheses:

#1: LCLU in the Semi-Arid rural zone of Senegal can be mapped reliably using recent classification algorithms applied to multi-seasonal Landsat satellite data.

#2: The temporal change in modeled SOC under future climate scenarios, assuming present day and unchanging LCLU, will be greater than the variability in modeled SOC due to remotely sensed data classification errors.

#3: Focus groups held with rural LCLU stakeholders provide insights into the climatic drivers of LCLU change; and these insights may be simplified in terms of particularly wet and dry years.

#4: Future LCLU under future climate change scenarios can be modeled in a spatially explicit manner using the simplified wet/dry year focus group insights.

Research hypothesis #1 Satellite data have been widely used to classify LCLU and to assess trends in vegetation cover (Hiernaux and Justice, 1986; Brandt et al., 2015;

Kaptué et al., 2015; Mbow et al., 2015). However, semi-arid vegetation often exhibits a marked seasonality in photosynthetic activity and leaf area in response primarily to seasonal precipitation (Hiernaux and Justice, 1986). Thus, multi-temporal satellite data is expected to provide improved land cover classification accuracies over single-date classifications assuming that the acquisitions capture seasonal and agricultural differences (Lo et al., 1986; Hansen and Loveland, 2012; Yan and Roy, 2015). Consequently, in this research, two Landsat scenes acquired over the study area in the early wet season (June - July) and one in the dry season (December - February) of the same year were used and bagged decision tree classification approaches were used to map LCLU. The ensemble classification accuracy of the tree classifications was quantified using a confusion matrix based statistical method.

Research hypothesis #2 follows on from hypothesis #1 and will be considered by comparing temporal change in modeled SOC with variability in modeled SOC due to the remotely sensed data classification errors. This hypothesis is worthy of interest as it unclear how variability in modeled SOC due to remotely sensed data classification errors compares to temporal change in modeled SOC. The general ensemble biogeochemical modeling system (GEMS) a well-established biogeochemical model developed for spatially and temporally explicit simulation of biogeochemical cycles (Liu et al., 2004; Tan et al., 2009) was used. In addition to LCLU maps, spatially explicit datasets of climate (monthly precipitation, monthly maximum and minimum air temperature), soils (including texture (fractions of sand, silt, and clay) and drainage) and management data (including crop and land management and additions of organic materials in quantities and over time) were used. Temporal change in modeled SOC will be assessed by running the model, under different climate change scenarios, repetitively each year during the time period 2000-2050. Variability in modeled SOC due to remotely sensed data classification errors will be assessed by using, for each model run during the same time period, different remotely sensed data classification approaches.

Research hypothesis #3 postulates the relevance of the perceptions that local population have of their changing environment and the resulting changes on LCLU, depending on the variability and change of climate parameters. In other words, hypothesis #3 postulates that in the study area change in rural LCLU is essentially influenced by human behavior with respect to precipitation. Social surveys, specifically focus group discussions, will be employed to capture local population attitudes and perceptions of their behavior to changes in the climate and their land use and livelihood strategies. Group discussions will be stratified by gender, ethnicity and dominant production systems in different representative villages of the study areas.

Research hypothesis #4 will be addressed in an attempt to conceptualize the implications of future regional climate predictions on LCLU (Ben Mouhamed et al., 2002; Sultan et al., 2010). Future LCLU scenarios will be developed (up to 2050) under current (average 1960-2010) and future (year 2050) climate scenarios (RCPs). Each pixel of the 2010 LCLU classified data will be modified using plausible future scenarios based on analysis of the attitudes and behaviors of stakeholders towards the socio-economic and climate drivers of how the land is used derived from the focus group discussions.

1.7 Significance of the Research

The capacity to model and project LCLU change is of considerable interest for mitigation and adaptation measures in response to climate change (Hansen, 2002; Blanc, 2012; Smith, 2014). This research aims to contribute to an understanding of future land cover land use change in the West African Sahel with respect to climate variability and human activities. It focuses on soil organic carbon with the assumption that a better understanding of climate LCLU interactions may provide insights to enable policy makers at local to national levels to formulate environmentally and economically adapted policy decisions.

Overall, the significance of this research could be attested with the following statements:

1 Africa is highly vulnerable to climate change and variability, a situation aggravated by the interaction of 'multiple stresses', occurring at various levels, and low adaptive capacity (Tschakert et al., 2004) while recent climate predictions suggest Africa could be 2-6 °C warmer in 100 years time (Hulme et al., 2001; IPCC, 2001; IPCC, 2007; IPCC 2014). However, regional climate models for West Africa are still inadequate to predict with confidence the impacts of climate change (Brooks, 2004; Boxel, 2004; Gaye et al., 2014).

2 While it is unclear how Africa's ecosystems will respond to future climate change, it is thought that "*environmental instabilities may be compounded by the strategies that inhabitants use to adapt to environmental and socioeconomic changes*" (IPCC, 2007). Therefore, the role of land cover land use change need to be further explored in order to enhance the understanding of the interaction

between multiple stresses and adaptation to such stresses in Africa (Tschakert et al., 2004).

3 Although, LCLU change has been generally considered as a local environmental issue, it is now recognized as an issue of global importance (Foley et al., 2005). Therefore, knowledge of the geographical extent and spatial patterns of LCLUC is crucial in this process. The need for more detailed local-level analyses of the role of multiple interacting factors, including development activities and climate risk-reduction in the African context, is evident.

4 There are still few detailed and rich compendia of studies on human dimensions of climate change (of both a historical, current, and future-scenarios nature) (IPCC, 2007).

1.8 Summary of Chapters

Chapter 2 addresses research **hypotheses #1 and #2.** It describes the processing methodology used to derive LCLU based on current state of the art classification approaches applied to multi-seasonal remotely sensed data. It describes also how variability of SOC due to satellite LCLU classification errors can be assessed and compared to temporal change in modeled SOC under future climate scenarios. This chapter was published in *Biogeosciences* in 2012 and to date has been cited twelve times.

Chapter 3 addresses research **hypothesis #3.** It describes how focus group discussions are undertaken to capture rural attitudes and perceptions of inhabitants behavior to changes in the climate and their land use and livelihood strategies. It discusses also possible implications for the development of scenarios of future land cover land use. This chapter was published in *Environmental Management* in 2012 and to date has been cited six times.

Chapter 4 addresses research **hypothesis #4.** It describes how future LCLU was modelled to provide insights into the likely implications of future climate predictions. This chapter will be submitted for publication to a peer reviewed journal.

Chapter 5 summarizes findings from the four research hypotheses and provides a general discussion, recommendations for future research, and is the conclusion of this dissertation.

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CHAPTER 2

SENSITIVITY ANALYSIS OF THE GEMS SOIL ORGANIC CARBON MODEL TO LAND COVER LAND USE CLASSIFICATION UNCERTAINTIES UNDER DIFFERENT CLIMATE SCENARIOS IN SENEGAL

Dièye, A.M, Roy, D.P., Hanan, N.P., Liu, S., Hansen, M. and Touré, A. (2012).

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2.0 Abstract

Spatially explicit land cover land use (LCLU) change information is needed to drive biogeochemical models that simulate soil organic carbon (SOC) dynamics. Such information is increasingly being mapped using remotely sensed satellite data with classification schemes and uncertainties constrained by the sensing system, classification algorithms and land cover schemes. In this study, automated LCLU classification of multi-temporal Landsat satellite data were used to assess the sensitivity of SOC modeled by the Global Ensemble Biogeochemical Modeling System (GEMS). The GEMS was run for an area of 1560 km^2 in Senegal under three climate change scenarios with LCLU maps generated using different Landsat classification approaches. This research provides a method to estimate the variability of SOC, specifically the SOC uncertainty due to satellite classification errors, which we show is dependent not only on the LCLU classification errors but also on where the LCLU classes occur relative to the other GEMS model inputs.

2.1 Introduction

Africa is experiencing rapid and substantial social, economic, climatic and environmental change (Brooks, 2004; Challinor et al., 2007; IPCC, 2007; Nkonya et al., 2011). Soil carbon is important in West African drylands for soil fertility and agricultural sustainability and the influence of land management under changing climate on soil carbon is of particular interest (Batjes, 2001; Lal, 2004; Tieszen et al., 2004). Biogeochemical model simulations of carbon dynamics in vegetation and soil in response to changes in land cover and land use (LCLU), land management and climate increasingly use spatially explicit LCLU data derived from satellite remote sensing (Turner et al., 2000; Liu et al., 2004; Kennedy et al., 2006; Liu et al., 2008, Tan et al., 2009). There is a recognition however that errors in satellite derived LCLU data, both in terms of classification errors and the degree of generalization of the landscape into the different LCLU classes, and differences between LCLU data sources and land cover classification approaches, may propagate into model outputs (DeFries et al., 1999; Reich et al., 1999; Turner et al., 2000; Quaife et al., 2008).

Remotely sensed satellite data have been used extensively to map land cover (Tucker et al., 1985; Pickup et al., 1993; Lambin and Strahler, 1994) although human influences are difficult to discern reliably except when using high spatial resolution data (Townshend and Justice, 1988). Consequently, high spatial resolution data, in particular from the Landsat satellite series, have been used for mapping land cover change over decadal periods (Skole and Tucker, 1993; Gutman et al., 2008). Satellite classification by visual photo interpretation is not suited to mapping large areas on the consistent and repeated basis required for long term monitoring. Automated techniques that use digital computer processing and statistical classification approaches largely overcome this issue, but also do not provide error free classifications. Furthermore, it is not usually possible to reliably map land use, i.e. the land's social, economical, and cultural utility, using automated techniques (Turner et al., 1997). In semi-arid areas, such as the West African Sahel, satellite land cover classification is particularly challenging because the vegetation types may be sparsely distributed across variable soil backgrounds and because they frequently transition and mix across the landscape at scales finer than the satellite pixel dimension (Frederiksen and Lawesson, 1992; Prince et al., 1990; Lambin and Ehrlich, 1997). Further, semi-arid vegetation often exhibits a marked seasonality in photosynthetic activity and leaf area in response primarily to seasonal precipitation, making the selection of appropriate satellite acquisitions important (Hiernaux and Justice, 1986).

The General Ensemble biogeochemical Modeling System (GEMS) is a well-established biogeochemical model developed for spatially and temporally explicit simulation of biogeochemical cycles (Liu et al., 2004; Tan et al., 2009). In this paper the sensitivity of GEMS modelled soil organic carbon to satellite LCLU mapping uncertainties is quantified for a semi-arid Sahelian region of Senegal. Supervised decision tree classification approaches are used to map LCLU from multi-temporal Landsat satellite data which are used to drive spatially explicit maps of GEMS soil organic carbon under different climate change scenarios. A description of the study area (Section 2), the Landsat data and pre-processing (Section 3) and the GEMS input data and parameterization (Section 4) are described. This is followed by description of the LCLU classification (Section 5) and carbon modeling and sensitivity analysis methodologies (Section 6). The results are presented and discussed (Section 7), preceding the concluding remarks (Section 8).

2.2 Study area

The study area is located in the north of Senegal, bordered by the Senegal River to the North and the Atlantic Ocean to the west, with the southern edge 100 km north of Dakar (Figure 1). It covers 1560 km^2 lying between 15º24' to 17º00' W and 15º00' to 16º42' N. The area has a semi-arid climate with a single rainy season from June-July through September-October; average rainfall decreased from 400-600 mm in the 1960s to 200-400mm in the 1990s, mean monthly temperature varies from 24.5ºC in January to 31.9ºC in May (Fall et al., 2006).

The study area includes a wide range of land covers and land uses, and consequently soil organic carbon, making it appropriate for the sensitivity analysis described in this paper. Most agricultural activities in the study area are undertaken during the rainy season, planting occurs in June followed by harvesting in late October through November. Flood recession farming is practiced in the Senegal River valley and irrigated crop production, largely dominated by vegetable production, is practiced where groundwater is available elsewhere. The dominant natural vegetation species are, trees: *Acacia raddiana, Balanites aegyptica, Sclerocarya birrea, Combretum glutinosum, Adansonia digitata* (boabab tree); shrubs: *Guiera senegalensis, Boscia senegalensis, Calotropis procera;* and grasses include primarily *Cenchrus biflorus, Schoenefeldia gracilis* and *Dactyloctenium aegyptium*. In order to summarize the region succinctly we refer to the Senegalese agro-ecological zones (also known as ecoregion) defined by Tappan et al. (2004). The study area encompasses four zones, and these are illustrated in Fig. 1 and are described below.

The smallest ecoregion (2% of the study area), is a narrow strip of land (10 to 30 km wide) along the Atlantic coast (120 km) from Saint-Louis to Dakar. The predominant soils are ferruginous tropical sandy soils, deep and well drained, low in organic matter and mineral content (Tappan et al., 2004). The ecoregion is characterized by geomorphological features composed of active littoral and stabilized continental sand dunes that alternate with longitudinal depressions. The sand dunes support shrub savanna used by pastoralists as gazing land. The longitudinal depressions, locally called *niayes*, have given their name to the region as a whole, and are used for irrigated agriculture owing to the shallow water table accessed by artisanal wells. The main irrigated agricultural land use is market gardening, primarily carrots, onions, and cabbages, for sale in Dakar. Beginning in the early 1980's, coastal sand dune stabilization projects planted drought-tolerant Whispering Pine (*Casuarina equisetifolia*) which cover much of the coastal zone from Dakar to Saint-Louis (Tappan et al., 2004; CSE, 2005). A second ecoregion, lying east of the smallest ecoregion, and covering 45% of the study area, includes much of the *peanut basin*, an area dedicated since the 1880s to groundnut cultivation. The predominant soils are slightly leached ferruginous tropical sandy soils lying in the plateau of the continental sedimentary basin. The main crops are millet, groundnuts, and sorghum in acacia tree parkland, which have replaced all vestiges of the pre-colonial woodland savanna landscape (Tappan et al., 2004). A third ecoregion, lying in the north east (east of Lake Guiers, Fig. 1) and covering 43% of the study area, is the *sandy ferlo*. It constitutes Senegal's main sylvo-pastoral zone, an area that is generally too dry for crop production, with mean annual precipitation less than 200 mm. The vegetation is composed of open grasslands with scattered shrubs and predominantly acacia trees on red-brown sandy and ferruginous tropical sandy soils. The last ecoregion (11% of the study area) is the Senegal River Valley, a floodplain previously covered by riverine woodland, today used for irrigated-agricultural projects that pump water from the Senegal River onto extensive rice and sugarcane fields. The predominant soils are hydromorphic and vertic with a sandy, clay loam, and clay. The natural vegetation is open steppe, shrub steppe, and riparian acacia woodland. <Insert Figure 1 near here>

Landsat Enhanced Thematic Mapper Plus (ETM+) satellite data were used in this study. All six 28.5m reflective, the two 57m thermal (low and high gain), and the single 15m panchromatic bands were used. Each ETM+ scene is approximately 180x180 km and is defined in the UTM coordinate system and referenced by a unique Landsat Worldwide Reference System (WRS-2) path and row coordinate (Arvidson et al., 2001).

Multi-temporal satellite data provide improved land cover classification accuracies over single-date classifications if the acquisitions capture seasonal and agricultural differences (Lo et al., 1986; Schriever and Congalton, 1993). Consequently, in this study two Landsat ETM+ scenes, acquired in 2002 in the early wet season (June 21) and the dry season (December 30) over the study area, WRS-2 scene path 205 row 49, were used. These acquisitions were selected because they were the only available scenes with very low (<1%) cloud cover. They are considered to be representative of the year 2000 in the subsequent GEMS modeling.

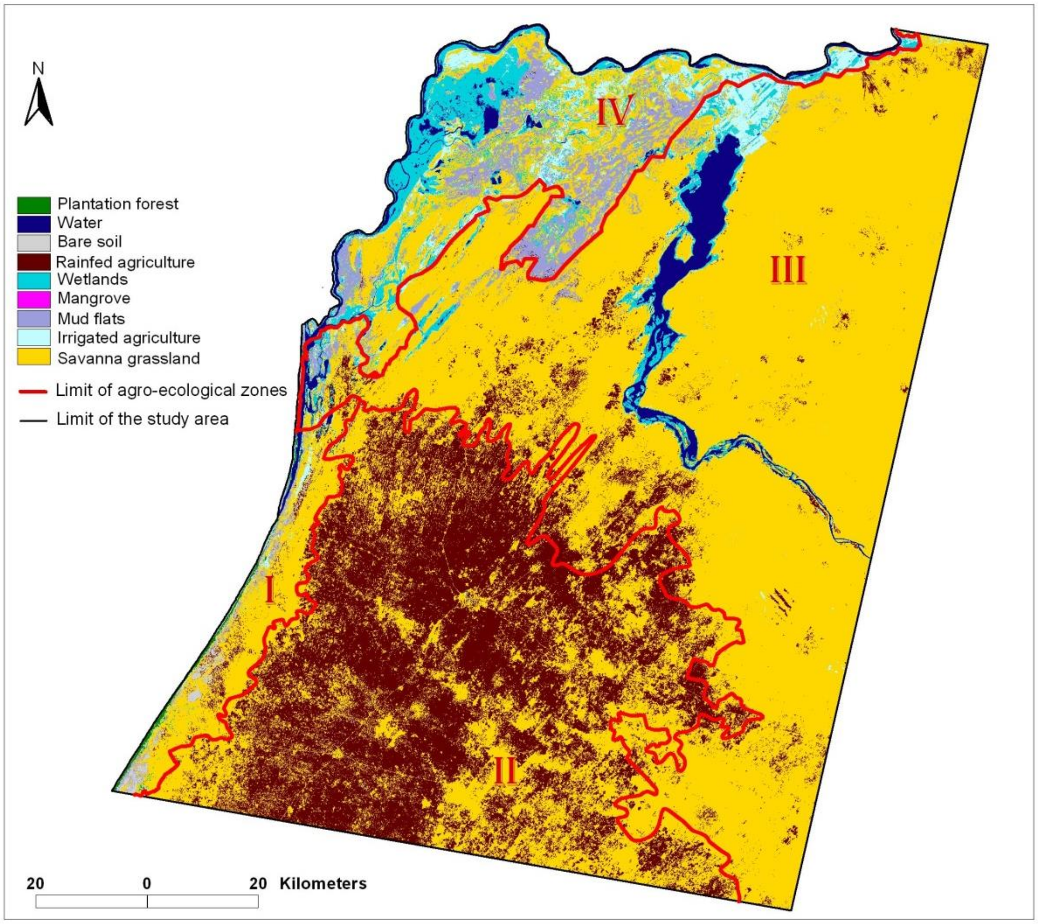

Figure 1 Landsat 28.5m hard decision tree classification of the study area in north-western Senegal, covering 1560 km^2 lying 15º24' - 17º00' W and 15º00' - 16º42' N. Dry and wet season 2002 Landsat data were classified using a bagged decision tree classification procedure into 9 land cover land use classes (plantation forest, water, bare soil, rainfed agriculture, wetlands, mangrove, mud flats, irrigated agriculture, and savanna grassland). The study area is shown bounded by a black vector. White shows unclassified (clouds, cloud shadows, settlement areas, or no Landsat data). The boundaries of the four main agro-ecological zones (I: Niayes; II: Peanut Basin; III: Sandy Ferlo; and IV: Senegal River Valley) are shown as red vectors

2.3 Satellite data

2.3.1 Landsat data

Landsat Enhanced Thematic Mapper Plus (ETM+) satellite data were used in this study. All six 28.5m reflective, the two 57m thermal (low and high gain), and the single 15m panchromatic bands were used. Each ETM+ scene is approximately 180x180 km and is defined in the UTM coordinate system and referenced by a unique Landsat Worldwide Reference System (WRS-2) path and row coordinate (Arvidson et al., 2001).

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2.3.2. Landsat data pre-processing

Landsat data are affected by several factors that need to be corrected before multi-date data can be compared reliably (Coppin et al., 2004). In this study, corrections for radiometric, atmospheric and geometric effects were undertaken. The ETM+ reflective bands were converted from digital numbers to at satellite reflectance using the best available ETM+ calibration coefficients and standard correction formulae taking into account the solar constant (Markham and Baker, 1986). The thermal bands were similarly converted from digital numbers to effective at satellite temperature using standard coefficients and Planck function formulae (USGS, 2001). The impact of the atmosphere is variable in space and time and is usually considered as requiring correction for quantitative and change detection applications (Ouaidrari and Vermote, 1999; Coppin et al., 2004). Several Landsat atmospheric correction methods have been proposed, with the dark-object subtraction (DOS) method widely used due to its methodological simplicity (Chavez, 1996). In the DOS approach, atmospheric path radiance is assumed to be equal to the radiance sensed over dark objects, such as dense vegetation or water, and is subtracted from each band. In this study, each Landsat acquisition was normalized using a dark object subtraction method to reduce scene-to-scene and within scene radiometric variations associated with atmospheric, phenological, and sun-sensor-target geometric variations. Surface reflectances were computed independently using inland water bodies and a small number of cloud shadows as dark objects. Clouds and cloud shadows were screen digitized manually and not considered in the subsequent analysis as they preclude optical wavelength remote sensing of the surface and deleteriously contaminate surface reflectance (Roy et al., 2010).

The two ETM+ acquisitions had already been ortho-rectified following established procedures (Tucker et al., 2004). However, to ensure precise sub-pixel co-registration, an image-to-image registration was performed using 25 ground control points identified in both scenes, and the December image was nearest neighbor resampled into reference with the June acquisition using a first-order polynomial warping transformation. The two 57 m at satellite temperature bands and the six 28.5 m at satellite reflectance bands were resampled in this way to 28.5 m to provide the same image spatial dimensions needed for the subsequent image classification.

2.4 GEMS model, input data and parameterization

2.4.1 GEMS model overview

The General Ensemble biogeochemical Modeling System (GEMS) was developed from the CENTURY model (Metherell et al., 1993) to enable integration of spatially explicit GIS data, including land cover, soils, climate, and land management practice information (Liu et al., 2008). CENTURY is an established plant-soil ecosystem model that simulates the dynamics of carbon, nitrogen, and phosphorus in various ecosystems including grassland, forest, savanna, and crop systems (Metherell et al., 1993; Parton et al., 2004). The input parameters comprise site specific biophysical data, plant characteristics, and management data, including monthly precipitation, monthly maximum and minimum air temperature, soil texture, bulk density, drainage, water holding capacity, cropping systems, fertilization, cultivation, harvesting, grazing, tree removal, and natural disturbances such as fire (Parton et al., 2004; Liu et al., 2004). GEMS couples CENTURY with various spatial databases to simulate biogeochemical cycles over large areas (Liu et al., 2004, Liu et al., 2008).

GEMS consists of three major components: an encapsulated ecosystem biogeochemical model (i.e., CENTURY), a data assimilation system (DAS), and an input/output processor (IOP). GEMS uses a Monte-Carlo based ensemble approach to incorporate the variability of state and the driving variables of the underlying biogeochemical models into simulations. Geographic information system software (ESRI,

2007) are used to group pixels that have the same combination of spatially explicit input data values. Each combination is described by a joint frequency distribution (JFD) that is used by the DAS to relate the spatially explicit data and model input parameters using look-up-tables (Liu et al., 2004). The IOP incorporates the assimilated data to the modeling processes and in return writes the selected output variables to a set of output files after each model run. The main output variable of interest for this study is the total soil organic carbon (SOC) (gCm^{-2}) in the top 0–20 cm soil layer. Soil organic matter is a key indicator of soil quality and is most usually determined by application of conversion factors to estimates of the soil organic carbon to some prescribed depth (Lal, 2004). The GEMS model includes three soil organic matter pools (active, slow and passive) with different potential decomposition rates of turnover: fast turnover (active SOM), intermediate turnover (slow SOM) and slow turnover (passive SOM) (Metherell et al., 1993).

In this study, 20 repeat GEMS model runs for each of 1081 JFDs were computed to incorporate the uncertainty of the input data and to provide stable spatially explicit soil organic carbon (SOC) estimates (Liu et al., 2004; Liu et al., 2008). Similarly, above ground net primary production (NPP) (gCm^{-2} $year^{-1}$) estimates were derived to check that the SOC and NPP values were plausible and spatially coherent. The GEMS model inputs are described below for the spatially explicit input data and the GEMS look up table parameterizations. In this study only the sensitivity of GEMS modeled SOC to land cover land use (LCLU) classification uncertainties are examined. Errors in the other input data and model parameterizations are not explicitly examined. Although, errors in the vegetation biomass and land management parameterizations are likely to be correlated to LCLU errors, other errors may change in space and time in ways that are only weakly correlated to LCLU.

2.4.2 GEMS spatially explicit input data

2.4.2.1 Land Cover Land Use (LCLU) data

Spatially explicit 28.5m LCLU maps representing the year 2000 were derived by multiple classifications of the Landsat ETM+ satellite data using a number of approaches described in detail in Section 5.

2.4.2.2 Climate data

Spatially and temporally explicit climate data were defined using 37 years of monthly average precipitation and minimum and maximum air temperature data defined in 0.05 degree grid cells (Hutchinson et al., 1996) nearest neighbor resampled to the 28.5m Landsat pixel dimensions. These monthly data were available for the period 1960-1996 and were used to “spin-up” the GEMS model to 1900 equilibrium, and then to run the GEMS model from 1990 to 2000 and to run the GEMS model for three future climate scenarios from 2000 to 2052. The future climate scenarios (no change, low and high change) were developed following the approach developed by Hulme et al. (2001) who assessed possible future (2000–2100) changes in temperature and rainfall for Africa using seven global climate models. The Hulme et al. (2001) approach and results are considered (Tan et al., 2009) to be compliant and comparable with those from the IPCC

Fourth Assessment Report (Christensen et al., 2007). Monthly climatologies of the 1960-1996 precipitation and minimum and maximum air temperature data were derived (i.e. 12 monthly values per 28.5m Landsat pixel). The no climate change scenario (NCCS) simply used the same monthly values of these data for each month of 2000 to 2052. The low climate change (LCCS) and high climate change (HCCS) scenarios were defined by weighting the monthly climatology values using the following equations derived from Hulme et al. (2001) for the study area:

Low Climate Change Scenario (LCCS):

$$\text{Temperature: change } (°\text{C}) = 0.0133 * \text{year} - 26.6 \quad (1)$$

$$\text{Precipitation: change } (\%) = -0.25 * \text{year} + 500 \quad (2)$$

High Climate Change Scenario (HCCS):

$$\text{Temperature: change } (°\text{C}) = 0.06 * \text{year} - 120 \quad (3)$$

$$\text{Precipitation: change } (\%) = -0.55 * \text{year} + 1100 \quad (4)$$

where *year* is set from 2000 to 2052. The additive constants in the above equations ensure that the LCCS and HCCS values are equal to the NCCS values in year 2000. In this way under the low climate change scenario by 2052 the temperature is 0.69ºC warmer with 13% less precipitation, and under the high climate change scenario by 2052 the temperature is 3.12ºC warmer with 28.6% less precipitation. We note that these scenarios do not model inter-annual variability in precipitation and minimum and maximum air temperature data, which is a limitation but not a concern for the purposes of this sensitivity study, and is the same approach used by Liu et al. (2004) and Tan et al. (2009) to prescribe climate scenarios in studies in Ghana and Senegal.

2.4.2.3 Soil, drainage and water holding capacity data

A map of static soil information was extracted from a Senegalese 1:500,000 vector soil atlas defined with 168 soil units (Stancioff et al., 1986). Soil characteristics were defined for the 45 soil units falling in the study area using a look up table with respect to texture (i.e., factions of sand, silt, and clay), drainage state, and water holding capacity. Sand fractions varied from 51% and 87%, silt fractions from 11% to 38%, clay fractions from 5% to 15%. The drainage state varied from poorly drained (=0) to overly well drained (=5), and the water holding capacity varied from high (clay=5) to low (sand=1).

2.4.2.4 Potential Natural Vegetation data

A static potential natural vegetation (PNV) map for 1900 was needed to run the GEMS model to equilibrium. In the absence of a PNV for Senegal, the earliest available vegetation map (Stancioff et al., 1986) developed by visual interpretation of 1985 Landsat data supplemented by intensive field survey was used. The map was nearest neighbor resampled to the 28.5m Landsat pixel dimensions, assigning to each output 28.5m pixel the value in the input data set nearest its centre. This map is considered as the most authoritative in its domain for Senegal for the 1980's (Tappan et al., 2004).

2.4.3 GEMS look-up-table parameterization

Vegetation biomass and land management practices were parameterized using look-up-tables related to the derived Landsat land cover land use (LCLU) classification data. Joint frequency distributions of the look-up-table variables values for each of the Landsat LCLU classes were developed following established GEMS conventions (Liu et al., 2004).

2.4.3.1 Vegetation biomass parameterization

Vegetation attributes required for the model parameterization were synthesized from an inventory of soil and biomass samplings conducted in Senegal during the last 20 years (CSE, 2004; Woomer et al., 2004b; Tschakert et al., 2004). Above-ground biomass (trees, herbs, and litter) and their carbon stocks were calculated using allometric formulae (Woomer et al., 2004a; Brown, 1997). The root biomass of trees and herbs were estimated as 0.35 and 0.15 of the above-ground biomass, respectively, based on field observations (Woomer et al., 2004a). The proportion of carbon in all biomass pools was set as 0.47 (Woomer et al., 2004a).

2.4.3.2 Management practices

Management practices that affect carbon dynamics were used: crop composition, crop rotation probability, temporal changes of harvest practices, cropping practices (including plowing and selective cutting), fertilizer use, fallow probability and fallow length, fire frequency, and frequency and intensity of grazing. These practices were compiled from annual agricultural acreage and yield statistics, and livestock census data defined by Senegalese administrative units (départements) (CSE, 2002) and from information collated in previous studies (Touré et al., 2003; Manlay et al., 2002; Tchakert et al., 2004a). The management practices are summarized in Table 1 and were considered in terms of non-arable (including pastoralism) and arable land uses defined by the Landsat classified LCLU class. The main crops grown are millet, sorghum, and groundnuts. Fallow lengths were set as 1-5 years with successive 5-10 years of cropping. Non-subsistence agriculture was assumed to have started in 1920 with current mineral fertilizer use varying from 0 to 300 kg/ha (Tschakert et al., 2004). Before this date, the study area was assumed to be savanna with low to moderate grazing (little influence on plant production) that rose to current high grazing rates of 12 to 30 tropical livestock units per km^2 (CSE, 2002), with an assumed linear effect on plant production (Woomer et al., 2004a).

Table 1 Summary of management practices used for the GEMS model parameterization. The crop rotation probabilities should be read horizontally from time 1 to time 2; each row sums to 1

<table>
<tr><td>Savanna</td><td colspan="5"></td></tr>
<tr><td>Grazing</td><td colspan="5">Moderate to high grazing intensity all year</td></tr>
<tr><td>Fire</td><td colspan="5">Once every year in February</td></tr>
<tr><td colspan="6"></td></tr>
<tr><td>Agriculture</td><td colspan="5"></td></tr>
<tr><td>Growing season</td><td colspan="5">June to September</td></tr>
<tr><td>Crop composition</td><td colspan="5">Millet, sorghum, groundnuts</td></tr>
<tr><td>Crop / fallow ratio (year)</td><td colspan="5">(5 – 10) / (1 – 5)</td></tr>
<tr><td>Tree removal</td><td colspan="5">Clear cut</td></tr>
<tr><td>Fertilizer</td><td colspan="5">Low to moderate use of NPK fertilizer</td></tr>
<tr><td>Cultivation</td><td colspan="5">Cultivation with cultivator tool (hoe) in July-September</td></tr>
<tr><td>Harvest</td><td colspan="5">Harvest with 90% straw removal in October</td></tr>
<tr><td>Grazing</td><td colspan="5">Winter grazing November – December</td></tr>
<tr><td rowspan="5">Crop rotation probabilities</td><td>time 2
time 1</td><td>Fallow</td><td>Millet</td><td>Sorghum</td><td>Groundnuts</td></tr>
<tr><td>Fallow</td><td>0.50</td><td>0.10</td><td>0.15</td><td>0.25</td></tr>
<tr><td>Millet</td><td>0.02</td><td>0.45</td><td>0.00</td><td>0.53</td></tr>
<tr><td>Sorghum</td><td>0.00</td><td>0.00</td><td>0.55</td><td>0.45</td></tr>
<tr><td>Groundnuts</td><td>0.06</td><td>0.34</td><td>0.00</td><td>0.60</td></tr>
</table>

2.5 Landsat Satellite Data Classification

The six 28.5m reflective, and the two 57m thermal (low and high gain) bands nearest neighbor resampled to 28.5m were classified together as described below. Clouds and cloud shadows were visually identified (< 1% of the image) and masked from both Landsat acquisitions and were not classified. The dry and wet season Landsat data were classified together, rather than independently.

2.5.1 Landsat LCLU Classification Scheme and Training Data

The state of the practice for automated satellite classification is to adopt a supervised classification approach where samples of locations of known land cover classes (training data) are collected. The optical and thermal wavelength values sensed at the locations of the training pixels are used to develop statistical classification rules, which are then used to map the land cover class of every pixel (Brieman et al., 1984; Foody et al., 2006). Supervised classification results depend on the appropriateness of the LCLU class nomenclature and on the quality of the training data used.

Table 2 summarizes the nine LCLU classes and the number of Landsat training pixels for each class. These nine classes were selected by examination of pre-existing land cover maps including a land cover map of the north of Senegal generated by the Centre de Suivi Ecologique (CSE, 2002) and were selected to ensure that the classes were mutually exclusive and that every part of the study area could be classified into one and only one class (Anderson et al., 1976). The CSE land cover map used the Yangambi vegetation classification scheme that contains 25 vegetation classes defined according to their physiognomy (i.e. structure and form of vegetation groups) (Monod, 1956; Trochain, 1957). The Yangambi scheme predates by two decades the availability of satellite data, and the different Yangambi vegetation classes were not always spectrally unambiguous from one another in the multi-date Landsat data. For these reasons several of the Yangambi classes were combined and three vegetation classes, savanna grassland, mangrove and wetlands, were considered. In addition, the study area includes non-vegetated surfaces not considered in the Yangambi scheme, and the classes water, bare soil, rainfed agriculture, mud flats, and irrigated agriculture) were identified based on our expert knowledge of the study area and multi-annual field visits.

Training pixels for each class were selected by visual analysis of the co-registered dry and wet season 2002 ETM+ imagery, augmented by our expert knowledge of the study area including information gathered during multi-annual field visits. Only training pixels that could be unambiguously identified were collected. A total of 11,717 Landsat 28.5m training pixels were selected (Table 2). Ideally, the training data should be representative of the area classified and of the classes in the classification scheme, although there is no statistical procedure to define a suitable number and spatial distribution without *a priori* information concerning the area (Stehman, 1997; Foody et al., 2006). Great care was taken in the training data collection. The land use-related classes (irrigated agriculture, rainfed agriculture, plantation forest) were the most difficult to reliably collect training data for. Irrigated agriculture is a unique characteristic of the Senegal River Valley and was interpretable on the Landsat data owing to the patterns of irrigation channels within and adjacent to agricultural fields. The *peanut basin* is the foremost rainfed agriculture area of Senegal, and polygonal rainfed agricultural fields were distinguishable by differences between the wet and dry season Landsat acquisitions.

Plantation forest in the *Niayes* ecoregion forms a distinctive strip observable on the Landsat data.

Table 2 Description of the 9 land cover land use (LCLU) classes and the number of training pixels used for the classification.

Code	LCLU class	Definition	Training pixels
1	Plantation Forest	Pine *Casuarina equisetifolia* plantation forest known only to occur in the Niayes coastal ecoregion.	113
2	Water	Permanent inland water (rivers, lakes); defined by visual interpretation of dry and wet season Landsat ETM+ data.	627
3	Bare Soil	Natural areas devoid of vegetation; defined by visual interpretation of dry and wet season Landsat ETM+ data.	280
4	Rainfed agriculture	Agricultural fields which crop development relies primarily on natural rainfall; defined by visual interpretation of dry and wet season Landsat ETM+ data and using contextual knowledge.	2,150
5	Wetlands	Areas inundated or saturated by surface or ground water in a permanent or temporary basis to support a prevalence of vegetation adapted for life in saturated conditions; defined after Yangambi classification.	922
6	Mangrove	Trees and shrubs that grow in saline coastal habitats; defined after Yangambi classification.	72
7	Mud flats	A mud area devoid of vegetation; seasonally inundated; defined by visual interpretation of dry and wet season Landsat ETM+ data.	149
8	Irrigated agriculture	Agricultural fields in proximity to the Senegal River and to artesian wells; defined by visual interpretation of dry and wet season Landsat ETM+ data and using contextual knowledge.	151
9	Savanna Grassland	Open savanna with annual grasses and scattered trees or shrubs (<10 % of cover); defined after Yangambi classification.	7,253
Total			11,717

Settlements contain different LCLU classes and consequently are difficult to classify reliably (Barnsely and Barr, 1997; Sun et al., 2003). This was particularly true for the rural villages occurring across the study area, which tended to be small and heterogeneous relative to the Landsat 28.5m pixel size. Consequently, all of the settlements were screen digitized manually and were not considered subsequently in the carbon modeling.

2.5.2 Classification Approaches

The Landsat ETM+ data were classified using bagged decision tree approaches. Decision trees are hierarchical classifiers that predict class membership by recursively partitioning data into more homogeneous subsets (Breiman et al., 1984). Trees can accept either categorical data in performing classifications (classification trees) or continuous data (regression trees). They accommodate abrupt and non-monotonic relationships between the independent and dependent variables and make no assumptions concerning the statistical distribution of the data. Currently, bagged decision tree classifiers are the state of the practice approach for supervised satellite data classification (Doan and Foddy, 2007; Hansen et al., 2008). Bagging tree approaches use a statistical bootstrapping methodology to improve the predictive ability of the tree model and reduce over-fitting whereby a large number of trees are grown, each time using a different random subset of the training data, and keeping a certain percentage of data aside (Breiman, 1996).

In this study, both hard and soft supervised classification approaches were undertaken. Classifications are described as “hard” when each pixel is classified into a single class category, i.e., full membership of a single class is assumed, and as “soft” when each pixel may have multiple partial class memberships (Foody, 2000).

Thirty bagged classification trees were generated, each time, 25% of the training data were used to generate a tree, and the remaining 75% were used to assess the classification accuracy. The 25% proportions were sampled at random with replacement. To limit overfitting, each tree was terminated using a deviance threshold: additional splits in the tree had to exceed 1% of the root node deviance or the tree growth was terminated. For each of the 30 trees, a soft classification result was generated defining for each 28.5m Landsat pixel the probability of it belonging to each of the nine LCLU classes.

A hard decision tree classification was generated from the 30 soft classifications. Each soft classification was converted to a hard classification by assigning to each pixel the class with the highest probability, and then assigning the single most frequently occurring class category over the 30 classifications (Breiman, 1996; Bauer and Kohavi, 1999). When the maximum probability corresponded to more than one class, one of the classes was selected randomly. The number of unique classes that a pixel was independently classified in this way over the 30 trees was also recorded.

2.5.3 Classification Accuracy Assessment

The ensemble classification accuracy of the 30 soft decision tree classifications was quantified using a confusion matrix based statistical method. The confusion matrix is a two dimensional matrix composed of *n* columns and rows, where *n* is the number of classes, and each column represents the number of instances of a predicted (i.e. classified) class and each row represents the number of instances of an actual true class (Congalton et al., 1983). The diagonal of the confusion matrix records the agreement between the “classified” and the corresponding “truth”. The off-diagonal records the disagreement. Conventional confusion matrix accuracy assessment approaches are inappropriate for application to soft classification results (Foody, 2000). Consequently a “soft-to-hard” confusion matrix generation methodology was developed following the method of Doan and Foody (2007).

Recall that each of the 30 classification trees was generated from 25% of the training data sampled at random with replacement. In the accuracy assessment, first each classification tree was used to classify the remaining (“out-of-bag”) 75% of the training data, deriving a vector of class probabilities for each out-of-bag pixel (Breiman, 1996). Then a single confusion matrix was generated from the 30 vectors of class probabilities. Throughout the 30 vectors of probabilities, each pixel was assigned to the LCLU class with the maximum probability. If several classes had the same probabilities then one class was selected at random.

Conventional accuracy statistics were then derived from the “soft-to-hard” confusion matrix. The *percent correct*, was calculated by dividing the total number of pixels correctly classified by the total number of pixels in the training data. The Kappa coefficient was also calculated as it provides another measure of overall classification accuracy, but that uses all the elements of the confusion matrix to compensate for chance agreement, although kappa values may be biased in areas with uneven proportions of the different classes (Stehman, 1997, 2004; Foody, 2004). The *producer’s* and the *user’s accuracies* were computed to assess the accuracies of each class (Foody, 2002). The *user’s accuracy* was calculated by dividing the number of all correctly classified pixels of a class by the sum of all pixels which had been assigned to that class; it indicates the probability that a pixel classified to a given class actually represents the reality on the ground (Congalton, 1991). The *producer's accuracy* was calculated by dividing the number of all correctly classified training pixels of a class by the sum of training data pixels for that class; it indicates the probability of a training pixel being correctly classified (Congalton, 1991).

2.6 Carbon Modelling and Sensitivity Analysis Methodology

2.6.1 Carbon Modelling

The GEMS model was used to estimate soil organic carbon SOC (gCm^{-2}) in the top 0-20 cm soil layer and also above ground net primary productivity (NPP) (gCm^{-2} $year^{-1}$). In this study we assumed that human disturbances in the study area were negligible before 1900 and that consequently carbon stocks and fluxes were at near equilibrium conditions in 1900. This is primarily justified since colonial impacts on Senegalese land use practices in the early colonial period were limited to small urban settlements and non-subsistence arable practices had largely not been developed (Gellar, 1976; Tschakert et al., 2004). Estimates of carbon stocks and fluxes in the study area in 1900 were obtained by running the model for 1500 years to a 1900 equilibrium (Liu et al., 2004; Tan et al., 2009) using the potential vegetation map, the 1960-1996 climate data, and the contemporary soil and drainage data described in Section 4.

The model was run from 1900 to 2000 using the 1900 carbon estimates to initialise the post-1900 model runs. The land cover of the study area was characterized in 1900 by the potential natural vegetation map and in 2000 was characterized by the Landsat classifications. The historical trajectory of land cover and land management between 1900 and 2000 is unknown, and so we assumed a linear change as a best estimate and following the approach used by other researchers (Liu et al., 2004, Liu et al., 2008 and Tan et al., 2009).

The GEMS model was run from 2000 to 2052 for the three climate change scenarios described in Section 4.2.2. The GEMS model was run independently parameterizing the 2000 land cover land use and associated land management parameterization (Table 1) from the 30 Landsat soft classifications and the single hard Landsat classification derived from the 30 soft classifications. These 31 runs were each repeated for the no, low, and high climate change scenarios.

We assumed there was no LCLU change after 2000 in order to assess *only* the sensitivity of the GEMS model outputs to the LCLU classification uncertainties under the different climate scenarios. Moreover, prediction of future LCLU is difficult, not least because even if appropriate statistical LCLU change trend data existed, it may not capture future changes in LCLU driving forces, such as economic and policy modifications, acting at varying scales (Moss et al., 2010). Further, as LCLU in the study region is extensively soil moisture limited, future LCLU scenarios can only be meaningfully developed when coupled with future climate scenarios. This will be examined in future research that is not described here.

2.6.2 Soil Organic Carbon Assessment & Sensitivity Analysis

Soil organic carbon (SOC) assessment and sensitivity analyses were performed to explore the variability imposed by the different land cover classification approaches for the three different climate scenarios. For the hard Landsat classification, where each

28.5m Landsat pixel is assigned to only one LCLU class, the SOC for each pixel and simulation year and climate scenario was defined as:

$$SOC_{year,scenario}(i,j) = C_{year,scenario,class}(i,j) \quad (5)$$

where $SOC_{year,scenario}(i,j)$ is the SOC estimated at pixel column and row (i,j) and $C_{year,scenario,class}(i,j)$ is the GEMS modeled SOC at that pixel assuming that the pixel is entirely LCLU class *class*. The net primary productivity (NPP) was similarly derived for each hard classification pixel so that the GEMS NPP could be compared to the SOC data to ensure the estimates were plausible and spatially coherent.

For each soft classification, where the probability of class membership is stored at each pixel, the SOC for each pixel was defined as:

$$SOC_{year,sceanrio}(i,j) = \sum_{class=1}^{n} C_{year,scenario,class}(i,j) \; P_{2000,class} \quad (6)$$

$$\sum_{class=1}^{n} P_{2000,\,class} = 1$$

where $SOC_{year,scenario}(i,j)$ is the SOC estimated at pixel column and row (i,j), $C_{year,\ class}(i,j)$ is the GEMS modeled SOC for that pixel assuming all the pixel is entirely class *class*, and $P_{2000,\ class}$ is the soft classification probability of the pixel belonging to class *class*.

2.7 Results

2.7.1 LCLU classification scheme and Classification Accuracy Assessment

Table 3 shows the ‘soft-to-hard’ confusion matrix results for the 9 LCLU classes. The classification accuracies tabulated in Table 3 provide an assessment of the ensemble classification accuracy of the 30 soft decision tree classifications and so also indicate the hard classification accuracy as it is derived from the 30 soft classifications. The percent correct and Kappa were 97.79% and 0.98 respectively. The producer's and user's classification accuracies were greater than 90% for all the classes except for the wetlands, irrigated agriculture and mangrove classes. No class was misclassified as another by a significant amount - the greatest misclassification was 0.19% between the rainfed agriculture and savanna grassland classes. These classification accuracies are high and reflect what we expect is the best classification typically achievable for the study area.

Table 3 Soft-to-hard confusion matrix results for the 9 land cover land use classes. The cell values report percentages of the total area; a total of 305 428 pixels were considered. The percent correct is 97.79% and Kappa-coefficient is 0.98. Grey fields, along the diagonal, represent for each class, the percentage correctly classified. The classes are: 1. Plantation; 2. Water; 3. Bare soil; 4. Rainfed agriculture; 5. Wetlands; 6. Mangrove; 7. Mud flats; 8. Irrigated agriculture; 9. Savanna grassland (Table 2).

		Classification										
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Row Total**	**Producer's Accuracy (%)**
True Class	**1**	3.30	0.00	0.00	0.00	0.03	0.00	0.00	0.02	0.00	3.4	98.4
	2	0.00	13.94	0.00	0.00	0.03	0.00	0.00	0.00	0.00	14.0	99.8
	3	0.00	0.00	1.43	0.01	0.00	0.00	0.02	0.00	0.02	1.5	96.1
	4	0.00	0.00	0.02	6.54	0.00	0.00	0.01	0.00	0.14	6.7	97.4
	5	0.02	0.00	0.00	0.00	1.04	0.04	0.04	0.05	0.07	1.3	82.0
	6	0.01	0.00	0.00	0.00	0.05	0.03	0.00	0.01	0.00	0.1	35.1
	7	0.00	0.00	0.05	0.03	0.01	0.00	4.06	0.01	0.12	4.3	94.8
	8	0.02	0.00	0.00	0.00	0.06	0.01	0.02	1.00	0.04	1.2	86.7
	9	0.00	0.00	0.01	0.19	0.06	0.00	0.13	0.08	67.21	67.7	99.3
	Column Total	3.4	13.9	1.5	6.8	1.3	0.1	4.3	1.2	67.6	100	
	User's Accuracy (%)	98.4	100.0	94.1	96.5	81.9	36.5	94.7	85.7	99.4		

Figure 1 shows the hard decision tree classification where each pixel is classified as one of the 9 LCLU classes. The classification indicates that in the study area, the dominant land cover is savanna grassland (61.5% of the area), followed by rainfed agriculture (20.58%), and then mud flats (5.67%), wetlands (4.92%), irrigated agriculture (3.25%), water (2.93%), plantation forest (0.70%), bare soil (0.44%), and mangrove (0.01%).

The hard classification was defined from the 30 soft classifications, assigning at each pixel the single most frequently occurring class category over the 30 classifications using a voting procedure. Pixels where all 30 soft classifications agreed are more likely to be reliable than those where there was disagreement. Figure 2 shows the number of unique classes (maximum 9) that a pixel was independently classified as over the 30 decision tree classifications. Approximately 82% of the pixels were classified into no more than 2 classes with 55% classified as one class and 27% as two classes. The least reliable areas, classified into 3 classes or more, occurred predominantly in areas classified as wetlands, mud flats, bare soil, irrigated agriculture, and mangroves; these classes also had the lowest producer’s and user’s accuracies (Table 3). Varying water levels present in all of these cover types may confound their discrimination, which is not unexpected when passive optical wavelength satellite data are classified (Ozesmi and Bauer, 2002). In addition, the peanut basin agricultural expansion zone in the South West of the study area, composed of a mix of savanna and rainfed agriculture, was less reliably classified. This is most likely because of the presence of abandoned rainfed agricultural fields in this region that are used for intermittent grazing and can physically resemble grassland (Tappan et al., 2004; Tschakert et al., 2004).

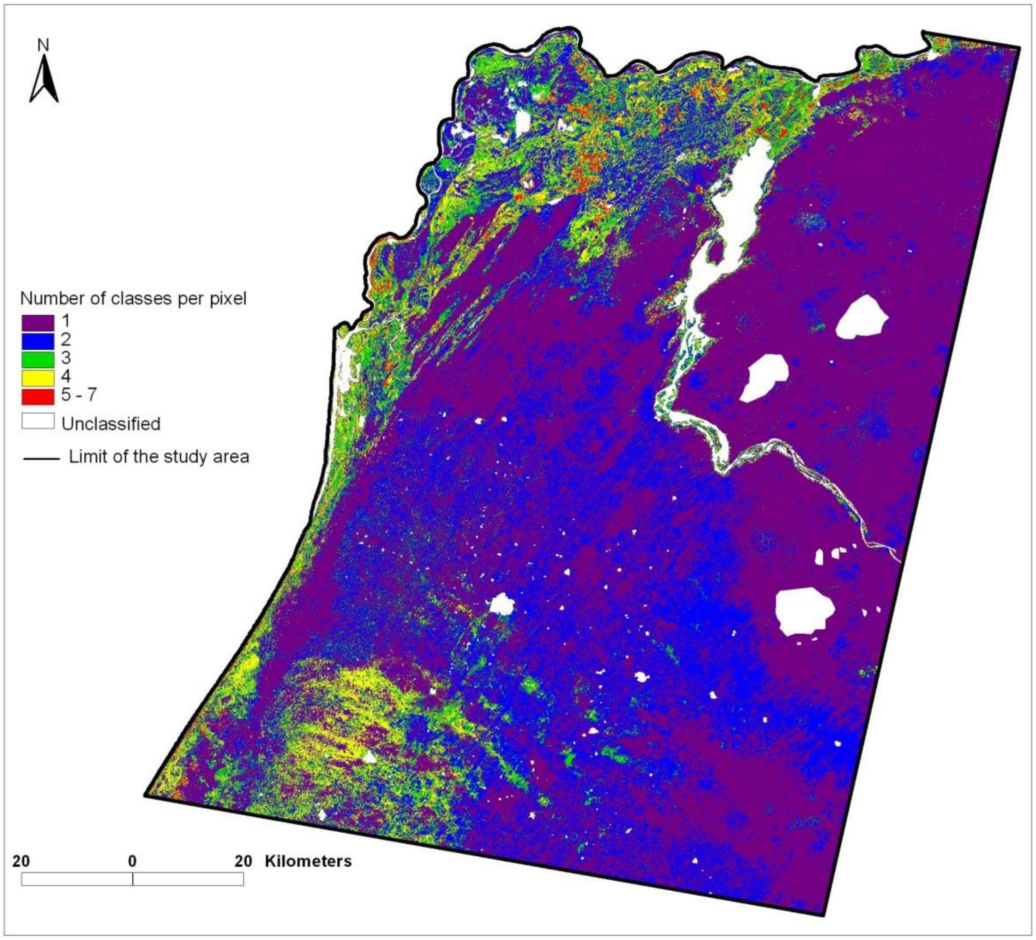

Figure 2 The "reliability" of the hard decision tree classification results shown in Figure 1. For each pixel the number of unique classes (maximum 9) that it could be independently classified as over the 30 decision tree classification runs is shown. Pixels reporting a value of 1 were always classified as one particular LCLU type, whereas pixels reporting values of 5-7 were variously classified into between 5-7 LCLU types. White shows unclassified (water bodies, clouds, cloud shadows, settlement areas, or no Landsat data)

2.7.2 Year 2000 Carbon Assessment and Land Cover Classification Sensitivity Analysis

2.7.2.1. Hard decision tree classification SOC and NPP model results

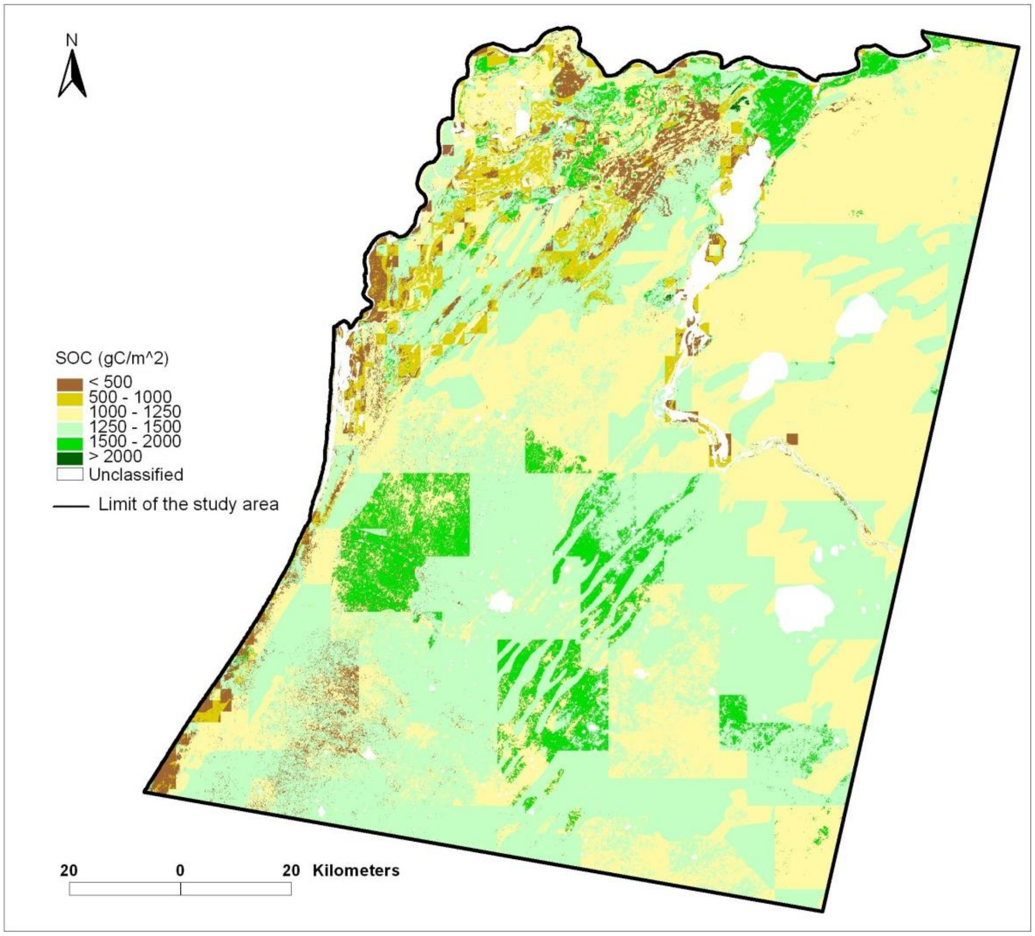

Figure 3 GEMS soil organic carbon (SOC) model output for 2000 using the 9 class 28.5m Landsat hard decision tree classification illustrated in Figure 1 and the corresponding spatially explicit model inputs for the 9 LCLU classes. White shows areas where no SOC was modeled (water bodies, clouds, cloud shadows, settlement areas, or no Landsat data).

Figures 3 and 4 illustrate year 2000 GEMS SOC in the top 0-20 cm soil layer and the above ground NPP respectively. The data were estimated as equation (5) using the 9 LCLU class hard Landsat classification illustrated in Figure 1 and using the corresponding spatially explicit GEMS model inputs for the 9 classes under the no climate change scenario. Some spatial discontinuities are evident and are due to changes in certain GEMS input data, including the soil and climate data that are defined at coarser spatial resolutions than the 28.5m Landsat pixel dimensions.

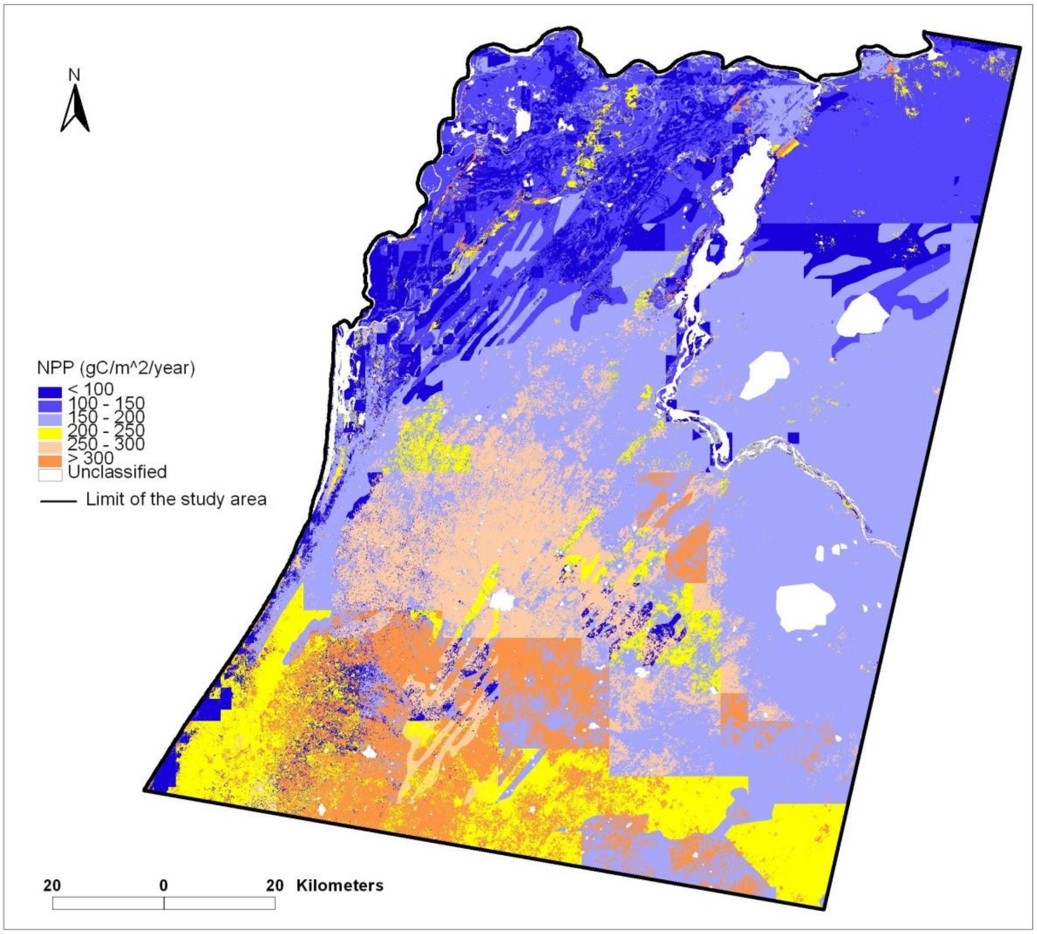

Figure 4 GEMS net primary productivity (NPP) model output for 2000 using the 9 class 28.5m Landsat hard decision tree classification illustrated in Figure 1 and the corresponding spatially explicit model inputs for the 9 LCLU classes. White shows areas where no NPP was modeled (water bodies, clouds, cloud shadows, settlement areas, or no Landsat data).

Table 4 summarizes the mean SOC and NPP for the 9 LCLU classes defined by the hard decision tree classification. The mean class SOC values range from 480.2 gCm^{-2} (Bare soil) to 1487.5gCm^{-2} (Irrigated agriculture) with a mean study area SOC of 1219.3gCm^{-2} or 12.193 $MgCha^{-1}$ which is in general agreement with other worker's Senegalese estimates (Touré, 2002; Manlay et al., 2002; Touré et al., 2003; CSE, 2004). Owing to the spatial differences in GEMS input data, within a given LCLU class, SOC values vary considerably. Thus, for Bare soil, SOC values range from a minimum of 358 to a maximum of 1491 gCm^{-2}; while for Irrigated agriculture they range from 417 to 4138 gCm^{-2}. In general, higher SOC values (Figure 3) occur where NPP is higher (Figure 4). The mean study area NPP is 185.1 gCm^{-2} $year^{-1}$, which is in agreement with the results of Parton et al. (2004) who estimated NPP values up to 200 gCm^{-2} $year^{-1}$ in this region using the CENTURY model and coarser 10km resolution input data. Similar differences of NPP values are also noted within LCLU classes.

Table 4 Comparison of the minimum, mean and maximum SOC (Figure 3) and NPP (Figure 4) simulated for the 9 LCLU classes using the year 2000 hard classification (Figure 1). Only pixels where SOC and NPP was modeled are considered (i.e., not water bodies, clouds, cloud shadows, settlement areas, or where there was no Landsat data).

LCLU class	**SOC (gC/m^2)**			**NPP ($gC/m^2/year$)**		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**
Plantation forest	452	1190.32	1525	0	162.55	756
Bare soil	358	480.22	1491	0	11.28	118
Rainfed agriculture	518	1441.5	2655	14	295.39	596
Wetlands	262	1094.6	2088	8	113.93	258
Mangrove	455	1010.11	1573	8	170.09	412
Mud flats	353	537.63	1537	0	45.36	149
Irrigated agriculture	417	1487.47	4138	0	200.99	720
Savanna	411	1212.44	1543	0	159.98	243
Over the study area	**262**	**1219.3**	**4138**	**0**	**185.1**	**756**

Table 5 summarizes the LCLU class minimum, mean and maximum SOC defined by the hard classification, and LCLU class percentage area, for each agro-ecological zone (Fig. 1). Comparison with the corresponding Table 4 study area LCLU class SOC statistics reinforces that geographic differences in the GEMS input data introduce SOC variability for any given LCLU class. For example, the savanna grassland class is highly prevalent in all four zones (varying from 41% to 87%), and although the mean savanna SOC for the entire study area is 1212 gCm^{-2} (Table 4) the zonal mean savanna SOC varies from 1127 gCm^{-2} (Senegal River Valley) to 1259 gCm^{-2} (Peanut Basin) (Table 5). The agro-ecological zone with the highest mean SOC is the Peanut basin (1344 gCm^{-2}), followed by the Sandy Ferlo (1214 gCm^{-2}), Niayes (1124 g C/m^2) and the lowest is the Senegal River Valley (1046 gCm^{-2}). This pattern reflects the SOC of the predominant LCLU classes. For example, the Peanut basin is predominantly rainfed agriculture (57%) and savanna (41%) which have high mean study area SOC (Table 4) and the Senegal River Valley zone includes the greatest proportion of mud flats (22%) which has nearly the lowest mean study area SOC (Table 4).

2.7.2.2. Soft decision tree classification SOC results

There is insufficient space to illustrate the GEMS SOC derived as equation (6) for each of the 30 soft decision tree classifications for the year 2000. The mean of the 30 soft decision tree SOC estimates has a similar spatial pattern as the hard decision tree SOC illustrated in Figure 3. Table 6 tabulates summary statistics of the 30 soft decision tree SOC estimates. Over the study area the mean SOC is 1217.4 gCm-2 and is very similar to the 1219.3 gCm-2 value estimated using the hard classification SOC (Table 4).

Table 5 Comparison by agro-ecological zone of the minimum, mean and maximum SOC (gC/m^2) (Fig. 3) for the 9 LCLU classes using the year 2000 hard classification (Fig. 1). The LCUC percentage area in each zone is shown in parentheses. Only pixels where SOC was modeled are considered (i.e., not water bodies, clouds, cloud shadows, settlement areas, or where there was no Landsat data).

	Agro-ecological zones											
	Niayes			**Peanut basin**			**Sandy Ferlo**			**Senegal River Valley**		
LCLU classes	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
Plantation forest	452	948.6 3.4%	1522	1108	1373.0 0.01%	1471	454	1296.1 0.4%	1525	452	1164.3 1.2%	1525
Bare soil	358	534.9 6.1%	1491	358	991.3 0.1%	1487	370	688.0 0.01%	1411	370	654.1 0.2%	1478
Rainfed agriculture	519	1385.8 5.7%	1858	518	1422.3 56.7%	1890	519	1390.2 5.8%	2183	534	1407.2 0.1%	2655
Wetlands	371	948.6 0.9%	1512	379	1075.1 0.02%	1471	353	1040.0 2.4%	2064	262	1106.7 22.8%	2088
Mangrove	455	969.3 0.01%	1474	_	_ 0.0%	_	_	_ 0.0%	_	483	1084.7 0.01%	1573
Mud flats	353	682.5 7.4%	1535	358	944.5 2.2%	1522	353	669.7 2.0%	1537	370	639.8 21.7%	1537
Irrigated agriculture	417	1174.6 3.0%	1830	576	1328.2 0.03%	1590	417	1507.7 2.7%	4138	417	1356.8 12.7%	2390
Savanna	411	1205.3 73.6%	1538	416	1258.6 41.0%	1541	411	1210.6 86.7%	1543	411	1127.2 41.4%	**1543**
Over the study area	353	1124.5	1858	358	1344.3	1890	353	1214.3	4138	262	1046.1	2655

For each class there is considerable variation between the minimum and maximum mean SOC statistics. For example, the irrigated agriculture class has mean SOC varying the most of all the classes from a minimum mean SOC of 457.9 gCm^{-2} to a maximum mean SOC of 4138.0 gCm^{-2}. This is explained in Section 7.2.3. The class mean SOC values in Table 6 are similar to the hard SOC classification equivalents tabulated in Table 4. For all classes the difference in the mean SOC between the 30 soft and the hard classification SOC results is less than 4%, except for mud flats (31%), bare soil (22%) and irrigated agriculture (8%), which were the most inconsistently classified over the 30 soft classification trees (Figure 2).

Table 6 Summary statistics of the mean of the 30 soft decision tree SOC estimates for year 2000. The statistics are summarized with respect to the 9 LCLU classes defined by the hard decision tree classification (Figure 1). The mean study area mean SOC is 1217.4 gC/m^2. Only pixels where SOC was modeled are considered (i.e., not water bodies, clouds, cloud shadows, settlement areas, or where there was no Landsat data).

LCLU class	Minimum Mean SOC (gC/m^2)	Mean Mean SOC (gC/m^2)	Maximum Mean SOC (gC/m^2)
Plantation forest	445.0	1203.26	1785.57
Bare soil	374.0	588.83	1491.0
Rainfed agriculture	474.6	1411.63	2655.0
Wetlands	150.0	1099.39	2278.73
Mangrove	439.0	979.5	1588.97
Mud flats	365.0	706.47	2207.17
Irrigated agriculture	457.93	1366.51	4138.0
Savanna	412.0	1211.9	2714.0
Over the study area	**150.0**	**1217.4**	**4138.0**

2.7.2.3 SOC Sensitivity to Land Cover Classification

The SOC derived from the hard classification (Figure 3) for a given LCLU class varies spatially due to spatial variation in the GEMS model inputs (soil, climate, land management, etc.). The SOC also varies between the 30 SOC soft decision tree classification estimates due to differences both in the LCLU classifications and to spatial differences in the GEMS model inputs. The 30 soft LCLU classifications are different because of differences in the training data sampling which causes differences in the LCLU class membership probabilities for each soft decision tree classification. For these reasons the sensitivity of the GEMS SOC model is dependent not only on the LCLU classification errors and the degree of generalization of the landscape into the LCLU classes, but also on where the classes occur relative to the other GEMS model inputs.

To examine this sensitivity in more detail, Figure 5 shows a map of the coefficient of variation (the standard deviation divided by the mean) of the 30 SOC soft decision tree classification estimates. The coefficient of variation, instead of the standard deviation, is used as it enables meaningful comparison between pixels that have markedly different mean SOC values. The SOC coefficient of variation varies from less than 0.15, for the majority of the study area, to more than 0.60. The highest SOC coefficient of variation values occur for the less accurately classified classes described in Section 7.1 and summarized in Table 3, i.e., for the bare soil, mud flats, wetland and rainfed agriculture classes situated along the coast and in the northwest. In addition, higher SOC coefficient of variation values occur in the peanut basin agricultural expansion zone in the south west where the hard classification “reliability” results illustrated in Figure 2 shows several classes per pixel. This is most likely because abandoned rainfed agricultural fields in this region are used for intermittent grazing and can physically resemble other LCLU classes such as savanna grassland (Tappan et al., 2004).

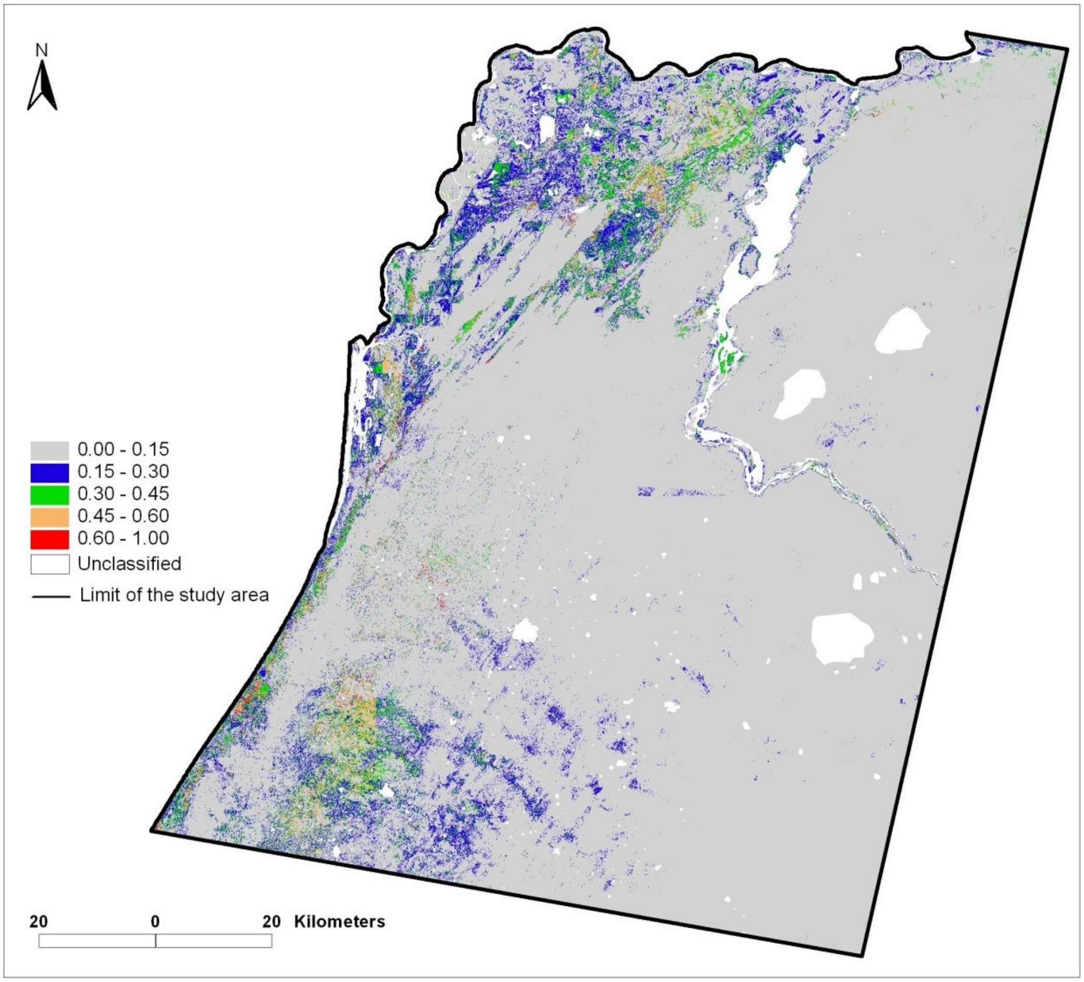

Figure 5 The soil organic carbon (SOC) coefficient derived from the 30 soft decision tree classification model runs. The coefficient of variation (standard deviation divided by mean) is dimensionless. The 2000 Landsat data were classified 30 times into one of more the 9 LCLU classes and the SOC modeled for the corresponding spatially explicit model inputs for those classes. White shows areas where no SOC was modeled (water bodies, clouds, cloud shadows, settlement areas, or no Landsat data).

Figure 6 shows histograms of the SOC coefficient of variation values for each land cover land use class defined by the hard decision tree classification (Figure 1). The less accurately classified classes, i.e., bare soil, mud flats, wetland and rainfed agriculture, have more widely distributed SOC coefficient of variation values with more than 20% of their pixels with SOC coefficient of variation values greater than 0.1. The results shown in Figures 5 and 6 illustrate that satellite classification uncertainties impact the GEMS model results not insignificantly. Similar SOC coefficient of variation histograms were observed for the SOC modeled under the low and high climate change scenarios.

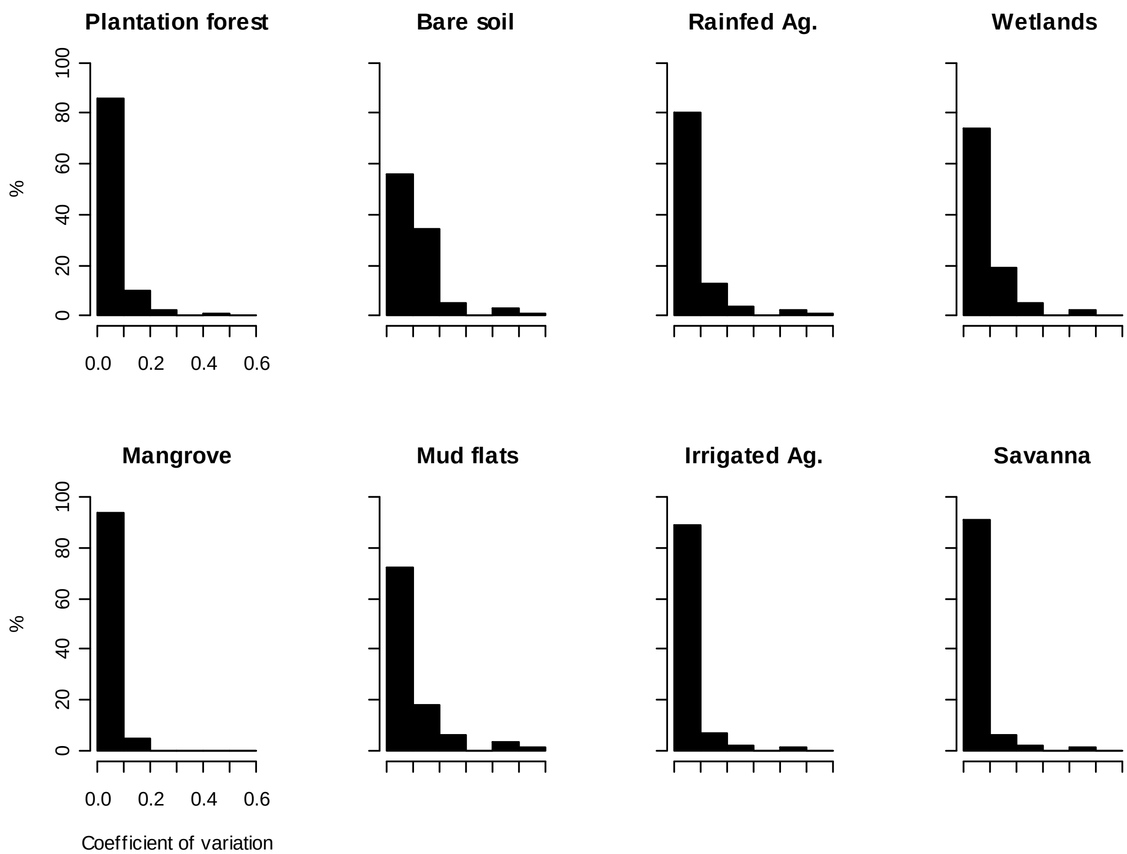

Figure 6 Histograms of the year 2000 SOC coefficient of variation (Figure 5) for each land cover land use class defined by the hard classification (Figure 1).

2.7.3 1900 to 2052 Carbon Assessment and Land Cover Sensitivity Analysis under Different Climate Change Scenarios

Figure 7 shows the mean SOC averaged over all the classified pixels in the study area for the no climate change scenario plotted every 4 years from 1900 to 2052. The open circles show the mean SOC from simulation using the 30 independent decision tree soft classifications; the orange filled circles show the mean of the 30 simulations. The green filled circles show the mean SOC derived from the hard decision tree classification carbon assignment approach. It is evident that from 1900 to 2000 the SOC is generally decreasing, by about 32% from approximately 1800 gCm^{-2} to approximately 1220 gCm^{-2}, this is due to human land cover land use, with some perturbations in this trend due to the growth and decay of the modelled vegetation.

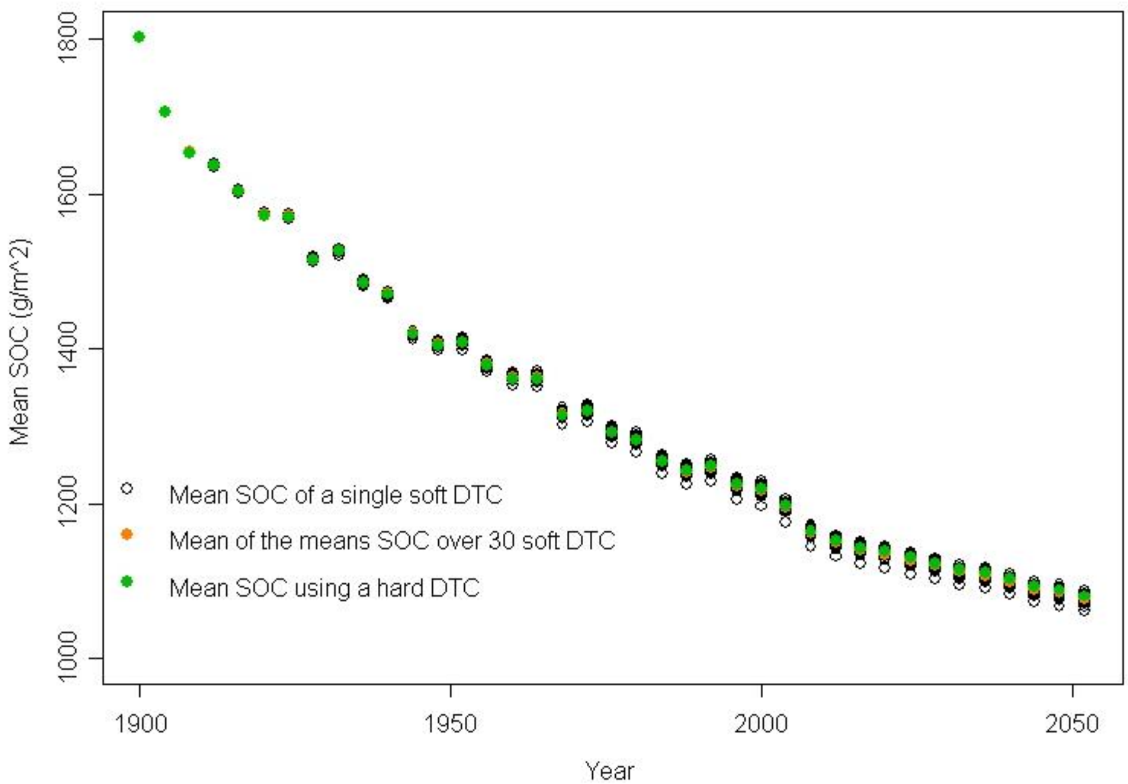

Figure 7 Mean GEMS modeled soil organic carbon (SOC) computed for the entire study area under the *no climate change scenario*, from 1900 to 2052 at 4 yearly intervals, using the 9 land cover land uses classes and different Landsat classification approaches. The open circles show the mean SOC for each of the 30 independent bagged decision trees computed using the soft classification-carbon assignment approach; the orange filled circles show the mean across 30 soft classification simulations; the green filled circles show the mean SOC derived simulations using the hard decision tree classification.

Figures 8 a-c show the mean SOC computed over all the classified pixels in the study area fo r the no, low, and high climate change scenarios plotted from 2000 to 2052. The SOC is estimated to decline from 2000 to 2052 under all climate change scenarios by approximately 11%, 14%, and 24%, for the no (Figure 8a), low (Figure 8b), and high (Figure 8c) climate change scenarios respectively. This trend has been observed elsewhere in West African drylands when temperature increases and precipitation decreases (Tan et al., 2009; Liu et al., 2004; Touré, 2002; Batjes, 2001). Summary statistics of the mean study area SOC results illustrated in these figures are tabulated in Table 7. These results reflect the spatial variability and uncertainty imposed by the different 2000 Landsat classifications and the spatio-temporal sensitivity of the GEMS model to that variability.

For all three climate scenarios, and for each simulation year, the mean study area SOC obtained running GEMS with the hard decision tree classification (green filled circles), is similar (within 4 gCm^{-2}) to the means of the 30 soft decision tree classification model results (orange filled circles) (Figures 7 and 8). This is not unexpected as the hard decision tree classification is generated by applying a voting procedure to the 30 soft classification trees and demonstrates that the hard decision tree classification approach does provide a representative single mean study area SOC estimate.

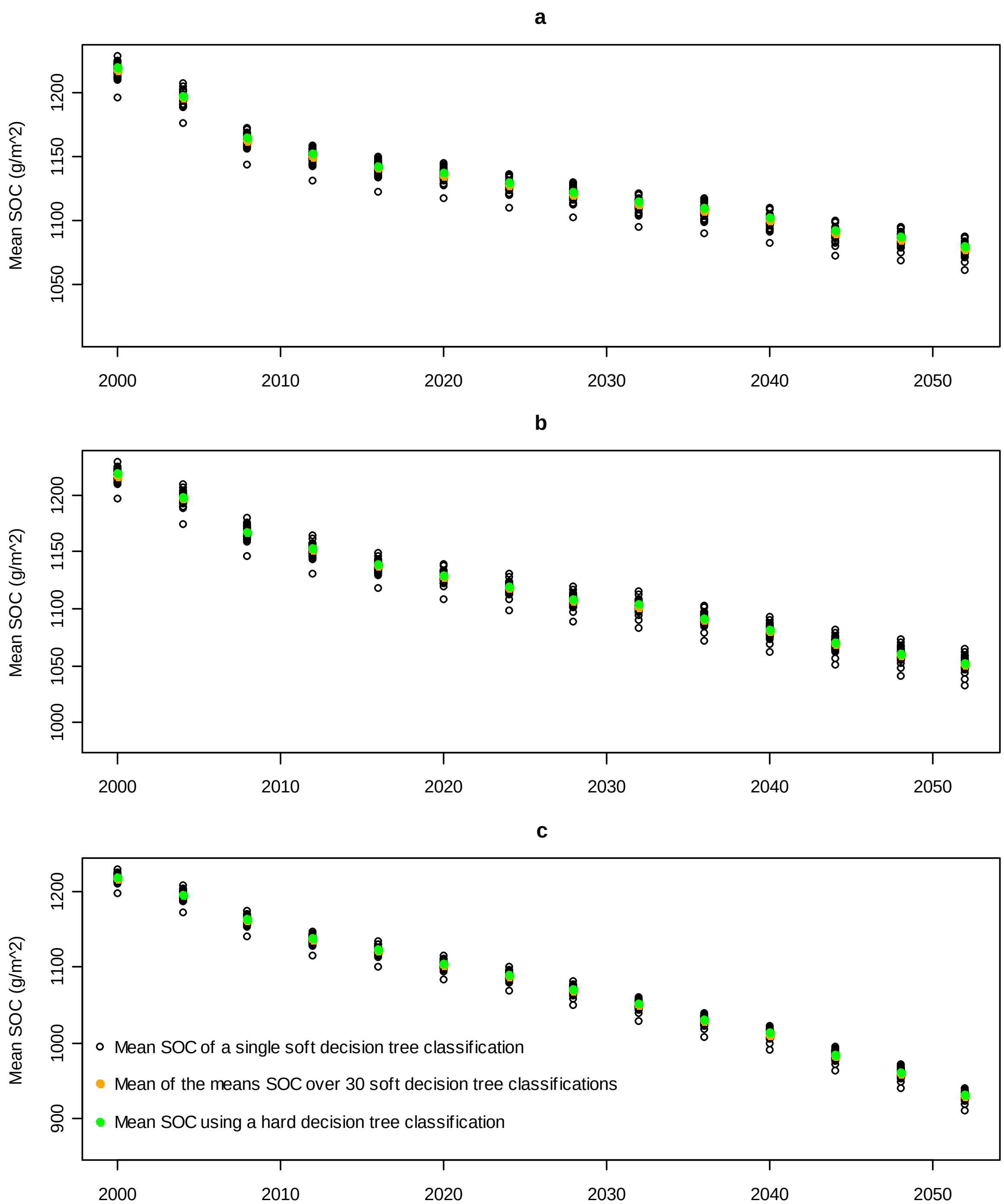

Figure 8 Mean GEMS modeled soil organic carbon (SOC) computed for all the study area for the period 2000 to 2052, under the a) *no*, b) *low*, and c) *high* climate change scenarios. See Figure 7 caption for details

Table 7 Summary statistics of the mean study area hard and soft decision tree (DT) soil organic carbon (SOC) (gC/m^2) model estimates illustrated in Figures 7 and 8, for the *no*, *low* and *high* climate change scenarios, for selected years

	Carbon dynamics 1900-2000			No climate change scenario		Low climate change scenario		High climate change scenario	
	1900	**1940**	**2000**	**2020**	**2052**	**2020**	**2052**	**2020**	**2052**
Hard DT SOC	1803.3	1470.6	1219.3	1138	1080.7	1129.3	1052.6	1104.8	931.5
Mean of 30 soft DT SOC estimates	1803.3	1471.1	1217.4	1135.4	1077.7	1128	1051.3	1103.2	929.7
Minimum of 30 soft DT SOC estimates	1803.2	1465.3	1196.6	1117.5	1061.2	1108.8	1032.8	1083.4	911.3
Maximum of 30 soft DT SOC estimates	1803.3	1474.2	1228.8	1145.1	1087.8	1139.8	1064.2	1114.6	941.2
Range of 30 soft DT SOC estimates and percent of mean (%)	0.1 (0.00)	8.9 (0.60)	32.2 (2.64)	27.6 (2.42)	26.6 (2.48)	31.0 (2.76)	31.4 (2.99)	31.2 (2.83)	29.9 (3.22)

The mean study area SOC for individual soft classifications varies for each simulation due to their different training data sampling which causes differences in the LCLU class membership probabilities *and* due to spatial differences in the GEMS model inputs as discussed in Section 7.2.3. In 2000, for the no climate change scenario, the mean study area SOC values vary over the 30 soft decision tree classifications from 1196.6 to 1228.8 gCm^{-2} (Figure 8a, Table 7). This 32.2 gCm^{-2} SOC range corresponds to a variation of 2.6% of the mean study area hard decision tree classification SOC. This variation decreases in time to 26.7 gCm^{-2} in 2052, equivalent to 2.5% of the mean study area hard classification SOC, and similarly it decreases to 31.4 gCm^{-2} (3%) and 29.9 gCm^{-2} (3.2%) for the low (Figure 8b, Table 7) and high (Figure 8c, Table 7) climate change scenarios. These results imply that using a state of the practice hard decision tree classification approach with a 9 class LCLU classification scheme imposes a variability of a maximum of 3.2% of the mean study area SOC.

2.8 Conclusion

Research has attested to the significance of land cover and land use (LCLU) change on carbon dynamics (Scholes and Hall, 1996; Houghton et al., 1999; Lal, 2004; Tieszen, 2004) and on the utility of biogeochemical models to simulate soil and carbon biomass under different land management (Metherell et al., 1993; Batjes, 2001; Liu et al., 2004; Tschakert et al., 2004). However, differences between LCLU data sources and classification approaches, and errors in the LCLU data both in terms of classification errors and the degree of generalization of the landscape into the LCLU classes, may influence model outputs. Despite this, relatively few studies have examined this issue. In this study, state of the practice bagged decision tree approaches for LCLU classification of dry and wet season Landsat satellite data were used to assess the sensitivity of SOC estimated using the spatially explicit Global Ensemble Biogeochemical Modeling System (GEMS) under different climate scenarios. The approach could be utilized by other biogeochemical models that use spatially explicit LCLU parameterizations. This study was undertaken in northern Senegal, where satellite LCLU classification is particularly challenging because of the semi-arid landscape, and where the coupling between future LCLU and climate change is poorly understood.

This research provides a new method to estimate the variability of SOC due to satellite LCLU classification errors. The single hard decision tree Landsat classification results, generated by applying a voting procedure to the 30 soft decision tree results, typically provided mean study area SOC values within about 4 gCm^{-2} of the mean of the 30 soft decision tree classification results. This is not unexpected, and demonstrates that hard decision tree classification provides an appropriate approach to define a single classification appropriate for GEMS modeling. The 30 SOC maps estimated independently using the 30 different soft classifications provide data that were used to quantify the variability of SOC imposed by satellite classification errors.

At the study area scale, considering the mean study area SOC, the variability of SOC imposed by satellite classification errors was not high. In 2000 the mean study area SOC values varied over the 30 soft decision tree classifications by 32.2 gCm^{-2} and corresponded to 2.6% of the mean study area hard decision tree classification SOC. In 2052 this relative SOC variation was 2.5%, 3% and 3.2% for the no, low and high climate change scenarios respectively. These variations are much less than the corresponding 11%, 14% and 24% declines from 2000 to 2053 in mean study area SOC modeled for the no, low and high climate change scenarios respectively.

At local, pixel, scale the impacts of satellite classification errors can be very apparent. The per-pixel coefficient of variation (the standard deviation divided by the mean) of the 30 SOC soft decision tree estimates was used to quantify the pixel-level spatial variability of SOC imposed by satellite classification errors. The highest coefficient of variations occurred for the least accurately classified classes and were not negligible. In this study, more than 20% of the bare soil, mud flat, wetland and rainfed agriculture pixels had SOC coefficient of variation values greater than 0.1 with some as great as nearly 0.6. These high local-scale SOC variations are due to differences in the satellite classification training data sampling, which causes differences in the mapped LCLU class membership probabilities, and due to the interaction of these differences with spatial differences in the other GEMS model inputs.

The findings of this study indicate that the high local variability of SOC due to satellite classification errors should be taken into consideration, for example, using the method described here. This is particularly important as local-scale SOC variations imposed by satellite classification errors may obscure modeled temporal changes in SOC due to climate influences that may be highly land cover specific. There are a number of recent and planned spaceborne sensors with very high (<10m) spatial resolution (Norris, 2011) and in conjunction with next generation freely available Landsat and similar high spatial resolution systems designed for land cover monitoring (Wulder et al., 2008, 2011) they provide opportunities for high resolution LCLU biogeochemical model parameterization and LCLU mapping uncertainty assessment.

This research has demonstrated a method to estimate the variability of GEMS modeled SOC due to satellite classification errors. The method can be applied to other biogeochemical models that use spatially explicit land cover land use (LCLU) parameterizations by running the model with a single hard and multiple soft LCLU classification inputs to infer model sensitivity. The Senegalese findings described in this paper can only be generalized to other process based models by repeating the described method with the new model. This is because of the non-linear dependency of the GEMS SOC estimates on LCLU and because, as we have demonstrated for specific LCLU classes at the study area scale and for four agro-ecological zones, the SOC uncertainty due to satellite classification errors is dependent not only on the LCLU classification errors but also on where the LCLU classes occur relative to the other biogeochemical model inputs.

As the goal of this study was to examine the sensitivity of GEMS modeled SOC to land cover land use (LCLU) classification uncertainties, the impacts of errors associated with the other GEMS spatially explicit input data and model parameterizations were not considered explicitly. The best available data sets and parameterizations were used. However, the degree to which all input data and model parameterization errors are captured by the GEMS simulations and by the LCLU bagged decision tree classification approach requires further research.

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CHAPTER 3

A STUDY OF RURAL SENEGALESE ATTITUDES AND PERCEPTIONS OF THEIR BEHAVIOR TO CHANGES IN THE CLIMATE

Dièye, A.M. and Roy, D.P. (2013). *Environmental Management,50*, 5, 929-941

3.0 Abstract

Semi-structured focus group discussions were employed to capture rural Senegalese attitudes and perceptions of their behavior to changes in the climate and their land use and livelihood strategies. Seven focus groups stratified by gender, ethnicity (Wolof and Peulh) and dominant production system (cultivators and pastoralists) in five villages in semi-arid northern Senegal revealed seven main themes. Rural livelihoods remain predominantly based on rainfall dependent practices, and although cultivators and pastoralists had a clear appreciation of changes in natural resources compared to a perceived more favorable past, few adaptive coping strategies beyond established ones were advocated. The seven themes are discussed in detail and their implications for rural livelihoods under future long term climate predictions discussed with the implications of this study for the development of scenarios of future land cover land use.

3.1 Introduction

The goal of this research is to capture rural Senegalese attitudes and perceptions of their behavior to climate change to enable the development of scenarios of future land cover land use (LCLU). The study was undertaken in five villages in the semi-arid North of Senegal in the Sahelian zone which experiences a high degree of spatial and temporal variability in precipitation and where rainfall is particularly an issue for arable and pastoral land uses. The Sahel was the cradle of the desertification debate, and desertification, land degradation and LCLU change are due not only to climatic factors but are influenced by human activities (Geist and Lambin 2004; Herrman and Hutchinson 2005; Nicholson 2005; Reynolds et al., 2011). Satellite data have been used to classify land cover and land use (LCLU) in this region (Hiernaux and Justice 1984; Frederiksen and Lawesson 1992; Dièye et al., 2012) but prediction of future LCLU from such data is challenging, not least because statistical contemporary LCLU change trend data may not capture future changes in LCLU driving forces, such as climatic, socioeconomic, technological, and policy related drivers acting at varying scales (Moss et al., 2010). The coupling between human LCLU induced changes and a changing climate is poorly understood, and currently there is no integrated regional scale coupled climate-human LCLU change model that has sufficient resolution to be meaningfully parameterized using satellite products (Barnes et al. 2012). Scenarios of future LCLU have been advocated to study alternative futures under different sets of assumptions given current understanding of the way that the drivers of LCLU interact (Strengers et al., 2004; Moss et al., 2010; Sleeter et al., 2012). Scenarios provide ‘‘descriptions of how the future may unfold based on ‘if-then’ propositions’’ (Alcamo et al., 2008). Plausible scenarios necessarily should capture inhabitant’s perspectives on their livelihood strategies. A number of studies have been undertaken on rural adaptation to climate change in West

Africa, including studies of inhabitant's perceptions and behavior, and have revealed that climate is only one of many factors influencing local adaptation strategies (Nielsen and Reenberg 2010; Mertz et al., 2010; Brown 2006; Tschakert 2007; Mbow et al., 2008). This study aims to capture rural inhabitant's attitudes and perceptions of their behavior to climate change to provide insights into how they may change their livelihood and land use strategies, and so the regional LCLU, given future regional climate predictions that suggest a warmer future with likely less available water (Hulme et al., 2001, Boko et al., 2007; Diallo et al., 2012).

Qualitative semi-structured focus group discussions were employed to capture inhabitant's perceptions in five villages. The villages, their environment and the past, current and likely future temperature and rainfall are described, followed by a description of the composition and structure of the focus groups. The results are organized according to seven main themes that emerged from the discussions. Concluding remarks are provided with a discussion of the focus group approach, the seven themes, and the implications of the study findings for rural livelihoods under future long term climate predictions and for the development of scenarios of future land cover land use.

3.2 Study Area and Five Focus Group Villages

Five villages, in the semi-arid North of Senegal were considered (Figure 1). The vegetation is predominantly open grasslands with scattered shrubs and trees. The villages encompass an approximate North West to South East rainfall gradient (annually 400-500 mm, Figure 1) with a single rainy season that lasts about four months and a seven to eight month dry season (Fall et al., 2006). Sufficient and timely rainfall is particularly an issue for arable and pastoral land uses in this area (Ecossen 1997; CSE 2002; Hulme 2003;

Tschakert et al., 2004). Since the 1960s, regional rainfall has been erratic and droughts are common (Ecossen 1997; Hulme et al., 2001; Tottrup and Rasmussen 2004). Figure 2 shows mean annual precipitation and temperature weather station records from 1950 collected at the nearby Saint-Louis and Louga meteorological stations. The inter-annual variability in these data is quite apparent. In recent decades there is thought to be an overall decreasing and increasing trend in precipitation and temperature respectively with 1951-1969 and 1970-1984 often considered as ‘wet’ and ‘dry’ periods, although since 1985 rainfall may be increasing again (Sene and Ozer 2002; Nicholson 2005). At the Louga weather station average decadal mean temperatures indicate an increasing trend from 1961-1970 (27.3 °C), 1971-1980 (27.6 °C), 1981-1990 (27.9 °C) to 1991-2000 (27.7 °C) (CSE 2002). There is speculation of a regional shift to a wetter climate, although whether recent observations imply a climatic shift that will continue throughout the coming decades is unknown (Brooks 2004; Boko et al., 2007; Lebel and Ali 2009). More certainly the region is expected to become warmer and with less available water due to enhanced evapotranspiration (Hulme et al., 2001; Hulme 2003; Boko et al., 2007; Diallo 2012; Blanc 2012).

The five villages are in the administrative regions of Louga and Saint-Louis, with 36% and 41% of households living under the poverty line (Senegal's PRSP 2006). The villages have no metaled roads, usually there are one to three cement buildings that are used for community activities including a mosque, and the houses are thatched buildings.

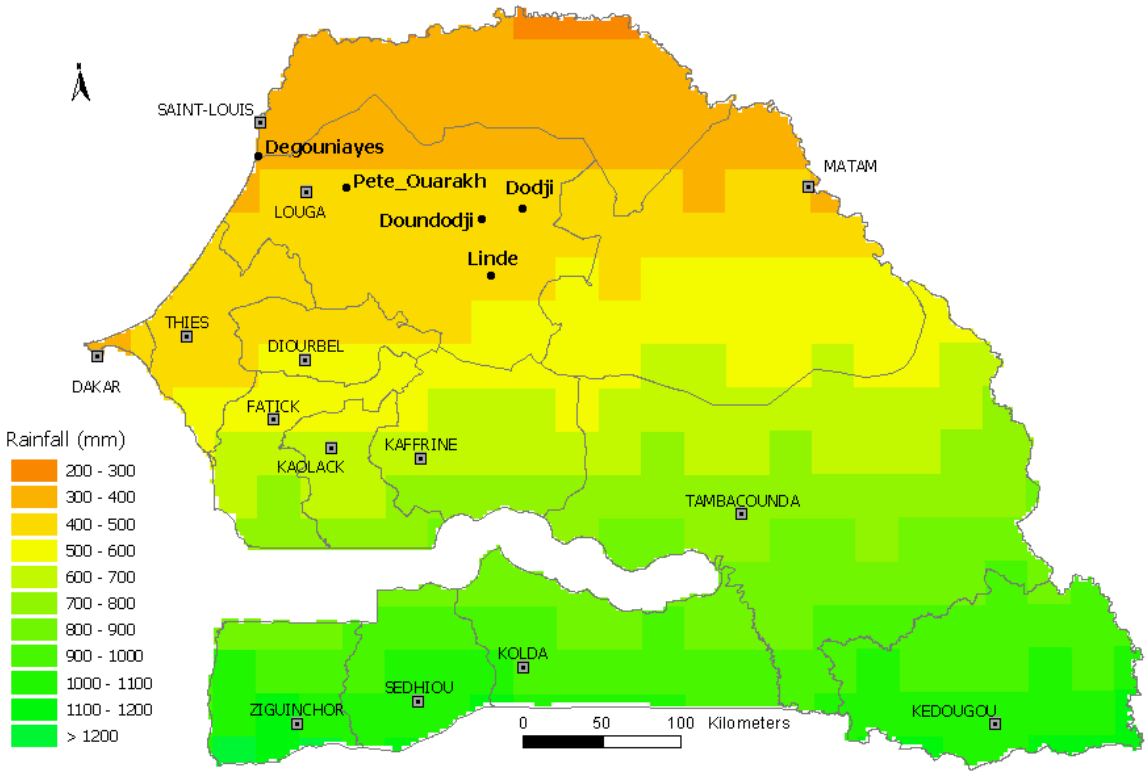
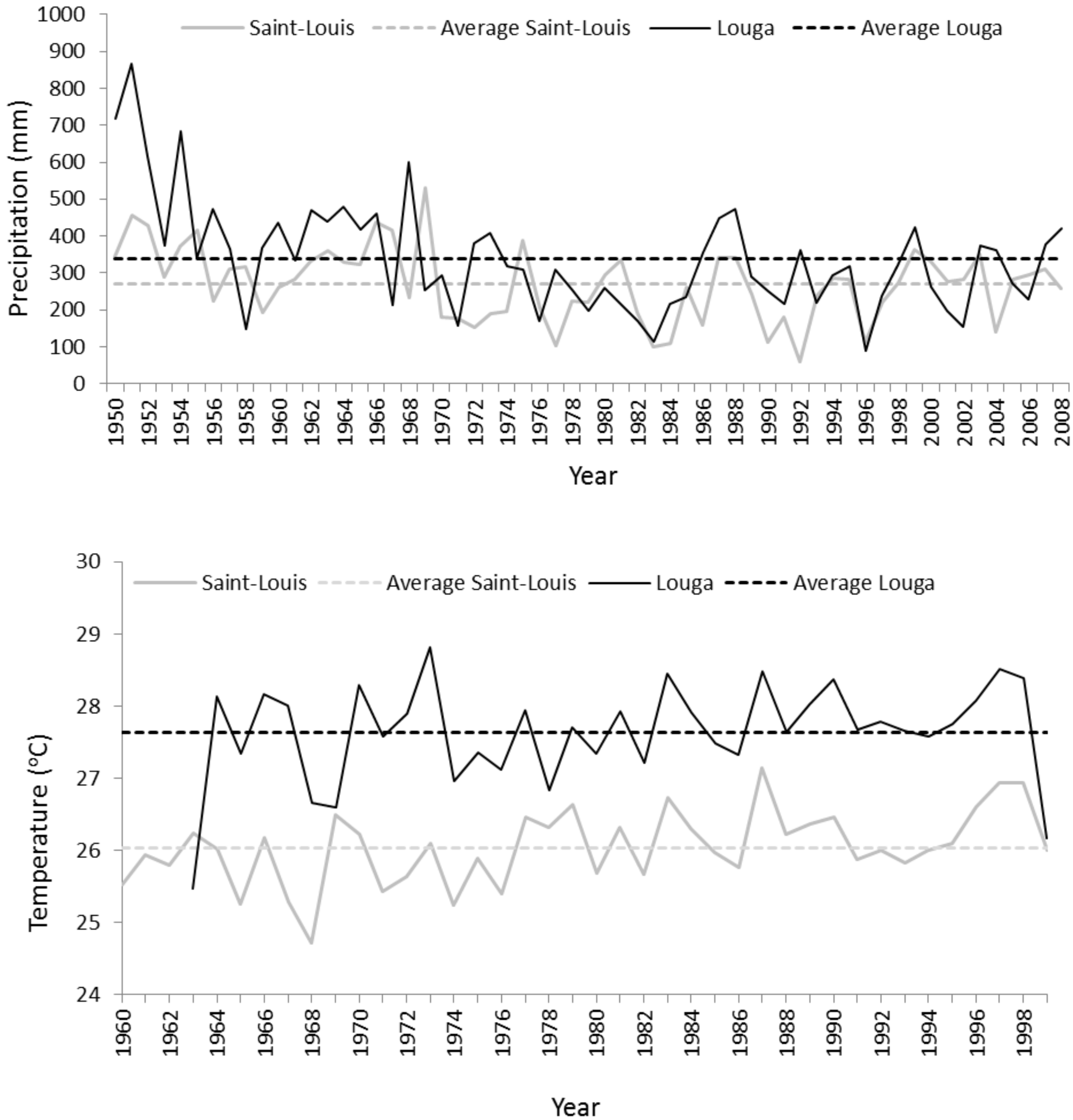


Figure 1. Location of the seven focus group sessions, in five villages (black dots), in the North of Senegal. Shown in the background is the mean 1998-2007 TRMM satellite estimated annual rainfall (mm), Senegalese administrative (Régions) boundaries are shown by grey lines and the major cities by grey squares

.

With the exception of Dodji, all the villages have electrical supply but only Pete Ouarakh has street lighting. The majority of the villages are Muslim and most families are polygamous, with the father having typically one to two wives, and about six to ten children. The village communities are ethnically Wolof (four villages) and Peulh (one village) with livelihoods typically based on irrigated or rain-fed agriculture, and pastoralism respectively (Marty 1993; Turner 2004).

Figure 2 Annual precipitation (top) and temperature (bottom) for Louga and Saint-Louis weather stations (Figure 1 shows Louga and Saint-Louis town locations), data from the Senegalese Meteorological Agency.



Nowadays, most Peulhs have a permanent village base and herds are moved only long distances if there are no local water resources and forage available (Adriansen, 2006, 2008; Moritz, 2009). In all villages the men and boys are responsible for cultivating the fields. The women typically cultivate their own small fields or gardens where they grow food to supplement what the men grow and to make the food more interesting. Both men and women are responsible for livestock, although in the pastoralist village of Dodji only the men are responsible for the cattle herds.

Dodji (240 inhabitants) is a Peulh village with a transhumant pastoralist tradition. The main animals kept are zebu cattle (*Bos primigenius indicus*), goats and sheep. During the rainy season, the livestock feed on the surrounding natural grassland and drink water from ephemeral ponds and a single village borehole. After the rainy season, when the ephemeral ponds start to dry out and the grasses decline, nearly half the village population (including whole families) travel with the majority of the village cattle and sheep, typically southwards to the more humid Sudanian zone, where the herds graze crop residues and fallow lands and have more easy access to perennial water resources. Hired herders from the village and elsewhere are also employed. Rain-fed agriculture is also practiced, with the main crops being millet (*Pennisetum typhoides*), groundnuts (*Arachis hypogaea*), sorghum (*Sorghum bicolor*), and cowpeas (*Vigna unguiculata*). The crops are stored for eating throughout the year. Some of the women also grow vegetables in gardens for household consumption using water from the village borehole, although this is limited owing to the cost of the water extraction.

Degouniayes is a Wolof community, of approximately 390 inhabitants, located on the Atlantic coast on the embouchure of the Senegal River. The villagers practice irrigated agriculture, with diesel pumps extracting water from artisanal wells, supplemented by some rain-fed agriculture. The agriculture is focused on market gardening, primarily of vegetables that are grown in all seasons and sold in the Senegalese capital Dakar (250 km to the South) or in Saint Louis (20 km to the North). This agriculture faces several constraints including a progressive salinity of the water table and nitrate pollution of the groundwater (Degeorges and Reilly 2006). The inhabitants of Degouniayes supplement their agricultural income by fishing in the Senegal River and in the Atlantic Ocean. Most of them rely on fish to supplement their protein intake and to make a living.

Pete Ouarakh (730 inhabitants), Doundodji (420 inhabitants), and Linde (500 inhabitants) are Wolof communities that are 60 to 180 km inland and rely primarily on rain-fed agriculture. Most rain-fed agricultural activities are undertaken during the rainy season, planting occurs in June followed by harvesting in late October through November. The main crops planted are millet (*Pennisetum typhoides*), groundnuts (*Arachis hypogaea*), sorghum (*Sorghum bicolor*), and cowpeas (*Vigna unguiculata*). Groundnuts are the most important cash crop, sold in regional weekly markets (*loumas*) and also to the government at fixed typically lower prices but with the guarantee then of receiving government seeds. Most households keep livestock, especially sheep and goats. Horses and donkeys are used for animal traction when they can be afforded.

3.3 Focus Groups

The focus group is an established qualitative interview technique designed to promote interaction between members of a group, in order to stimulate deeper discussion, reduce social and cultural constraints on participation, and reveal new facets of the discussion topics (Corbetta 2003). Focus groups involve discussion among a small number of participants, following a semi-structured format set by a moderator whose role is to promote discussion (Krueger 1994). The moderator poses open-ended discussion topics, clarifies participant's statements, and initiates new discussion when necessary. Of particular relevance to this study is their use to assess information on attitudes and perceptions of behavior toward phenomena (Miller and Dingwall 1997; Corbetta 2003). An advantage of focus groups is that the interaction of participants stimulates their thinking as well as an exchange of attitudes that may not emerge during direct questioning (interviews or questionnaires), and can reduce biases that may otherwise be introduced by social and cultural differences between the interviewer and the participants, and by the interviewer's preconceptions of the discussion topic (Cabañero-Versoza et al., 1993; Kitzinger and Barbour 1999).

The authors have previously undertaken focus group research with Southern African participants (Trigg and Roy 2007) and Rapid Rural Appraisals in Senegal (Freudenberger et al., 2000). A prototype focus group discussion guide was developed and tested in trial focus groups held in different (not reported in this paper) villages in northern Senegal. This initial testing produced poor focus group discussions, primarily due to cultural and linguistic differences between the Senegalese focus group participants and Dr. Roy who is a white European male who did not speak Senegalese languages. The prototype focus group discussion guide was refined and used in the following year in new focus group discussions with the lead author, a Senegalese citizen, as the focus group moderator speaking Wolof but allowing participant conversations in Pular the other main language spoken in northern Senegal.

A total of seven focus groups were held in the five villages. Each focus group was limited to ten adults (Krueger and Casey 2000), with groups stratified as agriculturalists or pastoralists, by gender and by ethnicity (Table 1). Emphasis was made on trying to have focus group participants that were from different families in the village and with diverse land use practice experiences so they could discuss a diversity of opinions and perspectives. Emphasis was also on inclusion of participants with a similar position in the village hierarchy in order to preclude focus group discussion dominated by a minority of speaker(s); in Senegalese rural society, individuals who hold leadership, customary, religious, or political, positions in the village tend to lead conversations. In Dodji (Peulh, pastoral) and Pete Ouarakh (Wolof, agricultural), separate female and male focus groups were conducted, in the other three villages the focus groups were male. Stratification by gender was undertaken as women are often not involved in key decision-making processes and they are not given voice or they avoid raising their voice in an assembly when men are present (Sheldon 1995; Perrinoa 2007; Badianky 2008).

Table 1 The composition of the seven focus groups, the village locations are shown in Figure 1

Village	**Gender**	**Ethnicity**	**Primary land cover land use practice**
Degouniayes	Men	Wolof	Irrigated Agriculture
Pete Ouarakh	Men	Wolof	Rain-fed Agriculture
Pete Ouarakh	Women	Wolof	Rain-fed Agriculture
Doundodji	Men	Wolof	Rain-fed Agriculture
Dodji	Men	Peulh	Pastoral
Dodji	Women	Peulh	Pastoral
Linde	Men	Wolof	Rain-fed Agriculture

The focus group discussion guide is described in Appendix A. The discussion guide questions were purposefully open ended and selected to solicit discussions to provide insights into how the participants may change their livelihood and land use strategies under future (not discussed) regional climate predictions. Sometimes the moderator would need to raise a non-controversial subject to allow the discussion to continue. Care was taken to ensure that the focus group participants always had opportunities to raise new topics (Krueger and Casey 2000). The focus group discussions lasted approximately 80 minutes and were recorded unobtrusively, but with participant permission, onto digital media. The recordings were subsequently transcribed. Summary notes made by the moderator after each session, were also retained for analysis.

3.4 Results

The transcripts for each focus group were analyzed individually and in concert and the findings were grouped into recurrent themes when the views of the participants coalesced around common opinions (Krueger 1994). Seven broad themes emerged; these are summarized in Table 2 and are discussed below. Where appropriate, example narrative statements are quoted to illustrate the discussion, with the gender and village specified in parenthesis.

3.4.1. Theme 1. There is a perceived decline in the state of the environment and natural resources

All focus groups included discussion of a perceived continuing degradation of the environment. In the Wolof language, the term "*diawji*" may refer either to the environment or to the climate, making it difficult to always distinguish unambiguously between these terms.

Table 2 The main themes that emerged from the seven focus group discussions

	Themes
1	There is a perceived decline in the state of the environment and natural resources.
2	Rainfall is perceived to have decreased and become irregular.
3	Rain-fed arable practices remain based on long-established practices.
4	Arable farming strategies are largely unaffected by the incidence of bad seasons but may be adapted to take advantage of the incidence of good seasons..
5	Pastoral practices are threatened.
6	There are a variety of alternative non-agricultural livelihood strategies but these are predominantly part time and related to informal small scale trading.
7	Government assistance is perceived as insufficient and inappropriate but is desired.

The predominantly Wolof cultivators expressed concerns in particular about declining soil fertility and vegetation, and also attacks of pests, plant diseases and parasitic weeds. The pastoralists expressed concerns primarily about the impacts of this perceived degradation on the quality of grazing and the value of livestock and products, an example narrative statement:

> "In the past, two cows could provide a milk bucket, but now, even a thousand of cows joined together cannot fill a cup with milk. And yet, they [cows] eat grass in sufficient quantity." [Dodji, male pastoralist]

The discussions revealed that perceived changes in the state of the environment and natural resources were perceived as an important challenge to rural livelihoods. This is not a new finding and was observed by other researchers using different survey techniques (Tschakert 2007; Mbow et al., 2008; Mertz et al., 2009).

3.4.2 Theme 2. Rainfall is perceived to have decreased and become irregular

All focus group discussions agreed that rains have decreased in living memory. Widely and uncontroversially, they commented on a perceived decline in the amount, and resulting agricultural efficacy, of the rains. In addition, all focus group discussions participants substantively commented on the irregularity of rainfall; mentioning changes in the onset and offset of the rainy and dry seasons, the duration of these seasons, and the occurrence of intermittent dry spells. Several focus group participants recalled occurrences of unusually dry and wet years, along with excessive off-season rains and floods; for example:

> "What I remember is that from 1966, 1970, until 1975, the drought was very tough." [Degouniayes, male cultivator]

Most of the perceived changes in rainfall, discussed in the focus groups, were substantiated by rain gauge measurements (Figure 2). The correspondence between scientific measurement and focus group recollections is not surprising given that participant agricultural and pastoral practices are reliant on prevailing seasonal weather conditions.

When the causes of the perceived changes in rainfall were discussed, they were not directly attributed to a changing climate, although it was ascribed to other climatic parameters, such as wind in some focus groups, and more typically, either in passing or explicitly, was ascribed to divine domain, for example:

"What a person has the best is hope. However, the *badoola* (poor) farmer, when the season approaches, he thinks of all kinds of crops; later, he will act according to the reality of the season. You program all, without knowing what you will collect. It is God who decides." [Linde, male cultivator]

"With the hot wind of this year, doors are open to believe that the season will be good. But, only God knows." [Dodji, male pastoralist]

From these focus group discussions, it appears that perception of changes and causes of changes is influenced by the participants' religious beliefs and ancestral traditions. Similarly, other studies have found that African farmers ascribe supernatural forces and also lack of respect to ancestral spirits and other customs as causing deleterious change (Bovin 1990, Kalinda 2011).

3.4.3 Theme 3. Rain-fed arable practices remain based on long-established practices

The focus group discussions in the rain-fed agricultural villages revealed a continuity of long-established agricultural practices.

"The crops we plant here are what our parents used to plant." [Pete, male cultivator]

Despite this, the participants expressed great interest in modern cash crops, as a means of revenue generation. However, the crops planted are determined, beside rainfall conditions, by the availability of seeds (discussed under Theme 7).

The rain-fed village focus group participants discussed a variety of indigenous knowledge they use to plan their agricultural activities, including the lunar calendar and the established dates of social/religious events, and by observing changes in the natural environment:

> "A clear sign of the approach of the season is given by the foliation of certain trees. Indeed, with the approach of the season, even before the first rains, certain trees such as *gouye* (baobab tree) or *dakhar* (tamarind) show remarkable clear green leaves." [Pete, male cultivator]

> "Most of our agricultural activities are based upon *werou woloff* (lunar calendar). Usually, when we return from *gamou* (religious event commemorating the birth of the Prophet Muhammad), if all goes well, we know that it is the start of *cooroon* (pre-rainy season) and rain will come soon…we start *roudji* (preparing the fields) and then *farassou* (sowing before rain)". [Pete, male cultivator]

From the discussions, it was apparent that radio weather forecasts were consumed by the rain-fed and also the irrigated agriculture focus group participants. It was unclear from the discussions how forecast information is used and is affecting farming strategies, although the necessity to provide African farmers with weather forecasts has been advocated (Ingram et al., 2002; Roncoli et al., 2006; Tschakert 2007; Roncoli et al., 2010). In summary, the rain-fed agriculture land management practices remain largely based on long-established practices, which has been observed in many other Senegalese rural communities (Brown 2006; Tschakert 2007; Mbow et al., 2008; Mertz et al., 2009, 2010).

3.4.4 Theme 4. Arable farming strategies are largely unaffected by the incidence of bad seasons but may be adapted to take advantage of the incidence of good seasons

The focus groups revealed that most cultivators will not dramatically change their farming strategies when they face bad seasons but rather they will continue to grow the same crops. Some of the recurrent farming adaptive strategies to bad seasons revealed were to concentrate efforts to fewer crops in smaller areas. Growing new varieties of crops, such as shorter cycle or more water tolerant seeds, was also discussed, but generally only envisioned through government support.

All focus groups, including pastoralists, advocated irrigation as the foremost solution to overcome the bad seasons and sustain the agricultural production. Notably, women, more than men, raised irrigated agriculture as an alternative. Some women mentioned pooling their efforts, through community based organizations, in order to irrigate some collective fields and share the benefits.

When they discussed how they will take advantage of the incidence of good seasons, most cultivators, with nostalgia, stated they will continue planting their usual crops while putting more effort and investment into their lands or that they will expand the size and/or number of their fields. Only in one focus group, the irrigated agriculture village, was the option to diversify and/or introduce new crop types explicitly expressed. In summary, arable farming strategies may be adapted to take advantage of the incidence of good seasons but most likely following intensification and/or extensification strategies and habitual practices (Theme 3).

3.4.5 Theme 5. Pastoral practices are threatened

Pastoralism in the Sahelian zone has been studied extensively and despite recurrent droughts and the threat of agricultural enchrochment has been reported as resilient and viable (Juul 2005; Adriansen 2006; Moritz et al., 2009). In the 1950s, many pastoralists became semi-sedentary, limiting their movement around boreholes installed by the French colonial administration and began to combine pastoral practices with rainfed subsistence crop production (Adriansen 2008). Only two pastoralist focus group discussions were held and from only one village (Table 1) and the way that their cattle, goats and sheep and crops were balanced in their livelihood strategies (Sumberg 2003) was not discussed with sufficient clarity to ascertain their actual reliance on livestock. The participant discussions suggest however that pastoral practices are threatened due to perceived concerns with access to water and grazing:

> "You know, that if it does not rain there is no pasture (grass). No rain, no pasture. If it does not rain and that there is no pasture, we pastoralists are desperate; thus, we are obliged to move our [cattle and sheep] herds where we can find grass." [Dodji, female pastoralist]

When the pastoralists discussed how they will take advantage of the incidence of good seasons, they predominantly discussed changes they would make to their non-pastoral activities. The apparent lack of emphasis on taking advantage of good seasons for pastoral activities may reflect that in the study region rain-fed crop cultivation is more sensitive to climate factors than livestock production (Mertz et al., 2011). When the pastoralists discussed bad seasons, the adaptive strategies they raised were to continue performing their agricultural activities and to move their cattle wherever pasture can be found further South, sometimes entrusted to paid herders. The discussions revealed that usually only the cattle are moved long distances and that the sheep and goats are herded and guarded against theft in the vicinity of the village by young men. Interestingly, nearly the majority of the pastoralist focus group attendees were observed to carry cell phones. However, they did not discuss explicitly the use of cell phones, or other technology such as global positing systems, to help them move their livestock.

The focus group discussions revealed that sometimes, the movement of cattle causes issues with people from neighboring villages:

> "Thanks to God we have space; however, there is a lot of cattle here and you know that the displacement of the herds poses problems on land under agriculture; and the lands do not belong to the stockbreeders exclusively; the stockbreeders need more space exclusively devoted to livestock." [Dodji, male pastoralist]

Cohabitation between pastoralists and cultivators was considered by several pastoralist focus group participants to be an issue that should be considered seriously by the authorities. For example, in response to the ending discussion point (Appendix A):

> "We will ask him [or her, government official] to definitely solve the existing problem of cohabitation between cultivators and pastoralists. We have to say that the relation between cultivators and pastoralists is still difficult." [Dodji, male pastoralist]

In Senegal several laws make mention of pastoral resources. Recently, in 2004 a "Law on Guidelines for Agriculture, Forestry and Livestock" was passed that was designed to "modernize family farming and promote agricultural and rural entrepreneurship and provide the legal framework for the development of Senegal's agriculture sector for the next twenty years" (JORS 2004). This law recognizes pastoralism as a proper land use and is a step towards securing better livelihood opportunities for pastoral and agro-pastoral communities. However this law and the 'Great Agricultural Offensive on Food and Abundance' program launched by the Senegalese Government in 2008 both encourage private investment and privatization of land (Resnick and Birner, 2010) which may exacerbate land competition. In reaction, pastoralists continue to organize themselves in order to claim land ownership and access rights while increasing their participation in land use and natural resource management dialogues (Freudenberger and Freudenberger 1993; Juul 1993, 2005).

3.4.6 Theme 6. There are a variety of alternative non-agricultural livelihood strategies but these are predominantly part time and related to informal small scale trading

When discussing alternative, non-agricultural, livelihood strategies, the focus group discussions revealed that small scale trading is the foremost strategy. Women play a prominent role, mostly buying and selling within the village when they have the time and opportunity:

> "[We do] small trade, like selling sugar and tea, rice and oil, vegetables, pepper, *bissap* (hibiscus); a little of everything." [Dodji, female pastoralist]

> "A fish truck passes here daily; among us [the women] some buy in wholesale and then sale in retail." [Pete, female cultivator]

Women envisaged (more than men) the future of their children in off-season activities. Education and training, in particular for young people was seen as an investment. In some families, children have been sent to find urban occupations during the off-season and return to the village during the rainy season. Rural exodus and emigration of young people is seen as a way to provide supplementary income to the emigrant family. However, in the focus group villages this does not happen frequently and the remittances were discussed as being very limited.

In Degouniayes, the focus group discussions mentioned fishing as an additional way of obtaining food and income. Although, the inhabitants of Degouniayes have this alternative livelihood strategy, their fisheries face several issues some imputable to the opening of the breach at the mouth of the Senegal River (Diop 2004). With the exception of Degouniayes, the focus group discussions revealed that the inhabitants have few consistently profitable agricultural alternatives. Overall, small scale trading was the main non-agricultural livelihood strategy revealed from the focus group discussions with a largely unfulfilled desire for more or new irrigated gardening and migration of family members to remit money back home. Brown (2006) and Mertz et al., (2009, 2010) reported similar findings in other Senegalese villages.

3.4.7 Theme 7. Government assistance is perceived as insufficient and inappropriate but is desired

When prompted to imagine talking to the number one government decision maker and what the focus group participants would advise him or her to help them better use their lands, the participants enumerated a lengthy list of rather general complaints. The cultivators generally disagreed on the importance and effectiveness of certain government actions/policies but stated a common wish that they should be consulted and give their views in some government policies that directly impact their livelihoods or the state of the natural resources. The more clearly articulated suggestions differed but were commonly concerned with irrigation, seeds and equipment.

In the majority of the rain-fed cultivator focus groups, access to irrigation was discussed as an important way to improve livelihoods given appropriate government assistance:

> “Everyone here would like to practice off-season agriculture. As rain-fed agriculture depends on rains and it happens that we are not getting enough rain, if ever irrigation water was available for off-season activities we would be able to overcome all food shortage and drought we are facing.” [Linde, male cultivator]

For the adoption of new varieties of seed and help with selling their products, the farmers articulated a high level of reliance and also trust in the government:

> "For the seeds, it is true we mostly depend on the government. However, if the season is good, we keep part of the harvest to supplement the seeds of the following season. At the moment when I speak to you, we cannot have another type of seeds different from that we cultivate, because we do not see any." [Linde, male cultivator]

> "It should be stressed that once, the Government introduced a new variety of "bissap" and facilitated access to the seeds with the promise to buy whatever amount of harvests we could have. The harvest was excellent but nobody came to buy it. We were very disappointed." [Linde, male cultivator]

The need for government assistance with farming equipment was less frequently discussed than for seed and irrigation. The Degouniayes focus groups were unanimous in commenting negatively on flood risk reduction programs and the opening of the breach at the embouchure of the Senegal River (Diop 2004). Another controversial action is what the focus group participants called "Radar", a government cloud-seeding program initiated to 'overcome rainfall irregularity and improve water availability in the Sylvo-Pastoral and the Peanut-basin zones' (ANAMS 2009). However, its success and effectiveness were diversely appreciated.

The pastoralist focus group discussions revealed attitudes that were less concerned with government assistance compared to the cultivators. However, they discussed the need for government help in resolving conflicts and cohabitation issues between cultivators and pastoralists, as discussed in Theme 5.

In summary, government assistance was perceived as insufficient and inappropriate but desired. This is not surprising. In the 1980s the Senegalese government engaged an era of economic structural adjustment and withdrew its support to the agriculture sector, reducing agricultural credits, price subsidies, and subsidized agricultural equipment, seeds, and fertilizer (Crawford et al., 1996). Consequently, few subsidies exist currently, although the government has initiated policies and programs to foster synergy among rural producers, research institutions and agricultural/pastoral extension services (Resnick and Birner, 2011). Interestingly, although mistrust towards the Government was perceptible, the focus group participants seemed to grant more credibility to the Government than to the other intervening organizations or individuals, such as private traders or non-governmental organizations, in providing needed assistance.

3.5 Conclusions

Semi-structured focus group discussions were employed to capture attitudes and perceptions of behavior which is particular strength of this qualitative survey approach (Miller and Dingwall 1997; Corbetta, 2003). Initial prototyping revealed problems with focus group discussions moderated by a non-indigenous person and conducted through a translator, including heightened participant expectations of the discussion outcomes, and moderator failure to interpret subtleties of spoken language, body language and facial expression, and indirect African discussion styles (Roncoli et al., 2010). The focus group discussion guide was refined from the prototyping and a Senegalese moderator used that reduced social, cultural and linguistic differences between the moderator and the participants. By holding focus group discussions a range of perceptions over a large number of villages stratified by gender, ethnicity and dominant production system (Wolof cultivators and Peulh pastoralists) was achieved in the same year and season. Analysis of seven focus group sessions in five villages revealed seven main themes (Table 2) and these are discussed below.

The focus group participants expressed views that they are living in a degrading environment which has been observed by other researchers in the region (Brown 2006; Tschakert 2007; Mbow et al., 2008; Mertz et al., 2009). The discussions revealed that perceived changes in the state of the environment and natural resources were an important challenge to rural livelihoods. In particular, the participants with unanimity agreed that rainfall had decreased and become both irregular and unpredictable. Notably, their recollections of anomalous wet and dry years since the 1970s are corroborated by Senegalese weather records. The correspondence between scientific measurement and the focus group recollections is not surprising given that participant agricultural and pastoral practices remain reliant on rainfall. Participant perceptions of the causes of environmental changes were not sought or discussed, although the participants ascribed decreasing rainfall to divine domain.

Despite perceived changes in rainfall and a degrading environment, rain-fed agriculture appeared from the discussions to remain largely based on long-established practices. A variety of indigenous knowledge was discussed as being used to plan rain-fed agricultural activities, including reference to the lunar calendar, the established dates of social/religious events, and by observation of changes in the natural environment. Radio weather forecasts were listened to but it was unclear from the focus groups how such information was used to affect farming strategies. Crops planted were typically reported as the same ones as those planted by the inhabitant's grandparents. Discussions of agricultural adaptive strategies when the seasons were bad, predominately when the growing season rainfall distribution resulted in poor yields, were focused on reduction of the cultivated land area and planting crops more tolerant to water stress. Adopting new crop varieties was only discussed as being conceivable however if the seeds were made available through the Government or if they were affordable. When the seasons were good, the discussion revealed an emphasis on planting usual crops using the land more intensively or expanding the size and/or number of fields. All the focus group discussions, including pastoralist, advocated irrigation as a perceived means to reduce reliance on rainfall and to increase local food production.

The pastoralist focus group discussions revealed that pastoral activities are perceived as being threatened due primarily to constraints concerned with insufficient access to water and grazing. However, only two pastoralist focus group discussions were held (female and male from the same village) and so these perceptions may be less regionally representative than the other village findings. Further the way that cattle, goats and sheep and crops were balanced in the participant livelihood strategies was not discussed with sufficient clarity to ascertain their reliance on livestock. Perhaps this is why when the pastoralists discussed how they would take advantage of the incidence of good seasons, they predominantly raised changes they would make to their non-pastoral activities. This may also reflect that in the study region rain-fed crop cultivation is more sensitive to climate factors than livestock production (Mertz et al., 2011). When the pastoralists discussed bad seasons, the adaptive strategies raised were to move cattle to where pasture could be found and to adopt agricultural adaptive strategies similar to those discussed in the cultivator focus groups. Cohabitation between pastoralists and cultivators was discussed as a source of conflict when livestock were moved.

The focus group discussions indicated that the participants have few consistently profitable agricultural alternatives; this is perhaps due to a lack of money to invest and also a lack of opportunities (Tschakert 2007; Mortimore 2010). Part time small scale trading was the predominant strategy discussed with women playing a prominent role. When government assistance was discussed, the focus participants enumerated a lengthy list of complaints and showed general disagreement on the effectiveness of specific governmental decisions and actions. However, government assistance with irrigation systems and the provision of seeds was commonly discussed.

This study revealed that cultivators and pastoralists have a clear appreciation of changes in natural resources and the environment compared to a perceived more favorable past. Nevertheless, few adaptive coping strategies beyond long-established ones were advocated. One conclusion is that the focus group participants rely on their knowledge and experience to overcome difficult conditions. Another potential reason why there was not more discussion of adaptive coping strategies was that the participant's rationale is shaped by their religious beliefs and ancestral traditions. Other studies have found that African farmers ascribe supernatural forces and also lack of respect to ancestral spirits and other customs as causing deleterious environmental change (Bovin 1990, Kalinda 2011). In this study the focus groups participants ascribed decreasing rain to divine domain. This raises considerable complexity in attempting to frame an understanding from a "scientific" perspective (Milton 1997) and for subsequent development of scenarios of future land cover land use (LCLU).

Scenarios of future LCLU have been advocated to study alternative futures under different sets of assumptions given current understanding of the way that the drivers of LCLU interact and provide ‘‘descriptions of how the future may unfold based on ‘if-then’ propositions’’ (Alcamo et al., 2008). The implications of this study given future regional climate predictions can be conceptualized in very simplified scenario terms of climate and external assistance. Climate change predictions for West Africa suggest increased temperatures in the next 100 years (2-6 °C warmer) with uncertain but most likely decreasing rainfall (Hulme et al., 2001; Hulme 2003; Boko et al. 2007; Diallo et al., 2012; Christensen et al., 2007). Given that the region is expected in the future to become warmer one important consequence of rising temperatures will be higher evaporative stress on cereal crops (Blanc 2012). If rural livelihoods continue to remain based on habitual rain-fed agriculture then these projected climate changes indicate that future rural livelihoods may not be viable in the next 100 years. This is especially likely if non-agricultural livelihood opportunities remain limited. If the incidence of bad seasons increases then without appropriate external assistance it is unclear but feasible that cultivators will ultimately abandon their land and move elsewhere or adopt non-agricultural activities when possible.

The results of the pastoralist discussions do not provide sufficient evidence for a clear future scenario. Pastoralists in the region are observed to be highly adaptive and able to re-invent their livelihoods in order to continue a predominantly pastoral way of life (Juul 2005; Adriansen 2006; Moritz et al., 2009). Consequently, this suggests that only under more extreme future climate and climate variation than experienced in the past will pastoralists sell their herds or move permanently elsewhere in search of pasture and better opportunities. The importance of appropriate and effective external assistance to help maintain rural livelihoods is suggested. Involving stakeholders in the formulation of assistance and development policies is important but a major challenge lies in transforming the outcomes of stakeholder participation into policies that can be feasibly implemented (Resnick and Birner, 2010). How the government and other external agencies will help rural inhabitants will likely be important in facilitating adaptation and resilience to climate change, although this and other studies highlight the complexity of such an endeavor (Kurukulasuriya et al., 2006; Tschakert 2007; Chalinor et al., 2007; Collier et al., 2008; Mertz et al., 2010). The Senegalese National Adaptation Program of Action (NAPA) (MEPN, 2006) and subsequent documents have been developed to address the potential impacts of climate change, including impacts on agriculture and livestock. Currently, however, the implementation of these programs is in the context of development policy and relies on international funding mechanisms (Collier et al., 2008).

Finally, we note some caution concerning the findings reported in this study. Despite the wide sampling across five villages and the culturally and socially easy discussion forum that was enabled, it is unknown to what extent the seven common themes that emerged captured all aspects of the participant's perceptions. Certain perceptions may not have been articulated simply because the participants considered them as obvious. For example, many of the pastoralist focus group attendees were observed to carry cell phones but they did not discuss their use, or other technology such as global positioning systems, to help them move their cattle to where forage and water were available. Another potential issue with focus groups is what people say and what they do may be different. We discount the notion that the participants would not hold truthful discussions – the participant's religious recommendations stress ethical and socially responsible living, and the community perception of individuals is considered important, particularly given the small population sizes of the villages. However, farmers may complain about the weather regardless of the country they live in, and as with the discussions of government assistance, it remains unclear how important the issues discussed really are in affecting participant livelihood strategies. Consequently, a recommendation of this work is to triangulate its findings using other social survey techniques and direct observations over a period of time in each of the five villages, although the resources to do this even in one village are considerable (Nielsen and Reenberg 2010).

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Appendix A. Moderator guide open end discussion questions

1. Opening question: First, I'd like you to introduce yourself to the group and briefly tell everyone who you are and what you do.
2. Introductory question: I'd like you to each discuss if you think the weather, has changed since you were a child and do you think it will change in the future?
3. Was there any unusual weather recently?
4. If there was any unusual weather recently do you think it was like the old days, like when you were a lot younger?
5. If there was any unusual weather recently did you benefit or suffer from it?
6. What I would like you to discuss now is the types of crops that you plant: Why do you plant those types of crops? Are there any other factors other than the land and the weather that affect what crops are planted?
7. How do you know when in the year to prepare the land and when to plant and harvest the crops?
8. What do you do if there is not enough rain? What do you do if there is too much rain?
9. If you look after livestock, what kinds and why those kinds of livestock?
10. When do you know when in the year to move the livestock and how do you know where to move them to?
11. For how long do you usually leave the village with your livestock and what routes do you take?
12. How else do you make a living other than crops and livestock and how much of your time is spent doing that?
13. I'd like to hear, what do you do when it's a bad season for the crops and the livestock or if there are a succession of bad seasons?
14. What do you do when it's a good season, do you change the way that you use the land ?
15. Ending question 1: Imagine you are talking to the number one decision maker in the government. What would you advise him or her to help you use the land better?
16. Ending question 2: Is there any information that you need?
17. Ending question 3: Have we missed anything?

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CHAPTER 4

USING DIFFERENT CLIMATE SCENARIOS AND FOCUS GROUP INSIGHTS TO MODEL THE IMPACTS OF CLIMATE CHANGE ON LAND COVER LAND USE IN RURAL SENEGAL 2010-2050

Dièye, A.M. and Roy, D.P. *To be submitted*

4.0 Abstract

We modelled in a simple but spatially explicit manner the likely implications of future predicted climate change on future LCLU by iteratively updating each pixel of a 2010 LCLU map every year up to 2050. LCLU class transitions occurred at a given pixel when precipitation, during a number of successive years, remains above or below "normal". We considered 3 GCM models along with two emission scenarios each, RCP8.5 (high emission scenarios) and RCP4.5 (mid-range mitigation emission scenarios) with regard to two land management scenarios, a “business as usual” scenario, where agriculturalists rely essentially on rainfall and their own experiences and possibilities, and an “external intervention” scenario, where agriculturalists get some external support such as some sort of irrigation systems or new seed varieties. The results show that, with certain GCM models and emission scenarios, within the study area, by 2050 agriculture activities could persist only with external intervention.

4.1 Introduction

In the West African Sahel, over 65% of the populations are thought to live in rural areas and rely predominantly on crop-livestock activities for their livelihoods (Ben Mouhamed et al., 2002; Blanc, 2012). In this region, agricultural production and pastoralism are particularly weather dependent (Sultan et al., 2010; Blanc 2012) and the means to improve agricultural livelihoods through technological improvements (including irrigation, fertilizer, new seed varieties) have been largely unavailable (Ingram et al., 2002; Sultan et al., 2010, Dièye and Roy, 2013). Erratic rainfall and previous loss of soil fertility have contributed to the deterioration of many rural livelihoods, although rural population in this region, pastoralists, in particular, are observed to be highly adaptive and able to re-invent their livelihoods (Adriansen, 2006; Moritz et al., 2009). However, appropriate and effective external intervention is seen to be important to help maintain rural livelihoods (Dièye and Roy, 2013; Tschakert, 2007; Collier et al., 2008; Mertz et al., 2010). Nevertheless, this external intervention is often implemented as part of the development policy and therefore relies on international financing mechanisms (Collier et al., 2008). Furthermore, the motivation of such development aid needs to be clearly defined, as some recent foreign investments in African agriculture have raised various suspicions of land grabbing by foreign companies (van Braun et al., 2009; Cotula, 2013).

Climate change predictions for West Africa suggest increased temperatures in the next 100 years (2-6 °C warmer) with uncertain, but most likely decreasing rainfall (Hulme et al., 2001, 2003; Christensen et al., 2007). Given that the region is expected in the future to become warmer, one consequence of rising temperatures will be higher evaporative stress on cereal crops (Blanc, 2012). The capacity to model and project LCLU change is of considerable interest for mitigation and adaptation measures in response to climate change (Hansen, 2002; Blanc, 2012; Smith, 2014). Therefore, it is not surprising that several studies have attempted to conceptualize the implications of future regional climate predictions on agriculture production (Ben Mouhamed et al., 2002; Sultan et al., 2010; Dièye et al., 2013). Scenarios of future LCLU have been advocated to study alternative futures under different assumptions given current understanding of the way that the drivers of LCLU interact and provide ‘‘descriptions of how the future may unfold based on ‘if-then’ propositions’’ (Alcamo et al., 2008). However, the prediction of LCLU is very difficult, due to the fact that statistical contemporary LCLU change trend data may not capture future changes in LCLU driving forces, such as socioeconomic, technological, and policy related drivers acting at varying scales (Lambin, 1997; Moss et al., 2010). Globalization of the economy has resulted in regional production patterns influenced by demands from distant urban areas and by food, fuel and fiber preferences among nations (Seto et al., 2012; Garrett et al., 2013). Moreover, long range (more than decadal) future LCLU can only be meaningfully considered when coupled with future climate.

The Intergovernmental Panel for Climate Change (IPCC) in the preparation of its Fifth Assessment Report (AR5) has requested the scientific communities to develop new sets of scenarios for the assessment of future climate change. This request came from the need to explore new sets of scenarios that incorporate different climate-policies in addition to the no-climate-policy scenarios such as the SRES (special reports on emission scenarios) used for the Forth Assessment Report (Moss et al., 2010; Taylor et al., 2012). These new set of scenarios or global climate models, called Coupled Model Intercomparison Project (CMIP5), are driven by concentration or emission scenarios and provide Representative Concentration Pathways (RCP) (Moss et al. 2010). The RCPs are mitigation scenarios, assuming possible policy actions could be taken to achieve certain emission targets. For CMIP5, four RCPs were formulated (RCP8.5, RCP4.5, RCP6 and RCP2.6) based on a range of projections of future population growth, technological development, and societal responses. The labeling of RCP reflects a rough estimate of the radiative forcing in the year 2100 (relative to preindustrial conditions). For example, the radiative forcing in RCP8.5 increases throughout the twenty-first century before reaching a level of about 8.5 W m^{-2} at the end of the century. In addition to this “high” scenario, there are two intermediate scenarios, RCP4.5 and RCP6, and a low so-called peak-and-decay scenario, RCP2.6 (Taylor et al., 2012).

Global climate models are complex mathematical representations of the major climate system components (atmosphere, land surface, ocean, and sea ice) and their interactions (Claussen et al., 2002). GCM produce data and variables related to each of these major climate system components at different spatial and temporal levels or scales. Data from GCM usually have a spatial resolution in the range 100–300 km, while temporal resolution may vary from few hours (e.g. 6-hourly data) to monthly values. GCM cover given periods, including historical periods (called control periods or baseline periods, e.g. 1961-1990) or future periods (called scenario simulation periods, e.g. 2000-2050) (Willems et al., 2012).

The study was undertaken in a 1560 km^2 region of the semi-arid North of Senegal in the West African Sahel zone which experiences a high degree of spatial and temporal variability in precipitation and where rainfall is particularly an issue for arable and pastoral land uses (Hulme, 2003). A recent focus group study of rural Senegalese attitudes and perceptions of their behavior to changes in the climate (Dièye and Roy, 2012) found that rural livelihoods in this region remain largely based on long-established practices. The focus group discussions indicated that the participants have very few consistently profitable agricultural alternatives; this is perhaps due to a lack of money to invest and also a lack of opportunities (Tschakert, 2007; Mortimore, 2010). For example, the adaptive strategies raised, including adopting new crop varieties, were only envisioned if the seeds were affordable or made available through the Government. Without appropriate external assistance, when incidences of bad seasons persist cultivators could ultimately abandon their land and move elsewhere or adopt non-agricultural activities. Thus, appropriate and effective external assistance to help maintain rural livelihoods appears critical for future LCLU.

This study is trying to model future land cover land use in rural Senegal rural in a simple but spatially explicit manner to provide tractable insights into the likely implications of future predicted climate changes. An accurate nine LCLU class 2002 satellite 28.5 m map (Dièye et al., 2012) is used to define a baseline LCLU data for 2000. Future LCLU is modelled iteratively by updating each pixel of the LCLU map every year up to 2050. The LCLU class label of each pixel in the map is updated independently of its neighbors by consideration of the previous LCLU class value and the preceding precipitation. LCLU class transitions occurred at a given pixel when precipitation, during a number of successive years, remains above or below normal; where according to the World Meteorological Organization's regulation, "normal" is defined as the arithmetic average of a climate element (e.g. precipitation) over a 30-year period (e.g. 1961-1990). To ensure a representative range of future climate scenarios, at first 9 GCM predictions from nine different modeling centers were assessed. For each GCM, two scenarios are considered, RCP8.5 (high emissions scenario) and RCP4.5 (mid-range mitigation emissions scenario), resulting to a total of 18 GCM runs. Based on RCP8.5 scenarios, the 3 GCM that provided the lowest, the median, and highest predicted change (1961-2050) in precipitation were selected. This allowed running the future LCLU modelling for a total six times (3 GCM each with 2 scenarios).

Further, two future local anthropogenic land use scenarios were considered, one based on a business as usual approach, i.e. limited external intervention with restricted technological and/or financial assistance scenario, and the other assuming a moderate level of external intervention by the Senegalese government or an external agency, such as an NGO or business interests, that provide technological and/or financial assistance. This provided a total of 12 possible temporally and spatially explicit future LCLU model runs (3 GCM each with 2 scenarios and 2 local anthropogenic land use scenarios).

The remainder of this paper is organized as follows. The Study area (Section 2), the Land cover land use data (Section 3.1) and the Climate data (Section 3.2) are first presented. Assessment of the GCM (Section 4.1 and 4.2), Definition of above and below normal rainfall (Section 4.3) and LCLU transition scenario development (Section 4.4) are then presented. The results are presented and discussed (Section 5), preceding the concluding remarks (Section 6).

4.2 Study area

The study area encompasses 1560 km^2 of northern Senegal, defined by a Landsat scene (159 x 157 km), bordered by the Senegal River to the North and the Atlantic Ocean to the west, with the southern edge 100 km north of Dakar (Figure 1). The study area lies between 15º24' to 17º00' W and 15º00' to 16º42' N and has a semi-arid climate. The mean monthly temperature varies from 24.5ºC in January to 31.9ºC in May with a single rainy season from June-July through September-October (Fall et al., 2006). The average rainfall decreased from 400-600 mm in the 1960s to 200-400 mm in the 1990s (Fall et al., 2006). The study area encompasses three main ecoregions (Tappan et al., 2004) briefly described hereafter. The *peanut basin (*45% of the study area) is used primarily for millet, groundnut, and sorghum cultivation in acacia tree parkland that has replaced all vestiges of the pre-colonial woodland savanna landscape (Tappan et al., 2004). The *sandy ferlo (*43% of the study area) constitutes the Senegal's main sylvo-pastoral zone, an area that is generally too dry for crop production, with mean annual precipitation less than 200 mm. The vegetation is composed of open grasslands with scattered shrubs and predominantly acacia trees on red-brown sandy and ferruginous tropical sandy soils. The *Senegal River Valley* (10% of the study area) in the north of the study area is a floodplain previously covered by riverine woodland, and used for irrigated agriculture, primarily rice and sugarcane.

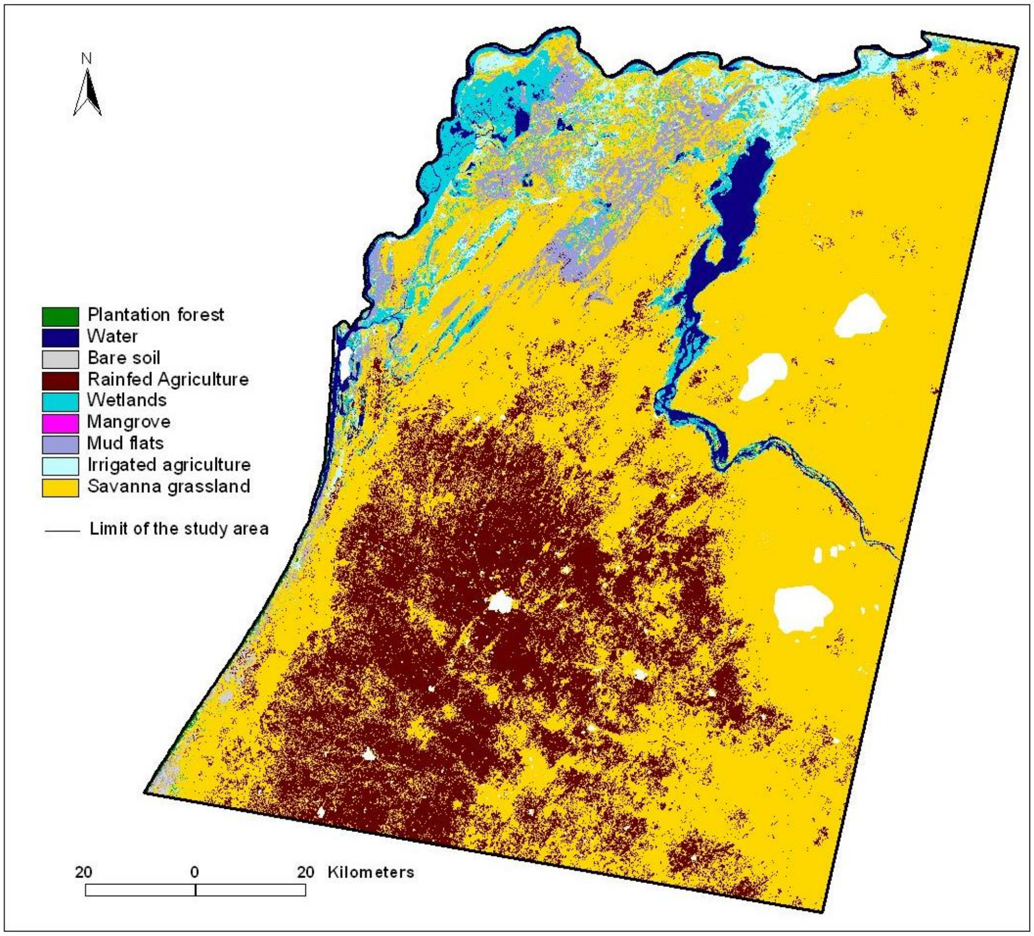

Figure 1 Landsat 28.5m decision tree classification of the study area in north-western Senegal, covering 1560 km^2 lying 15º24' - 17º00' W and 15º00' - 16º42' N. Dry and wet season 2002 Landsat data were classified using a bagged decision tree classification procedure into 9 land cover land use classes (Dieye et al., 2012). The study area is shown bounded by a black vector. White shows unclassified (clouds, cloud shadows, settlement areas, or no Landsat data).

4.3 Data

4.3.1 Land cover land use data

Remotely sensed satellite data have been used extensively to map land cover in the Sahel (Tucker et al., 1985; Pickup et al., 1993; Dièye et al., 2012); although, land use is difficult to discern reliably except when using high spatial resolution data and interpreter contextual geographic knowledge (Townshend and Justice, 1988). A Landsat satellite derived 28.5m land cover land use (LCLU) map, developed to examine soil organic carbon model sensitivity to LCLU classification uncertainties under different climate scenarios (Dièye et al. 2012) was used in this study as shown in Figure 1. Two Landsat 7 Enhanced Mapper Plus (ETM+) scenes, acquired in 2002 in the early wet season (June 21) and the dry season (December 30) to capture vegetation class differences in photosynthetic activity and leaf area in response to seasonal precipitation (Hiernaux and Justice, 1986), were classified by supervised bagged decision tree classification into nine mutually exclusive classes (Table 1). The map classification accuracies were high and reflect the best classification typically achievable for the study area - the percent correct and Kappa were 97.79% and 0.98 respectively (Dièye et al. 2012). The producer's and user's classification accuracies were greater than 90% for all the classes except for the wetlands, irrigated agriculture and mangrove classes. No class was misclassified as another by a significant amount - the greatest misclassification was 0.19% between the rainfed agriculture and savanna grassland classes. Clouds and cloud shadow areas were screen digitized manually and not classified. Settlements are difficult to classify reliably using Landsat data (Barnsely and Barr, 1997). This was particularly true for the rural villages occurring across the study area, which tended to be small and heterogeneous relative to the Landsat 28.5m pixel size. Consequently, all of the settlements were screen digitized manually and were not classified.

Table 1 Description of the 9 land cover land use (LCLU) classes and their spatial coverage (Figure 1). Classes 5 to 9 were not used in the LCLU scenario modeling analysis.

Code	**LCLU class**	**Definition**	**Percentage of the study area classified into class**
1	Bare Soil	Natural areas devoid of vegetation; defined by visual interpretation of dry and wet season Landsat ETM+ data.	0.44%
2	Rainfed agriculture	Agricultural fields which crop development relies primarily on natural rainfall; defined by visual interpretation of dry and wet season Landsat ETM+ data and using contextual knowledge.	20.58%
3	Irrigated agriculture	Agricultural fields in proximity to the Senegal River and to artesian wells; defined by visual interpretation of dry and wet season Landsat ETM+ data and using contextual knowledge.	3.25%
4	Savanna Grassland	Open savanna with annual grasses and scattered trees or shrubs (<10 % of cover); defined after Yangambi classification.	61.5%
5	Plantation Forest	Pine *Casuarinaequisetifolia* plantation forest known only to occur in the Niayes coastal ecoregion.	0.70%
6	Water	Permanent inland water (rivers, lakes); defined by visual interpretation of dry and wet season Landsat ETM+ data.	2.93%
7	Wetlands	Areas inundated or saturated by surface or ground water in a permanent or temporary basis to support a prevalence of vegetation adapted for life in saturated conditions; defined after Yangambi classification.	4.92%
8	Mangrove	Trees and shrubs that grow in saline coastal habitats; defined after Yangambi classification.	0.01%
9	Mud flats	A mud area devoid of vegetation; seasonally inundated; defined by visual interpretation of dry and wet season Landsat ETM+ data.	5.67%

4.3.2. Climate data

4.3.2.1. Weather station data

Monthly 0.05° average precipitation and minimum and maximum air temperature data for 1961-2010 were used. These data were compiled from monthly averages of climate measured at weather stations from a large number of global to local sources that were thin-plate smoothing spline interpolated (Hutchinson, 2004) to create climate surfaces for monthly precipitation and minimum, mean, and maximum temperature (Hijmans et al. 2005; Harris et al., 2013). The data are available for download at http://www.worldclim.org.

4.3.2.2. Global Climate Model data

A comprehensive dataset of GCM models is available at http://climexp.knmi.nl. Although, when we accessed the site, not all the models listed were complete in terms of climate variables and years covered. We selected 9 GCM datasets, based primarily on the availability of the three climate variables of interest in this study (monthly rainfall and minimum and maximum air temperature) at monthly time steps from 1961 to 2050. They were at variable grid spatial resolution, ranging from 1.2 degree to 3.7 degree (about 110 to more than 400 km) and are summarized in Table 2.

To reduce the number of GCM data set combinations a preliminary analysis with respect to predicted precipitation change from 2010 to 2050 was undertaken. It is well established that GCMs can predict future temperature more reliably then precipitation (Christensen et al., 2007). In the Western Africa Sahel, about 85% of the rainfall occurs during July-August-September (termed here for convenience as JAS) (Ben Mouhamed et al., 2002). Table 2 shows the total 2010 and 2050 JAS rainfall for each of the 9 GCMs under the RCP 8.5 scenario selected here because it is considered as the worst situation that can happen in the future. The three GCMS with the lowest, median and greatest percentage change in 2010 to 2050 JAS rainfall are -3.38%, -1.21% and 7.26%

respectively. Consequently, these three GCM data sets were used to capture the range of likely precipitation forecasts.

Table 2 List of the climate models initially considered in this study. July-August-September (JAS) rainfall for 2010 and 2050 from the original GCM are presented along with the percentage of change. The final three models selected (CSIRO-Mk3.6.0, CanESM2 andAccess1-3), marked with "*", have respectively the lowest, the median and the greatest percentage change in 2010 to 2050 JAS rainfall.

Model	**Modeling Center (or Group)**	**Spatial Resolution Lat. x Long. (degree)**	**2010 JAS Rainfall (mm)**	**2050 JAS Rainfall (mm)**	**Percent change in 2010 to 2050 JAS Rainfall**
ACCESS1-3*	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	1.875 x 1.250	358	384	7.26%
CanESM2 *	Canadian Centre for Climate Modelling and Analysis	2.812 x 2.780	330	326	-1.21%
CNRM-CM5	Centre National de Recherches Météorologiques	1.406 x 1.400	447	458	2.46%
CSIRO-Mk3.6.0*	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	1.895 x 1.875	355	343	-3.38%
HadGEM2-ES	National Institute of Met. l Research/Korea Met. Administration	1.241 x 1.875	313	329	5.11%
InmCM4	Institute for Numerical Mathematics	2.000 x 1.500	265	257	-3.02%
Ipsl-cm5b-lr	Institut Pierre-Simon Laplace	1.895 x 3.750	363	396	1.65%
MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (University of Tokyo), and National Institute for Environmental Studies	2.857 x 2.813	402	420	4.48%
MRI-CGCM3	Meteorological Research Institute	1.132 x 1.125	232	235	1.29%

4.4 Methods

4.4.1 Global climate model data bias correction

Global climate model (GCM) cannot be taken as a perfect representation of a true climate, as they can have large biases (Déqué, 2007; Bergeron et al., 2010). Several approaches have been suggested to undertake GCM climate model data bias correction (Déqué, 2007; Balshi et al., 2008; Bergeron et al., 2010; Xu and Yang, 2012), using almost similar methods, by correcting essentially climatology mean biases and inter-annual variability biases. In this study we used the approach from Xu and Yang (2012), consisting on the one hand, to adjust GCM predictions (temperature and precipitation) relative to the absolute difference of the mean of the observed data, and on the other hand, to adjust the inter-annual variability biases by setting the standard deviation of the GCM data to be similar to the one of the observed data. In this way, GCM bias correction is undertaken on a monthly basis, as:

$$GCM^{*}_{m,y} = GCM_{m,y} - \overline{G}^{a}_{m} \frac{\sigma O_m}{\sigma G^{p}_{m}} + \overline{O}_m + \left(\overline{G}^{f}_{m} - \overline{G}^{p}_{m}\right)$$

where $GCM^{*}_{m,y}$ and $GCM_{m,y}$ are the adjusted and original GCM values for the GCM grid cell covering the study area for month *m* and year *y* ;the straight horizontal lines and σ symbols denote mean and standard deviation from monthly climatology respectively computed over three time periods referenced by the superscripts *p* (past*:* 1961-2010), *f* (future: 2011-2050), and *a* (all: 1961-2050). The observed weather station data are defined at 0.05° so for this adjustment *O* is the observed weather station data and is available for *p* (past*:* 1961-2010). In this way the monthly GCM value for a given year and month is adjusted taking into account both climatology mean and inter-annual variability biases.

Figure 2 illustrates an example of the original and adjusted GCM as Equation [1] for the access1-3 GCM RCP8.5 scenario model data, which are the data that shows the highest percent of change in 2010 to 2050 in July-August-September (JAS) rainfall, on Table 2. The total July-August-September (JAS) precipitation data observed for 1961-2010 (black line), and the original GCM data (blue line) and adjusted GCM data (red line) for 1961-2050 are shown. The adjustment removed the original GCM biases of mean value and variance though shifting and scaling the original GCM predictions based on the observational data (Xu and Yang, 2012). In this way, by 2050 the change in JAS rainfall increased from 7.26% (original GCM) to 33.88% (adjusted GCM) while the standard deviation of the GCM adjusted equaled the one of the observational data.

Figure 3 illustrates the 1961-2050 monthly rainfall variation of the original (blue dots) and adjusted (red line) GCM access1-3 RCP8.5 data. This shows more clearly, following the bias corrections, the shift of the adjusted GCM over the original GCM. However as noted by Xu and Yang (2012), it appears that the adjustment does not alter the climatic trend and phase of inter-annual variability.

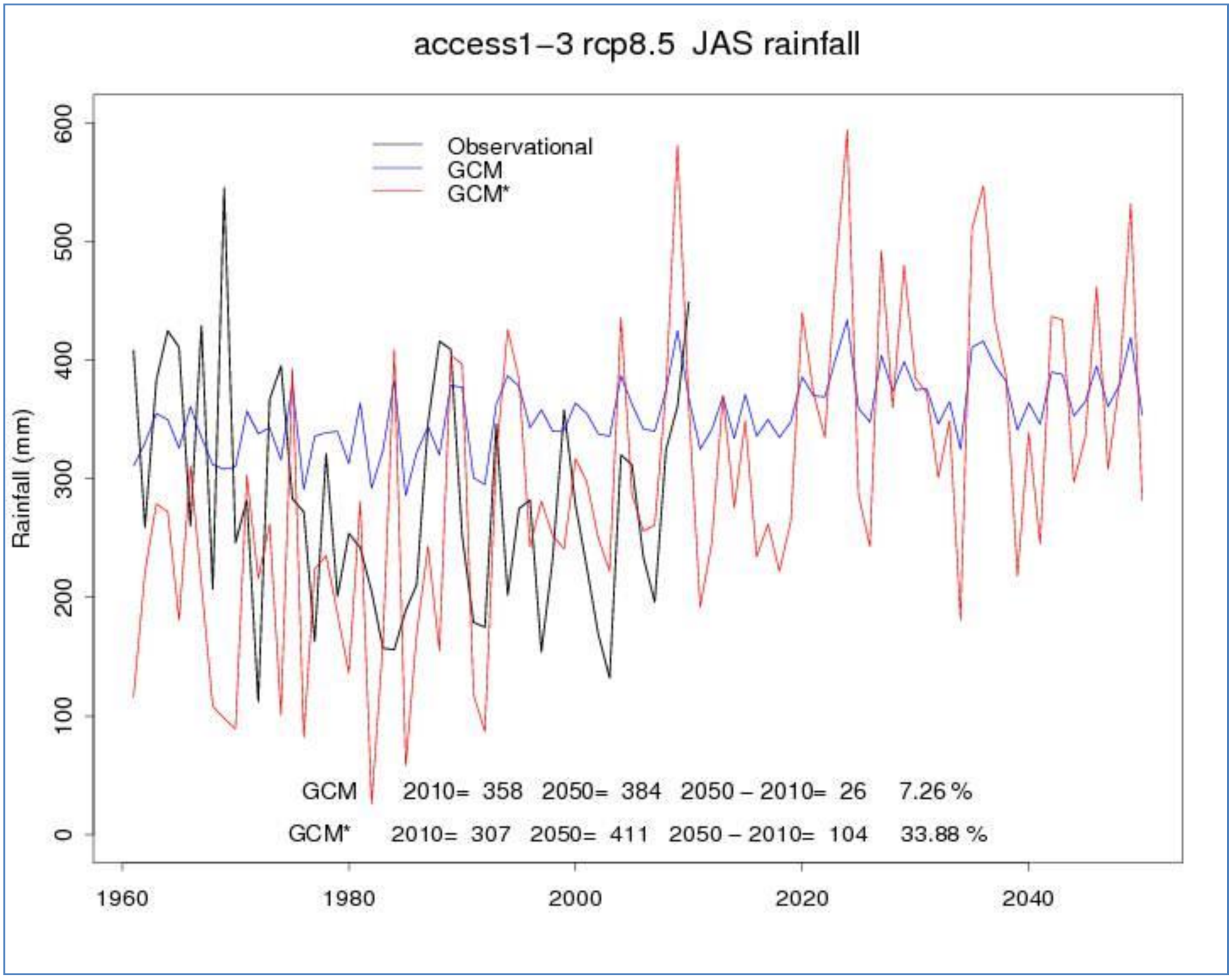

Figure 2 Illustration of the results of GCM mean value and variance bias corrections; example of access1-3 model for RCP8.5 with JAS rainfall over the study area. Observational indicates the observational data; GCM the original GCM; GCM* the GCM after both mean value and variance bias corrected, as indicated in Equation 1 (Xu and Yang, 2012)

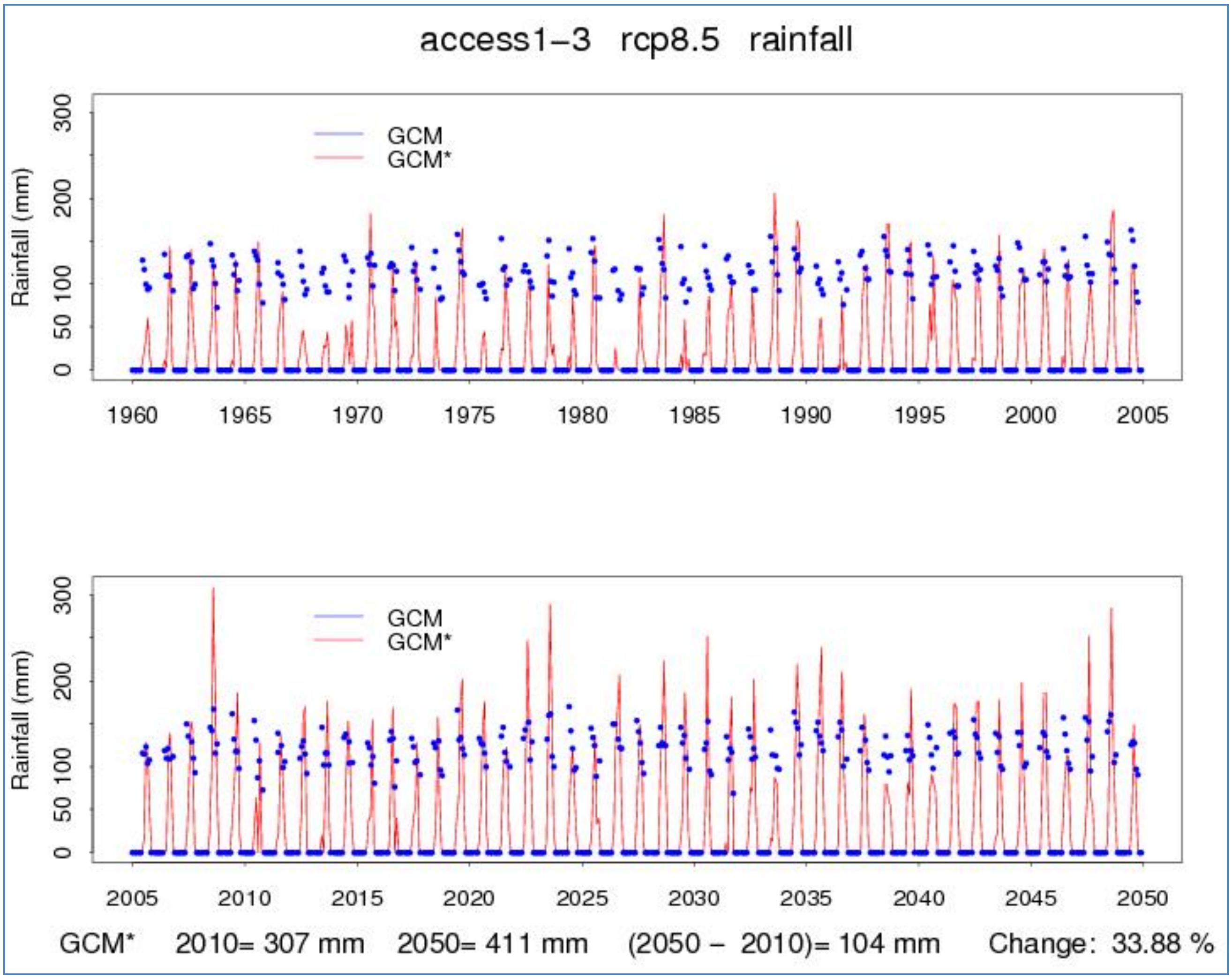

Figure 3 1961-2005 (top) and 2005-2050 (down) monthly rainfall variation of the original GCM and the corrected GCM*; example of access1-3 model for RCP8.5. Absolute change and percentage of change in rainfall of the GCM* values during the period 2010-2050 are indicated.

4.4.2 Global climate model data downscaling

Further to the bias correction performed in Section 4.1, the monthly adjusted GCM data (Equation 1) for the 3 GCM models and 2 RCPs were redefined in grid cells with size dimensions at 28.5m Landsat pixel dimension. This downscaling refers to the process of taking the coarse GCM and relate them to real points in the real world (Jones et al. 2005) for local-scale applications. Thus, monthly model predictions rainfall and minimum and maximum air temperature, downloaded as single values averaged over the study area (159 x 157 km), were statistically downscaled to the spatial resolution of the 1961-2010 monthly observation data (0.05° x0.05°) and then further nearest neighbor resampled to 28.5m Landsat pixel dimension, as:

$$GCM^{**}(i,j) = GCM^{*}(i,j) + \bar{\Delta}(i,j,month) \qquad (2)$$

$$\Delta(i,j\ month) = OBS(i,j,month,year) - \widetilde{OBS}(month,year)$$

Where $GCM^{**}(i,j)$ is the downscaled of GCM* bias corrected at pixel column and row (i,j), $\bar{\Delta}(i,j,month)$ is the mean (across all 1961-2010 years) of the differences between the monthly observation at pixel column and row (i,j) and the median value across that monthly observation based on rainfall and maximum and minimum air temperature at the 28.5 m scale.

Therefore, the downscaling to 28.5 m Lansdat pixel is simply done by adding the monthly GCM* (corrected as Equation 1) to the mean of the departures from the median of the corresponding month of the observation data.

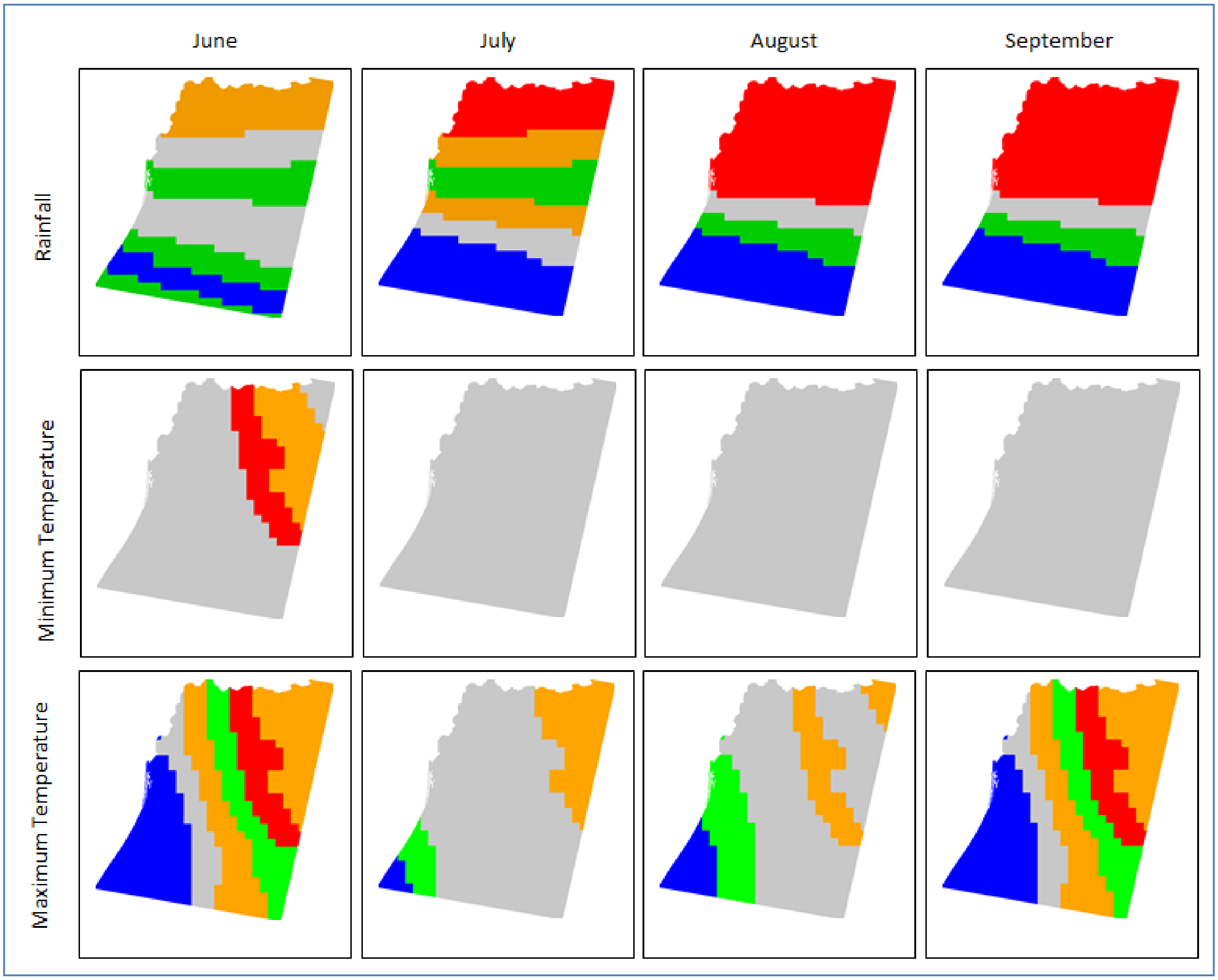

Figure 4 $\overline{\Delta}(i, j, month)$ Mean difference, i.e. departure, from the median of 1961-2010 monthly rainfall, minimum and maximum temperatures for June, July, August and September. Grey color indicates areas near median values. For rainfall, red color indicates values less than -7.5 mm from the median, orange values between -7.5 mm and -2.5 mm, grey between -2.5 mm and 2.5 mm, green values between 2.5 mm and 7.5 mm, and blue values more than 7.5 mm from the median. For minimum and maximum temperature, blue color indicates values less than -1 ^{o}C from the median, green values between -1.0 ^{o}C and -0.5 ^{o}C, grey between -0.5 and 0.5, orange between 0.5 ^{o}C and 1 ^{o}C, and red more than 1 ^{o}C.

Figure 4 show example of mean difference, i.e. departure, from the median of 1961-2010 monthly rainfall, minimum and maximum temperatures for June, July, August and September. Across the study area and between months, the departure from the median varies significantly. For example, for rainfall, the ranges, difference between the minimum and the maximum departures across the study area, in vary from a lowest of 14 mm (minimum -5 mm; maximum 9 mm) in June to a highest of 56 mm (minimum -32 mm; maximum 24 mm) in August temperature, blue color indicates values less than -1 ^{o}C from the median, green values between -1.0 ^{o}C and -0.5 ^{o}C, grey between -0.5 and 0.5, orange between 0.5 ^{o}C and 1 ^{o}C, and red more than 1 ^{o}C.

4.4.3 Definition of above and below normal rainfall

The Permanent Interstate Committee for Drought Control in the Sahel (CILSS) has setup a network of national Multidisciplinary Working Groups, with the mission to assess the food security situation in the Sahel countries. Every year, CILSS agro-meteorological experts express the annual rainfall as being either below normal, normal or above normal, with normal rainfall defined as the average rainfall during a 30-year period of observed rainfall (Ndione, 2005). In this way, for agricultural purpose, “precipitation below 80% of normal is considered as insufficient, while 80 to 110% is considered as regular and above 110% is excessive” (Ndione, 2005; Agrisystems, 2007). Based on this statement, we used the period 1981-2010 to derive the normal i.e. the 30-year average and define three categories of rainfall: above normal (>110% of the 30-year average), normal (80% to 110% of the 30-year average) and below normal (<80% of the

30-year average). Then, each observation from the GCM was classified in one of the three rainfall categories.

Figure 5, considering mean rainfall over the whole study area, shows the above and below rainfall lines along with the 1961-2010 observation data and the 2011-2050 GCM** data. Figure 6, shows for each pixel, across the study area, the value above (respectively below) which a total annual rainfall is considered as above normal (“wet”) or below normal (“dry”).

4.4.4 Land cover land use transition scenario development

We developed land cover land use transition scenarios based on several assumptions. Overall, we assumed that no major LCLU change will occur without rainfall change and transition between LCLU classes occurs only when rainfall remains above or below a threshold, referred as normal, during successive years. However, we recognize that drivers of LCLU may include, one the one hand, beside rainfall, several other climate variables, such as wind, solar radiation, temperature, evapotranspiration and humidity (Ben Mouhamed at al., 2002) and on the other hand, various and complex socio-economic drivers in space and time (Lambin, 1997).

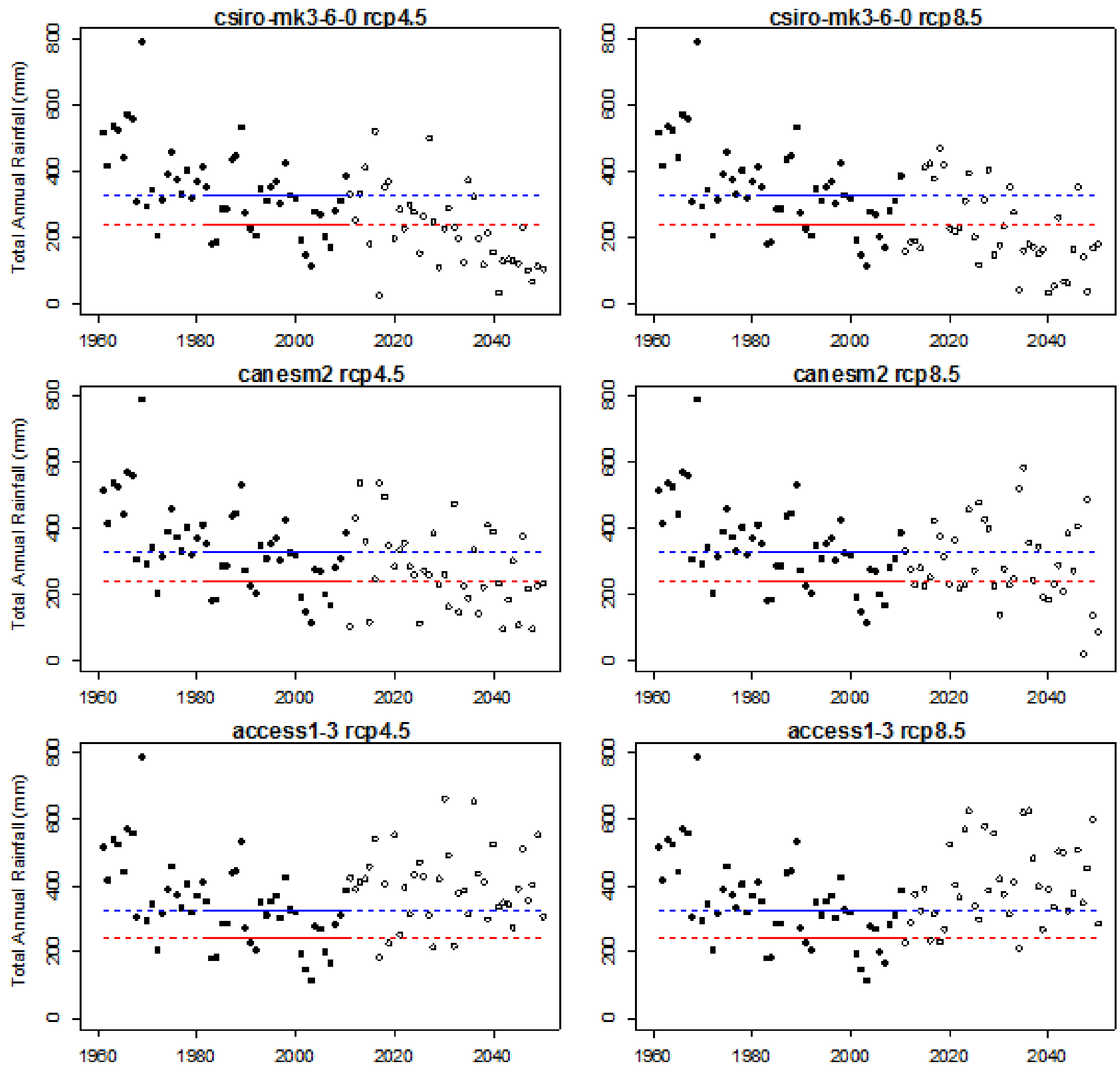

Figure 5 Study area mean rainfall inter-annual variability showing 1961-2010 observation data (black solid circles) and 2011-2050 GCM** data (black open circles). Above normal rainfall line (Y = 327 mm) is drawn in blue, with the 30-year period 1981-2010 used to derive it in solid line and the rest dashed. Similarly, below normal rainfall (Y = 238 mm) is in red with the 30-year period 1981-2010 used to derive it in solid line and the rest dashed.

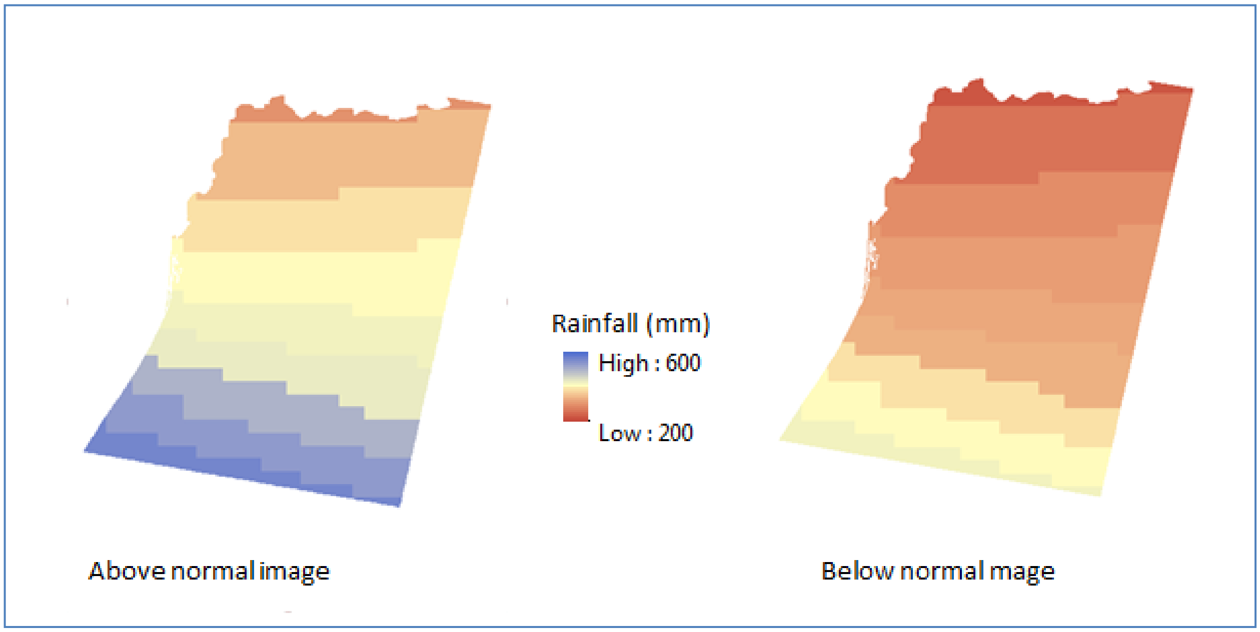

Figure 6 Image of above normal and below normal rainfall values per pixel. For each pixel, the 1981-2010 normal (i.e. the 30-year average) was calculated and used to derive above normal (>110% of the 30-year average) and below normal (<80% of the 30-year average) values.

Two scenarios were considered. First, a scenario based on "**business as usual**", where current practices will continue to prevail in the future, agriculturalists relying essentially on rainfall and their proper capabilities. Second, a scenario called "**external intervention**", where agriculturalists get some external support. For the "business as usual" scenario, year 2010 is considered as the starting point or reference for the land cover land use transition scenario development. Among the 9 classes of the 2000 LCLU map (Section 3.1), we only considered 4 LCLU classes: *Bare soil*, *Rainfed Agriculture*, *Irrigated Agriculture* and *Savanna Grassland*. Overall, we considered transitions from one class to another either as ecological processes (e.g. *Savanna* to *Bare soil*) or as land management practices (e.g. *Savanna* to *Rainfed Agriculture*). Those are explained below.

Based on the classification scheme used by Dièye et al. 2102, *Bare soil* is considered as a natural area devoid of vegetation, resulting among others, from successive dry years that led to the loss of the natural vegetation; inversely, under certain circumstances, such as successive wet years, vegetation can be reestablished. From the same authors (Dièye et al. 2102) *Savanna Grassland* is characterized by annual grasses and scattered trees or shrubs. Various studies have documented the 1970s and 1980s droughts that happened in the Sahel with dramatic losses of vegetation cover (Nicholson 2005; Lebel and Ali, 2009) while other studies have shown that annual grasses establish every wet season from seeds (Hiernaux and Justice, 1986; Herault and Hiernaux, 2004). More recent studies (Gonzales et al., 2011; Herrmann and Tappan, 2013) have found signs of re-establishment of the natural vegetation, including trees, in some areas previously classified as absent or of very low vegetation and the authors mostly attributed this recovery to favorable changes in rainfall patterns, particularly successive wet years. Although the cited studies did not explicitly mention the number of successive wet years or dry years that led either to loss or recovery of vegetation cover, they allowed to reasonably setting the transition from *Savanna Grassland* to *Bare soil* to 10 years of successive dry years and transition from *Bare soil* to *Savanna Grassland* to 10 years of successive wet years.

Considering *Rainfed Agriculture*, studies done in the study area (Tappan et al. 2004; Dièye and Roy, 2012) allow defining the transitions to and from other LCLU classes. Thus, we considered that after 3 successive dry years, *Rainfed Agriculture* fields are abandoned and then first, they appear as grazing land or grassy fallow to confound with *Savanna Grassland* (Tappan et al., 2004); second, if the dry years persist, after 7

years, *Rainfed Agriculture* will decline to *Bare soil*. Inversely, after successive years of normal to above normal rainfall, cultivators will regain confidence in rain-fed agriculture and will react by not only using their former agricultural fields but even expanding their fields in the *Savanna Grassland* and *Bare soil*, as it came out from the focus group sessions (Dièye and Roy, 2012). Thus, we set after 5 successive wet years *Savanna Grassland* transit to *Rainfed agriculture. Irrigated agriculture* relies primarily on the proximity to Senegal River and to artesian wells. A study from Oyebande and Odunuga (2010) shows that recharge of both river and groundwater is sensitive to rainfall patterns and a deficit of 10 to 30% in rainfall leads to a deficit of 20 to 60% in river discharge; furthermore, the authors stated that the recharge of the aquifers had noticeably recessed following successive dry years. From this study, we assumed that after 10 successive dry years, water availability will be too low to allow irrigated agriculture, and *Irrigated agriculture* will transit to *Bare soil.* In the same vein, we assume that after 5 successive wet years, *Irrigated agriculture* will transit to *Rainfed agriculture*. For agriculture, only crude class change is considered, i.e., no agriculture intensification within a pixel.
LCLU transition matrix for the “business as usual” scenario is shown in Table 3a.

Table 3a Land cover land use class transition matrix for "**business as usual**" scenario, where current practices will continue to prevail in the future, agriculturalists relying essentially on rainfall and their own experiences and possibilities. Red refers to dry years, blue wet years, "NA" not allowed.

		Previous Class			
		Bare Soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**
Change to new Class	**Bare Soil**	No change	When >7 years of below normal precipitation	When >10 years of below normal precipitation	When >7 years of below normal precipitation
	Rainfed agriculture	NA	No change	When >3 years of above normal precipitation	When >5 years of above normal precipitation
	Irrigated agriculture	NA	NA	No change	NA
	Savanna grassland	When >10 years of above normal precipitation	When >3 years of below normal precipitation	NA	No change

For the "**external intervention**" scenario we built from the "business as usual" transition matrix and we consider that with the external intervention *Rainfed Agriculture* could benefit, one hand from successive wet years by borrowing from *Bare Soil*, just after 5 years of successive wet years; one the other hand in case of successive dry years, *Rainfed Agriculture* will be able to resist longer and only move to *Bare soil* after 12 successive dry years (instead of 7 years considered in the "business as usual" scenario). LCLU transition matrix for "external intervention" scenario is shown in Table 3b.

Table 3b Land cover land use class transition matrix for "**external intervention**" scenario, where agriculturalists get some external support. Red refers to dry years, blue wet years, "NA" not allowed.

		Previous Class			
		Bare Soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**
Change to new Class	**Bare Soil**		When >12 years of below normal precipitation	When >10 years of below normal precipitation	When >7 years of below normal precipitation
	Rainfed agriculture	When >5 years of above normal precipitation	No change	When >3 years of above normal precipitation	When >5 years of above normal precipitation
	Irrigated agriculture	NA	When >3 years of below normal precipitation	No change	NA
	Savanna grassland	When >10 years of above normal precipitation	When >7 years of below normal precipitation	NA	No change

4.5 Results

Figure 7 show maps for the "business as usual" scenario applied to the GCM model ***access1-3*** (model that predicts a positive (+7.26%) percentage change in 2010-2050 JAS rainfall. For both (top row) ***RCP8.5*** scenario (high emission scenarios) and (bottom row) ***RCP4.5*** (intermediate emission scenarios), no remarkable LCLU transition change is noted up to 2050.

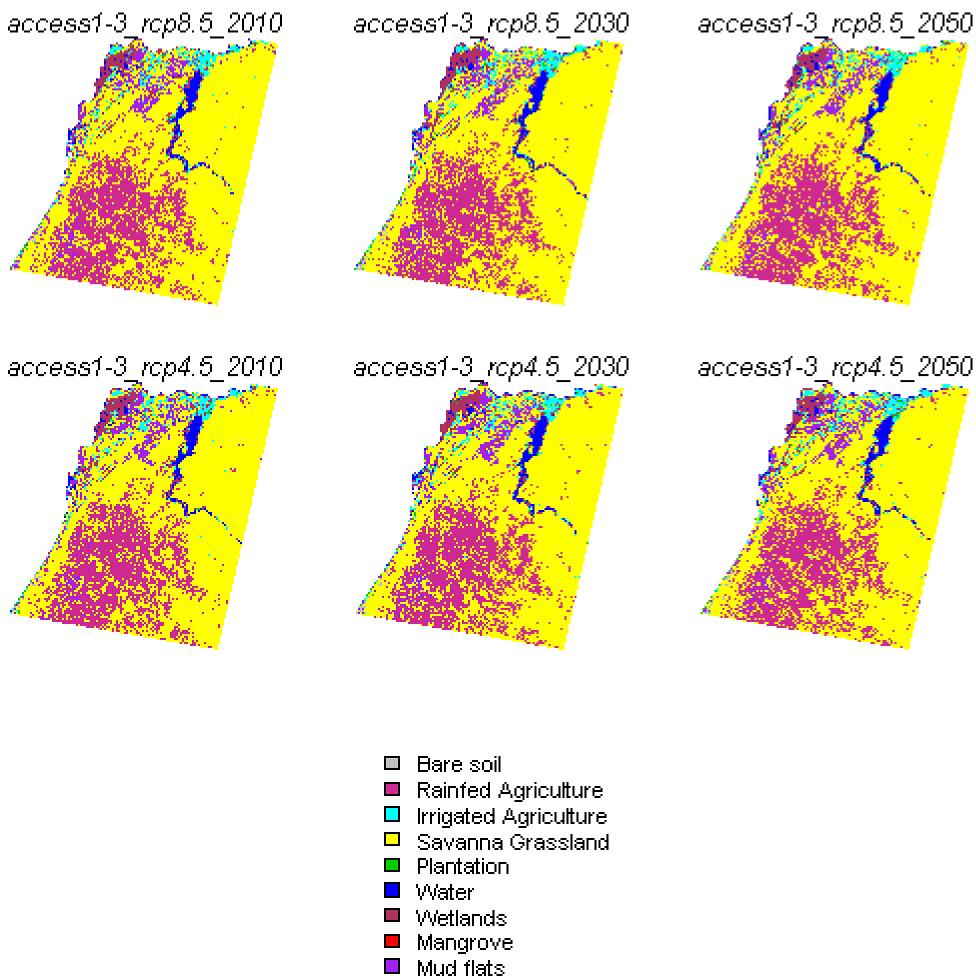

Figure 7 "Business as usual" scenario**,** LCLU change during the period 2010-2050 for GCM model ***access1-3*** (model that predicts a positive (+7.26%) percentage change in 2010-2050 JAS rainfall, Table 2).

Figure 8 shows maps for the "business as usual" scenario applied to the GCM model ***canesm2*** (model that predicts a neutral (-1.21%) percentage change in 2010-2050 JAS rainfall, Table 2). For both (top row) ***RCP8.5*** scenario (high emissions) and (bottom row) ***RCP4.5*** (intermediate emissions), by 2030 Rainfed Agriculture changes to Bare soil and the same situation remains by 2050.

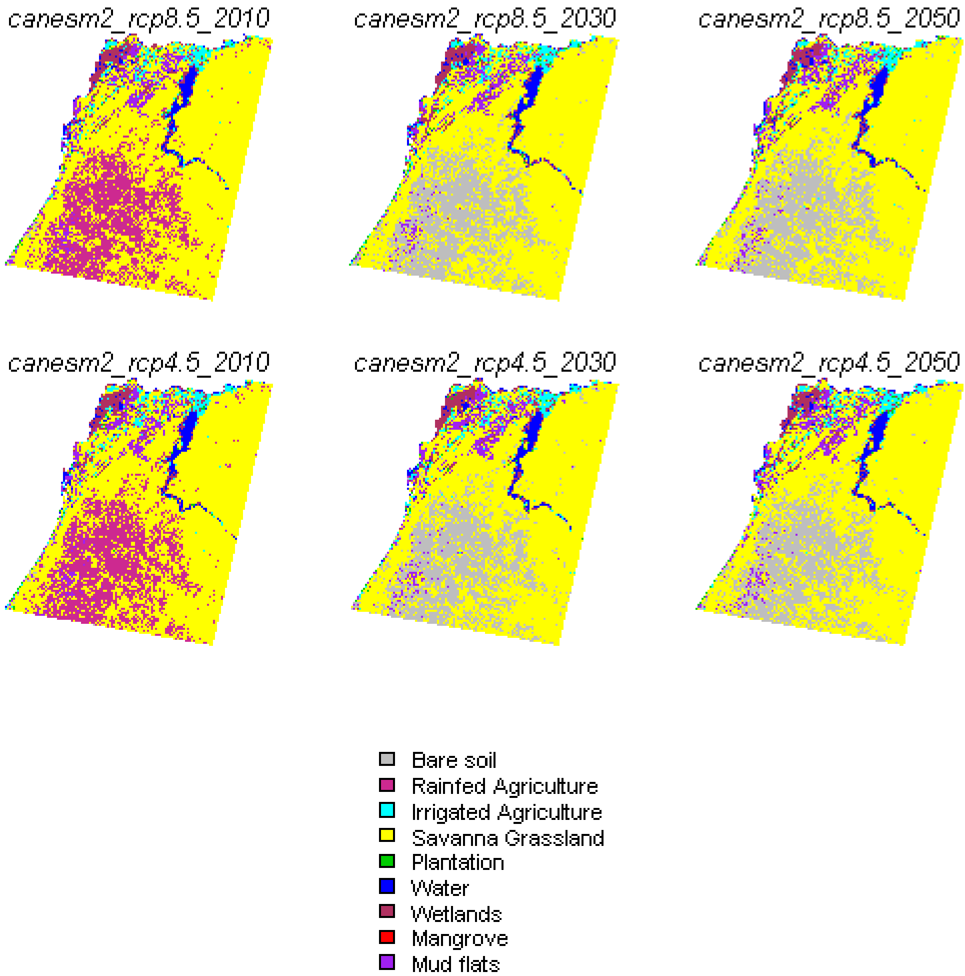

Figure 8 "Business as usual" scenario, LCLU change during the period 2010-2050 for GCM model ***canesm2*** (model that predicts a neutral (-1.21%) percentage change in 2010-2050 JAS rainfall, Table 2).

Figure 9 shows maps for the "business as usual" scenario applied to the GCM model ***csiro-mk3-6-0*** (model that predicts a negative (3.38%) percentage change in 2010-2050 JAS rainfall, Table 2). For both (top row) ***RCP8.5*** scenario (high emissions) and (bottom row) ***RCP4.5*** (intermediate emissions), by 2030 Rainfed Agriculture changes to Bare soil and by 2050 all classes considered in the LCLU transition development (Rainfed Agriculture, Irrigated Agriculture, and Savanna Grassland) change to Bare soil.

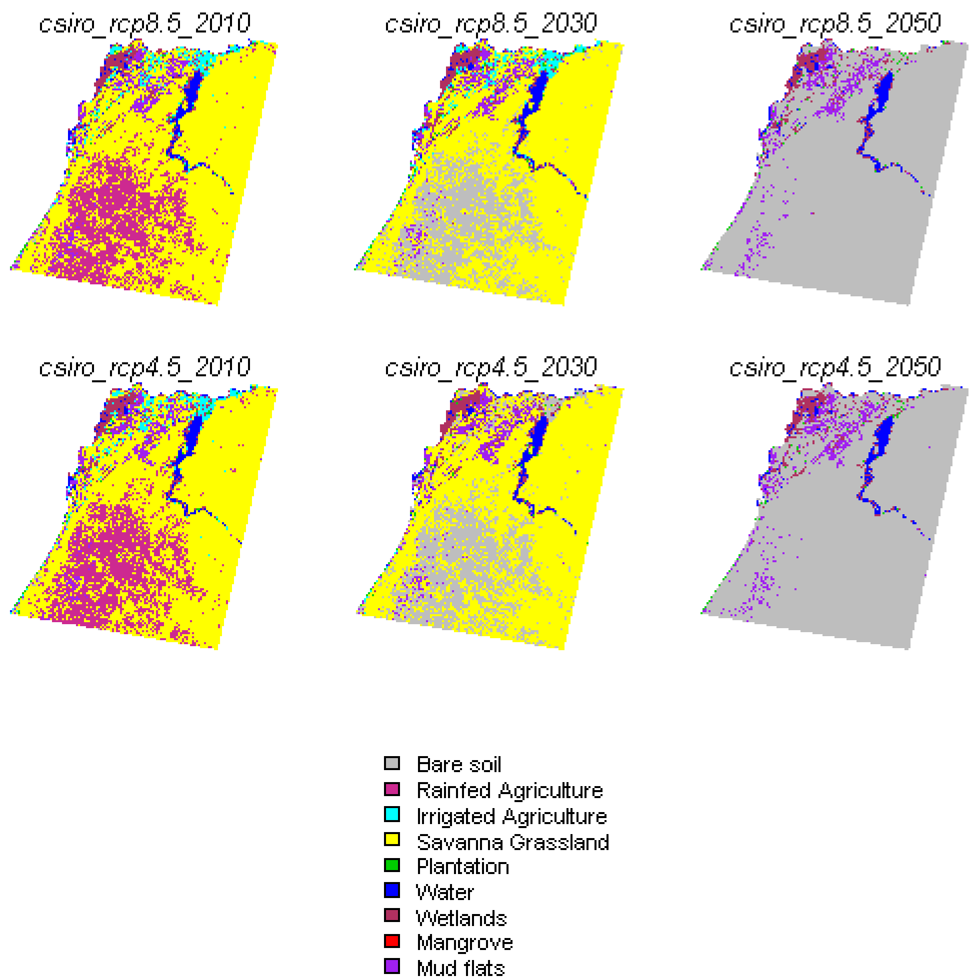

Figure 9 "Business as usual" scenario, LCLU change during the period 2010-2050 for GCM model ***csiro-mk3-6-0*** (model that predicts a negative (-3.38%) percentage change in 2010-2050 JAS rainfall, Table 2).

Under **access1-3** this is no remarkable change for both emission scenarios (Figure 7). Some changes are seen under **canesm2**, with by 2030, Bare soil replaces Rainfed agriculture by 2030 and the same situation remains by 2050 (Figure 8). More dramatic changes are seen under **csiro-mk3-6-0**, with by 2030, Bare soil replaces Rainfed agriculture and by 2050, all classes considered in the transition development change to Bare soil.

To examine these changes in more details, Table 4 show confusion matrices with changes and percentages of the total study area occupied by each of the LCLU in 2010 and 2050, considering **RCP8.5** emission scenarios and the 3 GCM access1-3, canesm2 and csiro-mk3-6-0.

Table 4 "Business as usual" scenario: confusion matrix showing change and percentage of the study area occupied by each of the LCLU class in 2010 (column total) and 2050 (row total), based on RCP8.5 emission scenarios and 3 GCM access1-3, canesm2 and csiro-mk3-6-0, shown from top to down respectively.

		Previous Class (2010)				
		Bare soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**	**Row total (%)**
Change to new Class (2050)	**Bare soil**	0.3	0.0	0.0	0.0	0.3
	Rainfed agriculture	0.0	21.7	0.0	0.0	21.7
	Irrigated agriculture	0.0	0.0	2.8	0.0	2.8
	Savanna grassland	0.0	0.0	0.0	64.5	64.5
	Column total (%)	0.3	21.7	2.8	64.5	89.3

		Previous Class (2010)				
		Bare soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**	**Row total (%)**
Change to new Class (2050)	**Bare soil**	0.3	21.7	0.0	0.0	22.0
	Rainfed agriculture	0.0	0.0	0.0	0.0	0.0
	Irrigated agriculture	0.0	0.0	2.8	0.0	2.8
	Savanna grassland	0.0	0.0	0.0	64.5	64.5
	Column total (%)	0.3	21.7	2.8	64.5	89.3

		Previous Class (2010)				
		Bare soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**	**Row total (%)**
Change to new Class (2050)	**Bare soil**	0.3	21.7	2.8	64.5	89.3
	Rainfed agriculture	0.0	0.0	0.0	0.0	0.0
	Irrigated agriculture	0.0	0.0	0.0	0.0	0.0
	Savanna grassland	0.0	0.0	0.0	0.0	0.0
	Column total (%)	0.3	21.7	2.8	64.5	89.3

Figures 10, 11 and 12 show the results from “external intervention” scenario. For **access1-3** model (7.26% increase in 2010-2050 JAS rainfall), for both RCP8.5 (high emission scenarios) and RCP4.5 (intermediate emission scenarios) no change is noted (Figure 10). For **canesm2** model (1.21% decrease in 2010-2050 JAS rainfall), both RCP8.5 and RCP4.5 show Rainfed agriculture changing to Irrigated agriculture in 2030 and the same situation remains by 2050. For **csiro-mk3-6-0** model (3.38% decrease in 2010-2050 JAS), both RCP8.5 and RCP4.5 show Rainfed agriculture changing to Irrigated agriculture by 2030 and Savanna grassland change to Bare soil by 2050.

Table 5 show confusion matrices with changes and percentages of the total study area occupied by each of the LCLU class in 2010 and 2050, considering RCP8.5 emission scenarios and the 3 GCM access1-3, canesm2 and csiro-mk3-6-0.

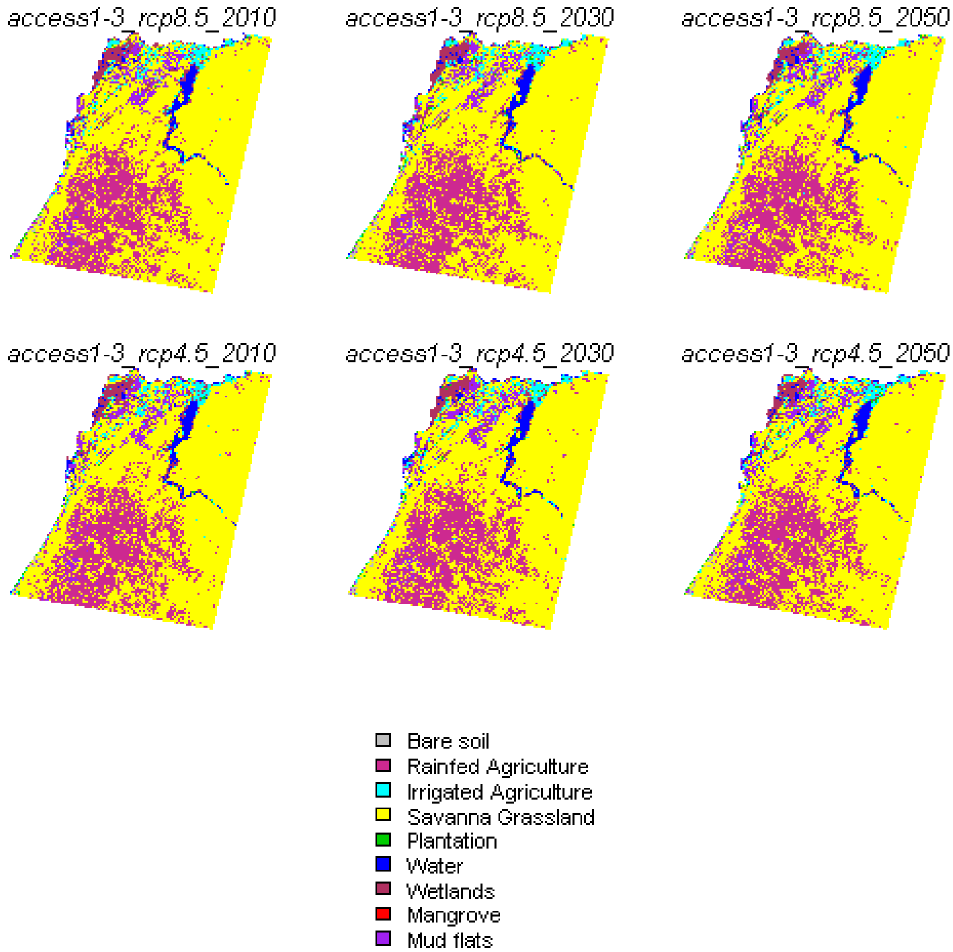

Figure 10 "External intervention" scenario**,** LCLU change during the period 2010-2050 for GCM ***access1-3*** (7.25% increase in 2010-2050 JAS RCP8.5 rainfall). By 2030 and 2050, for top row ***RCP8.5*** (high emission scenarios) and bottom row ***RCP4.5*** (intermediate emission scenarios) no change is noted.

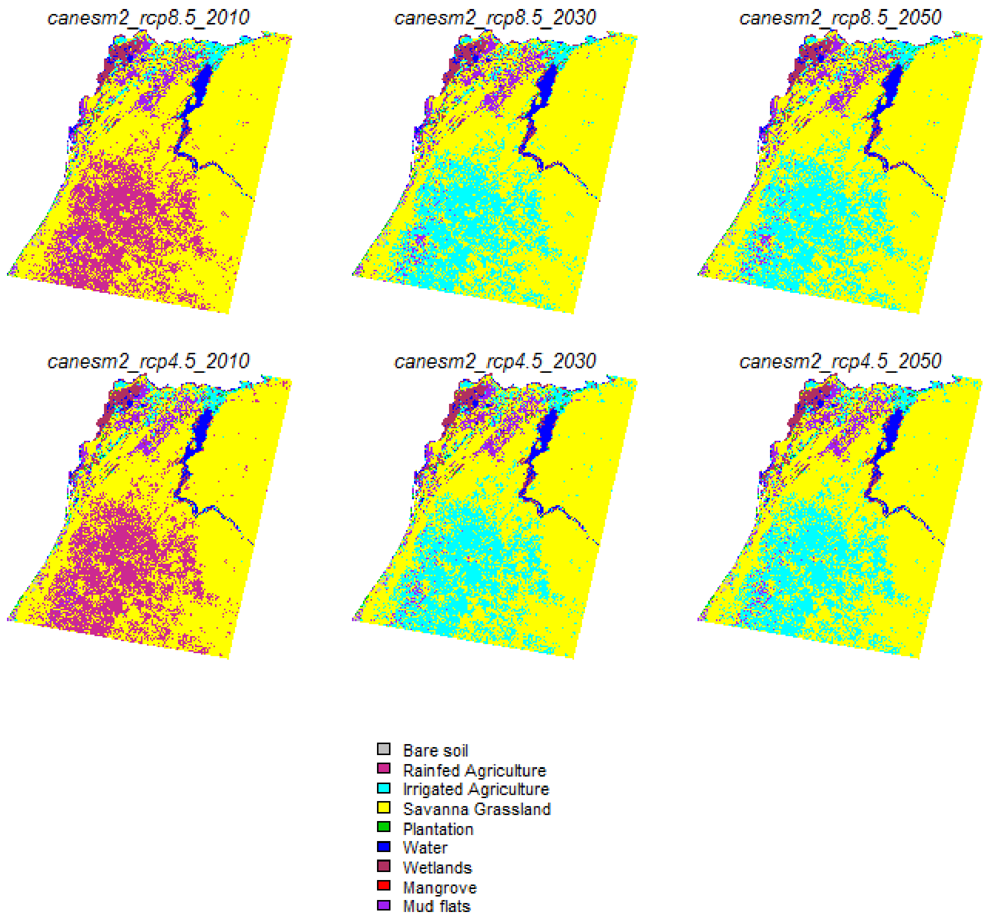

Figure 11 "External intervention" scenario, LCLU change during the period 2010-2050 for GCM ***canesm2*** (-1.21% decrease in 2010-2050 JAS RCP8.5 rainfall). By 2030, both (top row) ***RCP8.5*** scenario (high emission scenarios) and (bottom row) ***RCP4.5*** (intermediate emission scenarios) show Rainfed agriculture changing to Irrigated agriculture and the same situation remains by 2050.

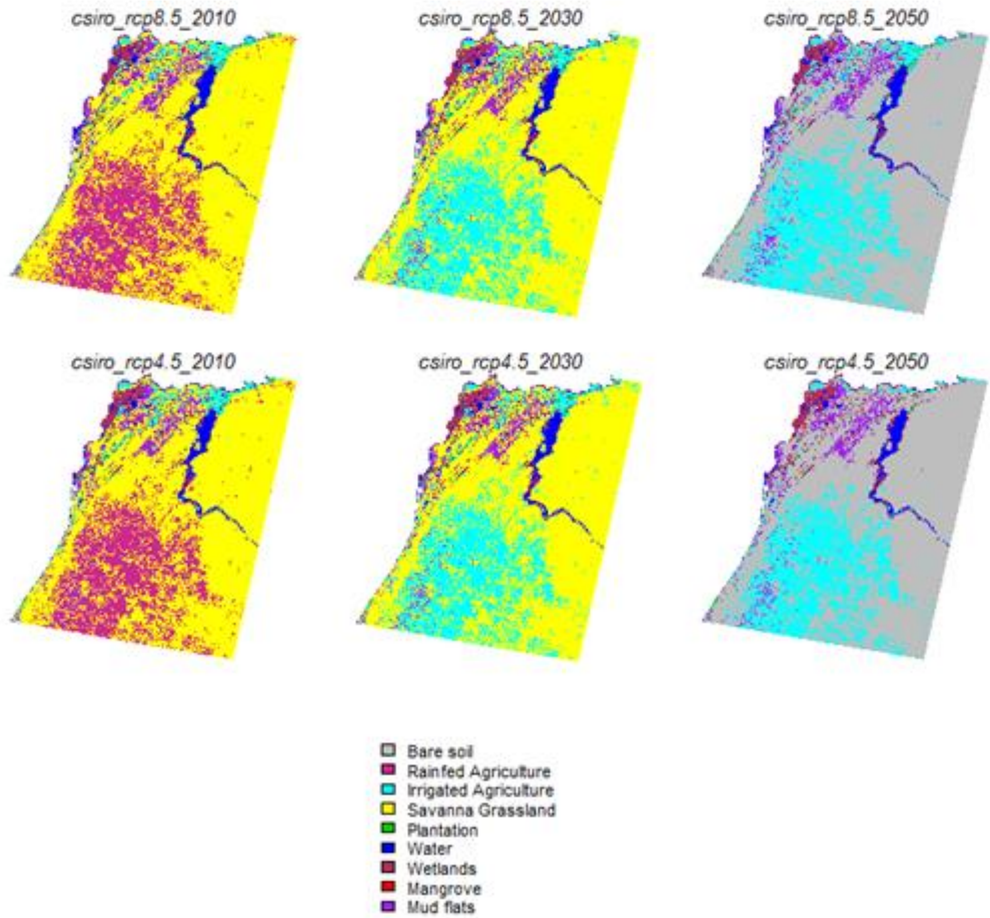

Figure 12 "External intervention" scenario, LCLU change during the period 2010-2050 for GCM model ***csiro-mk3-6-0*** (-3.38% decrease in 2010-2050 RCP8.5 JAS rainfall, Table 2). By 2030, both (top row) ***RCP8.5*** scenario (high emission scenarios) and (bottom row) ***RCP4.5*** (intermediate emission scenarios) show Rainfed agriculture changing to Irrigated agriculture and by 2050 Savanna grassland change to Bare soil.

Table 5 "External intervention" scenario: confusion matrix showing change and percentage of the study area occupied by each of the LCLU class in 2010 (column total) and 2050 (row total), based on RCP8.5 emission scenarios and 3 GCM access1-3, canesm2 and csiro-mk3-6-0, shown from top to down respectively.

	Previous Class (2010)					
		Bare soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**	**Row total (%)**
Change to new Class (2050)	**Bare soil**	0.3	0.0	0.0	0.0	0.3
	Rainfed agriculture	0.0	21.7	0.0	0.0	21.7
	Irrigated agriculture	0.0	0.0	2.8	0.0	2.8
	Savanna grassland	0.0	0.0	0.0	64.5	64.5
	Column total (%)	0.3	21.7	2.8	64.5	89.3

	Previous Class (2010)					
		Bare soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**	**Row total (%)**
Change to new Class (2050)	**Bare soil**	0.3	0.0	0.0	0.0	0.3
	Rainfed agriculture	0.0	0.0	0.0	0.0	0.0
	Irrigated agriculture	0.0	21.7	2.8	0.0	24.5
	Savanna grassland	0.0	0.0	0.0	64.5	64.5
	Column total (%)	0.3	21.7	2.8	64.5	89.3

	Previous Class (2010)					
		Bare soil	**Rainfed agriculture**	**Irrigated agriculture**	**Savanna grassland**	**Row total (%)**
Change to new Class (2050)	**Bare soil**	0.3	0.0	0.0	64.5	64.8
	Rainfed agriculture	0.0	0.0	0.0	0.0	0.0
	Irrigated agriculture	0.0	21.7	2.8	0.0	24.5
	Savanna grassland	0.0	0.0	0.0	0.0	0.0
	Column total (%)	0.3	21.7	2.8	64.5	89.3

4.6. Discussion and conclusions

In this study future LCLU was modelled in a simple but spatially explicit manner to provide tractable insights into the likely implications of future predicted climate given the study area focus group findings. An accurate nine LCLU class 2002 satellite 28.5 m map (Dièye et al. 2012) was used to define a baseline LCLU data for 2000. Future LCLU was modelled by iteratively updating each pixel of the LCLU map every year up to 2050.

The LCLU class label of each pixel in the map was updated independently of its neighbors by consideration of the previous LCLU class value and the preceding precipitation. LCLU class transitions occurred at a given pixel when precipitation, during a number of successive years, remains above or below normal; where according to the World Meteorological Organization's regulation, "normal" is defined as the arithmetic average of a climate element (e.g. precipitation) over a 30-year period (e.g. 1961-1990). To ensure a representative range of future climate scenarios, at first 9 GCM predictions from nine different modeling centers were assessed. For each GCM, two scenarios were considered, RCP8.5 (high emissions scenario) and RCP4.5 (mid-range mitigation emissions scenario), resulting to a total of 18 GCM runs. Based on RCP8.5 scenarios, the 3 GCM that provided the lowest, the median, and highest predicted change (1961-2050) in precipitation were selected. This allowed running the future LCLU modelling for a total six times (3 GCM each with 2 scenarios).

Further, two future local anthropogenic land use scenarios were considered, one based on a business as usual approach, i.e. limited external intervention with restricted technological and/or financial assistance scenario, and the other assuming a moderate level of external intervention by the Senegalese government or an external agency, such as an NGO or business interests, that provide technological and/or financial assistance. This provided a total of 12 possible temporally and spatially explicit future LCLU model runs (3 GCM each with 2 scenarios and 2 local anthropogenic land use scenarios).

The results show uncertain future for agriculture activities in the study area with regard to the three different GCM models (access1-3, canesm2, and csiro-mk3-6-0) whatever emission scenarios considered ***RCP8.5*** scenario (high emissions) and ***RCP4.5*** scenario (intermediate emissions). Interestingly, with the “external intervention” scenario, although similar dramatic changes could happen as noted in the “business as usual” scenario, agriculture activities could persist only as irrigated agriculture and especially if there is external support that can allow it.

The implications of this study given future regional climate predictions can be conceptualized in very simplified scenario terms of climate and external assistance. Climate change predictions for West Africa suggest increased temperatures in the next 100 years (2–6°C warmer) with uncertain but most likely decreasing rainfall (Hulme et al., 2001; Hulme 2003; Boko et al., 2007; Diallo et al., 2012; Christensen et al., 2007). Given that the region is expected in the future to become warmer one important consequence of rising temperatures will be higher evaporative stress on cereal crops (Blanc 2012). If rural livelihoods continue to remain based on rain-fed agriculture then these projected climate changes indicate that future rural livelihoods may not be viable in the next 100 years. This is especially likely if non-agricultural livelihood opportunities remain limited. If the incidence of bad seasons increases then without appropriate external assistance it is unclear but feasible that cultivators will ultimately abandon their land and move elsewhere or adopt non-agricultural activities when possible.

The transition development used in this study may raise several concerns. We considered that transition between LCLU classes occurs only when rainfall remains above or below a threshold, referred as *normal*, during successive years. Although, beside rainfall, many other parameters, internal as well external to the agriculturalists, may influence agriculture activities. In addition, for agriculture, we did not model agriculture intensification within a pixel but only crude class change was considered. This might be a limitation to our model, as a given pixel may remain agriculture from one period to another, without keeping the same characteristics or productivity owing for example to management or amendment it receives. Furthermore, we considered transitions between classes without evaluating their suitability, for example transforming bare soil to agriculture may not be always possible for many reasons, including soil characteristics and other agronomic requirements.

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CHAPTER 5

RESEARCH SUMMARY AND RECOMMENDATIONS

5.1 Summary of Research Hypotheses

A combination of remote sensing analyses, qualitative social survey techniques, and biogeochemical modeling was used to study the relationships between climate change, land cover land use change (LCLUC) and soil organic carbon in the Semi-Arid rural zone of Senegal between 1960 and 2050. For this purpose, four research hypotheses, were addressed. A summary of the research hypotheses and findings are described below:

Research hypothesis #1: LCLU in the Semi-Arid rural zone of Senegal can be mapped reliably using recent classification algorithms applied to multi-seasonal Landsat satellite data.

This hypothesis was *confirmed*. The results described in Chapter 2 (Dièye et al., 2012), in particular the soft-to-hard confusion matrix results for the 9 land cover land use classes, revealed a Percent correct and a Kappa-coefficient of **97.79%** and **0.98** respectively. These classification accuracies are high and reflect what was expected to be the best classification typically achievable for the arid study area. No class was misclassified as another by a significant amount - the greatest misclassification was **0.19%** between the rainfed agriculture and savanna grassland classes. This misclassification is most likely due to the presence of abandoned rainfed agricultural fields that are used for intermittent grazing, and are easily confound, from a satellite perspective, with grasslands (Tappan et al., 2004). In addition, using multi-temporal imagery (i.e., wet and dry season images) improved the discrimination of land cover classes, in particular classes that have varying seasonal water levels such as the wetlands, mud flats, bare soil, and mangroves classes.

The use of multi-temporal satellite data to provide improved land cover classification accuracy over single-date images, provided that the acquisitions capture seasonal and agricultural differences, is well established (Lo et al., 1986; Schriever and Congalton, 1993) and since this thesis was initiated has become even more common with the advent of freely available Landsat times series data (Hansen and Loveland, 2012; Yan and Roy, 2015).

Research Hypothesis #2: The temporal change in modeled SOC under future climate scenarios, assuming present day and unchanging LCLU, will be greater than the variability in modeled SOC due to remotely sensed data classification errors.

This hypothesis was *confirmed*. As described in Chapter 2 (Dièye at al., 2012) the variability in modelled soil organic carbon (SOC) imposed by satellite classification errors was not high. In 2000, the mean study area SOC values varied over the 30 soft decision tree classifications by 32.2 gCm^{-2} and corresponded to only **2.6%** of the mean study area hard decision tree classification SOC. Similarly, in 2050 the relative SOC variation due to satellite classification errors was **2.5%**, **3%** and **3.2%** for the no, low and high climate change scenarios, respectively. While during the same period (2000-2050), the mean study area modeled SOC declined by **11%**, **14%** and **24%** for the no, low and high climate change scenarios, respectively. Evidently, although not negligible, the temporal change in modeled SOC under future climate scenarios, assuming present day and unchanging LCLU, is greater than the variability in modeled SOC due to remotely sensed data classification errors.

Research hypothesis #3: Focus groups held with rural LCLU stakeholders provide insights into the climatic drivers of LCLU change; and these insights may be simplified in terms of particularly wet and dry years.

This hypothesis was *confirmed*. Focus groups held with rural LCLU stakeholders, Chapter 3 (Dièye and Roy, 2013), revealed that climate is the main driver of LCLU change. The seven focus groups, stratified by gender, ethnicity (Wolof and Peulh) and dominant production system (cultivators and pastoralists) in five villages revealed seven main themes. Evidently, cultivators and pastoralists had a clear appreciation of changes in natural resources, compared to a perceived more favorable past; rain-fed arable practices remain based on long-established practices; arable farming strategies are largely unaffected by the incidence of bad seasons but may be adapted to take advantage of the incidence of good seasons; and pastoral practices are threatened. Furthermore, focus groups recollections of anomalous wet and dry years since the 1970s were corroborated by Senegalese Meteorological Agency weather records.

Research hypothesis #4: Future LCLU under future climate change scenarios can be modeled in a spatially explicit manner using the simplified wet/dry year focus group insights.

The hypothesis was *partially confirmed*. The findings from Chapter 3 (Dièye and Roy, 2012), as stated in Research hypothesis #3, show that focus groups held with rural LCLU stakeholders provide insights into the climatic drivers of LCLU change and these insights may be simplified in terms of particularly wet and dry years. This statement was tested in

Chapter 4 to model future LCLU in a simple but spatially explicit manner to provide tractable insights into the likely implications of future predicted climate given the study area focus group findings. Scenarios of future land cover land use were successfully developed based on what focus groups participants said they did in the past when they faced climate variability (i.e., successions of bad or good years). It was expected that, with similar climate variability in the future, similar attitudes and behaviors will prevail (i.e., the business as usual scenario). In the same vein, attitudes and behaviors could be improved, if external factors allow it (i.e., the external assistance scenario). Indeed, West African LCLU, including rural livelihoods, will likely continue to be precipitation dependent and many other parameters (social, policy related, micro and macro-economic) will directly or indirectly influence land use decisions (ACPC, 2011; Sultan et al., 2015).

5.2 Recommendations for Future Research

Some limitations of this research, and recommendations for future research that could enhance the level of scientific understanding of the relationship between climate change, land cover land use (LCLU) and soil organic carbon, are presented below.

5.2.1 Improved LCLU classification

When this thesis was initiated Landsat data were not free; Landsat became free in 2008(Wulder et al., 2012), and consequently only two Landsat images were used for the classification experiments described in this thesis. Since the opening of the Landsat archive, classification techniques that use as many images as possible are being developed. Admittedly in much of Africa, prior to the availability of Landsat 8 data, Landsat data coverage has been limited (Roy et al., 2010; Wulder et al., 2015). The current state of the practice for large area land cover classification is to derive metrics from the time series and then classify the metrics bands with a supervised (i.e., training data dependent) non-parametric classification approach (Hansen and Loveland, 2012; Yan and Roy, 2015). The classification accuracies for the results presented in this thesis were high, due to the selection of cloud-free images and a large amount of training data. However, if the approach were to be extended to greater geographic regions then the use of the metrics approach is recommended to take advantage of the free-availability of Landsat data.

The spatially explicit LCLU maps used in this thesis were derived from 28.5m Landsat ETM+ satellite data. There are a number of ongoing, and planned, spaceborne sensors with high spatial resolution (<10m) designed for land cover monitoring (Wulder et al., 2011; Belward and Skøien, 2014; Johansen et al. 2008; Turker and Ozdarici, 2011) that could provide opportunities for higher spatial resolution LCLU biogeochemical model parameterization and LCLU mapping uncertainty assessment. In particular, the ESA Sentinel-2 satellite was successfully launched into a polar sun-synchronous orbit in 2015 and carries the Multi Spectral Instrument (MSI) that senses thirteen 10m, 20m and 60m Landsat-like bands (Drusch et al., 2012). The Sentinel-2 has a 10-day repeat coverage and therefore is likely to provide more-cloud free surface observations than Landsat 8 that has a 16-day repeat cycle (Whitcraft et al., 2015).

5.2.2 Sensitivity analysis with respect to key carbon model inputs

The SOC modelling method described in this thesis can be applied using other process based carbon models, i.e., not only using the general ensemble biogeochemical modeling system (GEMS) (Liu et al., 2004), and using spatially explicit LCLU parameterizations running the model with a single hard and multiple soft LCLU classification inputs to infer model sensitivity. In this thesis the impacts of errors associated with the other carbon model spatially explicit input data and model parameterizations (i.e., soil characteristics, including soil texture and drainage) were not considered explicitly. The best available data sets and parameterizations were used. However, the degree to which all input data and model parameterization errors are captured by the carbon model simulations and by the LCLU classification approach requires further research.

5.2.3 Confirmation of the focus group findings by triangulation with other social surveys

Chapter 3 described semi-structured focus group discussions that captured rural Senegalese attitudes and perceptions of inhabitants' behavior to changes to the climate and their environment. The particular strength of this qualitative survey approach is well recognized (Miller and Dingwall, 1997; Corbetta, 2003). However, despite the stratified sampling across five villages and the culturally and socially easy discussion forum that was enabled, it is unknown to what extent the seven common themes that emerged captured all aspects of the participant's perceptions or captured human perceptions across the study area. For example, findings relevant to a single village may be less regionally representative than other village findings. In addition, certain perceptions may not have been articulated simply because the participants considered them as obvious. Another potential issue is what people say and what they do may be different. Consequently, a recommendation for this research is to triangulate the findings using other social survey techniques and direct observations over a period of time in each of the five villages (Nielsen and Reenberg, 2010).

5.2.4 Develop more robust Land cover land use transitions

In this research, given future regional climate predictions, land cover land use transition developments were conceptualized in necessarily simplified scenario terms as being exclusively climate dependent (i.e., the business as usual scenario) or with some alternatives (i.e., the external assistance scenario). Future LCLU was modelled by iteratively updating each pixel of the 2010 LCLU map every year up to 2050. The LCLU class label of each pixel in the map was updated independently of its neighbors by consideration of the previous LCLU class value and the preceding years precipitation. LCLU class transitions occurred at a given pixel when precipitation, during a number of successive years, remained above or below normal. The transition development raises several concerns. Clearly, beside precipitation, other parameters, internal as well as external (socio-economic, political, etc.), may influence LCLU. The focus group discussions revealed small scale trading as the main non-agricultural livelihood strategy. Admittedly, public financing to the agricultural sector has greatly diminished in recent decades partly as a result of the structural adjustment embraced in many countries in the 1980s (Blanc, 2012; ACPC, 2011). It must be noted too that the LCLU transitions used in research did not model agriculture intensification within a pixel but only a LCLU class change was considered. This will limit the findings, as a given pixel may have an agricultural land use from one period to another, without keeping the same characteristics or productivity owing, for example, to the management it receives. Furthermore, transitions between classes were considered without evaluating their suitability, for example, transforming bare soil to agriculture may not be always possible for many reasons, including soil characteristics and other agronomic requirements. Therefore, future research should take in consideration these limitations.

5.2.5 Uncertainty in climate change predictions

It is agreed by scientists that climate projections are inherently uncertain. This comes partially from the imperfect ability of climate models to simulate climate system components, and the lack of methods to increase the temporal and spatial resolution of the outputs from the coarse climate models (GCMs) (Randall et al., 2007; ACPC, 2011; Willems et al., 2012). The uncertainty makes the quantification and evaluation of future LCLU less reliable. This thesis used global climate models because they were readily available, despite their coarse resolution (few hundred kilometers). Consequently, information on future LCLU precipitation driven changes were assessed at scales which do not capture within watershed precipitation variation and therefore are quite generalized.

In Africa, farm sizes are generally less than 2 ha (~150 m x150 m) (FAO, 1985; Valbuena et al., 2012) and are relatively much smaller than in other parts of the world (White and Roy 2015). Regional climate models (RCMs) are downscaled from GCMs and provide have higher spatial resolution climate predictions. However, they are not as available over Africa as GCMs and they are prone to error propagation from the GCMs (Willems et al., 2012). Significant disagreements still exist regarding long-term GCM and RCM precipitation predictions (Hulme et al., 2001; Hulme, 2003; Boko et al., 2007; Diallo et al., 2012; Christensen et al., 2007; ACPC, 2011). Therefore, this research will benefit from improved knowledge in climate change projections particularly those that are more accurate and defined at finer spatial and temporal scales and so are more appropriate for LCLU modeling.

5.2.5 Coupling future climate and future LCLU to provide insights into whether SOC will increase or decrease in the future

Finally, coupling future climate and future LCLU may provide future SOC scenarios that could provide insights into whether SOC will increase or decrease under future climate conditions due to changed rural land use practices. This was the original core question that this thesis, in its conceptualization, was to address for the study area. However, the complexity of the problem and time constraints, meant that instead this thesis laid the groundwork for addressing this question.

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