YANGON UNIVERSITY OF ECONOMICS

DEPARTMENT OF STATISTICS

TIME SERIES ANALYSIS OF TEMPERATURE FLUCTUATION IN YANGON REGION (JANUARY 2013 - DECEMBER 2023)

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ROLL NO. 26

MAS (4th BATCH)

JULY, 2024

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This thesis is submitted as a partial fulfillment toward the
degree of Master of Applied Statistics.
Approved by the Board of Examiners

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JULY, 2024

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ABSTRACT

This study investigates temperature trends and patterns within the Yangon Region through time series analysis. Monthly temperature data from January 2013 to December 2023 were examined using the SARIMA (Seasonal Autoregressive Integrated Moving Average) model, particularly effective in predicting temperature changes when trend patterns are not apparent. The results demonstrate the SARIMA model's capability in forecasting both minimum and maximum temperature fluctuations. Based on the analysis, the SARIMA(1,0,0) x $(1,1,1)_{12}$ model has been found as appropriate model of minimum temperature fluctuations in the Yangon Region, while the SARIMA(0,0,0) x $(3,1,0)_{12}$ model performs appropriate model in terms of maximum temperature fluctuations.

ACKNOWLEDGEMENTS

I would first like to express my sincere gratitude to Dr. Tin Tin Htwe, Rector of Yangon University of Economics, for allowing me to develop this thesis.

I wish to express my sincere appreciation to Dr. Mya Thandar, the Pro-Rector of Yangon University of Economics, for granting me permission to pursue this thesis. Her support and approval have been main in enabling me to start on this thesis endeavor. I am truly grateful for her confidence in my thesis and for the opportunities she has provided me.

I would also like to extend my gratitude to Dr. Kyaing Kyaing Thet, the Pro-Rector of Yangon University of Economics, for granting me approval to conduct this thesis. Her recommend and support have been instrumental in facilitating my thesis endeavors. I am sincerely thankful for her trust and confidence in my work.

I am profoundly grateful to Professor Dr. Aye Thida, who serves as the Head of the Department of Statistics at Yangon University of Economics. Her insightful recommendations and gracious permission to undertake this study have been invaluable to me. I am deeply indebted to her for her support and encouragement throughout this thesis endeavor.

I am deeply thankful to Daw Khin Nu Win, an Associate Professor (Retd.) at Yangon University of Economics' Department of Statistics for her meticulous evaluation of our coursework. Her constructive feedback and valuable suggestions have been instrumental in shaping our understanding of statistical methods and their applications in real-world scenarios.

I am deeply grateful to Professor Dr. Sanda Thein from the Department of Statistics at Yangon University of Economics. Her insightful suggestions and invaluable recommendations have significantly contributed to enhancing the quality of my thesis. My indebtedness to her expertise and guidance is immeasurable, and I am truly appreciative of her support throughout this study.

I would especially want to thank my supervisors, especially Dr. Khin Moh Moh, an Associate Professor at Yangon University of Economics' Department of Applied Statistics. Her insightful advice, encouraging direction, and careful oversight have greatly influenced my study pursuits.

Finally, I would like to express my sincere appreciation to my parents for their constant support and encouragement during my Master of Applied Statistics program. Their unwavering confidence in me has allayed my fears and freed me up to fully concentrate on my study endeavors.

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ABBREVIATIONS

ACF	=	Autocorrelation Function
AR	=	Autoregressive
ARIMA	=	Autoregressive Integrated Moving Average
ARMA	=	Autoregressive Moving Average
CSO	=	Central Statistical Organization
MA	=	Moving Average
PACF	=	Partial Autocorrelation Function
SACF	=	Sample Autocorrelation Function
SAR	=	Seasonal Autoregressive
SARIMA	=	Seasonal Autoregressive Integrated Moving Average
SARMA	=	Seasonal Autoregressive Moving Average
SMA	=	Seasonal Moving Average
SPACF	=	Sample Partial Autocorrelation Function

CAPTER I

INTRODUCTION

Global warming has already changed the world climate and changes in global climate become more and more significant with each passing decade and the long-term warming of the planet's overall temperature. Though this warming trend has been going on for a long time, its pace has significantly increased in the last hundred years due to the burning of fossil fuels. It is generally known that the increase of the earth surface temperature due to the global warming together with the land desertification by rapid urban development has caused severe climate and weather change(Jones & Wigley, 1990).

The consequences of climate change can already be seen in worldwide. Especially, temperatures are rising, rainfall patterns are shifting, glaciers are melting, sea levels are getting higher and hazards such as floods and droughts are becoming more common. The climate of an area is usually described as average weather condition experienced over a long period of time. Climate change is the change in climatic elements over the time period that ranges from decade to centuries. This change can be measured by changes of temperature, precipitation, and extreme weather events. Temperature fluctuation is induced in the region where hot and cold fluids are mixed, and it might cause thermal fatigue in the structure. This phenomenon is called thermal striping. When such high-cycle thermal stress acts in the structure, crack initiation and eventually crack penetration might occur under certain conditions(Jones & Wigley, 1990).

Temperature influences the geographical distribution of species. Temperature changes can affect migration patterns, breeding seasons, and the overall behavior of organisms. Temperature fluctuations can impact the diversity of species within an ecosystem. Some species may thrive in specific temperature ranges, while others may struggle or migrate in response to temperature changes. Temperature affects photosynthesis rates and nutrient cycling, influencing the productivity of ecosystems. Warmer temperatures can accelerate these processes, impacting the overall health of ecosystems. Temperature changes in water bodies can affect aquatic organisms. Temperature variations can influence the prevalence and distribution of pests and diseases. Warmer temperatures may extend the range of certain pathogens or insect vectors, impacting the health of plants and animals. These ecological impacts are crucial for conservation efforts and sustainable management of ecosystems, especially in the face of ongoing climate change and global warming(Jones & Wigley, 1990).

Extreme heat can lead to heat-related illnesses such as heat exhaustion and heatstroke. Vulnerable populations, including the elderly, children, and individuals with pre-existing health conditions, are particularly at risk. After the extreme weather has passed, mental health challenges can linger. The most common mental health impacts after disasters are post-traumatic stress disorder, depression, and general anxiety. Extreme weather isn't the only climate-challenge condition expected to cause mental health (Khraishah, et al.,2022).

As temperatures rise, more moisture evaporates, which exacerbates extreme rainfall and flooding, causing more destructive storms. The frequency and extent of tropical storms is also affected by the warming ocean. Cyclones, hurricanes, and typhoons feed on warm waters at the ocean surface. Understanding temperature fluctuations is crucial for various reasons. Firstly, it impacts ecosystems and biodiversity, influencing the distribution and behavior of species. Additionally, temperature fluctuations play a key role in weather patterns, affecting agriculture, water resources, and overall climate stability. Furthermore, in the context of human health, awareness of temperature changes is essential for preventing heat-related illnesses and adapting infrastructure to extreme conditions. Finally, addressing the global challenge of climate change requires a comprehensive understanding of temperature fluctuations to develop effective mitigation and adaptation strategies.

1.1 Rationale of the Study

In Yangon Region, a slight increase in rainfall is found at central part of the city than surrounding area. Peak monsoon rainfall is increasing but early and late monsoon rainfall is decreasing in Yangon Region. Yangon Region, the economic and cultural hub of Myanmar, experiences a tropical monsoon climate characterized by distinct wet and dry seasons. The temperature in Yangon Region typically ranges from 14.60°C to 38.60°C in 2023. The hottest months are usually from March to May, with temperatures peaking during April. The rainy season spans from May to October, bringing heavy rainfall and slightly cooler temperatures. November to February constitutes the cold season with lower humidity and milder temperatures. Understanding these temperature variations is crucial for residents, agriculture, and various sectors in adapting to seasonal changes in Yangon Region(Mon, et al., 2020).

Despite the region's prominence, there exists a noticeable gap in understanding of the intricate patterns of temperature fluctuations that unfold throughout the year. This lack of comprehensive knowledge has prompted the initiation of a groundbreaking study. This paper aspires to fill the existing void by employing advanced time series analysis techniques, with the primary aim of unraveling the intricate seasonal dynamics of temperature in Yangon Region(Mon, et al., 2020).

Any long-term variation of the typical weather patterns in a region is referred to as climate change. Yangon Region started its history from the current CBD (Central Business District) area, developed as a capital of lower Myanmar by the Britain in 1885. Urbanization expanded northward during 1950's to accommodate redevelopment of houses after devastation of houses and mitigation of developed slums and illegal settlements after the 2nd world war. Even though the capital of Myanmar was moved to Nay Pyi Taw in 2006, Yangon Region is still the national center of economy, business and communication. Current population of Yangon Region is approximately 8.8 million(CSO, 2023-2024 quarterly report).

Yangon Region's annual temperature has also shown no significant change over recent years, though fluctuations are observed. In 2019, the region experienced its highest recorded temperature, rapidly rising to 40.0ºC, marking occasional spikes amidst overall stability. Conversely, the average minimum temperature has typically hovered around 16.89 ºC annually.

Futhermore,as global temperatures continue to rise, Yangon Region and similar regions may encounter heightened seasonal and weather variations. This warming trend could increase the frequency of extreme cold spells, heavy rainfall, and intensified storm systems. These changes underscore the dynamic and evolving nature of climate patterns, presenting challenges to local environments and communities worldwide.

In addition, understanding temperature trend patterns and forecasting future trends are essential aspects of this study, particularly in Yangon Region, where climate variability significantly impacts multiple sectors. Evaluating temperature trends is increasingly crucial for predicting climate dynamics and guiding adaptive strategies effectively. This study aims to analyze temperature trend patterns from historical data, explain long-term trends, seasonal variations, and potential sudden changes, and utilize advanced forecasting models to predict future temperature trends in Yangon Region for the coming years. By providing actionable insights that support climate resilience planning, resource management, and policy formulation tailored to the region's specific climatic conditions

This study addresses critical knowledge gaps regarding recent temperature dynamics in Yangon Region. By studying trend patterns and forecasting future climate scenarios, the study contributes valuable information for stakeholders engaged in climatesensitive sectors such as agriculture, infrastructure development, and public health, facilitating informed decision-making and proactive measures to mitigate climate risks and enhance adaptive capacities in response to anticipated temperature fluctuations. To achieve comprehensive analysis and accurate forecasting, this study uses a combination of statistical techniques and modeling approaches. The initial analysis involved applying time series methods and seasonal decomposition to identify underlying trends and seasonal patterns in historical temperature data. Subsequently, forecasting models were employed to project future temperature trends based on historical patterns and potential influencing factors.

Therefore, understanding of temperature trend patterns and forecasting is very important role for the future year through meticulous analysis of historical data and advanced modeling techniques, by explaining current trends and providing forecasts to support evidence-based decision-making and proactive planning. And then, adaptation and mitigation strategies are increasingly crucial to guide these challenges, ensuring resilience against the impacts of a warming climate. Sustainable development, resource management, and community resilience efforts are vital in safeguarding against potential adverse effects of climate variability and change. Climate change give impacts on human life and also affecting the national economy and human health. Temperature changes had been afflicting and negatively impacting the agricultural sector. Moreover, elevated temperature have also resulted in respiratory and cardiovascular-related diseases that can lead to death. Therefore, the temperature prediction model is needed to help the authorities to have better preparation in temperature changes.

1.2. Objectives of the Study

The objectives of the study are:

(i) To describe monthly temperature fluctuations in Yangon Region from January 2013 to December 2023

(ii) To identify seasonal monthly temperature patterns in Yangon Region from January 2013 to December 2023

(iii) To forecast the monthly temperature for the year 2024 in Yangon Region.

1.3. Method of Study

This study utilizes secondary data obtained from the Department of Meteorology and Hydrology in Yangon Region, covering an extensive period from January 2013 to December 2023. The analysis includes descriptive methods to illustrate temperature trends and fluctuations in Yangon Region. To test the seasonality, the ratio to moving average method was applied in this study. The Box-Jenkins method was used to determine the most suitable model for predicting temperature fluctuations in Yangon Region.

1.4. Scope and Limitations of the Study

This study places a significant emphasis on investigating temperature fluctuations in Yangon Region. The comprehensive exploration of temperature dynamics is facilitated by utilizing secondary data sourced from the Department of Meteorology and Hydrology, Yangon Region, covering an extensive period from January 2013 to December 2023. This study focused to analyze the temperature trends over the specified timeframe, contributing to a comprehensive understanding of the climatic variations in Yangon Region.

1.5. Organization of the Study

This study consists of five chapters. Chapter I presents the introduction of the study which includes the rationale of the study, objectives of the study, method of study, scope and limitations of the study, and organization of the study. Chapter II discusses the literature review. Chapter III explains the methodology. Chapter IV provides data analysis of temperature fluctuations. Chapter V is the conclusion of the study.

CHAPTER II
LITERATURE REVIEW

In this chapter, the concept of temperature fluctuation and literature of the previous research studies which are related to the current study were presented.

2.1 The Concept of Temperature Fluctuation

Temperature fluctuation within a country refers to the variation in temperatures experienced across different regions or over time within the boundaries of a specific nation. These fluctuations can occur due to various factors, including geographical features, seasonal changes, weather patterns, and human activities. Understanding temperature fluctuations is crucial for numerous aspects of society, including agriculture, infrastructure planning, public health, and environmental management(Boltachev, G. S., & Schmelzer, J. W.2010).

(i) Geographical Diversity

Countries often encompass diverse geographical features, such as mountains, plains, deserts, and coastal areas, each of which can experience different temperature patterns(Boltachev, G. S., & Schmelzer, J. W.2010).

(ii) Seasonal Variations

Temperature fluctuations occur throughout the year due to seasonal changes in solar radiation, atmospheric circulation patterns, and the tilt of the Earth's axis. Countries located in the temperate zones typically experience distinct seasons with noticeable temperature variations between summer and winter(Boltachev, G. S., & Schmelzer, J. W.2010).

(iii) Microclimates

Within a country, microclimates can exist, leading to localized temperature fluctuations within relatively small areas. Factors such as topography, vegetation cover, and urbanization can influence microclimate conditions, resulting in variations in temperature, humidity, and wind patterns(Boltachev, G. S., & Schmelzer, J. W.2010).

(iv) Weather Patterns

Short-term temperature fluctuations within a country are often driven by weather systems, such as high and low-pressure systems, fronts, and atmospheric disturbances. These weather patterns can cause rapid changes in temperature over hours or days, leading to fluctuations in local weather conditions(Boltachev, G. S., & Schmelzer, J. W.2010).

(v) Climate Change

Climate change can exacerbate temperature fluctuations within a country by altering long-term temperature trends and increasing the frequency and intensity of extreme weather events, such as heat waves, droughts, and cold snaps(Boltachev, G. S., & Schmelzer, J. W.2010).

(vi) Impact on Society

Temperature fluctuations can have significant impacts on society and the economy. It affects agricultural productivity, energy demand, water resources, infrastructure resilience, and public health. Extreme temperature fluctuations, especially when coupled with other environmental stressors, can lead to adverse consequences for human well-being and ecosystems(Boltachev, G. S., & Schmelzer, J. W.2010).

(vii) Adaptation and Mitigation

Understanding and managing temperature fluctuations within a country require effective adaptation and mitigation strategies. This includes implementing measures to enhance resilience to extreme weather events, promoting sustainable land use and resource management practices, and reducing greenhouse gas emissions to mitigate the drivers of climate change. (Boltachev, G. S., & Schmelzer, J. W.2010)

2.2 Literature Review on Related Studies

Hecke (2010) investigated the evolution in time of economic issues in Belgium. Shows that the environmental field, where the progression of climate change is raising many concerns, may likewise benefit from the use of ARIMA models. Based on data gathered over the previous 150 years, it was shown that it is possible to forecast the evolution of temperature by utilizing ARIMA models. The temperature will still rise somewhat from that of the reference period of 1850–1899, according to the best-fitting model (particularly pronounced for Europe and Belgium). Naturally, the forecasts get less certain with time, thus these findings need to be regarded as preliminary.

Nury et al. (2017) investigated variability patterns as well as predicted short and long-term changes. Here, linear trends showed that the maximum temperature is increasing by 2.97°C and 0.59°C per hundred years, and the minimum, by 2.17°C and 2.73°C per hundred years at the Sylhet and Sreemangal stations. Anomaly of these regions also showed increasing temperature. The seasonal autoregressive integrated moving average (SARIMA) model was fitted for temperature time series with its traditional three steps: identification, diagnosis, and forecasting respectively. The results found that the monthly maximum and minimum temperature at Sylhet and Sreemangal stations, respective SARIMA models were (3, 1, 3) x $(1, 1, 1)_{12}$, (2, 1, 3) x $(0, 1, 1)_{12}$, (3, 1, 1) x $(1, 1, 1)_{12}$ and (2, 1, 1) x $(1, 1, 1)_{12}$.

Chen et al. (2018,August) investigated the use of SARIMA models for Monthly Mean Temperature Prediction in Nanjing, China. This study investigates the use of Seasonal Autoregressive Integrated Moving Average (SARIMA) techniques to analyze monthly mean temperatures in Nanjing, China, from 1951 to 2017. The research distinguishes between training and testing datasets, utilizing data from 1951 to 2014 for training and 2015 to 2017 for testing. The paper offers an in-depth discussion on model selection and assesses the accuracy of the forecasting methods employed, highlighting the effectiveness of the SARIMA approach. The results demonstrate that the proposed SARIMA model achieves satisfactory forecasting accuracy, confirming its suitability for predicting temperature trends in the given timeframe.

Odero (2019) investigated the use of SARIMA models for weather data estimates in South Carolina. This study makes use of the seasonal autoregressive integrated moving average (SARIMA) model. From January 2003 to December 2017, South Carolina used it for daily temperature time series data. The best-fitted model with the lowest AIC was SARIMA (5, 0, 0) × $(0, 1, 0)_{365}$ in Columbia, SARIMA (5, 0, 1) × $(0, 1, 0)_{365}$ in Greenville, and SARIMA (5, 0, 2) × $(0, 1, 0)_{365}$ in North Myrtle. The findings of this thesis demonstrate that proper preparation in the appropriate format or form is a crucial component of any data analysis process, even before the study itself is conducted. Following the identification of the optimal model or models for each of the three cities, strong models that are regarded as reliable for forecasting and prediction were created.

Kumar et al. (2020) investigated the prediction of future temperature values is the main goal of time series forecasting. The model has been trained using the past 137 years of data (1880-2017) and tested over 60 years to forecast maximum and minimum temperatures in India. Based on the inspection of the ACF, and PACF autocorrelation plots, the most appropriate orders of the ARIMA models are determined and evaluated using the AIC-criterion. For the maximum and minimum temperatures at the ARIMA model trend order (1,1,1), and ARIMA seasonal order $(1,1,0)_{12}$ are obtained. It found that based on the provided data, if the temperature on the earth is increasing over time or not. The goal is to prove whether the so-called Global Warming exists or not. a time series analysis can help to understand the underlying naturalistic process, the pattern of change over time, or evaluate the effects of either a planned or unplanned intervention It was demonstrated that obtained models can capture the dynamics of the time series data and produce sensible forecasts.

Gangshetty et al. (2021) investigated development of a SARIMA Model for Temperature Prediction in Pune, Maharashtra. This study focuses on creating a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to predict temperatures using historical data from Pune, Maharashtra, spanning 2009 to 2020. It highlights the advantages of SARIMA over manual decomposition in time series analysis, particularly in the presence of cyclical patterns. The SARIMA(1,1,1) x $(1,1,1)_{12}$ model demonstrated strong performance, achieving a Mean Absolute Error (MAE) of 0.60850 and a Root Mean Square Error (RMSE) of 0.76233. Model diagnostics confirmed that the SARIMA model is well-suited for temperature forecasting, effectively addressing unexpected changes in the system.

Zamri & Azmi (2021, November) investigated Forecasting Monthly Temperature in Cameron Highlands: A Comparative Study of SARIMA and ARAR. This research analyzes and forecasts the monthly temperature of Cameron Highlands for 2020 and 2021, comparing it to historical averages from January 1990 to December 2019. It found that The SARIMA model, specifically SARIMA (1, 1, 2) x $(1, 1, 1)_{12}$, outperformed the ARAR algorithm, demonstrating lower RMSE and MAPE values. The results demonstrate that the forecast indicates an estimated temperature increase of 1.6 °C in 2021, with monthly temperatures expected to continue rising over the next two years. This trend highlights the urgent need for action from higher authorities to address the impacts of climate change in the region.

CHAPTER III
METHODOLOGY

This chapter mentions the definition of time series, components of time series, two types of model, test of seasonality, method for finding seasonal variation by using ratio to moving average method, the Box- Jenkins methodology and seasonal time series models.

3.1 Definition of Time Series

A time series is a set of observations measured at successive points in time or over successive periods of time. A time series is a sequence of observations $Y_1, Y_2, \dots, Y_t, \dots, Y_n$ on a process at equally spaced points in time .

The main objective of studying a time series is to forecast or predict the future behavior or movements on the basis of its past and present situations. Managers and social scientists often deal with processes that vary over time observations. Time series are analyzed to understand, describe, control and predict the underlying process.

The analysis of time is a necessary technique in many areas such as industrial research, economics, marketing, physical and chemical sciences, etc. One of the important aspects of such a series is the dependence structure of adjacent observations; for the satisfactory analysis of the series, it is necessary to construct an appropriate stochastic model which can further be used in various ways, depending on the field of applications(Neter, et al.1993).

3.2 Components of a Time Series

It is convenient to represent the time series as sum of these four components and one of the objectives may be to break into its components, for individual study. However, in so doing, a model is imposed on the situation. It may be reasonable to suppose that trends are due to permanent forces operating uniformly in more or less the same direction that short-term fluctuations about these long movements are in same direction. There are four components: trend component, seasonal component, cyclical component and irregular (random) component(Neter, et al.1993).

Trend Component

In time series analysis, the measurements may be taken every hour, day, week, month, or year, or at any other regular interval. Although time series data generally exhibit random fluctuations, the time series may still show gradual shifts or movements to relatively higher or lower values over a longer period of time. The gradual shifting of the time series is referred to as the trend in the time series; this shifting or trend is usually the result of long-term factors such as changes in the population, demographic characteristics of the population, technology, and/or consumer preferences(Neter, et al.1993).

Seasonal Component

The trend of a time series can be identified by analyzing overlong movements in historical data. Seasonal pattern are recognized by seeing the same repeating patterns over successive periods of time. The pattern for a time series plot that exhibits a repeating pattern over a one-year period due to seasonal influences is called a seasonal component. Generally think of seasonal movement in a time series as occurring within one year, the seasonal component can also be used to represent any regularly repeating pattern that is less than one year in duration(Neter, et al.1993).

Cyclical Component

A time series may exhibit a trend over long periods of time all future values of the time series will not fall exactly on the trend line. In fact, time series often show an alternating sequence of points below and above the trend line. Any recurring sequence of points above and below the trend line lasting more than one year can be attributed to the cyclical component of the time series. Many time series exhibit cyclical behavior with regular runs of observations below and above the trend line. Generally, this component of the time series is due to overlong cyclical movements in the economy(Neter, et al.1993).

Irregular (Random) Component

The irregular component of the time series is the residual,' factor that accounts for the deviations of the actual time series values from those expected given the effects of the trend, cyclical, and seasonal components. The irregular component is caused by the short-term, unanticipated, and nonrecurring factors that affect the time series. Because this component accounts for the random variability in the time series, it is unpredictable(Neter, et al.1993).

3.3 Seasonality in Time Series

Seasonality refers to forecast changes that occur over a one- year period in a economy or business based on the seasons including commercial seasons or calendar. It can be used to help analyze economic trends and stocks. It refers to periodic fluctuations in certain business areas. A season may refer to calendar season such as winter or summer, or it may refer to a commercial season such as the holiday season. Seasonality is also important to consider when tracking certain economic data. Economic growth can be affected by different seasonal factors including the holidays and the weather. Economists have a better picture of how an economy is moving when adjust the analysis based on these factors. If this seasonality was not taken into account, economists would not have a clear picture of how the economy is truly moving(Kenton, 2020).

3.4 Test of Seasonality

In the study of seasonality, seasonal variation for each month of the year is usually considered. The following model for the randomized complete block design (Daniel & Terre, 1992) was used in testing seasonality in monthly temperature time series.

$$y_{ij} = \mu + \beta_i + \gamma_j + e_{ij} \quad ; 1 \le i \le n,\ 1 \le j \le k$$

where y_{ij} is a typical value from the overall population,

μ is an unknown constant,

β_i represents a yearly effect, reflecting the fact that the experimental unit fell in the i^{th} year,

γ_j represents a monthly effect, reflecting the fact that the experimental unit received the j^{th} month and

e_{ij} is a residual component representing all sources of variation other than months and years.

One make three assumptions when use the randomized complete block design.

(a) Each observed y_{ij} constitutes an independent random variable of size 1 from one of the kn populations represented.

(b) Each of these kn populations is normally distributed with mean μ_{ij} and the same variance σ^2. The e_{ij} are independently and normally distributed with mean 0 and variance σ^2.

(c) The block and treatment effects are additive. To state this assumption another way, one say that there is no interaction between months and years.

In general, one test

H_0: There is no seasonality.

H_1: There is a seasonality.

In other words, one test the null hypothesis that the monthly means are all equal or equivalently, which mean that there are no differences in monthly effects.

To analyze the data, the needed quantities are the total sum of squares SST, the sum of squares for months SSM, the sum of squares for years SSY and the error sum of squares SSE. When these sum of squares are divided by the appropriate degree of freedom, one have the mean squares necessary for computing the F statistic. For, monthly temperature fluctuation in Yangon Region during (2013-2023) data k = 12 and n = 11 years. The degree of freedom are computed as follows:

Total = Months + Years + Error

(kn-1) = (k-1) + (n-1) + (n-1) (k-1)

Where k = months, n = years

Short-cut formulas for computing the required sum of squares are as follows:

$$SSM = \sum_{j=1}^{k} \frac{y_{.j}^2}{n} - C \quad ; \ y_{.j} = \sum_{i=1}^{n} y_{ij}$$

$$SSY = \frac{\sum_{i=1}^{n} y_{i.}^2}{k} - C \quad ; y_{i.} = \sum_{j=1}^{k} y_{ij}$$

$$SSY = \sum_{i=1}^{n}\sum_{j=1}^{k} y_{ij}^2 - C$$

$$SSE = SST - (SSM + SSY)$$

Where $C = \frac{y_{..}^2}{nk}$; $y_{..} = \sum_{i=1}^{n}\sum_{j=1}^{k} y_{ij}$

The results of the calculations for the randomized complete block design are presented in the following analysis of variance (ANOVA) Table.

ANOVA Table for a Two-Way Analysis of Variance

Source	S.S	D.F	M.S	F-Ratio
Between Months	SSM	k-1	MSM = SSM/ k-1	F_1 = MSM/MSE
Between Years	SSY	n-1	MSY = SSY/ n-1	F_2 = MSY/ MSE
Error	SSE	(n-1)(k-1)	MSE = SSE/(n-1)(k-1)	
Total	SST	kn-1		

The computed ratios F_1 with critical values $K_1 = F_{\alpha,(k-1),(n-1)(k-1)}$ is then compared. If this ratios are equal to or exceed the critical values, reject the null hypothesis.

3.5 Methods for Finding Seasonal Variation

Seasonal variation is measured in terms of an index, called a seasonal index. The following are the methods of measuring seasonal variation:

(a) Simple Average method

(b) Simple Average Corrected to Trend

(c) Link Relative method

(d) Ratio to Moving Average method and

(e) Ratio to Trend method

Above the methods, ratio to moving average method is the most commonly used method for finding an index of seasonal variation.

Ratio to Moving Average Method

A seasonal index is a measure of how a particular season compares with the average season. Seasonal indices are calculated so that their average is 100. This mean that the sum of the seasonal indices equals the number of seasons.

The effect of seasonal fluctuations is quantified by using a technique called the ratio to moving average method. The following steps are using in this method.

(i) Construct a centered moving average of the time series.

(ii) Divide the original time series values by the corresponding centered moving average. Where, the first and last six months may not be obtained.

(iii) For each quarter (or month), identify the mean percentage from those obtained in step 2.

(iv) If the average value of the means is not 100, multiply each one by the same adjustment factor so that the average of 100 is obtained.

(v) Following the adjustment in step 4, the resulting values are the seasonal indexes (Weiers,2010).

3.6 The Box-Jenkins Methodology

The Box-Jenkins methodology has been expressed steps for model identification, methods of the estimation of the parameters in the ARIMA models, diagnostic checking and forecasting.

3.6.1 Steps for Model Identification

Consider the general ARIMA (p, d, q) model

$$(1-\phi_1 B-\ldots-\phi_p B^p)(1-B)\dot{Z}_t=\theta_0+(1-\theta_1 B-\ldots-\theta_q B^q)a_t$$

Model identification refers to the methodology in identifying the required transformations such as variance stabilizing transformation and differencing transformations, the decision to include the deterministic parameter θ_0 when $d \geq 1$ and the proper order of p and q for the model.

The following useful steps are used to identify a tentative model.

Step 1. Plot the time series data and choose proper transformations. In any time series analysis, the first step is to plot the data. One usually gets a good idea about whether the series contains a trend, seasonality, outliers, non-constant variance and other non-normal and non-stationary phenomena. This understanding often provides a basis for postulating a possible data transformation.

In time series analysis, the most commonly used transformations are variance-stabilizing transformations and differencing. Since differencing may create some negative values, one should always apply variance-stabilizing transformations before taking differences. A series with non-constant variance often needs a logarithmic transformation. More generally, to stabilize the variance, one can apply Box-Cox's power transformation.

Step2. Compute and examine the sample ACF and the sample PACF of the original series to further confirm a necessary degree of differencing. Some general rules are:

1. If the sample ACF decays very slowly and the sample PACF cuts off after lag 1 it indicates that differencing is needed. Try taking the first differencing $(1-B)Z_t$
2. More generally, to remove non-stationary that one may need to consider a higher order differencing $(1-B)^d \dot{Z}_t$ for d >1. In most cases, d is either 0, 1 or 2. Some authors argue that the consequences of unnecessary differencing are much less serious than those of under differencing.

Step3. Compute and examine the sample ACF and PACF of the properly transformed and differenced series to identify the orders of p and q, where p is the highest order in AR polynomial $(1-\phi_1 B-...-\phi_p B^p)$ and q is the highest order in MA polynomial $(1-\theta_1 B-...-\theta_q B^q)$.Usually the needed orders of these p and q are less than or equal to 3.

It is useful and interesting to note that a strong duality exists between the AR and MA model in terms of their ACFs and PACFs. To build a reasonable ARIMA model, one need a minimum of $n=50$ observations and the number of sample ACF and PACF to be calculated should be about $\frac{n}{4}$, although occasionally for data of good quality one may be able to identify and adequate model with a smaller sample size. To identify the order p and q by matching patterns in the sample ACF and PACF with the theoretical patterns of known models.

Table (3.1)

Characteristics Behavior of ACF, PACF for AR, MA and ARMA Processes

Processes	Autocorrelation	Partial Autocorrelation
AR(p)	Infinite (damped exponentials and/ or damped sine waves). Tail off according to $\rho_j = \phi_1\rho_{j-1} + \phi_2\rho_{j-2} + \ldots + \phi_p\rho_{j-p}$	Finite Spike at lag 1 through p, then cut off
MA(q)	Finite Spike at lag 1 through q, then cuts off	Infinite (dominated by damped exponentials and/ or damped sine waves) Tail off
ARMA(p,q)	Infinite (damped exponentials and/ or damped sine waves after first q-p lags). Irregular pattern at lag 1 through q, then tails off according to $\rho_j = \phi_1\rho_{j-1} + \phi_2\rho_{j-2} + \ldots + \phi_p\rho_{j-p}$	Infinite (dominated by damped exponentials and/ or damped sine waves after first q-p lags) Tail off

Sources: Univariate and Multivariate Methods (William W.S. Wei , 2006)

Step 4. Test the deterministic trend term θ_0 when d > 0 for non-stationary model, $\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t$, where the parameter θ_0 is usually omitted so that it is capable of representing series with random changes in the level, slope or trend. However, the differenced series contains a deterministic trend mean, one can test for its inclusion by comparing the sample mean $\overline{W}$ of the differenced series $W_t = (1-B)^d Z_t$ with its approximate standard error $S_{\overline{W}}$.

To derive $S_{\overline{W}}$

$$\lim_{n \to \infty} n\,Var(\overline{W}) = \sum_{j=-\infty}^{\infty} \gamma_j \quad \text{, and hence,}$$

$$\sigma^2_{\overline{W}} = \frac{\gamma_0}{n}\sum_{j=-\infty}^{\infty}\gamma_j = \frac{1}{n}\sum_{j=-\infty}^{\infty}\gamma_j = \frac{1}{n}\gamma(1) \qquad (3.1)$$

Where, $\gamma(B) = \sum_{-\infty}^{\infty} \gamma_k B^k = \sigma_a^2 \psi(B)\psi(B)^{-1}$is the autocovariance generating function and $r(1)$is its value at $B = 1$. Thus, the variance and hence the standard error for $\bar{w}$ is model dependent. For the ARIMA (1, d, 0) model, $(1 - \phi_1 B)W_t = a_t$

$$(1 - \phi_1 B)(1 - B)^d \dot{Z}_t = a_t$$

$$(1 - \phi_1 B)W_t = a_t \; ; \; W_t = \frac{1}{(1-\phi_1 B)} a_t$$

MA representation, $Z_t = \psi(B)a_t$

$$\psi(B) = \frac{1}{(1 - \phi_1 B)}$$

Autocovariance generating function is

$$\gamma(B) = \sigma_a^2 \psi(B)\psi(B)^{-1} = \frac{\sigma_a^2}{(1 - \phi_1 B)(1 - \phi_1 B^{-1})}$$

Where, $B = 1$, $\gamma(1) = \frac{\sigma_a^2}{(1-\phi_1 B)^2}$

$$\sigma_{\bar{w}}^2 = \frac{\sigma_a^2}{n(1-\phi_1)^2}$$

$$= \frac{\sigma_w^2(1-\phi_1^2)}{n(1-\phi_1)^2} \qquad (\because \sigma_w^2 = \frac{\sigma_a^2}{(1-\phi_1)^2})$$

$$= \frac{\sigma_w^2}{n}\left[\frac{1+\phi_1}{1-\phi_1}\right]$$

$$= \frac{\sigma_w^2}{n}\left[\frac{1+\rho_1}{1-\rho_1}\right] \qquad (\because \phi_1 = \rho_1) \qquad (3.2)$$

The required standard error is

$$S_{\bar{w}} = \sqrt{\frac{\hat{\gamma}_0}{n}\left[\frac{1+\hat{\rho}_1}{1-\hat{\rho}_1}\right]} \qquad (3.3)$$

Expression of $S_{\bar{w}}$ for other models can be derived similarly. However, at the model identification phase, since the underlying model is unknown, most available software use the approximation.

$$S_{\bar{w}} = \left[\frac{\hat{\gamma}_0}{n}(1 + 2\hat{\rho}_1 + 2\hat{\rho}_2 + \ldots + 2\hat{\rho}_k)\right]^{1/2} \qquad (3.4)$$

Where, $\hat{\gamma_0}$ is the sample variance and $\hat{\rho}_1$, $\hat{\rho}_2$,…., $\hat{\rho}_k$ are the first k significance sample autocorrelation function of(W_t).

Under null hypothesis$\rho_k = 0$; for $k \geq 1$

$$S_{\bar{w}} = \sqrt{\frac{\hat{\gamma_0}}{n}} \qquad (3.5)$$

Alternatively, one can include θ_0 initially and discard it at the final model estimation if the preliminary estimation result is not significant.

3.6.2 Methods of Parameters Estimation in ARIMA Models

After a model is identified for a given time series it is important to obtain efficient estimates of the parameters. To obtain the estimate of parameters $\phi_1, \phi_2, \ldots, \phi_p$, $\theta_1, \theta_2, \ldots, \theta_q$, one may use the least squares method since t_i can be proved that the least squares estimates are approximately maximum likelihood estimates in ARIMA models. If the least squares, method is used, to choose those value of ϕ'_s and θ'_s of the parameter set which minimize the sum of squared error $\sum_{t=1}^{n} = a_t^2$ obtained from the observed time series.

There arises two difficulties in estimation stage:

(i) The equation involve unknown starting values,

(ii) The sum of squared errors function is in general nonlinear in the coefficients to be estimated.

There are two approaches to (i)

(a) The unknown starting values are simply replaced by some appropriately assumed values and estimation is conditional on these assumed starting values.

(b) The estimation is based on estimated starting values from the sample data. This unconditional approach is more efficient than the conditional approach. For long series, the difference between the results obtained by the two approaches is negligible.

3.6.3 Diagnostic Checking

Time series model building is an iterative process. It starts with model identification and parameter estimation. After parameter estimation, one has to assess model adequacy by checking whether the model assumptions are satisfied. The basic assumption is that the $\{a_t\}$ are white noise. The a_t's are uncorrelated random shocks with zero mean and constant variance. For any estimated model, the residuals a_t's are estimates of these unobserved white noise a_t's. Hence, model diagnostic checking is accomplished through a careful analysis of the residual series($\hat{a}_t$). Because this residual series is the product of parameter estimation, the model diagnostic checking is usually contained in the estimation phase of a time series package.

(1) To check whether the errors are normally distributed, one can construct a histogram of the standardized residuals $\frac{\hat{a}_t}{\hat{\sigma}_a^2}$ and compare it with the standard normal distribution using the chi-square goodness of fit test.

(2) To check whether the variance is constant, one can examine the plot of residuals or evaluate the effect of different λ value via Box-Cox method.

(3) To check whether the residuals are approximately white noise, one can compute the sample ACF and sample PACF (or IACF) of the residuals to see whether they do not form any pattern and are all statistically insignificant.

Another useful test is the portmanteau Lack of fit test. This test uses the entire residual sample ACF's to check null hypothesis.

Hypothesis H_0: $\rho_1 = \rho_2 = \cdots = \rho_k = 0$

The residual are not autocorrelated.

H_1: The residual are autocorrelated.

Test statistic : $Q = n(n+2)\sum_{k=1}^{k}(n-k)^{-1}\hat{\rho}_k^2$

Critical value : $K = \chi^2_{(\alpha,K-m)}$

Decision Rule : Q > K ; Reject H_o

Otherwise ; Accept H_o

Where, m = the number of parameter estimated in the model. Based on the residual results, if the model is inadequate, a new model can be easily derived.

3.6.4 Model Selection Criteria

In time series analysis, several models may adequately represent a given data set. Sometimes, the best choice is easy; other times the choice can be very difficult. For these reasons, there are some model selection criteria based on residuals.

These criteria are

(i) Akaike's AIC and BIC

(ii) Schwartz's SBC

(iii) Parzen's CAT

AIC is called the Akaike's Information Criterion. This can be defined as follows:

$$AIC(M) = -2\ln[\text{ maximum likelihood}]+2M \qquad (3.6)$$

Where, M is the number of parameters in the model.

BIC developed minimizes of AIC. BIC is called the Bayesian information criterion. Which takes the form

$$\text{BIC(M)} = n\ln \hat{\sigma}_a^2 - (n-M)\ln\left[1-\frac{M}{n}\right] + \text{Mlnn} + \text{Mln}[\,(\frac{\hat{\sigma}_z^2}{\hat{\sigma}_a^2} - 1)/M\,] \tag{3.7}$$

Where $\hat{\sigma}_a^2$ is the maximum likelihood estimate of σ_α^2 , M is the number of parameters and $\hat{\sigma}_z^2$ is the sample variance of the series.

3.6.5 Forecasting

One of the most important objectives in the analysis of a time series is to forecast its future values. Even if the final purpose of time series modeling is for the control of a system, its operation is usually based on forecasting. In forecasting, the main objective is to produce an optimum forecast that has no error or as little error as possible. For these situation, minimum mean square error forecast is suitable.

Consider the general non-stationary ARIMA (p,d,q) model with d ≠ 0. i.e.,

$$\phi(B)(1-B)^d Z_t = \theta(B)a_t \tag{3.8}$$

where, $\phi(B) = (1- \phi_1 B - .. - \phi_p B^{\phi})$ is a stationary AR operator and

$\theta(B) = (1- \theta_1 B - .. - \theta_p B^{q})$ is an invertible MA operator, respectively.

For the general ARIMA model, rewriting the model at time t + l in and AR representation that exists because the model is invertible. Therefore,

$$Z_{t+l} = \sum_{j=1}^{\infty} \pi_j \, Z_{t+l-j} + a_{t+l} \tag{3.9}$$

By applying the operator

$$1 + \psi_1 B + \dots\dots\dots + \psi_{l-1} B^{l-1} \tag{3.10}$$

For a normal process, the (1-α)100 % forecast limits are

$$\widehat{Z_n}(l) \pm N_{\frac{\alpha}{2}}[\,1 + \sum_{j=0}^{l-1} \psi_j^2]^{\frac{1}{2}}\, \sigma_a$$

Where $N_{\frac{\alpha}{2}}$ is the standard normal deviate such that P (N > $N_{\frac{\alpha}{2}}$) = $\frac{\sigma}{2}$.

3.7 The General Multiplicative Seasonal ARIMA Model

Box and Jenkins (1976) proposed that the correlation between observations within seasonal periods may be introduced by supposing that the noise input to the seasonal ARIMA is serially correlated rather than independent. In particular, they suggest that Z_t be generated by the seasonal model of the form,

$$\Phi(B^s)\nabla_s^D Z_t = \Theta(B^s)\,\alpha_t \tag{3.11}$$

Where, $\nabla_s = 1 - B^s$ and $\Phi(B^s), \Theta(B^s)$ are polynomials in B^s of degree P and Q, respectively and, satisfying stationary and invertibility conditions. Similarly a model,

$$\Phi(B^s)\nabla_s^D Z_t = \Theta(B^s)\ \alpha_{t-1} \tag{3.12}$$

might be used to link the current behavior of a month (e.g. April) with previous April observation and so on, for each of the twelve months. Moreover, it would usually be reasonable to assume that the parameters Φ and Θ contained in these monthly models would be approximately the same for each month. Therefore, such a model relationship,

$$\phi(B)\nabla^d \alpha_t = \theta(B) a_t \tag{3.13}$$

Where, a_t is a white noise process and $\phi(B), \theta(B)$ are polynomials in B of degree p and q respectively, and satisfying stationary and invertibility conditions and $\nabla = \nabla_1 = 1 - B$

Combining equation (3.11) and (3.12), the following Box-Jenkins general multiplicative SARIMA model is finally obtained as,

$$\emptyset_P(B)\Phi_P(B^s)\nabla^d\nabla_s^D Z_t = \theta_q(B)\Theta_Q(B^s)a_t \tag{3.14}$$

In Equation (3.14), the subscripts p,P,q,Q has been added to remind the orders of the various operators. $\phi_p(B)$ and $\theta_q(B)$. $\Phi_P(B^s)$ are the regular autoregressive and moving average factors (polynomials) and $\Theta_Q(B^s)$ are the seasonal autoregressive and moving average factors (polynomials). The stationary series $(1 - B^s)^D(1 - B)^d\dot{Z}_t$ may have non-zero mean. The degree of seasonal differencing D and consecutive differencing d will usually be either 0 or 1. This model is often denoted as ARIMA(p, d, q)×(P, D, Q)$_s$ and s refer to the seasonal period.

3.7.1 PACF, IACF, and ESACF for Seasonal Models

The PACF and IACF for seasonal models are more complicated. In general, the seasonal and non-seasonal autoregressive components have their PACF and IACF cutting off at the seasonal and non-seasonal lags. The seasonal and non-seasonal moving average components produce PACF and IACF that show exponential decays or damped sine waves at the seasonal and non-seasonal lags. The ESACF for seasonal models is time consuming, and the patterns are in general very complicated. Because the ESACF provides only the information about the maximum order of p and q, its use in modeling seasonal time series is very limited. The standard ACF analysis is still the most useful method.

3.7.2 Multiplicative (0, 1, 1) × (0, 1, 1)$_{12}$ Model

Consider the multiplicative (0, 1, 1) ×(0, 1, 1)$_{12}$ model such a model,

$$\nabla_{12}\dot{Z}_t = (1 - \Theta_1 B^{12})\alpha_t \tag{3.15}$$

is employed for linking $\dot{Z}_t$'s one year apart. Suppose further that a similar model is employed,

$$\nabla\alpha_t = (1 - \theta_1 B)a_t \tag{3.16}$$

for linking α_t's one month apart, where in general θ and Θ will have difference values. The seasonal multiplicative model becomes,

$$\nabla\nabla_{12}\dot{Z}_t = (1 - \theta B)(1 - \Theta B^{12})a_t$$

Where, $\nabla = (1 - B)$ and $\nabla_{12} = (1 - B^{12})$

Now, $(1 - B)\,(1 - B^{12})\dot{Z}_t = \dot{Z}_t - \dot{Z}_{t-1} - \dot{Z}_{t-12} + \dot{Z}_{t-13}$ and

$$(1 - \theta_1 B)(1 - \Theta_1 B^{12})a_t = a_t - \theta_1 a_{t-1} - \Theta_1 a_{t-12} + \theta_1\Theta_1 a_{t-13}$$

Then, the model written explicitly is

$$\dot{Z}_t = \dot{Z}_{t-1} + \dot{Z}_{t-12} - \dot{Z}_{t-13} + a_t - \theta_1 a_{t-1} - \Theta_1 a_{t-12} + \theta_1\Theta_1 a_{t-13}$$

The invertability region for this model, required by the condition that the roots of $(1 - \theta_1 B)(1 - \Theta_1 B^{12}) = 0$ lie outside the unit circle, is defined by the inequalities.

$$-1 < \theta_1 < 1 \; and - 1 < \Theta_1 < 1$$

Note that the moving average operator

$(1 - \theta_1 B)(1 - \Theta_1 B^{12}) = 1 - \theta_1 B - \Theta_1 B^{12} + \theta_1\Theta_1 B^{13}$ is of order

q + sQ = 1+ (12)1= 13.

3.7.3 Autocorrelations Structure of Multiplicative (0, 1, 1) × (0, 1, 1)$_{12}$ Model

The autocorrelation structure of the stationary process $(1 - B^s)^D(1 - B)^d\dot{Z}_t$ is generally very complex. First of all if the polynomials in B on both sides of the model are combined, it is seen to be essentially an ARIMA process of order Ps + p and Qs + q. Many of the coefficients appearing in the explained model will, however be zero, resulting in certain simplifications in the autocorrelation structure. The multiplicative (0, 1, 1) x (0, 1, 1)$_{12}$ process is

$$(1 - B)(1 - B^{12})\dot{Z}_t = (1 - \theta_1 B)(1 - \Theta_1 B^{12})\, a_t$$

which is expanded form is

$$Y_t = (1 - \theta_1 B - \Theta_1 B^{12} + \theta_1\Theta_1 B^{13})\, a_t \tag{3.17}$$

where, Y_t is denotes the stationary series $(1 - B)(1 - B^{12})\dot{Z}_t$

Allowing the backshift operator to act on a_t Equation (3.17) can be described as

$$Y_t = a_t - \theta_1 a_{t-1} - \Theta_1 a_{t-12} + \theta_1 \Theta_1 a_{t-13} \tag{3.18}$$

which for analytical purpose is simply a MA process where only the first, twelfth and thirteenth coefficients are non-zero. The a_t's are random shocks with mean zero, constant variance ${\sigma_a}^2$ and are uncorrelated.

That is, $E[a_t] = 0$ for all t.

$V[a_t] = {\sigma_a}^2$ for all t, and

$\text{Cor}\,[a_t, a_t{}'] = E\,[a_t, a_t{}'] = 0$ for all $t \neq t'$

The autocovariance of Y_t is found by multiplying equation (3.18) with Y_{t-k} and taking expectation, that is,

$$\gamma_k = E[(a_t - \theta_1 a_{t-1} - \Theta_1 a_{t-12} + \theta_1 \Theta_1 a_{t-13})(a_{t-k} - \theta_1 a_{t-k-1} - \Theta_1 a_{t-k-12} + \theta_1 \Theta_1 a_{t-k-13})]$$

Therefore, the autocovariance function of Y_t is

$$\gamma_k = \begin{cases} (1+{\theta_1}^2)(1+{\Theta_1}^2){\sigma_a}^2 & ; k = 0 \\ -\theta_1(1+{\Theta_1}^2){\sigma_a}^2 & ; k = 1 \\ \theta_1 \Theta_2 {\sigma_a}^2 & ; k = 11 \\ -\Theta_1(1+{\theta_1}^2){\sigma_a}^2 & ; k = 12 \\ \theta_1 \Theta_1 {\sigma_a}^2 & ; k = 13 \\ 0 & ; k \neq 0, 1, 11, 12, 13, \ldots \end{cases}$$

The autocorrelation function of Y_t is

$$\rho_k = \begin{cases} 1 & ; k = 0 \\ \dfrac{-\theta_1}{(1+{\theta_1}^2)} & ; k = 1 \\ \dfrac{\theta_1 \Theta_1}{(1+{\theta_1}^2)(1+{\Theta_1}^2)} & ; k = 11 \\ \dfrac{-\Theta_1}{(1+{\Theta_1}^2)} & ; k = 12 \\ \dfrac{\theta_1 \Theta_1}{(1+{\theta_1}^2)(1+{\Theta_1}^2)} & ; k = 13 \\ 0 & ; k \neq 0, 1, 11, 12, 13, \ldots \end{cases}$$

Therefore, the only non-zero autocorrelation of Y_t are those at lags 1 ,11 ,12 and 13.Thus, the correlogram, of this process will display spikes at lags, 1, 11, 12and,13 with the latter 3 spikes being symmetric around ρ_{12}.

CHAPTER IV

DATA ANALYSIS AND FORECASTING

This study examines the monthly minimum and maximum temperatures fluctuation in Yangon Region from January 2013 to December 2023, sourced from selected climate indicators. The analysis employs descriptive methods to thoroughly investigate the variability and trends in both monthly minimum and maximum temperatures. Furthermore, employing the rigorous Box-Jenkins method underscores a statistical approach, involving model identification, precise parameter estimation, thorough diagnostic checking, and forecasting techniques. This methodological framework specifically addresses the presence and implications of seasonal patterns within the temperature data series, enhancing of understanding and predictive capabilities in this study.

4.1 Descriptive Statistics of Minimum Temperature Fluctuation in Yangon Region

Table (4.1) Minimum Temperature Fluctuation in Yangon Region (°C)

Year / Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
January	15.8	16.1	18.8	15.7	19.9	17.3	16.4	17.5	19.0	18.4	17.3
February	19.2	17.8	18.8	18.8	19.6	17.5	17.5	18.2	18.9	17.2	18.5
March	20.0	20.0	21.8	22.1	21.6	20.4	19.6	21.8	22.0	22.9	22.1
April	21.9	23.8	23.9	24.1	24.3	22.8	22.2	24.6	23.0	24.9	24.5
May	22.4	23.7	24.9	24.2	25.2	23.2	25.3	25.7	23.8	25.0	25.2
June	22.1	22.8	24.5	23.2	23.9	21.6	24.8	24.1	21.9	24.6	24.3
July	24.0	21.8	24.4	22.9	23.2	21.4	23.7	24.2	20.5	24.3	24.3
August	24.6	21.3	24.3	22.5	23.0	21.0	24.3	23.7	23.3	23.4	24.5
September	23.9	21.0	24.0	23.9	23.0	21.1	24	23.8	23.5	23.9	24.2
October	23.7	22.6	23.5	24	22.2	20.5	24.3	23.2	23.8	23.2	23.8
November	22.9	21.9	22	22.8	21.7	18.7	23	22.5	23.1	22.6	23.0
December	17.6	19.5	19.3	21.4	18.1	17.9	17.3	19.7	18.3	21.0	14.6

Source: Department of Meteorology and Hydrology in Yangon

According to Table (4.1), the minimum temperature data across the months from January to December for the years 2013 to 2023 provides insights into seasonal variations and long-term trends in Yangon Region. January starts the year with temperatures ranging from 15.7°C to 19.9°C. There is notable variability from year to year, reflecting fluctuations in early-year weather patterns. February shows temperatures fluctuating between 17.2°C and 19.6° cover the same period. While there are minor variations, February generally maintains a stable temperature range. March typically sees a rise in temperatures, ranging from 19.6°C to 22.9°C. This upward trend continues into April, where temperatures range from 21.9°C to 24.9°C, indicating the transition into warmer months. May, the warmest month, consistently shows temperatures between 22.4°C and 25.7°C across the years analyzed. June, July, and August maintain warm temperatures, ranging from 21.6°C to 24.8°C, 20.5°C to 24.6°C, and 21.0°C to 24.6°C respectively, with slight fluctuations noted year over year. September and October see temperatures stabilize between 20.5°C to 24.3°C and 20.5°C to 24.3°C respectively. November and December show cooler temperatures, with November ranging from 18.7°C to 23.1°C and December ranging. Overall, the data illustrates seasonal patterns in Yangon's climate. The months from January to May show a gradual increase in temperatures, peaking in May, which consistently registers the highest temperatures annually. This warm period is followed by relatively stable but warm conditions from June to August, September and October exhibit a mild to warm transition into cooler temperatures in November and December. The original dataset, which included the monthly minimum temperature from January 2013 to December 2023, shown in Figure (4.1).

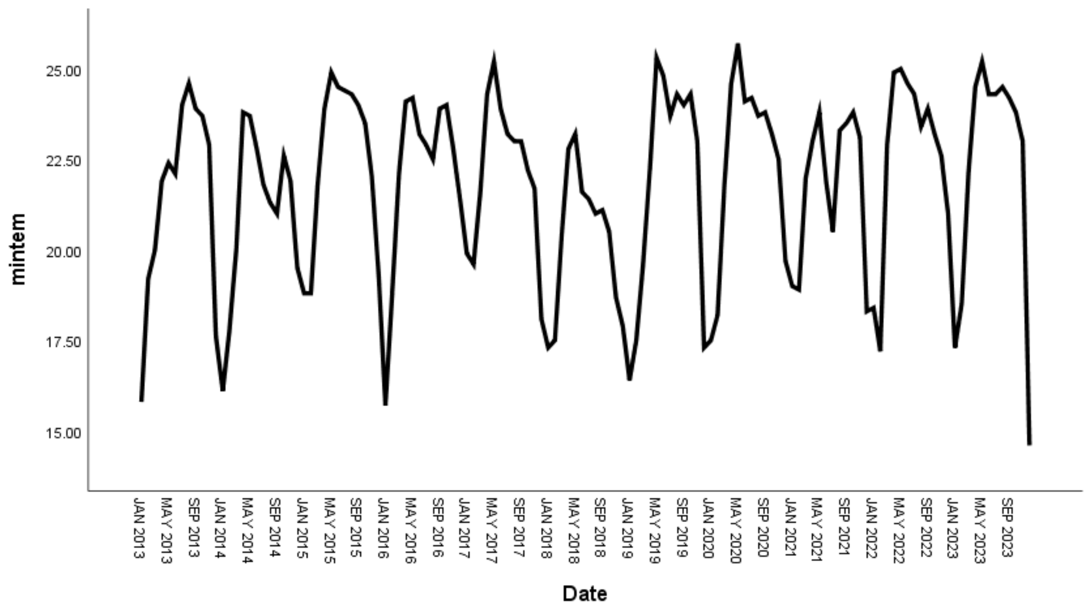


Figure (4. 1) Minimum Temperature Fluctuation in Yangon Region

According to the Figure (4.1), the minimum temperature fluctuation shows to vary around a fixed level. Data series that exhibit this characteristic are considered to be stationary in the mean. This stability in mean values indicate that the underlying factors influencing minimum temperatures are relatively consistent over the observed period, providing a stable baseline for understanding seasonal variations. Consequently, the test for seasonality of the minimum temperature data series in this region is as follows.

4.2 Test of Seasonality for Minimum Temperature Fluctuation in Yangon Region

Hypotheses

Null hypothesis: H_0 : Seasonality does not exist in the data series.

Alternative hypothesis: H_1 : Seasonality exists in the data series.

Table (4.2) ANOVA Table for Minimum Temperature Fluctuation in Yangon Region

Source of variation		Sum of Squares	Degree of Freedom	Mean Square	F-Ratio	Sig
Month	Hypotheses	419.275	10	41.927	42.983	.000***
	Error	87.789	90	0.975		
Year	Hypotheses	57.438	9	6.382	6.542	.005***
	Error	87.789	90	0.975		

Source: Own calculation

*denotes statistically significant at 10 % level, ** denotes statistically significant at 5 % level, ***denotes statistically significant at 1 % level.

As the result of the above Table (4.2), the observed value for monthly minimum temperature fluctuation of F statistic is 42.983 and it is significant since p-value is 0.000 which is less than 0.01. And also, the observed value for yearly minimum temperature fluctuation of statistic is 6.542 and it is significant since p-value is 0.000 which is less than 0.01. Therefore, it can be concluded that the monthly data of minimum temperature fluctuation in Yangon exists seasonality. Therefore, seasonality is existed in data series. The seasonal index of monthly minimum temperature data series from 2013 to 2023 is calculated by the ratio to moving average method which consists of 132 observations and it was shown in Appendix Table (A-1).

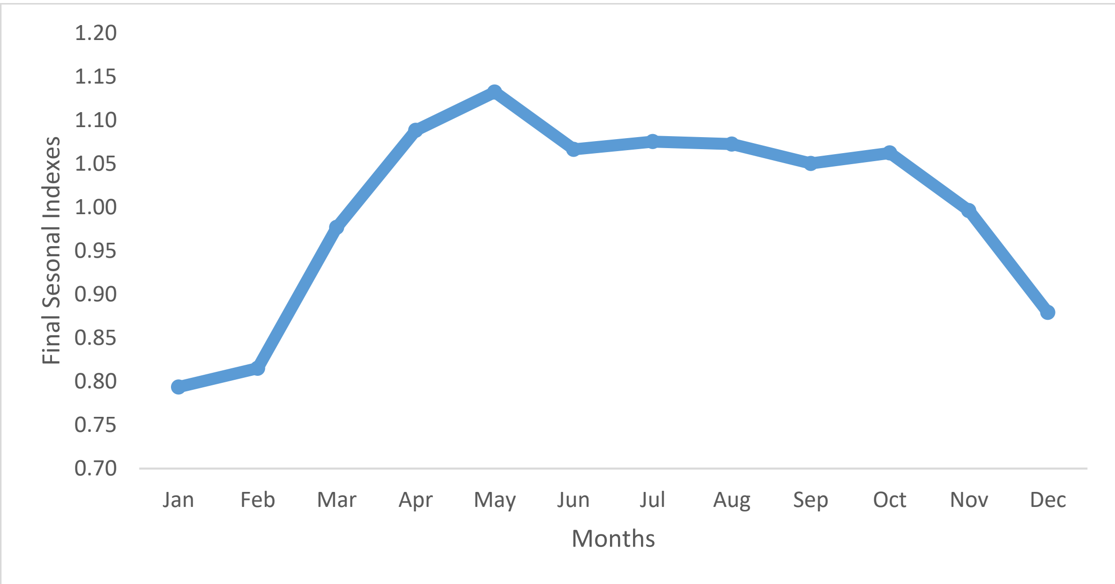


Figure (4.2) Seasonal Index for Minimum Temperature Fluctuation in Yangon Region

Table (4.3) Seasonal Indexes for Minimum Temperature Fluctuation in Yangon (2013 to 2023)

Month	Seasonal Index
January	0.79
February	0.81
March	1.00
April	1.08
May	1.13
June	1.06
July	1.08
August	1.07
September	1.05
October	1.06
November	0.99
December	0.88

According to the results from Table (4.3), the seasonal indexes for minimum temperature fluctuation has an average value of 1.00. March, April, May, June, July, August, September, and October are higher than 1.00. The seasonal index for minimum temperature was the lowest on January in Yangon. The seasonal index of January, February, November and December are 0.79, 0.81, 0.99 and 0.88 respectively. Therefore, it indicates that the data has seasonality.

4.3 Model Identification for Minimum Temperature Fluctuation in Yangon Region

It alludes to the process used to determine the necessary modifications. Table (4.4) and Figure (4.3) displayed the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) of the original series Z_t.

Table(4.4) Estimated Autocorrelation and Partial Autocorrelation Function for Original Series of Minimum Temperature Fluctuation in Yangon Region

(a) $\hat{\rho}_k$ for { Z_t } $\bar{Z}$ = 21.86 Sz = 2.57 n= 132

Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.66	0.23	-0.15	-0.32	-0.30	-0.28	-0.32	-0.31	-0.17	0.16	0.53	0.64
S.E	0.09	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
13-24	0.47	0.11	-0.22	-0.32	-0.32	-0.28	-0.31	-0.34	-0.20	0.14	0.46	0.60
S.E	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
25-36	0.40	0.06	-0.22	-0.33	-0.28	-0.27	-0.29	-0.27	-0.14	0.16	0.43	0.55
S.E	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.07	0.07	0.07
37-48	0.39	0.09	-0.16	-0.27	-0.26	-0.24	-0.28	-0.28	-0.13	0.14	0.40	0.51
S.E	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

(b) $\hat{\Phi}_{kk}$ for { Z_t } $\bar{Z}$ = 21.86 Sz = 2.57 n= 132

Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.66	-0.36	-0.25	-0.01	-0.01	-0.25	-0.27	-0.07	0.09	0.29	0.32	0.02
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	-0.06	-0.09	-0.14	0.03	-0.06	0.00	-0.12	-0.11	-0.06	0.15	0.03	0.09
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
25-36	-0.15	-0.03	-0.06	-0.03	0.03	-0.09	0.02	0.06	-0.10	0.02	-0.06	0.12
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
37-48	0.01	0.01	0.02	-0.09	-0.01	-0.01	-0.08	-0.01	0.01	-0.03	-0.03	0.02
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Source: SPSS output

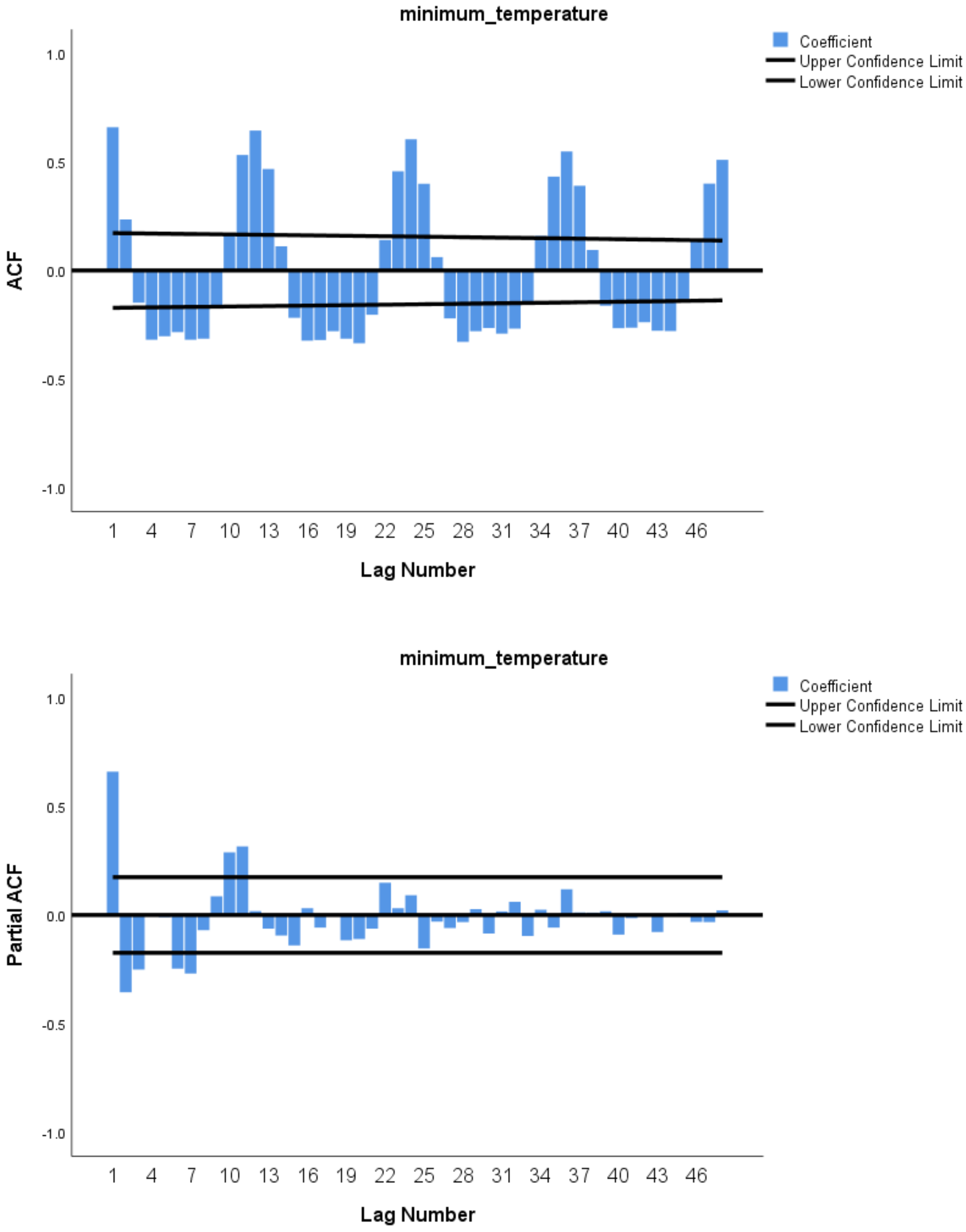


Figure (4.3) Sample ACF and Sample PACF of Minimum Temperature Fluctuation in Yangon Region

According to Table (4.5) and Figure (4.3) illustrate the ACF and PACF for this series. The sample ACF shows a damping sine-cosine wave and the sample PACF has significant spikes lag 1, lag 2 and lag 11. According to the test of seasonality, the seasonal differencing is also needed. Therefore, the sample ACF and PACF of the seasonal first difference series are described in Table (4.5) and Figure (4.4).

Table(4.5) ACF and PACF for First Seasonal Difference Series of Minimum Temperature Fluctuation in Yangon Region

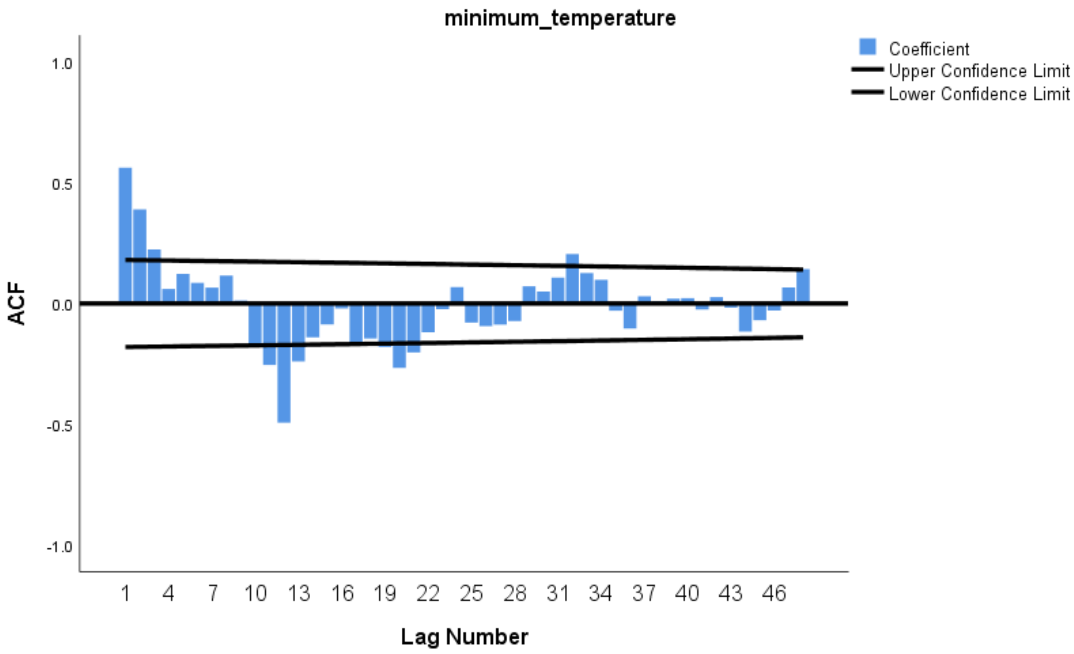
(a) $\hat{\rho}_k$ for { W_t= $(1-B^{12})Z_t$} $\bar{W}$= 0.003 S_w= 1.99 n=132

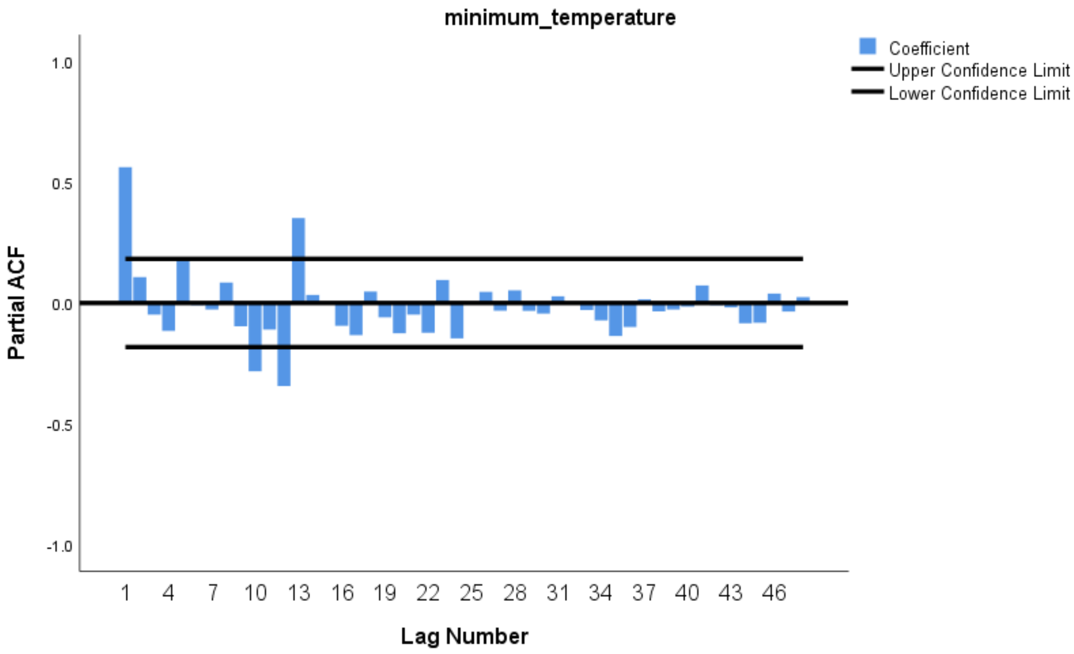
Lag K	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1-12	0.56	0.39	0.22	0.06	0.12	0.09	0.07	0.12	0.01	-0.17	-0.25	-0.49
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	-0.24	-0.14	-0.09	-0.02	-0.17	-0.15	-0.18	-0.27	-0.20	-0.12	-0.02	0.07
S.E	0.09	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
25-36	-0.08	-0.09	-0.09	-0.07	0.07	0.05	0.11	0.20	0.13	0.10	-0.03	-0.10
S.E	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
37-48	0.03	0.01	0.02	0.02	-0.02	0.03	-0.02	-0.12	-0.07	-0.03	0.07	0.14
S.E	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

(b) $\hat{\Phi}_{kk}$ for { W_t= $(1-B^{12})Z_t$} $\bar{W}$= 0.003 S_w= 1.99 n=132

Lag K	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1-12	0.56	0.11	-0.05	-0.12	0.18	-0.01	-0.03	0.08	-0.10	-0.28	-0.11	-0.34
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	0.35	0.03	-0.01	-0.09	-0.13	0.05	-0.06	-0.13	-0.05	-0.12	0.10	-0.15
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
25-36	0.00	0.05	-0.03	0.05	-0.03	-0.04	0.03	0.00	-0.03	-0.07	-0.14	-0.10
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
37-48	0.02	-0.03	-0.03	-0.02	0.07	-0.01	-0.02	-0.08	-0.08	0.04	-0.04	0.02
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Source: SPSS output





Figure(4.4) ACF and PACF for Seasonal First Difference Series of Minimum Temperature Fluctuation in Yangon Region

According to Figure (4.4), the ACF shows tailing off in the non-seasonal part, with a spike at lag 12 in the seasonal part, and the PACF exhibits a cutoff at lag 1 in the non-seasonal part and a spike at lag 12 in the seasonal part. Therefore, the Seasonal ARIMA $(1,0,0) \times (1,1,1)_{12}$ model was considered suitable to fit the series Z_t.

Hypotheses

Null hypothesis: H_0: There is no need for a constant term.

Alternative hypothesis: H_1: A constant term is needed.

Test statistics: $\overline{W}$, sample mean = 0.03 , S_w = 1.99 , n = 132

$$t = \frac{\overline{w}}{Sw/\sqrt{n}} = \frac{0.03}{\frac{1.99}{\sqrt{132}}} = -0.18$$

Critical value: k = $t_{\frac{\alpha}{2},n-1}$ = $t_{(0.025,131)}$=1.98

Decision Rule: If | t | ≥ k: reject H_0

Otherwise, accept H_0

Decision:Since | t | =0.18 ≤ k=1.98,accept H_0.

Conclusion: In the Model, there is no need for a constant term.

Therefore, the residual ACF and PACF for the tentative SARIMA (1,0,0) x $(1,1,1)_{12}$ model process, to represent the minimum temperature fluctuation in Yangon Region data series with no transformation, are also fitted as follows.

4.4 Parameter Estimation for SARIMA (1,0,0) x $(1,1,1)_{12}$ Model

Using SARIMA (1,0,0) x $(1,1,1)_{12}$ Model, the estimated parameters with their statistics were shown in Table (4.6).

Table (4.6) Estimated Parameter and Model Statistics for SARIMA (1,0,0) x $(1,1,1)_{12}$ Model

	Estimate	SE	t	Sig.
ϕ	0.667***	0.074	8.988	0.000
Φ_1	-0.417***	0.129	-3.230	0.002
Θ_1	0.591***	0.130	4.549	0.000

Source: SPSS Output

*denotes statistically significant at 10 % level, ** denotes statistically significant at 5 % level, ***denotes statistically significant at 1 % level

The estimated model is

$$(1-\Phi_1 B^{12})(1-B^{12})Z_t = \phi_1 Z_{t-1} + a_t + \Theta_1 a_{t-12}$$

$$(1+0.417B^{12})(1-B^{12})Z_t = 0.667Z_{t-1} + a_t + 0.591a_{t-12}$$

(0.129) (0.074) (0.130)

The estimation of the model SARIMA (1,0,0) x $(1,1,1)_{12}$ gives Φ_1=0.417 ϕ_1=0.667 and Θ_1=0.591 with the estimated standard error value of 0.129,0.074and 0.130 respectively. The test value of Φ_1, ϕ_1 and Θ_1 are statistically significant at the 1% level.

4.5 Diagnostic Checking for SARIMA (1,0,0) x $(1,1,1)_{12}$ Model

The estimated residual ACF and PACF for the above model are presented in Table (4.7).

Table(4.7) Estimated Residual ACF and PACF of SARIMA (1,0,0) x $(1,1,1)_{12}$ Model for Minimum Temperature Fluctuation in Yangon Region.

(a) $\hat{\rho}_k$

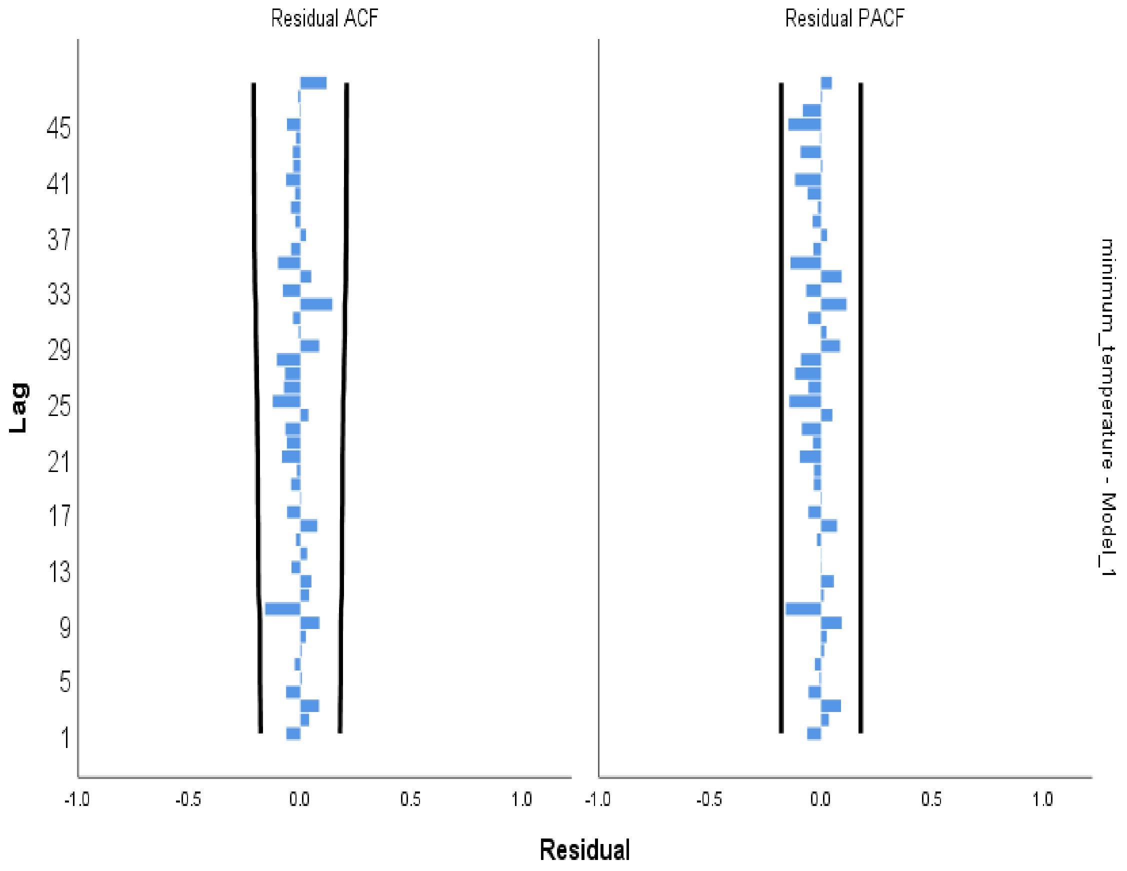
Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	-0.06	0.04	0.08	-0.06	0.01	-0.02	0.01	0.03	0.09	-0.16	0.04	0.05
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.10	0.10
13-24	-0.04	0.03	-0.02	0.08	-0.06	0.00	-0.04	-0.01	-0.08	-0.06	-0.07	0.04
S.E	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
25-36	-0.12	-0.07	-0.07	-0.11	0.09	-0.01	-0.03	0.14	-0.08	0.05	-0.10	-0.04
S.E	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.11
37-48	0.03	-0.02	-0.04	-0.02	-0.06	-0.03	-0.03	-0.02	-0.06	0.00	-0.01	0.12
S.E	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11

(b) $\hat{\phi}_{kk}$

Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	-0.06	0.04	0.09	-0.06	-0.01	-0.03	0.01	0.03	0.09	-0.16	0.01	0.06
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	0.00	0.00	-0.02	0.07	-0.06	0.00	-0.03	-0.03	-0.10	-0.04	-0.09	0.05
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
25-36	-0.14	-0.06	-0.12	-0.09	0.09	0.03	-0.06	0.12	-0.07	0.09	-0.14	-0.03
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
37-48	0.03	-0.04	-0.01	-0.06	-0.12	0.01	-0.09	0.00	-0.15	-0.08	0.01	0.05
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Source: SPSS Output

The residual ACF and PACF for the tentative SARIMA (1,0,0) x $(1,1,1)_{12}$ Model are described in Figure(4.5)



Figure(4.5) Sample ACF and PACF of Residual values for SARIMA (1,0,0) x $(1,1,1)_{12}$ Model of Minimum Temperature Fluctuation in Yangon Region

The residual values of the ACF and PACF for the minimum temperature fluctuation are all tiny and lie between two standard error bounds, as shown in Figure (4.5). Consequently, the residual series belong to the category of white noise processes. This indicates that the SARIMA (1,0,0) x $(1,1,1)_{12}$. Model is suitable for representing the minimum temperature fluctuation data series in Yangon Region. Consequently, analysis of the residual series ($\hat{a}_t$) autocorrelations may deviate significantly from zero. Table (4.8) presents the model statistics obtained from the SARIMA (1,0,0) x $(1,1,1)_{12}$ Model.

Table (4.8) Model Statistics for SARIMA (1,0,0) x $(1,1,1)_{12}$ Model

Model	Ljung- Box Q (18)		
	Statistics	df	Sig
SARIMA (1,0,0) x $(1,1,1)_{12}$	8.831	15	0.886

Source: SPSS output

According to the Table (4.8), statistics value is 8.831, and since the p-value is 0.886, which is larger than 0.05, it is not significant at the 5% level. It indicates that the residuals do not exhibit autocorrelation. As a result, the SARIMA (1,0,0) x $(1,1,1)_{12}$ model is suitable and it is used to forecast minimum temperature fluctuation in Yangon Region.

4.6 Forecasting of Minimum Temperature Fluctuation with SARIMA (1,0,0) x $(1,1,1)_{12}$ Model

Since SARIMA (1,0,0) x $(1,1,1)_{12}$ model is the best suitable model, this model is used to forecast the future value for minimum temperature fluctuation in Yangon Region. The forecast value for 12 months periods form January 2024 to December 2024 are shown in Table(4.9)and Figure (4.6).

Table (4.9) Forecast Values from January 2024 to December 2024 with 95 % Confidence Limit for Minimum Temperature Fluctuation in Yangon Region

Month	**Forecast Value**	**95% Limit**	
		Lower limit	**Upper Limit**
January	15.54	13.46	17.61
February	16.17	13.67	18.66
March	20.85	18.19	23.51
April	23.21	20.48	25.95
May	24.19	21.43	26.95
June	23.32	20.54	26.09
July	22.85	20.07	25.63
August	23.18	20.40	25.97
September	23.50	20.71	26.29
October	23.21	20.43	26.00
November	22.46	19.67	25.25
December	19.57	16.78	22.36

Source: SPSS Output

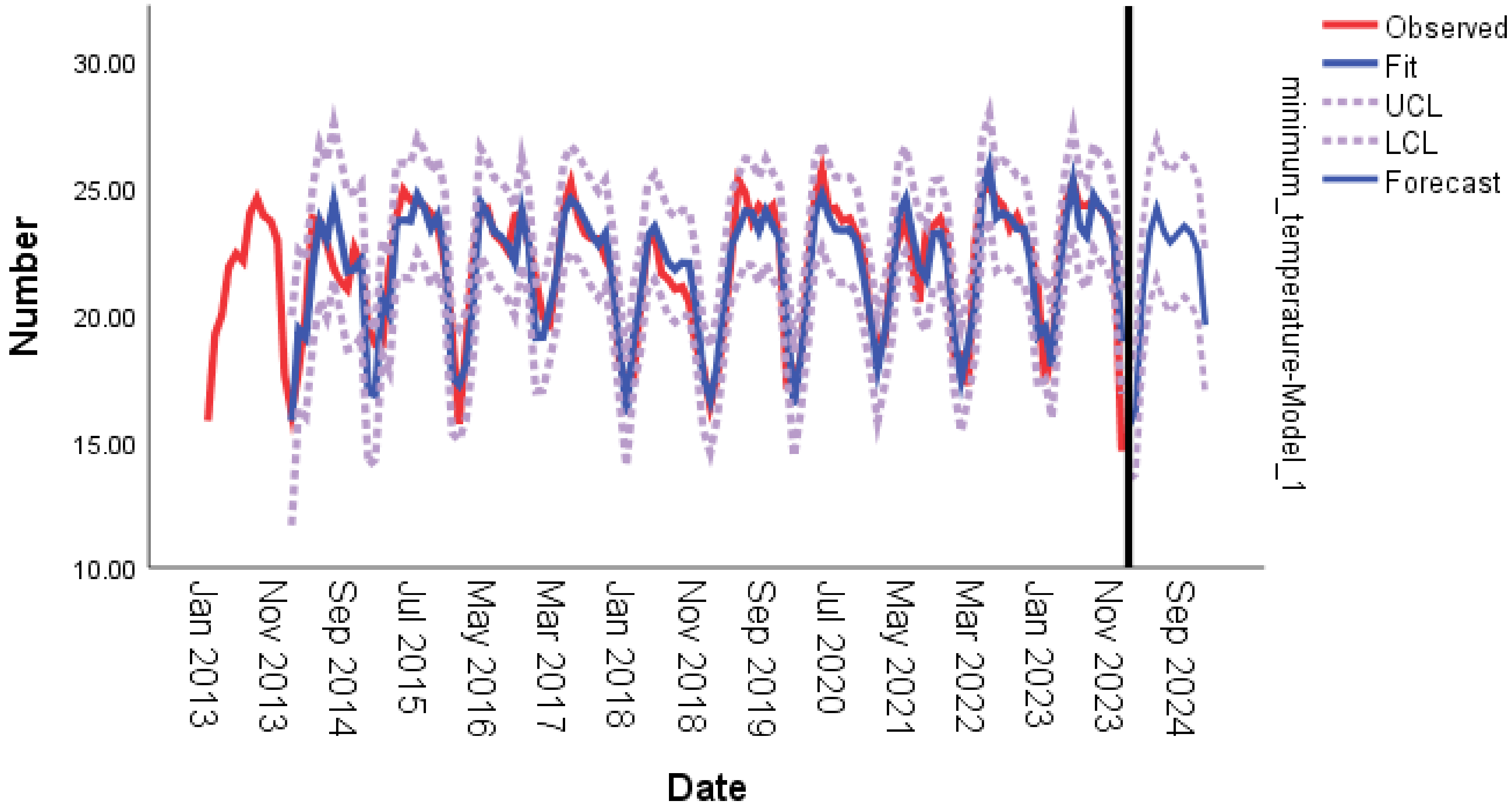


Figure (4.6) Forecast Values with 95% Confidence Limit for Minimum Temperature Fluctuation in Yangon Region

According to Table (4.9) and Figure (4.6), the forecast value of minimum temperatures for 2024 show a seasonal progression, starting with colder temperatures in January (15.54°C) and February (16.17°C), indicative of winter's peak. As spring arrives, temperatures rise steadily through March (20.85°C), April (23.21°C), and peak in May (24.19°C) and June (23.32°C), marking the onset of summer with progressively warmer conditions. July (22.85°C), August (23.18°C), and September (23.50°C) maintain relatively stable warmth, likely representing the peak summer months. October (23.21°C) onwards, temperatures gradually decline into late autumn and early winter, stabilizing around the low 20s°C until December (19.57°C), signaling the approach of cooler weather. The forecasted minimum temperatures for 2024 reveal a noticeable seasonal trend. This pattern suggests significant implications for the environment and ecosystems: fluctuating temperatures can influence biodiversity, migration patterns, and vegetation dynamics, and agricultural cycles. Stakeholders across various sectors, including agriculture, tourism, energy, and healthcare, can support these forecasts to make perfect planning and resource management. Adjusting strategies based on forecast temperature variations enables better preparedness for seasonal demands and challenges, fostering resilience and sustainable practices aligned with environmental dynamics.

4.7 Descriptive Statistics of Maximum Temperature Fluctuations in Yangon Region

Table (4.10) Maximum Temperature Fluctuation in Yangon Region(°C)

Year / Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
January	32.7	32.3	32.7	31.6	33.0	32.4	32.3	33.5	33.2	33.4	32.5
February	36.6	34.4	35	34.4	34.8	34.4	35.7	34.9	35.2	34.7	34.9
March	37.1	37.4	37.7	36.7	36.7	36.4	36.9	37.3	38.3	36.9	36.7
April	38.6	38.1	38.1	38.2	36.1	37.5	40.0	39.1	36.2	37.3	38.6
May	35.5	35.9	35.9	37.1	35.0	35.2	36.1	37.1	36.9	33.9	36.5
June	31.4	32.1	32.3	31.7	31.4	31.0	31.8	32.2	32.4	32.0	31.5
July	30.4	31.0	31.7	31.8	30.1	29.9	30.7	31.9	31.2	31.8	31.7
August	30.9	31.1	31.2	30.2	30.7	30.2	30.1	31.5	32.3	31.0	32.0
September	31.2	31.9	32.2	31.9	32.2	31.9	31.9	32.1	31.2	31.7	31.7
October	32.6	33.6	32.4	32.3	31.9	32.9	34.3	31.6	32.3	33.0	32.2
November	34.1	33.4	34.0	32.3	33.1	33.7	33.3	33.9	34.4	33.2	34.3
December	30.9	33.8	33.3	33.5	32.0	33.2	32.4	33.6	33.1	32.9	34.5

Source: Department of Meteorology and Hydrology

According to Table (4.10), the maximum temperature across the monthly data from January to December for the years 2013 to 2023 provides insights into seasonal variations and long-term trends in Yangon Region. January displays temperatures range from 31.60°C in 2016 to 33.50°C in 2019, with fluctuations suggesting no consistent trend over the decade. February shows variability from 34.40°C in 2014 to 35.70°C in 2018, indicating periodic fluctuations. Temperatures range notably from 36.40°C in 2016 to 38.30°C in March 2019, with occasional peaks and dips. April demonstrates pronounced variation, from 36.10°C in 2015 to 40.00°C in 2017, indicating possible local weather patterns. Moving to the mid-year months, temperatures range from 33.90°C in 2021 to 37.10°C in May 2013, with variations that suggest influence from seasonal shifts. June shows temperatures from 31.00°C in 2017 to 32.30°C in 2014, with modest fluctuations. July exhibits temperatures from 29.90°C in 2017 to 31.80°C in 2017, highlighting potential sensitivity to regional monsoonal effects. Temperatures range from 30.10°C in 2018 to 32.30°C in August 2019, indicating seasonal variability. In September, temperatures fluctuate between 31.20°C in 2019 to 32.20°C in 2015, with minor changes reflecting local climate dynamics. October shows temperatures from 31.60°C in 2018 to 34.30°C in 2017, indicating variability influenced by climatic conditions. Temperatures range from 32.30°C in 2019 to 34.40°C in November 2019, reflecting seasonal variability and potential climate oscillations. December exhibits temperatures from 32.90°C in 2017 to 34.50°C in 2023, indicating potential climate changes. Therefore, the temperature fluctuations in Yangon Region across these years and months highlight the region's sensitivity to seasonal shifts and potential climate variations. The original dataset, which included the monthly maximum temperature from January 2013 to December 2023, shown in Figure (4.7).

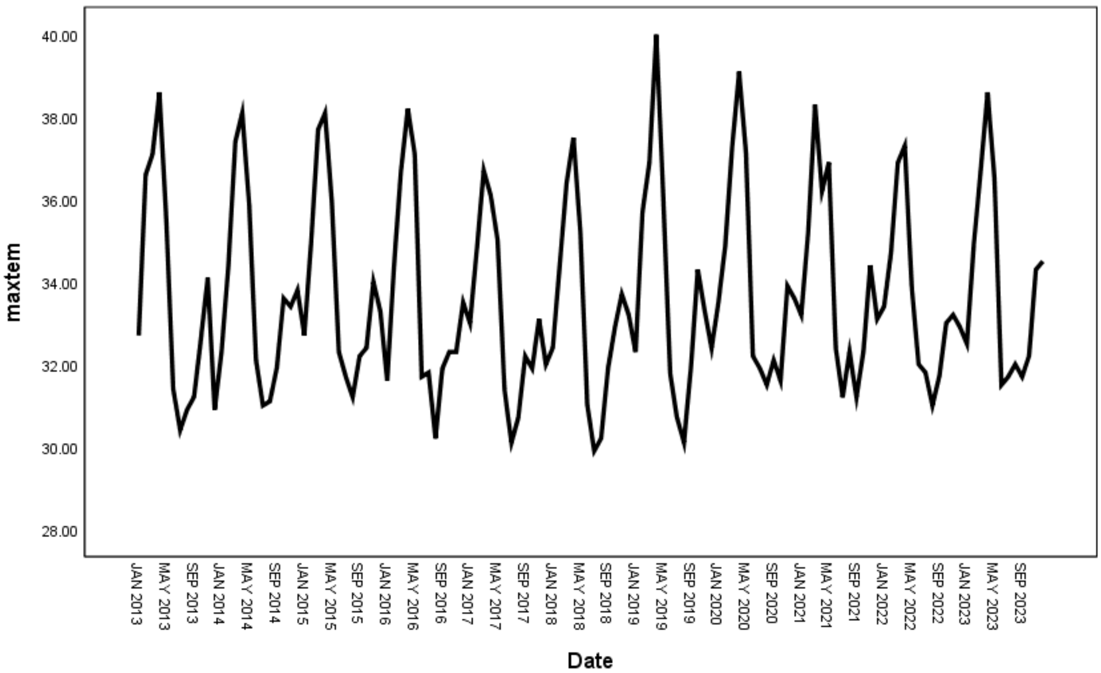


Figure (4. 7)   Maximum Temperature Fluctuation in Yangon Region

According , appears to vary around a fixed level. Data series that exhibit this characteristic are considered to be stationary in the mean. This stability in mean values suggests that the underlying factors influencing maximum temperatures are relatively consistent over the observed period, providing a stable baseline for understanding seasonal variations. Consequently, the test for seasonality of the maximum temperature data series is conducted as follows.

4.8 Test of Seasonality for Maximum Temperature Fluctuation in Yangon Region

Hypotheses

Null hypothesis: H_0: Seasonality does not exist in the data series.

Alternative hypothesis: H_1: Seasonality exists in the data series.

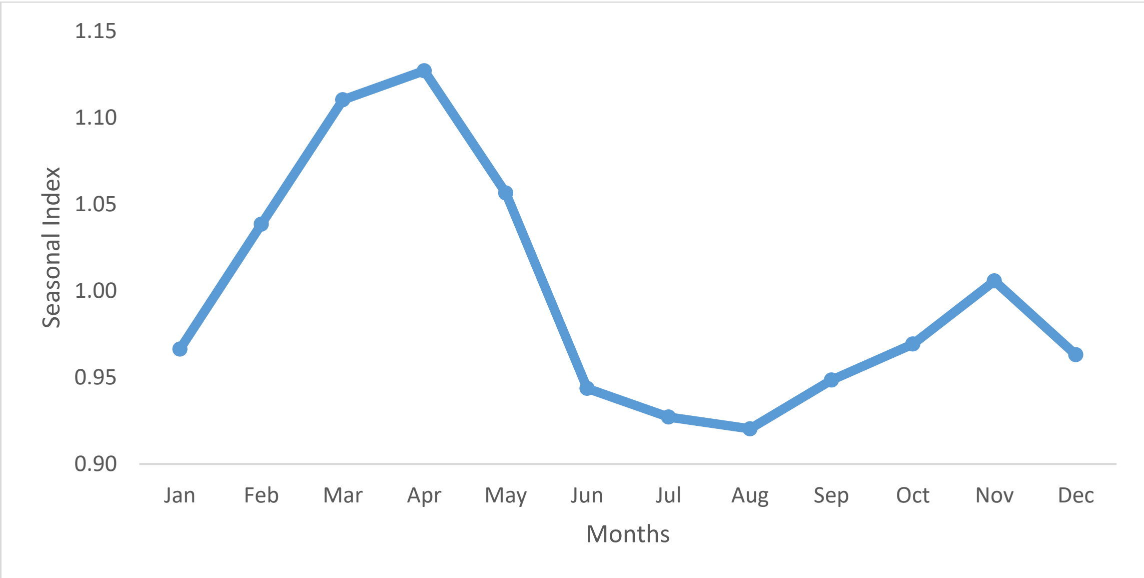
Table (4.11) ANOVA Table for maximum temperature fluctuation in Yangon Region

Source of Variation		Sum of Squares	Degree of Freedom	Mean Squares	F-Ratio	Significant level
Month	Hypotheses	573.855	10	57.3855	123.001	.000***
	Error	41.9891	90	0.46655		
Year	Hypotheses	11.8869	9	1.32077	2.831	.005***
	Error	41.9891	90	0.46655		

Source: Own calculation

*denotes statistically significant at 10 % level, ** denotes statistically significant at 5 % level, ***denotes statistically significant at 1 % level.

As the result of the above Table (4.11), the observed value for monthly maximum temperature fluctuation of F statistic is 123.001 and it is significant since p-value is 0.000 which is less than 0.01. And also, the observed value for yearly maximum temperature fluctuation F statistic is 2.831 and it is significant since p-value is 0.000 which is less than 0.01. Therefore, it can be concluded that the monthly data of maximum temperature fluctuation in Yangon exists seasonality. Therefore, seasonality is existed in data series. The seasonal index of monthly maximum temperature data series from 2013 to 2023 is calculated by the ratio to moving average method which consists of 132 observations and it was shown in Appendix Table (A-2).



Figure(4.8) Seasonal Index for Maximum Temperature Fluctuation in Yangon Region

Table (4.12) Seasonal Indexes for Maximum Temperature Fluctuation in Yangon (2013 to 2023)

Month	Seasonal Index
January	0.96
February	1.03
March	1.11
April	1.13
May	1.10
June	0.95
July	0.93
August	0.92
September	0.95
October	0.97
November	0.99
December	0.96

According to the results from Table (4.13), the seasonal indexes for maximum temperature fluctuation has an average value of 1.00. January, June, July, August, September, October, November and December are lower than 1.00. The seasonal index for maximum temperature was the highest on April in Yangon. The seasonal index of February, March, April and May are 1.03, 1.11, 1.13 and 1.10 respectively. Therefore, it indicates that the data has seasonality.

4.9 Model Identification for Maximum Temperature Fluctuation in Yangon Region

It alludes to the process used to determine the necessary modifications. Table (4.13) and Figure (4.9) displayed the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) of the original series Z_t.

Table (4.13) Estimated Autocorrelation and Partial Autocorrelation Function for Original Series of Maximum Temperature Fluctuation in Yangon Region

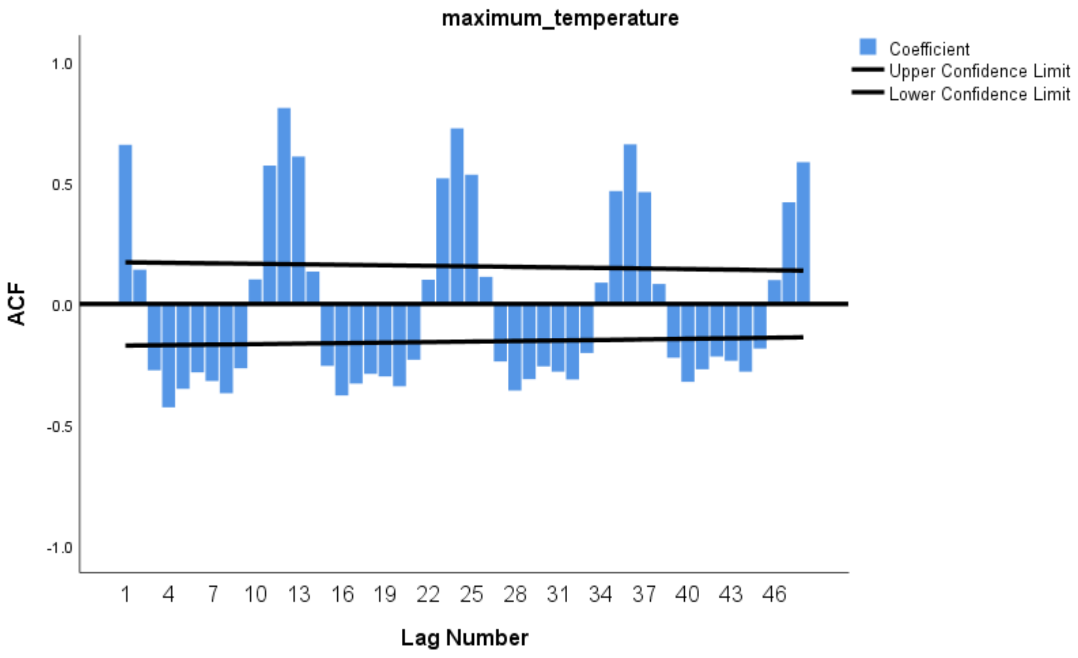
(a) $\hat{\rho}_k$ for { Z_t} $\bar{Z}$= 33.64 S_z =2.36 n = 132

Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.66	0.14	-0.27	-0.43	-0.35	-0.28	-0.32	-0.37	-0.27	0.10	0.57	0.81
S.E	0.09	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
13-24	0.61	0.13	-0.26	-0.38	-0.33	-0.29	-0.30	-0.34	-0.23	0.10	0.52	0.73
S.E	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
25-36	0.53	0.11	-0.24	-0.36	-0.31	-0.26	-0.28	-0.31	-0.20	0.09	0.47	0.66
S.E	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.07	0.07	0.07
37-48	0.46	0.08	-0.22	-0.32	-0.27	-0.22	-0.24	-0.28	-0.18	0.10	0.42	0.59
S.E	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

(b) $\hat{\Phi}_{kk}$ for { Z_t} $\bar{Z}$= 33.64 S_z =2.36 n = 132

Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.66	-0.51	-0.19	-0.03	-0.05	-0.34	-0.37	-0.31	-0.17	0.16	0.34	0.25
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	-0.07	-0.13	0.08	0.14	-0.07	-0.20	0.04	0.02	0.01	-0.04	0.05	0.01
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
25-36	-0.09	-0.04	0.01	-0.03	-0.05	0.00	-0.02	-0.07	0.01	-0.06	0.00	0.00
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
37-48	-0.18	-0.02	0.05	-0.02	-0.06	0.00	0.02	-0.08	0.02	0.03	-0.12	0.02
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Source: SPSS output



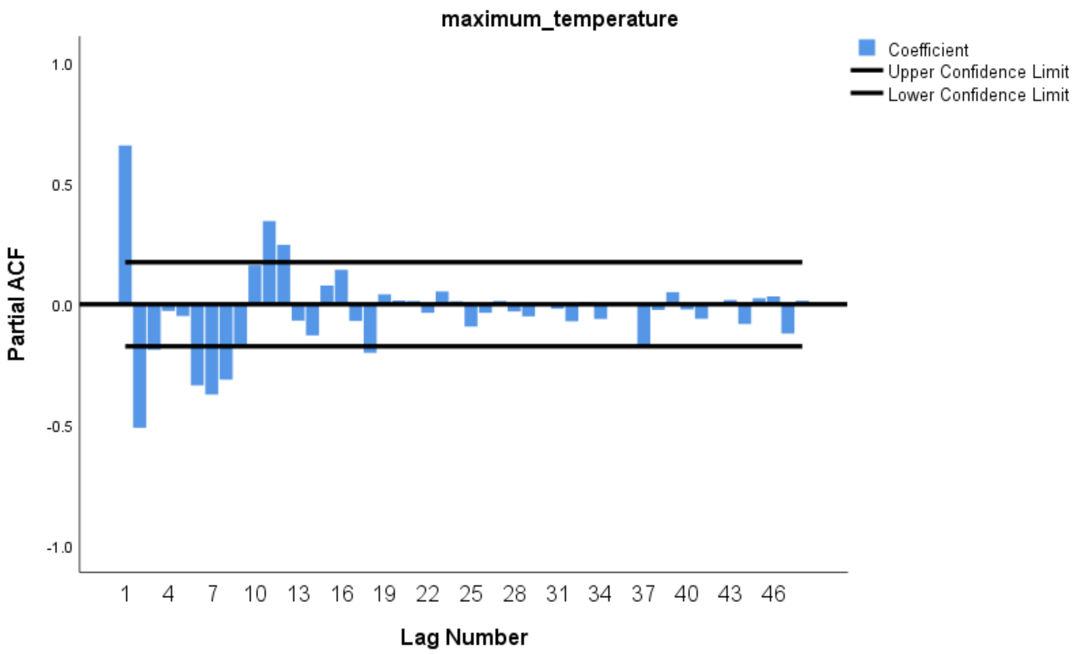


Figure (4.9) Sample ACF and Sample PACF of Maximum Temperature Fluctuation in Yangon Region

According to Figure (4.3) illustrate the ACF and PACF for this series. The sample ACF shows a damping sine-cosine wave and the sample PACF has significant spikes lag 1, lag 2 and lag 12. According to the test of seasonality, the seasonal differencing is also needed. So, the sample ACF and PACF of the seasonal first difference series are described in Table (4.14) and Figure (4.10).

Table(4.14) ACF and PACF for First Seasonal Difference Series of Maximum Temperature Fluctuation in Yangon Region

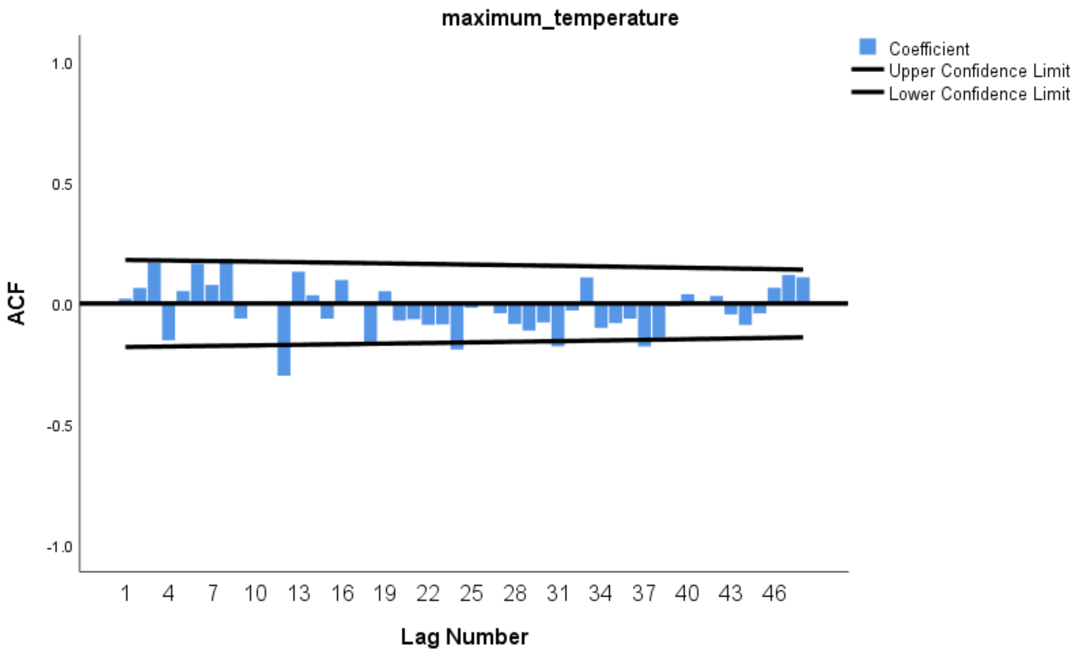
(a) $\hat{\rho}_k$ for { W_t= $(1-B^{12})$ Z_t} $\overline{W}$= 0.02 S_w= 2.05 n=132

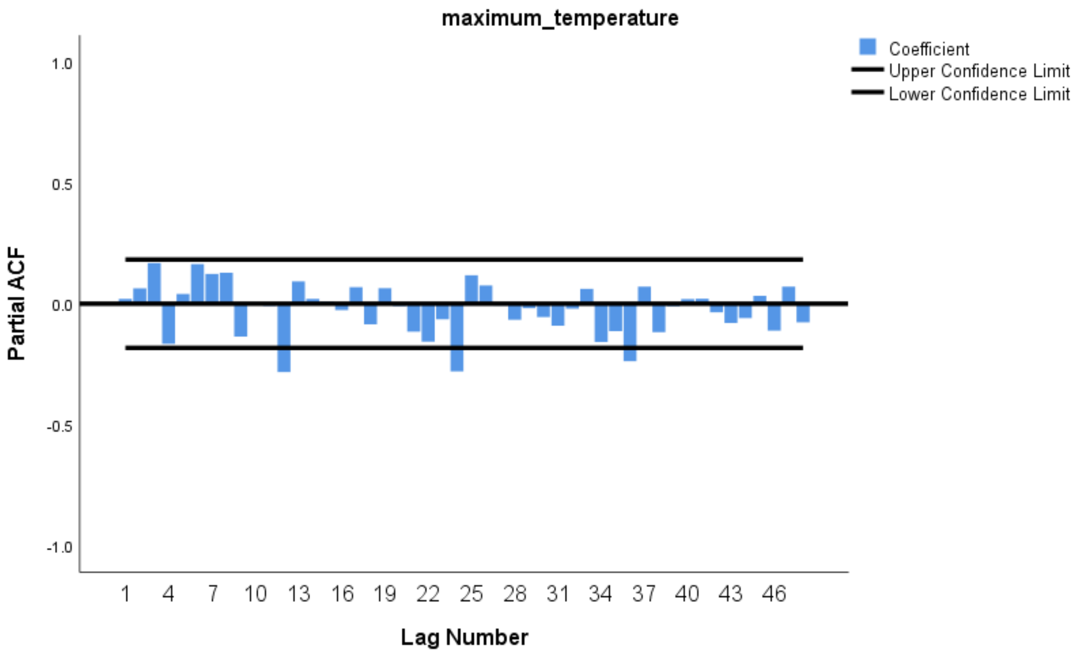
Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.02	0.06	0.17	-0.15	0.05	0.16	0.08	0.19	-0.06	0.00	0.01	-0.30
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	0.13	0.03	-0.06	0.10	-0.01	-0.17	0.05	-0.07	-0.06	-0.09	-0.09	-0.19
S.E	0.09	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
25-36	-0.02	0.00	-0.04	-0.08	-0.11	-0.08	-0.18	-0.03	0.11	-0.10	-0.08	-0.06
S.E	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
37-48	-0.18	-0.14	-0.01	0.04	0.00	0.03	-0.05	-0.09	-0.04	0.06	0.12	0.11
S.E	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

(b) $\hat{\Phi}_{kk}$ for { W_t= $(1-B^{12})$ Z_t} $\overline{W}$= 0.02 S_w= 2.05 n=132

Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.02	0.06	0.17	-0.17	0.04	0.16	0.12	0.13	-0.14	-0.01	-0.01	-0.28
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	0.09	0.02	0.01	-0.03	0.07	-0.09	0.06	-0.01	-0.12	-0.16	-0.06	-0.28
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
25-36	0.12	0.08	-0.01	-0.07	-0.02	-0.05	-0.09	-0.02	0.06	-0.16	-0.11	-0.24
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
37-48	0.07	-0.12	-0.01	0.02	0.02	-0.04	-0.08	-0.06	0.03	-0.11	0.07	-0.08
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Source: SPSS output





Figure(4.10) ACF and PACF for Seasonal First Difference Series of Maximum Temperature Fluctuation in Yangon Region

According to Figure (4.10), the ACF shows all tiny and lie between two standard error bounds in the non-seasonal part, with a spikes at lag 12 in the seasonal part and the PACF shows all tiny and lie between two standard error bounds in the non-seasonal part, with spikes at lag 12 , lag 24 and lag 36 in the seasonal part. Therefore, based on the observed patterns in ACF and PACF, the Seasonal ARIMA (0,0,0) x $(3,1,0)_{12}$ model was considered suitable to fit the Z_t series.

Hypotheses

Null hypothesis: H_0: There is no need for a constant term.

Alternative hypothesis: H_1: A constant term is needed.

Test statistics: $\bar{W}$, sample mean = 0.02 , S_w =2.05 , n= 132

$$t = \frac{\bar{w}}{Sw/\sqrt{n}} = \frac{0.02}{\frac{2.05}{\sqrt{132}}} = 0.14$$

Critical value: k = $t_{\frac{\alpha}{2},n-1}$ = $t_{(0.025,131)}$=1.98

Decision Rule: If ∣ t ∣ ≥ k: reject H_0

Otherwise, accept H_0

Decision:Since, ∣ t ∣ =0.14 ≤ k=1.98, accept H_0.

Conclusion: In the Model, there is no need for a constant term.

Therefore, the residual ACF and PACF for the tentative SARIMA (0,0,0) x $(2,1,0)_{12}$ model process , to represent the maximum temperature fluctuation in Yangon Region data series with no transformation, are also fitted as follows.

4.10 Parameter Estimation for SARIMA (0,0,0) x $(3,1,0)_{12}$ Model

Using SARIMA **(**0,0,0) x $(3,1,0)_{12}$ Model, the estimated parameters with their statistics were shown in Table (4.15).

Table (4.15) Estimated Parameter and Model Statistics for SARIMA (0,0,0) x $(2,1,0)_{12}$ Model

	Estimate	**SE**	**t**	**Sig.**
Φ_1	-0.635***	0.090	-7.096	0.000
Φ_2	-0.549***	0.097	-5.689	0.000
Φ_3	-0.408***	0.098	-4.170	0.000

Source: SPSS Output

*denotes statistically significant at 10 % level, ** denotes statistically significant at 5 % level, ***denotes statistically significant at 1 % level.

The estimated model is

$$(1- \Phi_1 B- \Phi_2 B^2- \Phi_3 B^3)(1-B^{12})Z_t= a_t$$

$$(1+0.635_1 B+0.549B^2+0.408B^3)(1-B^{12})Z_t= a_t$$

$$(0.090) \quad (0.097) \quad (0.098)$$

The estimation of the model SARIMA (0,0,0) x $(3,1,0)_{12}$ gives Φ_1= -0.635, Φ_2= -0.549and Φ_3= -0.408with the estimated standard error value of 0.090 ,0.097and 0.098 respectively. At the 5% level, the test value of Φ_1 and Φ_2 are statistically significant at the 1% level.

4.11 Diagnostic Checking for SARIMA (0,0,0) x $(3,1,0)_{12}$ Model

The estimated residual ACF and PACF for the above model are presented in Table(4.16).

Table(4.16) Estimated Residual ACF and PACF of SARIMA (0,0,0) x $(3,1,0)_{12}$ Model for Maximum Temperature Fluctuation in Yangon Region.

(a) $\widehat{\rho}_k$

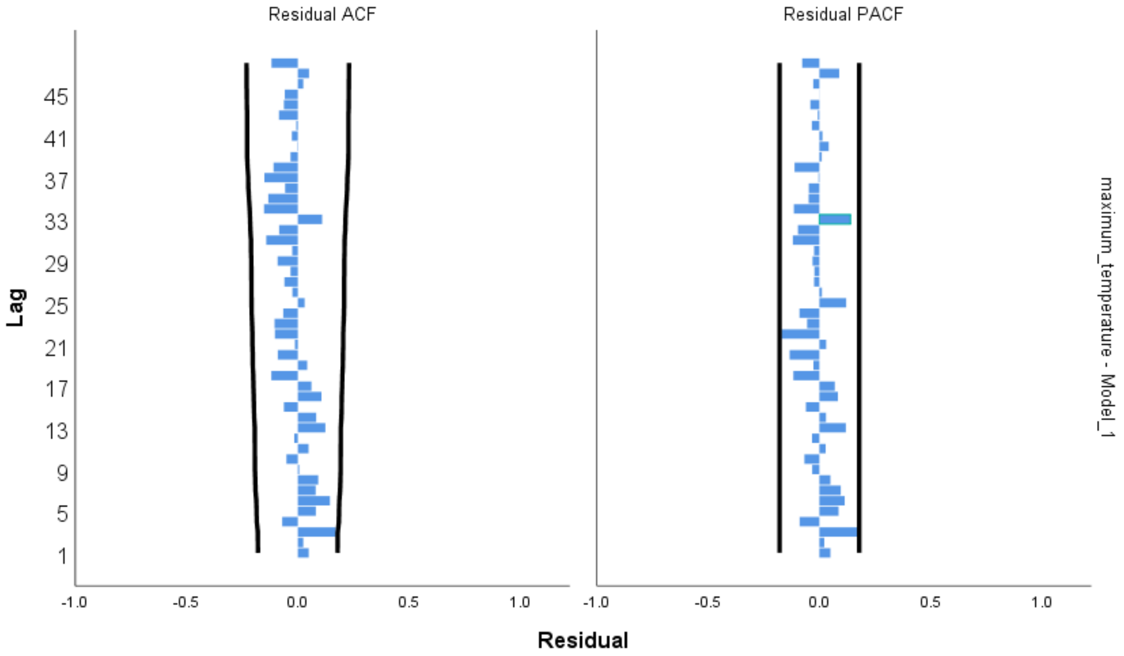
Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.05	0.02	0.17	-0.07	0.08	0.14	0.08	0.09	0.01	-0.05	0.05	-0.02
S.E	0.09	0.09	0.09	0.09	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10
13-24	0.12	0.08	-0.06	0.11	0.06	-0.12	0.04	-0.09	-0.01	-0.10	-0.10	-0.07
S.E	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.11
25-36	0.03	-0.02	-0.06	-0.03	-0.09	-0.03	-0.14	-0.08	0.11	-0.15	-0.13	-0.06
S.E	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
37-48	-0.15	-0.11	-0.03	0.00	-0.03	-0.01	-0.08	-0.06	-0.06	0.02	0.05	-0.12
S.E	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12

(b) $\widehat{\phi}_{kk}$

Lag K	1	2	3	4	5	6	7	8	9	10	11	12
1-12	0.05	0.02	0.17	-0.09	0.09	0.11	0.10	0.05	-0.03	-0.07	0.03	-0.03
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
13-24	0.12	0.03	-0.06	0.08	0.07	-0.12	-0.03	-0.13	0.03	-0.17	-0.05	-0.09
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
25-36	0.12	0.01	-0.02	-0.02	-0.03	-0.02	-0.12	-0.10	0.14	-0.11	-0.05	-0.05
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
37-48	0.00	-0.11	0.01	0.04	0.01	-0.03	-0.01	-0.04	0.00	-0.03	0.09	-0.08
S.E	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Source: SPSS Output

The residual ACF and PACF for the tentative SARIMA (0,0,0) x $(3,1,0)_{12}$ Model are described in Figure (4.11).



Figure(4.11) Sample ACF and PACF of Residual values for SARIMA (1,0,0) x $(3,1,0)_{12}$ Model of Maximum Temperature Fluctuation In Yangon Region

The residual values of the ACF and PACF for the Maximum Temperature Fluctuation are all tiny and lie between two standard error bounds, as shown in Figure (4.12). Consequently, the residual series belong to the category of white noise processes. This indicates that the SARIMA (0,0,0) x $(3,1,0)_{12}$. Model is suitable for representing the maximum temperature fluctuation data series in Yangon region. Consequently, analysis of the residual series ($\hat{a}_t$) autocorrelations may deviate significantly from zero. Table (4.17) presents the model statistics obtained from the SARIMA (0,0,0) x $(3,1,0)_{12}$ Model.

Table(4.17) Model Statistics for SARIMA (0,0,0) x $(3,1,0)_{12}$ Model

Model	Ljung- Box Q (18)		
	Statistics	df	Sig
SARIMA (0,0,0) x $(3,1,0)_{12}$	18.580	15	0.233

Source: SPSS output

According to the Table (4.17), statistics value is 18.580, and since the p-value is 0.233, which is larger than 0.05, it is not significant at the 5% level. It indicates that the residuals do not exhibit autocorrelation. As a result, the SARIMA (0,0,0) x $(3,1,0)_{12}$ model is suitable and it is used to forecast maximum temperature fluctuation in Yangon Region.

4.12 Forecasting of Minimum Temperature Fluctuation with SARIMA (0,0,0) x $(3,1,0)_{12}$ Model

Since SARIMA (0,0,0) x $(3,1,0)_{12}$ model is the best suitable model, this model is used to forecast the future value for maximum temperature fluctuation in Yangon Region. The forecast value for 12 months periods form January 2024 to December 2024 are shown in Table(4.18)and Figure (4.12).

Table(4.18) Forecast Values from January 2024 to December 2024 with 95 % Confidence Limit for Maximum Temperature Fluctuation in Yangon Region

Month	Forecast Value	95% Limit	
		Lower limit	Upper Limit
January	33.08	31.46	34.71
February	34.93	33.30	36.55
March	37.19	35.56	38.82
April	38.35	36.73	39.98
May	36.58	34.95	38.21
June	31.96	30.33	33.58
July	31.72	30.09	33.35
August	31.75	30.12	33.38
September	31.79	30.16	33.42
October	32.04	30.41	33.67
November	34.06	32.43	35.68
December	33.80	32.17	35.43

Source: SPSS Output

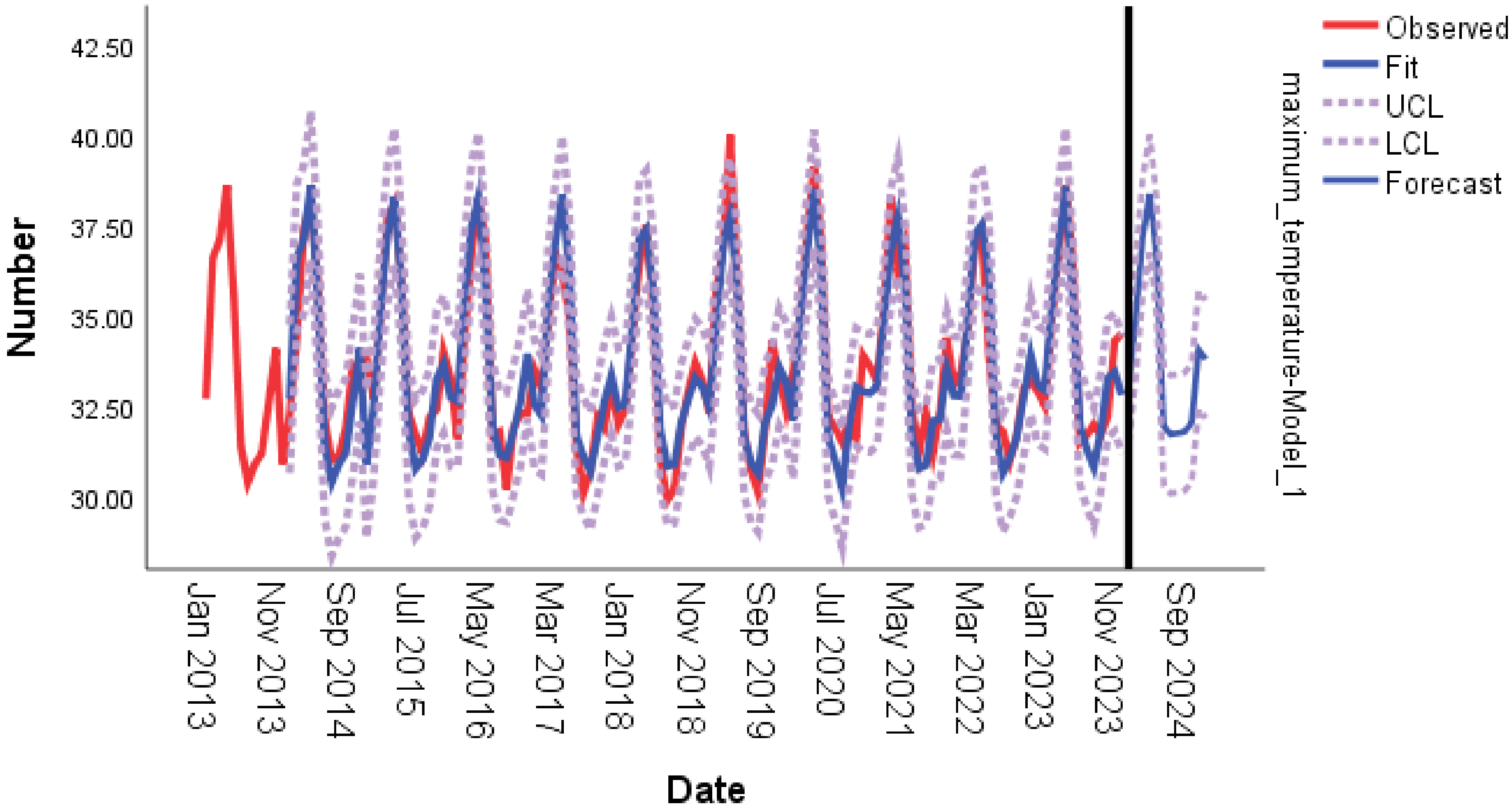


Figure (4.12) Forecast Values with 95% Confidence Limit for Maximum Temperature Fluctuation in Yangon Region

According to Table (4.18) and Figure (4.12) and the forecast value of maximum temperatures for 2024 illustrate a seasonal progression characterized by the temperature peaks and declines across the year. Starting in January (33.08°C) and February (34.93°C), temperatures rise steadily into early spring with March (37.19°C) and April (38.35°C) reaching their peak, indicating the height of summer. May (36.58°C) maintains warm conditions before temperatures begin to decline noticeably from June (31.96°C) through September (31.79°C), marking the transition towards cooler weather. October (32.04°C) sees a slight uptick before temperatures stabilize in November (34.06°C) and December (33.80°C), suggesting mild late autumn and early winter conditions. This seasonal pattern provides valuable insights into temperature trends that can influence planning and activities throughout the year, emphasizing the variability and changing nature of the climate across different seasons.

CHAPTER V
CONCLUSION

In this chapter, the findings, suggestions and recommendations and further study for the time series analysis of temperature fluctuation in Yangon Region was presented in details.

5.1 Findings

This study focuses on accurately modeling and forecasting temperature fluctuation in Yangon Region. It analyzes monthly data from January 2013 to December 2023, using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. This method is specifically designed to accurately show the seasonal variation and interdependencies essential in temperature data. Importantly, even in cases where the seasonal patterns do not exhibit a trend, the SARIMA model proves to be highly effective in fitting the data and producing precise forecasts. The findings emphasize the SARIMA model's effectiveness in forecasting temperature fluctuation across the Yangon Region, emphasizing its value as a strong and appropriate tool for time series forecasting.

According to the descriptive statistics, the minimum temperature fluctuations in Yangon Region from January to December between 2013 and 2023 highlight seasonal patterns and variability. It was found that Yangon Region recorded its highest temperature of 25.3°C in May 2019 and 25.7°C in May 2020, marking a notable deviation from the typical temperature patterns observed throughout the year. Overall, the data illustrates seasonal patterns in Yangon's climate, with the months from January to May showing a gradual increase in temperatures, peaking in May, which consistently registers the highest temperatures annually. This warm period is followed by relatively stable but warm conditions from June to August, and September and October exhibit a mild to warm transition into cooler temperatures in November and December.

Moreover, seasonal indices for March, April, May, June, July, August, September, and October are consistently higher than 1.00 for minimum temperatures, while January records the lowest seasonal index among all months, with specific values for January, February, November, and December being 0.79, 0.81, 0.99, and 0.88 respectively, highlighting clear seasonal patterns. The SARIMA $(1,0,0) \times (1,1,1)_{12}$ model estimation for minimum temperature fluctuation in Yangon Region reveals Φ_1=0.417, ϕ_1=0.667, and $\Theta 1$=0.591, with corresponding standard errors of 0.129, 0.074, and 0.130 respectively.

Statistical tests confirm that Φ_1, ϕ_1, and Θ_1 are all significant at the 1% level, indicating strong explanatory power. Residual analysis shows ACF and PACF values within two standard error bounds, suggesting white noise characteristics and validating the model's suitability for representing temperature fluctuations. Further model statistics indicate non-significant autocorrelation among residuals at the 5% level, supporting the SARIMA $(1,0,0) \times (1,1,1)_{12}$ model's adequacy for forecasting minimum temperature fluctuations in Yangon Region from January 2024 to December 2024.

Furthermore, the maximum temperature fluctuation in Yangon Region across months from January to December over the period from 2013 to 2023 highlight seasonal patterns and variability. It found that April generally exhibits moderate maximum temperatures, ranging from 31.60°C to 40.00°C in April from 2013 to 2023. In April 2019 and 2020, Yangon Region experienced its highest recorded temperature, reaching 40.00°C and 39.10°C. This spike in temperature stands out as an anomaly amidst the overall stability observed in the region's climate. Yangon Region typically shows consistent temperatures across the year with minor fluctuations between months, as evidenced by the data from 2013 to 2023.

In addition, seasonal indices for January, June, July, August, September, October, November and December are lower than 1.00 for maximum temperatures, indicating relatively milder variations compared to peak months, while April stands out with the highest seasonal index among all months in Yangon Region, suggesting consistent and pronounced temperature patterns during this time. Specific seasonal indices for February, March, April and May are 1.03, 1.11, 1.13 and 1.10 respectively, highlighting clear seasonal patterns. The SARIMA $(0,0,0) \times (3,1,0)_{12}$ model estimation for maximum temperature fluctuation in Yangon Region reveals Φ_1= -0.635, Φ_2= -0.549and Φ_3= -0.408 with the estimated standard error value of 0.090 ,0.097and 0.098 respectively.Both Φ_1 and Φ_2 , Φ_3 are statistically significant at the 1% level, indicating strong explanatory power. Residual analysis shows ACF and PACF values within two standard error bounds, suggesting white noise characteristics and validating the model's suitability for representing temperature fluctuations. Further model statistics indicate non-significant autocorrelation among residuals at the 5% level, supporting the SARIMA $(0,0,0) \times (3,1,0)_{12}$ model's adequacy for forecasting maximum temperature fluctuations in Yangon Region from January 2024 to December 2024.

In conclusion, the forecast for 2024 reveals notable seasonal variations and diverse month-to-month temperature patterns compared to 2023, underscoring significant climate variability in Yangon Region, where SARIMA models accurately modeled and forecasted temperature fluctuations from January 2013 to December 2023, demonstrating effectiveness in representing seasonal patterns and interdependencies and validating reliability for temperature forecasting in Yangon Region.

5.2 Suggestions and Recommendations

In accordance with the results, temperature data in Yangon Region from 2013 to 2023 reveals a nuanced understanding of seasonal variations and long-term trends. Implementing the SARIMA $(1,0,0) \times (1,1,1)_{12}$ model for monthly minimum temperature fluctuation predictions, and the SARIMA $(0,0,0) \times (3,1,0)_{12}$ model for monthly maximum temperature fluctuation predictions, alongside regular updates with data and performance comparisons with observed data, can facilitate the detection of pattern alterations necessitating model adjustments. These models have been chosen for strengthen explanatory capabilities, evidenced by significant findings in residual analysis. By applying these models, accurate predictions can be made for temperature changes in Yangon Region from January 2024 to December 2024. It is found that the forecast for 2024 reveals notable seasonal variations and diverse month-to-month temperature patterns compared to 2023, underscoring significant climate variability in Yangon Region

As a consequence, the temperature prediction model is needed to help the authorities to have better preparation in temperature changes. Based on the temperature trends in Yangon Region, stakeholders across environmental, health, economic, and local government sectors should accept strong matches approach to enhance sustainability and resilience. Environmental initiatives must focus on adapting to climate changes by enhancing green infrastructure, promoting energy efficiency, and control water resources while protecting biodiversity from extreme events like heat waves. Health strategies should prioritize preparing for temperature-related risks, including developing strong heat-wave response plans and maintaining alert against vector-borne diseases. Economic sustainability efforts should correspond with seasonal temperature variations, optimizing productivity in tourism and agriculture while managing energy demands effectively throughout the year. Local government plays a crucial role in urban resilience by combing climate forecasts into planning for green spaces, heat-reducing technologies, and sustainable building practices, ensuring the region's adequate and reducing energy consumption. These integrated strategies enable proactive management of resources and risks, it can better manage environmental impacts, support economic sustainability, and foster community resilience in the face of changing climatic conditions in Yangon Region.

5.3 Further Study

This paper on temperature fluctuations in Yangon Region would extremely severe study the structural variations using advanced statistical methods to gain a comprehensive understanding of local climate dynamics influenced by urbanization and land use changes. The analysis would be spanned decades, investigating long-term trends and using advanced models to forecast future climate scenarios accurately. Seasonal decomposition techniques would be applied to uncover repeat again seasonal patterns, while a significant focus would be placed on studying extreme events such as heat waves and various impacts. Utilizing multivariate time series models, the study would be explored the intricate interrelationships among temperature, humidity, and precipitation, particularly emphasizing the role of human activities in shaping local climate change dynamics. By using strong data analytics, the paper aims to enable real-time monitoring capabilities for adaptive responses and early warning systems. Collaboration with health scientists would be enhanced insights into how climate affects vulnerable populations, as a result fostering strategies to enhance climate resilience and sustainability in urban areas.

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APPENDIX

Appendix (A-1) Seasonal Index For Minimum Temperature Fluctuation in Yangon Region (°C)

Year / Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Seasonal Average	Final Seasonal Indexes
January		21.74	21.73	22.13	22.67	21.17	20.53	22.38	22.14	22.13	22.53	21.91	0.79
February		21.56	21.95	22.01	22.69	21.02	20.73	22.42	21.83	22.44	22.53	21.92	0.81
March		21.28	22.20	21.86	22.73	20.85	21.00	22.37	21.80	22.45	22.62	21.92	1.00
April		21.04	22.45	21.85	22.66	20.69	21.24	22.35	21.78	22.48	22.64	21.92	1.08
May		20.95	22.53	21.89	22.51	20.55	21.56	22.26	21.83	22.43	22.69	21.92	1.13
June		20.87	22.53	21.96	22.42	20.30	21.92	22.22	21.88	22.39	22.73	21.92	1.06
July	21.51	21.03	22.52	22.13	22.14	20.28	21.87	22.42	21.76	22.62		21.83	1.08
August	21.53	21.25	22.26	22.48	21.93	20.21	21.96	22.54	21.71	22.53		21.84	1.07
September	21.42	21.33	22.26	22.55	21.75	20.21	22.02	22.60	21.57	22.63		21.83	1.05
October	21.42	21.48	22.28	22.51	21.65	20.14	22.20	22.62	21.64	22.57		21.85	1.06
November	21.58	21.49	22.30	22.53	21.53	20.09	22.40	22.48	21.80	22.53		21.87	0.99
December	21.68	21.59	22.24	22.61	21.36	20.27	22.43	22.33	21.90	22.55		21.90	0.88
Total													**12.00**

Appendix (A-1) Seasonal Index For Maximum Temperature Fluctuation in Yangon Region (°C)

Year / Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Seasonal Average	Final Seasonal Indexes
January		33.36	33.88	33.71	33.25	33.08	33.72	33.90	33.90	33.56	33.69	33.60	0.96
February		33.41	33.93	33.72	33.11	33.06	33.78	34.00	33.84	33.61	33.68	33.61	1.03
March		33.43	33.94	33.63	33.15	33.02	33.78	34.12	33.91	33.50	33.77	33.62	1.11
April		33.48	33.97	33.61	33.18	32.99	33.78	34.13	33.83	33.54	33.77	33.63	1.13
May		33.57	33.87	33.60	33.14	33.08	33.89	33.91	33.89	33.60	33.70	33.62	1.10
June		33.51	33.92	33.46	33.21	33.13	33.86	33.96	33.93	33.50	33.79	33.63	0.95
July	33.50	33.75	33.88	33.48	33.08	33.23	33.79	34.06	33.89	33.48		33.61	0.93
August	33.47	33.78	33.78	33.59	33.03	33.22	33.89	34.03	33.91	33.41		33.61	0.92
September	33.28	33.83	33.73	33.63	33.00	33.33	33.83	34.06	33.87	33.43		33.60	0.95
October	33.31	33.86	33.65	33.63	32.98	33.37	33.86	34.14	33.75	33.41		33.59	0.97
November	33.27	33.86	33.66	33.45	33.09	33.58	33.78	33.90	33.84	33.52		33.59	0.99
December	33.30	33.86	33.76	33.28	33.11	33.65	33.87	33.88	33.59	33.73		33.60	0.96
Total													**12.00**