Spatiotemporal dynamics of crop phenology and crop yield: The influence of climate variability in the Upper Blue Nile basin

PhD Research Proposal

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Abstract

Climate variability/change imposes significant challenge on crop production by altering crop growth dynamics, phenology and yield. Vegetation phenology is an important input in crop yield modeling and an indicator of environmental change. Crop yield is a direct indicator of the vegetation growth response to climate and anthropogenic changes as well as a mechanism to assess the state of food security. Understanding the spatial and temporal dynamics of vegetation growth and productivity is vital for crop management and decision-making. Conventional production monitoring based on field survey is costly, time consuming and prone to error. Moreover, highly fragmented and topographically complex agricultural landscapes together with a high rate of climate variability becomes challenging to monitor crop growth and development processes. Lack of temporally frequent and spatially explicit data also constrains understanding of the inter-annual and seasonal dynamics of crop growth and development. Remote sensing data on the other hand provide a valuable opportunity for spatially explicit understanding of vegetation phenology and crop yield monitoring. Yet, existing remote sensing sensors do not provide temporally frequent and high spatial resolution data important for agricultural monitoring. In this regard, multi-sensor remote sensing data fusion is a valuable choice. It is therefore imperative that comprehensive assessment of the spatiotemporal dynamics of crop growth and production incorporating vegetation phenology and climate constraints using remote sensing method can provides a holistic understanding of the status of crop production. Thus, the main goal of this study is to investigate the spatiotemporal dynamics of vegetation phenology and the influence of climate variability on crop yield in Lake Tana basin, Ethiopia. To achieve this objective a spatiotemporal data fusion will be employed to determine vegetation growth dynamics and yield in heterogeneous landscapes. Furthermore, crop biomass productivity and yield estimation by coupling remote sensing data with a light- use efficiency-based crop model is envisioned. Landsat and MODIS data fusion will be utilized to detect phenology and estimate crop yield together with ground data calibration and climate data. Thereby, this research is expected to contribute to the literature on the current trend and dynamics of vegetation phenology and crop productivity in heterogeneous topography and crop ecosystem.

Key words

Phenology, Spatiotemporal fusion, Crop biomass and yield, Climate variability

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List of abbreviations

BFAST	Breaks for Additive Seasonal and Trend
CHIRPS:	Climate Hazards Group Infrared Precipitation with Station
DAM	Dry Aboveground biomass
EOS	End of the Season
ESTARFM:	Enhanced Spatial and Temporal Adaptive Reflectance Fusion Method
EVI:	Enhanced Vegetation Index
GLAI:	Green Leaf Area Index
HANTS:	Harmonic ANalysis of Time Series
IPCC:	Inter governmental panel for climate change
LOS	Length of the Season
LSP:	Land surface phenology
LST:	Land surface temperature
LUE:	Light Use Efficiency
MODIS:	MODerate-resolution Imaging Spectroradiometer
NDVI:	Normalized Vegetation Index
OAT	One factor at a time
RCP	Representative Concentration Pathway
RMSE	Root mean square error
SA	Sensitivity Analysis
SAFY:	Simple Algorithm For Yield estimates
SOS	Start of the Season

Introduction

Erratic and variable rainfall patterns, and temperature increases have significant impacts on crop production by altering crop growth dynamics, phenology and yield (Richardson et al., 2013). Vegetation phenology is a multi-purpose indicator of environmental change and productivity, which makes it an important variable in crop growth and production monitoring (Brown et al., 2012). Crop yield on the other hand is a direct response to climate and anthropogenic changes as well as a mechanism to assess the state of food security particularly in developing countries where the main source of livelihood is agriculture (Brown et al., 2017). Determining and monitoring crop growth dynamics, phenology and yield requires detailed spatiotemporal resolution. However, such efforts are challenged by a lack of reliable and up-to-date data in many developing countries including Ethiopia.

Remote sensing on the other hand provides alternative data source for a large geographical scale application (Atzberger, 2013). Yet, available satellite data doesn't satisfy the need for both high spatial resolution and temporal frequency which are essential for crop monitoring due to the trade-off between revisit period and spatial resolution (Zhu et al., 2018). One way to address this problem is with a spatiotemporal fusion of coarse and fine resolution data (Zhu et al., 2010). Furthermore, coupling remote sensing derived phenology and biophysical properties with semi-empirical crop model have been proven to provide a reliable crop biomass and yield estimation approach given ground calibration and validation applied (Sibley et al., 2014).

Subsistence farming, practiced dominantly by smallholders on heterogeneous environments, together with high inter-annual and seasonal climate variability in Ethiopia makes crop growth and production monitoring efforts difficult (Ahmed, 2003; Alemu and Henebry, 2017). There is limited research to understand vegetation growth dynamics and production using the wealth of remote sensing data in Ethiopia (Meshesha and Abeje, 2018). Furthermore, the impact of variability on critical phenological dates (SOS and EOS) on crop production has received little attention and divergent vegetation-climate trend have been reported in space and time (Gummadi et al., 2018; Workie and Debella, 2018). In this context, a reliable crop monitoring approach considering not only the final yield, but also understanding the growth and development process, drivers and response to the changing climate condition and applicability at larger geographic scale is vital which is the major starting point of this study.

Therefore, this study will focus on understanding the dynamics of vegetation phenology, the phenology - climate relationship, and on the estimation of crop biomass and yield based on spatiotemporal satellite image fusion. Thereby, the research will contribute to the literature on the current trend and dynamics of vegetation growth and phenology in heterogeneous tropical ecosystem. It will further extends the knowledge regarding the importance of integrating remote sensing to improve crop monitoring and production estimation in smallholders fragmented cropping system.

Objective of the study

The general objective of this study is to investigate the spatiotemporal dynamics of vegetation phenology and the influence of climate variability on crop yield in Lake Tana basin, Northwestern Ethiopia through:

- Detection of the spatial variation of vegetation phenology using a spatiotemporal MODIS -Landsat remote sensing data fusion technique
- Analysis of the trends in vegetation growth dynamics and the response to current climate variabilities in Lake Tana basin for the period between 2001 and 2020
- Estimation of crop biomass and yield by integrating Landsat-MODIS fused data with a LUE based crop model
- Analysis of the sensitivity of crop biomass and yield to variabilities of phenological and climate stress (temperature and water) factors

Conceptual framework

The general conceptual framework of this study is integrating multi-sensor remote sensing data to understand the dynamics of vegetation phenology, the trends and climate determinants as well as to estimate crop biomass and yield. This proposal is composed of four research chapters. Figure 1 shows the general conceptual framework of the study. The study starts with spatiotemporal fusion of MODIS and Landsat image during the 2019 growing season and detection of phenology across landscape and vegetation types to assess if fusion improves phenology detection (Chapter 1). By improving the resolution of satellite products using the fusion approach, calibrating, and evaluating phenology models, vegetation growth changes over time (2001 – 2020) and the response to climate variability will be analyzed (Chapter 2). Integrating phenological parameters and crop biophysical information with semi-empirical model will helps us to estimate crop biomass and yield of main staple crops (Chapter 3). Lastly, the impact of climate on biomass and yield estimation evaluated in space and time (Chapter 4).

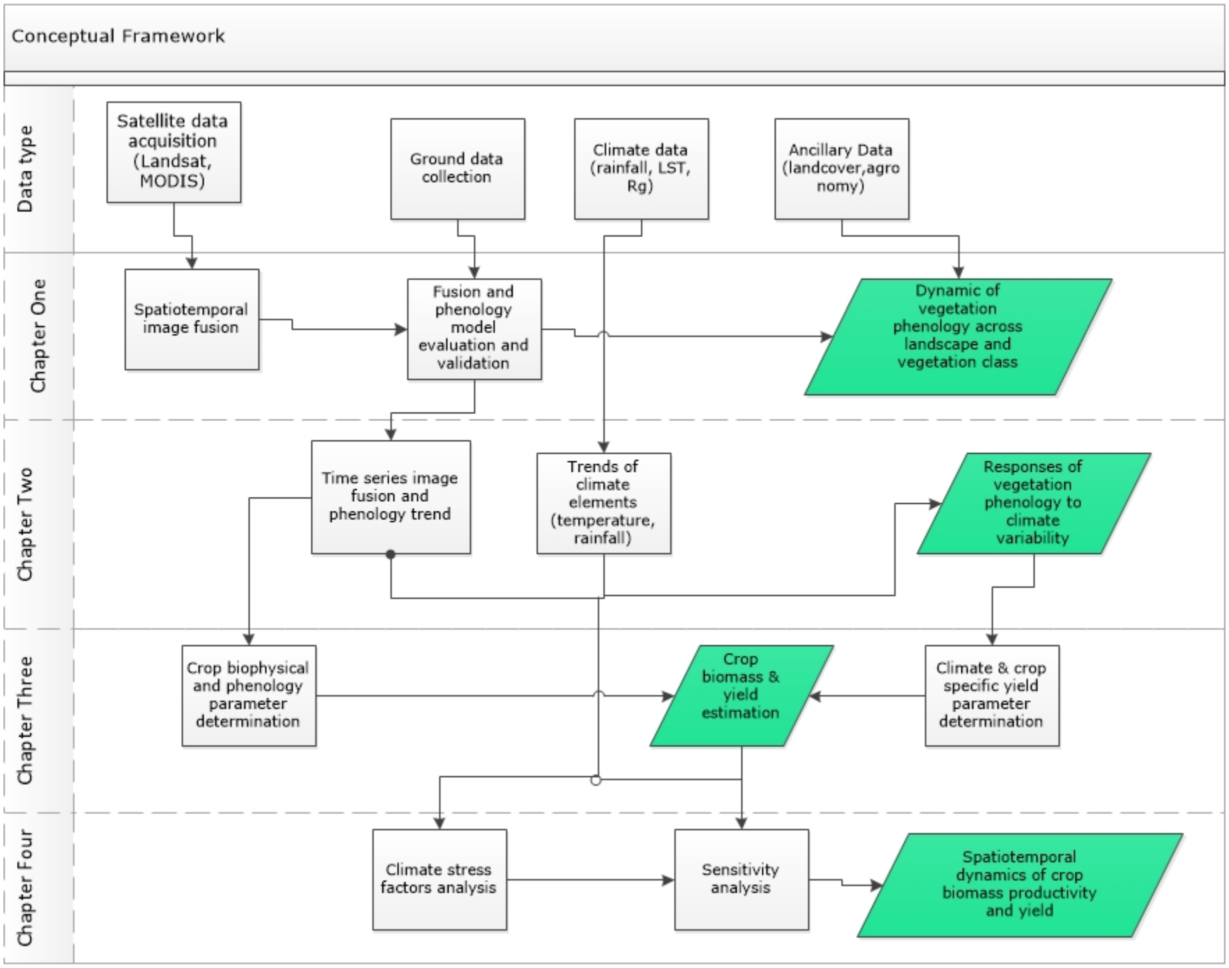

Figure 1: Workflow of the proposed study

The study area

Figure 2 shows the study will be conducted in the Lake Tana sub-basin of the Upper Blue Nile basin, parts of Ethiopia. It lies between latitude 10°29' N and 12°46'N, and longitude 36°44"E and 38°14'E with a total area of 15,100 km^2. Cultivated land accounts for 56% of the area, other natural vegetation includes grassland, shrub land, and natural forest covering about 25% of the total (BoEPLAU, 2015). The mean annual rainfall ranges between 970 mm to the north and 1900 mm in the southern part of the catchment, largely occurring during June to September (‘*kiremt*’) season. The entire Lake Tana sub-basin falls within three overlapping Landsat scenes; this study will focus on the scene number P170R52 path and row to apply image fusion with the corresponding MODIS tile since the majority of the study area lies within this scene and main crop-growing region containing almost environmental conditions of the basin

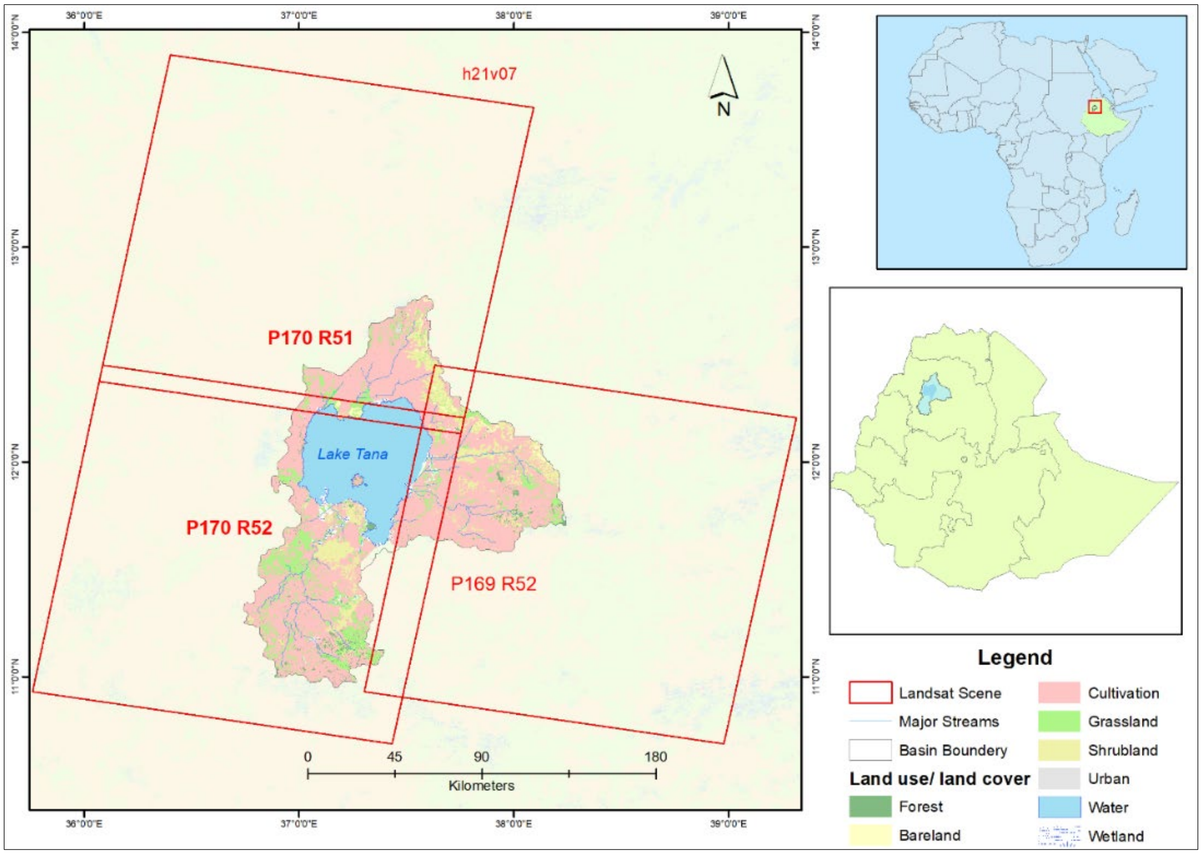

Figure 2: Overview of the study area Landsat raw and path, MODIS tile and Land use map (source: ETHIO_GIS)

1. Chapter One

Modeling the dynamics of Land Surface Phenology in Lake Tana basin

1.1. Introduction

Land surface phenology (LSP) - the periodic life cycle event of vegetation as determined from satellite imagery - is useful to characterize vegetation growth dynamics across space and time (de Beurs and Henebry, 2010). The start of the season (SOS), end of the season (EOS) and peak greenness are important seasonal phenological parameters that can be derived to indicate the growth progress of vegetation during the growing season (White et al., 2009). It is widely used to investigate the effect of climate variability and the state of ecosystem change (Brown et al., 2012) and to monitor crop growth and yield (Funk and Budde, 2009).

Various methodologies have evolved to determine LSP from remote sensing data, yet there no single ideal model to accurately determine phenological parameters since most are environment dependent (White et al., 2009). For instance, comparison of ten models by White et al. (2009) in North America and de Beurs and Henebry (2010) in the higher latitude region demonstrated a strong discrepancy on the estimated timing of parameters across environment and vegetation types. In comparison, HANTS and threshold methods have performed better in detecting phenology in different climate and vegetation classes (Vrieling et al., 2013; White et al., 2009). The double logistic curve change method has also been tested and evaluated across land cover types with multiple growing seasons (Beck et al., 2006; Dash et al., 2010) and has been shown to better reconstruct trends of phenlogical change (Guan et al., 2014a). Application of HANTS, threshold and double logistic methods in this study is expected to capture important phenological parameters useful for crop growth monitoring purposes.

However, the spatial and temporal resolution of available remote sensing data is a major challenge in regions characterized by heterogeneous topography, ecology and cropping systems (Zhu et al., 2010). The trade-off between spatial resolution and temporal frequency of existing satellite data limits vegetation phenology determination at the higher spatial and temporal details needed in such regions (Gao et al., 2017). Spatiotemporal data fusion between coarse and fine resolution sensors may be a feasible option for finer scale vegetation growth monitoring (Singh, 2012). In response to this, Gao et al. (2006) developed the Spatial and Temporal Adaptive Reflectance Fusion Method (STARFM). Consequently, improvements have been made to extend the model for various applications. For instance, Zhu et al. (2010) enhanced STARFM (ESTARFM) to capture surface reflectance in heterogeneous landscapes. Hilker et al. (2009) also developed a spatial and temporal adaptive algorithm for mapping reflectance change (STAARCH) to consider changes in the reflectance of coarse and fine resolution data. These methods have been widely used to detect cropland phenology (Liu et al., 2018; Schmidt et al., 2015), to generate of gross primary product (Singh, 2012) and estimate evapotranspiration (Cammalleri et al., 2014). These indicate that data fusion provides a valuable opportunity for vegetation growth monitoring efforts in heterogeneous environments.

Previous studies determining the phenology and seasonality in Sub-Saharan African applied different phenology detection methods and found spatially and temporally divergent result. For instance, Brown and de Beurs (2008) and de Beurs and Henebry (2010) in West Africa and Alemu and Henebry (2017) in East Africa, applied a quadratic model to estimate the SOS. Guan et al. (2014a) used a double logistic model to estimate seasonal trajectories in the growing season and Vrieling et al. (2013) employed a variable threshold method to determine LOS. Guan et al. (2014b) found asymmetric green up and green off rates and the occurrence of distinctive phenological features for cropland and natural vegetation. Heumann et al. (2007) reported a significant lengthening of the season in the Sudan and Guinean regions and Marshall et al. (2016) indicated a greening trend in the Sahel. Adole et al. (2018) on the other hand reported an absence of significant phenology change in recent decades. Workie and Debella (2018) reported lengthening of the growing season in the major ecoregions in Ethiopia. Even though, these studies contributed enormous efforts in phenology modeling, there are still uncertainties in the estimated parameters. The difference could be related to data resolution and methodology compared to the heterogeneous nature of the environment, which calls for more spatially explicit high-resolution investigation at local scale.

1.2. Problem Statement

Rugged topography, diverse climate, environment dependent socioeconomic activity and small scale agricultural system practiced on fragmented and small plots size are major drivers of ecological variability in Ethiopia (Gummadi et al., 2018). In such a heterogeneous environment the spatial and seasonal patterns of vegetation phenology may not be clearly detected and understood using coarse resolution data with little or no ground calibration (Brown et al., 2017). This was evident in previous studies reporting spatially and temporally inconsistencies results, which calls for high-resolution investigation. However, cloud contamination on the fine spatial resolution images during the growing season is also a constraining factor for high-resolution analysis. Studies demonstrated the feasibility of spatiotemporal data fusion to cope with such problem, which were not attempted in the context of the study area.

To this end, this study is aimed at employing a spatiotemporal image fusion based on Landsat-MODIS data for finer scale vegetation phenology characterization in Lake Tana basin. The ESTARFM fusion algorithm will be adopted, since it performs better in heterogeneous environments (Gao et al., 2015), retains spatial detail (Emelyanova et al., 2013) and captures phenological changes (Liu et al., 2016). The seasonal rate of change determined from MODIS and image pairing at the critical stages of vegetation development are expected to produce a reliable fusion. As a second line of this research, different phenology models will be employed to test if the image fusion capture major phenological parameters across landscapes and vegetation classes. The performance of the fusion and phenology models will be compared and validated using ground data acquired during 2019 growing period. Determination of vegetation growth dynamics based on high temporal resolution data and the use of different models is expected to improve detection of major phenological parameters.

1.3. Objective

The objective of this study is to determine the timing of vegetation phenology using a spatiotemporal Landsat – MODIS image fusion technique in Tana basin, Northwestern Ethiopia.

1.4. Research question

- Does high-resolution image acquired through spatiotemporal fusion capture vegetation phenology better in the heterogeneous environment in Lake Tana basin?
- What is the reliable model to determine the timing of vegetation phenology across different landscapes and vegetation class?

1.5. Data and methodology

1.5.1. Types and sources of data

Satellite Data acquisition and preprocessing

MODIS Tera version 6 (8-day) composites (MOD09Q1and MOD09A1) tile h21v07 and Landsat 8 Operational Land Imager (OLI) sensor surface reflectance data will be acquired from NASA LP DAAC (https://lpdaac.usgs.gov/) and Landsat archive (https://earthexplorer.usgs.gov/) respectively for the 2019 season. Low cloud coverage Landsat images will be selected for the entire season. Successful phenology detection using data fusion requires consistency between sensors. Landsat and MODIS have been found to have good consistency due to their similarity of data processing approaches (Gao et al., 2015). Cloud and cloud shadow masking for Landsat data and co-registration of the datasets using a common projection and coordinate system to WGS 84, UTM zone 37 will further improve consistency.

Land cover and field data

Data fusion and phenology parameters will be compared and validated using ground observed data collected from agricultural and non-agricultural fields during the 2019 growing season (June to October). Hence, the study area will be stratified into homogeneous unit (HU) based on topography, climate, soil mapping unit and cropping pattern identified through the existing land resource utilization survey conducted by the Amhara regional agriculture bureau (BoEPLAU, 2015). Within the HUs, crop and non-cropland will be identified using land cover maps acquired through the Ethiopian Geospatial Information System (EthioGISII) collection which is compiled and updated by the Water and Land Resource Centre (WLRC) (www.wlrc-eth.org) which was classified based on Landsat 8 and detail ground truth.

The actual plot location and size across the HU will be selected comparable with the size of the fused image and considering geolocation error considered following (McCoy, 2005). The timing of vegetative growth stages will be continuously monitored from planting to harvest period with the help of agricultural agents and farmers. Growth stage, crop type, density, height and management practices will also be collected during the field visit. Furthermore, to evaluate the performance of data fusion and phenology detection general vegetation characteristics and spectral information will be collected using handheld spectrometer and observation checklist during the peak vegetative period.

1.5.2. Method of analysis

Two major analysis covered in this study are data fusion and phenology extraction. The overall work flow is presented in Figure 3. ESTARFM model will be adopted for Landsat and MODIS data fusion. Pairs of Landsat-MODIS image acquired at the early and ends of the growing seasons (June and October for the main season and December to May for the dry season) are the main input requirement. Four main steps are required for fusion, searching for similar pixel, calculation of the weights for prediction, calculation of conversion coefficient (*vi*) and application of ESTARFM algorithm based on Zhu et al. (2010) with *w* searching window for the predicted high resolution central pixel ($x_{w/2}$,$y_{w/2}$) at date t_p as follows:

$$L\,(\frac{xw}{2},\frac{yw}{2},tp,b)\ =\sum_{i=1}^{N}L(\frac{xw}{2},\frac{yw}{2},to,b)\ +\ wi\ *\ vi\ *\ (M\ (xi,yi,tp,b\ )-(xi,yi,to,b))$$

Where, L, M denotes Landsat and MODIS pixels at xi and yi location in a *'b'* band, t_o pairs of images used for the prediction, N and wi are the number of similar pixel used to create the weight and the coefficient in the i^{th} date of prediction, respectively. To improve the temporal and land cover change detection performance of the model, the difference between the input and predicted MODIS images will be accounted for. One limitation of ESTARFM is similar pixels are identified by search from the entire study area, which results undesirable error in heterogeneous environment where several land cover class exists(Knauer et al., 2016a). To address this, ISODATA clustering of Landsat images will be applied based on the number of land cover classes acquired from existing land cover data to consider land cover change while selecting similar pixel as recommended by (Zhu et al., 2010) and applied by (Knauer et al., 2016b; Ma et al., 2018). To evaluate the accuracy of the prediction, a band-by-band linear correlation between the simulated and corresponding original Landsat image on the same date of the prediction will be used. Statistics will be computed across land cover types. A sample of the ground truth data will be used to validate the accuracy of the predicted image across different land cover types and environment. Once, the accuracy is tested and evaluated, NDVI and EVI will be calculated for the annual phenology detection.

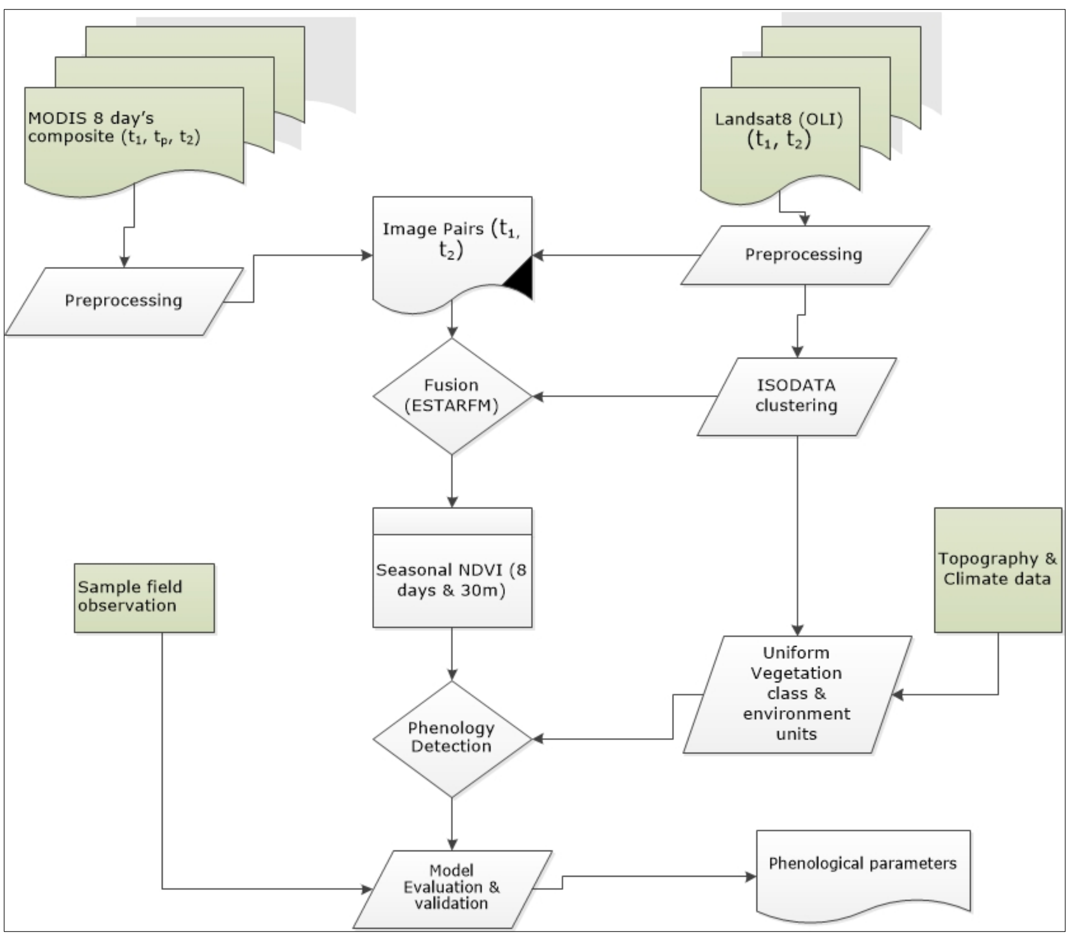

Figure 3: Workflow of image fusion and phenology detection

Phenology detection

Phenology extraction based on fused image on all cloud free pixels identified before fusion to evaluate how accurate the fusion detects phenology variation. The three proposed phenology models are the double logistic function (Beck et al., 2006; Zhang et al., 2003) based on inflection points; harmonic analysis of time series (HANTS) based on maximum increase (Moody and Johnson, 2001) and variable threshold methods (Vrieling et al., 2013; White et al., 1997). The main consideration in selection of these models include 1) applicability of detection in tropical and heterogeneous environments, 2) long-term trend detection capability and 3) applicability of models to detect cropland phenology. Given the complexity of the landscape, agricultural system and growing season variation in Ethiopia, the application of these models is expected to increase the predictive power across natural vegetation and agricultural landscapes. The application of different models will also minimize the errors and uncertainties associated data fusion procedures.

Model evaluation and validation

The spatial and seasonal pattern of phenology derived from the fused image based on the aforementioned models will be compared and evaluated at pixel and aggregate levels. The absolute difference of phenology parameters between pairs of models at each pixel will be used to test if they show similar characteristics and meaningful patterns for the determined parameters. At an aggregate levels homogeneous pixels stratified by vegetation type and uniform biophysical environment will be used to assess the predictability of models across different spatial and vegetation classes. In addition, the data acquired from ground observations will be correlated with the model outputs to validate phenology for agricultural land. The performance of models will be quantified statistically using the root mean square error (RMSE) calculated between observed NDVI and estimated values. Coefficient of determination (R^2) will be used to evaluate models bias and accuracy

1.6. Expected output

- High resolution (30m and 8 day) seasonal time series spectral and vegetation index
- The timing of vegetation growth cycle (SOS, EOS, peak period and LOS) across different vegetation and environment unit useful for crop monitoring and management

2. Chapter Two

Trends of vegetation phenology and the influence of climate variability/change in Lake Tana Sub basin, Northwestern Ethiopia from 2001 to 2020

2.1. Introduction

A better understanding of medium to long-term vegetation-climate trends and relationships is important in understanding complex atmospheric and terrestrial ecosystem dynamics (Brown et al., 2012; Forkel et al., 2013). Climate variability/change is predicted to impact 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 these elements during key phenological stages has a large influence on agriculture (Hmimina et al., 2013). For instance, a late SOS may lead to exposure to temperature and water stress during flowering and ripening periods which could result in crop loss or declining productivity (Brown et al., 2017). Yet, the effect climate on phenology and the current phenology – climate trends depend on climate regions of the world (Richardson et al., 2013). A lengthening of the growing season has been witnessed in the past few decades at global level and early green-up in high latitude climates because of global warming and CO2 increase (Brown et al., 2012; Chen et al., 2018). The trends and drivers of vegetation phenology over the tropics on the other hand is less clear (Vrieling et al., 2013). The IPCC fifth assessment report indicates that climate variability/change imposes a significant challenge on agricultural production in Africa by increasing water stress (Niang, 2014). The effect is not uniform across vegetation classes and regions in the continent (Guan et al., 2014a). Thus, understanding the trends and response of vegetation to climate variability/change is vital to understand future food production and food security trends in developing countries including Ethiopia.

Studies investigating the effects of climate variability and growing season dynamics in Ethiopia (Alemu and Henebry, 2017; Eastman et al., 2013; Workie and Debella, 2018) revealed that Ethiopia is perhaps the most vulnerable country in Africa to climate variability/change induced impacts because of complex topography, fragmented landscapes and a dependency on rain fed agriculture. Climate change has already altered the annual amount and distribution of rainfall (Meroni et al., 2014; Musau et al., 2016). Early green-up, an increase in the '*kiremt*' rainfall amount in the north and a shorter growing season in south and eastern Ethiopia have all resulted in water stress during critical crop growth stages (Brown et al., 2017; Funk et al., 2015). Whereas Gummadi et al. (2018) found substantial decreases in the amount and intensity of spring rainfall and a decline in the number of annual rainy days. Meroni et al. (2014) and Song Shuai (2018) argued that increasing temperature are also a limiting factor for vegetation growth in the highlands of Ethiopia. Divergent and spatially inconstant results on the trends and the response of vegetation to climate variabilities justifies the importance of a spatially explicit examination of the medium to long-term climate – vegetation trend.

Coarse resolution (≥250m) satellite data such as MODIS is unable to detect phenology trends in fragmented agricultural areas with small plots (<1 ha). Persistent cloud cover is also a major challenge for high-resolution phenological analysis in a tropical climate (Liang et al., 2014; Singh, 2012) which is a common problem in the highlands of Ethiopia. However, spatiotemporal data fusion techniques, such as ESTARFM combine coarse and fine resolution images to fill these gaps (Liu et al., 2016). In line with this,Schmidt et al. (2015); (2012) for example highlighted the applicability of time series spatiotemporal data fusion for phenology studies in Queensland, Australia. Gao et al. (2017) also derived a 15 years time series of MODIS-Landsat image fusion using three Landsat sensors data (TM, ETM+ and OLI) and found reliable phenology trend comparable with ground data in the US Corn Belt region. These studies were conducted in regions with relatively large farm sizes and there is limited research effort to apply such method in a fragmented landscape condition. Therefore, this study is intended to use spatiotemporal fusion to understand medium-term (20 years) phenology–climate trends in Ethiopia. Efforts to validate fusion and phenology methods across landscape and vegetation classes in chapter one will be the basis for the time series analysis.

2.2. Statement of the problem

Climate variability/change contributes to an unprecedented impact on crop production in Ethiopia (Brown et al., 2017). Variation in the timing of vegetation growth consistently leads to crop failure and an increase in diseases, invasive species, weeds and pests in the past few decades, suggesting that more detailed phenology and climate trend analysis is required to quantify the temporal and spatial scale of the variability (Evangelista et al., 2013). Previous studies indicate a lengthening trend of the growing season in northern Ethiopia (Brown et al., 2017; Workie and Debella, 2018).Yet, the response of vegetation to the current climate condition is overlooked and not well investigated with sufficient temporal detail. In addition, the existing few studies have relied on the analysis of annual climate variability and LOS, but variability during the critical vegetation growth periods are also the main constraining factors affecting agricultural production in Ethiopia, which remains unclear (Gummadi et al., 2018). Thus, given the diverse microclimate and cropping pattern, topographic and ecological heterogeneity there is a need to understand the phenology - climate trend based on multi-sensor spatiotemporal data fusion approach that may provide valuable information about the impact of current climates on crop growth and production.

In this regard, this study will characterize vegetation-climate trends during the critical growth stages- with particular emphasis on cropland - using information retrieved from multi-sensor satellite data for the period between 2001 to 2020. Time series vegetation phenology will be estimated first using the data fusion and phenology methods that evaluated and validated in the first chapter of this study. Secondly, the trends and pattern of vegetation phenology and climate variables (temperature and precipitation) pertinent to phenological timing will be investigated. Thirdly, the interaction of climate factors and vegetation phenology will be evaluated in space and time in an attempt to identify consistent phenology drivers. This will be useful to assess if the current climate has a significant impact on crop growth as well as to identify critical periods of the season affecting crop growth and production. Time series land surface phenology monitoring using high-resolution data is expected to detect trend in vegetation growth dynamics overtime.

2.3. Objective of the study

The main objective of this study is to investigate the trends of vegetation growth dynamics and the response to climate variabilities in Lake Tana basin, in Northwestern Ethiopia from 2001 to 2020.

2.4. Research question

- What is the medium-term seasonal and inter-annual trajectory of vegetation phenology and climate variability during the growing season?
- What is the interrelationship between vegetation phenology and climate variability during the critical phenological stages of vegetation in Lake Tana basin?

2.5. Data and Methods

2.5.1. Types and sources of data

Satellite image

Temporally frequent MODIS data and high spatial resolution Landsat data will be used in this study. MODIS Terra composite (8 day) data will be accessed for the period between 2001 to 2020 from NASA's LP DAAC website (https://lpdaac.usgs.gov/). Less cloudy atmospherically corrected surface reflectance Landsat TM (2001 to 2011) and Landsat 8 OLI (2013 to 2020) data, which is the base in many biophysical applications, will be acquired from Landsat archive (https://earthexplorer.usgs.gov/). Both data will be projected using common coordinate system using WGS84 UTM zone 37 and paired for fusion. The bands and spectral ranges involved in the data fusion in this study are as shown in Table 1 .

Table 1: Sensors spectral bands used in the study

Bands	**Landsat TM**		**Landsat8 (OLI)**		**Path/row**	**MODIS** (Tera)				**Tile**
	Bands	**Wavelength(µm)**	**Bands**	**Wavelength(µm)**	**170/52**	**Bands**	**Wavelength(µm)**	**Resolution**	**Type**	
Blue	B1	0.45 - 0.52	B2	0.45 - 0.51		B3	0.459–479	500	MOD09A1	h21v07
Green	B2	0.52 - 0.60	B3	0.53 - 0.59		B4	0.545–0.565	500	MOD09A1	
Red	B3	0.63 - 0.69	B4	0.64 - 0.67		B1	0.620– 0. 670	250	MOD09Q1	
NIR	B4	0.76 - 0.90	B5	0.85 - 0.88		B2	0.841–0.876	250	MOD09Q1	
SWIR1	B5	1.55 - 1.75	B6	1.57 - 1.65		B6	0.1628–0.1652	500	MOD09A1	
SWIR2	B7	2.08 - 2.35	B7	2.11 - 2.29		B7	0.2105–0.2155	500	MOD09A1	

Climate dataset

Precipitation and LST will be used as a climate factors in this study. The Climate Hazards Group Infrared Precipitation with Station (CHIRPS) gridded rainfall dataset (5km) which have been evaluated and found to be reliable for Ethiopia (Funk et al., 2015) and MODIS LST (1km), which includes daytime and nighttime records will be accessed from (http://chg.geog.ucsb.edu/data/chirps/). To match with the spatial resolution of the Landsat-MODIS fused data, the rainfall and LST data will be resampled. Then the climate variables will be aggregated to match the timing of the phenology parameters while considering time lag time effects.

For further phenology-climate relationship analysis, phenology parameters will be summarized within the resolution of climate dataset and uniform environmental zones.

Field data

Phenology and climate trends will be analyzed across homogeneous environmental units and per vegetation class, since croplands and other vegetation types respond differently to the inter annual and seasonal climate variation (Jong et al., 2012). Hence, a land cover mask will be used to identify major vegetation classes. For time series analysis during the study period, stable pixels will identified. Croplands have clear seasonality with high NDVI annual variance and standard deviation, which could be used to identify stable cropland pixels. The identified cropland will be used to collect phenological history from farmers. Farmers will be interviewed about sowing dates, green up, flowering, fruiting, harvest periods, final yield and other crop management information and the result will be compared with actual field observation identified in chapter one of this study. In addition, district level production statistics will be acquired from the regional agriculture bureau.

2.5.2. Method of Analysis

The analysis covered in this study includes vegetation-climate trend and the relationship using Breaks for Additive Seasonal and Trend (BFAST) and partial least square (PLS) regression methods, respectively based on time series phenology determined from Landsat – MODIS fused data as shown in Figure 4 and discussed below.

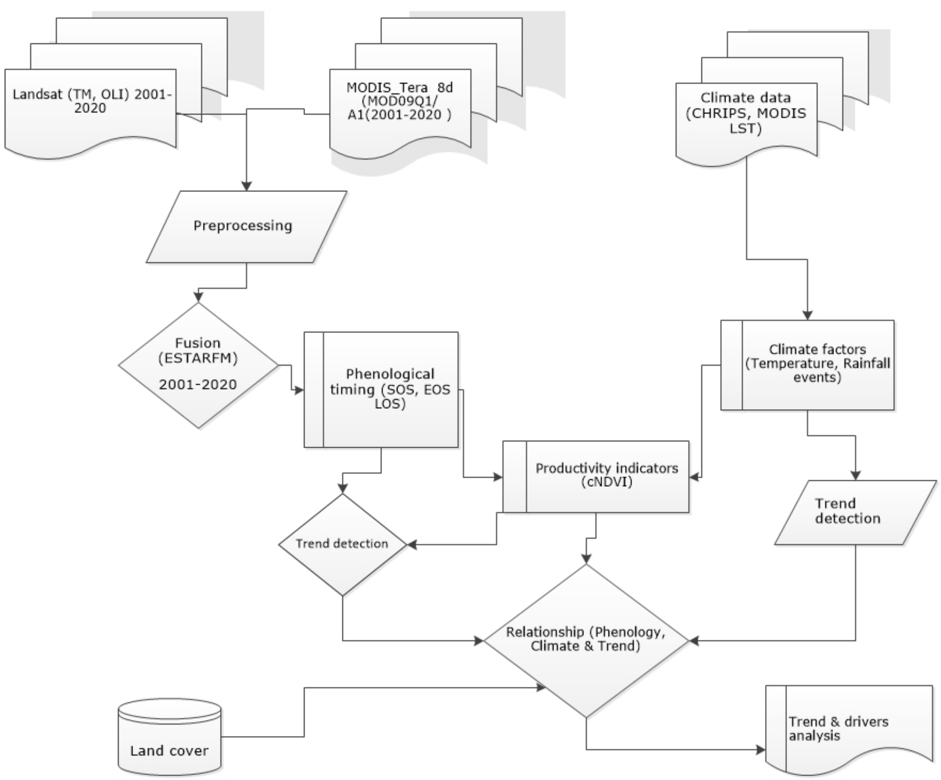

Figure 4: Workflow of phenology-climate trend analysis

Time series image fusion and phenology detection

To capture the spatial heterogeneity of phenology in fragmented landscapes, a time series of Landsat-MODIS data fusion using ESTARFM and phenology detection algorithms as evaluated and validated in the first objective of this study will be employed. Time series fusion will be conducted for periods between 2001 to 2003, 2005 to 2007, 2009 to 2011 using Landsat TM, 2013 to 2015, and 2017 to 2020 using Landsat8 OLI sensors. ESTARFM works when pairs of MODIS and Landsat data are available and thus these periods are selected considering Landsat data gaps and maintaining uniformity. Phenology parameters will be determined from an NDVI time series derived from the fused time series data and from MODIS NDVI for comparison. Data acquired from farmers will be used to evaluate the time series SOS, EOS and LOS, and district level production statistics peak greenness parameters considering the peak NDVI correlates with annual yield

Trends and climate determinants of vegetation growth dynamics

Vegetation phenology and climate factors (precipitation and Tmax, Tmin) trend and the inter-annual and seasonal variation will be analyzed using BFAST algorithm. BFAST is selected in this study since it accounts for seasonal and spatial change in the time series and suitable to detect medium to long-term trends and break points (Verbesselt et al., 2010). The algorithm integrates an iterative decomposition of the additive components of trend (*T*), seasonality (*S*) and residual error (*e*), with abrupt, gradual, and seasonal change (Musau et al., 2018; Verbesselt et al., 2010). The model iteratively decomposes the time series to fits a piecewise linear approximation to calculate trend and seasonality as:

$Yt = Tt + St + et$;

Where t is the time from 2001 to 2020 in case of this study and will be implemented in R-Package (https://CRAN.R-project.org/package=bfast). The algorithm was initially created for MODIS NDVI time series, but according to Verbesselt et al. (2010) the method can be used with any time series trend analysis such as weather data. This study proposes BFAST to analyze trends in vegetation growth dynamics and climate factors across land cover type and environment.

The relationship between phenological metrics and climate driving factors will be investigated using regression analysis (Chen et al., 2018; Wu et al., 2015). Prior to analyzing the vegetation – climate relationship, a time lag correlation analysis will be applied in weekly, biweekly and monthly time steps between climate variables and vegetation growth stages to identify the best-suited period for the relationship (Wu et al., 2015). Considering the lag-time effect, PLS regression model will be applied to analyze the response of vegetation growth to temperature and rainfall. PLS regression is proposed since it perform multiple correlation between variables (Ding et al., 2017; Zhang et al., 2017). One of the outputs of PLS regression, variable importance projection (VIP), that explains the importance of independent variables explaining the dependent will identify dominant factor affecting vegetation growth. VIP value greater or equal to one indicates the importance of climate factors during the season(Chen et al., 2018). This will give us an insight about the impact of seasonal climate variability on seasonal vegetation growth and critical vegetation growth stages.

2.6. Expected outputs

- Medium-term trends and patterns of vegetation growth dynamics for monitoring and management of crop growth such as sowing periods and harvesting time.
- Trends of climate variability and magnitude of climate influence on vegetation and crop growth

3. Chapter Three

Biomass and crop yield estimation for major cereal crops in the Lake Tana basin

3.1. Introduction

Climate variability/change can have a negative influence on crop production systems, particularly those that support a large population (Lobell and Gourdji, 2012). The inter-annual and seasonal variability of rainfall and temperature can have a large impact on agricultural production in sub-Saharan African countries where livelihoods dominantly depend on agriculture (Burke and Lobell, 2017). On the other hand, high population growth in the past few decades have led to increased demand for agricultural products (Niang, 2014). In such circumstances, timely and accurate information on crop yield and production is important for decision makers and planners (Lobell and Burke, 2010). Lack of reliable data hinders crop production monitoring and yield estimation efforts in Africa including Ethiopia (Mann and Warner, 2017). Remote sensing data due to their synoptic and repetitive coverage provides a means to detect crop biomass and yield variation (Lobell, 2013). Two popular approaches to estimate crop yield from remote sensing includes empirical statistical model and processed based crop growth model (Sibley et al., 2014).

Empirical statistical models are usually based on a correlation of historical yield statistics or vegetation biomass and remotely sensed vegetation indices (VI) such as NDVI integrated at phenological stages (Funk and Budde, 2009; Johnson, 2016; Zambrano et al., 2018). In these models, understanding the timing of the relationship between yield and VIs is the key to estimate yield (Battude et al., 2016). Incorporating remote sensing derived biophysical properties and spectral indices improves regional level yield prediction (Claverie et al., 2012). However, the main drawback of empirically based approaches is that they require recalibration when applied in other places and time periods (Marshall et al., 2018).
Process based crop models on the other hand simulate crop-soil atmosphere relationships to describe growth and development. Models such as AquaCrop (Silvestro et al., 2017), STICS (Constantin et al., 2015) and WOFOST (Huang et al., 2015) have all assimilated remote sensing derived biophysical properties such as FAPAR and LAI for regional level estimation. This approach accounts for different environmental stress

factors, which can be useful to capture yield variability (Marshall and Thenkabail, 2015). The problem is these models require a lot of ground-based and other input data and calibration (Battude et al., 2016).

Semi-empirical models based on Monteith (1972) light use efficiency (LUE) hoverer are easy to implement and translate remote sensing derived biophysical parameters into total biomass based on the assumption that biomass productivity is proportional to photosynthetically active radiation over the growing season (Lobell, 2013). Likewise model coupling LUE and process based models such as Simple Algorithm For Yield estimates (SAFY) developed by Duchemin et al. (2008) only require a few parameters, are designed for remote sensing application and can simulate crop biomass and yield over large geographic area (Claverie et al., 2012). SAFY combines Monteith (1972) LUE theory with a Maas (1993) leaf partitioning function to simulate daily time series of Dry Aboveground biomass (DAM), Green Leaf Area Index (GLAI) and actual yield (Y) (Claverie et al., 2012; Dong et al., 2016). Most of its parameters are linked with remote sensing derived phenology and biophysical properties.

Availability of high spatiotemporal remote sensing data that are comparable to field sizes throughout the growing season constrains the application of semi-empirical models (Liao et al., 2019). Similarly, accurate phenology determination at higher spatial and temporal time scales is an important input for field scale and inter-annual yield estimation, which can be achieved using a multi sensor spatiotemporal data fusion method (Dong et al., 2016; Gao et al., 2017). In this regard, Liao et al. (2019), (Gao et al., 2018) and Dong et al. (2016) for instance, fused Landsat8 and MODIS to estimate crop biomass and yield successfully at subfield scale and infer historical production trajectories. Such an approach has not been attempted in the context of the study area to support the traditional field survey methods, which are costly, untimely and less reliable. Therefore, optimization of SAFY model using phenology acquired through image fusion, calibration with remote sensing biophysical parameter (LAI) using *in-situ* measurement is envisioned in this study.

3.2. Statement of the problem

Crop production in Ethiopia is characterized by rain fed agriculture, a low level of productivity and substance smallholder farming practices (Ahmed, 2003; Alemu and Henebry, 2017). Moreover, climate variability and extreme weather events, periodic crop losses and food shortages are common phenomena (Brown et al., 2017). To minimize the vulnerability, sound spatiotemporal crop production monitoring and yield information is crucial. However, a lack of reliable, timely and accurate ground information is the major challenge in Ethiopia. Remote sensing based models can fill such gaps, but have uncertainties due to an absence of images satisfying both high spatial and temporal resolution. Furthermore, Ethiopia is also highly fragmented and topographically complex which requires high spatial remote sensing data to estimate crop yield. Integrating phenology and biophysical parameters determined from a Landsat-MODIS fused product with a semi empirical model might improve yield estimation in this data scarce environment. There are limited studies so far devoted to clarifying and understanding the unique advantages of remote sensing for crop production monitoring and yield prediction in Ethiopia (Meshesha and Abeje, 2018). Thus, this research will assimilate phenology information and crop biophysical properties derived from multi-sensor fused data to estimate crop biomass and yield in a fragmented agricultural landscape in the in Lake Tana basin. To achieve this, MODIS-Landsat fused image and phenology dynamics validated in (Chapter 1) will be assimilated in the SAFY crop model. Since this study will be evaluated and validated with field data, it can serve as a baseline for large area and time series production analysis in similar environments.

3.3. Objective

The objective of this study is to estimate crop biomass and yield by assimilating Landsat-MODIS fused data into SAFY in Lake Tana basin.

3.4. Research question

- Do fused spatial-temporal data improve crop yield estimates in a topographically complex and fragmented landscape?

3.5. Data and Methodology

3.5.1. Types and sources of data

Crop biomass and yield estimation in this study require biophysical field measurement, climate (daily temperature, rainfall and incoming solar radiation) and satellite imagery. Temperature data will be acquired from nearby meteorological stations from national metrological agency of Ethiopia located within 10km radius of the sample plots (http://www.ethiomet.gov.et). NDVI, EVI, and phenological date maps acquired through image fusion for the 2019 and 2020 seasons derived and calibrated in Chapter 1 will be used. Incoming short wave radiation data will be obtained from EUMESAT's land surface analysis website (https://landsaf.ipma.pt/en/) since it is one of the input for the yield estimation model.

Field measurement

Field data will be collected to calibrate and validate crop model input parameters. Leaf area index (LAI) which is the main input and state variable in this study will be collected during the 2019 and 2020 growing season. Available surveys by the Amhara agricultural bureau (BoEPLAU, 2015) show that the target crop types are dominantly produced in the *Dangla* (wheat, tef), *Mecha* (maize, tef), *Fogera* (rice and maize) *Sekela* and *Libo Kemkem* districts. Hence, agricultural test plots will be identified within a 10km radius of the local metrological station in these districts by stratifying the cultivated land based on environmental determinants of yield (topography, soil and climate). A total of 100 sample plots considering the combination of the number of districts and target crop types is proposed to be covered within two years of data collection. Considering 30m Landsat data and the small plot size of the area, farmer plots satisfying a 3 x 3-pixel window will be selected to collect the required sample data. For each crop types, we will sample

LAI in a non-destructive measurement approach (Marshall and Thenkabail, 2015) using a Plant Canopy Analyzer across plot transects during the main phenological stages of crops. Aboveground biomass and yield during the harvest period from the same sample plots will be measured with a destructive approach. Furthermore, crop height, intensity and crop type will be collected. The LAI and yield sample will be split for model calibration and validation. In addition, the district (*Woreda*) level '*Meher'* season official production statistics acquired from the Amhara Agricultural Bureau will be used to compare the model output at district level.

3.5.2. Method of analysis

Crop biophysical variables derived from Landsat8 - MODIS fused data assimilated with a semi-empirical crop model (SAFY) will be employed to estimate biomass and yield. The methodology consists of establishing a regression equation between ground bias corrected MODIS LAI and Landsat-MODIS fused NDVI/EVI; deriving input variables and calibrating model parameters based on estimated GLAI; and phenology and field measurement to estimate biomass and yield. Figure 5 shows the general workflow of the methodology.

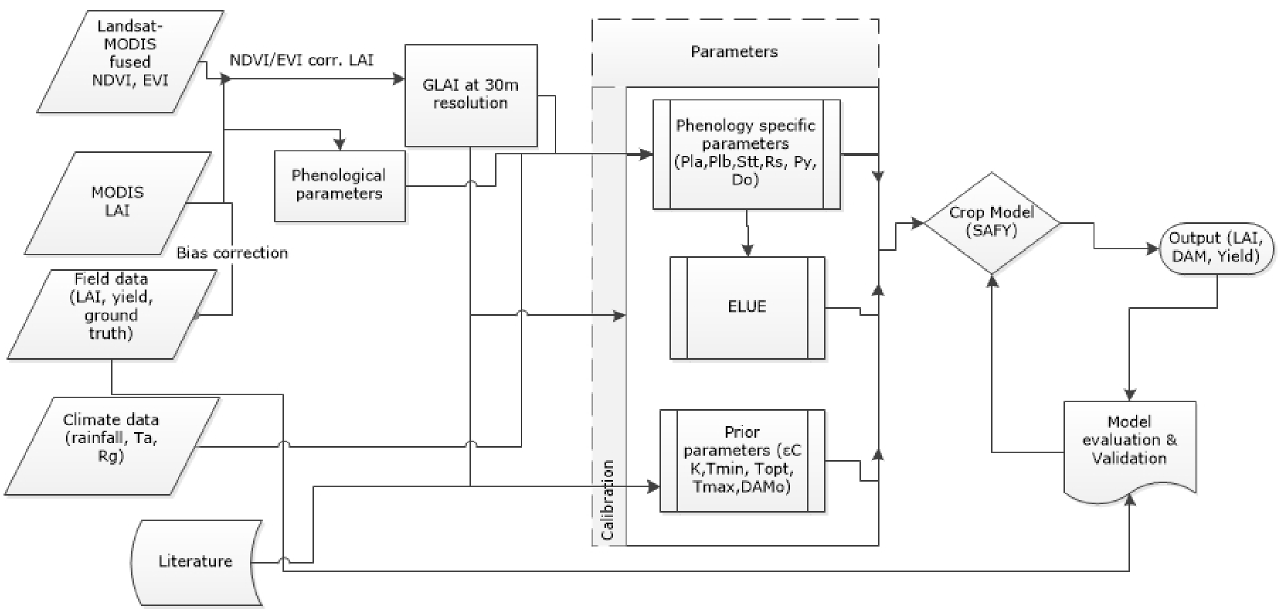

Figure 5: Biomass and Yield estimation workflow. Phenology parameter Pla and Plb are two leaf-partitioning factors, Stt is Temperature sum for senescence, Do refers days of emergence, Rs and Py are rate of senescence and rate of grain filling respectively. Prior parameters (Tmin, Topt and Tmax refers to the minimum, optimum and maximum temperature for growth, εC and k stands for climate efficiency and light interception coefficients, DAMo is the initial dry above mass). ELUE stands for effective light use efficiency.

Retrieving green LAI from remote sensing data

GLAI is the main state variable in SAFY model to determine light interception capacity of a crop and daily accumulation of DAM (Dong et al., 2016). It will be acquired through an empirical relationship between bias corrected MODIS LIA using field measured LAI and Landsat8 - MODIS fused NDVI/EVI. This should be successful since past studies have found an empirical relationship between satellite spectral indices and ground measured GLAI (Liao et al., 2019; Morel et al., 2014). Furthermore, because the widely used NDVI saturates at a relatively low LAI and is sensitive to soil background information (Liu et al., 2012), this study will also uses EVI for comparison. The kind of relationship and equation acquired will be evaluated at different phenological stages of crop development. The best performing equation that determines the relationship will be applied to the entire image time series. The performance of the relationship will be evaluated using RMSE between ground observed LAI and the estimated satellite GLAI and the coefficient of determination (R^2). This GLAI deduced from satellite image will be used to calibrate the biomass and yield model parameters.

Model development and parameter calibration

SAFY model is designed to estimate simulates daily GLA, DAM and final grain yield (Y) of crops from date of emergence to end of senescence (Duchemin et al., 2008). DAM is proportional to absorbed photosynthetically active radiation (APAR) estimated based on (Monteith, 1972) light use efficiency approach (equation 1). The main input variables GLAI will be established between Landsat-MODIS fused NDVI/EVI and ground measured GLAI (as discussed above). Daily temperature (Ta) is also the driving factors acquired from climate datasets. Subsequently other parameters will be calculated, calibrated and simulated. The parameters can be grouped in to fixed parameters acquired from literatures and field measurement, phenological parameters and agro environmental parameters based on GLAI estimated based on fused NDVI/EVI as shown in table 2.

$$DAM = ELUE * APAR * Ft(Ta) \ldots\ldots\ldots..1$$

$$APAR = Rg * \varepsilon\mathrm{C} * \mathrm{fAPAR} \ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

$$fAPAR = 1 - \exp\left(-\mathrm{k} * \mathrm{GLAI}\right) \ldots\ldots\ldots\ldots 3$$

Where, *DAM* is the Dry aboveground biomass, which is to the function photosynthetically active radiation (APAR) and effective light use efficiency (*ELUE)* and Ft (Ta) temperature stress function. APAR is the product of incoming short wave radiation (Rg), climate efficiency coefficient (εC) and light interception efficiency that link the fraction of photosynthetically active radiation (fAPAR) to green leaf area index (*GLAI*) via light interception coefficient (*K)* (equation 2&3).

Initial model parameters (*DAMo, εC, K, SLA and T (Tmin, Topt and Tmax*)) are parameters that will be selected according to the literature. Climate efficiency, which is the ratio of PAR to incoming shortwave radiation usually between 45% - 50%. *K* represent the light interception coefficient links fAPAR and GLAI in Beers law (equation 3). *SLA* is the ratio of leaf area per units of dry biomass which will be calculated after initial model simulation. *Tmin, Topt and Tmax* are decisive temperature for each crops where Tmin is the base temperature below which crop growth does not occurs; Topt is the optimal temperature and Tmax that leads to a decrease in crop growth. Temperature factors for major cereal crops in Ethiopia will be determined according to findings of local research centers and previous studies.

Table 2: SAFY Model parameters

No	Parameters	Units	No	Parameters	Unit
Initial values determined from literature/field			**Derived from time course of GLAI & phenology**		
1	Initial dry aboveground mass (*DAM₀*)	g m^{-2}	8	Day of plant emergence (*Do*)	Day
2	Climatic efficiency (εC)	-	9	Temperature sum for senescence (*Stt*)	^{0}C
3	Light-interception coefficient (*K*)	-	10	Rate of senescence (*Rs*)	-
4	Temperature for growth (min, opt, max)	^{0}C	11	Partition-to-leaf function (*Plb*)	-
5	Specific leaf area (*SLA*)	m^2 g^{-1}	12	Partition-to-leaf function (*Pla*)	^{0}C day
6	Polynomial degree (β)	-	13	Rate of grain filling (*Py*)	-
7	Effective light-use efficiency (*ELUE*)	g MJ^{-1}	14	Water stress (Ws)	

Phenological parameters (Do, Stt, Rs, Pla, Plb) will be determined from the phenology modeling procedure (Chapter 1) and daily temperature data. The key phenological stages required are SOS, day of senescence (DOS) and EOS that can be effectively retrieved using the double logistic inflection point method. Date of emergence (Do) will be replaced with SOS adjusted based on ground data validation. Temperature sum for senescence (Stt) is the cumulative temperature between SOS to DOS. The rate of senescence (Rs) determined from the beginning to end of senescence. Leaf partitioning –to-leaf fraction (Pla, Plb) are the ratio of leaf DAM and total dry biomass which capture the fraction of dry biomass partitioned per day during the plant vegetative stages calculated after (Maas, 1993). The effective light use efficiency (ELUE) is dependent on local agro-environmental conditions will be obtained from GLAI and stress factors.

These parameters will be calibrated based on the estimated GLAI and an optimization procedure aimed at reducing difference between observed GLAI and simulated GLAI by the model. In the first round of calibration, phenological parameters (Do, Stt, Rg Pla and Plb) will be calibrated by reducing RMSE between simulated GLAI and observed GLAI according to (Duchemin et al., 2008). This will be used to optimize the remaining remaining parameters. Finally, running the model based on these calibrated parameters will yield daily GLAI and dry biomass productivity. The total biomass will be aggregated for the growing period to estimate final grain yield. The final grain yield estimation will be based on total DAM and harvest index (HI). HI will be determined based on field experiment on selected field during the study period thus:

$$Y = DAM * HI \ldots\ldots\ldots 4$$

Model validation and evaluation

The model will be validated and evaluated using data from two growing seasons (2019 and 2020). To evaluate the improvement in model performance due to image fusion, the model will be run using MODIS only and Landsat-MODIS fused data. The relative difference between the simulated GLAI and the corresponding satellite image value will be compared for the two scenarios to evaluate the robustness of the model. Pairs of simulated and observed GLAI values on the same location will be compared based on coefficient of determination (R^2) and RMSE. To check the performance over crops with different photosynthetic capacity, the model will be evaluated for maize (C4), and C3 (wheat, *tef*, rice) crops. The variability of simulated DAM and yield will be evaluated across uniform cropping environments and based on actual field measurements obtained during the harvest. Farmers estimates of actual yield and district level crop yield statistics will also be used as independent data to evaluate the performance of the model at field and aggregate level respectively.

3.6. Expected output

- Spatially distributed crop biomass and yield estimates of major crops (*tef*, maize, rice, wheat).

4. Chapter Four

Sensitivity of crop biomass and yield to phenological and climate (temperature and rainfall) factors

4.1. Introduction

Implementing crop yield estimation model over time and across space is important to understand the dynamics of crop production (Lobell et al., 2003). However an apparent uncertainties in the estimated yield might be expected since crop models simplifies model parameters and do not take in to account every stress factor responsible for spatial and inter-annual variation of crop growth and development (Battude et al., 2016). Model parameters and inputs included in the model depend on the type of model used, environment and crop type under investigation (Vanuytrecht et al., 2014). In this regard, it is important to identify model parameters and input variables most influencing the output of the model over time. This can be done using sensitivity analysis (SA) (Liu et al., 2012). Parameter SA is vital for model understanding, for correct application to local environments and to screen important parameters (Campolongo et al., 2007). It could also be used for model parameter calibration in large-scale applications and for understanding the underlining causes of yield variability.

The biomass and yield estimation model proposed in Chapter 3 of this study (SAFY), is advantageous to apply at regional level since it integrates remote sensing data. Previous studies have shown that the model effectively estimates crop biomass and yield at a large geographical scale with few parameters (Bellakanji et al., 2018; Chahbi et al., 2014; Dong et al., 2016). However, due to its simplicity and uncertainties in integrating remote sensing data, uncertainty in the estimated biomass and yield is inevitable. For instance, the original SAFY does not account for the effect of water stress, and instead assumes it is accounted for by the remote sensing input (leaf area index) (Silvestro et al., 2017). However, this may lead to erroneous estimates in while implementing in the semi-arid climate where rainfall variability plays a significant role for crop yield variability (Lobell et al., 2003). In this regard, understanding and identifying the dominant input parameters that cause spatial and temporal yield variability is vital to implement remote sensing based production estimation over large geographical scale.

Similarly, phenological factors, particularly the start of emergence influences inter-annual crop yield variation since the model estimation runs from emergence to senescence (Claverie et al., 2012). Inter-annual variability of planting date can be attributed to climate variability or management factors. Furthermore, the importance of certain parameters may be higher in certain growth stages and their influence may gradually decrease as the importance of the other increases, implying performing SA at each stages of the phenological period (Wang et al., 2013). Therefore, this study is intended to use sensitivity analysis to assess how changes in temperature, rainfall and phenological variation affects crop production in space and time. This will be used to assess the projected impact of temperature and rainfall on yield.

4.2. Statement of the problem

Applying crop yield estimation using semi-empirical models such as SAFY over larger geographical areas over time requires adjustments of model parameters inherent to the environment under investigation (Battude et al., 2016). SA can be used to identify the dominant parameters and inputs responsible for spatiotemporal variation of the model output. Phenology related parameters and a remote sensing derived biophysical parameter (GLAI) are the main parameters responsible for spatial and temporal variability of yield in the SAFY model. Understanding how crop biomass and yield is sensitive to inter annual and spatial variability of phenology related parameters (SOS, LOS) and climate stress factors (temperature and rainfall) could be used to predict future impacts on production which is important for decision making. Therefore, this study is intended to evaluate the relative influence of model parameters and input variables of SAFY, and in turn analyze the impacts of projected rainfall and temperature on crop biomass/yield. The assumption is that spatiotemporal variability of biomass production and yield is explained by inter-annual variation of phenology and climate stress factors. The sensitivity of yield and biomass production to SAFY model input parameters will be analyzed to apply the model for time series analysis. Based on the parameters determined to be most influential via SA historical biomass and yield will be estimated for the period 2001 to 2020. Scenarios for early and late sowing and the impact on yield in relation to recent climate change projections based on representative concentration pathway (RCP 4.5 and RCP 8.5) will be evaluated. The sensitivity of biomass to rainfall and temperature during the phenological stages will indicate critical periods that influence the final yield. It will give us an insight about the temporal dynamics of crop production and the influence of phenology variation over time.

4.3. Objective

The objective of this study to analyze the spatiotemporal variability of biomass and yield based on trends of phenological metrics and climate stress factors from 2001 to 2020 in Lake Tana basin.

4.4. Research question

- What are the dominant parameters and input factors for the spatial and temporal variability of biomass and yield?

4.5. Data and Methodology

4.5.1. Data

Input parameters of SAFY and simulated LAI, DAM and yield obtained in Chapter 3 will be the main data for sensitivity analysis. Time series phenology derived from Landsat-MODIS image fusion in Chapter 2 will be used to run the crop estimation model over the entire study area and over time. Temperature and rainfall data will used to analyze biomass and yield sensitivity and uncertainty caused by variability temperature stress effect and water stress factor.

4.5.2. Method of Analysis

The analysis include the quantification of stress factors and SA of model outputs to input parameters. SA of the SAFY model to inputs and parameters based on a one factor at a time (OAT) method will be employed. Based on the SA result, biomass productivity and yield will be simulated for the period between 2001 and 2020. Inter annual variation of biomass productivity will be compared with seasonal integrated NDVI/EVI trajectories. The overall workflow of the study is illustrated in Figure 6.

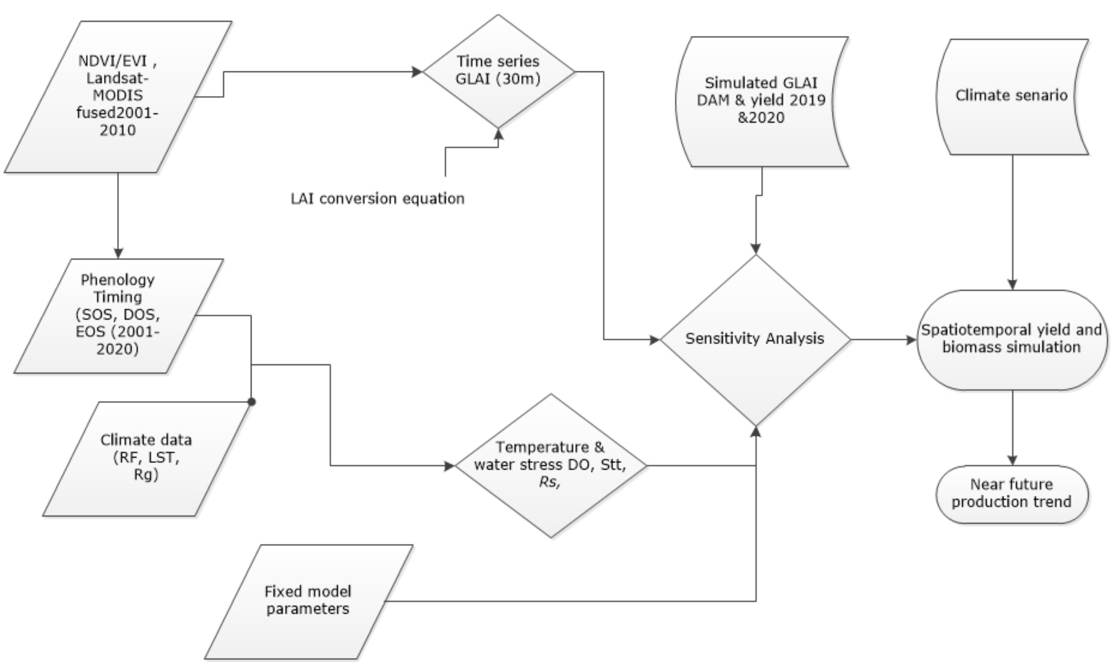

Figure 6: Methodological workflow of objective four

Input parameters related with spatial and temporal variation

Input parameters and stress factors responsible for spatial and temporal variation of biomass and yield including climate (temperature and rainfall), as well as phenological parameters (Do, EOS and DOS) will be characterized and mapped across the entire study area and for the period 2001 to 2020. Temperature stress which is part of SAFY model will be calculated based on critical temperatures (Tmax, Topt Tmin) and degree of the polynomial function (β) that defines the stress temperature function for major crops according to (Duchemin et al., 2008). On the other hand, crop water stress (Ws) which is not included in the original model will be considered according to (Duchemin et al., 2015) to assess the influence on the model performance in the context of the study area. Rainfall will be accumulated dekades before crop emergence to senescence to assess crop response to water availability.

Phenology parameters that include day of emergence (*Do*), *EOS* and *DOS* will be evaluated across space and time for SA. *Do* represent the effect of variability of sowing date that will be analyzed based on the *SOS* parameter adjusted according to data acquired from the field and farmers report of sowing date evaluated in the Chapter 1 of this study. Similarly, *DOS* and *EOS* during the study period (2001 to 2020) will be identified to parametrize the sum of senescence temperature (Stt). The temporal variation of PAR affecting APAR hence biomass accumulation. Therefore, APAR variation could be determined by variation in phenological stages or LOS.

Selectivity analysis

The SA aims at identifying the most and least influential model parameters for efficient simulation of the crop model. It may be also possible to perform a simple LUE model directly by evaluating model parameters, which is important for large area applications. In this study a SA using the OAT method (Campolongo et al., 2007) will be used since the number of parameters used in SAFY model is fairly small. Thus, the analysis focuses on how the model is sensitive to variation of GLAI and phenology determined from fused images as well as stress factor (Ta and Ws) variability. DAM and simulated GLAI will be considered as output reference to investigate the influence of phenological variation and other input parameters derived from fused Landsat-MODIS product. The model will be executed based on different combinations of input parameters and scenarios. For instance, the productivity response (DAM, LAI simulated) due to variability in the SOS, LOS and DOS across different environment (highland crops, crops on moderate topography) and the effects of early and late sowing will be investigated. The response of the parameters or factors may also vary in the wet and dry years and at different stages of the growing season. The level of influence of parameters will be determined based on relative sensitivity measure of mean and standard deviation in which larger mean indicates the parameter is influential as proposed by (Morris, 1991) and improved in (Campolongo et al., 2007).

Time series biomass and yield prediction

After important limiting and stress factors identified through SA, the SAFY model will be used to simulate time series DAM and yield over the study period for the period from 2001 to 2020. Once, the crop model will be calibrated for the period 2019 and 2020 and dominant parameters selected through SA, it will be applied to simulate the historical yield patterns. The patterns of variation will be analyzed across space and time. The performance in detecting inter annual and spatial variability will be evaluated across uniform environment using district level production statistics.

Apart from the historical production, the likelihood of phenology and yield deviation will be compared with respect to predicted temperature and rainfall change for near range. Future climate variables based RCP 4.5 and RCP 8.5 of the IPCC emission scenarios and different sowing date (depending on the historical trend) will be compared to get an insight about future impact of temperature and rainfall variability on phenology and crop yield of the major crops under investigation.

4.6. Expected output

- Ranking of model parameters to run the model with few parameters for regional scale application
- Time series crop biomass and yield prediction

Time plan

Table 3: Tentative Time plan of the research

No	Activities	2018		2019				2020				2021				2022	
		3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2
1	PhD proposal development and Qualifier																
2	Literature studies																
3	First round field data collection																
4	Draft journal article write-up on trend of phenology (objective 1)																
5	National workshop presentation																
6	Publication on objective one																
7	Data analysis and interpretation of objective 2																
8	Presentation on international workshop																
9	Publication of the second objective																
10	Second round field data collection																
11	Data analysis and interpretation of the third objective																
12	Publication of third objective																
13	Analysis and interpretation of objective four																
14	Submission of forth objective for publication																
15	Submission of thesis																
16	Admission to Defense																

Expected issues

- Data availability and quality: quality of climate data, crop mask and number of cloud free images
- Availability of field instrument to collect biophysical properties (LAI analyzer)
- Transportation and access to sample fields

Publications

These papers are expected to be published in the following journals

- Remote Sensing
- Remote Sensing of Environment
- International Journal of Applied Earth Observation and Geoinformation
- IEEE Transactions on Geoscience and Remote Sensing

Reference

Adole, T., Dash, J., and Atkinson, P. M. (2018). Characterising the land surface phenology of Africa using 500 m MODIS EVI. *Applied Geography* **90**, 187-199.

Ahmed, D. G. a. E. (2003). CROPS AND AGRO-ECOLOGICAL ZONES OF ETHIOPIA.

Alemu, W., and Henebry, G. (2017). Land Surface Phenology and Seasonality Using Cool Earthlight in Croplands of Eastern Africa and the Linkages to Crop Production. *Remote Sensing* **9**.

Atzberger, C. (2013). Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. *Remote Sensing* **5**, 949-981.

Battude, M., Al Bitar, A., Morin, D., Cros, J., Huc, M., Sicre, C. M., Le Dantec, V., and Demarez, V. (2016). Estimating maize biomass and yield over large areas using high spatial and temporal resolution Sentinel-2 like remote sensing data. *Remote Sensing of Environment* **184**, 668-681.

Beck, P. S. A., Atzberger, C., Hogda, K. A., Johansen, B., and Skidmore, A. K. (2006). Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI. *Remote Sensing of Environment* **100**, 321-334.

Bellakanji, A. C., Zribi, M., Lili-Chabaane, Z., and Mougenot, B. (2018). Forecasting of Cereal Yields in a Semi-arid Area Using the Simple Algorithm for Yield Estimation (SAFY) Agro-Meteorological Model Combined with Optical SPOT/HRV Images. *Sensors* **18**.

BoEPLAU (2015). Tana Sub Basin Integrated Land Use Planning and Environmental Impact Study Project Technical Report VI: Crop Resource Assessment.

Brown, M. E., de Beurs, K., and Vrieling, A. (2010). The response of African land surface phenology to large scale climate oscillations. *Remote Sensing of Environment* **114**, 2286-2296.

Brown, M. E., and de Beurs, K. M. (2008). Evaluation of multi-sensor semi-arid crop season parameters based on NDVI and rainfall. *Remote Sensing of Environment* **112**, 2261-2271.

Brown, M. E., de Beurs, K. M., and Marshall, M. (2012). Global phenological response to climate change in crop areas using satellite remote sensing of vegetation, humidity and temperature over 26years. *Remote Sensing of Environment* **126**, 174-183.

Brown, M. E., Funk, C., Pedreros, D., Korecha, D., Lemma, M., Rowland, J., Williams, E., and Verdin, J. (2017). A climate trend analysis of Ethiopia: examining subseasonal climate impacts on crops and pasture conditions. *Climatic Change* **142**, 169-182.

Burke, M., and Lobell, D. B. (2017). Satellite-based assessment of yield variation and its determinants in smallholder African systems. *Proc Natl Acad Sci U S A* **114**, 2189-2194.

Cammalleri, C., Anderson, M. C., Gao, F., Hain, C. R., and Kustas, W. P. (2014). Mapping daily evapotranspiration at field scales over rainfed and irrigated agricultural areas using remote sensing data fusion. *Agricultural and Forest Meteorology* **186**, 1-11.

Campolongo, F., Cariboni, J., and Saltelli, A. (2007). An effective screening design for sensitivity analysis of large models. *Environmental Modelling & Software* **22**, 1509-1518.

Chahbi, A., Zribi, M., Lili-Chabaane, Z., Duchemin, B., Shabou, M., Mougenot, B., and Boulet, G. (2014). Estimation of the dynamics and yields of cereals in a semi-arid area using remote sensing and the SAFY growth model. *International Journal of Remote Sensing* **35**, 1004-1028.

Chen, C., He, B., Guo, L., Zhang, Y., Xie, X., and Chen, Z. (2018). Identifying Critical Climate Periods for Vegetation Growth in the Northern Hemisphere. *Journal of Geophysical Research: Biogeosciences* **123**, 2541-2552.

Claverie, M., Demarez, V., Duchemin, B., Hagolle, O., Ducrot, D., Marais-Sicre, C., Dejoux, J.-F., Huc, M., Keravec, P., Béziat, P., Fieuzal, R., Ceschia, E., and Dedieu, G. (2012). Maize and sunflower biomass estimation in southwest France using high spatial and temporal resolution remote sensing data. *Remote Sensing of Environment* **124**, 844-857.

Constantin, J., Willaume, M., Murgue, C., Lacroix, B., and Therond, O. (2015). The soil-crop models STICS and AqYield predict yield and soil water content for irrigated crops equally well with limited data. *Agricultural and Forest Meteorology* **206**, 55-68.

Dash, J., Jeganathan, C., and Atkinson, P. M. (2010). The use of MERIS Terrestrial Chlorophyll Index to study spatio-temporal variation in vegetation phenology over India. *Remote Sensing of Environment* **114**, 1388-1402.

de Beurs, K. M., and Henebry, G. M. (2010). Spatio-Temporal Statistical Methods for Modelling Land Surface Phenology. *In* "Phenological Research", pp. 177-208.

Ding, C., Liu, X., Huang, F., Li, Y., and Zou, X. (2017). Onset of drying and dormancy in relation to water dynamics of semi-arid grasslands from MODIS NDWI. *Agricultural and Forest Meteorology* **234-235**, 22-30.

Dong, T., Liu, J., Qian, B., Zhao, T., Jing, Q., Geng, X., Wang, J., Huffman, T., and Shang, J. (2016). Estimating winter wheat biomass by assimilating leaf area index derived from fusion of Landsat-8 and MODIS data. *International Journal of Applied Earth Observation and Geoinformation* **49**, 63-74.

Duchemin, B., Fieuzal, R., Rivera, M., Ezzahar, J., Jarlan, L., Rodriguez, J., Hagolle, O., and Watts, C. (2015). Impact of Sowing Date on Yield and Water Use Efficiency of Wheat Analyzed through Spatial Modeling and FORMOSAT-2 Images. *Remote Sensing* **7**, 5951.

Duchemin, B., Maisongrande, P., Boulet, G., and Benhadj, I. (2008). A simple algorithm for yield estimates: Evaluation for semi-arid irrigated winter wheat monitored with green leaf area index. *Environmental Modelling & Software* **23**, 876-892.

Eastman, J., Sangermano, F., Machado, E., Rogan, J., and Anyamba, A. (2013). Global Trends in Seasonality of Normalized Difference Vegetation Index (NDVI), 1982–2011. *Remote Sensing* **5**, 4799.

Emelyanova, I. V., McVicar, T. R., Van Niel, T. G., Li, L. T., and van Dijk, A. I. J. M. (2013). Assessing the accuracy of blending Landsat–MODIS surface reflectances in two landscapes with contrasting spatial and temporal dynamics: A framework for algorithm selection. *Remote Sensing of Environment* **133**, 193-209.

Evangelista, P., Young, N., and Burnett, J. (2013). How will climate change spatially affect agriculture production in Ethiopia? Case studies of important cereal crops. *Climatic Change* **119**, 855-873.

Forkel, M., Carvalhais, N., Verbesselt, J., Mahecha, M., Neigh, C., and Reichstein, M. (2013). Trend Change Detection in NDVI Time Series: Effects of Inter-Annual Variability and Methodology. *Remote Sensing* **5**, 2113.

Funk, C., and Budde, M. E. (2009). Phenologically-tuned MODIS NDVI-based production anomaly estimates for Zimbabwe. *Remote Sensing of Environment* **113**, 115-125.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J. (2015). The climate hazards infrared precipitation with stations--a new environmental record for monitoring extremes. *Sci Data* **2**, 150066.

Gao, F., Anderson, M., Daughtry, C., and Johnson, D. (2018). Assessing the Variability of Corn and Soybean Yields in Central Iowa Using High Spatiotemporal Resolution Multi-Satellite Imagery. *Remote Sensing* **10**.

Gao, F., Anderson, M. C., Zhang, X. Y., Yang, Z. W., Alfieri, J. G., Kustas, W. P., Mueller, R., Johnson, D. M., and Prueger, J. H. (2017). Toward mapping crop progress at field scales through fusion of Landsat and MODIS imagery. *Remote Sensing of Environment* **188**, 9-25.

Gao, F., Hilker, T., Zhu, X., Anderson, M., Masek, J., Wang, P., and Yang, Y. (2015). Fusing Landsat and MODIS Data for Vegetation Monitoring. *IEEE Geoscience and Remote Sensing Magazine* **3**, 47-60.

Gao, F., Masek, J., Schwaller, M., and Hall, F. (2006). On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. *Ieee Transactions on Geoscience and Remote Sensing* **44**, 2207-2218.

Guan, K., Medvigy, D., Wood, E. F., Caylor, K. K., Li, S., and Jeong, S.-J. (2014a). Deriving Vegetation Phenological Time and Trajectory Information Over Africa Using SEVIRI Daily LAI. *IEEE Transactions on Geoscience and Remote Sensing* **52**, 1113-1130.

Guan, K., Wood, E. F., Medvigy, D., Kimball, J., Pan, M., Caylor, K. K., Sheffield, J., Xu, X., and Jones, M. O. (2014b). Terrestrial hydrological controls on land surface phenology of African savannas and woodlands. *Journal of Geophysical Research: Biogeosciences* **119**, 1652-1669.

Gummadi, S., Rao, K. P. C., Seid, J., Legesse, G., Kadiyala, M. D. M., Takele, R., Amede, T., and Whitbread, A. (2018). Spatio-temporal variability and trends of precipitation and extreme rainfall events in Ethiopia in 1980-2010. *Theoretical and Applied Climatology* **134**, 1315-1328.

Heumann, B. W., Seaquist, J. W., Eklundh, L., and Jönsson, P. (2007). AVHRR derived phenological change in the Sahel and Soudan, Africa, 1982–2005. *Remote Sensing of Environment* **108**, 385-392.

Hilker, T., Wulder, M. A., Coops, N. C., Linke, J., McDermid, G., Masek, J. G., Gao, F., and White, J. C. (2009). A new data fusion model for high spatial- and temporal-resolution mapping of forest disturbance based on Landsat and MODIS. *Remote Sensing of Environment* **113**, 1613-1627.

Hmimina, G., Dufrêne, E., Pontailler, J. Y., Delpierre, N., Aubinet, M., Caquet, B., de Grandcourt, A., Burban, B., Flechard, C., Granier, A., Gross, P., Heinesch, B., Longdoz, B., Moureaux, C., Ourcival, J. M., Rambal, S., Saint André, L., and Soudani, K. (2013). Evaluation of the potential of MODIS satellite data to predict vegetation phenology in different biomes: An investigation using ground-based NDVI measurements. *Remote Sensing of Environment* **132**, 145-158.

Huang, J., Tian, L., Liang, S., Ma, H., Becker-Reshef, I., Huang, Y., Su, W., Zhang, X., Zhu, D., and Wu, W. (2015). Improving winter wheat yield estimation by assimilation of the leaf area index from Landsat TM and MODIS data into the WOFOST model. *Agricultural and Forest Meteorology* **204**, 106-121.

Johnson, D. M. (2016). A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products. *International Journal of Applied Earth Observation and Geoinformation* **52**, 65-81.

Jong, R., Verbesselt, J., Schaepman, M. E., and Bruin, S. (2012). Trend changes in global greening and browning: contribution of short-term trends to longer-term change. *Global Change Biology* **18**, 642-655.

Knauer, K., Gessner, U., Fensholt, R., and Kuenzer, C. (2016a). An ESTARFM Fusion Framework for the Generation of Large-Scale Time Series in Cloud-Prone and Heterogeneous Landscapes. *Remote Sensing* **8**, 425.

Knauer, K., Gessner, U., Fensholt, R. K., 2016 #772}, and Kuenzer, C. (2016b). An ESTARFM Fusion Framework for the Generation of Large-Scale Time Series in Cloud-Prone and Heterogeneous Landscapes. *Remote Sensing* **8**, 21.

Liang, L., Schwartz, M. D., Wang, Z., Gao, F., Schaaf, C. B., Tan, B., Morisette, J. T., and Zhang, X. (2014). A Cross Comparison of Spatiotemporally Enhanced Springtime Phenological Measurements From Satellites and Ground in a Northern U.S. Mixed Forest. *IEEE Transactions on Geoscience and Remote Sensing* **52**, 7513-7526.

Liao, C., Wang, J., Dong, T., Shang, J., Liu, J., and Song, Y. (2019). Using spatio-temporal fusion of Landsat-8 and MODIS data to derive phenology, biomass and yield estimates for corn and soybean. *Science of The Total Environment* **650**, 1707-1721.

Liu, J., Pattey, E., and Jégo, G. (2012). Assessment of vegetation indices for regional crop green LAI estimation from Landsat images over multiple growing seasons. *Remote Sensing of Environment* **123**, 347-358.

Liu, M. X., Liu, X. N., Wu, L., Zou, X. Y., Jiang, T., and Zhao, B. Y. (2018). A Modified Spatiotemporal Fusion Algorithm Using Phenological Information for Predicting Reflectance of Paddy Rice in Southern China. *Remote Sensing* **10**, 18.

Liu, S., Zhao, W., Shen, H., and Zhang, L. (2016). Regional-scale winter wheat phenology monitoring using multisensor spatio-Temporal fusion in a South Central China growing area. *Journal of Applied Remote Sensing* **10**.

Lobell, D. B. (2013). The use of satellite data for crop yield gap analysis. *Field Crops Research* **143**, 56-64.

Lobell, D. B., Asner, G. P., Ortiz-Monasterio, J. I., and Benning, T. L. (2003). Remote sensing of regional crop production in the Yaqui Valley, Mexico: estimates and uncertainties. *Agriculture, Ecosystems & Environment* **94**, 205-220.

Lobell, D. B., and Burke, M. B. (2010). On the use of statistical models to predict crop yield responses to climate change. *Agricultural and Forest Meteorology* **150**, 1443-1452.

Lobell, D. B., and Gourdji, S. M. (2012). The influence of climate change on global crop productivity. *Plant Physiol* **160**, 1686-97.

Ma, J. H., Zhang, W. J., Marinoni, A., Gao, L. R., and Zhang, B. (2018). Performance assessment of ESTARFM with different similar-pixel identification schemes. *Journal of Applied Remote Sensing* **12**, 19.

Maas, S. J. (1993). PARAMETERIZED MODEL OF GRAMINEOUS CROP GROWTH .1. LEAF-AREA AND DRY MASS SIMULATION. *Agronomy Journal* **85**, 348-353.

Mann, M. L., and Warner, J. M. (2017). Ethiopian wheat yield and yield gap estimation: A spatially explicit small area integrated data approach. *Field Crops Research* **201**, 60-74.

Marshall, M., Okuto, E., Kang, Y., Opiyo, E., and Ahmed, M. (2016). Global assessment of Vegetation Index and Phenology Lab (VIP) and Global Inventory Modeling and Mapping Studies (GIMMS) version 3 products. *Biogeosciences* **13**, 625-639.

Marshall, M., and Thenkabail, P. (2015). Developing in situ Non-Destructive Estimates of Crop Biomass to Address Issues of Scale in Remote Sensing. *Remote Sensing* **7**, 808.

Marshall, M., Tu, K., and Brown, J. (2018). Optimizing a remote sensing production efficiency model for macro-scale GPP and yield estimation in agroecosystems. *Remote Sensing of Environment* **217**, 258-271.

McCoy, R. M. (2005). Field Method in Remote sensing *The Guilford Press*.
Meroni, M., Verstraete, M. M., Rembold, F., Urbano, F., and Kayitakire, F. (2014). A phenology-based method to derive biomass production anomalies for food security monitoring in the Horn of Africa. *International Journal of Remote Sensing* **35**, 2472-2492.
Meshesha, D. T., and Abeje, M. (2018). Developing crop yield forecasting models for four major Ethiopian agricultural commodities. *Remote Sensing Applications: Society and Environment* **11**, 83-93.
Monteith, J. L. (1972). SOLAR-RADIATION AND PRODUCTIVITY IN TROPICAL ECOSYSTEMS. *Journal of Applied Ecology* **9**, 747-766.
Moody, A., and Johnson, D. M. (2001). Land-surface phenologies from AVHRR using the discrete fourier transform. *Remote Sensing of Environment* **75**, 305-323.
Morel, J., Bégué, A., Todoroff, P., Martiné, J.-F., Lebourgeois, V., and Petit, M. (2014). Coupling a sugarcane crop model with the remotely sensed time series of fIPAR to optimise the yield estimation. *European Journal of Agronomy* **61**, 60-68.
Morris, M. D. (1991). Factorial Sampling Plans for Preliminary Computational Experiments. *Technometrics* **33**, 161-174.
Musau, J., Patil, S., Sheffield, J., and Marshall, M. (2016). Spatio-temporal vegetation dynamics and relationship with climate over East Africa. *Hydrology and Earth System Sciences Discussions*, 1-30.
Musau, J., Patil, S., Sheffield, J., and Marshall, M. (2018). Vegetation dynamics and responses to climate anomalies in East Africa. *Earth System Dynamics Discussions*, 1-27.
Niang, I., O.C. Ruppel, M.A. Abdrabo, A. Essel, C. Lennard, J. Padgham, and P. Urquhart (2014). Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.
Richardson, A. D., Keenan, T. F., Migliavacca, M., Ryu, Y., Sonnentag, O., and Toomey, M. (2013). Climate change, phenology, and phenological control of vegetation feedbacks to the climate system. *Agricultural and Forest Meteorology* **169**, 156-173.
Schmidt, M., Lucas, R., Bunting, P., Verbesselt, J., and Armston, J. (2015). Multi-resolution time series imagery for forest disturbance and regrowth monitoring in Queensland, Australia. *Remote Sensing of Environment* **158**, 156-168.
Schmidt, M., Udelhoven, T., Gill, T., and Roder, A. (2012). Long term data fusion for a dense time series analysis with MODIS and Landsat imagery in an Australian Savanna. *Journal of Applied Remote Sensing* **6**.
Sibley, A. M., Grassini, P., Thomas, N. E., Cassman, K. G., and Lobell*, D. B. (2014). Testing Remote Sensing Approaches for Assessing Yield Variability among Maize Fields. *Agronomy Journal* **106**.
Silvestro, P. C., Pignatti, S., Yang, H., Yang, G., Pascucci, S., Castaldi, F., and Casa, R. (2017). Sensitivity analysis of the Aquacrop and SAFYE crop models for the assessment of water limited winter wheat yield in regional scale applications. *PLOS ONE* **12**, e0187485.
Singh, D. (2012). Evaluation of long-term NDVI time series derived from Landsat data through blending with MODIS data. *Atmosfera* **25**, 43-63.
Song Shuai, L. F., LU Yonglong, Kifayatullah Khan, XUE Jianfang, Leng Peifang (2018). Spatio-Temporal Characteristics of the Extreme Climate Events and their Potential Effects on Crop Yield in Ethiopia.
Vanuytrecht, E., Raes, D., and Willems, P. (2014). Global sensitivity analysis of yield output from the water productivity model. *Environmental Modelling & Software* **51**, 323-332.
Verbesselt, J., Hyndman, R., Zeileis, A., and Culvenor, D. (2010). Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. *Remote Sensing of Environment* **114**, 2970-2980.

Vrieling, A., de Leeuw, J., and Said, M. (2013). Length of Growing Period over Africa: Variability and Trends from 30 Years of NDVI Time Series. *Remote Sensing* **5**, 982.

Wang, J., Li, X., Lu, L., and Fang, F. (2013). Parameter sensitivity analysis of crop growth models based on the extended Fourier Amplitude Sensitivity Test method. *Environmental Modelling & Software* **48**, 171-182.

White, M. A., de Beurs, K. M., Didan, K., Inouye, D. W., Richardson, A. D., Jensen, O. P., O'Keefe, J., Zhang, G., Nemani, R. R., van Leeuwen, W. J. D., Brown, J. F., de Wit, A., Schaepman, M., Lin, X., Dettinger, M., Bailey, A. S., Kimball, J., Schwartz, M. D., Baldocchi, D. D., Lee, J. T., and Lauenroth, W. K. (2009). Intercomparison, interpretation, and assessment of spring phenology in North America estimated from remote sensing for 1982-2006. *Global Change Biology* **15**, 2335-2359.

White, M. A., Thornton, P. E., and Running, S. W. (1997). A continental phenology model for monitoring vegetation responses to interannual climatic variability. *Global Biogeochemical Cycles* **11**, 217-234.

Workie, T. G., and Debella, H. J. (2018). Climate change and its effects on vegetation phenology across ecoregions of Ethiopia. *Global Ecology and Conservation* **13**, e00366.

Wu, D. H., Zhao, X., Liang, S. L., Zhou, T., Huang, K. C., Tang, B. J., and Zhao, W. Q. (2015). Time-lag effects of global vegetation responses to climate change. *Global Change Biology* **21**, 3520-3531.

Zambrano, F., Vrieling, A., Nelson, A., Meroni, M., and Tadesse, T. (2018). Prediction of drought-induced reduction of agricultural productivity in Chile from MODIS, rainfall estimates, and climate oscillation indices. *Remote Sensing of Environment* **219**, 15-30.

Zhang, X., Friedl, M. A., Schaaf, C. B., Strahler, A. H., Hodges, J. C. F., Gao, F., Reed, B. C., and Huete, A. (2003). Monitoring vegetation phenology using MODIS. *Remote Sensing of Environment* **84**, 471-475.

Zhang, Y., Li, L., Wang, H. B., Zhang, Y., Wang, N. J., and Chen, J. P. (2017). Land surface phenology of Northeast China during 2000-2015: temporal changes and relationships with climate changes. *Environmental Monitoring and Assessment* **189**, 13.

Zhu, X., Cai, F., Tian, J., and Williams, T. (2018). Spatiotemporal Fusion of Multisource Remote Sensing Data: Literature Survey, Taxonomy, Principles, Applications, and Future Directions. *Remote Sensing* **10**, 527.

Zhu, X., Chen, J., Gao, F., Chen, X., and Masek, J. G. (2010). An enhanced spatial and temporal adaptive reflectance fusion model for complex heterogeneous regions. *Remote Sensing of Environment* **114**, 2610-2623.