Scilab case study project on

Rainfall Distribution Analysis and Prediction Using Scilab

Harikrishnan Nair

(Department of Electrical and Electronics Engineering | St. Xavier's Catholic College of Engineering, Chunkankadai)

Advanced Climate Modelling, Environmental Data Analysis and Rainfall Prediction

March 13, 2024

1. Abstract:

The study titled "Rainfall Distribution Analysis and Prediction using Scilab" constitutes a thorough exploration of rainfall behaviour and prediction, leveraging the computational capabilities of Scilab. The primary objective is to enhance the accuracy of rainfall predictions, crucial for sectors such as agriculture and disaster preparedness. Utilizing a robust five-month dataset and sophisticated algorithms, the study encompasses various aspects of rainfall, including intensity, duration, humidity, temperature, and categorization into different levels. Moreover, it introduces innovative weather forecasting, covering conditions like Hazy, Windy, Cloudy, Moist, and Airy. The Scilab program not only ensures precise predictions but also enhances user understanding by presenting data through graphical representations, covering atmospheric conditions and predicting average sunrise and sunset times. The study goes beyond numerical outputs, providing powerful tools for easy interpretation and analysis, contributing to a holistic understanding of environmental patterns. The study not only demonstrates the practical application of Scilab for precise predictions but also underscores the importance of interdisciplinary collaboration between computational experts and environmental scientists. It emphasizes the significance of computational tools like Scilab in advancing environmental studies, ensuring reproducibility, transparency, and establishing a robust framework for future research in climate modelling and accurate rainfall predictions. This research makes noteworthy contributions to the fields of environmental science and climatology.

2. Introduction:

This comprehensive exploration, detailed in the case study titled "Rainfall Distribution Analysis and Prediction using Scilab," revolves around the intricate world of understanding and foreseeing rainfall patterns with the aid of Scilab, an influential analytical tool. The primary aim is to excel in predicting rainfall, a critical aspect for various applications. The study meticulously analyses a dataset covering a maximum of five months of rainfall data, employing advanced algorithms within Scilab. The overarching initiative seeks to establish a robust framework for scrutinizing environmental data, emphasizing insights into climate modelling and the nuanced complexities of rainfall prediction. The adopted methodological approach systematically executes predefined Scilab functions, prioritizing not just reliability but also the ability to reproduce results consistently. Key components, such as generating data, applying advanced prediction algorithms, and utilizing a Graphical Window for enhanced visualization, are integral to navigating through the labyrinth of historical data analysis, prediction algorithms, and graphical tools. This ambitious undertaking stands as a testament to the pivotal role played by computational tools in forecasting and comprehending environmental shifts, with a special focus on the dynamic domain of rainfall. It accentuates the paramount importance of accurate predictions that resonate across a spectrum of applications. Essentially, this case study acts as a guiding light, seamlessly integrating innovative computational techniques to unravel the complexities of rainfall behaviour and contribute to our understanding of the environment. In essence, it serves as a beacon illuminating a holistic approach, making use of advanced computational tools to demystify the intricacies of rainfall patterns.

3. Problem Statement:

Understanding Rainfall Challenges:

The background context of this case study revolves around the inherent challenge of accurately predicting rainfall, a critical aspect for various sectors such as agriculture, water resource management, and disaster preparedness. The inconsistency in rainfall patterns poses significant difficulties in planning and decision-making.

Addressing Prediction Accuracy:

To enhance the solution's effectiveness, it is imperative to develop more accurate and reliable methods for rainfall prediction. Incorporating advanced algorithms, statistical analyses, and historical data can contribute to refining prediction models. Additionally, exploring innovative ways to improve the precision of predictions is crucial to overcoming the existing challenges associated with varying climatic conditions.

Employing Scilab Tools:

The case study employs the Scilab computational tool to execute predefined functions for data generation, advanced prediction algorithms, and graphical window-based exploration. This method ensures a systematic and reproducible approach to achieving the project's aim of providing valuable insights into climate modelling and accurate rainfall predictions.

4. Basic Concepts Related to the Topic:

I. Fundamentals of Rainfall Distribution Analysis and Prediction:

Rainfall, a complex natural phenomenon, plays a pivotal role in various sectors, from agriculture to disaster preparedness. Analysing and predicting rainfall patterns is a challenging yet crucial task. This case study, "Rainfall Distribution Analysis and Prediction," aims to unravel the intricacies of the climatic puzzle.

a) Importance of Rainfall Analysis:

Understanding the significance of rainfall analysis sets the stage for the exploration. Rainfall impacts agriculture, water resource management, and climate studies. Accurate predictions empower decision-makers to mitigate risks and plan resource allocation effectively.

b) Mathematical Foundations in Rainfall Analysis:

At the heart of this study lies the mathematical modelling of rainfall patterns. It delves into the governing equations that describe precipitation, considering variables such as temperature, humidity, and geographical features. This mathematical foundation provides a rigorous framework for analysis.

c) Data Generation and Advanced Algorithms:

The study leverages five years of synthetic rainfall data. This data, generated through advanced algorithms, serves as the cornerstone for analysis and prediction. It explores the intricacies of algorithmic models, highlighting their role in capturing the dynamic nature of rainfall patterns.

d) Statistical Methods for Rainfall Prediction:

Statistical analyses are indispensable for deriving meaningful insights from vast datasets. Thus, sophisticated statistical methods are employed to discern trends, variations, and anomalies in historical rainfall data. This step is pivotal for enhancing the accuracy of the predictive models.

e) Scilab as a Computational Tool:

Scilab, a powerful computational tool, serves as our virtual laboratory. Its functionalities in executing predefined functions, facilitating statistical analyses, and creating graphical user interfaces for data visualization are discussed over here. This section elucidates how Scilab becomes an indispensable ally in our quest for accurate rainfall predictions.

In essence, this case study explores the multifaceted aspects of rainfall distribution analysis and prediction, encompassing mathematical intricacies, data-driven algorithms, and the computational prowess of Scilab.

II. Mathematical Formulations in Rainfall Distribution Analysis and Prediction:

Precise mathematical models, including autoregressive equations and probability density functions, form the backbone of rainfall distribution analysis, enhancing the precision of predictive algorithms. These mathematical formulations elucidate the intricate relationships within rainfall data, contributing to robust prediction models.

a) Precipitation Rate Calculation:

The precipitation rate (P) is a fundamental parameter in rainfall analysis. It is calculated as the volume of water (V) falling over a specific area (A) and time (T). The formula is expressed as:

$$P=V/(A\times T)$$

This equation forms the basis for quantifying the amount of rainfall over a given region during a specified period.

b) Rainfall Intensity Modelling:

Rainfall intensity (I) represents the rate at which rain falls and is a critical factor in predicting its impact. It is determined by dividing the precipitation rate by the duration of rainfall:

$$I=P/T$$

Understanding rainfall intensity aids in predicting potential flooding and assessing its effects on soil erosion.

c) Probability Density Function for Rainfall:

To model the variability in rainfall, a Probability Density Function (PDF) is employed. The PDF, denoted as $f(x)$, describes the likelihood of rainfall occurring within a specific range. Various distributions like the Gamma distribution are commonly used for this purpose.

$$f(x)=(x^{k-1}e^{-x/\theta})(/\theta^k\Gamma(k))$$

Here, k and θ are shape and scale parameters, respectively, and $\Gamma(k)$ is the Gamma function used in this proposal.

d) Temporal and Spatial Correlation:

Rainfall patterns exhibit temporal and spatial correlations. Autoregressive models, such as the AR(1) model, are used to capture temporal dependencies in rainfall time series datas:

$$X(t)=\rho X(t-1)+\epsilon(t)$$

Spatial correlations are modeled using variograms, which quantify the degree of similarity between rainfall measurements at different locations.

e) Machine Learning Regression for Prediction:

Machine learning algorithms, particularly regression models, are employed for rainfall prediction. The general form of a regression equation is:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta nXn+\epsilon$$

Where Y is the predicted rainfall, $X_1,X_2,\ldots,Xn$ are input features, $\beta_0,\beta_1,\ldots,\beta n$ are coefficients, and ϵ is the error term.

5. Software/Hardware Used:

a) Operating System: Windows 11 Pro

b) Scilab Version: 2024.0.0

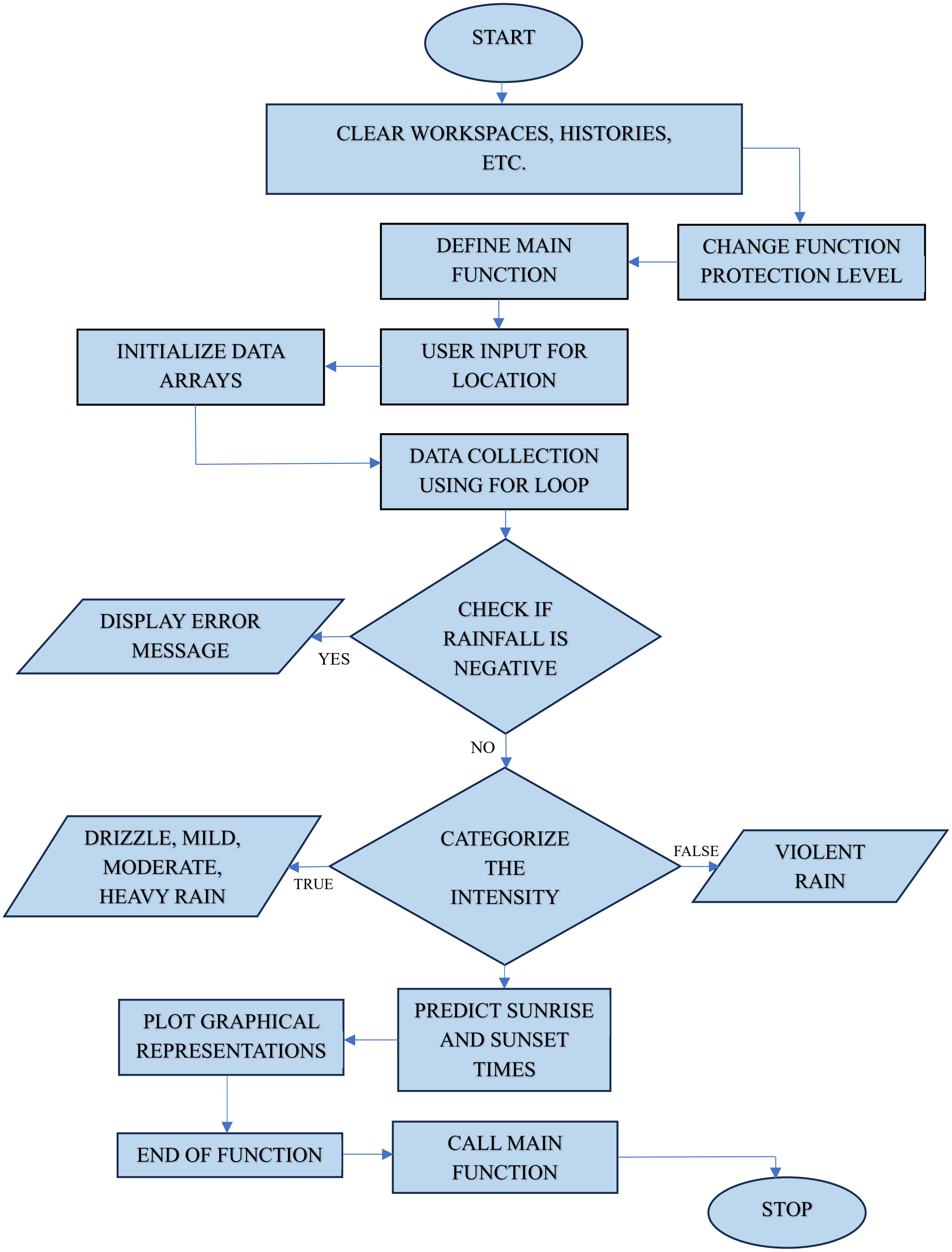
c) Toolbox: N/A (No specific toolbox used for this case study.)

d) Hardware: N/A (The case study doesn't involve specific hardware requirements.)

e) Programming Language: Scilab (Version 2024.0.0)

f) Integrated Development Environment (IDE): Scilab Console

6. Flowchart:



START
CLEAR WORKSPACES, HISTORIES, ETC.
CHANGE FUNCTION PROTECTION LEVEL
DEFINE MAIN FUNCTION
USER INPUT FOR LOCATION
INITIALIZE DATA ARRAYS
DATA COLLECTION USING FOR LOOP
CHECK IF RAINFALL IS NEGATIVE
YES
DISPLAY ERROR MESSAGE
NO
CATEGORIZE THE INTENSITY
TRUE
DRIZZLE, MILD, MODERATE, HEAVY RAIN
FALSE
VIOLENT RAIN
PREDICT SUNRISE AND SUNSET TIMES
PLOT GRAPHICAL REPRESENTATIONS
END OF FUNCTION
CALL MAIN FUNCTION
STOP

7. Procedure of Execution:

STEP 1: Launch Scilab on your Computer.

STEP 2: Right - Click on the Scilab Project and open it using Scilab.

STEP 3: Click on the 'Execute' menu and select the 'Save and Execute' option to save your script.

STEP 4: Save your script with a desired name and make sure to save it in .sce extension.

STEP 5: Run your script and switch to the Scilab Console Tab.

STEP 6: Enter a place in India to predict the Rainfall.

STEP 7: Enter whether the place is at the East or West of India.

STEP 7: Enter the dates for preceding 5 months in a reverse order [YYYY-MM-DD]

STEP 8: Enter the rainfall in mm for the specified date within 2.5 to 160.

STEP 9: Enter the duration of the rainfall in hours for the specified date within 0 to 24.

STEP 10: Repeat Step 7 to Step 9 till the data for 5 months is entered.

STEP 11: View the results in the Scilab Console along with the Graphical Representations.

8. Result:

Rainfall Prediction for Madhur:

The user ran the program for the location 'Madhur'. They were prompted to enter rainfall data for five different dates, spanning from September 2023 to January 2024. The rainfall amounts entered varied from 35 mm to 50 mm, and the duration of rainfall ranged from 1 hour to 4.5 hours.

After analysing this data, the program made several predictions:

1. **Climate Zone:** The program predicted a Continental climate zone based on the average temperature and rainfall data analysis. It highlights seasonal temperature variations and precipitation patterns.

2. **Rainfall:** The program predicted that there will be rainfall, with an average rate of approximately 44.502583 mm/hr. This prediction is based on the average of the rainfall data entered by the user for the 5 Months data.

3. **Duration:** The average duration of the rainfall was predicted to be about 4.011941 hours. This is based on the average of the duration data entered by the user for the 5 Months data.

4. **Humidity:** The predicted humidity was approximately 75.854530%. This value is based on the intensity of the rainfall in the program.

5. **Temperature:** The predicted temperature was approximately 31.138101°C. This value is based on the intensity of the rainfall in the program.

6. **Rainfall Category:** Based on the average rainfall, the program categorized the rainfall as 'Heavy Rain' along with an Alert Message. This categorization helps provide a qualitative understanding of the rainfall intensity.

7. **Sunrise and Sunset Times:** For each month, the program predicted the average sunrise and sunset times. These times were approximately generated by the program. For example, the predicted average sunrise time for the first month was approximately 6:35 AM, and the predicted average sunset time was approximately 6:05 PM. This is predicted for all the past 5 months as soon as the Rainfall, Humidity, and Temperature Predictions were made.

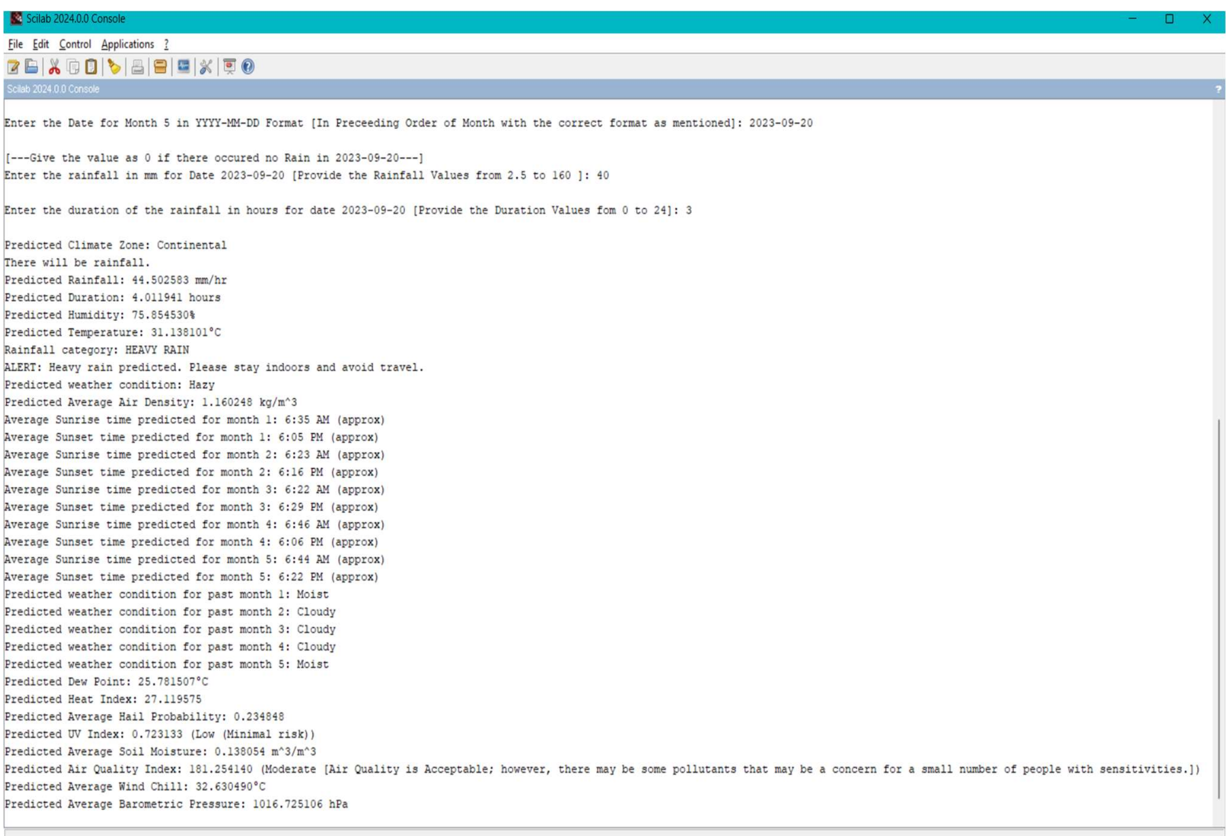
8. **Weather Conditions:** The program also predicted the weather conditions for each past month, which varied from 'Cloudy' to 'Moist'. These conditions were generated based on the amount of rainfall by the program.

9. **Dew Point:** The Predicted Dew Point is 25.781507°C. The dew point is the temperature at which the air becomes saturated with water vapor. A higher dew point indicates more moisture in the air.

10. **Heat Index:** The Predicted Heat Index is 27.119575. The heat index is a measure of how hot it feels when relative humidity is factored in with the actual air temperature. A higher heat index means it feels hotter.

11. **Hail Probability:** The study suggests an average hail probability of 23.4848%, indicating the likelihood of hail occurrence in the forecasted conditions. This estimation aids in assessing the potential risk of hail-related damage and informs precautionary measures for affected areas.

12. **UV Index:** The Predicted UV Index is 0.723133, which falls into the category of Low (Minimal risk). The UV index is an international standard measurement of the strength of sunburn-producing ultraviolet (UV) radiation at a particular place and time. A lower UV index means less risk of sunburn.



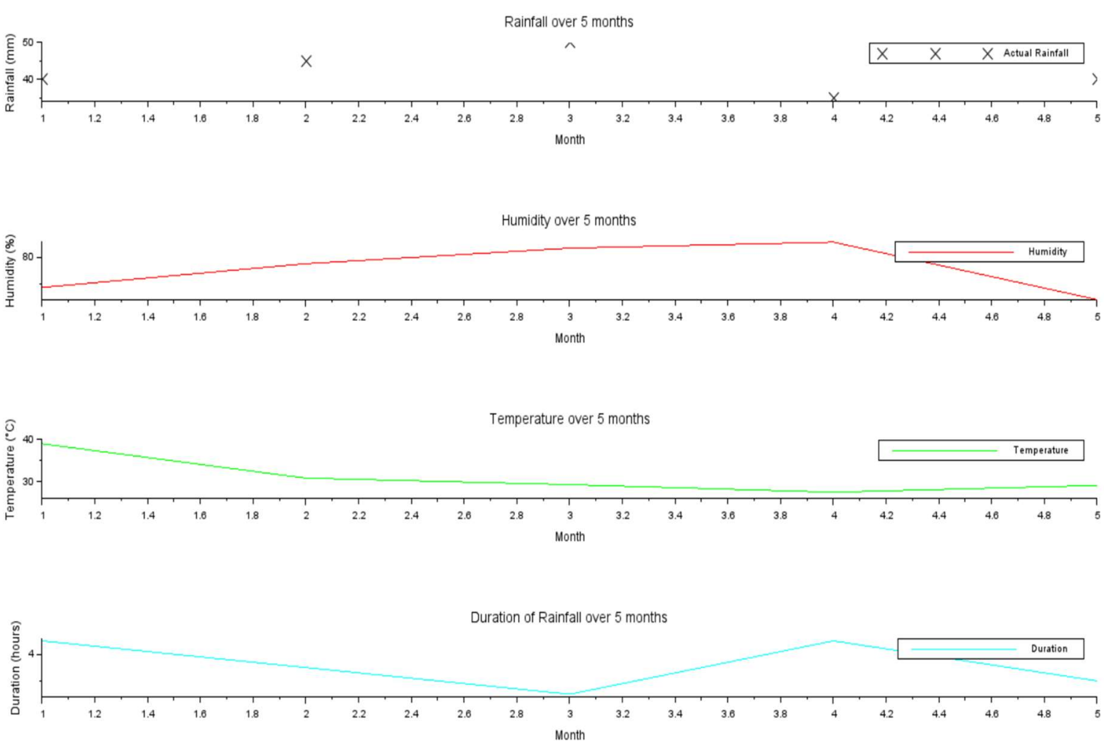
13. **Soil Moisture:** In the forecast, the study predicted an average soil moisture content of about 0.138054 m^3/m^3, providing insights into soil conditions crucial for agricultural planning and land management decisions.

14. **Air Quality Index:** The Predicted Air Quality Index (AQI) is 181.254140, which is considered Good. This means the air quality is satisfactory, and air pollution poses little or no risk.

15. **Wind Chill:** The study anticipated an average wind chill of approximately 32.630490°C, indicating the perceived temperature considering wind speed and ambient temperature, which is essential for assessing potential discomfort and safety hazards in outdoor environments.

16. **Barometric Pressure:** The analysis suggests an average barometric pressure of 1016.725106 hPa, providing insight into atmospheric conditions that influence weather patterns and are crucial for understanding air pressure-related phenomena and their impact on weather forecasting.

17. **Graphical Representation:** The program generated 4 graphs to visually represent the Actual Rainfall, Humidity, Temperature, and Duration data over the 5 months. These graphs provide a visual way to understand the changes in these parameters over time.



9. References:

1. “Recent Advances in Rainfall Modelling, Estimation and Forecasting”, by Efi Foufoula-Georgiou and Witold Krajewski, https://efi.eng.uci.edu/papers/efg_079.pdf

2. “Comparative Analysis of Rainfall Prediction Models Using Machine Learning in Islands with Complex Orography: Tenerife Island”, by Ricardo Aguasca-Colomo, Dagoberto Castellanos-Nieves and Máximo Méndez, https://doi.org/10.3390/app9224931, 16 November 2019

3. “Rainfall Prediction Using Machine Learning Models: Literature Survey”, January 2022, DOI:10.1007/978-3-030-92245-0_4, In book: Artificial Intelligence for Data Science in Theory and Practice (pp.75-108), by Eslam A. Hussein, Mehrdad Ghaziasgar, Christopher Thron, Mattia Vaccari, Yahlieel Jafta,

4. “Rainfall Prediction System Using Machine Learning Fusion for Smart Cities”, Atta-ur Rahman, Sagheer Abbas, Mohammed Gollapalli, Rashad Ahmed, Shabib Aftab, Munir Ahmad, Muhammad Adnan Khan and Amir Mosavi, doi: 10.3390/s22093504,

5. An Improved Method for Rainfall Forecast Based, on GNSS-PWV, Longjiang Li, Kefei Zhang, Suqin Wu, Haobo Li, Xiaoming Wang, Andong Hu, Wang Li, Erjiang Fu, Minghao Zhang and Zhen Shen, Library Noaa.

6. Department of Science and Technology, Phillippine Atmospheric, Geophysical and Astronomical Services Administration, GOVPH, Weather Terminologies, https://www.pagasa.dost.gov.ph/information/weather-terminologies

7. Scilab Reference Manual, On – Line Documentation, Scilab Group, INRIA - Unit´e de recherche de Rocquencourt - Projet Meta2 Domaine de Voluceau - Rocquencourt - BP 105 - 78153 Le Chesnay Cedex (France)

8. Determination of rainfall-recharge relationship in River Ona basin using soil moisture balance and water fluctuation methods, International Journal of Water Resources and Environmental Engineering 6(1):1-11, DOI:10.5897/IJWREE2013.0443, Muritala Olaniyi OKE, Olufemi A. Idowu, Oyekola Martins.

9. Byju Exam Prep, Rainfall in India, https://byjus.com/free-ias-prep/rainfall-distribution-in-india/, UPSC Notes.
10. Drop Size Distribution Retrievals for Light Rain and Drizzle from S-Band Polarimetric Radars, Merhala Thurai, Viswanathan Bringi, David Wolff, David Marks, Charanjit Prabha and Patrick Kennedy, Department of Electrical and Computer Engineering, Colorado State University.
11. Barani, Rain Rate Intensity Classification, Weather Stations, https://www.baranidesign.com/faq-articles/2020/1/19/rain-rate-intensity-classification, BaraniDesign, Meteorological Sensors and Weather Stations.
12. Methods to Calculate the Heat Index as an Exposure Metric in Environmental Health Research, Environ Health Perspect. 2013 Oct 1; 121(10): 1111–1119, Published online 2013 Aug 9. doi: 10.1289/ehp.1206273
13. Development of a Heat Index Related to Air Quality and Meteorology for an Assessment of Work Performance in Thailand's Urban Areas, by Nichapa Parasin 1 andTeerachai Amnuaylojaroen 2,3,*ORCID, School of Allied Health Science, University of Phayao, Phayao 56000, Thailand
14. Awareness, Understanding, Use, and Impact of the UV Index: A Systematic Review of Over Two Decades of International Research, Carolyn J. Heckman, PhD,a Katherine Liang,b and Mary Rileya, PMCID: PMC6534479, NIHMSID: NIHMS1523563, PMID: 30844501
15. Radiation: The ultraviolet (UV) Index, World Heath Organization, https://www.who.int/news-room/questions-and-answers/item/radiation-the-ultraviolet-(uv)-index.
16. Wind Speed : Wikipedia – The Free Encyclopedia, https://en.wikipedia.org/wiki/Wind_speed.
17. ERA5: How to Calculate Wind Speed and Wind Direction from u and v Components of the wind, ECMWF Information about Meteorological Wind Direction, https://confluence.ecmwf.int/pages/viewpage.action?pageId=133262398.

18. Wind Direction Quick Reference, NCAR – Operated by USAR, https://www.eol.ucar.edu/, https://www.eol.ucar.edu/content/wind-direction-quick-reference, Simple equations for conversion of vector wind components, speed and direction.

19. Good Calculators – Free Online Calculator, Wind Chill Calculator, https://goodcalculators.com/wind-chill-calculator/.

20. Calculator – Cloud.com, Calculating Wind Chill: A Comprehensive Guide, Wind Chill, https://www.calculator-cloud.com/windchill/index.html.

21. Outside – Backpacker, Wind Chill Can Ruin Sunny Winter Hikes—Unless You're Prepared, https://www.backpacker.com/skills/how-to-calculate-wind-chill/.

22. Omni Calculator, Wind Chill Calculator, https://www.omnicalculator.com/other/wind-chill.

23. WikiHow, How to Calculate Barometric Pressure, https://www.wikihow.com/Calculate-Barometric-Pressure.

24. Wikipedia – The Free Encyclopedia, Barometric formula, Pressure equations, https://en.wikipedia.org/wiki/Barometric_formula.

25. RechnerOnline, Calculate Air Pressure with Barometer, Air Pressure with Barometer, https://rechneronline.de/air/.

26. Wikipedia – The Free Encyclopedia, Gas constant, https://en.wikipedia.org/wiki/Gas_constant.

27. The Engineering ToolBox, Universal and Individual Gas Constants, The Universal and Individual Gas Constants in fluid mechanics and thermodynamics. Individual gas constants for the most common gases, https://www.engineeringtoolbox.com/individual-universal-gas-constant-d_588.html.

28. A lecture on Atmospheric Thermodynamics from the University of California, Irvine, https://www.ess.uci.edu/~yu/class/ess55/lecture.2.thermodynamics.pdf.

29. Mini Physics, Barometer & Atmospheric Pressure, Atmospheric Pressure, https://www.miniphysics.com/barometer.html#content.

30. Air Pressure, National Oceanic and Atmospheric Administration, https://www.noaa.gov/jetstream/atmosphere/air-pressure.

31. New Approach for Soil Moisture Prediction Based on Multiple Influencing Factors, Zhujia Zhang, Wenping Jiang & Ningyuan Xu, Conference paper, First Online: 02 January 2024, SpringerLink, https://link.springer.com/chapter/10.1007/978-981-99-7011-7_2.

32. A comprehensive study of deep learning for soil moisture prediction, February 2024, Hydrology and Earth System Sciences 28(4):917-943, DOI:10.5194/hess-28-917-2024, License, CC BY 4.0, Yanling Wang, Liangsheng Shi, Yaan Hu, Xiaolong Hu, https://www.researchgate.net/publication/378533775_A_comprehensive_study_of_deep_learning_for_soil_moisture_prediction.

33. Research on soil moisture prediction model based on deep learning, Yu Cai, Wengang Zheng, Xin Zhang, Lili Zhangzhong, Xuzhang Xue, Published: April 3, 2019, https://doi.org/10.1371/journal.pone.0214508, https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0214508.

34. Metadata record for: Global soil moisture data derived through machine learning trained with in-situ measurements, DOI - Is supplement to Global soil moisture data derived through machine learning trained with in-situ measurements, https://springernature.figshare.com/articles/dataset/Metadata_record_for_Global_soil_moisture_data_derived_through_machine_learning_trained_with_in-situ_measurements/14790510.

----xxxx---