Modeling and Forecasting of Average Yearly Temperature in Case of Mekelle City, Tigray, Ethiopia

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***Abstract*:- Temperature is the key natural resource on which the others depend. It influences food production, ground water and energy availability. The main objective of the research study is modeling and forecasting of temperature in case of Mekelle, which is found in north western zone of Tigray region . The goal of this research study was to examine the temperature of Mekelle city in the past 26 years, at present and forecasting the temperature of the city for the coming about 10 years. Source of the data and type of data are secondary source of data and secondary data respectively. The data is collected from the national metrology agency of Tigray region branch recorded from 1991 to 2016 of 26 years.**

***Key words:* temperature, modeling, ARIMA, forecasting**

I. INTRODUCTION

Climatic variability can be described as the annual difference in values of specific climatic variables within averaging periods such as a 30-year period. [18]Temperature is the key natural resource on which the others depend. It influences food production, water and energy availability. The modern communication media informs us almost daily of floods, droughts, hurricanes, blizzards, heat waves or other disasters that properly damage crop yields, famine or deaths. Dire views of the future promise global heating or cooling, advance or recession of polar ice, changing sea level, expanding deserts and unstable world hungry. Climate, weather manifested as extreme events or persistent conditions, is experienced first as a physical phenomenon. Temperature, wind and rainfall affect the biophysical environment when extreme events such as droughts and floods occur. People suffer injuries, and habitats are destroyed and the built environment is damaged. Socio-economic systems are sensitive to the frequency, paternity and persistence of these conditions, as well as potential changes in long term trends

Climate related hazards in Ethiopia include drought, floods, heavy rains, strong winds, frost, heat waves (high temperature), etc. Though the historical social and economic impacts of all of these hazards are not systemically well documented, the impacts of the most important ones, namely drought and floods, are discussed. Ethiopia is highly vulnerable to drought. Drought is the single most important climate related natural hazard impacting the country from time to time. Drought occurs anywhere in the world, but its damage is not as severe as in Africa in general and in Ethiopia in particular. Recurrent drought events in the past have resulted in huge loss of life and property as well as migration of people. The other climate related hazard that affects Ethiopia from time to time is flood. Major floods which caused loss of life and property occurred in different parts of the country. Climate change is expected to have adverse ecological, social and economic impacts. Quantitative climate change impact assessments made so far on various socio-economic sectors are limited in the country. However, effort was made to compile information on climate change impacts from such as the Initial National Communications of Ethiopia to the UNFCCC, the IPCC reports and other sources. Impact and vulnerability assessments in priority sectors were undertaken as part of the process of developing the Initial National Communication of Ethiopia to the UNFCCC. [7]

The climatic variations will have unexpected consequences with respect to frequency and intensity of temperature variability for many regions of the Earth. The focus on climate variability bases mostly on the detection of trends in instrumental records of temperature. Several researches of climatic trends have recently been conducted on rainfall and temperature data at different periods of records throughout the world. Ethiopia is among those areas in the world most likely to experience climatic variations for short and long time periods. Inter-annual variability of temperature in Ethiopia is relatively large from the annual mean. As a result of climatic variations, natural resources of the country, such as vegetation, and the existing resources are easily damaged by changes. In this study, we examined air temperature trends in Mekelle Illala station for the 1991-2016 time scale. The aim of this study is to evaluate temperature trends in Mekelle, Illala station to be able achieve our goals we conduct a thorough examination of climatic data from 1991-2016 in order to identify variability, trends and other characteristics of temperature at different time scales. The main purpose of this study is the detection of significant trends or fluctuations in the annual mean of temperature.

Objectives of the study

a) General objective

The general objective of this study is modeling and forecasting of climate condition based on the ARIMA model of temperature in case of Mekelle City.

b) Specific objectives

- To investigate the trend variations which require fitting an appropriate trend line on time series data
- To fit ARIMA model on the climate condition of Mekelle City
- To prepare as reference through forecasting of the distribution of temperature in case of Mekelle City.

II. METHODOLOGY

Description of study area

Mekelle is the capital city and commercial center of the Tigray National Regional State in the northern Ethiopia. The city is located at 39°33'E longitude and 13°32'N latitude, situated in the extension of the central highlands of Ethiopia. The altitude of Mekelle is between 1965 m and 2220 m above sea level. The city is bounded by mountain ranges in the east and north. Climatologically, the area is classified as "Woina Dega" (temperate) with an effective temperature between 14°C and 20°C (Ethiopian Mapping Agency, EMA, 1981), which for most of the time is comfortable. It has a moisture index (P/ ET) ranging in between 0.25 and 0.5, which indicates moderately dry area. The altitude varies from 2220 m at eastern side to 1965 m in the northwestern side of the town (lower reach of Illala River) [15].

Method of data collection

This study uses secondary data which are recorded by national metrology agency of the Tigray region which is centered at Mekelle, the capital city of the region. For convenience, the data is average yearly temperature for 26 (1991-2016) years.

Study variables

Dependent variables: Temperature in degree Celsius

Independent variable: Time

Method of Data Analysis

In this study, the investigator applies some statistical techniques to analyze data such as time series analysis and to minimize time consumption for analyzing the data the investigator uses the most appropriate statistical measures.

Descriptive Statistics

In general, the study has taken26 years of yearly average temperature and it has presented the data by plotting the graphs as well as other summary statistics.

Examining stationary of time series data

The first step for appropriate analysis is to determine whether the series is stationary or non-stationary. The widely used unit root tests are the Augmented Dickey Fuller (ADF) and Phillips Perron (PP) test.

Augmented Dickey Fuller (ADF) unit root test

The standard Dickey Fuller test is conducted in the following manner:

Y_t-Y_{t-1}= (p-1) Y_{t-1}+ε_t

Where ε_t is assumed to be white noise and p is parameter to be estimated. This can be written as:

$\Delta Y_t = \pi Y_{t-1} + \varepsilon_t$, where π=p-1.

The null and alternative hypothesis may be written as:

H_0: π=0 versusH_1: π<0

The test statistics is the conventional t-ratio for π.$t_\pi = \hat{\pi}/se(\hat{\pi})$

Where $\hat{\pi}$ is OLS estimate of π and se $(\hat{\pi})$ is standard error of $\hat{\pi}$. The ADF test constructs a parametric correction for higher order correlation by assuming that the series follows an AR (p) process adding lagged difference terms of the dependent variable Y_t to the right hand side of the test regression.

Test of the randomness

The check whether the given time series observations of recorded data of temperature is time dependent or not, the study will apply the test of the randomness of the given data. The null hypothesis will state that there is randomness in the series data and the alternative hypothesis will state opposite of the null hypothesis. There are various tests of randomness but by convenience for this study the turning point test will be held.

Turning point test

It is simple test by counting the number of peaks or trough from time series data. Peak is when the value is greater than the two neighboring values. Trough is when the value is less than the two neighboring values.

Let w be the number of turning points and define the variables for a set of observations:

Z_t=1=peak (trough) if there is turning point, 0 otherwise

W=$\sum Zi = numberofpeak + numberoftrough$

E (w) =2/3(n-2)

Var(w)=$\frac{16n-29}{90}$

Where n is the number of observations

The test statistics is:

$Z_{cal}=\frac{w-E(w)}{\sqrt{Var\,(w)}}$

Decision rule: reject H_0 if $|Z_{cal}|>Z_{\alpha/2}$, otherwise accept H_0

If H_0 is accepted we can conclude that there is randomness in the time series data.

Inferential statistics

Trend Analysis

Estimating the trend variations required fitting an appropriate trend line on the time series data. In such a manner that it passes through the middle of the high and low turning points of time series group as nearly as possible for attend time so drawn to be the best fit the average of all trend values must be the same as the average of all original values of the time series [21].

Trend time meetings are ferment candles out a typical path through the graph. Which the time series would have followed it no distribution of forces where depurating on the time series variable. The resultant trend values are therefore, those average values that perfectly balance the functions in the original time series data. The critically trend is however, more of frequently encountered because most business and economic time series trend to increase or decrease over a long period of time. The influence of trend generating force is always slow and gradual. Trend analysis is expressed in terms of three types of trend models [12].

Linear trend model:

$\mathbf{y_t=\beta_0+\beta_{1t}+\varepsilon_t}$

In this model beta represents the average change from one period to the next period.

Where $\mathbf{Y_t}$is the value of the variable at time t.

B_0: constant (intercept) and B_1: slope

Estimation of Betas:

$B_0=\bar{Y}_t-\beta_1\bar{t}andB_1=\frac{T\sum_{i=1}^{T}t\text{Y}t}{T\sum_{i=1}^{T}t^2-(\sum_{i=1}^{T}t)^2}-\frac{\sum_{i=1}^{T}t\sum_{i=1}^{T}t}{T\sum_{i=1}^{T}t^2-(\sum_{i=1}^{T}t)^2}$

Where $\bar{Y}_t$ is the sample mean of Y_t, $\bar{t}$ is the sample mean for t .

Box-Jenkins Approach

Most statistical methodologies are developing by assuming that, the observations are random. But there are some in which their successive observations correlated in such cases methods are designed to export this dependency and generally produce superior results. The Box Jenkins approach is one of the methods. Box –Jenkins model have frequently been used synonymously with the general autoregressive integrated moving average (ARIMA) model applied to time series and forecasting [9].

Autoregressive Integrated Moving Average (ARIMA)

ARIMA (p,d,q) model is the most general class of model forecasting time series, in which can be stationary by transformation such as different lagged. One possible way of handling non-stationary series is to apply differencing, so as to make them stationary. Differencing of a series can transform a non-stationary series to stationary. If an estimate of yt is essential, then de-trending maybe more appropriate. If the dual is to make the data stationary, then differencing maybe more appropriate. Therefore:

$Y_t=\Phi_1Y_{t-1}+\ \Phi_2Y_{t-2}+\ \Phi_3Y_{t-3}+\ldots\ldots\ldots\ldots+\ \Phi_pY_{t-p}-\ \Theta_1\varepsilon_{t-1}-\ \Theta_2\varepsilon_{t-2}-\ldots\ldots..-\ \Theta_q\varepsilon_{t-q}+\varepsilon_t$

Using the backward shift operator B (defined as ($B^pY_t=Y_{t-p}$)) the above equation can be written as: $\Phi(B)Y_t=\varepsilon_t$

Where: $\Phi(B)=1-\ \Phi_1B-\ \Phi_2B^2-\ \Phi_3B^3-\ldots\ldots\ldots.-\Phi_pB^p$ is polynomial in B of order p.

Where: p=Autoregressive parameter, d=the order of difference, q= moving average parameter.

Methodological tools for model identification

Autocorrelation

Autocorrelation coefficient describes the relation between various values of time series that are lagged by 1, 2 or more period. These autocorrelation coefficients at lag 1, 2, 3 …… make up the autocorrelation function (ACF).the correlation between observations at distance k period is given by:

$r_k=\frac{\sum_{t=1}^{T}(Yt-\bar{y})\ (\mathbf{Y(t-k)}-\bar{y})}{\sqrt{\sum_{t=1}^{T}\ (Yt-\bar{y})^2}\sqrt{\sum_{t=1}^{T}\ (Y(t-k)-\bar{y})^2}}$

Where: r_k=autocorrelation after lag k

Y_t=actual observations

$\bar{Y}$= the sample mean of Y_t

Partial Autocorrelation

Partial autocorrelation measures the degree of association between Y_t and Y_{t-1} when the effects other time lags 1, 2, ……, make up the partial autocorrelation of lag k denoted by $\partial(k)$ is the autocorrelation between Y_t and Y_{t+k} with the linear dependence of Y_{t+1} through to Y_{t+k-1} removed. Equivalently, it is the autocorrelation between Y_t and Y_{t+k} that is not accounted by lags 1 to k-1, inclusive $\partial(1)=\text{cor}(Y_{t+1},Y_t)$

$\partial(k)=\text{cor}(Y_{t+1}-p_{t,k}(Y_{t+k}),\ Y_t-p_{t,k}(Y_t))$, for $k\geq 2$

Where $p_{t,k}$ (x) denotes the projection of x onto the space spanned by $X_{t+1}, X_{t+2}, X_{t+3}, \ldots, X_{t+k-1}$.

Model selection criteria

Akaike's information criteria (AIC):

Defined as:AIC=-2logLK+2K

Where LK is maximized log-likelihood and K=p+q is number of parameters in the model. The best model is the one which minimize the AIC, and there is no requirement for the model to be nested.

Model estimation

The next step after identifying ARIMA model from the general classes of multiplicative models will be estimating the vector parameter $\Phi=(\Phi_1, \Phi_2, \Phi_3, \ldots, \Phi_p)$ and $\Theta=(\Theta_1, \Theta_2, \Theta_3, \ldots, \Theta_q)$. There various methods estimating the ARIMA parameter, such as maximum likelihood and least square method.

Diagnostic checking

Once a model has been identified and the parameter estimated diagnostic check are then applied to the fitted model. This includes test serial correlation and normality of residuals.

Ljung –Box Test of serial correlation

The Q statistic is then used as a test of whether the series is white noise or not. If the series represents the residuals from ARIMA estimation, the appropriate degree of freedom should adjusted to the number of autocorrelation less than the number of AR and MA terms. The Q statistics at lag n is a test statistics for null hypothesis that there is no autocorrelation up to n and is computed as:

$$Q = T(T+1)\sum_{k=1}^{n}\frac{r^2}{T-k} \sim X^2_{(n-1)}$$

Where r^2 is the k^{th} lag autocorrelation and T is the number observations.

Jarque –Bera (JB) test of normality

JB uses the property of normality distributed random variable that the entire distribution is characterized by the first two moments, the mean and variance. The standardized third and fourth moments of distribution are known as its skewness and kurtosis. The sample skewness and kurtosis's coefficients are computed as:

$$\hat{\mathbf{b}}_1 = \frac{1/T\sum_i^T(Yi-\bar{Y})^3}{1/T\sum_i^T\sqrt{(Yi-\bar{Y})^3}} \text{ and } \hat{\mathbf{b}}_2 = \frac{1/T\sum_i^T(Yi-\bar{Y})^4}{1/T\sum_i^T(Yi-\bar{Y})^2k}$$

Forecasting

Forecasting the future value of an observation time series is an important in time series in many areas. In this study it will use trend analysis and ARIMA model for forecasting. The last step in ARIMA modeling is forecasting. The general ARIMA (p,d,q) model can be written as:

$$\Phi(B)(1-B)^d Y_t = \Theta(B)\varepsilon_t$$

Where: $\Phi(B) = 1 - \Phi_1 B - \Phi_2 B^2 - \Phi_3 B^3 - \ldots\ldots - \Phi_p B^p$ is a stationary AR operator and

$\Theta(B) = 1 + \Theta_1 B + \Theta_2 B^2 + \Theta_3 B^3 + \ldots\ldots + \Theta_P B^P$ is uninvertible MA operator. Suppose at time t we have the observations $\mathbf{Y_t, Y_{t-1}, Y_{t-2}, \ldots\ldots}$ and wish to forecast the h step ahead future value $\mathbf{Y_{t+h}}$ as a linea1r combination of the observations. Let $\mathbf{F_t}$ be the information set at time t. The minimum mean square error forecast $\hat{\mathbf{Y}}_t(\mathbf{h})$ of $\mathbf{Y_{t+h}}$ is given by it's conditional expectation. That is: $\hat{\mathbf{Y}}_t(\mathbf{h}) = E(\mathbf{Y_{t+h}}/\mathbf{F}_t)$, h>1
For t is replaced by t+h, h≥1 we have:
$Y_{t+h} = \Phi Y_{t+h-1} + \Phi_2 Yt_{+h-2} + \Phi_3 Yt_{+h-3} + \ldots + \Phi_{p+d} Yt_{+h-p-d} + \varepsilon_{t+h} + \Theta_1\varepsilon_{t+h-1} + \Theta_2\varepsilon_{t+h-2} + \ldots.. + \Theta_q\varepsilon_{t+h-q}$

Forecasting accuracy measures

To the society of forecast, it is the accuracy of the future forecast that is most important.

If Y_{t+h}, h=1, 2, 3, ……k is the actual observation for the period(t+h) and $\bar{Y}_t(h)$ is the forecast of Y_{t+h} then the forecast error is defined as: $\hat{\boldsymbol{\varepsilon}}_t(\mathbf{h}) = \mathbf{Y_{t+h}} - \bar{\mathbf{Y}}_t(\mathbf{h})$

The fitness of trend line is determined by accuracy measures i.e. MSD, MAPE and MPE

Mean absolute deviation (MAD)

MAD is measures of the accuracy of fitted time series values. It expresses accuracy in the same units as the data, which helps conceptualize the amount of errors.

$MAD = \sum\frac{|Yt-\bar{y}|}{T}$ where Yt=the actual value

Ȳ= the forecasted or estimated value

T= the number of observations

Mean absolute percentage error (MAPE)

MAPE measures the accuracy of fitted time series values. It expresses accuracy as a percentage.

$$MAPE = \frac{\sum\left|\frac{Yt-\bar{y}}{Yt}\right|}{T}$$

Where Yt=the actual value

Ȳ=the forecasted value

T= the number of observations.

Mean squared deviation (MSD)

MSD is very similar to MSE, mean square error commonly used measure of accuracy of fitted time series values. Because MSD is always computed using the same denominator n, regardless of the model, it can be used to compare values across models. Because MSE's are computed using different degrees of freedom for different models, it can be always possible to compare MSE values across models (Kendall, 1998)

$$MSD = \frac{\sum(Yt-\bar{y}t)^2}{n}$$

Where: Yt=the actual values

Ȳt=the forecasted or estimated values

III. RESULTS AND DISCUSSION

Descriptive statistics of average yearly temperature

TABLE I SUMMARY STATISTICS

Variable	N	Mean	Median	Variance	St.Dev	Min	Max	Q1	Q3
	26	18.13	18.00	1.51	1.23	16.30	23.20	17.52	18.30

From the above Table I, the deviation of each year's average yearly temperature of Mekelle City from their mean of 18.13 was 1.23 for 26 years. The average temperature difference or variance of the City for 26 years was 1.51. From 1991 to 2016 the minimum and maximum yearly average temperatures of the City were 16.30 and 23.20 respectively.

Plot of the average yearly temperature of Mekelle City from 1991-2016

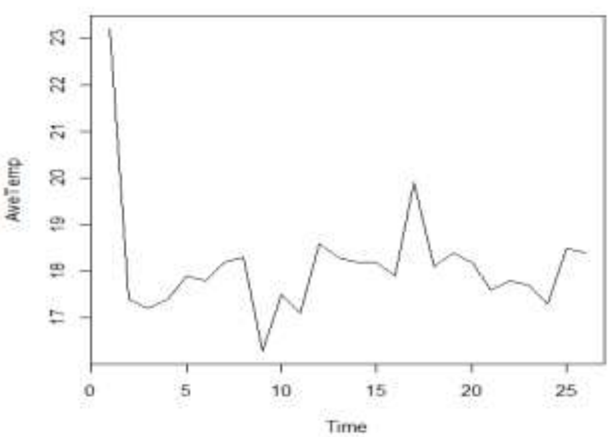

Fig 1. Average yearly temperature

As observed from the output of R software in the above figure1, the average yearly temperature of Mekelle City sharply decreased from 1991 to 1993, and then it increased slightly from1993 to 1998.It also decreased from 1998 to 1999. Again, it increased in the way zigzag from 1999 to2002, and continued at zigzag way around the mean average temperature until 2014. Finally, it increased from 2014 to 2015, and then to 2016.

Test of randomness

Based on the above figure, the graph shows 7 peaks and 8 troughs. In total, there are 15 turning points. From then at 5% level of significance, expected value and standard error of the turning point are 16 and 2.073 respectively. Then the $|Z_{cal}|$ is 1.59 which is less than 1.96.This indicates that the null hypothesis is accepted, so this tells that the data is random.

Linear Trend Analysis

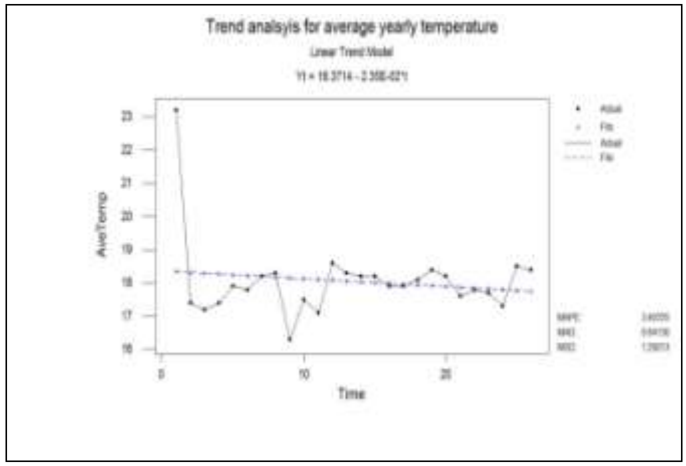

Fig. 2 Trend analysis of the average yearly temperature

As we see from the above figure, the linear trend of the graph of average yearly temperature of Mekelle City, it is slightly decreasing but not too much worrying of the temperature change in the city. As compared to 1991 for surly the temperature has decreased deeply but the changes for the past 10 years are almost constant. The accuracy measure of the MAPE of the average yearly temperature was 3.40.This shows that on average, the forecasting using linear trend is off by 34%.

The linear trend of the average yearly temperature of Mekelle City becomes:

Y_t=18.3714-2.35E-02*t

Interpretation: By keeping time constant, the average yearly temperature of Mekelle City will be 18.37.As the time increases by one year, the average yearly temperature of Mekelle city reduces by 2.35E-02.

ARIMA Model

Box-jenkin modeling of stationary time series data involves the following four steps. i.e. Model identification, Model estimation, Diagnostic checking, Forecasting.

The investigator has seen that th average yearly temperature of Mekelle City becomes stationary time series after first order differencing. Now the model that the investigator is looking at is ARIMA (p, 1, q). The investigator has to identify a good model and estimating its parameters and apply diagnostic checking for the residuals and finally the investigator used the model for forecasting the average yearly temperature.

Model identification

The researcher's first step was to identify preliminary values of the autoregressive p, and moving average order q. For this purpose, the researcher has computed the sample ACF and PACF of stationary series. These are given in Fig. 3 and Fig. 4 respectively below.

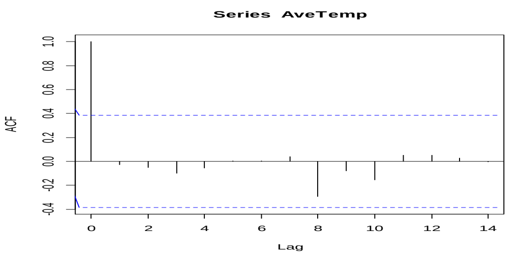

Fig. 2 Autocorrelation function test

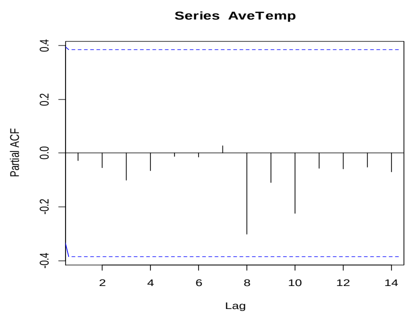

Fig.3 Partial Autocorrelation function test

From the Figs. 3 and 4 the researcher observed that ACF shows insignificance, but the PACF shows significance. For most of the lags, in most applications lower order ARIMA are considered. In this study, AR (0-3) and MA (0-3) order are considered. It is useful to compute different model selection statistics in order to suggest the best fit model of the entire ARIMA alternative at the simple stage. Here two statistics, AIC and BIC are used. The following table2 shows various ARIMA model with their corresponding AIC and BIC.

TABLE II. VARIOUS ARIMA MODEL WITH THEIR CORRESPONDING AIC AND BIC.

ARIMA	df	AIC	df	BIC
(0, 1, 0)	1	91.05	1	92.27
(0, 1, 1)	2	88.43	2	90.87
(0, 1, 2)	3	90.42	3	94.08
(0, 1, 3)	4	92.40	4	97.28
(1, 1, 0)	2	91.32	2	93.76
(1, 1, 1)	3	90.42	3	94.08
(1, 1, 2)	4	92.42	4	97.30
(1, 1, 3)	5	94.41	5	100.51
(2, 1, 0)	3	93.15	3	96.81
(2, 1, 1)	4	92.40	4	97.27
(2, 1, 2)	5	94.42	5	100.52
(2, 1, 3)	6	94.65	6	101.96
(3, 1, 0)	4	94.55	4	99.43
(3, 1, 1)	5	94.09	5	100.19
(3, 1, 2)	6	96.08	6	103.39
(3, 1, 3)	7	96.05	7	104.58

The model ARIMA (0, 1, 1) is the selected one, because it has the smallest value of both AIC and BIC. Based on these selection criteria, ARIMA (0, 1,1) is found to be the fit model for the average yearly temperature of Mekelle City.

Parameter Estimation

In this procedure, the researcher used maximum likelihood estimation method for average yearly temperature of Mekelle City to estimate the parameters. The results (output of MINITAB) are given in the table below (Table 3).

TABLE III PARAMETER ESTIMATION

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
MA 1	0.9487	0.0918	10.33	0.000
Constant	-0.01840	0.02167	-0.85	0.404

Differencing: 1 regular difference

Number of observations: Original series 26, after differencing 25

Residuals: SS = 13.2435 (backforecasts excluded)

MS = 0.5758 DF = 23

Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-Square	18.9	54.4	*	*
DF	10	22	*	*
P-Value	0.041	0.000	*	*

The estimated parameters of moving average are stationary at 5%, so the equation of the fitted model is given as: $Y_t = -0.01840+0.9487\epsilon_{t-1}+\epsilon_t$.

Interpretation: This model shows us that the predicted amount of average yearly temperature of Mekelle City is made up of 0.9487 of some random error at lag one plus some random error.

From the Minitab software output the investigator is able to conclude that the parameter has significant effect over the average yearly temperature of Mekelle city, because p-value is less than the significance level of effect.

Diagnostic check

Once the model has been identified and the parameters estimated, diagnostic check is applied to fit the model. The Box-pierce (andLjung-Box) test examines the null hypothesis of independent distributed residuals. From the data given below, the Box-Ljung test shows that the first 26 lags autocorrelation among the residuals are zero (p-value=0.05771), indicating that residuals are random and the model provided an adequate fit to the data.

```
model2=arima(AveTemp,order=c(0,1,1))
>tsdiag(model2)
>Box.test(model2$residuals,lag=1)
Box-Pierce test
data:  model2$residuals
X-squared = 3.6021, df = 1, p-value = 0.05771
```

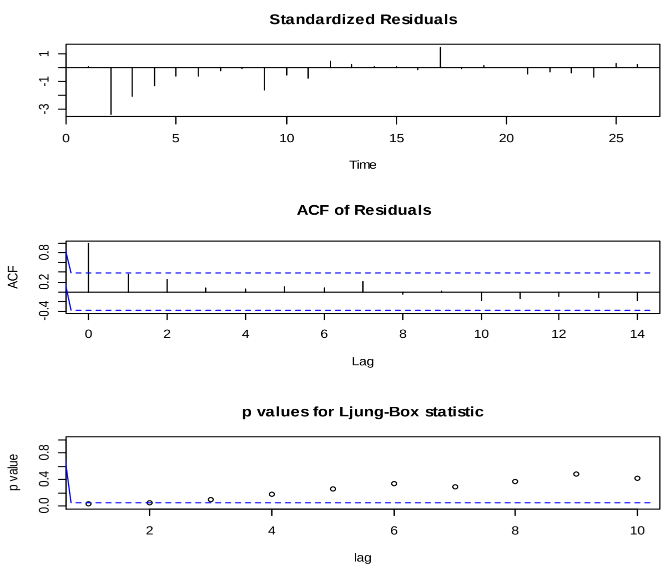

Fig. 5 diagnostic checking

Interpretation of autocorrelation plot: The autocorrelation plot of the above figure shows that for the first 14 lags, all the sample autocorrelations except at lag zero fall inside the 95% confidence bound indicating that the residuals appear to be random.

Prediction of ARIMA-Models

Using the ARIMA (0, 1, 1) model, the estimated average yearly temperature for the coming 8 years will look as follow:

TABLE IV PREDICTION USING THE SELECTED ARIMA MODEL

Forecasts from period 26			
		95 Percent Limits	
Period	Forecast	Lower	Upper
27	17.8612	16.3736	19.3488
28	17.8428	16.3532	19.3323
29	17.8244	16.3329	19.3159
30	17.8060	16.3125	19.2994
31	17.7876	16.2922	19.2830
32	17.7692	16.2718	19.2665
33	17.7508	16.2515	19.2501
34	17.7324	16.2312	19.2336

IV. CONCLUSIONS

In this study, the investigator has explained trend analysis and ARIMA model for the average yearly temperature of Mekelle city. Based on the result the following points could be concluded.

Unit root test of the series is non-stationary at the first level and becomes stationary at first order differencing.

In case of the linear trend model, the average yearly of temperature of Mekelle city is approximately constant. It is horizontal line with zero slop.But more confidently, it is better to say it is at decreasing rate.

On the other hand, ARIMA (0, 1, 1) becomes the best fitted model for the average yearly temperature of Mekelle city after examining different competitive models.

V. RECOMMENDATION

Based on the finding of this study, the following recommendations are given.

The people should challenge for the global phenomena due to climatically condition changes.

This shows the irregular changes of the weather of the environment, hence the people should protect themselves and their children from diseases which may come due coldness.

The people should wear thick clothes like jacket and cotton sweater to protect disease from coldness and take some preventive methods.

REFERENCES

[1] Akgiray U.U. Bollerserve T. Taylor S. (1989) condition in time series generalized Autoregressive conditional heteroscedasticity.
[2] AntonisAlexandridisk.,AchilleasD.Zapronis,(2007). Modeling and forecasting temperature based weather derivatives.
[3] Arthur Getis, TeromeFellmane(2000).Introduction of Geography MC Grow Hill companies.
[4] A.ZapranisandA.Alexandridis,"Waveletanalysisandweather derivatives pricing," in Proceedings of the 5th Hellenic Finance and Accounting Association (HFAA '06), Thessaloniki, Greece, December2006.
[5] A. Zapranis and A. Alexandridis, "Modelling the temperature time-dependent speed of mean reversion in the context of weatherderivativespricing,"AppliedMathematicalFinance,vol. 15,no.3-4,pp.355–386,2008
[6] B. Dischel, "Shaping history for weather risk management," EnergyPowerRisk, vol.12, no.8, pp.13–15, 1999
[7] BeyeneDollicho, EsayasShahl, FekadeShweakena (1996). Geography of Ethiopia press Addis Ababa University, Ethiopia.
[8] Box and piece D.(1970), Distribution of auto regression in autoregressive moving average time series odes Journal of American statistics association.
[9] Box D. and JenkisG.M (1996), Time series analysis forecasting and country revised edition, Oakland Al Haddemdoy.
[10] Bruce L., Bowerman and Richard T. O'connell,(1997), Applied statistics .
[11] C B Gupta and VIJAY GUPTA, (2004, Revised edition 23), An introduction to statistical methods. ISBN: 978-81259-1654.3

[12] Cheris Chris (1996). Time series Chapman and Hall, New Year
[13] Darin Brooks, Msc,college the north atlantic,(2015),Time series analysis and forecasting.
[14] Gardner RH, Hargrove WG, Turner MG, Romme WH (1996) Climate change, disturbances and landscape dynamics. In: Global Change and Terrestrial Ecosystems
[15] (Ed. by B. Walker and W. Steffen), Cambridge University Press, Great Britain, 149-172.
[16] Gebremedhin B (2002) Engineering Geological Investigation of Mekelle area, Tigray, Northern Ethiopia. M.Sc. Thesis, Addis Ababa University, Addis Ababa, pp. 163.
[17] Houghton J (1994) Global Warming, Cambridge University Press, Great Britain.
[18] KebedeTekle and TesfaShiferaw. Introduction of geography of Ethiopia (1996) press Addis Ababa University Ethiopia.
[19] Melillo JM, Callaghan TV, Woodward FI, Salati E, Sinha K (1990) Climate Change: Effects on Ecosystems. In: Houghton JT, Jenkins GJ, Ephraums JJ (eds.) Climate Change, Cambridge University Press, New York, 283-310.
[20] Md.Zuifequr Ahmed (1998). Text book of practical Geography published New Delhi 110059(India)
[21] Najd Hussain (1994) Climatology mol publication pub, Ltd New York.
[22] R.Lyman off, Michael longnecker, (2011, fifth edition), an introduction to statistical methods and data analysis.

National Meteorological Agency

Station: Mekelle(ap)				Element: Average Temp. ^{0}C									
Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
1991	21.7	23.3	24.4	25.4	26.0	27.6	23.2	20.4	22.8	22.5	20.2	20.8	23.2
1992	15.7	16.5	18.2	19.3	19.9	20.4	17.8	16.6	17.0	16.7	15.2	15.8	17.4
1993	15.1	15.7	17.6	17.3	18.6	19.1	17.5	17.7	18.1	17.6	16.3	15.6	17.2
1994	15.7	16.7	17.9	19.3	20.3	19.3	17.1	16.9	16.6	16.8	16.3	15.2	17.4
1995	15.7	16.9	18.2	19.3	20.1	21.0	17.8	17.7	17.6	17.2	16.5	16.6	17.9
1996	16.4	17.8	18.7	19.5	19.2	18.5	18.2	17.8	18.3	17.4	16.2	15.5	17.8
1997	16.3	16.8	19.1	19.3	20.1	20.5	18.0	17.9	19.0	17.8	17.5	16.7	18.2
1998	17.3	17.7	19.5	21.1	20.8	21.1	18.2	17.6	18.2	17.4	15.6	15.0	18.3
1999	15.8	17.7	18.0	19.9	20.9	20.8	17.2	17.1	17.8	11.5	9.5	9.5	16.3
2000	9.5	17.1	18.3	19.2	20.6	20.7	18.4	18.0	17.9	17.4	16.8	16.3	17.5
2001	15.6	17.3	18.3	20.1	21.3	19.4	13.3	17.6	18.4	18.2	9.6	16.5	17.1
2002	16.4	17.7	19.1	19.4	21.4	20.5	19.6	18.0	18.5	18.2	17.2	17.0	18.6
2003	16.6	18.7	19.0	20.2	21.7	20.2	18.6	17.5	18.0	17.2	16.7	15.7	18.3
2004	17.5	16.9	18.3	19.7	20.7	19.8	18.9	17.9	18.4	16.8	17.0	16.4	18.2
2005	16.3	18.5	19.3	19.9	20.1	20.3	18.3	18.1	18.4	16.9	16.6	15.3	18.2
2006	15.6	18.2	18.4	18.9	19.5	20.0	18.5	17.6	17.8	17.5	16.3	16.4	17.9
2007	16.1	18.1	18.8	19.3	20.9	20.5	17.8	17.8	17.5	16.6	16.0	15.2	17.9
2008	17.0	16.5	18.5	19.3	20.6	20.2	18.8	18.4	18.6	17.5	16.5	15.5	18.1
2009	16.2	17.7	18.9	19.6	20.1	21.9	18.5	18.4	18.6	17.5	16.7	17.0	18.4
2010	16.4	18.2	18.3	20.4	22.3	21.1	18.8	17.8	17.7	17.2	16.1	15.3	18.2
2011	15.6	17.0	17.4	19.8	19.7	20.0	18.6	17.6	17.2	16.8	16.7	15.4	17.6
2012	16.1	17.1	18.2	19.3	20.3	20.1	17.9	18.5	16.7	16.6	17.0	16.2	17.8
2013	16.3	17.6	18.7	19.3	20.3	20.2	16.4	18.5	16.8	17.3	16.8	14.6	17.7
2014	16.5	17.3	18.8	19.4	19.6	19.9	18.6	17.9	17.4	10.4	16.5	15.4	17.3
2015	16.6	17.7	19.6	19.7	19.9	19.9	18.7	18.5	18.9	18.5	17.4	16.7	18.5
2016	16.7	18.0	20.4	20.0	20.1	20.5	18.3	17.9	18.7	18.3	16.2	15.6	18.4

Source: National agency, Mekelle branch, Ethiopia