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Significance of soil moisture on vegetation greenness in the African Sahel from 1982 to 2008

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Significance of soil moisture on vegetation greenness in the African Sahel from 1982 to 2008

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Master Degree Thesis in Geomatics, 30 credits
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IN THE NAME OF ALLAH, THE MOST GRACIOUS, THE MOST MERCIFUL

AND SAY: "MY LORD! INCREASE ME IN KNOWLEDGE."

Abstract

This study investigates the temporal correlation relationship between vegetation greenness and soil moisture in the African Sahel from 1982 to 2008 at different time lags (maximum five lags used in this study) and determines the extent which soil moisture explains vegetation dynamics in the Sahel. Monthly composites of remotely sensed Normalized Difference Vegetation Index (NDVI) from National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (NOAA-AVHRR) were used in this study as a proxy for vegetation growth, whereas modeled soil moisture data (1.6m column depth) provided by the NOAA National Centers for Environmental Predictions (NCEP) Climate Prediction Center (CPC) Global Monthly high resolution Soil Moisture (GMSM) was used as an indicator of moisture availability for plants. The analyses were applied for all-year months data (dry season included) and only for growing months season (from July to October) to estimate the effect of long dry season on the association between vegetation growth and soil moisture. Trends in vegetation greenness, soil moisture and NDVI residuals were calculated separately in Sahel to investigate the changes occurred in vegetation growth and soil moisture during the study period. The correlations relationship were evaluated against land cover and soil texture data to estimate the influences of land cover and soil type on the strength of correlation relationship between vegetation growth and soil moisture.

The results showed a significant correlation relationship between vegetation greenness and soil moisture at lag0 (no time lag differences), lag1 (one month time lag) and lag2 (two months' time lag) with a better association in northern parts of Sahel region by using only the growing season data. However, the significant correlations covered a larger area by using all the year data (long dry season included). The results indicated that using AVHRR NDVI data for studying the vegetation growth in response to soil moisture availability is limited in the southern parts of the study area. The significant correlation coefficients (r) are varied between low and moderate values (0.1-0.6) in the study area, suggesting that soil moisture is not only the main driver of vegetation dynamics in Sahel. Vegetation greenness showed a significant increase during the study period in many locations in Sahel region (center of Chad, Senegal and south of Mali), whereas soil moisture showed a small significant locations in the study area (center of Sudan, center of Mali and east of Mauritania) during the study period from 1982-2008. Land cover type (Croplands and Grasslands) and soil texture (Entisols and Alfisols) showed a significant association and high influences on the correlation relationship between vegetation greenness and soil moisture at lag0, lag1 and lag2.

Keywords: NDVI, Soil moisture, Time series analysis, Sahel, Land cover, Soil type, remote sensing, temporal correlation

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Dedication

This thesis work is dedicated to my Family for their immense love

To my father and my mother

To my brothers- Mahmoud and Ahmed

To my sisters- Manal and Asmaa

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List of Abbreviations and Acronyms

ACF	Autocorrelation Function
AEJ	African Easterly Jet
AVHRR	Advanced Very High Resolution Radiometer
EMD	Empirical Mode Decomposition
ENSO	El Nino Southern Oscillations
ESRI	Environmental Systems Research Institute
EVI	Enhanced Vegetation Index
FAO	Food and Agricultural Organization of the United Nations
GIEWS	Global Information and Early Warning System-on food and agriculture
GIMMS	Global Inventory Modeling and Mapping Studies
GMSM	Global Monthly high resolution Soil Moisture
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter Tropical Convergence Zone
JASO	July, August, September and October
LAI	Leaf Area Index
mm	millimeter
MODIS	Moderate Resolution Imaging Spectroradiometer
MVC	Maximum Value Composites
NCEP-CPC	National Centers of Environmental Predictions-Climate Prediction Center
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infra Red
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Production
OR	Odds Ratio
PACF	Partial Autocorrelation Function
PAL	Pathfinder
ROC	Relative Operating Characteristics
RTA	Residual Trend Analysis
SM	Soil Moisture
SPOT	Système Pour l'Observation de la Terre
SZA	Solar Zenith Angle
TEJ	Tropical Easterly Jet
UNCCD	United Nations Convention to Combat Desertification
WAM	West African Monsoon

1. Introduction

The Sahel is a semi-arid eco-climatic transition zone in Africa that lies between the Sahara desert to the north and the humid tropical Savannas to the south, with distinctive vegetation cover ranging from very sparse vegetation cover in north of Sahel, to grasslands, shrubs and thorny trees interspersed with grasses in center of Sahel, to woodlands characterized by taller and higher amount of vegetation cover in south of Sahel (Le Houerou, 1980). Lately, the African Sahel has become one of the most investigated study areas relative to other regions in the world because of its dynamic ecosystem that responds to both land use practices and climate change (IPCC, 2007).Yet, there are still many unanswered questions connected to the assigning observed changes in Sahel ecosystems and direct human impacts.

Semi-arid African areas are more vulnerable to climate change and climate variability that causes massive impacts on their economic situations that are usually accompanied with existence of many developmental challenges such as ecosystem degradation, disasters and conflicts, and limited infrastructure and technology (IPCC, 2007). Mitigation and adaptation strategies were selected as two possibilities for overcoming and addressing climate change. Mitigation focuses on reducing greenhouse gases (GHG) emissions to avoid a dangerous increase in global temperatures, while adaptation strategies refer to any reaction or adjustment in response to actual or expected impacts of climate change (IPCC, 2001). Sahelian countries will need to adapt to climate change because they are expected to experience some of the most negative impacts in the future (IPCC, 2001). This is will be particularly challenging for them because of their already low adaptive capacity in the face of low and variable rainfall levels, combined with societal vulnerability.

Water availability is considered one of the most important climatic constraints on vegetation growth in Sahel. The projected number of Africans in semi-arid locations will suffer from increasing water stress by 2020s is between 75-250 million and this number is projected to increase to be between 350-600 million by 2050s (IPCC, 2007). However, other climatic constraints such as solar radiation, availability of nutrients and air temperature could also affect the vegetation growth as water becomes less limiting factor for plant growth in regions characterized by high amount of water availability (Herrmann et al., 2005). Owing to continuous presence of water shortages in the Sahel region, understanding the relationship between vegetation and soil moisture has become necessary for agriculture management in this region.

Soil moisture is a crucial factor linking rainfall with vegetation growth, it is considered to be the most important factor for vegetation production in arid and semi-arid regions because yield of crop is more linked to the amount of water availability rather than lack of nutrients (Wilhelmi and Wilhite, 2002). Soil moisture represents the rainwater accumulated over a period of time, and is considered to be more tightly coupled with vegetation greenness than instantaneous rainfall measurements, because soil moisture is more representing the actual water available or reached by plant roots. Besides, the best association between vegetation growth and rainfall occurs with rainfall total for concurrent month plus two previous months (Nicholson et al., 1990). However, the relationships between vegetation growth and soil moisture are complicated by other several factors such as land cover/vegetation type, land use and soil type. There are many studies that investigate the relation between vegetation growth and rainfall in Sahel region (e.g. Eklundh, 1997; Nicholson, 2001). However, a few of them analyze the relation between soil moisture and vegetation growth due to the lack of accurate spatial soil moisture data for vast area like Sahel (e.g. Huber et al., 2011; Owe et al. 1993).

Remotely sensed Normalized Difference Vegetation Index (NDVI) is a commonly used indicator for monitoring vegetation greenness. NDVI data have shown good association with rainfall fluctuations in semi-arid regions indicated by increasing NDVI values with increasing rainfall amounts at rainfall ranges from approximately 200 to 1200 mm yearly (Tucker et al., 1991; Nicholson et al., 1990). Vegetation phenology has a great role in different aspects not only in land use and environmental risk management but also modeling carbon exchange (Lucht et al., 2002). Moreover, vegetation production is considered a sensitive indicator for monitoring cause and effect of global climate change which is mainly driven by changes in rainfall, surface temperature, soil moisture, and human activity (Kartschall et al., 1995).

1.1. Aims and Objectives

The current study aims to evaluate the relationship between soil moisture and vegetation growth for the period spanning from 1982 to 2008 in Sahel at five different time lags (shifting the time of soil moisture back by five months) to recognize the best time of vegetation growth in response to concurrent and previous measurements of soil moisture, and to identify areas within Sahel region where vegetation growth shows a strong dependence on soil moisture. The specific objectives of this study are to: 1) Investigate changes that have occurred in the vegetation greenness and soil moisture during the study period, separately. 2) Analyze the correlation between vegetation growth and soil moisture. 3) Document the changes in strength of relationship between vegetation growth and soil moisture with time lag. 4) Assess if the maximum strength in the relationship between soil vegetation growth and soil moisture varies in space. 5) Investigate whether the strength of the relationship between vegetation growth and soil moisture varies with land cover and soil type.

1.2. Research questions

I. How does the soil moisture and vegetation greenness vary in Sahel from 1982 to 2008?

II. Is there a correlation between modeled soil moisture (SM) and vegetation growth (NDVI) during the study period from 1982 to 2008?

III. Does the relationship between soil moisture and vegetation growth vary with changing time lag across the study area?

IV. Does the lag of maximum correlation (optimal lag) vary across the Sahel?

V. Is the pattern from IV related to land cover types and soil textures?

1.3. Hypothesis

Based on the research questions stated above, the following are the research hypotheses:

Hypothesis 1
Null hypothesis: Trends in soil moisture and vegetation greenness in Sahel are not observed.
Alternative hypothesis: There is a significant trend in soil moisture and vegetation greenness in the Sahel.

Hypothesis 2
Null hypothesis: There is no significant relationship between NDVI and SM.
Alternative hypothesis: Significant relationship exists between NDVI and SM.

Hypothesis 3
Null hypothesis: Correlation relationship is showing the same pattern with changing time lag.
Alternative hypothesis: Correlation relationship is varying with changing time lag.

Hypothesis 4
Null hypothesis: Optimal lag correlation is not varying across the study area.
Alternative hypothesis: Optimal lag correlation shows different spatial variability in Sahel region.

Hypothesis 5
Null hypothesis: Correlation between NDVI and SM is not influenced by land cover type and soil texture across the Sahel region.
Alternative Hypothesis: Correlation between NDVI and SM is highly influenced by land cover type and soil texture across the Sahel region.

1.4. Thesis Outline

This thesis structure is organized in several chapters. The first chapter consists of a brief introduction, objectives, research questions and hypothesis. The second chapter consists of background and literature review about the study area. Description of materials and methods and the justification behind selecting the methodology is provided in the third chapter. The fourth chapter consists of results. Results discussed in more details in chapter five. Finally, the thesis ends with a brief summary, conclusions and references.

2. Background and Literature review

2.1. Study area

The Sahel word in Arabic language means “shore” or “coast” which is linguistically describes the appearance of vegetation in Sahel region as a shoreline defining the boundary of the Sahara desert (Le Houerou, 1980). The Sahel spans across northern Africa from the Atlantic Ocean in the west to the Red Sea in the east (about 5000 km) forming a belt extending roughly from 12° N to 18° N (about 1000 km). However, the biophysical characteristics are changing continuously in the Sahel region over time and space and leads to difficulty in pinpointing the precise geographic location of the Sahel (Le Houerou, 1980). Several different African countries are found in the Sahel (Fig.1). They not only share the same climatic conditions (Sahelian climate) but their inhabitants also share a lot in common in terms of their culture and livelihood systems (FAO/GIEWS, 1998). The study area covers most of Central and West Africa with geographic position extends roughly from 5°N to 20°N.

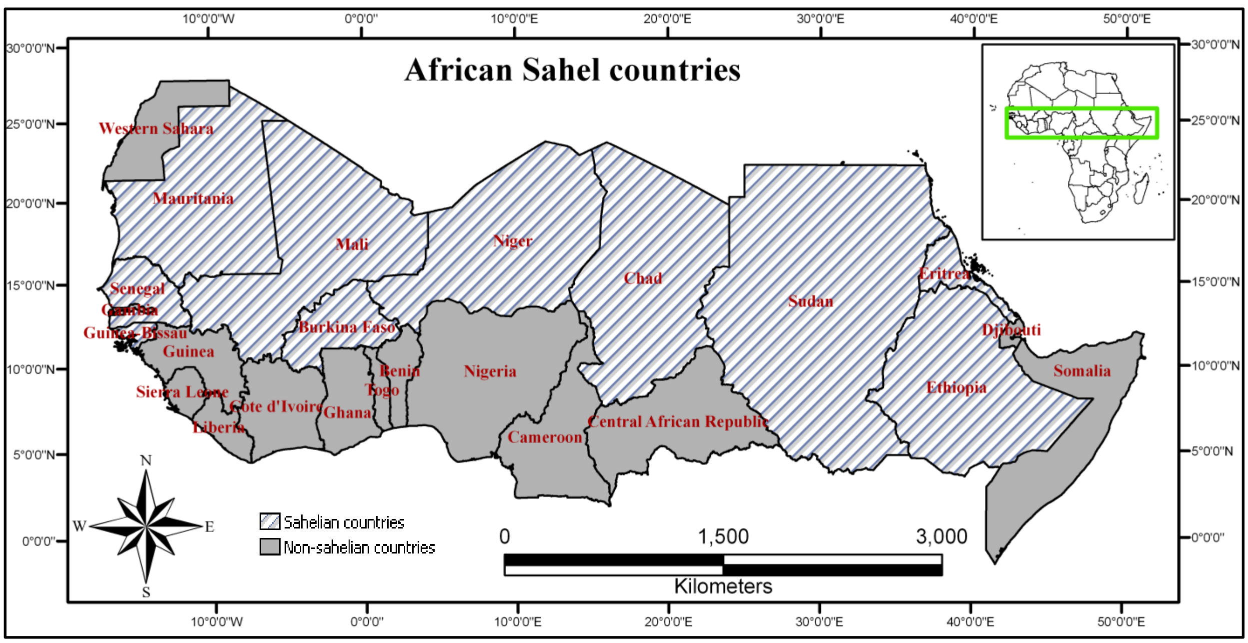
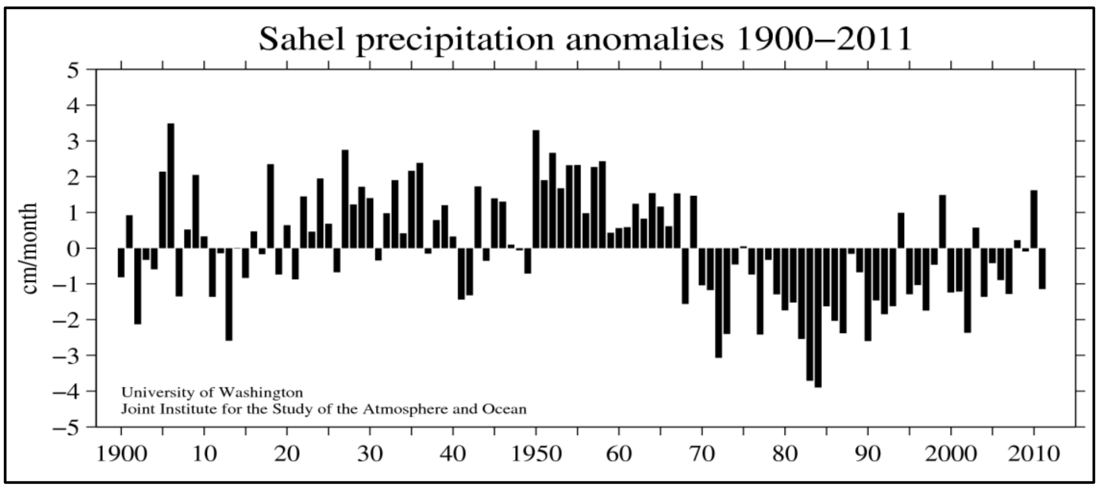


Figure 1: Overview of the geographic location of the Study area and Sahelian countries. Note that the Cape Verde islands, although not included in the map are also defined as Sahel.

The Sahel region is divided into four different eco-climatic zones based on the average annual rainfall and agricultural features, i.e. Sahelian, Sudano-Sahelian zone, Sudanian zone and Guinean zone (FAO/GIEWS, 1998). The Sahelian zone characterized by average annual rainfall between 250 and 500 mm, while the Sudano-Sahelian zone is receives average annual rainfall between 500 and 900 mm. Finally, the Sudanian zone and Guinean zones have average annual rainfall ranges from 900 to 1100 mm, and > 1100 mm, respectively (FAO/GIEWS, 1998, 2007).

2.1.1. Climate in Sahel

The Sahel climate is characterized by a distinct seasonality with a long dry season and a short humid season (JASO months) occurring approximately between July and October with August being the wettest month (Anyamba and Tucker, 2005). The rainfall regime in the Sahel is characterized by inter-annual and inter-decadal variability (Fig.2), and it varies spatially from year to year, which makes it difficult to predict future characteristics of rainfall. Rainfall amounts in the 1961-1989 periods showed a 40% lower amount than previous early period in 1931-1960 (Hulme, 2001). Rainfall in Sahel shows a steep north (low)-south (high) gradient distinguished by different vegetation species and agricultural crops that is mainly rain-fed and depends on 3 to 4 months of summer rainfall (Hulme, 2001). The Sahel is characterized by dry tropical climate with mean maximum temperature around 40-42° C, while the mean minimum temperature is around 15°C (Le Houerou, 1980).



[1]*Figure 2: Average precipitation over Sahel (20 N-10 N, 20W-10E) from 1900-2011 during June to October based on climatology NOAA NCDC Global Historical Climatology Network data.*

Reasons for rainfall variability in Sahel region are multiple and complex and several factors contribute, including the El Nino southern oscillation (ENSO) cycles (Nicholson, 2001), or non-ENSO-related variations in sea surface temperatures (Brooks, 2004). Many others may be related to changes in land cover and land-atmosphere interactions (Nicholson, 2001; Hulme et al., 2001) while other studies linked between rainfall variability in Sahel and anthropogenic global warming (e.g. Eltahir and Gong, 1995). Changes in the African Easterly Jet (AEJ) and the Tropical Easterly Jet (TEJ) intensity and localization could be other factors influencing rainfall variability (Nicholson and Grist, 2003).

[1]Available at: *http://jisao.washington.edu/data_sets/sahel/*

According to Lebel and Ali, 2009, the driving force that controls the amount, timing and distribution of rainfall in the Sahel region is the Intertropical Convergence Zone (ITCZ) However, the West African Monsoon (WAM) also has a great effect on the rainy season (JASO months) that varies between 3 and 6 months long. WAM dynamics comes from differences between temperature, pressure and humidity in the North African continent and the tropical Atlantic regions (Tucker et al., 2005). By the 2080s, Climate change and variability with interaction of human activity through deforestation can lead to increase in size of arid and semi-arid lands in Africa by 5-8% (IPCC, 2007).

2.1.2. Vegetation in Sahel

Vegetation in the Sahel area shows a gradient from north to south with denser vegetation in the south (Fig.3). The Sahelian zone is characterized by very sparse vegetation cover that is characterized by annual and perennial grasses with thorny shrubs interspersed in-between while the Sudanian and Guinean zones are characterized by higher amount of ground cover and more woody species with taller vegetation (Le Houerou, 1980). In the 20th century, the Sahel has been subjected to a long period of desiccation interspersed with major droughts causing serious impacts on the vegetation growth (Lamb, 1982). However, the Sahel has experienced a recovery and increase in rainfall over the last years compared to the amounts in the late of 1960s (Hulme et al., 2001; Nicholson, 2001).

2.1.3. Vegetation and rainfall in Sahel

Vegetation activity in the Sahel is powerfully linked to rainfall at continental and global scales (Zhang et al. 2005) and therefore the Normalized difference vegetation index (NDVI) index has been used by many researchers as a good indicator for monitoring and estimating the amount of rainfall in the Sahel. However, the relationship between NDVI and rainfall does not show a linear relationship in all regions as this relationship can be affected by other factors such as soil properties (Nicholson and Farrar 1994), region (Nicholson et al. 1990), vegetation type (Davenport and Nicholson 1993), and human factors through repeated burning (Parr et al. 2004), limited sensitivity of NDVI at higher vegetation densities or beyond 200mm monthly^{-1} (1200 mm yearly^{-1}) rainfall (Nicholson et al., 1990) and grazing strategies that are mainly associated with soil erosion (Wessels et al. 2004). Therefore, blaming only low and irregular rainfall alone for impeded vegetation growth is a misunderstanding and oversimplification of the situation even if rainfall variability is considered the major driver responsible.

The best relationship between vegetation growth and rainfall occurred at the concurrent month plus two previous rainfall months (two months' time lag), as the peak of vegetation growth responds to the peak of rainfall two months later (Davenport and Nicholson, 1993; Eklundh, 1997; Udelhoven et al., 2008). However, this relationship is highly variable in time and space and depends on the degree of aggregation of these variables in the time domain (Wang et al. 2003). Tucker and Nicholson (1999) found that the vegetation greenness margins in Sahel fluctuated by up to 150km from a wet year to a preceding dry year in response to rainfall variations.

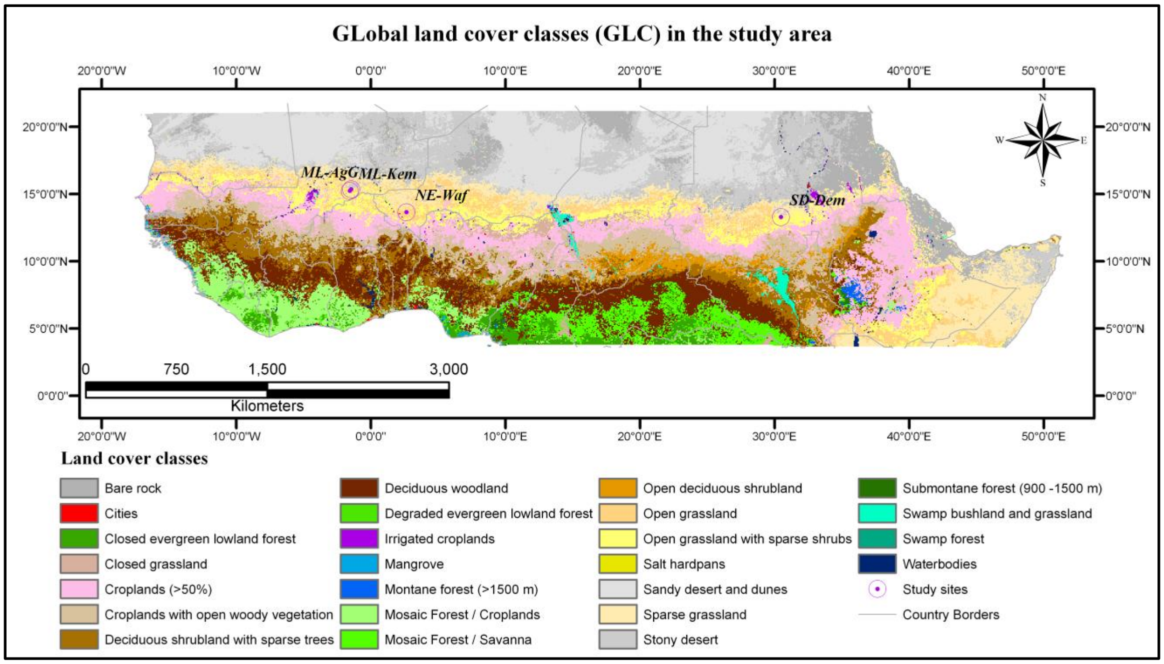


Figure 3: Major land cover classes across the study area based on global land cover (GLC 2000) classification with the selected study sites locations.

2.2. Desertification Debate

According to the current United Nations Convention to Combat Desertification (UNCCD), desertification means land degradation in arid and semi-arid areas that can be caused by many factors, such as climate change and human activities through over-use cultivation and soil nutrients (UNCCD website). Desertification is usually associated with a loss and reduction in areas of productivity. Desertification does not mean expansion of the existing deserts but occurs because dry lands are vulnerable to over-exploitation and mismanagement of land (FAO, 2011).

Tucker et al. (1991) and Tucker and Nicholson (1999) indicate that there is a southward movement of the Sahara desert as a result of the severe drought that occurred in the mid-1980s. However, many studies held by (Seaquist et al., 2006; Anyamba and Tucker, 2005; Olsson et al., 2005; Herrmann et al., 2005; Eklundh and Olsson, 2003) observed upturn in rainfall and vegetation growth in different regions in Sahel that prove there's recovery in rainfall in 1988s and contradict claims of widespread permanent desertification in the African Sahel. Owing to lack of uniformity increasing in the greening trend across the entire Sahel region, rainfall is not likely the only driving factor responsible for the vegetation dynamics in Sahel.

2.3. Agricultural Drought in Sahel

Drought occurred in the Sahel region during the 1970-1980's as a result of severe rainfall drop since the mid-1960s (especially in 1973, 1984 and 1990) that led to a large impact on the local economy. Food security was one of the reasons for establishing the United Nations Convention to Combat Desertification and Drought (UNCCD) to mitigate the effects of drought and improving the living conditions of people in dry-lands (Hulme, 2001).

Agricultural drought events are generally linked with reduction in crop yield and in many cases cause crop failure. The majority of the population in the Sahel region depends mainly on agriculture for their livelihood, and hence any long-term drought event is commonly associated with devastating hunger, famines, malnutrition and starvation (FAO, 2011). Droughts are natural and occur unexpectedly and slowly over time and their impacts could continue to be felt long after drought terminates (Wilhelmi and Wilhite, 2002). However, early warning of such drought events will minimize the risks that associated with droughts (Nicholson et al., 1990). Early warning can help the governments and international food aid agencies to plan in advance for redistributing food in the drought venerable areas to mitigate food insecurity and starvations.

2.4. Remote sensing and vegetation

Ecosystem monitoring has become much easier by using advanced remote sensing technology that is characterized by consistent delivery, presence of multi-decadal time series archive of several environmental variables, and datasets availability at different spatial, temporal and spectral resolution. Remote sensing is the art and science of collecting information about the Earth or any other object without a direct physical contact through using images acquired from satellite sensors or any synoptic perspective. The process is facilitated by analyzing the radiation emitted or reflected from the Earth's surface in one or several regions of the electromagnetic spectrum (Campbell, 1996). Nowadays, it is possible to derive information about the characteristics of vegetation cover at different scales by using the visible and near-infrared (NIR) spectral bands.

Owing to lack of spatially distributed climate data in the Sahel region, it is possible to use remote sensing at different scales from local to regional to observe vegetation growth or changes that cannot be easily observed from the Earth's surface. Normalized Difference Vegetation Index (NDVI) time series data from National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (NOAA AVHRR) sensor is used intensively in many studies for analyzing vegetation changes in semi-arid areas (in particular in the Sahel region) and analyzing the relationship between vegetation greenness and rainfall regime (e.g. Eklundh and Olsson, 2003; Anyamba and Tucker, 2005).

2.5. Normalized Difference Vegetation Index (NDVI)

Vegetation indices are used for measuring vegetation canopy "greenness" that refers to leaf chlorophyll, leaf area, canopy cover, and structure. There are many attempts to have an index that is maximizing the spectral contribution of vegetation greenness, but also minimizing the contribution of atmosphere and soil background. One of the most widely used vegetation indices is the Normalized Difference Vegetation Index (NDVI, Rouse et al. 1974). It is used for monitoring vegetation dynamics and the index is defined as $NDVI = \frac{QNIR-QRed}{QNIR+QRed}$, where QNIR is the reflectance in the Near-Infra Red (NIR) and QRED is the reflectance in Red band. NDVI is a relative measure of photosynthetic activity and green biomass because the healthy green leaves strongly reflects NIR radiation due to internal mesophyll structure and absorbs red radiations by leaf chlorophyll and other pigments (Tucker et al., 1985), good indicator for leaf area index (LAI) as reported by (Asrar et al., 1984) and Net Primary Production (NPP) as stated by many researchers (e.g. Nemani et al., 2003; Sjöström et al., 2009).

NDVI values range from -1 to 1, where high positive values are represent increasing vegetation greenness (+1 is healthy dense vegetation and 0.1 is a less dense vegetation) while negative magnitude values representing non-vegetated areas such as water, ice or clouds. However, NDVI has limited sensitivity to high dense vegetation or saturated leaf area index (LAI). NDVI values do not represent the amount of vegetation cover in low vegetation cover areas due to the effects of soil background, and using NDVI values as a proxy for vegetation growth in response to the water availability should be applied with caution as the relationship between NDVI and precipitation is not valid beyond 1200mm yearly since the moisture is no longer the limiting factor of vegetation growth (Nicholson et al., 1990).

NDVI composites satellite images derived from the NOAA AVHRR satellite are produced every two weeks by taking the maximum NDVI value during the two weeks period, this technique was done to minimize the effect of cloud coverage within the dataset (Wang et al., 2003). AVHRR NDVI data have been used in many early studies to monitor the vegetation greenness in response to changes in the climatic variables or other anthropogenic factors (e.g. Seaquist et al., 2006; Anyamba and Tucker, 2005; Olsson et al., 2005; Herrmann et al., 2005; Eklundh and Olsson, 2003).

2.6. Soil moisture and vegetation growth (NDVI)

Soil moisture (quantity of water contained in soil) has a great influence on the land surface energy fluxes, hydrological processes and the interaction between land surface and atmosphere (Zhang et al., 2011). Vegetation growth (NDVI) is influenced by soil moisture which is affected by changes in precipitation and temperature. Therefore, soil moisture is considered a key parameter linked between NDVI, precipitation and temperature (Wang et al., 2003). Using field investigation for such variable like soil moisture is time consuming, expensive and impractical for monitoring over large areas. Hence, modeled soil moisture data is used effectively and efficiently for covering vast geographic regions such as Sahel region. Modeled soil moisture can give an indication about the residence time of moisture in the soil and moisture availability for plant growth.

Root zone soil moisture represents a component of moisture that is accessible by plants roots linking surface vegetation with subsurface water stored in the soil, and varies with climate, type of vegetation and soil type (Guswa, 2008). Many studies suggested that NDVI data can be used as an indicator for the root zone moisture availability at large scale as any temporal variation in soil moisture affect the vegetation characteristics (e.g. Nicholson and Farrar, 1994; Schnur et al., 2010). Although much attention has been directed by many researchers to study the relationship between NDVI and climatic variables, few studies have emphasized the relationship between NDVI and soil moisture (e.g. Huber et al., 2011; Nicholson and Farrar, 1994).

The best relationship between NDVI and soil moisture occurred in the concurrent month, while the best relationship between NDVI and rainfall occurred at multi-months average of rainfall, according to the study reported by Nicholson and Farrar (1994) in Botswana. Another study reported by Owe and et al. (1993) stated that the relationship between NDVI and modeled soil moisture in semi-arid Botswana is poorly correlated at the same month (no time lag), while the relationship is improved by using one month time lag (current NDVI with the previous month's average soil moisture). Jamali et al. (2011) reported that the both NDVI and Enhanced vegetation Index (EVI) vegetation indices are highly correlated with soil moisture in the upper 1m depth with maximum correlation lag varies between 0-28 days in six different sites in Africa. Another study reported by Schnur et al. (2010) to estimate root zone soil moisture by using NDVI and EVI in southwestern of USA revealed that soil moisture values at distant sites and same depths are highly correlated (r= 0.53 to 0.85) and NDVI is more correlated with soil moisture than EVI and the correlation shows the maximum value when both NDVI and EVI lags soil moisture by 5 to 10 days.

The relationship between NDVI and root-zone soil moisture at five depths (5 cm, 10 cm, 20 cm, 50 cm, and 100 cm) in three sites in USA (New Mexico, Arizona, and Texas) was investigated to determine the possibility of using optical remote sensing techniques as an approach for assessing root zone soil moisture (Wang et al., 2007). Results showed that the significant correlation relationship between root zone soil moisture and deseasonalized NDVI varied between 0.46-0.55 at the three sites indicating that NDVI is a good proxy for root zone soil moisture mapping, and the vegetation in the humid site (Texas) need more time to respond to soil moisture than vegetation in the semi-arid sites (New Mexico and Arizona). The relationship between NDVI and soil moisture showed spatial-temporal variation in Sahel by using the rainy season (JASO months), the relationship strengthen in the north of Sahel and declined in south part of Sahel (Huber et al., 2011). The modeled root zone soil moisture showed a stronger correlation with NDVI than with precipitation in the Mongolian steppe during the period 1982-2005, suggesting that soil moisture has an important role on the vegetation dynamics (Nandintsetseg et al., 2010).

3. Materials and Methods

3.1. Datasets

Remotely-sensed NDVI and modeled soil moisture time series data sets for 27 years, spanning from 1982 to 2008 were used to perform this investigation. Descriptions of these data sets are provided below (in detail) with a description of other ancillary data such as land cover type and soil texture.

3.1.1. GIMMS Data Set (NDVI)

Advanced Very High Resolution Radiometer (AVHRR) Global Inventory Modelling and Mapping studies (GIMMS) NDVI time series data were used in this study. The data was monthly NDVI with maximum value composites (MVC) at 8 km spatial resolution. GIMMS NDVI data were processed by the GIMMS group at NASA's Goddard Space Flight Center (Tucker et al., 2005; Pinzon et al., 2005).

The GIMMS dataset is a normalized difference vegetation index (NDVI) product derived from the AVHRR instrument onboard of National Oceanic and Atmospheric Administration (NOAA) polar orbiting satellite series 7, 9, 11, 14, 16 and 17. AVHRR acquires data in five different spectral bands at 1.1 km spatial resolution; one visible, one infrared and three thermal bands; GIMMS data are using only the first and second band. Although, NOAA AVHRR satellite sensor series were originally designed as a weather satellites. However, it started from the early of 1980s to monitor the characteristics of land vegetation. The product NDVI dataset available for a 25 year period spanning from 1981 to 2006 (Note: 2007 and 2008 years data used in this study provided from *Eklundh, L.* by contacting the data provider).

The GIMMS NDVI dataset has been adjusted by the GIMMS group at NASA's Goddard Space Flight Center to eliminate and minimize the effect of inaccuracies produced by lack of on-board band calibration, atmospheric effects, variation in solar illumination, volcanic aerosols, effects of satellite drift and sensor view angles. According to Tucker et al. (2005), there is no atmospheric correction done to GIMMS data except for volcanic stratospheric aerosol periods (1982-1984 and 1991-1994), and even after correcting NDVI signals, there is still a reduction in NDVI over densely vegetated land covers for limited time periods. Pinzon et al. (2005) used a transformation method to correct the satellite orbital drift by using empirical mode decomposition (EMD) that removed common trends between time series of solar zenith angle (SZA) and NDVI to minimize the effects of orbital drift. Composite images were constructed (two 15-day composites per month) in order to have a cloud-free view of the Earth by choosing pixels with the MVC NDVI values during regularly spaced intervals, this method minimize the effects of water vapor and cloud cover that strongly reduce NDVI values (GIMMS data documentation).

AVHRR Pathfinder (PAL) and GIMMS NDVI are the two mostly commonly used datasets in Sahelian studies. According to McCloy *et al.* (2005), the pathfinder and GIMMS datasets are moderately correlated (r^2= 0.73) globally, however the NDVI in the Sahel has increased by 2-

20% by using the Pathfinder dataset and 6-50% by using the GIMMS dataset during 1981-2000 period.

Justification for Use of GIMMS NDVI Data

The GIMMS NDVI dataset was preferred for this study for several reasons. Firstly, it provided the longest, continuous NDVI time series from 1981 until 2008 and it is updated weekly with the shortest composition period (10 -15 days). Secondly, GIMMS NDVI dataset has been calibrated to be comparable with other newer vegetation remote sensing like Moderate Resolution Imaging Spectroradiometer (MODIS). A study by Fensholt et al. (2006) shows that the AVHRR GIMMS NDVI data is more consistent with SPOT-4 VGT NDVI data compared to other AVHRR data sets (e.g. PAL) and can therefore be considered highly accurate for monitoring the vegetation dynamics.

For more information about GIMMS NDVI data set or for downloading the product, go to: (http://glcf.umiacs.umd.edu/data/gimms/) [Data accessed in April, 2012].

3.1.2. Modelled Soil Moisture Data

Monthly soil moisture data sets spanning from 1982 to 2008 (covering the same period of time as the NDVI data) were used in this study. Modelled soil moisture data was provided by the NOAA National Centers for Environmental Predictions (NCEP) Climate Prediction Center (CPC) Global Monthly high resolution Soil Moisture (GMSM). The monthly soil moisture data sets were produced globally with a 0.5 degree spatial resolution by using one-layer "bucket" water balance (hydrological) model from 1948 until to the present (Fan and van den Dool, 2004). The data updated monthly which improves utility for near real-time purposes.

The model is driven by monthly Climate Prediction Center (CPC) global precipitation over land that uses over 17,000 gauges worldwide (Chen et al., 2002). For more recent years the analysis is based on radar and satellite measurements with gauge data. Monthly global temperatures from the CDAS- Re-analysis product were selected as the second input in this model owing to its availability and monthly updating (Kistler et al., 2001). The outputs from this model are global monthly soil moisture, evaporation and runoff.

Modelled soil moisture data validated with observed soil moisture measurements in different places around the world such as Russia, China, India and USA, the validation results shows that the modeled soil moisture simulates the seasonal to inter-annual variability of observed soil moisture very well in many locations (Fan and van den Dool, 2004). The anomaly correlation between modeled soil moisture and observed soil moisture is about 0.60-0.75 over the Illinois state in USA during the time period 1984 to 2001 (Van den Dool et al., 2003).

The model had set the effective water holding capacity to 76 cm of water, which is equal to 1.6 m deep "leaky" bucket at porosity of 0.047 (van den Dool et al., 2003). The maximum soil moisture value was set to 760 mm in the model with output units in mm for soil moisture data.

For more information about modelled soil moisture data set or for downloading the product, go to: (http://www.cpc.ncep.noaa.gov/soilmst/leaky_glb.htm) [Data accessed in April, 2012].

Table 1: Summary of NDVI and modelled soil moisture dataset characteristics.

Datasets	Spatial resolution	Spatial extent	Temporal resolution	Temporal extent	Availability and cost	Limitations
GIMMS NDVI datasets	8 km* 8km	Global	Monthly	1981 to 2008	Available online and free	In highly dense vegetation areas, NDVI has a lower accuracy.
CPC - GMSM	0.5º * 0.5º	Global	Monthly	1948 to present	Available online and free	Maximum soil moisture is 760 mm and the great modelled depth (=1.6 m)

3.1.3. Land Cover Data

Global land cover (GLC) 2000 map is based on observations made by the VEGETATION sensor on the SPOT 4 satellite from 1st November 1999 to 31st December 2000, to provide a harmonized land cover database over the whole globe. The land cover map was mainly produced by unsupervised classification aided by thematic maps and class spectral statistics. The GLC 2000 validation strategy includes systematic review by experts for the regional products, comparison with reference and ancillary data; and using stratified random sampling for quantitative accuracy assessment of the global products (Mayaux et al., 2006). The study area was clipped from the downloaded Africa land cover map (Fig.4), and then the land cover map was resampled to 8 km spatial resolution using nearest neighboring method as the original downloaded map had 1 km spatial resolution at the Equator. The GLC 2000 legends with 27 classes in Africa were based on the FAO LCCS (land cover classification system) (Mayaux et al., 2006). Land cover classes were merged in the study area to eight major classes based on similarity of their signatures for easier interpretation afterwards (Table A1, in appendix).

For more information about GLC 2000 Land cover data or for downloading the product, go to: (http://bioval.jrc.ec.europa.eu/products/glc2000/glc2000.php) [Data accessed in August, 2012].

3.1.4. Soil Texture Data

Soil texture data was provided by FAO-UNESCO soil map of the world. The digitized soil map by ESRI (Environmental Systems Research Institute) was classed by Soil Taxonomy suborders into twelve soil orders with their suborder classes. The Global soil regions were based on a reclassification of both FAO-UNESCO soil map of the world and the soil climate map. The soil map data produced in a global coverage in April, 1997 and revised in September, 2005 with a minimum scale equal to 1:5,000,000 and geographic projection. The Sahel study area clipped from the global soil map of the world and was resampled to 8 km spatial resolution using nearest neighbor method (Fig.4). Soil suborder classes were merged to a major order classes according to the USA Soil Taxonomy (Table A2, in appendix). [2]Descriptions of the twelve soil order characteristics with their percentage and location in the world can be found in (Table. 2).

For more information about FAO-UNESCO soil map of the world or for downloading the product, go to: (http://soils.usda.gov/use/worldsoils/mapindex/order.html) [Data accessed in August, 2012].

Table 2: Characteristics of the major soil order classes according to NRCS (Natural Resources Conversation Service) distribution center website.

Soil order	Location	Description	Area (%) in the world
Alfisols	Semiarid to moist areas	Characterized by holding water and nutrients to plants, occurs under high dense vegetation regions like as forest or mixed vegetation cover and it's a good productive soil for crops.	10%
Andisols	Cool areas with moderate to high precipitation	High water and nutrient-holding capacity associated with volcanic materials and tend to be highly productive soils.	1%
Aridisols	Deserts of the world	Highly dry soil for the growth of plants, characterized by lack of moisture and accumulating gypsum, and salt.	12%
Entisols	Occur in many environments	Characterized by absence of pedogenic horizon development and likely to found in flood plains, dunes and steep slopes.	16%
Gelisols	Common in higher latitudes or at high elevations	Characterized by a permafrost or ice aggregation near the soil surface.	9%
Histosols	Occur in highly saturated areas all the year round	Have a high content of organic matter and no permafrost and commonly called bogs, peats or mucks.	1%
Inceptisols	Semiarid to humid environments	Characterized by a moderate degree of soil weathering and development in a wide variety of climates.	17%
Mollisols	Occurs on the steppes of many countries.	Characterized by moderate to high moisture deficiency and high content of organic matter. Usually occurs under grass.	7%
Oxisols	Tropical and Subtropical regions	Characterized by low fertility and a low capacity to retain additions of lime and fertilizer.	8%
Spodosols	Under coniferous forests of humid regions	Occur in areas of coarse-textured deposits and it tends to be acid and infertile.	4%
Ultisols	Humid areas	Nutrients are concentrated in the upper zone of soil, and it is classified as acid soils that can't retain addition fertilizer and lime easily.	8%
Vertisols	Occur in many environments	Characterized by high content of expanding clay minerals that transmit water very slowly and tend to be high in natural fertility.	2%

[2]Descriptions of soil classes Available at: (http://www.soils.usda.gov/technical/soil_orders/) [Data accessed in August, 2012].

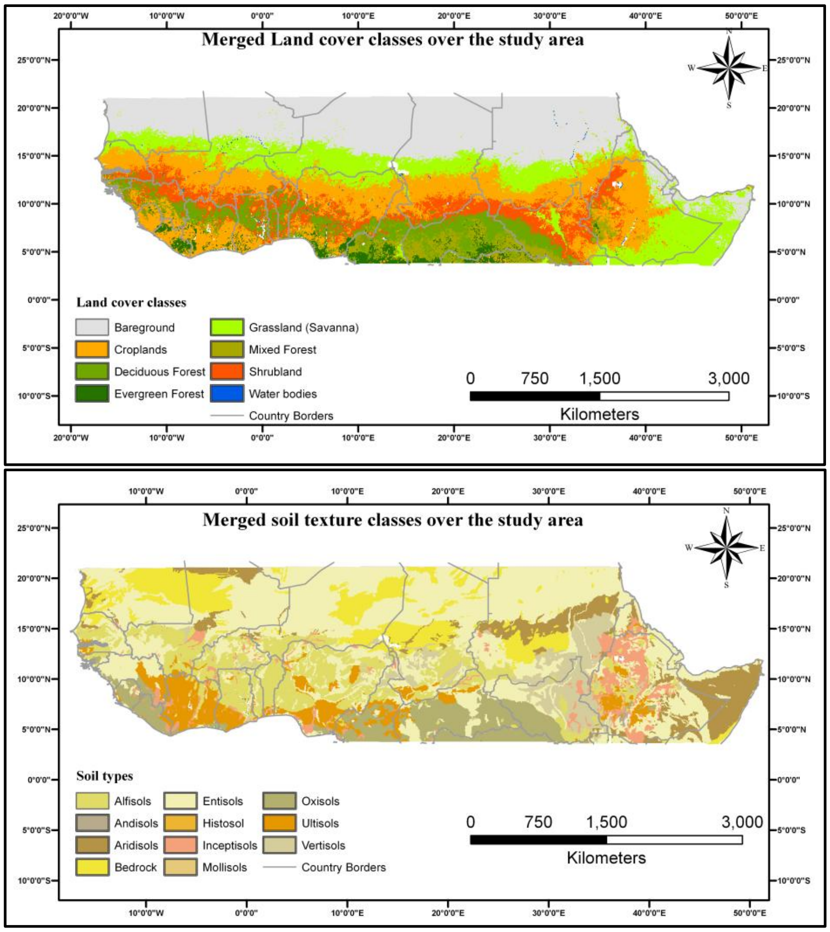


Figure 4: Major aggregated classes of land cover and soil types in the Sahel area.

3.2. Methodology

Procedures undertaken in this study can be categorized into three different steps beginning with a data pre-processing (data harmonization) step, a data processing step and data post-processing step. The analyses were applied for all the year data (dry season included) and only for the rainy season months from July to October (JASO months) that also representing the start and end of growing season. Flow chart of methodology analyses followed in this study will be found in Fig.8.

3.2.1. Data pre-processing

GIMMS NDVI data was converted from 8-bit into real NDVI. Raw NDVI values has been divided by 10000 (i.e. water pixels have a value of -10000 in the raw data) and to recover the -1 to 1 range of NDVI, the following formula used: (NDVI = (Raw NDVI/10000). The GIMMS data was projected to Albers Equal Area Conic projection using Clarke 1866 ellipsoid.

Soil moisture (SM) dataset was re-projected to Albers Conical Equal Area Projection and resampled from 0.5° to 8 km by using nearest neighbour algorithm that duplicating pixels without changing the original cell values to be in match with GIMMS NDVI data resolution and projection.

GIMMS NDVI data and SM data were provided in a global spatial cover and to emphasis only on Sahel region, the two datasets clipped only to the study area.

3.2.2. Data processing

NDVI and SM time series data can be decomposed into three main components: trend, seasonal and irregular fluctuations or errors (Fig.5). Any time series data characterized by autocorrelation and non-stationary properties affect the statistical relations between dependent and independent variable through violating the assumption of dependency or uncorrelated errors in the regression analysis (Salvatore and Reagle, 2001).

Autocorrelation or serial correlation occurs when the error term for one time period is positively or negatively correlated with the error term neighboring time periods. Autocorrelation will affect the cross correlation between variables through overestimating and sometimes underestimating cross correlation coefficients, and leads to downward-biased standard errors that give incorrect statistical tests and confidence intervals (Salvatore and Reagle, 2001). The presence of autocorrelation between NDVI and SM series data was tested by using Durbin –Watson statistics (Fig.6) and also by studying autocorrelation functions (ACF) and partial autocorrelation functions (PACF) for both NDVI and soil moisture data (Salvatore and Reagle, 2001).

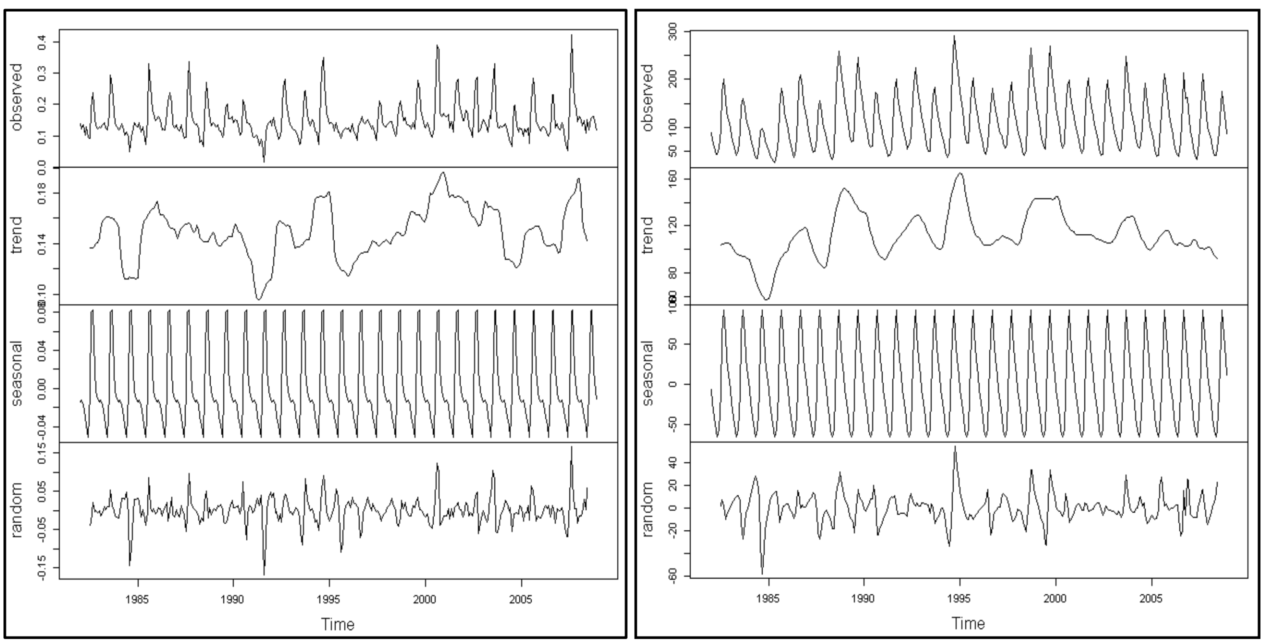


*Figure 5: Seasonal decomposition of NDVI (left) and SM (right) into trend, seasonal and irregular components based on one pixel size (8*8 km) at 15° 16' 20" N, 7° 28' 15" E.*

Non-stationarity is defined as the gradual change in mean and standard deviation of time series over time, which will affect or inflate cross correlation coefficients as the relationship should depend on difference of lag only and do not change with time (Milionis and Davies, 1994). The presence of non-stationarity is tested by plotting data over time and fitting first-order trend (Fig.7) and also by a parametric approach through the auto-correlation function (ACF) that shows very slowly decline (or trails off) to zero.

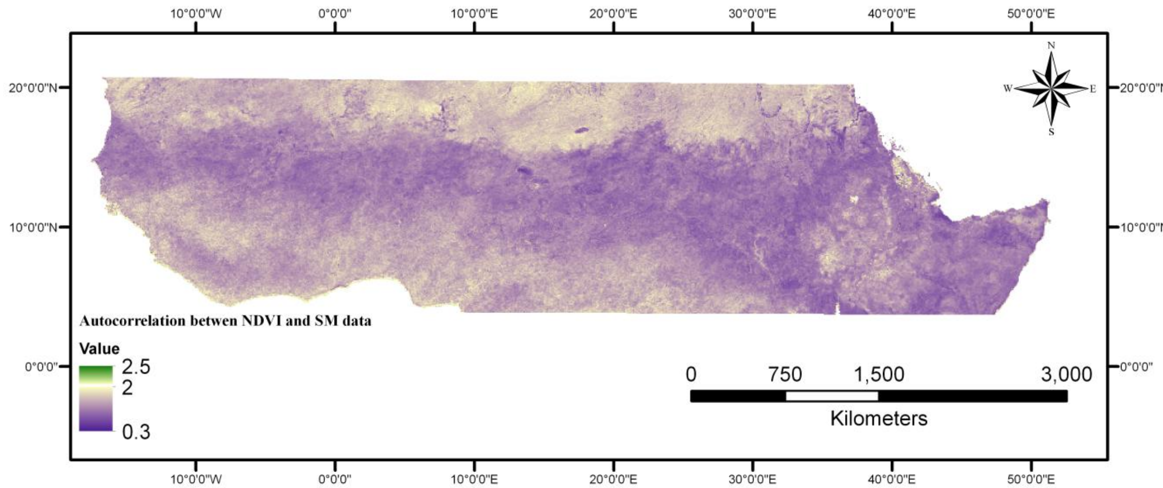


Figure 6: Showing the first order autocorrelation in residuals from a regression analysis between NDVI and soil moisture data before detrending and deseasonalizing. A value of 2 indicates no serial autocorrelation, values less than 2 indicates evidence of positive serial autocorrelation and values greater than 2 indicates evidence of negative serial autocorrelation.

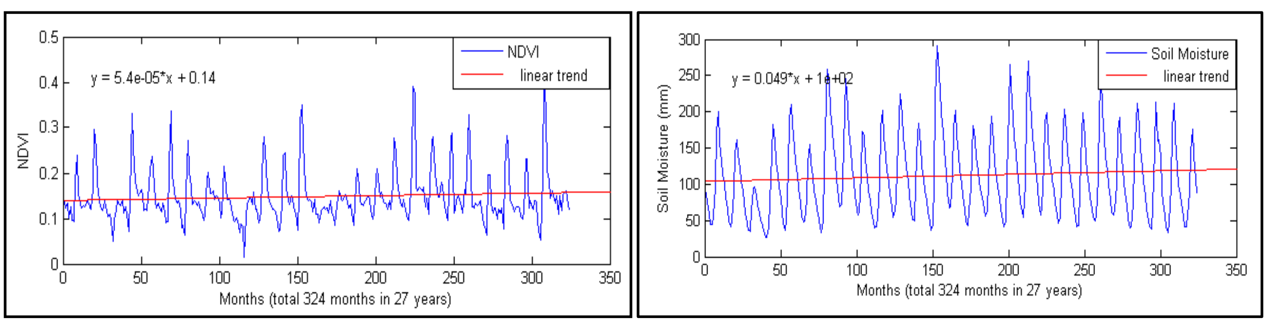


*Figure 7: Shows the presence of non- stationarity in the NDVI and soil moisture data, as the trend is increasing with increasing time. This figure is based on only one pixel (8*8 km) with geographic location 15° 16' 20" N, 7° 28' 15" E.*

3.2.2.1. Data De-trending

De-trending is the process of removing trend from the time series data to convert non-stationarity data to stationary data for a further analysis. Non-stationarity is identified as the long-term gradual change in the mean or variance over time or position in the time series data. De-trending by the differencing approach was applied in this study analysis. This method is implemented by differencing value of the series at times t and t-1 according to this equation: $W_t = X_t - X_{t-i}$, where W_t is the difference image series at time t, $X_t - X_{t-i}$ is the difference between original time series at time t and original time series at a previous time series step (t-1). The result from this approach is expected to remove the serial correlation that exists in the data. Another de-trending method is accomplished by the fitting low-order polynomials to the time series data through time by using TIMESAT software (Eklundh and Jonsson, 2004), and then subtracting the newly created trend images from TIMESAT from the original time series data. The two methods were applied for comparison and in order to identify which method is more effective for removing the trend from the NDVI and SM time series data.

3.2.2.2. De-seasonalization

Seasonality is one of the time series components and is identified by regularly spaced peaks and troughs around the trend line in one year or less. The presence of seasonal components in NDVI and soil moisture time series data spanning the same period of time will lead to a spurious cross correlation and it will influence the autocorrelation structure of the two time series data (Chartfield, 2004). So, removing the long-term effect of seasonal components from the two variables is necessary to correctly assessing the correlation relationship between NDVI and soil moisture. The standardized seasonal anomalies method was applied in our study to eliminate the effects of seasonality (Udelhoven et al., 2009) by using seasonal z-score transformation; $\mathrm{Z_{tj}} = \frac{\mathrm{X_{tj}}-\bar{\mathrm{x}}_{\mathrm{j}}}{\mathrm{S_j}}$, Where Z_{tj} is the standardized anomaly (z-score) for month (j) and a time index (t), Xtj is the original image series, $\bar{x}_j$ is the long term mean and S_j is the standard deviation. The standardized anomalies will not preserving the characteristic differences in the original data.

3.2.2.3. Data Pre-whitening

Errors characterized by time series structure will violate the assumption of errors independency in the ordinary least square regression, which will lead to inaccurate estimation of the standard errors and regression coefficients and give wrong statistical relationship between the dependent and independent variables. So, estimating the true serial correlation is essential to get a robust result from the relation between NDVI and SM. Pre-whitening is the approach used in our study analysis to remove the effect of serial correlation in the error components of NDVI and SM time series data. This procedure, described by Wang and Swail (2001), is used to remove the serial correlation through an iterative process until the error series becomes white noise (normally distributed errors with mean zero and variance σ^2).

3.2.3. Data post-processing

3.2.3.1. Trend analysis

The non-parametric median trend (Theil-Sen trend) was calculated for the GIMMS NDVI and SM dataset to investigate trends over time in both of time series data across the Sahel region. Non-parametric trend (Theil-Sen) calculates the non-parametric slope and intercept of data by determining the median of all estimates of the slopes from all pairs of observation (Sen, 1968; Then, 1950) and the trend have to be persistent for more than 29% of the length of the time series in order to be considered (Hoaglin et al., 2000). Significance of trend was calculated by Mann-

Kendall test (kendall, 1955; Mann, 1945) that gave image values in z-scores, where a positive slope or trend ($z \geq 1.96$) represents a significance increase at 5% significance level and a negative slope or trend ($z \leq -1.96$) represents a significance decrease at 5% significance level, while other pixels were indicated to have no trend. Non-linear monotonic trend "Mann-Kendall" test was calculated to indicate to what degree the trend is consistently increasing (values > 0) or decreasing (values < 0) and zero value represents absence of consistent trend.
Residual trend analysis (RTA) was calculated from the regression analysis between raw NDVI data as dependent variable and raw SM data as explanatory variable for both all-year data and JASO month's data, then searching for any significant long term trends in residuals. RTA was used to detect any possible trends that can be explained by any other factor than soil moisture.

3.2.3.2. Linear correlation "Pearson's correlation coefficients"

In order to test the strength of correlation relationship between GIMMS NDVI and SM time series data, Pearson's correlation coefficients were calculated for each pixel across the Sahel area with different time lags ranging from zero time lag (current values of NDVI versus current values of soil moisture) to five time lag (current values of NDVI versus previous five months lag soil moisture values). Significance correlation maps were produced at the 5% significance level (95% confidence intervals) for all the different time lags (lag0 to lag5) according to t-test analysis. The correlation analyses were done for all seasonal months and just for JASO rainy months. An optimal lag map was generated by calculating the highest correlation coefficient values for all the pixels when all the correlations coefficients of all the five lags were considered. Correlation relationship between NDVI and SM calculated based on the following equation:

$$r = \frac{\mathrm{COV}(X_1,\ X_2)}{S1\ S2} = \frac{\sum_{i=1}^{n} [(X_{1i}-\bar{x}_1)\ (X_{2i}-\bar{x}_2)]}{(n-1)S1S2}$$

Where r is the correlation coefficient, $\mathrm{COV}(X_1, X_2)$ is the covariance relationship between dependent and independent variable, S_1 and S_2 are the standard deviations of the two variables, n is the number of time series images, $(X_{1i}-\bar{x}_1)$ is the original time series data of the first variable subtracted from the long term mean of that variable and $(X_{2i}-\bar{x}_2)$ is the original time series data of the second variable subtracted from the long-term mean of that variable.

3.2.3.3. Logistic regression

Logistic regression analysis was calculated in this study to evaluate the effect of land cover and soil texture on the correlation relationship between NDVI and SM. Logistic binomial regression is a type of regression analysis used in estimating a model that describes the relationship between a binary dependent variable and one or more continuous independent variable(s). The logistic regression model in this analysis aims to gauge the direction and strength of the relationship between independent variables (land cover and soil texture) and a binary dependent variable (optimal lag correlation). The logistic regression was selected instead of a normal linear regression because the response values are categorical or not measured on a ratio scale (1 is the presence of significant correlation and 0 is the absence of significant correlation at this lag) and the error terms are not perfectly normally distributed. The logistic regression model uses the maximum likelihood estimation to find the best fitting of the parameters through finding the set of parameters for which their observed data probability is the greatest.

To evaluate the logistic regression model quality, the sensitivity which measures the ability to identify dependent variable “positive response” and specificity which measures the ability to identify the absence of independent variable were calculated. To determine the strength of association between independent variable and dependent variable, the odds ratio (OR) was calculated. The degree of association is calculated according to these values in (Table 3). In addition, the ROC (Relative Operating Characteristics) was calculated to measure the goodness of fit of logistic regression with values ranges from 0 to 1 (Table 3).

Table 3: Shows the description of logistic model parameters.

Parameters	Method	Interpretation
Sensitivity	a/ (a+c)	100% is a robust model and <50% is a weak model
Specificity	d/ (b+d)	100% is a robust model and <50% is a weak model
Odds Ratio (OR)	(a*d) / (b*c)	Strong (OR>3), moderate (OR= 1.5-3) and weak (OR<1.5)
Relative Operating Characteristics (ROC)	ROC module in IDRISI software	1 indicates a perfect fit and 0.5 indicates a random fit

Where,

a: number of correctly predicted occurrences

b: number of incorrectly predicted occurrences

c: number of incorrectly predicted absences

d: number of correctly predicted absences

2.2.3.4. Modeled Soil Moisture Evaluation

Four different sites were selected in the study area to evaluate the relationship between modeled soil moisture and in situ soil moisture measurements at 15cm, 30cm and 150cm depth with GIMMS NDVI (Fig.3). Soil moisture measurements were provided by the CarboAfrica project and Ardö, J. for the period 2005-2009 at different depths (Ardö, 2012). The soil moisture measurements were recorded each half-hour in (volumetric %). The measurements were converted to mm unit and then converted to monthly measurements (mm) by taking the average of the measured values during this month to be in match with monthly modeled soil moisture data. Pearson correlation coefficients (r) were calculated between GIMMS NDVI and both of soil moisture data (measured and modeled) at different locations and depths in the study area (Table 4).

Table 4: Biophysical characteristics of the selected four study sites.

Sites	Country	Location	Land cover (GLC)	Soil type (FAO)	Data time period (SM)	SM depth (cm)
ML-AgG (Agoufou G)	Mali	Lat: 15° 20' 35", Long: -1° 28' 50"	Open grassland with sparse shrubs	Entisols	2007	15
ML-Kem (Kelma)	Mali	Lat: 15° 13' 25", Long: -1° 33' 58"	Open grassland with sparse shrubs	Entisols	2007-2008	15
NE-Waf (Wankama fallow)	Niger	Lat: 13° 38' 51", Long: 2° 38' 1"	Open grassland	Alfisols	2005-2006	15,30,150
SD-Dem (Demokeya)	Sudan	Lat: 13° 16' 58", Long: 30° 28' 41"	Open grassland with sparse shrubs	Sand	2005-2009	15,30,150

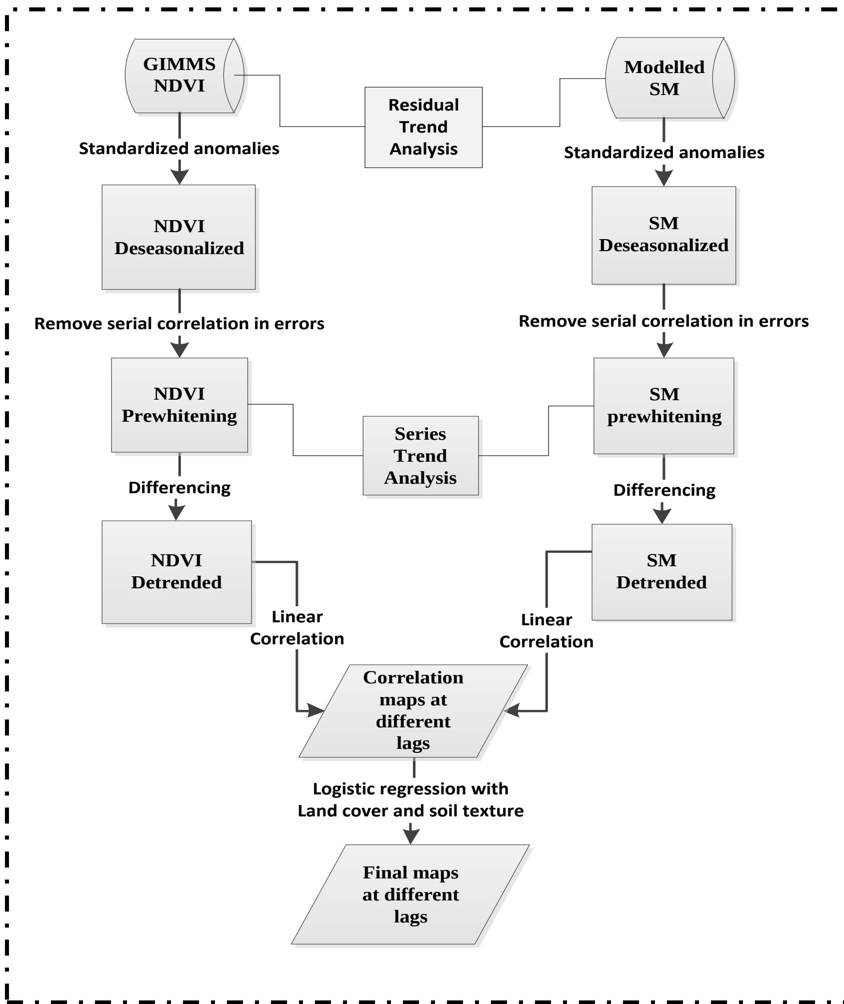


Figure 8: Flow chart showing the methodology analysis followed in this study.

4. Results

4.1. NDVI and SM data after de-trending and de-seasonality

Figure 9 shows the absence of autocorrelation in the NDVI-SM relationship after detrending, deseasonalizing and pre-whitening processes. A value of 2 indicates no serial correlation, values less than 2 indicates evidence of positive serial autocorrelation and values greater than 2 indicates evidence of negative serial autocorrelation. The study area characterized by absence of first order autocorrelation between NDVI and SM series data in major parts across the study area as the majority of values close or equal to 2 (Fig.9). However, northern parts of the study area still maintaining a small negative serial autocorrelation between NDVI and SM series data, also other few areas shows a small positive autocorrelation between the two datasets.

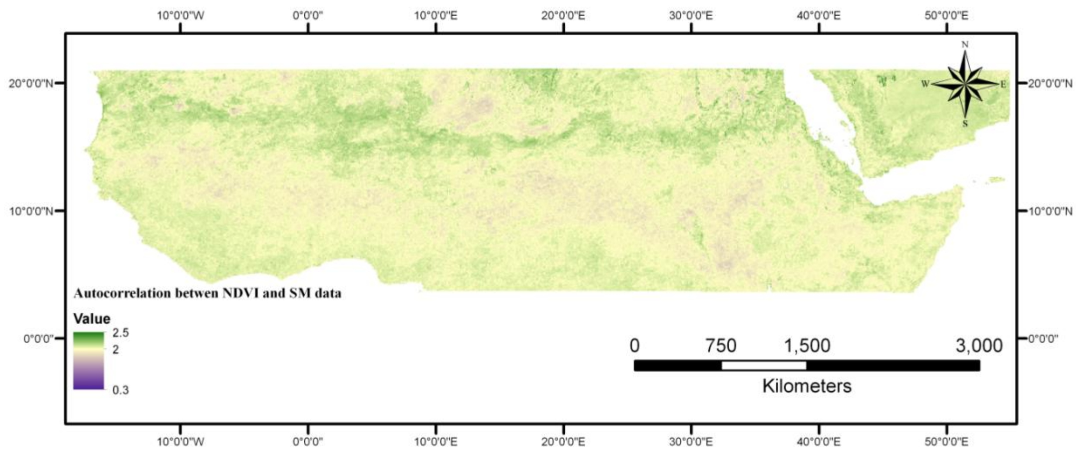


Figure 3: Showing the first order autocorrelation in residuals from a regression analysis between NDVI and soil moisture data after detrending and deseasonalizing.

Six different locations across the study area were selected in order to examine the differences between NDVI and SM data "before and after" de-trending and de-seasonalization. The selected locations are representing different eco-climatic zones in the study area (Table 5).

*Table 5: Biophysical characteristics of the selected locations, analysis based on only one pixel window (8km*8km) in the study area.*

Sites	Country	Latitude	Longitude	Land cover	Soil texture
Location 1	Niger	15° 16' 20" N	7° 28' 15" E	Grassland	Entisols
Location 2	Central African Republic	10° 17' 59" N	23° 7' 46" E	Shrubland	Inceptisols
Location 3	Mauritania	12° 55' 40" N	14° 17' 24" W	Cropland	Alfisols
Location 4	Central African Republic	6° 4' 34" N	23° 7' 47" E	Mixed forest	Oxisols
Location 5	Algeria	19° 29' 53" N	5° 47' 12" E	Bare ground	Entisols
Location 6	Ghana	10° 40' 31" N	1° 28' 16" W	Shrubland	Inceptisols

Figure 10 illustrates the differences between NDVI series before (a) and after (b) Z-score normalization in the selected six locations. The raw NDVI values were varying differently from 0.1 to 0.8 approximately in the six locations, while the detrended and deseasonalized NDVI values (Z-score) were deviating differently in the selected locations from the zero mean (approximately fluctuating from -10 to 10) represent monthly positive and negative NDVI anomalies.

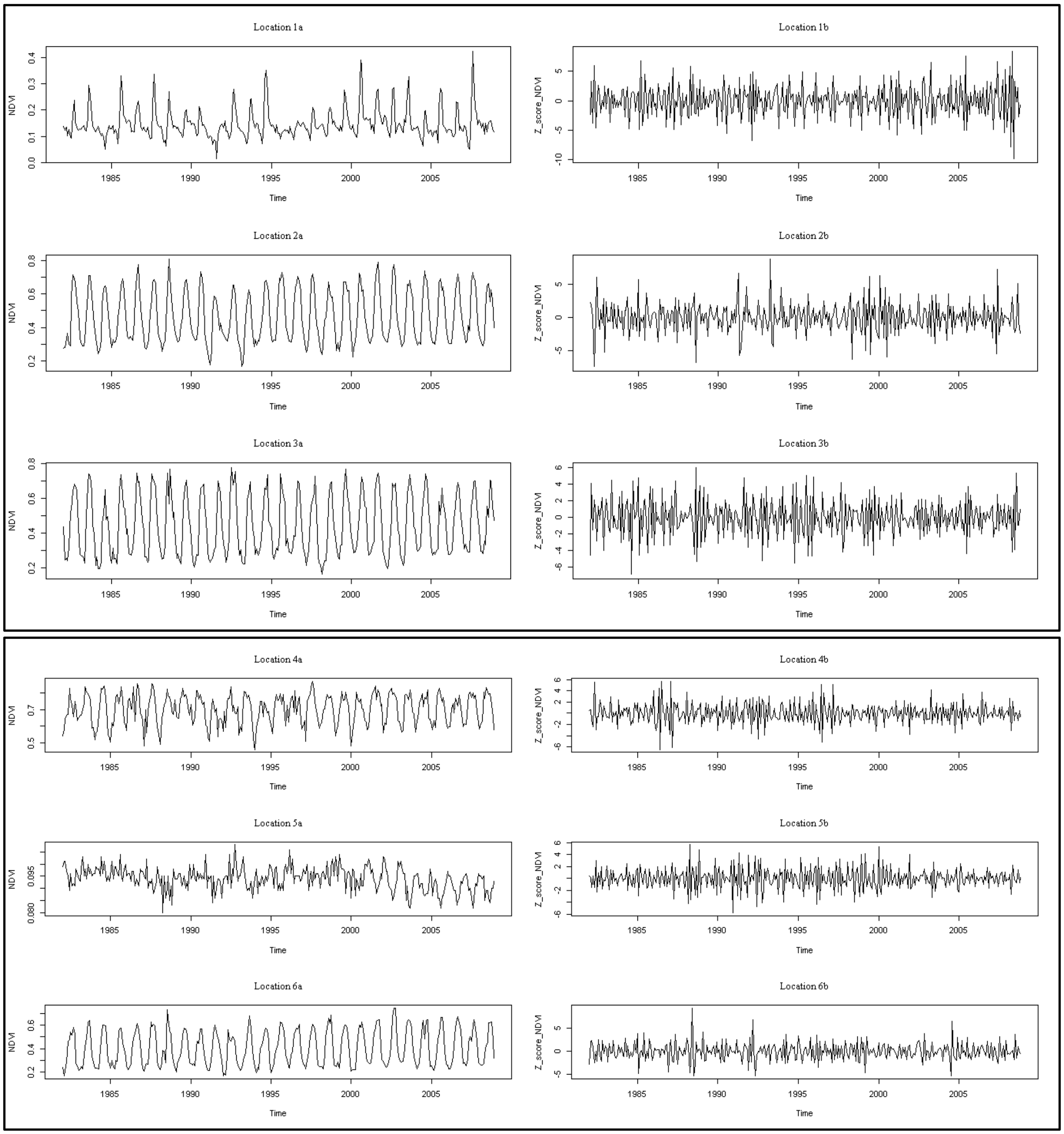


*Figure 10: Shows the differences between raw NDVI data (a) and detrended and deseasonalized NDVI data (b) in the selected six locations, based on 1 pixel size (8*8 km) in all the locations.*

Figure 11 presents the changes of soil moisture values before (a) and after (b) Z-score normalization in the selected six locations. The raw soil moisture values were varying approximately between 50-600 mm in the selected sites, while the soil moisture anomalies (Z-score values) after de-trending and de-seasonalizing were varying approximately from -20 to 40 around the zero mean represent monthly positive and negative soil moisture anomalies. The soil moisture Z-score values were fluctuated highly in the last three years of the study period especially in 2007 at locations 2, 3, 4 and 5.

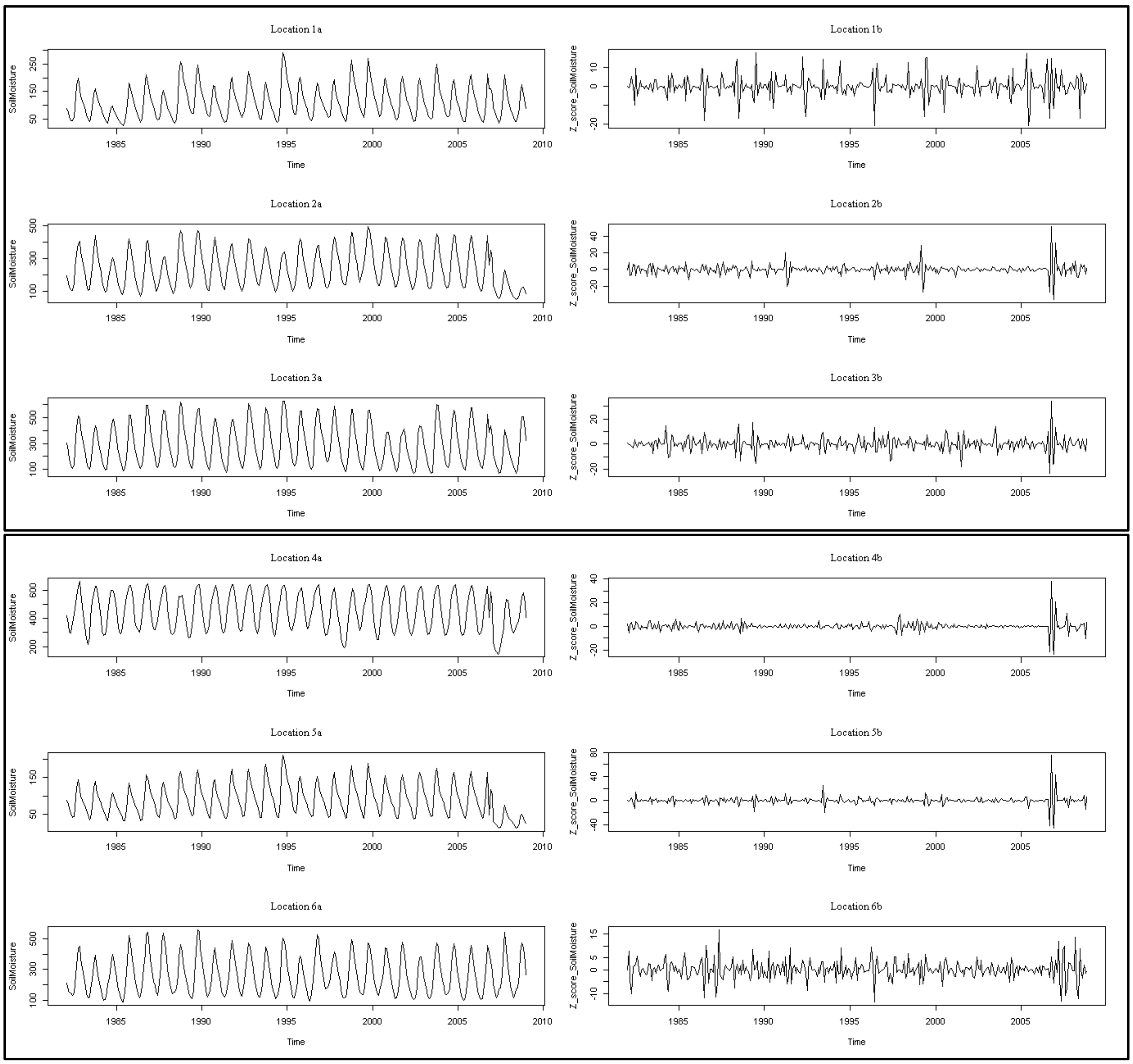


*Figure 4: Shows the differences between raw soil moisture data (a) and detrended and deseasonalized soil moisture data (b) in the selected six locations, based on 1 pixel size (8*8 km) in all the locations.*

Figure 12 illustrates the fluctuations of detrended and deseasonalized NDVI and soil moisture series at location 1. The soil moisture values are more strongly fluctuating around the mean zero value than NDVI values. NDVI and soil moisture series data displays absence of trend as the trend line occurred at zero in the two datasets.

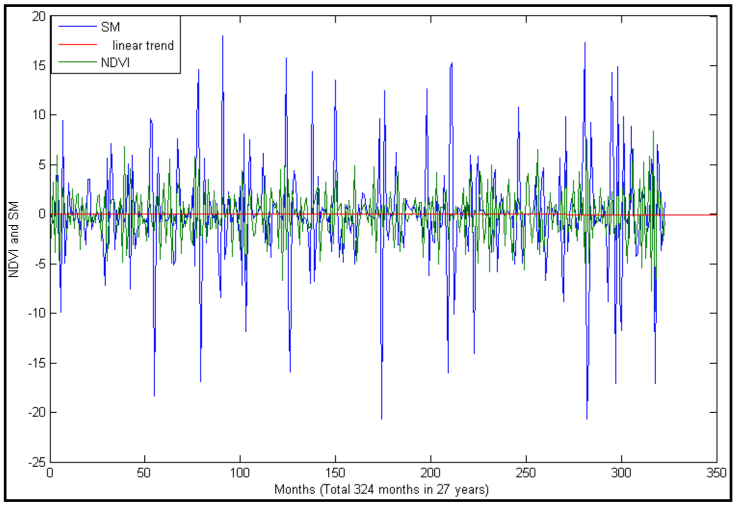


*Figure 5: shows stationarity (absence of trend) of NDVI and SM series data at location 1 through the study period from 1982-2008 (324 months), based on one pixel size (8*8 km).*

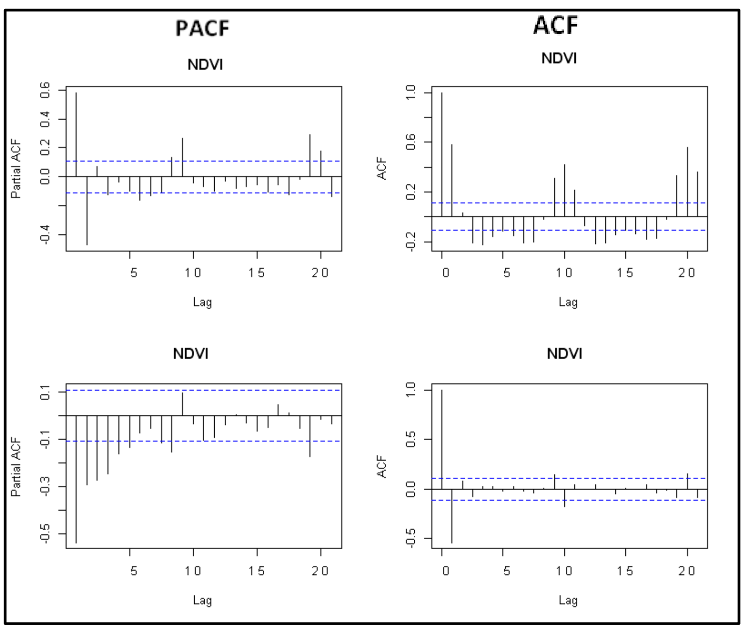


Figure 6: Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) for NDVI data detrended by curve fitting method in TIMESAT (upper left and right) and by differencing method (lower left and right) at location 1.

Autocorrelation Function (ACF) plots show the correlation coefficients between NDVI series and lags of itself at location 1 after detrending by using curve fitting method in TIMESAT (Fig.

13, upper right) and a differencing method (Fig. 13, lower right). Stationarity data with absence of trend shows a very quick decline of ACFs values to zero. The ACFs dies out or trails off quickly and became close to zero by using differencing method, whereas trails off slowly with ACFs not close to zero by using the curve fitting method in TIMESAT. The Partial Autocorrelation Function (PACF) describes the amount of correlation between NDVI series and lags of itself that is not explained by correlations at low order lags (previous lags) over time. PACFs plot of NDVI after detrending by differencing method shows a large significant spike at lag1 accompanied with gradual decaying of PACFs by increasing number of lags (Fig. 13, lower left), whereas PACFs plot for NDVI after using curve fitting method characterized by abruptly cuts off after high significant spike at lag1 (Fig. 13, upper left).

4.2. Trends in NDVI and SM data

Trend analyses were employed for both NDVI and SM data after deseasonalizing and removing the effect of serial correlations in errors by a multi-stage pre-whitening technique to investigate changes in NDVI and SM across the study area from 1982 to 2008.

Highest increase in vegetation greenness (NDVI) for the period 1982 to 2008 occurred in many locations in the study area especially in south-western Mali, central Chad, south of Sudan, east of Burkina Faso and north of Nigeria, whereas areas of significant decline in NDVI occurred in north of Mauritania, north of Niger and central of Sudan. Different locations in the study area display insignificant trend in NDVI at 5% significance level during the study period (Fig.14, right). NDVI trend show high consistency during the study period in southern parts of Sahel region. Soil moisture trend over the period 1982-2008 exhibits a significant increase in a few places in our study area especially at east of Mauritania, central Mali, west of Chad, south of Somalia and south of Sudan. Large areas in Sahel region does not exhibit any significant trend in soil moisture at 5% significance level over the last 27 years (Fig.14, left). Soil moisture trend displays a high consistency in a few locations across the study area especially in east of Mauritania, center of Mali and center of Sudan.

Trends in the residual time series data were calculated from the regression analyses between raw NDVI (dependent variable) and raw soil moisture data (independent variable) to investigate the effect of other factors than soil moisture in increasing vegetation greenness in our study area. All year data (include dry season) and JASO data (only rainy season) were used for this analysis. As can be seen in (Fig.15, left) most areas with significant increase in trends by using all year data at 5% significance level occurs in southern part of our study area especially in South Sudan and many locations in Nigeria and south of Mauritania. Areas with significant decline in trends occurred in many locations in northern part of the Sahel region. For JASO month’s data, the significant trends that shows increased vegetation greening over the 27-year study period were distributed mainly in the southern part of Sahel region with high significance in Chad, Senegal and south of Mali, whereas northern part of the study area shows absence of significance trend with a negative residual trends in many parts of the northern Sahel region (Fig.15, right).

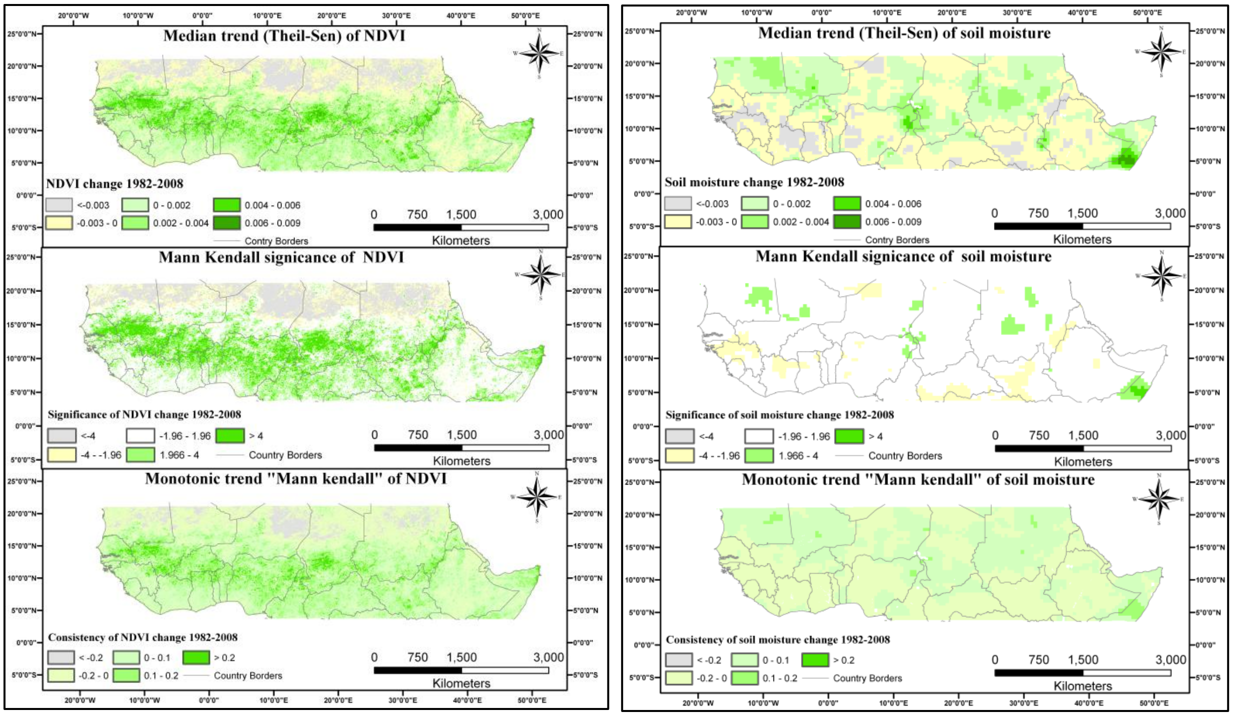


Figure 7: Trend maps of NDVI (right) and modeled soil moisture (left) in the study area from 1982 to 2008.

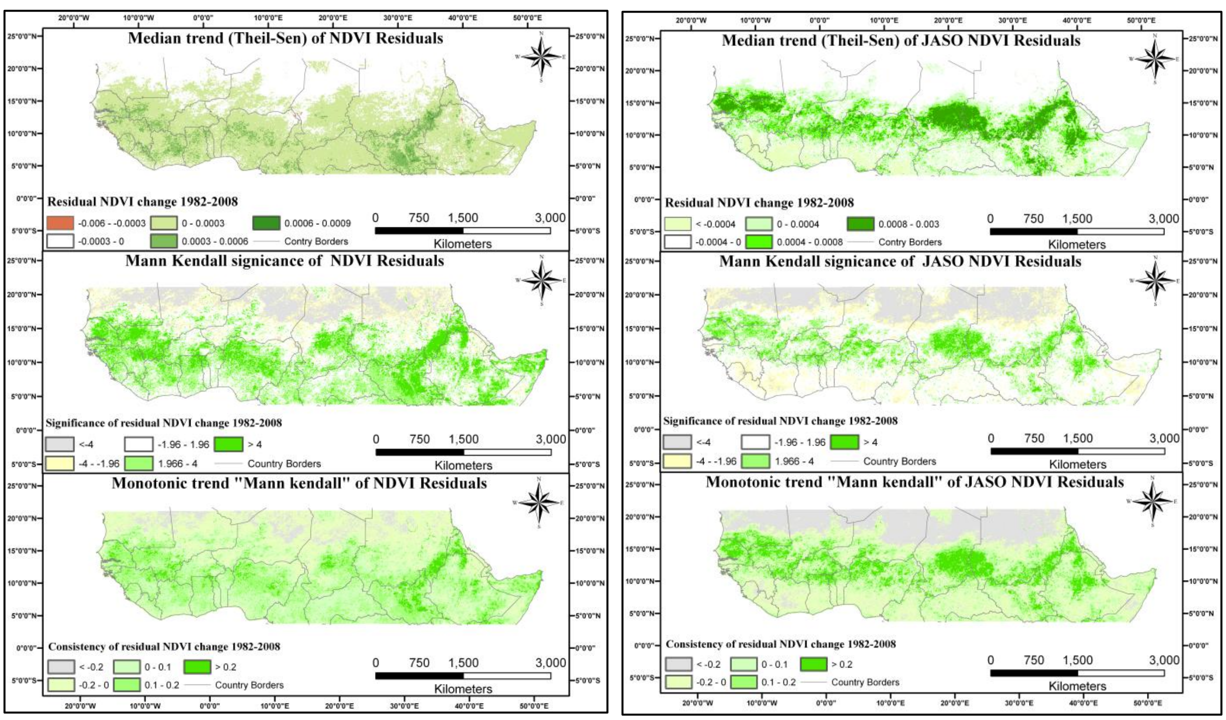


Figure 8: Residual trend map of all year data NDVI (left) and JASO NDVI (right) for 1982-2008, based on a regression analysis between NDVI (dependent variable) and modeled SM (independent variable).

4.3.Correlation between NDVI and SM

Pearson correlation coefficients between NDVI and modeled SM datasets throughout the study area were calculated for two different time frames on a pixel-by-pixel basis; full year data (long dry season and rainy season) from lag 0 to lag 5, as well as only to the rainy season (JASO months) from lag0 to lag 3. The correlation coefficients (r) were calculated at the 95% confidence intervals.

According to Fig. 16, significantly positive correlation coefficients (r) between NDVI and SM were not exceeding 0.5 with highest significant values at lag0, lag1 and lag2, while significant correlations at lag3, lag4 and lag5 were showing small values with also a limited spatial distribution in the study area. Highest values of lag0 occurred in Burkina Faso, south of Mali and north of Senegal, highest values of lag1 occurred in south of Sudan, central of Niger and east of Mali, whereas highest values of lag2 occurred in central of Mauritania and central of Chad with many insignificant locations in Sahel region.

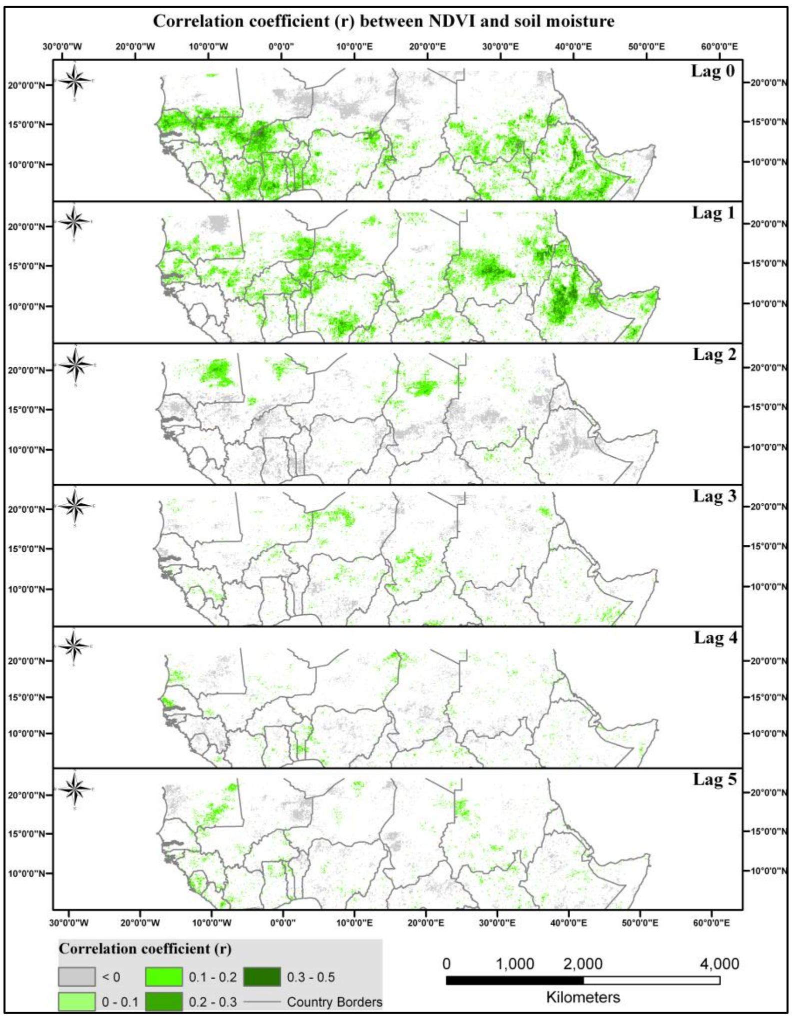


Figure 9: Temporal correlation relationship between NDVI and SM data (all seasons) at different time lags in the study area from 1982 to 2008.

For the JASO analyses, the significant correlations were tested from lag0 to lag3 (Fig. 17). JASO correlations at lag0 showed high significant correlation in many areas across the Sahel region with highest values in south of Sudan, south of Mali and north of Senegal. Correlation coefficient relationship (r) decreased with increasing number of lags. Highest values of lag1 occurred in central of Sudan and central of Mali, highest values of lag2 occurred in north central of Sudan, east of Mauritania, whereas highest values of lag3 occurred in central of Chad and western of Mauritania.

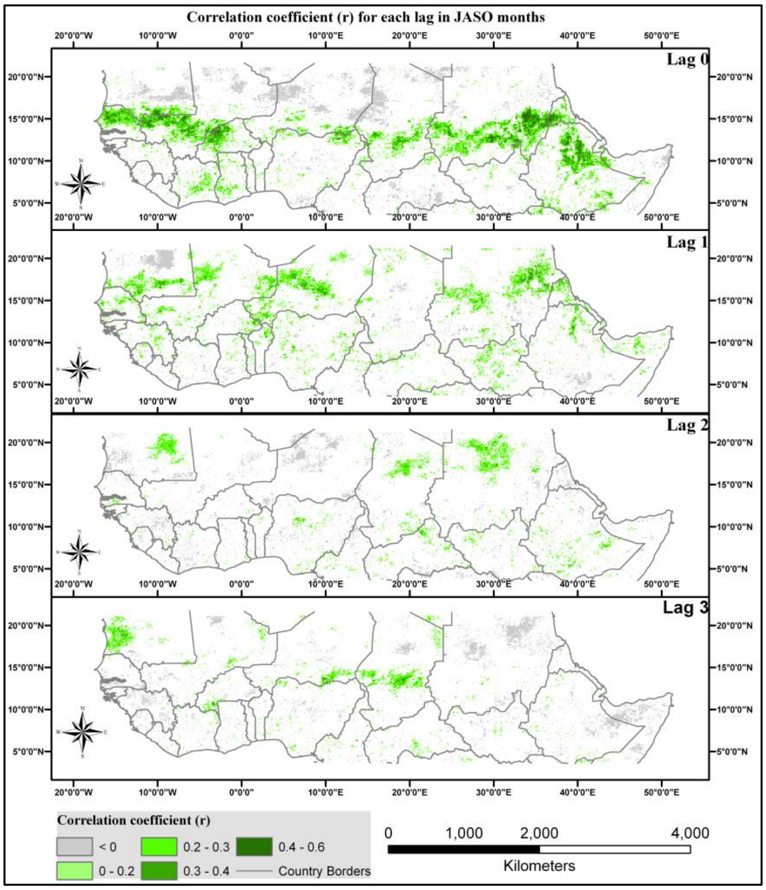


Figure 10: Temporal correlation relationship between NDVI and SM data (JASO months) at different time lags in the study area from 1982 to 2008.

Optimal correlation coefficient maps for all year-data and JASO months were calculated for each lag that reflects the best and highest significant correlation relationship between NDVI and SM when all the correlation coefficients of all lags were compared. An optimal lag map was produced in corresponding to the lag of highest correlation coefficient (Fig.18).

According to (Fig.18), the optimal lags for both time frames (all year data and JASO months) were mainly constrained to lag0, lag1and lag2 which correspond to the correlation between NDVI and SM with zero, one and two month time lags. For all year-data, the optimal lag0 dominates in the west of the Sahel region, whereas optimal lag1 dominates in east and central of

Sahel region and optimal lag2 in central Chad and east of Mauritania. For JASO month's correlation, optimal lag0 was spatially distributed in Sahel region with high domination in south of Sudan, south of Mali and Senegal, whereas optimal lag1 was focused in several location in northern part of Sahel especially in central of Sudan and Niger, optimal lag2 was dominated in Sudan and Mauritania and finally optimal lag3 was mainly found in central of Chad and west of Mauritania.

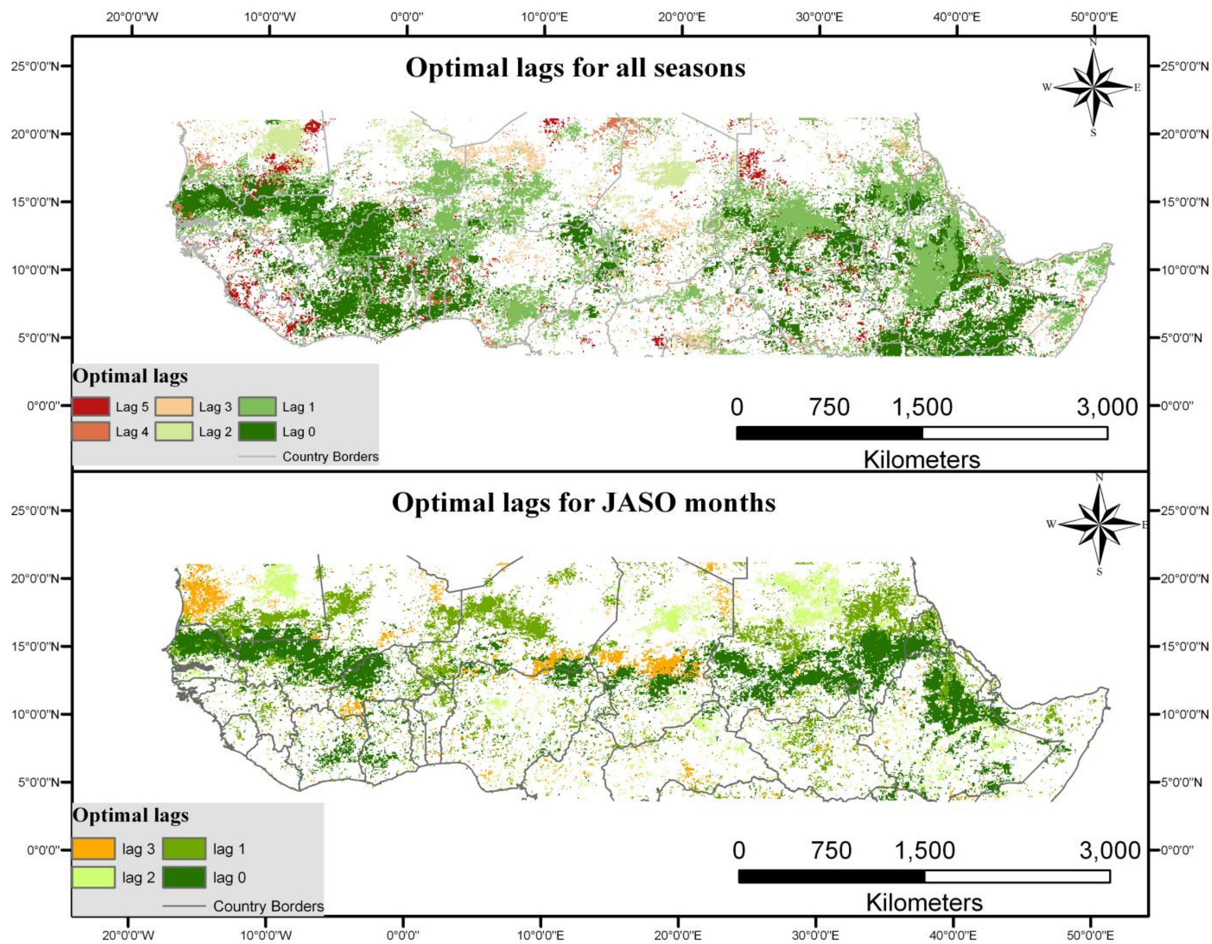


Figure 11: Optimal lags of NDVI and SM correlation in the study area from 1982 to 2008 for both all year data and JASO months.

Lag0 and Lag1 are considered the largest optimal lags in the study area with percentage covering area reaches to 40% and 39% respectively from the total significant areas by using all the year data. For JASO data, the significant percentage covering area reaches to 44% and 32% from total significant areas at optimal lag0 and optimal lag1 respectively. The percentage covering areas of other lags are lower than 10 % in all year data, whereas for JASO data the percentage covering areas of lag2 and lag3 are 14% and 10% respectively (Table 6).

Table 6: Shows significant area percentage of each optima lag in the study area.

Significant area of each lag in %	Lag0	Lag1	Lag2	Lag3	lag4	lag5
All year data	40 %	39 %	7 %	5 %	4 %	5 %
JASO data	44 %	32 %	14 %	10 %	−	−

4.4.Correlation coefficient differences between JASO data and all-year data

For a more in-depth investigation between correlation coefficient results by using only the JASO months or using all the year data, three locations were selected (Location1, Location2 and Location3) for further analysis (Table 5). Detrended and deseasonalized NDVI was plotted against detrended and deseasonlized modelled SM (five time lags) for both JASO and all-year data during the study period from 1982 to 2008 in the selected three locations.

Cross-correlations used as an indicator for the degree of the relationship between NDVI and SM data with values between -1(strong negative relationship) and +1 (strong positive relationship). Cross-correlations were calculated at different time lags to determine the best time delay between NDVI and SM, maximum cross-correlation value means this lag is considered the best time where the two variables are best aligned and the vice versa for lowest cross-correlation value. The analysis was based on only one pixel window (8*8 km).

The first location in Niger exhibited a low cross-correlation between NDVI and modelled SM by using all-year data at lag0 (0.08) and it was improved by using only JASO months (0.26). The correlation fluctuated in this site by using all-year data from positive to negative low correlation values through increasing the number of lags. Whereas for JASO months data, the correlation was negative at lag1 and lag4, and positive in the rest of lags with high positive correlation value in lag3 (Fig. 19).

The second location in Central African Republic country exhibited similar results to the first location in Niger with correlation results improved with using only the JASO month's data (0.16) than using all-year data (0.09) at lag0. At lag1, the correlation was positive by using all year data and negative by using JASO month's data. The rest of lags were fluctuated from low positive to low negative correlation values in the both of data (Fig. 20).

The last location in Mauritania displayed a negative correlation relationship in both timeframe data at lag0, and a positive correlation at lag1 with a high correlation value by using JASO month's data. At lag2, the correlation was negative by using JASO data and positive by using all-year data. The cross-correlation was fluctuated from a negative value at lag3 to positive values at lag4 and lag5 by using JASO data. Whereas the cross-correlation values were negative at lag3 and lag4 and turned to a positive value at lag5 by using all the year data (Fig. 21).

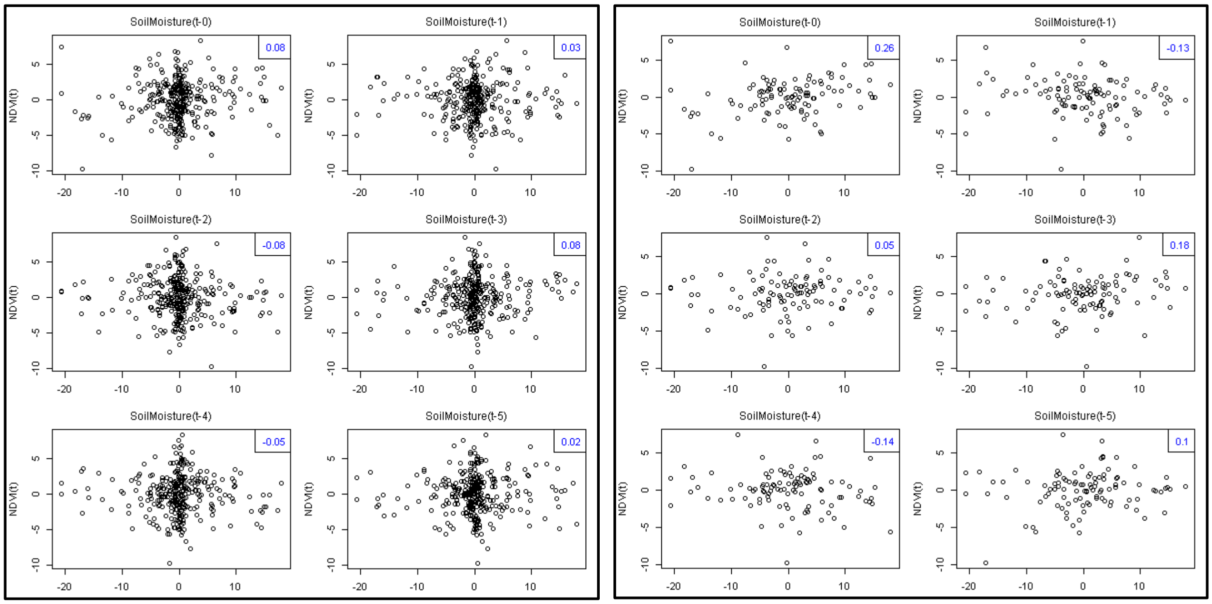


Figure 19: Scatterplots for detrended and deseasonalized NDVI and modeled SM by using all-year data (left) and JASO data (right) at location1 in Niger at different time lags during the study period from 1982-2008, with the cross-correlation values in blue.

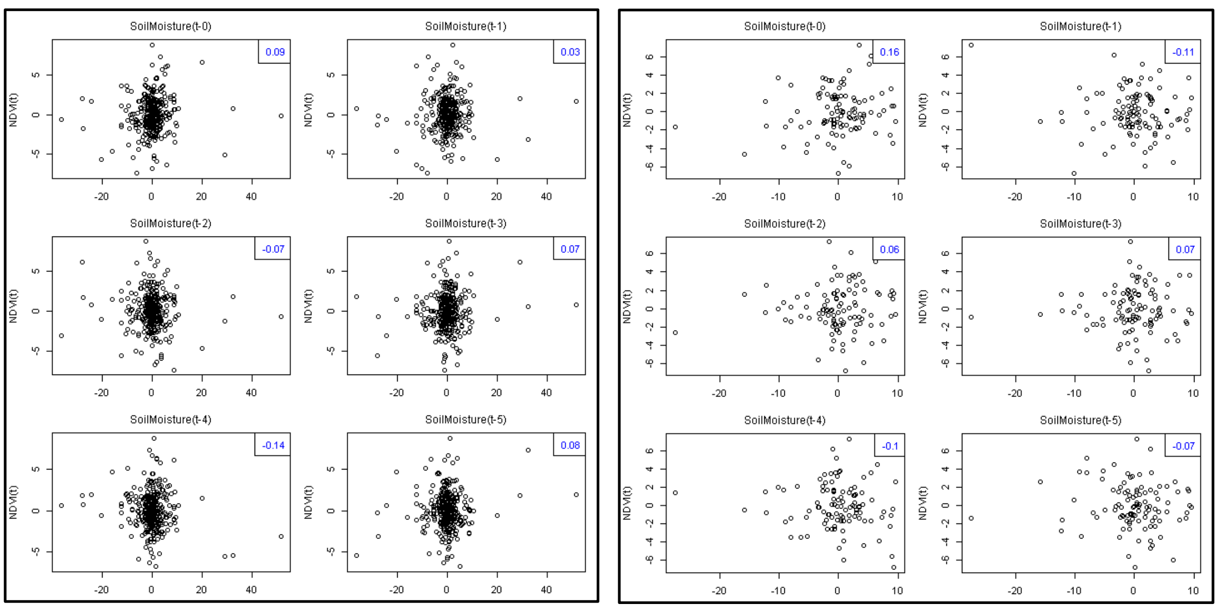


Figure 12: Scatterplots for detrended and deseasonalized NDVI and modeled SM by using all-year data (left) and JASO data (right) at location2 in Central African Republic at different time lags during the study period from 1982-2008, with the cross-correlation values in blue.

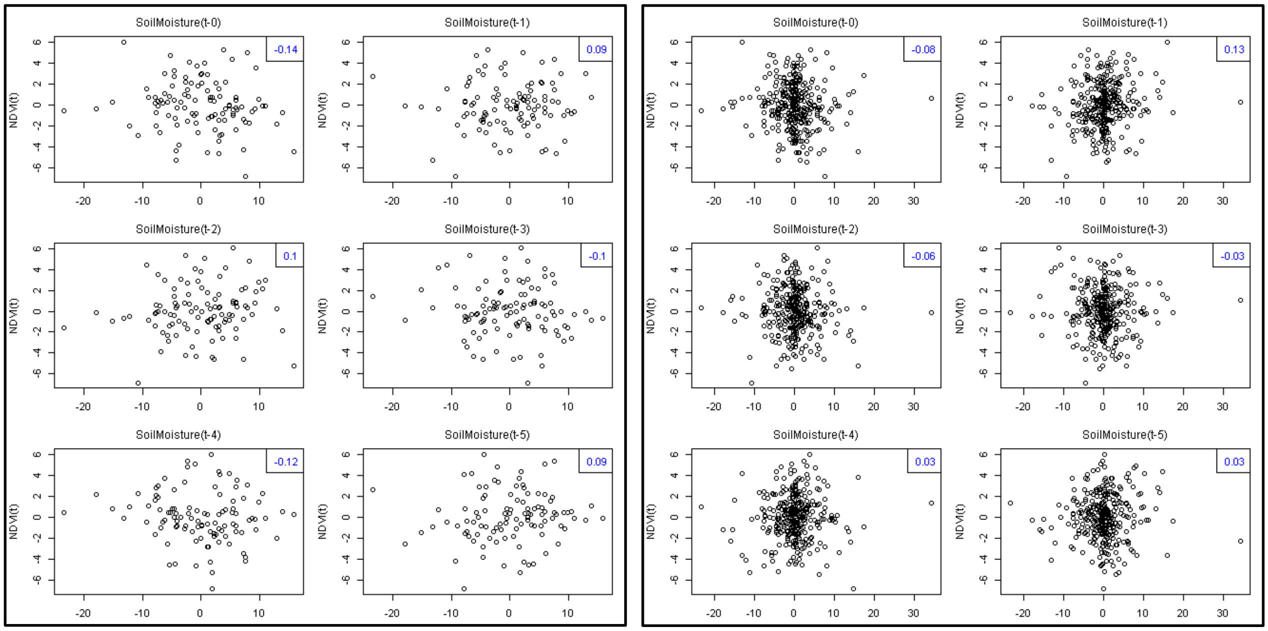


Figure 13: Scatterplots for detrended and deseasonalized NDVI and modeled SM by using all-year data (left) and JASO data (right) at location3 in Mauritania at different time lags during the study period from 1982-2008, with the cross-correlation values in blue.

4.5.Optimal correlation in relative to land cover and soil texture

The global land cover (GLC) map and soil texture map for Sahel region were used to evaluate the effect of land cover type and soil texture on the strength and direction of the correlation relationship between NDVI and modeled SM. Land cover and soil type were produced in correspondence to significant optimal correlation coefficients at each different lag in the study area. Significant areas in percentage for land cover classes and soil types were generated for both all the year data and JASO data.

According to Table.7 with including all year-data, the largest significant land cover type at lag0 in our study area was croplands followed by grassland “savanna” and shrublands, the largest significant land cover type occurred in lag1 was croplands, bare ground and Grasslands, whereas the dominant significant lands cover type at lag2 was bare ground class. The other three lags showed a low significant coverage in the remaining land cove classes. For JASO months, the major statistically significant land cover type occurred at lag0 is croplands and grasslands, while at lag1 the dominant land cover type is bare ground followed by grassland and cropland, lag2 and lag 3 showing large significant areas in bare ground and grassland classes (Table.8).

For all the year data, the largest significant soil type at lag0 is Entisols (minimal soil development with no diagnostic horizons) soil texture followed by Alfisols (moderately weathered and rich in iron and aluminum) and Vertisols (rich in expansive clay) soil textures. Major statistically significant soil type coverage at lag1 is Entisols, Alfisols and Aridisols (formed in arid and semi-arid areas and have a low content of organic matter). The other lags showed soil texture with area percentage less than 1% (Table.9). For JASO months, the major significant soil type at lag0 is Entisols, followed by Alfisols and Vertisols. The main statistically significant soil type at lag1 is Entisols, followed by Aridisols and Alfisols. Whereas at lag2, the dominant soil texture is Entisols. Lag3 showed a significant soil texture with percentage area coverage less than 1 % in all soil textures (Table.10).

Table 7: Describes the major significant land cover classes at 95% significant for different time lags by using all the year data during the study period from 1982 to 2008.

Lags	(Area % from the total significance area in Sahel) – all year data						
	Evergreen Forest	Mixed Forest	Deciduous Forest	Croplands	Bare Ground	Shrublands	Grassland "Savanna"
Lag0	0.20	0.25	1.77	6.75	0.51	2.24	4.92
Lag1	0.18	0.43	1.18	4.36	4.32	1.38	4.08
Lag2	0.01	0.03	0.02	0.17	2.22	0.14	0.12
Lag3	0.06	0.14	0.19	0.56	0.73	0.15	0.45
Lag4	0.05	0.08	0.23	0.22	0.63	0.15	0.16
Lag5	0.12	0.10	0.20	0.57	0.73	0.27	0.30

Table 8: Describes the major significant land cover classes at 95% significant for different time lags by using JASO data during the study period from 1982 to 2008.

Lags	(Area % from the total significance area in Sahel)– JASO data						
	Evergreen Forest	Mixed Forest	Deciduous Forest	Croplands	Bare Ground	Shrublands	Grassland "Savanna"
Lag0	0.06	0.04	0.34	6.02	0.91	0.64	4.50
Lag1	0.07	0.11	0.61	1.54	4.58	0.81	1.58
Lag2	0.07	0.14	0.26	0.56	2.31	0.43	0.28
Lag3	0.06	0.10	0.21	0.34	1.00	0.23	1.06

Table 9: Describes the major significant soil types at 95% significant for different time lags by using all the year data during the study period from 1982 to 2008.

Lags	(Area % from the total significance area in Sahel)- all year data							
	Bedrock	Oxisols	Vertisols	Aridisols	Ultisols	Alfisols	Inceptisols	Entisols
Lag0	0.71	0.54	1.66	1.23	1.76	4.28	1.21	5.27
Lag1	1.39	0.74	0.80	1.93	1.17	2.81	1.24	5.90
Lag2	1.06	0.02	0.17	0.21	0.04	0.05	0.02	1.16
Lag3	0.28	0.26	0.13	0.10	0.09	0.28	0.05	1.10
Lag4	0.18	0.19	0.04	0.13	0.09	0.26	0.05	0.60
Lag5	0.22	0.31	0.21	0.09	0.19	0.20	0.09	0.96

Table 10: Describes the major significant soil types at 95% significant for different time lags by using JASO data during the study period from 1982 to 2008.

Lags	(Area % from the total significance area in Sahel)– JASO data							
	Bedrock	Oxisols	Vertisols	Aridisols	Ultisols	Alfisols	Inceptisols	Entisols
Lag0	1.17	0.09	1.65	0.90	0.55	2.76	1.10	4.33
Lag1	1.20	0.38	0.54	1.21	0.37	1.06	0.28	4.30
Lag2	0.67	0.25	0.16	0.16	0.20	0.40	0.18	2.05
Lag3	0.97	0.18	0.12	0.17	0.12	0.37	0.08	0.99

4.6.Logistic regression based on all-year and JASO data

Logistic model parameters such as sensitivity, specificity, odds ratio (OR) and relative operating characteristics (ROC) were calculated to recognize time lags with the best logistic model and defines the importance of land cover and soil texture on the relationship between soil moisture and vegetation growth at each different lag. Lag with the best logistic model confirms that the degree of association of land cover and soil type with optimal correlation coefficient is high at this lag. Logistic regression was analyzed for all year data and JASO data.

The sensitivity of logistic model in all year data is decreasing with increasing the number of lags (Table 11). OR values showed the highest value in lag2 followed by lag3, lag 4 and lag0, whereas the best fit in all lags according to ROC values occurred in lag2. The best suitable logistic model that describes the association between dependent variable (optimal correlation) and independent variables (soil type and land cover) in all year data was found at lag2 and lag0. For the JASO months, the sensitivity was higher in lag1 with high OR value and a good fitting (ROC) between dependent and independent variables, while the other lags showed a low sensitivity with approximately similar ROC values (Table 12). The best suitable logistic model that describing the association between dependent and independent variable in JASO months data was found at lag1.

Table 11: Logistic regression models from the regression relationship between a binary dependent variable (optimal lag correlation) and independent variable (soil texture and land cover) for all the year data across the study area from 1982-2008.

Lags	Sensitivity	Specificity	Odds ratio (OR)	ROC
lag0	24 %	89 %	2.51	0.65
lag1	12 %	85 %	0.75	0.56
lag2	13 %	99 %	9.91	0.82
lag3	5 %	98 %	3.39	0.62
lag4	4 %	98 %	2.36	0.59
lag5	2 %	98 %	0.83	0.56

Table 12: Logistic regression model results from the regression relationship between a binary dependent variable (optimal lag correlation) and independent variable (soil texture and land cover) for JASO months data across the study area from 1982-2008.

lags	Sensitivity	Specificity	Odds ratio (OR)	ROC
lag0	2 %	89 %	0.15	0.64
lag1	18 %	93 %	3.14	0.66
lag2	2 %	97 %	0.54	0.69
lag3	5 %	98 %	2.51	0.67

4.7. Modelled SM data versus in situ SM measurements.

The relationships between modelled SM and in situ measurements of SM with GIMMS NDVI were calculated in different four sites (Table 4). The modelled SM at the first site in Mali (ML-AgG) showed a high correlation with NDVI than in situ SM measurements (15 cm depth) with the highest significant value at lag1; however the correlation relationship at lag0 was approximately similar for both modelled SM and in situ SM measurements (Fig. 22).

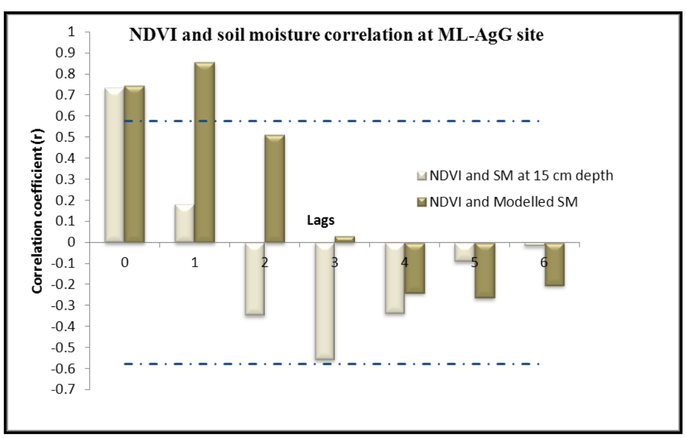


Figure 14: NDVI-soil moisture (modeled and measured) correlation coefficient vs. time lag of raw NDVI (six lags) in ML-AgG (Mali) study site, with the statistical significance at 95 % (dashed line).

Modelled SM showed a positive correlation until lag3, while the positive correlation in measured SM was only at lag0 and lag1and the both of them displayed a negative correlation at the last three lags with a higher negative values for measured SM at lag3 and lag4 (Fig. 22).

The highest correlation at the second site in Mali (ML-Kem) occurred at lag0 between measured SM (15 cm depth) and NDVI, while the correlation between Modelled SM and NDVI was significantly higher at lag1. The correlation relationship was positive at lag2 with modelled SM and negative with measured SM. Measured SM showed a significant negative relationship with NDVI at lag3 and lag4 and both of SM data (measured and modelled) were giving a negative correlation relationship from lag3 to lag6 (Fig. 23).

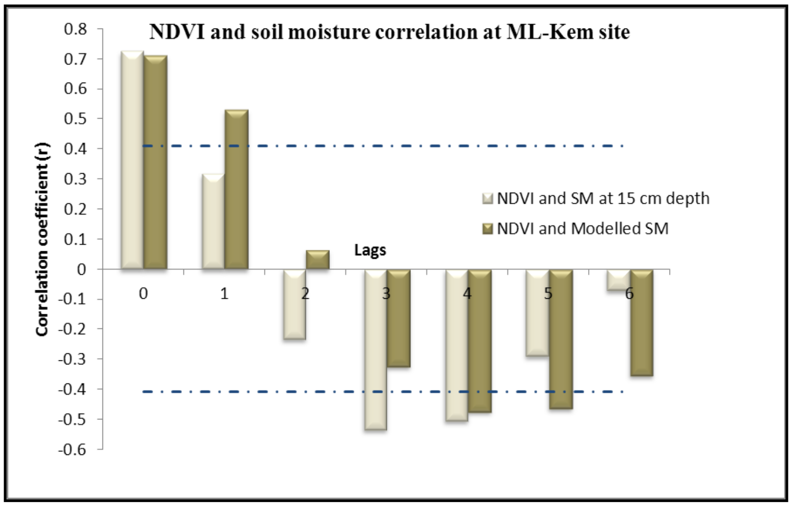


Figure 15: NDVI-soil moisture (modeled and measured) correlation coefficient vs. time lag of raw NDVI (six lags) in ML-Kem (Mali) study site, with the statistical significance at 95 % (dashed line).

The third site in Niger (NE-Waf) exhibited a strong significant correlation relationship between modelled SM and NDVI at lag0 and lag1 in comparison with measured SM at 15 cm, 30 cm and 150cm depth. Correlation of measured SM at 15cm depth with NDVI in lag1 was near from zero; while at 30 cm depth the correlation was significant and higher than at 150 cm depth. Modelled SM and SM at 30 cm depth preserved the positive correlation at lag2, while the measured SM at 15 cm and 150 cm exhibited a negative correlation. The two data (modelled SM and measured SM at 15 cm, 30 cm and 150 cm) displayed a negative correlation relationship from lag3 to lag6 with more significant negative correlation at lag3 and lag4 by using the measured SM data (Fig. 24).

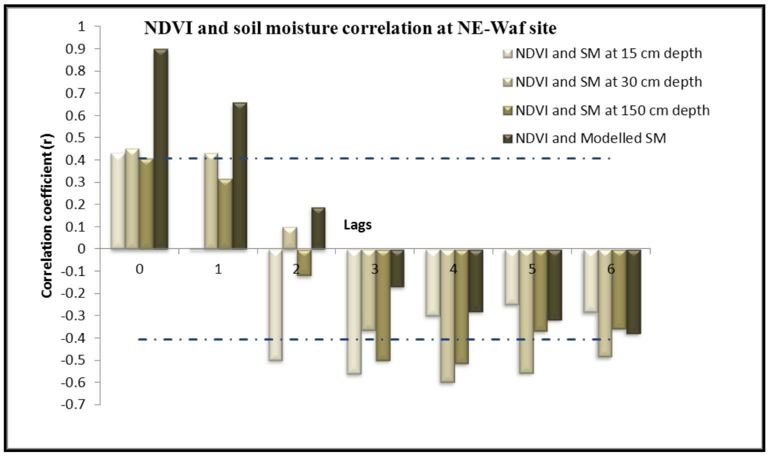


Figure 16: NDVI-soil moisture (modeled and measured) correlation coefficient vs. time lag of raw NDVI (six lags) in NE-Waf (Niger) study site, with the statistical significance at 95 % (dashed line).

The fourth site in Sudan (SD-Dem) showed high significant correlation between NDVI, modelled SM and measured SM at 150cm depth. Measured SM at 15 cm and 30 cm depths in lag1 showed a negative correlation, whereas measured SM (150 cm depth) and modelled SM displayed a positive correlation. In lag 2, modelled SM preserved the positive correlation and all of measured SM showed a negative correlation with NDVI. The last lags displayed a negative correlation between NDVI and SM (modelled and measured) with more negative correlation with the measured SM especially at 150cm depth (Fig. 25).

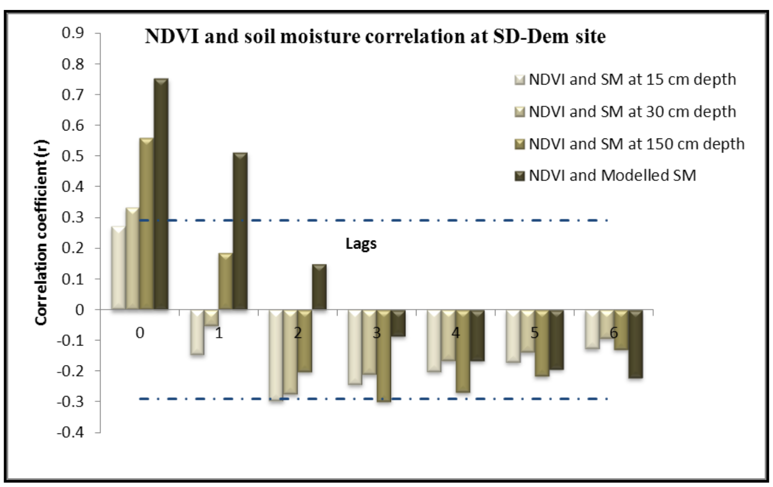


Figure 17: NDVI-soil moisture (modeled and measured) correlation coefficient vs. time lag of raw NDVI (six lags) in SD-Dem (Sudan) study site, with the statistical significance at 95 % (dashed line).

5. Discussion

5.1. NDVI and SM data after de-trending and de-seasonality

According to (Fig.9, Fig.10 and Fig.11), NDVI and SM datasets were de-trended and de-seasonalized effectively and the output data from this process were not showing any gradual changes in the mean value (Fig.12), and the seasonal effects has been eliminated. The Durbin Watson statistical map created after de-trending and de-seasonality process showed that the presence of first order correlations between NDVI and SM data were reduced and even eliminated in major areas in the study area. The autocorrelation function (ACF) and partial autocorrelation function (PACF) assured that differencing method removed the trend and helped in minimizing the serial correlation more efficiently than the curve fitting method used in TIMESAT software (Fig.13).

5.2.Trends in NDVI and SM data

Vegetation greenness (NDVI) during the study period (1982 to 2008) has significantly increased in several locations across the study area as illustrated in Fig. 14, and is consistent with earlier findings (Eklundh and Olsson, 2003; Anyamba and Tucker, 2005; Herrmann et al., 2005; Huber et al., 2011). NDVI trends mapped in this study is similar in spatial variability to those reported by Huber et al. (2011) from 1982-2007 as both studies used the "Theil-Sen method" for estimating the NDVI changes. However, NDVI trends in this study showed a stronger trend in the southern part of Sahel region in comparison with Huber et al. (2011) study. Similar results are also reported by Anyamba and Tucker, 2005 for the Sahel from 1981-2003. However, comparing the trend analysis with other studies is difficult because of differences in analysis techniques, differences in significant levels (5% in our analysis), length of study period and data pre-processing. For instance all the cited articles run the analysis on the raw NDVI, whereas in this study analysis the seasonality and also the autocorrelations in errors that can affect the trend relation were removed before calculating the trends in NDVI.

NDVI trends from 1982-2008 showed a persistent increase in central of Chad, Senegal, south of Mali and south of Sudan. This significance persistence trends could be related to the vegetation cover trees (*Acacia trees*) characterized by deep roots and being able to reach the water table without much depending on the fluctuation of rainfall and soil moisture (Do et al., 2008).

Few pixels are exhibiting a positive soil moisture trend at the 95% level across the study area from 1982-2008. The positive significant trends found in central Sudan, and the center of Mali and east of Mauritania as illustrated in Fig.14. The SM trends obtained in this study corresponds best with the results reported by Huber et al., 2011 except that the areas of significance were smaller in our study with presence of significant trends in central of Mali. The high positive SM trend in a few areas in central Sudan could be related to the presence of high volcanic mountains that complicate the modeled SM measurements and give overestimation for the real soil moisture data, a complex topography like that need more in situ measurements than that used in the modeled SM data to accurately estimate the diverse microclimatic process on a small scale. The high significant SM values in other parts of Sudan could be related to increasing water availability from the Nile River (IPCC, 2007), whereas in Mali the moisture support could be provided from the Niger River or Lake Faguibine that helped in keeping the moisture trend persisted through the study period (Herrmann et al., 2005). Other possibility for increasing soil moisture is related to advanced techniques used by farmers to improve water conversation (such as contour bunding) in response to long term droughts (Reij et al., 2005).

Comparing the significant trends of NDVI to the significant trends of SM in the study area (Fig. 14), indicates that maybe other factors than soil moisture have contributed to the vegetation greenness changes from 1982-2008 in the study area. For instance, central Chad showed a non-significant increasing in SM trend throughout the study period from 1982-2008, whereas the same area showed a significant increase in the vegetation greenness in the same study period. Low or non-significant of soil moisture trends in many parts of the Sahel region could be related to the great column depth (1.6 m) that used for modeling soil moisture data.

5.3. Trends in NDVI residuals

For all the year data, NDVI residual trends did not reveal statistically significant trends in many parts of the study area especially in the northern part of Sahel region (vegetation greenness trends corresponds with what is expected from soil moisture trend), whereas the southern part of the study area showed a positive significant trend (soil moisture is not enough for explaining the variation in vegetation greenness) especially in south of Sudan, south of Chad and many parts in Mauritania, Niger and Senegal (Fig. 15). The positive trend in southern parts of Sahel region could be related to other factors such as availability of nutrients (Ridder et al., 1982) or amount of solar radiation (Nicholson et al., 1990) as the moisture is not any longer the main driver of vegetation growth and maybe related to human induced factors through decisions on farming strategies and land use (Herrmann et al., 2005). Existence of positive trends in several locations in the northern part of Sahel could be explained by the direct influence of instantaneous rainfall as the vegetation start growing when the water starts travelling through the soil.

The relationship between NDVI and rainfall generally levels off beyond 200 mm monthly^{-1} rainfall (1000 mm yr^{-1}) as the water is no longer the limiting factor (Nicholson et al., 1990) and this also can be considered for NDVI-soil moisture relationship. The spatial variability of NDVI residual trend analysis was similar to what was reported by Herrmann et al. (2005) with differences in the degree of significance in many parts across the study area. The study done by Herrmann et al. (2005) calculated the overall trend in NDVI residuals from 1982-2003 based on a regression analysis of NDVI on 3-monthly cumulative rainfall.

For JASO data, the significant positive NDVI residual trends occurred in several parts in Sahel region with high significant values in south of Sudan, south of Chad, south of Mali and Senegal (Fig.15), which indicates that these regions do not depend on moisture availability especially during the rainy seasons when the availability of water is not a limiting factor. The degree of high positive NDVI residual values was much higher with JASO months than using all-year data, as the moisture factor in the growing season is less important for vegetation growth, and including the dry season in our calculation led to low positive NDVI residual values as the moisture is considered one of the limiting factors controlling the vegetation growth.

Compared to Huber et al. (2011) who calculated the residual NDVI for 1982-2007 based on a regression analysis of JASO NDVI and a 3-months sums rainfall, the spatial variability of significant positive trend was higher across the area in the present study. However, central Chad showed a high significant positive trend in this analysis, and exposed a low positive significant and non-significant trend in Huber et al. (2011). The differences between the two results might be due to the differences in the independent variables as in this study used soil moisture and the Huber et al. (2011) study used 3-month rainfall sums.

5.4. NDVI and SM correlation relationship

Significant correlations calculated from all-year data occupies a larger area than significant correlations calculated only by JASO month's data. However, the significant correlation areas are more present in the northern part of Sahel region by using JASO data at lag0 (no time lag difference). Differences in significant correlations between all-year data and JASO month's data could relate to the effect of movements of the ITCZ during the rainy season causing more water available during the growing season and a limited amount of water during the dry season (Hiernaux et al. 2009).

Soil moisture content in the upper 20-30 cm is more representative of soil moisture available for shorter plant roots in the northern and central parts of the Sahel, while water available at greater depths will not be accessed by plants (Fensholt et al., 2010). This likely explains low values of correlation coefficient between NDVI and SM or even absence of significant relationship in many areas across the study area, because the large column depth (1.6m) used in modeled soil moisture data does not reflect the characteristics of vegetation rooting depths in northern and central of Sahel region.

However, the correlation relationship between modeled SM and NDVI did not improved too much in the southern part of the study area, though the large column depth used in SM data which declaring that moisture is not anymore a limiting factor for vegetation growth in southern areas, as other factors such as solar radiation and availability of nutrients will be more important. Our results confirm the results found by Huber et al. (2011), that there is a shift in the variable that constrain vegetation growth in the Sahel region from moisture and rainfall in the northern and central of Sahel to the availability of plant nutrients (Ridder et al., 1982) or the effect of solar radiation especially in the humid areas in south of the study area (Nicholson, 1990).

According to (Fig. 19, Fig. 20 and Fig. 21), the strength of the relationship between NDVI and SM improved by using JASO data rather than using all-year data at lag0, because introducing dry months into the correlation relationship between the two variables reduces it. The SM introduces a larger bias during the dry periods in particular in the northern part of Sahel because SM values are very small and NDVI values oscillate independently of available soil moisture due to presence of vegetation cover that can tolerate or survive with a low amount of water availability which will introduce a bias in the correlation analysis when using all the year data (dry season included).

The existence of negative correlation in several parts in northern part of the study area might be related to the deep roots of trees (40m depth) that can reach water table during the dry season (Dupuy and Dreyfus, 1992). NDVI MVC products were selected in this study for its ability to reduce the effect of cloud cover. However, existence of negative correlation relationship between NDVI and SM in the southern part of the Sahel region might be related to the effect of cloud cover that influences the observed NDVI values as the higher rainfall is associated with more clouds and thereby reduced NDVI values recorded by satellite sensors.

The vegetation growth lags responses to rainfall in the Sahel region, varying from 10-20 days (Justice et al., 1991) to 2-3 months (Eklundh, 1997; Nicholson et al., 1990), whereas in this study the more effective relationship between the NDVI and SM in the Sahel are mainly restricted to one and two months' time lags and corresponds to the study based on field data, reported by Jamali et al. (2011) for different six sites in Africa. The areas of significant correlation are decreasing with increasing lags; the significant area at lag0 is 40% and 44% for all-year data and JASO data respectively, whereas at lag1 is 39% and 32% for both all-year data and JASO data respectively (Table 5). Lag0 and lag1 are considered the dominant optimal lags in the study area that best reflects the NDVI-SM relationship.

Low correlation coefficient values between NDVI and SM data indicate that using SM as the only explanatory variable for vegetation greenness in our study area is not sufficient and maybe other factors have their influences such as solar radiation, availability of nutrients, human impacts and actual plant available soil moisture. The estimation of trends and correlation relationships between NDVI and SM data is relevant for understanding the relationship between water availability and vegetation growth and can be used to help understand how these ecosystems might respond to projected climate change.

Relationship of land cover and soil texture with correlation

The optimal correlation coefficient was evaluated against the land cover types to determine the effect of land cover on NDVI-SM relationship. The results indicated that croplands and Grassland "savanna" are the most dominant significant land cover classes at lag0 and lag1 (0-1 months). The reasons for that are the majority of croplands and grasslands roots located at shallow depths and might be the vegetation starts growing when the water infiltrates from surface soil layer to the root zone (20-30 cm depth). Higher correlation for bare ground class at lag1 and lag2 indicated that the sparse tree covers and woody shrubs existing in the northern part of the study area acquired more time (1-2 months) to access accumulated moisture water in the soil (Table 6 and Table 7). The effect of soil moisture on vegetation growth in evergreen forest and mixed forest is not high in all of lags as the soil moisture availability is not anymore a constraining factor for vegetation increases in these classes.

Entisols and Alfisols soil classes are the highest significant classes at lag0 and lag1 in our study area, because both of these two classes allow quick infiltration of water to the root zone that helps the plants access quite quickly. The southern part of Sahel region is characterized by dense vegetation cover reaches to approximately 30% (Hanan et al. 1991) and with less sandy soil that slowing the time travelling of water from the surface zone to the root zone area. However, the vegetation cover in the southern part of Sahel region can reach the water table below surface by their roots making affecting of soil texture as a constraining factor are limited (Dupuy and Dreyfus, 1992).

5.5. Logistic regression

Land cover classes and soil textures were used as explanatory variables for the optimal correlation lags in our study area. For all year data, land cover and soil texture showed high influence on the relationship between soil moisture and vegetation growth at lag2. When using JASO data, the high influence of land cover and soil texture occurs at lag1. Bare ground and Grasslands are the two mainly land cover classes at lag2 (all year data) and lag1 (JASO data), whereas Entisols are the main soil type in the both lags. Importance of land cover and soil type on the NDVI-SM relationship at two months' time lags by using all year data and one month time lag by using JASO data might be related to time needed by water to infiltrate the soil or even generate enough soil moisture content to be accessed by plant roots. Our model cannot detect which factor (soil type or land cover) is most important on the relationship between NDVI and soil moisture as both of them used as explanatory variables inputs in the logistic model. However, our model gave an indication on the overall contribution effects of land cover and soil texture on the optimal correlation lags. For all year data, Lag2 showed a significant positive correlation between soil moisture and vegetation growth in east of Mauritania and central of Chad as the tree covers were mainly distributed on the alluvial fan deposits close to the high mountainous areas. Lag1 (by using JASO data) showed a significant positive correlation around the mountainous areas in western-central of Sudan, central of Chad and east of Mauritania.

5.6. Modelled SM versus measured SM

Modelled SM and measured SM at 15 cm depth displayed a similar correlation relationship with NDVI at lag0 in ML-AgG and ML-Kem sites indicating that both modelled and measured SM data are comparable with each other. However, the relationship between measured SM and NDVI decreased at lag 1 and even switched to negative correlation relationship in the greater lags indicating that the modelled SM is more correlated with vegetation growth (NDVI) more than measured SM at 15 cm depth even the modelled SM data was modelled for a column depth reaches to 1.6 m.

The two other selected sites in NE-Waf (Niger) and SD-Dem (Sudan) revealed that the modeled SM still shows high correlation more than measured SM at 15, 30, 150cm depths. The measured

SM showed a significant positive correlation at lag0 at both sites but it was still lower than correlation values obtained from modeled SM. The good correlation between modeled SM and NDVI could be related to presence of trend and seasonality in both of data that increase the autocorrelation and makes an overestimation for the correlation relationship between them. The raw modeled SM and NDVI data used in this analysis (instead of detrended and deseasonalized data) are comparable with the measured SM datasets that were not pre-processed by any kind of analysis.

5.7. Research answers

Based on the research questions and hypotheses stated in chapter 1, the following are the research questions with their answers:

I. ***How does the soil moisture and vegetation greenness vary in Sahel from 1982 to 2008?***

Vegetation greenness (NDVI) trend showed a significant increase at 5% significance level in many parts in central and south of Sahel region (in particular south-western Mali, central Chad, south of Sudan, east of Burkina Faso and north of Nigeria) during the study period from 1982-2008. When, soil moisture trend showed a significant trend in small areas in Sahel region especially at east of Mauritania, central Mali, west of Chad, south of Somalia and south of Sudan. NDVI trend increasing in these regions could be related to a recovery in rainfall or by humans through applying good farming strategies or due to presence of vegetation cover trees have accessibility to reach water table without much depending on the fluctuations of rainfall or soil moisture. Insignificant soil moisture in many parts in Sahel region might be related to the great modelled soil moisture depth (1.6 m) used in SM data or owing to lack of more in-situ measurements than that used in modelled SM data to accurately estimate soil moisture in diverse and complex topography regions.

Conclusion: There is a significant variation exists in trend of vegetation greenness (in many areas) and soil moisture (in small areas) in Sahel region during the study period.

II. ***Is there a correlation between modeled soil moisture (SM) and vegetation growth (NDVI) during the study period from 1982 to 2008?***

For all-year data (dry season included), the significant correlation coefficients (r) at 5% significance level based on pixel by pixel inspection were varying between low and moderate values (0.1-0.5). However, it varies between (0.1-0.6) by using only the JASO data (growing season only). These low and moderate values indicating that soil moisture is not only the main driver for vegetation dynamics in Sahel and might be related to other factors such as nutrient availability, solar radiation and human impacts.

Conclusion: There is a low and moderate significance correlation exists between soil moisture and vegetation growth during the study period from 1982-2008.

III. Does the relationship between soil moisture and vegetation growth vary with changing time lag across the study area?

Significance correlation relationship between soil moisture and NDVI by using all-year data are showing highest values at lag0 (especially in Burkina Faso, south of Mali and north of Senegal), lag1 (particularly in south of Sudan, central of Niger and east of Mali) and lag2 (mainly in central of Mauritania and central of Chad). For JASO data, the significant correlation values at lag0 are highly present in the northern parts of Sahel region (largely in south of Sudan, south of Mali and north of Senegal), whereas at lag1 occurred in central of Sudan and central of Mali and significant values of lag2 occurred in north central Sudan, east of Mauritania. This results indicating that the relationship between NDVI and SM is highly variable in time and space and depends on the degree of association of these variables in the time domain.

Conclusion: The significant relationship between NDVI and soil moisture is varying with changing the time lag.

IV. Does the lag of maximum correlation (optimal lag) vary across the Sahel?

Optimal lags (lag with the highest significant correlation coefficient in comparison to other lags) by using all the year data are mainly confined to lag0 and lag1 that were occupying areas reaches to 40% and 39% respectively from the total significance areas. For JASO data, the significant percentage areas were reaching to 44% and 32% for lag0 and lag1, respectively. The results showed that the best relationship between vegetation growth and soil moisture occurred at the concurrent month (no months' time lag) and one previous soil moisture month (one month time lag).

Conclusion: Optimal lag correlation was dominant at lag0 (no time lag) and lag1 (one month time lag).

V. Is the pattern from IV related to land cover types and soil textures?

The optimal correlation coefficients were evaluated against land cover and soil texture data by using all year data and JASO data. The results showed that croplands, grasslands and shrublands are the largest significant land covers at lag0, whereas at lag1 croplands, bare ground and grasslands are the major significant land cover classes. The largest significant soil types at lag0 and lag1 are Entisols and Alfisols in Sahel region.

Conclusion: The correlation relationship between NDVI and SM is highly influenced by land cover type and soil texture especially at lag2, lag0 and lag1 respectively across the Sahel region.

5.8. Uncertainties

NDVI and SM time series data characterized by seasonal variations and trends tends to make the data distribution skewed which contradicts many statistical assumptions. After de-trending and de-seasonalization, NDVI data showed a normal distribution curve more than SM data. This problem should be investigated properly to be sure that our results is robust. Uncertainties in the modelled soil moisture data itself, especially in areas of complex topography, need more in-situ measurements more than used to accurately estimate the diverse microclimatic process on a small scale. The depth of the modeled SM data does not represent plant available soil moisture and other types of vegetation with short roots especially, in the northern part of Sahel region.

The limited temporal (monthly) resolution of NDVI and SM data used in this analysis can also be another problem as the lag of best correlation between NDVI and SM cannot be precisely defined (it could be in the first ten days or in the last ten days during the month). According to Justice at al. (1993), the best correlation between rainfall and NDVI was consistent at 10-20 days for the Sahel region. Also, the limited spatial resolution (8*8 km) for both NDVI and SM data could be another factor for not accurately differentiate between different vegetation types and their responses to water availability. NDVI shows a limited sensitivity in the dense vegetation canopies (Field et al., 1995) and also effects of soil background in low vegetation cover areas can lead to inaccurately NDVI estimating values.

5.9.Future work

This study showed the importance of using the moisture as an indicator for vegetation growth, but for accurately estimating this relationship there is a need for modeling plant available soil moisture. So, future task would be to build a model that computes only the moisture accessed by plants and correlate this with NDVI. Other factors could also be included like farming strategies and land use change to strengthen the correlation relationship explanation and to have a good understanding on the human impacts through changes in grazing pressure, de- and afforestation and changes related to use fertilizers in cultivated areas.

Using radar techniques in estimating of soil moisture is also considered one of the promising techniques that can be used for estimating the amount of available soil moisture. Comparing NDVI with other vegetation index such as Enhanced Vegetation Index (EVI) could also be interesting for determining the responses of vegetation greenness to moisture availability in areas where the NDVI has limited sensitivity. Limitations of AVHRR sensor with 8*8km spatial resolution to detect the vegetation and land managements at finer scales could be another aspect to tackle, and maybe using data with a higher spatial resolution than used in this study could add more information for understanding the low correlation relationship between NDVI and SM.

6. Conclusions

This study has evaluated the correlation relationship between vegetation greenness (NDVI) and modeled soil moisture (SM) at different time lags in Sahel region from 1982-2008 depending on whether the dry season was included or not in the analyses, documented the changes that have occurred in NDVI and SM during the study period and investigated the influences of land cover and soil type on the correlation relationship. The most important results from this study can be concluded as follows:

- Highly significant NDVI-SM correlation relationship were found at no time lag and one month time lag, the strength of association between NDVI and SM increased in the northern part of Sahel region by using only growing season (JASO months) and this relationship was vague in central and southern area of the Sahel region.
- The significant correlation coefficients between NDVI and SM varied from 0.1 to 0.5 when using all year data (dry season included) and varied from 0.1 to 0.6 when using the growing season (JASO months). The correlation relationship decreased by increasing the number of time lags with high correlation at lag0, lag1 and lag2.
- Using NDVI as a proxy of vegetation response to moisture availability in the southern areas in Sahel region should be employed with caution as the soil reaches saturation or moisture water availability is not any longer a limiting factor for vegetation growth.
- Soil moisture data produced at a great column depth (1.6 m) is not representing the actual root zone depth in the northern and central part of Sahel region (20-30cm). However, the SM product performed quite well in our analysis when it was compared with measured soil moisture at different depths. Sahelian trees in dry season can reach water table at 40 m below the surface which makes the current soil moisture data inefficient in explaining the variation in vegetation growth (NDVI). Better to use soil moisture data describing the plant available soil moisture.
- The NDVI-SM correlation relationship is influenced by the land cover type (especially croplands and grassland) and soil type (especially Entisols and Alfisols) in our study area during the study period from 1982 to 2008.
- Low- moderate correlation coefficient values and presence of positive trends in the NDVI residuals from a regression analysis between NDVI and SM data indicated that there are other factors than SM affecting the vegetation growth in the study area such as instantaneous precipitation, plant nutrients, availability of solar radiation and human impacts.
- Vegetation greenness (NDVI) has increased over the study period from 1982 to 2008 in many locations in Sahel region, whereas modeled SM exhibited a significant increasing in a few locations in the study area during the study period.
- A good understanding of the relationship between vegetation greenness and soil moisture can help us to know how water affects plant growth, help in agricultural planning and food security to better understand the impact of climate change on these ecosystems.

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Appendices

Appendix A

Table A1: Major Global Land Cover (GLC) classes used in the study.

GLC classes	Major classes
Closed evergreen lowland forest	Evergreen Forest
Degraded evergreen lowland forest	
Submontane forest (900 -1500 m)	Mixed Forest (forest+savana)
Montane forest (>1500 m)	
Swamp forest	
Mangrove	
Mosaic Forest / Savanna	
Closed deciduous forest	Deciduous Forest
Deciduous woodland	
Deciduous shrubland with sparse trees	Shrublands
Open deciduous shrubland	
Closed grassland	Grassland "Savanna"
Open grassland with sparse shrubs	
Open grassland	
Sparse grassland	
Swamp bushland and grassland	
Mosaic Forest / Croplands	Croplands
Croplands (>50%)	
Croplands with open woody vegetation	
Irrigated croplands	
Tree crops	
Sandy desert and dunes	Bare Ground
Stony desert	
Bare rock	
Salt hardpans	
Cities	
Water bodies	water bodies

Table A2: Major soil order classes used in this study from aggregation suborders soil types.

Order	Suborders
Alfisols	Aqualfs, Cryalfs, Udalfs, Ustalfs, Xeralfs
Andisols	Aquands, Gelands, Cryands, Torrands, Ustands, Udands, Xerands, Vitrands
Entisols	Aquents, Arents, Fluvents, Orthents, Pasamments
Aridisols	Argids, Calcids, Cambids, Cryids, Durids, Gypsids, Salids
Oxisols	Aquox, Perox, Torrox, Ustox, Udox
Vertisols	Aquerts, Cryerts, Xererts, Torrerts, Usterts, Uderts
Histosol	Folists, Fibrists, Hemists, Saprists
Mollisols	Albolls, Aquolls, Cryolls, Gelolls, Rendolls, Udolls,Ustolls, Xerolls
Gelisols	Histels, Turbels, Orthels
Inceptisols	Anthrepts, Aquepts, Cryepts, Udepts, Ustepts, Xerepts
Ultisols	Aquults, Humutts, Udults, Ustults, Xerults
Spodosols "Podosols"	/

Appendix B

Figure B1: Scatter plot of raw NDVI values versus lagged raw soil moisture values at location 1 with the cross-correlation values in blue.

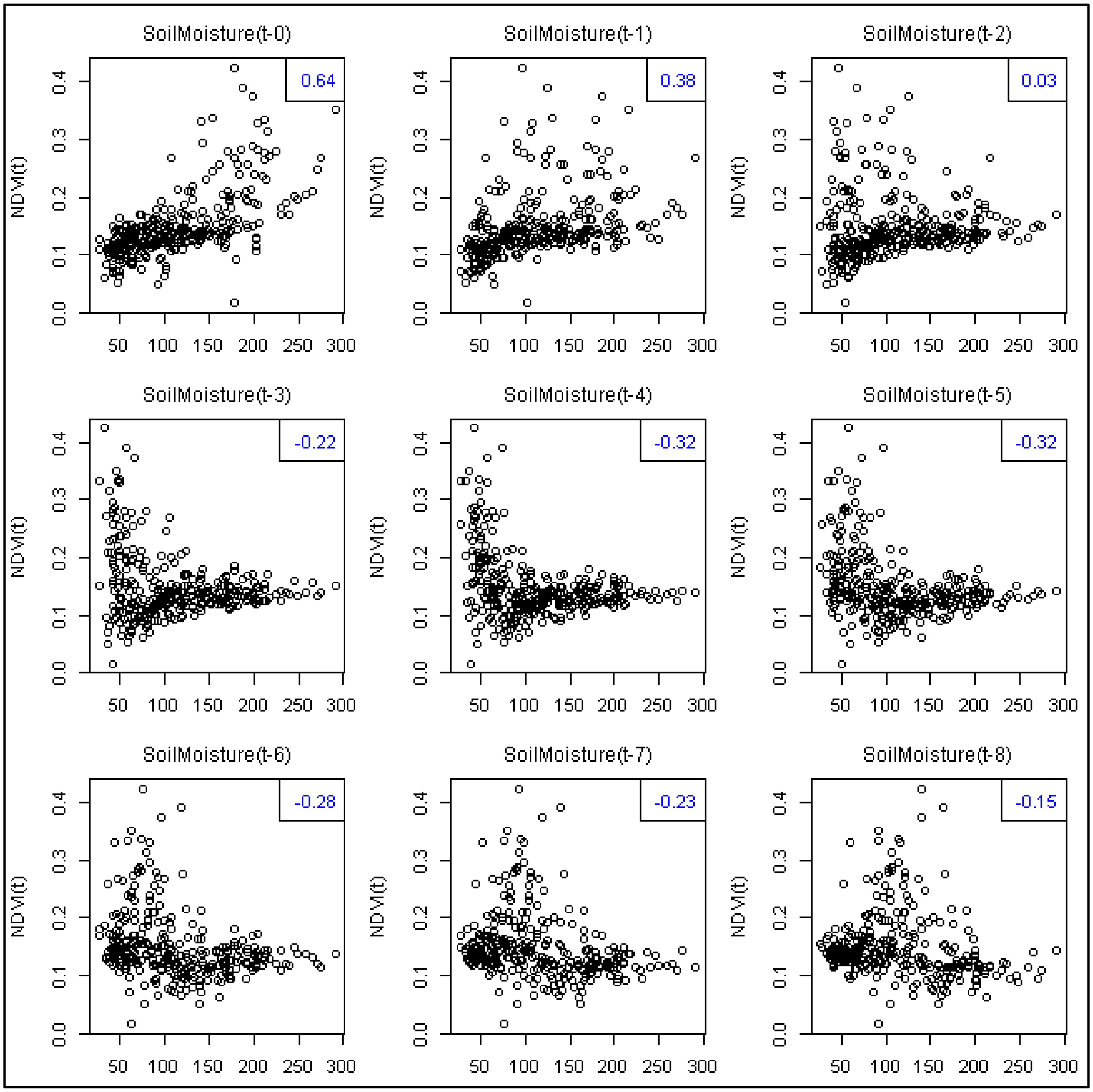


Figure B2: Scatter plot of raw NDVI values versus lagged raw soil moisture values at location 2 with the cross-correlation values in blue.

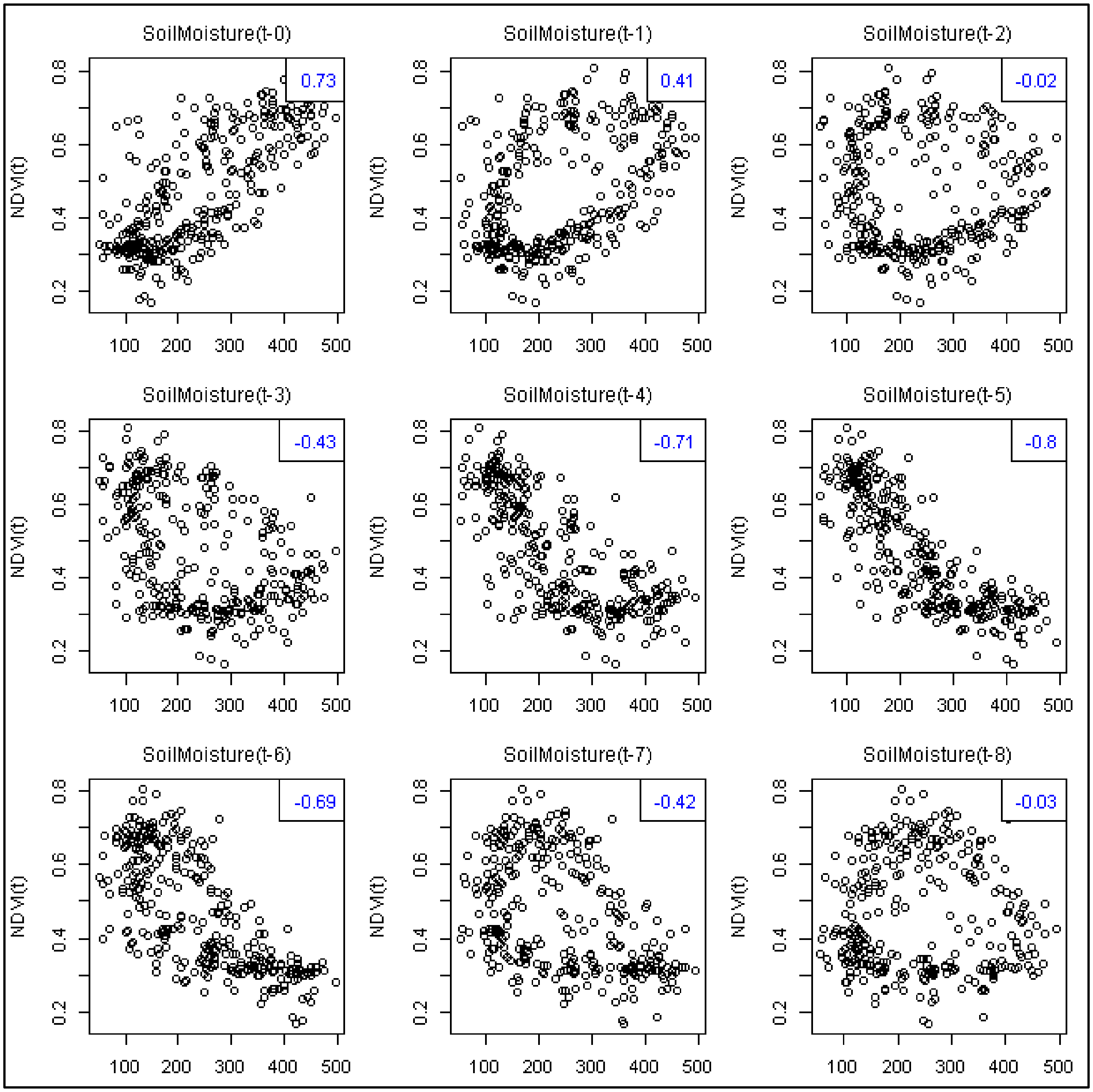
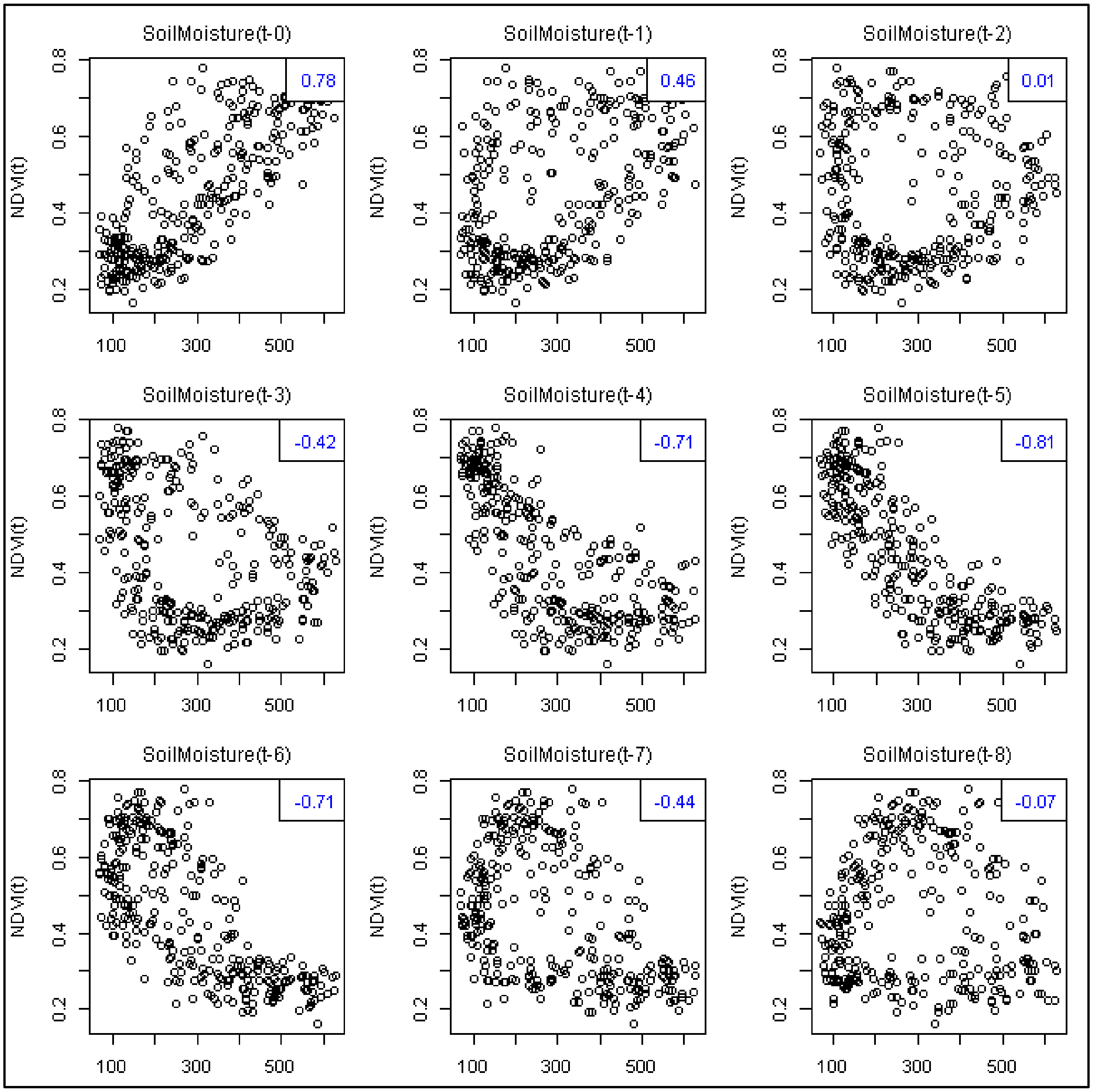


Figure B3: Scatter plot of raw NDVI values versus lagged raw soil moisture values at location 3 with the cross-correlation values in blue.



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