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Granger causality analysis of rainfall and temperature time series

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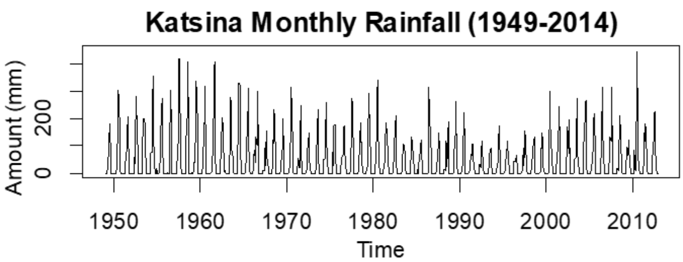
Abstract
Analysis of climate variables aims for scientifically establishing the influence of climatic variations on natural or anthropogenic factors. Several studies infer statistical cause effect relationships between meteorological variables. This paper has focused on the relationship between temperature and rainfall of Katsina metropolis. Being in a Tropical Continental region; it experiences rainfall between May and September with peak in August and is periodic in 12 months. A Granger-causality analysis was carried out in order to assess whether there is any prospective predictability power of one variable to the other. The conclusion was that temperature has a great impact on rainfall occurrence and can be used to predict rainfall, and vice-versa. These results will give an insight for developing bi-variate meteorological model.

Keywords: Meteorological Variables, Granger Causality, ADF test, Rainfall, Temperature

Introduction
In time series analysis phenomena, two or more random variables change over time. These variables not only have relationships with each other, but also are dependent. Generally, if variables are dependent, there is need to also consider all of these variables as a vector time series in a multivariate sense. Several studies infer statistical cause effect relationships between meteorological variables (Wan Zawiah, 2012; Norrulashikin, *et al*., 2015; etc) [6, 4]. The fluctuating nature of Meteorological Variables as a result of climate change has been a prospective subject of discussion in recent modelling framework (Wong *et al*. 2009) [7].

Since the last decade the concept of Granger causality has received more attention in accessing causality in the climate scheme. For example, Kaufmann *et al.* (2003) [3] tests the causal influences of snow cover and vegetation on temperatures in different seasons using satellite data. Elsner (2007) [2] applied a Granger causality analysis to time series of global temperatures and sea surface temperature and found a causal link from global temperature to sea surface temperature. Attanasio *et al.* (2013) [1] apply Granger causality technique to the study of the causes of recent global warming, in their findings the radiative forcing of green-house gases appear as the main temperature drivers, while natural forcing do not Granger cause temperature in the last decades, This paper has focused on the relationship between temperature and rainfall of Katsina metropolis being in a Tropical Continental region situated in North West zone of Nigeria.

Data Used
This work observed 30 years data of rainfall and temperature from Katsina which belong to steppe climates under Köppen Climate Classification system from 1946 to 2014.The time series plots of all the variables considered are plotted against time these plots are shown in fig.1.



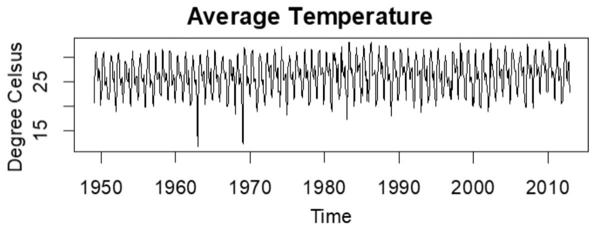


Fig 1: Rainfall and Temperature time plots of Katsina from 1949 to 2014

Relevant statistical information of these data is given in Table 1a & b, where all variables display a positive value of the mean. Their standard deviations are smaller than the mean values which indicates that the variation of the data sets were not far away from its mean. The coefficient of variation (CV) for rainfall is higher in the month of August and lower in the month of June. This means that rainfall is most stable in the month of August and least stable in the month of June. The coefficient of variation (CV) for temperature is higher in the months December to March and lower from the month of April to November.

Table 1: Descriptive statistics for monthly average rainfall from 1949 to 2014.

	Jan	Feb	Mar	Apr	May	Jun
Max	0	0	0	86.6	126.5	162.1
min	0	0	0	0.5	0.4	3.4
Mean	0	0	0	6.1	34.2	77.6
Std. dev	0	0	0	5.9	29.8	40.6
Skewness	0	0	0	4.1	0.9	0.4
Kurtosis	0	0	0	20.6	3.0	2.1
C V	0	0	0	61.4	47.1	42.4
	Jul	Aug	Sep	Oct	Nov	Dec
Max	341.2	448.9	210.3	0	0	0
min	38.1	24.7	21.1	0	0	0
Mean	162.7	217.7	96.7	0	0	0
Std. dev	70.7	95.2	44.9	0	0	0
Skewness	0.8	0.3	0.8	0	0	0
Kurtosis	3.1	2.5	3.2	0	0	0
CV	43.5	73.7	46.5	0	0	0

Table 2: Descriptive statistics for monthly average temperature from 1949 to 2014.

	Jan	Feb	Mar	Apr	May	Jun
Max	25.6	27.3	30.8	33.0	37.0	32.3
min	12.6	19.9	10.4	28.6	24.8	24.5
Mean	20.9	23.9	27.8	31.2	30.9	30.0
Std. dev	1.7	1.7	2.5	0.9	1.4	1.4
Skewness	-1.3	-0.1	-5.0	-0.4	-2.5	-2.1
Kurtosis	9.7	2.6	35.0	3.0	10.7	8.6
CV	8.1	7.3	9.2	2.99	4.6	4.7
	Jul	Aug	Sep	Oct	Nov	Dec
Max	31.7	28.9	28.2	28.0	27.2	25.0
min	21.7	24.8	24.1	9.5	21.9	5.6
Mean	28.2	26.3	25.9	25.8	24.6	21.2
Std. dev	1.1	0.9	0.9	2.3	1.2	2.5
Skewness	0.4	0.4	-0.02	-5.8	-0.05	-4.3
Kurtosis	3.7	3.2	2.7	42.7	2.3	27.0
CV	3.9	3.4	3.6	8.8	5.1	11.6

Various tests have been developed to test unit root with a view of checking stationary in time series analysis. Augmented Dickey Fuller (ADF) test is considered in this work.The ADF statistic tests the null hypothesis of presence of unit root against the alternative of stationary and the decision is to reject the null hypothesis when the value of test statistic is less than the critical value (Venus *et al.*, 2005) [5]. The ADF test involves regressing the first-difference of a variable on a constant, its lagged level, and k lagged first-difference:

$$\Delta\pi_t = \mu + \alpha\pi_{t-1} + \sum_{t=1}^{k} c_i \Delta\pi_{t-i} + \varepsilon_t$$

Where π_t is the variable? Table 1 offer the results of ADF tests for the rainfall and temperature series, It could be observed that the test reject the null hypothesis of unit root because the values of the tests statistic are less than the critical values, so there is evidence that the rainfall and temperature series does not behave as unit root. Therefore, Granger causality can be applied.

Table 1: The ADF unit root test results

Test	ADF								
	None			Drift			Trend		
Critical Level	10%	5%	1%	10%	5%	1%	10%	5%	1%
	-1.62	-1.95	-2.58	-2.57	-2.86	-3.43	-3.12	-3.41	-3.96
Parameter	Statistic			Statistic			Statistic		
Rainfall	-13.2768			-17.2228			-17.2676		
Temperature	-19.2320			-20.0948			-20.3082		

Granger causality

There are three different types of situation in which a Granger-causality test can be applied (Foresti, 2007):

1. In a simple Granger-causality test there are two variables and their lags.
2. In a multivariate Granger-causality test more than two variables are included, because it is supposed that more than one variable can influence the results.
3. Granger-causality can also be tested in a VAR framework, in this case the multivariate model is extended in order to test for the simultaneity of all included variables.

The concept of Granger causality is quite simple. For the two climate variables; temperature (x) and rainfall (y), first, we attempt to forecast y_{t+1} using past terms of y. We then try to forecast y_{t+1} using past terms of x and y. We say that x Granger causes y, if the second forecast is found to be more successful. If the second prediction is better, then the past of x contains useful information for forecasting y_{t+1} that is not in the past of y. Obviously, Granger causality is built on preference and predictableness.

In a more formal way, following (Attanasio *et al*, 2013) [1], we consider the vector time series $(y_t, x_t)'$ and the following information set $I_{yx}(t) = \{y_t, x_t, y_{t-1}, x_{t-1} \dots\}$ and $I_y(t) = \{y_t, y_{t-1}, \dots\}$. We denote with $P(y_{t+1} \backslash I(t))$ the optimal (minimum mean square error) linear forecast of the variable y_{t+1} based on the information set $I(t)$. We say that x does not Granger cause y, *in a bivariate case, if* $P\left(y_{t+1} \backslash I_y(t)\right) = P\left(y_{t+1} \backslash I_{yx}(t)\right)$for any t.

The result of Granger Causality for the climate variables is displayed in Table 3.

Table 4: Result of Granger Causality Test

Null Hypothesis	F-Statistic	P-Value	Decision
Rainfall does not Granger-cause Temperature	107.08	0.0	reject null
Temperature does not Granger-cause Rainfall	19.15	0.0	reject null

The estimated results show that rainfall Granger-cause temperature and temperature Granger-cause rainfall. Therefore, temperature could have a positive impact in predicting rainfall and rainfall could have a positive impact in predicting temperature.

Summary and Conclusion

Numerous attempts have been accomplished at applying the concept of Granger causality to climatic variables. After some pioneering works, where the choice of influencing variables is uncertain or the choice of the multivariate models probably exceeds the maximum number of parameters for obtaining reliable results, at present the application of Granger causality to the climate framework is well stood. This work present the result of Granger causality test on temperature and rainfall of Katsina, the findings revealed that temperature Granger-cause Rainfall and Rainfall Granger-cause Temperature. Therefore, temperature and rainfall have a positive impact in predicting one another. This could give insight for future research in joint modelling of climate variables of Katsina.

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