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Statistical Analysis of Meteorological Data

Sergio Perez Melo
spere047@fiu.edu

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FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

STATISTICAL ANALYSIS OF METEOROLOGICAL DATA

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in

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by

Sergio Perez Melo

2014

To: Interim Dean Michael R. Heithaus
College of Arts and Sciences

This thesis, written by Sergio Perez Melo, and entitled Statistical Analysis of Meteorological Data, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this thesis and recommend that it be approved.

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Florence George

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Wensong Wu

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Sneh Gulati, Major Professor

Date of Defense: May 28, 2014

The thesis of Sergio Perez Melo is approved.

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Interim Dean Michael R. Heithaus
College of Arts and Sciences

____
Dean Lakshmi N. Reddi
University Graduate School

Florida International University, 2014

DEDICATION

I dedicate this thesis to my parents, my sister and my nieces. This thesis would not have been possible without their love and support.

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I would like to express my gratitude to my main professor and committee members: Dr. Sneh Gulati, Dr. Florence George, and Dr. Wensong Wu. Thank you for your guidance, patience and kindness.

I would also like to express my appreciation to all my professors in the Master of Statistics program. Thank you all for being excellent educators.

Lastly, I wanted to thank my family and friends for their love and support. Thank you for helping me through all the ups and downs of life. Especially, I wanted to thank my parents and sister for being there for me unconditionally.

ABSTRACT OF THE THESIS

STATISTICAL ANALYSIS OF METEOROLOGICAL DATA

by

Sergio Perez Melo

Florida International University, 2014

Miami, FL

Professor Sneh Gulati, Major Professor

Some of the more significant effects of global warming are manifested in the rise of temperatures and the increased intensity of hurricanes. This study analyzed data on Annual, January and July temperatures in Miami in the period spanning from 1949 to 2011; as well as data on central pressure and radii of maximum winds of hurricanes from 1944 to present.

Annual Average, Maximum and Minimum Temperatures were found to be increasing with time. Also July Average, Maximum and Minimum Temperatures were found to be increasing with time. On the other hand, no significant trend could be detected for January Average, Maximum and Minimum Temperatures.

No significant trend was detected in the central pressures and radii of maximum winds of hurricanes, while the radii of maximum winds for the largest hurricane of the year showed an increasing trend.

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CHAPTER I

INTRODUCTION

Climate Change refers to "any significant change in the measures of climate lasting for an extended period of time. In other words, climate change includes major changes in temperature, precipitation, or wind patterns, among other effects, that occur over several decades or longer [1.]"Over the last decades evidence of rising global temperature has become stronger. According to the "Climate Change 2001 Synthesis Report," global mean surface temperature increased by 0.6±0.2°C during the 20th century, and land areas warmed more than the oceans. Also the Northern Hemisphere Surface Temperature Increase over the 20th century was greater than during any other century in the last 1,000 years, while 1990s was the warmest decade of the millennium [2].The intensity and impact of weather phenomena, like floods, droughts, hurricanes, etc. also seems to have increased. All these changes, as they become more pronounced will pose challenges to our society and the environment.

The objective of my study is to search for evidence of these climatological changes in South Florida. My main motivation in taking up this course of research is to apply statistical data analysis techniques to climatological data in order to quantitatively assess the effects of global warming in our region. My thesis focuses on two particular phenomena: temperature change and trends in the characteristics of hurricanes. For this purpose I have gathered and analyzed data on annual and monthly average, maximum and minimum temperatures for Miami for the period spanning from 1949 to the 2011. My research objective is to detect any statistically significant trend in these time series, and quantify the rate of change.

Also data on hurricanes (central pressure and radii of maximum winds) from 1944 to the present will be analyzed with the same objective.

I aim to make a modest contribution to the constantly increasing corpus of statistical evidence supporting the reality of global warming and its climatic consequences, with a special emphasis on how these changes are taking place in the region of South Florida.

CHAPTER II

LITERATURE REVIEW

One of the most significant effects of global warming is the rise in atmospheric temperature over time. Many studies have been done on this phenomenon in different parts of the world in order to quantify the rate of change of temperatures.

Easterling et. al.[3] carried out an analysis of the global mean surface air temperature showing that its increase is the result of differential changes in daily maximum and minimum temperatures, resulting in a narrowing of the diurnal temperature range (DTR). The analysis, used station metadata and improved areal coverage for much of the Southern Hemisphere landmass. The evidence collected indicated that the DTR is continuing to decrease in most parts of the world.

Karl et. al. [4] studied the year-month mean maximum and minimum surface thermometric record of three large countries in the Northern Hemisphere (the contiguous United States, Russia, and the People's Republic of China). They indicate that most of the warming which has occurred in these regions over the past four decades can be attributed to an increase of mean minimum (mostly nighttime) temperatures. Mean maximum (mostly daytime) temperatures display little or no warming. In the USA and Russia (no access to data in China) similar characteristics are also reflected in the changes of extreme seasonal temperatures, e.g., increase of extreme minimum temperatures and little or no change in extreme maximum temperatures. The continuation of increasing minimum temperatures and little overall change of the maximum leads to a decrease of the mean (and extreme) temperature range, an important measure of climate variability.

Vose, R. S., D. R. Easterling, and B. Gleason [5] used new data acquisitions to examine recent global trends in maximum temperature, minimum temperature, and the diurnal temperature range (DTR). On an average, the analysis covered the equivalent of 71% of the total global land area, 17% more than in previous studies. They found that minimum temperature increased more rapidly than maximum temperature (0.204 vs. 0.141°C dec^{-1}) from 1950–2004, resulting in a significant DTR decrease (−0.066°C dec^{-1}). In contrast, there were comparable increases in minimum and maximum temperature (0.295 vs. 0.287°C dec^{-1}) from 1979–2004, muting recent DTR trends (−0.001°C dec^{-1}). Minimum and maximum temperature increased in almost all parts of the globe during both periods, whereas a widespread decrease in the DTR was only evident from 1950–1980

Studies centered on local or national, rather than global, temperature trends have also been conducted. For example, Liu et. al. [6] analyzed daily climate data from 305 weather stations in China for the period from 1955 to 2000. The authors found that surface air temperatures in China have been increasing with an accelerating trend after 1990. They also found that the daily maximum and minimum air temperature increased at a rate of 1.27° and 3.23°C $(100\ yr)^{-1}$ between 1955 and 2000. Both temperature trends were faster than those reported for the Northern Hemisphere. The daily temperature range (DTR) decreased rapidly by −2.5°C $(100\ yr)^{-1}$ from 1960 to 1990; during the same time period, minimum temperature increased while maximum temperature decreased slightly.

Kothawale, D. R., and K. Rupa Kumar [7] focused on temperature trends in India, and found that while all-India mean annual temperature has shown significant warming trend of 0.05°C/10yr during the period 1901–2003, the recent period 1971–2003 has seen a relatively accelerated warming of 0.22°C/10yr, which is largely a result of unprecedented warming during the last decade. Further, in a major shift, the recent period is marked by rising temperatures during the monsoon season, resulting in a weakened seasonal asymmetry of temperature trends reported earlier. The recent accelerated warming over India is manifested equally in daytime and nighttime temperatures.

Rebetez, M, and M Reinhart [8] studied long-term temperature trends for 12 homogenized series of monthly temperature data in Switzerland for the 20th century (1901–2000) and for the last thirty years (1975–2004). Comparisons were made between these two periods, with changes standardized to decadal trends. Their results show mean decadal trends of +0.135 °C during the 20th century and +0.57 °C seen in the last three decades only. These trends are more than twice as high as the average temperature trends in the Northern Hemisphere.

Another study connected with the topic of this thesis is by Webster et. al.[9]. In it, the authors examined the number of tropical cyclones and cyclone days as well as tropical cyclone intensity over the past 35 years, in an environment of increasing sea surface temperature. A large increase was seen in the number and proportion of hurricanes reaching categories 4 and 5. The largest increase occurred in the North Pacific, Indian, and Southwest Pacific Oceans, and the smallest percentage increase occurred in the North Atlantic Ocean. These results hint at an overall increase in the intensity of hurricanes.

CHAPTER III

ANALYSIS OF AVERAGE, MAXIMUM AND MINIMUM TEMPERATURES

One of the most significant effects of global warming is the rise in atmospheric temperature over time. As we have seen in the review of literature, many studies have been done on this phenomenon in different parts of the world in order to quantify the rate of change of temperatures. For the most part the general consensus seems to be that temperatures are scaling up globally.

In this chapter the focus is on detecting trends and fitting statistical models for temperatures in Miami starting in 1948 to the present.The time series of average maximum, average minimum and average Annual temperatures , as well as the average maximum, average minimum and average temperatures for January (coldest month of the year) and July (one of the hottest months) will be analyzed to detect any statistically significant trend in annual, winter and summer temperatures.

Statistical Methodology

A **time series** is a time oriented or chronological sequence of observations on a variable of interest. **Time series analysis** comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data.

The time series analysis procedure that we have adopted in our thesis consists of first fitting a simple linear regression models to the corresponding times series. The basic model that we will fit to all of the previously mentioned Temperature time series is:

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t$$

where y_t is the temperature in period t, t is the time period (t = 1 for 1949, and increasing by one for each new observation), β_1 is the slope or trend of the line, β_0 is the y-intercept of our model, and ε_t is a random error term or stochastic component of the times series , which are assumed ideally to be independent and identically distributed normal random variables i.e: $\varepsilon_t \sim N(0, \sigma^2)$. We will obtain estimates of the model parameters (β_1 and β_0) through Ordinary Least Squares (OLS) estimation. For time series analysis purposes the OLS estimators take the following form:

$$\widehat{\beta_0} = \frac{2(2T+1)}{T(T-1)} \sum_{t=1}^{T} y_t - \frac{6}{T(T-1)} \sum_{t=1}^{T} t y_t$$

$$\widehat{\beta_1} = \frac{12}{T(T^2-1)} \sum_{t=1}^{T} t y_t - \frac{6}{T(T-1)} \sum_{t=1}^{T} y_t$$

where T is the number of observations. [10]

Once we compute the parameter estimates, we will perform a statistical test on the trend parameter β_1 to determine whether it is different from zero. In other words we want to know if the given temperature time series is stationary or not. The statistical test that we will perform is a t-test on β_1:

$$H_0: \beta_1 = 0 \ vs \ H_a: \beta_1 \neq 0$$

$$t = \frac{\widehat{\beta_1}}{se(\widehat{\beta_1})} \sim Student\ T(df = T-2)$$

We will test at $\alpha = 0.05$ level of significance as it is customary. If the null hypothesis is rejected we can conclude that the given temperature time series is not stationary, and the estimated slope will be an estimate of how fast the temperature is changing per year.

The models themselves will be fitted with a descriptive purpose; nevertheless checking of the assumptions will be made in every instance. Checking of the normality of residuals assumption will be made through QQ-plots and the Anderson-Darling Test for Normality on the residuals. Checking of the homoscedasticity of residuals will be made through visual inspection of residuals versus fits plots. Checking of the assumption of uncorrelated errors will be made through a plot of the autocorrelation function with 5% significance limits, and also through the Durbin-Watson test for auto-correlation.

When necessary, adjustments to the simple linear regression models will be done to account for violations on the simple linear regression assumptions. In particular, if auto-correlation in the residuals is detected, we will fit a simple linear regression model with first order autoregressive errors, of the type:

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t$$

$$\varepsilon_t = \phi\varepsilon_{t-1} + a_t$$

$$a_t \sim N(0, \sigma^2)$$

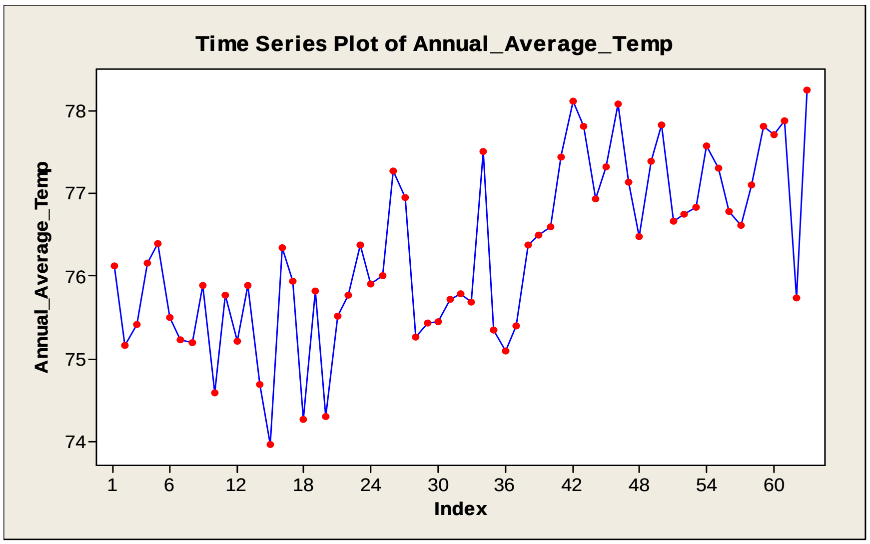
in order to account for the significant first order auto-correlation amongst the residuals. Theestimation of the model parameters will be done through maximum likelihood methods using PROC AUTOREG in SAS. The estimate of the slope parameter $\beta_1$will be the estimated rate of change for the temperatures [11].

Data Analysis

The data on temperatures comes from the website of the Southeast Regional Climate Center [12]. The data were collected in the meteorological station located in

Miami WSCMO Airport, in Miami, Florida, from 1949 and 2011, with no missing observations. All statistical data analysis was done with the software Minitab 16 and SAS 9.3. The following figures and tables show the result of the analysis:

Annual Average Temperature Time Series (1949-2011)




```
The regression equation is
Annual_Average_Temp = 75.0 + 0.0392 t


Predictor       Coef   SE Coef       T      P
Constant     75.0201    0.1971  380.57  0.000
t           0.039177  0.005356    7.31  0.000


S = 0.773022   R-Sq = 46.7%   R-Sq(adj) = 45.9%

Durbin-Watson statistic = 1.56527
```

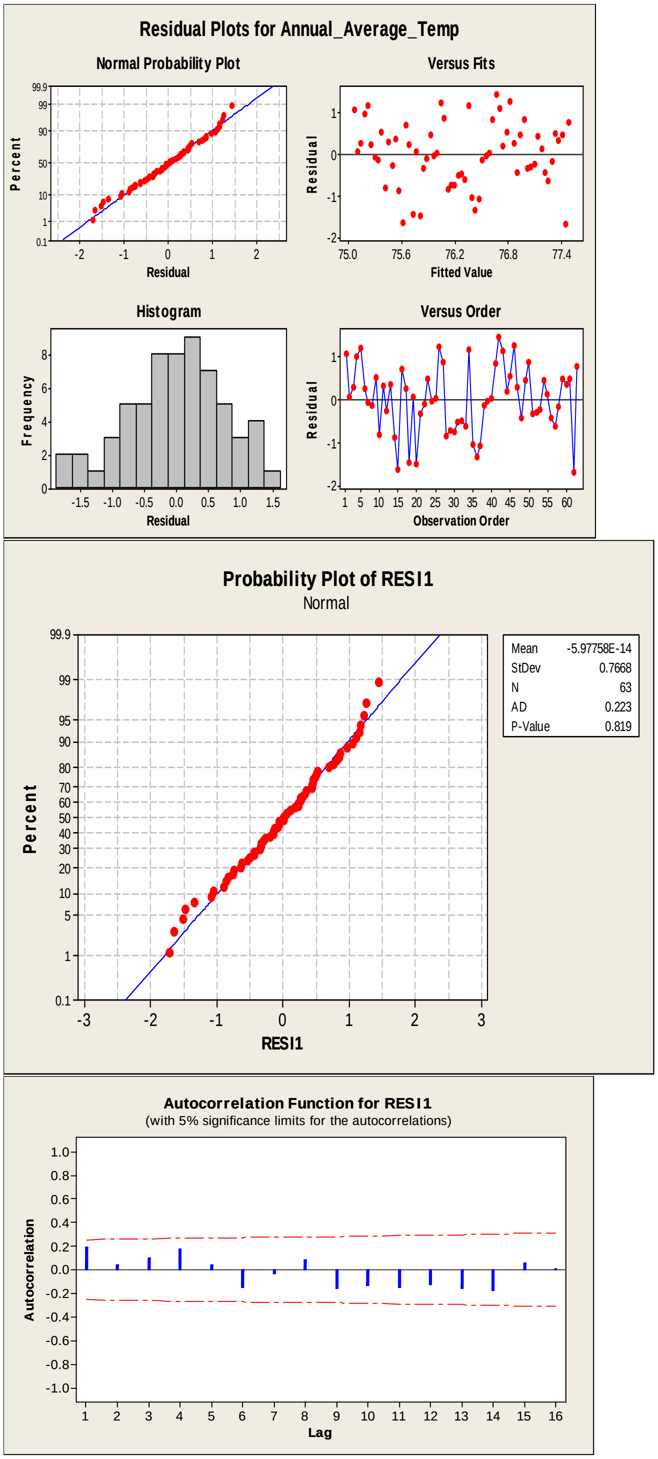
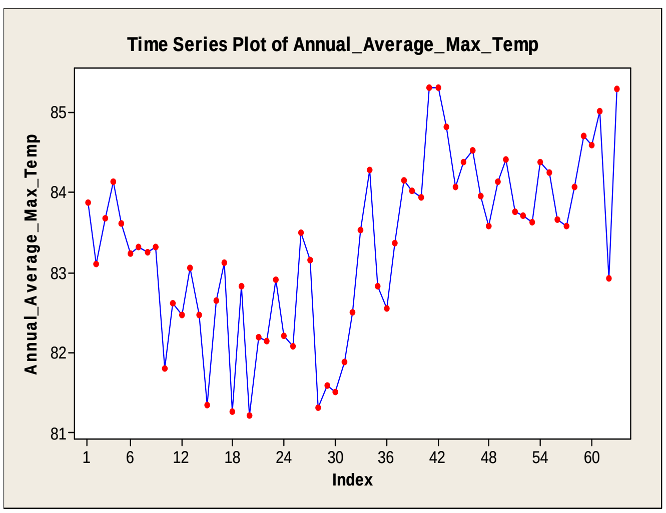


Figure 1: Annual Average Temperature Time Series

From the Minitab output we can conclude that there is a statistically significant positive trend in the Annual Average Temperature Time Series (p-value < 0.001). The estimate of the slope is 0.039177 degrees Celsius/ year (SE = 0.005356). From the residual analysis we cannot see any violations of the assumptions of the simple linear regression model. Residuals are normally distributed since the p-value of the Anderson-Darling Test is 0.819. Moreover, the residuals are uncorrelated because no significant autocorrelation is shown in the autocorrelation function graph, and the Durbin-Watson test statistic is not significant at 0.01 level of significance (DW= 1.565 > d_U = 1.52). Finally, the variance seems constant since there is no apparent pattern in the residuals vs fit plot.

Annual Average Maximum Temperatures Time Series (1949-2011)




```
The regression equation is
Annual_Average_Max_Temp = 82.4 + 0.0305 t


Predictor        Coef   SE Coef        T      P
Constant      82.3555    0.2324   354.32  0.000
t            0.030482  0.006315     4.83  0.000


S = 0.911467   R-Sq = 27.6%   R-Sq(adj) = 26.5%

Durbin-Watson statistic = 0.907803
```

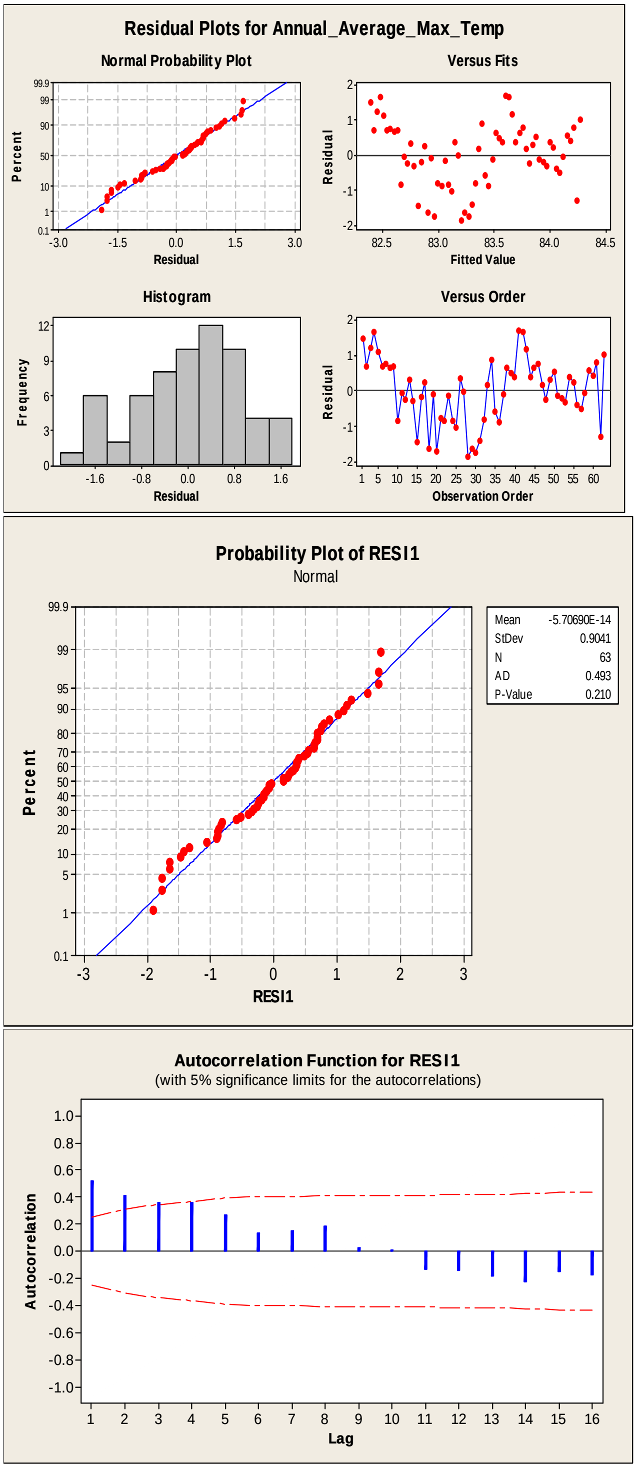


Figure 2:Annual Average Maximum Temperature Time Series

From the Minitab output for the annual average maximum temperature we can conclude that there is a statistically significant positive trend in the Annual Average Maximum Temperature Time Series (p-value < 0.001). The estimate of the slope is 0.030482 degrees Celsius/ year (SE = 0.006315). Residuals are normally distributed since the p-value of the Anderson-Darling normality test is 0.210. Also the variance seems constant because there is no apparent pattern in the residuals versus fit plot, but the residuals are correlated. We can observe in the autocorrelation function graph that the first, second and third lag autocorrelations are significantly different from zero, and the Durbin-Watson test statistic is also significant at 0.01 level of significance (DW= 0.9078 < d_L = 1.47). Therefore we will fit a simple linear regression model withfirst order autoregressive errors, in order to eliminate residual autocorrelation.

Maximum Likelihood Estimates

SSE	36.3364954	**DFE**	60
MSE	0.60561	**Root MSE**	0.77821
SBC	156.892356	**AIC**	150.462952
MAE	0.59270469	**AICC**	150.869731
MAPE	0.71346995	**HQC**	152.991668
Log Likelihood	-72.231476	**Regress R-Square**	0.1062
Durbin-Watson	2.0820	**Total R-Square**	0.4812
		Observations	63

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx

					Pr > |t|
Intercept	1	82.4257	0.4134	199.41	<.0001
t	1	0.0297	0.0111	2.66	0.0099
AR1	1	-0.5411	0.1097	-4.93	<.0001

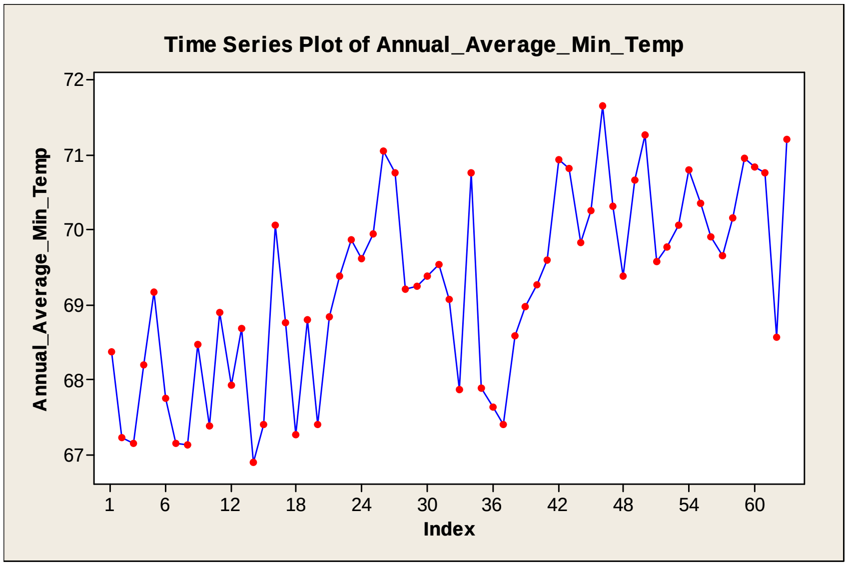
Miscellaneous Statistics

Statistic	Value	Prob	Label
Normal Test	1.5476	0.4613	Pr > ChiSq

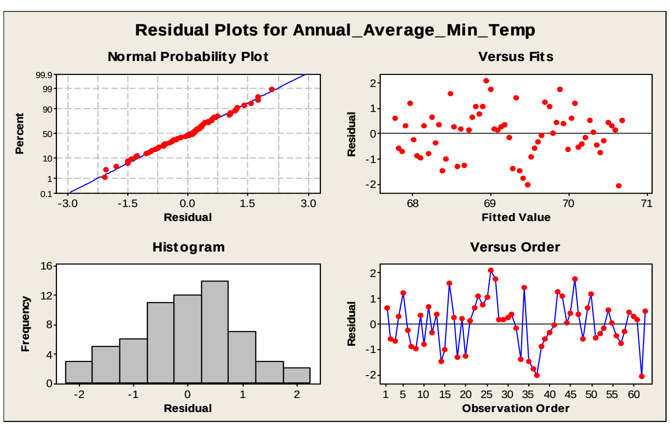
Figure 3: Annual Average Maximum Temperature Time Series (autoregressive)

This new model is an improvement over the previous one since the residuals are now uncorrelated and normally distributed (at 0.01 level of significance), and also the R-square of this new model is higher that of the previous model (goes up from 26.5% to 48.12 %). In this model, as in the previous model, it is clear that there is a significant positive trend in the time series (p-value = 0.0099). The estimate of the rate of change of the annual average maximum temperature with time is 0.0297 degrees Celsius/ year (SE=0.0111), having been controlled for the significant autocorrelation.

Average Minimum Temperature Time Series (1949-2011)




```
The regression equation is
Annual_Average_Min_Temp = 67.7 + 0.0472 t


Predictor       Coef   SE Coef       T      P
Constant     67.7199    0.2441  277.38  0.000
t           0.047187  0.006633    7.11  0.000


S = 0.957384   R-Sq = 45.3%   R-Sq(adj) = 44.4%


Durbin-Watson statistic = 1.50042
```



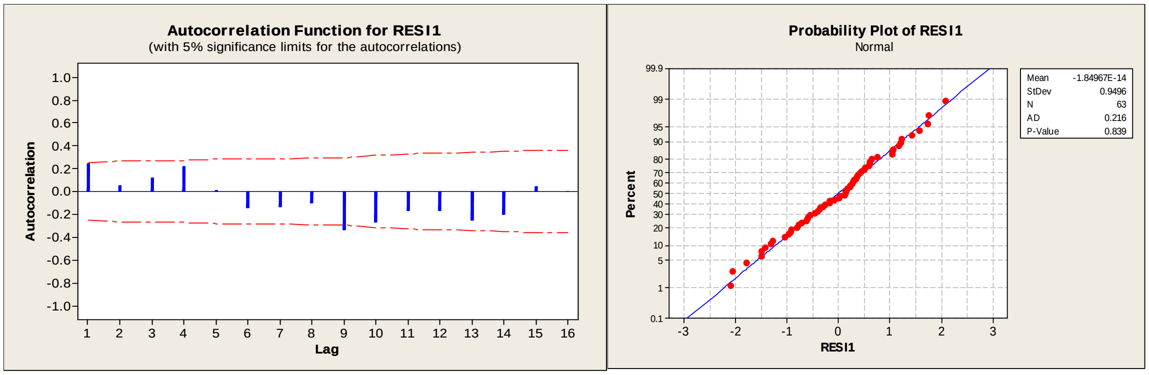


Figure 4: Annual Average Minimum Temperature Time Series

From the Minitab output for the Annual Average Minimum Temperature Time Series we can conclude that there is a statistically significant positive trend in the Annual Average Minimum Temperature Time Series (p-value < 0.001). The estimate of the slope is 0.047187 degrees Celsius/ year (SE = 0.006633). Residuals are normally distributed since Anderson-Darling normality test doesn't show departure from normality (p-value = 0.839). Also the variance seems constant since there is no apparent pattern in the residuals vs fit plot, but the residuals are correlated. We can observe from the autocorrelation function graph that the first lag autocorrelation is marginally significant, while the Durbin-Watson test statistic is significant at the 0.05 level of significance (DW= 1.50042 < d_L = 1.55). Therefore we will fit a simple linear regression model with first order autoregressive errors, in order to eliminate residualautocorrelation.

Maximum Likelihood Estimates

SSE	52.5386337	**DFE**	60
MSE	0.87564	**Root MSE**	0.93576
SBC	179.836696	**AIC**	173.407292
MAE	0.74085066	**AICC**	173.814072
MAPE	1.07240266	**HQC**	175.936008

Log Likelihood	-83.703646	**Regress R-Square**	0.3422
Durbin-Watson	1.9626	**Total R-Square**	0.4864
		Observations	63

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	67.7269	0.3113	217.54	<.0001
t	1	0.0471	0.008439	5.59	<.0001
AR1	1	-0.2432	0.1254	-1.94	0.0573

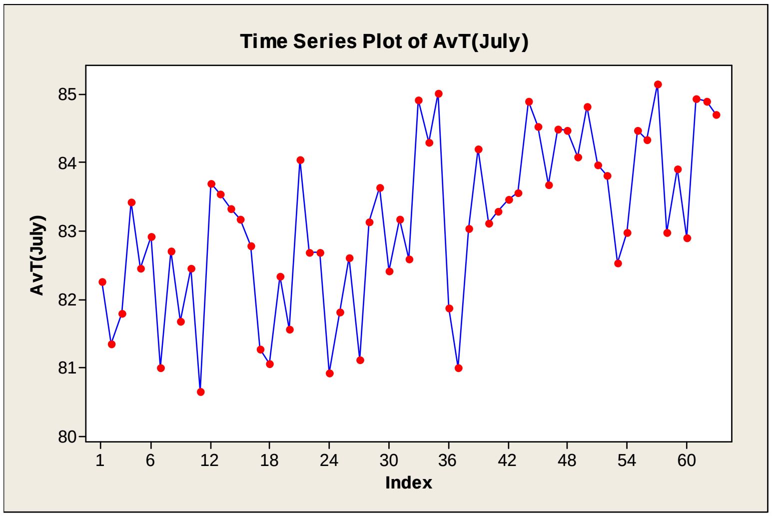
Miscellaneous Statistics

Statistic	Value	Prob	Label
Normal Test	0.4296	0.8067	Pr > ChiSq

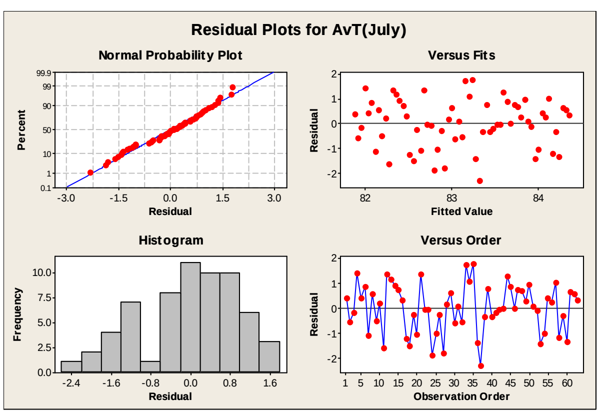
Figure 5: Annual Average Minimum Temperature Time Series (autoregressive)

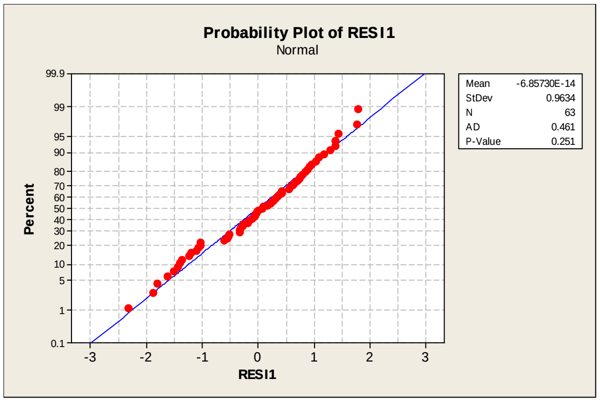
This new model is an improvement over the previous one since the residuals are now uncorrelated and normally distributed, and also the R-square of this new model is higher that of the previous (increases from 44.4% to 48.6 %). In this model, as in the previous, it is shown that there is a significant positive trend in the time series (p-value < 0.001). The estimate of the rate of change of the annual average maximum temperature with time is 0.0471 degrees Celsius/ year (SE=0.008439), having controlled for the significant autocorrelation.

July Average Temperature Time Series(1949-2011)




```
The regression equation is
AvT(July) = 81.8 + 0.0403 t


Predictor       Coef    SE Coef       T      P
Constant     81.8282     0.2477  330.39  0.000
t           0.040295   0.006729    5.99  0.000


S = 0.971228   R-Sq = 37.0%   R-Sq(adj) = 36.0%


Durbin-Watson statistic = 1.66800
```





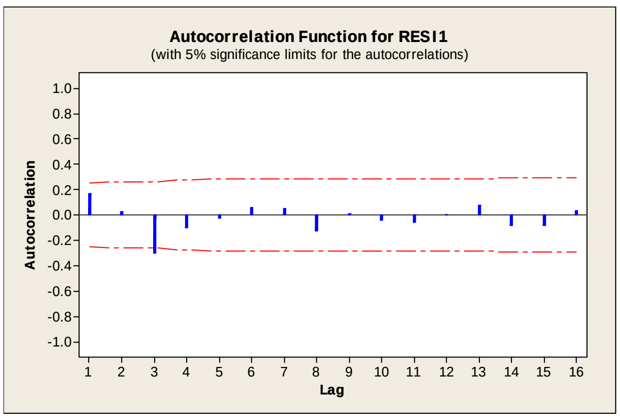
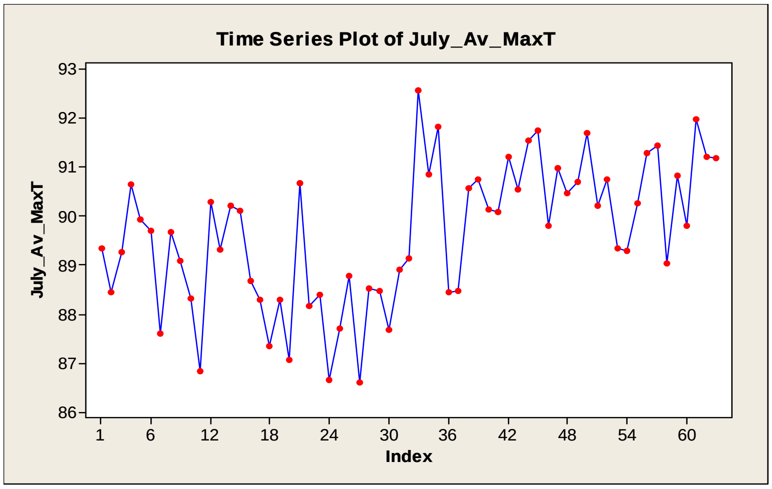


Fig 6.July Average Temperature Time Series

From the Minitab output for the July Average Temperature Time Series we can conclude that there is a statistically significant positive trend in the July Average Temperature Time Series (p-value < 0.001). The estimate of the slope is 0.0403 degrees Celsius/ year (SE=0.006729). Residuals are normally distributed since Anderson-Darling normality test doesn't show departure from normality, p-value = 0.251. Also the variance seems constant since there is no apparent pattern in the residuals vs fit plot. The residuals are uncorrelated as can be observed from the autocorrelation function graph. Durbin-Watson test statistic is not significant at 0.05 level of significance (DW= 1.66800 > d_U = 1.62).

Therefore we will not fit an autoregressive model because the present one is compliant with the assumptions.

July Average Maximum Temperature Time Series (1949-2011)




```
The regression equation is
July_Av_MaxT = 88.4 + 0.0403 t


Predictor        Coef    SE Coef       T      P
Constant      88.3553     0.3194  276.61  0.000
t            0.040271   0.008679    4.64  0.000


S = 1.25260   R-Sq = 26.1%   R-Sq(adj) = 24.9%


Durbin-Watson statistic = 1.39805
```

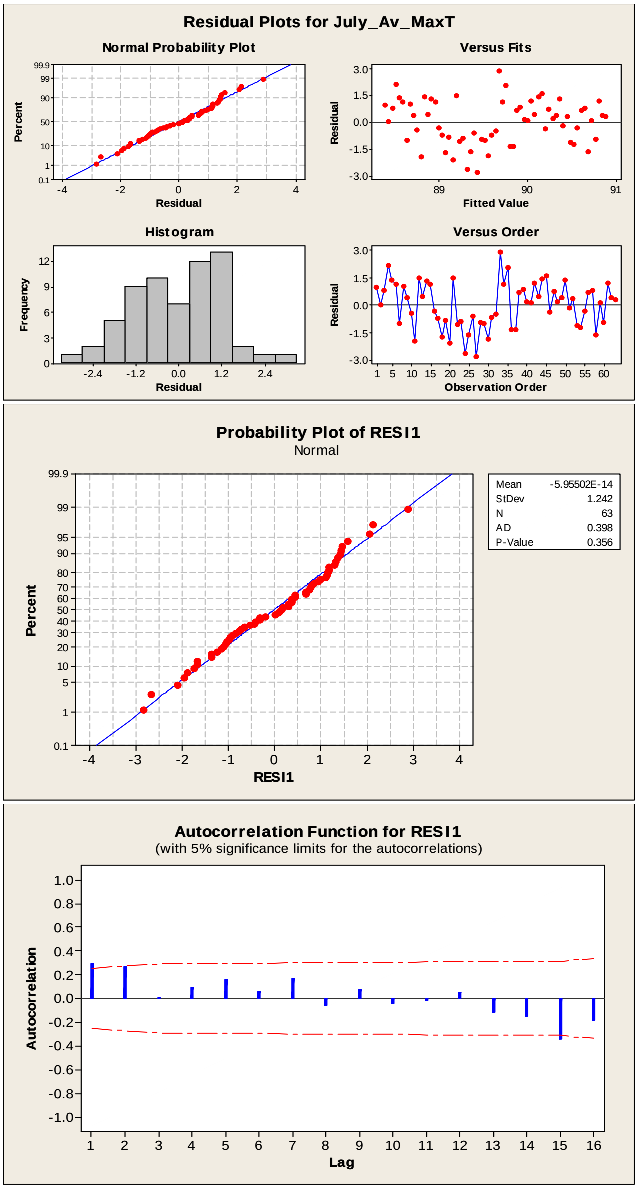


Fig 7. July Average Maximum Temperature Time Series

From the Minitab output we can conclude that there is a statistically significant positive trend in the **July Average Maximum Temperature Time Series** (p-value < 0.001). The estimate of the slope is 0.0403 degrees Celsius/ year (SE=0.008679). Residuals are normally distributed since Anderson-Darling normality test doesn't show departure from normality, p-value = 0.356. Also the variance seems constant since there is no apparent pattern in the residuals vs fit plot, but the residuals are correlated. We can observe from the autocorrelation function graph that the first lag autocorrelation is significant , while the Durbin-Watson test statistic is significant at 0.05 level of significance (DW= 1.39805 < d_L = 1.55). Therefore we will fit a simple linear regression model with first order autoregressive errors, in order to eliminate residualautocorrelation.

Maximum Likelihood Estimates

SSE	87.2467245	**DFE**	60
MSE	1.45411	**Root MSE**	1.20587
SBC	211.819394	**AIC**	205.389989
MAE	0.94068792	**AICC**	205.796769
MAPE	1.05159428	**HQC**	207.918706
Log Likelihood	-99.694995	**Regress R-Square**	0.1643
Durbin-Watson	2.1000	**Total R-Square**	0.3262
		Observations	63

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	88.3766	0.4286	206.18	<.0001
t	1	0.0399	0.0116	3.43	0.0011
AR1	1	-0.2943	0.1233	-2.39	0.0201

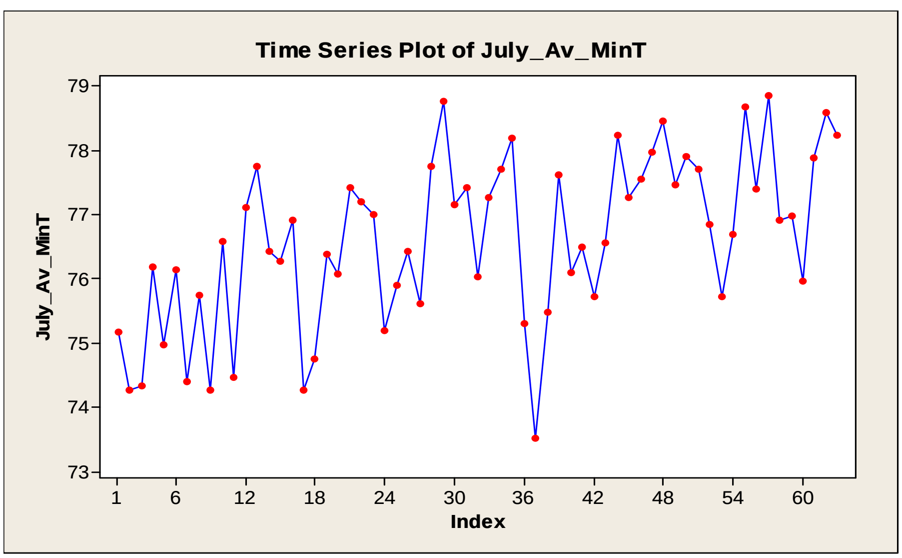
Miscellaneous Statistics

Statistic	Value	Prob	Label
Normal Test	1.0719	0.5851	Pr > ChiSq

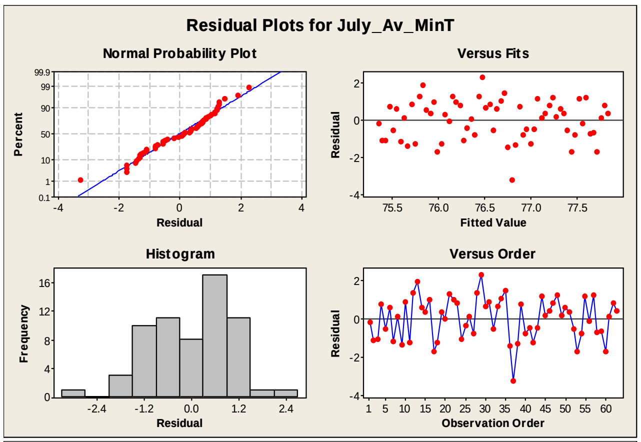
Fig 8.July Average Maximum Temperature Time Series (autoregressive)

This new model is an improvement over the previous one since the residuals are now uncorrelated and normally distributed, and also the R-square of this new model is higher that of the previous model (goes up from 24.9% to 32.6 %). In this model, as in the previous model, it is clear that there is a significant positive trend in the time series (p-value = 0.0011). The estimate of the rate of change of the annual average maximum temperature with time is 0.0399 degrees Celsius/ year (SE=0.0116), having been controlled for the significant autocorrelation.

July Average Minimum Temperature Time Series (1949-2011)



```
The regression equation is
July_Av_MinT = 75.3 + 0.0402 t


Predictor       Coef   SE Coef       T      P
Constant     75.3038    0.2772  271.64  0.000
t           0.040240  0.007532    5.34  0.000


S = 1.08711   R-Sq = 31.9%   R-Sq(adj) = 30.8%


Durbin-Watson statistic = 1.54232
```



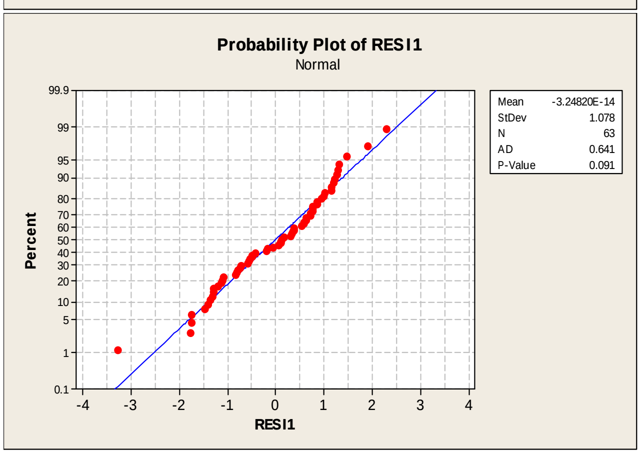


Fig 9. July Average Minimum Temperature Time Series

From the Minitab output for the **July Average Minimum Temperature Time Series** we can conclude that there is a statistically significant positive trend in the July Average Minimum Temperature Time Series (p-value < 0.001). The estimate of the slope is 0.0402 degrees Celsius/ year (SE=0.007532). Residuals are normally distributed since

Anderson-Darling normality test doesn't show departure from normality, p-value = 0.091. Also the variance seems constant since there is no apparent pattern in the residuals vs fit plot, but the residuals are correlated. We can observe from the autocorrelation function graph that the first lag autocorrelation is marginally significant , while the Durbin-Watson test statistic is significant at 0.05 level of significance (DW= 1.54232< d_L = 1.55). Therefore we will fit a simple linear regression model with first order autoregressive errors, in order to eliminate residualautocorrelation.

Maximum Likelihood Estimates

SSE	68.3485652	**DFE**	60
MSE	1.13914	**Root MSE**	1.06731
SBC	196.401038	**AIC**	189.971634
MAE	0.87198725	**AICC**	190.378414
MAPE	1.14176733	**HQC**	192.50035
Log Likelihood	-91.985817	**Regress R-Square**	0.2359
Durbin-Watson	1.9592	**Total R-Square**	0.3541
		Observations	63

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	75.2967	0.3470	216.98	<.0001
t	1	0.0405	0.009408	4.30	<.0001
AR1	1	-0.2246	0.1258	-1.78	0.0793

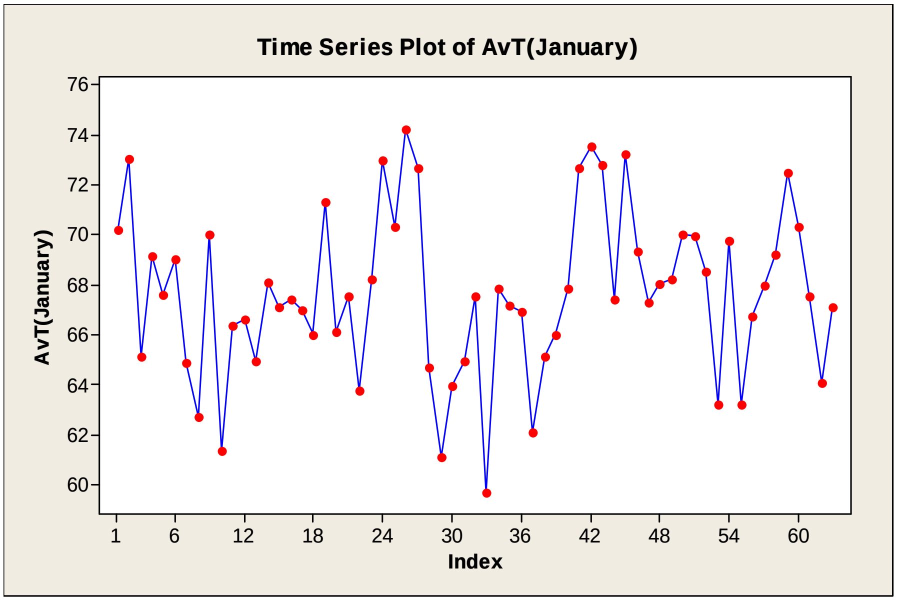
Miscellaneous Statistics

Statistic	Value	Prob	Label
Normal Test	1.6808	0.4315	Pr > ChiSq

Fig 10. July Average MinimumTemperature Time Series (autoregressive)

This new model is an improvement over the previous one since the residuals are now uncorrelated and normally distributed, and also the R-square of this new model is higher than that of the previous model (goes up from 30.8% to 35.4 %). In this model, as in the previous model, it is evident that there is a significant positive trend in the time series (p-value <0.0001). The estimate of the rate of change of the annual average maximum temperature with time is 0.0405 degrees Celsius/ year (SE=0.009408), having been controlled for the significant autocorrelation

January Average Temperature Time Series (1949-2011)

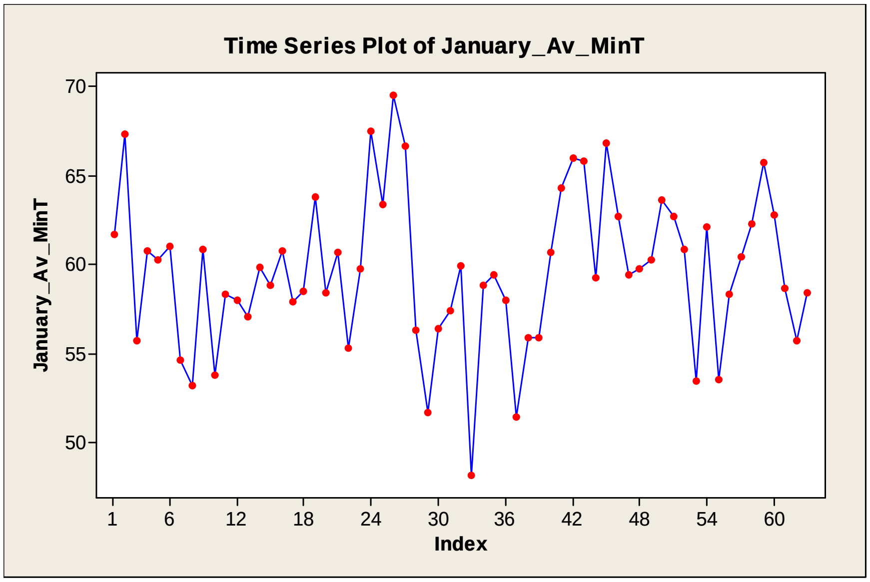



```
The regression equation is
AvT(January) = 67.1 + 0.0164 t


Predictor       Coef   SE Coef      T      P
Constant     67.1221    0.8455  79.39  0.000
t            0.01645   0.02297   0.72  0.477


S = 3.31555   R-Sq = 0.8%   R-Sq(adj) = 0.0%


Durbin-Watson statistic = 1.44655
```

Fig 11.JanuaryAverage Temperature Time Series

From the Minitab output we can conclude that there is no statistically significant trend in the January Average Temperature Time Series (p-value = 0.477).

January Average Minimum Temperature Time Series (1949-2011)

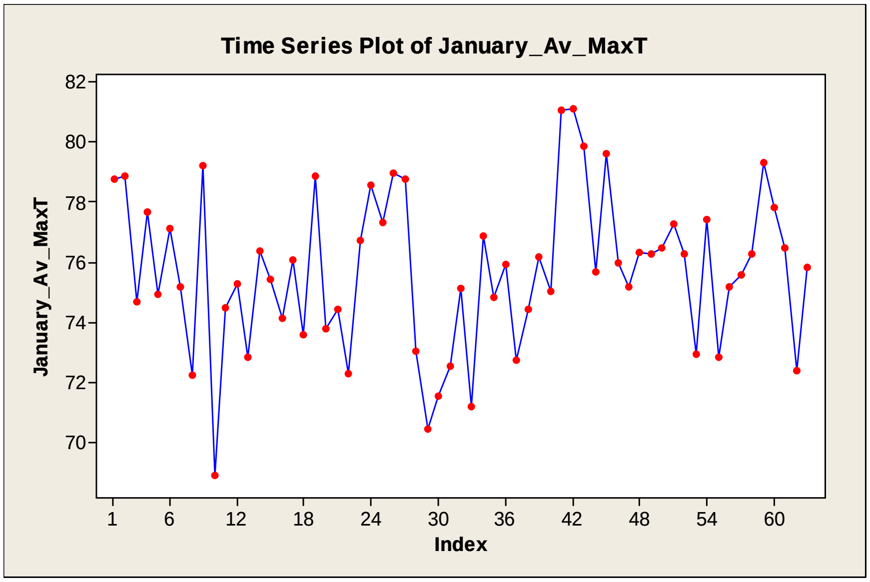



```
The regression equation is
January_Av_MinT = 59.0 + 0.0189 t


Predictor      Coef  SE Coef      T      P
Constant     59.012    1.093  54.01  0.000
t           0.01887  0.02969   0.64  0.527


S = 4.28486   R-Sq = 0.7%   R-Sq(adj) = 0.0%


Durbin-Watson statistic = 1.39967
```

Fig 12. January Average Minimum Temperature Time Series

From the Minitab output we can conclude that there is no statistically significant trend in the January Average Minimum Temperature Time Series (p-value = 0.527).

January Average Maximum Temperature Time Series(1949-2011)




```
The regression equation is
January_Av_MaxT = 75.2 + 0.0140 t


Predictor      Coef  SE Coef       T      P
Constant    75.2318   0.6611  113.79  0.000
t           0.01401  0.01796    0.78  0.439


S = 2.59256   R-Sq = 1.0%   R-Sq(adj) = 0.0%

Durbin-Watson statistic = 1.61565
```

Fig 13.January Average Maximum Temperature Time Series

From the Minitab output we can conclude that there is no statistically significant trend in the January Average Maximum Temperature Time Series (p-value = 0.439).

CHAPTER IV

ANALYSIS OF HURRICANES CENTRAL PRESSURES AND RADII OF MAXIMUM WINDS

A **hurricane** is a rapidly-rotating storm system characterized by a low-pressure center, strong winds, and a spiral arrangement of thunderstorms that produce heavy rain. The central pressure of a hurricane is inversely related to the speed of maximum winds, which in turn determines the intensity and destructive power of the hurricane. In other words, the lower the central pressure of a hurricane, the more intense the winds will be. That is why central pressures are used as an indicator of intensity of tropical storms. Also, it has been determined that one of the best predictor of potential losses is the minimum central pressure [13].

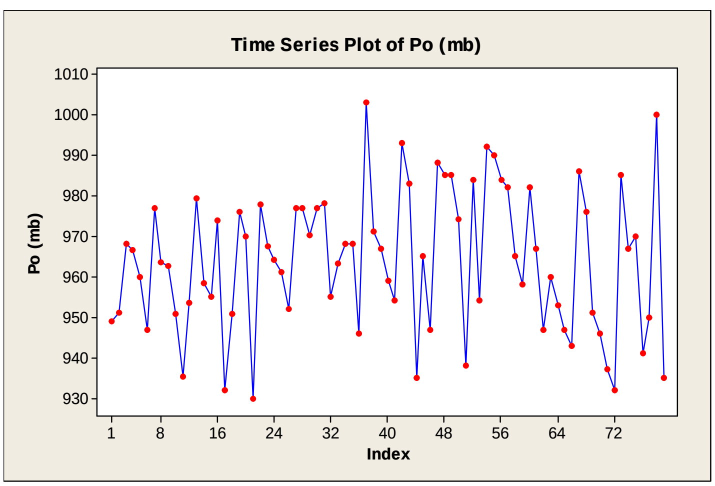
The radius of maximum winds is another important characteristic of hurricanes. It is defined as the distance between the center of a cyclone and its band of strongest winds. It is a parameter in atmospheric dynamics and tropical cyclone forecasting. The highest rainfall rates occur near the RMW of tropical cyclones. The extent of a cyclone's storm surge and its maximum potential intensity can be determined using the RMW [14].

In this chapter I will analyze the time series of hurricanes central pressures, radii of maximum winds and radii of maximum winds of the largest hurricane in the year, for all hurricanes affecting the Atlantic Coast since year 1944. Although there is information on hurricanes going back to 1851, I have decided not to use data previous to 1944.Data before 1944 are not as reliable, because it was not until 1944 that reconnaissance airplanes started to go into hurricanes to collect data. In the analysis, simple linear regression models will be fitted to the time series in order to detect any existing statistically significant trend. This will be done as explained in the Statistical Methodology section in the previous chapter.

The data set used comes from NOAA (National Oceanic and Atmospheric Administration), and it is analyzed using Minitab 16.The data are maintained in a data base called HURDAT. HURDAT has information on all tropical cyclones in the Atlantic Ocean, Gulf of Mexico and Caribbean Sea, since 1851. It consists of 6 hourly records of the position, intensity and other parameters of the storm.

Data Analysis

Hurricanes Central Pressure Time Series




```
The regression equation is
Po (mb) = 962 + 0.0335 Index


Predictor      Coef  SE Coef       T      P
Constant    962.489    3.941  244.25  0.000
Index       0.03348  0.08558    0.39  0.697
```

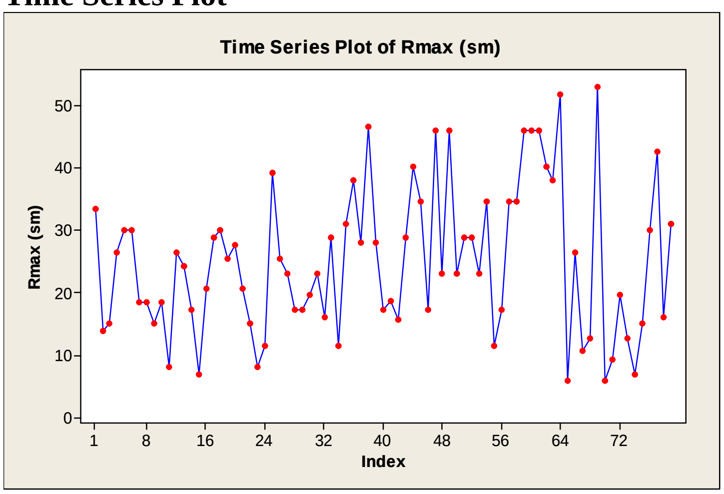
```
S = 17.3462   R-Sq = 0.2%   R-Sq(adj) = 0.0%

Durbin-Watson statistic = 1.9392
```

Fig 14. Hurricanes Central Pressure Time Series

From the Minitab output we can conclude that there is no statistically significant trend in the Hurricanes Central Pressure Time Series (p-value = 0.697).

Hurricanes Radius of Maximum Winds Time Series

Time Series Plot

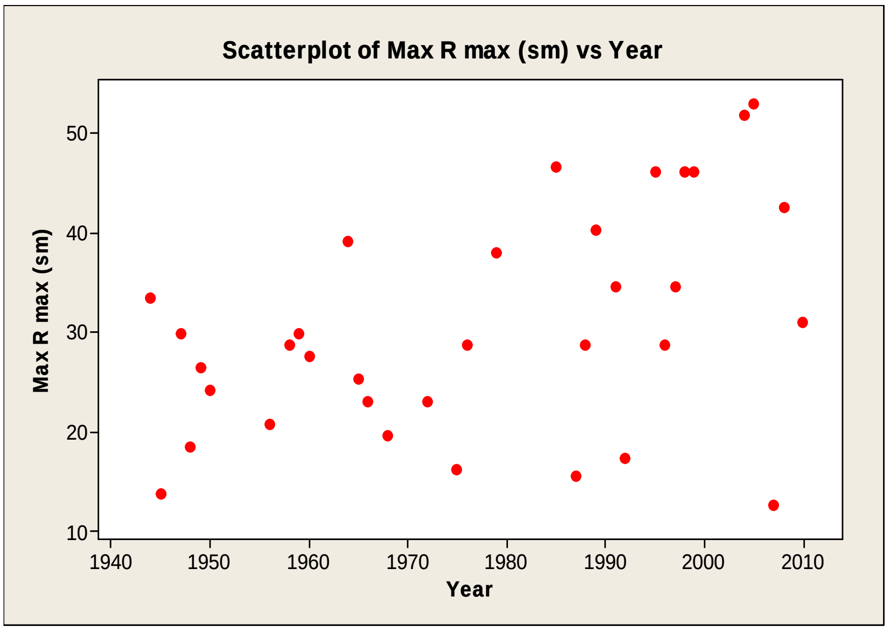



```
The regression equation is
Rmax (sm) = 21.4 + 0.0885 Index


Predictor      Coef  SE Coef     T      P
Constant     21.381    2.660  8.04  0.000
Index       0.08853  0.05776  1.53  0.129


S = 11.7071   R-Sq = 3.0%   R-Sq(adj) = 1.7%

Durbin-Watson statistic = 1.63515
```

Fig 15. Hurricane Radius of Maximum Winds Time Series

From the Minitab output we can conclude that there is no statistically significant trend in the Hurricanes Radius of Maximum Winds Time Series (p-value = 0.697). Now we analyze the time series of the largest hurricane every year, that is the one with the largest RMW on a given year.

Largest Hurricanes Radius of Maximum Winds Time Series




```
The regression equation is
Max R max (sm) = - 454 + 0.245 Year


34 cases used, 33 cases contain missing values


Predictor      Coef  SE Coef      T      P
Constant     -453.7    164.6  -2.76  0.010
Year        0.24494  0.08324   2.94  0.006


S = 10.0747   R-Sq = 21.3%   R-Sq(adj) = 18.8%
```

Fig 16. Largest Hurricanes Radius of Maximum Winds Time Series

From the Minitab output we can conclude that there is a statistically significant positive trend in the Largest Hurricanes Radius of Maximum Winds Time Series(p value= 0.006).

CHAPTER V

CONCLUSIONS

From the previously explained statistical analysis it can be concluded that the Annual Average, Annual Average Maximum and Annual Average Minimum Temperatures in Miami are increasing with time. The estimated rates of change of the aforementioned temperatures are 0.039177 degrees Celsius/ year (SE = 0.005356),0.0297 degrees Celsius/ year (SE=0.0111) and 0.0471degrees Celsius/ year (SE=0.008439) respectively, according to our statistical models.

Also July Average, July Average Maximum and July Average Minimum Temperatures in Miami are increasing with time. The estimated rates of change of these temperature time series are 0.0403 degrees Celsius/ year (SE=0.006729), 0.0399 degrees Celsius/ year (SE=0.0116), 0.0405 degrees Celsius/ year (SE=0.009408) respectively. This result could be taken as an indication of a rise in summer temperatures.

On the other hand, no statistically significant trend could be detected in the time series of January Average, Average Maximum and Average Minimum Temperatures. This result indicates that, on an average, January, and by extension, winter temperatures are not changing over time in Miami.

As for the hurricanes, no statistically significant trend was detected in the central pressures and radii of maximum winds time series, but the time series of the radii of maximum winds for the largest hurricane of the year showed a statistically significant increasing trend. This result indicates that the largest hurricanes are getting larger with time.

All in all, this study has shown that Miami annual and summer temperatures are increasing with time, which is consistent with the global warming phenomenon described in literature. Surprisingly, that tendency was not detected in January (winter) temperatures.Also a tendency to larger hurricanes was seen.

Further research could be done to improve this study. A way of improving it could be to carry out a detailed analysis of the time series of every month of the year to investigate what the tendencies and rates of change are for the temperatures of each of the twelve months. This could give a more detailed picture than our more restricted analysis. Also other valid modeling approaches, such as Exponential Smoothing and ARIMA, could be considered to quantify rates of change, and to describe the previously analyzed time series.

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