Analysis of Rainfall and Temperature at Kamembe in Western Province of Rwanda.

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Abstract

This research was conducted using monthly average temperature and rainfall data measured at Kamembe weather station located in Western province of Rwanda to estimate in separate section the trends, the seasonal variability, to identify all possible ARIMA models and the best model to be used in forecasting the future temperature and rainfall condition at Kamembe, and also to make a linkage of temperature and rainfall to the lighting. R programming and R studio was used to achieve on our objectives. From 1961 to 2017 for both parameters the monthly average rainfall and temperature varies between 0-287mm and 22.32-28.34°C. The minimum monthly rainfall intensity was obtained during long dry season exactly June and the maximum intensity was observed during shorter rainy season mainly October but during long rainy season in February the intensity of rainfall is nearly close to that of October, and minimum temperature was observed during long rain season mainly during May and very close to that observed during November while the maximum monthly average temperature was observed during long dry season exactly during August. We have estimating all possible ARIMA models to be used and we identify the best model for analyzing monthly average rainfall and monthly average temperature data and forecasting which was ARIMA (3,0,3) (2,1,2) [12] and ARIMA (5,1,0) (2,0,0) [12] respectively. By forecasting we realize that the temperature will continue to increase up to 2022, thus higher water will be deposited in atmosphere as thunderstorms which are GHG and this phenomenon together with others mainly such as ITCZ and Kamembe topography will cause the increase of lighting.

Keywords: Temperature, Rainfall, Autoregressive Processes (AR), Moving Average Processes (MA), Auto Regressive Integrated Moving Average (ARIMA) model, forecast, Kamembe, Rwanda.

1. Introduction

Rainfall and temperature are among the basic parameters that determine weather condition. It is also the most investigated meteorological parameters due to its spatial and temporal changes affecting environmental communities (Ferrari and Coscarelli, 2018). These two parameters are only to be considered in this study and analyzed separately even if there are more others parameters that affect weather including pressure, relative humidity, solar radiation, winds, clouds, visibility and so on (Seinfeld and Pandis, 2006). Such parameters may exploit for different purpose like energy production simply solar energy, wind energy etc. There is some science needed for production of such energy, for wind energy there is a need of wind speed, direction, continuity and also its availability (Safari and Gasore, 2011). The atmosphere is transparent to the incoming solar radiation from the sun (short waves radiation) and opaque to the long waves from the earth's surface as infrared (Wallace and Hobbs, 2006). The main five goals of this study was: (i) to estimate the trends of monthly average rainfall and temperature at Kamembe (ii) the evaluation of the seasonal and monthly variability and (iii) evaluate the all ARIMA models and the best model among them (iv) the assessment of the ability of the best model to predict the future condition using ARIMA models (v) the link between temperature, rainfall to the lighting.

In the second half of the 21st century and beyond, global temperature will increase diverges across emission scenarios (IPCC, 2014). The global scale increase in temperature up to 2100 ranging from 1.8 to 4 °C (Nshombo and Laleye, 2018). And in this study we focus on case study which is kamembe and we forecast very few years for the accuracy of the model results. The relative humidity at Kamembe station decrease from 1971 up to 2013 and wind speed decrease from1971 to 1995 where it start to increase up to 2015, the annual mean wind speed at Kamembe sites is 2.97ms^{-1} with dominant wind direction of 150^{o} (Ndeda, 2015). And also, the water level of lake Kivu decrease from 1960 to 2012 (Nshombo and Laleye, 2018). And this implies that the lake water body evaporate and this affect the rainfall of the surrounding area including Kamembe but not for long distance as the wind speed was decreased. The western region of Rwanda along with volcanic region is the wettest compared to other remaining part of country (U. N. F. C. C., 2018).

By prediction the temperature across Rwanda will increase from 1°C to 2.5°C between 2000 and 2050 and 1°C to 6°C by 2100. This increase is said to be consistent across the country and seasons even if dry season may have higher temperature increase (Warner *et al*., 2015). But globally it is estimated that at 2˚C of temperature increment, global sea levels would rise by 10cm due to the melting of ice and ice sheets, thus between the increase of 40cm to 50cm will be reached by 2100 (Pringle, 2018), the National Academy of Sciences (2011) state that the main contributors of this warming are anthropogenic activities emitting greenhouse gases (GHGs) and aerosols particles which alter the Earth's energy budget. The GHGs drive the global warming while aerosols drive cooling effect (Trenberth *et al.,* 2000). While the prediction of rainfall using annual rainfall models are between -100 mm and +400 mm during 2000 to 2050. Here the rainfall is expected to be intense during rainy season (Warner *et al*., 2015). Rainfall is a major factor in shaping the vegetation, hydrology, and water quality all over the world (Nkuna and Odiyo, 2016). Rainfall intensity projection is very necessary due to the intense rainfall events may cause direct effects such as disasters including landslides, mudslides, floods (Ndayisenga, 2020) and significant erosion particularly in the steep, mountainous terrain due to its highest slope mainly that of Kamembe and commonly western part of Rwanda (Siebert *et al.,* 2019) and even in the indirect pathways (WHO, 2014) the indirect effect of such disaster include malaria and diarrhea and other related burden diseases (Henninger, 2013). The relative humidity increase slightly from 1955 to 1992 and fall down directly at this year and then start to increases slightly as usual up to 2010 (Mcsweeney and Cole 2011). The prediction is very important tools to understand the expected future change and expect the impact driven by that change and variability (Muhire *et al,*. 2015) and the magnitude of variability varies according to the locations (Panda, 2019).

2. Drivers of weather and climatology variability

As some others part of Rwanda, the weather and climate systems in Kamembe is affected by many international and even regional drivers, some of them include El Niño and La Niña phenomena due to their effect of shifting walker circulation which cause heavy rain and dry condition in different region (Byamukama *et al.,* 2011). Other moisture are due to the movement of the Inter Tropical Convergence Zone (ITCZ) along Hadley cell controlled by Mascarene, St. Helena, Azores, Arabian and Sahara high pressure systems (anticyclones). ITCZ experiencing two rainfall seasons across Rwanda and generally in East Africa, and govern the transport of moisture during MAM season which shifts from South to North due to the southeast monsoon, another driver of weather condition variability include Indian Ocean by altering the Walker circulation (Ntwali *et al.,* 2016). And we do not neglect the contribution of Subtropical anticyclones, Atlantic and Congo air mass accompanied by very strong southerly winds, Inter-seasonal wave variation, Regional topography, anabatic and katabatic wind, large water bodies (e.g. Lake Kivu, Victoria, Tanganyika), and large forests (Byamukama *et al.,* 2011) mainly Nyungwe forest, the most intense species in this forest is dependent to the seasonal rainfall and temperature (Kormos *et al*., 2017). In agriculture sector the seasonal variation of rainfall and even temperature reduce crops yield (Cong and Brady, 2012).

3. Study area

In this study the rainfall data and temperature data used was collected at Kamembe Meteorological Weather Station located in Rusizi district, Western province of Rwanda. This station has Meteorological Station, World Meteorological Organization ID of 641750-99999 and N/A respectively. It is located at +1588.0 m of elevation -2.46 latitude and 28.91 of longitude (Siebert *et al.,* 2019). This station is not so far from lake Kivu and Nyungwe forest.

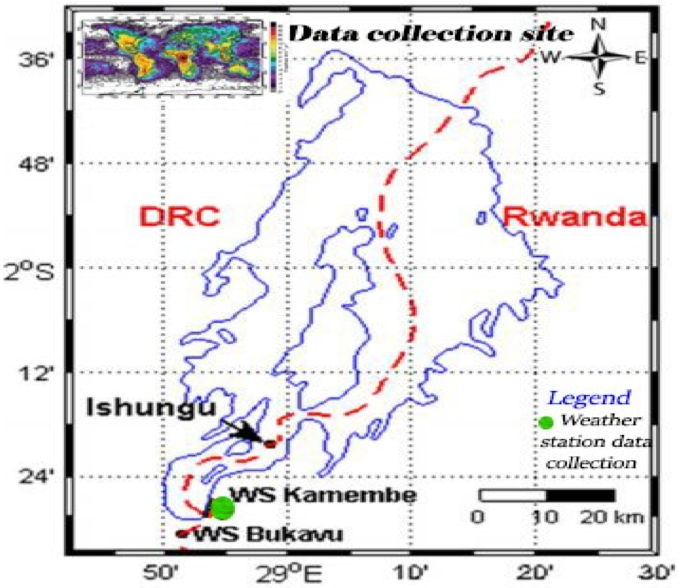


Figure 1: Kamembe weather station

4. Methodology

We use data of monthly average rainfall and monthly average temperature collected at Kamembe weather station, and we use R programming and R Studio by time series analysis. Our data firstly both monthly average temperature and rainfall data was time series class, yearly data, no missing data realized and for rainfall the data started since January 1981and end November 2017 while for temperature the data started since January 1961 and end June 2017 but we prefer to start since 1961 for both parameters. The results for rainfall and temperature data are presented in separate sections in this study.

5. Results and discussion

Table 1 summarize the basic six statistics, mean ($\bar{X}$) is the average of the data values, and the median is the 50th percentile

(p_{50}) of the data set or second quartile. This is the point that splits the data base in half while 25th percentile is called the first (lower or p_{25}) quartile, and the 75th percentile is called the third (upper or p_{75}) quartile, in other word the first quartile is the median (middle value) of the first half of a set of values and the third quartile is the median of the second half quartile. The minimum and maximum values indicate the range of our data.

Where $w_t \sim wn(0, \sigma_w^2)$, and $\theta_1, \theta_2, \ldots, \theta_p$ ($\theta_p \neq 0$) are parameters.

For MA (1) series is represented by $X_t = w_t + \theta_1 w_{t-1}$ where only one θ_1 is involved, clearly Expectation E(X_t) $= 0$ and

$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}$, $Range = (Max - Min)$ and

percentile $(i^{th} = \frac{p}{100} \times n)$ (1)

Table 1: Basic data summary statistics

Data	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Monthly Average temp.	22.32	24.47	25.16	25.26	25.93	28.34
Monthly average Rainfall	0	58.79	116.71	106.35	150.1	287

5.1. Autoregressive Processes AR(p)

The autoregressive model of order 1, AR (1), is defined as;

$$X_t = \phi\, X_{t-1} + w_t \quad (2)$$

Autoregressive processes are as their name suggests regressions on themselves. Specifically, a pth-order autoregressive process {X$_t$} satisfies the equation (3):

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + w_t = \sum_{i=1}^{p} \phi_i X_{t-i} + w_t \quad (3)$$

Where X_t is stationary, $w_t \sim wn(0, \sigma_w^2)$, and $\Phi_1, \Phi_2, \ldots, \Phi_p$ ($\Phi_p \neq 0$) are model parameter and the hyperparameter p represent the length of the direct look back in the series.

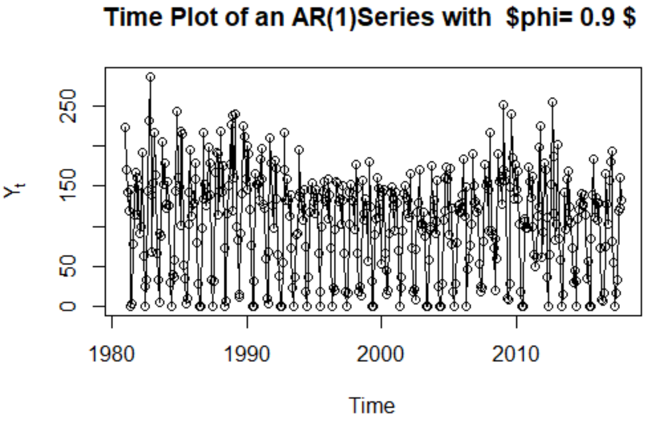


Figure 2: AR (1) rainfall Kamembe

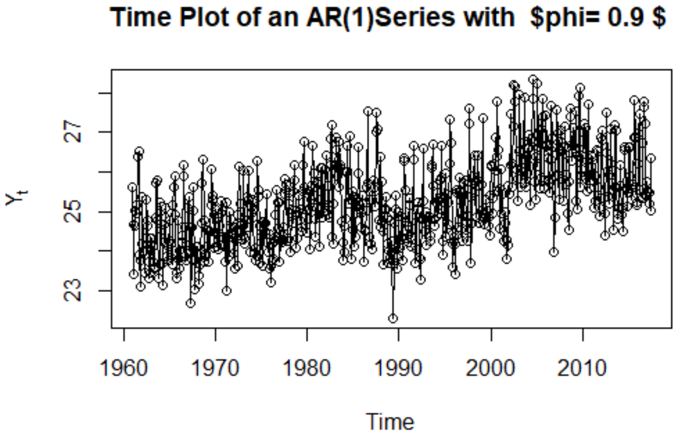


Figure 3: AR(1) Temperature Kamembe

The equation for figure 2 and 3 is: $X_t = 0.9\, X_{t-1} + w_t$ and some parameter are summarized in table 1. And Expectation

E$[X_t] = 0$, Var$(X_t) = \frac{\sigma_w^2}{(1-\phi_1^2)}$ (4)

For ACF $\rho h = \phi_1^h$ and for PACF $\rho_{11} = \rho_1 = \phi_1$, $\phi_{hh} = 0$ for all h ≥ 2

5.2. Moving Average Processes (MA)

ACF for MA(1):

A general linear process is expressed by this equation:

$$X_t = w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots + \theta_q w_{t-q} \quad (5)$$

$$X_t = w_t + \sum_{j=1}^{q} \theta_j w_{t-j} \quad (6)$$

$$Var(X_t) = \sigma_w^2(1 + \theta_1^2) \quad (7)$$

$$\gamma_1 = -\theta_1 \sigma_w^2$$

$\rho_1 = \frac{-\theta_1}{(1+\theta_1^2)}$ where $\rho_h = 0$ $for\ h \geq 2$ (8)

While for PCAF for MA(1):

$$\phi_{hh} = \frac{(-\theta_1)^h(1-\theta_1^2)}{1-\theta_1^{2(h+1)}} \qquad h \geq 1 \quad (9)$$

5.3. Auto Regressive Integrated Moving Average (ARIMA) model

ARIMA model is specified by three order parameter: p, d, q (p: number AR terms, d: how many non-seasonal differences are needed to achieve stationary, q: number of lagged forecasters in the prediction equation MA). And generally this model can be written as:

$$\phi(\mathrm{B})(1-\mathrm{B})^{d}X_t = \theta(B)w_t \qquad (10)$$

Use of ACF and PACF to identify potential AR and MA model

We can now create autocorrelation factor (ACF) and partial autocorrelation factor (PACF) plots to identify stationality in our data on both mean and variance for all possible lag. The idea is to identify presence of AR and MA components in the residuals. ACF tells us how correlated points are with each other, based on how many times steps they are separated by. It is used to determine how past and future data point are related in a time series, ACF is defined mathematically as:

$$\rho(s,t) = \frac{\gamma(s,t)}{\sqrt{\gamma(s,s)\gamma(t,t)}} \qquad (11)$$

and according to Cauchy-Schwarz inequality;

$|\gamma(s,t)|^2 \leq \gamma(s,s)\gamma(t,t)$, Then can be used to derive the range of ACF: $-1 \leq \rho(s,t) \leq +1$

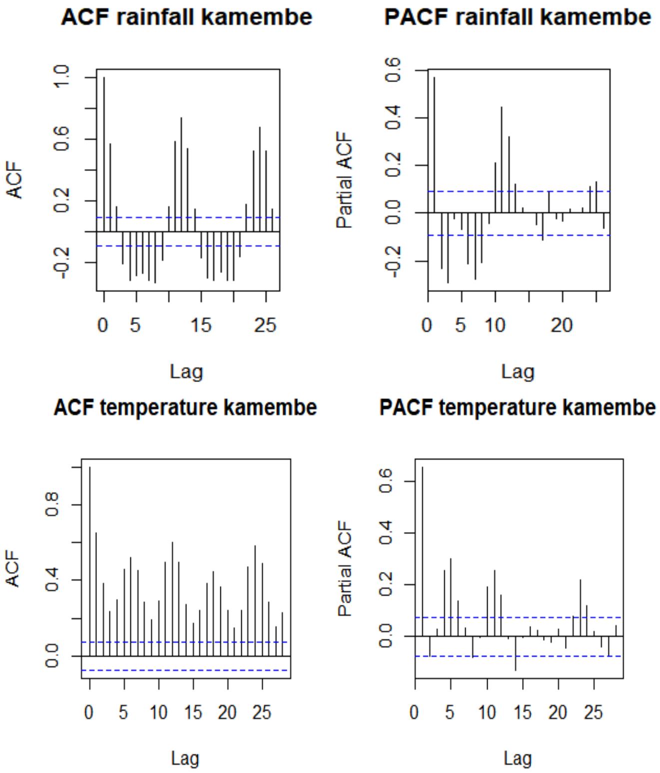


Figure 5: ACF and PACF plot

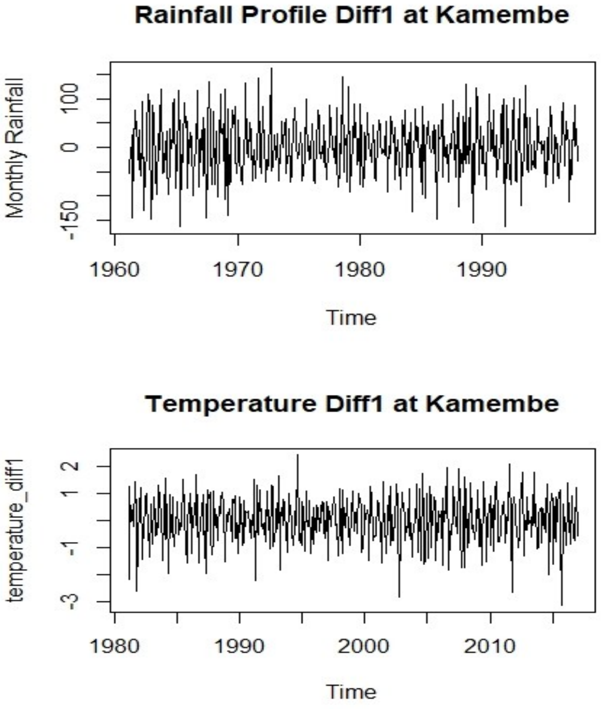
This show that our data are not stationary and some values goes beyond the range (blue line) and thus it indicate that those values are correlated, now let find out those values using R programming and are listed as annex1. Then we continue by differencing technics to make our series stationary, this is done in different order. It is also the process of subtracting one observation from another, it is used for transforming non stationary data into stationary data.

For first differencing order (d=1) $X_t' = X_t - X_{t-1}$ (12)

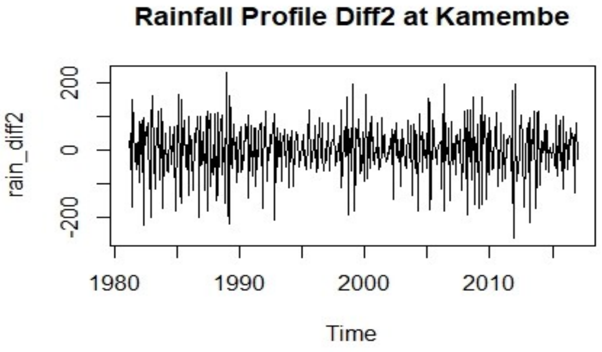
(d=2): $X_t' = X_t - X_{t-1} - X_{t-2}$

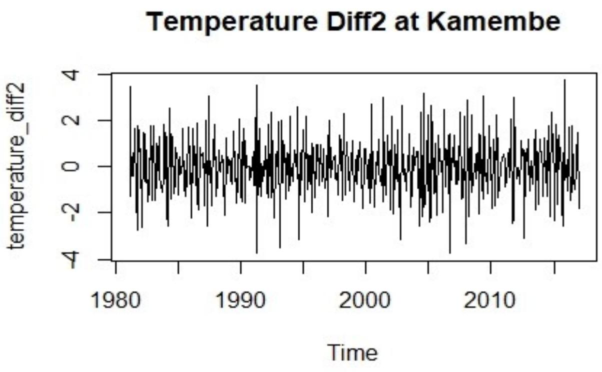
$\vdots$

(d=n): $X_t' = X_t - X_{t-1} - X_{t-2} - \cdots - X_{t-n}$ (13)



Figures 6: Rainfall and temperature Diff-1





Figures 7: Rainfall and temperature Diff-2

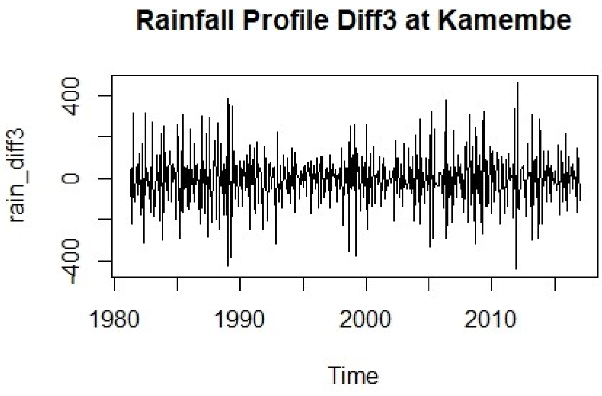


Figure 8: Rainfall Diff-3

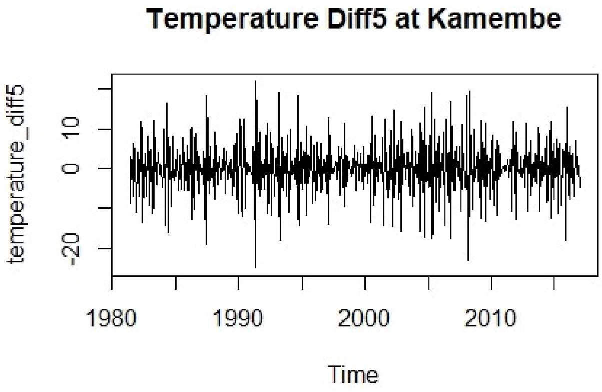


Figure 9: Temperature Diff-5

Simply this series looks stationary on both mean and variance to be specific you may check stationarity using ACF and PACF plot.

Now by expanding AR(1) representation:

$$X_t = \phi_1 X_{t-1} + w_t$$

$$= \phi_1(\phi_1 X_{t-2} + w_{t-1}) + w_t$$

$$= \phi_1^2 X_{t-2} + \phi_1 w_{t-1} + w_t$$

$$\vdots$$

$$= \phi_1^k X_{t-k} + \sum_{j=0}^{k-1} \phi_1^j w_{t-j} \qquad (14)$$

As $\phi_1 < 1$ and $sup_t Var(X_t) < \infty$, we have:

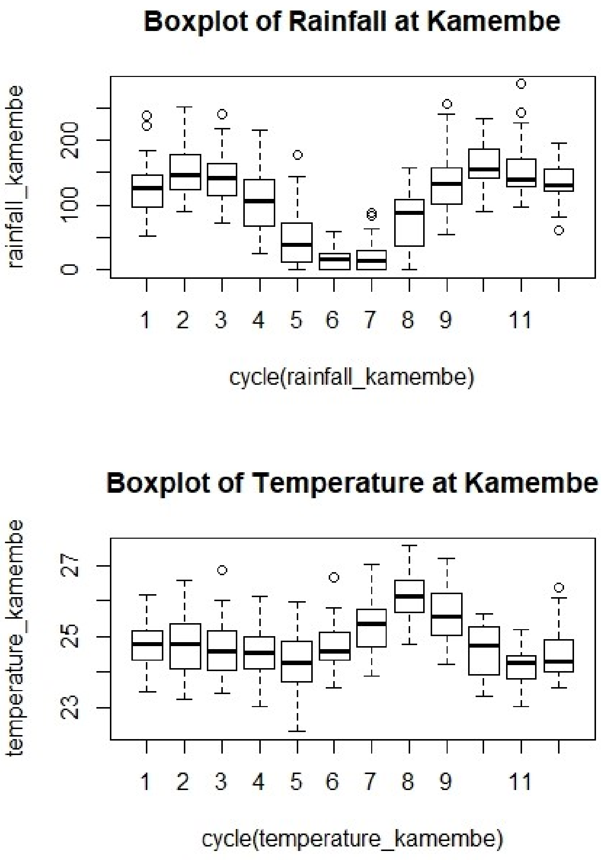
$$X_t = \sum_{j=0}^{\infty} \phi_1^j w_{t-j} \qquad (15)$$

Thus this is called the stationary solution.

In general, for AR(p) when $h > p$, theoretical PACF is zero,

$$\phi_{hh} = corr(X_{t+h} - \hat{X}_{t+h}, X_t - \hat{X}_t) = corr w_{t+h}, X_t - \hat{X}_t = 0 \qquad (16)$$

And when $h \leq p$, ϕ_{pp} is not zero and $\phi_{11}, \phi_{22}, \ldots, \phi_{h-1,h-1}$ are not necessarily zero.



Figures 10: Temperature and rainfall cycle.

This figures 10 shows the mean of all monthly data from January up to December. Each box indicate the minimum value, 1st quartile, median, 3rd quartile and the maximum value respectively for each month. As for rainfall cycle there are outlier values which affect the mean it is best to use the median as the measure of central tendency instead of mean. This is more helpful to analyze the monthly based intensity of rainfall and temperature. From January 1981 to November 2017 the least rainfall intensity is obtained during long dry season exactly June and the highest intensity is observed during shorter rainy season mainly October but during long rainy season in February the intensity of rainfall is nearly to that of October. For temperature profile between January 1961 to June 2017 the least temperature is observed during long rain season mainly during May and very close to that observed during November while the highest temperature is observed during long dry season exactly during August. The best way for looking full information is to consider the observed, trend, seasonal and random profile separately as figure 11 and 12 summarized.

The mathematical expression of decomposing this data is:

$$X = S_t \times T_t \times E_t \tag{17}$$

Where: S_t is Seasonal variation, T_t is the trend, E_t is the remaining error.

Trend show the general tendency of a time series to increase, decrease or stagnate over our data ranging period of time and Seasonal variation explains fluctuations within a year during the season, usually caused by climate factors, emissions, land surface cover, urbanization etc. Random variations are driven by unpredictable influences, not necessary to be regular or to repeat in a particular pattern, some of the main general causes of random variation include war, strike, earthquake, flood, revolution.

Table 2: Rainfall and temperature best model coefficient

Rainfall Kamembe related coefficients

	ar1	ar2	ar3	ma1	ma2	ma3	sar1	sar2	sma1	sma2
	0.4666	-0.3919	0.8541	-0.3556	0.4220	-0.9029	-0.4195	-0.0195	-0.3378	-0.3716
s.e.	0.0539	0.0423	0.0463	0.0413	0.0291	0.0408	0.6271	0.0801	0.6262	0.5143

Temperature Kamembe related coefficients

	ar1	ar2	ar3	ar4	ar5	sar1	sar2	drift
	-0.5148	-0.4060	-0.4038	-0.3710	-0.1748	0.2035	0.2597	-0.0001
s.e.	0.0404	0.0406	0.0422	0.0417	0.0382	0.0400	0.0406	0.0176

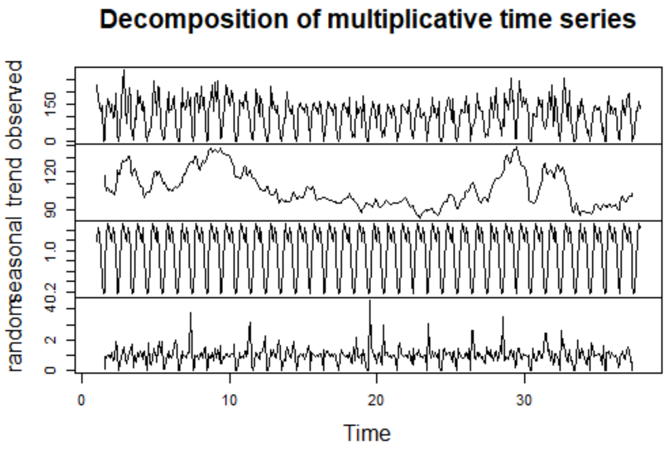


Figure 11: Rainfall profile

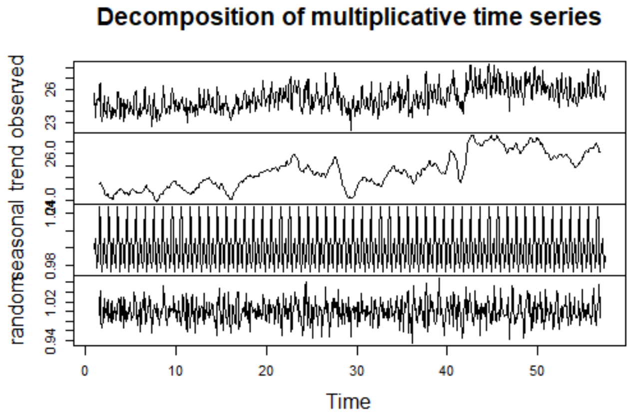


Figure 12: Temperature profile

6. Forecasting

There are at least three major steps to consider in order to make an ARIMA forecast model including: Model specification, Parameter estimation, Diagnostics and potential improvement. During this study all steps was covered.

For modelling specification we identify p, d, q. where d was obtained after checking stationarity of data, generally if data is stationary d=0, if not we take the first difference and check for stationarity again until a stationary output obtained as figure 8 and 9 shows. While p and q was obtained from PACF to get AR order p (PACF cuts off after some lags, that number obtained was the order of AR) and ACF to get MA order q (ACF cuts off after some lags, that number obtained was the order of MA). For parameter estimation the commonly used are least square, maximum likelihood, method of moments. And finally diagnostics by checking auto correlation of the residuals and look for improvement possible as figure 15 shows.

Here it was very necessary to fit model and the best model obtained were ARIMA(3,0,3)(2,1,2)[12] for rainfall data with sigma square estimated of 1223 and log likelihood -2144.44, Akaike information criteria (AIC)=4310.89 AICc=4311.52 and (Baysian information criteria) BIC=4355.61 while for temperature data was ARIMA(5,1,3)(2,0,0)[12], ARIMA(4,1,2)(2,0,

0), ARIMA(5,1,1)(2,0,0)[12], ARIMA(4,1,1)(2,0,0)[12] and ARIMA(5,1,0)(2,0,0)[12] but among these models the most best was ARIMA(5,1,0)(2,0,0)[12] with sigma square estimated of 0.5237, log likelihood of -739.38, Akaike information criteria AIC=1496.77, AICc=1497.04, (Baysian information criteria) BIC=1537.43 the other related coefficient is in table (2) and all model as annex 2.

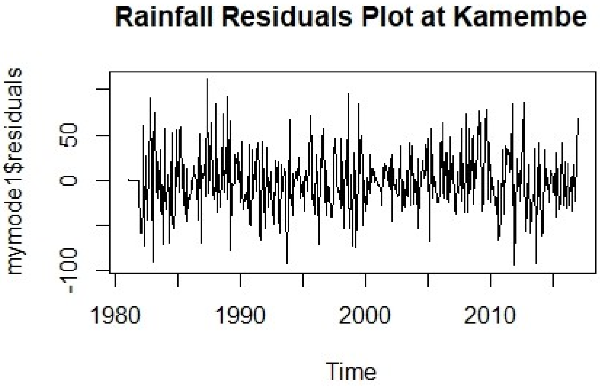


Figure13: Rainfall residual plot

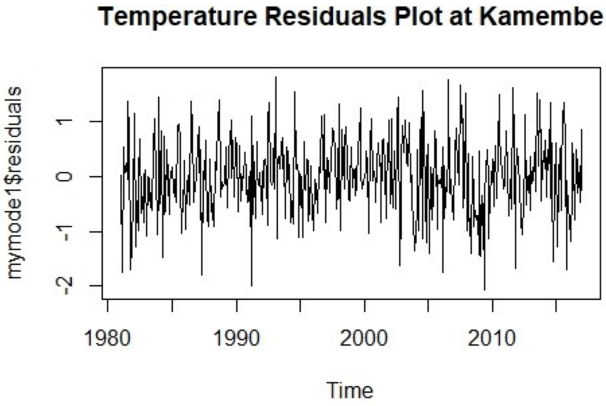
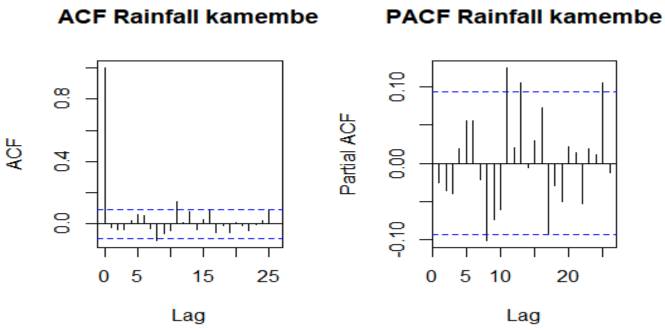
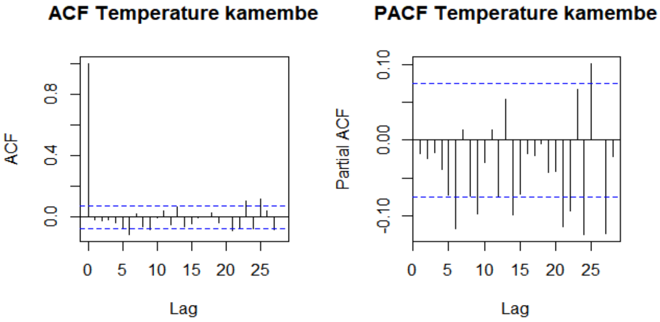


Figure14: Temperature residual plot

Now we check stationarity of our data using the following obtained residual plot and ACF and PACF for data stationarity:





Figures15: ACF and PACF plot

Thus these figures 15 shows that there is no time variability in the residual plots figure 13 and figure 14, in other ways our series becomes stationary, there is no further improvement needed and then based on this recent data we have, we can predict the future rainfall and temperature trends as shown on the figures 16 and 17 respectively.

Here the confidence interval (μ) is 95 and forecast 5 years from January 2017.

$$\mu = \bar{X} \pm z - \frac{\sigma}{\sqrt{n}} \tag{18}$$

Where standardized score or z-score is: $z = \frac{x-\mu}{\sigma}$ $(\mu\colon mean, \sigma\colon standard\ deviation)$

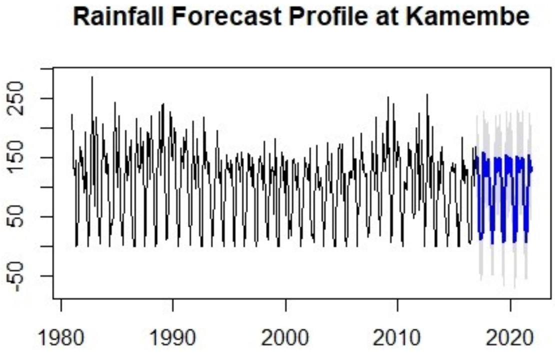


Figure 16: Rainfall forecast

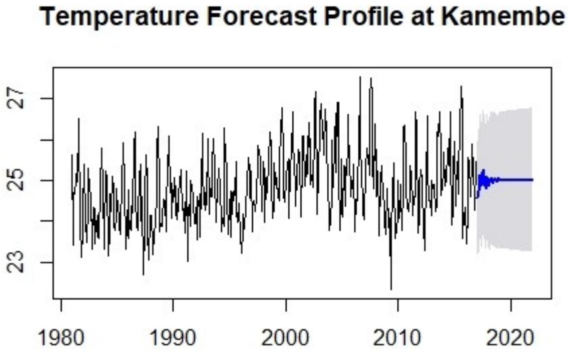


Figure 17: Temperature forecast

Models Validation

We use Box-Ljung test to validate our models, the Ljung-Box test can be defined as:

H_0: The data are random

H_a: The data are not random

Here we test: $Q_{LB} = n(n+2)\sum_{j=1}^{h}\frac{\rho^2(j)}{n-j}$ (19)

And the critical region is: $Q_{LB} = X^2_{1-\alpha;h}$ (20)

Where n is the sample size, ρ_j is the autocorrelation at lag j, and h is the number of lags being tested, α is Significance level and $X^2$is the percent point function of the chi-square distribution.

Table 3: Box-Ljung test parameters

Rainfall			Temperature		
df	X-squared	p-value	df	X-squared	p-value
5	2.8754	0.7195	5	1.9495	0.8561
10	11.998	0.2852	10	10.684	0.3826
15	24.318	0.05989	15	38.653	0.0007218

7. Conclusion

Price, (2008) observe that for different timescale for only one increased degree of surface warming, lighting increase 10-100%. Christian *et al.,* (2003) shows that the annualized distribution of total lightning activity was mostly intense in East Africa than any where allover the world. This study shows that the temperature at kamembe will continue to increase up to 2022 based on confidence interval, this implies that the more water evaporate and the unequal surface heating influence ITCZ which are among the drivers of Kamembe climate as mentioned above and thunderstorms formation which is directly proportional to the regional weather. The risk of lighting at this region will continue to increase due to higher water deposited in atmosphere by thunderstom formation which is one of the major GHGs. Even if it is difficult to quantify the concentration of NO_x produced by lighting through $NO + NO_2 \rightarrow NO_x$, this NO_x produce O_3 in troposphere which is also GHG and continue warming the surface. Thus the hiher temperature of Kamembe as it will continue to increase the lighting probability increase with an influence of ITCZ and Kamembe topography.

Acknowledgement

The Kamembe weather station is acknowledged for providing the monthly average rainfall and temperature data.

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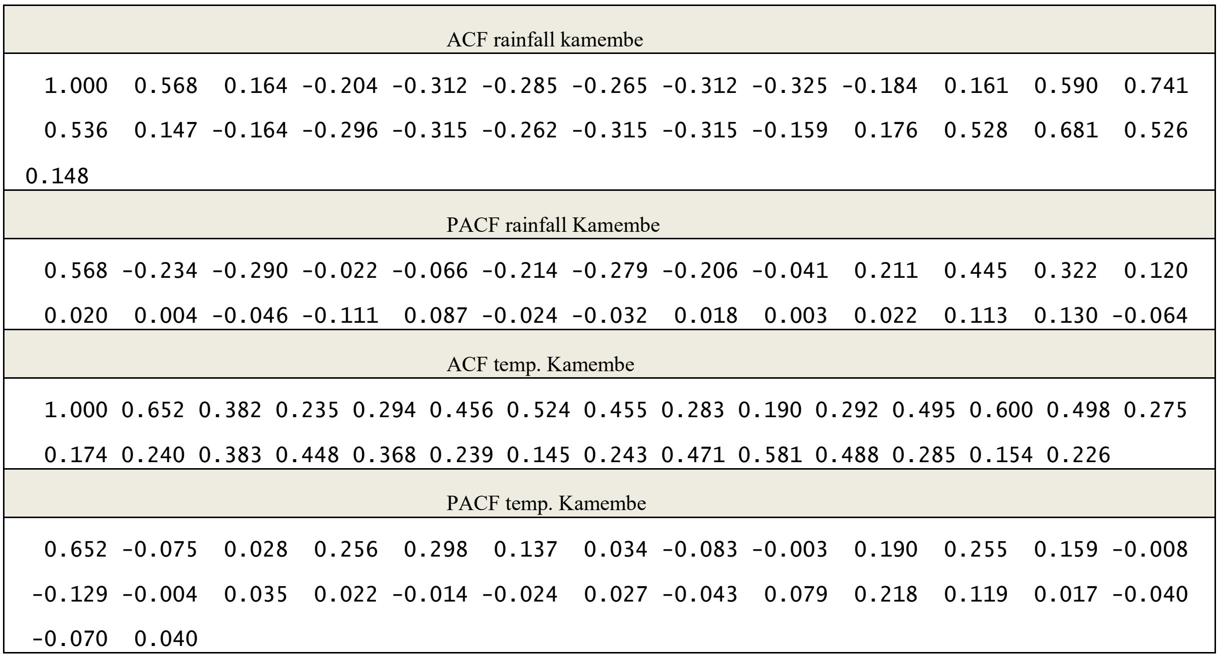
Detector Global frequency and distribution of lightning as observed from space by the Optical Transient Detector. (May 2014). https://doi.org/10.1029/2002JD002347

Annex 1: Correlated values



ACF rainfall kamembe
1.000 0.568 0.164 -0.204 -0.312 -0.285 -0.265 -0.312 -0.325 -0.184 0.161 0.590 0.741 0.536 0.147 -0.164 -0.296 -0.315 -0.262 -0.315 -0.315 -0.159 0.176 0.528 0.681 0.526 0.148
PACF rainfall Kamembe
0.568 -0.234 -0.290 -0.022 -0.066 -0.214 -0.279 -0.206 -0.041 0.211 0.445 0.322 0.120 0.020 0.004 -0.046 -0.111 0.087 -0.024 -0.032 0.018 0.003 0.022 0.113 0.130 -0.064
ACF temp. Kamembe
1.000 0.652 0.382 0.235 0.294 0.456 0.524 0.455 0.283 0.190 0.292 0.495 0.600 0.498 0.275 0.174 0.240 0.383 0.448 0.368 0.239 0.145 0.243 0.471 0.581 0.488 0.285 0.154 0.226
PACF temp. Kamembe
0.652 -0.075 0.028 0.256 0.298 0.137 0.034 -0.083 -0.003 0.190 0.255 0.159 -0.008 -0.129 -0.004 0.035 0.022 -0.014 -0.024 0.027 -0.043 0.079 0.218 0.119 0.017 -0.040 -0.070 0.040

Annex 2: All ARIMA models fitted

Series: Temp. Kamembe		Series: Rainfall Kamembe	
ARIMA(2,1,2)(1,0,1)[12] with drift	: Inf	ARIMA(2,0,2)(1,1,1)[12] with drift	: 4222.363
ARIMA(0,1,0) with drift	: 1787.233	ARIMA(0,0,0)(0,1,0)[12] with drift	: 4386.246
ARIMA(1,1,0)(1,0,0)[12] with drift	: 1659.924	ARIMA(1,0,0)(1,1,0)[12] with drift	: 4283.111
ARIMA(0,1,1)(0,0,1)[12] with drift	: 1666.449	ARIMA(0,0,1)(0,1,1)[12] with drift	: 4246.159
ARIMA(0,1,0)	: 1785.234	ARIMA(0,0,0)(0,1,0)[12]	: 4384.289
ARIMA(1,1,0) with drift	: 1776.217	ARIMA(2,0,2)(0,1,1)[12] with drift	: 4220.313
ARIMA(1,1,0)(2,0,0)[12] with drift	: 1595.13	ARIMA(2,0,2)(0,1,0)[12] with drift	: 4387.88
ARIMA(1,1,0)(2,0,1)[12] with drift	: Inf	ARIMA(2,0,2)(0,1,2)[12] with drift	: 4220.483
ARIMA(1,1,0)(1,0,1)[12] with drift	: Inf	ARIMA(2,0,2)(1,1,0)[12] with drift	: 4277.356
ARIMA(0,1,0)(2,0,0)[12] with drift	: 1673.494	ARIMA(2,0,2)(1,1,2)[12] with drift	: 4195.012
ARIMA(2,1,0)(2,0,0)[12] with drift	: 1570.357	ARIMA(2,0,2)(2,1,2)[12] with drift	: 4191.318
ARIMA(2,1,0)(1,0,0)[12] with drift	: 1639.888	ARIMA(2,0,2)(2,1,1)[12] with drift	: 4199.748
ARIMA(2,1,0)(2,0,1)[12] with drift	: Inf	ARIMA(1,0,2)(2,1,2)[12] with drift	: 4202.827
ARIMA(2,1,0)(1,0,1)[12] with drift	: Inf	ARIMA(2,0,1)(2,1,2)[12] with drift	: 4204.492
ARIMA(3,1,0)(2,0,0)[12] with drift	: 1551.396	ARIMA(3,0,2)(2,1,2)[12] with drift	: 4193.617
ARIMA(3,1,0)(1,0,0)[12] with drift	: 1601.059	ARIMA(2,0,3)(2,1,2)[12] with drift	: 4193.27
ARIMA(3,1,0)(2,0,1)[12] with drift	: Inf	ARIMA(1,0,1)(2,1,2)[12] with drift	: 4203.775
ARIMA(3,1,0)(1,0,1)[12] with drift	: Inf	ARIMA(1,0,3)(2,1,2)[12] with drift	: 4202.774
ARIMA(4,1,0)(2,0,0)[12] with drift	: 1506.335	ARIMA(3,0,1)(2,1,2)[12] with drift	: 4205.871
ARIMA(4,1,0)(1,0,0)[12] with drift	: 1540.616	ARIMA(3,0,3)(2,1,2)[12] with drift	: 4189.865
ARIMA(4,1,0)(2,0,1)[12] with drift	: Inf	ARIMA(3,0,3)(1,1,2)[12] with drift	: 4196.974
ARIMA(4,1,0)(1,0,1)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,1)[12] with drift	: 4201.919
ARIMA(5,1,0)(2,0,0)[12] with drift	: 1484.273	ARIMA(3,0,3)(1,1,1)[12] with drift	: 4231.544
ARIMA(5,1,0)(1,0,0)[12] with drift	: 1518.936	ARIMA(4,0,3)(2,1,2)[12] with drift	: 4201.141
ARIMA(5,1,0)(2,0,1)[12] with drift	: Inf	ARIMA(3,0,4)(2,1,2)[12] with drift	: 4195.533
ARIMA(5,1,0)(1,0,1)[12] with drift	: Inf	ARIMA(2,0,4)(2,1,2)[12] with drift	: 4192.3
ARIMA(5,1,1)(2,0,0)[12] with drift	: 1462.404	ARIMA(4,0,2)(2,1,2)[12] with drift	: 4196.833
ARIMA(5,1,1)(1,0,0)[12] with drift	: 1485.056	ARIMA(4,0,4)(2,1,2)[12] with drift	: 4196.293
ARIMA(5,1,1)(2,0,1)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.259
ARIMA(5,1,1)(1,0,1)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.260
ARIMA(4,1,1)(2,0,0)[12] with drift	: 1476.657	ARIMA(3,0,3)(2,1,2)[12]	: 4188.261
ARIMA(5,1,2)(2,0,0)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.262
ARIMA(4,1,2)(2,0,0)[12] with drift	: 1462.265	ARIMA(3,0,3)(2,1,2)[12]	: 4188.263
ARIMA(4,1,2)(1,0,0)[12] with drift	: 1499.699	ARIMA(3,0,3)(2,1,2)[12]	: 4188.264
ARIMA(4,1,2)(2,0,1)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.265
ARIMA(4,1,2)(1,0,1)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.266
ARIMA(3,1,2)(2,0,0)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.267
ARIMA(4,1,3)(2,0,0)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.268
ARIMA(3,1,1)(2,0,0)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.269
ARIMA(3,1,3)(2,0,0)[12] with drift	: Inf	ARIMA(3,0,3)(2,1,2)[12]	: 4188.270
ARIMA(5,1,3)(2,0,0)[12] with drift	: 1456.417		
ARIMA(5,1,3)(1,0,0)[12] with drift	: Inf		
ARIMA(5,1,3)(2,0,1)[12] with drift	: Inf		
ARIMA(5,1,3)(1,0,1)[12] with drift	: Inf		
ARIMA(5,1,4)(2,0,0)[12] with drift	: Inf		
ARIMA(4,1,4)(2,0,0)[12] with drift	: Inf		
ARIMA(5,1,3)(2,0,0)[12]	: Inf		