STUDY OF CLIMATE CHANGE EFFECTS ON RAIN HEIGHT FOR SATELLITE MICROWAVE LINKS

YONG XIN YU

UNIVERSITI TUNKU ABDUL RAHMAN

STUDY OF CLIMATE CHANGE EFFECTS ON RAIN HEIGHT FOR SATELLITE MICROWAVE LINKS

YONG XIN YU

A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Electrical and Electronic Engineering with Honours

Lee Kong Chian Faculty of Engineering and Science
Universiti Tunku Abdul Rahman

May 2024

DECLARATION

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

Signature :

Name : Yong Xin Yu

ID No. : 19UEB03733

Date : 15 May 2024

APPROVAL FOR SUBMISSION

I certify that this project report entitled **"STUDY OF CLIMATE CHANGE EFFECTS ON RAIN HEIGHT FOR SATELLITE MICROWAVE LINKS"** was prepared by **YONG XIN YU** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Electrical and Electronic Engineering with Honours at Universiti Tunku Abdul Rahman.

Approved by,

Signature : ____________________

Supervisor : Hafiz Basarudin

Date : 16/05/2024

Signature : ____________________

Co-Supervisor : ____________________

Date : ____________________

ACKNOWLEDGEMENTS

I would like to thank everyone who had contributed to the successful completion of this project. I would like to express my gratitude to my research supervisor, Dr. Hafiz bin Basarudin for his invaluable advice, guidance and his enormous patience throughout the development of the research.

In addition, I would also like to express my gratitude to my loving parents and friends who had helped and given me encouragement and moral support whenever I am working on my final year project.

ABSTRACT

In this research paper, the study of climate change effects on rain height for satellite microwave links in Malaysia is being conducted. Rain height is one of the important variables in determining the effective slant path for signal transmission of satellite communication systems. When the height of the rainfall increases, the length of the slant path increases which causes the signal being attenuated by the raindrops increase. Since the rain height is widely depends on the global surface temperature, the issues of climate change might cause effects on the rain height. Data being used in this research are obtained from NCEP/NCAR reanalysis database which including the reanalysis data for altitude and temperature. Furthermore, the ITU-R recommendation method such as ITU-R P.839 and ITU-R P.618 recommendation model had been adopted in obtaining the rain height values as well as the rain attenuation values respectively. Then, a simple AI predictive model for rain height is being developed by using Artificial Neural Network (ANN) algorithms with Python programming language. The rain height value is found to have a positive correlation with the global temperatures and both of them have a significant increase throughout the past 30 years in Malaysia. This rain attenuation also proved to have an increasing trend. Lastly, an AI predictive model with Artificial Neural Network (ANN) algorithms that have the good performance and acceptable accuracy in predicting the future rain height values had been developed. This can provide accurate data for future design work of satellite-based communication systems.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS / ABBREVIATIONS

p	probability of exceedance
γ_R	specific attenuation, dB/km
k	coefficient of horizontal polarization or vertical polarization
R	rain rate, mm/h
α	coefficient of vertical polarization or horizontal polarization
d_{eff}	effective path length, km
d	actual path length, km
r	distance factor
$R_{0.01}$	point rainfall rate for the location for 0.01% of an average year, mm/h
h_s	height above mean sea level of the earth station, km
φ	latitude of the earth station, degrees
R_e	effective radius of the Earth, km
θ	elevation angle, degrees
A_s	attenuation along the slant path
D	rain cell diameter, km
L	horizontal projection
L_s	slant path length
γ_p	specific attenuation
k_n	number of rain cells involved

ZDI	zero-degree isotherm
ITU-R	International Telecommunication Union Radiocommunication Sector
TRMM	Tropical Rainfall Measuring Mission
AI	Artificial Intelligence
ANN	Artificial Neural Network
MSE	mean squared error
MAE	mean absolute error
R^2	r-squared score

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 General Introduction

In this modern era, telecommunication technology is the necessary part for transferring of data, sharing of information and communication (Jessica, 2023). In general, there are two ways for telecommunication networks to transmit information which are by using the cable or wireless channel. Since wireless channels do not need laying of cables, the cost effectiveness is higher which causes the rapidly growth of wireless communication in telecommunication field. Most of the rural and remote areas are depending on the wireless communication since it is more affordable.

Among the types of wireless communications networks, satellite communications services play an important role in telecommunication field (Hafiz, et al., 2016). Satellite communications operate by transmitting the signal from ground station to the artificial satellite and retransmit the amplified signal back to the Earth (Labrador, 2023). High frequency signals are used in satellite communication which is normally at Ka and Ku band of frequency range. Ku band is at the frequency range of 12 - 18 GHz and Ka band is at 26.5 - 40 GHz (Marine Satellite Systems, 2012). A satellite microwave links normally included multiple components such as ground station, satellite, and others as shown in Figure 1.1.

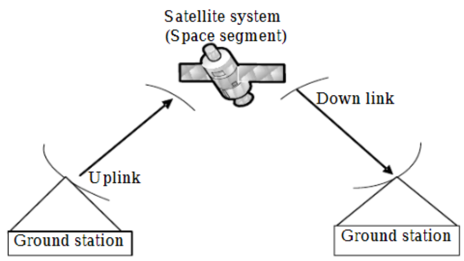

Figure 1.1: Picture of Ground Station and Satellite (Ukommi, et al., 2022).

Due to the high demand of wireless communication for satellite microwave links, the stability and performance of wireless transmission systems should be maintained as stable as possible. Since the signal wave is transmitted at high frequency in the atmosphere, the signal will distort more severe by rain precipitation (Albendag and Zain, 2020). The attenuation of the signal that caused by the rain precipitation is known as rain attenuation which may affect the performance of the satellite communication system. For satellite, the magnitude of rain attenuation is mostly relied on the rain height, intensity of rain, frequency and other factors.

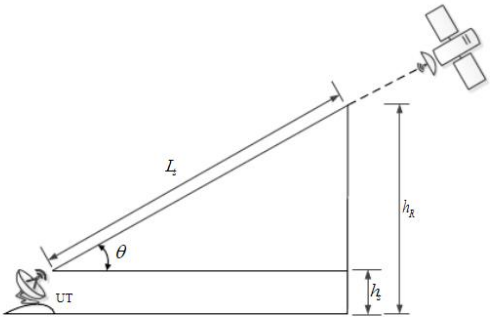

Figure 1.2: Geometry of the Satellite Microwave Links (Gharanjik, et al., 2018).

As shown in Figure 1.2, the propagation path of the signal wave for satellite microwave links is measured between the ground station and the rain height, h_R. This path is known as the slant path, L_S. Within the slant path, the signal wave will have the possibility to attenuate due to the rain events. When the rain height is longer, the slant path length increases which causes the magnitude of the rain attenuation increase since the area of the path being affected by raindrops is larger. Furthermore, the rain attenuation will increase when the rain rate as well as the operating frequency is higher.

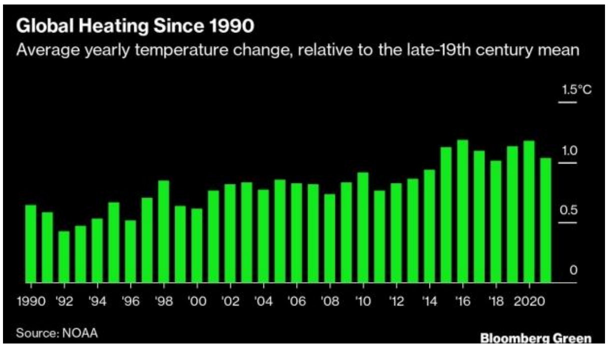

Figure 1.3: Graph of Global Heating Temperature since Year 1990 (Roston, 2023).

Furthermore, as shown in Figure 1.3, due to climate change issues, the global heating temperature increases which causes the world to become warmer and thus result in increasing of rain height (Paulson, 2011). Other than the temperature, climate change had caused the increase of occurrence for extreme rain that increase the intensity of rainfall rate which affecting the magnitude of rain height and rain attenuation (Marzuki, et al., 2018).

Recently, there are multiple empirical models being used to predict the value of rain height. For example, International Telecommunication Union (ITU) had proposed a recommendation model in estimating the value of rain height. Based on ITU-R P.839 recommendation model, the mean annual freezing level height above the mean sea level, h_0 is provided in terms of a digital map and the fixed mean value of rain height, h_R can be obtained as 360 meters above the zero-degree Celsius isotherm height, h_0 (Benarroch, et al., 2022). However, due to the high rainfall rate in tropics and the effects of climate change issues, the fixed value of rain height obtained from ITU-R model is not accurate since it assumes a static climate for the whole region (Paulson, 2011).

Therefore, in this research, the relationship between rain height and climate change will be investigated. A more accurate rain height model that associated with the geographic location and temperature parameters will be developed. Other than that, an Artificial Intelligence (AI) prediction model for rain height will be deployed.

1.2 Importance of the Study

According to Hendri, et al. (2023), climate change has become a serious environmental issue that cause the variations of global temperature and precipitation patterns. The precipitation patterns may vary in terms of the rain height and the rain rate. By understanding the climate change effects on the rainfall patterns, the prediction for the rain attenuation will be more precise and accurate. Due to the temperature level for each region in the world is different, a rain height model that included the effects of climate change which can specify different longitude and latitude of the region is useful in determining the precipitation patterns in different region more specifically. Furthermore, although the ITU-R model can provide accurate results in estimating the statistics for rainfall in subtropical countries, but its accuracy in estimating the rainfall statistics for tropics is lower due to the rainfall in tropics are varying in terms of time as well as the location (Marzuki, et al., 2018). Therefore, the findings that obtained from this study is mainly focusing on the tropical countries. Moreover, this study is estimating the rainfall statistics with the duration of 30 years which is the minimum years needed for climate study.

By knowing how the rainfall height patterns being affected by climate change, the effects on satellite-based communication systems can also be analyse. The predicted value of the rain height can be used to determine the effective slant path for the microwave satellite links which then used as an important parameter to estimate the rain attenuation. This can help to ensure the systems are able to provide reliable and robust communication services despite of climate change. Besides, instead of using the historical data or an assumed static data, a rain height model that are using the real-time data such as NCEP/NCAR reanalysis data can provide a more accurate predicted value for rain attenuation. By using the real-time data, a more detailed and accurate data can be obtained for research purposes and the design work of satellite-based communications systems. The occurrence of the most severe rain attenuation can also be investigated based on the real-time data being used in the rain height model.

1.3 Problem Statement

In the process of transmitting the data through telecommunication channels, the strength of the signals might loss due to external factors. The attenuation of the signals become more significant at high frequencies which is mainly caused by hydrometeors such as rain and clouds. The signals that being transmitted through satellite-earth communication system suffered more losses that caused by rain since the satellite communications operate at high frequencies (Hassan, et al., 2011). When more severe rain attenuation happened, the extreme condition will cause a complete loss of signal.

Rain attenuation become a severe issue especially in tropical countries such as Malaysia since the yearly precipitation of the countries in tropics is higher. To predict the effective slant path length for the satellite microwave links, there are many models being used such as ITU-R model, Bryant model and Stutzman model to estimate the rain height since rain height is one of the dominant factors which affects the amount of rain attenuation (Ali et al., 2014). However, the research results for these models to estimate the rain height were not up to date and do not take considerations on the effects of climate change. Without accurate estimating values of the rain height, the fade mitigation techniques (FMTs) will not be efficient in reducing the fading of signal for satellite microwave links.

In this research, the effects of climate change on the rain height will be investigated and a simple prediction model for predicting the rain height will be deployed. The data being used in this research is based on the reanalysis data of air temperature and geopotential height at different pressure level that obtained from NCEP/NCAR reanalysis data. Therefore, a new model that can obtain more accurate results for rain height enable the engineer to assign the fade margin which is needed to be built in for reducing the attenuation of signals in satellite-Earth communications and improve the performance of the satellite links.

1.4 Aim and Objectives

This project targets to build a rain height model associated with climate change model to study the effects of climate change on rain height. A better understanding of how climate change will alter the rainfall height and how these rain height patterns affected the magnitude of rain attenuation are expected after completing this project. The objectives of the project are listed as shown below.

(i) To obtain the rain height by using the NCEP/NCAR reanalysis data.

(ii) To study the relationship between climate change and the rain height in Malaysia.

(iii) To simulate the rain attenuation model for satellite links with the input of rain height values obtained in this project.

(iv) To deploy an Artificial Intelligence (AI) predictive model in predicting the rain height for rain attenuation estimation in designing the application for satellite microwave links.

1.5 Scope and Limitation of the Study

The scope of this project is to develop a rain height model that including the climate change model by using the simulation software. The rain height model is using the real time data that are obtained from the database of NCEP/NCAR reanalysis data. In this project, the location being chosen for analysis is Malaysia which is one of the tropical regions. After the rain height model is being developed, the effects of climate change on rain height of satellite microwave links are being investigate. Prediction model that forecast the rainfall height will then be developed by using simple Artificial Intelligence (AI) algorithms.

One of the limitations of this project is that the developed model is mainly depending on the data collected in Malaysia. This might cause the results obtained from this project is not applicable to other region such as temperate regions. Next, since NCEP/NCAR reanalysis data only provided data that starts from year 1979 to recent year, therefore this project is developing the rain height model over 30 years which is from year 1992 to year 2022. Other than that, choosing thirty years as the period for the observation of the data is sufficient to analyse the effects of climate change since the climate change issues is becoming more severe in past few years which is in the late-19th century.

After that, another limitation is that the NCEP/NCAR reanalysis data are being sampled for every 6 hours. This sample size might consider precise enough. However, with a smaller sampled time, the data will be more accurate. Furthermore, Google Colaboratory has limited runtime for free accounts. The progress of the model's training will be automatically terminated if the user does not perform any interaction more than 90 minutes (Kanjee, 2021). This will cause an issue when the model is needed to be train for overnights or for many days.

1.6 Contribution of the Study

This study has investigated the effects of climate change on rain height and provided a more accurate estimated values for rain height in Malaysia which is one of the tropical regions. The results obtained by the study serves as an important parameter which helps in deploying a more accurate fade margin model in predicting and mitigating the rain attenuation. This allows the satellite system designers to perform a better planning and design for the satellite system which can reduce the effects of rain attenuation more efficiently. This can ensure a better performance and quality of the satellite communications systems.

1.7 Outline of the Report

The outline of the report consists of total five chapters which as shown below:

Chapter 1: Introduction

(i) Provide an introduction about satellite communication systems, rain attenuation and rain height.
(ii) Discuss about the importance and contribution of the study.
(iii) State the problem statements, objectives of the project and the scope as well as the limitations of the study.

Chapter 2: Literature Review

(i) Review about the issues of climate change and rain attenuation.
(ii) Explain about the concept of rain height, freezing level height and rain rate.
(iii) Discuss about the different types of rain attenuation prediction models and techniques.
(iv) Explore the concept and working of AI predictive model.

Chapter 3: Methodology and Work Plan

(i) Make planning for the project and the overall workflow.
(ii) Discuss about all the software being used in this project and methodology of the project.
(iii) Discuss about the steps being taken to obtain the results for the project.

Chapter 4: Results and Discussion

(i) Display all the results obtained for this project.

(ii) Discuss and analyse the results obtained concisely.

(iii) Discuss about the accuracy of the AI prediction model developed in this project.

Chapter 5: Conclusion and Recommendation

(i) Conclude and summarize the findings of the project.

(ii) Suggest recommendations for future work to improve the project.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, climate change issues will be reviewed to understand the effects of climate change to the world. Then, the concept of rain attenuation on satellite communications networks will be emphasized. Besides, literatures that discuss about the relationship between rain height and magnitude of signal attenuation on satellite microwave links had been reviewed. Furthermore, several models that are currently being used to estimate the rain attenuation in the industry were also being reviewed to have a deep understanding on the theory that applied in these models. After that, the working of an Artificial Intelligence (AI) predictive model will be discussed comprehensively and including the concept for different method of AI predictive modelling techniques.

2.2 Issues of Climate Change

According to NASA (n.d.), the climate change issues have become more serious due to the increment of greenhouse gases emissions that causes the heat trapping in the environment. The global temperature had an obvious rise about one degree Celsius from 1901 to 2020 (National Oceanic and Atmospheric Administration, 2021). Although there is only around one-degree Celsius increase in the global average surface temperature, but it causes a notable increase in accumulated temperature unit, ATU (Lindsey and Dahlman, 2024). As shown in Figure 2.1, the global average temperature had a significant increase from year 1880 to year 2023.

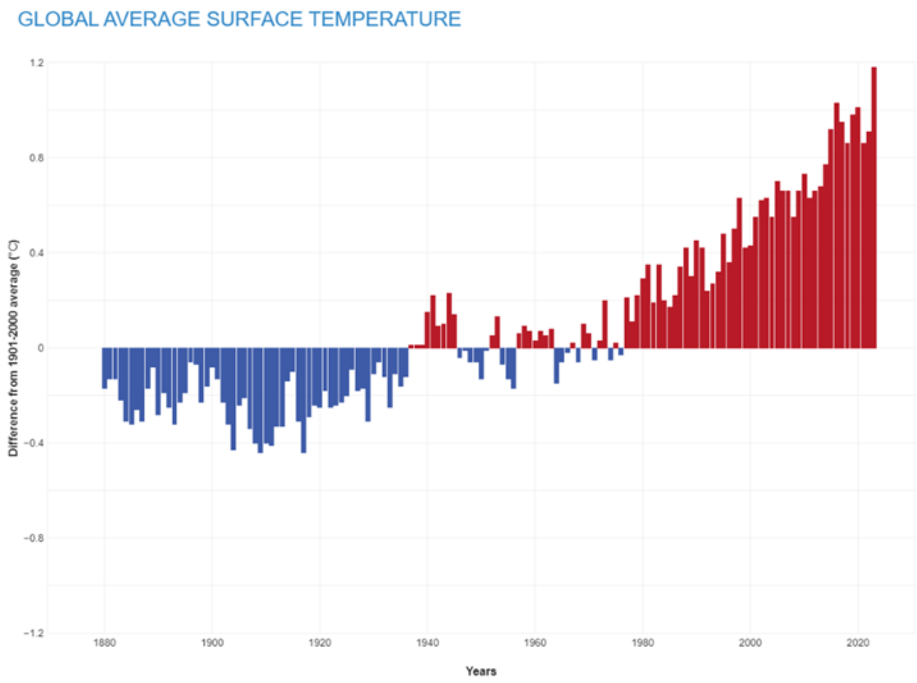

Figure 2.1: Yearly Global Average Surface Temperature from Year 1880 to Year 2023 (Lindsey and Dahlman, 2024).

Climate change not only affecting the global temperature but also affecting the weather which causes frequent extreme weather events such as droughts, wildfires, floods and unpredictable fluctuations in rainfall patterns (Bolan, et al., 2024). Due to climate change, the precipitation changes in terms of frequency and its intensity (United States Environmental Protection Agency, 2023). When the air temperature become warm, more water evaporates into the air which causes the intensity of precipitation increases. With increasing in global temperature, the hydrological cycle become more active due to the change of atmospheric circulation (Mohammed, 2005). Besides, the water-holding capacity increases by 7% for every 1 degree Celsius of increasing in global temperature (Trenberth, 2011). In tropics regions, the precipitation extremes are more sensitive to the climate change as compared to extratropic (Gorman, 2015). Furthermore, Gorman (2015) states that when the carbon dioxide concentration increases in the atmosphere, the heavy rain occurred more frequently. When the precipitation patterns changes, the rain height and rain rate parameters will vary.

2.3 Rain Attenuation

Rain attenuation is the phenomenon of electromagnetic wave being attenuated due to the rainfall. The attenuation of the signal wave is mainly depending on the rainfall rate, the slant path distance and the operating frequency level of the signal (Mukesh, et al., 2014). When the signal wave is transmitted at a higher operating frequency, rain attenuation will be more severe. A complete loss of signal may happen when there are large losses of signal due to rain attenuation (Hafiz, et al., 2016). According to Nazar, et al. (2005), the attenuation of the signal that caused by the rainfall has a significant effect at the frequencies of signal above 10 GHz which is the operating frequencies for satellite microwave links. Due to the rain attenuation, the losses of signals that travel between the path of Earth-satellite communications will increase and the coverage area of the signal path is limited which causes the reliability and the performance of the satellite communications systems degraded (Mukesh, et al., 2014).

The attenuation of the electromagnetic (EM) wave signal is normally caused by the absorption and the scattering of the wave during the rain. Absorption of the electromagnetic wave energy will be formed due to the damping effect that happen from the interaction between the rainwater particle then the attenuation of the EM wave will increase when the wavelength of the Ka-band is nearly the same to the diameter of the raindrops (Zhang, et al., 2017). Furthermore, rain height is another dominant aspect that will affects the magnitude of rain attenuation. The higher the rain height, the larger the magnitude of rain attenuation since the slant path among the satellite and the ground station will be longer (Hafiz, et al., 2016). Besides that, when rain rate increases, the attenuation of the signal transmitted at satellite microwave links will increase. The magnitude of rain attenuation is mainly depending on the slant path length among the satellite and ground station on Earth that passing through the rain (Paulson and Al-Mreri, 2011).

2.4 Rain Height and Zero-Degree Isotherm Height (ZDI)

Rain height is one of the most important parameters that being used by researchers to estimate the attenuation of rain. Hafiz, et al. (2016) states that rain height is the distance that measured from the ground surface to the atmosphere level where melting of ice particles started and raindrops are then formed. Rain height is also described as the level where the diameter of the raindrops is larger than 0.1 mm during rainfall (Ojo, et al., 2014). Rain height is considered as a function for multiple parameters such as temperature (Yusuf, et al., 2021). This means that the rain height is depends on these parameters. For example, when the atmospheric temperature changes, the rain height will be affected since the temperature is different due to climate change.

Next, zero-degree isotherm (ZDI) is also known as the freezing level height in which the temperature at this height is zero-degree Celsius. According to ITU-R P.839-4 (2013), the average rain height per year is predicted to be at 360 m above the freezing level. This shows that the rain height is at a temperature below the freezing point. This is because the rainwater exists as supercooled water droplets which can remain in liquid form at the temperature below the freezing point (Clayton, 2023). The ZDI height can be determined by using the linear interpolation method between the smallest temperature-height points with increase of altitude (Paulson and Al-Mreri, 2011).

2.5 Rain Rate

Rain rate is defined as the intensity of rain per unit of time and it is an important parameter in predicting the attenuation of rain. The rainfall rate is measured in the unit of mm/h. According to World Meteorological Organization, the intensity of rain is normally categorized into four categories which is shown in Table 2.1.

Table 2.1: Categories of Rain Rate (Marsico et al., 2021).

Rain Rate Category	**Rain intensity (mm/h)**
Light	less than 2.5
Moderate	2.6 ~ 7.5
Heavy	7.6 ~ 50
Violent	more than 50

The intensity of rain can be measured by using the tipping bucket rain gauges, disdrometer and weather radar (Gires, 2018). For example, the tipping bucket rain gauge operates by counting the amount of water that entered the rain gauge funnel in terms of pulses per time (Syahrul, 2017). The function of the rain gauge is to determine the rain rate for a particular location. Next, disdrometer is a device that being used to continuously measure the size distribution of the raindrop and the speed of the rainfall (Sinclair and Weigel, 2020).

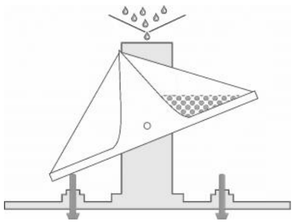

Figure 2.2: Tipping Bucket Rain Gauge (Erbakanov, et al., 2018).

2.6 Rain Attenuation Prediction Model

Due to the significant impact of rain attenuation on the performance of Earth-satellite communications systems, the estimation of rain attenuation is important for the design of reliable communication systems for satellite-microwave links. There are multiple prediction models being applied to evaluate the rain attenuation for the development of rain fade counter-measure algorithms (Hassan, et al., 2011).

There are two categories of prediction model for rain attenuation which are the empirical models and physical models. Empirical models are using the statistical data from the past measurement to analyze the mathematical relationships between those parameters to predict the rain fade margin (Yeo, et al., 2014). While physical models are more depends on the physical characteristics of rain such as the total power absorbed and scattered by a rainwater droplet (Tan, et al., 2021). Both categories of prediction models have its own advantages and disadvantages. The empirical model has simpler mathematical expressions and it is less costly as compared to physical model. Although the physical model needs a longer time and more complex set up of experiment, but it can obtain a more accurate results as compared to empirical model.

2.7 ITU-R Recommendations Model

ITU-R is the International Telecommunication Union Radiocommunication Sector. This is one of the sectors in ITU which is mainly responsible for developing the standards for the radiocommunication systems (RF Editorial Team, 2021). This sector also ensures that the radio frequency spectrums are being utilized in an efficient way by all radiocommunication services around the world (RF Editorial Team, 2021). Furthermore, it also provides various of recommendation models for the development of high performance radiocommunication systems. Those ITU-R recommendation models that are related to this project will be reviewed in the following subchapters.

2.7.1 ITU-R P.839 Recommendation Model

ITU-R P.839 Recommendation Model provides the prediction method for rain height for the use of propagation prediction. This model is assuming the mean annual rain height is 360 m higher than the freezing height level. The ZDI height is considered as the essential part in this recommendation model. However, this prediction model for rain height is updated until year 2013 which is not the latest data. Besides, this recommendation model is initially fixing an assumed value for the rain height in different regions that is needed for the prediction of the rain fade (Olurotimi, et al., 2017). The estimated value for the freezing height level at Malaysia is 4.5 km from assumption made by ITU-R P.839 recommendation model. This make the rain height data being used for prediction of rain attenuation become inaccurate since the rain height value provided is a static value. Other than that, this recommendation model does not include the climate change model for prediction of rain height.

Figure 2.3 is showing the digital global map for this recommendation model. It is showing the mean annual zero-degree isotherm height above the mean sea level in kilometer with respect to different latitude and longitude.

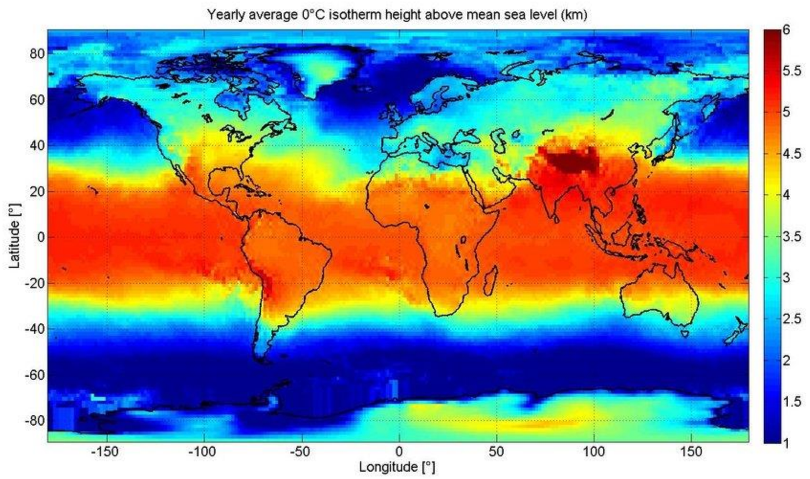

Figure 2.3: Freezing Level Height for ITU-R P.839 (Claudia, et al., 2021).

2.7.2 ITU-R P.837 Recommendation Model

ITU-R P.837 Recommendation Model is a model that discussed about the characteristics of precipitation for prediction of propagation for radio signals. It provides the method to compute the statistics for rain rate with the integration of one minute for the estimation of rain attenuation for terrestrial links and satellite links. Since a long integration time for rain rate has the higher chances to get failure when capturing the high intensity and short durations of rain, therefore, all calculations for rainfall are applying the integration time of one minute (Mohanty, et al., 2016). The parameters that needed for this rain rate prediction model are the annual probability of exceedance (p), latitude and longitude for specific locations. The unit of rain rate that can be obtained by using this model is in mm/h.

This recommendation model provides the global digital map that indicate the annual data for intensity of rainfall rate that exceeded 0.01% in each region. By providing the latitude and longitude data, the respective rainfall rate that exceeded 0.01% of the average year for specific region can be obtained from the global digital map in Figure 2.4. The 0.01% of the average year is approximately equal to 20 minutes in a year. The data being used by this ITU-R P.837 Recommendation Model are from the GPCC Climatology database and European Centre of Medium-range Weather Forecast (ECMWF) data (ITU-R P.837-7, 2017). Due to the data being used by this model is historical data and the newest updated result from this model is until year 2017, therefore, this model did not provide the latest data for research work. Furthermore, another weak point of this recommendation model is that the spatial resolution is low which is only 1.125° × 1.125° for the latitude/longitude grid (Singh and Acharya, 2018). This caused the information derived from the digital global map is not precise on the specific region of precipitation field.

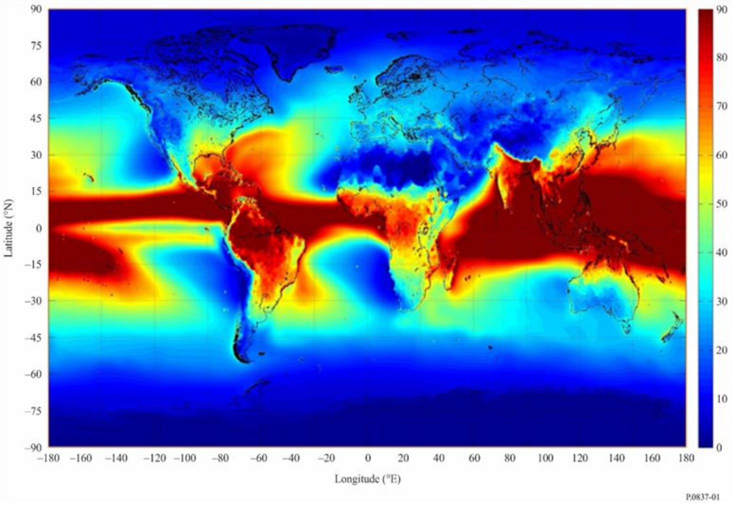

Figure 2.4: Global Map that Visualized the Rainfall Rate which exceeded 0.01% Annually (ITU-R P.837-7, 2017).

2.7.3 ITU-R P.838 Recommendation Model

ITU-R P.838 Recommendation Model provided the method to obtain specific attenuation for rain by using the rain rate data. Specific attenuation has a considerable impact on the propagation of radio wave in the millimeter-wave band (Riera, et al., 2023). This mm-wave band is defined as the frequency level in the range of 30 - 300 GHz with a wavelength among 1 to 10 mm in the air (Everything RF, 2023). This model is using the rain rate data, R in the unit of mm/h to obtain the specific attenuation γ_R (dB/km).

$$\gamma_R = kR^{\alpha} \tag{2.1}$$

where

R = rain rate, mm/h

γ_R = specific attenuation, dB/km

From Equation 2.1, the specific attenuation, γ_R is proportional to the rain rate, R which show that when the rain rate is high, the specific attenuation will rise. The regression coefficients which are k and α are the functions of drop size distribution of rain, frequency and the radio wave's polarization (Ulaganathen, et al., 2018). The rain attenuation can be obtained by integrating the specific attenuation value along the link of path (Riera, et al., 2023).

2.7.4 ITU-R P.530 Recommendation Model

ITU-R P.530 Recommendation Model provided the prediction methods for rain attenuation that should be considered in the design of link-to-link terrestrial communication systems. This prediction method required the rain rate parameters with the one-minute integration time. This parameter can be acquired by using the estimation given in ITU-R P.837 Recommendation Model or data collected from rain gauge. By referring to ITU-R P.530, (2021), the effective slant path length of the terrestrial communication systems can be calculated using the Equation 2.2 as shown below. While the distance factor can be calculated by using the Equation 2.3 as shown below.

$$d_{eff} = dr \tag{2.2}$$

where

d_{eff} = effective slant path length, km

d = actual path length, km

r = distance factor

$$r = \frac{1}{0.477 d^{0.633} R_{0.01}^{0.073\alpha} f^{0.123} - 10.579(1 - e^{-0.024d})} \tag{2.3}$$

where

f = frequency, GHz

α = exponent obtained from the specific attenuation model

$R_{0.01}$ = rain rate that exceeded for 0.01% of time, mm/h

Then, the method for estimation of the rain attenuation that exceeded 0.01% of the time being used in this model is calculated by obtaining the products between the specific attenuation with the effective slant path length of the terrestrial communication system. The estimation of the attenuation that exceeded for 0.01% of the time can be computed by utilizing the Equation 2.4.

$$A_{0.01} = \gamma_R dr = \gamma_R d_{eff} \qquad (2.4)$$

where

$A_{0.01}$ = Path attenuation exceeded for 0.01% of time, dB

2.7.5 ITU-R P.618 Recommendation Model

ITU-R P.618 Recommendation Model showed how the data of propagation and prediction methods being used in the design of satellite-based communication systems. When designing the Earth-satellite telecommunication systems, propagation loss of the data through the transmission path between Earth and satellite should be take into consideration. The propagation loss may be due to the attenuation by hydrometeors, atmospheric gases, focusing and defocusing issues, wave-front incoherence and others (ITU-R P.618-13, 2017). This recommendation is mainly focused on the attenuation due to the precipitation which is normally become a severe issue for frequency above 10 GHz.

The prediction method for long-term attenuation by precipitations and clouds' statistics is being presented in this recommendation model. This prediction method calculates the attenuation which at 0.01% exceedance of an average year in Decibel (Foo, 2019). A good system needs to have 99.99% of the reliability, therefore rain attenuation that exceeded 0.01% is being examined (Alui, 2012). The parameters that are required for this prediction model are the point rainfall rate for 0.01% ($R_{0.01}$), the height above average sea level for the ground station (h_s), the latitude of the ground station in degrees (φ), frequency, Earth's effective radius (R_e) which is around 8500 km and the elevation angle (θ). The figure below shows the schematic of the path between Earth and space with the input parameters.

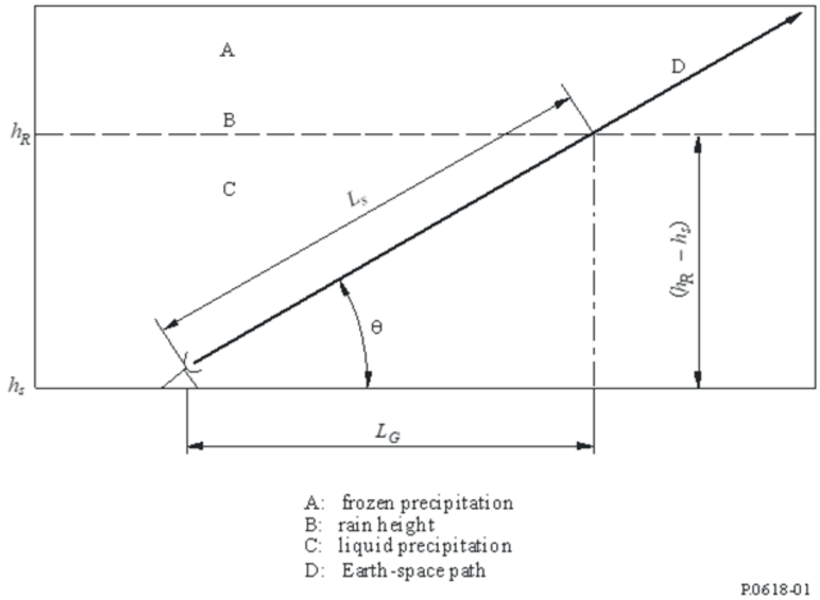

Figure 2.5: Schematic of Earth-Space Path for Attenuation Prediction Process (ITU-R P.618-13, 2017).

Furthermore, the computation method for the probability of rain attenuation on the slant path is shown in this recommendation model. The parameters needed for this computation method are the probability of rain at earth station per year, the elevation angle and the slant path length between the height of the rain and the ground station (ITU-R P.618-13, 2017). However, the data being used for ITU-R model are old or historical data which causes the rain attenuation data obtained by using this model is not update to current situation. Besides, this ITU-R model is said to be underestimate for rain attenuation in tropical region since it is mainly built by using the measurements data from the country that have temperate climate (Yeo, et al., 2014).

2.8 Crane Model

Crane Model is a model that provide the prediction for the slant path's attenuation exceedance (Yusuf, et al., 2014). Geophysical data are being used in this model to determine the surface point rain rate, the dependency of attenuation on height and the point-to-path variations in rain rate (Muhammad Rezza, 2012). The rain climate region that obtained by using Crane's Global Model is used to determine the climate zone for different geographical locations and the distribution values of the rain rate can be obtained by the Global Crane rain rate distribution's table for specific rain climate zone region (Muhammad Rezza, 2012). Then, the Crane Model is basically depending on the measurements of atmospheric rain rate and variation of temperature in atmosphere (Monga, et al., 2022). According to research done by Monga, et al. (2022), the ITU-R model is being proved to have a better performance as compared to Crane Model. ITU-R model can provide an improvement of signal attenuation results by 7% and 36% at low and high frequencies respectively as compared to Crane Model.

2.9 Singh Model

Singh Model is considered as the modified model of ITU-R model. This model is developed by utilizing the cumulative distribution of the rain attenuation for tropics. The cumulative distribution for the rain fade is calculated by applying the full set of rain rate's cumulative distribution and the length of the horizontal path (Singh, et al., 2006). This model is more suitable for tropical region since the input parameters being used by this model are taken from the measurement site that located at tropical region. For example, the horizontal projection of the slant path will be adjusted according to the rain height, elevation angle of the Earth station, rate of rainfall and the reduction factor for the measurement site at tropical region (Singh, et al., 2006). This model is proved to perform better than ITU-R model in tropical regions and for application of different elevation angles of antenna. However, the data being used by this model are static data and this model does not include the climate change model.

2.10 Bryant Model

Bryant model is a model that utilizes the idea of variable rain height and effective rain cell to obtain the distribution of rain attenuation at the desired location (Mandeep, 2009). The input parameters that are required by this model are the intensity of rain, rain height and the angle of elevation at the antenna. The capable frequency range for this model is the frequency level larger than 15 GHz. This model is applicable to temperate region as well as tropical region and is valid for high Earth station's elevation angle

(Chakraborty, et al., 2020). For Bryant model, the expression being used for computation of rain attenuation along the slant path is shown in below.

$$A_s = 1.57 D_m k_n \gamma_p \frac{L_S}{\xi L + D} \tag{2.5}$$

where

D = rain cell diameter

L = horizontal projection

L_S = slant path length,km

γ_p = specific attenuation, dB/km

k_n = number of rain cell involved

Yussuff and Kasali, (2018) claims that Bryant model performs better when the percentage probability, p is lesser or equal to 0.01% of exceedance. This model is more suitable to estimate the rain attenuation at Ku-band as compared to at Ka-band (Igwe, et al., 2019).

2.11 Tropical Rainfall Measuring Mission (TRMM)

Tropical Rainfall Measuring Mission (TRMM) is aiming to measure the rainfall mainly at tropical and subtropical regions by using the rain radar system and sensors that operate in the microwave as well as visible infrared spectrums (Graham, 1999).

Figure 2.6: Earth-Observation Satellite for TRMM Project (Platnick, et al., 2015).

TRMM satellite precipitation radar is considered as one of the popular instruments in estimating the rainfall height mostly in tropical regions (Nor Azlan, et al., 2011). TRMM satellites will fly over each position on the Earth surface daily at different local time by following its orbit ranges (Graham, 1999). The main radar system being used for TRMM is the precipitation radar. This radar system will detect the bright-band height that eventually gives the highest level of reflectivity to the radar system (Foo, 2019). By determining the bright-band height, the zero-degree isotherm (ZDI) level can be known since both are normally lie close to each other (Nor Azlan, et al., 2011).

The TRMM radar normally analysed during the stratiform rain event yearly due to the present of bright band during stratiform. By comparing the results obtained from TRMM with the ITU-R P.839 Recommendation Model, it shows the ZDI height in Malaysia is much higher than 4.5 km which is the assumed value of ZDI height made by ITU-R P.839 Recommendation Model (Nor Azlan, et al., 2011). However, due to fuel of the satellite had been used up completely, the TRMM project had ended in year 2015 (NASA, 2015).

2.12 Artificial Intelligence (AI) Predictive Model

Predictive modelling is defined as a statistical method that utilizing the machine learning and data analysis on past and existing data to predict the future outcomes (Ali, 2020). There are multiple predictive modelling techniques and algorithms available in machine learning. For example, regression, classification, artificial neural network, clustering, time series, decision tree and ensemble. The selection of the predictive modelling techniques is depending on the types of data and what type of prediction needed to be done (Abdullahi, 2024). Accuracy of the predictive model will be higher if a suitable technique is being chosen. By developing a mathematical model that able to capture and analyse the relationship between the variables, predictive models can estimate the future trends, events and behaviours (Kothari, 2023).

2.12.1 Regression Analysis for Predictive Modelling

One of the most used methods for predictive modelling is regression analysis. Regression model is the statistical method that used for determining the value of the dependent variable according to one or more independent variables and analysing the relationship between the variables (Ogunleye, 2022). There are different variety of regression techniques such as linear, polynomial and logistic regression. The linear regression is being applied to establish a linear relationship between the dependent and independent variables (Anjanakrishnan, 2023). Then, polynomial regression is establishing the curvilinear relationship between the variables (Ostertagová, 2012).

Furthermore, logistic regression is an algorithm that performs the binary classification works by providing the probability of the outcome (Kanade, 2022). There are only two possible outcomes for logistic regression since this model provides a binary output. Regression model normally being used for forecasting the continuous outcomes and plotting for a best fit line along the data points. In general, the regression model being used is the linear regression which assume the linear relationship between the target variable and the predictor variables.

2.12.2 Artificial Neural Network (ANN) for Predictive Modelling

Artificial neural network (ANN) is an algorithm that inspired by the human brain structure which consists of multiple layers of neurons interconnected together and using the mathematical operations to process the data in parallel (Agbemenou, et al., 2023). ANNs play significant role in wide range of applications such as social media, facial recognition, aerospace industry, weather forecasting, healthcare and others (Muzammil, 2023). The layered structure of ANN is composed of mainly three layers which are the input layer, few numbers of hidden layers and the output layer. Then, the amount of input and output variables are same as the amount of neurons in the input and output layers for ANN while the number of neurons in hidden layers are determined by using trial and error methods(Abebe and Endalie, 2023).

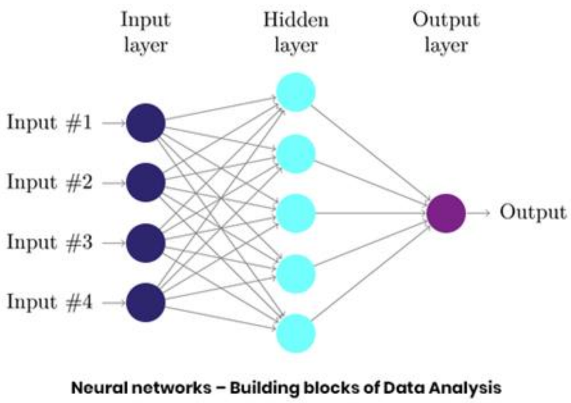

Figure 2.7: Illustration of the Building Blocks for Artificial Neural Networks (Ariwala, 2023).

In Artificial Neural Network (ANN), activation functions are being used to transform the input signal into output signal. There are different types of activation functions which are being applied into different application of ANN. Each layer that made up interconnected neurons in the neural network is associated with activation function (Sharma, et al., 2020). Activation functions can be classified into linear and non-linear. For linear activation function, it is mainly being used in regression problems in which the activation function does not transform the output but returned the actual predicted output value (All, 2023).

For non-linear activation function, it can extract more complicated and complex information from the input data as compared to linear activation function (Sharma, et al., 2020). There are multiple types of non-linear activation function. For example, Rectified Linear Unit (ReLU), Sigmoid, and Hyperbolic tangent. Sigmoid activation function is most commonly being used when probability is the desire prediction output (Sharma, 2017). The output value for neural network that applying the sigmoid activation function will be the number that range between zero and one (Topper, 2023). Hyperbolic tangent (Tanh) function is much alike to the sigmoid activation function. However, it produces the output in the range between -1 to 1 and tanh function have a larger derivative than sigmoid function which can minimize the cost function more rapidly (Baruah, 2021). Tanh activation function is commonly being applied for classification between two classes (Sharma, 2017). While for rectified linear unit (ReLU) activation function, it consists of two linear functions which its output is zero for negative input values and provides a continuous linear output mapping for non-negative input values (Thuy Le, 2024). This activation function manages to solve the gradient dispersion problem and has faster convergence speed as well as provide a better sparsity (Bai, 2022).

2.13 Summary

In summary, the effects of climate change issues to the atmosphere had been reviewed and discussed in the beginning of this chapter since climate change is the main issues that this project is focusing on. Next, the concept of rain attenuation and its effect on the satellite microwave links is being reviewed in this chapter. Besides, the concepts of rain height, ZDI height and the rain rate are also being discussed in this chapter. The mean annual rain height can be obtained by adding 0.36 km to the zero-degree isotherm (ZDI) height.

After that, multiple types of prediction model for rain attenuation had been reviewed and evaluated in terms of their prediction method and its accuracy. ITU-R recommendation models are currently the most used prediction model by engineers in designing the satellite-based communication systems. However, static data are being used in this recommendation model and it does not include climate change model which then cause the accuracy of the prediction decrease.

Next, the Crane Model is a model that used to estimate the slant-path attenuation exceedance. Research shows that ITU-R model can performed better as compared to Crane Model. While for the Singh Model, it can be applied for different elevation angles of antenna and it is suitable to be used in tropical region. However, Singh Model is also using the static data and does not include any climate change model. Besides, for Bryant Model, it is more suitable for estimating rain attenuation at Ku-band instead of Ka-band. Lastly, for the Tropical Rainfall Measuring Mission (TRMM) project, it was considered as one of the accurate methods to obtain the rain height value. However, due to the run out of fuels for the satellite, the TRMM project had come to an end.

Furthermore, the concept and the working of AI predictive model had been reviewed and explained. Different types of methods for AI predictive modelling had been compared and evaluated to determine which model is suitable for this project. Regression analysis is suitable for application with binary outputs while Artificial Neural Network (ANN) is suitable for more complex applications in which it is using the mathematical operations to process the data.

In short, a rain height model associated with a climate change model that will be developed in this research project is aiming to achieve a more accurate result as compared to those models that have been reviewed in this chapter. Then, the AI predictive model in this project will be applying the Artificial Neural Network (ANN) techniques.

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Introduction

In overall, this project can be classified into two parts, in which the first part is literature review and research part, while the second part is results analysis part. The first step in the first part is to understand the objectives of the project. After that is to start research for the concept of climate change, rain height, rain rate and rain attenuation as well as understand the relationship between them. Then, the next step is to understand the effects of rain attenuation on the satellite microwave links. Fourthly, various ITU-R recommendation models will be reviewed and comparison between different type of rain attenuation prediction model will be performed. Lastly in the literature review part, different types of Artificial Intelligence (AI) predictive model will be reviewed to understand their working and select the suitable model for this project.

Furthermore, in the second part of this project, the NCEP/NCAR reanalysis data will be downloaded from the NCEP/NCAR official website. Next, the reanalysis data will be decoded by using MATLAB simulation code to obtain the rain height in Malaysia over 30 years which is from year 1992 to year 2022. The following step is to observe and analyse the climate change effects on the patterns and trends of rainfall over time. Until this step were all done in the previous trimester.

In this trimester, the work is mainly focused on the results analysis and development of the simple AI prediction model for rain height. In the beginning of this trimester, further analysis of data will be done by adopting the prediction method from ITU-R P.618 Recommendation Model to obtain the probability of rain attenuation on a slant path with the input of rain height values obtained in the previous step. Then, correlation between the average rain height and the global temperature will be performed. Lastly, a rainfall height prediction model will be developed by using Google Colaboratory application associated with Python programming language.

3.2 Overall Flowchart of the Project

In this subchapter, the overall flow for the literature review and research part as well as the results analysis part for this project are shown in different flowchart.

3.2.1 Flowchart of Literature Review and Research Part

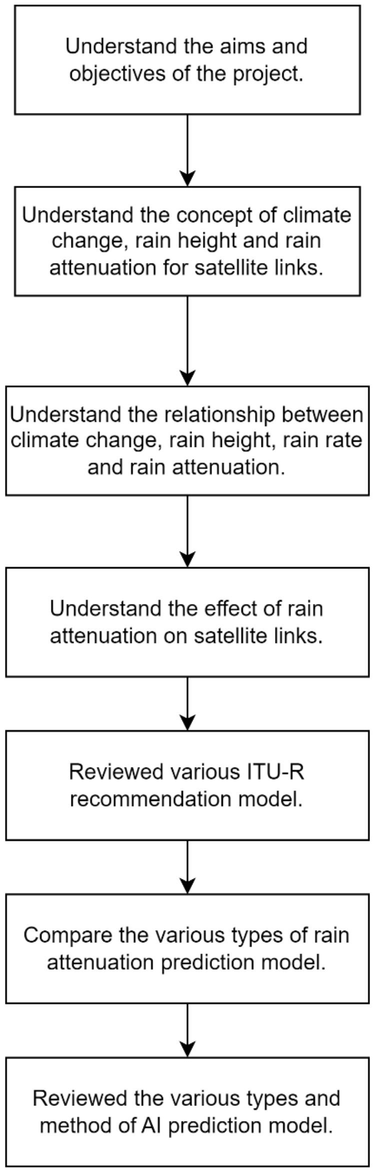

Figure 3.1: Flowchart for Literature Review and Research for this Project.

3.2.2 Flowchart of Results Analysis Part

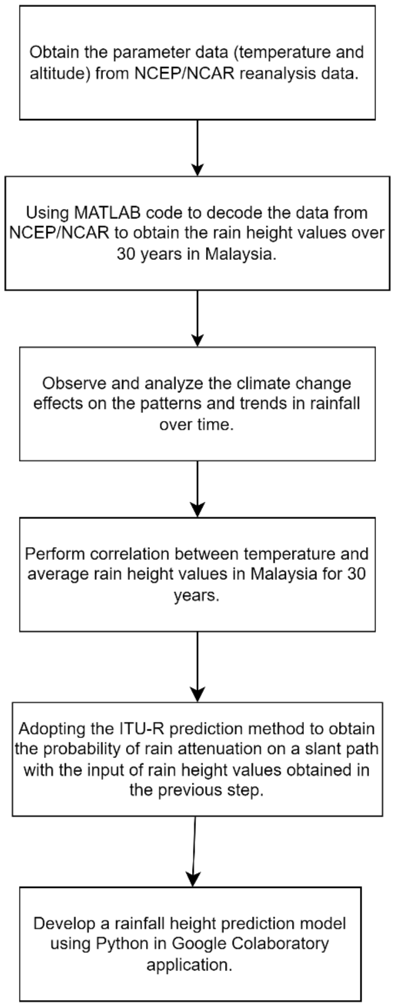

Figure 3.2: Flowchart for Development of Rain Height Prediction Model and Results Analysis Part

3.3 Gantt Chart of the Project

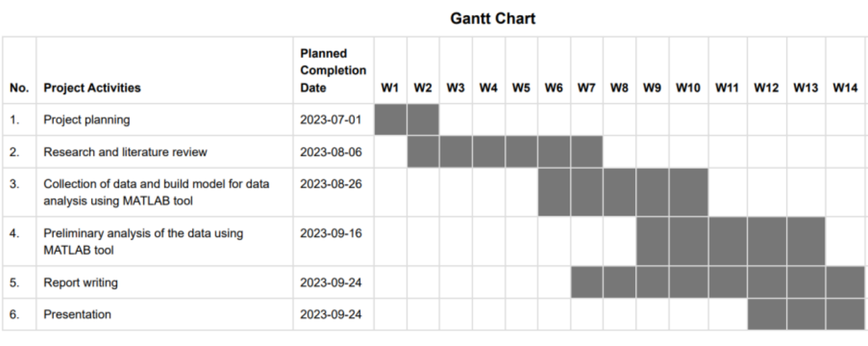

Figure 3.3: Gantt Chart for FYP Part 1

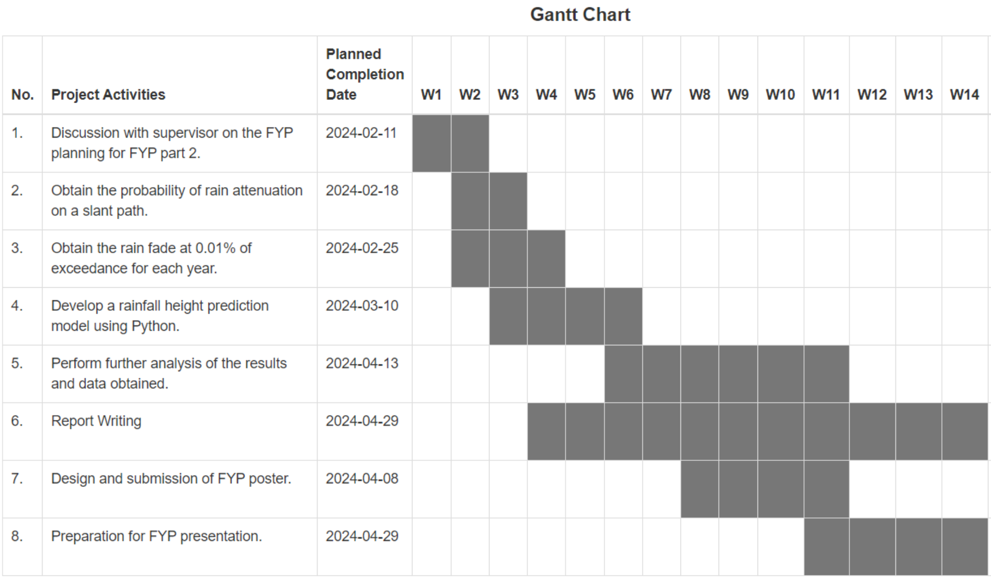

Figure 3.4: Gantt Chart for FYP Part 2

3.4 Project Methodology

The project methodology will be discussed about the method that being conducted to carry out this project. This project can be classified into quantitative research that mainly involved the work of collecting the numerical data and performing the mathematical analyses for prediction and observation of trends. There is no hardware involved in this project and this project is fully utilizing the software tools.

3.4.1 NCEP/NCAR Reanalysis Data

The data being applied in this project are mainly from NCEP/NCAR reanalysis data which are the free resources that can be obtained in NCEP/NCAR official website. According to re3data (n.d.), the NCEP/NCAR reanalysis project is the combined project between these two centers which are National Centers for Environment Prediction (NCEP) as well as National Center for Atmospheric Research (NCAR). This reanalysis data is the meteorological data that obtained by integrating the Numerical Weather Prediction model and the global climate observations at 17 different pressure levels which in the range of 1000mBar to 10mBar (Hafiz, et al., 2016). This reanalysis data has the temporal resolution of 6-hour which are 12am, 6am, 12pm and 6pm UTC time and the spatial resolution of global grid with the area of 144 km × 73 km.

The historical data of NCEP/NCAR reanalysis database are started from the year 1979 to present. Since the available data provided by this database are until the present time, which is until year 2023, therefore, the real time data can be obtained from this database which ensure the results of this project become more accurate and precise. This reanalysis dataset provides a large amount and various types of parameters data such as air temperature, convective precipitation rate, average sea level pressure, geopotential height and others. The main parameters that are needed for this project are the air temperature and the geopotential height. The data being used for this research project is from year 1992 to 2022 which is a total of 30 years. The NCEP/NCAR reanalysis data are provided in the format of .nc file which is the file type of netCDF file. Most of the meteorological data are being store in file format to reduce the size of the file. Each of the yearly data file have the file size of around 300 MB.

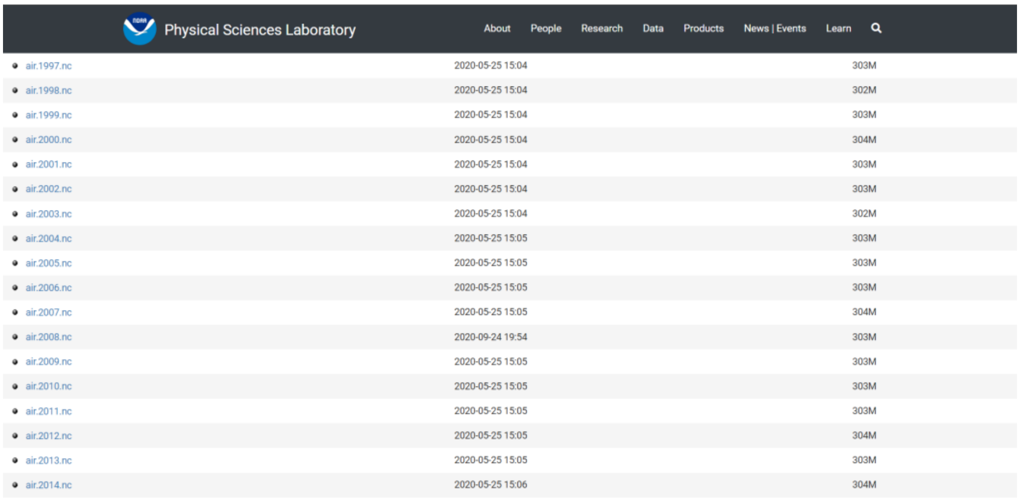

Figure 3.5: Website for NCEP/NCAR Reanalysis Data for Air Temperature.

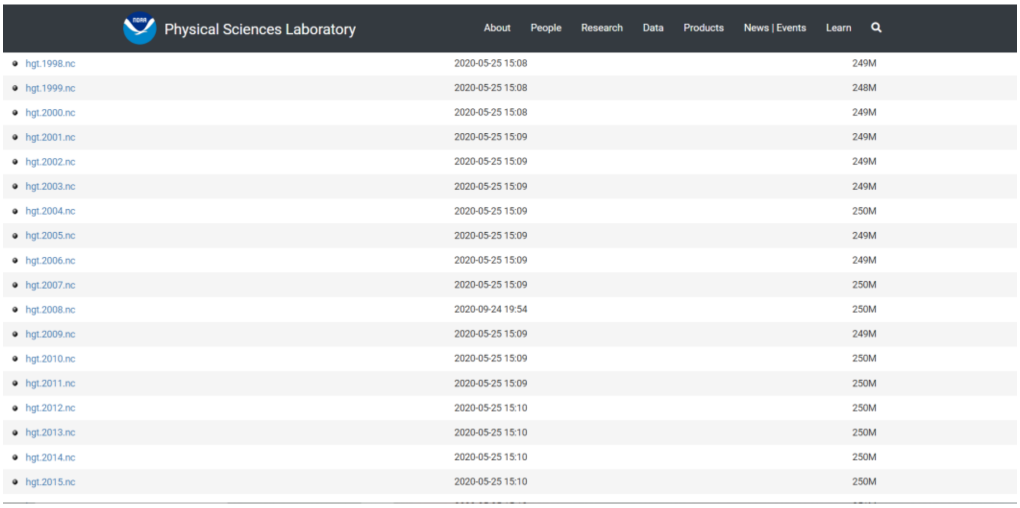

Figure 3.6: Website for NCEP/NCAR Reanalysis Data for Geopotential Height

3.4.2 Overview of Software

3.4.2.1 MATLAB

MATLAB tool is mainly being used in this project as the main simulation tool to simulate desired results and developing the rain height model. This is because it consists of multiple functions that are needed in this project. First, it has the function to read the netCDF file which is the file format for the NCEP/NCAR reanalysis data. Next, it has the graph plotting function that can be utilized in plotting graphs that are needed in this project for results analysis work.

MATLAB is one of the user-friendly software since it is using the high-level language that ease the works of users in expressing complex mathematical computations, data analysis and modelling tasks (Altena, 2023). It also has a large library of predefined functions that ease the development process of the model. With the build-in integrated development environment, the program code can be edited and debugged easily by using the debugger in MATLAB. Furthermore, MATLAB simulation tool can run the large input files without any clashing. This feature is important in this project since each of the input file being applied in this project is large which is about 300 MB per file. As compared to Python, MATLAB have faster performance when the data sets are large.

Figure 3.7: MATLAB Logo.

3.4.2.2 Python

Python programming language will be used in the stage of developing the prediction rain height model. Python is a high-level language that is easy to use and understand by users. It also provided a huge library of functions that allow users to use for different applications of task. The function to plot graph is available in Python software which is important in visualizing the predicted data for the prediction model developed in this project. Furthermore, Python is being considered as the better choice for machine learning works as compared to MATLAB. This is because Python provides lots of libraries and packages for various types of machine learning models but the machine learning algorithms in MATLAB only have limited code portability (Rane, 2021).

Figure 3.8: Python Logo.

3.4.2.3 Google Colaboratory (Google Colab)

In this project, Google Colab is being used to execute the Python code for the Artificial Intelligence (AI) prediction model for rain height. Basically, one of the advantages of Google Colab is that it can be use through the browser which does not require any download action for this application. Then, Google Colab is using the Jupyter notebook service which does not require any setup for the computing resources which including the GPUs and it is free for public to use (Dolinay, 2023). The notebooks provide autosave function that direct save all the changes of the notebook to the respective Google Drive files

(Burke, 2023). Furthermore, Google Colab provides various of pre-installed libraries which including NumPy, PyTorch, TensorFlow and others that are required for the training of Artificial Intelligence (AI) model (Das, 2023).

Figure 3.9: Google Colab logo.

3.4.2.4 PyTorch

In this project, PyTorch is being used as the machine learning framework in the development of Artificial Intelligence (AI) prediction model for rain height. PyTorch is a free open-source framework for machine learning that based on the Python programming language (Yasar, 2022). It can be used to build wide range of neural networks and graph-based execution in machine learning applications. PyTorch is convenient to be used since it supports variety of computation environment such as CPU and GPU (Stokes, et al., 2023). The data structure for PyTorch is Tensors which worked as an array that able to store and manipulate the parameters, inputs and outputs variables of the model. By using PyTorch, the training time for the prediction model is faster as compared to other machine learning frameworks.

Figure 3.10: PyTorch Logo.

3.5 Planning and Methodology of Work

The work of this project included decoding the NCEP/NCAR reanalysis data, plotting and analysis of the rain height graph and rain attenuation graph in Malaysia using MATLAB software and the development of the Artificial Intelligence (AI) predictive model for rain height prediction using Google Colab with Python coding.

3.5.1 Decode the NCEP/NCAR Reanalysis Data

Since this project is focusing on the tropical region which is Malaysia, the latitude and longitude of Peninsular Malaysia as well as Sabah and Sarawak are being specified when decoding the NCEP/NCAR reanalysis data. This step is important since NCEP/NCAR reanalysis data are providing the globally grided dataset. The latitude and longitude of Peninsular Malaysia is 3.9743°N and 102.4381°E respectively. While for the latitude and longitude of Sabah/Sarawak is 3.7035°N and 114.5243°E.

To estimate the distance between the specific location and North pole based on the latitude and longitude, the following calculations are performed.

$$distance_{latitude} = \frac{91-latitude}{2.5} \tag{3.1}$$

$$distance_{longitude} = \frac{91-longitude}{2.5} \tag{3.2}$$

Next, since the reanalysis data have temporal resolution of 6-hour, therefore the amount of samples data per day and amount of samples data per year are calculated to be 4 samples per day and 1460 samples per year.

3.5.2 Calculate the Freezing Level Height and Rain Height

The calculation of the freezing level height depends on the air temperature and the geopotential height parameters obtained from the reanalysis data. All 1460 samples will be run to obtain the freezing height level for one year. First, the freezing height level is determined from the large dataset by using linear interpolation between the decreasing of lowest temperature height position when the temperature is zero degree Celsius with the increasing of geopotential altitude. After obtaining the ZDI height, the rain height is calculated by using the Equation 3.3. This equation is adopted from the ITU-R P.839 Recommendation Model which provide the method to predict the rain height with respect to the freezing height level. Since the atmospheric pressure level is quite low at higher sea level, therefore, the actual freezing temperature is lower than zero degrees Celsius. This is mainly due to the super-cooled water droplets that have the characteristics to exist as liquid at the temperature below freezing point (Clayton, 2023). Therefore, the rain formation is assumed to be higher than the height of the freezing level.

$$Rain\ height = ZDI\ height + 0.36\ km \quad (3.3)$$

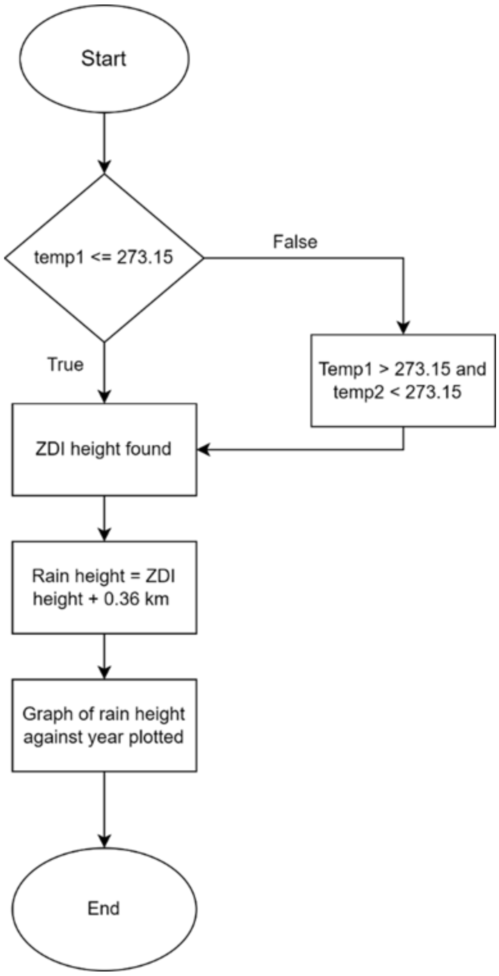

Figure 3.11: Simplified Flowchart for Obtaining the Rain Height using MATLAB.

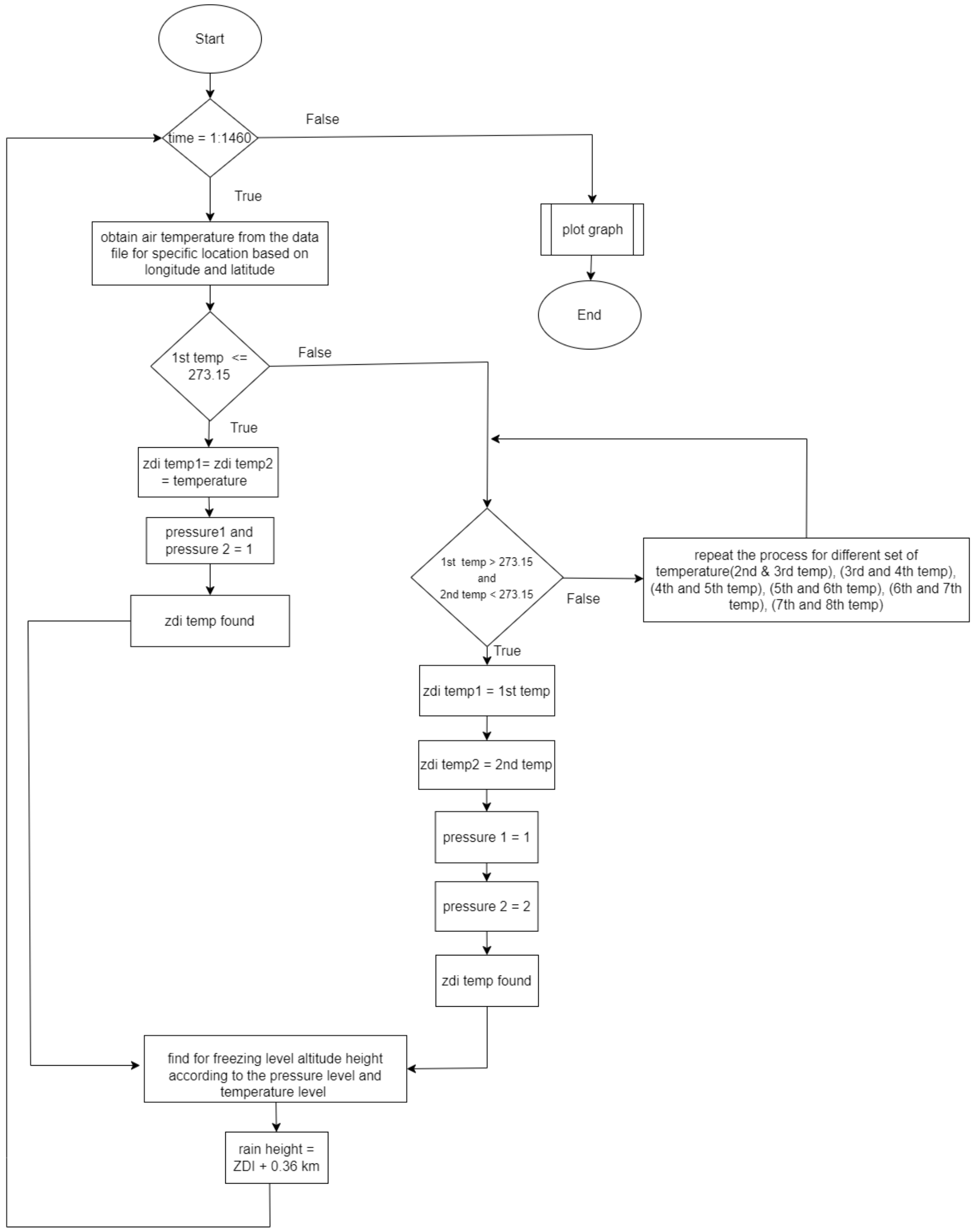

Figure 3.12: Detailed Flowchart for Obtaining the Rain Height

3.5.3 Obtain the Probability of Rain Attenuation on a Slant Path

To obtain the probability curve of rain attenuation on a slant path, the method that recommended in ITU-R P.618 Recommendation Model will be adopted in this part of the project. In overall, the value of rain height that is needed as an input parameter for this recommendation model will be the rain height that is obtained from the previous steps in this project instead of using the static data that is provided by ITU-R model. Other parameters required for this method are the elevation angle, altitude of the earth station and the latitude of the location. According to the Ground Control Look Angle Calculator, the elevation angle for Peninsular Malaysia and East Malaysia for MEASAT satellite is 76.3° and 62.7° respectively.

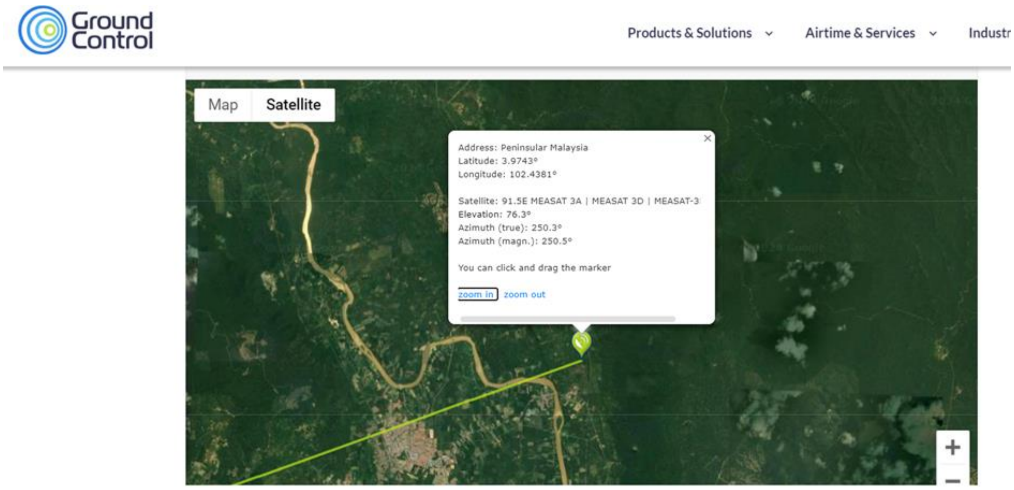

Figure 3.13: Elevation Angle for Peninsular Malaysia Obtained from Ground Control Look Angle Calculator.

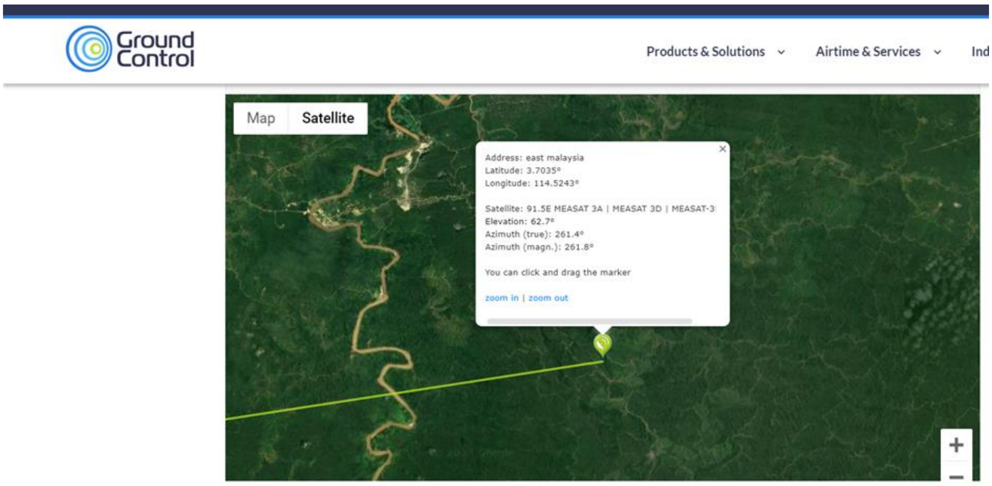

Figure 3.14: Elevation Angle for East Malaysia Obtained from Ground Control Look Angle Calculator.

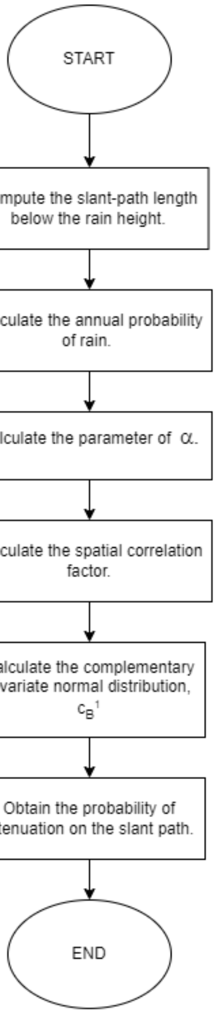

Figure 3.15: Simplified Flowchart for the Method of Obtaining the Probability Curve of Rain Attenuation on the Slant Path.

3.5.3.1 Detailed Formula for Obtaining the Probability Curve of Rain Attenuation on the Slant Path

To compute the length of the slant path:

For elevation angle, $\theta \geq 5^\circ$:

$$L_S = \frac{(h_R - h_s)}{\sin\theta} \tag{3.4}$$

where

L_S = slant path length, km

h_R = rain height, km

h_S = height above average sea level of the ground station, km

θ = elevation angle, °

For elevation angle, $\theta < 5^\circ$:

$$L_S = \frac{2(h_R - h_S)}{(sin^2\theta + \frac{2(h_R - h_S)}{R_e})^{\frac{1}{2}} + \sin\theta} \tag{3.5}$$

where

R_e = effective radius of the Earth

To calculate the annual probability of rain, $P_{0_{annual}}$:

$$P_{0_{annual}} = \frac{\sum_{ii=1}^{12} N_{ii} \times P_{0_{ii}}}{365.25} \tag{3.6}$$

To compute the spatial correlation function, ρ:

$$\rho = 0.59e^{-\frac{|d|}{31}} + 0.41e^{-\frac{|d|}{800}} \tag{3.7}$$

To compute the complementary bivariate normal distribution, c_B[1]:

$$c_B = \frac{1}{2\pi\sqrt{1-\rho^2}} \int_{\alpha}^{\infty} \int_{\alpha}^{\infty} e^{-\frac{x^2 - 2\rho xy + y^2}{2(1-\rho^2)}} \, dxdy \tag{3.8}$$

To calculate the probability of attenuation on the slant path:

$$P(A > 0) = 100\left[1 - \left(1 - \frac{P_{0_{annual}}}{100}\right)\left(\frac{c_B - \left(\frac{P_{0_{annual}}}{100}\right)^2}{\frac{P_{0_{\mathrm{annual}}}}{100}\left(1 - \frac{P_{0_{annual}}}{100}\right)}\right)^{\frac{P_{0_{annual}}}{100}}\right] \tag{3.9}$$

3.5.4 Development of Artificial Intelligence (AI) Predictive Model for Prediction of Rain Height

In this part, Google Colab is being chosen as the platform for the training of predictive model with the utilization of Python code. The dataset being applied to train the AI predictive model consists of the temperature and rain height data from year 1992 to year 2019. The AI predictive model learned from the historical data of rain height and temperature values. After the training of the predictive model, it will output the target variable which is the rain height values for the future years with assumed temperature values.

The type of model being applied is linear regression associate with Artificial Neural Network (ANN) since the relationship between both independent as well as the dependent variables is linear. Both variables will be split into training and validation sets with the test size of 0.2 which indicates that 20% of the data will be utilized as validation set and 80% of the data will be the training set. Then, the data will be normalized and being converted to PyTorch tensors for further manipulation and representation of data. Data normalization is necessary in deep learning to ensure all the attribute data are in the same range for achieving a higher accuracy (Chernysheva, 2023).

After that, the neural network model is being defined as the machine learning algorithm for this predictive model. In general, neural network will have three layers which are the input layer, output layer as well as the hidden layers that will be fully connected in linear. By training the model multiple times, the optimum values for the number of neurons can be determined. In this project, the neural network consists of the first layer that have two input features, the second layer with eight hidden neurons, third layer with four hidden neurons and one output value for the layer of output.

Then, in order to allow the neural network to develop a more complex functions based on the input, non-linear activation functions will be introduced. The rectified linear unit (ReLU) function is being employed in this model. Next, Adams optimization algorithms is being selected as the optimizer in this model with a learning rate of 0.001 since it can perform more effective for a wide range of scenarios.

In the training loop, the number of training epochs is being determined through trial-and-error method. The training loss is being computed by using the mean squared error (MSE) functions to determine the MSE loss between the model's prediction and the actual training data. Then the model is being set to evaluation mode for validation purpose to evaluate the performance of the predictive model throughout the training. After the training of model completed, the trained model will undergo an evaluation process. This step is to pass the test data through the trained model for prediction work for the evaluation of the model's accuracy by using the computation of mean squared error (MSE), R^2 score and mean absolute error (MAE).

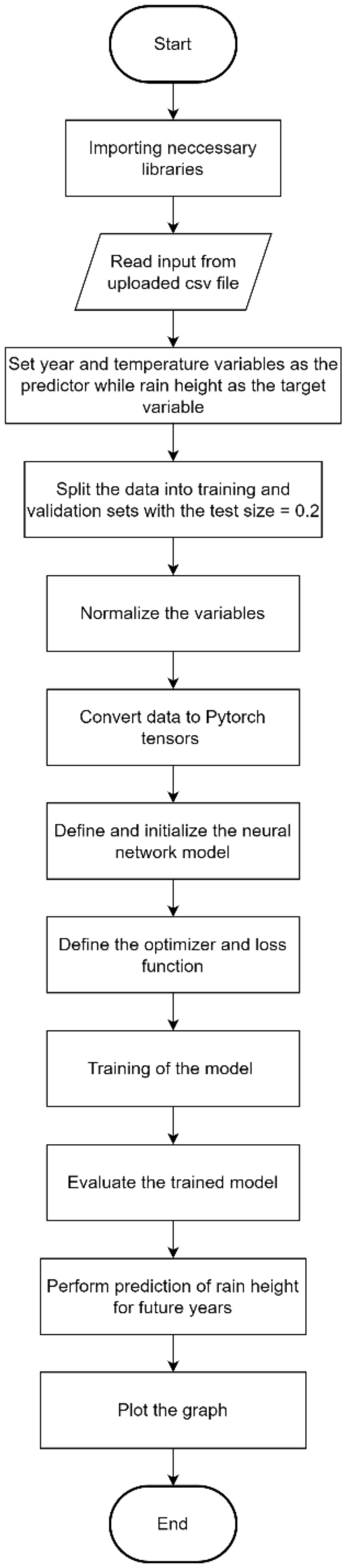

Figure 3.16: Flowchart for the Workflow of AI Prediction Model for Rain Height.

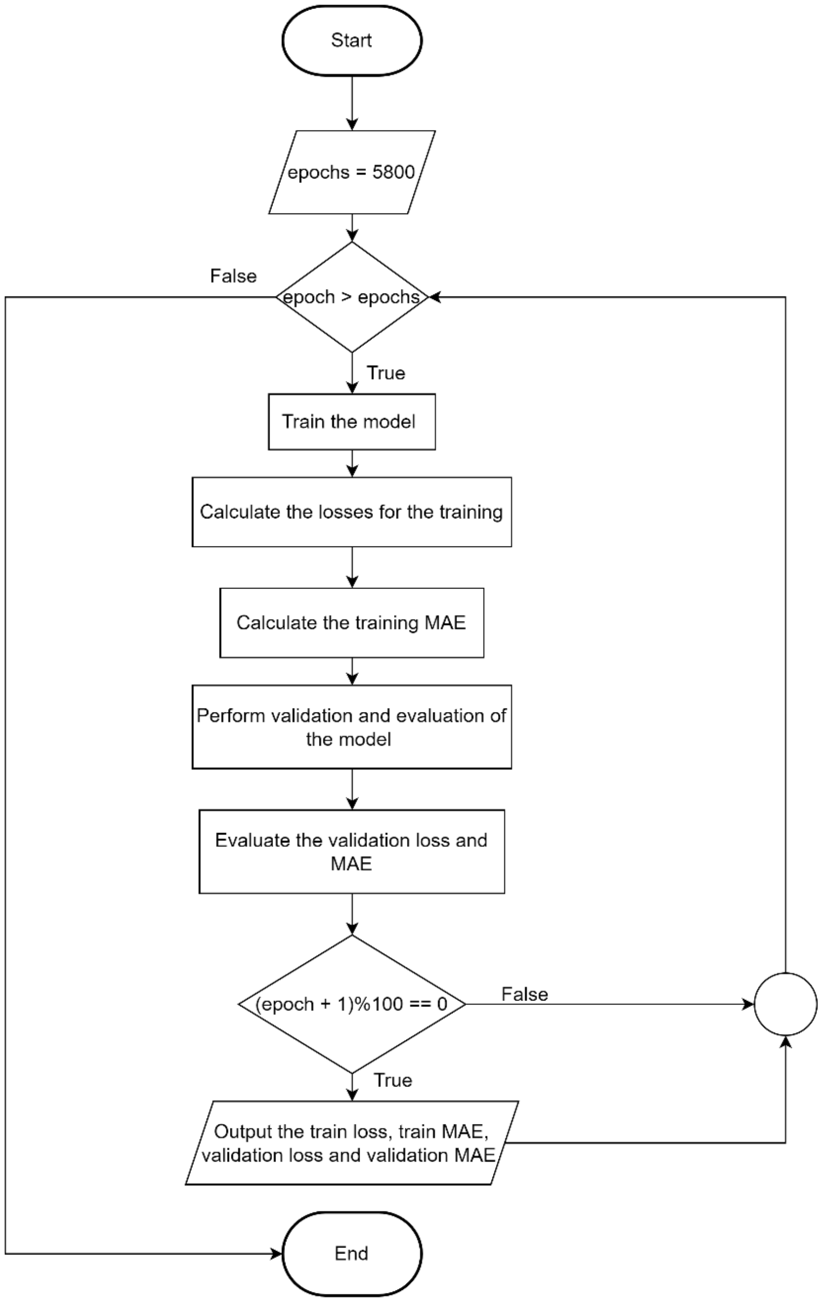

Figure 3.17: Detailed Flowchart for the Training Loop of the AI Prediction Model for Rain Height.

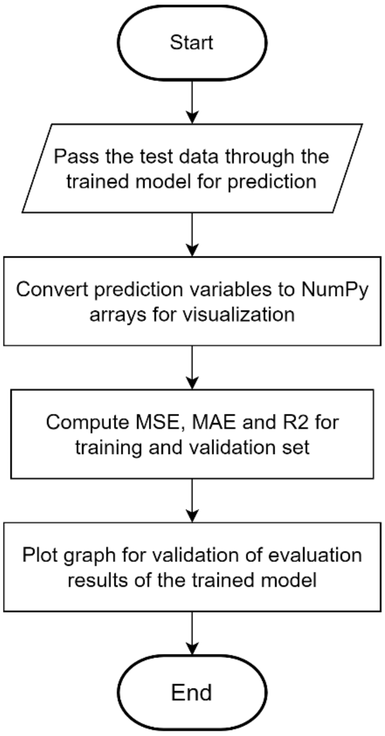

Figure 3.18: Detailed Flowchart for the Validation Part of the AI Prediction Model for Rain Height.

After the training and evaluation of the AI predictive model, the model is being used to predict the rain height for future years. The prediction is started from year 2020 to year 2024 which is five years period. The reason for starting the predictions from past few years is to compare the predicted results with the actual historical results for accuracy checking. As mentioned by World Meteorological Organization (2023), in the year between 2023 to 2027, the mean global temperature for each year is forecasted to be in the range of 1.1 °C to 1.8 °C higher. Therefore, the predicted average global temperature in the future years is being assumed and set to 0.1 °C higher between each year.

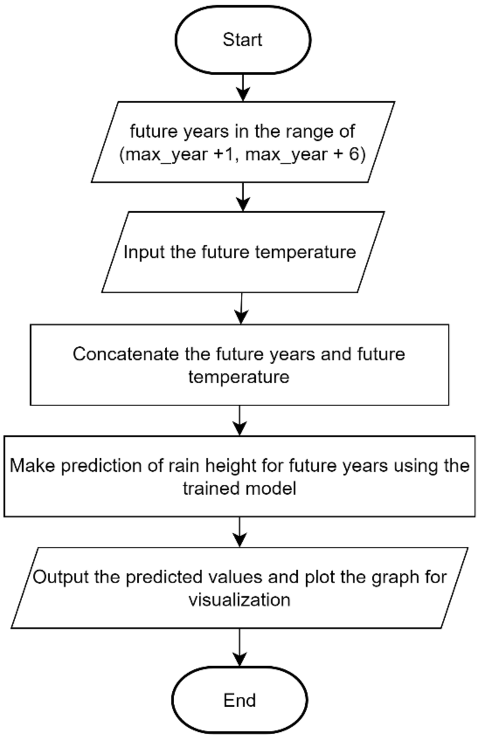

Figure 3.19: Flowchart for the Prediction Part of the AI Prediction Model for Rain Height.

3.6 Summary

In this chapter, the overall flow of the project was discussed and illustrated in the flowcharts. Next, since this research project is simulation-based, therefore, the resources that will be utilized such as software and databases were being discussed. All the data that being applied in this project are from NCEP/NCAR reanalysis database. MATLAB, Python programming languages, Google Colab and PyTorch will be the mainly utilized in this project for the development of rain height model and the AI predictive model.

Next, the work plan for the whole project is explained and discussed in detail in this chapter. The work started from decoding the data from the database, then obtain the rain height from ZDI height, afterwards the probability curve of rain attenuation on a slant path will be plotted by adopting the method being used in ITU-R Recommendation Model. All these stated tasks will be done by using MATLAB simulation tool.

After that, the AI predictive model for rain height will be developed in Google Colab using Python programming language and associated with

PyTorch. The AI predictive model is applying the Artificial Neural Network (ANN) machine learning algorithms.

In overall, this project will be carried out according to the work plan that had been discussed in this chapter to ensure that the project will be conducted in a correct way and can be completed in time.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, the results are presented in two sections which are the results obtained from MATLAB software and the results obtained from the AI predictive model. Firstly, the NCEP/NCAR reanalysis data will be visualized and the graph of average rain height in Malaysia for past 30 years will be discussed. After that, the correlation between average rain height and global temperatures will be performed and analysed. Then, the rain attenuation at 0.01% exceedance in Malaysia will be analysed. All the results mentioned is obtained using the MATLAB software.

While for the results of AI prediction model will be displayed by using tables and graphs. The prediction results of rain height from year 2020 to year 2024 will be listed and compared with the actual rain height values to find out the percentage error between them. Then, the mean squared error (MSE) values and R^2 values that computed by the model will be displayed to analyse the accuracy of the predictive model.

4.2 Visualization for NCEP/NCAR Reanalysis Data

The NCEP/NCAR reanalysis data for the air temperature and geopotential height parameters are visualized in Figure 4.1 as well as Figure 4.2 respectively. These two figures are showing the global data for both parameters. In Figure 4.1, the colour map shows the air temperature in Kelvin unit. Yellow colour means higher temperature and blue colour means lower temperature. On the other hand, in Figure 4.2, the colour map shows the geopotential height level which indicates that yellow colour is representing the highest altitude while blue colour is representing the lowest altitude.

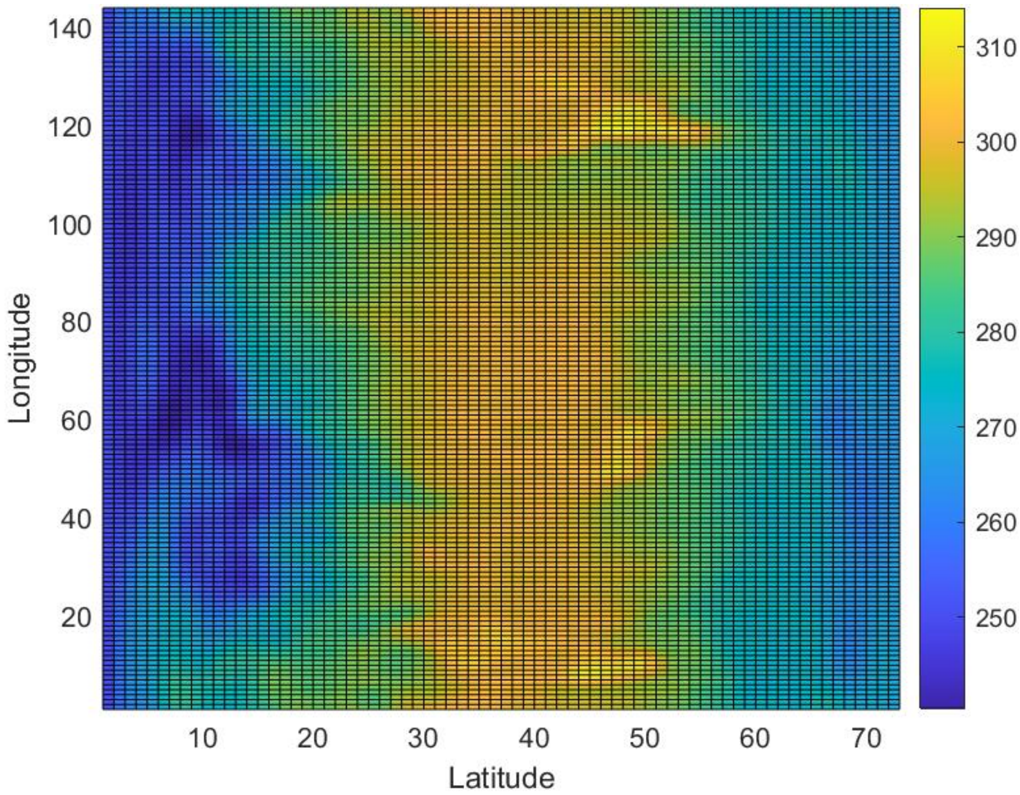

Figure 4.1: Global Map that Visualized the Air Temperature in Kelvin for Year 2022.

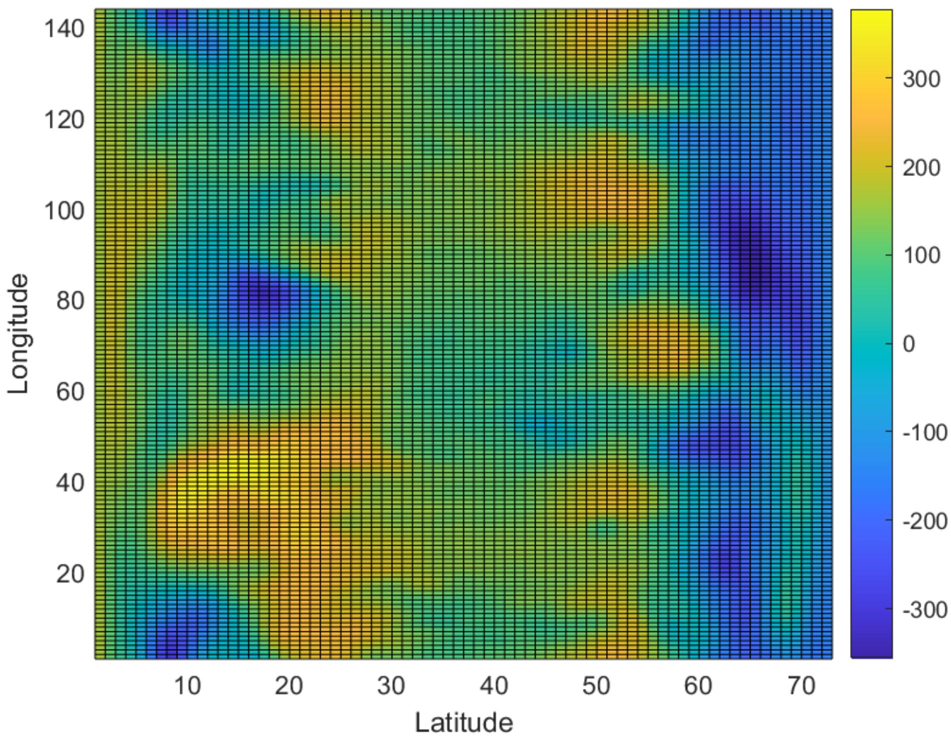

Figure 4.2: Global Map that Visualized the Geopotential Height in kilometer for Year 2022.

4.3 Analysis of Rain Height Level in Malaysia

The year chosen for the analysis work of yearly rain height level is 2022. This allow the most current data can be presented and current situation can be known and analysed. The graph of rain height level for Peninsular Malaysia as well as East Malysia for year 2022 are shown in Figure 4.3 and Figure 4.4 respectively.

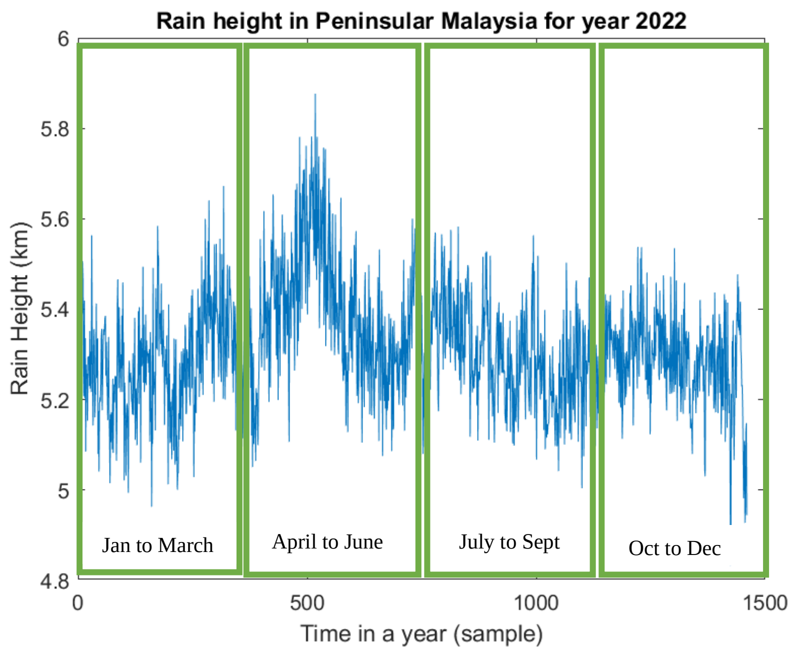

Figure 4.3: Rain Height in Peninsular Malaysia for Year 2022.

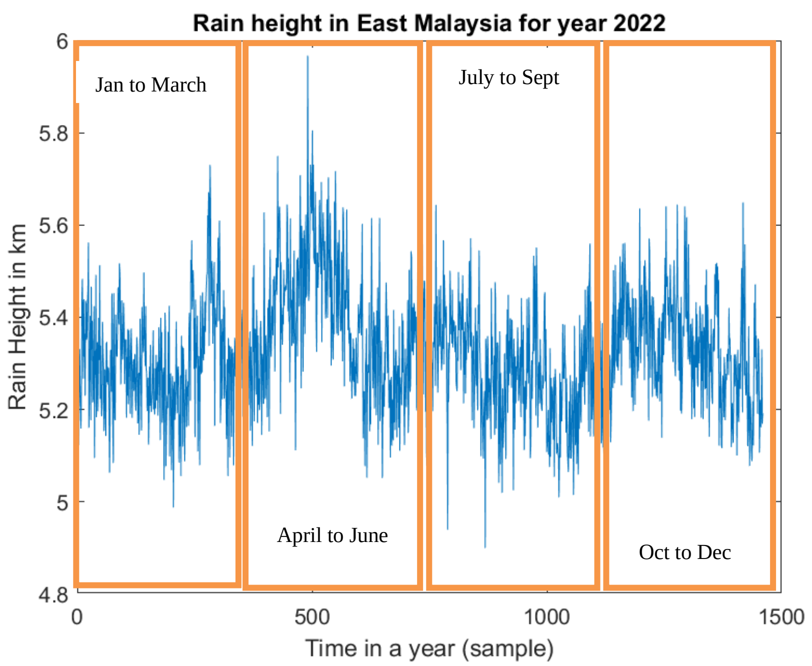

Figure 4.4: Rain Height in East Malaysia for Year 2022.

Since there are 1460 samples per year that provided by the reanalysis data, the respective month for the rain height level is being estimated. The months are divided into four parts equally for a better analysis of the graph. First, by observing the graph shown in Figure 4.3 which is the rain height in Peninsular Malaysia, the rain height levels for the whole year are at the range of 5 to 5.7 km. However, in the month of May, the rain height level reached the highest value which is approximately 5.9 km and the rain height in the month of May is higher as compared to other months. On the other hand, the rain height levels in East Malaysia are also at the range of 5 to 5.7 km but the highest rain height in East Malaysia reached up to 6 km in the month of May.

4.4 Rain Height Level of Malaysia from Year 1992 to Year 2022

The average mean rain heights for both West and East Malaysia over 30 years is shown in Figure 4.5 and Figure 4.6 respectively. The red least square linear regression line is plotted in both graphs to show the trend of the rain height levels.

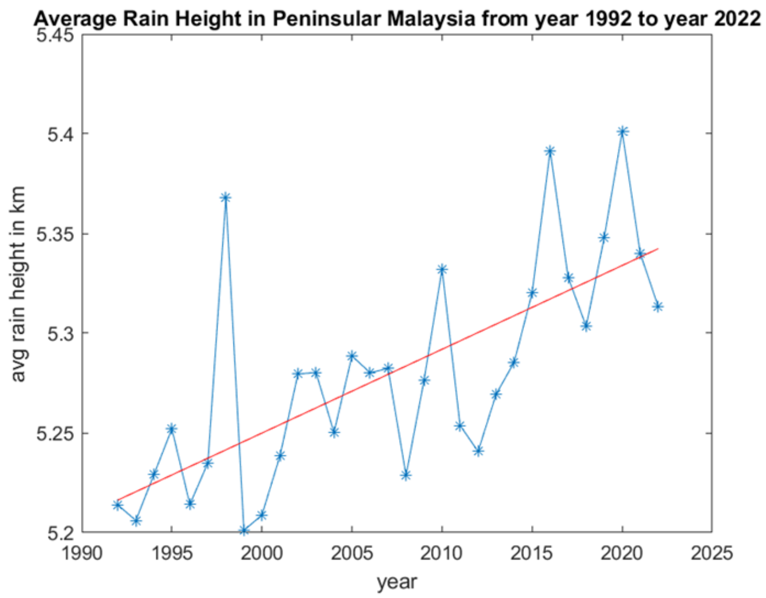

Figure 4.5: Average Rain Height in Peninsular Malaysia from Year 1992 to Year 2022.

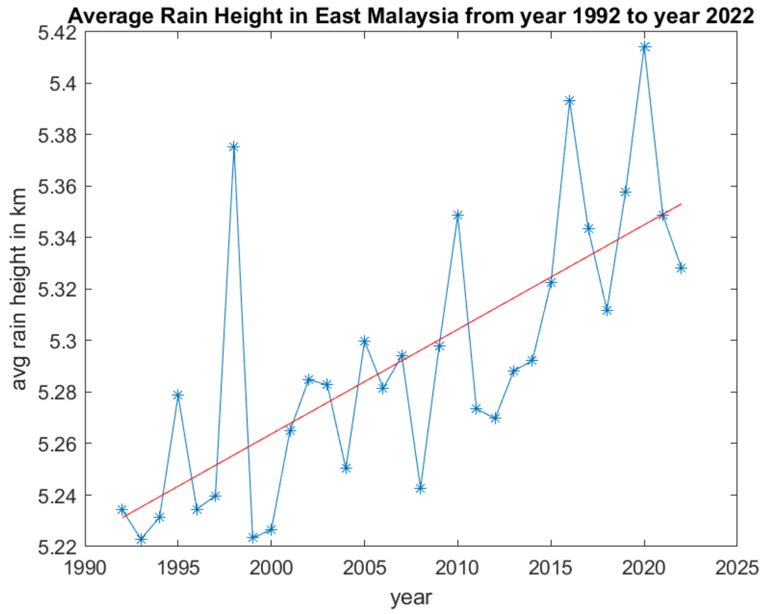

Figure 4.6: Average Rain Height in East Malaysia from Year 1992 to Year 2022.

Figure 4.5 and Figure 4.6 show an increasing trend of the average rain height in Peninsular Malaysia and East Malaysia respectively from year 1992 to year 2022. Then, the highest average rain height in Peninsular Malaysia is at 5.4 km which is in the year of 2020. While in East Malaysia, the highest average rain height is at 5.42 km which is also in the year of 2020. Furthermore, it can be observed that after year 2015, the average rain height stayed above 5.3 km in both Peninsular Malaysia and East Malaysia.

The lease square linear regression line in both Figure 4.5 and Figure 4.6 have the positive slope which proves that the average rain height is increasing over 30 years in Malaysia. Based on the regression line, linear equation that show the linear relationship between the average rain height with time of year can be obtained. The linear equation that being obtained for the average rain height in Peninsular Malaysia and East Malaysia from year 1992 to year 2022 is being shown in Equation 4.1 and Equation 4.2 respectively. According to the linear equation that being derived from the regression line, it shows that in every one year, there will be an increment of around 4.2 meters for the rain height when the global temperature increases.

$$h_R = 0.0042\ yr + (-3.1547) \tag{4.1}$$

$$h_R = 0.0041\ yr + (-2.8649) \tag{4.2}$$

where

h_R = rain height, km

yr = year

4.5 Correlation between Average Rain Height and Global Temperature in Malaysia

Correlation between average rain height and global temperature in both Peninsular Malaysia and East Malaysia from year 1992 to year 2022 had been performed to investigate the relationship between them. Furthermore, the trend for global temperature from year 1992 to year 2022 in both region in Malaysia can be analysed by plotting a red dotted linear regression line in Figure 4.7 and Figure 4.8 respectively.

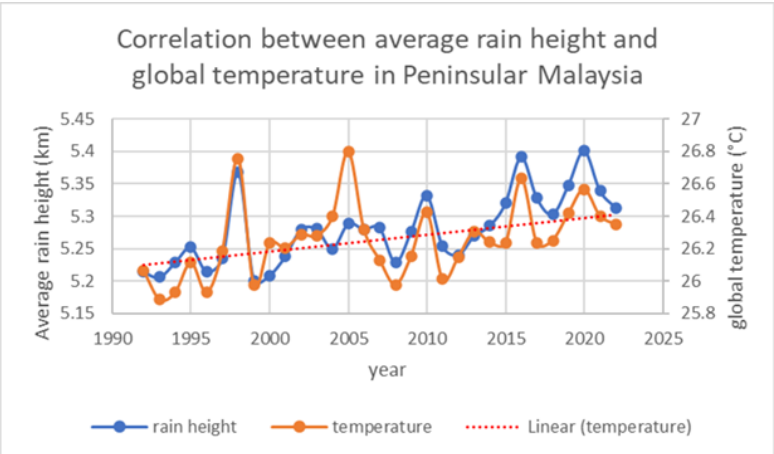

Figure 4.7: Graph of Correlation between Average Rain Height and Global Temperature in Peninsular Malaysia.

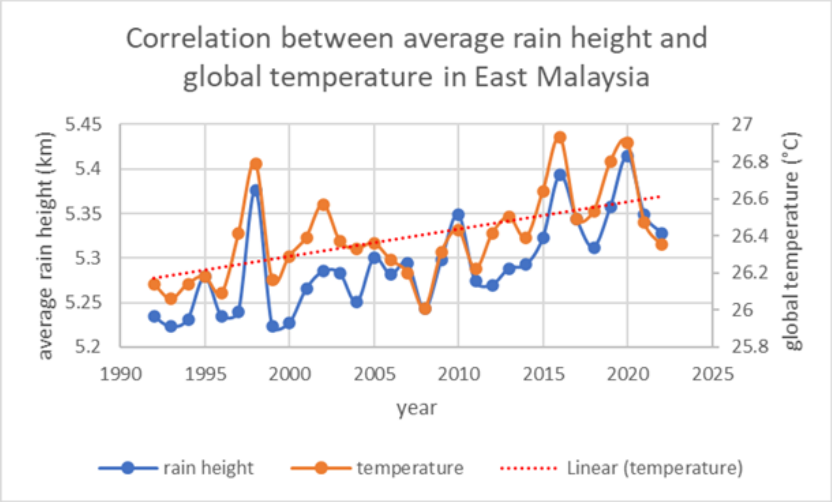

Figure 4.8: Graph of Correlation between Average Rain Height and Global Temperature in East Malaysia.

Based on Figure 4.7 and Figure 4.8, in overall, it can be observed that when the global temperature increase, the average rain height increases. This proved that there is a linear relationship between global temperature and average rain height. For example, in Figure 4.7, there is an increment of global temperature from 26.4 °C to 26.6 °C in the year of 2019 to year 2020. At the same year, the average rain height also had an increment from 5.35 km to 5.4 km in Peninsular Malaysia. Moreover, the red dotted lines show that the global temperature had a positive trend throughout year 1992 to year 2022.

4.6 Analysis of Rain Attenuation at 0.01% Exceedance in Malaysia

The rain attenuation at 0.01% probability exceedance in Malaysia is being obtained by using rain height values acquired in previous part. Figure 4.9 and Figure 4.10 are showing the graph for rain attenuation at 0.01% probability exceedance from year 1992 to year 2022 in Peninsular Malaysia and East Malaysia respectively. Then, the red linear regression line is plotted to show the trend of the rain attenuation.

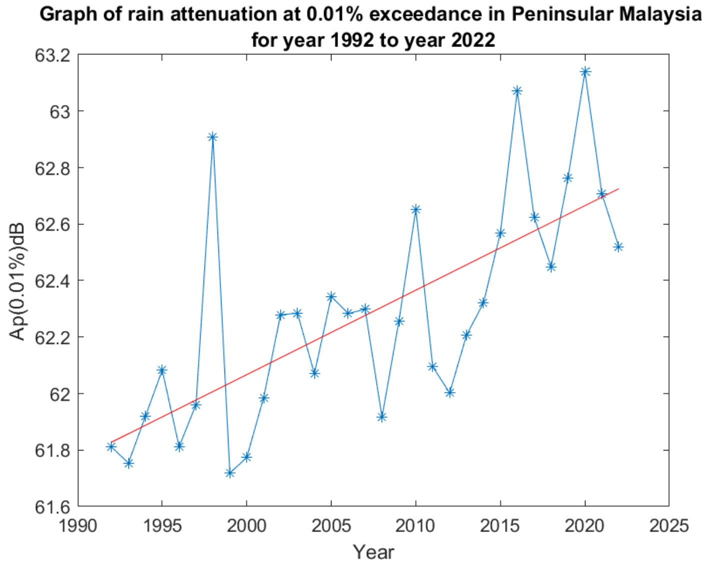

Figure 4.9: Rain Attenuation at 0.01% Exceedance in Peninsular Malaysia for Year 1992 to Year 2022.

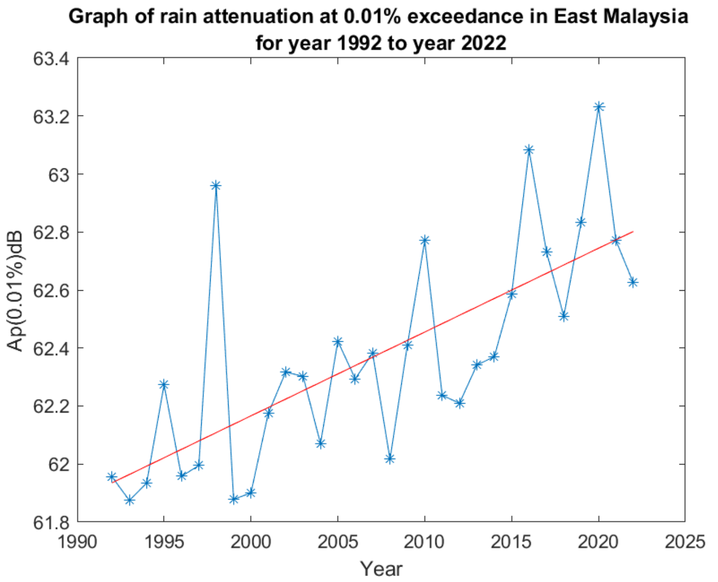

Figure 4.10: Rain Attenuation at 0.01% Exceedance in East Malaysia for Year 1992 to Year 2022.

According to Figure 4.9 and Figure 4.10, the rain attenuation at 0.01% exceedance in both region in Malaysia have an obvious increment from year 1992 to year 2022. Then, the highest rain attenuation is at 63.1 dB in Peninsular Malaysia for the year 2020. While in East Malaysia, the highest rain attenuation is at 63.25 dB for the year 2020.

The red linear regression line in both figures also shown an increasing trend for the rain attenuation in these 30 years. Linear equation that being shown in Equation 4.3 and Equation 4.4 were obtained from the regression line in each of the graph to investigate the linear relationship between the rain attenuation at 0.01% exceedance with respect to year in Peninsular Malaysia and East Malaysia respectively.

$$A_{0.01} = 0.0299\,yr + 2.2484 \tag{4.3}$$

$$A_{0.01} = 0.0289\,yr + 4.3753 \tag{4.4}$$

where

$A_{0.01}$ = attenuation at 0.01% exceedance of an average year, dB

yr = year

According to the linear equation that shown in Equation 4.3 and Equation 4.4, it shows that in every average year, the attenuation at 0.01% exceedance will increase with 0.03 dB in either Peninsular Malaysia or East Malaysia.

4.7 Results of AI Predictive Model for Rain Height

The AI predictive model being built in this project provided the predicted rain height values from the year 2020 to year 2024. The input parameters being used for the learning of the AI predictive model is the historical temperature and rain height values from year 1992 to year 2019. With the use of historical temperature values as one of the parameters for the AI predictive model, the effects of the climate change can be included in the prediction to increase the accuracy of the results. The predicted results for rain height in Peninsular Malaysia and East Malaysia from year 2020 to year 2024 are shown in Table 4.1 and Table 4.2 respectively. After that, the graph for predicted and historical rain height values in Peninsular Malaysia and East Malaysia are shown in Figure 4.11 and Figure 4.12 respectively. A red linear regression line is plotted in both figures to show the trend of the rain height data.

Table 4.1: Table of Predicted Rain Height in Peninsular Malaysia from Year 2020 to Year 2024.

Year	Predicted Rain Height, km
2020	5.369
2021	5.347
2022	5.343
2023	5.389
2024	5.404

Table 4.2: Table of Predicted Rain Height in East Malaysia from Year 2020 to Year 2024.

Year	Predicted Rain Height, km
2020	5.372
2021	5.315
2022	5.300
2023	5.363
2024	5.378

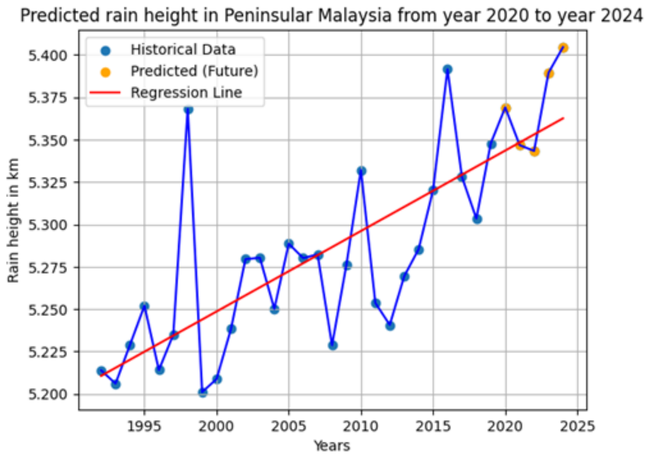

Figure 4.11: Graph of Predicted Rain Height and Historical Data in Peninsular Malaysia.

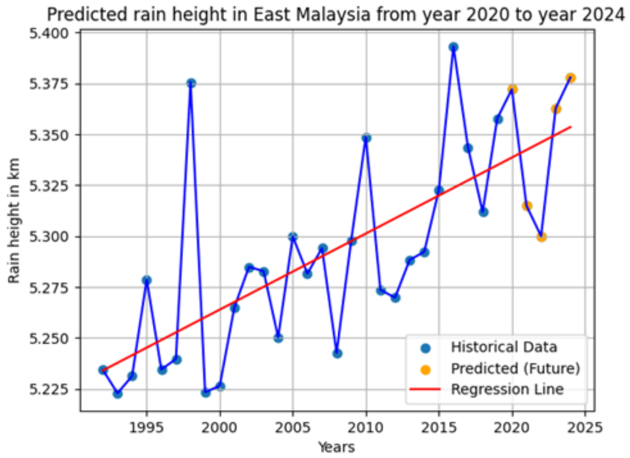

Figure 4.12: Graph of Predicted Rain Height and Historical Data in East Malaysia.

According to the results obtained from the AI predicted model, it can be observed that in both regions, the predicted rain height had a slight decrease from year 2021 to 2022 and rise until year 2024. Furthermore, the red regression lines that plotted in Figure 4.11 and Figure 4.12 show that the trend for historical data with predicted results for rain height have a positive trend.

4.8 Validation for the Accuracy of AI Predictive Model

The accuracy of the AI predictive model for rain height is being validated by calculating the percentage error between the actual rain height and predicted rain height values. Then, mean-squared error (MSE) and the R-squared (R^2) score for the model were being computed for the accuracy checking of the predictive model. The percentage error between actual and predicted rain height in Peninsular Malaysia and East Malaysia is shown in Table 4.3 and Table 4.4 respectively. While for the mean squared error (MSE) and R-squared score (R^2) are shown in Table 4.5.

Table 4.3: Table of Percentage Error between Actual and Predicted Rain Height in Peninsular Malaysia from Year 2020 to Year 2022.

Year	**Actual Rain Height, km**	**Predicted Rain Height, km**	**Percentage error, %**
2020	5.401	5.369	0.59
2021	5.34	5.347	0.13
2022	5.313	5.343	0.56

Table 4.4: Table of Percentage Error between Actual and Predicted Rain Height in East Malaysia from Year 2020 to Year 2022.

Year	**Actual Rain Height, km**	**Predicted Rain Height, km**	**Percentage error, %**
2020	5.414	5.372	0.77
2021	5.349	5.315	0.63
2022	5.328	5.300	0.52

Table 4.5: Table of Mean Squared Error and R-squared Score for AI Predictive Model.

Region / **Evaluation metrics**	**Peninsular Malaysia**	**East Malaysia**
Mean Squared Error (MSE)	0.0004	0.0004
R- Squared Score (R^2)	0.8306	0.8013

Based on the percentage error being calculated, it can be seen that in overall, the percentage errors do not exceed 1%. The highest percentage error for the result obtained is 0.77% while for the lowest percentage error for the result obtained is 0.13%.

After that, mean squared error (MSE) is measuring the average squared difference between the forecast value and the actual value. The smaller the value for MSE indicates that the overall model's performance is better. While for R-squared score (R^2) is determining how well the data fit the model and the value are between 0 to 1. In which value of 1 shows a perfect fit.

According to Table 4.5, the MSE value for predictive model of rain height in both regions is computed to be 0.0004. While the R^2 value for predictive model in Peninsular Malaysia and East Malaysia is 0.8306 and 0.8013 respectively. This shows that the AI predictive model for rain height has a good overall performance with the data is well-fitted to the predictive model since the computed MSE value is low and the R^2 value is closed to 1.

4.9 Summary

In summary, it can be understood that the rain height will be affected by the temperature level in which when the temperature increases, the rain height will increase. Then, the rain attenuation also being proved that from year 1992 to year 2022, there is an increasing trend for the rain attenuation in Malaysia.

After that, the AI predictive model being developed in this project is applying the input of historical data for rain height and global temperatures. This can ensure that the predicted rain height values are considering the effects of climate change. Furthermore, the predictive model had proved to achieve an acceptable accuracy and with the ability to predict the rain height values in the future.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In conclusion, all the aims and objectives of this project had been achieved. The data obtained from NCEP/NCAR reanalysis database had been successfully decoded using MATLAB software and the rain height values had been obtained by adding the ZDI height with 0.36 km. Then, the average rain height had been proved to have an increasing trend in both Peninsular Malaysia and East Malaysia from year 1992 to year 2022. The results showed that the average rain height will increase approximately 4 m with the increase in global temperature. A positive correlation relationship between average rain height and global temperature had been shown and the global temperature had a significant increase in Malaysia from year 1992 to year 2022.

Furthermore, the rain attenuation at 0.01% exceedance in Malaysia from year 1992 to year 2022 had a growing trend with the increasing of rain height and global temperature. The equation obtained showed that the rain attenuation value increased approximate 0.03 dB per year.

Moreover, a simple AI predictive model for rain height had been successfully deployed in this project. Since the AI predictive model had included the global temperature variable as one of the input parameters, therefore the predicted rain height values will be more accurate as compared to the static data for rain height. After that, due to the percentage error between the actual and predicted results is low, MSE values is low and the R^2 scores of the model is near to value of 1, therefore, it can be concluded that the AI predictive model had a good performance, acceptable accuracy and the data are well fitted to the model.

Lastly, the AI predictive model that can predict accurate rain height values can be applied to the future design work of satellite communication systems in determining the effective slant path of the satellite microwave links to reduce the effects of rain attenuation.

5.2 Recommendations for future work

The first recommendation for future work is to include more factors such as pressure and rain rate that might have the effects on the targeted variable for the learning of the AI predictive model so that it can have a complex learning algorithm. With a more complex AI predictive model, the results obtained will be more accurate and suitable for more applications.

The second recommendation would be to involve more tropical countries for analysis so that the results obtained can be compared with different tropics and to allow the application of results to other countries instead of only one country.

Furthermore, the datasets being learned by the AI predictive model can be larger by adding more historical data. This can allow the model can have sufficient inputs to analyse and to provide a more accurate result. Other than that, instead of using yearly data, future work can focus on monthly or weekly data for the rain height values. This can enable analysis for seasonal variation of the rain height.

REFERENCES

Abdullahi, A., 2024, *Generative AI vs predictive AI: What is the difference* [Online]. Available at: 〈https://www.eweek.com/artificial-intelligence/generative-ai-vs-predictive-ai/> [Accessed: 11 March 2024].

Abebe, W.T. and Endalie, D., 2023. Artifcial intelligence models for prediction of monthly rainfall without climatic data for meteorological stations in Ethiopia. *Journal of Big Data*, 10(2). Available at: <https://journalofbigdata.springeropen.com/articles/10.1186/s40537-022-00683-3#citeas> [Accessed: 11 March 2024].

Agbemenou, A.K.H., Motamed, R. and Amir, T.-K., 2023. A predictive analytics model for designing deep underground foundations using artificial neural networks. *Decision Analytics Journal*, 7. Available at: <https://www.sciencedirect.com/science/article/pii/S2772662223000607> [Accessed: 11 March 2024].

Albendag, A. and Zain, A., 2020. Improving the estimation of Earth-space link in ITU rain attenuation model. *ICEMIS'20: The 6th International Conference on Engineering & MIS 2020*. September 2020 pp. 1–4.

Ali, K.L., Md. Rafiqul, I. and Mohamed, H., 2014. Analysis of the synthetic storm technique using rain height models to predict rain attenuation in tropical regions. *5th International Conference on Computer & Communication Engineering*. 2014 IEEE, Kuala Lumpur, Malaysia, pp. 220–223.

Ali, R., 2020. Predictive modeling: Types, benefits and algorithms. *Oracle Net Suite*. Available at: <https://www.netsuite.com/portal/resource/articles/financial-management/predictive-modeling.shtml> [Accessed: 10 March 2024].

All, M., 2023, *Introduction to activation functions in neural networks* [Online]. Available at: <https://www.datacamp.com/tutorial/introduction-to-activation-functions-in-neural-networks> [Accessed: 11 March 2024].

Altena, K., 2023, *Matlab and Azure: A match made in performance heaven.* [Online]. Available at: <https://techcommunity.microsoft.com/t5/azure-high-performance-computing/matlab-and-azure-a-match-made-in-performance-heaven/ba-p/3788737> [Accessed: 5 September 2023].

Alui, M.R., 2012. *Study of rain rate and rain attenuation for finding the optimum frequency uses by maritime radar at Malaysia*. Universiti Teknologi MARA , Shah Alam, Malaysia.

Anjanakrishnan, 2023, *Predictive Modelling - An beginner's overview of linear regression model* [Online]. Available at: <https://medium.com/@anjanakrishnan3100/predictive-modelling-an-beginners-overview-of-linear-regression-model-b01d820da57e> [Accessed: 11 March 2024].

Ariwala, P., 2023, *How machine learning can boost your predictive analytics* [Online]. Available at: <https://marutitech.com/machine-learning-predictive-analytics/> [Accessed: 11 March 2024].

Bai, Y., 2022. RELU-function and derived function review. *SHS Web of Conferences 144*. 2022 Hainan, China.

Baruah, I.D., 2021, *Activation functions and loss functions for neural networks: How to pick the right one?* [Online]. Available at: <https://medium.com/analytics-vidhya/activation-functions-and-loss-functions-for-neural-networks-how-to-pick-the-right-one-542e1dd523e0> [Accessed: 15 March 2024].

Benarroch, A., Siles, G.A. and Riera, J.M., 2022. Height of the 0°C Isotherm and the Melting Layer in Madrid: Comparison of Estimations from Different Sensors. *16th European Conference on Antennas and Propagation (EuCAP)*. 2022 IEEE, Madrid, Spain, pp. 1–5.

Bolan, S. et al., 2024. Impacts of climate change on the fate of contaminants through extreme weather events. *Science of The Total Environment*, 909. Available at: <https://www-sciencedirect-com.libezp2.utar.edu.my/science/article/pii/S004896972307016X> [Accessed: 24 February 2024].

Burke, J., 2023, *Why and how to use Google Colab.* [Online]. Available at: <https://www.techtarget.com/searchenterpriseai/tutorial/Why-and-how-to-use-Google-Colab#:~:text=Google%20Colaboratory%2C%20or%20Colab%2C%20is,creation%20from%20the%20Jupyter%20Project.> [Accessed: 17 March 2024].

Chakraborty, S., Chakraborty, M. and Das, S., 2020. Experimental Studies of Slant-Path Rain Attenuation Over Tropical and Equatorial Regions: A Brief Review. *IEEE Antennas and Propagation Magazine*. Available at: <https://www.researchgate.net/publication/340151731_Experimental_Studies_of_Slant-Path_Rain_Attenuation_Over_Tropical_and_Equatorial_Regions_A_Brief_Review> [Accessed: 9 September 2023].

Chernysheva, A., 2023, *Exploring data transformation for PyTorch Tensors in Python.* [Online]. Available at: <https://medium.com/@anna_che/exploring-data-transformation-for-pytorch-tensors-in-python-36ad97e5e2bf#:~:text=A%20PyTorch%20tensor%20is%20an,for%20data%20representation%20and%20manipulation.> [Accessed: 20 March 2024].

Claudia, B., Mario, C. and Giuseppe, D., 2021. Analysis of the downlink system for low earth orbit cubesats. Available at: <https://www.researchgate.net/publication/354572152_Analysis_of_the_Downlink_System_for_Low_Earth_Orbit_CubeSats> [Accessed: 14 May 2024].

Clayton, A., 2023, *What is supercooled water?* [Online]. Available at: <https://www.wkbn.com/weather/what-is-supercooled-water/> [Accessed: 19 March 2024].

Das, T., 2023, *Google Colab: Everything you need to know*. [Online]. Available at: <https://geekflare.com/google-colab/> [Accessed: 17 March 2024].

Dolinay, A., 2023, *An introduction to Google Colab*. [Online]. Available at: <https://adriandolinay.medium.com/an-introduction-to-google-colab-2023-6c26792827b3> [Accessed: 16 March 2024].

Erbakanov, L., Staneva, L. and Vardeva, I., 2018. Using a long time constant integrator in rainfall intensity measuring via acoustic method. *2018 20th International Symposium on Electrical Apparatus and Technologies (SIELA)*. 2018

Everything RF, 2023, *What are mmwaves or millimeter waves?* [Online]. Available at: <https://www.everythingrf.com/community/what-are-millimeter-waves> [Accessed: 7 March 2024].

Foo, Y.L., 2019. Rain attenuation factor in the Earth-space links of tropical regions. *Journal of Telecommunication, Electronic and Computer Engineering*, 11(3).

Gharanjik, A., Mysore, B.S., Zimmer, F. and Ottersten, B., 2018. Centralized Rainfall Estimation Using Carrier to Noise of Satellite Communication Links. *IEEE Journal on Selected Areas in Communications*, 36(5), pp.1–1. Available at: <https://www.researchgate.net/publication/324939953_Centralized_Rainfall_Estimation_using_Carrier-to-Noise_of_Satellite_Communication_Links> [Accessed: 8 February 2024].

Gires, A., 2018, *How do we measure rainfall?* [Online]. Available at: <https://kids.frontiersin.org/articles/10.3389/frym.2018.00038> [Accessed: 3 September 2023].

Gorman, Paul.A.O., 2015. Precipitation extremes under climate change. *Current Climate Change Reports*, 1(2015), pp.49–59. Available at: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4542457/pdf/40641_2015_Article_9.pdf> [Accessed: 3 September 2023].

Graham, S., 1999, *Tropical Rainfall Measuring Mission* [Online]. Available at: <https://earthobservatory.nasa.gov/features/TRMM> [Accessed: 12 September 2023].

Hafiz, B., Aizat, F., Mohamad, I. and M, H., 2016. Effect of Climate Change on Satellite Communication Links in Malaysia. *Journal of Artificial Intelligence*, 9(4), pp.78–81. Available at: <https://scialert.net/abstract/?doi=jai.2016.78.81> [Accessed: 22 July 2023].

Hassan, D., Md.Rafiqul, I., Khalid, A.-K. and Sheroz, K., 2011. Preliminary Analysis of Ku-Band Rain Fade Data for Earth-to-Satellite Path Measured in Malaysia . *2011 IEEE 10th Malaysia International Conference on Communications*. 2011 IEEE, Sabah, Malaysia, pp. 93–96.

Hendri, I., Mohammad, Syamsul.R. and Mart, T., 2023. Effects of Climate change on temperature and precipitation in the Lake Toba region, Indonesia, based on ERA5-land data with quantile mapping bias correction. *Scientific reports*, 2542(2023). Available at: <https://www.nature.com/articles/s41598-023-29592-y> [Accessed: 3 September 2023].

Igwe, K.C., Oyedum, O.D., Ajewole, M.O. and Aibinu, A.M., 2019. Evaluation of some rain attenuation prediction models for satellite communication at Ku and Ka bands. *Journal of Atmospheric and Solar-Terrestrial Physics*, 188(2019), pp.52–61. Available at: <http://repository.futminna.edu.ng:8080/jspui/bitstream/123456789/2722/1/Evaluation%20of%20rain%20Atten_JASTP.pdf> [Accessed: 9 September 2023].

ITU-R P.618-13, 2017. Propagation data and prediction methods required for the design of Earth-space telecommunication systems. *International Telecommunication Union*.

ITU-R P.837-7, 2017. Recommendation ITU-R P.837-7: Characteristics of precipitation for propagation modelling.

ITU-R P.839-4, 2013. Rain height model for prediction methods: P series, radiowave propagation. . *International Telecommunication Union*.

Jessica, 2023, *Understanding Telecommunication: A Comprehensive Guide To How It Work and Its Applications.* [Online]. Available at: <https://www.openworldlearning.org/understanding-telecommunication-a-comprehensive-guide-to-how-it-works-and-its-applications/> [Accessed: 15 July 2023].

Kanade, V., 2022, *What is logistic regression? Equation, assumptions, types and best practices.* [Online]. Available at: <https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-logistic-regression/> [Accessed: 11 March 2024].

Kanjee, R., 2021, *The 4 problems with training models in Colab.* [Online]. Available at: <https://medium.com/augmented-startups/the-4-problems-with-training-models-in-colab-9135d9702359> [Accessed: 10 April 2024].

Kothari, S., 2023, *Predictive modeling: Revolutionizing decision-making with AI* [Online]. Available at: <https://www.simplilearn.com/predictive-modeling-article> [Accessed: 11 March 2024].

Labrador, V., 2023. Satellite Communication. Available at: <https://www.britannica.com/technology/satellite-

communication/Development-of-satellite-communication> [Accessed: 22 July 2023].

Lindsey, R. and Dahlman, L., 2024. Climate Change: Global temperature. Available at: <https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature#:~:text=According%20to%20NOAA’s%202023%20Annual,0.20%C2%B0%20C)%20per%20decade.> [Accessed: 20 February 2024].

Mandeep, J.S., 2009. Slant path rain attenuation comparison of predicted models for satellite applications in Malaysia. *Journal of Geophysical Research,* 114. Available at: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2009JD011852> [Accessed: 8 September 2023].

Marine Satellite Systems, 2012, *Satellite Frequency Bands* [Online]. Available at: <http://www.marinesatellitesystems.com/index.php?page_id=101> [Accessed: 22 July 2023].

Marsico, A., Vincenzo, D.S. and Capolongo, D., 2021. Erosion rate of the Aliano Biancana Badlands based on a 3D multi-temporal high-resolution survey and implications for wind-driven rain. *Land*, 10(8). Available at: <https://www.researchgate.net/publication/353769617_Erosion_Rate_of_the_Aliano_Biancana_Badlands_Based_on_a_3D_Multi-Temporal_High-Resolution_Survey_and_Implications_for_Wind-Driven_Rain> [Accessed: 5 March 2024].

Marzuki et al., 2018. Long-term Change in Rainfall Rate and Melting Layer Height in Indonesia. *2018 Progress in Electromagnetics Research Symposium (PIERS-Toyama)*. 2018 IEEE, Toyama, Japan.

Mohammed, H.I.D., 2005. Climate change and changes in global precipitation patterns: What do we know? *Environment International*, 31(2005), pp.1167–1181. Available at: <https://www.mobot.org/MOBOT/Research/climateChange/pdf/Dore2005-EnvironmenInternational.pdf> [Accessed: 3 September 2023].

Mohanty, S., Singh, C. and Tiwari, V., 2016. Estimation of rain attenuation losses in signal link for microwave frequencies using ITU-R model. *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. 2016 Beijing, China, pp. 532–535.

Monga, S. et al., 2022. Estimation of rain attenuation over 10GHz to 80GHz radio band. *2022 3rd International Conference on Computing, Analytics and Networks (ICAN)*. 2022 IEEE, Rajpura, Punjab, India, pp. 1–6.

Muhammad Rezza, bin A., 2012. *Study of rain rate and rain attenuation for finding the optimum frequency uses by Maritime Radar at Malaysia.* Universiti Teknologi MARA.

Mukesh, C.K., Sumit, J. and Lalit, S.G., 2014. Prediction of rain attenuation and impact of rain in wave propagation at microwave frequency for tropical region (Uttarakhand, India). *International Journal of Microwave Science and Technology*, 2014. Available at: <https://www.hindawi.com/journals/ijmst/2014/958498/> [Accessed: 6 August 2023].

Muzammil, K., 2023, *Application of Neural Network* [Online]. Available at: <https://www.aalpha.net/articles/applications-of-neural-networks/> [Accessed: 16 March 2024].

NASA, *The effects of climate change: Earth will continue to warm and the effects will be profound.* [Online]. Available at: <https://climate.nasa.gov/effects/#:~:text=%E2%80%9CClimate%20change%E2%80%9D%20encompasses%20global%20warming,in%20flower%2Fplant%20blooming%20times.> [Accessed: 26 August 2023].

NASA, 2015, *TRMM comes to an end after 17 years* [Online]. Available at: <https://gpm.nasa.gov/missions/trmm/mission-end#:~:text=NASA%20and%20the%20Japan%20Aerospace,of%20the%20world's%20rainfall%20occurs.> [Accessed: 12 September 2023].

National Oceanic and Atmospheric Administration, 2021, *Climate change impacts* [Online]. Available at: <https://www.noaa.gov/education/resource-collections/climate/climate-change-impacts> [Accessed: 26 August 2023].

Nazar, E., Zia, N., Md. Abdus Salam and Jegathese, R., 2005. Microwave attenuation studies due to rain for communication links operating in Malaysia. *Georgian Electronic Scientific Journal: Computer Science and Telecommunications*, 1(5). Available at: <https://www.researchgate.net/profile/Zia-Nadir/publication/256086499_Microwave_attenuation_studies_due_to_rain_for_communication_links_operating_in_Malaysia/links/00b49521866713a88c000000/Microwave-attenuation-studies-due-to-rain-for-communication-links-operating-in-Malaysia.pdf> [Accessed: 6 August 2023].

Nor Azlan, M.A., Din, J. and Lam, H.Y., 2011. Rain height information from TRMM precipitation radar for satellite communication in Malaysia. *2011 IEEE International Conference on Space Science and Communication (IconSpace)* . 2011 Penang, Malaysia.

Ogunleye, J.O., 2022. *Predictive data analysis using linear regression and random forest*. Data Integrity and Data Governance. Available at: <https://www.intechopen.com/chapters/84394> [Accessed: 11 March 2024].

Ojo, J.S., Falodun, S.E. and Odiba, O., 2014. 0°C isotherm height distribution for Earth-space communication satellite links in Nigeria. *Indian Journal of Radio & Space Physics*, 43, pp.225–234. Available at: <https://nopr.niscpr.res.in/bitstream/123456789/29055/1/IJRSP%2043%283%29%20225-234.pdf> [Accessed: 15 April 2024].

Olurotimi, E.O., Sokoya, O., Ojo, J.S. and Owolawi, P.A., 2017. Observation of bright-band height data from TRMM-PR for satellite communication in South Africa. *Journal of Atmospheric and Solar-Terrestrial Physics*, 160, pp.24–33. Available at: <https://www.sciencedirect.com/science/article/abs/pii/S1364682616302772> [Accessed: 12 September 2023].

Ostertagová, E., 2012. Modelling using polynomial regression. *Procedia Engineering*, 48, pp.500–506. Available at: <https://www.sciencedirect.com/science/article/pii/S1877705812046085> [Accessed: 11 March 2024].

Paulson, K and Al-Mreri, A., 2011. Trends in the incidence of rain height and the effects on global satellite telecommunications. . *IET Microwaves Antennas & Propagation*, 5(14), pp.1710–1713. Available at: <https://www.researchgate.net/publication/260502254_Trends_in_the_incidence_of_rain_height_and_the_effects_on_global_satellite_telecommunications> [Accessed: 15 April 2024].

Paulson, Kevin. S., 2011. The effects of climate change on microwave telecommunications. *Proceedings of the 11th International Conference on Telecommunications*. 2011 IEEE, Graz, Austria, pp. 157–160.

Platnick, S., Przyborski, P. and Hanson, H., 2015, *Tropical Rainfall Measuring Mission (TRMM)* [Online]. Available at: <https://eospso.nasa.gov/missions/tropical-rainfall-measuring-mission> [Accessed: 12 September 2023].

Rane, Z., 2021, *There's a clear winner between matlab vs python.* [Online]. Available at: <https://towardsdatascience.com/theres-a-clear-winner-between-matlab-vs-python-f6bb56b2b930> [Accessed: 16 March 2024].

re3data, *NCEP/NCAR Reanalysis Project* [Online]. Available at: <https://www.re3data.org/repository/r3d100011760> [Accessed: 19 August 2023].

RF Editorial Team, 2021, *ITU Radiocommunication Sector (ITU-R): What is the ITU-R? What do they do?* [Online]. Available at: <https://www.everythingrf.com/community/itu-radiocommunication-sector> [Accessed: 12 September 2023].

Riera, J.M. et al., 2023. Characterization of rain attenuation in 80-200GHz from experimental drop size distributions. *IEEE Transactions on Antennas and Propagation*, 74(5), pp.4371–4379. Available at: <https://oa.upm.es/73233/1/TAP3259682%20Author%20version.pdf> [Accessed: 7 March 2024].

Roston, E., 2023. These are the climate numbers to watch in 2023. *The Malaysian Reserve*. Available at: <https://themalaysianreserve.com/2023/01/12/these-are-the-climate-numbers-to-watch-in-2023/> [Accessed: 20 February 2024].

Sharma, S., 2017, *Activation functions in neural networks* [Online]. Available at: <https://towardsdatascience.com/activation-functions-neural-networks-1cbd9f8d91d6> [Accessed: 11 March 2024].

Sharma, Siddharth, Sharma, Simone and Athaiya, A., 2020. Activation functions in neural networks. *International Journal of Engineering Applied Sciences and Technology*, 4(12), pp.310–316. Available at: <https://ijeast.com/papers/310-316,Tesma412,IJEAST.pdf> [Accessed: 11 March 2024].

Sinclair, L. and Weigel, A., 2020, *Instrument: 2DVD Disdrometer* [Online]. Available at: <https://ghrc.nsstc.nasa.gov/home/micro-articles/instrument-2dvd-disdrometer#:~:text=A%20disdrometer%20is%20an%20optical,raindrops%2C%20snowflakes%2C%20and%20hail.> [Accessed: 3 September 2023].

Singh, Mandeep.Singh.J. et al., 2006. Earth-To-Space Improved Model for Rain Attenuation Prediction at Ku-Band. *American Journal of Applied Sciences*, 3(8), pp.1967–1969. Available at: <https://thescipub.com/pdf/ajassp.2006.1967.1969.pdf> [Accessed: 8 September 2023].

Singh, R. and Acharya, R., 2018. Development of a new global model for estimating one-minute rainfall rate. *IEEE Transactions on Geoscience and Remote Sensing*, 556(11), pp.6462–6468. Available at: <https://www.researchgate.net/publication/325860357_Development_of_a_New_Global_Model_for_Estimating_One-Minute_Rainfall_Rate> [Accessed: 14 April 2024].

Stokes, K., Brown, M., Zala, S. and Hargrave, B., 2023. AI model training with PyTorch. Available at: <https://developer.ibm.com/articles/awb-ai-model-training-with-pytorch/> [Accessed: 9 April 2024].

Syahrul, M.G., 2017. Design and implementation of tipping-bucket rain gauge. *2017 1st International Conference on Informatics and Computational Sciences*. 2017 IEEE.

Tan, Y.H. et al., 2021. Rain attenuation prediction based on theoretical method with realistic drop shape for millimeter-wave radio in tropical region. *IEICE Communications Express*, 10(5), pp.260–265. Available at: <https://www.jstage.jst.go.jp/article/comex/10/5/10_2021XBL0025/_pdf> [Accessed: 6 August 2023].

Thuy Le, T.L., 2024, *How does ReLU enable neural networks to approximate continuous nonlinear functions?* [Online]. Available at: <https://towardsdatascience.com/how-relu-enables-neural-networks-to-approximate-continuous-nonlinear-functions-f171b7859727> [Accessed: 16 March 2024].

Topper, N., 2023, *Sigmoid activation function: An introduction* [Online]. Available at: <https://builtin.com/machine-learning/sigmoid-activation-function> [Accessed: 15 March 2024].

Trenberth, Kevin.E., 2011. Changes in precipitation with climate change. *Climate Research*, 47(2011), pp.123–138. Available at: <https://www.int-res.com/articles/cr_oa/c047p123.pdf> [Accessed: 3 September 2023].

Ukommi, U., Ubom, E. and Ikpaya, I., 2022. Ground station design for satellite and space technology development. *American Journal of Engineering Research*, 10(8), pp.12–19. Available at: <https://www.researchgate.net/publication/358511532_Ground_Station_Design_for_Satellite_and_Space_Technology_Development> [Accessed: 29 July 2023].

Ulaganathen, K., Islam, M.R., Khaizuran, A. and Tharek, A.R., 2018. Specific rain attenuation analysis and modeling for 5G communication. *2018 7th International Conference on Computer and Communication Engineering (ICCCE)*. 2018 IEEE, Kuala Lumpur, Malaysia, pp. 1–4.

United States Environmental Protection Agency, 2023, *Climate change indicators: heavy precipitation* [Online]. Available at: <https://www.epa.gov/climate-indicators/climate-change-indicators-heavy-precipitation#:~:text=Climate%20change%20can%20affect%20the,heavier%20rain%20and%20snow%20storms.> [Accessed: 3 September 2023].

World Meteorological Organization, 2023. Global temperatures set to reach new records in next five years. Available at: <https://wmo.int/news/media-centre/global-temperatures-set-reach-new-records-next-five-years> [Accessed: 20 March 2024].

Yasar, K., 2022, *Definition: PyTorch* [Online]. Available at: <https://www.techtarget.com/searchenterpriseai/definition/PyTorch> [Accessed: 5 April 2024].

Yeo, J.X., Lee, Y.H. and Ong, J.T., 2014. Rain Attenuation Prediction Model for Satellite Communications in Tropical Regions. *IEEE Transactions on Antennas and Propagation*, 62(11), pp.5775–5781. Available at: <https://ieeexplore-ieee-org.libezp2.utar.edu.my/document/6899607> [Accessed: 6 August 2023].

Yussuff, Abayomi.Isiaka.O. and Kasali, Ololade.F., 2018. Slant path rain attenuation models evaluation for Lagos at Ka band. *Engineering & Technology Research Journal*, 3(1), pp.24–30. Available at: <https://etrj.com.ng/files/04.pdf> [Accessed: 9 September 2023].

Yusuf, A. et al., 2014. Comparison of measured rain attenuation in the 10.982-GHz band with predictions and sensitivity analysis. *International Journal of Satellite Communications and Networking,* , 33(3).

Yusuf, B.L., Joseph, S.O. and Sunday, E.F., 2021. Rain height statistics from GPM data for satellite communication systems in Nigeria. *IOP Conf. Series: Earth and Environmental Science*. 2021

Zhang, F., Zuo, Y. and Sun, H., 2017. Techniques of rain fade countermeasures in Ka-band satellite communication on ships. *2017 16th International Conference on Optical Communications and Networks (ICOCN),*. 2017 IEEE, Wuzhen, China, pp. 1–3.

APPENDICES

Appendix A: MATLAB Code of Obtaining the Rain Height Value

```
year= 1995;

lat=36;
longi=41;

s=['air.' int2str(year) '.nc'];
ncid= netcdf.open(s, 'NC_NOWRITE');
temperature_global_map = netcdf.getVar(ncid,4);


s=['hgt.' int2str(year) '.nc'];
ncid= netcdf.open(s, 'NC_NOWRITE');
height_global_map = netcdf.getVar(ncid,4);

status=0;


for time=1:1460

      temp_data = temperature_global_map(longi,lat,1,time);
       temp1st=temp_data;

       if temp1st <= 273.15
           temp2a=temp1st;
           temp1a=temp1st;

           press2=1;
           press1=1;

           status=1;
       end

       if status==0;

       temp_data = temperature_global_map(longi,lat,2,time);
       temp2nd=temp_data;

              if temp1st > 273.15 && temp2nd < 273.15
                  temp1a=temp1st;
                  temp2a=temp2nd;

                   press1=1;
                   press2=2;

                   status=1;

              end


       end


       if status==0;
```

```
temp_data = temperature_global_map(longi,lat,3,time);
temp3rd=temp_data;

        if temp2nd > 273.15 && temp3rd < 273.15
          temp1a=temp2nd;
          temp2a=temp3rd;

          press1=2;
          press2=3;

          status=1;

         end


end


if status==0;

temp_data = temperature_global_map(longi,lat,4,time);

temp4th=temp_data;


       if temp3rd > 273.15 && temp4th < 273.15
          temp1a=temp3rd;
          temp2a=temp4th;

          press1=3;
          press2=4;

          status=1;

       end


end


if status==0;

temp_data = temperature_global_map(longi,lat,5,time);
temp5th=temp_data;



       if temp4th > 273.15 && temp5th < 273.15
          temp1a=temp4th;
          temp2a=temp5th;

          press1=4;
          press2=5;

          status=1;

       end
```

```
end


if status==0;

temp_data = temperature_global_map(longi,lat,6,time);
temp6th=temp_data;



          if temp5th > 273.15 && temp6th < 273.15
             temp1a=temp5th;
             temp2a=temp6th;

             press1=5;
             press2=6;

             status=1;

         end


end


if status==0;

temp_data = temperature_global_map(longi,lat,7,time);
temp7th=temp_data;


          if temp6th > 273.15 && temp7th < 273.15
             temp1a=temp6th;
             temp2a=temp7th;

             press1=6;
             press2=7;

             status=1;

         end


end


if status==0;

temp_data = temperature_global_map(longi,lat,8,time);
temp8th=temp_data;



          if temp7th > 273.15 && temp8th < 273.15
             temp1a=temp7th;
             temp2a=temp8th;

             press1=7;
             press2=8;
```

```
                status=1;

            end


      end

      height_data = height_global_map(longi,lat,press1,time);
      height1a=height_data;


      height_data = height_global_map(longi,lat,press2,time);
      height2a=height_data;


      temp_data2 = temperature_global_map(longi,lat,1,time);
      temp_lista=temp_data2;



      height1=double(height1a);
      height2=double(height2a);

      temp1=double(temp1a);
      temp2=double(temp2a);

      temp_list=double(temp_lista);

    if temp2 <= 273.15 && temp1 <= 273.15
      temp=((temp_list-273.15)-(temp2-273.15));
      height=height2;
      heightkm=height/1000;
      lapse_rate=temp/heightkm;
      lapse_rate_list(:,time)=lapse_rate;
      altitude=((temp1-273.15)/lapse_rate)+(height1/1000);
      altitude( altitude < 0 ) = 0;
      altitude (altitude==inf)=0;

      alt1995(:,time)=altitude;

    else
      temp=((temp1-273.15)-(temp2-273.15));
       height=height2-height1;
       heightkm=height/1000;
       lapse_rate=temp/heightkm;
       lapse_rate_list(:,time)=lapse_rate;
       altitude=((temp1-273.15)/lapse_rate)+(height1/1000);
       altitude (altitude==inf)=0;

       alt1995(:,time)=altitude;
       rain_h1995(:,time) = altitude + 0.36;
    end
       near_surface_temp(:,time)=temp_lista;


time
status=0;

end
```

Appendix B: Python Code of AI Prediction Model in Google Colab

```
import torch
import torch.nn as nn
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, r2_score,
mean_absolute_error
import io
import numpy as np

# Read the dataset
data = pd.read_csv(io.BytesIO(uploaded['rain height.csv']))

# Preprocess the data
X = data[['year','temp']].values
y = data['rain height peninsular malaysia'].values

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
random_state=42)

# Normalize/Scale the features
scaler = StandardScaler()
X_train_normalize = scaler.fit_transform(X_train)
X_val_normalize = scaler.transform(X_val)

# Convert data to PyTorch tensors
tsr_year_train = torch.tensor(X_train_normalize, dtype=torch.float32)
tsr_rainh_train = torch.tensor(y_train, dtype=torch.float32)
tsr_year_val = torch.tensor(X_val_normalize, dtype=torch.float32)
```

```
tsr_rainh_val = torch.tensor(y_val, dtype=torch.float32)

# Define the neural network model
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.fc1 = nn.Linear(2,8)
        self.fc2 = nn.Linear(8, 4)
        self.fc3 = nn.Linear(4, 1)

    def forward(self, x):
        x = torch.relu(self.fc1(x))
        x = torch.relu(self.fc2(x))
        x = torch.relu(self.fc3(x))
        return x

# Initialize the model
model = Model()

# Define optimizer and loss function
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
criterion = nn.MSELoss()
# Training the model
epochs = 5800
train_losses = []
val_losses = []
train_MAE = []
val_MAE = []

for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    outputs = model(tsr_year_train)
```

```
    train_loss = criterion(outputs, tsr_rainh_train.view(-1, 1))
    train_losses.append(train_loss.item())

    #calculate training MAE
    train_mae = mean_absolute_error(tsr_rainh_train,
outputs.detach().cpu().numpy().flatten())
    train_MAE.append(train_mae)
    train_loss.backward()
    optimizer.step()

    # Validation
    model.eval()
    with torch.no_grad():
        val_outputs = model(tsr_year_val)
        val_loss = criterion(val_outputs, tsr_rainh_val.view(-1, 1))
        val_losses.append(val_loss.item())

        val_mae = mean_absolute_error(tsr_rainh_val,
val_outputs.detach().cpu().numpy().flatten())
        val_MAE.append(val_mae)
# Evaluate the trained model
model.eval()

# Pass the test data through the trained model for prediction
with torch.no_grad():
    predicted_train = model(tsr_year_train)
    predicted_val = model(tsr_year_val)

# Convert predictions to NumPy arrays for visualization
predicted_train_np = predicted_train.cpu().numpy().flatten()
predicted_val_np = predicted_val.cpu().numpy().flatten()

# Calculate MSE, MAE, and R2 for training set
```

```
mse_train = mean_squared_error(y_train, predicted_train_np)
mae_train = mean_absolute_error(y_train, predicted_train_np)
r2_train = r2_score(y_train, predicted_train_np)

# Calculate MSE, MAE, and R2 for validation set
mse_val = mean_squared_error(y_val, predicted_val_np)
mae_val = mean_absolute_error(y_val, predicted_val_np)
r2_val = r2_score(y_val, predicted_val_np)

# Maximum year in the dataset
max_year = data['year'].max()
# Generate future years for prediction (e.g., next 5 years)
future_years = np.arange(max_year + 1, max_year + 6).reshape(-1, 1)
future_temp = np.array([26.6,26.4,26.35,26.7,26.8]).reshape(-1,1)

#concatenate future_years and future_temp into a single array
future_data = np.concatenate((future_years, future_temp),axis = 1)

# Scale the future years using the same scaler used for training data
#future_years_scaled = scaler.transform(future_years)
#future_temp_scaled = scaler.transform(future_temp)
future_data_scaled = scaler.transform(future_data)

#extract scaled future years and temp
future_years_scaled = future_data_scaled[:,0].reshape(-1,1)
future_temp_scaled = future_data_scaled[:,1].reshape(-1,1)

# Convert future years to PyTorch tensor
tsr_future_years = torch.tensor(future_years_scaled, dtype=torch.float32)
tsr_future_temp = torch.tensor(future_temp_scaled, dtype=torch.float32)

#concatenate future_years and future_temp tensors
tsr_future_combined = torch.cat((tsr_future_years,tsr_future_temp), dim=1)
```

```
# Make predictions for future years using the trained model
with torch.no_grad():
    predicted_future = model(tsr_future_combined)

# Convert predicted values to NumPy array
predicted_future = predicted_future.cpu().numpy()

# Assuming total_year and hist_and_pred are your data arrays
# Fit a linear regression model
regression_model = LinearRegression()
regression_model.fit(total_year[:,0].reshape(-1,1), hist_and_pred[:,0])

# Plot historical data
plt.scatter(total_year[:,0], hist_and_pred[:,0], label='Historical Data')

# Plot predicted values for new years
plt.scatter(new_years[:,0], predicted_future.flatten(), label='Predicted
(Future)', color='orange')

# Predict values using the model
predicted_values = regression_model.predict(total_year[:,0].reshape(-1,1))

# Plot the data points
plt.plot(total_year[:,0], hist_and_pred, color='blue')
plt.plot(total_year[:,0], predicted_values, color='red', label='Regression Line')
```