International Journal of Research in Environmental Science (IJRES)
Volume 5, Issue 2, 2019, PP 23-28
ISSN No. (Online) 2454-9444
DOI: http://dx.doi.org/10.20431/2454-9444.0502004
www.arcjournals.org

Modeling the Relative Humidity in New Halfa Agricultural Scheme (Sudan)

Tariq Mahgoub Mohamed[1*], Hisham Mohamed Hassan[2], Mahmoud Abdelrahim Abdelgiom[3]

[1,3]*Department of Civil Engineering, Jazan University, Jazan, KSA*

[2]*Department of Econometrics, University of Khartoum*

Corresponding Author:** ***Tariq Mahgoub Mohamed, *Department of Civil Engineering, Jazan University, Jazan, KSA*

Abstract: *In this paper, linear stochastic approach with the Seasonal Autoregressive Integrated Moving Average (SARIMA) based methods are used to model relative humidity for New Halfa Agricultural Production Scheme. Relative humidity has main influences on the crop production, crop protection and storage and this factor should be modeled for future design purposes. The realization analyzed spans from 2000 to 2014. An inspection of the original series confirms a yearly seasonal pattern. The results of Phillips-Perron (PP) test shows that this series is not stationary. This non-stationarity was removed using first order seasonal differencing (i.e. twelve-monthly) prior to the selection of the model. The SARIMA (1,0,0)×(0,1,1)12 model was choose as the most suitable for modeling monthly relative humidity for New Halfa Agricultural Production Scheme.*

Keywords: *Relative Humidity, Stochastic models, New Halfa Agricultural Production Scheme, Sudan*

1. Introduction

The construction of the Aswan High Dam, in the early 1960's, was a huge disaster to the Sudanese Nubians living in the border town of Wadi Halfa and the neighboring villages. The dam buried the oldest civilization land in Africa which back to more than 3000 B.C under its water. Consequently, more than 50,000 Sudanese Nubians (Halfawien) had to be relocated to new villages in northeastern Sudan near to the Atbara River called New Halfa, about 850 kilometers southeast of their original homes [1,2]. It is one of the largest centrally planned and executed human relocations in the world history [3]. Several observers of the exodus operations alarm that a large amount of Nubian's mineral wealth might have been obscured in the lake waters. But the humanitarian factor in the evacuation of Nubians to their new residences is definitely the worst one.

The New Halfa Agricultural Production Scheme is constructed to residence the displaced Nubians. The scheme has been produced different crops like cotton, wheat, sugar and sorghum. It draws its water from the Khashm al Girba dam on the Atbara River.

Crops production is mainly affected by many climatic variables, such as, precipitation, temperature, relative humidity and solar radiation. Relative humidity directly influences the water relations of plant and indirectly affects leaf growth, photosynthesis, pollination, occurrence of diseases and finally economic yield [4]. Modeling and forecasting relative humidity is predominant factor for the agricultural operations and for future design purposes.

SARIMA modes have been extensively used to model different types of seasonal time series. For example, Nasiru and Solomon [5] applied a SARIMA model to forecast short term inflation in Ghana. Ette [6] used an Additive SARIMA model for daily exchange rates of the Malaysian Ringgit and Nigerian Naira. Bazrafshan et al. [7] found that the application of SARIMA modeling was appropriate for the forecasting of hydrological drought in the Karkheh Basin, Iran. Arumugam and Anithakumari, [8] fitted SARIMA $(2,1,2)x(1,1,1)_{12}$ model to forecast natural rubber production in India. Li etal [9] proposed SARIMA $(0,1,1)(0,1,1)_{12}$ model for forecasting outpatient amount in China. Kibunja et al. [10] applied a SARIMA $(1,0,1)x(1,0,0)_{12}$ model to monthly rainfall in Mt. Kenya region, Kenya. Mohamed and Etuk [11] used a SARIMA $(2,0,0)x(0,1,1)_{12}$ to predict monthly flow of Rahad River, Sudan. These are just to mention a few.

This work applied the seasonal autoregressive integrated moving average (SARIMA) approach to simulate the monthly relative humidity for the New Halfa Agricultural Production Scheme.

2. MATERIALS AND METHODS

2.1. Study Area and Data

The New Halfa Agricultural Production Scheme is bounded between latitudes 14.75°N and 16.00° N and longitude 35.00° E and 36.00° E with altitude 450 masl. It covers an area of about half a million feddans of which about eighty percent was under irrigation from Khashm al Girba dam on the Atbara River. It is characterized by annual rainfall of [78 – 543] mm during the period from 1940-2004 [12].

Climate Forecast System Reanalysis (CFSR) of the National Centers for Environmental Prediction (NCEP) readily gives climate data for any position on the earth between 1979 and 2014. Numerous studies used the CFSR data set as a source for their works [13,14,15,16,17]. The CFSR data (globalweather.tamu.edu) were obtained for the entire region (bounding box: latitude 14.0–17.0° N and longitude 34.0–37.0° E) before choosing the closest station for the scheme. It includes temperature, daily rainfall, wind speed and relative humidity.

2.2. Modeling by SARIMA Methods

A time series is said to be stationary if it has constant mean and variance. A stationary time series can be modeled in several ways: an autoregressive (AR) process, a moving average (MA) process, or an autoregressive and moving average (ARMA) process. Although, an ARMA model deal with stationary data, ARMA models can be applied to non-stationary series by permitting differencing of data series. These models are called autoregressive integrated moving average (ARIMA) models. A time series may have non-seasonal and seasonal characteristics.

The general structure of non-seasonal ARIMA model is AR to order p and MA to order q and operates on dth difference of the time series X_t; therefore a model of the ARIMA family is classified by three parameters (p, d, q) that can have zero or positive integral values. The general non-seasonal ARIMA model may be written as

$$\phi(B)\nabla^d X_t = \theta(B)\varepsilon_t \tag{1}$$

Where:

$\phi(B)$ *and* $\theta(B)$ = polynomials of order p and q, respectively.

$$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_P B^p) \tag{2}$$

and

$$\theta(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q\right) \tag{3}$$

Commonly time series have a seasonal part that repeats every s observations. For monthly observations s = 12 (12 in 1 year), for quarterly observations s = 4 (4 in 1 year). Box et al, [18] has generalized the ARIMA model to deal with seasonality, and define a general multiplicative seasonal ARIMA model, which are generally known as SARIMA models. In short form the SARIMA model expressed as ARIMA (p, d, q) x (P, D, Q) s, which is written as

$$\phi_p(B)\Phi_p(B^s)\nabla^d \nabla_s^D (X_t) = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{4}$$

Where p is the order of non-seasonal autoregression, d the number of regular differencing, q the order of non-seasonal MA, P the order of seasonal autoregression, D the number of seasonal differencing, Q the order of seasonal MA, s is the length of season, Φ_p and Θ_q are the seasonal polynomials of order P and Q, respectively.

SARIMA models development consists of the next three steps: model identification, parameters estimation and diagnostic checking. The model that gives the minimum Akaike Information Criterion (AIC) [19] is chosen as best fit model. The statistical and econometric software Eviews-9 was applied for the analytical work.

3. RESULTS AND DISCUSSION

The time plot of the monthly relative humidity in Figure 1 shows that there is a seasonal pattern in the series and the series is non-stationary. The Phillips-Perron (PP) test proved the non-stationarity of the series, as shown in Table 1. The data is seasonal of period 12 months and must therefore be differenced by one seasonal degree of differencing to attain stationary . The PP test was done again on the seasonally differenced data. The results of the test adjudge that the differenced series is stationary, Table 2.

Figure 2 shows the ACF and PACF plots of the data after we take seasonal difference. It appears that the majority of the seasonality is disappeared and the data became stable. The autocorrelation structure in Figure 2 suggests many models. The suggested models, the Akaike Information Criterion (AIC) are shown in Table 3. Clearly, model SARIMA$(1,0,0)x(0,1,1)_{12}$ has the smallest values of AIC in that case one would temporarily have this model.

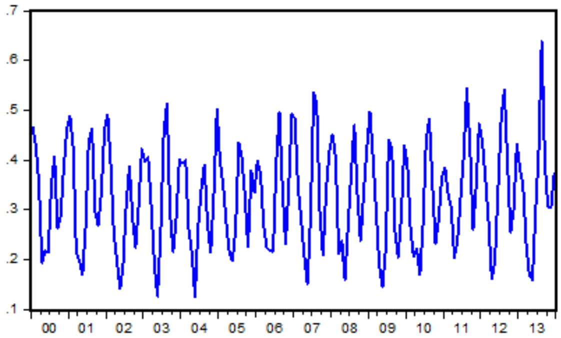


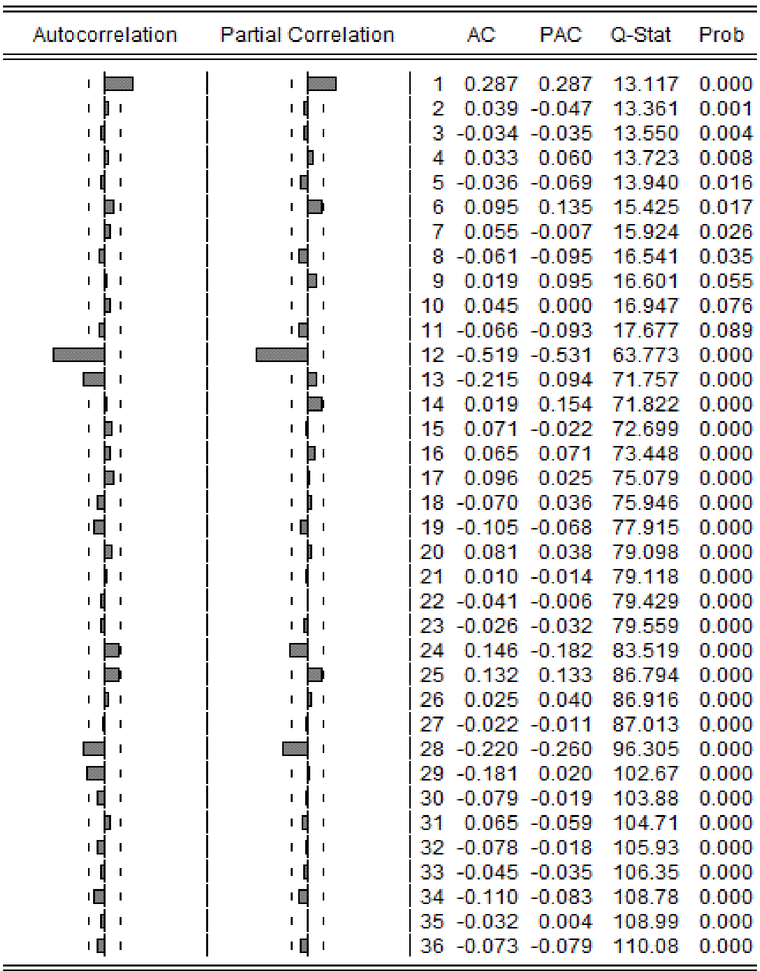
Figure1. *Monthly relative humidity for New Halfa Scheme [2000-2013]*

Table1. *Unit root test of the monthly flow data*

Test	Static	P-value
Phillips-Perron	-1.4866	0.1280

Table2. *Unit root test of the differenced data*

Test	Static	P-value
Phillips-Perron	-9.1880	0.0000



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.287	0.287	13.117	0.000
		2	0.039	-0.047	13.361	0.001
		3	-0.034	-0.035	13.550	0.004
		4	0.033	0.060	13.723	0.008
		5	-0.036	-0.069	13.940	0.016
		6	0.095	0.135	15.425	0.017
		7	0.055	-0.007	15.924	0.026
		8	-0.061	-0.095	16.541	0.035
		9	0.019	0.095	16.601	0.055
		10	0.045	0.000	16.947	0.076
		11	-0.066	-0.093	17.677	0.089
		12	-0.519	-0.531	63.773	0.000
		13	-0.215	0.094	71.757	0.000
		14	0.019	0.154	71.822	0.000
		15	0.071	-0.022	72.699	0.000
		16	0.065	0.071	73.448	0.000
		17	0.096	0.025	75.079	0.000
		18	-0.070	0.036	75.946	0.000
		19	-0.105	-0.068	77.915	0.000
		20	0.081	0.038	79.098	0.000
		21	0.010	-0.014	79.118	0.000
		22	-0.041	-0.006	79.429	0.000
		23	-0.026	-0.032	79.559	0.000
		24	0.146	-0.182	83.519	0.000
		25	0.132	0.133	86.794	0.000
		26	0.025	0.040	86.916	0.000
		27	-0.022	-0.011	87.013	0.000
		28	-0.220	-0.260	96.305	0.000
		29	-0.181	0.020	102.67	0.000
		30	-0.079	-0.019	103.88	0.000
		31	0.065	-0.059	104.71	0.000
		32	-0.078	-0.018	105.93	0.000
		33	-0.045	-0.035	106.35	0.000
		34	-0.110	-0.083	108.78	0.000
		35	-0.032	0.004	108.99	0.000
		36	-0.073	-0.079	110.08	0.000

Figure2. *ACF and PACF plots after one seasonal difference*

Following the selection of the best model using the AIC criteria, estimation of the parameters was done. The value of the parameters, associated standard errors, *t*- statistic and *p*-values are accessible in Table 4. The results verified that the parameters are significant since their *p*-values are lesser than 0.05. All the absolute values of the inverted AR and MA roots are smaller than one; hence the model is stationary and invertible.

Once the best model is selected, the Box-Jenkins methodology requires examining the residuals of the model. The residuals must behave like Gaussian white noise, which is appearing random, homoscedastic and normal [18]. Many confirmation tests were used on the residual series. The selected tests are the Box-Ljung test, the Durbin-Watson Statistic test, the Jarque-Bera test and ARCH LM test. These tests are discussed in the next paragraphs.

The residuals autocorrelation function (RACF) and partial autocorrelation function (RPACF) are valuable tools to judge the presence of correlation between the residuals. The ACF and PACF of residuals of the model are shown in Figure 3. All values of the RACF and RPACF lie within the confidence limits. The figure supports the absence of significant correlation between the residuals.

Table3. *Comparison of the proposed Models*

Variable	Station	Model	AIC
Monthly Relative Humidity	New Halfa Scheme	$SARIMA(1,0,1)X(0,1,1)_{12}$	-3.285
		$SARIMA(1,0,0)X(0,1,1)_{12}$	-3.303
		$SARIMA(1,0,1)X(1,1,1)_{12}$	-3.272
		$SARIMA(1,0,1)X(1,1,0)_{12}$	-3.199
		$SARIMA(0,0,1)X(1,1,1)_{12}$	-3.273
		$SARIMA(0,0,1)X(1,1,0)_{12}$	-3.206

Table4. *Estimation of the SARIMA (1,0,0)x(0,1,1)12 model*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.337454	0.083119	4.059898	0.0001
MA(12)	-0.736566	0.071517	-10.29913	0.0000
SIGMASQ	0.001949	0.000199	9.808004	0.0000
R-squared	0.440774	Mean dependent var		-0.000127
Adjusted R-squared	0.433463	S.D. dependent var		0.059224
S.E. of regression	0.044577	Akaike info criterion		-3.303220
Sum squared resid	0.304033	Schwarz criterion		-3.244569
Log likelihood	260.6512	Hannan-Quinn criter.		-3.279398
Durbin-Watson stat	2.010565			
Inverted AR Roots	.34			
Inverted MA Roots	.97	.84+.49i	.84-.49i	.49-.84i
	.49+.84i	.00-.97i	-.00+.97i	-.49-.84i
	-.49+.84i	-.84+.49i	-.84-.49i	-.97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.010	-0.010	0.0174	
		2	0.044	0.044	0.3309	
		3	-0.027	-0.026	0.4463	0.504
		4	0.012	0.009	0.4687	0.791
		5	-0.098	-0.096	2.0308	0.566
		6	0.106	0.104	3.8855	0.422
		7	-0.066	-0.057	4.5953	0.467
		8	-0.054	-0.068	5.0746	0.534
		9	0.032	0.046	5.2505	0.629
		10	0.046	0.039	5.6146	0.690
		11	0.112	0.130	7.7299	0.562
		12	-0.083	-0.113	8.9117	0.541
		13	-0.043	-0.052	9.2358	0.600
		14	0.128	0.170	12.072	0.440
		15	0.083	0.077	13.264	0.428
		16	-0.059	-0.069	13.867	0.460
		17	0.069	0.030	14.708	0.473
		18	-0.121	-0.085	17.312	0.366
		19	-0.151	-0.127	21.411	0.208
		20	0.078	0.056	22.525	0.210
		21	0.020	0.008	22.599	0.255
		22	-0.077	-0.048	23.698	0.256
		23	0.003	-0.007	23.700	0.308
		24	0.095	0.091	25.386	0.279
		25	0.049	0.045	25.830	0.309
		26	0.079	0.037	27.025	0.303
		27	0.040	0.067	27.335	0.339
		28	-0.177	-0.205	33.389	0.151
		29	-0.040	-0.018	33.699	0.175
		30	-0.165	-0.156	39.053	0.080
		31	0.031	-0.025	39.240	0.097
		32	-0.075	-0.023	40.344	0.098
		33	-0.013	0.026	40.378	0.121
		34	-0.098	-0.089	42.308	0.105
		35	0.042	-0.056	42.668	0.121
		36	-0.016	0.056	42.722	0.145

Figure3. *ACF and PACF plots for SARIMA (1,0,0)x(0,1,1)$_{12}$ Residual*

The Ljung-Box test is applied for checking independence of residual. From Figure 3, the goodness of fit values for the autocorrelations of residuals from the model up to lag 36 was greater than 0.05. The result proves the acceptance of the null hypothesis of model adequacy at the 5% significance level and the set of autocorrelations of residuals was considered white noise.

The Durbin-Watson (DW) statistic measures the serial correlation in the residuals. If the residuals are not correlated, the Durbin-Watson statistic will be 2 [20]. The Durbin-Watson test statistic value in Table 4 is found to be 2.0105, which does not deviate from 2 by more than 0.0105. Hence, there is no serial correlation between the residuals.

The result for the Jarque-Bera tests show that the residuals are normally distributed as the skewness is close to zero and kurtosis close to 3. (See Figure 4: JB = 2.242, *p* value = 0.3258). Homoscedasticity is the expression applied to identify that the variance of the residual in each observation is constant. In this work, we apply ARCH LM test. The test statistics value of ARCH LM test for the homoscedasticity of the residuals is presented in Table 5. The *p*-value for the test is greater than 0.05, which indicating that the residual variance is constant.

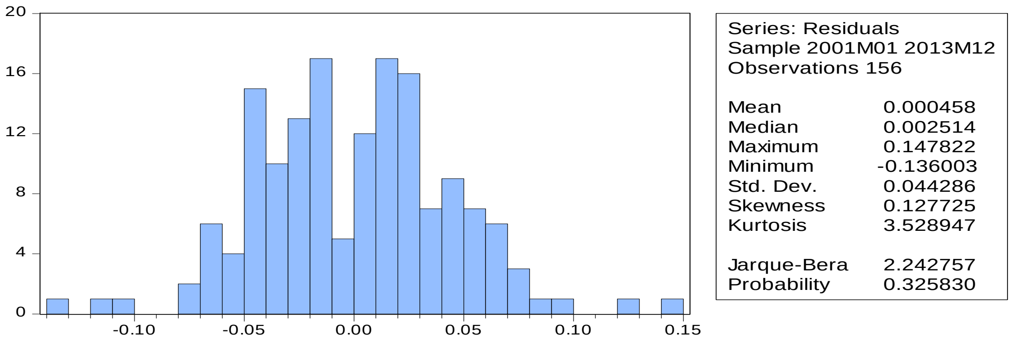


Figure4. *Histogram of the Residuals*

Table5. *ARCH test*

F-statistic	0.376934	Prob. F(2,151)	0.6866
Obs*R-squared	0.765025	Prob. Chi-Square(2)	0.6821

4. CONCLUSION

In this paper, linear stochastic approach with the Seasonal Autoregressive Integrated Moving Average (SARIMA) based methods are used to model relative humidity for New Halfa Agricultural Production Scheme, Sudan.

The time plot of the monthly relative humidity shows that there is a seasonal pattern in the series and the series is non-stationary. This non-stationarity was removed using first order seasonal differencing (i.e. twelve-monthly) prior to the selection of the model. The SARIMA (1,0,0)×(0,1,1)12 model was choose as the most suitable for modeling monthly relative humidity for New Halfa Agricultural Production Scheme.

REFERENCES

[1] Sorbo,G.M, (1985). Tenants and Nomads in Eastern Sudan: A Study of Economic Adaptations in the New Halfa Scheme, Scandinavian Institute of African Studies, Uppsala.

[2] Salman, M.A.(2010). Water Resources in the Sudan North-South Peace Process: Past Experience and Future Trends, African Yearbook of International Law, 299-328.

[3] Dafalla H.,(1975) The Nubian Exodus, C. Hurst and Company, London.

[4] http://agritech.tnau.ac.in/agriculture/agri_agrometeorology_relativehumidity.html

[5] Nasiru, S. & Solomon, S. (2012). Empirical Approach to Modeling and Forecasting Inflation in Ghana. Current Research Journal of Economic Theory, 4(3), 83-87.

[6] Etuk, EH. An Additive SARIMA Model for Daily Exchange Rates of the Malaysian Ringgit (MYR) and Nigerian Naira (NGN). International Journal of Empirical Finance, 2014, 2(4): 193-201.

[7] Bazrafshan, O., Salajegheh, A., Bazrafshan, J., Mahdavi, M. and Marj, A.F. (2015) 'Hydrological drought forecasting using ARIMA models (a case study: Karkheh Basin)', Ecopersia, Vol. 3, No. 3, pp.1099–1117.

[8] Arumugam, P., and Anithakumari, V. (2013). SARIMA model for Natural Rubber production in India. International Journal of Computer Trends and Technology (IJCTT), Vol. 4, No. 8, pp. 2480-2484.

[9] Xiaosheng Li,Chunliu Ma,Haike Lei &Haixia Li . Applications of SARIMA Model in Forecasting Outpatient Amount. Chinese Medical Record English Edition , Volume 1, 2013 - Issue 3, Pages 124-128. https://doi.org/10.3109/23256176.2013.798456

[10] Kibunja, H. W., Kihoro , J.M., Orwa , G.O., Yodah , W.O., (2014), Forecasting Precipitation Using SARIMA Model: A Case Study of Mt. Kenya Region, Mathematical Theory and Modeling, Vol.4, No.11, pp:50-58.

[11] Mohamed, T.M., Etuk, E.H, (2017). Application of linear stochastic models to monthly streamflow data of Rahad River, Sudan, Int. J. Hydrology Science and Technology, 7(2), 197-212.

[12] [12] Elhag, MM. Causes and Impact of Desertification in the Butana Area of Sudan. Ph. D. Thesis, University of Free State, South Africa, pp. 171, 2006.

[13] Fuka, D,R etal (2013)Using the climate forecast system reanalysis as weather input data for watershed models , Hydrol.Process,Wiley online liberary.

[14] Diro, G. T., Grimes, D. I. F., Black, E., O'Neill, A., and PardoIguzquiza, E. (2009) Evaluation of reanalysis rainfall estimates over Ethiopia, Int. J. Climatol., 29, 67–78.

[15] Yu, M., Chen, X., Li, L., Bao, A., and Paix, M. J. D. L.(2011) Streamflow Simulation by SWAT Using Different Precipitation Sources in Large Arid Basins with Scarce Raingauges, Water Resour. Manage. 25, 2669–2681.

[16] Roth, V and Lemann T, Comparing CFSR and conventional weather data for discharge and soil loss modelling with SWAT in small catchments in the Ethiopian Highlands, Hydrol. Earth Syst. Sci., 20, 921–934, 2016, doi: 10.5194/hess-20-921-2016

[17] Dile, Y T and Raghavan S, 2014. Evaluation of CFSR Climate Data for Hydrologic Prediction in Data-Scarce Watersheds: An Application in the Blue Nile River Basin. Journal of the American Water Resources Association (JAWRA) 1-16. DOI: 10.1111/jawr.12182

[18] Box, G.E.P., Jenkins, G.M., Reissel, G.C., (1994) *Time Series Analysis Forecasting and Control*, 3rd edition, Prentice Hall, USA.

[19] Akaike, H.,(1974) "A New look at the statistical model identification, " *IEEE Trans Automatic Control*, AC- 19:716–723.

[20] Montgomery, D.C., Peck, E.A., Vining, G.G.,(2006) *Introduction to Linear Regression Analysis*. 4th Edition, John Wiley & Sons, UK.

Citation: *Tariq Mahgoub Mohamed, et.al, " Modeling the Relative Humidity in New Halfa Agricultural Scheme (Sudan)", International Journal of Research in Environmental Science (IJRES), vol. 5, no. 2, pp. 23-28, 2019. Available: DOI: http://dx.doi.org/10.20431/2454-9444.0502004*