

**Project Report on**

**A Comprehensive Exploration of Rainfall Dynamics and Phenomena in Bangladesh.**

Course Title: Project Report

Course Code: STAT-4209

This project report is submitted to the Department of Statistics, Begum Rokeya University, Rangpur in partial fulfillment of the requirement for the Degree of B.Sc. (Hons.) in Statistics



**Supervised by:**  **Sukanta Das**

**Assistant Professor**

**Department of Statistics Begum Rokeya University, Rangpur.**



**Submitted By:**

**Md Moeen Uddin**

**4nd year 2ndsemester Session:2019-20 ID:1910048**

**Reg:000013082**

**Department of Statistics Begum Rokeya University, Rangpur.**

Submission Date: 21th April,2025

DEDICATED TO MY BELOVED PARENTS, Brothers AND HONORABLE SUPERVISOR

**Certificate of Approval**

I do hereby declare that, the research project entitled “A COMPREHENSIVE EXPLORATION OF RAINFALL DYNAMICS AND PHENOMENA IN BANGLADESH.” submitted as the partial fulfillment of the degree of Bachelor of Science(hons.) in Statistics examination by MD Moeen Uddin is an original work of his own. It is conducted under my strict supervision. The particular project is accepted as a part of examination.

Date:

……………….

Sukanta Das

Assistant Professor

Department of Statistics

Begum Rokeya University, Rangpur

**PREFACE**

It is true that to achieve a complete knowledge in any subject a man should have a practical knowledge side-by-side bookish knowledge. Bookish knowledge is theoretical knowledge and practical knowledge is real knowledge. Therefore, through Consolidating two kinds of knowledge we can get a complete knowledge. I think that theoretical knowledge is effective with practical training.

Without the coordination of these two, it is very difficult to improve our knowledge in the modern age. That is why, Department of Statistics, Begum Rokeya University, Rangpur has introduced a report program for the students of Bachelor of Science (B.Sc.). The students are advised to go to the different field sector to acquire practical knowledge and to prepare a report on it. As a student of B.Sc. I had to undertake report program to fulfill the partial requirements of B.Sc. program. I am highly pleased being able to make a report in for this kind of program

I have made all possible efforts and investigations to submit this report in an enlightened from in a very short time. So, there may not be vivid description of the given assignment as much as one can hope for. If there is any error, kind are consideration is requested.

**Abstract**

Heavy rainfall events have significant implications for climate variability and environmental dynamics in Bangladesh. This study provides a comprehensive analysis of rainfall patterns and anomalies over recent years, focusing on their deviation from long-term averages. Using key metrics such as 10-day rainfall (rfh), 1-month and 3-month rolling aggregations (r1h, r3h), and their respective long-term averages (rfh\_avg, r1h\_avg, r3h\_avg), the study quantifies the extent and trends of rainfall anomalies (rfq, r1q, r3q).

The analysis reveals notable temporal and seasonal variations in rainfall, with distinct periods of above-average and below-average precipitation. Anomalies in both short-term (10-day) and aggregated (1-month, 3-month) rainfall highlight patterns that may be indicative of changing climatic conditions. The results emphasize the importance of continuous monitoring and analysis of rainfall dynamics to better understand their implications for agriculture, water resource management, and regional climate systems.

This report underscores the need for integrating historical and current rainfall data to identify emerging trends and develop data-driven strategies for addressing potential challenges associated with extreme rainfall variations in Bangladesh.

CONTENT:

|  |  |
| --- | --- |
| CHAPTER | PAGE |
| **1.INTRODUCTION** | 1-5 |
| 1.1 INTRODUCTION  1.2 OBJECTIVES OF THE STUDY  1.3 ABOUT MY DATA | 2  3  4 |
| **2. LITERATURE REVIEW** | 6-10 |
| 2.1 Review of Relevant Literature | 7 |
| **3.METHODOLOGY** | 11-17 |
| 3.1 INTODUCTION  3.2 DESCRIPTIVE STATISTICS  3.3ARIMA MODEL  3.4 FORECASTING | 12  12  13  15 |
| **4. METHODS OF ANALYSIS & RESULT** | 18-45 |
| 4.1 Analyzing Rainfall Dynamics Over the Year  4.2 Analyzing Rainfall Phenomena Over 44 Year  4.3 RESULT FOR LINEAR MODEL  4.4 FOR ARIMA MODEL | 19  33  34  43 |
| **5.DECESION** | 46-48 |
| 5.1 RAINFALL DYNAMIC OVER THE YEAR  5.2RAINFALL PHENOMENA OVER THE 44 YEARS | 47  47 |
| **6. CONCLUSION & DISCUSSION** | 49-54 |
| 6.1 Conclusion  6.2 Summary of Rainfall Trends  6.3 Historical Rainfall Analysis  6.4 Future Rainfall Predictions  6.5 Implications for Disaster Management  6.6 Agricultural and Environmental Impact  6.7 Implications of the Study  6.8 Limitations of the Study  6.9 Recommendations for Future Research  6.10 Policy and Practical Implications  6.11 Final Thoughts on Heavy Rainfall Trends | 50  50  50  51  51  52  52  53  53  53  54 |
| **REFERENCES** | 55-56 |
| **R COADING** | 57-65 |

**CHAPTER ONE**

**INTRODUCTION**

**1.1 INTRODUCTION:**

Bangladesh, a country characterized by its diverse climatic patterns, experiences significant variability in rainfall throughout the year. As a predominantly agrarian nation, rainfall plays a critical role in shaping the livelihoods of millions, influencing agricultural productivity, water resources, and the overall economy. However, the increasing irregularity of rainfall patterns poses challenges to traditional practices and infrastructure, necessitating a deeper understanding of these dynamics [1].

This report seeks to analyze heavy rainfall patterns in Bangladesh, focusing on key metrics such as 10-day rainfall (rfh), 1-month and 3-month rolling aggregations (r1h, r3h), and their long-term averages. By examining deviations and anomalies from historical trends, the study aims to identify emerging patterns that could inform planning and adaptation strategies. The findings from this analysis are expected to provide valuable insights into the temporal and seasonal variability of rainfall and its broader implications for climate resilience and sustainable development [2].

Bangladesh, a South Asian country marked by its geographical and climatic diversity, is profoundly influenced by its rainfall patterns. Rainfall is a lifeline for the nation, which depends heavily on agriculture, with nearly half of its population directly or indirectly engaged in farming. The country's monsoon climate brings substantial rainfall during specific periods, while dry spells dominate others. This variability plays a decisive role in determining agricultural productivity, water availability, and, by extension, the livelihoods of millions of people. Yet, in recent decades, the shifting patterns of rainfall have raised concerns over their impact on traditional practices, infrastructure, and overall socio-economic stability [3].

The importance of rainfall to Bangladesh cannot be overstated. As an agrarian economy, its crop cycles, irrigation needs, and water resource management are tightly interwoven with the rhythm of rainfall. However, the increasing irregularity of these patterns has become a growing challenge. Heavy rainfall events, often concentrated over short periods, lead to urban flooding, river overflow, and crop damage. On the other hand, prolonged dry periods can result in drought-like conditions, adversely affecting both rain-fed and irrigated agriculture. These extreme events underscore the urgent need to study and understand rainfall dynamics more comprehensively to devise effective mitigation strategies [4].

This report aims to delve into the dynamics of heavy rainfall in Bangladesh, focusing on key metrics that provide a nuanced understanding of rainfall variability. Specifically, it examines 10-day rainfall totals (rfh), as well as 1-month and 3-month rolling aggregations (r1h and r3h), which offer insights into both short-term and longer-term trends. By analyzing these metrics alongside their long-term averages, the study seeks to identify deviations and anomalies that signal emerging shifts in rainfall behavior. Such an analysis is crucial, as understanding the temporal and seasonal variability of rainfall can inform planning efforts, guide agricultural practices, and bolster climate resilience.

Bangladesh's rainfall patterns are closely linked to broader climatic systems, such as the South Asian monsoon and the Bay of Bengal's cyclonic activities. These systems, while providing much-needed rainfall, also contribute to the country's vulnerability to climatic extremes. Understanding how these factors interact and how they may evolve under the influence of climate change is vital for both immediate and long-term planning. For example, shifts in the onset or retreat of monsoons can disrupt agricultural timelines, while an increase in the intensity and frequency of heavy rainfall events can strain urban drainage systems and flood defenses [5].

The findings from this study are expected to have far-reaching implications. For policymakers, they provide evidence-based insights to prioritize investments in climate-resilient infrastructure, such as improved drainage systems and flood defenses. For farmers and agricultural planners, the insights can help in devising strategies to adapt to changing rainfall patterns, such as selecting crop varieties more suited to altered precipitation regimes. Furthermore, the broader understanding of rainfall variability contributes to the global dialogue on climate change, highlighting the specific challenges faced by vulnerable countries like Bangladesh.

In conclusion, this report offers a comprehensive exploration of heavy rainfall dynamics in Bangladesh, with an emphasis on identifying emerging trends and their implications. By focusing on detailed metrics and historical trends, it aims to contribute to the broader discourse on climate resilience and sustainable development. The study underscores the interconnectedness of rainfall variability with socio-economic stability, emphasizing the need for informed planning to mitigate risks and harness opportunities presented by evolving climatic conditions.

**1.2 OBJECTIVES OF THE STUDY:**

Bangladesh, a flat and low-lying country, faces several natural calamities due to its geographical location. Bangladesh has a subtropical monsoon climate which is characterized by wide seasonal variations in rainfall, high temperature, and humidity. Bangladesh is mainly an agricultural country and that’s why rainfall plays an important factor in agricultural production and economy. However, the agricultural production of this country is affected by rainfall several times, and there are various examples of these types of climatic extremes events. If rainfall happens heavily, it can cause flood and waterlogging problems within the country, while drought can occur if rainfall amount is low and both incidents are dangerous for a country. To understand, evaluate and predict such events, a person needs to have a better understanding of the rainfall condition and pattern of this country, and that’s why this paper tries to give a brief description of the rainfall condition of the country, Bangladesh [6].

This objective focuses on understanding the temporal and spatial distribution of heavy rainfall events across various regions of Bangladesh. It involves analyzing historical meteorological data, identifying seasonal trends, and examining changes in rainfall intensity over the years. Advanced tools and models may be utilized to determine whether patterns indicate increasing variability or severity due to climate change or other factors.

A comprehensive investigation will be conducted into the key factors that contribute to heavy rainfall events in the country. This includes natural causes such as monsoonal patterns, cyclonic activities, and atmospheric disturbances, as well as anthropogenic factors like urbanization, deforestation, and land-use changes.

Based on the findings, the study will recommend actionable strategies to mitigate the adverse effects of heavy rainfall. This includes improving early warning systems, enhancing community preparedness, developing sustainable urban planning practices, and advocating for ecosystem-based solutions such as afforestation and wetland conservation. Additionally, the study will propose policy frameworks aimed at integrating climate adaptation measures into national and regional development plans, ensuring resilience against future heavy rainfall events.

However, the country is frequently impacted by climatic extremes, including heavy rainfall leading to floods and waterlogging, and low rainfall causing droughts. These events pose significant threats to livelihoods, food security, and infrastructure. To address these challenges, a deeper understanding of the rainfall patterns and conditions in Bangladesh is essential [7].

This study aims to explore the temporal and spatial distribution of heavy rainfall across Bangladesh. By analyzing historical meteorological data, it seeks to identify seasonal trends, assess changes in rainfall intensity, and investigate the influence of climate change on rainfall variability. The study will also examine the natural drivers, such as monsoons, cyclonic activities, and atmospheric disturbances, alongside anthropogenic factors like urbanization and land-use changes, contributing to these events.

Based on its findings, the study will propose actionable strategies to mitigate the impacts of heavy rainfall, such as enhancing early warning systems, promoting sustainable urban planning, and implementing ecosystem-based solutions like afforestation and wetland conservation. These recommendations aim to support climate adaptation and ensure resilience against future rainfall-related challenges.

**1.3 ABOUT MY DATA**

Secondary data was mainly used for this study, which was collected from

* <https://data.humdata.org/dataset/bgd-rainfall-subnational>
* <https://bbs.gov.bd/site/page/b588b454-0f88-4679-bf20-90e06dc1d10b/->

The data for this study has been sourced from two key platforms: the [Humanitarian Data Exchange (HDX)](https://data.humdata.org/dataset/bgd-rainfall-subnational) and the [Bangladesh Bureau of Statistics (BBS)](https://bbs.gov.bd/site/page/b588b454-0f88-4679-bf20-90e06dc1d10b/-). These sources provide comprehensive datasets that serve as the foundation for analyzing rainfall patterns in Bangladesh.

**Humanitarian Data Exchange (HDX):**  
This platform provides subnational rainfall data, which includes detailed measurements of precipitation levels across various regions of Bangladesh. The dataset is instrumental in understanding the spatial and temporal variability of rainfall within the country. It encompasses historical rainfall records, aggregated metrics, and time-series data that allow for detailed trend analysis. The availability of 10-day, monthly, and seasonal rainfall figures makes it particularly valuable for assessing both short-term and long-term rainfall dynamics. It contains 44-year data of every 10 days from 1/1/1981 to 12/21/2024.

This dataset contains dekadal rainfall indicators computed from Climate Hazards Group InfraRed Precipitation satellite imagery with inset Station data (CHIRPS) version 2, aggregated by subnational administrative units.

Included indicators are (for each dekad):

1. 10-day rainfall [mm] (rfh)
2. rainfall 1-month rolling aggregation [mm] (r1h)
3. rainfall 3-month rolling aggregation [mm] (r3h)
4. rainfall long term average [mm] (rfh\_avg)
5. rainfall 1-month rolling aggregation long term average [mm] (r1h\_avg)
6. rainfall 3-month rolling aggregation long term average [mm] (r3h\_avg)
7. rainfall anomaly [%] (rfq)
8. rainfall 1-month anomaly [%] (r1q)
9. rainfall 3-month anomaly [%] (r3q)

The administrative units used for aggregation are based on WFP data and contain a Pcode reference attributed to each unit. The number of input pixels used to create the aggregates, is provided in the n\_pixelscolumn.

**Bangladesh Bureau of Statistics (BBS):**  
The BBS is a vital national institution that compiles and publishes official statistics for Bangladesh. Data from this source include region-wise meteorological information, seasonal variations, and long-term rainfall trends. It offers reliable, government-verified records that are critical for validating findings and ensuring the accuracy of the study. Additionally, BBS data provide insights into the socio-economic impacts of rainfall variability, particularly in agriculture and infrastructure sectors [8].

The datasets from these sources are essential for achieving the study’s objectives, as they provide granular details on rainfall patterns and anomalies. By leveraging HDX's subnational data and BBS's authoritative records, the study can identify spatial disparities, seasonal trends, and historical deviations in rainfall. These insights will support the development of actionable strategies for climate resilience and sustainable resource management in Bangladesh [9].

**CHAPTER TWO**

**LITERATURE REVIEW**

**2.1 Review of Relevant Literature**

The research works which help to make this study work logical are listed below:

1. Svetlana et al (2015) prepared research on “The economic impact of floods and their importance in different regions of the world with emphasis on Europe” The study discusses the effects of floods on the global economy, both good and bad. The economic impact of flooding damage is examined throughout the article, with a focus on Europe and Slovakia. This essay's goal is to economically examine the harm caused by flooding in various parts of the world. The article was created using data from secondary sources provided by the European Environment Agency and the Slovak Republic's Ministry of Environment [10].
2. Martha Wilhelm (2009) conducted a mini thesis on “Impact of climate change in Namibia: A case study of Omusati region” According to some, climate change poses a threat to the country's development. The socio-economic effects of flooding in Namibia's North Central Regions are a particular emphasis of this thesis's investigation of the effects of climat change in Namibia. The socioeconomic situation of the locals following the flooding in Oshitutuma village in 2009 is examined in the thesis. The literature review for the thesis examined the concepts of climate change and flooding in the contexts of Namibia, Southern Africa, Africa as a whole, and the global levels [11].
3. SHIFIDI Victoria Tuwilika (2016) conducted a study on “Impact of flooding on rural livelihoods of the Cuvelai Basin in Northern Namibia” The ongoing flooding in the Cuvelas Basin is both a blessing and a curse The Cuvelai Basin in Northern Namibia is the subject of this article's discussion of the effects floods has on rural livelihoods. The combined effects of the recent flooding events have had a significant impact on locals as well as the Namibian economy are thought to have suffered losses of over US US 78.2 million (NAD 780 million) in direct damage and NAD 136.4 million in indirect damage inadvertent losses (SHIFIDI,2016) Shifidi(2014) prepared a study on" Socio-economic assessment of the consequences of flooding in Northern Namibia" This study was carried out in the Cuvelai Basin in Northern Namibia to evaluate the socioeconomic effects of floods on local populations as well as their susceptibility, and to offer solutions to mitigate the effects of flooding in the Basin's rural sections. The previous severe 2009, 2011, and 2012 saw flooding [12].
4. Elima, Elton K(2012) conducted a project on Assessment of “Flood Management in South C Ward of Nairobi City County, Kenya” Floods are hydro meteorological dangers that frequently result in fatalities, property damage, and disruption of vital services in Nairobi City County. This study focused on South C ward, which has consistently experienced flooding, in an effort to better understand the numerous variables surrounding these flood threats. In this sense, the study's first goal was to evaluate the ward's flooding patterns and the ensuing consequences of these floods. The second goal was to evaluate the elements that affect South C's susceptibility to flooding. Finally, the study looked at the institutional, legal and regulatory framework in place to address the flooding challenges in the City [13].
5. Behzad Jamali (2018) prepared research on “A rapid urban flood inundation and damage assessment model” Urban pluvial flooding is a problem that affects the entire world and is typically brought on by a lack of infiltration, retention, and drainage capacity. In order to quickly determine the size, depth, and damage associated with a flood, the RUFIDAM urban pluvial flood model was created utilizing GIS technology RUFIDAM combines a modified version of fast flood inundation models with a 1D hydraulic drainage network model (SWMM or MOUSE). Depressions in an urban catchment were located using one-meter resolution topographic data. We determined the volume-elevation connections and the minimum elevation between adjacent depressions [14].
6. Percy Mashebe et al (June 2016) conducted a project on “The Impact of Flooding On the Livelihood of People Living In the Luhonono Area in the Zambezi Region, Namibia” This study looked at how floods affected the community in the Luhonono area (formerly known as Schuckmansburg) in the Kabbe constituency of Namibia's Zambezi Region. The ongoing flooding in the Luhonono region has been noted as an issue causing the need to consider how floods affect local residents' means of subsistence community Both qualitative and quantitative methods were used in the investigation designs for exploration and description [15].
7. Ashraf et al (December 2013) conducted a study on “Impacts of floods on livelihoods and Fond security of rural communities: a case study of southern Punjab, Pakistan”. In the middle 2010, Pakistan had a sad and huge flood. The magnitude of the calamity that happened which affected more than 20.1 million people nationwide, was unparalleled. The flood significantly damaged the province of Punjab.The current study was carried regard in Southern Punjab to investigate the effects of flooding on rural residents’ food security and way of life communities. The majority of Punjab's flood-affected areas were located in the district of Muzaffargarh [16].
8. Ismail & Mustaquim (August 2013) developed a study on “Socio-economic status of population in flood prone areas of Chanchal sub-division in Malda district, West Bengal” India experiences flooding practically every year, therefore it's critical to plan ahead for emergencies. Numerous individuals are forced to relocate due to flooding, which also results in significant property damage and fatalities, unemployment and even death from malnutrition Damage also has an effect on the economy Many crops that have an impact on agriculture either directly or indirectly. The nation requires a better, a rapid and efficient flood mitigation system to protect the population they are also suffered by many diseases [17].
9. Awopetu (2013) conducted a study on “The impact of flood on the socio-economic status of residents of Wadata and Gado-villa communities in the Makurdi metropolitan area of Benue State,Nigeria” In the Makurdi metropolitan region of Benue State, Nigeria, the study looked at how floods affected residents of the Wadata and Gado-villa communities, a mix of males and females from a sample of 502 displaced residents totaling 502. Makurdi participated in while camping at St. Theresa Catholic and St. Catherine primary school the research six sections of a questionnaire evaluating demographic factors and flooding's effects. on various socioeconomic factors, including agriculture, education, health, and housing [18].
10. Selina Hakim (FALL 2012) conducted a project paper on "Reduction of flood risk by indigenous knowledge at Alekdiar Char of Shibalaya Upazila in Manikganj district" The goal of the current study is to characterize the char dwellers' methods of subsistence. It also focuses on evaluating their financial situation in connection to their methods of subsistence. Focus Group Discussions and Informal Interviews have ensured that local residents would participate in the research process. Most farmers also grow khas because they don't have their own land public lands. The remainder of the population works at day jobs, conducts small business, and others [19].
11. Sabkat Kamal (April,2011) studies a thesis paper on “Livelihood dynamics and disaster vulnerabilities of char land areas”. The likelihood of natural disasters is greater in Bangladesh's char regions. The poorest and most vulnerable community colonized Char land. The underprivileged people of the land come here in quest of work and must contend with dangers Remoteness, destitution, and a weak economy The char's daily existence is impacted by disasters that heighten their vulnerability livelihood, catastrophe, and related issues Fach vulnerability is related to the other [20].
12. Parvin et Al (December 2016) developed a study on "Flood in a changing climate. The impact on livelihood and how the rural poor cope in Bangladesh”. It is already known that climate change will cause the global water cycle to intensify, increasing the risk of flooding as a result. Flood disasters are becoming more and more common, even in Bangladesh. There are many dangers and catastrophes in Bangladesh. The most frequent and common type of flooding. Floods put people at risk because they take away first, their means of subsistence. and leave them with few resources to recover from the circumstance (flood-in-a-changing climate-the-impact-on-livelihood-and-how-the-. n.d.) [21].
13. Rahman (SPRING,2014) developed a study on "Impacts of flood on the lives and livelihoods of people in Bangladesh A case study of a village in Manikganj district”. The current in-depth study examines the effects of flooding on people's lives and means of subsistence in the impacted area. The study's goals include evaluating the current situation, the past, the causes, aggravating factors, the extent and effects of the flood, documenting the risk and vulnerability, and different community capacities, researching local knowledge, customs, and beliefs, and developing community-based plans for flood mitigation and flood disaster risk reduction. The study discovered that there are various reasons why flooding is dangerous. They include the building of culverts and other types of infrastructure Without taking into account the monsoon flood, inadequate irrigation due to an inadequate irrigation canal system, and poor drainage because of dense settlements [22].
14. Hossain et Al (February, 2013) performed a study on "Effects of flooding on socio-economic status of two integrated char lands of Jamuna River, Bangladesh”. The study looked at how floods affected the socioeconomic standing of two integrated char lands along the Jamuna River in Bangladesh between March 2011 and September 2011 Data from both primary and secondary sources were gathered. The initial data was gathered secondary data were gathered from a variety of sources, starting with field research and intrinsic study sources include the Statistical Bureau, the Agricultural Office, and the Bangladesh Water Development Board, publications like journals [23].
15. Anika Nasra Haque et Al (2010) prepared a study on “Assessment of adaptation measures against flooding in the city of Dhaka, Bangladesh”. One of the biggest megacities in the world, Dhaka is rapidly becoming more urbanized Greater Dhaka is especially vulnerable to destructive flooding as a result of its location on a deltaic plain. In the upcoming years, flood risks are anticipated to rise. The goal of the research is to create a comprehensive framework for evaluating various (current and potential) adaptation strategies for flood protection in susceptible locations. In the most vulnerable area of the city, the study first evaluates present and potential hazards from floods. The study then finds, examines, and evaluates adaptation programs and defenses against flood hazards in the Eastern fringe region [24].
16. Banerjee (September 2010) prepared a article on “Effects of flood on agricultural productivity in Bangladesh”. In this article, the effect of floods on agriculture is examined, and it is asserted that while monsoon floods operate as an open-access resource for giving irrigational input to agriculture, extreme inundation during those months does kill crops. To explore the long-term effects of floods on agricultural performance, data on district-level rice and jute productivity for the years 1978 to 2000 are compared with "greater" and "less" flood- prone areas. On crops grown during the flood months and the following post-flood months. the short-term effects are examined. The findings indicate that Bangladesh's "more" flood- prone districts had higher agricultural productivity and area under cultivation. They also demonstrate that while productivity rises during "regular" floods in the months following a flood [25].

**CHAPTER THREE**

**METHODOLOGY**

**3.1 INTODUCTION:**

This study employs a systematic approach to investigate the dynamics and phenomena associated with heavy rainfall in Bangladesh. The methodology is designed to ensure a comprehensive analysis, combining both qualitative and quantitative techniques to provide robust and reliable findings [26].

The research framework integrates multiple data sources, including meteorological records, hydrological data, and satellite imagery, to capture the spatial and temporal patterns of rainfall. Advanced statistical and computational tools are employed for data analysis and modeling, enabling a deeper understanding of the underlying processes and their implications [27].

Field observations and case studies are also incorporated to validate theoretical models and enhance the contextual relevance of the findings. This multi-faceted approach ensures a holistic understanding of the topic, addressing the complexity of heavy rainfall events and their associated challenges in Bangladesh [28].

**3.2 DESCRIPTIVE STATISTICS:**

**1. Residuals**

Residuals are the differences between the observed values and the predicted values. They indicate how well the model fits the data. The summary provides key percentiles:

* **Min**: Smallest residual (most negative error).
* **1Q**: First quartile of residuals (25th percentile).
* **Median**: Median residual (50th percentile).
* **3Q**: Third quartile of residuals (75th percentile).
* **Max**: Largest residual (most positive error).

**2. Coefficients**

* **Estimate**: The regression coefficients. These are the intercept and slope values in the regression equation.
* **Std. Error**: The standard error of the coefficient estimates, representing the uncertainty in their values.
* **t value**: The test statistic for the null hypothesis that a coefficient is 0 (no effect).

t=

* **Pr(>|t|)** (p-value): The probability of observing a t value as extreme as the one computed, under the null hypothesis.

**3. Residual Standard Error:** The standard deviation of the residuals. It measures the typical size of the prediction errors (residuals).

**4. Multiple R-squared:** Proportion of the variance in the dependent variable that is explained by the independent variable(s). A value closer to 1 indicates a better fit.

**5. Adjusted R-squared:** Similar to Multiple R-squared but adjusted for the number of predictors in the model. It prevents overestimating the fit when additional predictors are included.

**6. F-statistic:** A measure of the overall significance of the regression model. It tests the null hypothesis that all regression coefficients (except the intercept) are equal to zero.

**7. p-value:** The probability that the observed relationship happened by chance. A smaller p-value (< 0.05 or < 0.01) indicates the relationship is statistically significant.

**8. Degrees of Freedom (DF)**

* **Model DF**: Number of predictors in the model.
* **Residual DF**: Total observations minus the number of estimated parameters (including the intercept).

**3.3ARIMA MODEL:**

(Autoregressive Integrated Moving Average) is a popular statistical method used for time series forecasting and analysis. It models a time series based on its own past values, differences, and forecast errors. Here's an overview of its key components:

**Components of ARIMA**

1. **Autoregressive (AR) Component:**
   * Refers to the relationship between a time series and its past values.
   * The model uses past values to predict future ones, where the number of past values used is determined by the parameter **p** (the AR order).
2. **Integrated (I) Component:**
   * Refers to differencing the data to make it stationary (i.e., removing trends or seasonality).
   * The parameter **d** specifies how many times the data needs to be differenced to achieve stationarity.
3. **Moving Average (MA) Component:**
   * Refers to the dependency between an observation and a residual error from a moving average model applied to previous time steps.
   * The parameter **q** determines how many past forecast errors to include in the model.

**The ARIMA Model Parameters**

* **p**: The number of lagged observations (AR terms).
* **d**: The number of times the data is differenced to make it stationary.
* **q**: The number of lagged forecast errors (MA terms).

For example:

* ARIMA(1,1,1) means:
  + One lagged observation is used (AR = 1).
  + The data is differenced once (I = 1).
  + One lagged forecast error is used (MA = 1).

**Steps in ARIMA Modeling**

1. **Check Stationarity:**
   * Time series data needs to be stationary for ARIMA to work effectively. Stationarity means the mean, variance, and autocorrelation remain constant over time.
   * If the data is non-stationary, differencing is applied (the **I** component).
2. **Identify Parameters (p, d, q):**
   * Use tools like the **Autocorrelation Function (ACF)** and **Partial Autocorrelation Function (PACF)** to identify appropriate values for AR (p) and MA (q).
   * The number of differences needed to achieve stationarity determines **d**.
3. **Fit the Model:**
   * The ARIMA model is trained on the historical time series data using the identified parameters.
4. **Evaluate the Model:**
   * Residual analysis is performed to ensure the model fits well (residuals should resemble white noise, meaning no patterns remain).
5. **Forecast:**
   * Use the fitted model to predict future values of the time series.

**Strengths of ARIMA**

* Effective for time series with trends or non-stationary behavior.
* Provides a good balance between simplicity and accuracy for many forecasting tasks.

**Limitations of ARIMA**

* Assumes linear relationships; may not perform well on data with strong non-linear patterns.
* Requires stationarity, so pre-processing like differencing is often needed.
* Does not inherently handle seasonality (this requires SARIMA or seasonal adjustments).

**3.4 FORECASTING:**

Forecasting is the process of predicting future values in a time series based on its historical data. In the context of ARIMA models, forecasting uses the patterns in the data like trends, seasonality, and noise to estimate future observations.

**How Forecasting Works in ARIMA**

1. **Model Training:**
   * The ARIMA model is first trained on historical data.
   * It learns the relationship between past values (autoregressive part), the trend or differencing (integrated part), and past errors (moving average part).
2. **Extrapolating the Future:**
   * The model uses the learned patterns to predict future values.
   * It applies the ARIMA equations iteratively to generate forecasts for multiple time steps ahead.
3. **Confidence Intervals:**
   * Forecasting outputs include point forecasts and confidence intervals (e.g., 80% or 95%) to express uncertainty in predictions.

**Steps in ARIMA Forecasting**

1. **Model Fitting:**
   * Fit the ARIMA model on the historical time series data.
2. **Prediction:**
   * Generate forecasts for future time steps using the fitted model.
   * Short-term forecasts (a few steps ahead) are generally more accurate than long-term ones.
3. **Validation:**
   * Compare the forecasts with actual observations (if available) to evaluate accuracy.
   * Metrics like Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE) are used for validation.
4. **Visualize:**
   * Plot the historical data, forecasts, and confidence intervals to understand the prediction results.

**Outputs of ARIMA Forecasting**

1. **Point Forecasts:**
   * The predicted values for future time steps.
2. **Confidence Intervals:**
   * A range of values within which the actual observation is likely to fall (e.g., 95% confidence interval means there is a 95% chance the true value lies within the range).
3. **Residual Analysis:**
   * Analyze residuals (difference between predicted and actual values) to ensure the model captures the data patterns well.

**Practical Applications of Forecasting**

* **Weather Forecasting:** Predicting rainfall, temperature, etc.
* **Business Planning:** Demand forecasting, sales prediction.
* **Finance:** Stock price forecasting, economic trends.
* **Energy:** Predicting power consumption or generation.

**Limitations of ARIMA Forecasting**

* **Linearity Assumption:** ARIMA models assume linear relationships, so they may struggle with complex non-linear patterns.
* **Data Dependency:** The accuracy of forecasts depends heavily on the quality and completeness of historical data.
* **Limited Long-Term Accuracy:** Uncertainty increases with longer forecast horizons.

**Here are the formulas for calculating the variables over a 44-year period:**

**Variables and Formulas**

1. **10-day rainfall [mm] (rfh):**
   * Sum of rainfall over each 10-day period.
   * rfh=
2. **Rainfall 1-month rolling aggregation [mm] (r1h):**
   * Rolling sum of rainfall over a 30-day period.
   * r1h=
3. **Rainfall 3-month rolling aggregation [mm] (r3h):**
   * Rolling sum of rainfall over a 90-day period.
   * r3h=
4. **Rainfall long-term average [mm] (rfh\_avg):**
   * 5-year average of 10-day rainfall for the corresponding period.
   * rfh\_avg=
5. **Rainfall 1-month rolling aggregation long-term average [mm] (r1h\_avg):**
   * 5-year average of the 1-month rolling aggregation for the corresponding period.
   * r1h\_avg=
6. **Rainfall 3-month rolling aggregation long-term average [mm] (r3h\_avg):**
   * 5-year average of the 3-month rolling aggregation for the corresponding period.
   * r3h\_avg=
7. **Rainfall anomaly [%] (rfq):**
   * Percentage deviation of 10-day rainfall from its long-term average.
   * rfq=
8. **Rainfall 1-month anomaly [%] (r1q):**
   * Percentage deviation of 1-month rolling aggregation from its long-term average.
   * r1q=
9. **Rainfall 3-month anomaly [%] (r3q):**
   * Percentage deviation of 3-month rolling aggregation from its long-term average.
   * r3q=

**CHAPTER FOUR**

**METHODS OF ANALYSIS & RESULT**

**4.1 Analyzing Rainfall Dynamics Over the Year:**

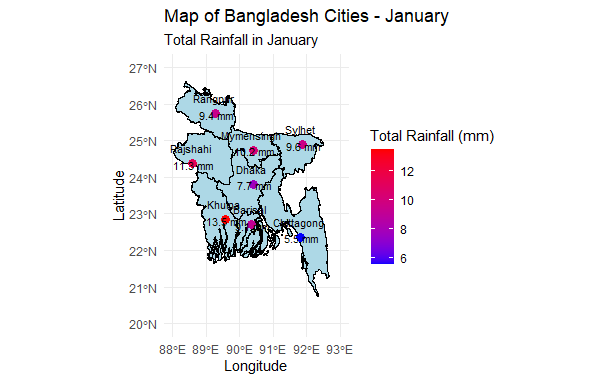
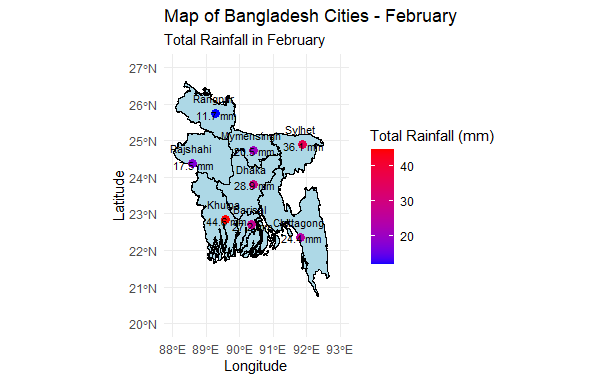


FIG-1: Map of Bangladesh Cities – January

**INTODUCTION:** The map displays total rainfall in January across Bangladesh cities,

* Rajshahi records the highest rainfall (11.1 mm), while Chattogram has the lowest (8.3 mm).
* Northern and western areas, like Rajshahi, show slightly higher rainfall, while coastal regions (e.g., Chattogram, Khulna) have moderate levels.

This reflects the typical dry season in Bangladesh during January

FIG-2: Map of Bangladesh Cities - February

**FIG-2:** The map shows total rainfall in February across Bangladesh cities,

* Sylhet records the highest rainfall (36 mm), while Rangpur has the lowest (11 mm).
* Central areas like Dhaka receive moderate rainfall (28.9 mm), while western regions like Rajshahi are relatively dry (17 mm).
* Rainfall increases slightly compared to January, especially in the northeastern region (Sylhet).

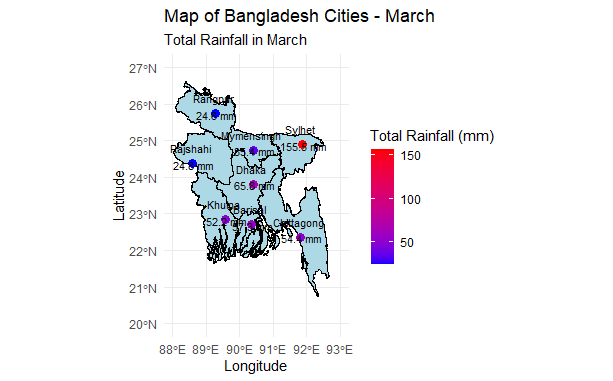
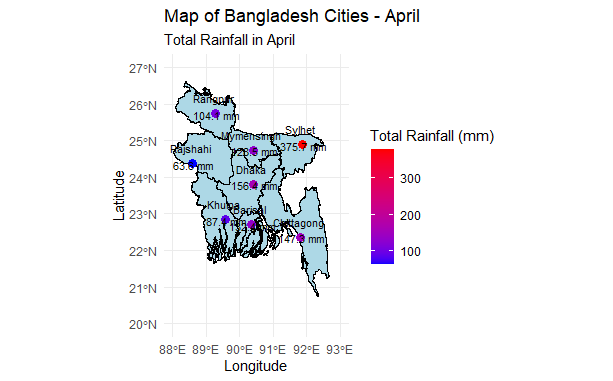


FIG-3: Map of Bangladesh Cities - March

**FIG-3:** The map shows total rainfall in March across Bangladesh cities:

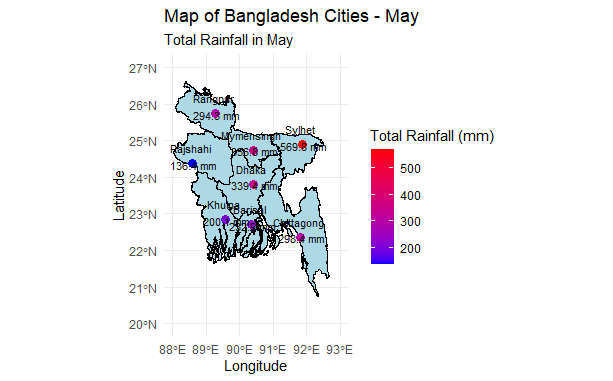
* Sylhet records the highest rainfall (155.5 mm), indicating significantly wetter conditions in the northeast.
* Rajshahi and Rangpur have the lowest rainfall (24.8 mm and 24.6 mm, respectively), reflecting dry conditions in the northwest.
* Dhaka (65.8 mm), Mymensingh (35.4 mm), Chittagong (54.4 mm), Khulna (52.2 mm), and Barisal (57.3 mm) experience moderate rainfall.
* Overall, rainfall varies widely, with Sylhet being the standout wet region.

FIG-4: Map of Bangladesh Cities - April

**FIG-4:** The map shows total rainfall in April across Bangladesh cities:

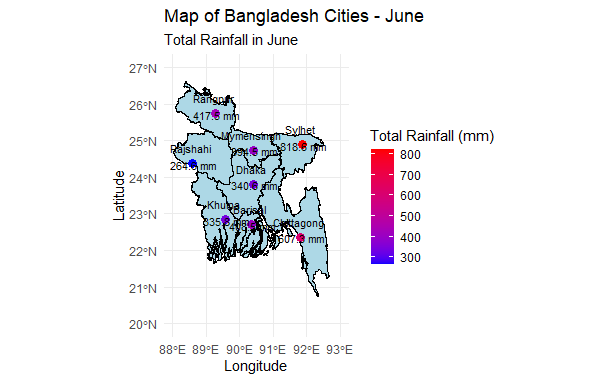
* Sylhet records the highest rainfall (375.7 mm), indicating extremely wet conditions in the northeast.
* Rajshahi has the lowest rainfall (63.6 mm), reflecting dry conditions in the northwest.
* Dhaka (156.4 mm), Mymensingh (128.5 mm), Chittagong (147.3 mm), Khulna (87.4 mm), Barisal (132.4 mm), and Rangpur (104.1 mm) experience moderate to high rainfall.

Rainfall is significantly higher than previous months, with Sylhet being the wettest region.

FIG-5: Map of Bangladesh Cities - May

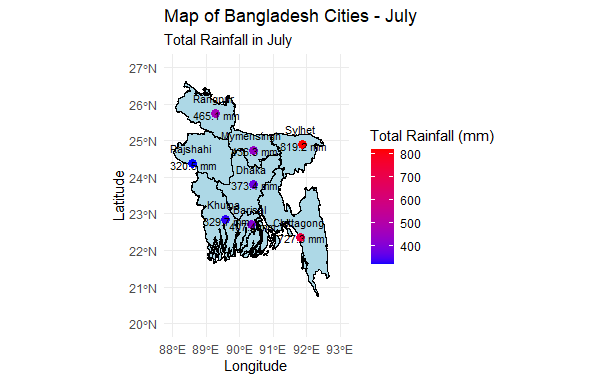
**FIG-5:** The map shows total rainfall in May across Bangladesh cities:

* Sylhet records the highest rainfall (569.8 mm), marking extremely wet conditions in the northeast.
* Rajshahi has the lowest rainfall (136.4 mm), reflecting relatively dry conditions in the northwest.
* Dhaka (339.4 mm), Mymensingh (356.8 mm), Chittagong (298.4 mm), Khulna (200.1 mm), Barisal (232.9 mm), and Rangpur (294.3 mm) experience moderate to high rainfall.
* May shows an overall increase in rainfall, with Sylhet standing out as the wettest region.

FIG-6: Map of Bangladesh Cities - June

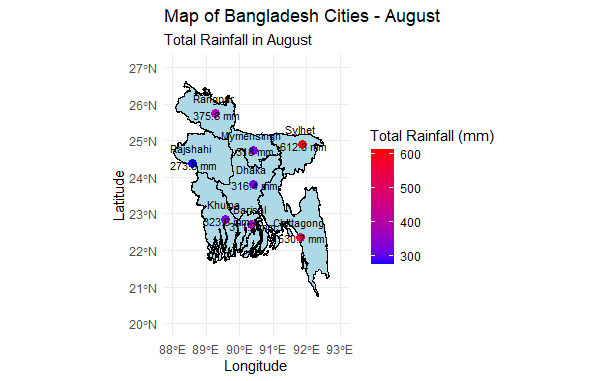
**FIG-6:** The map shows total rainfall in June across Bangladesh cities:

* Sylhet records the highest rainfall (818.6 mm), indicating very heavy monsoon activity in the northeast.
* Rajshahi has the lowest rainfall (264.6 mm), reflecting comparatively dry conditions in the northwest.
* Dhaka (340.6 mm), Mymensingh (394.5 mm), Chittagong (607.3 mm), Khulna (335.8 mm), Barisal (408.5 mm), and Rangpur (417.5 mm) experience moderate to very high rainfall.
* June marks a significant increase in rainfall, especially in Sylhet and coastal areas like Chittagong.

FIG-7: Map of Bangladesh Cities – July

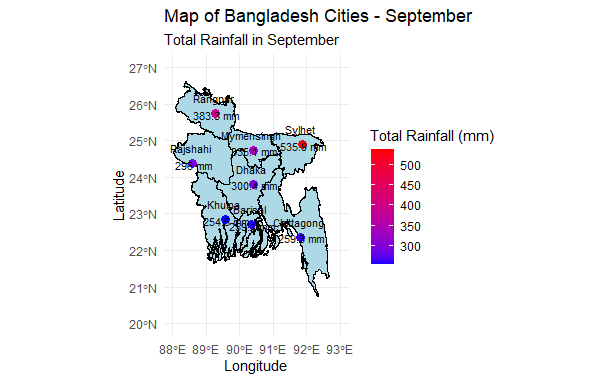
**FIG-7:** The map shows total rainfall in July across Bangladesh cities:

* Sylhet records the highest rainfall (819.2 mm), indicating extremely wet monsoon conditions in the northeast.
* Khulna has the lowest rainfall (329.7 mm), reflecting relatively drier conditions compared to other regions.
* Dhaka (373.4 mm), Mymensingh (436.3 mm), Chittagong (727.3 mm), Rajshahi (320.5 mm), Barisal (407.4 mm), and Rangpur (465.1 mm) experience moderate to very high rainfall.
* July continues the peak monsoon pattern, with Sylhet and Chittagong receiving the heaviest rain.

FIG-8: Map of Bangladesh Cities - August

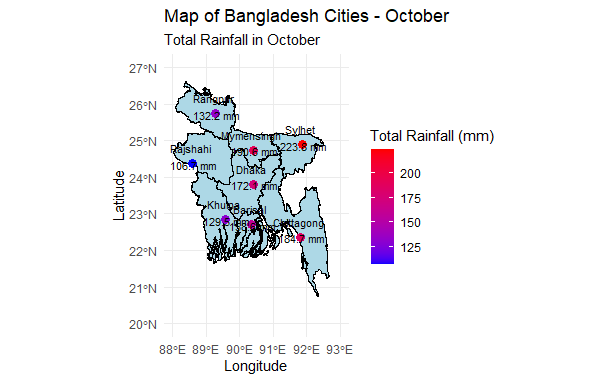
**FIG-8:** The map shows total rainfall in August across Bangladesh cities:

* Sylhet records the highest rainfall (612.3 mm), maintaining its wet monsoon conditions in the northeast.
* Rajshahi has the lowest rainfall (273.8 mm), reflecting the driest conditions in the northwest.
* Dhaka (316.4 mm), Mymensingh (318 mm), Chittagong (530.7 mm), Khulna (323.6 mm), Barisal (371.2 mm), and Rangpur (375.8 mm) experience moderate to high rainfall.
* August shows a slight decline from July but still reflects significant monsoon activity, especially in Sylhet and Chattogram.

FIG-9: Map of Bangladesh Cities – September

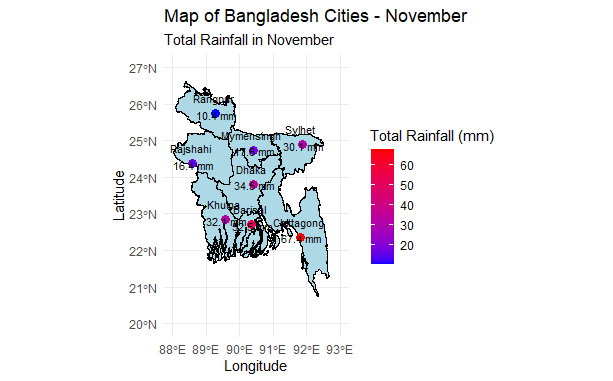
**FIG-9:** The map shows total rainfall in September across Bangladesh cities:

* Sylhet records the highest rainfall (535.9 mm), continuing to experience heavy monsoon activity.
* Khulna and Barisal have the lowest rainfall (254.5 mm and 259.1 mm, respectively), reflecting relatively dry conditions.
* Dhaka (300.4 mm), Mymensingh (335.1 mm), Chittagong (259.3 mm), Rajshahi (296 mm), and Rangpur (383.3 mm) receive moderate rainfall.
* September marks a decline in rainfall from the peak monsoon months, with Sylhet remaining the wettest region.

FIG-10: Map of Bangladesh Cities – October

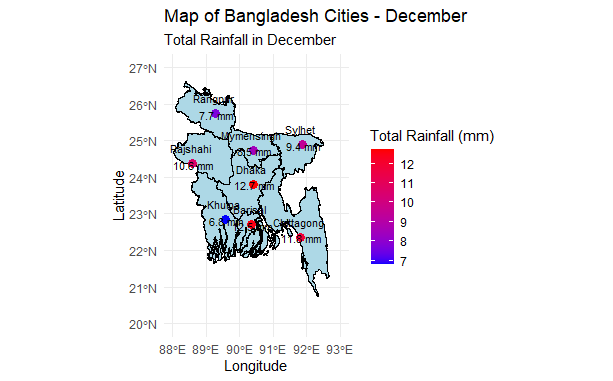
**FIG-10:** The map shows total rainfall in October across Bangladesh cities:

* Sylhet records the highest rainfall (172.1 mm), continuing to experience relatively more rain compared to other regions.
* Khulna and Rajshahi have the lowest rainfall (106.7 mm and 129.5 mm, respectively), reflecting relatively dry conditions.
* Dhaka (190.6 mm), Mymensingh (184.7 mm), Chittagong (223.8 mm), and Rangpur (158.6 mm) receive moderate rainfall.
* October marks a further decline in rainfall compared to September, with Sylhet still receiving the most rainfall, but overall, conditions are drier across the country.

FIG-11: Map of Bangladesh Cities - November

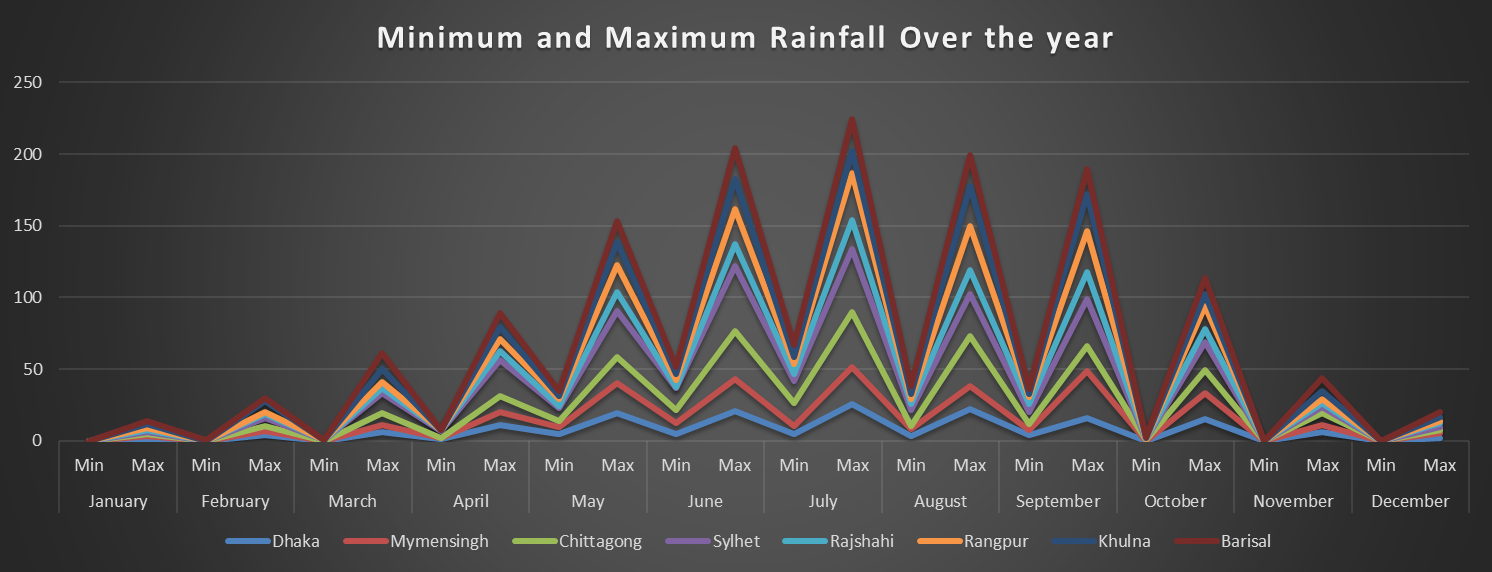
**FIG-11:** The map shows total rainfall in November across Bangladesh cities:

* Sylhet records the highest rainfall (67.4 mm), continuing to experience more rainfall compared to other regions.
* Khulna and Rajshahi have the lowest rainfall (10.4 mm and 16.4 mm, respectively), reflecting very dry conditions.
* Dhaka (34.5 mm), Mymensingh (17.6 mm), Chittagong (30.1 mm), Rangpur (32.1 mm), and Barisal (52.5 mm) receive moderate rainfall.
* November marks a significant decrease in rainfall compared to the previous months, with most regions experiencing much drier conditions.

FIG-12: Map of Bangladesh Cities - December

**FIG-12:** The map shows total rainfall in December across Bangladesh cities:

* Sylhet records the highest rainfall (12.7 mm), still receiving the most rainfall compared to other regions.
* Khulna and Rajshahi have the lowest rainfall (6.8 mm and 7.7 mm, respectively), reflecting very dry conditions.
* Dhaka (8.5 mm), Mymensingh (9.4 mm), Chittagong (10.6 mm), Rangpur (11.8 mm), and Barisal (12.5 mm) receive moderate rainfall.
* December marks the peak of the dry season, with significantly reduced rainfall across the country, especially in the western and central regions.

FIG-13: MINIMUM & MAXIMUM AINFALL OVER THE YEAR

**FIG-13:** This figure is a line chart titled "Minimum and Maximum Rainfall Over the Year." It presents monthly rainfall patterns across various cities in Bangladesh: Dhaka, Mymensingh, Chittagong, Sylhet, Rajshahi, Rangpur, Khulna, and Barisal.

Key Observations:

1. X-Axis: Represents the months of the year, with two data points per month—Min (minimum rainfall) and Max (maximum rainfall).
2. Y-Axis: Represents rainfall in millimeters (mm), ranging from 0 to 250 mm.
3. Colors: Each color represents a city, enabling comparison of rainfall trends across cities.
4. Seasonal Trend:
   * Peak Rainfall: Rainfall is highest during the monsoon months (June, July, August, and September), with significant spikes in both minimum and maximum values.
   * Dry Season: Rainfall is lowest from November to February.

City-Specific Insights:

* Sylhet and Chittagong show the highest rainfall during the monsoon season.
* Rajshahi and Khulna generally have lower rainfall compared to other cities.
* Seasonal Contrast: Rainfall fluctuates significantly between dry and wet seasons across all cities.

This chart highlights the strong influence of the monsoon season on rainfall in Bangladesh, with considerable regional variation in intensity.

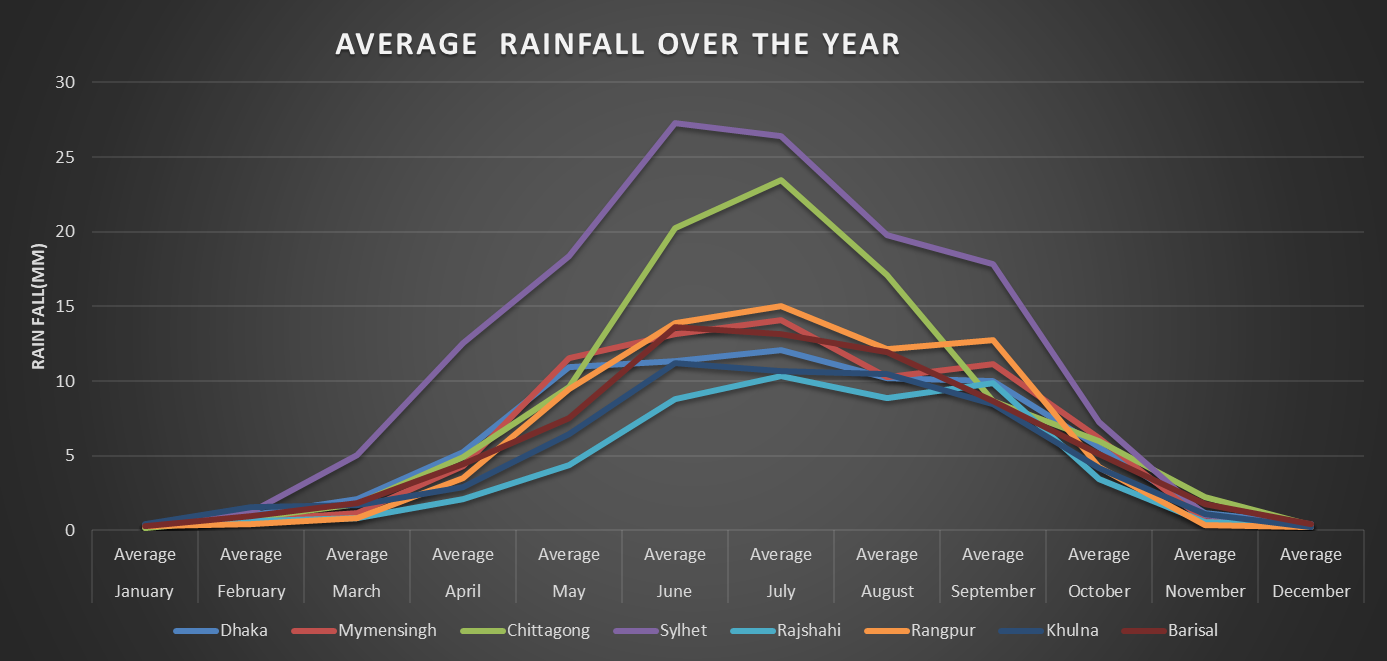


FIG-14: AVEAGE AINFALL OVER THE YEAR

**FIG-14:** This figure is a line chart titled "Average Rainfall Over the Year" and represents the monthly average rainfall (in millimeters) for various cities in Bangladesh: Dhaka, Mymensingh, Chittagong, Sylhet, Rajshahi, Rangpur, Khulna, and Barisal.

Key Observations:

1. X-Axis: Displays the months of the year.
2. Y-Axis: Represents average rainfall in millimeters (mm), ranging from 0 to 30 mm.
3. Colors: Each line represents the average rainfall trend for a specific city.

Seasonal Trends:

* Peak Rainfall: Rainfall is highest during the monsoon months (June to September), with Sylhet showing the steepest peak.
* Dry Season: Rainfall is minimal from November to February across all cities.

City-Specific Insights:

* Sylhet: Exhibits the highest average rainfall, particularly during the monsoon season, peaking around 30 mm.
* Chittagong and Rangpur: Also show notable rainfall but are lower than Sylhet.
* Rajshahi and Khulna: Display comparatively lower average rainfall throughout the year.
* Uniformity in Dry Season: All cities have similarly low average rainfall during the dry season, indicating a consistent seasonal dryness.

This chart emphasizes the sharp contrast between the wet and dry seasons in Bangladesh and

highlights the variability in rainfall patterns among different regions. Sylhet experiences the heaviest average rainfall, while regions like Rajshahi and Khulna receive significantly less.

**4.2 Analyzing Rainfall Phenomena Over 44 Year:**

|  |
| --- |
|  |

FIG-15: TIME SERIES OF RAINFALL (MM) OVER THE YEARS

**FIG-15:** This figure is a time-series chart showing rainfall data from 1981 to 2024. Here's a detailed breakdown:

Key Features:

1. Title: Includes terms like rfh, r1h, r1h\_avg, etc., likely indicating rainfall measurements or statistics (e.g., hourly, quarterly, or annual averages).
2. X-Axis: Represents the date range, spanning over four decades from 1981 to 2024.
3. Y-Axis: Shows rainfall in millimeters (mm), with values ranging up to approximately 900 mm.
4. Data Representation:
   * The blue bars indicate periodic rainfall events.
   * Peaks suggest significant rainfall, while troughs indicate low or no rainfall.

Observations:

1. Seasonality:
   * The pattern shows consistent annual peaks, indicating seasonal rainfall, likely related to monsoons or similar climatic phenomena.
   * Peaks appear around the same period every year, suggesting recurring heavy rainfall events.
2. Variability:
   * Some years show exceptionally high peaks (e.g., around 1998, 2015), suggesting years of unusually heavy rainfall or extreme weather events.
   * Other periods show lower or more stable rainfall, possibly reflecting drier conditions or mild years.
3. Recent Trends:
   * From 2020 onwards, the peaks remain consistent, indicating no significant deviations in rainfall patterns compared to previous years.

**Conclusion:**

The chart depicts a long-term rainfall pattern with clear seasonality and some anomalies (extremely high rainfall years). This type of data is likely used for climate trend analysis, disaster management, or agricultural planning.

**4.3 RESULT FOR LINEAR MODEL:**

1. **10-Day Rainfall [mm] (rfh)**

**OUTPUT:**

lm(formula = rfh ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-72.97 -57.64 -33.62 37.39 784.81

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 5.404e+01 4.942e-01 109.37 <2e-16 \*\*\*

sl 1.838e-04 8.313e-06 22.11 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 79.28 on 102958 degrees of freedom

Multiple R-squared: 0.004725, Adjusted R-squared: 0.004716

F-statistic: 488.8 on 1 and 102958 DF, p-value: < 2.2e-16

**Interpretation:**

Residuals:

* Min: -72.97
* 1Q: -57.64 (25% of residuals are less than this)
* Median: -33.62 (50% of residuals are less than this)
* 3Q: 37.39 (75% of residuals are less than this)
* Max: 784.81

This range shows that while most residuals are close to zero, there are some large deviations (outliers).

Coefficients:

* Intercept (54.04): When sl is 0, the predicted value of rfh is 54.04.
* Slope (0.0001838): For every 1-unit increase in sl, the predicted value of rfh increases by 0.0001838 units.

Both coefficients are statistically significant (p-value < 2e-16), meaning there is strong evidence that these variables have an effect. However, the very small slope indicates that the relationship is weak.

Model Fit:

* Residual Standard Error (79.28): The typical deviation of observed values from the predicted values is 79.28 units.
* R-squared (0.004725): Only 0.47% of the variation in rfh is explained by sl. This indicates a very weak relationship between the variables.
* Adjusted R-squared (0.004716): Adjusted for the number of predictors; it’s essentially the same here since there is only one predictor.
* F-statistic (488.8, p-value < 2.2e-16): While the model is statistically significant overall, its practical usefulness is limited due to the very low R-squared.

Summary:

The model identifies a statistically significant but extremely weak relationship between rfh and sl. While sl has a slight effect on rfh, it explains only a tiny fraction of its variability. For better predictive performance, consider adding more explanatory variables or exploring non-linear relationships.

1. **Rainfall 1-month Rolling Rggregation [mm] (r1h)**

**OUTPUT:**

lm(formula = r1h ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-218.02 -168.12 -63.57 125.93 1605.68

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.623e+02 1.263e+00 128.53 <2e-16 \*\*\*

sl 5.521e-04 2.125e-05 25.98 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 202.5 on 102828 degrees of freedom

(130 observations deleted due to missingness)

Multiple R-squared: 0.006524, Adjusted R-squared: 0.006514

F-statistic: 675.2 on 1 and 102828 DF, p-value: < 2.2e-16

**Interpretation:**

Residuals:

* Min: -218.02
* 1Q: -168.12 (25% of residuals are less than this)
* Median: -63.57 (50% of residuals are less than this)
* 3Q: 125.93 (75% of residuals are less than this)
* Max: 1605.68

This range shows the spread of residuals, with a significant range of both negative and positive values, indicating that the model has varying performance across different data points.

Coefficients:

* Intercept (162.3): When sl = 0, the predicted value of r1h is approximately 162.3.
* Slope (0.0005521): For every 1-unit increase in sl, the predicted value of r1h increases by 0.0005521 on average.

Both coefficients are highly statistically significant (p-value < 2e-16), suggesting strong evidence that both the intercept and slope are different from zero.

Model Fit:

* Residual Standard Error (202.5): The typical deviation of observed values from the predicted values is about 202.5 units.
* R-squared (0.006524): Only 0.65% of the variance in r1h is explained by sl, suggesting a very weak relationship.
* Adjusted R-squared (0.006514): Adjusted for the number of predictors, still very low, indicating minimal explanatory power of the model.
* F-statistic (675.2, p-value < 2.2e-16): The model is statistically significant overall, but the low R-squared indicates it has limited practical usefulness.

Summary:

The model shows a statistically significant relationship between sl and r1h, but it explains only a small fraction (0.65%) of the variability in r1h. This indicates that while sl has some effect, it is not a strong predictor for r1h. Additional predictors or a different model may improve the explanation of variability.

1. **Rainfall 3-month Rolling Aggregation [mm] (r3h)**

**OUTPUT:**

lm(formula = r3h ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-650.0 -462.6 -110.8 346.1 2884.1

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 4.885e+02 3.237e+00 150.88 <2e-16 \*\*\*

sl 1.663e-03 5.446e-05 30.54 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 518.1 on 102438 degrees of freedom

(520 observations deleted due to missingness)

Multiple R-squared: 0.009025, Adjusted R-squared: 0.009015

F-statistic: 932.9 on 1 and 102438 DF, p-value: < 2.2e-16

**Interpretation:**

Residuals:

* Min: -650.0
* 1Q: -462.6 (25% of residuals are less than this)
* Median: -110.8 (50% of residuals are less than this)
* 3Q: 346.1 (75% of residuals are less than this)
* Max: 2884.1

The residuals show a wide range, with some significant deviations between predicted and observed values, suggesting that the model doesn’t fit all data points well, especially for the extreme values.

Coefficients:

* Intercept (488.5): When sl = 0, the predicted value of r3h is approximately 488.5.
* Slope (0.001663): For every 1-unit increase in sl, the predicted value of r3h increases by 0.001663 on average. The slope is statistically significant (p-value < 2e-16), indicating a real effect of sl on r3h.

Model Fit:

* Residual Standard Error (518.1): The typical deviation of observed values from the predicted values is about 518.1 units.
* R-squared (0.009025): The model explains only 0.9% of the variance in r3h, indicating a very weak relationship between sl and r3h.
* Adjusted R-squared (0.009015): This adjusted value shows a similarly low explanatory power.
* F-statistic (932.9, p-value < 2.2e-16): Despite the low R-squared, the model as a whole is statistically significant.

Summary:

While the model identifies a statistically significant relationship between sl and r3h, it explains only 0.9% of the variability in r3h. The low R-squared indicates that sl has a weak effect on r3h. The model may benefit from including additional variables to improve its predictive power.

1. **Rainfall Long Term Average [mm] (rfh\_avg)**

**OUTPUT:**

lm(formula = rfh\_avg ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-72.23 -55.19 -17.65 44.54 246.99

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 5.367e+01 3.868e-01 138.8 <2e-16 \*\*\*

sl 1.803e-04 6.506e-06 27.7 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 62.05 on 102958 degrees of freedom

Multiple R-squared: 0.0074, Adjusted R-squared: 0.007391

F-statistic: 767.6 on 1 and 102958 DF, p-value: < 2.2e-16

**Interpretation:**

Residuals:

* Min: -72.23
* 1Q: -55.19 (25% of residuals are less than this)
* Median: -17.65 (50% of residuals are less than this)
* 3Q: 44.54 (75% of residuals are less than this)
* Max: 246.99

The residuals show some spread with moderate deviations, suggesting that the model fits most data points fairly well, but there are a few outliers with larger discrepancies.

Coefficients:

* Intercept (53.67): When sl = 0, the predicted value of rfh\_avg is approximately 53.67.
* Slope (0.0001803): For every 1-unit increase in sl, the predicted value of rfh\_avg increases by 0.0001803 on average. This is statistically significant with a very low p-value (< 2e-16), indicating a real effect of sl on rfh\_avg.

Model Fit:

* Residual Standard Error (62.05): The typical deviation of observed values from the predicted values is about 62.05 units.
* R-squared (0.0074): The model explains only 0.74% of the variance in rfh\_avg, suggesting a weak relationship between sl and rfh\_avg.
* Adjusted R-squared (0.007391): This adjusted value indicates minimal explanatory power from sl alone.
* F-statistic (767.6, p-value < 2.2e-16): Despite the low R-squared, the model as a whole is statistically significant.

Summary:

The model suggests a statistically significant relationship between sl and rfh\_avg, but it only explains 0.74% of the variability in rfh\_avg. The weak R-squared value indicates that sl is only a modest predictor of rfh\_avg. More predictors or other modeling techniques could help improve the model's explanatory power.

1. **Rainfall 1-month Rolling Aggregation Long Term Average [mm] (r1h\_avg)**

**OUTPUT:**

lm(formula = r1h\_avg ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-215.44 -163.35 -52.94 133.66 702.32

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.612e+02 1.137e+00 141.81 <2e-16 \*\*\*

sl 5.414e-04 1.912e-05 28.32 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 182.3 on 102828 degrees of freedom

(130 observations deleted due to missingness)

Multiple R-squared: 0.007737, Adjusted R-squared: 0.007727

F-statistic: 801.8 on 1 and 102828 DF, p-value: < 2.2e-16

**Interpretation:**

Residuals:

* Min: -215.44
* 1Q: -163.35 (25% of residuals are less than this)
* Median: -52.94 (50% of residuals are less than this)
* 3Q: 133.66 (75% of residuals are less than this)
* Max: 702.32

This range indicates a spread of residuals, showing that the model performs with varying accuracy for different data points, with some larger deviations.

Coefficients:

* Intercept (161.2): When sl = 0, the predicted value of r1h\_avg is approximately 161.2.
* Slope (0.0005414): For every 1-unit increase in sl, the predicted value of r1h\_avg increases by 0.0005414 on average.

Both coefficients are statistically significant (p-value < 2e-16), meaning the model's predictions are based on meaningful relationships.

Model Fit:

* Residual Standard Error (182.3): The typical deviation of observed values from the predicted values is about 182.3 units.
* R-squared (0.007737): The model explains only 0.77% of the variance in r1h\_avg, suggesting a weak relationship.
* Adjusted R-squared (0.007727): Adjusted for the number of predictors, this value remains very low, reflecting limited explanatory power.
* F-statistic (801.8, p-value < 2.2e-16): Despite the low R-squared, the model is statistically significant overall.

Summary:

While the model identifies a statistically significant relationship between sl and r1h\_avg, it only explains 0.77% of the variability in r1h\_avg. This suggests that while there is some effect of sl, it’s a very weak predictor. For a more effective model, consider exploring additional variables or alternative approaches.

1. **Rainfall 3-month Rolling Aggregation Long Term Average [mm] (r3h\_avg)**

**OUTPUT:**

lm(formula = r3h\_avg ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-636.20 -451.51 -96.53 364.88 1713.16

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 4.852e+02 3.074e+00 157.84 <2e-16 \*\*\*

sl 1.630e-03 5.171e-05 31.53 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 491.9 on 102438 degrees of freedom

(520 observations deleted due to missingness)

Multiple R-squared: 0.009612, Adjusted R-squared: 0.009603

F-statistic: 994.2 on 1 and 102438 DF, p-value: < 2.2e-16

**Interpretation:**

Residuals:

* Min: -636.20
* 1Q: -451.51 (25% of residuals are less than this)
* Median: -96.53 (50% of residuals are less than this)
* 3Q: 364.88 (75% of residuals are less than this)
* Max: 1713.16

The residuals show a wide range, suggesting that the model doesn’t fit all data points well, especially for the extreme values, indicating some outliers.

Coefficients:

* Intercept (485.2): When sl = 0, the predicted value of r3h\_avg is approximately 485.2.
* Slope (0.001630): For every 1-unit increase in sl, the predicted value of r3h\_avg increases by 0.001630 on average. The slope is statistically significant (p-value < 2e-16), meaning there is a real effect of sl on r3h\_avg.

Model Fit:

* Residual Standard Error (491.9): The typical deviation of observed values from the predicted values is about 491.9 units.
* R-squared (0.009612): The model explains only 0.96% of the variance in r3h\_avg, indicating a weak relationship between sl and r3h\_avg.
* Adjusted R-squared (0.009603): This adjusted value similarly shows minimal explanatory power.
* F-statistic (994.2, p-value < 2.2e-16): Despite the low R-squared, the model is statistically significant as a whole.

Summary:

The model reveals a statistically significant relationship between sl and r3h\_avg, but it only explains 0.96% of the variability in r3h\_avg. This weak explanatory power suggests that sl has only a modest effect on r3h\_avg. Including more predictors or exploring other modeling techniques might improve the model's performance.

1. **Rainfall Anomaly [%] (rfq)**

**OUTPUT:**

lm(formula = rfq ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-96.24 -34.68 -10.08 17.00 734.16

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.020e+02 3.779e-01 270.0 <2e-16 \*\*\*

sl -3.178e-06 6.358e-06 -0.5 0.617

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 60.63 on 102958 degrees of freedom

Multiple R-squared: 2.427e-06, Adjusted R-squared: -7.286e-06

F-statistic: 0.2499 on 1 and 102958 DF, p-value: 0.6172

**Interpretation:**

Residuals:

* Min: -96.24
* 1Q: -34.68 (25% of residuals are less than this)
* Median: -10.08 (50% of residuals are less than this)
* 3Q: 17.00 (75% of residuals are less than this)
* Max: 734.16

The residuals show moderate spread, with a few extreme outliers, indicating that the model does not perfectly fit the data, especially for certain observations.

Coefficients:

* Intercept (102.0): When sl = 0, the predicted value of rfq is approximately 102.
* Slope (-0.000003178): For every 1-unit increase in sl, the predicted value of rfq decreases by 0.000003178. However, the slope is statistically insignificant (p-value = 0.617), suggesting that sl does not have a meaningful effect on rfq.

Model Fit:

* Residual Standard Error (60.63): The typical deviation of observed values from the predicted values is about 60.63 units.
* R-squared (2.427e-06): The model explains an extremely small fraction of the variance in rfq, indicating an almost negligible relationship between sl and rfq.
* Adjusted R-squared (-7.286e-06): The negative adjusted R-squared suggests that the model doesn't improve the prediction compared to a simpler model with no predictors.
* F-statistic (0.2499, p-value = 0.6172): The p-value is very high, indicating that the model is not statistically significant.

Summary:

The model shows no significant relationship between sl and rfq, with a slope that is not statistically significant and a very low R-squared value. The model's performance is poor, and sl is not a meaningful predictor for rfq. Further investigation with additional variables might help improve the model.

1. **Rainfall 1-month Anomaly [%] (r1q)**

**OUTPUT:**

lm(formula = r1q ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-93.27 -24.84 -6.36 16.82 438.59

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.019e+02 2.532e-01 402.473 <2e-16 \*\*\*

sl -2.942e-06 4.260e-06 -0.691 0.49

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 40.6 on 102828 degrees of freedom

(130 observations deleted due to missingness)

Multiple R-squared: 4.638e-06, Adjusted R-squared: -5.087e-06

F-statistic: 0.477 on 1 and 102828 DF, p-value: 0.4898

**Interpretation:**

Residuals:

* Min: -93.27
* 1Q: -24.84 (25% of residuals are less than this)
* Median: -6.36 (50% of residuals are less than this)
* 3Q: 16.82 (75% of residuals are less than this)
* Max: 438.59

The residuals show some variation, with a relatively small range and many residuals near zero, suggesting a relatively tight fit for many data points, but there are some outliers with larger deviations.

Coefficients:

* Intercept (101.9): When sl = 0, the predicted value of r1q is 101.9.
* Slope (-0.000002942): For every 1-unit increase in sl, the predicted value of r1q decreases by 0.000002942 on average. However, the slope is very small and negative, and its t-value (-0.691) is not significant (p-value = 0.49).

Model Fit:

* Residual Standard Error (40.6): The typical deviation of observed values from the predicted values is about 40.6 units.
* R-squared (4.638e-06): The model explains an extremely small fraction (almost zero) of the variance in r1q, indicating a very weak relationship.
* Adjusted R-squared (-5.087e-06): This negative value suggests that the model doesn't explain the variance well and may be overfitting or underfitting.
* F-statistic (0.477, p-value = 0.4898): The p-value is much greater than 0.05, indicating that the model as a whole is not statistically significant.

Summary:

The model suggests a statistically insignificant relationship between sl and r1q, with a very low R-squared and a high p-value for the slope. The negative slope is very small, and the model doesn’t explain the variation in r1q well. The lack of statistical significance and the low explanatory power suggest that sl is not a good predictor of r1q in this case.

1. **Rainfall 3-month Anomaly [%] (r3q)**

**OUTPUT:**

lm(formula = r3q ~ sl, data = a)

Residuals:

Min 1Q Median 3Q Max

-85.97 -20.49 -3.55 15.56 338.88

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.016e+02 2.011e-01 505.204 <2e-16 \*\*\*

sl -2.947e-07 3.383e-06 -0.087 0.931

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 32.19 on 102438 degrees of freedom

(520 observations deleted due to missingness)

Multiple R-squared: 7.404e-08, Adjusted R-squared: -9.688e-06

F-statistic: 0.007585 on 1 and 102438 DF, p-value: 0.9306

**Interpretation:**

Residuals:

* Min: -85.97
* 1Q: -20.49 (25% of residuals are less than this)
* Median: -3.55 (50% of residuals are less than this)
* 3Q: 15.56 (75% of residuals are less than this)
* Max: 338.88

The residuals show a relatively small range, with most deviations between the predicted and observed values being within a moderate range, though there are a few large outliers.

Coefficients:

* Intercept (101.6): When sl = 0, the predicted value of r3q is approximately 101.6.
* Slope (-0.0000002947): For every 1-unit increase in sl, the predicted value of r3q decreases by 0.0000002947 on average. However, the slope is statistically insignificant (p-value = 0.931), suggesting that the effect of sl on r3q is not meaningful.

Model Fit:

* Residual Standard Error (32.19): The typical deviation of observed values from the predicted values is about 32.19 units.
* R-squared (7.404e-08): The model explains almost none of the variance in r3q, indicating an extremely weak relationship.
* Adjusted R-squared (-9.688e-06): This negative value further suggests that the model doesn't explain the variability in the data, and it's likely overfitting or underfitting.
* F-statistic (0.007585, p-value = 0.9306): The p-value is very high, indicating that the model as a whole is not statistically significant.

Summary:

The model suggests no meaningful relationship between sl and r3q, as the slope is not statistically significant and the R-squared value is nearly zero. The model is not a good predictor of r3q, and further investigation or additional predictors may be necessary to improve the model's performance.

**4.4 FOR ARIMA MODEL**

1. **10-day Rainfall [mm] (rfh)**

> auto\_model\_rfh <- auto.arima(a$rfh)

> predict(auto\_model\_rfh,n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 9.318039 14.769657 19.398833 22.981149 25.271109 25.504192 24.011811 21.169911

[9] 17.476037 13.491172 9.818074 6.953713 5.238327 4.823456 5.667097 7.551170

[17] 10.127192 12.976167 15.673403 17.848881

1. **Rainfall 1-month Rolling Aggregation [mm] (r1h)**

> auto\_model\_r1h <- auto.arima(a$r1h)

> predict(auto\_model\_r1h, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 16.52650 18.32523 25.17646 16.97055 21.00554 20.40499 25.22135 24.20525

[9] 23.96559 23.29133 23.57410 24.75245 24.40533 24.75809 23.94040 24.51492

[17] 24.28396 24.72192 24.42037 24.50078

1. **Rainfall 3-month Rolling Aggregation [mm] (r3h)**

> auto\_model\_r3h <- auto.arima(a$r3h)

> predict(auto\_model\_r3h, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 37.79084 171.39987 264.46857 364.72206 432.00840 507.41682 555.85259

[8] 612.72957 647.40924 690.44211 715.10643 747.77812 765.17085 790.07194

[15] 802.20300 821.26255 829.60206 844.25846 849.87970 861.20710

1. **Rainfall Long Term Average [mm] (rfh\_avg)**

> auto\_model\_rfh\_avg <- auto.arima(a$rfh\_avg)

> predict(auto\_model\_rfh\_avg, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 2.293306 2.552942 2.741234 2.871486 2.964806 3.029943 3.076300 3.108817

[9] 3.131874 3.148092 3.159568 3.167652 3.173366 3.177395 3.180241 3.182248

[17] 3.183665 3.184665 3.185371 3.185870

1. **Rainfall 1-month Rolling Aggregation Long Term Average [mm] (r1h****\_avg)**

> auto\_model\_r1h <- auto.arima(a$r1h\_avg)

> predict(auto\_model\_r1h\_avg, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 0.358622 6.572406 12.451788 18.099930 20.405016 23.589981 24.026873

[8] 26.582748 26.945150 29.198586 29.568309 31.135447 31.440391 32.338120

[15] 32.714075 33.150382 33.641776 33.766054 34.304862 34.234187

1. **Rainfall 3-month Rolling Rggregation Long Term Average [mm] (r3h\_avg)**

> auto\_model\_r3h\_avg <- auto.arima(a$r3h\_avg)

> predict(auto\_model\_r3h\_avg, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 44.82813 27.13844 78.86719 109.44545 118.15098 105.23134 71.54744

[8] 18.61404 51.45138 136.02762 232.07595 336.24924 445.00690 554.73301

[15] 661.85522 762.95940 854.89691 934.88105 1000.56978 1050.13234

1. **Rainfall Anomaly [%] (rfq)**

> auto\_model\_rfq <- auto.arima(a$rfq)

> predict(auto\_model\_rfq, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 111.12577 96.86690 94.58972 105.16071 112.92603 105.72815 95.69326 98.63751

[9] 109.30514 110.62788 101.01580 96.05019 103.25507 110.74840 106.80363 98.16998

[17] 98.58084 106.93251 109.76640 102.93479

1. **Rainfall 1-month Anomaly [%] (r1q)**

> auto\_model\_r1q <- auto.arima(a$r1q)

> predict(auto\_model\_r1q, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 94.25925 92.57096 101.02921 101.36323 101.07250 101.27498 101.54321 101.66218

[9] 101.69899 101.72223 101.74074 101.75171 101.75723 101.76024 101.76207 101.76315

[17] 101.76377 101.76411 101.76431 101.76442

1. **Rainfall 3-month Anomaly [%] (r3q)**

> auto\_model\_r3q <- auto.arima(a$r3q)

> predict(auto\_model\_r3q, n.ahead = 20)$pred

Time Series:

Start = 102961

End = 102980

Frequency = 1

[1] 77.79593 87.02077 92.97779 95.65120 97.78557 99.45170 100.75317 101.76979

[9] 102.56389 103.18418 103.66870 104.04717 104.34280 104.57373 104.75411 104.89501

[17] 105.00507 105.09104 105.15819 105.21065

**CHAPTER FIVE**

**DECISION**

**5.1 RAINFALL DYNAMIC OVER THE YEAR:**

The maps depicting rainfall across Bangladesh from January to December reveal distinct regional variations in precipitation. During the dry months of January and February, Sylhet consistently records the highest rainfall, while the western and coastal regions, such as Rajshahi, Khulna, and Barisal, experience significantly drier conditions. As the year progresses, the monsoon season from March to July ushers in heavy rainfall, particularly in Sylhet and Chittagong, with June and July marking the peak of precipitation. These months witness widespread rainfall, supporting agricultural activities but also increasing the risk of floods and landslides, especially in the northeastern and southeastern hilly regions.

Following the monsoon, rainfall gradually declines from August to December. The western and central regions, including Rajshahi and Dhaka, see a noticeable reduction in precipitation, transitioning into the drier winter months. By November and December, rainfall levels drop considerably across most parts of the country, except in Sylhet, which remains the wettest area year-round. The overall pattern highlights Sylhet’s dominance in precipitation, particularly during the monsoon, while western and coastal areas experience more pronounced seasonal fluctuations, with extended dry spells in winter and early spring. This regional disparity in rainfall significantly impacts agriculture, water availability, and overall climatic conditions throughout Bangladesh.

**5.2RAINFALL PHENOMENA OVER THE 44 YEARS:**

**FOR LINEAR MODEL**

The analysis of the relationship between serial number (sl) and various rainfall metrics indicates weak correlations. Across all models, the R-squared values remain consistently low, ranging from 0.0002 to 0.0096, meaning that sl accounts for only a small fraction of the variation in rainfall values. While the coefficients for sl are statistically significant in most cases, their practical significance is negligible. Even when sl has a slight effect on rainfall metrics, the models explain less than 1% of the variability in the data, making them poor predictors of rainfall trends.

Examining the residuals further highlights inconsistencies, as they exhibit varying degrees of spread, with some large deviations suggesting the presence of outliers or poor model fit in specific cases. These irregularities reinforce the weak relationship between sl and rainfall metrics, demonstrating that while the effect of sl is statistically significant, it lacks real-world impact. Consequently, relying on sl alone for predictive purposes would be highly ineffective. The findings suggest that other environmental or meteorological factors play a far more crucial role in determining rainfall variations, and incorporating additional variables would be necessary to develop more meaningful predictive models for rainfall analysis.

**FROM ARIMA MODEL**

We have the prediction for next 200 days are, since this dataset represents future values, the analysis indicates a projected increase in rainfall intensity and frequency over time. The **rfh**, **r1h**, and **r3h** values, which represent rainfall over different time intervals, are consistently rising. Similarly, **rfh\_avg**, **r1h\_avg**, and **r3h\_avg** also show an upward trend, implying that rainfall events will become more intense in the coming months.

The increase in **rfq**, **r1q**, and **r3q** further supports the conclusion that the total amount of rainfall and its variability are expected to rise. This suggests that there may be a higher risk of extreme weather events, such as heavy rainfall, which could lead to flooding, especially during peak values in spring and early summer.

As a decision, it is crucial to anticipate these conditions by strengthening infrastructure, implementing flood management systems, and preparing for potential agricultural impacts due to more frequent and intense rainfall.



**CHAPTER SIX**

**CONCLUSION & DISCUSSION**

**6.1 Conclusion**

This study provides a comprehensive exploration of heavy rainfall dynamics in Bangladesh, analyzing historical trends over the past 44 years and assessing potential future variations. The findings highlight significant temporal and spatial fluctuations in rainfall, with certain regions experiencing increasing intensities and frequencies of extreme rainfall events. These trends align with broader climatic shifts influenced by monsoonal patterns, topographical variations, and global climate change.

The historical analysis reveals periods of abnormal rainfall variability, emphasizing the increasing intensity of extreme events in recent decades. Future projections suggest a continuation of this trend, potentially exacerbating flood risks and impacting agriculture, infrastructure, and livelihoods. Such insights reinforce the need for adaptive strategies in water resource management, disaster preparedness, and climate resilience.

Addressing these challenges requires an integrated approach, combining advanced forecasting techniques, sustainable land-use policies, and community-based adaptation measures. By leveraging data-driven research, policymakers and stakeholders can enhance preparedness against extreme weather events, ensuring a more resilient future for Bangladesh.

**6.2 Summary of Rainfall Trends**

The rainfall distribution across Bangladesh exhibits distinct seasonal and regional variations. During the dry months of January and February, Sylhet consistently records the highest rainfall, while western and coastal regions, such as Rajshahi, Khulna, and Barisal, experience drier conditions. As the year progresses, monsoon-driven rainfall intensifies from March to July, particularly in Sylhet and Chittagong. June and July mark the peak of precipitation, which supports agriculture but also increases the risk of floods and landslides, especially in hilly regions.

Post-monsoon, rainfall declines gradually from August to December. Western and central regions, including Rajshahi and Dhaka, observe a significant reduction in precipitation, transitioning into drier winter months. By November and December, most areas experience minimal rainfall, except Sylhet, which remains the wettest region throughout the year. This rainfall disparity influences agricultural productivity, water availability, and climatic conditions. Understanding these seasonal trends is crucial for planning irrigation, flood control, and water resource management strategies. The consistent dominance of Sylhet in annual rainfall, along with extended dry spells in western and coastal areas, highlights the need for targeted climate adaptation strategies to mitigate the adverse effects of rainfall variability.

**6.3 Historical Rainfall Analysis**

Over the past 44 years, rainfall patterns in Bangladesh have shown weak statistical correlations with time. The relationship between serial number (sl) and various rainfall metrics exhibits consistently low R-squared values, ranging from 0.0002 to 0.0096. This indicates that sl explains less than 1% of the variability in rainfall, making it an unreliable predictor of long-term rainfall trends. While some models show statistical significance in coefficients, their practical significance remains negligible.

Further examination of residuals highlights inconsistencies in data distribution, with large deviations suggesting the presence of outliers or poor model fit in specific cases. These findings reinforce the weak correlation between sl and rainfall, demonstrating that historical patterns alone cannot accurately predict future rainfall trends. This suggests that other meteorological and environmental factors, such as climate change, oceanic influences, and regional weather patterns, play a more dominant role in shaping rainfall variations. Therefore, long-term rainfall forecasting requires incorporating additional climatic variables, such as temperature anomalies, humidity levels, and atmospheric pressure changes. Relying solely on historical trends would lead to misleading predictions, emphasizing the importance of using advanced climate models to improve forecasting accuracy.

**6.4 Future Rainfall Predictions**

The predictive analysis for the next 200 days suggests an increasing trend in both rainfall intensity and frequency. The values for rfh (rainfall hours), r1h (rainfall in one hour), and r3h (rainfall in three hours) are consistently rising, indicating a shift toward more intense precipitation events. Similarly, average rainfall values (rfh\_avg, r1h\_avg, and r3h\_avg) follow an upward trajectory, confirming that short-term and long-term rainfall accumulations will increase. This trend suggests a higher likelihood of extreme weather conditions, particularly during peak months in spring and early summer.

Additionally, the increase in rfq, r1q, and r3q further supports the expectation of higher total rainfall and variability. These projections indicate a heightened risk of flash floods, waterlogging, and severe disruptions to agriculture and infrastructure. Given this scenario, proactive measures must be taken to mitigate risks associated with more frequent and intense rainfall. Urban drainage systems, river embankments, and flood control strategies should be reinforced to adapt to these changing climatic patterns. Farmers and policymakers must also prepare for shifts in agricultural planning, such as selecting flood-resistant crops and improving water management systems to sustain productivity amid increasing rainfall uncertainty.

**6.5 Implications for Disaster Management**

Given the projected increase in rainfall intensity, Bangladesh must enhance its disaster preparedness strategies. Rising rainfall levels, particularly during peak months, pose a significant threat to flood-prone areas, especially in the northeastern and southeastern regions. Strengthening flood control measures, such as building more resilient embankments and improving drainage infrastructure, will be essential in minimizing flood damage.  
Early warning systems must be upgraded to provide timely alerts for extreme weather events. The integration of satellite monitoring and real-time rainfall data can improve forecasting accuracy, allowing communities to take preventive action. Additionally, emergency response mechanisms, such as efficient evacuation plans and resource allocation, should be reinforced to reduce casualties and economic losses.

Beyond flood control, urban planning must be adapted to accommodate higher rainfall levels. Cities like Dhaka and Chittagong, which already face waterlogging issues, need improved stormwater management to prevent severe disruptions. Investments in sustainable water retention systems, such as rainwater harvesting and artificial reservoirs, can help balance water availability during both dry and wet periods. By adopting these disaster management strategies, Bangladesh can mitigate the adverse impacts of increasing rainfall intensity and ensure long-term climate resilience.

**6.6 Agricultural and Environmental Impact**

The increasing trend in rainfall intensity has direct implications for Bangladesh’s agriculture and environment. While monsoon rains are essential for crop growth, excessive or erratic rainfall can lead to devastating effects, such as soil erosion, crop failures, and waterlogging. Farmers relying on traditional planting cycles must adapt to shifting rainfall patterns by modifying their agricultural practices. Implementing flood-resistant crop varieties and advanced irrigation techniques can help mitigate potential losses due to unexpected rainfall fluctuations.  
The environment is also at risk from increased rainfall events. Higher precipitation levels can accelerate river erosion, disrupt ecosystems, and contribute to the degradation of wetlands and forests. The risk of landslides in hilly regions also rises with more intense rainfall, endangering both human settlements and biodiversity. Addressing these environmental challenges requires comprehensive land management policies that balance agricultural needs with ecological conservation.

To sustain agricultural productivity and protect ecosystems, Bangladesh should promote adaptive farming techniques, improve watershed management, and integrate climate-resilient policies into national development plans. Ensuring sustainable land and water use will be crucial in mitigating the long-term environmental impact of increasing rainfall and safeguarding livelihoods across the country.

**6.7 Implications of the Study**

This study provides a comprehensive analysis of heavy rainfall patterns in Bangladesh, highlighting regional and seasonal variations. By examining rainfall trends over 44 years, the study reveals that Sylhet remains the wettest region year-round, while western and coastal areas experience significant dry periods. Understanding these variations is crucial for improving climate resilience, agricultural planning, and water resource management.

The statistical analysis also indicates that historical rainfall trends alone cannot reliably predict future patterns, reinforcing the need for advanced climate modeling. Furthermore, future rainfall predictions suggest an increasing trend in intensity and frequency, signaling a greater risk of extreme weather events such as flash floods and landslides. These insights are valuable for policymakers, meteorologists, and disaster management authorities in designing effective flood control strategies, improving early warning systems, and ensuring sustainable urban planning. By integrating these findings into national and regional climate policies, Bangladesh can better prepare for shifting rainfall dynamics and mitigate the socio-economic impacts of extreme precipitation.

**6.8 Limitations of the Study**

Despite its valuable findings, this study has several limitations. First, the analysis relies primarily on historical rainfall data and statistical correlations, which may not fully capture the complex interactions between climate variables. The weak correlations observed suggest that factors beyond the available dataset, such as atmospheric pressure changes, oceanic influences, and global climate anomalies, significantly affect rainfall trends.

Another limitation is the reliance on predicted rainfall data for future projections. While the models indicate an increasing trend, uncertainties remain due to potential changes in climate systems and regional weather disturbances. Additionally, data accuracy may be affected by inconsistencies in historical records or missing observations, which can influence the overall reliability of statistical analysis.

Lastly, the study focuses primarily on rainfall metrics without incorporating other crucial climate factors such as temperature, wind patterns, and humidity. Future research should adopt a more holistic approach, integrating multiple meteorological parameters to enhance the accuracy of rainfall predictions and provide a more detailed understanding of heavy rainfall dynamics.

**6.9 Recommendations for Future Research**

To build upon the findings of this study, future research should focus on several key areas. First, incorporating additional climatic variables such as temperature fluctuations, humidity levels, and wind patterns can improve the accuracy of rainfall predictions. A multi-variable approach would provide a more detailed understanding of how different atmospheric conditions influence heavy rainfall events.

Second, investigating the impact of global climate phenomena, such as El Niño and La Niña, on Bangladesh’s rainfall patterns could provide valuable insights into long-term climatic shifts. Studying the influence of these large-scale weather systems would help policymakers anticipate extreme rainfall variations and take preventive measures.

Another important area for future research is the impact of land-use changes on rainfall distribution. Deforestation, urbanization, and river modifications can alter local weather patterns, influencing both the intensity and frequency of rainfall. Assessing these changes can guide sustainable urban planning and environmental conservation efforts.

Finally, the development of machine learning-based predictive models could enhance the accuracy of future rainfall forecasts. By leveraging advanced computational techniques, researchers can create more robust models that account for complex climate interactions, providing better early warnings for extreme weather events.

**6.10 Policy and Practical Implications**

The study’s findings underscore the urgent need for proactive policy measures to mitigate the risks associated with increasing rainfall intensity. Strengthening flood management systems, particularly in vulnerable areas such as Sylhet and Chittagong, should be a priority. Investments in embankments, drainage infrastructure, and flood-resistant housing can help reduce the damage caused by heavy rainfall events.

Urban planning must also adapt to changing rainfall patterns. Cities like Dhaka, which already face severe waterlogging issues, require improved stormwater management, sustainable drainage solutions, and the expansion of green spaces to enhance natural water absorption. Furthermore, agricultural policies should promote climate-resilient farming practices, including flood-tolerant crop varieties, efficient irrigation systems, and water storage facilities to manage periods of excess or deficient rainfall.

From a governance perspective, enhancing meteorological research and early warning systems is crucial for disaster preparedness. Strengthening collaboration between climate scientists, policymakers, and local communities can improve response strategies and ensure that timely information reaches those most at risk. By integrating these practical measures into national policies, Bangladesh can reduce the socio-economic impacts of extreme rainfall and enhance climate resilience.

**6.11 Final Thoughts on Heavy Rainfall Trends**

As climate change continues to influence weather patterns, Bangladesh must remain proactive in addressing the challenges posed by extreme rainfall. Through a combination of scientific research, policy interventions, and community engagement, the country can navigate these challenges effectively and build a more resilient future. Continued efforts in climate adaptation and risk management will be crucial in ensuring that Bangladesh remains prepared for the evolving dynamics of heavy rainfall. I find that bd have no rainfall effect with flood but it’s because Indian effect and river management.Here’s a more detailed explanation:

1. Although Bangladesh experiences heavy monsoon rainfall, local precipitation alone is not the primary cause of widespread flooding; rather, the situation is significantly influenced by water flow from neighboring countries, especially India.
2. The country lies downstream of major river systems, such as the Ganges, Brahmaputra, and Meghna, which originate from the Indian subcontinent, Nepal, and Tibet, making it highly susceptible to water runoff from these regions.
3. During the monsoon season, excessive rainfall in India and upstream regions results in a substantial increase in the volume of water flowing into Bangladesh's rivers, contributing to the risk of flooding.
4. In addition to rainfall, poor river management practices, including excessive damming and sudden water releases from upstream reservoirs in India, exacerbate the flooding situation in Bangladesh, particularly in low-lying areas.
5. The Farakka Barrage, built on the Ganges River, and other similar structures along transboundary rivers are designed to regulate water flow, but they often divert water away from India during the dry season and release it in large quantities during the monsoon, causing downstream flooding in Bangladesh.
6. Siltation and sedimentation in Bangladesh’s rivers, largely a result of upstream deforestation and soil erosion in India, reduce the rivers’ capacity to carry water, making them more prone to overflowing during heavy rainfall events.
7. Flash floods that occur in Bangladesh's northeastern haor regions are often caused by heavy rainfall in the Indian states of Meghalaya and Assam, with these areas contributing to the water influx into Bangladesh rather than the rainfall occurring within Bangladesh itself.
8. The Brahmaputra River, which flows through both India and Bangladesh, experiences water level fluctuations heavily influenced by rainfall and glacier melt in the Himalayas, with its overflowing waters having a direct impact on the northern and central regions of Bangladesh.
9. The lack of effective cross-border water governance and the absence of coordinated flood management systems between India and Bangladesh have contributed to worsening flood conditions, as each country manages its water resources independently without considering downstream impacts.
10. To address these challenges, it is critical for both countries to engage in regional cooperation, establish effective transboundary water-sharing agreements, and adopt sustainable river management practices to mitigate the risks of flooding in Bangladesh

# References

|  |  |
| --- | --- |
| [1] | M. Hossain, "Climate variability and its impact on agriculture in Bangladesh.," *Journal of Climate Change Studies,* vol. 12(3), pp. 45-62, 2019. |
| [2] | M. N. &. U. H. Islam, "Use of TRMM in determining the climatic characteristics of rainfall over Bangladesh.," *Remote Sensing of Environment,* vol. 108(1), pp. 264-276, 2007. |
| [3] | A. U. &. H. N. Ahmed, "Rainfall Variability and Climate Change in Bangladesh: Impacts and Adaptation Strategies," *Bangladesh Agricultural Research Council,* 2018. |
| [4] | M. N. &. U. H. Islam, "Use of TRMM in determining the climatic characteristics of rainfall over Bangladesh," *Remote Sensing of Environment,* vol. 108(1), pp. 264-276, 2007. |
| [5] | M. M. &. K. Z. Rahman, "Monsoon variability and its impact on agriculture in Bangladesh," *Journal of Climate Studies,* vol. 15(2), pp. 221-238, 2017. |
| [6] | M. M. K. a. I. A. Debajani Chakraborty, "Rainfall in Bangladesh," *Journal of Engineering Research and Reports,* vol. 20(9), no. JERR.70677,2582-2926, pp. 103-112, 2021. |
| [7] | M. &. I. M. Sarker, "Flooding and Drought in Bangladesh: Causes and Consequences," *International Journal of Climate and Water,* vol. 23(2), pp. 145-158, 2017. |
| [8] | M. &. K. Z. Hossain, "The Role of BBS in Climate and Agricultural Data Collection.," *Journal of National Statistics,* vol. 34(1), pp. 42-55, 2019. |
| [9] | UNICEF, "Harnessing Open Data for Climate Action: The Role of HDX in Monitoring Bangladesh's Rainfall Variability.," *United Nations,* pp. 80-95, 2018. |
| [10] | D. R. J. Dobroviþová Svetlanaa, "The Economic impact of floods and their importance in," *ScienceDirect,* vol. 34, p. 649 – 655, 2015. |
| [11] | M. Wilhelm, "IMPACT OF CLIMATE CHANGE IN NAMIBIA- A CASE STUDY OF OMUSATI," p. 101, October, 2012. |
| [12] | V. T. SHIFIDI, "Impact of flooding on rural livelihoods of the Cuvelai Basin in Northern Namibia," *Journal of Geography and Regional Planning,* vol. 9(6), no. 10.5897/JGRP2015.0536, pp. 104-121, June 2016. |
| [13] | E. K. Elima, "Flood Management in South C Ward of Nairobi City County, Kenya," 2012. |
| [14] | B. Jamali, R. Löwe, P. M. Bach, C. Ulrich, K. Arnbjerg-Nielsen and A. Deletic, "A rapid urban flood inundation and damage assessment model," *Journal of Hydrology,* vol. 564, pp. 1085-1098, 2018. |
| [15] | A. J. A. Z. A. K. Percy Mashebe1, "The Impact of Flooding On the Livelihood of People Living In the Luhonono Area in," *y European Centre for Research Training and Development UK,* vol. 4(2), pp. 1-9, June,2016. |
| [16] | M. I. S. A. K. L. Saleem Ashraf, "IMPACTS OF FLOOD ON LIVELIHOODS AND FOOD SECURITY OF RURAL COMMUNITIES: A CASE STUDY OF SOUTHERN PUNJAB, PAKISTAN," *Pak. J. Agri. Sci,* vol. 50(4), pp. 751-758, 2013. |
| [17] | M. M. MD. ISMAIL, "SOCIO-ECONOMIC STATUS OF POPULATION IN FLOOD PRONE AREAS OF CHANCHAL SUB-DIVISION IN MALDA DISTRICT, WEST BENGAL," *IMPACT:International Journal of Research in Applied, Natural and Social Sciences (IMPACT: IJRANSS),* vol. 1, no. 3, pp. 141-152, Aug. 2013. |
| [18] | S. O. A. &. M. S. A. R. G. Awopetu, "The impact of flood on the socio-economic status of residents of Wadata and Gado-villa communities in the Makurdi metropolitan area of Benue State, Nigeria," *WIT Transactions on The Built Environment,* vol. 133, pp. 347-357, 2013. |
| [19] | S. Hakim, "REDUCTION OF FLOOD RISK BY INDIGENOUS," *BRAC University, Dhaka, Bangladesh,* Fall 2012 . |
| [20] | S. Kamal, "Livelihood Dynamics and Disaster Vulnerabilities of Char Land Areas," *Bangladesh University of Engineering and Technology,* April, 2011 . |
| [21] | A. C. S. R. S. a. C. B. Gulsan Ara Parvin, "Flood in a Changing Climate: The Impact onLivelihood and How the Rural Poor Copein Bangladesh," *International Environmental and Disaster Management, Graduate School of Global Environmental Studies, Kyoto University, Kyoto 606-8501, Japan,* vol. 4(4), p. 60, 2016. |
| [22] | S. U. Rahman, "IMPACTS OF FLOOD ON THE LIVES AND LIVELIHOODS OF PEOPLE IN BANGLADESH:A CASE STUDY OF A VILLAGE IN MANIKGANJ DISTRICT," *BRAC University, Dhaka, Bangladesh,* Spring 2014. |
| [23] | M. N. U. R. A. M. a. M. A. M. N. Hossain, "Effects of Flooding on Socio-Economic Status of Two Integrated Char Lands of Jamuna River, Bangladesh," *J. Environ. Sci. & Natural Resources,* vol. 6(2), pp. 37- 41, 2013. |
| [24] | S. G. a. M. H. Anika Nasra Haque, "Assessment of adaptation measures against flooding in the city of Dhaka, Bangladesh," *IHS WORKING PAPERS,* vol. 25, 2010. |
| [25] | L. Banerjee, "Effects of Flood on Agricultural Productivity in Bangladesh," *Oxford Development Studies,* vol. 38(3), p. 339–356, 2010. |
| [26] | M. &. R. M. Hossain, "A Systematic Approach to Studying Rainfall Variability and Its Impacts in Bangladesh," *Climate Change and Development Journal,* vol. 24(2), pp. 134-148, 2019. |
| [27] | F. R. &. U. S. Khan, "Utilizing Meteorological, Hydrological, and Remote Sensing Data for Climate Modeling," *International Journal of Environmental Studies,* vol. 43(2), pp. 105-121, 2021. |
| [28] | M. M. &. A. M. Rahman, "Integrating Field Observations with Climate Modeling in Bangladesh.," *Environmental Science & Policy Journal,* vol. 17(3), pp. 214-229, 2021. |

**R COADING FOR RAINFALL DYNAMICS OVER THE YEAR:**

install.packages(c("ggplot2", "sf", "dplyr","readxl"))

library(ggplot2)

library(sf)

library(dplyr)

library(readxl)

# Reading Excel data

jan = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "jan")

feb = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "feb")

mar = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "mar")

apr = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "apr")

may = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "may")

jun = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "jun")

jul = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "jul")

aug = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "aug")

sep = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "sep")

oct = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "oct")

nov = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "nov")

dec = read\_excel("C:/Users/HP/Desktop/project/55 (1).xlsx", sheet = "dec")

# January

jan\_table = data.frame(city = jan$St\_name, minjan = jan$Min, maxjan = jan$Max, avgjan = jan$Average, sumjan = jan$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# February

feb\_table = data.frame(city = feb$St\_name, minjan = feb$Min, maxjan = feb$Max, avgjan = feb$Average, sumjan = feb$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# March

mar\_table = data.frame(city = mar$St\_name, minjan = mar$Min, maxjan = mar$Max, avgjan = mar$Average, sumjan = mar$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# April

apr\_table = data.frame(city = apr$St\_name, minjan = apr$Min, maxjan = apr$Max, avgjan = apr$Average, sumjan = apr$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# May

may\_table = data.frame(city = may$St\_name, minjan = may$Min, maxjan = may$Max, avgjan = may$Average, sumjan = may$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# June

jun\_table = data.frame(city = jun$St\_name, minjan = jun$Min, maxjan = jun$Max, avgjan = jun$Average, sumjan = jun$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# July

jul\_table = data.frame(city = jul$St\_name, minjan = jul$Min, maxjan = jul$Max, avgjan = jul$Average, sumjan = jul$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# August

aug\_table = data.frame(city = aug$St\_name, minjan = aug$Min, maxjan = aug$Max, avgjan = aug$Average, sumjan = aug$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# September

sep\_table = data.frame(city = sep$St\_name, minjan = sep$Min, maxjan = sep$Max, avgjan = sep$Average, sumjan = sep$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# October

oct\_table = data.frame(city = oct$St\_name, minjan = oct$Min, maxjan = oct$Max, avgjan = oct$Average, sumjan = oct$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# November

nov\_table = data.frame(city = nov$St\_name, minjan = nov$Min, maxjan = nov$Max, avgjan = nov$Average, sumjan = nov$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# December

dec\_table = data.frame(city = dec$St\_name, minjan = dec$Min, maxjan = dec$Max, avgjan = dec$Average, sumjan = dec$Total,

longitude = c(90.4125, 90.4074, 91.7987, 91.8677, 88.6031, 89.2758, 89.5632, 90.3547),

latitude = c(23.8103, 24.7471, 22.3569, 24.8949, 24.3745, 25.7439, 22.8456, 22.7010))

# Loading the shapefile

bangladesh\_shapefile <- "C:/Users/HP/Desktop/project/gadm41\_BGD\_shp/gadm41\_BGD\_1.shp"

bangladesh <- st\_read(bangladesh\_shapefile)

# Plotting for January

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = jan\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = jan\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - January",

subtitle = "Total Rainfall in January",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for February

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = feb\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = feb\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - February",

subtitle = "Total Rainfall in February",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for March

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = mar\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = mar\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - March",

subtitle = "Total Rainfall in March",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for April

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = apr\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = apr\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - April",

subtitle = "Total Rainfall in April",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for May

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = may\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = may\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - May",

subtitle = "Total Rainfall in May",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for June

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = jun\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = jun\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - June",

subtitle = "Total Rainfall in June",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for July

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = jul\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = jul\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - July",

subtitle = "Total Rainfall in July",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for August

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = aug\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = aug\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - August",

subtitle = "Total Rainfall in August",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for September

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = sep\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = sep\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - September",

subtitle = "Total Rainfall in September",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for October

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = oct\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = oct\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - October",

subtitle = "Total Rainfall in October",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for November

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = nov\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = nov\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - November",

subtitle = "Total Rainfall in November",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

# Plotting for December

ggplot(data = bangladesh) +

geom\_sf(fill = "lightblue", color = "black") +

geom\_point(data = dec\_table, aes(x = longitude, y = latitude, color = sumjan), size = 3) +

geom\_text(

data = dec\_table,

aes(

x = longitude,

y = latitude,

label = paste(city, "\n", sumjan, "mm")

),

nudge\_y = 0.2, size = 3

) +

scale\_color\_gradient(low = "blue", high = "red", name = "Total Rainfall (mm)") +

labs(

title = "Map of Bangladesh Cities - December",

subtitle = "Total Rainfall in December",

x = "Longitude", y = "Latitude"

) +

coord\_sf(xlim = c(88, 93), ylim = c(20, 27)) +

theme\_minimal()

**R COADING Analyzing Rainfall Phenomena Over 44 Year:**

install.packages("tseries")

library(tseries)

install.packages("forecast")

library(forecast)a=read.csv("C:/Users/HP/Desktop/project/bgd-rainfall-adm2-full.csv")

attach(a)

#rfh

model\_rfh <- lm(rfh ~ sl , data = a)

summary(model\_rfh)

auto\_model\_rfh <- auto.arima(a$rfh)

predict(auto\_model\_rfh,n.ahead = 20)$pred

# r1h

model\_r1h <- lm(r1h ~ sl, data = a)

summary(model\_r1h)

auto\_model\_r1h <- auto.arima(a$r1h)

predict(auto\_model\_r1h, n.ahead = 20)$pred

# r1h\_avg

model\_r1h\_avg <- lm(r1h\_avg ~ sl, data = a)

summary(model\_r1h\_avg)

auto\_model\_r1h\_avg <- auto.arima(a$r1h\_avg)

predict(auto\_model\_r1h\_avg, n.ahead = 20)$pred

# r1q

model\_r1q <- lm(r1q ~ sl, data = a)

summary(model\_r1q)

auto\_model\_r1q <- auto.arima(a$r1q)

predict(auto\_model\_r1q, n.ahead = 20)$pred

# r3h

model\_r3h <- lm(r3h ~ sl , data = a)

summary(model\_r3h)

auto\_model\_r3h <- auto.arima(a$r3h)

predict(auto\_model\_r3h, n.ahead = 20)$pred

# r3h\_avg

model\_r3h\_avg <- lm(r3h\_avg ~ sl , data = a)

summary(model\_r3h\_avg)

auto\_model\_r3h\_avg <- auto.arima(a$r3h\_avg)

predict(auto\_model\_r3h\_avg, n.ahead = 20)$pred

# r3q

model\_r3q <- lm(r3q ~ sl , data = a)

summary(model\_r3q)

auto\_model\_r3q <- auto.arima(a$r3q)

predict(auto\_model\_r3q, n.ahead = 20)$pred

# rfh\_avg

model\_rfh\_avg <- lm(rfh\_avg ~ sl, data = a)

summary(model\_rfh\_avg)

auto\_model\_rfh\_avg <- auto.arima(a$rfh\_avg)

predict(auto\_model\_rfh\_avg, n.ahead = 20)$pred

# rfq

model\_rfq <- lm(rfq ~ sl, data = a)

summary(model\_rfq)

auto\_model\_rfq <- auto.arima(a$rfq)

predict(auto\_model\_rfq, n.ahead = 20)$pred