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Modelling The Dynamic Relationship Between Rainfall and Temperature Time Series Data In Niger State, Nigeria.

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Abstract

Vector Autoregression (VAR) has some very attractive features and has provided a valuable tool for analysing dynamics among time series processes. This paper examined the dynamic relationship between rainfall and temperature time series data in Niger State, Nigeria, collected from the Meteorological station, NCRI, Badeggi, Niger State, Nigeria which spanned from January 1981 to December 2010. The VAR model favoured VAR at lag 8 which indicated bi-directional causation from rainfall to temperature and from temperature to rainfall. The Impulse Response Functions and the Forecast Error Variance Decomposition were further used to interpret the VAR model. We concluded that modelling rainfall and temperature together in Niger State will further improved the forecast of rainfall and temperature respectively.

Keywords: Rainfall; Temperature; Modelling; Meteorological data; Time series; Vector Autoregression (VAR).

1.0 Introduction

Vector Autoregression (VAR) is a widely use econometrics technique for multivariate time series modelling. The VAR model specifically resembles the form of simultaneous model (SEM), but VAR approach imposes fewer and weaker restrictions in specifying a model than SEM (Sims, 1980; Chowdhury, 1986). VAR has some very attractive features and has provided a valuable tool for analysing dynamics among time series processes. A VAR model posits a set of relationship between lagged values of all variables and the current values of all variable in the system (Mcmillin, 1991; Lu, 2001).

VAR models have been used in many empirical studies. Park, (1990) used VAR models in forecasting the U.S cattle market; Bessler, (1984) used VAR models to study Brazillian agricultural prices, industrial prices and money supply; Kaylen, (1988) used VAR and other forms of model to forecast the U.S Hog market; Haden and VanTassell, (1988) applied VAR to study the dynamic relationships in the diary sector of U.S.; Holtz-Eakin, Newey and Rosen, (1988) estimated VAR model using Panel data; Estenson, (1992) used VAR model to explore the dynamics of the Keynesian theory; McCarty and Schmidt, (1997) used the VAR model to study State-Government expenditure; Enders and Sandler, (1993) used VAR and Intervention analysis to study various attack modes used by transnational terrorists; Freeman, Williams and Lin, (1989) compared VAR model and familiar Structural equation (SEQ) to study politics; Backus, (1986) use VAR to elicit the empirical facts concerning the movement of the Canadian-U.S exchange rate; Lu, (2001) apply a VAR model for the dynamics of the U.S population between 1910 and

1990; Saluwa and Olubusoye, (2006) compared VAR and other estimation techniques on macroeconomic models in Nigeria; Andersson, (2007) in his thesis compared the forecast performance of RW, AR and VAR models to forecast Swedish real GDP growth; Adenomon, Oyejola and Adenomon, (2012) applied VAR approach on the relationship between savings and investment in Nigeria. In fact, the empirical applications of VAR model are numerous.

The aim of this paper therefore is to study the dynamic relationship between rainfall and temperature time series data in Niger State. And also, to investigate whether rainfall Granger caused temperature or whether temperature Granger caused rainfall or whether rainfall and temperature are independent in relation to forecasting.

2.0 Literature Review

Evidence is building that human-induced climate change (global warming), is changing precipitation and the hydrological cycle, and especially the extremes (Trenberth2011).

Precipitation is the general term for rainfall, snowfall, and other forms of frozen or liquid water falling from clouds (Dai 2006a). There is a very strong relationship between total column water vapour (TCWV, also known as precipitable water) and sea-surface temperatures (SSTs) over the oceans (Trenberth 2000). Precipitation is intermittent, and the character of the precipitation when it occurs depends greatly on temperature and the weather situation (Willet *et.al.*2008). He further explained that, heated by the sun's radiation, the ocean and land surface evaporate water, which then moves around with winds in the atmosphere, condenses to form clouds, and falls back to the Earth's surface as rain or snow, with the flow to oceans via rivers completing the global hydrological (water) cycle. The same process is essential for creating precipitation. As air rises into regions of lower pressure, it expands and cools, and that cooling causes water vapor to condense and precipitation to form. The Clausius-Clapeyron (C-C) equation describes the water-holding capacity of the atmosphere as a function of temperature, and typical values are about 7% change for 1°C change in temperature. Consequently, changes in temperature through the C-C relationship provide a very fundamental constraint on the amount and type of precipitation through the water vapor content of the air. (Trenberth2011)

Precipitation varies from year to year and over decades, and changes in amount, intensity, frequency, and type (e.g. snow vs. rain) affect the environment and society. Steady moderate rains soak into the soil and benefit plants, while the same amounts of rainfall in a short period of time may cause local flooding and run off, leaving soils much drier at the end of the day.

Among variables relevant to climate change, rainfall and temperature are two important factors which have a large effect on crop yield (Abbate *et. al* 2004). Typically, temperature affects the length of the growing season and rainfall affects plant production (leaf area and the photosynthetic efficiency) (Cantelaube, 2005).

In summary, it is well established that rainfall and temperature are two important climatic factors affecting agricultural production. (Lobell and Field 2007; Kaufmann and Snell 1997; Riha, Wilks, and Simoens 1996).

3.0 Model Specification

VAR is a generalized reduced form which helps to detect the statistical relationship among the variables in the system. It allows all the variables in the system to interact with self and with each other, without having to impose a theoretical structure on the estimates. It also provide additional method that help in analysing the impact of a given variable on itself and on all other variables using Impulse Response Functions (IRFs) and Variance Decompositions(VDCs) (Ansari and Ahmed, 2007).

We consider a VAR(p) model as

$$y_t = \mathrm{C} + \mathrm{A}_1 y_{t-1} + A_2 y_{t-2} + \ldots + \mathrm{A}_p y_{t-p} + \ell_t \qquad t = 0, \pm 1, \pm 2 \ldots$$

where $y_t = [y_{it}, \ldots \mathrm{y}_{\mathrm{Kt}}]'$ is a (kx1) random vector, the A_i are fixed (kxk) coefficient matrices, C is a k x 1 vector of constants (intercept) allowing for the possibility of non zero mean E(y_t). Finally, $u_t = [u_{1t} . . . \mathrm{u}_{\mathrm{Kt}}]'$ is a k-dimensional white noise or innovation process, that is $E(\ell_t) = 0$, $E(\ell_t \ell_t') = \Sigma_u$ and $E(\ell_t \ell_s') = 0$ $\mathrm{s} \neq \mathrm{t}$. The Covariance matrix $\sum_u$ is assumed to be non-singular (Lütkepohl, 2005).

We say that y_t is stable VAR(p) process if $\det(I_K - A_1 z - \ldots - A_p z^p) \neq 0 \text{ for } |z| \leq 1$

Hence this condition provides an easy tool for checking the stability of a VAR process. Since the explanatory variables are the same in each equation, the Multivariate Least Squares is equivalent to the Ordinary Least Squares (OLS) estimator applied to each equation separately, as was shown by Zellner, (1962).

3.1 Unit Root and Causality Tests

In VAR, it is useful to tests for time series characteristics such as unit root, Granger causality and cointegration (Engle and Kozicki, 1993; Ansari and Ahmed, 2007). Broadly speaking, a stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed (Gujarati, 2003). A test of stationarity (or non stationarity) that has become widely popular over the past several years is the unit root test known as Augmented Dickey-Fuller (ADF) test (Engle and Granger, 1987; Ajayi and Mougoue, 1996).

To distinguish a unit root, we can run the regression

$$\Delta Y_t = b_o + \sum_{j=1}^{k} b_j \Delta Y_{t-j} + \beta t + \gamma Y_{t-1} + u_t$$

The model can be estimated with or without trend. If there is unit root, differencing Y should be in a white noise series. The Augmented Dickey-Fuller (ADF) test of the null hypothesis of no unit root tests can be carried out as follows: If the trend is of interest, that is, H_o: $\beta = \gamma = 0$, we then use the F-test, and if the trend is not of interest, that is, H_o: $\gamma = 0$, we then use the t-test. And if the null hypothesis is accepted, we assume that there is a unit root and difference the data before running a regression. If the null hypothesis is rejected, the data are stationary and can be used without differencing (Dominick and Derrick, 2002).

3.2 Causality Test

Granger causality test is a technique for determining whether one time series is useful in forecasting another (Granger, 1969). The series x_t is said to Granger cause y_t if the past of x_t has additional power in forecasting y_t after controlling for the past of y_t (Gelper and Croux, 2007). Gujarati, (2003) distinguished four cases of causality. They are unidirectional causality from X to

Y; unidirectional causality from Y to X; bilateral causality of Y and X; and independence of Y and X. The steps involved in implementing Granger causality test can be found in Gujarati, (2003).

3.3 Lag length Selection in Vector Autoregressive Models

The optimal lag length (p) is usually determined using one of the following popular criteria and p is chosen to be the order that minimizes the following criterion (Gujarati, 2003; Beenstock and Felsenstein, 2007). The criteria are

$$AIC_{(p)} = \ln\left|\hat{\Sigma}_{(p)}\right| + \frac{2}{T} pk^2$$

$$SIC_{(p)} = \ln\left|\hat{\Sigma}_{(p)}\right| + \frac{\ln T}{T} pk^2$$

$$HQIC_{(p)} = \ln\left|\hat{\Sigma}_{(p)}\right| + \frac{2\ln\ln T}{T} pk^2$$

where $\hat{\Sigma}$ = estimated covariance matrix and T= number of observations

Akaike Information Criterion (AIC); Schwarz Information Criterion (SIC); Hannan and Quinn information Criterion (HQIC).

Finally the lag length (p) that is associated with the minimum AIC, SIC and HQIC values from a set of AIC, SIC and HQIC values is selected as the appropriate lag length (p) for the VAR model.

3.4 Impulse Response Function (IRF)

The Impulse Response Function (IRF) is used to determine how each endogenous variable responds over time to a shock in its own value and in every other variable. Again any VAR can be modelled as a triangular moving average process (Beenstock and Felsenstein, 2007).

$$Y_t = \eta + \theta_o \eta_t + \theta_1 \eta_{t-1} + \theta_2 \eta_{t-2}$$

From this equation we can observe changes in Y_t given a change in the residual. Plotting the IRF maps out the "cyclic" created in all variables given a 'shock' in one variable

$$\frac{\partial y_i, t+s}{\partial \eta_i, t} = \frac{\partial y_i, t}{\partial \eta_i, t-s} = \theta^s_{i,j} \quad \mathrm{i, j} = 1, 2, \ldots, \mathrm{n}, \mathrm{s} > 0$$

It is common to draw bootstrapped confidence intervals around IRF.

3.5 Forecast Error Variance Decompositions (FEVDs)

If the innovation which actually drive the system can be identify, a further tool used to interpret VAR model is forecast error variance decompositions. It is denoted as $w_{jk,h} = \sum_{i=0}^{h-1} (e'_j \Theta_i e_k)^2 \Big/ \left(\sum_{i=0}^{h-1} e'_j \Phi_i \Sigma_\varepsilon \Phi'_i e_j \right)$ which denote the k-th column of I_k by e_k, the proportion of the h-step forecast error variance of the variable k. Detailed can be found in Lütkepohl, (2005); Lütkepohl and Saikkonen, (1997).

4.0 Data

The data set consist of monthly rainfall and Maximum Temperature from January 1981 to December 2010. The data were obtained from the National Cereals Research Institute (NCRI), Meteorological Station, Badeggi, Niger State. The data were used in the Statistical analysis without further transformation.

5.0 Empirical Results

The descriptive statistics on rainfall and temperature are presented in table 1. For the period considered the average rainfall is 96.6497mm with maximum rainfall of 440.60mm and the minimum rainfall is 0.000mm, while the average temperature is 33.8444^{o}C with maximum temperature as 40.00^{o}C and minimum temperature as 21.00^{o}C. The standard deviation is high in rainfall data and low in temperature data.

Table 1:Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
rainfall	360	.00	440.60	96.6497	104.90354
temperature	360	21.00	40.00	33.8444	2.96652
Valid N (listwise)	360				

In Fig 1 and Fig 2 show some level of stationarity because the graph did not show any level of trend. But we will test the Series with the ADF test to confirm there stationarity.

5.1 Stationarity Test

To examine whether the two time series data are nonstationary, the ADF unit root will be employed. The null hypothesis is that the series are nonstationary(That is, presence of a unit root), and the alternative hypothesis is that they are stationary (that is, absence of a unit root).

The ADF test for rainfall and temperature series are presented in table 2 and table 3. The test was carried with and without trend. The results revealed that at 1%, 5% and 10% the null hypothesis was rejected for both series for with and without trend. The results signified that both series are stationary. The implication of this result means that the VAR model is suitable for modelling the time series data.

5.2 The VAR Model and Lag selection

In Lütkepohl and Saikkonen, (1997) showed that the fitted VAR model order is assumed to increase with the sample size that is, $h \sim o(T^{1/3})$ where T is the size of the time series. And they concluded that VAR(h+1) are fitted to data such that h goes to infinity with sample size. Using this idea, in this work T=360, then $h \approx (360^{1/3}) \approx 7$. Then using VAR(h+1)=VAR(7+1), we considered VAR models from lag 1 to lag 8, and VAR model at lag 8 was chosen by AIC and HQIC criteria, that is, the minimum AIC and HQIC. Detailed are found in table 4 and table 5.

5.3 The Granger causality test

The Granger causality test in table 6 revealed a bi-directional relationship between Rainfall and Temperature that is, the relationship is running from rainfall to temperature (rainfall→temperature) with p-value <0.001 also the relationship runs from temperature to rainfall (temperature→rainfall) with p-value<0.001. These results indicated that rainfall is useful in forecasting temperature, and temperature is useful in forecasting rainfall in Nigeria.

5.4 Stability Condition of VAR model

The table 7 show the results on the stability condition of VAR model at lag 8. The results revealed that all the eigenvalues lie inside the unit circle, because all the modulus values are less than 1.suggesting that the VAR satisfies stability condition. This further suggests that both series (rainfall and temperature) are stationary as specified by the ADF test in table 2 and table 3

5.5 Impulse Response Functions and Variance Decompositions

As started earlier, the individual VAR coefficients are difficult to interpret, but the IRF and FVDCs help us to interpret the dynamic relationship between time series data.

In Fig. 3a we have the positive impact of rainfall on rainfall; Fig. 3b shows the positive impact of rainfall on temperature as well which shows some level of sensitivity of the series. In Fig 3c shows the impact of temperature on rainfall and Fig 3d shows the impact of temperature on temperature. The IRF do not show the magnitude of these relationships. For these reasons, it is necessary to examine the Variance Decompositions.

The Variance decomposition in Fig 4a and Fig 4d appear in the same manner, also Fig 4b and Fig 4c appear to be the same, which revealed some striking results. The results of the FEVDs are presented in table 9 in the appendix. The result revealed that over 86% of the variance in Rainfall appears to have been explained by innovations in Rainfall, while over 8% was explained by innovations in temperature. Also, over 91% of variance in temperature appears to have been explained by innovations in temperature, while over 13% was explained by innovations in rainfall. This result is similar to the result obtain by Granger causality test of bi-directional relationship. These results suggest that modelling rainfall and temperature together will further improve the forecast of rainfall and temperature respectively.

6.0 Summary and Conclusion

We set out to investigate the dynamic relationship of rainfall and temperature in Niger State, using monthly data from January 1981 to December 2010. The ADF test was used to test the nonstationarity of the series, the test revealed that rainfall and temperature time series are both stationary which was also confirmed by the VAR stability condition that the series are both stationary this revealed the suitability of the VAR model for studying the dynamic relationship between rainfall and temperature. The VAR models favoured VAR at lag 8 using AIC and HQIC criteria, the results from the Impulse Response Functions and Forecast Error Variance Decompositions revealed that over 91% of variance in temperature appears to have been explained by innovations in temperature, while over 13% was explained by innovations in rainfall. This result is similar to the result obtain by Granger causality test of bi-directional relationship.

The work therefore concludes that modelling rainfall and temperature together will further improve the forecast of rainfall and temperature respectively in Niger State.

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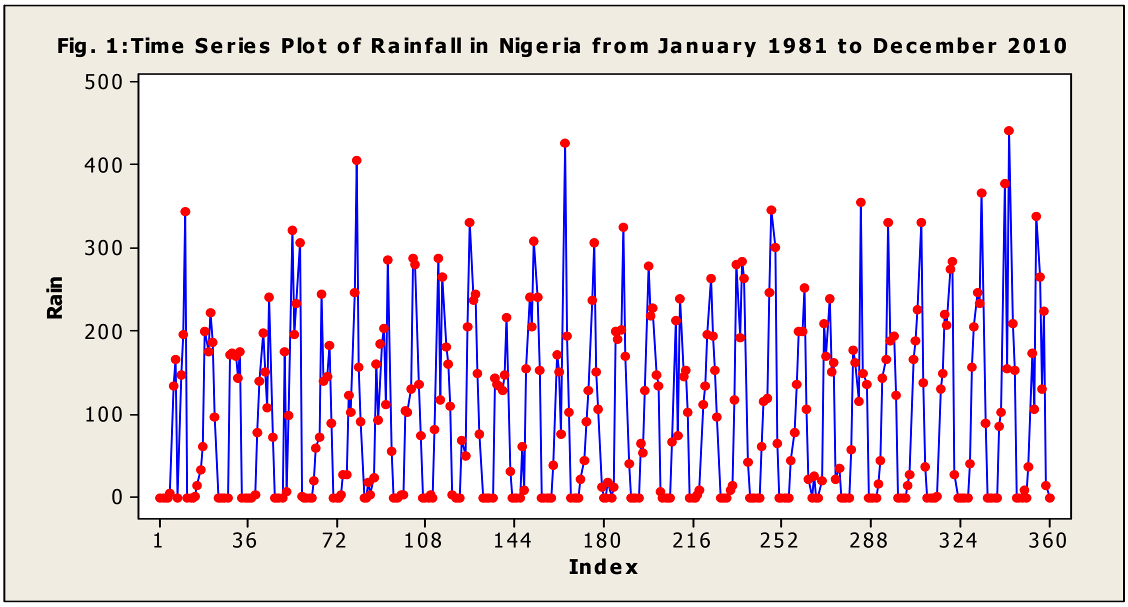
Time Plots for Rainfall and Temperature in Nigeria from January 1981 to December 2010



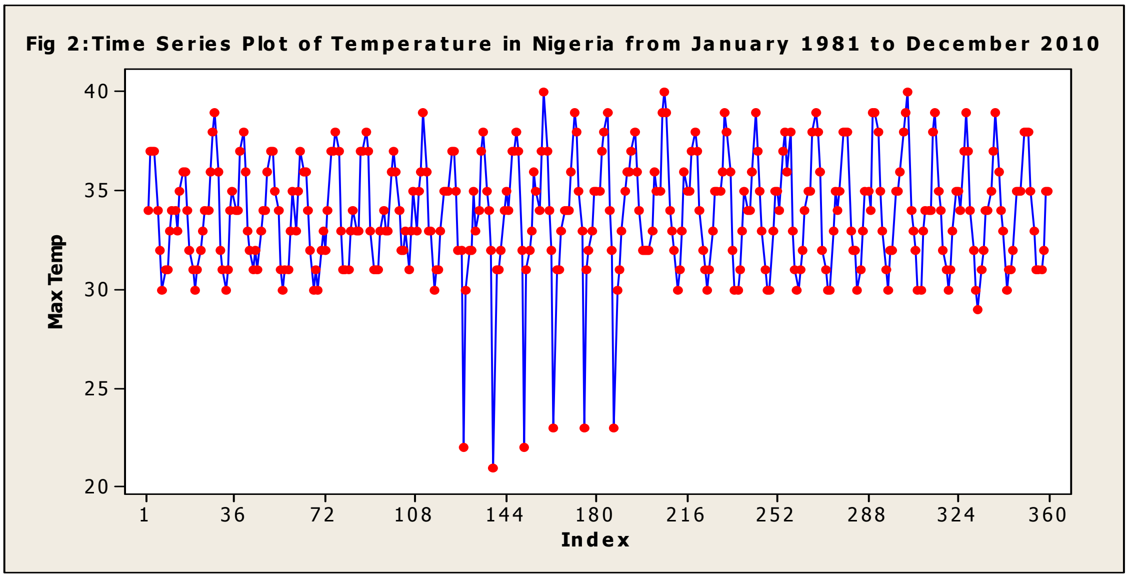


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Table2: ADF test for Rainfall and Temperature Series with Trend

```
Augmented Dickey-Fuller test for unit root        Number of obs   =      358
                        ---------- Interpolated Dickey-Fuller ---------
             Test        1% Critical      5% Critical      10% Critical
           Statistic         Value            Value            Value
------------------------------------------------------------------------------
 Z(t)          -8.904          -3.986          -3.426          -3.130
------------------------------------------------------------------------------
* MacKinnon approximate p-value for Z(t) = 0.0000
------------------------------------------------------------------------------
D.rainfall  |     Coef.     Std. Err.     t     P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
rainfall    |
        L1 |    -.4260259 .0478474    -8.90   0.000    -.5201267    -.331925
        LD |    .0510459  .0531088    0.96   0.337    -.0534026    .1554944
_trend      | .020217   .0433539    0.47   0.641    -.0650466    .1054806
_cons       |  37.75413  9.849594   3.83   0.000     18.38305     57.12521
------------------------------------------------------------------------------
Augmented Dickey-Fuller test for unit root        Number of obs   =      358
                        ---------- Interpolated Dickey-Fuller ---------
             Test        1% Critical      5% Critical      10% Critical
           Statistic         Value            Value            Value
------------------------------------------------------------------------------
 Z(t)         -10.095          -3.986          -3.426          -3.130
------------------------------------------------------------------------------
* MacKinnon approximate p-value for Z(t) = 0.0000
------------------------------------------------------------------------------
D.temperat~e |     Coef.   Std. Err.      t      P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
temperature  |
        L1 |     -.441097   .0436925   -10.10   0.000    -.5270266   -.3551675
        LD |      .2290004   .0515927     4.44   0.000     .1275336    .3304672
_trend      |  .0009352   .0011378    0.82   0.412   -.0013026     .003173
_cons       |  14.75204   1.484327     9.94   0.000    11.83283     17.67125
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Table 3: ADF test for Rainfall and Temperature series without Trend

Augmented Dickey-Fuller test for unit root   Number of obs = 358

	Interpolated Dickey-Fuller			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-8.905	-3.451	-2.876	-2.570

* MacKinnon approximate p-value for Z(t) = 0.0000

D.rainfall	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
rainfall						
L1	-.4242522	.0476434	-8.90	0.000	-.5179509	-.3305535
LD	.0499545	.0529987	0.94	0.347	-.0542764	.1541854
_cons	41.23096	6.429151	6.41	0.000	28.58695	53.87497

Augmented Dickey-Fuller test for unit root   Number of obs = 358

	Interpolated Dickey-Fuller			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-10.068	-3.451	-2.876	-2.570

* MacKinnon approximate p-value for Z(t) = 0.0000

D. temperature	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
temperature						
L1	-.4388046	.0435835	-10.07	0.000	-.5245189	-.3530904
LD	.2279515	.0515534	4.42	0.000	.1265631	.3293399
_cons	14.84327	1.479495	10.03	0.000	11.93359	17.75295

Table 4: Lag Selection Criteria

Lag	AIC	HQIC	SBIC
1	15.803053	15.867955	15.867955
2	15.605223	15.648332	15.713618
3	15.418469	15.478953	15.570537
4	15.223757	15.301693	15.419681
5	15.138641	15.234104	15.378603
6	15.022575	15.135644	15.306761
7	14.952235	15.082986	15.28083
8	14.813664	14.962176	15.186856

Table 5: VAR model at lag 8 for rainfall and temperature time series

```
Vector autoregression
Sample: 1960m10   1990m1
------------------------------------------------------------------------
Equation        Obs  Parms      RMSE     R-sq      chi2       P
------------------------------------------------------------------------
rainfall        352     17    56.9997   0.7201   905.7201   0.0000
temperature     352     17    1.63566   0.7112   866.7275   0.0000
------------------------------------------------------------------------
Model lag order selection statistics
-----------------------------------
 FPE        AIC        HQIC        SBIC        LL        Det(Sigma_ml)
   9303  14.813664   14.962176   15.186856   -2573.2049    7667.3633


----------------------------------------------------------------------------
          |     Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
rainfall     |
rainfall     |
        L1 | -.0438991   .0523728   -0.84   0.402    -.146548    .0587497
        L2 | -.0462281    .052185   -0.89   0.376   -.1485088    .0560525
        L3 |  .0020681   .0513406    0.04   0.968   -.0985576    .1026938
        L4 | -.0601173   .0496824   -1.21   0.226   -.1574929    .0372583
        L5 | -.1129724    .048784   -2.32   0.021   -.2085874   -.0173575
        L6 | -.1956262   .0490811   -3.99   0.000   -.2918234    -.099429
        L7 | -.1968896   .0510134   -3.86   0.000   -.2968741   -.0969052
        L8 | -.1299306   .0518125   -2.51   0.012   -.2314814   -.0283799
temperature  |
        L1 | -7.688047   1.786025   -4.30   0.000   -11.18859   -4.187502
        L2 |  1.100741   1.858709    0.59   0.554   -2.542263    4.743744
        L3 |  3.404807   1.840216    1.85   0.064   -.2019489    7.011563
        L4 |  6.152467   1.850445    3.32   0.001    2.525661    9.779272
        L5 |  3.897059   1.885462    2.07   0.039    .2016213    7.592497
```

L6	3.142034	1.891085	1.66	0.097	-.5644243	6.848491
L7	-.5891503	1.908795	-0.31	0.758	-4.33032	3.152019
L8	-2.391352	1.841534	-1.30	0.194	-6.000692	1.217988
_cons	-64.19275	160.5199	-0.40	0.689	-378.8061	250.4206
temperature						
rainfall						
L1	-.0026712	.0015029	-1.78	0.076	-.0056168	.0002744
L2	.0006798	.0014975	0.45	0.650	-.0022553	.0036148
L3	-.0001178	.0014733	-0.08	0.936	-.0030054	.0027697
L4	-.002271	.0014257	-1.59	0.111	-.0050653	.0005233
L5	.0013318	.0013999	0.95	0.341	-.0014119	.0040756
L6	.0060679	.0014084	4.31	0.000	.0033074	.0088284
L7	.0049342	.0014639	3.37	0.001	.002065	.0078033
L8	.0065018	.0014868	4.37	0.000	.0035877	.0094159
temperature						
L1	.2548849	.0512516	4.97	0.000	.1544335	.3553362
L2	-.0593777	.0533374	-1.11	0.266	-.163917	.0451616
L3	-.0888727	.0528067	-1.68	0.092	-.1923719	.0146264
L4	-.197279	.0531002	-3.72	0.000	-.3013535	-.0932045
L5	-.0264664	.0541051	-0.49	0.625	-.1325103	.0795776
L6	.1205344	.0542664	2.22	0.026	.0141742	.2268946
L7	.0068929	.0547746	0.13	0.900	-.1004633	.1142492
L8	-.1820181	.0528445	-3.44	0.001	-.2855914	-.0784448
_cons	38.27358	4.606266	8.31	0.000	29.24546	47.30169

Table 6: Granger Causality Test

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
rainfall	temperature	74.2114	8	0.0000
rainfall	ALL	74.2114	8	0.0000
temperature	rainfall	80.9265	8	0.0000
temperature	ALL	80.9265	8	0.0000

Table 7: VAR stability Condition

Eigenvalue stability condition

Eigenvalue	Modulus
.8598821 + .49686041	.99310999
.8598821 - .49686041	.99310999
.4515828 + .80715762	.92489484
.4515828 - .80715762	.92489484
.7236031 + .22003161	.75631696
.7236031 - .22003161	.75631696
.1493898 + .78230925	.79644529
.1493898 - .78230925	.79644529
-.2981741 + .73656616	.79463043
-.2981741 - .73656616	.79463043
-.3914914 + .68809827	.79167212
-.3914914 - .68809827	.79167212
-.6803016 + .36985289	.77433936
-.6803016 - .36985289	.77433936
-.7089978 + .19217735	.73458154
-.7089978 - .19217735	.73458154

Fig 3: The IRF for rainfall and Temperature time series data

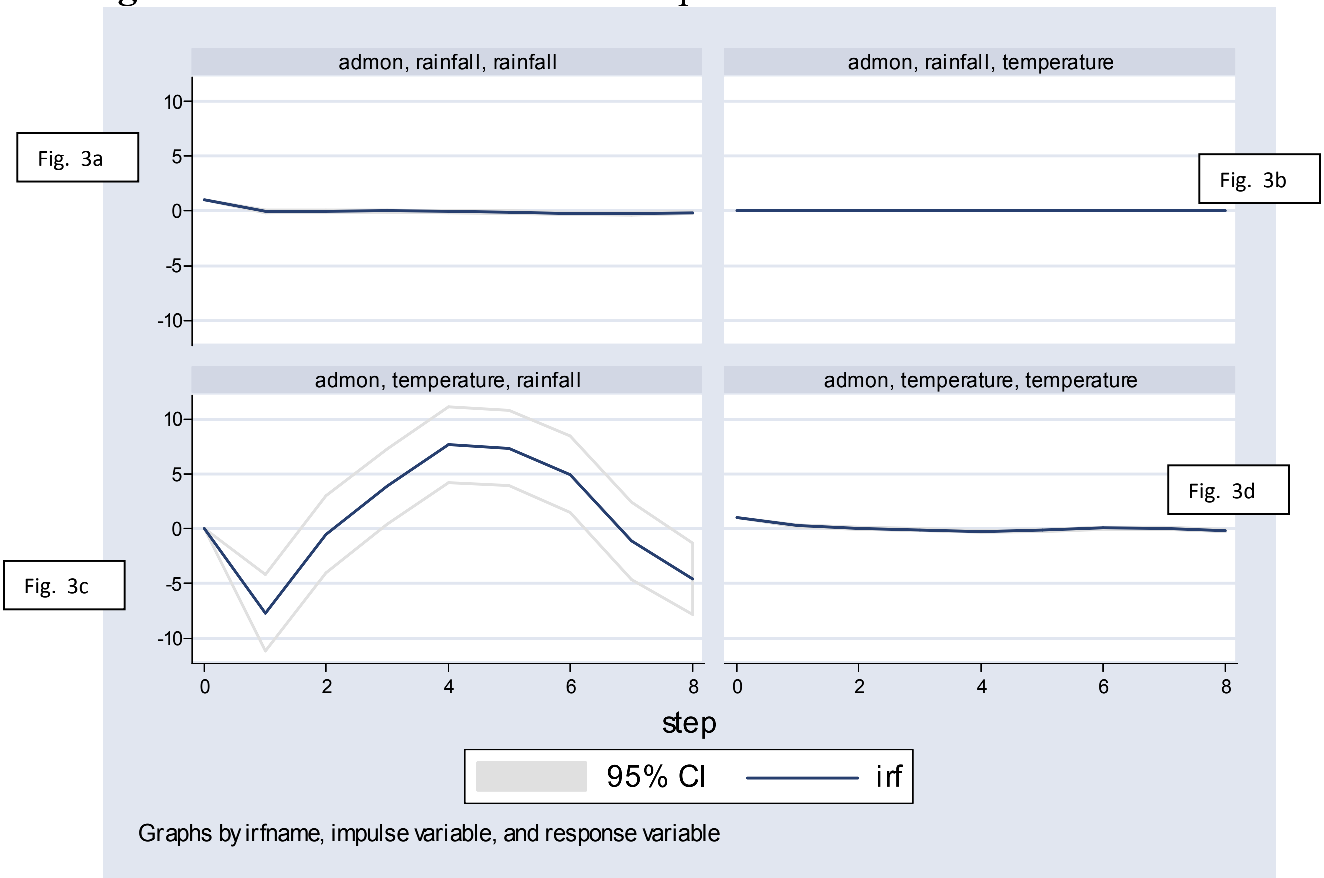

Fig 4: Decomposition of Variance from VAR

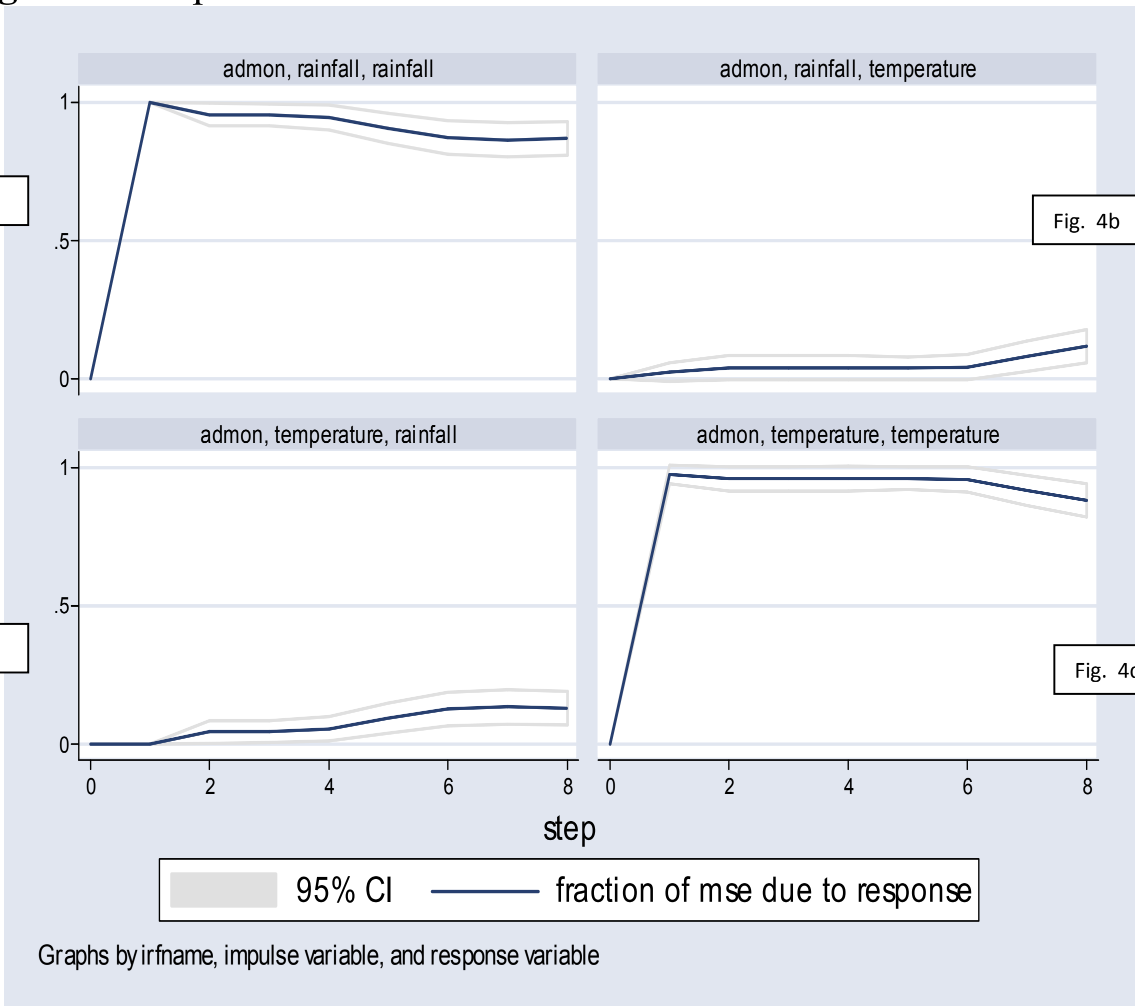

Fig. 4a

Fig. 4b

Fig. 4c

Fig. 4d

Table 8: Result on Forecast Error Variance Decompositions

. varirf table fevd, stderror step(10) Results from admon

(1) step	(1) fevd	(1) Lower	(1) Upper	(2) S.E.	(2) fevd	(2) Lower	(2) Upper	S.E.
0	0	0	0	0	0	0	0	0
1	1	1	1	1.1e-17	.026109	-.006769	.058988	.016775
2	.954748	.914382	.995114	.020595	.040819	-.003174	.084812	.022446
3	.954569	.914357	.99478	.020516	.040794	-.003181	.084769	.022437
4	.943808	.898846	.988771	.02294	.040772	-.003232	.084776	.022451
5	.90459	.850173	.959007	.027764	.03921	-.001282	.079702	.02066
6	.872926	.812274	.933578	.030946	.043613	-.000818	.088044	.022669
7	.864437	.801687	.927188	.032016	.083421	.028653	.138188	.027943

(3) step	(3) fevd	(3) Lower	(3) Upper	(4) S.E.	(4) fevd	(4) Lower	(4) Upper	S.E.
0	0	0	0	0	0	0	0	0
1	0	0	0	0	.973891	.941012	1.00677	.016775
2	.045252	.004886	.085618	.020595	.959181	.915188	1.00317	.022446
3	.045431	.00522	.085643	.020516	.959206	.915231	1.00318	.022437
4	.056192	.011229	.101154	.02294	.959228	.915224	1.00323	.022451
5	.09541	.040993	.149827	.027764	.96079	.920298	1.00128	.02066
6	.127074	.066422	.187726	.030946	.956387	.911956	1.00082	.022669
7	.135563	.072812	.198313	.032016	.916579	.861812	.971347	.027943

95% lower and upper bounds reported
(1) irfname = admon, impulse = rainfall, and response = rainfall
(2) irfname = admon, impulse = rainfall, and response = temperature
(3) irfname = admon, impulse = temperature, and response = rainfall (4) irfname = admon, impulse = temperature, and response = temperature