Climate Change, Savanna grassland, Autoregressive model, Time series data

OLILA, Dennis Opiyo, Oliver V. Wasonga

Invited paper presented at the 5th International Conference of the African Association of Agricultural Economists, September 23-26, 2016, Addis Ababa, Ethiopia

Time Series Analysis and Forecasting of Carbon Dioxide Emissions: A Case of Kenya's Savanna Grasslands

OLILA, Dennis Opiyo*, Oliver V. Wasonga

Department of Land Resource Management and Agricultural Technology

University of Nairobi, Kenya

P.O. BOX 29053-00625, NAIROBI, KENYA

E-mail: oliladennis@gmail.com

Abstract

Climate change and climate variability is perhaps one of the major challenges facing the world today. There is an equivocal agreement that climate change is not only a threat to the economies of developing world, but also to those of the developed economies. One of the key drivers of global warming is the greenhouse gas (GHG) emissions. Even though several studies have in the recent past evaluated various sources of GHG emissions and their associated impacts, little empirical information exists on the role played by burning savanna grasslands as far as global warming is concerned. This study is an attempt to determine the emission pattern over time and consequently forecast the linear trend in GHG emissions from the Kenya' Savanna. Using Autoregressive (AR) modelling, the study analyzes and forecasts time series data ranging from the year 1993 to 2012. The key finding of the study indicate that emissions resulting from continual burning of Savanna grasslands will continue in an upward trend if no serious mitigation measure is put in place to revert the statusquo. Averting the current state of affairs requires policies aimed at reducing the levels of GHGs in the atmosphere for instance promotion of Climate Smart Agricultural (CSA) Practices.

Key words: Climate Change, Savanna grassland, Autoregressive model, Time series data

1. Introduction

Ending poverty and addressing climate change are perhaps the two defining challenges facing the world (World Bank 2016). The recent twenty-first session of Conference of Parties commonly dubbed Paris agreement report that climate change represents an urgent and potentially irreversible threat to human societies and the planet and therefore requires countries to cooperate in terms of adaptation and mitigation (UNFCCC, 2015). There is unequivocal evidence that climate change and climate variability is real and its negative effects are already manifested in different parts of the world (Jianjun *et al*., 2015). According to the United Nations Convention to Combat Desertification (UNCCD 2009), climate crisis is one of the greatest challenges facing the world with indications depicting change as occurring faster compared to previous predictions. The threats posed by climate change are likely to change the food security equation particularly in developing countries where its impacts are more prominent. According to Pandey and Jha (2012), climate change and extreme events has adversely impacted on the functioning of the ecosystems and provisions of environmental goods and services critical for livelihoods.

It is common knowledge that climate change and climate variability impacts are more rampant in developing nations (Ndegwa *et al.*, 2011). Moreover, it has now emerged that the impacts of climate variability are likely affect livelihoods living in fragile environments such as the Arid and Semi-Arid (ASALs) regions of the world (Jat *et al.*, 2012). Similarly, Ngigi *et al*. (2016) and Knaepen *et al*. (2015) argue that severe impact of climate variability will be felt in Sub-Saharan Africa where a significant portion of land fall under ASALs. This is likely to be exacerbated by the fact that Africa's agricultural systems are highly climate dependent.

In the Kenyan context, empirical evidence such as that done by Mwenzwa (2011) point out that four-fifths of Kenya's is classified as ASALs. Indeed, this current state of scenario has negative implications of agricultural transformation agenda. Specifically, the Kenya's Vision 2030 and the second Medium term Plan (MTP II) recognizes agriculture as one of the flagship project under economic pillar. According to the second Republic of Kenya (2013), agricultural sector employs approximately 3.8 million Kenyans directly on the farm, livestock production as well as fishing. Additionally, statistics indicate that about 4.5 million Kenyans are employed in off-farm informal sector activities. However, despite the positive progress made by agricultural sector in creation of employment opportunities, climate change and climate variability is posing a serious threat to this positive progress.

Climate change and variability in Kenya's drylands has manifested in various forms. For instance, land degradation is a major impediment to building resilience among dryland livelihoods (Wasonga *et al.*, 2009). In addition, deforestation, loss of soil nutrient as well as reduction in ecosystem services resulting from declining ecological integrity are some of the impediments to agricultural productivity in the Kenyan ASALs. Consequently, building resilient livelihoods capable of combating the inevitable climate variability has drawn a lot of interest among Governments all over the world. For instance, Kenya's National Climate response

Strategy aims at strengthening and focusing nationwide actions towards climate change adaptation and Green House Gas (GHG) emission (GoK 2010).

Climate change and climate variability jeopardizes economic and social progress in many sectors of the economy. For instance, IPCC (2014) indicate that Africa is the most vulnerable continent globally and climate change and climate variability is already impacting the agricultural sector negatively. The reduction in viable agricultural land and food production is likely to impact the poor and marginalised groups such as subsistence farmers in rural areas as well as the urban poor (CUTS, 2014). Interestingly it has been shown that climate change also impacts trade particularly in agricultural products. This emanates from the fact that it impedes the supply side thus hampering farmers' ability to have the surplus for sale.

In the phase of climate change and climate variability, the consequence of global warming has drawn a lot of interest among policy makers and government world over. For instance, the Intergovernmental Panel on Climate Change (IPCC, 2007) synthesis report argue that warming of climate system is unequivocal with indications of increases in global average air and ocean temperatures, widespread melting of snow and ice accompanied by rising average sea levels. Further, IPCC (2007) posit that some of the key drivers of climate change are the increase in global GHG emissions. In regard to this, the recently adopted Paris agreement takes into cognizance the fact that reducing global emissions will play a key role in achieving the goal of the convention while at the same time emphasizing the need for addressing climate change (UNFCCC, 2015).

According to Nhemachena and Hassan (2008), mitigation efforts to combat climate change by reducing sources of GHG's and enhancing sinks is usually a progressive process. The GHG emissions are attributed to anthropogenic activities that have grown since pre-industrial era. According to Thomas *et al.*(2009), global warming observed over the past fifty years is primarily due to human-induced emissions of heat trapping gases in the atmosphere. Moving away from the Millennium Development Goals (MDGs) and embracing the Sustainable Development Goals (SDGs) requires countries to incorporate climate change programmes into their development strategies and policies. According to the study done by Osborn *et al.* (2015) where developing countries ranked SDGs by level of transformational challenge, SDG thirteen (13) namely taking urgent action to combat climate change and its impacts was ranked number one with an average target score of 7.1. This suggests that climate change should be given priority by developing countries as they come up with plans and strategies to implement the SDGs in their countries.

In the Kenyan context, issues of climate change and whether variability continues to surface the government's top agenda as far as economic development and prosperity is concerned. According to the Kenya National Climate Change Action Plan 2013-2017, changes in climate presents one of the most serious global challenges (GoK, 2013). The key aim of the aforementioned plan is to address the unprecedented challenge of climate change impacts as well as reducing the socio-economic losses (GoK, 2013).

According to Kenya's National Climate Change Response Strategy, climate change is a key threat to sustainable development globally (GoK, 2010). A study by Parry *et al.*(2012*)* argues that Kenya is characterized by a complex climate that varies significantly between the coastal, interior and highland regions. In addition, Climate change and weather variability have in the recent past manifested in terms of seasonality in both temperature and rainfall patterns (GoK 2010). There is a unanimous agreement that one common cause of climate change is GHG emissions. For instance, IPCC (2014) acknowledges that the recent anthropogenic emissions of GHGs is the highest in history. This evidence reinforces that of IPCC (2007) indicating that global GHG emissions grew by 70 percent between 1970 and 2004. Generally, one of the key anthropogenic GHG is Carbon Dioxide (CO_2). Other known GHGs arising from human activities are methane (CH_4) and Nitrous Oxide (N_2O).This calls for the need for adaptation particularly in Africa where a majority of the population are vulnerable to climate shocks (Nhemachena and Hassan, 2008).

Even though emission of GHGs into the atmosphere is historically known to result to global warming, there is limited empirical information on sector specific evolution of GHG emissions over the years in many countries. It is common knowledge that GHGs cause global warming phenomenon. Global warming is the continuing rise in the average temperature of earth's climate system. Generally, GHG emissions brought about by combustion of fossil fuels in industries have significantly contributed to global warming. According to IPCC (2007), global increases in CO_2 are attributed to fossil fuel and land use change that provides a smaller amount though a significant driver of climate change in the long-term. Agricultural sector is believed to contribute to global warming through emissions of methane ($CH_{4)}$ and Nitrogen Dioxide (N_2O) (IPCC 2007). Other GHGs include water vapor (H_2O (g) as well as Ozone (O_3).

It is now clear that the activities of human beings are perhaps the major cause of global warming. The most obvious and visible impact of global, warming has been witnessed in the rising earth's average temperatures since the genesis of industrial age. Other impacts are manifested in the reduction in quality of atmosphere, longer summers, shorter and warmer winters, inconsistent rainfall patterns in the tropics, irregular floods and storms among others.

Even though GHG's are largely attributed to industrial emissions, it is increasingly becoming clear that burning of Savanna Grasslands significantly contributes to global warming through emission of CO_2 (g). This is what we term as the "unforgotten contributor of global warming". In addition, Savanna fires cause disturbance to fauna as well as pollution through the smoke. Importantly, Savanna fires if not well managed would significantly contribute to global warming. According to Trollope (2007), there is a serious deficiency of knowledge concerning the behavior of fires particularly in the context of Savanna grasslands.

In the Kenyan context, burning of Savanna grasslands is an indigenous practice aimed at regenerating new grass with uniform and good growth. This is done with less consideration on the role it plays as far as global warming is concerned. This problem is enhanced by the fact that over the years, marginalization of such regions has taken root. Even though a plethora of empirical research has been done in the Kenya's Savanna grassland, there is limited empirical evidence on time series emission patterns and future projections as well as the likely contribution to global warming. To understand how fires influence and interact with Savanna ecosystem, quantitative information on time series patterns and forecasting of GHG emissions resulting from burning of Kenya's Savanna grassland is vital.

2. Overview of Savanna Grassland GHG emissions

The drylands of Africa, exclusive of hyper-arid zones occupy 43 percent of the continent, and are a home to a rapidly growing population of approximately 325 million (UNCCD, 2009). A majority of people inhabiting the drylands are mainly pastoralists and agro-pastoralists. Even though the key livelihood activity is pastoralism, dryland agriculture is gaining recognition. With the evolution of Climate Smart Agriculture (CSA) concept, a lot of interest is focused on building resilience of livelihoods through adoption of CSA practices. According to the Food and Agricultural Organization of the United nations, CSA refers to agriculture that sustainably increases productivity, resilience, reduces GHGs, and enhances the attainment of national food security and development goals (FAO, 2010).

Generally, a majority of dryland livelihoods live under conditions of abject poverty owing to resource limitation as well as fragility of the environment to both endogenous and exogenous shocks. As pointed out by Olila *et al*. (2015), risk and uncertainty are ubiquitous in Kenya's agricultural system thereby calling for appropriate risk management mechanisms such as crop and livestock insurance. However, amidst these challenges, agro-pastoralists have an opportunity of reducing potential damage by making tactical responses to the inevitable climate change and climate variability (Nhemachena and Hassan (2008).

Savannas grasslands are tropical ecosystems having a continuous grass layer and discontinuous canopy of trees and shrubs. According to O'Higgins (2007), population growth in the savannas have led to the intensification of land use thus threating livestock production besides impacting negatively on the livelihoods. In addition, managing savanna grasslands resources places a huge challenge among resource managers. The existence of equilibrium and non-equilibrium paradigms within the ASALs further present management challenges (Nyangito *et al.*, 2015). For instance, the stock of grass and the rate of harvest (usage by cattle) may exhibit dynamic behavior including deterministic chaos where steady state equilibrium is never reached.

One of the key contributors of GHG emissions in the context of Savanna grassland is the inevitable fires. According to the Global Fire Monitoring Center (GFMC, 2004), fire is a widespread seasonal phenomenon in Africa with Savanna burning accounting for 50 percent. Generally, fires are started by lightening, volcanoes as well as anthropogenic factors (FAO, 2001). The burning of Savanna grasslands by humans contributes to global warming. In the context of pastoral livelihoods, burning of savanna grassland is known to possess merits such as stimulating grass growth for livestock while subsistence agro-pastoralists use fire to clear unwanted biomass as well as eliminating unused residues after harvest (GFMC, 2004). According to the Global Forest Fire Assessment Report of 1990 – 2000, indicate that fires play a myriad of roles including regulating plant succession, regulating fuel accumulations, controlling age, structure of species composition of vegetation, as well as influencing nutrient cycles and energy flow among others (FAO, 2001).

Other studies by Sheuyange *et al.* (2005) point out that anthropogenic fires in the African continent is an antiquity form of environmental disturbance. The burning have shaped savanna vegetation more than any other human induced disturbance (Sheuyange *et al.*, 2005). This implies that burning of savanna grasslands dates back to many centuries in Africa. The indigenous people used indigenous knowledge to determine when to set the grasses on fire for the reasons that confer benefits to the communities. For instance Walters *et al.* (2010) report that in some parts of the world, fires was the primary tool used to subsist; used as hunting technique, grazing, gathering, agriculture and thus linked to survival of humanity. Interestingly, despite the benefits conferred by burning, currently, emphasis on ecosystem management calls for the maintenance of interactions between fire disturbance processes vis a vis ecosystem functions (FAO, 2001).

Over the years, savanna grasslands have evolved with fires creating a unique adaptation. Walters *et al.* (2010) argue that there exists a strong nexus between anthropogenic fire regimes and society. In other words, social change is a key driver on how fire is used in the savanna. One of the most common justification for continual use of fire is that it contributes positively to biodiversity as well as enhancing forage growth. For instance Walters *et al*. (2010) posit that burning particularly during dry season plays a significant role in maintaining biodiversity. Similarly, FAO (2001) indicate that fire is key in regulating biotic productivity, diversity and stability as well as determining the habitat for wildlife.

The evolution of Savanna ecosystems with fires has indeed a plethora of benefits as outlined in the various empirical literatures. Indeed, past scholars have played a vital role in unveiling the significance of fires in the context of grassland burning. Despite the benefits derived from ecosystem management using fires, little attention seems to focus on the negative impacts posed by Savanna fires. Some of the negative benefits of fire within savannas are livelihood disruption, mortality among livestock and destroying soil organisms. The little focus on the demerits of savanna fires is pegged on the marginalization of such drylands in many regions of Africa, Kenya included.

According to FAO (2001), understanding of fire effects is increasingly becoming important to land managers since the disturbance caused by fires is closely linked to the concept of ecosystem management. In simple terms, ecosystem management refers to conservation of environmental goods and services with an objective of ensuring delivery of goods and services for the benefit of current and future generations.

This study attempts to understand the evolution pattern of GHG emissions from Kenya's' grassland. Second, the study forecasts the time series emissions data to give a glimpse of how the situation will be under business as usual scenario. Ultimately, we unpack the nexus between such emissions and the current policy debate on global warming. Although there have been a growing attention among researchers, policy makers, as well as governments on the importance of reducing GHG emissions (UNFCCC, 2015), linking Savanna grassland fires and global warming has been given limited attention.

Therefore, the contributions of this study are three fold as far as the on-going global debate on climate change and climate variability is concerned. First, it establishes the dynamic pattern of carbon emissions within the Savanna grassland ecosystem. Second, simulating carbon emission pattern is imperative for *ex-ante* formulation of relevant policy to reduce the levels of emission. Finally, the study contributes to the thin body of existing on the role of fires in shaping Savanna grassland in Kenya.

3. Methodology

3.1 Data

In this study, we use time series secondary data of emissions from Kenya's Savanna grassland during the period 1993 - 2012. The data was retrieved from the Food and Agricultural Organization of the United Nations statistics website (FAOSTAT). The emissions are measured in Gigagrams (Gg). A Gg refers to a decimal multiple of the base unit of mass in the international System of Units (SI) kilogram, which is defined as being equal to the mass of the international prototype Kilogram. Note that 1 Gg is equal to 10^6 Kg.

3.2 Model specification

A time series is a collection of observations made sequentially through time (Chatfield, 2000). Similarly, Maddala (1992) refers to time series as sequence of numerical data in which each item is associated with a particular instant in time. Generally, these observations are spaced at equal time intervals. Some examples of time series data comprise rainfall and temperature data over time, greenhouse gas emissions over time, sales of a product in successive months, and trade data among others. The main objective of analysis of time series data is to find a mathematical model capable of explaining data behavior. Following Nemec (1996), the objective of time series analysis range from data summary and prediction, model development and parameter estimation, prediction of future values, as well as detection description or removal of trend and cyclic components.

A growing interest in comprehending the behavior of time series data emanates from the need to predict the future values of the series. Understanding the future values (forecasts) of time series data is vital for *ex-ante* policy formulation and planning. According to Chatfield (2000), time series data provides an excellent opportunity to look at *out of sample* behavior (forecasted values), thus providing an opportunity to benchmark with the actual observations. For instance, forecasting of GHG emissions enables formulation of appropriate policies aimed at reducing emissions thus enhancing efficient decision-making process.

From econometric context, we use an autoregressive (AR) model. An AR model is one where a variable is regressed on itself by one lag period. Chatfield (2000) stipulates that a process (x_t) is said to be an autoregressive process of order p (abbreviated $AR(p)$) if it is a weighted linear sum of the past p values plus a random shock formulated as:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_p x_{t-p} + z_t \qquad (1)$$

Where z_t denotes a purely random process with zero mean and variance σ_z^2. If the backward shift operator B such that $Bx_t = x_{t-1}$. It is important to note that the backward shift operator has the effect of changing the period t to a period $t-1$. The $AR(p)$ model is formulated as follows:

$$\phi(B)x_t = z_t \qquad (2)$$

Where $\phi(B) = 1 - \phi_1 - \phi_2(B^2) - \ldots - \phi_p B^p$ is polynomial in B of order p. According to Chatfield (2000), the properties of AR processes defined by equation (1) is examined by focusing on the properties of the function ϕ. Since B is an operator, the algebraic properties of ϕ have to be investigated by examining the properties of $\phi(x)$, where x denotes a complex variable rather than by looking at $\phi(B)$.

It can be shown that equation (2) has a unique causal stationarity solution if the roots of $\phi(x) = 0$ lie outside the unit circle. The solution is follows the following formulation:

$$x_t = \sum_{j \geq 0}^{\infty} \varphi_j z_{t-j} \qquad (3)$$

Taking into cognizance that for some constants φ_j should conform to $\sum \left|\varphi_j\right| < \infty$. Equation (3) above simply postulates that AR process is stationary provided the roots of $\phi(x) = 0$ lie outside the unit circle.

Generally, the simplest is the first order formulated as:

$$X_t = \phi X_{t-1} + Z_t \quad (4)$$

It is imperative to note that the stationarity of AR times series is crucial as far as time series analysis is concerned. This is possible if the following condition if $|\phi| < 1$ is satisfied. One way to test for stationarity is the use of Autocorrelation Function (ACF)

According to Chatfield (2000), the ACF of stationarity $AR(1)$ process is given by $\rho_k = \phi^k$ for $k = 1,2,...n$. The ACF is a convenient way of summarizing the dependence between observations in a stationary time series (Nemec, 1996). It is vital to note that when it comes to higher order stationarity AR processes, the ACF is a mixture of terms which cline exponentially. In order to obtain ACF, a set of difference equations commonly referred to as Yule-Walker equations are applied. Yule-Walker equation is formulated as:

$$\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + ... + \phi_k \rho_{k-p} \quad (5)$$

Where $k = 1,2,...n$, $\rho_0 = 0$. One of the important useful property of $AR(\rho)$ process is the ability to show that the partial ACF is zero at all lags greater than ρ; implying that the sample ACF can be used to determine the order of an AR process. This is done by focusing the lag value at which the sample's partial ACF "cuts-off" i.e. should be approximately zero or at least not significantly different from zero for higher lags (Chatfield, 2000).

4. Results and discussions

4.1 Graphical representation of GHG emissions

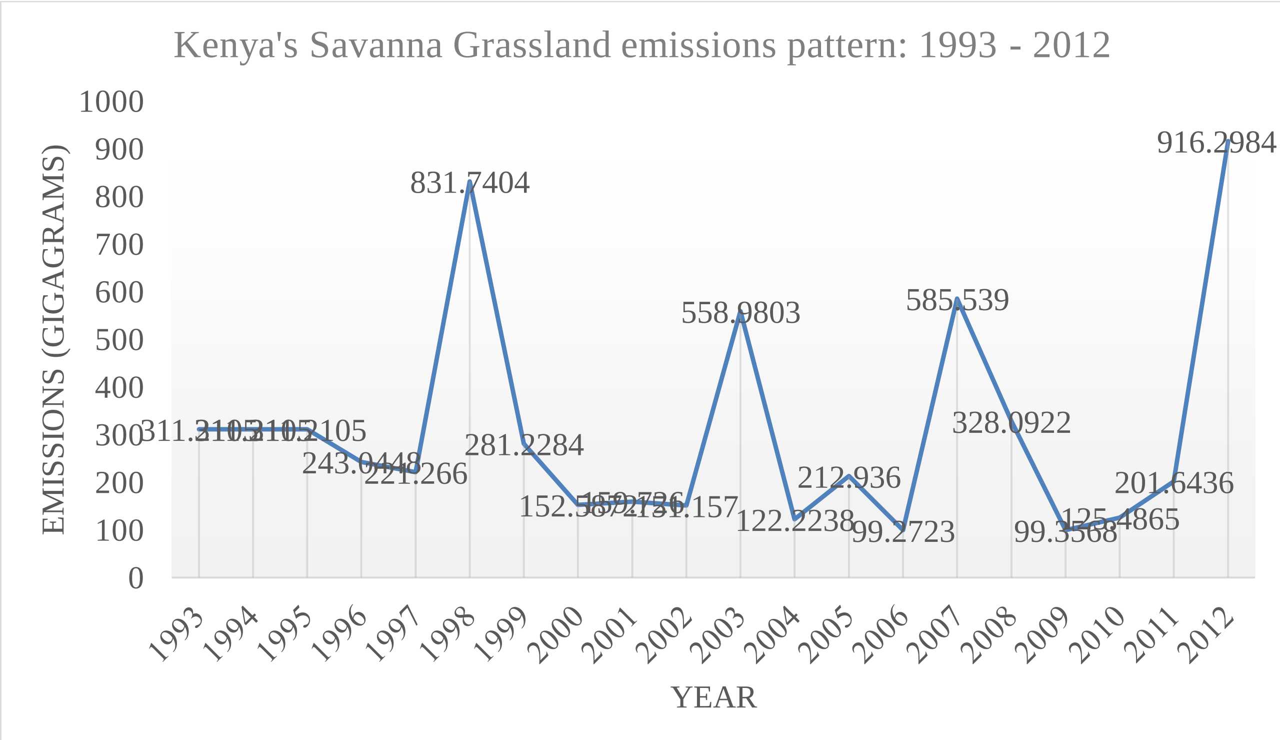


Figure 1: Savanna grassland GHG emissions from 1993 – 2012 in Kenya.

Data source: FAOSTAT

Figure 1 shows the pattern of GHG emissions from Kenya's Savanna grassland. The graph indicates that there has been variability in the level of emissions. For instance, between 1993 and 1997, there was no significant variation in emissions. However, it is evident that much fluctuations began during after 1997. During the year 1998, emissions level increased significantly from 221 to 832 gigagrams (Gg). Interestingly, between 1999 and 2002, there emission levels reduced significantly. Other peaks in emission level are evident during 2003, 2007 and 2012. During the year 2012, the emission level rose to 916 Gg. representing the highest ever under the period of study. For a summary of descriptive statistics (see table 1).

Table 1: Descriptive statistics of emissions from Kenya's Savanna grassland

Minimum	Maximum	Range	Mean	Median	Variance	Skewness	Kurtosis
99.2723	916.298	817.026	311.211	232.155	54897.2	1.01222	3.74187
N=20							

4.2 Results of AR model

Table 1 shows the results of the AR model. The estimation of the AR model follows the regression of the emission variable y_t over its lags. Specifically, the AR model was formulated in Eviews version 9 statistical software as $y_t\ c\ y_t$ (-1 to -3)... (6)

Where y_t is the dependent variable, c is the constant term y_t (-1 to -3) represents the lags of the dependent variable by periods one, two and three respectively.

Table 2: AR model results

Variable	Coefficient	Std. Error	t-statistic	Prob.
Constant	742.247	178.688	4.154	0.001
YT(-1)	-0.375	0.295	-1.272	0.226
YT(-2)	-0.509	0.289	-1.760	0.102*
TT(-3)	-0.629	0.303	2.077	0.058**
R-Squared		0.344		
Adjusted R-Squared		0.193		
S.E Regression		229.335		
Log likelihood		-114.240		
F-statistic		2.277		
Prob (F-statistic)		0.128*		
Durbin-Watson stat		1.977		

Table 2 shows the results of the AR (dynamic) model. Data analysis was done by using The Least Squares Method (LSM). The AR model is the preliminary model estimated before forecasting is done. The existence of a relatively high R-squared value (34%) in the estimated model is an important pre-condition for forecasting of time series data. The value of R-squared is an indicator of model fitness. In simple terms, 34 percent of the variation in the dependent variable y_t is accounted for by the lags i.e. the three lags as indicated in equation six (6). However, Greene (2008) point out that R^2 as a measure of goodness of fit suffers from challenges relating to degrees of freedom used in estimating the parameter. In regard to this, R^2 does not decrease as one adds additional variable thus resulting in improper goodness of fit. This implies that one can push R-squared value higher simply by adding more regressors (Greene, 2008). Further, our regressors are statistically significant at ten and one percent thereby conforming to the normal guideline that at least 50 percent of the variables should be statistically significant for the model to be acceptable. Interestingly, the F-statistic and the corresponding probability value is statistically significant at 10 percent.

Even though the results of the AR preliminary model are acceptable, the model has to be tested further for serial correlation. We therefore use Breusch-Godfrey Serial Correlation LM test to determine whether seral correlation exists of not. The results are as indicated in Table 2 below.

Table 3: Results of serial correlation test

Breusch-Godfrey Serial Correlation LM Test			
F-statistic	1.528	Prob. F(2,11)	0.260
Obs*R-squared	3.696	Prob.Chi-square (2)	0.158

Results show that the probability value of the observed R-squared (0.158) is statistically insignificant. This implies non-existence of serial correlation thus leading to failure to reject the null hypothesis. The existence of no serial correlation in the model is indeed a good indicator as far as the usefulness of the model is concerned in time series forecasting.

In order to validate the finding of non-existence of serial (autocorrelation), the study uses the correlogram approach. Drawing from the work of Nemec (1996), the correlogram or sample autocorrelation function is obtained by replacing $COV\left(y_t, y_{t-k}\right)$ and $Var\left(y_t\right)$ in the true autocorrelation function with the corresponding sample covariance formulated as:

$$\hat{ACF}(k) = \frac{\sum_{t=1}^{n-k}\left(y_t - \bar{y}\right)\left(y_{t+k} - \bar{y}\right)}{\sum_{t-1}^{n}\left(y_t - \bar{y}\right)2} = r_k \quad \text{...} \quad (7)$$

Thereafter, the autocorrelation coefficient r_k is plotted against k. If the estimates are reliable, then the sample size n should be large relative to k with the assumption of non-existence of outliers in the data set. The correlogram results are as presented graphically (see figure 2), the AC values above are close to zero.

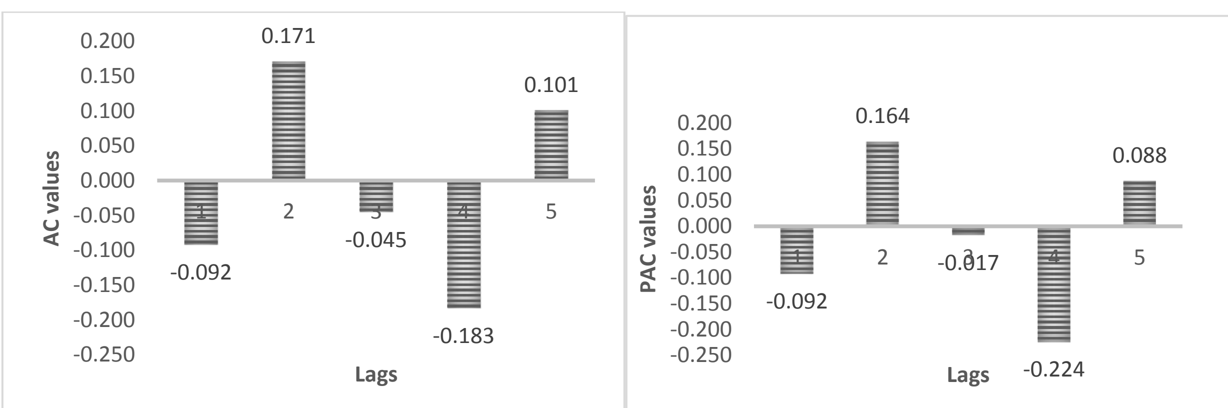


Figure 2: AC and PAC functions respectively.

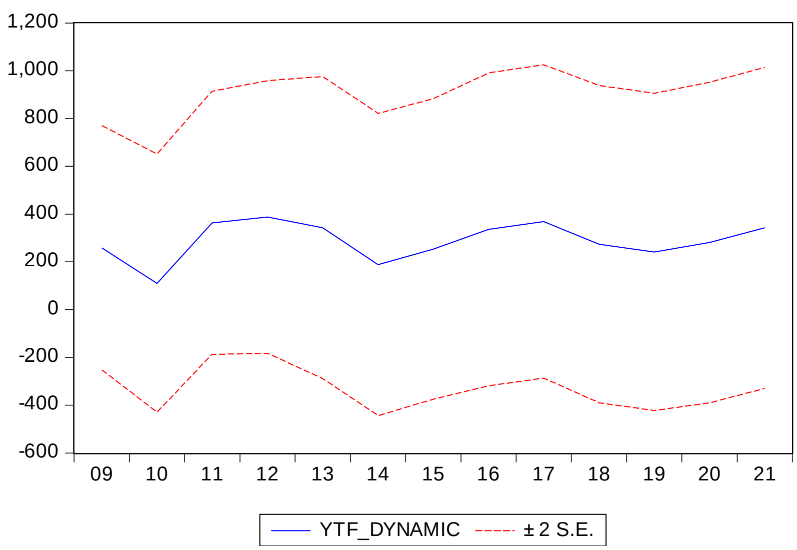
According to Nemec (1996), the sample ACF for a purely random or "white noise: series should be zero for all non-zero lags. In addition, a time series with a trends, the ACF should fall slowly as the number of lags increase. Conversely, a time series with seasonal or cyclic component exhibits a correlogram with oscillatory pattern (Nemec, 1996). This is the case of the aforementioned correlogram in the context of this study. However, even though the correlogram indicate no serial correlation, we confirm the results using Q-statistic values. Focusing on the p-values of the Q-statistics, it is evident that they are greater than 5 percent degree of statistical significance. Therefore, we fail to reject the null hypothesis of no serial correlation in the model. The existence of no serial correlation therefore implies that our model is fit for forecasting.

Table 4: Correlogram results

Lag	AC	PAC	Q-stat.	Prob.
1	-0.092	-0.092	0.172	0.678
2	0.171	0.164	0.805	0.669
3	-0.045	-0.017	0.852	0.837
4	-0.183	-0.224	0.682	0.794
5	0.101	0.088	0.955	0.855

4.3 Forecastig results

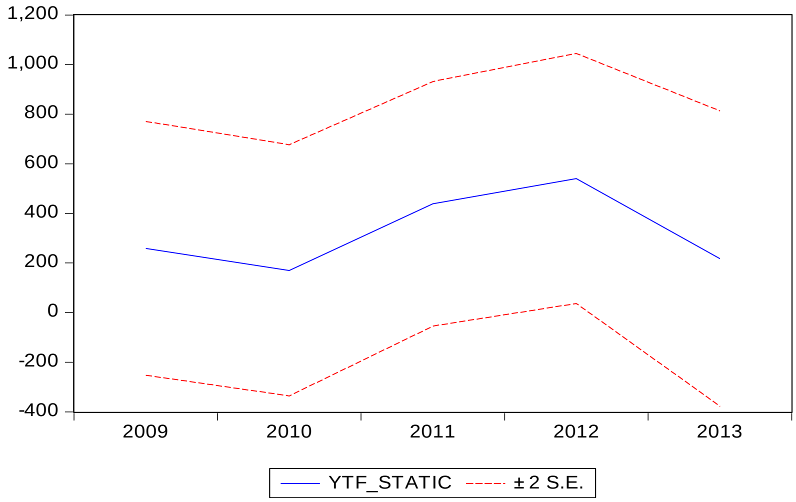
The study used both dynamic and static forecasting techniques. The actual GHG emissions data was from the year 1993 to 2012. The out of sample forecasting covers the period of 2009 to 2021. This implies that the forecasting will cover twelve years. Figure 3 shows some values of forecasting evaluation.



Forecast: YTF_DYNAMIC	
Actual: YT	
Forecast sample: 2009 2021	
Included observations: 4	
Root Mean Squared Error	287.8816
Mean Absolute Error	216.2889
Mean Abs. Percent Error	77.63285
Theil Inequality Coefficient	0.370845
Bias Proportion	0.037641
Variance Proportion	0.627843
Covariance Proportion	0.334515

Figure 2: Forecast of equation YTF_Dynamic

The values on the right side of the graph are known as forecasting evaluation. One of the most critical values is the Root Mean Square Error (RMSE) and the smaller the value the better the predictability of model. In other words, the RMSE offers the basis for benchmarking the forecasted model since it measures the gap between the actual value and the forecasted value. The blue line is the forecasted value of the dependent variable YT sandwiched between the 95 percent confidence interval. The fact that the forecasted equation passes through 95 percent confidence interval is important aspect of forecasting. Figure 4 presents the values of forecasting using a static model.



Forecast: YTF_STATIC
Actual: YT
Forecast sample: 2009 2021
Adjusted sample: 2009 2013
Included observations: 4

Root Mean Squared Error	237.0838
Mean Absolute Error	204.1879
Mean Abs. Percent Error	88.61850
Theil Inequality Coefficient	0.276740
Bias Proportion	0.004672
Variance Proportion	0.654240
Covariance Proportion	0.341088

Figure 3: Forecast of equation YTF_Static

The values of the static model also indicate that the forecasted equation lies between the 95 percent confidence levels with a RMSE of 237.08. The static model has a smaller RMSE as compared to the dynamic model meaning that a static model has exhibits a greater predictive power. Figure 5 shows a combination of both dynamic and static forecasting.

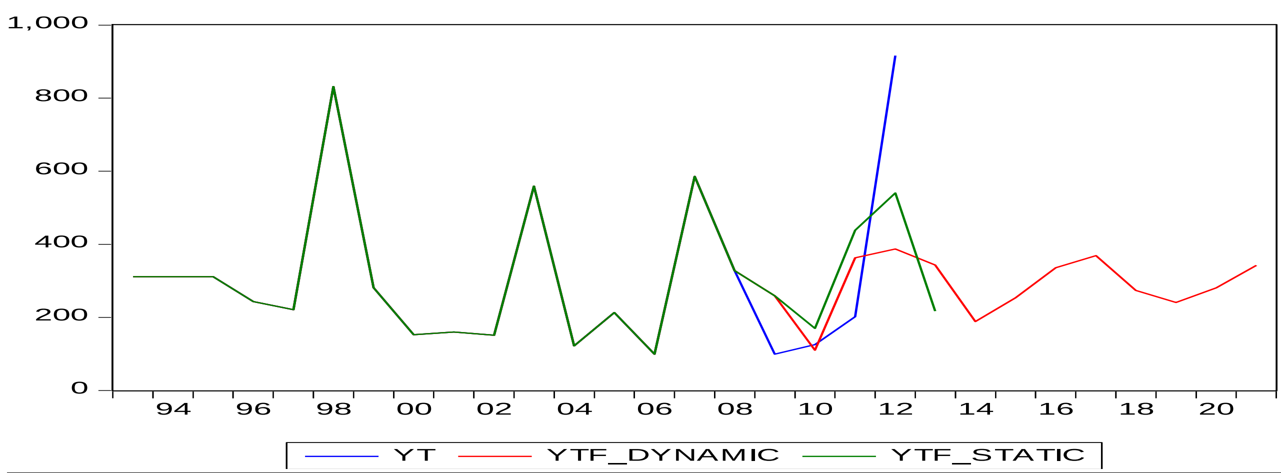


Figure 4: Dynamic and static forecasting.

It is evident from the results of figure 5 that both static and dynamic forecasting are moving towards a similar trend. However, it is worth pointing out that static forecasting only allows to prediction by one year ahead while dynamic forecasting allows several years. However, one has to be careful how far to project since as you proceed much into the future, the values may not be accurate owing from the uncertainty.

Table **5: Trend analysis Model Summary for Savanna emissions**

R	R-Squared	R-Squared Adjusted	Sum Squared Error (SSE)	Mean Squared Error (MSE)
0.06195	0.999023	0.999023	1039044.834	57724.71298
N = 20				

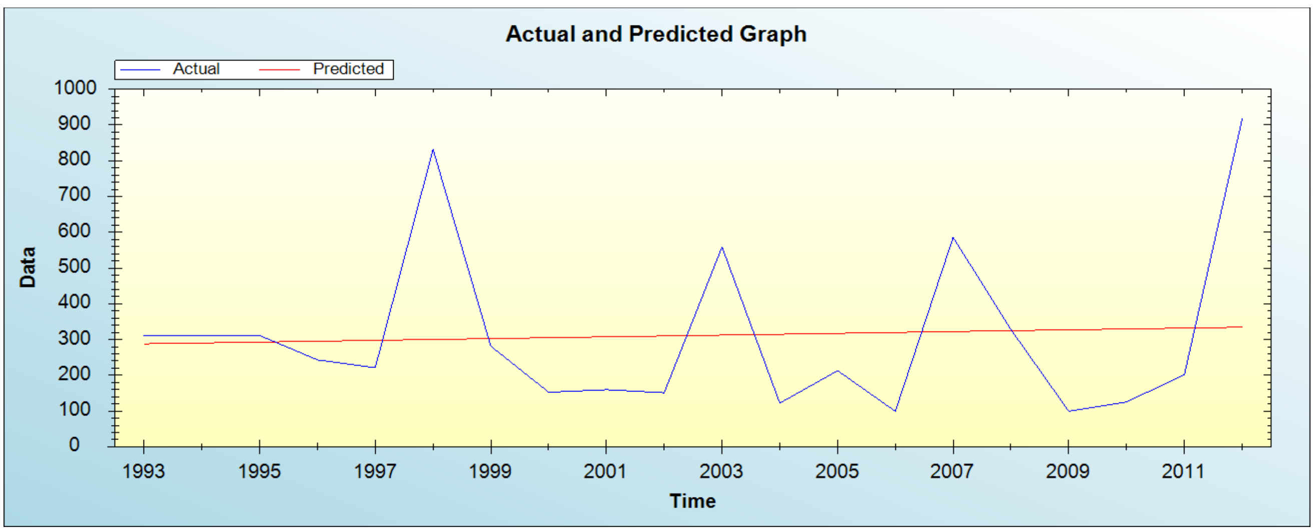


Figure 5: Actual and predicted graph

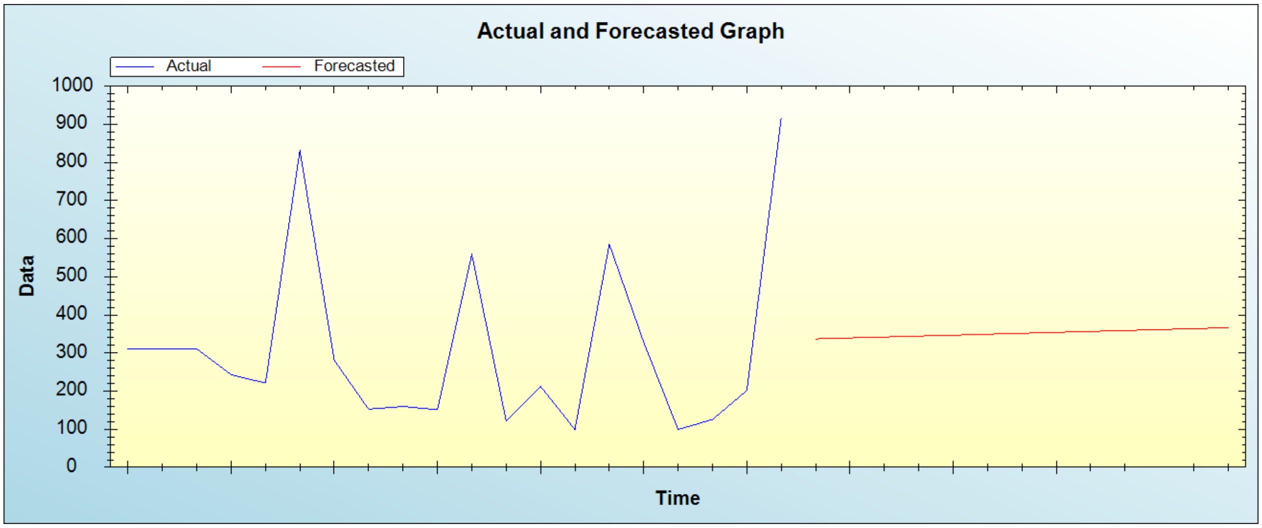


Figure 6: Actual and forecasted graph (No differencing)

When we carry out seasonal differencing with logarithm base 10, the following results are gotten.

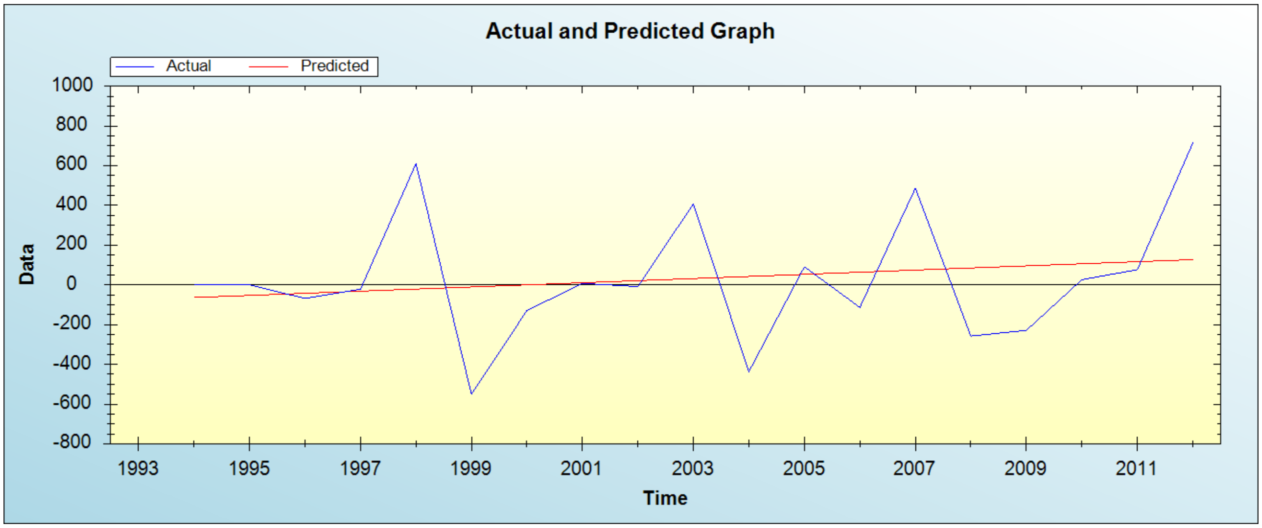


Figure 7: Actual and predicted after differencing

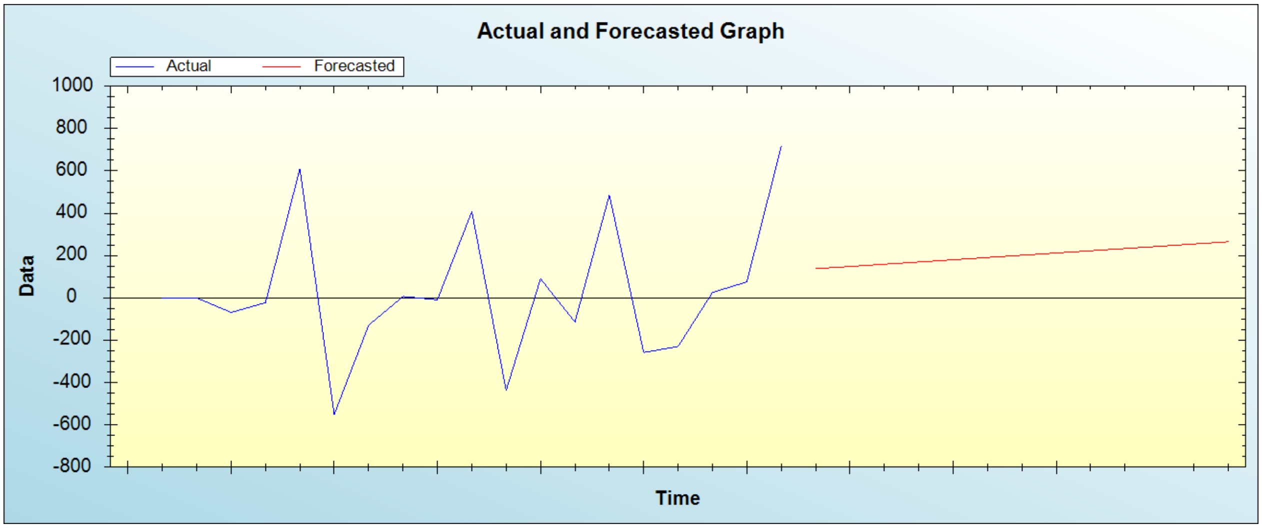


Figure 8: Actual and forecasted after differencing

The figure below presents the results of neural network with sigmoid and bipolar sigmoid as activation functions respectively.

Table 6: Results of the neural network

Activation function	Iteration	Error	MAE	MSE
Sigmoid	10,000	0.006	35.93	3174
Bipolar Sigmoid	10,000	0.001	5.568	103
Semi Linear	10,000	0.0078	51.693	3628.6

Table 7: Neural Network Model summary

Input layer neuron	9
Network architecture	
Hidden layer neurons	12
Output layer neurons	1
Back propagation learning	
Learning rate	0.05
Momentum	0.5
Criteria	
Error	0.0078
MSE	3628.6
MAE	51.693
Included observation (after adjusting endpoints)	10

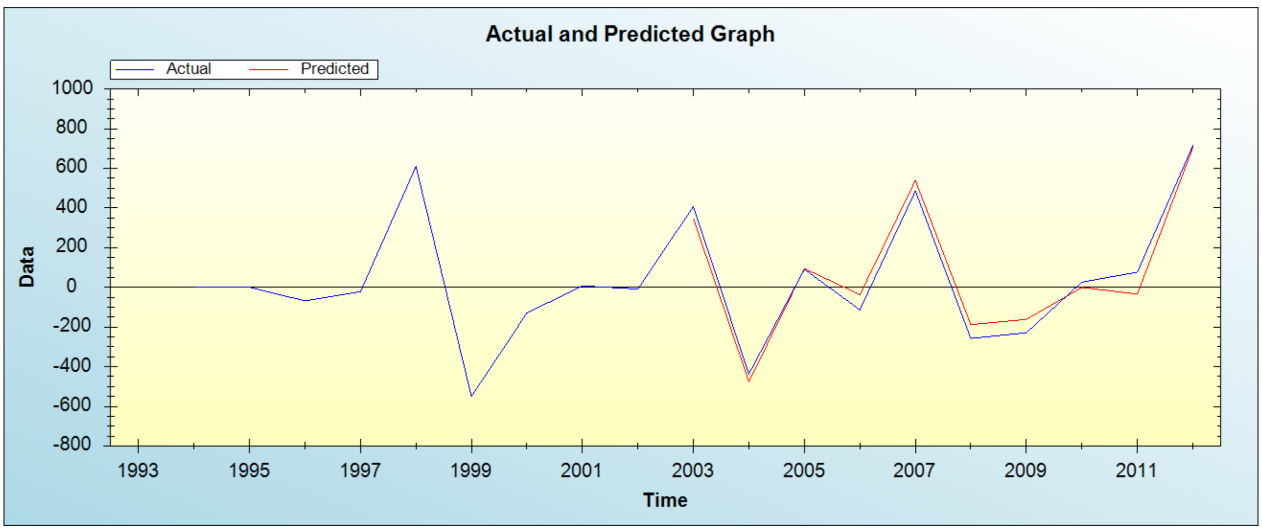


Figure 9: Actual and predicted neural network model

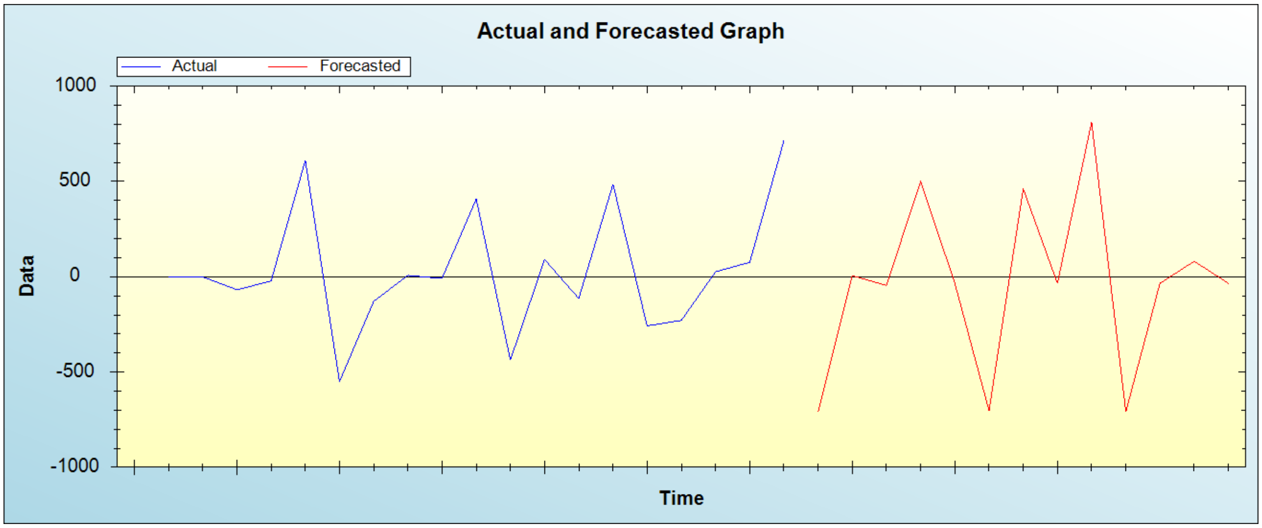


Figure 10: Actual and forecasted Neural Network model

5. Conclusions and policy recommendation

Following the findings of this study, it is evident that under business as usual scenario, GHG emissions from Savanna grasslands will continue posing threat not only to the dryland livelihoods but also to the global arena at large. This is due to the fact that GHG emission is an international negative externality with no boundaries. The study envisages that if the worrisome trend is not addressed, it is likely to reinforce poverty among pastoralists and agro-pastoralists. In terms of the policy, the government should take acute measures to ensure that GHG emission from such vulnerable environments is reduced significantly. Further, promotion of the adoption of Climate Smart Agriculture (CSA) technologies will play a key role in reducing the impact of emissions. Such CSA technologies include conservation agriculture, agroforestry among others.

References

Chatfield, C., 2000. *TIME-SERIES FORECASTING*,

CUTS, 2014. *Climate Change , Food Security and Trade : Evidence from East African Community*,

FAO, 2010. Climate-Smart Agriculture: Policies, Practices and Financing for Food Security, Adaptation and Mitigation. , p.49. Available at: http://www.fao.org/docrep/013/i1881e/i1881e00.htm.

FAO, 2001. *Global forest fire assessment 1990-2000*,

GFMC, 2004. *Wildland Fire Management Handbook for Sub-Sahara Africa*,

GoK, 2010. National Climate Change Response Strategy National Climate Change Response Strategy. , (April).

Greene, W.H., 2008. *ECONOMETRIC ANALYSIS* Sixth. David Alexander, ed., Pearson eDUCATION, Inc,.

IPCC, 2007. *Climate Change 2007 Synthesis Report*,

IPCC, 2014. Climate Change 2014 Synthesis Report Summary Chapter for Policymakers. *Ipcc*, p.31.

Jat, R.A. et al., 2012. Climate change and resilient dryland systems : experiences of ICRISAT in Asia and Africa. *Currenty Science*, 102(12).

Jianjun, J. et al., 2015. Land Use Policy Farmers ' risk preferences and their climate change adaptation strategies in the Yongqiao District , China. *Land Use Policy*, 47, pp.365–372. Available at: http://dx.doi.org/10.1016/j.landusepol.2015.04.028.

Knaepen, H., Torres, C. & Rampa, F., 2015. *Making agriculture in Africa climate-smart From continental policies to local practices*,

Maddala, G.S., 1992. *Introduction to* Second., Canada: Maxwell Macmillan.

Mwenzwa, E.M., 2011. Dryland farming and food security in Kenya : challenges and research priorities. , 41, pp.5832–5836.

Ndegwa, W., Ngugi, R.. & Laishena, J., 2011. *Mapping vulnerability of climate variability on agriculture systems in machakos and makueni counties*,

Nemec, A.T.L., 1996. *Analysis of Repeated Measures and Time Series: An Introduction with Forestry Examples*,

Ngigi, M.W., Mueller, U. & Birner, R., 2016. *Gender differences in climate change perceptions and adaptation strategies: an intra-household analysis from rural Kenya*,

Nhemachena, C. & Hassan, R., 2008. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *AfJARE*, 2(1), pp.83–104.

Nyangito, M.., 2015. Range use and dynamics in the agropastoral system of southeastern Kenya. *African Journal of Environmental Science and Technology*, 2(8), pp.222–230.

O'Higgins, R.C., 2007. Savannah Woodland Degradation Assessments in Ghana : integrating ecological indicators with local perceptions . *Earth & Environment*, 2893, pp.246–281.

Olila, D.., Nyikal, R.. & Otieno, D.., 2015. *AN ASSESSMENT OF MAIZE FARMERS' PREFERENCES FOR CROP INSURANCE FEATURES IN TRANS-NZOIA COUNTY, KENYA*. University of Nairobi, College of Agriculture and Veterinary Sciences.

Osborn, D., Cutter, A. & Ulla, F., 2015. *UNIVERSAL SUSTAINABLE DEVELOPMENT GOALS: Understanding the Transformational Challenge for Developed Countries*,

Pandey, R. & Jha, S., 2012. Climate vulnerability index - measure of climate change vulnerability to communities: a case of rural Lower Himalaya, India. *Mitig ation and Adaptation Strategies for Global Change*, 10(2), pp.487–506.

Parry, J.-E. et al., 2012. *Climate Risks, Vulnerability and Governance in Kenya: A review*, Available at: http://www.preventionweb.net/files/globalplatform/entryhttps://www.google.com/?gws_rd=ssl#q=climate+change+in+Kenya+pdf.

Republic of Kenya, 2013. *The Second Medium Plan (MTP II, 2013 - 2017)*,

Sheuyange, A., Oba, G. & Weladji, R.B., 2005. Effects of anthropogenic fire history on savanna vegetation in northeastern Namibia. *Journal of Environment Management*, 75, pp.189–198.

The Republic of Kenya, 2013. *National Climate Change Action Plan 2013 -2017*,

Thomas R. Karl, J.M.M. and T.C.P. (eds), 2009. *Global Climate Chnage Impacts in the United States*, Available at: http://www.ncbi.nlm.nih.gov/pubmed/15003161.

Trollope, W.S.W., 2007. Fire—a key factor in the ecology and management of African grasslands and savannas. *Proceedings of the 23rd Tall Timbers Fire Ecology Conference: Fire in Grassland and Shrubland Ecosystems*, pp.2–14.

UNCCD, 2009. Climate change in the African drylands. , p.-.

UNFCCC, 2015. *Conference of Parties: Twenty-first Session*,

Walters, B.G. et al., 2010. *Savanna burning yesterday and today in Gabon ' s Bateke Plateaux : foraging-fires and ecosystem effects*,

Wasonga, O. V., Nyariki, D.M. & Ngugi, R.K., 2009. *Linkages between Land-use , Land Degradation and Poverty in Semi-Arid Rangelands of Kenya : The Case of Baringo District*. University of Nasirobi.

World Bank, 2016. *Shock waves: Managing the Impacts of Climate Change on Poverty*,