

**TIME SERIES ANALYSIS OF PRECIPITATION IN BAGUIO CITY BETWEEN
2001 AND 2012 USING HOLT-WINTERS FORECASTING**

A Research Paper Submitted to the Research Committee
Science, Mathematics, Computer and Technology Department
Philippine Science High School
Cordillera Administrative Region Campus

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In Partial Fulfillment of the Requirements
for the Course
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CERTIFICATION

This is to certify that this research paper entitled, "**TIME SERIES ANALYSIS OF PRECIPITATION IN BAGUIO CITY BETWEEN 2001 AND 2012 USING HOLT-WINTERS FORECASTING**" and submitted by **SHEANNE ERIC P. CABANTAC, MIKHAIL ANTONI A. OSBUCAN, and JOHN CHRISTOPHER C. YODONG**, to fulfill part of the requirements for the course Science and Technology Research II was successfully defended and approved on 4 March 2013.

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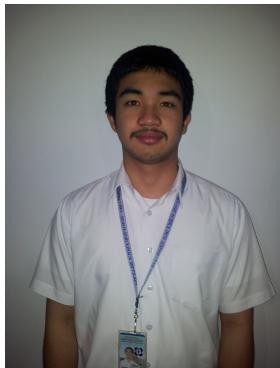
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This Thesis Paper is dedicated to the People of Baguio who have been our constant source of inspiration. They have given us the drive and discipline to tackle any task with enthusiasm and determination. Without their support this project would not have been made possible.

Biographical Sketch



John Christopher C. Yodong, born on October 06, 1996, is a graduate of SPED Center Elementary School and is currently a fourth year student in PSHS-CAR campus. He is a citizen of the Republic of the Philippines and he is a resident of Baguio City. He is a consistent learner and he is able to perform well in school. He, along with Sheanne Eric P. Cabantac and Mikhail Antoni A. Osbucan, is one of the proponents of the research on the series analysis of rainfall in Baguio City.

Mikhail Antoni Azul Osbucan is currently studying at Philippine Science High School. He is currently a member of the section IV-Photon. He was born on the 30th day of March on 1997 in Baguio City. He is the first child of Ma. Lourdes Osbucan and Rommel Paolo Osbucan. He is of Igorot, Bisayan, and Tagalog decent. He likes to play basketball a lot and he also watches NBA a lot. He is a big fan of alternative music. He is also a big fan of action and suspense movies. When he grows older, he wants to become either a successful pilot or a successful cardiologist. He also believes in the saying that "Hardwork beats talent when talent fails to work hard."



Sheanne Eric P. Cabantac is a Filipino citizen, born and raised in Baguio City on January 14, 1997. He completed his primary education in Star Educational School in La Trinidad and graduated as an academic achiever. He then pursued his elementary education at SPED Center Baguio City, before getting to Philippine Science High School CAR Campus. He is a son to Eduardo R. Cabantac and Sheryl Anne P. Cabantac, and an older brother to three siblings.

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Cabantac, Sheanne Eric P.
Osbucan, Mikhail Antoni A.
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ABSTRACT

CABANTAC, SHEANNE ERIC P., OSBUCAN, MIKHAIL ANTONI A., and YODONG, JOHN CHRISTOPHER C., Philippine Science High School - Cordillera Administrative Region Campus, March 2013. **Time Series Analysis of Precipitation in Baguio City between 2001 and 2012 Using Holt-Winters Forecasting.**

Adviser: **Joseph S. Tabadero, Jr.**

The research was conducted to provide a rainfall amount forecast for Baguio City, using time series data from January 2001 to December 2011 gathered from PAG-ASA. Using Holt Winters simple exponential smoothing technique through the statistical software R-statistics, the data gathered were used to create a model to produce a forecast for the year 2012.

Through the auto-correlation function, it was found out that the model derived through Holt-Winters exponential smoothing might be improved upon. However, the Ljung-Box test showed that there is little evidence of non-zero autocorrelations in the in-sample forecast errors, and the distribution of forecast errors seems to be normally distributed with mean zero. These suggest that the exponential smoothing, Holt-Winters method provides an adequate predictive model for rainfall, which probably cannot be improved upon. Furthermore, the assumptions that the 80% and 95% predictions intervals were based upon (that there are no auto-correlations in the forecast errors, and the forecast errors are normally distributed with mean zero and constant variance) are probably valid.

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Chapter 1

Introduction

Precipitation is any form of humidity that falls from the clouds in the air to the exterior of the Earth. Since precipitation refers to the liquid quantity and how much of it is isolated on the Earth within a given time, it is measured in volumes and concentration of precipitation on specific areas where the study is focused on. (Ramsey, 1998)

Rain is a group of droplets that tends to fall towards the land of the Earth. The cloud cannot already include the amount of cloud droplets present within it that is why the cloud needs to release these droplets and when they are released, these droplets are already called as rain. Rain is the only type of liquid precipitation, as opposed to non-liquid types of precipitation, which are sleet, snow, and hail. A presence of a thick layer of our atmosphere is needed by rain to maintain temperatures above the melting point of water on the surface of the Earth. When ice crystals within a specific cloud collide against each other, precipitation is formed. Ice crystals have different shapes. There are oblate crystals, round-shaped crystals, and crystals that look like a small sphere. (Ramsey, 1998) The major cause of rain production is moisture contrasts that are commonly called as weather fronts and some moisture moving along the zones of temperature. Based on the location of the Philippines, this country only experiences rain, drizzle, and hail among the other types of precipitation. ("Earth Science: The Philippines in Focus," 1983)

Since the precipitation is measured in volumes of water in a specific area, the best way to measure the amount of precipitation is to gather all fallen liquid on a specific area with the use of waterproof walls and bases to see how high the water

would increase from ground level. An instrument used in this process with a similar mechanism is the rain gauge. The rain gauge is the most widely used weather instrument in measuring precipitation. The rain gauge is composed of a funnel and a cylindrical container where the water accumulates and is collected. However, a rain gauge is most effective when used in a perfectly flat area with its surroundings of the same level. When used in mountainous regions or areas with uneven ground levels, either the measurements would be inaccurate or multiple rain gauges must be used for each ground level. Rainfall varies in amounts depending on the altitude. The measurements on a rain gauge are only applicable on a fairly small radius or area around it, any data that would need more information about the amount of rainfall on a specific radius would be erroneous.

The most common rain detector used in electronic weather stations is the “tipping bucket” type of rain sensor. This fascinating type of technology uses two small “buckets” mounted on a swivel. The tiny buckets are manufactured with tight tolerances to guarantee that they hold an exact quantity of precipitation. The tipping bucket assembly is to be found underneath the rain collector, which funnels the precipitation to the buckets. As rainfall fills the tiny bucket, it becomes overbalanced and tips down, emptying itself as the other bucket pivots into place for the next reading. The action of each tipping episode triggers a small control that activates the electronic circuitry to transmit the count to the indoor console. On a wireless rain gauge, records are transmitted through a radio signal. (“WW2010,” 2003)

These methods aforementioned are some methods that PAGASA Weather Station is implementing to gather records of rainfall during the entire day, where they collect data every after three hours starting at two in the morning until eleven in the evening.

The PAGASA Weather Station, also recognized as Philippine Atmospheric, Geophysical and Astronomical Services Administration, is a nationwide institution of the Philippines that provides warnings about flood and typhoon. They also provide a lot more services like public advisories and forecasts concerning the up to date weather report of the country. PAGASA furthermore provides meteorological, astronomical, and climatological information for the security of life and property

of the Filipino people. This government agency started operating on the 8th of December in 1972.

This agency has a mandate that states that they need to provide protection against natural calamities to ensure the safety of the Filipino citizens, well-being and economic security of all the people, and for promotion of national progress.

Residents in the Philippines would expect to have a huge amount of rainfall every month of the year. The rainy season starts on the end of May and ends on late November or early December. ("Earth Science: The Philippines in Focus," 1983)

In Batanes, Northeastern Luzon, Western part of Camarines Norte, Camarines Sur, Albay, Bondoc Peninsula, Eastern Mindoro, Marinduque, Western Leyte, Northeastern Cebu, Bohol, and most of the Central and Southern Mindanao experience rainfall that is more or less evenly distributed all throughout the year. ("Earth Science: The Philippines in Focus," 1983)

Upon observing the rainfall pattern in Baguio City, the proponents also observed some factors that could massively affect the rainfall in our city. One factor that would affect the rainfall pattern of Baguio City is the season. According to some references, high precipitation occurs during the humid season of the year while low precipitation occurs during the dry season of the year. Since the city is located at a high altitude, the elevation could also affect the pattern of rainfall that will occur. Mountains affect the amount of rainfall. Rains fall more often on the slopes facing the wind than on the slope away from the wind. The reason is that a wind hitting the side of the mountain tends to rise along the slope reaching heights of low temperature. There, the moisture in the wind condenses to form rain. By the time it reaches the other side of the mountain there is not enough amount of moisture to further condense. The eastern coastal areas generally receive more rainfall than the western parts. The eastern areas have high rainfall from October to March when the monsoon blows over the country. For the Philippines as a whole, June to December are the rainy months while January to May are the dry months. ("Earth Science: The Philippines in Focus," 1983)

Background of the Study

Baguio City is a highly urbanized city located in the province of Benguet. It has an altitude of 1610 meters and covers a total land area of 57.5 km². Landslide and flashflood occurrences are highly unpredictable in some areas of the city because rainfall amount does not have a recognizable pattern. Thus, many parts of Baguio City are suffering from landslides and flashfloods during periods of unpredicted heavy rainfall. In order to increase the safety, awareness against such environmental disasters and an analysis regarding the rainfall patterns of Baguio City has to be done to provide basic information.

Such study has been done in different countries such as Northeastern Thailand, India, and Australia. The necessary data shall be collected from the weather station of Baguio City to produce a forecast for the amounts of rainfall every year.

Statement of the Problem

The amount of precipitation in Baguio City has become very unpredictable, to a point where landslides and flashfloods have become unforeseeable. The aim of the study is to provide a basic forecast about how much precipitation would fall on Baguio City on the succeeding year, based on the ten-year data gathered from PAGASA.

Significance of the study

This study can be a reference for preparations for certain agricultural activities like cultivating, planting, and harvesting. It can also be a reference as a precautionary measure for flash floods and landslides.

Scope and Delimitation

The study is limited only to analyzing rainfall amounts and no other weather factors. The study has been limited to only analyzing the rainfall amounts in Baguio City because it ensures the safety of the researchers and it gives the easiest access to the needed data. This study was also limited to determining the coefficients of

the Holt-Winters additive seasonal model and not all the set of the equations in the model. This study is further delimited to the prediction of the average monthly rainfall for the months of 2012.

Definition of Terms

For clearer understanding of terms used in this study, below are the operational definitions of the terms used in this research paper.

Time series analysis concerns the analysis of data collected over time. Usually the intent is to discern whether there is some pattern in the values collected to date, with the intention of *short term* forecasting

Seasonality is defined to be the tendency of time-series data to exhibit behavior that repeats itself over regular periods.

Additive seasonality shows steady seasonal fluctuations, regardless of the overall level of the series.

Multiplicative seasonality, the size of the seasonal fluctuations vary, depending on the overall level of the series.

Exponential smoothing is a procedure for continually revising a forecast in the light of more recent experience. Exponential Smoothing assigns exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the older observations.

Forecasting is the process of making projections about future performance on the basis of historical and current data.

Holt-Winters is a set of equations which handle time series data that show trend, seasonality, and a random effects.

Additive Seasonal Model is the Holt-Winters model used when the data exhibits Additive seasonality. In this model, we assume that the time series is represented by the model

$$y_t = a + bt + S_t + \epsilon_t \quad (1.1)$$

where,

y_t response of interest at time t

a is the base signal also called the permanent component

b is a linear trend component

S_t is a additive seasonal factor

ϵ_t is the random error component

Let the length of the season be L periods.

The seasonal factors are defined so that they sum to the length of the season, that is

$$\sum_{1 \leq t \leq L} S_t = 0. \quad (1.2)$$

The trend component b if deemed unnecessary, maybe deleted from the model.

The application of the model and further description of the rest of the set of equations in the model can be found in Kalekar (2004, p 7).

Precipitation is a deposit on earth of hail, mist, rain, sleet, or snow. It is also the quantity of water deposited.

Rainfall is the amount of precipitation usually measured by the depth in millimeters.

Rainy day refers to the period where precipitation occurs at any time of the day.

Chapter 2

Review of related literature

Time Series Analysis on hourly rainfall (Cutrim et al 2000)

Time Series Analysis was used on an average hourly precipitation. The method determined whether statistically significant differences existed from each season. The data gathered is a 20-year period consisting of 2-hour intervals per day. In a seasonal analysis it was defined that winter, spring, summer, and fall are the seasons to be used. The Box-Jenkins methodology, a sample autocorrelation function (ACF) and a partial auto correlation function (PACF) plot were employed for each of the 12 periods of the day, for both precipitation accumulations and counts. A plot of ACF values at different lags was used to find a working series of stationary time points for the precipitation parameters accumulation and counts. For both precipitation parameters, the ACF plots clearly indicated the time series to be a non-seasonal component, but the same plot showed the need for further differencing of the seasonal component of the series, which occurs every four time periods. The periods of differencing, therefore, are 1 for the seasonal component of order 4. This differencing scheme produced a stationary time series, which is a prerequisite in ARIMA Modeling.

The ACF and PACF plots of the differentiated series were then used to determine the autoregressive (AR) component and a moving average (MA) component of the series. Except for precipitation count at 6 a.m. the ARIMA model for cache of the differenced precipitation time series year were identified. (See Figure (2.1)).

A large set of data involving more than 50 years of rainfall and temperature data

Time Series Analysis of Hourly Precipitation

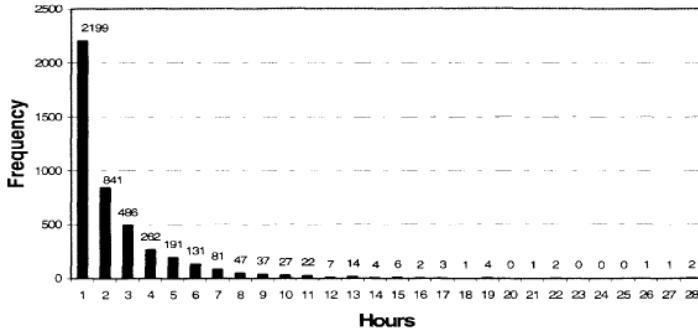


Figure 2.1: Time Series Analysis on a 50 year data of rainfall and temperature (Cutrim et al 2000).

were examined using Spectral Analysis, Time Series Analysis-ARIMA Methodology to analyse climatic trends and interactions. Fourier analysis, linear regression and ARIMA based time series models were used to analyze the large data sets using Mat-lab, SPSS and SAS programs. The results that came up showed that the rainfall data was variable and appeared seasonal while the temperature data appeared stationary. Spectral analysis also showed variations in rainfall and temperature over 50-60 years but the results showed that rainfall and temperature varied coherently, with a cycle of about 2-3 years. An inverse relationship in trend was noted between rainfall and daily temperature range using linear regression among the variables. The ARIMA models showed autocorrelation and seasonality providing time series models.

It was concluded that: There is a cyclic pattern noted in both the rainfall and temperature time series and a cycle of about 3 years in the rainfall and temperature data sets suggesting a coherent variance in the relationship. This finding suggested a cyclic nature of large rainfall events over time and was confirmed by the recent large rainfalls events in 2009-10. Linear regression showed an inverse relationship in trend between rainfall and temperature range only even though the r value was around 0.27.

Time Series Analysis on the Agricultural Commodities Prices

Other than prices, the data includes variables reflecting demand and supply factors affecting agricultural prices. Series are on a monthly basis. On the demand side it has been considered that monetary aggregate will be the proxy for world real aggregate expenditure, production of ethanol and biodiesel, several proxies for trading activity in futures markets, and the U.S. dollar–Euro exchange rate. On the supply side the price of oil, price of fertilizers, and volume of exports by major world producers are used.

The data gathered was from 2002 to 2009. The end of the series was restricted due to unavailable data, and restrictions at the beginning of the series were due to the presence of structural changes based on Chow tests. All price data and other variables will be taken in log form when analyzed.

The distribution of monthly rainfall

Monthly distributions of rainfall in space and time can provide guidelines for crop scheduling and for introducing better cropping patterns in the region.

To determine the periodicity of the monthly rainfall sequence at a station, the method developed by Vujica M. Yevjevich was used, in which the parameters involved are clearly defined.

It was found that monthly rainfall sequences at all the stations under consideration have six significant harmonics, which means that the monthly rainfall has a periodic part that consists of components corresponding to the following six periods: 12, 6, 4, 3, 2.4 and 2 months. The variances of the monthly means and the monthly standard deviations are explained up to more than 90% by these six significant harmonics. These findings show that after removing the first six periodic components, the residual rainfall sequence at a station can be considered to be stationary at least in the mean and standard deviation. (See Table 1.)

For most cases, the serial correlation coefficient between two successive monthly rainfall sequences at a station were found not to be significantly different from zero. Nonsignificance of correlation does not necessarily imply statistical independence,

Station	Mean	Standard Deviation
Buriram	0.925	0.917
Chaiyaphum	0.940	0.938
Kalasin	0.924	0.920
Khon Kaen	0.927	0.937
Loei	0.924	0.921
Maha Sarakham	0.935	0.921
Nakhon Phanom	0.924	0.979
Nakhon Ratchasima	0.931	0.920
Nongkhai	0.919	0.929
Roi Et	0.922	0.919
Sakhon Nakhon	0.917	0.941
Ubon Ratchatani	0.922	0.942
Udon Thani	0.917	0.927
Yasothon	0.927	0.939

Table 2.1: The residual rainfall sequence in agricultural provinces in Thailand.

monthly rainfall totals were analysed separately and a probability distribution was fitted month by month.

It was concluded that each monthly rainfall sequence has a periodic part consisting of six constituents corresponding to the following six periods: 12, 6, 4, 3, 2.4 and 2 months. At each station the rainfall sequence in a month is independent of the rainfall sequences in the other months. Since many monthly rainfall sequences in the Northeast have zero values, the leakage law is most appropriate for fitting these sequences. Monthly rainfall in the region varies greatly from month to month, resulting in high degrees of irregularity, ranging from 45 to 70 per cent. Monthly rainfall also varies greatly from year to year as indicated by the high values for the coefficient of variation. The eastern and north-eastern sections of the region are the wettest areas of the Northeast from April to September but they are the driest parts from October to December. The maximum amount of rainfall for the entire region usually occurs in August or September while the minimum normally occurs in December or January.

Chapter 3

Methodology

Research Design

The study, which is about the rainfall patterns of Baguio, involves quantitative research on the rainfall amounts of Baguio. A statistical analysis shall be done on the gathered data, particularly a Time Series Analysis. The Holt-Winters Method will be applied to the time series data from January 2001 to December 2011 to make determine the coefficients of the mathematical model for forecasting values from January 2012 to December 2012 which were retrieved from PAG-ASA. Auto-correlation function, Ljung-Box test, and test for normality were used to test for the validity of the model.

Sources of Data

The data were the rainfall amounts per month in Baguio City. The sample, which will be taken from the population, were the rainfall amounts ranging from January 2000 to December 2011. Rainfall amount was measured using either a tipping bucket or rain gauge. It is measured and recorded in millimeters every three hours starting from 2a.m. to 11p.m.. The data was gathered from the weather station of PAGASA located in Baguio City.

Locale of the Study

There have been a series of occurrences of unforeseen flashfloods and landslides in Baguio City, especially in areas such as City Camp Lagoon, so the researchers

chose that the study should be done in Baguio City.

Population/Sampling

The study involved the analysis of rainfall amounts gathered daily by PAGASA. The research would only take into consideration the data gathered from January 2000 to December 2011 since the study was proposed before several months before the year 2012 ended.

Instrumentation and Data Collection

The data was then summarized and classified by year on Microsoft Excel. However, the amount of rainfall for May 2006 was missing, so a statistical method called Bootstrapping method was done to generate a forecasted value.

Bootstrapping method is a method developed by B. Efron on 1979. It is a computer-based method for assigning accurate sample estimates. This method allows estimation of the sample distribution of almost any value using only very simple methods (Varian 2005). Using R-statistics, a computer statistical software, bootstrapping method was used to generate an estimate for May 2006.

The data from January 2001 to December 2005 was used to generate an estimate for May 2006, through R-statistics. Then, a time-series analysis was conducted. A time-series analysis is a method used to obtain an understanding of the forces, which produced the data. The time series analysis is a set of data used and collected sequentially at fixed intervals of time. The amount of rainfall , is a time series data, which is measured and recorded at successive time intervals.

Protocol

The time series analysis and forecasting will be done using a statistical software called R-statistics. R is a free software environment for statistical computing and graphics. It compiles and runs on a wide variety of UNIX platforms, Windows and MacOS.

Research Paradigm

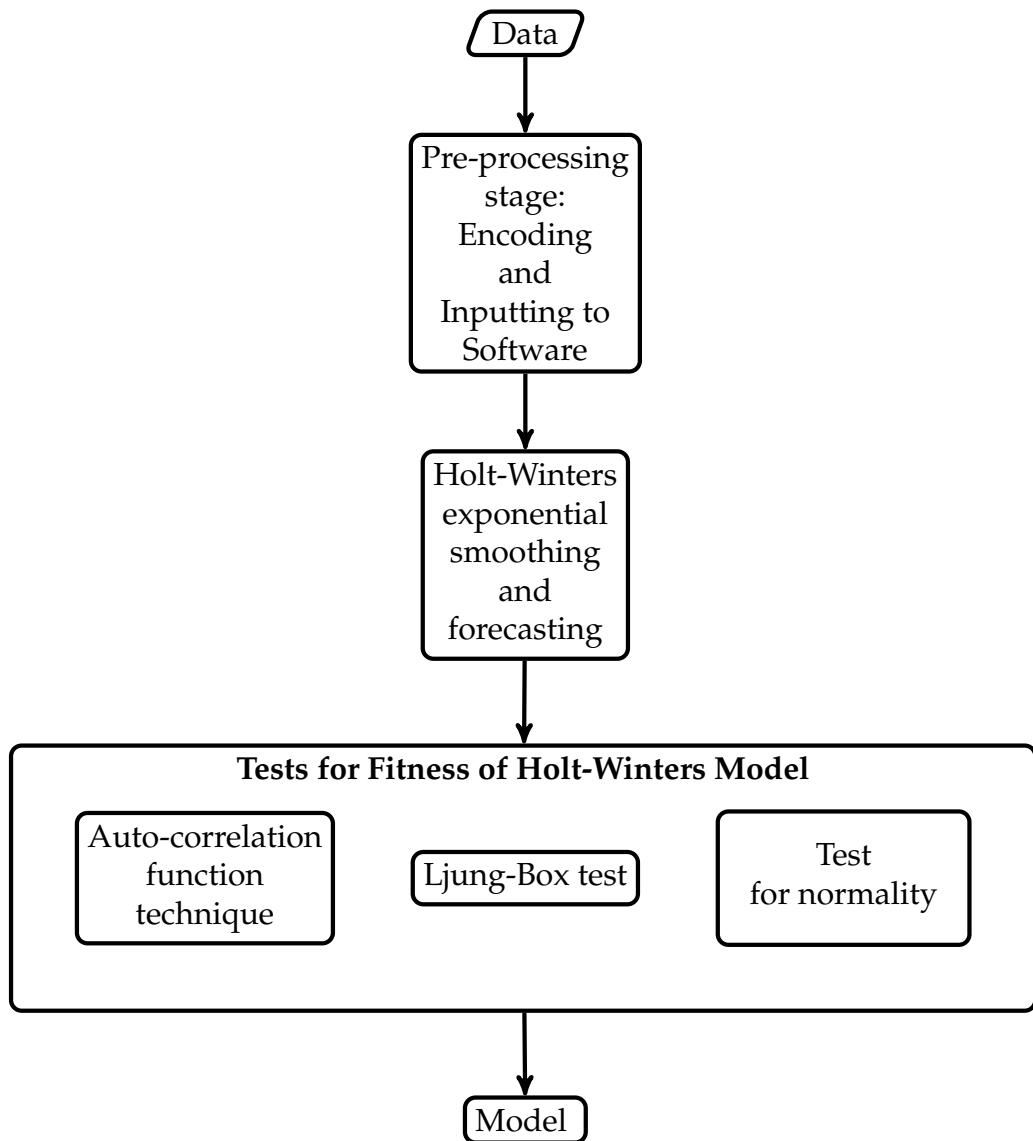


Figure 3.1: Flow chart for time rainfall time series analysis.

Chapter 4

Results and discussion

Table (4.1) shows the raw data from January of 2001 to December of 2012. The initial data collected were from January 2001 to December 2011. The rainfall data for January 2012 to December 2012 were collected after one year for comparison of the predicted values. The data for May 2006 was initially missing. Using bootstrapping method in R, the missing May 2006 data was generated.

Table 4.1: Amount of Precipitation Per Month in mm, from 2001 to 2012

Month	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
JANUARY	14.6	5	0*	17	0.2	160.6	0*	24	8	0*	94	17.5
FEBRUARY	39.5	2	25.4	128.6	0*	8.8	0.6	97	64.5	0*	13.8	80.3
MARCH	289.8	0.6	4.8	0*	54.6	38.4	31.8	78.7	82.9	15.3	88.9	151.9
APRIL	76	71.2	46.8	37.8	32	29.6	25.4	149.8	407.3	148.6	11.9	72.6
MAY	291	264.4	662.7	428.6	291	245.5048 [△]	308.6	839.8	298.5	248.6	462.5	207.7
JUNE	451.4	411	792.4	1306.5	425.7	188.2	358.4	302	810	254	529.1	659
JULY	1642	1883.4	721.3	445.4	292.4	1769.8	219	681.2	758.4	543.7	435.9	1020.2
AUGUST	274	525.6	1089.4	1432.9	690.2	735.8	1201.6	999.5	1087.7	536.6	1096.3	2,207
SEPTEMBER	842.2	301.5	303.2	225.6	694.6	207.6	408.4	761	516.9	296.8	819.2	288.3
OCTOBER	97	224.8	179.7	42.4	256.6	316	410.3	178.1	1981.8	920.1	332.4	72.4
NOVEMBER	61.6	67.3	60.4	114.5	55.2	72.4	444.8	82.6	22.2	226.4	81.6	57.8
DECEMBER	23.2	10	4.4	154.9	68	43.2	21.6	0*	0*	47.4	67.4	10.8

* Trace amount, < 0.01 mm

△ Bootstrapped value

Analysis of Data

The data was saved in a file named baguiorainfall.dat. This data was then inputted in R and stored in a variable baguiorainseries using the ts function.

```
baguiorain ← read.table("baguiorainfall.dat")
baguiorainseries ← ts(baguiorain, frequency = 12, start = c(2001, 1))
```

Figure (4.1) shows the graph of the rain fall time series from January 2001 to December 2011. It can be seen that the data is seasonal, peaking every July to August every year.

```
plot.ts(baguiorainseries)
```

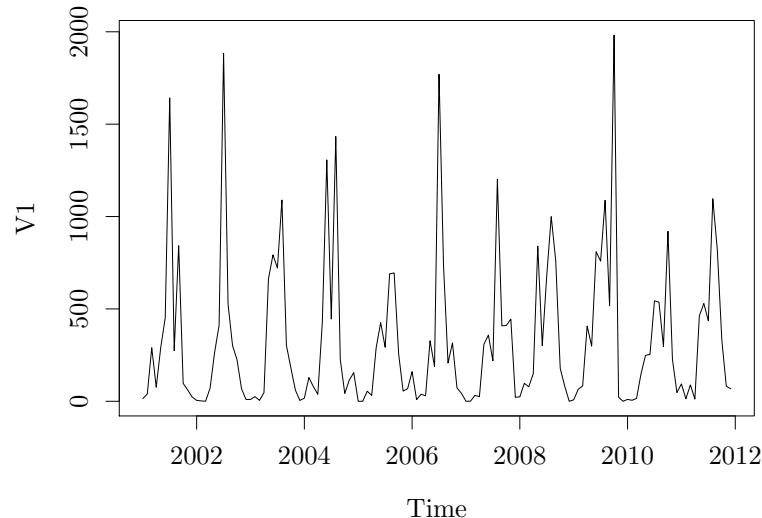


Figure 4.1: Plot of Baguio rain fall time series, from January 2001 to December 2011.

Here, the time series data is broken down into its components. This is done in preparation to eliminating the seasonal component of the data. Only the partial results are shown in (4.2). The full results are in Listing (2).

Figure 4.2: Partial results of the seasonal, trend, and random components.

```
baguiorainseriescomponents ← decompose(baguiorainseries)
baguiorainseriescomponents
```

\$x	Jan	Feb	Mar	Apr	May	Jun	Jul
2001	14.600	39.500	289.800	76.000	291.000	451.400	1642.000
2002	5.000	2.000	0.600	71.200	264.400	411.000	1883.400
2003	9.800	25.400	4.800	46.800	662.700	792.400	721.300
.							
.							
.							
	Aug	Sep	Oct	Nov	Dec		

2001	274.000	842.200	97.000	61.600	23.200							
2002	525.600	301.500	224.800	67.300	10.000							
2003	1089.400	303.200	179.700	60.400	4.400							
.												
.												
.												
\$seasonal												
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug				
2001	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65				
2002	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65				
2003	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65				
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.												
.												
	Sep	Oct	Nov	Dec								
2001	122.05	128.05	-212.33	-296.84								
2002	122.05	128.05	-212.33	-296.84								
2003	122.05	128.05	-212.33	-296.84								
.												
.												
.												
\$trend												
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	
2001	NA	NA	NA	NA	NA	NA	341.5	339.5	325.9	313.6	312.3	
2002	317.9	338.4	326.4	309.2	314.8	314.4	314.1	315.3	316.4	315.6	331.2	
2003	331.1	306.2	329.8	327.9	325.8	325.3	325.3	329.9	337.4	340.1	330.0	
.												
.												
.												
	Dec											
2001	309.5											
2002	363.7											
2003	341.6											
.												
.												
.												
\$random												
	Jan	Feb	Mar	Apr	May	Jun	Jul					
2001	NA	NA	NA	NA	NA	NA	NA	739.334				
2002	-16.360	-43.257	-42.248	-2.012	-130.491	-107.820	1008.092					
2003	-24.773	12.401	-41.398	-45.158	256.792	262.771	-165.233					
.												
.												
.												
	Aug	Sep	Oct	Nov	Dec							
2001	-588.150	394.268	-344.686	-38.390	10.510							
2002	-312.329	-136.973	-218.836	-51.528	-56.807							

```

2003  236.821 -156.201 -288.458 -57.242 -40.400
.
.
.

$figure
[1] -296.55 -293.19 -283.56 -235.99    80.13  204.37  561.21  522.65
[9] 122.05 128.05 -212.33 -296.84

$type
[1] "additive"

attr(,"class")
[1] "decomposed.ts"

```

It can be seen in Figure (4.2) that the data is of additive type. The plot is in Figure (4.3).

```
plot(baguiorainseriescomponents)
```

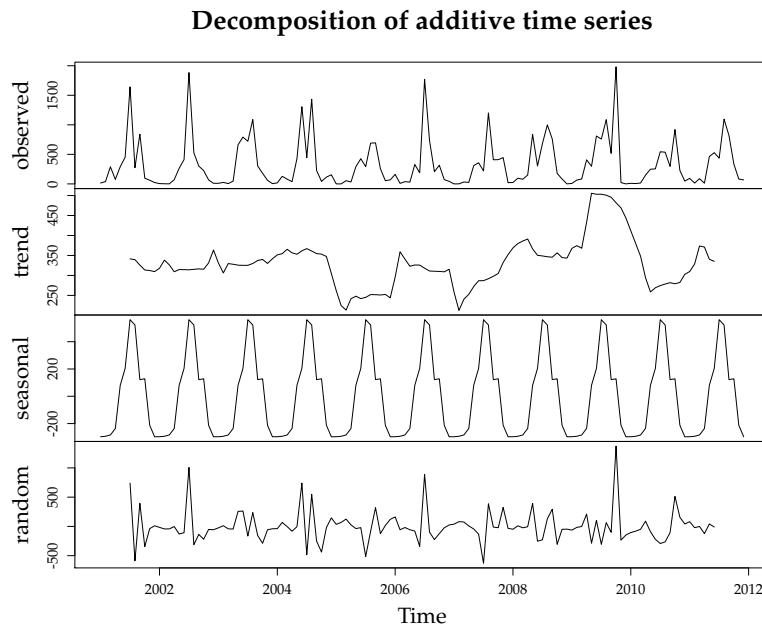


Figure 4.3: The plot of the components of the rainfall time series data.

To use exponential smoothing to make forecasts for the time series of monthly rainfall in Baguio City, the `HoltWinters()` function was used.

The output of `HoltWinters()` made forecast for the same time period covered by the original time series, the time series included rainfall for Baguio City for

```

rainforecasts ← HoltWinters(raintimeseries)
rainforecasts

Holt-Winters exponential smoothing with trend and additive seasonal
component.

Call:
HoltWinters(x = raintimeseries)

Smoothing parameters:
alpha: 0.001826
beta : 0.422
gamma: 0.3554

Coefficients:
[,1]
a     267.1477
b      0.5062
s1   -208.3311
s2   -227.2503
s3   -194.1851
s4   -136.7234
s5    147.8871
s6    216.3476
s7    338.7154
s8    673.8567
s9    321.0458
s10   430.4775
s11  -130.6776
s12  -215.8636

```

Figure 4.4: The output of `HoltWinters()` function.

the period January 2000 to December 2011. So the forecasts were also for that period. An α of 0.001826 indicates that the forecasts were based on both recent and less recent observations—although somewhat more weight was placed on recent observations (Coghlan 2011). A β of 0.422 and a low γ of 0.3554 meant that the estimate of both the trend and seasonal components at the current time point are based upon both recent observations and some observations in the more distant past. The graph of the original time series against the fitted forecast of the model can be seen in Figure (4.5).

```
plot(baguiorainseriesforecasts)
```

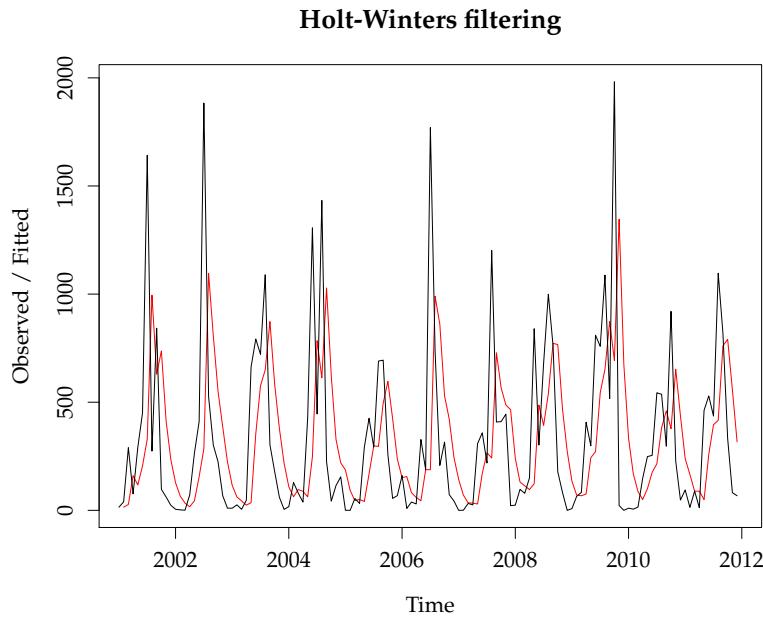


Figure 4.5: The original rainfall time series with the predicted values of the derived model in the same period.

The output of `HoltWinters()` function was stored in the variable `baguiorainseriesforecasts$fitted`. The forecast for the period January 2000 to December 2011 is shown partially in Figure (4.6), and in full in Figure (B.1) of **Appendix B**.

```
baguiorainseriesforecasts$fitted
```

	xhat	level
Feb 2001	14.60	14.60
Mar 2001	27.22	27.22
Apr 2001	160.31	160.31
May 2001	117.58	117.58
Jun 2001	205.48	205.48
.		
.		
.		
Oct 2011	790.45	790.45
Nov 2011	558.28	558.28
Dec 2011	316.67	316.67

Figure 4.6: The forecast for the period January 2000 to December 2011 using Holt Winters.

We now make forecasts for further time points by using the `forecast.HoltWinters()` function in the R `forecast` package. `forecast.HoltWinters()` uses the predictive model derived using the `HoltWinters()` function. The result is in Figure (4.7).

```
library(forecast)
```

```
This is forecast 4.01
```

```
baguiorainseriesforecasts2 ← forecast.HoltWinters(
  baguiorainseriesforecasts ,
  h = 12)
baguiorainseriesforecasts2
```

	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan	2012	59.32	-366.29	484.9	-591.60	710.2
Feb	2012	40.91	-384.70	466.5	-610.01	691.8
Mar	2012	74.48	-351.14	500.1	-576.44	725.4
Apr	2012	132.45	-293.17	558.1	-518.48	783.4
May	2012	417.57	-8.06	843.2	-233.37	1068.5
Jun	2012	486.53	60.90	912.2	-164.42	1137.5
Jul	2012	609.41	183.77	1035.0	-41.56	1260.4
Aug	2012	945.05	519.40	1370.7	294.07	1596.0
Sep	2012	592.75	167.08	1018.4	-58.25	1243.7
Oct	2012	702.69	277.01	1128.4	51.66	1353.7
Nov	2012	142.04	-283.66	567.7	-509.02	793.1
Dec	2012	57.36	-368.37	483.1	-593.73	708.4

```
rainforecasts$SSE
```

```
[1] 13193425
```

Figure 4.7: The 12-month forecast for the year 2012 based on Holt Winters smoothing.

Figure (4.8) shows the original time series with the graph of the predicted values (in blue color) and the low and high values (shown in light blue-gray color).

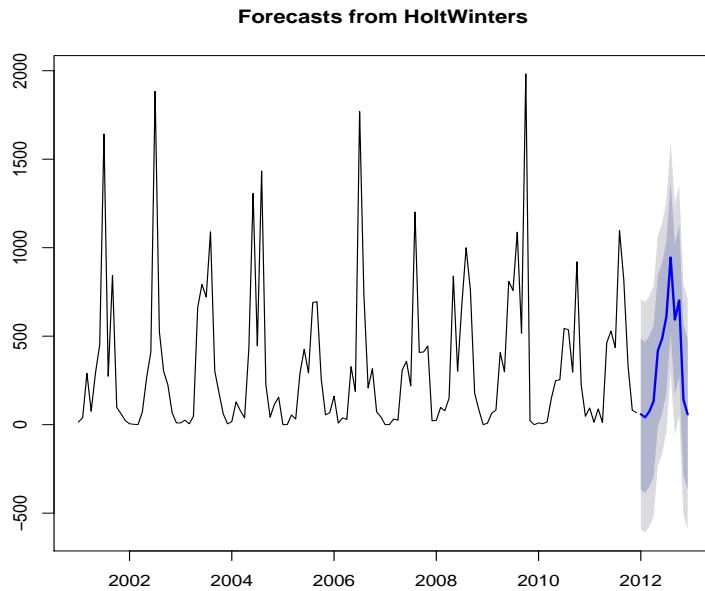


Figure 4.8: The graph of the time series with the forecasted values.

The ‘forecast errors’ are calculated as the observed values minus predicted values, for each time point. We can only calculate the forecast errors for the time period covered by our original time series, which is January 2011 to December 2011 for the rainfall data. One measure of the accuracy of the predictive model is the sum-of-squared- errors (SSE) for the in-sample forecast errors. The in-sample forecast errors are stored in the named element “residuals” of the list variable returned by `forecast.HoltWinters()`. If the predictive model cannot be improved upon, there should be no correlations between forecast errors for successive predictions. In other words, if there are correlations between forecast errors for successive predictions, it is likely that the exponential smoothing forecasts could be improved upon by another forecasting technique. The function `acf()` function was used here to test for autocorrelation in the errors.

```
acf(rainforecasts2$residuals, lag.max = 20)
```

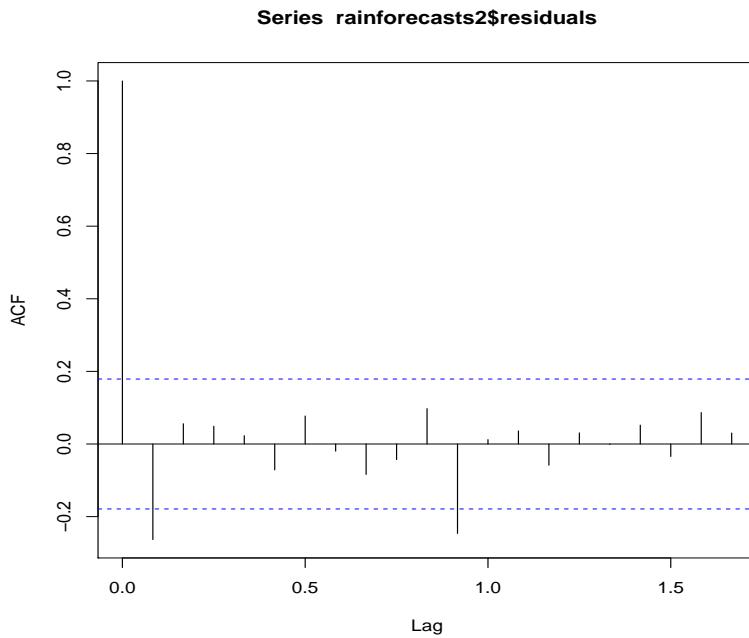


Figure 4.9: `acf()` output.

Here the correlogram shows that the sample autocorrelation for the in-sample forecast errors at lags 1 and 11 exceed the significance bounds. This is more than the 1 than the one in 20 of the autocorrelations for the first twenty lags to exceed the 95% significance bounds by chance alone indicating possible auto-correlation in internal errors.

```
Box.test(rainforecasts2$residuals, lag = 20, type = "Ljung-Box")
```

```
Box-Ljung test

data: rainforecasts2$residuals
X-squared = 23.91, df = 20, p-value = 0.2465
```

```
plot.ts(rainforecasts2$residuals)
```

The Ljung-Box test, with p-value of 0.2465 on the other hand shows no evidence of non-zero autocorrelations in the in-sample forecast errors at lags 1-20.

To be sure that the predictive model cannot be improved upon, the researchers checked whether the forecast errors are normally distributed with mean zero and constant variance. To check whether the forecast errors have constant variance, the researchers made a time plot of the in-sample forecast errors:

```
plot.ts(rainforecasts2$residuals)
```

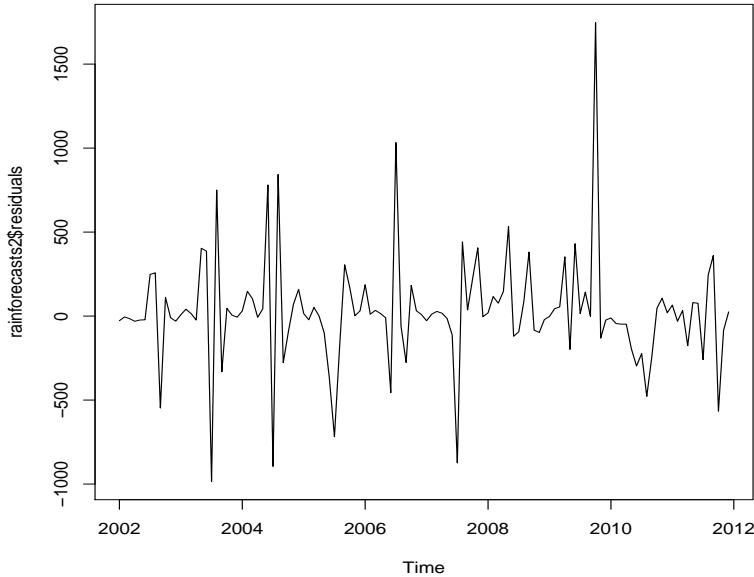


Figure 4.10: Plot of the in-sample forecast errors.

The plot shows that the in-sample forecast errors seem to have roughly constant variance over time with some fluctuations between 2000 and 2011.

To check whether the forecast errors are normally distributed with mean zero, a histogram of the forecast errors, with an overlaid normal curve that has mean zero and the same standard deviation as the distribution of forecast errors can be plotted. Here the R function `plotForecastErrors()` was used.

```
plotForecastErrors <- function(forecasterrors) {
  # make a red histogram of the forecast errors:
  mybinsize <- IQR(forecasterrors)/4
  mymin <- min(forecasterrors) * 3
  mymax <- max(forecasterrors) * 3
  mybins <- seq(mymin, mymax, mybinsize)
  hist(forecasterrors, col = "red", freq = FALSE, breaks = mybins)
  # freq=FALSE ensures the area under the histogram = 1
  mysd <- sd(forecasterrors)
  # generate normally distributed data with mean 0 and standard
  # deviation
  # mysd
  mynorm <- rnorm(10000, mean = 0, sd = mysd)
  myhist <- hist(mynorm, plot = FALSE, breaks = mybins)
  # plot the normal curve as a blue line on top of the histogram of
  # forecast errors:
  points(myhist$mid, myhist$density, type = "l", col = "blue", lwd =
  2)
```

```
}
```

```
plotForecastErrors(rainforecasts2$residuals)
```

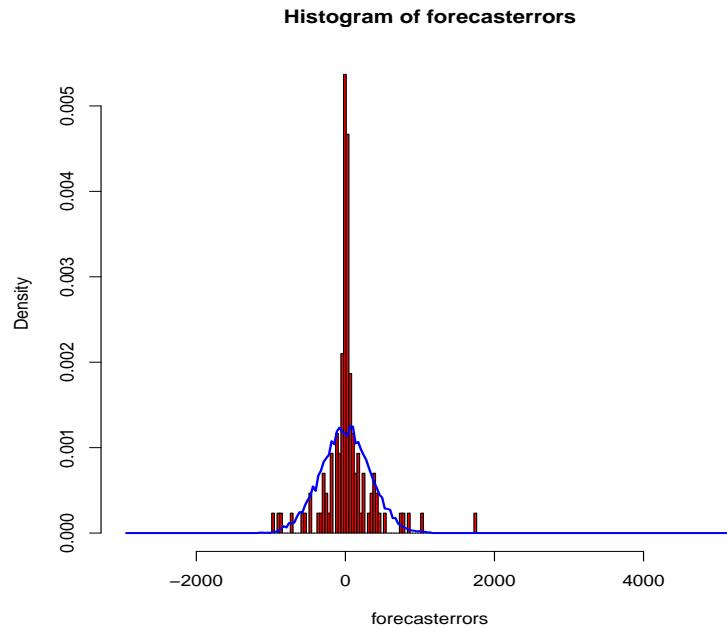


Figure 4.11: A histogram of the forecast errors, with an overlaid normal curve that has mean zero and the same standard deviation as the distribution of forecast errors.

The plot shows that the distribution of forecast errors is roughly centred on zero, and is more or less normally distributed, although it seems to be slightly skewed to the right compared to a normal curve. However, the right skew is relatively small, and so it is plausible that the forecast errors are normally distributed with mean zero.

Chapter 5

Summary, Conclusion, and Recommendations

Summary and Conclusion

The research was conducted to provide a rainfall amount forecast for Baguio City, using time series data from January 2001 to December 2011 gathered from PAG-ASA. Using Holt Winters simple exponential smoothing technique through the statistical software R-statistics, the data gathered were used to create a model to produce a forecast for the year 2012.

Through the auto-correlation function, it was found out that the model derived through Holt-Winters exponential smoothing might be improved upon. However, the Ljung-Box test showed that there is little evidence of non-zero autocorrelations in the in-sample forecast errors, and the distribution of forecast errors seems to be normally distributed with mean zero. These suggest that the exponential smoothing, Holt-Winters method provides an adequate predictive model for rainfall, which probably cannot be improved upon. Furthermore, the assumptions that the 80% and 95% predictions intervals were based upon (that there are no auto-correlations in the forecast errors, and the forecast errors are normally distributed with mean zero and constant variance) are probably valid.

Recommendations

The proponents recommend that a better statistical study be done to further prove the validity of the forecasts. It is also possible that a better and more accurate

forecast be produced through other statistical models. It is also recommended that this research be done on other weather factors such as temperature, air pressure, humidity, and number of rainy days.

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Appendix A

Summary of R Codes Used

Code for Time Series

Listing 1: Summary of R codes used.

```
rain=scan("baguiorainfall.dat")
rain
raintimeseries=ts(rain, frequency=12, start=c(2001,1))
raintimeseries
plot.ts(raintimeseries)
rainforecasts<- HoltWinters(raintimeseries)
rainforecasts
rainforecasts$SSE
plot(rainforecasts)
library(forecast)
rainforecasts2=forecast.HoltWinters(rainforecasts,h=12)
rainforecasts2
plot.forecast(rainforecasts2)
acf(rainforecasts2$residuals, lag.max=20)
Box.test(rainforecasts2$residuals, lag=20, type="Ljung-Box")
plot.ts(rainforecasts2$residuals)
plotForecastErrors=function(forecasterrors)
{
# make a red histogram of the forecast errors:
mybinsize=IQR(forecasterrors)/4
mymin=min(forecasterrors)*3
mymax=max(forecasterrors)*3
mybins=seq(mymin, mymax, mybinsize)
hist(forecasterrors, col="red", freq=FALSE, breaks=mybins)
# freq=FALSE ensures the area under the histogram = 1
mysd=sd(forecasterrors)
# generate normally distributed data with mean 0 and standard deviation mysd
mynorm=rnorm(10000, mean=0, sd=mysd)
myhist=hist(mynorm, plot=FALSE, breaks=mybins)
# plot the normal curve as a blue line on top of the histogram of forecast
# errors:
points(myhist$mids, myhist$density, type="l", col="blue", lwd=2)
}
plotForecastErrors(rainforecasts2$residuals)
```

Appendix B

Full output for the decomposed Bagiuo rainfall time series data

Listing 2: The seasonal, trend, and random components.

```
baguiorainseriescomponents ← decompose(baguiorainseries)
baguiorainseriescomponents
```

\$x	Jan	Feb	Mar	Apr	May	Jun	Jul	
2001	14.600	39.500	289.800	76.000	291.000	451.400	1642.000	
2002	5.000	2.000	0.600	71.200	264.400	411.000	1883.400	
2003	9.800	25.400	4.800	46.800	662.700	792.400	721.300	
2004	17.000	128.600	79.870	37.800	428.600	1306.500	445.400	
2005	0.200	0.000	54.600	32.000	291.000	425.700	292.400	
2006	160.600	8.800	38.400	29.600	327.509	188.200	1769.800	
2007	0.000	0.600	31.800	25.400	308.600	358.400	219.000	
2008	24.000	97.000	78.700	149.800	839.800	302.000	681.200	
2009	8.000	64.500	82.900	407.300	298.500	810.000	758.400	
2010	10.037	5.499	15.300	148.600	248.600	254.000	543.700	
2011	94.000	13.800	88.900	11.900	462.500	529.100	435.900	
	Aug	Sep	Oct	Nov	Dec			
2001	274.000	842.200	97.000	61.600	23.200			
2002	525.600	301.500	224.800	67.300	10.000			
2003	1089.400	303.200	179.700	60.400	4.400			
2004	1432.900	225.600	42.400	114.500	154.900			
2005	690.200	694.600	256.600	55.200	68.000			
2006	735.800	207.600	316.000	72.400	43.200			
2007	1201.600	408.400	410.300	444.800	21.600			
2008	999.500	761.000	178.100	82.600	0.000			
2009	1087.700	516.900	1981.800	22.200	0.000			
2010	536.600	296.800	920.100	226.400	47.400			
2011	1096.300	819.200	332.400	81.600	67.400			
\$seasonal	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
2001	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65
2002	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65

2003	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2004	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2005	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2006	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2007	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2008	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2009	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2010	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
2011	-296.55	-293.19	-283.56	-235.99	80.13	204.37	561.21	522.65			
	Sep	Oct	Nov	Dec							
2001	122.05	128.05	-212.33	-296.84							
2002	122.05	128.05	-212.33	-296.84							
2003	122.05	128.05	-212.33	-296.84							
2004	122.05	128.05	-212.33	-296.84							
2005	122.05	128.05	-212.33	-296.84							
2006	122.05	128.05	-212.33	-296.84							
2007	122.05	128.05	-212.33	-296.84							
2008	122.05	128.05	-212.33	-296.84							
2009	122.05	128.05	-212.33	-296.84							
2010	122.05	128.05	-212.33	-296.84							
2011	122.05	128.05	-212.33	-296.84							
\$trend											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
2001	NA	NA	NA	NA	NA	NA	341.5	339.5	325.9	313.6	312.3
2002	317.9	338.4	326.4	309.2	314.8	314.4	314.1	315.3	316.4	315.6	331.2
2003	331.1	306.2	329.8	327.9	325.8	325.3	325.3	329.9	337.4	340.1	330.0
2004	351.6	354.4	365.5	356.5	353.0	361.6	367.1	361.1	354.7	353.4	347.4
2005	261.9	224.6	213.2	241.6	248.1	242.0	245.1	252.1	251.8	251.0	252.4
2006	295.7	359.2	340.8	323.0	326.2	325.9	318.1	311.1	310.5	310.0	309.1
2007	257.8	212.6	240.4	252.7	272.2	286.8	286.9	291.9	297.9	305.0	332.3
2008	369.0	379.8	386.1	391.1	366.4	350.4	348.8	346.8	345.6	356.5	344.7
2009	367.7	374.6	368.1	433.1	505.7	503.2	503.3	500.9	495.6	482.0	469.2
2010	411.8	379.9	347.8	294.4	258.6	269.1	274.6	278.4	281.8	279.2	282.4
2011	309.8	328.6	373.7	371.0	340.4	335.2	NA	NA	NA	NA	NA
	Dec										
2001	309.5										
2002	363.7										
2003	341.6										
2004	305.0										
2005	244.1										
2006	315.4										
2007	352.1										
2008	343.3										
2009	443.9										
2010	302.8										
2011	NA										
\$random											
	Jan	Feb	Mar	Apr	May	Jun	Jul				
2001	NA	NA	NA	NA	NA	NA	NA	739.334			
2002	-16.360	-43.257	-42.248	-2.012	-130.491	-107.820	1008.092				

2003	-24.773	12.401	-41.398	-45.158	256.792	262.771	-165.233
2004	-38.020	67.408	-2.038	-82.722	-4.572	740.561	-482.947
2005	34.856	68.622	124.989	26.355	-37.216	-20.666	-513.866
2006	161.414	-57.200	-18.845	-57.396	-78.796	-342.030	890.458
2007	38.698	81.151	74.939	8.675	-43.687	-132.745	-629.083
2008	-48.460	10.347	-23.861	-5.345	393.305	-252.745	-228.816
2009	-63.135	-16.882	-1.623	210.225	-287.329	102.446	-306.076
2010	-105.222	-81.207	-48.910	90.231	-90.157	-219.482	-292.093
2011	80.773	-21.612	-1.236	-123.083	41.921	-10.520	NA
	Aug	Sep	Oct	Nov	Dec		
2001	-588.150	394.268	-344.686	-38.390	10.510		
2002	-312.329	-136.973	-218.836	-51.528	-56.807		
2003	236.821	-156.201	-288.458	-57.242	-40.400		
2004	549.165	-251.118	-439.028	-20.565	146.777		
2005	-84.563	320.752	-122.478	15.089	120.772		
2006	-97.955	-224.932	-122.087	-24.336	24.668		
2007	387.054	-11.511	-22.753	324.818	-33.657		
2008	130.058	293.343	-306.465	-49.753	-46.457		
2009	64.151	-100.768	1371.724	-234.631	-147.076		
2010	-264.483	-107.090	512.835	156.306	41.439		
2011	NA	NA	NA	NA	NA		

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$figure
[1] -296.55 -293.19 -283.56 -235.99    80.13   204.37   561.21   522.65
[9] 122.05 128.05 -212.33 -296.84

$type
[1] "additive"

attr(,"class")
[1] "decomposed.ts"
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baguiorainseriesforecasts\$fitted

	xhat	level
Feb 2001	14.60	14.60
Mar 2001	27.22	27.22
Apr 2001	160.31	160.31
May 2001	117.58	117.58
Jun 2001	205.48	205.48
Jul 2001	330.13	330.13
Aug 2001	995.07	995.07
Sep 2001	629.58	629.58
Oct 2001	737.35	737.35
Nov 2001	412.78	412.78
Dec 2001	234.78	234.78
Jan 2002	127.54	127.54
Feb 2002	65.43	65.43
Mar 2002	33.28	33.28
Apr 2002	16.72	16.72
May 2002	44.33	44.33
Jun 2002	155.88	155.88

Jul	2002	285.19	285.19
Aug	2002	1095.26	1095.26
Sep	2002	806.52	806.52
Oct	2002	550.55	550.55
Nov	2002	385.44	385.44
Dec	2002	224.19	224.19
Jan	2003	115.62	115.62
Feb	2003	61.99	61.99
Mar	2003	43.44	43.44
Apr	2003	23.86	23.86
May	2003	35.49	35.49
Jun	2003	353.40	353.40
Jul	2003	575.91	575.91
Aug	2003	649.60	649.60
Sep	2003	872.52	872.52
Oct	2003	583.95	583.95
Nov	2003	379.05	379.05
Dec	2003	217.54	217.54
Jan	2004	109.51	109.51
Feb	2004	62.62	62.62
Mar	2004	96.06	96.06
Apr	2004	87.86	87.86
May	2004	62.48	62.48
Jun	2004	248.05	248.05
Jul	2004	784.54	784.54
Aug	2004	612.64	612.64
Sep	2004	1028.40	1028.40
Oct	2004	621.49	621.49
Nov	2004	327.97	327.97
Dec	2004	219.77	219.77
Jan	2005	186.89	186.89
Feb	2005	92.26	92.26
Mar	2005	45.50	45.50
Apr	2005	50.11	50.11
May	2005	40.93	40.93
Jun	2005	167.68	167.68
Jul	2005	298.46	298.46
Aug	2005	295.39	295.39
Sep	2005	495.50	495.50
Oct	2005	596.42	596.42
Nov	2005	424.18	424.18
Dec	2005	237.16	237.16
Jan	2006	151.42	151.42
Feb	2006	156.07	156.07
Mar	2006	81.43	81.43
Apr	2006	59.62	59.62
May	2006	44.40	44.40
Jun	2006	187.90	187.90
Jul	2006	188.05	188.05
Aug	2006	989.78	989.78
Sep	2006	861.05	861.05
Oct	2006	529.84	529.84

Nov	2006	421.45	421.45
Dec	2006	244.53	244.53
Jan	2007	142.48	142.48
Feb	2007	70.26	70.26
Mar	2007	34.95	34.95
Apr	2007	33.36	33.36
May	2007	29.32	29.32
Jun	2007	170.88	170.88
Jul	2007	265.93	265.93
Aug	2007	242.14	242.14
Sep	2007	728.45	728.45
Oct	2007	566.23	566.23
Nov	2007	487.20	487.20
Dec	2007	465.71	465.71
Jan	2008	240.61	240.61
Feb	2008	130.82	130.82
Mar	2008	113.68	113.68
Apr	2008	95.95	95.95
May	2008	123.24	123.24
Jun	2008	486.44	486.44
Jul	2008	392.95	392.95
Aug	2008	539.05	539.05
Sep	2008	772.44	772.44
Oct	2008	766.64	766.64
Nov	2008	468.33	468.33
Dec	2008	272.82	272.82
Jan	2009	134.54	134.54
Feb	2009	70.40	70.40
Mar	2009	67.41	67.41
Apr	2009	75.26	75.26
May	2009	243.56	243.56
Jun	2009	271.41	271.41
Jul	2009	544.40	544.40
Aug	2009	652.87	652.87
Sep	2009	873.27	873.27
Oct	2009	692.64	692.64
Nov	2009	1346.07	1346.07
Dec	2009	675.05	675.05
Jan	2010	332.89	332.89
Feb	2010	169.25	169.25
Mar	2010	86.25	86.25
Apr	2010	50.29	50.29
May	2010	100.12	100.12
Jun	2010	175.38	175.38
Jul	2010	215.23	215.23
Aug	2010	381.72	381.72
Sep	2010	460.22	460.22
Oct	2010	377.39	377.39
Nov	2010	652.47	652.47
Dec	2010	436.51	436.51
Jan	2011	239.29	239.29
Feb	2011	165.65	165.65

Mar 2011	88.68	88.68
Apr 2011	88.79	88.79
May 2011	49.82	49.82
Jun 2011	258.99	258.99
Jul 2011	395.90	395.90
Aug 2011	416.17	416.17
Sep 2011	760.90	760.90
Oct 2011	790.45	790.45
Nov 2011	558.28	558.28
Dec 2011	316.67	316.67

Figure B.1: The full forecast for the period January 2000 to December 2011 using Holt Winters.