UNIVERSITY OF SOUTHAMPTON

FACULTY OF ENVIRONMENTAL AND LIFE SCIENCES

Academic Unit of Geography and Environment

Land Surface Phenology of Africa, its drivers and relationship with climate variability

by

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ABSTRACT

FACULTY OF ENVIRONMENTAL AND LIFE SCIENCES

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The study of vegetation phenology is very important because it is a sensitive indicator of climate changes. In the last few decades, phenological studies have focussed on using satellite sensor data because of it benefits. Nevertheless, despite being home to the second-largest area of rainforest and wetlands, and the largest area of savanna in the world with a diverse range of vegetation types, Africa is still one of the most poorly studied regions in the world. Very little is known about its vegetation phenology and it drivers. Hence, this study aimed (i) to identify major research gaps by providing a synthesis of studies of related Africa's vegetation phenology and classify them based on the methods and techniques used (ii) to provide seasonal vegetation phenological pattern of the major land cover types in different geographical sub-regions in Africa using medium spatial resolution data (iii) to understand the recent trends in Africa's vegetation phenology over the period 2001 – 2015 (iv) to understand the influence of land cover changes on LSP trends and (v) to investigate the relationship between vegetation phenological pattern and climatic factors. Significant increases in the number of phenological studies in the last decade were observed, mostly remote sensing, whereas ground based studies occurred rarely in the continent. Even more evident was the lack of phenological networks in the continent. In addition, a more detailed and up-to-date characterisation of Africa's LSP was reported. Furthermore, longer vegetation growing season and the influence of land cover changes were observed. Relating to the climate-LSP relationships, this study showed a wider spread of pre-rain green-up over Africa than previously reported and the localised post-rain green-up. The major climatic drivers of LSP parameters in the continent was also reported. In general, therefore, these results alongside recommendations can significantly improve our understanding of vegetation-climate interactions, and ultimately improve vegetation phenological and climatic studies in Africa.

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DECLARATION OF AUTHORSHIP

I, Tracy Adole, declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

Land Surface Phenology of Africa, its drivers and relationship with climate variability

I confirm that:

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Definitions and Abbreviations

AVHRR	Advanced Very High Resolution Radiometer
BFAST	Breaks for Additive Seasonal and Trend
BISE	Best Index Slope Estimation
CACAO	Consistent Adjustment of the Climatology to Actual Observations
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
CN	Carbon–nitrogen
CWF	Changing Weight Filter
DFT	Discrete Fourier Transform
DMA	Delayed Moving Average
DOY	Day of Year
ECMWF	European Centre for Medium-Range Weather Forecasts
EOS	End of season
EOS	Earth Observing System
ERS	End of rainy season
EVI	Enhanced Vegetation Index
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FFT	Fast Fourier Transform
GPP	Gross Primary Production
HANTS	Harmonic Analysis of Time Series
IDR	Iterative Interpolation for Data Reconstruction
IGBP	International Geosphere Biosphere Programme
IntEVI	Integrated EVI
ITCZ	Inter-Tropical Convergence Zone
LAI	Leaf Area Index
LGS	Length of Growing Season
LOS	Length of Season
LRS	Length of rainy season
LSP	Land Surface Phenology
LWSI	Land Surface Water Index
MCTI	MERIS Terrestrial Chlorophyll Index
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate-resolution Imaging Spectroradiometer
MSG	Meteosat Second Generation
MVC	Maximum Value Compositing
MVI	Mean-Value Iteration
MWHA	Moving Weighted Harmonic Analysis

NAO	North Atlantic Oscillation
NAOO	National Oceanic and Atmospheric Administration
NASA	National Aeronautics and Space Administration
NCAR	National Centre for Atmospheric Research
NDII	Normalized Difference Infrared Index
NDVI	Normalized Difference Vegetation index
NDWI	Normalized Difference Water Index
PCA	Principal Component Analysis
PDO	Pacific Decadal Oscillation
PRI	Photochemical Reflectance Index
QA	Quality Assurance
Rcum	Cumulative annual rainfall
Rtmax	Time of maximum rain
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SeaWIFS	Sea-Viewing Wide Field-of-View Sensor
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SOS	Start of season
SPOT	Satellites Pour l'Observation de la Terre
SRS	Start of rainy season
STA	Seasonal Trend Analysis
STD	Standard Deviation
TBM	Terrestrial biosphere models
Temp	Temperature
TLS	Terrestrial Laser Scanning
TRMM	Tropical Rainfall Measuring Mission
TSF	Two-Step Filtering
TSF	Temporal Spatial Filter
VIs	Vegetation Indices
VItmax	Maximum EVI
WDRVI	Wide Dynamic Range Vegetation Index
WS	Whittaker Smoother

Chapter 1: Introduction

The phenology of plants which refers to the timing of cyclical biological events of plant growth offers better understating of vegetation dynamics and their relationship with climatic and non-climatic factors (Cleland *et al.*, 2007; Zhao *et al.*, 2013). Apart from it being an indicator of environmental changes (Cleland *et al.*, 2007), it is also very important in monitoring other anthropogenic activities like land-use management/evaluations and agricultural production (Brown & de Beurs, 2008; Vrieling *et al.*, 2011). Globally, in the last few decades, this study of vegetation phenology has gained much attention especially in relation to quantifying climate change impacts and the development of mitigation strategies (Cleland *et al.*, 2007; Peñuelas *et al.*, 2009; Richardson *et al.*, 2013). These concerns have led to studies focusing on understanding vegetation phenology and its drivers, with most using remote sensing techniques. The use of remote sensing techniques offers resources for long-term observations and at broad-scale especially areas void of ground data (Jeong *et al.*, 2011; Dawson *et al.*, 2016a). It also provide the capability to synchronise LSP data with large scale climatic data at regional to global scales (Cleland *et al.*, 2007; Richardson *et al.*, 2013).

Nevertheless, despite Africa being home to the second-largest rainforest and wetlands, as well as having 17% of global tropical forest and 12% of global tropical mangroves (Spiers, 1999; Food and Agriculture Organization of the United Nations, 2010; Betbeder *et al.*, 2014; Zhou *et al.*, 2014), very little is known about the African vegetation phenology and the factors regulating its vegetation growth and dynamics (IPCC, 2014; Adole *et al.*, 2016; Ryan *et al.*, 2017; Stock, 2017). The continent is also known to have very complex vegetation dynamics with multi-annual seasons and landscape heterogeneity, and potentially high vulnerability to climate change impacts (Boko *et al.*, 2007; Favier *et al.*, 2012; Guan *et al.*, 2014b; Niang *et al.*, 2014). Its vegetation is also a major contributor to the global climate-carbon cycle feedback (Friedlingstein *et al.*, 2010) and provides numerous ecosystem services, including rangelands for grazing and livestock production (Skowno *et al.*, 2016), and croplands for agricultural production (Brown & de Beurs, 2008).

In view of the above, and considering the variability of vegetation growing pattern, detailed and up to date phenological information for the African continent is essential especially in the wake of climate change studies. Therefore, this study aimed:

(1) to identify major research gaps by providing a synthesis of studies of related Africa’s vegetation phenology and classify them based on the methods and techniques used

(2) to characterise the spatial distribution of Land Surface Phenology (LSP) in Africa using medium spatial resolution of 500 m 8-day MODIS EVI time series data with a long temporal range of 15 years (2001 – 2015)

(3) to understand the recent trends in vegetation phenology of Africa over the period 2001 – 2015 using 500 m 8-day MODIS EVI time-series data

(3) to understand the influence of land cover changes on vegetation phenological trends, and

(5) to investigate the relationship between vegetation phenological pattern and climatic factors.

As previously mentioned, the use of remote sensing techniques has offered a way out of some of the difficulties posed by ground-based studies. Given that, the extent of study area is large and the issue of physical accessibility, remote sensing-based approaches have been adopted for this entire study. Based on this, the second chapter focuses on the Land Surface Phenology (LSP) (essentially remote sensing methods) smoothing and estimation techniques. Chapter three then gives a comprehensive systematic appraisal of the literature on vegetation phenology in Africa and identified the research gaps needed to be filled.

A more recent and detailed characterisation of the Land Surface Phenology (LSP) of Africa was described in chapter four. Chapter five focuses on the recent LSP trends in the continent controlling for trends influenced by land cover changes in order to determine trends affected by climatic factors only. Chapter six and seven gives an appraisal of the controlling climatic drivers of LSP in the African continent. Finally, chapter eight discusses the implications of this study, its benefits and future recommendations for both scientific research and policy makers.

Chapter 2: Land Surface Phenology (LSP) estimation techniques

2.1 Introduction

There has been a surge in phenological studies over the decades occasioned by a changing climate (Cleland *et al.*, 2007; Richardson *et al.*, 2013). As a result, more researchers are developing different approaches in measuring phenology which is the study of periodic life-cycle events, the impact of changes in climate and environment on the different phases of these events, and the interrelations among these phases either from the same or different species (Lieth, 1974). More of this attention has been geared towards vegetation phenology considering the dynamic and significant functions of plants within the biosphere. This sequence of events of the life cycle of plants, which can be the onset of bud break, leaf growth, shoot growth, flowering, fruiting and greenness to the end of senescence (litter fall,/leaf abscission) (Childes, 1989; Chidumayo, 1994; Seghieri *et al.*, 1995; Chapman *et al.*, 2005; O'Farrell *et al.*, 2007) can be measured either through ground observations or by remote sensing methods (White *et al.*, 2005; Studer *et al.*, 2007). Table 2.1 and Figure 2.1 show key phenological parameters measured and their interpretation using remote sensing techniques.

Table 2.1 Phenological parameters and their interpretations

Phenological parameters	**Phenological Interpretation**
Time of onset of greenness	Beginning of measurable photosynthesis in the vegetation
Value of onset of greenness	Level of photosynthetic activity at the beginning of measurable photosynthesis
Time of end of greenness	Cessation of measurable photosynthesis in the vegetation
Value of end of greenness	Level of photosynthetic activity at the end of measurable photosynthesis
Green-up duration	Length of photosynthetic activity (difference between onset of greenness and end of greenness)
Peak of growing season	Maximum measureable level of photosynthetic activity
Time of peak of growing season	Time of maximum measureable photosynthesis
Amplitude	Maximum increase in canopy photosynthetic activity above the baseline (difference between peak of growing season and onset of greenness)
Small season integral	Seasonal active vegetation or the net primary production calculated as the area above the baseline but within the growing season curve
Large seasonal integral	Total vegetation production calculated as the area within the growing season curve between the fitted function and the zero level

The use of remote sensing methods also called "Land Surface Phenology (LSP)", is defined "*as the seasonal pattern of variation in vegetated land surfaces observed from remote sensing"* (Friedl *et al.*, 2006). It involves the use of spatially aggregated satellite data ranging from fine (30 m) to coarse (25 km) spatial resolutions in determining timings of vegetation growth, senescence and dormancy at seasonal and inter-annual time scales (Friedl *et al.*, 2006). Overtime however, other forms of LSP have emerged, making use of non- satellite data. For example the use of Terrestrial Laser Scanning (TLS), also known as terrestrial LiDAR (Calders *et al.*, 2015) and the use of digital cameras also known as near-surface remote sensing (Ide & Oguma, 2010; Hufkens *et al.*, 2012; Soudani *et al.*, 2012). Nevertheless, common to all forms of LSP, the timings of vegetation phenophases are mostly determined through vegetation indices derived from the band combination of reflectance values in the electromagnetic spectrum or sometimes through biophysical variables (Myneni *et al.*, 1997; Dash *et al.*, 2010; Boyd *et al.*, 2011; Bobée *et al.*, 2012), and hemispherical photography in the case of TLS (Calders *et al.*, 2015). These vegetation phenophases or phenological parameters can be estimated from a time-series of remotely sensed data. This mostly requires a stepwise approach, involving the initial calculation of vegetation indices from time-series of satellite data, removal of "bad" pixels in the time-series, interpolation of the missing values, smoothing of the complete time-series, and estimation of phenological parameters from the already smoothed data.

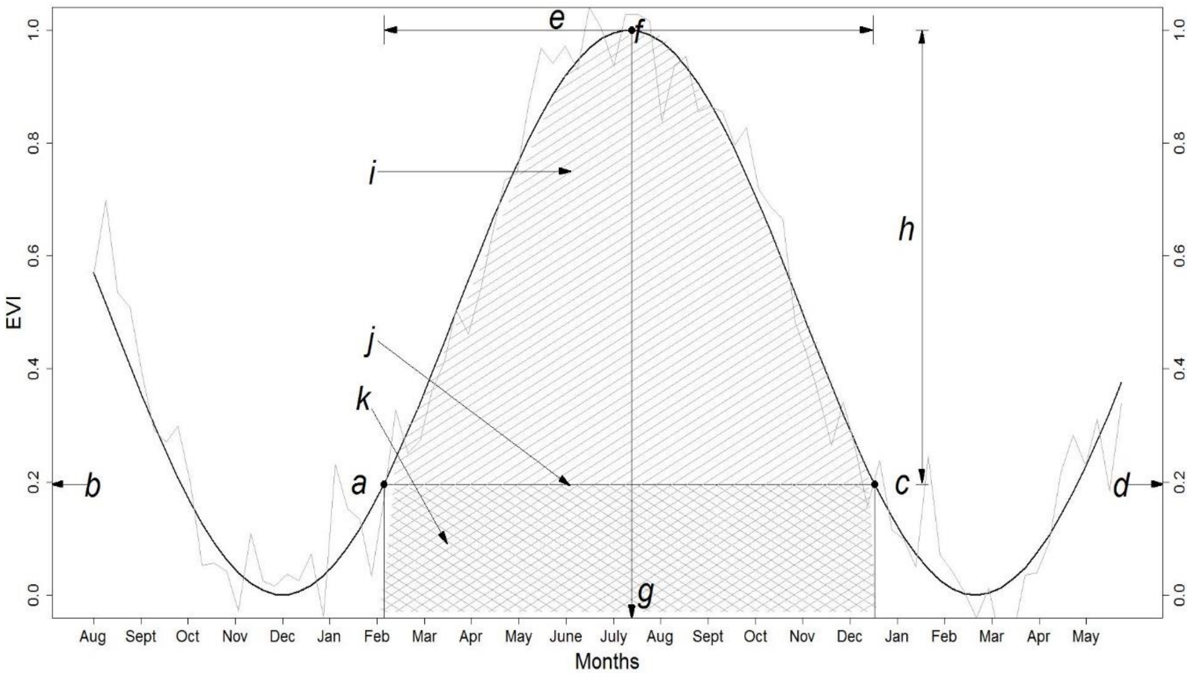

Figure 2.1 Graphical representation of key phenological parameters. (a) Time of onset of greenness, (b) Value of onset of greenness, (c) Time of end of greenness, (d) Value of end of greenness, (e) Green-up duration, (f) Peak of growing season, (g) Time of peak of growing season, (h) Amplitude, (i) Small season integral, (j) Baseline, and (k) Large seasonal integral.

2.2 Advantages of LSP

A number of parameters such as vegetation indices and biophysical variables have been employed in measuring LSP. Table 2.2 gives an overview of the different types used in LSP and the type of smoothing and estimation techniques employed in those studies. The Normalized Difference Vegetation index (NDVI) and the Enhanced Vegetation Index (EVI) are the most commonly used parameters. These are Vegetation Indices (VIs) that optically measures the “greenness” of vegetation based on a photosynthetically active signal, and calculated in the same way across all pixels in an image (Huete *et al.*, 2002, 2011). These indices are closely related to other biophysical variables which are also used in LSP like the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) and the Leaf Area Index (LAI) (Verstraete *et al.*, 2008; Bobée *et al.*, 2012; Jin *et al.*, 2013). Other VIs used in LSP are the Normalized Difference Water Index (NDWI) (Gao, 1996; Delbart *et al.*, 2006), the normalized difference infra-red index (NDII) (Thompson & Paull, 2017), the Backscatter (Ringelmann *et al.*, 2004; Ryan *et al.*, 2014), the Land Surface Water Index (LSWI) (Xiao *et al.*, 2005), Wide Dynamic Range Vegetation Index (WDRVI) (Sakamoto *et al.*, 2010), the MERIS Terrestrial Chlorophyll Index (MCTI) (Dash & Curran, 2004; Dash *et al.*, 2010), and the Photochemical Reflectance Index (PRI) (Ulsig *et al.*, 2017).

The advantages of LSP range from monitoring the inter-annual variability of plant's life cycle in climate-vegetation interactions (Ma *et al.*, 2008; Seghieri *et al.*, 2009; Broich *et al.*, 2014; Rodriguez-Galiano *et al.*, 2015c) to understand animal behavioural pattern, livestock production practices, ecosystem diversity and predicting animal phenology (Pons & Wendenburg, 2005; O'Farrell *et al.*, 2007; Yamagiwa *et al.*, 2008; Barrett *et al.*, 2010; Butt *et al.*, 2011; Brottem *et al.*, 2014; Maeda *et al.*, 2014; Cole *et al.*, 2015). It has provided means for long-term observations both at small-scale, especially in places void of ground data and at broad-scale (regional, continental and global) (Zhang *et al.*, 2006, 2014b; Julien & Sobrino, 2009; Jeong *et al.*, 2011; Guan *et al.*, 2013; Rodriguez-Galiano *et al.*, 2015a).

Notwithstanding these advantages, LSP has its limitations and challenges, particularly knowing that different vegetation types with different periodic life cycle could be in one pixel (Delbart *et al.*, 2015), hence the emphasis on validation of results with ground data. Major challenges of LSP are; the uncertainties generated by noisy satellite data caused by sensor resolution and calibration uncertainties (Viovy *et al.*, 1992), ground and atmospheric conditions and variability (Tanre *et al.*, 1992; Huete *et al.*, 1994; Xiao *et al.*, 2003), and orbital and sensor degradation (Kaufmann *et al.*, 2000). In order to overcome this, a number of researchers have developed several noise-reduction smoothing techniques for time-series of satellite data.

2.3 LSP smoothing techniques

There are a diverse range of smoothing techniques applied to the vegetation indices and biophysical variables derived from time-series of satellite data. These techniques can be grouped into four broad categories: the threshold-based local filter methods, the frequency-based methods, the function-based methods and the integrated methods.

2.3.1 The threshold-based local filter methods

The threshold-based local filter methods are time-domain techniques that set-up thresholds when deriving values of VIs used in reconstructing the time-series profile. They use one or more moving windows to apply local criteria, which identifies and remove spurious values in a time-series. One of the most widely used method is the Maximum Value Compositing (MVC) technique (Holben, 1986), carried out to minimize the effects of noise on pre-processed NDVI time-series. This method retains the maximum VI value for all location in a pixel over a composite period. Another technique is the Best Index Slope Estimation (BISE) method which takes into account the asymmetric growth of vegetation during the estimation of NDVI profiles from daily satellite data (Viovy *et al.*, 1992). Although, smoothing techniques like the Maximum Value Compositing (MVC) have already been carried out on pre-processed satellite data, there still remains a significant residual noise level in data. For this reason, some researchers have developed other noise-reduction smoothing techniques to further apply on pre-processed MVC data. Examples are the Savitzky–Golay filter method (Savitzky & Golay, 1964; Chen *et al.*, 2004), the Mean-Value Iteration filter (MVI) (Ma & Veroustraete, 2006), Iterative Interpolation for Data Reconstruction (IDR) method (Julien & Sobrino, 2010), Changing Weight Filter (CWF) method (Zhu *et al.*, 2012b), two-step gap filling method (Xiao *et al.*, 2003), the Principal Component Analysis (PCA) (Eklundh & Singh, 1993) and Seasonal Auto Regressive Integrated Moving Average (SARIMA) (Jiang *et al.*, 2010).

Major disadvantages of these local filter methods are; the requirement of a uniformly spaced intervals of time-series data (Zhu *et al.*, 2012b), and the dependency on user expertise (Chen *et al.*, 2004). Others disadvantages are the overestimation of the upper envelope for vegetation dormancy period in the IDR (Julien & Sobrino, 2010) and the instability of reconstruction results due to irregular fluctuations (Chen *et al.*, 2004; Zhu *et al.*, 2012b).

2.3.2 The frequency-based methods

These are curve fitting techniques that reduce noise in a time-series by estimating the main data at different time-frequency resolutions using polynomials or Fourier functions. These techniques can also be applied on already pre-processed MVC data. A classic example of this technique is the Fourier smoothing method (Sellers *et al.*, 1994). This technique decomposes a time-series from temporal space into a frequency domain using several sine or cosine functions. After which noisy values are removed by multiple iterations while maintaining the upper envelope of VI values in the time-series. Within the Fourier smoothing methods, we have the “classical” Fourier methods (Discrete Fourier Transform (DFT) (Moody & Johnson, 2001), Fast Fourier Transform (FFT) (Azzali & Menenti, 2000)), and the “non-classical” Fourier methods (Sellers *et al.*, 1994; Hermance, 2007). This technique readily indicates actual growth dynamics of vegetation and unlike the local filter methods, very minimal user input is required (Dash *et al.*, 2010). Although very smooth results are achieved using this technique, when applied on an irregular seasonal profile, the result is a large displacement from the original time-series (Chen *et al.*, 2004).

Other methods in this group are the wavelet-based method (Lu *et al.*, 2007), the Two-Step Filtering (TSF) (Sakamoto *et al.*, 2010), the smoothing spline (Bradley *et al.*, 2007), the Harmonic Analysis of Time Series (HANTS) method (Verhoef, 1996; Roerink *et al.*, 2000), Seasonal Trend Analysis (STA) (Eastman *et al.*, 2009) and the Moving Weighted Harmonic Analysis (MWHA) (Yang *et al.*, 2015a).

2.3.3 The function-based methods

Function-based methods are asymmetric function fitting techniques based on least squares of the piecewise functions, which capture annual seasonal vegetation growth signals while removing spurious values in a time-series data. Examples of these methods are the Gaussian function fitting method (Jönsson & Eklundh, 2002), logistic function (Zhang *et al.*, 2003; Kandasamy & Fernandes, 2015), double logistic function fitting method (Fischer, 1994; Beck *et al.*, 2006; Julien & Sobrino, 2009), generalized additive models (Cole *et al.*, 2015), and the Whittaker Smoother (WS) (Eilers, 2003; Atzberger & Eilers, 2011). There are no threshold sets in function based method and most can also be used in estimating phenological parameters (Butt *et al.*, 2011; D’Odorico *et al.*, 2015). Additionally, unlike threshold-based method, function-based methods are less sensitive to noise (Jönsson & Eklundh, 2004) and can be applied to unevenly spaced intervals of time-series data (Zhu *et al.*, 2012b). However, like frequency based methods, irregularities in time-series prolife pose serious difficulty in fitting the data. In addition, these methods may be difficult to implement in large areas with different types biomes (Zhu *et al.*, 2012b).

2.3.4 Integrated methods

Methods in this category consider other factors in reducing contamination in time-series data. They also combine two or three of the above methods in constructing a smoothed time-series data. Amongst some of the other factors considered are: climatology (de Beurs & Henebry, 2005; Verger *et al.*, 2013), the integration of both spatial and temporal information (Moody *et al.*, 2005; Fang *et al.*, 2008), etc. The ecosystem-dependent, temporal-interpolation technique developed to fill missing or snow-covered pixels derived from the MODIS albedo product (Moody *et al.*, 2005) is one of the few in this group. This technique imposes the spatial and spectral behaviour of a pixel unto another pixel’s temporal data in the same ecosystem (Moody *et al.*, 2005). Other integrated methods are: Temporal Spatial Filter (TSF) (Fang *et al.*, 2008), Consistent Adjustment of the Climatology to Actual Observations (CACAO) (Verger *et al.*, 2013), and temporally integrated inversion method (Xiao *et al.*, 2009).

Table 2.2 Examples of different smoothing technique used in LSP studies showing estimation techniques, VIs, biophysical variables and senor types

Smoothing technique	**Classification**	**LSP Estimation technique**	**Parameters**	**Sensor**	**Reference**
A two-step gap filling method	Threshold-based local filter	Function model fitting [The Vegetation Photosynthesis Model (VPM)]	LSWI	MODIS	Jin *et al.* (2013)
Best Index Slope Estimation (BISE)	Threshold-based local filter	Threshold-based	NDWI	SPOT VEGETATION	Delbart *et al.* (2006)
Changing Weight Filter (CWF) method	Threshold-based local filter	Curve-derived	NDVI	MODIS	Zhu *et al.* (2012b)
Median smoothing	Threshold-based local filter	Curve-derived	NDVI	AVHRR	Reed *et al.* (1994)
Savitzky-Golay filter	Threshold-based local filter	Curve-derived	Backscatter	Sea Winds Scatterometer	Ryan *et al.* (2014)
Seasonal Auto Regressive Integrated Moving Average (SARIMA)	Threshold-based local filter	Function model fitting	LAI	MODIS	Bobée *et al.* (2012)
Discrete Fourier Transformation (DFT)	Frequency-based	Curve-derived	MCTI	MERIS	Dash *et al.* (2010)
Fast Fourier Transform (FFT)	Frequency-based	Function model fitting	LAI	MODIS	Hanes & Schwartz (2011)
Smoothing spline	Frequency-based	Threshold-based	NDVI	AVHRR	Bradley *et al.* (2007)
Two-Step Filtering (TSF)	Frequency-based	Function model fitting	WDRVI	MODIS	Sakamoto *et al.* (2010)
Modified logistic functions	Function-based	Function model fitting	NDVI	LANDSAT	Fisher *et al.* (2006)
Parametric sigmoid model	Function-based	Function model fitting	FAPAR	SeaWIFS	Verstraete *et al.* (2008)
Piecewise logistic functions	Function-based	Function model fitting	EVI	MODIS	Zhang *et al.* (2003)
Whittaker smoother	Function-based	Function model fitting	NDVI	SPOT VEGETATION	Atzberger & Eilers (2011)

2.4 LSP estimation techniques

As mentioned above, a stepwise approach is usually employed when estimating phenological parameters (see section 2.1). The last step involves the estimation of phenological parameters from already smoothed data. Unlike smoothing techniques, methods for exploring and estimation of LSP are limited in number, but they can also be grouped into three broad categories: threshold-based, curve-derived and function model fitting methods (Reed *et al.*, 2009b; de Beurs & Henebry, 2010; Zhu *et al.*, 2012a). It is important to note that visual observation of remotely sensed data have been used to estimate LSP. This was carried out by Tappan *et al.* (1992), where LSP was estimated from smooth NDVI AVHRR data with the help of soil polygon maps and visual interpretation of the plots.

2.4.1 Threshold-based methods

This is the most commonly used method for estimating LSP. In this method, a reference value of the parameter or VIs is pre-defined and used in determining LSP parameters (White *et al.*, 1997). This method is further divided into two sub-types: (1) the global or absolute threshold method which uses the same user-defined threshold for every pixel in a study area to determine LSP parameters (Fischer, 1994; Myneni *et al.*, 1997; White *et al.*, 2009), and (2) the local or dynamic threshold method wherein a locally tuned threshold is used to identify LSP parameters for each pixel (per-pixel basis) or a group of pixels in the study area (White *et al.*, 1997; Jönsson & Eklundh, 2002).

The major setback of using this method is the high probability of having later times for onset of greenness and earlier times for end of greenness. This is because onset of greenness may begin way before the user-defined threshold (Vrieling *et al.*, 2008). Moreover, spatial variation cannot represent temporal variation (de Beurs & Henebry, 2010).

2.4.2 Curve-derived methods

Curve-derived method detects phenological phases by comparing variable values to a moving average of the previous observations, specifically to identify any change in an established trend or the point where the curve crosses the moving average curve (Reed *et al.*, 1994; Tateishi & Ebata, 2004; Zhu *et al.*, 2012a). These points of maximum rate of change are extracted as the LSP parameters. Techniques under this method such as inflection points (Moulin *et al.*, 1997; Dash *et al.*, 2010), maximum curvature (Zhang *et al.*, 2001), Delayed Moving Average (DMA) (Reed *et al.*, 1994; Schwartz *et al.*, 2002; Archibald & Scholes, 2007) employ empirical equations in detecting these points of maximum rate of change. Unlike the threshold-based methods, these methods explicitly capture onset and end of growing seasons as there are no pre-defined thresholds. However, it is very challenging when using these methods in estimating LSP parameters from time-series profiles that do not follow the pattern of sudden increases or decreases (de Beurs & Henebry, 2010).

2.4.3 Function model fitting methods

These are both smoothing functions and LSP estimation techniques. They are complex mathematical models used in deriving LSP parameters by fitting mathematical functions to a time-series (Zhang *et al.*, 2003). Some examples are the conceptual-mathematical phenology models in de Beurs & Henebry (2005), double-logistic curve in Beck *et al.* (2006) and Guan *et al.* (2014a) , piecewise logistic functions Zhang *et al.* (2003), Two-Step Filtering (TSF) (Sakamoto *et al.*, 2010). One of the advantages of mathematical models over other traditional method of LSP estimation is that results can be easily interpreted because of their strong mathematical and physical connotation (Menenti *et al.*, 1993).

It is important to note that some studies have employed methods of estimating LSP which cannot be fully classed into any of the categories above. For example, the phase-spaces (sometimes referred to as feature-or band-spaces) which involves developing an algorithm that can estimate phenological descriptor dates from the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Infrared Index (NDII) phase-spaces (Thompson *et al.*, 2015), the combination of threshold and inflection point in Whitcraft *et al.* (2015), the Breaks for Additive Seasonal and Trend (BFAST) method, an additive decomposition model for detecting long-term phenological change (Verbesselt *et al.*, 2010b).

2.5 Conclusion

Land surface phenology has not only offered the opportunity for long-term and broad-scale phenological assessment, but provided means to assess vegetation dynamics of remote areas. Regardless of these advantages, results from LSP vary a great deal due to the different smoothing techniques and estimation methods used. Comparing several methods of estimating LSP, several researchers have found large discrepancies in LSP parameters (Beck *et al.*, 2006; Verstraete *et al.*, 2008; Vrieling *et al.*, 2008; White *et al.*, 2009; de Beurs & Henebry, 2010; Guan *et al.*, 2014a). White *et al.* (2009) reported a difference of ±60 days in onset of growing season and de Beurs & Henebry (2010) also had large differences in all LSP parameters, an average of 60 days for onset of growing season, 63 days for end of senescence and 98 days for LOS. Similarly, the performance of different smoothing techniques have been assessed and this varies depending on the type of data/study area and the user input (e.g. determining the number of harmonics for Fourier) (Bachoo & Archibald, 2007; White *et al.*, 2009; Atkinson *et al.*, 2012; Mo *et al.*, 2015).

Apart from the techniques, the sensor type also influences the LSP parameters (Atzberger *et al.*, 2013). Hence, considering that associated with the advantages of each smoothing and/or phenology estimation techniques are several limitations, it is very important to have proper knowledge of the study area. While is it is important to consider the study area before selecting these techniques, as suggested by Atkinson *et al.* (2012), there is the need to evaluate and combine these different parameters in order to have robust phenological records.

Chapter 3: A systematic review of vegetation phenology in Africa

3.1 Introduction

Vegetation phenology, which deals with the phenology of plants and their seasonal cycles, focuses on the onset of the growing season to the end of senescence in a plant's annual cycle and its relationship with climatic and non-climatic factors (Zhang *et al.*, 2012; Zhao *et al.*, 2013). The relationship between vegetation phenology and climatic factors has been researched since the 1950s (Schnelle, 1955). However, it was formally established in the early 1990s that vegetation phenology is strongly dependent on climatic variables, making it a sensitive marker of seasonal changes in climate variables and their manifestation on the ground (Van Schaik *et al.*, 1993; Wright & van Schaik, 1994).

An important advantage of phenological studies is the ability to carry-out long-term and broad-scale natural experiments, which can be synchronised readily with large scale climatic data (Myneni *et al.*, 1997; Menzel *et al.*, 2006). This has facilitated monitoring the impacts that changes in climate may have on vegetation growth (Chmielewski & Rötzer, 2001; Cleland *et al.*, 2007) and has aided in characterising climate-related events like droughts (White *et al.*, 1997; Brown *et al.*, 2012; Ivits *et al.*, 2014). Vegetation phenology also plays an important role in controlling the global carbon, water, and nitrogen cycles, especially the global carbon cycle, as the timing and duration of growing seasons greatly influences terrestrial energy budgets and atmospheric CO_2 exchange (Keeling *et al.*, 1996; Higgins & Scheiter, 2012). This makes vegetation phenology an important factor to consider in planning and developing climate change mitigation strategies (Peñuelas *et al.*, 2009; Richardson *et al.*, 2013).

In the last few decades, the study of vegetation phenology has gained attention especially in relation to investigating climate change and its impacts on terrestrial ecosystem. Several studies have shown that increases in global temperature can influence photosynthetic activity, litterfall and the length of the growing-season of plants (Chmielewski & Rötzer, 2001; Chmielewski *et al.*, 2004; Zhang *et al.*, 2004). These studies are either ground-based or remote sensing studies or a combination of both. This increase in temperature, in particular during the spring, has been shown to increase vegetation greenness, advance the arrival of spring, and significantly alter growing season length especially in most parts of the Northern hemisphere (Myneni *et al.*, 1997; Menzel & Fabian, 1999; Zhou *et al.*, 2001). Similarly, other studies involving controlled experiments that simulate increases in temperature have provided further evidence of a lengthened growing season driven by changes in climatic conditions (Matsumoto *et al.*, 2003; Wolkovich *et al.*, 2012). This further emphasises the importance of a greater understanding of vegetation phenology and its drivers, especially in poorly studied regions. Unfortunately, one of those regions is the African continent as identified by the IPCC (2014) report on climate change.

3.2 Vegetation phenology in Africa

Despite increased interest in phenological studies, the phenology of the African vegetation has received far less attention than that of the Northern hemisphere, notwithstanding the African forest's important contributions to the global carbon cycle. Given that Africa is home to the second-largest rainforest in the world (central African rainforests) (Zhou *et al.*, 2014), and the second and third largest wetlands in the world: the *Cuvette Centrale* of the Congo River Basin (Betbeder *et al.*, 2014) and the Niger Delta region of Nigeria (Spiers, 1999), vegetation dynamics in this region greatly influence regional and global land-atmosphere feedbacks. Also, 17% of global forest cover (Food and Agriculture Organization of the United Nations, 2010), and approximately 12% of tropical mangroves, which are the most productive natural ecosystem and the most carbon rich forest in the world, are found in Africa (Giri *et al.*, 2010; Donato *et al.*, 2011; Record *et al.*, 2013). Specific areas in the African forest have been mapped to have very high potential for carbon offsetting by reforestation (Greve *et al.*, 2013). In addition to the abundance of forest, Africa also has a diverse range of vegetation types, ranging from deserts, grasslands, savannas and scrublands to woodlands, including broadleaved evergreen, needleleaved evergreen and deciduous forest (see Figure 3.1) (Mayaux *et al.*, 2004; Gritti *et al.*, 2010; Arino *et al.*, 2012; Faber-Langendoen *et al.*, 2012; Day *et al.*, 2013) with complex vegetation dynamics (Favier *et al.*, 2012).

The African continent has been recognised as one of the most vulnerable to climate change impacts (Boko *et al.*, 2007; Niang *et al.*, 2014). Warming in Africa has been projected to be larger than global annual mean warming, and land temperatures have been projected to rise faster than the global land average (Boko *et al.*, 2007; Christensen *et al.*, 2007; Niang *et al.*, 2014). For the rainforest region, a mean warming rate of 0.8–1.0^{o}C per 1^{o}C of global warming has been projected (Malhi *et al.*, 2013). Also, annual precipitation, both observed and projected, across Africa has changed significantly (Niang *et al.*, 2014) over last few decades. These changes vary greatly across the continent, increasing or decreasing depending on spatial and seasonal factors (Orlowsky & Seneviratne, 2012). There is also the threat of contamination of freshwater with saltwater, due to sea level rise, which can impact negatively on coastal vegetation (Nicholls & Cazenave, 2010; Nicholls *et al.*, 2011). In addition, Africa's vegetation has experienced significant change over recent years. Between 2000-2010 the continent experienced a net loss of forest cover of approximately 3.4 million hectares annually (Food and Agriculture Organization of the United Nations, 2010). East Africa in particular, was shown to have increased tropical woody vegetation over grasslands (Doherty *et al.*, 2010), while Mitchard *et al.*, (2009) demonstrated forest encroachment into grassland areas in central Cameroon. There has also been a reported increase in vegetation greenness in the Sahel region (Olsson *et al.*, 2005; Heumann *et al.*, 2007). However, this phenomenon of increasing vegetation is not universal across all regions in Africa. Other studies show quite the opposite (Allen *et al.*, 2010; Mayaux *et al.*, 2013), including a detectable reduction in tree cover in the parts of the African Sahel attributable to climate variability and global climate change (Gonzalez *et al.*, 2012).

Despite the above studies, the phenology of the African forest and its role in the global biogeochemical cycle are not clearly understood. Very few studies have attempted to characterise the highly irregular phenological patterns of Africa's vegetation (De Bie *et al.*, 1998; Linderman *et al.*, 2005; Zhang *et al.*, 2005; Guan *et al.*, 2013, 2014b). Moreover, unlike the Northern hemisphere phenological system which is driven mainly by temperature (Myneni *et al.*, 1997; Zhou *et al.*, 2001; Zhang *et al.*, 2004), vegetation growth in Africa is controlled by combination of three factors (temperature, precipitation and irradiance) (Chidumayo, 2001; Grab & Craparo, 2011; Brown *et al.*, 2012; Polansky & Boesch, 2013; Guan *et al.*, 2014b; Wolkovich *et al.*, 2014; Zhou *et al.*, 2014), thus, making it a complex system to study. In addition, the multi-annual life cycles of tropical rainforests makes it even more challenging to characterise vegetation phenology (Viennois *et al.*, 2013).

While there generally exist sufficient phenological data and numerous field phenological observation networks worldwide, the same cannot be said for regions outside the temperate latitudes (Zhang *et al.*, 2012; Wolkovich *et al.*, 2014), especially for Africa. Although research on African vegetation phenology is limited, more can be done by refining and integrating these studies, to identify the particular *foci* of phenological assessments that have been conducted, the specific research gaps and the appropriate approaches needed to fill these gaps. However, to date there has been no comprehensive review that summarizes the phenological studies in Africa, which highlights the specific gaps in knowledge and research, and identifies the suitable research methods required. Through this review, we provide a summary of the current state of research in the continent of Africa and some recommendations for future research. This review, thus, aims to contribute to the ongoing debates over climate change in Africa and, most importantly, its effects on vegetation phenology and attempts to mitigate its effects through climate change adaptation and mitigation strategies.

3.3 Conceptual framework

Phenological studies have increased in number over the last decade, with studies focusing more on higher latitude regions, and including both small on-the-ground or *in situ* field studies (Chmielewski & Rötzer, 2001; Seghieri *et al.*, 2009; Calle *et al.*, 2010) and large scale remote sensing (Moulin *et al.*, 1997; Dash *et al.*, 2010; Jeganathan *et al.*, 2010; Stockli *et al.*, 2011; Brown *et al.*, 2012; Clinton *et al.*, 2014). On-the-ground measurements are made by visual observation and recording of the different stages of a plant's life cycle (Chmielewski *et al.*, 2004), *in situ* spectral measurements and near-surface remote sensing from laboratory-made sensors (Ide & Oguma, 2010; Hufkens *et al.*, 2012; Sonnentag *et al.*, 2012; Soudani *et al.*, 2012; Hmimina *et al.*, 2013), and gas exchange measurements from flux towers (Migliavacca *et al.*, 2011; Jin *et al.*, 2013). Remote sensing measurement on the other hand, is based primarily on deriving Vegetation Indices (VIs) and other vegetation parameters like the leaf area index (LAI) or the fraction of absorbed photosynthetically active radiation (FAPAR) from satellite-based sensors (Gobron *et al.*, 1999; Huete *et al.*, 2002; Dash & Curran, 2004; Delbart *et al.*, 2005; Boyd *et al.*, 2011; Bobée *et al.*, 2012; Guan *et al.*, 2014a; Meroni *et al.*, 2014b).

Based on the above two different approaches to estimating vegetation phenological parameters, a conceptual framework was developed as a systematic basis for reviewing the scientific literature on vegetation phenological studies in Africa (Figure 3.2). Selected scientific literature was then classified based on geographical area and method of phenological assessment (Figure 3.2).

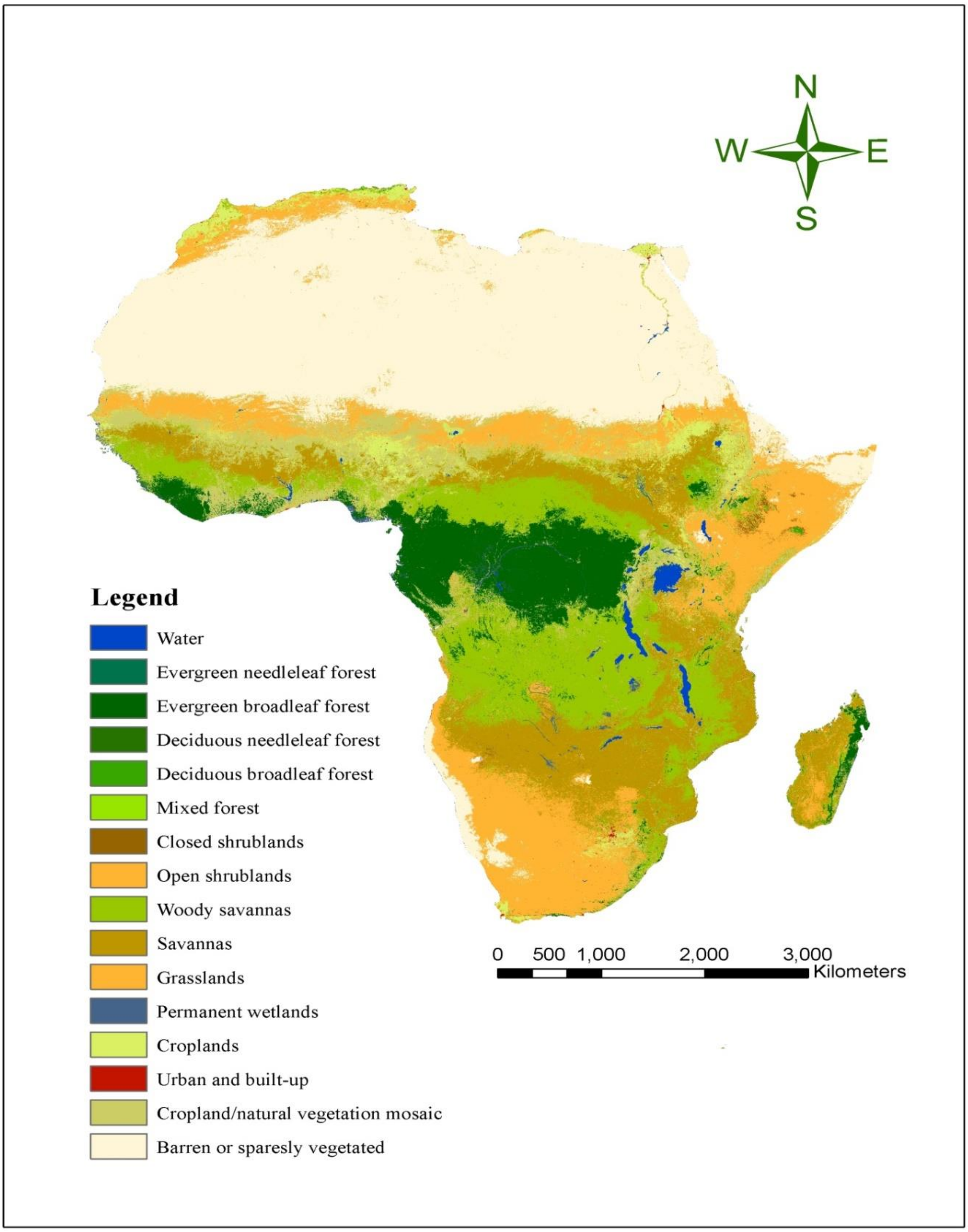

Figure 3.1 Land cover map of Africa derived from the MODIS land cover type product (MCD12Q1) data for 2012, downloaded from NASA's LP DAAC (https://lpdaac.usgs.gov/).

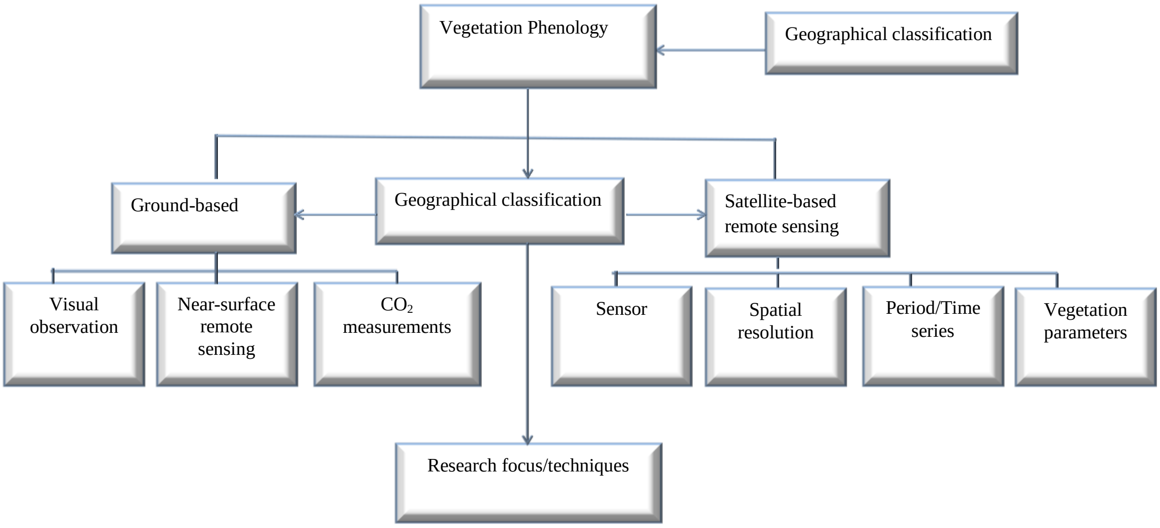

Figure 3.2 Conceptual frameworks for this systematic review showing the stepwise approach to classifying the selected literature based on geographical area and methodology, including the specific methods undertaken and the research focus.

3.4 Literature search and study selection

A search was conducted within the peer-reviewed literature on the Web of Knowledge (http://www.webofknowledge.com) and Scopus (http://www.scopus.com) databases spanning the years 1960 to 2015. A combination of the search terms and keywords *"Phenology",* and *"Vegetation phenology"* were used, with the results further refined with keywords such as *"Africa"*, *"Asia"*, *"Australia"*, *"North America", "South America",* and *"Europe"*, and also keywords representing the major countries in the world such as *"USA", "UK", "China"*, to provide a set of studies undertaken across several continents and, thus, provide a comparison with the set of studies in Africa.

The following criteria were used to select the articles for this review:

- **i.** English-language publications
- **ii.** Published in peer-reviewed scientific journals
- **iii.** A major or secondary assessment of vegetation phenology should have been conducted in the article

Based on the conceptual framework, all peer-reviewed literature on Africa's vegetation phenology was examined to determine the following: the year of publication, the study area, the methods of phenological assessment, the spatial and temporal scale of the study, the sensor types and vegetation indices and parameters used (if derived from satellite sensor data), the techniques employed, and the research focus. Further studies were added to the total set of studies by reviewing the literature found in the reference lists of already included papers which evaluated Africa's vegetation phenology and which also conformed to the criteria above. Figure 3.3 is a schematic representation of the methodology used in this systematic review and the final number of articles selected.

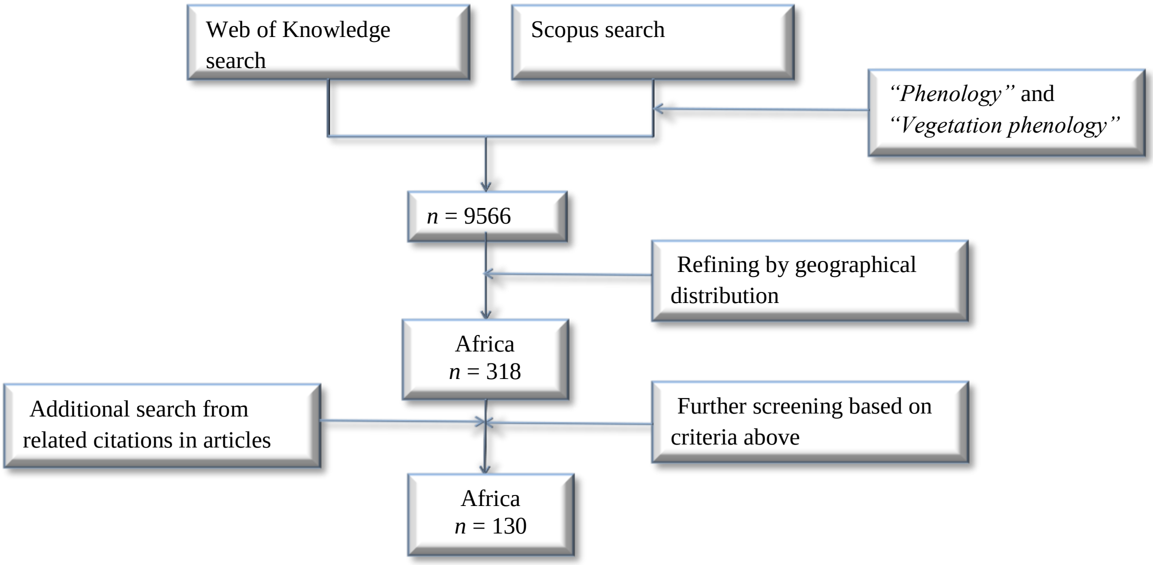

Figure 3.3 Schematic diagram of literature search and article selection process.

3.5 Results

Approximately 9,566 articles were found based on the first search terms and keywords; "*Phenology*", and *"Vegetation phenology"*. Refining by geographical distribution based on further keywords, which included the names of continents and major countries in the world, Europe produced the maximum number of articles at 823, while North America and Asia produced 783 and 714 articles, respectively. South America and Africa had 394 and 318 articles, respectively, while for Africa only 130 articles were selected for this review having satisfied the necessary criteria described in section 3.4 (Figure 3.3).

3.5.1 Publication year and geographical distribution of studies

The results appear to support the claim that there has been a surge in phenological studies over the past decade, as over 75% of the articles were published between 2000 and 2015 (Figure 3.4). This surge can be attributed to an increased focus on climate change issues globally, with vegetation phenology having been shown to have a significant relationship with changes in climate (Chmielewski *et al.*, 2004).

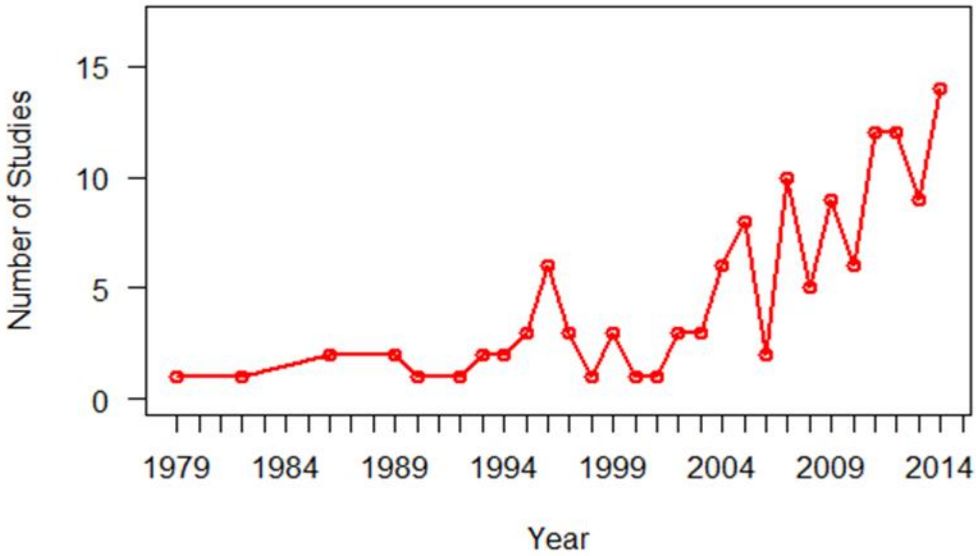

Figure 3.4 Number of publications on Africa's vegetation phenology plotted against time in years. This figure shows the increase in vegetation phenology studies since 1979.

Further regional analysis within Africa revealed that more phenological studies have been carried out in Western and Southern Africa (Figure 3.5 and Figure 3.6). Western Africa also recorded the most satellite-based remote sensing phenological studies, while Northern Africa had the least satellite-based remote sensing phenological studies and the least studies in general.

It is important to note that, while some countries recorded no phenological studies, at a regional scale, some studies may have covered part of their vegetation within a continental (semi-continental) study. Examples are in studies which covered parts of all countries in Western Africa (e.g. Philippon *et al.*, 2007; Vrieling *et al.*, 2011).

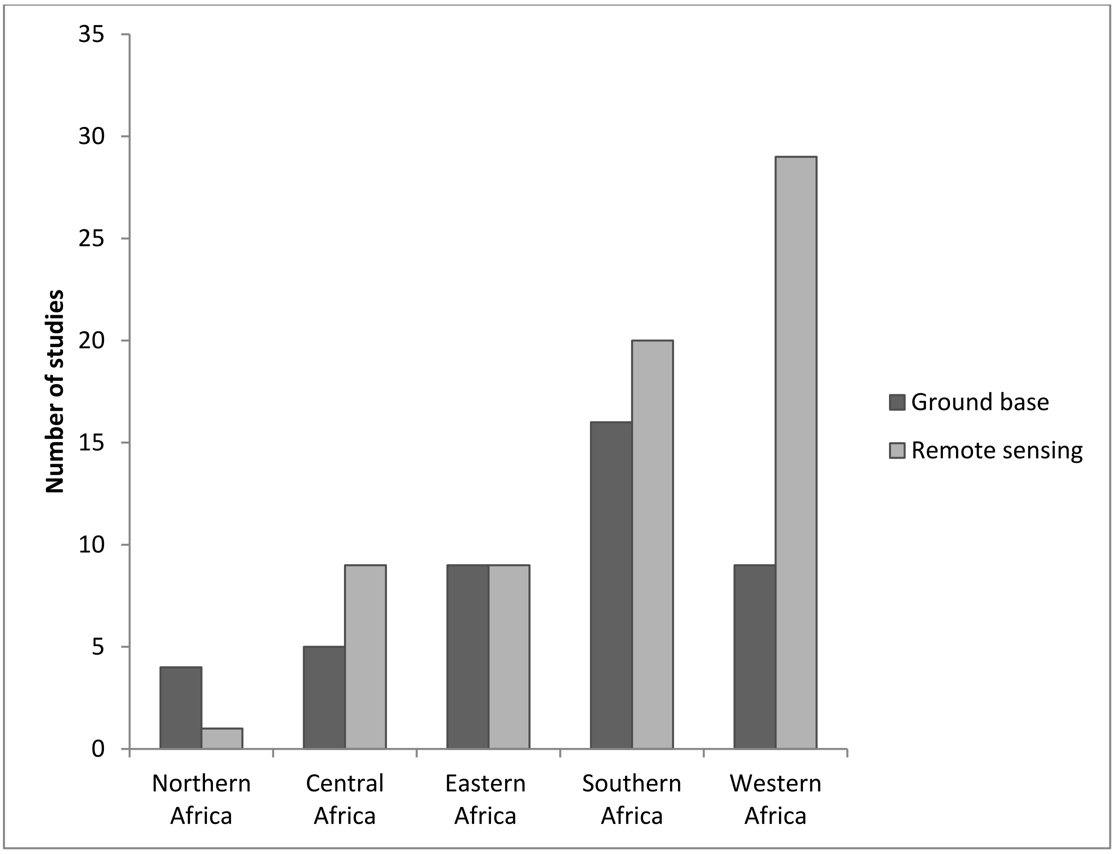

Figure 3.5 Regional distribution of studies based on method of measurement showing the larger number of remote sensing studies compared to ground studies in most regions except Northern and Eastern Africa.

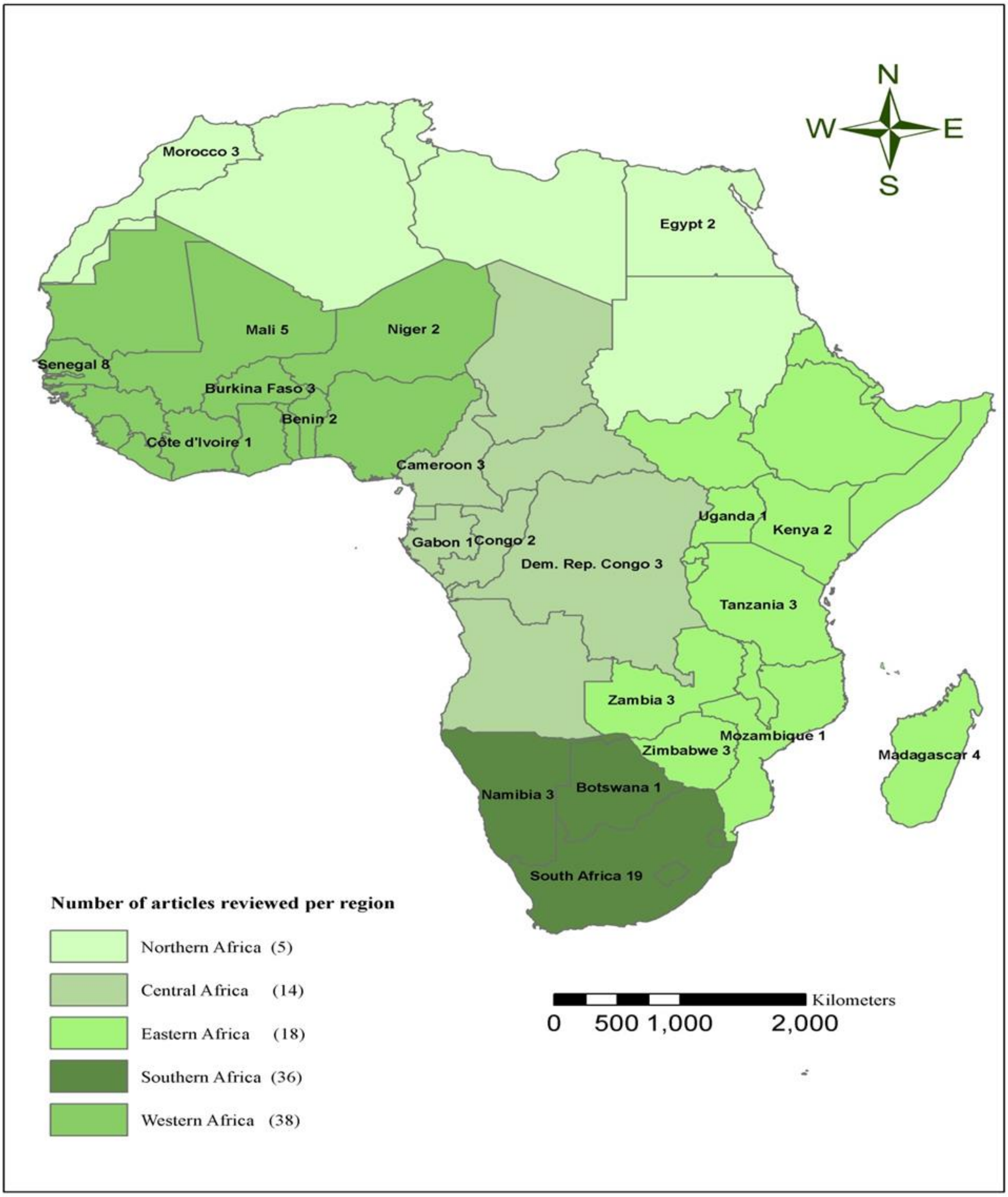

Figure 3.6 Geographical distribution of studies showing the number of studies per country (numbers) and per region (coloured shading). The number of studies in a region includes studies carried out at the regional level and at the country level.

3.5.2 Measuring phenology in Africa

Estimation of vegetation phenology, either by ground-based methods or satellite-based remote sensing techniques, commonly involves characterising the timing of a plant's life cycle by estimating the major phenological parameters: Start of Season (SOS), End of Season (EOS), Length of Growing Season (LGS) and time of maximum growth (Jönsson & Eklundh, 2004; de Beurs & Henebry, 2010). Other parameters like the date of maturity onset and dormancy onset (Boyd *et al.*, 2011), rate of green-up, rate of senescence and modality (Reed *et al.*, 1994), plant phenophases (leaf growth, shoot growth, flowering, fruiting and leaf abscission) (Childes, 1989; Chidumayo, 1994; Seghieri *et al.*, 1995; Chapman *et al.*, 2005; O'Farrell *et al.*, 2007) are also used in some phenological assessments.

3.5.2.1 Ground-based approaches

Using *in situ* field techniques, ground-based measurements can provide detailed and fine temporal resolution data on plant phenology, although these data may suffer from very limited spatial coverage (Studer *et al.*, 2007). From the literature search, 33% of the phenological studies carried out in Africa were ground-based, and the absolute number of ground studies has increased in recent years (Figure 3.7). However, over 37% of these studies were done in Southern Africa, mostly in South Africa (Figure 3.5, Figure 3.7). The spatial coverage of ground-based studies in Africa is limited, ranging from study areas of 4.35 km^2 (Janecke & Smit, 2011) to 7500 km^2 (O'Farrell *et al.*, 2007), and these were carried out at specific sites only. Also, the temporal duration of these studies is limited and most measure the phenology of individual plant species only. The longest recorded phenological record for a ground-based study was 37 years and this was carried out for three apple species and one pear species in the south-western Cape of South Africa (Grab & Craparo, 2011). Only about seven studies (De Bie *et al.*, 1998; Esler & Rundel, 1999; Chapman *et al.*, 2005; Do *et al.*, 2005; Pons & Wendenburg, 2005; O'Farrell *et al.*, 2007; Yamagiwa *et al.*, 2008) measured phenology at the community level.

A general concern for all ground-based measurements globally, is the evident lack of a standard approach to measuring vegetation phenological stages in Africa. While some studies measured the emergence of reproductive structures (Sekhwela & Yates, 2007; Wang'ondu *et al.*, 2010; Seghieri *et al.*, 2012; Polansky & Boesch, 2013) in determining SOS, others measured leaf opening (Do *et al.*, 2005) and above ground biomass (Wakeling *et al.*, 2012).

The types of technique applied in ground-based measurements of vegetation phenology in Africa are still, in some ways, limited. Over 80% of ground-based studies estimated phenology by visual observation of the timing of the developmental cycles or different stages of a plant's life cycle, from germination/flowering to litter-fall. Only one study (Jin *et al.*, 2013), as part of its assessment used CO_2 fluxes observed with the eddy covariance technique to estimate Gross Primary

Production (GPP), from which phenological parameters were estimated. Similarly, near-surface remote sensing involving the use of hand-held or aircraft carrying sensors has been utilized for phenological studies. However, only five of the 43 ground-based phenological studies employed this technique: Duchemin *et al.* (2006), Higgins *et al.* (2011), Soudani *et al.* (2012) and Mbow *et al.* (2013) employed the use of laboratory made sensors (e.g., the cosine corrected SKYE Instruments sensors, CMOS sensor, hand-held MSR87 multispectral radiometer) while Fuller (1999) used a light aircraft to capture aerial photography at a scale of 1:30,000 for measuring canopy phenology. The reflectance values in the red and near-infrared spectra of the images acquired in these studies were used to determine the normalized difference vegetation index (NDVI). Unlike the traditional visual observation technique used in most ground-based studies, mathematical methods were used to estimate phenological parameters from NDVI, just like satellite-based remote sensing studies (see section 3.5.2.3). Examples used for estimating phenological stages are the Bayesian model fitting method used in Higgins *et al.* (2011), and a histogram thresholding algorithm in Fuller (1999).

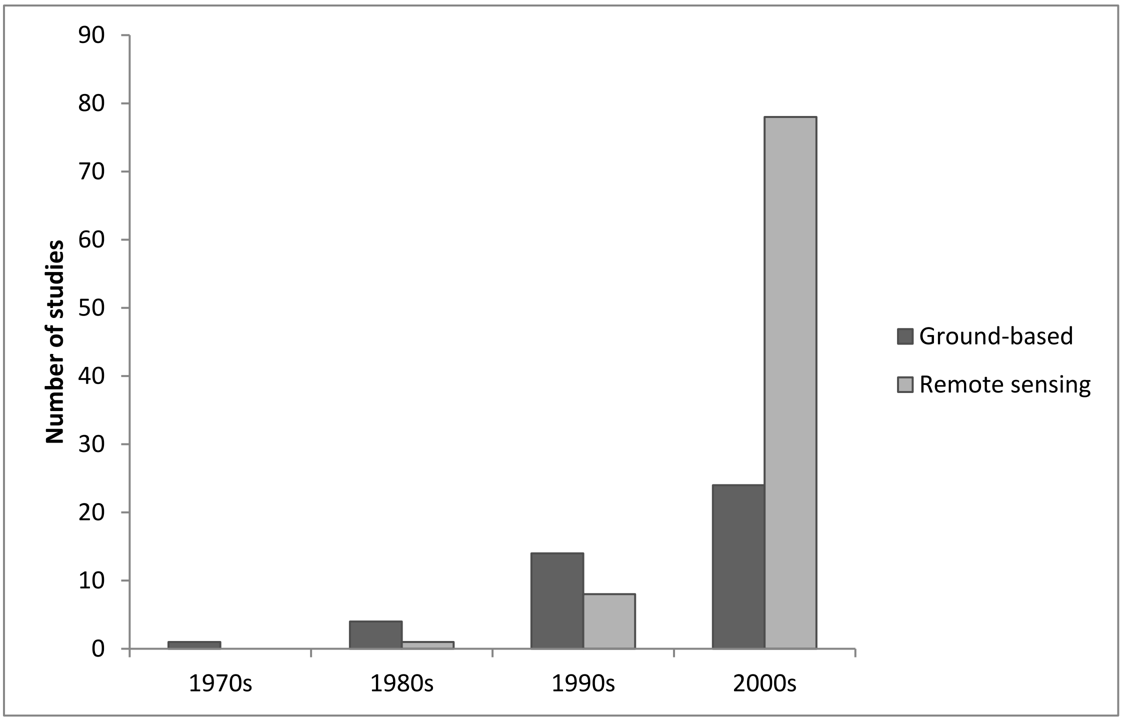

Figure 3.7 Number of studies by decade by method of measurement showing the dramatic increase in remote sensing studies in the 2000s.

3.5.2.2 Remote sensing

As observed with ground-based studies, the number of satellite-based remote sensing phenological studies in Africa has increased with a surge in the 2000s (Figure 3.7). They account for over 70%

of all phenological studies in Africa (Figure 3.7). However, unlike ground-based studies, many of the satellite-based remote sensing phenological assessments in Africa have been able to provide full spatial coverage of the entire continent.

3.5.2.2.1 Sensor types, spatial resolution and geographical coverage

The merit and strength of satellite-based remote sensing phenological assessments are highly dependent on the temporal and spatial resolution of the sensor type used for analysis, and the length of the temporal record (Boyd *et al.*, 2011). Table 3.1 shows the characteristics of the different types of sensors used for phenological studies in Africa.

As shown in Figure 3.8 and Table 3.1, six different satellite sensors were identified as having been used for phenological studies in Africa. With a daily orbiting frequency and spatial resolutions of 1 km and 8 km, the Advanced Very High Resolution Radiometer (AVHRR) on-board the National Oceanic and Atmospheric Administration (NOAA) satellites were the most widely used sensor (Figure 3.8). Additionally, because of its available data records from 1981-to-date, the AVHRR sensor is well suited for long-term studies and was used for all studies in this review that had time-series of data longer than 20 years, with the longest time-series of 30 years in Vrieling *et al.* (2013). Moreover, over 65% of studies covering the entire continent employed the 8 km spatial resolution NDVI datasets, while the 1 km datasets were used mainly for regional and individual country assessments (see Figure 3.9).

Table 3.1 Characteristics of sensor types used in satellite-based remote sensing phenological studies in Africa.

Sensor	Satellite	Orbiting frequency	Spatial resolution in studies	Temporal resolution in studies	Time-series range in studies	Vegetation indices and parameters in phenological studies
AVHRR	NOAA	Daily	1 km 7 km and 8 km	15-day, 10-day	1981 - 2011	NDVI
MODIS	Terra and Aqua	1-2 days	250 m, 500 m, 1 km and 5 km	8-day, 16-day	2000 - 2013	NDVI, EVI, LAI and LSWI
SPOT-Vegetation	SPOT	1-2 days	1 km	10-day	1998 - 2013	NDVI, EVI and FAPAR
SEVIRI	Meteosat Second Generation (MSG) geostationary satellite series (EUMET-SAT)	Daily	3 km	15 mins	2007 - 2011	LAI
METEOSAT B2	Meteosat	Daily	5 km	30 mins	1983 – 1984	NDVI
Sea Winds Scatterometer	QuikSCAT	Daily	25 km	4-day	2000 - 2003	Backscatter

The second most used sensor compared to the AVHRR is the Moderate-resolution Imaging Spectroradiometer (MODIS) sensor with a total number of 37 studies (Figure 3.8). This sensor is on-board the Terra Earth Observing System (EOS) AM and the Aqua EOS PM satellites with spatial resolutions of 250 m, 500 m, and 1 km (Barnes *et al.*, 1998; Justice *et al.*, 1998) (Table 3.1). Apart from the finer spatial resolution of the MODIS data products, they also provide data with lower noise from clouds or atmospheric haze, aerosols and negligible water vapour impacts (Huete *et al.*, 2002). Only four studies (Linderman *et al.*, 2005; Zhang *et al.*, 2005; Guan *et al.*, 2013, 2014b) assessed the LSP of the entire African continent using MODIS data at spatial resolutions of 1 km (Linderman *et al.*, 2005; Zhang *et al.*, 2005) and 5 km (Guan *et al.*, 2013, 2014b), with time-series of 3 years and 12 years, respectively (Figure 3.9). Other MODIS-based phenological studies with finer spatial resolution were carried out either regionally or in individual countries (Figure 3.9).

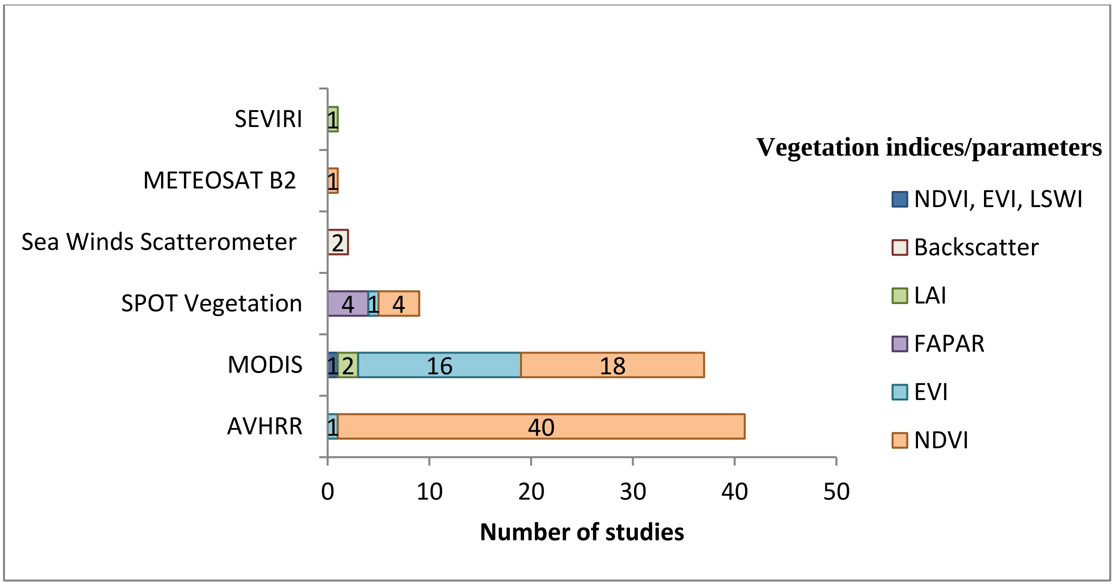

Figure 3.8 The sensor types used for phenological studies in Africa plotted against the number of studies using them, and showing the VIs and/or vegetation parameters estimated from them.

Another fairly well used sensor is the Satellite Pour l'Observation de la Terre (SPOT) Vegetation with a total of nine studies. These sensors (VEGETATION 1 and VEGETATION 2) were launched on-board the SPOT satellites in 1998 and 2002, respectively (Aitkenhead, 2014). The main advantage of the SPOT-Vegetation sensor is its consistent temporal reconstructed reflectance time-series data of three times per month (Guyon *et al.*, 2011) (a rationale for selection by some of the studies in this review, e.g., Verhegghen *et al.*, 2012). Another reason for its use, is the improved radiometric calibration and geometric distortion corrections of the SPOT-Vegetation sensor, especially when compared to the AVHRR (Boschetti *et al.*, 2013).

Other sensors used for LSP estimation in Africa include, Meteosat Second Generation (MSG), Spinning Enhanced Visible and Infrared Imager (SEVIRI) (Guan *et al.*, 2014a), METEOSAT B2 (Amram *et al.*, 1994) and the Sea Winds Scatterometer (Ringelmann *et al.*, 2004; Ryan *et al.*, 2014) (Table 3.1).

From Figure 3.9 it can be observed that most studies that utilized sensors with fine spatial resolution data were carried out either within individual countries or at the regional scale and none were yet undertaken for the entire continent. The most applicable spatial resolution with the longest time series for applications at the continent scale is the 8 km resolution.

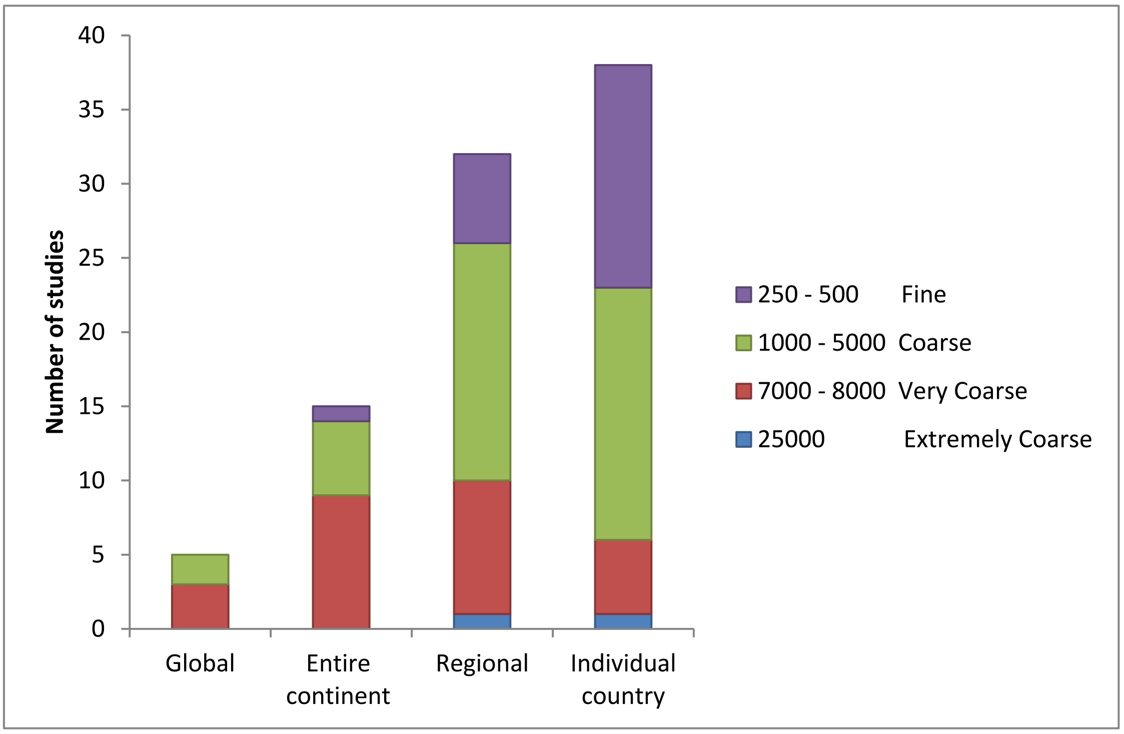

Figure 3.9 The range of spatial resolutions and the geographical extent employed by the reviewed studies. This shows that a coarse spatial resolution was used generally at the regional scale (extent) and a very coarse spatial resolution at the continental scale (extent).

3.5.2.2.2 Vegetation indices, biophysical variables and phenological parameters

Phenological parameters in remote sensing are usually estimated from Vegetation Indices (VIs). They are usually estimated from an arithmetic combination of different spectral reflectance values mainly in the red (R) and near infrared (NIR) region of the electromagnetic spectrum. Figure 3.8 shows the VIs and vegetation parameters in each study and the sensor type that these parameters were estimated from. The NDVI was the most commonly estimated VI (see Figure 3.8) which, as mentioned above, is the most widely used for vegetation studies globally (Reed *et al.*, 2009a).

The NDVI was used in over 90% of the longer-term studies of 20 to 30 years (Heumann *et al.*, 2007; Philippon *et al.*, 2007; Vrieling *et al.*, 2008, 2011, 2013; Torbick *et al.*, 2009; Brown *et al.*, 2010, 2012) and was commonly derived from spectral data of the AVHRR sensor (see Figure 3.8). An exception to this is the 30 years global inter-annual LSP study of Zhang *et al.* (2014) using the Enhanced Vegetation Index (EVI) specifically the EVI2 (Jiang *et al.*, 2008) derived from AVHRR data. Despite the advantages of the EVI over the NDVI, only 21% of studies (see Figure 3.8) used the EVI, mostly derived from MODIS data.

Other variables that can be used to estimate vegetation phenology include the fraction of absorbed photosynthetically active radiation (FAPAR) and the Leaf Area Index (LAI), which are both closely related to vegetation canopy structure (Gobron & Verstraete, 2009; Huete *et al.*, 2011), and these have been used sparsely over Africa (see Figure 3.8). The FAPAR of the incoming solar radiation in the photosynthetically active radiation (PAR) spectral region that is absorbed by leaves (Gobron & Verstraete, 2009), was used by four studies only (Meroni *et al.*, 2013, 2014c, b,a), and was derived from 1 km SPOT-Vegetation data. Likewise, the LAI was used in only 3% of studies, and was derived from MODIS data in Huemmrich *et al.* (2005) and Bobée *et al.* (2012) and SEVIRI data in Guan *et al.* (2014a) (Figure 3.8).

The backscatter derived from the Sea Winds Scatterometer in Ringelmann *et al.* (2004) and Ryan *et al.* (2014) and the Land Surface Water Index (LSWI) (Xiao *et al.*, 2005) derived from MODIS data in Jin *et al.* (2013) were other vegetation parameters also used in phenology studies in Africa.

3.5.2.3 Phenology estimation

Estimation of phenological parameters from satellite sensor data commonly requires a stepwise methodology, which involves the initial calculation of VIs from satellite sensor data, removal of “bad” pixels in the time-series, interpolation of the missing values, smoothing of the complete time-series, and estimation of phenological parameters from the smoothed data. There are several smoothing techniques used for smoothing VI data and for estimating phenological parameters from the smoothed data. The smoothing techniques can be classified into three broad categories: statistical, curve fitting and data transformation (Atkinson *et al.*, 2012). Likewise, phenological parameter estimation techniques can also be classified into three broad categories: threshold, curve-derived and function model fitting methods (Reed *et al.*, 2009b; de Beurs & Henebry, 2010; Zhu *et al.*, 2012a).

Table 3.2 gives an overview of the different types of techniques and the number of studies that employed the use of these techniques in Africa. Although, threshold methods have been identified as the most commonly used technique globally (de Beurs & Henebry, 2010), only 40 studies estimated phenological parameters using this technique, while 37 studies used the model fitting method, of which one was a ground-based study (section 3.5.2.1 and Table 3.2).

Visual observation, the traditional approach of estimating phenological parameters, was employed in 39 studies in this review. However, one of these studies (Tappan *et al.*, 1992), a satellite-based remote sensing study, used this technique in estimating phenological parameters from already smooth VI images with the help of soil polygon maps and by visual interpretation of the plots.

Other non-conventional approaches have been used in phenological assessment in Africa. Viennois *et al.* (2013) characterised canopy phenology in central African tropical forests by averaging MODIS EVI data over the wet and dry seasons. Cook & Vizy (2012) and Roehrig & Laudien (2009) without the use of VIs, were able to estimate the length of growing seasons from climatic data, using approaches previously undertaken by other researchers (White *et al.*, 1997; Linderholm, 2006). Only Jin *et al.* (2013), as a part of their assessment, defined phenology from GPP estimated from eddy covariance CO_2 fluxes.

Table 3.2 Summary of studies, their research areas, methods and techniques

Technique / Research aim	Visual observation	Threshold	Curve-derived	Model fitting	Other	Grand Total
Ground-based	**38**	**4**		**1**		**43**
Characterisation	3	1				4
Explanation	31	3		1		35
Ecosystem management	4					4
Remote sensing	**1**	**36**	**11**	**36**	**3**	**87**
Characterisation	1	12	1	15	1	30
Explanation		23	10	19	2	54
Ecosystem management		1		2		3
Grand Total	**39**	**40**	**11**	**37**	**3**	**130**

3.5.2.4 Ground validation of LSP

The validation of remotely sensed phenological parameters is important to establish the reliability of estimates of vegetation growth stages from satellite sensor data, and yet this is rarely undertaken due to a lack of sufficient coverage of ground data (Reed, 2007; Walker *et al.*, 2012; Zhang *et al.*, 2014b). One of the major challenges with LSP estimation in Africa is ground validation. Validating satellite-derived phenology estimates in Africa is currently near-impossible, especially on a large scale, either due to the complete absence of, or very few, available ground-based phenological studies. Only 15 studies carried out some form of validation and these were done over very small study areas, and with a temporal scale range of one to three years (Bachoo & Archibald, 2007; Brown & de Beurs, 2008; Jin *et al.*, 2013). Some of these studies adopted non-conventional approaches in validating phenological data. Examples are Vintrou *et al.*, (2014) who in the absence of ground-based phenology, used a crop model SARRA-H (System for Regional Analysis of Agro-Climatic Risks) to validate phenological variables from MODIS EVI data, and Ringelmann *et al.* (2004) who used *in situ* soil moisture time-series, weather station data, satellite-derived rainfall estimates (RFE) and NDVI to validate planting dates estimated from Backscatter Sea Winds Scatterometer data. These studies also presented results which demonstrated a significant correlation between satellite-based phenological data and field observations (Jin *et al.*, 2013; Marinho *et al.*, 2014; Meroni *et al.*, 2014b,c).

3.5.3 Focus of vegetation phenological research

The focus or aim of all 130 studies in this review was categorised into three major groups: characterisation, explanation and ecosystem management. The characterisation group comprises studies that focus on: methodological approaches in estimating and mapping vegetation phenology, variation in vegetation phenology overtime, and the use of vegetation phenology in land cover classification/mapping and characterisation of land cover changes. Explanation on the other hand includes studies involved in determining the drivers of phenology or the relationship between vegetation phenology and other parameters, including phenological responses to climate change. Lastly, ecosystem management comprises studies that evaluated vegetation phenological dynamics to understand and make decisions on the environment. It is important to note that these groups potentially are non-exclusive, that is, some studies may overlap between categories and so a judgement was made in each case to determine the main focus.

From Table 3.2 it can be observed that approximately 26% of studies were categorised under characterisation, with most focusing on mapping vegetation phenology and temporal trend analysis (Jönsson & Eklundh, 2002, 2004; Heumann *et al.*, 2007; Steenkamp *et al.*, 2008; Vrieling *et al.*, 2008, 2011, 2013, Wessels *et al.*, 2009, 2011; Verhegghen & Defourny, 2011; Zurita-Milla *et al.*, 2013). For the Sahel, Soudan, and Guinean regions in Africa, Heumann *et al.* (2007) investigated phenological trends and reported significant changes in the Length of Growing Season (LGS) mostly in the Soudan and Guinean regions. On a continental scale, phenological trend analysis was undertaken by Vrieling *et al.* (2013), and observed that inter-annual variability in LGS was high in arid and semi-arid regions.

For land cover classification and mapping, variation in phenological parameters was used to classify and map different vegetation types especially in cases where there was insufficient ground data (Höpfner & Scherer, 2011; Betbeder *et al.*, 2014). An example is given by Betbeder *et al.*

(2014) who mapped the *Cuvette Centrale* of the Congo River Basin using phenological differences of EVI from MODIS time-series to characterise different forested wetlands.

The group explanation included over 68% of studies of which the majority focused on phenological patterns and their relationship with climatic variability (Malo & Nicholson, 1990; Fuller & Prince, 1996; Esler & Rundel, 1999; Eklundh, 2003; Zhang *et al.*, 2005; Fox *et al.*, 2005; Colditz *et al.*, 2007; Philippon *et al.*, 2007; Brown *et al.*, 2010; Wang'ondu *et al.*, 2013; Guan *et al.*, 2013, 2014b; Dubovyk *et al.*, 2015). Across the entire African continent, studies like Zhang *et al.* (2005) and Guan *et al.* (2013, 2014b) identified precipitation as the major environmental factor controlling variability in the seasonality of vegetation growth, canopy structure and function. In contrast, variability in temperature was attributed to be the major determinant of phenological patterns in South Africa's savanna vegetation (Chidumayo, 2001) and some apple varieties in South Africa (Grab & Craparo, 2011). Also, the inter-annual growth trends of some tropical rainforest trees in West Africa were not related with rainfall patterns; rather solar radiation was suggested to be responsible for growth trends (Polansky & Boesch, 2013).

Notwithstanding the growing interest in climate change studies, only four studies (Chapman *et al.*, 2005; Grab & Craparo, 2011; Brown *et al.*, 2012; Cook & Vizy, 2012) focused on climate change, specifically how a changing climate is impacting on the growing seasons of plants in Africa. These studies demonstrated significant correlations between climatic variables and the phenophases of plants, like the associated temperature increases and advance in flowering dates of apple and pear trees in South Africa (Grab & Craparo, 2011), and the global shift in SOS and LGS of crops in response to increases in temperature and moisture availability (Brown *et al.*, 2012).

The ecosystem management group constituted less than 10% of the 130 studies. These studies used vegetation phenology to understand animal behavioural pattern, livestock production practices, and ecosystem diversity (Pons & Wendenburg, 2005; O'Farrell *et al.*, 2007; Yamagiwa *et al.*, 2008; Barrett *et al.*, 2010; Butt *et al.*, 2011; Brottem *et al.*, 2014; Maeda *et al.*, 2014). They showed that vegetation phenological parameters, and their variability across time and latitudinal gradients, influence the timing and direction of transhumance movements and livestock management practices. This is because foliage (and, thus, forage) quality largely depends on the phenophases of vegetation (O'Farrell *et al.*, 2007; Butt *et al.*, 2011; Brottem *et al.*, 2014). Additionally, the relationship between the timings of the abundance of vegetation resources, derived from vegetation phenophases and animal behavioural pattern was established in these studies (Pons & Wendenburg, 2005; Yamagiwa *et al.*, 2008; Barrett *et al.*, 2010).

3.6 Discussion: Challenges and opportunities for research and development

Vegetation phenological assessments in Africa, in terms of the numbers of studies, their spatial and temporal coverage and their research focus, are still very limited especially when compared to other continents. This review has identified several gaps in vegetation phenological assessments and some challenges specific to the African continent.

3.6.1 Number and spatial coverage/resolution of studies

Ground-based phenological observations are seriously lacking in Africa both in terms of the spatial coverage and in terms of temporal records. While most regions in the temperate latitudes have observation networks with long time-series of data acquired through extensive ground-based measurement of vegetation phenology (e.g., the US National Phenology Network and the Woodland Trust, UK) (Graham *et al.*, 2010; Boyd *et al.*, 2011; Zhang *et al.*, 2012; Wolkovich *et al.*, 2014) there are no known phenological observation networks in the African continent. Also absent are any digital camera networks for phenological observation in Africa, networks which have already been established in other continents (Richardson *et al.*, 2009; Nasahara & Nagai, 2015). Only one study (Higgins *et al.*, 2011) used digital cameras for phenological observation. However, this was achieved by capturing images in scheduled flights by a helicopter on which the camera was mounted rather than fixed cameras taking continuous photograph of the landscape. Additionally, the use of different measurement protocols in ground-based studies makes it challenging to compare between the few existing measurements. Hence, there is an urgent need for a systematically organized long-term monitoring network for ground-based phenological assessment for the entire African continent. This is required to support systematic and well-documented ground-based observations with unifying standards of measurements to provide detailed characterisation of species and community level responses to climatic changes. This is more important considering that most satellite-based remote sensing phenological assessments lack ground validation due to the complete absence or very limited records of ground observed phenology (Reed, 2007; Walker *et al.*, 2012; Zhang *et al.*, 2014b).

Although, phenological studies have been increasing in number over recent years, the spatial coverage of studies has been limited to regions and individual countries, with some regions having a relatively higher proportion of studies than others, and with very few covering the entire continent. For example, Southern Africa had 47 studies while Central Africa had 17, and only 10% of the total number of studies reviewed covered the entire continent. These studies were mostly satellite-based phenological studies. Furthermore, those studies which covered the entire continent, were at relatively coarse spatial scale (i.e. 8 km), thus, masking out the complexity and the inter-annual variability of the vegetation phenology of Africa's forest types. Hence, a relatively fine spatial resolution LSP mapping is essential for Africa to ensure: (1) a more accurate characterisation of the phenology of the African vegetation, (2) a detailed description of the phenological trends especially at local scales which may have been previously undetected when using coarse spatial resolutions, and (3) an increased knowledge of the inter-annual variability of the LSP and other environmental factors.

Before improved measurement protocols can be implemented it is important to note some of the major challenges responsible for the concerns raised above. These are the inadequate research capacity of institutions, financial constraints and lack of funding for physical science based research across the continent (Irikefe *et al.*, 2011; Njuguna & Itegi, 2013; World Bank, 2014). The financial constraint is a major concern that has prohibited ground-based survey or observations in Africa (Wagenseil & Samimi, 2006) as field studies would require intensive resource from the already financially constrained national governments of African countries. Furthermore, physical accessibility issues and political instability in some regions of Africa (Laurance *et al.*, 2006) are other challenges that have been associated with deterring field acquisition of both scientific and social data.

3.6.2 LSP estimation method

The type of sensor and spatial resolution used for remote sensing studies are very important and can greatly influence assessment results (Pelkey *et al.*, 2003). The MODIS sensor has several advantages over the AVHRR sensor (Barnes *et al.*, 1998; Justice *et al.*, 1998; Huete *et al.*, 2002). One major advantage is reduced cloud and atmospheric contamination, noting that cloud is prevalent in tropical regions of the world (Justice *et al.*, 1985; Moulin *et al.*, 1997). Several studies have highlighted the significant influence that cloud contamination has on VI values (especially NDVI values from AVHRR data) and the uncertainty that this brings in estimating phenological parameters (Moulin *et al.*, 1997; Anyamba & Tucker, 2005; de Beurs & Henebry, 2010; Vrieling *et al.*, 2013). Despite these advantages, at the African continent scale the advantages of this sensor have not been fully utilized as only three studies measured the LSP of the entire African continent using the MODIS sensor. In addition, the potential of the next generation of satellite instruments, such as the Sentinel series from the European Space Agency, for addressing some of these constraints in vegetation monitoring needs to be explored. This sensor series, especially the recently launched Sentinel-2 which is designed for terrestrial observation with a possible resolution of 10 m and potential temporal coverage of 5 days, is likely to provide unparalleled opportunities for local scale monitoring (Laurent *et al.*, 2014; Zhu *et al.*, 2015).

Notwithstanding the reduction of cloud and atmospheric contamination in the MODIS data, these phenomena still have significant effects on MODIS VI values (Höpfner & Scherer, 2011; Hmimina *et al.*, 2013), hence the use of smoothing techniques or time-series filters like Fourier analysis (Wagenseil & Samimi, 2006), the double logistic model (Zhang *et al.*, 2004; Beck *et al.*, 2006), asymmetric Gaussian model (Jönsson & Eklundh, 2002, 2004; Hird & McDermid, 2009), Savitzky-Golay filter (Chen *et al.*, 2004; Hird & McDermid, 2009) and the Whittaker filter (Atkinson *et al.*, 2012; Verhegghen *et al.*, 2014) in smoothing out noise from VI time-series data. These techniques all have their advantages and disadvantages which are also dependent on the frequency of cloud contamination and the seasonality strength of VIs in the time-series (Atkinson *et al.*, 2012). However, these techniques can result in variation in estimated phenological parameters. Therefore, it is important to consider the purpose of each study and the specific study area when selecting smoothing and estimation techniques (de Beurs & Henebry, 2010; Atkinson *et al.*, 2012). The results, shown clearly in Table 3.2, revealed that reviewed studies employed a wide range of techniques in estimating phenological parameters, from visual observations to mathematical and climate models. Knowing that these studies were applied both at regional and individual country levels, a means by which these metrics can be evaluated and combined together to give broader phenological records of the entire continent is an open area for further research. This possibility has also been highlighted by Atkinson *et al.* (2012) who suggested the use of a statistical ensemble-based approach.

3.6.3 Forecasting and climate change

It has been well established that vegetation phenology is an important indicator of climate change (Cleland *et al.*, 2007; Richardson *et al.*, 2013). However, studies focusing on vegetation phenology and its relationship with climate change are lacking in Africa (IPCC, 2007, 2014) despite Africa being identified as potentially especially vulnerable to climate change (Boko *et al.*, 2007; Niang *et al.*, 2014). This position was confirmed from the search results, as only four studies (see section 3.5.3) evaluated the relationship between vegetation phenology and climate change. Amongst these studies, only one (Cook & Vizy, 2012) assessed climate change impacts on the growing season at the continental scale, but based on a different approach of determining LGS by using climate models rather than the conventional satellite-derived VIs. However, it is also important to acknowledge that the coverage of fine spatial resolution climate data records over Africa is sparse.

Another aspect is to understand the influence of natural climatic drivers on vegetation phenology. Although, several studies have shown the relationship between the phenological patterns of the African vegetation and climatic drivers, precipitation-driven studies are more numerous than temperature and solar radiation studies (see section 3.5.3),. Furthermore, owing to the complexity and the highly irregular phenological patterns of Africa's vegetation, which has multi-annual life cycles and is driven by a combination of three climatic drivers (i.e. Precipitation, temperature and solar radiation), an enhanced understanding of the interplay of all these factors is needed. Consequently, there exist opportunities to investigate and forecast the possible responses of vegetation phenology to changes in climatic conditions. While it is imperative that this opportunity is realized, it is also important that the associated challenges are considered when carrying out such research. Some of these challenges are, the numerous uncertainties with regards to the regulatory mechanisms of vegetation phenology, model parameterization and forecasting future climate systems (Zhao *et al.*, 2013), the evolutionary trends of individual plants (Visser *et al.*, 2010), and integrating individual plants to ecosystem level phenology (Cleland *et al.*, 2007).

3.7 Conclusion

The phenology of vegetation is an important measure of terrestrial ecosystem processes. In addition to being an indicator of climate change, it is also useful in studying ecological processes like energy exchanges (e.g., water and carbon exchange), habitat provision, food insecurity and other ecosystem services. Given the increasing occurrences of climate change impacts in the 21st century, it is important to understand vegetation phenological responses to natural climatic variability and to anthropogenic activities, especially its role in local climate feedback mechanisms. Consequently, based on several studies across the globe and as reported by the IPCC, there is high confidence that changes in climatic factors have impacted on vegetation phenology in Europe, Asia, Australasia and North America (IPCC, 2014). However, that same confidence has not been attributed to reported climate change impacts on vegetation phenology in Africa. Rather, research gaps were identified which include assessing the effect of natural climate variability on ecosystems and the development of monitoring networks for long-term change assessment (IPCC, 2013, 2014).

This review corroborates the findings of the IPCC Fifth Assessment Report (AR5) and other peer reviewed literature. It identified several research gaps and opportunities associated with vegetation phenological studies in Africa. Based on this review, the following recommendations are made for future studies and for decision-makers and policy-makers:

- Development of a widespread monitoring network for vegetation phenology across the entire continent with presence in all countries, with a view to facilitating extensive country-based vegetation phenology studies.
- Characterisation of the vegetation phenological parameters at a relatively fine spatial resolution to capture the complexity due to multi-annual seasons and landscape heterogeneity.

- Investigation of vegetation phenological feedbacks (or the role of vegetation phenology in vegetation-climate feedback mechanisms), and the relationship between climate change and vegetation phenological changes.

Addressing these issues will provide greater understanding of the role of the African forest in the global carbon cycle and climate system, ultimately contributing to current climate change adaptation and mitigation strategies.

Chapter 4: Characterisation of the Land Surface Phenology (LSP) of Africa

4.1 Introduction

The study of vegetation phenology, which deals with the timing of plant growth stages and their inter-annual variation, can increase our understanding of global climate-vegetation relationships, and in particular can be used to characterise impact of climate change on terrestrial ecosystem (Chmielewski & Rötzer, 2001; Cleland *et al.*, 2007; Richardson *et al.*, 2013; Broich *et al.*, 2014; Clinton *et al.*, 2014). Consequently, the study of vegetation phenology has received increased attention in recent years, providing detailed characterisation of spatio-temporal changes in terrestrial biogeochemical cycles.

Ground-based observations of vegetation phenology, offer detailed and fine temporal resolution data for different vegetation types (Rodriguez-Galiano *et al.*, 2015b). However, these observations are limited in spatial coverage (Studer *et al.*, 2007). On the other hand, satellite-based remote sensing techniques, which measure *land surface phenology* (LSP), offer wide spatial coverage, and can monitor the inter-annual variability of vegetation dynamics in areas without ground data (Julien & Sobrino, 2009; Guan *et al.*, 2013; Zhang *et al.*, 2014b; Rodriguez-Galiano *et al.*, 2015a). These techniques also offer the capability of quantifying vegetation response to climate variability (Ma *et al.*, 2008; Zhu *et al.*, 2012c; Broich *et al.*, 2014; Guan *et al.*, 2014b). Other advantages can be seen in studies covering ecosystem processes and diversity, for example, in studies of the phenology of bird communities from space (Cole *et al.*, 2015), and understanding transhumance patterns (Butt *et al.*, 2011; Brottem *et al.*, 2014).

In the northern high latitude regions such as Europe and North America, numerous studies have detailed the characteristics of vegetation phenology at both fine and coarse temporal and spatial resolutions, either through ground-based measurements or by remote sensing techniques (Chmielewski & Rötzer, 2001; Zhang *et al.*, 2004; Menzel *et al.*, 2006; Ganguly *et al.*, 2010; Wu *et al.*, 2012; Jeganathan *et al.*, 2014; Walker *et al.*, 2014; Rodriguez-Galiano *et al.*, 2015a). There are also robust ground-based observation networks in these regions. Examples of such networks are: the US National Phenology Network, the Woodland Trust, UK, International Phenological Gardens (IPG) in Europe and the German phenological network (Chmielewski *et al.*, 2004; Graham *et al.*, 2010; Boyd *et al.*, 2011; Zhang *et al.*, 2012; Menzel, 2013; Wolkovich *et al.*, 2014).

In Africa, there have also been several phenological studies, both ground-based and satellite-based (Adole *et al.*, 2016). However, despite being home to 17% of the world's forest cover (Food and Agriculture Organization of the United Nations, 2010), approximately 12% of the world's tropical mangroves (Giri *et al.*, 2010; Donato *et al.*, 2011), and with a diverse range of vegetation types (Figure 4.1), compared to other continents, the number of phenological studies in Africa is very limited (Adole *et al.*, 2016). Similarly, unlike other regions, there are no phenological networks in Africa (Adole *et al.*, 2016).

A recent systematic review by Adole *et al.* (2016) revealed that of 9,566 articles on vegetation phenology globally, only 130 focused on Africa. Moreover, despite the advances in LSP, particularly with the availability of fine spatial resolution data, and knowing that at coarser spatial resolutions phenological information may be misread (Fisher & Mustard, 2007), only 15 studies evaluated LSP at a continental scale using coarse spatial resolution (ranging from 1 to 8 km) data (Adole *et al.*, 2016). Adole *et al.* (2016, Table 4.1) found that studies over longer periods used coarse spatial resolution datasets while those with a shorter duration of five years or less commonly used a spatial resolution of 1 km. Additionally, the temporal resolutions of most of these studies were relatively coarse (10 – 16 day), thereby increasing the potential for errors in vegetation phenology estimation (Zhang *et al.*, 2009). Although the MODIS Land Cover Dynamics product (MCD12Q2) provides global LSP information at a spatial resolution of 500 m there are large uncertainties, and sometimes unrealistic LSP parameter values, associated with this product (Ganguly *et al.*, 2010; Vintrou *et al.*, 2012) and, thus, may not be reliable for detail characterisation of LSP. Also, this product which was last released in 2012 is not as recent as other MODIS data and does not benefit from the recent reprocessing of MODIS data products. Based on these findings, we have summarized the identified research gaps which are relevant to this below:

(1) There has been no study characterising LSP of the major land cover types in the different geographical sub-regions in Africa.
(2) At a continental scale, only coarse spatial resolution datasets ranging from 1 to 8 km have been used for LSP studies in Africa, and
(3) 10 – 16 day temporal resolution datasets were used with the exception of only two studies which used daily datasets, albeit at coarse spatial resolutions of 3 and 5 km (see Table 4.1).

In addition to the above highlighted gaps, Africa is known to have complex vegetation dynamics (Favier *et al.*, 2012) and its vegetation types are very distinct in their responses to climatic factors, resulting in great variability in phenological patterns. Although there are generally two major maximum rainfall seasons in Africa (the June-to-August season in the northern latitudes and the December-to-February season in the southern latitudes) (Griffiths, 1971), the distribution of these seasons varies considerably across the continent. This can be seen in the rainfall seasons in the extreme north falling into the December-to-February season and southwestern Africa falling into the June-to-August season (Griffiths, 1971). Also, the Horn of Africa, which is greatly affected by the Inter-Tropical Convergence Zone (ITCZ) (Thompson, 1965), and the Guinea coast in West Africa exhibit a unique double peak or two seasonal rainfall patterns (Herrmann & Mohr, 2011; Liebmann *et al.*, 2012). This variation in the climate of the different geographical sub-regions in Africa (see Figure 4.1) plays a significant role in the vegetation dynamics in these regions, hence the requirement to characterise LSP regionally.

In view of the above, it is apparent that there is a need to provide more detailed LSP information for the African continent. This detailed LSP information is likely to be very important in climate-vegetation modelling and can potentially help in increasing our understanding of carbon, energy and water cycles, characterisation of soil-vegetation-atmospheric feedbacks, and predictive phenology modelling. This would also aid in-depth monitoring of agricultural production and livestock management practices which would be unique to the different geographical regions in African farmlands and rangelands. Therefore, the aim was to characterise the spatial distribution of LSP in Africa using medium spatial and temporal resolution (500 m, 8-day) MODIS EVI time-series data with a long temporal range of 15 years (2001 – 2015). The specific objectives were to:

(1) establish a baseline of LSP over Africa at a fine spatial resolution of 500 m
(2) determine the latitudinal variation and inter-annual variability of LSP in Africa at a fine spatial resolution of 500 m compared to previous work.

(3) Using these data, characterise the LSP of the major land cover types in different geographical sub-regions in Africa, and

(4) demonstrate the advantages of the medium fine spatial resolution of 500 m.

Comprehensive ground-based validation of the LSP maps from this research is not possible presently due to the absence of a broad-scale ground-based observation network across the African continent. Therefore, comparisons were made between the estimated LSP and previous vegetation phenology studies, and the ground-based vegetation phenology data for the few areas for which data were available.

Table 4.1 Number of LSP studies in Africa undertaken at a continental scale with the Advanced Very High Resolution Radiometer (AVHRR), Moderate-resolution Imaging Spectroradiometer (MODIS), and Spinning Enhanced Visible and Infrared Imager (SEVIRI) sensors.

Authors	**Period**	**Temporal frequency**	**Sensor**	**Spatial Resolution (km)**	**Index**	**Research findings**
Brown *et al.* (2010)	1981 - 2008	15-day	AVHRR	8	NDVI	LSP is significantly affected by climate oscillations
Camberlin *et al.* (2007)	1981 - 2000	15-day	AVHRR	8	NDVI	Significant correlation between annual NDVI values and rainfall variations
Guan *et al.* (2013)	2000 - 2012	16-day	MODIS	5	EVI	Strong seasonality coupling between vegetation function and structure which is controlled by precipitation in tropical forest
Guan *et al.* (2014a)	2007 - 2011	Daily	SEVIRI	3	LAI	New algorithm that can be used to derive LSP across other carbon related datasets
Guan *et al.* (2014b)	2000 - 2011	Daily	MODIS	5	NDVI	Distinct responses of African savannas and deciduous woodlands LSP to rainy season
Jönsson & Eklundh (2002)	1982 - 2000	10-day	AVHRR	8	NDVI	New algorithm for estimating LSP
Jönsson & Eklundh (2004)	1998 - 2000	10-day	AVHRR	8	NDVI	TIMESAT programme for processing time-series of satellite data
Justice *et al.* (1989)	1981	15-day	AVHRR	8	NDVI	Microwave polarization difference temperature (MPDT) relationship with NDVI seasonal variations
Linderman *et al.* (2005)	2000 - 2004	16-day	MODIS	1	EVI	Interannual changes in vegetation activity not linked to shifts in phenology
McCloy & Tind (2011)	1982 - 2008	15-day	AVHRR	8	NDVI	Changes in vegetation phenology overtime
Stroppiana *et al.* (2009)	1990 - 2002	10-day	AVHRR	8	NDVI	A new anomaly indicator (AI) for abstract environmental status assessment and monitoring using phenological data
Vrieling *et al.* (2008)	1981 - 2006	15-day	AVHRR	8	NDVI	Temporal trend analysis of crop phenology showing both positive and negative yield across Africa
Vrieling *et al.* (2011)	1982 - 2006	15-day	AVHRR	8	NDVI	Understanding variability and trends in seasonal cumulated NDVI (cumNDVI) is important in characterising farming systems
Vrieling *et al.* (2013)	1981 - 2011	15-day	AVHRR	8	NDVI	The variability and trend of length of growing period (LGP) in Africa
Zhang *et al.* (2005)	2000 - 2003	16-day	MODIS	1	EVI	Vegetation green-up strongly dependent on rainfall seasonality in Africa

4.2 Methodology

4.2.1 Data acquisition and pre-processing

4.2.1.1 MODIS land surface reflectance data

MODIS data, which are significantly improved in terms of spatial and spectral resolution, atmospheric corrections, cloud screening and sensor calibration (Soudani *et al.*, 2008) compared to AVHRR, were acquired for this study. Only the MODIS tiles covering vegetation areas in Africa were considered. For this reason, 16 years (18 Feb 2000 – 29 Aug 2015) of 44 MODIS/Terra Surface Reflectance 8-Day L3 Global 500 m SIN Grid V005 data (MOD09A1) tiles with collection numbers ranging from h16v07 to h22v11 were downloaded from NASA's LP DAAC (https://lpdaac.usgs.gov/). These data provide a long temporal record of a medium spatial resolution product. Apart from the seven spectral bands [bands 1 (620-670 nm), 2 (841-876 nm), 3 (459-479), 4 (545-565 nm), 5 (1230-1250 nm), 6 (1628-1652 nm), and 7 (2105-2155 nm)], this product has an additional 32-bit Quality Assurance (QA) layer which was used for quality assessment to filter out residual atmospheric and sensor effects, ensuring that the best quality pixels were selected for study. This involved computing 36 different combinations of MODIS land surface reflectance quality parameters from the 32-bit Science Data Set (SDS) Quality Assurance (QA) layer (the 500 m Reflectance Band Quality). All measurements not within these 36 parameters were filtered out, ensuring that only pixels that were atmospherically and adjacently corrected, and of the highest quality on all bands were retained. (see https://lpdaac.usgs.gov/sites/default/files/public/modis/docs/MODIS_LP_QA_Tutorial-3.pdf for more details on the QA assessment procedures).

The Enhanced Vegetation Index (EVI), which overcomes the saturation problems of the Normalized Difference Vegetation Index (NDVI) especially in areas with high biomass vegetation (Huete *et al.*, 2002), was selected as the vegetation index for use in this study. It was developed with the inclusion of the blue reflectance band (B) to correct for atmospheric and soil background influences (Huete *et al.*, 2011; Rowhani *et al.*, 2011), and derived according to the following equation:

$$EVI = G * \frac{(NIR - Red)}{(L + NIR + C1 * Red - C2 * Blue)}$$

The coefficients of the EVI equation are L=1(canopy background adjustment factor); C1= 6 and C2 = 7.5 (aerosol correction factors); and G = 2.5 (gain factor) (Huete *et al.*, 2002, 2011; Reed *et al.*, 2009a; Rowhani *et al.*, 2011).

4.2.1.2 MODIS Land Cover Type data

To represent the land cover of Africa, 44 tiles of 2012 MODIS/Terra Land Cover Type Yearly L3 Global 500 m SIN Grid V005 data (MCD12Q1) (h16v05 to h22v11) were downloaded from NASA's LP DAAC (https://lpdaac.usgs.gov/). This product was chosen because of its relatively fine spatial resolution, high temporal frequency and highest overall accuracy when compared to other land cover data (Bai, 2010; Bontemps *et al.*, 2012; Giri *et al.*, 2013). Also, it has been shown to be consistent with other land cover classification outputs (He *et al.*, 2017). This product has five different land cover classification schemes. The 17-class International Geosphere Biosphere Programme (IGBP) global vegetation classification scheme, shown to be the best among the five schemes, was selected for analysis (Scepan & Estes, 2001; Friedl *et al.*, 2010; Liang *et al.*, 2015) (Figure 4.1).

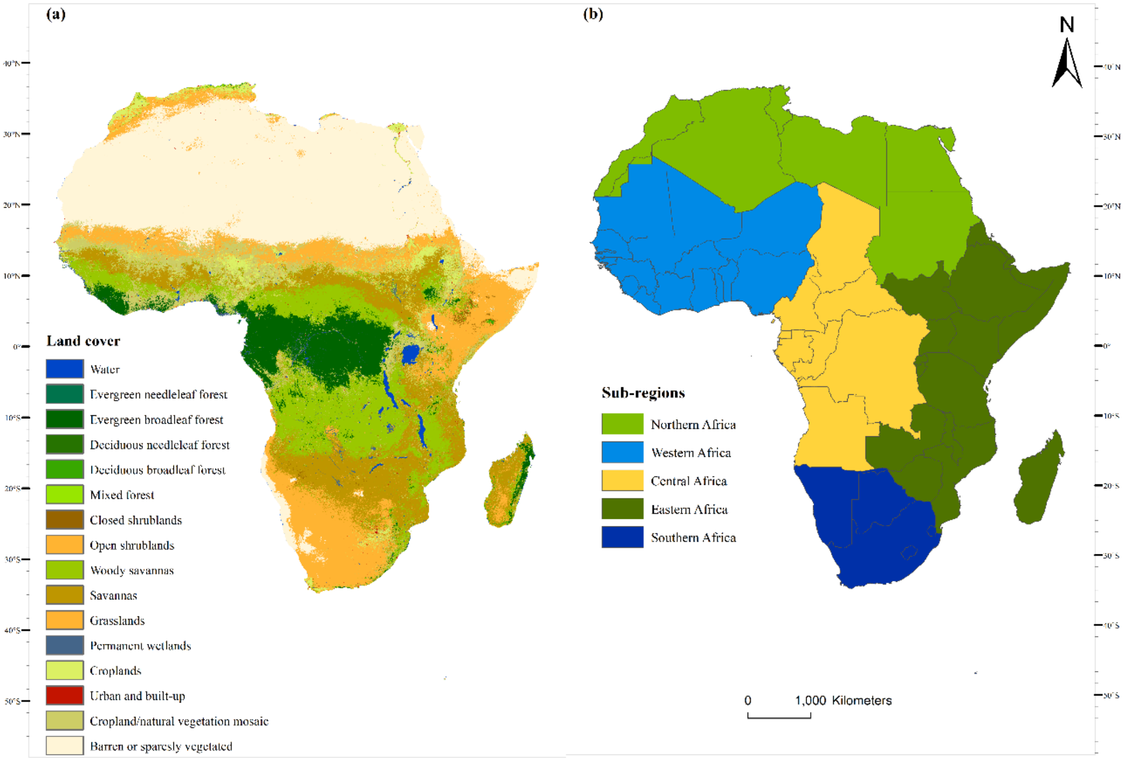

Figure 4.1 (a) Land cover map of Africa derived from the 500 m MODIS land cover type product (MCD12Q1) data for 2012, downloaded from NASA's LP DAAC (https://lpdaac.usgs.gov/). (b) Map of Africa, showing the five different geographical sub-regions (Griffiths, 1971; United Nations, 2014).

4.2.2 Data analysis

4.2.2.1 LSP estimation

To begin LSP estimation, EVI data were stacked into 86 layers (Figure 4.2) (a layer being one composite EVI image), which defined a “cycle” to include two years (i.e., July of year 1 to June of year 3). This is to account for the non-uniform growing seasons across Africa, where start of season is much earlier in the northern latitudes compared to southern latitudes, ensuring that seasonal phenological parameters are estimated yearly.

Four steps were carried out to estimate LSP from the EVI time-series data (Figure 4.3).

1) Removal of drop outs in the EVI time-series with a temporal moving average window
2) Linear interpolation for gap filling (Dash *et al.*, 2010)
3) Data smoothing to further reduce residual noise in data using the inverse Discrete Fourier Transform (DFT)
4) A search process to find the phenological parameters (e.g., minima in the smoothed time-series).

The Discrete Fourier Transform (DFT), a frequency-based smoothing technique was applied to the EVI time-series. This method undertakes a frequency decomposition of the temporal profile of a time-series using Fourier analysis and then reconstructs back to the temporal domain via an inverse Fourier transform, in the present case based on only the smoother components (Moody & Johnson, 2001; Atkinson *et al.*, 2012). One major advantage of this technique is the minimal user input, as users need to specify only the number of harmonics required to reconstruct the time-series (Dash *et al.*, 2010). It has been established that the first two harmonics can adequately represent annual or semi-annual cycles (Jakubauskas *et al.*, 2001). Considering the bimodal seasonality and double cropping agricultural systems found in some parts of Africa, the first six harmonics, as used in Dash *et al.* (2010), were used to generate the smoothed time-series (Figure 4.2).

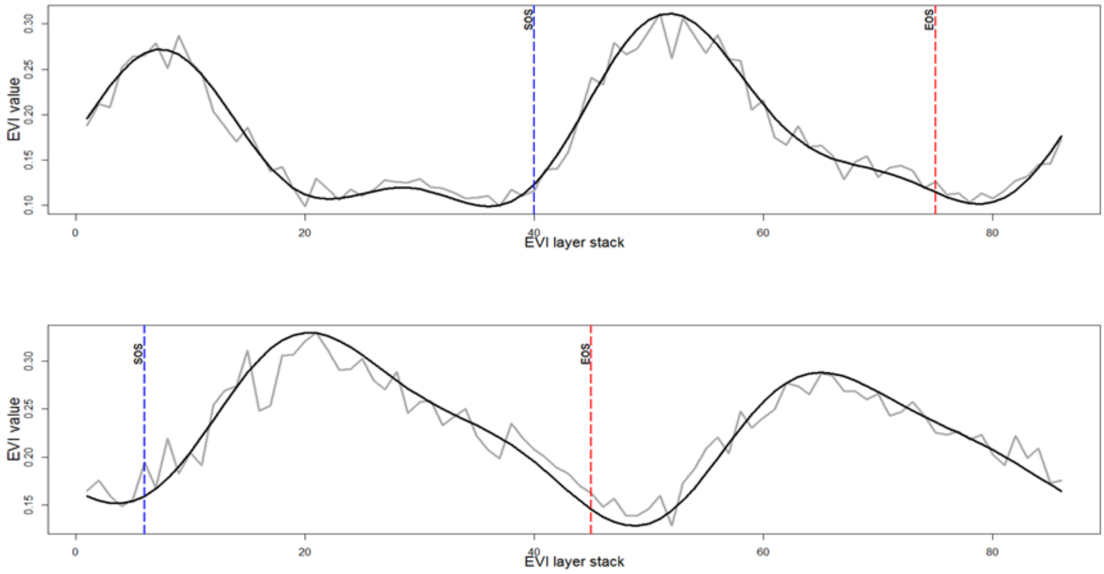

Figure 4.2 Example of pixels showing the smoothed temporal profile of an 86 layer-stacked EVI time-series in black superimposed on the raw EVI data in grey. Blue dotted lines are the SOS and red dotted lines are EOS estimated for each time-series.

Finally, LSP parameters were estimated using the inflection point method based on points of maximal curvature in the time-series (Figure 4.2) (Reed *et al.*, 1994; Moulin *et al.*, 1997; Zhang *et al.*, 2001; Dash *et al.*, 2010). This method overcomes the uncertainties of using a pre-defined threshold which may lead to later onset and earlier end of vegetation growing season. We used an algorithm which departs at the maximum peak, and iteratively searches for valley points (change in derivative value) at the beginning of the growing cycle (Start of Season (SOS), i.e. a change in derivative value from positive to negative) and at the decaying end of the phenology cycle (End of Season (EOS), i.e. a change in derivative value from negative to positive) (Dash *et al.*, 2010). To ensure the appropriate valley points are identified especially in irregular time-series two major conditions were incorporated into this algorithm: (1) at least four consecutive rising EVI values must be identified before key LSP parameters are defined, and (2) the difference between peak and the valley points must be greater than one fifth of the maximum EVI value. The length of season (LOS) was determined as the difference between the estimated SOS and the EOS, converted to number of days. The median values for these parameters for the period of 2001 to 2015 were estimated and then converted to their corresponding Julian days (i.e. day of year (DOY)).

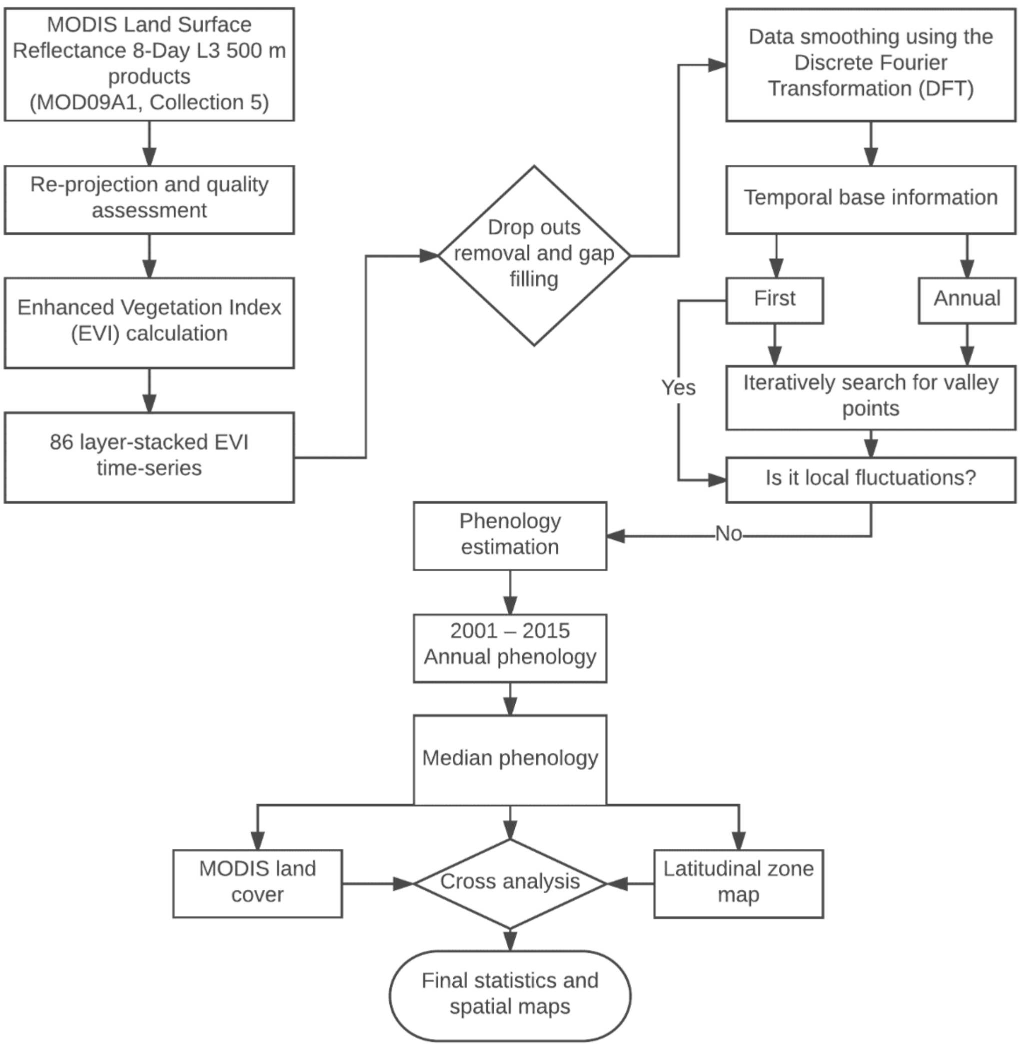

Figure 4.3 Schematic diagram illustrating the research methodology adopted in this study.

4.2.2.2 MODIS Land cover masking

A further reclassification was carried out on the MODIS land cover 17-class International Geosphere Biosphere Programme (IGBP) global vegetation classification scheme, by merging classes with very similar phenological behaviour into broad vegetation classes. For example, evergreen needleleaf forest and evergreen broadleaf forest were merged together to give one class of “evergreen forest”. Pixels belonging to other land cover types that are not vegetation were masked out. Additionally, pixels which remained as the same class over the time-series of 12 years were extracted and used to mask the phenology estimates based on the geographical sub-regions in Africa.

4.2.3 Analysis of LSP

To analyse the variation in phenology with latitude, the majority of LSP parameters were calculated per degree increase in latitude. Thereafter, a simple linear regression model was used to estimate the expected change in phenological parameter per degree increase in latitude (LSP parameters as the dependent variable and latitude as the independent variable) and the significance of the models assessed.

To determine the inter-annual variability of LSP parameters over the entire time-series, the temporal Standard Deviation (STD) values for each LSP parameter in each pixel were estimated. A large magnitude of STD can reveal areas that have unstable seasons in Africa. Additionally, to quantify the spatial distribution of LSP parameters across Africa the percentage of pixels of LSP parameters belonging to each land cover type in the different geographical sub-regions was determined. Finally, to demonstrate the effect of spatial resolution, the STD of the SOS values were estimated with spatial resolutions of 1 km, 3 km, 5 km and 8 km obtained by image degradation (linear averaging).

4.3 Results

4.3.1 Spatiotemporal variation in vegetation phenological parameters

Figure 4.4 shows the median phenological map of Africa for the study period of 2001 to 2015. Between the latitudes of 0^0 and 20^0N which covers the Sahel, Sudan and Guinean regions of Africa, the beginning of the growing season (SOS) has a wide range between late February and early August with most SOS estimates occurring in late February and June. The end of the growing season in these regions falls between late November and the following February, with a long growing season of 150 – 310 days. These very long growing seasons have also been observed by Yan *et al.* (2016). However, some parts of Eastern Africa have SOS dates that are between August and October and EOS between late June and August of the following year. Further north, above 27^0N, most SOS dates occurred between September and November. The corresponding EOS dates are between May and August. This can be attributed to the different seasonal rainfall patterns observed in the extreme north which begins around September with peaks in December and February (Griffiths, 1971; Liebmann *et al.*, 2012). No clear seasonality was detected in most parts of Central Africa, due to the presence of very dense canopies of evergreen forest, and persistent cloud prohibited sufficient cloud free data collection.

In contrast to most areas in the north, for the south of Africa, between latitudes 0^0 and 34^0S, the majority of SOS dates fell between August and November and corresponding EOS dates between

May-June and August of the following year. In the southwestern region, different SOS and EOS dates were observed; February to April for SOS and November to the following year February for EOS. This can be explained by the distinct rainfall pattern observed in this region (rainfall peaks in June to August) (Griffiths, 1971; Liebmann *et al.*, 2012).

Bimodality was also observed in the Horn of Africa and some parts of Western Africa particularly in the coast of Guinea (Figure 4.5). This could be as a result of dual seasonal rainfall patterns, with peaks in April-May and October-November observed in these regions (Herrmann & Mohr, 2011; Liebmann *et al.*, 2012) or artificial bimodality due to residual noise in the EVI data, especially where the bimodality lacks consistency in space and time. Vegetation growth for this second season starts between late August and November and ends between December and February. A shorter LOS of 112 – 144 days was also observed in the Horn of Africa for both the first and second seasons (see Figure 4.4 and Figure 4.5).

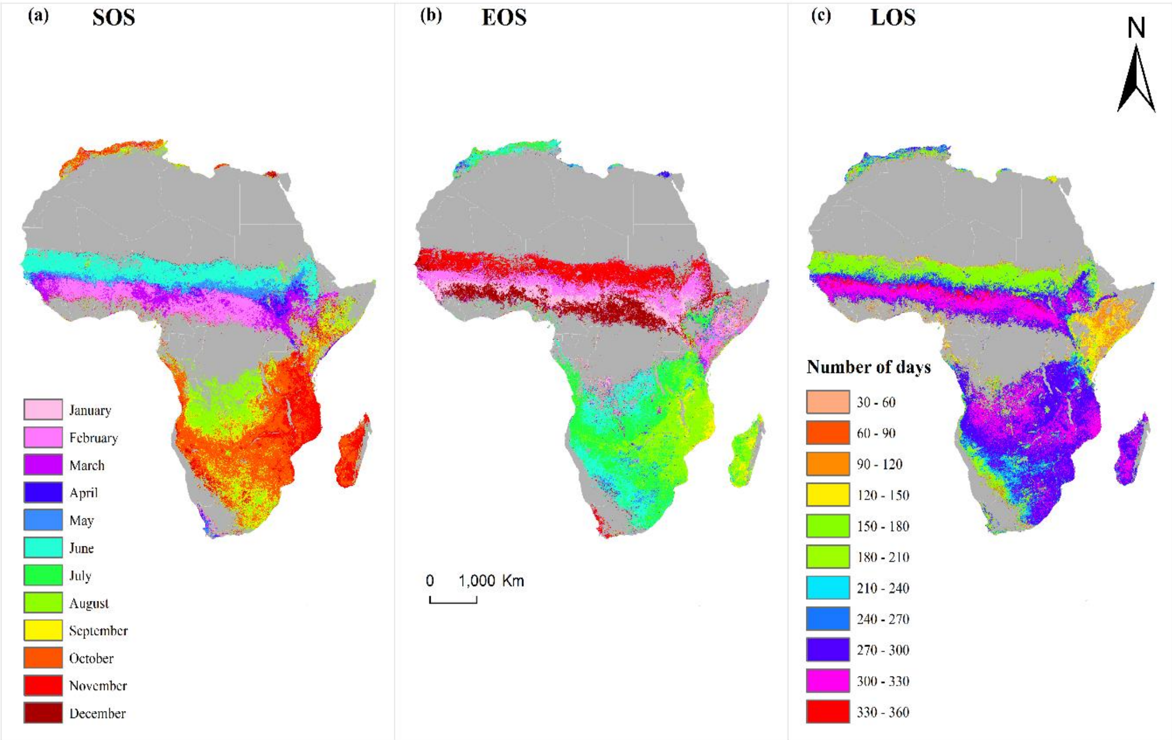

Figure 4.4 The median values of phenological patterns derived from MODIS EVI data. (a) Start of Season (SOS) and (b) median End of Season (EOS) shown in months; (c) median Length of Season (LOS) shown in number of days.

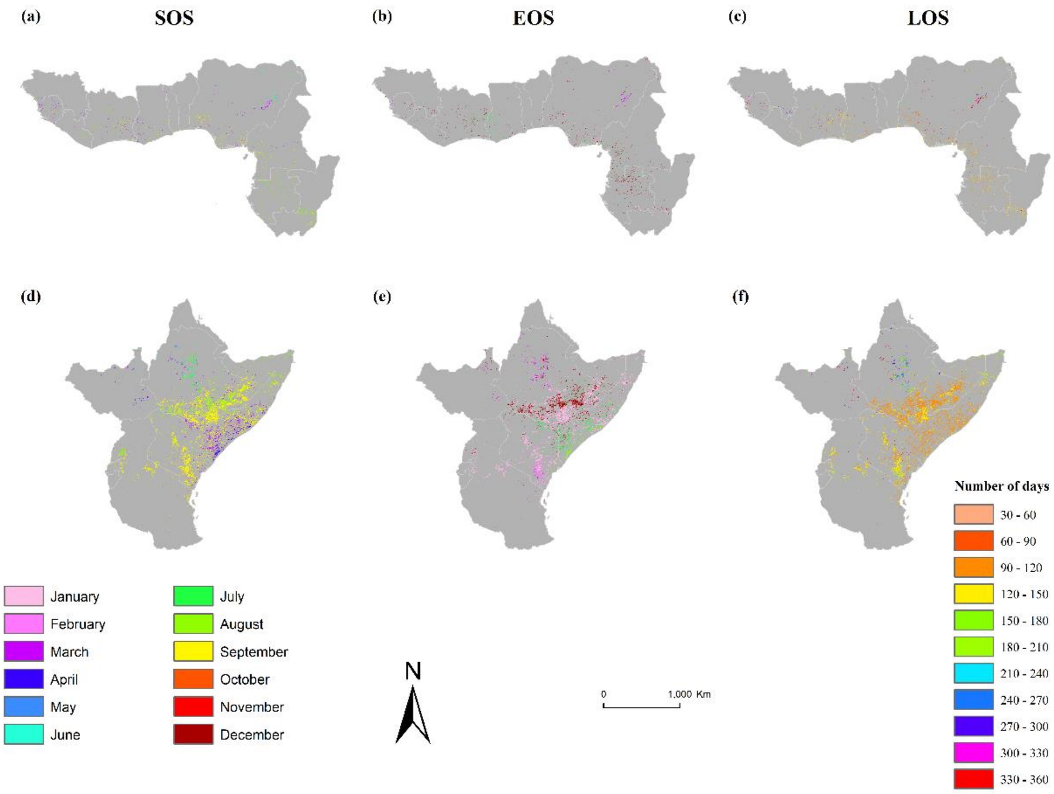

Figure 4.5 The median values of phenological patterns derived from MODIS EVI data. (a,b,c) median (a) start, (b) end and (c) length of season for areas with second seasonal cycle in Western Africa and (d,e,f) median (d) start, (e) end and (f) length of season for areas with second seasonal cycle in Eastern Africa.

4.3.2 Latitudinal gradient

The variability of the majority values of LSP parameters across the African latitudinal gradient, from north above the equator to south below the equator is illustrated in Figure 4.6. Latitude had more influence on SOS and EOS in the northern part of Africa than in the south. Approximately 43% of SOS dates and 59% of EOS dates north of the equator can be explained by latitude ($p<0.0001$). A one degree increase in latitude will result in an approximately 5 days delay in SOS and 5 days advance in EOS dates (0.05 days km^{-1}) (see Table 4.2). However, the correlation between LOS and latitude was insignificant ($p=0.870$).

Table 4.2 *y*-intercept, slope and coefficient of determination for linear regression between LSP parameters and latitude.

Latitude	*y*-intercept			Slope			R^2			*p* (Sig.)		
	SOS	EOS	LOS	SOS	EOS	LOS	SOS	EOS	LOS	SOS	EOS	LOS
North	106.959	320.978	216.349	5.091	5.511	-0.185	0.430	0.589	0.001	<0.0001	<0.0001	0.870
South	277.648	556.786	225.771	1.295	1.155	-1.035	0.122	0.029	0.044	0.0400	0.325	0.225

However, no significant relationship was observed between EOS and latitude south of the equator (R2= 0.029, p=0.325), while a relatively small correlation was observed between SOS and latitude (R2= 0.212, p=0.005).

For a specific land cover type, the latitudinal variation in the phenology also follows the same pattern as explained before (i.e. a very small phenology-latitude correlation in the Southern hemisphere, and a large dependence on latitude in the Northern hemisphere of Africa). However, this trend was interrupted at latitude 300N northwards and latitude 310S southwards. This could be because of the different climatic conditions operating in these regions (see section 4.3.1).

4.3.3 Variability in LSP parameters

Figure 4.7 presents the inter-annual variability in the LSP parameters for the first season for the entire study period. Across the whole of Africa most STD values for all LSP parameters range from 0 – 80 days. However, greater variability was observed in SOS compared to EOS and LOS, and these occurred mostly in the Sahelian region, and mainly in croplands (see Figure 4.7). Although representing less than 1% of the total number of pixels, some areas in Western Africa and the Horn of Africa, mainly croplands, produced very large STDs for SOS of up to 128 days. The same large STDs were observed for both EOS and LOS. This could be attributed to failed season occasioned by several factors like fire, severe drought and human-induced land cover changes. Examples are the severe drought reported to have occurred in the Horn of Africa between late 2010 and late 2011 (Meroni *et al.*, 2014c) and rainfall anomalies in the Sahelian region (Anyamba & Tucker, 2005).

No significant inter-annual variability was observed for the evergreen and deciduous forest across Africa. The same observation was recorded for STD of SOS for shrublands and grasslands, with the exception of a few pixels in Eastern and some parts of Western Africa that had SOS STD values of up to 128 days. Nevertheless, EOS and LOS for both land cover types had STD values ranging from 0 to 48 days and these were mainly in the Sahelian and eastern sub-regions. On the other hand, the STD of SOS for savannas (woody savannas/savannas) ranged from 0 to 40 days, and the number of days increased in EOS (0 to 48 days) and LOS (0 to 56 days).

Contrasting with the first season, no significant variability was observed in LSP for the entire second season, as STDs were very small, with values of less than a day.

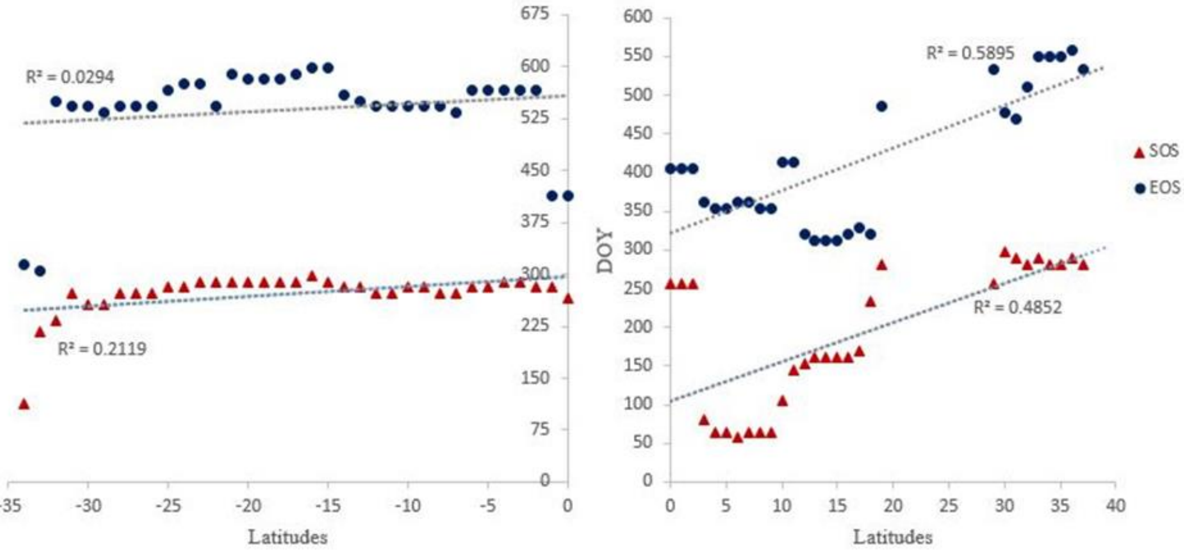

Figure 4.6 Latitudinal variation in the LSP parameters, SOS and EOS, the left showing variations in the southern hemisphere while right showing variations in the northern hemisphere.

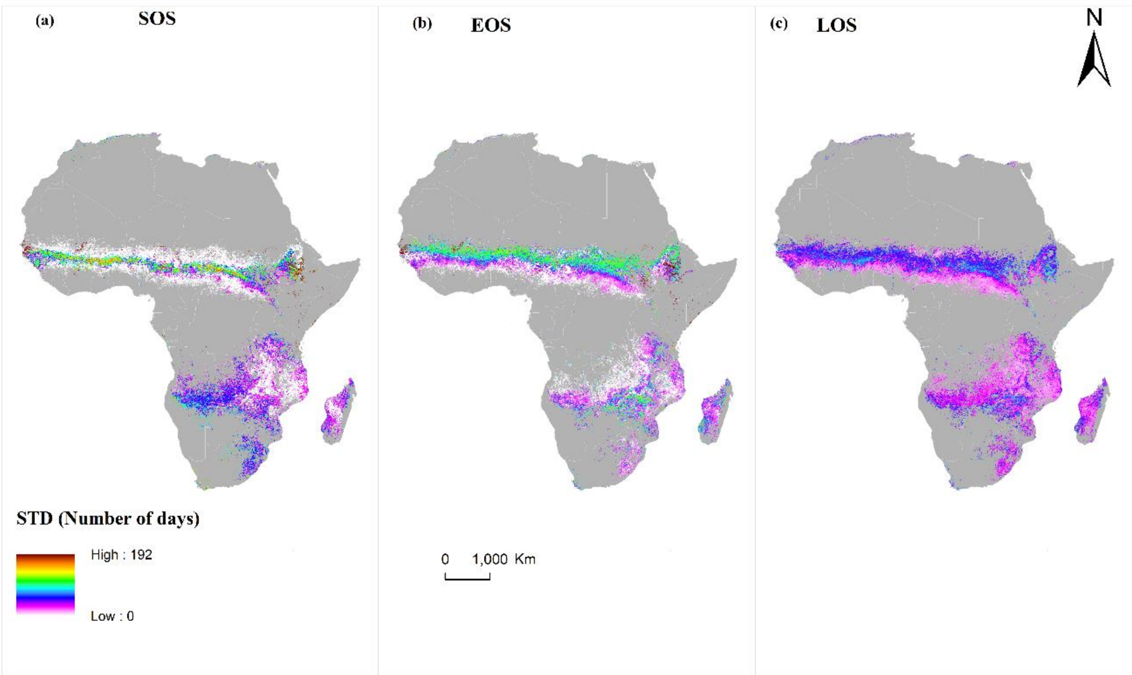

Figure 4.7 Standard deviation of LSP parameters in number of days for the period of 2001 to 2014 for (a) SOS, (b) EOS, and (c) LOS.

4.3.4 Characterisation of the LSP of the major land cover types in different geographical sub-regions

The spatial and temporal variability of the vegetation phenological pattern in Africa is greatly influenced by the different climatic factors operational in the geographical sub-regions, and the vegetation type. Figure 4.8 shows the pattern in the LSP parameters across the six types of land cover based on the five geographical sub-regions in Africa.
Croplands/natural vegetation in Western Africa and some parts of Eastern Africa had over 70% of the SOS dates (homogeneous pixels) from late February to June (with over 36% occurring in June), and EOS between November and February. In geographical sub-regions south of the equator, there was an observed shift in SOS dates, occurring later between August to November, with their corresponding EOS dates between May and August. However, some locations in Northern Africa also exhibited similarly advanced SOS dates (see section 4.3.1 for explanation), which also has been reported by an earlier study (Höpfner & Scherer, 2011). When LOS is compared to other vegetation land cover types, croplands/natural vegetation had the longest growing season of approximately 12 months. These were mostly located in Western Africa predominantly known for cassava production, usually harvested 9 – 18 months after planting (Oshunsanya, 2013; Ezui *et al.*, 2016).
One unique feature of croplands/natural vegetation is the bimodality observed in Eastern Africa. Although this was seen in very few pixels (see Figure 4.4), this nevertheless indicates double cropping activities made possible by bimodal rainfall regimes (Haugerud & Collinson, 1990).
The phenologies of deciduous forest and evergreen forest are somewhat similar, with both having growing seasons starting later between August and November, and ending mostly in January, June, July and August. The average LOS of both land cover types is 10 months. As expected with most land cover types, the spatial location influences the phenology of both forest types, as SOS dates are much earlier in Western Africa and parts of Eastern Africa.

Grasslands, unlike most other land cover types, exhibit very distinct SOS and EOS dates, occurring mainly in the month of June and November, respectively, for all geographical sub-regions in the north of Africa, while southern and some eastern grasslands have a diverse range of SOS and EOS dates. Shrublands also have very diverse SOS and EOS dates across the geographical sub-regions, especially Southern Africa, resulting in a wide range of LOS from 3 to 11 months. However, shrublands in Western Africa have a distinct LSP, with the growing season beginning in early June and ending towards late November.

Woody savanna and savanna are very different from most land cover types. In Western Africa, their SOS dates were mainly in February and March, unlike grasslands, which have most SOS dates in June. Over 85% of the homogeneous pixels of the woody savanna/savanna land cover type have a growing season length between 9 to 10 months.

4.3.5 Heterogeneity of LSP parameters in coarse resolutions

We demonstrate the effect of spatial resolution on the analysis in Table 4.3. The table shows the range of STD of SOS in grids of 8 km, 5 km, 3 km and 1 km, and the percentage of pixels having those values. 22% of the pixels with an 8 km resolution have STD values ranging from 37 – 180 (DOY). As expected, this number reduces as spatial resolution increases: 19% for 5 km, 16% for 3 km and 6% for 1 km. The reverse was observed for percentage of pixels with smaller STD values (i.e., the finer the spatial resolution the greater the number of pixels with smaller STD deviation values) (see Table 4.3).

Table 4.3 Percentage of pixels in four different resolutions of 8000 m, 5000 m, 3000 m and 1000 m with their STD range of values

STD (SOS)	8000 m	5000 m	3000 m	1000 m
0 - 18	62.69	67.36	74.29	89.86
19 - 36	15.77	13.99	10.20	4.58
37 - 54	5.27	4.44	3.64	0.98
55 - 72	3.43	2.95	2.43	0.35
73 - 90	3.48	3.00	2.46	0.60
91 - 108	3.98	3.41	2.81	0.93
109 - 126	4.17	3.59	2.88	1.60
127 - 144	1.06	1.10	1.12	0.88
145 - 162	0.11	0.12	0.14	0.18
163 - 180	0.02	0.03	0.03	0.04

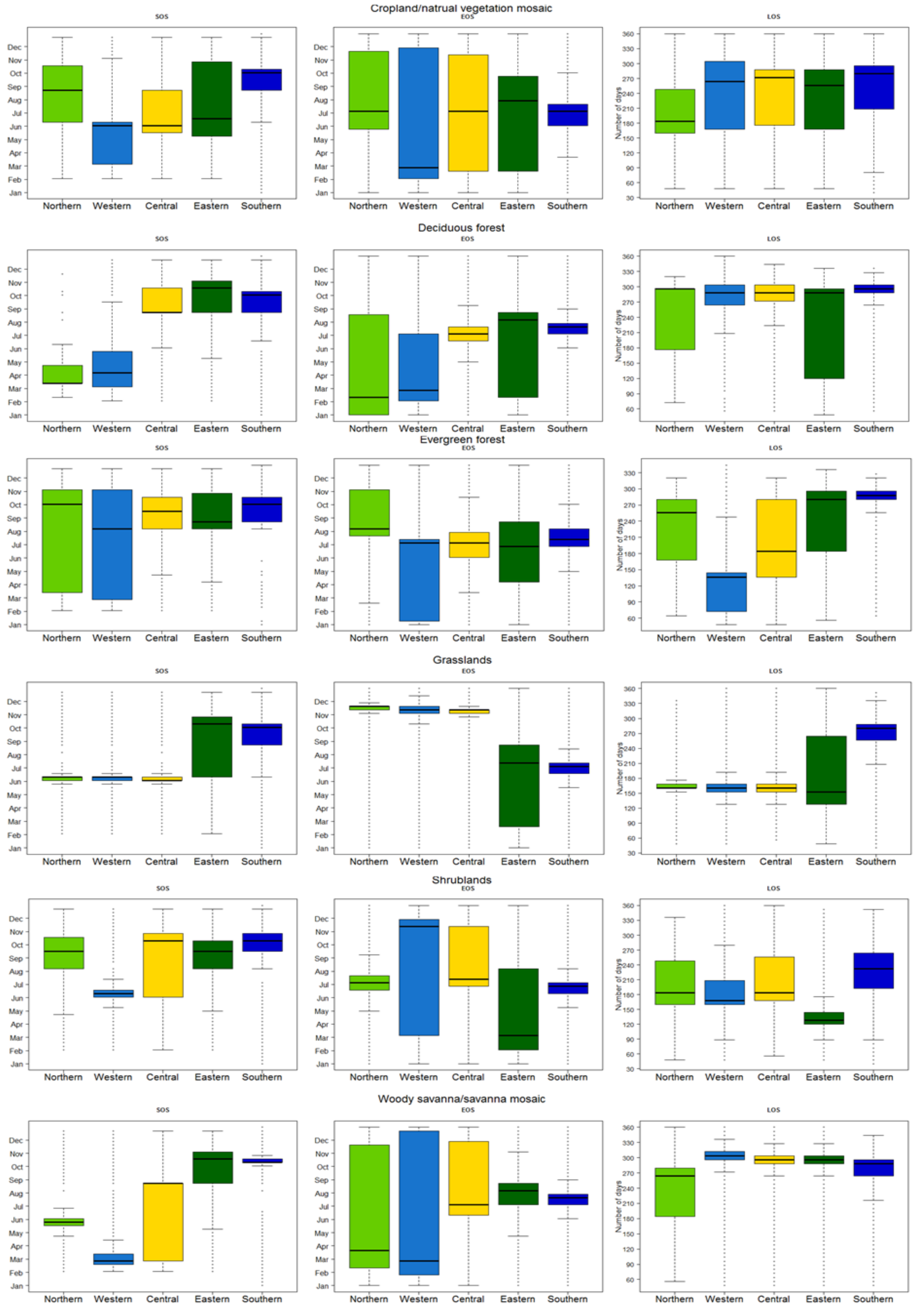

Figure 4.8 Box plots showing the distribution of pixels of LSP parameters in the six major land cover types based on five geographical sub-regions.

4.4 Discussion

The phenological pattern of vegetation cross different land covers and across different African sub-regions is important in understanding the vegetation dynamics of different biomes especially in relation to climate changes. This research provides a detailed characterisation of the LSP of the major land cover types in Africa at a continental scale based on the different geographical sub-regions at the finest spatio-temporal resolution to-date.

4.4.1 Latitudinal variation in LSP

Latitude was found to have some controlling effect on phenological patterns which is consistent with results from previous studies (Zhang *et al.*, 2005; Butt *et al.*, 2011; Brottem *et al.*, 2014; Guan *et al.*, 2014b). The latitudinal variation in phenology across Africa revealed greater spatial variability at lower latitudes, that is, Africa in the Southern hemisphere. However, increases in DOY SOS were observed as latitude increases, especially in the northern hemisphere (see Figure 4.6). Similar results were found in Seghieri *et al.*(2009); with the same coverage of shrubs in West Africa, leafing dates were earlier at lower latitudes when compared to leafing dates at higher latitudes. Also Guan *et al.* (2014b) and Zhang *et al.* (2005) showed that in Northern Africa LSP parameters were more correlated with latitude than in the Southern hemisphere. Our study, which used a much finer spatial resolution, not only confirms this phenology-latitude relationship but also provides the average rate of increase per one degree increase in latitude. This average rate of a 0.05 days km^{-1} for both SOS and EOS is supported by previous studies: (0.12 days km^{-1} and 0.05 days km^{-1} for the period 2000 to 2003 in Zhang *et al.* (2005), 0.05 days km^{-1} and 0.03 days km^{-1} for the period 2000 to 2008 in Bobée *et al.* (2012) and 0.09 days km^{-1} and 0.05 days km^{-1} for the period 2000 to 2010 in Butt *et al.* (2011), respectively).

One major reason for this north-south discrepancy is the climatic factors operational in these regions. The North is mostly controlled by the northwards movement of the Intertropical Convergence Zone (ITCZ) which migrates latitudinally defining the seasonality of rainfall in the northern region (Giannini *et al.*, 2008). However, the south has multiple climatic factors at play: the east-west oriented component of the African ITCZ, the North Atlantic Oscillation index (NAO), the Pacific Decadal Oscillation (PDO) (Nicholson, 2001, 2003; Brown *et al.*, 2010) and the Agulhas and Benguela current systems (Walker, 1990)(Walker, 1990), each exerting their influence along the east-west to the south-west coasts.

The present results show that in some places in the African continent LSP does not vary linearly with latitude, and more importantly quantify the degree of variation.

4.4.2 Inter-annual variability

The broad spatial distribution of inter-annual variability of LSP indicated in this study is consistent with outcomes from previous studies. Interesting is the different pattern of inter-annual variability shown by the different geographical sub-regions and the different land cover types. As shown in Figure 4.7, inter-annual variability was greater in Eastern and some parts of Western Africa, which corresponds with some areas identified as hotspots of change by Linderman *et al.* (2005). Most land cover types in these regions had a large STD representing inter-annual variability except for the evergreen and deciduous forest types. These vegetation types across Africa were found not to have significant changes in LSP parameters, a similar outcome reported for vegetation activity by Linderman *et al.* (2005) for the period 2000 to 2004. In contrast, croplands had a large STD, with SOS having the largest values. This confirms results from previous studies of crop failures in the Sahelian region and Eastern Africa (Vrieling *et al.*, 2013; Landmann & Dubovyk, 2014; Meroni *et al.*, 2014c). Similarly, shrublands and grasslands across Africa had moderately large STDs for EOS and LOS, but large STD for SOS in the Eastern and Western sub-regions. This implies that between 2001 and 2014, some factors may have affected the onset of growing season in these regions. Factors that could be responsible, and have been identified by previous studies are: human-induced land transformations (Landmann & Dubovyk, 2014), climatic factors like droughts and rainfall anomalies (Anyamba & Tucker, 2005; Meroni *et al.*, 2014c), and vegetation-type transitions occasioned by both climatic and human factors (Linderman *et al.*, 2005; Mitchard *et al.*, 2009).

Contrary to Vrieling *et al.* (2013), there was no observable relationship between the duration of LOS and STD values of LOS (i.e., no heteroscedasticity). Additionally, no significant relationship was detected between inter-annual variability and latitudinal gradient.

4.4.3 Comparison with ground-based studies

Owing to the absence of a comprehensive ground-based observation network in Africa and the very limited number of ground-based studies (Rutherford & Panagos, 1982; Childes, 1989; Seghieri *et al.*, 2009; February & Higgins, 2016; Whitecross *et al.*, 2017a,b), direct or indirect validation of the results of this study was not possible. Hence, a comparison was made with the limited existing literature on ground-based studies. In Western Africa, several species of shrubs and woodland savannah, and mosaic of crops and natural vegetation have been found to start leafing in February just before the rainy season, and in June during the rainy reason (Seghieri *et al.*, 2009). This agrees well with our findings as results from our study in the same geographical locations showed SOS to begin in DOY 57 – 65 and DOY 161 - 169 (see Table 4.4). This early onset of growing season before the rains has also been reported to occur in numerous evergreen and mostly woody plants in the African Sahel by Seghieri and Do (2012); Guan *et al.* (2014b) and Brandt *et al.* (2016). More recent studies have reported the ubiquitous nature of this pre-rain onset in southern Africa (Ryan *et al.*, 2017; Whitecross *et al.*, 2017a,b). Similarly, in Southern Africa, some species of savanna trees were found to begin their growing season and attain tree canopy fullness between October and November. These savanna trees were also found to have no leaves at the end of the dry season in October (February & Higgins, 2016; Whitecross *et al.*, 2017b,a). Again, our results for the same geographical location are in agreement with these findings.

Increased air temperature and atmospheric vapour pressure/relative humidity, with scleromorphic features and access to deeper groundwater or stored water in plants have been proposed to be responsible for this early onset of greening (De Bie *et al.*, 1998; Do *et al.*, 2005; Seghieri *et al.*, 2012). Comparison was not possible with all the existing literature on ground-based studies due to the type of vegetation phenological parameters measured. For example, plant phenophases such as budding, shoot growth, flowering and fruiting measured by some studies (Chapman *et al.*, 2005; Do *et al.*, 2005; O'Farrell *et al.*, 2007; Sekhwela & Yates, 2007; Yamagiwa *et al.*, 2008; Wang'ondu *et al.*, 2010, 2013; Seghieri *et al.*, 2012; Polansky & Boesch, 2013) cannot be compared directly to onset of greenness or leaf emergence/leafing in remote sensing studies. Regardless of this limitation, the phenological patterns of major vegetation types from these ground-based studies are very similar to our results. Notwithstanding, this limitation further drives home the need for more ground-based observations and a phenological network for the African continent.

Table 4.4 Comparison of locations in West Africa showing results from literature and current study.

Location	**Study period**	**Vegetation type**	**Results from Literature**	**Authors**	**Results from study SOS (DOY)**
$9^0$40' - $9^0$54'N and $1^0$34' - $1^0$58'E	2004 - 2006	Shrubs, woodland savannah, forest, mosaic of crops and young fallows	Leafing began in February	Seghieri *et al.*(2009)	57 - 65
$15^0$08'- $15^0$35'N and $1^0$23' - $1^0$39'E	2005 - 2006	Shrubs and woodland Sparse vegetation	Leafing began in June	Seghieri *et al.* (2009)	161 - 169

4.4.4 Comparison with other remote sensing studies

The present results differ from most earlier remote sensing studies of LSP over Africa (Brown *et al.*, 2010, 2012; Jacquin *et al.*, 2010; Vrieling *et al.*, 2013) which used a threshold method in estimating LSP parameters. In comparison, the present analysis detected SOS approximately 30 to 60 days earlier across Africa. Similarly, EOS was detected approximately 30 – 60 days later. Consequently, the present study produced longer LOS values of about 30 – 90 days. This supports the findings of Vrieling *et al.* (2008) and de Beurs & Henebry (2010), that threshold methods estimate SOS later and EOS earlier because the point of maximum curvature may be below the user-defined threshold.

On the other hand, the present results are in agreement with remote sensing studies (Zhang *et al.*, 2005; Archibald & Scholes, 2007; Butt *et al.*, 2011; Bobée *et al.*, 2012; Brottem *et al.*, 2014; Guan *et al.*, 2014a,b; Ryan *et al.*, 2014) that applied the inflection point or the function model fitting methods in estimating LSP. This consistency was very evident in the early green-up observed before the rainy seasons, especially in evergreen forest and woodlands (Archibald & Scholes, 2007; Guan *et al.*, 2014b), and the distinct phenological pattern observed in the extreme northern and southern tips of Africa (Guan *et al.*, 2014a).

While there exists strong agreement with previous studies, minor discrepancies of an estimated 5 – 20 days were observed. This could be the result of the different spatial resolution used in the studies. At coarser spatial resolutions, phenological parameters are usually averaged across an area that may have different vegetation types with distinct phenological patterns. This can be seen in the STDs of SOS with spatial resolutions of 1 km, 3 km, 5 km and 8 km. As the spatial resolution becomes finer, the STD in number of days reduces (see Table 4.3). This suggests that with a finer spatial resolution there is less conditional bias (under-estimating highs and over-estimating lows) from spatial averaging and aggregation.

Aside from the type of estimation technique and the spatial resolution of data, the smoothing techniques (Atkinson *et al.*, 2012), sensor type (Atzberger *et al.*, 2013) and the temporal resolution of data (Zhang *et al.*, 2009) could also be responsible for such discrepancies between outcomes.

4.5 Conclusion

The LSP of the major vegetation types in Africa was described for the first time using homogeneous pixels from 12 years (2001 – 2012) MODIS land cover data (MODIS MCD12Q1) and EVI derived from the MODIS MOD09A1 product at a medium spatial resolution of 500 m and a high temporal frequency of 8-days. Indeed, the maps of LSP parameters (SOS, EOS, LOS) produced here represent the finest spatial resolution and most detailed maps of the phenology of Africa to-date. Additionally, the inter-annual variability of all LSP parameters for all of Africa was reported for the first time.

The well-known phenology-latitude relationship in Africa was quantified at an unprecedented fine resolution, with a greater correlation found in northern latitudes. . Moreover, the dependence of the LSP parameters (SOS, EOS and LOS) on land cover type and geographical sub-region was analysed in detail, revealing a complex interaction between the three dimensions of vegetation timing, geographical location and land cover type.

The results reported here support previous studies and while providing a more refined quantification with some significant variations to existing maps. The spatial detail (500 m) with which the LSP parameters are mapped here provides a platform to support further applied environmental research in the African continent. In particular, it is anticipated that the mapped outputs from this research will be important for ecosystem management and climate-related research and can be of value for further studies on climate change impacts and phenology-climate modelling.

While it was not possible to conduct an extensive empirical validation of the maps of LSP produced (due to the lack of a comprehensive African ground observation network measuring vegetation phenology), comparison of the results with the available ground-based studies published in the literature found close agreement. Moreover, the methods applied in this research to estimate LSP parameters have been applied widely and tested extensively in other studies, including through comparison with empirical ground data in those studies. Further studies should be undertaken to provide a comprehensive, continental scale validation of the LSP predictions across Africa when suitable ground data become available.

Chapter 5: Major trends in the Land Surface Phenology (LSP) of Africa, controlling for land cover change

5.1 Introduction

Remote sensing techniques for mapping land surface phenology (LSP) provide the capability for long-term observation across large areas, especially those where ground data are lacking (Zhang *et al.,* 2006, 2014b; Julien & Sobrino, 2009; Jeong *et al.*, 2011). Remote sensing has been used to study the response of LSP to climatic and non-climatic factors and has, thus, contributed to increased understanding of climate change impacts on the terrestrial ecosystem. Several authors have used remote sensing to estimate inter-annual trends in LSP (usually related to the timing of specific events). Myneni *et al.* (1997) was one of the first studies to report a 12 days increase in the length of growing season (LOS) for the Northern Hemisphere during the period 1982–1991 using satellite sensor data. Several other studies have been carried out since then, mostly focusing on LSP trends in the Northern Hemisphere (e. g., Zhou *et al.*, 2001; de Beurs & Henebry, 2005; Delbart *et al.*, 2005; Piao *et al.*, 2007; Julien & Sobrino, 2009; Jeong *et al.*, 2011; Zhu *et al.*, 2012, 2014; Ivits *et al.*, 2012; Zhang *et al.*, 2014; Yang *et al.*, 2015; Liu *et al.*, 2016) with a limited number of studies covering the Southern Hemisphere (Heumann *et al.*, 2007; Vrieling *et al.*, 2008, 2011, 2013, Verbesselt *et al.*, 2010a,b; Garonna *et al.*, 2016).

The above studies estimate LSP trends over a particular inter-annual period and evaluate the possible drivers for such trends, but do not consider land cover changes as a confounding driver that can significantly influence the observable changes in LSP. This lack of research into the influence of land cover changes on LSP trends has been highlighted previously (Reed, 2007; Zhang *et al.*, 2014b; Tang *et al.*, 2015). Additionally, only a limited number of studies have recognised that other non-climatic factors can significantly influence trends in LSP. For example, Krishnaswamy *et al.* (2014) suggested that other factors besides temperature and precipitation were responsible for browning and greening trends in tropical mountain regions; Olsson *et al.* (2005) suggested that changes in vegetation type were responsible for an increase in greening in the Sahel as rainfall only partially explained increasing vegetation cover; and Verbesselt *et al.* (2010a,b), Ivits *et al.* (2012) and Begue *et al.* (2014) identified land management practices as a major factor influencing phenological changes in South Eastern Australia, Europe and Mali, respectively.

Because of the potentially confounding influence of land cover changes, it would be preferable to control for these changes, for example, by ensuring that only homogeneous pixels (i.e., those that have a constant land cover throughout the entire time-series) are used to characterise inter-annual trends for comparison with changing climate drivers. This would allow separation of those LSP trends that are solely climate-driven from those that are influenced by non-climatic factors. To the best of our knowledge, Jeganathan *et al.* (2014) may be the only study to have deliberately controlled for land cover changes while analysing inter-annual and seasonal vegetation dynamics.

In addition to the above gaps in research methodology, substantial gaps exist with respect to the study of the vegetation phenology of Africa (IPCC, 2014; Adole *et al.*, 2016). While it has been shown that other factors besides climate are responsible for some variation in phenology and increases in greenness in different regions of the African continent (Herrmann *et al.*, 2005; Martínez *et al.*, 2011; Polansky & Boesch, 2013), studies investigating this phenomenon across the whole of Africa are limited.

This chapter represents the first analysis of inter-annual LSP trends in Africa that controls for land cover changes, using MODIS data. The aim was to separate out the LSP trends that are not influenced by (mainly) anthropological disturbances such as deforestation, agricultural land conversion, land management, land degradation, land transformation and urbanization, from trends that may have been influenced by these disturbances.

5.2 Data and methodology

The LSP parameters estimated from the Enhanced Vegetation Index (EVI) derived from 500 m surface reflectance Moderate Resolution Imaging Spectroradiometer (MODIS) (MOD09A1) were used for this study. Methodology of LSP estimation and EVI derivation are detailed in chapter four. However, only the first season LSP parameters results were considered for this analysis. 13 years (2001 – 2013) of MCD12Q1 tiles covering the entire African continent was also used for this study.

5.2.1 Land cover change detection and trend analysis

As explained in chapter four a reclassification was carried out on the MODIS land cover 17-class International Geosphere Biosphere Programme (IGBP) global vegetation classification scheme. A further grouping was done to other classes comprising water, permanent wetlands, barren or sparsely vegetated and urban/built-up areas which were grouped into the class "*others*" (see Table 5.1).

To estimate the inter-annual LSP trends, two main categories of pixel were analysed based on the nature of their time-series: (1) only pixels with the same land cover in all years of the time-series of 13 years were used to estimate the temporal trends, and these were separable based on the type of land cover and (2) pixels which changed from one land cover class to another were also analysed, but this time to determine if land cover changes significantly influenced the estimated LSP parameters. The latter category was further characterised into sub-groups based on the number of times the land cover had changed in the entire time-series. Only changes in vegetative land cover were considered. These were classified in the following way: 1) changes between two classes only were labelled as "one change", for example, a change from grasslands to croplands; 2) changes between three classes were labelled as "two changes", for example a change from woody savanna to croplands and then to grasslands or back to savanna; 3) and those pixels that changed land cover types more than three times were labelled as "> two changes", (Woody savanna/savanna - cropland/natural vegetation - grasslands - cropland/natural vegetation). (See Figure 5.1 for spatial patterns of land cover types and the different classes of pixels used in this study).

The Spearman's non-parametric rank correlation coefficient was used to characterise the magnitude and direction of temporal trends in day of year with significance testing (*F*- test at the 95% confidence level). This test was used because of its robustness in relation to identifying trends in non-Gaussian distributed data (Yue *et al.*, 2002; Vrieling *et al.*, 2008). Simple linear regression was then fitted to estimate the magnitude of the trends in number of days per year.

Table 5.1 Reclassification of land cover types into broad categories based on the International Geosphere Biosphere Programme (IGBP) global vegetation classification scheme.

Merged land cover type	**Initial land cover types**
Evergreen forest	Evergreen needleleaf forest
	Evergreen broadleaf forest
Deciduous forest	Deciduous needleleaf forest
	Deciduous broadleaf forest
Shrublands	Closed shrublands
	Open shrublands
Woody savanna/savanna	Woody savannas
	Savannas
Grasslands	Grasslands
Croplands	Croplands
Croplands/natural vegetation mosaic	Croplands/natural vegetation mosaic

Table 5.2 Number and proportion of pixels showing significant increasing and decreasing trends (p-value < 0.05) in each land cover change class. The “no change” class is of greatest interest when analysing trends in LSP because it controls for land cover change (i.e., there was no land cover change in this group).

Land cover change category	**Proportion of pixels in each category**	**SOS**				**EOS**				**LOS**			
		Number of pixels		**Proportion of pixels**		**Number of pixels**		**Proportion of pixels**		**Number of pixels**		**Proportion of pixels**	
		Sig. pos.	**Sig. neg.**	**Sig. pos.**	**Sig. neg.**	**Sig. pos.**	**Sig. neg.**	**Sig. pos.**	**Sig. neg.**	**Sig. pos.**	**Sig. neg.**	**Sig. pos.**	**Sig. neg.**
No change	75%	676823	286722	2.78%	1.18%	687864	387520	2.83%	1.59%	264082	155223	1.09%	0.64%
One change	18%	854507	217825	3.52%	0.90%	838527	352015	3.45%	1.45%	307371	160246	1.26%	0.66%
Two changes	3%	467500	110228	1.92%	0.45%	474940	162754	1.95%	0.67%	241246	89551	0.99%	0.37%
> Two changes	3%	144460	52850	0.59%	0.22%	195508	54218	0.80%	0.22%	144022	28400	0.59%	0.12%
Total	100%	2143290	667625	8.82%	2.75%	2196839	956507	9.04%	3.93%	956721	433420	3.94%	1.78%
Overall sig. (+ & -)		**2810915**		**11.56%**		**3153346**		**12.97%**		**1390141**		**5.72%**	

5.3 Results

5.3.1 LSP trend analysis

LSP trends found to be significant (95% confidence levels) were mapped for all LSP parameters. The mapped trends for SOS and EOS are shown in Figure 5.2 and Figure 5.3. A summary of the significant statistical trends (p-value < 0.05) for all LSP parameters by land cover change group are displayed in Table 5.2. Overall, less than 13% of pixels in each LSP parameter showed significant trends (see Table 5.2) and an estimated 70% of these pixels had trends that were significantly positive (i.e., the LSP event date becoming later). For example, of the 12.97% (3,153,346) significant pixels in EOS, 9.04% (i.e., 70% of the total number of significant pixels) were significantly positive.

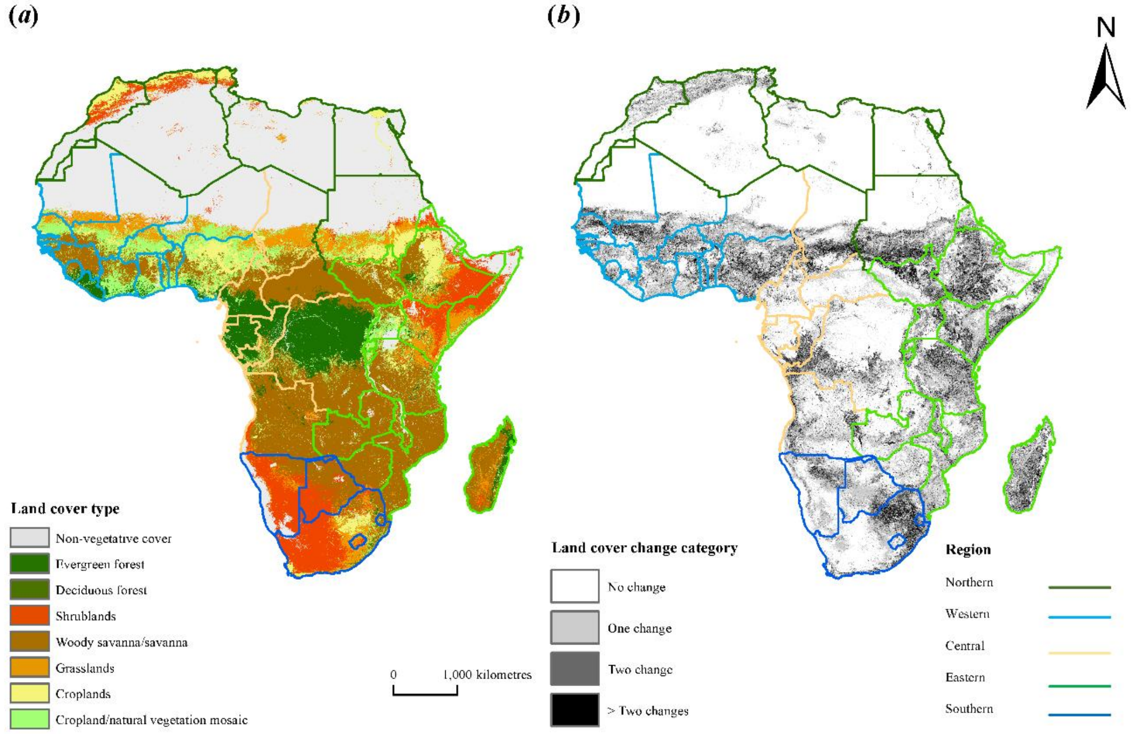

Figure 5.1 (a) Reclassified 2013 MODIS land cover product (MCD12Q1). (b) Change classification based on number of land cover changes in the time-series of 13 years.

Table 5.3 also shows the different combinations of LSP trends in this study. An estimated 9% of the entire continent had delayed SOS dates, with 0.75% resulting in "*delayed longer season*" (i.e. delayed SOS and increased LOS), 1.36% resulting in *"delayed shorter season"* (i.e. delayed SOS and reduced LOS), and 6.62% with no significant LOS trend. Similarly, of the estimated 3%

advancing SOS dates, 1.54% led to *"earlier longer season"* (i.e. advanced SOS and increased LOS), 0.05% resulted in *"earlier shorter season"* (i.e. advanced SOS and reduced LOS), and 1.19% resulted in no significant LOS trend (see Table 4). These observations suggest that despite significant shifts in SOS and/or EOS dates, there was less change in LOS, indicating that both SOS and EOS are becoming later or earlier in synchrony, as shown in Table 5.3.

There were significant EOS trends which led to apparent changes in LOS. For example 0.38% of earlier EOS led to *"shorter season"* and 1.65% of delayed EOS resulted in *"longer season"*. In general, significant increases in LOS were associated mostly with delayed EOS (2.4%). That is, over 60% of the significant LOS positive trends was influenced by delayed EOS dates. These were mostly observed in western and eastern Africa. On the other hand, a shorter LOS was mostly due to a delayed SOS and earlier EOS (see Table 5.3). This shorter LOS was seen in similar geographical sub-regions as observed longer LOS. However, observations were confined to certain regions like northern Nigeria, western Angola and the savannas of central Africa.

Table 5.3 Observed combinations of changes in SOS and EOS (leading to changes in LOS), showing the percentage of pixels in each combination.

Change in SOS	**Change in EOS**	**Change in LOS**	**Proportion of area (%)**
Earlier	Earlier	Longer season	1.45
Earlier	Earlier	Shorter season	0.05
Earlier	Earlier	-	1.19
Earlier	Delayed	Longer season	0.01
Earlier	-	Longer season	0.08
Earlier	-	Longer season	0.38
Delayed	Delayed	Longer season	0.75
Delayed	Delayed	Shorter season	0.01
Delayed	Delayed	-	6.62
Delayed	Earlier	Shorter season	0.85
Delayed	-	Shorter season	0.50
Delayed	-	Shorter season	1.65

5.3.2 LSP trends based on land cover type

Figure 5.5 shows the magnitude of the observed significant LSP trends in SOS (i.e., magnitude and direction of the slope from linear regression) in days year^{-1}. These represent only stable land cover types and were identified mainly in woody savanna/savanna and croplands/natural vegetation. More specifically, 72% of these significant pixels were found in woody savanna/savanna, 16% in croplands/natural vegetation mosaic, 7% in croplands, 4% in grasslands and 1% in shrublands.

Corresponding to the general pattern of SOS becoming later (i.e., more significant positive trends compared to negative trends), woody savanna/savanna had more pixels with a trend towards a delayed SOS with a slope of between 2 to 2.4 days year^{-1} across all Africa. (spatial pattern of slope magnitudes and frequency distributions are detailed in Figure 5.5 and Figure 5.6). A very small proportion of woody savanna/savanna pixels of about 0.4%, distributed in central and eastern Africa, had a trend towards an earlier SOS with a slope of -3 to -4 days year^{-1}. The EOS and LOS trends for woody savanna/savanna were similar to the SOS trends, having more significant positive pixels. However, for woody savanna/savanna the positive LOS trends observed were mostly a result of earlier SOS dates leading to an *"earlier and longer season"*. Croplands/natural vegetation mosaic on the other hand had more *"longer season"* LOS trends. This was due to a delayed EOS only, particularly in West African countries like Mali and Senegal. Although there were delayed SOS trends of approximately 2.3 days year^{-1}, similar rates of change in EOS were observed.

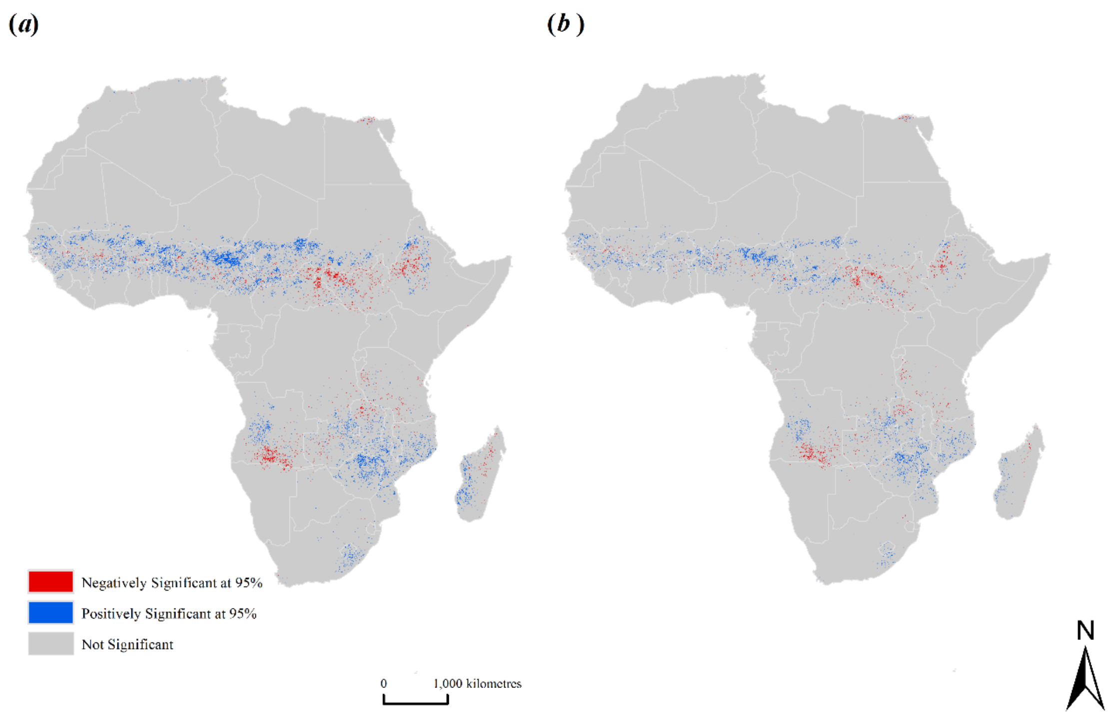

Figure 5.2 Spatial distribution of significant inter-annual Start of Season (SOS) trends in Africa estimated from 8-day 500 m MODIS-EVI time-series for 2001-2015. (a) All significant LSP trends in both "*no change*" land cover and changed land cover pixels. (b) Significant trends in *"no change"* land cover pixels only. Spatially contiguous areas of positive change (later SOS) and negative change (earlier SOS) are apparent.

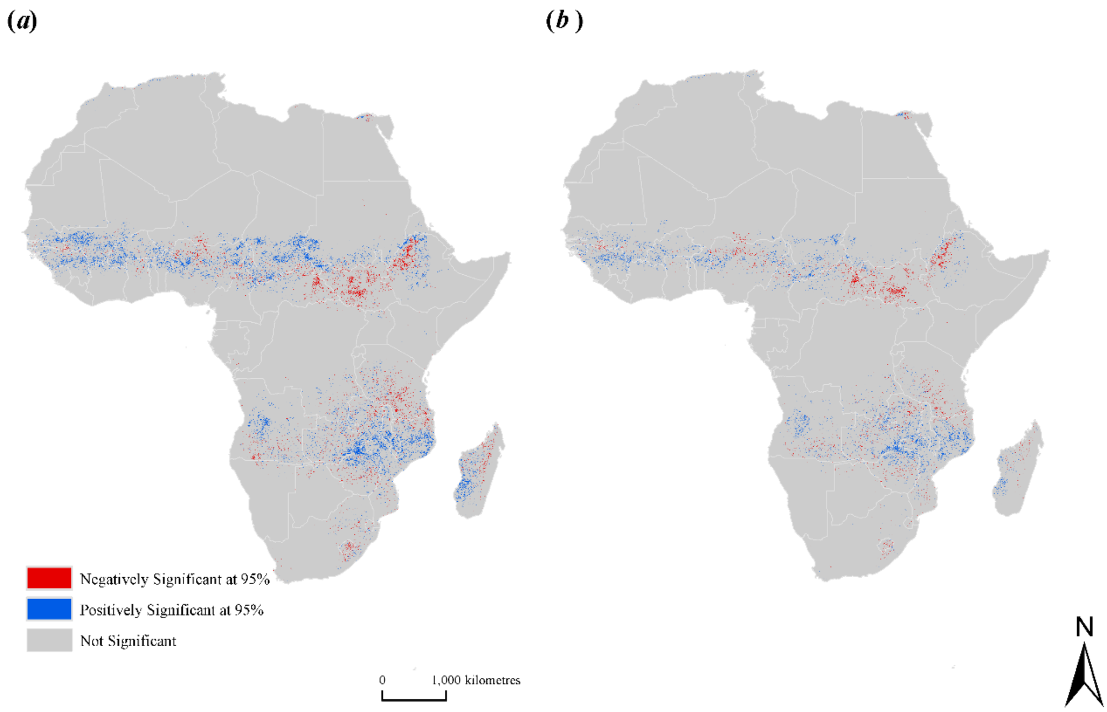

Figure 5.3 Spatial distribution of significant inter-annual End of Season (EOS) trends in Africa estimated from 8-day 500 m MODIS-EVI time-series for 2001-2015. (a) All significant LSP trends in both *"no change"* land cover and changed land cover pixels. (b) Significant trends in *"no change"* land cover pixels only. Spatially contiguous areas of positive change (later EOS) and negative change (earlier EOS) are apparent.

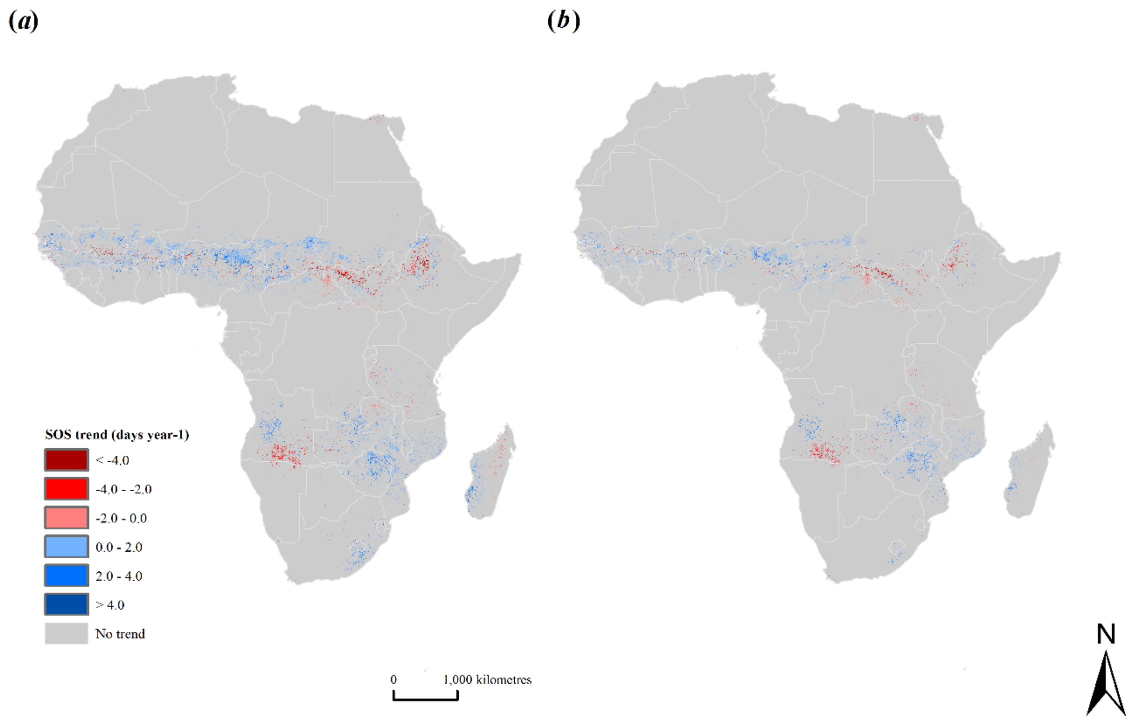

Figure 5.4 Spatial pattern of the magnitude of inter-annual Start of Season (SOS) trends (i.e., magnitude and direction of slope based on linear regression) while controlling for land cover change and using only significant pixels at p<0.05. (a) Magnitude of slope in all pixels. (b) Magnitude of slope in *"no change"* land cover pixels only. Spatially contiguous areas of positive change (later SOS; blue) and negative change (earlier SOS; red) are apparent.

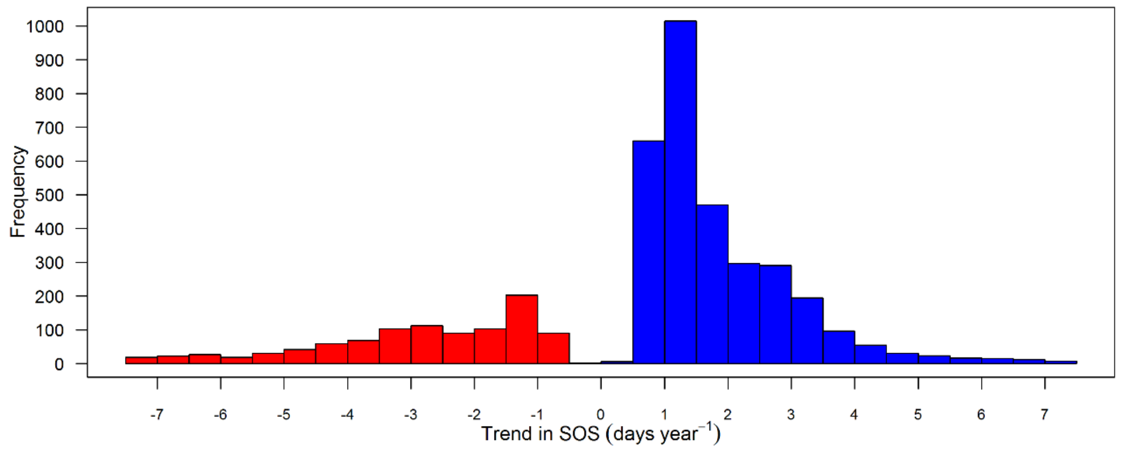

Figure 5.5 The pixel distributions of SOS trends in days year^{-1}.

5.3.3 LSP trends based on land cover change

Table 5.2 shows the number and proportion of land cover change events and their corresponding significant trends. The significant SOS trends in the *"one change"* category with 18% of the total number of pixels had 4.41% of the total significant trend, while the *"no change"* category with 75% of the total number of pixels had 3.96% of the total significant trend. In addition, linear regression of a 13 years profile of significant pixels in both the "*one change"* and *"two changes"* categories showed significant shifts in LSP parameters. This can be seen in Figure 5.6 which shows the time-series for two pixels, one in the (a) *"one change"* category and the other in the (b) *"two changes"* category. In both cases, the SOS dates shifted from February to June as the land cover changed from woody savanna/savanna to croplands and/or grasslands. The results show that SOS dates were delayed with an average of 9.5 days year^{-1} in both categories of change. In the same way, EOS dates shifted from December to February with an average increase of 5 days year^{-1}. Inevitably, LOS shortened by an average rate of 4 days year^{-1} for both categories of change. However, there was no significant difference between the rate of change in the different land cover change categories.

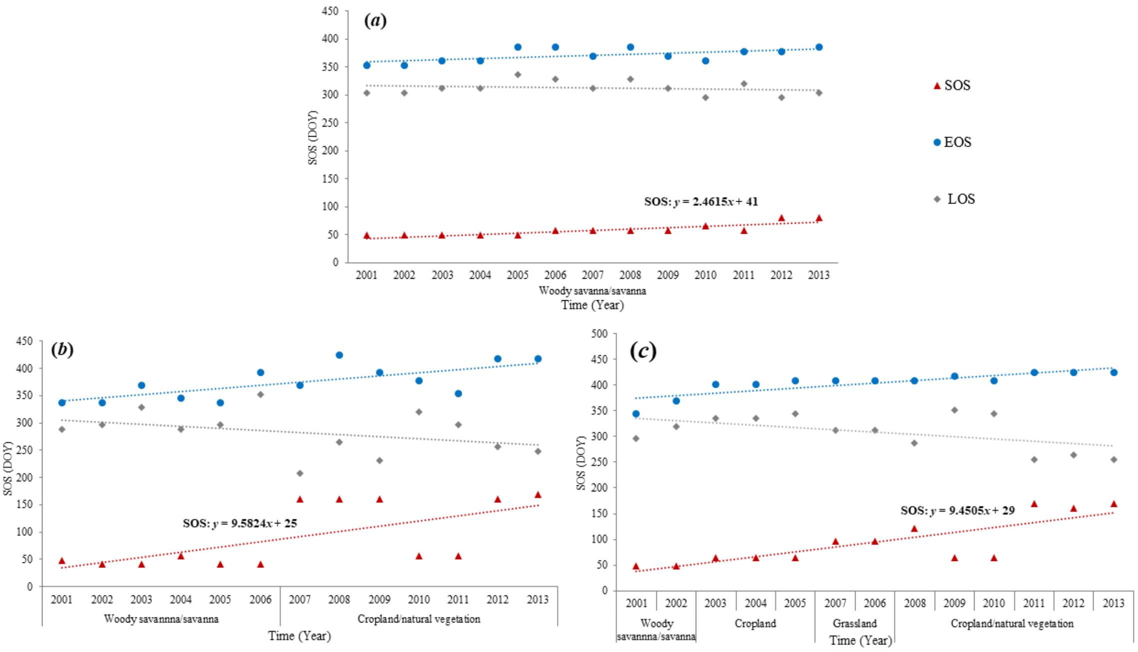

Figure 5.6 Examples of temporal profiles of phenological parameters plotted against year and showing the land cover changes through time. Dotted lines show fitted regression models, which illustrate the rate of change in land cover per year. (a) *"no change"*, (b) *"one change"* and (c) *">two changes"* land cover categories. The trends in the phenological parameters is greater in the *"changed"* pixel categories than in the *"no change"* category.

5.4 Discussion

Several studies have suggested that significant changes have occurred in Africa's vegetation in recent decades (Eklundh, 2003; Herrmann *et al.*, 2005; Martínez *et al.*, 2011; Zhou *et al.*, 2014). It has also been implied that changes in land cover can equally drive changes in the rate of green-up observed from remote sensing methods (Hoscilo *et al.*, 2015), and the findings of this research support this view. It is, therefore, accepted that changes in land cover can significantly influence observed LSP trends and, consequently, any inferences made about the impact of climate changes on vegetation phenology. Analysis of the set of LSP trends across all of Africa revealed that of the 11.56% (SOS), 12.97% (EOS) and 5.72% (LOS) of pixels that were significantly trending, an estimated 65 – 70% belong to "*changed*" land cover change categories (i.e., pixels that have changed land cover type in the time period 2001 to 2013). Although, climatic factors may have contributed to these LSP trends, as shown in Figure 5.6, changes in land cover can also influence LSP trends. This is because phenological response to environmental cues varies based on the type of land cover (Guan *et al.*, 2014b; Ryan *et al.*, 2017). Additionally, pixels with a greater slope magnitude were observed more frequently in the "*changed*" pixels category compared to the *"no change"* category.

Previous studies are generally in agreement with our findings (Heumann *et al.*, 2007; Vrieling *et al.*, 2013) with respect to the overall pattern of LSP trends and the observation of significant positive LOS being associated mostly with delayed EOS. This was seen irrespective of the datasets and study periods of the different studies, therefore, indicating the influence of other common drivers of LSP.

Some interesting differences with previous studies were observed. While Heumann *et al.* (2007) found significant positive trends for LOS across the whole of western Africa, the present results revealed *"delayed shorter seasons"* in LOS in northern Nigeria (i.e. significant negative trends in LOS were associated mainly with significant positive trends in SOS). Similarly, the magnitude of the rate of change in days year^{-1} in this analysis was greater than those from Julien and Sobrino (2009); Vrieling *et al.* (2013) and Zhang *et al.* (2014). These differences could be attributed to the types of dataset and the duration of the study periods used in these studies (de Beurs & Henebry, 2005; Zhang *et al.*, 2014b). While these previous studies used the 8 km AVHRR NDVI datasets with longer duration ranging from 1981 to 2011, none exceeding 2011, the present study used the EVI derived from the MODIS/Terra Surface Reflectance 8-Day L3 Global 500 m product. This much finer spatial resolution is expected to reveal greater variation in trends due to the well-known spatial convolution associated with the measurement process. Also, the present study period (2001 to 2015), while not as long as for some previous studies, accounted for more recent seasonal vegetation events across the continent. However, there are some issues associated with these data. The degradation of the blue band (Band 3, 470 nm) in these data has been recorded as having a negative influence on temporal trend analysis previously (Wang *et al.*, 2012). In addition, sensor degradation have been shown to influence magnitude of vegetation indices derived from this data, but not seasonality (Zhang *et al.*, 2017). Furthermore, the accuracy of the land cover data which is not very high may have influenced the areas of changes observed in the different change categories. Additionally, as a result of the availability of land cover data not exceeding 2013, an assumption that no significant changes in land cover occurred between 2013 and 2015 was made (while noting that Terra MODIS 500 m data are the earliest with the longest time-series; 2000-present). Another assumption in this research was the consistency of the unchanged land cover pixels of cropland/natural vegetation mosaic. Changes in the percentage composition of this land cover type and inter-annual crop rotation to a different crop type can significantly influence LSP timings. Also, the analysis of LSP trends to determine the magnitude of change based on land cover changes was restricted to the time period 2001 to 2013.

5.5 Conclusion

Trends in phenology are increasingly being used to infer the effects of climate changes on vegetation development and growth patterns. Understanding the drivers of vegetation phenological trends is, therefore, paramount in vegetation-climate studies. However, most studies analyse the relation of phenology with these drivers without due consideration for confounding land cover changes which may also significantly impact LSP. Considering the magnitude of the land cover changes taking place across the African continent, this research controlled for land cover change such as to analyse inter-annual time-series of LSP parameters independent of these effects. For the purposes of comparison, we also analysed LSP trends for pixels for which the land cover changed.

When controlling for land cover change, significant trends were observed in all groups of pixels, and an estimated 70% of these trends in both SOS and EOS were significantly positive, that is, mostly delayed SOS and EOS dates. These occurred more in the Sudano-Sahelian and Sudanian regions of Africa. Importantly, the land cover changes significantly affected the LSP trends; larger trends were observed in the “changed” land cover groups. If these land cover changes were not controlled for in the LSP trend analysis, some of the reported trends would have been erroneously significantly larger. Based on these results, we suggest that future analyses of LSP trends should control for land cover changes such as to isolate those LSP trends that are solely climate-driven and/or those influenced by other anthropogenic activities or a combination of both.

Chapter 6: Large scale pre-rain vegetation green up across Africa

6.1 Introduction

The African continent contains the world's largest area of savanna and around 17% of the world's tropical forests. Savannas alone account for 30% of the primary production from global terrestrial vegetation, underlining the importance of the African vegetation (Grace *et al.*, 2006). Indeed, African vegetation contributes 38% of the global climate-carbon cycle feedback (Friedlingstein *et al.*, 2010). In spite of this, African vegetation is relatively under-studied (Adole *et al.*, 2016), and the few existing vegetation models are associated with significant uncertainties (Scheiter & Higgins, 2009; Hemming *et al.*, 2013). Another fundamental concern is the vulnerability of African vegetation to climate change, further worsened by interactions between changes in climatic drivers and anthropogenic land use, which puts at risk both the condition and the amount of overall vegetation cover (IPCC, 2014). Apart from their role in global carbon sequestration, the savannas and forests of Africa support a large number of ecosystem services, which are also vulnerable to climatic and anthropogenic changes; for example, the perceived threat to livestock farming and production due to expanding woodlands (Skowno *et al.*, 2016), and reduced crop productivity caused by increasing temperatures and changes in precipitation (Brown & Funk, 2008). These ecosystem services, in addition to their functions, are influenced heavily by the condition of vegetation and its seasonality (Brottem *et al.*, 2014), which could lead to multiple feedbacks into the climate system (Keenan *et al.*, 2014; Buitenwerf *et al.*, 2015; Wu *et al.*, 2016). In the context of anthropogenic, agro-climatic and climate changes, which may affect future ecosystem services, greater understanding of vegetation dynamics across Africa and its drivers is crucial.

In recent years, the importance of phenology has increased as a result of a wide range of empirical-, modelling- and meta-analysis-based evidence, suggesting that long-term changes in key phenological parameters such as the start of season and end of season are key indicators of biological impact resulting from climate change (Cleland *et al.*, 2007; Richardson *et al.*, 2013). Moreover, the role of several climatic factors has been identified in the seasonal timing and seasonal productivity of vegetation cycles (Ma *et al.*, 2015; Shen *et al.*, 2016). Specifically, in arid and semi-arid environments water availability is deemed to be the primary factor controlling vegetation seasonality and growth (Zhang *et al.*, 2005; Chidumayo, 2015). Of particular interest is the close linkage between precipitation and vegetation growth. Studies have suggested that rainfall control of vegetation greening trends (Hickler *et al.*, 2005; Martínez *et al.*, 2011) was associated with the 1980s recovery of vegetation growth from the Sahelian droughts (Olsson *et al.*, 2005). Likewise, parameters estimated from seasonal growth patterns of vegetated land surfaces have been shown to be correlated with derivatives of rainfall data (Zhang *et al.*, 2005; Guan *et al.*, 2014b; Verger *et al.*, 2016). The start of vegetation growing season (SOS) and start of raining season (SRS) have been shown to be highly correlated by several researchers (Zhang *et al.*, 2005; Guan *et al.*, 2014b). Despite these general findings, the dynamics of vegetation growth are not identical in areas with similar rainfall regimes, suggesting that rainfall alone does not satisfactorily explain vegetation growth patterns. For example, non-climatic greening was observed in some parts of sub-Saharan Africa (Hoscilo *et al.*, 2015), and no significant relationship was found between SOS and SRS in the northern Sahara desert (Yan *et al.*, 2016).

"Pre-rain green-up" is an interesting phenomenon whereby vegetation growth starts at the end of the dry season, just before the start of the rainy season (Ryan *et al.*, 2017). This phenomenon has been observed as far back as the 1940s in some woody species at the field scale (Miller, 1949). With the emergence of remote sensing of land surface phenology (LSP) (defined as *"the seasonal pattern of variation in vegetated land surfaces observed from remote sensing"* (Friedl *et al.*, 2006)), pre-rain green-up has now been observed across larger areas, but mostly in African woodlands (Guan *et al.*, 2014b; Ryan *et al.*, 2017; Yan *et al.*, 2017). However, the number of studies is limited and does not describe the nature and extent of this relationship at the continental scale. Similarly, only a few studies undertaken at the regional scale have attempted to investigate the lag between the end of rainy season (ERS) and the end of vegetation growing season (EOS) in Africa (Zhang *et al.*, 2005; Yan *et al.*, 2017). Therefore, detailed quantification of the magnitude and frequency of this pattern across different vegetation types at the continental scale is currently needed. Consequently, this research seeks to answer the following questions:

(1) what is the magnitude and spatial distribution of the time lags between vegetation phenophases and rainfall parameters across the different vegetation types in Africa?

(2) what is the magnitude of the association between vegetation phenological and rainfall parameters across the different vegetation types in Africa?

Understanding the relationships between LSP and rainfall parameters is critical in developing a robust phenological model and LSP representation in terrestrial ecosystem models. Currently, most global land-atmosphere models have shown varying projections of vegetation response to climate change, associated with large uncertainties in the terrestrial carbon cycle (Shao *et al.*, 2013). These uncertainties are known to arise from inaccurate estimation of seasonal productivity patterns

(Restrepo-Coupe *et al.*, 2017), incorrect assumptions in biosphere–atmosphere process models driven by vegetation growth (Whitley *et al.*, 2016), and poor understanding of functional responses of vegetation phenology to climate change (Richardson *et al.*, 2012). Moreover, current climate change models predict uneven rainfall distribution both in terms of timing and amount across the continent; some areas are expected to receive excess rainfall, whereas other regions are expected to receive less (Res *et al.*, 2001; Niang *et al.*, 2014). This in turn, will affect the vegetation phenology and the resulting vegetation-atmosphere feedbacks such as albedo, water, energy and gas fluxes across the region (Wu *et al.*, 2016).

We used satellite remote sensing and meteorological data to quantify the lag in number of days between SRS and SOS, and ERS and EOS. We further examined the relationships between a range of LSP and rainfall parameters, including the length of growing season (LOS) with length of raining season (LRS), and time of maximum vegetation growth (VItmax) with time of maximum rain (Rtmax), across all of Africa. The productivity-based relationship between Integrated EVI (IntEVI) and cumulative annual rainfall (Rcum) was also explored.

By investigating the above relationships, we provide the most comprehensive and detailed view of the response of vegetation phenological variables to rainfall across Africa, by vegetation type. This greater insight into the mechanisms underlying African vegetation dynamics provides useful information necessary to support and increase the accuracy of future terrestrial biosphere models (TBMs) and global ecosystem models.

6.2 Data and methodology

6.2.1 Data processing and analysis

6.2.1.1 MODIS data and LSP estimation

The LSP parameters estimated from the Enhanced Vegetation Index (EVI) derived from 500 m surface reflectance Moderate Resolution Imaging Spectroradiometer (MODIS) (MOD09A1) were used for this study. Methodology of LSP estimation and EVI derivation are detailed in chapter four. Similarly, only the first season LSP parameters results were considered for this analysis. 13 years (2001 – 2013) of MCD12Q1 tiles covering the entire African continent was also used for this study. Homogeneous pixels over the 13 years record of the MCD12Q1 were extracted and used to stratify the land cover into their different vegetation types. Only five major classes were used for this analysis: (1) Croplands, (2) Forest (Deciduous and evergreen forest) (3) Grasslands (4) Shrublands (Closed and open shrublands), and (5) Woodlands (Woody savannas and savannas) (Table 6.1 and Figure 6.1). The derived MODIS Land cover classes were then used as a mask to select class-specific LSP parameters. A schematic diagram of the methodology is provided in Figure 6.2. Five LSP parameters (Start of growing season (SOS), End of growing season (EOS), Length of growing season (LOS), time of maximum EVI (VItmax), and Integrated EVI (IntEVI)) were estimated for each cycle (Figure 6.3). This led to estimates of each LSP parameter in each of a total of 15 years (2001 – 2015).

Table 6.1 Reclassification of land cover types into broad categories based on the International Geosphere Biosphere Programme (IGBP) global vegetation classification scheme.

IGBP number	Initial land cover types	Merged land cover type
1	Evergreen needleleaf forest	Forest
2	Evergreen broadleaf forest	
3	Deciduous needleleaf forest	
4	Deciduous broadleaf forest	
5	Mixed forest	
6	Closed shrublands	Shrublands
7	Open shrublands	
8	Woody savannas	Woodlands
9	Savannas	
10	Grasslands	Grasslands
12	Croplands	Croplands
14	Croplands/natural vegetation mosaic	Croplands/natural vegetation mosaic
11	Permanent wetlands	Non-vegetative cover
13	Urban and built-up land	
15	Permanent cnow and ice	
16	Barren or sparsely vegetated	
17	Water	

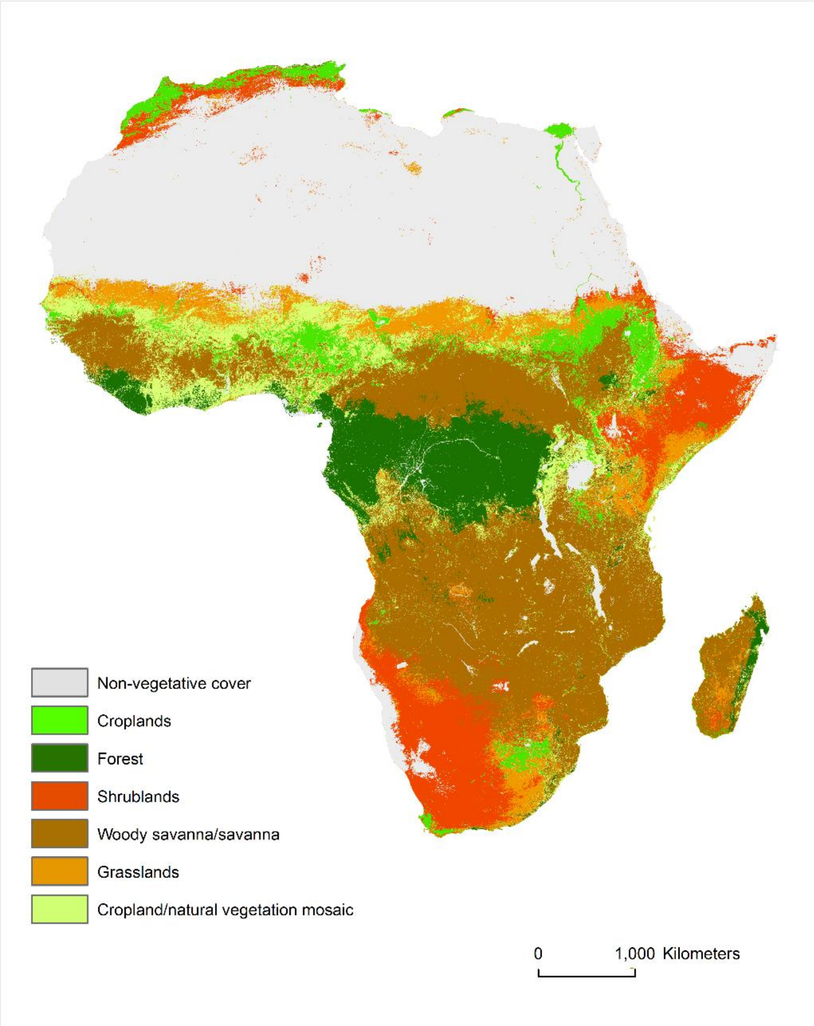

Figure 6.1 Reclassified 2013 MODIS land cover product (MCD12Q1).

6.2.1.2 CHIRPS data and rainfall parameters estimation

This study used the 0.05^{O} gridded rainfall dataset from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). This dataset was generated by combining satellite sensor and station data using smart interpolation techniques, and has been shown to have less bias in examining wet seasons than most other products, especially in data-sparse regions in Africa (Funk *et al.*, 2015). It has also been shown to be more precise in estimating the entire seasonal cycle of rainfall because it is spatially more detailed and corresponds more closely to ground data (Toté *et al.*, 2015). As with the MODIS data, 16 years of daily rainfall data from 2000 to 2016 were downloaded from CHIRPS (http://chg.geog.ucsb.edu/data/chirps/).

The SRS (SRS) and end of rainy season (ERS) have been determined in a variety of ways, and there is still no consensus on the most appropriate definition. Examples can been seen in Liebmann *et al.* (2012) and Yan *et al.* (2016) who employed the climatological anomalous accumulation method in determining start and end of rainy season, and Zhang *et al.* (2005) and Guan *et al.* (2014) who employed the percentage method. In this research, we adopted the definition first proposed by Stern *et al.* (1981), and used by several researchers (Sarria-dodd & Jolliffe, 2001; Segele & Lamb, 2005; Mupangwa *et al.*, 2011; Rosell, 2011). This method defines SRS as the first period of two to 10 days where specified amounts of rainfall (10, 20, 30 mm) are reached or exceeded followed by no continuous dry period of specified length (7, 8, 10 days). This approach was selected as it is designed to also account for sowing dates in croplands to remove false start dates. First, a threshold was set to differentiate between wet and dry days. All wet days had at least 0.1 mm rainfall and others below this threshold were classed as dry days (Sarria-dodd & Jolliffe, 2001). To follow the same cycle for the EVI time-series, two sets of criteria were adopted to determine the SRS: (1) the first wet day in a 40 day duration after a dry spell where the total rainfall in the first consecutive 10 days is 25 mm or more, which is followed by no consecutive dry period of seven days or more, (2) the first wet day in a 30 day duration after a dry spell where the total rainfall in the first consecutive three days in a row is 15 mm or more which is followed by no consecutive dry period for 10 days or more. If one the criterion is not met, then testing resumes considering the other.

End of season dates were defined as dates after the start of season where no rain occurs over a period of 20 days or in a 30 day duration, the total number of wet days is less than four (Sivakumar, 1988; Zhang *et al.*, 2005).

Due to the complexity of rainy seasons in Africa, especially for regions with a bimodal annual rainfall cycle, results were rigorously cross-checked again for false starts. This involved an iterative procedure to check if start dates occurred around 10% of the total annual precipitation and end dates occurred around 99% of total annual precipitation. In addition, spatial agreement was seen in the results when compared with previous studies on seasonal rainfall onset and end dates retrievals (Zhang *et al.*, 2005; Brown & de Beurs, 2008; Liebmann *et al.*, 2012; Guan *et al.*, 2014b)

Other rainfall parameters derived were: the length of rainy season (LRS) which is the number of days between SRS and ERS, time of maximum rainfall (Rtmax) and cumulative annual rainfall (Rcum).

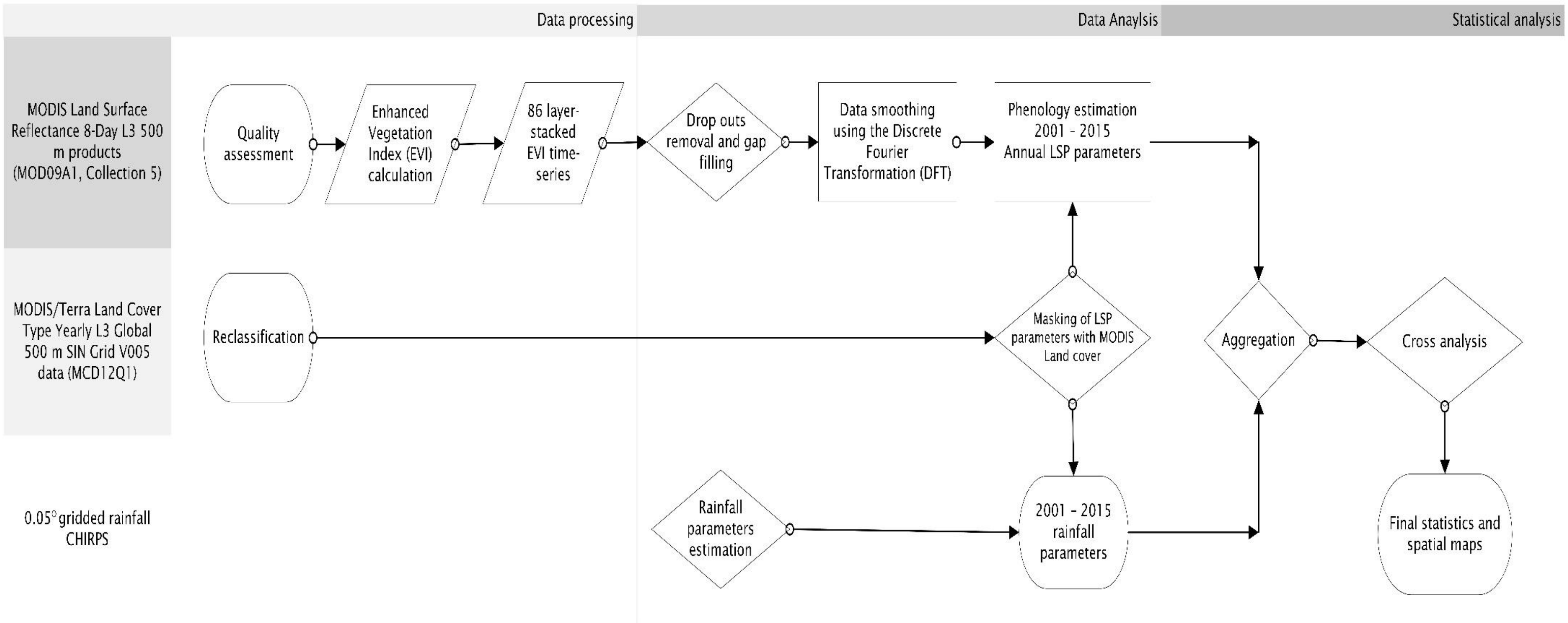

Figure 6.2 Flow chart describing the study methodology in three major steps: (1) data processing, (2) data analysis and (3) statistical analysis.

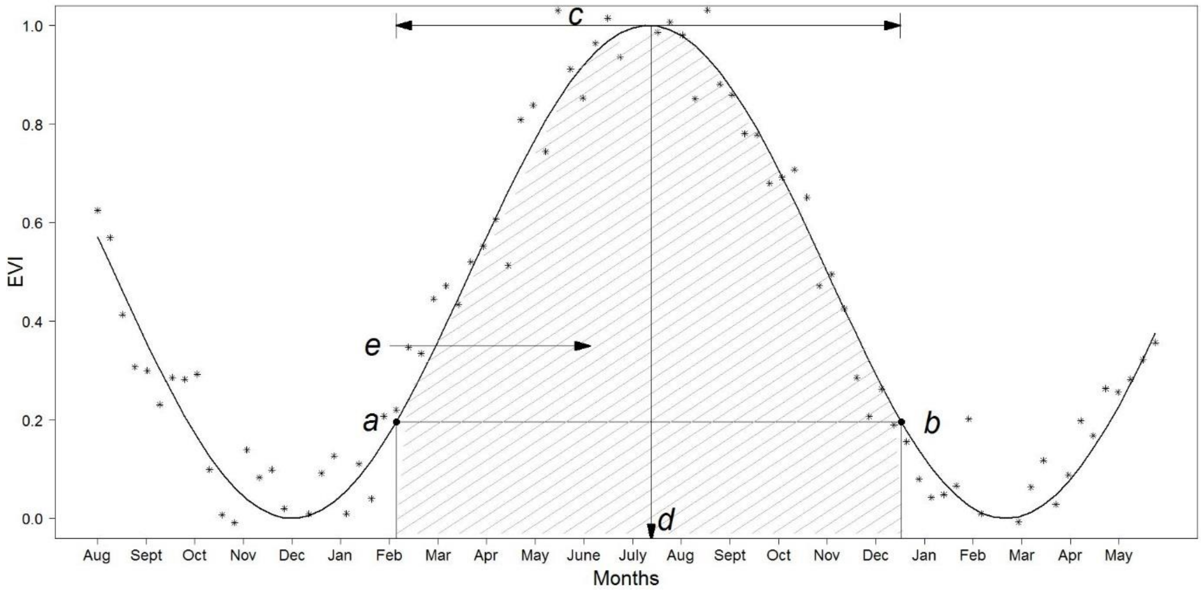

Figure 6.3 An illustration of LSP parameters used in this study. Black line illustrates smoothed time-series, (a) Start of season (SOS), (b) End of season (EOS), (c) Length of season (LOS), (d) Time of maximum EVI (VItmax), and (e) Integrated EVI (IntEVI).

6.2.1.3 Statistical approach

All LSP parameters were aggregated to match the spatial resolution of the rainfall data by assigning the modal value in 10 by 10 0.005^0 grid cells to a 0.05^0 grid cell. The mode was used because the mean can be skewed due to the occurrence of outliers, and the median is less representative of the average of a dataset. Pixels showing no clear vegetation seasonality were excluded from the analysis. Pixels with no distinct rainfall seasonality for the entire time-series were also excluded.

The lag, which is the time difference in number of days between SOS and SRS, and EOS and ERS, was calculated for each land cover type. A -10 and 10 days “no change” category was applied to the start of growing and rainy season lags to account for uncertainties in the SOS and SRS estimates and the MODIS 8-day composites. This range was selected because lags of less than 10 days may sometimes arise due to the difference in the Julian date of the MODIS 8-days composite and the daily rainfall data. Further analysis involved fitting linear regression models to determine the association of spatial shifts with the means of different combinations of LSP and rainfall parameters (Table 6.2).

6.3 Results

6.3.1 Frequency of lags between LSP and rainfall parameters across Africa

The difference between the start of rainfall and start of season and can be categorised into three categories: (a) SOS arriving much before the SRS, (b) SOS arriving after the SRS and (c) SOS arriving at the same time as SRS. Figure 6.4 presents these differences for croplands, grassland and woodlands pixels. Cropland pixels were in the second category showing SOS arrival after SRS, while grasslands were in two categories: SOS arriving at the same time as SRS and SOS arriving before SRS. Woodlands, on the other hand, showed SOS arriving much before the SRS.

Across all Africa, SOS generally occurred prior to the SRS except in the Sudano-Sahelian region were SOS occurred after the SRS (Figure 6.5). The distribution of the pixels seen in Figure 6.5c is skewed towards positive lag values with more occurring between 15 and 45 days (i.e., SOS before SRS). More than 88% of the studied vegetative area had SOS arriving more than 10 days before the SRS, of which 90% of this amount was found in woodlands. These were distributed all across Africa, but ubiquitous in southern Africa, having longer lags concentrated more in Angola and Zambia. An estimated 9% had lag days between -10 and 10 days (i.e. SOS and SRS arriving almost at the same time), with over 90% occurring in woodlands. As seen in Figure 6.5, approximately 3% of the studied vegetation, mainly along the Sudano-Sahelian region, had SOS arriving 10 days or more after the SRS (i.e. < -10 days lag), with over 35% of this area belonging to croplands and about 46% to woodlands. More of these croplands with longer lag time were seen in eastern Africa particularity in Ethiopia, while the woodlands were mostly located in western Africa.

Figure 6.6 shows the distribution of the lag occurrences within each land cover type. Within the croplands pixels, an estimated 10% had SOS arriving at the same time as the SRS, and over 80% had SOS arriving after the SRS. The average lag times for croplands were -18 days in the north and 54 days in the south. In contrast, over 89% of woodlands had SOS arriving before the SRS, with averages of 29 days in the north and 36 days in the south, clearly showing longer lag times in southern woodlands as seen in Figure 6.5.

Grasslands and shrublands had very similar onset lag patterns of an early SOS before the SRS in over 80% of pixels with averages of 38 and 34 days, respectively. However, 11% of shrublands compared to 1% of grasslands had SOS arriving after the SRS.

In contrast to the SOS, the EOS generally lagged behind the ERS across all Africa (Figure 6.4 and Figure 6.7) with a longer lag duration in southern Africa. Interestingly, the Sudano-Sahelian region also showed a distinct pattern of lag range between 90 to 120 with peaks in western and eastern Africa of 120 -150. In addition, the distribution of pixels (Figure 6.7c) unlike SOS had several peaks within a wide range of values (50 to 120 days). Over 90% of pixels had a lag between 30 to

150 days, with the longest durations occurring in woodlands. While most land cover types had varied lags, over 70% of grasslands varied between 30 to 60 days.

It is interesting to analyse these results in relation to the season lengths (length of growing season (LOS) and length of rainy season (LRS)). In general, pixels with SOS arriving after SRS had shorter LOS (Figure 6.8), when compared to those with SOS arriving before SRS. The average LOS within these pixels varied between 220±30 days to 250±40 days while those with SOS arriving before SRS varied between 270±45 days to 300±30 days. The length of rainy season (LRS) within both categories of pixels varied greatly, and no observable pattern was detected.

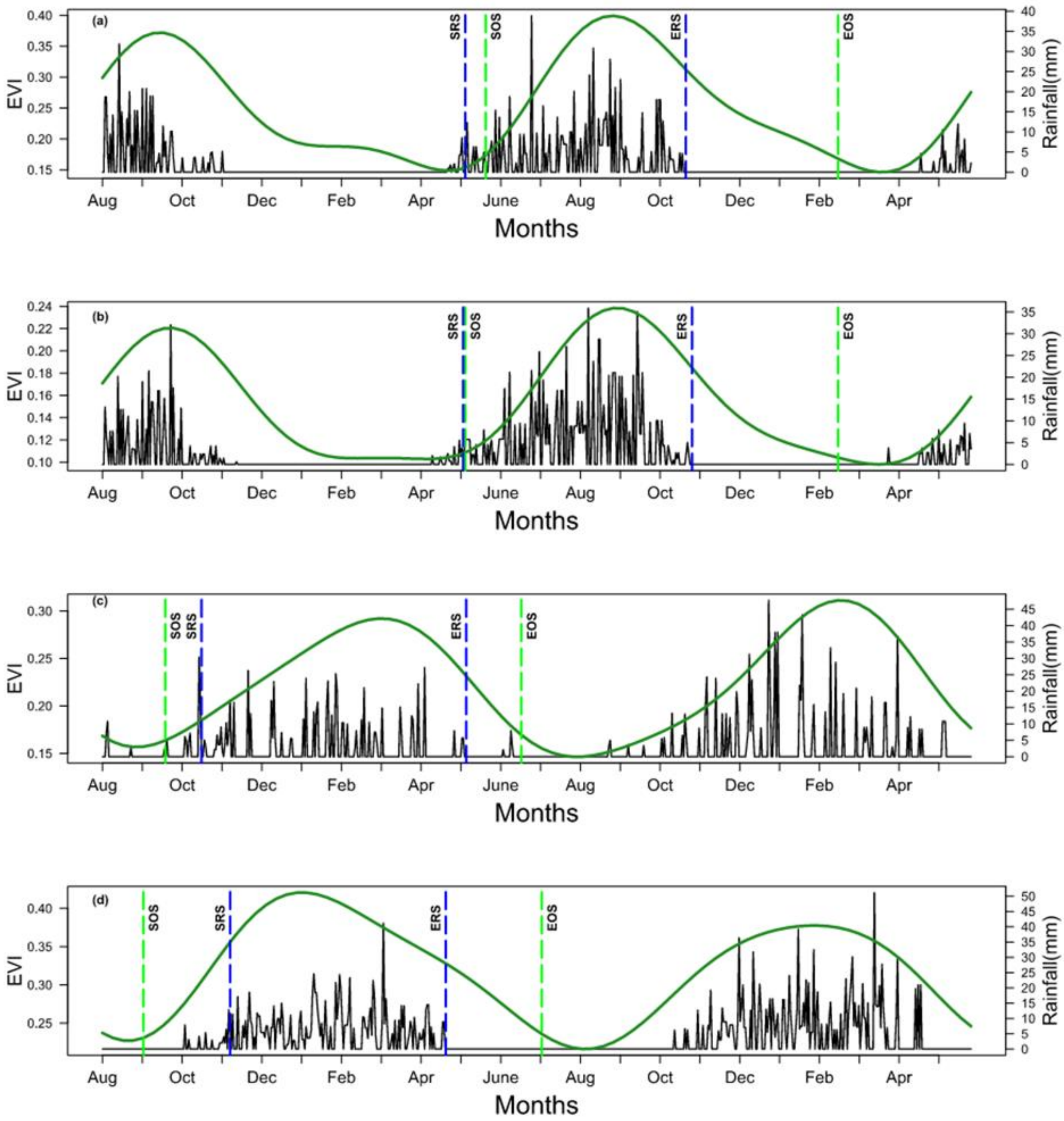

Figure 6.4 Examples of pixel profiles for a complete cycle of EVI and daily rainfall time-series. EVI time-series is represented by green curved lines while rainfall is represented by black bars. Vertical dashed lines show LSP and rainfall parameters (SOS and EOS in green and SRS and ERS in blue). (a) Croplands in the Sudano-Sahelian region showing SOS arriving after SRS, (b) Grasslands in the Sudano-Sahelian region showing SOS and SRS arriving approximately at the same time, (c) Grasslands in southern Africa showing SOS arriving before SRS, and (d) Woodlands in southern Africa showing SOS arriving well before SRS.

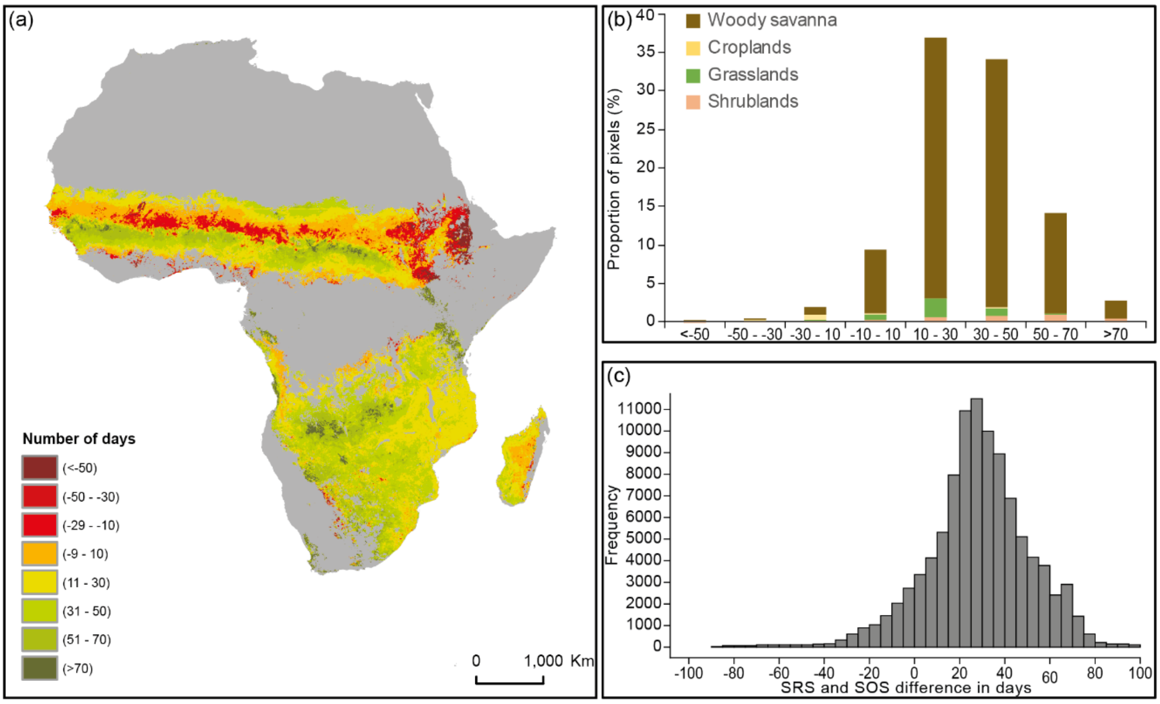

Figure 6.5 Difference in days between SRS and SOS (i.e., SRS - SOS in days). Positive values indicate SOS arriving before SRS while negative values indicate SOS arriving after SRS. (a) Spatial distribution of SOS and SRS difference in number of days. (b) Proportion of pixels by land cover in different categories of SOS and SRS lag. (c) Frequency distribution of SRS and SOS difference.

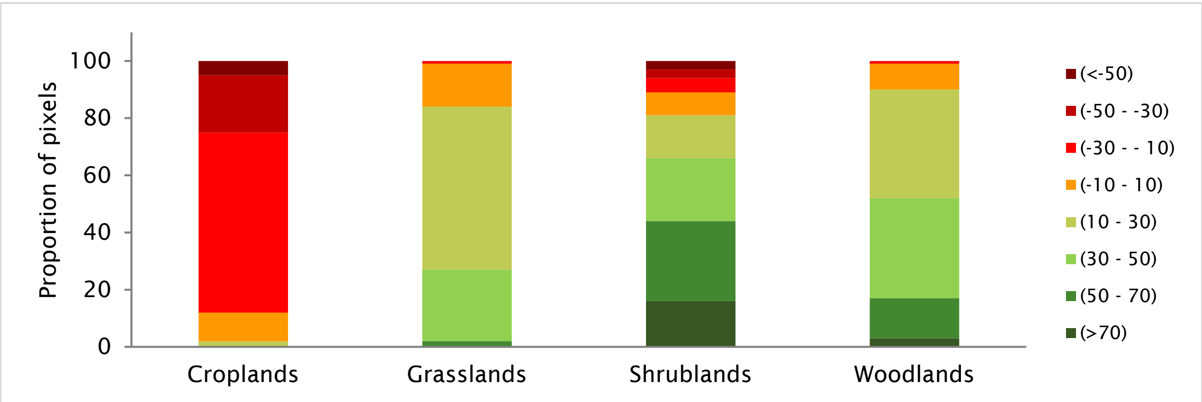

Figure 6.6 Proportion of pixels in each land cover type in the different categories of SOS and SRS lag.

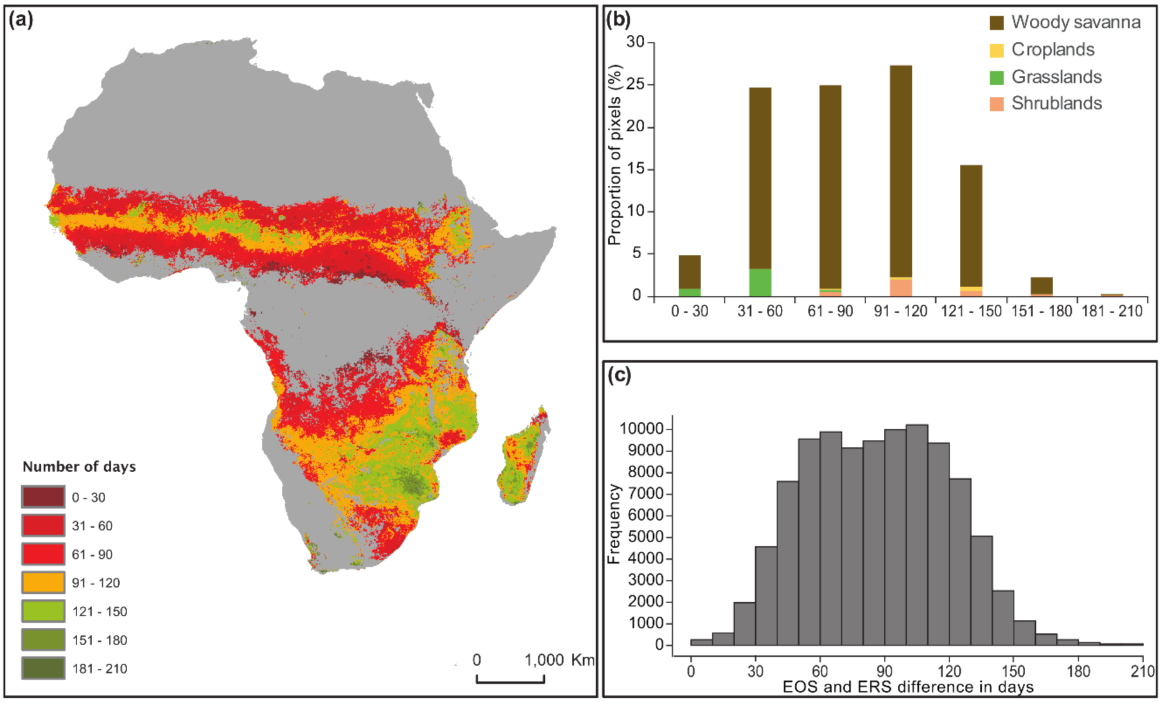

Figure 6.7 Differences in days between EOS and ERS (i.e., EOS - ERS in days. Positive values indicate EOS arriving after ERS while negative values indicate EOS arriving before ERS. (a) Spatial distribution of EOS and ERS difference in number of days, (b) Proportion of pixels by land cover type in different categories of EOS and ERS lag, (c) Frequency distribution of EOS and ERS difference.

6.3.2 Summary of spatial patterns of LSP and rainy seasons

The spatial distributions of LSP and rainfall parameters are broadly similar following latitudinal patterns. Figure 6.8 shows the averages over the entire period of 2001 – 2015 for the three LSP parameters (SOS, EOS and LOS) and three rainfall parameters (SRS, ERS and LRS). The SOS and SRS occur earlier (shifting from 0^0 to 20^0 N around late February to early August) in the north, and later in the south of Africa roughly between August and December (Figure 6.8a**)**. Inter-annual variation in both SOS and SRS is much greater in the south (Figure 6.9 and Figure 6.10), with average standard deviation (STD) values of 22 and 19 days, respectively. Similarly, EOS and ERS were later in the northern latitudes and earlier in the southern latitudes. However, large spatial variation was observed in EOS in the Sudano-Sahelian region (Figure 6.8b), and mostly in croplands. This variation was also apparent in the STD pattern for EOS, with large STD (>60 days) in this region, and only about 58% of pixels with STD values of <30 days (Figure 6.9). The durations of LOS and LRS were generally longer for LOS across Africa, with lengths >300 days mostly in the Sudano-Sahelian region. In addition, compared to LOS, the latitudinal pattern of LRS in northern Africa was more distinct from 60 to 270 days duration than that of LOS (Figure 6.8c).

Other LSP and rainfall parameters also revealed visible spatial patterns (Figure 6.11). For example, VItmax and Rtmax were earlier in the south and later in the north. Also large IntEVI values were observed in the Sudano-Sahelian, Sudanian and Guinean regions, while small IntEVI values were seen mostly in the Sahelian and some parts of southern Africa.

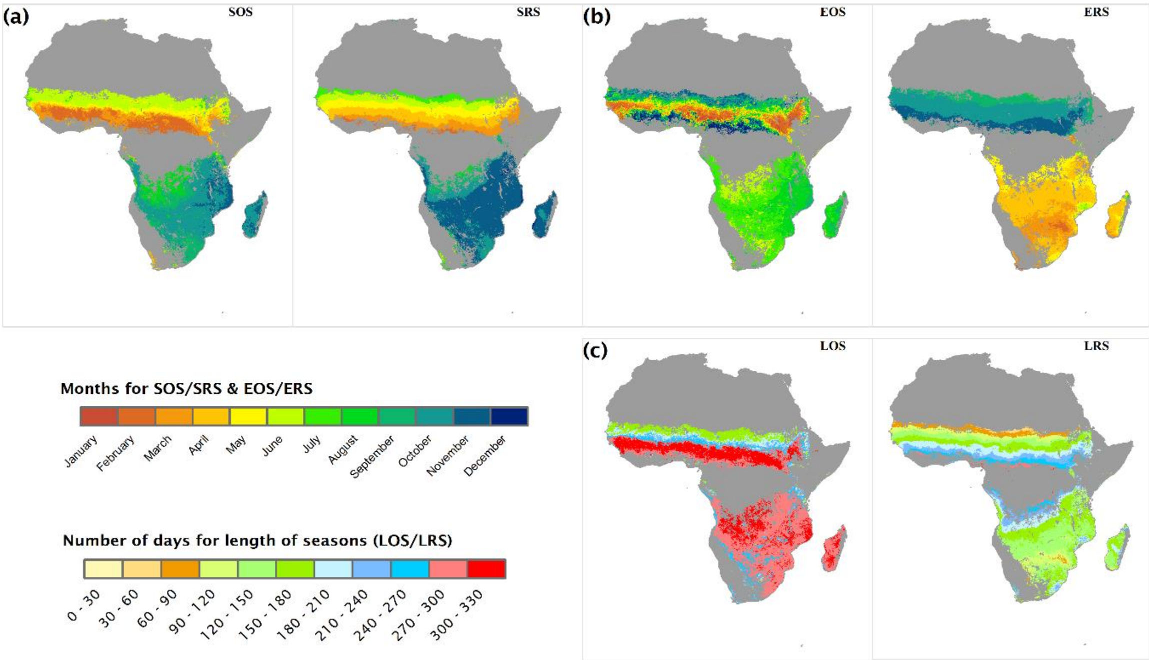

Figure 6.8 Spatial pattern of the average of LSP and rainfall parameters between 2001 and 2015. (a) SOS and SRS and (b) EOS and ERS (shown in months of the year). (c) LOS and LRS (shown in number of days).

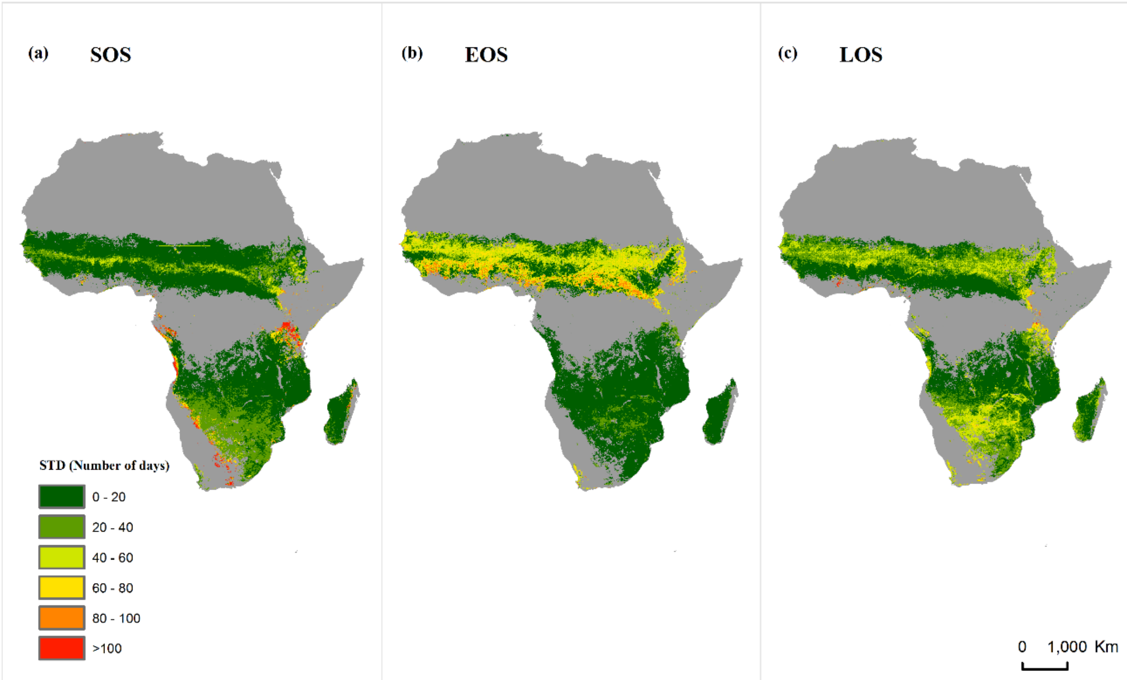

Figure 6.9 Standard deviation of LSP parameters in number of days for the period of 2001 to 2015 for (a) SOS, (b) EOS and (c) LOS.

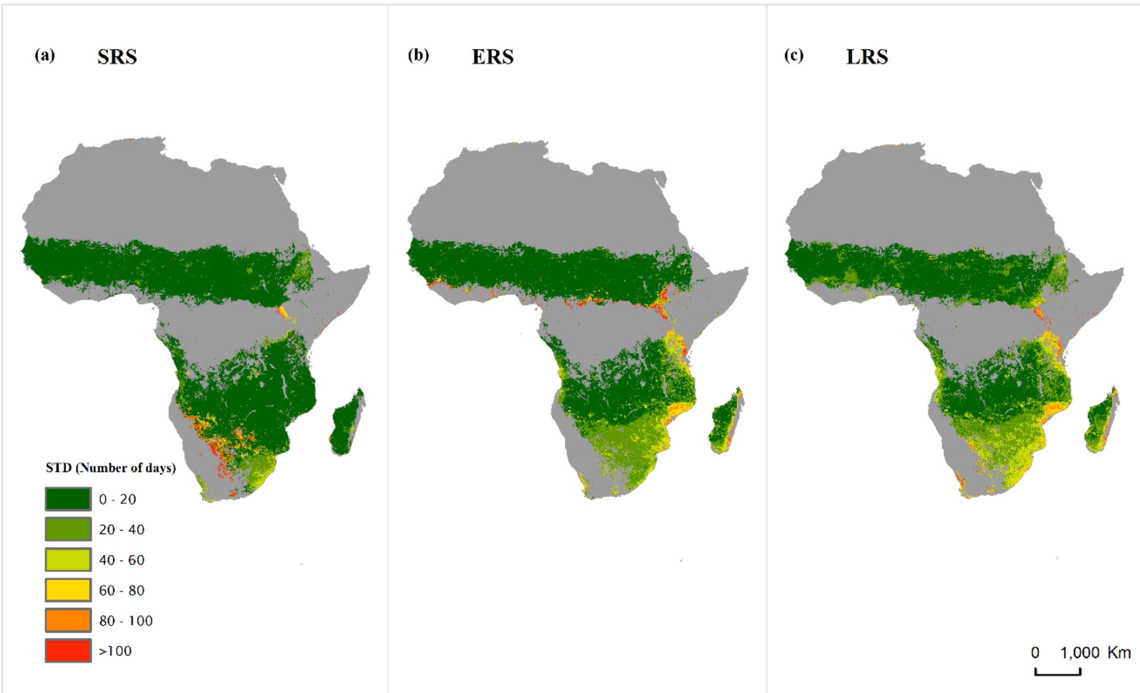

Figure 6.10 Standard deviation of rainfall parameters in number of days for the period of 2001 to 2015 for (a) SRS, (b) ERS and (c) LRS.

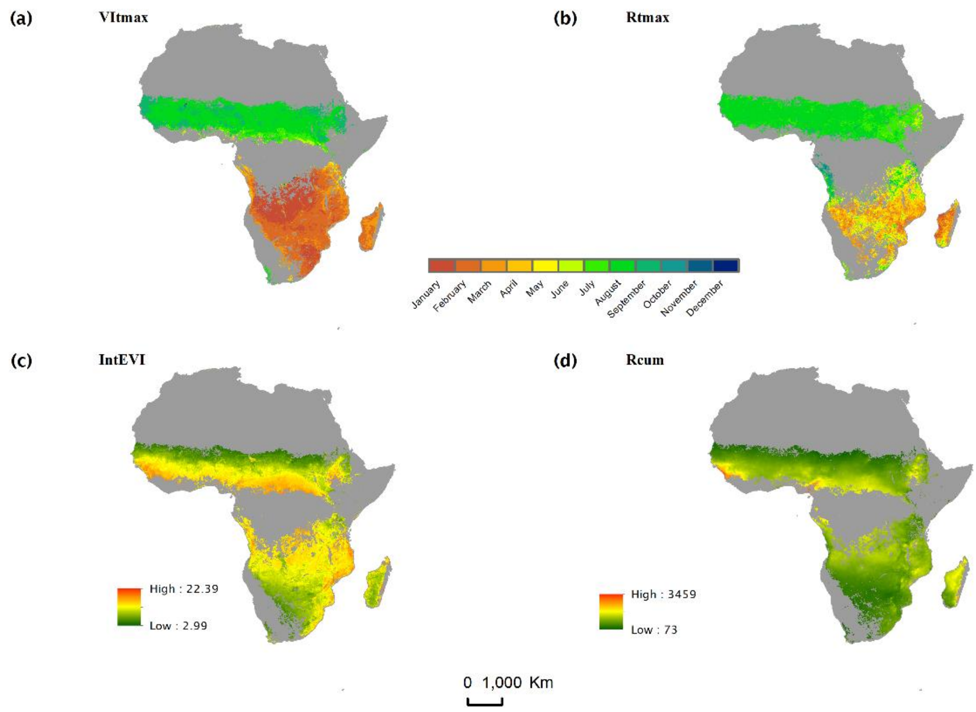

Figure 6.11 Spatial pattern of the average of LSP and rainfall parameters between 2001 and 2015. (a) VItmax and (b) Rtmax (shown in months of the year). (c) IntEVI and (d) Rcum (shown as annual cumulative figures).

6.3.3 Spatial relationships between LSP and rainfall parameters

Table 6.2 shows the results of the spatial association between LSP and rainfall parameters (all statistically significant at $p < 0.0000$). A complex relationship was observed. While a large association was seen between SOS and SRS (R^2= 0.92), IntEVI and Rcum (R^2= 0.58), and VItmax and Rtmax (R^2= 0.52), other combinations of LSP and rainfall parameters showed very little correlation, especially between EOS and ERS, and LOS and LRS. Interestingly, for grasslands, EOS and ERS, and LOS and LRS produced large R^2 values of 0.76 and 0.87, respectively. The same large association was seen across all LSP and rainfall parameters in grasslands, suggesting tight coupling of grasslands with water availability. In contrast, only the timings of onsets (i.e. SOS and SRS) and of maximums (i.e. VItmax and Rtmax), and production (IntEVI and Rcum) produced large R^2 values for woodlands. Although, statistically significant, the relationship between EOS and ERS, LOS and LRS, and LOS and Rcum were very small for woodlands. The same very small association was observed in shrublands between LOS and Rcum. However, in contrast is the weak association seen between SOS and SRS, and between IntEVI and Rcum, in shrublands when compared to all other land cover types.

For croplands, similar to most land cover types (excluding grasslands) the correlation between LOS and LRS was small. In addition, only a small association was observed between VItmax and Rtmax for croplands. However, large correlations were observed for SOS and SRS, and LOS and Rcum.

Table 6.2 Spatial relationship between LSP and rainfall. The spatial associations are reported in R squared values all at p-value <0.000.

Pheno-rain combinations	**Spatial correlation (R^2) (*p*-value<0.000) by land cover class**				
	All	**Croplands**	**Grasslands**	**Shrublands**	**Woodlands**
SOS and SRS	0.92	0.70	0.95	0.31	0.97
EOS and ERS	0.10	0.23	0.76	0.50	0.07
LOS and LRS	0.27	0.18	0.87	0.28	0.09
LOS and Rcum	0.34	0.79	0.82	0.04	0.09
IntEVI and Rcum	0.58	0.37	0.55	0.12	0.57
VItmax and Rtmax	0.52	0.28	0.75	0.72	0.69

6.4 Discussion

6.4.1 Early and late greening response of vegetation to rainfall

Our results suggest that pre-rain vegetation green-up occurs across most of Africa. The results are corroborated by the pre-rain green-up reported previously by a limited set of studies, both ground-based (Childes, 1989; De Bie *et al.*, 1998; Higgins *et al.*, 2011; Seghieri & Do, 2012; February & Higgins, 2016) and satellite-based (Guan *et al.*, 2014b; Ryan *et al.*, 2017; Yan *et al.*, 2017). However, we show that the pre-rain green-up is far more widespread across the entire African continent than previously reported. In addition, we were able to determine quantitatively its occurrence across all the major vegetation types studied, confirming its prevalence mostly in woodlands and grasslands in northern and southern Africa. Our findings show that more pre-rain green-up occurred in woodlands, sometimes as much as 3 months before the onset of rain. This pattern of pre-rain green-up in woodlands was more widespread in the southern part of Africa, consistent with previous work (Ryan *et al.*, 2017).

Several explanations have been proposed for the observed pre-rain green-up. It was suggested that a form of memory mechanism developed from adaptation to previous climatic cues could be responsible for early greening (by about two months) in Miombo woodland in central and southern Africa (Goward & Prince, 1995). Also implicated were daylength and temperature thresholds being responsible for early greening of certain woody plant species in southern Africa (Van Rooyen *et al.*, 1986a). Responses of plants to other anticipatory climatic factors besides rainfall have also been reported in the Australian savanna (Prior *et al.*, 2004; Bowman & Prior, 2005). In Senegal, where we also observed pre-rain green-up, it was suggested that air relative humidity occasioned by the Inter-Tropical Convergence Zone (ITCZ) is a major determinant of early leaf flush in this region (Do *et al.*, 2005). Other mechanisms primarily located within plants have been proposed by several researchers. One of these is the rehydration of stem tissues in the dry season caused by reduction in water stress levels following leaf shedding (Reich & Borchert, 1982; Borchert, 1994; Williams *et al.*, 1997). During this rehydration process, when the required water potential for plant cellular development is attained, early leafing begins (Reich & Borchert, 1982). The phreatophytic nature of some woody plants (their ability to tap underground water reserves with deep root systems, and utilize the previous season's water and nutrients) and low water consumption have also been suggested to cause early green up (Roupsard *et al.*, 1999; Guan *et al.*, 2014b). Similarly, the ability of some woody plants to withdraw and conserve nitrogen and carbon for later use to construct new leaves from these stored reserves has been implicated in early green up (February & Higgins, 2016). These features give savanna trees competitive advantage over their herbaceous neighbours, which can drive temporal niche separation; a possible explanation for pre-rain green-up (Higgins *et al.*, 2011; February & Higgins, 2016; Ryan *et al.*, 2017). Another interesting phenomenon, which may have influenced the pre-rain green-up observed in western Africa, is the reverse phenology of the widely distributed *Faidherbia albida* (Acacia) tree (Roupsard *et al.*, 1999; Seghieri & Do, 2012). This species enters leaf out during the dry season and sheds leaves during the rainy season. As described above, its unique facultative phreatophytism and low water consumption are responsible for the reversed phenological pattern. Besides climatic or endogenously plant-controlled causes of early greening, biotic factors such as pressures from herbivory have been hypothesised as reasons for early initiation of leafing in some woody plants (Aide, 1988, 1992). It was suggested that this is an antiherbivore defence mechanism by plants, essentially to escape seasonally from herbivores in order to avoid nutrient losses caused by herbivory (Aide, 1992; Rossatto *et al.*, 2009). However, evidence supporting this strategy in Africa savannas is unavailable (Higgins *et al.*, 2011).

Contrary to previous work (Guan *et al.*, 2014b), our findings showed pre-rain green-up occurring in the vast majority of grasslands across Africa, albeit with a short duration, mostly within 10 to 30 days. This can be attributed to SOS being triggered by the small bouts of rains that occur just before the actual start of the rainy season. This is possible because grasslands have very high sensitivity to water fluctuations (Scholes & Archer, 1997; Whitecross *et al.*, 2017b). In addition, the large R^2 values in Table 6.2 also suggest this tight coupling of grasslands and water availability across the continent. Our results also showed that pre-rain green-up occurred in some of the shrublands which can be explained by their deep root systems (Childes, 1989).

In contrast to other land cover types, post-rain green-up was largely observed in croplands, all located in the Sudano-Sahelian region (Figure 6.5 and Figure 6.6). This region consists mainly of croplands (Figure 6.1), and is known to have a short rainy season and prolonged dry season (Liebmann *et al.*, 2012; Dunning *et al.*, 2016) (Figure 6.8). This lengthened dry season usually influences farmers' decision to begin sowing, because despite relying to some extent on climatological history, they generally wait for a major burst of rain and ascertain the status of the soil moisture before commencing sowing (Marteau *et al.*, 2011). The variety of crops being cultivated can also explain the post-rain green-up observed. For example, the different species of millet and sorghum sown are largely dependent on water availability for growth, and these are the main staple crops in the Sudano-Sahelian region, cultivated mostly under rainfed conditions (Guan *et al.*, 2015).

Woodlands and shrublands found in the Sudano-Sahelian region revealed post-rain green-up. Leafing of dominant woody plants in this region is controlled by rainfall and, as mentioned above, this is caused by the occurrence of marked shorter rainy seasons (Seghieri *et al.*, 2009). The woody plants in this region endure long dry seasons of over 8 months. Hence, they depend on the occurrence of the first rains to begin leafing (Seghieri *et al.*, 2009; Seghieri & Do, 2012).

The early and late greening responses of vegetation also influence the lag between ERS and EOS. For example, longer EOS lags were evident in vegetation with pre-rain green-up phenological patterns. According to several researchers, this early greening before the onset of rains enables plants to obtain early access to, and optimally utilize, nutrients released during the first rains; hence, the longer growing season for such plants (Do *et al.*, 2005). Nevertheless, long EOS lag durations were observed in the Sudano-Sahelian region, especially in croplands with post-rain green-up. As mentioned above, the variety of crops affects the phenological pattern. Crops such as cassava, grown mostly in western Africa, are usually harvested 9 to 18 months after sowing (Ezui *et al.*, 2016), thus, leading to long lags between the ERS and EOS.

6.4.2 Relationships between LSP and rainfall parameters

Consistent with previous studies (Zhang *et al.*, 2005; Guan *et al.*, 2014b), our analysis revealed large correlations between SOS and SRS across Africa. Notwithstanding this large correlation, vegetation green-up is not driven by rainy season onset as plants green-up early, prior to the rainy season onset. This phenomenon suggests that other factors may have a much greater influence over the onset of the vegetation growing season. However, large correlations were observed for all the major vegetation types in this study, except for shrublands (Table 6.2), and this is influenced by the spatial variability in SOS dates across Africa (Adole *et al.*, 2018a).

The EOS and ERS had a small association for woodlands and croplands, but large association for shrublands and grasslands. This was expected as the EOS for woodlands extends much later than for ERS. Similarly, because the end of the crop growing season depends largely on sowing date and the variety of crops grown (Brown & de Beurs, 2008), only a small correlation between ERS and crop EOS was expected. The tight coupling of grasslands to water explains the large correlation observed for grasslands, and the large associations between all other grassland LSPs and rain parameters analysed in this study (Table 6.2).

The LOS and the total amount of annual rainfall across Africa produced a large association. However, only a small association was observed for woodlands between LOS and the total amount of annual rainfall, and between LOS and LRS. This suggests that the length and total amount of annual rainfall does not significantly influence the length of growing season for woody vegetation. One reason for this could be the ability of woody plants to minimise transpiration over a long period, especially during dry seasons and at the same time maximise photosynthesis (De Bie *et al.*, 1998), thus, leading to a longer LOS than LRS. Nevertheless, the time of maximum greenness produced a large association with time of maximum rainfall, and seasonal integrated EVI produced a large association with total amount of annual rainfall (Table 6.2). This suggests that rainfall amount affects the seasonal productivity of woodlands. This is in broad agreement with reported increases in productivity in areas with larger amounts of rainfall in some woody species in South Africa (Shackleton, 1999).

From this research, it is evident that while pre-rain green-up is ubiquitous in Africa, post-rain green-up was limited to the Sudano-Sahelian region. From previous studies (Berg *et al.*, 2011; Marteau *et al.*, 2011) and the results of this research, it can be inferred that the post-rain green-up pattern observed in the Sudano-Sahelian region can be explained by the very short, marked rainy season in the region.

The above observations pose serious challenges for existing terrestrial biosphere models (TBMs) and climate change predictions (Ryan *et al.*, 2017). Currently, TBMs like the dynamic global vegetation models (DVGM) use only precipitation or soil moisture thresholds in modelling the response of dry deciduous plants to climatic factors (Sitch *et al.*, 2008; Zhao *et al.*, 2013). Some examples of phenological models are the meteorological data-based phenology model (Jolly *et al.*, 2005) and the carbon–nitrogen dynamics (CN) model (Wang *et al.*, 2016). They both depend on seasonal water availability as a cue for vegetation phenology in the tropics. This potentially creates a large bias in estimating phenological events because the parametrisation process in these models does not account for the ubiquitous pre-rain greening phenomenon, which may be triggered by other environmental factors.

Another aspect worthy of consideration in these global change models is the feedback role of phenology on climate, mostly through CO_2 uptake (Peñuelas *et al.*, 2009; Wu *et al.*, 2016). As previously mentioned, the African vegetation contributes 38% of the global climate-carbon cycle feedback, mostly coming from its savanna comprised mainly of woodlands (Friedlingstein *et al.*, 2010). In a changing climate of projected increases in temperatures, droughts, soil moisture drying, and decreases in precipitation in Africa, especially southern Africa (Niang *et al.*, 2014), there could be an accompanying shift in precipitation seasonality and intensity. This could result in the delay or absence of the anticipated moisture support for plant growth at the time needed in pre-rain green up woodlands, with likely consequences on net primary productivity. Consequently, this may influence the vegetation-mediated feedbacks on climate systems (a positive feedback on climate change), because of the possible reduction in CO_2 uptake from the African savannas. Similarly, increasing temperatures may influence vegetation-mediated feedbacks on climate change estimates in pre-rain green up plants. Studies have suggested that temperature increases might have caused increased productivity and growth in some southern African woodlands (Bunting *et al.*, 2016; Davis *et al.*, 2017), therefore, potentially leading to greater CO_2 uptake.

In summary, this research presents a comprehensive classification of the different patterns of LSP responses to rainfall in Africa. It confirms the prevalence of pre-rain green-up in Africa, and further demonstrates that this pattern is more widespread across the continent than previously reported. Additionally, we found that both pre-rain and post-rain green-up had a significant influence on EOS lags across different vegetation types. We were also able to quantify the frequencies of these LSP responses (pre-rain and post-rain) across different vegetation types in Africa and provided supporting evidence from previous studies, mostly ground-based. These findings and other advances in phenological studies were possible because of remote sensing methods (Archibald & Scholes, 2007; Studer *et al.*, 2007). As such, the findings are subject to the common limitations associated with these techniques. Examples of limitations are the potential influences from smoothing and LSP estimation techniques, and influences from the type of sensor (Atzberger *et al.*, 2013). Notwithstanding these limitations, the findings and the supporting literature suggest that rainfall is not the only major environmental factor controlling initiation and cessation of vegetation seasonality in Africa. It proposes that although rainfall is important in vegetation growth (as seen in the large correlations between the rainfall and phenological parameters), other environmental factors, and the interplay between these factors, are likely to exert a greater influence on the onset and end of seasonal vegetation growth patterns. Temperature and photoperiodicity have been suggested to be among the most important factors triggering onset of growing season across Africa. The effect of these other factors and the related role of rainfall in seasonal vegetation growth needs to be investigated at the continental scale to advance our understanding of natural ecosystem processes in Africa and their representation in terrestrial biosphere models. This is especially important, considering the need to understand the likely responses of pre-rain green-up under a changing climate, and how these responses might influence global climate change on vegetation-atmosphere feedbacks.

Chapter 7: Understanding the effect of climatic drivers on the seasonal dynamics of Land Surface Phenology (LSP) across a range of vegetation types in Africa

7.1 Introduction

Vegetation phenology involving the study of plants photosynthetic cycle at a seasonal time scale is known to be sensitive to seasonal variation of environmental drivers such as precipitation, temperature, insolation and nutrient availability (Myneni *et al.*, 1997; White *et al.*, 1997; Jolly *et al.*, 2005). Likewise, variations in vegetation phenology also affect changes in climate, a phenomenon known as vegetation phenological feedbacks (Peñuelas *et al.*, 2009; Strengers *et al.*, 2010; Richardson *et al.*, 2013). Consequently, vegetation phenology is a suitable indicator in monitoring ecosystems responses to climate variability and climate change (Cleland *et al.*, 2007; Broich *et al.*, 2014).

Numerous studies both ground-based and satellite-based remote sensing studies have documented evidence of environmental drivers controlling effect on vegetation phenology. A number of these studies which have been satellite-based remote sensing studies, commonly termed land surface phenology (LSP), offer the means to synchronise with large scale climatic data at regional to global scales (Cleland *et al.*, 2007; Richardson *et al.*, 2013). These studies have reported that in mid and high latitudes, LSP is mostly controlled by temperature and photoperiod (Jolly *et al.*, 2005; Menzel *et al.*, 2006; White *et al.*, 2009; Jeong *et al.*, 2011; Piao *et al.*, 2015), while precipitation has been said to play a more controlling effect on LSP in the tropics (Fuller & Prince, 1996; Zhang *et al.*, 2006; Vrieling *et al.*, 2011; Zhu *et al.*, 2014; Verger *et al.*, 2016)**.** These factors sometimes together at the same time of the year or separately at different time of the year exert their effect on LSP (White *et al.*, 1997; Jolly *et al.*, 2005). Generally, besides the dependable controlling effect, these factors in a changing climate can alter the usual timing of phenological events. This has been observed across the northern hemisphere were warmer spring temperature resulted in earlier start of season and delayed end of season, leading to longer growing seasons (Myneni *et al.*, 1997; Julien & Sobrino, 2009; Jeong *et al.*, 2011).

While there have been ample studies on the controlling effects of these environmental drivers on LSP in the northern hemisphere, few detailed studies quantifying vegetation phenological responses to these environmental drivers have been carried out in Africa (IPCC, 2014; Adole *et al.*, 2016). Very little is known about what triggers the onsets of vegetation growth and the beginning of dormancy in Africa. The same also can be said of ground-based studies on vegetation phenology (Van Schaik *et al.*, 1993; Sekhwela & Yates, 2007). Common with most studies in Africa is the ambiguity of the environmental drivers of vegetation growth and pattern. Examples of these are: the pre-rain green up of most woody plants in Africa (Ryan *et al.*, 2017; Adole *et al.*, 2018b), the irregularities in the relationship between onset of growing season and the beginning of rainy season in the Sahara desert (Yan *et al.*, 2016), the uncertainty of drivers of changing vegetation greenness in the Sahel (Hickler *et al.*, 2005). In addition, apart from Guan *et al.* (2013) who found out that insolation controls tropical evergreen vegetation development, remote sensing-based studies investigating LSP relationship with other climatic factors besides precipitation are scarce. Moreover, these other climatic factors such as temperature, photoperiod and insolation have been shown to play significant roles in vegetation development (Sekhwela & Yates, 2007; Calle *et al.*, 2010; Polansky & Boesch, 2013; Borchert *et al.*, 2015). For instance, Van Rooyen *et al.* (1986) discovered that rainfall is only effective in the growth pattern of some woody species in southern Africa only when certain threshold of temperature and photoperiod have been exceeded. Njoku (1963 & 1964) also found out that vegetation seasonality in some rain forest species in Nigeria is not marked by seasonality in rainfall but by seasonal changes in day length. Furthermore, the multifaceted association of environmental drivers with LSP parameters have not been investigated for the entire African continent. As a result, the sensitivity of the precipitation-controlled African phenology to other environmental drivers is not well understood. This is particularly important especially in the context of climate change and the recent observed lengthen of growing season in western Africa (Adole *et al.*, 2017).

This research, therefore, seeks to carry out a systematic analysis of the relationship between LSP parameters and a range of climatic driver's averages, in order to offer improved understanding of the climate-driven phenology in Africa. Since several studies have shown that certain thresholds of temperature, insolation and water availability (Yu *et al.*, 2003; Shen *et al.*, 2014; Liu *et al.*, 2015; Piao *et al.*, 2015) are needed to be attained before vegetation growth or dormancy is initiated, "preseason" climatic drivers were used for this study. The preseasons are well-defined periods before phenological dates. We, therefore, aim to quantify the LSP responses to these preseason climatic drivers spatially, and more specifically determine the dominant climatic driver of the LSP of the different land cover types in Africa. This is much needed knowing that there have been few or no study demonstrating the effects of preseason climatic factors on LSP in Africa, especially at a continental scale. This would meaningfully improve our understating of ecosystem functioning and climate-vegetation modelling.

7.2 Data and methodology

7.2.1 LSP estimation and land cover datasets

As previously mentioned in the preceding chapters, LSP parameters were estimated from the Enhanced Vegetation Index (EVI) derived from 500 m surface reflectance Moderate Resolution Imaging Spectroradiometer (MODIS) (MOD09A1). Detailed methodology of LSP estimation and EVI derivation can be found in chapter four. Also, only the first season LSP parameters results were considered. Similarly, homogenous pixels stable through the 13 years (2001 – 2013) time-series of the MCD12Q1 land cover data were extracted. These homogenous area of each land cover type were then used to mask out the LSP estimates of four major land cover types: croplands, grasslands, shrublands and woodlands.

7.2.2 Climatic data sets

The 0.05^{O} gridded rainfall dataset from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) was used for this study. Further details of this data can be seen in chapter six.

Owing to the sparse availability of air temperature data over Africa, daily day and night skin temperature with spatial resolution of 0.125^{O} were acquired from the ERA-Interim developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) (http://apps.ecmwf.int/datasets/). This data unlike surface temperature is the interface between the soil and the atmosphere, and generated using a series of improved data assimilation techniques (4D-Var analysis) and simple empirical interpolation (Uppala *et al.*, 2005; Dee *et al.*, 2011). The values in Kelvin were converted to degrees Celsius.

Daily surface solar radiation downwards data, which is the sum of shortwave radiation reaching the surface of the earth were also downloaded from the ERA-Interim. This data was generated from the ECMWF forecast atmospheric model with a T255 horizontal resolution and vertical resolution of 60 model layers (Dee *et al.*, 2011).

Daily photoperiod which is the length of time a plant receives sunlight in a day was also generated for this analysis. This was estimated using a standard equation based on latitude and day of year (Monteith & Unsworth, 2013) in the ‘geosphere’ package in R (Hijmans, 2017). A summary of all datasets used in this study is shown in Table 7.1.

The preseason periods used in this analysis were defined as the period preceding the LSP event from 0 to 90 days in a step of 10 days. Preseasons sum of each time-series of gridded climactic data (rain, solar, temperature and photoperiod) were estimated before each start of season dates and end of season dates for each year.

7.2.3 LSP driver analysis

All parameters were aggregated to match the spatial resolution of the coarser climatic dataset. In order to statistically investigate the relationship between each LSP parameters (SOS and EOS) and a single preseason climatic driver, we developed two types of spatial models; a simple linear regression and a partial correlation analysis. The partial correlation analysis measures the correlation between two variables after controlling the effects of other variables. This method has been commonly used in several remote sensing studies determining drivers of LSP (Liu *et al.*, 2015, 2016; Piao *et al.*, 2015; Yang *et al.*, 2015b). Due to dominance of different climatic factors at different geographical areas, and species-specific responses of vegetation to climatic factors (He *et al.*, 2015), different models were developed and performed each at regional and vegetation type levels (i.e. a model is developed for a vegetation type and in a specific region). Furthermore, occasioned by the reported effects of SOS on EOS (Fu *et al.*, 2014b; Keenan & Richardson, 2015; Liu *et al.*, 2016), in order to eliminate this influence of SOS, dates of SOS were included in the partial correlation analysis for the EOS models. The significance of the spatial correlations at 95% confidence level were assessed for each vegetation type in the different geographical regions.

Table 7.1 LSP parameters and preseason climatic predictor used in this study showing their spatial resolution and data sources.

Parameters	**Symbol/Units**	**Datasets**	**Resolution**	**Source**
Start of season	SOS/DOY	8-Day MODIS Surface Reflectance SIN Grid V005 data (MOD09A1)	500m	https://lpdaac.usgs.gov/
End of season	EOS/DOY	8-Day MODIS Surface Reflectance SIN Grid V005 data (MOD09A1)	500m	https://lpdaac.usgs.gov/
Preseason cumulative rainfall	Rain/mm	CHIRPS	0.05^{O}	http://chg.geog.ucsb.edu/data/chirps/
Preseason cumulative solar radiation	Solar/Wm^{-2}	ERA-Interim	0.125^{O}	http://apps.ecmwf.int/datasets/
Preseason cumulative temperature	Temp/^{O}C	ERA-Interim	0.125^{O}	http://apps.ecmwf.int/datasets/
Preseason cumulative photoperiod	Photo/h		0.125^{O}	Grid created from 'geosphere' package in R (Hijmans, 2017)

7.3 Results

7.3.1 Correlations between SOS and climatic factors

Results reveal differences in the associations between SOS DOY and climatic drivers which may be dependent on the vegetation type and/or the geographical region. The correlation analysis showed that photoperiod had the highest significant correlation with the DOY of SOS in all vegetation types and geographical region (Figure 7.1; Figure 7.2; Figure 7.3; and Table 7.2; Table 7.3; Table 7.4), implying SOS DOY are mainly controlled by photoperiod in Africa. However, partial correlation results revealed that a combination of other climatic factors also exerts significant effect on SOS dates.

The linear relationship between SOS DOY and the four climatic variables in the different vegetation types in the northern hemisphere of Africa are shown in Figure 7.1. The SOS DOY of all studied vegetation type in Sudano-Sahel region of western Africa were significantly and positively correlated with photoperiod in both models (Figure 7.1 and Table 7.2). These results suggest that the longer the hours of daylight the later the SOS dates. No significant linear relationship was seen with other climatic factors except for temperature in grasslands and shrublands (Figure 7.1). However, partial correlation analysis revealed that a combination of these factors tend to improve correlation values for all climatic drivers, especially in the 30 and 40 day preseason periods (Table 7.2). The partial correlation results revealed that preseason amount of rainfall was significantly and positively correlated with SOS of croplands, grasslands and woodlands except for the first two preseason periods of shrublands with insignificant correlations values. Correspondingly, preseason temperature was significantly and negatively correlated with SOS of croplands, grasslands and shrublands with exception to woodlands showing low positive correlation values. For preseason solar averages, all preseason periods for shrublands, and the first three periods for croplands were generally not significantly correlated with SOS DOY. In contrast, preseason solar sums and SOS were negatively correlated in grasslands, and positively correlated in woodlands.

Results in the southern hemisphere of Africa are somewhat similar to those in the northern hemisphere except for major differences in croplands and shrublands (Figure 7.2 and Table 7.3). In both models, SOS DOY were positively correlated with photoperiod, implying that later vegetation onset dates in the southern hemisphere relate strongly with longer hours of daylight. However, exceptions were croplands SOS dates in the South-western region, which had much more earlier SOS dates similar to those in the western Africa but negatively correlated with photoperiod (Figure 7.2 and Table 7.3). In the same way, SOS dates in the extreme north of Africa for croplands and shrublands were significantly and negatively correlated with photoperiod (Figure 7.3). These outcomes suggests that preseason periods with longer hours of daylight, decreases in daylength is associated with earlier SOS dates, while preseason periods with shorter hours of daylight, increases in daylength is associated with earlier SOS dates. For preseason temperature averages, significant negative correlation values were observed in preseason periods of 10 to 40 days for croplands and grasslands. While, for shrublands and woodlands, significant negative values were seen in preseason periods of 60 to 80 days. These significant negative correlations suggest that higher preseason temperatures are associated with earlier SOS dates. In contrast, SOS dates for both croplands and shrublands in the extreme north of Africa were significantly positively correlated with preseason temperature averages of 10 to 60 days, thus implying that at lower preseason temperature, SOS dates are earlier and vice versa. On the other hand, cumulative solar radiation for all preseason periods for croplands and grasslands in the southern hemisphere, and shrublands in the extreme north were not significantly correlated with SOS (Table 7.4). In cases of significant correlations between preseason solar averages and SOS dates, correlation values were very low, suggesting that solar radiation may not have very substantial effect on onset of vegetation growth in these regions. Similarly, all models results showed that the cumulative rainfall averages had no or very little remarkable impact on SOS DOY.

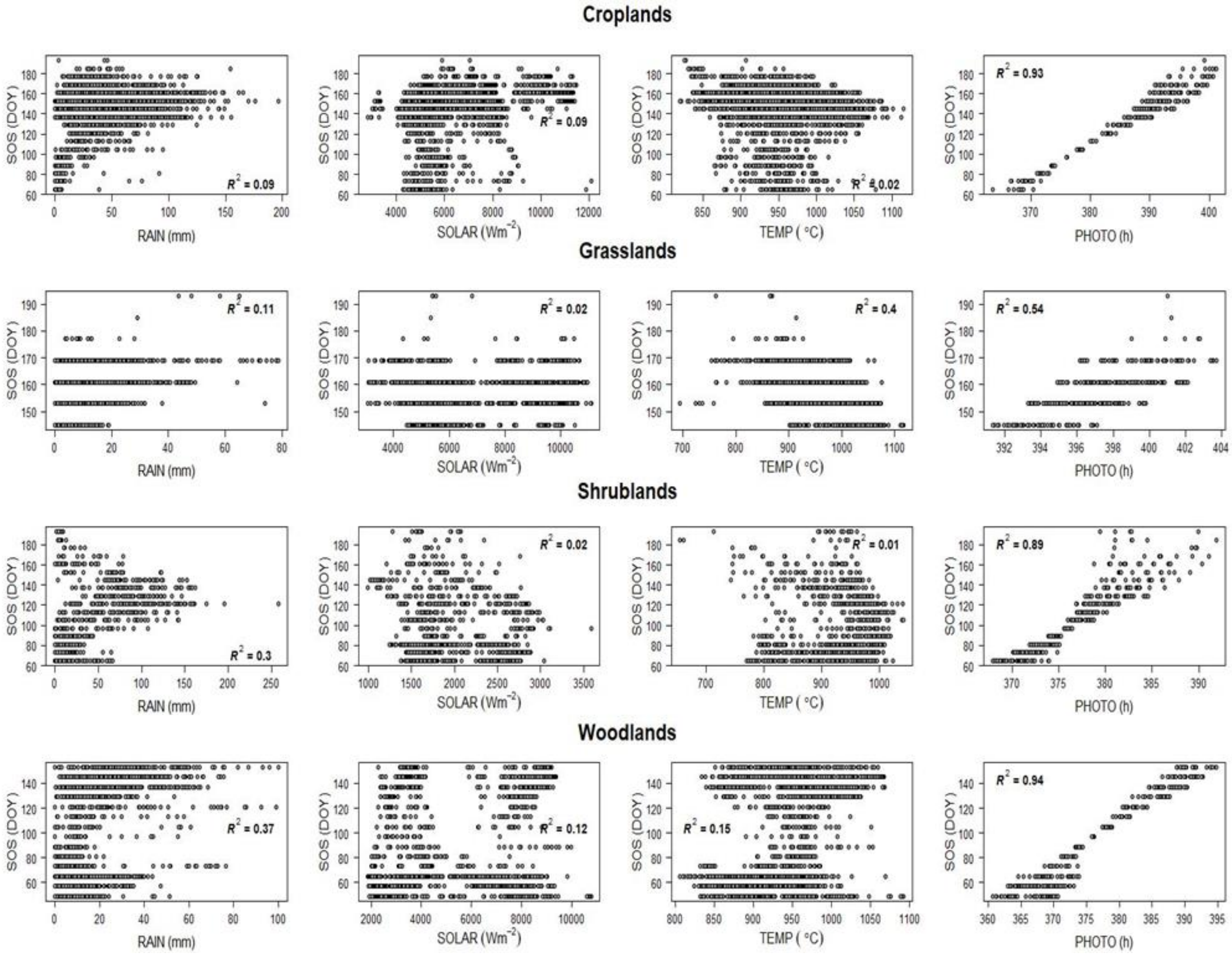

Figure 7.1 Scatterplots between SOS and preseason cumulative climatic drivers (30 days preseason) across different vegetation types in the Northern hemisphere of Africa (All at P<0.05). Shrublands were located in the horn of Africa.

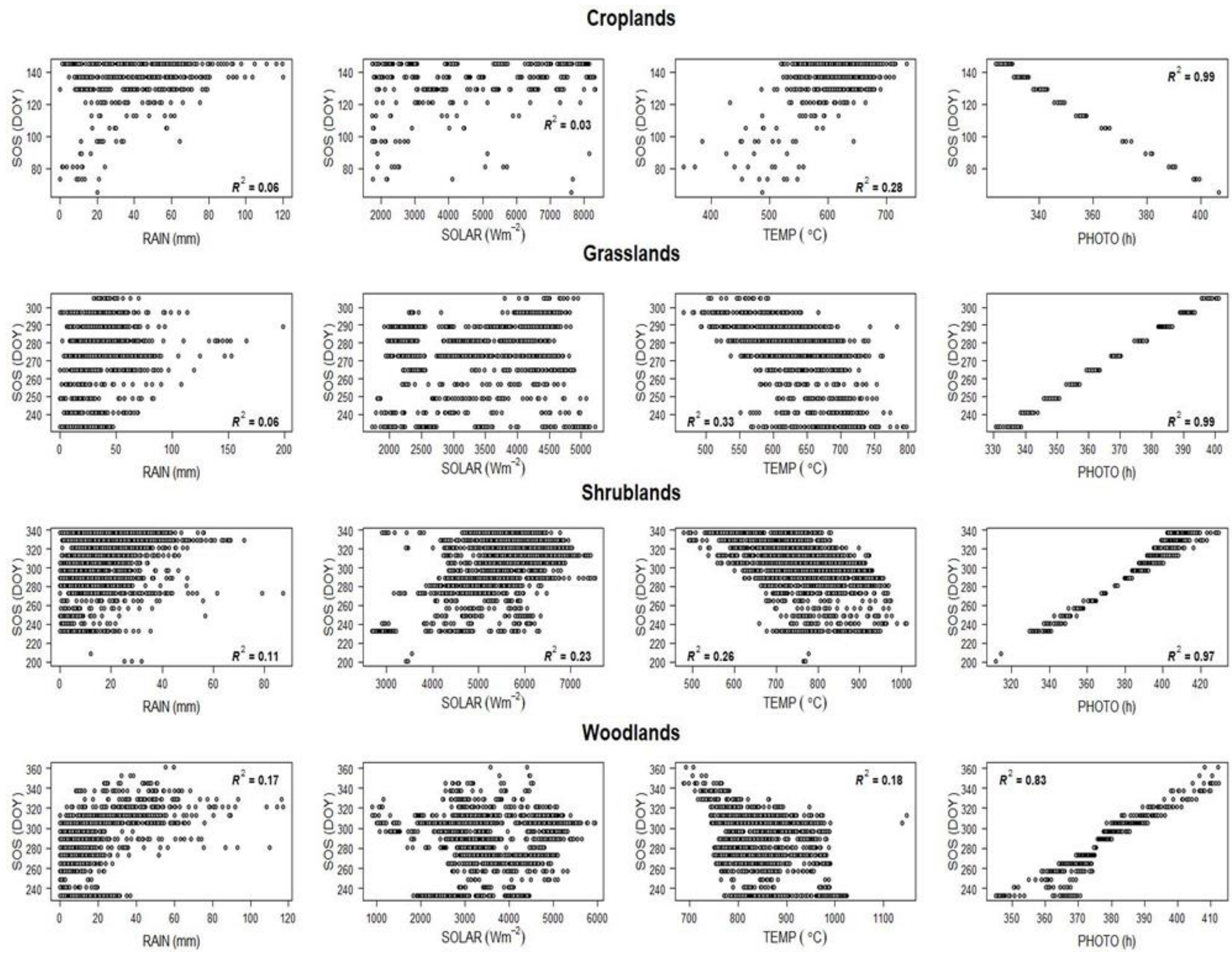

Figure 7.2 Scatterplots between SOS and preseason cumulative climatic drivers (30 days preseason) across different vegetation types in the Southern hemisphere of Africa (All at $P<0.05$). Croplands were located in the south-western region of Africa with a similar climate to the Sudano-Sahel region of western Africa.

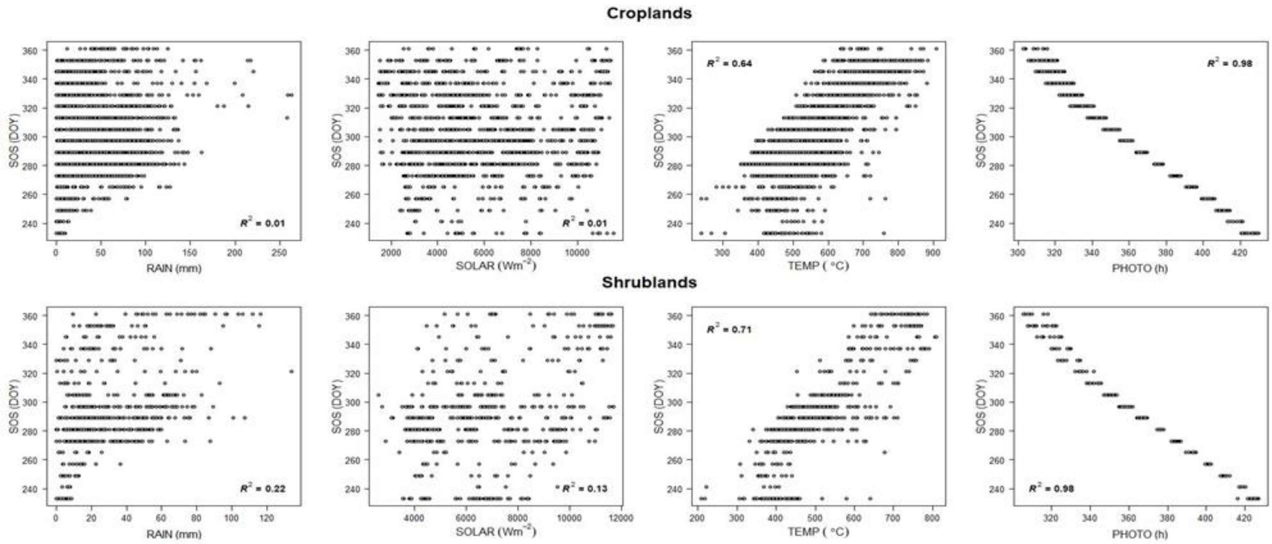

Figure 7.3 Scatterplots between SOS and preseason cumulative climatic drivers (30 days preseason) across different vegetation types in the extreme northern part of Africa (All at $P<0.05$).

Table 7.2: Partial correlation coefficient in northern latitudes of Africa between SOS DOY and cumulative climatic drivers summed over a 90 day period in a step of 10 days. (* means insignificant at P>0.05)

	Northern Africa															
	Croplands				Grasslands				Shrublands				Woodlands			
Preseason	Rain	Solar	Temp	Photo	Rain	Solar	Temp	Photo	Rain	Solar	Temp	Photo	Rain	Solar	Temp	Photo
10	0.35	0.12*	-0.35	0.71	0.25	-0.37	-0.46	0.51	0.06*	-0.00*	-0.19	0.97	0.24	0.29	0.16	0.77
20	0.40	0.08*	-0.33	0.79	0.23	-0.43	-0.45	0.53	0.11*	-0.08*	-0.28	0.96	0.32	0.31	0.15	0.69
30	0.42	-0.07*	-0.34	0.87	0.34	-0.50	-0.38	0.69	0.20	-0.11*	-0.39	0.95	0.30	0.31	0.10	0.66
40	0.47	-0.23	-0.24	0.93	0.36	-0.52	-0.35	0.78	0.24	-0.02*	-0.39	0.93	0.24	0.30	0.09	0.65
50	0.48	-0.29	-0.19	0.95	0.36	-0.53	-0.36	0.81	0.28	-0.01*	-0.39	0.92	0.23	0.28	0.11	0.64
60	0.46	-0.33	-0.14	0.96	0.34	-0.52	-0.37	0.85	0.31	-0.01*	-0.40	0.90	0.10*	0.22	0.16	0.66
70	0.47	-0.34	-0.11	0.97	0.34	-0.52	-0.34	0.88	0.32	-0.02*	-0.42	0.87	0.06*	0.24	0.12	0.66
80	0.47	-0.39	-0.05*	0.98	0.34	-0.51	-0.33	0.92	0.33	-0.10*	-0.45	0.84	0.05*	0.24	0.12	0.66
90	0.46	-0.40	-0.05*	0.98	0.33	-0.50	-0.34	0.93	0.32	-0.09*	-0.45	0.81	-0.02*	0.22	0.14	0.70

Table 7.3: Partial correlation coefficient in southern latitudes of Africa between SOS DOY and cumulative climatic drivers summed over a 90 day period in a step of 10 days. (* means insignificant at P>0.05)

	Southern Africa															
	Croplands (South-western)				Grasslands				Shrublands				Woodlands			
Preseason	Rain	Solar	Temp	Photo	Rain	Solar	Temp	Photo	Rain	Solar	Temp	Photo	Rain	Solar	Temp	Photo
10	0.13*	0.10*	-0.16	-0.96	0.07*	0.02*	-0.42	0.98	-0.13*	0.27	0.07*	0.92	-0.01*	0.03*	-0.06*	0.95
20	0.12*	0.03*	-0.15	-0.96	0.13*	0.01*	-0.34	0.98	-0.12*	0.17	0.12*	0.94	-0.04*	0.19	-0.19	0.96
30	0.11*	0.04*	-0.15	-0.96	0.16	0.01*	-0.27	0.98	-0.13*	0.16	0.11*	0.94	-0.09*	0.28	-0.13*	0.96
40	0.11*	0.05*	-0.16	-0.96	0.28	0.04*	0.01*	0.98	-0.14*	0.19	0.06*	0.95	-0.14*	0.31	-0.03*	0.97
50	0.08*	0.04*	-0.12*	-0.96	0.32	0.13*	0.09*	0.98	-0.11*	0.24	-0.02*	0.96	-0.14*	0.30	-0.05*	0.93
60	0.10*	0.05*	-0.10*	-0.96	0.34	0.06*	0.36	0.98	-0.14*	0.29	-0.07*	0.97	-0.11*	0.28	-0.19	0.92
70	0.03*	0.05*	-0.11*	-0.96	0.33	0.03*	0.15	0.98	-0.08*	0.35	-0.13*	0.98	-0.05*	0.30	-0.15	0.91
80	0.05*	0.03*	-0.11*	-0.96	0.32	0.02*	0.17	0.98	-0.04*	0.37	-0.24	0.98	-0.00*	0.42	-0.21	0.90
90	0.10*	0.07*	-0.08*	-0.96	0.33	0.06*	0.21	0.98	-0.09*	0.38	-0.26	0.99	-0.01*	0.39	-0.28	0.86

Table 7.4: Partial correlation coefficient in the extreme north of Africa between SOS DOY
and cumulative climatic drivers summed over a 90 day period in a step of 10 days.
(* means insignificant at *P*>0.05)

	Extreme North							
	Croplands				Shrublands			
Preseason	Rain	Solar	Temp	Photo	Rain	Solar	Temp	Photo
10	-0.08*	-0.08*	0.35	-0.97	0.26	0.07*	0.42	-0.98
20	-0.08*	-0.09*	0.34	-0.98	0.23	-0.02*	0.48	-0.98
30	-0.04*	-0.10*	0.31	-0.98	0.24	-0.04*	0.45	-0.97
40	-0.05*	-0.08*	0.23	-0.98	0.19	-0.07*	0.37	-0.97
50	-0.06*	-0.12	0.13	-0.98	0.20	-0.06*	0.21	-0.97
60	0.00*	-0.15	0.10	-0.98	0.22	-0.02*	0.08*	-0.97
70	0.05*	-0.17	0.07*	-0.99	0.25	-0.04*	0.00*	-0.98
80	0.10	-0.20	0.06*	-0.99	0.26	-0.08*	-0.03*	-0.98
90	0.15	-0.22	0.08*	-0.99	0.28	-0.09*	-0.07*	-0.98

7.3.2 Correlations between EOS and climatic factors

Contrary to the results for SOS, the statistical models results for EOS revealed the influence of factors which in addition to photoperiod are major factors controlling EOS dates in Africa (Figure 7.4; Figure 7.5; Figure 7.6 and Table 7.5; Table 7.6; Table 7.7). For example, in shrublands, SOS DOY had higher correlation values than any of the preseason climatic factors, suggesting that EOS dates are largely controlled by the date of onset of vegetation growing season. Also, in the northern region of Africa, while preseason photoperiod was most important for croplands, grasslands and shrublands, in woodlands preseason rainfall had the highest correlation values (Table 7.5). The preseason rainfall was significantly negatively correlated with EOS, suggesting that the more amount of preseason rainfall the earlier the EOS dates. Equally important in woodlands were the preseason solar averages for 10 to 30 days period, showing a significant positive correlation. Although significantly negative, the preseason photoperiod correlation values were very low, suggesting that the duration of sunlight may not have strong effect on senescence of woodlands in northern Africa. However, for croplands and grasslands, the results showed preseason photoperiod as the most important controlling climatic factor (Table 7.5). Similar to SOS, the EOS DOY for croplands were significantly and positively correlated with photoperiod. On the contrary, for grasslands and shrublands preseason photoperiod were significantly and negatively correlated with EOS DOY. These differences may be due to the length of growing season of croplands, and the photoperiod seasonality in the Sudano-Sahel region, which increases at the start of the year, peaks in the middle and declines towards the end of the year.

As previously mentioned, preseason temperature like photoperiod plays an equally important driver of EOS onsets in the southern hemisphere (Table 7.6), and the primary factor in the extreme north of Africa (Table 7.7). Exception to this are preseason temperature for croplands in south-western Africa. Partial correlation results revealed that though preseason temperature were significantly and negatively correlated with EOS DOY, correlation values in all preseason periods were less than that of photoperiod (Table 7.6). For grasslands, shrublands and woodlands in southern Africa, preseason temperature were significant and positively correlated with EOS DOY, suggesting that increases in preseason temperature may delay EOS dates. On the other hand, preseason temperature for croplands and shrublands in the extreme north of Africa were significant and negatively correlated with EOS DOY, suggesting that increases in preseason temperature may result in earlier EOS dates (Table 7.7). These negative correlations at very high latitudes and positive correlations a lower latitudes suggest that preseason temperature increases at higher temperatures contribute to earlier EOS while temperature increases at lower temperatures contribute to later EOS.

Results for preseason photoperiod were somewhat different from those of temperature. In the southern hemisphere, for grasslands, shrublands and woodlands, increasing preseason photoperiod were associated with earlier EOS dates, while in the extreme north, increasing preseason photoperiod were associated with later EOS dates.

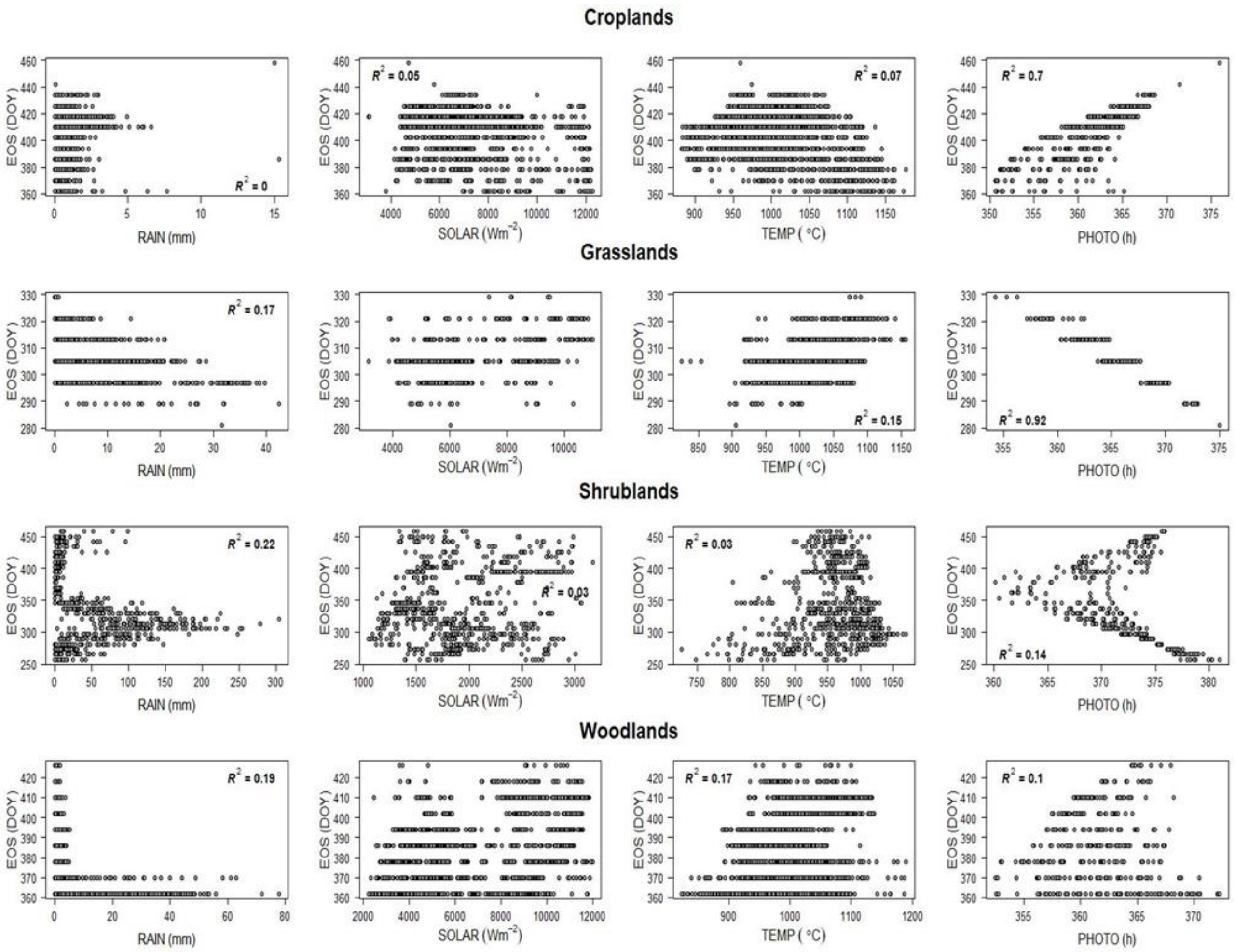

Figure 7.4 Scatterplots between EOS and preseason cumulative climatic drivers (30 days preseason) across different vegetation types in the Northern hemisphere of Africa (All at *P*<0.05). Shrublands were located in the horn of Africa.

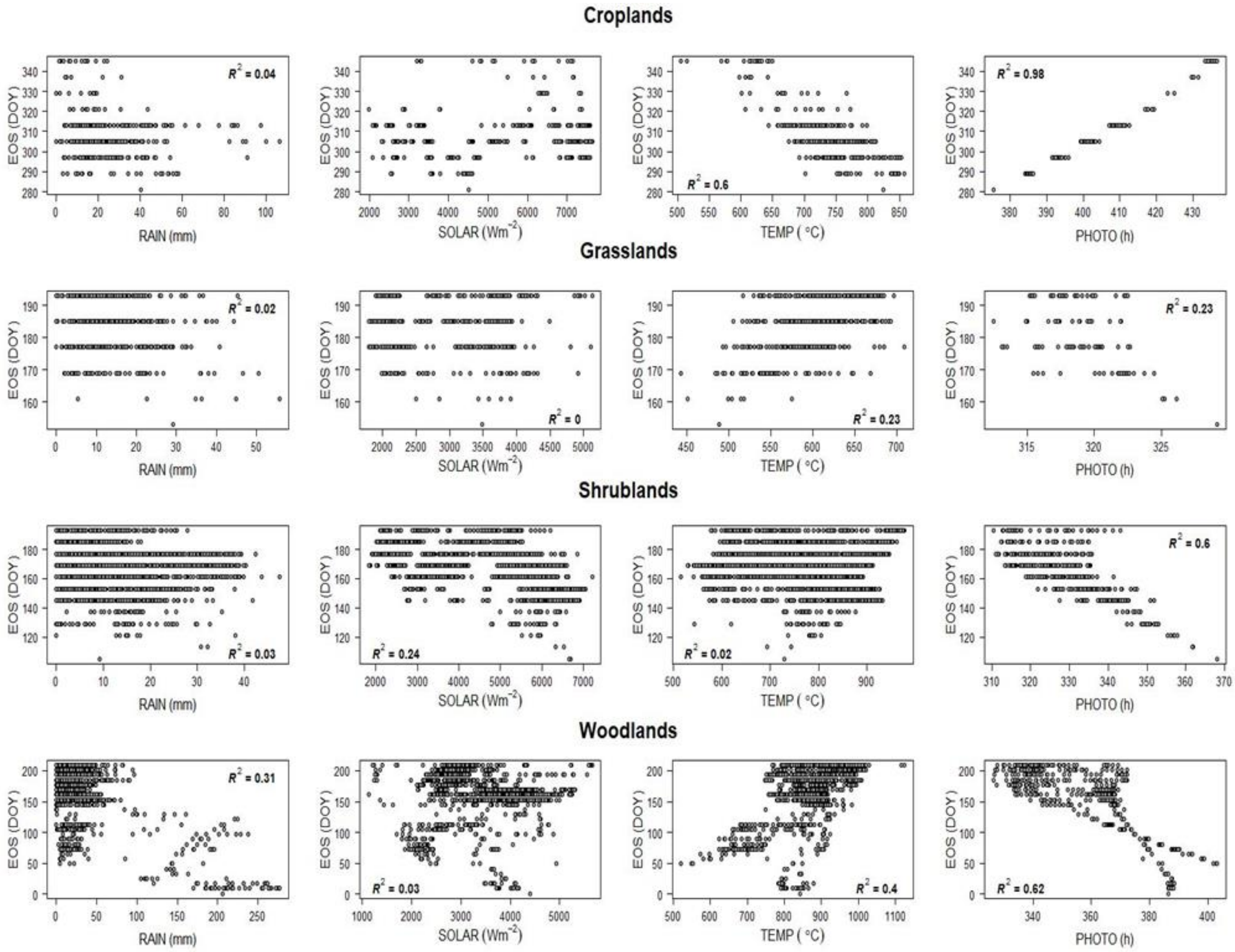

Figure 7.5 Scatterplots between EOS and preseason cumulative climatic drivers (30 days preseason) across different vegetation types in the Southern hemisphere of Africa (All at *P*<0.05). Croplands were located in the south-western region of Africa with a similar climate to the Sudano-Sahel region of western Africa.

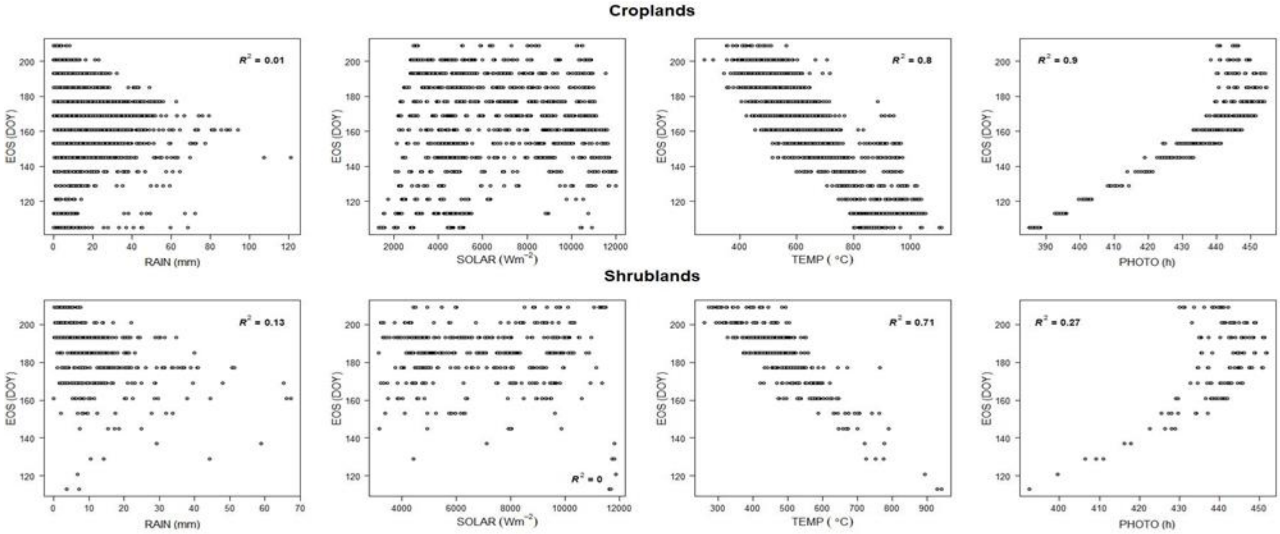

Figure 7.6 Scatterplot between EOS and preseason cumulative climatic drivers (30 days preseason) across different vegetation types in the extreme northern part of Africa (All at *P*<0.05).

Table 7.5: Partial correlation coefficient in northern latitudes of Africa between EOS DOY and cumulative climatic drivers summed over a 90 day period in a step of 10 days, while controlling for SOS. (* means insignificant at *P*>0.05)

	Northern																			
	Croplands					Grasslands					Shrublands					Woodlands				
Preseason	SOS	Rain	Solar	Temp	Photo	SOS	Rain	Solar	Temp	Photo	SOS	Rain	Solar	Temp	Photo	SOS	Rain	Solar	Temp	Photo
10	0.36	-0.12	0.36	0.01*	0.93	0.08	-0.18	-0.30	0.32	-0.86	0.66	-0.31	0.08*	0.00*	-0.08*	0.02*	-0.33	0.40	0.29	-0.07*
20	0.37	-0.19	0.35	0.02*	0.92	0.12	-0.11	-0.27	0.45	-0.86	0.64	-0.34	0.07*	-0.02*	-0.18	0.08*	-0.44	0.41	0.09*	-0.12
30	0.39	-0.22	0.31	0.04*	0.88	0.18	0.01*	-0.31	0.29	-0.85	0.62	-0.34	0.07*	-0.01*	-0.27	0.13*	-0.51	0.30	0.02*	-0.11
40	0.42	-0.24	0.28	0.04*	0.83	0.17	0.09*	-0.36	0.26	-0.87	0.60	-0.31	0.09*	-0.01*	-0.36	0.18	-0.55	0.18	-0.10	-0.13
50	0.44	-0.25	0.27	0.04*	0.75	0.18	0.04*	-0.33	0.28	-0.87	0.57	-0.29	0.13	0.00*	-0.45	0.22	-0.62	0.09*	-0.21	-0.15
60	0.47	-0.26	0.24	0.02*	0.65	0.21	-0.22	-0.18	0.15	-0.84	0.54	-0.29	0.16	0.03*	-0.52	0.22	-0.67	0.01*	-0.31	-0.24
70	0.47	-0.29	0.20	0.00*	0.51	0.18	-0.37	-0.07	0.13	-0.83	0.50	-0.28	0.21	0.06*	-0.58	0.20	-0.68	-0.14	-0.38	-0.40
80	0.44	-0.36	0.19	0.00*	0.42	0.15	-0.33	-0.16	-0.11	-0.87	0.46	-0.35	0.26	0.10*	-0.66	0.22	-0.67	-0.14	-0.39	-0.50
90	0.39	-0.42	0.16	0.02*	0.30	0.16	-0.29	-0.14	-0.19	-0.87	0.45	-0.26	0.28	0.11*	-0.70	0.19	-0.66	-0.15	-0.39	-0.58

Table 7.6: Partial correlation coefficient in southern latitudes of Africa between EOS DOY and cumulative climatic drivers summed over a 90 day period in a step of 10 days while controlling for SOS. (* means insignificant at *P*>0.05)

	Southern																			
	Croplands(South-western)					Grasslands					Shrublands					Woodlands				
Preseason	SOS	Rain	Solar	Temp	Photo	SOS	Rain	Solar	Temp	Photo	SOS	Rain	Solar	Temp	Photo	SOS	Rain	Solar	Temp	Photo
10	0.15	-0.19*	0.05*	-0.26	0.94	-0.12*	-0.12	0.10	0.46	-0.29	-0.14	-0.16	-0.39	0.44	-0.44	0.19	-0.44	-0.02*	0.35	-0.46
20	0.20	-0.10*	0.06*	-0.30	0.93	-0.15*	-0.11	0.12	0.57	-0.18	-0.17	-0.10	-0.40	0.53	-0.56	0.12	-0.36	-0.04*	0.33	-0.50
30	0.19	-0.08*	0.00*	-0.21	0.94	-0.07*	-0.21	0.19	0.57	-0.15	-0.21	-0.16	-0.36	0.57	-0.70	0.19	-0.28	-0.03*	0.32	-0.52
40	0.20	-0.22*	0.04*	-0.20	0.95	0.00*	-0.31	0.30	0.48	-0.39	-0.20	-0.16	-0.31	0.57	-0.75	0.19	-0.26	-0.04*	0.30	-0.55
50	0.20	-0.12*	0.05*	-0.20	0.95	0.05*	-0.33	0.36	0.38	-0.59	-0.18	-0.15	-0.28	0.61	-0.82	0.16	-0.33	-0.04*	0.30	-0.58
60	0.13	-0.01*	0.06*	-0.13	0.95	0.09*	-0.32	0.34	0.30	-0.75	-0.17	-0.17	-0.28	0.65	-0.87	0.13	-0.33	-0.11*	0.28	-0.62
70	0.10	0.12*	0.05*	-0.13	0.95	0.12*	-0.42	0.34	0.23	-0.83	-0.15	-0.10	-0.28	0.70	-0.91	0.12	-0.33	-0.12*	0.28	-0.63
80	0.11	0.08*	0.03*	-0.18	0.95	0.07*	-0.49	0.30	0.22	-0.87	-0.13	0.04	-0.29	0.76	-0.94	0.11	-0.31	-0.12*	0.28	-0.65
90	0.08	0.13*	-0.01*	-0.24	0.96	0.02*	-0.54	0.25	0.25	-0.91	-0.14	0.08	-0.28	0.77	-0.95	0.10	-0.30	-0.09*	0.29	-0.68

Table 7.7: Partial correlation coefficient in extreme north of Africa between EOS DOY and cumulative climatic drivers summed over a 90 day period in a step of 10 days, while controlling for SOS.
(* means insignificant at *P*>0.05)

Extreme North										
	Croplands					Shrublands				
Preseason	SOS	Rain	Solar	Temp	Photo	SOS	Rain	Solar	Temp	Photo
10	-0.03*	-0.25	-0.09*	-0.75	0.54	0.05*	-0.31	-0.26	-0.64	0.29
20	-0.06*	-0.35	0.01*	-0.75	0.65	0.10	-0.30	-0.24	-0.69	0.05*
30	-0.06*	-0.39	0.07*	-0.72	0.73	0.20	-0.34	-0.27	-0.75	0.10*
40	-0.05*	-0.40	0.12	-0.67	0.81	0.21	-0.38	-0.08*	-0.72	0.26
50	-0.04*	-0.36	0.18	-0.65	0.87	0.19	-0.43	0.05*	-0.77	0.37
60	-0.04*	-0.32	0.17	-0.63	0.92	0.23	-0.42	0.18	-0.76	0.49
70	-0.02*	-0.28	0.26	-0.59	0.94	0.17	-0.40	0.29	-0.72	0.59
80	-0.03*	-0.29	0.29	-0.58	0.95	0.16	-0.38	0.32	-0.68	0.66
90	-0.01*	-0.21	0.28	-0.57	0.96	0.14	-0.36	0.37	-0.63	0.72

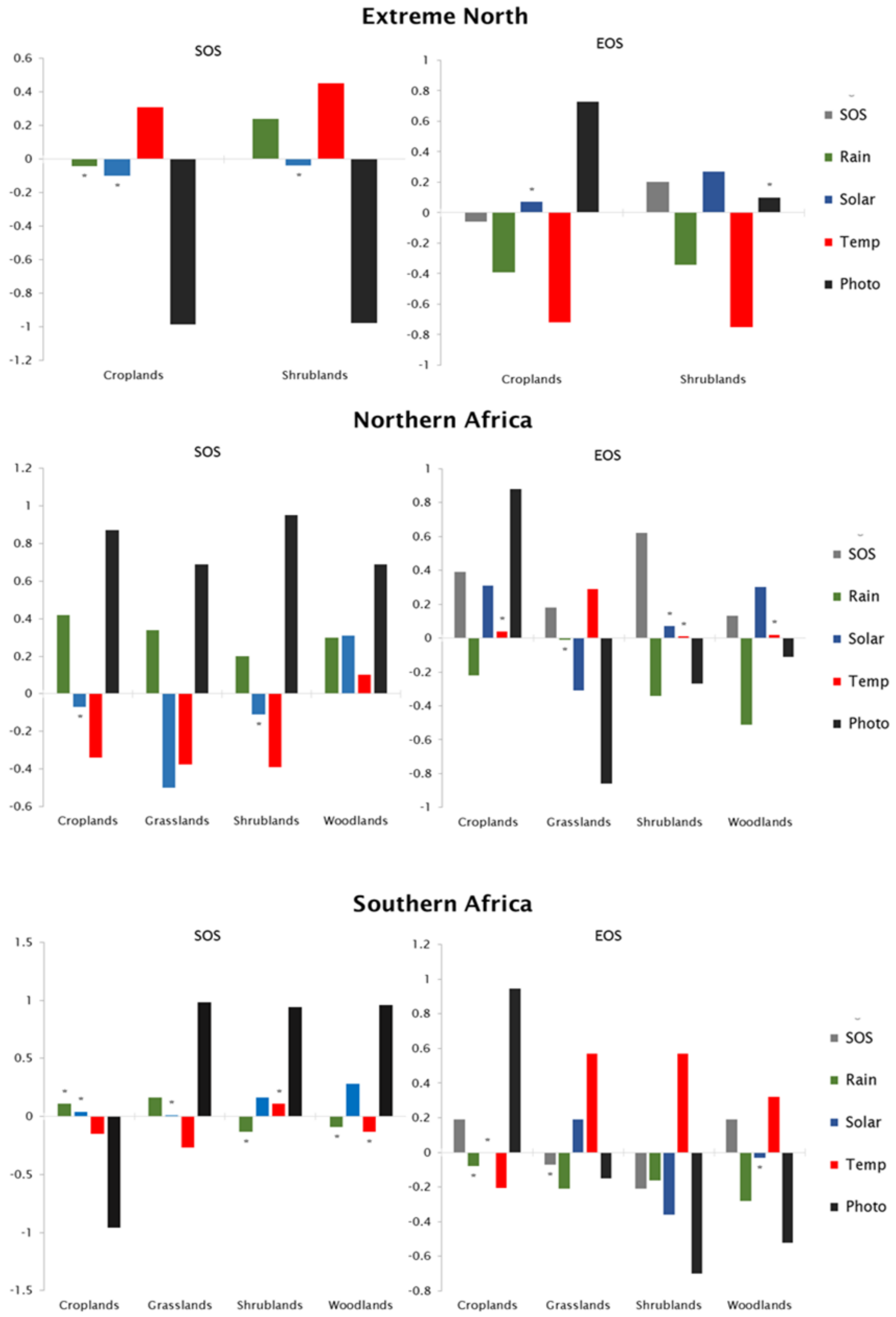

Figure 7.7 Partial correlation coefficients between LSP parameter and 30 days preseason cumulative climatic drivers all across Africa. (* means insignificant at *P*>0.05).

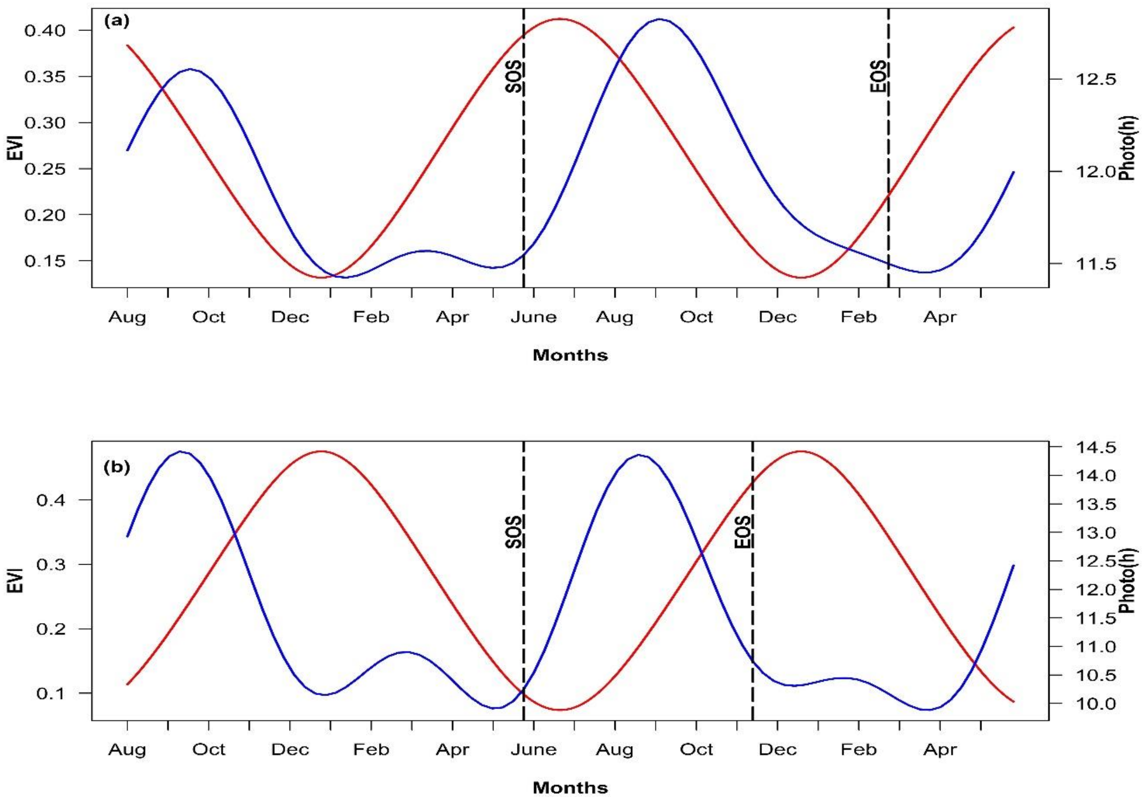

Figure 7.8 Example of pixel profile for a complete EVI and Photoperiod daily time-series. EVI time-series represented by blue curved lines while photoperiod is represented by red curved lines. Vertical dashed black lines show LSP parameters (SOS and EOS). (a) Croplands in the Sudano-Sahel region showing longer growing season with increasing preseason photoperiod at the start of vegetation growing season, (b) Croplands in the south-western region showing shorter growing season with decreasing preseason photoperiod at the start of vegetation growing season.

7.4 Discussion

This present research was designed to determine the dominant preseason climatic drivers of the LSP across the different land cover types in Africa and the summary of the findings are shown in

Figure 7.7. In that respect, the findings indicate that all across Africa, photoperiod is the most dominant factor controlling the onset and end of vegetation growing season. It clearly highlights the high sensitivity of plants to photoperiod, a phenomenon that has been documented as early as the 1950s and 1970s (Wareing, 1956; Njoku, 1963, 1964; Heide, 1974; Van Rooyen *et al.*, 1979). This dominant control by photoperiod tends to corroborates earlier submissions which attributes photoperiodic thresholds to be the major determinant that allows for other climatic-driven development to occur (Körner, 2007; Körner & Basler, 2010; Basler & Körner, 2012). The results

are also in agreement with earlier studies indicating that a combination of climatic factors, either occurring simultaneously or preceding one another, controls LSP patterns, with their effects sometimes biome-dependent (White *et al.*, 1997; Keatinge *et al.*, 1998; Jolly *et al.*, 2005; Prieto *et al.*, 2009). It further supports the idea of incorporating photoperiod into the terrestrial biosphere model for improved predictions (Bauerle *et al.*, 2012; Migliavacca *et al.*, 2012; Ma *et al.*, 2014; Xin *et al.*, 2015; Liu *et al.*, 2018). These findings can be observed in the patterns of statistical correlations with LSP parameters which are further explained below.

7.4.1 Drivers of LSP in the northern hemisphere of Africa

In the northern latitudes of Africa, photoperiod and temperature were found to be the major climatic factors controlling the onset and end of vegetation growing season. This result for Africa is nevertheless consistent with other research which concluded that photoperiod is the major factor controlling phenological events in tropical ecosystems (Njoku, 1964; Borchert & Rivera, 2001).

In the extreme north of Africa, the wet season is usually accompanied by a declining daylength duration and an increasing temperature. With this research revealing negative correlations between SOS and preseason photoperiod, and positive correlations between SOS and preseason temperature, it can be inferred that a combination of lower temperature limits and higher photoperiod limits are the cues required for the initiation of vegetation growth in the extreme north of Africa. For onset of dormancy, the result suggests that the reverse (higher temperatures and lower photoperiod) may be the environmental cue, with temperature playing a more predominant role.

In the Sahel region, onset of growing season for all studied vegetation types is predominantly controlled by photoperiod, suggesting their strong sensitivity to sunshine duration. This sensitivity have been reported in a wide range of vegetation types in the Sudanian region (Seghieri *et al.*, 2009) and also known to be genetically-based in some cereal crops, including major varieties grown in West Africa (Buerkert *et al.*, 2001; Dingkuhn *et al.*, 2008; Kouressy *et al.*, 2008; Marteau *et al.*, 2011). Nonetheless, in this region, the role of other factors and their combinations are still important as shown in the results. For example, the onset of vegetation growing season is characterised by increasing daylength duration and increasing temperatures. The photoperiod seasonality from the beginning of the year usually begins with longer day length of over 11 hours, and rising temperatures of over 20^0C. With both factors having significant correlations values (photoperiod with the highest), these observations, therefore, suggest that lower photoperiod limits and warmer temperatures (negative effect of preseason temperatures), coupled with the timing of the onset of raining season could be responsible for the initiation of vegetation green-up in this region. These conditions are particularly favourable to tropical plants, known to grow well in warmer temperatures and shorter photoperiods (Keatinge *et al.*, 1998). Surprisingly, preseason rainfall had little or no significant effect on onsets dates, suggesting that the amount of precipitation plays a secondary or no role when compared to photoperiod and temperature in regulating the start of vegetation growing season in the Sahel. Moreover, a large percentage of pre-rain green-up have been observed in this region (Adole *et al.*, 2018b). In addition, contrary to expectations, significant positive correlations were observed between preseason rainfall and SOS dates. A possible explanation for this might be that higher amounts of rainfall are usually accompanied by clouds, thus, reducing temperatures and sunshine intensity below growth initiation thresholds, hence the later onset dates (Piao *et al.*, 2006; Ge *et al.*, 2016).

For the onset date for grasslands, smaller positive values of preseason photoperiod and a slightly greater negative effect of solar radiation and temperatures were observed in this region, compared to other land cover types. Studies have shown that the grasses (mainly of C4 type) found in many African ecosystems are strongly associated with high solar radiation and temperatures (Ehleringer *et al.*, 1997; Ségalen *et al.*, 2007). It has been established that this C4 plants types are better adapted to warm climates because of its enzyme sensitivity to chilling temperatures (Sage & Kubien, 2007). They are also known to have greater photosynthetic capacity at higher sunlight and temperature levels (Kellogg, 2013; Yamori *et al.*, 2014). These factors may explain the relatively significant negative effect of solar radiation and temperature on the onset dates of grasslands. This further supports the recommendation that thermal scenarios should be considered when investigating grassland phenology (Chen *et al.*, 2014), since increased amount and duration of rainfall had no effect on its phenology events. These findings in general, raise the likelihood of a vegetation type dependency of LSP responses to climatic factors. Additionally, it also highlights the much reduced role of rainfall seasonality in the vegetation growth cycle. However, it is important to note that although most studies have shown large correlation between rainfall and vegetation seasonality, this association is more related to timing and productivity than to rainfall amounts (Hiernaux *et al.*, 2009). As shown in this research, the amount of rainfall has little or no significant influence on onset dates. Rather, the association is largely a time-based relationship as shown in previous studies (Zhang *et al.*, 2005; Proud & Rasmussen, 2011; Adole *et al.*, 2018b).

Unlike the onset of vegetation growing season, for dormancy onsets, preseason photoperiod was not the only major determining factor. While preseason photoperiod was the predominant factor controlling dormancy onsets in croplands and grasslands, other factors were shown to be more significantly associated with EOS dates. In shrublands, SOS and preseason rain were more dominant, and in woodlands, preseason rain and solar radiation showed more dominance, although their effect is dependent on the preseason period. This negative effect of preseason rainfall could be caused by the accompanying reduced temperatures not favourable to vegetation growth as explained above.

Apart from the human factor in agricultural lands (irrigation/farmers' decision of sowing dates) (White *et al.*, 1997; Marteau *et al.*, 2011), the length of growing season as a function of the vegetation type could also be a factor that can contribute to the effect of preseason climatic factor on end of season dates. For example, in croplands preseason photoperiod was significantly positive, whereas that of grasslands was significantly negative. In croplands the length of growing season extends to periods at the beginning of the year where we have low but increasing photoperiodicity. While, in grasslands with a short growing season of approximately six months, the photoperiodicity towards the end of the season is high but declining. This phenomenon can be seen clearly in the relationship between EOS and preseason photoperiod for shrublands (Figure 7.4 and

Figure 7.7). Also, in shrublands, photoperiod had larger significantly negative correlation values in preseason periods of 2-3 months before the onset of dormancy dates, suggesting that photoperiod 2-3 months before onset of dormancy plays a major role in regulating EOS in shrublands. In contrast, the SOS in shrublands was positively associated with EOS dates, implying that the timing of the growing seasons in shrublands to a large extent determines the end of growing season.

7.4.2 Drivers of LSP in the southern hemisphere of Africa

In the southern hemisphere, like the northern hemisphere, photoperiod was the major climatic factor controlling onset of vegetation growing season while other factors showed significant control of vegetation dormancy onset. These findings are consistent with results from Garonna *et al.* (2018) and corroborate the idea that photoperiod is the most reliable predictor of onset dates for southern African savanna trees (Archibald & Scholes, 2007; Higgins *et al.*, 2011; Whitecross *et al.*, 2017a). Equally, like observations in the north, the apparent positive effect of preseason photoperiod was as a result of higher and increasing preseason photoperiod. However, the observed negative effect of preseason photoperiod on croplands in south-western Africa can be attributed to the declining duration of day length which is similar to the photoperiodicity of the extreme north of Africa. Also significant were preseason temperatures for grasslands and croplands which had a negative effect, with warmer temperatures favouring earlier vegetation green up. These results confirm previous suggestions that a combination of photoperiod and temperature thresholds are environmental cues for vegetation growth in southern Africa (Van Rooyen *et al.*, 1986b; Childes, 1989; De Bie *et al.*, 1998).

As presumed, preseason rainfall amounts had no significant effect on onset of vegetation growing season, except for preseason periods in grasslands. This was expected as pre-rain green-up has been reported to be ubiquitous in southern African savanna, with as early as 60 days before the first rains (Ryan *et al.*, 2017; Adole *et al.*, 2018b). In addition, these results seem to be consistent with other research which found out that rainfall clearly had no effect on the development of leaves in some southern Africa savanna trees (Higgins *et al.*, 2011). This further confirms that most of the associations between rainfall and vegetation seasonality are mainly related to time and productivity (Davis *et al.*, 2017). For example, the memory mechanism of miombo woodlands: greening-up in anticipation of onset of rains (Goward & Prince, 1995) (time-based), and the intra-seasonal rainfall variability effect on sorghum yield (Guan *et al.*, 2015) (productivity-based).

The onset of vegetation dormancy was influenced not only by photoperiod but also by other climatic factors. In croplands, a positive effect of preseason photoperiod was dominant, while in other studied vegetation types, preseason photoperiod had a negative influence. However, this negative influence of photoperiod is secondary to the positive influence exerted by preseason temperature in grasslands. Also in shrublands and woodlands, the influence of preseason temperature was significantly high, suggesting that temperature increases postpone the onset date of vegetation dormancy. This observation is consistent with earlier studies which showed that increases in temperature may have extended the vegetation growing season in the Namaqualand, southern Africa (Davis *et al.*, 2016, 2017). On a contrary, the significant effect of preseason rainfall suggests that increasing rainfall led to earlier onset date of vegetation dormancy. Again, the accompanied reduced temperature during rainfall could be responsible for such negative effect (Cong *et al.*, 2016).

In general, we observed an overall synchrony between photoperiod and LSP parameters across all of Africa. A possible explanation for this may be due to the fact that photoperiod is the most consistent environmental signal from year to year (Borchert *et al.*, 2005; Jolly *et al.*, 2005). As result of this consistency, plants may tend to rely more on specific day length signals to regulate their growth (Kouressy *et al.*, 2008). This can be seen in the results showing that increasing preseason photoperiods of above 12 hours duration tend to be associated with later SOS and earlier EOS, while increases of above 10 hours were associated with earlier SOS and later EOS. Similarly, decreasing preseason photoperiods of below 12 hours were associated with earlier SOS and later EOS. Hence, it is possible to hypothesise that longer day length duration of above 12 hours tends to delay the onset of vegetation growing season and initiate dormancy, while a duration of less than 12 hours but above 10 hours may initiate SOS and delay EOS. This distinct change in the response of plants to small changes of 2 hours or less in photoperiods have been reported previously (Borchert & Rivera, 2001; Rivera & Borchert, 2001; Rivera *et al.*, 2002). This ability of plants to detect light and measure time very accurately has been attributed to an *"endogenous time-keeping mechanism called the circadian clock"* (Jackson, 2009), and the perception of light signals by photoreceptors (Singh *et al.*, 2017). However, there are still many unanswered questions about how this mechanism works especially in different plant types, and more investigations are required as recommended by Richardson *et al.* (2013) and Way & Montgomery (2015).

A particular interesting observation which further supports the sensitivity of plants to small changes in photoperiods is the distinct response of croplands in the Sudano-Sahel region of western Africa and the croplands in south-western Africa. Although, estimated SOS beginning around May/June were similar for both croplands, however their responses to photoperiodic signals were very distinct. This can be attributed to the increasing preseason photoperiod at the start of the year observed in Sudano-Sahel region, and the decreasing preseason photoperiod observed at the same period in south-western Africa (Figure 7.8). As previously mentioned, the length of growing season as a function of the crop type may also play a role in these responses, especially relating to EOS and preseason photoperiod. For example, maize crop mostly grown in the south-western region have shorter growing season and harvested much earlier than those (millet/sorghum/cassava) in the Sudano-Sahel region (Leff *et al.*, 2004; Zinyengere *et al.*, 2015; Ezui *et al.*, 2016).

Additionally, irrespective of the observed dominance of photoperiod, the partial correlation results also showed that LSP is influenced not just by a single factor but a combination of these factors, which is in agreement with previous studies (White *et al.*, 1997; Jolly *et al.*, 2005). It revealed the significance of other factors and in some cases, these factors were shown to having more influence than photoperiod. Therefore, investigations into LSP response to interactions between a consistent photoperiod and inter-annual variations in climatic driver, especially under a changing climate is paramount. The importance of such interactions has been brought to the fore recently by other researchers (Way & Montgomery, 2015; Liu *et al.*, 2018). In addition, understanding such interactions would help in identifying the confounding drivers of the reported inter-annual variations of vegetation phenology in Africa (Adole *et al.*, 2017), especially knowing that photoperiod is consistent and reliable year to year. Nevertheless, it is important to state that the findings from this study highlights the very important role of photoperiod in vegetation phenology, hence a key factor that should be incorporated into all vegetation phenological models. This importance can be corroborated by Liu *et al.* (2018) who reported significant improvement of vegetation phenology model performance, and uncertainties reduction resulting from the integration of photoperiod.

7.5 Conclusion

In comparison with studies on climatic controls of vegetation phenology in the northern hemisphere, knowledge of the climatic drivers of vegetation seasonality in Africa is very limited, particularly at the continental scale. This issue is also made worse by lack of sufficient and continuous ground-based observations. In trying to fill this void, remotely sensed data were used to investigate the relationship between LSP parameters and preseason climatic drivers. The statistical analysis performed revealed a predominately photoperiodic control on vegetation growth (SOS and EOS) across all of Africa. This provides evidence that, contrary to widely held expectation, rainfall is not a direct driver of vegetation onset and end dates in Africa. The partial correlation analysis, across the different land cover types, provided evidence of vegetation sensitivity to photoperiod. The onsets and ends dates were either significantly positively or negatively correlated with preseason photoperiod which is largely dependent on the seasonality of photoperiod, and synonymous with the wet and dry season in Africa. The results also revealed that over the preseason periods, photoperiod was predominantly associated with SOS dates. For EOS, in addition to photoperiod, controls included rain, temperature and SOS date depending on the vegetation type and preseason period. Additionally, in drier areas like the extreme north of Africa, increases in preseason temperature exerted a greater influence on vegetation dormancy onset that any other climatic variable.

Generally, this research suggests that photoperiod is, thus, a more important environmental cue than previously thought, while also acknowledging the significance of other factors. The partial correlation results also supports the proposition that vegetation phenology is influence by the combination of two or more factors rather than a single factor. It also supports previous ideas that LSP response is biome dependent. The combination of these findings will enhance our understanding of how LSP will respond to climatic variations in a changing climate with consistent photoperiod. Additionally, findings are crucial for the future development of phenological models and climate change studies. They highlight the importance of incorporating photoperiod and temperature settings when developing phenological models for tropical regions such as Africa.

Chapter 8: Discussion and conclusion

8.1 Introduction

This chapter gives an overview of the set objectives and aims in this study, how these were achieved, and its major contributions. A synopsis of the entire study is discussed in chronological order, focusing on identified knowledge gaps, its methodological approach, its major findings, limitations and future directions. Further, it discusses its recommendations, which possess potential policy implications for future ecosystem management and climate change concerns in Africa.

8.2 Identified knowledge gaps

The seasonal events of vegetation life cycle also known as vegetation phenology is very important in understanding ecosystem response to climate variability and change (Cleland *et al.*, 2007; Richardson *et al.*, 2013). With the increasing danger from climate change impacts, a clearer understanding of ecosystem climate interactions is very essential in today's world. The emergence of land surface phenology (LSP) promises to fill the gaps in the study of vegetation dynamics, offering wider spatial and temporal scale assessments especially in remote regions of the globe (Guan *et al.*, 2013; Rodriguez-Galiano *et al.*, 2015b). It also offers a better understanding of how different ecosystems are responding to climate variability and change at regional to global scale (White *et al.*, 2005; Kong *et al.*, 2017), thus, improving our capabilities of predicting terrestrial ecosystem adaptations to global changes. Using this technique has also provided very cost-effective means for environmental monitoring and management when compared to most traditional ground-based methods (Studer *et al.*, 2007). Notwithstanding these gains, further gaps still exist in the study of LSP, which limits our thorough understanding of vegetation growth and dynamics. In this study after a systematic review of existing scientific literature on vegetation phenology, several gaps in study of seasonal vegetation patterns were identified. The gaps relevant to reported results in this study are:

1) The very limited number of ground-based studies and the complete absence of phenological network in Africa
2) Absence of a continental scale characterisation of the land surface phenology (LSP) in the different geographical sub-regions in Africa carried out with a medium spatial and temporal resolution satellite data

3) The recent trends in Africa’s LSP, and influence of land cover changes on LSP trend analysis studies is particularly absent
4) A comprehensive analysis of the different patterns of LSP response to rainfall in Africa by vegetation type is currently lacking, and
5) There is ambiguity on what are the dominant climatic drivers of the start and end of vegetation growing season of major vegetation types are in Africa.

8.3 Major findings and implication of study

This study with more details in chapter three has shown for the first time the current state of phenological research in the African continent. It revealed the recent increasing trend in vegetation phenological studies; both ground-based and remote sensing studies and the regions were these studies were carried out. However, the vast majority of these studies were remote sensing based using very coarse resolution data at continental scale. The review also showed the complete absence of any form of phenological network in Africa, like digital camera or field observations networks. Several recommendations emerged based on these findings, some of which this study further investigated and presented subsequent outcomes in chapters four, five, six and seven.

This study is the first to comprehensively investigate and characterise the LSP of Africa’s major vegetation type and their responses to climatic and non-climatic drivers. In chapter four, for the first time addresses the LSP of the major vegetation types in Africa using homogeneous pixels from 12 years (2001 – 2012) MODIS land cover data and EVI derived from the MODIS MOD09A1 product at a medium spatial resolution of 500 m and a high temporal frequency of 8-days. As previously highlighted by other researchers, coarse spatial resolution datasets which have been mostly used for LSP studies in Africa are inadequate to provide accurate description of vegetation phenology in heterogeneous areas (Melaas *et al.*, 2013; Guan *et al.*, 2014b; Cho *et al.*, 2017). Zhang *et al.* (2009) also showed that errors in LSP estimates increases with reduction in temporal resolution. However, this study occasioned by its spatial and temporal resolution has significantly improved our understanding of these heterogeneous areas. It has provided more detailed characteristics of the LSP in Africa, including its variability in the different geographical sub-region with improved estimation accuracy. For example, it has shown the consistency of the LSP patterns of grasslands all across the different geographical sub-regions, and the variations in LSP patterns of shrublands especially in the southern part of Africa. Being able to clearly distinguish these LSP patterns would also help to determine their unique responses to different environmental cues, an assessment that was further carried out in this study.

Currently, there is insufficient knowledge regarding the drivers of vegetation dynamics in Africa, which also should include impacts from anthropogenic factors that can led to land cover changes.

The influence of these land cover changes on LSP significantly limits our understanding of the temporal trends of LSP that are solely driven by climatic factors. Besides, these changes have not been taken into account and investigated by most LSP trend analysis studies. In filling this gap, in chapter five, details of an assessment into the influence of land cover changes on LSP trends were discussed. The results showed that influences from land cover changers were highly significant. Also reported for the first time are the most recent LSP trends in Africa not influenced by land cover changes. These results suggested that most previously reported climate-driven LSP trends may not have be solely influenced by climatic factors as continuing or abrupt changes in vegetation cover may result in changes in LSP responses. It further suggested that the magnitude of trends reported in days year^{-1} may have been occasioned by both climatic and non-climatic drivers. Consequently, future studies should control for land cover changes, and also take care when interpreting climate change impacts on LSP as absence of control could lead to reported trends been erroneously larger.

Also discussed in chapter five are the recent trends devoid of land cover change influences, of which the results demonstrated significant changes in LSP parameters across Africa leading to longer vegetation growing season. This increase in vegetation growing season is a reoccurring outcome from quite a number of research across the world both ground-based and remote-sensing studies (Myneni *et al.*, 1997; Linderholm, 2006; Julien & Sobrino, 2009; Dong *et al.*, 2012; Fu *et al.*, 2014a; Liu *et al.*, 2016; Davis *et al.*, 2017). The implication of this suggest likely increases in vegetation productivity because longer growing season have been associated with increases in plant productivity (Wu *et al.*, 2012). This may affect the terrestrial carbon cycle, considering that changes in phenology can exert significant influence on the carbon cycle (Peñuelas *et al.*, 2009; Richardson *et al.*, 2013; Gonsamo *et al.*, 2017). Therefore, more research is required to determine the contributions of Africa's vegetation feedbacks to the overall global climate system.

To determine LSP responses to rainfall, chapter six focuses on how remotely sensed meteorological data was used to analyse the lags between vegetation phenophases and rainfall parameters across the different vegetation types in Africa. A comprehensive classification quantifying the magnitude and frequency of the different patterns of LSP responses across different vegetation types in Africa was reported. Interestingly, was the observed wider spread of pre-rain green-up all across Africa than was previously reported, and the post-rain green-up, mostly limited to the Sudano-Sahelian region. Until now, detailed understanding of the occurrence of both pre- and post- rain green-up is lacking in Africa. One critical issue with current terrestrial ecosystem models are large uncertainties in modelling different vegetation growth pattern occasioned by ambiguous understanding of vegetation dynamics (Dahlin *et al.*, 2015, 2017; Restrepo-Coupe *et al.*, 2017). Thus, with these findings arise an opportunity to improve parametrisation of current models to properly capture the seasonal pattern of all vegetation types. It is anticipated that this would reduce these uncertainties especially in Africa and ensure high confidence in predicting vegetation response to climate change.

As mentioned above, one important finding from this study is the pre-grain green-up phenomenon, which clearly indicates onset of vegetation growing season is not driven by rainfall in the vast majority of Africa's vegetation. Consequently, chapter seven went further in detailing the investigation into the role of preseason climatic variables in initiating vegetation growth onset and dormancy in different vegetation types across Africa. To the best of my knowledge, this is the first study to have assessed the effects of preseason climatic factors on LSP parameters in Africa. The results revealed that contrary to common knowledge of a rainfall controlled LSP in Africa, vegetation growth onsets and end all across Africa is predominately controlled by photoperiod, and sometimes temperature. It also suggest that not one but a combination of environmental factors control vegetation seasonal growth patterns. Emphasis was placed on the incorporation of photoperiod into vegetation-climate modelling studies, to clearly define how vegetation would respond to interactions between a consistent photoperiod and inter-annual variations in climatic drivers, especially under a changing climate.

8.4 Limitations and Uncertainties

A number of remote sensing data and approaches were used in this study in attempting to evaluate LSP of Africa and it drivers. Associated with these data types and approaches are several limitations, and where feasible, the steps taken to overcome them. These limitations and uncertainties, including the steps taken to reduce and/or overcome them are explained below.

8.4.1 Uncertainties relating to sensor, vegetation indices and mixed pixels

The type of sensor and vegetation indices used in remote sensing studies have been known to influence estimates of LSP parameters (Atzberger *et al.*, 2013; White *et al.*, 2014). The LSP parameters estimated from the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) in certain seasons in Europe were shown to have high discrepancies (Atzberger *et al.*, 2013). Additionally, the normalized difference vegetation index (NDVI) which is the most commonly used vegetation index (VI) is known to be associated with clouds and aerosols saturation issues (Huete *et al.*, 2011). Consequently, to minimise the possibilities of these uncertainties occurring, data from only one sensor (8-day MODIS surface reflectance data) was used to estimate LSP for this study. In addition, the enhanced vegetation index (EVI), suggested to be less sensitive to high biomass and shown to outperform the

NDVI (Xiao *et al.*, 2005; White *et al.*, 2014; Wu *et al.*, 2014; Zhang *et al.*, 2014a) was selected for this study. It is also important to note that before the choice of EVI, the preference of this 8-day over the daily MODIS data was because of the vulnerability of the daily data to clouds, atmospheric, aerosols, haze etc. Hence, the use of the 8-day MODIS composites which was developed to improve the acquisition of cloud-free images (Chen *et al.*, 2013).

The mixed pixels effect especially those associated with leafing from understory is also known as a source of limitation in LSP studies (Liu *et al.*, 2017b; Helman, 2018), which may result in earlier estimation of start of vegetation growing season (Tremblay & Larocque, 2001; Ahl *et al.*, 2006). However, the magnitude of this effect on LSP estimation is still very uncertain, nevertheless researchers have suggested that using radar or lidar technology, and more ground based studies may reduce this mixed signal from these multi-canopy layers (Chen *et al.*, 2018; Helman, 2018).

8.4.2 Uncertainties relating to smoothing and LSP estimation techniques

Numerous smoothing and estimation techniques have been used for LSP studies (see chapter two). Despite a comprehensive evaluation of the performance of smoothing techniques by several researchers , (Bachoo & Archibald, 2007; White *et al.*, 2009; Atkinson *et al.*, 2012; Lara & Gandini, 2016), there is still no agreement on which smoothing technique is best in estimating LSP as they all have their unique advantages as well as limitations. However, because of the less user involvement and the production of very smooth time-series, the Discrete Fourier Transform (DFT) (Moody & Johnson, 2001; Dash *et al.*, 2010) was used for this study. Nevertheless, this frequency-based technique assumes that noise in a time-series are regular and generally symmetrical which can result in distorted signals or large displacement from the original time-series when faced with irregular signals (Chen *et al.*, 2004). In response to this limitation, before applying the DFT, this study with a temporal moving average window limited to size two, first removed obvious outliers. This was done by implementing a threshold which identifies outliers, removes them and then fills these gaps by a linear interpolation using neighbouring pixels to ensure the interpolated values retain the local trend (Dash *et al.*, 2010).

Similarly, in estimating LSP parameters from already smoothed time-series data, there is no consensus in the scientific community as to which technique is best suited for estimating LSP parameters. However, the inflection point method adapted for this study, overcomes the uncertainties of using a pre-defined threshold which could result in later start of season and earlier end of season (see section 2.4.1 and 2.4.2) (Vrieling *et al.*, 2008; de Beurs & Henebry, 2010; Shang *et al.*, 2017). Nevertheless, this method has been associated with uncertainties resulting from the fitting accuracy of the mathematical function (Chen *et al.*, 2016) especially when faced with a time-series profile of irregular patterns of abrupt rises or falls (de Beurs & Henebry, 2010). To overcome this, two major conditions were incorporated into this study's mathematical function in order to reduce these uncertainties: (1) at least four consecutive rising EVI values must be identified before key LSP parameters are defined, and (2) the difference between peak and the valley points must be greater than one fifth of the maximum EVI value.

8.4.3 Limitation relating to validation from ground studies

This is a major limitation plaguing the study of LSP especially in Africa due to insufficient or the complete absence of field observation data. It is practically impossible to carry out proper validation of LSP estimates across the continent because of this scarce availability of ground data. Where available, the parameters measured by these studies cannot be easily matched with those measured by satellite-based remote sensing studies (Adole *et al.*, 2016). There are no digital camera networks for phenological studies in Africa (Adole *et al.*, 2016), and the number of eddy covariance towers (currently between 19 to 21 sites) is very insufficient (see http://fluxnet.fluxdata.org/sites/site-summary/). In addition, most of these eddy covariance sites only have data for a limited number of years (mostly less than five) and data acquisition is not constant. Notwithstanding, in an effort to reduce this uncertainty, results from limited existing literature on ground-based studies were compared with those from this study (see section 4.4.3). In addition, comparison was made with previous remote-sensed based studies (see section 4.4.4).

8.4.4 Other uncertainties

Other uncertainties and limitations associated with this study are related to the climatic datasets and techniques used in estimating rainfall parameters. The uncertainties with regard to the climatic datasets always arise from input data quality and applied interpolation method (Hijmans *et al.*, 2005). For example, the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data is associated with uncertainty issues related to the algorithm used in merging satellite observations and ground station data (Funk *et al.*, 2015). The algorithm is unable to provide detail information of the associated statistical errors biases. Another climatic data used in this study is the European Centre for Medium-Range Weather Forecasts (ECMWF) data, most of which are primarily estimated parameters that are consistent with observations (Dee *et al.*, 2011). Similarly, there several uncertainties associated with this data. They include: quality and scarcity of observational data coverage, bias correction of observed data and the data assimilation techniques used (Uppala *et al.*, 2005; Dee *et al.*, 2011). Other concerns associated with climatic datasets are their very coarse spatial resolutions. The spatial resolutions of datasets used in this study are 0.05^0 and 0.125^0, the implication being that some spatial variation in rainfall magnitude may not be explicitly captured (Janowiak *et al.*, 2001; Joyce *et al.*, 2004).

The uncertainties with regard to the rainfall parameters estimation techniques are usually related to detection of onset and end of raining seasons. Like LSP smoothing and estimation methods, there is no universal acceptable technique in detecting onset and end of rains. Most methods are susceptible to false detection of the start of raining season especially in cases were onset are preceded by a sequence of isolated showers (Ati *et al.*, 2002; Araya *et al.*, 2012). Nevertheless, to reduce this uncertainty, this study from Stern *et al.* (1981) implemented series of iterations setting adequate predefined thresholds and conditions to ensure sufficient precipitation amount is achieved for vegetation growth without very long dry spells before onset dates are detected (see section 6.2.2.2).

Another limitation associated with this study is the assumption that no significant land cover changes occurred between 2013 and 2015 in Africa. This assumption was made because of the year differences between the MODIS land cover product, which was until 2013 and no further, and the MODIS surface reflectance product which had LSP estimated till 2015. In other to reduce the uncertainties that could arise from this difference, land cover change analysis used LSP parameters from 2001 to 2013 only (see section 5.3.4).

8.5 Policy implications, challenges and future prospects

The African continent has one of the fastest growing population and is also one of the most vulnerable continent to climate change impacts (Food and Agriculture Organization of the United Nations, 2014; Niang *et al.*, 2014), especially those impacts bothering on food security (Dawson *et al.*, 2016b). Coupled with the impacts from climate change and rapid expansion of agricultural lands, other issues facing the continent are increases in the conflicts between herdsmen's and farmers especially in the Sudanian and Sahelian region. In addition, the livelihood of its population, which is sustain by its ecosystem, is under threat. Therefore, is it hoped that an accurate and up-to-date spatial pattern of vegetation growth and its response to climate variability can be of importance in providing evidence-based information that can aid in addressing some of these dire issues. Hence, the findings from this study do not only have strong implications for the vegetation-climate modelling communities but also can influence decision and policy makers in the following ways:

- Provide an up-to-date distinct mapped out region suitable for grazing fields and agricultural lands.
- Provide current vegetation phenological data and maps important for conservation and management of terrestrial ecosystem.

- Identify potential areas vulnerable to vegetation loss if faced with high significant shifts in rainfall seasonality and temperature increases.
- Provide data to help in prioritising understudied regions requiring pheno-networks, and in prioritising areas of vegetation-climate research requiring funding.

In spite of the above, it is important to note that enormous challenges are still facing the continent. Besides the problems of poverty, famine, spread of infectious diseases e.t.c, inadequate research capacity of institutions, internet access constraints, lack of skilled researchers, financial constraints and wars/conflicts are major challenges hampering science research development in Africa (Roy *et al.*, 2010; Irikefe *et al.*, 2011; World Bank, 2014).

Financial constraints which eventually leads to lack of funding is one of the major challenges facing phenological studies in Africa. In addition to that is the scarcity of field observational data, which limits the validation, and accuracy of LSP studies done in Africa. This dearth of observational data is one of the major challenges faced in this study. As previously mentioned, no field validation was carried out because of this. Another major challenge had to do with applying LSP trend analysis to a data period of 15 years only. One major contribution of this study was to describe the LSP of the major vegetation types in Africa using a medium spatial resolution of 500m MODIS data. However, this data product were only available from February 2000, hence confining analysis to a period of 15 years only. Also, the unavailability of long term soil moisture data (soil moisture data were monthly averages with a temporal range of 2000 – 2009) for Africa prevented this study from incorporating soil moisture into climatic driver analysis.

Notwithstanding, this study has been able to bridge some of the identified research gaps in phenological studies in Africa. However, more work is still required to further close these gaps especially those related to vegetation-climate research (IPCC, 2014; Adole *et al.*, 2016). Below are suggestions for ways in which these gaps can be addressed.

(1) Investigate in detail the response mechanism of the different vegetation types to the different climatic cues. In addition, examine ways in which the effect of hydrological control from soil moisture and irrigation system can be investigated.

(2) Carry out continental scale studies on modelling the climate-driven phenological changes and inter-annual climate variability and predictability. These studies should also focus on understanding vegetation phenological feedbacks (or the role of vegetation phenology in vegetation-climate feedback mechanisms). The inter-annual anomalies of vegetation phenology and climatic variables, and their relationship should also be investigated.

(3) Promote and improve cost effective methods of field phenological observational data collection that can be easily synchronised with remotely sensed satellite data. One major

setback with ground validation of LSP studies is the inability to match field and satellite data due to different methods of measuring vegetation phenological stages. Having a comprehensively acceptable standard approach on ground-based measurements of vegetation phenology in Africa would improve validation of LSP parameters.

(4) The importance of having a continental phenology network cannot be overemphasised. This is particularly essential in establishing standardised field observational techniques and a comprehensive record of ground measurements, thereby improving the validity of phenological data. This network can also be involved in capacity building particularly of local citizens and/or students across the continent on scientific data collection techniques ensuring standardisation across board. In addition, such networks should promote data sharing among countries and at regional level in the continent.

(5) As suggested by Atkinson *et al.* (2012),investigate the possibility of merging LSP parameters derived with different methods and from different sensors in order to develop a comprehensive and very long phenological record.

(6) Explore the use of new generation satellites, the Sentinels constellations (Sentinel-1A and 1B) in monitoring LSP especially in regions of very high cloud cover. Limitations from cloud coverage are often associated with traditional optical sensors. Recently, researchers are beginning to explore the possibilities of fusing optical data with satellite synthetic aperture radar (SAR) data in monitoring vegetation dynamics (Vuolo *et al.*, 2016; Torbick *et al.*, 2017). Other possible areas of future research that need more attention is in real-time phenological monitoring (De Bernardis *et al.*, 2016; Liu *et al.*, 2017a), and the incorporation of biomass combustion estimates in vegetation-climate modelling studies (Roberts *et al.*, 2009)

8.6 Conclusion

The African human population still rely on vegetation and its services for its basic existence and survival (Food and Agriculture Organization of the United Nations, 2014). Hence, it is quite pertinent to constantly update and enhance our understanding of vegetation dynamics and growth pattern in the continent. The seasonal vegetation pattern, and its recurrence of life cycle events, observed remotely (also known as land surface phenology, LSP), offers the opportunity to understand vegetation dynamics and its responses to climate variability and change at a much wider spatial and temporal scale (Cleland *et al.*, 2007; Peñuelas *et al.*, 2009; Richardson *et al.*, 2013). Therefore, this study set out to first systematically identify the gaps in the analysis of remotely sensed and ground-based observed seasonal vegetation pattern commonly referred to as vegetation phenology in Africa. It went further to evaluate some of the identified gaps relating to the description of vegetation phenological patterns, its trends and responsible drivers.

Significant increases in the number of phenological studies in the last decade were observed, with majority of the studies adopting a satellite-based remote sensing approach to monitor vegetation phenology. Whereas ground based studies that provide detailed characterisation of vegetation phenological development, occurred rarely in the continent. Even more evident was the lack of phenological networks in the continent.

Further results from these investigations showed a more detailed up-to-date characterisation of Africa's LSP. It also identified significant trends in LSP parameters leading to longer vegetation growing season. Importantly, LSP trends that were not affected by land cover changes were distinguished from those that were influenced by land cover changes such as to map LSP changes that have occurred within stable land cover classes and which might, therefore, be reasonably associated with climate changes through time. As expected, greater slope magnitudes were observed more frequently for pixels with land cover changes compared to those without, indicating the importance of controlling for land cover.

One of the most interesting findings is the ubiquitous nature of pre-rain green-up across the continent and the localised Sudanian and Sahelian post-rain green-up. Remarkably also was the predominantly photoperiodic control of LSP in Africa which is contrary to previously held views of drivers of onset and end of vegetation growing season.

In general, these findings while complementing those of earlier studies have strong implications for the vegetation and climate change modelling communities as well as for decisions and policy makers. It offers the possibility of reducing the uncertainties in vegetation phenological modelling and increasing the confidence level in predicting vegetation response to climate variability and change.

One key strength of this study is its enhancement of the general understating of Africa's LSP by employing recent satellite remote sensed data with relatively finer spatial and temporal resolution. Another is its contribution to the current literate on drivers of LSP of different vegetation types both regionally and globally.

Notwithstanding these contributions, it is important to state that the results of this study were subject to certain limitations. These limitations and uncertainties cut across the type of remotely sensed data used, the vegetation indices adopted, smoothing, LSP estimation and rainfall parameters estimation techniques, and availability of field observational data and up-to-date land cover data. However, several steps were taken to reduce some of these uncertainties in order to improve the reliability of study outcomes.

Although there has been significant improvement on our understanding of the climate-driven vegetation phenology in Africa, the representation of Africa's LSP in current vegetation models is still very challenging. Still required are further investigations into vegetation-climate interactions, including vegetation-climate feedbacks. Further insights into future research is the possibility of linking and merging data derived from different sources and/or different estimation techniques. Also important is the recommendation of developing a widespread monitoring phenological network for the African continent, which is very much needed to ultimately improve vegetation phenological studies in Africa.

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