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Assessment of crop Phenology Trends and Climate Drivers Based on Earth Observation System In Lake Tana basin, northwestern Ethiopia

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By

Ayenew Gezie

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A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES OF BAHIR DAR UNIVERSITY, FOR PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN GEOINFORMATICS

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February 2022

BAHIR DAR

Declaration

This is to certify that the thesis entitled "Assessment of crop phenology trends and climate drivers based on Earth observation system in Lake Tana Basin, Northwestern Ethiopia ", submitted in partial fulfillment of the requirements for the degree of Master of Science in Geoinformation Science of Department of Geography and Environmental Studies, Bahir Dar University, is a record of original work carried out by me and has never been submitted to this or any other institution to get any other degree or certificates. The assistance and help I received during the course of this investigation have been received during the course of this investigation have been duly acknowledged.

Ayenew Gezie	24/02/2022	Bahir Dar	______________
Name of Candidate	Date	Place	Signature

CERTIFICATION

This is to certify that the thesis entitled as Assessment of crop phenology trends and climate drivers based on Earth observation system in Lake Tana Subbasin, Northwestern Ethiopia is an authenticated work carried out by Ayenew Gezie under our guidance and supervision. This is the actual work done for the partial fulfillment of the award of the Degree of Master of Science in Geo-Information Science from Bahir Dar University, Bahir Dar.

GRADUATE PROGRAM

As thesis research advisor, I hereby certify that I have read and evaluated this thesis prepared under my guidance by Assessment of crop phenology trends and climate drivers based on Earth observation system in Lake Basin, Northwestern Ethiopia. I recommend that it be submitted as fulfilling the thesis requirement.

Mr. Biniam Sishebre ________________ ________________

Advisor name Signature Date

Dr. Daniel Ayalew Mengistu ________________ ________________

Advisor name Signature Date

As members of the Board of Examiners of the M.Sc. Master of Science thesis open defense examination, we certify that we have read and evaluated the thesis prepared by Ayenew Gezie and examined the candidate. We recommend that the thesis be accepted as fulfilling the thesis requirements for the degree of Master of Science in Geo-Information Science.

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Final approval and acceptance of the thesis is contingent upon the submission of final copy of the thesis to postgraduate office (PGO) through the departmental or school graduate committee (DGC or SGC) of the candidate.

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ABSTRACT

Understanding trends in crop phenological variables and the climate drivers is indispensable for devising precision agricultural system. Studies conducted using remote sensing technologies at the national scale in Ethiopia have focused on the relationships of climate variability with vegetation greenness. However, assessment of crop phenological variable trends and the climate drivers were unexplored. Therefore, the study aimed to understand the trends in crop phenological variables and the climate derivers. To this end, phenological variables extracted from Normalize Difference Vegetation Index (NDVI), Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperatures and Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) were used. Savitzky–Golay filter method employed to smooth NDVI time series data and relative threshold method applied to extract phenological variables such as start of season (SOS), length of grow the season (LOS) end of growing season (EOS) and peak greenness time (POS). Trend analysis of crop phenological variables, precipitation and land surface temperature examined by Mann Kendall test and slope of the trend calculated by Sen's slope method. Linear regression model used to evaluate the influence of changes in climate variables on crop phenological variables. End of crop growing season showed strong decreasing trend in the past twenty years ($p < 0.05$). May precipitation amount showed substantial increasing trend ($p = 0.013$). Minimum land surface temperature in May portrayed positive statistically significant trend. Peak greenness time had showed significant correlations with May, July and October precipitations ($P < 0.05$). Precipitation amount in May and June had showed strong positive correlation with start of crop growing season ($p < 0.001$), whereas length of crop growing period showed positive significant correlation with precipitation amount in July and August ($p < 0.001$). On the other hand, maximum land surface temperatures in May and June had strong positive correlation with start of crop growing season. In conclusion, the trends of crop phenological variables are advanced and shorten. Hence, farmers should consider crop varieties or types that need short development period. The research results can be used as an input in adaptive crop management guideline preparations.

Keywords: CHIRPS, MODIS, land surface temperature, phenology, precipitation

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CHAPTER ONE

1. INTRODUCTION

1.1. Background

Crop phenology refers to the study of crop seasonal life cycles. It focuses on the start of the growing season to the end of aging in the life cycles of crops and the connection of the life cycles with the drivers (Adole et al 2016). Crop phenological variables such as start of growing season, end of growing season, and lengthen of growing period and peak greenness time are driven by variability (Adole et al.2019; Xiao et al. 2021). A warmer climate certainly leads to shift in crop phenology and eventually determine crop yields (Zhao et al. 2019). Declining of precipitation results in water stress and stagnates crop growth and development, thereby affect primary productivity (Liu et al. 2021). Hence, monitoring crop phenology variables in connection with climate variability helps in selecting crop types or varieties and modeling net primary production (Sakamoto et al. 2005). It is also useful to determine crop growth period conditions for modeling crop yields. Information found by monitoring crop phenology helps to decide when and how to utilize water resource efficiently (Digkuhn and Gal 1996). Therefore, monitoring trends of crop phenology is necessary for evaluating crop productivity and crop management (Sakamoto et al. 2005). Time series analysis in crop phenology in light with climate variability or change help formulate effective climate change adaptation strategies (Mo et al. 2016).

However, traditional crop monitoring is costly and susceptible to error. There is also lack of time series data that can be used in developing countries. The aforementioned gabs can be alleviated by remote sensing technologies. Remote sensing technologies provides time series data that helps understand long term trend of crop phenology (Zhao et al. 2019). The technologies are also used for detecting seasonal crop phenological changes and climate variability (Zhao et al. 2019). The most commonly used remote sensing technology for crop monitoring is MODIS data because of its moderate spatial and high temporal resolutions. The time series data of this technology used for studying trend of long term crop phenological variables. The MODIS NDVI product widely used to extract crop phenological variables such as SOS, end of the season EOS, length of the season LOS, and peak greenness POS (White et al. 2009). Such information helps to perform adaptive agricultural system to be based on informed decision.

Climate variables are key parameters influencing the growth, phenology and crop productivity. Cool summers for instance could result in delayed growth and decreased crop yields (Xu et al. 2020). Rain fed agricultural system is prone to climate variability. Climate variability profoundly affects crop phenological variables (Hmimina et al. 2013). Precipitation and temperature are considered very important elements in climate description (Mahmood et al. 2019).Variations in these climate variables result in advanced or delayed, prolonged or shortened of crop and development (Richardson et al. 2013). Late start of the growth season leads to exposure to harmful temperatures and water deficit in flowering and ripening periods (Brown et al. 2017). Early onset of the growth season on the contrary negatively affects crop production by delaying plant growth and restricting full development (Membold et al. 2014). However, the impact of climate variability on the trends of crop growth periods depends on climate regions (Brown et al. 2012; Richardson et al. 2013; Vrieling et al. 2013; Fatima et al 2020; Brown et al. 2012; Chen et al. 2018).

1.2.Statement of the problem

Ethiopia is characterized by complex topography, recurrent drought and climate variability. The country also located where the trade winds from North and South come together. The climate conditions in Northern and Southern hemispheres therefore affect the climate condition of Ethiopia. The climate variability influences crop production (Evangelista et al. 2013; Brown et al. 2017; Gummadi et al. 2018).The Ethiopian Agricultural system is rainfed and it is a backbone of Ethiopian economy. Rainfed agriculture is more susceptible to climate variability. For long time, crop maturity failure and yield decline have been frequently observed in the country (Evangelista et al. 2013). However, how crop phenological variables respond to climate variability at local scale have hardly been studied.

Rainfed agricultural system is highly susceptible to climate conditions. The livelihoods of nearly 85% of the population in the country are dependent of rainfed agriculture. Studies conducted at global, regional and national scales showed that Ethiopia is most vulnerable country to climate change (Brown et al. 2012; Eastman et al. 2012, Vrieling et al. 2013; Guan et al. 2014; Alemu and Henebry 2017). Rainfall onset, duration and intensity are highly variable in time and space in the country (Vrieling et al. 2013; Musau et al. 2016). Studies conducted regarding phenology and climate variability show different findings. Advance of SOS and positive trends of rainfall amount in the north, but shortening LOS and negative trend in rainfall amount in the south and eastern part of the Ethiopia were reported (; Funk et al. 2015; Brown et al. 2017). Climate models project increasing rainfall, but frequency of drought occurrence increased in recent decades (Vrieling et al. 2013; Evangelista et al. 2013). On the contrary, some other authors profound decreasing of rainfall amount and intensity all over the country (Vrieling et al. 2013; Evangelista et al. 2013). These inconsistent reports indicate that studies on crop phenology and the climate drivers need to be conducted at local scales.

Several research have been undertaken regarding climate interactions with phenology at the country or global level in Ethiopia (Brown et al. 2012; Richardson et al. 2013; Vrieling et al. 2013; Fatima et al 2020; Brown et al. 2012; Chen et al. 2018). However, the findings of the research results are inconsistent. Early SOS and increasing trends of rainfall amount in the north, but shortening LOS and decreasing of rainfall amount in the south and eastern parts Ethiopia were reported (Brown et al. 2017; Funk et al. 2015). On the contrary, profound decreasing of rainfall amount and intensity all over the country is reported (Vrieling et al. 2013; Envangelista et al. 2013). Climate models project increasing rainfall, but frequency of drought occurrence increased in recent decades (Vrieling et al. 2013; Envangelista et al. 2013). Hence, researches are needed to be conducted at local scales for informed decision. Therefore, this research aimed to assess the trends in crop phenological variables and climate drivers in Lake Tana basin northwest Ethiopia. Long time-series of crop phenological variables and their drivers could can provide information in preparation of adaptive agronomic management guidelines. Studies conducted regarding phenology using remote sensing technologies at the national scale in Ethiopia have focused on the relationships of climate variability with vegetation greenness (Kabthimer 2012; Teferi et al. 2015; Getahun and Shefine 2015; Zewdie et al. 2017; Workie and Debella 2018; Dagnachew et al. 2019). However, assessment of crop phenological variable trends and their response to climate drivers were unexplored at local level. This kind of research helps to select suitable crop varieties or crop types and perform informed agricultural management. Assessment of trends in crop phenology and climate drivers is necessary for developing climate adaptation strategy guideline.

1.3.Objectives of the study

1.3.1.General objective

The purpose of the study was to assess trends in crop phenology and climate drivers (2001 – 2020) based on Earth observation system in Lake Tana Subbasin, Northwestern Ethiopia

1.3.2.Specific objectives

- Investigating trends in crop phenological variables in the past twenty years
- Detecting trends in precipitation in crop growing months in the past twenty years
- Exploring trends in land surface temperatures in crop growing months in the past twenty years
- Analyzing the relationships of crop phenological variables with the climate variables

1.4.Significant of the study

Climate change is real, and environmental change is inevitable. In this dynamic environment, enhance productivity agricultural system has to be based on informed decisions. To this end, understanding the trends in crop phenological variables connections with climate variables is necessary. This information helps to select suitable crop type or varieties that could adapt the existing climate conditions and establish supplementary irrigation system in crop growth stages. In this study, decreasing trends in start of growing season, end of crop growth season, length of crop growth season, and peak greenness time observed. Besides, cool trend in land surface temperatures also detected in the present study in crop growing season. On the other hand, in crop growing season, increasing trends in precipitation has been detected except in June precipitation. The aforementioned information generated in this study can be used by different stakeholders, engaged in farming. This information helps understand how crop phenological variables respond to climate conditions. Hence, the results could be used in selecting suitable of crop types or varieties and establish accompanying irrigation system in crop growth stages accordingly. Besides, the results of this study could be used as a baseline to advance using remote sensing time-series for modeling crop productivity and establish modern agricultural system. Understanding how crop phenology respond to climate variability is also vital to understand future food production and food security trends in developing countries like Ethiopia. Generally, the findings of this research might be used as a base for further research and an input for planning precision agriculture.

1.5.Scope of the study

The study carried at subbasin scale on investigating trends in crop phenological variables, land surface temperatures and precipitation in crop growth period for the past two decades (2001- 2020). Besides, the study has focused on investigating the relationships of climate variables with crop phenological variables such as start of crop growing season, end of crop growing season, length of growth period and peak greenness time. In this study NDVI constructed from MODIS time series data. Crop phenological variables generated from MODIS NDVI products by using TIMESAT software version 3.3. MODIS land surface temperatures have been used in the study. Besides, CHRIPS data was used in the study.

1.6.Organization of the thesis

This research work document is organized into five chapters. Chapter one included a brief introduction of the research, statement of the problem, research objectives, describe significance of the study and scope of the study. Chapter two consists of briefly review of scholars works. Chapter three encompasses description of the study area, method and materials sections. Chapter four consists of result, discussion conclusion and recommendation sections of the thesis.

CHAPTER TWO

2. REVIEW LITERATURE

2.1. Phenology

Vegetation phenology is the study of the recurrent patterns, behaviors and life cycles of plants in response to insolation, temperature, and precipitation (Jönsson and Eklundh, 2004). Phenological events have been found to be sensitive to climate change (Adole et al. 2016), and hence they are considered as bioindicators of climate variabilities and climate change (Adole et al, 2018). Studies showed higher spring temperature triggers earlier leaf-on, and thereby it leads to a prolonged growth season (Piano et al. 2015). Additionally, it has been reported that warming land surface temperature in Northern Hemispheric ecosystem resulted in uneven effects on vegetation activity (Peng et al. 2013) and phenology such as spring leaf onset (Piao et al. 2015; Shen et al. 2018), autumn-leaf senescence, and summer greenness (Shen et al. 2016). These changes of vegetation activity and phenology alter functioning and structure of ecosystems. These in turn result in changes in the carbon balance, land surface water and energy balances (Wu et al. 2014). Therefore, studying how phenology responses to climate change/ variability is essential for better understanding of ecosystems functioning and the nutrient cycle.

Information on crop phenology is essential for precision farming and efficient resource utilizations. It help the farming system to be implemented based on comprehensive scientific information to enhance crop productivity. Precision agriculture is systems of farming in which crops and soil receive exactly what they need in order to optimum health and productivity of crop growth. Studies on timing of crop phenological variables and the climate drivers provide valuable data for planning, organizing and timely effecting of certain standard and special agricultural activities that require advanced information on the dates of specific stages of crop development (Xiao et al. 2021).

Climate variables are key primary drivers of crop seasonal biological events. The variability of climate elements impacts agricultural production through affecting crop growth stages, phenological events and crop yields. Variations in climate variables result in advanced or delayed, prolonged or shortened key sensitive crop growth stages (Richardson et al. 2013). Thus, changes in the rhythm of different phenological events are considered as a key biological indicator of climate change (Piao et al. 2019). Global average temperature change has resulted in spring phenological events to occur sooner as well as a delay of autumn phenological events (Jeong et al. 2011). An increase in the length of the growth duration generally favors an increase in net primary production resulting by increase carbon dioxide assimilation and potentially contributes to regulating atmospheric greenhouse gases (Keenan et al. 2014). On the other hand, lengthening of growth duration can also have negative impact of atmospheric greenhouse gases. Piao et al. (2008) reported longer of growth season in warmer autumn results in increased respiration. Consequently, it leads to an increase in the amount of carbon dioxide. This largely counteracts the positive impact of springtime carbon dioxide assimilation on the total amount of atmospheric greenhouse gases.

In addition to the impact on carbon dioxide, longer growth duration with increased temperature influences the transpiration of plants and impact the processes involved in hydrological cycle between the Earth's surface and the atmosphere (Huntington 2004). Furthermore, a longer growth season also leads to a decreased surface albedo. This in turn could lead to increased warming of the Earth's surface due to increased solar energy absorption by vegetation. Finally, changes in the biological cycles of plants may also have consequence on species interaction, affecting their ecological relationship, which could result in a loss of biodiversity (Caparros-Santiago et al. 2021). Therefore, studying the phenological dynamics of vegetation has paramount importance in understanding the behavioral responses of the Earth's ecosystems in the face of climate change.

In the past decades, satellite remote sensing has played a vital important role in monitoring how vegetation response to environmental changes because of its repeat monitoring capabilities and global coverage. Land surface phenology a term commonly used to refer to vegetation phenology derived from satellite data (Helman 2018). It is generally estimated based on vegetation indexes or biophysical variables. Time series data of vegetation indexes or biophysical variables can be used to study phonological events and obtain specific phenological variables based on functional analyses. Phenological variables include start of the growth season, end of the growth season or the length of growth duration. These help monitoring of vegetation phenological dynamics at global scales (Aragones et al. 2019). Hence, land surface phenology has made a great effort to determine ecologically expressive variables from multispectral satellite observations (Caparros-Santiago et al. 2021).

2.2.Vegetation indexes

Vegetation indexes are spectral transformations of two or more bands that are developed to understand the response of vegetation photosynthetic activity and canopy structural variations to various factors (Huete et al. 2002).The most commonly used remote sensing technology for crop monitoring in developing countries is Moderate Resolution Imaging Spectroradiometer (MODIS) because of its moderate spatial resolutions and high temporal resolution. The Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation index products are designed to offer consistent, spatial, and temporal comparisons of global vegetation conditions for monitoring photosynthetic activity (Running et al.1994). The time series data of this technology is used for studying trend of long term crop phenological variables. However, normalized difference vegetation index (NDVI) has been widely used for monitoring, analyzing, and mapping spatiotemporal distributions of physiological and crop phenological stages characterization (Yu et al. 2003). This is because the NDVI is chlorophyll sensitive and sufficiently stable to permit expressive comparisons of seasonal and inter-annual changes in vegetation growth and activity (Huete et al. 2002). The most commonly used vegetation index is Normalized Difference Vegetation Index (NDVI) (Huete et al. 2002; Gitelson 2004).

Analysis of remote sensing based vegetation index data which transformed from individual spectral bands has been the basis for most phenology studies. The use of vegetation indexes has been well established in the literatures as they represent spectral transformations that integrate two or more spectral bands sensitive to different plant characteristics and have been found to be more useful indicators of the state and condition of vegetation (Adole et al, 2018; Vrieling et al. 2018). Commonly used remote sensing vegetation indexes in phenology literatures are normalized difference vegetation index, enhanced vegetation index, leaf area index, and wide dynamic range vegetation index. Whereas, fraction of absorbed photosynthetically active radiation, perpendicular vegetation index, green-red vegetation index, two-band enhanced vegetation index, plant phenology index, and soil adjusted vegetation index are the less frequently used indices (Caparros-Santiago et al. 2021).

Physical-based indexes like fraction of absorbed photosynthetically active radiation and leaf area indices represent direct biophysical measures of vegetation can be estimated by empirical or physical models, instead of a certain combination of the multispectral reflectance properties (Gobron et al. 2006). The modified vegetation indexes such as perpendicular vegetation index, soil adjusted vegetation index, enhanced vegetation index, and 2 bands enhanced vegetation index are designed to minimize the index's sensitivity to various environmental factors that introduce non-vegetation-related variations into normalized difference vegetation index that include effects from the soil background, snow or aerosols. In addition, several studies suggest that a collectively analysis of multiple vegetative indexes may improve the accuracy of phenology estimation (Wu et al. 2014).

2.3.Climate variability impacts on phenology

An understanding of vegetation-climate trends along with their relationships is essential to visualize the complex interactions of Earth systems and their dynamics (Brown et al. 2012). Climate variability/change impacts agricultural system by shifting phenology timing (Brown et al. 2010). The variability of climate variables such as temperatures and precipitations in key phenological stages impose challenges on agriculture (Hmimina et al. 2013). For instance, a late start of season may cause exposure to temperature and water stresses in flowering and fruit ripening periods. These in turn could result in crop growth failures and declining productivity (Brown et al. 2017). However, the impact of climate on phenology timing trends varies from region to region across the world (Richardson et al. 2013). An expansion of the growth period has been reported in the previous decades at global level and early green-up in high latitudes owing to global warming (Chen et al. 2018). However, the trends and the drivers of vegetation phenology timing over the tropics is less clear (Vrieling et al. 2013). The impact of climate variability or changes varies across vegetation types and from regions to regions in the continent (Adole et al 2019; Wang and Shafeeque 2019). These clearly indicate that detail studies on the trends and response of vegetation to climate conditions at local scales is necessary to envisage the possible agricultural systems, future food production and food security trends in developing countries.

Ethiopia is vulnerable to climate variability/change as it is reported by several researches (Alemu and Henebry 2017; Eastman et al. 2013; Workie and Debella, 2018). This is brought about due to the country’s latitude position, complex topography, fragmented landscapes and rain fed agriculture system. Agriculture is the backbone of Ethiopia economy. Climate change altered the annual amount, intensity and distribution of rainfall in the country (Musau et al. 2016). Early green up, an increase the rainfall amount in summer in the north and a shorter growth duration in south and eastern Ethiopia have all resulted in water stress in crop growth season (Brown et al. 2017; Funk et al. 2015). On the other hand, significant declining in the amount and intensity of spring rainfall and a decline in the number of annual rainy days have been reported by Gummadi et al. (2018). According to Meroni et al. (2014), increasing temperature is also a limiting factor for vegetation growth in the highlands of Ethiopia. Conflicting and spatially inconstant study results on the trends and the response of vegetation to climate variabilities justify the importance of a spatially explicit examination of the trends and connections of climate and vegetation critical growth timing period in the country.

2.4.Satellite data smoothing methods

Remotely sensing data quality contaminated by various noises such as aerosols, sun angle shadow effects, cloud and cloud shadow, and sensors/platform conditions. To reduce the noise, maximum value composite method is commonly applied to the satellite derived observations to generate temporally composite data. However, composite data alone cannot ensure quality of remote sensing data. Consequently, various techniques have been developed to minimize the residual noise and reconstruct a more representative data time series vegetation condition. The specific method selected can influence the performance of the phenology extraction from the smoothed time series (Atkinson et al. 2012). The techniques used to smooth and reconstruct the time-series data categorized into empirical methods, curve fitting methods and data transformations (Atkinson et al. 2012).

2.4.1. Empirical methods

Empirical smoothing methods operate over a local temporal window within the time series based on empirical knowledge or assumptions. This smoothening technique is based on the assumption that noise signals usually reduce the vegetation index value and temporal variation of the vegetation indexes signal from vegetation should be a smooth, continuous response across the growth season under favorable conditions. To this end, running sliding window, moving average filter, iterative interpolation, and changing-weight filter proposed to replace the low vegetation index values caused by residual noise (Zhu et al. 2012).

The advantage of empirical smoothing techniques is that they are simple to apply, but they are usually sensitive to the empirical parameters such as the threshold for noise, the length of compositing period for the maximum value composite method and the length of sliding window. Specifically, they performed poorly as the original time series contains continuous missing data. Recently, the methods integrating spatial and/or temporal information have been proposed to reconstruct vegetation time-series data (Cao et al. 2018).

Only applying traditional empirical methods to create a smoothed time series representative of detail phenological responses can still retain some residual noise artifacts in the form of localized, anomalous peaks or dips in the time-series vegetation index data. Accordingly, other data smoothing methods like curve fitting and data transformation can be used after the application of empirical methods to further reduce these remaining noise artifacts (Caparros-Santiago et al. 2021).

2.4.2. Curve fitting method

Curve fitting methods apply mathematical functions to fit the vegetation index time-series curves to a specified function. Commonly used approaches include logistic models, improved logistic method, asymmetric Gaussian functions, Savitzky–Golay filter, quadratic function and nonlinear spherical model. The most commonly used smoothing technique in phenology detection are curve fitting methods (Caparros-Santiago et al. 2021). The model fitting methods can effectively suppress the noise of data. In addition, they are expected to be more objective approaches and easier to adapt to a wide range of situations. However, the time series vegetation index curves derived from remote sensing data are not always regular curves, and hence the accuracy of function fitting will directly affect the precision and accuracy of extracting phenological features. An inadequately calibrated data record can introduce artefactual changes in the time series data and an overfitting of the time series may affect important phenological features. The greenness trajectory in the senescence phase of the growth season for instance can drop more rapidly than the rapid vegetation indexes value increase in the green up phase for most vegetation types, or even appear as a two-stage decline, which results in estimates of end of growth season in autumn often being inherently more uncertain (Caparros-Santiago et al. 2021).

2.4.3. Data transformation methods

Data transformation methods decompose the time series into cyclical, trend, seasonal and irregular components based on mathematical manipulation. Fourier transforms and wavelet analysis are the most widely used data transformation methods to characterize the phenological stages which are derived from satellite observations (Caparros-Santiago et al. 2021). Generally, the model with higher resolution can better capture refined phenological information as they are able to describe more detailed changes of time-series curves (Beck et al. 2006). Accordingly, compared to Fourier analysis, wavelet transform based on local basis of functions has advantage in the feasibility of localization in the time domain and flexible scales in both frequency and time domains, which can capture the high frequency variability (Sakamoto et al. 2005).

2.5. Phenological variable extraction methods

Several methods have been applied to extract various phenology variable. The methods, however, can be categorized into threshold-based methods and vegetation index change detection methods. The most commonly methods used in phenological event extraction approaches are briefly discussed as follows.

2.5.1. Thresholds methods

Threshold methods represent the simplest approach to extract phenological indexes from vegetation time-series data, assuming that the phenological stage commences as the smoothed vegetation index values reach a specific index value. Thresholds commonly are either fixed or dynamic. In the case of fixed threshold, arbitrarily a single fixed index value establishes. The dynamic threshold is generally based on a metric calculated from the vegetation index time-series data such as the vegetation index ratio, long-term mean or median vegetation indexes, vegetation index of the time-series data record (White et al. 1997).

Albeit the threshold method is simple and easy to apply, there is no underlying biophysical meaning for the threshold selected and a single threshold value may not be appropriate for different plant species and/or different locations. Fixed threshold methods can be sensitive to various noise in the vegetation index time series. On the other hand, dynamic thresholds are established directly from the vegetation index data characteristics over the study area. Thus, they are more customized as the threshold accounts for differences among vegetation types or the inter-annual variation of vegetation that occur within the targeted area. However, these dynamic thresholds might not be stable over time and can be sensitive to the noise (White et al. 1997). The baseline year method developed by Shabanov et al. (2002) is based on the value from a selected baseline year in the time series to represent the normal phenological behavior of vegetated landscape and phenological events for other years are detected as time series values reach the values from the baseline year (Shabanov et al. 2002). However, the baseline year method is sensitive to the inter-annual variations and the selection of a representative year is subjective and challenging.

5.3.2. Change detection methods

Change detection methods determine the phenological dates by directly identifying the changing characteristics of the vegetation index time-series curve such as the point with largest derivative or the inflection point with the local extreme in the first derivative or the rate of change of curvature. It is assumed that the start of the growth season and the end of the growth season can be determined as the time starting the maximal increase or the time marking the maximal decrease in vegetation index in the green up and senescence phases of the growth season, respectively. The primary difference among existing methods is how they determine the points with specific change characteristics in vegetation index time series. Reed et al. (1994) proposed a moving averaged method to determine the start of growth season and the end of growth season as the dates that an observed vegetation index time series crossed a curve established from moving average models. This is an innovative in the change detection method for estimating the start of the growth season and end of the growth season dates.

Change detection methods are usually combined with curve fitting or data transformation methods to extract the phenological features from the smoothed data, as the fitted time series data are continuous in first derivative or change rate of curvature. Change detection methods are widely documented in literatures and considered an effective way to extract the phenological metrics (Zhang et al. 2003). The reliability depends on the assumption that the phenological stages are corresponding to the rapid changes of vegetation index values and the smoothed time series data approximates the true phenological characteristics of the vegetation.

2.6. Applications of remote sensing technology in agriculture

Remote sensing is the acquisition of information about an object or phenomenon from distance. This involves an instrument or a sensor mounted on a satellite, an aircraft, an unmanned aerial vehicle or unmanned ground vehicle or a probe. The sensor typically measures the electromagnetic radiation that is either reflected or emitted by the target (Wang and Shafeeque 2019).

The type of information accessible from remote sensing depends on the specific properties of the instrument and its platforms. In the field of agriculture, the information of interest consists of traits or features of the agricultural systems, and especially how the features r vary in space and time. According to Nock et al. (2016) functional traits that influence organism performance or fitness are morphological, biochemical, physiological, structural, phenological or behavioral characteristics. The nature of agronomic traits can be crop type, physical, chemical, biological, structural or geometrical. Crop productivity is resulted from a series of intertwined biophysical processes and agricultural managements in the crop growth season (Nock et al. 2016).

The agronomic traits mentioned in the aforementioned are hardly measured directly by remote sensing sensors. However, it is possible to make inference about the traits by modeling the relationships of radiance measured by remote sensors and the traits themselves. Crop yield can be linked to remote sensing observations. However, in this regard characterizing driving factors of crop yield such as solar radiation, temperature, wind speed, humidity precipitation, crop growth stages, transpiration and photosynthesis, redistribution of assimilates within plant organs, nutrient and water supplies, pruning need to be considered.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1.Description of the study area

Geographical location of Lake Tana basin ranges from 10°29′N to 12°46′N latitude, 36°44′E to 38°14′E longitude (Figure 1). The total area coverage of the basin including the Lake area is around 15096 km^2. Lake Tana basin is located in the Amhara National Regional State in the north-western part of Ethiopia. The basin is the headwater catchment of the Upper Blue Nile River. Lake Tana basin support the production of Ethiopia's main staple grains such teff, maize, millet, and rice. The spatial distribution of crops in the Lake Tana Basin mainly influenced by heterogeneous topography and highly localized climate patterns (Sisheber et al. 2022).

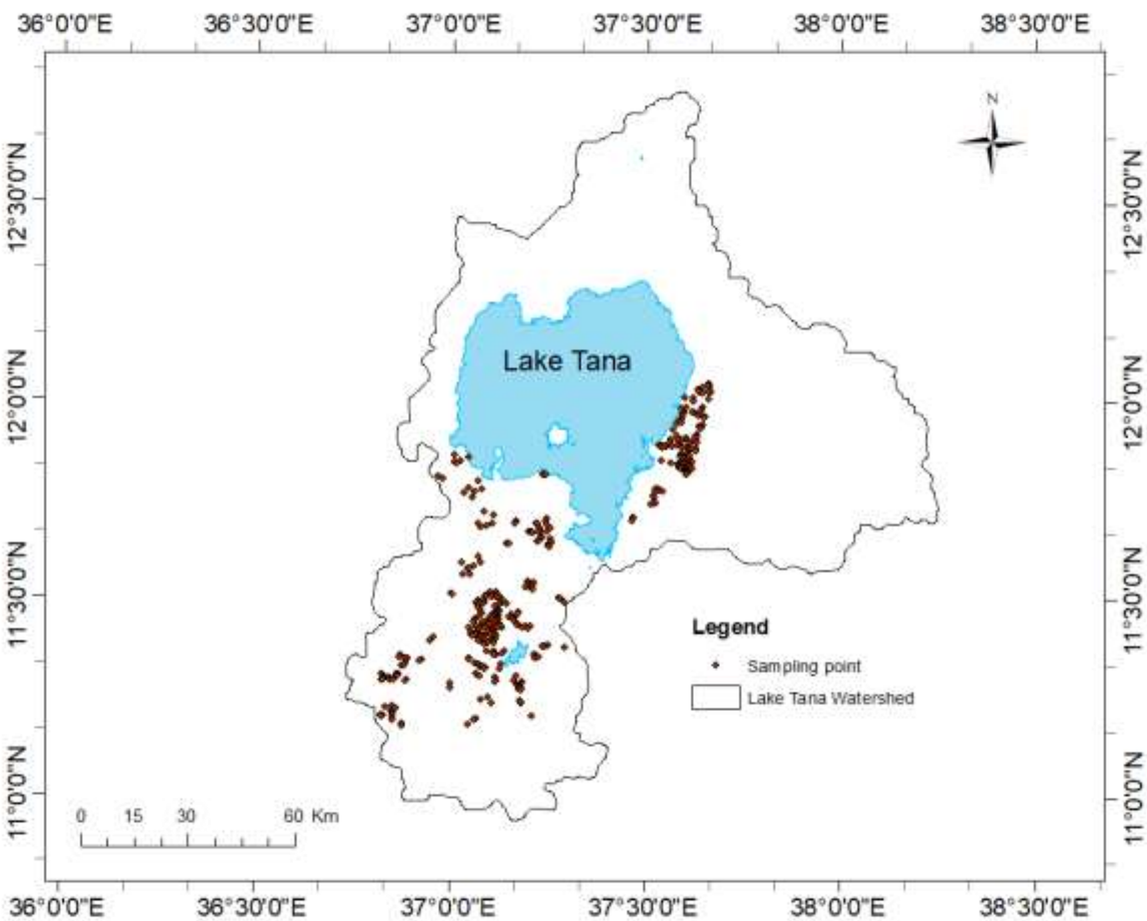


Fig. The study area map

3.2.Characteristics of Lake Tana Basin

3.2.1. Topography of Lake Tana

Lake Tana is located in a wide depression of the Ethiopian plateau. It drained by several rivers flowing into Lake Tana. (Sisheber et al. 2022).The landscape is characterized by floodplains, peak highlands, mountain chains, hills and steeply slope lands that mostly divide the sub-basin from its surrounding drainage basin and serves as a water tower for whole sub-basin area. According to BoEPLAU (2015), the largest area of Lake Tana basin area is characterized by moist tepid (79.4%) followed by sub-humid tepid (12%) and moist cool (5%). The rest of the areas characterized by sub-humid cool, moist warm, moist cold, moist very cold, and sub-humid cold which cover 2.8%, 0.64%, 0.2% , 0.01%, 0.01% of the basin, respectively . Moist tepid agroclimatic condition found up to 2700 m and of which 25.75% and 19.33% is found within the elevation range from 1327 to 1800 m and 1800 to 1900 m, respectively. It is surrounded by high hills and mountains except where the outflow leaves the lake by a narrow valley in the southeast. The lake catchment has a minimum elevation of approximately 1784m at around the south tips of Lake Tana, and a maximum elevation of 4107 (BoEPLAU 2015).

3.2.2.Climate

The Lake Tana basin has a comparatively mild climate as of its high elevation. The annual climatic conditions of Lake Tana basin is categorized into rainy and dry season. The rainy season further categorized into major rainy season which ranges from June to September, and minor rainy season which is in April to May. The dry season occurs between October and April. The mean annual rainfall ranges from 970 mm to 1900 mm (Sisheber et al. 2022). The annual average air temperature in the basin ranges from 13.2 °C to 27.3° C. The mean annual relative humidity is around 58% (Setegn et al. 2008).

3.2.3.Land use land cover

According to the information in BoEPLAU (2015), Lake Tana basin is characterized by diverse land use and land cover types dominantly by cultivated land. From the total area of Lake Basin , 55.71% of the area covered by cultivated land, 19.69% by water, 7.22% infrastructure, 6.3% grassland, 4.9% by bush and shrub land, 3.79% by forest, and 1.52% by wetland. In the basin, around 0.85% of the land in Guna Mountain range covered by afroalpine and sub-afroalpine vegetation.

3.2.4. Vegetation

Natural forests in Lake Tana basin are characterized into dry evergreen Afromontane and riverine forest. Evergreen Afromontane forests found ranges from 1500 to 2700 m above sea level. Riverine forest is mainly found in the vicinity of Lake Tana and rivers of the basin. *Combretum–Terminalia* and *Acacia–Commiphora* woodland are the two types of woodland mostly found in the Lake Tana basin. *Combretum–Terminalia* woodlands found in the altitude range from 500–1900 m. They are usually located in humid lowland areas or in river valleys of Lake Tana basin. *Acacia–Commiphora* woodlands usually found within the altitude ranging from 1000 to 1900 m. *Eucalyptus* species, *Cupressus lusitanica* and pine species as well as *Acacia mearnsii* are most common planted plants in the Lake Tana basin. Bushland commonly found in areas with shallow soil and steep slopes such as hills, escarpments, mountains, and gorge slopes. While grasslands are mainly distributed along rivers, around villages, on mountains and hilltops, on slopes, and on highlands with stony and shallow soils. Teff, sorghum, chickpea, rice, maize, and sesame are the most commonly cultivated in the Lake Tana basin (Song et al. 2018).

3.2.5.Agronomic practices

Lake Tana basin is characterized by having high potential for agriculture, livestock, water resource, forest and wildlife, tourism, and fishery development compounded with high biological diversity. The basin has also fertile soil and cultivable land for intensive agriculture. The agroecosystem are also suitable to produce more than once per year. More than million people expected to live in the Lake Tana basin (BoEPLAU 2015). The basin is characterized its multiple benefits such as economic, social, political, religious, ecological benefits.

In Lake Tana basin, mixed agronomic practices such as crop production and the rearing of livestock carried out in small farms. The basin is most suitable for irrigation agricultural development. It is estimated that 8% of the basin is irrigable land, which makes the water shed a major growth corridor in Ethiopia. However, the agricultural system in the basin is rain fed which is highly susceptible to climate variability or changes. Based on the origin, formations, morphology and other profiles, the soils in the basin is classified into Vertisols, Luvisols, Nitosols, Leptosols, Alisols, Cambisols, Regosols, Fluvisols, Ferralsols, Gleysols, Acrisols and Lixisols (BoEPLAU 2015).

3.2.6.Population

Lake Tana basin is one of the most densely populated area. It is estimated that 250 people live within a square kilometer. Around 76.9 % of the proportion live in the rural areas while the remaining percent live in urban and semi urban centers. Linguistically, main ethnic families live in the basin is Amhara (BoEPLAU 2015).

3.3.Materials

In this study, MODIS Conversion Toolkit used for reprojection sinusoidal projection of MODIS imageries into UTM projection in ENVI 3.5 software. While TIMSAT software version 3.3 and Matlab software version 2018b used for the purpose of analysis of time series data and extracting phenological variables. ArcGIS 10.2 used for the purpose of calculating NDVI.

3.4.Research design

The research designed used in this study was a longitudinal research design. This research approach was performed as the study focused exploring the relationships of crop phenological variables with climate variables, and the trends in the climate variables as well crop phenological variables in relation to time repeatedly for twenty from 2001 to 2020. In this study, the researchers have looked into the correlations of land surface temperatures and precipitations with crop phenological variables such as SOS, EOS, LOS, and POS. Longitudinal research design selected as the research aimed to assess the trend of crop phenological variables and the climate variables for the past twenty years, time series analysis.

3.5.Satellite data acquisition and preprocessing

3.5.1.MODIS data

Terra MODIS eight day maximum value composite stellate archives (MOD09Q1/A1) accessed from NASA's LP DAAC website https://lpdaac.usgs.gov/. Then, data reprojected into Universal Transverse Mercator projection (UTM Zone 37N, WGS84) using MODIS Conversion Toolkit. MODIS imageries from May to October for the past twenty years (2001 -2020) processed for this study. A total of 480 imageries processed for constructing MODIS NDVI time series data. The spatial resolution of the MODIS sensor data used in this study is 250m. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor time series data used because it has high temporal and moderate spatial resolution, and is accessible free of charge. Cloud and cloud shadow effects on MODIS LST removed by MODIS state quality flags (NourEldeen et al. 2020). The NDVI is chlorophyll sensitive vegetation index and commonly used in crop phenology trend assessment and monitoring (Wang and Shafeeque 2019). Besides, the NDVI is sufficiently stable to provide expressive comparisons of seasonal and interannual changes in vegetation growth and activity (Huete et al. 2002). The NDVI is a normalized ratio of the near infrared (NIR) and red bands and it is calculated as below:

$NDVI = \frac{\rho NIR - \rho red}{\rho NIR + \rho red}$ Where pNIR and $p$red are the surface bidirectional reflectance factors for their respective MODIS bands.

3.5.2. Climate data

3.5.2.1. MODIS Land surface temperatures

MODIS Land surface temperatures (MODIS LST) used in the study. Terra MODIS LST with a resolution of 1km were accessed from https://lpdaac.usgs.gov/products/mod21a2v061/. Land surface temperature (LST) is an important parameter related to surface atmosphere interactions. It has been widely used for agriculture scientific studies (NourEldeen et al. 2020). The change in LST can cause surface air temperature, precipitation and vegetation cover to vary by altering terrain materials and energy balances (Vancutsem et al. 2010). MODIS LST is considered the most suitable data source because of its free accessible, high observation frequency and moderate spatial resolution (NourEldeen et al. 2020). The MODIS Reprojection Toolkit software also used to reprojection Sinusoidal data to the UTM (Zone 37N, WGS84). Cloud and cloud shadow effects on MODIS LST removed by MODIS state quality flags (NourEldeen et al. 2020).

3.5.2.2. Climate Hazard Infrared Precipitation with Stations

Climate Hazard Infrared Precipitation with stations (CHIRPS) were as a climate element. CHIRPS dataset at a spatial resolution of 0.05◦ x 0.05◦ which is found to be reliable to Ethiopia (Funk et al. 2015, Bayissa et al. 2017) accessed from http://chg.geog.ucsb.edu/data/chirps/. Then, the land surface temperatures and the precipitation data were resampled to match with the spatial resolution of the MODIS NDVI time series products data. Then, the climate variables aggregated into months of crop growing periods (May, June, July, August, September, October) to match the timing of the phenology parameters in exploring the relationships of crop phenological seasonal parameters and climate parameters. The data used in this study summarized in (Table 1).

Table 1: Data sources of the study

Data Type	Source	Spatial resolution	Temporal resolution	Unit
NDVI	MODIS terra sensor	250m	8 day composite	m
Precipitation	CHRIPS	5km	pentad	mm
Maximum land surface temperature, Minimum land surface temperature and average land surface temperature	MODSLST	1km	8 day composite	^{o}c

3.5.3. Data extraction

Nine thousand points sampled from croplands using Google history Earth imageries. Then, the reliable croplands for the past twenty years (2001 to 2020) identified from Google Earth history. From the total sample, the four hundred fifty two points were found to be consistently croplands for the past twenty years. Then, the NDVI, land surface temperatures, and CHRIPS time series data were extracted by using these reliable cropland points to construct time series data for the past twenty years.

Phenological variables extracted from NDVI using TIMSAT software 3.3. The software is widely used to extract phenological information from time series of satellite data. Maximum value composition technique lessens cloud and cloud shadow effects ((Jönsson and Eklundh, 2004).). However, the technique cannot remove the noises completely, and hence original NDVI products are insufficiently accurate as residual noises. Several techniques proposed to further remove residual noises. For NDVI time series data characterized by fine spike noises, the Savitzky-Golay filtering method works very well (Jönsson and Eklundh, 2004). And hence, Savitsky-Golay filter smoothing model used to minimize the noises of MODIS NDVI time series in TIMESAT software version 3.2 during extracting crop phenological variables in this study.

During extracting the phenological variables, we used the relative threshold method to detecting crop phenology and determine the crop phenological variables as Lake Tana basin characterized by mixed crop agricultural practices (Jönsson and Eklundh, 2004). The date of the phenological variables occurs as NDVI values measured increased/decreased from the base level to a specified fraction of the amplitude. A relative threshold of 0.1 for start of crop growing season, and a relative threshold 0.3 for end of crop growing season used in extracting phenological variables. These relative thresholds are found to be reliable in the study area (Sisheber et al. 2022). The date of peak greenness represents date of the period as crop greenness reaches at least 80 % of NDVI maximum seasonal value (Jönsson and Eklundh, 2004). The length of crop growing period is the difference between the end of crop growing season and start of crop growing season (Zhou et al. 2016).

3.5.4. Data analysis

Trend analysis was carried out by XLSTAT version 2021.1.software. The Mann-Kendall test widely employed to detect trends in time series data, however, the result of the test may contain an error if significant autocorrelation exists in the data series (Mahmood et al. 2019). We calculated autocorrelation coefficient (R) to identify existence of significant autocorrelation within time series as below:

$$\left[\frac{-1 - 1.645 * (N-2) * 0.5)}{N-1}\right] =< R <= \left[\frac{1 = 1.465 * (N-2) * 0.5}{N-1}\right]$$

Where N represents the number of observations, R indicates autocorrelation coefficient. If the autocorrelation coefficient values R lies in between the lower and the upper confidence boundary, it shows that there is no significant autocorrelation among the observations (Mahmood et al. 2019). We have calculated autocorrelation coefficient in crop phenological variables, land surface temperatures and precipitation time series data using the aforementioned model. We found that the autocorrelation coefficients of crop phenological variables, land surface temperatures and precipitation time series data falls in between the lower confidence level and upper confidence level (-0.75 = < R= < 0.75). And hence, we applied Mann Kendall test to identify statistically significant trends in phenological variables, land surface temperature and precipitation for the period of 2001- 2020. Mann-Kendall test is the most commonly used nonparametric method in trend analysis (Mahmood et al. 2019). Mann-Kendall test statistic (S), the variance of Mann-Kendall test statistic V(S), and the associated standard normal test statistic (Z) were calculated as below.

$$Z = \begin{bmatrix} \frac{S-1}{\sqrt{V(S)}} \text{for S} > 0 \\ 0 \qquad S = 0 \\ \frac{S-1}{\sqrt{V(S)}} \text{for S} < 0 \end{bmatrix}$$

$$\sum_{I=1}^{n-1} \sum_{J=I+1}^{n} sign(xj - xi)$$

$$sign(xj - xi) = \begin{bmatrix} 1\ for\ (xj - xi) > 0 \\ 0\ for\ (xj - xi) = 0 \\ -1\ for\ (xj - xi < 0 \end{bmatrix}$$

$$V(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p\ (t_p - 1)(2t_p + 5)\right]$$

Where q designates total number of tied groups. A set of the same values in a dataset is referred to as a tied group. Each tied group is denoted by t_p. The positive values of Z denotes indicate increasing trends in time series, and the negative Z values means decreasing trends in time series. Trends are tested against the critical values ($Z1-\alpha$) to show that either they are statistically significant or not.

The Sen's slope estimator applied to quantify the magnitude of detected trends. It is a commonly used nonparametric method. We applied the Sen's slope method this present study. The method is robust against outliers in a time series (Mahmood et al. 2019). Declining slope indicates that the phenological period is advanced/shortened whereas increasing slope denotes the phenological period is delayed/prolonged. Sen's slope (SS) is estimated as below:

$SS = median\left[\frac{xj-xi}{j-i}\right]\ for\ all\ i < j$ Where xi is the value of data at time step i & xj at time step j

Partial correlation analysis was carried out in order to weight the contributions of climate variables for variation of crop phenological variables. Different periods selected for the partial correlation analysis to set fitting time scales for the phenological variables and climatic variables. For SOS, May, June, and July; for EOS, July, August, and September; and for POS May, June, July, and August; and for LOS May, June, July, August, September and October were selected. Then, we used linear regression analysis to estimate the influence of climatic variables effect on crop phenology. The correlation coefficient (r), coefficient of determination, and p value ($p < 0.05$) were used to determine the extent of the correlation and significances of the relationships between crop phenological variables and climate variables. The correlation coefficient measures the strength of the relationships while coefficient determination expresses the percentage of variation in a crop phenological variable explained by a climate variable.

CHAPTER FOUR

4. RESULTS

The major findings of the study described in this chapter. This section included trends in crop phenology, precipitation and land surface temperatures during crop growing months. Besides, the relationships of crop phenological variables with the climate variables are also detected.

The result shows (Table 2) the beginning of SOS ranges from 170th to 187th DOY. EOS ranges from 318th to 337th DOY. LOS ranges from 134 to 165 days. The peak greenness time ranges from 252 to 268 days in the pat twenty years in the studied area.

Table 2: Crop phenological indices in Lake Tana Subbasin (2001-2020)

Years	SOS (DOY)	EOS (DOY)	LOS (Days)	POS (day)
2001	177	336	159	264
2002	179	331	152	262
2003	186	336	150	268
2004	183	327	144	265
2005	187	330	143	265
2006	172	337	165	258
2007	182	325	144	259
2008	179	331	153	261
2009	187	331	144	260
2010	184	326	142	263
2011	177	332	155	260
2012	184	333	149	266
2013	185	328	143	263
2014	172	324	153	252
2015	179	326	147	257
2016	184	318	134	263
2017	170	324	154	259
2018	174	327	153	255
2019	179	326	146	260
2020	180	328	148	263

4.1.1. Trends in crop phenological variables

The result of time series MODIS data showed that trend in crop phenological variables advanced and shortened in the past twenty years. SOS (figure 2A) (slope = -0.203, p = 0.436), EOS (figure 2B) (slope = -0.469, p = 0.021), POS (figure 2C) (slope = -0.230, p = 0.112) and length of crop growing period (figure 3D) (Slope = - 0.171, p = 0.496) showed decline trends in the past two decades. However, EOS showed substantial negative trend in the past twenty years ($p < 0.05$). The results implied that crop types or varieties that need short crop growth season should be considered in agricultural practices.

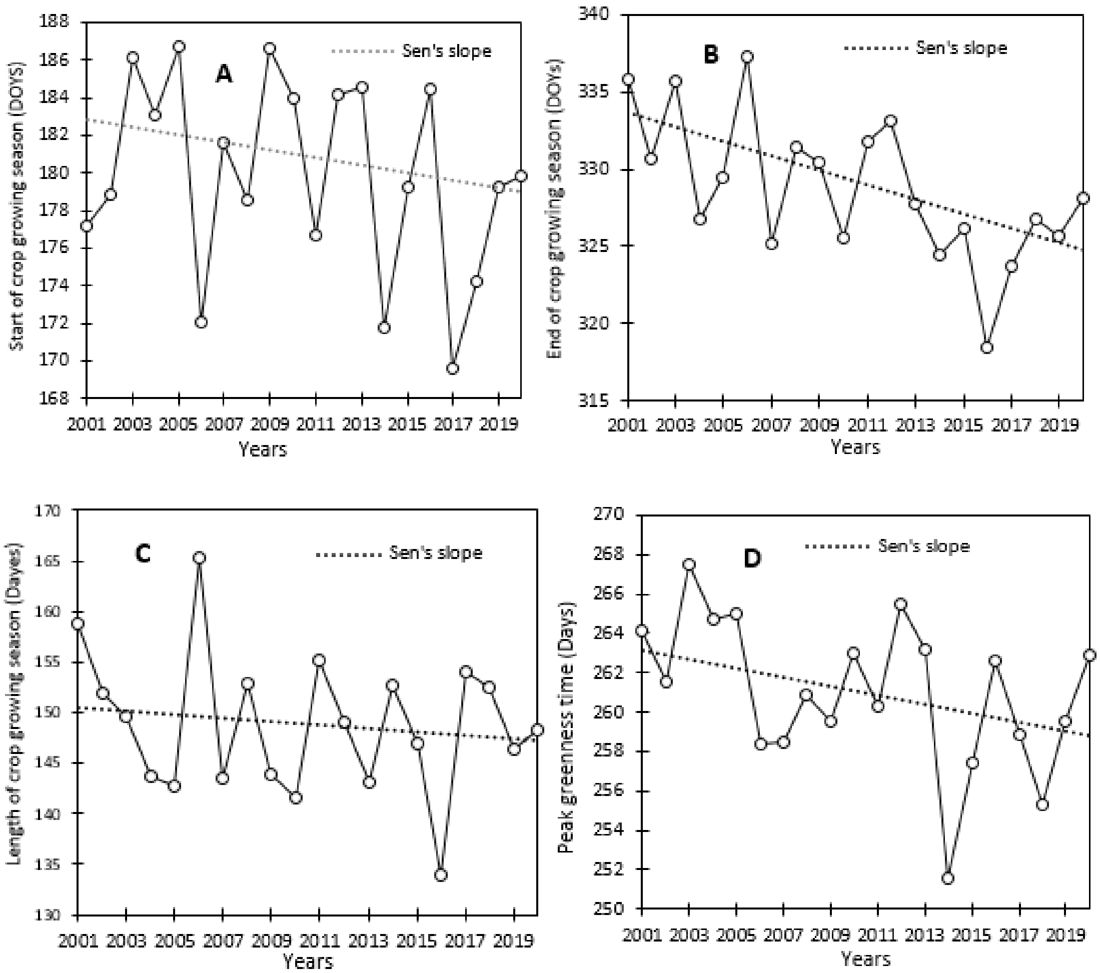
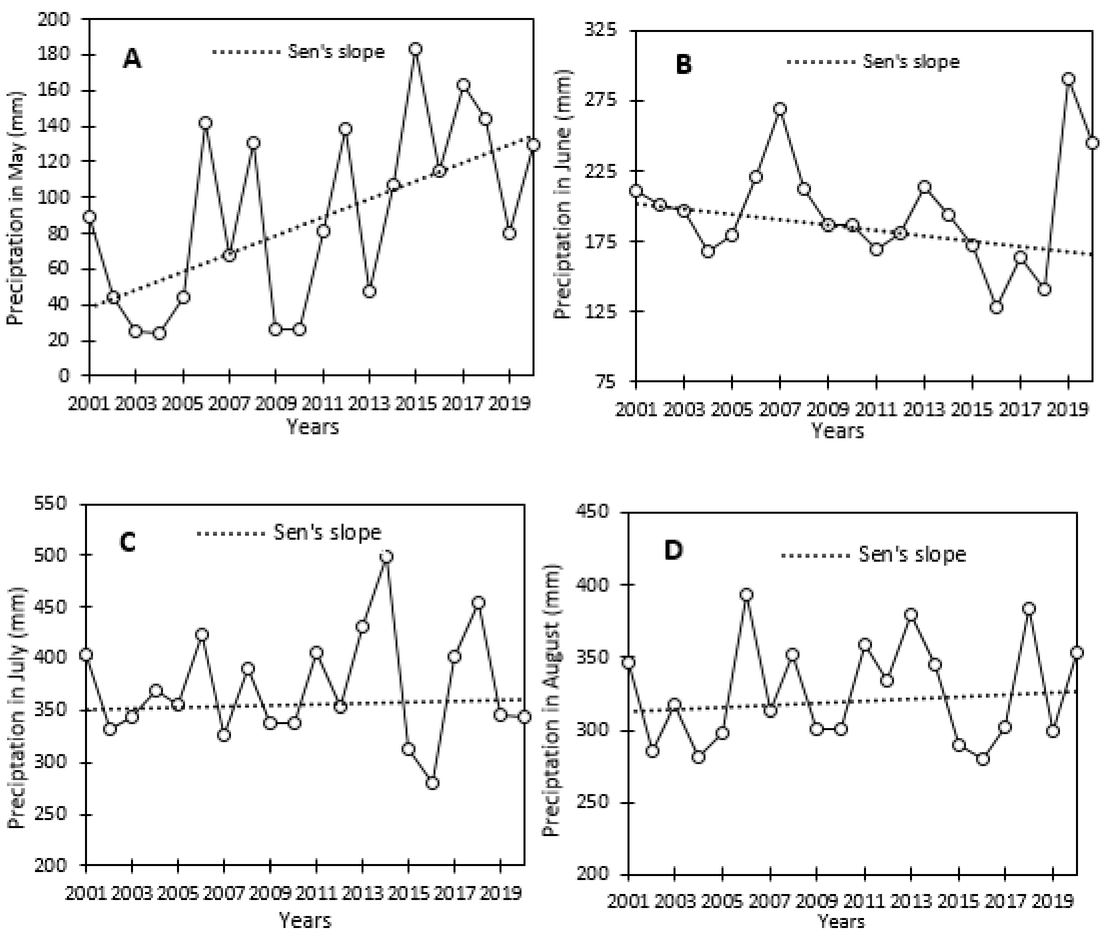


Figure 2. Trend in crop phenological variables in Lake Tana basin: start of crop growing season (A), end of crop growing season (B), length of crop growth period(C), peak greenness time (D)

4.2. Trends in climate variables

4.2.1. Trend in precipitation

Figure 3 shows trends in precipitation in crop growing months. In the past twenty years, precipitation showed positive trends in May (figure 3A) (slope = 5.025, p = 0.013), in June (figure 3B) (slope = -1.305, p = 0.363), in July (figure 3C) (Slope = 0.482, p = 0.864), in August (figure 3D) (Slope = 0.768, p = 0.09), in September(figure 3E) (slope = 2.407), p = 0.23, and in October (figure 3F) (slope = 1.275, p = 0.299). Whereas, June precipitation trend showed negative trend (Slope = -1.305, p = 0.363) for the past twenty years. However, substantial increasing trend observed in May precipitation in the past twenty years (p = 0.013). As observed in the graph (Figure 3), precipitation showed increasing trend in crop growing season except in June in the past twenty years.



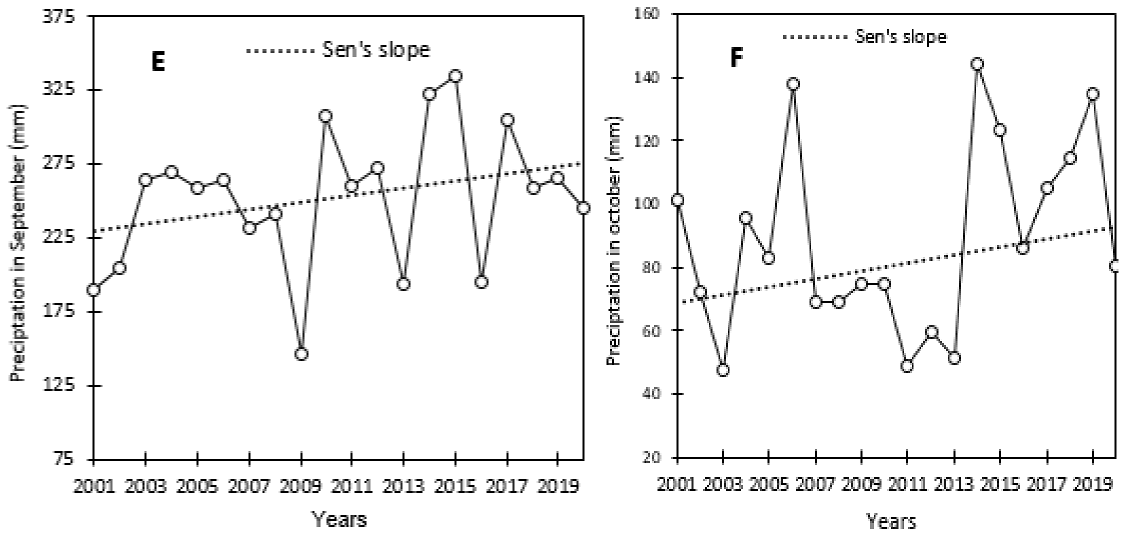


Figure 3. Trends in precipitations in crop growing months: precipitation in May (A), precipitation in June (B), precipitation in July (C) precipitation in August (D) precipitation in September (E) precipitation in October (F)

4.2.2. Trends in land surface temperatures

Land surface temperatures showed declining trends (Figure 4) in crop growing months. For the past twenty years, maximum land surface temperature showed negative trend in May (figure 3A) (slope = -0.50, p = 0.002), and in June (figure 3B) (slope = -0.081, p = 0.284). The mean maximum land surface temperature also showed negative trend (figure 4C) in the crop growing months (slope = -0.118, p = 0.006). May minimum land surface temperature (Figure 4D) also showed declining trend. According to the study finding implies substantial heat stress has not been observed in the past twenty years.

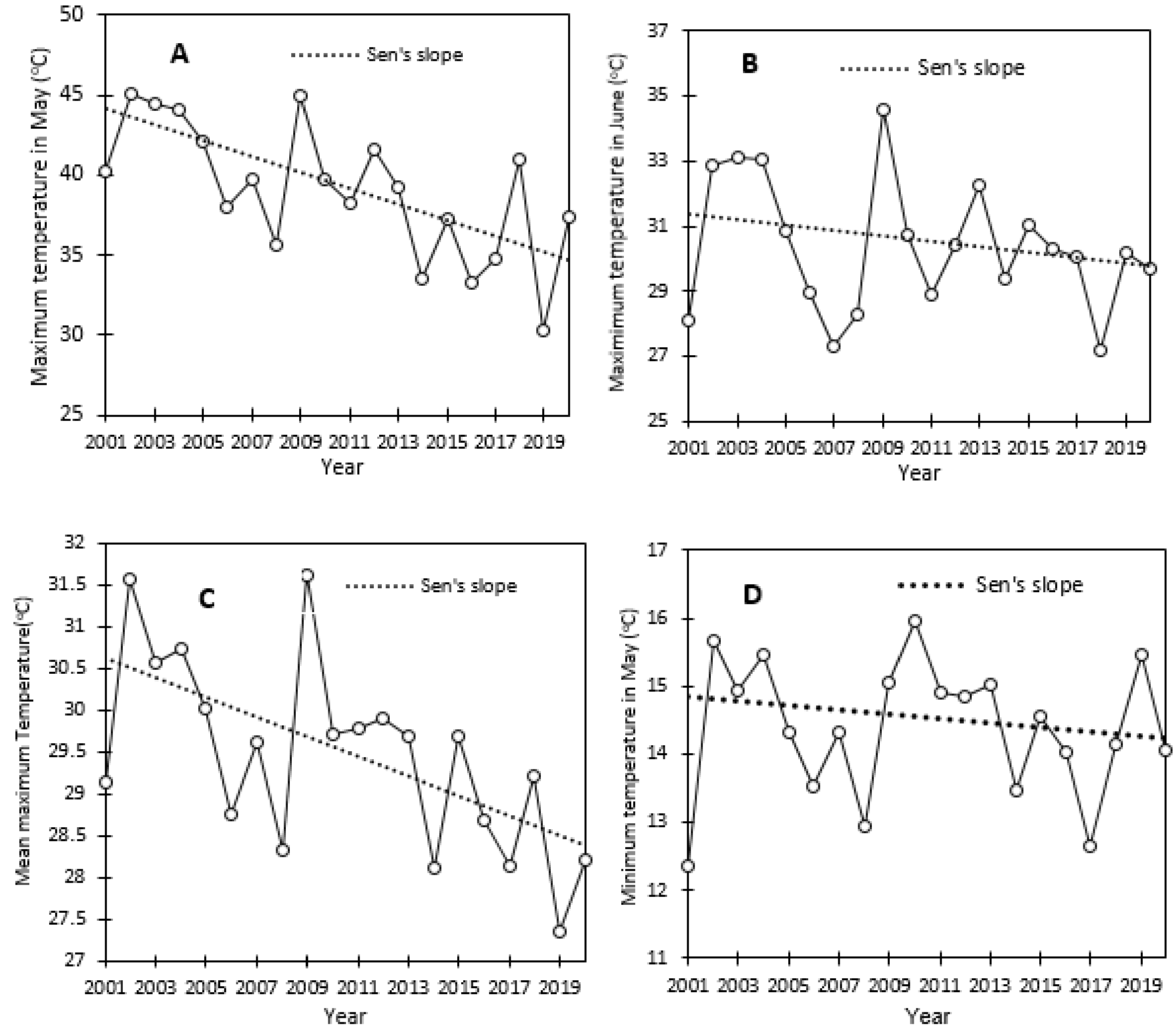
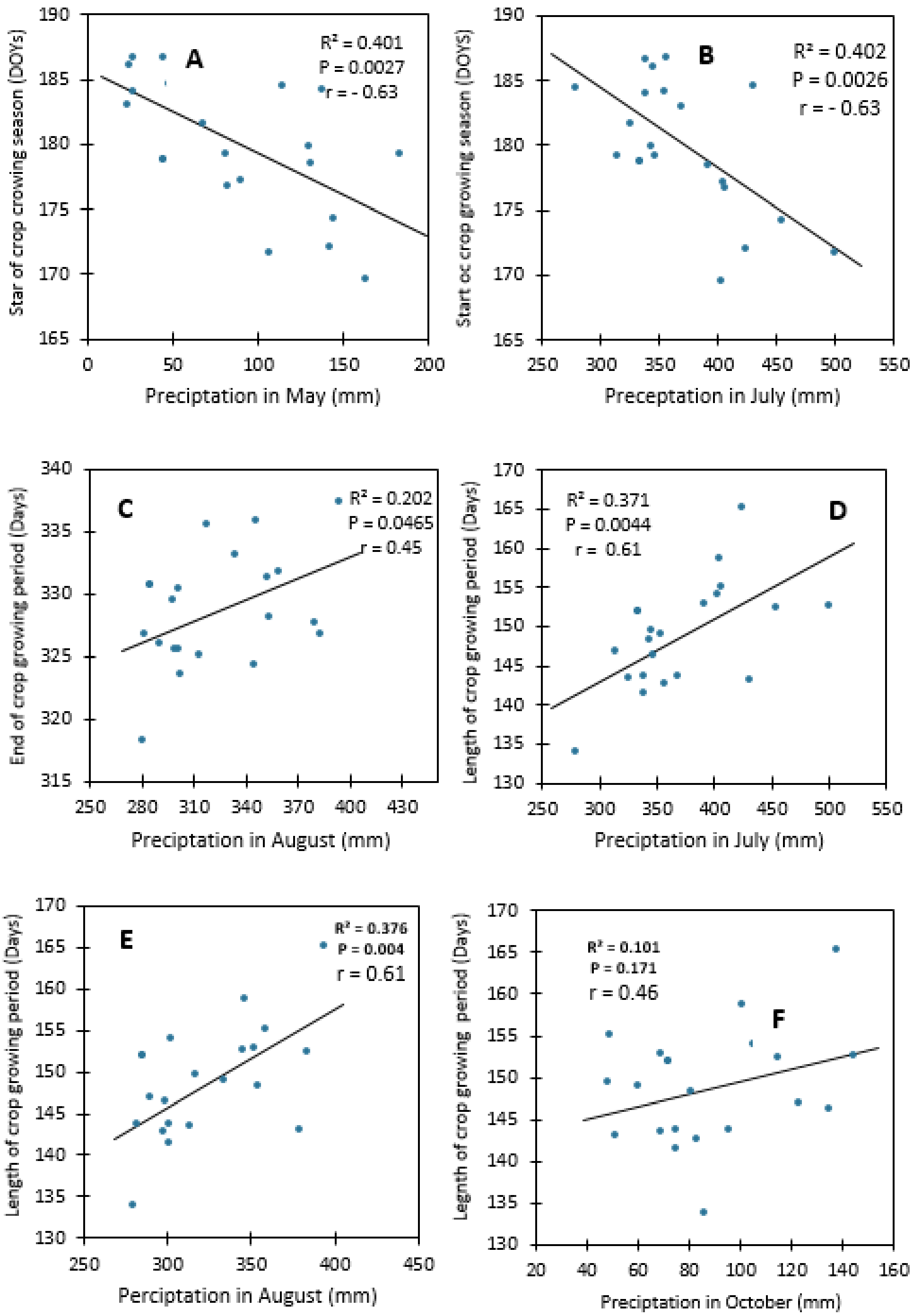


Figure 4. Trends of land surface temperatures in crop growing months in the study area: maximum temperature in May (A), maximum temperature in June (B), mean maximum temperature (C), mean minimum temperature (D)

4.3. Crop phenological variables relationships with climatic variables

4.3.1. Crop phenological variables relationships with precipitation

Precipitation showed negative correlations with SOS and POS, but positive correlation with EOS and LOS (Figure 5). 40.1% variation of SOS explained by variation in May precipitation amount (Figure **5A**), and 40.2 % variation of SOS explained by variation of amount of precipitation in July (figure **5B**). 20.2% of variation of EOS explained by precipitation amount variation in August (figure **5C**) ($p = 0.0465$). 37.1% of variation in LOS in July (Figure **5D**), 37.6% variation of LOS in August (Figure **5E**), and 10.1% of variation of LOS in October (figure **5F**) explained by the variations of precipitation amount in the last twenty years. 21% of variation of POS in May (figure **5G**); 24.3% of variation of POS in July (figure 5**H**), and 43.3% of variation of POS in October (figure 5**I**) explained by variation of precipitation in the months. The correlations of amount precipitation with phenological metrics in crop growing season were statistically significant ($p < 0.05$).



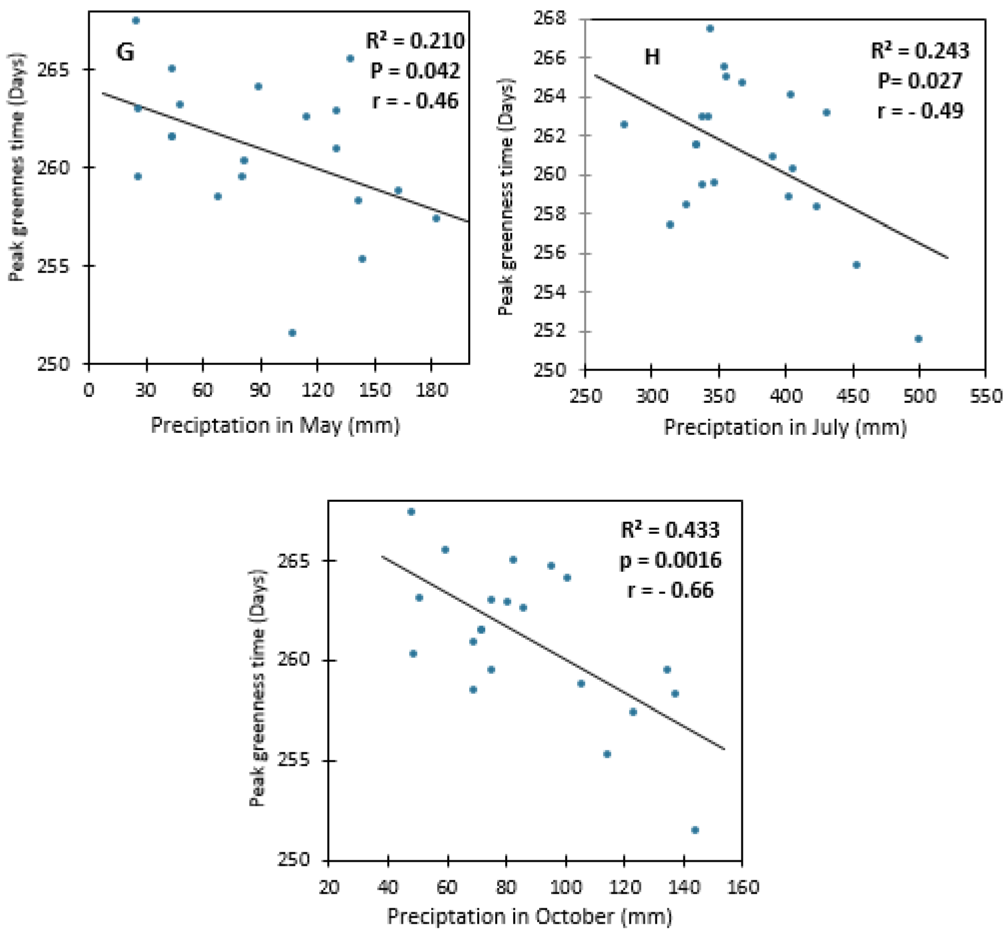
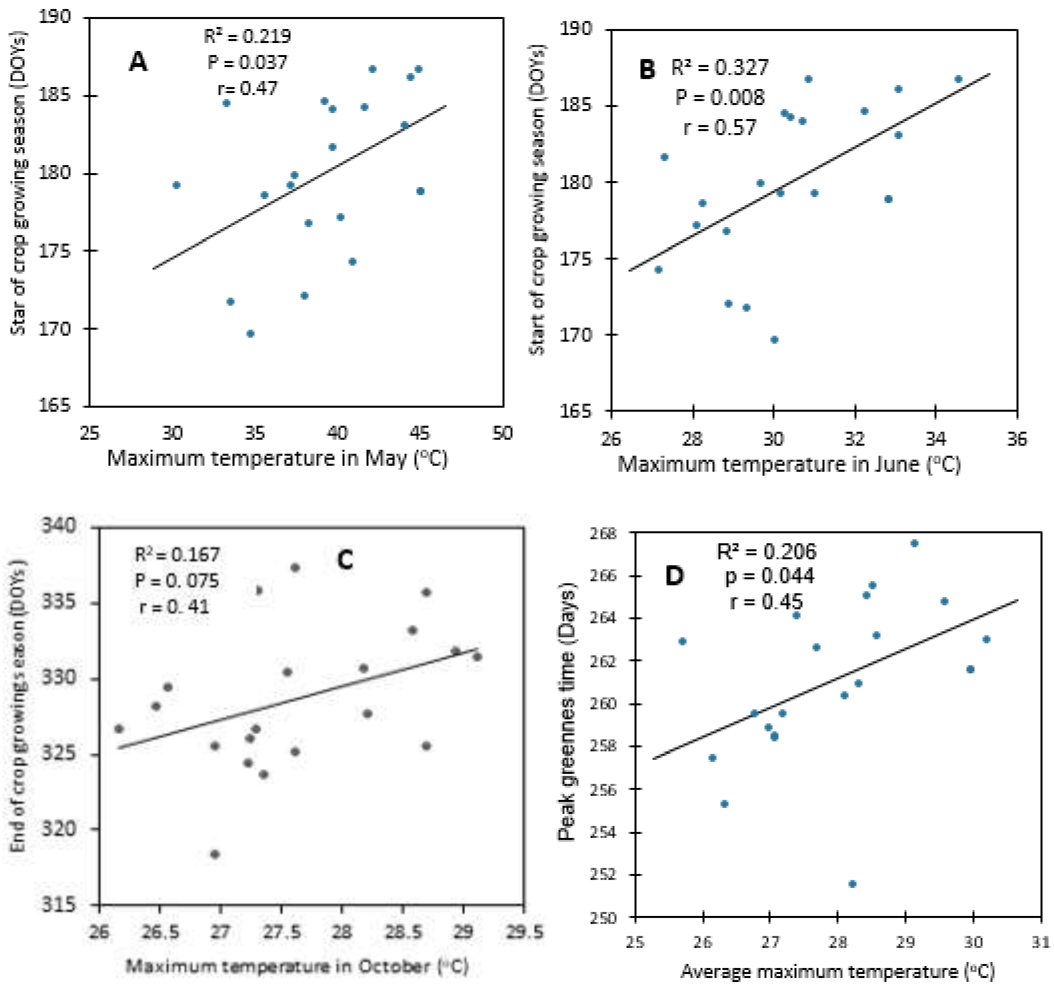


Figure 5 Crop phenological variables relationships with monthly precipitations: start of growing season relationship with precipitation in May (**A**), start of growing season relationship with precipitation in July (**B**), end of growing season relationship with precipitation August (**C**), length of growing period relationship with precipitation in May (**D**), length of growing period relationship with precipitation in July (**E**), length of growing period relationship with precipitation in August (F), peak greenness time relationship with precipitation in July(**G**), peak greenness time relationship with precipitation in October(**I**)

4.3.2.Crop growth relationships with land surface temperatures

Maximum land surface temperature showed strong positive correlations with SOS and POS (Figure 5). Maximum land surface temperature in May (Figure **5A**) explained 20.9 % variation of day of the year of SOS, and 32.7% variation of day of the year of SOS in July (figure **5B**) in the past twenty years. The mean land surface temperature of crop growth period from May to October (figure **5**C) explained around 30.5 % variations of day of the years of start of crop growing season. On the other hand, 24% of variation in date of EOS explained by maximum land surface temperature in June (figure **5D)**. The correlation of maximum land surface temperature with SOS and POS was statistically significant ($p < 0.05$). May minimum land surface temperature explained 34% of the variation in start growing season. Besides May minimum temperature explained 25% variation in length of growing period.



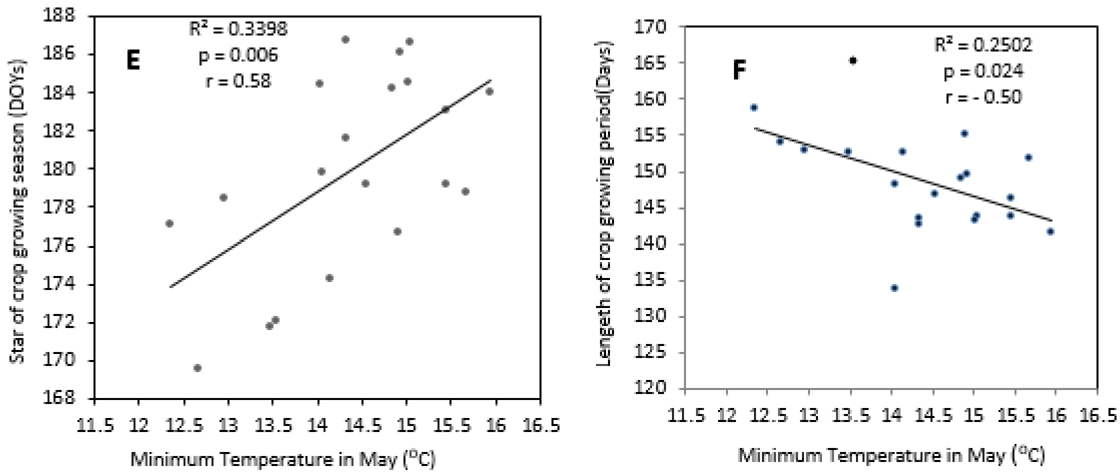


Figure 6 Crop phenological variables relationship with monthly land surface temperatures: start of growing season relationship with maximum surface temperatures in May (**A**), start of growing season relationship with maximum temperatures in July (**B**), start of growing season relationship with maximum temperatures in June (**C**), end of growing season relationship with maximum temperature in October (**D**), start of growing season relationship with minimum temperatures in May (E), Length of crop growing period relationship with minimum temperatures in May (F)

4. DISCUSION

Our research findings revealed that the trends of crop phenological variables advanced and the length of crop growing duration shorten. The substantial advanced of end of crop growing season has led shortening of length of the growing season. This implies consideration of types or varieties of crops which need short growth and development duration is indispensable in agronomic activities in the studied area. A delayed start of crop cropping season results to water stress in flowering and ripening periods, lead to crop failure (Brown et al.2017). Early green up and water stress in flowering and fruiting stages of crop reported in the northern Ethiopia (Brown et al. 2017; Funk et al. 2015). Monitoring trends in crop phenological variables and the climate drivers supports in devising adaptive agricultural system. Information on crop phonology in connection with climate variability uses as an input to predict crop yield and monitoring the state of food security. Besides climate variability, crop phenology influenced by anthropogenic activities such as agricultural management (Wakjira et al. 2021).

In past twenty years, precipitation amount increased in crop growth season except in June the present study. The ground data supported this finding. This implies that water deficit in growing season may face in June in the studied area, and the deficit needs to be regulated through precision agriculture. However, May precipitation amount revealed substantial increasing trend. Precipitation is a key climate element in crop growing season. Rainfall periodic fluctuations and timing affect crop yield in rained agricultural system (Wakjira et al. 2021). Amorality of amount precipitation found be high in the study area although the trends of precipitation found to be positive in the past twenty years. Wakjira et al. (2021) reported amorality of rainfall in the northern Ethiopia in crop growing periods. Rainfed agriculture practices is influenced by the temporal distribution of rainfall in the cropping period in a given season of the year (Hao et al. 2013).

Crop phonological variables showed strong correlation with climate variables of crop growth periods in the studied area. Start of crop growing season positively influenced by the amount precipitation in May and in July. Whereas, lengths of crop phenology considerably influenced by the amount of precipitation in July and August. Furthermore, peak greenness period portrayed strong negative correlation with amount of precipitation in crop growth periods. Climate variables affect crop development by influencing crop phenology, growth, and yield productivity (Brown et al.2017). The onset of the main rainy season starts in advance in the northeast Ethiopia (Wakjira et al. 2021). Generally, amount precipitation in crop development months more importantly affected crop development in the studied area.

Land surface temperature showed negative trend in the study area in crop growing months. However, mean land surface temperature and May land surface temperature showed substantial decreasing trends for the past twenty years. This implies heat stress were important limiting factors for the past twenty years. Maximum land surface temperature and minimum land surface temperature in May positively influence start of crop growing season. Crop phenology showed strong correlations with land surface temperatures. However, May minimum land surface temperature negatively influenced length of crop growing period. Temperature influence the growth, rate of development and yields of crops (Luo 2011). Land surface temperature changes rapidly in space as well as in time. It is strongly affected by high land surface heterogeneity such as surface albedo, vegetation, topography, and soil moisture (Wan et al. 2002; Khandelwal 2018). The declining of land surface temperature in the study area in crop growing period might be due to the vegetation cover and high soil moisture due to increasing precipitation amount in the crop growth season. This study, decreasing of mean maximum temperature in crop development period positively influenced crop greenness period. Climate variability impacts agriculture by shifting phenology timing mainly due to increases in temperature and/or the seasonality of rainfall amount and rainfall intensity (Brown et al. 2010). Variability of climate elements in key phenological stages has a large influence on agriculture (Brown et al. 2010; Hmimina et al. 2013). The variability of climate variables such as temperatures and precipitations in key phenological stages impose challenges on agriculture (Hmimina et al. 2013). For instance, a late start of season may cause exposure to temperature and water stresses in flowering and fruit ripening periods. These in turn could result in crop growth failures and declining productivity (Brown et al. 2017).

Though shorten and advance of crop phenological variables, increasing of precipitation and decline of land surface temperatures observed in crop growing period in the study area, high irregularity patterns have been observed. Information on trends in crop growth development in relation with climate variables help agricultural stakeholders to formulate effective climate change adaptation strategies (Mo et al.2016; Bai et al. 2019; Zhao et al.2019; Liu et al. 2021). Crop phenology is affected by both climate conditions and agricultural management processes such as sowing date adjustment and cultivar improvement (Zhao et al. 2015). Implementing practical agricultural management measures is an effective means to deal with climate variable impacts on crop phonology (He et al. 2020). Advancing sowing dates and sowing crop varieties or types that need shorter growing duration as well as precision agriculture are management adaptations to cope up climate impacts on crop phenology, growth and yield (Zhao et al.2015; Ye et al.2019). With the cooling of climate condition and increasing of precipitation, the growing period has advanced and shorten. Trend analysis in temperature and precipitation is very indispensable for rainfed agricultural system, where farmland is primarily dependent on precipitation. It supports better water resource management in agricultural water use and regulation as well as for better planning in agricultural activities.

5. Conclusion and recommendations

Anomaly trend anomaly in crop phenological variables, land surface temperature and precipitation found to be highly in the study area. Declining trend in crop phenological variables detected in the present study. However, end of crop growing season showed substantial advanced and shorten trend. Crop phenological variables showed strong correlations with amount of precipitations in crop growing months. Start of crop growing season showed strong negative correlation with increasing amount precipitation in May and in July. The length of crop growing period showed strong positive correlation with the amount of precipitation in July and August. The trends in precipitation amount in crop growth season were positive except trend in June. On the other hand, peak greenness period negatively influenced by the amount of precipitation in May, July and October. While amount of precipitation increase, dates of peak greenness time advanced in the study area. Maximum land surface temperature in May and June, and minimum land surface temperature in May positively influence start of crop development. The higher the minimum land surface temperature in May lead to the shorter length of crop growing period. Mean maximum temperature of crop growing period positively influenced crop greenness period. Generally, crop phenological variables extracted from the MODIS NDVI time series, MODIS LST time series data, and CHRIPS data provided a valuable information on trends in crop phenology and the climate variables.

The findings indicated that farmers should consider crop types or varieties which need short growing duration. However, this research have not addressed the knowhow of the farmers about changing trends in the crop phenological variable and how the farmers respond for the changes. Besides, the agricultural system in the studied basin is characterized by fragmented agriculture. In this study, information synthetized using data constructed from satellite observations having moderate spatial resolution, MODIS sensor. Therefore, cross validation of the findings through data extracted from satellite sensors which have fine resolution is indispensable.

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