DETECTION AND QUANTIFICATION OF FALSE START OF THE MAIN GROWING SEASON AS EXPERIENCED BY FARMERS

Case-study relating NDVI, Rainfall and Interview Data for Arable Cropping Systems in Uganda

OCEN EMMANUEL

Enschede, The Netherlands, March 2019

SUPERVISORS:

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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Natural Resource Management

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DEDICATION

This piece of work is dedicated to my friends, brothers, sisters and colleagues staffs of CLUSA Uganda Chapter who lost their lives in a tragic accident 18th-Dec 2018. Oliver Okello, Robert Bills Okello, Gloria Muhairwe, Linda Acheng, OB Dona Ssekitoloko, Gloria Oweta, Benard Kyambbade, Nelson Agatu, Sandra Akullo, Justus, Silvia Aceng and the other seven. Your passion and commitment towards climate smart agriculture and youth empowerment will forever remain alive

ABSTRACT

Growing seasonal false start is a component of the onset variability that has recently been reported by farmers in Uganda; it is a phenomenon that results from rainfall retreat following planting of the crops by the farmers leading to failure and/or poor germination. We adopted an integrated approach moving from indigenous knowledge to scientific data-driven conclusions to detect and quantify these phenomena over a period of 19 years (1999 to 2017). Farmer's perception and recall of the onset variability were obtained using interviews, with data collected in the districts of Pallisa, Kumi, Soroti, Dokolo and Kole and analyzed using simple descriptive statistics, this allowed indigenous knowledge to be incorporated in the analysis. The quantitative data used are; the 19 years Proba V NDVI data of 1km*1km resolution, from which long term dekadal means of standard deviation, 10^{th}, 50^{th} & 90^{th} percentile, was used to identify and map areas at risk of dry spell at the onset of the season. CHIRPs daily & dekadal data obtained at 0.05^{0} *0.05^{0} resolution facilitated the comparison with the information provided by the farmers and NDVI leading to a definition of a false start as the dekad that had atleast two rainy days and the subsequent two-dekad having no rainy days. Following the comparative analysis, we concluded that NDVI is not an effective indicator for assessing the occurrence of a false start. Subsequently, we applied the derived definition on CHIRPs dataset to detect, map and quantify the false start of the season that occurred in the 19 years within Uganda. The first result was the NDVI 25 classes that were created from the statistic parameters and, generating their respective temporal profile information resulted in the identification of areas at risk. We found out that 70.6% of the cropland areas within Uganda was at risk of dry spell at the onset of 1^{st} planting season, of which 8.8% throughout the year, meanwhile 3.7% at risk in the 2^{nd} planting seasonal onset, with 23.2% showing no indication of risk during the start as well through the growing period. Secondly, field interview results obtained from the farmers proved that in the 19 years the onset of the season had been varying between early, late and normal, which are sometimes characterized by a false start. In this aspect, when we considered three years (2015-2017) of vivid farmer recall, 43% confirmed the occurrence of a false start of the season, reporting it to have suffered from the failure of their seed to germinate and others reporting poor emergence. Finally, we detected, quantified and mapped spatial coverage of Fsos phenomena for the 19 years at a pixel level, we found out that the years 2016, 2003 & 2002 were the most affected years, registering 46%, 37% &32% of pixel affected by Fsos respectively. The analysis indicates that the highest chance of Fsos occurring is 53% and mainly in the North Eastern region, while other parts in South Western had no indication of Fsos in the years considered for the analysis. Comparing the spatial coverage of Fsos with cropland areas, we noted that cropland areas categorized as 20-70% cropland are more at risk compared to >70% cropland areas, this was reflected in timing of Fsos where areas with 20-70% cropland, the Fsos dates tend to coincide with normal start of the season. Hence farmers are easily duped into planting. These results point to the potential of integration of remote sensing products and farmers indigenous knowledge in monitoring Fsos and variability in the onset of the growing season. Therefore, future studies need to be motivated by the prospect of assessing the duration of a dry spell after Fsos and planting, coupled with increasing the sample size of farmers interviewed per pixel to allow for evaluation of the severity of the impact on the farmers and overall their livelihood.

Keywords; False start, Onset variability, start of the season, farmers recall, NDVI, CHIRPS

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My Inspiration: Mrs. Joy G. Adiele

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ACRONYMS AND ABBREVIATION

CHIRPS	Climate Hazard Group InfraRed Precipitation with Station data
Dekad	10-day period
ENSO	Pacific El Nino Southern Oscillation
EoS	End of the growing season
FAO	Food and Agriculture Organization
Fsos	False start of the main growing season
IOD	Indian Ocean Dipole
IPCC	Intergovernmental Panel for Climate Change
MAM	March April May growing season
NDVI	Normalized Difference Vegetation Index
RD	Rainy Day
SD	Standard deviation
SON	September October November growing season
SoS	Start of the growing season
SST	Sea surface temperature

1. INTRODUCTION

1.1. Background and motivation

Rainfall is one of the most important natural resource supporting rainfed agricultural production systems; its onset is a major indicator to the start of the growing season by many farmers. Farmers in Africa have over time developed knowledge using phenology of existing permanent vegetation within their communities such as trees, rangeland vegetation (Example *"Opok," Terminalia mollis and Termarich tree leave regrowth)* and changes in the movement of wind as a signal to seasonal onset. This has made them align their farming practices to follow particular events at the time of year where they expect the season to commence. To them, the onset of the rainfall is not only critical to informing their decision on when to commence land preparation and planting, but also it is a crucial determinant to successful crop production (Laux, Jäckel, Tingem, & Kunstmann, 2009). Benoit, (1977) acknowledge that it after sowing of seeds and during flowering, that the ability of the soil to store water is significantly critical and essential. Thus any shortage of water will affect germination and eventually yield. Therefore, before planting, farmers need to be sure that the rainy season has started, and it will be consistent to support the planted crops to germinate and grow to maturity. This would enable farmers to reduce or avoid the risk associated with the false start of rainy season and thereby avoiding crop failure (Drake N. Mubiru, Komutunga, Agona, Apok, & Ngara, 2012; Laux et al., 2009).

The uncertainty in rainfall & seasonality has triggered research relating to climate change, example; development of drought tolerant varieties, agrometeorology studies for early warning system & adaptation and the establishment of institutions such as Famine Early Warning Systems Network (FEWS-Net). In this regard, any effort towards achieving UN sustainable development goal No.2 of Zero hunger will require sustainable farm production & productivity that meets the demand of the growing population. However, this comes amidst the existing climatic extremes, interannual and intra-annual weather variability in the forms of floods, drought, delayed onset, early onset and short-term breaks ("false start") that severely affects agriculture.

Recent reports by Intergovernmental Panel for Climate Change (IPCC) 2007, points out that due to climate change, the frequency, intensity, and severity of extreme climate events are likely to increase, with spatial, temporal variation globally. There are changing rainfall patterns, shown in the variability and unpredictable onset dates of the rainy season. These changes have had an a dire impact on agroecosystems and other natural system's production and productivity (Winkler, Gessner, & Hochschild, 2017)and more explicitly inflicting heavy economic losses to smallholder farmers. Thus, resulting in food insecurity and poor social livelihood. For example, in sub-Saharan Africa, rainfall amount is expected to reduce with increasing variability within the years and because most of the agriculture is heavily dependent on rainfall, reports projects 50% reduction in yield by the year 2020. This implies that African agricultural sectors and its resources are at severe risks, requiring preparation and strategic planning to counter such threats. The research will play a crucial role in providing evidence-based information to support this.

In East Africa, Uganda in particular, where agriculture is the backbone of the economy and serves as a means of livelihood for over four million households (Epule, Ford, Lwasa, & Lepage, 2017), agricultural production & productivity is heavily dependent on rainfall, making farmers extremely vulnerable to the changing climate conditions (Agutu et al., 2017). Incidentally, recent climatic conditions in Uganda are characterized by extreme weather phenomena, particularly those related to precipitation. These phenomena are manifested via the increasing frequency and duration of droughts, storms, and floods, which directly affects agricultural productivity (Kaggwa, Hogan, & Hall, 2009) in reduced yields and hence less food to meet the needs of the ever growing population. Furthermore, rainfall seasons have been characterized by sporadic rainfall events, a situation with short term breaks, inconsistent and light rains during the crop growing season (Diem, Hartter, Salerno, McIntyre, & Stuart Grandy, 2017), all directly having an impact of agricultural production.

In Uganda, these uncertainties are reported by farmers to occur at the onset of the growing seasons, leaving farmers in doubt on whether to plant or delay planting activities, which may lead to wasting resources such as labour, seed and finances invested (Cooper & Wheeler, 2017; Mubiru et al., 2015; Wetterhall, Winsemius, Dutra, Werner, & Pappenberger, 2015), thereby threatening food security. The Eastern part of the country is one of the regions that have had variabilities in rainfall event, experiencing recurrent droughts, floods and mudslides in the last dekad directly affecting peoples livelihood and nature vegetation in the area, while in other parts of the country, the same phenomena has resulted in loss of crops in the field, famine (Nsubuga et al., 2014). Notably early onset of the season may result in long growing season and late onset of rainy season short growing season; however, this may not be the case when short dry spells follow the rainy season onset "false start", therefore farmers who plant early would be affected when their crop fails to germinate due to dry spell following planting. While delaying planting would reduce the length of growing season, thus have a direct effect on the yield of the crop.

The phenomena relating to dry spell affecting normal crop growth is considered as agricultural drought and results from the inadequate soil moisture available to support either crop emergence or healthy growth, this often leads into the failure of emergency or wilting of the crop, eventually causing crop failure and thus food insecurity. It may happen before, extending into the growing season or during the growing season. Hence it is vital to understand the onset of the rainy season since it informs decisions and planning of farming activities covering the growing season.

Growing seasonal onset variability are categorized as early, late or false start. Early onset referred here is when rainfall sets in earlier than usual and will remain consistent to sustain crop production, late onset is when there is delayed rainfall often resulting in shortening of the growing. Critical is the false start of the season; it is related to the false onset of the rainy season occurring at the beginning of crop growing seasons. The question here is, "what's the difference between true start and a false start." Different criteria have been proposed to define the actual onset of the season, with many relying on threshold values relating to recorded data by gauge stations.

Example, Benoit (1977), while referring to the growing season and not rainy season, used a criterion of rainfall of atleast 0.5 ETp over any period with no five days of dry spell immediately following as the SoS and if it coincides with five of days dry spell, he refers to it as a false start. In his definition he accounts for evapotranspiration, which relates to the amount of the cumulative rainfall stored by the soil, thus Total Water Available (TAW) for the plant. Nassib 1987, as cited in Camberlin and Okoola (2003) defined the onset of rainy season in Tanzania as the first week during which more than 15mm of rainfall is received based on defined local climatology and agricultural demands without the occurrence of 2 weeks dry spell in the subsequent four weeks. While Stern et al. (1982) utilize criteria of atleast 20mm of rainfall received in 2days and if it is followed by 10 days dry spell in the next days, this he regards as a false start. On the other hand, SivaKumar (1988), defines onset to be the day during which a cumulative total of 20mm is received in 3 consecutive days, and no dry spell is received in 7 successive days in the 30 days, if such dry spell is experienced, such onset would be a false start. Finally, Dunning et al. (2016), defined false start as the occurrence of an extended dry period shortly after heavy rains have been received in the wet season. Most importantly for all the definitions, a false start is related to dry spell immediately following the onset of the rainy season, the threshold proposed are of agronomic relevance that trigger farming activities. None the less, these definitions perform differently in many locations and thus cannot be applied universally.

Growing season false start as part of onset variability is attributed to the existence of seasonal variability relating to weather patterns and have been linked to several teleconnections. As a result of these onset variabilities and uncertainty, farmers do not know what to expect, "when is the start of the growing season?" keeps lingering in the minds of farmers, they are in dire needs of information regarding the start of season (Orlove, Roncoli, Kabugo, & Majugu, 2010). For this reason, it is essential to understand SoS and drivers influencing variation in the onset of the growing season (Dunning et al., 2016). Hence, timely accurate detection of the actual beginning of the growing season is crucial for farmer decision making in a rainfed agricultural system where production is dependent on start & duration of rains (Indeje, Semazzi, & Ogallo, 2000; Sobowale, Sajo, & Ayodele, 2016). These information helps farmers to decide on what type & when to plant a specific type of crop. The challenge, however, has been to assess the occurrence of these variabilities and identify which climate forcing's/parameters can effectively be used to explain the phenomena to aid the planning of rainfed agriculture.

In Uganda, growing season are usually between March to June (MAM) as the first season and 2nd season start in July to November (SON). Recent studies relating to rainfall variability during the growing season have shown that the total amount of rainfall and the number of wet days in the MAM are decreasing (Nsubuga et al., 2014). Additional efforts have been made to investigate onset of growing season, applying different techniques based on the rainfall considered drivers, example Reason, Hachigonta, & Phaladi (2005) used El Nino 3.4 in Limpopo South Africa to explain the false onset of growing season, and suggested that predictability of rainfall variability may be possible at seasonal scale. While (Bello, 1997) used potential evapotranspiration and Inter Tropical Discontinuity (ITD) to explain the onset of seasons. This however, requires continuous studies to provide in-depth understanding.

Monitoring of the of rainfall, its onset, and consistency requires adequate, consistent in-situ meteorological data, for which this is not the case for Uganda, the country has minimal meteorological stations and data is not consistently recorded. This is partly due to the heavy initial financial investment required for installations of effective and efficient automated gauge stations and long-term maintenance. Remote sensing technique in the absence and uncertainty of meteorological in situ data offers an opportunity for this phenomenon to be monitored and predicted. We can use vegetation indices like NDVI to monitor crop conditions, identify areas under drought risk (Tonini, Lasinio, & Hochmair, 2012) and also apply it in ecosystem studies (Huete, Miura, Yoshioka, Ratana, & Broich, 2014), from which varied information relating to crop phenology can be derived, for example start of the season (SoS), length of growing season (LGS), end of growing season (EoS), characteristics of growing season (Unimodal, bimodal season).

NDVI application in agronomic drought monitoring is essential because it is a valid indicator for biophysical characteristics of vegetation and also requires no calibration in applying to a particular location (Gebre, Berhan, & Lelago, 2017), making it one of the most important indices for studying vegetation health and anomalies. According to Zambrano, Lillo-Saavedra, Verbist, & Lagos (2016), NDVI is significant for monitoring drought during crop growing season, aiding planning of agronomic management practices and has become an integral part of precision agriculture, famine early warning systems. NDVI integrated with rainfall estimate offers the opportunity to achieve robust investigation relating to crop performance in the field.

Satellite-derived rainfall products and derived indices such as standard precipitation index (SPI), Standard Precipitation and Evapotranspiration Index (SPEI), are applied in the studying meteorological droughts. Rainfall anomalies and cumulative seasonal, monthly, daily values relating to specific growing season, specific period have been used to study rainfall variability. In Uganda for example studies conducted by (Nakalembe, 2018; Mulinde, Majaliwa, Twesigomwe, & Egeru, 2016; Drake N. Mubiru et al., 2012) all focused on variability affecting growing season. This weather variability has links to long distance climatic anomalies changes referred to as teleconnections.

For example, in East Africa and Uganda, the linkage between NDVI and El Nino La Nina events have currently been considered, many studies have been conducted to establish the connection of ENSO event to the seasonal variability and the teleconnections, with attention to rainfall variability over regional East Africa. Dunning et al. (2016) using SST indices, found out that ENSO and the Atlantic Sea Surface Temperature (SST) contributes to rainfall variability. They noted that the variation within a particular dekad had an influence on the strength of the teleconnection for both Atlantic and East SST, while for East Africa, they suggested that the abnormally short rains are attributable to weaken the power of the ENSO of equatorial Walker cell occurring over the Indian Ocean during the season. Using simulation models, Zaroug, Giorgi, Coppola, Abdo, & Eltahir (2014), establish a negative correlation between Pacific SST and rainfall anomalies and it relation to drought event between April to June, therefore suggesting the use of ENSO as a predictor of drought for East Africa.

Furthermore, in the study of NDVI anomaly patterns for Africa, Anyamba, Tucker, & Eastman (2001), evaluated the teleconnection between El Nino Southern Oscillation and NDVI anomaly analysis technique, using both correlation and cross-correlation. They were able to show that the 1997/98 ENSO warm event showed that there was a continuous above normal NDVI anomalies; Phillips & McIntyre (2000) using correlation for the month July to September found a significant negative relationship between SST Nino3.4 and rainfall variability for Uganda. However, the analysis relied on station data which is not spatially explicit; therefore the derived information falls short to account for the existence of local variability influenced by different climatic forcing, examples vegetation, physical features, the contribution of land surface & water surface temperature.

In conclusion, Inspite of the existing remote sensing technology and historical data, there is limited knowledge on the variability in onset MAM growing season for Uganda and more especially in relation to the occurrence of a false start with linkage to nature and the ability of existing atmospheric climatic forcing in explaining variability on the onset of the season. Studies carried in East Africa and Uganda have linked and suggested that ENSO event can be used as a predictor of drought and beginning of the season, they have been at continental or regional levels and mainly relied on a single parameter to explain the interannual variability. Most used either SST or SOI of the Pacific region Nino3.4 and not accounting for other factors modulating the variabilities. Therefore, they provide a more generalized conclusion falling shot to explain sub-regional variability drivers. Moreover, by using gauge data, the studies fail to account for the spatially heterogeneous nature of weather variability, vegetation cover and response of farmers to such risk event, leave alone their ability to predict the onset and avoid false start correctly. This would allow for consideration of all prevailing climatic variation.

In this study, its acknowledged that the processes modulating weather patterns in Uganda are complex and run from global, regional and local scale associated with orographic effects of physical features, influence of large inland water bodies; example for Uganda, Lake Victoria, Albert and Kyoga that influence Land-Lake breeze movements (Indeje et al., 2000), local circulations, solar radiation, temperature patterns, precipitation and rainfall drivers/systems all playing role in addition to the El Nino (ENSO), La Nina, monsoon winds, Indian Ocean Dipole (IOD), Madden Julian Oscillation (MJO) and Sea Surface Temperature (SST) (Anyamba, Tucker, & Mahoney, 2002; Nicholson, 2017).

Therefore, in detecting growing seasonal false start for Uganda, NDVI time series, CHIRPS as a proxy rainfall data and farmer indigenous recall data is used to map out areas at risk of experiencing dry spell during the onset of the season, a basis to link the phenomena to crop production and productivity. Thus, the significance of this study is;

- The mapping of areas within Uganda that experiences dry spell at the onset of the growing season
- The detection of variability in the start of growing seasonal relating to crop production in Uganda, through NDVI derived climatology, rainfall, and perspective of the farmers
- Documenting farmers point of view concerning onset variability and occurrence false start of the growing season.
- Explain the relationship on farmers perspective to information derived from remotely sensed data
- To propose a definition of the false start of the growing season considering both farmers knowledge and remote sensing acquired information.
- Detection and mapping of Fsos phenomena spatial coverage over Uganda to reveal variation in threats it pauses to different areas.

1.2. Conceptual diagram and theory underlining the study

In this study, the earth as a system is a perfect model of itself; the atmosphere has no boundary. Thus distant phenomena, such as ENSO, Oceanic circulation, and pressure differences will have an influence on weather pattern at far places as it is for those within its vicinity of Uganda. The conceptual diagram **(Figure 1.),** provides an overview of the interaction between different systems and influences they have over crop growing seasons in Uganda. Rainfall drivers influence the movement of clouds which eventually fall as precipitation. Crops, however, do not necessarily depend on the amount of rainwater received, but rather ability of the soil to hold water to meet plant's needs, rates of evapotranspiration (ET), yet farmer's management practices such as tillage influences soil aeration properties, net ET, thereby eventually determining growth of the crop. Uganda has three major lakes; therefore, land surface and lake surface temperature are assumed to contribute to experience whether variabilities. This has been shown in the study by (Sun, Xie, Semazzi, & Liu, 2015); where rainfall intensity/decrease has a positive relationship with lake surface temperature. Accordingly, from the **Figure 1**, farmers will assess the rainfall received and decide if its adequate to allow planting of seeds, however if its followed by a dry spell and seeds fail to germinate or do indeed germinate but wilts out due to dry spell, such onset dekad would be defined as a false start date. Farmers ability to correctly or incorrectly detect false start determines whether he/she will be affected by this weather variability.

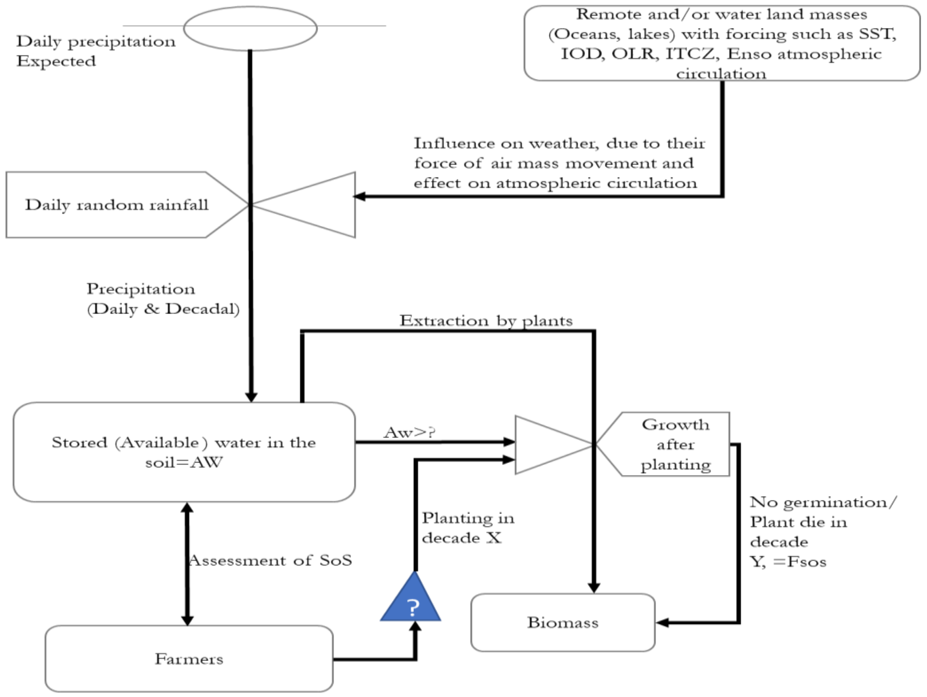

Figure 1: System diagram showing the interaction of different drivers and component relating to growing seasonal false start in Uganda

1.3. The aim and objective of the study

The study aims to define, quantify and map the occurrence and probability of a false start of the main growing season using NDVI time series, rainfall estimates, and farmer recall data, covering the years 1999-2017.

Specifically, this study seeks:

1. To map out areas within Uganda that have been at risk of a dry spell during the onset of the growing season from the year 1999-2017 using NDVI time series data. *The assumption here is that NDVI can explicitly be used to identify variability in the start of the growing season, revealing it spatial-temporal characteristics and that variability is solely due to changes in climatic conditions, not in any way related to the decision of the farmers to plant late considering that farmers are reluctant to take the risk.*

2. To prepare a Sampling scheme for conducting a field survey, identifying cropland areas at risk.

3. To describe farmers perceptions on the variability of the onset of the main growing season, as experienced between 1999-2017. *To explore this aspect of the study, we assume the farmers can recall weather variability especially those that directly affect their farming activities.*

4. To derived a clear definition with criteria to identify the occurrence of a false start of the main season using NDVI, CHIRPS and farmer recall data. The assumption is that farmers correctly recall SoS and Fsos, both NDVI and CHIRPS dataset can be used to identify Fsos

5. To detect and map aspects of the occurrence of Fsos during the period 1999-2017 in relation to probability, timing and weather aspects.

Research questions

1. Which areas within Uganda have been at risk of a dry spell at the onset of the growing season during the period 1999-2017 based on NDVI analysis?

2. Can we map cropland areas in Uganda at risk of a dry spell at the onset of the growing season using NDVI data in order to develop an appropriate sample scheme?

3. How did farmers experience variability at the onset of the season and what variability where experienced between 1999-2017 as recalled by farmers?

4. Is it possible to integrate NDVI, CHIRPs and farmer recall data to derive the definition and criteria for identifying the false start of the main growing season?

5. What is the probability of the occurrence of a false start in the main growing season in the last 19 years, what is its spatial extent and when did it occur?

Hypothesis

1. H1: Farmer's identification of false start are influenced by crop type, the start of the season and planting date.
2. H1: Farmers in Uganda correctly reported the occurrence of a false start of the main growing season

2. STUDY AREA AND DATA

2.1. Study area

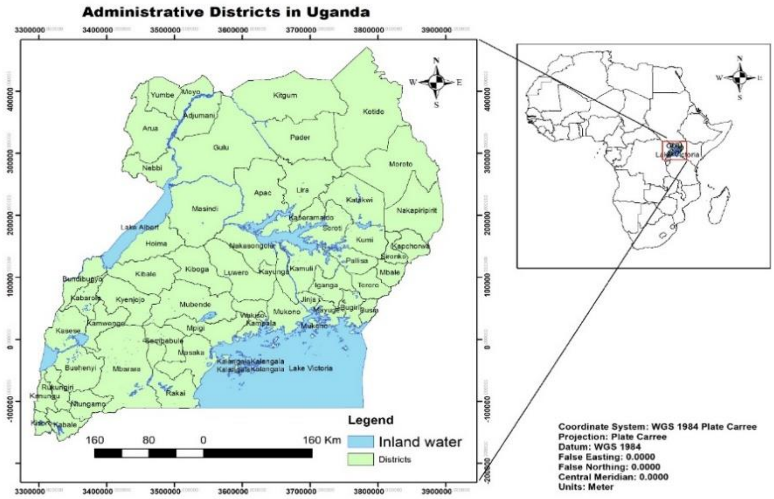

Figure 2: Administrative districts of Uganda

The study domain is Uganda, a landlocked country located in the Eastern region of Africa, crossed by the equator lying between the latitude of 4°N and 2 °S and longitudes 29 °W and 35°E (**Figure 2**). Its bordered by Kenya to the East, Tanzania to the south, Sudan & South Sudan to the North and Democratic Republic of Congo to the West. Uganda has an estimated land mass of 241,155Km² and is rich in numerous natural resources such as forest, wetlands, freshwater lakes, mountains (Mt. Elgon, Rwenzori, Virunga and Tororo rocks) and the Albertine rift valley along its western borders. The country is at an altitude of about 1100 meters above sea level sloping downwards to towards the northern part of the Sudanese plain.

The climate of Uganda is naturally tropical, influenced by different earth's systems, such as the Inter-Tropical Convergence Zone (ITCZ), the subtropical anticyclones, the moist Westerly winds originating from Congo basin and the monsoon winds (Nsubuga 2011). These forces couples with the contribution of the local geographical features such as large water bodies (Lakes), Swamps, rivers, mountains interacting with the earth solar systems and interception of convective air determines the existing weather patterns (Ogalla, 1989 as cited in Phillips & McIntyre, 2000). Rainfall is triggered by the movement of air masses related to intercontinental convergence of the monsoon. Uganda being crossed by the equator have the sun over it, on the 21st of March, in the tropic of cancer on the 21st June and again at the equator on 21st September then retreating to the tropic of Capricorn on 21st Decembers. It is these overhead passes of the sun with a deviation of 4-6 weeks that is linked to the onset variability of rainfall and distinction of seasonality type for different parts of the country (Asadullah, Mcintyre, & Kigobe, 2010).

Because of this, the country has different climatic regimes shown in local variability in temperature & rainfall occurring across the country (Majaliwa J.G.M, Tenywa M. M., Bamanya D., Isabirye P., Nandozi C., Nampijja J., Musinguzi P, Luswata K C, Rao KPC, Bonabana J.; Bagamba, F.; Sebuliba, & Azanga, 2015). Most regions of the country receive rainfall in two distinct seasons, between March to May (MAM) and September to November (SON), with Karamoja region "a semi-arid and North Eastern region being characterized mostly by the single rainy season." Although towards the northern part the time lag between the first and 2nd rainy seasons is short and so often appears to have unimodal rainfall. The above notwithstanding, there is evident notable variation in the timing, frequency, and distribution of the rainfall amount received in Uganda from one region to another and the same is for temperature. The average rainfall amount received is between 850-1700mm, while the average temperature in 16-30°C. For this reason, Uganda is divided into sixteen climatic zones and 09 Agro-Ecological Zones (AEZ) based on different agricultural farming systems dictated by different soil types, climate, landforms and socio-economic factors. Different zones experience variation in seasonality and thus different growing season (Majaliwa J.G.M, Tenywa M. M., Bamanya D. et al., 2015)

Agriculture is the primary sector of the country's economy, contributing up to 23% of the GDP and accounted for 48.5% of the total export in 2012. The production system is mostly subsistence, heavily relying on the timing, duration and amount of rainfall received. A more significant population of farmers are involved in the cultivation of major food crops such maize, millet, cassava, banana, beans, sweet potatoes, groundnuts, and sorghum, and most important cash crop are coffee, cotton, sunflower, sugar cane, and tea. Planting dates for annual crops vary with the onset of the rains. Depending on soil moisture, maize may be planted from mid-August to mid-September in the first season and mid-February to mid-March in the second season. Beans are often planted well into April and October. Given the dependence of planting time and crop choice on rainfall distribution, there could be potential for utilizing forecasts of season arrival date and duration in crop management These crops are the source of livelihood for farmers and generally feeds other sectors of the economy.

2.2. Data

In this study, Spot/Proba V NDVI time series data, CHIRPS rainfall estimate, together with both seasonal and agronomic information obtained directly from the farmers during fieldwork have been used to support the analysis and discussion of the findings of the study. Details description of the datasets is provided below.

2.2.1. NDVI time series data for the period 1999 to 2017

SPOT/PROBA V NDVI time series data covering 19 years was obtained from ITC Copernicus catalogue using GDAL command prompt. The data is provided by Copernicus, available at a near real-time, making it one of the most reliable data sources for remotely sensed vegetation indicators. These data are accessible both online and on EUMET cast at no cost (https://land.copernicus.eu/global/products/ndvi) and are derived from the Red (0.61-0.68um) and Near infra-red (NR; 0.78-0.89um) reflectance (equation 1), provided at a spatial resolution of 1km & 300m in Digital Numbers (DN) from 0-255. The images are obtained every day, making it an essential aspect in supporting monitoring of phenomenal dynamic changes such as drought.

$$\text{NDVI} = \frac{(NIR-RED)}{(NIR+RED)} \qquad \text{Equation (1)}$$

In equation 1, NIR is the reflectance in the near infra-red band and RED is for the red band. However, the product, used in this study is available in digital number based on the information in Table 1 and 2 i.e., equation 2 defines the physical range and scale factors of the product

$$\text{PhyVal=DN*scale\_Factor+add\_offset} \qquad \text{Equation (2)}$$

The values provided in table 1 and 2, documented by Vito (https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/GIOGL1_ATBD_NDVI1km-V2.2_I2.21.pdf)

Table 1: Information used to derive DN values

Variable	Physical Minimum	Physical Maximum	Max DN value	Scale factor	Add offset
NDVI	-0.08	0.92	250	0.004	-0.08

Table 2: Information on values flag off the data during preliminary processing

Flag value	Flag Name	Description
251	Missing	Error in RED/NIR
252	Cloud	Cloud/Shadow
253	Snow	Snow/ice
254	Sea	Water (Land Mask=0)
255	Background	SM=0

AVHRR is another sensor from which most extended NDVI time series is available for studying drought and phenology. However, at a continental scale, NDVI time series product from SPOT-4 10 day composite at 1km spatial resolution performs better with higher dynamic range compared to AVHRR GIMMS NDVI & Pathfinder (Fensholt, Nielsen, & Stisen, 2006). Thus, SPOT4 NDVI is considered an improvement of AVHRR NDVI.

For this study, a 10-day temporal resolution data of maximum value composite NDVI are obtained at a spatial resolution of 1km^2 and 19 years (1999-2017) temporal window. The product is version 2.2, created from top of canopy reflectance by the Flemish Technical and Research Institute (VITO) (Eklundh & Jönsson, 2015) and have been corrected for system errors and atmospheric conditions; thus it's reliable. Each month in years; 1998 Nov/December 1999-2017 and 2018 Jan/Feb have three images, this is the maximum value composite for every ten days in that month, therefore for each MVC, the model takes the maximum value of NDVI recorded of the 10 days; thus each year has 36 images. By taking the maximum value in compositing the daily images, the effects of clouds are minimized, and other atmospheric effects are reduced and thus referred to as "declouded image" (Chen et al., 2004; C. A. J. M. de Bie et al., 2011).

In this case, only pixels with good quality have been considered to produce the images without overlapping into another temporal window. This would, however, be a challenge, if we were to use remote sensing product from platforms such as Landsat with 16days revisit time. Compositing even two images would result into overlapping into the preceding month, leading to loss of vital information in between the days of the month or complete lack of information where images used in the composite both have clouds covering the same spatial extent. Although these corrections have been made, not all the temporal images of maximum value composite will be cloud-free. The presence of clouds in the image results into a sudden and high reduction in the NDVI, thus requires further cleaning. Finally, we acknowledge that 10 days NDVI composite of 8km spatial resolution collected by Advanced Very High-Resolution Radiometer (AVHRR) available at https://earlywarning.usgs.gov/fews/africa/index.php with a more extended period, the 1km Spot/Proba V is better in terms of spatial resolution.

NDVI as an indicator has been chosen in this study because it gives indicative information on the health status and condition of the vegetation which is vital for the identification of the start of the season, its variability or the false start in this case. NDVI is a function of spectral variation between the reflected Near Infrared (NIR) and Visible (VIS) radiation. The changes are usually higher for vegetation than for soil, and hence the higher the vegetation index, the denser the cover and health of vegetation. It's on this basis that many studies have used NDVI. Therefore, the adoption of NDVI for this study is partly due to its effectiveness as an indicator for biophysical characteristics of vegetation and also that it requires no calibration in applying to a particular location (Gebre et al., 2017). They further point out that it has been used widely used in studies relating to droughts and its strength lies in its ability to provides information on both spatial and temporal effects of drought.

Furthermore, carrying out NDVI stratification makes it possible to identify vegetation stress areas, and for which period (s), this enables investigation of spatial, temporal variability. For example (Rembold et al., 2017), demonstrated the application of NDVI in providing early warnings relating to food security using NDVI anomaly maps in which they focused on agricultural drought. **Table 3** provides a summary of the NDVI dataset used for purposes of this study

Table 3: Summary of metadata for Spot/Proba V NDVI dataset

Dataset	RS products	RS indicator
Source	Copernicus	NDVI
Sensor from which product was developed	Spot/PROBA V	NDVI
Temporal coverage	18 Years	Temporal profile
Spatial coverage	Global	
Temporal resolution	Every day	
Spatial resolution	1km	
Data format	.nc	

2.2.2. CHIRPS Data (Rainfall Estimate product)

Rainfall data obtained from gauge station provide reliable and accurate localized data, in Uganda; however there is lack of long term, and inadequate gauge stations which are unevenly distributed and because achieving a highly dense network of gauge station require substantial initial capital investment and maintenance, this has hindered its acquisition in Ugandan case. Therefore, satellite RFE is used since it provides spatial-temporal information including those from inaccessible places and is freely available spanning up to 35 years, thereby facilitating food security early warning studies, drought & flood monitoring and modeling. Thus, accounting for weather variability localized level.

In this study, Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) based on a 30+ year quasi-global rainfall dataset, developed by United States Geological Survey (USGS) teaming up with Climate Hazard Group, Department of Geography University of California at Santa Barbara is chosen for this study. The dataset is generated from a combination of in situ station observation data and interpolated precipitation estimates from satellites that are derived from Cold Clouds Duration (CCD) to represent areas/regions with few distributions of gauge station. Its available from 1981 to near real-time at $0.05^0*0.05^0$ spatial resolution of daily, pentad and monthly temporal resolution, with a spatial coverage from 50^0S to 50^0N in different formats (NetCDF, TIFF, BIL, PNG) (Chris Funk et al., 2015).

CHIRPS products were developed with the ultimate aim to support assessment and monitoring drought affecting the agricultural sector (Agronomic drought), hence supporting delivery of valid information relevant for food security early warning information systems. Funk et al. (2015) used CHIRPS product to quantify hydrologic impact of decreasing precipitation and rising air temperature in the greater horn of Africa, concluding that, it has potential application in hydrologic forecasting and trend analysis in southern Ethiopia. In East Africa, where Uganda is part, validation of CHIRPS rainfall estimates with in situ gauge, demonstrate high level performance in estimating gauge station data, showing a correlation r=0.73 and bias of 0.99 (Muthoni et al., 2018), because of this, it has been applied in drought monitoring and hydrology related studies in the region (eg Shukla, Funk, & Hoell, 2014; Shukla et al., 2014; Agutu et al., 2017b). CHIRPS dekadal and monthly data compared with other satellite-derived products (TAMSAT3,6 IMERG, CMORPH, ARC2) upon considerable analysis was found to perform better with pixel by pixel correlation of 0.73/8-0.87 and 0.95-1.13 bias, while point to pixel correlation of 0.65-0.77 & 94%-110% bias (Dinku et al., 2018). The selection of CHIRPS product for this study is informed by these findings and its application in the East African region

Furthermore, to date, the product has been used by Famine Early Warning Systems Network (FEWS Net), in providing seasonal forecast information for East Africa and Africa in general. For these reasons, both daily and dekadal CHIRPS version 2.0 product for Africa in TIFF format, was obtained from the Climate Hazard group data FTP portal (ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/) and clip to Uganda extent for the purposes of this study.

Technical description of CHIRPS

Funk et al. (2014; 2015), provides a comprehensive technical description for the CHIRPS product. Never the less effort is made to give a brief description of how the product is produced. To create and ensure the product is available for users, CHIRPS algorithm uses a combination of data sources. First, the monthly precipitation climatology referred to as CHPClim; a global precipitation climatology is used. It is obtained $0.05^0*0.05^0$ spatial resolution and has been temporally disaggregated for each month for particular grid cells in relation to specific gauge station data, elevation, latitude, and longitude into 72 pentadal (6 pentads per month) of long term average accumulation values in millimeter (C. C. Funk et al., 2014). The 72 pentadal values are the expected annual sequence of rainfall for that specific location.

CHPClim is based on a regression approach, applying a moving window regression and inverse distance weighting interpolation. Using a collection of 27453 monthly station averages acquired from the Agromet group of the Food and Agricultural Organization (FAO) and 20591 stations data of the Global Historical

Climate Network (GHCN) version2. A regression model is performed on the FAO dataset to generate gridded moving weighted regression estimates (MWR) and residuals. The outputs are then corrected using the GHCN stations average, and finally, it is interpolated following modified IDW interpolation procedure resulting into five days temporal resolution rainfall accumulation data (C Funk et al., 2015).

The second input is the Thermal Infra Radiation (TIR) satellite-based precipitation estimate obtained from a combination of two NOAA sources; Climate Prediction Centre (CPC), whose data is acquired at 0.5hrs temporal resolution, 4km spatial resolution covering the period year 2000-present) and the National Climatic Data Centre (NCDC). It is obtained at a temporal resolution of 3hrs, at 8 km spatial resolution from the year 1981 -2008. The third input is the Tropical Rainfall Measuring Mission (TRMM) 3B42 product developed by NASA (Huffman & Bolvin, 2017). Finally, the atmospheric model rainfall field generated by NOAA Climate Forecast System, version2 (CFSv2) and data from gauge station acquired from various sources, both at regional and national meteorological service centres are in cooperated. This eventually leads to the final output of 5 days rainfall accumulations dataset.

2.2.3. Field data `and field work

Field data were collected through farmer interviews starting 26th of September to 12th October, from 14 pixels each covering an area of 1km^2, located in the districts of Soroti, Kumi, Kole, Dokolo, and Pallisa. A pre-test to 10 farmers in Pallisa was done, this allowed re-adjusting of questions. Finally, data were collected with the support of 6 field assistants and District Agricultural extension staff facilitating mobilization. A total of seventy-two (72) adult farmers who had been practicing farming for atleast 15 years, was available and willing to participate in the interview process were surveyed. These criteria were adopted in consideration of the ability of the farmer to recall seasonality information, onset variability and long-term cropping practices that are relevant for the study and duration for which field data was to be collected. This allowed retrieval of farmers historical insight on the onset of the growing season, which is considered critical to their decisions to commence cropping activities such as ploughing and planting.

With a GPS navigation tool, selected pixels were located, and once in a pixel, semi stratified sampling method was employed, interviewing a farmer that was available at the time when the pixel was visited. In coordination with the local council one of the areas, the community members were informed of the data collection activities and requested to participate voluntarily. Interviews were conducted from the identified farmers crop field within the pixel to facilitate better recall to questions that follow historical perspective and further allowing for visual validation of the land cover type compared to that in google earth image.

Guided by structured interview schedule, probing technique and interactive discussion with the individual farmers, data on; "normal" start of the season in a year that the farmers considered were not characterized by variability and extreme event during its onset was recorded. Additionally, years during which there was an early onset, late and false start with corresponding indicators as recalled by the farmers; common crops grown during the first planting, specific crop grown during first planting for all the years that farmers could vividly remember and false SoS, rainfall retreat period before its return and general crop calendar information were recorded (**Appendix figure 11**).

This information helped to understand farmers perspective of seasonal variability, in this context information based on farmers' experience about the growing seasonal variability, for example; the definition/distinction between the start of the growing season and false start of the growing season; farmer responses to aspects of seasonal variabilities;

2.2.4. Auxiliary data

The following datasets were additionally obtained to support the study;

i. The land cover dataset that is freely available since 2008 resulting from the initiative of European Space Agency launched in 2004 was acquired from FAO - UN (2009) in different classes and follows the FAO Global Land Cover Land Use classification generated from original raster base Global cover regional archive. The dataset comes with data on areas in square km, Grid code representing global cover cell value, unique land cover classification system code.

Most importantly, agricultural areas categorized as; 20-50%, 50-70% mosaic cropland area, and rainfed croplands were utilized in preparation for fieldwork, this enables selection of the only pixels that are covered by cropland areas. The assumption is, there is a negligible land cover change in the 19 years, although crop rotational practice is acknowledged to have taken place, the land use and land cover remained relatively the same between the year 1999-2017 and variability in NDVI over the cropland areas are not caused by changes in land use types.

ii. Uganda roads data downloaded from https://download.geofabrik.de/africa/uganda.html that is provided by OpenStreetMap data. The roads data was used to guide the sampling procedure on pixel selection to ensure that sites to visit were easily accessible.

iii. World imagery; High-resolution land cover data of the 14 preselected pixels was acquired through the ArcGIS baseline data. World imagery makes this data available for most parts of the world in one meter or better spatial resolution obtained from both satellite and aerial images. The product includes the integration of 15m Terracolor imagery, 2.5m SPOT Imagery (288 to 72k) covering the world, and 15m Landsat imagery for Antarctica. For the United States, it's of 0.3m spatial resolution, and 0.6m in some regions of western Europe obtained from Digital Globe. Also available for other parts of the world is the 1m resolution of GeoEye, IKONOS, AeroGRID, and IGN Spain. Additionally, imagery at different resolutions has been contributed by the GIS User Community.

2.3. Software

In this study, different software & applications were used in various aspects of the research, starting from fieldwork preparation, analysis to final production of the report. They include;

- GDAL, used for data acquisition and format translation into workable ".img" format in Erdas and Uganda administration boundary
- Notepad application for the creation of batch files that were implemented in both GDAL and Erdas processes
- Erdas Imagine 2016 product of the hexagonal Geospatial community used for image preprocessing and stratification
- Envi classic 5.5, used to apply the upper envelop filter to address the problem of signal to noise ratio on the NDVI time series data.
- Argis 10.5.1; used for the creation of NDVI grid cell, vectorization, rasterization, integration of landcover data, world imagery data access through base data, extraction of temporal pixel values from the stack images and CHIRPS, raster calculation and map making.
- R studio and SPSS IBM for simple statistical data exploration and analysis
- Microsoft Excel, word, and ppt; area calculation, generation of temporal graphs and comparative analysis among the different dataset

3. METHODOLOGY

An introductory overview of the approach

The study applies both qualitative and quantitative methods to study the variability in relation to false onset of the growing season for Uganda using satellite products; NDVI time series data (1999-2017), CHIRPs rainfall product, integrating it with the indigenous knowledge of farmers. The qualitative aspects, farmers perception on growing seasonal onset variability, rely on their experience and local knowledge gained over a more extended period and subsequently informed their detection and anticipation of weather (Orlove et al., 2010) and was obtained using the interview method. This method provided an opportunity to strengthen scientifically derived information, allowing a local narrative to play a critical role in the analysis and presentation of the results of the study (Twomlow et al., 2008). Thereby contributing evidence base information that supports farming community response to climatic risk & uncertainty. Notably, the integration of farmers perspectives has not been widely explored in the climate studies due to the limited participatory tool for rainfall weather variability, yet this information is vital for contextual understanding and adaptation approaches in response to such variability (Simelton et al., 2011).

In this study, semi-structured interviews strengthened by the extension approach of "one on one" farmer interaction was the basis on which data is collected from farmers (Niles & Mueller, 2016). The data are later analyzed using explorative simple descriptive statistic and thematic coding of farmers responses to facilitate their integration in answering the postulated research questions.

The quantitative methods utilized data from CHIRPS, NDVI times series to derived general seasonality information for the different regions, detect areas at risk of onset variability and 1st dekad of SoS for the season for the three years (2015-2017). Results from the satellite products are later compared with both rainfall and farmer information corresponding to the pixel surveyed to facilitate modification of the definition of the start of the season as proposed by (Sivakumar, 1988). Following this, rainy day rather than rainfall amounts only were considered to distinguish between the actual onset of the rainy season and false beginning "false start."

Limitation: although the methodology applied is consistent and had the intention to identify links of onset variability to teleconnections (ENSO, ORL, SST, IOD, LST & LWST), this could not be included in this study due to time scale hence this links has not been analyzed and so not elaborated in this work, however efforts will be made to provide brief insights in relation to the findings. This aspect, however, remains elusive and opens up the opportunity for further research to evaluate relative correlation among these potential predictors on which basis an extensive investigation can be done. In relation to field data challenges was that farmers had different perceptions and sometimes imply different aspect when referring to variability, thus requiring comprehensive exploration and possible addition of focus group discussion, key informants to generate consensus. Never the less with the explorative analysis vital information have been was utilized for purposes of this study.

In section 3.1-3.5, details techniques applied to explain the fact of this study is provided, giving comprehensive information on the; study area, method, and analysis conducted to derive relevant details.

A general overview of the research design and approach

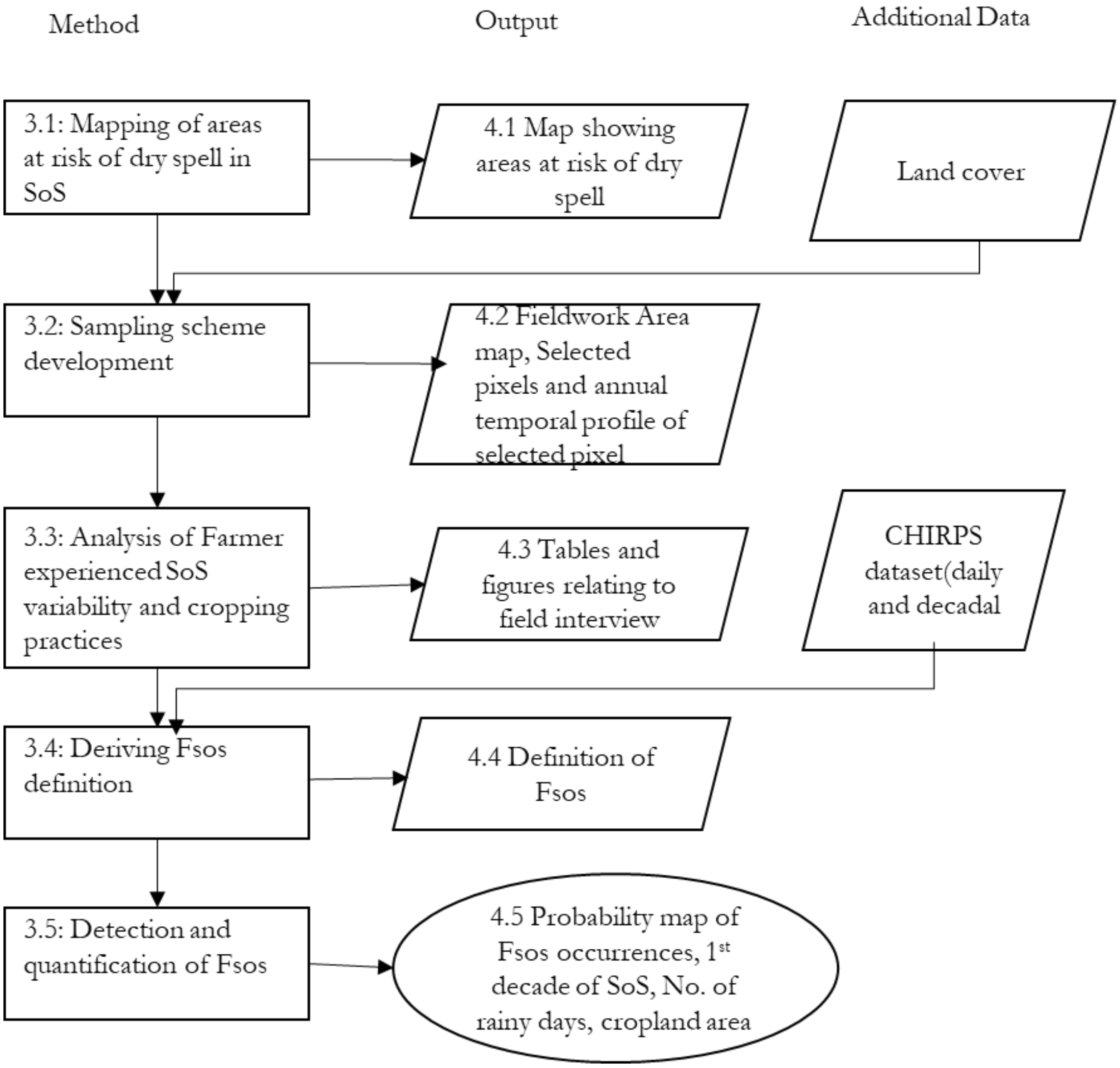

Figure 3: Schematic diagram illustrating the steps applied in answering the research questions as set in the study. Providing an overview of methods, output and additional data used in the analysis.

3.1. Mapping of areas within Uganda ar risk of a dry spell in SoS

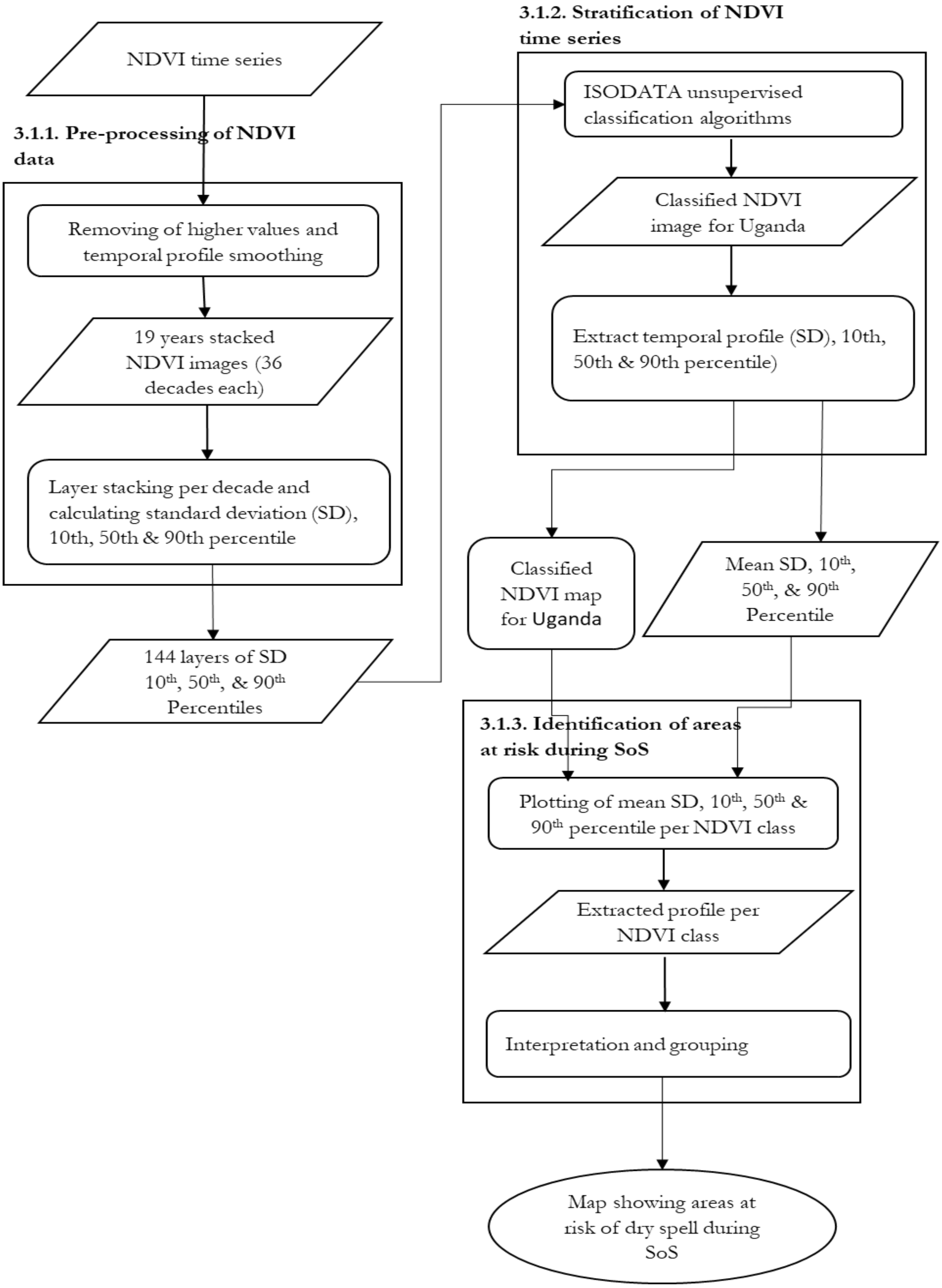

Figure 4: Flow diagram illustrating the mapping of the areas at risk of a dry spell in Uganda during the year 1999-2017

3.1.1. Pre-processing and preparation of NDVI time series.

The NDVI as guided by the quality assessment described by Vito in its Gio GMES initial operational report issue I2.21(https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/GIOGL1_ATBD_NDVI1km-

V2.2 I2.21.pdf) in table 1&2; is affected by numerous factors, including those that are sensor specific. Samples of the acquired image were inspected for values that have been described in table 2.2.1-2. Yearly stacks were created for all the 19 years (19 images) and later the pixel values of 251 to 255 were removed using Erdas imagine. The output was 19 images (1998-2018) each with 44 temporal band with no pixel value in the range of 251-255. By eliminating these values, the process results in the loss of some data which would otherwise affect the final analysis in relation to the study. Additionally, the stack images now have signal noise spike and outliers resulting into the unsmooth temporal profile, and yet with regard to the growing seasons, the NDVI temporal profile is assumed to be smooth when plotted (Eklundh & Jönsson, 2015). Time-Series Processing and Assessment of Vegetation Dynamics (TIMESAT) an integrated application in ENVI classic software were used to remove the signal noise, spike, and outliers.

The operation is based on earlier mentioned assumptions of temporal NDVI profile for growing season being smooth to address the signal noise problem. TIMESAT algorithms perform three processes built on least square fits to apply the upper envelope filter on the NDVI data; it starts by applying a local polynomial function which is an adaptive Savitzky-Golay filter, then least square regression during which all the data values are fitted in a nonlinear model functions (Eklundh & Jönsson, 2017). In the process recalculating all the value for the NDVI stack images and seasonal parameters. Using 44 temporal band images (4 images before 1999 and four after 2017), an upper envelope filter was applied to each of the 19 stack images, allowing for the gap filling of the lost data. Finally, from each of the output, the eight extra images were removed to have images with 36 temporal bands each, representing data of the first to last dekad in a particular year.

The layers were then stacked per dekad and georeferenced to WGS_1984_Plate_Carree, generating 19 years dekadal stack to allow an assessment about the performance of vegetation during each dekad over the study window. This was important because it enables determination of which dekad(s) is a risk of dry spell most common which is the heart of this research. Finally, 10th, 50th, 90th percentiles and standard deviation (here referred to as SD in this study) was derived and used in the classification of the image to facilitate derivation of climatology and precursor for risk mapping

3.1.2. Stratification of NDVI time series

Studying growing seasonal onset variability has attracted the attention of many scholars, informed by reports on changing weather patterns, seasonality, and overall climate change. To the farmers' onsets of rainy season logically defines the start of the growing season, thus critical factor driving their decision on starting to plant their crops. Therefore, since NDVI reveals the photosynthetic activities of vegetation, variability in the onset of rainy season in relation to annual cropping will determine the date during which after the minimum, the NDVI value will start rising. NDVI has already been applied in the monitoring of agronomic droughts and assessment of its impact on crop productivity.

In this study, dekadal 10th, 50th, 90th and SD for each year have been derived to stratify and support the detection of areas within Uganda that are at risk of a dry spell at the start of growing season, suggesting a possibility of the occurrence of a false start of the season in some years. A stack of each dekad for all the 19 years was created (d1_1999 to d36_2017) and percentiles values for each dekad was obtained using ENVI software, while SD generated using Erdas imagine and finally stacked of the 144-image made.

An unsupervised classification was performed on the 144 "standard deviation-percentile stacks" image using Iterative Self-Organizing Data Analysis Technique (ISODATA). This technique applies a minimum distance clustering method. Unlike K-means, it operates taking maximum advantage of the variability in the image and does not assume that the number of classes is known before the run of the algorithm, but the clusters present in the data are dense and close together. Secondly, it assumes that the clusters are separated adequately so that their inter-centre distances are more than the defined threshold (Mather & Koch, 2011, p. 235).

The ISODATA algorithm applied here is in accordance to approach described by (Khan, de Bie, van Keulen, Smaling, & Real, 2010; Gumma, Nelson, & Yamano, 2018) and was implemented in ERDAS Imagine 2016, classifying the image into 25 classes at 0.99 convergence with a maximum iteration of 50 and applied divergent static to measure the distance between the signatures of the classes created from the model

run. Therefore, each iteration gives results for the defined number of classes before the model run. By using the SD-percentile stack, we were able not only to reduce the volume of data for analysis from 684 to 144 data but also the duration of the model run during the classification process. The choice of 25 classes threshold was informed by prior classification carried out by (Kees de Bie) that concluded that Uganda was not very heterogeneous and therefore 25 classes were appropriate for ISODATA clustering.
To display the variation within Uganda, a static stratified map was created in ArcGIS environment, enabling visual interpretation of spatial representation of the different classes with a view of understanding the dekadal variability over the 19 years. The mean values of SD, 10th, 50^{th,} and 90th percentile was extracted per class and plotted in excel, thereby facilitating the regrouping of the classes into areas at risk and those not at risk at the onset of SoS.

3.1.3. Identification of areas at risk of a dry spell at the start of the growing season

In detecting the areas at risk, NDVI temporal profile variability depicted by annual, dekadal 10th, 50th, 90th and SD plots is used. Where the peak of the standard deviation coincides with the start of season dekads, such a class is at risk while others are not. Base on this approach, an index based insurance model in Ethiopia has been implemented and has been proven to be reliable (Kees, Ben, & Anton, 2018). This approach significantly relies on information revealed by groups of pixels that exhibits similar characteristic to the variation in weather patterns. Because of the similar local climatic conditions prevailing, including anomalies, such as short terms dry spell during the growing season, false start, the timing of drought, duration and gravity of its impact to vegetation, the groups of pixels have identical land cover & land use types (Kees et al., 2018).

Meanwhile in another study; Yang, Seager, Cane, & Lyon (2014) used the 5th, 95th percentile as climatological indicators in comparison with long times series in East Africa. They used the gap existing between the standard deviation and percentiles (5th &95th) to demonstrate the occurrence of interannual variability in relation to MAM season. However, in this research, we included standard deviation as the basis of revealing risk information.

Additionally, unlike the application by C. A. de Bie, Khan, Toxopeus, Venus, & Skidmore (2008) to map out areas with different crop types and deriving cropping calendar. In this study we apply a similar approach but map out areas at risk of a dry spell as depicted by the spatial-temporal profile from SD and percentile plots, the output from this process does not only allow for mapping areas at risk but also visualization of seasonality differences and average changes of NDIV during the 36 dekads. Subsequently, the 10th, 50th, 90th and SD statistics for each NDVI class for 19 years derived per dekad was extracted and plotted in excel revealing the temporal variations from the first dekad to the 36th dekad. Comparison between the percentiles values and the SD profiles was used to describe the onset of the season variability depicted by each class, thus flagged to either be at risk of a dry spell or not. Subsequently, the temporal profiles revealed characteristics of the growing season within the different location and potential land cover types. This was crucial in aiding the decision to select which areas are characterized by annuals vs. perennials and those that are forest land cover. Finally, a map showing areas at risk was created.

3.2. Sampling scheme development

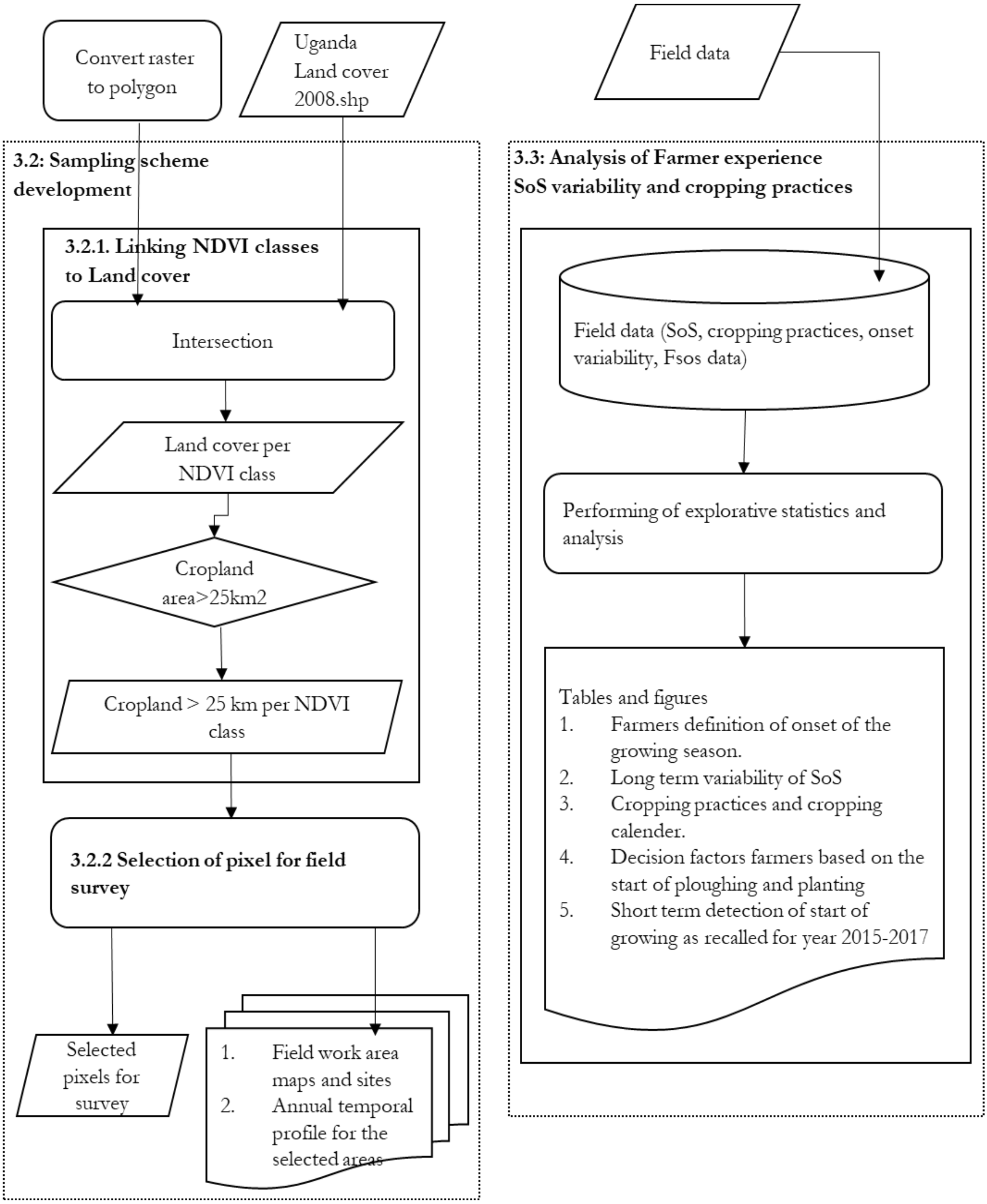

Figure 5: The schematic representation for the process leading to answering research question two and three.

3.2.1. Linking NDVI Classes to Land cover data

Linking stratified NDVI to land cover types allowed the creation of classes with the different land cover types and their correspondent spatial coverage are calculated. This is vital to ensure the selection of relevant pixel in the context of this research (C. A. J. M. de Bie et al., 2011). Uganda land cover data obtained was reclassified into four relevant classes; rainfed cropland (3), 50-70% mosaic cropland (2), 20-50% mosaic cropland (1) and others (0)-includes forest cover, water bodies among others), while the classified NDVI map was converted into vector to facilitate the integration of the two data.

The reclassified land cover map was then crossed with a classified NDVI vector map resulting into land cover per NDVI class, after which cropland area was masked out and the area calculated in square kilometers for each NDVI class in ArcGIS. By masking out the agricultural areas, we minimize the influence of non-agricultural vegetation on the results of the analysis. Using the NDVI Land cover type map, a grid cells of 1km*1km was created in the ArcGIS environment, and a land cover type(s) per class was obtained at "pixel" size. This guided the process of selecting survey sites.

3.2.2. Selection of Pixel for Field Survey

A stratified partial random sampling was applied in selecting pixels to be surveyed, using the classes as strata where the pixels are to be selected. This was done by mainly focusing on pixels that met a predefined criterion of, in that;

- The pixel should be in a class identified to have been at risk for a dry spell at the beginning of the growing season.
- The site pixel in the area covered by cropland area, it is within cropland areas of atleast 25km^2 and is accessible during the field survey.

Prior to implementation of the above conditions, the preliminary process of selection involved a three-stage process, first to identify relevant total area according to the land cover types, secondly relevance for a specific class. Cropland category of 50-70% and >70% cropland (referred to as rainfed in the metadata) was considered most important in the selection. Thus, in Table 4, classes with a higher proportion of land covered with these types combined were preselected and later within each category only classes with more than 20% of land covered with cropland was selected. Classes 9, 10, 13, 14, 18 and 21 were considered as most appropriate in this study since they had 67.5%, 67.4%, 37.6% 34.3% mosaic cropland area of 50-70% while class 21 had 25.5% rainfed cropland area. Finally, the criteria defined was implemented on the selected classes ensuring that pixels with minimal contamination are selected.

Table 4: The selection of classes to be surveyed as per the proportion of land area coverage within the 25 classes

Class Name	Other Land cover	20-50% Mosaic cropland	50-70% Mosaic cropland	> 70% cropland	50-70% Mosaic + >70% cropland	Percentage of cover per class	%age of cropland
Class 1	0.1	0.0	0.0	0.0	0.00	0.1	0.0
Class 2	0.2	0.1	0.0	0.0	0.06	0.4	0.2
Class 3	1.9	0.9	0.2	0.1	0.26	3.1	1.1
Class 4	3.3	0.5	0.4	0.0	0.49	4.3	1.0
Class 5	0.7	0.2	0.1	0.0	0.06	1.0	0.2
Class 6	2.4	0.0	0.8	0.0	0.84	3.3	0.9
Class 7	3.6	0.0	0.6	0.0	0.60	4.2	0.6
Class 8	4.6	0.1	0.6	0.0	0.64	5.3	0.7
Class 9	1.4	0.4	3.6	0.2	3.71	5.5	4.1
Class 10	5.3	0.0	0.9	0.0	0.86	6.2	0.9
Class 11	0.8	0.1	0.1	0.0	0.12	1.0	0.2
Class 12	2.3	0.1	0.3	0.0	0.30	2.6	0.4
Class 13	1.7	0.7	4.9	0.1	4.96	7.4	5.7
Class 14	2.9	2.9	3.5	0.0	3.51	9.3	6.5
Class 15	2.0	0.6	0.3	0.0	0.26	2.8	0.8
Class 16	1.1	2.5	0.0	0.1	0.06	3.7	2.6
Class 17	1.2	4.4	0.7	0.0	0.71	6.3	5.1
Class 18	0.9	2.0	1.5	0.0	1.52	4.4	3.5
Class 19	2.5	3.0	0.1	0.8	0.84	6.4	3.8
Class 20	0.4	0.4	0.0	0.0	0.00	0.9	0.4
Class 21	3.1	2.9	0.0	2.0	2.08	8.2	5.0
Class 22	1.6	6.7	0.0	0.3	0.38	8.7	7.1
Class 23	0.2	0.0	0.0	0.0	0.00	0.2	0.0
Class 24	1.3	1.9	0.0	0.1	0.07	3.3	2.0
Class 25	1.1	0.5	0.0	0.0	0.01	1.7	0.6
	46.6	**31.1**	**18.6**	**3.8**	**22.3**	**100.0**	**53.4**

Class Name	Other Land cover	20-50% Mosaic cropland	50-70% Mosaic cropland	Rainfed cropland	50-70% Mosaic + rainfed cropland
Class 6	74.0	0.3	25.7	0.0	25.7
Class 9	25.4	6.7	65.0	2.8	67.9
Class 10	85.8	0.196	13.88	0.1276	14.00492
Class 13	23.1	9.6	66.6	0.7	67.4
Class 14	30.9	31.5	37.5	0.1	37.6
Class 18	21.0	44.7	33.6	0.7	34.3
Class 21	38.5	36.0	0.5	25.0	25.5

3.3. Analysis of farmers perception of variability on SoS and cropping practice

As illustrated in **Figure 5**: in section 3.2, farmer knowledge about the onset of the season variability was clustered into awareness of early, normal, late start and false start of the season. It was inquired and analyzed in general terms for the 19 years, evaluating farmer definition of SoS, long term farmer recalls of weather-related variability and specifically for the year with vivid recall (2015-2017). The data are analyzed at a pixel level and aggregated to the district level; this is because of the existing local variability both in terms of weather and farmer practices.

Excel, R-studio and SPSS packages are used to explore, analyze and summarize the information derived from the field survey data using simple descriptive statist and graphical representation have. This includes cross-tabulation of the different parameters to facilitate interpretation of data provided by the farmer during the interview. Information is presented in a bar graph, tables and box & whisker plots revealing cropping practices characteristics at the onset of the season for the regions surveyed and recall of variability by farmers. In carrying out the analysis related to farmers responses, it was to help identify relevant parameters that could support the definition of the Fsos and subsequently allowing for determination, quantification and mapping of the onset variability.

3.4. Deriving the definition of the false start of the season for Uganda

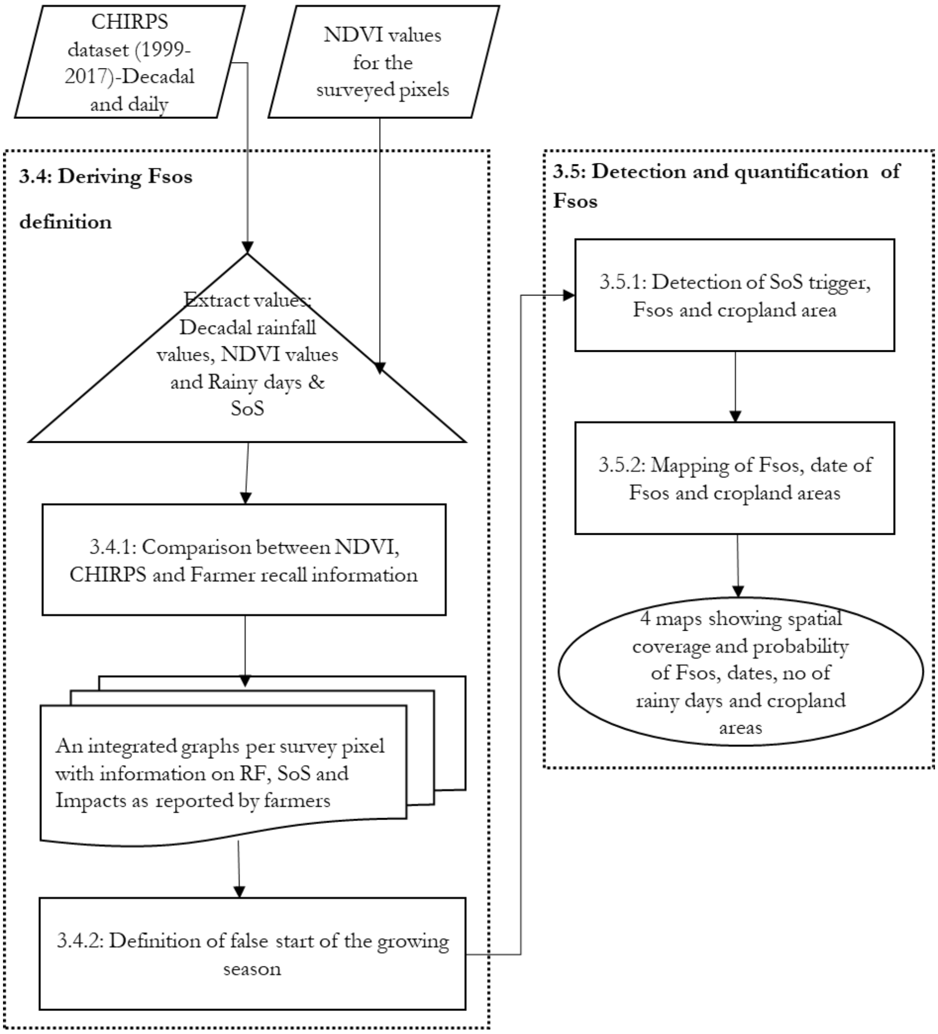

Figure 6: Schematic diagram, illustrating the steps in answering research questions four and five.

3.4.1. Comparison between NDVI, CHIRPS and farmer recall information

Most approaches to establishing the relationship between two or more variables are by performing statistical regression analysis, in this study qualitative and non-linear methods have been used in exploring (dis)agreement between the different parameters. The qualitative approach involved creating an integrated representation of information derived from farmers, NDVI and CHIRPS in a graph and through visual interpretation relationship among them were established by considering three years of fresh farmer memory.

To begin with; three years (2015-2017) time series climatological data derived from CHIRPS and NDVI for the survey areas were analyzed and compared with farmers recall information & perception on growing seasonal onset variability. The choice of these years is based on the ability of farmers to recall anomaly information and their cropping activities during these years. Information provided by farmers relating to onset of rainy season, planting date and a false start was annotated on the graph for all the surveyed pixels, this qualitative approach allows for comparison of what the farmers reported and that revealed by both NDVI and CHIRPS products. While comparing the data, attention was placed on the identification of SoS in relation Fsos reported date by the farmers; this process facilitated detection of first rainfall peak and related numbers of rainy days corresponding to this peak thereby leading adjustment of the definition of SoS in view of detecting the occurrence of a false start. Rainy days per dekad other than rainfall events that are often applied in many studies was used to arrive at the definition of Fsos.

3.4.2. Definition of the false start of the growing season

According to the analysis in section 3.4.1, the definition proposed by Sivakumar in 1988, where SoS is that date, when accumulated rainfall in three consecutive is atleast 20mm and is not followed by more than seven days of dry spell in the proceeding 30 days, was modified to factor in rainy days other than just rainfall events. This modification was informed by field survey data, where the number of rainy days to the farmers was more relevant than just rainfall events, thereby allowing for the distinction between the true and false start of the rainy season. Subsequently, a definition of Fsos was arrived at.

3.5. Detection and quantification of false start

3.5.1. Detection of SoS 1st dekad, Fsos and Rainy Day for the 19 years

The definition arrived at in section 3.4.2 was implemented on the CHIRPS data for all the 19 years at the pixel level to determine the SoS that triggers Fsos, and the corresponding number of rainy days leading to the dates of the SoS. This step was crucial in determining the spatial-temporal characteristic of the Fsos phenomenon and enable its representation in a map. It further enabled us to establish the frequency with which Fsos occurred in the 19 years and this ascertains the severity.

Using the daily CHIRPS data, pixels values were obtained in an ArcGIS environment with corresponding coordinates in a tabular form. Using the Fsos definition, the SoS date was identified and checked against the condition to ascertain whether it’s an actual start or a Fsos. This was done for all the 6818 pixels and corresponding rainy days values recorded. The information was then tabulated per year in excel, sheet and cross tabulated to ensure the quantification of the number of pixels that were affected per year and relationship between the actual SoS and Fsos

3.5.2. Mapping of Fsos, date of Fsos, number of rainy days and cropland areas

To show the spatial-temporal characteristic of the Fsos, three static maps were created. This includes the probability raster maps for the occurrence of Fsos in the nineteen years, means dates of SoS corresponding to Fsos and average number of rainy days. Finally, a map showing these parameters was displayed side by side allowing for visual interpretation and comparison with cropland areas to highlight the areas vulnerable and at risk of the impact of Fsos.

3.5.3. Hypothesis testing

We explored the factors influencing farmer identification of Fsos using Fisher's exact test statistic. Fishers statistics were used because in certain categories identified by farmers the number of counts was less than five. Thus Pearson Chi-square test could not be applied. The hypothesis in relation to farmers ability to correctly recall false start could not be tested considering that, no accuracy assessment on the detected Fsos was done and also farmer recalls varied from one farmer to another thus requiring detailed inquiry and more number of farmers to have a greater perspective.

4. RESULTS AND DISCUSSION

4.1. Mapping of areas within Uganda at risk of a dry spell at SoS

4.1.1. Pre-processing and data preparation

Data pre-processing is a crucial step to the achievement of accurate analysis and delivery of robust research piece of work. The process was mainly done for satellite products Spot/Proba V 1999-2017, and CHIRPS. A smoothen NDVI dataset was generated after implementing the algorithm in section 3.1.1, the 19 years NDVI time series was available to facilitate the analysis. Addressing the problem of temporal fluctuation. On the other hand, CHIRPS information was extracted in a table and ready for analysis.

The NDVI temporal profile in **Figure 7** showed a smooth profile after the filtering process, at this stage the characteristic of sample pixels already displayed the growth patterns of vegetation in Uganda, thereby providing prior information on seasonality. This was important, pointing out the vegetation dynamics for Uganda.

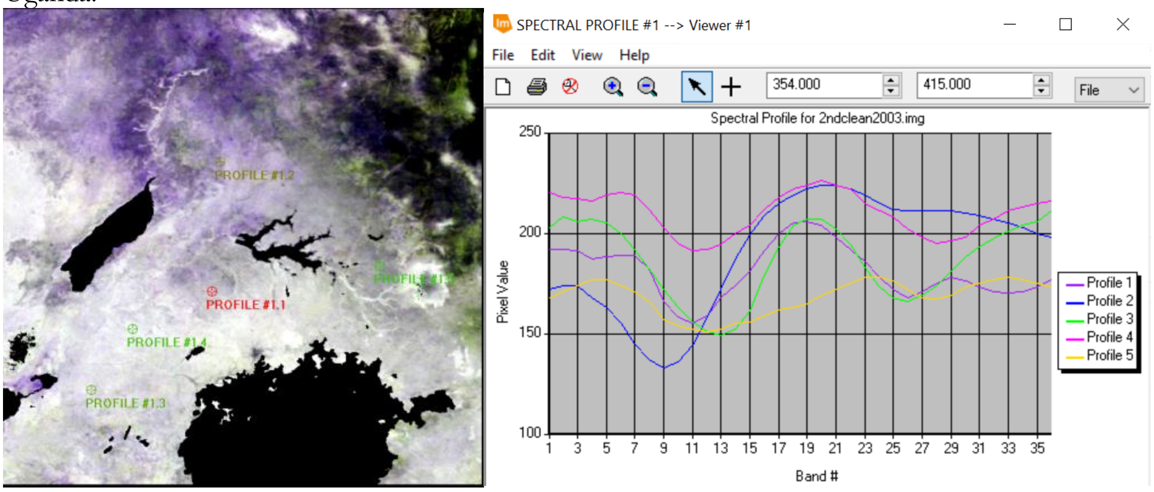

Figure 7: Temporal characteristic of the pixels after the smoothing filter application.

The benefits relating to the data used here is the ability to revealed both phenological information and risk information. It presents the opportunity for a comprehensive description of the vegetation characteristics than we could achieve using a single date image. For example, in profile 2, its shows longer monomodal growing season, while profile three show bimodal growing seasons with the 1st season being shorter (15-25th) than the 2nd (29-11th). Meanwhile, profile 5 relatively have lower mean NDVI values through the year 2003, remaining quite uniform.

4.1.2. Stratification of NDVI time series 1999-2017

In Figure 8 is an ISODATA classification for the NDVI into 25 classes generated from the reduced 144 stack layers of 10th, 50th, 90th and standard deviation values of each dekad from all the 19 years used for this study. It shows a static representation of the spatial-temporal variability of vegetation performance during the 19 years. The colours in the legend indicate variation in mean values from the lowest to the highest, i.e., magenta to red respectively. The ISODATA clustering provided insights on the variation and characteristics of the vegetation cover types over the last 19 years which were verified from the field during the farmer's interview in the selected pixels.

The analysis, derived 19 years spatial, temporal dynamics of the land cover for Uganda obtained by extracting the temporal profile per class and through visualization, inferred the seasonality information across the land mass indicating bimodal versus monomodal short and long term single growing season mainly in the north-central part around the Kyoga basin (as represented in section 4.1.3 **Figure 10**) and have been described by Jameson and McCallum as cited in Phillips & McIntyre (2000) to relate to the short period of dry spell in Jun-July 1st -2nd season transition, thus the NDVI values do not fall to a minimum value since planting is done immediately following the 2nd season rainfall onset. These aspects provided prior information which was useful to group the classes in relation to risk during a dry spell at the beginning of specific seasonality type (**Table 5**).

Additionally, we noted that the NDVI annual temporal profile differed distinctively from one year to another in both minimum value and amplitude, thus pointing out the annual variability within the different classes that are displayed by the profile, hence the differences in the characteristic of each class show incredible homogeneity existing within a given class. Strikingly the onset window from 7th -14th dekad have revealed the same information indicating an early start, a late start in some years and hints on the possibility of a false start in a particular year. Anyhow, this approach cannot provide a conclusion on the occurrence of Fsos for specific areas without the inclusion of meteorological data.

The approach demonstrates that image classification can be done using derived statistical parameters of standard deviation and percentile, generating important information like variability in onset of the season, seasonality variation and annual variability as has been revealed by the timing of the first increase of NDVI from the minimum in a given year. A similar approach was applied by (Höpfner & Scherer, 2011) in Morocco to derived information on intra-annual & interannual variation in vegetation and is considered a stable classifier, thus justifying the effectiveness of applying these parameters. Meanwhile, Gasmi, Gomez, Zouari, Masse, & Ducrot (2016) while using ASTER dataset for geological mapping applied principle component analysis to reduce 9 bands of ASTER so as to compare with the reference geological map in an effort to reduce the volume of data for analysis. Thus, the use of statistical parameter as it is in this study addresses the problems of large data dimensionality in the long-term time series that we were supposed to work with, allowing improvement in computational time and analysis, yet revealing the relevant required information.

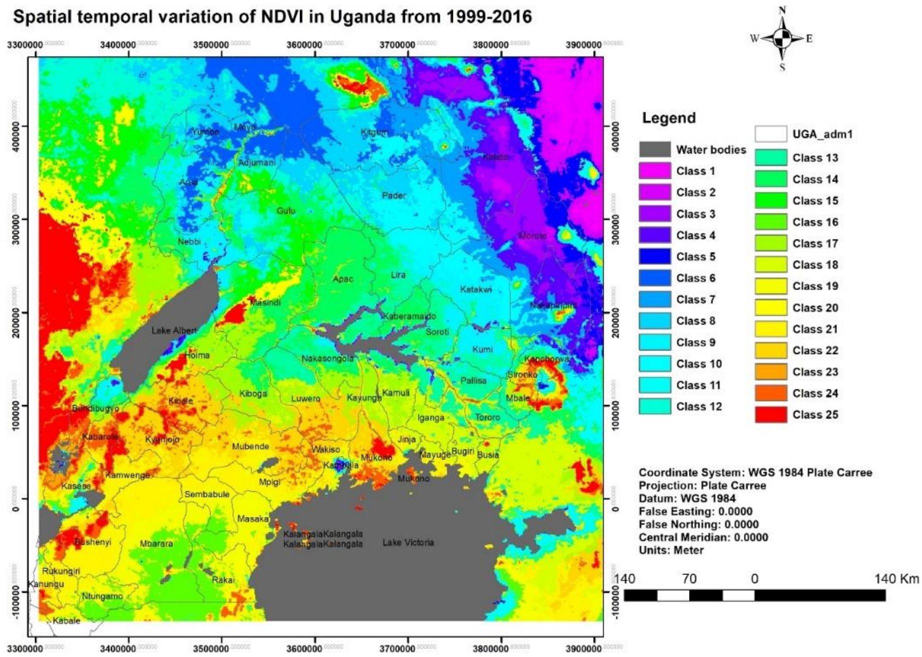

Figure 8: Spatial representation of the variation in vegetation performance within Uganda from the period 1999-2019

We can accordingly infer that NDVI has strength and capability in describing the variability during the growing season in relation to weather & climatic changes that affect vegetation performance and consequently reveal information captured through remote sensing. The advantage of this approach is the ability to derive the temporal information from which further characterization can be made (C. A. J. M. de Bie et al., 2011) as applied in answering the questions in the next section 4.1.3

4.1.3. Identification of areas at risk of a dry spell during the start of the growing season

In the **Table 5**, most of the regions within Uganda in the 19 years were at risk of a dry spell at the onset of the first planting season, except for some location in the southwestern region that revealed risk during the 2nd growing season (category 3 in **Figure 9 & 10**). The 90th & 10th mean NDVI values are low around 4th to 6th dekad, increasing from 8th dekad to a maximum in the 23rd dekad for most areas in the first planting season. This is because for cropping areas during this time, most of the annual crops have already been harvested from the field and its dry season where even the deciduous trees loose their leaves to reduce the rate of evapotranspiration, consequently resulting into lowering of the NDVI value since even the permanent vegetation are less active. However, classes 23,24, 25 the NDVI profile remains high throughout the year; this represents forested areas and land cover around Mount Elgon in Eastern part where vegetation tends to stay active throughout the year because of the high density of tree cover in this area. The NDVI temporal profiles in **Figure 10**, show known seasonality information for different regions in the study area with associated vegetation characteristics.

In total, 12 classes are part of the monomodal rainfall regime that are at risk at the onset of the season, 5 classes at risk in both seasons and the 16th class of bimodal season characteristic indicating risk during the beginning of the 2nd growing season. This suggests the possibility of the occurrence of a false start. Notably classes 19, 21 and 22 in purple colour in **Figure 9** did not show sign of dry spell during the onset of the season.

Table 5: Grouping of classes at risk of dry spell and type of season associated with the risk

Class Name	Total No of classes	%age of cropland area	Group by type of growing seasonal regime	Risk of dry spell during the 1st planting season	Risk of dry spell during the 2nd planting season
01,02,03, 04,05-Category 1	5	8.8	mono modal	√	√
6,7,8,9,10,12,13,14,15,17,18,20-	12	58.1	2 planting seasons with short dry spell (mono modal)	√	
19,21,22	3	23.2	Bimodal	Not at risk	
11, 23,24,25	4	6.2	Bimodal	Permanent vegetation cover type	
16	1	3.7	Bimodal		√
Total	25	100			

From the **Figure 9**, four distinctive areas categories have been delineated indicating that overall, 70.6% of cropland area within Uganda is at risk of a dry spell during the onset of the growing season, 8.8% all throughout the year, 58.1% during 1st planting, while 3.7% during the 2nd season planting. This is supported by finding in revealed in **Figure 20** where Fsos in shown to be experienced generally across the country. Obviously, this does not imply the dry spell is experienced at the same time period in all areas but provides evidence that within the last 19 years, they were at risk during the onset of the season. This dry spell can be attributed to Fsos or an extending dry spell into the growing season resulting into the late start of the growing season. The latter has been reported by (Jury, 2018) pointing out the years 2005 and 2009 as the affected years experienced in the kiyoga basin. While similar reports have been documented in the recent studies (Orlove et al. 2010; Kansiime, Wambugu, & Shisanya, 2013; Cooper & Wheeler, 2017; Mugume et al., 2016) and (Nakalembe, 2018) pointing to the facts of dry spell during the growing season, with the later mainly characterizing prolonged dry experienced in Karamoja region.

Specifically, for these groupings, their mean SD as seen in the extended legend **(Figure 10)** is higher at the onset of growing season indicating variability within this temporal window, thus the classification as at risk. While for areas not at risk the standard deviation is high during the dry season, i.e., in dekad 7-11 (March-April) for monomodal and 26-27 (September) which are a window for start of the season in Uganda and the 34-6th dekad in the dry season. The application of SD in this study is similar to the one used by Hall-Beyer (2012) to quantify the interannual variability over the 25 year period in Canada and just like in this study the mean value for standard deviation for specific areas were used, thus appropriate for risk mapping.

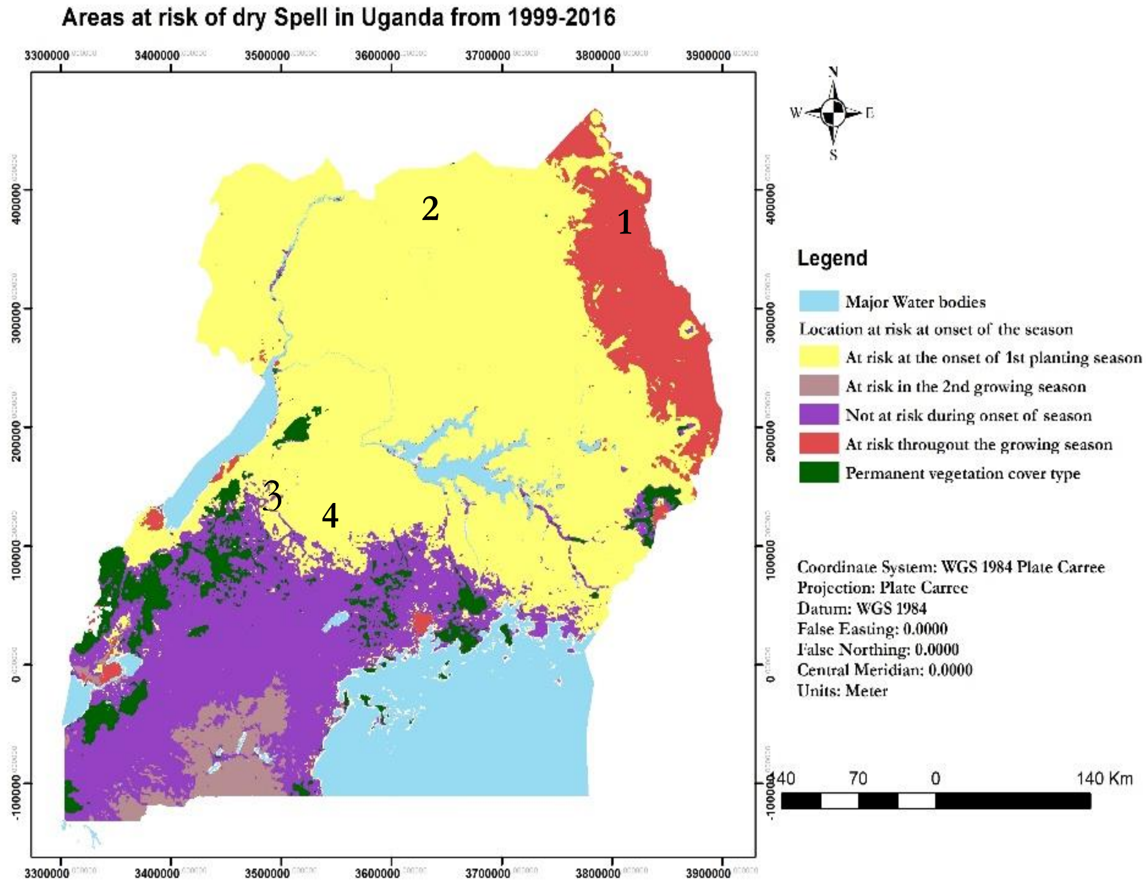

Figure 9: Areas within Uganda that are at risk of dry spell during SoS, indicating the spatial coverage of different categories as shown in the legend. The grouping follows generalization of classes with similar temporal profiles in relation to risk at the onset

Extended Legend

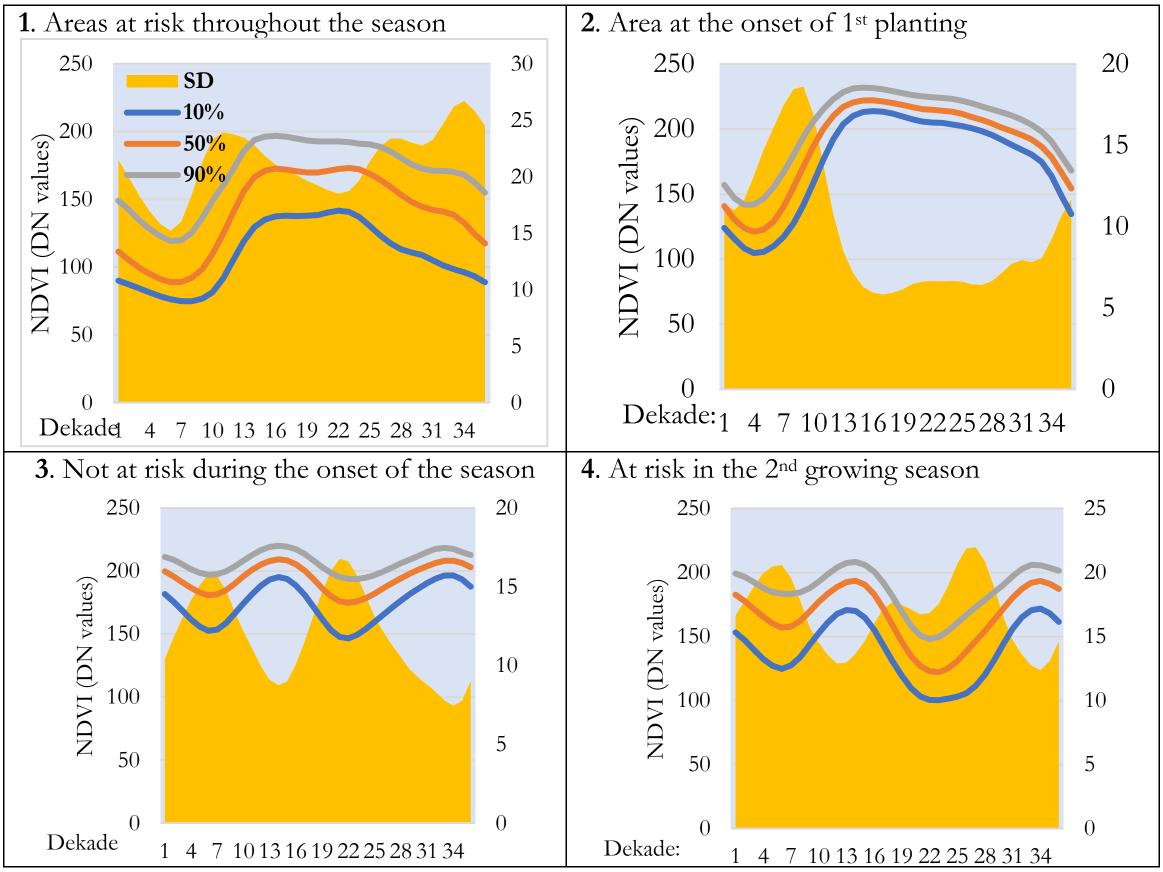

Figure 10: Anomaly pattern revealed by the NDVI profile for different areas at risk of dry spell during the onset of the growing season

The variability as depicted by the profile in the **Figure 10** highlights areas at risk of dry spell whose information formed the basis for field surveys and also seasonality differences among the classes. Category 1 shows higher vulnerability to the risk; this section covers the monomodal semi-arid regions of Uganda often experiencing occasional dry spell not only at the onset of the season but all through the year. Nakalembe (2018) highlight the risk among the farmers here, that “farmers follow their cropping calendar and once seeds are sown, many are not in a position to replant if rains fail at the start of the season.” Therefore, the occurrence of a dry spell in this region will severely impact on agricultural productivity. Category 2 monomodal long growing season, show the profile of areas at risk during first planting season, meanwhile in category 3, indicates that these locations had not been at risk of a dry spell during the onset of the season. However, this is likely not the case; perhaps it is because of the existing cropping system in this region of Banana-Coffee, the mean NDVI will tend to remain relatively less variable since the perennial crops would have an effect. Conducting field surveys and using of gauge station data would allow for validation of this finding, hence proving the application of this model in drought monitoring assessment.

The findings relating to class 16 belonging to the fourth category is a location in the western part of Uganda indicates risk of a dry spell during the onset of the 2nd growing season. This is algins with the results of the study conducted by Cooper & Wheeler, (2017) in which farmers revealed that in recent years they had experienced variability in the SoS in SON season, pointing out increasing uncertainty in relation to false start. Which accordingly, has been reported to cause confusion on planting activities among farmers.

Overall, dry spell occurring during the start of the growing season has a substantial negative impact on the general productivity of the agricultural sector due to reduced yields and low production among the farming community. The implication, therefore, is that correct detection of SoS by farmers and stakeholders delivering forecast information would translate into a successful season and wrong detection, otherwise.

4.2. Sampling scheme for field survey

4.2.1. Integration of NDVI stratified map and land cover data

Upon linking the classified image with land cover type, area coverage were calculated in square kilometers for each NDVI class and analyzed for percentage of coverage of cropland area in each class, results gave the proportion of cropland areas as a percentage of total cropland areas ranging from 0.00% (the lowest belonging to class1 and 7.1% in class 22 and 6.5% in class 14 (3.1.1-1). The strata represented by class 1 is one of the three classes (1,2,3) located in the Karamoja region which is a semi-arid area with vast coverage of rangeland areas, and their significant economic activity is pastoralism and has less cropland areas. While class 22 is part of cropland areas in the southern region and 14 represents the cropland areas around the lake Kyoga basin stretching to the section of the North Western part of the country which constitutes a farming community of Lango, Acholi, and Westnile region characterized as a millet-cassava farming season. This finding is corroborated by the fieldwork results in which most farmers interviewed around the lake kiyoga basin revealed their principal crops like maize, cassava, millet, and soybeans.

The land cover data attributes were; forest, buildings, cropland areas, wetlands, water bodies and was regrouped into three dominant cropland cover type and other cover types (other type, 20-50%, 50-70%, >70% cropland area as in Table 4). The proportion of the land cover type per NDVI class is summarized in the same table. In isolation of "other type" land cover type and attention to cropland areas, we note that Southwestern Uganda is the only region majorly covered by rainfed cropland areas while mosaic cropland areas predominate other parts of the country. This explains the heterogeneity of the vegetation characteristic detected by the satellite, and it is associated challenges towards crop performance monitoring during the growing season as is the case in this study.

58.1% of cropland area are at risk of a dry spell during the 1st planting season, 8.8% all through the growing and 3.7% are at risk during the 2nd season planting while 23.2%% of cropland areas in the western region did not show signs of risk during SoS. The integration of land cover data with the NDVI indicates that most of the cropland area in Uganda are covered by mosaic cropland areas and not specifically pure field for crop production, therefore this result imply broad coverage of cropland area would suffer in case of the risk. The risk map derived from the stratification and risk detection, show that the agricultural land falls in the areas mapped to be at risk, thus highlighting the vulnerability of the rainfed agricultural systems of Uganda

4.2.2. Selected classes and corresponding pixel surveyed

Analysis of the land cover per NDVI classes provided information on the proportions of each land cover type class (**Table 4**). Classes 11, 23, 24 and 25 identified as permanent vegetation cover type depicted by their respective profile were flagged off since they are not of interest in this study. In total, they constitute 6.2% of the total land cover.

Before the application of the selection criteria, classes 9, 10, 13, 14, 18 and 21constituting 3.7%, 0.86% 4.6%, 3.5%, 1.5 & 2.1% respectively of the total land cover and having 67.9%, 14.0%, 67.4%, 37.6%, 34.3% and 25.5% respectively within their classes covered by cropland cover were selected. Finally, classes 10, 18 and 21 were dropped for field survey to allow collection of adequate data, since class 10 had less 20% cover with 50-70% of mosaic cropland while class 21 located far south of the country was considered far and thus dropped for the survey. The four classes (9, 13 &14) form the sampling frame from which pixels were selected for field survey. The selection of classes ensures coverage of a few classes that were manageable within the study time frame. Notably class 18 was not surveyed while in the field due to time limitation; however the 72 farmers interviewed from the other three pixel was considered substantial to support the analysis.

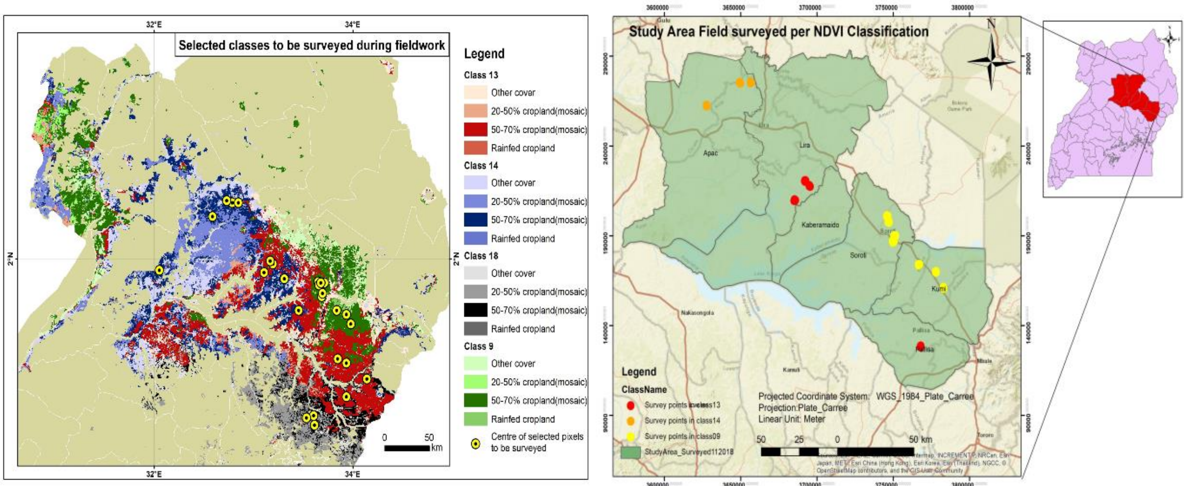

Figure 11: Location of plan sites for field survey and the surveyed sites per NDVI class

A total of 14 pixels were selected and their respective temporal profile extracted (**Figure 12**), providing insightful information of the year during which the SoS where either early, normal or late, therefore, ensuring farmer responses were compared directly during the field survey.

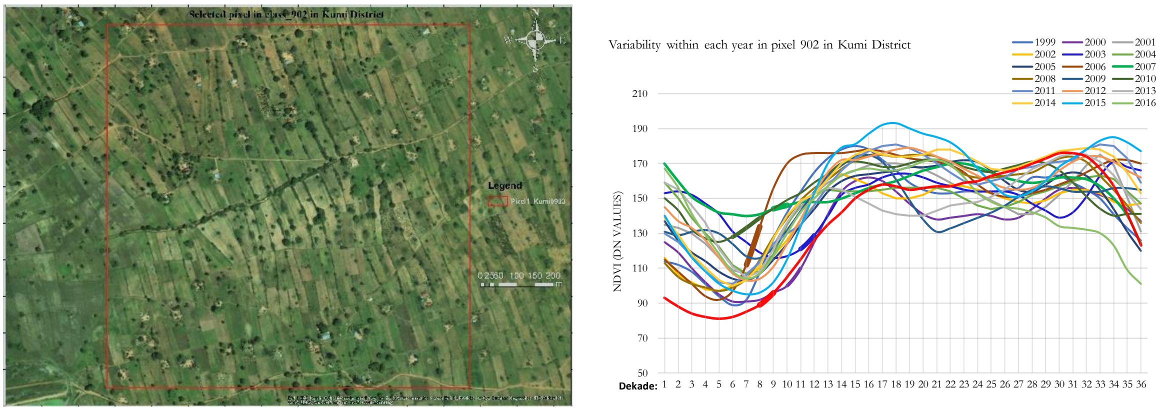

Figure 12: One of the surveyed pixels in class 9 and its temporal variation for the years 1999-2016

In selecting pixels with more 25km2 of cropland area, we eliminate the possibility of polluted pixels being included in the analysis which would otherwise affect the results. It was further noted that even within a class there were temporal variations within selected pixels, this points to the contribution of localized climatic drivers.

4.2.3. Field surveyed area

The field sites covered administrative districts of Soroti, Pallisa, & Kumi districts in the eastern and Kole & Dokolo district in central northern regions of Uganda. The surveyed areas points are represented in Figure 13; fields data were collected from 72 crop fields corresponding to the number of farmers interviewed. Soroti district surveyed pixel belongs to NDVI class no.9, with 25 sites (4 pixels) in Soroti and 15 (3 pixels) in Kumi, meanwhile in Pallisa the surveyed site is part of class 13 and only two pixels were covered with the first pixel having 5 sites all of which were used for pretesting the questionnaire and the last covering four sites. On the other hand, in the central north, in Kole covered by class 14(3pixel) and Dokolo (3) class had 15 sites that were surveyed

The map below gives spatial details of the surveyed sites within Uganda from which field information was collected

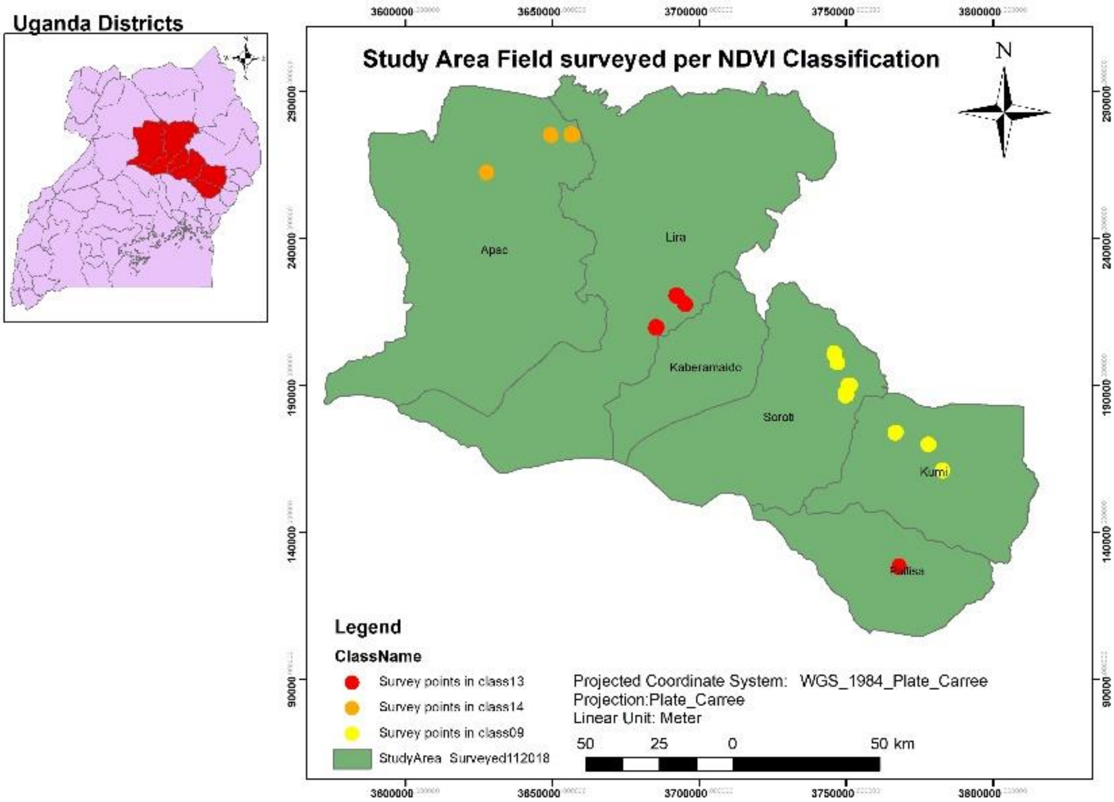

Figure 13: Location of surveyed pixels per NDVI class

4.3. Farming Experience and Perception on Start of Growing Season

4.3.1. Farmer's definition of the onset of the season

To understand farmers perspective on the start of the growing season and the beginning of rainy season, farmers were asked separate questions on this aspect. They provided general information on SoS over the last 19 years in relation to their cropping practices. In the **Appendix table 2**, we note that 42 % of farmers interviewed in all the districts covered, reported that the usual onset of the rainy season is in dekad 8, 10% saying it is in dekad 7, 17% in dekad 9. When referring to the start of the growing season, 67% states that the SoS is between the 7th-11th dekad and others referring to 4th, 5th and 6th dekad. This disparity is likely due to the cropping activities by farmers, for example, those who start preparing the land prior to rainfall onset regards it as the SoS and this may be the associated with dry planting as is for millet. Significantly this definitions and perception varied from one location to another as is shown **Appendix figure 3.**

Further analysis revealed that there is a relationship between SoS and cropping practices. For example, the farmers who referred to the start of rains to be in February mainly planted millets that rely on the short and less intense rains that are used for dry planting, while majority planting maize, beans and Gnuts mainly refer to the SoS as associated to rainfall onset (Appendix figure 7). Accordingly, in this study, we focus more on the start of the rainy season as a determinant of the start of the growing season because of the relationship between the two concepts as defined by the farmers. The small variation here acknowledged.

4.3.2. Long term variability in the onset of the growing season

During the interview process, the farmers were asked whether within a particular year the SoS was normal, early or late and proceeding to probe whether it was a true or false start. The variability component is indicative of when the farmers commence their farming activities or are at risk of the effect of a false start.

The **Appendix figure 4**, indicates that the onset of the season has been typical for most of the years according to farmers recall, strikingly as revealed **Appendix table 1**; the years 2003, 2006,2010,2013,2016 and 2017 were identified by atleast 10% of the respondents as years during which the SoS was early. The years 2015, 2016, 2017 were identified by a 32%, 40% and 43% of farmers respectively as years of late SoS, although atleast 10% of the farmers also reported the year 2006, 2007 and 2012.

A close analysis of the last three years, we note an almost equal number of farmers reporting the normal onset versus late onset, while comparatively, a ratio of 1:2 reporting late to early onset. This finding aligns with the study done by Okonya, Syndikus, & Kroschel (2013) across six agro-ecological zones of Uganda, with farmers revealing that they were experiencing an early and late start of SoS recently. In the same study, 47.6% percentage of farmers reported late start, while 47.1% noticed early SoS. These perceptions provided by farmers is by no doubt dependent on farmers ability to recall the long-term onset date, hence having an influence on the recall recorded.

On the other hand, there was the perception of Fsos, a phenomenon where farmers explained that it would start raining normally and later after they have planted, the rains retreat into dry spell affecting their planted crops. The false start years are reported **in Figure 14**, showing its relationship with the timing of the season. In this regard, 15 farmers reported Fsos in the year 2009, 5 farmers reporting that it occurred in both the year 2012, 2013& 2014 and 14, 16,18 farmers reporting it occurred in the years 2015, 2016, 2017respectively. Statistically these numbers are low, however, by the fact that among the interviewed farmers, reports of false start have been highlighted, this brings out information that was probably not remembered by other farmers due to poor memory or because they did not suffer the effects of false start having avoided it by planting late.

The variability in the responses generated from farmers has been underscored further by Simelton et al. (2011) where they state that "bad year for one farmer may be a good one for another.", Thus different experiences inform recall of the farmers. On the other hand, farmers rarely keep weather related records and therefore relies on their ability to recall and thus a temporal window as is considered in this study would present challenges to them. This was proven as we noted that farmers had better recall of weather event in the close five years from the current one, this is probably because the event is still fresh in their memory and impact felt aids the recall process. Specifically, at district level there exist variation in the time and characteristic on the SoS**,** in the **Appendix figure 5,** suggesting the contribution of the local factors in the SoS and above all overall weather condition experienced in such districts.

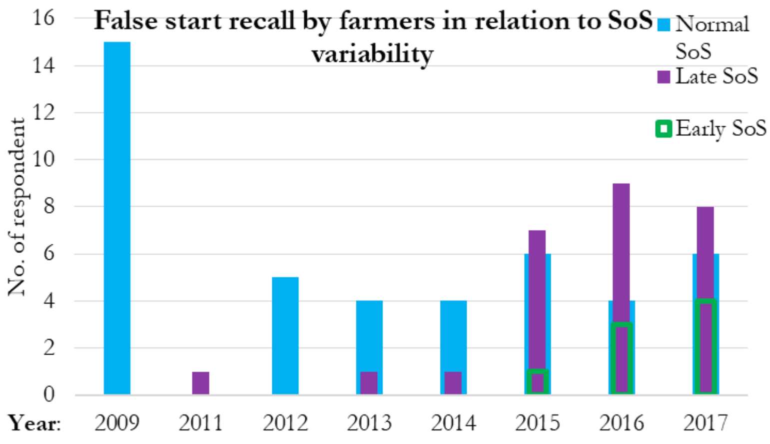

Figure 14: Years during which farmers recalled the occurrence of the false start

4.3.3. Cropping practices and cropping calendar

Farmers were interview on the three major crops that are grown in a crop field of the reference during the first planting season. Thus every farmer gave atleast 2 crops commonly grown in that field. This information was collected at a pixel and crop field level. The common crops reported from the interview varied from district to district, although within one district, farmers tend to grow similar types of crops **(Appendix figure 6)**. The farmers in Dokolo for example mainly grow maize, cassava, beans, millet & sesame; in Kole the common crops are maize, cassava, beans & soybeans while their counterpart in the eastern region in Soroti commonly plant Gnuts, cassava & millet and those in Kumi grow most farmers plant Gnuts, cassava & millet in this sequence. This crops somewhat influences the timing of cropping activities.

Besides, from section 4.3.1. We note that the start of growing season differs from one location to another, so is the start of farming activities. The start of cropping activities such as land preparation proceeds the start of the rainy season as shown in **Appendix figure 7**. At the district level, in Dokolo for example farmers interviewed start land preparation for crops such as maize, beans, sesame, and cassava start in 2nd, 3rd & 4th dekad respectively until 10th dekad for maize crop. Planting then proceeds from the 6 -12th dekad where mainly cassava is planted. Meanwhile, In Kole district as displayed; land preparation starts in the 3rd dekad until the 10th dekad. Many farmers ensure that their land is ready by 7th dekad to allow them to begin planting in the 7th dekad when they expect the SoS. Planting then starts in the 7th dekad running until 12th dekad. Meanwhile in Kumi district in the; land preparation usually begins in the 2nd dekad until the 9th dekad, this mainly related to millet as a crop that is dry planted in 4th dekad and Gnuts in 5th.

4.3.4. Decision factors farmers base on to start ploughing and planting

The start of cropping activities such as land preparation and planting by farmers are informed by certain factors. The farmers identified the following factors; labour availability, the onset of the rainfall, health of the oxen, crop types, wetness of the soil and 2-3 days of consecutive rainfall as key decision factor that drives them to start ploughing and planting. In Table 7, on a case by case basis, 59.7% of the respondents consider the availability of labour as the most important factor to start land preparation, on the same scales 52.8% regards crop type and 43.1% say its onset of the rains. When all the highlighted factors are integrated, 32.6%, 28.8%,23.5% and 15% of the respondent regards availability of labour, crop type, the onset of the rains and health of oxen respectively as important decision criteria. However, the health of oxen only become significant upon analysis at district level, its mainly a factor for farmers in Soroti district where 52% of farmers interviewed consider it as a factor to start land preparation, while in other districts it's of less importance. This Suggest that oxen ploughing is common among the farmers in Soroti as opposed to the use of hand hoe; hence the health of the oxen is crucial for land preparation to take place.

Labour availability stands out among other factors to drive farmers decision to commence ploughing activities; this is likely because the 1st growing season for Uganda, follows a period of the festive season that starts in December 23rd until 2nd of the new year. During this time most farmers have completed harvesting of 2nd season crops, and therefore most manpower is available and redundant, hence driving their decision to commence land preparation so as to have seedbed ready in time for planting of the crops when rains return.

Table 6: Drivers for the start of ploughing according to farmers

		Responses		
		N	Percent	Percent of Cases
Ploughing decision driving factors	Labour availability	43	32.6%	59.7%
	Onset of rain	31	23.5%	43.1%
	Health of the oxen	20	15.2%	27.8%
	Crop type	38	28.8%	52.8%
Total		132	100.0%	183.3%
a. Dichotomy group tabulated at value 1.				

Table 7: Driving factors for planting according to the farmers interviewed

Planting Frequencies				
		Responses		Percent of Cases
		N	Percent	
Planting Decision driving factors	Onset of rain	42	24.9%	58.3%
	2-3 three days of consecutive rainfall	47	27.8%	65.3%
	Wetness of soils	39	23.1%	54.2%
	Crop type	20	11.8%	27.8%
	Labour availability	21	12.4%	29.2%
Total		169	100.0%	234.7%

The start of planting as indicated in Table 8 is informed mainly by rainy days, with 65.3% of the farmers report 2-3 days of consecutive rainfall as important, 58.3% considers the onset of the rains and 54.2% associating it to the wetness of the soil. When these factors are integrated, 27.8%, 24.9% & 23.1% points 2-3 rainy days, the onset of the rainy season and wetness of soil respectively as important decision factors.

To have a better idea of which factors are most relevant, a rank order list was generated per district according to the numbers of farmers in relation to the identified factors. Primarily for all the districts, availability of labour ranked first except for Dokolo district that had both labour availability and crop type registering the same number of responses (refer to Table 8). While in regards to planting, the main factor is rainfall considering that the factors that ranked first for all the districts. In Table 9 & 10, these factors are linked to rainfall with the wetness of the soil as an important factor for Dokolo, 2-3 days & labour availability for Kole, the onset of the rainy season for Soroti and Kumi District. Since rainfall is the only source of water used to irrigate the crops, it’s no extraordinary that its very vital factor for planting. Meanwhile, labour is also a factor since most of the farmers do not only own a single parcel of farm fields that need to be planted, because of the limited labour, they cannot sow all on the same day, hence priority crops will be planted first.

Table 8: Rank order list of decision factors that informs farmers to start ploughing

Northern Regional districts		Dokolo District		Kole District	
Decision factors		**No. of respondents**	**Rank**	**No. of respondents**	**Rank**
1	Labour availability	8	1	13	1
2	Onset of the rainy season	9	3	7	2
3	Health of the oxen	0	4	3	4
4	Crop type	8	1	5	3
Eastern Regional Districts		**Soroti District**		**Kumi District**	
Decision factors		**No. of respondent**	**Rank**	**No. of respondent**	**Rank**
1	Labour availability	12	3	8	1
2	Onset of rainy season	9	4	6	2
3	Health of the oxen	13	2	3	3
4	Crop type	19	1	3	3

Note Dokolo: Labour availability and crop type, Kole: Labour availability, Soroti: Crop type, Kumi: Labour availability. Pallisa district was not considered since only four farmers were interviewed.

Table 9: Rank order list of decision factors that informs farmers to start planting in Soroti and Kumi

Northern Regional districts		Dokolo District		Kole District	
Decision factors		**No. of respondent**	**Rank**	**No. of respondent**	**Rank**
1	Onset of rainy season	4	3	6	4
2	2-3 three days of consecutive rainfall	10	2	9	1
3	Wetness of the soil	11	1	8	3
4	Crop type	4	3	4	5
5	Labour availability	1	5	9	1

Table 10: Rank order list of decision factors that informs farmers to start planting in Dokolo and Kole

Eastern Regional districts		Soroti District		Kumi District	
Decision factors		**No. of respondent**	**Rank**	**No. of respondents**	**Rank**
1	Onset of rainy season	18	1	11	1
2	2-3 three days of consecutive rainfall	17	2	9	2
3	Wetness of the soil	12	3	6	3
4	Crop type	10	4	2	4
5	Labour availability	9	5	2	4

Key: Green colour indicate highly ranked factors, according to the number of farmers who mentioned it as a factor

4.3.5. Short term detection of the start of the growing season as recalls for the period 2015-2017

In following up to the responses provided for long term recall, a three years window was used to gain specific insight into farmer cropping practices and experienced weather variability within these years, generating information on actual rainy season onset, actual planting date, the experience of false start and impact if affected by Fsos. **Appendix table 3** provides details on the actual onset of the rainy season by district for three years (2015-2016). The start of the rainy season as revealed by farmers was between the 5th -13th dekad. On close analysis, we can conclude that in the year 2015, the rainy season started in the 7th dekad to 10th varying from one district to another, in the year 2016 the rainy season was late by about a dekad as reported by most farmers, in this year, it starts the 8th dekad. In the year 2017, there is an indication that the rains were back early in Dokolo with 3/25 farmers interviewed reporting the start in the 5th dekad and most reporting start in 8th -11th dekad. Overall, we can conclude the start of the season in the surveyed areas are mainly from March (7th dekad) to April (10th dekad). Furthermore, the findings suggest that the year 2015 and 2016, registered normal start of the season, while 2017 had an early start of the season thus an increase in the LGS. A situation as such can be exploited by farmers planting early leading to a timely harvest in a given year; this opportunity may only be taken by farmers who are willing to take the risk hoping that the first rains will remain consistent to support their crops.

Appendix table 4, provides planting date information for the three years. Planting mainly was done between 4-14th dekad, varying from one district to another, with planting in the year 2015 starting in 8th - 12th dekad although 3 farmers in Soroti planted late in the 13th dekad mainly related to cassava as a crop type. In the year 2016, the start of planting was from 5th -12th dekad, with 12/30 farmers interviewed from the north planting in the 9th dekad while 16/37 in the eastern region sow their seeds in the 11th and 12th dekad with other 5 and 3 planting in 8th, 13th dekad respectively. This pattern is consistent with results in **Figure 14** that points the year 2016 to have had late onset of the season. The year 2017 saw farmers commence planting as early as the 7th through to the 12th dekad in all the surveyed areas since rains were early

Finally as a verification of historical seasonal onset information provided by a farmers, a box and whisker plots (where S_ploughing=ploughing dates, G_SOR=long term recall of the start of rainy season, planting=long term recall of start of planting , S_planting= start of planting generated from the three considered years) was used to compare with the information derived from the three years specific data. In Figure 15, we note that the long-term historical information provided by farmers in Dokolo show SoS in the 5th dekad with small range compared to that derived in three years where SoS is in the 4th and larger range until 12th dekad. Regarding planting, there is agreement on the earliest start date of planting with that of three indicating planting was done until 13th dekad. In general terms the farmers in Dokolo delay to start planting after the onset of the rains, implying in the event of dry spell immediately after the rains, they are likely to escape the risk associated with such dryness.

Meanwhile, in Figure 16, there is an agreement in the earliest start date for both SoS and when farmers start planting. Strikingly the minimum and maximum date revealed by the long term SoS and SoS short term intersect and so is the range of start of planting. We observe that some farmers in Kole start planting immediately after the rains, this exposes them to higher risk in the event of dry spell following the onset of rains, these farmers may loose their crops due to the failure of germination or wilting resulting from this low soil moisture. They may become frustrated, foregoing production activity for that season as they wait for the next planting season.

On the other, in the eastern districts as shown in Figure 17&18, the SoS in usually earlier (4th dekad) in Soroti than in Kumi (5th dekad), while the farmers in Kumi starts land preparation earlier than farmers Soroti. There is an agreement in the earliest start date of SoS (4th dekad) between the long term and short-term reporting in Soroti with a dekad deviation between the earliest date and latest of planting. Meanwhile, in Kumi, there is a dekad deviation in SoS earliest date ($5^{th}/6^{th}$ dekad) and two-dekad deviation for the latest SoS date ($9^{th}/11^{th}$ dekad). However, both long term and short-term earliest planting date are the same (5^{th} dekad) with a dekad deviation in the latest planting date ($12^{th}/13^{th}$). Importantly for these two districts is that farmers tend to plant immediately after onset of the rains, this exposes them to high risk if it is a Fsos.

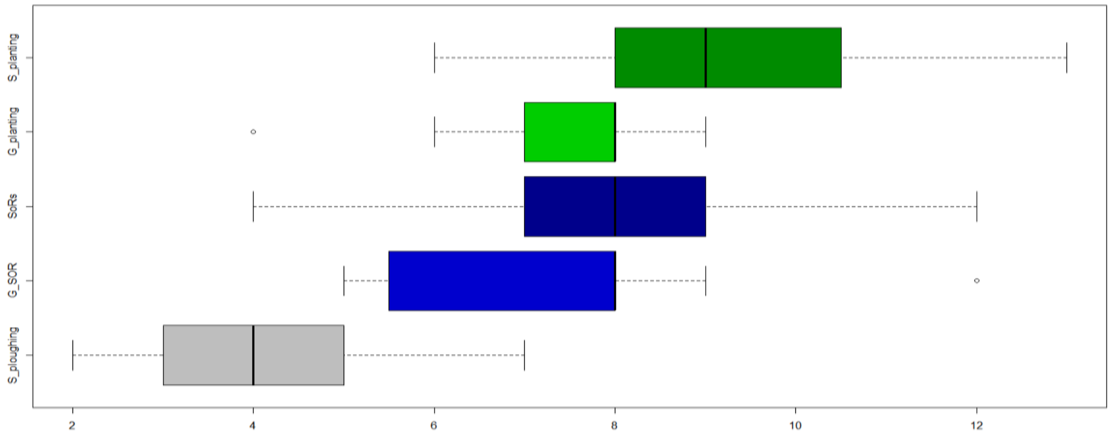

Figure 15: Comparison of the long-term farmer recall of start of the season and planting, with the inclusion of generally derived information of land preparation in Dokolo district

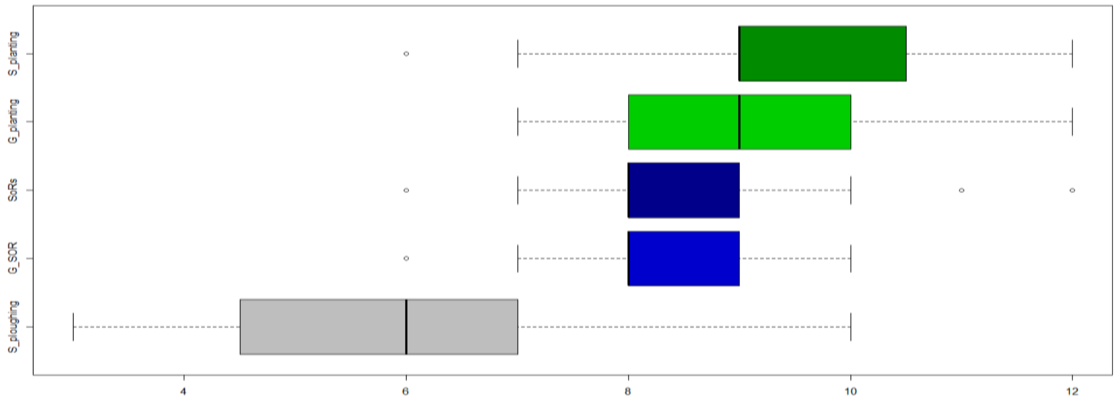

Figure 16: Comparison of the long-term farmer recall of start of the season and planting, with the inclusion of generally derived information of land preparation in Kole district

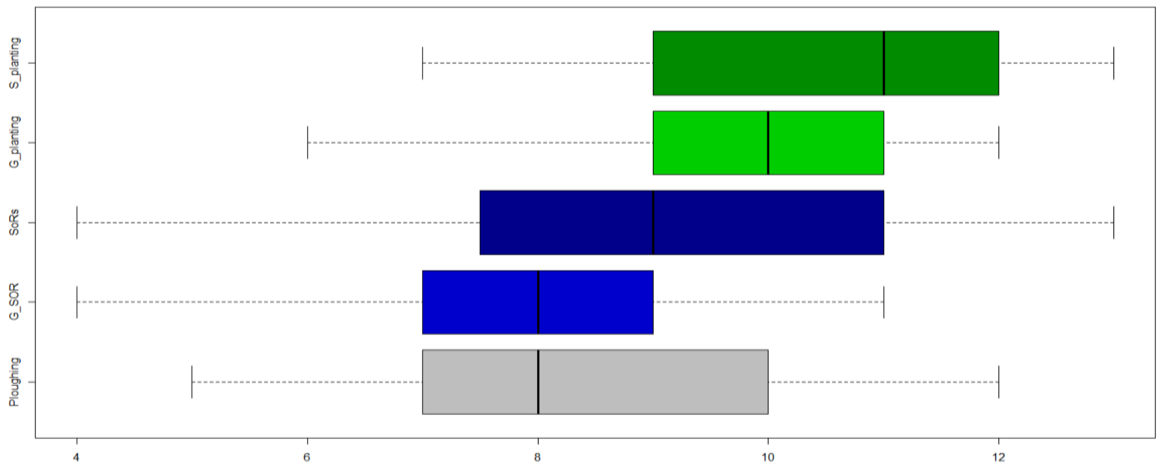

Figure 17: Comparison of the long-term farmer recall of start of the season and planting, with the inclusion of generally derived information of land preparation in Soroti district

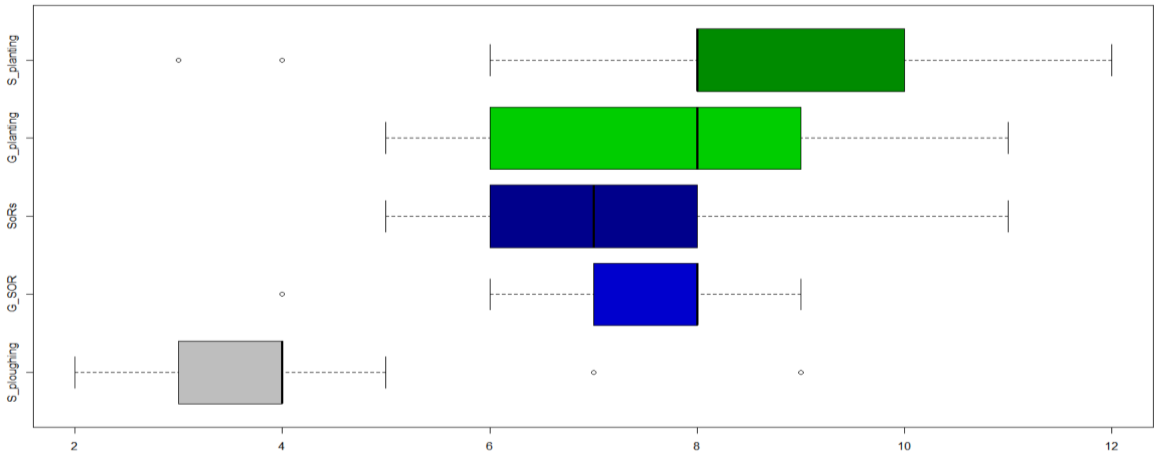

Figure 18: Comparison of the long-term farmer recall of start of the season and planting, with the inclusion of generally derived information of land preparation in Kumi district

Reflecting on the revealed information, we realize that the median for the SoS identified by farmers is dekad 8, this is consistent with the analysis conducted for a closes gauge station of Serere that indicate 16th pentad as median onset and planting window 12th -20th pentad (6-10th dekad)(Botai & Combrinck, 2012). These findings are inferred in the NDVI SoS reveal information where the mean is the 9th dekad for the 14 pixels surveyed, pointing out vegetation development following rainfall onset. Additionally, during this window, the sun is overhead the equator triggering radiation impact on land surface and atmospheric clouds to drop as rainfall.

According to a study conducted by Kansiime, Wambugu, & Shisanya (2013) in Lake Kyoga basin, the farmers reported that they had had late onset of the season in recent years, emphasizing that the first planting season of MAM had had its onset shifting from early March to late March. These findings align to that of this study where from the year 2005-2017 farmers in Soroti and Kumi reported the late onset of the season. The years 2012, 2014, 2015, 2015 and 2017 had 25% of farmers interviewed in these areas reporting late onset, 17% reporting an early start while 58% reporting season to have been typical. The farmers further point out that there is an increasing problem of a dry spell during the start of the season and sometimes flash floods in other years this suggest increased risk during the production period over the years

The perception of farmers about onset variability corresponds to the information revealed by the rainfall data, pointing to early SoS, late SoS and Fsos in some years. We noted that from the 14 pixels surveyed that, there were variations in the way farmers experience the onset of the season and a pixel analysis of the SoS proved the same with an early onset as 6th and late SoS as the 11th dekad and standard deviation of 1.22 dekads.

Accordingly, the perception of farmers on variability on the SoS as identified in this research are in tandem with related work on the same subject. Example, in studies conducted in Uganda; (Osbahr, Dorward, Stern, & Cooper, 2011), (Okonya et al., 2013), farmer perception points out that temperature is increasing and seasonal variation that has made first season unreliable and less favourable for crop production. Other studies around Africa like one by Simelton et al. (2013); Reason et al., (2005) in south Africa assessed the perception of farmers about onset, duration and cessation exploring the degree and frequency of characterized variability. The farmers in Southern Africa reported the shift in the onset and that it is becoming unpredictable, highlighting the occurrence dry spell after planting. In West Africa similar studies (Sobowale et al., 2016; Laux et al., 2009; Odenkunle, 2004).

The implication of this variability is the direct impact on crop productivity. The late onset of the season results in shortening of the growing season; therefore only crops with short growing periods can be grown during search time. Furthermore in this study we note that dry spell after planting is really damaging to the farmers because they start sowing almost immediately after the rainfall onset. If the rains stop they will loose the seeds and many cannot afford to replant for the second time thereby no production in such a planting season leading an overall low crop production in such an area (Salack et al., 2015). Evidently from this study, in the year 2016 only two out 13 farmers who were affected by Fsos, indicated they carried out replanting. This made analysis about replanting impossible as several farmers that were reportedly affected did not replant.

In relation to the seasonality information, its inferred that there is a relationship between the cropping practices among farmers from different areas. This is not surprising, agro-ecological zoning includes an aspect of local climatic variability in its delineation, thus the existing cropping practice. Two facts are noteworthy, first; that across the different districts land preparation tends to commence prior to the onset of the season and planting proceeds the onset, this is only logical that it follows this sequence. Secondly, different areas have different major crops, therefore will suffer differently the impacts relating to the variability in the onset of the growing season. The differences in the crops planted is arguably determined by the local climatic condition, elevation, slope and soil characteristic, where certain types of crops will thrive better than others.

4.4. Deriving False start of the season Definition

4.4.1. Comparison between NDVI, CHIRPS and Farmer Recall

A qualitative approach was adopted in comparing of the NDVI; rainfall revealed information and farmer recall data for the years 2015-2017. In the **Tables 11,** we note that only 43% (31 farmers) of farmers interviewed were able to provide Fsos information in the three years and from them, 42%, 48% and 58% reported Fsos in the year 2015, 2016 and 2017 respectively. The low number of farmers reporting Fsos is likely due to the inability of the farmers to recall long term historical events. Farmers do not usually keep records of weather variability but instead relies on memory. Recall of events is particularly possible especially when a risk scenario occurred, in which case it remains stack in their minds. Majority of the farmers that reported these phenomena did not suffer its impact, its therefore likely that they were able to correctly identify it and delay their planting activities, thus avoiding the risk associated with the short-term dry spell that prevailed in these years. This is observable from (**Appendix table 6**), were farmers who reported Fsos, ended up planting their crops from the 10-12th dekad in the year 2016 that had a Fsos.

Table 11: Three-years farmer identification of the occurrence of false start of the season

	False start reporting by the farmer (2015-2017)		
	Year 2015	Year 2016	Year 2017
False start	13	15	18
No false start	18	16	13
%age when considering false start reporting	42%	48%	58%
Overall %age over all the farmer interviewed	18%	21%	25%

Furthermore, the **Figure 19** indicates that in the 7th dekad of the year 2016 up to 31.26 mm accumulate rainfall was received, this triggered start of the season and likely drove farmers into planting of their crops, yet also in the same figure we observed that in the next dekad (8th) only total of 1.28mm of rainfall was accumulated. This suggests that the SoS in the 7th dekad is a false onset. A situation like this will be problematic when farmers plant, their crops are likely to fail to germinate due to inadequate moisture availability, thus resulting in loss of seeds.

Inspite of the receipt of rainfall of inadequate amount in 7th dekad, we observe that the NDVI values remain low and only started to rise in the 10th dekad. Thus suggesting that either farmer did not plant immediately in this area following the onset or that the planted crops suffered from stress and never germinated or wilted out immediately after thus no lag response resulting in observed low mean NDVI values pixels, in which Fsos occurred. Alternatively, correct detection by farmers or the risk-averse nature of farmers could be likely explanation of the no response from NDVI. These findings suggest that it would be very challenging to use NDVI in the detection of the false start of the growing season, however where Fsos corresponds to an early start, there is a strong relationship between Fsos and late SoS in a particular year. This fact is supported by results from **Table 13** where onset on 6,7 and 8th dekad are strongly associated with Fsos and thus leading to the late onset of the rainfall. In regards to this, the other school of thought highlighted by Geerken, Zaitchik, & Evans (2005) points out the possibility of the signal to noise ratio resulting into the irregular patterns in the NDVI profile. Pointing it to have links to the intermittent rainfalls that is followed by dry spell that would eventually affect plant growth and if the short rainfall retreat is at the onset of the growing season it would be possible to associate it to Fsos. Additionally Jury (2018) highlights that the vegetation sensitivity in Uganda for MAM is low, thereby having the potential influence on the initial response of rainfall to the short variability (Fsos) investigated in this study.

Interestingly, two farmers from the pixel represented by **Figure 19** correctly reported Fsos in the year 2016, with one who planted millet to have been affected severely, while farmer that planted Gnuts had poor germination. Meanwhile, among those that did not have successful germination (**Appendix figures 8**), only two carried out replanting while the rest opted to prepare their garden waiting for the next planting season, this according to them was due to limited labour that had to be directed into another crop fields.

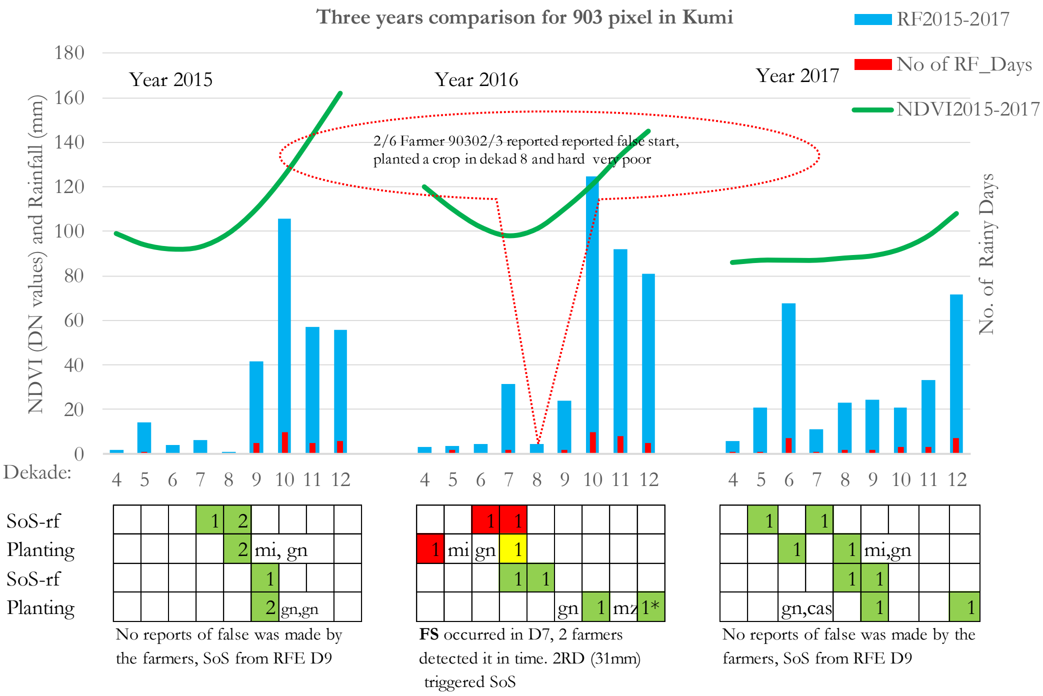

Figure 19: Relationship between NDVI and rainfall revealed information

As presented in **Table 20**, 12.9% who reported Fsos had poor germination, 14.0% had 50% success in emergence while 73.1% did register successful germination, this is probably because most farmers interviewed were able to detect and avoid the Fsos correctly. However, it important to note that, since only six farmers were interviewed per pixel, we cannot conclude the degree Fsos had on the farmers within this pixel.

Impact table

	Poor germination	50% germination	Successful germination
No of responses in three years	12	13	68
Percentage of responses	12.9%	14.0%	73.1%

Figure 20: Report on the impact of false start according to the farmers affected by Fsos

Strikingly for all the surveyed pixels (**Appendix figure 8**) in all the districts, the year 2017 had the season starting early in 6th dekad remaining consistent throughout the dekad with no indication of Fsos. We further note the inconsistency between the farmers recall of the occurrence of Fsos to that revealed by the satellite product in the year 2015 and 2017 were farmers in pixels 901, 902, 906, 1303, 1403 (the year 2015) and 906,1304, 1403, 1404 (the year 2017) wrongly reported Fsos. Example of this is illustrated in **Figure 21**, In the year 2015, two farmers wrongly identified Fsos in dekad 8th, yet in the previous two-dekad, no rainy days were registered, although a relatively low amount of rainfall of 3mm, 5mm in 6th & 7th dekad respectively were received. For these farmers, there are high chances that they were gambling and/or taking the risk, which did not pay off since the amount of rainfall received continued to be lower in 8th dekad thus their maize and sorghum failed to germinate. The actual SoS was in the 9th dekad for which the other two farmers planted and had successful germination of their crops.

Notably in the year 2016 for this pixel there was an early SoS in 7th dekad and farmers did not report any problem associated with Fsos. While in the year 2017 the season as early as the 6th dekad, however, farmers waited until 8th dekad to start planting, this may be attributable to the decision made by the farmers not to plant immediately following onset of the rains as is revealed in **Appendix table 6** . The existence of spatial variability even at pixel levels in the case of Kumi district have been revealed in this comparative analysis, that at district level different place will have different onset date, for example while in pixel 902 (**Appendix figure 8**) the SoS in the year 2016 was 7th dekad, in **Figure 21**, the 7th dekad was a Fsos, it was followed immediately by dry spell in dekad 8th with no rains. Therefore, farmers who planted in the 7th dekad were affected by the dry spell that occurred. This points to the fact that local factors have an influence on the rainfall events and thus the timing of the SoS will vary even at low tier localize area.

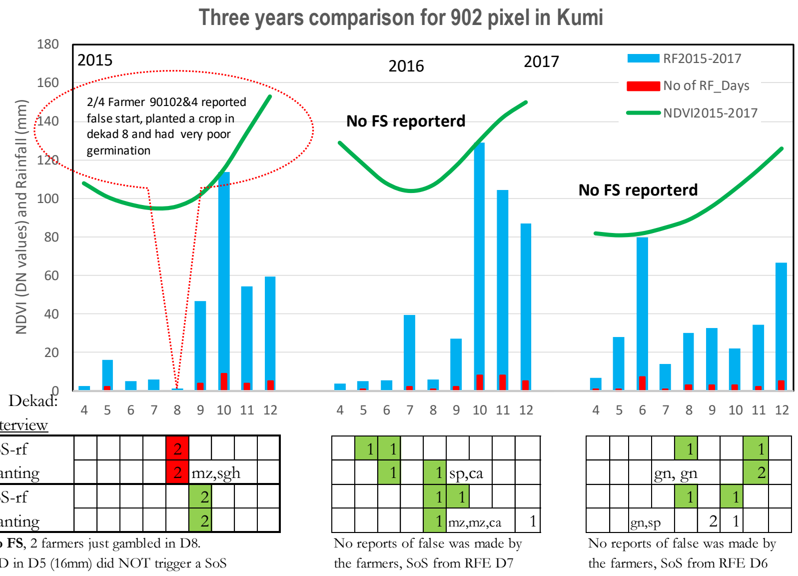

Figure 21: Comparison between farmer reported information and that revealed by remote sensing products

Finally, as shown in **Table 12,** we note that the SoS, planting date and crops types significantly influences farmers identification of Fsos. Fisher's exact test indicates p-value of 0.018 for SoS, 0.006 for both planting date and crops type. These results suggest that planting date and crop types are most important in influencing farmers recall of Fsos, perhaps this is because the effect of this phenomena is felt following planting where farmers fail to identify the onset as a false start.

Table 12: Statistic test for the influencing of farmer crop practices and SoS on identification Fsos

Variables	Fishers Exact test	DF	P_value	Decision
SoS (by farmers)	17.16	08	0.018	Reject the null
Planting date	20.74	09	0.006	Reject the null
Crop type	20.80	09	0.006	Reject the null

4.4.2. Definition of the false start of the growing season

In using the integrate information derived from the 14-pixel analysis, definition of the false start was arrived at with the 6th dekad as the initial date on which in a given year the season would start. The 6th dekad is taken because any rainfall occurring prior to this date is assumed not to be the onset of the season, it's expected that there will be a dry spell following it. It's also based on historical records and definition of the start of the season of Uganda that is usually between March and April.

Rainy days in a given dekad other than rainfall events were used to define the Fsos where following criteria of atleast two rainy days in a given dekad and less no rainy day (RD) in two subsequent dekads
Where RD is defined as the day on which more than 5mm of rainfall is received. The threshold of above 5mm/day of rainfall was arrived at in relation to average reference evapotranspiration (ETo) for Uganda that lies in the latitude 1.2 South to 4.5 North. Additionally, a threshold of atleast two rainy days for the whole country allowed for detection of SoS triggers including in the semi-arid regions (Karamoja) of Uganda and accounting for farmers perception of 2-3days of rainfall that drives their planting decision. This would otherwise have been a challenge if the method of Sivakumar (1988) was applied, where a threshold of atleast 20mm in 3 days would be required, this problem has been pointed out by (Ati, Stigter, & Oladipo, 2002)

4.5. Detection and quantification of false start (1999-2017)

4.5.1. Detection of False start, SoS & rainy days in the 19 years

The equation derived in section 4.4.2 was applied for each pixel to identify the 1st dekad of SoS and analyze such a date for Fsos or a true start of the season. In **Table 13**, generally, all the years where affected by the Fsos, with the spatial extent varying from one year to another. The table display with green to read depicts good to worst years, with the latter indicating a more significant percentage of the pixels are affected by Fsos. The year 2002, 2003 and 2016 were the most affected according to the findings, having 32%, 37% and 46% proportion of pixels respectively were affected. Meanwhile, the year 1999, 2009, 2010,2011 and 2013 indicate an insignificant number of pixels where affected. **Appendix figure 9**, provides an insight into the yearly spatial occurrence of Fsos.

Table 13: The proportion of pixels and frequency of occurrence of Fsos from the year 1999-2017

	No. of pixels			Proportion in Percentage	
Years	**FSoS**	**SoS**	**Total**	**Fsos**	**SoS**
1999	38	6780	6818	1%	99%
2000	603	6122	6725	9%	91%
2001	525	6291	6816	8%	92%
2002	2203	4615	6818	32%	68%
2003	2550	4268	6818	37%	63%
2004	1007	5811	6818	15%	85%
2005	611	6182	6793	9%	91%
2006	404	6414	6818	6%	94%
2007	1062	5730	6792	16%	84%
2008	1164	5645	6809	17%	83%
2009	178	6637	6815	3%	97%
2010	168	6650	6818	2%	98%
2011	141	6652	6793	2%	98%
2012	1292	5526	6818	19%	81%
2013	65	6753	6818	1%	99%
2014	491	6324	6815	7%	93%
2015	706	6112	6818	10%	90%
2016	3153	3665	6818	46%	54%
2017	1736	5001	6737	26%	74%

Accordingly focusing on the dates, it alludes to a relationship between Fsos occurrence and early or normal SoS and not late start. In **Table 14,** it indicates that majority of pixel affected by Fsos, had SoS 1st date between the 6 to 9th dekad, with the year 2002 event relating to 7th dekad, while 2003 in 9th and 2016 in 7th. Consequently, the years characterized by Fsos will possibly result in late SoS in a given area, although the late start of the season may also be due to an extended dry spell into the start of the growing season in a given year.

Table 14: Dekads in the 19-year period frequently associated with Fsos

	Dekad						
Year	**6**	**7**	**8**	**9**	**10**	**11**	**Total**
2002	0	2187	1	15	0	0	2203
2003	864	19	0	1667	0	0	2550
2007	49	8	997	7	1	0	1062
2008	0	113	0	1051	0	0	1164
2012	4	1234	54	0	0	0	1292
2016	0	3153	0	0	0	0	3153
2017	1353	16	0	367	0	0	1736

4.5.2. Mapping of areas affected by Fsos

In the **Figure 22**, we observe that Fsos during the first planting season frequently occurred in the northern part of the country with some areas having experience atleast 10 times in the last 19 years (0.53) and it is in these regions that the Fsos date is usually from the 7-9th dekad, while the significant crop covers are mosaic cropland composing of 50-70% of pure crop cover. The North Eastern part had the most frequent occurrence of Fsos compared to the rest of the country, notably this area coincides with the dryland areas classified as the part of the cattle corridors, frequently suffering from drought and thus highly prone to rainfall variability. Comparatively, analysis by Netherlands Space Office (2019), that mapped out areas at risk of dry spell for overall growing season for Uganda (**Appendix figure 10**), show a correlation with our results, in that the areas identified to be at high risk has a high probability of Fsos and Southern western having low risk characterised by low probability.

These findings complement the argument put forward by Orindi V A and Eriksen S (2005) that the SoS for northern Uganda is highly variable and uncertain. The Fsos occurrence is therefore conceivably a major contributor to the variation being experienced, thus creating conflict with the known farmers cropping calendar and affecting yields. Additionally, areas around the major water bodies also as seen from the figure frequently experience this risk and are mainly associated with early onset, this includes a section of the surveyed areas in which reports of Fsos where recorded for the year 2016 and 2017 by few farmers. Comparatively, in Nigeria, the timing Fsos is usually on dates before the long term mean onset (Benoit, 1977) as its observed in the SoS trigger dates.

The ITCZ has significant influence in the onset and duration of rainfall in Uganda, with the movement towards the north during the MAM season, accordingly, because of its sensitivity to the variability of the Indian Ocean sea surface temperature that varies annually, it alludes to a relation with Fsos (Karmalkar, Mcsweeney, New, & Lizcano, 2012).

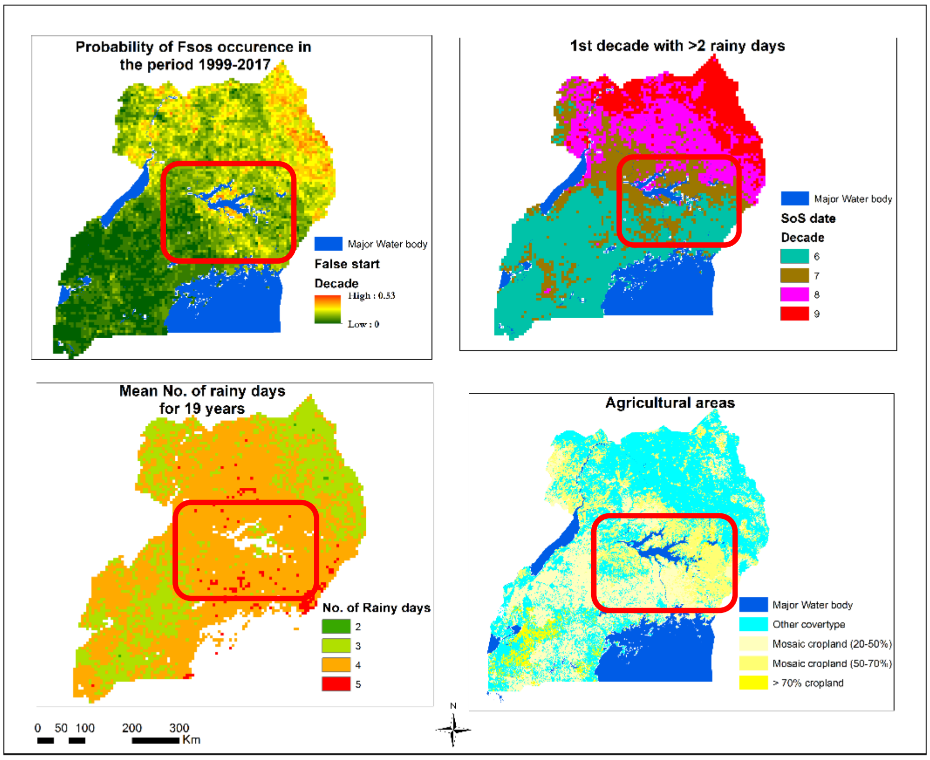

Figure 22: Comparison of probability of Fsos, it is timing in relation to the cropping areas affected by the event in a given year

From the **Figure 22**, we note that the probability of occurrence of Fsos in mainly higher in the Northern part of the country, with highest being in the North Eastern part that constitutes the semi-arid Karamoja region. This suggests that the farmers within this region are often confronted with this risky, the rains are very tempting to farmers and failure to correctly identify that it's a Fsos puts them in great jeopardy if the triggered SoS is not proceeded by sustained rainfall to support the planted crops. The implication of this will be frustration due to not only the loss of seeds but the wastage labour and capital investment placed towards planting the crops but above all, it will influence the length of the growing season, shortening it. Additionally, from the same figure as pointed out by the red boxes, there is evidence that start of rainy season in the 7-9th dekad following 4 rainy days are associated with Fsos compared with the 6th dekad.

Coincidentally the areas with frequent Fsos falls in the areas indicated in **Figure 9** as being at risk of a dry spell during the SoS; this suggests that the risk identified in the section 4.1.3 is perhaps associated to the Fsos. Furthermore, the areas around the major water bodies as indicated in a red box in **Figure 22** also registered a relatively high probability of Fsos; this points to probably the relation between seasonal variation and lakes forces. It is known that the seasonal rainfall total decreases with distance from the lakes, thus areas around the Lake Victoria and Kyoga are often characterized by higher rainfall seasonal total compared to other parts of the country. The Fsos is possibly due to the early arrival of ITCZ that results in early onset followed by early cessation whose drivers to this point unknown.

4.6. Reflection on results, methods, data and assumption

In this study, we acknowledge that in principle most meteorological definition of SoS relies on a threshold of 20mm in two or three days. However, farmers rarely have access to such information and/or apply such a threshold to inform their decision to start planting. Local forecast by experienced farmers, observations, generally practice long term cropping calendar and available agricultural extension services guides their addition on deciding whether its actual SoS or Fsos, suggesting possible planting dates. From the interviews conducted farmers enlisted factors they consider in deciding when to start ploughing and planting as the season begins discussed in section 4.2.

At the initial stage of the growing season, the farmers often have their land ready for planting in Uganda, this has been revealed in **Appendix figure 7**, they are waiting for a start of the season signal. The farmers are however conscious that the success of germination of their crops is reliant on the amount of rainfall and consistency in terms of rainy days, thus use indicators to guide their decision to plant. Additionally, other factors such; crop type, climatic condition (soil environment), the planting date are essential factors and later this determines the effective crop cover during the initial stage of crop development. Therefore, the occurrence of a dry spell after planting of crops will result into wastage energy stored by the seed as it attempts to transit into the vegetative stage and once the energy has been exhausted, the seed eventually dies, thereby failing to germinate, thus the definition of Fsos.

We further observed that the risk of farmers falling for or being fooled is higher when there is a higher probability of Fsos in a given location when SoS date is 7th, 8th or 9th dekad accompanied by atleast 3 rainy days within in that dekad. This is not surprising since farmers are looking for certainty and often less willing to take risk; thus, the number of rainy days and onset date plays a very critical role in their decision to commence planting activities. Farmers are easily canned in these dekads' because they coincide with the normal onset of the season which has been revealed in **Appendix figure 8** according to the farmers, supported by (Okonya et al., 2013)

We used the long term dekadal mean standard deviation, 10th, 50th, and 90th percentile for 19 years 1km*1km resolution NDVI to stratify and map areas at risk of a dry spell during the onset of the growing season. The approach revealed areas within Uganda that are at risk and differentiating those at risk during the primary growing season (MAM), 2nd growing season (SON) and those at risk through the growing season for the 19 years considered in the analysis. In comparison to other studies, we note that the North Eastern and Eastern part of the country as has been revealed by this study have been found to be at risk of a dry spell (Nakalembe, 2018; Kansiime, Wambugu, Shisanya, et al., 2013). However, these results can be validated by conducting studies using long term records of dry spell during the primary growing season, determining the timing, duration and frequency and exploring the potential impact it had on crop production. Limitation of the approach used in mapping the dry spell risk here is that we cannot conclude on the timing of the dry spell with certainty, although we can conclude that the risk is higher between the 6-10th dekad for the main growing season and 21-25th for the 2nd growing season. Using this approach also we cannot determine the frequency of the occurrence of a dry spell in the 19 years. To determine the frequency using the same data a separate approach is recommended.

While we used dekadal NDVI time series dataset in this study to map out areas at risk of a dry spell, it is also possible to use gauge station historical data to achieve the same output since in situ data are considered more accurate compared to model data. However, this is challenging for Uganda where there is a limited network of gauge station and its associated data consistency.

Effort was made to derive the criteria for the definition of false start of the growing season by comparing NDVI, CHIRPS and farmer recall data for the three years (2015-2017). One striking findings was the year 2016 for all the fourteen pixel, where the rainfall estimate revealed the occurrence of Fsos in dekad 7 with farmers correctly identifying this dekad as Fsos, however the NDVI did show a rise from the minimum value. In this scenario, correct detection by farmers imply they were able to delay planting as they waited for the actual onset of the season, hence its this decision by the farmers that explains the delayed response of the NDVI as is expected in the 8th dekad.

Through this comparative analysis, a definition of Fsos was arrived at which we used to map the areas affected by Fsos, 1st dekad of SoS and the corresponding number of rainy days leading to the SoS date for each of the 19 years. This definition facilitated the generation of probability maps for Fsos for the Uganda and associate means SoS dates and mean the number of rainy days. We noted that the 1st date occurred between the 6-9th dekad which is the window period for start of the season in most part of the country, hence suggesting the occurrence of Fsos around these dates, it would be highly likely for farmers to be duped into planting. Challenge however was that we could not calculate the accuracy of the detection of 1st SoS dates, where it could also be that our definition was detecting early SoS dates. However, on checking Fsos corresponding dates with rainfall amount below 15mm, we noted that the years with the highest early detection in the 6th dekad was the year 2003 with 50% of Fsos detected pixels. Notably, this opens up an opportunity for a validation study in respect of Fsos mapping and monitoring

Admissibly, farmers knowledge plays a role in the detection of Fsos as it is in this study, the number of rainy days is vital to them other than rainfall amount. By comparing both farmers recall data and quantitative data, we hard opportunity to explore agreement and existing disagreement, such as aspect of wrong detection of Fsos in the years 2015 and 2017 thus opening potential new opportunities for further investigation to explore and understand what could possibly have influenced their recall or what other factor affected crop production that prompted the farmers to identify it as a Fsos.

5. CONCLUSIONS AND RECOMMENDATIONS

This study was set out to provide evidence on the occurrence of Fsos in light of reports by the farmers in Uganda. Both farmer's indigenous knowledge and remote sensing products were applied in answering the research questions. We proposed an approach to define Fsos that builds on the characterization of areas at risk at the onset of the growing season using atleast 2 rainy days followed no rainy days in the subsequent two dekads to detect Fsos. We applied statistic parameters (SD, 10^{th}, 50^{th} & 90^{th} percentiles) and demonstrated the strength of statistic parameters in mapping areas at risk of dry spell during the onset of the season. Thus, providing a framework for the detection of the occurrence of false start in the first planting season in Uganda, a phenomenon that critically hampers crop productivity and affects general livelihood of the farming community. Using ISODATA classification, 25 classes were generated and grouped into five categories in relation to the risk of a dry spell during the onset of the growing season. This revealed that 70.6% of cropland areas are at risk and indicating that almost all regions in Uganda are at risk of dry spell during the onset of the season, although the timing and severity vary from place to place. This could be due to influence the ITCZ to have across the country, were areas close to the equator are less affected by the Fsos and rainfall onset tends to be early. Associating this to seasonality variation, 8.8% of the cropland was found to be at risk of dry spell in two planting seasons, 58.1% of the extended monomodal season display at risk of dry spell during the 1^{st} planting meanwhile 3.7% of bimodal seasonality is at risk mainly in the 2^{nd} planting season and on the other hand 6.2% of bimodal season behavours showed no signs of risk.

Farmers were interviewed on the variability at the onset of the growing season and asked to identify years during which they experience Fsos. The field survey information was compared with satellite data allowing local farmer narratives to play a role in the definition of the false start of the season. From the field survey data and comparative analysis; farmers indicated that there is variation in the onset of the growing season, characterized by early, late or occurrence of Fsos as opposed to normal rainy season onset. 43% of the farmers reporting the occurrence of Fsos event in the period year 2015-2017, suffering the impact in relation to the failure of their crops to germinated and subsequent failure of season production. This information was back up by Fsos detection and quantification from CHIRPs product, which showed that years 2016 was the most affected, with 46% pixels recording Fsos. While the year 2002 and 2003 had 32% & 37% of the area experiencing Fsos, however the spatial coverage and probability of occurrence varied, ranging from 0 to 53% for the 19 years analysed.

Accordingly, this approach has demonstrated great potential in the monitoring of short-term agronomic drought and application in risk management relating to onset variability. It is however important to investigate alternative methods that can be used to detect Fsos, for example, the inclusion of soil moisture parameters into the analysis and/or temperature thus would allow accounting for net water balance and following rainfall retreats and areas of potential threat. Subsequently, research on Fsos should further be motivated by prospects of assessing duration of a dry spell after the Fsos detection and interview of atleast 50 farmers per pixel to allow for evaluation of the severity of the impact. Furthermore, identifying the predictors that can/are effective to provide information ahead of time to the farmers distinguishing between the true and false start of the season is another aspect to be explored. This will facilitate effective and efficient agricultural resources & farm planning by different actors in the production chain. Thereby the early warning system contributing to overall food security planning. El nino and La-Nina is one such potential predictor that has been linked to variable weather conditions. Besides, the Indian Ocean dipole too recently has been pointed out to contribute to early and late retreats of rainfall in Uganda and East African region in general, the Oceanic and atmospheric forcing's in combination with existing lake systems contribution presents possible option to explore in the analysis of Fsos through climatic models.

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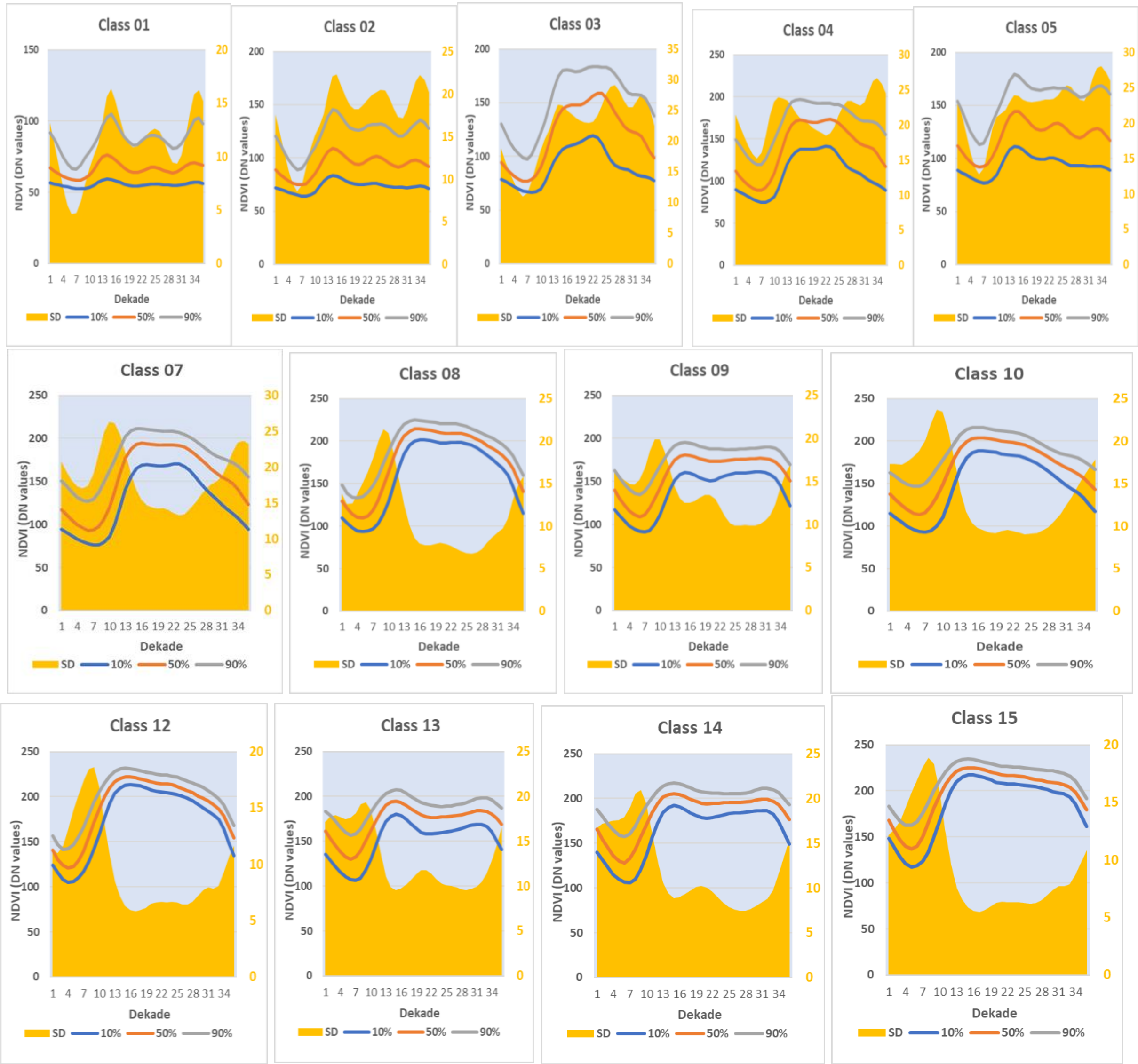
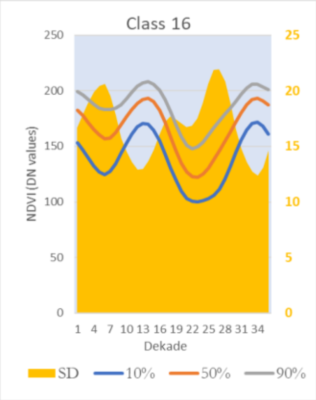
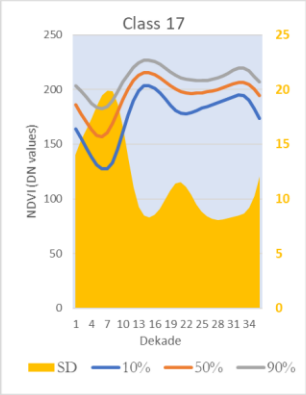
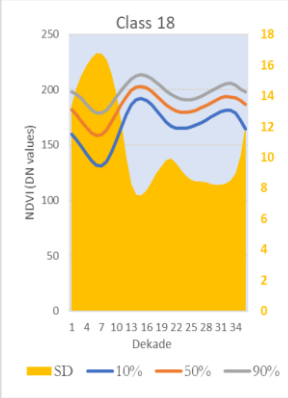
7. APPENDICES

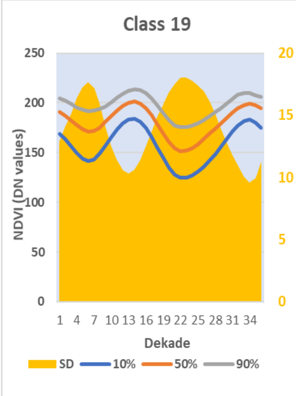
Appendix Figures 1: SD, 90th, 50th, 10th long term (19 years) temporal variation in the 25 classes

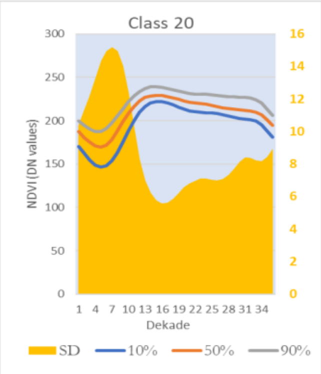


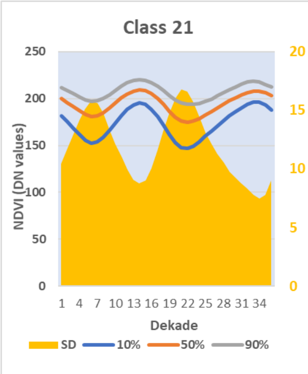

Class 16
NDVI (DN values)
Dekade
SD 10% 50% 90%

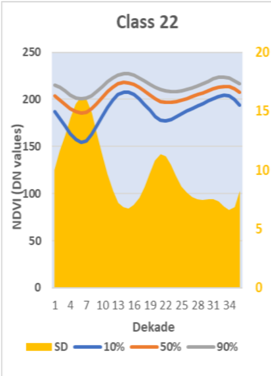

Class 17
NDVI (DN values)
Dekade
SD 10% 50% 90%

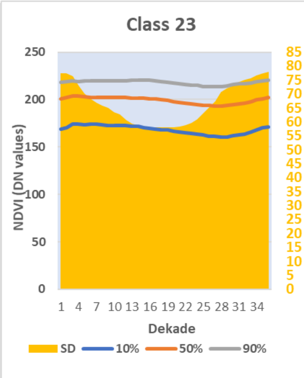

Class 18
NDVI (DN values)
Dekade
SD 10% 50% 90%

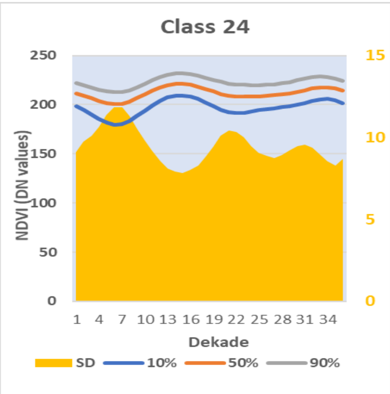

Class 19
NDVI (DN values)
Dekade
SD 10% 50% 90%

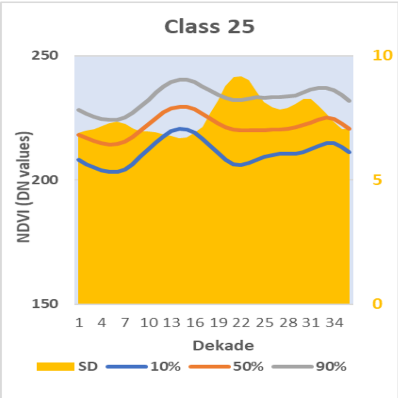

Class 20
NDVI (DN values)
Dekade
SD 10% 50% 90%


Class 21
NDVI (DN values)
Dekade
SD 10% 50% 90%

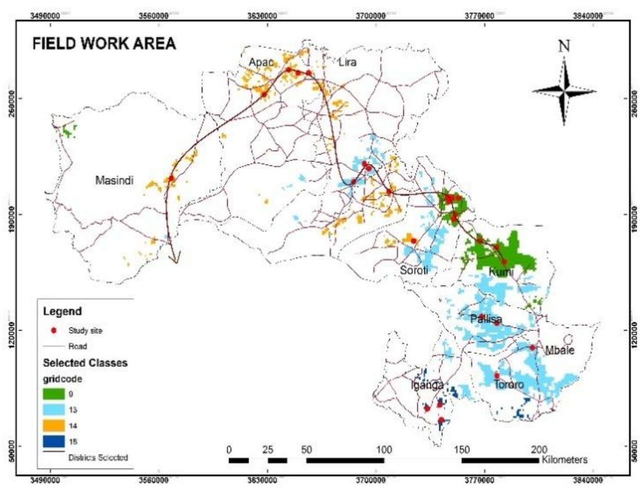

Class 22
NDVI (DN values)
Dekade
SD 10% 50% 90%


Class 23
NDVI (DN values)
Dekade
SD 10% 50% 90%


Class 24
NDVI (DN values)
Dekade
SD 10% 50% 90%


Class 25
NDVI (DN values)
Dekade
SD 10% 50% 90%

Appendix Figures 2: Selected classes and field surveyed pixels with common crops grown in that pixel



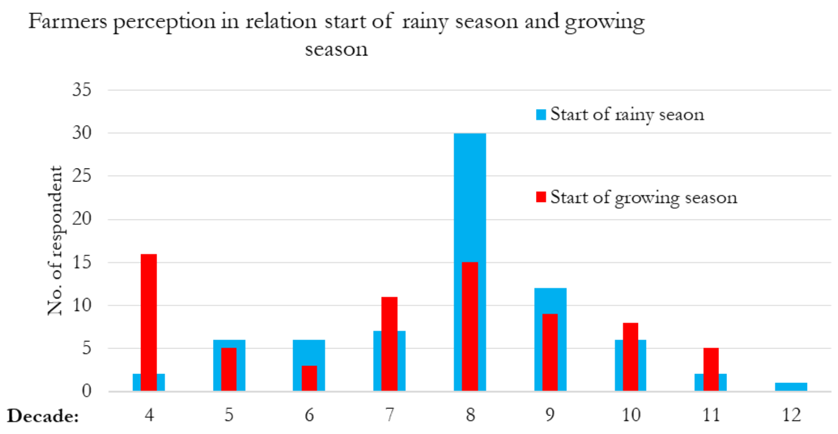
Appendix Table 1: Long term farmer recall of the variability in the onset of the season indicates the proportion of farmers that identified the characteristics of variability

No. of respondent in percentage	Year								
	1999	2000	2001	2002	2003	2004	2005	2006	2007
Normal	31%	58%	57%	50%	40%	50%	54%	63%	71%
Early SoS	1%	1%	0%	1%	11%	7%	8%	10%	1%
Late SoS	0%	1%	1%	1%	0%	3%	8%	10%	10%
Total no. of farmers able to recall	23	44	42	38	37	43	51	59	59
	Year								
	2009	2010	2011	2012	2013	2014	2015	2016	2017
Normal SoS	76%	67%	83%	79%	79%	78%	60%	43%	39%
Early SoS	3%	10%	7%	8%	15%	15%	8%	17%	18%
Late SoS	1%	3%	4%	10%	6%	7%	32%	40%	43%
Total no. of farmer able to recall	58	57	68	70	72	72	72	72	72

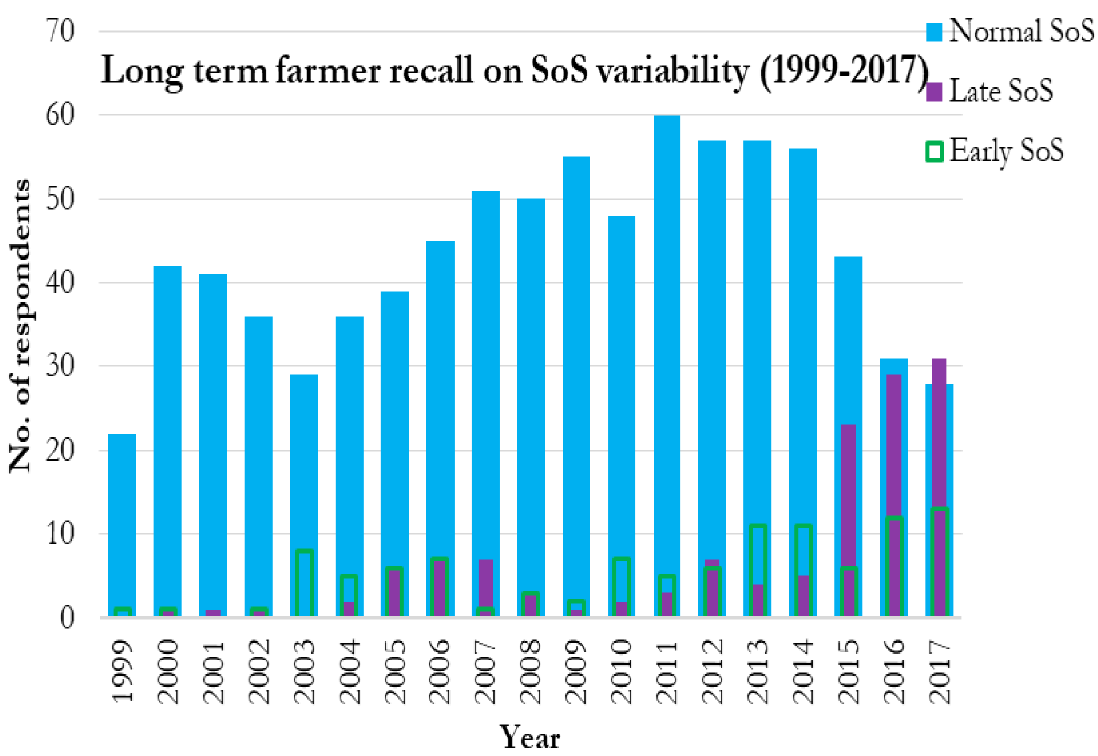
Appendix Table 2: Farmer perception on the definition of the start of the growing season

Dekad	Month	**Start of rainy season**	**Start of growing season**	%age of the respondent (Start of rainy season	%age of the respondent (SoS)
d4	February	2	16	3%	22%
d5		6	5	8%	7%
d6		6	3	8%	4%
d7	March	7	11	10%	15%
d8		30	15	42%	21%
d9		12	9	17%	13%
d10	April	6	8	8%	11%
d11		2	5	3%	7%
d12		1	0	1%	0%
Total no of the respondent		**72**	**72**		

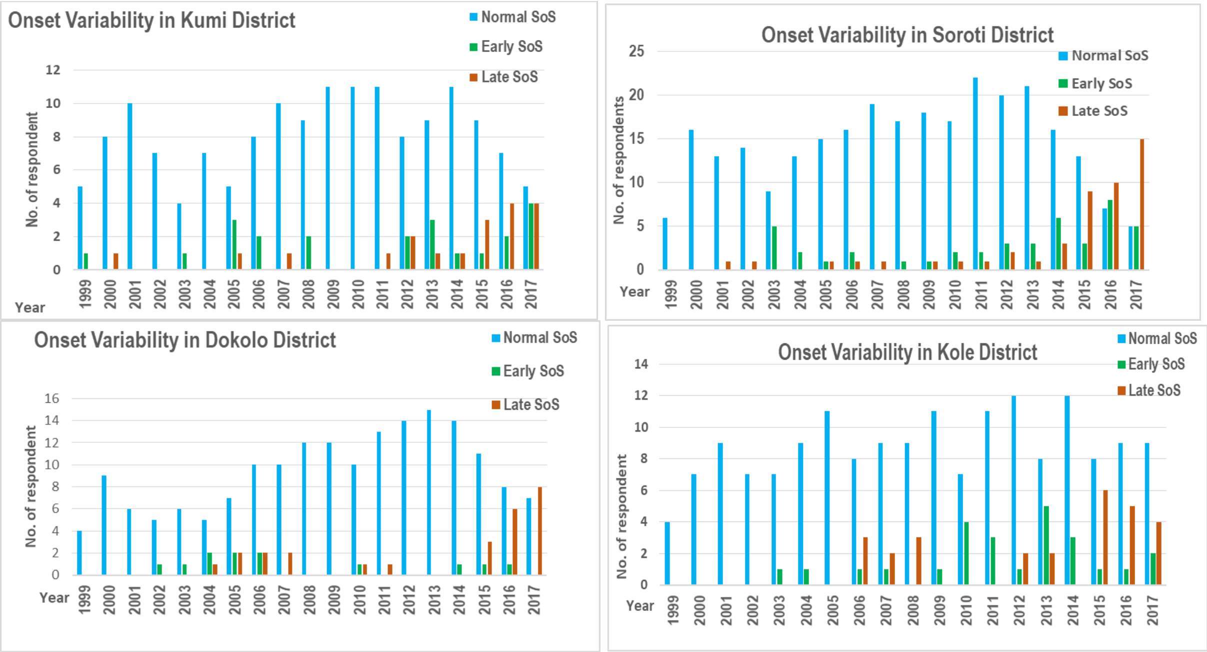
Appendix Figures 3: Comparison of the start of rainy season and growing season as identified by farmers



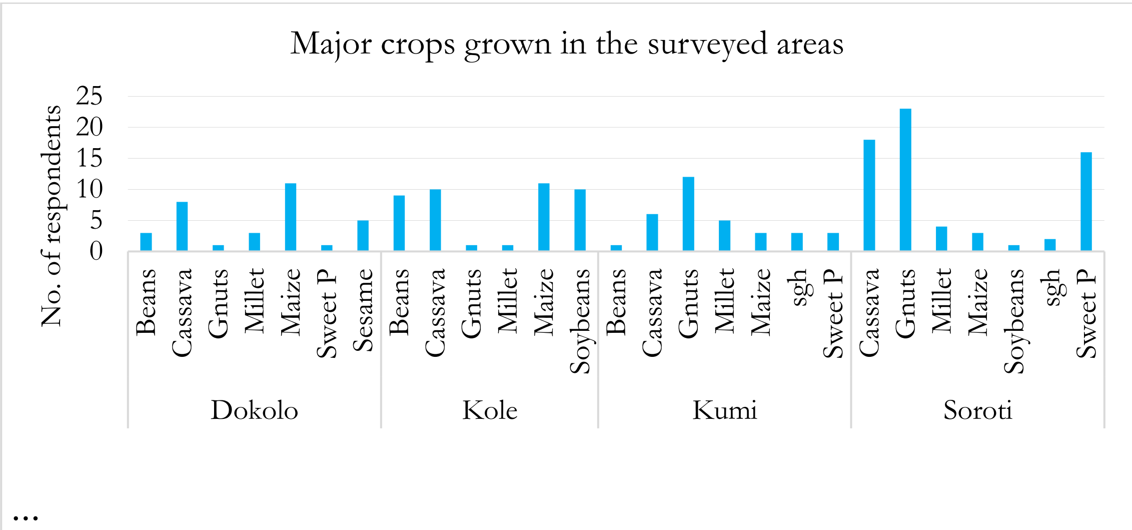
Appendix Figures 4: The characteristics of the onset of the season as explained by the interviewed farmers to recollect historical SoS information



Appendix Figures 5: District level variability identified by farmers in relation to growing seasonal onset



Appendix Figures 6: The different types of crops commonly grown by farmers during the main growing season for the different districts.



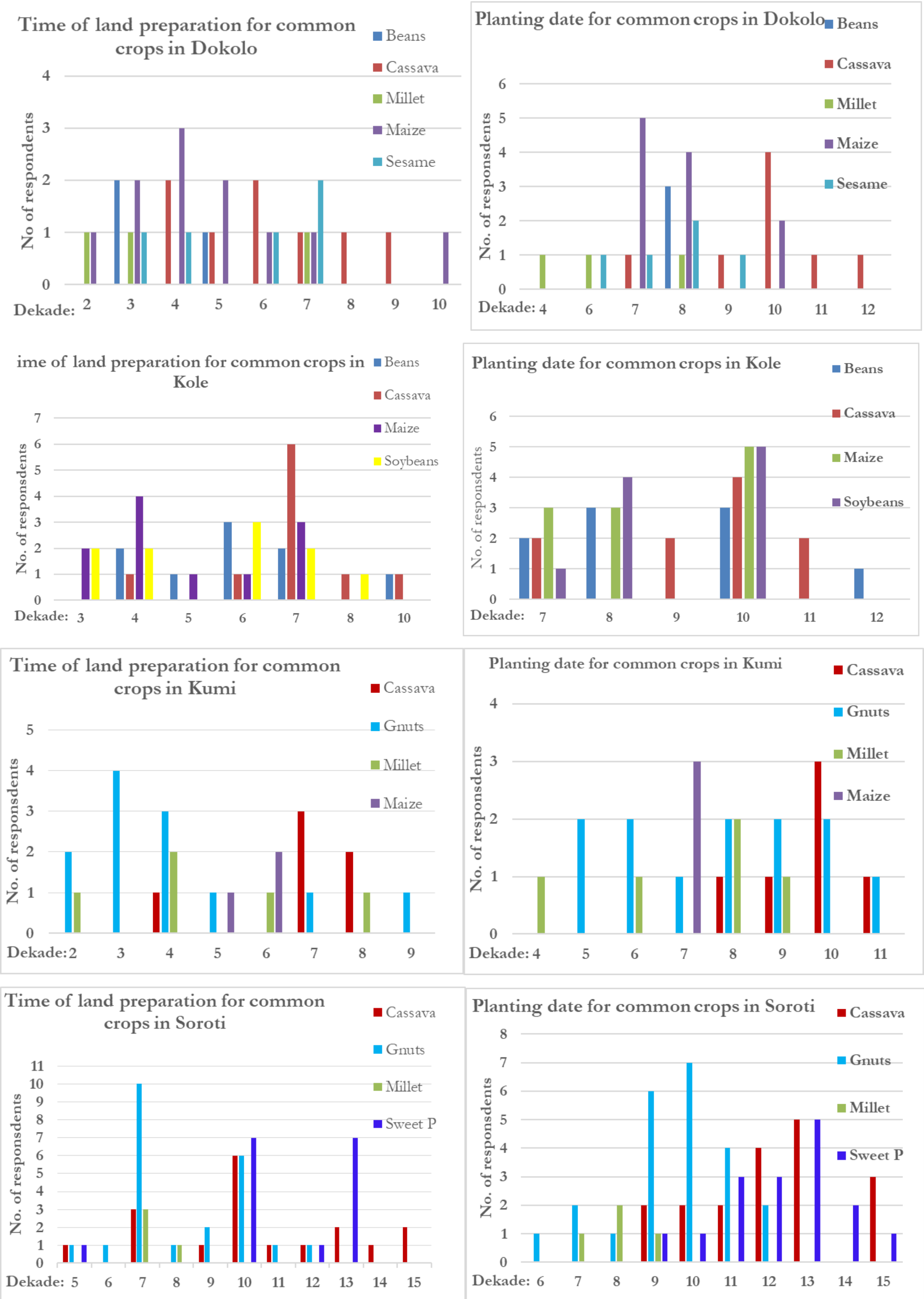
Appendix Table 3: The short-term farmer recall per district on the start of the season for the year 2015-2016

Districts	Year	5th	6th	7th	8th	9th	10th	11th	12th	13th	Total
Dokolo	**2015**	0	2	1	4	6	1	1	0	0	15
Kole	**2015**	0	0	2	4	6	2	0	1	0	15
Kumi	**2015**	1	0	4	3	2	2	0	0	0	12
Soroti	**2015**	0	0	2	2	4	8	2	2	1	21
	Total	**1**	**2**	**9**	**13**	**18**	**13**	**3**	**3**	**1**	63
Dokolo	**2016**	0	0	2	4	5	1	1	2	0	15
Kole	**2016**	0	0	3	3	4	2	2	1	0	15
Kumi	**2016**	1	2	2	5	2	0	0	0	0	12
Soroti	**2016**	1	3	0	3	4	5	6	3	0	25
	Total	**2**	**5**	**7**	**15**	**15**	**8**	**9**	**6**	**0**	**67**
Dokolo	**2017**	3	0	2	3	4	2	1	0	0	15
Kole	**2017**	0	1	2	3	4	3	2	0	0	15
Kumi	**2017**	1	0	2	4	2	1	2	0	0	12
Soroti	**2017**	1	0	2	5	3	3	7	4	0	25
	Total	**5**	**1**	**8**	**15**	**13**	**9**	**12**	**4**	**0**	**67**

Appendix Table 4: Planting date information per district as reported by the farmers for the period 2015-2017

Districts	Yearly Specific planting dates in dekad										Total
	4th	**6th**	**7th**	**8th**	**9th**	**10th**	**11th**	**12th**	**13th**	**14th**	
					Year 2015						
Dokolo	0	0	0	2	8	3	1	1	0	0	15
Kole	0	0	1	1	4	4	3	2	0	0	15
Kumi	0	0	0	5	4	2	1	0	0	0	12
Pallisa	0	0	0	0	1	0	1	2	0	0	4
Soroti	0	0	0	2	3	6	4	3	3	0	21
Total	0	0	1	10	20	15	10	8	3	0	67
					Year 2016						
Dokolo	0	0	0	1	5	0	3	6	0	0	15
Kole	0	0	0	0	7	3	3	2	0	0	15
Kumi	1	1	1	3	2	1	1	1	0	1	12
Pallisa	0	0	0	0	3	0	0	1	0	0	4
Soroti	0	0	1	1	4	2	3	11	3	0	25
Total	1	1	2	5	21	6	10	21	3	1	71
					Year 2017						
Dokolo	0	1	3	2	6	0	0	3	0	0	15
Kole	0	0	1	3	4	3	1	3	0	0	15
Kumi	0	1	0	3	2	2	2	2	0	0	12
Pallisa	0	0	0	0	4	0	0	0	0	0	4
Soroti	0	0	1	2	2	2	7	10	1	0	25
Total	0	2	5	10	18	7	10	18	1	0	71

Appendix Figures 7: Appendix A: Time of land preparation in comparison to planting by farmers in Dokolo, Kole, Kumi and Soroti district



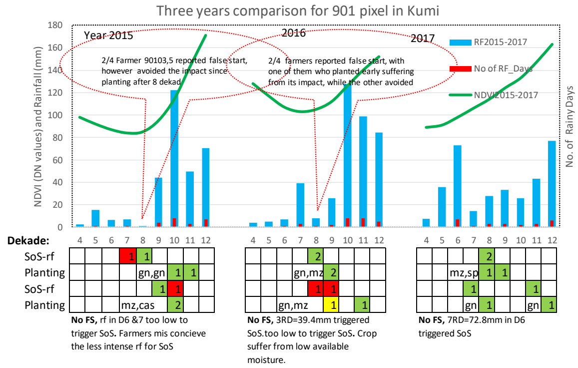
Appendix Table 5: Indicators of the start of the season and variability according to the farmers as reported by the farmers

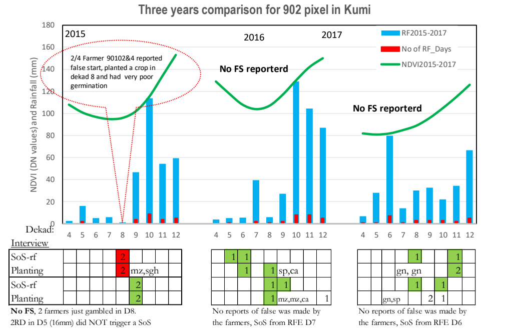
Summary of Indicator of Onset of the season as reported by farmers			
Region	**Indicators onset of the rainy season**	**Indicators of Late onset of Rainy season**	**Indicators of false onset of Rainy season**
Teso Region (Kumi, Pallisa and Soroti districts)	1. Winds blowing eastwards in mid- February 2. Cloudy skies 3. Start of rains in between February and 1st week of March 4. Mist and dew formation 5.Mivule tree starting to bare leaves late February 6. Most farmers starting to plant their crops	1. Wind blowing towards the west 2. Extended dry spell to end of march 3. Start of rainfall in late March to mid-April in a particular year (no rain in February) 4. Clear skies, observed during the period of expected normal onset of the season 5. Heavy and high speedy winds blowing 6. Delayed flowering of "Opok tree"	1. Normal start of rainfall and breaks after planting or the emergence of planted crops 2. Rainfall for 7days and breaks and returns again 3. Dry soils after rainy days 4. Withering of crop due to lack of moisture 5. Dry spell setting in after first weeding of crops
Lango region (Dokolo and Kole)	1. Rainfall experience for 3-4days consecutive 2. Farmers starting to plant their crops 3.Farmers preparing the seedbed for crop planting	1. Continuous rainfall is extending into the January in the new year. 2. Excessive heat and high temperature 3. Frequent winds 4. Plants drying up at juvenile age. 5. A lot of weeds in the crop fields 6. The onset of rain in mid-April to may 7.Late planting by farmers	1. Normal start of rainfall and later dry spell for 2weeks-one month after planting of seeds 2. Poor emergency of planted crop due to the dry spell

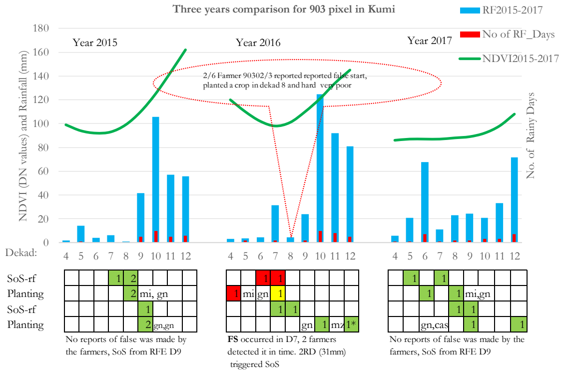
Appendix Table 6: False start recall and impact as reported by farmers

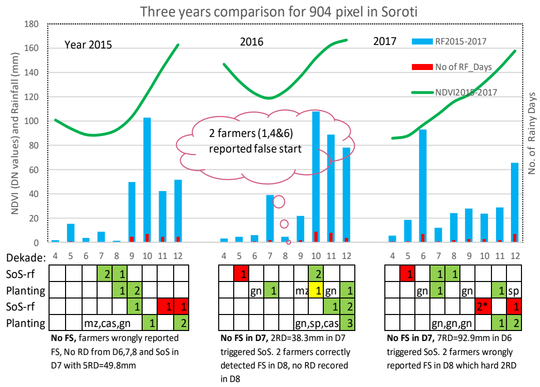
	False Recall by farmers												
		Farmer response			Planting date			Crop Planted			Impact suffered		
	District	Farmers ID	2015	2016	2017	PD2015	PD2016	PD2017	Crop2015	Crop2016	Crop2017	E2015	E2016	E2017
	Kumi	3	1	1	0	11	9	10	G/nuts	Maize	Gnuts	3	3	3
901		5	1	1	0	8	8	8	G/nuts	Gnuts	Maize	1	2	3
		2	1	0	0	8	8	8	Sorghum	Cassava	G/nuts	2	3	3
902		4	1	0	0	8	6	11	Maize	Sweet P	Gnuts	2	3	3
		2	0	1	0	9	5	8	G/nuts	Millet	G/nuts	3	1	3
903		3	0	1	0	8	7	8	G/nuts	G/nuts	Maize	1	2	2
	Soroti	1	1	1	0	13	13	12	G/nuts	G/nuts	Gnuts	3	3	3
904		4	0	1	1	8	7	7	Cassava	Gnuts	Gnuts	3	2	3
		6	1	0	1	12	12	12	Cassava	Sweet P	Gnuts	3	3	3
		2	0	1	0	0	12	0	Millet	Cassava	Sweet P	3	3	3
905		6	0	1	1	0	0	12	Sweet P	Sweet P	Sweet P	3	3	3
		1	1	0	1	13	12	8	G/nuts	G/nuts	G/nuts	1	3	2
		2	0	1	1	9	8	10	G/nuts	G/nuts	G/nuts	3	3	3
906		4	1	0	1	11	9	12	Sorghum	G/nuts	Sweet P	3	3	3
		3	1	1	1	12	12	12	G/nuts	G/nuts	G/nuts	3	3	3
		6	0	1	0	13	12	12	G/nuts	G/nuts	G/nuts	3	3	3
909		7	0	0	1	10	9	11	Maize	G/nuts	G/nuts	3	3	2
1303	Pallisa	1	0	1	1	10	9	9	G/nuts	G/nuts	G/nuts	3	2	1
		3	0	1	0	12	12	9	Maize	Cassava	Maize	3	3	3
		4	1	0	0	9	9	9	Maize	G/nuts	Maize	1	3	1
1304	Dokolo	2	0	0	1	9	9	8	Maize	Maize	Gnuts	3	3	3
		5	0	0	1	9	12	12	Maize	Maize	Maize	3	3	1
1305		1	0	1	1	9	9	7	Sorghum	Maize	Millet	1	3	3
		1	1	0	1	12	9	9	Millet	Sesame	Sesame	3	3	1
1306		3	1	0	0	11	11	7	Soybeans	Maize	Sesame	3	3	3
		6	0	0	1	10	8	12	Maize	Beans	Cassava	3	3	3
	Kole	1	0	1	0	12	9	12	Cassava	Beans	Maize	3	2	3
		4	1	0	1	11	8	10	Sesame	Beans	Cassava	2	2	2
1403		6	0	0	1	10	9	8	Maize	Maize	Cassava	3	3	1
1404		2	0	0	1	9	9	9	Soybeans	Beans	Cassava	3	3	3
		3	0	1	1	10	9	8	Soybeans	Maize	Beans	3	3	1
			13	16	18									

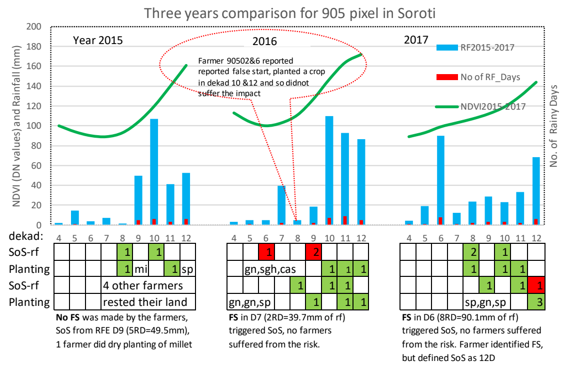
Appendix Figures 8: Appendix A: Comparison of farmer derived information and remote sensing products

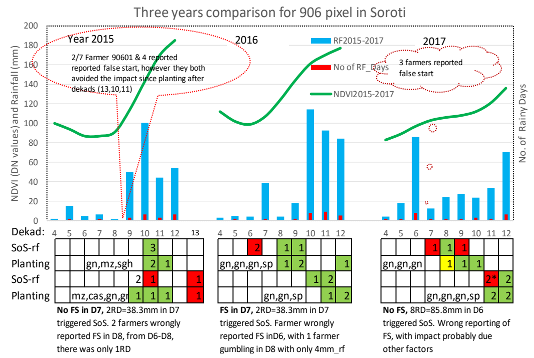


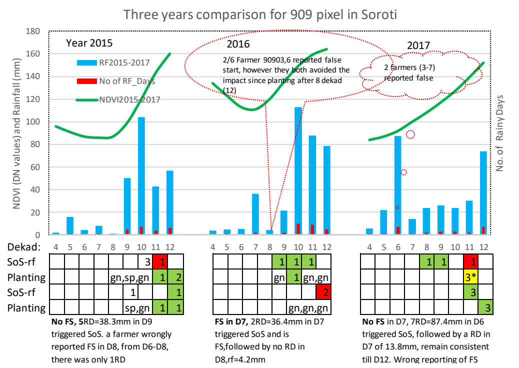


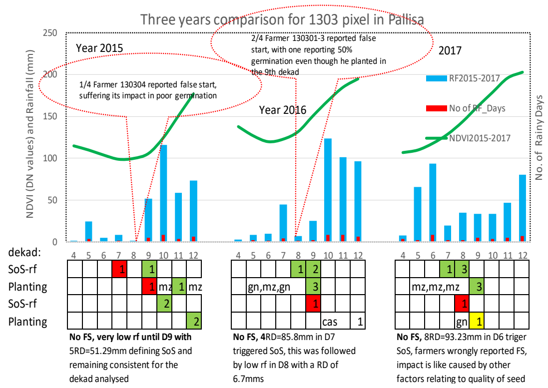






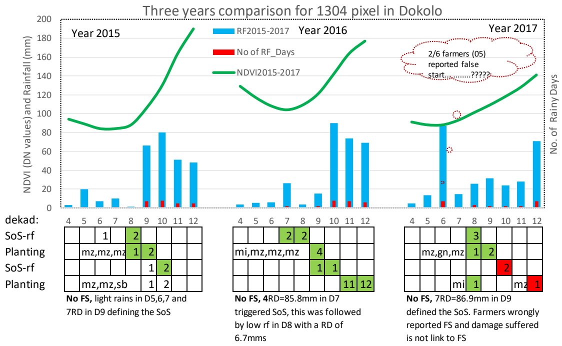


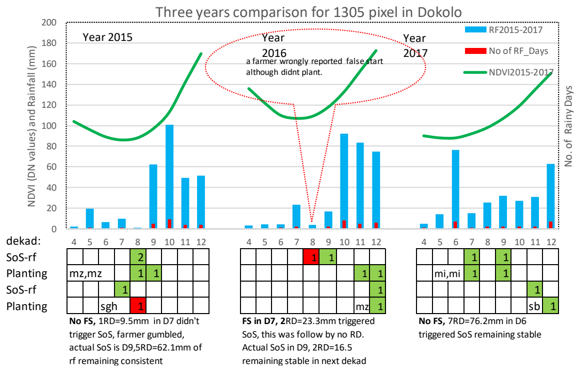


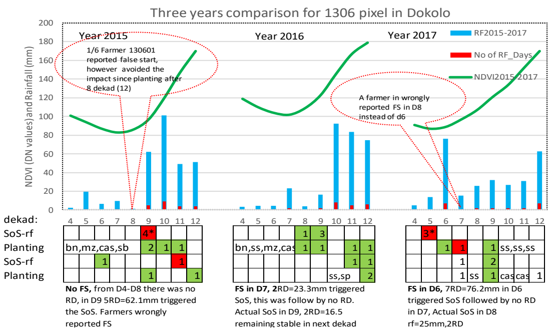


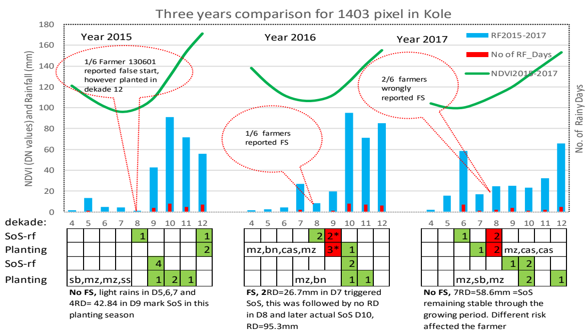
Key:

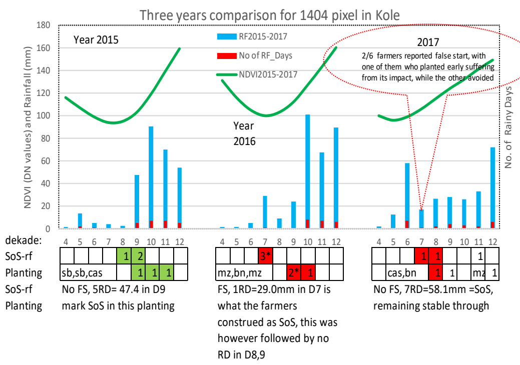
gn	Gnuts	RF	Rainfall
mz	Maize	RD	Rainy days
cas	Cassava	FS	False start
Sp	Sweet Potatoes	(green)	Successful germination
mi	Millet	(yellow)	Poor germination
sgh	Sorghum	(red)	Failure of germination

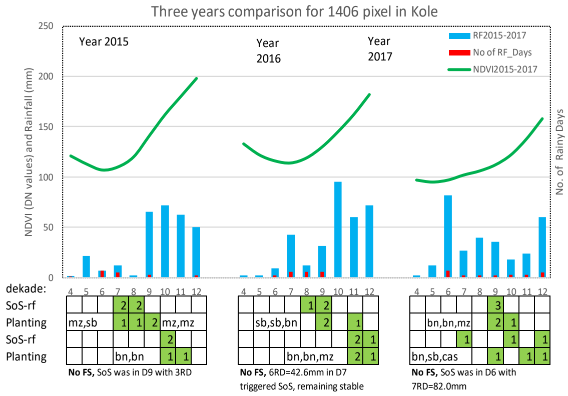








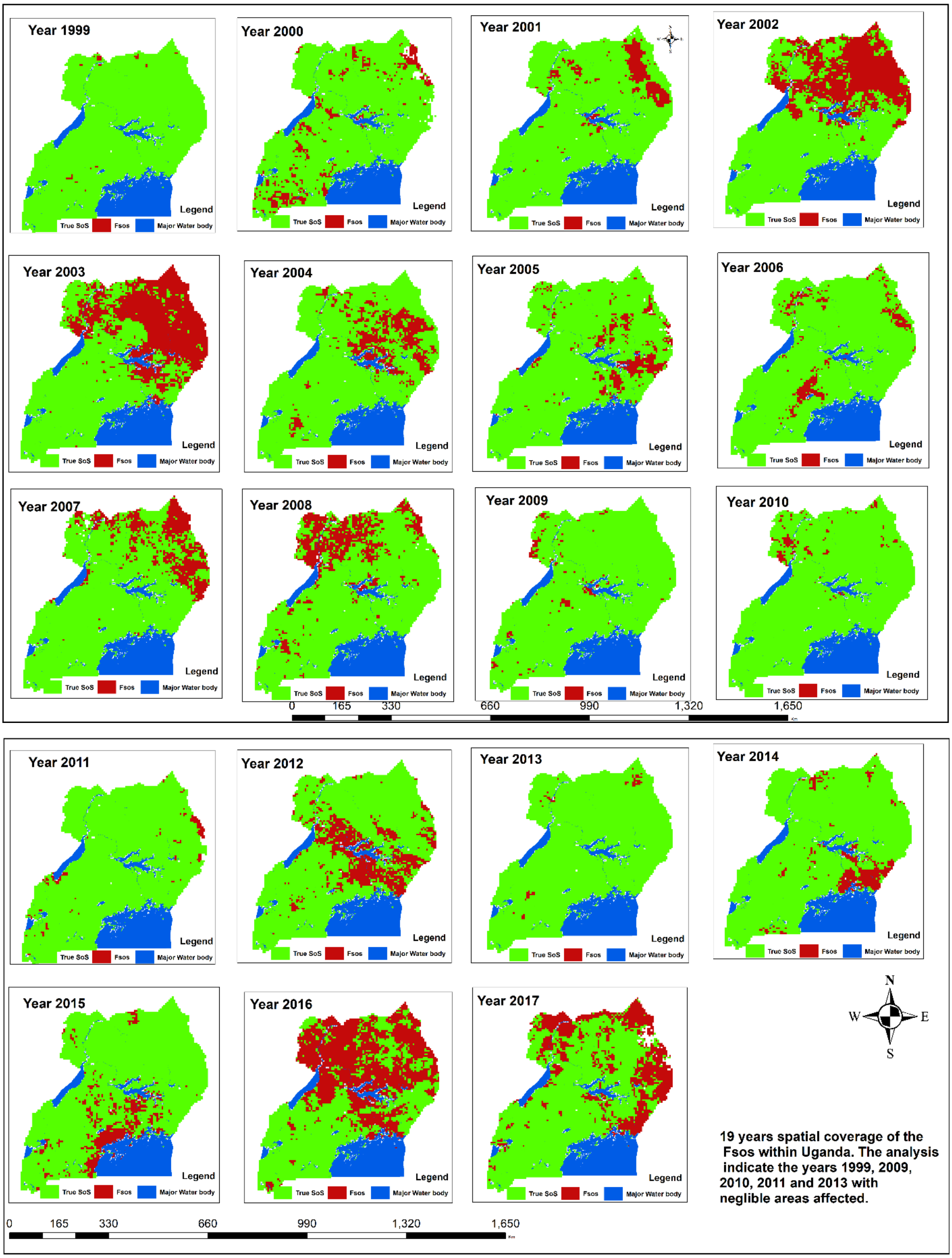




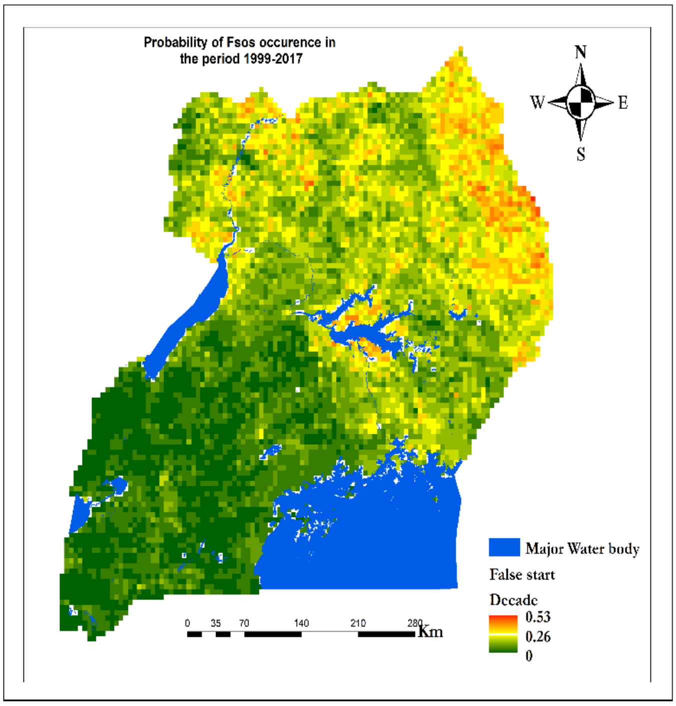
Key

gn	Gnuts	RF	Rianfall
mz	Maize	RD	Rainy days
cas	Cassava	FS	False start
Sp	Sweet Potatoes	(green)	Successful germination
mi	Millet	(yellow)	Poor germination
sgh	Sorghum	(red)	Failure of germination

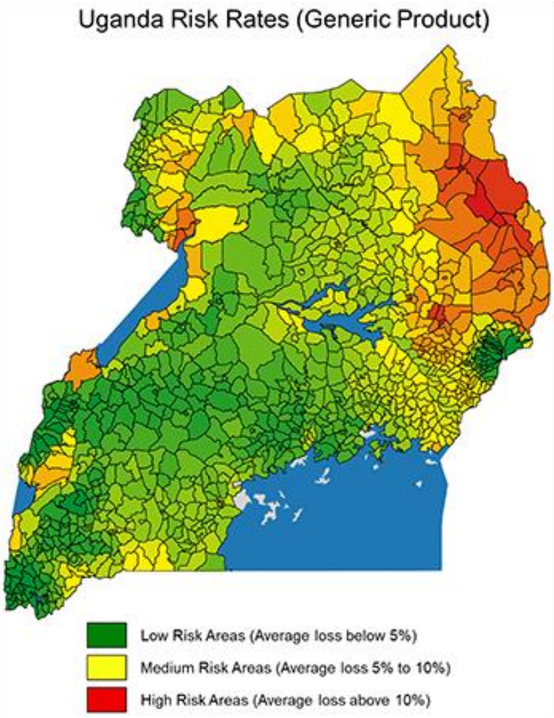
Appendix Figures 9: Yearly representation of the occurrence of Fsos during the period 1999-2015



Appendix Figures 10: Comparison Fsos mapping and Uganda Risk rate by NSO



Source: Author of the study



Source: Netherlands Space Office, the SUM Africa Project

Appendix figure 11: **Field data interview sheet**

Farmer Field Interview data sheet

***Introduction** : My name is Ocen Emmanuel, a student at the University of Twente, pursuing Master degree in Geo-information Science and Earth's Observation. I am conducting a study on variability of the start of the growing season in Uganda, with aim of understanding the underlying drivers of this variability in the last 18 years. Information you provide will strickly be used for this purpose.*

Section A: General questions on Seasonal and its variability

1 When is the normal beginning of the season in this area?

Month...Week...date.......................................

2 On a normal year when does it usually starts raining in this area

Month...Week...date.......................................

3 How do you define an/or	Indicator	How frequent and when did it occur, which years?					
Early start of the season		Frq	Yr	ES	LO	FS	Response
			1999				
			2000				
			2001				
Late onset of the season Probe: *How late has the onset of the season been*			2002				
			2003				
			2004				
			2005				
			2006				
False start of the growing season			2007				
			2008				
			2009				
			2010				
False start of the season			2011				

Section B: Farmer agricultural practices and underlying decision

4 When do you carry out the following activities based dominant/common annual food crops grown in this area?

What crops are grown mainly in this area by you	Field	crop type1	Date (Month,	crop type2	Date (Months, Early, mid or end of	Crop type3	Date (Month, Early, mid, or end of
Land preparation							
What are the underlying decisions on which you base on to decide on start ploughing							
Planting dates							
What are the underlying decision on which you base on to decide on date to plant							
Harvesting dates							

Generate potential list after interviewing atleast 5 farmers in particular district

A B C D

Generate potential list after interviewing atleast 5 farmers in particular district

A B C D E

Section C: Relating findings from A & B

5 Now we want to relate to specific crop you pointed out earlier, base on your recall,

Years	Crop of choice	Start of the 1st season (Month- early, mid, late	Start of rainfall(Date-Month)	Date started planting(Days in a month)	Emergency success of planted seeds	Why	Did you replant
2018							

specific year identified by the farmer and proceed to specifics of date and month