J. Environ. Sci. & Natural Resources, **10(2): 163–170, 2017** ISSN 1999-7361

Forecasting of Climatic Variables in Dinajpur of Bangladesh

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Abstract

An attempt was made to forecast the 17 monthly climatic variables for 2005-2012 of Dinajpur using the univariate Box-Jenkinôs ARIMA (autoregressive integrated moving average) modeling techniques for 1948-2004. The 8 years data for 1973-1980 were missing and those data were replaced with the 4 years monthly forecasted data for 1948-1972 and 1981-2004 (reversing the years). The well fitted ARIMA (autoregressive integrated moving average) models were selected from the possible 16 ARIMA models based on the minimum root mean square forecasting errors (RMSFE) with the last 24 observations for all the cases and the residuals followed stationarity and normality. Several outliers were detected in the data which were replaced by the forecasted value. The fitted model for sunshine data (1989-2004) was found ARIMA $(1, 1, 1)(1, 1, 1)_{12}$ and for evaporation data (1987-2000) was ARIMA $(1, 1, 2)(1, 1, 1)_{12.}$. The findings supports that the changing term of the climatic variables may have adverse impacts on the crop production in this country.

Key words: ARIMA, Climate, Forecasting

Introduction

Climatic pattern has significant impact on the agricultural field, soil moisture regime, crop phenology, crop productivity and so on. Climatic variables may vary from time to time and from space to space and these variations may hamper agricultural crop production.

Wheat is the second most important cereal crop after rice in Bangladesh and Dinajpur is the highest wheat producing district having long tradition of its cultivation. Wheat is much sensitive to climatic variation and change. So, forecasting of climatic variables are necessary for the planning of wheat production in this district. The prediction of atmospheric parameters is essential for various applications like climate monitoring, drought detection, severe weather prediction, agriculture and production, planning in energy and industry, communication, pollution dispersal etc. But the weather prediction is a complex process and a challenging task for researchers. The accurate prediction of weather parameters is a difficult task due to the dynamic nature of atmosphere. So, for proper planning of expected crop yields, the study of the temporal rainfall and its forecasting are much needed. In this study, it was tried to forecast 17 climatic variables using the monthly data by fitting the ARIMA model.

Methodology

Sources of data

The daily data were taken from Bangladesh Meteorological Department, Dhaka. The monthly data used in the analyses were total rainfall in millimeter (TR), maximum rainfall in millimeter (MXR), total frequency of insignificant (<5mm) rain (TFIR), average dry bulb temperature in celcius (ADBT), average maximum temperature in celcius (AMXT), average minimum temperature in celcius (AMNT), average range temperature in celcius (ARNT), average wet bulb temperature in celcius (AWBT), Average difference of dry bulb and wet bulb temperature in celcius {AT(D-W)}, average relative humidity in percentage (ARH), Average difference of relative humidity between morning and evening in percentage ARH(0-12), average wind speed in knots (AWS), average maximum wind speed in knots (AMWS), average sea level pressure in millibar (ASLP) and average cloud in octas (AC) were collected for 1948-1972 and 1981-2004. The monthly data of TR, MXR and TFIR were made by accumulating the daily data but the monthly data for the rest of the variables were obtained from the average of the daily data. The missing values for 1973-1976 and 1977-1980 were replaced by the forecasted values which were obtained from the fitted ARIMA models for 1948-1972 and 1981-2004 (reversing the year). The average sunshine hour (ASH) during 1989-2004 and average evaporation during 1987-2000 were collected too. Finally, ARIMA models were fitted with the missing replaced data taking the 684 monthly observations for 1948-2004 and the values for 2005-2008 were forecasted. Again, the data for 2009-2012 were forecasted from the missing replaced and forecasted data taking the 780 observations for 1948 - 2008 by the similar process. The variables ASH and AE were forecasted for 2005-2008 from the fitted ARIMA model for 1987-2004 and 1989-2000, respectively.

Methodologies

In this section, the methodologies used in the analyses have been discussed. Univariate Box-Jenkinôs ARIMA model was fitted to forecast the monthly data for January 2008-December 2012. After confirmed the stationary series, an effort was made for an ARIMA model to express each observation as a linear function of the previous value of the series (autoregressive parameter) and of the past error effect (moving average parameter). The available data were divided into training, validation and test sets. The training set was used to build the model, the validation set was used for parameter optimization and the test set was used to evaluate the model. The adequacy of the above model was checked by comparing the observed data with the forecasted results. In this study, the data for the last two years were used to compare with the fitted model forecasts for the years and the models were selected for the minimum root mean square forecasting error (MRMSFE) of the data set of those two years. The diagnostic techniques namely histogram of residuals, normal probability plot of residuals, autocorrelation function (ACF) and Partial autocorrelation (PACF) display of residuals, Time series (TS) plots for residual versus fitted values and TS plots for residual versus order of the data were used for checking residuals of ARIMA models. Box-Cox transformation was used for variance stabilization and the transformation of the data to get stationary series from non-stationary series, Pankraiz (1991). The software package Minitab 13 was used to fit the ARIMA models. A detailed description of the non-seasonal and seasonal ARIMA models and the standardized notation used in this paper is set in the Appendix 1.

Box Jenkins modelling strategy and ARIMA model

Box Jenkins (1976) formalized the ARIMA modeling framework in the three steps: (I) Identification, (II) Estimation and (III) Verification. In the identification stage, it is tried to identify that how many terms to be included is based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the differenced and/or transformed time series (Box Jenkins, 1976). In the estimation stage, the coefficients of the model are estimated by means of the maximum likelihood method. The verification of the model is done through diagnostic checks of the residuals (histogram or normal probability plot of residuals, standardized residuals and ACF and PACF of the residuals). The performance of the ARIMA models is often tested through comparison of prediction with observation not used in the fitted model. An appropriate ARIMA model provides minimum mean squared error forecasts among all linear univariate models with fixed coefficients. It can produce point forecasts for each time period and interval forecasts constructing a confidence interval around each point forecast. To have the 95% interval for each forecast the formulae $f \pm 2s$ is used, where f denotes a forecast and s is its standard error. The forecasts for a stationary model converge to the mean of the series and the speed of converging movement depends on the nature of the model. For non-stationary model the forecasts do not converge to the mean.

Results and Discussions

The well fitted ARIMA models for all the variables during 1948-1972, 1981-2004 (reversing the years), 1948-2004 and 1948-2004 were selected from the 16 possible ARIMA models on the basis of minimum root mean square forecasting error (MRMSFE) for the last two years of 24 observations. The ACF displays for residual autocorrelations for the estimated models were fairly small relative to their standard errors for all the variables. The histograms of the residuals were symmetrical suggesting that the shocks may be normally or approximately normally distributed. The normal probability plots of the residuals did not deviate badly from straight lines (fairly close to a straight line), again suggesting that the shocks are normal. The outliers of 1981 for AMNT, ARNT, ARH, AWS, AWBT and ARH(0-12) were replaced by the forecasted value of 1981 from the fitted ARIMA models for January 1982-December 2004 by reversing the years and those models are presented in the Tables 1-16. The data for April 1948 of ASLP (989.48) and September 1960 of ASLP (978.51) were detected as outliers from the two drops in the TS plot of ASLP for 1948-1972. Firstly, the data for September 1960 of ASLP (978.51) was replaced by the forecasted value of 1000.13 for September 1960 from the well fitted ARIMA models for 1961-1972 (reversing the years). After replacing the outlier by the forecasted value, ARIMA model for 1949-1972 (reversing the years) was fitted and the year 1948 was forecasted. Afterwards, the data for April 1948 of ASLP (989.48) was replaced by the forecasted value of 1006.52 taken from the forecasted year 1948. The fitted ARIMA Models selected from the possible 16 ARIMA (autoregressive integrated moving average) models based on minimum root mean square forecasting error (RMSFE) with the last 24 observations for all the cases are presented in the Tables 1-16 and TS plots of point and interval forecasts for the models of the variables are shown in the figures 1-18. Furthermore, some obtained point forecasts are presented in the Tables 1-16 but interval forecasts are not shown.

Table 1. Models for total rainfall (TR) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
SQ RT of TR(1948-72)	ARIMA(1, 0, 1)(0, 1, 1)	$(1 - 0.8739B)\ \nabla^{12} y_t = -0.00555 + (1 - 0.7768B)(1 - 0.9217B^{12})\ \varepsilon_t$	5.2150	15.06
SQ RT of TR(1981-04)	ARIMA(1, 0, 0)(1, 1, 1)	$(1 - 0.0324B)\ (1 + 0.0449\ B^{12})\ \nabla_{12} y_t = -0.02654 + (1 - 0.9295\ B^{12}))\ \varepsilon_t$	4.8578	15.94
S QRT of TR(1948-04)	ARIMA(1, 0, 0)(1, 1, 1)	$(1 - 0.089B)(1 - 0.0131B^{12}))\ \nabla_{12} y_t = 0.037875 + (1 - 0.9616B^{12})\ \varepsilon_t$	3.8943	13.66
SQ RT of TR(1948-08)	ARIMA(2, 0, 0)(1, 1, 1)	$(1 - 0.0774B)(1 - 0.0777B^2)(1 - 0.0287\ B^{12})\ \nabla_{12} y_t = 0.035531 + (1 - 0.9996\ B^{12})\ \varepsilon_t$	0.0132	12.43

* *MRMSFE = Minimum root mean square forecasting error* *MSE = Mean square error*

Table 2. Models for total frequency of insignificant rain (TFIR) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
TFIR (1948-72)	ARIMA(1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.1692B)\ \nabla_{12}\ y_t = 0.05077 + (1 - 0.9348)\ \varepsilon_t$	2.6427	6.53
TFIR(1981-04)	ARIMA(1, 0, 0)(1, 1, 1)$_{12}$	$(1 - 0.0521B)\ (1 + 0.0654B^{12})\ \nabla_{12}\ y_t = 0.01848 + (1 - 0.9327B^{12})\ \varepsilon_t$	2.4707	6.14
TFIR(1948-04)	ARIMA(1, 1, 1)(0, 1, 1)$_{12}$	$(1 - 0.0758\ B)\ \nabla_{12}\ \nabla\ y_t = -0.00031 + (1 - 0.9562B)(1 - 0.9528B^{12})\ \varepsilon_t$	2.3263	5.70
TFIR(1948-08)	ARIMA(0, 1, 1)(1, 1, 1)$_{12}$	$(1 - 0.0303B^{12})\ \nabla_{12}\ \nabla\ y_t = -0.0003176 + (1 - 0.9492B)\ (1 - 0.9925B^{12})\ \varepsilon_t$	0.1755	5.29

Table 3. Models for maximum rainfall (MXR) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
SQRT of MXR(1948-72)	ARIMA(1, 0, 1)(1, 0, 1)$_{12}$	$(1 - 0.7381B)(1 - 0.9984B^{12})\ y_t = -0.003462 + (1 - 0.6737B)(1 - 0.9328\ B^{12})\ \varepsilon_t$	2.9494	6.16
SQRT of MXR(1981-04)	ARIMA(1, 1, 1)(1, 0, 1)$_{12}$	$(1 + 0.0168B)(1 - 0.9986B^{12})\ \nabla\ y_t = -0.000099 + (1 - 0.8923\ B^{12})\ \varepsilon_t$	3.8419	7.33
SQRT of MXR(1948-04)	ARIMA(1, 0, 0)(1, 1, 1)$_{12}$	$(1 - 0.0227B)(1 - 0.0109\ B^{12})\ \nabla_{12}\ y_t = 0.024318 + (1 - 0.9588\ B^{12})\ \varepsilon_t$	2.8846	5.74
SQRT of MXR(1948-08)	ARIMA(1, 0, 0)(1, 1, 1)$_{12}$	$(1 - 0.0197B)(1 - 0.0354\ B^{12})\ \nabla_{12}\ y_t = 0.023802 + (1 - 0.9989\ B^{12})\ \varepsilon_t$	0.0247	5.23

Table 4. Models for average relative humidity (ARH) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
ARH(1948-72),(λ=3)	ARIMA(1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.3606B)\quad \nabla_{12} y_t = -248.19 + (1 - 0.9658B^{12})\ \varepsilon_t$	13987.52	288869809
ARH (1982-04),(λ=3)	ARIMA(0, 1, 1)(1, 1, 1)$_{12}$	$(1 - 0.0854\ B^{12})\quad \nabla\nabla_{12} y_t = -30.13 + (1 - 0.6956\ B)(1 - 0.8266\ B^{12})\ \varepsilon_t$	18290.84	423950172
ARH (1981-04),(λ=3)	ARIMA(1, 1, 1)(0, 1, 1)$_{12}$	$(1 - 0.3959\ B)\ \nabla\nabla_{12} y_t = -9.650 + (1 - 0.9771\ B)(1 - 0.8247\ B^{12})\ \varepsilon_t$	16825.02	365751625
ARH (1948-04),(λ=3)	ARIMA(1, 1, 1)(0, 1, 1)$_{12}$	$(1 - 0.3956B)\ \nabla\nabla_{12}\ yt = -2.053 + (1 - 0.9415\ B)(1 - 0.8642\ B^{12})\ \varepsilon_t$	25268.87	315734934

Table 5. Models for average maximum temperature (AMXT) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
Ln of AMXT(1948-72)	ARIMA(0, 1, 1)(1, 1, 1)$_{12}$	$(1 + 0.0269B^{12})\ \nabla\nabla^{12} y_t = 0.000048 + (1 - 0.776\ B)(1 - 0.9474B^{12})\ \varepsilon_t$	0.0463	0.0013
Ln of AMXT (1981-04)	ARIMA(0, 1, 1)(0, 1, 1)$_{12}$	$\nabla\nabla^{12} y_t = -0.00005 + (1 - 0.8682\ B)\ (1 - 0.9177\ B^{12})\ \varepsilon_t$	1.8907	0.0018
SQRT of AMXT (1948-04)	ARIMA(1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.628B)\ \nabla_{12} y_t = -0.0007 + (1 - 0.9084B^{12})\ \varepsilon_t$	0.1330	0.0120
SQRT of AMXT (1948-08)	ARIMA(1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.6281B)\quad \nabla_{12} y_t = -0.0007 + (1 - 0.9085\ B^{12})\ \varepsilon_t$	0.00003	0.0112

Table 6. Models for average minimum temperature (AMNT) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
AMNT(1948-72)	ARIMA(1, 0, 1) (0, 1, 1) $_{12}$	$(1 - 0.8234B)\ \nabla_{12}y_t = 0.004446 + (1 - 0.5666B)(1 - 0.9606B^{12})\ \varepsilon_t$	0.4539	0.728
AMNT (1982-04)	ARIMA (1, 1, 1)(0, 1, 1) $_{12}$	$(1 - 0.2559B)\nabla\nabla_{12}y_t = -0.0004017 + (1 - 0.9088B)(1 - 0.9129B^{12})\ \varepsilon_t$	0.6902	0.560
AMNT (1981-04)	ARIMA(1, 0, 0)(0, 1, 1) $_{12}$	$(1 - 0.3414B)\nabla_{12}y_t = -0.025249 + (1 - 0.9388B^{12})\ \varepsilon_t$	0.3501	0.512
AMNT (1948-04)	ARIMA (1, 0, 1)(1, 1, 1) $_{12}$	$(1 - 0.85B)(1 + 0.0646B^{12})\nabla_{12}y_t = 0.001553 + (1 - 0.5812B)(1 - 0.948)\ \varepsilon_t$	0.8889	0.550
AMNT (1948-08)	ARIMA (1, 1, 1)(1, 1, 1) $_{12}$	$(1 - 0.1925B)(1 + 0.0849B^{12})\nabla\nabla_{12}y_t = 0.000002 + (1 - 0.864B)(1 - 0.9686B^{12})\ \varepsilon_t$	0.0592	0.529

Table 7. Models for average range temperature (ARNT) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
ARNT(1948-72)	ARIMA (0, 1, 1)(1, 1, 1) $_{12}$	$(1 + 0.0874B)\ \nabla\nabla_{12}y_t = 0.0024 + (1 - 0.5504B)(1 - 0.9459B^{12})\ \varepsilon_t$	2.2115	1.302
ARNT(1982-04)	ARIMA (0, 1, 1)(0, 1, 1) $_{12}$	$\nabla\nabla_{12}y_t = 0.00099 + (1 - 0.7659B)(1 - 0.9193B^{12})\ \varepsilon_t$	0.9431	1.034
ARNT(1981-04)	ARIMA (0, 1, 1)(1, 1, 1) $_{12}$	$(1 + 0.1437B^{12})\ \nabla\nabla_{12}y_t = 0.000665 + (1 - 0.8157B)(1 - 0.9023B^{12})\ \varepsilon_t$	0.7979	0.980
ARNT(1948-04)	ARIMA (1, 0, 0)(0, 1, 1) $_{12}$	$(1 - 0.6911B)\ \nabla_{12}y_t = -0.00065 + (1 - 0.8594B^{12)})\ \varepsilon_t$	0.1062	0.010
ARNT(1948-08)	ARIMA (1, 0, 0)(0, 1, 1) $_{12}$	$(1 - 0.6939B)\ \nabla_{12}y_t = (1 - 0.8598)\ \varepsilon_t$	0.0002	0.009

Table 8. Models for average wind speed (AWS) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
SQRT of AWS(1948-72)	ARIMA (2, 0, 0)(1, 0, 1) $_{12}$	$(1 - 0.4642B - 0.1508B^2)(1 - 0.9864B^{12})y_t = 0.0049 + (1 - 0.7602B^{12})\ \varepsilon_t$	0.2200	0.0553
SQRT of AWS(1982-04)	ARIMA (0, 1, 1)(0, 1, 1) $_{12}$	$\nabla\nabla_{12}y_t = -0.00014 + (1 - 0.6871B)(1 - 0.8781B^{12})\ \varepsilon_t$	0.2251	.01910
SQRT of AWS(1981-04)	ARIMA (1, 0, 1)(1, 1, 1) $_{12}$	$(1 - 0.9389B)(1 - 0.0082B^{12})\ \nabla_{12}y_t = 0.00079 + (1 - 0.6122B)(1 - 0.8805B^{12})\ \varepsilon_t$	0.1320	0.0178
SQRT of AWS(1948-04)	ARIMA (1, 1, 1)(0, 1, 1) $_{12}$	$(1 - 0.2864B)\ \nabla\nabla_{12}y_t = 0.00006 + (1 - 0.8755B)(1 - 0.8255B^{12})\ \varepsilon_t$	0.0765	0.0311
SQRT of AWS(1948-08)	ARIMA (0, 1, 1)(0, 1, 1) $_{12}$	$\nabla\nabla_{12}y_t = 0.00007 + (1 - 0.7376B)(1 - 0.8359B^{12})\ \varepsilon_t$	0.0018	0.0306

Table 9. Models for average maximum wind speed (AMWS) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
SQRT of AMWS (1948-72)	ARIMA (1, 0, 0)(1, 1, 1) $_{12}$	$(1 - 0.437B)(1 - 0.0481B^{12})\ \nabla_{12}y_t = 0.0039 + (1 - 0.9009B^{12})\ \varepsilon_t$	1.013	0.541
Ln of AMWS (1981-04)	ARIMA (2, 0, 0)(1, 1, 1) $_{12}$	$(1 - 0.0452B - 0.26B^2)(1 + 0.0189B^{12})\ \nabla_{12}y_t = 0.0211 + (1 - 0.9107B^{12})\ \varepsilon_t$	0.4937	0.161
SQRT of AMWS (1948-04)	ARIMA(0, 1, 1)(1, 0, 1) $_{12}$	$(1 - 0.9938B^{12})\ \nabla y_t = -0.000001 + (1 - 0.8649B)(1 - 0.9317B^{12})\ \varepsilon_t$	0.3388	0.424
SQRT of AMWS(1948-08)	ARIMA(0, 1, 1)(1, 0, 1) $_{12}$	$(1 - 0.994B^{12})\ \nabla y_t = -0.0000008 + (1 - 0.8645B)(1 - 0.9334B^{12})\ \varepsilon_t$	0.0028	0.396

Table 10. Models for average cloud (AC) and their tesults

Variable	Model	Equation of Model	MRMSFE	MSE
AC(1948-72)	ARIMA (1, 0, 0)(0, 1, 1) $_{12}$	$(1 - 0.026B)\ \nabla_{12}y_t = -0.0194 + 1 - 0.9417B^{12})\ \varepsilon_t$	0.4270	0.340
AC(1981-04)	ARIMA (0, 1, 1)(1, 1, 1) $_{12}$	$(1 + 0.1167B^{12})\ \nabla\nabla_{12}y_t = 0.000543 + 1 - 0.9633B)(1 - 0.8713B^{12})\ \varepsilon_t$	0.9452	0.447
AC(1948-04)	ARIMA (0, 1, 1)(1, 1, 1) $_{12}$	$(1 + 0.0548B^{12})\ \nabla\nabla_{12}y_t = 0.000183 + (1 - 0.9047B)(1 - 0.9163B^{12})\ \varepsilon_t$	0.7844	0.375
AC(1948-08)	ARIMA (0, 1, 1)(1, 1, 1) $_{12}$	$(1 + 0.0532B^{12})\ \nabla\nabla_{12}y_t = 0.00018 + (1 - 0.9047B)(1 - 0.9176B^{12})\ \varepsilon_t$	0.0024	0.350

Table 11. Models for average dry bulb temperature (ADBT) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
ADBT(1948-72)	ARIMA (1, 0, 1)(0, 1, 1) $_{12}$	$(1 - 0.4814B)\ y_t = 0.004596 + (1 - 0.2037B)(1 - 0.9529B^{12})\ \varepsilon_t$	0.6312	0.761
ADBT(1981-04)	ARIMA (0, 1, 1)(1, 1, 1) $_{12}$	$(1 - 0.038B^{12})\ \nabla\nabla_{12}y_t = -0.00148 + (1 - 0.694B)(1 - 0.8926B^{12})\ \varepsilon_t$	1.8147	1.062
ADBT(1948-04)	ARIMA (0, 1, 1)(1, 0, 1) $_{12}$	$(1 - 0.9997B^{12})\ \nabla y_t = 0.000181 + (1 - 0.7266B)(1 - 0.8189B^{12})\ \varepsilon_t$	0.00003	0.899
ADBT(1948-08)	ARIMA (0, 1, 1)(1, 0, 1) $_{12}$	$(1 - 0.9997B^{12})\ \nabla y_t = 0.000181 + (1 - 0.7266B)(1 - 0.8189B^{12})\ \varepsilon_t$	0.00003	0.840

Table 12. Models for average wet bulb temperature (AWBT) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
AWBT(1948-72)	ARIMA (2, 0, 0)(1, 1, 1)$_{12}$	$(1 - 0.1809B - 0.1303B^2)(1 + 0.0974 B^{12}) \nabla_{12}y_t = 0.000398 + (1 - 0.9482 B^{12}) \varepsilon_t$	0.5422	0.543
AWBT(1982-04)	ARIMA (1, 0, 1)(1, 1, 1)$_{12}$	$(1 - 0.6488B)(1 + 0.0676 \nabla_{12}y_t = -0.00925 + (1 - 0.349B)(1 - 0.8822 B^{12}) \varepsilon_t$	0.7175	0.440
AWBT(1981-04)	ARIMA (1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.3423B) \nabla_{12}y_t = -0.01649 + (1 - 0.9206 B^{12}) \varepsilon_t$	0.3653	0.422
AWBT(1948-04)	ARIMA (1, 0, 1)(1, 1, 1)$_{12}$	$(1 - 0.7958B) (1 + 0.0443 B^{12}) \nabla_{12}y_t = 0.003359 + (1 - 0.5849B)(1 - 0.9164 B^{12}) \varepsilon_t$	0.8464	0.428
AWBT(1948-08)	ARIMA(1, 0, 1)(1, 1, 1)$_{12}$	$(1 - 0.7958B)(1 + 0.0439B^{12}) \nabla_{12}y_t = 0.003359 + (1 - 0.5849B)(1 - 0.9165 B^{12}) \varepsilon_t$	0.0002	0.400

Table 13. Models for average difference of dry bulb and wet bulb temperature {AT (D-W)} and their results

Variable	Model	Equation of Model	MRMSFE	MSE
Ln of AT(D-W)(1948-72)	ARIMA(2, 0, 0)(1, 0, 1)$_{12}$	$(1 - 0.4213B + 0.0817B^2)(1 - 1.0007 B^{12}) y_t = -0.0004 + (1 - 0.9291 B^{12}) \varepsilon_t$	0.1630	0.0284
Ln of AT(D-W)(1981-04)	ARIMA(1, 0, 1)(0, 1, 1)$_{12}$	$(1 - 0.2865B) \nabla_{12}y_t = 0.019375 + (1 + 0.1822B)(1 - 0.9075 B^{12}) \varepsilon_t$	0.3660	0.0387
Ln of AT(D-W)(1948-04)	ARIMA(1, 0, 1)(1, 0, 1)$_{12}$	$(1 - 0.4744B)(1 - 0.9925 B^{12}) y_t= 0.002626 + (1 + 0.0287B)(1 - 0.7837 B^{12}) \varepsilon_t$	0.2326	0.0327
Ln of AT(D-W)(1948-08)	ARIMA(1, 0, 1)(1, 0, 1)$_{12}$	$(1 - 0.4855B)(1 - 0.9927 B^{12}) y_t= 0.002492 + (1 + 0.0209B)(1 - 0.7885 B^{12}) \varepsilon_t$	0.0018	0.0305

Table 14. Models for average sea level pressure (ASLP) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
ASLP (1960-72)	ARIMA(1, 0, 0)(1, 1, 1)$_{12}$	$(1 - 0.1482 B)(1 + 0.1299 B^{12}) \quad \nabla_{12}y_t = -0.03685(1 - 0.8997 B^{12}) \quad \varepsilon_t$	0.8095	0.912
ASLP(1949-72)	ARIMA(1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.2325 B) \nabla_{12}y_t = 0.023107 + (1 - 0.9253 B^{12}) \quad \varepsilon_t$	1.0190	1.024
ASLP(1948-72)	ARIMA(1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.2615B) \quad \nabla_{12}y_t = -0.019005 + (1 - 0.9382 B^{12}) \quad \varepsilon_t$	0.9884	1.033
ASLP (1981-04)	ARIMA(1, 0, 1)(1, 1, 1)$_{12}$	$(1 - 0.8405B)(1 + 0.0344 B^{12}) = -0.000162 + (1 - 0.6583B)(1 - 0.9199 B^{12}) \varepsilon_t$	1.1241	1.328
ASLP(1948-04)	ARIMA(0, 1, 1)(1, 0, 1)$_{12}$	$(1 - 0.9999 B^{12}) = -0.0000467 + (1 - 0.8297B)(1 - 0.9620 B^{12}) \varepsilon_t$	1.3548	1.033

Table 15. Models for average difference of morning and evening relative humidity (ARH 0-12)) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
Ln of ARH(0-12)(1948-72)	ARIMA(1, 0, 0)(1, 1, 1)$_{12}$	$(1 - 0.287B)(1 + 0.0713 B^{12}) \nabla_{12} y_t= 0.00028 + (1 - 0.9404 B^{12}) \varepsilon_t$	0.2308	0.029
ARH(0-12)(1982-04)	ARIMA(1, 0, 0)(0, 1, 1)$_{12}$	$(1 - 0.3191B) \nabla_{12} y_t= 0.07771 + (1 - 0.913 B^{12}) \varepsilon_t$	3.1082	13.62
ARH(0-12)(1981-04)	ARIMA(0, 1, 1)(1, 0, 1)$_{12}$	$(1 - 1.0005 B^{12}) \nabla y_t= 0.000054 + (1 - 0.8686 B)(1 - 0.9514 B^{12}) \varepsilon_t$	2.4036	14.89
Ln of ARH(0-12)(1948-04)	ARIMA(2, 0, 0)(1, 0, 1)$_{12}$	$(1 - 0.2929B - 0.0306B^2)(1 - 0.9973B^{12}) y_t = 0.005229+(1- 0.9006 B^{12}) \varepsilon_t$	0.2002	0.028
Ln of ARH(0-12)(1948-08)	ARIMA(1, 0, 1)(1, 0, 1)$_{12}$	$(1 - 0.4175 B)(1 - 0.9973 B^{12}) y_t = 0.0045025 + (1 - 0.1276 B)(1- 0.9008 B^{12}) \varepsilon_t$	0.00007	0.026

Table 16. Models for average sunshine-hour (ASH) and average evaporation (AE) and their results

Variable	Model	Equation of Model	MRMSFE	MSE
ASH(1989-04)	ARIMA(1, 1, 1)(1, 1, 1)$_{12}$	$(1 - 0.1007B)(1 + 0.2393 B^{12}) = -0.0015 + (1 - 0.9487 B)(1- 0.8494 B^{12}) \varepsilon_t$	1.0670	1.04
AE(1987-00)	ARIMA(1, 1, 2)(1, 1, 1)$_{12}$	$(1 - 0.2759 B)(1 - 0.0111 B^{12}) \nabla \nabla_{12}y_t = -0.0105 + (1- 0.774 B - 0.2304B^2)(1 - 0.882B^{12})\varepsilon_t$	7.6465	27.6

Some residual and TS plots for climatic variables with forecasted values

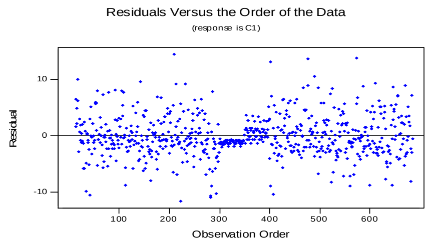

Fig. 1. Resid. vs order of the SQRT TR (1948-2004)

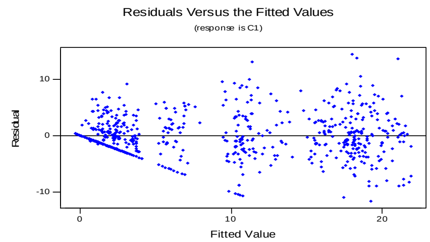

Fig. 2. Resid. vs the fitted SQRT TR (1948-2004)

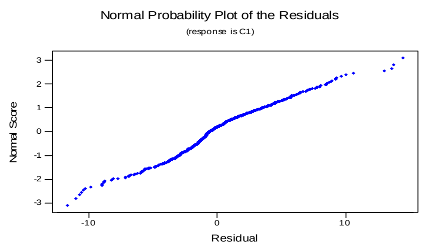

Fig. 3. Np plot of resid. for SQRT TR (1948-2004)

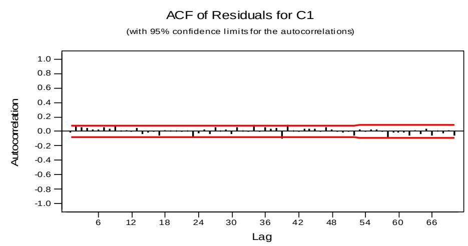

Fig. 4. ACF plot of resid. for SQRT TR (1948-2004)

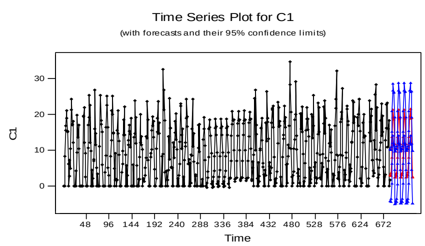

Fig. 5. TS plot of 48 forecasted SQRT TR (1948-2004)

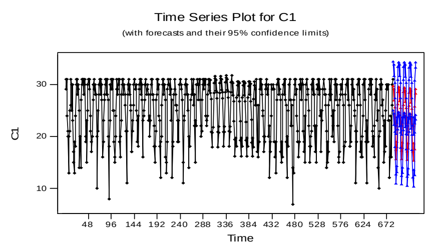

Fig. 6. TS plot of forecasted TFIR (1948-2004)

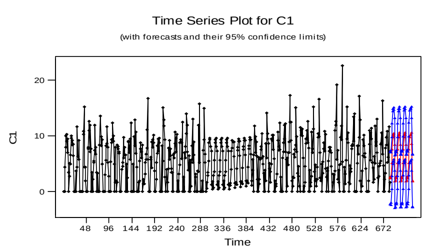

Fig. 7. TS plot of forecasted MXR (1948-2004)

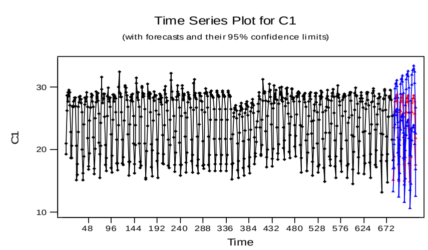

Fig. 8. TS plot of forecasted ADBT (1948-2004)

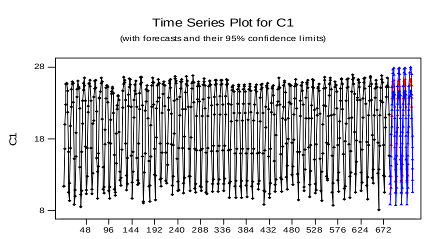

Fig. 9. TS plot of forecasted ORAMNT (1948-2004)

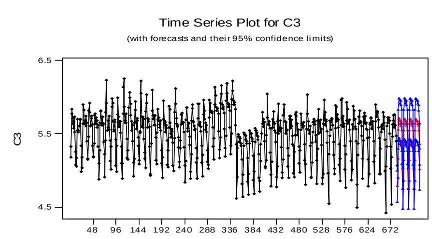

Fig. 10. TS plot of forecasted SQRT of AMXT(1948-2004)

Note: OR-Outlier replaced, SQRT-Square root transformed, resid.-Residual Fig.-Figure

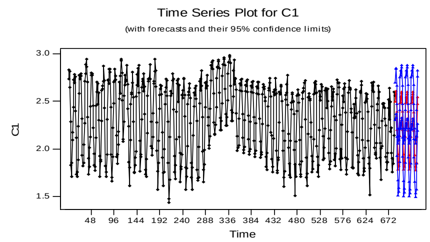

Fig. 11. TS plot of forecasted ORARNT (1948-2004)

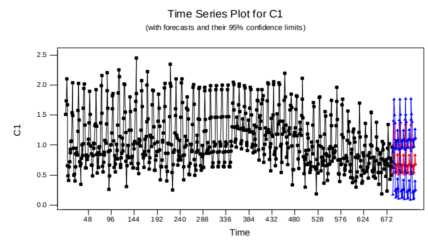

Fig. 12. TS plot of forecasted AT(D-W) (1948-2004)

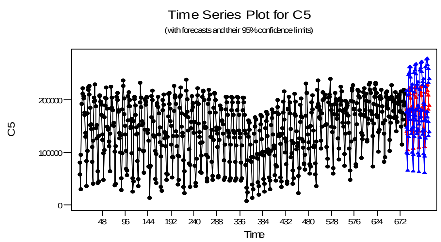

Fig. 13. TS plot of forecasted ORARH (1948-2004)

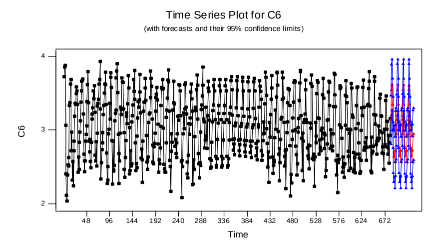

Fig. 14. TS plot of forecasted ARH(0-12) (1948-2004)

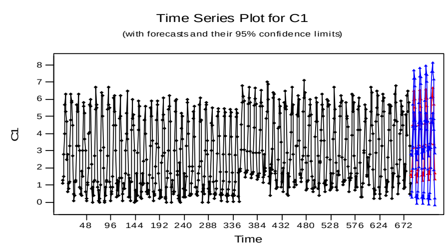

Fig. 15. TS plot of forecasted AC (1948-2004)

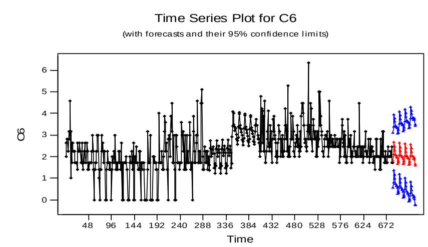

Fig. 16. TS plot of forecasted AMWS (1948-2004)

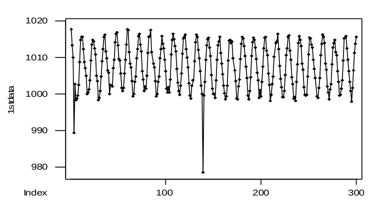

Fig. 17. TS plot of ASLP (1948-1972)

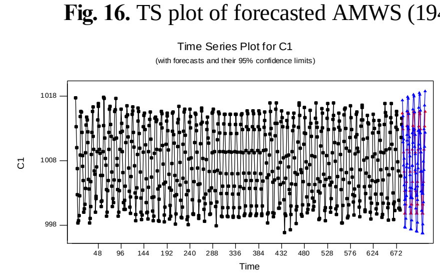

Fig. 18. TS plot of forecasted ORASLP (1948-2004)

Conclusions

The earlier presented ARIMA models for the monthly data during 1948-1972, 1981-2004 (reversing the years), 1948-2004 and 1948-2008 on the basis of minimum root mean square forecasting error. Those models were selected from the possible 16 ARIMA (autoregressive integrated moving average) models based on minimum root mean square forecasting error (RMSFE) with the last 24 observations for all the cases and all the residuals followed stationarity and normality. The 17 ARIMA models of the climatic variables (with the required transformations) during 1948-2004 were selected. These were ARIMA (1, 0, 0) $(1, 1, 1)^{12}$ for SQRT of TR; ARIMA (1, 1, 1) $(0, 1, 1)^{12}$ for TFIR; ARIMA (1, 0, 0) $(1, 1, 1)^{12}$ for SQRT of MXR ; ARIMA (1, 0, 1) $(1, 1, 1)^{12}$ for AMNT; ARIMA (1, 0, 0) $(0, 1, 1)^{12}$ for SQRT of AMXT; ARIMA (1, 0, 0) $(0, 1, 1)^{12}$ for ARNT; ARIMA (1, 1, 1) $(0, 1, 1)^{12}$ for ARH (λ=3); ARIMA (1, 1, 1) $(0, 1, 1)^{12}$ for SQRT of AWS; ARIMA (0, 1, 1) (1, 0, 1) for SQRT of AMWS; ARIMA (0, 1, 1) $(1, 1, 1)^{12}$ for AC; ARIMA (0, 1, 1) $(1, 0, 1)^{12}$ for ADBT; ARIMA (1, 0, 1) $(1, 1, 1)^{12}$ for AWBT; ARIMA (1, 0, 1) $(1, 0, 1)^{12}$ for Ln of AT(D-W); ARIMA (0, 1, 1) $(1, 0, 1)^{12}$ for ASLP; ARIMA (2, 0, 0) $(1, 0, 1)^{12}$ for Ln of ARH(0-12); ARIMA (1989-04) (1, 1, 1) $(1, 1, 1)^{12}$ for ASH and ARIMA (1987-00) (1, 1, 2) $(1, 1, 1)^{12}$ for AE. The data of 1981 for AMNT, ARNT, ARH, AWS, AWBT and ARH(0-12) were detected as outliers which were replaced by the forecasted value of 1981 from the fitted ARIMA models for January 1982-

December 2004 by reversing the years So, the findings pinpoints that the changing term of the climatic variables may have adverse impacts on the crop production in this country. Hence, judicious planning is very much essential to suit with the changes for sustainable development in agriculture.

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Appendix 1: Standardized ARIMA Notations

The ARIMA models have a general form of p, d, q where p is the order of the standard autoregressive term AR, q is the order of the standard moving average term MA, and d is the order of differencing AR describes how a variable y_t such as evaporation depends on some previous values y_{t-1}, y_{t-2} etc. while MA describes how this variable y_t depends on a weighted moving average of the available data y_{t-1} to $y_{t-n.}$ For example, for a one step ahead forecast (suppose: for t being September) with an AR-1, all weight is given to the evaporation in the previous month (September), while with an AR-2 the weight is given to the evaporation of the two immediately previous months (September and August). By contrast, with a MA-1, MA-2, a certain weight is given to the evaporation of the immediately previous month (September), a smaller weight is given to the evaporation observed two months ago (August) and so forth, i.e., the weights decline exponentially.

The combined multiplicative seasonal ARIMA (p, d, q) × 12 (P, D, Q) model gives the following:

$$\phi_p(B)\Phi_p(B^s)\nabla_s^D\nabla^d z_t = C + \theta_q(B)\Theta_Q(B^s)\varepsilon_t$$

The standard expression of ARIMA model where B denotes the backward shift operator where

- $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p$

The standard autoregressive operator of order p

- $\Phi_p(B^s) = 1 - \Phi_1 B - \Phi_2 B^2 - ... - \Phi_p B^{ps}$

The seasonal autoregressive operator of order p

- ∇_s^D is the seasonal differencing operator of order D

- ∇^d is the differencing operator of order d

-y_t is the value of the variable of interest at time t

- $C = \mu\phi_p(B)\Phi_p(B^s)$ is a constant term, where ε is the true mean of the stationary time series being modeled. It was estimated from sample data using the approximate likelihood estimator approach.

- $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$

The standard moving average operator of order q

- $\Theta_Q(B^s) = 1 - \Theta_1 B^1 - \Theta_2 B^2 - ... - \Theta_Q B^{QS}$

The seasonal moving average operator of order Q

- ϕ_1, ϕ_2,é é ,ϕ_p; Φ_1, Φ_2,é ,Φ_p; θ_1, θ_2, é ,θ_q; Θ_1 Θ_2 ,é , Θ_Q are unknown coefficients that are estimated from sample data using the approximate likelihood estimator approach.

-Ů is the error term at time at time t

-S is the annual period, i,e. 12 months

Thus, the multiplicative seasonal modeling approach with the general form of ARIMA (p, d, q) ×S (P, D, Q) has been used in this paper. In this form, p is the order of the seasonal autoregressive term (ARS), Q is the order of the seasonal moving average term, D is the order of the seasonal differencing and s is the annual cycle (e.g, s = 12 using the monthly data). ARS describes how the variable y depends on y_{t-12} (ARS-1), y_{t-24} (ARS-2), etc., while MAS describes how y depends on a weighted moving average of the available data y_{t-12} to y_{t-12n}. For example, for a one step ahead forecast (suppose: for t being September and with an ARS-1, all weight is given to the evaporation in the previous September while with an ARS-2, the weight is given to the September evaporation 1 and 2 years ago. By contrast, with a MAS-1, MAS-2, the model gives a certain weight to September evaporation 1 year ago, to the September evaporation 2 years ago, and so on. These weights decline exponentially.