HYPER-TEMPORAL NDVI-DERIVED INDICATORS TO ESTIMATE MAIZE YIELDS IN KENYA

John Joseph Essien
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SUPERVISORS:
Dr. Ir. C.A.J.M, (Kees) de Bie
Dr. Ir. A. Vrieling

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JOHN JOSEPH ESSIEN
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SUPERVISORS:
Dr. Ir. C.A.J.M. (Kees) de Bie
Dr. Ir. A. Vrieling

THESIS ASSESSMENT BOARD:
Prof.Dr.Ing, W, Verhoef (Chair)
Dr. B. Sonneveld (External Examiner) Centre for Food Studies-University of Amsterdam

ABSTRACT

Food insecurity remains high in many parts of Kenya due to recurrent seasons of failed rains occurring during crop growing seasons. This has resulted in drought situations which have led to extensive loss of yields, displacement of people, malnutrition, epidemics and sometimes resulting to famine. Variability in climatic conditions is projected to be more severe in subsequent years. This calls for concern because large part of Kenya's population is dependent on rain-fed agriculture. Maize which is a rain-fed crop accounts for >80% cereals used at household level. Accurate and timely information on crop yields estimation in the stages of crop growth is fundamental towards ensuring food security. The use of satellite derived NDVI data for monitoring of crops is of key importance in providing accurate and timely estimation of yields to warn against impending poor or failed harvest. This study is centred on exploiting effectively the use of hyper-temporal SPOT-VGT NDVI-derived indicators to estimate maize yields. Three distinct steps, the ISODATA clustering technique, disaggregation of published maize statistics and simple linear regression model using hyper-temporal NDVI derived indicators as independent variable and maize yields as dependent variables were performed in this study. The ISODATA clustering produced useful temporal NDVI profiles for classification. The disaggregation of maize areas statistic data by NDVI classes gave reasonable fractions of maize per districts. Two NDVI-derived indicators, maximum NDVI and the sum of NDVI were used in establishing correlations with maize yields. Strong and significant correlations were found from both NDVI-derived indicators in estimating maize yields. A coefficient of determination (R^2) of 0.71 was obtained between maximum NDVI and maize yields while R^2 of 0.84 was obtained between sum of NDVI and maize yields at district level.. The results show the effectiveness of the NDVI-derived indicators in estimating maize yields. Thus this study has demonstrated that hyper-temporal NDVI-derived indicators from SPOT -VGT data can be used for simple, early and reasonably accurate estimation of maize yields.

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1. INTRODUCTION

There are various challenges facing the African continent among which is food insecurity. Ensuring food security has been a burning issue on the mantles of the developed and developing nations. Several government institutions, organizations both nationally and globally, private sectors and non-governmental organizations have proposed and implemented several programs to tackle this problem. It is a major agenda on the United Nations Millennium development Goals (MDG) project. Food security exist "when all people at all times have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and daily life" (FAO, 1996). This is not the situation in many developing countries especially Africa due to socio-economic and political factors like rapid population growth, civil strife, absence of good governance, poor economic policies, political crisis that sometimes culminate into civil wars which exacerbates the problem. Natural factors such as drought, pest infestation, floods, earthquake, and other underlying natural constraints has been a major contributor to food insecurity. Drought has been a major cause of food insecurity experienced in the semi-arid and arid regions in Africa.

Drought is a condition of moisture deficit sufficient to have an adverse effect on yields over a sizeable area. The National Drought Mitigation Centre (NDMC, 2011) defined drought as "a protracted period of deficient precipitation resulting in extensive damage to crops, resulting in loss of yield". This deficiency results in a water shortage for some activity, group, or environmental sector. Thus short term drought on its own is not necessarily a disaster but when it occurs consecutively for several years to cause significant drop in agricultural production resulting in famine, then it becomes a natural disaster. The effects of drought may also lead to displacement of people, malnutrition and epidemics (Rojas et al, 2011) . Drought can be categorized into three types, meteorological drought, hydrological drought and agricultural drought.

Agricultural droughts affect whole societies, leading to higher food costs, threatened economies, and even famine (Wilhite, 2000). This type of drought has adverse and consequent effects on African countries whose population derive their livelihood from subsistence farming which is mostly rain-fed agriculture. This variability in climatic condition has resulted in frequent occurrence of drought due to low precipitations. This has led to crop failures, decline in animal productivity and generally famine which has attracted world attention and thus the need to develop measures to guard against this threat, through early warning using remotely sensed data.

The introduction of the first earth observation satellite revolutionized the space industry and brought about new methods of acquiring information by satellite data. This also gave rise to the development of early warning systems by using remote sensing. A whole range of early warning systems such as the United Nations Food and Agricultural Organization Global Information and Early Warning System (FAO-GIEWS), the United States Agency for International Development Famine Early Warning Systems (USAID-FEWSNET), the European Joint Research Centre (JRC)-MARS project with specific interest in Africa, the Africa Real Time Environmental Monitoring using Imaging Satellites (ARTEMIS) of the UN/FAO are some of the organizations that are using satellite imageries together with ground observations, historical and statistical data to make predictions

Satellite remote sensing is widely used for monitoring crops and agricultural drought assessment for early warning systems. This is because it provides high quality spatial and temporal information about the behaviour of agricultural crops (Lewis et al.,1998). It also provides an efficient and reliable means of collecting timely information for various purposes, such as mapping crop types, crop acreage, crop health, phenology, etc. It is used for deriving indicators for crop production assessment Genovese et al. (2001). Coarse resolution satellites sensors have been used to monitor vegetation and detect the impact of moisture stress on vegetation over the last twenty years. Since one key aspect of food security on regional or continental scale is timely monitoring of the food production conditions , therefore use of repetitive satellite remote sensing data is a key aspect for systematically monitoring the different aspects of the resource base over the entire region (Huber et al.,2009). Remote sensing data has the potential to capture the spatial and temporal variations in climatic conditions which is characteristic of large areas of the African continent. The most commonly used satellite-sensors are the Advanced Very High Resolution Radiometer (NOAA-AVHRR), the Moderate Imaging Spectroradiometer (MODIS) and the *System Pour l' Observation de la terre* (SPOT) VGT sensor. It has been shown that data obtained from these polar orbiting satellite platforms can be used as a sole source of information, and can also be used complimentary to weather data, for the purposes of monitoring crop conditions and productivity on a large scale area (Groten, 1993b).

Vegetation indices (VI) have been extensively used for monitoring vegetation and land cover changes using the above sensors (Swain & Davis, 1981). It is a mathematical combination of the satellite bands sensitive to the presence and conditions of green vegetation. These VIs are algorithms for simplifying data from multiple reflectance bands to a single value correlating to physical vegetation parameters such as biomass, leaf area index, vegetation ground cover or productivity (Tucker 1979). They are the most widely used in remote sensing measurements (Brown, 2008). .One of such vegetation indices is the Normalized Difference Vegetation Index (NDVI). NDVI is a broadband index known to correlate well with leaf area index and green biomass (Inman et al.,2007) it is representative of the various spectral vegetation indices (Rouse et al, 1974). It is probably one of the most popular remote sensing vegetation indices used to monitor vegetation conditions such as plant vigour, biomass, moisture stress, yield and other parameters and calculated as the ratio of the difference between the red and infrared reflectance to their sum (de Bie et al., 2011a) and is computed;

NDVI= (NIR-VIS)/ (NIR+VIS)

Where NIR= reflectance in the near infrared band (Band4) and VIS= reflectance in the red (visible) band (Band3)

NDVI measurements range between -1 and +1 in theory, but practically is observed at between 0.1 and 0.7 for vegetated land with values greater than 0.5 indicating dense vegetation. Large NDVI values are expected to occur in areas where the amount of green vegetation increases. Bare soils also record NDVI values between -0.1 and +0.1 whereas negative values are observed in clouds, water, snow and ice. In general, higher values of NDVI indicate greater vigour and amounts of vegetation (FEWSNET, 2011). Low values of NDVI have been associated with the lack of vegetation, dormant states of existing vegetation or stress caused by drought, over-irrigation, or diseases (Hastings, 2005). NDVI has been used as an indicator to measure of the amount and vigour of vegetation by the level of photosynthetic activity in the observed vegetation , as well as an effective method for drought detection and also for estimating the impacts of moisture deficits on vegetation (Malingreau, 1989), (John et al,1993) . NDVI from remote sensing products alone has been used in estimating crop yields (Lewis et al.,1998), (Hochheim & Bullock, 1994). Rasmussen(1992) and Groten (1993a) for Burkina Faso, Krause(1992) for Ethiopia, and Maselli et al., (1992) for Niger which showed strong relationship between the radiant components of NDVI (the red and near-infrared band) and grain production.

There are various NDVI phenological metrics such as green-up onset, green peak onset, senescence onset and length of growing season (Sibanda & Murwira, 2012). Vrieling et al., (2008) also described phenological indicators to include start of season (SOS), time of maximum NDVI, maximum NDVI, length of season (LOS) and cumulated NDVI over the season. SOS as defined by Rojas et al.(2011) is "the moment between maximum and minimum when NDVI reaches the average between maximum and minimum (i.e. 50% threshold) and EOS is the moment after maximum when the NDVI-curve again reaches the same level." NDVI phenological indicators have been extensively used in crop yields as illustrated by (Funk & Budde, 2009). Furthermore, NDVI-derived indicators from hyper-temporal imageries can monitor crop production growth and timely estimation of crop yields. Also hyper-temporal NDVI imageries can capture variability over time due to frequent changes in agro-ecosystem and can be observed in the temporal profiles. Therefore, higher temporal variability can be seen more than a spatial one using hyper-temporal data (de Bie et al, 2008) . Since crop monitoring is a critical component of famine early warning, the use of hyper-temporal NDVI-images is of immeasurable value.

The use of hyper-temporal data from MODIS, MERIS, AVHRR AND SPOT-VGT has given insight into the dynamics of temporal variability due to the 8 -16 days maximum value composites imagery as compared to their spatial resolution of 250m-1km. NDVI hyper-temporal data have been used in estimating crop yields through mapping and analyses of vegetation indices. De Bie et al.,(2011b) showed how most frequently annual changes in NDVI class profiles reflected changes in cropped areas in small scale land use mapping using hyper temporal NDVI data. Consequently, using hyper temporal NDVI data derived from the SPOT-VGT (1998-2010) can capture variability and provide information which can be incorporated into early warning system. Early warning of impending poor crop harvests in highly variable environments can allow policy makers the time needed to take appropriate action to ameliorate the effects of regional food shortages on vulnerable rural and urban populations (Thornton et al., 1997).

Traditionally, maize or other crop yields were estimated either through agro-meteorological parameters or by compiling information on crop growth throughout the growing season (Bognár et al., 2011). Recently, several remote sensing models have been developed using hyper-temporal imageries from NOAA-AVHRR and SPOT VGT data to relate between NDVI indicators and crop yields. Some of these remote sensing models have been enumerated by Funk & Budde (2009), where specific studies have been carried put in Kenya. These studies have concentrated mostly on national and sub-national levels and crop production estimates.

This study looks beyond the national and sub-national levels to provide a simple method for maize yield estimation by exploiting more effectively indicators derived from hyper-temporal SPOT VGT NDVI data and its correlation with maize yield data at district level. This is because most natural variations and differences are concealed when agricultural data are aggregated over larger areas (Walker & Mallawaarachchi, 1998).

1.1 Research problem

Food insecurity remains high in many parts of Kenya due to extremes in climate variability and consecutive seasons of poor rainfall. This variability in climatic conditions has resulted to drought situations and is projected to be more severe in subsequent years (Boko et al., 2007). Large parts of Kenya's population are dependent on rain-fed agriculture and the growing climate unpredictability and low precipitation result in poor yields and sometimes total crop failure. In some districts in Kenya, fluctuating crop production levels affects the socio-economic and living quality of the people due to the effects of drought. Inaccurate and less timely information on crop production estimation in the early stages of growth portends a problem in ensuring food security. As earlier stated, most of the crop yield estimation models do not capture variability at district levels because most often, agricultural production data collected over large statistical zones tends to smoothen out the natural variations and conceal differences (Walker & Mallawaarachchi, 1998).

1.2 Research Objective

The objective of this study is to relate NDVI derived indicators from hyper-temporal SPOT NDVI data with maize yield statistics to establish their functional utility.

1.3 Research Questions

- How well can hyper-temporal SPOT NDVI data disaggregate published maize area statistics per districts in Kenya?
- To what extent can hyper-temporal SPOT NDVI data capture maize areas with variability for various districts in Kenya?
- What is the strength per districts in Kenya of the relationship between NDVI derived indicators and maize yields?
- Which of the two tested NDVI derived indicators performed better?

1.4 Research Hypothesis

- H_o: There is no significant correlation between indicators derived from hyper-temporal NDVI and maize yields with coefficient of determination (R^2) > 0.65
- H_a: There is significant correlation between indicators derived from hyper-temporal NDVI and maize yields with coefficient of determination (R^2) > 0.65.

1.5 Research Assumptions

- The yield data obtained from the Ministry of agriculture (MoA) is correct
- The fractions of maize obtained from the stepwise regression analysis in disaggregating published maize statistics are correct
- Choices made in defining the growing seasons and the derived indicators are correct.
- The up-scaling of administrative boundaries in relationship to maize yields are correct.

2. MATERIALS AND METHOD

2.1 Study Area

Kenya was chosen as a study area due to the growing food insecurity as a result of recurrent seasons of poor or failed rains, its relative richness in data and thirdly, the agro-ecological heterogeneity of the districts. It is a country in East Africa situated at the equator. It lies between latitude 5^0N and 5^0S and longitudes 34^0 and 42^0E. The country has a population of nearly 41,000,000 people presently and occupies an area of about 580,367km^2. It consists of 8 provinces and several districts. The country's geography is as diverse as its people and agriculture is practiced in coastal, low land and high land areas which have diverse climate conditions (Rojas, 2007). Kenya's agro-ecological zones are characterized by the following; humid, sub-humid, semi-humid, semi humido/semi-arid (transitional), semi-arid and arid. The production systems are high potential (mixed farming), high potential (cereal and dairy), marginal agriculture, agro-pastoral and mostly pastoral. There are six Agro-Ecological Zones (AEZs) and five major production systems in Kenya (USDA, 2004). These AEZs are humid, sub-humid, semi-humid, semi-humido/semi-arid (transitional) semi-arid and arid. These zones vary from tropical along the coast to temperate inland to arid in the north and northeast parts of the country with long rains beginning from march-June (or sometimes late February- August/ September) and short rains from October- December. The average temperature is 19^0C.

Agriculture plays an important role in the livelihood of the people and about 80 percent of Kenyans derive their livelihoods from this activity. The livelihood/production systems are the high potential (mixed farming), high potential (cereal and dairy), marginal agriculture, agro-pastoral and mostly pastoral. There are other ecosystem services that contribute to the livelihood of the people as well such as the tourism sector with its array of mountains, rangelands, wildlife, beaches and timber production. Maize (*Zea mays*) is the major food crop cultivated in Kenya and represents 90 percent of the country's total national cereal production (Rojas, 2007). It is an annual crop with solid jointed stem and its mode of photosynthesis is very efficient and growth is rapid with a life cycle of 90-270 days (FAO, 2012) . Three provinces are known for high maize cultivation and these are Rift Valley, Nyanza and Western and they produce more than 80 percent of the national maize production. Also, these three provinces are characterized by one period of rainfall while Central, Eastern and Coast provinces have two periods of rainfall and thus have two cropping seasons per year (Rojas, 2007). The large and widely dispersed rural populations in the semiarid zone make their living out of rain-fed agriculture and pastoral farming and this is greatly affected by agricultural drought which has resulted in poor yields sometimes leading to crop failures and death of animals. This persistent rainfall variability makes subsistence farming difficult and as such, results in food insecurity. Estimation of crop yields prior to harvest is required for early intervention in case of a deficit. Figure 1 below represents the maize area statistics per district collected from by the Ministry of Agriculture presented in spatial context. It is the study area and shows the area of maize from 20000 hectares (ha) to greater than 100000ha.

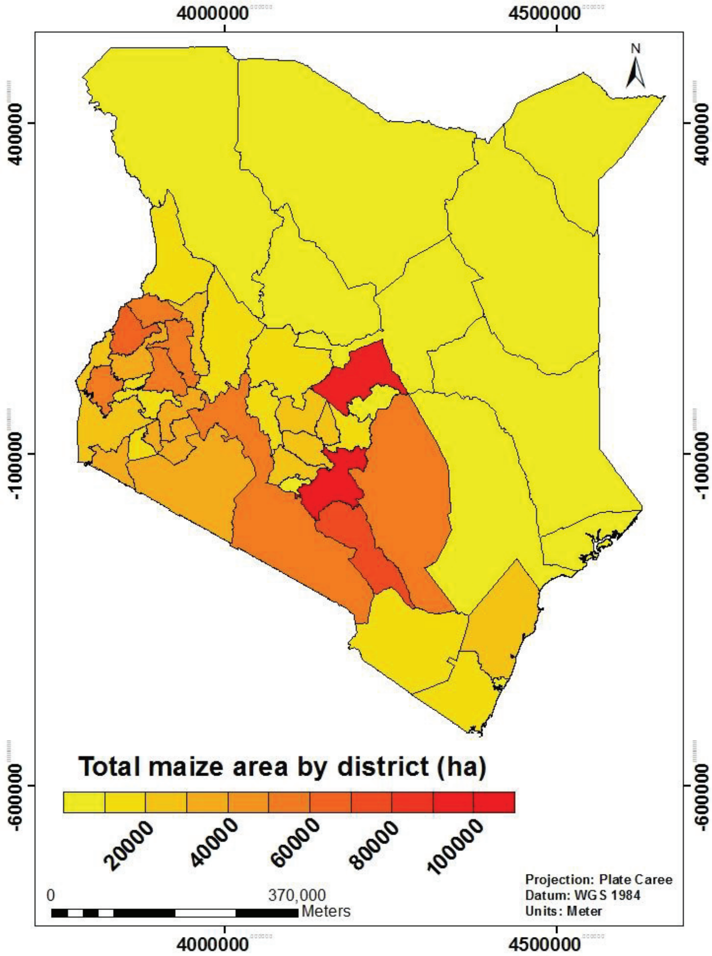

Figure 1: Maize areas in Kenya ('000 ha/district)

2.2 Data used

Hyper temporal SPOT NDVI data

The major data source for this research was the SPOT VEGETATION (VGT) NDVI data from http://www.VGT.vito.be. This dataset consist of 10-day Maximum-Value Composites (MVC), synthesis (S10) images at 1km x 1km resolution from April 1998 to July 2011. The images were corrected for atmospheric, radiometric and geographically effects. The maximum value compositing of the data corrects for cloudy days which might interfere with the NDVI values. A total of 475 images were geo-referenced and de-clouded. De-clouded as explained by de Bie et al(2008) are "those pixels with good radiometric quality, not having cloud or uncertainty, but clear image". The NDVI image was in the Plate Caree projection system and comprised of four bands:

Blue band- 0.43 to 0.47μm
Red band (R) - 0.61 to 0.68 μm
Near infrared (NIR) - 0.78 to 0.89μm
Short- wave infrared (SWIR) - 1.58 to 1.75μm.

The red and near infrared bands are the main wavelengths used by VITO in deriving the NDVI. The NDVI measure the greenness of vegetation and is calculated from NIR-R / NIR+R. It ranges from 0-1 but mostly represented as Digital Numbers (DN) ranging from 0-255 by applying the formula: DN = NDVI + 0.1/ 0.004.

Africover map of Kenya

The Africover map was obtained from International Livestock Research Institute (ILRI). The land cover data was produced using LANDSAT TM at 30m spatial resolution under the FAO/UNEP international standard LCCS classification system at a scale of 1: 100,000 or 1:200,000 respectively for small or large countries. It has a planimetric accuracy of 50m. The projection system was in WGS _1984_ UTM_Zone_37N but was re-projected to Plate Caree projection system to enable the calculation of areas in hectares. It consists of various land cover classes in which a section is described below in table1.

Table 1: Description of the land cover classes from Africover that were assigned to fields

Africover land cover classification	Fields
AG 1- Rainfed Herbaceous Crop	
AG 1B- Scattered (in natural vegetation or others) Rainfed herbaceous crop (field density 20-40% of polygon area)	
AG 1C- Isolated (in natural vegetation or others) Rainfed herbaceous crop (field density 10-20% of polygon area)	
AG2- Irrigated herbaceous crop	
AG-2B Scattered (in natural vegetation or others) irrigated herbaceous crop (field density 20-40% of polygon area)	
AG 3 Rainfed shrub crop	
AG 3B Scattered (in natural vegetation or others) Rainfed shrub crop (field density 20-40% of polygon area)	
AG 3C Isolated (in natural vegetation or others) Rainfed shrub crop crop (field density 10-20% of polygon area)	
AG 5B Scattered (in natural vegetation or others) rainfed tree crop (field density 20-40% of polygon area)	
AG 6 Rice fields	

The above land cover description assigmned fields is srepresented below in figure2. The fields were extracted from the Africover land cover data using the extraction function in ArcGIS.

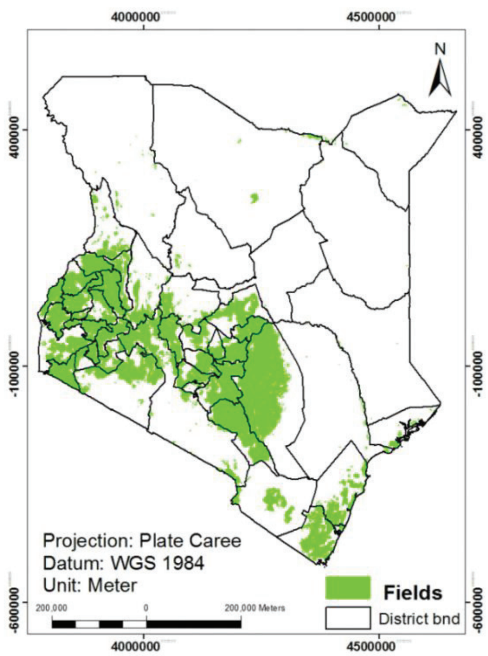

Figure 2: Map showing fields extracted from Africover data

District map of Kenya

This was equally obtained from ILRI comprising the 47 districts in Kenya with D-WGS_1984 Datum, Zone 37N and Universal Transverse Mercator (UTM) projection system but re-projected to Plate Caree projection system.

Maize crop statistics

Maize crop statistics by districts was collected (part of the fieldwork) from the department of crop development in the Ministry of Agriculture (MoA). Kenya started collecting disaggregated agricultural crop statistics in 1997 (Rojas, 2007). The government agencies routinely gathers crop data, including planted and harvested areas on periodic basis through districts agricultural officers and are aggregated at provincial levels. This data reported by the MoA is considered as a standard source of information although other agencies are also involved in the final publishing of the crop statistics data. The data consist of maize cultivated areas in hectares (ha) and maize production some in tonnes per hectares (t/ha), or 90 kilograme bag per hectare (90kgbag/ ha). The data was reported in EXCEL format consisting of Provinces, Districts and Counties. The data were in two formats, one with data from 1976-2006 and the other from 2007 -2010. The first format had maize production data in tonnes per hectare while the second format had maize production in 90kg bags per hectare. To obtain uniform units, the number of bags was converted to tonnes using the formula: Tonnes=No. of Bags*90/1000. The yield data (Y) was obtained from the maize statistics data by dividing maize production(P) in tons by the area of cultivation (A) in hectares(ha) represented as Y=P/A

Crop calendar data

This was obtained from the Food and Organization (FAO) website (FAO, 2012). Table 2 below shows planting, length of days and harvesting periods for the different provinces and selected districts.

Table 2: Part of maize crop calendar for some provinces and selected districts from FAO website:

Administrative areas	Crop	Additional Information	Planting period	Length of days	Harvesting period
Western province (Embu, Meru) Central province Rift valley province	Maize	First season	28/02	180-270	01/09
Western province , (Embu, Meru) Central province (Except Kirinyaga), Rift valley,	Maize	Second season	01/09	180-270	01/02
kisumu, (Busia, , Embu, Meru, Kirinyaga	Maize	First season	01/03	110-150	01/08
Kisumu, Busia, , Embu, Meru, Kirinyaga	Maize	Second season	15/10	110-150	01/02
Meru, T/Nzoia,	Maize	Second season	15/10	210-280	01/05
Kisumu	Maize	First season	15/02	135-160	01/08
Kisumu	Maize	Second season	01/08	135-160	15/12
Embu, Meru, Kirinyaga, T/Nzoia	Maize	First season	15/03	135-160	01/08
Embu, Meru,, Kirinyaga, T/Nzoia	Maize	Second season	01/08	135-160	15/12
Lamu	Maize		15/04	90-120	15/07
Lamu	Maize		15/03	90-120	15/07

2.3 Method

The method employed in this study comprised of three distinct steps depicted below in figure 3, ISODATA clustering, disaggregating crop statistics into NDVI classes and selecting NDVI derived indicators, their relationship to yields and comparison of the indicators.

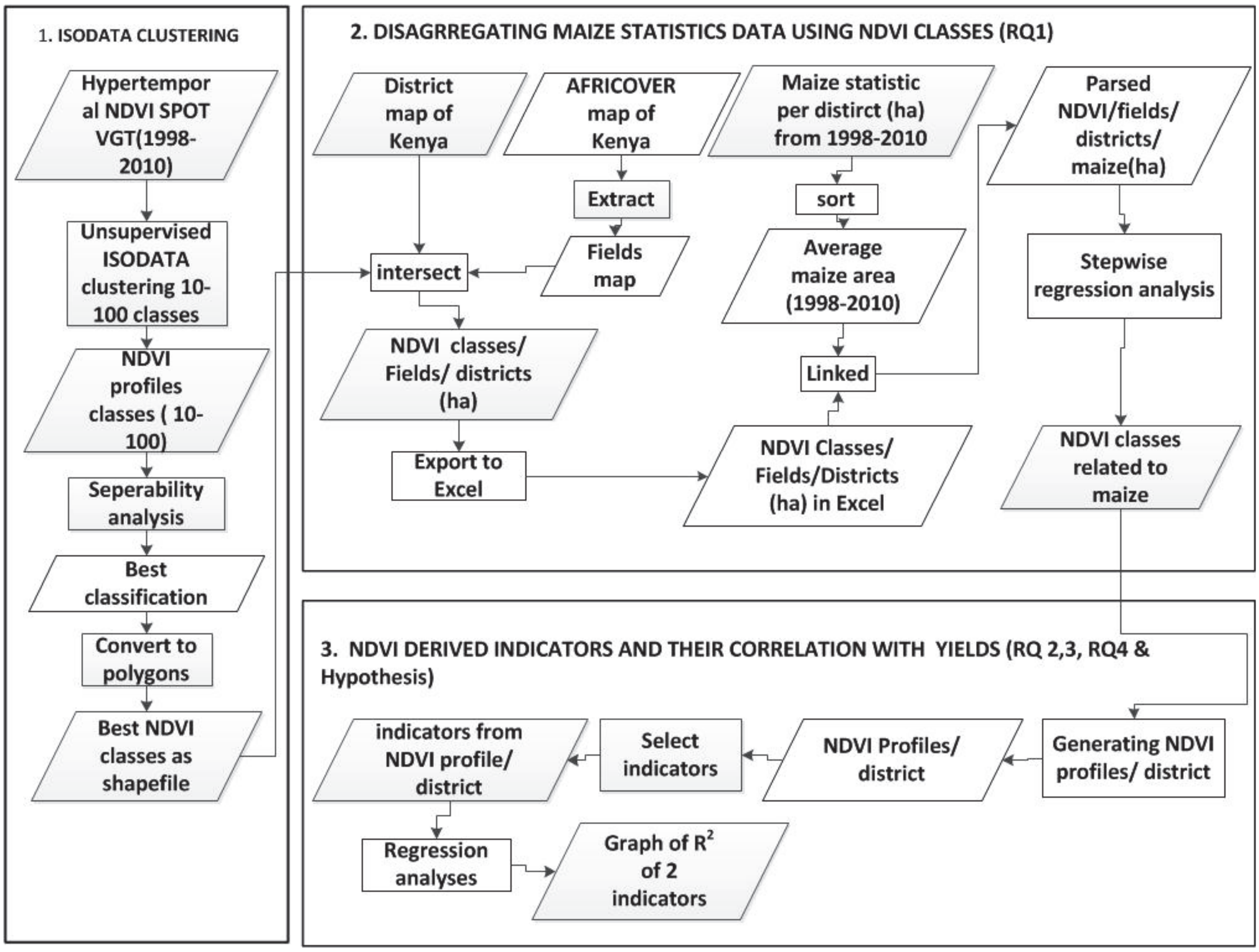

Figure 3: Flowchart of work process and hypothesis test.

The first step was the ISODATA clustering (unsupervised classification) to determine the useful number of classes to be used for further analysis. The second step was to disaggregate published maize statistics data by NDVI classes and the third step was to select NDVI-derived indicators and establish their correlation with maize yields.

ISODATA Clustering

The ISODATA (Iterative Self Organizing Data Technique Analysis) was performed to derive spectral classes from 475 stacked NDVI image layers. It is an unsupervised classification algorithm in the ERDAS Imagine software to naturally group the study area into clusters (group of pixels with similar characteristics). This method as described by de Bie et al.(2008), Campbell (2006) and Swain & Davis (1981), was carried out to generate temporal profiles for the land cover classes. The method uses minimum spectral distance to assign a cluster for each candidate pixel beginning with a specified number of arbitrary clusters and then processes repetitively (ERDAS, 2003). Separate ISODATA runs were carried out with number of iterations set at 50 and convergence threshold at 1.0. A predefined number of classes were optimized at 100. Iteration is explained as the process of repeatedly performing an entire classification resulting to thematic layers, and then the statistics are recalculated (ERDAS, 2003). The convergence threshold was set at 1.0 to ensure that the maximum percentage of classes of pixels whose values are to be unchanged do not run indefinitely between iterations. The signatures from the runs were evaluated using the divergence statistics analysis to determine the most useful or best classes for analysis (i.e. grouping similar NDVI profiles into meaningful classes). This was achieved by selecting the highest peak values recorded from the minimum seperability measure of distance above the exponential line curve (see figure 4). The selected classes were then exported to excel and plotted to visualize the NDVI temporal profiles of all the classes. The selected classes called best NDVI classes were converted to polygons without simplying. The method of classification is simpler than the supervised classification because the cluster signatures are automatically generated Khan et al.(2010).

Disaggregating maize statistics data using NDVI classes

This step involved Geographic information systems (GIS) analysis in ArcGIS. The NDVI classes derived from the ISODATA clustering technique after converting to polygons were intersected with the districts shapefile. Thus the intersection produced a shapefile consisting of districts and NDVI classes and a new area was calculated in hectares. The fields (crops) map which was extracted from the Africover land cover data was intersected with the district/ NDVI classes' shapefile. This intersection resulted in a shapefile consisting of district, NDVI classes (as grid codes) and fields and a final area calculated in hectares. The data was exported to EXCEL and parsed which enabled the easy interpretation and management of data. The maize area statistics data was sorted by averaging maize areas from 1998-2010 relevant for the purpose of this study though only data from 2000-2006 were finally used. The average maize area was linked to the parsed data in

EXCEL with equal representation of the districts to ensure spatial compatibility in EXCEL. This resulted in a matrix (table 3) showing districts, reported maize areas and areas of NDVI classes.

Table 3: Part of table showing parsed districts, averaged maize area (ha) statistics with NDVI classes (ha)

	Areas by NDVI classes (ha)											Reported maize areas
Districts	1	2	3	--------------------	30	31	32	33	34	35	36	(ha)
Baringo												3354
Bomet	0	0	893		0	0	0	32300	0	24703		11488
Bungoma	0	0	0		0	0	13297	32735	0	0	18771	37547
Busia	0	0	0		0	0	0	34233	198	138122	2386	65644
Elgeyo-	0	0	0		227	0	6195	82140	0	20502	86	21557
Marakwet	0	0	0		29	0	0	48716	4030	15209	13793	29946
Embu	0	49	0		0	69950	3870	2515	0	0	8327	17403
Garissa	0	0	0		0	2	0	0	47	0	0	267
Homa Bay	25	81	282		25795	66	56657	63923	0	16835	6	24921
Isiolo	0	0	0		0	0	0	0	0	0	0	1114
Kakamega	0	0	0		0	0	0	71249	8954	57809	1280	32043

The linking of the districts/ 36 NDVI classes/fields with averaged maize area statistics produced the statistical function: Maize area by district (ha) =f [Area of NDVI classes by district (ha)]. The function was estimated through stepwise regression as illustrated by Khan et al., (2010).

$$Y = \sum_{i=1}^{n} bi \text{ xi} + \text{ei}$$

Y= Maize area per district (ha)

b= Regression coefficient for NDVI class $_i$ per district

x= Average area (ha) of NDVI class $_i$ per district

n= Number of NDVI classes

$\epsilon_=$ Residual error

A stepwise linear regression analysis was performed using average area of maize per district as dependent variable and the fields (crops) covered by the 36 NDVI classes as independent variables to estimate the contribution of NDVI classes in predicting maize in the various districts. No constant was applied and no coefficient was constrained to the 0.0 -1.0 because as explained by Khan et al (2010), "the area of a crop in a district can neither be negative or more than the area of that particular district". Model performance was evaluated by removing negative values until only coefficients with positive values were attained. This produced the NDVI classes that related to maize. Thus this produced a map showing the fractions of maize per district.

NDVI derived indicators and their relation to maize yields.

To derive NDVI indicators, mean temporal NDVI profiles were generated per districts. The NDVI classes that related to maize were individually clipped to respective districts (as shape files) in which the classes were found. The extent of the NDVI class in the district was found by calculating the area in ArcGIS. These shapefiles consisting of the districts and respective NDVI classes were defined as area of interest (AOI) and superimposed over the original SPOT VEGETATION NDVI stacked image in ERDAS. This process calculated the mean temporal NDVI value of the pixels per district for the 475 layers. The mean value and the standard deviation were obtained from the statistics properties window in Arc catalogue and exported as XML format. These were parsed to obtain the mean NDVI values in digital numbers (DN) per pixels per districts. These values were used in generating the temporal NDVI profiles per districts. To avoid the complexity of having more than a single temporal profile in a district, weighted averages were applied to the respective NDVI classes. Weighted averages were obtained by dividing the extent (area in ha) of each NDVI class by the total area (ha) of all NDVI classes in that district and multiplied by the fractions of the maize predicted by the NDVI classes. The weighted average for each class was multiplied to the DN values of the classes per district. The summation of the product was divided by the sum of weighted averages to produce a single mean NDVI profile per district.

The NDVI growth seasonal curves derived from the mean temporal NDVI profiles per districts were generated by defining the growing seasons for the maize crop using fixed calendar dates from February to September from the FAO website (FAO, 2012) and also by adjusting the NDVI values and smoothing it. A sudden rise in NDVI values indicated the onset of greenness (significant photosynthetic activity) while a sudden decrease in NDVI values signaled the end of greenness thus the growing season (GS) and non-growing season (NGS) were established. The growing season represents period from onset of greenness, maximum greenness and decrease in greenness. Non growing season represents period after the growing season for the long rains. To establish the correlation between NDVI and maize yields, two indicators were considered, the maximum NDVI and the sum of NDVI. The highest DN value recorded within the growing season depicted the highest greenness value on the curve and was selected as the maximum NDVI. This indicator was considered as a potential indicator for estimation of maize yields before harvest. The maximum NDVI was regressed with the annual maize yield data for the respective years for selected districts. Below (table4) is an example showing the selection of maximum NDVI–derived indicator. Maximum NDVI generally occurred in May for most of the districts.

Table 4: A sample showing the selection of maximum NDVI in a growing season.

NDVI DATA		GS (DNvalues)	MaxNDVI (DNvalues)	YIELD (t/ha)	NGS (DNvalues)
Month/Year	DN values				
Feb'02	150				150
	143				143
	140				140
Mar'02	141	141			
	145	145			
	150	150			
Apr'02	156	156			
	163	163			
	175	175			
May'02	186	186			
	193	193	193	3.1	
	191	191			
Jun'02	183	183			
	170	170			
	160	160			
Jul'02	150	150			
	142	142			
	134	134			
Aug'02	126	126			
	121	121			
	118				118
Sep'02	116				116
	114				114
	111				111

Another indicator considered was the sum of NDVI above a defined threshold and its relationship to maize yields. This threshold was based on selecting the highest DN value of the onset of greenness (hereby used as start-of-season) from the growing seasons of individual years and subtracting this value from the proceeding NDVI values for the entire growing seasons. The differences in each of the growing seasons were summed up to give the sum of NDVI above the threshold.

A simple linear regression analysis was used in developing the maize yield model using the derived NDVI indicators as independent variables and the maize yields as dependent variable.

$$Y = \alpha + \beta I$$

Where Y is Yield (t/ha), α is constant, β is the coefficient (slope) and I is the NDVI indicator (dimensionless)

Coefficient of determination (R^2) was obtained between NDVI derived indicators and maize yields in EXCEL. The districts were selected based on Agro-Ecological Zones (AEZ) and also from high potential maize areas.

3. RESULTS

3.1. ISODATA clustering

The ISODATA clustering algorithm of Erdas Imagine software was used in carrying out unsupervised classification of 475 NDVI image data layers with a predefined number of 100 classes. The result of this runs produced minimum and average divergence indicators that best suited the data (debie, 2008). The minimum separability distance measure considered minimum seperability between two most similar classes while average separability indicator considered values between all pairs of classes. The minimum seperability distance measure was used in identifying the best number of classes to be used for further analysis. The highest peak observed from the minimum seperability distance measure (arrowed in figure 4) was used in defining the suitable number of classes for analysis. Thus the unsupervised classification produced 36 NDVI classes as the best classification for the data from 1998-2011 as seen in figure 4 below.

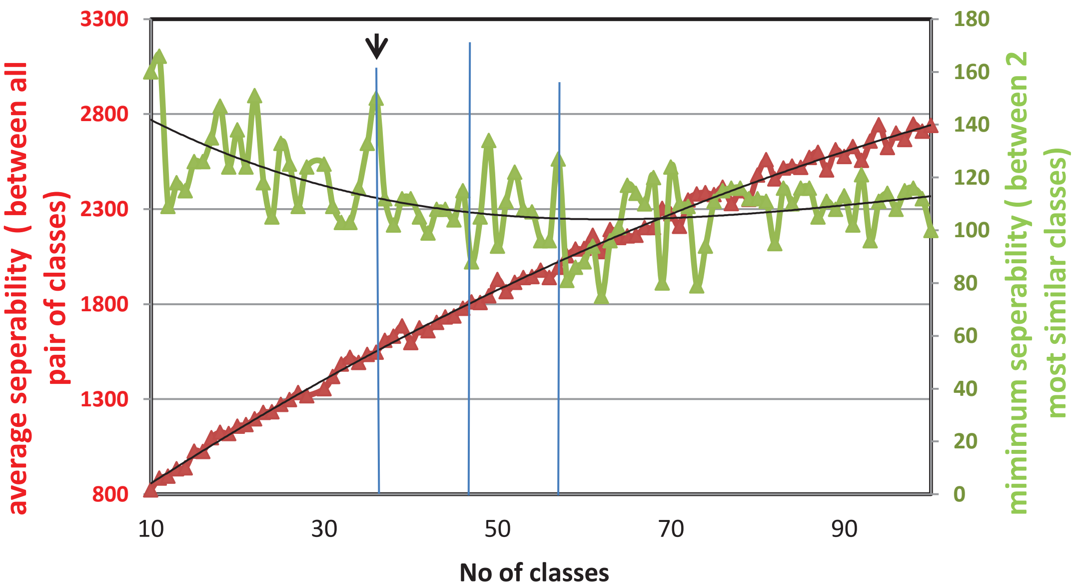

Figure 4: Result of seperability analysis to identify the best classes.

These 36 classes were converted into polygons and intersected with the district map. Figure 5 below shows the representation of the 36 NDVI classes within the districts.

The unsupervised classification analysis produce the useful number of classes to used for further analysis and is presented below (Figure 5)

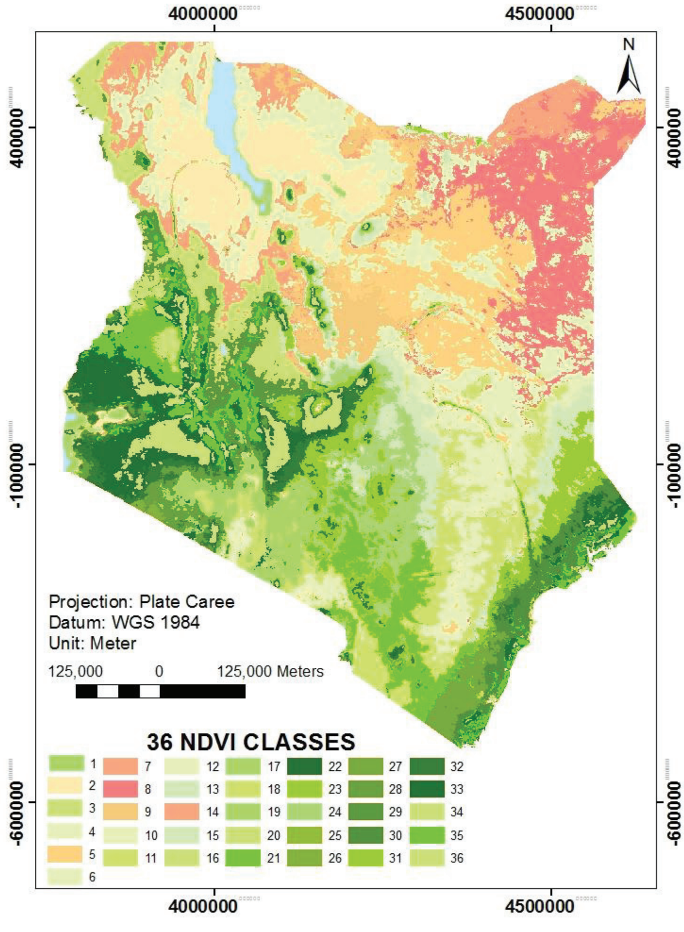

Figure 5: Map showing NDVI classes based on unsupervised classification

3.2. Disaggregating maize statistics data into NDVI classes

The result of the stepwise linear regression analysis displayed a model summary showing four steps with adjusted R^2 of 0.32, 0.62, 0.72 and 0.79 respectively shown in table5 below.

Table 5: Summary results of the 4 steps of the stepwise linear regression analysis

Step	NDVI classes	Coefficient	Adjusted R^2
1	31	.727	0.32
2	31, 35	.716, .475	0.62
3	31, 35, 33	.697, .333, .347	0.72
4	31, 35, 33 and 17	.597, .312, .308 and .851	0.79

Therefore Maize area (ha)= 0.597**(Class 31) + 0.312** (Class 35) +0.308** (Class 33) +0.851*(Class 35)

** = Signifcant at P= 0.000

* = Significant at P=0.001

Regression parameters were considered to be significant at the $p \leq 0.05$ level of significance. Independent variables that were significant at the $p \leq 0.05$ level of significance were retained in the model and thus the four models were highly significant but the best was the fourth model that had more NDVI classes related to maize. Figure 7 below shows the representation of the fractions of maize(%) per 1Km² .

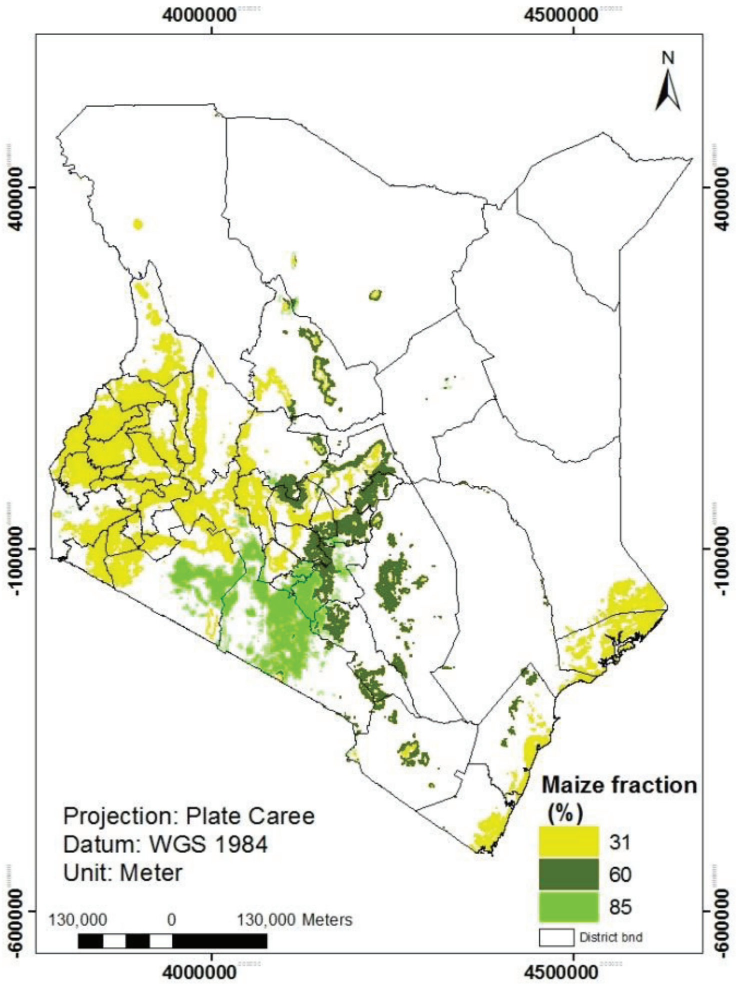

Figure 6: Maize fractions in percentage per 1Km2 per district obtained from the stepwise regression analysis

3.3. NDVI –derived indicators and their relationship with yields

Temporal NDVI profiles

In order to derive indicators from NDVI, single mean temporal profiles were generated from the four NDVI classes that related to maize. Figure 8 below shows mean temporal profiles of the four classes. Meru district was one of the districts that had all the four NDVI classes that related to maize.

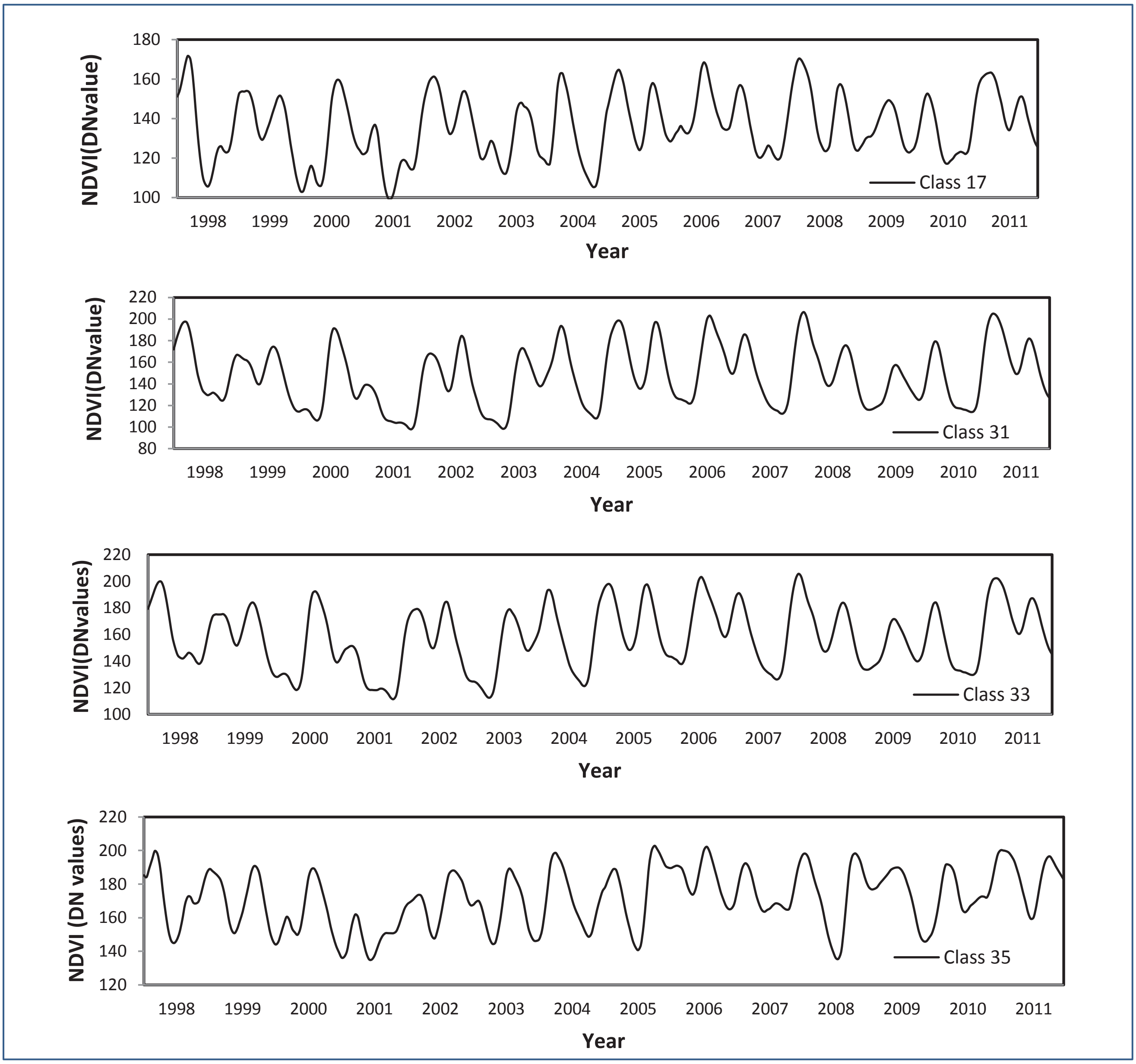

Figure 7: Mean NDVI temporal profile for four classes

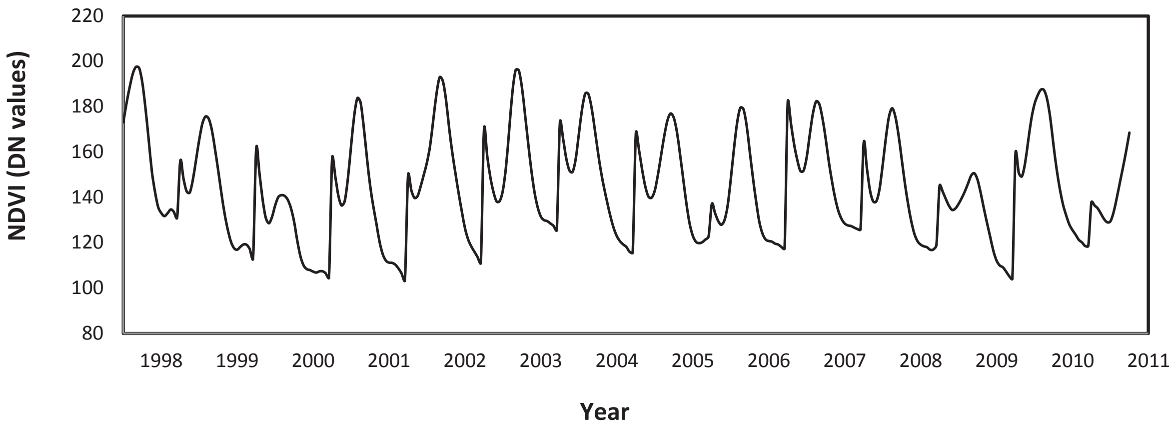

Figure 7: Single mean temporal NDVI profile for Meru district.

Simple linear regression between indicators and maize yields

The selected indicators were regressed with maize yields to determine their correlations. The growing season (GS) represents period from onset of greenness, to end of greenness for the long rains while non-growing season (NGS) represents period after the growing season for the long rains. The blue lines across in the NDVI profile represents the threshold which was the highest value recorded during the onset of greenness for the growing period. Graphical representation showing the derived indicators and maize yields and their correlations for selected districts are presented below.

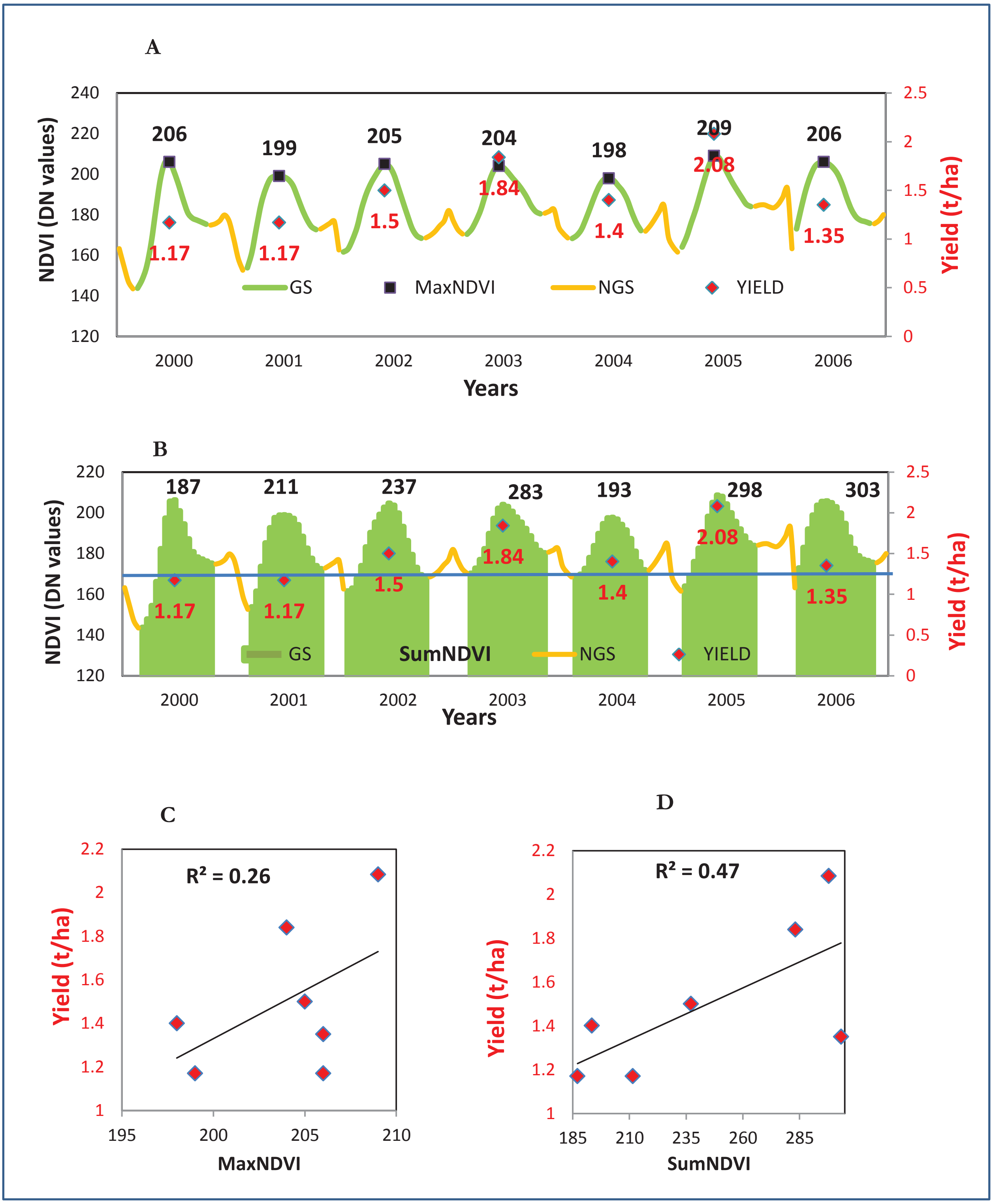

Figure 8: A=NDVI profile showing maximum NDVI and maize yields, B= NDVI profile showing sum of NDVI and maize yields, C=Linear relationship between maximum NDVI and maize yields and D= Linear relationship between sum of NDVI and maize yields for Busia district.

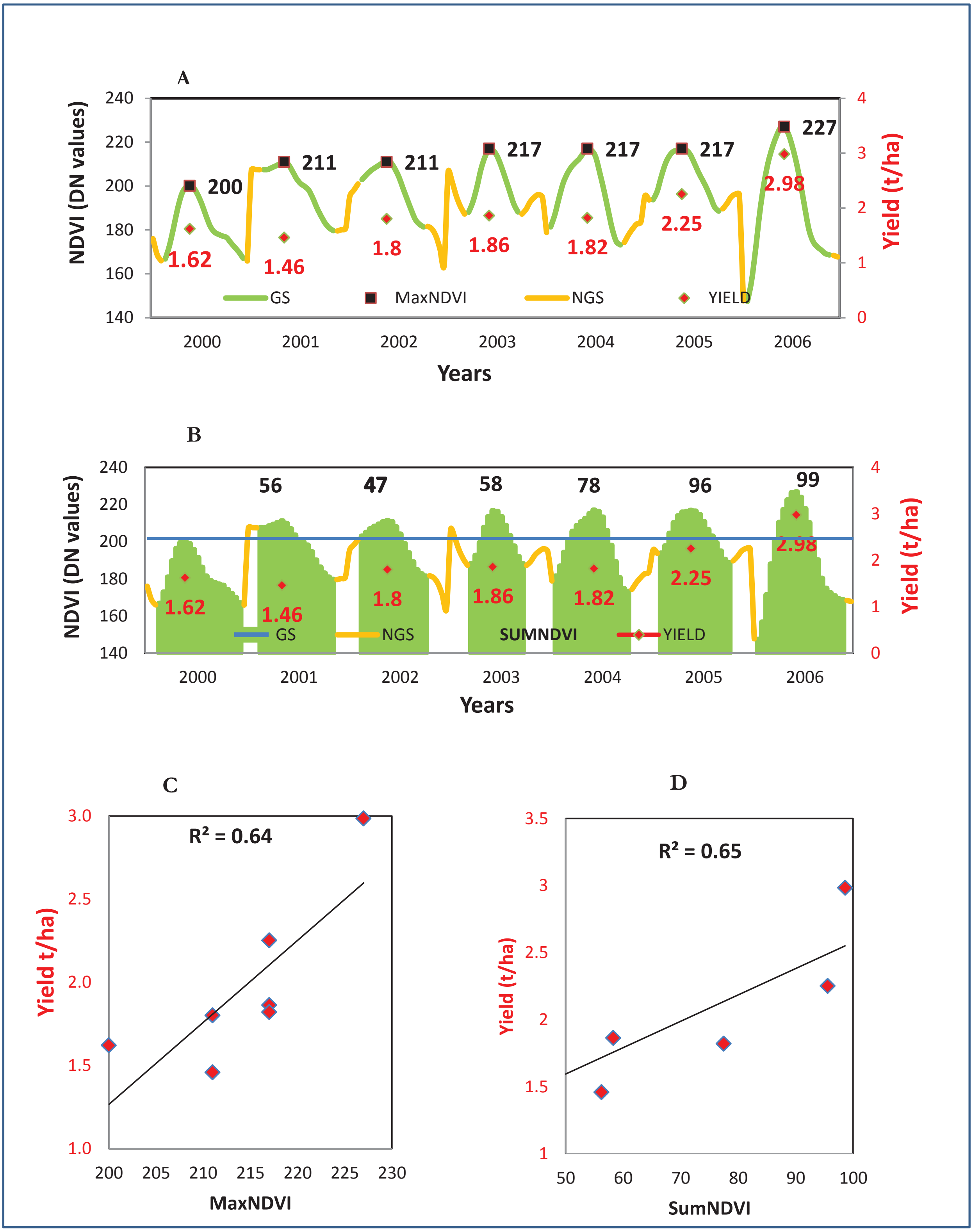

Figure 9: A=NDVI profile showing maximum NDVI and maize yields, B= NDVI profile showing sum of NDVI and maize yields, C=Linear relationship between maximum NDVI and maize yields and D= Linear relationship between sum of NDVI and maize yields for Bomet district.

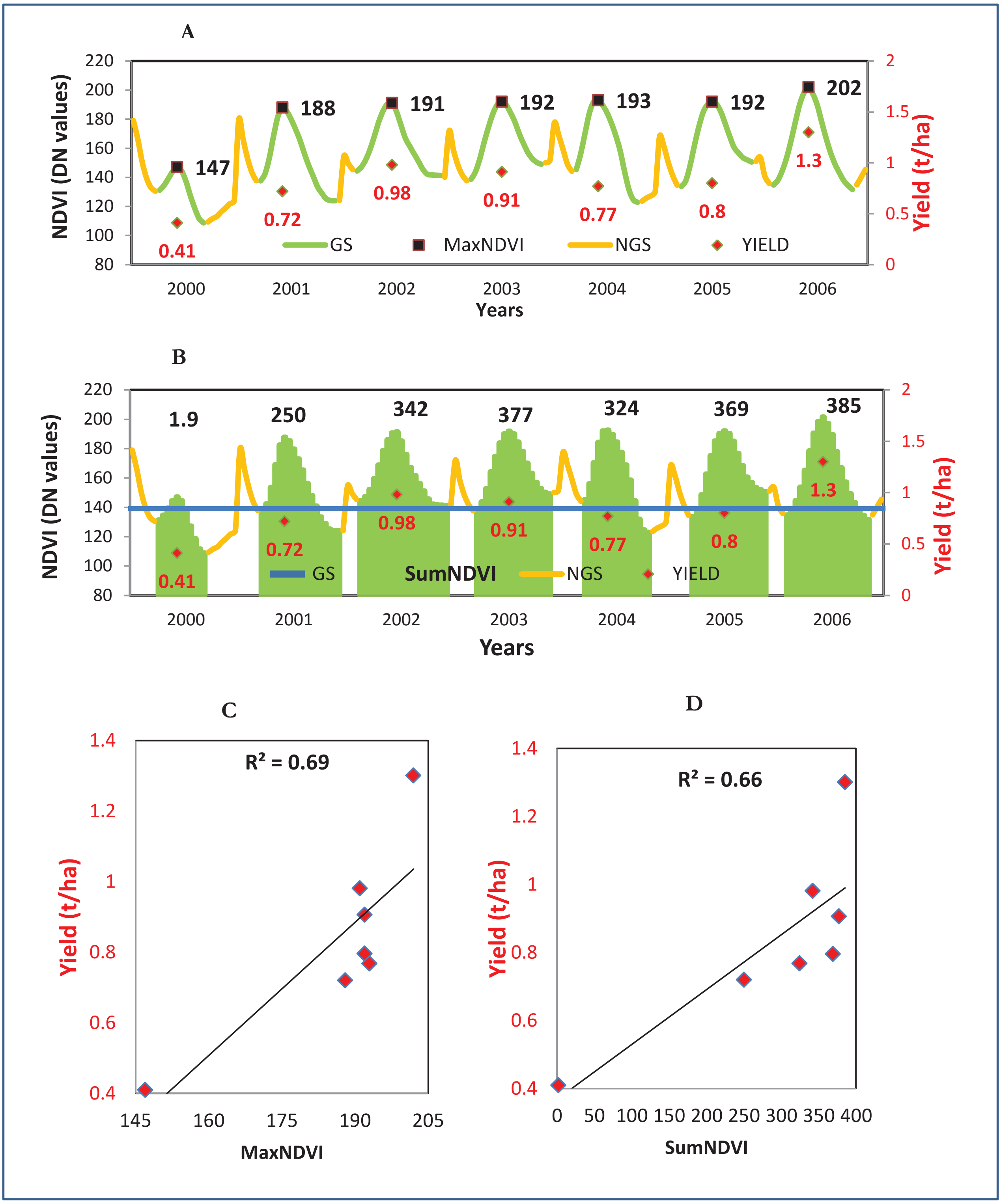

Figure 10: A=NDVI profile showing maximum NDVI and maize yields, B= NDVI profile showing sum of NDVI and maize yields, C=Linear relationship between maximum NDVI and maize yields and D= Linear relationship between sum of NDVI and maize yields for Kirinyaga district.

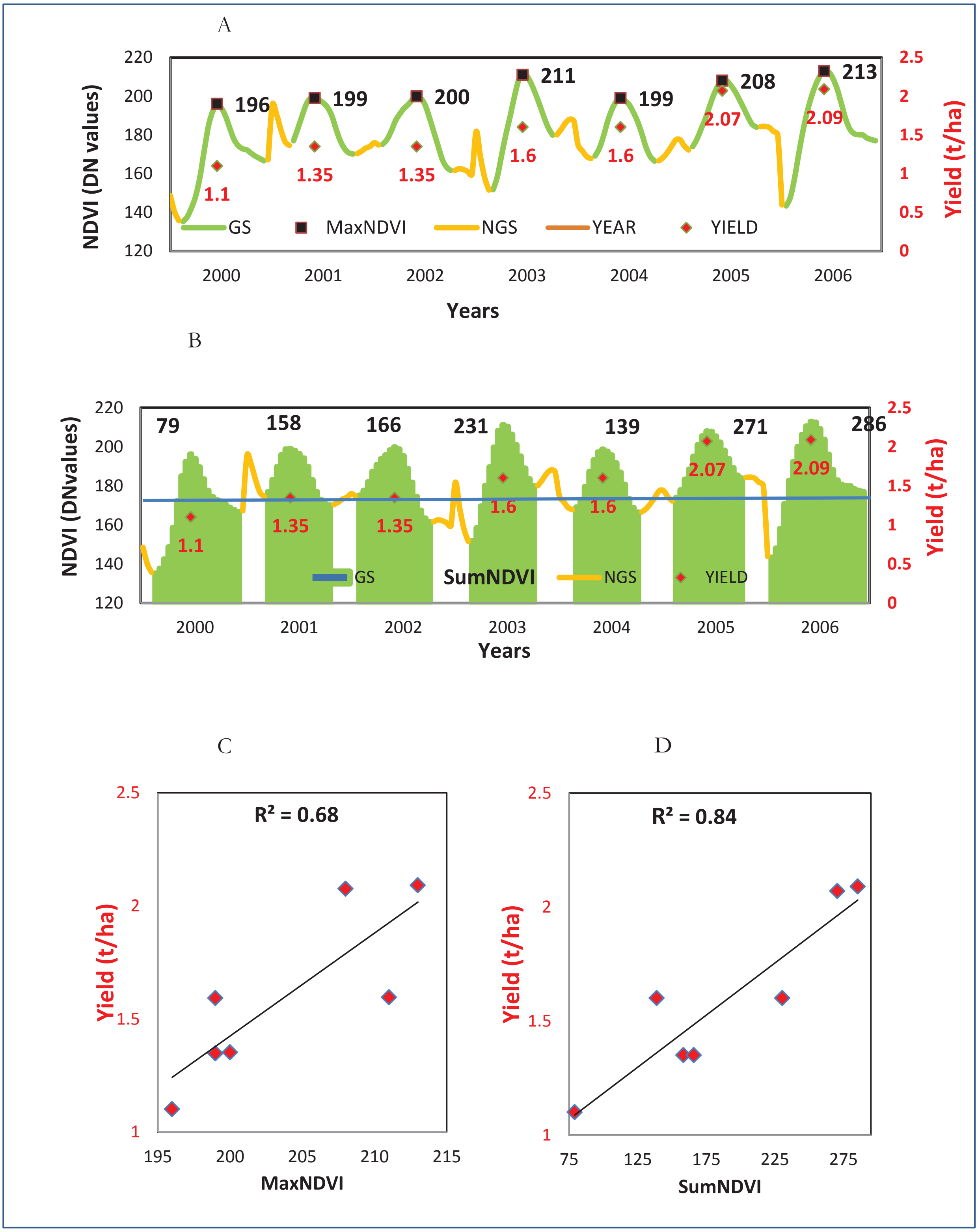

Figure 11: A=NDVI profile showing maximum NDVI and maize yields, B= NDVI profile showing sum of NDVI and maize yields, C=Linear relationship between maximum NDVI and maize yields and D= Linear relationship between sum of NDVI and maize yields for Kisumu district.

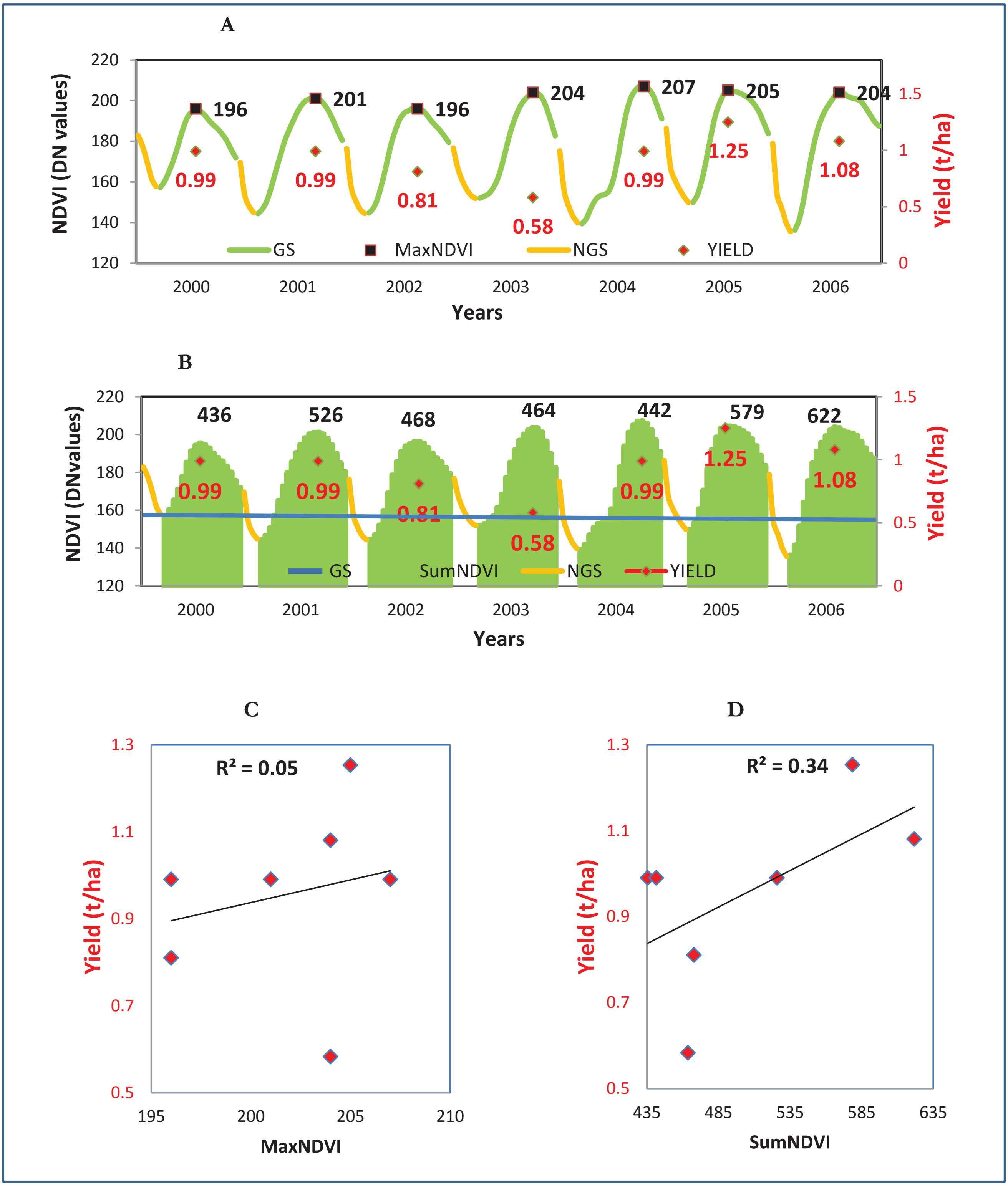

Figure 12: A=NDVI profile showing maximum NDVI and maize yields, B= NDVI profile showing sum of NDVI and maize yields, C=Linear relationship between maximum NDVI and maize yields and D= Linear relationship between sum of NDVI and maize yields for Lamu district.

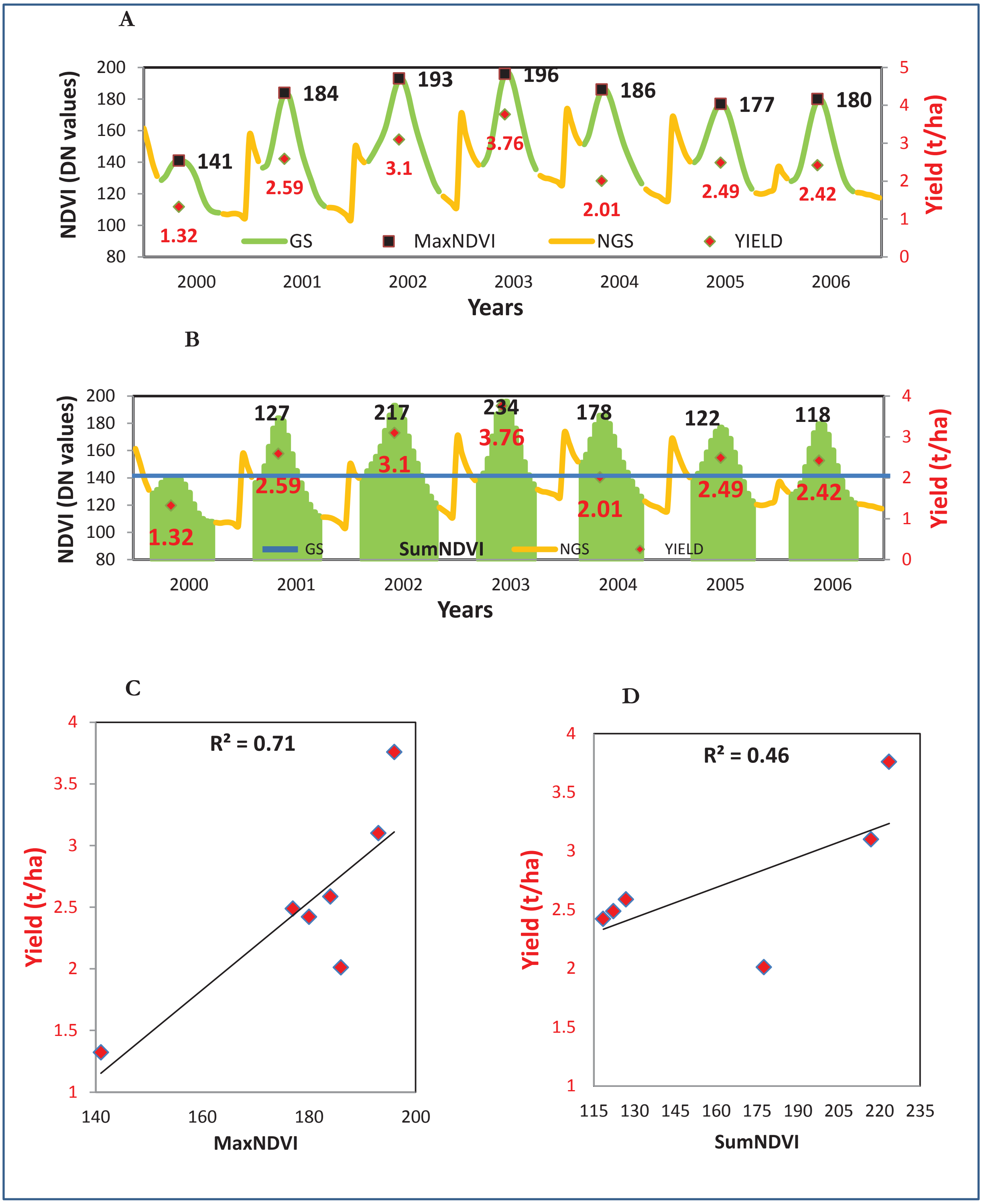

Figure 13: A=NDVI profile showing maximum NDVI and maize yields, B= NDVI profile showing sum of NDVI and maize yields, C=Linear relationship between maximum NDVI and maize yields and D= Linear relationship between sum of NDVI and maize yields for Meru district.

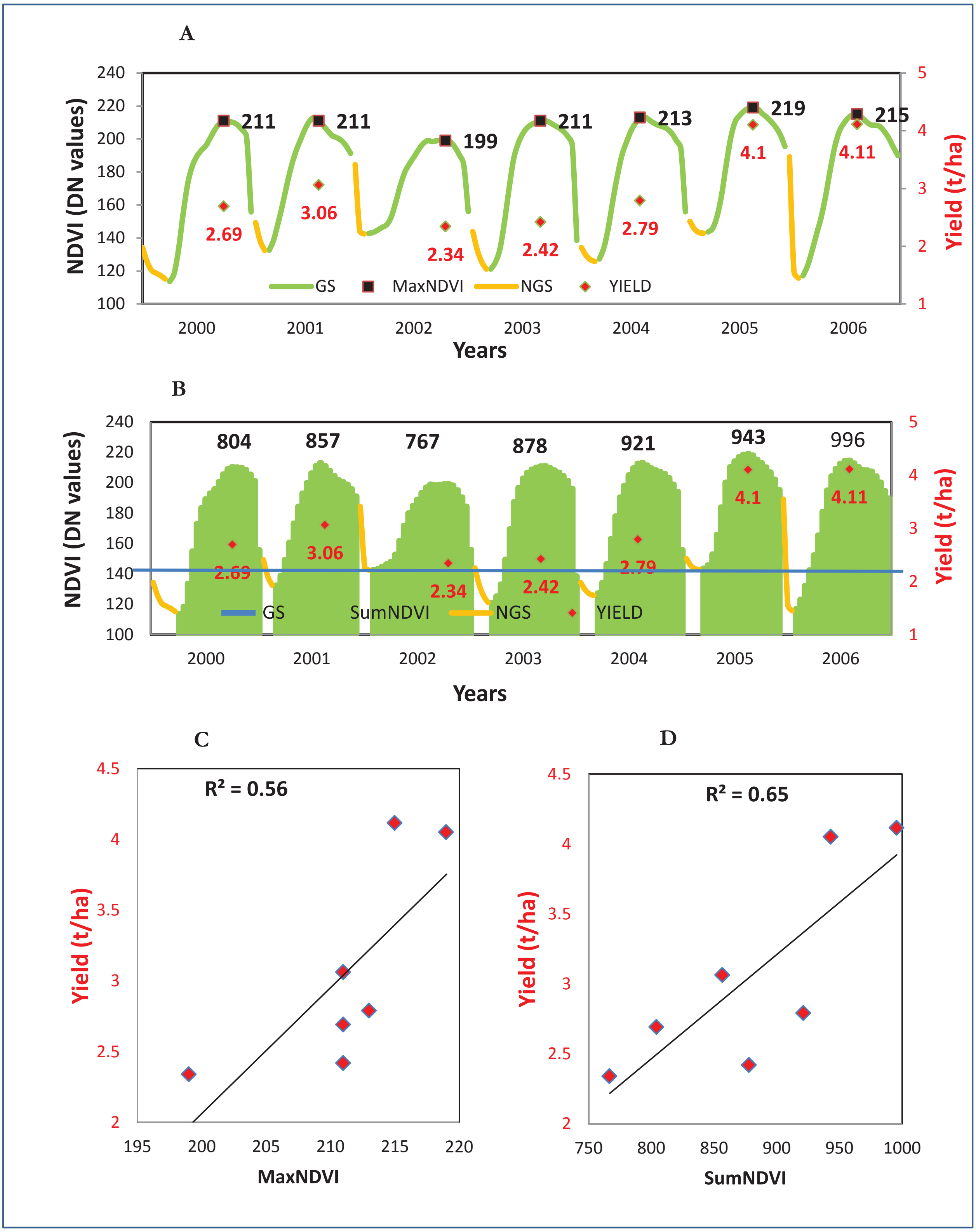

Figure 14: A=NDVI profile showing maximum NDVI and maize yields, B= NDVI profile showing sum of NDVI and maize yields, C=Linear relationship between maximum NDVI and maize yields and D= Linear relationship between sum of NDVI and maize yields for Trans-Nzoia district

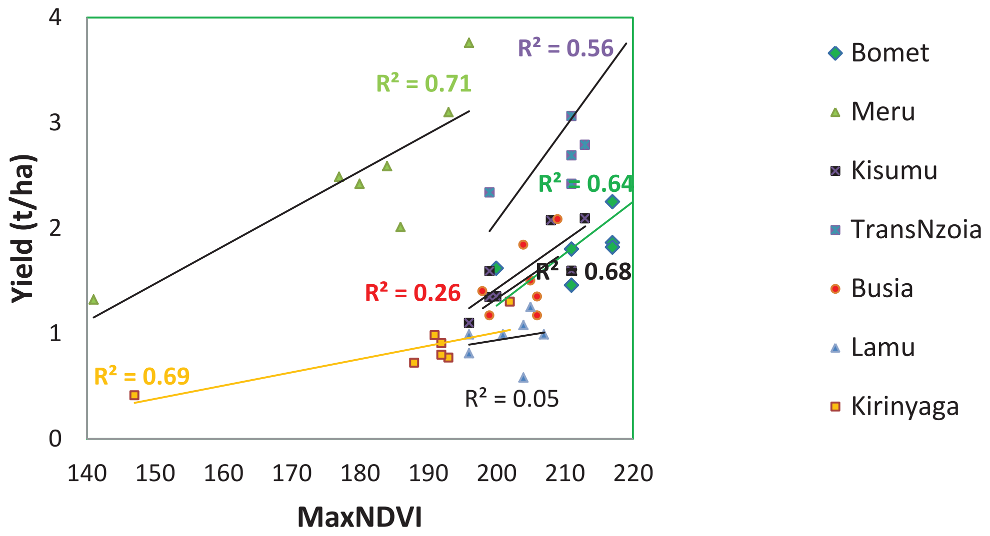

Figure 15: Linear relationship between maximum NDVI and maize yields for seven selected districts

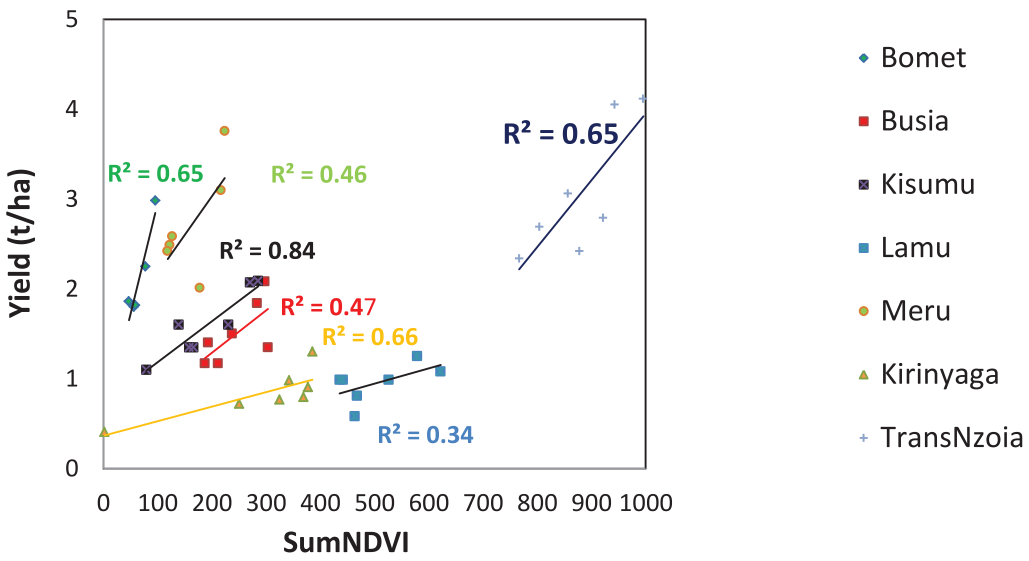

Figure 16: Linear relationship between sum of NDVI and maize yields for seven selected

The above graphical representation of the linear relationship between maximum NDVI and yields show the variability that exists in the different districts from the different AEZs.

Table 6: Summary of simple linear relationship between maximum NDVI and maize yields

Selected Districts	Simple Linear Relationship	R^2	Significance
Busia	Yield =0.04MaxNDVI - 7.54	0.26	0.2
Bomet	Yield =0.05MaxNDVI- 8.59	0.64	0.03
Kirinyaga	Yield =0.01MaxDNVI- 1.51	0.69	0.02
Kisumu	Yield =0.05MaxNDVI- 7.7	0.68	0.02
Lamu	Yield=0.01MaxNDVI-1.15	0.05	0.64
Meru	Yield =0.04MaxNDVI- 3.87	0.71	0.01
Trans-Nzoia	Yield =0.09MaxNDVI- 15.74	0.56	0.05

Table 7: Summary of simple linear relationship between sum of NDVI and maize yields

Selected districts	Simple Linear Relationship	R^2	Significance
Busia	Yield= 0.004SumNDVI +0.34	0.47	0.09
Bomet	Yield= 0.02SumNDVI +0.62	0.65	0.05
Kirinyaga	Yield= 0.002SumNDVI +0.37	0.66	0.02
Kisumu	Yield= 0.005SumNDVI +0.73	0.84	0.003
Lamu	Yield=0.002SumNDVI+0.10	0.34	0.17
Meru	Yield= 0.001SumNDVI +1.32	0.46	0.14
Trans-Nzoia	Yield= 0.007SumNDVI -3.49	0.65	0.03

The results of the statistical analyses showed varying coefficient of determination for the selected districts. These ranged from R^2 of 0.05-0.71 for maximum NDVI derived indicator versus yield and R^2 of 0.34-0.84 for the sum of NDVI derived indicator. Both indicators showed strong positive linear correlation with maize yields and were significant estimators of yield in most of the districts selected (Tables 6 and 7) except for Lamu and Busia districts that had R^2 of 0.05 and 0.26 respectively for maximum NDVI versus yields. Lamu, Meru and Busia districts equally had low correlations between sum of NDVI versus maize yields.

The best fitting model was an R^2 of 0.71 significant at 0.01 estimated for Meru district between maximum NDVI and maize yields and for sum of NDVI versus yield, it was an R^2 of 0.84 estimated for Kisumu district and significant at 0.003. It is evident from the results (tables 6 and 7) that NDVI derived indicators with R^2 above 0.55 were significant at $P \leq 0.05$ and strongly correlated with maize yields.

4 DISCUSSION

4.1 Baseline information on fractions of maize per district by NDVI classes

Given the complexity of spectrally determining maize areas due to the mixes of crops in a field, the ISODATA algorithm was able to produce the useful number of classes to be used for analysis. The minimum seperability measure distance was used in selecting the best number of NDVI classes. The disaggregation of the published maize area statistics data by these NDVI classes provided the reasonable information on the fractions of maize per districts by NDVI classes (see also table 4). The fractions of maize compare favourably with the maize area statistics from the MoA (figure1).

Khan et al.,(2010) also showed the usefulness of the above procedure in stratifying a study area into map units or classes. The advantages of the ISODATA clustering algorithm are the capability at finding spectral clusters that are inherent in the data, not geographically biased due to its iterative nature and it produces results similar to the minimum distance classifier on signatures created (ERDAS, 2003). This shows that analyses of NDVI time series with coarse resolution together with crop statistics data can provide useful information on the fractions of crop on a field.

4.2 Capturing variability in the various districts using Hypertemporal data

. Mean temporal NDVI profiles were generated per districts. These profiles reflected the NDVI time series growth cycle of maize and change that occured throughout the growing season. These changes can be seen by the behavior of the NDVI-profiles for each growing season. In the year 2000, there was considerable variability in some of the selected districts especially in Bomet, Kirnyaga and Meru districts. (Figures 10, 11 and 14). This is an indication of possibly a bad year equally noticeable in the yields. de Bie et al.(2008) also proved this procedure to be a useful tool in image analysis for crop mapping, monitoring and change detection. .The varying results obtained from the simple regression analysis explained substantial variability. Thus the use of hyper-temporal NDVI SPOT data was able to capture variability. These trends in variability can be used to detect drought years and thus estimate their re-occurrence which is fundamental towards ensuring food security (Rojas et al., 2011).

4.3 Relationship between indicators derived from NDVI and maize yield

To establish relationships between NDVI-derived indicators and maize yields, only yields from the long rains were considered even though Kenya is characterized by two growing seasons. According to Lewis et al.(1998) about 95 percent of the yields are obtained from the first season. This is also supported by Rojas (2007) more than 82 percent and Galu & Gideon (2007) that about 80 percent of the yields are obtained from the first season. Maize yield data for seven years were used. (2000-2006). Yield data from 2007-2011 were excluded due to missing data and inconsistency as a result of the fragmentation of districts and the aftermath of post-election violence which caused the temporary displacement of farmers across Nairobi, Rift Valley, Nyanza, Western and the coastlands (USAID, 2009). Thus there were disruptions in agricultural production in the three provinces responsible for producing maize. The third important reason was that the released crop production data compendium of the Kenyan Agricultural Sector Data Compendium volume2 compiled by the Kenyan Institute for Public Policy Research and Analysis (KIPPRA) in collaboration with the Ministry of Agriculture (MoA), Ministry of Livestock & Fisheries Development (ML&FD) and Ministry of Cooperative Development (MoCD) officially published crop production data from 1976 to 2006.

The maximum NDVI and the sum of NDVI were selected as indicators to estimate yields based on their functional utility in providing information on yields before harvest. The maximum NDVI as a median area NDVI (Lewis et al., 1998) recorded the peak of greenness (grain filling) stage and the sum of NDVI which is often used as a proxy for biomass, thus accumulation of biomass should correlate with crop yields (Wiegand & Richardson). Furthermore, Labus et al.(2002) explained that the inclusion of the summation of entire NDVI growth profile through each consecutive month could detect early and accurate estimation of yields. Maximum NDVI were recorded in the month of May, three months before harvest for most districts selected except in Meru where it was recorded in April year 2000 (Figure 14).

The results of the statistical analyses showed varying coefficient of determination for the selected districts. (Tables 6 and 7). The regression model between maximum NDVI and maize yield was highest in Meru district and recorded an estimation of R^2 of 0.71. The regression model between sum of NDVI and maize yield recorded the highest R^2 of 0.84 in Kisumu district. The high correlations recorded in these districts indicated that NDVI was a major influence on yields and thus is a good indicator for early estimation of maize yields. With such strong correlations, estimation of yields will be of great significance because only then can timely monitoring be effective to safeguard against food insecurity which manifest as a chronic problem in marginal agricultural areas (Galu & Ng'anga, 2007). There were low correlations with yields in a few of the districts selected indicating that other factors could be responsible for yield. Mkhabela et al.,(2005) explains that even with high rainfall leading to high NDVI, yields could still be low. Other factors that could be responsible for correlation with low yields are soil fertility, pest and disease infestation (Prasad et at., 2006) . However, in

Kenya, USAID(2009) reported that low yields resulted from flooding caused by the October- December heavy rains which affected the un-harvested maize crops. These crops require dry conditions. Again, the heavy rains resulted in flooding of the riverine and coastal areas damaging crops and potentially decreasing yields. This may explain why there were low correlations in Lamu district even with the high maximum NDVI values and sum of NDVI recorded. Another possible reason for low correlations even with high NDVI values, apart from the reasons mentioned above could be that officials from the MoA do not always go the farms to collect data and as such data collected on maize yields might be subjective.

Though other studies have been carried out in Kenya such as the Crop Specific water balance (CSWB) model (Rojas, 2007) where the cumulative NDVI and maximum NDVI metrics throughout the crop season were used to correlate maize yields and the beta--version stand-alone Geospatial Water Requirement Satisfaction Index (GeoWSRI) crop model (Galu & Ng'anga, 2007) which incorporated locally available agro-meteorological datasets and crop phenology to estimate maize production, these were carried out at sub-national levels. Thus, this method used in this study is a simplified procedure which has demonstrated that reliable estimates on maize yields can be obtained from NDVI-derived indicators at district level.

5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Results obtained from the analysis explained sufficiently the variability that exist between district and thus interpretations between districts differed considerably and therefore targeting a nation-wide (aggregated) relationship is not recommended. This method is suitable for district specific aspect of crop monitoring therefore timely information on the specific districts on estimation of yields is valuable for adequate and prompt response by relevant government institutions targeted at those districts with poor yields estimation. The study also shows both NDVI derived indicators can be used in estimating maize yields, although the maximum NDVI regression model showed significant levels in one or more districts than the sum of NDVI, the sum of NDVI had the best fit model. This can be explained that increase in biomass reflects increase in yields, thus as the season progresses, higher correlations are attained. (Labus et al., 2002). The use of seven years yield data were marginal to reach firm conclusions because in order to adequately identify critical periods such as drought and monitor crop yields for firm estimations, long term seasonal growth profiles are required (Labus et al., 2002). However, the method applied and results obtained can be used for simple, early and reasonably accurate estimation of maize yields and therefore can be adopted as an operational tool for ensuring timely estimation of maize yields in Kenya and countries that have similar agro-ecological heterogeneity.

5.2 Recommendation

- The study recommends that further analysis with hyper-temporal SPOT-VGT NDVI data and crop yield data the analysis should be carried out with longer time frame to be able to study temporal trends and thus make concrete predictions.
- An independent collection of crop production/yield data would be ideal.

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