# FORECASTING REFERENCE EVAPOTRANSPIRATION DURING YALA AND MAHA SEASONS IN DRY ZONE SRI LANKA: A STATISTICAL APPROACH

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Dissertation submitted in partial fulfilment of the requirements for the Degree of Master of Science in Business Statistics

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Signature of the supervisor:

Prof. T. S. G. Peiris Date

# Dedication

"I dedicate this thesis to my husband, parents, supervisors and lecturers and to all of those who are willing to gather knowledge about application of statistical knowledge to forecast reference evapotranspiration during Yala and Maha seasons in dry zone of Sri Lanka."

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# Abstract

Sri Lanka is heavily dependent on both rain-fed and irrigated agriculture and thus irrigation has had a unique contribution towards country`s agro economy from history to this date. The established patterns of rainfall in different parts of the country have changed and the demand for agricultural water has to be balanced with the municipal and industrial water demand. The improved procedures for estimating agricultural water requirements both for irrigation and rain-fed agriculture have become an important research particularly due to erratic rainfall patterns and inadequate water resources in dry season. The aim of this study is therefore to develop time series models to predict weekly reference evapotranspiration ($ET_o$) for Yala and Maha seasons in Polonnaruwa district using climate data from 2010 to 2015. As actual evapotranspiration is not available, those values on weekly basis were computed using Pan Evaporation method based on relative humidity, wind speed and pan evaporation. 85% of the data computed were used for training and balance of 15% was kept for validation. The weekly evapotranspiration during Yala varied from 2.23mm (6 – 12 September 2013 ) to 5.37mm (1 – 7 May 2015) with mean of 3.62mm and SD of 0.53 and that during Maha varied from 0.76mm (21 – 27 December 2012) to 5.56mm (17 – 23 October 2014) with mean of 2.29mm and SD of 0.85. Both series were able to make stationary by taking one short-term difference and one long-term difference with the length of 26. The identified best fitted ARIMA models for Yala and Maha weekly evapotranspiration were SARIMA (1,1,1) $(1,1,1)_{26}$. The errors produced by two models were found to be white noise. The percentage errors in both models for validation data set were within the range of ± 3% and it was found that the correlations between observed and predicted values for Yala (r=0.90) and for Maha (r = 0.88) were highly significant ($p<0.05$). The best fitted model identified for the pooled weekly series was SARIMA (0,1,2) $(0,1,1)_{52}$. Though the errors found to be satisfied all the diagnostic tests, the percentage error was higher in the combined model than the corresponding values for two separate models. Therefore, it is recommended to use the developed separate models to forecast $ET_0$ on short-term or long-term basis which will be useful for the appropriate water management for real time irrigation scheduling in Dry Zone of Sri Lanka.These models can also be used for estimating irrigation water requirements for different crops. It is suggested to use Artificial Neural Network (ANN) techniques to improve the accuracy of the developed models.


**Keywords:** Dry Zone, Maha, Reference Evapotranspiration, Yala, SARIMA.

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## Abbreviations

| | | |
|---|---|---|
| ACF | - | Auto Correlation Function |
| ANN | - | Artificial Neural Network |
| AR | - | Auto Regressive |
| ARIMA | - | Auto Regressive Integrated Moving Average |
| CEA | - | Central Environmental Authority |
| cm | - | centimeter |
| CWR | - | Crop Water Requirement |
| ECA | - | Evaporation Class A |
| ET | - | Evapotranspiration |
| ETo | - | Reference crop evapotranspiration |
| ETc | - | Crop Evapotranspiration |
| FAO | - | Food and Agriculture Organization |
| FIM | - | First Inter Monsoon |
| IR | - | Irrigation Requirement |
| IWRM | - | Integrated Water Resources Management |
| Kc | - | Crop Coefficient |
| Ks | - | Water Stress Coefficient |
| m | - | Meters |
| MA | - | Moving Average |
| mm | - | Millimeters |
| MSE | - | Mean Squared Error |
| NEM | - | North East Monsoon |
| PACF | - | Partial Auto Correlation Function |
| PM | - | Penman-Monteith |
| RVM | - | Relevance Vector Machines |
| SAR | - | Seasonal Auto Regressive |
| SARIMA | - | Seasonal Auto Regressive Integrated Moving Average |
| SIM | - | Second Inter Monsoon |
| SMA | - | Seasonal Moving Average |
| SSE | - | Sums Squared Error |

| | | |
|---|---|---|
| SVM | - | Support Vector Machines |
| SWM | - | South  West Monsoon |

# CHAPTER 1
# INTRODUCTION

## 1.1 Background

Water scarcity is considered, along with climate change, as one of the most pressing environmental issues of the 21st century. About 67% of the global water withdrawal is related to agricultural production, and 87% of the consumptive water is for irrigation purposes. Agriculture is greatly concerned with water shortage, and in areas characterized by arid or semi-arid climates, irrigation is often the only option to secure productivity (Mancosu, *et al*., 2015).

Sri Lanka being an agricultural country, the irrigation has had a unique contribution towards country`s agro economy from history to this date. Sri Lanka is heavily dependent on both rain-fed and irrigated agriculture form the backbone of rural livelihoods. Scientists have suggested that the overall rainfall received by Sri Lanka has decreased in many areas of the country. The established patterns of rainfall have changed and the distribution of rainfall in different parts of the country also appears to be undergoing changes. Therefore, demand for agricultural water has to be balanced with the municipal and industrial water demand (Anon., 2013).

Sri Lanka is a humid tropical island, situated in the path of two monsoons, the south-west and the north-east monsoons. The average annual rainfall over Sri Lanka is approximately 1850 mm. Though the average water potential is high in the country, there exists three climatic regions as wet, dry and intermediate due to the variation in range of rainfall (Department of Agriculture, 2006). Location, climate and topography are the main factors that influence precipitation and water availability (Wijesekara, *et al*., 2005).

Ever growing population and projected shifts in precipitation patterns, which are likely to increase the trend of prolong droughts in some areas, in the other hand it is expected that irrigation demand will increase in future with the growth of population. Clearly, only a prudent choice of irrigation strategies, based on quantitative estimates of the water requirements, will allow sustainable use of water resources (Smith, *et al*., 2012).

Planning and coordinating irrigation water is also very important to save the excess use of water. Farmer organizations, local institutions and state agencies such as the Agrarian Development Department, Department of Agriculture, Department of irrigation, and the Department of Meteorology all have an important role to play in water management by working closely and sharing knowledge and information. It will help for better management of irrigation water through an IWRM approach (Rajakaruna, 2014).

Agricultural managers have relied on evapotranspiration (ET) measurements or estimations, for purposes of timely and efficient water application. Therefore, an accurate assessment of ET is essential to improving water management practices. ET is one of the main components of the hydrological cycle. It is a complex process driven mainly by weather parameters. Accurate estimation of ET is very important, but providing a reliable short-term forecast of ET plays as the critical constituent for management of irrigation systems (Bachour, 2013).

## 1.2 Irrigation in Sri Lanka

Sri Lanka is greatly reliant on agriculture, both rain-fed and irrigated agriculture. In relation to current statistics, the total cultivated area in Sri Lanka is valued at 1.86 million ha. About 632,000 ha of this area is irrigated; the rest is rain-fed. Irrigated agriculture is mainly consist of of major irrigation schemes. Furthermore, there are numerous minor schemes, which can be named as semi rain-fed systems. They include over 15,000 village tanks disseminated over the dry zone areas of the country (Rajakaruna, 2014).

Majority of the irrigated land in Sri Lanka is used for paddy cultivation. The demand for water is high in paddy cultivation compared to many other crops. Water is essential for the preparation of land, and the planting and maintenance of the crop throughout the planting-harvest cycle (Facon, 2000).

Two main cropping seasons associated with rainfall pattern. The Second Inter Monsoonal (SIM) and North East Monsoon (NEM) rainfall seasons together forms major cultivation season known as “Maha” (October– March) while the First Inter Monsoonal (FIM) and South West Monsoon (SWM) collectively forms the minor cultivation season recognized as “Yala” (April – Septeber) (FAO, 1997). Nearly eighty per cent of the annual rainfall is experienced in heavy storms during a period from September to January. In general, this period is cool and wet. Although dry spells are not uncommon, rainfall during this period is evenly distributed (Mahendrarajah, 1981). Following this period, a dry spell occurs. The ensuing three months are under the full dominance of the south-west monsoon with a pronounced drought during months from June to August. The few occasional rains are also ineffective in the sense that they are relatively small compared with the evaporation. The drying wind together with persistent high temperatures leads to aridity (Rajakaruna, 2014).

## 1.3 Irrigation and Water Resources Management in Sri Lanka

Significant efforts have been put by governments over the past few years to establish novel infrastructure, rehabilitate or renovate existing dams, reservoirs and canals, and encourage agro wells and micro-irrigation technologies to meet the increasing demand for agricultural water. In spite of such efforts, the problem of water scarcity is growing continously. Therefore, innovative approaches are needed to cater the future demand of agricultural water (Rajakaruna, 2014).

Agriculture is the highest water use sector in Sri Lanka (Amarasinghe,*et al.,* 1999). In many parts of the country, productivity of the rice is below optimum levels due to inadequate irrigation water deliveries. The major challenge is, therefore, to produce more food with less water in order to meet the rising food demand. Best management strategies is essential to putting into practice for efficient irrigation water use to maximize production per unit of water being used (Mancosu, *et al*., 2015).

Irrigation scheduling is one of the most effective tools to preserve water (Fereres, 1996) and it makes possible an increase in crop yield, water economy by identifying the crop water requirements during the growth season and avoiding excessive water consumption (Werner, 1996). Crop evapotranspirations are an important components used in the planning, design, implementation, operation, and maintenance of agro economical conditions (Ertek,*et al*., 2002).

### 1.4 Evapotranspiration (ET)

ET is a combination of two independent processes, namely evaporation and transpiration. Evaporation is a process in which water is evaporated or lost from the wet soil into the atmosphere. In transpiration water is breathed or lost into the atmosphere from small openings on the surface of the leaves. Evaporation and transpiration occur simultaneously, and there is no easy way to distinguish between the two processes (Allen,*et al*., 1998).

Actual evapotranspiration is a main process of hydrological cycle which driven by climatic parameters, crop characteristics, management practices and environmental aspects. Evapotranspiration plays a vital role in mimicking hydrological impact on climate change, and a thorough study on evapotranspiration estimation methods in hydrological models is of vital important (Zhao, *et al*., 2013). And also accurate estimation of evapotranspiration is required for efficient irrigation management as water losses in irrigation schemes occur mainly due to Evapotranspiration. So the total water demand of crop is directly proportional to ET. Therefore, ET is often referred to as crop water demand terminology. As a result, the knowledge of ETs becomes even more important when designing and maintaining irrigation plans (Brouwer & Heibloem, 1986).

But the relationship between ET and its driving factors are complex and not easy to model (Partal 2009; Torres,*et al*., 2011). Therefore, the concept of reference evapotranspiration (ETo) is introduced because it is not related to crop types, crop development stages and management practices. Associating evapotranspiration with a specific surface provides a reference that can be related to evapotranspiration from other surfaces.

### 1.5 Modelling and Predicting Reference Evapotranspiration

Seeing the real-world limitations of large-scale and complex hydrological models, the objective of the current work was to develop a simple modeling mechanism to interpret the refeence evapotranspiration.

Numerous equations have been proposed to develop refeence evapotranspiration (ETo) on the basis of measured weather parameters, classified as temperature-based, radiation-based, pan evaporation-based and combination-type. The Food and Agricultural Organization of the United Nations (FAO) has developed Penman-Monteith (PM) model that has become a generally accepted standard for calculating ETo (Allen,*et al*., 1998, 2006). This method is the most widely used in the world, and has been proven to accurately estimate ETo in different climates (Allen,*et al*., 1998; De Bruin and Stricker, 2000; Hussein and Al-Ghobari, 2000; Smith, 2000; Walter,*et al*., 2000).

A major drawback to application of the PM, is the relatively high data demand, where the method requires air temperature, wind speed, relative humidity, and solar radiation data that are not always available, especially in developing countries. The number of meteorological stations where all of these parameters are observed is limited in many areas of the globe. The number of stations where reliable data for these parameters exist is an even smaller subset. This is true in Sri Lanka where reliable collection of wind speed, humidity, and radiation is limited (Allen, *et al*., 1998).

This lack of meteorological data leads to the development of simpler approaches to estimate ETo that require only a few climatic parameters. As a result of that researchers have developed numerous approaches to retrieve ETo. The internationally accepted equations for estimating ETo based on the limited climatic variables are as follows: Hargreaves- Samani (Hargreaves and Samani1985), Jensen-Haise (Jensen and Haise, 1963; Jensen and Burman,1990), Makkink (Makkink, 1957), Priestley-Taylor (Priestley and Taylor, 1970) and Blaney–Criddle (Blaney and Criddle, 1962). Though there are many equations available to estimate ETo, due to their different weather data requirements and climate specificity statistical analysis came to action. Time series analysis is one of the statistical technique that has been widely used for modeling and predicting different hydrological parameters including ETo (Mariño,*et al*., 1993; Cigizoglu 2003; Gorantiwar,*et al*., 2011) as ETo is characterized by high non-linearity and non-stationarity (Hernandez,*et al*., 2011). Several researchers have found that the seasonal autoregressive integrated moving average (SARIMA) model provides good forecasts of monthly and weekly ETo (Trajkovic 1998; Landeras,*et al*., 2009). However, researchers have motivated to look for other modeling approaches including the use of data-driven tools or statistical learning machines, such as artificial neural networks (ANN), multiple regression methods, support vector machines (SVM), and relevance vector machines (RVM). Satellite remote sensing can be identified as one of the other promising techniques that is widely used for estimating global or regional reference evapotranspiration (ETo) (Adhikai & Agrawal, n.d.).

## 1.6 Problem Statement

The dry zonal area in Sri Lanka contributes 70% of national paddy cultivation by depending on irrigated water. As the report on Climate Change Vulnerability in Sri Lanka states, the dry zonal area is highly vulnerable due to a prolonged drought season and diminishing precipitation (Ministry of Environment, 2011). Erratic rainfall patterns and inadequate water resource during the dry season and poor water management practices in irrigation systems significantly contributed to the low agricultural production and water productivity in dry zone of Sri Lanka.

Since 2011, erratic rainfall during the northeast monsoon characterized by flood/drought cycles has led to increased number of disaster affected people in Dry Zone. In 2013 the northeast monsoon, which supplies water for the main rain-fed agriculture (Maha) season across the key paddy producing areas in the country was delayed and brought the lowest reported precipitation (less than 40 percent) (Source: Dept. of Meteorology Sri Lanka). Climate change and delayed monsoon has caused 20% loss of paddy harvest in the country during Maha 2013. By April 2014, the

Department of Agriculture reported that lack of rain has damaged 83,746 hectares of paddy planted area resulting an estimated production loss of 280,000 MT of rice.
All these cases are clearly described that, thousands of acres of paddy cultivation are on the verge of being destroyed due to lack of sufficient water since their cultivations totally depend on irrigation water.

Therefore, every possible effort have to be put in order to optimize the water usage to achieve increased crop production. Recent reports on water management activities of several irrigation schemes in the Dry Zone indicates that the water distribution is not meeting the demands of farmers in terms of adequacy, reliability & timeliness. In order to address these issues a proper water management system has to be introduced to the area.

## 1.7 Significance of the Study

Water scarcity conditions have forced to devote considerable efforts to increase water efficiency based on the assertion. Better water management usually refers to improvements in allocation of irrigation water effectively. This can be achieved by irrigation scheduling in the area. Irrigation scheduling is the process used by irrigation system managers to determine the correct frequency and duration of watering, or in other words the decision of when and how much of water to apply to a field. This can be calculated once the volume of water needed for crop productivity at their different growth stages, is known (Pechlivanidis & Arheimer, 2015). In order to define the crop water requirements reference evapotranspiration (ETo) are widely used in irrigation engineering. These estimates can be used to manage water distribution in existing schemes as well as to develop the planning process for irrigation schemes (Ahmed & Liu, 2013).

This study will contribute to accurate estimates of weekly crop evapotranspiration (ET) which will be important for irrigation and water management in Dry Zone of Sri Lanka where crop water demand exceeds rainfall.

## 1.8 Objectives of the Study

On view of the above explanations the primary objective of the present study is to develop a statistical models to predict weekly evapotranspiration in Yala and Maha seasons from the historical data of selected meteorological area.

The secondary objectives of this study are to:

- Study the temporal variability of evapotranspiration during both Yala and Maha period
- Develop a statistical model for pooled data using both Yala and Maha
- Validate the models
- Forecast the ETo values for upcoming weeks

## 1.9 Structure of the Dissertation

This thesis consists of five chapters. The first chapter presents the Introduction to this study, outlined the objectives and scopes of this research. The descriptions of the current irrigation patterns and related problems also discussed in this chapter.

The first section following this Introduction presents a review of the relevant literature starting with Hydrology by describing the hydrological cycle, evapotranspiration mechanism and ETo modelling approaches. The next section of the literature review briefly describes the pan evaporation method used to calculate reference evapotranspiration. Then applications of ETo in agricultural management is described. At last previous studies related to analysis of evapotranspiration using Time Series were explained along with Chapter Summary.

The proposed models for evapotranspiration modelling and methodologies, secondary data and details of the study area are described in Chapter 3.

The results and discussions are presented in Chapter 4. Results of the three different time series models are discussed with the performance, the robustness and limitations and the applications of the proposed models were discussed.

Chapter 5 of the study conclude the findings of the statistical analysis and recommendations are sugested for future analysis to improve the outcomes.

# CHAPTER 2
# LITERATURE REVIEW

## 2.1 Hydrological Cycle

Water is one of the most valuable natural resources in the world. Without it, there would be no life on earth. Hydrology is the science that prevalence the occurrence, circulation, movement and properties of the water of the earth and their association with the environment in each stage of the hydrologic cycle (U.S. Department of the Interior, 2016). Water cycle, additionally known as hydrologic cycle that encompasses the continual circulation of water within the Earth-atmosphere system (Figure 2.1). Beyond the various processes concerned within the water cycle, the foremost vital are evaporation, transpiration, condensation, precipitation, and runoff. Though the full quantity of water inside the cycle remains basically constant, its distribution among the varied processes is regularly dynamical (Britannica, 2018).

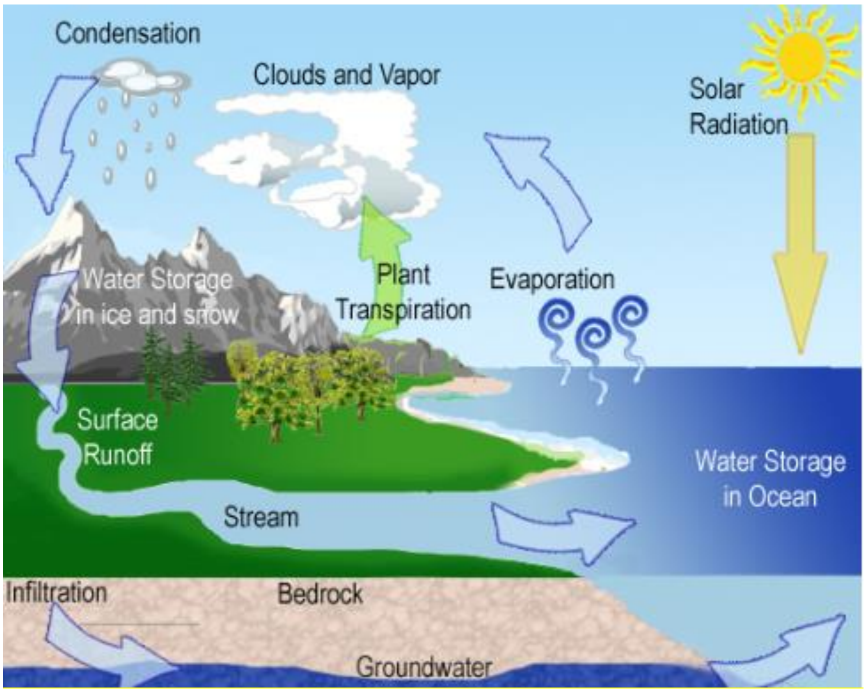


**Figure 2.1**: Hydrological cycle
(Source: RMB Environmetal Laboratories, 2018)

Evaporation, one in all the main processes within the cycle, is that the transfer of water from the surface of the planet to the atmosphere. By evaporation, water within the liquid state is transferred to the gasiform, or vapour, state. This transfer happens once some molecules during water mass have earned sufficient kinetic energy to eject themselves from the water surface. The factors touching the measure of evaporation are temperature, humidity, wind speed, and radiation. The direct measuring of evaporation, although fascinating, is challenging and attainable solely at point locations. The principal supply of vapour is that the oceans, however evaporation moreover happens in soils, snow, and ice. Evaporation from snow and ice, the direct conversion from solid to vapour, is understood as sublimation. Transpiration is that the evaporation of water through minute pores, or stomata, within the leaves of plants. For reasonable purposes, transpiration and the dissipation from all water, soils, snow, ice, vegetation, and different surfaces are lumped together and called evapotranspiration, or total evaporation (Britannica, 2018).

The transition method from the vapour state to the liquid state is named condensation. Condensation could manifest itself as before long when the air contains a lot of water vapour evaporated at the prevailing temperature. This condition happens because the consequence of either cooling or the blending of air lots at various temperatures. Water vapour subjected to condensation is discharged to form precipitation (USGS, 2016).

There are four main ways to distribute precipitation that falls to the Earth: some is returned to the atmosphere by evaporation, some may be captured by vegetation and then evaporated from the surface of leaves, some percolates into the soil by infiltration, and the remainder flows directly as surface runoff where water runs overland into nearby streams and lakes; the steeper the land and the less porous the soil, the bigger the runoff. Overland flow is mainly visible in urban areas. Rivers be a part of one another and eventually form one major watercourse that carries all of the sub-basins' runoff into the ocean. Some of the infiltrated precipitation may later percolate into streams as groundwater runoff. Direct measure of runoff is created by stream gauges and plotted against time on hydrographs (USGS, 2016).

Most groundwater that has percolated through the soil comes from precipitation. Groundwater flow rates, compared with those of surface water, are terribly slow and vary from millimetres to metres on a daily basis. Movement of groundwater is studied by tracer techniques and remote sensing (USGS, 2016).

Ice and snow on the Earth’s surface come about in numerous forms such as to frost, sea ice, and glaciers, once vapour in the soil get freezes. Ice also forms underneath the Earth’s surface, forming permafrost. About 18,000 years ago approximately one-third of the Earth’s land surface covered by glaciers and ice caps. Nowadays it has been reduced to 12% of the land surface due to melting of ice as a result of global warming (USGS, 2016).

The engineering hydrologists, or water resources engineers, are engaging, planning, analysis, design, construction and operation of projects for the control, utilization, and management of water resources with the use of analytical knowledge on hydrological process (Dyck, 1990).

## 2.2 Evapotranspiration Process

The combination of two separate processes whereby water is lost on the one hand from the soil surface by evaporation and on the other hand from the crop by transpiration is referred to as evapotranspiration (ET) (Savva & Frenken, 2002).

### 2.2.1 Evaporation

Evaporation is the method whereby liquid water is transformed to water vapour (vaporization) and removed from the evaporating surface (vapour removal). Water evaporates from a various surfaces, such as lakes, rivers, soils and wet vegetation. In order to change the state of the molecules of water from liquid to vapour, energy is the must. This energy is provided by direct solar radiation and the ambient temperature of the air, to a lesser extent (Savva & Frenken, 2002).

Difference between the water vapour pressure at the evaporating surface and that of the surrounding atmosphere play as the driving force of removing water vapour from the evaporating surface. As evaporation continues, the surrounding air becomes progressively saturated and the process will slow down and might stop when the air get fully saturated where no more wet air is not transferred to the atmosphere (Savva & Frenken, 2002).

Replacement of the saturated air by drier air depends greatly on the wind speed. Hence, to assess the process of evaporation, climatological parameters such as solar radiation, air temperature, air humidity and wind speed have to be considered. Where the evaporating surface is the soil surface, the degree of shading of the crop canopy and the amount of water available at the evaporating surface are other factors that affect the evaporation process further to the above (Savva & Frenken, 2002).

### 2.2.2 Transpiration

Transpiration comprises of the vaporization of fluid water contained in plant tissues and the vapour expulsion to the atmosphere. Crops predominately lose their water through stomata. These are tiny openings on the plant leaf through which gases and water vapour pass. The water, together with nutrients, is taken up by the roots and transported to the plant. The vaporization happens inside the leaf, to be specific in the intercellular spaces, and the vapour exchange with the air is controlled by the stomata opening. Almost all water taken up is lost by transpiration and just a little portion is utilized inside the plant. Transpiration, as immediate dissipation, relies upon the energy supply, vapour pressure gradient and wind. Subsequently, radiation, air temperature, air humidity and wind terms ought to be considered while surveying transpiration. The soil water content and the capacity of the soil to lead water to the roots also decide the transpiration rate, as do waterlogging and soil water saltiness. The transpiration rate is furthermore affected by crop characteristics, environmental aspects and cultivation practices. Various types of plants may have diverse transpiration rates. The variety of crop, as well as the crop development, environment and management ought to be considered while evaluating transpiration (Savva & Frenken, 2002).

### 2.2.3 Evapotranspiration (ET)

Evaporation and transpiration happen at the same time and there is no simple method for recognizing the two procedures separately (Figure 2.2). The evaporation from the cropped soil is mainly determined by the water availability in the top soil layer and fraction of the solar radiation reaching the soil surface. Fraction of solar radiation that touch the soil layer get decreases over the growing period of the crop as the crop develops, the crop canopy shades increasingly over the ground area. When the crop is small, water is predominately lost by soil evaporation, but once the crop is well developed and completely covers the soil, transpiration becomes the main process (Savva & Frenken, 2002).

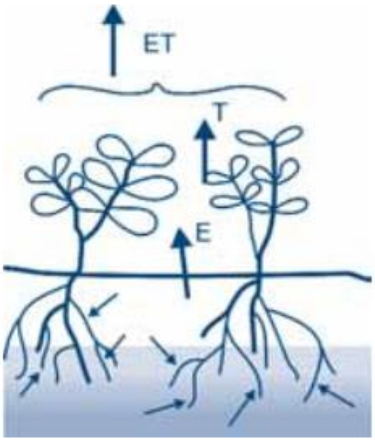


**Figure 2.2:** Process of Evapotranspiration
(Source: Savva & Frenken, 2002)

### 2.2.4 Reference Evapotranspiration (ETo)

The evapotranspiration from the reference surface is defined as reference crop evapotranspiration or reference evapotranspiration, denoted as ETo. The reference surface is a hypothetical grass reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s $m^{-1}$ which implies a moderately dry soil surface resulting from about a weekly irrigation frequency and an albedo of 0.23. The reference surface closely looks like a widespread surface of green, well-watered grass of uniform height, actively growing and completely shading the ground (Savva & Frenken, 2002).

The reason for introducing the concept of ETo was to study the evaporative demand of the atmosphere without any effect of the crop type, crop development stage and management practices. In other words it removes the need to define a separate evapotranspiration level for each crop and stage of growth. Once water is ample at the evapotranspiring surface, soil factors do not affect evapotranspiration. Relating evapotranspiration to a specific surface provides a reference to which evapotranspiration from other surfaces can be related (Savva & Frenken, 2002).

Only climatic parameters affect ETo. Therefore, ETo can be identified as a climatic parameter that can be computed from weather data. ETo expresses the evaporative demand of the atmosphere at a specific location and time of the year and does not consider crop and soil factors (Savva & Frenken, 2002).

## 2.3 Determining Evapotranspiration

Measuring Evapotranspiration is difficult. To determine evapotranspiration, specific devices and precise measurements of various physical parameters or the water balance of the soil in lysimeters are required. These methods are often expensive and demanding in terms of accuracy of the measurements. Therefore, these methods are not considered as practicable measures for routine measurements (Savva & Frenken, 2002).

### 2.3.1 Energy Balance and Microclimatological Methods

Relatively large volume of energy, either in the form of sensible heat or radiant energy is required by the water evaporation. Therefore, the evapotranspiration process is directed by energy interchange at the vegetation surface and is restricted by the amount of energy available. Because of this limitation, it is possible to predict the evapotranspiration rate by applying the principle of energy balance. The energy that reaches the surface must be equal to the energy that leaves from the surface during the same time period. All fluctuations of energy should be considered when deriving the equation of energy balance (Lin, *et al.*, 2008). The equation for an evaporating surface can be written as shown in Equation 2.1

$$R_n - G - \lambda ET - H = 0 \qquad \textbf{(2.1)}$$

Where,

$R_n$ - Net radiation,
H - Sensible heat,
G - Soil heat flux and
$\lambda$ ET - Latent heat flux.

These various terms can be either positive or negative. Positive net radiation implies energy to the surface and positive G, $\lambda$ ET and H remove energy from the surface. In above equation only vertical fluxes are considered and the net rate at which energy is being transferred horizontally is ignored. Therefore, the equation is applicable to large, widespread surfaces of homogeneous vegetation only. When all the other variables are known, energy balance equation can be used to calculate the latent heat flux ($\lambda$ ET) or the energy that is used to evaporate water representing the fraction of evapotranspiration (Allen, *et al*., 2006).

### 2.3.2 Mass Transfer Method

The mass transfer method is another method of estimating evapotranspiration. This method reflects the vertical movement of small packs of air (eddies) above a large homogeneous surface. Eddies transport material (water vapour) and energy (heat, momentum) from and towards the evaporating surface. By assuming steady state conditions and that the eddy transfer coefficients for water vapour are proportional to those for heat and momentum, the evapotranspiration rate can be computed via the Bowen ratio which use the vertical gradients of air temperature and water vapour. Other direct measurement methods use are gradients of wind speed and water vapour. These methods and several other methods such as eddy covariance require precise measurement of vapour pressure, and air temperature or wind speed at different levels above the surface. Therefore, this application is restricted to primarily research situations (Renuka, n.d.).

### 2.3.3 Soil Water Balance

Measuring the different components of the soil water balance can also use to determine Evapotranspiration. The method consists in evaluating the flow of water entering and leaving for a certain period of time into the crop root zone over same time period. Irrigation (I) and rainfall (P) add water to the root zone. Part of I and P might be lost by surface runoff (RO) and by deep percolation (DP) that will eventually recharge the water table. Water transport upward by capillary rise (CR) from a shallow water table towards the root zone or even transferred horizontally by subsurface flow in ($SF_{in}$) or out of ($SF_{out}$) the root zone. However, except under conditions with large slopes, in many surfaces, $SF_{in}$ and $SF_{out}$ are negligible and can be ignored. Soil evaporation and crop transpiration exhaust water from the root zone. If all fluxes other than evapotranspiration (ET) can be measured, the evapotranspiration can be deduced from the variation in soil water content (ΔSW) over the time period (Feddes & lenselink, 1994) as given by Equation 2.2.

$$ET = I + P - RO - DP + CR \pm \Delta SF \pm \Delta SW \quad \textbf{(2.2)}$$

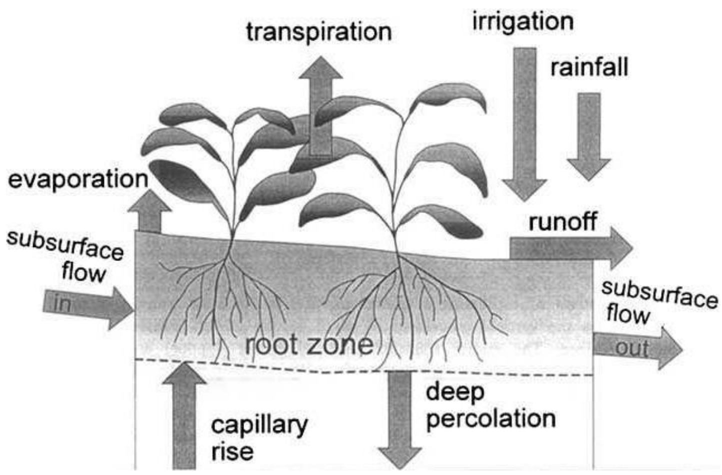


**Figure 2.3:** Process of soil water balance
(Source: Allen, *et al*., 2006)

Some fluxes such as subsurface flow, deep percolation and capillary rise from a water table are difficult to measure and even challenging for short time periods. ET assessments given by the soil water balance method are typically only for long time periods of the order of week-long or ten-day periods (Allen, *et al*., 2006).

### 2.3.4 Lysimeters

Lysimeters are also use the soil water balance equation by isolating the crop root zone from its environment and governing processes. In lysimeters the crop grows in isolated tanks filled with moreover disturbed or undisturbed soil. In precision weighing lysimeters, where the loss of water is measured directly by changing mass, the evapotranspiration can be obtained with an accuracy of a few hundredths of a millimeter and can be considered a short time of one hour. In lysimeters that do not weigh, the evapotranspiration for a given period of time is determined by subtracting the drainage water, collected in the lower part of the lysimeters, from the total water input. A requirement of lysimeters is that the vegetation both inside and immediately outside the lysimeter will fit perfectly (same height and leaf area index). This requirement has not been closely complied in majority of lysimeter studies in history and has resulted in severely erroneous and unrepresentative ETc and Kc data (Allen, *et al*., 2006). The use of lysimeters is limited to specific research purposes due to their difficultness and expensiveness to construct and as their operation and maintenance require special care (Allen, *et al*., 2006).

### 2.3.5 ET Computed from Meteorological Data

Owing to the problem of getting accurate field measurements, weather data is employ to compute ET. Empirical or semi-empirical equations have been developed largely for assessing crop or reference crop evapotranspiration using meteorological data (Yoder, *et al*., 2005). Some of these methods can only be used under specific climatic and agronomic conditions and cannot be applied under any other conditions apart from the originally developed (Kale, *et al*., 2013).

#### *2.3.5.1 FAO Penman-Monteith method*

As a result of an Expert Consultation held in May 1990, the FAO Penman-Monteith method is now recommended as the standard method for the definition and computation of the reference evapotranspiration, ETo. The ET from crop surfaces under standard conditions is determined by crop coefficients (Kc) that relate ETc to ETo. The ET from crop surfaces under non-standard conditions is adjusted by a water stress coefficient (Ks) and/or by modifying the crop coefficient (Savva & Frenken, 2002). The formula for ETo is given by Equation 2.3.

$$\mathrm{ETo} = \frac{0.408\,\Delta\,(\mathrm{R_n} - \mathrm{G}) + \gamma\,\frac{900}{\mathrm{T}+273}\,\mathrm{u_2}\,(\mathrm{e_s} - \mathrm{e_a})}{\Delta + \gamma\,(1 + 0.34\,\mathrm{u_2})} \quad \textbf{(2.3)}$$

Where,

ETo – Reference evapotranspiration [mm $day^{-1}$],

Rn – Net radiation at the crop surface [MJ $m^{-2}$ $day^{-1}$],

| | | |
|---|---|---|
| G | – | Soil heat flux density [MJ $m^{-2}$ $day^{-1}$], |
| T | – | Air temperature at 2 m height [°C], |
| $u_2$ | – | Wind speed at 2 m height [m $s^{-1}$], |
| $e_s$ | – | Saturation vapour pressure [kPa], |
| $e_a$ | – | Actual vapour pressure [kPa], |
| $e_s$-$e_a$ | – | Saturation vapour pressure deficit [kPa], |
| $\Delta$ | – | Slope vapour pressure curve [kPa °$C^{-1}$], |
| $\gamma$ | – | Psychrometric constant [kPa °$C^{-1}$] |

#### *2.3.5.2 ET estimated from pan evaporation*

Evaporation from an open water surface provides an index of the integrated effect of radiation, air temperature, air humidity and wind on evapotranspiration. However, differences in the water and cropped surface produce significant differences in the water loss from an open water surface and the crop. The pan has proved its practical value and has been used successfully to estimate reference evapotranspiration by observing the evaporation loss from a water surface and applying empirical coefficients to relate pan evaporation to ETo (Pereira & Pires, 2011).

## 2.4 Pan Evaporation Method

The Pan Evaporation method is still widely used because this method is very practical and simple as the evaporation rate from pans filled with water can be easily obtained. The amount of water evaporated during a period (mm/day) matches with the decrease in water depth in that period, in the absence of rain. Pans provide a measurement of the combined effect of radiation, wind, temperature and humidity when they evaporate from the surface of the open water. There are many factors that create significant differences in water loss from water surface and from cropped surface, but the pan responds similar way to the same climatic factors which affect crop transpiration. Reflection of solar radiation from water in the shallow pan might be different from the assumed 23% for the grass reference surface. Storage of heat within the pan can be appreciable and may cause significant evaporation. Some crops transpire only during the night while most crops transpire only during the daytime.

There are also differences in turbulence, temperature and humidity of the air immediately above the respective surfaces. Energy balance can be affected by the heat transfer through the sides of the pans. (Ali & Faraj, 2017).

Notwithstanding the difference between pan-evaporation and the evapotranspiration of cropped surfaces, the use of pans to predict ETo for longer periods may be acceptable. The pan evaporation is related to the reference evapotranspiration by an empirically derived pan coefficient (Beg, 2014) as given in the Equation 2.4.

$$ETo = K_p \times E_{pan} \tag{2.4}$$

Where,

ETo - Reference evapotranspiration [mm/day],

Kp - Pan coefficient [],

$E_{pan}$ - Pan evaporation [mm/day].

### 2.4.1 Pan Types and Environment

There are different types of pans. As the colour, size, and position of the pan can be influence significantly on the measured results and the pan coefficients are very much pan specific (Allen, *et al*., 2006).

#### 2.4.1.1 The Class A Pan

This kind of pan is very common to determining evaporation rate. This is a circular pan with 120.7cm in diameter and 25 cm deep (Figure 2.4). It is made of galvanized iron or Monel metal (0.8 mm). The pan is mounted on a wooden open frame platform which is 15cm above ground level. The soil built up to within 5 cm of the bottom of the pan. The pan must be levelled. The pan is filled with water to 5cm below the rim, and the water level should be not allowed to drop to more than 7.5cm below the rim. The water should be regularly renewed, at least weekly, to eliminate extreme turbidity. If galvanized, the pan needs to be painted annually with aluminium paint. Screens over the pan are not a standard requirement and should preferably not be used. Pans should be protected by fences to keep animals from drinking (Allen, *et al*., 1998).

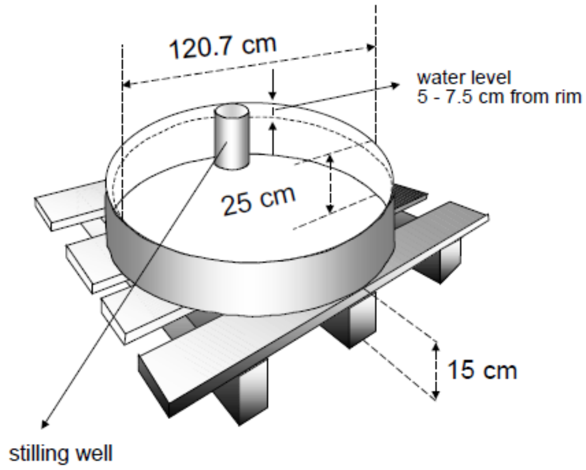


**Figure 2.4:** Schematic diagram of Class A pan
(Source: Allen, *et al*., 2006)

The site should preferably be under grass, 20m by 20m, open on all sides to permit free circulation of the air. It is preferable that stations be located in the center or on the sheltered side of large cropped fields. Pan readings are taken daily in the early morning at the same time that precipitation is measured. Measurements are made in stilling well that is situated in the pan near one edge. The stilling well is a metal cylinder of about 10cm in diameter and some 20cm deep with a small hole at the bottom (Abubaker, 2007).

#### 2.4.1.2 Class B Pan

Class B is a square pan with a 92cm square and 46cm deep, made of 3mm thick iron, placed in the ground with rim 5cm above the soil level (Figure 2.5). Also, the dimensions 1m square and 0.5m deep are frequently used. The pan is painted with black tar paint. The water level is maintained at or slightly below ground level, i.e., 5cm - 7.5cm below the rim. The measurements are taken similarly to those for the circular pan. The sitting and environment requirements are also similar to those for circular pan. Sometimes the square pan is preferred in crop water requirement studies, as these pans gives a better direct estimation of reference evapotranspiration than does the circular pan. The disadvantage is that maintenance is more difficult and leaks are not always visible (Abubaker, 2007).

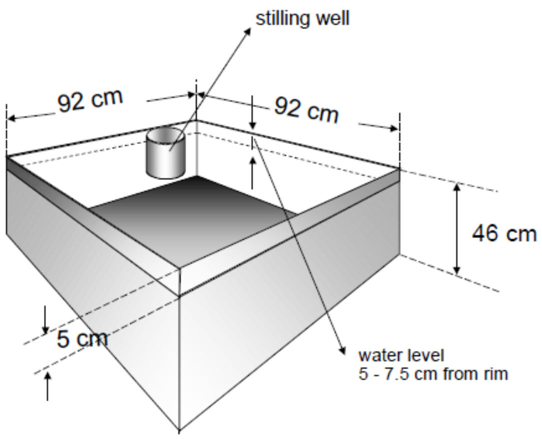


**Figure 2.5:** Schematic diagram of Class B pan
(Source: Allen, *et al.*, 2006)

Together with the pan type, ground cover in the station, its surroundings, general wind and humidity conditions, should also be checked in selecting the appropriate pan coefficient.

Pans are categorized with the sittings of the pans and the environment (Allen, *et al.*, 2006). This is particularly when the pan is placed in fallow rather than cropped fields. Two cases are commonly considered (Figure 2.6): Case A where the pan is sited on a short green (grass) cover and surrounded by fallow soil; and Case B where the pan is sited on fallow soil and surrounded by a green crop (Abubaker, 2007) .

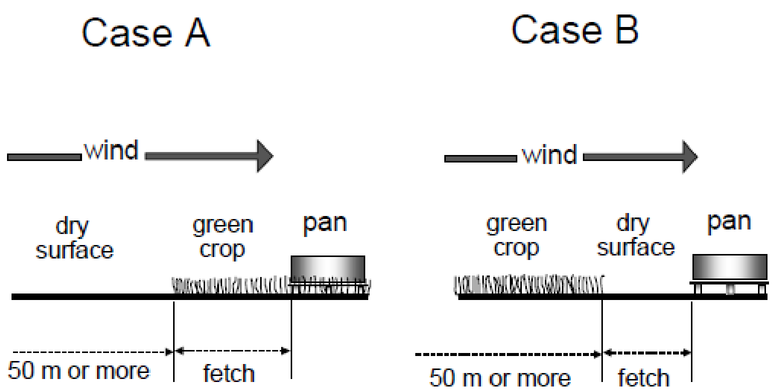


**Figure 2.6:** Two cases of evaporation pan sitting and their environment
(Source: Allen, *et al.*, 2006)

### 2.4.2 Pan Coefficients

Pan coefficients are pan specific as the colour, size and position of the pan have influence on the measured results. In selecting the correct pan coefficient, factors such as pan type, the groundcover in the station where the pan is sited, its surroundings and the general wind and humidity conditions should be considered.

#### 2.4.2.1 Methods of Estimating Kp

There are several methods to estimate Kp, all of them use data such as wind speed (U), relative humidity (H), and fetch length (F). The values of Kp were estimated from the following methods (Sentelhas & Folegatti, 2003) as described below:

a) FAO Irrigation and Drainage Paper No. 24

Appropriate Kp values applicable to the Class A& Class B pans for different groundcover and climatic conditions, Wind Speed and Relative Humidity can be read from the Table 2.1.

**Table 2.1:** Estimation of Kp using FAO Irrigation and Drainage Paper No. 24 (Source: Doorenbos & Pruitt, 1977)

| Class A pan | Case A: Pan placed in short green cropped area | | | | Case B: Pan placed in dry fallow area | | | |
|---|---|---|---|---|---|---|---|---|
| RH mean (%) → | | low < 40 | medium 40 -70 | high > 70 | | low < 40 | medium 40 -70 | high > 70 |
| Wind speed $(m\ s^{-1})$ | Windward side distance of green crop (m) | | | | Windward side distance of dry fallow (m) | | | |
| Light | 1 | .55 | .65 | .75 | 1 | .7 | .8 | .85 |
| < 2 | 10 | .65 | .75 | .85 | 10 | .6 | .7 | .8 |
| | 100 | .7 | .8 | .85 | 100 | .55 | .65 | .75 |
| | 1 000 | .75 | .85 | .85 | 1 000 | .5 | .6 | .7 |
| Moderate | 1 | .5 | .6 | .65 | 1 | .65 | .75 | .8 |
| 2-5 | 10 | .6 | .7 | .75 | 10 | .55 | .65 | .7 |
| | 100 | .65 | .75 | .8 | 100 | .5 | .6 | .65 |
| | 1 000 | .7 | .8 | .8 | 1 000 | .45 | .55 | .6 |
| Strong | 1 | .45 | .5 | .6 | 1 | .6 | .65 | .7 |
| 5-8 | 10 | .55 | .6 | .65 | 10 | .5 | .55 | .65 |
| | 100 | .6 | .65 | .7 | 100 | .45 | .5 | .6 |
| | 1 000 | .65 | .7 | .75 | 1 000 | .4 | .45 | .55 |
| Very strong | 1 | .4 | .45 | .5 | 1 | .5 | .6 | .65 |
| > 8 | 10 | .45 | .55 | .6 | 10 | .45 | .5 | .55 |
| | 100 | .5 | .6 | .65 | 100 | .4 | .45 | .5 |
| | 1 000 | .55 | .6 | .65 | 1 000 | .35 | .4 | .45 |

b) Cuenca (1989)

$$\mathbf{K_p = 0.475 - 2.4 \times 10^{-4}U + 5.16 \times 10^{-3}H + 1.18 \times 10^{-3}F - 1.6 \times 10^{-5}H^2 - 1.01 \times 10^{-6}F^2 - 8.0 \times 10^{-9}H^2U - 1.0 \times 10^{-8}H^2F} \qquad \textbf{(2.5)}$$

Where,

U = mean daily wind speed at 2 m height in km $d^{-1}$;

H = mean daily relative humidity in percentage; and

F = upwind fetch of low-growing vegetation,

c) Snyder (1992)

$$\boldsymbol{K_p = 0.482 + 0.024 \ln(F) - 0.000376\, U + 0.0045\, H} \qquad \textbf{(2.6)}$$

d) Pereira, *et al*., (1995)

$$\mathbf{K_p = 0.85 \times \frac{(s + \gamma)}{\left[s + \gamma \left(1 + \frac{r_c}{r_a}\right)\right]}} \qquad \textbf{(2.7)}$$

Where,

s = Slope of the vapour pressure curve at the daily average air temperature;

γ = Psychrometric coefficient; and

$r_c/r_a$ = Relationship between the grass canopy resistance to the water vapour diffusion ($r_c$) and the resistance offered by the air layer to exchange water vapour from the evaporating surface ($r_a$) given by an empiric relation with the wind speed, suggested by Allen *et al*. (1989) and adopted by FAO (Smith, 1991; Allen,*et al*., 1998):

$$\frac{r_c}{r_a} = 0.34\ \mathrm{U} \qquad \textbf{(2.8)}$$

e) Raghuwanshi & Wallender (1998)

$$\mathbf{K_p = 0.5944 + 0.024\,X_1 - 0.0583\,X_2 - 0.1333\,X_3 - 0.2083\,X_4 - 0.0812\,X_5 + 0.1344\,X_6} \quad \textbf{(2.9)}$$

Where,

$X_1$ = ln of the fetch distance (F) in m;

$X_2$, $X_3$, and $X_4$ = wind speed categories of 175-425, 425-700, and >700 km $d^{-1}$, respectively, and were assigned values of one or zero depending upon their occurrence (a zero value for these variables represented a wind speed < 175 km $d^{-1}$)

$X_5$ and $X_6$= relative humidity categories of 40-70% and >70%, respectively (a zero value for these variables represent a relative humidity < 40%).

f) Estimation of Kp using FAO Irrigation and Drainage Paper No. 56

$$\boldsymbol{K_p = 0.108 - 0.0286\,U + 0.0422\ln(F) + 0.1434\ln(H) - 0.000631\,[\ln(F)]^2\ln(H)} \quad \textbf{(2.10)}$$

Where,

U = mean daily wind speed at 2 m height in km $d^{-1}$;

H = mean daily relative humidity in percentage; and

F = upwind fetch of low-growing vegetation,

g) Constant Kp

This value was determined for Piracicaba, SP, Brazil, by the relationship between ETo and ECA with data from December 1995 to December 1996, during 112 days, and tested with independent data obtained in the same conditions described above, from January 1997 to October 1997, during 123 days.

### 2.4.2.2 Estimation of Kp using FAO Irrigation and Drainage Paper No. 56

In some conditions not accounted under the equation 2.10, the presented Kp coefficients may need some adjustment. Specially in the areas with no agricultural development, or where the pans are enclosed by tall crops. Not maintaining the standard colour of the pan or installing screens can affect the pan readings and will require some adjustment of the pan coefficient.

The pan coefficients presented apply to galvanized pans annually painted with aluminium and to stainless steel pans. Little difference in Epan will occur where the inside and outside surfaces of the pan are painted white. The level at which the water is maintained in the pan is important; resulting errors may be up to 15% when water levels in the Class A pan fall 10cm below the accepted standard of between 5cm and 7.5cm below the rim. To prevent animals from entering and drinking, the evaporation pan should be placed in a large, secure, wire enclosure, also affect the readings of the pans (Allen, *et al*., 2006).

The above considerations and adjustments indicate that the use of the corresponding equations may not be sufficient to consider all local environmental factors influencing Kp and that local adjustment may be required. To overcome the above problems following standard are recommended for installation and maintenance of evaporation pan (Allen, *et al*., 2006).

It is recommended that the pan should be installed inside a short green cropped area with a size of a square of at least 15m by 15m. The pan should not be installed in the centre but at a distance of at least 10m from the green crop edge in the general upwind direction (Allen, *et al*., 2006).

Where observations of wind speed and relative humidity, required for the computation of Kp, are not available at the site, estimates of the weather variables from a nearby station have to be utilized. And then these variables be averaged for the computation period and that Epan be averaged for the same period is recommended (Allen, *et al*., 2006).

| | | |
|---|---|---|
| **Class A pan with green fetch** | $K_p = 0.108 - 0.0286\,u_2 + 0.0422\ln(FET) + 0.1434\ln(RH_{mean}) - 0.000631[\ln(FET)]^2\ln(RH_{mean})$ | |
| **Coefficients and parameters** | $K_p$ | pan coefficient [ ] |
| | $u_2$ | average daily wind speed at 2 m height ($m\ s^{-1}$) |
| | $RH_{mean}$ | average daily relative humidity [%] = $(RH_{max} + RH_{min})/2$ |
| | FET | fetch, or distance of the identified surface type (grass or short green agricultural crop for case A, dry crop or bare soil for case B upwind of the evaporation pan) |
| **Range for variables** | $1\ m \le FET \le 1\ 000\ m$ | (these limits must be observed) |
| | $30\% \le RH_{mean} \le 84\%$ | |
| | $1\ m\ s^{-1} \le u_2 \le 8\ m\ s^{-1}$ | |

**Table 2.2:** Parameters and Variables described in Equation 2.10

(Source: Allen, *et al*., 1998)

## 2.5 Application of ETo in Agriculture

Estimating the crop water and irrigation requirements for a proposed cropping pattern is an essential part of the planning and designing of an irrigation system (Doorenbos & Pruitt, 1977).The irrigation requirement (IR) is one of the principal parameters for the planning, design and operation of irrigation and water resources systems. Detailed knowledge of the IR quantity and its temporal and spatial variability is essential for assessing the adequacy of water resources, for evaluating the necessity of storage reservoirs and to determine the capacity of irrigation systems. It is a major important parameter in formulating the policy for optimal allocation of water resources as well as in decision-making in the day-to-day operation and management of irrigation systems (A.C.C.Ltd., 2016). Incorrect estimation of the IR may lead to serious failures in the system performance and to the waste of valuable water resources (Savva & Frenken, 2002).

### 2.5.1 Crop Water Requirement

The crop water requirement is the amount of water required to compensate the evapotranspiration loss from the cropped field. Although the values for crop evapotranspiration and crop water requirement are identical, crop water requirement refers to the amount of water that needs to be supplied, while crop evapotranspiration refers to the amount of water that is lost through evapotranspiration. FAO (1984) defined crop water requirements as ‘the depth of water needed to meet the water loss through evapotranspiration of a crop, being disease-free, growing in large fields under non restricting soil conditions, including soil water and fertility, and achieving full production potential under the given growing environment’(Allen, *et al*., 2006). Crop evapotranspiration, ETc, is calculated using the Equation 2.11

$$ETc = Kc \times ETo \tag{2.11}$$

Where

| | | |
|---|---|---|
| ETc | - | crop evapotranspiration [mm $d^{-1}$], |
| Kc | - | crop coefficient [dimensionless], |
| ETo | - | reference crop evapotranspiration [mm $d^{-1}$]. |

#### 2.5.1.1 Crop Coefficient

Experimentally determined ratios of ETc/ETo, called crop coefficients (Kc), are used to relate ETc to ETo. Differences in leaf anatomy, stomatal characteristics, aerodynamic properties and even albedo cause the crop evapotranspiration to differ from the reference crop evapotranspiration under the same climatic conditions. Kc for a given crop changes from sowing till harvest, due to variations in the crop characteristics throughout its growing season. Kc represents an integration of the effects of four primary characteristics that distinguish the crop from reference grass. These characteristics are (Allen, *et al*., 2006):

- Crop height. The crop height influences the aerodynamic resistance term, $r_a$, of the FAO Penman-Monteith equation and the turbulent transfer of vapour from the crop into the atmosphere. The $r_a$ term appears twice in the full form of the FAO Penman-Monteith equation (Allen, *et al*., 2006).
- Albedo (reflectance) is the crop-soil surface. The albedo is affected by the fraction of ground covered by vegetation and by the soil surface wetness. The albedo of the crop-soil surface influences the net radiation of the surface, $R_n$, which is the primary source of the energy exchange for the evaporation process (Allen, *et al*., 2006).

- Canopy resistance. The resistance of the crop to vapour transfer is affected by leaf area (number of stomata), leaf age and condition, and the degree of stomatal control. The canopy resistance influences the surface resistance, $r_s$ (Allen, *et al*., 2006).
- Evaporation from soil, especially exposed soil.

The surface resistance, $r_s$ is influenced by soil surface wetness and the fraction of ground covered by vegetation. Following soil wetting, the vapour transfer rate from the soil is high, especially for crops having incomplete ground cover. The combined surface resistance of the canopy and of the soil determines the (bulk) surface resistance, $r_s$. The surface resistance term in the Penman-Monteith equation represents the resistance to vapour flow from within plant leaves and from beneath the soil surface (Allen, *et al*., 2006).

### 2.5.2 Irrigation Water Requirement

Irrigation requirements (IR) refer to the water that must be supplied through the irrigation system to ensure that the crop receives its full crop water requirements. If irrigation is the sole source of water supply for the plant, the irrigation requirement will always be greater than the crop water requirement to allow for inefficiencies in the irrigation system. The irrigation requirement will be considerably less than the crop water, if the crop receives some of its water from other sources (rainfall, water stored in the ground, underground seepage, etc.) (Letey, 2007)

The irrigation water requirement basically represents the difference between the crop water requirement and effective precipitation. The irrigation water requirement also includes additional water for leaching of salts and to compensate for non-uniformity of water application (Allen, *et al*., 2006). The net irrigation requirement is derived from the field balance Equation 2.12:

$$IRn = ETc - (Pe + Ge + Wb) + LR \qquad \textbf{(2.12)}$$

Where,

IRn - Net irrigation requirement (mm)

ETc - Crop evapotranspiration (mm)

| | | |
|---|---|---|
| Pe | - | Effective dependable rainfall (mm) |
| Ge | - | Groundwater contribution from water table (mm) |
| Wb | - | Water stored in the soil at the beginning of each period (mm) |
| LR | - | Leaching requirement (mm) |

### 2.5.3 Irrigation Scheduling

Once the crop water and irrigation requirements have been calculated, the next step is the preparation of field irrigation schedules. It is very critical to schedule irrigation for obtaining optimal crop yields. For optimum irrigation scheduling, sound knowledge of the soil water status, crop water requirements, crop water stress status, potential yield reduction under water-stressed conditions is prerequisite to maximize profits and optimize the use of water and energy (Zegbe, *et al.*, 2003; Kang, *et al.*, 2002). Irrigation scheduling involves the timing of irrigation and the amount of water applied (Brouwer & Prins, 1989). Three parameters have to be considered in preparing an irrigation schedules are;

- The daily crop water requirements
- The soil, particularly its total available moisture or water-holding capacity
- The effective root zone depth

Irrigation scheduling is conventionally based on Irrigation Water Requirement. Plant response to irrigation is influenced by the physical condition, fertility and biological status of the soil. Soil condition, texture, structure, depth, organic matter, bulk density, salinity, sodicity, acidity, drainage, topography, fertility and chemical characteristics all affect the extent to which a plant root system penetrates into and uses available moisture and nutrients in the soil. Many of these elements influence the water movement in the soil, the water holding capacity of the soil, and the ability of the plants to use the water. Soils to be irrigated must also have sufficient surface and subsurface drainage, especially in the case of surface irrigation. Internal drainage within the crop root zone can either be natural or from an installed subsurface drainage system. The irrigation system used should have the potential to match all or most of these conditions (Murray & Grant, 2007).

## 2.6 Historical Preference

Gautham and Sinha have used ARIMA for forecasting mean monthly reference crop evapotranspiration using data series of 102 years of Bokaro District, India the identified best fitted model is ARIMA (0, 1, 4) $(0, 1, 1)_{12}$ for the considered data set. The model has not been tested for an independent data set.

Mohan and Arumugam (1995) have carried out a study on “Forecasting weekly reference crop evapotranspiration”. Two techniques: namely a seasonal ARIMA model and Winter's exponential smoothing model have been investigated in their study. A seasonal ARIMA model with one autoregressive of order one and order one moving average process and with a seasonality of 52 weeks, ARIMA $(1,1,1)_{52}$ was found as the best fitted model. The ARIMA and Winter's models were compared with a simple ET model to assess their performance in forecasting. The forecast errors produced by these models were found to be very small and the models would be promisingly of great use in real-time irrigation management.

A study conducted by Meshram, Gorantiwar, Sangale, Nagraj and Pal (2017), investigated for forecasting the weekly reference crop evapotranspiration (ETo) at Maharashtra, India. The daily values of climatic parameters were collected for 33 years (1984 to 2016) and daily values of ETo were estimated by using Penman-Monteith method. These weekly ETo values were used to fit the ARIMA models and SARIMA models by comparing 256 models. The results from an analysis shows that, the model fitted best is SARIMA (0,0,1) $(1,0,2)_{52}$.

Another study has carried out by Manikumari andVinodhini in year 2016 to model the reference evapotranspiration by two different regression models based on the daily evapotranspiration data collected during the period 1987 –2008 in India. Best model has been selected by comparing the results with Penman – Monteith (FAO-PM). As per the findings of the study, Support Vector Regression gives the better estimates than multi-layer regression.

The objective of the study carried out by Landeras, Ortiz-Barredo and Lópezin year 2009was to compare the weekly evapotranspiration using ARIMA and artificial neural network (ANN)-, in Northern Spain. The application of both ARIMA and

ANN models improved the performance of one week in advance weekly evapotranspiration predictions compared to the model based on means (mean year model based on historical averages).

Arca *et al*. (2004) have developed both ARIMA and ANN models using four years of reference evapotranspiration which were calculated hourly Penman-Monteith equation with weather data. Two year data set has used to validate the model by comparing the forecasted ETo with values calculated using weather data.

## 2.7 Summary

Chapter 02 provides a superficial introduction to process of evapotranspiration and its applications in agriculture. Evapotranspiration is a combination of two separate processes whereby water is lost on the one hand from the soil surface by evaporation and on the other hand from the crop by transpiration (ET). The evapotranspiration from the reference surface, is defined as reference crop evapotranspiration or reference evapotranspiration, denoted as ETo. The reason for introducing the concept of ETo was to study the evaporative demand of the atmosphere without any effect of the crop type, crop development stage and management practices where only climatic parameters affect. Energy Balance and Microclimatological Methods, Mass Transfer Method, Soil Water Balance, Lysimeters are the methods used for calculating evapotranspiration which are often expensive and demanding in terms of accuracy of the measurements. To overcome this issue, weather data is employ to compute ET. FAO Penman-Monteith method is recommended as the standard method for computation of the reference evapotranspiration. Due to the high data demand in PM method, the Pan Evaporation method is used in this study to calculate ETo. The pan evaporation is related to the reference evapotranspiration by an empirically derived pan coefficient, Kp. There are several methods to estimate Kp and out of those, equation derived through FAO/56 (Allen, et al., 1998) is used in this analysis. Reference evapotranspiration can be used in field of agriculture to compute crop water requirement that is the amount of water required to compensate the evapotranspiration loss from the cropped field and it can be further used to calculate the irrigation requirement. Once the crop water and irrigation requirements have been calculated, field irrigation schedules can be prepared. These estimates can be used to manage water distribution and develop the planning process of irrigation schemes.

# CHAPTER 3
# MATERIALS AND METHODS

Previous chapter described the background of reference evapotranspiration analysis. This section refers to the data and methodology that are going to apply for the forecast of ETo in Polonnaruwa.

## 3.1 Study Area

To simplify the study, ETo is analyzed for both Maha and Yala seasons of Polonnaruwa district which is in the dry zone of the Sri Lanka. Polonnaruwa District is a major agricultural area in the North Central province of the Sri Lanka with the engagement of the traditional farmers who are lacking of water (Upali, *et al*., 2016).

Polonnaruwa District is located between longitudes 81° 0' East, and Latitudes 7° 56' North with annual rainfall ranges between 1180 mm – 1800 mm in short period with long dry spell. Generally, average temperature is $28^{0}$C and shows seasonal variation. Average temperature during December and January were found as approximately 27 °C (80.6 °F) and during the warmest months of the year from April through September it seemed 30-32 °C (CEA, 1990).

Land cover map (Figure 3.1) shows that the predominant type in the area is forest while paddy is the next major type. This reflects that the agriculture, both irrigated or rainfed is influencing the living patterns of the population in the district. As per the records of Department of Census and Statistics, the second highest Paddy production is reported from Polonnaruwa district and agriculture in Polonnaruwa mainly depends on traditional tank based system. Today traditional tank based system is not sufficient to fulfill the water requirement of crops grown in Polonnaruwa district; therefore it is vital to develop a crop plan, which can optimize the use of rainfall to reduce the irrigation water demand from tanks. The objective of this study is to investigate ETo trends, in order to have better management of surface water resources and agricultural activities in Polonnaruwa.

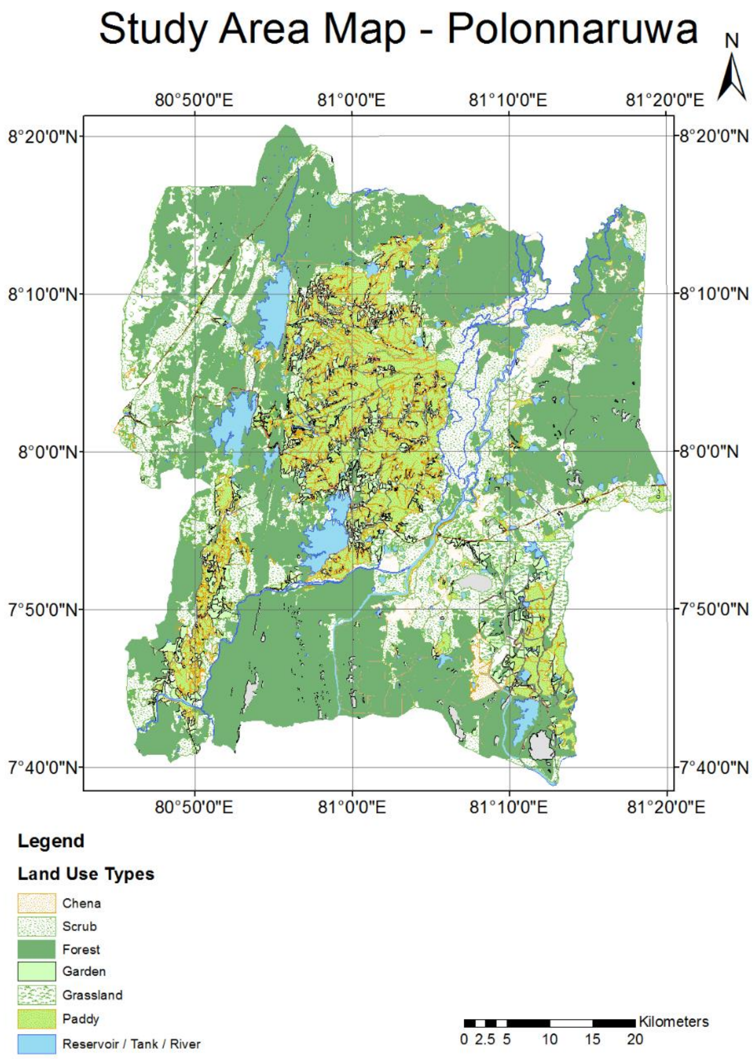


**Figure 3.1: Location of Polonnaruwa District.**

## 3.2 Data

Data used for this study were obtained from Department of Meteorology Sri Lanka. Pan evaporation, relative humidity and wind speed collected on weekly basis at Polonnaruwa Meteorology station, for the period of January 2010 to December 2015. Data from April 2010 to May 2015 covering the period from April to September in five years span was used to train the model for Yala season. In order to train the model for Maha season data used from January 2010 to February 2015covering the period from October to March in five years span. Third model was fitted by pooling the data used for Yala and Maha. The balance data was used to validate the fitted model.

### 3.3 Method Statement

Models for weekly reference evapotranspiration were developed by covering five successive stages as shown in Figure 3.2.

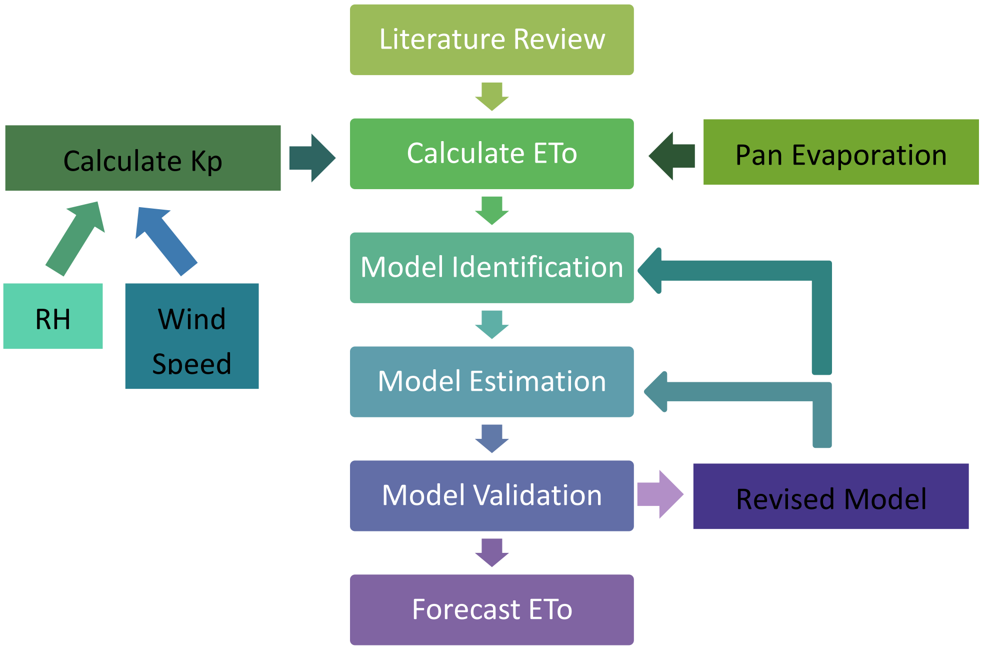


**Figure 3.2:** Flow chart of the methodology

First stage of research methodology was devised to acquire and process the data. During the second stage of the methodology, reference evapotranspiration is calculated using pan evaporation method. At the next stage ARIMA and SARIMA time series analysis were developed using Minitab and EViews softwares for Yala and Maha seasons separately.

### 3.4 Calculation of Reference ETo

The pan evaporation is related to the reference evapotranspiration by an empirically derived pan coefficient ($K_p$) as shown in Equation 3.1.

$$ET_0 = K_p \times E_{pan} \quad \textbf{(3.1)}$$

where:

ETo – reference evapotranspiration (mm/day);

Kp – pan coefficient,

Epan – pan evaporation (mm/day).

The details of computing Kp has been defined in Equation 2.10. It should be noted that the evaporation pan at Polonnaruwa agromet is installed inside a short green cropped area with a size of a square of at least 15 by 15 m and the pan is in the centre but at a distance of nearly 10 m from the green crop edge in the general upwind direction.

## 3.5 Developing Time Series Models

A time series is a sequence of data points, typically consisting of successive measurements or observations on quantifiable variable(s), made over a time interval (Cochrane, 2005). Usually the observations are chronological and taken at regular intervals (days, months, years), but the sampling could also be irregular (Adhikari & Agrawal, n.d.).

Time series analysis comprises methods or processes that breakdown a series into components and explainable portions that allows trends to be identified, estimates and forecasts to be made. Basically time series analysis attempts to understand the underlying context of the data points through the use of a model to forecast future values based on known past values. Such time series models include MA, AR, ARIMA, GARCH, TARCH, EGARCH, FIGARCH, CGARCH and ARIMA among others but the main focus of this study is based on MA, AR, ARIMA, and SARIMA models (Gahirwal & Vijyalakshmi, n.d.).

According to (Cochrane, 2005), time series can be represented as a set of observations $X_T$, each one being recorded at a specific time T; written as:

$\{X_1, X_2,...X_t\}$ or $\{X_T\}$, where T = 1, 2,...t

If a time series has a regular pattern i.e. trend, then a value of the series should be a function of previous values. If X is the target value that is to be modelled and predicted, and Xt is the value of X at time t, then the goal is to create a model of the form (Equation 3.2):

$$X_t = f(X_{t-1}, X_{t-2}, X_{t-3}, \ldots, X_{t-n}) + e_t \qquad \textbf{(3.2)}$$

Where $X_{t-1}$ is the value of X for the previous observation, $X_{t-2}$ is the value two observations ago, etc., and $e_t$ represents noise that does not follow a predictable pattern (this is called a random shock). Values of variables occurring prior to the current observation are called lag values.

#### 3.5.1.1 Basic Concepts and Definitions of Time Series

Time series can be categorized into two major classes namely: univariate or multivariate. A univariate time series is a sequence of measurements of the same variable collected over time. Most often, the measurements are sequence of events made at regular time intervals (Fawumi, 2015).

However, when a time series involves more than one variable, it is said to be multivariate. Most economic and financial information is structured in the form of multivariate time series. Multivariate time series can be further categorized into homogenous and heterogeneous multivariate time series, based on the relationships between the measured variables. If a variable X is useful to predict future values of another variable Y, the multivariate time series is said to be homogeneous, else it is heterogeneous (Fawumi, 2015).

The following is a brief definition of the commonly used terminologies in describing time series.

- Lag

Lag is the time period between two observations. For example, lag 1 is between $X_t$ and $X_{t-1}$. Lag 2 is between $X_t$ and $X_{t-2}$. Time series can also be lagged forward, $X_t$ and $X_{t+1}$. The observation at the current time, $X_t$ , depends on the value of the previous observation, $X_{t-1}$ ( Fawumi, 2015).

- Autocorrelation and Partial Autocorrelation Functions (ACF and PACF)

ACF is the linear dependence of a variable with itself at two points in time of lag h, like equation 3.3

$$\text{ACF}(h) = \text{Corr}(x_t, x_{t-h}) = \gamma_h = \frac{\sum_{i=1}^{n-h}(x_i - \bar{x})(x_{i+h} - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad \textbf{(3.3)}$$

PACF is the autocorrelation of a signal with itself at different points in time, with linear dependency with that signal at shorter lags removed, as a function of lag between points of time. Informally, the partial correlation between $x_t$ and $x_{t+h}$ is the autocorrelation between $x_t$ and $x_{t+h}$ without the contribution of $x_{t+1}, x_{t+2}, \ldots, x_{t+h-1}$.

- Differencing

Differencing simply means subtracting the value of an earlier observation from the value of a later observation. Calculating differences among pairs of observations at some lag to make a non-stationary series stationary (Hyndman &Athanasopoulos, 2012).

Differencing the scores is the easiest way to make a non-stationary mean stationary (flat). The number of times you have to difference the scores to make the process stationary determines the value of d. If $dC_0$, the model is already stationary and has no trend. When the series is differenced once, $dC_1$ and linear trend is removed. When the difference is then differenced, $dC_2$ and both linear and quadratic trend are removed. For non-stationary series, d values of 1 or 2 are usually adequate to make the mean stationary (Hyndman &Athanasopoulos, 2012).

- Stationary Data

This describes a time series variable which exhibits no significant upward or downward trend over time (Hyndman &Athanasopoulos, 2012). In other words it can be known as a series vary around a constant mean level, neither decreasing nor increasing systematically over time, with constant variance (NIST/SEMATECH, 2012).

- Non-stationary Data

A non-stationary time series data is a data with variable exhibiting a significant upward or downward trend over time. Seasonal Data: This describes a time series variable exhibiting repeating patterns at regular intervals over time (Anderson, *et al*., 2014).

### 3.5.2 Autoregressive Process.

Autoregressive models are based on the idea, that values of process $X_t$are linearly dependent on some number of past values of the same process$X_t$. In this model, the actual value of the process is expressed as a sum of finite linear combination of previous values and the impulses, called white noise. This can be summarized in the Equation 3.4& 3.5(Wildi, 2013):

$$X_t = \delta + \theta_1 X_{(t-1)} + \theta_2 X_{(t-2)} + \theta_3 X_{(t-3)} + \ldots\ldots.. + \theta_p X_{(t-p)} + \varepsilon_t \qquad \textbf{(3.4)}$$

$$\theta\ (\beta) = 1 - \theta_1\beta - \theta_2\beta^2 - \ \ldots\ldots\ldots - \ \theta_p\beta^p \qquad \textbf{(3.5)}$$

Where

δ is a constant (intercept), and

$\theta_1$,$\theta_2$, $\theta_3$ are the autoregressive model parameters.

The formula describes the autoregressive model of order p. This model is often denoted as AR (p). In AR (p) model, the present value is made up of a random error component (random shock, $\varepsilon_t$) and a linear combination of prior observations. The parameters$\delta$ and $\theta_1$are usually estimated by mean least squares or maximum likelihood methods (Wildi, 2013).

### 3.5.3 Moving Average Process.

Independent from the autoregressive process, each element in the series can also be affected by the past error (or random shock) that cannot be accounted by the autoregressive component, that is shown in Equation 3.6 & 3.7 (Wildi, 2013):

$$X_t = \mu + \varepsilon_t - \varphi_1\,\varepsilon_{(t-1)} - \varphi_2\,\varepsilon_{(t-2)} - \varphi_3\,\varepsilon_{(t-3)} - \varphi_4\,\varepsilon_{(t-4)} - \ldots\ldots \qquad \textbf{(3.6)}$$

$$\varphi(\beta) = 1 - \varphi_1\beta - \varphi_2\beta^2 - \ \ldots\ldots\ldots - \ \varphi_p\beta^p \qquad \textbf{(3.7)}$$

Where,

μ is a constant, and

$\varphi_1, \varphi_2, \varphi_3, \ldots \ldots$ are the moving average model parameters.

That is the present values of MA(q) model is made up of a present random error component (random shock, $\varepsilon_t$ ) and a linear combination of prior random shocks $(\varepsilon_1, \varepsilon_2, \ldots \ldots \ldots \varepsilon_{t-1})$.

### 3.5.4 Autoregressive and Moving Average Model

In order to achieve better prediction quality, two previous models are often merged into one model, autoregressive and moving average model. Common model is denoted as ARMA(p; q) and it unites a moving average filter of order q and auto regression of filtered values of order p (Wildi, 2013).

If the time series data show evidence of non-stationarity, then the initial differencing step can be applied to reduce the non-stationarity. This model is usually denoted as ARIMA(p; d; q). The parameter d represents the degree of differencing, it corresponds to the integrated part of the model (Wildi, 2013).

$$Y_t = \delta + \theta_1 Y_{(t-1)} + \theta_2 Y_{(t-2)} + \ldots \ldots \ldots + \theta_p Y_{(t-p)} + \varepsilon_t - \varphi_1\, \varepsilon_{(t-1)} - \varphi_2\, \varepsilon_{(t-2)} - \ldots \ldots \ldots \ldots - \varphi_q \varepsilon_{(t-q)} \quad \textbf{(3.8)}$$

Where, $Y_t = X_{(t)} - X_{(t-\mathrm{d})}$

This can be further describe by backshift operator as follows (Equation 3.9&3.10).

$$\left(1 - \theta_1 \beta - \theta_2 \beta^2 - \ldots \ldots \ldots - \theta_p \beta^p\right) Y_t = \delta + \left(\varphi_1\, \beta - \varphi_2\, \beta^2 - \ldots \ldots \ldots - \varphi_q \beta^q\right) \varepsilon_t \quad \textbf{(3.9)}$$

$$(1 - \beta^d)\left(1 - \theta_1 \beta - \theta_2 \beta^2 - \ldots \ldots \ldots - \theta_p \beta^p\right) X_t = \delta + \left(\varphi_1\, \beta - \varphi_2\, \beta^2 - \ldots \ldots \ldots - \varphi_q \beta^q\right) \varepsilon_t \quad \textbf{(3.10)}$$

### 3.5.5 Seasonal Autoregressive and Moving Average Model

A time series is said to be seasonal if there is a sinusoidal or periodic pattern in the series. These periodic patterns of the data series has to be taken into consideration separately. In these models seasonal differencing of appropriate order is used to remove non-stationarity from the series. Box and Jenkins (1970) incorporated seasonality into existing ARIMA approaches, arriving at the seasonal autoregressive moving average model or SARIMA (p,d,q)(P,D,Q)$_S$, which can be written as Equation 3.11 or 3.12

$$\begin{aligned}\left(1-\theta_1\beta-\theta_2\beta^2-\ \dots\dots-\ \theta_p\beta^p-\theta_S\beta^S-\ \theta_{2S}\beta^{2S}-\ \dots\dots\right.\\ \left.-\ \theta_{SP}\beta^{SP}\right) Z_t\\ =\delta\\ +\left(\varphi_1\,\beta\ -\ \varphi_2\,\beta^2\ -\ \dots\dots\ -\ \varphi_q\beta^q-\ \varphi_{\mathrm{S}}\,\beta^S\right.\\ \left.-\ \varphi_{2\mathrm{S}}\,\beta^{2S}-\ \dots.\dots-\ \varphi_{\mathrm{SQ}}\,\beta^{SQ}\right)\varepsilon_t\end{aligned} \tag{3.11}$$

Where, $Z_t=\ \left(X_{(t)}-X_{(t-\mathrm{d})}\right)-\ \left(X_{(t-DS)}-X_{(t-\mathrm{DS}-\mathrm{d})}\right)$

Or

$$\begin{aligned}(1-\ \beta^d)(1-\ \beta^{SD})\left(1-\theta_1\beta-\theta_2\beta^2-\ \dots\dots-\ \theta_p\beta^p-\theta_S\beta^S\right.\\ \left.-\ \theta_{2S}\beta^{2S}-\ \dots\dots-\ \theta_{SP}\beta^{SP}\right) X_t\\ =\ \delta\\ +\ \left(\varphi_1\,\beta\ -\ \varphi_2\,\beta^2\ -\ \dots\dots\ -\ \varphi_q\beta^q-\ \varphi_{\mathrm{S}}\,\beta^S\right.\\ \left.-\ \varphi_{2\mathrm{S}}\,\beta^{2S}-\ \dots.\dots-\ \varphi_{\mathrm{SQ}}\,\beta^{SQ}\right)\varepsilon_t\end{aligned} \tag{3.12}$$

Where, $\beta$ denotes the backward shift operator ($\beta\, X_t\ =\ X_{t-1}$), ‘S’ the seasonal lag and $'\,\varepsilon_t'$ a sequence of independent normal error variable with mean 0 and variance $\sigma^2$. $'\theta'$and$'\varphi'$ are respectively the autoregressive and moving average parameters. ‘p’ and ‘q’ are order of non seasonal auto regression and moving average parameters respectively. Whereas ‘P’ and ‘Q’ are that of seasonal auto regression and moving average parameters respectively. Also ‘d’ and ‘D’ denote non seasonal and seasonal differences and $\delta$ is a constant.

### 3.5.6 ARIMA / SARIMA Model Building

Box – Jenkins studied the simplified steps to obtain comprehensive information of ARIMA models. Four steps as per the Box – Jenkins studies are: (1) model identification, (2) estimation of model parameters, (3) diagnostic checking, and (4) application of the model forecasting (Box, Jenkins, and Reinsel 1994).

#### 3.5.6.1 Model identification

The model identification stage help to decide whether the time series may be modelled by ARIMA, and if so, what order of autoregressive and moving average terms should be chosen for the validation stage. The first step in developing a Box–Jenkins model is to determine if the time series is stationary and if there is any significant seasonality that needs to be modelled.

- Detecting Stationarity

A run sequence plot of the data is generated to determine time series stationarity i.e., whether the time series exhibits constant mean and scale. It can also be detected from an autocorrelation plot. Specifically, non-stationarity is often indicated by an autocorrelation plot with very slow decay. Finally, unit root tests provide a more formal approach to determining the degree of differencing.

- Differencing to achieve Stationarity

Box and Jenkins recommend the differencing approach to achieve stationarity. However, fitting a curve and subtracting the fitted values from the original data can also be used in the context of Box-Jenkins models.

- Seasonal Differencing

At the model identification stage, the goal is to detect seasonality, if it exists, and to identify the order for the seasonal autoregressive and seasonal moving average terms. For many series, the period is known and a single seasonality term is sufficient. However, it may be helpful to apply a seasonal difference to the data and regenerate the autocorrelation and partial autocorrelation plots. This may help in the model identification of the non-seasonal component of the model. In some cases, the seasonal differencing may remove most or all of the seasonality effect.

- Identifying p and q

Once stationarity and seasonality have been addressed, the next step is to identify the order (i.e. the p and q) of the autoregressive and moving average terms. These are determined by examining the values of the autocorrelations and the partial autocorrelations with their corresponding plots as explained below. The autocorrelation function (ACF) measures the degree of correlation between lagged values of the times series. The autocorrelation value is bounded by the interval [-1,1] where a value close to 1 indicates strong, positive correlation; a value close to -1 indicates strong negative correlation;

The partial autocorrelation coefficient at lag k is the autocorrelation between observations $X_t$ and $X_{t-k}$ that is not explained by lag k = 1 through to lag k-1. Similar to the ACF, the PACF is bounded on the [-1,1] interval; the numerical interpretation of the PACF with respect to correlative behaviour and strength are also similar to the ACF.

At the identification stage, one or more parsimonious models are tentatively chosen that seem to provide statistically adequate representations of the available data. Precise estimation of the parameters can be obtained using statistical techniques, such as the maximum likelihood, least-squares, or Yule–Walker method.

#### 3.5.6.2 Diagnostic checking

The diagnostic checking stage involves assessing the adequacy of the identified and fitted models through possible statistically significant test on the residuals to verify its consistency with the white noise process e.g. the Ljung-Box test, residual correlograms (ACF and PACF) and residual plots.

#### 3.5.6.3 Model forecasting

As a final step for modeling, once an appropriate time-series model is estimated, future values can be forecasted. Forecast precision can be evaluated against performance measures.

### 3.5.7 ARIMA Modelling: Advantages and Disadvantages

Time series models have been commonly used in a broad range of scientific applications, including hydrology; however, as per the studies it can be basically concluded that the SARIMA model has good model fitting degree in decision-making for agricultural irrigation.

Some of the major advantages of time series models include the systematic search capability for identification, estimation, and diagnostic checking. Time series models, like the Autoregressive Integrated Moving Average (ARIMA), effectively consider serial linear correlation among observations, whereas Seasonal Autoregressive Integrated Moving Average (SARIMA) models can satisfactorily describe time series that exhibit non-stationary behaviours both within and across seasons. It is found that ARIMA as a proper way in especially short term time series forecasting (Box, 1970; Jarrett, 1991). Taking advantage of its strictly statistical approach, the ARIMA method only requires the prior data of a time series to generalize the forecast. Hence, the ARIMA method can increase the forecast accuracy while keeping the number of parameters to a minimum (Zhai, 2005).

Some major disadvantages of ARIMA forecasting are: the traditional model identification techniques use for identifying the correct model from the class of possible models are difficult to understand and usually computationally expensive. This process is also subjective and the reliability of the chosen model can depend on the skill and experience of the forecaster. The underlying theoretical models and structural relationships are not distinct as some simple forecasts models such as simple exponential smoothing and Holt-Winters (Thomas 1983). Moreover, the ARIMA models, as all forecasting methods, are essentially "backward looking". Such that, the long term forecast eventually goes to be straight line and poor at predicting series with turning points (Zhai, 2005).

# CHAPTER 4
# RESULTS AND DISCUSSION

After a thorough discussion on theoretical background of Reference Evapotranspiration and Time Series analysis, from the previous chapters, this chapter describes the development of ARIMA models for weekly reference evapotranspiration over six years period from 2010 to 2015 of Polonnaruwa area.

## 4.1 Time Series Analysis for Yala Season

The descriptive statistics for the weekly reference evapotranspiration over six years period from 2010 to 2015 during Yala Season is shown in Table 4.1. This analysis was made in an attempt to find more information about pattern of ETo in Polonnaruwa during the Yala season.

### 4.1.1 Temporal Variability of Yala Season

Table 4.1 clearly explains descriptive statistics of the data set that used to have a general idea of the original data set, the distribution of ETo in Polonnaruwa during the period of April – September in five years span. The mean reference evapotranspiration varied between 2.23 mm (minimum) to 5.37 mm (maximum) with a mean of 3.62 mm and SD of 0.53. The chance of reference evapotranspiration exceeds the 3.96 mm is 25% and chance of being lower than 3.23mm is also 25%.

**Table 4.1:** Descriptive Statistics of the average weekly reference evapotranspiration from 2010 to 2015 in Polonnaruwa during Yala Season (April to September) (in mm)

| Mean | SE Mean | StDev | Minimum | Q1 | Median | Q3 | Range | Maximum |
|---|---|---|---|---|---|---|---|---|
| 3.62 | 0.05 | 0.53 | 2.23 (Week 102) | 3.23 | 3.67 | 3.96 | 3.14 | 5.37 (Week 136) |

Figure 4.1 shows the average weekly ETo time series during the Yala Season at Polonnaruwa from 01.01.2010 to 31.12.2015.The time series plots display calculated reference evapotranspiration in mm on the y-axis against equally spaced time

intervals on the x-axis. This can be used to evaluate patterns, knowledge of the general trend and behaviors of ETo at Polonnaruwa during the Yala season. There is no clear trend can be observed in the reference evapotranspiration time series and seasonality of the data series is doubtful (Figure 4.1).

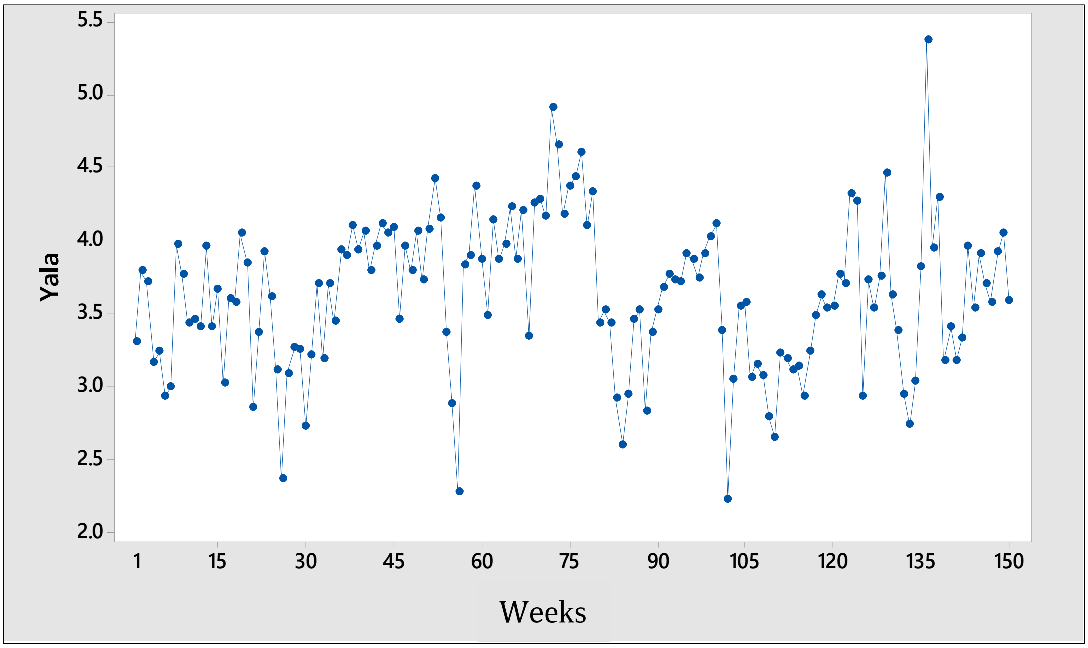


**Figure 4.1:** Time series plot of average weekly reference evapotranspiration from 2010 to 2015 in Polonnaruwa in Yala season $\{Y_t\}$

### 4.1.2 ACF of Original Yala Data Series

A plot of the autocorrelation of a time series by lag is called the **A**uto **C**orrelation **F**unction, or the acronym ACF. This plot is sometimes called a correlogram or an autocorrelation plot. Autocorrelation plot is a commonly-used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero. In addition, autocorrelation plots are used in the model identification stage for Box-Jenkins autoregressive, moving average time series models.

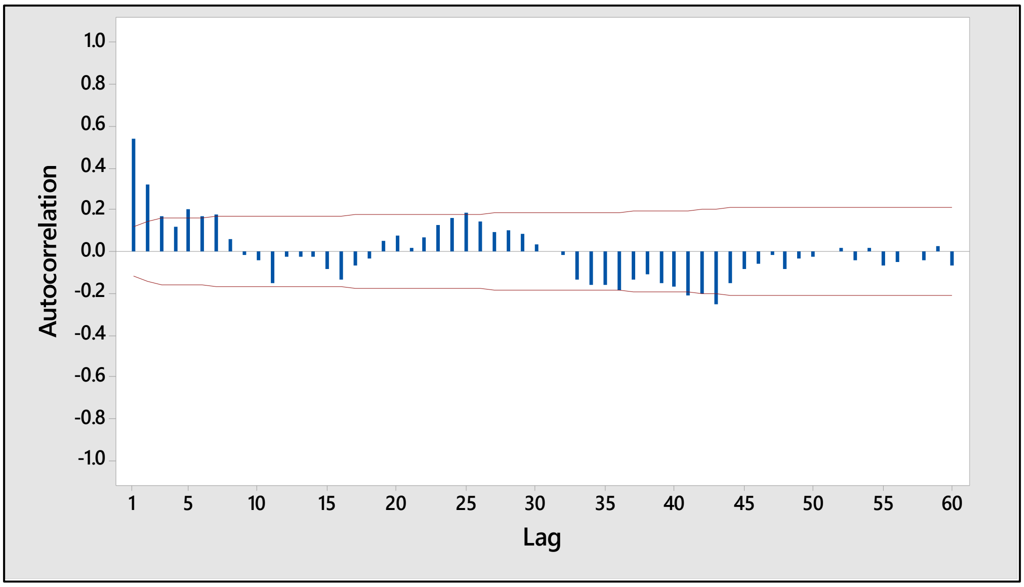


**Figure 4.2:** Autocorrelation function of reference evapotranspiration in Polonnaruwa training data set (Yala){$Y_t$}

The autocorrelation graph was plotted for the reference evapotranspiration data series in Yala (Figure 4.2), to check the randomness of the data. In Figure 4.2 data set shows that the time series is not random. The autocorrelations remain strong in first few lags and slightly decreasing when increasing the number of lags following a kind of sinusoidal pattern. This emphasize that previous ETo values are obviously correlated to future ETo data.

And also seasonal patterns of time series can be examined via correlograms. Seasonality in a time series refers to predictable and recurring trends and patterns over a period of time. It is hard to find seasonality in the calculated weekly ETo data series from figure 4.2.

### 4.1.3 ACF of Stationary Series - Non Seasonal

A common assumption in many time series techniques is that the data are stationary. A stationary process has the property that the mean, variance and autocorrelation structure do not change over time. Stationarity can be defined a series, without trend, constant variance over time, a constant autocorrelation structure over time and no periodic fluctuations (seasonality). A stationarized series is relatively easy to predict.

The two most common ways to make a non-stationary time series curve stationary are: differencing & transforming.

ARIMA models a non-stationary time series is made stationary by applying finite differencing of the data points. Consider the 1st difference of the series (Figure 4.3) to model ARIMA for ETo in Yala season.

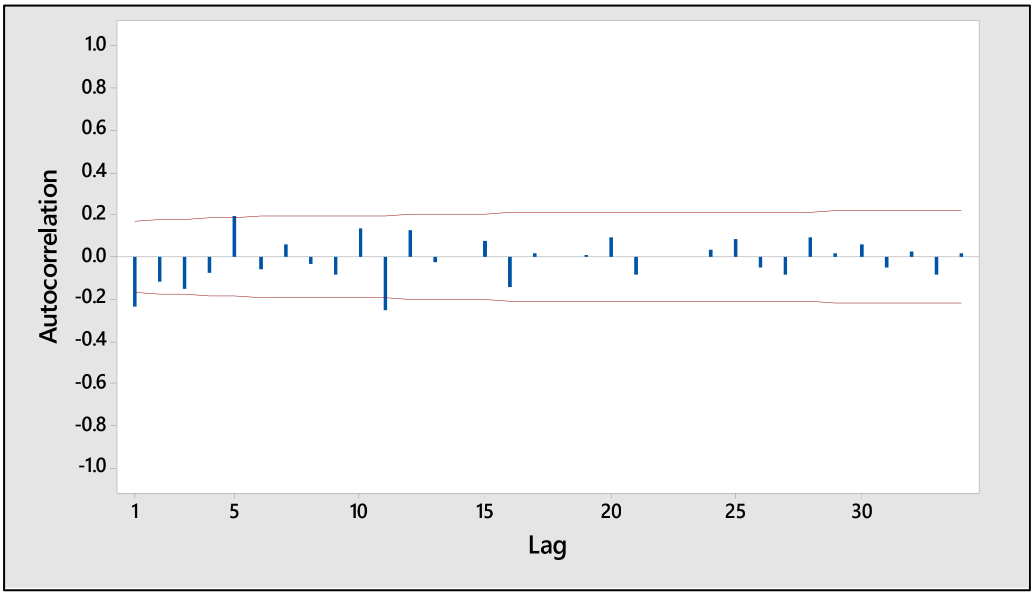


**Figure 4.3:** ACF for 1st difference of original ETo data series (Yala) $\{Y_t - Y_{t-1}\}$

The ACF property defines a distinct pattern for the autocorrelations. 1st difference of the series shows that significant correlations at the first lag, followed by correlations that are not significant, which implies that 1st difference of the reference evapotranspiration series is stationary. This looks like a pattern of moving average terms in the data, MA(1) as the number of significant correlations indicates the order of the moving average term. If large correlation occurs at the first season lag and decreases over several seasonal lags, have to difference the data using a lag equal to the seasonal length before attempt to identify a model. But in this case no seasonal lags are identified as significant.

### 4.1.4 PACF of Stationary Series - Non Seasonal

Another useful method to examine serial dependencies is to examine the partial autocorrelation function (PACF). Partial Autocorrelation to calculate and plot the correlation between observations in a time series. A partial autocorrelation is a summary of the relationship between an observation in a time series with observations at prior time steps with the relationships of intervening observations removed.

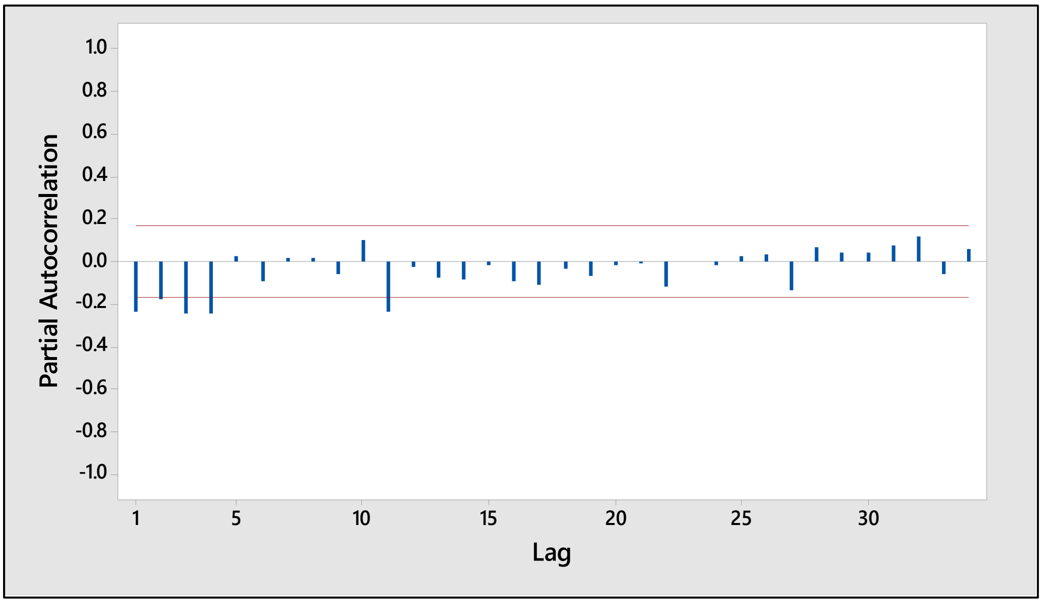


**Figure 4.4:** PACF for 1st difference of original ETo data series (Yala){$Y_t$- $Y_{t-1}$}

In this plot (Figure 4.4) first few lags are identified as significant and followed by correlations are gradually tapers to 0. For an AR model, the theoretical PACF "shuts off" past the order of the model. It means that the number of non-zero partial autocorrelations gives the order of the AR model. For an MA model, the theoretical PACF does not shut off, but instead tapers toward 0.Therefore figure 4.4 further confirms the pattern of MA observed from ACF.

### 4.1.5 Identification of Parsimonious ARIMA Models

Examining the ACF and PACF of the first differenced series, the order of the model (p, d, q) was determined as follows: ACF looks like the pattern of moving average terms in the data, MA(1) while PACF indicates also a moving average term, therefore both these patterns indicate an ARIMA (0, 1, 1) model. However this is only a tentative choice. There will ARIMA models with values of AR and/ or MA less than the parameters of the considered ARIMA. In this case following five parsimonious models were chosen to identify the best fit model.

**Table 4.2:** Comparison of the selected non seasonal parsimonious time series model for ETo in Yala season

| No | Model | AR (1) | AR (2) | AR (3) | AR (4) | MA (1) | C | MSE | BP Statistic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 12 | 24 | 36 | 48 |
| 1 | ARIMA(4,1,1) | (-0.6670, p=0.020) | (-0.3920, p=0.003) | (0.4150, p=0.000) | (-0.3500, p=0.001) | (-0.2970, p=0.324) | (0.0164, p=0.743) | 0.202 | 0.082 | 0.634 | 0.655 | 0.806 |
| 2 | ARIMA(0,1,1) | | | | | (0.5085, p=0.000) | (0.0057, p=0.774) | 0.220 | 0.002 | 0.057 | 0.165 | 0.370 |
| 3 | ARIMA(1,1,1) | (0.5629, p=0.000) | | | | (0.9892, p=0.000) | (0.0003, p=0.808) | 0.197 | 0.034 | 0.304 | 0.494 | 0.388 |
| 4 | ARIMA(2,1,1) | (0.5443, p=0.000) | (0.0178, p=0.840) | | | (0.9741, p=0.000) | (0.0007, p=0.701) | 0.200 | 0.024 | 0.271 | 0.470 | 0.413 |
| 5 | ARIMA(3,1,1) | (-0.4000, p=0.988) | (-0.1800, P=0.977) | (-0.0300, P=0.993) | | (-0.2000, p=0.994) | (0.0312, p=0.536) | 0.232 | 0.000 | 0.014 | 0.076 | 0.173 |

Table 4.2 describes the results obtained for selected ARIMA models for original data series such as coefficients of the parameters and corresponding p value and mean square of error (MSE). None of the parameters are significantly different from zero (p value > 0.05) in the fifth model. Model 1 and 4 are also having none significant parameters where p value is greater than 0.05, which are marked in red colour. Parameters of Model 2, ARIMA (0,1,1) and Model 3, ARIMA(1,1,1) reject the null hypothesis " coefficients are equal to zero" with p values <0.05. Compared to the model 2, model 3 is having lesser MSE and SSE values. The Ljung-Box chi-square statistics are considered for the selected two models to determine whether the models meet the assumption that the residuals are independent. None of the two models are met the assumption, as the p-values for the Ljung-Box chi-square statistics of first few lags are lesser than 0.05. Therefore Model 2 and 3 are rejected since the model residuals are not independent and have to search further for a best fit model.

### 4.1.6 ACF of Stationary Series - Seasonal

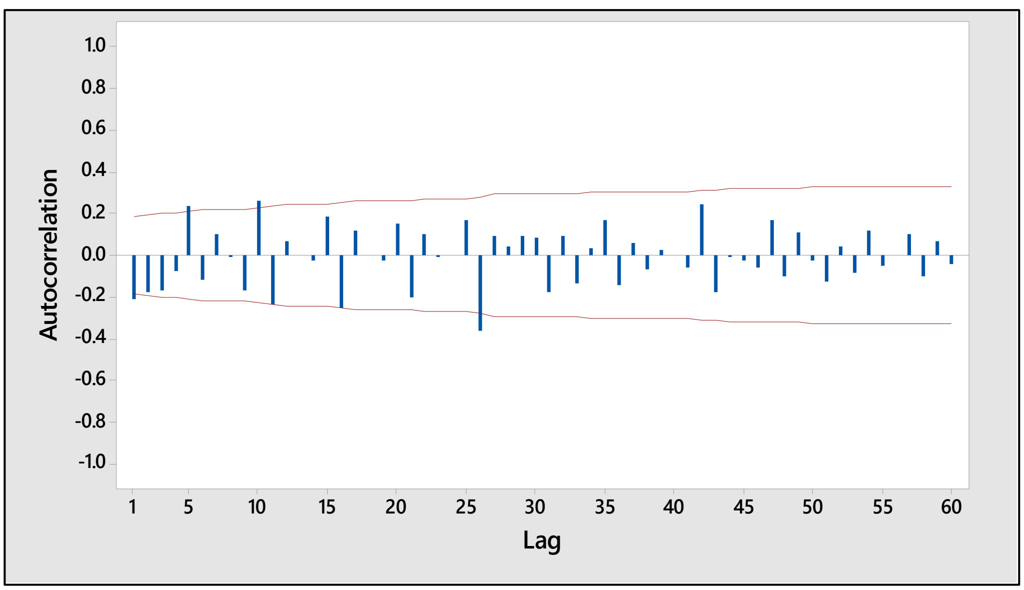


**Figure 4.5:** ACF plot of 26th difference of the 1st difference series of original data set (Yala) $\{(Y_t - Y_{t-1}) - (Y_{t-26} - Y_{t-27})\}$

Though the ACF of 1st difference of original series was not indicate a significant lag at lag 26, ACF plot of original data series implies a pattern of seasonal with time length of 26. Therefore, now consider the seasonal effect of the original series to observe the best fit model for Yala. In order to identify the seasonal ARIMA model, ACF plot of 26th difference of the 1st difference series of original data was plotted (Figure 4.5).

At the non seasonal levels ACF has significant spikes at lag 1 and cuts off after lag 1. At the seasonal level, the ACF has significant lag at lag 26 and tails off thereafter. Therefore, conclusion can be made that 26th difference of the 1st difference series of original data is stationary at both seasonal and non seasonal lengths. And also this indicate the order of moving average terms in both seasonal and non seasonal. MA(1) & SMA(26) as the moving average components that can be visualized by the figure 4.5.

### 4.1.7 PACF of Stationary Series - Seasonal

Identification of AR component of the SARIMA model is often best done with the PACF (Figure 4.6). Few significant “spikes” were identified at non seasonal lags, followed by the pattern gradually tapers to 0. For seasonal component, first seasonal lag is identified as significant, lag at 26 and shuts off thereafter.

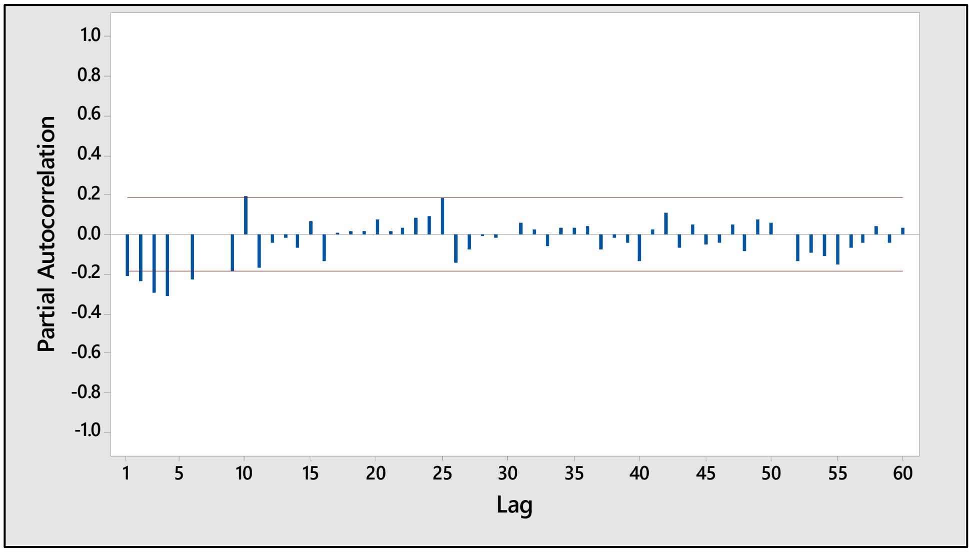


**Figure 4.6:** PACF plot of 26th difference of the 1st difference series of original data (Yala){$(Y_t - Y_{t-1}) - (Y_{t-26} - Y_{t-27})$ }

In other words lags 52, 78 etc. were not identified as significant lags. For an AR model, the theoretical PACF "shuts off" past the order of the model. It means that the number of non-zero partial autocorrelations gives the order of the AR model. For an MA model, the theoretical PACF does not shut off, but instead tapers toward 0. Therefore figure 4.6 further confirms the pattern of MA observed from ACF plot for non seasonal lengths while order 1 of AR for seasonal lengths.

### 4.1.8 Identification of Parsimonious SARIMA Models

Examining the ACF and PACF of the both seasonal and non-seasonal differenced data, the order of the model $(p, d, q) \times (P, D, Q)_s$ was determined as follows: As per the ACF plot of Figure 4.5, First and Twenty Sixth lags are significantly different from zero. This implies that this data series is having MA(1) and SMA(26) components. Non seasonal decaying pattern of PACF of differenced series describe that there may be no AR component in non seasonal and significant autocorrelation at lag 26 implies that there may be a seasonal AR component. Both these patterns indicate an SARIMA (0, 1, 1) $(1, 1, 1)_{26}$.

A model comparison was carried out to find the best fit time series model for observed weekly ETo durinng Yala season at Polonnaruwa from selected models. Out puts of the considered 04 different models are as follows.

Table 4.3 describes the results obtained for selected SARIMA models for original data series such as coefficients of the parameters and corresponding p values, sums square of errors (SSE) and mean square of errors (MSE). All the models are having parameters significantly different from zero where p value is less 0.05 which accept the null hypothesis “coefficients are equal to zero”. Comparing the MSE values of the parsimonious models, model with least MSE is selected as the best fit model. Comparing all the four models model 4, SARIMA $(1,1,1)(1,1,1)_{26}$ is selected as the best fit model for reference evapotranspiration during Yala in Polonnaruwa as it is having the lowest MSE of 0.184.Mean Absolute percentage error of the selected model is varying between ± 1.5%.

**Table 4.3:** Comparison of selected seasonal ETo time series models in Yala

| No | Model | AR (1) | MA (1) | SAR (26) | SMA (26) | C | SSE | MSE |
|---|---|---|---|---|---|---|---|---|
| 1 | SARIMA 0,1,1) $(1,1,1)_{26}$ | | (0.6239, p=0.000) | (-0.4680, p=0.000) | (0.8247, p=0.000) | (0.0036, p=0.415) | 20.9486 | 0.1958 |
| 2 | SARIMA (0,1,1) $(0,1,1)_{26}$ | | (0.7026, p=0.000) | | (0.7830, p=0.000) | 0.0066, p=0.197) | 25.142 | 0.2327 |
| 3 | SARIMA (1,1,1) $(0,1,1)_{26}$ | (0.3790, p=0.003) | (0.8757, p=0.000) | | (0.7800, p=0.000) | (0.0021, p=0.373) | 22.764 | 0.2127 |
| 4 | SARIMA (1,1,1) $(1,1,1)_{26}$ | (0.3770, p=0.004) | (0.8600, p=0.000) | (-0.4200, p=0.000) | (0.8140, p=0.000) | (0.0020, p=0.276) | 19.483 | 0.1838 |

### 4.1.9 Estimation of Best Fitted Model – Yala Data Series

Then selected best fitted model was analyzed. Seasonal ARIMA model $(1,1,1)(1,1,1)_{26}$ has a constant value which is not significantly different from zero. MSE of the SARIMA model is 0.184 which is less compared to the other parsimonious models. Mean Square of Error (MSE) is use to determine how well the model fits the data. Smaller values indicate a better fitting model. Therefore, $(1,1,1)(1,1,1)_{26}$ model is selected as the best fit model for the original ETo data series for Yala season.

To determine whether the association between the response and each term in the model is statistically significant, the p-value for the term is compared with the considered significance level to assess the null hypothesis. The null hypothesis is that the term is not significantly different from 0, which indicates that no association exists between the term and the response. Usually, a significance level (denoted as α or alpha) of 0.05 works well. A significance level of 0.05 indicates a 5% risk of concluding that the term is not significantly different from 0 when it is significantly different from 0. If the p-value is less than or equal to the significance level, then the coefficient is statistically significant. But, if the p-value is greater than the significance level, then the coefficient is statistically not significant, where the model has to be refit without the term.

The moving average and seasonal moving average terms, autoregressive and seasonal autoregressive terms except the constant value have a p-value that are less than the significance level of 0.05 (Table 4.4). It describes that the coefficients of the fitted model are statistically significant by rejecting the null hypothesis, and can proceed with the fitted model.

Fitted model is as shown in Equation 4.1

$$\begin{aligned}(1-0.377\,B)(1+0.42\,B^{26})(1-B)(1-B^{26})\,Y_t \\ = (1+0.86\,B)(1+0.814\,B^{26})e_t\end{aligned} \qquad \textbf{(4.1)}$$

**Table 4.4:** Final estimates of parameters of SARIMA $(1,1,1)(1,1,1)_{26}$ for Yala ETo

| Type | Coefficient | SE Coefficient | T-Value | P-Value |
|---|---|---|---|---|
| AR 1 | 0.377 | 0.128 | 2.96 | 0.004 |
| SAR 26 | -0.420 | 0.114 | -3.67 | 0.000 |
| MA 1 | 0.8600 | 0.0748 | 11.50 | 0.000 |
| SMA 26 | 0.814 | 0.103 | 7.92 | 0.000 |
| Constant | 0.00196 | 0.00179 | 1.09 | 0.276 |

### 4.1.10 Model Diagnostic

When conducting any statistical analysis it is important to evaluate how well the model fits the data and that the data meet the assumptions of the model. There are numerous ways to do this and a variety of statistical tests to evaluate deviations from model assumptions.

#### 4.1.10.1 Ljung-Box chi-square statistics

The Ljung-Box chi-square statistics are used to determine whether the model meets the assumption that the residuals are independent. If the assumption is not met, the model may not fit the data and use caution when you interpret the results and have to search for best fit model. In these results, the p-values for the Ljung-Box chi-square statistics are all greater than 0.05 where conclusion can be made that the model meets the assumption that the residuals are independent (Table 4.5).

**Table 4.5:** Modified Box-Pierce (Ljung-Box) Chi-Square Statistic of SARIMA $(1,1,1)(1,1,1)_{26}$ for Yala ETo

| Lag | 12 | 24 | 36 | 48 |
|---|---|---|---|---|
| Chi-Square | 9.44 | 13.84 | 22.18 | 31.84 |
| DF | 7 | 19 | 31 | 43 |
| P-Value | 0.222 | 0.793 | 0.877 | 0.895 |

#### 4.1.10.2 Residual Plots

Residuals are estimates of experimental error obtained by subtracting the observed responses from the predicted responses. Examining residuals is a key part of all statistical modeling, including DOE's. Carefully looking at residuals can tell whether the assumptions are reasonable and the choice of the model is appropriate. Residuals can be thought of as elements of variation unexplained by the fitted model. For a best fit model, the general assumptions apply to the group of residuals that them to be (roughly) normal and (approximately) independently distributed with a mean of 0 and constant variance.

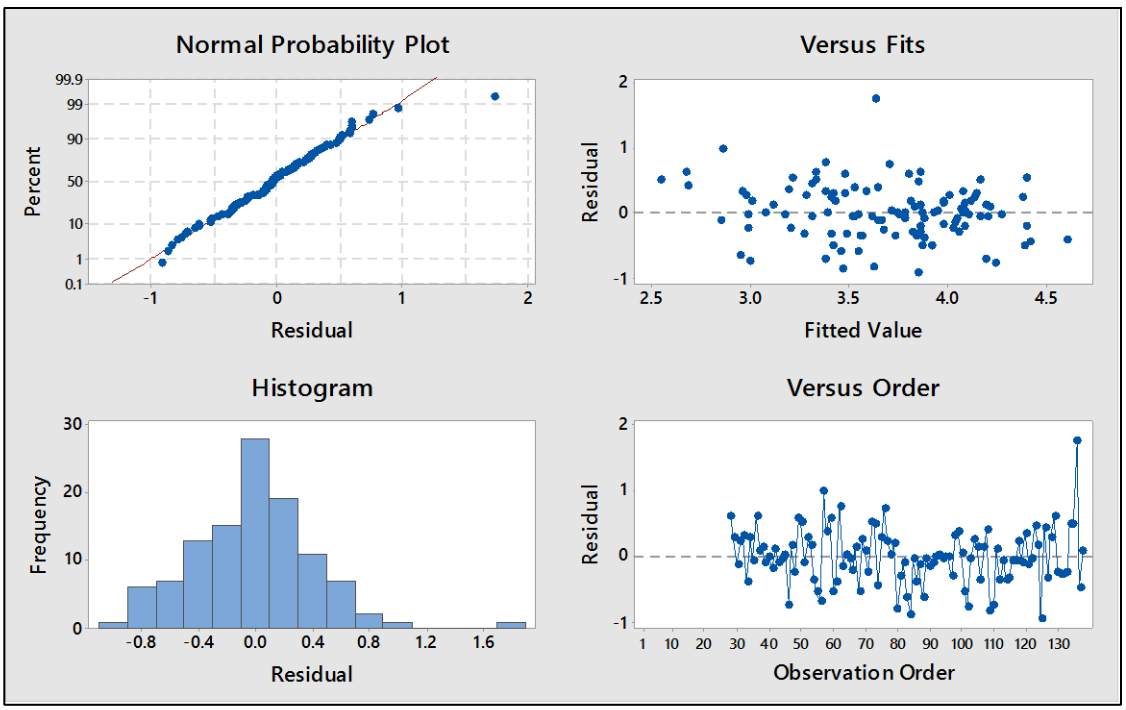


**Figure 4.7:** Residual plot for Yala obtained from SARIMA $(1,1,1)(1,1,1)_{26}$

Errors were analyzed further for the fitted model of SARIMA $(1,1,1)(1,1,1)_{26}$ for average weekly ETo in Polonnaruwa. During Yala. Figure 4.7 shows the residual plot for ETo.

Use the normal plot of residuals to verify the assumption that the residuals are normally distributed. The normal probability plot should produce an approximately straight line if the points come from a normal distribution. The following probability plot of residuals suggests that the residuals are normally distributed as residual are on a straight line with single extreme outlier.

The histogram is a frequency plot obtained by placing the data in regularly spaced cells and plotting each cell frequency versus the center of the cell. Use the histogram of residuals to determine whether the data are skewed or whether outliers exist in the data. Figure 4.7 illustrates an approximately normal distribution of residuals of the fitted model.

Use the residuals versus fits plot to verify the assumption that the residuals are randomly distributed and have constant variance. Ideally, the points should fall randomly on both sides of 0, with no recognizable patterns in the points. The patterns may indicate the model does not meet the model assumptions. There could be a non-linear relationship between predictor variables and an outcome variable and the pattern could show up in the plot if the model doesn't capture the non-linear relationship. Equally spread residuals around a horizontal line without distinct patterns, is a good indication of having non-linear relationships. Figure 4.7 also shows that residuals are scattered along a horizontal line of 0, implying that residuals have a constant variance.

Residuals versus order plot is use to verify the assumption that the residuals are independent from one another or in other words residuals are uncorrelated with each other. Independent residuals show no trends or patterns when displayed in time order. Patterns in the points may indicate that residuals near each other may be correlated, and thus, not independent. Ideally, the residuals on the plot should fall randomly around the center line. Figure 4.7 shows that residuals are independent as they spread around the center line.

#### 4.1.10.3 ACF of Residuals

It is assumed that the residuals are independent of (not correlated with) each other. Further ACF plot of residuals can be used to test the residuals. Use a graph of residuals versus data order (1, 2, 3, 4, n) to visually inspect residuals for autocorrelation. A positive autocorrelation is identified by a clustering of residuals with the same sign. A negative autocorrelation is identified by fast changes in the signs of consecutive residuals. If no significant correlations are present, conclusion can be made that the residuals are independent. However, 1 or 2 significant correlations at higher order lags that are not seasonal lags are usually caused by random error instead and are not a sign that the assumption is not met. In this case (Figure 4.8), conclusion can make that the residuals are independent as none of the correlations for the autocorrelation function of the residuals are significant.

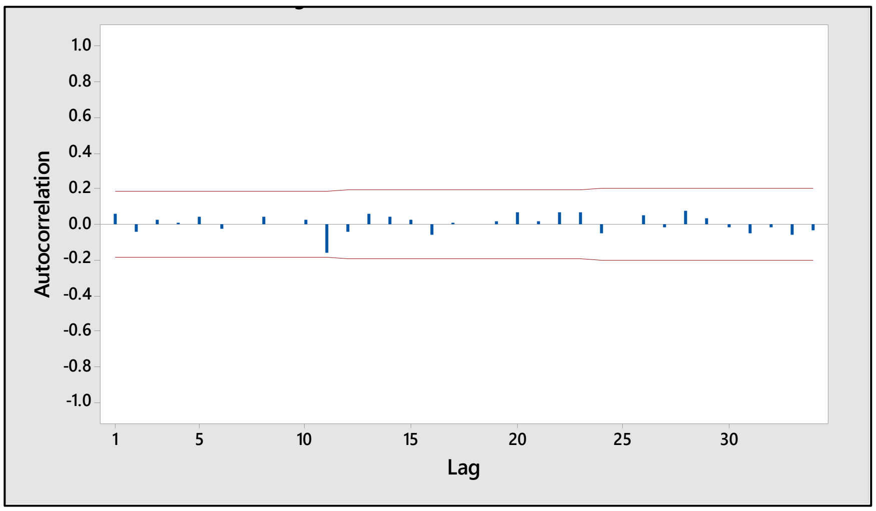


**Figure 4.8:** ACF of residual plot of SARIMA (1,1,1)(1,1,1)$_{26}$ for Yala ETo

### 4.1.10.4 Predicted vs Observed

Test data kept for validation is compared with the forecasted values. After selecting the ARIMA model, it is used for forecasting. Three months weekly ETo was forecasted by using selected model. Figure 4.9 shows the scatter plot between observed and forecasted ETo. The $R^2$ value 0.81 presents good correlation ($\gamma$ = 0.9) between observed and forecasted value.

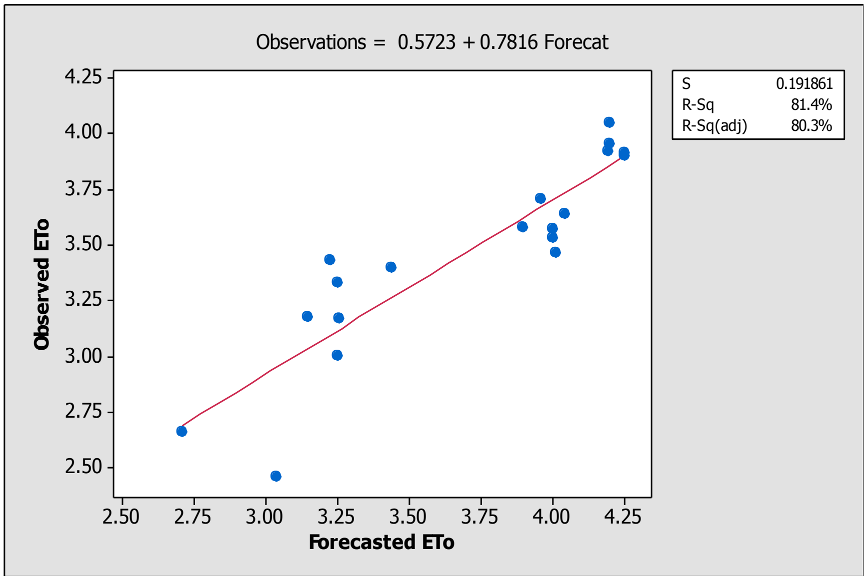


**Figure 4.9:** Scatter plot of observed vs forecasted ETo in Yala Season Polonnaruwa

### 4.1.11 Forecasting

Next step was to forecast the weekly ETo for coming months. Weekly ETo was forecasted 10 weeks ahead during the Yala season in Polonnaruwa area (Table 4.6). These results will be helpful to the water management officials of the area as well as the researchers who are willing to conduct their studies based on ETo.

**Table 4.6:** Forecasted weekly ETo for Yala season in Polonnaruwa

| Year | Month | Week | Forecasted ETo (mm) |
|---|---|---|---|
| 2016 | April | 1 | 3.97 |
| | | 2 | 3.95 |
| | | 3 | 3.54 |
| | | 4 | 3.62 |
| | May | 5 | 3.30 |
| | | 6 | 3.87 |
| | | 7 | 4.11 |
| | | 8 | 4.01 |
| | June | 9 | 3.98 |
| | | 10 | 4.03 |

## 4.2 Time Series Analysis for Maha Season

This section will present the results of an analysis of the weekly reference evapotranspiration during Maha season over six years period from 2010 to 2015 of Polonnaruwa area.

### 4.2.1 Temporal Variability of Maha Season

Table 4.7 clearly explains descriptive statistics of the data set to have a general idea of the original data series, the distribution of ETo in Polonnaruwa during the period of October – March in five years span. The mean reference evapotranspiration varied between 0.76 mm (minimum) to 5.56 mm (maximum) with a mean of 2.29 mm and SD of 0.85. The chance of reference evapotranspiration exceeds the 2.85 mm is 25% and chance of being lower than 1.63mm is also 25%.

**Table 4.7:**Descriptive Statistics of the average weekly reference evapotranspiration from 2010 to 2015 in Polonnaruwa during Maha Season (October – March) (in mm)

| Mean | SE Mean | StDev | Minimum | Q1 | Median | Q3 | Range | Maximum |
|---|---|---|---|---|---|---|---|---|
| 2.29 | 0.07 | 0.85 | 0.76<br>(Week 77) | 1.63 | 2.24 | 2.85 | 4.80 | 5.56<br>(Week 120) |

In order to identify the best fit model for the weekly observed ETo in Maha season at Polonnaruwa model estimation was carried out by following several stages. As first step of model estimation, time series plot of the test data was analyzed.

Figure 4.10 shows the average weekly ETo time series during the Maha Season at Polonnaruwa from 01.01.2010 to 31.12.2015. The time series plots display calculated reference evapotranspiration in mm on the y-axis against equally spaced time intervals on the x-axis. This can be used to evaluate patterns, knowledge of the general trends and behaviors of ETo at Polonnaruwa during the Maha season. There is no clear trend can be observed in the reference evapotranspiration time series and seasonality of the data series is doubtful.

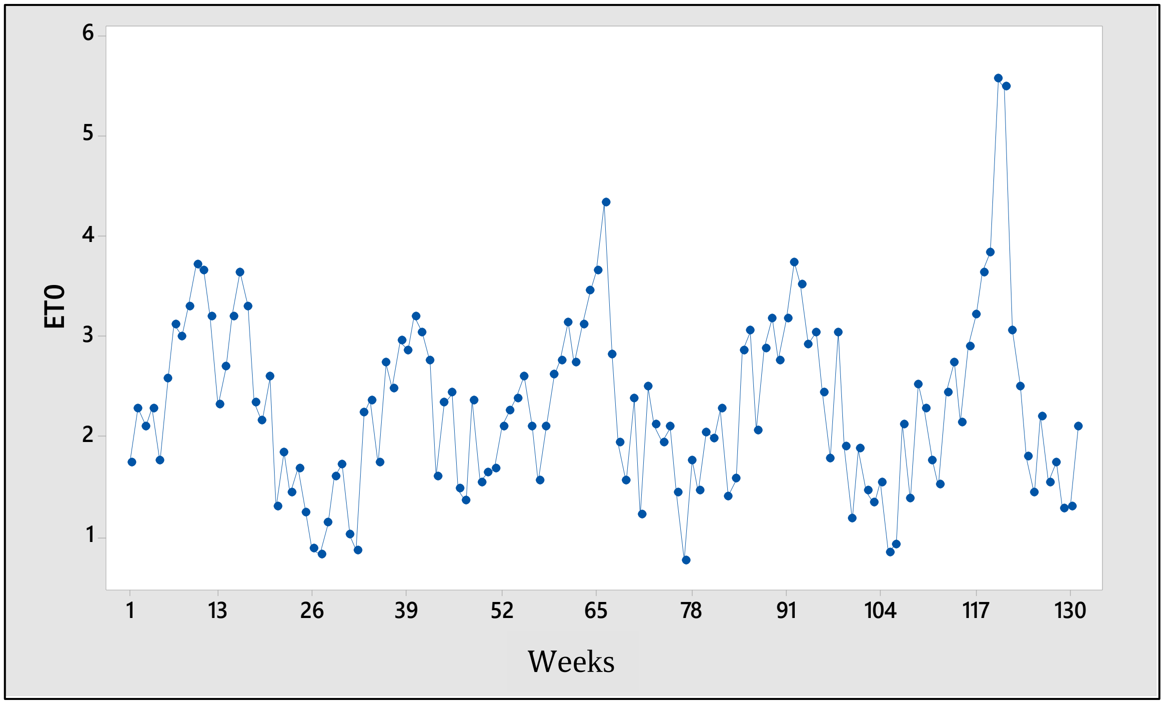


**Figure 4.10:** Time series plot of average weekly reference evapotranspiration from 2010 to 2015 in Polonnaruwa in Maha season$\{Y_t\}$

### 4.2.2 ACF of Original Maha Data Series

The first step in identifying a preliminary model was to examine the autocorrelations for the raw data. The autocorrelation graph was plotted for the reference evapotranspiration data series to check the randomness of the data (Figure 4.11). The autocorrelations, which were very large at first, did not tail off towards zero quickly. They appeared to be forming a sine wave pattern, but because the damping process was so slow, it was concluded that the process was non-stationary and this emphasize that previous ETo values are obviously correlated to future ETo data. Seasonal patterns of time series also can be examined via correlograms. It confirms that there is a seasonality in the calculated weekly ETo data series with lag of 26.

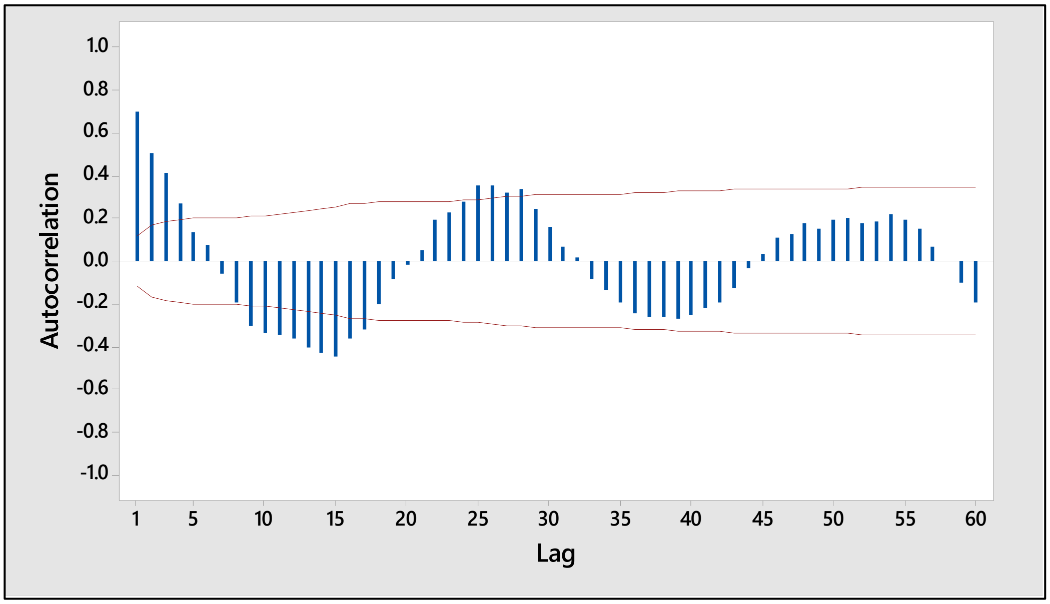


**Figure 4.11:** Autocorrelation function of reference evapotranspiration in Polonnaruwa training data set (Maha){$Y_t$}

### 4.2.3 ACF of Stationary Series - Non Seasonal

A common assumption in many time series techniques is that the data are stationary. As ARIMA models a non-stationary time series transforming to stationary by applying finite differencing of the data points. Consider the 1$^{st}$ difference of the series (Figure4.12) to model ARIMA for ETo in Maha season.

Figure 4.12 contains the autocorrelation of the first differences. The ACF property defines a distinct pattern for the autocorrelations. 1$^{st}$ difference of the series shows none of the significant correlations are significant, which implies that 1$^{st}$ difference of the reference evapotranspiration series is non stationary.

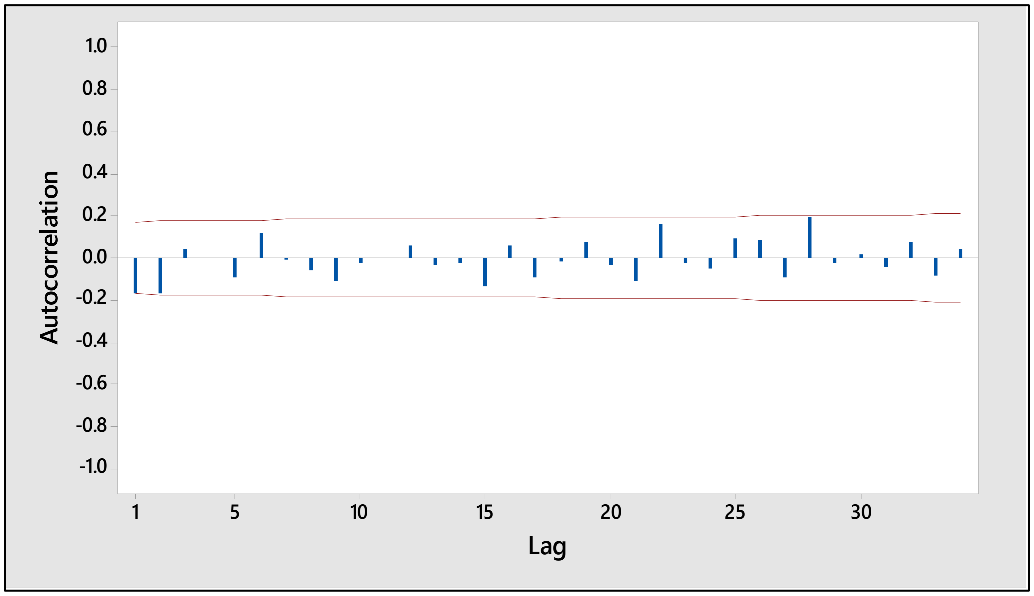


**Figure 4.12:** ACF for 1st difference of original ETo data series (Maha){$Y_t$- $Y_{t-1}$}

In order to make the series stationary consider the 2nd difference of original data series, ETo at polonnaruwa during Maha season (Figure 4.13).

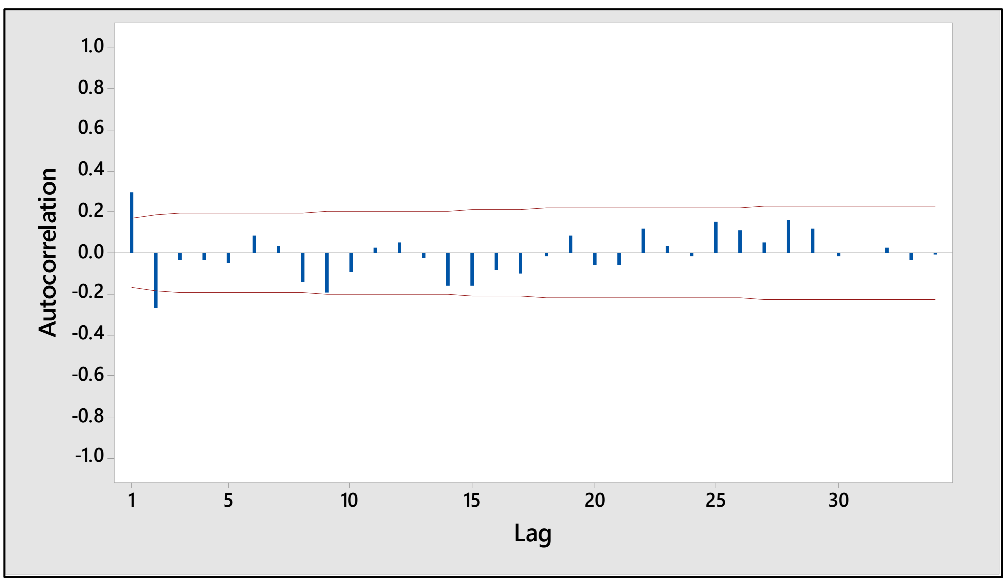


**Figure 4.13:** ACF for 2nd difference of original ETo data series (Maha)

The ACF property defines a distinct pattern for the autocorrelations. 2nd difference of the series shows that significant correlations at the first and second lag, followed by correlations that are not significant, which implies that 2nd difference of the reference evapotranspiration series is stationary. This looks like the pattern of moving average terms in the data, MA(1) & MA(2) as the number of significant correlations indicates the order of the moving average term. In this case no seasonal lags are identified as significant to consider the stationarity of seasonal component.

### 4.2.4 PACF of Stationary Series - Non Seasonal

In figure 4.14 few significant "spikes" were identified at first few lags, followed by the pattern gradually tapers to 0. Therefore figure 4.14 further confirms the pattern of MA observed from ACF plot.

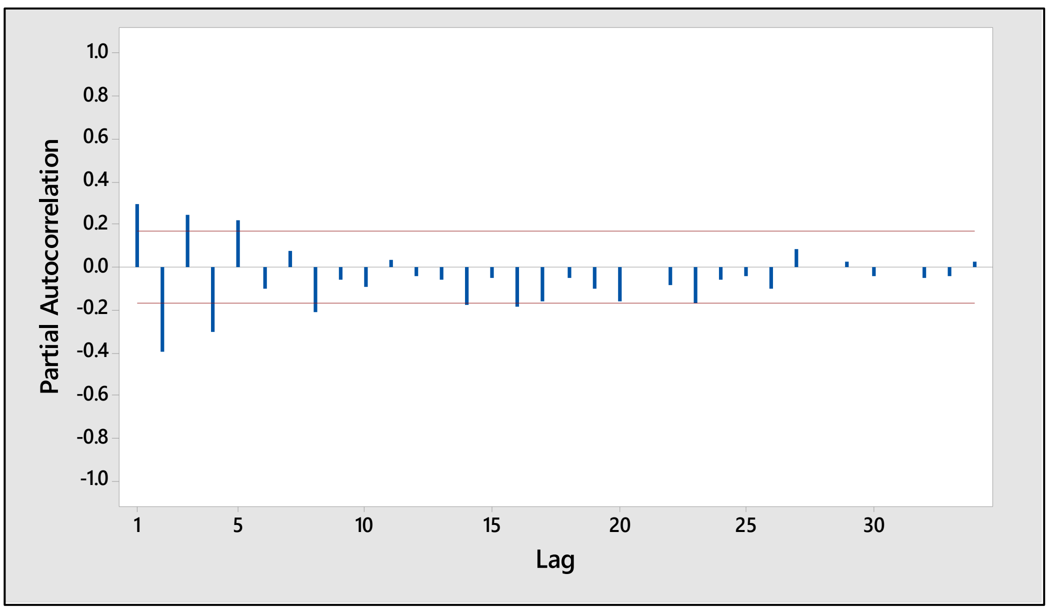


**Figure 4.14:** PACF for 2nd difference of original ETo data series (Maha){$Y_t$- $Y_{t-1}$}

### 4.2.5 Identification of Parsimonious ARIMA Models

Examining the ACF and PACF of the differenced data, the order of the model (p, d, q) was determined as follows: ACF looks like the pattern of moving average terms in the data, MA(1) & MA(2) while PACF further confirms the MA terms observed in ACF, therefore both these patterns indicate an ARIMA (0, 2, 2) model. However this is only a tentative choice. There will ARIMA models with values of AR and/ or MA less than the parameters of the considered ARIMA. In this case following seven parsimonious models were chosen to identify the best fit model.

**Table 4.8:** Comparison of the selected non seasonal time series model for ETo for Maha

| No | Model | AR (1) | AR (2) | MA (1) | MA (2) | C | MSE | BP Statistic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | 12 | 24 | 36 | 48 |
| 1 | ARIMA(0,2,2) | | | (0.8349, P=0.000) | (0.1489, P=0.044) | (-0.0005, p=0.923) | 0.4913 | 0.017 | 0.024 | 0.010 | 0.022 |
| 2 | ARIMA(1,2,2) | (-0.5280, p=0.300) | | (0.5270, p=0.317) | (0.4510, p=0.389) | (-0.0003, p=0.950) | 0.4608 | 0.055 | 0.087 | 0.081 | 0.200 |
| 3 | ARIMA(1,2,1) | (-0.1783, p=0.040) | | (0.9843, p=0.000) | | (0.0002, p=0.915) | 0.4464 | 0.145 | 0.179 | 0.165 | 0.333 |
| 4 | ARIMA(2,1,2) | (-0.0810, p=0.912) | (-0.0680, p=0.872) | (0.1380, p=0.851) | (0.1220, p=0.824) | (0.0001, p=0.976) | 0.4246 | 0.334 | 0.181 | 0.058 | 0.083 |
| 5 | ARIMA(0,1,2) | | | (0.2171, p=0.012) | (0.1695, p=0.051) | (0.0009, p=0.980) | 0.41847 | 0.519 | 0.242 | 0.068 | 0.091 |
| 6 | ARIMA(2,1,0) | (-0.2104, p=0.015) | (-0.2053, p=0.018) | | | (0.0020, p=0.972) | 0.4192 | 0.50 | 0.346 | 0.179 | 0.241 |
| 7 | ARIMA(1,1,1) | (0.6951, p=0.000) | | (0.9798, p=0.000) | | (0.0004, p=0.850) | 0.3898 | 0.328 | 0.095 | 0.027 | 0.039 |

Table 4.8 describes the results obtained for selected ARIMA models for original data series such as coefficients of the parameters and corresponding p value and mean square of error (MSE). Model 2, 4 and 5 are having none significant parameters where p value is greater than 0.05, which are marked in red colour. Parameters of Model 1, ARIMA (0,2,2), Model 3, ARIMA (1,2,1) Model 6 ARIMA (2,1,0) and Model 7, ARIMA(1,1,1) reject the null hypothesis " coefficients are equal to zero" with p values <0.05. Considering the BP statistics Model 1 and Model 7 were rejected as p-values for the Ljung-Box chi-square statistics of some lags are lesser than 0.05 which implies that residuals are not independent. Compared to the Model 3, Model 6 is having lesser MSE value, therefore model 6, ARIMA (2,1,0) is selected as the best fit model.

### 4.2.6 ACF of Stationary Series - Seasonal

Though the 1$^{st}$ and 2$^{nd}$ difference of original series was not indicate a significant lag at lag 26, ACF plot of original data series implies a pattern of seasonal with time length of 26. Therefore, now consider the seasonal effect of the original series to check any improvements to the above selected model. In order to identify the seasonal ARIMA model, ACF plot of 26$^{th}$ difference of the 1$^{st}$ difference series of original data was plotted (Figure 4.15).

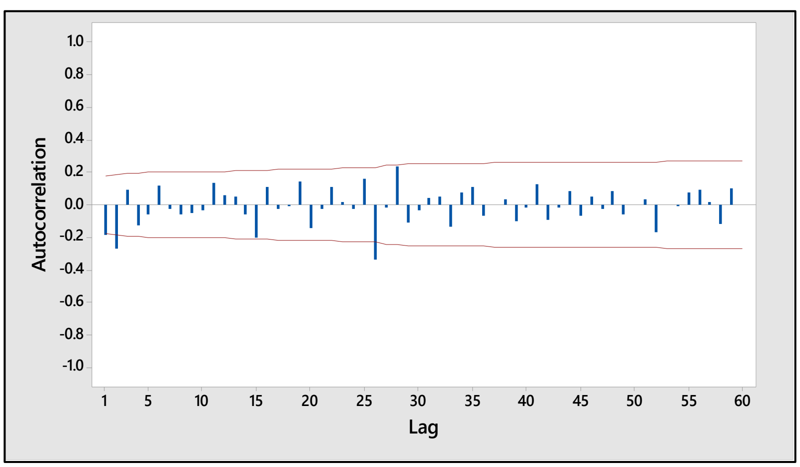


**Figure 4.15:** ACF plot of 26$^{th}$ difference of the 1$^{st}$ difference series of original data set (Maha){$(Y_t - Y_{t-1}) - (Y_{t-26} - Y_{t-27})$ }

At the non seasonal levels ACF has significant spikes at lag 1 & lag 2 and cuts off after lag 2. At the seasonal level, the ACF has significant lag at lag 26 and tails off thereafter. Therefore, conclusion can be made that 26$^{th}$ difference of the 1$^{st}$ difference series of original data is stationary at both seasonal and non seasonal lengths. And also this indicate the order of moving average terms in both seasonal and non seasonal. MA(1), MA(2) & SMA(26) are the moving average components can be visualized by the figure 4.15.

### 4.2.7 PACF of Stationary Series - Seasonal

In this PACF plot (Figure 4.16)two spikes are identified as significant and followed by correlations are tails off. This indicates an autoregressive terms in the data. The number of significant correlations indicate the order of the autoregressive term. This pattern indicates an autoregressive term of order 1 and order 2. For seasonal component seasonal lags are considered. Significant spike at lag 26 is identified with Figure 4.16 illustrating an seasonal AR term of order 1.

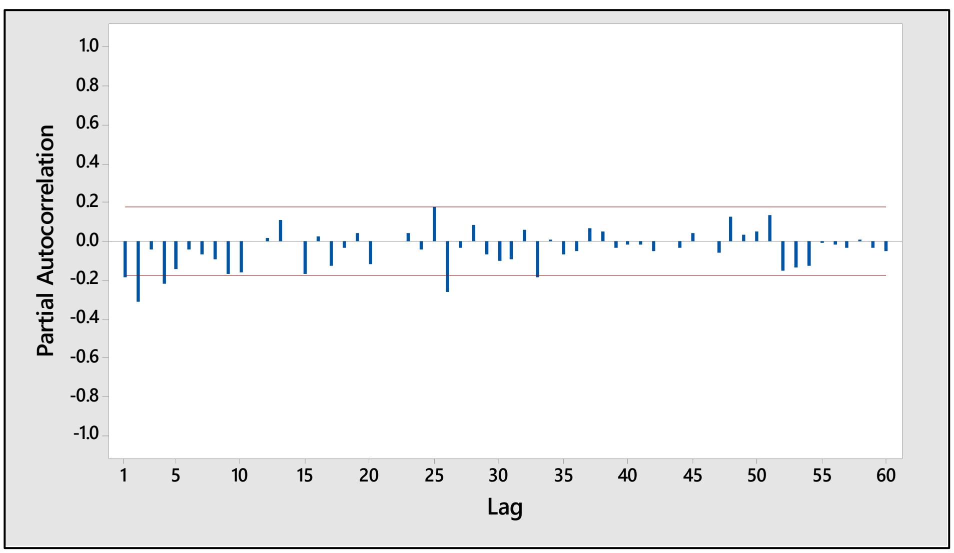


**Figure 4.16:** PACF plot of 26$^{th}$ difference of the 1$^{st}$ difference series of original data (Maha){($Y_t$- $Y_{t-1}$) - ($Y_{t-26}$ - $Y_{t-27}$) }

### 4.2.8 Identification of Parsimonious SARIMA Models

Examining the ACF and PACF of the both seasonal and non-seasonal differenced data, the order of the model (p, d, q) × (P, D, Q) $_s$ was determined as follows: As per the ACF plot of Figure 4.17, First two and twenty sixth lags are significantly different from zero. This implies that this data series is having MA(1), MA(2) and SMA(26) components. PACF of differenced series describe two AR components in non seasonal and order 1 of seasonal AR component. Both these patterns indicate an SARIMA (2, 1, 2) (1, 1, 1)$_{26.}$

A model comparison was carried out to find the best fit time series model for observed weekly ETo at Polonnaruwa for Maha season from selected models. Out puts of the considered 04 different parsimonious models are as follows.

Table 4.9 describes the results obtained for selected SARIMA models for original data series. Third and fourth models are having none significant parameters where p value is greater than 0.05, which are marked in red colour. Model 2 is having none of the parameters significant. Only Model 1, SARIMA (1,1,1)(1,1,1)$_{26}$ reject the null hypothesis “ coefficients are equal to zero” with p values <0.05. Therefore model 1 is selected as the best fit model.

**Table 4.9:** Comparison of selected seasonal ETo time series models in Maha

| No | Model | AR (1) | AR (2) | MA (1) | MA (2) | SAR (26) | SMA (26) | C | SSE | MSE |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | SARIMA (1,1,1) $(1,1,1)_{26}$ | (0.5157, p=0.000) | | (0.9819, P=0.000) | | (-0.2860, P=0.042) | (0.7900, P=0.000) | (0.0003, P=0.750) | 26.7968 | 0.2528 |
| 2 | SARIMA (2,1,2) $(0,1,1)_{26}$ | (-0.1110, P=0.770) | (0.0580, P=0.796) | (0.3510, P=0.327) | (0.5450, P=0.123) | (-0.2510, P=0.095) | (0.7780, P=0.000) | (0.0050, P=0.037) | 37.7137 | 0.3626 |
| 3 | SARIMA (2,1,1) $(0,1,1)_{26}$ | (0.4510, P=0.000) | (0.8884, P=0.088) | (0.8884, P=0.000) | - | (-0.3040, P=0.041) | (0.7730, P=0.000) | (0.0030, P=0.209) | 39.3861 | 0.3751 |
| 4 | SARIMA (1,1,2) $(1,1,1)_{26}$ | (-0.0500, P=0.819) | | (0.4100, P=0.041) | (0.4870, P=0.004) | (-0.2520, P=0.089) | (0.7820, P=0.000) | (0.0050, P=0.024) | 37.7525 | 0.3595 |

### 4.2.9 Estimation of Best Fitted Model – Maha Data Series

Then selected two models, seasonal and non seasonal were analyzed. ARIMA (2,1,0) model is having insignificant constant with MSE of the 0.40. Seasonal ARIMA model $(1,1,1)(1,1,1)_{26}$ is also has a constant value which is not significantly different from zero. MSE of the SARIMA model is 0.25 which is less compared to the ARIIMA (1,1,1). Therefore, $(1,1,1)(1,1,1)_{26}$ model is selected as the best fit model for the original ETo data series. The identified best fitted model is having a mean absolute percentage error of ± 3.1%

To determine whether the association between the response and each term in the model is statistically significant, the p-value for the term is compare with the considered significance level to assess the null hypothesis. The null hypothesis is that the term is not significantly different from 0, which indicates that no association exists between the term and the response.

**Table 4.10 :** Final estimates of parameters SARIMA $(1,1,1)(1,1,1)_{26}$

| Type | Coefficient | SE Coefficient | T-Value | P-Value |
|---|---|---|---|---|
| AR 1 | 0.5157 | 0.0891 | 5.79 | 0.000 |
| SAR 26 | -0.286 | 0.139 | -2.05 | 0.042 |
| MA 1 | 0.98191 | 0.00122 | 801.78 | 0.000 |
| SMA 26 | 0.790 | 0.133 | 5.92 | 0.000 |
| Constant | 0.000266 | 0.000832 | 0.32 | 0.750 |

The non seasonal and seasonal terms except the constant value have p-values that are less than the significance level of 0.05 (table 4.10). It describes that the coefficients of the fitted model are statistically significant by rejecting the null hypothesis except the constant value, and can proceed with the fitted model.

Equation 4.2 illustrate the fitted model for Maha season

$$(1-0.5157\,B)(1+0.286\,B^{26})(1-B)(1-B^{26})\,Y_t = (1+0.982\,B)(1+0.79\,B^{26})e_t \quad \textbf{(4.2)}$$

### 4.2.10 Model Diagnostic

When conducting any statistical analysis it is important to evaluate how well the model fits the data and that the data meet the assumptions of the model.

#### 4.2.10.1 Ljung-Box chi-square statistics

The Ljung-Box chi-square statistics are used to determine whether the model meets the assumption that the residuals are independent. In these results, the p-values for the Ljung-Box chi-square statistics are all greater than 0.05 where conclusion can be made that the model meets the assumption that the residuals are independent (Table 4.11).

**Table 4.11:** Modified Box-Pierce (Ljung-Box) Chi-Square Statistic of SARIMA $(1,1,1)(1,1,1)_{26}$

| Lag | 12 | 24 | 36 | 48 |
|---|---|---|---|---|
| Chi-Square | 12.19 | 23.69 | 33.43 | 39.19 |
| DF | 7 | 19 | 31 | 43 |
| P-Value | 0.095 | 0.208 | 0.350 | 0.637 |

#### 4.2.10.2 Residual Plots

Errors were analyzed for the fitted model of SARIMA $(1,1,1)(1,1,1)_{26}$ for average weekly ETo in Polonnaruwa. Figure 4.17 shows the residual plot for ETo in Maha season.

Use the normal plot of residuals to verify the assumption that the residuals are normally distributed. The normal probability plot should produce an approximately straight line if the points come from a normal distribution. The following probability plot of residuals suggests that the residuals are normally distributed as residual are on a straight line with the presence of two extreme outliers, which can be neglected.

Histogram of residuals is used to determine whether the data are skewed or whether outliers exist in the data. Figure 4.17 illustrates an approximately normal distribution of residuals.

Residuals versus fits plot, verify the assumption that the residuals are randomly distributed and have constant variance. Figure 4.17 also shows that residuals are scattered along a horizontal line of 0, implying that residuals have a constant variance.

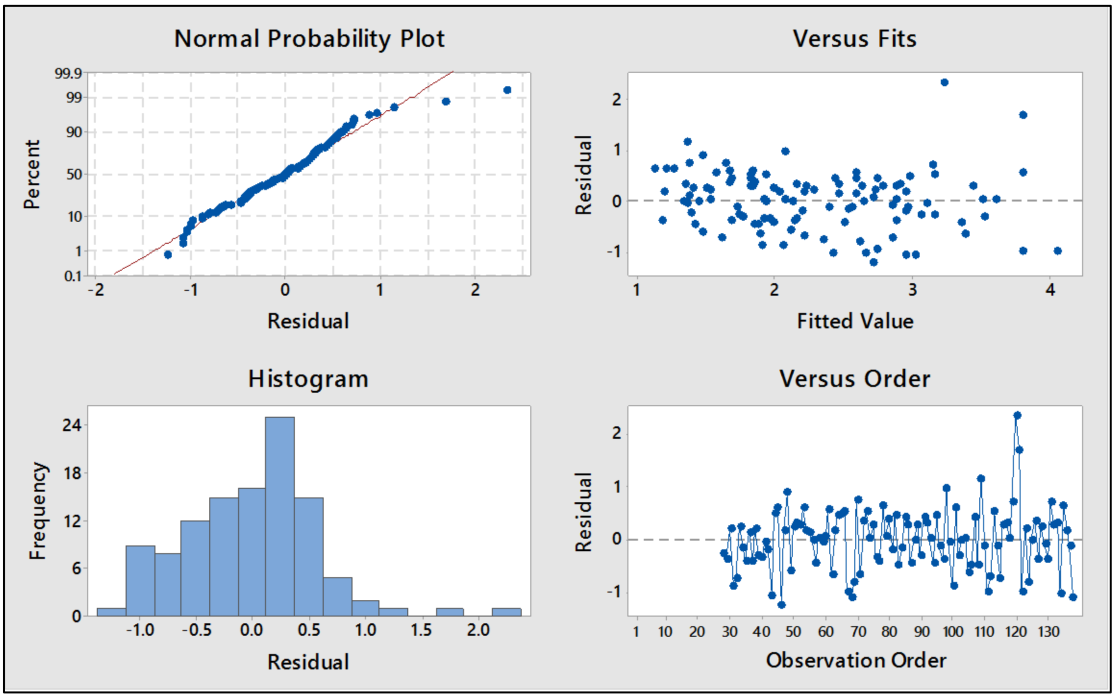


**Figure 4.17:** Residual plot for Maha obtained from SARIMA (1,1,1)(1,1,1)$_{26}$

Use the residuals versus order plot to verify the assumption that the residuals are independent from one another or in other words residuals are uncorrelated with each other. Figure 4.17 shows that residuals are independent as they spread around the center line.

#### 4.2.10.3 ACF of Residuals

Further, ACF plot of residuals can be used to test the residuals. In this case, conclusion can make that the residuals are independent as none of the correlations of the autocorrelation function for the residuals are significant (Figure 4.18).

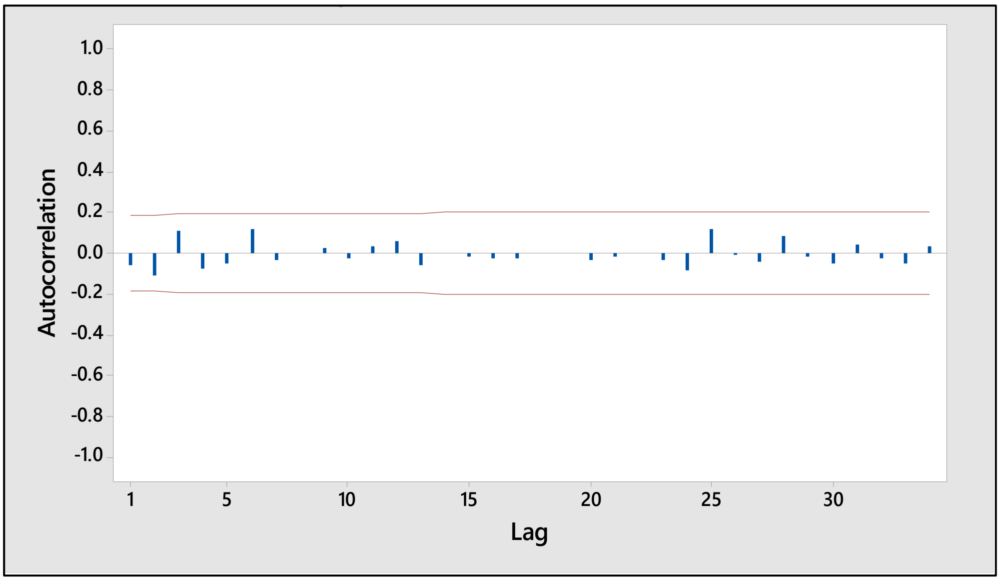


**Figure 4.18:** ACF of residual plot of SARIMA (1,1,1)(1,1,1)$_{26}$ for Maha ETo

### 4.2.10.4 Predicted vs Observed

Test data kept for validation is compared with the forecasted values. Three months, weekly ETo was forecasted by using the selected model. Figure 4.19 shows the scatter plot between observed and forecasted ETo. The $R^2$ value, 0.78 presents good correlation ($\gamma$ = 0.88) between observed and forecasted values.

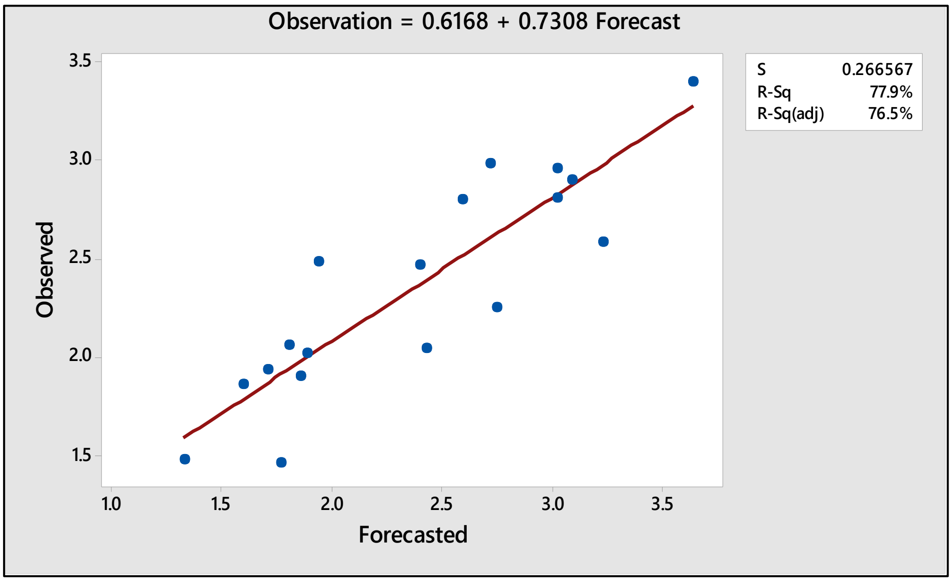


**Figure 4.19:** Scatter plot of observed vs forecasted ETo in Maha Season Polonnaruwa

### 4.2.11 Forecasting

Next step was to forecast the weekly ETo for coming months. Weekly ETo was forecasted 10 weeks ahead during the Maha season in Polonnaruwa area (Table 4.12). These results will be helpful to the water management officials of the area as well as the researchers who are willing to conduct their studies based on ETo.

**Table 4.12:** Forecasted weekly ETo for Maha season in Polonnaruwa

| Year | Month | Week | Forecasted ETo (mm) |
|---|---|---|---|
| 2016 | January | 1 | 3.91 |
| | | 2 | 4.07 |
| | | 3 | 3.96 |
| | | 4 | 3.55 |
| | February | 5 | 3.97 |
| | | 6 | 3.82 |
| | | 7 | 3.83 |
| | | 8 | 3.86 |
| | March | 9 | 3.62 |
| | | 10 | 3.54 |

## 4.3 Time Series Analysis for Pooled Data

This section will present the results of an analysis of the weekly refeence evapotranspiration over six years period from 2010 to 2015 of Polonnaruwa area.

### 4.3.1 Temporal Variability of Pooled Data Series

Descriptive statistics of the data set are used to have a general idea of the original data set which clearly shows in Table 4.13, the distribution of ETo in Polonnaruwa. The mean reference evapotranspiration varied between 0.76 mm (minimum) to 5.56 mm (maximum) with a mean of 2.98 mm and SD of 0.95. The chance of reference evapotranspiration exceeds the 3.71 mm is 25% and chance of being lower than 2.27mm is also 25%.

**Table 4.13:** Descriptive Statistics of the average weekly reference evapotranspiration from 2010 to 2015 in Polonnaruwa (in mm)

| Mean | SE Mean | StDev | Minimum | Q1 | Median | Q3 | Maximum |
|---|---|---|---|---|---|---|---|
| 2.98 | 0.055 | 0.95 | 0.76 (Week 156) | 2.27 | 3.12 | 3.71 | 5.56 (Week 251) |

Figure 4.20 shows the average weekly ETo time series at Polonnaruwa meteorological station in Polonnaruwa District from 01.01.2010 to 31.03.2015. This can be used to evaluate patterns, knowledge of the general trend and behaviors of ETo at Polonnaruwa over the time. There is no clear trend can be observed in the reference evapotranspiration time series and it seems to have seasonal pattern of the dataset annually.

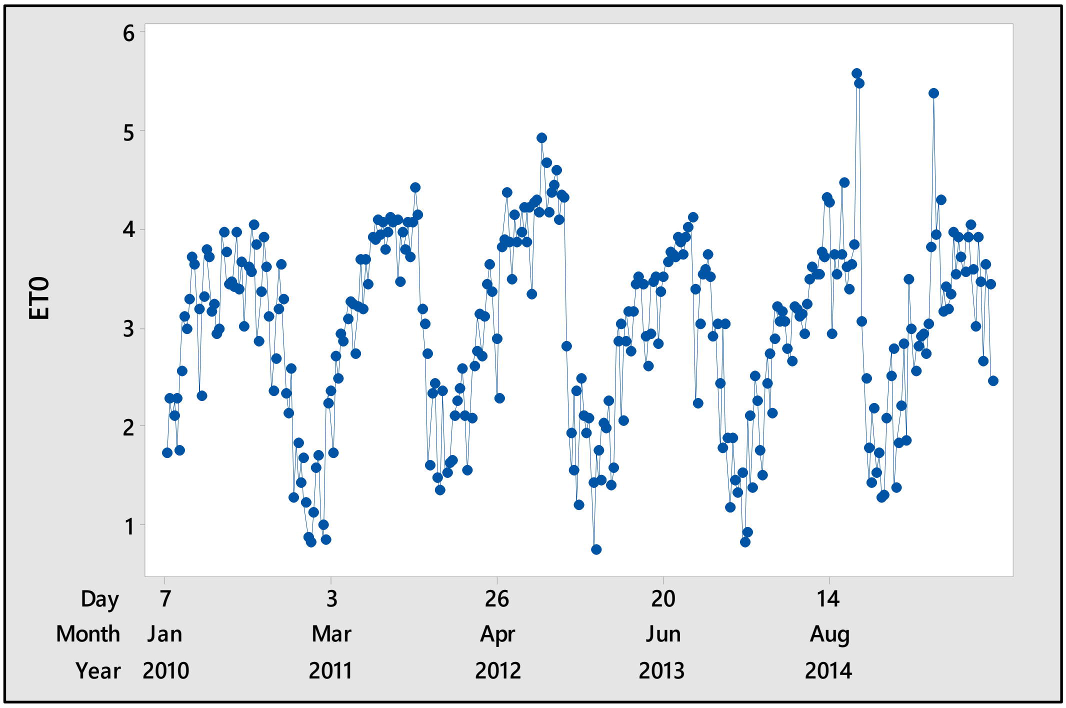


**Figure 4.20:** Time series plot of average weekly reference evapotranspiration from 2010 to 2015 in Polonnaruwa$\{Y_t\}$

### 4.3.2 ACF of Original Pooled Data Series

The first step in the application of the methodology is to check whether the time series (weekly reference evapotranspiration) is stationary and has seasonality. The autocorrelation graph was plotted for the reference evapotranspiration data series to check the randomness of the data. In Figure 4.21 data set shows that the time series is not random, but has a high degree of autocorrelation between adjacent and near-adjacent observations. The autocorrelations remain strong in first few lags and slightly decreasing when increasing the number of lags following a sinusoidal pattern as shown. This emphasize that previous ETo values are obviously correlated to future ETo data. ACF plot of reference evapotranspiration confirms that there is a seasonality in the calculated weekly ETo data series with lag of 52.

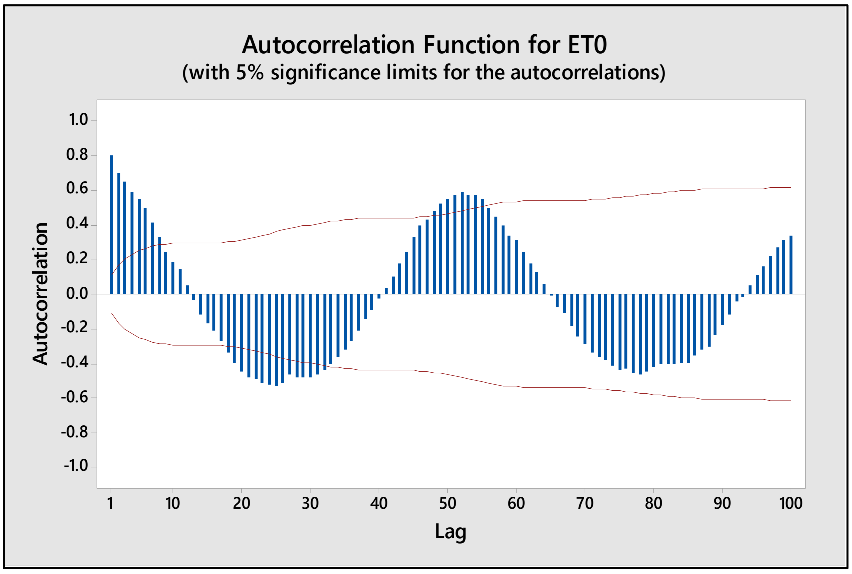


**Figure 4.21:** Autocorrelation function of reference evapotranspiration in Polonnaruwa training data set$\{Y_t\}$

### 4.3.3 ACF of Stationary Series - Non Seasonal

ARIMA models a non-stationary time series by applying finite differencing of the data pointsto make stationary. Consider the 1st difference of the series (Figure 4.22) to model ARIMA for ETo.

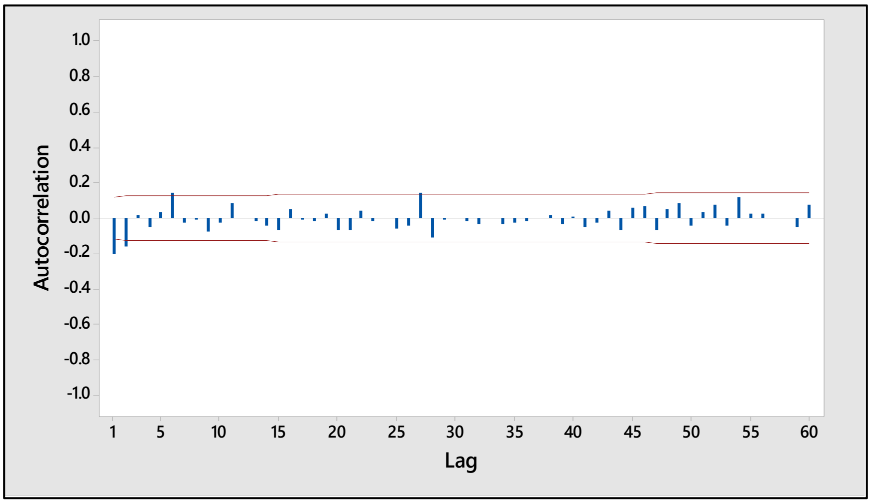


**Figure 4.22:** ACF for 1st difference of original ETo data series$\{Y_t - Y_{t-1}\}$

### 4.3.4 PACF of Stationary Series - Non Seasonal

Another useful method to examine serial dependencies is to examine the partial autocorrelation function (PACF). In this plot (Figure 4.23) two spikes are identified as significant and followed by correlations are tails off. This indicates an autoregressive terms in the data. The number of significant correlations indicate the order of the autoregressive term. This pattern indicates an autoregressive term of order 1 and order 2.

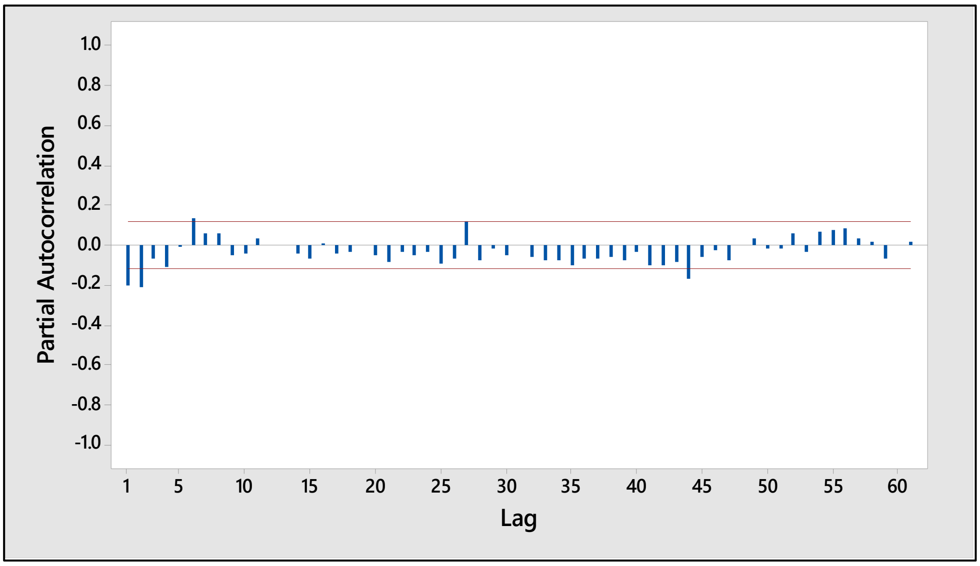


**Figure 4.23:**PACF for 1st difference of original ETo data series$\{Y_t - Y_{t-1}\}$

### 4.3.5 Identification of Parsimonious ARIMA Models

Examining the ACF and PACF of the first differenced series, the order of the model (p, d, q) was determined as follows: ACF looks like the pattern of moving average terms in the data, MA(1) & MA(2) while PACF indicates an autoregressive term of order 1 and order 2, therefore both these patterns indicate an ARIMA (2, 1, 2) model. However this is only a tentative choice. There will ARIMA models with values of AR and/ or MA less than the parameters of the considered ARIMA. In this case following five parsimonious models were chosen to identify the best fit model.

Table 4.14 describes the results obtained for selected ARIMA models for original data series. None of the parameters are significantly different from zero (p value > 0.05) in the first model that assumed through the ACF and PACF plots.

**Table 4.14:** Comparison of the selected non seasonal time series model for ETo

| No | Model | AR(1) | AR(2) | MA(1) | MA(2) | C | SSE | MSE | BP Statistic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 12 | 24 | 36 | 48 |
| 1 | ARIMA (2,1,2) | (-0.1500, p=0.771) | (-0.6370, p=0.893) | (0.1150, p=0.823) | (0.1760, p=0.641) | (0.0043, p=0.857) | 81.899 | 0.304 | 0.124 | 0.242 | 0.172 | 0.227 |
| 2 | ARIMA (1,1,1) | (0.2960, p=0.076) | | (0.5840, p=0.000) | | (0.0024, p=0.861) | 82.703 | 0.305 | 0.116 | 0.213 | 0.148 | 0.194 |
| 3 | ARIMA (0,1,2) | | | (0.2573, p=0.000) | (0.1563, p=0.010) | (0.0035, p=0.858) | 82.049 | 0.303 | 0.246 | 0.329 | 0.204 | 0.242 |
| 4 | ARIMA (2,1,0) | (-0.2461, p=0.000) | (-0.2106, p=0.000) | | | (0.0055, p=0.868) | 82.642 | 0.305 | 0.063 | 0.232 | 0.261 | 0.406 |
| 5 | ARIMA (1,1,2) | (-0.2110, p=0.552) | | (0.0530, p=0.879) | (0.2240, p=0.045) | (0.0043, p=0.858) | 81.914 | 0.303 | 0.180 | 0.295 | 0.206 | 0.264 |

Model 2 and 5 are also having none significant parameters where p value is greater than 0.05, which are marked in red colour. AR and MA parameters of Model 3, ARIMA (0,1,2) and Model 4, ARIMA(2,1,0) reject the null hypothesis " coefficients are equal to zero" with p values <0.05. BP statistic of the Model 3 and Model 4 is significant (p value > 0.05). Compared to the model 4, model 3 is having lesser MSE and SSE values, therefore model 3, ARIMA (0,1,2) is selected as the best fit non seasonal model.

### 4.3.6 ACF of Stationary Series - Seasonal

In general the seasonality in a time series is a regular pattern of changes that repeats over time periods. Though the 1st difference of original series was not indicate a significant lag at lag 52 ACF plot of original data series implies a pattern of seasonal with time length of 52. Therefore, now consider the seasonal effect of the original series to check any improvements to the above selected model.

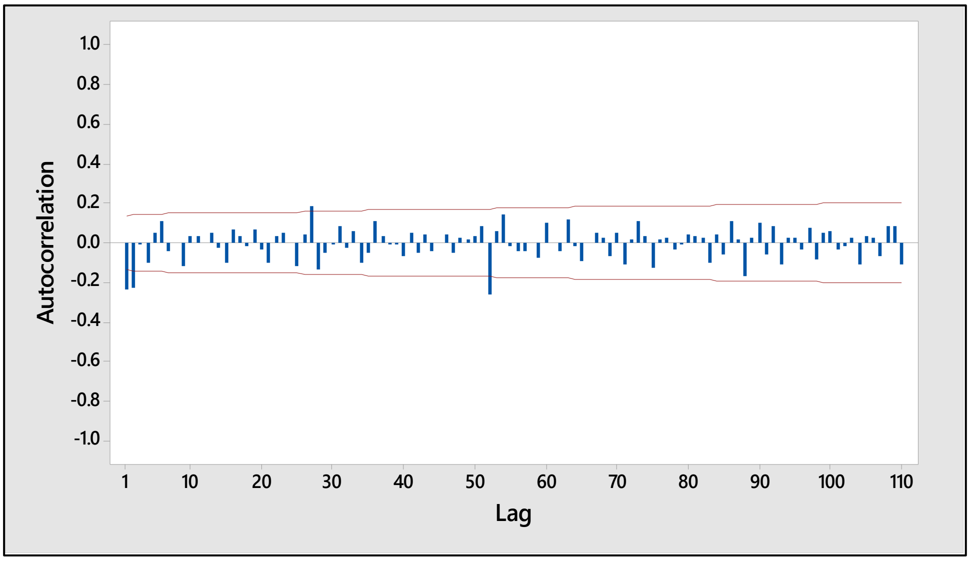


**Figure 4.24:** ACF plot of 52nd difference of the 1st difference series of original data set$\{(Y_t - Y_{t-1}) - (Y_{t-52} - Y_{t-53})\}$

In order to identify the seasonal ARIMA model, ACF plot of 52nd difference of the 1st difference series of original data was plotted (Figure 4.24). At the non seasonal levels ACF has significant spikes at lag 1 & lag 2 and cuts off after lag 2. At the seasonal level, the ACF has significant lag at lag 52 and tails off thereafter.

Therefore, conclusion can be made that 52nd difference of the 1st difference series of original data is stationary at both seasonal and non seasonal lengths. And also this indicate the order of moving average terms in both seasonal and non seasonal. MA(1), MA(2) & SMA(52) are the moving average components can be visualized by the figure 4.24.

### 4.3.7 PACF of Stationary Series - Seasonal

Identification of AR component of the SARIMA model is often best done with the PACF (Figure 4.25). Few significant "spikes" were identified at first lags, followed by the pattern gradually tapers to 0.

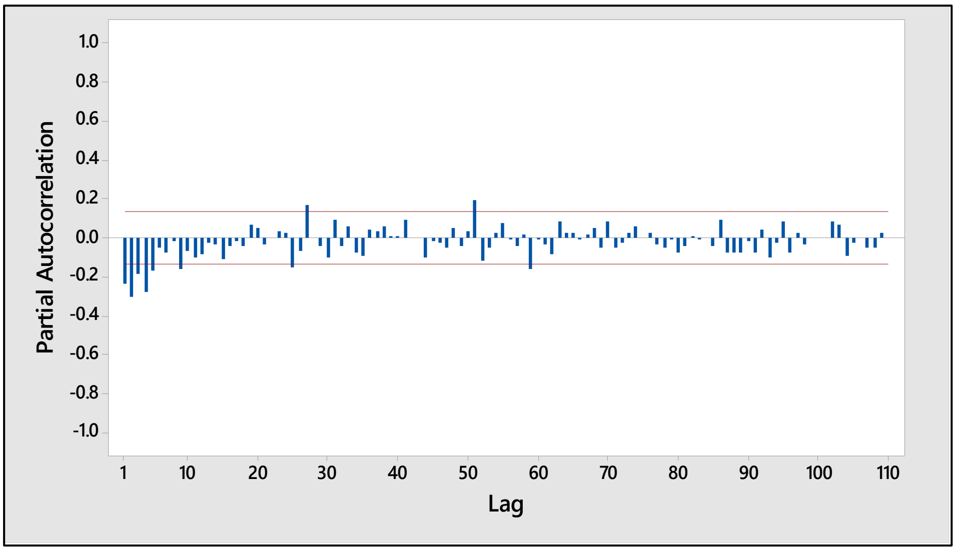


**Figure 4.25:** PACF plot of 52nd difference of the 1st difference series of original data $\{(Y_t - Y_{t-1}) - (Y_{t-52} - Y_{t-53})$

For seasonal component, first seasonal lag is identified as significant, lag at 52 and shuts off thereafter. In other words lag 104, 156 etc. were not identified as significant lags. Therefore figure 4.25 further confirms the pattern of MA observed from ACF plot for non seasonal lengths while order 1 of AR for seasonal lengths.

### 4.3.8 Identification of Parsimonious SARIMA Models

Examining the ACF and PACF of the both seasonal and non-seasonal differenced data, the order of the model $(p, d, q) \times (P, D, Q)_s$ was determined as follows: As per the ACF plot of Figure 4.24, First two and Fifty Second lags are significantly different from zero. This implies that this data series is having MA(1), MA(2) and SMA(52) components. PACF of differenced series describe that there may be no AR component in non seasonal and order 1 of seasonal AR component. Both these patterns indicate an SARIMA (0, 1, 2) $(0, 1, 1)_{52}$.

A model comparison was carried out to find the best fit time series model for observed weekly ETo at Polonnaruwa from selected models. Out puts of the considered 04 different parsimonious models are as follows.

Table 4.15 describes the results obtained for selected SARIMA models for original data series. First three models are having none significant parameters where p value is greater than 0.05, which are marked in red colour. Only Model 4, SARIMA $(0,1,2)(0,1,1)_{52}$ reject the null hypothesis " coefficients are equal to zero" with p values <0.05. Therefore model 4 is selected as the best fit model.

**Table 4.15:** Comparison of selected seasonal ETo time series models

| No | Model | AR(1) | MA(1) | MA(2) | SAR(52) | SMA(52) | C | SSE | MSE |
|---|---|---|---|---|---|---|---|---|---|
| 1 | SARIMA $(0,1,2)(1,1,1)_{52}$ | | (0.4906, p=0.000) | (0.3507, p=0.000) | (-0.0407, p=0.683) | (0.7894, p=0.000) | (0.0017, p=0.433) | 58.664 | 0.270 |
| 2 | SARIMA $(1,1,2)(1,1,1)_{52}$ | (-0.0180, p=0.927) | (0.4750, p=0.010) | (0.3630, p=0.012) | (-0.0416, p=0.676) | (0.7899, p=0.000) | (0.0017, p=0.442) | 58.637 | 0.271 |
| 3 | SARIMA $(1,1,2)(1,1,1)_{52}$ | (0.3246, p=0.000) | (0.8978, p=0.000) | (0.8127, p=0.000) | (-0.0240, p=0.806) | (0.8127, p=0.000) | (0.0014, p=0.320) | 59.345 | 0.273 |
| 4 | SARIMA $(0,1,2)(0,1,1)_{52}$ | | (0.4920, p=0.000) | (0.3518, p=0.000) | | (0.7954, p=0.000) | (0.0016, p=0.452) | 59.241 | 0.272 |

### 4.3.9 Estimation of Best Fitted Model – Pooled Data Series

Then selected two models, seasonal and non seasonal were analyzed. ARIMA (0,1,2) model is having insignificant constant. MSE of the fitted model is 0.30. Seasonal ARIMA model $(0,1,2)(0,1,1)_{52}$ is also has a constant value which is not significantly different from zero. MSE of the SARIMA model is 0.272 which is less compared to the ARIIMA (0,1,2). Mean Square of Error (MSE) is use to determine how well the model fits the data. Smaller values indicate a better fitted model. Therefore, $(0,1,2)(0,1,1)_{52}$ model is selected as the best fitted model for the original ETo data series. The mean absolute percentage error of the best fitted model is varying between ±4.8%.

To determine whether the association between the response and each term in the model is statistically significant, the p-value for the term is compare with the considered significance level to assess the null hypothesis. The moving average and seasonal moving average terms except the constant value have a p-values that are less than the significance level of 0.05 (Table 4.16). It describes that the coefficients of the fitted model are statistically significant by rejecting the null hypothesis, and can proceed with the fitted model. Only the constant value is having a p value > 0.05 of the significance level.

Fitted model for pooled data is shown in Equation 4.3

$$(1-B)(1-B^{52})\,Y_t = (1+0.492\,B)(1+0.3518\,B^2)(1+0.795\,B^{52})e_t \tag{4.3}$$

**Table 4.16:** Final estimates of parameters for SARIMA $(0,1,2)(0,1,1)_{52}$

| Type | Coefficient | SE Coefficient | T-Value | P-Value |
|---|---|---|---|---|
| MA 1 | 0.4920 | 0.0646 | 7.61 | 0.000 |
| MA 2 | 0.3518 | 0.0649 | 5.42 | 0.000 |
| SMA 52 | 0.7954 | 0.0670 | 11.88 | 0.000 |
| Constant | 0.00162 | 0.00214 | 0.75 | 0.452 |

### 4.3.10 Model Diagnostic

When conducting any statistical analysis it is important to evaluate how well the model fits the data and that the data meet the assumptions of the model.

#### 4.3.10.1 Ljung-Box chi-square statistics

The Ljung-Box chi-square statistics is used to determine whether the model meets the assumptions that the residuals are independent. In these results, the p-values for the Ljung-Box chi-square statistics are all greater than 0.05 where conclusion can be made that the model meets the assumption that the residuals are independent (Table 4.17).

**Table 4.17:** Modified Box-Pierce (Ljung-Box) Chi-Square Statistic of SARIMA $(0,1,2)(0,1,1)_{52}$

| Lag | 12 | 24 | 36 | 48 |
|---|---|---|---|---|
| Chi-Square | 8.94 | 18.84 | 30.10 | 38.88 |
| DF | 8 | 20 | 32 | 44 |
| P-Value | 0.347 | 0.532 | 0.563 | 0.690 |

#### 4.3.10.2 Residual Plots

Errors were analyze for the fitted model of SARIMA $(0,1,2)(0,1,1)_{52}$ for average weekly ETo in Polonnaruwa. Figure 4.26 shows the residual plot for ETo.

Use the normal plot of residuals to verify the assumption that the residuals are normally distributed. The following probability plot of residuals suggests that the residuals are normally distributed as residual are on a straight line with two extreme outliers.

The histogram is a frequency plot obtained by placing the data in regularly spaced cells and plotting each cell frequency versus the center of the cell. Figure 4.26 illustrates an approximately normal distribution of residuals produced by a model for a calibration process.

Residuals versus fits plot use to verify the assumption that the residuals are randomly distributed and have constant variance. Figure 4.26 also shows that residuals are scattered along a horizontal line of 0, implying that residuals have a constant variance.

Residuals versus order plot, verify the assumption that the residuals are independent from one another or in other words residuals are uncorrelated with each other. Ideally, the residuals on the plot should fall randomly around the center line. Figure 4.26 shows that residuals are independent as they spread around the center line.

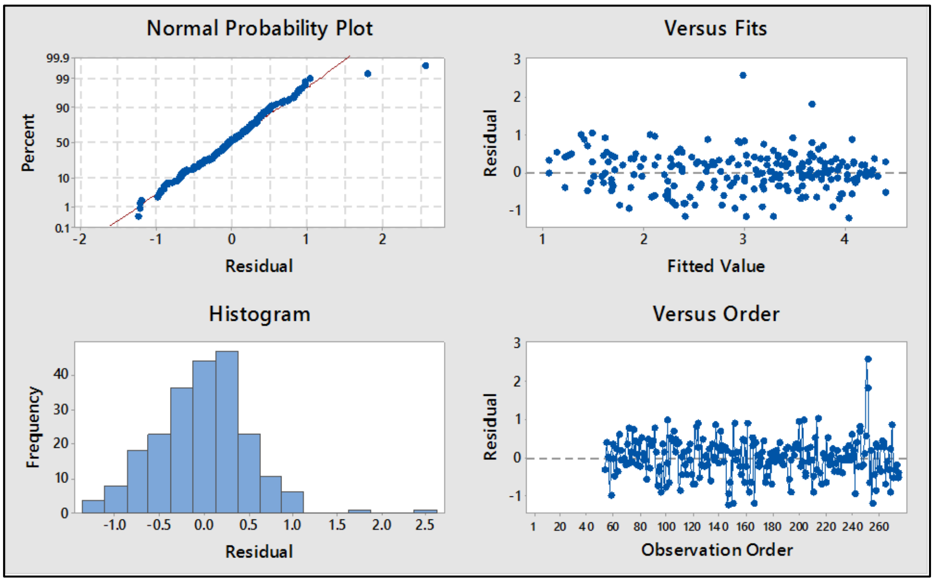


**Figure 4.26:** Residual plot of ETo for the fitted model of for SARIMA $(0,1,2)(0,1,1)_{52}$

### 4.3.10.3 ACF of Residuals

Further, ACF plot of residuals can be used to test the residuals (Figure 4.27). In this case, conclusion can make that the residuals are independent as none of the correlations for the autocorrelation function of the residuals are significant

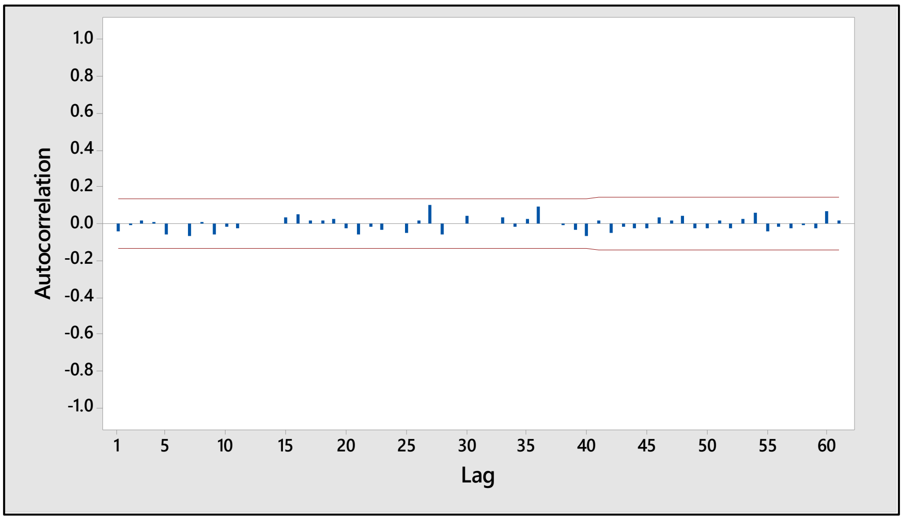


**Figure 4.27:** ACF plot of residuals for fitted model of SARIMA (0,1,2)(0,1,1)$_{52}$

#### 4.3.10.4 Predicted vs Observed

Test data kept for validation is compared with the forecasted values. After selecting the ARIMA model, it is used for forecasting. Three months weekly ETo was forecasted by using selected model. Figure 4.28 shows the scatter plot between observed and forecasted ETo. The $R^2$ value 0.62 presents good correlation ($\gamma$ = .78) between observed and forecasted value.

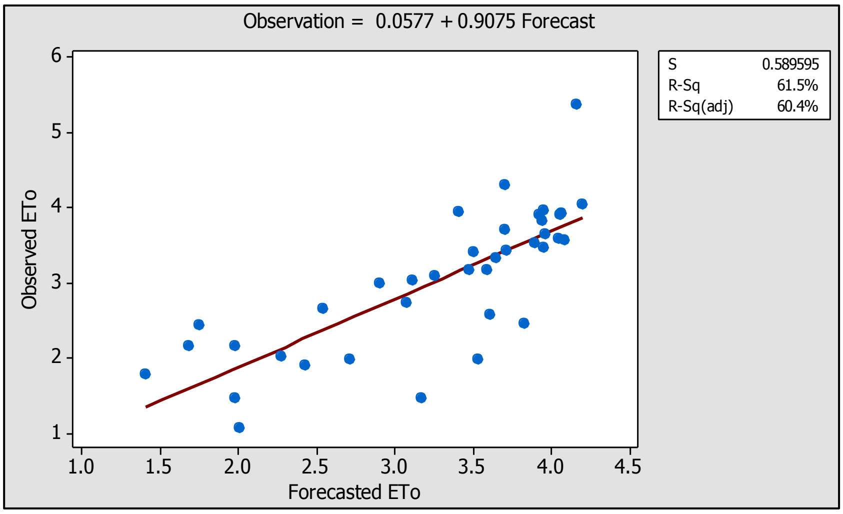


**Figure 4.28:** Scatter plot of observed vs forecasted ETo in Polonnaruwa

### 4.3.11 Forecasting

Next step was to forecast the weekly ETo for coming months. Weekly ETo was forecasted three months ahead in Polonnaruwa area based on the previous six years of ETo (Table 4.19). These results will be helpful to the water management officials of the area as well as the researchers who are willing to conduct their studies based on ETo.

**Table 4.18:** Forecasted weekly ETo in Polonnaruwa

| Year | Month | Week | Forecasted ETo (mm) |
|---|---|---|---|
| 2016 | January | 1 | 1.91 |
| | | 2 | 2.09 |
| | | 3 | 2.43 |
| | | 4 | 1.78 |
| | February | 5 | 2.15 |
| | | 6 | 2.55 |
| | | 7 | 2.82 |
| | | 8 | 2.57 |
| | March | 9 | 3.22 |
| | | 10 | 3.24 |
| | | 11 | 3.10 |
| | | 12 | 3.23 |

## 4.4 Summary

Chapter 04 presented the results of the analysis of weekly reference evapotranspiration over six years period from 2010 to 2015 of Polonnaruwa area in Sri Lanka. The time series plots were used to evaluate patterns, knowledge of the general trend and behaviors of ETo at Polonnaruwa during the Yala and Maha seasons separately and pooled data series. No clear trend and seasonality can be observed in the reference evapotranspiration time series of both Yala and Maha seasons, while time series plot of pooled data indicate a seasonal pattern with no trend. Then autocorrelation graphs were plotted for above three scenarios to check the randomness of the data series. ACFs confirmed that the time series are not random and follow a sinusoidal pattern during three cases. Differencing were considered to make the series stationary and as a result of that 1$^{st}$ difference of the original series were identified as the stationary series for all the three cases. After making the series stationary, different parsimonious models were identified with the help of ACF and PACF. Selected parsimonious models were compared separately for three different scenarios by considering the significance of the model parameters and randomness of the errors.

SARIMA models were considered by using seasonal differences of the data series along with the non seasonal differences. 26$^{th}$ difference of the 1$^{st}$ difference series were considered for both Yala and Maha data series separately in order to model a SARIMA while 52$^{nd}$ difference of 1$^{st}$ difference series was used for pooled data. Above differences made the series stationary. Hence parsimonious SARIMA were fitted for three cases by analyzing the ACF and PACF of differenced series. Finally, significance of the model parameters and randomness of the errors were considered to select the best fit models for three different scenarios.

After comparing the fitted ARIMA and SARIMA models, SARIMA $(1,1,1)(1,1,1)_{26,}$ SARIMA $(1,1,1)(1,1,1)_{26}$ and SARIMA $(0,1,2)(0,1,1)_{52}$ were identified as best fit model for Yala, Maha and Pooled data respectively with minimum MSE. Fitted model were validated using the validation data set, and accuracy of the three fitted models were obtained above 75%.

# CHAPTER 5
# CONCLUSIONS AND RECOMMENDATIONS

This chapter highlights the conclusions and recommendations based on the models developed in this study along with few suggestions.

## 5.1 Conclusions

- Seasonal Auto Regressive Integrated Moving Average (SARIMA) models well demonstrated the weekly reference evapotranspiration (ETo) in Polonnaruwa
- Two separate SARIMA models were developed to predict ETo during Yala and Maha seasons.
- Models were tested for an independent data sets and found that percentage errors are within 3%.
- The best fitted model developed for Yala season is SARIMA $(1,1,1)(1,1,1)_{26}$
- The best fitted model developed for Maha season is SARIMA $(1,1,1)(1,1,1)_{26}$
- For the pooled data, the best fitted model developed is $(0,1,2)(0,1,1)_{52}$
- The errors of all three models were found to be white noise.
- The accuracy is higher in separate models than the common model.
- Therefore, it is recommended to use separate models to predict reference evapotranspiration.
- Results obtained through this study can be used effectively to plan and establish an appropriate strategy to manage and sustain water resources in Polonnaruwa area.
- Findings can also be helpful for making local and national water policy, and for irrigation scheduling.

## 5.2 Recommendations

- In order to predict short-term and long-term reference evapotranspiration in Polonnaruwa, it is recommend to use two models developed for Yala and Maha seasons.
- Similar approaches can be investigated for other areas as well as where evapotranspiration is not measured.
- Accurate ETo observations, can be further fine-tuned the fitted models to adjust the actual ETo scenarios.
- The study can be considered as a pre-feasibility study for any water management program of the Polonnaruwa area conducted by any government or non-government agencies.

## 5.3 Suggestions

- To use lysimeters or other precision measuring devices to collect evapotranspiration data in future studies.
- To fit a Multi-Layer Artificial Neural Network method with all the correlated parameters of $ET_o$ for higher accurate time series model.

# REFERENCES


ABS. (2005). *Australian Bureau of Statistics*. Retrieved 03 12, 2018, from http://www.abs.gov.au/websitedbs/D3310114.nsf/home/Time+Series+Analysis:+The+Basics

Abubaker, J. (2007). *Irrigation scheduling for efficient water use in dry climates.* Swedish: Swedish University of Agricultural Sciences .

A.C.C.Ltd., A. C. (2016). *Irrigation Agronomy Training Manual on Farm Water Management.* Hawassa.

Adhikai, R., & Agrawal, R. K. *An Introductory Study on Time Series Modeling and Forecasting.*

Adhikari, R., & Agrawal, R. K. *An Introductory Study on Time Series Modeling and Forecasting* .

Ahmed, H. I., & Liu, J. (2013). Evaluating Reference Crop Evapotranspiration (ETo) in the Centre of Guanzhong Basin. *Engineering , 5*, 9.

Al-Ghobari, H. M. (2000). Estimation of reference evapotranspiration for southern region of Saudi Arabia. *ResearchGate , 19* (2), 7.

Ali, H. Z., & Faraj, S. H. (2017). Estimation of Daily Evaporation from Calculated Evapotranspiration in Iraq. *Journal of Madent Alelem College , 9* (2), 13.

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration - Guidelines for computing crop water requirements.* Rome: FAO.

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (2006). *FAO Irrigation and Drainage Paper No 56, Crop Evapotranspiration.* Rome: Food and Agriculture Organization of the United Nations.

Amarasinghe, U., Mutuwatta, L., & Sakthivadivel, R. (1999). *Water scarcity variations within a country:.* Colombo: International Water Management.

Anderson, D. R., Sweeney, D. J., Williams , T. A., Camm, J. D., & Cochran, J. J. (2014). Time Series Analysis and Forecasting. In *Statistics for Business & Economics, Revised* (p. 1090). CENGAGE Learning.

Arca, B., Duce, P., Spano, D., & Fiori, M. (2004). Use of Numerical Weather Forecast and Time Series Models for Predicting Reference Evapotranspiration. *Acta horticulturae , 664* (2).

Bachour, R. (2013). *Modeling and forecasting evapotranspiration for better management of irrigation command areas.* Utah State: Utah State University.

Beg, M. (2014). PREDICTION OF CROP WATER REQUIREMENT: A REVIEW. *International Journal of Advanced Technology in Engineering and Science , 2* (1), 8.

Blaney, H. F., & Criddle, W. D. (1962). *Determining Consumptive Use and Water Requirements.* US: UNITED STATES DEPARTMENT OF AGRICULTURE.

Britannica, E. o. (2018, February 02). *Water cycle*. Retrieved from Encyclopædia Britannica: https://www.britannica.com/science/water-cycle

Brouwer, C., & Heibloem, M. (1986). *Irrigation Water Management: Irrigation Water Needs.* Rome: FAO.

Brouwer, C., & Prins, K. (1989). DETERMINATION OF THE IRRIGATION SCHEDULE FOR PADDY RICE. In *Irrigation Water Management: Irrigation Scheduling.* Rome: FAO.

Bruin, H. A., & Stricker, J. N. (2000). Evaporation of grass under non-restricted soil moisture conditions. *Hydrological Sciences Journal , 45* (3), 7.

Chai, Q., Gan, Y., Turner, N. C., Zhang, R., Yang, C., Niu, Y., et al. (2014). Chapter Two - Water-Saving Innovations in Chinese Agriculture. *ELSEVIER , 126*, 149-201.

Chakravarti, A., Joshi, N., & Panjiar, H. (2015). Rainfall Runoff Analysis Using Artificial Neural Network. *Indian Journal of Science and Technology* .

Chithranayana, R. D., & Punyawardena , B. V. (2008). Identification of drought prone agro-ecological regions in. *JOURNAL OF THE NATIONAL SCIENCE FOUNDATION , 36* (2), 7.

Cigizoglu, H. K. (2003). Estimation, forecasting and extrapolation of flow data by artificial neural networks. *Hydrological Sciences Journal , 48* (3), 349-361.

Cuenca, R. H. (1989). *Irrigation system design. An engineering approach.* Oregon State, USA: Prentice Hall.

Dar , L. (2017). RAINFALL-RUNOFF MODELING USING ARTIFICIAL NEURAL NETWORK TECHNIQUE. *International Research Journal of Engineering and Technology* , pp 424 - 427.

De Silva, M., Weerakoon, S., Herath, S., Ratnayake, U., & Mahanama, S. (2012). Flood Inundation Mapping along the Lower Reach of Kelani River Basin under the Impact of Climatic Change. *ENGINEER* , pp 23-29.

De Vos, N. (2003). *Rainfall-Runoff Modelling Using Artificial Neural Networks.* Netherlands: Delft University of Technology.

Doorenbos, J., & Pruitt, W. O. (1977). *Guidlines for Predicting Cropwater Requirement.* Rome: FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS.

Dyck, S. (1990). *Integrated Planning and Management of Water Resources* . Paris: United Nations Educational, Scientific and Cultural Organization.

Eijkelkamp. (2014). *Evaporation Pan - Operating Instructions*. Retrieved 02 26, 2018, from https://www.eijkelkamp.com

Facon, T. (2000). WATER MANAGEMENT IN RICE IN ASIA: SOME ISSUES FOR THE FUTURE . Bangkok: Food and Agricultural Organization.

FAO. (1984). *Land, Food and People. Economic and Social Development Series No. 30.* Rome: FAO.

FAO. (1997, 04 19). *SPECIAL REPORT - FAO/WFP CROP AND FOOD SUPPLY ASSESSMENT MISSION TO SRI LANKA.* Retrieved 12 01, 2017, from http://www.fao.org/docrep/004/W4931e/W4931e00.htm

Fawumi, K. (2015). *DESIGN OF AN INTERACTIVE AND WEB-BASED SOFTWARE FOR THE MANAGEMENT, ANALYSIS AND TRANSFORMATION OF TIME SERIES.*

Feddes, R., & lenselink, K. J. (1994). Evapotranspiration. In H. P. Ritzema (Ed.), *Drainage Principles and Applications* (p. 130). Wageningen, Netherlands: ILRI Publications.

Fereres, E. (1996). Irrigation scheduling and its impact on the 21st Century. San Antonio: American Society of Agricultural Engineers.

Gahirwal, M., & Vijyalakshmi, M. (n.d.). Inter Time Series Sales Forecasting.

Gautam, R., & Sinha, A. K. (2016). Time series analysis of reference crop evapotranspiration for Bokaro District, Jharkhand, India. *JOURNAL OF WATER AND LAND DEVELOPMENT , 30* (69), 51-56.

Gorantiwar, S. D., Meshram, D. T., & Mittal, H. K. (2011). Seasonal ARIMA model for generation and forecasting evapotranspirtion of Solapur district of Maharashtra. *Journal of Agrometeorology , 13* (2), 119-122.

Govindaraju, R. (2000). Artificial neural networks in. *Journal of Hydrologic Engineering, Vol. 5* , pp. 115-123.

Gunasekara, I. (2008). Flood Hazard Mapping in Lower Reach of Kelani River. *ENGINEER* , 149-154.

Hargreaves, G. H., & Samani, Z. (1985). Reference Crop Evapotranspiration From Temperature. *Applied Engineering in Agriculture* .

Hegb, B; Bety, N; Vwrry, L;. (2015). *BVJHBJK.* LKJ: JKHLK.

Hyndman, R., & Athanasopoulos, G. (2012). ARIMA models. In *Forecasting: principles and practice.*

IUCN. (2015). *Management and conservation of the Kelani River Basin*. Retrieved from IUCN: https://www.iucn.org/asia/countries/sri-lanka/management-and-conservation-kelani-river-basin

Jensen , M. E., Burman, R. D., & Allen, R. G. (1990). Evapotranspiration and irrigation water requirements: a manual. *ASCE manuals and reports on engineering practice (USA). no. 70.* , 360p.

Jensen, M. E., & Haise, H. R. (1963). Estimating evapotranspiration from solar radiation. *Journal of Irrigation and Drainage Engineering , 89* (4), 203-205.

Joshi, J., & Patel, V. (2011). Rainfall-Runoff Modeling Using Artificial Neural Network. *National Conference on Recent Trends in Engineering & Technology* .

Kale, M. U., Nagdeve, M. B., & Bagade, S. J. (2013). ESTIMATION OF EVAPOTRANSPIRATION WITH ANN TECHNIQUE . *Jounal of Indian Water Resources Society , 33* (1), 7.

landeras, G., Barredo, A. O., & Lopez, J. J. (2009). Forecasting Weekly Evapotranspiration with ARIMA and Artificial Neural Network Models. *Journal of Irrigation and Drainage Engineering , 135* (3), 323-334.

Landeras, G., Ortiz-Barredo, A., & Lopez, J. J. (2009). Forecasting Weekly Evapotranspiration with ARIMA and Artificial Neural Network Models. *Journal of Irrigation and Drainage Engineering , 135,* 323-334.

Letey, J. (2007). Optimizing Irrigation for Agricultural Water Management: Scientific Principles. Tunisia: National Academies Press.

Lin, W., R. V., & Su, Z. (2008). SATELLITE BASED REGIONAL-SCALE EVAPOTRANSPIRATION IN THE HEBEI. *Dragon Symposium, Dragon 1 Programme, Final Results 2004 2007* (p. 9). China: European Space Agency.

Liyanage, C., Marasinghe, A., & Yamada, K. (2016, 07 31). Comparison of Optimized Selection Methods of Sampling Sites Network for Water Quality Monitoring in a River. *International Journal of Affective Engineering* .

Loucks, D. P. (2008, 12 03). *Water Resource Management Models*. Retrieved from National Academy of Engineering: https://www.nae.edu/19582/Bridge/V38N2/WaterResourceManagementModels.aspx

Mahendrarajah, S. (1981). *WATER RESOURCE OPTIMISATION IN SMALL DAMS IN THE DRY ZONE OF SRI LANKA: A TIME SERIES ANALYSIS AND STOCHASTIC.* Australia: A dissertation submitted in partial fulfilment of the requirements for the degree of Master of Agricultural Development Economics in ANU.

Mahesh, P., & Kayesth, B. (2017). Prediction of Runoff using Matlab. *International Journal for Scientific Research & Development* , 1727-130.

Makkink, G. F. (1957). Testing the Penman formula by means of lysimeters. *Journal of Water Process Engineering , 11* (3), 277-278.

Mancosu, N., Snyder, R., Kyriakakis, G., & Spano, D. (2015). Water Scarcity and Future Challenges for Food Production. *water* , 18.

Manikumari, N., & Vinodhani, G. (2016). Regression Models for Predicting Reference Evapotranspiration. *International Journal of Engineering Trends and Technology , 38* (3), 134-139.

Marino, M. A. (1993). Forecasting of Reference Crop Evapotranspiration. *Agricultural Water Management , 24*, 163-187.

Mesbram, D. T., Gorantiwar, S. D., Sangale, U. R., Nagraj, B. K., & Pal, R. K. (2017). ARIMA MODEL FOR FORECASTING REFERENCE CROP EVAPOTRANSPIRATION OF SOLAPUR REGION, MAHARASHTRA, INDIA . *CONTEMPORARY RESEARCH IN INDIA , 7* (2), 286-295.

Mohan, S., & Arumugam, N. (1995). Forecasting weekly reference crop évapotranspiration series . *Hydrological Sciences -Journal , 40* (6), 689-702.

Mörtberg, U. (2016, 06 03). *Hydrological modeling as a tool for water resources management*. Retrieved from KTH: https://www.seed.abe.kth.se/om/avd/lwr/grupper/forskningsomraden/ema/research/water-resources-decision-support/hydrological-modeling-tool-1.84735

Murray, R. S., & Grant, C. D. (2007). *The Impact of Irrigation on Soil Structure*. Canberra: The National Program for Sustainable Irrigation (Land & Water Australia)

NIST/SEMATECH. (2012). *Handbook of Statistical Methods*. Retrieved 02 23, 2018, from https://www.itl.nist.gov/div898/handbook/pmc/section4/pmc442.htm

Nor, N. (2005). *RAINFALL-RUNOFF MODELLING USING ARTIFICIAL NEURAL NETWORK METHOD.* University of Technology Malaysia.

ORIENTAL CONSULTANTS. (2009). *COMPREHENSIVE STUDY ON DISASTER MANAGEMENT IN sRI LANKA.* JAPAN INTERNATIONAL COOPERATION AGENCY.

Pannikar, A. (2008). Water profile of Sri Lanka. *National Conference on Water, Food Security and Climate.* FAO.

Pechlivanidis, I., & Arheimer, B. (2015). Large-scale hydrological modelling by using modified PUB recommendations: the India-HYPE case. *Hydrology and Earth System Sciences , 19*, 20.

Pereira, A. R., Villa Nova, N. A., Pereira, A. S., & Barbieri, V. A. (1995). A modelfor the class A pan coefficient. *Agricultural and Forest Meteorology , 76*, 75-82.

Pereira, A., & Pires, L. (2011). Evapotranspiration and Water Management for Crop Production. In G. Gerosa (Ed.), *Evapotranspiration - From Measurements to Agricultural and Environmental Applications* (p. 410). Brazil: In Tech.

Priestley, C. H., & Taylor, R. J. (1970). ‘On the Assessment of the Surface heat Flux and Evaporation using Large-scale Parameters. *Monthly Weather Review 100* , 81-92.

Raghuwanshi, N., & Wallender, W. W. (1988). Converting from pan evaporation to evapotranspiration. *Journal of Irrigation and Drainage Engineering , 118*, 977-980.

Rajakaruna, R. M. (2014). New Approach for the Success of Yala cultivation in Dry zone under Drought Condition. *ENGINEER , 47* (4), 7.

Renuka, G. (n.d.). *Agriculture in India*. Retrieved 02 06, 2018, from http://www.agricultureinindia.net/evapotranspiration/how-to-measure-evapotranspiration-plant-water-relationships-agronomy/13507

RMB Environmetal Laboratories. (2018). *Water Cycle*. Retrieved 01 13, 2018, from https://www.rmbel.info/primer/water-cycle/

Samanthi, W. G. (1999). *FITTING MATHEMATICAL MODELS FOR RAINFALL-RUNOFF RELATIONSHIPS.* University of Sri Jayewardenepura.

Savva, A. P., & Frenken, K. (2002). *Crop Water Requirements and Crop Water Requirements and.* Harare: FAO.

Savva, A. P., & Frenken, K. (2002). *Crop Water Requirements and Irrigation Scheduling.* Harare: Food and Agriculture organization of United States.

Senevirathne. (2015, 02 20). *Sustainable water resources management in Sri Lanka: present situation and way forward*. Retrieved from RURAL WATER SUPPLY NETWORK – BLOG: https://rwsn.blog/2015/02/20/sustainable-water-resources-management-in-sri-lanka-present-situation-and-way-forward/

Sentelhas, P. C., & Folegatti, M. V. (2003). Class A pan coefficients (Kp) to estimate daily reference evapotranspiration (ETo). *Revista Brasileira de Engenharia Agrícola e Ambiental , 7* (1), 9.

Smith, P., Calanca, P., & Fuhrer, J. (2012). A Simple Scheme for Modeling Irrigation Water Requirements at the Regional Scale Applied to an Alpine River Catchment. *Water , 4* (4), 17.

Snyder, R. (1992). Equation for evaporation pan to evapotranspirationconversion. *Journal of Irrigation and Drainage Engeneeringof ASCE , 118* (6), 977-980.

*Sri Lanka: Mapping Flood Extent for Kelani Ganga River Basin and its surrounding using RISAT-1 Satellite imagery*. (2016, 05 19). Retrieved from Reliefweb: https://reliefweb.int/map/sri-lanka/sri-lanka-mapping-flood-extent-kelani-ganga-river-basin-and-its-surrounding-using

Tessema, S. (2011). *HYDROLOGICAL MODELING AS A TOOL FOR SUSTAINABLE WATER RESOURCES MANAGEMENT: A CASE STUDY OF THE AWASH RIVER BASIN.* Sweden: Department of Land and Water Resources Engineering, Royal Institute of Technology (KTH).

Trajkovic, S. (1998). Comparison of Prediction of Reference Crop Evapotranspiration. *The Scientific Journal FACTA UNIVERSITATIS , 1* (5), 617-620.

U.S. Department of the Interior, U. G. (2016, December 02). *What is hydrology and what do hydrologists do?* Retrieved from The USGS Water Science School: http://water.usgs.gov/edu/hydrology.html

Upali, J., Sugirtharan, M., & Dasinaa, S. (2016). Associated Problems and Farmers' Satisfaction in the Use of Mahaweli Irrigation Water during Maha and Yala Season at Mahaweli C Zone of Sri Lanka . Faculty of Management and Commerce- SEUSL.

USGS. (2016). *The Water Cycle - USGS Water Science School*. Retrieved 03 01, 2018, from https://water.usgs.gov/edu/watercyclesummarytext.html

Walter, M. J., Newsom, H. E., Ertel, W., & Holzheid, A. (2000). Siderophile elements in the Earth and Moon; Metal/silicate partitioning and implications for core formation. In R. M. Canup, & K. Righter (Eds.), *Origin of the Earth and Moon* (pp. 265-289). Tuscon: University of Arizona Press.

Werner, H. D. (1996). Checkbook irrigation tables developed from Ag. Met. Data. In C. Camp, E. Sadler, & R. Yoder (Eds.), *Evapotranspiration and Irrigation Scheduling* (p. 5). San Antonio,: A.S.A.E.

Wijesekara, S., Imbulana, K., & Neupane, B. (2005). *Proceedings of the Preparatory Workshop on Sri Lanka National Water Development Report.* Paris: United Nations World Water Assessment Programme .

Wildi, M. (2013). *Econometrics 1: Time Series Analysis.*

Will Sri Lanka Run Out of Water for Agriculture or Can it Be Managed? (2013). The Island.

Xu, C.-y. (2002). *HYDROLOGIC MODELS.* Uppsala : Department of Earth Sciences and Hydrology, Uppsala University.

Yoder, R. E., Odhiambo, L., & Wright, W. (2005). Evaluation of methods for estimating daily reference crop evapotranspiration at a site in the humid south United States. *Applied engineering in agriculture , 22* (2), 6.

Zhai, Y. (2005). *TIME SERIES FORECASTING COMPETITION AMONG THREE SOPHISTICATED PARADIGMS.* University of North Carolina Wilmington.

Zhao, L., Xia, J., Yu Xu, C., & Long, C. (2013). Evapotranspiration estimation methods in hydrological models. *Journal of Geographical Sciences , 23* (2), 10.

# APPENDICES

## APPENDIX A: Week No. Referring Period in Yala Season

| Week No | From | To |
|---|---|---|
| 1 | 2-Apr-2010 | 8-Apr-2010 |
| 2 | 9-Apr-2010 | 15-Apr-2010 |
| 3 | 16-Apr-2010 | 22-Apr-2010 |
| 4 | 23-Apr-2010 | 29-Apr-2010 |
| 5 | 30-Apr-2010 | 6-May-2010 |
| 6 | 7-May-2010 | 13-May-2010 |
| 7 | 14-May-2010 | 20-May-2010 |
| 8 | 21-May-2010 | 27-May-2010 |
| 9 | 28-May-2010 | 3-Jun-2010 |
| 10 | 4-Jun-2010 | 10-Jun-2010 |
| 11 | 11-Jun-2010 | 17-Jun-2010 |
| 12 | 18-Jun-2010 | 24-Jun-2010 |
| 13 | 25-Jun-2010 | 1-Jul-2010 |
| 14 | 2-Jul-2010 | 8-Jul-2010 |
| 15 | 9-Jul-2010 | 15-Jul-2010 |
| 16 | 16-Jul-2010 | 22-Jul-2010 |
| 17 | 23-Jul-2010 | 29-Jul-2010 |
| 18 | 30-Jul-2010 | 5-Aug-2010 |
| 19 | 6-Aug-2010 | 12-Aug-2010 |
| 20 | 13-Aug-2010 | 19-Aug-2010 |
| 21 | 20-Aug-2010 | 26-Aug-2010 |
| 22 | 27-Aug-2010 | 2-Sep-2010 |
| 23 | 3-Sep-2010 | 9-Sep-2010 |
| 24 | 10-Sep-2010 | 16-Sep-2010 |
| 25 | 17-Sep-2010 | 23-Sep-2010 |
| 26 | 24-Sep-2010 | 31-Mar-2011 |
| 27 | 1-Apr-2011 | 7-Apr-2011 |
| 28 | 8-Apr-2011 | 14-Apr-2011 |
| 29 | 15-Apr-2011 | 21-Apr-2011 |
| 30 | 22-Apr-2011 | 28-Apr-2011 |
| 31 | 29-Apr-2011 | 5-May-2011 |
| 32 | 6-May-2011 | 12-May-2011 |
| 33 | 13-May-2011 | 19-May-2011 |
| 34 | 20-May-2011 | 26-May-2011 |
| 35 | 27-May-2011 | 2-Jun-2011 |
| 36 | 3-Jun-2011 | 9-Jun-2011 |
| 37 | 10-Jun-2011 | 16-Jun-2011 |

## APPENDIX A (Continued)

| Week No | From | To |
|---|---|---|
| 38 | 17-Jun-2011 | 23-Jun-2011 |
| 39 | 24-Jun-2011 | 30-Jun-2011 |
| 40 | 1-Jul-2011 | 7-Jul-2011 |
| 42 | 15-Jul-2011 | 21-Jul-2011 |
| 43 | 22-Jul-2011 | 28-Jul-2011 |
| 44 | 29-Jul-2011 | 4-Aug-2011 |
| 45 | 5-Aug-2011 | 11-Aug-2011 |
| 46 | 12-Aug-2011 | 18-Aug-2011 |
| 47 | 19-Aug-2011 | 25-Aug-2011 |
| 48 | 26-Aug-2011 | 1-Sep-2011 |
| 49 | 2-Sep-2011 | 8-Sep-2011 |
| 50 | 9-Sep-2011 | 15-Sep-2011 |
| 51 | 16-Sep-2011 | 22-Sep-2011 |
| 52 | 23-Sep-2011 | 29-Sep-2011 |
| 53 | 30-Sep-2011 | 5-Apr-2012 |
| 54 | 6-Apr-2012 | 12-Apr-2012 |
| 55 | 13-Apr-2012 | 19-Apr-2012 |
| 56 | 20-Apr-2012 | 26-Apr-2012 |
| 57 | 27-Apr-2012 | 3-May-2012 |
| 58 | 4-May-2012 | 10-May-2012 |
| 59 | 11-May-2012 | 17-May-2012 |
| 60 | 18-May-2012 | 24-May-2012 |
| 61 | 25-May-2012 | 31-May-2012 |
| 62 | 1-Jun-2012 | 7-Jun-2012 |
| 63 | 8-Jun-2012 | 14-Jun-2012 |
| 64 | 15-Jun-2012 | 21-Jun-2012 |
| 65 | 22-Jun-2012 | 28-Jun-2012 |
| 66 | 29-Jun-2012 | 5-Jul-2012 |
| 67 | 6-Jul-2012 | 12-Jul-2012 |
| 68 | 13-Jul-2012 | 19-Jul-2012 |
| 69 | 20-Jul-2012 | 26-Jul-2012 |
| 70 | 27-Jul-2012 | 2-Aug-2012 |
| 71 | 3-Aug-2012 | 9-Aug-2012 |
| 72 | 10-Aug-2012 | 16-Aug-2012 |
| 73 | 17-Aug-2012 | 23-Aug-2012 |
| 74 | 24-Aug-2012 | 30-Aug-2012 |
| 75 | 31-Aug-2012 | 6-Sep-2012 |
| 76 | 7-Sep-2012 | 13-Sep-2012 |
| 77 | 14-Sep-2012 | 20-Sep-2012 |

## APPENDIX A (Continued)

| Week No | From | To |
|---|---|---|
| 78 | 21-Sep-2012 | 27-Sep-2012 |
| 79 | 28-Sep-2012 | 4-Apr-2013 |
| 80 | 5-Apr-2013 | 11-Apr-2013 |
| 81 | 12-Apr-2013 | 18-Apr-2013 |
| 82 | 19-Apr-2013 | 25-Apr-2013 |
| 83 | 26-Apr-2013 | 2-May-2013 |
| 84 | 3-May-2013 | 9-May-2013 |
| 85 | 10-May-2013 | 16-May-2013 |
| 86 | 17-May-2013 | 23-May-2013 |
| 87 | 24-May-2013 | 30-May-2013 |
| 88 | 31-May-2013 | 6-Jun-2013 |
| 89 | 7-Jun-2013 | 13-Jun-2013 |
| 90 | 14-Jun-2013 | 20-Jun-2013 |
| 91 | 21-Jun-2013 | 27-Jun-2013 |
| 92 | 28-Jun-2013 | 4-Jul-2013 |
| 93 | 5-Jul-2013 | 11-Jul-2013 |
| 94 | 12-Jul-2013 | 18-Jul-2013 |
| 95 | 19-Jul-2013 | 25-Jul-2013 |
| 96 | 26-Jul-2013 | 1-Aug-2013 |
| 97 | 2-Aug-2013 | 8-Aug-2013 |
| 98 | 9-Aug-2013 | 15-Aug-2013 |
| 99 | 16-Aug-2013 | 22-Aug-2013 |
| 100 | 23-Aug-2013 | 29-Aug-2013 |
| 101 | 30-Aug-2013 | 5-Sep-2013 |
| 102 | 6-Sep-2013 | 12-Sep-2013 |
| 103 | 13-Sep-2013 | 19-Sep-2013 |
| 104 | 20-Sep-2013 | 26-Sep-2013 |
| 105 | 27-Sep-2013 | 3-Apr-2014 |
| 106 | 4-Apr-2014 | 10-Apr-2014 |
| 107 | 11-Apr-2014 | 17-Apr-2014 |
| 108 | 18-Apr-2014 | 24-Apr-2014 |
| 109 | 25-Apr-2014 | 1-May-2014 |
| 110 | 2-May-2014 | 8-May-2014 |
| 111 | 9-May-2014 | 15-May-2014 |
| 112 | 16-May-2014 | 22-May-2014 |
| 113 | 23-May-2014 | 29-May-2014 |
| 114 | 30-May-2014 | 5-Jun-2014 |
| 115 | 6-Jun-2014 | 12-Jun-2014 |
| 116 | 13-Jun-2014 | 19-Jun-2014 |

## APPENDIX A (Continued)

| Week No | From | To |
|---|---|---|
| 117 | 20-Jun-2014 | 26-Jun-2014 |
| 118 | 27-Jun-2014 | 3-Jul-2014 |
| 119 | 4-Jul-2014 | 10-Jul-2014 |
| 120 | 11-Jul-2014 | 17-Jul-2014 |
| 121 | 18-Jul-2014 | 24-Jul-2014 |
| 122 | 25-Jul-2014 | 31-Jul-2014 |
| 123 | 1-Aug-2014 | 7-Aug-2014 |
| 124 | 8-Aug-2014 | 14-Aug-2014 |
| 125 | 15-Aug-2014 | 21-Aug-2014 |
| 126 | 22-Aug-2014 | 28-Aug-2014 |
| 127 | 29-Aug-2014 | 4-Sep-2014 |
| 128 | 5-Sep-2014 | 11-Sep-2014 |
| 129 | 12-Sep-2014 | 18-Sep-2014 |
| 130 | 19-Sep-2014 | 25-Sep-2014 |
| 131 | 26-Sep-2014 | 2-Apr-2015 |
| 132 | 3-Apr-2015 | 9-Apr-2015 |
| 133 | 10-Apr-2015 | 16-Apr-2015 |
| 134 | 17-Apr-2015 | 23-Apr-2015 |
| 135 | 24-Apr-2015 | 30-Apr-2015 |
| 136 | 1-May-2015 | 7-May-2015 |
| 137 | 8-May-2015 | 14-May-2015 |
| 138 | 15-May-2015 | 21-May-2015 |

## APPENDIX B: Week No. Referring Period in Maha Season

| Week No | From | To |
|---|---|---|
| 1 | 1-Jan-2010 | 7-Jan-2010 |
| 2 | 8-Jan-2010 | 14-Jan-2010 |
| 3 | 15-Jan-2010 | 21-Jan-2010 |
| 4 | 22-Jan-2010 | 28-Jan-2010 |
| 5 | 29-Jan-2010 | 4-Feb-2010 |
| 6 | 5-Feb-2010 | 11-Feb-2010 |
| 7 | 12-Feb-2010 | 18-Feb-2010 |
| 8 | 19-Feb-2010 | 25-Feb-2010 |
| 9 | 26-Feb-2010 | 4-Mar-2010 |
| 10 | 5-Mar-2010 | 11-Mar-2010 |
| 11 | 12-Mar-2010 | 18-Mar-2010 |
| 12 | 19-Mar-2010 | 25-Mar-2010 |
| 13 | 26-Mar-2010 | 30-Sep-2010 |
| 14 | 1-Oct-2010 | 7-Oct-2010 |
| 15 | 8-Oct-2010 | 14-Oct-2010 |
| 16 | 15-Oct-2010 | 21-Oct-2010 |
| 17 | 22-Oct-2010 | 28-Oct-2010 |
| 18 | 29-Oct-2010 | 4-Nov-2010 |
| 19 | 5-Nov-2010 | 11-Nov-2010 |
| 20 | 12-Nov-2010 | 18-Nov-2010 |
| 21 | 19-Nov-2010 | 25-Nov-2010 |
| 22 | 26-Nov-2010 | 2-Dec-2010 |
| 23 | 3-Dec-2010 | 9-Dec-2010 |
| 24 | 10-Dec-2010 | 16-Dec-2010 |
| 25 | 17-Dec-2010 | 23-Dec-2010 |
| 26 | 24-Dec-2010 | 30-Dec-2010 |
| 27 | 31-Dec-2010 | 6-Jan-2011 |
| 28 | 7-Jan-2011 | 13-Jan-2011 |
| 29 | 14-Jan-2011 | 20-Jan-2011 |
| 30 | 21-Jan-2011 | 27-Jan-2011 |
| 31 | 28-Jan-2011 | 3-Feb-2011 |
| 32 | 4-Feb-2011 | 10-Feb-2011 |
| 33 | 11-Feb-2011 | 17-Feb-2011 |
| 34 | 18-Feb-2011 | 24-Feb-2011 |
| 35 | 25-Feb-2011 | 3-Mar-2011 |
| 36 | 4-Mar-2011 | 10-Mar-2011 |
| 37 | 11-Mar-2011 | 17-Mar-2011 |
| 38 | 18-Mar-2011 | 24-Mar-2011 |
| 39 | 25-Mar-2011 | 6-Oct-2011 |
| 40 | 7-Oct-2011 | 13-Oct-2011 |

## APPENDIX B (Continued)

| Week No | From | To |
|---|---|---|
| 41 | 14-Oct-2011 | 20-Oct-2011 |
| 42 | 21-Oct-2011 | 27-Oct-2011 |
| 43 | 28-Oct-2011 | 3-Nov-2011 |
| 44 | 4-Nov-2011 | 10-Nov-2011 |
| 45 | 11-Nov-2011 | 17-Nov-2011 |
| 46 | 18-Nov-2011 | 24-Nov-2011 |
| 47 | 25-Nov-2011 | 1-Dec-2011 |
| 48 | 2-Dec-2011 | 8-Dec-2011 |
| 49 | 9-Dec-2011 | 15-Dec-2011 |
| 50 | 16-Dec-2011 | 22-Dec-2011 |
| 51 | 23-Dec-2011 | 29-Dec-2011 |
| 52 | 30-Dec-2011 | 5-Jan-2012 |
| 53 | 6-Jan-2012 | 12-Jan-2012 |
| 54 | 13-Jan-2012 | 19-Jan-2012 |
| 55 | 20-Jan-2012 | 26-Jan-2012 |
| 56 | 27-Jan-2012 | 2-Feb-2012 |
| 57 | 3-Feb-2012 | 9-Feb-2012 |
| 58 | 10-Feb-2012 | 16-Feb-2012 |
| 59 | 17-Feb-2012 | 23-Feb-2012 |
| 60 | 24-Feb-2012 | 1-Mar-2012 |
| 61 | 2-Mar-2012 | 8-Mar-2012 |
| 62 | 9-Mar-2012 | 15-Mar-2012 |
| 63 | 16-Mar-2012 | 22-Mar-2012 |
| 64 | 23-Mar-2012 | 29-Mar-2012 |
| 65 | 30-Mar-2012 | 4-Oct-2012 |
| 66 | 5-Oct-2012 | 11-Oct-2012 |
| 67 | 12-Oct-2012 | 18-Oct-2012 |
| 68 | 19-Oct-2012 | 25-Oct-2012 |
| 69 | 26-Oct-2012 | 1-Nov-2012 |
| 70 | 2-Nov-2012 | 8-Nov-2012 |
| 71 | 9-Nov-2012 | 15-Nov-2012 |
| 72 | 16-Nov-2012 | 22-Nov-2012 |
| 73 | 23-Nov-2012 | 29-Nov-2012 |
| 74 | 30-Nov-2012 | 6-Dec-2012 |
| 75 | 7-Dec-2012 | 13-Dec-2012 |
| 76 | 14-Dec-2012 | 20-Dec-2012 |
| 77 | 21-Dec-2012 | 27-Dec-2012 |
| 78 | 28-Dec-2012 | 3-Jan-2013 |
| 79 | 4-Jan-2013 | 10-Jan-2013 |

## APPENDIX B (Continued)

| Week No | From | To |
|---|---|---|
| 80 | 11-Jan-2013 | 17-Jan-2013 |
| 81 | 18-Jan-2013 | 24-Jan-2013 |
| 82 | 25-Jan-2013 | 31-Jan-2013 |
| 83 | 1-Feb-2013 | 7-Feb-2013 |
| 84 | 8-Feb-2013 | 14-Feb-2013 |
| 85 | 15-Feb-2013 | 21-Feb-2013 |
| 86 | 22-Feb-2013 | 28-Feb-2013 |
| 87 | 1-Mar-2013 | 7-Mar-2013 |
| 88 | 8-Mar-2013 | 14-Mar-2013 |
| 89 | 15-Mar-2013 | 21-Mar-2013 |
| 90 | 22-Mar-2013 | 28-Mar-2013 |
| 91 | 29-Mar-2013 | 3-Oct-2013 |
| 92 | 4-Oct-2013 | 10-Oct-2013 |
| 93 | 11-Oct-2013 | 17-Oct-2013 |
| 94 | 18-Oct-2013 | 24-Oct-2013 |
| 95 | 25-Oct-2013 | 31-Oct-2013 |
| 96 | 1-Nov-2013 | 7-Nov-2013 |
| 97 | 8-Nov-2013 | 14-Nov-2013 |
| 98 | 15-Nov-2013 | 21-Nov-2013 |
| 99 | 22-Nov-2013 | 28-Nov-2013 |
| 100 | 29-Nov-2013 | 5-Dec-2013 |
| 101 | 6-Dec-2013 | 12-Dec-2013 |
| 102 | 13-Dec-2013 | 19-Dec-2013 |
| 103 | 20-Dec-2013 | 26-Dec-2013 |
| 104 | 27-Dec-2013 | 2-Jan-2014 |
| 105 | 3-Jan-2014 | 9-Jan-2014 |
| 106 | 10-Jan-2014 | 16-Jan-2014 |
| 107 | 17-Jan-2014 | 23-Jan-2014 |
| 108 | 24-Jan-2014 | 30-Jan-2014 |
| 109 | 31-Jan-2014 | 6-Feb-2014 |
| 110 | 7-Feb-2014 | 13-Feb-2014 |
| 111 | 14-Feb-2014 | 20-Feb-2014 |
| 112 | 21-Feb-2014 | 27-Feb-2014 |
| 113 | 28-Feb-2014 | 6-Mar-2014 |
| 114 | 7-Mar-2014 | 13-Mar-2014 |
| 115 | 14-Mar-2014 | 20-Mar-2014 |
| 116 | 21-Mar-2014 | 27-Mar-2014 |
| 117 | 28-Mar-2014 | 2-Oct-2014 |
| 118 | 3-Oct-2014 | 9-Oct-2014 |

## APPENDIX B (Continued)

| Week No | From | To |
|---|---|---|
| 119 | 10-Oct-2014 | 16-Oct-2014 |
| 120 | 17-Oct-2014 | 23-Oct-2014 |
| 121 | 24-Oct-2014 | 30-Oct-2014 |
| 122 | 31-Oct-2014 | 6-Nov-2014 |
| 123 | 7-Nov-2014 | 13-Nov-2014 |
| 124 | 14-Nov-2014 | 20-Nov-2014 |
| 125 | 21-Nov-2014 | 27-Nov-2014 |
| 126 | 28-Nov-2014 | 4-Dec-2014 |
| 127 | 5-Dec-2014 | 11-Dec-2014 |
| 128 | 12-Dec-2014 | 18-Dec-2014 |
| 129 | 19-Dec-2014 | 25-Dec-2014 |
| 130 | 26-Dec-2014 | 1-Jan-2015 |
| 131 | 2-Jan-2015 | 8-Jan-2015 |
| 132 | 9-Jan-2015 | 15-Jan-2015 |
| 133 | 16-Jan-2015 | 22-Jan-2015 |
| 134 | 23-Jan-2015 | 29-Jan-2015 |
| 135 | 30-Jan-2015 | 5-Feb-2015 |
| 136 | 6-Feb-2015 | 12-Feb-2015 |
| 137 | 13-Feb-2015 | 19-Feb-2015 |
| 138 | 20-Feb-2015 | 26-Feb-2015 |

## APPENDIX C: Week No. Referring Period in Pooled Data Series

| Week No | From | To |
|---|---|---|
| 1 | 1-Jan-2010 | 7-Jan-2010 |
| 2 | 8-Jan-2010 | 14-Jan-2010 |
| 3 | 15-Jan-2010 | 21-Jan-2010 |
| 4 | 22-Jan-2010 | 28-Jan-2010 |
| 5 | 29-Jan-2010 | 4-Feb-2010 |
| 6 | 5-Feb-2010 | 11-Feb-2010 |
| 7 | 12-Feb-2010 | 18-Feb-2010 |
| 8 | 19-Feb-2010 | 25-Feb-2010 |
| 9 | 26-Feb-2010 | 4-Mar-2010 |
| 10 | 5-Mar-2010 | 11-Mar-2010 |
| 11 | 12-Mar-2010 | 18-Mar-2010 |
| 12 | 19-Mar-2010 | 25-Mar-2010 |
| 13 | 26-Mar-2010 | 1-Apr-2010 |
| 14 | 2-Apr-2010 | 8-Apr-2010 |
| 15 | 9-Apr-2010 | 15-Apr-2010 |
| 16 | 16-Apr-2010 | 22-Apr-2010 |
| 17 | 23-Apr-2010 | 29-Apr-2010 |
| 18 | 30-Apr-2010 | 6-May-2010 |
| 19 | 7-May-2010 | 13-May-2010 |
| 20 | 14-May-2010 | 20-May-2010 |
| 21 | 21-May-2010 | 27-May-2010 |
| 22 | 28-May-2010 | 3-Jun-2010 |
| 23 | 4-Jun-2010 | 10-Jun-2010 |
| 24 | 11-Jun-2010 | 17-Jun-2010 |
| 25 | 18-Jun-2010 | 24-Jun-2010 |
| 26 | 25-Jun-2010 | 1-Jul-2010 |
| 27 | 2-Jul-2010 | 8-Jul-2010 |
| 28 | 9-Jul-2010 | 15-Jul-2010 |
| 29 | 16-Jul-2010 | 22-Jul-2010 |
| 30 | 23-Jul-2010 | 29-Jul-2010 |
| 31 | 30-Jul-2010 | 5-Aug-2010 |
| 32 | 6-Aug-2010 | 12-Aug-2010 |
| 33 | 13-Aug-2010 | 19-Aug-2010 |
| 34 | 20-Aug-2010 | 26-Aug-2010 |
| 35 | 27-Aug-2010 | 2-Sep-2010 |
| 36 | 3-Sep-2010 | 9-Sep-2010 |
| 37 | 10-Sep-2010 | 16-Sep-2010 |
| 38 | 17-Sep-2010 | 23-Sep-2010 |
| 39 | 24-Sep-2010 | 30-Sep-2010 |
| 40 | 1-Oct-2010 | 7-Oct-2010 |

## APPENDIX C (Continued)

| Week No | From | To |
|---|---|---|
| 41 | 8-Oct-2010 | 14-Oct-2010 |
| 42 | 15-Oct-2010 | 21-Oct-2010 |
| 43 | 22-Oct-2010 | 28-Oct-2010 |
| 44 | 29-Oct-2010 | 4-Nov-2010 |
| 45 | 5-Nov-2010 | 11-Nov-2010 |
| 46 | 12-Nov-2010 | 18-Nov-2010 |
| 47 | 19-Nov-2010 | 25-Nov-2010 |
| 48 | 26-Nov-2010 | 2-Dec-2010 |
| 49 | 3-Dec-2010 | 9-Dec-2010 |
| 50 | 10-Dec-2010 | 16-Dec-2010 |
| 51 | 17-Dec-2010 | 23-Dec-2010 |
| 52 | 24-Dec-2010 | 30-Dec-2010 |
| 53 | 31-Dec-2010 | 6-Jan-2011 |
| 54 | 7-Jan-2011 | 13-Jan-2011 |
| 55 | 14-Jan-2011 | 20-Jan-2011 |
| 56 | 21-Jan-2011 | 27-Jan-2011 |
| 57 | 28-Jan-2011 | 3-Feb-2011 |
| 58 | 4-Feb-2011 | 10-Feb-2011 |
| 59 | 11-Feb-2011 | 17-Feb-2011 |
| 60 | 18-Feb-2011 | 24-Feb-2011 |
| 61 | 25-Feb-2011 | 3-Mar-2011 |
| 62 | 4-Mar-2011 | 10-Mar-2011 |
| 63 | 11-Mar-2011 | 17-Mar-2011 |
| 64 | 18-Mar-2011 | 24-Mar-2011 |
| 65 | 25-Mar-2011 | 31-Mar-2011 |
| 66 | 1-Apr-2011 | 7-Apr-2011 |
| 67 | 8-Apr-2011 | 14-Apr-2011 |
| 68 | 15-Apr-2011 | 21-Apr-2011 |
| 69 | 22-Apr-2011 | 28-Apr-2011 |
| 70 | 29-Apr-2011 | 5-May-2011 |
| 71 | 6-May-2011 | 12-May-2011 |
| 72 | 13-May-2011 | 19-May-2011 |
| 73 | 20-May-2011 | 26-May-2011 |
| 74 | 27-May-2011 | 2-Jun-2011 |
| 75 | 3-Jun-2011 | 9-Jun-2011 |
| 76 | 10-Jun-2011 | 16-Jun-2011 |
| 77 | 17-Jun-2011 | 23-Jun-2011 |
| 78 | 24-Jun-2011 | 30-Jun-2011 |
| 79 | 1-Jul-2011 | 7-Jul-2011 |

## APPENDIX C (Continued)

| Week No | From | To |
|---|---|---|
| 80 | 8-Jul-2011 | 14-Jul-2011 |
| 81 | 15-Jul-2011 | 21-Jul-2011 |
| 82 | 22-Jul-2011 | 28-Jul-2011 |
| 83 | 29-Jul-2011 | 4-Aug-2011 |
| 84 | 5-Aug-2011 | 11-Aug-2011 |
| 85 | 12-Aug-2011 | 18-Aug-2011 |
| 86 | 19-Aug-2011 | 25-Aug-2011 |
| 87 | 26-Aug-2011 | 1-Sep-2011 |
| 88 | 2-Sep-2011 | 8-Sep-2011 |
| 89 | 9-Sep-2011 | 15-Sep-2011 |
| 90 | 16-Sep-2011 | 22-Sep-2011 |
| 91 | 23-Sep-2011 | 29-Sep-2011 |
| 92 | 30-Sep-2011 | 6-Oct-2011 |
| 93 | 7-Oct-2011 | 13-Oct-2011 |
| 94 | 14-Oct-2011 | 20-Oct-2011 |
| 95 | 21-Oct-2011 | 27-Oct-2011 |
| 96 | 28-Oct-2011 | 3-Nov-2011 |
| 97 | 4-Nov-2011 | 10-Nov-2011 |
| 98 | 11-Nov-2011 | 17-Nov-2011 |
| 99 | 18-Nov-2011 | 24-Nov-2011 |
| 100 | 25-Nov-2011 | 1-Dec-2011 |
| 101 | 2-Dec-2011 | 8-Dec-2011 |
| 102 | 9-Dec-2011 | 15-Dec-2011 |
| 103 | 16-Dec-2011 | 22-Dec-2011 |
| 104 | 23-Dec-2011 | 29-Dec-2011 |
| 105 | 30-Dec-2011 | 5-Jan-2012 |
| 106 | 6-Jan-2012 | 12-Jan-2012 |
| 107 | 13-Jan-2012 | 19-Jan-2012 |
| 108 | 20-Jan-2012 | 26-Jan-2012 |
| 109 | 27-Jan-2012 | 2-Feb-2012 |
| 110 | 3-Feb-2012 | 9-Feb-2012 |
| 111 | 10-Feb-2012 | 16-Feb-2012 |
| 112 | 17-Feb-2012 | 23-Feb-2012 |
| 113 | 24-Feb-2012 | 1-Mar-2012 |
| 114 | 2-Mar-2012 | 8-Mar-2012 |
| 115 | 9-Mar-2012 | 15-Mar-2012 |
| 116 | 16-Mar-2012 | 22-Mar-2012 |
| 117 | 23-Mar-2012 | 29-Mar-2012 |
| 118 | 30-Mar-2012 | 5-Apr-2012 |

## APPENDIX C (Continued)

| Week No | From | To |
|---|---|---|
| 119 | 6-Apr-2012 | 12-Apr-2012 |
| 120 | 13-Apr-2012 | 19-Apr-2012 |
| 121 | 20-Apr-2012 | 26-Apr-2012 |
| 122 | 27-Apr-2012 | 3-May-2012 |
| 123 | 4-May-2012 | 10-May-2012 |
| 124 | 11-May-2012 | 17-May-2012 |
| 125 | 18-May-2012 | 24-May-2012 |
| 126 | 25-May-2012 | 31-May-2012 |
| 127 | 1-Jun-2012 | 7-Jun-2012 |
| 128 | 8-Jun-2012 | 14-Jun-2012 |
| 129 | 15-Jun-2012 | 21-Jun-2012 |
| 130 | 22-Jun-2012 | 28-Jun-2012 |
| 131 | 29-Jun-2012 | 5-Jul-2012 |
| 132 | 6-Jul-2012 | 12-Jul-2012 |
| 133 | 13-Jul-2012 | 19-Jul-2012 |
| 134 | 20-Jul-2012 | 26-Jul-2012 |
| 135 | 27-Jul-2012 | 2-Aug-2012 |
| 136 | 3-Aug-2012 | 9-Aug-2012 |
| 137 | 10-Aug-2012 | 16-Aug-2012 |
| 138 | 17-Aug-2012 | 23-Aug-2012 |
| 139 | 24-Aug-2012 | 30-Aug-2012 |
| 140 | 31-Aug-2012 | 6-Sep-2012 |
| 141 | 7-Sep-2012 | 13-Sep-2012 |
| 142 | 14-Sep-2012 | 20-Sep-2012 |
| 143 | 21-Sep-2012 | 27-Sep-2012 |
| 144 | 28-Sep-2012 | 4-Oct-2012 |
| 145 | 5-Oct-2012 | 11-Oct-2012 |
| 146 | 12-Oct-2012 | 18-Oct-2012 |
| 147 | 19-Oct-2012 | 25-Oct-2012 |
| 148 | 26-Oct-2012 | 1-Nov-2012 |
| 149 | 2-Nov-2012 | 8-Nov-2012 |
| 150 | 9-Nov-2012 | 15-Nov-2012 |
| 151 | 16-Nov-2012 | 22-Nov-2012 |
| 152 | 23-Nov-2012 | 29-Nov-2012 |
| 153 | 30-Nov-2012 | 6-Dec-2012 |
| 154 | 7-Dec-2012 | 13-Dec-2012 |
| 155 | 14-Dec-2012 | 20-Dec-2012 |
| 156 | 21-Dec-2012 | 27-Dec-2012 |
| 157 | 28-Dec-2012 | 3-Jan-2013 |

## APPENDIX C (Continued)

| Week No | From | To |
|---|---|---|
| 158 | 4-Jan-2013 | 10-Jan-2013 |
| 159 | 11-Jan-2013 | 17-Jan-2013 |
| 160 | 18-Jan-2013 | 24-Jan-2013 |
| 161 | 25-Jan-2013 | 31-Jan-2013 |
| 162 | 1-Feb-2013 | 7-Feb-2013 |
| 163 | 8-Feb-2013 | 14-Feb-2013 |
| 164 | 15-Feb-2013 | 21-Feb-2013 |
| 165 | 22-Feb-2013 | 28-Feb-2013 |
| 166 | 1-Mar-2013 | 7-Mar-2013 |
| 167 | 8-Mar-2013 | 14-Mar-2013 |
| 168 | 15-Mar-2013 | 21-Mar-2013 |
| 169 | 22-Mar-2013 | 28-Mar-2013 |
| 170 | 29-Mar-2013 | 4-Apr-2013 |
| 171 | 5-Apr-2013 | 11-Apr-2013 |
| 172 | 12-Apr-2013 | 18-Apr-2013 |
| 173 | 19-Apr-2013 | 25-Apr-2013 |
| 174 | 26-Apr-2013 | 2-May-2013 |
| 175 | 3-May-2013 | 9-May-2013 |
| 176 | 10-May-2013 | 16-May-2013 |
| 177 | 17-May-2013 | 23-May-2013 |
| 178 | 24-May-2013 | 30-May-2013 |
| 179 | 31-May-2013 | 6-Jun-2013 |
| 180 | 7-Jun-2013 | 13-Jun-2013 |
| 181 | 14-Jun-2013 | 20-Jun-2013 |
| 182 | 21-Jun-2013 | 27-Jun-2013 |
| 183 | 28-Jun-2013 | 4-Jul-2013 |
| 184 | 5-Jul-2013 | 11-Jul-2013 |
| 185 | 12-Jul-2013 | 18-Jul-2013 |
| 186 | 19-Jul-2013 | 25-Jul-2013 |
| 187 | 26-Jul-2013 | 1-Aug-2013 |
| 188 | 2-Aug-2013 | 8-Aug-2013 |
| 189 | 9-Aug-2013 | 15-Aug-2013 |
| 190 | 16-Aug-2013 | 22-Aug-2013 |
| 191 | 23-Aug-2013 | 29-Aug-2013 |
| 192 | 30-Aug-2013 | 5-Sep-2013 |
| 193 | 6-Sep-2013 | 12-Sep-2013 |
| 194 | 13-Sep-2013 | 19-Sep-2013 |
| 195 | 20-Sep-2013 | 26-Sep-2013 |
| 196 | 27-Sep-2013 | 3-Oct-2013 |

## APPENDIX C (Continued)

| Week No | From | To |
|---|---|---|
| 197 | 4-Oct-2013 | 10-Oct-2013 |
| 198 | 11-Oct-2013 | 17-Oct-2013 |
| 199 | 18-Oct-2013 | 24-Oct-2013 |
| 200 | 25-Oct-2013 | 31-Oct-2013 |
| 201 | 1-Nov-2013 | 7-Nov-2013 |
| 202 | 8-Nov-2013 | 14-Nov-2013 |
| 203 | 15-Nov-2013 | 21-Nov-2013 |
| 204 | 22-Nov-2013 | 28-Nov-2013 |
| 205 | 29-Nov-2013 | 5-Dec-2013 |
| 206 | 6-Dec-2013 | 12-Dec-2013 |
| 207 | 13-Dec-2013 | 19-Dec-2013 |
| 208 | 20-Dec-2013 | 26-Dec-2013 |
| 209 | 27-Dec-2013 | 2-Jan-2014 |
| 210 | 3-Jan-2014 | 9-Jan-2014 |
| 211 | 10-Jan-2014 | 16-Jan-2014 |
| 212 | 17-Jan-2014 | 23-Jan-2014 |
| 213 | 24-Jan-2014 | 30-Jan-2014 |
| 214 | 31-Jan-2014 | 6-Feb-2014 |
| 215 | 7-Feb-2014 | 13-Feb-2014 |
| 216 | 14-Feb-2014 | 20-Feb-2014 |
| 217 | 21-Feb-2014 | 27-Feb-2014 |
| 218 | 28-Feb-2014 | 6-Mar-2014 |
| 219 | 7-Mar-2014 | 13-Mar-2014 |
| 220 | 14-Mar-2014 | 20-Mar-2014 |
| 221 | 21-Mar-2014 | 27-Mar-2014 |
| 222 | 28-Mar-2014 | 3-Apr-2014 |
| 223 | 4-Apr-2014 | 10-Apr-2014 |
| 224 | 11-Apr-2014 | 17-Apr-2014 |
| 225 | 18-Apr-2014 | 24-Apr-2014 |
| 226 | 25-Apr-2014 | 1-May-2014 |
| 227 | 2-May-2014 | 8-May-2014 |
| 228 | 9-May-2014 | 15-May-2014 |
| 229 | 16-May-2014 | 22-May-2014 |
| 230 | 23-May-2014 | 29-May-2014 |
| 231 | 30-May-2014 | 5-Jun-2014 |
| 232 | 6-Jun-2014 | 12-Jun-2014 |
| 233 | 13-Jun-2014 | 19-Jun-2014 |
| 234 | 20-Jun-2014 | 26-Jun-2014 |
| 235 | 27-Jun-2014 | 3-Jul-2014 |

## APPENDIX C (Continued)

| Week No | From | To |
|---|---|---|
| 236 | 4-Jul-2014 | 10-Jul-2014 |
| 237 | 11-Jul-2014 | 17-Jul-2014 |
| 238 | 18-Jul-2014 | 24-Jul-2014 |
| 239 | 25-Jul-2014 | 31-Jul-2014 |
| 240 | 1-Aug-2014 | 7-Aug-2014 |
| 241 | 8-Aug-2014 | 14-Aug-2014 |
| 242 | 15-Aug-2014 | 21-Aug-2014 |
| 243 | 22-Aug-2014 | 28-Aug-2014 |
| 244 | 29-Aug-2014 | 4-Sep-2014 |
| 245 | 5-Sep-2014 | 11-Sep-2014 |
| 246 | 12-Sep-2014 | 18-Sep-2014 |
| 247 | 19-Sep-2014 | 25-Sep-2014 |
| 248 | 26-Sep-2014 | 2-Oct-2014 |
| 249 | 3-Oct-2014 | 9-Oct-2014 |
| 250 | 10-Oct-2014 | 16-Oct-2014 |
| 251 | 17-Oct-2014 | 23-Oct-2014 |
| 252 | 24-Oct-2014 | 30-Oct-2014 |
| 253 | 31-Oct-2014 | 6-Nov-2014 |
| 254 | 7-Nov-2014 | 13-Nov-2014 |
| 255 | 14-Nov-2014 | 20-Nov-2014 |
| 256 | 21-Nov-2014 | 27-Nov-2014 |
| 257 | 28-Nov-2014 | 4-Dec-2014 |
| 258 | 5-Dec-2014 | 11-Dec-2014 |
| 259 | 12-Dec-2014 | 18-Dec-2014 |
| 260 | 19-Dec-2014 | 25-Dec-2014 |
| 261 | 26-Dec-2014 | 1-Jan-2015 |
| 262 | 2-Jan-2015 | 8-Jan-2015 |
| 263 | 9-Jan-2015 | 15-Jan-2015 |
| 264 | 16-Jan-2015 | 22-Jan-2015 |
| 265 | 23-Jan-2015 | 29-Jan-2015 |
| 266 | 30-Jan-2015 | 5-Feb-2015 |
| 267 | 6-Feb-2015 | 12-Feb-2015 |
| 268 | 13-Feb-2015 | 19-Feb-2015 |
| 269 | 20-Feb-2015 | 26-Feb-2015 |
| 270 | 27-Feb-2015 | 5-Mar-2015 |
| 271 | 6-Mar-2015 | 12-Mar-2015 |
| 272 | 13-Mar-2015 | 19-Mar-2015 |
| 273 | 20-Mar-2015 | 26-Mar-2015 |
| 274 | 27-Mar-2015 | 2-Apr-2015 |
| 275 | 3-Apr-2015 | 9-Apr-2015 |