FLOOD FORECASTING IN LANGAT RIVER BASIN USING STOCHASTIC ARIMA MODEL

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Hons.) Civil Engineering

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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ABSTRACT

Floods have huge environmental and economic impact. Therefore, flood forecasting is given a lot of attention due to its importance. This study analysed the annual maximum stage readings of three rivers in Langat River Basin for flood forecasting using ARIMA model. Stage readings were taken from four stations: Dengkil, Kg. Lui, Kg. Rinching and Kajang. The Kajang series was found to be a white noise series so no modelling could be done. The white noise tests carried out for the Kajang series were the Box-Pierce test, the Ljung-Box test and the McLeod-Li test which gave the p-values of 0.408, 0.214 and 0.218 respectively. The modelling approach was based on the Box-Jenkins approach, which starts with model identification followed by parameter estimation and lastly model verification. The significance level adopted was 0.05. The ADF test, KPSS test and Mann-Kendall trend test were performed to determine data stationarity. The Mann-Kendall trend test gave p-values of 0.438 and 0.072 for the Dengkil and Kg. Lui series respectively, indicating the absence of trend while the p-value for the Kg. Rinching series was less than 0.0001 so a trend was present. The p-values from the ADF test were 0.35, 0.138 and 0.411 while the p-values from the KPSS test were 0.001, 0.005 and 0.03 for the Dengkil, Kg Lui and Kg. Rinching series respectively. All three series were non-stationary.

The main tool used in ARIMA modelling was the XLSTAT statistical software. Model identification was done by visual inspection on the ACF and PACF. XLSTAT computed the model parameters using the Maximum Likelihood (ML) method. For model verification, the chosen criterion for model parsimony was the AICC and the diagnostic checks included residuals' independence, homoscedasticity and normal distribution. The best ARIMA models for the Dengkil, Kg. Lui and Kg.

Rinching series were (1,1,0), (1,1,0) and (1,1,1) respectively with their AICC values of 133.736, 55.348 and 42.292. The RACF and RPACF showed residuals' independence while the histograms showed approximately normally distributed residuals. Homoscedasticity was confirmed with the Breusch-Pagan test giving p-values of 0.145, 0.195 and 0.747 for the Dengkil, Kg. Lui and Kg. Rinching models respectively. Forecast series up to a lead time of eight years were generated using the accepted ARIMA models. Model accuracy was checked by comparing the synthetic series with the original series. Results showed that the ARIMA models for the rivers and the forecast series were adequate. By visual inspection, the Dengkil model and the Kg. Lui model looked more convincing than the Kg. Rinching model. In conclusion, the Box-Jenkins approach to ARIMA modelling was found to be appropriate and adequate for the rivers under study in Langat River Basin. The flood forecast up to a lead time of eight years for the three models exhibited a straight line with near constant streamflow values showing that the forecast values were similar to the last recorded observation.

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LIST OF SYMBOLS / ABBREVIATIONS

r_k	autocorrelation coefficient
ρ_k	autocorrelation function
c_k	autocovariance function
$\hat{\phi}_p$	autoregressive parameter
k	lag
ξ	location parameter
μ	mean
$\hat{\theta}_q$	moving-average parameter
N	number of observations
p	order of autoregressive model
d	order of differencing
q	order of moving-average model
ϕ_k	partial correlation coefficient
ε	residual
σ_ε^2	residual variance
β	scale parameter
α	shape parameter for Log Pearson Type 3 distribution
κ	shape parameter for Gumbel distribution
σ	standard deviation

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AICC	Akaike Information Criteria Corrected
AMAK	Autoregressive Moving-average Markov
AMS	Annual Maximum Series
AR	Autoregressive

ARCH	Autoregressive Conditional Heteroscedastic
ARMA	Autoregressive Moving-average
ARIMA	Autoregressive Integrated Moving-average
BL	Broken Line
DID	Department of Irrigation and Drainage
EV	Extreme Value
EV1	Extreme Value Type 1
FEH	Flood Estimation Handbook
FGN	Fractional Gaussian Noise
FFGN	Fast Fractional Gaussian Noise
FSR	Flood Studies Report
GEV	Generalized Extreme Value
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LN	Log Normal
LP	Log Pearson
LP3	Log Pearson Type 3
MA	Moving-average
ML	Maximum Likelihood
MOM	Method of Moments
MSE	Mean Squared Error
NERC	Natural Environment Research Council, UK
PACF	Partial Autocorrelation Function
PDF	Probability Density Function
PDS	Partial Duration Series
POT	Peak Over Threshold
PWM	Probability Weighted Moments
P3	Pearson Type 3
Qt	Quantile Lower Bound Estimation
RACF	Residuals Autocorrelation Function
RPACF	Residuals Partial Autocorrelation Function
ReFH	Revitalised Flood Hydrograph
SARIMA	Seasonal Autoregressive Integrated Moving-average
WMO	World Meteorological Organization

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CHAPTER 1

INTRODUCTION

1.1 Background

Flood analysis is a form of extreme value analysis. The main interest in analyzing extreme hydrological events is not in what has occurred but possibilities that further extreme events will occur in the future. Flood analysis in particular, allows statisticians, mathematicians and hydrologists to estimate future flood occurrence probabilities as well as the peak magnitude of streamflow. It is a subject of great importance due to its large environmental and economic impact. According to a study conducted by KTA Tenaga in 2002, the total flood affected area in Malaysia in 2000 was 29799 km^2, which is about 9.04 % of 329,735 km^2, the total land area of Malaysia (DID Malaysia, 2003). The population in flood affected areas in 2000 was 4,819,265, which is 22 % of the total population at that time and the Annual Average Damage estimated was RM 915 million (at year 2000 prices). The study shows how flood has a huge impact on Malaysia. Another reason flood analyses are important is that the design and operation of hydraulic structures such as dams and reservoirs are determined based on them.

Flood modelling depends on available data to generate efficient estimations. There are two approaches to hydrological modelling; at-site modelling and regional modelling. At-site modelling uses historical data of the site being studied which includes rainfall data, flood records and runoff data. On the other hand, regional modelling uses data from different sites in a region that is assumed to have similar hydrological behaviour. It is more frequently used in ungauged sites and sites with limited historical data. Regionalization also reduces the sampling uncertainty because more data is introduced (Madsen, 1996). Regional modelling is a popular approach in developing and undeveloped countries with low density of gauging stations due to lack of funds and qualified personnel.

Statistical analysis of flood data does not always provide a true answer because hydrological events are subjected to great variability and uncertainties. The uncertainties include sampling uncertainty and model uncertainty (Madsen, 1996). They are more prevalent especially when the estimated return periods are beyond observable period (when extrapolation is required). Sampling uncertainty arises when estimating the parameters of a particular statistical distribution due to a limited set of data. On the other hand, model uncertainty arises when selecting the type of frequency distribution to be used. It is essential that a suitable distribution model is chosen for hydrological analysis. No particular model is considered superior for all applications (WMO, 2009). The selection of model ultimately has to depend on the problem encountered and the available data.

The chosen method of study falls under the category of time series modelling. Time series is commonly used in the financial sectors and also in the field of hydrology. The beauty of time series modelling is that future values of a variable can be estimated using its historical values.

The study area is the Langat River Basin which spans two states in Malaysia, namely Selangor and Negeri Sembilan. The Langat River Basin is shown in Figure 1.1. It has a catchment area of approximately 2,348 km^2. The Langat River is the main stream while other major tributaries include the Semenyih River, the Labu River and the Beranang River. Two dams are located at the upper region of the river basin; the Semenyih dam and the Langat dam. The Semenyih dam has a catchment area of 56.7 km^2 while the Langat dam has a catchment area of 41.1 km^2.

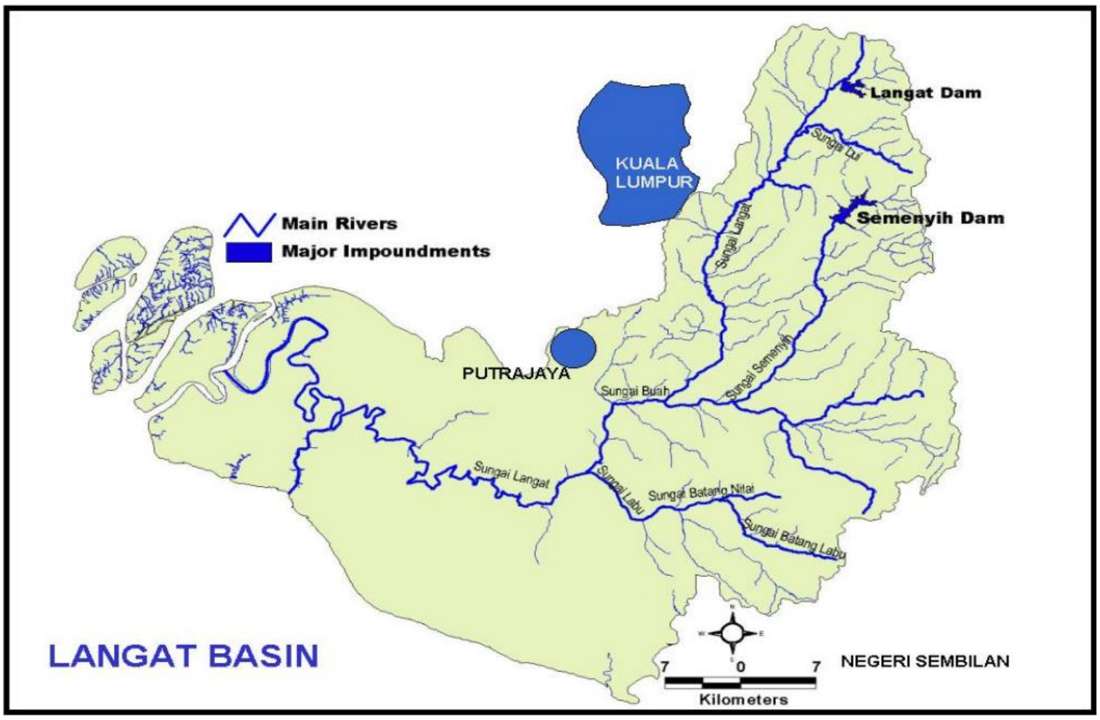

Figure 1.1: The Langat River Basin

1.2 Problem Statement

The event of flood can cause significant damage to the lives and properties of those living within the affected area. The high water level causes disruption to their daily activities. Children will be unable to attend school, adults will be unable to work and consequently the nation’s economy will be affected. In year 2000 alone the damage caused by flood in Malaysia was estimated to cost more than RM 915 million (DID Malaysia, 2003).

The design of hydraulic structures such as dams and reservoirs also depends on the design flood of the particular river. An inaccurate design flood can lead to inefficiency of those hydraulic structures. Modifications to an existing structure are extremely costly and troublesome. Therefore, flood analysis is important to address these key issues. The main obstacle in flood analysis is the lack of sufficient data to predict future occurrences. The available data may be insufficient to guarantee an acceptable confidence level.

1.3 Aim and Objectives

The aim of this study is to mitigate the flood problems in Langat River Basin through developing a stochastic model for forecasting annual maximum streamflows in the study rivers. The objectives of this study are:

i. To develop stochastic ARIMA models for the study rivers using Box-Jenkins approach;
ii. To forecast future annual maximum streamflow values in the study rivers using the developed ARIMA models.

1.4 Significance of Study

Through this study, the forecasted annual maximum streamflow values for the chosen rivers in Langat River Basin are available for future use. The results from this study are beneficial to engineers, researchers and hydrologists in the field of hydrology, especially in flood forecasting and flood management. A better understanding towards flood study may limit the environmental and economic impact of flood and subsequently reducing flood damage.

The results also contribute to a better understanding towards stochastic flood forecasting modelling, particularly time series modelling. This study can be a reference for future development of time series modelling in hydrological studies.

1.5 Scope of Work

The scope of work of the present study includes the study of statistical models in the field of hydrology and the application of time series model, namely the Autoregressive Integrated Moving-Average (ARIMA) model, onto the study area. Stage readings from four water level stations in the Langat River Basin were analysed and the future annual maximum streamflow magnitudes were forecasted using ARIMA model.

CHAPTER 2

LITERATURE REVIEW

2.1 Stochastic, Probabilistic and Deterministic Modelling

The primary focus of this study is on stochastic modelling for flood analysis. However, it is important to highlight other methods of modelling for a better understanding on the similarities and differences of these methods.

The stochastic models are related to the probability models in the sense that both types of models have random variables. The former are models of dependent random variable while the latter are models of independent variables. Although models of independent random variables are much simpler to understand compared to models of dependent random variables, the concepts involved are actually common to both types of models. For example, concepts of probability, probability distribution and estimation are essential in expressing random variables. In fact, having a good understanding on the simpler probability models is useful in understanding the more complex stochastic models.

The main difference between probability models and stochastic models lies on the dependence between random variables. The incorporation of dependence between random variables is the major difficulty in modelling dependent random variables. To overcome the difficulty in estimation, time series analysis and regression techniques are applied in order to build a stochastic model in flood analysis.

Goldman (1985) uses an example of designing a system of reservoirs to examine the different approaches of stochastic and deterministic models. In order to estimate the required storage capacity of the system, the future inflows and water demands have to be estimated. One possible way to estimate future inflows is to create a mathematical model which simulates future weather conditions and then couple it with a watershed model to predict future streamflow. In this way, the weather conditions and the inflows are predicted before they are observed. This type of model is a deterministic model. The common presumption used in deterministic models is that future inflows are identical to past inflows, which is highly unlikely in real life. Alternatively, another approach is to assume that past inflows are observations of a random or stochastic process, in which future observations cannot be estimated with certainty. By treating the inflows as a random process, a mean for identifying the underlying probability law governing the process, or equivalently, a stochastic model, must be developed.

2.2 Design Flood

The design flood in the form of frequency-based flood is determined by applying frequency analysis of flood flows or rainfall data by carrying out one of the following (WMO, 2009):

i. Frequency analysis of rainfall data to obtain a frequency-based storm, which is then converted to design flood;
ii. Frequency analysis of flood flows;
iii. Regional frequency analysis.

Sutcliffe (1978) discussed on the choice between the method of frequency analysis of flood flows and the method of design storm (or method of unit hydrograph). The unit hydrograph method is necessary if:

i. The detailed shape of the flood is required;
ii. The estimate of the maximum flood is required.

2.2.1 Rainfall-Runoff Approach

The rainfall-runoff approach involves coupling rainfall frequency statistics with a catchment model to estimate flood. This approach can be divided according to their spatial structure (lumped, semi-distributed or distributed) and time representation (event-based simulations and continuous simulations).

For event-based simulations the rainfall-runoff model is fed by a design rainfall of a defined probability (Paquet et al., 2013). A very popular method is the revitalised flood hydrograph (ReFH) method (Kjeldsen, 2007), which is commonly used in England and Wales and has replaced the earlier Flood Studies Report/Flood Estimation Handbook (FSR/FEH) rainfall-runoff method for most applications. The ReFH model converts a design rainfall event into a design flood. The three components of the ReFH model include a loss model, a routing model and a baseflow model. Figure 2.1 shows the structure of ReFH model.

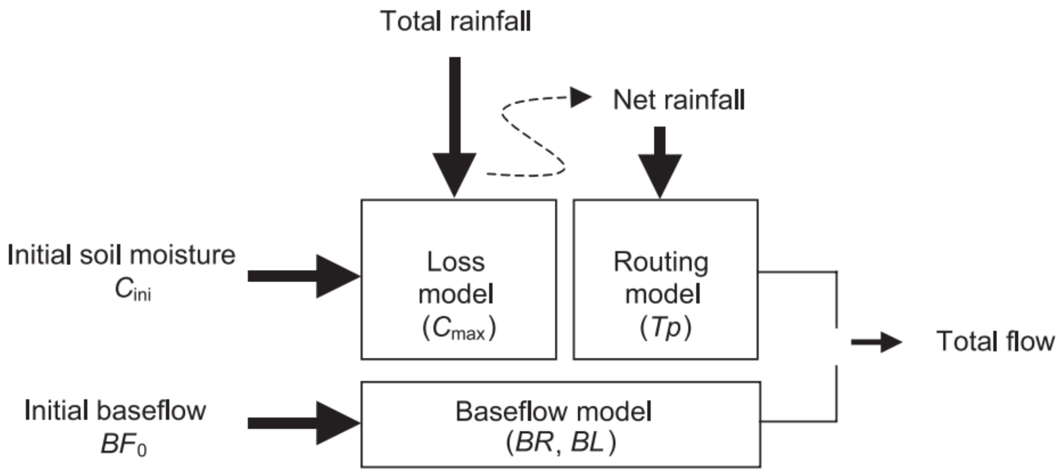

Figure 2.1: Structure of ReFH Model

For continuous simulations, Boughton and Droop (2003) presented a very comprehensive review on this type of method. Calver and Lamb (1995) performed flood frequency estimation for a sample of ten UK catchments using continuous rainfall-runoff modelling. This continuous simulation is also known as the Monte Carlo simulation whereby a stochastic rainfall model is coupled with a rainfall-runoff model. Cameron et al. (2000) coupled a stochastic rainfall model with the TOPMODEL to estimate flood peaks for four UK catchments and the results compared well with the traditional statistical approach.

There had been some studies done to compare the rainfall-runoff method with flood frequency analysis. Boughton and Hill (1997) compared the continuous approach with flood frequency statistics for a 108 km^2 catchment in Victoria, Australia. Their results concluded that long flood records are important for better estimates using flood frequency statistics. In another case study, Boughton et al. (2002) compared the estimates from continuous simulation method and design storm approach with the estimates from flood frequency analysis in three small catchments (62 km^2, 108 km^2, 259 km^2). Very short flood records used in flood frequency analysis resulted in estimates that were up to 50 % smaller. In an Austrian case study, Gutknecht et al. (2006) concluded that for very low probability floods, the design flood from an event-based approach is larger than the estimates from flood frequency statistics and regional methods. McKerchar and Macky (2001) compared design flood estimates from a design storm approach and regional flood analysis to the estimates from flood frequency analysis of six catchments in Australia. It was found that the estimates from design storm approach tend to be more than 100 % larger compared to the other estimates.

Thus, in most catchments, the event based runoff model generally gives larger flood estimates than flood frequency analysis (Rogger et al., 2012). For better estimates from the flood frequency statistics, long flood records are necessary.

2.2.2 Flood Frequency Analysis Approach

Generally, flood frequency analysis is the study on streamflow records in order to make estimations on future streamflow values.

There are two prevalent methods for flood frequency analysis; the annual maximum series (AMS) method and the partial duration series (PDS) method. The

PDS method is also known as the peak over threshold (POT) method. The main difference between the two methods is the extreme values used. The AMS method takes into account only the annual maximum while the PDS method includes all the values exceeding a certain threshold level. One significant drawback of the AMS method is that secondary events in a year may give higher values than annual maxima of other years (Madsen, 1996). However, the AMS method is commonly used in frequency analyses compared to the PDS method (WMO, 2009). The AMS method is easier to define and the assumption that annual maxima are independent is reasonable. The PDS method, on the other hand, requires its user to choose an appropriate threshold value as well as ensuring independence between successive peaks.

Cunnane (1973) compared estimates in the PDS model with exponential distribution to the corresponding AMS model with Gumbel distribution and discovered that if the PDS has more than 1.65 exceedances per year, then the PDS model is more efficient than the AMS model. Madsen (1996) compared the AMS model with the PDS model using three methods of estimation and concluded that since heavy-tailed distribution are the most common in flood frequency analysis, the preferred model would be the PDS model.

According to Takara (2009), the important issues to be considered in a frequency analysis are:

i. Data characteristics;
ii. Sample size;
iii. Parameter estimation;
iv. Model evaluation;
v. Accuracy of quantile estimates.

The frequency curve is deemed complete when a suitable distribution has been fitted to the observed flood peak data (Sivandran, 2002). As shown in Figure 2.2, the fitted curves relates the return period to a flood magnitude.

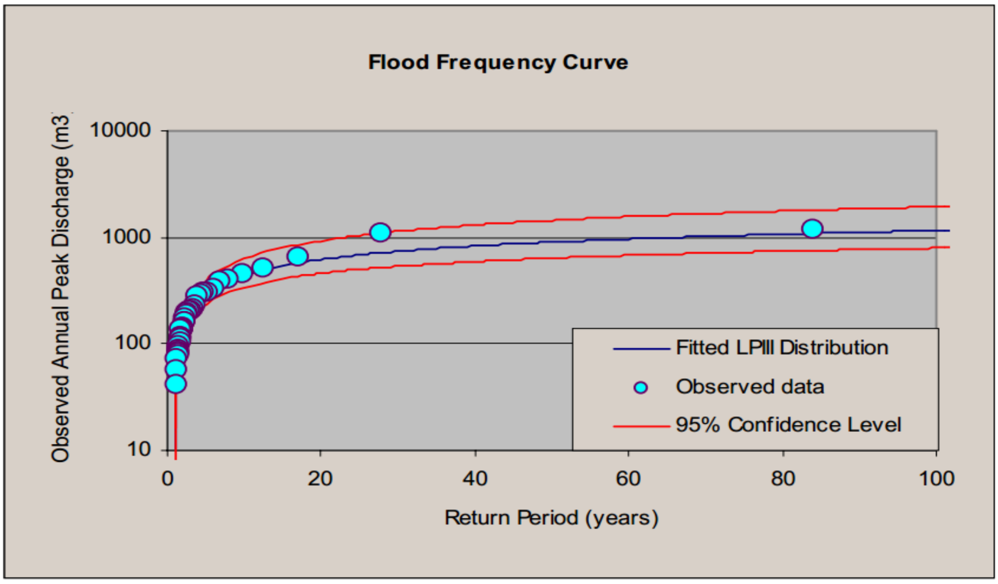

Figure 2.2: Example of Flood Frequency Curve (Source: Sivandran, 2002)

2.2.3 Types of Distribution

NERC (1975) studied the frequency distributions used in flood analyses by most countries and the results are tabulated in Table 2.1.

Table 2.1: Frequency Distributions Used in Flood Analysis Studied by NERC (1975)

Distribution	Percentage of countries recommended	Percentage of total countries using it
Log-Normal (LN)	18.9	15
Log-Pearson Type 3 (LP3)	15.4	23
Pearson Type 3 (P3)	11.9	12
Generalized Extreme Value (GEV) including Extreme Value Type 1 (EV1)	24.9	32

There are other relatively less used distributions such as the Gamma distribution, the Wakeby distribution and the exponential distribution. Many frequency distributions for flood analysis are described in details by Cunnane (1989).

A very informative research was done by Haktanir and Horlacher (1993) whereby various distributions were evaluated for flood frequency analysis. Nine different probability distributions were applied to the annual flood peak series in two streams in Scotland and the Rhine Basin in Germany. It was found that the GEV and the log-normal distributions predict floods with return periods of more than 100 years better than other distributions. The GEV type 2, log-Pearson type 3 and the Wakeby distributions would usually give conservative peaks. The log-logistic distribution coupled with the ML method tends to overestimate high return period floods.

2.2.3.1 Normal Distribution

The normal distribution is useful for describing well-behaved hydrologic phenomena such as total annual flow. It has a symmetrical, unbounded, bell-shaped curve. The maximum value for a normal distribution occurs at the mean and due to its symmetrical nature, half of the values will be below the mean and another half will be above the mean.

For the purpose of flood analysis, the normal distribution is not suitable to be used. It has an unbounded lower limit whereas streamflows observed in flood analyses have a lower bound of zero. Besides, streamflows observed in flood analysis normally have a skewed distribution, which cannot be represented by the symmetrical shape of the normal distribution.

2.2.3.2 Log-Normal Distribution

Streamflows in flood analysis are non-negative and typically have skewed distributions. The log-normal distribution is one of the frequently used models for skewed distributions. By definition, if the natural logarithm of a random variable is normally distributed, then it has a log-normal distribution.

A random variable represented by the log-normal distribution takes on values in the range of zero to positive infinity. The parameter μ determines the scale of the distribution while σ^2 determines the shape of the distribution. Figure 2.3 shows different shapes of log-normal distributions under different σ.

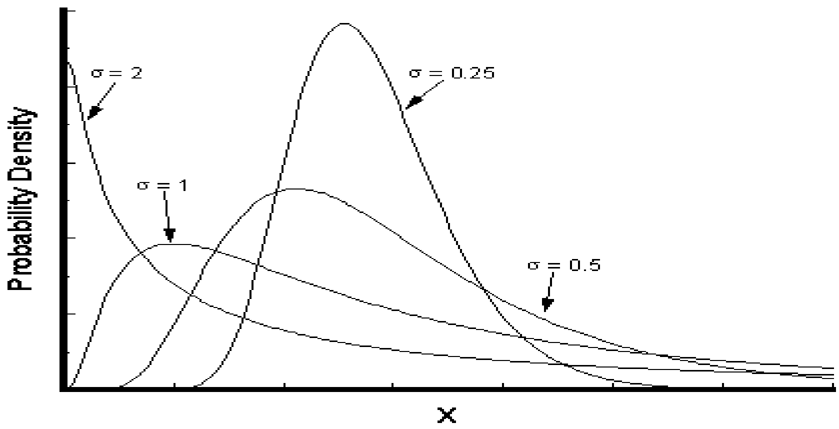

Figure 2.3: Log-Normal Distributions under Different σ

2.2.3.3 Log-Pearson Type 3 Distribution

The log-Pearson type 3 distribution is widely used in flood frequency modelling in the United States of America and it had been recommended for that purpose by Interagency Advisory Committee on Water Data (1982).

Its probability density function (PDF) is defined by three parameters: the location parameter (ξ), the scale parameter (β) and the shape parameter (α) with $\alpha > 0$ and β either positive or negative. For $\beta < 0$, its values are in the range of zero to exponential (ξ) and for $\beta > 0$, its values have a lower bound so they are more than exponential (ξ).

2.2.3.4 Gumbel Distribution

The Gumbel distribution belongs to a type of distribution termed extreme value distribution. There are three types of extreme value distributions which describe the distribution of the maximum and minimum values in a large sample defined by Gumbel (1958). The Gumbel distribution is also known as the extreme value type 1 distribution because it is actually a special case of generalized extreme value distribution with its shape parameter, $\kappa = 0$.

The location parameter is denoted by ξ and the moments for the distribution are μ_x, σ_x^2 and γ_x.

2.2.3.5 GEV Distribution

The generalized extreme value distribution is an expression that includes the type 1, 2 and 3 extreme value distributions (Gumbel, 1958; Hosking et al., 1985). The GEV distribution is commonly used as a general model for extreme events such as flood flows, especially in the regionalization procedures (NERC, 1975; Stedinger and Lu, 1995).

2.2.4 Parameter Estimation

Parameter estimation is done on the distributions chosen to describe flood flows so that the required quantiles and expectations can be obtained with the fitted model. There are different methods for parameter estimation and the most commonly used in flood analysis are the method of moments (MOM), the maximum likelihood (ML) method and the probability weighted moments (PWM) method. The PWM method is regarded as one of the best parameter estimation methods (Cunnane, 1989).

Monte Carlo studies comparing various fitting methods for the log-normal (LN), Gumbel (EV1), generalized extreme value (GEV) and log-Pearson type 3 (LP3) distributions were summarized by Takara and Stedinger (1994) and it was noticed that:

i. For two-parameter distributions (LN(2), EV1(2)), the maximum likelihood method gave accurate quantile estimators;
ii. The quantile lower bound estimation method coupled with the maximum likelihood method or methods of moments (Qt & MOM or Qt & ML) gives more accurate quantile estimates for three-parameter distributions such as LN(3), P3(3) and LP3(3);
iii. The probability weighted moments method (PWM) is best for the GEV(3) distribution. The PWM is also known as the L-moments method (Hosking and Wallis, 1997).

2.3 Stochastic Processes and Time Series

Chow (1969) gave a brief but comprehensive introduction on stochastic hydrologic phenomenon: "The hydrologic phenomenon changes with time in accordance with the law of probability as well as the sequential relationship between its occurrences." For example, the event of a flood follows the law of probability and is affected by the previous flood condition.

In flood analysis, stochastic modelling can be applied in many ways. One of them is to perform a stochastic rainfall modelling which is then coupled with a watershed model to make flood estimates. Another way is to apply stochastic modelling on the streamflow itself. The focus of this study is on stochastic streamflow modelling.

An in-depth review on stochastic processes in hydrologic system is given by Chow and Meridith (1969). Time series analysis is an important component in stochastic modelling and Matalas (1967) and Kisiel (1969) provided a general survey of hydrologic time series analysis. Figure 2.4 shows the components of a time series. The components in a time series can be divided into deterministic component (trends, periodicities and catastrophic events) and random component.

Chow (1969) reviewed three time series models which have been used in hydrologic study: the moving-average model, the sum-of-harmonics model and the autoregression model. The approaches used to select the best model were also reviewed and they are the correlogram and the spectrum analysis.

Since the focus is on stochastic streamflow modelling, the type of dependence that is focused is the serial dependence. Serial dependence is used to model the relationship between past and current observation of streamflow (Goldman, 1985). Goldman also discussed on using linear regression and correlation to determine the dependence between random variables or in the case of serial dependence, between observations of the same variable.

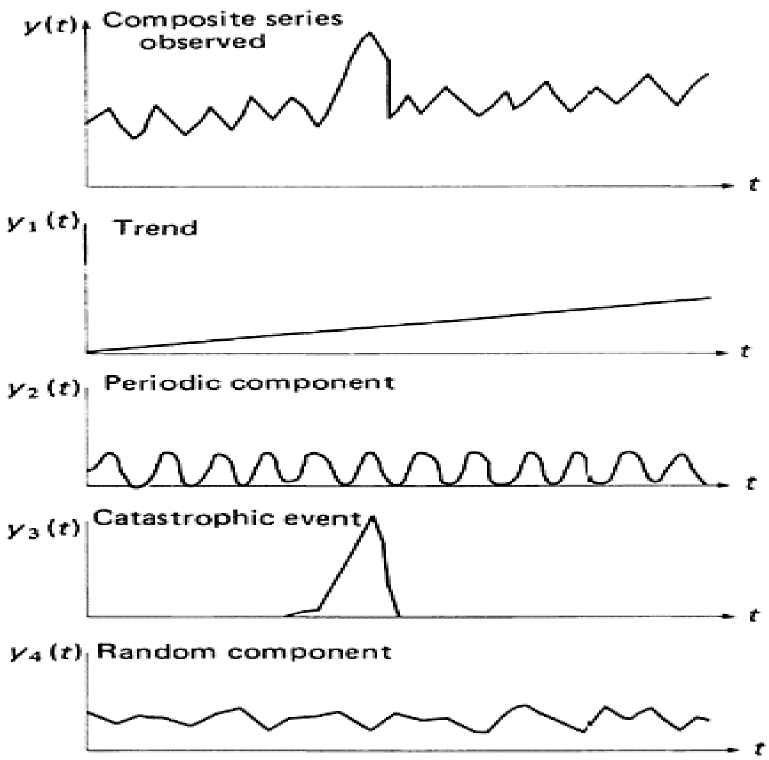

Figure 2.4: Components of Time Series

Most of the conventional statistical methods deal with models in which the observations are assumed to be independent. However, a lot of data in daily applications have dependent observations. Engineering, economics and natural sciences have a great deal of data in the form of time series. According to Akgun (2003), the main objective of a time series analysis is to determine the stochastic process that governs the observed series and subsequently forecast future values from the observed series.

Naturally, streamflow has a random component. However, it is also observed that a high flow tends to follow high flow and a low flow tends to follow low flow so it is not fully random. In statistics, the term ‘stochastic’ denotes randomness but in hydrology it can be used to refer to a partial random sequence as well.

The autocorrelation coefficient is a time series parameter that indicates serial dependence between successive values of a time series. This coefficient is calculated for successive observations as well as for observations that are separated by various time intervals. These time intervals are known as lag period. A graph of autocorrelation coefficient against lag period is known as a correlogram. The correlogram is an excellent indicator of the behaviour of the underlying stochastic process of the series. If a correlogram shows nearly zero values for all lag periods, the process is a white noise process, which is purely random. On the other hand, if a correlogram shows values close to one, it indicates a deterministic process (Gupta, 1989). No modelling or forecasting could be done on a white noise series because there is no more information which could be extracted from the series.

2.4 Stochastic Modelling

According to Box and Jenkins (1976), time series modelling can be carried out in the following stages:

i. Selection of model type;
ii. Identification of model form;

iii. Estimation of model parameters;
iv. Diagnostic check of the model.

Salas et al. (1980) further explained the stages of time series modelling. At the first stage, a type of model representing the dependence of time series is selected. For example, the Markov chain model and the autoregressive model are two common types of models for that purpose. Once a type of model is selected, the form or the order the model has to be identified. For instance, if the autoregressive model is chosen, it has to be identified whether it is an autoregressive model of order one (one autoregressive coefficient), order two, et cetera. Next, estimation is done on the parameters of the model identified and finally diagnostic checks are done to verify the quality of the model. The whole process is an iterative process with feedback and interaction between the stages.

Salas and Smith (1980) on the other hand, proposed a systematic approach to hydrologic time series modelling which consists of six phases:

i. Identification of model composition;
ii. Selection of model type;
iii. Identification of model form;
iv. Estimation of model parameters;
v. Goodness-of-fit testing;
vi. Evaluation of uncertainties.

This systematic approach by Salas and Smith retains some of the components of the Box-Jenkins approach while also adding some steps which improve the modelling process.

There are many models which have been proposed in the past for stochastic modelling. They include: the autoregressive (AR) models (Thomas and Fiering, 1962; Yevjevich, 1963; Matalas, 1967); the autoregressive moving-average (ARMA) models (Carlson et al., 1970; O'Connell, 1971); the ARMA-Markov models (Letternmaier and Burges, 1977); the fractional Gaussian noise (FGN) models

(Matalas and Wallis, 1971); the broken-line (BL) models (Mejia et al., 1972); and the disaggregation models (Valencia and Schaake, 1973).

According to Salas et al. (1980), these models have been criticized for: inability to reproduce short term dependence; inability to reproduce long term dependence; parameters estimation difficulties; inability to generate large samples of synthetic data; lack of physical basis; and too many parameters. The advantages and limitations of the mentioned models can be found out through the original publications as well as through the reviews mentioned.

Bowles et al. (1980) investigated the range of applicability of the lag two autoregressive (AR) model, the ARMA model, the BL model, the fast fractional Gaussian noise (FFGN) model and the ARMA-Markov (AMAK) model in drought analysis based on these criteria:

i. Ability to preserve annual persistence statistics and the run properties of the seasonal statistics;
ii. Model cost and ease to use;
iii. Magnitude of economic damage associated with flows generated by each model;
iv. Reservoir capacity and critical design parameters.

The results showed that the FFGN and BKL were much more costly than the AR(2), ARMA and AMAK. The parameter estimation for the AR(2) was the easiest. Based on criteria (i), all models are effective in preserving the Hurst coefficient except the AR(2) model, with the ARMA model being most effective. In terms of estimating the required reservoir capacity based on criteria (iv), the ARMA and AMAK were the most conservative followed by the AR(2) model and then the BKL and FFGN models.

2.5 The ARMA Family

An autoregressive integrated moving-average (ARIMA) model is basically an ARMA model. The difference is that ARIMA is used when the raw data is non-stationary and it requires differencing to become stationary. Once the data is differenced, the procedure becomes an ARMA procedure. The outcomes from the ARMA procedure are then integrated to reverse the effect of the initial differencing.

The seasonal autoregressive integrated moving-average (SARIMA) model on the other hand, takes into account the seasonal effect in the data series. If there is any seasonal or cyclic pattern in the series, the SARIMA model would be more appropriate to be used. There are actually other models which have similar concept with the ARMA model. One example would be the autoregressive conditional heteroscedastic (ARCH) model. However, the more commonly used models from the ARMA family are the ARMA model itself, the ARIMA model and the SARIMA model.

2.6 ARIMA Model

The ARIMA modelling is actually an approach that has the flexibility to fit a model which is adapted from the data structure itself. With the help of the computed autocorrelation function and partial autocorrelation function, the time series' stochastic nature can be modelled and vital information such as trend, periodic components, random components and serial correlation can be obtained.

The Box-Jenkins approach to ARIMA modelling is an iterative model building process where the best models have to be determined through trial and error. However, with the advent of computers and statistical software packages, this iterative process can be simplified. Commonly used software packages include Statgraphics, Minitab and Statistica.

The ARIMA model has three main components:

i. Autoregressive (AR);
ii. Integrated (I);
iii. Moving-Average (MA).

The AR component represents the autocorrelation between current and past observations while the MA component describes the autocorrelation structure of error. The integrated component represents the level of differencing required to transform a non-stationary series into a stationary series (Hasmida, 2009). A non-seasonal ARIMA model is usually denoted by (p,d,q). The order of the AR component is denoted by p, the order of differencing is denoted by d and q is the order of the MA component.

Throughout the years researchers have used the ARIMA model for different scientific and technical applications. Ahlert and Mehta (1981) described the random component of streamflow time series by examining the stochastic structure of the flow data for the Upper Delaware River. Forecasting monthly rainfall data using various ARIMA models was done by Fernando and Jayawardena (1994). Ahmad et al. (2001) analysed water quality data whereas Hsu et al. (1995) carried out streamflow prediction on a medium sized basin in Mississippi. The ARIMA model was applied to monthly data from Kelkit Stream watershed by Yurekli et al. (2005). Kurunc et al. (2005) reviewed the performance of two stochastic models (Thomas-Fiering and ARIMA) on Yesilirmak River, Turkey.

There have been a lot of reviews on the performance of the ARIMA model. Tang et al. (1991) argued that the ARIMA model is only suitable for short term forecasting. The ARIMA model needs a long input series to produce forecasts that are more accurate. Therefore, the ARIMA model may not work well for short input series. Maia et al. (2008) showed that the performance of ARIMA is satisfactory in forecasting either a linear or non-linear interval series. It is also a good forecasting alternative to inter-valued time series. However, it was shown that the hybrid model of ARIMA and artificial neural network gives a better average performance.

2.6.1 Stationarity

The Box-Jenkins approach is a stationary time series approach. If a time series is non-stationary, differencing is required to make it stationary before the Box-Jenkins approach can be carried out. There are many ways to determine non-stationarity. The common tests used include unit root tests and trend tests. Figure 2.5 shows the examples of stationary and non-stationary time series.

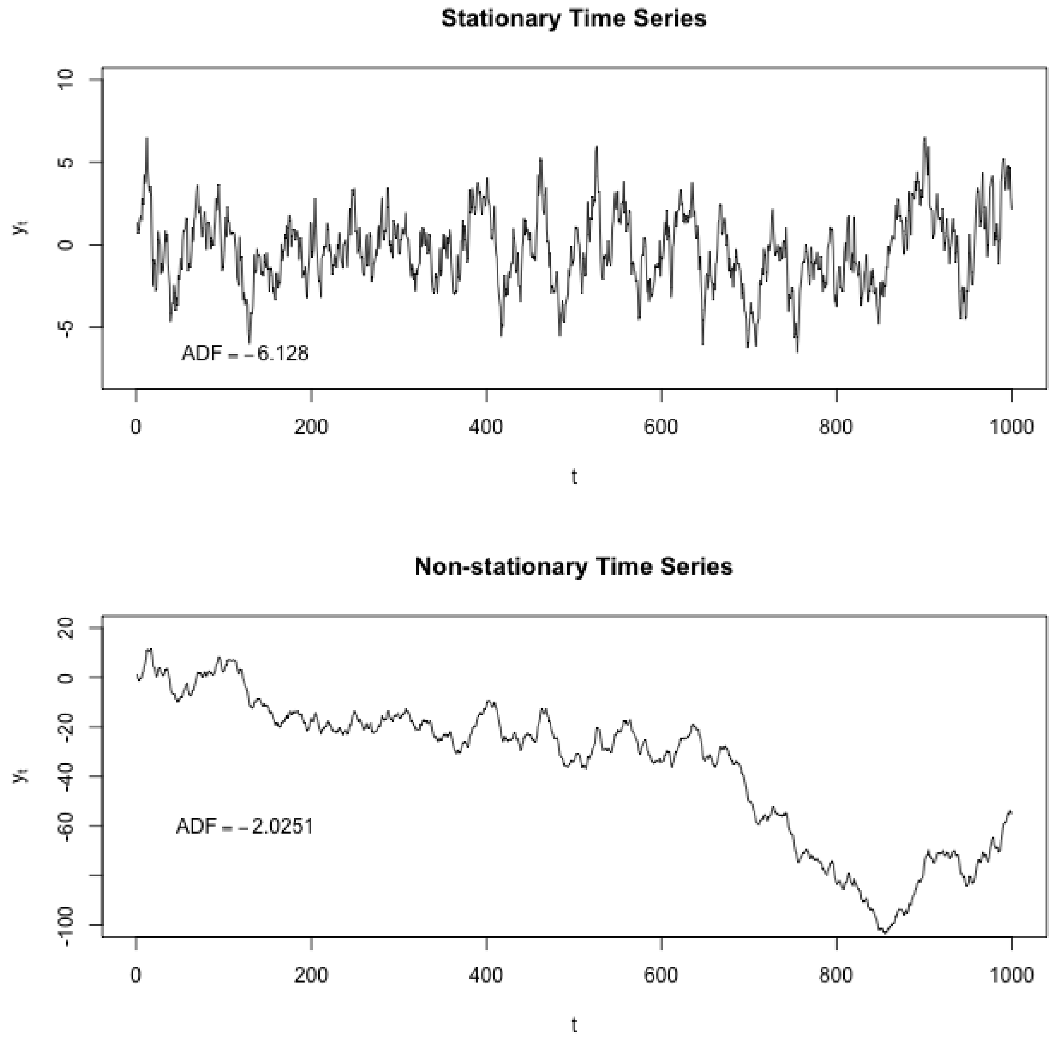

Figure 2.5: Examples of Stationary and Non-stationary Time Series

2.6.1.1 ADF Test

The testing for unit root's presence in a time series is a normal starting point of applied work in macroeconomics. One of the popular tests for unit root is the Augmented Dickey-Fuller (ADF) test. This test is based on estimates from an augmented autoregression. One of the main issues in the ADF test is the choice of lag length *k*. Schwert (1989) and Harris (1992) found that the autoregression order has important size and power implications. Ng and Perron (1995) provided a formal analysis on the relevance of lag length *k* in the ADF test procedure.

2.6.1.2 KPSS Test

Another well known test for stationarity in econometrics is the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. It tests for the null hypothesis of stationarity as opposed to the ADF test which tests for the null hypothesis of non-stationarity. One of the important arguments against the use of tests with stationarity as the null hypothesis is that it is very difficult to control their size when the process is stationary and extremely autoregressive (Hobijn et al., 1998).

The KPSS test is oversized for processes that are highly autoregressive because it uses a semiparametric heteroscedasticity and autocorrelation consistent covariance estimator with positive finite sample bias. However, one can choose other bandwidths other than the ones suggested by KPSS for the estimator. Care should be taken when choosing a bandwidth because a bandwidth that is too large implies that the long run variance is overestimated and if common nominal significance levels are used, the test will have little or no power in finite samples. On the other hand, a bandwidth that is too small for a highly autoregressive process implies that the long run variance is underestimated and thus the test is oversized. Hobijn et al. (1998) suggested an automatic form of KPSS test that minimizes the size distortion without facing the problem of inconsistency.

2.6.1.3 Mann-Kendall Trend Test

The Mann-Kendall trend test is commonly used to test the presence of trend in a time series. It is not a parametric test so the data do not have to be normally distributed and it has low sensitivity to sudden changes due to non-homogeneous time series. The Mann-Kendall S Statistic shows the behaviour of a trend. A positive S indicates an upward trend while a downward trend is indicated by a negative S. Another statistic obtained from the test is the Kendall's tau, which measures the strength of the dependence between two variables. A positive value of Kendall's tau shows that the variables' ranks increase together while a negative value shows that as one variable's rank increases, the other variable's rank decreases. Figure 2.6 shows an example of trend in a time series.

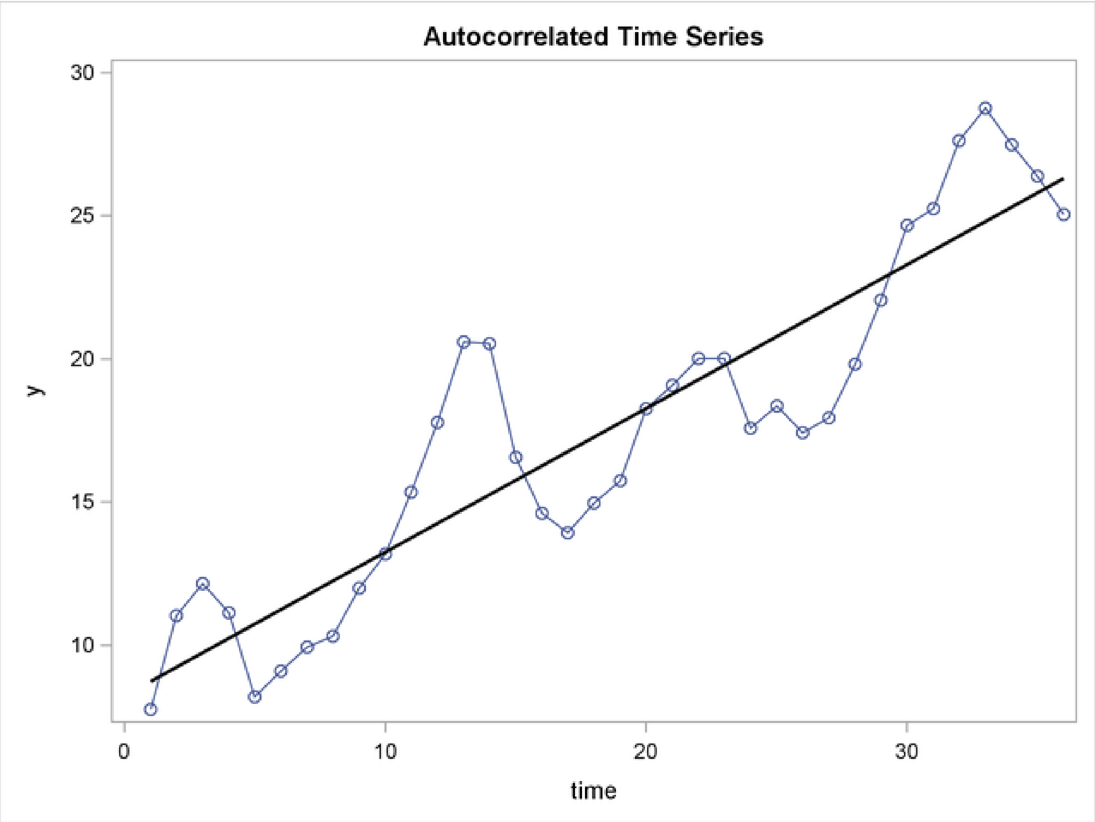

Figure 2.6: Example of Trend in a Time Series

2.6.2 Independence

The basic assumption is that the residuals of an ARIMA model are white noise. A white noise series have uncorrelated random shock with zero mean and constant variance. If the residuals are independent, it means that there is no more information that could be extracted from the series. One of the ways to determine the independence is to visually inspect the correlogram of the residuals. If the correlogram shows values that are close to zero, the residuals are uncorrelated and independent. Figure 2.7 shows an example correlogram or autocorrelation function (ACF) that exhibits white noise.

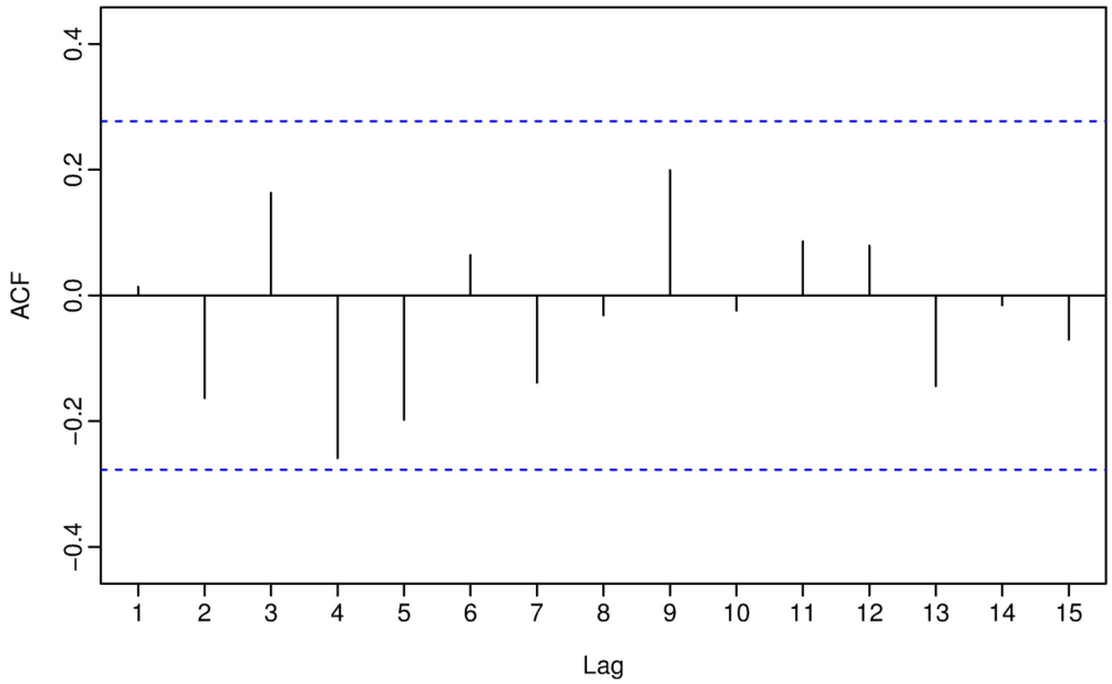

Figure 2.7: Example of ACF Exhibiting White Noise (Source: Hyndman and Athanasopoulos, 2013)

2.6.3 Homoscedasticity

Homoscedasticity is the term used to define that the variance of the disturbance term in each observation is constant. If the residuals are homoscedastic, their variances are stable. The probability of the disturbance terms reaching a given positive or negative value will be the same in all observations, which means that they have the same dispersion. Figure 2.8 illustrates an example of homoscedastic dispersion.

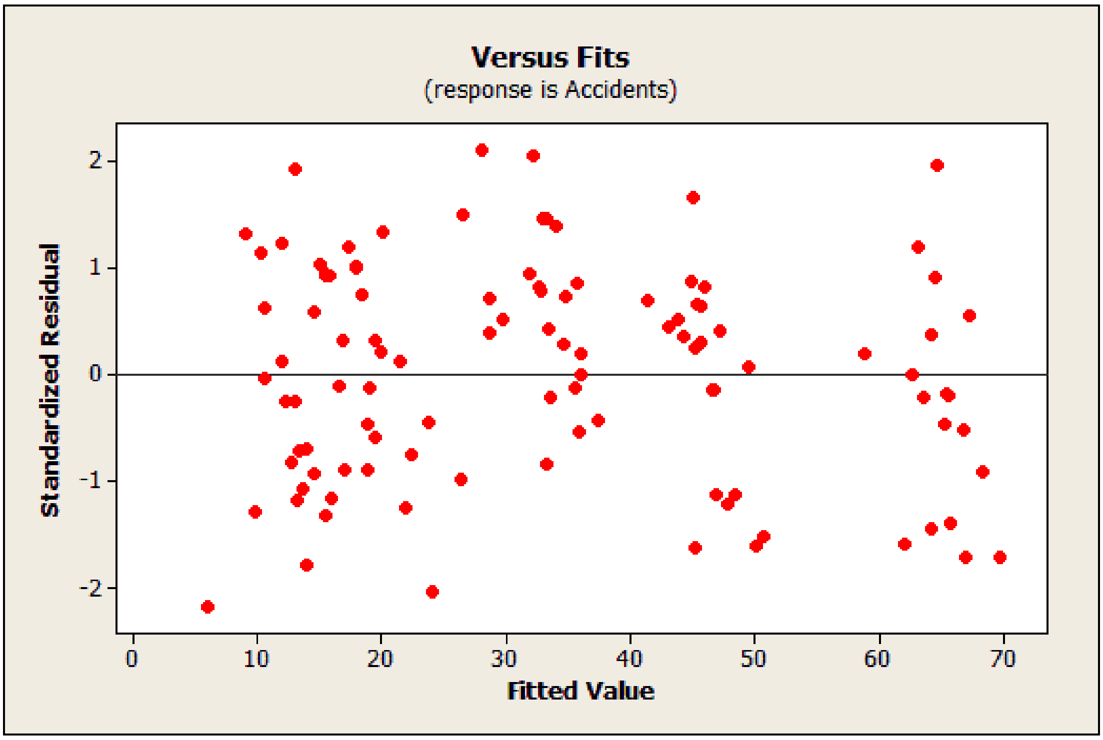

Figure 2.8: Example of Homoscedastic Dispersion

There are two main reasons why homoscedasticity is important. The first involves the regression coefficients' variances. The variances should be as small as possible in order to produce maximum precision. The second reason is the chances that the estimators of the standard errors of the regression coefficients could be wrong. These estimators are computed on the assumption that the disturbance terms are homoscedastic.

Heteroscedasticity can be detected by using different tests which include the Spearman Rank Correlation test, the Goldfield-Quandt test, the Glejser test and the Breusch-Pagan test.

2.7 Transformation

Many statistical analyses are done based on the assumption that the population being investigated is normally distributed with a common variance. In situations where the relevant assumptions are violated, a few options are available:

i. Ignore the violation of the assumptions and continue with the analysis;
ii. Decide on a correct assumption in place of the violated one and proceed with the new assumption taken into account;
iii. Design a new model that retains the important aspects of the original model and satisfies the assumptions;
iv. Select a distribution-free method that can be used even if the assumptions are violated.

Most researchers have opted for the third option which includes applying a transformation to the original data. One of the popular transformation methods is the Box-Cox transformation (Box and Cox, 1964). In ARIMA modelling, if the normality assumption for the residuals is not true, it is usually well satisfied when a Box-Cox transformation is done onto the original observations (Yurekli and Kurunc, 2005).

Although it is widely used, Sakia (1992) found that the Box-Cox transformation seldom fulfills the assumptions of linearity, normality and homoscedasticity simultaneously. This transformation has more practical use in the determination of functional relationships, especially in the field of econometrics.

2.8 Forecasting

Forecasting can be categorized into short-term forecasting and long-term forecasting. Short-term forecasting can predict values that are a few time periods (a few years) into the future. Long-term forecasting on the other hand, can predict values for time periods that extend far beyond that. In terms of applications, long-term forecasts are used for strategic planning while short-term forecasts are used for project developments as well as operation management. Statistical methods are good for short-term forecasting because the historical data normally exhibit inertia and do not show drastic changes (Montgomery et al., 2008). Short-term forecasting is based on identifying, modelling and extrapolating the patterns found in the data.

Box et al. (1994) stated that the use of available observations to forecast future values can provide a basis for:

i. Business and economic planning;
ii. Production planning;
iii. Production and inventory control;
iv. Control and optimization of industrial processes.

It shows a wide range of applications for time series forecasting. In the field of hydrology, which is the field of interest in the present study, there have been a lot of researches and studies done that are related to time series forecasting.

It is essential to specify the accuracy of forecasts. The accuracy is expressed by calculating a set of probability limits on either side of the forecast. The range of this set of limits is also sometimes called the confidence interval or prediction interval. It means that the future observations will be within these limits. Figure 2.9 shows a forecast function with 50 % probability limits.

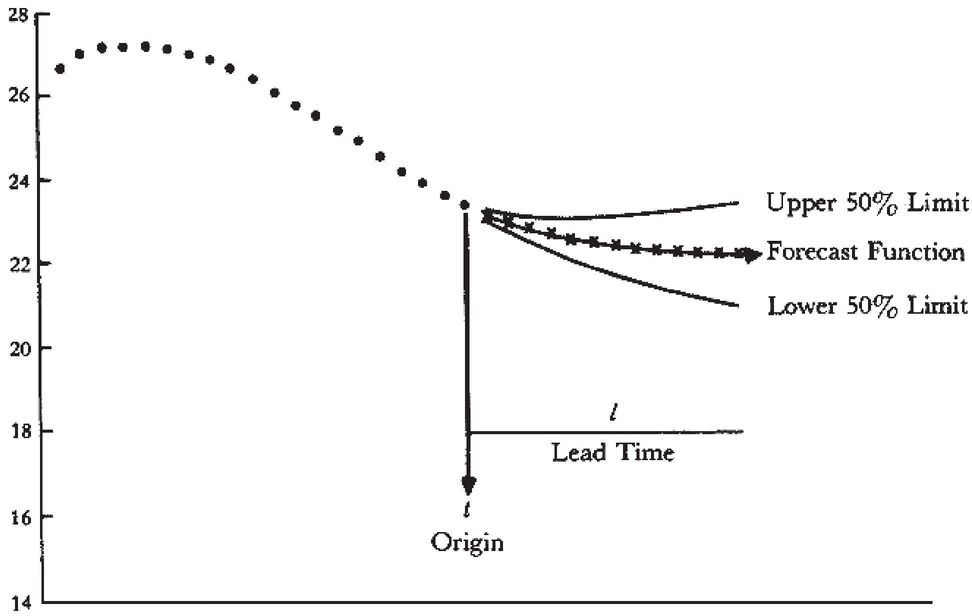

Figure 2.9: Forecast Function at 50 % Probability Limits (Source: Box et al., 1994)

2.9 Summary

There are two main approaches in performing a flood analysis; the rainfall-runoff analysis approach and the flood frequency analysis approach. The first approach uses rainfall statistics and a catchment model to estimate flood. In the second approach, only peak flow data is used to make the estimation. The comparisons between the two approaches had been done by researchers mentioned.

Another method of predicting flood is by using stochastic modelling. A time series has four main components which are the trend component, the periodic component, the catastrophic component, and the random component. Different researchers had come up with different approaches to model a time series and a very popular and widely used systematic approach was done by Box and Jenkins (1976). The comparisons for some of the commonly used stochastic models were also done by many researchers.

It is noteworthy that the outcome of an ARMA/ARIMA/SARIMA model is different from the outcome of a flood frequency analysis. A flood frequency analysis produces a flood frequency curve whereas an ARMA/ARIMA/SARIMA model generates a synthetic series and a forecast series.

The stationarity of a series can be tested by using the ADF test, the KPSS test and the Mann-Kendall trend test. The residuals of an ARIMA model are required to be independent, homoscedastic and normally distributed. Transformations are sometimes required to normalize a series and a widely used transformation method is the Box-Cox transformation.

CHAPTER 3

METHODOLOGY

3.1 Location of Study and Data Acquisition

The river basin under study was the Langat River Basin located in the state of Selangor. The stage readings from four water level stations were collected for analysis. The stations were the Sg. Langat at Dengkil station (ID: 2816441), the Sg. Lui at Kg. Lui station (ID: 3118445), the Sg. Semenyih at Kg. Rinching station (ID: 2918401), and the Sg. Langat at Kajang station (ID: 2917401). Figure 3.1 shows the locations of the stations.

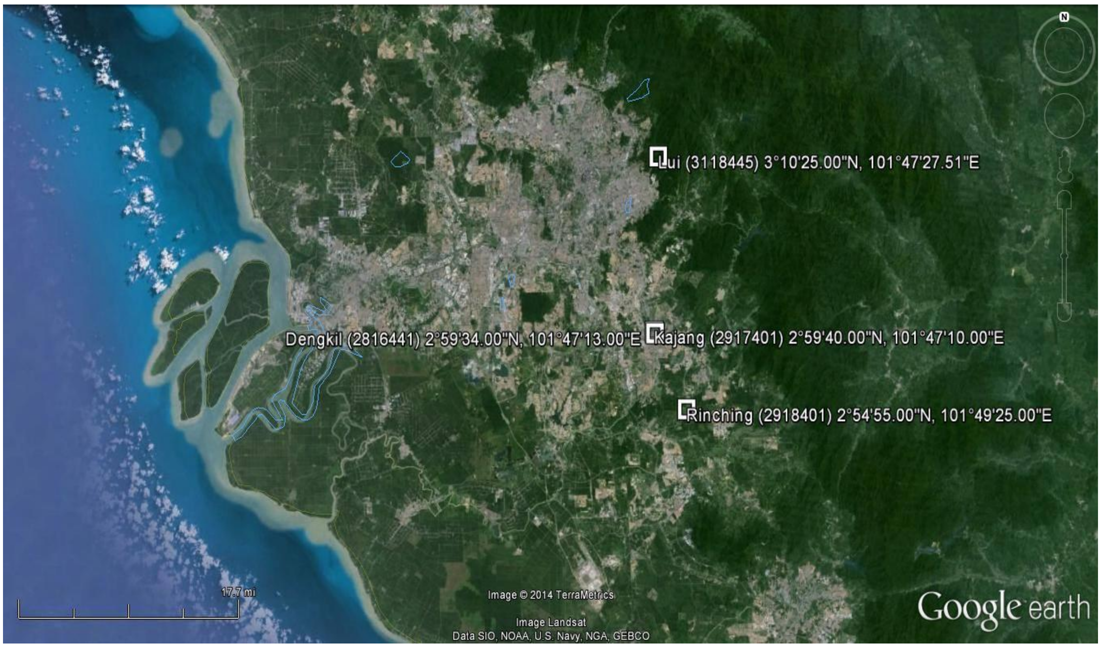

Figure 3.1: Locations of Water Level Stations in Langat Basin

Having obtained the stage readings, they were sorted so that the annual maximum stage for each of the stations could be obtained. The annual maximum stage readings were then subjected to ARIMA modelling, resulting in forecasts of future annual maximum stage readings. The stage readings generated by the ARIMA model were then converted to streamflow readings using rating curves developed for the respective rivers. Therefore, the outputs were stage readings which were interchangeable with streamflow readings. Both stage and streamflow readings are useful and the choice of using which one of them depends on the hydrological application.

3.2 Tools and Instruments

The main tool used for this study was the Microsoft Excel program. The Excel add-on statistical software XLSTAT was also used in addition to basic Microsoft Excel functions.

3.3 ARIMA Modelling of Annual Maximum Stage

The autoregressive integrated moving-average (ARIMA) model is one of the most popular stochastic models used to analyse a time series. It was chosen for this study because it is relatively simple to use and effective. It is made up of three main components; the autoregressive (AR) component, the moving-average (MA) component, and the differencing and integrating component. The properties of the ARIMA model were discussed in details by Salas et al. (1980). In this study, the time series that was subjected to ARIMA modelling was an annual time series.

The general ARIMA (*p*,*d*,*q*) model is

$$U_t = \phi_1 U_{t-1} + \phi_2 U_{t-2} + \ldots + \phi_p U_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \tag{3.1}$$

where

$$U_t = X_t - X_{t-d}$$

(3.2)

ϕ_p = autoregressive parameter

ε_t = residual

θ_q = moving-average parameter

X = dependent variable

U = d-th difference of the dependent variable.

An iterative approach to model building was proposed by Box and Jenkins (1976). It consists of three stages; (i) model identification, (ii) parameter estimation and (iii) model verification. The use of statistical software enables faster parameter calculation. The steps carried out for ARIMA modelling are explained in the following subsections.

3.3.1 Plotting the Series and Its ACF and PACF

The main tools used for identification of model were the visual displays of the series, which included the autocorrelation function (ACF) and the partial correlation function (PACF). Using the annual maximum stage readings as the input time series, the autocovariance function (c_k), the autocorrelation coefficients (r_k) and the partial correlation coefficients ($\phi_k(k)$) were calculated and the series with its ACF and PACF were plotted using XLSTAT. The number of lags *k* should fall between *N*/4 and *N*, therefore the chosen number of lags in this study was sufficient.

$$c_k = \frac{1}{N}\sum_{t=1}^{N-k}(x_t - \bar{x})\,(x_{t+k} - \bar{x}), \qquad 0 \le k \le N$$

(3.3)

$$r_k = \frac{c_k}{c_0} = \frac{\sum_{t=1}^{N-k}(x_t - \bar{x})\,(x_{t+k} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2}$$

(3.4)

$$\hat{\phi}_{k+1}(k+1) = \left[r_{k+1} - \sum_{j=1}^{k} \hat{\phi}_k(j) r_{k+1-j}\right] / \left[1 - \sum_{j=1}^{k} \hat{\phi}_k(j) r_j\right]$$

(3.5a)

$$\hat{\phi}_{k+1}(j) = \hat{\phi}_k(j) - \hat{\phi}_{k+1}(k+1)\hat{\phi}_k(k-j+1)$$

(3.5b)

The ACF and PACF were then analysed to determine behaviour and stationarity of the series. If all the ACF and PACF values are insignificant and fall within the confidence band, it indicates that the observations are independent. In such a case the time series is a white noise process and no modelling could be performed.

A stationary time series has a rapidly decaying ACF. If the ACF is slow decaying, it indicates that the series may be non-stationary and requires differencing. Further tests should be carried out to confirm the non-stationarity.

3.3.2 Stationarity Tests

Unit root tests such as the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test were carried out to test the presence of a unit root while the Mann-Kendall trend test was performed to check for the presence of a trend. The presence of a unit root or a trend should indicate non-stationarity of the series. The significance level used was 5 %.

If the series is non-stationary, differencing is required to transform it into a stationary series. On the other hand, if the series is stationary, the series is modelled as an ARMA process instead, which requires no differencing.

3.3.3 Differencing

Differencing is normally done onto non-stationary series to make it stationary. If the series is originally stationary, this step is skipped. In an ARIMA model, the order of differencing (*d*) is determined by trial and error.

The series was initially differenced once (d = 1) and the ACF and PACF of the differenced series were plotted and analysed. If the ACF and PACF decay rapidly then it indicates stationarity is achieved. Another indicator is the standard deviation of the differenced series. The optimum differenced series should have the lowest standard deviation.

The differenced series was then differenced again (d = 2) to check for underdifferencing or overdifferencing. Similarly, the ACF and PACF were plotted and analysed. The lag 1 ACF and PACF of an overdifferenced series will be lower than negative 0.5. If the standard deviation of the current series is lower than that of the previous series, then the current series has the optimum order of differencing.

It is noteworthy that some researchers argue that the effect of overdifferencing is much less serious than the effect of underdifferencing.

3.3.4 Identifying *p* and *q*

Having identified the optimum order of differencing (*d*), the next step was to identify the order of the autoregressive and moving-average parameters. The ACF (symbolized as ρ_k) and the PACF for the optimum differenced series were analysed to determine the *p* and *q* of the ARIMA model. Table 3.1 shows the identification properties of AR, MA and ARMA processes.

Table 3.1: Identification Properties of AR, MA and ARMA Processes

Process	Autocorrelation	Partial Autocorrelations
AR(*p*)	Infinite in extent. Consists of damped waves. Attenuates as $\rho_k = \sum_{j=1}^{p} \phi_j \rho_{k-j}$ (3.6)	Finite in extent. Peaks at lags 1 through *p* and then cuts off.
MA(*q*)	Finite in extent. Peaks at lags 1 through *q* and then cuts off.	Infinite in extent. Consists of damped waves.
ARMA(*p*,*q*)	Infinite in extent. First *q*-*p* lags: irregular then damped waves. Attenuates as $\rho_k = \sum_{i=1}^{p} \phi_i \rho_{k-i}$ $(k \geq q + 1)$ (3.7)	Infinite in extent. First *p*-*q* lags: irregular then damped waves.

3.3.5 Choosing the Best ARIMA Model

The previous step gave an indication of the order of *p* and *q* that should be fitted in the model. However, it was recommended to try a few different values of *p* and *q* to get the best model while preserving the parsimony of the parameters. To test for the parsimony of parameters, the corrected Akaike Information Criteria (AICC) was used. The model with the minimum AICC was selected as the best model.

The XLSTAT software can find the best model based on the AICC values calculated for a range of p and q. In this study the maximum p selected was 3 and the maximum q selected was also 3. The model with the minimum AICC was then subjected to diagnostic checks.

According to Salas et al. (1980), there are three levels of parameter estimation. The parameters can be estimated with increasing accuracy by: a preliminary estimate, a likelihood method and a nonlinear estimation. XLSTAT only estimated the parameters in the first and second level. Preliminary estimation was done by applying Yule-Walker equations. The Yule-Walker equations can be used to estimate the autoregressive parameters ($\hat{\phi}$) and the moving-average parameter ($\hat{\theta}$). The maximum likelihood estimates were more efficient estimates that took into account all the information stored in the data.

3.3.6 Diagnostic Checks

After the best initial model was determined, the next step was running the diagnostic checks. Its purpose was to verify the proposed model's validity. Before any checking was done onto the residuals, the values of the estimated ARIMA parameters first had to be in an interval computed using the Hessian standard errors. If the values are out of that interval, then they are not significant and the ARIMA model should not be used.

The first checking on the residuals was to test for independence. In this approach, the consideration was that the observed data was transformed into a series of purely independent residuals through the modelling of time series. The independence of residuals can be determined by inspecting its ACF and PACF plot. If the residuals autocorrelation function (RACF) and residuals partial autocorrelation function (RPACF) are not significant, which means none of their values exceed the significance interval, then the residuals are independent. The value of residual at any lag will not affect the value of residual at the next lag.

The next criterion that required checking was residuals homoscedasticity. Homoscedasticity means having a stable set of variances and an ARIMA model should have homoscedastic residuals. This particular criterion was tested using the Breusch-Pagan test. The significance level used was 5 %.

The third checking was done to determine whether the residuals' distributions were approximately normal. The residuals had to be approximately normal in order to produce a good forecast confidence interval. Strictly normal distribution was not necessary as long as the residuals were approximately normal. The normality of the residuals was tested using normality tests, namely the Jarque-Bera test, the Shapiro-Wilk test and the Anderson-Darling test. Visual inspection was also done on the Q-Q plot and histograms of the residuals.

In order for the chosen model to be accepted, the residuals had to be independent, homoscedastic, and approximately normally distributed. If the chosen model fails any of the three criteria then it will be rejected and the next model with the least AICC will be applied and checked.

3.3.7 Series Comparison and Forecasting

The best model that passed the diagnostic checking will then have its synthetic series compared to the original data series. This determined the degree of resemblance between the synthetic series and the original data series. If the pattern of the synthetic series appears similar to the pattern of the original series, then the fitted model is a good model.

The final step was to generate a forecast of future values. The ARIMA model can predict future values as well as its confidence interval using the calculated model parameters. In this study the chosen number of forecasted values was eight, which means that the values were forecasted for the next eight years after the last observation.

3.4 Summarized Steps to Flood Modelling Using ARIMA

Flood modelling began with data collection in the form of stage readings. The readings were sorted to produce a series of annual maximum stage readings for the ARIMA modelling procedure. After the ARIMA procedure, the results were forecasted stage readings which can then be converted into streamflow readings by using the rating curves provided by the Department of Irrigation and Drainage (DID) Malaysia. The summarized steps are shown in Figure 3.2.

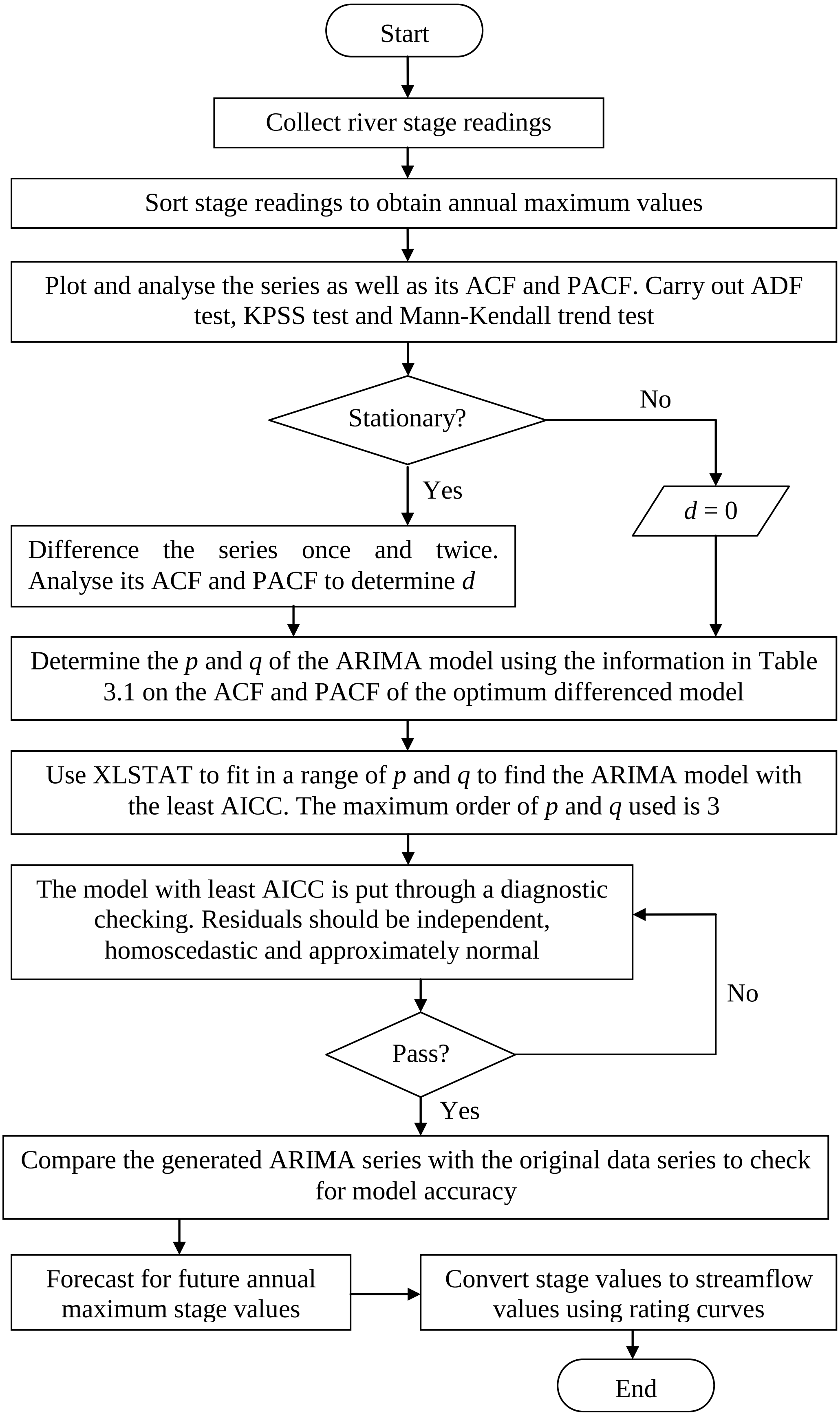

Figure 3.2: Flowchart of Flood Modelling Using ARIMA

3.5 Summary

In summary, the raw data obtained from the four water level stations was in the form of historical stage records. They were sorted to produce four series of annual maximum stage readings which were then modelled using ARIMA models. The outputs from the ARIMA models were the generated synthetic series as well as the forecasted series of annual maximum stage readings. These stage values can then be converted to streamflow values by using the rivers' rating curves.

The main tool used in this study was Microsoft Excel spreadsheet program. A statistical computing program called XLSTAT was also studied and used as an add-on to Microsoft Excel.

The steps in ARIMA modelling included analyzing the series' ACF and PACF, carrying out stationarity tests, differencing the series, running the XLSTAT software to find the best model, diagnostic checking, comparing generated series with original series, and forecasting.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Data Collected

The stage readings collected from the four stations and their graphical forms are presented in Table 4.1 and Figure 4.1 respectively.

Table 4.1: Annual Maximum Stage Values in Meter

Year	Dengkil	Kg. Lui	Kg. Rinching	Kajang
1960	7.50			
1961	7.67			
1962	7.83			
1963	7.81			
1964	7.34			
1965	7.57	76.38		
1966	7.56	75.92		
1967	7.66	76.34		
1968	7.20	75.73		
1969	7.19	76.41		
1970	5.87	75.65		
1971	6.19	77.36		
1972	5.89	77.46		
1973	6.70	77.30		
1974	5.46	77.80		
1975	5.64	77.45	23.54	
1976	5.25	77.26	23.62	23.33
1977	4.59	78.20	23.33	24.58
1978	4.36	77.66	23.16	24.18
1979	4.90	77.25	23.02	24.04
1980	5.16	77.48	23.31	24.26
1981	4.91	77.77	22.90	24.38

1982	5.97	77.53	23.44	26.52
1983	5.38	77.72	23.06	24.43
1984	6.18	77.76	23.72	24.74
1985	5.93	77.78	23.26	25.30
1986	5.74	77.85	22.95	24.04
1987	5.95	77.91	23.69	24.14
1988	5.71	77.72	23.16	24.77
1989	6.29	78.24	24.12	24.40
1990	5.35	77.41	23.21	23.87
1991	7.62	77.70	23.04	24.95
1992	9.30	77.44	23.34	25.63
1993	6.65	78.25	23.37	25.39
1994	7.30	77.55	22.69	25.09
1995	8.26	77.64	22.53	25.30
1996	6.28	77.57	22.55	24.86
1997	6.29	77.34	22.67	24.87
1998	5.46	77.25	22.60	23.60
1999	5.17	77.54	21.89	23.90
2000	5.67	77.57	22.81	24.57
2001	5.09	77.47	22.49	23.8
2002	5.95	77.56	22.52	24.24
2003	6.28	77.61	22.60	23.57
2004	8.09	77.79	21.95	24.53
2005	5.77	76.79	21.78	23.48
2006	6.58	77.40	21.47	25.28
2007	5.98	77.10	21.96	25.18
2008	6.53	77.25	22.47	24.54
2009	6.52	77.47	22.49	26.59
2010	6.40	77.22	21.53	23.72
2011	6.51	77.58	21.85	25.00
2012	6.84	77.96	22.25	25.42
2013	6.11	78.46	21.83	24.31

The Dengkil station had the longest historical record of stage readings, followed by the Kg. Lui station, the Kg. Rinching station and lastly the Kajang station. Most time series reference materials recommended that the number of observations should at least be fifty but in real hydrological modelling the historical record may be short and in this study only the Dengkil series exceeded fifty observations. Nonetheless, modelling can still be done even if the number of observations was less than fifty.

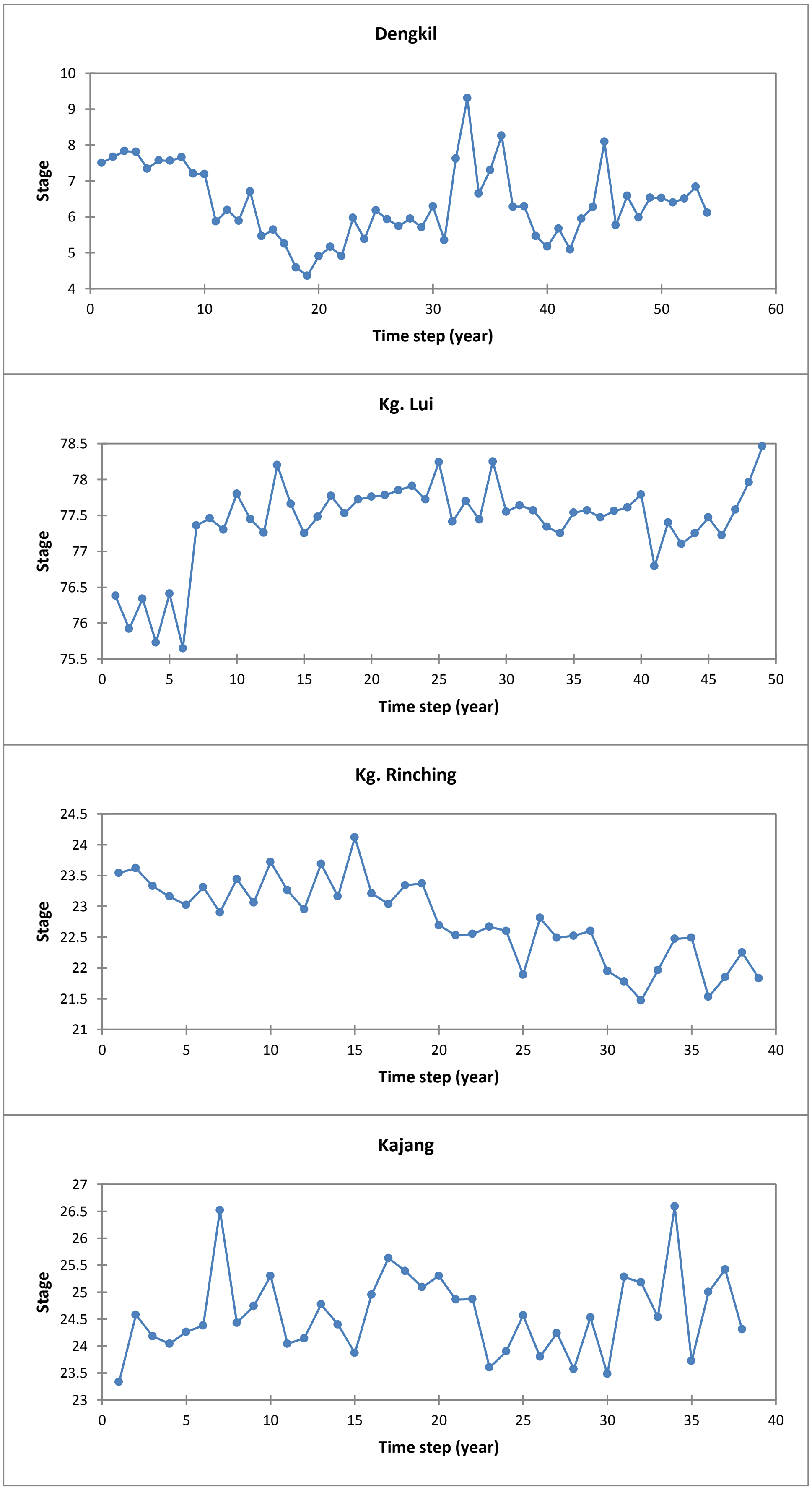

Figure 4.1: Annual Maximum Stage Readings

From the graphical representation of the series, there was a lack of seasonality in the data. This was not surprising because the data used was the annual maximum stage readings, which more often than not, do not have seasonality. Therefore, modelling was simpler since seasonal effects were absent.

4.2 ACF and PACF Plots

The ACF and PACF for the four series are presented in Figure 4.2, Figure 4.3, Figure 4.4 and Figure 4.5.

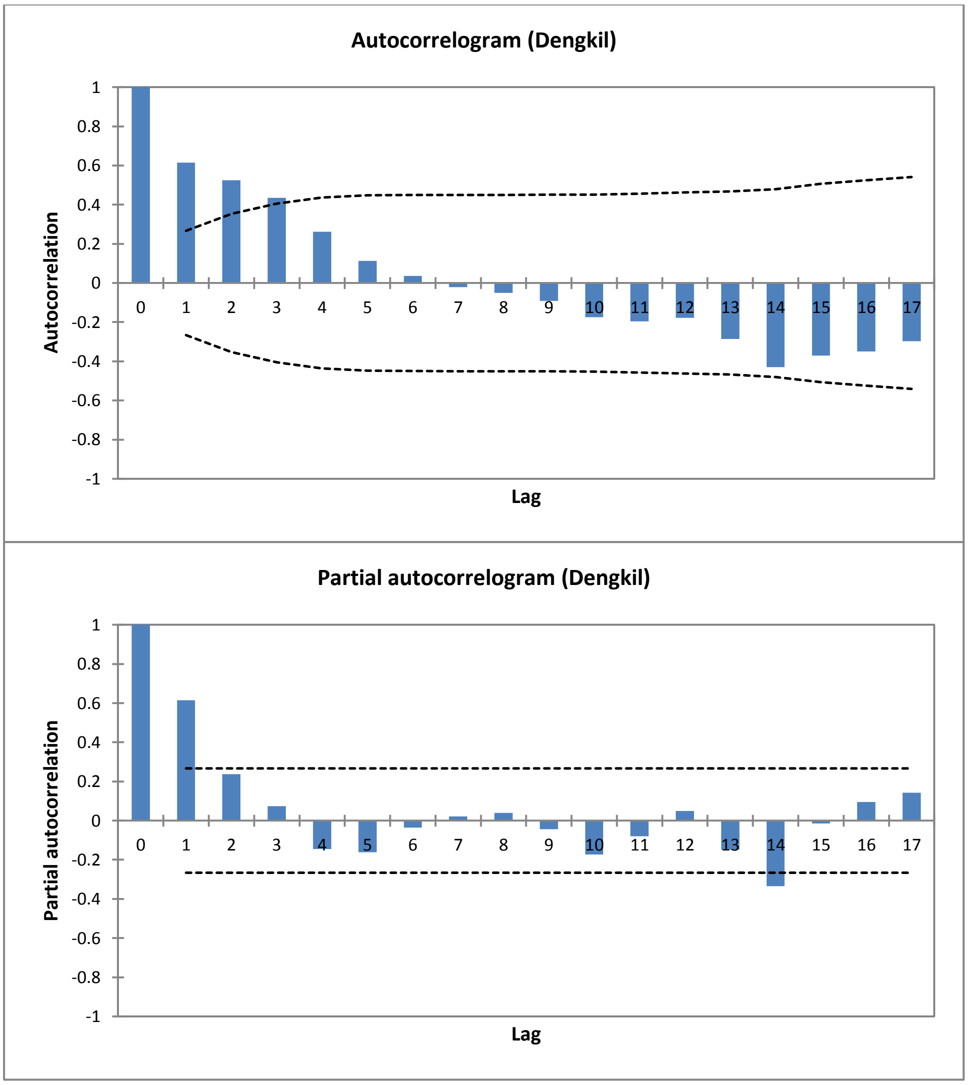

Figure 4.2: ACF and PACF of Dengkil Series

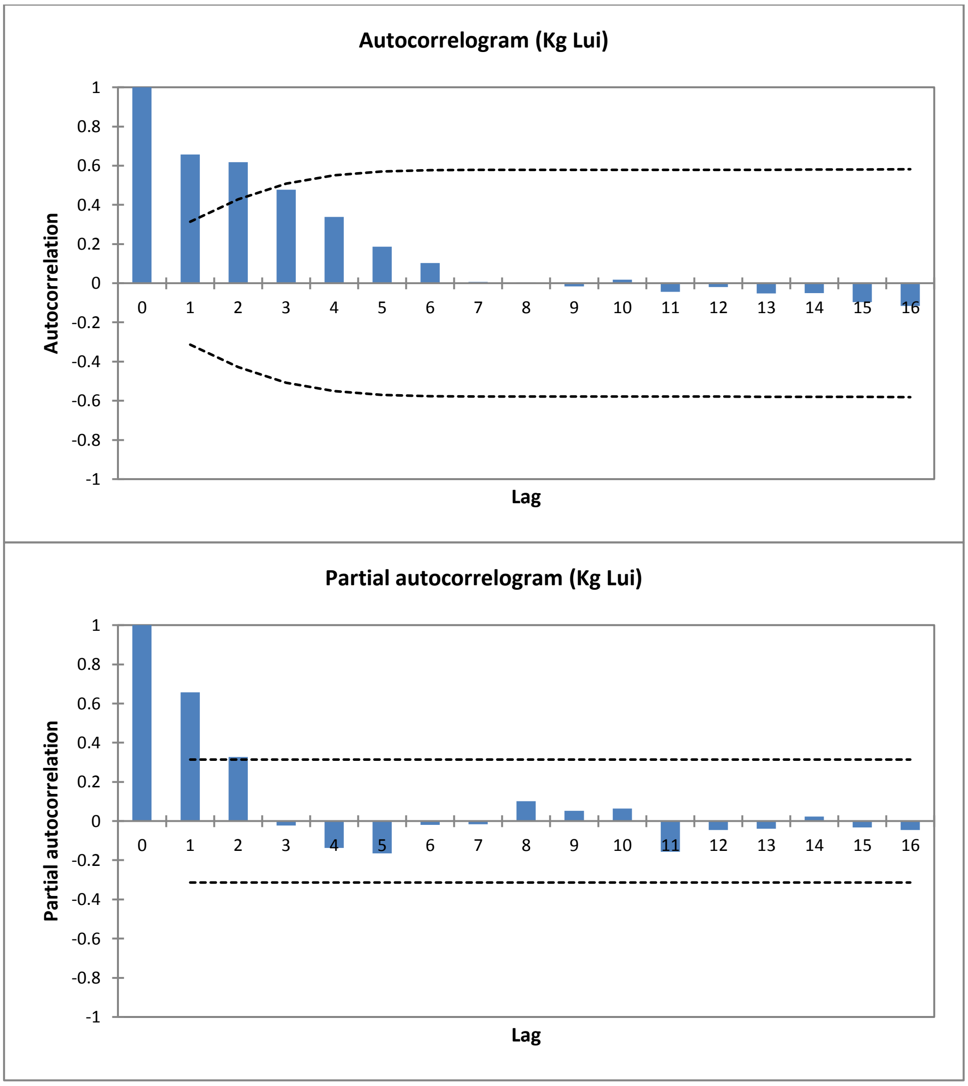

Figure 4.3: ACF and PACF of Kg. Lui Series

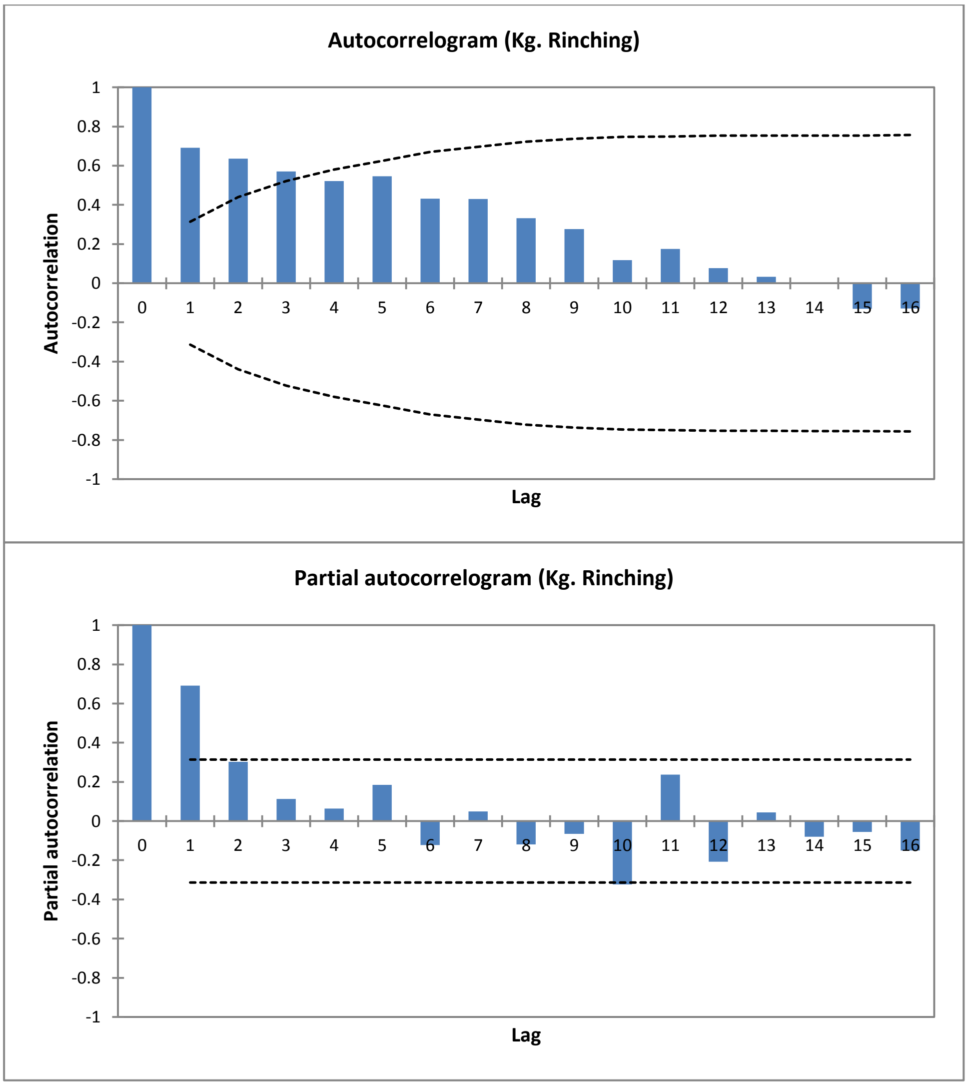

Figure 4.4: ACF and PACF of Kg. Rinching Series

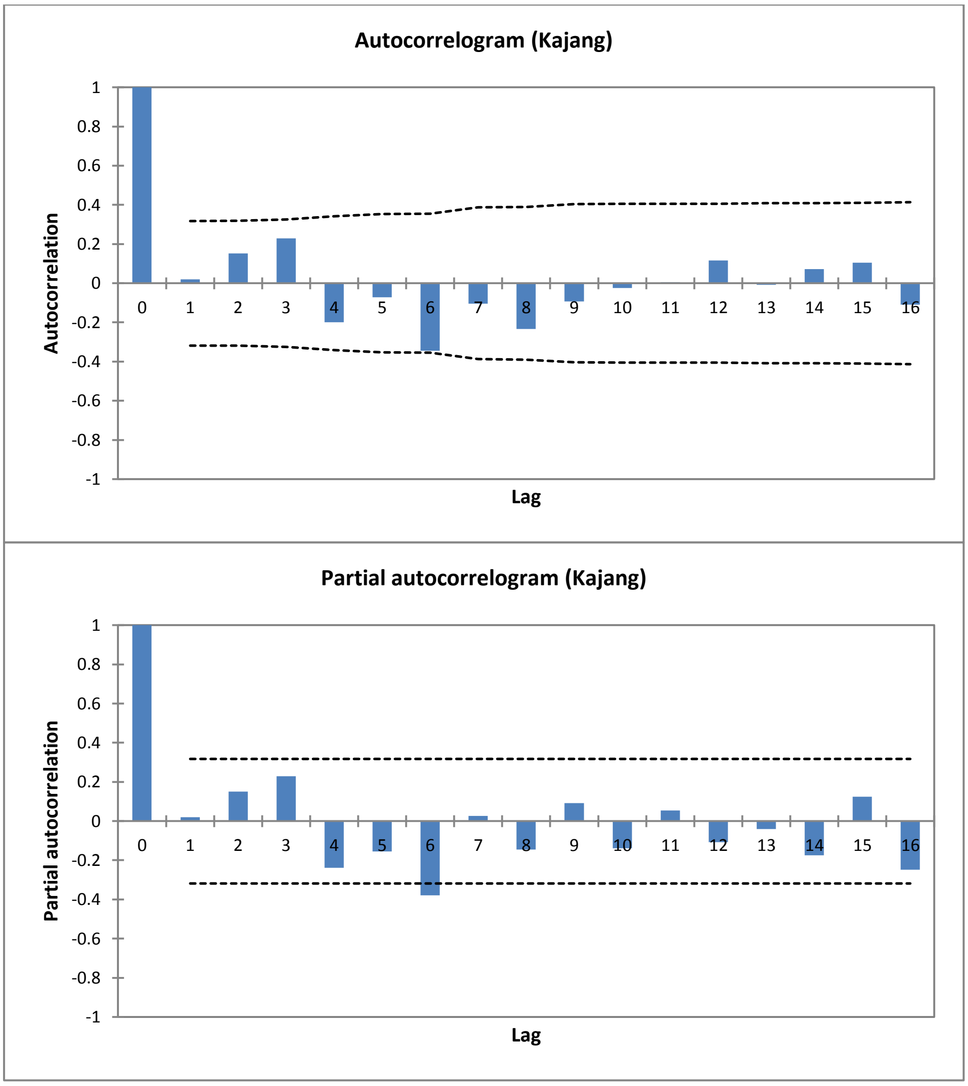

Figure 4.5: ACF and PACF of Kajang Series

The ACF plots for the Dengkil series, the Kg. Lui series and the Kg.Rinching series exhibited slow decay, indicating the possibility of non-stationarity. The ACF plot for the Kajang series indicated that the series may be white noise because its values were not significant. Further white noise tests (Box-Pierce test and Ljung-Box test) were applied to the Kajang series and they showed that the series was indeed a white noise series. Table 4.2 shows the results of the white noise tests. Therefore, no further modelling was done onto the Kajang series.

Table 4.2: Results of White Noise Tests

Test	Value	p-value	Remarks
Box-Pierce	12.477	0.408	White noise
Ljung-Box	15.525	0.214	White noise
McLeod-Li	15.445	0.218	White noise

4.3 Stationarity Tests

Stationarity tests were carried out for the remaining three series to confirm the initial presumption that they were non-stationary. The results for the ADF test, KPSS test and Mann-Kendall trend test are presented in Table 4.3.

Table 4.3: Results of Stationarity Tests

Station	ADF test	KPSS test	Mann-Kendall trend test	Remarks
	p-value	p-value	p-value	
Dengkil	0.350	0.001	0.438	Non-stationary
Kg. Lui	0.138	0.005	0.072	Non-stationary
Kg. Rinching	0.411	0.030	<0.0001	Non-stationary

The tests confirmed that all the data series were non-stationary. The Augmented Dickey-Fuller test and the KPSS test showed that all three series had unit roots. The Mann-Kendall test also detected a trend in the Kg. Rinching series. A series that has either a unit root or a trend was considered as non-stationary and therefore required differencing.

The ADF test and the KPSS test are actually similar in the sense that both of them are used to test for unit roots. The difference is that the null hypothesis and alternative hypothesis for both tests are inverted. The ADF has the following hypotheses:

H_0 = The series is non-stationary (presence of unit root);
H_1 = The series is stationary.

The KPSS test, on the other hand, has the following hypotheses:

H_0 = The series is stationary;
H_1 = The series is non-stationary (presence of unit root).

The KPSS test is commonly used to confirm the results of the ADF test or vice versa. Since both tests showed the same outcomes, the stationarity results were convincing.

Now that the series were known to be non-stationary, a simple ARMA model may not be sufficiently good enough to model those series. Instead, an ARIMA model was used. Thus, the optimum order of differencing, *d* had to be determined first.

4.4 Differencing the Series

The series were differenced once and twice to obtain the optimum *d*. The ACF and PACF of the differenced series are shown in Figure 4.6, Figure 4.7 and Figure 4.8 while the standard deviations of the original and differenced series are shown in Table 4.4.

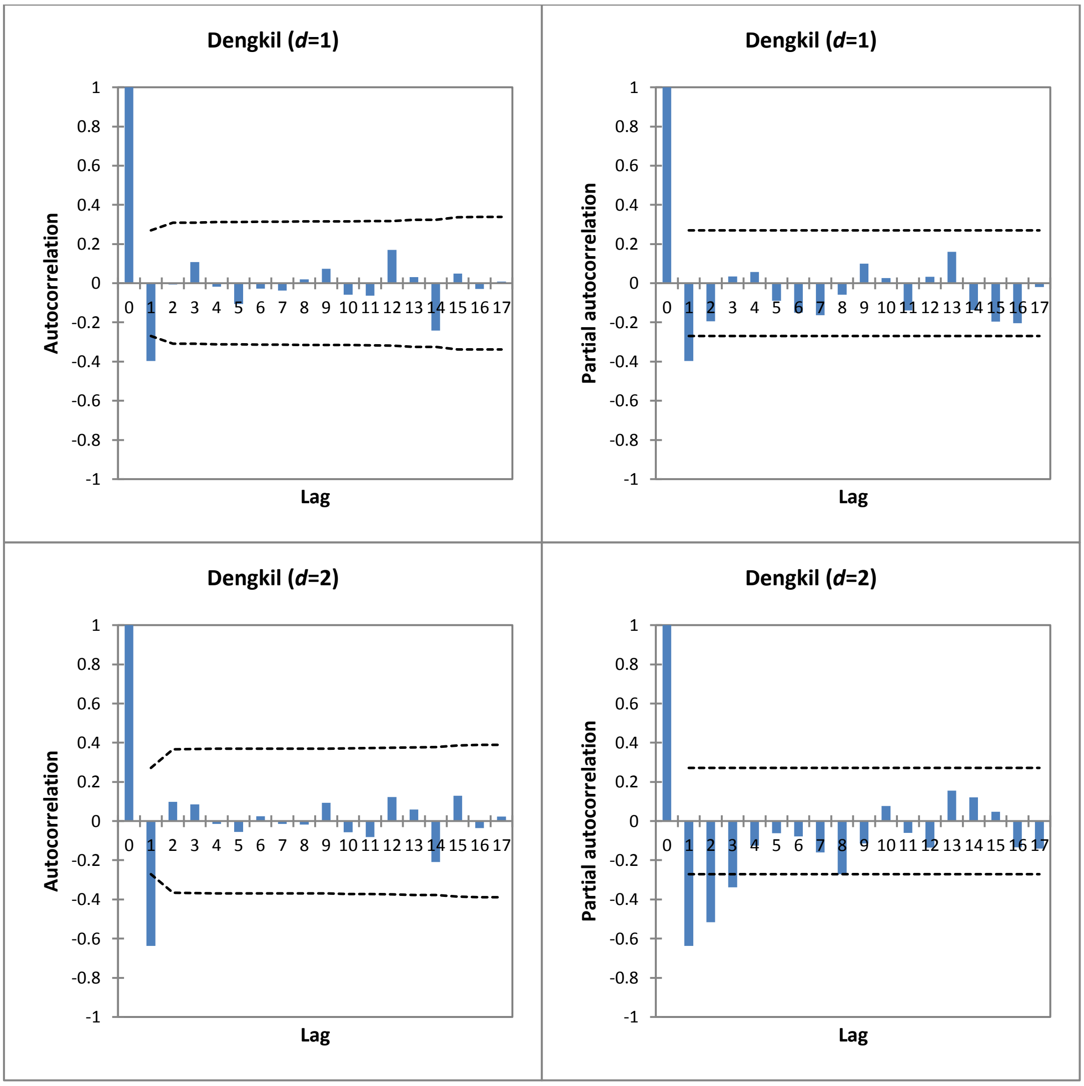

Figure 4.6: ACF and PACF of Differenced Dengkil Series

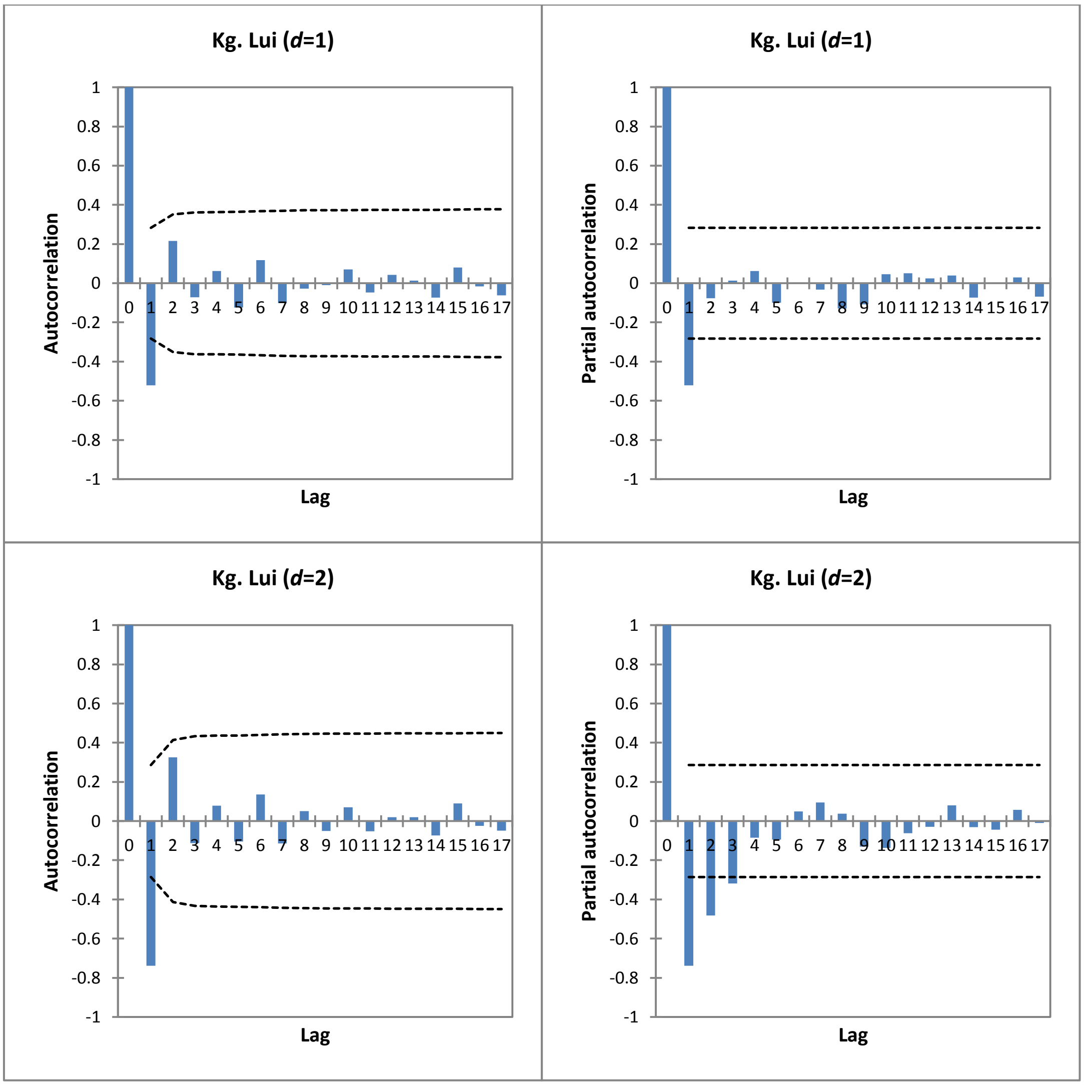

Figure 4.7: ACF and PACF of Differenced Kg. Lui Series

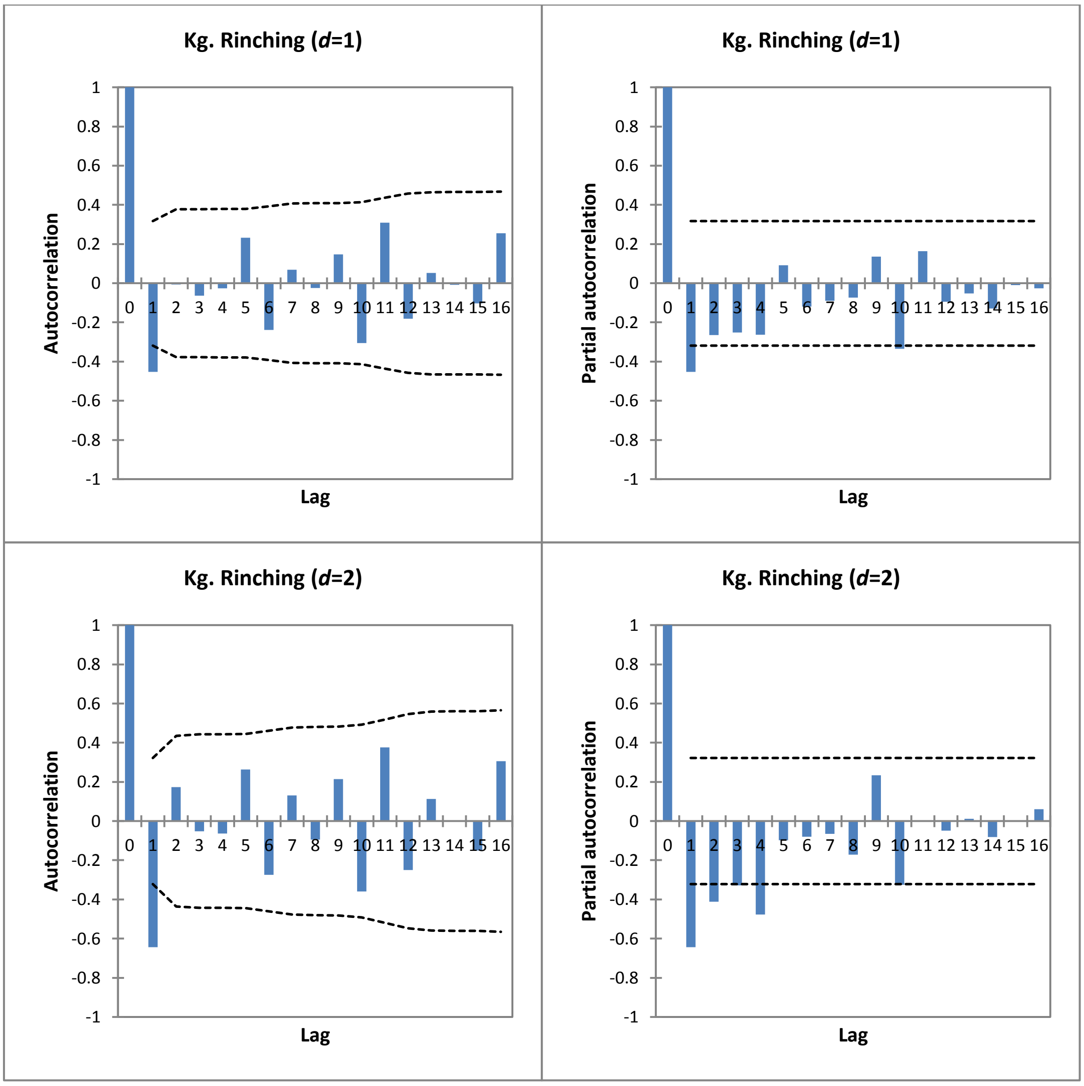

Figure 4.8: ACF and PACF of Differenced Kg. Rinching Series

Table 4.4: Standard Deviations of Original Series and Differenced Series

Order, *d*	Dengkil	Kg. Lui	Kg. Rinching
0	1.035	0.597	0.658
1	0.903	0.490	0.481
2	1.521	0.858	0.829

The ACF and PACF of the once differenced (d = 1) series decayed rapidly compared to the ACF and PACF of the original series. Comparing the standard deviations of the series, the minimum standard deviations were obtained from the series with d = 1. The results also showed that the first lags of the twice differenced

(d = 2) series were lower than -0.5, indicating overdifferencing. Therefore, the optimum level of differencing for the three series was one and the d value used in the ARIMA model would be one.

The ACF and PACF of the series with d = 1 were then analysed using Table 3.1. The PACF of each series was significant at lag 1, indicating the presence of a first order autoregressive (AR) component. The ACF of each series was also significant at lag 1 so a moving-average (MA) component may be present. Therefore, the ARIMA models that seem reasonable to be tested were (1,1,0) and (1,1,1). However, with the computing capabilities of the XLSTAT software, the orders of p and q were tested up to three.

4.5 ARIMA Modelling and Diagnostic Checking

XLSTAT was used to compute the AICC for ARIMA models with p starting from one to three and q starting from zero to three. The models tested were (1,1,0), (1,1,1), (1,1,2), (1,1,3), (2,1,0), (2,1,1), (2,1,2), (2,1,3), (3,1,0), (3,1,1), (3,1,2) and (3,1,3). For each station, the model having the minimum AICC was chosen as the best model. The best models along with their estimated parameter values are tabulated in Table 4.5.

Table 4.5: Best ARIMA Models

	Dengkil	**Kg. Lui**	**Kg. Rinching**
Best model	(1,1,0)	(1,1,0)	(1,1,1)
AICC	133.736	55.348	42.292
MSE	0.672	0.169	0.137
AR(1)	-0.395	-0.532	0.241
MA(1)	-	-	-1.000
Constant	-0.023	0.044	-0.047

The results showed that the preliminary models determined from the ACF and PACF of the differenced series were indeed the best models. The Hessian standard errors were calculated and all the estimated parameters successfully fell within the significance interval. The RACF and RPACF for the best ARIMA models were plotted and shown in Figure 4.9, Figure 4.10 and Figure 4.11.

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The RACF and RPACF for all the three series fell within the confidence interval. They were not significant and this showed that the residuals were independent, therefore satisfying the first residual criterion. The next requirement was residuals' homoscedasticity and Table 4.6 shows the results of Breusch-Pagan test. Figure 4.12 shows the distribution of the standardized residuals.

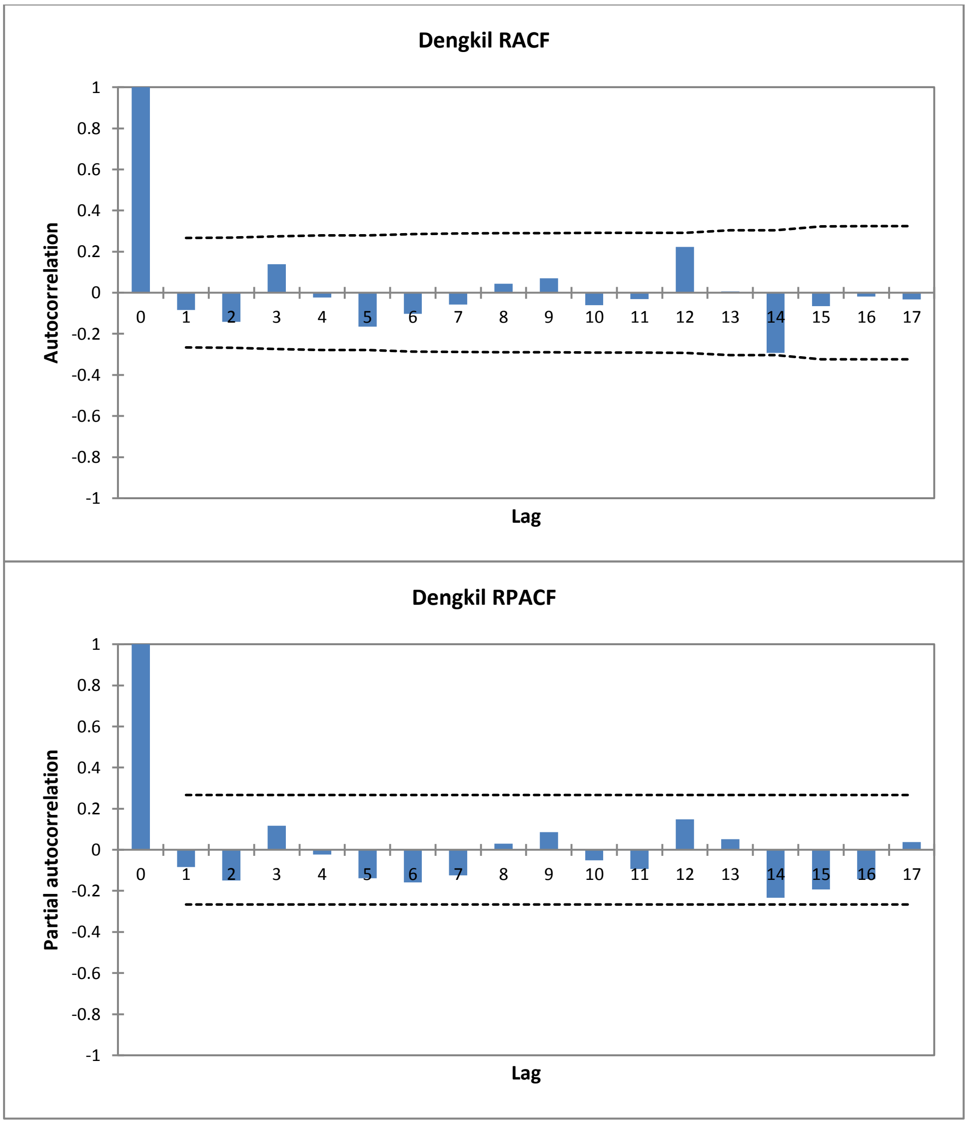

Figure 4.9: RACF and RPACF of Dengkil Model

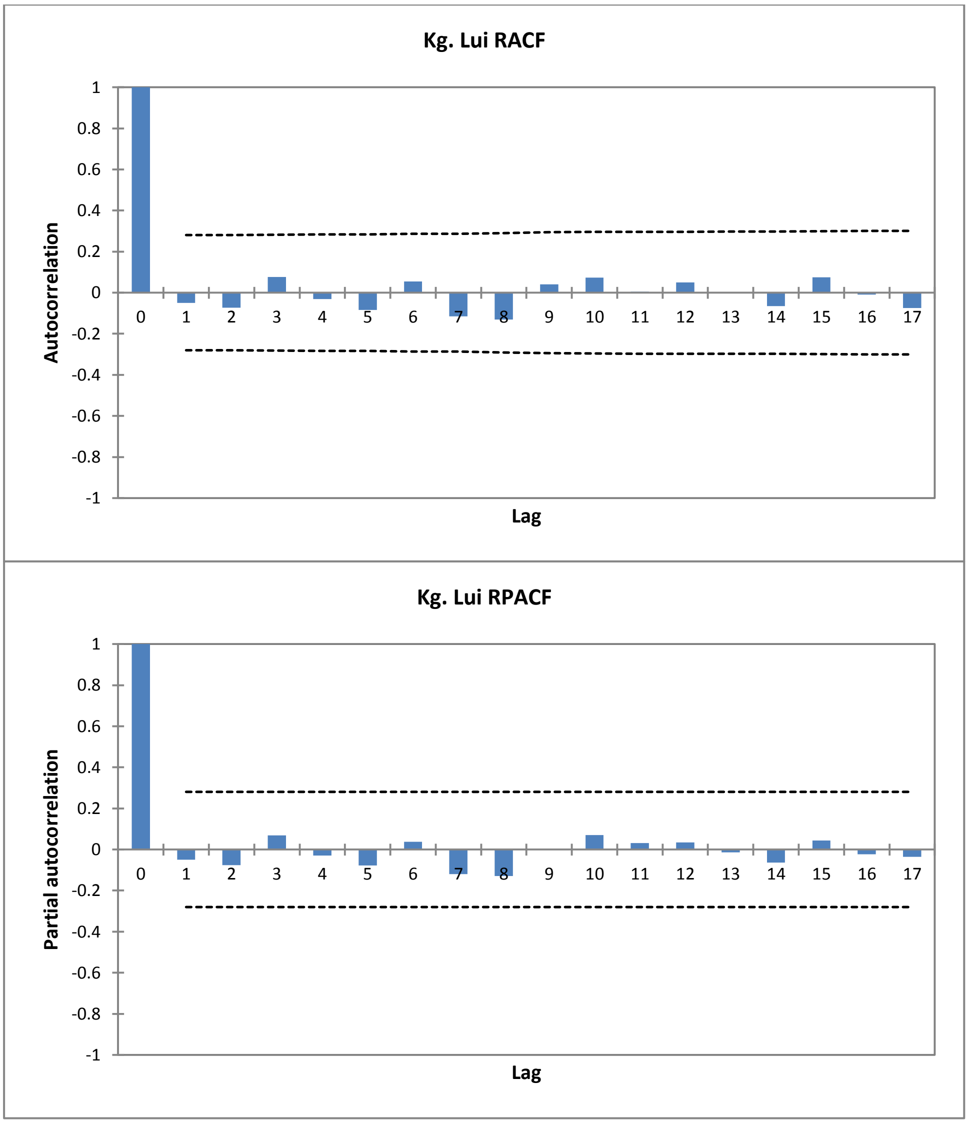

Figure 4.10: RACF and RPACF of Kg. Lui Model

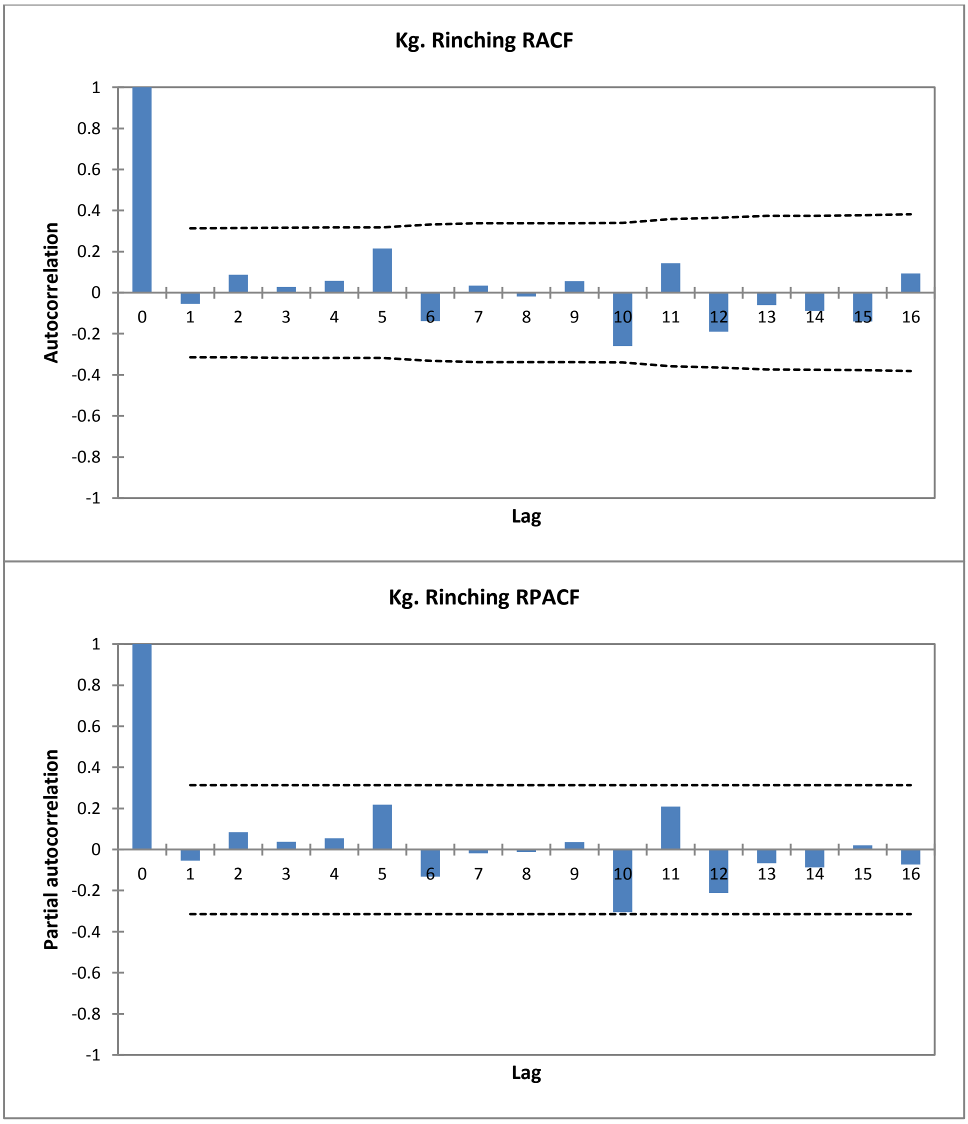

Figure 4.11: RACF and RPACF of Kg. Rinching Model

Table 4.6: Results of Breusch-Pagan Test

Station	p-value	Remarks
Dengkil	0.145	Homoscedastic
Kg. Lui	0.195	Homoscedastic
Kg. Rinching	0.747	Homoscedastic

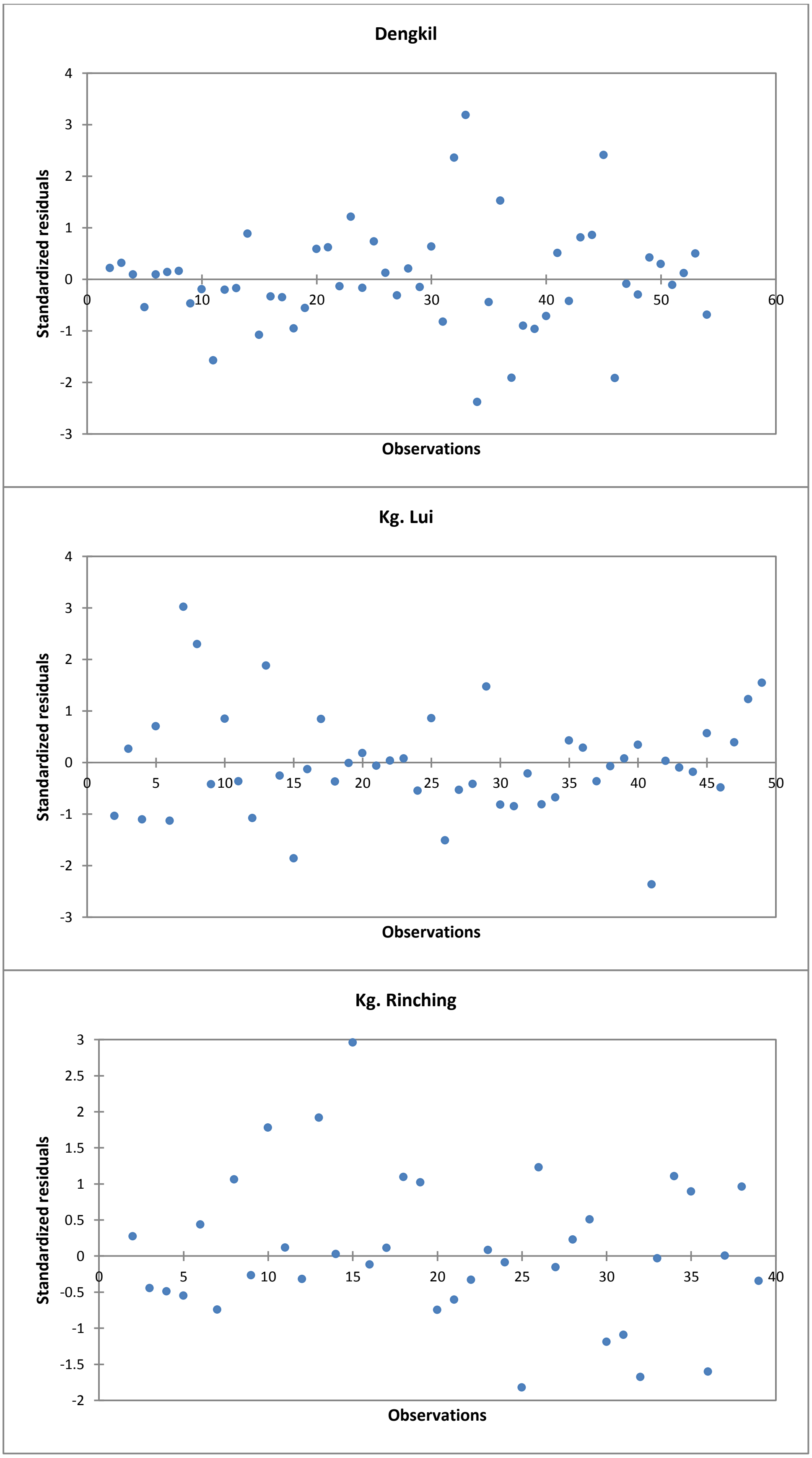

Figure 4.12: Distribution of Standardized Residuals

The residuals were homoscedastic which meant that they had constant variances. It was important for the residuals to be homoscedastic because it determined whether the model's ability to predict variable values was consistent. A model with heteroscedastic residuals cannot give results that are trustworthy and transformation of the data is required (Yurekli and Kurunc, 2005). The most commonly used transformation method is the Box-Cox transformation. Although primarily used to normalize a series, it may also be used onto the raw data before modelling in order to obtain homoscedastic residuals. However, Sakia (1992) argued that the Box-Cox transformation seldom fulfils the assumptions of linearity, homoscedasticity and normality simultaneously. In short, it may not be useful in obtaining homoscedastic residuals. Since the results showed homoscedastic residuals for the three models, no transformation was required.

The third criterion for diagnostic checking was the distribution of the residuals. The residuals were subjected to normality tests and histograms were also plotted to give a visual representation of their distributions. The results of normality tests are presented in Table 4.7 while the histograms are shown in Figure 4.13. The significance level used was 5 % and the test results that gave p-values higher than 0.05 indicated normality.

Table 4.7: Results of Normality Tests

Station	Shapiro-Wilk test	Anderson-Darling test	Jarque-Bera test
	p-value	p-value	p-value
Dengkil	0.017	0.012	0.007
Kg. Lui	0.140	0.066	0.064
Kg. Rinching	0.315	0.223	0.331

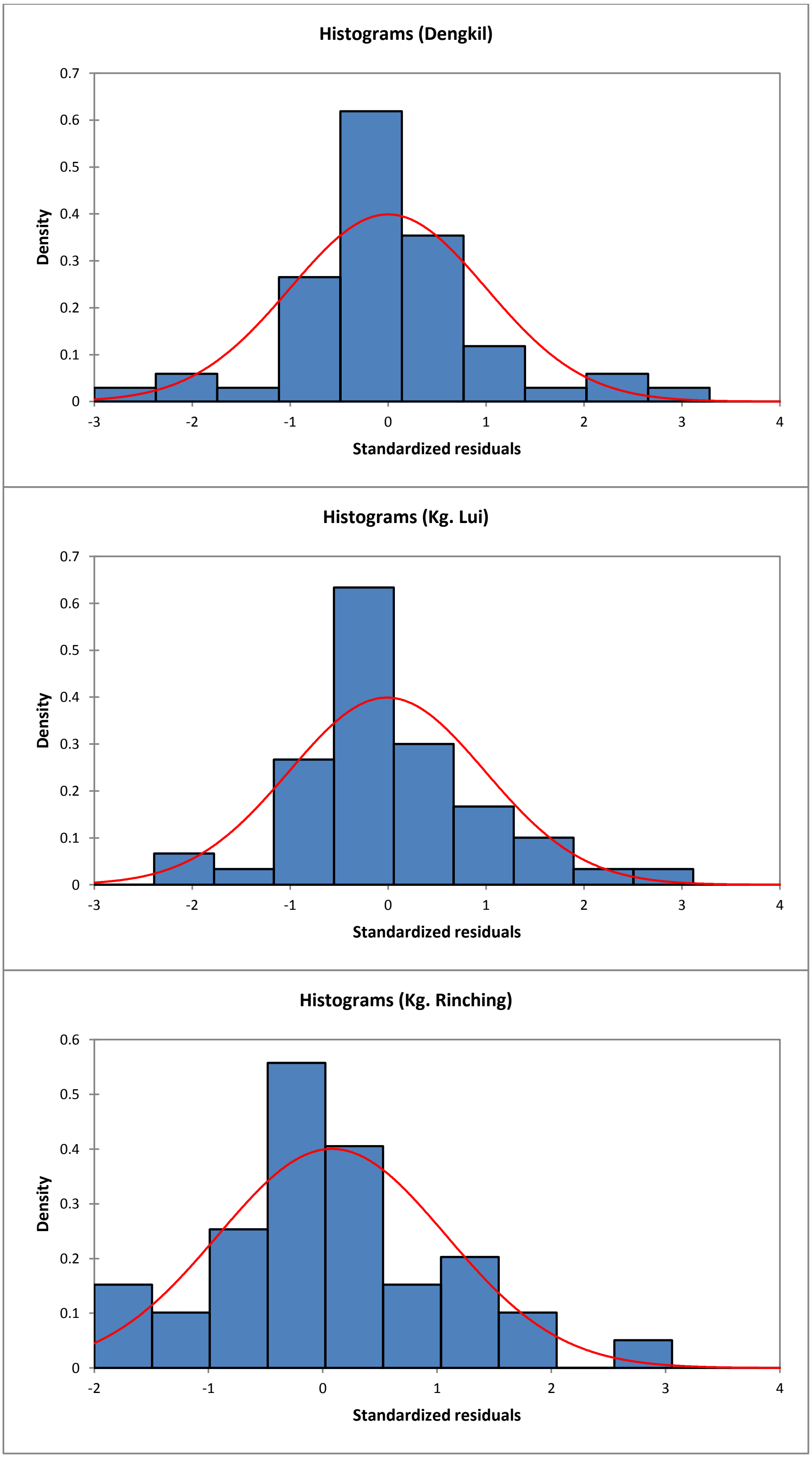

Figure 4.13: Histograms of Residuals

Both the normality tests and histograms showed that the Kg. Lui series and the Kg. Rinching series had normally distributed residuals. The Dengkil series however, failed the normality tests but its histograms showed that it was very close to a normal distribution, which was good enough. The normality of residuals' distribution was important to produce a satisfactory confidence interval for the forecast. Improving the normality can improve the trustworthiness of the confidence interval but it has little effect on the parameter estimates of the model (Osbourne, 2013). Again, the Box-Cox transformation can be applied to obtain normally distributed residuals but it was not done in this study because it was not really necessary to normalize the residuals which were already close to normality.

Therefore, all three series generated by the ARIMA model passed the diagnostic checking stage. The estimated parameters were significant and the models had independent, homoscedastic and approximately normally distributed residuals.

4.6 Comparison of Series and Forecasting

The synthetic series generated by the ARIMA models were compared to the original series to check for model accuracy. Forecast series were also generated for a lead time of eight years with 95 % confidence intervals. Figure 4.14 shows the original series, the synthetic series and the forecast series for the three stations while Table 4.8 lists the exact forecast values as well as their confidence intervals.

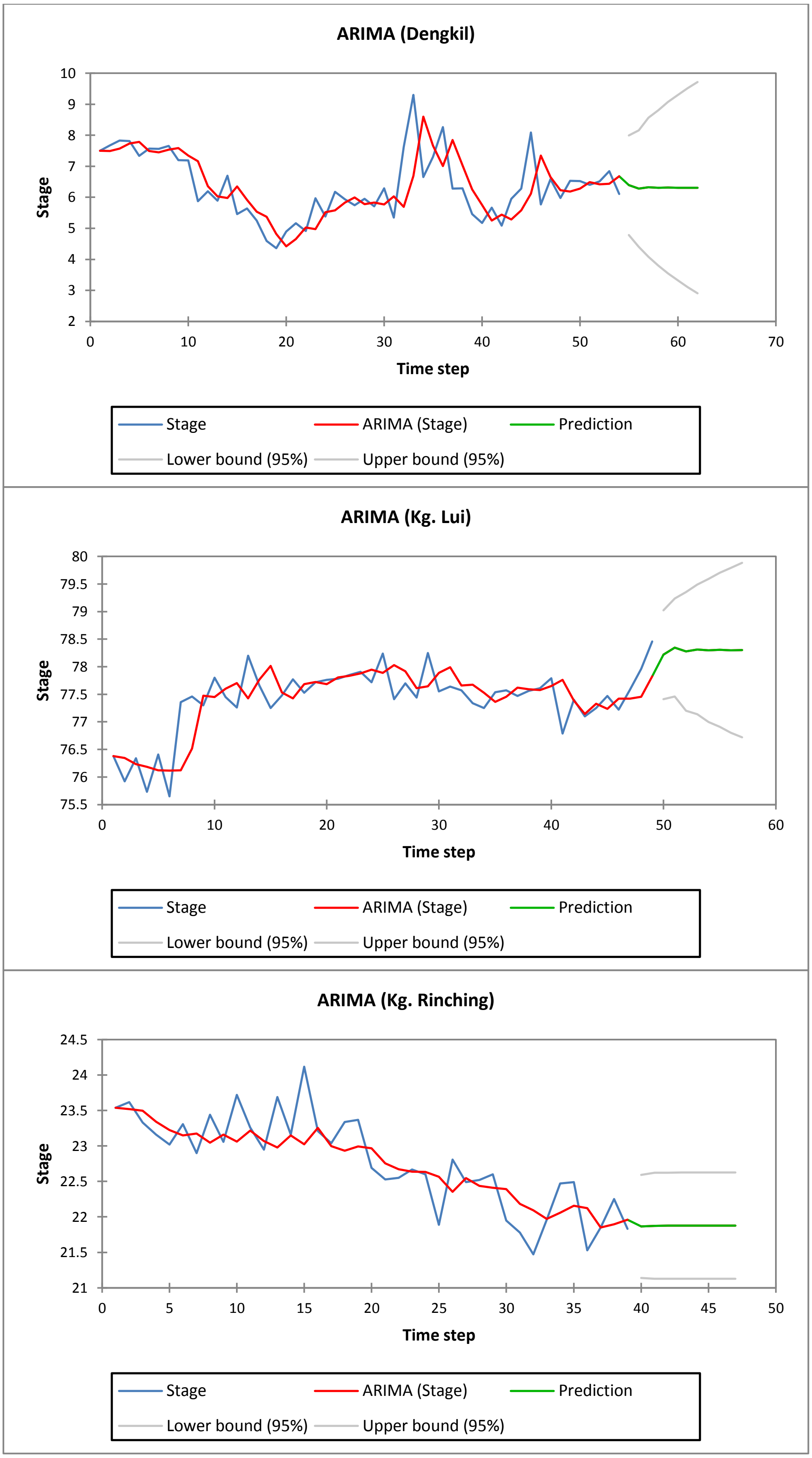

Figure 4.14: Original Series, Synthetic Series and Forecast Series

The Dengkil model and the Kg. Lui model were considerably satisfactory because their synthetic series had similar pattern to the original series. The Kg. Rinching model on the other hand, was adequate but less convincing compared to the other two models. Its synthetic series still maintained the general trend of the original series but some of its values were very different from the original values. Overall, all three models were adequate but the Dengkil model and the Kg. Lui model were more convincing than the Kg. Rinching model. The exact stage values can be found in Appendix C.

The forecast series for all three models presented in Figure 4.14 were similar because they looked like a straight line. There were fluctuations in the beginning of the forecast but as the time step increased, the fluctuations became smaller and barely noticeable. The three forecast series looked reasonable because they seemed to continue the trends of their original series.

Table 4.8: Forecast Values and Confidence Interval

Lead	Dengkil		Kg. Lui		Kg. Rinching	
	Forecast	**Interval**	**Forecast**	**Interval**	**Forecast**	**Interval**
1	6.389	(4.783, 7.996)	78.217	(77.413, 79.022)	21.865	(21.139, 22.592)
2	6.279	(4.401, 8.156)	78.346	(77.458, 79.235)	21.874	(21.127, 22.621)
3	6.322	(4.082, 8.563)	78.278	(77.203, 79.352)	21.876	(21.128, 22.625)
4	6.305	(3.799, 8.812)	78.314	(77.136, 79.492)	21.877	(21.128, 22.625)
5	6.312	(3.549, 9.075)	78.295	(76.996, 79.594)	21.877	(21.128, 22.625)
6	6.309	(3.318, 9.301)	78.305	(76.908, 79.702)	21.877	(21.128, 22.625)
7	6.310	(3.104, 9.517)	78.300	(76.805, 79.794)	21.877	(21.128, 22.625)
8	6.310	(2.903, 9.517)	78.303	(76.720, 79.886)	21.877	(21.128, 22.625)

The confidence intervals are also known as prediction intervals. According to Chatfield (1998), these prediction intervals are important to enable forecasters to

i. Assess future uncertainties;
ii. Come up with different strategies for the range of possible outcomes;
iii. Compare different forecasting methods thoroughly;
iv. Explore different scenarios with different assumptions.

4.7 Conversion to Streamflow Series

The original series, synthetic series and forecast series of stage readings were converted to streamflow series using the rating curves provided by DID. Figure 4.15 shows the converted streamflow series.

The streamflow series and the stage series had the same shapes. Both streamflow and stage values can be used in hydrological applications. The conversion process involved basic interpolation technique using the values from the rating curves.

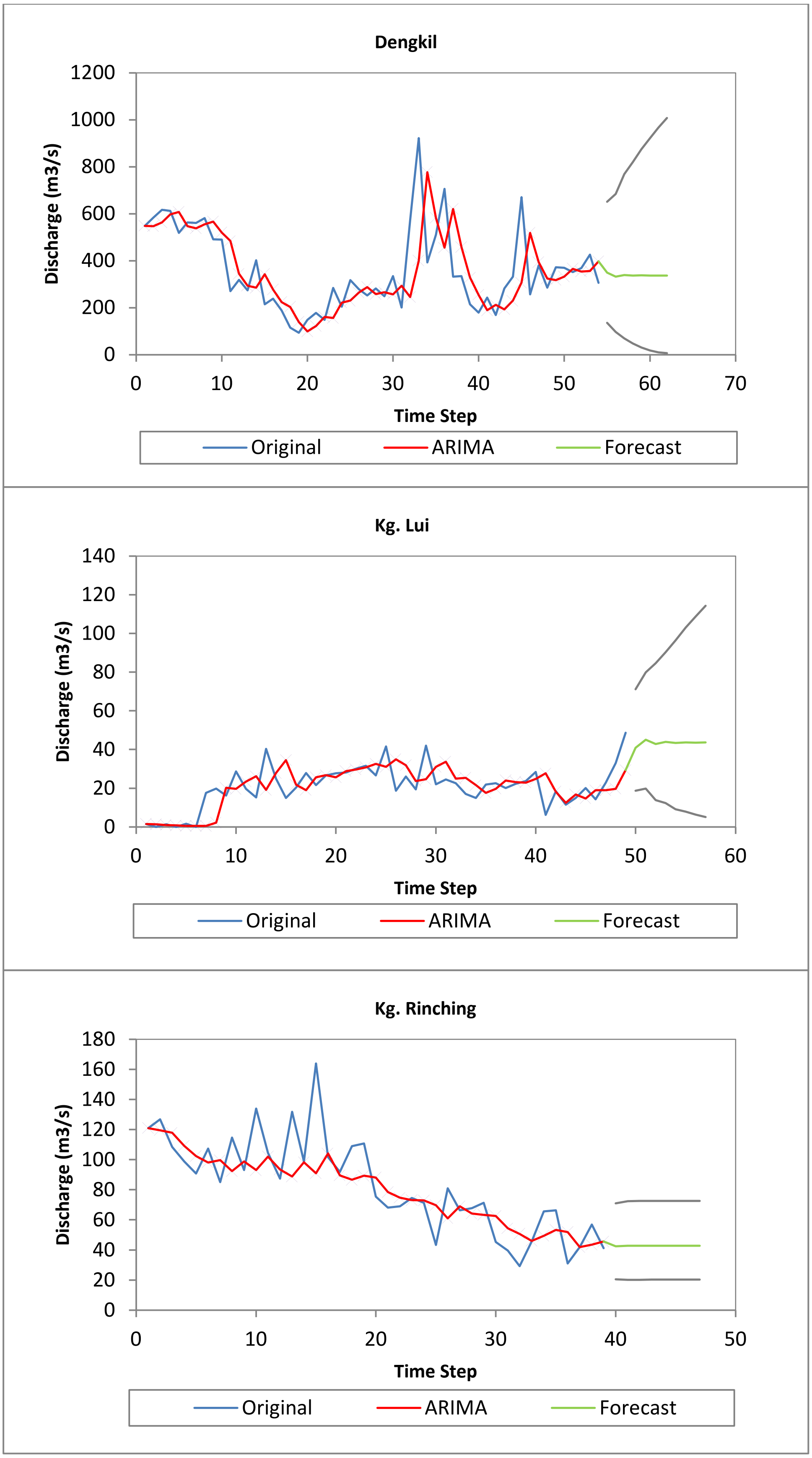

Figure 4.15: Streamflow Series

4.8 Summary

The data collected were in the form of stage readings. These readings were then sorted to obtain the annual maximum values. The Dengkil station had the most observations while the Kajang station had the least.

The ACF and PACF showed that the Kajang series was a white noise series. Further white noise tests confirmed it so no modelling was done onto that series. The other three series seemed non-stationary from the ACF and PACF so stationarity tests (ADF, KPSS and Mann-Kendall trend test) were carried out to confirm it. They were indeed non-stationary so differencing was required.

The series were differenced twice and the optimum level of differencing was found to be one. The ACF and PACF of the differenced series suggested the ARIMA models (1,1,0) and (1,1,1) to be tested. However, since the XLSTAT can model for a range of p and q easily, the order of p and q was increased to 3. The models with the least AICC along with their parameters were given in Table 4.5.

Diagnostic checks showed that the models had parameters that were significantly different from zero and residuals that were independent, homoscedastic and approximately normally distributed. Therefore, all three models passed the requirements.

The synthetic series were compared to the original series and it was found that all the models were adequate but the Dengkil model and the Kg. Lui model seemed more convincing than the Kg. Rinching model. Forecast series were also obtained and they appeared to be straight lines with minor fluctuations. The forecast series also looked reasonably convincing.

Lastly, all the stage series were converted to streamflow series using the rating curves provided by DID and it was found that the patterns of the stage series and the streamflow series were the same.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Ultimately, the objectives of this study had been achieved. Statistical modelling was successfully performed onto the study rivers using the time series approach, specifically the autoregressive integrated moving-average (ARIMA) method. Forecast series were also generated by the models to give sequences of future stage and streamflow values.

One of the series, the Kajang series, could not be modelled because it was a white noise series and no dependence existed between its successive streamflow values. The future values cannot be predicted using the historical values. The best ARIMA models for the other three series, Dengkil, Kg. Lui and Kg. Rinching series were (1,1,0), (1,1,0) and (1,1,1) respectively.

The best models were the models with the least AICC and passed the diagnostic checks. Their residuals were independent, homoscedastic and approximately normally distributed. By comparing the models' synthetic series with the original series, their accuracies were checked. All three models were adequate models.

The critical step in ARIMA modelling was model identification. The values of p, q and d had to be determined visually and they depended on the modeller's experience and judgement. The selection of p and q had been made easier because XLSTAT can quickly compute the AICC for models with different p and q.

The ARIMA model is suitable for short term forecasting because the ARMA family models can model short term persistence very well. Goldman (1985) argued that the autoregressive model is a finite memory model, thus it does not fare well in long term forecasting.

In conclusion, the Box-Jenkins approach for ARIMA modelling was found to be appropriate and adequate for the rivers under study in Langat River Basin. The flood forecast up to a lead time of eight years for the three models exhibited a straight line with near constant streamflow values showing that the forecast values were similar to the last recorded observation.

5.2 Recommendations

Although the ARIMA modelling in this study was considerably successful, generally there are still doubts on the application of ARIMA models. There are some recommendations that can be useful for further understanding and improvement of the ARIMA model:

i. The length of historical record of input data affects the model's performance so longer input series should be used to predict more accurately;
ii. Apply transformations such as the Box-Cox transformation onto the data series to improve the desired residuals' characteristic if necessary;
iii. Compare the ARIMA model with other models such as the Thomas-Fiering model and the Markov model;
iv. Apply a combination of ARIMA and artificial neural network in a hybrid model;
v. Apply and compare the ARIMA model for both short term forecasting and long term forecasting.

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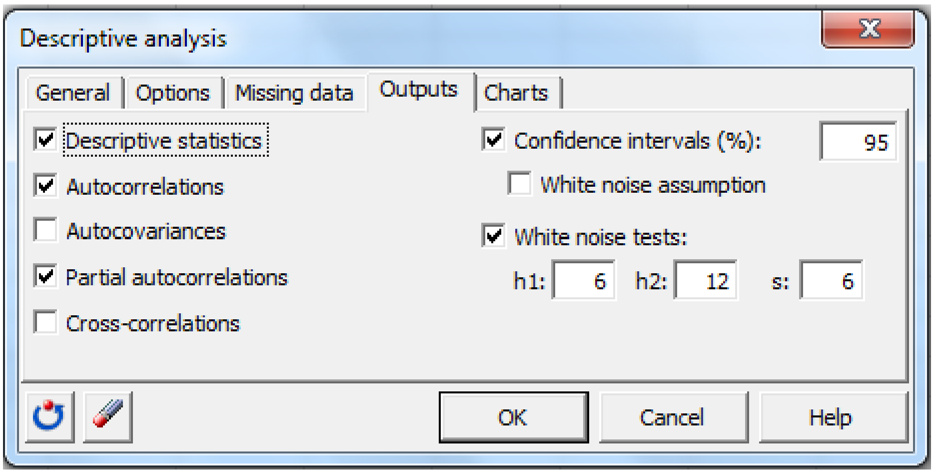
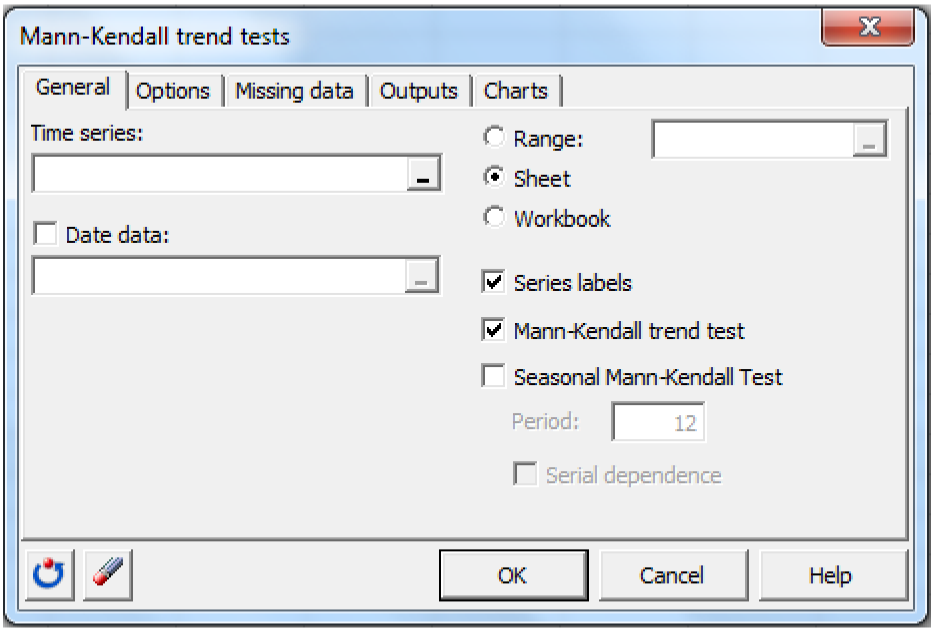
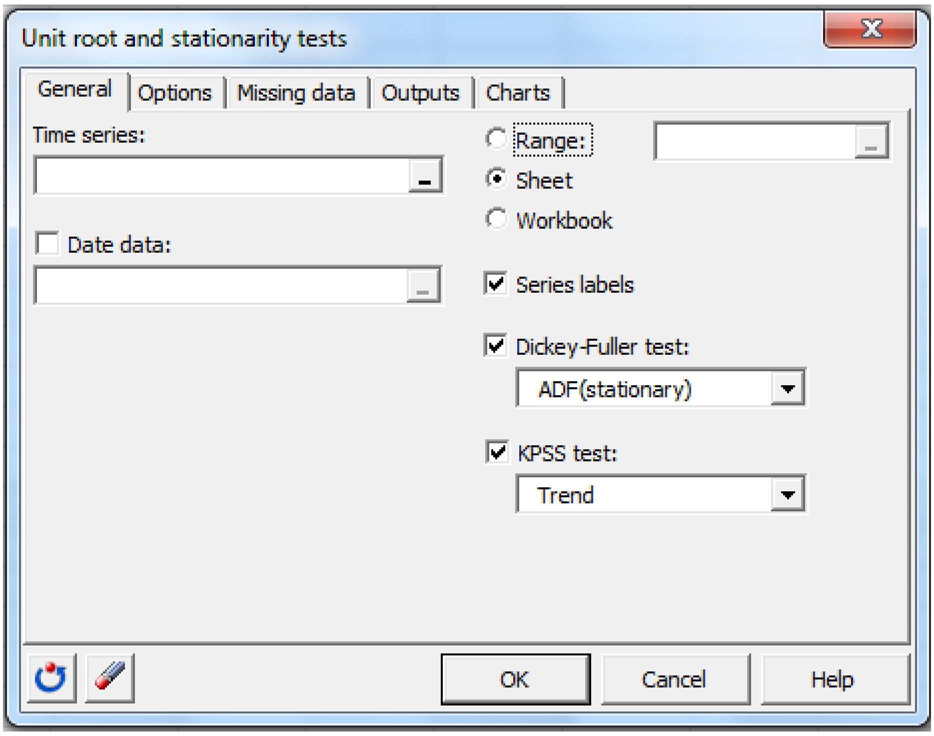
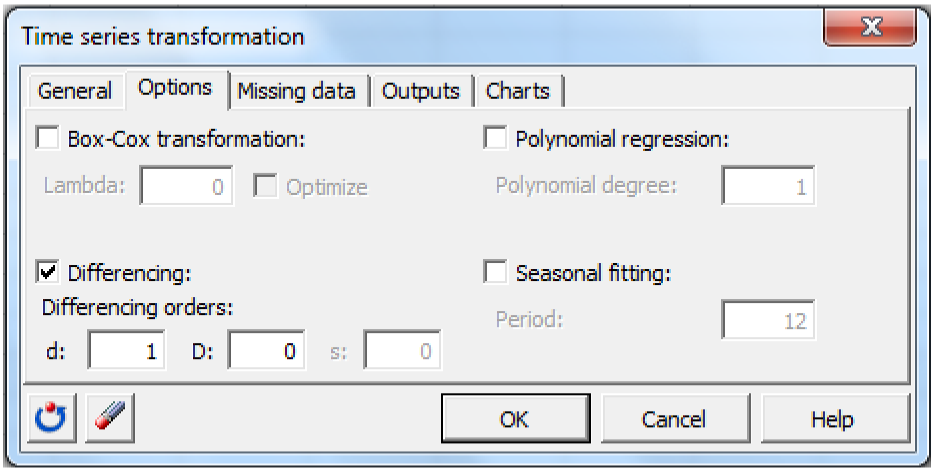
APPENDICES

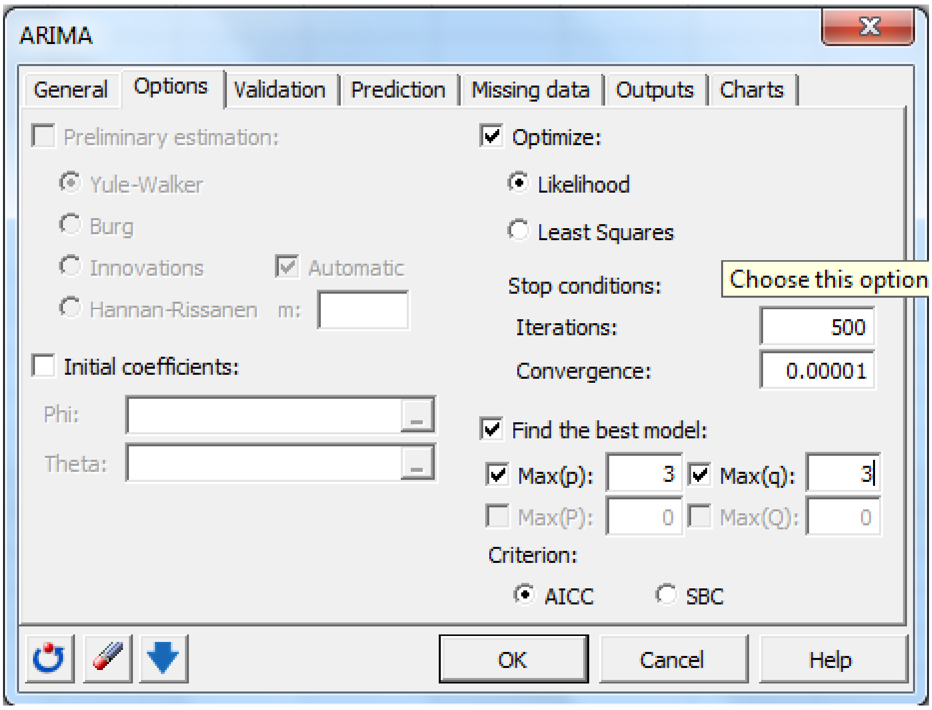
APPENDIX A: XLSTAT Program

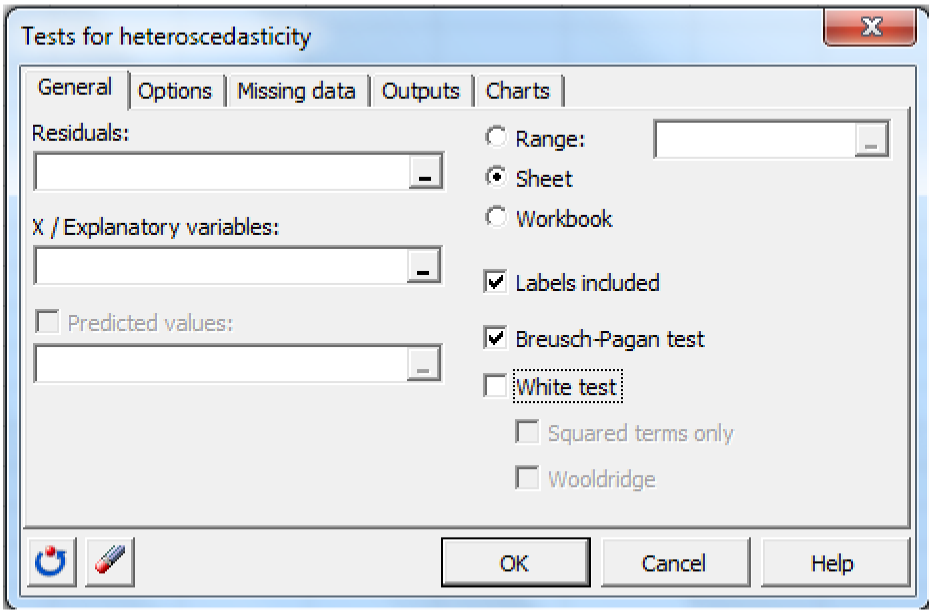


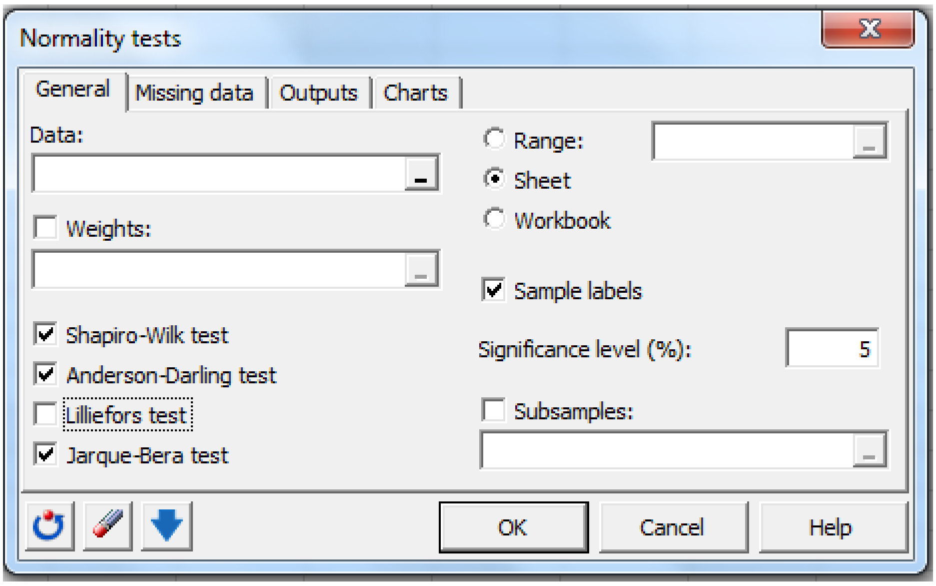



Unit root and stationarity tests
General
Options
Missing data
Outputs
Charts
Time series:
Range:
Sheet
Workbook
Date data:
Series labels
Dickey-Fuller test:
ADF(stationary)
KPSS test:
Trend
OK
Cancel
Help


Time series transformation
General
Options
Missing data
Outputs
Charts
Box-Cox transformation:
Lambda:
0
Optimize
Polynomial regression:
Polynomial degree:
1
Differencing:
Differencing orders:
d:
1
D:
0
s:
0
Seasonal fitting:
Period:
12
OK
Cancel
Help


ARIMA
General
Options
Validation
Prediction
Missing data
Outputs
Charts
Preliminary estimation:
Yule-Walker
Burg
Innovations
Automatic
Hannan-Rissanen
m:
Initial coefficients:
Phi:
Theta:
Optimize:
Likelihood
Least Squares
Stop conditions:
Choose this option
Iterations:
500
Convergence:
0.00001
Find the best model:
Max(p):
3
Max(q):
3
Max(P):
0
Max(Q):
0
Criterion:
AICC
SBC
OK
Cancel
Help


Tests for heteroscedasticity
General
Options
Missing data
Outputs
Charts
Residuals:
X / Explanatory variables:
Predicted values:
Range:
Sheet
Workbook
Labels included
Breusch-Pagan test
White test
Squared terms only
Wooldridge
OK
Cancel
Help


Normality tests
General
Missing data
Outputs
Charts
Data:
Weights:
Shapiro-Wilk test
Anderson-Darling test
Lilliefors test
Jarque-Bera test
Range:
Sheet
Workbook
Sample labels
Significance level (%):
5
Subsamples:
OK
Cancel
Help

APPENDIX B: Results of Statistical Tests

White noise tests (Kajang):

Statistic	DF	Value	p-value
Box-Pierce	12	12.477	0.408
Ljung-Box	12	15.525	0.214
McLeod-Li	12	15.445	0.218

Mann-Kendall trend test / Two-tailed test (Dengkil):

Kendall's tau	-0.073
S	-105.000
Var(S)	17963.000
p-value (Two-tailed)	0.438
alpha	0.05

The exact p-value could not be computed. An approximation has been used to compute the p-value.

Test interpretation:
H0: There is no trend in the series
Ha: There is a trend in the series
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 43.78%.

Mann-Kendall trend test / Two-tailed test (Kg. Lui):

Kendall's tau	0.179
S	210.000
Var(S)	13452.000
p-value (Two-tailed)	0.072
alpha	0.05

The exact p-value could not be computed. An approximation has been used to compute the p-value.

Test interpretation:
H0: There is no trend in the series
Ha: There is a trend in the series
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 7.15%.

Mann-Kendall trend test / Two-tailed test (Kg. Rinching):

Kendall's tau	-0.636
S	-470.000
Var(S)	6830.667
p-value (Two-tailed)	< 0.0001
alpha	0.05

The exact p-value could not be computed. An approximation has been used to compute the p-value.

Test interpretation:
H0: There is no trend in the series
Ha: There is a trend in the series
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.

Dickey-Fuller test (Dengkil):

Tau (Observed value)	-2.431
Tau (Critical value)	-0.718
p-value (one-tailed)	0.350
alpha	0.05

Test interpretation:
H0: There is a unit root for the series.
Ha: There is no unit root for the series. The series is stationary.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 34.96%.

KPSS test (Dengkil):

Eta (Observed value)	0.269
Eta (Critical value)	0.147
p-value (one-tailed)	0.001
alpha	0.05

Test interpretation:
H0: The series is stationary.
Ha: The series is not stationary.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.11%.

Dickey-Fuller test (Kg. Lui):

Tau (Observed value)	-2.980
Tau (Critical value)	-0.709
p-value (one-tailed)	0.138
alpha	0.05

Test interpretation:
H0: There is a unit root for the series.
Ha: There is no unit root for the series. The series is stationary.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 13.78%.

KPSS test (Kg. Lui):

Eta (Observed value)	0.765
Eta (Critical value)	0.451
p-value (one-tailed)	0.005
alpha	0.05

Test interpretation:
H0: The series is stationary.
Ha: The series is not stationary.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.50%.

Dickey-Fuller test (Kg. Rinching):

Tau (Observed value)	-2.294
Tau (Critical value)	-0.619
p-value (one-tailed)	0.411
alpha	0.05

Test interpretation:
H0: There is a unit root for the series.
Ha: There is no unit root for the series. The series is stationary.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 41.07%.

KPSS test (Kg. Rinching):

Eta (Observed value)	0.161
Eta (Critical value)	0.145
p-value (one-tailed)	0.030
alpha	0.05

Test interpretation:
H0: The series is stationary.
Ha: The series is not stationary.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 3.05%.

Breusch-Pagan test (Dengkil):	
LM (Observed value)	2.119
LM (Critical value)	3.841
DF	1
p-value (Two-tailed)	0.145
alpha	0.05
Test interpretation:	
H0: Residuals are homoscedastic	
Ha: Residuals are heteroscedastic	
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	
The risk to reject the null hypothesis H0 while it is true is 14.55%.	

Breusch-Pagan test (Kg. Lui):	
LM (Observed value)	1.682
LM (Critical value)	3.841
DF	1
p-value (Two-tailed)	0.195
alpha	0.05
Test interpretation:	
H0: Residuals are homoscedastic	
Ha: Residuals are heteroscedastic	
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	
The risk to reject the null hypothesis H0 while it is true is 19.47%.	

Breusch-Pagan test (Kg. Rinching):	
LM (Observed value)	0.104
LM (Critical value)	3.841
DF	1
p-value (Two-tailed)	0.747
alpha	0.05
Test interpretation:	
H0: Residuals are homoscedastic	
Ha: Residuals are heteroscedastic	
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	
The risk to reject the null hypothesis H0 while it is true is 74.69%.	

Dengkil			
Variable\Test	Shapiro-Wilk	Anderson-Darling	Jarque-Bera
(Standardized residuals)	**0.017**	**0.012**	**0.007**

Kg. Lui			
Variable\Test	Shapiro-Wilk	Anderson-Darling	Jarque-Bera
(Standardized residuals)	0.140	0.066	0.064

Kg. Rinching			
Variable\Test	Shapiro-Wilk	Anderson-Darling	Jarque-Bera
(Standardized residuals)	0.315	0.223	0.331

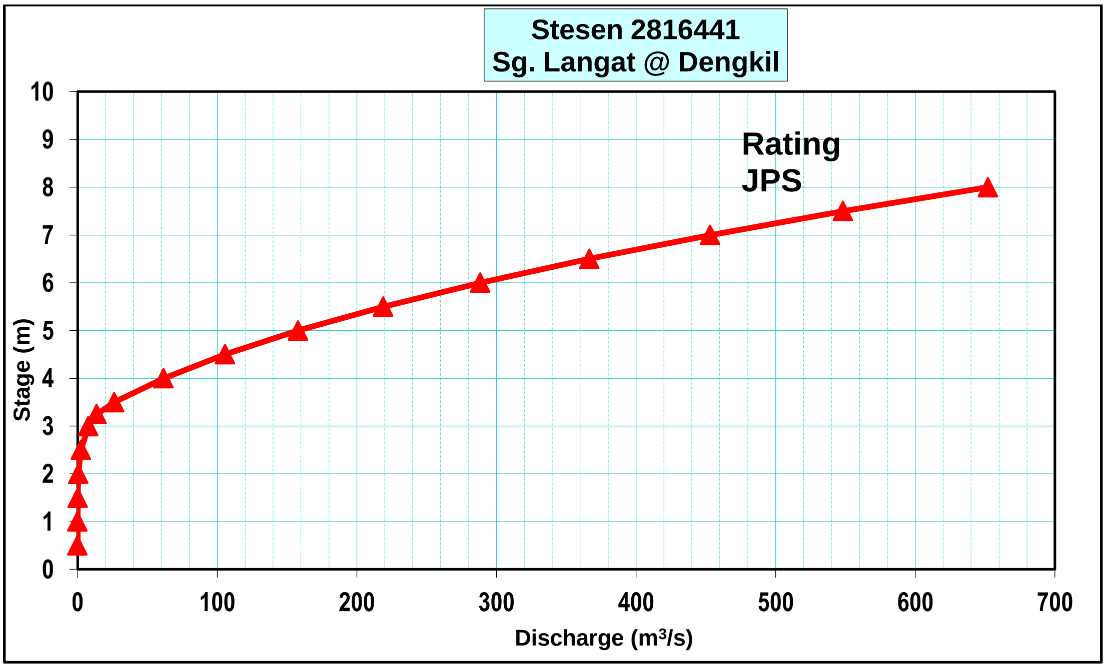
APPENDIX C: ARIMA Model Stage Readings

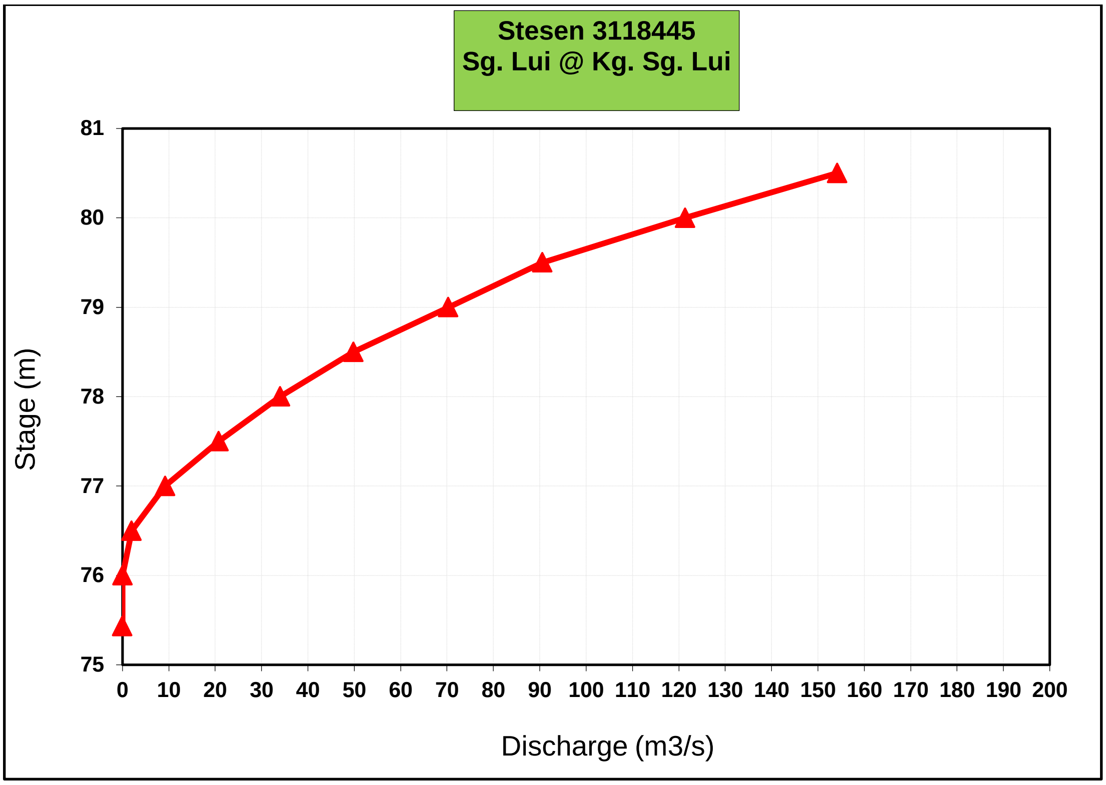
Dengkil							
Observations	Stage	ARIMA(Stage)	Residuals	Standardized residuals	Standard error	Lower bound (95%)	Upper bound (95%)
1	7.500	7.500	0.000	0.000			
2	7.670	7.492	0.178	0.217			
3	7.830	7.570	0.260	0.317			
4	7.810	7.734	0.076	0.093			
5	7.340	7.785	-0.445	-0.543			
6	7.570	7.493	0.077	0.094			
7	7.560	7.446	0.114	0.139			
8	7.660	7.531	0.129	0.157			
9	7.200	7.588	-0.388	-0.473			
10	7.190	7.349	-0.159	-0.194			
11	5.870	7.161	-1.291	-1.575			
12	6.190	6.359	-0.169	-0.206			
13	5.890	6.031	-0.141	-0.172			
14	6.700	5.976	0.724	0.884			
15	5.460	6.347	-0.887	-1.082			
16	5.640	5.917	-0.277	-0.338			
17	5.250	5.536	-0.286	-0.349			
18	4.590	5.371	-0.781	-0.953			
19	4.360	4.818	-0.458	-0.559			
20	4.900	4.418	0.482	0.588			
21	5.160	4.654	0.506	0.617			
22	4.910	5.025	-0.115	-0.140			
23	5.970	4.976	0.994	1.213			
24	5.380	5.519	-0.139	-0.169			
25	6.180	5.580	0.600	0.732			
26	5.930	5.831	0.099	0.121			
27	5.740	5.996	-0.256	-0.312			
28	5.950	5.782	0.168	0.205			
29	5.710	5.834	-0.124	-0.152			
30	6.290	5.772	0.518	0.632			
31	5.350	6.028	-0.678	-0.827			
32	7.620	5.689	1.931	2.356			
33	9.300	6.691	2.609	3.184			
34	6.650	8.604	-1.954	-2.383			
35	7.300	7.664	-0.364	-0.444			
36	8.260	7.010	1.250	1.524			
37	6.280	7.848	-1.568	-1.913			
38	6.290	7.029	-0.739	-0.902			
39	5.460	6.253	-0.793	-0.968			
40	5.170	5.755	-0.585	-0.714			
41	5.670	5.252	0.418	0.510			
42	5.090	5.440	-0.350	-0.427			
43	5.950	5.286	0.664	0.810			
44	6.280	5.578	0.702	0.857			
45	8.090	6.117	1.973	2.407			
46	5.770	7.342	-1.572	-1.918			
47	6.580	6.654	-0.074	-0.090			
48	5.980	6.227	-0.247	-0.302			
49	6.530	6.184	0.346	0.422			
50	6.520	6.280	0.240	0.293			
51	6.400	6.491	-0.091	-0.111			
52	6.510	6.415	0.095	0.116			
53	6.840	6.434	0.406	0.496			
54	6.110	6.677	-0.567	-0.692			
55		6.389			0.820	4.783	7.996
56		6.279			0.958	4.401	8.156
57		6.322			1.143	4.082	8.563
58		6.305			1.279	3.799	8.812
59		6.312			1.410	3.549	9.075
60		6.309			1.526	3.318	9.301
61		6.310			1.636	3.104	9.517
62		6.310			1.738	2.903	9.717

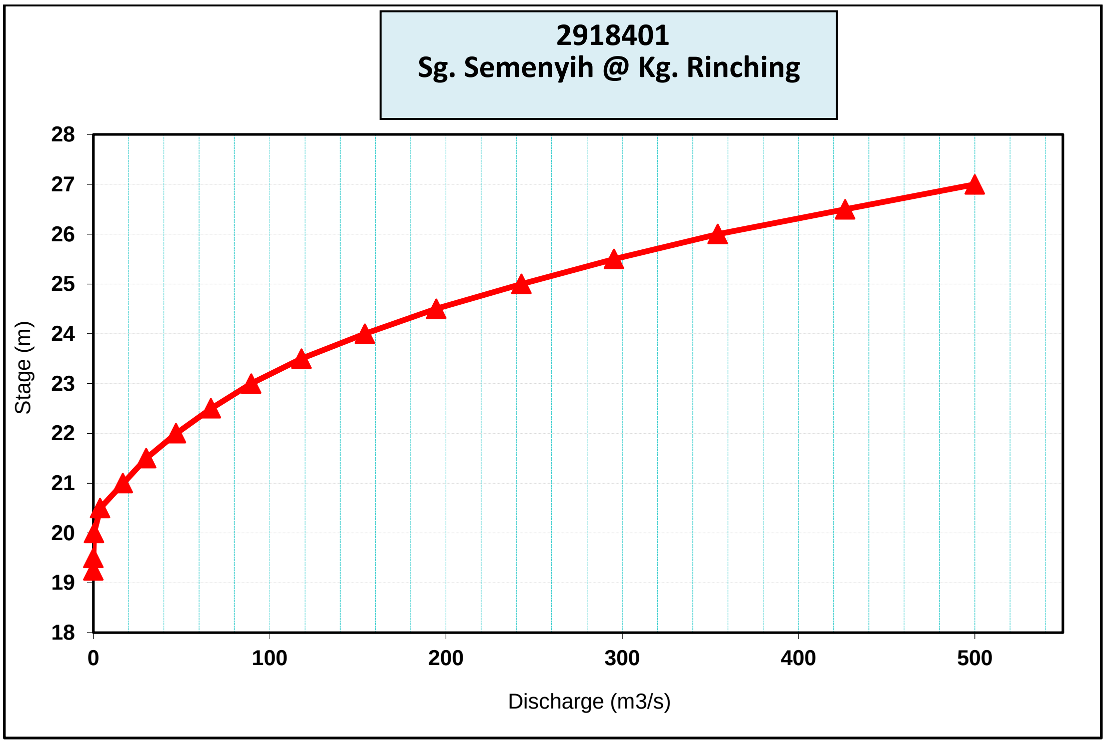
Kg. Lui							
Observations	Stage	ARIMA(Stage)	Residuals	Standardized residuals	Standard error	Lower bound (95%)	Upper bound (95%)
1	76.380	76.380	0.000	0.000			
2	75.920	76.346	-0.426	-1.039			
3	76.340	76.232	0.108	0.264			
4	75.730	76.183	-0.453	-1.105			
5	76.410	76.121	0.289	0.703			
6	75.650	76.115	-0.465	-1.133			
7	77.360	76.121	1.239	3.017			
8	77.460	76.517	0.943	2.297			
9	77.300	77.474	-0.174	-0.423			
10	77.800	77.452	0.348	0.848			
11	77.450	77.601	-0.151	-0.368			
12	77.260	77.703	-0.443	-1.079			
13	78.200	77.428	0.772	1.880			
14	77.660	77.767	-0.107	-0.260			
15	77.250	78.014	-0.764	-1.862			
16	77.480	77.535	-0.055	-0.134			
17	77.770	77.425	0.345	0.842			
18	77.530	77.683	-0.153	-0.372			
19	77.720	77.725	-0.005	-0.011			
20	77.760	77.686	0.074	0.181			
21	77.780	77.806	-0.026	-0.062			
22	77.850	77.836	0.014	0.033			
23	77.910	77.880	0.030	0.074			
24	77.720	77.945	-0.225	-0.548			
25	78.240	77.888	0.352	0.857			
26	77.410	78.030	-0.620	-1.511			
27	77.700	77.919	-0.219	-0.532			
28	77.440	77.613	-0.173	-0.420			
29	78.250	77.645	0.605	1.473			
30	77.550	77.886	-0.336	-0.818			
31	77.640	77.989	-0.349	-0.851			
32	77.570	77.659	-0.089	-0.217			
33	77.340	77.674	-0.334	-0.814			
34	77.250	77.529	-0.279	-0.680			
35	77.540	77.365	0.175	0.427			
36	77.570	77.453	0.117	0.286			
37	77.470	77.621	-0.151	-0.368			
38	77.560	77.590	-0.030	-0.073			
39	77.610	77.579	0.031	0.075			
40	77.790	77.650	0.140	0.340			
41	76.790	77.761	-0.971	-2.366			
42	77.400	77.389	0.011	0.027			
43	77.100	77.142	-0.042	-0.103			
44	77.250	77.327	-0.077	-0.186			
45	77.470	77.237	0.233	0.567			
46	77.220	77.420	-0.200	-0.487			
47	77.580	77.420	0.160	0.390			
48	77.960	77.455	0.505	1.229			
49	78.460	77.825	0.635	1.547			
50		78.217			0.411	77.413	79.022
51		78.346			0.453	77.458	79.235
52		78.278			0.548	77.203	79.352
53		78.314			0.601	77.136	79.492
54		78.295			0.663	76.996	79.594
55		78.305			0.713	76.908	79.702
56		78.300			0.763	76.805	79.794
57		78.303			0.808	76.720	79.886

Kg. Rinching							
Observations	Stage	ARIMA(Stage)	Residuals	Standardized residuals	Standard error	Lower bound (95%)	Upper bound (95%)
1	23.540	23.540	0.000	0.000			
2	23.620	23.520	0.100	0.270			
3	23.330	23.496	-0.166	-0.448			
4	23.160	23.342	-0.182	-0.491			
5	23.020	23.224	-0.204	-0.549			
6	23.310	23.149	0.161	0.435			
7	22.900	23.176	-0.276	-0.744			
8	23.440	23.047	0.393	1.059			
9	23.060	23.160	-0.100	-0.270			
10	23.720	23.061	0.659	1.779			
11	23.260	23.218	0.042	0.114			
12	22.950	23.068	-0.118	-0.319			
13	23.690	22.980	0.710	1.915			
14	23.160	23.150	0.010	0.026			
15	24.120	23.024	1.096	2.958			
16	23.210	23.254	-0.044	-0.119			
17	23.040	22.999	0.041	0.112			
18	23.340	22.934	0.406	1.094			
19	23.370	22.992	0.378	1.019			
20	22.690	22.967	-0.277	-0.746			
21	22.530	22.755	-0.225	-0.606			
22	22.550	22.672	-0.122	-0.330			
23	22.670	22.639	0.031	0.083			
24	22.600	22.633	-0.033	-0.088			
25	21.890	22.566	-0.676	-1.824			
26	22.810	22.354	0.456	1.230			
27	22.490	22.548	-0.058	-0.157			
28	22.520	22.436	0.084	0.227			
29	22.600	22.412	0.188	0.507			
30	21.950	22.392	-0.442	-1.192			
31	21.780	22.185	-0.405	-1.093			
32	21.470	22.092	-0.622	-1.679			
33	21.960	21.972	-0.012	-0.032			
34	22.470	22.060	0.410	1.105			
35	22.490	22.159	0.331	0.894			
36	21.530	22.124	-0.594	-1.603			
37	21.850	21.849	0.001	0.004			
38	22.250	21.895	0.355	0.958			
39	21.830	21.959	-0.129	-0.347			
40		21.865			0.371	21.139	22.592
41		21.874			0.381	21.127	22.621
42		21.876			0.382	21.128	22.625
43		21.877			0.382	21.128	22.625
44		21.877			0.382	21.128	22.625
45		21.877			0.382	21.128	22.625
46		21.877			0.382	21.128	22.625
47		21.877			0.382	21.128	22.625

APPENDIX D: Rating Curves




Stesen 3118445
Sg. Lui @ Kg. Sg. Lui
Stage (m)
81
80
79
78
77
76
75
0 10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180 190 200
Discharge (m3/s)


2918401
Sg. Semenyih @ Kg. Rinching
Stage (m)
28
27
26
25
24
23
22
21
20
19
18
0 100 200 300 400 500
Discharge (m3/s)