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Evaluating the Relationship between Drought and Vegetation Greenness in Chyulu-Amboseli Rangeland, Kenya

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ABSTRACT: Remote sensing techniques have been widely used to monitor moisture-related vegetation conditions. Vegetation vigour response to drought however is complex and has not been adequately studied using satellite sensor data. This paper investigated the time lag response of vegetation to drought in Kenya's Chyulu-Amboseli ecosystem based on Standardized Precipitation Index (SPI) derived from monthly precipitation data for the period January 2000-October 2016 downloaded from the Climate Hazards group InfraRed Precipitation with Stations and Normalized Difference Vegetation Index (NDVI) computed from Moderate Resolution Imaging Spectro-radiometer (MODIS) pre-processed images downloaded from the University of Natural Resources and Life Sciences (BOKU) database. Statistical analysis showed that drought severity increased over the study period while corresponding vegetation conditions degenerated. Results further revealed that the relationship between drought and vegetation greenness was significant ($R^2 = 0.6$) with 2 months optimal lag. This calls for policy makers and programme managers to integrate the lag effect in measures to cope with drought in the rangelands.

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Drought is one of the biggest threats to Kenya's socio-economic and environmental development particularly in arid and semi-arid lands (ASALs) (RoK, 2015). Defined as the extreme persistence deficiency in precipitation over an extended period usually a season or more (Tale and Gustard, 2000) drought results in a water shortage causing adverse impacts on ecosystems, livelihoods or societies (Kassahun *et al*., 2008; Opiyo, *et al*., 2015; Tuqa *et al*., 2014). The precipitation deficiency prompts meteorological drought which subsequently affects soil moisture content, water availability and vegetation growth and production (Wilhite, 2000; Son *et al*., 2012; Udmale *et al*., 2014). Pastoral livestock production is the dominant economic activity in ASAL areas of Kenya. Although drought is a normal characteristic of these areas, rise in frequency and severity has adversely affected livestock production, both directly and indirectly (RoK, 2012; Ngaina *et al.,* 2014). Whilst direct effects result from associated high temperature which influence animal growth, milk production, and reproduction; indirectly drought affects the quantity and quality of feedstuffs such as pasture, forage, and the severity and distribution of livestock diseases and parasites (Houghton *et al*., 2001; Seo and Mendelsohn, 2007).

The focus of this study was Chyulu-Amboseli ecosystem, Kajiado County, a drought hotspot in Kenya. In recent years the area experienced rapid transformation driven by rising human population and land fragmentation limiting free movement of livestock and wildlife and diminished dispersal areas (Okello *et al.*, 2005). Similarly, there has been a dramatic increase in incidences of drought both short and long-term (Thornton *et al*., 2006) causing a reduction in pasture and water resource necessary for sustaining the animals. The most recent drought of 2016 - 2017 caused pasture failure and prevalence of foot and mouth diseases causing livestock mortality, emaciation, reduced milk yields and reduction in overall livestock productivity (NDMA, 2017). In planning for drought mitigation, there has been a shift from disaster management to drought risk management (Wilhite *et al*., 2014) which is often difficult to design when the behaviour and characteristic of drought and expected losses are not easily predictable (Wilhite *et al*., 2007). Although previous studies (Vicente-Serrano *et al*., 2013) have examined the influence of drought on vegetation, few studies have paid attention to this relationship in dryland areas. This paper therefore sought to investigate how quickly vegetation vigour as measured by greenness responded to drought events in the

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Chyulu-Amboseli ecosystem. Such knowledge is important in informing the design of drought risk reduction strategies in rangelands.

MATERIALS AND METHODS

Study area: The study was carried out in the Chyulu-Amboseli ecosystem located within latitudes 2.21º S and 2.77º S and longitudes 37.40º E and 37.94º E covering 1,352.2 square kilometres (Figure 1). The physiography of the area is greatly influenced by the Chyulu Hills which bound the area to the east and the slopes of Kilimanjaro located to the south-east. The area is low lying with small interruptions of hills towards the western and northern parts. It is characterized by basement and saline plains with fresh water springs flowing from the volcanic slopes of the Mt. Kilimanjaro to form wetlands on the lowlands. A large part of the area falls within climatic zones V-2 and VI-2 (Okello *et al*., 2016), is generally arid to semi-arid savannah environment with low agricultural potential (Croze *et al*., 2006). It is characterized by spatial and temporal variation in hydrology with surface water only found in few permanent streams and rivers. The area receives bimodal rainfalls with the short rains occurring between October and December, while the long rains are experienced between March and May (Okello and D'Amour, 2008). Mean annual rainfall ranges from 400 to 1000 mm (Reid *et al*., 2004) and is influenced either by the rain-shadow effects from the neighbouring mountains or by divergent wind flow between the Chyulu Hills and Mt. Kilimanjaro (Ntiati, 2002). The Chyulu- Amboseli-rangeland epitomizes the impacts of a history of most destructive droughts in the Horn of Africa (Notenbeart *et al*., 2012).

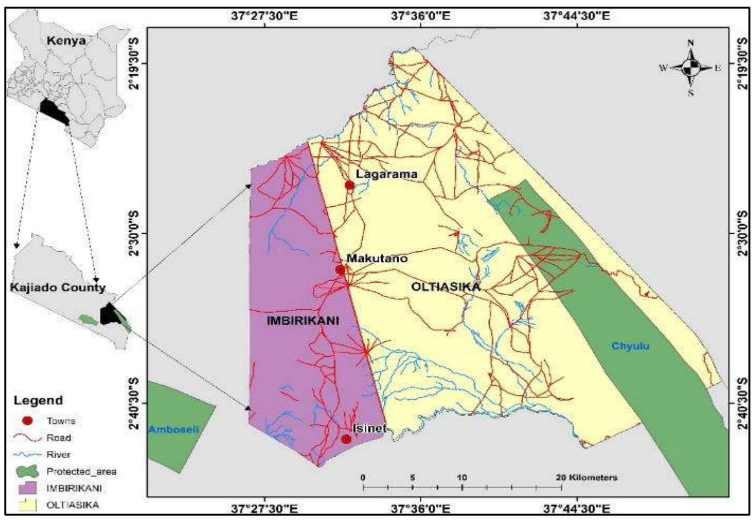

Fig 1: Location of Chyulu-Amboseli Ecosystem

The vegetation of the region is typical of a semi-arid environment. High immigration of non-pastoral communities in search of land for cultivation have put pressure on natural resources within the group ranch. At the same time, the land within the group ranches has experienced extensive changes over the past 30 years in response to a variety of economic, cultural, political, institutional, and demographic processes (Reid *et al*., 2004). Pastoralism, which was once the backbone of the Maasai livelihood, has declined tremendously in recent years due to land use changes and recurrent drought (Ntiati, 2002).

Data Collection: For drought assessment monthly rainfall data from January 2000 to December 2016 was downloaded from the Climate Hazards group Infra-Red Precipitation with Stations (CHIRPS) dataset, a 0.05° (~5 km) spatial resolution global gridded dataset http://chg.geog.ucsb.edu/data/chirps/ (Funk *et al*., 2015). Computation of vegetation greenness was based on data derived from gapless pre-processed images downloaded from the University of Natural Resources and Life Sciences (BOKU), Vienna (http://ivfl-info.boku.ac.at/index.php/eo-data-processing/dataprocess-global), using the bounding box coordinates of the study area. MODIS data was preferred in this study because it is free, is more frequent and has higher spatial resolution for semi-arid areas compared to other datasets. Further, MODIS images do not suffer data inconsistency from multiple sensors. Images from BOKU are already corrected to remove the effects of solar angle and sensor errors and have been found effective in studies that monitor long-term vegetation activities (Nemani *et al*., 2003; Mao *et al*., 2012; Klisch and Atzberger, 2016).

Data Analysis: Drought was assessed using the Standardized Precipitation Index (SPI)- a probability index designed to quantify the precipitation deficiency for multiple time scales. The index is calculated by fitting long-term precipitation data to a gamma probability distribution function then transforming it to a normal distribution with mean zero and one standard deviation (McKee *et al*., 1993; Bordi and Sutera, 2007). SPI values were classified into seven categories; extremely wet (z > 2.0), very wet (1.5 to 1.99), moderately wet (1.0 to 1.49), near normal (-0.99 to 0.99), moderately dry (-1.49 to -1.0), severely dry (-1.99 to -1.5), and extremely dry (< -2.0) (McKee *et al.*, 1995). SPI was used over other indices because it is relatively easy to compute, is flexible allowing observation of water deficits at different time scales and can monitor dry and wet conditions over a wide spectrum of time (Hayes *et al*., 2000; Wu *et al*., 2001).

The sum of absolute values for SPI for a drought event represent a drought magnitude that measure the persistence of a drought.

Assessment of vegetation greenness was based on the Normalized Difference Vegetation Index (NDVI) developed by Tucker (1979). NDVI is a quantitative measure of biomass quantitative an indication of changes in vegetation patterns (Todd *et al*., 1998). It is dimensionless with values ranging between -1 and +1 to correspond to non-vegetated and forest surfaces respectively (Tucker, 1979; Justice *et al*., 1991). Kogan (1993) found NDVI effective in detecting drought and estimating its impacts on vegetation in East African.

The effect of drought on vegetation greenness was analysed using autoregressive model of the form shown in equation (1).

$$NDVI_t = \beta_0 + \beta_1 SPI_t + AR(1) + AR(2) + \mu_t \quad 1$$

$$\mu_t = \rho\mu_{t-1} + \varepsilon_t \quad 2$$

Where, $NDVI_t$ is the current NDVI, $AR(1)$ is NDVI for the past one month, AR (2) is the NDVI for the past two months SPI_t is current standardized precipitation β_0 and β_1 are coefficients of the model, while ε_t is the error term.

The number of lags was determined by the lowest Akaike Information Criterion (AIC), while the Breusch-Pagan-Godfrey test was performed to test for serial correlation between the model variables.

RESULTS AND DISCUSSION

Descriptive Statistics: Results of the Standardized Precipitation Index had a mean of -0.26, median -0.35, maximum 3.26, minimum -4.64, and a standard deviation of 1.32. Months with the lowest SPI values were September 2008 (-2.19), July 2012 (-2.19), July 2007 (-2.11), June 2005 (-2.11), June 2003 (-2.08) and September 2004 (-2.08). The years 2000, 2004, 2009, and 2012 recorded multiple extreme dry months. The highest SPI were recorded in April 2013 (4.68), February 2014 (3.36), December 2013 (3.32), March 2013 (3.12), April 2012 (3.00), March 2014 (2.90), November 2011 (2.85), and March 2011 (2.56). Analysis of the NDVI yielded a mean value of 0.34 and a standard deviation of 0.01. A value of 0.5 represents normal vegetation conditions; those below 0.5 represent depressed vegetation, while those above 0.5 show abnormal conditions. The year 2009 had the most prolonged period when NDVI values were below the mean, thereafter, there were quick succession of droughts events resulting in some years like 2012 recording rapid changes in vegetation conditions. This has implication on pastoralism as the pasture does not get adequate time to regenerate and re-establish. The maximum NDVI value of (0.62) was recorded in December 2006, while the minimum (0.20) was in September 2004. Overall, 2005 and 2009 were the two driest years with the lowest annual NDVI mean values. In these years, the highest NDVI values were recorded in February and the lowest in September, with remarkable differences in between these extremes. When a cut-off of 0.5 was used, 93.5 % of the total months registered depressed vegetation conditions, with only 6.5 % months experiencing above normal vegetation conditions. The highest number of months with normal vegetation greenness fell in November (4) followed by March and April (each 3) and December (1). It is evident that NDVI can be an effective measure in monitoring drought patterns in the area and thus an important tool in rangeland management. The findings amplify those of BurnSilver and Mwangi (2007) who found that vegetation greenness in the Chyulu hills varied across a calendar year and reflected the bimodal distribution of rainfall.

Relationship between SPI and NDVI: Prior to estimating the Autoregression model the NDVI and SPI values were plotted in a graph (Figure 2) and the result revealed that the two variables exhibited similar behaviour throughout the study period. This meant that the variables could be subjected to statistical tests to examine the strength of their relationship.

Initial results of the regression analysis between NDVI and SPI were significant with p- value = 000 and coefficient of relationship (R^2 = 0.49). Being time series variables, tests for serial correlation performed by Breusch-Godfrey test produced a P-value = 0.000 an indication that the model suffered the problem of serial correlation suggesting that the standard errors and test statistics were no longer valid even asymptotically.

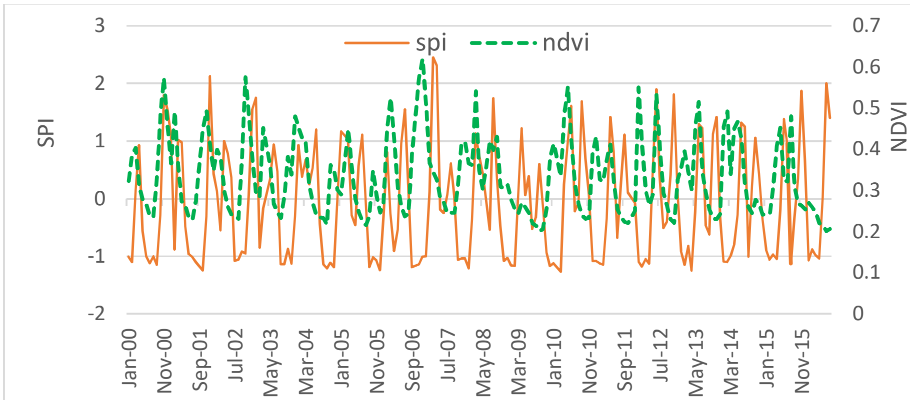

Fig 2: Normalized Difference Vegetation Index and Standardized Precipitation Index patterns in Chyulu-Amboseli rangeland

Table 1: Regression Analysis using Lagged Normalized Difference Vegetation Index for Chyulu-Amboseli

	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	C	0.244	0.021	11.528	0.000
	SPI	0.030	0.004	6.799	0.000
	NDVI (-1)	0.515	0.081	6.324	0.000
	NDVI (-2)	-0.218	0.068	-3.205	0.002
R-squared	**0.596**			Mean dependent var	0.336
Adjusted R^2	0.589			S.D. dependent var	0.096
Prob (F-statistic)	0.000				

Table 2: Breusch-Godfrey Serial Correlation test for Lagged Model

F-statistic	2.181			Prob. F (2,167)	0.116
Obs*R-squared	4.404			Prob. Chi-Square (2)	**0.111**
	Variable	Coef.	Std. Error	t-Statistic	Prob.
	C	0.019	0.032	0.591	0.554
	SPI	0.002	0.004	0.471	0.637
	NDVI (-1)	-0.188	0.137	-1.373	0.171
	NDVI (-2)	0.133	0.093	1.432	0.154
	RESID (-1)	0.261	0.137	1.902	0.058
	RESID (-2)	-0.046	0.105	-0.436	0.663
R-squared	0.025			Mean dependent var	-7.50E-18
Adjusted R^2	-0.003			S.D. dependent var	0.061
Prob (F-statistic)	0.501				

As a remedy, the first and second differences of NDVI (NVDI (-1) and NDVI (-2)) were used as independent variables in the autoregression model. By so doing the model was able to correlate the vegetation condition from the current month with that of the previous two months. The selection of the second lag was informed by model with the highest Akaike Information Criterion (AIC). Table 1 summarizes the results of this analysis, while Table 2 gives the corresponding test for serial correlation. The lagged model was highly significant with P-value = 0.00 implying that the long-time relation between NDVI and SPI were not by chance. The resultant R^2 improved to 0.60 suggesting that 60% of the vegetation greenness can be explained by drought for that particular month as well as that of the previous two months. Our results closely mirror those of Karnieli *et al*. (2010) who found a significant relationship between drought and vegetation response with an R^2 of 0.69, 0.51, and 0.61, while Ji and Peters (2003) found an R^2 of 0.58. The impacts of drought on vegetation persist for a period of up to two months, implying that following a drought event, it takes up to 2 months for vegetation to regenerate. These results are critically important in designing measures to assuage drought effects in drylands. Our lag period is longer than the 3 months reported by Udelhoven *et al*., (2009) due to differences in vegetation response to drought human factors, and the structural features of the vegetation (Musau *et al*., 2018).

Conclusion: On the basis of the results presented in this paper, drought appears to be the greatest factor contributing to vegetation greenness in the Chyulu-Amboseli rangeland accounting for 60 per cent of changes in vegetation conditions. The results further reveal that after drought occurrence vegetation takes up to two months to regain its vigour. This knowledge is critically important in informing policy and designing programmes on drought management in rangelands. In particular, measures to cope with drought events must consider the two months lag period if they are to be effective.

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