Forecasting of Temperature and Rain in the City of Baghdad Using Seasonal Vector Autoregressive Moving Average Modelsvarma

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Abstract

In this research , theinteraction between two variable was studied and analyzed , the firstrepresenting the amount of monthly rainfall and the secondrepresenting the monthly temperature in Baghdad city , Abu Ghraib station for the period from Jan 2015 to Dec 2019 so it will be 60 values ,each variable represents a time series of 60 values , the two series were standardized with zero mean and one variance ,then the stationarity of the two series was tested by the Diekey Fuller test, for the purpose of choosing the best order of the model , the corrected Akaike information standard AICC was calculated,It was found that the best model has the lowest value for the AICCstandard is SVARMA(2,0) , then the model was estimated , some tests were conducted including Portmanteau test on the residual series of the estimated model, AR disturbance test , and then forecast for this model for a period of 24 months , starting from Jan 2020 to Dec 2021.The aim of this research is to analyze the relationship between rain and temperature with forecasting , due to importance of the amount of rainfall and the temperature on agriculture and the economy in general , it was concluded that The optimal model is SVARMA(2,0) ,the rain influenced by temperature at lag 1 , while temperature is influenced by temperature at lag 1 and 2 andthe variance increases as the forecast period increases . SAS programing was used to estimate and forecast the model .

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1.Introduction

Rain and temperature are important climatic factors that have a significant impact on agricultural production and that have a significant impact on the economy , as well as the forecasting of these two factors , and the rain is of great importance , it enables the competent agriculture authorities to grow agriculture crops that are commensurate with the Amount of forecasting rainfall , as well as with regard to temperature and its impact on agricultural crops , especially in the recent period of time and the damage caused by global warming to the environment in general and to agricultural crops in particular ,

One of the important models in analyzing the relationship between variables is seasonalvector autoregressive moving average models, it is a model used to measure the effects between varaibles , It is used in the field of climatic factorReinsel,1993 measure the impact of each climatic factor and the relationship between them . It is also used to determine the relationship between economic variables , The topic of multivariate time seriesattracted the attention by researchers such asTiao and Box (1981) [1] [7]

2.method

There are seasonal phenomena that appear in several time series repeat itself after each regular period , these phenomena appear in time series related to agriculture , construction and travel sector , they will have seasonal models because of the relationship between these time series and the weather .The appropriate way to represent these seasonal phenomena through seasonal vector autoregressive moving average models as following :

for *n* variables , a seasonalvector ARMA(p)$(P)_s$(q)$(Q)_s$ modelhas the following form:

$$\phi(B)\boldsymbol{\Phi}(\boldsymbol{B^s})\boldsymbol{y_t} = \boldsymbol{\theta}(\boldsymbol{B})\Theta(B^s)u_t \qquad \cdots\ 1$$

Where

$$\phi(B) = I_n - \phi_1 B - \cdots - \phi_p B^p$$

$$\boldsymbol{\Phi}(B^s) = I_n - \boldsymbol{\Phi}_1 B^s - \cdots - \boldsymbol{\Phi}_P B^{Ps}$$

$$\boldsymbol{\theta}(B) = I_n - \boldsymbol{\theta}_1 B - \cdots - \boldsymbol{\theta}_q B^q$$

$$\Theta(B^s) = I_n - \Theta_1 B^s - \cdots - \Theta_Q B^{Qs}$$

$y_t = (y_{1t} . \cdots . y_{nt})'$representesan ($n$ $x1$)vectorof variables , B is the backshift operator , $\phi_s . \Phi_s$. , an (n x n) matrices of autoregression parameters , $\boldsymbol{\theta}_s . \Theta_s$ an (n x n) matrices of moving average parameters , s is the smallest time period , u_t an (n $x1$) vector of white noise $u_t = (u_{1t} \ldots u_{nt})'$ zeromean white noise withcovariance matrix $\Sigma_u = E(u_t u_t')$. [8]

2.1 Model optimum lag length selection

For the purpose of determining the model order,CorrectedAkaike information criterion was adopt , the formula is defined as follows :

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$$AICC = log(|\Sigma_{\hat{u}}|) + \frac{2r}{(T - r)/n} \qquad (2)$$

Were $\Sigma_{\hat{u}} = T^{-1}\Sigma_{t=1}^{T}\hat{u}_t\hat{u}_t^{'}$the maximum likelihood estimator of the residual covariance matrix , ndenote the number of variables , r denote the number of parameters and T denote the number of observation[3][1]

2.2 Multivariate Portmantau test

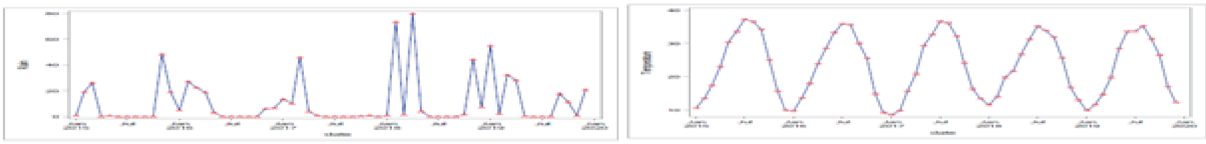
the statistics for the Ljung-Boxtest is the following form :

$$Q_{\mathrm{h}} = T^2 \sum_{l=1}^{\mathrm{h}} (T - l)^{-1}\, tr\{\hat{C}_{\epsilon}(l)\hat{C}_{\epsilon}(0)^{-1}\hat{C}_{\epsilon}(-l)\hat{C}_{\epsilon}(0)^{-1}\} \qquad (3)$$

Were$\hat{C}_{\epsilon}(l)$ represent the residualsof cross correlation, h is the maximum lag to be tested [2][1][5][6]

3. Application

Two time series were used , represented by the monthly rainfall and the monthly temperature series in Baghdad city , Abu Ghraib station for the period from Jan 2015 to Dec 2019



$(1._{A})$ $(1._{B})$

Figure.(1.($_{A}$) . ($_{B}$)) rain and temperature series

After standardized the two series to mean zero and variance one [4] , to test the stationarity of the series the dicky - fuller test has been calculated , The null hypothesis which states there exists a unit root is not accepted , and then the two series are stationary , table(1).

Table (1). The test of Dickey-Fuller

Variable	Type	Rho	Pr< Rho	Tau	Pr< Tau
Rain	Zero Mean	-33.95	<.0001	-4.05	0.0001
	Single Mean	-33.95	0.0005	-4.01	0.0025
	Trend	-34.53	0.0007	-4.01	0.0138
Temperature	Zero Mean	-120.03	0.0001	-6.49	<.0001
	Single Mean	-120.06	0.0001	-6.47	0.0001
	Trend	-129.62	0.0001	-6.47	<.0001

For the purpose of determining the order of the appropriate model , the value of corrected Akaike information criterion was calculated, table(2)shows that the model SVARMA(2,0) has the lowest value of the AICC criterion .

Table (2). The Corrected Akaike Information Criterion

Lag	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	-0.188471	-0.17852	-0.213882	-0.108475	0.0056006	0.0617678
AR 1	-1.288552	-1.136496	-1.20605	-1.239905	-1.333445	-1.338471
AR 2	-2.138846	-2.091439	-2.066039	-2.02936	-1.939573	-1.765191
AR 3	-2.045322	-2.057932	-1.952669	-1.823278	-1.720026	-1.542618
AR 4	-1.982337	-2.046527	-1.90615	-1.704758	-1.647116	-1.47061
AR 5	-1.858597	-1.878725	-1.76146	-1.528186	-1.503641	-1.15574

Table (3) shows the parameters estimates for SVARMA(2,0) model , it is clear from the significant parameter A1_1_2 that rain influenced by temperature at t-1 , while temperature is influenced by temperature at t-1 , AR1_2_2 and t-2 , AR2_2_2respectively .

Table(3). Estimated parameters of SVARMA(2,0) model

Equation	Parameter	Estimate	Standard Error	t	Pr > |t|	Variable
Rain	Constant1	0.01339	0.11742	0.11	0.9096	1
	AR1_1_1	-0.27227	0.13860	-1.96	0.0547	Rain(t-1)
	AR1_1_2	-0.61008	0.22623	-2.70	0.0094	Temperature(t-1)
	AR2_1_1	0.14608	0.13775	1.06	0.2937	Rain(t-2)
	AR2_1_2	0.10381	0.24462	0.42	0.6730	Temperature(t-2)
Temperature	Constant2	0.02926	0.04786	0.61	0.5436	1
	AR1_2_1	0.04577	0.05649	0.81	0.4214	Rain(t-1)
	AR1_2_2	1.53980	0.09221	16.70	0.0001	Temperature(t-1)
	AR2_2_1	-0.01004	0.05614	-0.18	0.8587	Rain(t-2)
	AR2_2_2	-0.84239	0.09970	-8.45	0.0001	Temperature(t-2)

Table (4) shows the cross – correlation structure for the residuals of the SVARMA(2,0) model , as it turns out that the residuals are uncorrelated .

Table(4). The Representation ofResiduals SchemeofCross Correlations forSVARMA(2,0)model

Variable/Lag	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Rain	+-	..	..	..	..	..	..	..	..	..	..	..	..
Temperature	-+	..	..	..	..	..	..	..	..	..	..	..	..

Table (5) shows portmanteau test , as it turns out that the test statistic insignificant for all lagged , this means that there is no autocorrelation in the residuals .

Table(5). Portmanteau test ofresiduals for SVARMA(2,0)model

Lag	df	Chi-Square	Pr > ChiSquare
3	4	4.84	0.3043
4	8	8.63	0.3747
5	12	10.65	0.5590
6	16	13.08	0.6670
7	20	13.53	0.8536
8	24	15.43	0.9077
9	28	19.99	0.8648

10	32	21.55	0.9189
11	36	23.16	0.9518
12	40	24.08	0.9781

Table (6) shows R- Square explanatory ability for each variable , the P value of F statistics show that the univariate model is significant .

Table(6). Diagnostics of Univariate Model for SVARMA(2,0) model

Variable	R-Square	Standard Deviation	F	Pr > F
Rain	0.2762	0.89378	5.06	0.0016
Temperature	0.8744	0.36429	92.28	<.0001

Table(7) shows F test for Autoregressive Conditional HeteroscdasticARCH , to test that thecovariances of residuals are equal , as it turns out that the test statistics are insignificant , this indicates that the residuals are homogeneous . [5]

Table(7).ARCH test for SVARMA(2,0) model

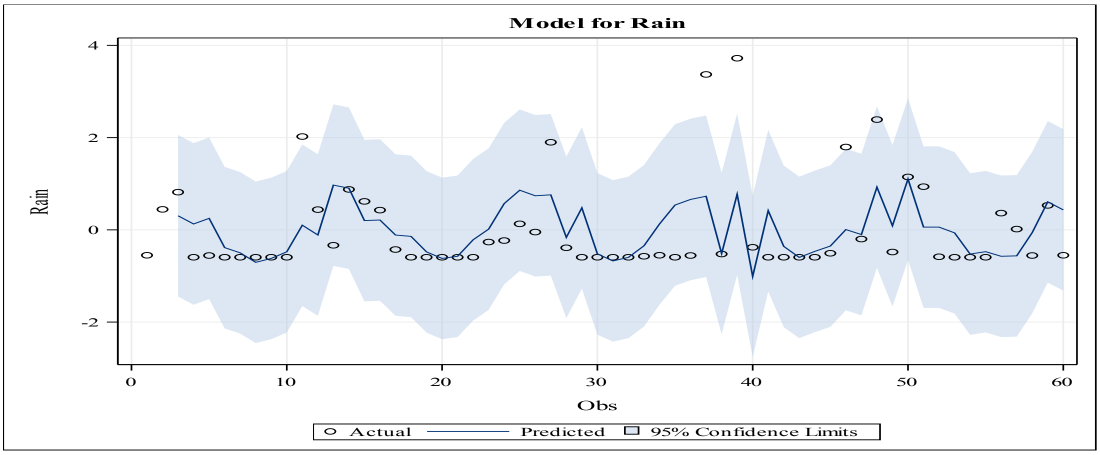
Variable	ARCH	
	F	Pr > F
Rain	0.20	0.6589
Temperature	0.25	0.6203

Table (8) shows the test ofdisturbance for ARUnivariate Model ,for the purpose of testing the null hypothesis that the residualsare independent, as it turns out that the residuals have no AR effects .[5]

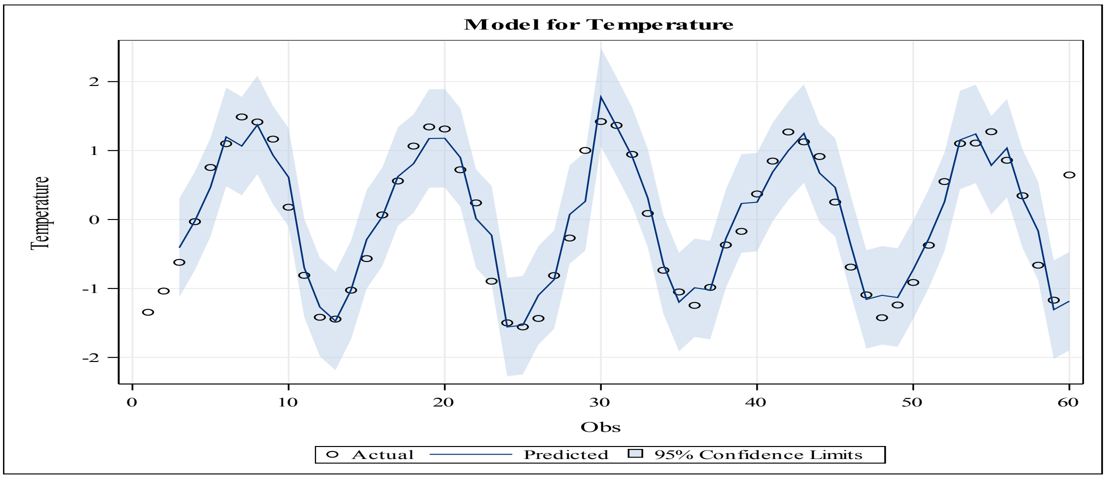
Table(8). The test of AR Univariate Model

Variable	AR1		AR2		AR3		AR4	
	F	Pr > F	F	Pr > F	F	Pr > F	F	Pr > F
Rain	0.01	0.9184	0.01	0.9864	0.18	0.9064	0.60	0.6643
Temperature	1.78	0.1870	1.14	0.3281	0.73	0.5414	0.95	0.4413

Figure(2) , (3)shows actual with predicted value for the rain series , and actual with predicted value for the temperature series respectively .



Figure(2). predicted rain series



Figure(3). predicted temperature series

3.1 Simple impulse response

Response impulse can be defined as the response of one variable to the shock in another variable[5], table (9) shows the response of rain →temperature at lag 2is 0.67 , this represent the impact on rain of one unit change in temperature at lag 2 , and the responseof temperature

→temperature at lag 3 is 0.99 this represent the impact on temperature of one unit change in temperature at lag 3 .

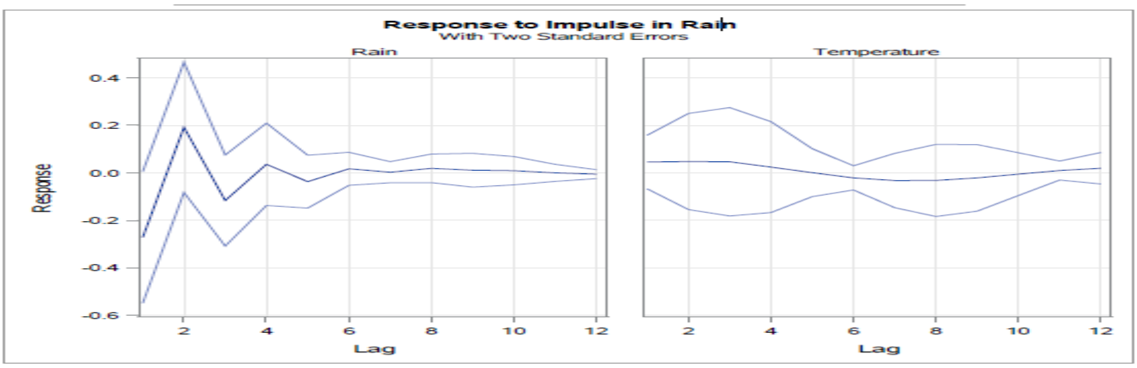
Table(9). Simple Impulse Response function

Lag	Variable Response\Impulse	Rain	Temperature
1	Rain	-0.27227	-0.61008
	STD	0.13860	0.22623
	Temperature	0.04577	1.53980
	STD	0.05649	0.09221
2	Rain	0.19229	-0.66949
	STD	0.13732	0.17515
	Temperature	0.04798	1.50067
	STD	0.10131	0.20630
3	Rain	-0.11664	-0.66253
	STD	0.09596	0.20291
	Temperature	0.04685	0.98910
	STD	0.11421	0.28834
4	Rain	0.03625	-0.36507
	STD	0.08677	0.22159
	Temperature	0.02446	0.23527
	STD	0.09582	0.31503
5	Rain	-0.03697	-0.03825
	STD	0.05575	0.21127
	Temperature	0.00102	-0.48100
	STD	0.05055	0.31300
6	Rain	0.01728	0.27495
	STD	0.03478	0.20293
	Temperature	-0.02108	-0.93691
	STD	0.02545	0.33167
7	Rain	0.00287	0.44122
	STD	0.02226	0.19863
	Temperature	-0.03216	-1.02450

	STD	0.05724	0.37613
8	Rain	0.01918	0.44781
	STD	0.03016	0.20994
	Temperature	-0.03181	-0.77085
	STD	0.07600	0.40986
9	Rain	0.01126	0.30646
	STD	0.03562	0.21911
	Temperature	-0.02103	-0.30785
	STD	0.07015	0.41573
10	Rain	0.00927	0.08978
	STD	0.02987	0.21789
	Temperature	-0.00527	0.18485
	STD	0.04508	0.40985
11	Rain	0.00015	-0.12441
	STD	0.01797	0.21184
	Temperature	0.00991	0.54500
	STD	0.01998	0.41416
12	Rain	-0.00528	-0.26632
	STD	0.00945	0.20877
	Temperature	0.01962	0.67687
	STD	0.03320	0.42583

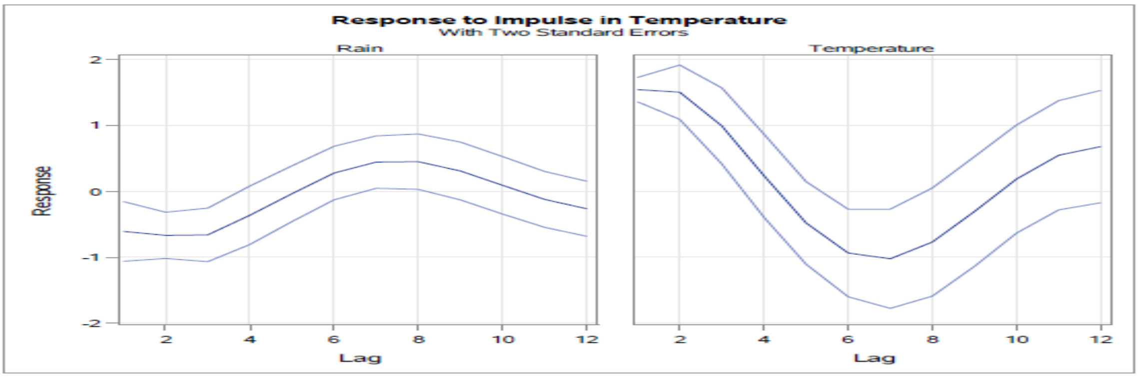
Figure (4)shows the responses of rain and temperature to a forecast error in rain impulse

Figure(4).response to impulsein rain



Figure(5)shows the responses of rain and temperature to a forecast error in temperature impulse

Figure(5).response to impulse in temperature



the forecasting process based on The optimal minimum mean squared error (minimum MSE)i-step-ahead forecast (8),tabel (10) shows forecasting values for rain and temperature series fromJan 2020 to Dec 2021 **,** we note that the standard deviation increases for both series as the forecast period increases **,** this indicates that the variance increases as the forecast period increases . figure (6) , (7) .

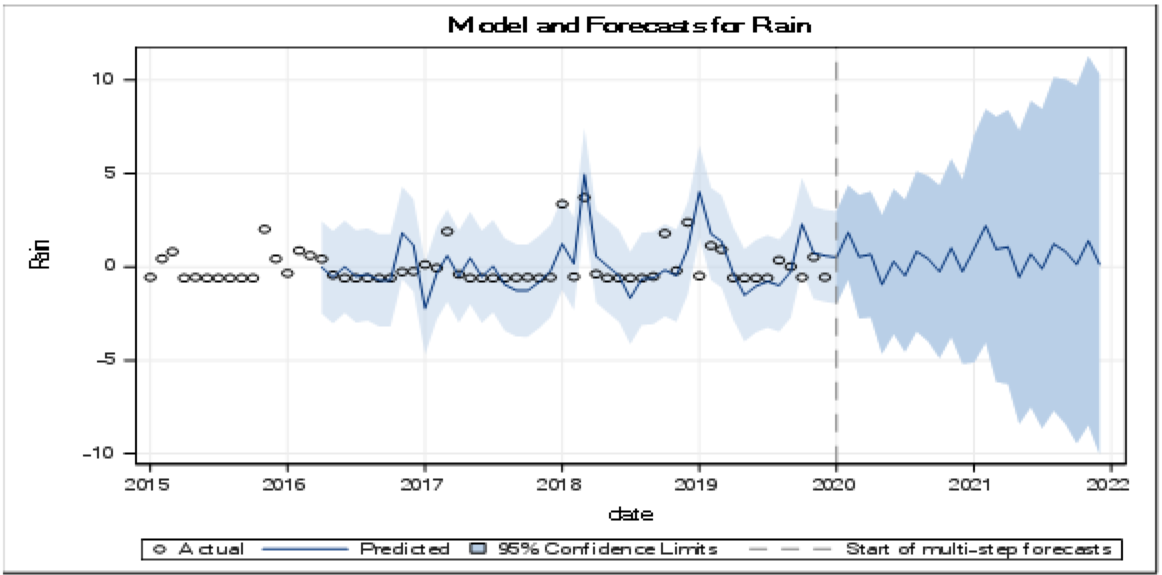
Table(10). TheForecasts for SVARMA(2,0)model

Variable	Obs	Time	Forecast	Standard Error	95% Confidence Limits	
Rain	61	2020m1	0.51255	1.26288	-1.96264	2.98774
	62	2020m2	1.84620	1.28850	-0.67922	4.37163
	63	2020m3	0.54614	1.68767	-2.76164	3.85392
	64	2020m4	0.67870	1.71745	-2.68743	4.04483
	65	2020m5	-0.93681	1.89581	-4.65252	2.77891
	66	2020m6	0.29254	1.98413	-3.59628	4.18137
	67	2020m7	-0.47004	2.07707	-4.54102	3.60094
	68	2020m8	0.83411	2.18711	-3.45256	5.12077
	69	2020m9	0.43936	2.25923	-3.98864	4.86736
	70	2020m10	-0.25604	2.35924	-4.88008	4.36799

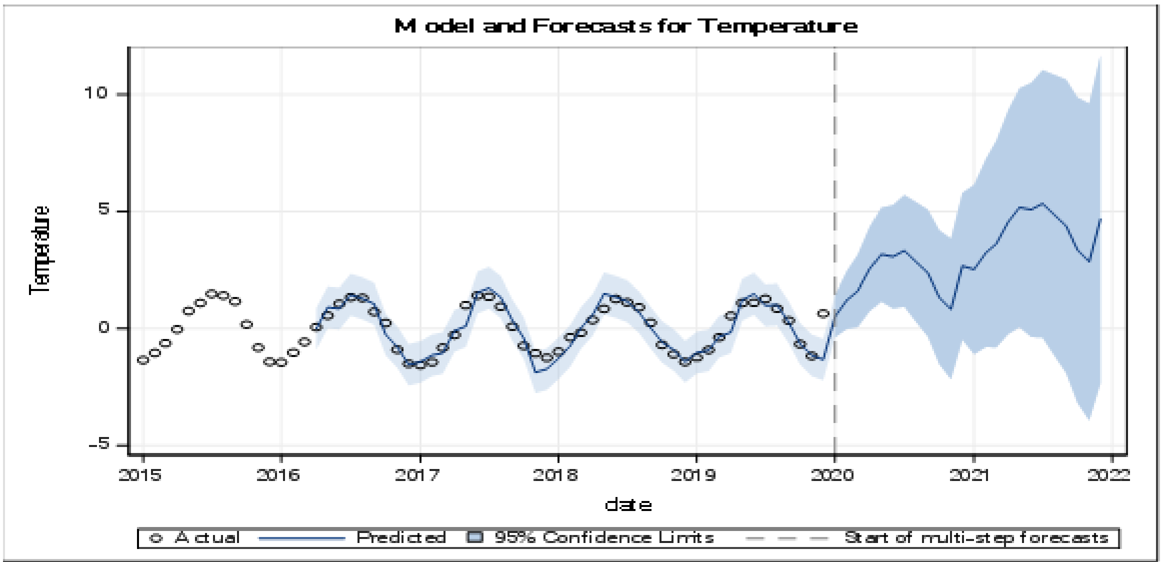
	71	2020m11	1.01852	2.43228	-3.74866	5.78569
	72	2020m12	-0.24527	2.51677	-5.17805	4.68751
	73	2021m1	0.95850	3.09833	-5.11413	7.03112
	74	2021m2	2.20511	3.18643	-4.04018	8.45040
	75	2021m3	0.94483	3.62246	-6.15506	8.04471
	76	2021m4	1.07160	3.74130	-6.26121	8.40441
	77	2021m5	-0.55764	4.00625	-8.40973	7.29446
	78	2021m6	0.69297	4.18294	-7.50544	8.89137
	79	2021m7	-0.09032	4.36299	-8.64162	8.46097
	80	2021m8	1.22976	4.55553	-7.69891	10.15844
	81	2021m9	0.82508	4.70913	-8.40465	10.05481
	82	2021m10	0.13424	4.88732	-9.44474	9.71322
	83	2021m11	1.40811	5.03683	-8.46389	11.28012
	84	2021m12	0.14278	5.19560	-10.04041	10.32598
Temperature	61	2020m1	0.51794	0.45495	-0.37375	1.40963
	62	2020m2	1.21361	0.62676	-0.01483	2.44205
	63	2020m3	1.60928	0.78596	0.06883	3.14973
	64	2020m4	2.53094	0.91587	0.73586	4.32602
	65	2020m5	3.15832	1.02147	1.15628	5.16036
	66	2020m6	3.06444	1.12678	0.85599	5.27289
	67	2020m7	3.32118	1.21448	0.94085	5.70151
	68	2020m8	2.83967	1.30221	0.28739	5.39195
	69	2020m9	2.36490	1.38099	-0.34179	5.07159
	70	2020m10	1.34129	1.45690	-1.51418	4.19676
	71	2020m11	0.83448	1.52895	-2.16220	3.83116
	72	2020m12	2.65876	1.59719	-0.47167	5.78919
	73	2021m1	2.51927	1.84296	-1.09287	6.13141
	74	2021m2	3.22536	2.04758	-0.78782	7.23855
	75	2021m3	3.61337	2.25192	-0.80031	8.02705
	76	2021m4	4.53955	2.43732	-0.23751	9.31661
	77	2021m5	5.16507	2.60352	0.06227	10.26788
	78	2021m6	5.07122	2.76762	-0.35321	10.49565

79	2021m7	5.32892	2.91531	-0.38498	11.04283
80	2021m8	4.84613	3.06104	-1.15339	10.84565
81	2021m9	4.37254	3.19711	-1.89368	10.63877
82	2021m10	3.34806	3.32890	-3.17647	9.87259
83	2021m11	2.84177	3.45555	-3.93098	9.61451
84	2021m12	4.66583	3.57723	-2.34541	11.67707

Figure(6). Forecasts and predicted for rain series



Figure(7). Forecasts and predicted for temperature series



4. Conclusions

- The optimal model is SVARMA(2,0) , which isdetermined by AICCstandard ,

- The residuals for SVARMA(2,0) model are random , based on the results of the portmanteau test, ARCH test and AR disturbance test .
- the rain influenced by temperature at lag 1 , while temperature is influenced by temperature at lag 1 and 2
- the variance increases as the forecast period increases .

5. proposal

among the models that are suggested to be estimated are multivariate GARCH modes such as BEKK , CCC , DCC .

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