

Assessing Differences in Practiced Maize Crop Calendars using Hyper- temporal NDVI data in Rwanda

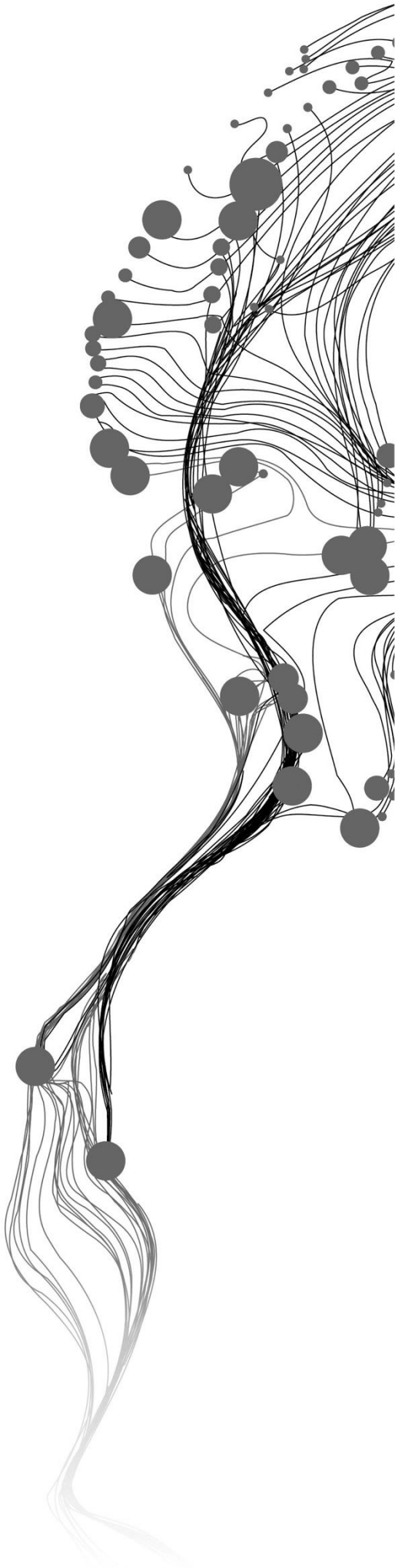
ALINE MUYIZERE

February, 2016

SUPERVISORS:

Drs. Eduard Westinga

Dr. Ir. C.A.J.M. (Kees) de Bie



Assessing Differences in Practiced Maize Crop Calendars using Hyper- temporal NDVI data in Rwanda

ALINE MUYIZERE

Enschede, The Netherlands, February, 2016

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: Geo-information Science and Earth Observation for Natural resources management

SUPERVISORS:

Drs. Eduard Westinga (First supervisor)

Dr. Ir. C.A.J.M. (Kees) de Bie (Second supervisor)

THESIS ASSESSMENT BOARD:

Dr. Y.A. Hussin (Chair)

Dr. Ir. B.G.J.S. (Ben) Sonneveld (External Examiner, VU Amsterdam)

Drs. Eduard Westinga (First supervisor)

Dr. Ir. C.A.J.M. (Kees) de Bie (Second Supervisor)

DISCLAIMER

This document describes work undertaken as part of a programme of study at the Faculty of Geo-Information Science and Earth Observation of the University of Twente. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the Faculty.

ABSTRACT

Crop calendar is an important tool providing relevant information on crop cycles in a specific area. It allows effective planning of various agricultural activities leading to a better agriculture management. The crop calendars are different from an area to another given differences in natural systems and agroecosystems characteristics of the areas. However, this was not the case for Rwanda, a country with natural differences from East to West due, mainly, to altitude and rainfall patterns. Focusing on the maize crop, the country has known a single maize crop calendar for the entire country.

This research used hyper-temporal NDVI stratification to study whether there are differences in maize crop calendars in different areas of Rwanda, and also assess if the hyper-temporal NDVI stratification can differentiate the differences in the practiced maize crop calendars in the country. The research used hyper-temporal MODIS NDVI 250 m of 16 days composites data recorded for 10 years (from 2004 till 2014) for land stratification. The NDVI images were stacked together and imploded using unsupervised classification through ISODATA clustering algorithm in Erdas-Imagine software. Through separability analysis, 95 best separable NDVI classes were identified, from which four sample NDVI classes: 24, 54, 70 and 82 were selected given dominance of agriculture in the classes and notable different temporal behaviours between the classes from 2004 till 2014. 45 representative sample areas were selected to represent the four NDVI classes in field data collection.

From the field, maize planting and harvesting times were recorded through the interviews with farmers. 96 farmers were interviewed in NDVI class 24, 113 farmers in NDVI class 54, 105 farmers in NDVI class 70 and 119 farmers in NDVI class 82. Maize crop calendars for each NDVI class were generated from the interviews with farmers.

All the planting and harvestings time data from the field were also classified using K-means unsupervised clustering algorithm in order to produce the groupings of practiced maize crop calendars irrespective of the NDVI classes. 4 practiced maize crop calendars independent of NDVI classes were produced. To assess differences in maize crop calendars for Rwanda, analysis of variance (ANOVA) indicated that the maize crop calendars for NDVI classes were significantly different between the four sample NDVI classes, and also, the practiced maize crop calendars were significantly different between the four maize crop calendars groupings at $p=0.05$.

To analyse the relationship between maize growing seasons and NDVI classes, the chi-square test showed that the number of maize growing seasons was highly related to the clustering of NDVI profiles into NDVI classes at $p = 0.05$. Moreover, to assess spatial stratification of hyper-temporal NDVI data into NDVI classes can differentiate differences in practiced maize crop calendars for Rwanda, chi-square test showed that the practiced maize crop calendars were highly related to the maize crop calendars for NDVI class at $p = 0.05$. Conclusively, spatial stratification of hyper-temporal NDVI data can significantly differentiate differences in practiced maize crop calendars for Rwanda.

Keywords: Hyper-temporal, NDVI data stratification, Crop calendar, Crop growing season

ACKNOWLEDGEMENTS

This journey of 18 months at ITC, the Netherlands, has been a great achievement in my life. I have learned a lot, not only in the academic area but also in social life.

First of all, I thank The Almighty God for everything done during this academic journey, especially for this thesis.

I am so grateful for the financial support from NUFFIC, without the support, I could not have reached this goal today.

I would like to express my deepest gratitude to my first supervisor drs. Eduard Westinga for his support, advices and guidance to accomplish this MSc thesis.

I extremely appreciate my second supervisor dr. ir. C.A J.M. (Kees) de Bie for his support, advices and guidance during this MSc thesis.

I would like also to thank all lecturers from NRS department at ITC for their teachings, I learned a lot from you.

I would like to thank Mr. Raymond, NRM course coordinator, for his help, advice and flexibility from the core modules time till our final academic works.

I would like to express my gratitude to my NRM and GEM students especially Maurice, Steve and Edossa for the brainstorming activities, advices and your moral support.

To the whole Bible study group members, especially Claudine who has been always praying for our theses, and her husband Prosper for his advices and comfort throughout the thesis period.

To my family back home, my Dad, my Mom, my brothers and sisters and my brother in law for their love, care and moral support during this time here in the Netherlands, especially during the thesis period.

TABLE OF CONTENTS

1.	Introduction.....	1
1.1.	Background and motivation	1
1.2.	Research problem	2
1.3.	Research objectives, research questions and hypothesis	4
2.	Literature review	5
2.1.	Agriculture in Rwanda.....	5
2.2.	Currently used methods to generate crop calendars	8
3.	Materials and methods	10
3.1.	Study area description.....	10
3.2.	Data acquisition and pre-processing.....	10
3.3.	Data processing.....	12
3.4.	Data analysis and interpretation.....	15
3.5.	Methodology flow chart.....	17
4.	Results.....	18
4.1.	Hyper-temporal MODIS NDVI data stratification	18
4.2.	Maize crop calendars per sample area for different NDVI classes	22
4.3.	Assessment of relationship between number of maize growing seasons and NDVI classes	31
4.4.	Practiced maize crop calendars and maize crop calendars for NDVI classes	32
4.5.	Assessment of relationship between practiced maize crop calendars and NDVI classes	36
5.	Discussion.....	38
5.1.	Maize crop calendars of sample NDVI classes through interviews with farmers	38
5.2.	Relationship between practiced crop calendars and crop calendars per NDVI classes	39
6.	Conclusions and recommendations.....	41
6.1.	Conclusions	41
6.2.	Recommendations.....	41

LIST OF FIGURES

Figure 1: Major crops' calendar for Rwanda (FAO/GIEWS, 2015)	3
Figure 2: Agro-ecological zones of Rwanda	6
Figure 3: Study area map	10
Figure 4: Flow chart of the applied research methodology	17
Figure 5: The best separable NDVI classes for MODIS data from 2004 to 2014	18
Figure 6: 95 NDVI classes of hyper-temporal MODIS images from 2004 to 2014	19
Figure 7: The location of 24 NDVI classes with more than 50% of agriculture	20
Figure 8: NDVI profiles for 24 NDVI classes with above 50% agriculture	20
Figure 9: Temporal behaviour of 4 sample NDVI classes	21
Figure 10: Location of 4 sample NDVI classes and the sample areas in Rwanda	22
Figure 11: Maize crop calendars per sample area per cluster for NDVI class 24	23
Figure 12: NDVI profiles per cluster for NDVI class 24	23
Figure 13: Maize crop calendars per sample area per cluster for NDVI class 54	25
Figure 14: NDVI profiles per cluster for NDVI class 54	25
Figure 15: Maize crop calendars per sample area per cluster for NDVI class 70	27
Figure 16: NDVI profiles per cluster for NDVI class 70	27
Figure 17: Maize crop calendars per sample area per cluster for NDVI class 82	29
Figure 18: NDVI profiles for NDVI class 82 (From August 2014 to August 2015)	29
Figure 19: Generalized maize crop calendars for the 4 sample NDVI classes	31
Figure 20: Four groupings of practiced maize crop calendars	33

LIST OF TABLES

Table 1: Characteristics of 12 Rwanda agro-ecological zones (Clay & Dejaegher, 1987).....	6
Table 2: Number of interviewed farmers per sample area per cluster per NDVI class.....	14
Table 3: Dominant land covers and their area (%) in cluster 1 of NDVI class 24.....	24
Table 4: Dominant land covers and their area (%) in cluster 2 for NDVI class 24.....	24
Table 5: Dominant land covers and their area (%) in cluster 3 for NDVI class 24.....	24
Table 6: Dominant land covers and their area (%) in cluster 1 for NDVI class 54.....	26
Table 7: Dominant land covers and their area (%) in cluster 2 of NDVI class 54.....	26
Table 8: Dominant land covers and their area (%) in cluster 3 of NDVI class 54.....	26
Table 9: Dominant land covers and their area (%) in cluster 1 of NDVI class 70.....	28
Table 10: Dominant land covers and their area (%) in cluster 2 of NDVI class 70.....	28
Table 11: Dominant land covers and their area (%) in cluster 3 of NDVI class 70.....	28
Table 12: Dominant land covers and their area (%) in cluster 1 of NDVI class 82.....	30
Table 13: Dominant land covers and their area (%) in cluster 2 for NDVI class 82.....	30
Table 14: Dominant land covers and their areas in cluster 3 of NDVI class 82.....	30
Table 15: Contingency table of observed and expected frequency of maize growing seasons per NDVI class.....	32
Table 16: Number of plots with same practiced maize crop calendar per NDVI class.....	32
Table 17: One-way ANOVA results on season A planting dates between four NDVI classes.....	33
Table 18: One-way ANOVA results for season A harvesting dates between four NDVI classes.....	34
Table 19: T-test results for season B planting dates between NDVI class 24 and 82.....	34
Table 20: T-test results for season B harvesting dates between NDVI class 24 and 82.....	35
Table 21: One-way ANOVA results for season A plating dates of practiced maize crop calendars groupings.....	35
Table 22: One-way ANOVA results for season A harvesting dates of practiced maize crop calendars groupings.....	36
Table 23: Contingency table of observed and expected frequency of practiced maize crop calendar per NDVI class.....	37

LIST OF ABBREVIATION

AMIS:	Agricultural Market Information System
ESAANet:	East and South African Agribusiness Network
FAO:	Food and Agriculture Organization
GDP:	Gross Domestic Product
GIEWS:	Global Information and Early Warning System
GIS:	Geographical Information System
IPAQ:	International Physical Activity Questionnaire
ISODATA:	Iterative Self Organizing Data Analysis Technique
MINAGRI:	Ministry of Agriculture and Animal Resources
MINALOC:	Ministry of Local Government
MINITERE:	Ministry of Lands Environment, Forests, Water and Mines
MODIS:	Moderate Resolution Imaging Spectroradiometer
NAEB:	National Agricultural Export Development Board
NASA:	National Aeronautics and Space Administration
NDVI:	Normalized Difference Vegetation Index
NISR:	National Institute of Statistics of Rwanda
REMA:	Rwanda Environmental Management Authority
RIU:	Research Into Use
UN:	United Nations
USAID:	United States Agency for International Development
USGS:	United States Geological Survey

1. INTRODUCTION

1.1. Background and motivation

Agriculture is the most important economic sector in the world. It offers the very basic need; food for the population and plays a key role in the economy of the countries (Christiaensen, Demery, & Kuhl, 2011). In Rwanda, agriculture is regarded as a keystone for the country's population, and a catalyst for economic development (NAEB, 2015). The sector employs about 87% of the working population, making around 46% of the country's GDP, and produces about 80% of the total export revenues (Kanyarukiga, 2004). Eventually, it is very important to know relevant information about agriculture like crops grown, their specific areas, their planting periods, their growing periods and their harvesting periods to ensure sustainable development of the sector and timely interventions in case of need. Most importantly, crop calendar is one of the crucial information needed and used by various stakeholders in this regard.

Crop calendar is a brief way of presenting crop cycle information (Patel & Oza, 2014). In order to promote local crops production for a specific zone, crop calendar provides relevant timely information about crops in that zones, which contribute to the food security (Guo, 2013). More specifically, crop calendar is regarded as “a sequential summary of the dates/periods of essential operations, including land preparation, planting and harvesting for a specific land use; it may apply to a specific plot, but is frequently generalized to characterize a specified area” (de Bie, 2002).

The information contained in crop calendar is very beneficial to various categories of population, most importantly farmers and agriculture extensionists worldwide in taking a decision regarding agriculture (FAO, 2015). On one hand, the information helps the farmers to take decisions and effective measures for their agricultural products, including market price for their crops (Guo, 2013). On another hand, the information helps the investors to know about periods and cycles of specific crops in different areas, allowing them to plan for optimal time to invest in agriculture. Moreover, governments use the crop calendar information for various planning and decisions making regarding agricultural sector including, for instance, planning for the provision of inputs and seeds to the farmer in the right time (ESAANet, 2007). Regarding the contribution to the economy of a country, crop calendar helps in estimating supply, demand and prices of various agricultural products on global and regional markets (AMIS, 2012).

However, crop calendar is not common. It differs from an area to another and even within the same country. It differs based on differences in ecological conditions including soil types, climate conditions and many other natural factors which influence adaptation and growth of crops in an area (Bailey, 2004; FAO, 1996). In addition, FAO (1996) indicates that these differences make agro-ecological zone be a general unit for crop calendar, where the influencing natural factors are considered not so different. This indicates that effective method for crop calendar development should be able to detect these differences in different areas, especially in the same country.

Different methods have been in use in order to estimate, and thus be able to map different crop calendars for various crops in different parts of the world. Kotsuki and Tanaka (2015) indicate that there exist three different methods to estimate crop calendars: census-based, model-based and satellite (remote sensing) based methods. The methods have points of strength and downfalls. The census-based method collects

crops data based on country's administrative units to develop a crop calendar. However this method is time, money and labour consuming, so, it is not applied frequently (UN, 2011). Model-based methods use meteorological data to simulate crops growth for the calendar's development (Vintrou et al., 2014). This method uses forced data and does not incorporate the farmer's decision, which constrains the accuracy of a produced crop calendar (Kotsuki & Tanaka, 2015; Oettli, Sultan, Baron, & Vrac, 2011). Lastly, satellite-based methods use remote sensing data. This method is regarded as powerful regarding the accuracy and possibility of frequent applications because it can observe a variety of areas depending not only on natural conditions but also on farmer's decisions over the area (Kotsuki & Tanaka, 2015). In addition, the method can be applied frequently with up-to-date data.

There exist a variety of remote sensing techniques among which Normalized Difference Vegetation Index (NDVI) data (Rouse, Haas, Schell, & Deering, 1974) has been applied by different scientists in finding differences in cropland. For instance, researchers including de Bie (2002); Upadhyay, Ray and Panigrahy (2008) used NDVI data to map different agricultural land uses. The technique has been optimistically perceived by many scientists for crops mapping, as it is able to differentiate areas with different crop types (Gamon et al., 1995; Ji-hua et al., 1999; Wardlow & Egbert, 2010), and thus be able to identify crops according to their calendars.

Hyper-temporal temporal NDVI data: NDVI data rich in temporal characteristic of an area according to vegetation dynamics through time (de Bie, 2014), have been potential and showed the ability in mapping land use changes, ecosystem's heterogeneity, crops performance, land management, and importantly in mapping different crops' crop calendars (Ali, de Bie, Skidmore, Scarrott, & Lymberakis, 2014; de Bie et al., 2008; de Bie, 2002).

This research applied MODIS hyper-temporal data for 10 years from 2004 to 2014, to detect the differences in practiced maize crop calendars in Rwanda. Maize, one of the important crops contributing a lot to livelihood and food security of the majority of Rwandan population, has been considered as having the same crop calendar in the country (FAO/GIEWS, 2015). However, by applying the NDVI data to find different areas in the country, the research found significantly different maize crop calendars in the different NDVI classes.

1.2. Research problem

The great importance of crop calendar requires that it should be accurate: conforming almost exactly to its area's ground reality (Miller, Lanier, & Brandt, 2001) for the ability to serve its contribution to ensure country's food security (AMIS, 2012). Inaccurate crop calendar may lead to food insecurity, due to lack of reliable information about important aspects such as crop cycles, and the right time for planting and harvesting.

In order to have good crop calendar's accuracy, Bailey (2004) and FAO (2015) indicate that the calendar should differ from one place to another depending of differences in natural factors influencing crops growth, including soil, topography, climate conditions, etc... These differences result in an area or a country with a diversity in agro-ecosystems characteristics, which would diversify also the crop calendars.

In regard to Rwanda, the country is made of a complex landscape different from West to East (Twagiramungu, 2006). The natural differences in Rwanda are mainly due to topography, rainfall, landform, soil types (Clay & Dejaegher, 1987). This led to the country to be composed of 12 different

agro-ecological zones, which were delineated based on differences in topography, rainfall and soil types. This indicates that the country should have different crop calendars for different crops.

However, even though Rwanda presents major natural differences in different areas, currently, one crop calendar is attributed to the country for maize and sorghum crops (FAO/GIEWS, 2015), as presented in the following figure 1.

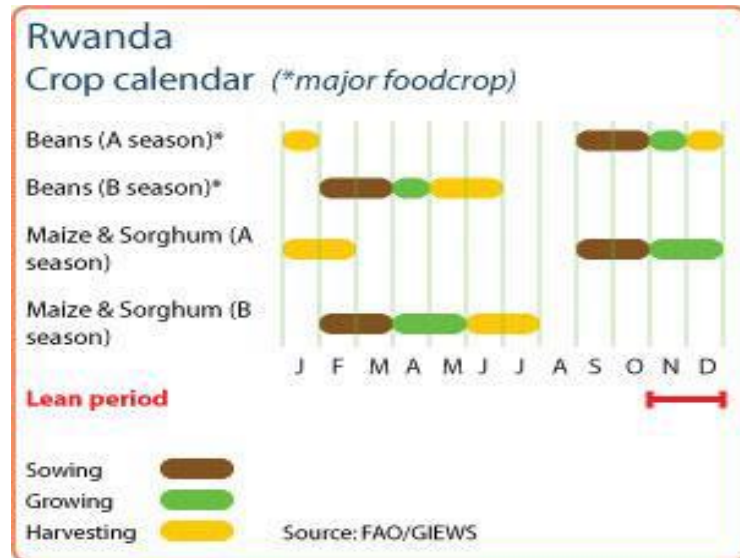


Figure 1: Major crops' calendar for Rwanda (FAO/GIEWS, 2015)

Regarding the differences in country's natural system, the above crop calendar is too generalized. It is not showing the variation exist in the country while the crops are grown in different ways and periods in order to adapt to specific area's local conditions (Westengen & Brysting, 2014). The differences are not only viewed as spatial but also temporal. The farmers' attitudes and decisions change over time in order to adapt to local climate conditions which vary or change in time (Foody & Boyd, 1999). This indicates that there is a need to apply a method which captures both the spatial and temporal differences of different areas, in order to be able to generate different crop calendars for different areas of the country.

Remote sensing methods for crop calendar development is the method with the ability to incorporate areas' both spatial and temporal changes, and actions taken from farmers' decisions including planting and harvesting time (Kotsuki & Tanaka, 2015). In addition, remote sensing methods have been found to be effective in agriculture monitoring (Ji-hua et al., 1999), and cost-effective for crops calendars estimation (Ozdogan, Yang, Allez, & Cervantes, 2010).

One of the remote sensing methods used to monitor crops and capture the spatio-temporal changes of an area based on vegetation cycles over the area, is hyper-temporal NDVI (de Bie et al., 2008). NDVI which is an index characterizing different areas according to the amount of vegetation and their health condition, considers photosynthetic activity over an area and quantifies it using satellites' red and near-infrared bands (Govaerts & Verhulst, 2010).

In order to consider both spatial and temporal changes in crops over different areas of the country, this research used hyper-temporal NDVI data from MODIS, with 250m spatial resolution and regularly available every 16 days as maximum value composite images. To incorporate temporal changes in the

country, 10 years data from 2004 to 2014 have been used to classify areas of the country according to similarities in vegetation cover changes over time.

This research aimed at assessing whether the hyper-temporal NDVI stratification can significantly differentiate the differences in practiced crop calendars in Rwanda. The maize crop calendars were generated from interviews with farmers from sample NDVI classes and the calendars were different from one NDVI class to another. Also, practiced maize crop calendars were generated irrespective of NDVI classes and also were different from each other.

1.3. Research objectives, research questions and hypothesis

1.3.1. General objective

The general objective of this research was to assess if spatial stratification of hyper-temporal NDVI data into NDVI classes can differentiate differences in practiced maize crop calendars for Rwanda.

1.3.2. Specific objectives

1. To generate maize crop calendars for different NDVI classes through interviews with farmers
2. To assess the number of growing seasons per NDVI class
3. To generate maize crop calendar groupings and assess if they relate to the different NDVI classes

1.3.3. Research questions

1. Do the number of maize growing seasons per year differ from one NDVI class to another?
2. Does the grouping of maize crop calendars relate to maize crop calendars of NDVI classes?

1.3.4. Hypotheses

Hypothesis 1:

- ❖ H_0 : The number of maize growing seasons is not significantly related to the clustering of NDVI profiles into NDVI classes (at $p=0.05$)
- ❖ H_1 : The number of maize growing seasons is significantly related to the clustering of NDVI profiles into NDVI classes (at $p=0.05$)

Hypothesis 2:

- ❖ H_0 : The grouping of maize crop calendars is not significantly related to the clustering of NDVI profiles into NDVI classes (at $P=0.05$)
- ❖ H_1 : The grouping of maize crop calendars is significantly related to the clustering of NDVI profiles into NDVI classes (at $P=0.05$)

2. LITERATURE REVIEW

2.1. Agriculture in Rwanda

Agriculture in Rwanda is diverse and influenced by different factors. It is influenced by exogenous factors such as biophysical environment factors, government policies and economic conditions (Smit, McNabb, & Smithers, 1999). The authors also indicate that the agriculture is affected by endogenous factors like farmer's experience, perceptions, the location of the farms and financial capacity. The applicability of the combination of these factors characterises agriculture of the region (Iisd, 1997).

2.1.1. Exogenous factors influencing agriculture in Rwanda

Rwanda is characterised by a great variety in agriculture due to different exogenous factors (Clay & Dejaegher, 1987). One of the principal cause of diversity in the country is topography which divides Rwanda into three main altitude zones: high altitude in West, medium altitude in the Centre, and low altitude in East (Twagiramungu, 2006). In the Western part of the country, the highest altitude goes beyond 2000 meters, and ranges from 2000 m to 1500 m in Central part, and below 1500 m in Eastern part (Cole & Mcsweeney, 2011). Topography also influences other biophysical environmental factors including temperature, rainfall and soil quality (Chemonics International Inc, 2003).

The temperature, which also affects agriculture by influencing crop growth through photosynthetic activity (NC State University, 2010), varies according to the topography as well. The higher the altitude, the lower the temperature. In the North and Western part of the country, the temperature ranges between 15°C and 17°C and it can be lower than 0°C in some parts of the volcanic region (Rema, 2011). In central medium altitude, temperature varies between 19°C and 21°C. In lowland of East and South West is high temperature which can go above 30°C. In North and West where the temperature is low, there are longer crops growing seasons compared to other parts of the country (REMA, 2009b).

Likewise, the rainfall which also affects crops by the providing of water, varies following the variation in altitude. The higher the altitude the more the rainfall (Barrow, 2013). The annual rainfall in the North and Western part of the country is 1500 mm, and 900 mm in the East and South East (REMA, 2009b). There is a bimodal pattern of rainfall which causes four seasons: short rain season which starts from September to November, short dry season from December to February of the following year, long rain season starting from March to May, and long dry season which starts from June to August (Brouwer, van Bodegom, Satijn, & Buit, 2015).

The high topography and abundant rain in the Western part of the country are the main factors of soil vulnerability to erosion which most of the times leads to landslide and affects soil fertility (USAID, 2008). The soil in Central plateaus also is prone to erosion, while in lowland soils in East and South Eastern regions like Bugesera are not prone to erosion as their topographical and geological structure allow rain water to infiltrate deeply (MINITERE, 2006).

The areas with similarities in altitude, rainfall and soil, have the similar potential for a particular land use. The areas with the similarities in Rwanda were divided into 12 agro-ecological zones (Clay & Dejaegher, 1987), as presented by the following figure 2.

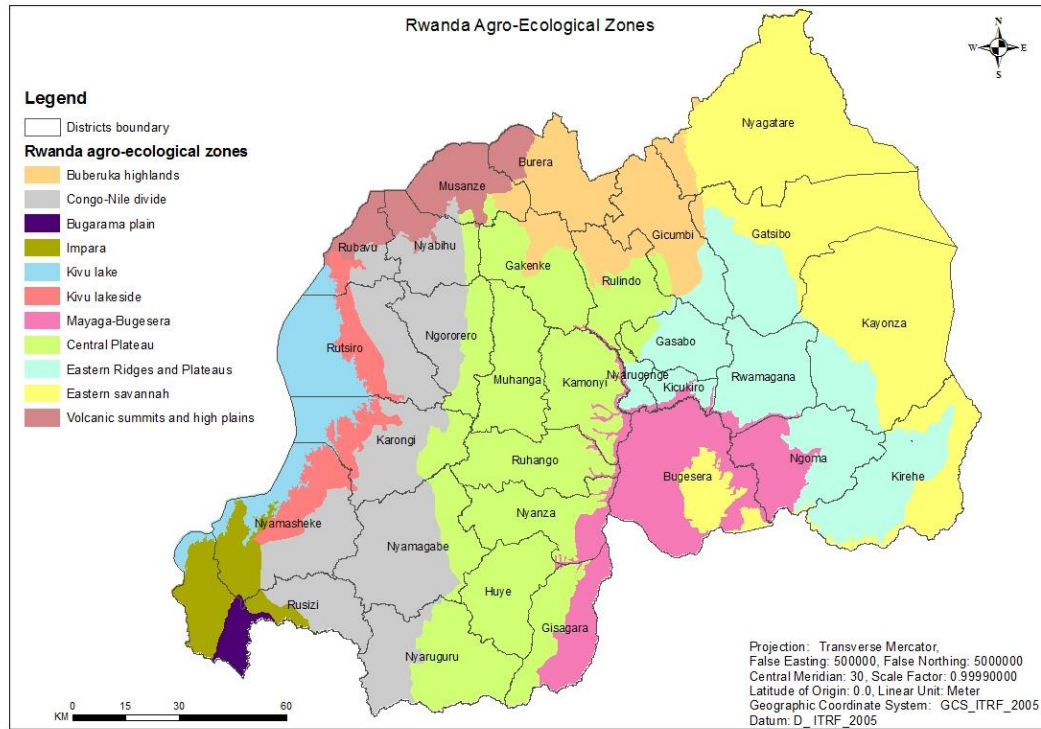


Figure 2: Agro-ecological zones of Rwanda

Figure 2 shows that from West to East of the country, also from South to North, the areas of Rwanda are characterized by different agro-ecological zones. The following table 1 summarizes differences between the 12 agro-ecological zones of Rwanda in terms of altitude, rainfall and soil type.

No	Agro-ecological zone	Average altitude (m)	Average rainfall (mm)	Soil type
1	Buberuka highlands	2000	1200	Oxisols at high altitude
2	Congo-Nile divide	2100	1600	Humic acid soils
3	Bugarama plain	1100	1200	Alluvial soils
4	Impara	1700	1400	Heavy clayey soils derived from basalt
5	Kivu lake	1600	1100	Gravelly sandy loam soils
6	Kivu lake side	1600	1200	Clay loam soil
7	Mayaga	1450	1050	Clayey soils derived from shale
8	Bugesera	1400	900	Oxisols
9	Central plateaus	1700	1200	Humic soils at medium altitude
10	Eastern ridges and plateaus	1500	950	Oxisols with high iron oxide
11	Eastern savannah	1400	850	Old infertile soils with texture variable
12	Volcanic summits and high plains	2200	1500	Ultisols derived from volcanic materials

Table 1: Characteristics of 12 Rwanda agro-ecological zones (Clay & Dejaeger, 1987)

Farming system in the 12 agro-ecological zones is complex based on a diversity of crops and crops requirements. Each agro-ecological zone counts different crops due to different crops requirements, also, different crops cycles, and time of planting and harvesting are different from a zone to another.

Government policy is another exogenous factor influencing agriculture in the country. For instance, the government formulates and helps in implementation of various agricultural policies in order to address agricultural issues and improve agricultural production at different administrative levels. The policies generally affect positively agriculture but in some cases, the impact may also be negative in case of general policies which normally do not consider natural variability in different administrative units of the country (Tyrchniewicz & Wilson, 1994). An example is of crop intensification program (Cantore, 2011) which failed in some regions of the country at its beginning, because some crops could not adapt in their defined areas by the policy.

2.1.2. Endogenous factors influencing agriculture in Rwanda

Endogenous factors; those that farmers can control, also influence agriculture in different aspects. The farmers know historical information about their farms which eventually play a big role in making decisions about appropriate inputs, preferable crop seeds to grow, the right time for ploughing, planting, weeding and harvesting (Iisd, 1997).

In addition to the knowledge and experience of the farmer over his/her farm, there is a financial factor which also influences the farming. Farmer's financial capacity gives the farmer option to decide about types and quality of crop seeds and other input to use. It also affects the time of application of the inputs, as farmer tends to buy and uses the inputs early or late, which affects also planting time, according to the financial capacity (ESAANet, 2007).

In a nutshell, the combination of both the exogenous and endogenous factors determines the structure of the country's agriculture and practiced crop calendar (Iisd, 1997)

2.1.3. Seasonal agriculture in Rwanda

Rwanda has three agricultural seasons per agricultural year. Season A starts in September of one calendar year and ends in February of the following calendar year. Season B starts in March and ends in July of the same calendar year. Season C starts in August and ends with September of the same calendar year (NISR, 2015a). These seasons are sometimes subject to climate uncertainties and then present differences from one region to another, and from one year to another. Season A and B are the main agricultural seasons for the country (Takeuchi, Shin'ichi, & Marara, 2006). For season C which is composed of months when the country is under a dry period of a year (from June till August), agriculture is practiced in marshlands using residual moisture from previous rainy seasons and through irrigation practices in some areas (FAO/GIEWS, 2015).

2.1.4. Maize crop in Rwanda

Maize crop is one of the major crops in Rwanda. It has been identified as a priority crop by the government in the recent program of crop intensification (RIU Rwanda, 2012). The crop has a big positive impact on the country's population in contribution to income generation, food security and poverty reduction in general. With the crop intensification programme, the maize crop increased by 300% in the area where cultivated, and the production increased by more than 400% by 2011 (MINAGRI, 2011).

The crop is cultivated countrywide and mainly intercropped with beans (N2Africa, 2014). It is influenced by various factors including abiotic factors such as climatic conditions resulting in varying rainfall regimes and temperature, soil conditions such as fertility, acidity and vulnerability to erosion (REMA, 2009a).

Maize crop requires the following ecological conditions to grow properly (Chand, 2015; Heisse, 2011; “Maize production,” 2013):

- Well drained soils with a worthy resource of nutrients and humidity. In a small quantity of water, the crop cannot survive, instead, it easily fades if it stands in water for a day.
- The crop necessitates optimal rainfall of 200 mm while the first 5 weeks after planting, if not available, irrigation should be applied. It requires both cool and warm areas.
- Regarding the altitude; generally maize crop grows well at all attitudes. But, it is more suitable for the range between 0 and 2, 900 m altitudes above sea level, and 30°C is its optimum temperature for growth.

The above mentioned required ecological conditions, explains the reason why Nyagatare district; one of the areas for sample areas by this study in North East of the country, was chosen by institutions such as RIU, as a major maize producing region. This district meets almost all required ecological conditions based on its altitude, temperatures and rainfall (RIU Rwanda, 2012).

Regarding the differences in the above mentioned maize requirements countrywide, it clarifies that also the crop calendars should be different to the different areas of Rwanda.

2.2. Currently used methods to generate crop calendars

This section explains different methods used to generate different crop calendars, their strengths and their drawbacks. According to Kotsuki & Tanaka (2015), there are three methods to estimate crop calendar: census based, model based and satellite (remote sensing) based methods. From the three methods, the focus has been remote sensing methods which was applied by this research.

2.2.1. The census based method

The census based method estimates crop calendar based on collected agricultural census data from administrative levels such as district, provincial or country level. Crop calendar from this method is highly reliable for the regions where there is sufficient census data but poorly reliable for regions where there is insufficient census data or no census data at all (Kotsuki & Tanaka, 2015). Although the census data are collected on an administrative level, the administrative boundaries are not based on climate conditions which are relevant in determining crop calendars (Manakov & Mikhaylova, 2015). Additionally, the authors argue that administrative boundaries are not stable and their instability is based on political decisions instead of natural behaviour. Also, the census method is criticised for being time consuming, labour-intensive, and it is difficult to replicate the process (HarvestChoice, 2013). Yet, the method has a good ability in separating the mixture of sample crops.

2.2.2. Model-based Method

The model-based method determines crop calendars using crop growth models through simulations by the use of meteorological data including weather, temperature, solar radiation, and soil data (Rafi & Ahmad, 2005). One of acknowledged strength of the method, is that it can identify different crop calendars in the same administrative unit, and it can be applicable to future simulation (Kotsuki & Tanaka, 2015). Though, the method requires special skills in modelling, mainly regarding crops and water modelling. This method is applied by various renowned institutions for agricultural development and food security including the Food and Agricultural Organization of the United Nations (Raes, Steduto, Hsiao, & Fereres, 2009).

2.2.3. Satellite based Method

Satellite data-based method has been used in mapping and identifying field crops at country or local level (Bailey & Boryan, 2010). One of the most used remote sensing techniques is NDVI time series data, by which it is possible to monitor crop health conditions; where high NDVI value is related to good crop conditions, and low NDVI indicating bad crop health (Ji-hua et al., 1999). From a variety of NDVI products offered by number of satellites, Wardlow, Egbert and Kastens (2007) showed that spatial-temporal information from MODIS NDVI 250m 16 days composites is suitable to identify crop types and their calendars. NDVI profiles allow crop monitoring from the start of growing period to the end of the growing period (Wardlow & Egbert, 2008).

The NDVI is given by a ratio of satellite red band and satellite near-infrared band as presented by the formulae below:

$$NDVI = \frac{NIR - R}{NIR + R}$$

Where: NIR is Near Infra-Red band
R is Red Band

Formulae 1: Calculation of NDVI

3. MATERIALS AND METHODS

3.1. Study area description

Rwanda is located in central Africa between 1°04' and 2°51' latitude South, and 28°45' and 31°15' longitude East. The total area of the country is 26,338 km², in which 67.7% is occupied by agriculture. The country is made of different administrative units: 4 provinces and Kigali city, 30 districts, 416 sectors, then cells and villages which are the smallest levels of administration (MINALOC, 2011).

Delineation of the study area in the country by this research, was based on differentiation of areas according to NDVI data from 2004-2014, as detailed the next sections. The following figure 3 presents the location of four surveyed sample NDVI classes making the study area for the research.

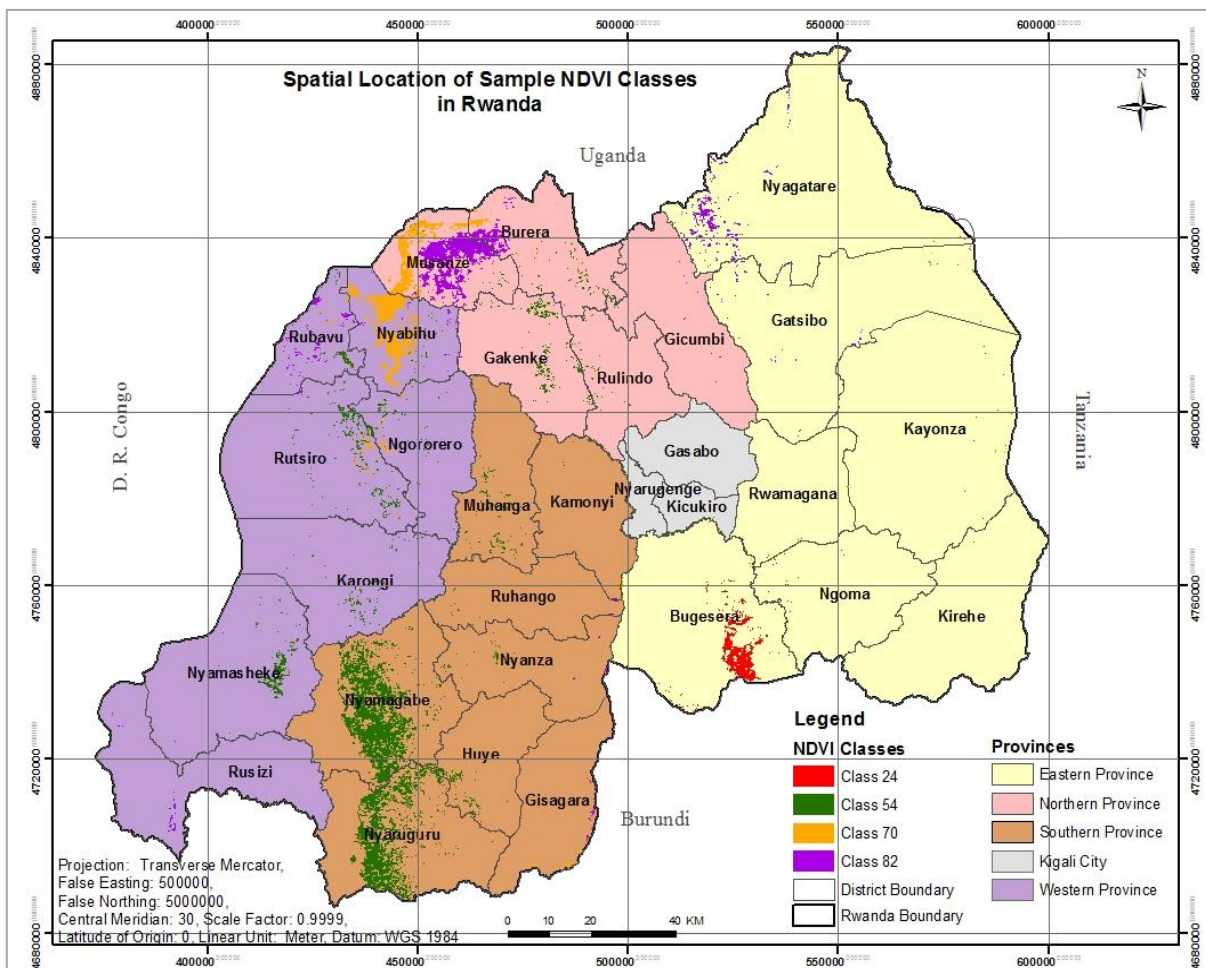


Figure 3: Study area map

3.2. Data acquisition and pre-processing

This section presents the data and data processes performed for land stratification, sampling, and collection of the field data in order to respond to research questions and hypotheses. The stratification of land was done through the use of MODIS NDVI images from 2004 till 2014, which were acquired from

USGS/NASA. The stratification of MODIS NDVI data was overlaid with land use data of Rwanda, from which sample NDVI classes were selected and surveyed. The information collected were about maize planting and maize harvesting dates for the agricultural year 2014-2015.

3.2.1. MODIS images data collection

MODIS NDVI data were chosen by this research over NDVI products from other different satellites sensors such as SPOT VGT, AVHRR GIMMS and MERIS which are also used for vegetation monitoring (Fensholt, Sandholt, & Stisen, 2006; Tucker, Pinzon, & Brown, 2004; VITO, 2015), because of a better spatial resolution compared to the others, and most importantly the ability in providing useful information on radiometric and biophysical characteristics of surface features (Yin, Udelhoven, Fensholt, Pflugmacher, & Hostert, 2012).

MODIS NDVI data were acquired using MODIS reprojection tool web interface. The tool allowed mosaicking process, as the study area was covered by two different tiles. With the tool, it was possible to specify and limit the download to the geographic area of interest. The product name for the downloaded data is MOD13Q1; referring to MODIS NDVI data with 250 m spatial resolution, with 16 days composites.

3.2.2. MODIS images data pre-processing

In order to make the data ready for use, the following pre-processing steps were performed using different software including ENVI 5.2, ERDAS Imagine and Arcgis 10.2

Step 1: Importing and rescaling: Downloaded NDVI images were imported into ERDAS imagine, and saved as .img files, and have been rescaled in order to range from 0 to 255 as a normal image digital number. The data were originally ranging from -3,000 to 10,000

Step 2: Stacking and filtering: this was done to enable further analysis, by cleaning possible outliers in the data. Using ERDAS IMAGINE 2014, the layer stack was produced containing all downloaded NDVI data from 2004 to 2014, and likewise for the data from 2014 to 2015. The latter images were used to observe the temporal behaviour of NDVI profiles for study area during the agricultural year of focus (2014-2015). By the use of timesat functionality in ENVI software, smoothing and filtering of the data was performed and provided the smoothed NDVI data which were used for the further land classification process.

Step 3: Classification: Using ERDAS IMAGINE 2014 software, the unsupervised classification was run for the smoothed layer stack by applying ISODATA clustering algorithm. The algorithm classified the NDVI data based on differences in NDVI values; which correspond to the vegetation cover over different areas of the country from 2004 to 2014. The output signature was used to generate a legend for NDVI profiles of different produced NDVI classes, from which the differences in classes' temporal behaviour was observed.

Step 4: Converting classified image into polygon: The process was done using arcmap software, by the help of its toolbox. The conversion into shapefiles allowed subsequent processes that involved combination of the NDVI classes with existing Rwanda land use data shapefiles, in order to determined amount of every land use present in every NDVI class, and then focus on those dominated by agriculture.

Step 5: Re-projection: All previous processes were done with original projection system of NDVI data (sinusoidal) in order to ensure the minimal risks of pixels shifts. At final pre-processing step, the data were re-projected into new projection system (transverse Mercator), which was the projection system used by other polygon data used afterwards. It was done in Erdas software; which is more effective for dealing with the sinusoidal projection system.

3.3. Data processing

After data pre-processing, sample areas selection was the next step, in order to prepare the field data collection. Unsupervised classification using ISODATA was applied on the data layer stack, and classification was run from 10 to 100 classes as minimum to maximum number of classes. The maximum number of iterations was set to 50 and the convergence threshold was set to 1. After obtaining the results for all NDVI classes from 10 to 100, the separability analysis was performed to decided optimal number of NDVI classes to use for sampling and other processes. Through the separability analysis, 95 NDVI classes were found to be the best separable NDVI classes from 2004-2014 in Rwanda

As the focus of this research was on agricultural areas, existing land use data in Rwanda were overlaid with the 95 NDVI classes to obtain NDVI classes dominated by agriculture. The process resulted in 24 NDVI classes with more than 50% of agriculture.

In order to assess the way the 24 agricultural NDVI classes have been behaving from 2004 till 2014, for the impression of their differences to be observed, the medians of their NDVI values were plotted in excel software.

It was observed that the 24 agricultural NDVI classes have been behaving differently over 10 years. For the purpose of field data collection, four sample NDVI classes have been selected based on notable differences in their median NDVI profiles, so that maximum of the variation existing in the study area in terms of crops cover can be represented. In addition, within each sample NDVI class, 12 sample areas were selected, making final representative sample size to be 48 sample areas for the entire study area. The number of sample areas was due to the possibility to be covered during the field work, because of limited research time. Sample areas were selected randomly, but with restrictions to avoid areas at the edge NDVI class which may influenced by other external classes. Also, sample areas had to be close to the road in order to ease the access while field work. The sample areas were distributed per clusters, to facilitate transport and quick field work process. Three clusters per NDVI class were designed, and a cluster contained four sample areas.

Though, after field work, only 45 sample areas remained useful for the study. Among the three not used sample areas include an area where was no more vegetation due to new industrial construction in the district. In another sample area was an issue of buffaloes escaping from the close national park and eat the planted maize, so farmers gradually do not grow maize time after time. But, in this area was very small patches of maize, but no farmer was found to be interviewed. For the final sample area, there was no presence of maize in the fields. So, the research only used the collected data from the rest 45 sample areas for the analysis.

3.3.1. Field data collection

The field work was conducted in the four sample NDVI classes, within the 45 sample areas, and the focus was on maize crop. The main data collected were dates of planting and harvesting of the maize crop. The data were collected through interview with farmers randomly found inside a sample area, given that they grow maize within the same area.

Interviewed farmers and sampling technique

In Rwanda, the average agricultural land is 0.35 ha per person (Premier Consulting Group, 2009). Sample area was of the size of the MODIS NDVI data, which was equal to 231.92 * 230.37 m (5.34 ha), which by average is occupied by 16 farmers. In order to capture much of the variations, interviewed farmers ranged between 50% and 81% of the average farmers per sample area. In total, 433 farmers were interviewed in all 4 sample NDVI classes.

The farmers for interview were randomly selected based on the following conditions: they were found within the sample areas while the field work, and they grew maize in the same sample area for the agricultural year 2014-2015.

The following table 2 presents number of farmers interviewed per each sample area per NDVI class.

NDVI class	Cluster	Sample area ID*	No. farmers
24	1	2411	10
		2412	9
		2414	11
		Total	30
	2	2421	9
		2422	10
		2423	10
		Total	29
	3	2431	11
		2432	9
		2433	8
		2434	9
Total	37		
54	1	5411	12
		5412	10
		5413	9
		5414	11
Total	42		
	2	5421	9
		5422	10
		5423	8
		5424	9
Total	36		
	3	5431	9
		5432	8
		5433	10
		5434	8
Total	35		
70	1	7011	8
		7012	9
		7013	10
		7014	11
Total	38		
	2	7021	9
		7022	9
		7023	9
		7024	9
Total	36		
	3	7031	10
		7033	10
		7034	11
		Total	31
82	1	8211	11
		8212	10
		8213	9
		8214	13
Total	43		
	2	8221	10
		8222	10
		8223	10
		8224	9
Total	39		
	3	8231	9
		8232	9
		8233	11
		8234	8
Total	37		
Overall total			433

Table 2: Number of interviewed farmers per sample area per cluster per NDVI class

* Sample area ID is made by four digits: first two digits are for NDVI class, the third digit is for cluster number within the class, and the fourth digit is for the sample area number within the cluster.

3.4. Data analysis and interpretation

To analyse the collected data, first, maize crop calendars for the plots were generated and generalized per sample area, and then to NDVI classes.

Second, the practiced crop calendars as collected from the interviews with farmers were entered into SPSS regardless of which NDVI class they were collected from. Using K-means classification method, the practiced maize crop calendars were grouped into four groupings.

Third, using chi-square test, it was assessed whether the number of maize growing seasons is significantly related to the NDVI classes, and also, it was assessed if the groupings of practiced maize crop calendars as grouped using K-means are significantly related to the maize crop calendars for NDVI classes.

3.4.1. Maize calendars for different NDVI classes

Based on interviews with farmers, four maize crop calendars were generated according to the four different NDVI classes. First, single crop calendar was generated per plot, then generalize the calendar on sample areas, and then, the maize crop calendars were generalized per NDVI class.

The following are steps taken to generate the maize crop calendars per NDVI class:

1st step: Translating date given by farmer into Julian day

The farmers provided maize planting and harvesting dates in a normal calendar year from January to December. In order to allow crop calendar generation and further statistical analysis, the normal calendar days were transformed into Julian calendar from 1 to 365 days of a year.

2nd step: Dividing into weeks

This study generated a weekly interval crop calendars. To do so, the dates from 1 to 365 were transformed into 52 weeks of a year, and then every day of a year was assigned to its corresponding week.

3.4.2. Grouping of maize crop calendars

To group practiced maize crop calendars according to their differences irrespective of NDVI classes, the following steps were taken:

1st step: Determining the number of practiced maize crop calendars groupings: In order to determine the number of practiced maize crop calendars groupings (K), the agglomerative hierarchical clustering algorithm was applied to the data, to have hierarchy structure of the data (Blei, 2008). This was a prior step to allow application of k-means clustering method, which was applied for the determination of conclusive maize crop calendar groupings.

The method applies different consecutive steps, from grouping nearby points into one group, then groups closest groups into a new bigger group based on the short distance between small groups, and finally builds hierarchical tree called dendrogram; from which all the formed groups from initial stage can be observed (Zhu, 2010). In case of this research, input data were the data as collected from interviews with farmers (planting and harvesting days in Julian days) for all the farmers regardless of their NDVI classes, so that the algorithm groups the similar groups and distinguishes the different ones according to their differences. To identify manageable different groups from the data, a threshold is arbitrarily set at a certain distance in the dendrogram, allowing to identify non-overlapping groupings (Ryan, 2013). From the

dendrogram, this study found 4 separable and non-overlapping groupings from the collected data, which were manageable for the study.

2nd step: Clustering the practiced maize crop calendars into four groupings. K-means clustering method, an unsupervised classification algorithm which divides n observations into K groups by assigning an observation to a nearest mean (Pham, Dimov, & Nguyen, 2005), was performed over all the collected maize crop calendars data, so that they are grouped into the 4 groupings according to similar (nearest) means.

3.4.3. Analysis of variance, t-test and chi-square test

By this stage, the four practiced maize crop calendars groupings independent of the NDVI classes had been obtained, and there was still observed a relationship between the 4 practiced maize crop calendars groupings and the maize crop calendars per NDVI classes: some maize crop calendars from the same NDVI class were also grouped into the same practiced crop calendar grouping. This led to the next analysis; first, using ANOVA (Miller & Haden, 2006) to assess whether the maize crop calendars for NDVI classes were significantly different, and also assess whether the practiced maize crop calendars groupings were significantly different. Then, Fisher’s least significant differences was applied to evaluate specific pairs’ differences for NDVI classes and practiced maize crop calendar groupings. For assessing differences in planting and harvesting for season B, t-test instead of ANOVA, was carried out given only two groups for comparison: NDVI class 24 and 82.

Second, Chi-square (Griffiths, Miller, & Suzuki, 2000) test was performed to evaluate whether the number of maize growing seasons are significantly related to the maize crop calendars according to NDVI classes, and also examine whether the practiced maize crop calendar groupings are significantly related to the different maize crop calendars according to NDVI classes. The analysis directed to the conclusion about the ability of NDVI data to differentiate differences in the practiced crop calendars.

For chi-square test, both to assess the relationship between the number of maize growing seasons and NDVI classes, and between practiced maize crop calendars and NDVI classes, first contingency table was constructed containing frequency number of farmers from different NDVI classes with the same number of maize growing seasons. The second contingency table was constructed containing frequency numbers of farmers from the same practiced maize crop calendar grouping and found in the same maize crop calendars per NDVI class. Then, according to the total number of observations (interviews with farmers), expected values were computed for every cell in the contingency tables by applying the following formulas (Diener-West, 2008):

$$Expected_{ij} = \frac{Row\ Total_i \times Col\ Total_j}{Grand\ Total}$$

Formula 2: Calculation of expected values in contingency tables

After getting the expected values, the following formulae was applied to calculate the chi-square value:

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

Where: χ^2 is chi-square calculated
O is observed value (observed frequency of the same calendar)
E is expected value (expected frequency the same calendar)

Formula 3: Calculation of Chi-square (χ^2)

After getting the chi-square value calculated, it was compared with the chi-square critical from the chi-square distribution table. The latter was obtained by taking the degrees of freedom (calculated according to the following formulae 4), at a significance level of 0.05 in order to find whether the relationship was significant (if chi-square calculated was greater than chi-square critical).

Where: **DF** is degree of freedom

$$DF = (r - 1)(c - 1)$$

r is the number of the contingency table's rows

c is the number of the contingency table's columns

Formula 4: Calculation of degrees of freedom for chi-square test

3.5. Methodology flow chart

The following figure 4 contains a flowchart presenting a sequence of activities carried out in order to reach the objectives and test hypotheses of this research.

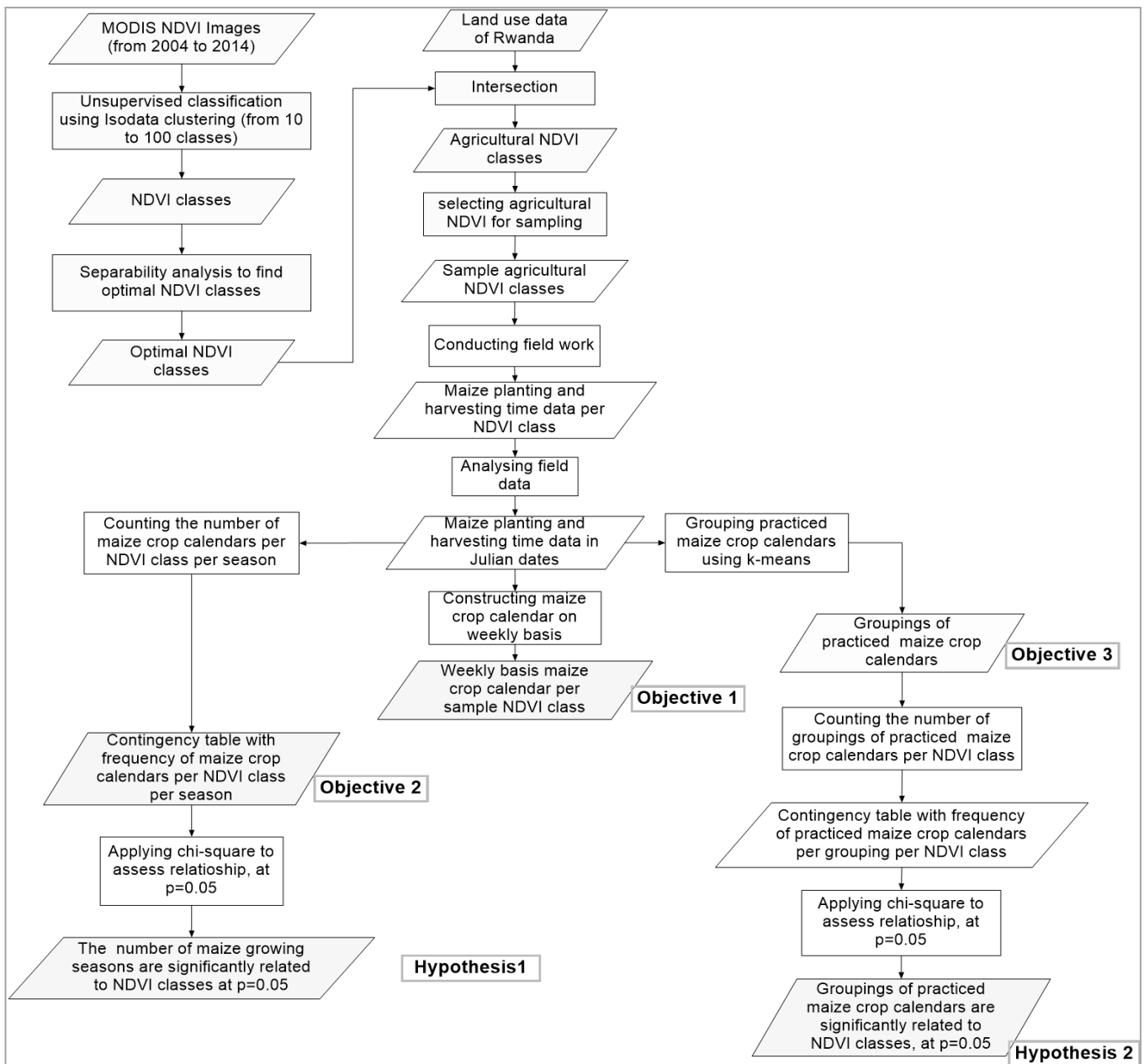


Figure 4: Flow chart of the applied research methodology

4. RESULTS

This section presents the results from hyper-temporal MODIS NDVI data stratification process, and the results from the field data analysis to respond to the research's objectives, answer the research questions and test hypotheses.

4.1. Hyper-temporal MODIS NDVI data stratification

The hyper-temporal MODIS NDVI data of 10 years from (2004-2014), was stratified using ISODATA unsupervised classification technique. Through the separability analysis, 95 NDVI classes were found to be the best separable NDVI classes from 2004-2014 for Rwanda, as shown by the following figure 5.

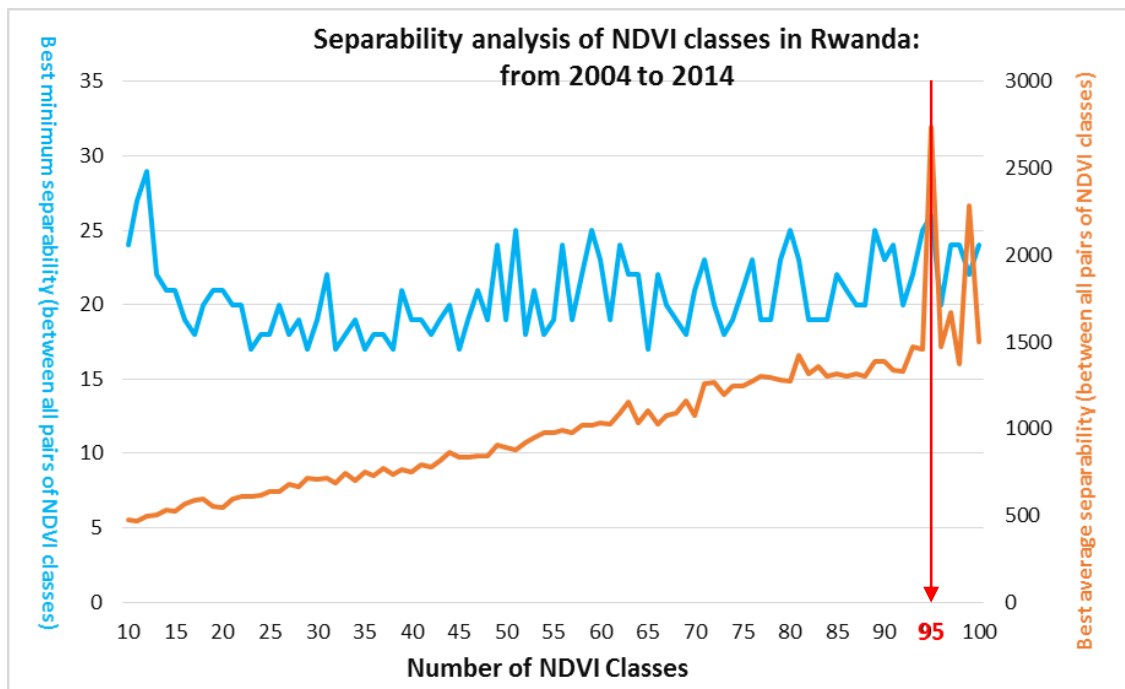


Figure 5: The best separable NDVI classes for MODIS data from 2004 to 2014

The red arrow in figure 5 shows the peaks for both best minimum and best average separability values pointing out 95 to be the best separable NDVI classes for Rwanda

The spatial distribution of the 95 classes in Rwanda is presented by the map in the following figure 6

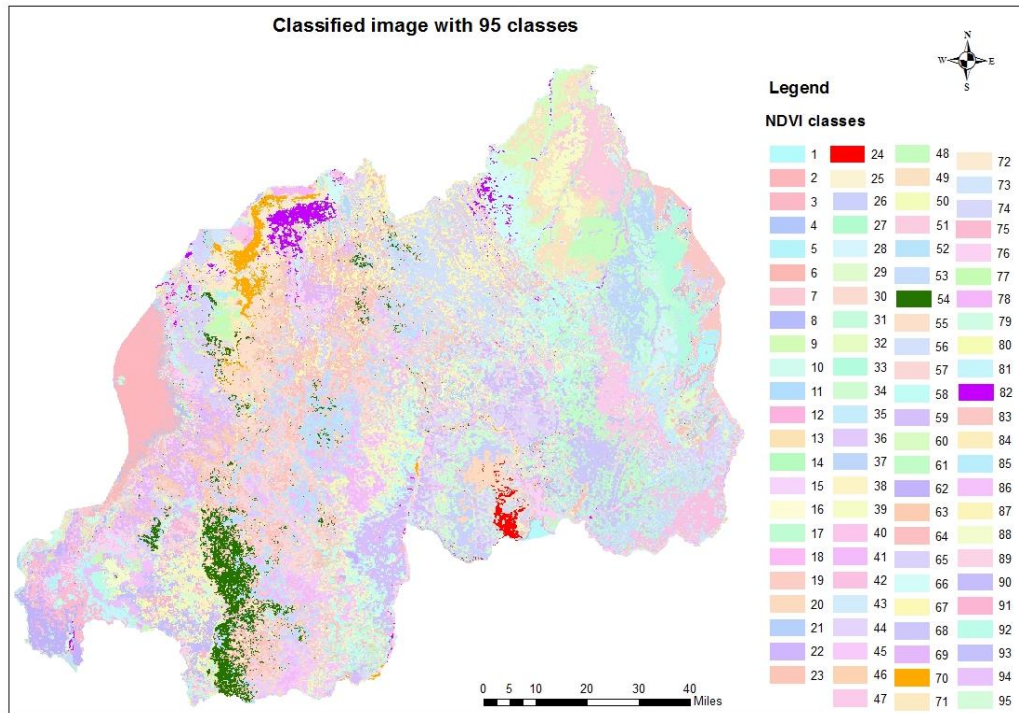


Figure 6: 95 NDVI classes of hyper-temporal MODIS images from 2004 to 2014

As the focus of this research was on agricultural areas, to distinguish NDVI classes with the dominance of agriculture, existing land use data in Rwanda were overlaid with the 95 NDVI. The process resulted in 24 NDVI classes with more than 50% of agriculture. Figure 7 below shows the spatial location of the 24 NDVI classes dominated by agriculture in Rwanda.

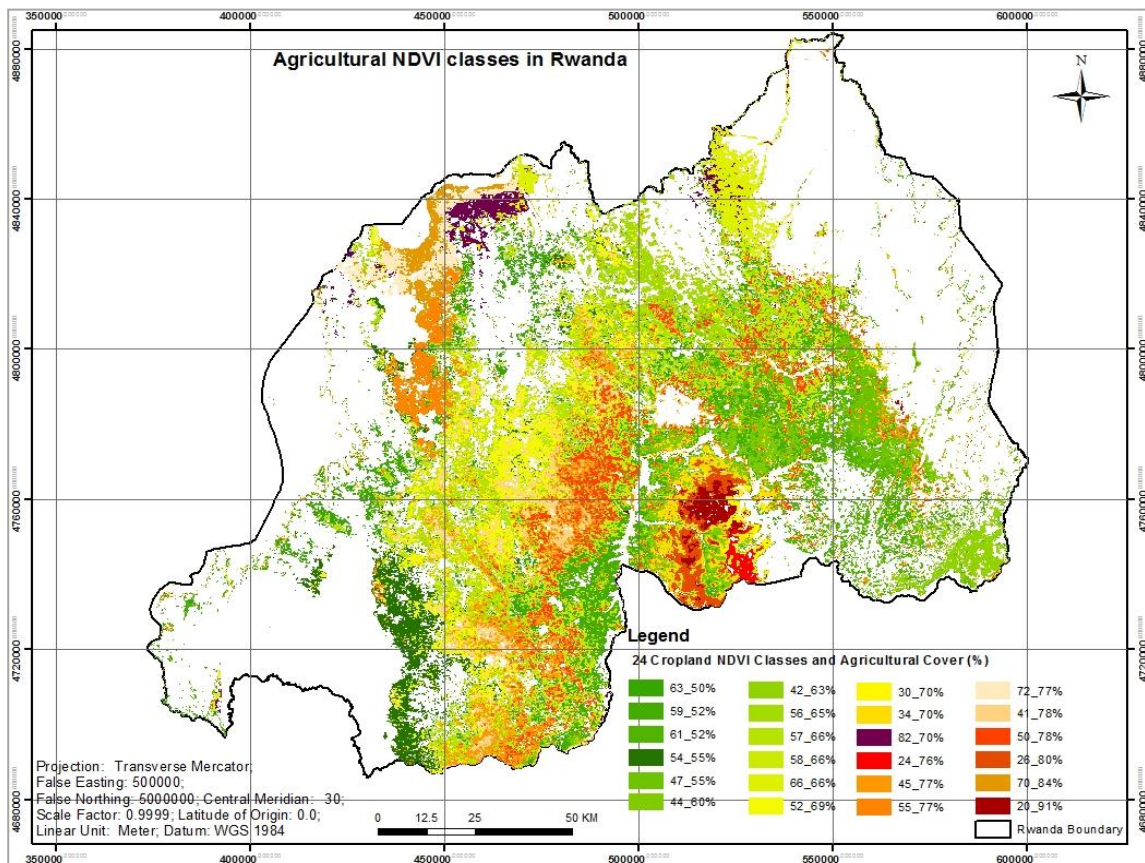


Figure 7: The location of 24 NDVI classes with more than 50% of agriculture

The map in figure 7 showed that agriculture is generally dominant in central part of Rwanda than any other part of the country.

To visualize temporal behaviour of the agricultural NDVI classes, the annual NDVI profiles medians were generated, as presented in the following figure 8

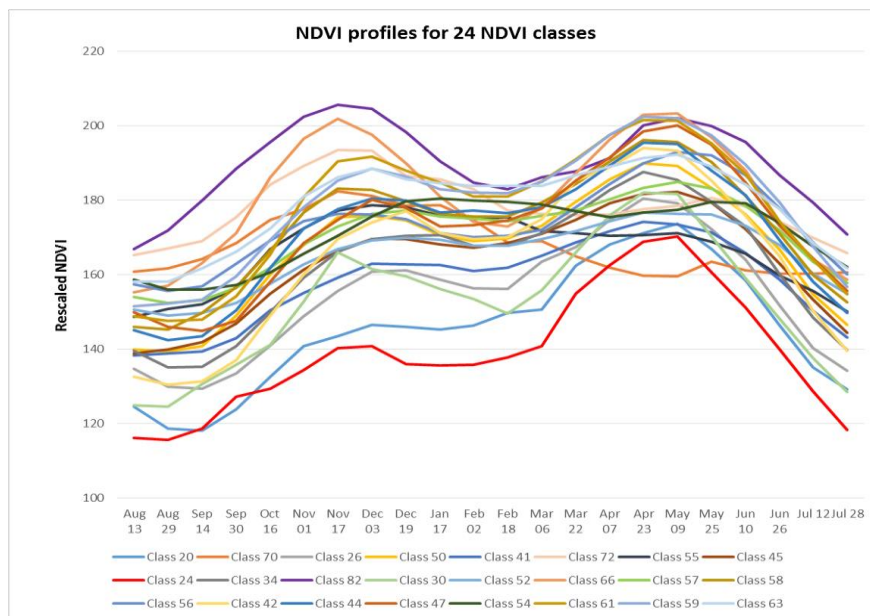


Figure 8: NDVI profiles for 24 NDVI classes with above 50% agriculture

Figure 8 shows differences in temporal behaviour of the agricultural NDVI classes, and also indicates the seasonality (by NDVI peaks) in the classes. From the above figure 8, 4 sample NDVI profiles of 4 NDVI classes were selected based on eminent differences in behaviour in order to represent the rest while field data collection. The profiles of the four selected sample NDVI classes are presented in figure 9 below:

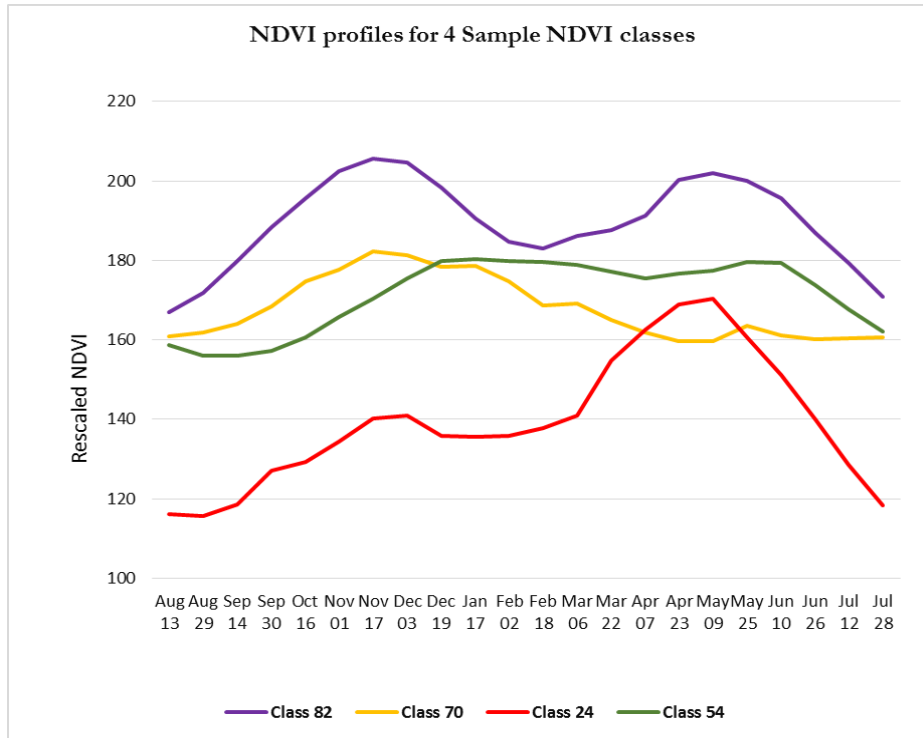


Figure 9: Temporal behaviour of 4 sample NDVI classes

The selected sample NDVI classes in figure 9, had differences that were chosen in order to represent other NDVI classes given different characteristics including: two distinguished agricultural seasons (NDVI class 82), remarkable season A than B (NDVI class 70), remarkable season B than A (NDVI class 24), and no distinguishable seasonality (NDVI class 54). Regarding the spatial location of the four sample NDVI classes, the following figure 10 shows their spatial distribution in the country.

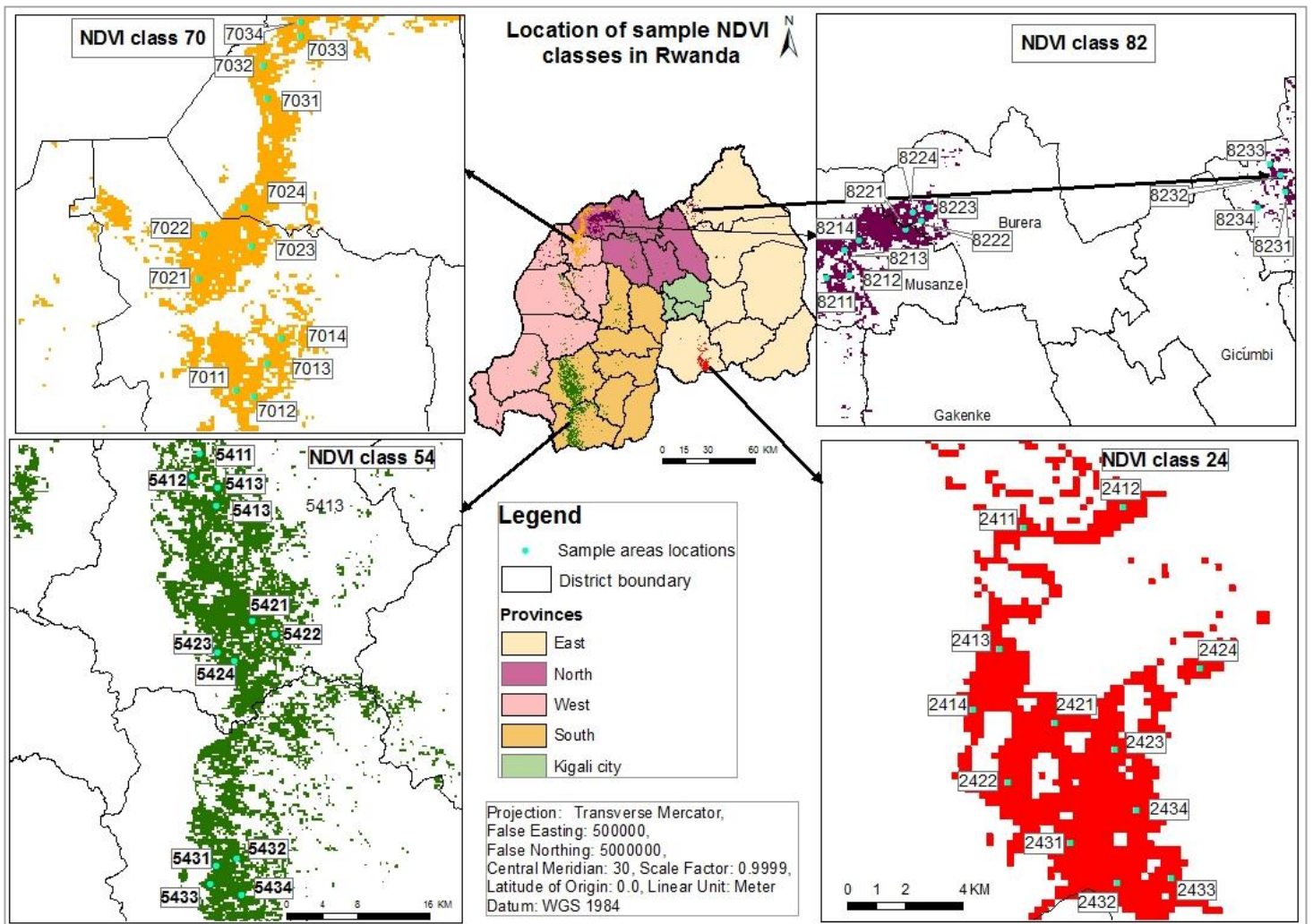


Figure 10: Location of 4 sample NDVI classes and the sample areas in Rwanda

As shown in the above figure 10, the sample areas within NDVI class were distributed according to cluster, as each cluster was containing 4 sample areas represent the cluster and 12 sample areas represent the whole NDVI class.

4.2. Maize crop calendars per sample area for different NDVI classes

The Generated maize crop calendars were for one agricultural year of 2014 – 2015, through the interviews with farmers on planting and harvesting time in the four sample NDVI classes (24, 54, 70 and 82). NDVI profiles for sample NDVI classes also were presented to compare their spatial and temporal behaviours and produced maize crop calendars.

4.2.1. Maize crop calendar and NDVI profiles for NDVI class 24

In NDVI class 24, the interviewed farmers were 96. There were 2 maize growing seasons (season A and B) and were no much differences in planting and harvesting time for different sample areas of this class (Appendix 5). For season A, planting started with September 2014 and ended with the first week of October 2014. Harvesting started with the last week of December 2014 and ended with the first week of February 2015. For season B, plating started in the second week of February and finished in the first week of March 2015. Harvesting period started in the last two weeks of May till the third week of June. Figure 11 below presents the maize crop calendar for NDVI class 24, per sample area per cluster.

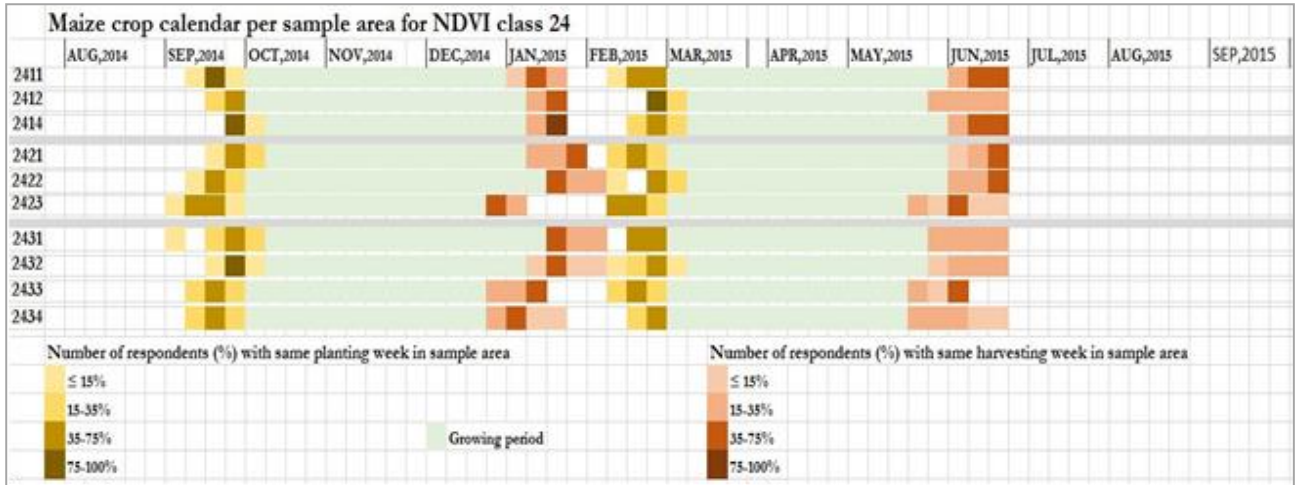


Figure 11: Maize crop calendars per sample area per cluster for NDVI class 24

To compare the above maize crop calendar (figure11) with the sample areas’ phenology temporal behaviour, MODIS NDVI data for the agricultural year 2014-2015 (from August 2014 till September 2015) were used and NDVI profile per sample area per cluster were visualized. The profiles visualization is presented in figure 12 below, with highlights in red for sample areas in cluster 1, green for sample areas in cluster 2, and blue for sample areas in cluster 3. For thorough information, the profiles per sample area are presented in appendix 9.

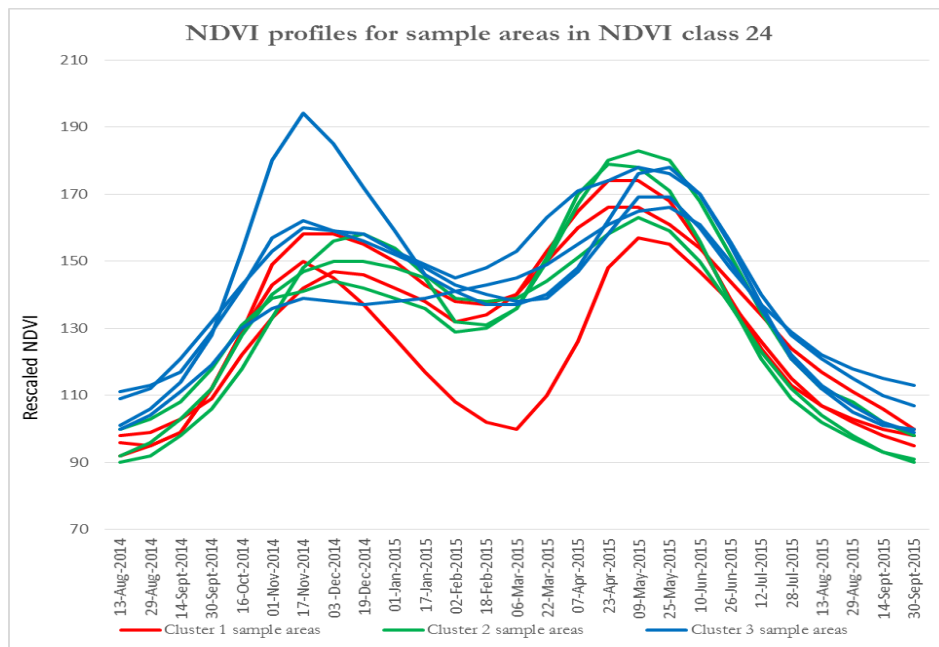


Figure 12: NDVI profiles per cluster for NDVI class 24

As shown in figure 12, the NDVI profiles show two agricultural seasons for the agricultural year 2014-2015 corresponding to the two growing seasons of maize crop calendar for NDVI class 24. However, focusing on the vegetation cover, within the one sample area was many various vegetation covers and the maize crop was not dominant (table 3, 4 and 5). So, the temporal behaviour of NDVI profiles reflected behaviour of a mixture of the vegetation covers, and the maize had a small contribution. The following table 3, 4 and 5 present area in percentage of different land covers sample area per cluster in NDVI class 24, as they were found from the field. The detailed NDVI profiles per sample areas are presented in appendix 9.

Sample area	Maize	Banana	Forest	Bare soil	Sorghum	Sisal	Grass	Cassava	Beans	Total
2411	10.91	5.82	1.50	6.42	2.87	0	12.15	50.60	5.73	96.01
2412	5.39	10.44	9.25	2.27	5.46	0	10.36	43.91	5.07	92.15
2414	3.01	2.83	6.78	1.46	6.00	39.83	11.12	25.82	1.10	97.96

Table 3: Dominant land covers and their area (%) in cluster 1 of NDVI class 24

Table 3 above shows that cluster 1 of NDVI class 24 was mainly dominated by cassava crop and grass, then maize. The following table 4 shows the percentage of dominant land covers per sample area in cluster 2 of NDVI class 24

Sample area	Maize	Banana	Forest	Ploughed	Sorghum	Grass	Cassava	Total
2421	8.22	0	11.03	9.81	8.73	31.01	31.20	100
2422	8.55	0	0	20.17	0	68.19	3.10	100
2423	5.13	2.86	9.95	0	10.20	21.08	50.24	99.45

Table 4: Dominant land covers and their area (%) in cluster 2 for NDVI class 24

Table 4 shows that grass and cassava were dominant in cluster 2 of NDVI class 24. The following table 5 presents the percentage cover of dominant land covers per sample areas in cluster 3 of class 24.

Sample area	Maize	Banana	Forest	Bare soil	Sorghum	Grass	Cassava	Total
2431	9.60	22.03	0	2.17	9.41	0	54.44	97.66
2432	1.82	1.13	66.09	3.38	2.30	13.38	11.40	100
2433	37.05	0	0	3.63	11.29	4.07	34.72	96.54
2434	6.48	0.38	18.69	5.19	23.03	11.69	34.41	100

Table 5: Dominant land covers and their area (%) in cluster 3 for NDVI class 24

Table 5 indicates that cassava was the most dominant crop in cluster 3 of class 24, followed by maize and sorghum.

In brief, they were different land covers in different sample areas per cluster in NDVI class 24 that contributed to the temporal behaviours in figure 12 and appendix 9, and the maize crop had a small contribution. Only maize crop contributed much in one sample area (2433). This indicates that different other crops might have had the same calendar as maize in the year 2014-2015 in NDVI class 24.

4.2.2. Maize crop calendars and NDVI profiles for NDVI class 54

In NDVI class 54, the interviewed farmers were 113, and there was one maize growing season (season A). In the NDVI class 54, planting started with June 2014 and ended in the third week of September the same year. Harvesting started in the last week of December 2014 and ended in the second week of March 2015. The following figure 13 summarises the maize crop calendar per sample area per cluster, with the percentage of respondents with the same calendar per sample area. The crop calendar is presented on a weekly basis for planting and harvesting times.

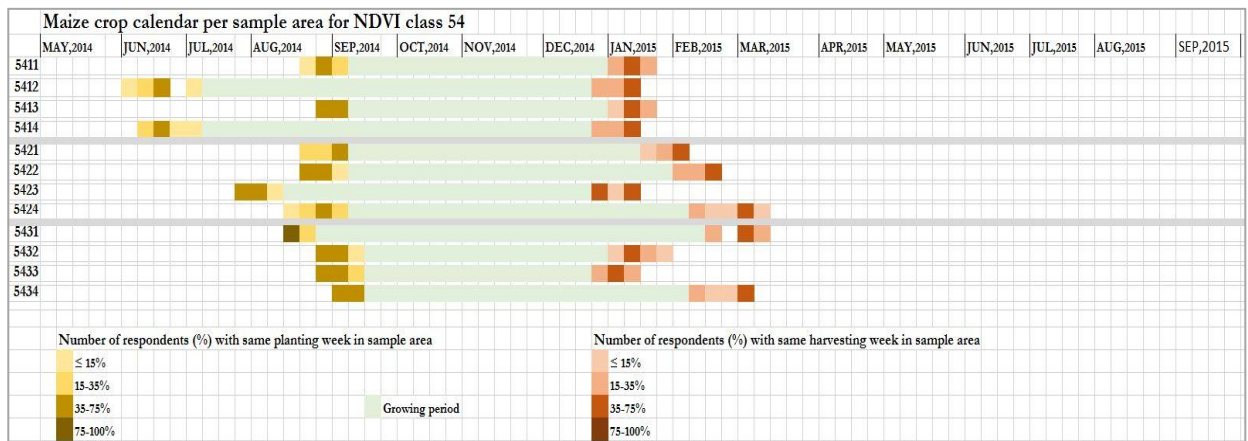


Figure 13: Maize crop calendars per sample area per cluster for NDVI class 54

The farmers from two sample areas (5412 and 5414) in cluster 1 planted maize earlier than others, in the first week of June till the first week of July. The farmers from sample area 5423 were the next, where they started to plant maize in the fourth week of July 2014 till the second week of August 2014. Farmers from the rest of the sample areas did not have much variation. The rest planted from the third week of August 2014 till the third week of September 2014. The harvesting started in the fourth week of September 2014 till the second week of March 2015.

To be compared to the generated maize crop calendars and sample areas' NDVI profiles, MODIS NDVI data from May 2014 till September 2015 were used and the profiles per sample area per cluster were visualized (cluster 1 in red, cluster 2 in green and cluster 3 in blue) as shown in the following figure 14.

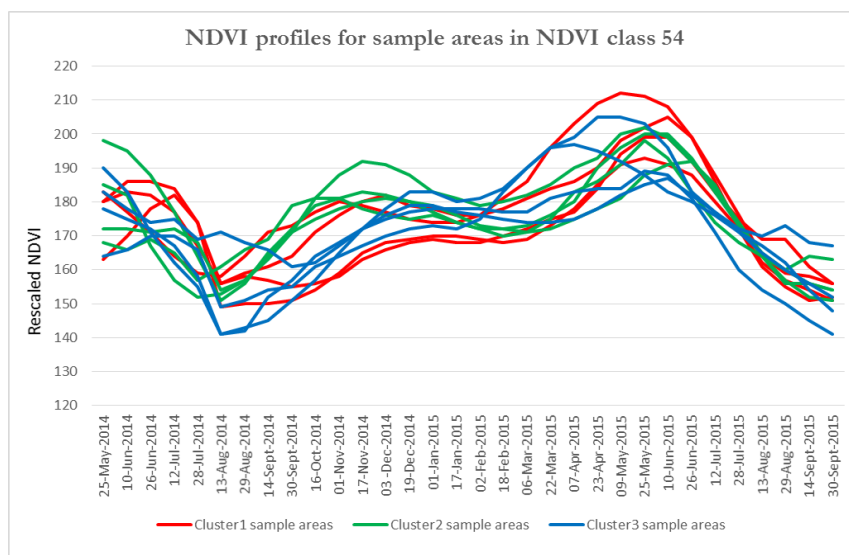


Figure 14: NDVI profiles per cluster for NDVI class 54

As presented by the figure 14, there had been two agricultural seasons in NDVI class 54, though the first season did not show high NDVI peak as the second one. Based on maize crop calendars of this class (figure 13), maize was grown only in season A, a season characterized by low pick in figure 14.

To know about the contribution of the maize crop to the NDVI profiles, the following tables 6, 7 and 8 present dominant land covers and their areas in percentage per sample area per cluster, as observed from the field. The detailed NDVI profiles per sample areas are presented in appendix 10.

Sample area	Maize	Banana	Forest	Eggplant	Sweet potatoes	Peas	Irish potatoes	Grass	Cassava	Beans	Total
5411	8.12	11.49	5.94	5.07	13.32	3.54	3.69	19.35	11.01	14.47	96.01
5412	6.28	6.55	11.48	5.63	8.17	1.97	4.35	23.35	6.87	9.74	84.40
5413	5.28	11.09	13.01	5.75	10.61	2.46	4.85	20.57	5.97	10.83	90.42
5414	1.10	5.94	14.07	0.52	11.96	1.68	1.43	26.40	4.93	21.21	89.24

Table 6: Dominant land covers and their area (%) in cluster 1 for NDVI class 54

As shown in table 6, cluster 1 of NDVI class 54 was dominated by grass, beans, sweet potatoes and forest. The contribution of maize was small in the cluster. The following table 7 shows the percentage of dominant land covers per sample area in cluster 2 of NDVI class 54

Sample area	Maize	Banana	Forest	Tea	Sweet potatoes	Peas	Irish potatoes	Grass	Beans	Total
5421	5.79	22.60	6.19	0	13.39	2.06	0.56	18.00	19.77	88.35
5422	6.83	8.39	14.93	0	19.40	1.69	7.22	18.95	12.43	89.84
5423	7.69	5.44	6.84	13.84	9.28	3.81	9.32	18.69	14.09	89.00
5424	4.01	6.79	29.61	13.70	4.28	3.59	6.37	14.31	10.74	93.39

Table 7: Dominant land covers and their area (%) in cluster 2 of NDVI class 54

From table 7, it was realized that, though maize had some contribution to the NDVI profiles in cluster 2 of NDVI class 54, the cluster was dominated by beans, grass and sweet potatoes. The following table 8 presents the percentage of dominant land covers per sample area in cluster 3 of NDVI class 54.

Sample area	Maize	Banana	Forest	Wheat	Sweet potatoes	Peas	Irish potatoes	Grass	Beans	Total
5431	6.57	5.64	4.73	3.25	15.27	4.62	7.10	21.44	12.64	81.24
5432	6.26	1.98	35.98	2.00	9.21	2.20	3.22	16.47	15.09	92.42
5433	24.53	0.50	20.73	3.16	10.14	3.52	12.11	13.74	4.05	92.48
5434	9.10	2.73	22.39	0	7.65	3.30	5.75	13.26	14.12	78.30

Table 8: Dominant land covers and their area (%) in cluster 3 of NDVI class 54

Also, cluster 3 was dominated by beans, grass and sweet potatoes as indicated by table 8. Maize still contributed less to the NDVI profiles. This indicated that the two seasonality profiles in figure 14 might have been determined mainly by many other land covers, with a small contribution of maize.

4.2.3. Maize crop calendars and NDVI profiles for NDVI class 70

In NDVI class 70, 105 farmers were interviewed. Maize crop was grown also for one agricultural season (season A). There were many variations in planting time (Appendix 7). Planting started in the last week of April 2014 and end in the first week of August 2014. Growing period started in the third week of May 2014 and ended in the first week of January 2015. Harvesting started in the second week of December

2014 and ended with January 2015. The following figure 15 summarizes maize crop calendars per sample area per cluster in NDVI class 70, according to the interviews with farmers in this NDVI class.

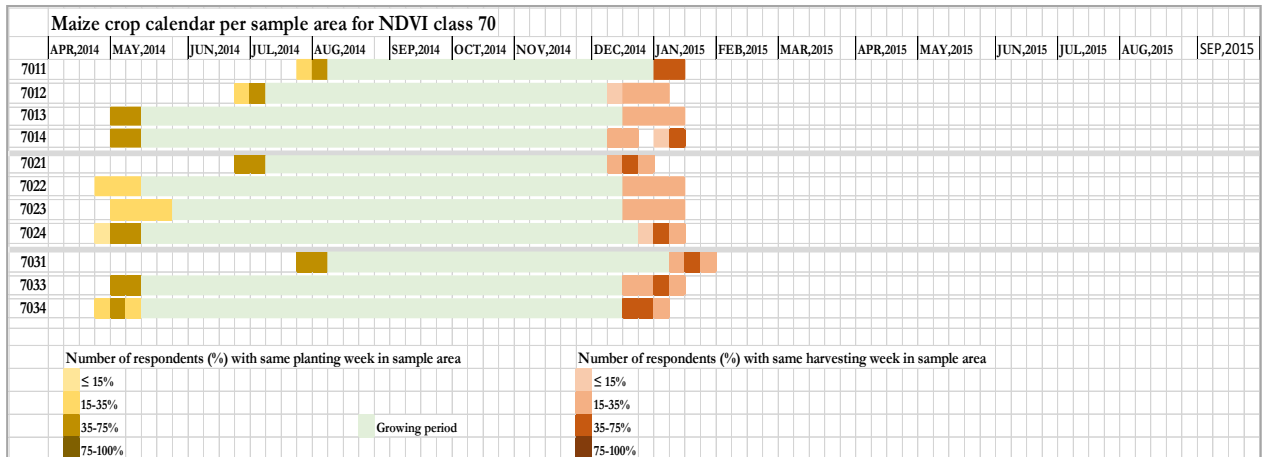


Figure 15: Maize crop calendars per sample area per cluster for NDVI class 70

Considering the NDVI profiles temporal behaviours in NDVI class 70, they behaved differently from other 3 sample NDVI classes. Also, as shown by maize crop calendar in figure 15, sample areas crop calendars were also different from other NDVI classes' maize crop calendars. The following figure 16 presents the NDVI profiles per sample areas with highlights of cluster 1 sample areas in red, cluster 2 sample areas in green, and cluster 3 sample areas in blue.

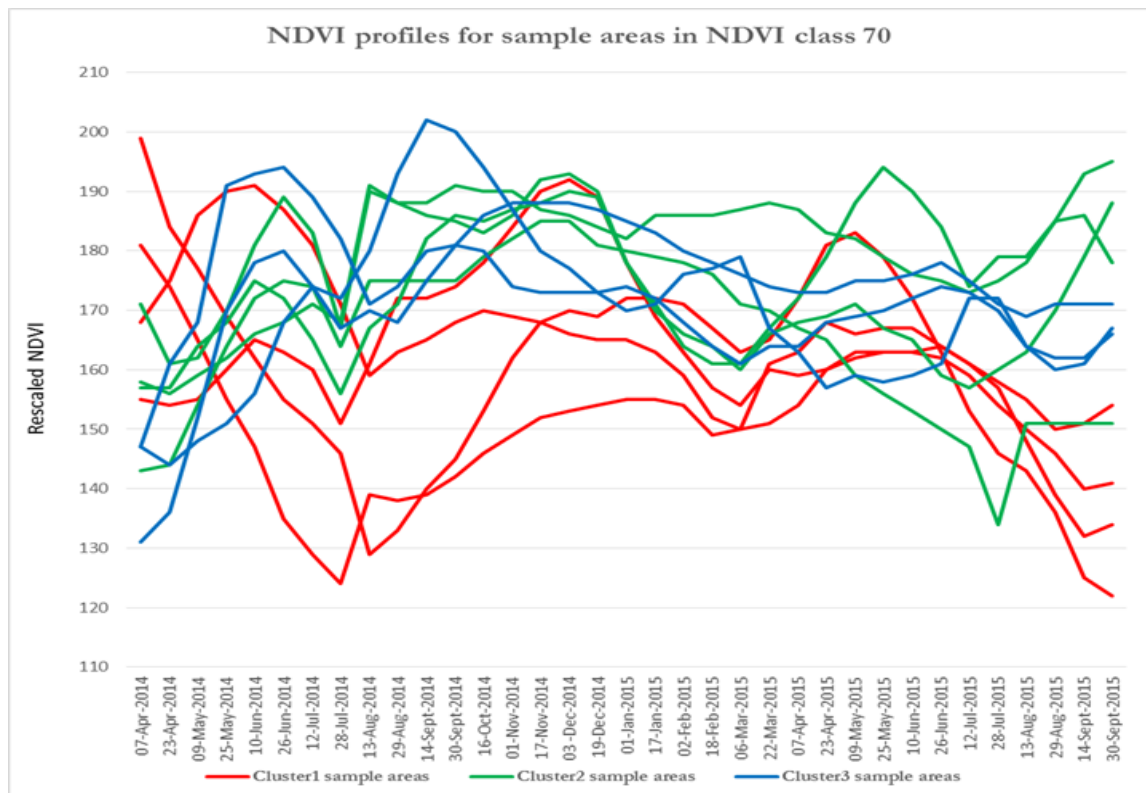


Figure 16: NDVI profiles per cluster for NDVI class 70

As shown in figure 16, most of the sample areas had two phenological growing seasons, though maize was grown for only one growing season (figure 15). Maize might not have had a great influence on the profiles

given its small area coverage in the sample areas, as presented by the following tables 9, 10 and 11. The detailed NDVI profiles per sample areas in NDVI class 70 are presented in appendix 11.

Sample area	Maize	Forest	Tea	Peas	Irish potatoes	Grass	Beans	Total
7011	4.81	8.58	0	7.03	53.79	13.68	5.20	93.10
7012	12.94	2.46	0	8.71	15.99	10.91	48.75	99.76
7013	3.44	6.98	22.77	0.51	9.35	6.69	43.53	93.28
7014	8.79	9.82	0	2.88	11.06	9.66	44.16	86.36

Table 9: Dominant land covers and their area (%) in cluster 1 of NDVI class 70

As shown by table 9, cluster 1 of NDVI class 70 was dominated by beans, irish potatoes and grass. The following table 10 shows the percentage of dominant land covers per sample area in cluster 2 for NDVI class 70.

Sample area	Maize	Forest	Pyrethrum	Peas	Irish potatoes	Grass	Beans	Total
7021	2.40	6.99	26.76	1.73	37.13	8.02	12.22	95.25
7022	3.01	5.19	8.48	2.37	57.53	9.85	5.09	91.51
7023	23.88	0.61	1.47	1.62	31.05	9.00	30.03	97.68
7024	4.25	13.63	27.00	3.16	29.35	11.87	9.39	98.64

Table 10: Dominant land covers and their area (%) in cluster 2 of NDVI class 70

Table 10 shows that cluster 2 of NDVI class 70 was dominated by irish potatoes, beans and pyrethrum though maize was dominant only in sample area 7023. The following table 11 shows the percentage of dominant land covers per sample area in cluster 3 of NDVI class 70

Sampled area	Maize	Forest	Pyrethrum	Irish potatoes	Grass	Beans	Total
7031	14.87	5.68	24.98	24.72	10.86	6.11	87.23
7033	3.95	3.69	61.34	19.55	6.75	4.72	100
7034	5.01	3.16	39.34	32.99	8.35	9.21	98.07

Table 11: Dominant land covers and their area (%) in cluster 3 of NDVI class 70

Table 11 shows that cluster 3 was dominated by pyrethrum, irish potatoes and maize. The contribution of maize also is not dominant like in the other clusters of the class. So, NDVI profiles in figure 16 had a great influence from other crops than maize.

4.2.1. Maize crop calendars and NDVI profiles for NDVI class 82

In NDVI class 82, the interviewed farmers were 119 among whom 82 farmers planted maize in one agricultural season (season A) and were from two first clusters (1 & 2), and other 37 farmers planted maize in two agricultural seasons (season A and B) and were from cluster 3, as detailed per single plot crop calendars in class 82 in Appendix 8. Generally, for season A, planting started with August and ended with the third week of September 2014. Harvesting started in the last week of December 2014 and finished with February 2015.

For season B in cluster 3 of class 82, planting started in mid-February and ended with the second week of March 2015. Growing period started with March and ended in the third week of June 2015, and harvesting started with the second week of June 2015 till mid-July of the same year. The following figure 17

summarizes information about maize planting and harvesting time per sample area in class 82 as from interviews with farmers.

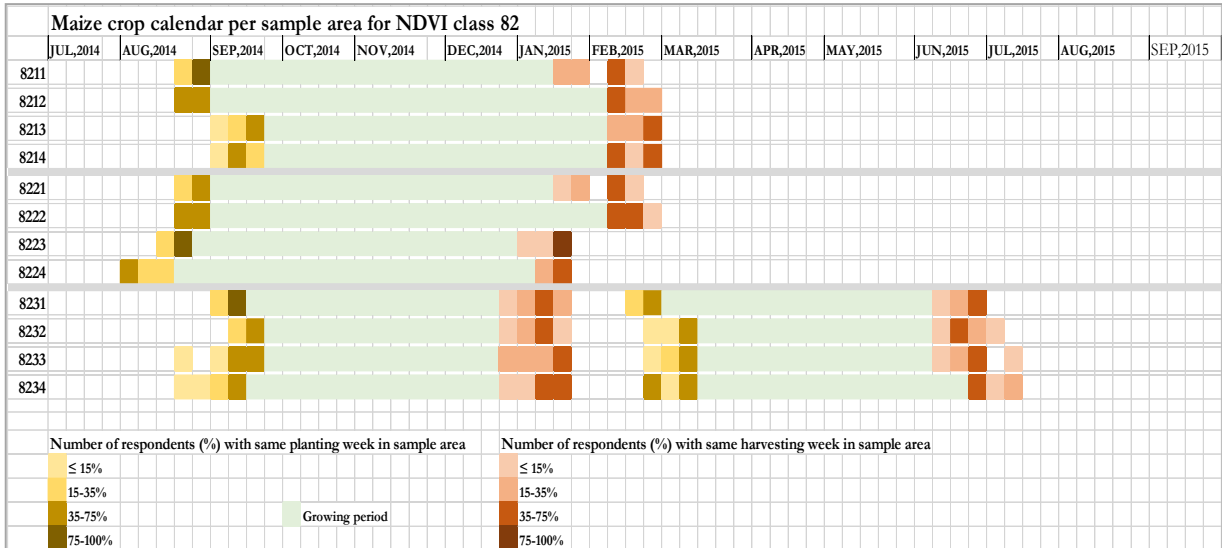


Figure 17: Maize crop calendars per sample area per cluster for NDVI class 82

In this NDVI class 82 also, in regard to sample areas temporal behaviours, the behaviours were observed through their NDVI profiles from MODIS NDVI data from last week of July 2014 till the end of the agricultural year 2015. In this NDVI class, NDVI profiles were behaving almost similar and showed two agricultural seasons for the agricultural year 2014–2015, as shown in the following figure 18 with highlights of cluster 1 sample areas in red, cluster 2 sample areas in green, and sample areas of cluster 3 in blue.

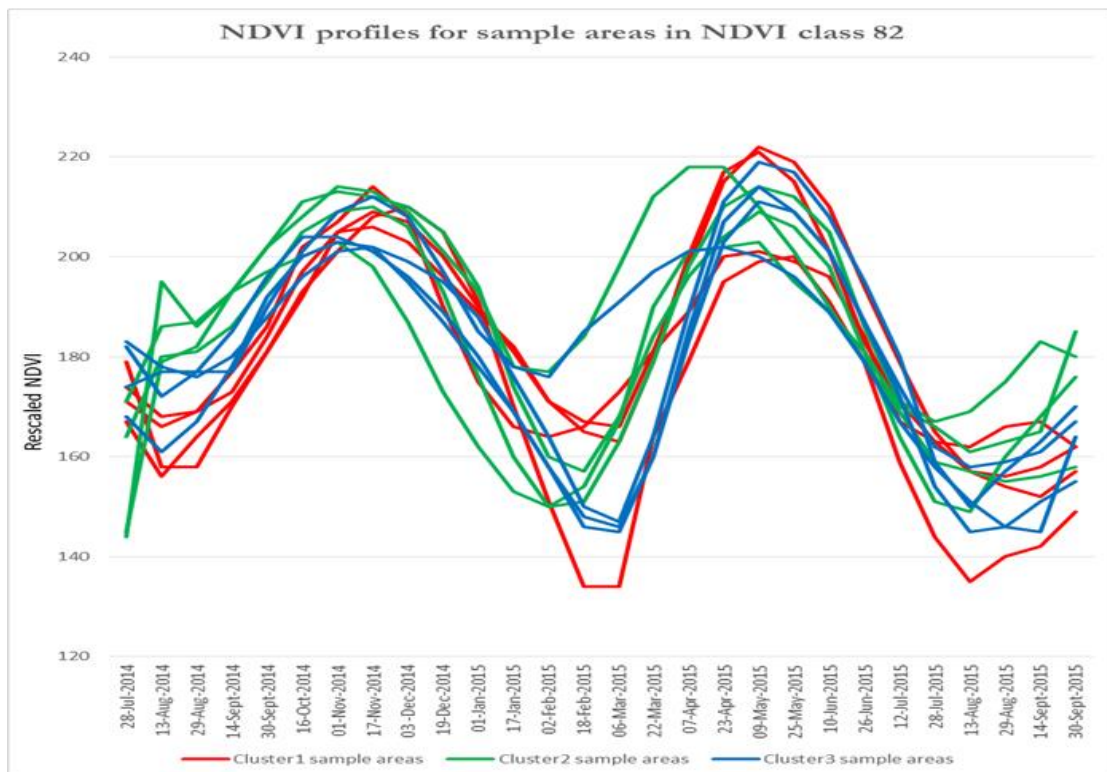


Figure 18: NDVI profiles for NDVI class 82 (From August 2014 to August 2015)

Though the figure 18 presents two phenological growing seasons for NDVI class 82, referring to its maize crop calendars in figure 17; in 8 sample areas farmers responded that maize crop was cultivated only for

one agricultural season (season A) in the year 2014 – 2015, while in the rest four sample areas maize was cultivated for two seasons (both in season A and B). Regarding the contribution of maize to the NDVI profiles, the following table 12, 13 and 14 present dominant land covers and their area in percentage per sample area per cluster, as observed from the field. The detailed NDVI profiles per sample areas in NDVI class 82 are presented in appendix 12.

Sample areas	Maize	Banana	Forest	Sorghum	Irish potatoes	Grass	Beans	Total
8211	47.64	6.87	6.83	0	1.30	6.34	26.88	95.86
8212	20.84	3.05	23.53	0	3.01	4.31	37.13	91.86
8213	16.93	0	3.06	0	2.08	1.48	74.46	98.02
8214	13.73	5.56	0.93	59.73	7.89	0	10.65	98.49

Table 12: Dominant land covers and their area (%) in cluster 1 of NDVI class 82

As shown by table 12, cluster 1 of NDVI class 82 was dominated by beans and maize. The table 13 below presents dominant land covers and their percentage in cluster 2.

Sample areas	Maize	Banana	Forest	Baresoil	Sorghum	Irish potatoes	Grass	Beans	Total
8221	1.91	4.11	8.90	0.30	32.19	2.59	4.04	44.93	98.97
8222	6.23	4.12	5.38	1.48	45.83	3.10	5.16	27.81	99.11
8223	21.90	0	11.32	0	7.24	8.44	4.51	46.61	100
8224	6.59	3.57	2.58	0.55	65.52	2.68	3.15	14.73	99.38

Table 13: Dominant land covers and their area (%) in cluster 2 for NDVI class 82

Table 13 shows that beans and sorghum were the dominant land covers in cluster 2 of NDVI class 82. The following table 14 shows the percentage of dominant land covers and their area in percentage per sample area in cluster 2 for NDVI class 82.

Sample areas	Maize	Banana	Forest	Sorghum	Irish potatoes	Grass	Cassava	Beans	Total
8231	24.67	3.43	3.42	18.47	2.18	5.65	2.16	32.19	92.16
8232	21.76	25.67	0	13.02	5.26	3.74	0.71	28.35	98.51
8233	8.76	33.67	4.08	9.23	2.98	2.00	0	28.34	89.05
8234	12.11	19.16	2.52	16.55	0.78	4.56	3.74	33.98	93.40

Table 14: Dominant land covers and their areas in cluster 3 of NDVI class 82

Table 14 shows that cluster 3 of NDVI class 82 was dominated by beans, banana, maize and sorghum. From table 12, 13 and 14, it was realized that it was in NDVI class 82 where maize dominated some sample areas. So, maize might have contributed much to the NDVI profiles in figure 18, but also, influence from other vegetation was high because the figure shows two distinguished seasons, but maize crop was planted only in one season in cluster 1 and 2 of the class.

To summarize the crop calendars per NDVI classes, the following figure 19 presents overall maize crop calendars summarized per the sample NDVI classes.

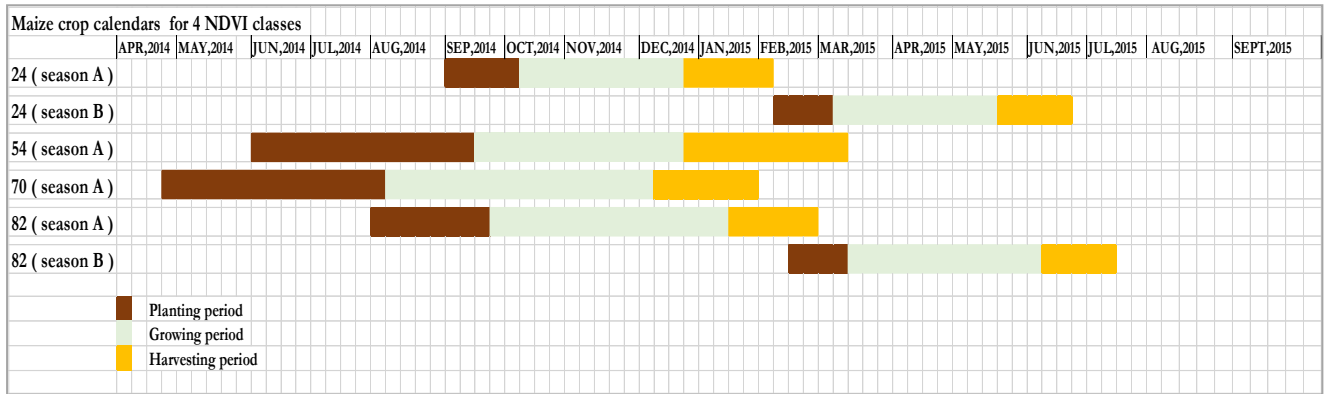


Figure 19: Generalized maize crop calendars for the 4 sample NDVI classes

Figure 19 shows that, in general, there were different maize crop calendars in different NDVI classes. NDVI classes 24 and 82 had two maize growing seasons, and the rest had only one maize growing season.

From the results of maize crop calendars, NDVI profiles and dominant land covers per NDVI class, the following observations were made:

- The start of maize planting and end of planting time were different from one NDVI class to another, but not much differences between NDVI class 24 and NDVI class 82.
- The start of maize harvesting and end of harvesting time also were different from one NDVI class to another, but also, no much differences were between NDVI class 24 and NDVI class 82.
- The NDVI profiles of the same NDVI class were behaving almost similar for all NDVI classes except for NDVI class 70, and there were different from one NDVI class to another.
- In regard to the dominant land covers per NDVI class, there were almost similar trends in the data in clusters of the same NDVI class. But, every NDVI class had particular dominant crops.
- Maize was not dominant in most of the sample areas. So, it had small contribution to the behaviour of NDVI profiles of different sample areas. This resulted in the fact that the number of maize growing seasons as from interviews with farmers was not conforming to the temporal behaviours of all the different sample areas in NDVI profiles. This showed the big influence in NDVI profiles from other variety of crops.

4.3. Assessment of relationship between number of maize growing seasons and NDVI classes

As observed from previous results, there was only one maize growing season in NDVI class 54 and 70 and partly NDVI class 82, and two growing seasons in NDVI class 24 and partly in NDVI class 82. To assess whether the number of maize growing seasons significantly relate to NDVI class, in order to respond to the second objective of the study and test the first hypothesis, the chi-square test was carried out.

To perform the test, first, a contingency table was constructed establishing the relationship between maize growing seasons and NDVI classes, according to the frequency number of plots with the same number of

growing seasons per NDVI class (table 15). The table also contains the expected values per every cell, according to the total number of interviewed farmers found in the same NDVI class with the same number of maize growing season:

NDVI class \ Number of Seasons	24	54	70	82	Total
1	0	113	105	82	300
	66.5	78.3	72.7	82.4	
2	96	0	0	37	133
	29.5	37.7	32.3	36.6	
Total	96	113	105	119	433

Table 15: Contingency table of observed and expected frequency of maize growing seasons per NDVI class

From table 15, values in black are the number of plots with the same number of maize growing seasons and located in the same NDVI class as from interviews with farmers. The values in red are the expected number of farmers with the same number of maize growing season and found in the same NDVI class. The expected values were given by a ratio between the product of total farmers with the same number of growing seasons and total number of farmers found in the same NDVI class, and the grand total (formulae 2).

From the values in table 15, chi square test was performed. Chi square value was calculated by applying formulae 3 from methodology section, and was found to be:

$$\chi^2 = 316 \text{ at } p = 0.05.$$

In order to assess whether the results are significant, chi-square critical was looked up from chi-square distribution table, with degrees of freedom =3 (given formulae 4) at $p = 0.05$. The chi square critical was found to be 7.815 on the chi square distribution table (appendix 13).

By comparing the results, the chi-square calculated was greater than chi-square critical. So, the number of maize growing periods was significantly related to the clustering of NDVI profiles into NDVI class at $p=0.05$.

4.4. Practiced maize crop calendars and maize crop calendars for NDVI classes

After that the hierarchical clustering showed that it is possible to cluster the interviews with farmers into four groupings, k-means clustering algorithm was then performed on the data, and the four practiced crop calendars groupings were identified irrespective of NDVI classes. Then, the number of plots in the same practiced maize crop calendar grouping were put together and related to the NDVI class where they are located, as presented in the following table 16.

NDVI classes \ Grouping	24	54	70	82
1	0	18	75	0
2	96	0	0	37
3	0	50	30	25
4	0	45	0	57

Table 16: Number of plots with same practiced maize crop calendar per NDVI class

From the interviews with farmers, the four practiced maize crop calendars were generated in the four groupings, as presented in the following figure 20.

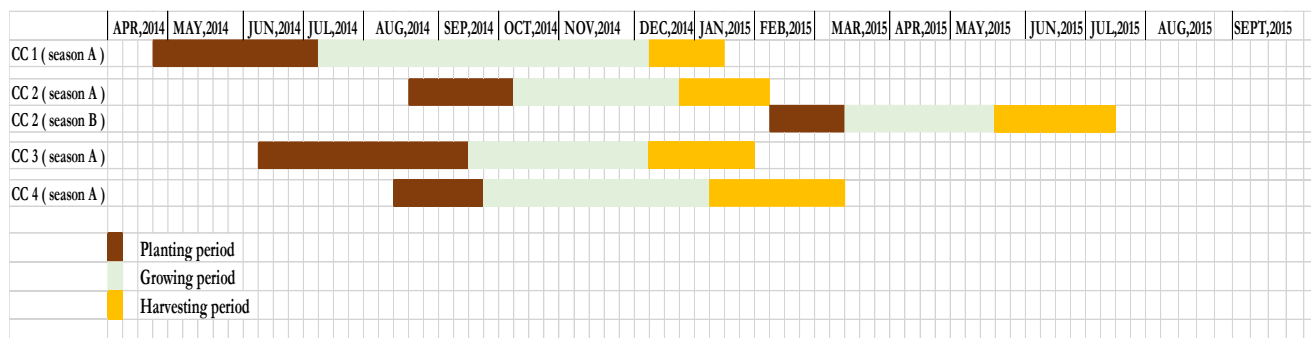


Figure 20: Four groupings of practiced maize crop calendars

From figure 20, it was observed that three groupings (CC1, CC3, and CC4) had only one maize growing season, whereas only one grouping (CC2) had two maize growing seasons according to the k-means unsupervised classification.

To continue the analysis, it was considered important to analyse how significantly different the maize crop calendars are, for both NDVI classes and practiced crop calendar groupings. This was in order to see if significant differences in practiced maize crop calendar, can be significantly detected by NDVI class; an analysis made later through assessing whether there is a strong relationship between the practiced maize crop calendars and NDVI classes.

✓ **Analysis of variance and t-test for crop calendars between NDVI classes**

One way ANOVA was carried out following the number of seasons per NDVI class. First, it was carried out for season A planting dates (in Julian calendar) for the four sample NDVI classes as presented in table 18 below:

Anova: Single Factor						
SUMMARY						
Groups	Count	Sum	Average	Variance		
NDVI class 24	96	25514	265.7708	33.12588		
NDVI class 54	113	25704	227.469	863.7513		
NDVI class 70	105	15812	150.5905	1225.763		
NDVI class 82	119	29204	245.4118	183.329		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	787931.7	3	262643.9	452.5082	1.8E-132	2.625699
Within Groups	248999.3	429	580.418			
Total	1036931	432				

Table 17: One-way ANOVA results on season A planting dates between four NDVI classes

Table 17 shows that the four NDVI classes were significantly different in terms of maize planting time for season A in the year 2014-2015 at $p=0.05$, given that F statistic (452.5) which was greater than F critical

(2.6), and p-value (3.6 E-128) which was smaller than p (0.05). Moreover, the pairwise analysis also showed that all the pairs of the NDVI classes are significantly different in terms of planting time, as presented in appendix 14.

Second, one-way ANOVA was carried out between the four NDVI classes using season A harvesting days, as presented in table 18 below:

Anova: Single Factor						
SUMMARY						
Groups	Count	Sum	Average	Variance		
NDVI class 24	96	36377	378.9270833	97.12094298		
NDVI class 54	113	43860	388.1415929	480.6940582		
NDVI class 70	105	38328	365.0285714	104.6626374		
NDVI class 82	119	46681	392.2773109	307.3715995		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	47921.89048	3	15973.96349	62.17468076	2.14291E-33	2.625699
Within Groups	110218.9871	429	256.9207159			
Total	158140.8776	432				

Table 18: One-way ANOVA results for season A harvesting dates between four NDVI classes

Table 18 shows that sample NDVI classes are different in terms of harvesting time in season A in the year 2014-2015 at $p=0.05$ given that F statistic (62.2) was greater than F critical (2.6), and p-value (2.14 E-33) was smaller than p (0.05). Furthermore, the pairwise comparison showed that all the NDVI classes' pairs are significantly different in terms of harvesting times, as presented in appendix 15.

Third, the analysis was carried out on maize planting times in season B. Given that the NDVI classes with season B were only two: NDVI class 24 and 82, so, the t-test was carried out, as presented in the following table 19.

t-Test: Two-Sample Assuming Unequal Variances		
	NDVI class24	NDVI class 82
Mean	50.83	61.30
Variance	36.62	43.49
Observations	96	37
Hypothesized Mean Di	0	
df	61	
t Stat	-8.39	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.67	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.00	

Table 19: T-test results for season B planting dates between NDVI class 24 and 82

T-test results in table 19 showed that, though both NDVI class 24 and NDVI class 82 had two maize growing seasons, they were significantly different in terms of planting dates at $p=0.05$, given the p-value that was smaller than the p (0.05).

Lastly, a t-test was carried out between NDVI class 24 and 82 in terms of season B harvesting time. The results are presented in the following table 20.

t-Test: Two-Sample Assuming Unequal Variances		
	NDVI class 24	NDVI class 82
Mean	162.16	176.84
Variance	73.69	47.25
Observations	96	37
Hypothesized Mean Difference	0	
df	81	
t Stat	-10.27	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.66	
P(T<=t) two-tail	0.00	
t Critical two-tail	1.99	

Table 20: T-test results for season B harvesting dates between NDVI class 24 and 82

The t-test results in table 20 show that, also, NDVI class 24 and class 82 were significantly different in terms of harvesting dates of season B, at $p = 0.05$.

In summary, the results in tables 17, 18, 19 and 20 show that the crop calendars for the four NDVI classes were significantly different in terms of planting and harvesting dates at $p = 0.05$.

✓ **Analysis of variance for practiced maize crop calendars**

One way ANOVA was carried out between the four groupings of practiced maize crop calendars to assess whether they are significantly different as they were grouped differently. First, the analysis was carried out in terms of season A planting dates, as presented in the following table 21:

Anova: Single Factor						
SUMMARY						
Groups	Count	Sum	Average	Variance		
CC 1	93	12823	137.8817204	417.3228144		
CC 2	133	34957	262.8345865	64.91182502		
CC 3	105	23517	223.9714286	458.7972527		
CC 4	102	24937	244.4803922	103.9154533		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	931758.6275	3	310586.2092	1266.885984	1E-212	2.6256992
Within Groups	105172.4349	429	245.1571909			
Total	1036931.062	432				

Table 21: One-way ANOVA results for season A planting dates of practiced maize crop calendars groupings

As presented by table 21, the four practiced maize crop calendars were significantly different in terms of season A planting dates at $p=0.05$. Also, the pairwise comparison showed that all pairs of the practiced maize crop calendars are significantly different in terms of planting time, at $p=0.05$, as presented in appendix 16.

Second, the analysis was carried to assess the difference in terms of season A harvesting dates, as presented in table 22 below:

Anova: Single Factor						
SUMMARY						
Groups	Count	Sum	Average	Variance		
CC 1	93	33897	364.4839	71.23072		
CC 2	133	50219	377.5865	89.59285		
CC 3	105	39286	374.1524	91.11117		
CC 4	102	41844	410.2353	113.2312		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	118849.5	3	39616.49	432.5496	2.7E-129	2.625699
Within Groups	39291.4	429	91.58834			
Total	158140.9	432				

Table 22: One-way ANOVA results for season A harvesting dates of practiced maize crop calendars groupings

Table 22 shows that, also, the four practiced crop calendar groupings were significantly different in terms of season A harvesting dates. Moreover, the pairwise comparison, in appendix 17, showed that all pairs of the practiced maize crop calendars are significantly different in terms of planting time, at $p=0.05$.

The season B was not analysed because only one practiced crop calendar (CC 2) had season B, indicating one of its uniqueness among other practiced crop calendars groupings.

In summary, table 21 and 22 show that, as the k-means clustering algorithm separated the practiced maize crop calendars into 4 groupings, the groupings were also significantly different in terms of planting and harvestings dates. Furthermore, only one crop calendar, among the four, had two maize growing seasons.

4.5. Assessment of relationship between practiced maize crop calendars and NDVI classes

As observed from previous sections, there were significant differences in practiced maize crop calendars and also in the maize crop calendars for NDVI classes. To assess if NDVI classes can significantly detect the differences existing in the practiced crop calendars, the chi-square test was performed in order to evaluate whether there is a relationship between crop calendars by NDVI classes and the practiced maize crop calendars. The following table 23 presents the constructed contingency table, with observed values from interviews with farmers and expected values, in order to run the test.

NDVI class \ Grouping	24	54	70	82	Total
1	0 20.6	18 24.3	75 22.6	0 25.6	93
2	96 29.5	0 34.7	0 32.3	37 36.6	133
3	0 23.3	50 27.4	30 25.5	25 28.9	105
4	0 22.6	45 26.6	0 24.7	57 28	102
Total	96	113	105	119	433

Table 23: Contingency table of observed and expected frequency of practiced maize crop calendar per NDVI class

From table 23, values in black are the number of plots with the same observed practiced maize crop calendars per NDVI class, and the values in red are the expected number of plots with the same practiced maize crop calendars per NDVI class. Then, chi-square value was calculated using formulae 3, and was:

$$\chi^2 = 519.56 \text{ at } p = 0.05.$$

Looking up the chi-square critical in the chi-square distribution table (appendix 13) using 9 as a degree of freedom at $p=0.05$, the chi-square critical was 16.919. By comparison, the chi-square calculated is much greater than the chi-square critical. So, the results were highly significant, indicating that the practiced maize crop calendars are highly related to the maize crop calendars for NDVI classes, at $p = 0.05$.

In summary, the previous results showed that the spatial stratification of hyper-temporal NDVI data into NDVI classes can significantly differentiate differences in practiced maize crop calendars.

5. DISCUSSION

In this section, the findings are discussed and compared with previous studies in line with the research objectives and hypotheses.

5.1. Maize crop calendars of sample NDVI classes through interviews with farmers

For the first objective, crop calendars for sample NDVI classes were produced. The generated crop calendars were for the agricultural year 2014-2015 through the interviews with farmers. The research found that maize crop had different crop calendars in the 4 different sample NDVI classes, with differences in duration of one agricultural activity to another, from one area to another, as detailed in the results section.

The obtained results of crop calendars by this research were compared to the existing maize and sorghum crop calendar for Rwanda by FAO/GIEWS (2015). The existing crop calendar shows that in season A, maize is planted in September and October, and then the two crops undergo a growing period of two months from November to December, and harvesting time takes place afterward also for two months from January to February. In season B, planting takes place in February and March, and then the growing period takes place from April to May, and finally harvesting takes place from June to July.

On another side of comparing the results of this research with the general agricultural seasons in Rwanda: season A, season B and season C as detailed by NISR (2015), there were found also differences. Especially, agricultural seasons in NDVI classes 54 and 70 were very different from the Rwanda three general agricultural seasons. For NDVI classes 24 and 82, there were no much differences though there were still some differences. The differences might have been the effect of differences in applied methodologies for mapping the crops calendars.

Considering the methodologies applied, the three normal agricultural seasons in Rwanda are based on surveyed data at administrative level NISR (2015). One of the side effects of the method is that the demarcation of administrative boundaries do not consider environmental conditions and temporal variation which are the base for different crop calendars (Eagleson, Escobar, & Williamson, 2000).

The methodology as applied by this research on the other hand, one of the main advantages of using hyper-temporal NDVI data for land stratification for crop calendars mapping is that there is consideration of the natural relevant factors like climate conditions, soil characteristics, human activities on ground and consideration of areas' spatial temporal change (de Bie et al., 2008) which influence different crop calendars.

As said by Clay and Dejaegher (1987) and FAO (1996), in Rwanda there is a lot of diversity based on its topography, environmental factors including soil characteristic, land forms and other climatic conditions such as temperature and rainfall. The factors lead to much diversity in agriculture as well. But, in addition to the climate conditions, agriculture is controlled by human decisions (Iisd, 1997). This was observed by this research where maize crop calendars were produced based on the data from interviews with farmers, and it was found that in some cases were big differences even between the neighbouring farmers located in the same sample area (Appendices: 5, 6, 7, and 8).

Referring to de Bie (2002), while defining crop calendar he mentioned that a parcel can have its own crop calendar but the calendar is often generalized to a specific area. In this regard, though there were differences at plot and sample area level, the maize crop calendars were generalized to NDVI class level (figure 11, 13, 15 and 17) which led to less detailed crop calendars.

By generalizing different agricultural activities (planting and harvesting) of different sample areas in one maize crop calendar at NDVI class level, obviously, there was a loss of information. Additionally, due to the generalization, there were cases where successive agricultural periods for a certain activity (like planting and growing period, or growing period and harvesting) happened simultaneously in the same agricultural season. The example is presented in figure 19, where in NDVI class 82 planting time for season B started while harvesting of season A was not finished yet.

Regarding the agricultural seasons in the country, they were also different from NDVI class to another. Season A was the most important period for maize cultivation, where for the sample NDVI classes all farmers cultivated maize in season A. For season B, only farmers from NDVI class 24 and 82 planted maize. Specifically, all interviewed farmers in NDVI class 24 cultivated maize in both season A and B, but for NDVI class 84, all farmers cultivated maize in season A but only 31% cultivated maize for season B. This finding was similar to the findings in 2014-2015 season A for Rwanda national agricultural survey report, where maize was among the main and dominant crops in season A in the country. For season A of the year 2014-2015, maize crop occupied 12.3% of the country's cultivated area and 5.2% for season B (NISR, 2015b).

In brief, this research found different maize crop calendars for different NDVI classes. Also, as shown by their NDVI profiles, the sample NDVI classes' temporal behaviours were different. As observed on the field in the dates from 9th October till 5th November, 2015, in some areas of NDVI class 54 and NDVI class 70 were maize crops in leaf growing stages (V7 and V10) and maize crops in tasseling stage (VT and R1), while for NDVI class 24 and NDVI class 82 the maize crops were only on leaf growth stage (V3, V7 and V10) (Odell's World, 2010).

5.2. Relationship between practiced crop calendars and crop calendars per NDVI classes

Regarding the maize growing seasons in Rwanda, it was found that the number maize growing seasons is significantly related to the NDVI class. This indicates that different areas in Rwanda have different number of maize growing seasons. It was observed that among the surveyed sample NDVI classes, two classes: 54 and 70 had only one maize growing season (Season A) for the year 2014-2015 whereas another NDVI class: 24 had two maize growing seasons and the NDVI class 82 had partly (69%) only one maize growing season (season A) and partly (31%) two maize growing season (both season A and B).

These differences in a number of maize growing season per year in different NDVI classes answered the first research question about whether the number of maize growing seasons per year differ from one NDVI class to another. In addition, the number of maize growing seasons was found to highly relate to the NDVI classes by this research, using chi-square test.

Furthermore, the maize crop calendars for NDVI classes were significantly different in terms of planting time and harvesting time. This diversity in maize crop calendars with significant differences in different areas in Rwanda indicates that in case a crop calendar would be generalized to the country level, there are many significant differences that would be ignored, leading to different consequences in case of using the generalized crop calendar for various agricultural interventions in the country.

Likewise, the practiced maize crop calendar groupings as grouped by k-means unsupervised classification, were found to be significantly different in terms of planting and harvesting times. For the practiced maize crop calendars, only one grouping had two maize growing seasons. Still, this emphasised the significant differences in maize crop calendars for different areas in Rwanda.

In order to relate the significant differences in the practiced maize crop calendars groupings and the significant differences in maize crop calendars for NDVI classes, the chi-square test showed that there is a strong relationship between practiced maize crop calendars groupings and crop calendars per NDVI classes. This answered the second research question about whether the groupings of maize crop calendars relate to maize crop calendars of NDVI classes. Moreover, it revealed the ability of hyper-temporal NDVI stratification to capture the differences existing in the practiced maize crop calendars in Rwanda.

This relationship is explained by the fact the crop calendar is a reflection of a particular crop and cropping system seasonal progression from planting to harvesting in a certain area (HarvestChoice, 2013), and also the hyper-temporal stratification bases on area's vegetation cover photosynthetic activity in order to classify the land into different NDVI classes (Govaerts & Verhulst, 2010).

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

Conclusively, this research showed that there were more than one maize crop calendars for Rwanda. The research showed, also, the potential of hyper-temporal MODIS NDVI data to classify different areas with different maize crop calendars in Rwanda. Each NDVI class had different maize crop calendars, and also there existed different practiced maize crop calendars with different maize growing seasons.

Moreover, the research found that the number of maize growing seasons were highly related to the maize crop calendars for NDVI classes at $p = 0.05$. Similarly, the practiced maize crop calendars were highly related to the maize crop calendars for NDVI classes at $p = 0.05$. Hence, the spatial stratification of hyper-temporal NDVI data into NDVI classes can significantly differentiate differences in practiced maize crop calendars in Rwanda.

6.2. Recommendations

From this research, the following recommendations are suggested for prospective researchers:

- Assessing differences in practiced maize crop calendars for Rwanda using other 20 NDVI classes dominated with agriculture which were not used for this study due to time limitations.
- Assessing differences in practiced crop calendars for Rwanda for other seasonal main crops in Rwanda such as beans, sorghum, and irish potatoes, using hyper-temporal NDVI stratification.
- Mapping differences in practiced crop calendars in Rwanda at detailed level including more information about agricultural activities such as land preparation time and weeding.
- Derive different crop calendars of a specific crop using NDVI profiles from NDVI hyper-temporal data, taking a study area to be an area where the crop of interest is dominant.
- To know different crops and their growing seasons in order to be aware of how different crops contribute to their NDVI profiles of their areas, and relate crop calendars of dominant crops to their respective areas' NDVI profiles.

LIST OF REFERENCES

- Ali, A., de Bie, C. a J. M., Skidmore, a. K., Scarrott, R. G., & Lymberakis, P. (2014). Mapping the heterogeneity of natural and semi-natural landscapes. *International Journal of Applied Earth Observation and Geoinformation*, 26(1), 176–183. <http://doi.org/10.1016/j.jag.2013.06.007>
- AMIS. (2012). AMIS crop calendar. Retrieved July 29, 2015, from http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/Crop_Calendar/121206-AMIS-online-crop-calendar_REDUCED3.pdf
- Bailey, J. T., & Boryan, C. G. (2010). Remote sensing applications in agriculture at the USDA national agricultural statistics service, 22030, 14. Retrieved from http://www.fao.org/fileadmin/templates/ess/documents/meetings_and_workshops/ICAS5/PDF/ICASV_2.1_048_Paper_Bailey.pdf
- Bailey, R. (2004). Role of landform in differentiation of ecosystems at the mesoscale (landscape mosaics), (1993), 22.
- Barrow, M. (2013). The mountain environment. Retrieved January 8, 2016, from <http://www.primaryhomeworkhelp.co.uk/mountains/climate.htm>
- Blei, D. M. (2008). Hierarchical clustering. Princeton.
- Brouwer, M., van Bodegom, A. J., Satijn, B., & Buit, G. L. (2015). *Climate change profile: Rwanda*. Kigali.
- Cantore, N. (2011). *The crop intensification program in Rwanda: a suitability analysis*. London.
- Chand, S. (2015). Maize cultivation: suitable geographical conditions required for maize cultivation. Retrieved from <http://www.yourarticlelibrary.com/cultivation/maize-cultivation-suitable-geographical-conditions-required-for-maize-cultivation/25501/>
- Chemonics International Inc. (2003). *Rwanda environmental threats and opportunities*. Retrieved from http://www.encapfrica.org/documents/biofor/Rwanda_2003.pdf
- Christiaensen, L., Demery, L., & Kuhl, J. (2011). The (evolving) role of agriculture in poverty reduction- An empirical perspective. *Journal of Development Economics*, 96(2), 239–254. <http://doi.org/10.1016/j.jdeveco.2010.10.006>
- Clay, D. C., & Dejaegher, Y. M. J. (1987). Agro-ecological zones: The development of regional classification scheme for Rwanda. *Tropicultura*. Retrieved from <http://www.tropicultura.org/text/v5n4/153.pdf>
- Cole, M., & Mcsweeney, R. (2011). Rwanda s Climate : Observations and Projections, (July).
- de Bie, C. A. J. M. (2002). Novel approaches to use RS-products for mapping and studying agricultural land use systems.
- de Bie, C. A., Khan, M. R., Toxopeus, A. G., Venus, V., & Skidmore, A. K. (2008). Hypertemporal image analysis for crop mapping and change detection. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B7. Beijing 2008*, 2, 803–814. Retrieved from http://isprserv.ifp.uni-stuttgart.de/proceedings/XXXVII/congress/7_pdf/5_WG-VII-5/13.pdf

- de Bie, K. (2014). Integrating census data with hyper-temporal NDVI data, to prepare detailed crop intensity and crop growing period maps. Addis Abeba.
- Diener-West, M. (2008). Use of the Chi-Square Statistic. Retrieved from <http://ocw.jhsph.edu/courses/fundepiii/pdfs/lecture17.pdf>
- Eagleson, S., Escobar, F., & Williamson, I. (2000). Hierarchical spatial reasoning applied to the automated design of administrative boundaries using GIS.
- ESAANet. (2007). Crop guide. Retrieved September 23, 2015, from http://www.esaanet.com/reports/index.php?option=com_content&view=article&id=619:kenya-relief-as-ncpb-begins-distribution-of-subsidised-fertiliser-after-delay&catid=43:crop-guide&directory=133
- FAO. (1996). Agro-ecological zoning guidelines, 78. Retrieved from <https://www.mpl.ird.fr/crea/taller-colombia/FAO/AGLL/pdffdocs/aeze.pdf>
- FAO. (2015). Crop Calendar. Retrieved July 30, 2015, from <http://www.fao.org/agriculture/seed/cropcalendar/welcome.do>
- FAO/GIEWS. (2015). *GIEWS Country brief- Rwanda*. Retrieved from <http://www.fao.org/giews/countrybrief/country/RWA/pdf/RWA.pdf>
- Fensholt, R., Sandholt, I., & Stisen, S. (2006). Evaluating MODIS, MERIS, and VEGETATION vegetation indices using in situ measurements in a semiarid environment. *IEEE Transactions on Geoscience and Remote Sensing*, 44(7). Retrieved from http://hydrology1.nmsu.edu/Teaching_Material/Agro500/Refernces/SpecIssuePapers/Fensholt et al 2006 Veg_Indices_Arid.pdf
- Foody, G. M., & Boyd, D. S. (1999). Fuzzy mapping of tropical land cover along an environmental gradient from remotely sensed data with an artificial neural network, 35, 23–35.
- Gamon, J. A., Field, C. B., Goulden, M. L., Griffin, K. L., Hartley, A. E., Joel, G., ... Valentini, R. (1995). Relationships between NDVI, canopy structure, and photosynthesis in three Californian vegetation types. *Ecological Applications*, 5(1), 28–41. Retrieved from http://www.crea.uab.es/global-ecology/Pdfs_UEG/EcolAppl1995.pdf
- Govaerts, B., & Verhulst, N. (2010). *The Normalized Difference Vegetation Index (NDVI) Greenseeker handheld sensor: toward the integrated evaluation of crop management*. Leuven. Retrieved from <http://www.plantstress.com/methods/Greenseeker.PDF>
- Griffiths, A. J. F., Miller, J. H., & Suzuki, D. T. (2000). Chi-square test. In *An introduction to genetic analysis* (7th ed.). New York: W. H. Freeman. Retrieved from <http://www.ncbi.nlm.nih.gov/books/NBK21907/>
- Guo, Z. (2013). Mapping the planting dates: An effort to retrieve crop phenology information from MODIS NDVI time series in Africa. *International Geoscience and Remote Sensing Symposium (IGARSS)*, 3281–3284. <http://doi.org/10.1109/IGARSS.2013.6723528>
- HarvestChoice. (2013). *A time to sow: how HarvestChoice is mapping the life cycle of crops*. Washington, DC. Retrieved from <http://harvestchoice.org/node/8862>

- Heisse. (2011). *Maize production*. Kampala. Retrieved from [http://teca.fao.org/sites/default/files/technology_files/MAIZE PRODUCTION_0.pdf](http://teca.fao.org/sites/default/files/technology_files/MAIZE_PRODUCTION_0.pdf)
- Iisd. (1997). *Agriculture and climate change: A prairies perspective*. Toronto.
- Ji-hua, M., Bing-fang, W., Monitoring, C. C., Trend, D., Pei, L., Jiulin, S., ... Aeronautics, N. (1999). Study on the Crop Condition Monitoring Methods. *Archives*, 945–950.
- Kanyarukiga, S. G. (2004). Strategic plan of agriculture transformation financing , coordination and monitoring and evaluation, (October), 1–27. Retrieved from <http://www.ifad.org/english/operations/pf/rwa/i671rw/web/theme/coordination.pdf>
- Kotsuki, S., & Tanaka, K. (2015). SACRA – a method for the estimation of global high-resolution crop calendars from a satellite-sensed NDVI. *Hydrology and Earth System Sciences*, 19(11), 4441–4461. <http://doi.org/10.5194/hess-19-4441-2015>
- Maize production. (2013). Retrieved from [http://www.naads.or.ug/files/downloads/MAIZE Production guide.doc.pdf](http://www.naads.or.ug/files/downloads/MAIZE_Production_guide.doc.pdf)
- Manakov, A. G., & Mikhaylova, A. A. (2015). Changes in the Territorial and Administrative Division of Northwest Russia over the Soviet Period, 5, 37–40.
- Miller, J., & Haden, P. (2006). *Statistical analysis with the general linear model*. San Francisco.
- Miller, P., Lanier, W., & Brandt, S. (2001). *Using growing degree days to predict plant stages*. Montana. Retrieved from <http://store.msuextension.org/publications/AgandNaturalResources/MT200103AG.pdf>
- MINAGRI. (2011). *National post-harvest staple crop strategy*. Kigali.
- MINALOC. (2011). Administrative units. Retrieved January 8, 2016, from <http://www.minaloc.gov.rw/index.php?id=450>
- MINITERE. (2006). *National adaptation programmes of action to climate change*. Kigali.
- N2Africa. (2014). *Better beans: through good agricultural practices*.
- NAEB. (2015). *Profiling and mapping suitable land for horticulture in Rwanda*. Kigali.
- NC State University. (2010). Temperature relation to agriculture/K-12: How does this relate to agriculture?
- NISR. (2015a). *Seasonal agricultural survey 2013 (Version 2)*.
- NISR. (2015b). *Seasonal agricultural survey 2014*.
- Odell's World. (2010). Corn growth stages. Retrieved December 20, 2015, from <http://odells.typepad.com/blog/corn-growth-stages.html>
- Oettli, P., Sultan, B., Baron, C., & Vrac, M. (2011). Are regional climate models relevant for crop yield prediction in West Africa? *Environmental Research Letters*, 6(1), 014008. <http://doi.org/10.1088/1748-9326/6/1/014008>

- Ozdogan, M., Yang, Y., Allez, G., & Cervantes, C. (2010). Remote sensing of irrigated agriculture: opportunities and challenges. *Remote Sensing*. <http://doi.org/10.3390/rs2092274>
- Patel, J. H., & Oza, M. P. (2014). Deriving crop calendar using NDVI time-series. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-8*(December), 869–873. <http://doi.org/10.5194/isprsarchives-XL-8-869-2014>
- Pham, D. T., Dimov, S. S., & Nguyen, C. D. (2005). Selection of K in K-means clustering. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*. <http://doi.org/10.1243/095440605X8298>
- Premier Consulting Group. (2009). Land Reform in Rwanda - Technology & the Land Tenure Regularisation Process -. *Matrix*, (May).
- Raes, D., Steduto, P., Hsiao, C. T., & Fereres, E. (2009). *AquaCrop-The FAO crop model to simulate yield response to water*. Rome.
- Rafi, Z., & Ahmad, R. (2005). Wheat crop model based on water balance for agrometeorological crop monitoring. *Pakistan Journal of Meteorology Vol, 2*(3), 23–33. Retrieved from http://www.pmd.gov.pk/rnd/rnd_files/vol2_Issue3/3.WHEAT_CROP_MODEL_BASED_ON_WATER_BALANCE_FOR_AGROMETEOROLOGICAL_CROP_MONITORING.pdf
- REMA. (2009a). Overview of the agriculture sector. Retrieved December 8, 2015, from <http://www.rema.gov.rw/soe/chap3.php>
- REMA. (2009b). Rwanda state of environment and outlook, 98. Retrieved from <http://www.rema.gov.rw/soe/>
- Rema. (2011). Atlas of Rwanda's Changing Environment — Implications for Climate Change Resilience, 92. Retrieved from <http://na.unep.net/siouxfalls/publications/REMA.pdf>
- RIU Rwanda. (2012). Maize innovation platform and warrantage. Retrieved November 17, 2015, from <http://www.researchintouse.com/programmes/riu-rwanda/riu-rw41innovplat-maize.html>
- Rouse, J. W. J., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the great plains with Ert. *Third Earth Resources Technology Satellite-1 Symposium, I: Technic*(NASA SP-351).
- Ryan, T. (2013). Clustering 2: Hierarchical clustering. Retrieved from <http://www.stat.cmu.edu/~ryantibs/datamining/lectures/05-clus2-marked.pdf>
- Smit, B., McNabb, D., & Smithers, J. (1999). Agricultural adaptation to climatic variation. Retrieved from [http://www.uoguelph.ca/gecg/images/userimages/Smit et al. \(1996\)_Climatic Change.pdf](http://www.uoguelph.ca/gecg/images/userimages/Smit%20et%20al.%20(1996)%20Climatic%20Change.pdf)
- Takeuchi, Shin'ichi, & Marara, J. (2006). Characteristics of agriculture and rural areas in Rwanda.
- Tucker, C. J., Pinzon, J. E., & Brown, M. E. (2004). Global inventory modeling and mapping studies (GIMMS) satellite drift corrected and NOAA-16 incorporated Normalized Difference Vegetation Index (NDVI). Retrieved November 15, 2015, from http://iridl.ldeo.columbia.edu/SOURCES/.UMD/.GLCF/.GIMMS/.NDVIg/.global/.dataset_documentation.html

- Twagiramungu, F. (2006). Environmental Profile of Republic of Rwanda. Retrieved from <http://www.vub.ac.be/klimostoolkit/sites/default/files/documents/rwanda-environmental-profile.pdf>
- Tyrchniewicz, A., & Wilson, A. (1994). *Sustainable development for the great plains: policy analysis*. Winnipeg, Manitoba. Retrieved from https://www.iisd.org/pdf/sd_for_gp.pdf
- United Nations. (2011). Report on the results of a survey on census methods used by countries in the 2010 census round. *Working Paper: UNSD/DSSB/1*, 69. Retrieved from <http://unstats.un.org/unsd/census2010.htm>
- Upadhyay, G., Ray, S. S., & Panigrahy, S. (2008). Derivation of crop phenological parameters using multi-date SPOT-VGT-NDVI data: A case study for Punjab. *Journal of the Indian Society of Remote Sensing*, 36(1), 37–50. <http://doi.org/10.1007/s12524-008-0004-4>
- USAID. (2008). Rwanda environmental threats and opportunities assessment 2008 update. Retrieved from http://pdf.usaid.gov/pdf_docs/Pnadm537.pdf
- Vintrou, E., Bégué, A., Baron, C., Saad, A., Seen, D. Lo, & Traoré, S. B. (2014). A comparative study on satellite- and model-based crop phenology in West Africa. *Remote Sensing*, 6(2), 1367–1389. <http://doi.org/10.3390/rs6021367>
- VITO. (2015). Copernicus global land service. Retrieved November 14, 2015, from <http://land.copernicus.eu/global/products/ndvi>
- Wardlow, B. D., & Egbert, S. L. (2008). Large-area crop mapping using time-series MODIS 250 m NDVI data: An assessment for the U.S. Central Great Plains. *Remote Sensing of Environment*, 112(3), 1096–1116. <http://doi.org/10.1016/j.rse.2007.07.019>
- Wardlow, B. D., & Egbert, S. L. (2010). A comparison of MODIS 250-m EVI and NDVI data for crop mapping: a case study for southwest Kansas. *International Journal of Remote Sensing*, 31(3), 805–830. <http://doi.org/10.1080/01431160902897858>
- Wardlow, B., Egbert, S., & Kastens, J. (2007). Analysis of time-series MODIS 250 m vegetation index data for crop classification in the U.S. Central Great Plains. *Remote Sensing of Environment*, 108(3), 290–310. <http://doi.org/10.1016/j.rse.2006.11.021>
- Westengen, O. T., & Brysting, A. K. (2014). Crop adaptation to climate change in the semi-arid zone in Tanzania: the role of genetic resources and seed systems. *Agriculture & Food Security*, 3(1), 3. <http://doi.org/10.1186/2048-7010-3-3>
- Yin, H., Udelhoven, T., Fensholt, R., Pflugmacher, D., & Hostert, P. (2012). How normalized difference vegetation index (NDVI) trends from advanced very high resolution radiometer (AVHRR) and système probatoire d'observation de la terre vegetation (SPOT VGT) time series differ in agricultural areas: An inner mongolian case study. *Remote Sensing*, 4(11), 3364–3389. <http://doi.org/10.5829/idosi.mejsr.2012.12.3.64113>
- Zhu, X. (2010). Clustering. Retrieved from <http://pages.cs.wisc.edu/~jerryzhu/cs769/clustering.pdf>

APPENDICES

Sample area	Plant A	Harvest A	Plant B	Harvest B
2411	15-Sep-14	05-Jan-15	15-Feb-15	05-Jun-15
2411	20-Sep-14	10-Jan-15	10-Feb-15	12-Jun-15
2411	20-Sep-14	10-Jan-15	15-Feb-15	05-Jun-15
2411	20-Sep-14	10-Jan-15	15-Feb-15	15-Jun-15
2411	30-Sep-14	10-Jan-15	15-Feb-15	12-Jun-15
2411	20-Sep-14	10-Jan-15	25-Feb-15	20-Jun-15
2411	20-Sep-14	10-Jan-15	25-Feb-15	20-Jun-15
2411	20-Sep-14	15-Jan-15	25-Feb-15	20-Jun-15
2411	20-Sep-14	15-Jan-15	25-Feb-15	20-Jun-15
2411	20-Sep-14	15-Jan-15	15-Feb-15	15-Jun-15
2412	20-Sep-14	10-Jan-15	25-Feb-15	15-Jun-15
2412	20-Sep-14	10-Jan-15	25-Feb-15	01-Jun-15
2412	25-Sep-14	10-Jan-15	01-Mar-15	15-Jun-15
2412	20-Sep-14	15-Jan-15	20-Feb-15	20-Jun-15
2412	25-Sep-14	15-Jan-15	20-Feb-15	10-Jun-15
2412	25-Sep-14	15-Jan-15	01-Mar-15	01-Jun-15
2412	25-Sep-14	15-Jan-15	20-Feb-15	20-Jun-15
2412	25-Sep-14	20-Jan-15	20-Feb-15	05-Jun-15
2412	25-Sep-14	20-Jan-15	25-Feb-15	10-Jun-15
2414	25-Sep-14	10-Jan-15	25-Feb-15	10-Jun-15
2414	25-Sep-14	15-Jan-15	20-Feb-15	15-Jun-15
2414	25-Sep-14	15-Jan-15	20-Feb-15	20-Jun-15
2414	25-Sep-14	15-Jan-15	25-Feb-15	20-Jun-15
2414	25-Sep-14	15-Jan-15	20-Feb-15	20-Jun-15
2414	30-Sep-14	15-Jan-15	25-Feb-15	20-Jun-15
2414	30-Sep-14	20-Jan-15	03-Mar-15	15-Jun-15
2414	05-Oct-14	20-Jan-15	01-Mar-15	20-Jun-15
2414	25-Sep-14	20-Jan-15	25-Feb-15	15-Jun-15
2414	25-Sep-14	20-Jan-15	01-Mar-15	10-Jun-15
2414	05-Oct-14	20-Jan-15	03-Mar-15	20-Jun-15
2421	20-Sep-14	10-Jan-15	20-Feb-15	20-Jun-15
2421	30-Sep-14	10-Jan-15	10-Feb-15	20-Jun-15
2421	01-Oct-14	15-Jan-15	20-Feb-15	20-Jun-15
2421	30-Sep-14	15-Jan-15	20-Feb-15	20-Jun-15
2421	25-Sep-14	20-Jan-15	10-Feb-15	15-Jun-15
2421	25-Sep-14	25-Jan-15	15-Feb-15	10-Jun-15
2421	25-Sep-14	25-Jan-15	15-Feb-15	15-Jun-15
2421	01-Oct-14	25-Jan-15	15-Feb-15	20-Jun-15
2421	25-Sep-14	25-Jan-15	15-Feb-15	25-Jun-15
2422	15-Sep-14	15-Jan-15	10-Feb-15	10-Jun-15
2422	20-Sep-14	15-Jan-15	25-Feb-15	15-Jun-15
2422	20-Sep-14	20-Jan-15	20-Feb-15	15-Jun-15
2422	25-Sep-14	20-Jan-15	01-Mar-15	20-Jun-15
2422	20-Sep-14	25-Jan-15	20-Feb-15	20-Jun-15
2422	20-Sep-14	25-Jan-15	01-Mar-15	20-Jun-15
2422	25-Sep-14	25-Jan-15	25-Feb-15	20-Jun-15
2422	20-Sep-14	30-Jan-15	20-Feb-15	20-Jun-15
2422	25-Sep-14	30-Jan-15	25-Feb-15	10-Jun-15
2422	20-Sep-14	30-Jan-15	28-Feb-15	20-Jun-15
2423	11-Sep-14	01-Jan-15	25-Feb-15	13-Jun-15
2423	22-Sep-14	03-Jan-15	07-Feb-15	26-May-15
2423	27-Sep-14	05-Jan-15	05-Feb-15	11-Jun-15
2423	13-Sep-14	24-Dec-14	15-Feb-15	26-May-15
2423	13-Sep-14	24-Dec-14	15-Feb-15	07-Jun-15
2423	05-Sep-14	26-Dec-14	09-Feb-15	22-May-15
2423	22-Sep-14	26-Dec-14	17-Feb-15	28-May-15
2423	13-Sep-14	28-Dec-14	17-Feb-15	30-May-15
2423	20-Sep-14	31-Dec-14	23-Feb-15	05-Jun-15
2423	22-Sep-14	31-Dec-14	09-Feb-15	28-May-15

Appendix 1: Data from the interviews with farmers for 24 NDVI class

Sample area	Plant A	Harvest A	Plant B	Harvest B
2431	05-Oct-14	15-Jan-15	15-Feb-15	15-Jun-15
2431	20-Sep-14	15-Jan-15	20-Feb-15	05-Jun-15
2431	27-Sep-14	18-Jan-15	25-Feb-15	19-Jun-15
2431	25-Sep-14	20-Jan-15	15-Feb-15	21-Jun-15
2431	27-Sep-14	20-Jan-15	17-Feb-15	30-May-15
2431	23-Sep-14	20-Jan-15	15-Feb-15	10-Jun-15
2431	25-Sep-14	25-Jan-15	22-Feb-15	16-Jun-15
2431	29-Sep-14	25-Jan-15	25-Feb-15	31-May-15
2431	20-Sep-14	01-Feb-15	25-Feb-15	07-Jun-15
2431	01-Oct-14	01-Feb-15	20-Feb-15	15-Jun-15
2431	03-Sep-14	01-Feb-15	25-Feb-15	19-Jun-15
2432	25-Sep-14	10-Jan-15	25-Feb-15	20-Jun-15
2432	25-Sep-14	20-Jan-15	15-Feb-15	30-May-15
2432	20-Sep-14	20-Jan-15	25-Feb-15	10-Jun-15
2432	25-Sep-14	20-Jan-15	15-Feb-15	15-Jun-15
2432	25-Sep-14	20-Jan-15	01-Mar-15	12-Jun-15
2432	25-Sep-14	20-Jan-15	10-Feb-15	20-Jun-15
2432	25-Sep-14	25-Jan-15	25-Feb-15	15-Jun-15
2432	25-Sep-14	25-Jan-15	20-Feb-15	20-Jun-15
2432	05-Oct-14	04-Feb-15	15-Feb-15	10-Jun-15
2433	20-Sep-14	01-Jan-15	15-Feb-15	30-May-15
2433	20-Sep-14	05-Jan-15	15-Feb-15	05-Jun-15
2433	25-Sep-14	10-Jan-15	25-Feb-15	05-Jun-15
2433	30-Sep-14	10-Jan-15	15-Feb-15	05-Jun-15
2433	15-Sep-14	10-Jan-15	15-Feb-15	05-Jun-15
2433	20-Sep-14	10-Jan-15	25-Feb-15	05-Jun-15
2433	20-Sep-14	26-Dec-14	10-Feb-15	25-May-15
2433	15-Sep-14	31-Dec-14	10-Feb-15	25-May-15
2434	20-Sep-14	01-Jan-15	22-Feb-15	10-Jun-15
2434	20-Sep-14	02-Jan-15	20-Feb-15	30-May-15
2434	22-Sep-14	04-Jan-15	15-Feb-15	01-Jun-15
2434	20-Sep-14	05-Jan-15	25-Feb-15	05-Jun-15
2434	15-Sep-14	05-Jan-15	20-Feb-15	25-May-15
2434	25-Sep-14	10-Jan-15	20-Feb-15	20-Jun-15
2434	30-Sep-14	15-Jan-15	25-Feb-15	15-Jun-15
2434	15-Sep-14	25-Dec-14	15-Feb-15	25-May-15
2434	19-Sep-14	30-Dec-14	18-Feb-15	03-Jun-15

Appendix 1 (continued): Data from the interviews with farmers for NDVI class 24

Sample area	Plant A	Harvest A	Plant B	Harvest B
5411	05-Sep-14	01-Jan-15	_	_
5411	06-Sep-14	02-Jan-15	_	_
5411	30-Aug-14	05-Jan-15	_	_
5411	05-Sep-14	08-Jan-15	_	_
5411	30-Aug-14	10-Jan-15	_	_
5411	31-Aug-14	10-Jan-15	_	_
5411	30-Aug-14	10-Jan-15	_	_
5411	30-Aug-14	10-Jan-15	_	_
5411	25-Aug-14	12-Jan-15	_	_
5411	06-Sep-14	12-Jan-15	_	_
5411	09-Sep-14	15-Jan-15	_	_
5411	05-Sep-14	15-Jan-15	_	_
5412	18-Jun-14	01-Jan-15	_	_
5412	20-Jun-14	02-Jan-15	_	_
5412	05-Jun-14	05-Jan-15	_	_
5412	15-Jun-14	08-Jan-15	_	_
5412	15-Jun-14	10-Jan-15	_	_
5412	11-Jun-14	10-Jan-15	_	_
5412	20-Jun-14	10-Jan-15	_	_
5412	05-Jul-14	12-Jan-15	_	_
5412	20-Jun-14	25-Dec-14	_	_
5412	20-Jun-14	31-Dec-14	_	_
5413	06-Sep-14	05-Jan-15	_	_
5413	20-Aug-14	08-Jan-15	_	_
5413	03-Sep-14	08-Jan-15	_	_
5413	30-Aug-14	10-Jan-15	_	_
5413	25-Aug-14	10-Jan-15	_	_
5413	30-Aug-14	10-Jan-15	_	_
5413	05-Sep-14	12-Jan-15	_	_
5413	05-Sep-14	15-Jan-15	_	_
5413	09-Sep-14	20-Jan-15	_	_
5414	22-Jun-14	05-Jan-15	_	_
5414	20-Jun-14	05-Jan-15	_	_
5414	15-Jun-14	08-Jan-15	_	_
5414	15-Jun-14	09-Jan-15	_	_
5414	20-Jun-14	10-Jan-15	_	_
5414	15-Jun-14	10-Jan-15	_	_
5414	05-Jul-14	10-Jan-15	_	_
5414	30-Jun-14	10-Jan-15	_	_
5414	20-Jun-14	25-Dec-14	_	_
5414	20-Jun-14	30-Dec-14	_	_
5414	20-Jun-14	31-Dec-14	_	_
5421	25-Aug-14	20-Jan-15	_	_
5421	20-Aug-14	22-Jan-15	_	_
5421	30-Aug-14	25-Jan-15	_	_
5421	05-Sep-14	01-Feb-15	_	_
5421	31-Aug-14	01-Feb-15	_	_
5421	03-Sep-14	01-Feb-15	_	_
5421	05-Sep-14	01-Feb-15	_	_
5421	09-Sep-14	02-Feb-15	_	_
5421	30-Aug-14	04-Feb-15	_	_
5422	20-Aug-14	01-Feb-15	_	_
5422	20-Aug-14	02-Feb-15	_	_
5422	25-Aug-14	05-Feb-15	_	_
5422	20-Aug-14	10-Feb-15	_	_
5422	25-Aug-14	10-Feb-15	_	_
5422	06-Sep-14	12-Feb-15	_	_
5422	05-Sep-14	12-Feb-15	_	_
5422	30-Aug-14	15-Feb-15	_	_
5422	30-Aug-14	15-Feb-15	_	_
5422	30-Aug-14	15-Feb-15	_	_

Appendix 2: Data from the interviews with farmers for NDVI class 54

Sample area	Plant A	Harvest A	Plant B	Harvest B
5423	02-Aug-14	01-Jan-15	_	_
5423	10-Aug-14	10-Jan-15	_	_
5423	02-Aug-14	10-Jan-15	_	_
5423	05-Aug-14	10-Jan-15	_	_
5423	01-Aug-14	10-Jan-15	_	_
5423	25-Jul-14	25-Dec-14	_	_
5423	28-Jul-14	30-Dec-14	_	_
5423	25-Jul-14	31-Dec-14	_	_
5424	05-Sep-14	10-Feb-15	_	_
5424	06-Sep-14	10-Feb-15	_	_
5424	25-Aug-14	15-Feb-15	_	_
5424	25-Aug-14	25-Feb-15	_	_
5424	15-Aug-14	29-Feb-15	_	_
5424	03-Sep-14	29-Feb-15	_	_
5424	30-Aug-14	01-Mar-15	_	_
5424	30-Aug-14	03-Mar-15	_	_
5424	06-Sep-14	09-Mar-15	_	_
5431	15-Aug-14	15-Feb-15	_	_
5431	15-Aug-14	15-Feb-15	_	_
5431	20-Aug-14	29-Feb-15	_	_
5431	25-Aug-14	29-Feb-15	_	_
5431	20-Aug-14	29-Feb-15	_	_
5431	20-Aug-14	01-Mar-15	_	_
5431	13-Aug-14	03-Mar-15	_	_
5431	18-Aug-14	04-Mar-15	_	_
5431	15-Aug-14	09-Mar-15	_	_
5432	30-Aug-14	05-Jan-15	_	_
5432	30-Aug-14	09-Jan-15	_	_
5432	05-Sep-14	10-Jan-15	_	_
5432	08-Sep-14	10-Jan-15	_	_
5432	15-Sep-14	10-Jan-15	_	_
5432	27-Aug-14	15-Jan-15	_	_
5432	05-Sep-14	20-Jan-15	_	_
5432	25-Aug-14	25-Jan-15	_	_
5433	30-Aug-14	01-Jan-15	_	_
5433	03-Sep-14	01-Jan-15	_	_
5433	01-Sep-14	05-Jan-15	_	_
5433	06-Sep-14	05-Jan-15	_	_
5433	15-Sep-14	08-Jan-15	_	_
5433	15-Sep-14	10-Jan-15	_	_
5433	08-Sep-14	12-Jan-15	_	_
5433	27-Aug-14	25-Dec-14	_	_
5433	05-Sep-14	27-Dec-14	_	_
5433	30-Aug-14	31-Dec-14	_	_
5434	03-Sep-14	10-Feb-15	_	_
5434	15-Sep-14	10-Feb-15	_	_
5434	05-Sep-14	15-Feb-15	_	_
5434	03-Sep-14	28-Feb-15	_	_
5434	10-Sep-14	29-Feb-15	_	_
5434	12-Sep-14	29-Feb-15	_	_
5434	05-Sep-14	01-Mar-15	_	_
5434	15-Sep-14	04-Mar-15	_	_

Appendix 2(continued): Data from the interviews with farmers for NDVI class 54

Sample area	Plant A	Harvest A	Plant B	Harvest B
7011	23-Jul-14	01-Jan-15	_	_
7011	02-Aug-14	03-Jan-15	_	_
7011	25-Jul-14	05-Jan-15	_	_
7011	05-Aug-14	05-Jan-15	_	_
7011	01-Aug-14	08-Jan-15	_	_
7011	28-Jul-14	10-Jan-15	_	_
7011	25-Jul-14	10-Jan-15	_	_
7011	05-Aug-14	12-Jan-15	_	_
7012	02-Jul-14	01-Jan-15	_	_
7012	30-Jun-14	05-Jan-15	_	_
7012	08-Jul-14	10-Dec-14	_	_
7012	05-Jul-14	17-Dec-14	_	_
7012	05-Jul-14	20-Dec-14	_	_
7012	05-Jul-14	20-Dec-14	_	_
7012	30-Jun-14	25-Dec-14	_	_
7012	25-Jun-14	25-Dec-14	_	_
7012	02-Jul-14	30-Dec-14	_	_
7013	12-May-14	01-Jan-15	_	_
7013	10-May-14	05-Jan-15	_	_
7013	08-May-14	10-Jan-15	_	_
7013	03-May-14	10-Jan-15	_	_
7013	05-May-14	10-Jan-15	_	_
7013	10-May-14	19-Dec-14	_	_
7013	10-May-14	20-Dec-14	_	_
7013	01-May-14	25-Dec-14	_	_
7013	05-May-14	27-Dec-14	_	_
7013	08-May-14	30-Dec-14	_	_
7014	08-May-14	01-Jan-15	_	_
7014	10-May-14	08-Jan-15	_	_
7014	05-May-14	10-Jan-15	_	_
7014	10-May-14	10-Jan-15	_	_
7014	10-May-14	10-Jan-15	_	_
7014	01-May-14	10-Jan-15	_	_
7014	10-May-14	12-Jan-15	_	_
7014	05-May-14	10-Dec-14	_	_
7014	08-May-14	15-Dec-14	_	_
7014	01-May-14	20-Dec-14	_	_
7014	12-May-14	22-Dec-14	_	_
7021	25-Jun-14	10-Dec-14	_	_
7021	05-Jul-14	10-Dec-14	_	_
7021	30-Jun-14	17-Dec-14	_	_
7021	25-Jun-14	18-Dec-14	_	_
7021	05-Jul-14	20-Dec-14	_	_
7021	30-Jun-14	20-Dec-14	_	_
7021	05-Jul-14	25-Dec-14	_	_
7021	08-Jul-14	30-Dec-14	_	_
7021	05-Jul-14	30-Dec-14	_	_
7022	05-May-14	01-Jan-15	_	_
7022	05-May-14	05-Jan-15	_	_
7022	25-Apr-14	10-Jan-15	_	_
7022	10-May-14	20-Dec-14	_	_
7022	01-May-14	20-Dec-14	_	_
7022	25-Apr-14	22-Dec-14	_	_
7022	05-May-14	25-Dec-14	_	_
7022	10-May-14	25-Dec-14	_	_
7022	28-Apr-14	30-Dec-14	_	_

Appendix 3: Data from the interviews with farmers for NDVI class 70

Sample area	Plant A	Harvest A	Plant B	Harvest B
7023	05-May-14	01-Jan-15	_	_
7023	15-May-14	05-Jan-15	_	_
7023	15-May-14	10-Jan-15	_	_
7023	01-May-14	17-Dec-14	_	_
7023	10-May-14	20-Dec-14	_	_
7023	25-May-14	20-Dec-14	_	_
7023	05-May-14	25-Dec-14	_	_
7023	10-May-14	25-Dec-14	_	_
7023	25-May-14	30-Dec-14	_	_
7024	08-May-14	01-Jan-15	_	_
7024	10-May-14	03-Jan-15	_	_
7024	01-May-14	05-Jan-15	_	_
7024	05-May-14	05-Jan-15	_	_
7024	25-Apr-14	05-Jan-15	_	_
7024	01-May-14	05-Jan-15	_	_
7024	10-May-14	10-Jan-15	_	_
7024	05-May-14	10-Jan-15	_	_
7024	10-May-14	25-Dec-14	_	_
7031	25-Jul-14	10-Jan-15	_	_
7031	05-Aug-14	10-Jan-15	_	_
7031	01-Aug-14	10-Jan-15	_	_
7031	05-Aug-14	15-Jan-15	_	_
7031	25-Jul-14	15-Jan-15	_	_
7031	02-Aug-14	20-Jan-15	_	_
7031	25-Jul-14	20-Jan-15	_	_
7031	25-Jul-14	20-Jan-15	_	_
7031	25-Jul-14	25-Jan-15	_	_
7031	02-Aug-14	25-Jan-15	_	_
7033	01-May-14	01-Jan-15	_	_
7033	05-May-14	01-Jan-15	_	_
7033	08-May-14	05-Jan-15	_	_
7033	05-May-14	05-Jan-15	_	_
7033	10-May-14	10-Jan-15	_	_
7033	01-May-14	10-Jan-15	_	_
7033	10-May-14	20-Dec-14	_	_
7033	12-May-14	22-Dec-14	_	_
7033	12-May-14	25-Dec-14	_	_
7033	10-May-14	30-Dec-14	_	_
7034	05-May-14	01-Jan-15	_	_
7034	25-Apr-14	05-Jan-15	_	_
7034	25-Apr-14	05-Jan-15	_	_
7034	05-May-14	20-Dec-14	_	_
7034	12-May-14	20-Dec-14	_	_
7034	05-May-14	20-Dec-14	_	_
7034	05-May-14	22-Dec-14	_	_
7034	30-Apr-14	25-Dec-14	_	_
7034	10-May-14	25-Dec-14	_	_
7034	10-May-14	30-Dec-14	_	_
7034	25-Apr-14	30-Dec-14	_	_

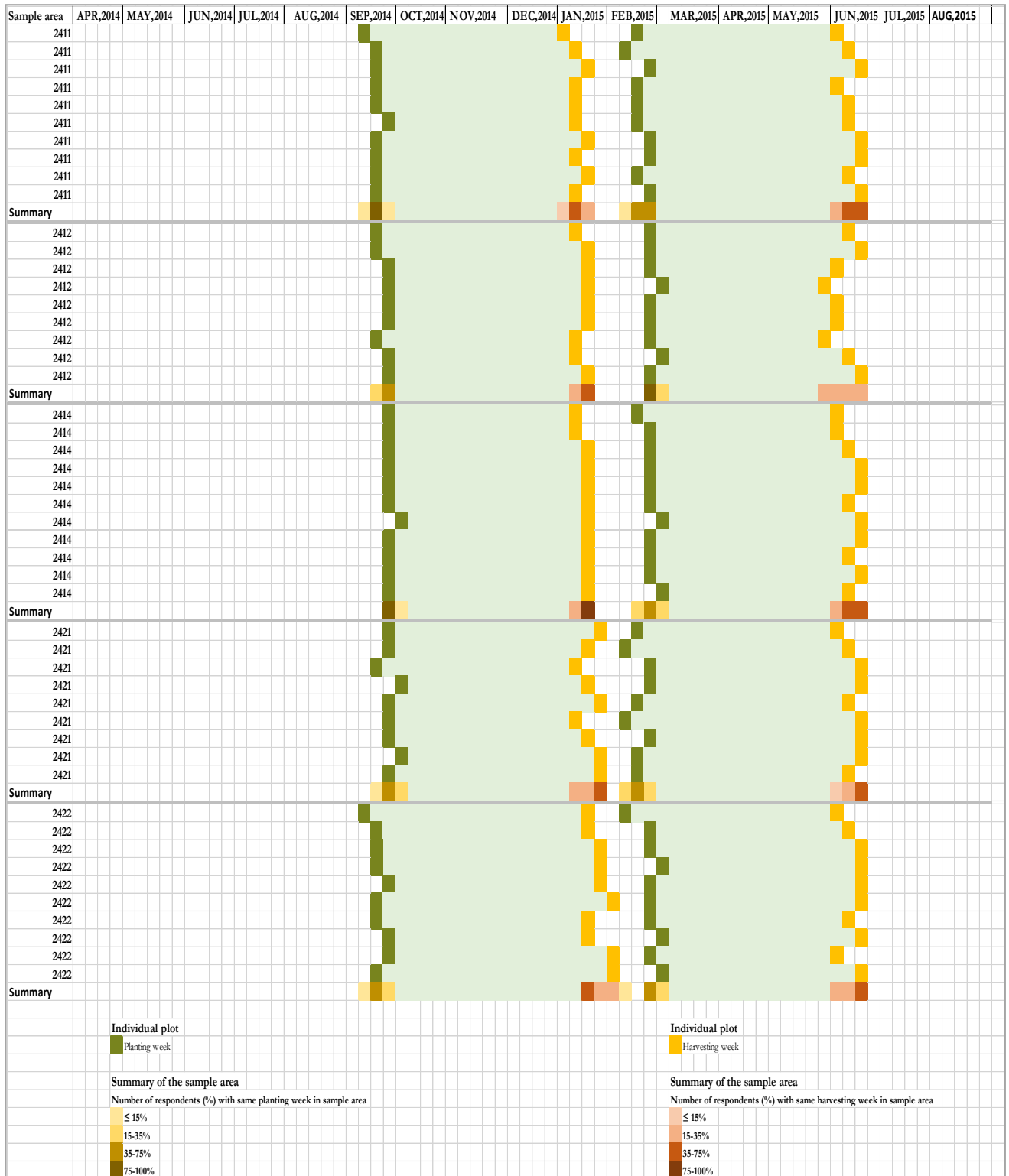
Appendix 3(continued): Data from the interviews with farmers for NDVI class 70

Sample area	Plant A	Harvest A	Plant B	Harvest B
8211	06-Sep-14	20-Jan-15	—	—
8211	25-Aug-14	20-Jan-15	—	—
8211	25-Aug-14	25-Jan-15	—	—
8211	06-Sep-14	25-Jan-15	—	—
8211	31-Aug-14	05-Feb-15	—	—
8211	30-Aug-14	05-Feb-15	—	—
8211	30-Aug-14	10-Feb-15	—	—
8211	30-Aug-14	10-Feb-15	—	—
8211	06-Sep-14	10-Feb-15	—	—
8211	06-Sep-14	10-Feb-15	—	—
8211	30-Aug-14	15-Feb-15	—	—
8212	25-Aug-14	10-Feb-15	—	—
8212	30-Aug-14	10-Feb-15	—	—
8212	25-Aug-14	10-Feb-15	—	—
8212	30-Aug-14	10-Feb-15	—	—
8212	30-Aug-14	10-Feb-15	—	—
8212	30-Aug-14	10-Feb-15	—	—
8212	25-Aug-14	15-Feb-15	—	—
8212	20-Aug-14	15-Feb-15	—	—
8212	31-Aug-14	25-Feb-15	—	—
8212	20-Aug-14	25-Feb-15	—	—
8213	20-Sep-14	05-Feb-15	—	—
8213	18-Sep-14	10-Feb-15	—	—
8213	15-Sep-14	10-Feb-15	—	—
8213	10-Sep-14	12-Feb-15	—	—
8213	15-Sep-14	15-Feb-15	—	—
8213	23-Sep-14	20-Feb-15	—	—
8213	05-Sep-14	25-Feb-15	—	—
8213	20-Sep-14	25-Feb-15	—	—
8213	23-Sep-14	25-Feb-15	—	—
8214	05-Sep-14	08-Feb-15	—	—
8214	10-Sep-14	08-Feb-15	—	—
8214	10-Sep-14	10-Feb-15	—	—
8214	23-Sep-14	10-Feb-15	—	—
8214	15-Sep-14	10-Feb-15	—	—
8214	20-Sep-14	11-Feb-15	—	—
8214	20-Sep-14	15-Feb-15	—	—
8214	15-Sep-14	15-Feb-15	—	—
8214	15-Sep-14	20-Feb-15	—	—
8214	10-Sep-14	20-Feb-15	—	—
8214	05-Sep-14	22-Feb-15	—	—
8214	15-Sep-14	25-Feb-15	—	—
8214	20-Sep-14	25-Feb-15	—	—
8221	20-Aug-14	15-Jan-15	—	—
8221	15-Aug-14	25-Jan-15	—	—
8221	20-Aug-14	25-Jan-15	—	—
8221	15-Aug-14	25-Jan-15	—	—
8221	20-Aug-14	05-Feb-15	—	—
8221	15-Aug-14	05-Feb-15	—	—
8221	25-Aug-14	10-Feb-15	—	—
8221	25-Aug-14	10-Feb-15	—	—
8221	25-Aug-14	10-Feb-15	—	—
8221	25-Aug-14	25-Feb-15	—	—
8222	20-Aug-14	05-Feb-15	—	—
8222	30-Aug-14	05-Feb-15	—	—
8222	25-Aug-14	10-Feb-15	—	—
8222	30-Aug-14	10-Feb-15	—	—
8222	30-Aug-14	10-Feb-15	—	—
8222	25-Aug-14	15-Feb-15	—	—
8222	01-Sep-14	15-Feb-15	—	—
8222	25-Aug-14	15-Feb-15	—	—
8222	20-Aug-14	15-Feb-15	—	—
8222	30-Aug-14	25-Feb-15	—	—

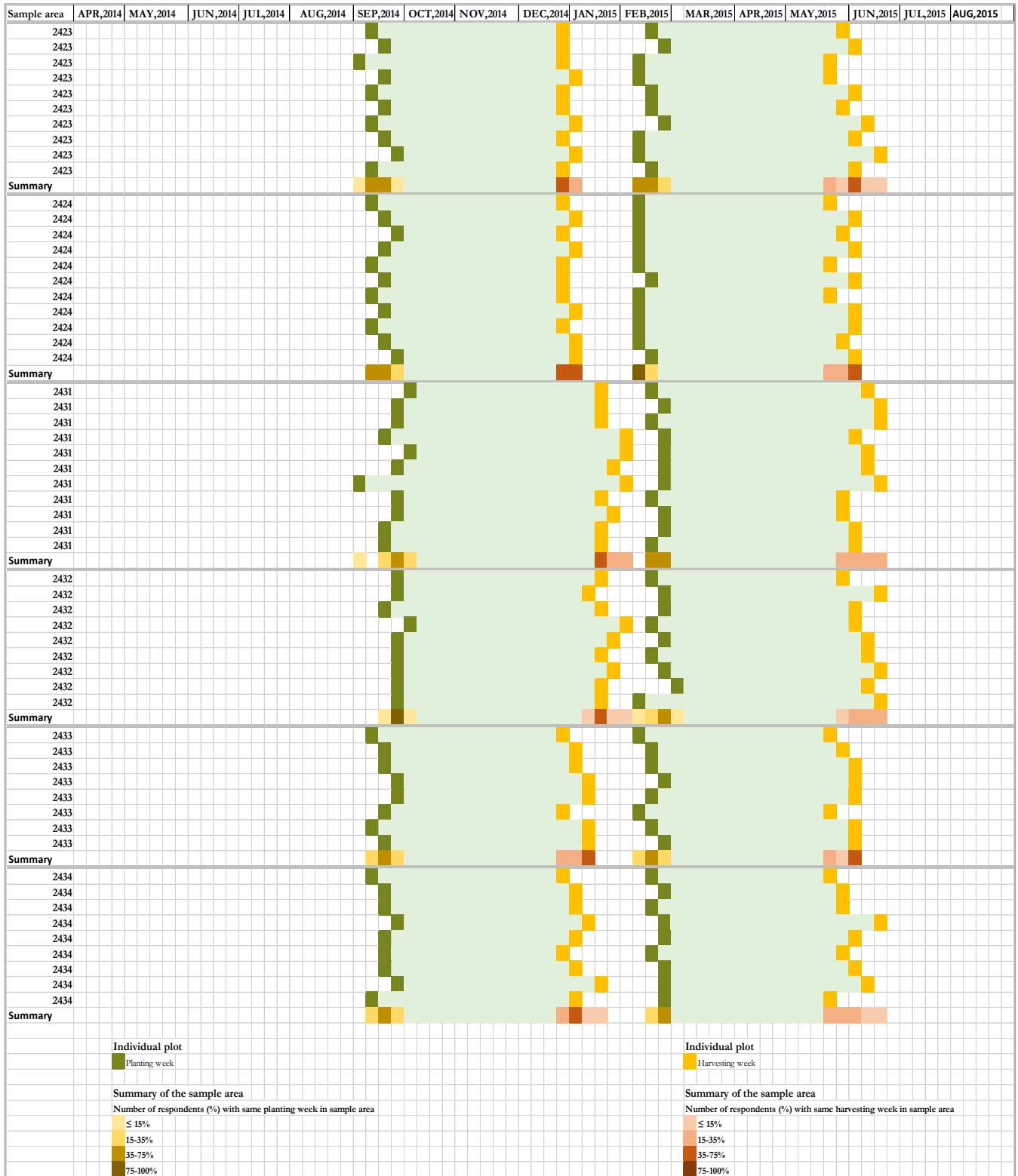
Appendix 4: Data from the interviews with farmers for NDVI class 82

Sample area	Plant A	Harvest A	Plant B	Harvest B
8223	20-Aug-14	05-Jan-15		
8223	15-Aug-14	10-Jan-15		
8223	20-Aug-14	15-Jan-15		
8223	20-Aug-14	15-Jan-15		
8223	25-Aug-14	15-Jan-15		
8223	25-Aug-14	15-Jan-15		
8223	25-Aug-14	15-Jan-15		
8223	25-Aug-14	20-Jan-15		
8223	15-Aug-14	20-Jan-15		
8223	20-Aug-14	20-Jan-15		
8224	10-Aug-14	08-Jan-15		
8224	06-Aug-14	10-Jan-15		
8224	15-Aug-14	10-Jan-15		
8224	01-Aug-14	15-Jan-15		
8224	10-Aug-14	15-Jan-15		
8224	02-Aug-14	15-Jan-15		
8224	05-Aug-14	20-Jan-15		
8224	15-Aug-14	20-Jan-15		
8224	02-Aug-14	20-Jan-15		
8231	12-Sep-14	01-Jan-15	25-Feb-15	20-Jun-15
8231	15-Sep-14	05-Jan-15	25-Feb-15	22-Jun-15
8231	10-Sep-14	10-Jan-15	25-Feb-15	30-Jun-15
8231	10-Sep-14	10-Jan-15	25-Feb-15	30-Jun-15
8231	10-Sep-14	10-Jan-15	15-Feb-15	25-Jun-15
8231	05-Sep-14	10-Jan-15	25-Feb-15	30-Jun-15
8231	15-Sep-14	15-Jan-15	15-Feb-15	15-Jun-15
8231	15-Sep-14	20-Jan-15	25-Feb-15	25-Jun-15
8231	05-Sep-14	25-Dec-14	25-Feb-15	20-Jun-15
8232	20-Sep-14	01-Jan-15	10-Mar-15	30-Jun-15
8232	23-Sep-14	05-Jan-15	05-Mar-15	05-Jul-15
8232	20-Sep-14	05-Jan-15	01-Mar-15	25-Jun-15
8232	22-Sep-14	08-Jan-15	10-Mar-15	15-Jun-15
8232	10-Sep-14	10-Jan-15	10-Mar-15	25-Jun-15
8232	10-Sep-14	10-Jan-15	10-Mar-15	20-Jun-15
8232	23-Sep-14	12-Jan-15	03-Mar-15	20-Jun-15
8232	20-Sep-14	20-Jan-15	25-Feb-15	22-Jun-15
8232	15-Sep-14	30-Dec-14	08-Mar-15	20-Jun-15
8233	10-Sep-14	01-Jan-15	25-Feb-15	25-Jun-15
8233	23-Sep-14	05-Jan-15	05-Mar-15	10-Jul-15
8233	15-Sep-14	08-Jan-15	03-Mar-15	25-Jun-15
8233	15-Aug-14	10-Jan-15	10-Mar-15	15-Jun-15
8233	20-Sep-14	10-Jan-15	05-Mar-15	22-Jun-15
8233	10-Sep-14	15-Jan-15	10-Mar-15	20-Jun-15
8233	10-Sep-14	20-Jan-15	01-Mar-15	25-Jun-15
8233	15-Sep-14	20-Jan-15	10-Mar-15	30-Jun-15
8233	23-Sep-14	20-Jan-15	05-Mar-15	25-Jun-15
8233	05-Sep-14	25-Dec-14	05-Mar-15	20-Jun-15
8233	15-Sep-14	30-Dec-14	10-Mar-15	30-Jun-15
8234	09-Sep-14	05-Jan-15	05-Mar-15	05-Jul-15
8234	05-Sep-14	10-Jan-15	10-Mar-15	25-Jun-15
8234	15-Sep-14	10-Jan-15	01-Mar-15	25-Jun-15
8234	30-Aug-14	10-Jan-15	05-Mar-15	10-Jul-15
8234	10-Sep-14	15-Jan-15	10-Mar-15	15-Jul-15
8234	15-Sep-14	20-Jan-15	20-Feb-15	25-Jun-15
8234	15-Sep-14	20-Jan-15	25-Feb-15	25-Jun-15
8234	25-Aug-14	30-Dec-14	25-Feb-15	30-Jun-15

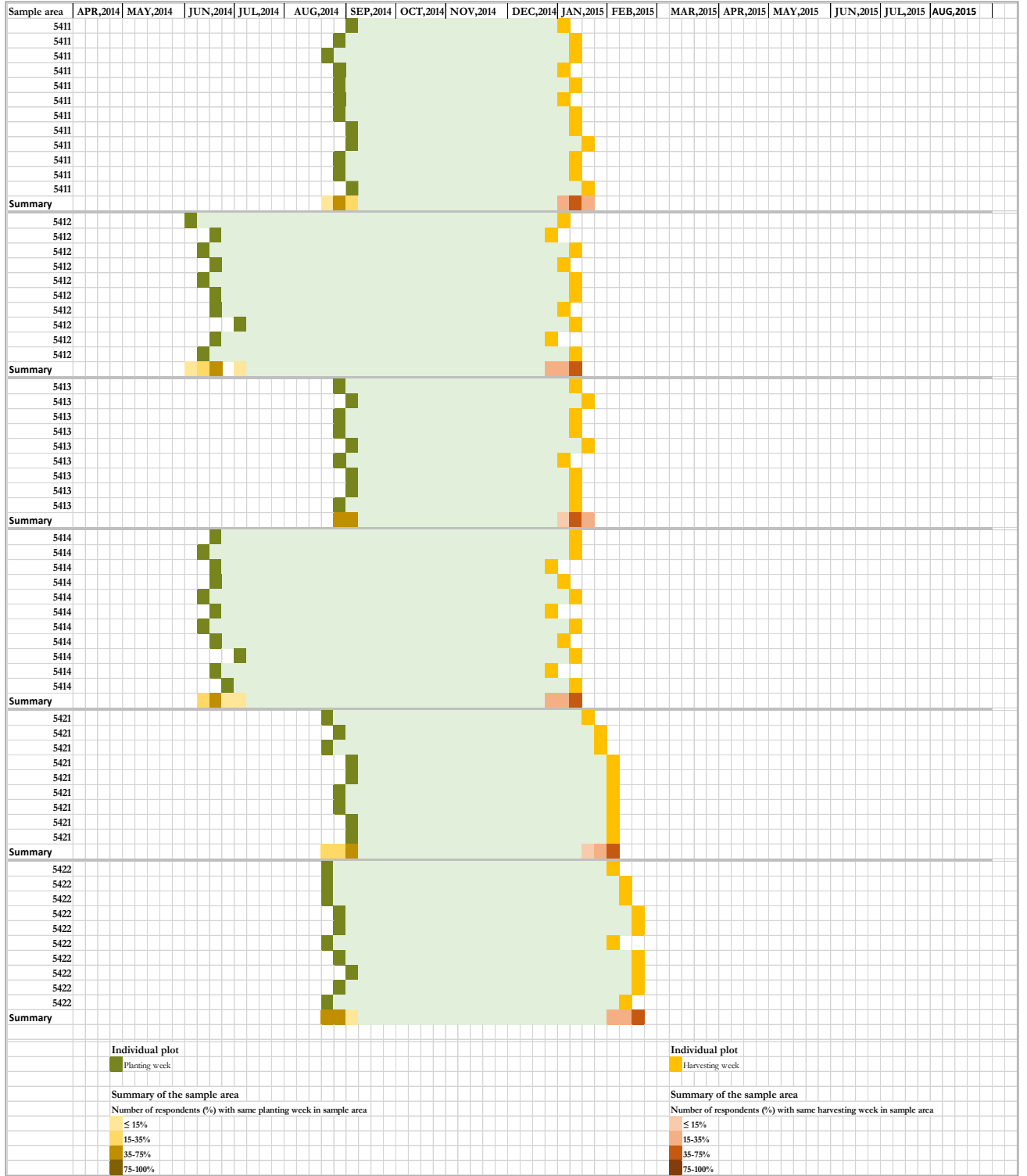
Appendix 4(continued): Data from the interviews with farmers for NDVI class 82



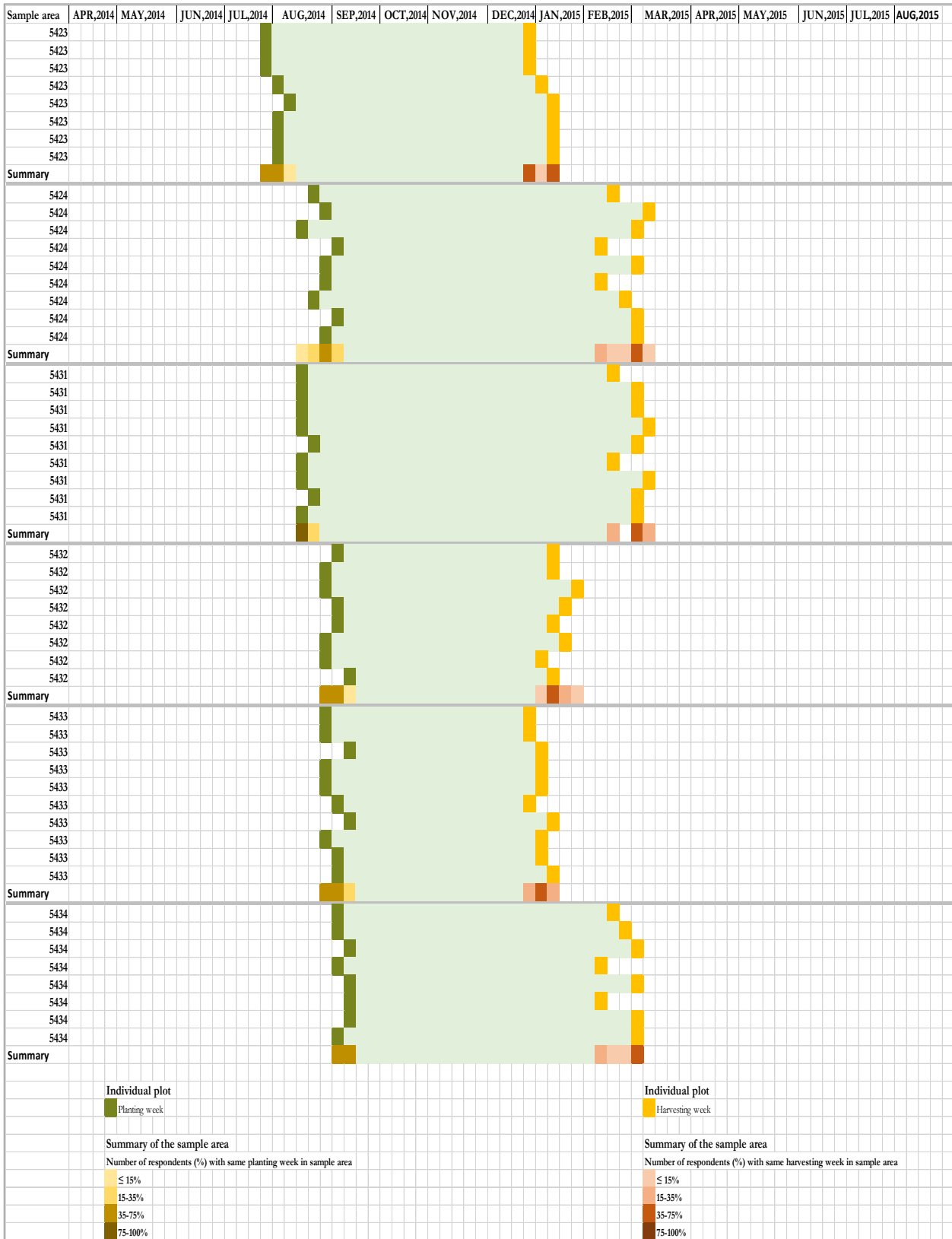
Appendix 5: Maize crop calendars for each plot of interviewed farmer in NDVI class 24



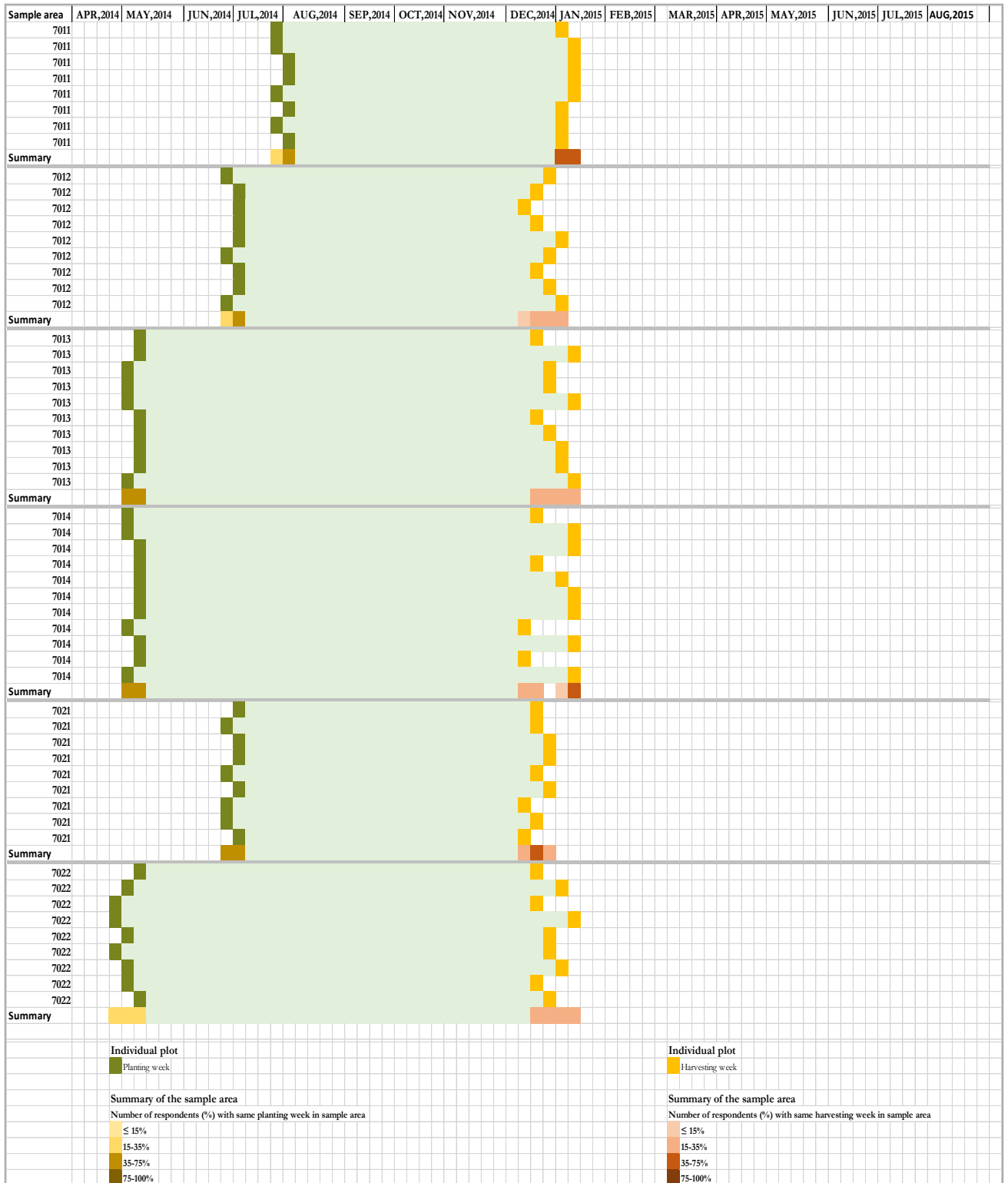
Appendix 5(continued): Maize crop calendar for each plot of interviewed farmer in NDVI class 24



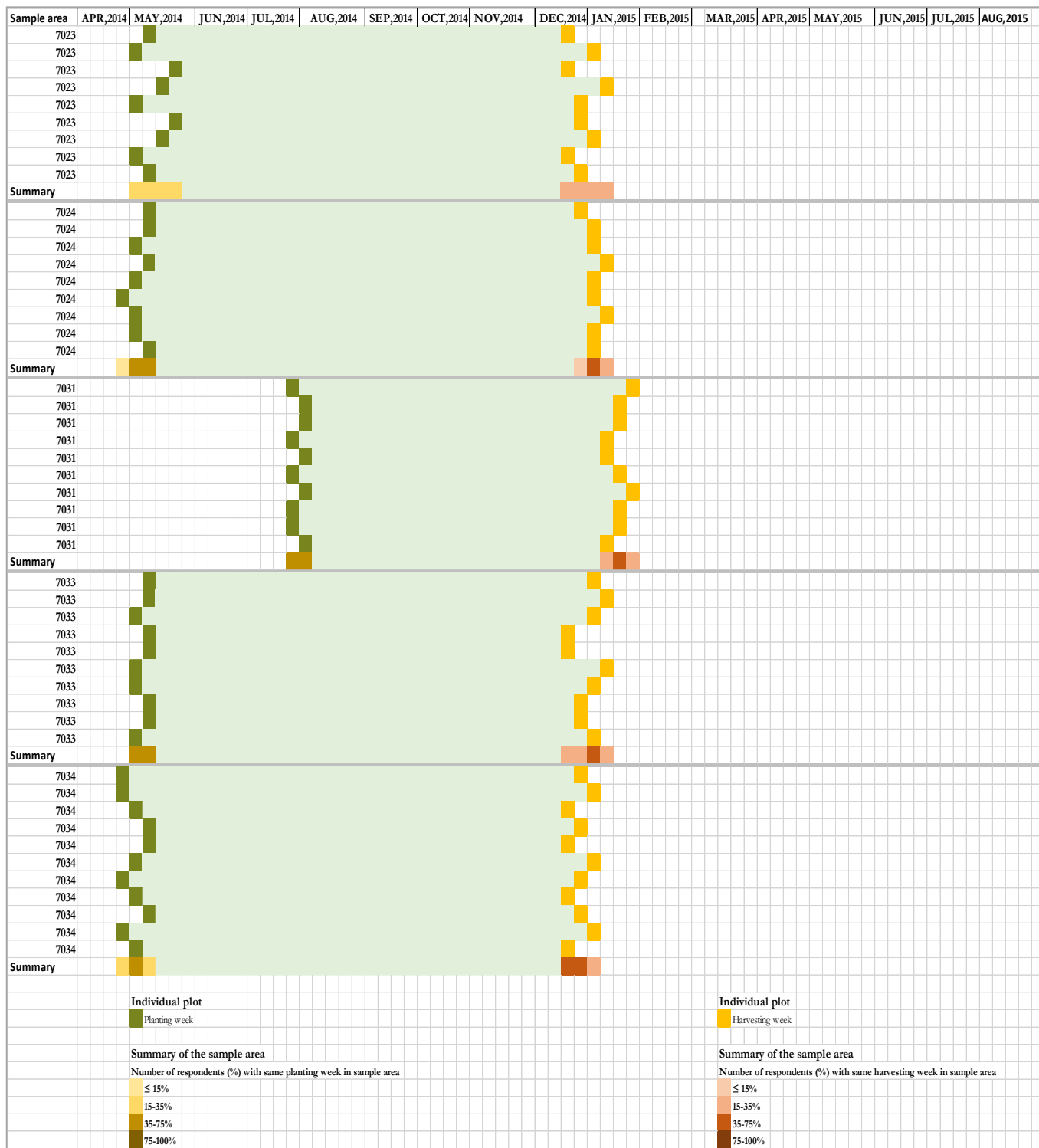
Appendix 6: Maize crop calendar for each plot of interviewed farmer in 54 NDVI class



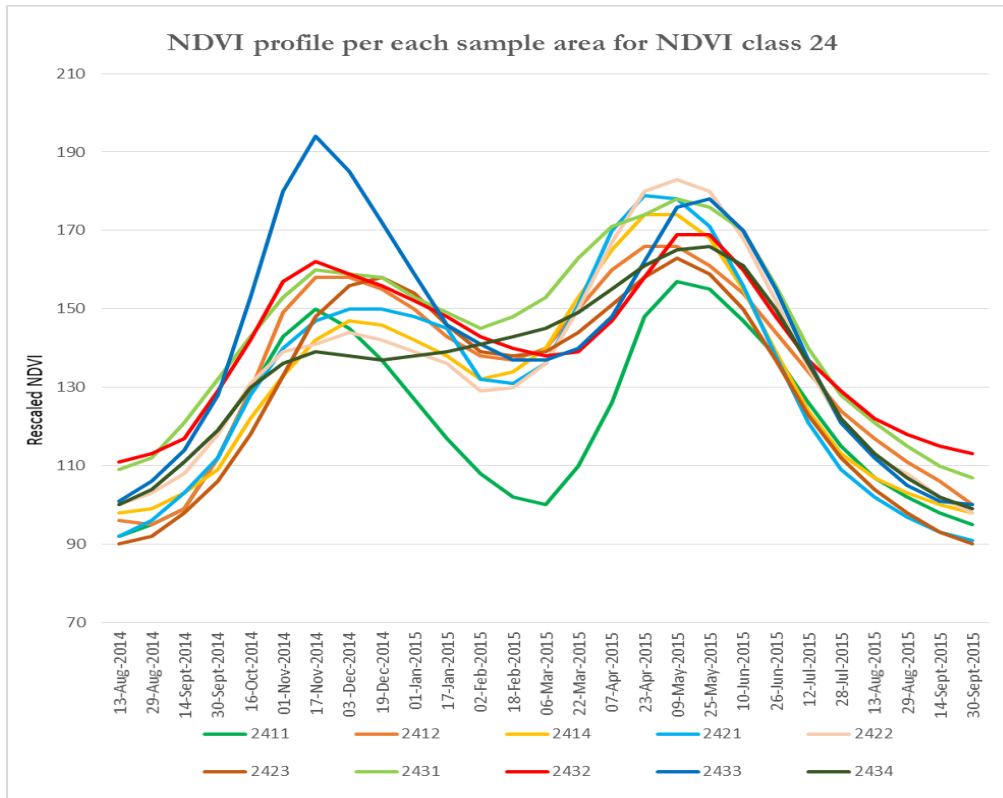
Appendix 6(continued): Maize crop calendar for each plot of interviewed farmer in 54 NDVI class



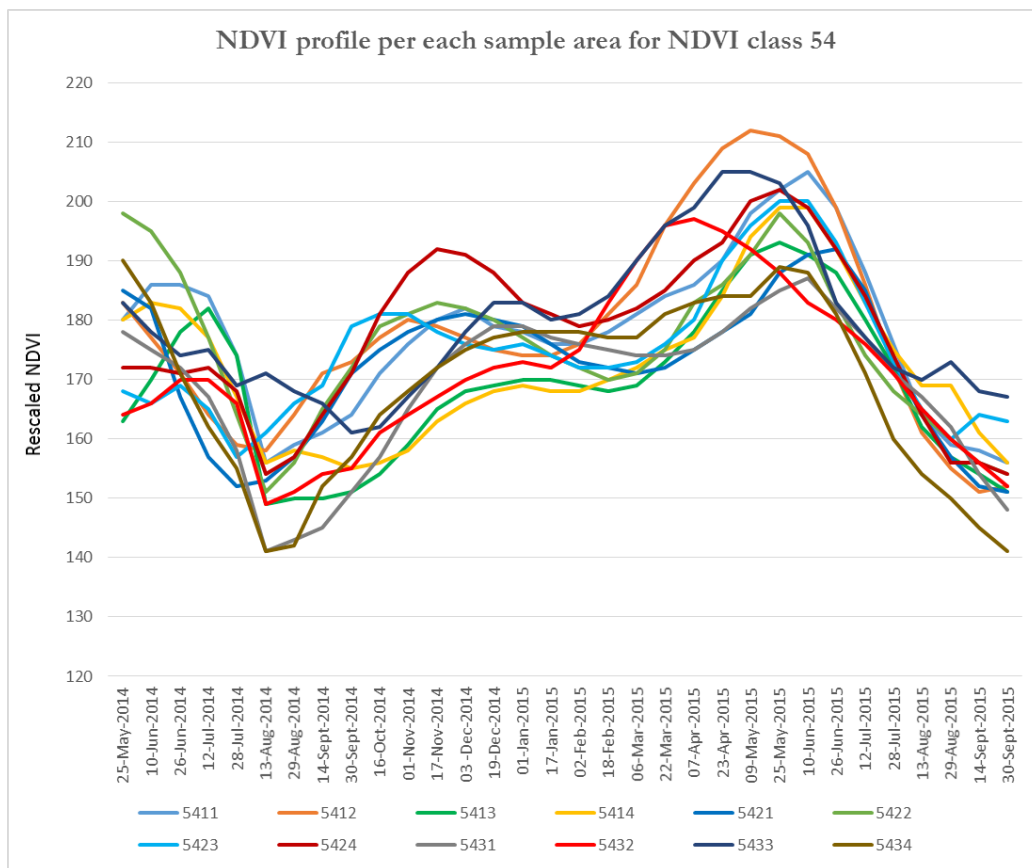
Appendix 7: Maize crop calendar for each plot of interviewed farmer in 70 NDVI class



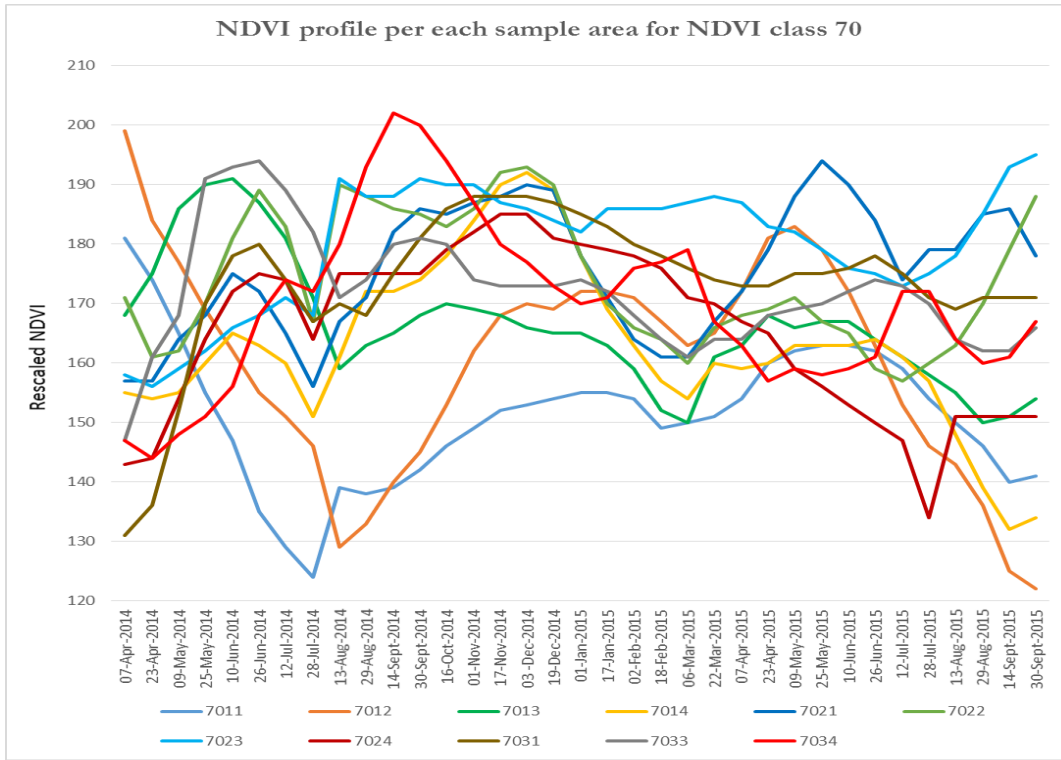
Appendix 7 (continued): Maize crop calendar for each plot of interviewed farmer in 70 NDVI class



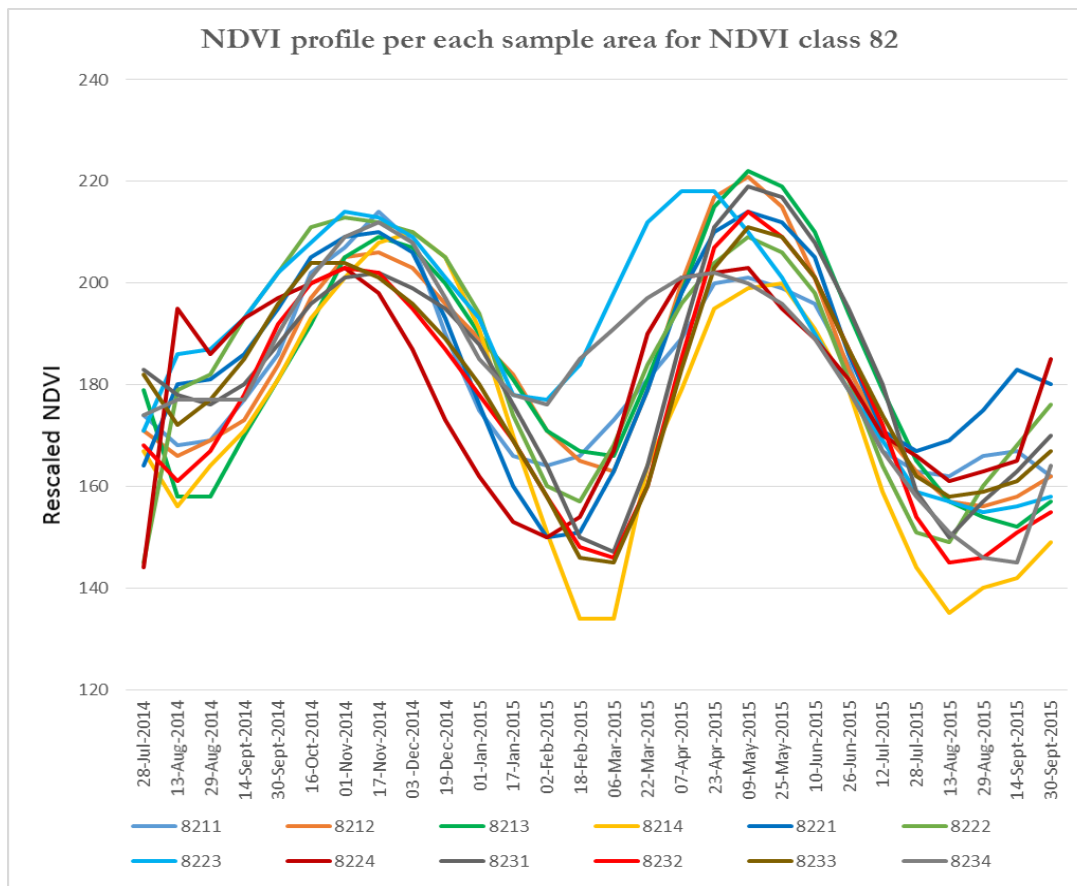
Appendix 9: NDVI profiles per sample area for NDVI class 24



Appendix 10: NDVI profiles per sample area for NDVI class 54



Appendix 11: NDVI profiles per sample area for NDVI class 54



Appendix 12: NDVI profiles per sample area for NDVI class 54

df	Level of Significance α								
	0.200	0.100	0.075	0.050	0.025	0.010	0.005	0.001	0.0005
1	1.642	2.706	3.170	3.841	5.024	6.635	7.879	10.828	12.116
2	3.219	4.605	5.181	5.991	7.378	9.210	10.597	13.816	15.202
3	4.642	6.251	6.905	7.815	9.348	11.345	12.838	16.266	17.731
4	5.989	7.779	8.496	9.488	11.143	13.277	14.860	18.467	19.998
5	7.289	9.236	10.008	11.070	12.833	15.086	16.750	20.516	22.106
6	8.558	10.645	11.466	12.592	14.449	16.812	18.548	22.458	24.104
7	9.803	12.017	12.883	14.067	16.013	18.475	20.278	24.322	26.019
8	11.030	13.362	14.270	15.507	17.535	20.090	21.955	26.125	27.869
9	12.242	14.684	15.631	16.919	19.023	21.666	23.589	27.878	29.667
10	13.442	15.987	16.971	18.307	20.483	23.209	25.188	29.589	31.421
11	14.631	17.275	18.294	19.675	21.920	24.725	26.757	31.265	33.138
12	15.812	18.549	19.602	21.026	23.337	26.217	28.300	32.910	34.822
13	16.985	19.812	20.897	22.362	24.736	27.688	29.820	34.529	36.479
14	18.151	21.064	22.180	23.685	26.119	29.141	31.319	36.124	38.111
15	19.311	22.307	23.452	24.996	27.488	30.578	32.801	37.698	39.720
16	20.465	23.542	24.716	26.296	28.845	32.000	34.267	39.253	41.309
17	21.615	24.769	25.970	27.587	30.191	33.409	35.719	40.791	42.881
18	22.760	25.989	27.218	28.869	31.526	34.805	37.157	42.314	44.435
19	23.900	27.204	28.458	30.144	32.852	36.191	38.582	43.821	45.974
20	25.038	28.412	29.692	31.410	34.170	37.566	39.997	45.315	47.501
21	26.171	29.615	30.920	32.671	35.479	38.932	41.401	46.798	49.013
22	27.301	30.813	32.142	33.924	36.781	40.289	42.796	48.269	50.512
23	28.429	32.007	33.360	35.172	38.076	41.639	44.182	49.729	52.002
24	29.553	33.196	34.572	36.415	39.364	42.980	45.559	51.180	53.480
25	30.675	34.382	35.780	37.653	40.646	44.314	46.928	52.620	54.950
26	31.795	35.563	36.984	38.885	41.923	45.642	48.290	54.053	56.409
27	32.912	36.741	38.184	40.113	43.195	46.963	49.645	55.477	57.860
28	34.027	37.916	39.380	41.337	44.461	48.278	50.994	56.894	59.302
29	35.139	39.087	40.573	42.557	45.722	49.588	52.336	58.302	60.738
30	36.250	40.256	41.762	43.773	46.979	50.892	53.672	59.704	62.164
40	47.269	51.805	53.501	55.759	59.342	63.691	66.766	73.403	76.097
50	58.164	63.167	65.030	67.505	71.420	76.154	79.490	86.662	89.564
60	68.972	74.397	76.411	79.082	83.298	88.380	91.952	99.609	102.698
70	79.715	85.527	87.680	90.531	95.023	100.425	104.215	112.319	115.582
80	90.405	96.578	98.861	101.880	106.629	112.329	116.321	124.842	128.267
90	101.054	107.565	109.969	113.145	118.136	124.117	128.300	137.211	140.789
100	111.667	118.498	121.017	124.342	129.561	135.807	140.170	149.452	153.174

Appendix13: Chi-square distribution table

NDVI classes pairs	Absolute value of means differences	LSD	Conclusion
24, 54	38.30	6.63	There are significant differences
24, 70	115.18	6.75	There are significant differences
24, 82	20.36	6.56	There are significant differences
54, 70	76.88	6.48	There are significant differences
54, 82	17.94	6.28	There are significant differences
70, 82	94.82	6.40	There are significant differences

Appendix 14: Pairwise comparison for planting dates of NDVI classes maize crop calendars, at $p=0.05$

NDVI classes pairs	Absolute value of means differences	LSD	Conclusion
24, 54	9.21	4.41	There are significant differences
24, 70	13.90	4.49	There are significant differences
24, 82	13.35	4.36	There are significant differences
54, 70	23.11	4.31	There are significant differences
54, 82	13.35	4.18	There are significant differences
70, 82	27.25	4.26	There are significant differences

Appendix 15: Pairwise comparison for harvesting dates of NDVI classes maize crop calendars, at $p=0.05$

Pairs of Practiced maize crop calendar groupings	Absolute value of means differences	LSD	Conclusion
CC1, CC2	124.95	4.20	There are significant differences
CC1, CC3	86.09	4.42	There are significant differences
CC1, CC4	106.60	4.45	There are significant differences
CC2, CC3	38.86	4.06	There are significant differences
CC2, CC4	18.35	4.09	There are significant differences
CC3, CC4	20.51	4.32	There are significant differences

Appendix 16: Pairwise comparison for planting dates for practiced maize crop calendar groupings, at $p=0.05$

Pairs of Practiced maize crop calendar groupings	Absolute value of means differences	LSD	Conclusion
CC1, CC2	13.10	2.57	There are significant differences
CC1, CC3	9.67	2.70	There are significant differences
CC1, CC4	45.75	2.72	There are significant differences
CC2, CC3	3.43	2.48	There are significant differences
CC2, CC4	32.65	2.50	There are significant differences
CC3, CC4	36.08	2.64	There are significant differences

Appendix 17: Pairwise comparison for harvesting dates for practiced maize crop calendar groupings, at $p=0.05$