Assessing the impact of agricultural drought on maize prices in Kenya with the approach of the SPOT-VEGETATION NDVI remote sensing

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Abstract

The high cost of maize in Kenya is basically driven by East African regional commodity demand forces and agricultural drought. The production of maize, which is a common staple food in Kenya, is greatly affected by agricultural drought. However, calculations of drought risk and impact on maize production in Kenya is limited by the scarcity of reliable rainfall data. The objective of this study was to apply a novel hyperspectral remote sensing method to modelling temporal fluctuations of maize production and prices in five markets in Kenya. SPOT-VEGETATION NDVI time series were corrected for seasonal effects by computing the standardized NDVI anomalies. The maize residual price time series was further related to the NDVI seasonal anomalies using a multiple linear regression modelling approach. The result shows a moderately strong positive relationship (0.67) between residual price series and global maize prices. Maize prices were high during drought periods (i.e. negative NDVI anomalies) and low during wet seasons (i.e. positive NDVI anomalies). This study concludes that NDVI is a good index for monitoring the evolution of maize prices and food security emergency planning in Kenya. To obtain a very strong correlation for the relationship between the wholesale maize price and the global maize price, future research could consider adding other price-driving factors into the regression models.

Introduction

Drought is one of the most frequent climate-related disasters occurring across large portions of the African continent, often with devastating consequences for food security and agricultural households (Andrea et al., 2011; Rojas et al., 2011; FEWSNET, 2010; Dinku et al., 2007). Understanding the probability of drought occurrence is of basic importance for risk management programs and for efficient food-aid delivery (Rojas et al., 2011). Drought is an extended period of abnormally dry weather that causes water shortage and damage to vegetation (Singh et al., 2003). It can further be defined as a creeping and recurrent natural phenomenon which creates impacts that can affect large areas of land, lasting for several months (Wilhite, 2005). For example, Rojas et al. (2011) reported that countries in Eastern Africa (Ethiopia, Eritrea, Somalia and Kenya) were worst hit with water shortage between 1984 and 2000. The consequence of this prolonged water shortage was famine (Andrea et al., 2011). Agricultural drought impacts food security because it can disrupt crop development and productivity (Ifejika et al., 2008), and consquently, hinder food availability. Agricultural drought is referred to as a period with declining soil moisture, which consequently leads to crop failures in areas where it is not possible to implement irrigation (Mishra et al., 2010).

Kenya is an agrarian country that primarily relies on rainfed agriculture. However, rainfall is erratic in most parts of the country (Kangasniemi et al., 1993). Usually, food insecurity occurs between August and November of

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every year. Additionally, food insecurity can extend beyond this period in times of drought, flooding, and social strife (FEWSNET, 2010). In Kenya, maize is a widely consumed staple food (Grace et al., 2014). Kenya has experienced variations in maize production over the years. This is mainly due to weather variability (Kangasniemi et al., 1993). In order to bridge the gap between the quantity produced and quantity demanded, high amounts of maize were imported into the country over the years (Kibaara, 2005). Also, the Kenyan government introduced a livelihood zoning system (Grace et al., 2014). The livelihood zoning mechanism divides the country into homogenous areas such that the people within a particular zone share almost the same pattern of livelihood options, including their pattern of obtaining food and generating income, as well as their market opportunities (Grace et al., 2014; FEWSNET, 2010; Lewis et al., 1998). According to Famine Early Warning Systems Network (FEWSNET) (2011, 2010, 2009) and Nyoro (2002), there is always a small population group that suffers from some form of food insecurity. The National Cereals and Produce Board (NCPB) has the mandate of procuring and selling maize at administratively determined prices in Kenya (Jayne et al., 2008). NCPB maize prices are usually uniform at all depots throughout the country and typically remain fixed within a particular market season; however, in some cases the prices are reviewed by the government within the same year in response to changes in crop yield forecast (Jayne et al., 2008).

Monitoring agricultural production in Kenya can provide important information about food security over time (AATF, 2010; Dinku et al., 2007). A hyperspectral remote sensing approach has been widely used to model spatial and temporal variability of crop vegetation over large areas (Rojas et al., 2011; Jacquin et al., 2010; Dinku et al., 2007; Wylie et al., 2002). The most widely used hyperspectral remote sensing technique is the Normalized Difference Vegetation Index (NDVI) developed by Rouse et al. (1974). According to Rouse et al. (1974), NDVI can generally be calculated from vegetation canopy reflectance in the red (670 – 680 nm) and near-infrared (750 – 850 nm) wavelengths using broad-band remotely sensed data. Therefore, NDVI is the most commonly used multi-spectral index of canopy greenness in relation to vegetation structural aspects, such as canopy cover and leaf area index (LAI) (Nguyen & Lee, 2006). Previous studies on NDVI indicate the possibility of estimating visible vegetation reflectance indices, such as chlorophyll a and b pigments (Gitelson & Merzlyak, 1997). Blackburn (1998) further states that estimating the concentrations of vegetation pigments with NDVI techniques is dependent on factors such as structure of the canopy, phenology and environmental stress (e.g. drought). Calculation of drought risk and its impact on maize production in Kenya is limited by the scarcity of reliable rainfall data (Dinku et al., 2007). Despite the coverage of operational weather stations in Kenya, large spatial gaps and independent stations often provide discontinuous data (FEWSNET, 2011). For these reasons, rainfall measurements are commonly replaced by data generated by atmospheric calculation models or satellite observations (Rojas et al., 2011). Nowadays, free data are available for vegetation indices derived from NDVI approaches. An NDVI approach is capable of identifying spatial and temporal patterns of seasonal change in vegetation health and in distinguishing forest from other vegetation types, such as grasses and shrubs, so it is very useful for calculating and monitoring greenness condition in agricultural crops (Mutanga & Skidmore, 2004; Wylie et al., 2002).

The aim of this study is to apply a novel remote sensing method to modelling temporal fluctuations of maize production and prices in five markets in Kenya. In doing so, we assessed how maize price relates to drought conditions during the period from September 1998 to August 2011. The SPOT-VEGETATION NDVI remote sensing approach was adopted to investigate and model the relationship between agricultural drought and maize prices in order to improve food security in Kenya.

Materials and Methods

Study area

Kenya lies along the equator in east-central Africa on the coast of the Indian Ocean. The country has a total area of 582,650 square kilometres (Andrea et al., 2011). Kenya shares borders with Somalia to the east, Ethiopia to the north, South Sudan to the northwest, Uganda to the west, Tanzania to the southwest, and the Indian Ocean to the southeast (FEWSNET, 2011). In the north, the land is arid, while the fertile Lake Victoria Basin is located in the south-western corner. The eastern depression of the Great Rift Valley separates the western highland from the lowland coastal strip. The country is situated between a latitude of 5^0 South and 5.5° North and longitude of 34° and 42°East (Andrea et al., 2011). **Figure 1** illustrates the distribution of sampled markets.

The World Resources Institute (2007) reported that the average annual rainfall in Kenya ranges between 250 mm and 2,500 mm. The country experiences bimodal rainy seasons: one from March to May (featuring long periods of rain) and one from October to December (featuring short periods of rain). Ariga et al. (2006) specifically state that the water footprint of Kenya in relation to crop production was 18.1 Gm^3/year between 1996 and 2005. However, Kenya was hit with severe droughts in the past quarter century, including the following years: 1983/1984, 1991/1992, 1995/1996, 1999/2001,

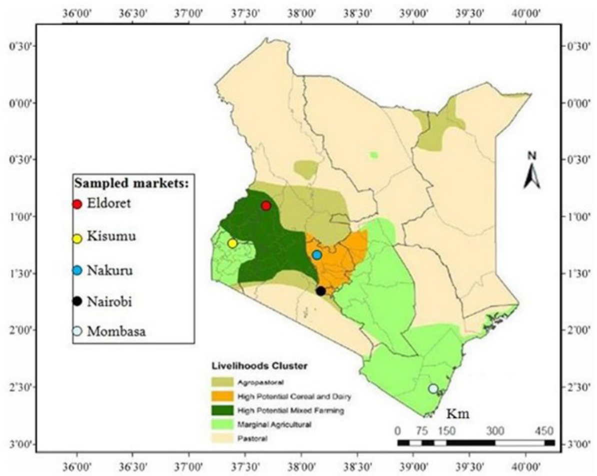

Figure 1 : Livelihood map of Kenya showing the distribution of sampled markets
Source: modified from FEWSNET, 2013

Table 1 : 2006 – 2009 Average maize production
Source: Kangethe, 2011

Kenyan Regions	Maize Production (90kg/bag)	Maize Yield (bags/ha)
Rift Valley	13, 225, 039	20.50
Nyanza	3, 711, 215	14.10
Eastern	3, 903, 141	08.40
Western	4, 163, 878	18.50
Coast	1, 079, 389	08.30
Central	1, 047, 879	06.70
North Eastern	5, 520	02.20
Nairobi	6, 420	14.04

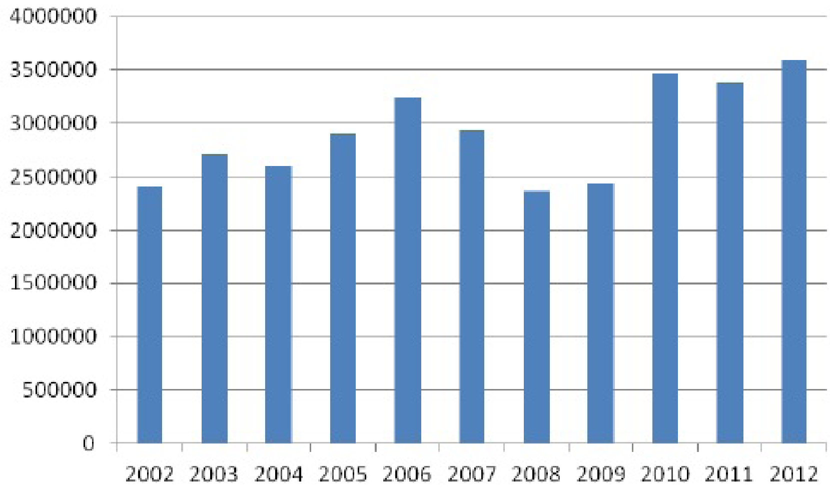

Figure 2 : 2002 – 2012 maize production (metric tonnes) in Kenya
Source: FEWSNET, 2013

2004/2005 and 2009/2010 (Andrea et al., 2011; Boken et al., 2005). The areas most affected by the droughts were the marginal agricultural lands in the north-eastern, north-western, southern and south-eastern parts of Kenya (FEWSNET, 2011; Andrea et al., 2011; Boken et al., 2005). These regions also faced variations in maize production between July and November, 2011 (FEWSNET, 2011), primarily because the drought occurrences caused the average maize production outputs (**Table 1**) in Kenya to fluctuate.

Over the decade of 2002 to 2012, maize production varied greatly in Kenya (**Figure 2**) because of a high incidence of agricultural droughts, as well as limited use of technologies to overcome drought (Short et al., 2012; FEWSNET, 2011; Kangethe, 2011).

Jayne et al. (2008) asserts that the Kenyan government influenced wholesale maize market prices in the country through four main processes: (a) the official price setting process of the NCPB, with the difference between its purchase and sale prices relative to private sector market prices being the major determinant; (b) the restrictions on inter-district maize trade that were in operation; (c) stockholding policies of the NCPB as indicated by net inflows and outflows from NCPB depots; and (d) tariff and trade policy, including informal transaction costs of illegal cross-border trade. However, FAO (2011) showed that the quantity of maize imports and exports in Kenya fluctuated between 1998 and 2009 (**Figure 3**) due to weather variability.

Since the last decade, the price of domestic staple foods in Kenya, such as maize, has been volatile and high (Kangethe, 2011; Nyoro, 2002). Furthermore, the outcome of Kangethe's (2011) comparative analysis shows that imported maize was more expensive than locally produced maize in the period from 2000 to 2010 due to restrictive import policies implemented by the government. Also, the rising dependence of Kenya on maize

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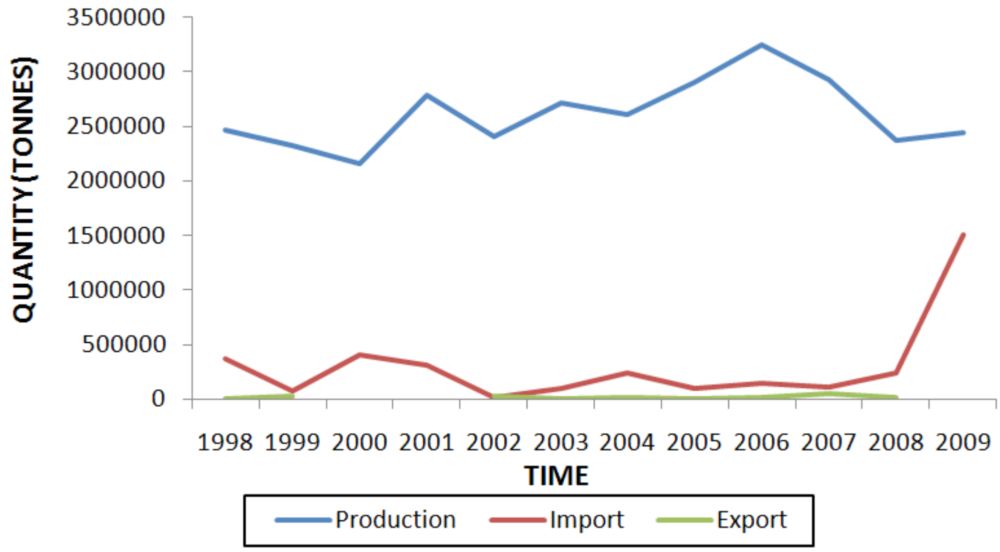

Figure 3 : Maize production, imports and exports (metric tonnes), 1998-2009 (FAO, 2011)

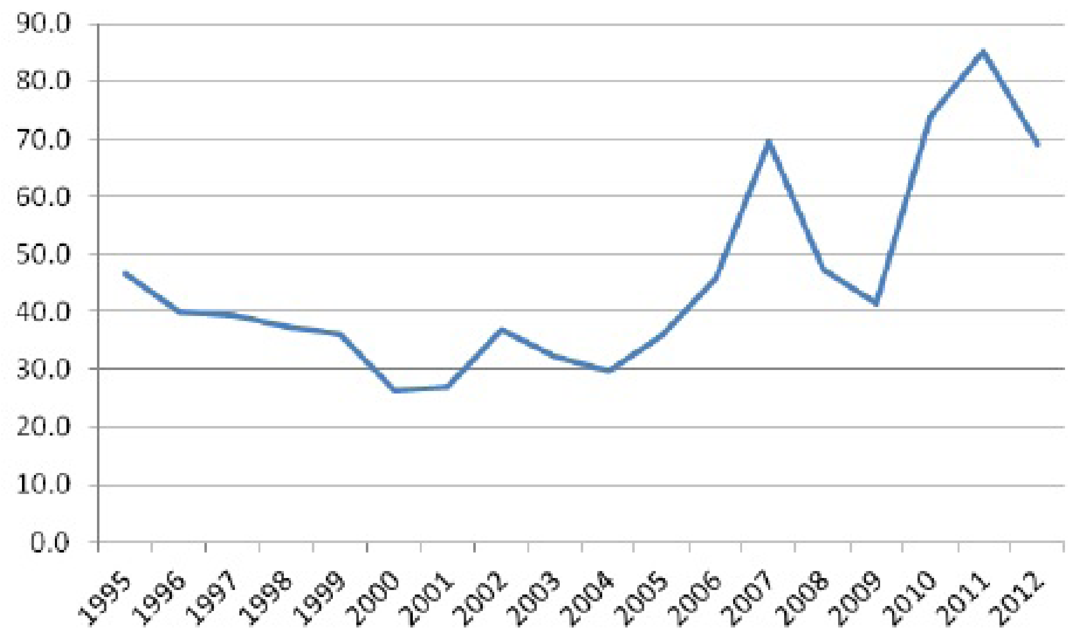

Figure 4 : Kenyan domestic staple food price volatility (including maize), 1995 - 2012 (FAO, 2012)

imports increases vulnerability to regional and global food price fluctuations (FAO, 2011; Nyoro, 2002). In other words, an increase or decrease in maize prices in any part of the World accordingly results in domestic food price volatility in Kenya. **Figure 4** indicates the Kenyan domestic staple food price volatility for the period 1995-2012, which includes maize.

Data

a. SPOT VEGETATION Image Data: The data from satellite SPOT VEGETATION (Satellite Pour l'Observation de la Terre) is freely available for vegetation studies. SPOT VEGETATION has four spectral imaging bands ranging from about 0.45 µm (blue light) to 1.67 µm (mid-infrared radiation). SPOT satellite has a field of view of 0 – 55° on both sides of the satellite tracking path. The SPOT satellite has a pixel size of 1.15 km x 1.15 km at nadir. The major dataset used in this study is the high temporal frequency SPOT VEGETATION (SPOT VGT)[1] S10 imagery. The SPOT time series data consist of 10-day maximum-value composites at 1 km spatial resolution for the period September 1998 to August 2011. The advantages of using maximum-valued composite satellite imagery are two-fold: (a) a composite image is less influenced by cloud effects, sun-angle/shadow effects, aerosols, and water vapour effects; and (b) reduces directional reflectance and off-nadir viewing effects. To further reduce the remaining atmospheric effects, an iterative Savitzky-Golay filter, as described by Huete et al. (2006), was applied to the time series of each pixel for temporal smoothing.

b. **Land Cover Map:** The land cover GIS shapefile for Kenya was freely obtained from AFRICOVER[2]. The AFRICOVER map for Kenya was produced from 1995 Landsat Thematic Mapper imagery with spectral bands: Red (band 4), Green (band 3) and Blue (band 2).The purpose for using this mono-date land cover map of Kenya was to assess which areas were classified as water, bare, or urban in order to exclude these from further analysis.

c. **Field data**: The Kenyan wholesale maize prices used in this study were sampled at five market sites, namely, Nairobi, Mombasa, Kisumu, Eldoret and Nakuru. Maize wholesale price data collected in Kenya were further compared with Global maize price data.[3] Maize prices were expressed in Kenyan shillings per 90 kg bag. Global wholesale prices (in US dollars per tonne) were converted to Kenyan shillings using the official exchange rate.[4]

Methods

1. Analyses of market locations and maize prices in GIS software:

Each sampled market is named after the Kenyan district[5] in which it is situated. The center of each town was selected as the market place in ArcGIS 10.1 software. Afterwards, a buffer of 25 km was generated around each market to indicate the potential area of maize farms that supplies each market. The 25 km buffered areas were intersected with the predicted maize fields to extract the maize growing areas around each market. Monthly SPOT-VGT NDVI was aggregated within the buffered maize areas to extract the time series of mean NDVI values for the maize area around every sampled market.

The maize map that was used for this study was generated using an unsupervised classification on the 1998 – 2011 SPOT-VGT NDVI time series. A total of 100 legend classes were tested and evaluated using the separability model approach. The optimal number of classes was chosen as the one which had the highest average separability among all classes. The separabilty analysis produced a legend with 36 classes, with each class representing a separate NDVI profile. To assess which class best corresponds to maize area, a stepwise regression analysis was performed on the 36 NDVI class image data.

2. Temporal Dependence of Kenyan Wholesale Maize Price on Global Price:

The price data used in this study was obtained from the MIB (Kenyan Ministry of Agriculture's Market Information Bureau). The following four criteria were adopted to select the markets used in this research: (a) the sites were selected because the remote sensed images obtained over their locations were almost cloud-free; (b) sampled markets were located within the grain basket zones of Kenya; (c) for the Nairobi district, where there is more than one market, an average of three markets was sampled. Selected Nairobi markets for urban maize consumers were in proximity to rural communities that are located within the grain basket zones[6] of Kenya; and (d) apart from Nairobi, the other sampled districts have only one particular day per week set aside as their market day. As such, maize price data were only recorded on the respective market days for the districts other than Nairobi.

3. Temporal Dependence of Wholesale Maize Price on NDVI Seasonal Anomalies:

a. Mean-NDVI series and price series for each buffer during the observation period were visualized in a graph to analyse their temporal behaviours (Lewis et al., 1998). Both NDVI and wholesale price series were decomposed into three components: observed, trend and seasonal. The NDVI values were calculated with a simple additive R-statistical model:

$$X_t = m_t + s_t + z_t \qquad \text{Eq. 1}$$

Where, t = time, x = observed series, m = the trend, s = seasonal components and z = an error term.

The purpose of Mean-NDVI analysis is to visualize the seasonal and trend variations in both series. This is because many time series are characterized by a trend and/or seasonal effects (Metcalfe et al., 2009) which could result in spurious regression (Udelhoven et al., 2009).The NDVI series is more affected by seasonal variations than the trend. Seasonal variation strongly affects the structure of autocorrelation of a time series and could also result in spurious regression (Udelhoven et al., 2009). Price series, on the other hand, exhibit more of a trend variation than seasonal variation; therefore, the price series was not corrected for the seasonal variation. The seasonal variation

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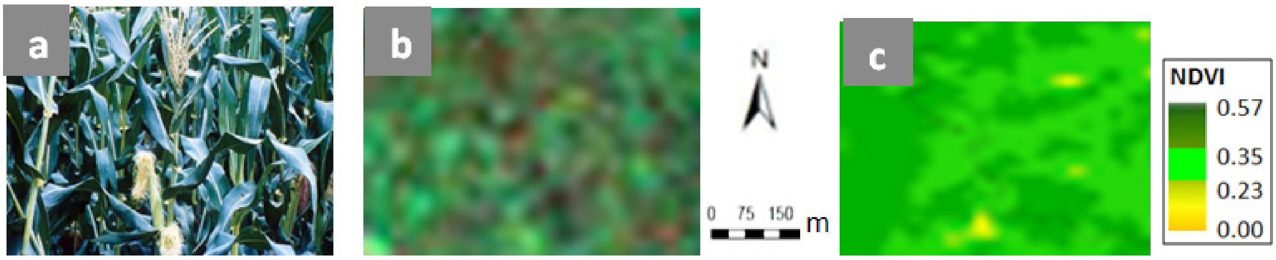

Figure 5 : SPOT VGT NDVI spectral reflectance of mature maize: 5 (a) = mono-cropped maize field at inflorescence stage at 01^0 21' 59" S and 36^0 44' 17" E (WGS84) in Nairobi Kenya; 5 (b) = 1 km² SPOT VGT Satellite image (RGB =421); and 5 (c)= pixel-based NDVI output.

of the NDVI series was removed by computing the standardized seasonal anomalies (z-score) in Timestat V1.0 GIS software. The baseline period was September 1998 to August 2011. This method was used by Udelhoven et al. (2009) while assessing the relationship between temperature and rainfall in Spain as in **Equation 2**:

$$Z_{tj} = \frac{NDVI_{tj} - \text{Mean}(NDVI)_j}{S(NDVI)_j} \qquad \text{Eq. 2}$$

Where Mean(NDVI)j and S denote the long term means and standard deviation of month j and t are the time index indicating the respective years.

b. Maize residual price series and NDVI seasonal anomalies were visualized prior to regression analysis. The purpose of doing this was to visually examine whether a temporal relationship exists between these variables. Residual price series and lagged NDVI seasonal anomalies were also visualized in a scatter plot to determine the direction of the correlation between these variables. Furthermore, Pearson correlation coefficient was used to evaluate the strength of the relationship between residual price series and lagged NDVI seasonal anomalies of the aggregated pixel of the buffered areas. Several other studies have demonstrated that NDVI is correlated with net primary production and crop yield (Malmström et al., 1997; Pettorelli et al., 2005; Prince et al., 1995). Hence, the residual price series after the growing season was related to the lagged NDVI anomalies during the growing season using multiple linear regression. In this case, only four lags of NDVI seasonal anomalies were computed (**Equation 3**) because the total length of the growing season was approximately six months. The purpose of carrying out this computation is based on the fact that a vegetation production anomaly during the growing season is an indicator for price after harvest (Brown et al., 2006).

$$\mu_1 = a + b_1(NDVIA)_t + b_2\,(NDVIA)_{t-1} + \dots\dots\dots\, b_2\,(NDVIA)_{t-4} + NDVIA_{max} + \mu_t \quad \text{— Eq. 3}$$

Where NDVIA = monthly NDVI anomalies, b= the impulse response weight vectors describing the weight assigned to the current and past monthly NDVI anomalies series, a = constant, μ_1 = the model residual, and μ_t = the residuals from the optimal lag identified from the model of wholesale price and global price. Note that NDVIA in this case is the NDVI of seasonal anomalies.

Results and Discussion

1. Temporal Dependence of Kenyan Wholesale Maize Price on Global Price:

Figure 5 shows the NDVI output (**5 c**) derived from the SPOT VGT image on 23 August, 2011 of a maize farm in Nairobi. The spectral heterogeneity observed in the NDVI image could be attributed to the appearance of the maize cobs (yellow) and the variation in the greenness of the maize leaves in **Figure (5a)** since the crop is at a mature stage.

Figure 6 shows a price distribution for wholesale maize at each of the study sites and the global price of maize for the period under study. The wholesale maize prices in major urban centres of Kenya are more related with one another than with the global price. However, the regression results show a moderately strong correlation (0.67) between the Kenyan market wholesale prices and the global maize prices. This outcome corresponds to the fact that Kenya is one of the countries in Africa that is exposed to higher international prices for food commodities due to insufficient stocks and budgetary resources to adequately protect the food security of the country (Grace et al., 2014; FAO, 2011; Jayne et al., 2008). Kenya was a net importer of maize and had appealed for external assistance and food aid during seasons of maize shortage (Jayne et al., 2008). There is a deviation of the wholesale market prices in Kenya from the global prices in 2009. This could be the result of one of the

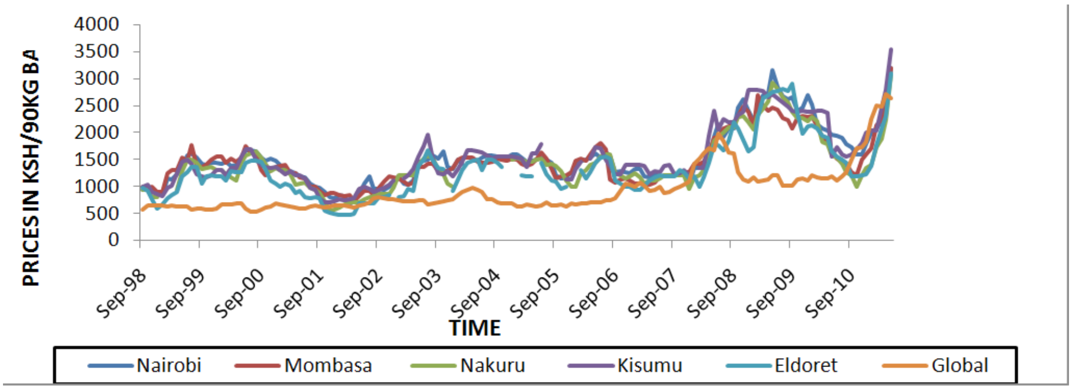

Figure 6 : Temporal plot of Kenyan wholesale maize prices compared to global prices

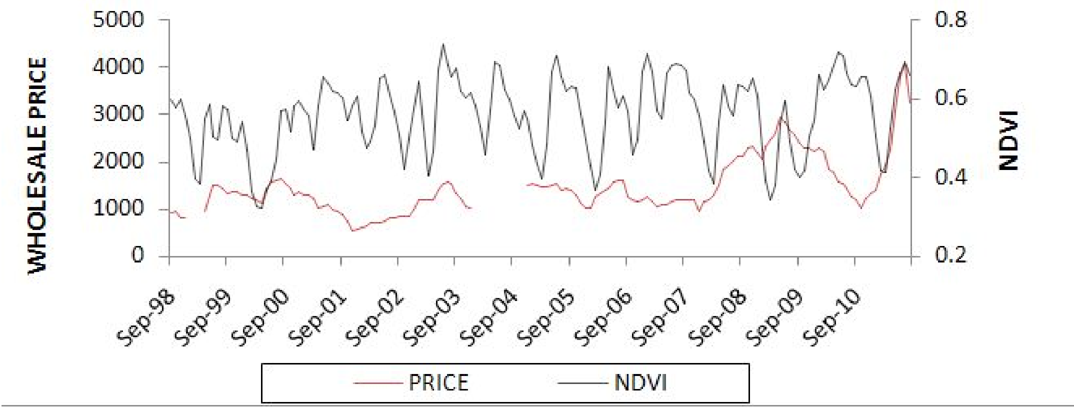

Figure 7 : Maize residual price series (in Kenyan shillings/90 kg bag) and mean NDVI of Nakuru from September 1998 - August 2011

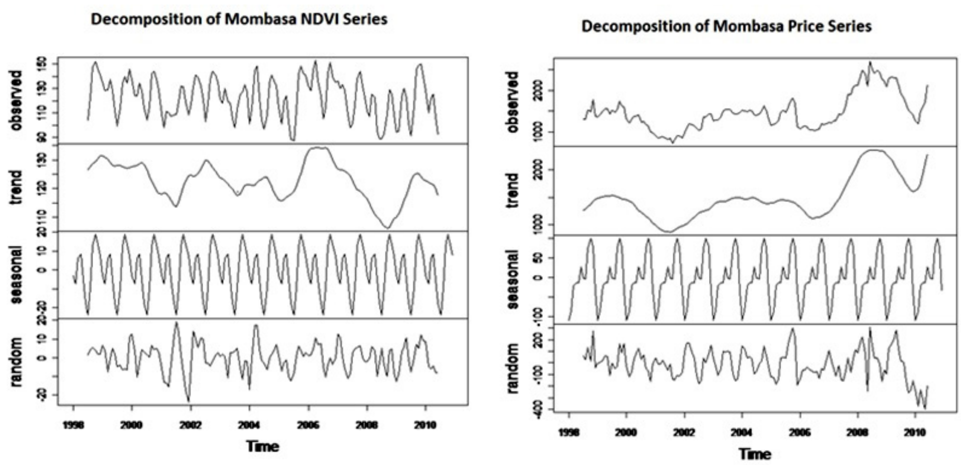

Figure 8 : Results for the decomposed NDVI and price series data of the Mombasa market

worst droughts experienced in Kenya occurring during that period. The wholesale prices were generally high in 2011 due to the delay of the long rains in the country. The global shocks in food prices could, therefore, have impacted local food prices in Kenya. Global shocks in food prices are due to multiple factors, such as: (a) drought in Australia, (b) policies to promote the use of biofuels, which increases demand for maize, (c) depreciation of the US Dollar and d) long-term economic growth in several large developing countries (FAO, 2011). For example, increases in oil prices made biofuels more profitable, thereby diverting maize from food markets to biofuel factories. Furthermore, depreciation of the US dollar was responsible for 15 - 27% of the increase in dollar-denominated food prices between 2007 and 2008 (Minot, 2010).

The outcomes of this study could have been affected by limited price data. Brown et al. (2006) used 445 markets in the analysis of millet price-NDVI correspondence. The assumption that most of the maize sold in each market are from the 25 km buffer region could possibly be

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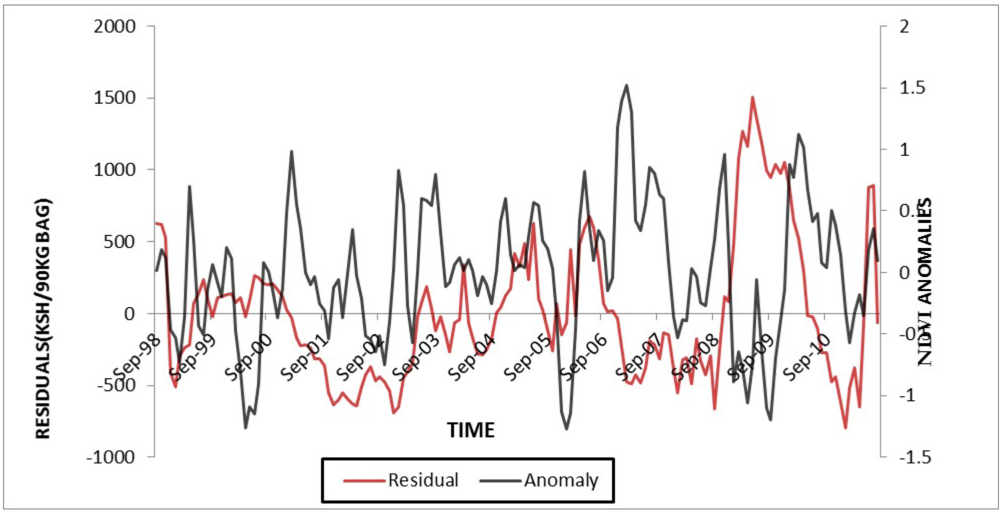

Figure 9 : Maize residual price series versus NDVI seasonal anomalies aggregated for the buffered areas of the five markets, illustrating the temporal relationship between these variables

the reason why the results of this present study do not agree with that of Brown et al. (2006). For our study, the maize coming into the sampled markets may not only be supplied from within a 25km market buffer zone. Therefore, an on-spot data collection of maize prices could possibly improve the outcome of this experiment. Furthermore, an inclusion of other price-driving factors (such as regional pricing regime, export restrictions, cost of farm implements, social strife, etc.) into the regression models could produce a stronger regression result from the correlation between Kenyan maize wholesale price and the NDVI anomalies.

2. Temporal Dependence of Kenyan Wholesale Maize Prices on NDVI Seasonal Anomalies

Figure 6 illustrates the temporal characteristics of mean-NDVI and price series for the Nakuru market. The NDVI series follows a seasonal pattern, while price series fluctuates without a clear seasonal pattern. **Figure 7** does not indicate a strong correspondence (r = - 0.479) between price and NDVI. Nevertheless, the trend is evident that maize prices were high during drought period (i.e. negative NDVI anomalies) and low during wet seasons (i.e. positive NDVI anomalies).

The reason for this outcome is because of the effect of the global prices on the Kenya wholesale price and seasonal variation in NDVI (Brown et al., 2006). Although, stepwise regression statistical models have the limitation of over-predicting the significance of results (Chartfield, 1995). In addition, since NDVI time series data are usually affected by seasonal variations and trends, the requirement of normally distributed data for a regression analysis was not fully met. Hence, future research should consider the use of finer resolution (0.5 m) NDVI data that can accurately capture maize fields.

Figure 8 presents the results of the profile analysis of maize in Mombasa, Kenya. The time series profiles indicate variations based on the decomposition analysis of trend, seasonal, and random components for both the NDVI maize phenology and the Maize wholesale price series.

Figure 9 below illustrates the maize residual price series and standardized NDVI anomalies for the five markets. Values that fall below zero represent NDVI negative anomalies (drought conditions) and values that are above zero indicate NDVI positive anomalies (productive years). 2009 was found by FEWSNET to be one of the worst drought years, and maize prices rose by 130 percent in Nairobi and 85 percent in Mombasa compared to maize prices in 2008 (FEWSNET, 2009). The NDVI anomalies were below zero (indicating a drought) and the residual price series was also high. Therefore, drought had an impact on maize wholesale price in 2009. However, there are other drought years mentioned in the literature (Andrea et al., 2011) that do not show a clear relationship between these variables (FEWSNET, 2009; Dinku et al., 2007).

The results of the temporal correlation between maize residual price series and NDVI seasonal anomalies correspond with Brown et al. (2006), who found an association of negative NDVI anomalies with high price and positive NDVI anomalies with low price. Brown et al. concluded that NDVI anomalies can provide information on areas where food price and food production instability exists. Furthermore, maize price in Kenya seems to be more correlated with global maize prices because Kenya is a major importer of maize even in favourable production years (Kibaara, 2005). This assertion further suggests that correction of the NDVI variable with maize prices, including global market prices, could be helpful for countries like Kenya that import food.

Conclusion and Recommendation

This study evaluates the relationship between remotely sensed vegetation indices and the wholesale price of maize in Kenya from September 1998 to August 2011. To achieve this, the monthly wholesale price was isolated from the lagged global prices using a linear regression model. The residuals of the linear regression model of the optimal lag were regarded as the wholesale price corrected for the effect of global prices. Distributed lag and multiple linear regression models were used to establish a link between the residual price series and NDVI anomalies. A negative correlation (r = - 0.479) exists between the average residual price series and monthly NDVI anomalies for markets in Kenya. This study concludes that NDVI is a good index for monitoring the evolution of maize prices and food security emergency planning in Kenya. It is recommended that future research should consider correlating the wholesale maize prices with the global maize prices and other price-driving factors in order to obtain an even stronger regression result.

End Notes

1. Further details of the SPOT VGT data and their pre-processing approaches are available at www.spot-vegetation.com and *www.spotimage.fr.*
2. AFRICOVER website: *http://www.fao.org/docrep/003/X0596E/X0596e00.HTM*
3. Global maize prices were obtained from *http://www.indexmundi.com/commodities/?commodity=corn&months=300*
4. Global price in US dollars was converted to Kenyan shillings via *www.oanda.com/currency-converter*
5. District shapefiles were obtained from *http://www.un-spider.org/links-and-resources/data-sources/land-cover-kenya-africover-fao*
6. Information about grain basket zonation in the study area was obtained from both the MIB and the National Cereals and Produce Board (NCPB)

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Conflict of Interests

The authors hereby declare that there are no conflicts of interest.

References

AATF - African Agricultural Technology Foundation. (2010, May 4). Policy Brief. Reducing Maize Insecurity in Kenya. Retrieved from *http://www.aatf-africa.org/userfiles/WEMA-KE-policy-brief1.pdf*

Andrea, M. B., Prakash, N.K. D., & Zhuohua, T. (2011). *Strengthening Institutional Capacity for Integrated Climate Change Adaptation and Comprehensive National Development Planning in Kenya*. Millenium Institute, Washington DC, USA. pp 51.

Ariga, J., Jayne, T.S. & Nyoro, J. (2006). Factors driving the growth in fertilizer consumption in Kenya, 1990 -2005: Sustaining the momentum in Kenya and lessons for broader replicability in Sub-Saharan Africa. *Tegemeo working paper 24/2006*, Tegemeo Institute of Agricultural Policy and Development, Egerton University, Nairobi, Kenya.

Blackburn, G.A. (1998). Quantifying chlorophylls and ceroteniods at leaf and canopy scales: An evaluation of some hyperspectral approaches. *Remote sensing of Environment*, 66(2), 273 - 285.

Boken, V. K., Cracknell, A. P., Heathcote, R. L., & World Meteorological, O. (2005). *Monitoring and predicting agricultural drought: a global study* (Eds.). GB: Oxford University Press.

Brown, M. E., Pinzon, J. E., & Prince, S. D. (2006). The effect of vegetation productivity on millet prices in the informal markets of Mali, Burkina Faso and Niger. *Climatic Change*, 78(1), 181-202.

Chatfield C. (1995). Model uncertainty, data mining and statistical inference. J*ournal of the Royal Satistical Society*, A(158), 419-466.

Dinku, T., Ceccato, P., Grover-Kopec, E. Lemma, M., Conner, S.J., & Ropelewski, C.F., (2007). Validation of satellite rainfall products over East Africa's complex topography. *International Journal of Remote Sensing* 28(7), 1503 - 1524.

FAO - Food and Agriculture Organization (2011, June 5). The state of food security in the World: How does international price volatility affect domestic economies and food security. Retrieved from *http://www.fao.org/docrep/014/i2330e/i2330e.pdf*

FAO - Food and Agriculture Organization (2013, June). Kenyan domestic staple food price volatility for the period 1995-2012. Retrieved from *http://faostat.fao.org*

ISSN-Internet 2197-411x OLCL 862804632

FEWSNET - Famine Early Warning Systems Network (2011, June). Kenya Food Security Outlook. Retrieved from *http://www.fews.net/docs/Publications/Kenya%20 Food%20Security%20Outlook_April%202011_final.pdf*

FEWSNET - Famine Early Warning Systems Network (2013, December). Kenya Food Security Brief. *http:// www.fews.net/sites/default/files/documents/reports/Kenya_Food%20Security_In_Brief_2013_final_0.pdf*

FEWSNET - Famine Early Warning Systems Network (2011, June). Kenya Food Security Outlook. Retrieved from *http://www.fews.net/docs/Publications/Kenya%20 Food%20Security%20Outlook_April%202011_final.pdf*

FEWSNET - Famine Early Warning Systems Network (2010, May). Food Security Framework. Retrieved from *http://www.fews.net/ml/en/info/Pages/fmwkfactors.aspx?gb=ke&l=en&loc=2*

FEWSNET - Famine Early Warning Systems Network (2009, April). KENYA Food Security Outlook Update. Retrieved May 29, 2011, from *http://www.fews.net/docs/ Publications/Kenya_FSU_2009_03_final.pdf*

Gitelson, A.A. & Merzlyak, M.N. (1997). Remote estimation of chlorophyl content in higher plant leaves. *International Journal of Remote Sensing*, 18 (12), 2691 - 2697.

Grace, K., Brown, M. & McNally, A. (2014). Examining the link between food prices and food insecurity: A multi-level analysis of maize price and birthweight in Kenya. *Journal of Food Policy*, 46, 56–65.

High Level Panel of Experts on Food Security and Nutrition. (2013, June). *Biofuels and food security. A report by the HLPE of the Committee on World Food Security*, Rome .

High Level Panel of Experts on Food Security and Nutrition. (2011, July). *Price volatility and food security*. A report by the HLPE of the Committee on World Food Security, Rome.

Huete, A. R., Karl, F. H., Tomoaki, M., Xiangming, X., Didan, K., Willem, L., et al. (2006). *Vegetation Index greenness global data set*. National Aeronautics and Space Administration. USA. pp 56.

Ifejika, S., Chinwe, Kiteme, B., & Wiesmann, U. (2008). Droughts and famines: The underlying factors and the causal links among agro-pastoral households in semi-arid Makueni district, Kenya. *Global Environmental Change Journal*, 18 (1), 220-233.

Jayne, T. S., Myers, Robert, J., & James Nyoro. (2008). The effects of NCPB marketing policies on maize market prices in Kenya. *Journal of International Association of Agricultural Economics*, 38, 313–325.

Kangasniemi, J., Staatz, J., Phillips, C., Diskin, P., & Diagne, A. (1993). *Food Sector Instability and Food Aid in Sub-Saharan Africa*: Michigan State University,East Lansing, Michigan.

Kangethe, E. (2011, October 10). Situational Analysis: Improving food safety in the maize value chain in Kenya. FAO Technical Report. Retrieved from *http://www.fao.org/fileadmin/user_upload/agns/pdf/WORKING_PAPER_AFLATOXIN_REPORTDJ10thOctober.pdf*

Kibaara, B. W. (2005). *Technical efficiency in kenyan maize production: An application of the stochastic frontier approach*. Colorado State University, Fort Collins. pp 23 - 28.

Kogan, F. N. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in Space Research*, 15, 91-100.

Jacquin, A., Sheeren, D., & Lacombe, J.P. (2010). Vegetation cover degradation assessment in Madagascar savvana based on trend analysis of MODIS NDVI time series. *International Journal of Applied Earth Observation and Geoinformation*, 12(S1), 3-10.

Lewis, J. E., Rowland, J., & Nadeau, A. (1998). Estimating maize production in Kenya using NDVI: Some statistical considerations. *International Journal of Remote Sensing*, 19(13), 2609-2617.

Malmström, C. M., Thompson, M. V., Juday, G. P., Los, S. O., Randerson, J. T., & Field, C. B. (1997). Interannual variation in global-scale net primary production: Testing model estimates. Global Biogeochem. Cycles, 11(3), 367-392.

Metcalfe, A. V., & Cowpertwait, P. S. P. (2009). *Time Series Data. Introductory Time Series with R* (pp. 1-25). New York, NY: Springer.

Minot, N. (2010). *Transmission of World Food Price Changes to Markets in sub-Saharan Africa*. Washington: International Food Policy Research Institute.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. Journal of Hydrology, 391(1-2), 202-216.

Mutanga, O. & Skidmore, A.K. (2004). Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing*, 57, 263 - 272.

Mutanga, O. & Skidmore, A.K. (2004). Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing*, 57, 263 - 272.

Nguyen, H.T. & Lee, B. W. (2006). Assessment of rice leaf growth and nitrogen status by hyperspectral canopy reflectance and partial least square regression. *European Journal of Agronomy*, 24(4), 349 - 356.

Nyoro, J. K. (2002). *Kenya's Competitiveness in Domestic Maize Production: Implications for Food Security*. Nairobi: Tegemeo Institute, Egerton University, Kenya.

Nyoro, J. K., Kirimi, L., & Jayne T.S. (2004). *Competitiveness of Kenyan and Ugandan Maize Production: Challenges for the Future*. Nairobi: Tegemeo Institute of Agricultural Policy and Development.

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J.-M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution*, 20(9), 503-510.

Prince, S. D., & Goward, S. N. (1995). Global Primary Production: A Remote Sensing Approach. *Journal of Biogeography*, 22(4/5), 815-835.

Rojas, O., Vrieling, A., & Rembold, F. (2011). Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. *Remote Sensing of Environment*, 115(2), 343-352.

Rouse, J. W., Haas, R.H., Schell, J.A., Deering, D.W. & Harlan, J.C. (1974). *Monitoring the vernal advancement and retrogradation of natural vegetation. NASA/GSFC, Type III Final Report*, M.D. Greenbelt, pp. 371.

Rowland, J. D., Brock , J. C., Nadeau, C. A., Klaver, R. W., Moore, D. G., & Lewis, J. E. (1996). *Use of Vegetative index to characterize drought patterns in East Africa. In Raster Imagery in Geographic Information System* (Santa Fe, NM: Onward Press. pp. 247-255.

Singh, R. P., Roy, S., & Kogan, F. (2003). *Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. International Journal of Remote Sensing*, 24(GEOBASE), 4393-4402.

Short C., Mulinge W. & Witwer M. (2012). *Analysis of incentives and disincentives for maize in Kenya*. Technical notes series, MAFAP, FAO, Rome

Udelhoven, T., Stellmes, M., del Barrio, G., & Hill, J. (2009). Assessment of rainfall and NDVI anomalies in Spain (1989–1999) using distributed lag models. International *Journal of Remote Sensing*, 30(8), 1961-1976.

Wilhite, D., (2005). *Drought and water crisis: science, technology and management issues*. Taylor and Francis Group.

World Resources Institute. (2007). *Nature's benefits in Kenya: An atlas of ecosystems and human well-being. World Resources Institute*. Washington DC (USA) and Nairobi (Kenya).

Wylie, B.K., Meyer, D.J., Tieszen, L.L. & Mannel, S. (2002). Satellite mapping of surface biophysical parameters at the biome scale over the North American grasslands: A case study. *Remote sensing of Environment*, 79(2-3), 266-278.

ISSN-Internet 2197-411x OLCL 862804632