IOSR Journal of Humanities And Social Science (IOSR-JHSS)
Volume 25, Issue 7, Series 4 (July. 2020) 17-31
e-ISSN: 2279-0837, p-ISSN: 2279-0845.
www.iosrjournals.org

Predicting and Forecasting of Changes in Weather Patterns in the CoastalLowlands along the Western Indian Ocean Shoreline, Kenya

Bertha Othoche[1], Maarifa Mwakumanya[2], Tunje Joseph[3], Kiti Lenard[4]
[1]*(Department of Environmental Science, Pwani University, Kenya)*
[2]*(Department of Environmental Science, Pwani University, Kenya)*
[3]*(Department of Environmental Science, Pwani University, Kenya)*
[4]*(Department of Mathematics and Computer Sciences, Pwani University, Kenya)*

ABSTRACT
Background: This study assessed weather variability and climate change in the coastal lowlands along the western Indian ocean coastline, Kenya. The aim of the study was to establish the trend of rainfall and temperature and their variations as indicators of climate change. The objectives of the study included: i) To determine the trend and variability of rainfall in the coastal lowlands along the western Indian ocean coastline, Kenya; ii) To determine the trend of land and sea temperatures in the coastal lowlands along the western Indian ocean coastline, Kenya iii) To forecast and predict future trends in rainfall using ARIMA model and Holt-Winters Forecasting method in the in the coastal lowlands along the western Indian ocean coastline Kenya.
Materials and Methods:A retrospectiveresearch design was used to obtain long term data from meteorological stations to establish the emerging trends.Rainfall and temperature data for a period of 37 years from 1975 to 2015 was used. The study used descriptive statistics and time series model. Predictive model (ARIMA) and Holt-Winters forecasting method were used to establish future trends.
Results: The results from analysis of rainfall and temperature showed a strong seasonality within each year, and some strong cyclic behavior. Mean rainfall was 923.6 with a standard deviation of over 429.2. Time series and ARIMA Predictive Model used in forecasting the rainfall trends indicated marginal positive and negative anomalies in the next six years in the study area.
Conclusion: The study concludes that there are observed manifestations of weather variability and climate change in the form of erraticand poorly distributed rainfall as well as increasing temperatures in the study area. This trend requires closer monitoring for informed decisions in sectors that are closely associate with weather patterns such as agriculture, transport, tourism, sports and other socio-economic and cultural activities.
KEY WORDS: Climate Change, Weather Variability, ARIMA Model, Forecasting, Prediction, Indicators of Climate Change, Seasonality, Manifestations.

Date of Submission: 18-06-2020 Date of Acceptance: 06-07-2020

I. INTRODUCTION

This study focused on weather variability and climate change in the coastal lowlands of the weather Indian Ocean coastline in Kenya. These lowlands have experienced weather patterns associated with both the dry land and the Indian ocean seas surface processes. The lowlands share the shoreline or coastline of the western part of the Indian Ocean. The exact study areas included Tana River and Tana Delta sub-counties in the coastal lowlands in Kenya. The local communities in these areas have experienced adverse weather patterns which have affected them adversely.There is therefore the need for research that would inform policies and decisions in addressing the adverse impacts of climate change and weather variability.

Weather and climate variability includes variations in the mean state and other statistics of climate on all temporal and spatial scales and which are beyond individual events. Climate variability is therefore measured by deviations (anomalies) from the general patterns of climatic elements over the years. Variability may be due to natural processes within the climate system (internal variability), or due to variations in natural or anthropogenic external factors (external variability). Climate change on the other hand is a change of climate attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which in addition to natural climate variability over comparable time periods. It is a significant and long lasting change in the statistical distribution of weather patterns over periods ranging from a decade to millions of years (Blast, 2010). It is a change in the average distribution of weather conditions, including the distribution of extreme weather events on the earth's surface. The most significant elements of climate that are associated with climate change and also addressed in this study are temperature and rainfall. Climate change and weather variability have been attributed to both natural and anthropogenic factors. The natural factors include oceanic, tectonic, radiation and biotic processes, (Stern & Kaufmann, 2014). Human induced alteration of global atmospheric conditions has led to accumulation of greenhouse gases that act as a blanket thereby trapping terrestrial radiation and eventually warming the lower atmosphere.

Indeed, components of climate change process include natural influence, human activities, direct and indirect changes in climate drivers, radiative forcings as well as climate perturbation and response (Goose, et al 2010). The climate forcings, natural forcings and human forcings have resulted in the process of global warming which shows no signs of decreasing and is expected to bring about long term changes in weather patterns, as global warming continues over the years, (Hughes, et al, 2017; Goose, et al 2010). A climate forcing is an imposed perturbation of the earth's energy balance whose consequences include change in global temperatures.Evidence of climate change are inferred from changes in indicators that reflect climate, such as sea level rise and the climate and weather variability to include rainfall variability; erratic rainfall, that is, the rains coming either too early or too late, ending abruptly or prolonging beyond the seasons, rainfall being too little or too much; and increase in temperature conditions. Earth observations by NOAA have showed that the year 2018 was the fourth hottest year in NOAA's 139-year climate record (Meng, et al, 2019). Indeed, the five hottest years have occurred since 2015.Other evidence of climate change includes changes in agricultural production, as well as changes in water resources, low water volumes and drying of wells (Petit *et al*.,1999; Hughes*et al*.,2018). Manifestations of climate change have been captured in literature from different parts of the world including Russia, USA, Canada, and India (Seneviratne, 2006; (Seneviratne, 2006;Rasmijn et al., 2018; Rosenzweig, 2008; Rushydromet, 2015; Agafonova et al., 2017;Schwartz, 2003; Jones, 2007;Radić, & Hock, 2011; Choi, et al 2009).

In Africa, it has been established that climate change contributed or resulted in a 30% loss of corals in the western Indian Ocean region between 1997 and 1998 which resulted in financial losses of about US$ 12-18 million, (Funk et al., 2008). The changes affected the endangered animal and bird species associated with these ecosystems (Funk et al., 2008).Other manifestations of climate change have been observed in other countries in Africa such as Ethiopia, Aklilu&Desalegn (2013); and Botswana, Kulthoum, (2010), (Kulthoum, 2010;Rossati, 2017). In Kenya climate change manifests itself in the form of warming of ocean surface waters (Darling, et al, (2010). The Indian Ocean waters along the shoreline of Kenya, have warmed by 0.2 to 0.7°C since the early 1900s, (WWF, 2013; WWF, 2008; Nyamwaro et al., 2015; Kizito, et al.,2015; Silvestri, et al., 2012; 2015 and Senaratna et al., 2015; Leauthaud, 2012; GoK, 2009; 2014; 2018; Amuyunzu-Nyamongo, et al, 2011).

Climate models which are simplified mathematical representations of the Earth's climate system have been developed to help understand the changing climatic conditions by simulating or imitating the components and processes at work in an actual climate system (Harper, 2018; (IGPCC-TGCIA, 1999; Seneviratne, 2006; Rushydromet, 2015; Agafonova et al. (2017). The national and global community have recognized the changing climatic conditions and the likely adverse impacts, hence have put in place measures and strategies to address the same. Examples of global effort include the establishment on climate change related bodies including the United Nations Framework °Convention on Climate Change, (UNFCCC), Intergovernmental Panel on Climate Change, (IPCC); United Nations Environmental Program, (UNEP);and World Meteorological Organizations, (WMO), among others. There a number Protocols that have also been put in place to address climate change and weather variability. Notable exmpale is the Kyoto Protocol which extended the 1992 UNFCCC committing countries to reduce greenhouse gas emissions and hence address aspects of global warming. Through the various Conference of Parties, (COPs), and especially the 2015 Paris Agreement, the international community to engage strategies to limit global greenhouse gas emissions to 2°C above preindustrial levels and thereafter aim at limiting increase of the harmful gases to 1.5°C.

II. MATERIALS AND METHODS

Study Design: Retrospective research design was used in the study. It is where the outcome of interest has occurred at the time the study is initiated. This design enables the researcher to formulate ideas about possible associations and investigate potential relationships.

Study Location: The study was carried out in the coastal lowlands along the western Indian Ocean coastline in Kenya.

Study duration: January – December 2014

Sample Size: The study was based on secondary data on rainfall and temperature for a period of 37 years and sea surface temperatures for on a period of 37 and 55years

Procedure methodology

Research variables included weather elements of temperature and rainfall as observed over a longer period of time. The study used probability sampling method. Purposive sampling technique was used to identify the study area and to select a meteorological station that would give data on the meteorological variables of temperature and rainfall. The main meteorological station located in the coastal region of Kenya and within the vicinity of the study areais Kipini. Another main meteorological station along the coastline in the neighboring regions which was also used was Msabaha.

Statistical Analysis

Data analysis was done using descriptive statistics. Descriptive statistics were used to calculate average values, establish trends in rainfall, temperature and crop yields. ARIMA model and Holt-Winters Holt-Winters forecasting method were used to predict future rainfall trends. The main statistical and data analysis tool or software used was Microsoft Excel. The results were presented in thematic and graphical forms.

III. RESULT

Thissection present results or findings on weather variability and climate change in the study area. The section covers rainfall and temperatures trends as climatic and weather variables. The aim is to observe the trend in order to capture any significant variability that would inform opinions on whether the study area is experiencing climate change beyond the allowable climatic variability perimeters.

Rainfall Distribution

The annual rainfall in coastal lowlands along the Indian Ocean shoreline in Kenya shows strong seasonality over the period between 1975 to 2014 year and 1960-2015 from two different stations. There is no apparent trend in the data over this period, Figure 1. The results show that rainfall in the study area is erratic and unpredictable as marked fluctuations are observed over the 37-year period. This observation has also beenmade and exist in literature supporting views that fluctuations in the patterns of weather elements of temperature and rainfall, especially when they are frequent and prolonged are manifestations of climate change (Byg&Salick, 2009; Asante, et, al 2017; Sousa, et al 2010).

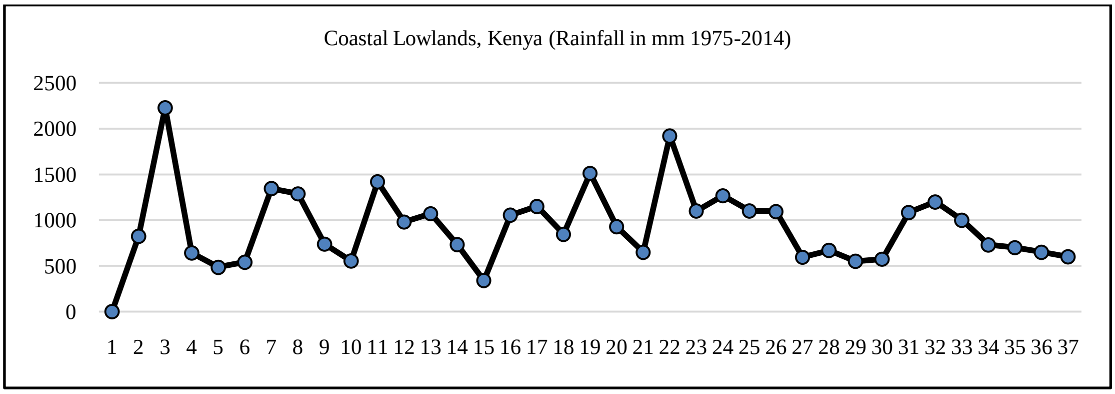

Figure 1: Rainfall Distribution in the Coastal Lowlands, Kenya

Scatter diagram for rainfall in the coastal lowlands, Kenya also confirms the variabilityof rainfall with existing extremes of outliers. Highest values were recorded between 1960 to the year 2000. A downward trend is seen between the year 2000 and 2015. (Figures 2).

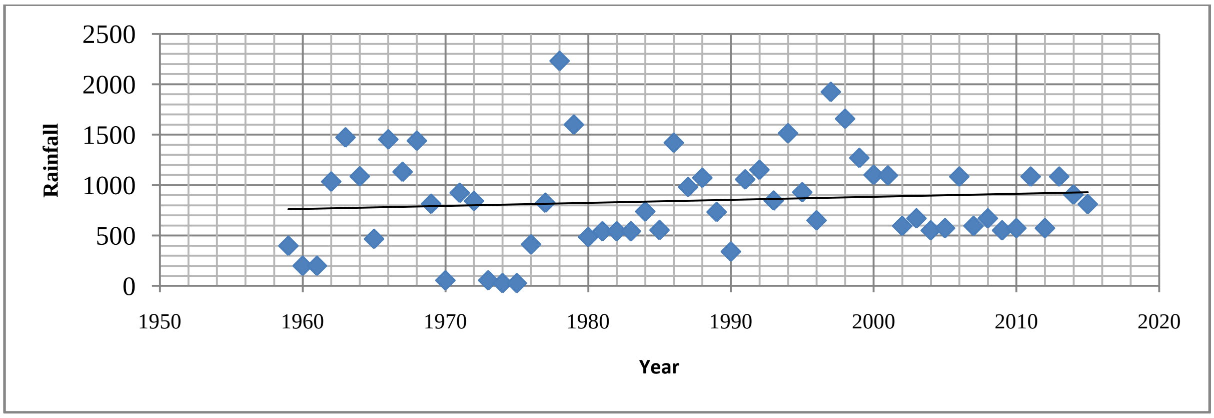

Figure 2: Rainfall Variability in the Coastal Lowlands, Kenya (1959-2015)

Forecasts of Rainfall in the Study Area Using Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA Modelis usually fitted to time series data to enhance level of understanding of the data in question. It is also used to predict future scenarios hence is useful in forecasting. According to this model, the value of time series today depends on the lagged or historical values, hence history is used to predict the future. The ARIMA Model is based on certain assumptions. The first assumption is that data should be stationarymeaning that the properties of the series don't depend on the time when it is captured. A white noise series and series with cyclic behaviour can also be considered as stationary series. The second assumption is that the data should be univariate since ARIMA works on a single variable. Auto-regression is all about regression with the past values. This is illustrated in the Figure 3.

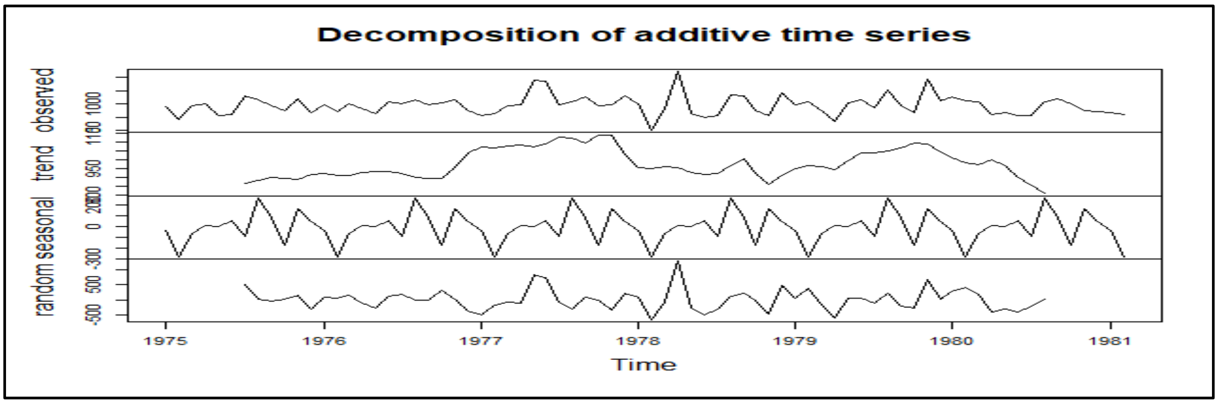

Figure 3: ARIMA Model Random Seasonal Trend Observed

From the figure above, it can be inferred that the data points have no trend but have some outliers in terms of sudden higher values between 1978 and 1979. The figure gives 4 components to include:

i) Observed – the actual data plot
ii) Trend – the overall upward or downward movement of the data points -no obvious trend in the data
iii) Seasonal – any monthly/yearly pattern of the data points -there are seasonal variations in the data
iv) Random – unexplainable part of the data

Figure 4 shows the autocorrelations of residuals and partial autocorrelations of residuals. The figure shows that there are no significant autocorrelations between the observed values of the time series and the lagged values. The data is therefore stationary. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was conducted to check for stationarity of the time series.

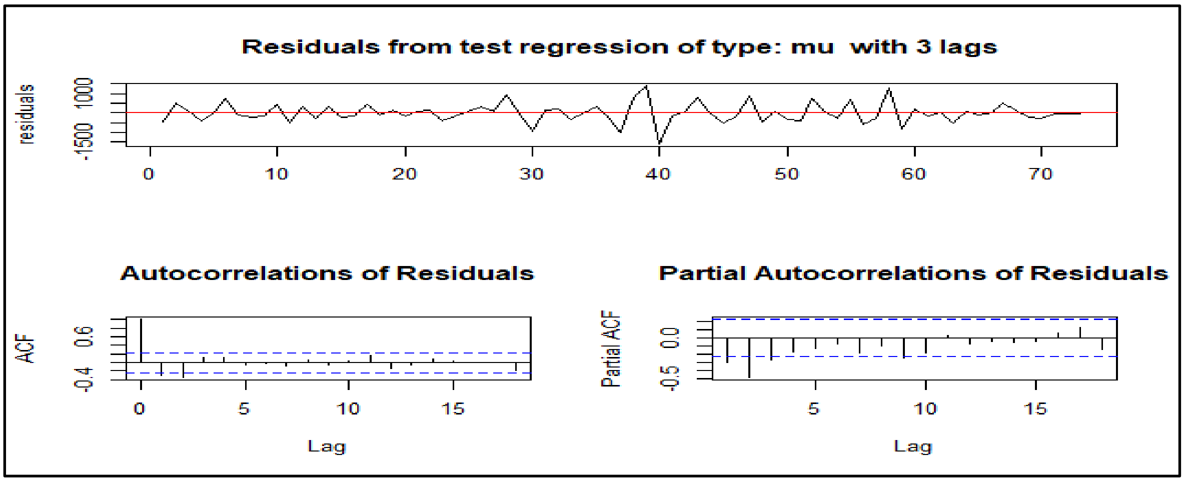

Figure 4: Autocorrelations of Residuals and Partial Autocorrelations of Residuals

After satisfying all the assumptions of modelling, a model was fitted to the data. This was done by finding the three variables: p, d, and q which are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. Going through Table 1, it is possible to determine the type of the ARIMA Model to select and establish what the values of p, d and q are.

Table 1: Types of ARIMA Models

Shape	**Indicated Model**
Exponential Series Decaying to Zero	Autoregressive Model. Partial autocorrelation function will be used to identify the order of the model
Alternative positive and negative spikes decaying to Zero	Autoregressive Model. Partial autocorrelation function will be used to identify the order of the model
One or more spikes in series, rest are all zero	Moving Average model, Identify order where plot becomes zero
After a few lags, overall a decaying series	Mixed Autoregressive and Moving average model
Total Series is Zero or nearly Zero	Data is Random
Half values at fixed intervals	We need to include a seasonal Autoregressive term
Visible spikes, no decay to zero	Series is not stationary

Choosing the Best Model

The method used to estimate the ARIMA model is the maximum likelihood estimation (MLE). It tries to maximize the log-likelihood for given values of p, d, and q when finding parameter estimates so as to maximize the probability of obtaining the data that has been observed. As a start an ARIMA (1,1,1) was fit to the data. Table 2 shows the coefficients of the model.

Table 2: Coefficients of the ARIMA Model

	Estimate	Standard Error	Z-value	p-value	95% CI	
AR1	0.148963	0.117026	1.2729	0.2031	-0.08040481	0.3783303
MA1	-1.000000	0.045355	-22.0485	<2e-16 ***	-1.08889286	-0.9111062
SAR1	-0.101623	0.117779	-0.8628	0.3882	-0.33246453	0.1292195

This process was then done recursively with different (p,d,q) values to find out the most optimized and efficient model.The Akaike's Information Criterion (AIC) for a set of models were found and investigated and the models with lowest AIC value selected. Another criterion that was used is the Schwarz Bayesian Information Criterion (BIC) where the model with lowest BIC values is selected. When estimating model parameters using maximum likelihood estimation, it is possible to increase the likelihood by adding additional parameters, which may result in over fitting. The BIC resolves this problem by introducing a penalty term for the number of parameters in the model. Along with AIC and BIC, there is also need to closely watch those coefficient values and decide whether to include that component or not according to their significance level. Table 3 shows the models under recursion and the final model chosen.

Table 3: Models Under Recursion

Model		**AIC**
ARIMA(2,0,2)(1,0,1)[12]	with non-zero mean	1095.798
ARIMA(0,0,0	with non-zero mean	1089.885
ARIMA(1,0,0)(1,0,0)[12]	with non-zero mean	1092.159
ARIMA(0,0,1)(0,0,1)[12]	with non-zero mean	1090.711
ARIMA(0,0,0)	with zero mean	1236.948
ARIMA(0,0,0)(1,0,0)[12]	with non-zero mean	1091.262
ARIMA(0,0,0)(0,0,1)[12]	with non-zero mean	1091.179
ARIMA(0,0,0)(1,0,1)[12]	with non-zero mean	1093.375
ARIMA(1,0,0)	with non-zero mean	1090.831
ARIMA(0,0,1)	with non-zero mean	1089.548
ARIMA(0,0,1)(1,0,0)[12]	with non-zero mean	1090.786
ARIMA(0,0,1)(1,0,1)[12]	with non-zero mean	1093.004
ARIMA(1,0,1)	with non-zero mean	1089.669
ARIMA(0,0,2	with non-zero mean	1087.817
ARIMA(0,0,2)(1,0,0)[12]	with non-zero mean	1089.254
ARIMA(0,0,2)(0,0,1)[12]	with non-zero mean	1089.182
ARIMA(0,0,2)(1,0,1)[12]	with non-zero mean	1091.523
ARIMA(1,0,2)	with non-zero mean	1089.981
ARIMA(0,0,3	with non-zero mean	1089.894
ARIMA(1,0,3)	with non-zero mean	1091.606
ARIMA(0,0,2)	with zero mean	1166.675
Best Model: ARIMA (0,0,2) with non-zero mean		
Coefficients:		
ma1 ma2 mean		
0.1678 -0.2227 949.8904		
s.e. 0.1149 0.1099 39.2218		
σ^2estimated as 131370: log likelihood=-539.62		
AIC=1087.24 AICc=1087.82 BIC=1096.45		

Diagnostic measures

This involves finding out the pattern in the residuals of the chosen model by plotting the ACF of the residuals, and doing a portmanteau test. Once the residuals look like white noise, the forecasts can be calculated.

Final forecasting using an ARIMA Model

The parameters of the ARIMA model can be used as a predictive model for making forecasts for future values of the time series once the best-suited model is selected for time series data. The forecasts for the next 6 years are shown in the Figure 5. The figure shows that in the next six years there will be slight upward and downward fluctuations in rainfall patterns.

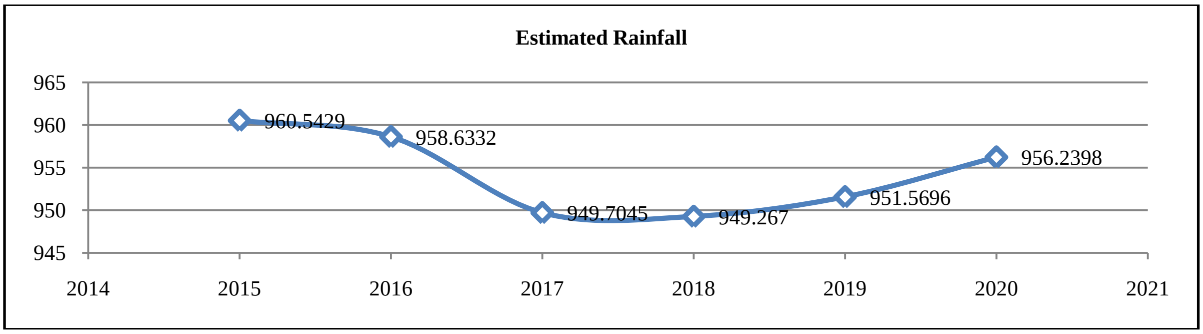

Figure 5: Estimated Rainfall (Average Rainfall Forecasts for Coastal Lowlands, Kenya) for the Next Six Years

Temperature variability/distribution in the study area

The distribution of temperature in the study area shows some relatively weak fluctuations in the annual temperatureover the period between 1975 to 2014 year.The averagetemperature was 34.784 with a standard deviation of 0.5838. Figure 6 gives the general trend of temperature in the study area.

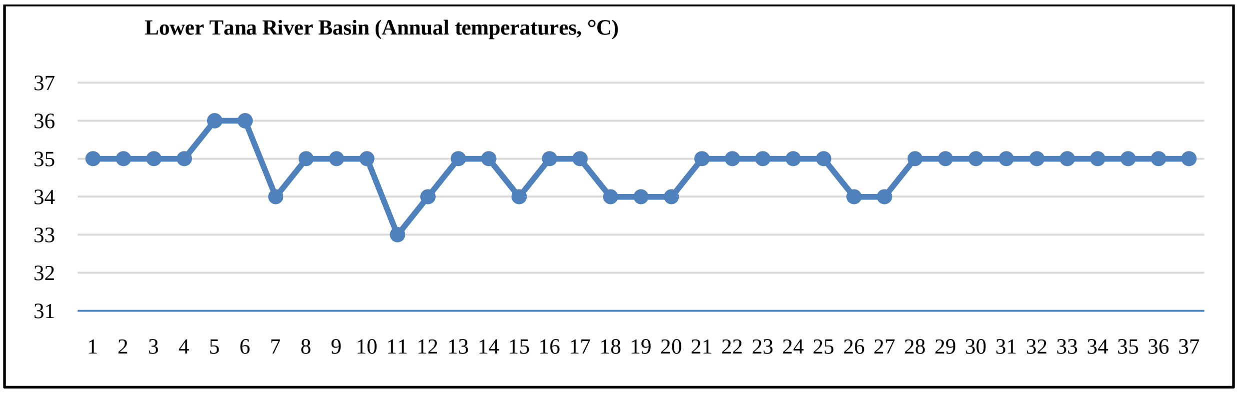

Figure 6: Temperature Distribution in the Coastal Lowlands, Kenya

Temperature variability is further ascertained using scatter diagrams, Figure 7. Scatter diagram for temperature shows a positive trend with a slight annual increase. Both maximum and minimum values are slightly on the upward trend. The period of 1980s recorded the highest values while the lowest temperatures were recorded in the late 1980s.The trend of temperature has remained upward since 2015.

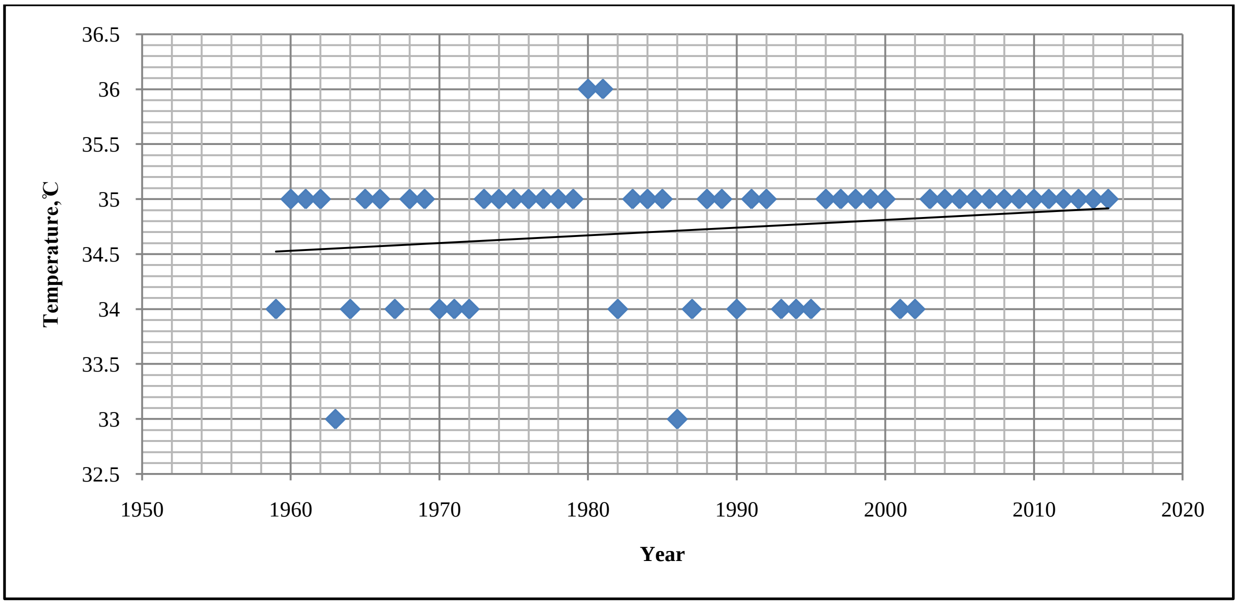

Figure 7: Temperature variability for the Coastal Lowlands, Kenya

Increasing trend in temperatures is a manifestation of climate change. The very slight upward fluctuations translate into changing environmental conditions that cause alarm at the global arena. The COP 15 requires nations to reduce the margin of production of GHGs in order to retain the temperature conditions to a level that will not accelerate global warming and hence reduce the side effects.

Trends of sea surface temperatures in the study area

Studies have shown that the oceans have warmed up from the upper layers to 700 meters below sea level by 0.59°C in the last 135 years (Roemmich*et al*, 2012). Generally, the average temperature of the ocean surface waters is about 17°C. Temperature and salinity affect the density of water. This results in water moving up or down through the ocean layers as currents around the ocean. As the oceans absorb more heat, sea surface temperature increases and the ocean circulation patterns that support cold and warm water around the globe change. The changes in sea surface temperatures is caused by excess heat from greenhouse gases emissions. It means that the increasing temperature conditions have not only been experienced on land but also in the ocean. Research has indicated that ocean heat has risen drastically over the past decade leading to potential warming. The study area lies along the western Indian ocean coastline or shoreline. The Indian Ocean warming affects the Indian Monsoon which is one of the most important climate patterns in the world. The Indian ocean dipole events are becoming more common with the warming in the last fifty years. Models suggest a tendency for such events to become more frequent and stronger in the study area. Global heating is “supercharging” and this is an increasingly dangerous climate mechanism in the Indian Ocean that has played a role in disasters experienced in the year 2019 and which was characterized by floods in the study area (Beamont, P. and Readfearn, Graham 2019).

Summary statistics for the period 1981 t0 2019 indicate the mean temperature conditions are 27.44°C; the maximum and minimum temperatures values are 30.14°C and 24.979°C, respectively. The mode is 28; the standard deviation is 1.258 with a sample variance of 1.58; the range is 5.159. Figure 5 gives the trend of Indian ocean sea temperatures along the coastline of the study area. The Sea Surface Temperature for the study area’s coastline shows a larger deviations based on the range and this has also been documented in literature (Reynolds, 2002).

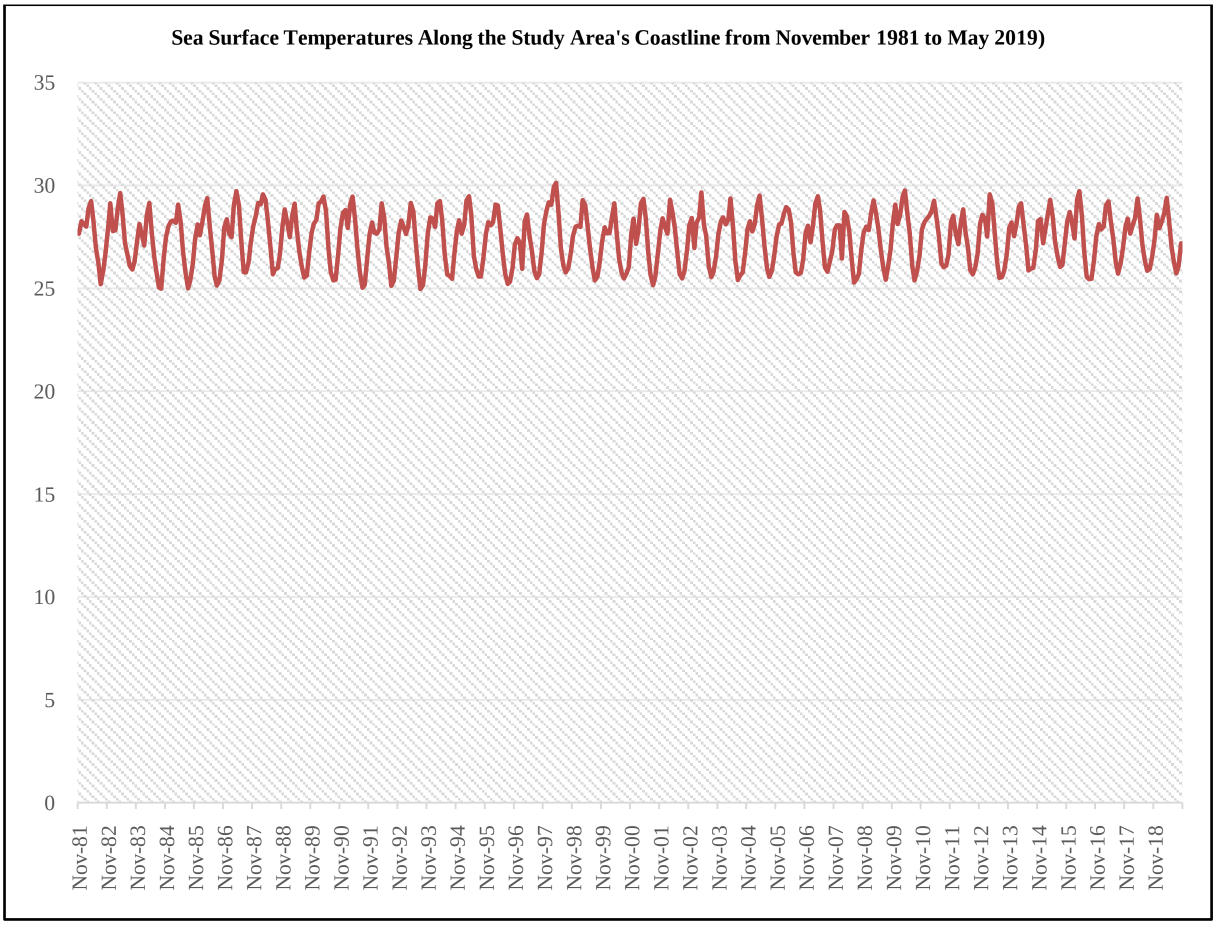

Figure 5: Sea Surface Temperatures Along the Study Area’s Indian Ocean Coastline

Source: The IRI/LDEO Collection of Climate Data

Using ARIMA model when temperature is plotted over time, the process has constant mean and constant variance, Figures6, 7, 8, 9, 10 and Tables1 and 2.

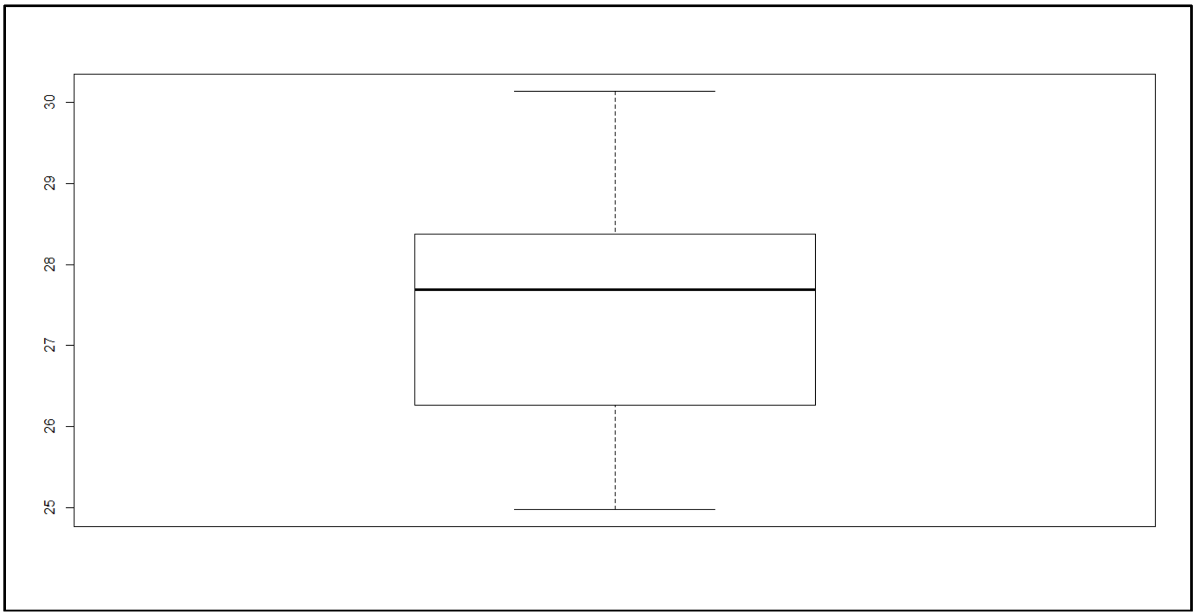

Figure 6: Temperature Plot for Sea Surface Temperature

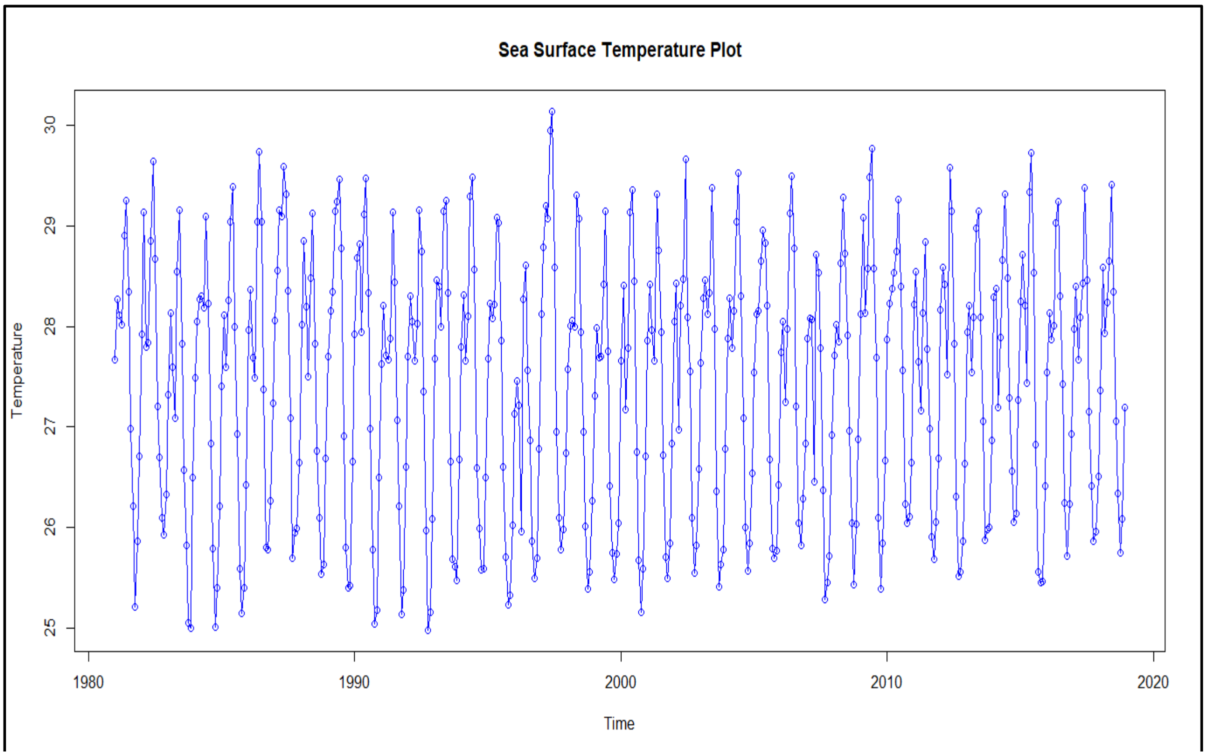

Figure 7: Sea Surface Temperature Plot

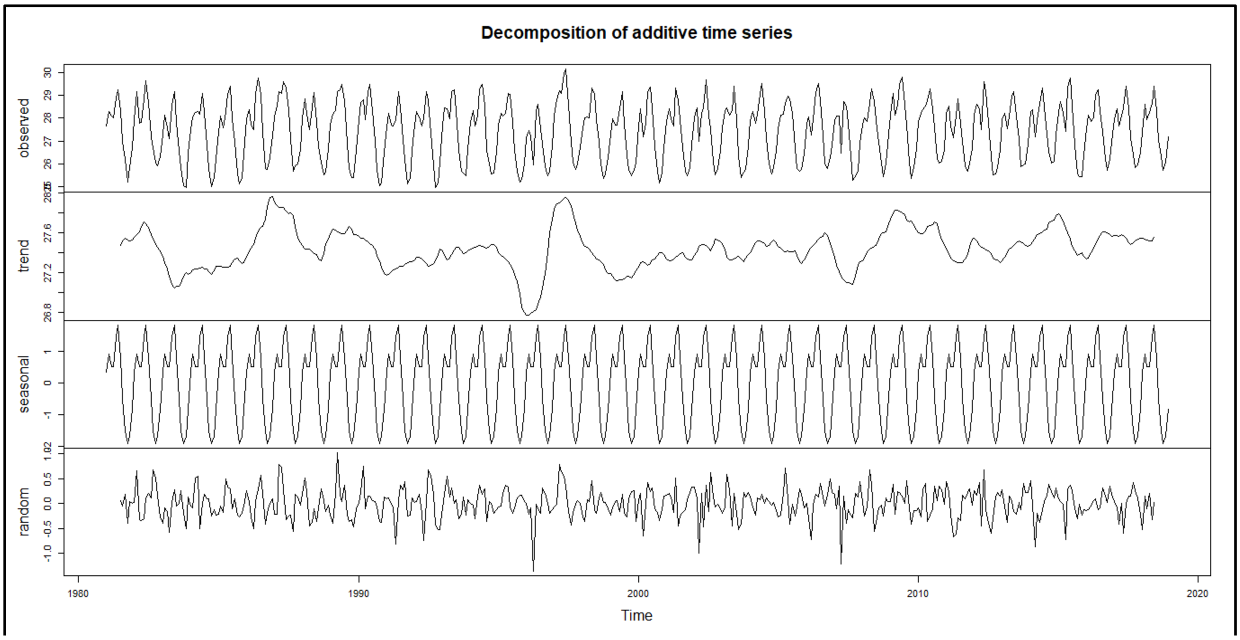

Figure 8: Decomposition of Additive Time Series

The decomposition of the time series shows that there is constant trend and variance of time suggesting that the time series is stationary. The ACG oscillates across the lags while the PACF has two spike at lags one and two. This suggests an autoregressive model.An iteration of the time series selected an ARIMA model of order one as illustrated in the iteration log.This model was used for forecasting.

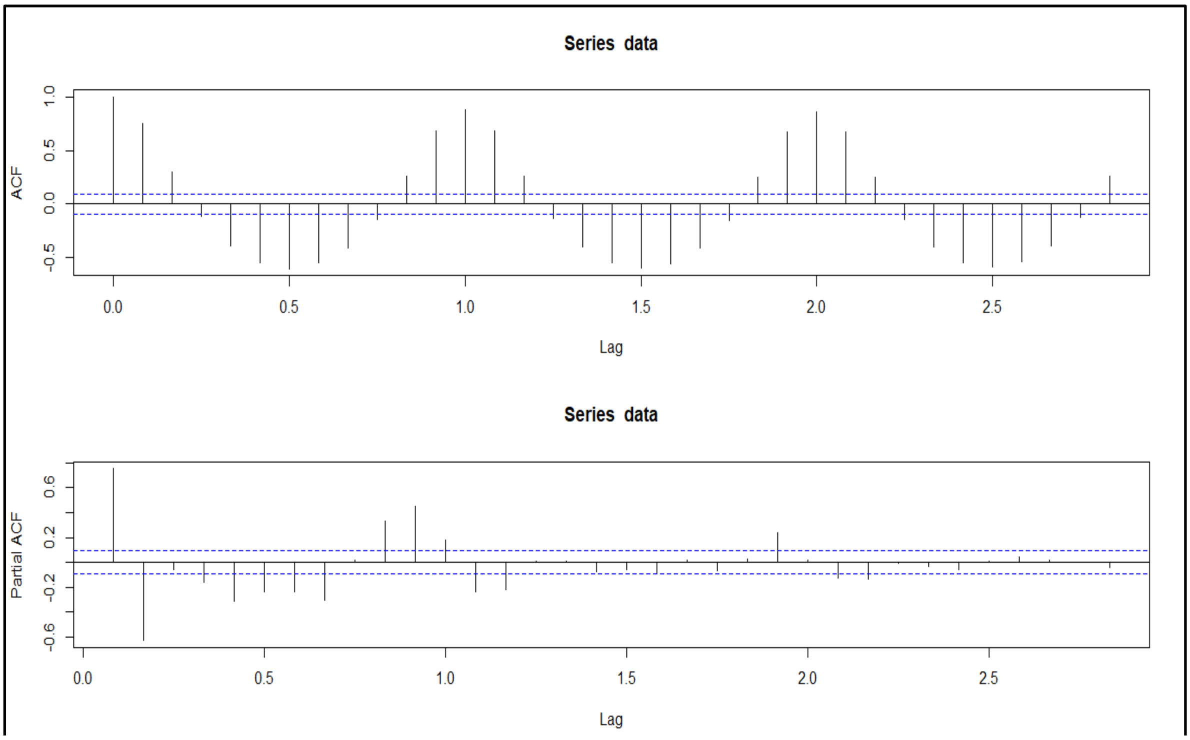

Figure 9: Time Data

Table 1: Fitting Models Using Approximations and Re-writing the Model

ARIMA(2,0,2)(1,1,1)[12] with drift	: 374.6425
ARIMA(0,0,0)(0,1,0)[12] with drift	: 777.4106
ARIMA(1,0,0)(1,1,0)[12] with drift	: 506.056
ARIMA(0,0,1)(0,1,1)[12] with drift	: Inf
ARIMA(0,0,0)(0,1,0)[12]	: 775.4059

ARIMA(2,0,2)(0,1,1)[12] with drift : 365.6538
ARIMA(2,0,2)(0,1,0)[12] with drift : 633.3207
ARIMA(2,0,2)(0,1,2)[12] with drift : 365.5038
ARIMA(2,0,2)(1,1,2)[12] with drift : Inf
ARIMA(1,0,2)(0,1,2)[12] with drift : Inf
ARIMA(2,0,1)(0,1,2)[12] with drift : 364.6368
ARIMA(2,0,1)(0,1,1)[12] with drift : 364.7781
ARIMA(2,0,1)(1,1,2)[12] with drift : Inf
ARIMA(2,0,1)(1,1,1)[12] with drift : 372.733
ARIMA(1,0,1)(0,1,2)[12] with drift : Inf
ARIMA(2,0,0)(0,1,2)[12] with drift : 362.6658
ARIMA(2,0,0)(0,1,1)[12] with drift : 362.8328
ARIMA(2,0,0)(1,1,2)[12] with drift : Inf
ARIMA(2,0,0)(1,1,1)[12] with drift : 374.7075
ARIMA(1,0,0)(0,1,2)[12] with drift : Inf
ARIMA(3,0,0)(0,1,2)[12] with drift : 374.4671
ARIMA(3,0,1)(0,1,2)[12] with drift : 376.2938
ARIMA(2,0,0)(0,1,2)[12] : 360.6268
ARIMA(2,0,0)(0,1,1)[12] : 360.8212
ARIMA(2,0,0)(1,1,2)[12] : Inf
ARIMA(2,0,0)(1,1,1)[12] : 372.9751
ARIMA(1,0,0)(0,1,2)[12] : Inf
ARIMA(3,0,0)(0,1,2)[12] : 372.479
ARIMA(2,0,1)(0,1,2)[12] : 362.5813
ARIMA(1,0,1)(0,1,2)[12] : Inf
ARIMA(3,0,1)(0,1,2)[12] : 374.3286

Re-fitting the best model(s) without approximations

ARIMA(2,0,0)(0,1,2)[12] : Inf
ARIMA(2,0,0)(0,1,1)[12] : Inf
ARIMA(2,0,1)(0,1,2)[12] : Inf
ARIMA(2,0,0)(0,1,2)[12] with drift : Inf
ARIMA(2,0,0)(0,1,1)[12] with drift : Inf
ARIMA(2,0,1)(0,1,2)[12] with drift : Inf
ARIMA(2,0,1)(0,1,1)[12] with drift : Inf
ARIMA(2,0,2)(0,1,2)[12] with drift : Inf
ARIMA(2,0,2)(0,1,1)[12] with drift : Inf
ARIMA(3,0,0)(0,1,2)[12] : Inf
ARIMA(2,0,1)(1,1,1)[12] with drift : Inf
ARIMA(2,0,0)(1,1,1)[12] : Inf
ARIMA(3,0,1)(0,1,2)[12] : Inf
ARIMA(3,0,0)(0,1,2)[12] with drift : Inf
ARIMA(2,0,2)(1,1,1)[12] with drift : Inf
ARIMA(2,0,0)(1,1,1)[12] with drift : Inf
ARIMA(3,0,1)(0,1,2)[12] with drift : Inf
ARIMA(1,0,0)(1,1,0)[12] with drift : 493.3944

Best model: ARIMA(1,0,0)(1,1,0)[12] with drift

Table 2: The Coefficients of the Model

	Coefficient	**95% Confidence Interval**	
AR1	0.520587	0.44131	0.59986
SAR1	-0.50937	-0.58848	-0.43028
DRIFT	0.000117	-0.004371735	0.004605

The forecast in Figure 10 shows a tendency to remain constant at 80-95% confidence interval and with fluctuation towards increasing temperatures for the next six years.

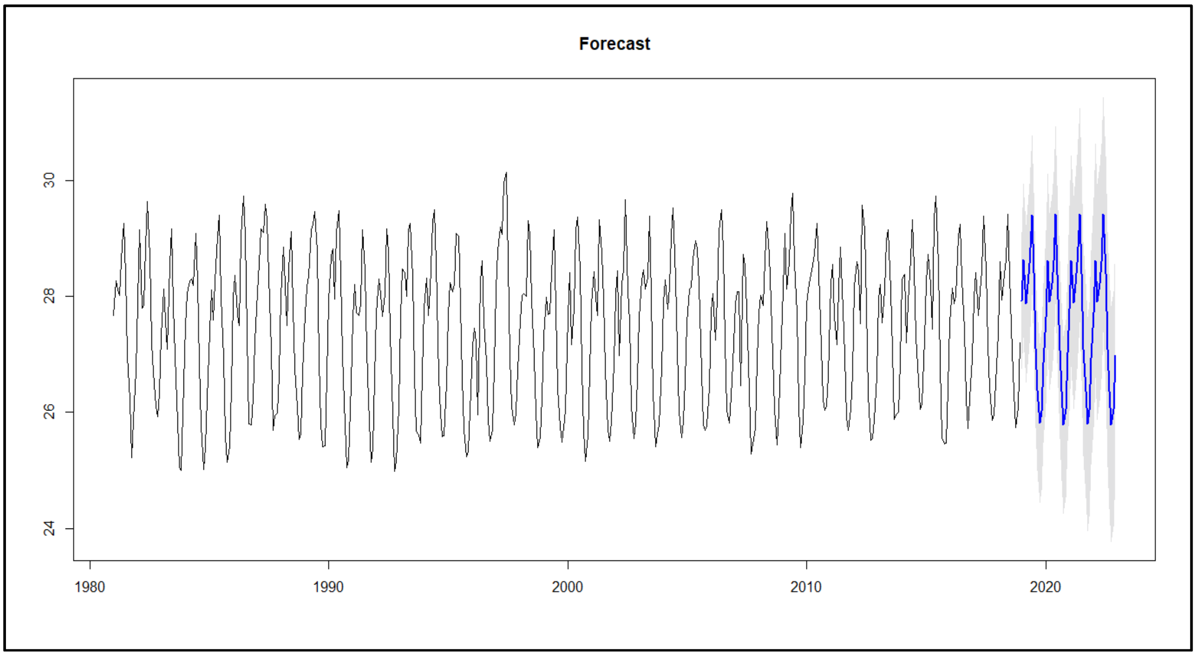

Figure 10: The Forecasted Values of Sea Surface Temperature

The study also used the Holt-Winters forecasting method which applies a triple exponential smoothing for level, trend and seasonal components. Alpha specifies the coefficient for the level smoothing, Beta specifies the coefficient for trend smoothing and Gamma specifies the coefficient for seasonal smoothing. The graphical representation is given in Figure 11.

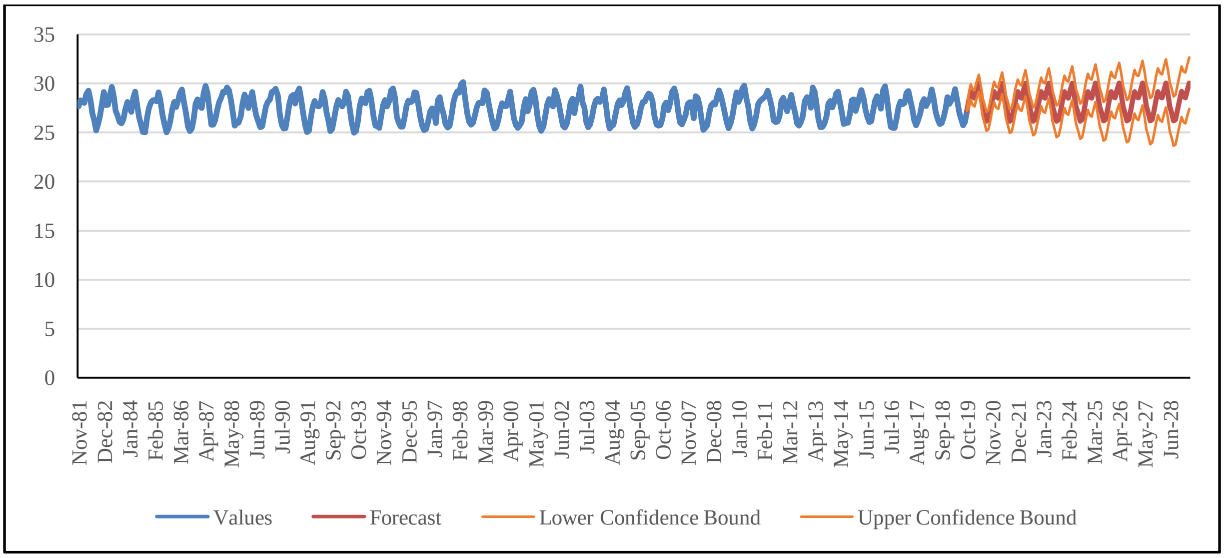

Figure 11: The Forecasted Values of Sea Surface Temperature Using Holt-Winters Forecasting Method

The Holt-Winters forecasting gave the following results: Gama 0.00, Beta 0.00 and Alpha 0.25. The Mean Absolute Scale Error, (MASE) was 0.39. MASE is a measure of the accuracy of forecasts. It is the mean absolute values divided by the mean absolute error of the sample one-step naïve forecast. The MASE of >1 implies the actual forecast is not good enough. MASE of <1 means that the actual forecast performance is better than a naïve method. It means that the lower the MASE value the lower the absolute error and the better the method. In this study the MASE value for SST is 0.39 hence a better prediction.

IV. DISCUSSION

The trend of rainfall in the coastal lowlands along the western Indian Ocean shorelineis random with outliers of very high and low rainfall figures. There are marked spatial and temporal variations. The findings indicate that there will be increasing temperature trends in the study area. Floods and drought are expected along the coastal lowlands as well as in the immediate hinterland.

The trends of rainfall and temperature observed in the study area are in line with MAMJ and MAM observed and projected change in precipitation from 1975 to 2025 for the study area, as projected in literature (FEWSNET, 2010). The FEWSNET projections indicate that the north western part of the study area will experience a negative trend of precipitation of up to <-100mm; the central part of the study area will experience a negative of <-50mm; while the southern part will experience either a positive or negative precipitation of <±50mm. In fact, the general trend of precipitation in the whole study area will be downward except for the far north eastern part that will experience positive trends of <+50. The study also confirmed long term variations of precipitation. The Coefficient of Variations(CoV) for rainfall between 30- >50mm. Rainfall variability is not only a confine of the study area but has been documental for the continent of Africa (Janowiak, 1988; Nicholson, 2000; Haarsma, et al, 2005).

The upward trend of temperature in the study area has been established. The results on temperature indicate that the trend of temperature also fluctuates but with minimal margins. The area has maintained higher temperature figures of above 30°C.It has been confirmed in literature that the temperature fluctuatingtrends impact in different ways on the environment as high temperatures are associated with moisture availability. This poses a serious challenge to the local communities in the study area.

Similar observations have been made on increasing temperature conditions in the area and elsewhere (Makenzi, et al., (2013; Ray *et al*, 2015; Rowhani, *et al*, 2011).Also the FEWSNET observed and projected trend in temperature conditions indicate that in the northern and central part of the study area , there will be an upward trend or positive trend , that is <+0.7°C. The southern part of the study area will also experience an upward trend of between <0.5°C to <+0.75°C (FEWSNET, 2010). There is therefore agreement in both empirical data and existing projections in literature on increasing temperature conditions in the study area.

The observed and predicted trends of temperature and rainfall in the study area confirm the variability of these climatic parameters. Weather variability or temperature and rainfall anomalies are some of the manifestations of climate change (IPCC, 2007; 2008; 2013). This variability impacts on various anthropogenic activities and are considerably significant issues to be addressed (Osborne & Wheeler, 2013; Chen, et al, 2004).

The sea surface temperatures have remained warmer along the coastline of the study area. This has generated heat in the Indian Ocean which eventually has affected climatic patterns in the region and hence resulted in high frequency of extreme weather events, especially floods, drought, heat waves and stronger wind patterns in the study area.The sea surface temperatures for the study area ranges between average maximum values of 30°C and minimum values of 25°C. These values are both above the average sea surface temperatures of about 17°C.

The western coastline of the Indian Ocean shows a positive trend, meaning increasing temperatures. Indeed, using 1971-2000 as average baseline for depicting change, NOAA confirmed that most of the world's Oceans have changed since 1880 (NOAA, 2016). The seas surface temperatures along the western Indian Ocean coastline in Kenya had a positive change per decade of 0.13F and a cumulative figure of 1.5-2°F in the entire period which was statistically significant between 1901 to 2015. The increase in seas temperatures intensified in the last three decades even though there are a few areas where cooling has occurred that include parts of the North Atlantic. Global seas surface temperatures are expected to rise by approximately 0.4-1.1C by 2025, (IPCC, 2016). Understanding seas surface temperature is important because it can be used to infer the response of the ocean to global warming and hence how the response can influence other changes in climate. Sea surface temperature also has environmental, economic, ecological as well as human health impacts.

Changes in sea surface temperatures can also alter marine ecosystems thereby impacting directly and indirectly on local community livelihoods. In the coastline of the study area, studieshave confirmed that bleaching of coral has indeed taken place (Ateweberhan and McClanahan, 2010; Wilkinson, et al, 1999). These findings therefore have direct and indirect policy implications for line ministries dealing with weather related disasters, marine, agriculture and sustainable livelihoods.

V. CONCLUSION

The trend in temperature in the study area is upward. Rainfall is erratic hence lacks any significant pattern. Extreme weather events were observed in the study area in the form of prolonged drought, floods and delayed, unpredictable rainfall. The rains sometimes start early or late, the rains end abruptly and alternating light and heavy rains makes prediction difficult. There is therefore need for proper documentation of the changing weather and climatic variables for informed decision making at local, national, regional and global levels. This is because of the cumulative effect of small scale spatial and temporal patterns of studies.

REFERENCES

[1]. Agafonova, S. A., Frolova, N. L., Krylenko, I. N., Sazonov, A. A., &Golovlyov, P. P. (2017). Dangerous ice phenomena on the lowland rivers of European Russia. Natural Hazards, 88(1), 171-188.

[2]. Aklilu, A., Desalegn, W., Mesfin, K., &Negash, T. (2013). Climate change impacts on Pastoral Women in Ethiopia: some evidences from the Southern lowlands. PHE Ethiopia Consortium.

[3]. Asante, W. A., Acheampong, E., Kyereh, E., &Kyereh, B. (2017). Farmers' perspectives on climate change manifestations in smallholder cocoa farms and shifts in cropping systems in the forest-savannah transitional zone of Ghana. Land Use Policy, 66, 374-381.

[4]. Ateweberhan, M., & McClanahan, T. R. (2010). Relationship between historical sea-surface temperature variability and climate change-induced coral mortality in the western Indian Ocean. Marine Pollution Bulletin, 60(7), 964-970.

[5]. Blast J., (2010). Seven Theories of Climate Change. The Heartland Institute, USA Borenstein, S. (2012). Climate Change Report from NOAA Reveals Rising Seas, Snow Melt and More Warming. The Climate of 2012 Report: Http://Www.Ncdc.Noaa.Gov/Bams-State-Of-The-Climate/2012.Php

[6]. Byg, A., &Salick, J. (2009). Local perspectives on a global phenomenon—climate change in Eastern Tibetan villages. Global Environmental Change, 19(2), 156-166.

[7]. Chen, Z., Grasby, S. E., &Osadetz, K. G. (2004). Relation between climate variability and groundwater levels in the upper carbonate aquifer, southern Manitoba, Canada. Journal of Hydrology, 290(1-2), 43-62.

[8]. Choi, S. J., Kim, I. W., Kang, C. G., Jeong, M. S., & Lim, Y. J. (2009). U.S. Patent No. 7,532,598. Washington, DC: U.S. Patent and Trademark Office.

[9]. Creswell, J.W., (2003): Qualitative, Quantitative and Mixed Methods Approaches. SAGE Publications, London

[10]. FEWSNET, (2010). A Climate Trend Analysis of Kenya—August 2010. Famine Early Warning Systems Network Informing Climate Change Adaptation Series. USGS Fact Sheet 2010–3074August 2010

[11]. GoK, (2009): Flood Mitigation Strategy, Ministry of Water and Irrigation 2009

[12]. GoK, (2014): Drought Monitoring. National Drought Management Authority, Tana River County

[13]. GoK, (2008-2012): District Development Plans, Kilifi (Various Years)

[14]. GoK, (2015). Economic Survey. Kenya Bureau of Statistics. Government Printer. Nairobi

[15]. GoK, (2015). Statistical Abstracts. Kenya Bureau of Statistics. Government Printer. Nairobi

[16]. Goose, J. E., First, E. L., & Clancy, P. (2010). Nature of step-edge barriers for small organic molecules. Physical Review B, 81(20), 205310.

[17]. Haarsma, R. J., Selten, F. M., Weber, S. L., &Kliphuis, M. (2005). Sahel rainfall variability and response to greenhouse warming. Geophysical

[18]. Research Letters, 32(17).

[19]. Harper, A. B., Powell, T., Cox, P. M., House, J., Huntingford, C., Lenton, T. M., ... &Comyn-Platt, E. (2018). Land-use emissions play a critical role in land-based mitigation for Paris climate targets. Nature communications, 9(1), 1-13.

[20]. Hughes, T. P., Kerry, J. T., Álvarez-Noriega, M., Álvarez-Romero, J. G., Anderson, K. D., Baird, A. H., ... & Bridge, T. C. (2017). Global warming and recurrent mass bleaching of corals. Nature, 543(7645), 373-377.

[21]. Hughes, T. P., Anderson, K. D., Connolly, S. R., Heron, S. F., Kerry, J. T., Lough, J. M., ... &Claar, D. C. (2018). Spatial and temporal patterns of mass bleaching of corals in the Anthropocene. Science, 359(6371), 80-83.

[22]. IPCC, (2007; 2013). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, (2008). "Glossary". Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. (http://www.grida.no/climate/ipcc_tar/wgI/518.htm)

[23]. Janowiak, J. E. (1988). An Investigation of Inter-Annual Rainfall Variability in Africa. Journal of Climate, 1(3), 240-255.

[24]. Nicholson, S. E. (2000). The nature of rainfall variability over Africa on time scales of decades to millenia. Global and planetary change, 26(1-3), 137-158.

[25]. Kizito, K., Ndegwa, W., Esilaba, A.O., Nyamwaro, S.O., Wamae, D. K., Matere, S.J., Kisua, J.W., Ruttoh, R.J., Kibue, A.M., (2015). Climate Change Adaptation Planning in Kenya: Do Scientific Evidence Really Count? Climate Change Management, pp 35-42. 27th, Nov. 2015

[26]. Kulthoum, O., Masego, M., Hepworth, N., Tigere, C., Oladipo, E., (2010). Climate Governance in Africa - Adaptation Strategies and Institutions. Camco Advisory Services (K) Ltd. (Kenya)

[27]. Leauthaud, C., Durvall, S., Belaud, G., Moussa, R., Grunberger O., and Albergel, J., (2012). Floods and Wetlands: Combining a Water-Balance Model and Remote Sensing Techniques to Characterize

Hydrological Processes of Ecological Importance in the Tana River Delta (Kenya). Hydrology and Earth Sciences Discussions. 9, 11269-11318, 2012. DOI: 10.5194/hessd-9-11267-2012
[28]. Makenzi, et al., (2013). Trend Analysis of Climate Change and its Impacts on Crop Productivity in the Lower Tana River Basin, Kenya, October, 2013. Journal of Environmental Resources, Vol. 1(4): 237-248 240
[29]. Meng, X., Cheng, J., Zhao, S., Liu, S., & Yao, Y. (2019). Estimating land surface temperature from landsat-8 data using the NOAA JPSS enterprise algorithm. Remote Sensing, 11(2), 155.
[30]. Nyamwaro, S.O., Kizito, K., Ndegwa, W., Esilaba, A.O., Wamae, D. K., Matere, S.J., Kisua, J.W., Ruttoh, R.J., Kibue, A.M., (2015). Situation Analysis of Climate Change Aspects in Kenya. Climate Change Management 2015. 27th, Nov. 2014
[31]. Osborne, T. M., & Wheeler, T. R. (2013). Evidence for a climate signal in trends of global crop yield variability over the past 50 years.
[32]. Environmental Research Letters, 8(2), 024001.
[33]. Petit, R.A., Humberto, R. M, Bressani, R, J.M. Barnola, I. Basile, M. Bender, J. Chappellaz, M. (1999). "Climate and Atmospheric History of the Past 420,000 Years from the Vostok Ice Core, Antarctica". Nature 399 (1): 429 – 436.
[34]. Radić, V., & Hock, R. (2011). Regionally differentiated contribution of mountain glaciers and ice caps to future sea-level rise. Nature Geoscience, 4(2), 91-94.
[35]. Rasmijn, L. M., Van der Schrier, G., Bintanja, R., Barkmeijer, J., Sterl, A., &Hazeleger, W. (2018). Future equivalent of 2010 Russian heatwave intensified by weakening soil moisture constraints. Nature Climate Change, 8(5), 381-385.
[36]. Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. Nature communications, 6, 5989.
[37]. Redfern, R. C., DeWitte, S. N., Beaumont, J., Millard, A. R., & Hamlin, C. (2019). A new method for investigating the relationship between diet Reynolds, R.W., N.A. Rayner, T.M. Smith, D.C. Stokes, and W. Wang, 2002: An Improved in Situ and Satellite SST Analysis for Climate. J.
[38]. Climate, 15, 1609-1625 - he IRI/LDEO collection of climate data Last updated: Mon, 09 Dec 2019 08:02:11 GMT. Expires: Mon, 06 Jan 2020 00:00:00 GMT
[39]. Roemmich, D., Gould, W. J., & Gilson, J. (2012). 135 years of global ocean warming between the Challenger expedition and the Argo Programme. Nature Climate Change, 2(6), 425-428.
[40]. Rowhani, P., Lobell, D. B., Linderman, M., &Ramankutty, N. (2011). Climate variability and crop production in Tanzania. Agricultural and forest meteorology, 151(4), 449-460.
[41]. Rosenzweig, C, Karoly, D. Marta, V., Neofotis, P. Qigang, W., Gino, C., Annette, M., Terry, L. R., Estrella, N., Seguin, B., Piotr, T., Chunzhen, L., Rawlins, S., Anton, I., (2008). Attributing physical and biological Impacts to Anthropogenic Climate Change.Nature453, 353-357 (15th May 2008) | DOI: 10.1038/nature06937; Received 28 January 2008; Accepted 19 March 2008
[42]. Rossati, A. (2017). Global warming and its health impact. The international journal of occupational and environmental medicine, 8(1), 7.
[43]. Schwartz, P., & Randall, D. (2003). An Abrupt Climate Change Scenario and Its Implications for United States National Security. California Institute of Technology Pasadena Ca Jet Propulsion Lab.
[44]. Senaratna, N., Marie-Anji, B. Oluoko-Odingo, A.A., Ajwang, L., Wepukhulu, D.W., Mwadali, A.S., (2014). Natural Hazards and Climate Change in Kenya: Minimizing Impacts on Vulnerable Communities through Early Warning Systems. Reducing Disaster: Early Warning Systems for Climate Change, 2014, pp 355-375. Jan. 27th 2014
[45]. Seneviratne, S. I., Lüthi, D., Litschi, M., and Schär, C. (2006). Land–Atmosphere Coupling and Climate Change in Europe.Nature, 443(7108), 205-209.
[46]. Silvestri, S., Broyan, E., Ringler, C., Mario, H., Okoba, B., (2012). Climate Change Perceptions and Adaptation of Agro-Pastoral Communities in Kenya. Regional Environmental Change. Volume 12, Issue 4, pp 791-802. 4th March, 2012
[47]. Stern, D. I., & Kaufmann, R. K. (2014). Anthropogenic and natural causes of climate change. Climatic change, 122(1-2), 257-269.
[48]. Sousa, A., García-Murillo, P., Sahin, S., Morales, J., &García-Barrón, L. (2010). Wetland place names as indicators of manifestations of recent climate change in SW Spain (Doñana Natural Park). Climatic change, 100(3-4), 525-557.
[49]. Wilkinson, C., Lindén, O., Cesar, H., Hodgson, G., Rubens, J., & Strong, A. E. (1999). Ecological and socioeconomic impacts of 1998 coral mortality in the Indian Ocean: An ENSO impact and a warning of future change? Ambio, (2).
[50]. WWF, (2008; 2013). "Global Warming". 18 Oct 2007; 8 Nov 2008. <http://www.panda.org/about_wwf/what_we_do/climate_change/problems/global_warming/index.cfm>.