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EDITORIAL

Statement from the Editor-in-Chief

It is my pleasure to present the fourth volume of the Journal of Meteorology, Sri Lanka, which continues our commitment to advancing high-quality research in meteorology and climate science. Building on the foundation established in previous volumes, the journal has evolved as a trusted platform for the dissemination of rigorous, peer-reviewed scientific knowledge with relevance to both regional and global atmospheric processes.

Sri Lanka's strategic location in the tropical Indian Ocean region provides a unique natural laboratory for studying monsoon dynamics, extreme weather events, climate variability, and climate change impacts. This volume features contributions that enhance understanding across observational, modeling, and applied aspects of meteorology, reflecting the journal's interdisciplinary scope.

The journal remains committed to maintaining high editorial standards through a transparent and robust peer-review process. I sincerely acknowledge the dedication of our authors, reviewers, and Editorial Board members, whose collective efforts ensure the scientific quality and credibility of the journal.

As we publish this fourth volume, we reaffirm our mission to support scientific excellence, encourage innovation, and strengthen collaboration among meteorologists and climate scientists in Sri Lanka and beyond.

A.R.P. Warnasooriya,

Chief Editor

Sri Lanka Journal of Meteorology, Vol 4

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ACKNOWLEDGEMENT

I am pleased to express my sincere appreciation to the Editorial Board and all contributors of this research journal for their valuable efforts in advancing scientific knowledge in the fields of meteorology and climate science. This publication demonstrates a strong commitment to rigorous research, innovation, and the dissemination of evidence-based findings that are highly relevant to Sri Lanka and the wider region.

The Department of Meteorology recognizes the vital role of such scholarly platforms in strengthening climate research, enhancing national capacity, and supporting informed decision-making in climate-sensitive sectors. I commend the researchers for their dedication and the Editorial Board for upholding high academic and professional standards in the production of this journal.

I trust that this publication will serve as a valuable reference for researchers, practitioners, policymakers, and students, and will contribute meaningfully to the understanding of weather and climate variability and change.

I wish the journal continued success in its future endeavors.

A. K. Karunanayake
Director General
Department of Meteorology
Sri Lanka

Spatiotemporal Analysis of PM_{2.5} and PM₁₀ Concentrations in Relation to Meteorological Variables Over Colombo and Kandy Sri Lanka (2021–2023)

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ABSTRACT

Air pollution, especially from fine particulate matter, PM_{2.5} and PM₁₀ in urban areas are unsafe and at a risk to human health and environment. This study investigates the relationship between temporal distribution and meteorological influences on PM_{2.5} and PM₁₀ concentrations in Colombo and Kandy, Sri Lanka from 2021 to 2023. Statistical and graphical analysis were performed to examine seasonal, monthly and weekly variations in the PM mass concentrations and also the influence of the rainfall and wind on the PM levels. Correlation matrices and regression methods were developed to establish relationships between air pollutants and meteorological variables. Results indicate that PM_{2.5} and PM₁₀ concentration varies closely with monsoonal cycle and meteorological condition. Pollution levels were higher during dry weather, whereas rainfall exhibited a cleansing effect. Pollutant dispersion was influenced mainly by wind direction and wind speed, illustrated using pollution rose diagrams and sectoral wind analysis. Most importantly the study shows that PM_{2.5} is more controlled by regional scale wind patterns than local wind conditions. These points to the role of transboundary transport and large-scale atmospheric circulation in urban air quality. The study also shows a clear difference between the two cities due to geographical and climatic differences. This highlights the need to include regional meteorology in air quality monitoring and forecasting frameworks. This research can be used for policy making, public health planning and early warning systems for pollution events in Sri Lanka.

Keywords: PM_{2.5}, PM₁₀, Air Pollution, Meteorological Parameters, Seasonal Variation, Sri Lanka.

1. Introduction

Air pollution has become a global environmental issue (*World Health Organization [WHO], 2021; Cohen et al., 2017*) especially in urban areas with rapid industrialization, increased vehicle emissions and land use changes. Among the pollutants, fine particulate matter PM_{2.5} (particles with diameter $\leq 2.5 \mu\text{m}$) and PM₁₀ (particles with diameter $\leq 10 \mu\text{m}$) pose significant threat to human health. Deeply in the respiratory system, these pollutants flourish; they are responsible for causing respiratory and cardiovascular diseases (*Brook et al., 2010; Pope & Dockery, 2006*) leading to higher mortality.

In recent years Sri Lanka has seen a noticeable increase in urban air pollution (*Ekanayake et al., 2020; NBRO, 2022*) especially in major cities like Colombo and Kandy. Colombo, the commercial capital and most populated city in Sri Lanka has high traffic congestion and industrial activities that contributes to poor air quality. Kandy, a city in the central highlands is affected by its topography, meteorology and urban growth making it a unique location to study the behaviour of air pollutants in a valley.

Air pollutants dispersion, transformation and removal are controlled by a number of meteorological factors (*Zhang et al., 2015; Tai et al., 2010; Baldasano et al., 2003*) such as temperature, relative humidity, wind speed, direction and rainfall. Rain can wash out pollutants, wind can scatter or dilute them if you get the direction/force right. It is essential to understanding this interaction amongst the meteorological variables and PM concentrations in order to formulate pollution abatement measures or early warning systems.

Although several global studies have examined the relationship (*Gunawardena et al., 2019*) between meteorology and air pollution, such comprehensive studies are limited in the Sri Lankan context. This study aims to bridge this gap by analyzing temporal variation and meteorological impacts on PM_{2.5} as well as PM₁₀ concentrations in Colombo and Kandy through 2021–2023.

The main objectives of this study are analyzing the temporal variations (daily, monthly and seasonal) of PM_{2.5} and PM₁₀ in Colombo and Kandy, investigate the effect of some meteorological variables on particulate matter (PM) levels, and identify high pollution events and determine what impact the rainfall and wind have on these events.

This study hopes to contribute insights for informed mitigation by policy makers, urban environmental agencies and public health authorities to better understand the mechanisms of air quality in urban settings in Sri Lanka.

2. Methodology

2.1 Study Area and Period

This study focuses on analyzing air quality in the cities of Colombo and Kandy, Sri Lanka, using PM_{2.5} and PM₁₀ data collected from January 2021 to December 2023.

2.2 Data Sources

Hourly PM_{2.5} and PM₁₀ data were obtained from the National Building Research Organization (NBRO), Sri Lanka. Corresponding meteorological parameters, including temperature, relative humidity (RH), wind speed, wind direction, and rainfall, were obtained from the Department of Meteorology, Sri Lanka. The wind charts used in this study were sourced from the Integrated Terminal Area Climate Services (ITACS) operated by the Japan Meteorological Agency (JMA), which provides global wind analyses (<https://www.data.jma.go.jp/itacs/>). The ITACS dataset used was JMA global reanalysis at $1.25^{\circ} \times 1.25^{\circ}$ spatial resolution, Version 5.

2.3 Data Processing

The data were concatenated and synchronized in a date time index by converting the columns for year, month and day. All analyses were done in Python (Pandas, Matplotlib, Seaborn, Scikit-learn and Wind rose libraries).

2.4 Statistical and Visual Analysis

Due to the complexity of PM_{2.5} and PM₁₀ behaviour in relation to time and the atmospheric condition, an overall assessment of the behaviours was conducted. The different temporal and meteorological dimensions were assessed by plotting time series and bar plots to visualize various daily, monthly, and seasonal variations in pollutant concentrations. The interrelated behaviours of pollutant concentrations in regard to meteorological variables were examined through Pearson correlation analysis. The effect of wind was illustrated as pollution rose diagrams and wind sector boxplot figures that presented PM_{2.5} concentrations in relation to wind direction. PM_{2.5} concentrations were compared between rainy days and dry days using boxplots to investigate rainfall effects.

3. Preliminary Analysis

3.1 Temporal Trends

The study of daily and monthly variability in PM_{2.5} and PM₁₀ showed very clear seasonal patterns, with seasonal peaks in pollution during the drier months of South East Asia. Time series diagrams indicated repeated periods of higher concentrations for PM_{2.5} and PM₁₀, indicating repeated periods of seasonal outdoor air pollution. Analysis of weekly averages of pollution levels indicated a general trend of higher PM_{2.5} and PM₁₀ concentrations on weekdays compared to weekends indicating a correlation to human activity and vehicular emissions during the work week. Furthermore, seasonal variations illustrated higher particulate concentrations associated with the Northeast related to local weather (e.g. wind and humidity).

3.2 Meteorological Influences

Precipitation had a distinct effect on air quality; PM_{2.5} levels were much lower on rainy days, which represents the scavenging effect of rain on airborne pollutants. Relative humidity also seemed to have an impact on pollution concentrations; in general, higher humidity levels corresponded with lower PM_{2.5} levels, most likely due to the enhanced settling of particles as humidity increased. Wind conditions also influenced pollution patterns; wind speed increased generally caused particulate levels to decrease because increased air movement can make dispersion more efficient. Wind direction, also influenced PM levels related to the weather systems. Temperature had a positive relationship with

PM_{2.5} levels indicating that it is possible that high temperatures are related to photochemical reactions or stagnant atmospheric conditions keeping pollutants closer to the surface.

3.3 High Pollution Events

Several high PM_{2.5} events occurred during the 2021–2023 period. These were mostly located in months/seasons, corresponding to some weather conditions or anthropogenic processes.

4. Results and Discussions

4.1 Daily PM_{2.5} and PM₁₀ levels

This analysis presents the daily variability of particles PM_{2.5} and PM₁₀ concentrations in Colombo and Kandy from 2021 to 2023, highlighting the key aspects of monthly variations in particle concentration and a possible scenario for pollution episodes in both cities. Graphs for comparison between particles PM_{2.5} and PM₁₀ concentrations are presented to provide an overall picture for understanding the spatial distribution and environmental influence in both locations.

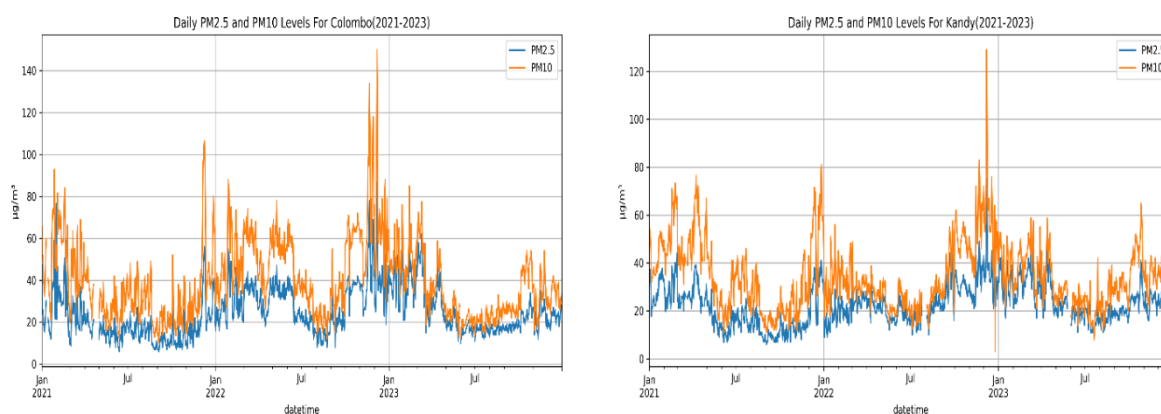


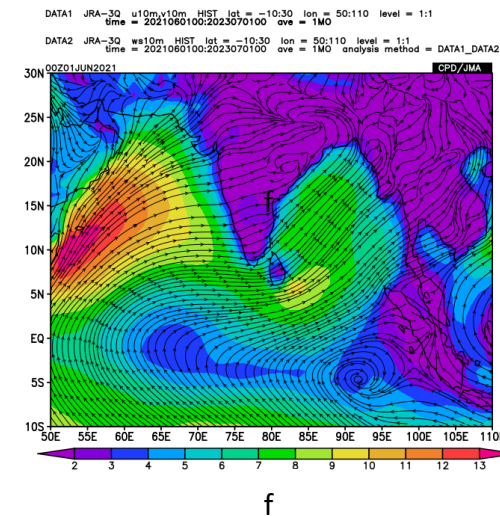
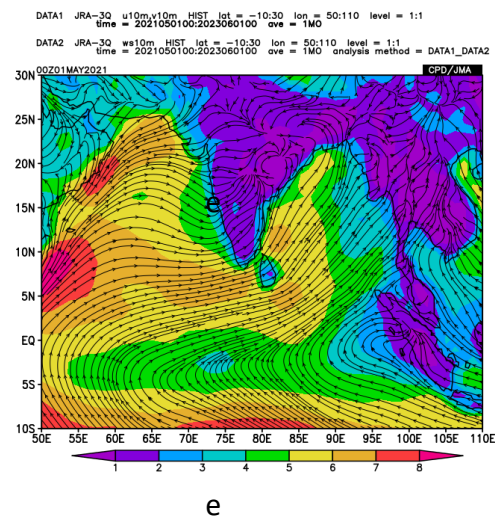
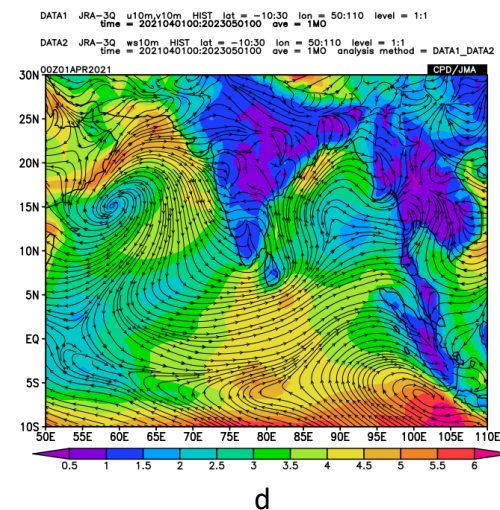
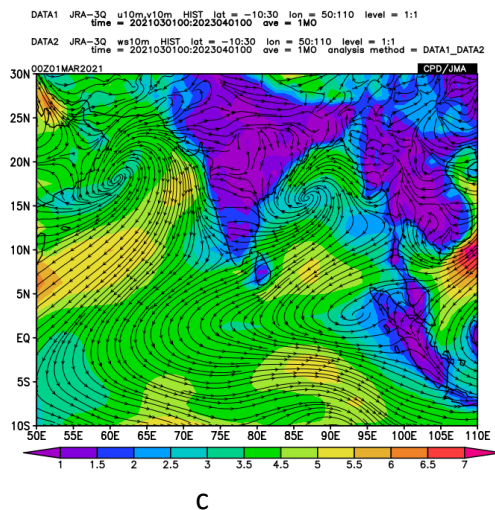
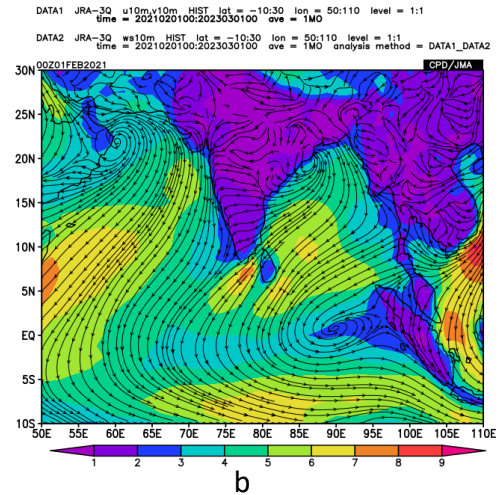
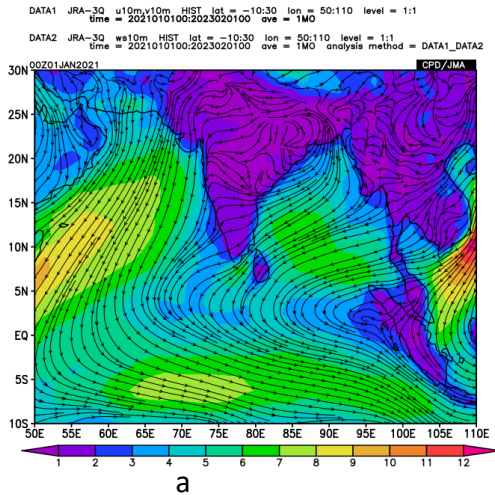
Figure 1: Daily PM_{2.5} and PM₁₀ Levels for Colombo and Kandy (2021-2023)

The daily PM_{2.5} and PM₁₀ plots for Colombo and Kandy (2021–2023) depict seasonal patterns of variation, with concentrations being higher in dry months. Colombo has more frequent and severe pollution spikes, with PM₁₀ levels sometimes exceeding 140 $\mu\text{g}/\text{m}^3$, most likely because of traffic and urban activities. On the other hand, Kandy has relatively lower concentrations, although some short-term spikes are present.

Both cities have lower polluted days during the Southwest Monsoon, probably due to higher rain and dispersion. In general, PM₁₀ concentrations are greater than PM_{2.5}, therefore showing that coarse particles are abundant, especially in Colombo. Those observations highlight the necessity to design air quality management plans for each city.

4.2 Monthly Average Wind Patterns for South Asia

The images below show the monthly average wind patterns across Sri Lanka, highlighting how wind speed and direction vary throughout the year. These patterns critically influence the transport and distribution of PM_{2.5} pollutants, especially during the Northeast Monsoon seasons.



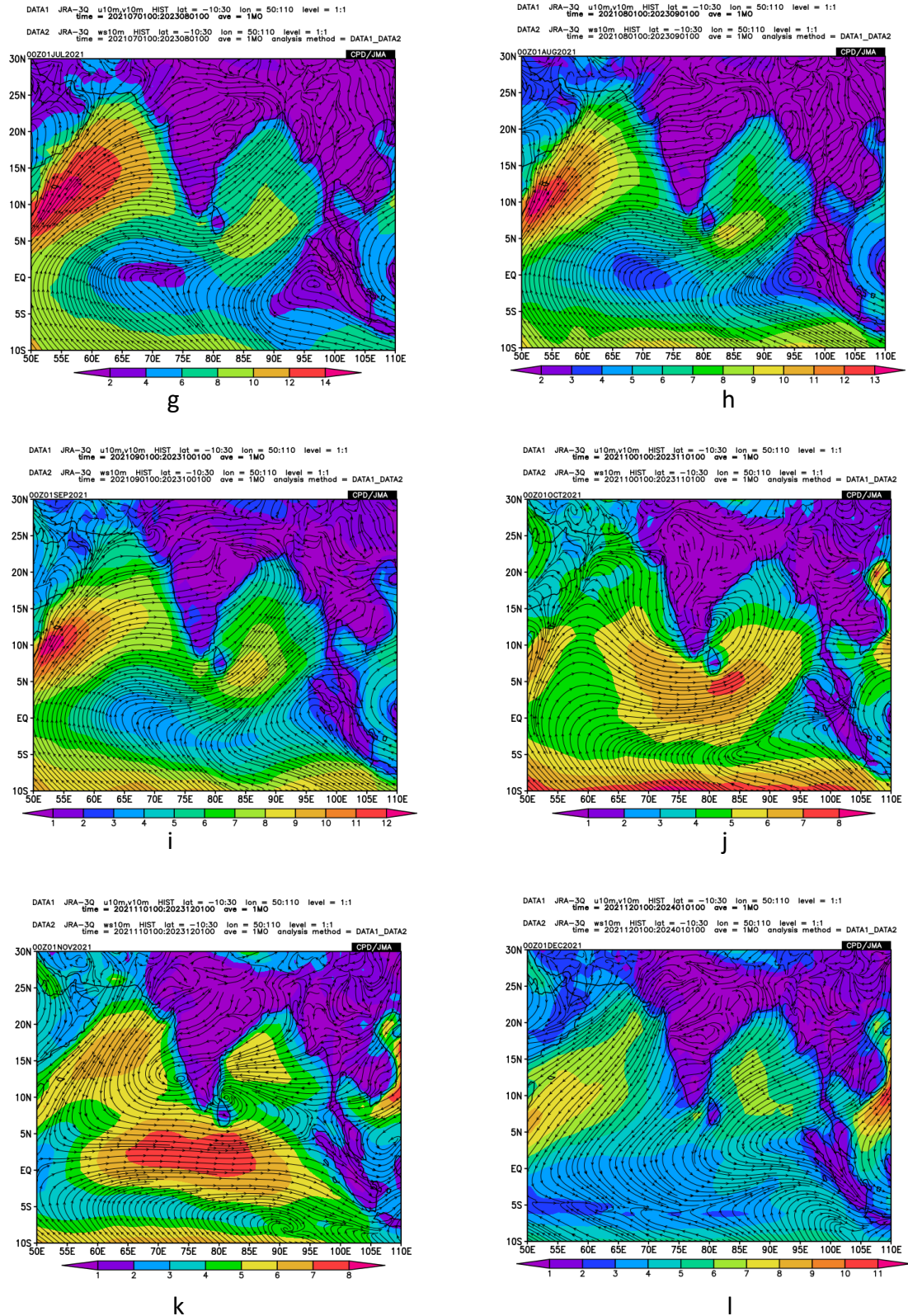


Figure 2: Monthly Average Surface winds for South Asia region (2021-2023) (a) January, (b) February, (c) March, (d) April, (e) May, (f) June, (g) July, (h) August, (i) September, (j) October, (k) November and (l) December

Figure 02 shows monthly wind patterns over South Asian region sourced from the Integrated Terminal Area Climate Services (ITACS), Japan Meteorological Agency (JMA, <https://www.data.jma.go.jp/itacs/>), accessed on 24 June 2025. South Asia experiences seasonal changes in winds owing to the monsoon system that directly influence the transport of PM_{2.5} to Sri Lanka. The prevailing winds during the Northeast Monsoon (December–February) are from over the Indian subcontinent and northeast, which allows dry air masses to carry fine particulate matter (PM_{2.5}) from northern and north-eastern continental areas towards Sri Lanka. It can lead to elevated PM_{2.5} concentrations because pollutants are transported over the Bay of Bengal and deposited on the island. On the other hand, during the Southwest Monsoon season (May–September), winds blow mostly from the sea to land, limiting the long-distance transportation of PM_{2.5} from the continent to Sri Lanka but enhancing the dispersal of local emissions due to increased wind speeds. In months of inter-monsoon periods (March–April and October–November), incoherent and weaker winds reduce pollutant dispersion, setting the stage for regionally and locally accumulating PM_{2.5}. These seasonal wind patterns play an important role in spatial and temporal PM_{2.5} concentration variation in Sri Lanka, especially the role of transboundary sources during the Northeast Monsoon.

4.3 Monthly Average PM_{2.5} and PM₁₀ levels

The analysis provides monthly average PM_{2.5} and PM₁₀ concentrations in Colombo and Kandy for the period 2021–2023. Graphs show temporal and seasonal variations in air quality and help identify periods with higher particulate matter levels in both urban and coastal environments.

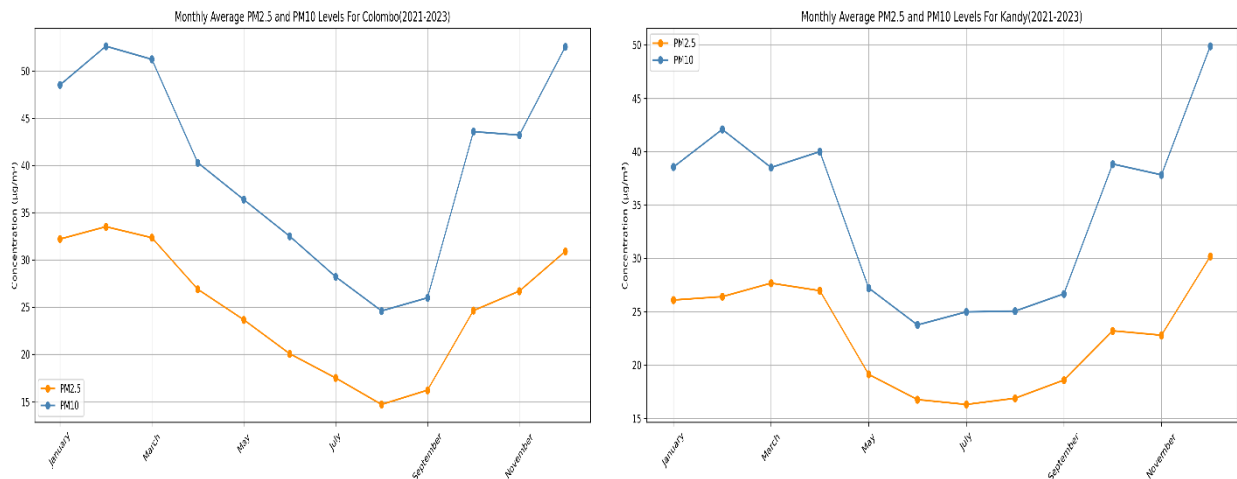


Figure 3: Monthly Average PM_{2.5} and PM₁₀ levels for Colombo and Kandy (2021-2023)

The average monthly concentrations of PM_{2.5} and PM₁₀ in Kandy and Colombo (2021-2023) have a distinct seasonal variation with peaks in the dry months (January, December, March) and lower peaks during the Southwest Monsoon (June-August). This pattern corresponds to the Rainfall and Regional

wind influence, which enhances the dispersion of the atmosphere and the removal of pollutants during the monsoon season.

The Southwest Monsoon brings in stronger winds and frequent showers and these along with the rains help reduce PM concentration by scattering and washing away suspended particulate matter. In contrast, the inter-monsoon period along with the Northeast Monsoon is usually marked with stagnate weak winds which leads to the accumulation of pollutants, particularly in cadent urban valleys like Kandy. Regional wind patterns and biomass burning associated with seasonal practices peak these months as well. In both cities, PM₁₀ concentrations consistently exceed PM_{2.5} which indicates that coarse particles are from road dust and construction.

Kandy's topographical setting may amplify pollution retention during calm wind conditions while Colombo is bound to have higher level of pollution due to its urban-industrial profile.

4.4 Pollution Rose

This paper presents pollution rose diagrams of PM_{2.5} in Colombo and Kandy from 2021 to 2023 that show the variations in particulate matter concentrations due to the wind direction. These graphs allow for the identification of dominant sources of pollution and to estimate the effect of the local wind patterns on air quality in urban and coastal environments.

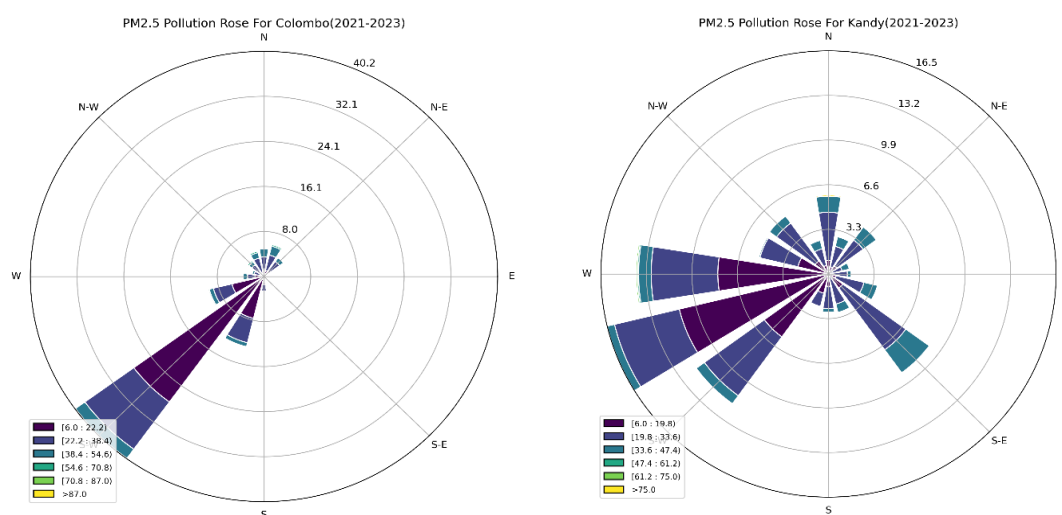


Figure 4: PM 2.5 Pollution Rose for Colombo and Kandy (2021-2023)

The analysis indicates that high pollution events in both Colombo and Kandy predominantly occur when local winds originate from the west (W) and southwest (SW). While these directions suggest

cleaner maritime air, the elevated pollution levels are strongly influenced by broader regional atmospheric circulation patterns.

Specifically, during periods when regional winds originate from the northwest (NW), north (N), and northeast (NE) particularly during the Northeast Monsoon and inter-monsoonal seasons, polluted air masses from the industrial zones of South Asian landmass are transported over the Bay of Bengal toward Sri Lanka. As these transboundary pollutants reach the island, local meteorological conditions, such as sea breezes from the W and SW, can trap these particles near the surface, particularly over urban areas like Colombo and Kandy.

This combination of regional long-range transport and local wind convergence significantly contributes to elevated levels of PM_{2.5} and PM₁₀, resulting in frequent high pollution episodes, particularly during dry and stagnant atmospheric conditions.

Such events highlight the critical role of transboundary air pollution, where air quality in Sri Lanka is influenced not only by local sources but also by atmospheric dynamics involving pollution inflow from NW, N, and NE regions of South Asia.

4.5 PM_{2.5} vs Relative Humidity

The present study focuses on relationship between PM_{2.5} concentrations and relative humidity in both Colombo and Kandy from 2021 to 2023. Graphs presented show the effect of atmospheric moisture on particulate matter concentration in cities as well as coastal environments.

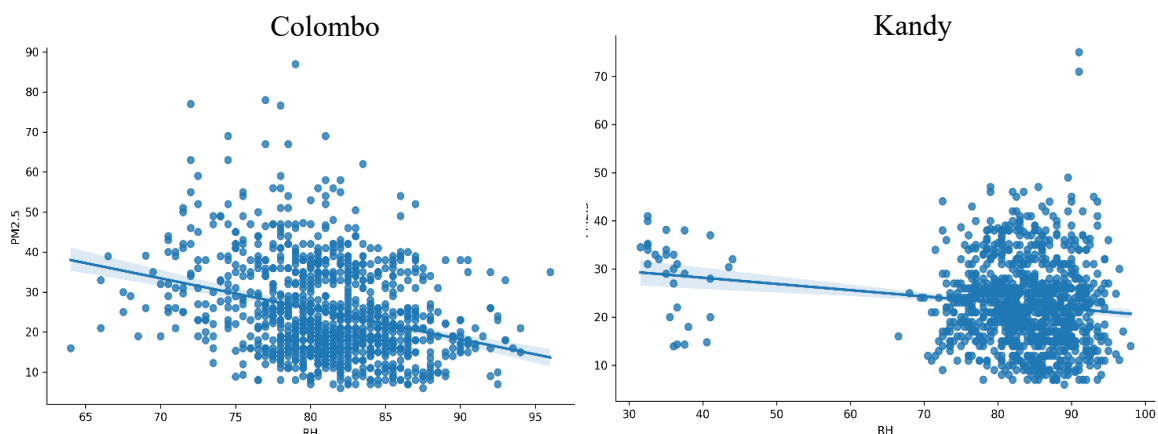


Figure 5: PM 2.5 vs Relative Humidity for Colombo and Kandy (2021-2023)

In Colombo, a moderate negative correlation is observed, indicating that PM_{2.5} levels generally decrease as relative humidity increases. This suggests that higher humidity contributes to the reduction of particulate matter, likely through mechanisms such as wet deposition or enhanced particle settling.

In contrast, the relationship in Kandy appears weaker, with data points more tightly clustered and less variation in PM_{2.5} levels across different humidity ranges. This may be attributed to Kandy's geographic and environmental conditions, such as its higher elevation, greater vegetation cover, and lower industrial activity, which can influence the local air quality dynamics. Overall, the analysis indicates that while increased humidity is associated with lower PM_{2.5} levels in both cities, the strength and consistency of this relationship vary due to local climatic and anthropogenic factors.

4.6 High pollution events

Graphs (*Figure 06*) Show the frequency and distribution of high pollution events which days with PM_{2.5} concentrations greater than 50 $\mu\text{g}/\text{m}^3$ on the basis of data collected during the Periodic Environmental Reporting Period for the city of Colombo and Kandy for the period 2021–2023. They illustrate those periods of poor air quality, which presents public health concerns in the urban and coastal regions.

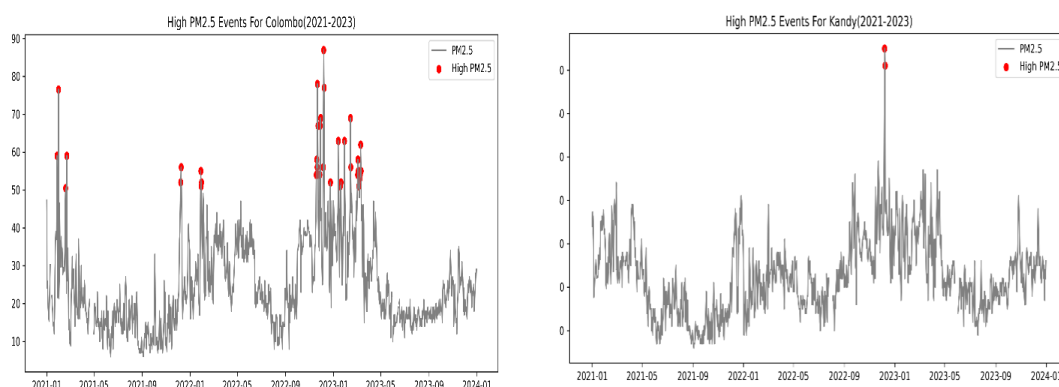


Figure 6: High PM_{2.5} events for Colombo and Kandy (2021-2023)

A widely accepted reference that considers PM_{2.5} concentrations above 50 $\mu\text{g}/\text{m}^3$ as high pollution is from air quality standards and related research. The exact threshold is somewhat inconsequential at different countries and organizations, but the WHO (World Health Organization) and many national guidelines support the threshold in short-term exposure assessment.

The data indicates that Colombo endured more days of severe pollution than Kandy. This may be a result of higher urban concentration, vehicle exhaust, industrial work, as well as coastal areas which may hold pollution ('trap' them) within calm weather conditions. Kandy, although less often impacted, registered significant increases in pollution levels during dry and still weather.

While this study primarily relies on ground-based observations, the inclusion of Copernicus CAMS (*Copernicus Atmosphere Monitoring Service [CAMS], 2023*) reanalysis data could provide additional insight into the long-range transport of PM_{2.5} into Sri Lanka. CAMS data would allow tracking of regional pollution episodes and help distinguish between locally generated and transboundary

particulate matter. Integrating such reanalysis datasets could strengthen the scientific soundness of future analysis and inform more effective air quality policies and mitigation strategies.

4.7 Statistical Values

The linear regression analysis was conducted to assess the influence of key meteorological variables temperature, relative humidity, wind speed, and rainfall on PM_{2.5} concentrations during 2021–2023 in Colombo and Kandy.

Table 1: Linear Regression(R^2) and Root Mean Squared Error (RMSE) for Colombo and Kandy (2021-2023)

Station	R^2	RMSE
Colombo	0.10494608	11.21782
Kandy	0.09342394	8.234021

In the case of Colombo, the model's R^2 result was 0.105, signifying that a mere 10.5% of PM_{2.5} concentration variation could be correlated with the incorporated weather factors. The Root Mean Squared Error (RMSE) was 11.22 $\mu\text{g}/\text{m}^3$ which demonstrates a relatively high prediction error. For Kandy, the model demonstrated a slightly lower R^2 value of 0.093, which indicates that the model captured 9.3% of the PM_{2.5} variability. As for the RMSE, it was 8.23 $\mu\text{g}/\text{m}^3$ which is lower than the value for Colombo, but expected given the generally lower and less variable PM_{2.5} concentrations in Kandy.

The statistical analysis revealed low R^2 values between PM concentrations and individual meteorological parameters. While this may suggest weak correlations, it is consistent with findings from previous studies showing that particulate matter variability is governed not only by meteorology but also by emissions, urban morphology, and transboundary transport (Jacob & Winner, 2009; Zhang & Fu, 2022). In Sri Lanka, local factors such as traffic congestion, biomass burning, and industrial activities contribute significantly to particulate levels, which explains why meteorology alone cannot fully capture the variability.

5. Conclusion

This research analyses the parameters affecting the air quality in Colombo and Kandy from 2021 to 2023, including seasonal, spatial, and meteorological parameters. The concentration of both PM_{2.5} and PM₁₀ showed obvious seasonal patterns with higher concentrations during the dry spells (January to March and December), while the Southwest Monsoon tends to have lower concentrations due to rainfall washout and enhanced dispersion. Compared to Kandy, Colombo endured more severe and more frequent pollution episodes due to urbanization, traffic congestion, and the presence of industries.

An important observation is the occurrence of high pollution episodes in conjunction with certain regional wind directions. Most undisturbed local winds from west and south west monsoon towards the seasonal in the east do align with the local winds, however, the most polluted days tend to be when regional winds from north, north east and north west transboundary air pollution are coming from industrial northern India and Bangladesh. These air masses transport fine particulate matter over large distances which greatly hinders the air quality in Sri Lanka, especially in western and central provinces.

With regard to both cities, the R^2 values suggest that Sri Lanka's meteorological stimuli alone could not explain the discrepancy in PM_{2.5} levels identified. Such results highlight the lack of integrated approaches that combine meteorological drivers with emission inventories, land use characteristics, and transboundary transport, which are essential for developing more accurate air quality assessments in Sri Lanka.

Acknowledgments

We would like to express our sincere gratitude to the Department of Meteorology, Sri Lanka, for providing essential meteorological data and technical support for this study. We also thankful to the National Building Research Organization (NBRO) for supplying PM_{2.5} and PM₁₀ air quality data.

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Five-Year (2019-2023) Wind Pattern Analysis at Bandaranaike International Airport, Katunayake: Implications for Aviation Safety and Operational Efficiency

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ABSTRACT

This study investigates wind patterns at Bandaranayake International Airport, Katunayake, over a five-year period (2019–2023), emphasizing their significant impact on flight safety and operational efficiency. Wind speed and direction are crucial factors in aviation, particularly during take-off and landing. Using observational data recorded at the airport, the research provides a comprehensive analysis of prevailing wind behaviour to support improved runway utilization, flight planning, and overall airport operations. The analysis shows distinct variations on a seasonal and daily basis, mostly affected by the monsoon cycle. Winds from the southwest brings in stronger winds from May to September and more north easterly winds are calmer from January to March and in November to December. The crosswind components with a clear diurnal cycle have a peak during late morning and significant decrease in the evening. These findings offer critical insights for optimizing runway usage, enhancing flight safety, and informing strategic planning. The current study increases local knowledge of the prevailing winds, aids in the predictive estimations precision and improves short- to medium-term wind forecasting. The implications of these research results improve the security and efficiency with which regional airport operations can be conducted during varying wind conditions.

Keywords: Wind Analysis, Bandaranaike International Airport, Seasonal wind patterns, Airport safety, Wind rose.

1. Introduction

Sri Lanka is a tropical island located in the Indian Ocean, southeast of the Indian subcontinent, between latitudes 5°55'N–9°51'N and longitudes 79°41'E–81°53'E. The country's diverse geographical setting, comprising low-lying coastal plains and elevated central highlands, exerts a strong influence on regional and local weather systems (Zubair, 2002; Chandrasekara et al., 2018). Variability in wind regimes is of particular importance, since wind systems are strongly modulated by monsoon circulations, sea-breeze interactions, and synoptic-scale features (Amador et al., 2006; Chand et al., 2017).

Bandaranaike International Airport (BIA), situated in Katunayake about 30 km north of Colombo, is the primary aviation hub of Sri Lanka, connecting the island with South Asia, the Middle East, Europe, and beyond (Civil Aviation Authority of Sri Lanka [CAASL], 2021). As the gateway for most international air traffic, reliable meteorological information at BIA is critical for aviation safety and operational efficiency. Wind is among the most influential meteorological factors for airport operations, shaping runway orientation, flight routing, and delay management (FAA, 2019; ICAO, 2007; Bazargan & Kaighobadi, 2017).

Among meteorological parameters, wind speed and wind direction are particularly important for aviation. Accurate wind observations are essential for all stages of flight take-off, cruising, and landing,

as adverse wind conditions can lead to turbulence, runway safety issues, and increased fuel consumption (ICAO, 2018; Gultepe et al., 2019). Aircraft performance and fuel efficiency are strongly influenced by wind components: tailwinds shorten flight time and reduce fuel consumption during cruising but can significantly increase landing distance and accident risk on wet runways; headwinds enhance lift during take-off and landing but increase fuel requirements in cruise; and crosswinds pose a hazard during critical phases of take-off and landing, sometimes necessitating runway changes and operational delays (van Es & Karwal, 2001; Storer et al., 2019). The authors stated that the majority of accidents occurred when tail wind exceeding 10 knots on contaminated runways.

Globally, several studies highlight the growing role of meteorological variability and climate change in shaping aviation operations, with increasing turbulence, wind variability, and weather-related delays expected in the future (Connor & Hurley, 2019; Storer & Connolly, 2017; Zhang & Fu, 2022). For Sri Lanka, however, systematic investigations into wind climatology in the context of airport operations remain limited.

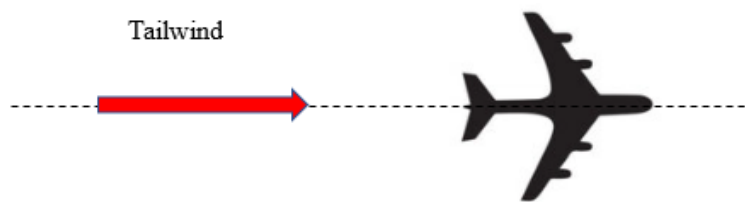


Figure 1: Aircraft Tailwind

Tailwind (Figure 1) blows same direction of aircraft while headwind blows in the opposite direction the aircraft is facing. Headwind (Figure 2) increases fuel consumption in cruise mode, but it enhances safety during take-off and landing by enabling more lift at lower ground speeds, shortening runway requirements.



Figure 2: Aircraft Headwind

Crosswinds (Figure 3) blow perpendicular to the flight path and the runway. It is especially dangerous during the take-off and landing phases, as the directional change can potentially blow the aircraft off

course. In order to stay correctly aligned, pilots will have to change their heading which leads to airport reporting crosswind conditions or recommending to use other runways when certain thresholds are surpassed.

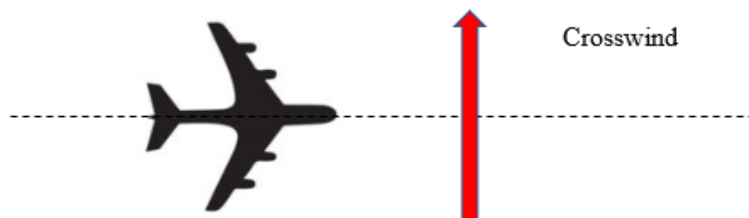


Figure 3: Aircraft Crosswind

Therefore, this study analyses wind patterns at Bandaranaike International Airport over a five-year period (2019–2023). The research aims to identify seasonal and directional wind trends, assess their implications for aviation safety, and provide evidence-based insights to enhance flight planning, operational efficiency, and runway utilization through improved meteorological understanding (WMO, 2020; Gultepe et al., 2019).

2. Methodology

2.1 Research strategies and techniques

This descriptive study focuses on surface wind patterns at Bandaranaike International Airport, utilizing secondary data provided by the airport's Meteorological Office. The dataset includes hourly wind speed and direction observations, along with half hourly METAR reports, spanning from January 2019 to December 2023. Surface wind data, which significantly influences airport operations, were processed using the windrose method. For analysis, wind speed and direction data were grouped by month across the five-year period. Python and Microsoft Excel were employed as the primary tools for data processing and visualization. The airport meteorological station's anemometer provided the direction and speed of the wind.

2.2 Processing and data analysis

2.2.1 Windrose Method

A wind rose is a graphical representation that illustrates the frequency and distribution of wind speed and direction at a specific location over a defined time period. It visually displays how often the wind blows from each direction and at what speed, typically using radial bars extending outward from the centre of a circle.

In this study, wind rose analysis is used to identify prevailing wind directions associated with dominant wind speeds. Average wind direction and surface wind speed were calculated as part of the analysis

process. Wind speeds are represented by concentric circles on the wind rose, while wind directions or gust degrees are shown by radial lines. Each cell on the diagram is framed by two circular segments and radial lines, indicating different percentages of wind occurrences.

Hourly data on wind direction and speed from January 2019 to December 2023 serves as the input for the wind rose construction.

2.2.2 Headwind, Tailwind and Crosswind

The crosswind component is the vector component of wind acting perpendicular to the runway, derived from the angle between the wind direction and the runway orientation. It is calculated by multiplying the wind speed by the Sine of the angle (θ) between the runway heading and wind direction. Figure 4 illustrates examples of crosswind component calculations.

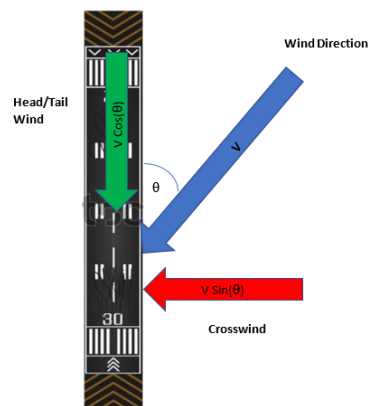


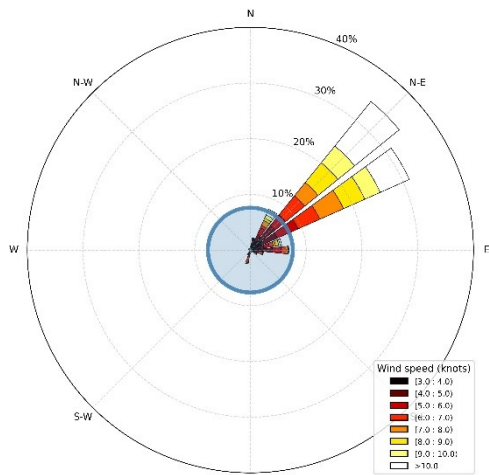
Figure 4: Crosswind Calculation

3.0 Results and Discussion

3.1 Windrose

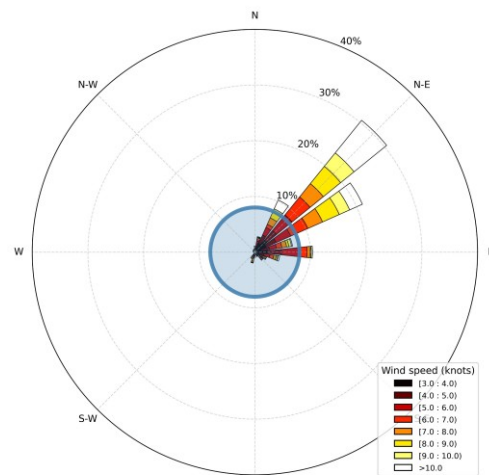
The wind rose illustrates the distribution of wind speed and direction, emphasizing dominant wind patterns and their intensities over the study period. This visualization is essential for understanding local wind climatology, supporting applications such as aviation operations, runway orientation, and meteorological evaluations. The Figure 05 provides a visualization of surface wind data at Bandaranaike International Airport for the period from January 2019 to December 2023. At Bandaranaike International Airport, the wind direction changes with the seasons due to the monsoon cycle. From January to March, most winds come from the northeast, especially in January where they reach 66.8%. In April, the wind starts to change more frequently. From May to September, the southwesterly wind becomes stronger, peaking in August at 63.6%, which is when the southwest monsoon, while October and November exhibit a mix of southwest, south, east, and northeast winds.

Monthly Wind Rose - January (2019-2023)



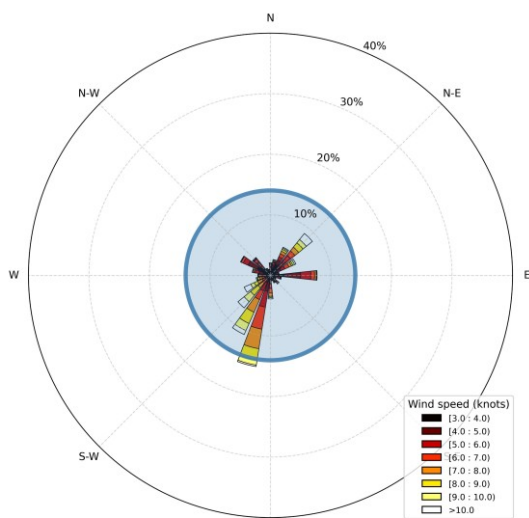
(a)

Monthly Wind Rose - February (2019-2023)



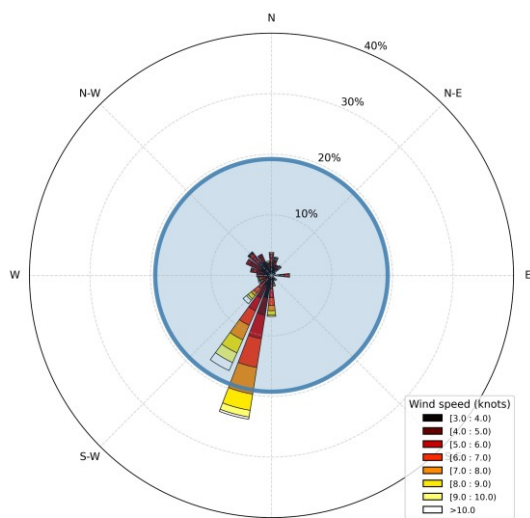
(b)

Monthly Wind Rose - March (2019-2023)



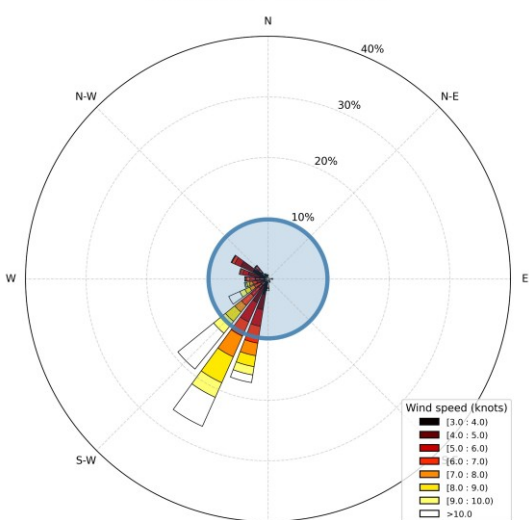
(c)

Monthly Wind Rose - April (2019-2023)



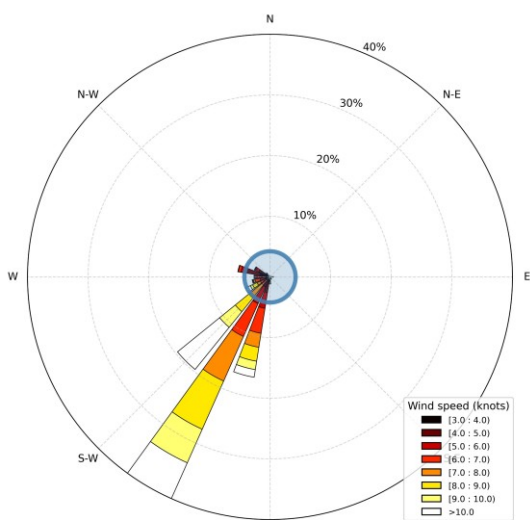
(d)

Monthly Wind Rose - May (2019-2023)



(e)

Monthly Wind Rose - June (2019-2023)



(f)

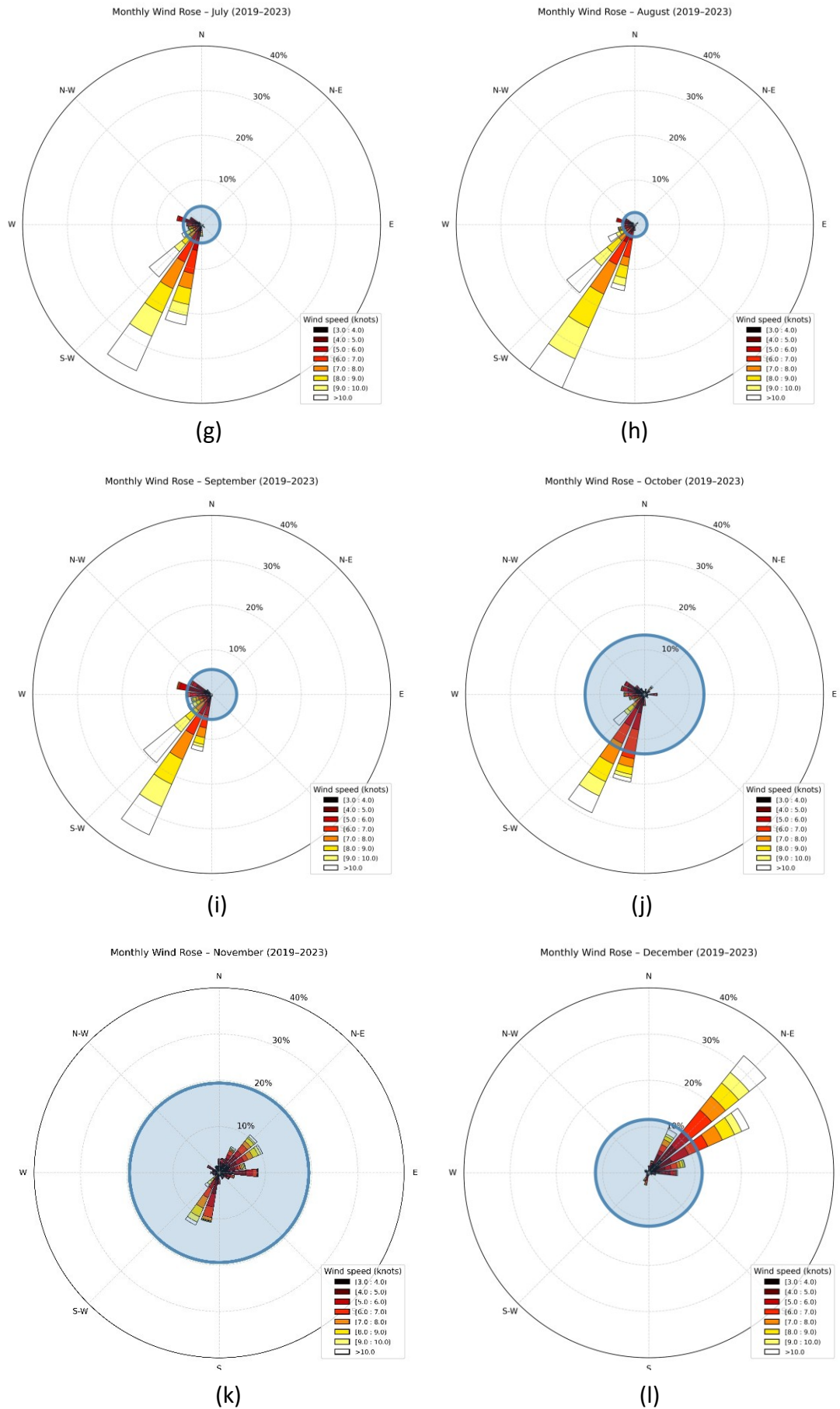


Figure 5: Windrose for Months(a) January, (b) February, (c) March, (d) April, (e) May, (f) June, (g) July, (h) August, (i) September, (j) October, (k) November and (l) December

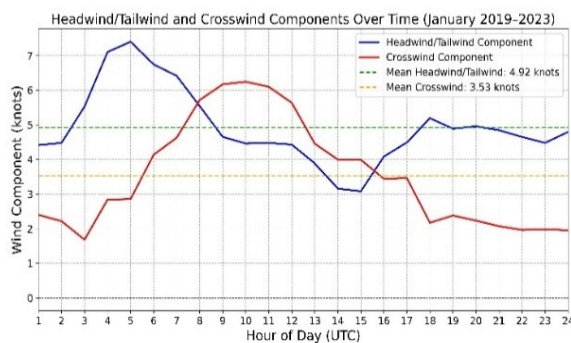
Figure 05 presents the surface wind climatology at Bandaranaike International Airport for the period January 2019 to December 2023, illustrating clear seasonal variations in wind direction associated with the regional monsoon cycle.

The wind rose is expressed in terms of percentage frequency, enabling direct comparison of wind direction and speed distributions. Near-calm wind conditions, defined as wind speeds less than 3 kt, are excluded from the directional bins and are represented separately by the central circle. The size of this central circle indicates the relative contribution of calm winds to the overall wind climatology.

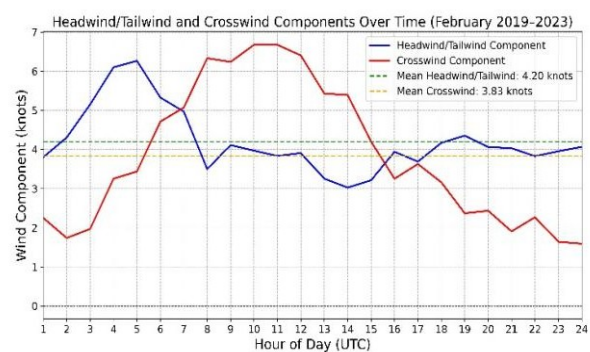
Overall, wind speeds at Bandaranaike International Airport are predominantly moderate, with most occurrences falling within the 3–7 kt range. The relative frequency of wind speeds remains broadly consistent throughout the year, although directional dominance varies with the seasonal monsoon regime. These wind characteristics are operationally important for airport activities, as variations in wind direction and the occurrence of calm conditions can influence runway usage, aircraft handling, and flight safety, particularly during monsoon transition periods.

3.2 Crosswind and Headwind/Tailwinds Components

The Figure 6 shows the hourly variation of headwind/tailwind and crosswind components at Bandaranaike International Airport. Positive values indicate headwind, negative values indicate tailwind, while crosswind acts perpendicular to the runway. These diurnal patterns, influenced by local meteorology, are critical for runway selection, flight safety, and operational planning.



(a)



(b)

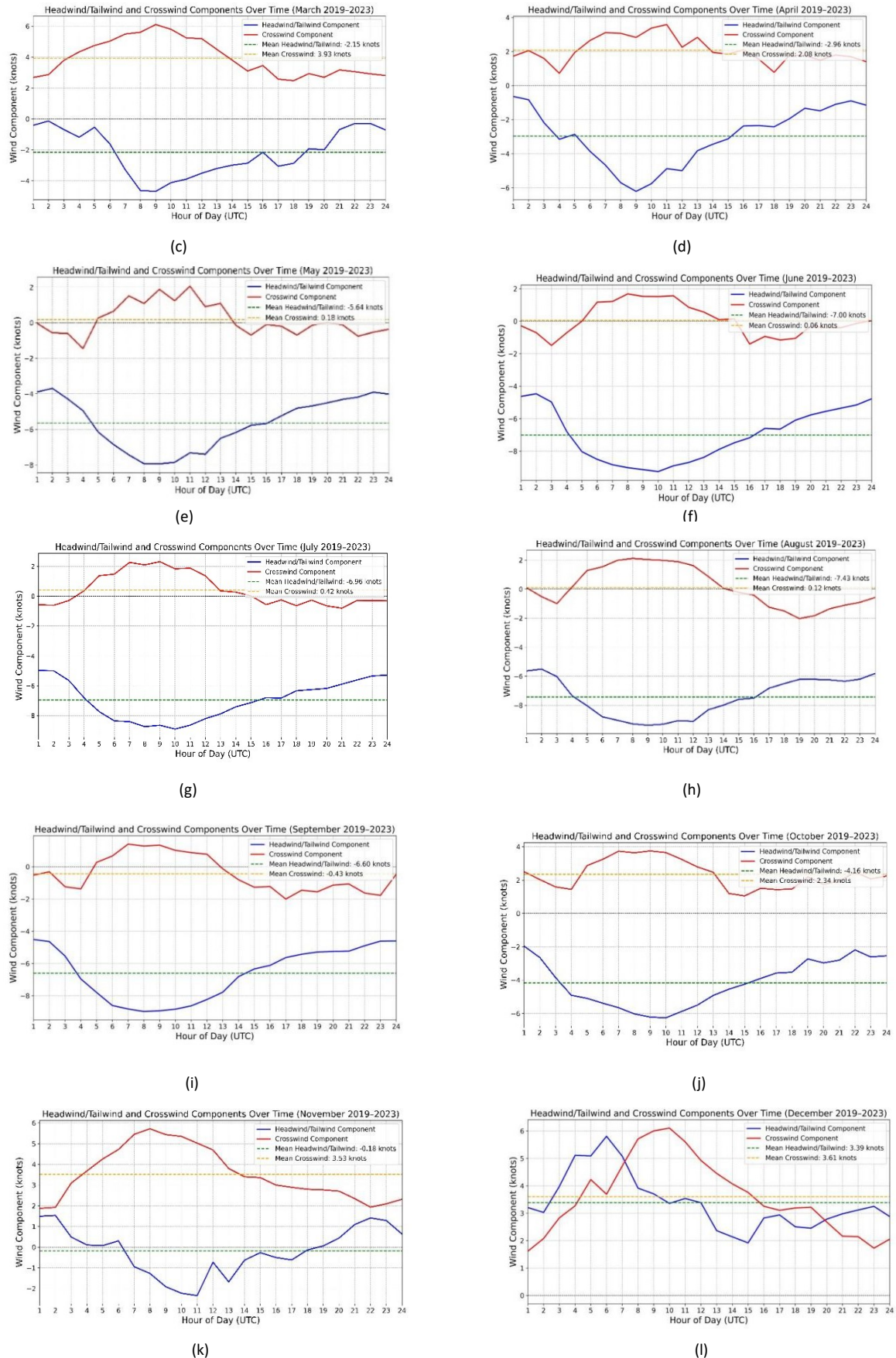


Figure 6: Hourly variation of headwind/tailwind (blue) and crosswind (red) components (knots) over a 24-hour UTC cycle, dashed lines indicate the mean headwind/tailwind (green) at 4.92 knots and mean crosswind (orange) at 3.53 knots. Crosswind, Headwind and tailwind over the time based on (a) January, (b) February, (c) March, (d) April, (e) May, (f) June, (g) July, (h) August, (i) September, (j) October, (k) November and (l) December 2019–2023 data.

The y axis is crosswind and headwind or tailwind in knots and the x axis is the hour of the day in UTC, which ranges from 1 to 24, and displays how headwind and tailwind change by the hour of the day. The solid blue line represents the hourly headwind or tailwind component, and the solid red line represents the crosswind component.

Bandaranaike International Airport wind component from January 2019 to December 2023 exhibits unambiguous diurnal patterns in headwind/tailwind as well as crosswind conditions, mostly due to local land breeze and sea breeze interactions. Headwind and tailwind components peak to around 7 knots at 6–8 UTC and decline to around 3 knots during 14–16 UTC, indicating low afternoon wind conditions. Crosswind components share the same diurnal cycle with a maximum of approximately 6 knots at 7–14 UTC and less than 2 knots after 16 UTC, with minimum values in the early morning (02–04 UTC).

These variations are of the utmost significance for aeronautical meteorology and aviation operations, as they affect runway selection, take-off and landing performance, and overall flight safety (ICAO, 2018; FAA, 2019; Bazargan & Kaighobadi, 2017). Understanding these diurnal patterns enables more accurate flight scheduling, fuel-efficient planning, and reduced risk from severe crosswinds (Liu et al., 2017; Rojek et al., 2019). Awareness of these patterns can streamline airport operations and enhance operational efficiency and safety, particularly during peak traffic periods (Storer & Connolly, 2017; Gultepe et al., 2019).

4. Conclusion

Wind observations at Bandaranaike International Airport from 2019 to 2023 reveal clear seasonal variations in wind direction and speed that are closely aligned with the regional monsoonal circulation. South westerly winds dominate during the Southwest Monsoon period (May–September), while northeasterly and easterly winds prevail during the Northeast Monsoon (December–February) and transitional inter-monsoon periods. Wind speeds generally range between 3 and 7 knots throughout the year, with calm conditions (wind speed < 3 kt) represented by the central circle in the wind rose analysis.

The crosswind component exhibits a distinct diurnal cycle, with peak values of approximately 6 knots occurring between 07 and 14 UTC, corresponding to late morning and early afternoon, while crosswinds decrease significantly after 17 UTC and remain below 2 knots overnight. A secondary minimum during the early morning hours (02–04 UTC) indicates calmer conditions. These recurring seasonal and diurnal wind patterns, governed by monsoon reversal and mesoscale coastal processes, are of direct relevance to airport operations, including flight planning, runway utilization, and aviation safety. Incorporating these wind characteristics into operational forecasting and decision-support systems can enhance aeronautical meteorological services and contribute to improved operational efficiency and safety.

5. Operational Recommendations

Based on the analysis of wind patterns at Bandaranaike International Airport (2019–2023), it is recommended that runway usage and scheduling be aligned with prevailing seasonal wind trends to enhance safety and operational efficiency. Runways should be prioritized according to dominant wind directions, minimizing exposure to crosswinds and optimizing take-off and landing performance. Seasonal runway rotation schedules can further reduce delays by matching runway assignments with monsoonal wind patterns, while crosswind monitoring systems should trigger timely adjustments when thresholds are exceeded. Integrating historical and forecasted wind data into flight planning and dispatch operations will improve fuel efficiency, reduce pilot workload, and ensure safer runway operations. Continuous evaluation of runway utilization against wind trends will support evidence-based refinement of operational guidelines over time.

Acknowledgments

We would like to express our sincere gratitude to the Department of Meteorology, Sri Lanka, for providing the necessary resources and data for this study. Special thanks go to our colleagues at Katunayake International Airport for their invaluable support and assistance in collecting and verifying the wind data.

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Long-Term Trends in Maximum, Minimum, and Diurnal Temperature Range in South-Western Sri Lanka

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ABSTRACT

This study investigates long-term (1920-2023) temperature variability across the south-western region of Sri Lanka, focusing on maximum temperature (Tmax), minimum temperature (Tmin), and the Diurnal Temperature Range (DTR). Daily temperature data from seven meteorological stations were analyzed to examine temporal trends and diurnal variability. Using Python with Pandas, Matplotlib, and SciPy, monthly mean Tmax, Tmin, and DTR were computed and statistically assessed through linear regression to estimate slope, R^2 , and significance levels. Results indicate significant warming across most stations, with Tmin increasing more rapidly than Tmax, resulting in a narrowing DTR, particularly at Katunayake (Tmax: $0.008\text{ }^{\circ}\text{Cyr}^{-1}$ / Tmin: $0.017\text{ }^{\circ}\text{Cyr}^{-1}$) and Nuwara Eliya (Tmax: $0.002\text{ }^{\circ}\text{Cyr}^{-1}$ / Tmin: $0.024\text{ }^{\circ}\text{Cyr}^{-1}$). Conversely, some coastal stations (e.g., Galle, Ratmalana) exhibited stable or slightly increasing DTR, reflecting localized climatic influences. The asymmetric warming pattern aligns with global and regional climate change signals, suggesting the influence of both large-scale drivers and local factors such as urbanization and elevation. These findings highlight the vulnerability of Sri Lanka's climate to ongoing warming and underscore the importance of sustained monitoring and adaptive strategies to address the rising temperatures. The observed increases in Tmax, Tmin, and DTR have significant implications for agriculture, water resource management, and urban planning, as higher daytime and nighttime temperatures can exacerbate heat stress, alter crop productivity, and intensify urban heat island effects.

Key words: Temperature trends, Sri Lanka

1. Introduction

Climate change has become one of the defining environmental challenges of the twenty-first century, with rising temperatures posing significant risks to ecosystems, economies, and human well-being worldwide. Global mean surface temperature has increased markedly since the late nineteenth century, with an accelerated pace of warming in recent decades (IPCC, 2021). This warming, however, is not uniform; it varies across space and time, with some regions and climatic variables responding more strongly than others. Among the most critical indicators of such variability are changes in maximum temperature (Tmax), minimum temperature (Tmin), and the Diurnal Temperature Range (DTR), which together reflect key aspects of atmospheric and surface processes (Karl et al., 1993; Easterling et al., 1997).

Globally, both Tmax and Tmin have increased, though Tmin often rises faster, leading to a narrowing DTR (Vose et al., 2005). This narrowing DTR has been linked to elevated greenhouse gas concentrations, enhanced cloud cover, and urbanization (Braganza et al., 2004; Dai et al., 1999). Such asymmetric warming affects agricultural productivity, pest and disease dynamics, and public health,

particularly in tropical regions (Donat & Alexander, 2012; You et al., 2017). Conversely, coastal or maritime regions may exhibit stable or even increasing DTR due to oceanic moderation and local climatic effects (Chowdhury & Beecham, 2010).

South Asia is recognized as a climate change hotspot due to its exposure to temperature extremes and dependence on climate-sensitive sectors (Krishnan et al., 2020; Roxy et al., 2017). Within this region, Sri Lanka occupies a unique position influenced by monsoonal dynamics, the Intertropical Convergence Zone (ITCZ), and ocean–atmosphere interactions such as the IOD and ENSO (Zubair, 2002; Chandrapala, 1996). The country’s climatic diversity arising from topography, coastal proximity, and land use makes it essential to examine localized temperature trends (Domroes & Ranatunge, 1993).

Previous studies have identified general warming trends across Sri Lanka, often with stronger nighttime warming (Basnayake, 2007; Zubair et al., 2005; Wijeratne et al., 2018). However, detailed assessments of DTR patterns remain limited, particularly for the south-western region, which includes urbanized, agricultural, and high-elevation zones such as Colombo, Galle, and Nuwara Eliya. Understanding how Tmax, Tmin, and DTR evolve across these diverse environments is crucial for bridging the existing research gap and supporting climate-resilient development.

Accordingly, this study analyzes long-term temperature records from seven south-western stations Colombo, Galle, Katugastota, Katunayake, Nuwara Eliya, Ratmalana, and Ratnapura using Python-based tools (McKinney, 2010; Virtanen et al., 2020). The objectives are to (1) quantify long-term trends in Tmax, Tmin, and DTR, (2) assess their statistical significance, (3) explore spatial differences linked to geography and urbanization, and (4) discuss sectoral implications.

By integrating high-resolution daily data with robust statistical analysis, this research strengthens understanding of regional temperature behavior and addresses a key scientific gap in Sri Lanka’s climate studies. The findings have significant policy relevance, providing evidence to guide agricultural planning, water management, urban design, and climate adaptation strategies in vulnerable regions.

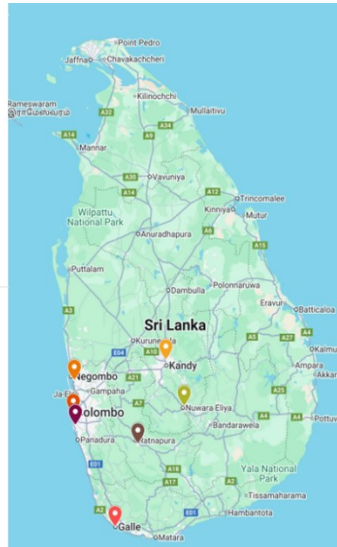
2. Methodology

Study Area

The study was carried out in the south-western region of Sri Lanka, a climatically sensitive area influenced by the Southwest Monsoon and inter-monsoonal rainfall. Seven long-term meteorological stations Colombo, Galle, Katugastota, Katunayake, Nuwara Eliya, Ratmalana, and Ratnapura were selected to represent diverse geographic conditions, ranging from coastal to inland and mid-elevation environments.

Met Stations-SWM.xlsx

KATUGASTOTA
KATUNAYAKA
COLOMBO
NUWARA ELIYA
RATNAPURA
GALLE
RATMALANA



Station	Latitude (°N)	Longitude (°E)	Elevation /m
Colombo	6.90	79.87	7
Galle	6.03	80.21	12
Katugastota	7.33	80.63	417
Katunayaka	7.17	79.88	8
Nuwara Eliya	6.97	80.78	1894
Ratmalana	6.82	79.89	5
Ratnapura	6.68	80.40	86

Table 1: locations and elevations of the selected stations.

2.1 Data Collection and Quality Control

- Data Source: Daily maximum (Tmax) and minimum (Tmin) temperature observations were obtained from the Department of Meteorology, Sri Lanka.
- Study Period: Each station provided long-term records spanning ~100 years (period varies slightly by station).
- Quality Control:
 - Missing values were identified; short gaps were interpolated while longer gaps were excluded.
 - Outliers were screened using ± 3 standard deviations and validated against station metadata, including possible relocations and instrument changes.

2.2 Computation of Derived Variables

- The Diurnal Temperature Range (DTR) was calculated as: $DTR = T_{max} - T_{min}$
- Daily data were aggregated to monthly means and then to annual means for Tmax, Tmin, and DTR, to reduce short-term variability and emphasize long-term climatic signals.

2.3 Data Processing and Analysis Tools

The analysis was conducted entirely in Python (v3.x) using the following scientific libraries:

- pandas → importing, cleaning, and managing station-wise daily temperature datasets.
- numpy → numerical operations and array-based calculations.
- matplotlib → generation of time-series plots for monthly mean Tmax, Tmin, and DTR. Linear trend lines were overlaid to illustrate long-term changes.
- scipy.stats.linregress → linear regression analysis to estimate slope ($^{\circ}\text{C yr}^{-1}$), intercept, correlation coefficient (r), coefficient of determination (R^2), and p-values.

- os → managing output directories and systematically saving plots and tabulated results to ensure reproducibility.

This integrated computational approach ensured efficient handling of large datasets, robust trend detection, and transparent reproducibility of results.

2.4 Trend Analysis and Graphical Representation

1. Linear Regression

- Annual time series of Tmax, Tmin, and DTR were analyzed using linear regression.
- Slopes represent the rate of change ($^{\circ}\text{C yr}^{-1}$).
- R^2 quantified the goodness-of-fit, while p-values tested the statistical significance of trends.
- A p-value < 0.05 was interpreted as statistically significant, while $p \geq 0.05$ indicated no significant trend.

2. Statistical Significance in Visualization

- p-values and R^2 values were included directly in the plots.
- This approach allowed a clear visual assessment of whether an observed increase or decrease was statistically meaningful or potentially due to random variability.

3. Moving Average Smoothing

- A 5-year moving average was calculated for all temperature indices to suppress short-term variability and highlight decadal-scale changes.

3. Results

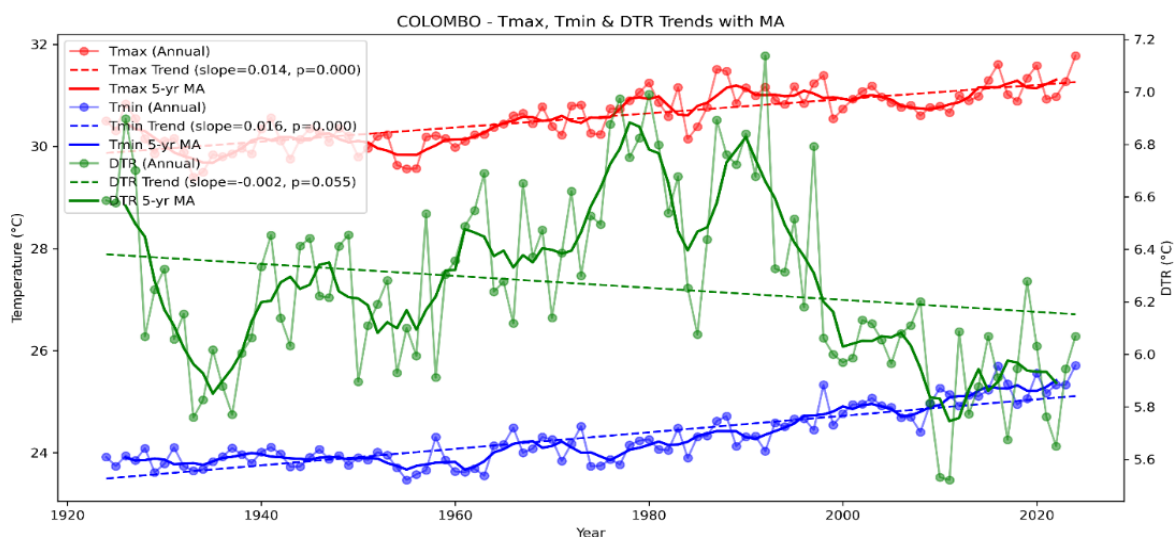


Figure 1: Long-term Tmax, Tmin, and DTR trends at Colombo (1920–2023)

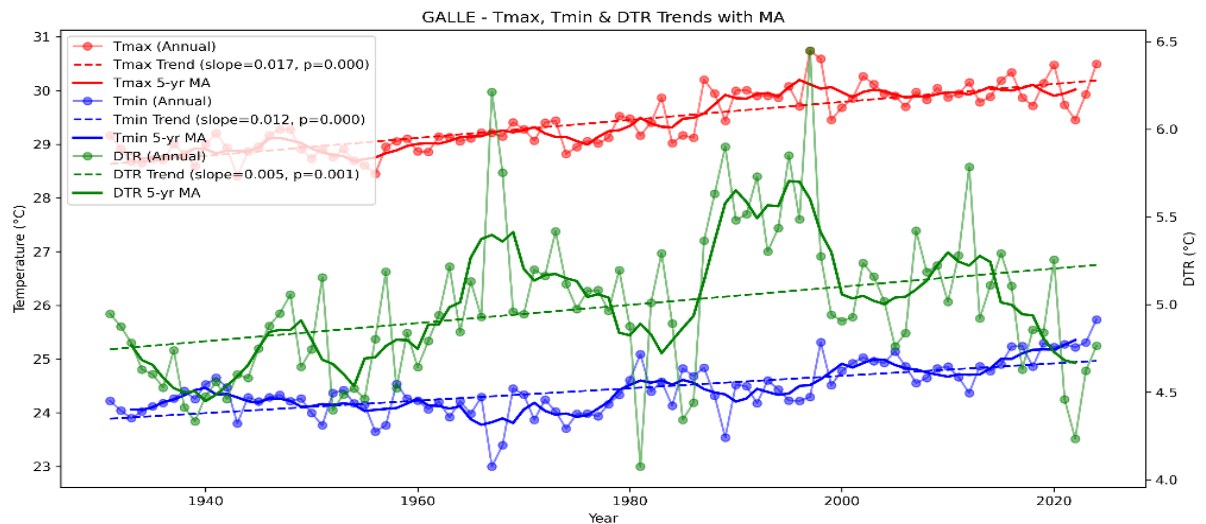


Figure 2: Long-term Tmax, Tmin, and DTR trends at Galle (1930–2023)

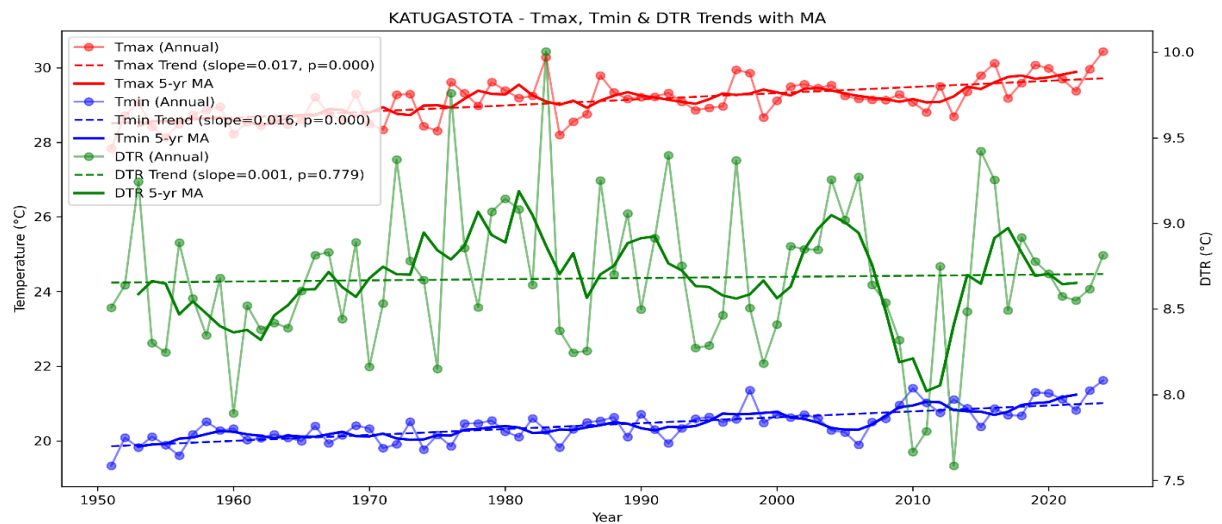


Figure 3: Long-term Tmax, Tmin, and DTR trends at Katugastota (1950–2023)

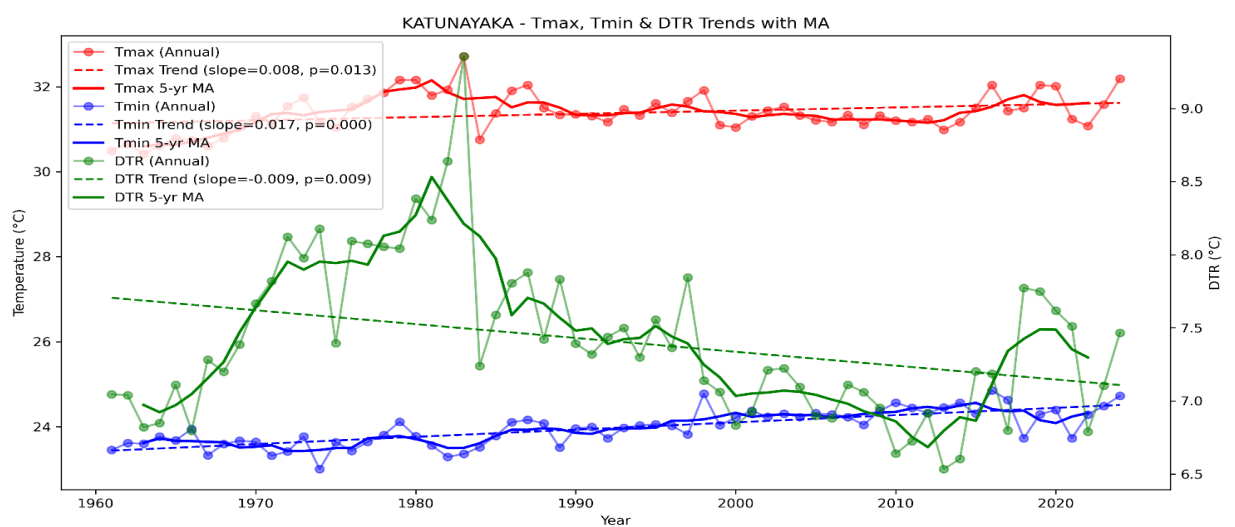


Figure 4: Long-term Tmax, Tmin, and DTR trends at Katunayaka (1960–2023)

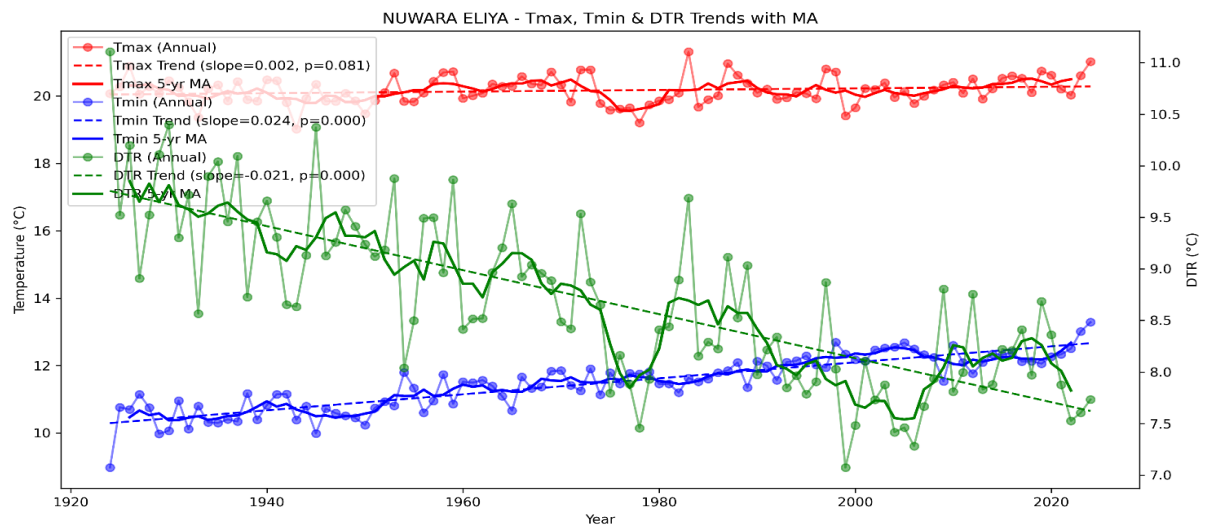


Figure 5: Long-term Tmax, Tmin, and DTR trends at Nuwara Eliya (1920–2023))

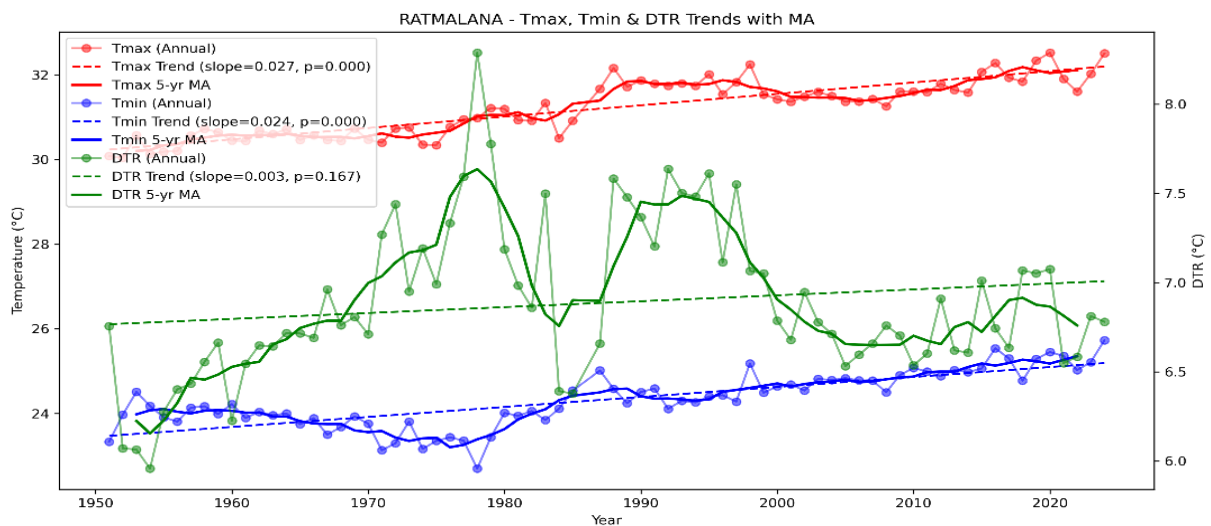


Figure 6: Long-term Tmax, Tmin, and DTR trends at Ratmalana (1950–2023)

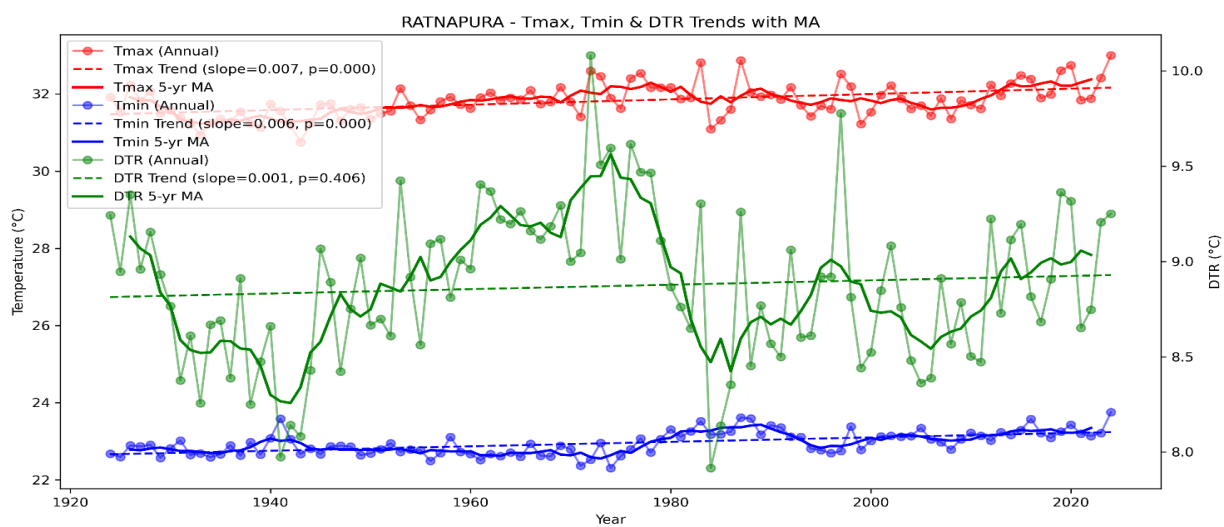


Figure 7: Long-term Tmax, Tmin, and DTR trends at Ratnapura (1920–2023)

Table 2: Trends in annual Tmax, Tmin, and DTR for selected stations in southwestern parts in Sri Lanka

Station	Slope $^{\circ}\text{Cyr}^{-1}$			R^2			P-Value		
	Tmax	Tmin	DTR	Tmax	Tmin	DTR	Tmax	Tmin	DTR
Colombo	0.014	0.016	-0.002	0.77	0.84	-0.19	P<0.001	P<0.001	P=0.055
Galle	0.017	0.012	0.005	0.83	0.66	0.33	P<0.001	P<0.001	P<0.01
Katugastota	0.017	0.016	0.0007	0.65	0.75	0.03	P<0.001	P<0.001	P=0.78
Katunayaka	0.008	0.017	-0.009	0.31	0.77	-0.33	P=0.01	P<0.001	P=0.009
Nuwara Eliya	0.002	0.024	-0.021	0.17	0.88	0.76	P=0.08	P<0.001	P<0.001
Ratmalana	0.027	0.024	0.003	0.88	0.79	0.16	P<0.001	P<0.001	P=0.17
Ratnapura	0.007	0.006	0.001	0.46	0.56	0.08	P<0.001	P<0.001	P=0.41

The analysis of long-term temperature trends across seven south-western Sri Lankan stations reveals a consistent warming signal in both maximum (Tmax) and minimum (Tmin) temperatures, though the magnitude and statistical significance vary regionally. Coastal and lowland stations such as Colombo, Galle, Ratmalana, and Katunayake exhibit clear positive trends in both Tmax and Tmin, with high R^2 values (0.31–0.88) and strong statistical significance ($P<0.001$ –0.01), indicating robust warming patterns. In contrast, high-elevation Nuwara Eliya shows a modest increase in Tmax ($0.002\text{ }^{\circ}\text{C yr}^{-1}$) but a pronounced rise in Tmin ($0.024\text{ }^{\circ}\text{C yr}^{-1}$), resulting in a significant decline in diurnal temperature range (DTR), reflecting stronger nighttime warming in cooler upland environments. Inland stations such as Katugastota and Ratnapura also show positive trends in Tmax and Tmin, although changes in DTR are generally small and not statistically significant, suggesting relatively stable diurnal variability. Across all seven stations, the regional average trends are approximately Tmax: $0.015\text{ }^{\circ}\text{C yr}^{-1}$, Tmin: $0.016\text{ }^{\circ}\text{C yr}^{-1}$, and DTR: $-0.0035\text{ }^{\circ}\text{C yr}^{-1}$, highlighting an overall warming pattern with a slight reduction in DTR. The 5-year moving averages reveal that this warming was relatively gradual until the 1960s, after which a consistent rise is observed, followed by a notable acceleration in temperature increase from the 1980s onward, particularly in Tmin. Overall, the results underscore spatial heterogeneity in temperature responses, with coastal and urbanized lowlands experiencing more uniform warming, while high-elevation and inland areas display distinct diurnal dynamics.

4. Discussion

The results of this study demonstrate a clear long-term warming trend across the south-western region of Sri Lanka, with both maximum (Tmax) and minimum (Tmin) temperatures increasing at most stations. Tmin generally rises faster than Tmax, leading to a slight overall fall in diurnal temperature range (DTR). The 5-year moving averages indicate that warming was gradual until the 1960s, followed by a consistent rise and a notable acceleration from the 1980s onward. This pattern is consistent with previous studies in Sri Lanka, which also reported stronger nighttime warming and modest declines in DTR (Basnayake, 2007; Zubair et al., 2005; Wijeratne et al., 2018). The observed temperature and DTR changes carry important implications for climate-sensitive sectors. Rising Tmin and narrowing DTR may increase agricultural stress by reducing nighttime recovery for crops, alter pest and disease cycles,

and exacerbate heat-related health risks in both urban and rural populations. Conversely, areas with relatively stable DTR, such as Galle, may experience slightly moderated heat stress but are not immune to broader warming trends. These results underscore the need for targeted adaptation measures, including heat-resilient crop selection, irrigation planning, urban greening, and infrastructure design that account for site-specific temperature dynamics.

For future research, integrating additional high-resolution climate data from more stations and expanding analyses to include precipitation, humidity, and extreme event metrics would strengthen the understanding of regional climate change impacts. Mechanistic studies linking local land-use change, urbanization, and topography to diurnal and seasonal temperature responses are also recommended to improve predictive modeling and inform climate adaptation policy at both local and regional scales.

5. Conclusion

The long-term analysis of temperature trends across seven meteorological stations in south-western Sri Lanka indicates a clear and statistically significant warming in both maximum (Tmax) and minimum (Tmin) temperatures, with a slight overall decline in diurnal temperature range (DTR). Regional averages show increases of approximately Tmax: $0.015^{\circ}\text{C yr}^{-1}$ and Tmin: $0.016^{\circ}\text{C yr}^{-1}$, while DTR decreased slightly at $-0.0035^{\circ}\text{C yr}^{-1}$, reflecting stronger nighttime warming in many locations. The 5-year moving averages demonstrate that warming was gradual until the 1960s, became consistent afterward, and accelerated notably from the 1980s, particularly in Tmin.

Spatial variability is evident: coastal and urbanized lowlands exhibit uniform warming, whereas inland and high-elevation stations, such as Nuwara Eliya, show distinct diurnal patterns with significant nighttime warming. These findings have important implications for climate-sensitive sectors, including agriculture, water management, and urban planning, as rising temperatures and falling DTR can increase heat stress, affect crop productivity, and exacerbate urban heat island effects.

Overall, this study provides a detailed, station-specific assessment of temperature trends and diurnal variability in south-western Sri Lanka, filling a critical knowledge gap and offering a scientific basis for climate adaptation and policy planning in vulnerable regions. Continued monitoring and localized strategies are essential to mitigate the impacts of ongoing warming.

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Sensitivity of Cumulus and Microphysics Parameterization Schemes in WRF Model for Southwest Monsoon in Sri Lanka

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ABSTRACT

Accurate simulation of precipitation during the Southwest Monsoon (SWM) remains a critical challenge for numerical weather prediction over Sri Lanka. This study evaluates the forecast skill of the Weather Research and Forecasting (WRF) model for SWM conditions—an aspect not previously assessed in this region—and investigates the spatial sensitivity of various Cumulus Parameterization Schemes (CPS) and Microphysics Parameterization Schemes (MPS) incorporated within the model. Using 13 CPS–MPS combinations, we found that most simulations performed poorly in reproducing observed rainfall, particularly along inflow-side coastal zones. Root Mean Square Error (RMSE) and Bias values ranged from 20–40 mm/day and 5–20 mm/day, respectively, with True Skill Statistics (TSS) as low as 0.07. Among the tested schemes, the Betts-Miller-Janjic (BMJ) CPS combinations demonstrated relatively better performance, achieving TSS values between 0.1 and 1.2, and RMSE/Bias near 20 mm/day and –2 mm/day. Inter-comparison of parameterization schemes revealed strong regional sensitivity, underscoring the importance of ensemble forecasting in operational settings. Overall, the BMJ CPS and WRF Double-Moment six-class (WDM6) MPS emerged as the most skillful configuration for simulating SWM precipitation over Sri Lanka.

1. Introduction

As a tropical country in the Indian Ocean, the climate of Sri Lanka can generally be categorized as tropical and monsoonal (Malmgren et al., 2003). The seasons in Sri Lanka are divided into four (4) regimes and Southwest monsoon (SWM) from May to September is the most prominent season with respect to precipitation and vulnerability. However, predicting these extreme events is still a challenge due to complex dynamics of atmosphere. To face this challenge, several type of Numerical Weather Prediction (NWP) models are used by the hydro-meteorological agencies (Lynch, 2015).

Many past studies have shown that the prediction of a model highly depend on model parameterization options (Argüeso et al., 2011; Jankov et al., 2005; Krishnamurti et al., 2012; Kumar et al., 2010; Pattanayak et al., 2012). However, the performance of cumulus parameterization schemes (CPS) and microphysics parameterizations schemes (MPS) over Sri Lanka has not yet been evaluated for the SWM. This study focused on testing the sensitivity of CPS and MPS on spatial variation of predictability during SWM period given that most of the studies conducted on this territory are based on few rainy cases (Mukhopadhyay et al. 2010; Rajeevan et al. 2010; Kumar et al. 2013). This study can be highly beneficial for issuing accurate forecast not only for the effective disaster preparedness plan but also for general public and other sectors.

The meteorological model, Weather Research and Forecasting - Advanced Research WRF (WRF-ARW) by the National Center for Atmospheric Research's (NCAR) is a new generation NWP model which helps meteorologists to identify several kinds of weather information. Like other numerical models, WRF model also provides parameterization schemes that is used to evaluate small scale atmospheric processes: cloud process; planetary boundary layer process; long wave radiation process; etc, which cannot be resolved explicitly by the model itself (Skamarock et al., 2008). Many studies have shown that model results such as rainfall amount, patterns, and localization are highly dependent on the parameterization schemes (Venkata et al. 2006); (Viterbo et al. 2016). In NWP, the precipitation is the most important and critical element that highly volatile. Precipitation parameterizations are used to produce precipitation by consuming excess moisture in the model atmosphere. Basically, two types of parameterizations such as CPS and MPS are used to resolve precipitation process.

Since convective processes can occur over a few kilometers to tens of kilometers, parameterized cloud processes are needed in NWP models to resolve sub-grid-scale effects of convection, such as the release of latent heat, which distributes heat through the grid column on a realistic time scale when the model runs at lower resolution. Thus, CPS are able to represent mechanisms such as vertical fluxes and compensating motion outside the cloud to provide vertical heating, moistening profiles, and surface precipitation when triggered in the individual grid column (Skamarock et al. 2008). Since most CPS were designed to resolve sub-grid-scale convective eddies, the assumptions made for this scale (>10 km) break down for finer grid sizes. However, some studies have found that CPS are capable of triggering convection in fine grid resolutions of 5–10 km.

MPS refers to the explicit model emulation of cloud and precipitation processes that remove excess atmospheric moisture directly resulting from the dynamically driven forecast wind, temperature, and moisture fields. In MPS, moisture variables and their interactions are taken into account. These MPS have the ability to explicitly emulate sub-grid convection in fine grid resolutions less than 2 km (Bryan et al. 2003).

2. Methodology and Data

Combinations of four CPS and three MPS, totaling 12 CPS–MPS permutations, plus the “default” combination specified in the WRF 3.7.1 were used to simulate rainfall over Sri Lanka. Therefore, a matrix of 13 different combinations of CPS and MPS was used. The domain shown in Fig. 2.1 has three-way nesting at 36 km, 12 km, and 4 km. The National Centers for Environmental Prediction (NCEP)'s final analysis (FNL) 1-degree data were used as the initial and boundary conditions for the model, which was updated every six hours (<http://rda.ucar.edu/datasets/ds083.2/>).

SWM rainfall in Sri Lanka from 2013 to 2015 showed notable year-to-year variation, with 2013 marking the end of a long-term declining trend and 2015 experiencing relatively higher rainfall. Accordingly, to reduce the influence of event-specific anomalies, data spanning 2013 to 2015 were chosen for this analysis. The model was run separately for each year, starting from April 15 to September 30 (five and a half months), allowing a 16-day spin-up period from April 15 to 30. Simulated precipitation from each combination was validated against observational data using statistical scoring methods such as contingency tables, bias, and root mean square error. Figure 2.2 represents the spatial distribution of 450 rainfall observation sites.

The predictive ability of each combination was analyzed on a spatial basis. For this, daily rainfall stations were grouped district-wise to assess the skill of each combination for individual districts. The district-wise spatial distribution was further re-grouped into regions based on the performance of the model.

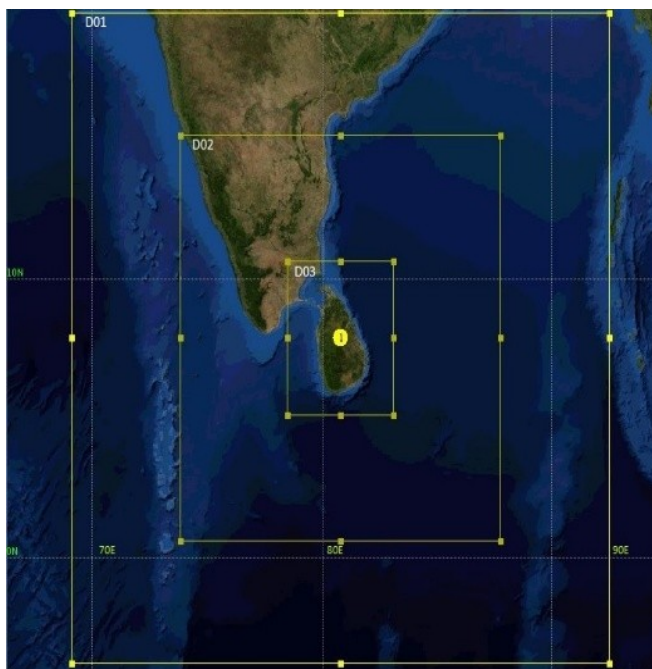


Figure 2.1. Study area of the experiment. Out puts from the inner most domain (D03) is considered in this study.

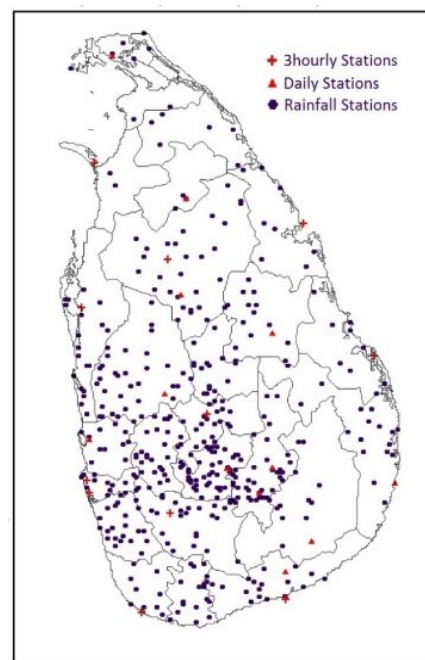


Figure 2.2 Distributions of 3hourly meteorological stations (red cross), Daily Meteorological stations (triangle) and daily Rainfall observation stations (blue dots) network.

2.1 WRF model configurations

The WRF Version 3.7.1 was used in this study to simulate atmospheric conditions with different combinations of parameterization options. The model setup included a three-way nested domain, with the third domain consisting of 124×148 grid points at 4 km grid spacing (Figure 2.1). A total of 28 vertical levels from the surface to 50 mb were used to run the model. Experimental ID and the details are provided in the table 2.1. The other WRF physical parameterization schemes, which were kept

identical through out the experiment, include the Rapid Radiative Transfer Model (RRTM) longwave radiation, Dudhia shortwave radiation, Monin- Obukhov surface layer, Noah land surface, and YSU planetary boundary layer scheme. The Mercator was used as projection method.

Table 2.1. Experiment ID and details

No	Exp. ID	CPS	MPS
1	KF-SM5	Kain-Fritsch (KF)	WRF Single-Moment 5-class scheme (SM5)
2	KF-SM6	Kain-Fritsch	WRF Single-Moment 6-class scheme (SM6)
3	KF-DM6	Kain-Fritsch	WRF double-moment 6-class scheme (DM6)
4	BMJ-SM5	Betts–Miller–Janjic (BMJ)	WRF Single-Moment 5-class scheme
5	BMJ-SM6	Betts–Miller–Janjic	WRF Single-Moment 6-class scheme
6	BMJ-DM6	Betts–Miller–Janjic	WRF double-moment 6-class scheme
7	GF-SM5	Grell- Freitas (GF)	WRF Single-Moment 5-class scheme
8	GF-SM6	Grell- Freitas	WRF Single-Moment 6-class scheme
9	GF-DM6	Grell- Freitas	WRF double-moment 6-class scheme
10	G3-SM5	Grell 3D (G3)	WRF Single-Moment 5-class scheme
11	G3-SM6	Grell 3D	WRF Single-Moment 6-class scheme
12	G3-DM6	Grell 3D	WRF double-moment 6-class scheme
13	No-SM3	0	WRF Single-Moment 3-class scheme (SM3)

2.2 Data analysis

To evaluate the performance of each simulated output produced by different CPS and MPS combinations, two evaluation methods providing distinct skill scores were used: statistical analysis and contingency tables. The evaluation of simulated model precipitation against observations employed statistical parameters such as BIAS, MAE, and RMSE (Litta & Idicula, 2011).

Contingency tables (Table 2.2) were used to quantify the ability of model predictions to simulate precipitation for each CPS–MPS configuration. In general, contingency tables are commonly used to verify categorical forecasts such as rainfall (Maussion et al., 2011; Wilson, 2014; McBride & Ebert, 2000). Since contingency tables can be applied to assess spatiotemporal variations, they were used in this study to verify rainfall forecasts on a spatial basis. Here, 0.1 mm daily rainfall was used as the threshold value for rainfall occurrence (Yes ≥ 0.1 mm and No < 0.1 mm) (Pereira et al., 2013)

Table 2.2. Contingency table for yes-no events

Event Forecast	Event observed		
	Yes	No	Marginal Total
Yes	a	b	$a + b$
No	c	d	$c + d$
Marginal Total	$a + c$	$b + d$	$a + b + c + d$

Where,

a – Hit

b – False alarm

c – Miss

d – Correct negative

Threat score (TS) critical success index is another score which is takes into account: hits, misses and false alarms. This vary from 0 to 1, 0 has no skill while the 1 is the perfect.

$$TS = a/(a+b+c) \quad \text{Equation 2.1}$$

Hanssen & Kuipper's Skill Score, True Skill Statistic (TSS) and also known as Pierce's Skill Score, the score has a range of -1 to +1, with 0 representing no skill. The best possible score value is 1, which is obtained when the hit rate (HR) is 1 and the false alarm ratio (FA) is 0. If HR = FA, then the score goes to 0, which is the worst value possible. The KSS is also the difference between the hit rate and false alarm rate, KSS=HR-FA

$$KSS = TSS = HR - FA = \frac{(ad-bc)}{[(a+c)(b+d)]} \quad , \text{ Where, } FA = b/(b+d) \quad \text{Equation 2.2}$$

3. Results and Discussions

3.1. Daily precipitation distribution

The spatial distribution of total simulated rainfall for each CPS and MPS combination is shown in Figure 3.1. Observed rainfall distribution in Southwestern parts is around 1000-3000 mm. However, simulated rainfall by KF and G3 reached around 6000 mm, and GD produced approximately 4000 mm. These elevated simulated rainfall amounts peaked along the coastal areas of the western and southwestern parts of the country. No-SM3 produced less than 600 mm of rainfall in this coastal area, indicating poor skill in rainfall prediction. Observed rainfall was also high on the western slopes of the central hills, with more than 2000 mm recorded at some stations. However, none of the precipitation outputs simulated by the model combinations matched the observations. It should be noted that the spatial distribution of rainfall is highly dependent on cumulus scheme choices, while the influence of microphysics options was negligible. The spatial distribution of TSS values for model-simulated precipitation over land for each parameterization combination, with respect to observed rainfall, is shown in Figure 3.2. TSS values depict large spatial differences across the island, with the southwestern half showing very low scores, whereas the northeastern half exhibited comparatively better and higher TSS values. Very low TSS values (less than 0.1) were observed in the western and southwestern coastal areas. The BMJ-DM6 combination was found to be the best-performing configuration for the coastal districts in the southwestern part, while G3-DM6 performed best in the central/highland districts such as Ratnapura, Kandy, and Nuwara Eliya. All KF combinations showed high TSS values in the rest of the country.

An intercomparison of RMSE values for the simulated combinations revealed that all KF combinations had the highest RMSE values, followed by G3 combinations in the coastal districts and on the windward side of the central hilly areas, which feature complex topography (Figure 3.3). Combinations with BMJ,

GF, and No-SM3 showed relatively lower RMSE values in those areas; however, they still exhibited significantly higher values on the windward side of the central hills. Compared to other combinations, BMJ-DM6 emerged as the best-performing configuration for the country in terms of RMSE.

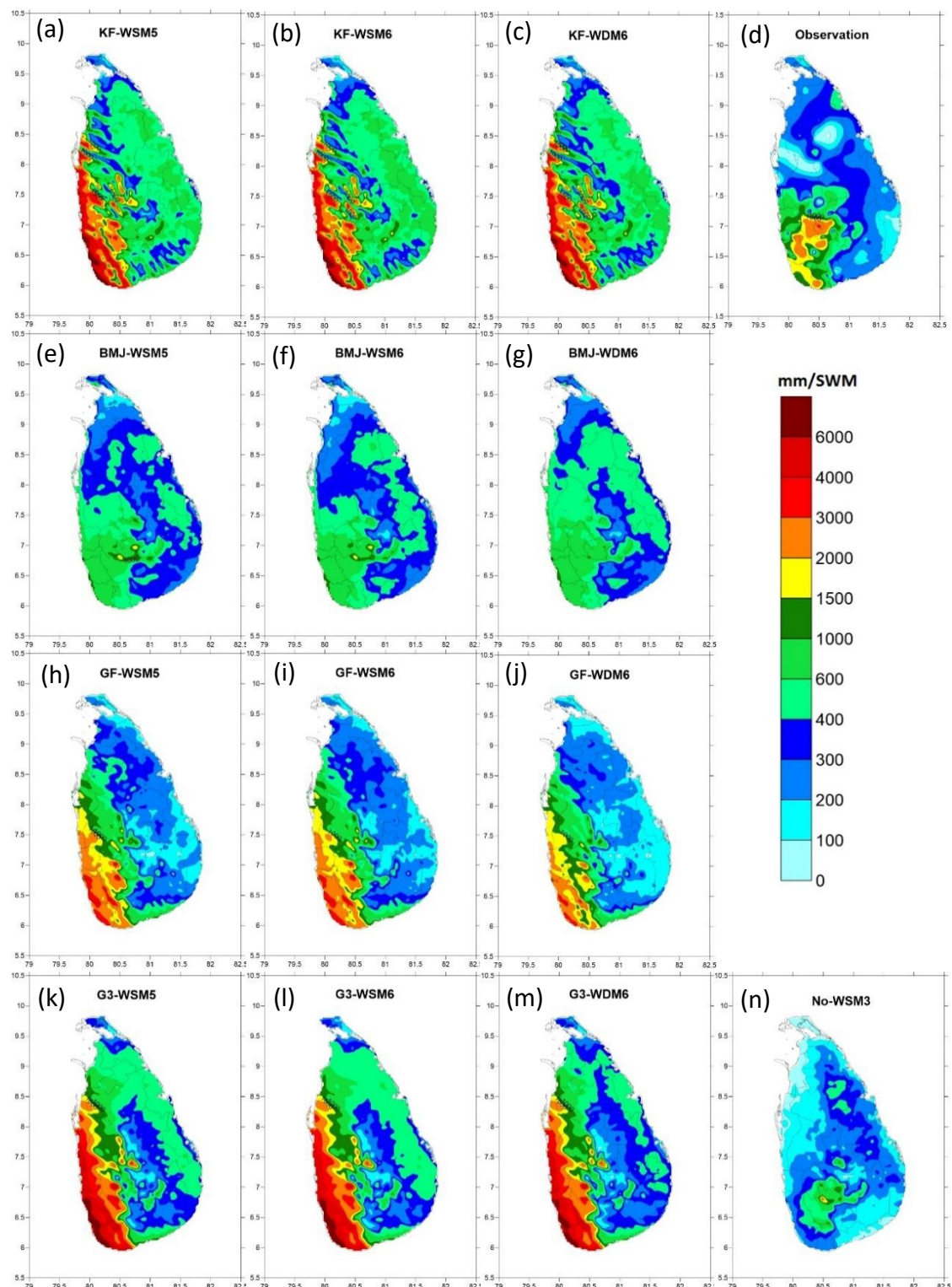


Figure 3.1 Spatial distribution of mean precipitation simulated by each CPS-MPS combination, along with observed daily precipitation during the SWM, 2013–2015.

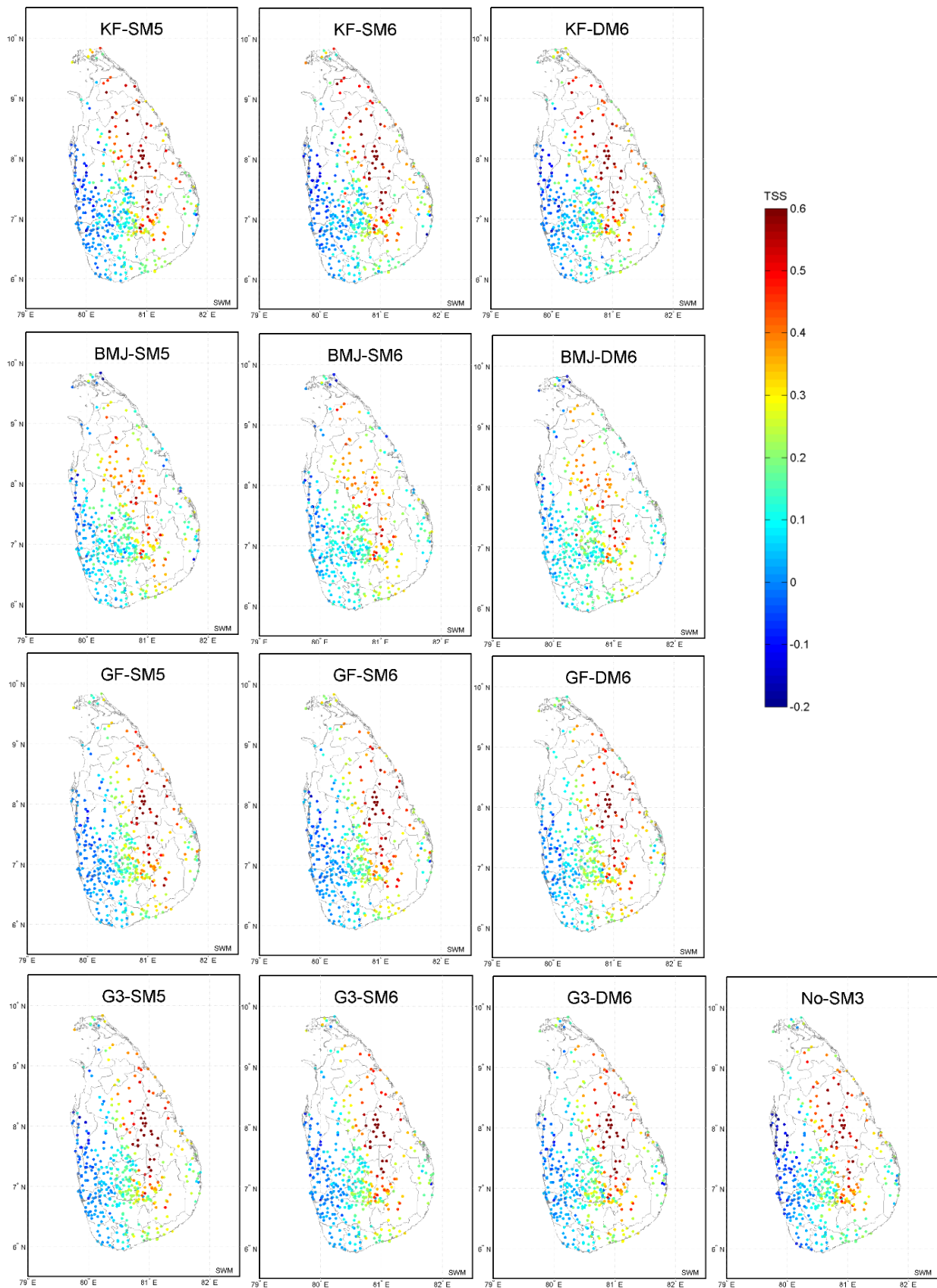


Figure 3.2 Spatial distribution of TSS for simulated precipitation by each CPS-MPS combination, compared against DOM daily rainfall observations during the SWM period, 2013–2015.

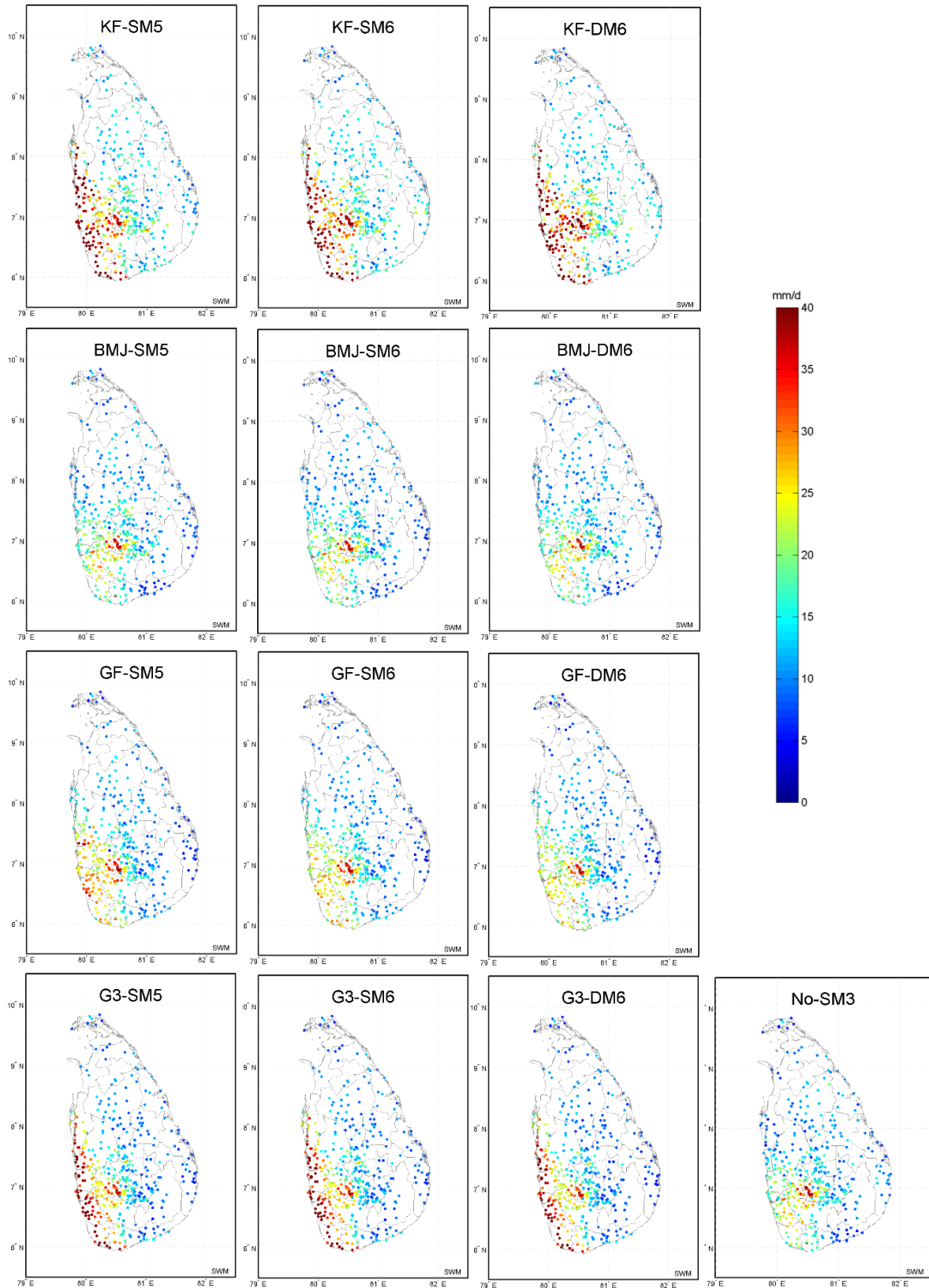


Figure 3.3 Same as figure 3.2 but for RMSE

3.2. Region wise TSS, RMSE, TS and BIAS of daily precipitation

To simplify the intercomparison of the performance of each combination, station-wise skill scores and error statistics TSS, TS, RMSE, and Bias were grouped by district. Similarities in skill across certain districts revealed clusters with comparable performance, allowing further grouping into broader regions. Three (3) regions were identified based on consistent district-wise performance during the SWM, as outlined below.

- Region-1: Southwestern coastal districts (Puttalam, Gampaha, Colombo, Kalutara, Galle, Matara, Hambatota, Kurunegala and Kegalle districts)
- Region-2: Southwestern inland districts where having complex topographical features (Rathnapura, Kandy and Nuwara-Eliya districts)
- Region-3: Rest of the country.

All combinations showed very low accuracy during the Southwest Monsoon (SWM), particularly in Region-1. Figure 3.4(a) represents the regions identified during the SWM period, while Figures 3.4(b), (c), (d), and (e) illustrate TSS, TS, RMSE, and Bias, respectively, for each combination across the regions. For Region-1, the BMJ–DM6 combination recorded the highest TSS value of 10.8%, while other BMJ combinations also exceeded 10%, though they remained below BMJ–DM6. Combinations using GF and G3 CPS exhibited the lowest TSS values when paired with SM5 and SM6 MPS. All DM6 configurations demonstrated better capability in capturing rainfall events compared to other microphysics options, as indicated by higher TSS scores. BMJ combinations were the only ones to show the lowest Bias values, even though rainfall was underestimated in this region. Bias values for the simulated combinations indicate that, in the coastal region (Region-1), the sensitivity of the parameterization schemes is highly dependent on the cumulus choices. All combinations showed positive bias except for BMJ, which exhibited dry biases. The largest bias was observed in the G3 combinations, followed by KF, while BMJ combinations showed the lowest bias. Here, mass-flux type convective schemes show high sensitivity at the coastal regions where the wind interacts with shore line. As example, the KF convective scheme uses CAPE removal method to eliminate atmospheric instability and the scheme triggers convection whenever the grid column is found to be lower level unstable layer with lower level CAPE values (Kain, 2004) Hence, the lower level instability due to coastal convergence and warm higher moisture amount seem to over active the scheme to develop excessive convection producing three to two times higher precipitation relative to the observations over coastal region.

TS and RMSE results were consistent, indicating that BMJ–DM6 is the most appropriate combination for the coastal areas of the southwestern parts (Region-1). The explicit convection scheme with SM3 MPS the current default combination assigned by the WRF preprocessing system showed moderate skill across all metrics, though it also exhibited a dry bias.

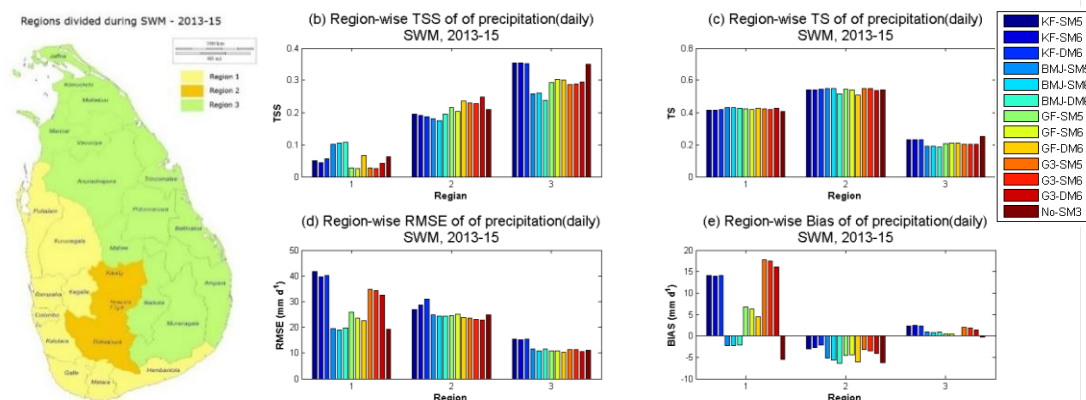


Figure 3.4 (a) Regions Divided during SWM (b) TSS, (c) TS, (d) RMSE & (e) Bias of region-wise daily precipitation simulated by each combination

For Region-2, TSS and TS accuracy for all combinations were significantly higher than in Region-1, with approximately 20% TSS (Figure 3.4b) and 50% TS accuracy (Figure 3.4c). Bias values indicated underestimated rainfall across all combinations, which was further influenced by cumulus scheme choices. KF combinations continued to show lower bias, while BMJ combinations exhibited higher bias. Notably, RMSE values were highest for KF-based configurations. In this region, the G3–DM6 combination demonstrated the greatest potential for capturing rainfall, with a maximum TSS of 24.76% and the lowest RMSE of 9.46 mm/day. However, combinations such as KF, GF, and G3 showed location bias, as heavy rainfall was simulated around the western border of the region. None of the combinations successfully captured the heavy rainfall observed in the central highlands, particularly in the Nuwara Eliya and Kandy districts.

Region-3, which includes the districts of Badulla, Monaragala, Batticaloa, Ampara, Trincomalee, Polonnaruwa, Matale, Anuradhapura, Vavuniya, Mannar, Kilinochchi, Mullaitivu, and Jaffna, represents the leeward area during the SWM. This region exhibited distinct skill scores compared to the others. Except for Badulla and Monaragala, isolated rainfall distributions between 600–1000 mm were reported, with an accumulated average rainfall of less than 400 mm during the 2013–2015 SWM period.

TSS values around 0.30 were observed for KF, GF, and G3 combinations, while BMJ showed the lowest TSS at approximately 0.25. The KF–SM6 combination recorded the highest TSS value (0.354), followed by KF–SM5. Among non-KF combinations, No-SM3 showed a strong performance with a TSS of 0.351. The GF–SM6 combination had the lowest RMSE value at 8.12 mm/day. Except for No-SM6 schemes, all combinations overestimated rainfall in this region, with a small negative bias of –0.33 mm/day. GF–DM6 showed the least bias at 0.01 mm/day. Overall, combinations involving KF, BMJ, and G3 simulated more rainfall than was observed, as evident in the spatial distribution maps (Figure 3.1). A well-distributed rainfall pattern was found in the GF and No-SM3 combinations, with No-SM3 demonstrating the best overall performance for Region-3.

3.3 Precipitation production by Cumulus and microphysics schemes (non-convective)

The precipitation output from each CPS and MPS combination near coastal stations in the western to southern parts of Sri Lanka is illustrated in Figure 3.5. Except for the Kurunegala station, all other stations are located very close to the shoreline. It is notable that the majority of simulated total rainfall at these coastal stations was produced by CPS, while the contribution from microphysics schemes was minimal. At stations such as Katunayake, Colombo, and Galle where observed rainfall during the SWM exceeded 1000 mm all combinations except BMJ and No-SM3 produced less rainfall than observed, resulting in higher errors in accumulated rainfall. This overestimation is attributed to overly active CPS, with KF and G3 showing the greatest deviations, particularly in coastal areas. It is evident that all MPS failed to adequately simulate precipitation along the coastal belt. In contrast, the fraction of precipitation produced by CPS and MPS at inland stations such as Kandy, Nuwara Eliya, and Ratnapura (Region-2) indicates that MPS contributed more significantly to rainfall in these areas compared to coastal regions. This contribution was especially pronounced at the Nuwara Eliya station, which is situated at higher altitude and features complex topography. Except for the G3–DM6 combination, all other configurations produced more than 50% of non-convective rainfall, whereas G3–DM6 showed a lower proportion of non-convective precipitation. Stations in Region-3 exhibited a higher fraction of precipitation generated by MPS across all combinations, as shown in Figure 3.6.

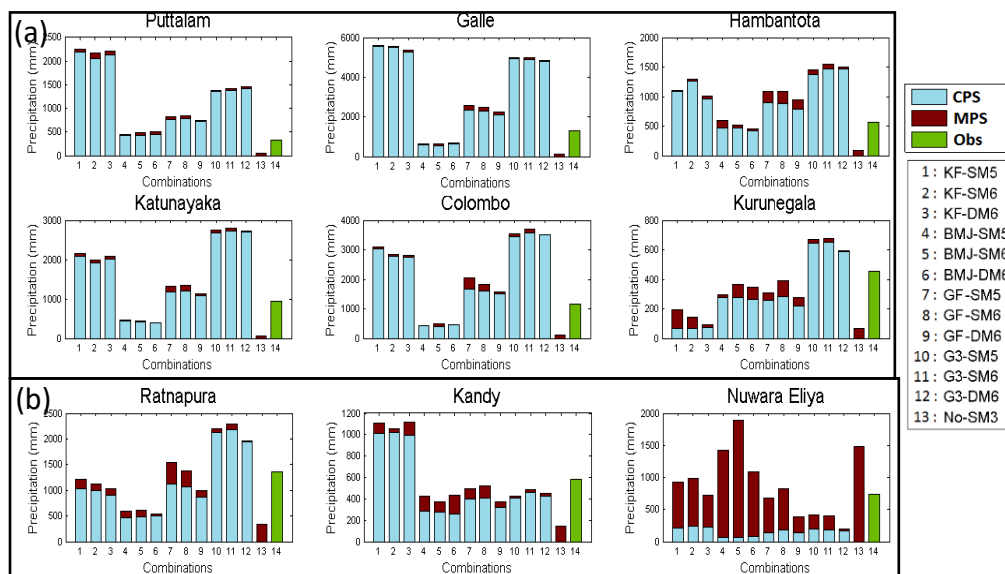


Figure 3.5 Simulated precipitation from the convective parameterization (blue) and micro-physics (non-convective) (red) as a fraction of total in each combination and observation (green) at the near coastal stations in (a) Region-1 and (b) Region-2 during the SWM, 2015

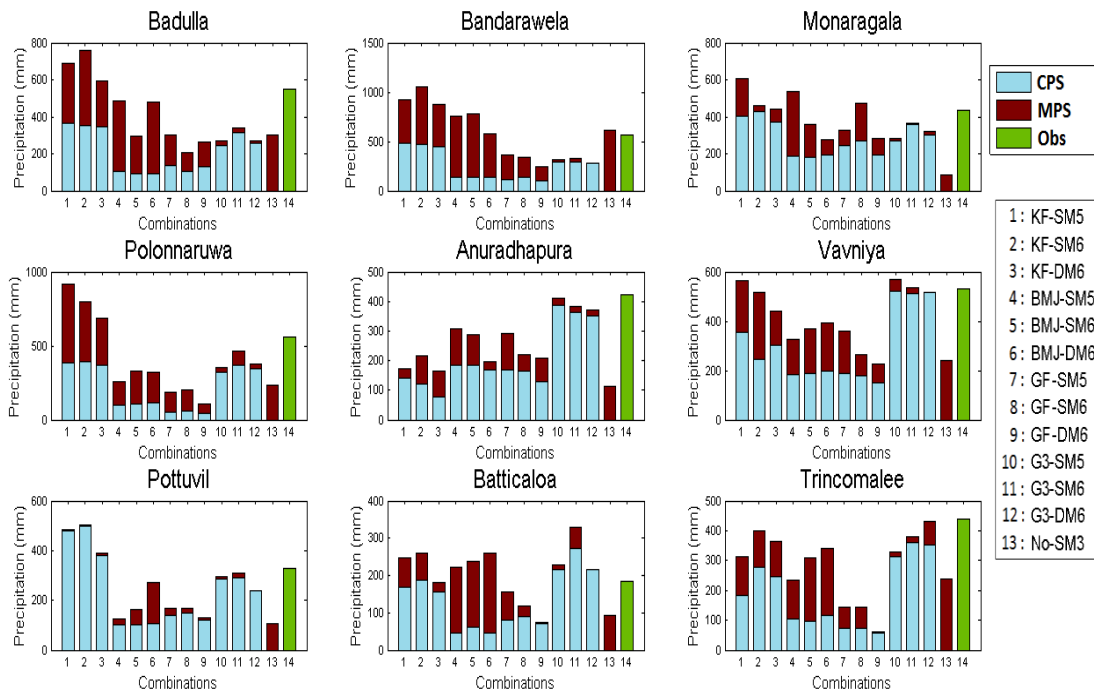


Figure 3.6 same as 3.5 but for the Region-3

4. Summary and Conclusion

The amount of precipitation produced by each combination is highly dependent on CPS, particularly in coastal areas. Mass-flux type convective schemes show very high sensitivity in these regions, where wind interacts with the shoreline. For example, the KF convective scheme uses a CAPE removal method to eliminate atmospheric instability and triggers convection whenever the grid column exhibits a lower-level unstable layer with low-level CAPE values (Kain, 2004). Consequently, lower-level instability caused by coastal convergence and warm, moisture-rich inflow appears to over-activate the CPS, leading to excessive convection. This results in precipitation amounts two to three times higher than observed values over the western and southwestern coastal regions. In contrast to mass-flux type CPS, the BMJ scheme produced underestimated precipitation. This may be due to its triggering mechanism. BMJ does not redistribute moisture within the grid column and does not account for processes occurring below the cloud base (Betts and Miller, 1993). As a result, it is not activated by mixed-layer instability that may arise from air–land interactions. Additionally, the post-convective reference profile used by BMJ to adjust temperature and moisture may not be suitable for real monsoon conditions in Sri Lanka. On the other hand, the contribution of non-convective precipitation to total rainfall was minimal in these areas. Even the No-SM3 combination, which excludes a convective scheme, failed to simulate rainfall amounts explicitly along the coast. This implies that the model’s predicted upward motion is insufficient to generate grid-scale precipitation via MPS. The amount of moisture transported by winds and the wind speed seem to be directly linked to excessive triggering of convection over coastal inflow zones. These findings align with those of Mukhopadhyay et al. (2010), who similarly reported overestimation of

precipitation by the KF scheme and comparatively lower errors associated with the BMJ scheme during the Indian summer monsoon.

However, MPS contributions were notably higher in inland areas and on the leeward side of the central hills. Therefore, to simulate precipitation effectively in coastal areas on the low-level inflow side, cumulus parameterization is necessary even at 4 km grid resolution despite recent studies suggesting that explicit convection may be feasible in “gray scale” resolutions ($dx = 2\text{--}10\text{ km}$) (Pieri et al., 2015). In precipitation prediction, the WRF model shows strong sensitivity to the selected cumulus parameterization scheme, more so than to microphysics schemes. Furthermore, intercomparison of station skill scores reveals significant regional variation in model performance. Across all simulations using the 13 CPS–MPS permutations, most model runs performed poorly in predicting precipitation, especially along the inflow-side coastal region. RMSE and Bias values ranged from 20–40 mm/day and 5–20 mm/day, respectively, while TSS values were as low as 0.07. For BMJ combinations, TSS accuracy ranged from 0.1 to 1.2 still relatively low while RMSE and Bias were around 20 mm/day and –2 mm/day, respectively. Overall, BMJ showed the most skillful simulation runs among all experiments.

The sensitivity of simulated precipitation to different MPS configurations was negligible. MPS produced significantly lower precipitation along windward coastal areas and were extremely inactive during the SWM period in these zones. At Nuwara Eliya station, which is surrounded by complex topography in the highlands, MPS tended to be overactive and appeared to control all orographically induced rainfall. The contribution of MPS to total rainfall also increased with distance from the coast. Generally, MPS produced less rainfall in GF and G3 combinations than in KF and BMJ combinations. Additionally, WDM6 showed low contribution when paired with G3.

Based on the results presented in this study, it can be concluded that to improve rainfall forecasting in Sri Lanka, an ensemble approach using CPS–MPS combination model runs tailored to specific regions and seasons should be implemented operationally. Future studies may consider the sensitivity of other CPS and MPS together with other parameterizations options such as Planetary Boundary Layer (PBL) parameterizations options. The best-performing combinations by region are:

- Region 01: BMJ–DM6
- Region 02: G3–DM6
- Region 03: No-SM3

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Verification of Monthly Rainfall Forecasts in Sri Lanka (2020–2024)

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ABSTRACT

This study evaluates monthly rainfall forecasts, produced via a subjective synthesis approach integrating large-scale climate driver behavior, WMO Global Producing Centers (GPCs) outputs, and relevant research against observed rainfall across 25 districts of Sri Lanka from 2020 to 2024. Verification employed qualitative visual-based (eyeball) assessment, recognized by WMO as a valid method, alongside contingency tables to derive six key metrics: Bias Score, Proportion Correct (PC), Probability of Detection (PoD), False Alarm Ratio (FAR), Probability of False Detection (PoFD), and Critical Success Index (CSI). Results show that while forecasts captured rainfall events reasonably well (PoD), they exhibited systematic over-forecasting, reflected in elevated FAR values. Spatial patterns were evident: northern and eastern districts showed stronger over-forecasting, whereas southern and central regions were more balanced or slightly under-forecasting. The findings suggest that incorporating high-resolution dynamical model outputs and AI-based statistical post-processing into the subjective framework could improve forecast skill, reduce biases, and enhance operational utility for agriculture, water resource management, and disaster preparedness.

Key words: Monthly rainfall forecast, Forecast verification, Skill scores, Seasonal dependence

1. Introduction

Accurate rainfall forecasting is essential for Sri Lanka, where more than 60% of the population relies, directly or indirectly, on agriculture and water-dependent livelihoods (World Bank 2022). Monthly and seasonal rainfall outlooks support farm-level decision-making, reservoir operation, and early warning systems for droughts and floods. Rainfall variability exerts a strong influence on key socio-economic sectors, including rain-fed agriculture, hydropower generation, irrigation scheduling, and inland fisheries. Given the country's dependence on monsoon-driven rainfall, skillful monthly and seasonal rainfall forecasts are critical for climate-resilient planning and the effective management of water and agricultural resources.

1.1 Rainfall Forecasting in Sri Lanka

At present, the Department of Meteorology (DoM), Sri Lanka issues monthly rainfall forecasts primarily based on statistical and dynamical assessments of key large-scale climate drivers, including the El Niño–Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD), and the Madden–Julian Oscillation (MJO). These climate modes significantly modulate rainfall variability across the South Asian region. In Sri Lanka, where rainfall patterns are influenced by monsoonal systems and inter-

annual climate variability, such as the El Niño–Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD), verification of rainfall forecasts is particularly important. A robust understanding of forecast performance enables meteorological agencies and decision-makers to better manage agricultural activities, mitigate disaster risks, and plan for climate resilience.

To enhance predictive skill, the DoM integrates model guidance from the World Meteorological Organization's (WMO) Global Producing Centres (GPCs) for Long-Range Forecasts. The GPCs such as the European Centre for Medium-Range Weather Forecasts (ECMWF), Japan Meteorological Agency (JMA), UK Met Office (UKMO), Australian Bureau of Meteorology (BoM), and National Centers for Environmental Prediction (NCEP) operate advanced coupled ocean–atmosphere general circulation models (CGCMs). These models produce global ensemble forecasts of temperature, precipitation, and circulation anomalies, which are disseminated through the WMO Lead Centre for Long-Range Forecast Multi-Model Ensemble (LC-LRFMME) and the Global Seasonal Climate Update (GSCU) frameworks.

The DoM applies subjective interpretation and statistical downscaling techniques to these global outputs, blending them with local climatological data, historical analogues, and expert judgment to produce country-specific rainfall forecasts. The resulting outlooks are disseminated to national stakeholders in agriculture, irrigation, water resources, power generation, and disaster risk management, supporting evidence-based decision-making and enhancing climate resilience.

To ensure the reliability and continuous improvement of these forecast products, systematic forecast verification is undertaken to evaluate their accuracy, monitor performance over time, and guide model development.

1.2 Forecast Verification

Forecast verification is the process of assessing the accuracy and skill of a forecasting system. The forecast is verified against a corresponding observation of what actually occurred. Verification gives an insight into weaknesses and strengths of forecasting systems, thus allowing a more complete use of the information contained in the forecasts (Anna Ghelli and Francois, 2001). Forecast Verification provides an objective means of quantifying the performance of prediction systems, revealing both their strengths and weaknesses (Jolliffe & Stephenson, 2012; Wilks, 2019). The three most important reasons to verify forecasts are to monitor forecast quality, that is, to assess how accurate the forecasts are and whether they are improving over time, to improve forecast performance through continuous evaluation and feedback, and to compare the quality of different forecasting models, determining the extent to which one provides better forecasts than another.

Commonly used categorical metrics such as Bias Score, Probability of Detection (PoD), False Alarm Ratio (FAR), and Critical Success Index (CSI) offer insight into model behavior under different rainfall regimes (Doswell et al., 1990; Ebert, 2001). Verification studies not only help to identify sources of systematic errors but also guide model improvements and calibration efforts to enhance forecast credibility for end users (Murphy & Winkler, 1987).

Verification results are analyzed to assess spatial and temporal variations in forecast skill, particularly during key monsoon seasons, the Southwest (May–September) and Northeast (December–February) monsoons. These assessments help the DoM refine its forecast methodologies, adjust model weighting strategies, and improve the interpretation of global model outputs from the WMO Global Producing Centres (GPCs). Ultimately, the systematic verification process strengthens user confidence and ensures that forecast information remains credible, actionable, and fit for purpose in climate-sensitive decision-making.

Verification of monsoon forecasts is inherently challenging because observational datasets contain uncertainties arising from sparse station coverage, measurement errors, and representativeness limitations. In addition, scale mismatches between observations and the relatively coarse resolution of many forecast models can influence the assessed performance. These factors highlight the need for careful interpretation when evaluating seasonal forecast skill.

2. Methodology

2.1 Verification Approach

Verification of the Sri Lanka's monthly rainfall forecasts issued by DOM was carried out by using visual based, eyeball verification, the standard procedures recommended by the World Meteorological Organization (WMO).

The verification process was primarily based on contingency table analysis, in which forecasted and observed rainfall categories above-normal, near-normal, and below-normal were compared. From these contingency tables, several key categorical skill scores were derived, including the Hit Rate (H), False Alarm Ratio (FAR), and Bias Score (B). These indices provide quantitative measures of forecast accuracy, reliability, and systematic bias (WMO Guidelines on the Verification of Hydrological Forecasts).

2.2 Data Sources and study area

Monthly rainfall forecasts for Sri Lanka, during the period from 2020 to 2024, were obtained from the operational climate forecasting system developed and maintained by the DoM. The corresponding

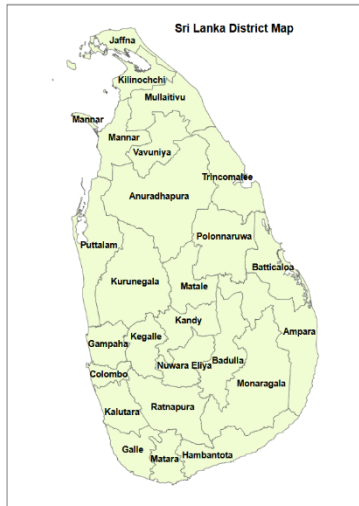


Figure 1: Map of Sri Lanka showing the distribution of 25 districts

observed rainfall data were sourced from the network of regional meteorological stations operated by the DoM and other collaborative rainfall stations supervised by DoM. The analysis encompassed all 25 administrative districts, providing comprehensive spatial representation across Sri Lanka's wet, intermediate, and dry climatic zones.

Prior to analysis, both forecasts and observed rainfall datasets were first aggregated to a common monthly temporal resolution. A comprehensive data quality control procedure was then applied to identify and address inconsistencies. This included screening for missing values, outliers, and unrealistic rainfall amounts (e.g., negative or excessively high values relative to climatology). Records

identified as erroneous through range checks and internal consistency checks were flagged and removed. Stations/datasets with more than a predetermined threshold of missing values (e.g., >10–15% of the total record) were excluded from subsequent verification to maintain statistical validity. The final dataset used for verification therefore consists only of stations with sufficient temporal completeness and reliability, ensuring data integrity throughout the analysis.

2.3 Forecast Categorization

In this study, the three rainfall categories were defined using the percentage-of-normal method, where rainfall amounts within 90–110% of the long-term mean were classified as 'normal', values below 90% as 'below normal', and values above 110% as 'above normal'. This approach is commonly applied in operational climate monitoring to distinguish meaningful wet and dry anomalies from typical variability around the climatological mean.

Although some countries, such as Japan and Bangladesh, use probabilistic tercile classifications with equal appearance probabilities (33%, 33%, and 33%) for below-normal, near-normal, and above-normal categories, percentage-based ranges are also widely applied in South and East Asia. For example, the India Meteorological Department (IMD) defines "normal" seasonal rainfall as within $\pm 15\%$ of the long-term mean. The slightly narrower 90%–110% range adopted in this study was selected to provide a more conservative definition of near-normal conditions while maintaining consistency with operational climatological practice in the region. This event-based classification enables the computation of categorical skill metrics such as Hit Rate, False Alarm Ratio, and Probability of Detection (POD).

2.4 Contingency Table

For each district, a 2×2 contingency table, which is a standard practice to use two-dimensional contingency table was used to compare forecasted and observed rainfall categories. In this study, rainfall forecasts were expressed as above-normal or near normal or below normal relative to the climatological mean, 30 year average 1981-2010. Each pair of forecast observation outcomes was classified into one of four possible incidents:

Table 1. 2×2 Contingency Table Structure

	Event Forecasted	No Event Forecasted
Event Occurred	a (Hits)	c (Misses)
No Event Occurred	b (False Alarms)	d (Correct Negatives)

The raw counts (a, b, c, d) were aggregated for each district over the entire study period. These totals were then used to calculate the following standard forecast verification scores. These metrics collectively describe different aspects of model performance, including accuracy, bias, and detection capability (Doswell et al., 1990; Ebert, 2001). The categorical verification metrics (PC, POD, FAR, POFD, and CSI) were computed following WMO standard definitions (WMO-No. 485; WMO-No. 1364). In general, higher values of PC, POD, and CSI, and lower values of FAR and POFD, indicate better forecast performance.

Table 2 key verification metrics are computed for each district to assess forecast performance

Metric	Formula
Proportion Correct (PC)	(Hits + correct negatives) / observed total
Bias (for each category)	(Forecast total) / (Observed total)
Probability of Detection(POD) (for each category)	Hits / Observed total
False Alarm Ratio(FAR) (for each category)	False Alarms / (Hits + False Alarms)
CSI (Critical Success Index)	Hits / (Hits + Misses + False Alarms)
Probability of False Detection(POFD)	False Alarms / Observed Non-Event

The categorical verification of forecasts was performed using standard contingency-table-based indices following the definitions provided in the WMO Manual on the Global Data-Processing and Forecasting System (WMO-No. 485) and the WMO Guidelines on the Verification of Hydrological Forecasts (WMO-No. 1364). The verification measures include Bias Score (B), Proportion Correct (PC), Probability of Detection (POD), False Alarm Ratio (FAR), Probability of False Detection (POFD), and Critical Success Index (CSI).

These indices were calculated using the relationships described by WMO (2023) and Ebert (2008). Table 3 summarizes the definitions, value ranges, and general interpretation of each index. Higher values of PC, POD, and CSI and lower values of FAR and POFD indicate better forecast skill, whereas a Bias Score close to 1 represents an unbiased forecast system.

Table 3. Interpretation and Definitions of Categorical Verification Indices

Index	Range	Interpretation
Bias Score (B)	0 – 3	Indicates the ratio of forecasted to observed events. A value of 1 represents an unbiased forecast. $0.75 \leq B \leq 1.25$ indicates acceptable/good forecast performance. $B > 2$ indicates a significant over forecasting (over-warning) tendency, while $B < 0.5$ indicates a strong under forecasting (miss) tendency. $B = 0$ means no events were detected.
Proportion Correct (PC)	0 – 1	Fraction of forecasts that are correct. $PC = 1$ means all forecasts are correct; $PC = 0$ means all are incorrect.
Probability of Detection (POD)	0 – 1	Fraction of observed events correctly forecasted. $POD = 1$ means all observed events were predicted; $POD = 0$ means none were detected.
False Alarm Ratio (FAR)	0 – 1	Fraction of forecasted events that did not occur. $FAR = 0$ means no false alarms; $FAR = 1$ means all forecasted events were false.
Probability of False Detection (POFD)	0 – 1	Fraction of non-events incorrectly forecasted as events. $POFD = 0$ represents a perfect forecast (no false detection); $POFD = 1$ means all non-events were falsely forecasted as events.
Critical Success Index (CSI) / Threat Score	0 – 1	Measures overall forecast skill for events: $CSI = a/(a+b+c)$, where a = hits, b = false alarms, c = misses. $CSI = 1$ indicates perfect forecast; $CSI = 0$ indicates no skill.

3. Result and Discussion

3.1 Detailed Analysis of Monthly Forecast Performance Metrics:

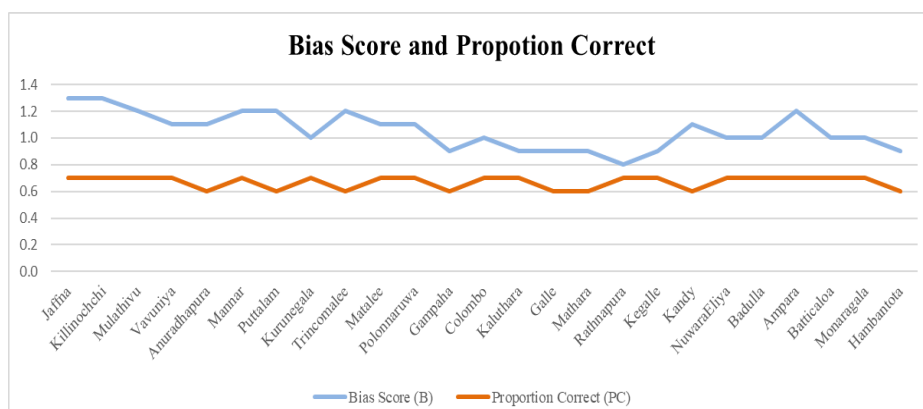


Figure 1: Bias Score (B) and Proportion Correct (PC) calculated for monthly rainfall forecasts across districts. The Bias Score indicates whether events were over-forecast ($B > 1$) or under-forecast ($B < 1$), while the Proportion Correct represents the overall percentage of correctly predicted outcomes. The graph highlights spatial variations in forecast performance among the districts.

3.1.1 Bias Score (B): Tendency to Over- or Under-Forecast

The Bias Score shows a clear spatial pattern across Sri Lanka. The forecast tends to over-predict above-normal rainfall in the northern and eastern districts ($B \approx 1.2$ – 1.3), notably in Jaffna, Kilinochchi, Mullaitivu, Mannar, Puttalam, Trincomalee, and Ampara. In contrast, several southern and western districts exhibit slight under-forecasting ($B \approx 0.8$ – 0.9), including Gampaha, Kalutara, Galle, Matara, Hambantota, Ratnapura, and Kegalle. Meanwhile, Kurunegala, Colombo, Badulla, Nuwara Eliya, Monaragala, and Batticaloa show values close to 1, indicating relatively unbiased forecasts. Overall,

the system appears more sensitive in the north/east and more conservative in the south/west, reflecting a regionally varying forecast behavior.

3.1.2 Proportion Correct (PC): Overall Accuracy

The Proportion Correct (PC) metric shows minimal spatial variation across Sri Lanka, with all districts recording values between 0.60 and 0.70. This indicates that the monthly forecasts correctly classify events and non-events about 60–70% of the time throughout the country. Although this level of accuracy is moderate, the uniformity of PC values suggests that the baseline forecast performance is consistent, with no district exhibiting markedly better or poorer overall accuracy.

3.1.3. Probability of Detection (PoD): Ability to Capture Events

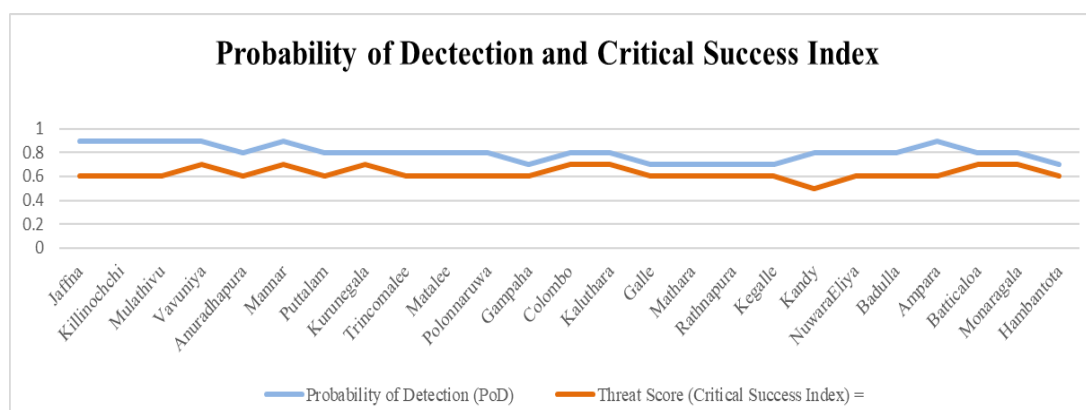


Figure 2: Probability of Detection (PoD) and Critical Success Index (CSI) for monthly rainfall event forecasts across districts. PoD indicates the fraction of observed events that were correctly forecast, while CSI accounts for hits, misses, and false alarms, providing an overall measure of forecast skill. The spatial variation in both metrics illustrates differences in forecast performance among districts.

The Probability of Detection (PoD) is a notable strength of the forecasting system, with consistently high values across all districts (0.7–0.9). Exceptional detection skill ($PoD \approx 0.9$) is evident in Jaffna, Kilinochchi, Mullaitivu, Vavuniya, Mannar, and Ampara where the forecasts correctly identified most above-normal rainfall events. The remaining districts also demonstrate good detection capability, with PoD values between 0.7 and 0.8. Overall, the forecasts are highly effective at identifying actual above-normal rainfall events.

3.1.4 Critical Success Index (CSI): Overall Skill for Events

The Critical Success Index (CSI) indicates moderate forecast skill across the country, with values ranging from 0.5 to 0.7. The highest-performing districts Vavuniya, Mannar, Kurunegala, Colombo, Kalutara, Monaragala and Batticaloa record CSI values around 0.7, reflecting a favourable balance of high event detection and relatively few false alarms or misses. In contrast, Kandy shows the weakest

performance with a CSI of 0.5. Overall, the forecasts demonstrate moderate but meaningful skill, with several districts achieving a strong combination of detection capability and reliability.

3.1.5. False Alarm Ratio (FAR): Reliability of Forecasts

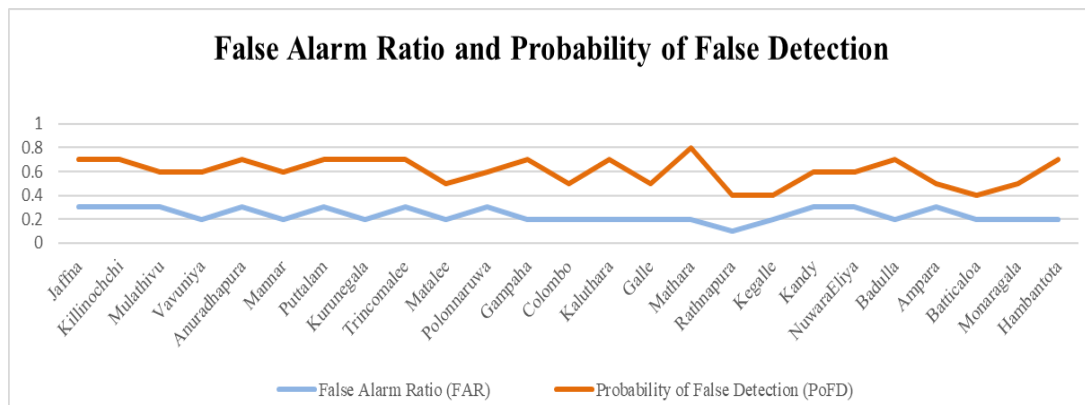


Figure 3: False Alarm Ratio (FAR) and Probability of False Detection (PoFD) calculated for monthly rainfall event forecasts across districts. FAR represents the proportion of forecasted rainfall events that did not occur; whereas PoFD indicates how often non-events were incorrectly forecast as events. Higher values of these metrics indicate reduced forecast reliability. Spatial variation shows differences in false alarm tendencies among districts.

The False Alarm Ratio (FAR) remains consistently low across all districts (0.1–0.3), indicating high forecast reliability. Ratnapura exhibits the best performance (FAR = 0.1), while Western, Southern, and Uva provinces and Vavuniya, Mannar, Kurunegala, Matale, Kegalle and Batticaloa districts also record low FAR values (~0.2). These results imply that approximately 80–90% of the forecasted rainfall events were realized. Overall, the forecasts demonstrate strong reliability, with minimal false alarms, thereby enhancing user confidence in above-normal rainfall predictions.

3.1.6. Probability of False Detection (PoFD): Inability to Identify Non-Events

The Probability of False Detection (PoFD) reveals a notable limitation in forecast performance, with values ranging from 0.4 to 0.8 across districts. Several regions including Jaffna, Kilinochchi, Anuradhapura, Puttalam, Trincomalee, Gampaha, Kalutara, Badulla, Hambantota, and Kurunegala exhibit PoFD values exceeding 0.6, indicating a systematic tendency to falsely predict above-normal rainfall. Relatively better performance is observed in Kegalle, Ratnapura, Ampara, Monaragala, Galle, Colombo, Matale, and Batticaloa (PoFD = 0.4–0.5); however, false detections remain substantial even in these areas. Overall, the forecasts show limited skill in discriminating between rainfall and non-rainfall conditions, with the weakest performance occurring in regions that also display the strongest over-forecasting bias.

3.1.7 Overall forecast performance across different regions and skill indicators.

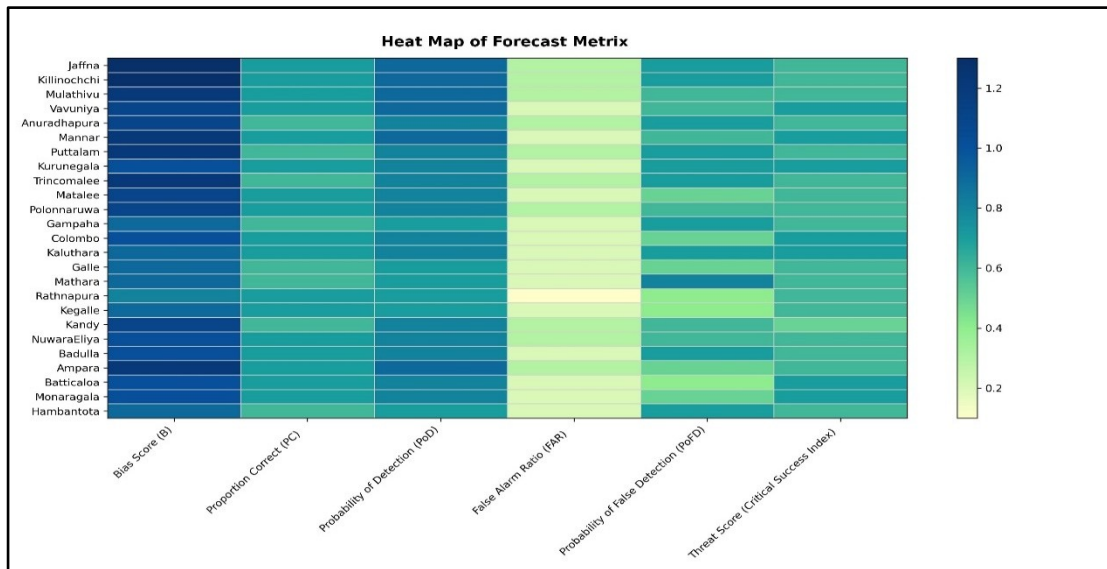


Figure 4: Heatmap of forecast verification metrics (Bias, Proportion Correct (PC), Probability of Detection (PoD), False Alarm Ratio (FAR), Probability of False Detection (PoFD), and Critical Success Index (CSI)) for monthly rainfall forecasts across districts. The colour gradient represents the magnitude of each verification score, enabling of forecast performance across different regions and skill indicators.

The heatmap, Figure 4 provides a consolidated view of the forecast verification metrics across districts. Districts such as Jaffna, Mannar, and Puttalam generally exhibit higher PoD and CSI, indicating relatively stronger forecast skill in capturing above normal rainfall events. In contrast, districts including Rathnapura and Badulla show higher FAR and PoFD, suggesting more frequent false alarms and lower reliability. Overall, the spatial variability observed in the heatmap indicates that forecast performance is not uniform across regions and may be influenced by local climatic conditions and rainfall regimes.

3.1.8 Monthly forecasts verification during Southwest monsoon season

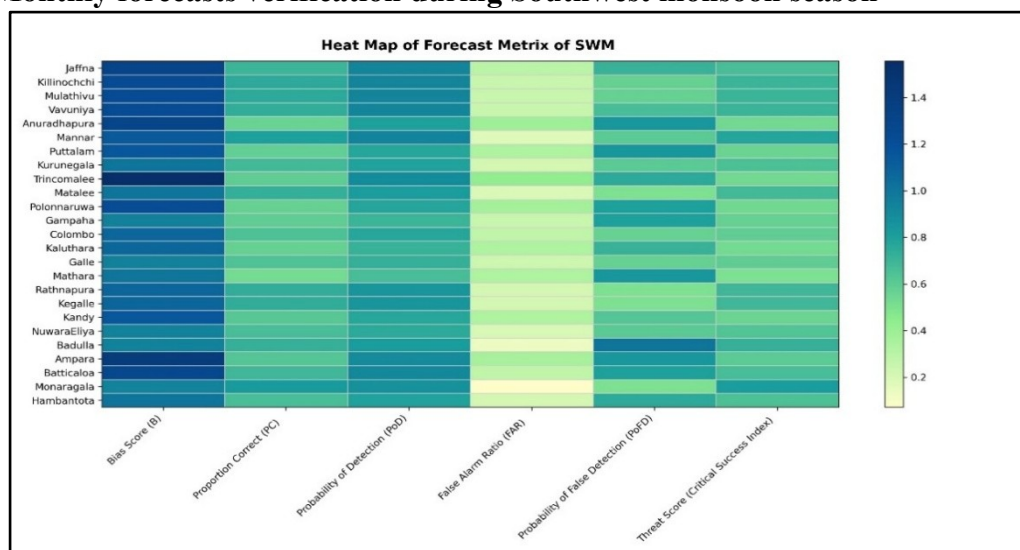


Figure 5. Heat map of monthly rainfall forecast verification metrics for the Southwest Monsoon (SWM) season across Sri Lanka. Spatial patterns in Bias, PC, POD, FAR, POFD, and TS indicate higher forecast skill in western and central districts, with reduced performance in northern and eastern regions where rainfall variability is greater.

The heat map (Figure 5) summarizes the spatial performance of the monthly rainfall forecast across Sri Lanka using multiple verification metrics during SW monsoon which starts from May to September. Bias scores are predominantly greater than 1 across most districts, indicating a widespread tendency to over-forecast above-normal rainfall. This overestimation is particularly pronounced in districts such as Amapara, Anuradhapura and Trincomalee, which are mostly in dry zones.

Probability of Detection (POD) values are generally moderate (≈ 0.4 – 0.6), suggesting that the model captures a reasonable fraction of observed above-normal rainfall events. However, this skill is offset by relatively high Probability of False Detection (PoFD) values in many districts, reflecting frequent false alarms when rainfall does not occur. The False Alarm Ratio (FAR) remains comparatively low to moderate across most regions except some districts in dry Zone, implying that a substantial proportion of forecasted events are realized, despite the presence of false detection.

The Threat Score (Critical Success Index) is consistently low to moderate, highlighting limited overall forecast skill when both missed events and false alarms are considered. Spatially, relatively better performance is evident in wet-zone districts such as Ratnapura, Kegalle, Colombo, and Galle, while poorer performance is observed in several dry-zone districts, where high bias and PoFD dominate.

3.1.9 Monthly forecasts verification during Northeast monsoon season

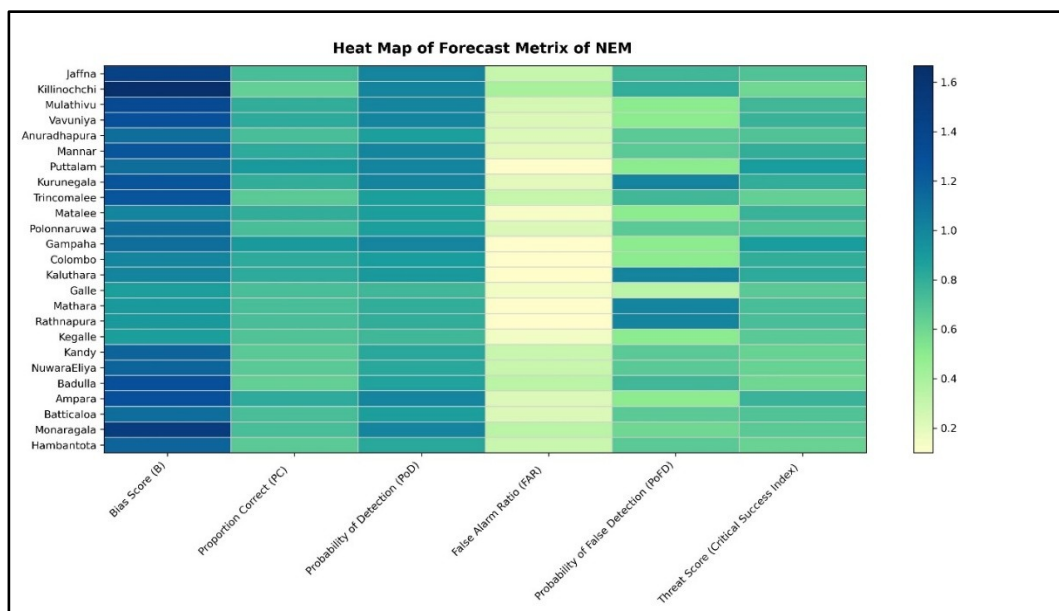


Figure 6. Heat map of monthly rainfall forecast verification metrics for the Northeast Monsoon (NEM) season, across Sri Lanka. Spatial variations in Bias, PC, POD, FAR, POFD, and TS highlight higher forecast skill in northern and eastern districts—where NEM rainfall is most prominent—and lower skill in western, southern, and central areas due to more variable and localized rainfall.

The heat map illustrates the spatial performance of the monthly rainfall forecast skill across Sri Lanka using multiple verification metrics during the Northeast Monsoon (NEM) season starting from December to February. Bias scores are consistently greater than 1 for most districts, indicating a systematic over-forecasting of above-normal rainfall during the NEM season. This wet bias is particularly strong at some districts in northern, eastern, and north-central provinces such as Jaffna, Kilinochchi, Mullaitivu, Vavuniya, Anuradhapura, and Trincomalee, which are climatologically dominant under NEM influence. Probability of Detection (POD) values are generally moderate to high (≈ 0.5 – 0.7), suggesting that the forecasts are relatively effective at capturing observed rainfall events during NEM. However, this improved detection skill is accompanied by moderate to high Probability of False Detection (PoFD) across many districts, indicating frequent false alarms. Although False Alarm Ratio (FAR) values remain low to moderate, the elevated PoFD highlights persistent difficulty in correctly identifying non-rainfall periods. The Threat Score (Critical Success Index) is moderate overall, with comparatively higher values in eastern and wet-zone districts such as Ampara, Gampaha and Kalutara reflecting better combined performance in these regions. In contrast, lower CSI values in several inland and transitional districts point to reduced forecast skill where over-forecasting and false detection dominate. Overall, the heat map demonstrates that the forecasting system performs best in areas dominated by large-scale NEM monsoon flows, while predictive uncertainty increases in regions where rainfall is low, sporadic, or influenced by localized convection.

4. Discussion

The interpretation of forecast skill is subject to several sources of uncertainty associated with both observational data and model representation. Rainfall observations are affected by random and systematic measurement errors, sampling limitations, and representativeness issues arising from the spatially uneven distribution of rain-gauge stations. Additional uncertainty is introduced when station data are interpolated or aggregated to monthly and district scales to match the forecast resolution. Furthermore, the relatively coarse spatial resolution of monthly forecast products limits their ability to resolve localized convection and sub-regional rainfall variability, leading to spatial scale mismatches that can suppress apparent skill even when large-scale circulation signals are captured. The analysis is also constrained by the relatively short five-year verification period, which limits the statistical robustness of the results and the ability to assess forecast performance under a wider range of climate conditions.

5. Conclusion

The verification results indicate that Sri Lanka's monthly rainfall forecasting system, based on expert-driven subjective assessments, demonstrates moderate skill in detecting above-normal rainfall events

but is strongly constrained by a persistent wet bias. Across both the Southwest (SWM) and Northeast (NEM) monsoons, Bias scores exceed unity in most districts, leading to elevated false detections and consistently low Threat Scores, which limit overall forecast reliability. Spatial contrasts are weak during SWM, with uniformly low skill across climatic zones, whereas NEM forecasts exhibit relatively stronger event detection and slightly higher skill in monsoon dominant eastern and wet-zone regions, albeit with a more pronounced over forecasting tendency. Reduced performance in transition regions highlights ongoing challenges in capturing localized and intermittent rainfall processes.

These findings underscore the need for systematic calibration of subjective forecasts using objective model guidance and region specific climatological baselines. Routine verification and structured feedback can help reduce judgment bias and improve forecast consistency. As forecasting systems evolve toward multi-model ensembles and advanced downscaling approaches, continuous verification will be critical to ensure that technical advances translate into meaningful gains in reliability and user confidence. Integrating high resolution dynamical model outputs and AI-based statistical post-processing within the subjective forecasting framework offers a promising pathway to reducing bias and enhancing operational utility for agriculture, water resource management, and disaster preparedness.

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Southwest Monsoon Rainfall Pattern Analysis Across Climatic Zones in Sri Lanka

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ABSTRACT

Sri Lanka experiences two major monsoons the Southwest Monsoon (SWM) and the Northeast Monsoon (NEM) which together shape the island's climate and socio-economic activities. The SWM, occurring from May to September, contributes approximately 30% of annual rainfall, with strong influence on the wet, intermediate, and dry climatic zones. This study analyzes the spatial and temporal variability of SWM rainfall anomalies across Sri Lanka using long-term station data (1961–2024) from more than 200 rainfall-monitoring stations maintained by the Department of Meteorology. Station data were interpolated to district level using Ordinary Kriging, and visualizations were produced using ArcGIS (ArcMap 10.x). Rainfall anomalies were computed as percent of normal relative to the 1961–1990 baseline. Linear trends were assessed for the full period and for key sub-periods. Trend significance was tested using linear regression p-values and corresponding R^2 values. Results show no statistically significant long-term trend in SWM rainfall at national or zonal levels. However, recent years indicate emerging patterns: an upward tendency in the wet and intermediate zones, and a declining, though statistically non-significant, tendency in the dry zone. These findings highlight the need for continued monsoon monitoring and improved climate-resilient planning in Sri Lanka.

1. Introduction

Sri Lanka experiences two major monsoons: the Southwest Monsoon (SWM) and the Northeast Monsoon (NEM). The SWM (May–September) is a dominant climatic system, bringing strong southwesterly winds and significant rainfall to the southwestern and western parts of the island. This rainfall is crucial for agriculture, hydropower generation, water resource management, and flood mitigation.

Based on rainfall distribution, soil characteristics, and geography, Sri Lanka is divided into three climatic zones: wet, intermediate, and dry zones (Fig i). Understanding long-term variability in SWM rainfall across these zones is essential for risk management, climate adaptation, and early-warning systems.

This study investigates rainfall anomalies, trends, and variability during the SWM season from 1961 to 2024, including zonal differences and recent decadal changes.

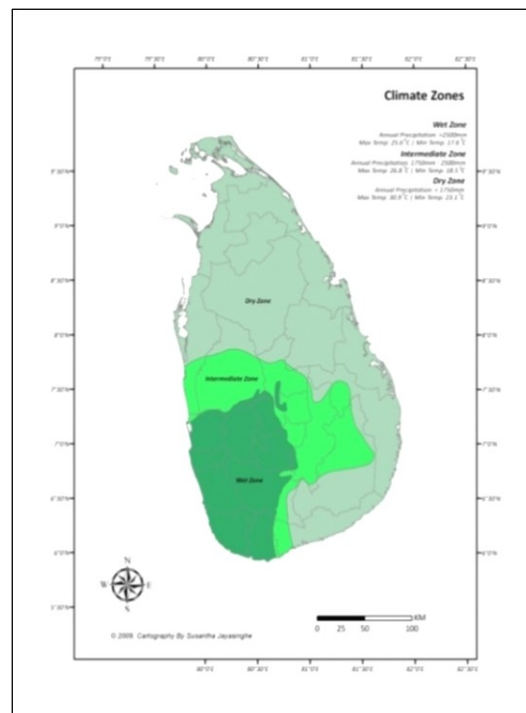


Figure (i): Climate zones in Sri Lanka (source: Department of Meteorology, Sri Lanka)

2. Data and Methodology

2.1 Data Sources

Rainfall data were obtained from more than 200 meteorological stations including synoptic meteorological and rain-gauge stations maintained by the Department of Meteorology. Seasonal totals were calculated for the Southwest Monsoon (SWM) period from May to September for each year from 1961 to 2024.

2.2 Computation of SWM Rainfall and anomaly

For each year, accumulated SWM rainfall was calculated using monthly station rainfall data from May to September. Rainfall anomalies were expressed as percent of normal, based on the 1961–1990 climatological baseline, following WMO guidelines.

2.3 Spatial Interpolation and Visualization

Spatial interpolation and mapping were carried out using the Geostatistical Analyst toolset in ArcGIS (ArcMap 10.x). The Ordinary Kriging method was selected because it provides a statistically optimal estimator for spatially dependent variables such as rainfall.

2.3.1. Interpolation method: Kriging

- Kriging incorporates both distance and spatial autocorrelation, improving accuracy compared with deterministic methods.
- SWM rainfall is strongly influenced by topography and monsoon wind patterns; Kriging captures these spatial structures through the semi variogram.
- Kriging provides prediction error surfaces, enabling assessment of uncertainty.

2.3.2 Kriging Procedure in ArcGIS

- Exploratory Spatial Data Analysis (ESDA)
- Semi variogram modeling (spherical/exponential models)
- Ordinary Kriging interpolation with optimized parameters
- Generation of interpolated rainfall anomaly raster
- Visualization using ArcMap with standardized symbology

2.4 Trend Analysis

Trends were assessed using: Linear regression for the full period (1961–2024) and sub-periods:

- 1961–1990
- 1991–2020
- 2015–2024
- Trend significance: p-values
- Explained variance: R^2 values

3. Results

3.1 SWM Rainfall Trends over Sri Lanka (1961–2024)

The SWM rainfall anomaly time series shows substantial interannual variability. The long-term SWM rainfall trend is weakly positive (+0.09% per year), but not statistically significant ($p = 0.640$, $R^2 = 0.00$), indicating no meaningful long term increase or decrease (Table i).

Sub-periods:

- 1961–1990: slight negative trend (−0.32%/yr, $p = 0.443$)
- 1991–2020: weak positive trend (+0.28%/yr, $p = 0.697$)
- 2015–2024: positive but non-significant trend (+0.26%/yr, $p = 0.871$)

Table i: SWM rainfall analysis over Sri Lanka

	Sri Lanka			
	1961-2024	1961-1990	1991-2020	2015-2024
Tend	+ 0.09	- 0.32	+ 0.28	+ 0.26
P value	0.640	0.443	0.697	0.871
R ²	0.00	0.02	0.01	0.00

3.2 SWM Rainfall Trends in Dry Zone

The dry zone shows a weak long-term positive trend (+0.16%/yr; $p = 0.470$), but all sub-periods are statistically non-significant (Table ii).

- 1961–1990: $-0.26\%/yr$ ($p = 0.621$)
- 1991–2020: $+0.71\%/yr$ ($p = 0.411$)
- 2015–2024: sharp negative trend ($-2.71\%/yr$, $p = 0.232$)

Although statistically non-significant, the recent decade indicates a noticeable downward pattern suggesting increasing rainfall deficits.

Table ii: SWM rainfall analysis over Dry zone

	Dry zone			
	1961-2024	1961-1990	1991-2020	2015-2024
Trend	+ 0.16	- 0.26	+ 0.71	- 2.71
P value	0.470	0.621	0.411	0.232
R ²	0.01	0.01	0.02	0.17

3.3 SWM Rainfall Trends in Wet Zone

The wet zone shows a weak long-term negative trend $-0.03\%/yr$ ($p = 0.851$) (Table iii).

Sub-periods:

- 1961–1990: $-0.06\%/yr$ ($p = 0.139$)
- 1991–2020: $-0.37\%/yr$ ($p = 0.540$)
- 2015–2024: $+4.53\%/yr$ (not significant; $p = 0.002$)

Table iii: SWM rainfall analysis over wet zone

	Wet zone			
	1961-2024	1961-1990	1991-2020	2015-2024
Trend	- 0.03	- 0.60	- 0.37	+ 4.53
P value	0.851	0.139	0.540	0.002
R ²	0.00	0.08	0.01	0.72

Recent years show a mild upward tendency consistent with high rainfall events.

3.4 SWM Rainfall Trend in Intermediate Zone

Long-term: $-0.01\%/yr$ ($p = 0.939$) with no significant trend (Table iv). Recent decade: $+2.79\%/yr$ ($p = 0.279$), indicating a short-term upward shift similar to the wet zone.

- 1961–1990: $-0.15\%/yr$ ($p = 0.139$)
- 1991–2020: $-0.13\%/yr$ ($p = 0.847$)
- 2015–2024: $+2.79\%/yr$ (not significant; $p = 0.279$)

Table iv: SWM rainfall analysis over Intermediate zone

	Intermediate zone			
	1961-2024	1961-1990	1991-2020	2015-2024
trend	- 0.01	- 0.15	- 0.13	+ 2.79
P value	0.939	0.719	0.847	0.279
R ²	0.00	0.00	0.00	0.14

The overall thirty-year variation of Southwest Monsoon (SWM) rainfall 199 across the climatic zones is illustrated in Fig. (ii).

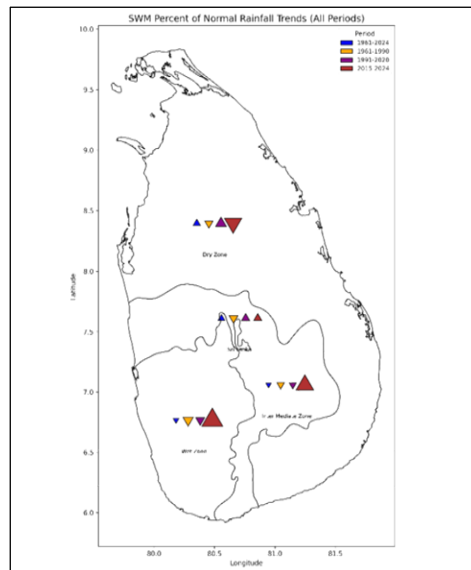


Figure (ii): SWM rainfall variation across the climatic zones

4. Discussion

Although overall SWM rainfall across Sri Lanka has remained statistically stable over the past six decades, emerging short-term signals deserve attention. Recent upward tendencies in the wet and intermediate zones align with increased extreme rainfall events reported in regional monsoon literature. Conversely, the declining tendency in the dry zone may indicate increasing drought risk.

These contrasting signals highlight the complexity of SWM responses to broader climate drivers such as ENSO, IOD, and monsoon circulation variability. Data limitations, such as station density changes and the need for homogenization, represent areas requiring further research.

5. Conclusion

Overall, the analysis confirms that no significant long-term trend exists in SWM rainfall over Sri Lanka from 1961–2024. However, the recent decades reflect an upward tendency over Sri Lanka.

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Cloudburst-Scale Rainfall Triggered by an Atmospheric River–Trough Interaction over Southwestern Sri Lanka on 1 June 2024

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ABSTRACT

An extreme rainfall event affected south-western Sri Lanka on 1 June 2024, producing widespread flooding and landslides. Several stations recorded more than 430 mm of rainfall within 24 h, with cloudburst-like hourly intensities exceeding 130 mm h^{-1} , making this one of the most intense short-duration rainfall events observed in the region. This study investigates the synoptic, dynamical, and thermodynamic processes responsible for the event using surface rainfall observations, satellite imagery, and ERA5 and JRA-3Q reanalysis data. Results show that the event was driven by a rare combination of multi-scale atmospheric processes. A deep, vertically coherent cyclonic circulation extending from the lower to mid-troposphere, together with pronounced upper-level divergence, provided sustained dynamical support for ascent. The circulation was supplied by a long, narrow corridor of enhanced tropical moisture transport from the equatorial Indian Ocean, exhibiting characteristics consistent with an Atmospheric River (AR) like moisture plume. Thermodynamic analysis revealed a deeply moist atmospheric column from 850 to 500 hPa, with a pronounced dry line like moisture gradient in the lower troposphere that focused convective development. The interaction of these features with a blocking trough near $81\text{--}82^\circ\text{E}$ and strong orographic uplift along the central highlands resulted in persistent, localized, and extreme rainfall. This case study highlights the critical role of AR, like moisture transport, blocking dynamics, and orographic enhancement in generating short-duration extreme rainfall over Sri Lanka. The findings also underscore the substantial challenges associated with forecasting such events in complex tropical terrain and emphasize the need for convection-permitting models, improved satellite and radar monitoring, and integration of atmospheric river diagnostics into operational early-warning systems.

Keywords: Extremely heavy rainfall, Atmospheric River, cloud burst, wind shear, Sri Lanka

1. Introduction

Sri Lanka, a tropical island in the Indian Ocean, receives rainfall primarily from two monsoon seasons the Southwest (SW) monsoon (May–September) and the Northeast (NE) monsoon (December–February) interspersed with two inter-monsoonal periods. The SW monsoon contributes approximately 30% of the annual rainfall and is frequently associated with heavy precipitation episodes linked to low-pressure systems, wind convergence zones, monsoon troughs, and occasional cyclones originating in the Bay of Bengal. The south-western slopes of the central highlands are particularly vulnerable to extreme rainfall, floods, and landslides, where strong orographic lifting enhances monsoon precipitation.

Several recent extreme rainfall events, including the May 2010 and May 2017 floods and the September 2020 rainfall episode (Warnasooriya et al., 2022), produced large daily rainfall totals but typically over longer durations. In contrast, the event of 1 June 2024 was exceptional in both magnitude and intensity,

delivering more than 430 mm of rainfall within 24 h, with cloudburst-scale hourly intensities approaching 130 mm h^{-1} . Extreme rainfall events in the tropics are commonly associated with strong low-level convergence and cyclonic vorticity coupled with upper-tropospheric divergence, which together create a dynamically favorable environment for deep convection (Houze, 2014; Trenberth et al., 2015).

A cloudburst is a localized extreme rainfall phenomenon characterized by highly concentrated precipitation over a limited area (typically not exceeding $20\text{--}30 \text{ km}^2$) and lasting for a short duration, often only a few hours (Sravan Kumar et al., 2012). Such events represent an extreme form of rainfall, sometimes accompanied by hail and thunder, and are capable of producing devastating flash floods, landslides, infrastructure damage, and loss of life (Sati and Maikhuri, 1992). Meteorologically, cloudbursts are associated with rainfall rates exceeding 100 mm h^{-1} , with several centimeters of rain potentially falling within minutes (Govind et al., 2012).

Unlike the gradual intensification with embedded low pressure systems typically observed during SW monsoon onsets, the June 2024 event was characterized by the presence of a deep lower-tropospheric trough interacting with an atmospheric river (AR), leading to rapid moisture flux convergence. A moisture plume is defined as a long, narrow, and transient corridor of enhanced horizontal water vapor transport originating from lower latitudes. When such a plume satisfies specific criteria related to its length, width, and vertically integrated water vapor transport, it is classified as an atmospheric river (Ralph et al., 2004; Guan and Waliser, 2015; Cordeira et al., 2013; Guan et al., 2018; American Meteorological Society, 2020).

Recent studies have highlighted the growing importance of atmospheric rivers in shaping hydroclimatic extremes across South Asia. Mahto et al. (2023) documented AR activity over the Bay of Bengal and its association with flood-producing rainfall in eastern India, while Nanditha et al. (2023) demonstrated that interactions between ARs and monsoon circulations can significantly enhance short-duration extreme precipitation over peninsular India. Extending this perspective, You et al. (2024) analyzed long-term AR climatology across South Asia and reported increasing frequency and intensity of AR landfalls in recent decades. Atmospheric rivers are long, narrow corridors of enhanced water vapor transport that can produce extreme rainfall when interacting with regional circulation and topography (Zhu and Newell, 1998; Ralph et al., 2017).

Despite increasing recognition of ARs in both mid-latitudes and South Asia (e.g., Lyngwa and Nayak, 2021; Wu et al., 2023), their role in driving extreme rainfall over Sri Lanka remains largely unexplored. The June 2024 event therefore provides a unique opportunity to examine how AR–trough interaction and orographic enhancement combined to produce unprecedented rainfall over the island’s south-western region.

Accordingly, this study investigates the synoptic and dynamical conditions leading to the 1 June 2024 extreme rainfall event, with particular emphasis on the novel contribution of atmospheric river trough blocking and orographic processes. High intensity rainfall events of this nature frequently trigger flash floods, resulting in severe damage to infrastructure and agriculture and, tragically, loss of life. While reliable forecasts and early warning systems can substantially reduce societal impacts, such extreme events remain difficult to predict due to their low-probability and highly localized nature. Detailed case studies of extreme rainfall events are therefore essential for improving predictive understanding and early warning capabilities, particularly for small tropical islands like Sri Lanka, where complex topography strongly modulates rainfall extremes.

2. Data and Methodology

2.1 Data sources

This study integrates observational, reanalysis, and satellite-based datasets to examine the extreme rainfall event on 1 June 2024.

Daily and sub-daily rainfall observations were obtained from the Department of Meteorology (DoM), Sri Lanka, and were used to characterize the spatial distribution and intensity of precipitation during the event. These data form the basis for identifying rainfall maxima and assessing the temporal evolution of the extreme rainfall.

Atmospheric fields were derived from two global reanalysis datasets: ERA5 produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) and JRA-3Q from the Japan Meteorological Agency. These datasets were used to analyze large-scale and regional atmospheric conditions, including wind fields, pressure patterns, vorticity, divergence, and moisture transport at multiple pressure levels. Using two independent reanalysis products provides additional confidence in the robustness of the diagnosed synoptic and dynamical features.

Geostationary satellite imageries were used to examine cloud evolution and convective organization associated with the event, supporting interpretation of the dynamical analyses.

2.2 Methodology

The analysis focuses on diagnosing the synoptic and dynamical mechanisms responsible for the extreme rainfall over south-western Sri Lanka. Synoptic-scale conditions were examined using horizontal wind and pressure fields at multiple pressure levels (1000, 850, 700, 500 and 200hPa) to identify the presence of low-level convergence, cyclonic circulation, and upper-level flow patterns.

Vertical atmospheric structure was assessed using vertical wind profiles and thermodynamic indicators, including dew point depression ($T-T_d$), to evaluate moisture availability and column saturation. Dynamical fields, including relative vorticity and divergence, were analyzed to assess the coupling between low–mid-tropospheric forcing and upper-level support for ascent. In addition, moisture transport pathways were examined to identify the role of long, narrow moisture plumes consistent with atmospheric river characteristics.

All analysis were performed at hourly resolution during the peak period of the event to capture the rapid evolution of atmospheric conditions leading to extreme rainfall.

3. Results

3.1 Rainfall observations

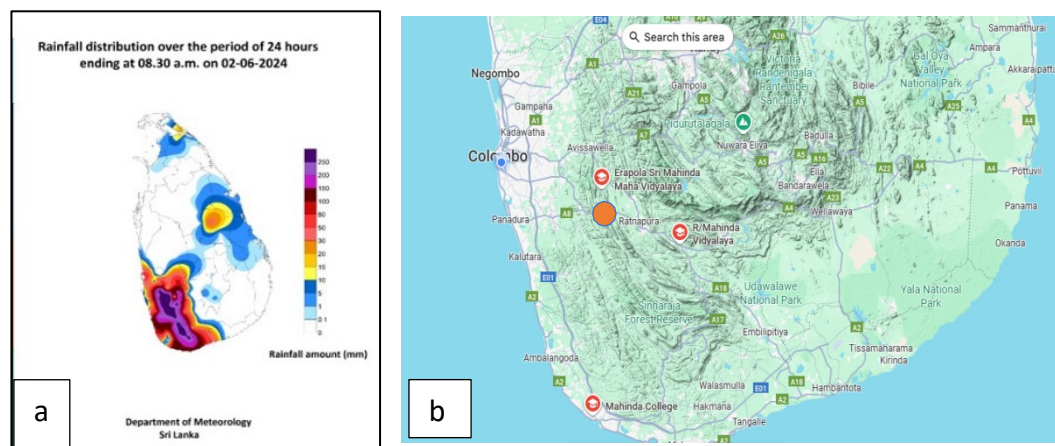
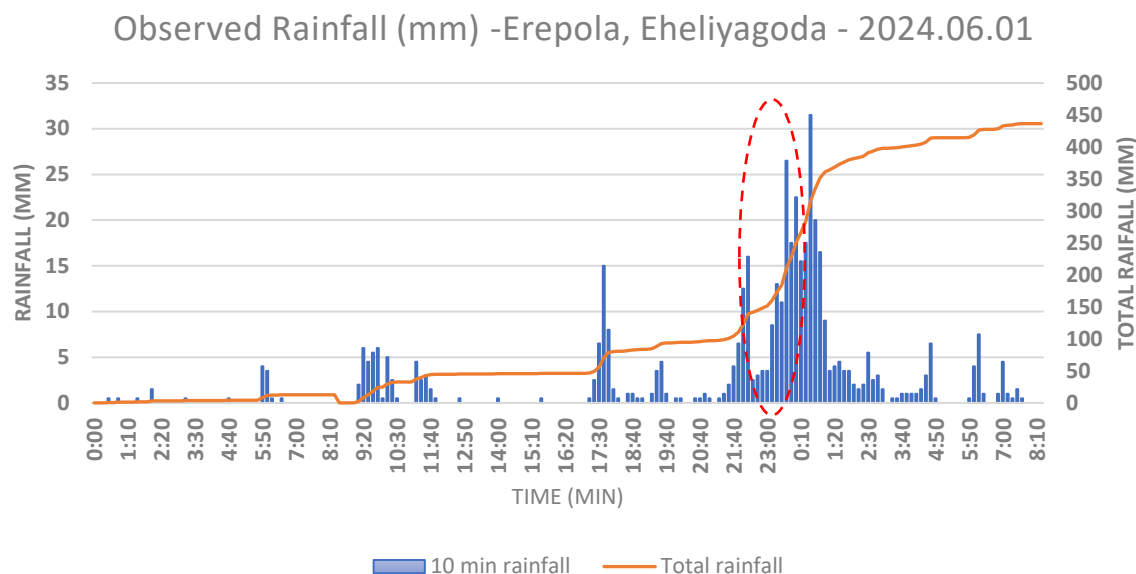


Figure 1. (a) Spatial distribution of 24-h accumulated rainfall (mm) over Sri Lanka ending at 08:30 LST on 2 June 2024, based on observations from the Department of Meteorology. (b) Locations of reported rainfall-affected sites.

The spatial distribution of 24-h rainfall is shown in Fig. 1(a), while Fig. 1(b) depicts the regional topography. The affected areas are located along the foothills of the central highlands, where steep terrain enhances orographic uplift as moist south-westerly flow ascends the windward slopes. This terrain-forced ascent likely intensified convective development, producing localized rainfall maxima in valley locations such as Kalatuwawa, Labugama, and Ehaliyagoda.



Graph 1. Observed 10-min rainfall (mm; bars) and corresponding cumulative rainfall (mm; line) at Erepola–Eheliyagoda on 1 June 2024, highlighting short-duration high-intensity rainfall leading to extreme daily totals.

The 10-min rainfall record at Erepola–Eheliyagoda on 1 June 2024 shows a short-duration episode of extreme rainfall during the night hours. Rainfall intensity increased abruptly, with several consecutive 10-min intervals reaching extreme values and producing a rapid rise in cumulative rainfall. The most intense precipitation occurred between 16:30 and 20:10 UTC, with hourly rainfall intensities exceeding 130 mm h^{-1} between 19:10 and 20:10 UTC, reflecting the combined influence of synoptic-scale forcing and topographically enhanced mesoscale processes.

Table 1. Twenty-four-hour rainfall totals recorded on 1 June 2024 at selected stations in south-western Sri Lanka, compared with historical maximum daily rainfall and long-term mean June rainfall (1981–2010).

	24-h rainfall (mm) on 1 st June 2024	Ever recorded highest rainfall/year/month Rainfall(mm)	Average monthly (June) total rainfall (mm) (1981-2010)
Kalatuwawa	490.0	548.3(2017 May)	306.9
Labugama	464.8	643.5(2017 May)	369.8
Ehaliyagoda	430.0	299.7(1939 May)	437.4

Table 1 Lists stations that recorded extreme rainfall exceeding 400 mm within 24 h on 1 June 2024. Kalatuwawa and Labugama registered 490.0 mm and 464.8 mm, respectively. The Ehaliyagoda Automatic Weather Station (AWS) in the Ratnapura District recorded 430.0 mm within 24 h, including an exceptionally intense rainfall burst of nearly 130 mm in one hour (*Graph 1*). This total exceeded all previously documented daily rainfall records at the station, surpassing the earlier maximum of 297.7 mm recorded in May 1939, highlighting the unprecedented intensity and short-duration accumulation of the event.

3.2 The driving circulation pattern/Synoptic conditions

Winds over 1000mb at 2024060120Z Winds over 850mb at 2024060120Z

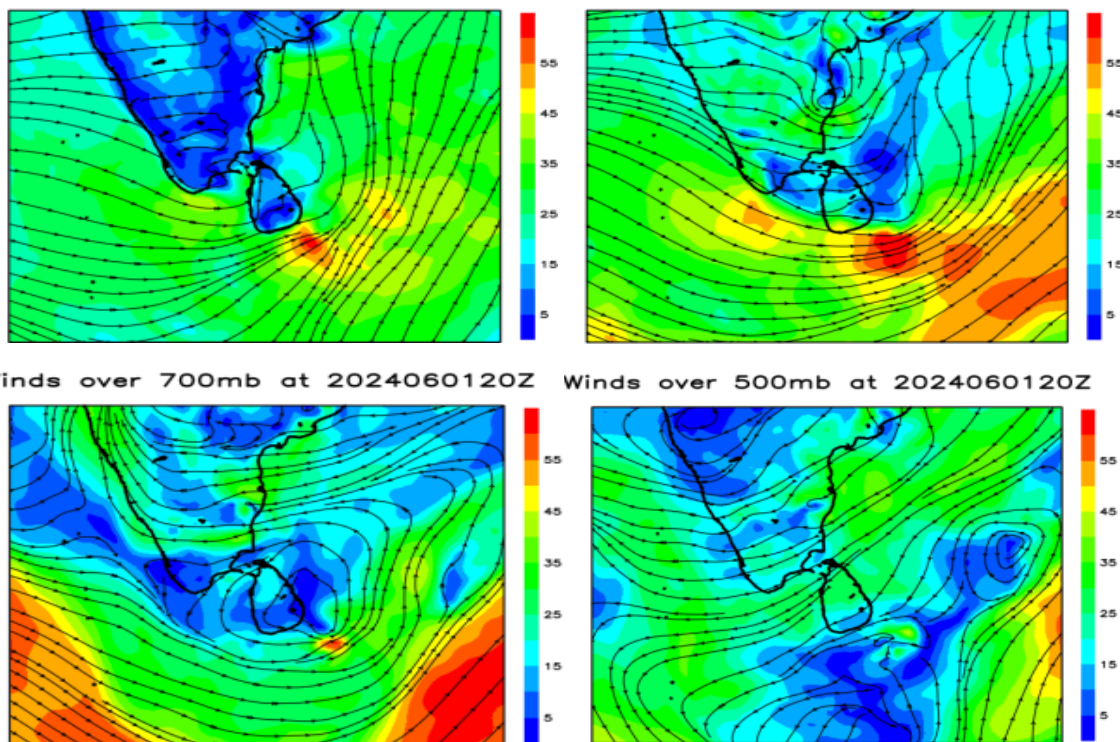


Figure 2. Horizontal wind speed (shaded, $m s^{-1}$) and streamlines at 1000, 850, 700, and 500 hPa over Sri Lanka at 20Z on 1 June 2024, illustrating the vertical structure of the circulation during the peak phase of the extreme rainfall event.

The wind fields at 20Z on 1 June 2024 reveal a vertically coherent circulation extending from the lower to the mid-troposphere. At 1000 hPa, strong south-westerly low-level inflow converges toward the south-western coast of Sri Lanka, indicating pronounced moisture transport from the adjacent ocean. This inflow intensifies at 850 hPa, where North West – South East oriented deep trough is evident, consistent with enhanced low-level convergence. At 700 hPa, a well-defined cyclonic circulation is observed, demonstrating vertical coupling between the boundary layer and mid-levels. At 500 hPa, broader-scale flow exhibits diffluent characteristics, providing upper-level dynamical support for sustained ascent. The vertical alignment of these features indicates a deep, dynamically supported system favorable for persistent and intense convection during the extreme rainfall event.

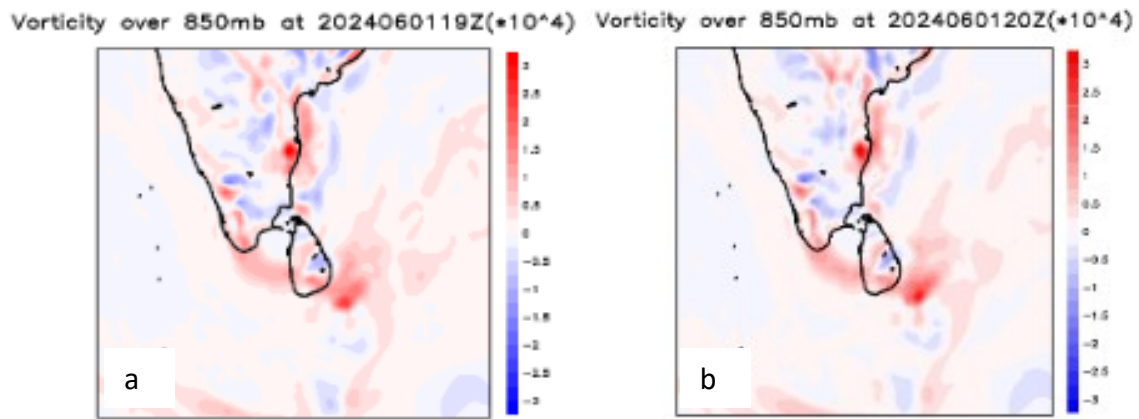


Figure 3. Relative vorticity ($\times 10^{-4} \text{ s}^{-1}$) at 850 hPa over Sri Lanka and adjacent regions at (a) 19Z and (b) 20Z on 1 June 2024. Positive values (red shading) denote cyclonic vorticity

The two panels show 850-hPa relative vorticity during the core development stage of the event (19Z–20Z, 1 June 2024). At 19Z, a distinct band of positive (cyclonic) vorticity is already established along the western to south-western coastal sector, indicating an organized low-level circulation and enhanced shear/convergence in the boundary-layer inflow region. By 20Z, the cyclonic vorticity signal intensifies and becomes more spatially coherent, with a strengthened core near the south-western coastal waters and a meridionally extended vorticity ribbon along the west coast.

The persistence and strengthening across these consecutive hours support the presence of a quasi-stationary low-level cyclonic circulation, favorable for sustained moisture convergence and the maintenance of organized deep convection during the extreme rainfall period.

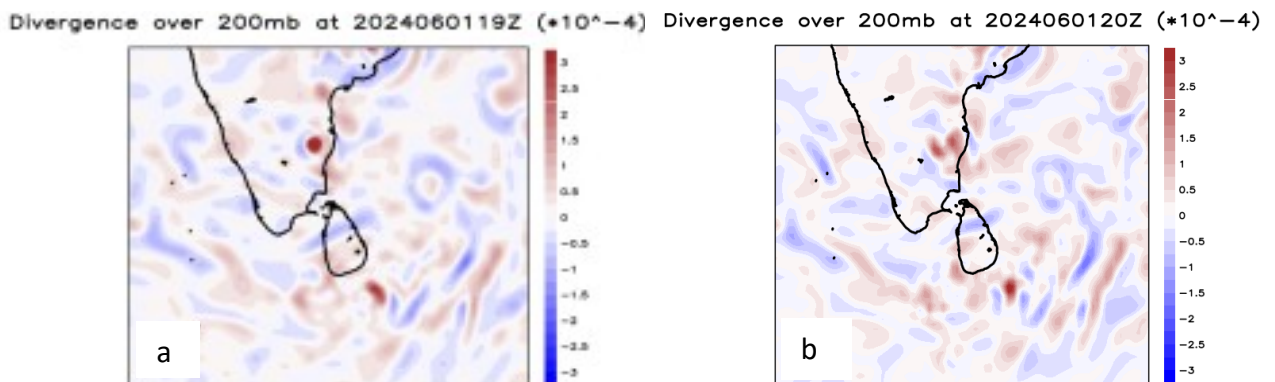


Figure 4. Divergence ($\times 10^{-4} \text{ s}^{-1}$) at 200 hPa over Sri Lanka and surrounding regions at (a) 19Z and (b) 20Z on 1 June 2024. Positive (negative) values indicate divergence (convergence). The Sri Lankan coastline is shown in black.

The 200-hPa divergence fields at 19Z and 20Z on 1 June 2024 show a persistent region of upper-level divergence over and immediately upstream of south-western Sri Lanka. At 19Z, positive divergence is already established over the western and central parts of the island, indicating favorable upper-tropospheric conditions for ascent. By 20Z, the divergent signal becomes more spatially coherent and

slightly intensifies, remaining collocated with the underlying low- and mid-level cyclonic circulation. The temporal persistence of upper-level divergence during these consecutive hours suggests sustained dynamical support for deep convection, consistent with the observed extreme rainfall during this period.

3.3 Moisture transport

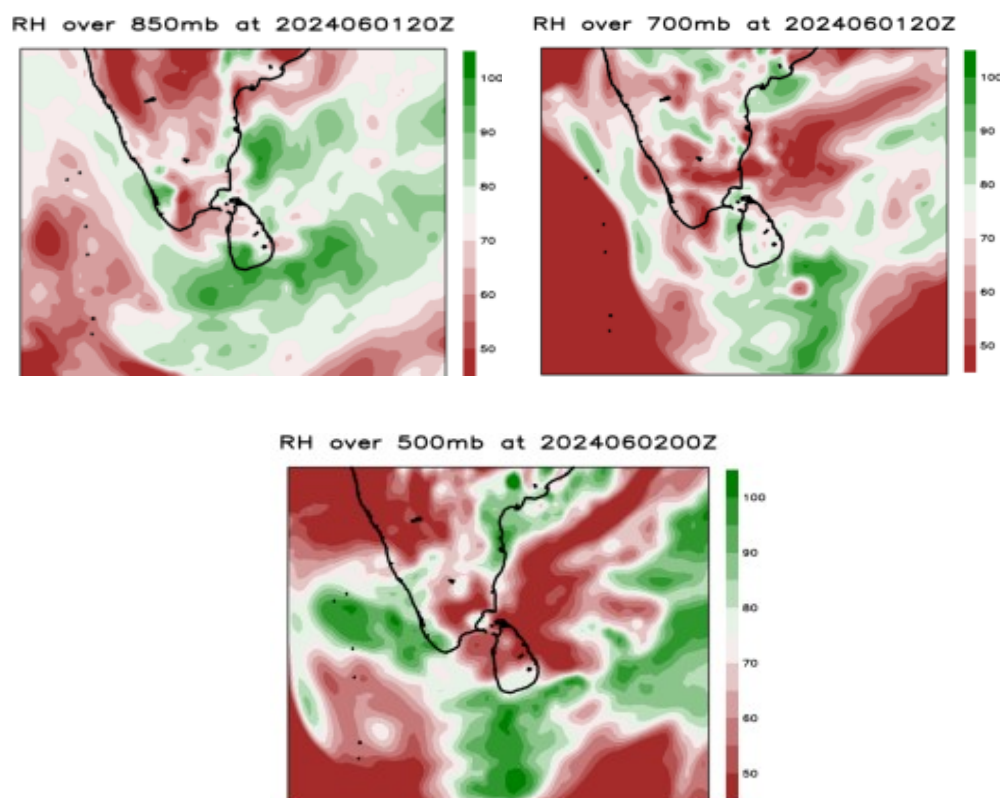


Figure 5. Relative humidity (%) at 850 hPa, 700 hPa, and 500 hPa over Sri Lanka and adjacent regions at 20Z on 1 June 2024, illustrating the vertical moisture structure during the peak phase of the extreme rainfall event. The Sri Lankan coastline is shown in black.

The relative humidity fields at 850, 700, and 500 hPa at 20Z on 1 June 2024 reveal a pronounced horizontal moisture gradient over south-western Sri Lanka and the adjacent Indian Ocean. At 850 hPa, a sharp transition is evident between a moist air mass ($RH > 80\text{--}90\%$) advected from the south-west and comparatively drier air to the north and west, forming a dry-line-like boundary in the lower troposphere. This moisture contrast is collocated with the region of intense low-level convergence identified in the wind and vorticity fields, indicating a favored zone for convective initiation.

At 700 hPa, the moisture gradient remains evident, with high humidity persisting over the south-western sector while drier air occupies the surrounding region, suggesting vertical coherence of the dry-line-like structure. At 500 hPa, although overall humidity is lower, enhanced moisture remains present above the affected region, indicating that deep convection had effectively moistened the mid-troposphere. The vertical alignment of a low-level moisture boundary with a deeply moist column implies that the dry-

line like feature acted as a focus for sustained uplift, contributing to the rapid intensification and persistence of convection during the peak rainfall period.

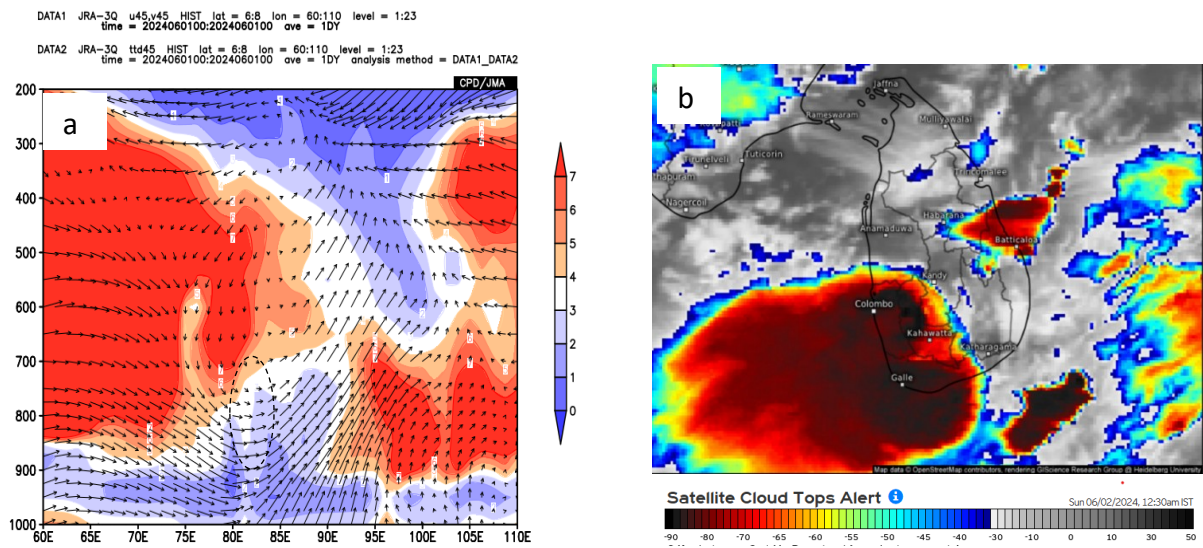


Figure 6 (a) illustrates a vertical cross-section of horizontal wind components (u, v) and dew point depression ($T-T_d$), averaged over 6° – 8° N, while Figure 6 (b) shows satellite-derived cloud-top temperatures around 19:00 UTC on 1 June 2024. Satellite imagery indicates rapid convective development between 19:00 and 20:00 UTC, coinciding with the period of peak rainfall.

The vertical cross-sectional analysis reveals a deep, vertically coherent moisture plume extending from the equatorial Indian Ocean toward south-western Sri Lanka, with enhanced low- to mid-tropospheric moisture and strong horizontal flow directed toward the island. The concentration of low $T-T_d$ values below approximately 700 hPa indicates intense moisture transport within the lower troposphere, consistent with the structural characteristics of an atmospheric river like moisture plume (Ralph et al., 2004; Guan and Waliser, 2015; AMS, 2020). The upward tilt of the flow with height and the convergence of vectors near Sri Lanka suggest forced ascent as the moisture-laden air impinges on the regional circulation and topography.

Moisture convergence was further enhanced by the presence of a blocking trough near 81° – 82° E, which limited the eastward progression of the synoptic system and promoted quasi-stationary conditions. Such blocking configurations are known to focus and prolong moisture transport into confined regions by disrupting the background westerly flow (Rex, 1950; Nakamura and Huang, 2018). In this case, the interaction between the AR-like moisture plume and the blocking trough effectively anchored moisture delivery over south-western Sri Lanka, while persistent south-westerly flow and orographic uplift sustained deep convection and extreme rainfall.

The right panel (satellite cloud-top temperature imagery) shows a large, organized convective cloud mass over the south-western Indian Ocean and Sri Lanka, with very cold cloud tops ($< -70^{\circ}\text{C}$) during

the same period. The spatial alignment between the deep convective system and the upstream moisture transport corridor indicates that the sustained supply of tropical moisture directly supported the development and persistence of intense convection over south-western Sri Lanka.

3.4 Weather Forecasts

Despite substantial advances in numerical weather prediction and satellite-based monitoring, forecasting short duration, cloudburst like rainfall events of this intensity remains a major challenge in Sri Lanka and across South Asia. While synoptic-scale precursors such as atmospheric river associated moisture transport, dry line formation, and trough blocking can often be identified in advance, the precise timing, location, and magnitude of extreme hourly rainfall are difficult to resolve using current operational forecasting systems. This limitation underscores the need for enhanced high-resolution forecasting capabilities, improved utilization of satellite observations and the incorporation of atmospheric river diagnostics into early warning frameworks. The absence of real time weather radar observations in Sri Lanka further constrains the ability to monitor and nowcast rapidly evolving convective systems.

Accurate prediction is further complicated by the interaction of multiple spatial and temporal scales. Although low-mid-level cyclonic vorticity and upper level divergence establish a favorable large scale environment for convection, the occurrence of extreme rainfall is strongly modulated by local orographic forcing and mesoscale convective processes. Numerical weather prediction models often struggle to capture these localized enhancements due to coarse horizontal resolution, uncertainties in cloud microphysical parameterizations, and the complex terrain of the central highlands. Moreover, the rapid intensification of convection within a short time window, as observed at Ehaliyagoda, presents a significant challenge for both deterministic forecasts and ensemble-based guidance. These limitations highlight the urgent need for convection permitting models, enhanced radar and satellite monitoring, and improved data assimilation strategies to support more reliable early warning of extreme rainfall events in terrain-influenced regions.

4. Discussion

The extreme rainfall event on 1 June 2024 over south-western Sri Lanka resulted from an efficient coupling of synoptic-scale forcing, mesoscale organization, and local orographic enhancement. Observations show that a large fraction of the daily rainfall accumulated within a short nocturnal window, with hourly intensities exceeding 130 mm h^{-1} , exhibiting a cloudburst-like rainfall structure indicative of highly concentrated, short-duration precipitation.

At the synoptic scale, the event was associated with a low-level convergence, trough and cyclonic circulation accompanied by pronounced upper-level divergence, providing a dynamically favorable environment for sustained ascent. Embedded within this circulation was a long, narrow corridor of enhanced moisture transport from the equatorial Indian Ocean toward Sri Lanka, consistent with an atmospheric river like moisture plume. Although integrated vapor transport was not explicitly quantified, the vertical structure, persistence, and spatial coherence of the moisture plume resemble AR-associated transport documented in other tropical extreme rainfall events.

Thermodynamic conditions further supported intense convection, with a deeply moist atmospheric column extending from 850 to 500 hPa during the peak phase. Superimposed on this moist background, a pronounced dry line like moisture gradient in the lower troposphere marked a sharp transition between moist south-westerly inflow and drier surrounding air. The alignment of this moisture boundary with regions of enhanced low-level convergence likely acted as a mesoscale trigger, focusing convective initiation and intensification.

The persistence of extreme rainfall was enhanced by the presence of a blocking trough near 81–82°E, which limited the eastward propagation of the synoptic system and anchored moisture delivery over south-western Sri Lanka. Such blocking configurations disrupt the background westerly flow and promote quasi-stationary conditions, focusing moisture transport over confined regions (Rex, 1950; Nakamura and Huang, 2018). Within this environment, the moisture plume exhibited characteristics consistent with an atmospheric river-like structure, defined as a long, narrow corridor of enhanced water vapor transport (Zhu and Newell, 1998; Ralph et al., 2004; Guan and Waliser, 2015). The interaction between AR-like moisture transport and blocking dynamics has been widely associated with prolonged heavy rainfall and flood events in various regions worldwide (Ralph et al., 2017).

This quasi-stationary configuration, combined with strong orographic uplift along the windward slopes of the central highlands, amplified convective development and produced highly localized rainfall maxima at stations such as Kalatuwawa, Labugama, and Ehaliyagoda.

From a forecasting perspective, this event highlights the difficulty of predicting short duration extreme rainfall in complex tropical terrain. While large scale precursors such as moisture plumes, troughs, and favorable upper-level dynamics may be identifiable, the precise timing and localization of cloudburst-like rainfall remain challenging for current operational models. Improving early warning capabilities will require convection permitting models, enhanced satellite and radar observations, and the integration of atmospheric river diagnostics into operational forecasting frameworks, particularly for terrain influenced countries such as Sri Lanka.

5. Conclusions

This study investigated the synoptic, dynamical, and thermodynamic processes responsible for the extreme rainfall event on 1 June 2024 over south-western Sri Lanka. The event was exceptional in both magnitude and intensity, with more than 430 mm of rainfall recorded within 24 h at several locations and cloudburst-like hourly intensities exceeding 130 mm h^{-1} , resulting in severe flooding and landslides.

The analysis demonstrates that the event resulted from a rare and highly efficient combination of atmospheric processes operating across multiple spatial scales. At the synoptic scale, convergence, a deep trough and vertically coherent cyclonic circulation, coupled with pronounced upper-level divergence, provided sustained dynamical support for ascent. This circulation was supplied by a long, narrow corridor of enhanced tropical moisture transport, exhibiting characteristics consistent with an atmospheric river like moisture plume, which continuously replenished moisture over the affected region.

Thermodynamic conditions further favored intense convection, with a deeply moist atmospheric column extending from 850 to 500 hPa during the peak phase of the event. The presence of a dry line like moisture gradient in the lower troposphere acted as a mesoscale focusing mechanism for convection, while a blocking trough near $81\text{--}82^\circ\text{E}$ restricted eastward system progression and prolonged moisture convergence. These large-scale and mesoscale processes were strongly amplified by orographic uplift along the windward slopes of the central highlands, producing highly localized rainfall maxima at stations such as Kalatuwawa, Labugama, and Ehaliyagoda.

The findings highlight the significant challenges associated with forecasting short duration, high impact rainfall events in complex tropical terrain. Although large-scale precursors such as moisture plumes, troughs, and favorable upper-level dynamics may be detectable in advance, the precise timing and localization of cloudburst like rainfall remain difficult to predict using current operational forecasting systems. Enhancing early warning capabilities in Sri Lanka will require the adoption of convection-permitting numerical models, improved satellite-based monitoring, the introduction of weather radar observations, and the systematic incorporation of atmospheric river diagnostics into operational forecasting and decision-support frameworks.

Overall, this case study provides new insight into the role of AR-like moisture transport, blocking dynamics, and orographic enhancement in producing extreme rainfall over Sri Lanka. As climate variability and warming may increase the likelihood of such high impact events, improved understanding of these mechanisms is essential for strengthening disaster preparedness, risk reduction, and early warning systems in the region

Acknowledgements

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Integrated Drought Monitoring in Sri Lanka Using an SPI based CDI–CDSI Framework (1981–2025)

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ABSTRACT

Drought is a recurrent and spatially heterogeneous hazard in Sri Lanka, exerting severe impacts on agriculture, water resources, and socio-economic stability. This study develops an integrated drought monitoring framework to support early detection of emerging drought conditions using rainfall anomalies. A Composite Drought Index (CDI) derived from multi-scale Standardized Precipitation Index (SPI) values were used to characterize drought intensity and duration at the Divisional Secretariat Division (DSD) scale across Sri Lanka for the period 1981–2025. To capture national scale drought severity, a Composite Drought Severity Index (CDSI) was formulated by integrating mean CDI intensity with the proportion of drought affected DSDs, thereby jointly representing temporal severity and spatial extent. Drought severity was normalized and classified into standardized categories ranging from mild to extreme. Analysis of the 45-year record identified 14 major drought events, including long duration and high-intensity droughts, as well as prolonged nationwide episodes consistent with historically documented drought impacts in Sri Lanka. The CDI–CDSI framework effectively captures the multi-temporal evolution and spatial propagation of drought conditions, demonstrating strong capability in distinguishing localized, regional, and national-scale drought events. The proposed approach provides a robust and operationally relevant tool for drought monitoring, early warning, and hazard mapping, with direct applicability for national climate resilience planning and agricultural risk management in Sri Lanka.

1. Introduction

Drought is a multi-stage phenomenon that typically originates from rainfall deficits and progressively propagates into agricultural, hydrological, and ultimately socio-economic impacts. Sri Lanka's economy and food security are particularly vulnerable to drought due to the country's strong dependence on monsoon rainfall and rain fed agriculture. As one of the most frequent and damaging natural hazards, drought affects nearly all agro ecological zones in Sri Lanka, resulting in substantial agricultural losses, water scarcity, and socio-economic disruption (Disanayake et al., 2021; Bayissa et al., 2022). The national rainfall regime is governed by the Southwest (May–September) and Northeast (December–February) monsoons, two inter-monsoonal periods, and localized convective rainfall, producing pronounced spatial and temporal variability (Punyawardena & Kulasiri, 2013; Chandrapala, 2020). This inherent variability leads to recurrent and regionally diverse drought patterns across the island.

Sri Lanka has experienced numerous severe and widespread droughts over recent decades, including major events in 1968, 1974, the early 1980s, the mid-1990s, 2001–2002, 2016–2017, and 2019, which

caused significant impacts on crop production, reservoir storage, and rural livelihoods (Amaraweera et al., 2018; Naveendrakumar et al., 2018; Abeysingha, 2020; DMC, 2016; Kajendram et al., 2024). These droughts were characterized by persistent rainfall deficits, particularly across the Dry and Intermediate Zones, with several events extending into parts of the Wet Zone (Abeysingha, 2020; Ampitiyawatta & Wimalasiri, 2023). Multi-timescale analyses using the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) further confirm the severity, duration, and spatial extent of these historical droughts, including extreme conditions during 2016–2017 (Somasundaram et al., 2024). Together, these events underscore the critical need for robust drought monitoring and early warning systems in Sri Lanka.

Among available drought indicators, the SPI remains one of the most widely used tools for operational drought monitoring due to its simplicity, robustness, and modest data requirements (McKee et al., 1993; WMO, 2012). However, SPI assessments at a single temporal scale are insufficient to fully characterize drought processes that evolve across multiple temporal and spatial scales (Mishra & Singh, 2010). Short term droughts primarily affect soil moisture and crop growth, whereas prolonged droughts influence groundwater recharge, reservoir storage, and broader hydrological systems. Consequently, a multi scale approach is essential for capturing the compound behavior of drought as it develops and propagates through successive stages. Early detection of rainfall driven meteorological drought is particularly critical, as agricultural, hydrological, and socio-economic droughts represent subsequent phases of drought evolution.

To address these limitations, recent research has increasingly adopted composite drought indicators that integrate multiple SPI time scales or combine meteorological indices with evapotranspiration, soil moisture, and vegetation-based information (e.g., NDVI) to better represent drought dynamics and impacts (Vicente-Serrano et al., 2010; Zargar et al., 2011; Hao & AghaKouchak, 2013). Such composite approaches have been successfully applied across diverse climatic regions, including South Asia, enhancing sensitivity to both agricultural and hydrological drought conditions (Zhou et al., 2021; Bayissa et al., 2022; Shahid et al., 2023). For example, Şerban and Maftai (2025) demonstrated the effectiveness of a high resolution Composite Drought Index (CDI) in capturing spatiotemporal drought patterns in Romania through strong relationships with SPI and SPEI. In the Sri Lankan context, integrating meteorological and remote-sensing-based indices has also proven effective in improving spatial drought characterization and agricultural impact assessment (De Silva et al., 2023).

Despite these advances, existing drought studies in Sri Lanka have largely focused on single index analyses, sector specific drought characterization, or spatial assessments without explicitly integrating drought intensity and national-scale spatial extent into a unified severity metric. While composite indices have improved drought characterization at local or sectoral scales, a clear gap remains in the

development of an operational, rainfall driven framework capable of capturing the onset, persistence, and nationwide propagation of meteorological drought using a consistent multi-scale approach.

This study addresses this gap by focusing on the early stage of drought development and capturing emerging drought conditions driven by rainfall anomalies. By integrating multi-scale precipitation-derived SPI with a Composite Drought Index (CDI), this study develops a Composite Drought Severity Index (CDSI) that jointly represents drought intensity and spatial extent across Sri Lanka. The proposed CDI–CDSI framework is designed to identify the onset, persistence, and spatial coherence of meteorological drought, providing early warning signals of potential downstream agricultural and hydrological impacts rather than directly quantifying those impacts.

This study introduces a novel CDI–CDSI framework for Sri Lanka that integrates multi-scale SPI derived drought intensity with national spatial extent to enable early detection of meteorological drought.

1.1 Objectives of the Study

This study aims to the early detection of drought by focusing on rainfall-driven meteorological drought, recognizing that agricultural, hydrological, and socio-economic droughts represent subsequent stages of drought propagation. It does so by developing an integrated framework for monitoring and assessing drought conditions across Sri Lanka using a multi-scale (spatial and temporal) approach.

The specific objectives are to:

- Develop a Composite Drought Index (CDI) by integrating Standardized Precipitation Index (SPI) values at 3, 6, and 9-month timescales, optimized through weighted combination to represent short, medium, and long term drought conditions.
- Quantify drought severity and classify drought hazards at the Divisional Secretariat Division (DSD) level using normalized CDI values and categorical drought classes.
- Formulate a Composite Drought Severity Index (CDSI) by integrating national scale CDI averages and the percentage of drought affected DSDs to assess the temporal and spatial extent of droughts.
- Examine the temporal dynamics of drought across the 45-year period (1981–2025) to identify major drought episodes, their duration, and severity characteristics.

2. Data and Methodology

2.1 Study area

Sri Lanka is a tropical island in the northern Indian Ocean ($5^{\circ}55' - 9^{\circ}51' \text{ N}$, $79^{\circ}41' - 81^{\circ}53' \text{ E}$) with a land area of approximately 65,610 km². The country exhibits strong spatial variability in rainfall, reflected in the Wet, Intermediate, and Dry Zones, which display distinct drought characteristics. In this study, drought conditions are assessed at the Divisional Secretariat Division (DSD) level ($n = 331$), enabling a detailed national-scale analysis of spatial drought variability.

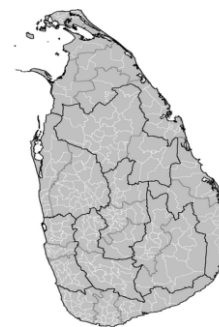


Figure 1. Administrative boundary data sourced from the Humanitarian Data Exchange (HDX), Sri Lanka administrative divisions.

2.2 Data Sources and Quality Control

Monthly precipitation data for 331 Divisional Secretariat Divisions (DSDs) covering the period 1981–2025 were obtained from the Department of Meteorology, Sri Lanka.

All rainfall series underwent a multi-step quality control and homogenization process to ensure data reliability and spatial consistency:

- Visual inspection was conducted to identify and correct apparent outliers, missing segments, and discontinuities.
- Cross-validation was performed using the inter-quartile range and double mass curve methods to detect inconsistencies relative to neighbouring stations.
- Gap filling was applied for short-term data gaps (≤ 3 months) using the Kriging interpolation method based on adjacent DSDs.

These steps collectively improved the spatial completeness and temporal continuity of the national rainfall data set, forming a reliable foundation for subsequent drought analysis.

2.3 Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) (McKee et al., 1993) was computed at 3, 6 and 9 months accumulation periods to represent short, medium, and long-term precipitation anomalies, respectively. Monthly precipitation totals were fitted to a gamma probability distribution using maximum likelihood estimation, then transformed into a standard normal distribution. Zero-rainfall months were adjusted following the World Meteorological Organization (WMO, 2012) recommended procedure.

Each SPI value reflects the standardized deviation of observed precipitation from the 1981–2025 climatological baseline, expressed in standard deviation units. Negative SPI values indicate dry

conditions, while positive values denote wet anomalies. These multi temporal SPI series provided the basis for the Composite Drought Index (CDI) development described in the next section.

2.4 Composite Drought Index (CDI)

To capture the multi-temporal characteristics of drought, a Composite Drought Index (CDI) was developed by integrating three Standardized Precipitation Index (SPI) time scales 3 month (SPI₃), 6 month (SPI₆), and 9 month (SPI₉) representing short, medium, and long-term moisture anomalies, respectively. Each scale contributes distinct hydrological and agricultural relevance. SPI₃ captures immediate meteorological and soil moisture deficits, SPI₆ reflects seasonal agricultural impacts, and SPI₉ identifies prolonged hydrological drought conditions.

The CDI for each DSD and month was computed as a weighted linear combination of the three SPI series:

$$CDI = 0.40(SPI_3) + 0.35(SPI_6) + 0.25(SPI_9)$$

The weighting scheme was optimized through sensitivity analysis to balance responsiveness to short-term rainfall anomalies and stability in longer-term drought signals. The 0.40, 0.35, 0.25 weighting combination provided the best representation of observed drought progression and recovery patterns across different climatic zones of Sri Lanka. To ensure comparability across regions and seasons, SPI values were normalized to a 0–1 scale using the min–max normalization method:

SPI is defined such that negative values indicate dry conditions. Therefore, a monotonic mapping was applied to transform SPI into a positive drought severity metric that is comparable across accumulation periods. To maintain continuity in drought severity representation, SPI-3, SPI-6, and SPI-9 were normalized to a common scale, preserving the relative magnitude of drought conditions while facilitating cross time scale comparison. For each SPI value s , define severity $S = \max(0, -s)$. That yields 0 for no drought ($SPI \geq 0$) and positive severity increasing with negative SPI. Optionally scale by an upper cap (e.g., 3) so severity is bounded:

$$S' = \frac{\min(S, 3)}{3} \in [0, 1].$$

Following relationship is used the transformation:

$$S' = \frac{\min(\max(0, -SPI), 3)}{3}$$

where:

- $SPI < 0 \rightarrow$ dry conditions, $SPI \geq 0 \rightarrow$ no drought,
- $S' \in [0, 1] \rightarrow$ normalized drought severity index.

Thus: For calculate CDI,

$$0.0 = \text{No drought and } 1.0 = \text{Extreme drought (similar to } \text{SPI} \leq -3))$$

This follows the standardized drought severity mapping framework originally proposed by McKee et al. (1993). Accordingly, CDI thresholds adopted are shown in following Table 1.

Table 1. Classification of drought severity based on Composite Drought Index (CDI) ranges and their corresponding Standardized Precipitation Index (SPI) thresholds, with associated drought categories and descriptions.

Equivalent SPI Threshold	Drought Category	CDI Range (for a DSD)	Mean_CDI Range (average for Sri lanka)	Description
≤ -2.0 to -3.00	Extreme	≥ 0.833	≥ 0.213	Exceptional and widespread drought
-1.5 to -1.99	Severe	$0.667 - 0.832$	$0.170 - 0.212$	Serious hydrological and agricultural drought
-1.0 to -1.49	Moderate	$0.500 - 0.666$	$0.127 - 0.169$	Noticeable moisture deficit
-0.5 to -0.99	Mild	$0.333 - 0.499$	$0.084 - 0.126$	Light dryness
> -0.5	No Drought	< 0.333	< 0.084	Near-normal to wet

This classification enabled spatial mapping of drought hazard intensity at the DSD level and facilitated the identification of both localized and nationwide drought episodes.

2.5 Composite Drought Severity Index (CDSI)

While the Composite Drought Index (CDI) provides detailed drought characterization at the Divisional Secretariat Division (DSD) level, national-scale drought monitoring requires a metric that simultaneously represents drought intensity and spatial extent. To achieve this, a Composite Drought Severity Index (CDSI) was formulated by integrating the monthly national average CDI and the proportion of drought affected DSDs. The Composite Severity Coverage Index (CDSI) Composite Drought Severity Index (CDSI) was formulated following the severity area integration approach widely used in drought monitoring studies (Hayes et al., 1999; Svoboda et al., 2002), where drought severity classes are weighted by their spatial coverage.

Mean CDI was calculated across DSDs to obtain national drought severity. Additionally, drought extent (% area under drought) was computed per month to derive the Composite Drought Severity Index (CDSI).

The Composite Drought Severity Index (CDSI) quantifies the combined influence of drought intensity and spatial extent as a weighted sum of area under different severity classes (Moderate, Severe or Extreme).

The CDSI for a month was computed as:

- National monthly mean CDI (CDI_{mean}) = average of all DSD CDI values (drought intensity).

$$CDI_{national,month} = \frac{1}{N} \sum_{i=1}^N CDI_{i,month}$$

Where

- $N=331$ (number of DSDs)
- $CDI_{i,month}$ = composite drought index for DSD i at that month
- The threshold of $CDI \geq 0.5$ was adopted to delineate drought-affected areas, as the CDI is normalized to a 0–1 scale and values above 0.5 represent the upper half of drought severity. This threshold effectively captures DSDs experiencing persistent and concurrent drought signals across multiple time scales, corresponding to moderate, severe, and extreme drought conditions, while excluding weak or transient anomalies. The use of this mid-scale cut-off ensures a robust and policy-relevant estimation of drought spatial extent.

Let $I_t = CDI_{mean}_t$ (already in $[0,1]$).

Let $E_t = PctArea_t / 100$ (in $[0,1]$).

$PctArea_t$ = percentage of Divisional Secretariat Divisions (DSDs) experiencing drought at time t .

$CDSI_t = I_t * E_t$

Interpretation

- Higher CDSI $\rightarrow$ drought is more widespread and/or more severe
- Units are composite (severity $\times$ % area)

The CDSI ranges from 0 (no drought) to 1 (nationwide extreme drought), thereby providing an integrated measure of drought severity that accounts for both the intensity of local drought conditions and the spatial coverage of drought-affected areas.

The classification thresholds for CDSI were empirically defined in this study based on the distribution of drought intensity and spatial coverage (Table 2).

Table 2. The classification thresholds for CDSI :

CDSI Range	Drought Category	Description
0.0 – 0.083	No Drought	Normal to wet conditions
0.084 – 0.126	Mild	Localized short-term dryness
0.127 – 0.169	Moderate	Regional drought with notable impacts
0.170 – 0.213	Severe	Widespread drought affecting multiple regions
0.214 – 1.0	extream	National scale drought

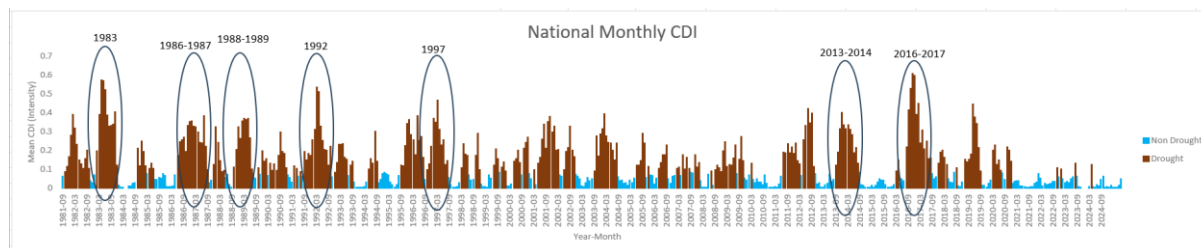
A normalized monthly drought severity index (S'), ranging from 0 to 1, was computed at the Divisional Secretariat Division (DSD) scale. National mean seasonal severity was then derived by averaging S' across all 331 DSDs for each season. As spatial averaging tends to attenuate severity magnitudes, adjusted absolute thresholds were applied to the national S' to classify drought intensity: In addition, a relative classification based on standardized anomalies (z-scores) was employed to identify anomalous seasons, with threshold values calibrated against historically documented drought events.

Drought is a complex, multi-stage phenomenon that typically evolves from meteorological drought, driven by rainfall deficits, to agricultural and hydrological drought, and ultimately to socio-economic drought as impacts propagate through natural and human systems. The present study focuses on the early stage of drought development by capturing emerging drought conditions using rainfall-based anomalies. By integrating precipitation-derived SPI with CDI, the proposed CDSI is designed to identify the onset, persistence, and spatial coherence of meteorological drought, thereby providing early warning signals of potential downstream agricultural and hydrological impacts rather than directly quantifying those impacts.

3. Results and Discussion

3.1 Temporal drought variability based on CDI

The temporal evolution of drought conditions was first examined using the national monthly Composite Drought Index (CDI), which primarily reflects drought severity and persistence at the national scale.



Graph 1. Temporal evolution of the national monthly Composite Drought Index (CDI). Magnitude and duration reflect drought severity and persistence at the national scale across Sri Lanka during 1980-2025.

Notably, the severe drought events of 1983, 1986–1987, 1988–1989, 1992, 1997, 2013–2014 and 2016–2017 are evident as sustained higher CDI values extending over several months. Frequent minor CDI excursions between these major events demonstrate the country's susceptibility to recurrent short-term meteorological droughts.

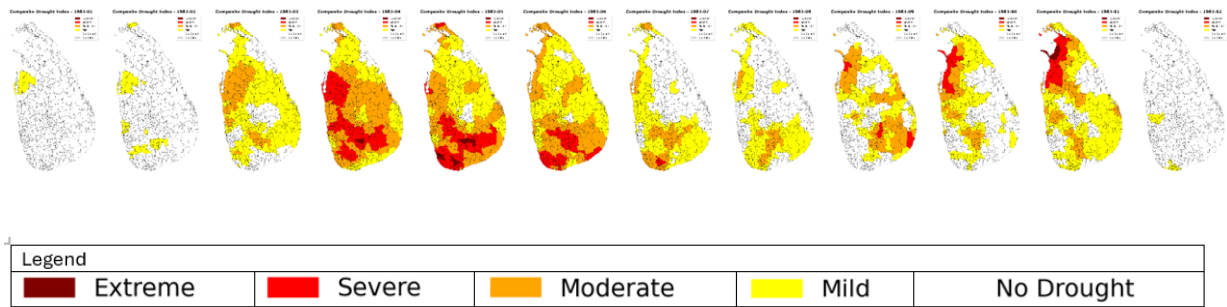


Figure 2. Monthly Composite Drought Index (CDI) maps and drought-affected area (%) depicting the progression of meteorological drought across Sri Lanka during January to December 1983.

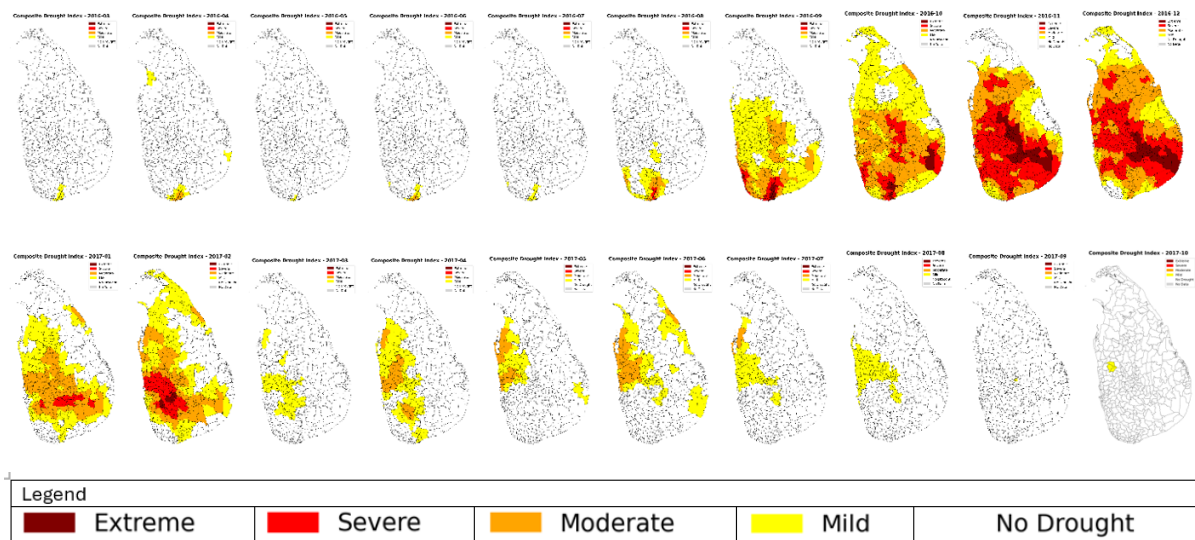
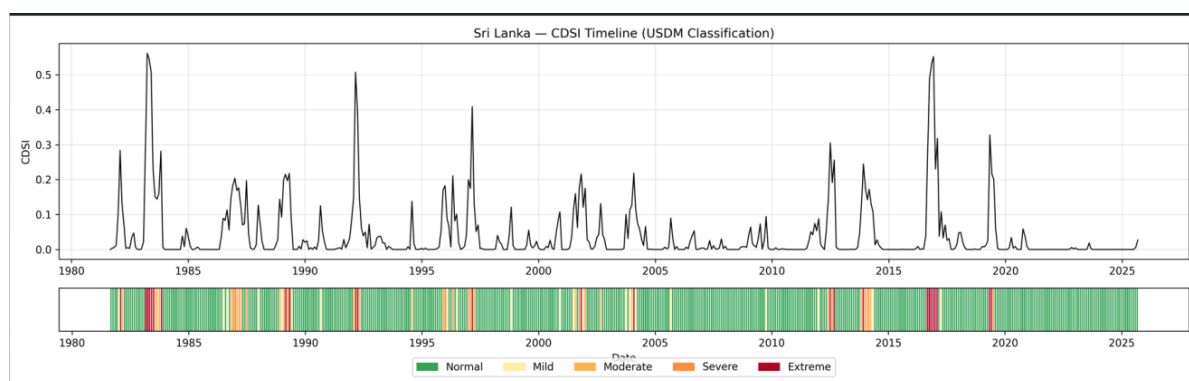


Figure 3. Monthly Composite Drought Index (CDI) maps and drought-affected area (%) depicting the progression of meteorological drought across Sri Lanka during January to December 2016 (upper) & 2017 (lower)

The monthly CDI maps (Figure 2 & 3) for 1983 and 2016–2017 show a clear progression from localized drought onset to widespread and persistent drought conditions across Sri Lanka. Drought severity intensifies early 1983 and during mid–late 2016 and extends into 2017, with high CDI values expanding across the dry, intermediate and wet zones. Both events characterized by rapid spatial expansion and sustained monthly severity. The CDI maps demonstrate a clear ability to capture monthly drought conditions, resolving both the timing and spatial evolution. Month-to-month changes in CDI values reflect the rapid development, persistence, and decay of drought conditions, highlighting the index's suitability for sub-seasonal and operational drought monitoring.

3.2 Composite Severity Coverage Index (CDSI).

While CDI effectively characterizes the temporal dimension of drought, it does not explicitly capture spatial coherence, necessitating the use of an integrated index for comprehensive drought assessment. Drought severity is defined temporally by CDI anomalies and spatiotemporally by CDSI, which integrates severity with spatial extent.



Graph 2. Temporal evolution of the national Composite Drought Severity Index (CDSI) for Sri Lanka from 1980 to 2024. The upper panel shows the continuous CDSI time series, while the lower panel presents corresponding drought classifications based on U.S. adopted categories, ranging from normal to extreme drought.

The Graph 2, CDSI time series shows distinct episodic peaks indicating drought events of varying severity and spatial coherence across Sri Lanka. Moderate droughts occur frequently, while severe and extreme events are less common but marked by higher CDSI values and greater spatial extent. Several events persist over multiple months, reflecting sustained and coherent drought conditions rather than short-lived anomalies. Overall, the CDSI clearly distinguishes isolated drought signals from major, long-duration drought episodes, highlighting strong interannual variability in national drought severity.

Table 3. Top 10 drought events in Sri Lanka ranked by duration, identified using the Composite Drought Severity Index (CDSI), showing event start and end dates, duration (months), peak drought class, and corresponding CDSI values.

Sri Lanka CDSI_Top10_Events_By_Duration				
start	end	duration_months	peak_class	peak_value
1983-03-01 00:00:00	1983-11-01 00:00:00	9	Extreme	0.561460777
1988-12-01 00:00:00	1989-06-01 00:00:00	7	Extreme	0.217543066
2013-11-01 00:00:00	2014-05-01 00:00:00	7	Extreme	0.244556846
1986-11-01 00:00:00	1987-04-01 00:00:00	6	Severe	0.203940191
2016-09-01 00:00:00	2017-02-01 00:00:00	6	Extreme	0.552112089
1992-02-01 00:00:00	1992-05-01 00:00:00	4	Extreme	0.507440198
1997-01-01 00:00:00	1997-04-01 00:00:00	4	Extreme	0.408806054
2001-10-01 00:00:00	2002-01-01 00:00:00	4	Extreme	0.216193663
2003-12-01 00:00:00	2004-03-01 00:00:00	4	Extreme	0.218510024
2012-06-01 00:00:00	2012-09-01 00:00:00	4	Extreme	0.304793032

The top 10 drought events ranked by duration show that Sri Lanka's longest droughts are seasonal to sub-annual, lasting 4–9 months, with extreme droughts dominating nearly all events. The most prolonged and severe episode occurred during March–November 1983, while other extended droughts recur in the late 1980s, early 1990s, early 2000s, and mid-2010s, indicating multi-decadal repetition of high-impact droughts. Peak CDSI values are consistently high for longer events, suggesting that drought persistence is commonly accompanied by increased severity, and reinforcing the episodic yet high-impact nature of drought risk in Sri Lanka.

Table 4. Top 10 drought events in Sri Lanka ranked by intensity, identified using the Composite Drought Severity Index (CDSI), showing event start and end dates, duration (months), peak drought class, and corresponding CDSI values.

Sri Lanka CDSI_Top10_Events_By_Intensity				
start	end	duration_months	peak_class	peak_value
1983-03-01 00:00:00	1983-11-01 00:00:00	9	Extreme	0.561460777
2016-09-01 00:00:00	2017-02-01 00:00:00	6	Extreme	0.552112089
1992-02-01 00:00:00	1992-05-01 00:00:00	4	Extreme	0.507440198
1997-01-01 00:00:00	1997-04-01 00:00:00	4	Extreme	0.408806054
2019-05-01 00:00:00	2019-07-01 00:00:00	3	Extreme	0.327939593
2012-06-01 00:00:00	2012-09-01 00:00:00	4	Extreme	0.304793032
1982-01-01 00:00:00	1982-03-01 00:00:00	3	Extreme	0.283660306
2013-11-01 00:00:00	2014-05-01 00:00:00	7	Extreme	0.244556846
2003-12-01 00:00:00	2004-03-01 00:00:00	4	Extreme	0.218510024
1988-12-01 00:00:00	1989-06-01 00:00:00	7	Extreme	0.217543066

The results highlight the recurring nature of droughts in Sri Lanka, with several events (e.g., 1983, 1992, 1997, 2016–2017) affecting extensive areas and exhibiting multi-season persistence. These patterns correspond well with historical reports of agricultural droughts and observed monsoon failures in the respective years.

The integration of CDI intensity and drought-affected area into the Composite Drought Severity Index (CDSI) provided a coherent and comprehensive measure of national-scale drought severity. The CDSI successfully identified all 14 major drought events between 1981 and 2025, capturing both their magnitude and spatial persistence. It effectively distinguished between localized short-duration droughts (e.g., 1982, 1995–1996, 2001, 2019), medium-duration droughts (e.g., 1992, 1997, 2001–2002, 2003–2004, 2012), long-duration droughts (e.g., 1983, 1986–1987, 1988–1989, 2013–2014, 2016–2017), and high-intensity events (e.g., 1983, 1992, 1997, 2016–2017), demonstrating its potential utility for operational monitoring, early warning, and policy-level decision support.

3.3 A temporal (interannual–seasonal) evolution of national drought severity.

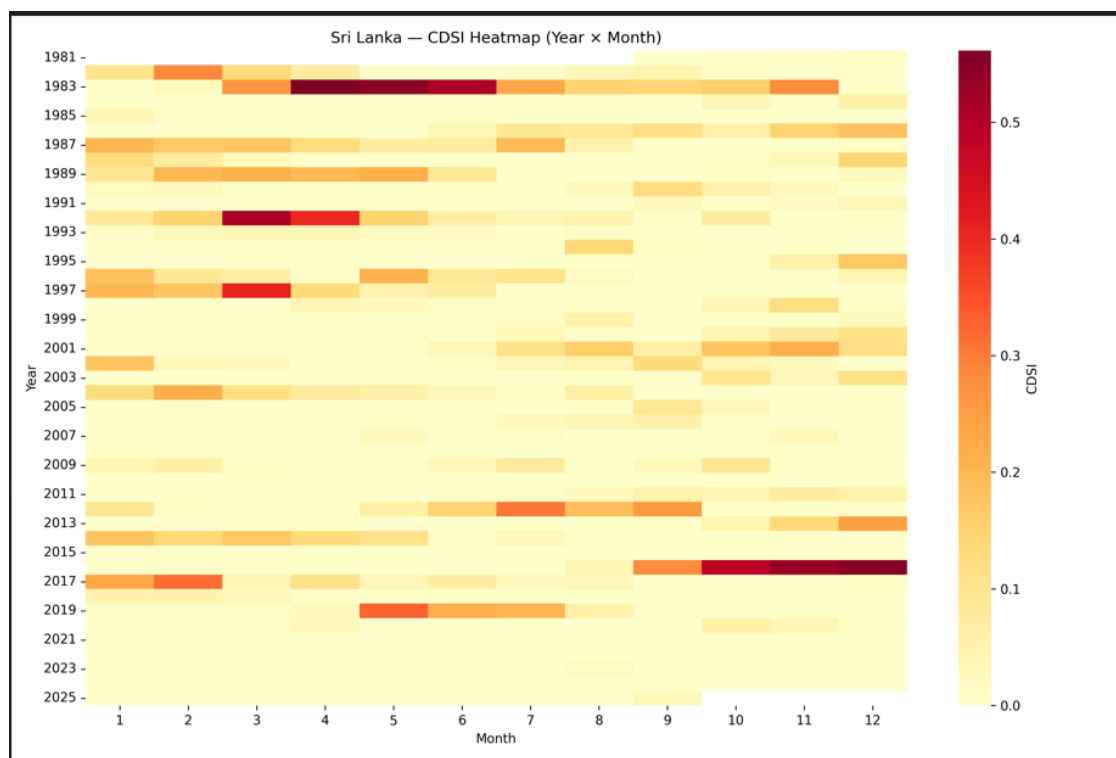


Figure 2. Heatmap of the composite Drought Severity Index (CDSI) showing temporal drought variability across Sri Lanka from 1981 to 2025. with darker colors representing more severe drought conditions.

The Figure 02, heatmap reveals pronounced temporal variability in drought severity across Sri Lanka during 1981–2025, with distinct vertical bands indicating nationally coherent drought episodes. Major droughts are evident in the early 1980s (1982–1984), late 1980s (1987–1989), early 1990s (1992–1993), late 1990s (1997–1998) and the prolonged 2016–2017 event, all characterized by elevated CDSI values across multiple districts. In contrast, fragmented and short-lived drought signals occur intermittently, reflecting localized or intra-seasonal rainfall deficits.

The 1987 drought occurred during a strong El Niño event, a large-scale climate mode previously linked to reduced monsoonal precipitation and persistent negative rainfall anomalies over Sri Lanka, which is consistent with the drought patterns captured by the (CDSI)during this period.

3.4 District-wise spatiotemporal variability of drought severity in Sri Lanka (1981–2025)

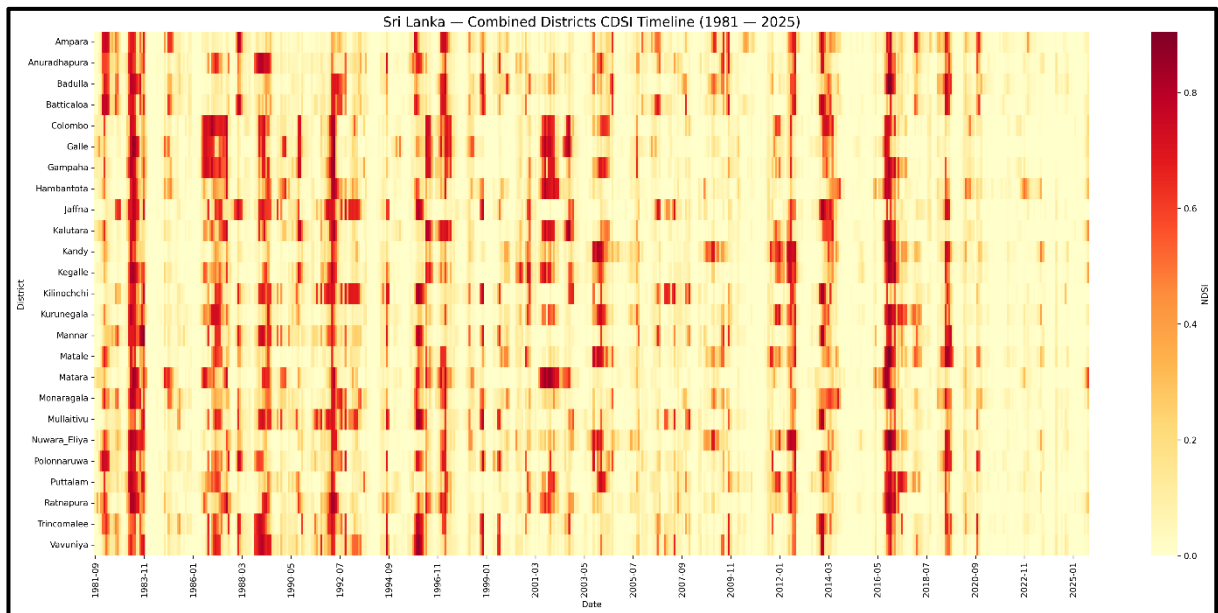


Figure 3. Heatmap showing district-level spatio-temporal variability of drought severity in Sri Lanka (1981–2025) derived from the Composite Drought Severity Index (CDSI), which integrates Composite Drought Index (CDI) intensity and spatial extent. Darker colors denote more severe drought conditions.

The district-wise CDSI heatmap (Figure 3) shows strong spatial contrasts in drought severity across Sri Lanka (1981–2025). Dry-zone districts experience more frequent and persistent high-severity droughts, while wet-zone and highland districts exhibit mainly episodic and lower-intensity events. Vertically coherent high CDSI bands indicate major national droughts, whereas fragmented patterns reflect localized or short-duration droughts, demonstrating the CDSI's ability to resolve district-level drought variability.

3.5 Temporal variability of drought severity in Kurunegala district (1981–2025)

The Kurunegala CDSI heatmap (Figure 4) shows a combination of short-duration droughts (1–3 months) and prolonged severe droughts lasting up to 7–8 consecutive months. Short events occur sporadically across the record and are typically confined to single inter-monsoon periods, reflecting transient rainfall deficits. In contrast, the longer duration droughts most evident during 1983, 1986–1987, 2003–2004, and 2016–2017 span multiple seasons, indicating compounded rainfall failures across successive monsoon phases and a substantially higher risk to agriculture and water availability.

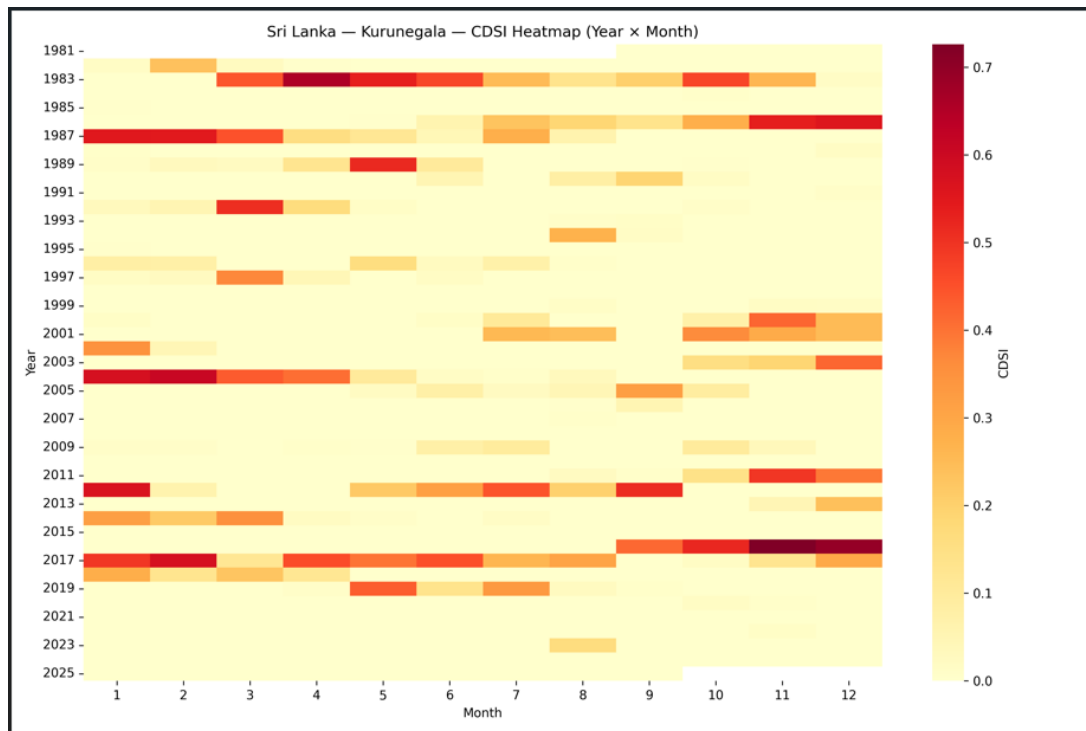


Figure 4. Monthly Composite Drought Severity Index (CDSI), heatmap for Kurunegala District (1981–2025), illustrating the timing and intensity of localized drought events, with darker colors indicating higher drought severity.

3.6 Temporal variability of drought severity in Hambantota district (1981–2025)

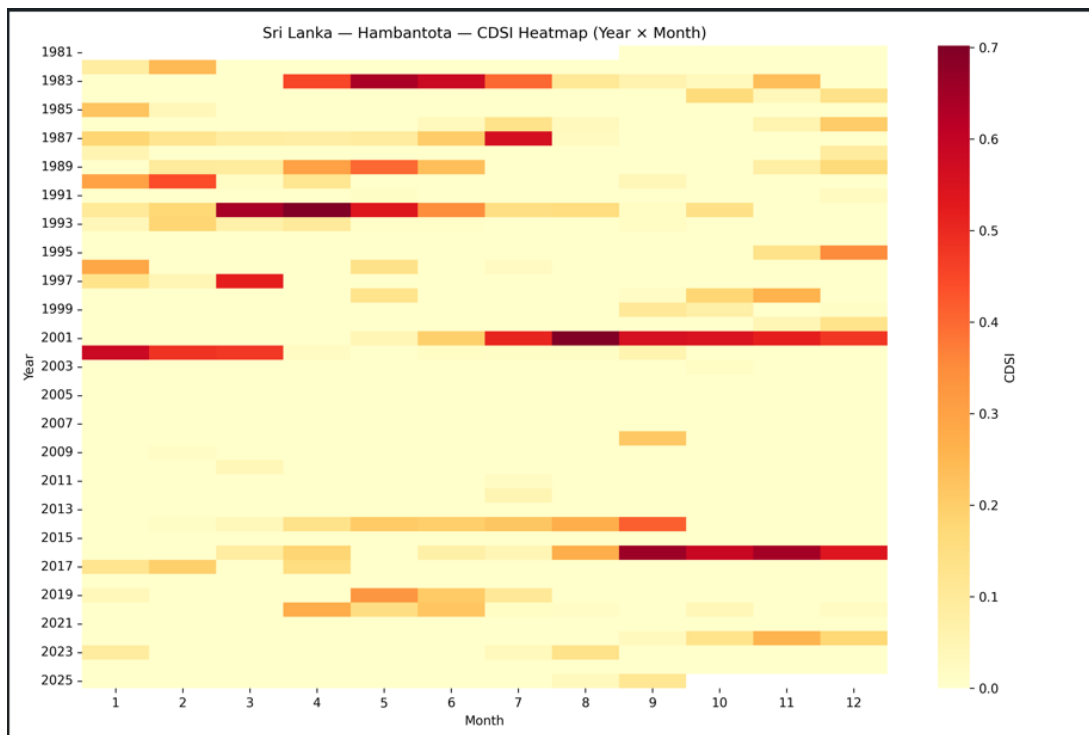


Figure 5. Monthly Composite Drought Severity Index (CDSI) heatmap for Hambantota District (1981–2025), showing the timing, duration, and intensity of localized drought events, with darker colors indicating higher drought severity.

The Hambantota CDSI heatmap (Figure 5) indicates frequent and persistent drought conditions, with several severe events spanning multiple consecutive months. Pronounced droughts are evident during 1983–1984, 1992–1993, 2001–2002, and 2015–2016, often extending for 6–8 months, particularly during the Yala season and late inter-monsoon periods.

4. Discussion

The integration of drought intensity and spatial extent through the Composite Drought Index (CDI) and the Composite Drought Severity Index (CDSI) provides a robust framework for national scale drought assessment in Sri Lanka. The CDSI successfully captures all major drought episodes during 1981–2025, reflecting both their temporal persistence and spatial coherence. Droughts identified in 1992, 1997, 2016, and 2019 show strong agreement with independent SPI-based assessments and documented historical records, confirming that the adopted CDSI thresholds reliably represent real drought occurrences across the country. In particular, the 2016–2017 drought widely recognized as one of the most severe national droughts in recent history is clearly characterized by sustained high CDSI values, indicating its prolonged duration and extensive spatial impact.

The temporal characteristics of CDSI detected events indicate that Sri Lanka's drought regime is predominantly episodic, with recurrent but generally short-lived high severity droughts lasting between 2 and 9 months, rather than persistent long-term drought conditions. Although extreme droughts occur infrequently, they dominate the severity spectrum and exhibit rapid intensification once drought conditions develop. The most intense and persistent events were observed during the early 1980s, mid-1990s, early 2000s, and mid to late 2010s, with peak severity during 1983 and 2016–2017. These findings are consistent with previous drought climatology studies for Sri Lanka, further reinforcing the credibility of the CDI/CDSI framework.

The CDSI time series shows strong coherence with CDI derived temporal patterns, demonstrating that national drought peaks arise from the combined influence of elevated drought intensity and widespread spatial coverage. By jointly accounting for mean CDI severity and the proportion of drought-affected Divisional Secretariat Divisions (DSDs), the CDSI effectively distinguishes between localized short-duration droughts, medium-duration regional events, and prolonged nationwide droughts. This balanced formulation ensures that both intense but spatially limited droughts and widespread moderate droughts are proportionally represented in the national severity signal. Consequently, the CDI/CDSI framework offers a practical and scalable indicator for operational drought monitoring, early warning, and policy-level decision support in Sri Lanka.

5. Conclusions

This study demonstrates the effectiveness of a CDI/CDSI based framework for quantifying drought severity, duration, and spatial extent across Sri Lanka. The Composite Drought Index (CDI) successfully captures monthly drought intensity and spatial variability at the Divisional Secretariat Division scale, while severity normalization enables consistent and interpretable drought hazard mapping. By integrating drought intensity with spatial extent, the Composite Drought Severity Index (CDSI) reliably identifies major national drought events during 1981–2025 and distinguishes between localized, regional, and nationwide drought conditions in close agreement with documented historical records. The CDI/CDSI framework therefore provides a practical and scalable national drought hazard indicator suitable for operational monitoring, early warning system calibration, and policy-oriented risk zoning when coupled with DSD-level hazard maps. Future work should focus on incorporating soil moisture, temperature anomalies, and hydrological indicators to advance toward impact-based drought risk assessment, while probabilistic drought outlooks derived from model-forecast SPI offer additional potential provided that forecast skill is rigorously calibrated and validated using hindcasts.

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Changes in Spatial Rainfall Distribution in climate zones of Sri Lanka under the Changing Climate

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ABSTRACT

The climate of Sri Lanka is predominantly governed by the monsoon system and the associated air masses that are part of the hemispheric wind regime over Indian sub-continent and surrounding Indian Ocean. Therefore, the climate of Sri Lanka can be characterized as a tropical monsoon climate.

Sri Lankan climate is traditionally categorized into three zones, Wet, Intermediate and Dry zone. (Figure 1). The central highlands, which control the prevailing moisture-laden monsoon winds, act as an important physiographical climatic barrier. These three climatic zones can be distinguished to the west and east of the central highlands. The Wet Zone essentially comprises the southwest parts, which are directly exposed to the South West Monsoon (SWM) winds, whereas the rest of Sri Lanka constitutes the Intermediate & Dry Zone.

This study aims to review that the climatic changes related to rainfall in the climatic zones in Sri Lanka. In order to understand the changes related to rainfall in the climatic zones, rainfall data from around 170 locations over the last two distinct 30-year periods from 1961 to 1990 and 1991 to 2020 respectively mapping using “kriging” interpolation method to see the changes in spatial rainfall distribution.

Key words: Monsoon, Rainfall, Climate, Climatic Zones

1. Introduction:

The island of Sri Lanka is located at the southern tip of the Indian sub-continent, extending from 5°55' to 9°51'N and from 79°42' to 81°53'E. The total area of the country is 65,610 Km². Sri Lanka has a maximum length of 435km in the north-south direction and a width of 240 km in the east-west direction. Given its tropical location, the main climatic variations relate to rainfall. The rainfall of Sri Lanka is predominantly governed by the seasonally varying monsoon system and the associated air masses that are part of the hemispheric wind regime over South Asia. Therefore, the climate of Sri Lanka can be characterized as a tropical monsoon climate. (*Rajendram, K. 2021*).

Sri Lanka is influenced by two monsoons and the weather systems within the inter-tropical convergence zone (ITCZ). The western, central, and southern parts experience wet and humid conditions throughout the year. The two monsoon seasons are the South West Monsoon (SWM - summer monsoon) from May to September and the North-East Monsoon (NEM - winter monsoon) from December to February. During the SWM season, heavy rainfall receives by the low land areas in the southwestern part of Sri Lanka and the western slopes of the hill country. The NEM brings rain mainly to the northern and eastern parts of the country. (*Rajendram, K.2021*). The two Inter monsoon rainfall seasons, the First Inter monsoon (FIM; March to April) and Second Inter monsoon (SIM; October to November) occur in association with the respective northward and southward migrations of the intertropical convergence

zone (ITCZ) over Sri Lanka. During the Inter monsoon seasons, convectional type rainfall are frequent and tropical depressions (mainly during the SIM) originating in the Bay of Bengal may triggered to, heavy rainfall spells within a short period of time.

Based on rainfall, Sri Lanka is divided into three major climatic regions, viz. Wet Zone (WZ), Intermediate Zone (IZ) and Dry Zone (DZ). (Figure 1) The south-western part of Sri Lanka, including a part of central highlands, is wet; while the north and eastern regions are dry. In-between above two zones Intermediate zone is from north western coast of the island to Southern coast via a part of central highland. The western wet zone is generally the water surplus area in the country dominated by southwest monsoon (SWM) rainfall. In contrast, water deficit areas exist in the northern, eastern, and south eastern regions conquered by the northeast monsoon (NEM). The availability of rainfall, particularly in the dry zone in Sri Lanka, is frequently affected by the failure or poor monsoon. (*Punyawardena BVR, Kulasiri D, 1998*).

The variability of rainfall is indeed higher in the dry zone than in the wet zone.

The higher rainfall variability is closely associated with water scarcity, perhaps creating uncertainty in agriculture, drinking water supply.

There are two major cropping seasons in Sri Lanka, namely, Maha (Second Inter-monsoon from October to November and the North-East monsoon from December to February) and Yala (First Inter-monsoon from March to April and the South-West monsoon from May to September) (*Amarasingha, et al., 2015*).

A particular season is defined considering the land preparation activities during inter-monsoon periods and harvesting activities at the tail end of the monsoonal seasons. The deviation in sown and harvested extent and the average yield of paddy in Sri Lanka are directly correlated with the deviations of the seasonal rainfall. (*Yoshino and Suppiah, 1983; Suppiah, 1985; Chithranayana and Punyawardena, 2014; Amarasingha et al., 2018*).

This study is out to extract the changes in annual and seasonal rainfall in Sri Lanka over the last two distinct 30-year periods from 1961 to 1990 and 1991 to 2020 and the study's main objectives are to analyse the annual and seasonal rainfall changes with particular reference to understand the changes related to rainfall in Sri Lanka.

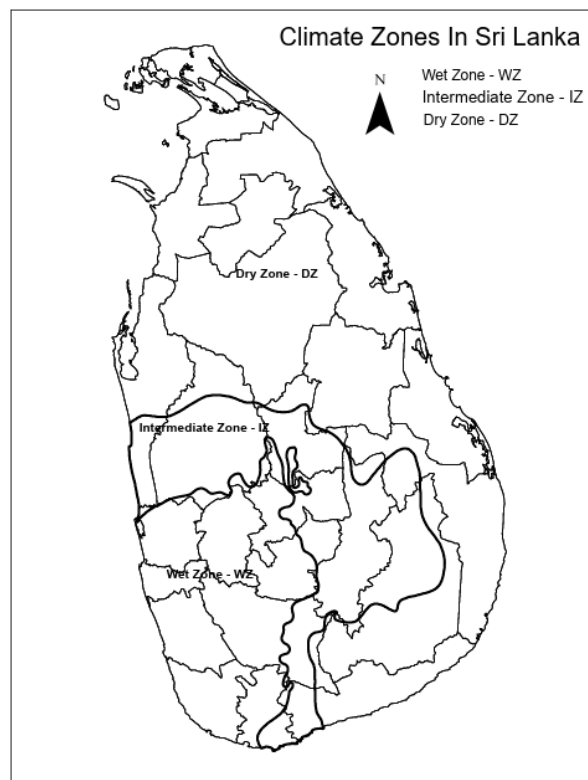


Figure 1: Major climatic regions, viz. Wet Zone (WZ), Intermediate Zone (IZ) and Dry Zone (DZ).

Above mentioned two consecutive periods of 30 years are selected according to Technical Standards of World Meteorological Organization (WMO) to calculate Climatological normal. (<https://community.wmo.int/en/wmo-climatological-normals>)

2. Methodology:

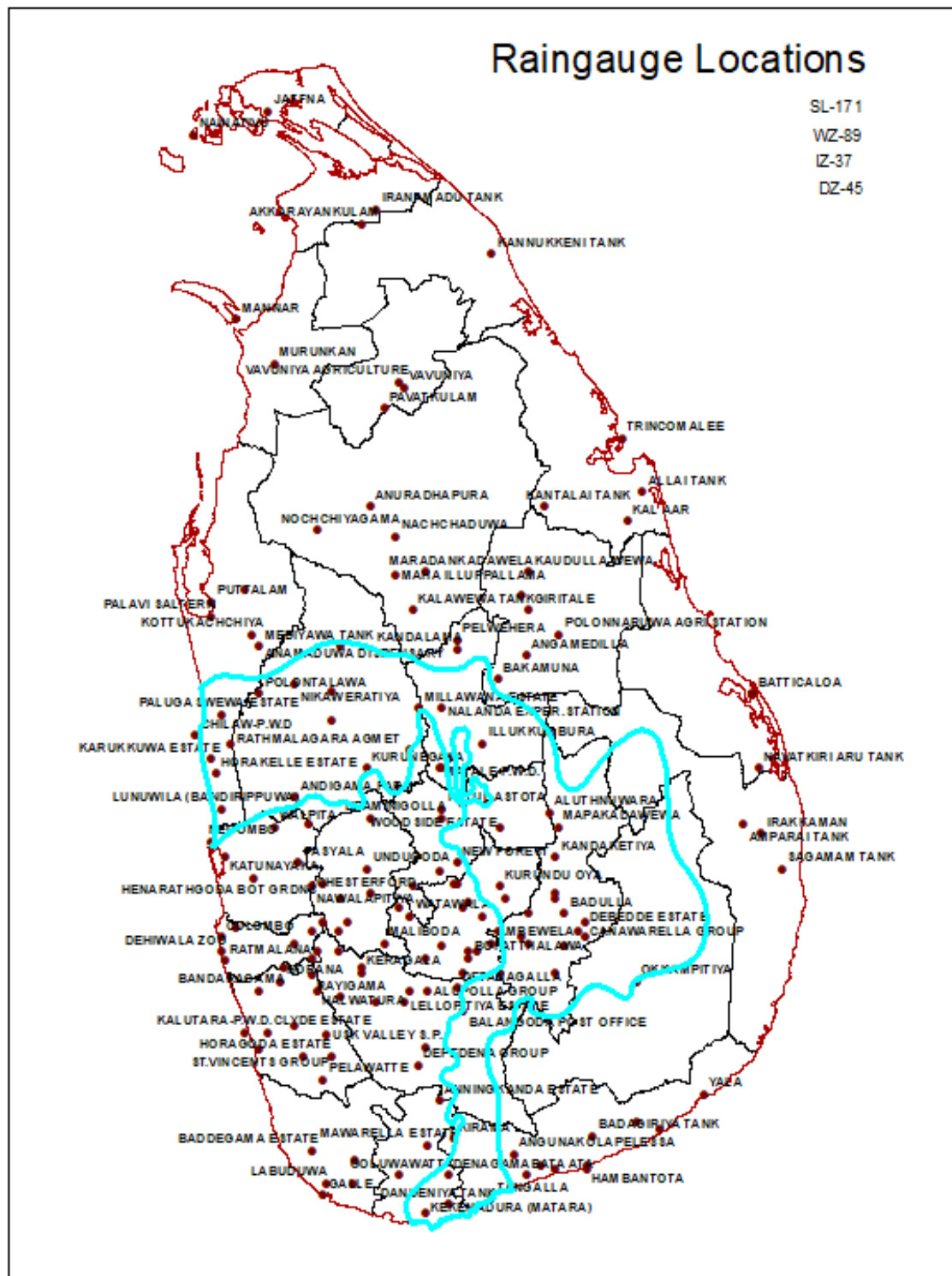
Data for this study were obtained from database of Department of Meteorology. Monthly total rainfall for a period of 60 years from 1961 to 1990 and 1991 to 2020 recorded at 18 meteorological synoptic stations and 153 rain gauges, with the data availability more than 90 percent of selected each 30-year period representing all three major climatic zones of Sri Lanka (Map 1). The data represent 89 stations for wet zone, 37 stations for intermediate zone and 45 stations for dry zone. Stations are selected to represent at least one station to an administrative district.

The analysis was carried out for monthly averages of rainfall data in 2 separate periods within the years from 1961 to 1990 and 1991 to 2020. It is very important in rainfall measurements to confirm whether the data were recorded at the same time daily with the same instrument at the same location. However, this is a big task when it comes to recording of daily rainfall measurements in longer time spans (like 60 years) as the measuring techniques may not change over the period, but the measuring instruments may have been reinstalled, and so on, the data contained a fair number of missing values

Therefore, prior to the analysis, missing values were removed from the daily time series records. A month which contained at least one missing day was taken as a missing month.

2.1 Spatial distribution mapping to visualize Rainfall variations across Sri Lanka.

30-year average monthly total rainfall values at selected 18 meteorological stations and 153 rain gauges in two distinct 30-year periods: 1961-1990 and 1991-2020 are mapped monthly-wise using Geographic Information System (GIS) and the Kriging geostatistical estimation technique method which were used to create a comprehensive over-view of rainfall trends across the country. The results were categorized into annual, two monsoonal seasons, two inter-monsoonal seasons and two cultivation seasons, namely, South West Monsoon (SWM), North East Monsoon (NEM), First Inter Monsoon (FIM), Second Inter Monsoon (SIM), YALA and MAHA season to providing better view into average rainfall patterns during these periods.



2.2 Kriging:

Kriging is a geostatistical estimation technique that originated in the field of mining geology as is named after South African mining engineer Danie Krige for. Kriging is one of several methods that uses to spatial interpolation using a linear combination of surrounding observed values to make predictions. To make

such predictions, one must estimate the weights for each surrounding observation. Kriging allows us to derive weights by minimizing the error variance and systematically setting the mean of errors to zero. Ordinary kriging was used assuming the absence of trend in observations over the considered area. In kriging, the spatial correlation or the spatial dependence structure is quantified by a ‘semivariogram’, which provides a measure of variance as a function of distance between data points. The experimental semivariance $\gamma(h)$ is calculated from the observed data using the equation

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{x_i - x_{i+h}\}^2$$

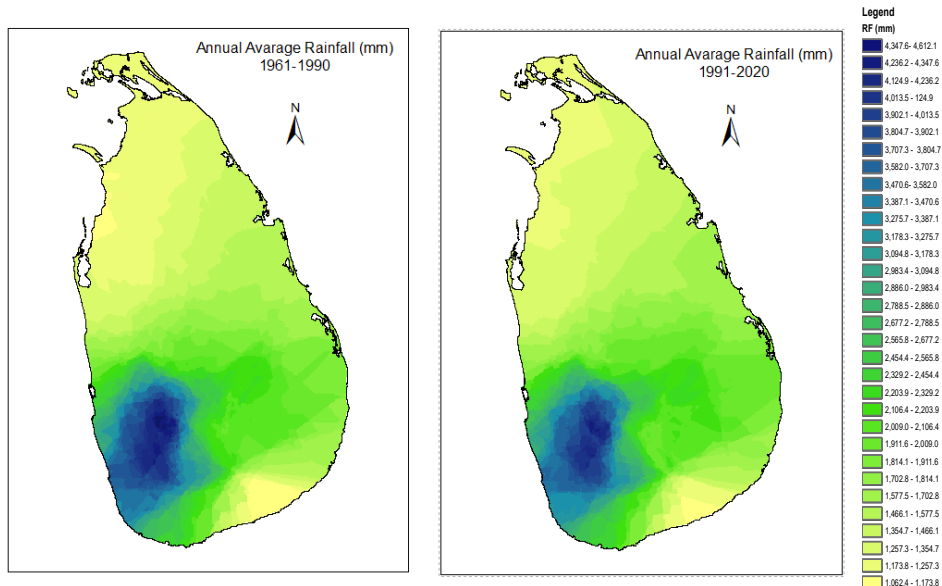
Here $N(h)$ is the number of pairs of observed points separated by distance h or lag. x_i and x_{i+h} refers to observed rainfall values at locations around the station to be estimated. A semivariogram is the graphical display of $\gamma(h)$ versus h . Usually, $\gamma(h)$ will increase with h and after a certain distance, called the ‘range’ (L), $\gamma(h)$ will level out at a value called the ‘sill’ ($C1$). At a distance beyond L the deviations in observations are no longer correlated. The experimental semivariogram was modelled by fitting a theoretical function to ensure that the solution is unbiased and has minimum variance. Since the rainfall data display high spatial correlation between nearby points (i.e. an S-shaped behaviour at short lags in the semivariogram), a Gaussian function was chosen to model the experimental semivariogram.

$$\gamma(h) = C_0 \left\{ 1 - \exp \left[- \left(\frac{h}{L} \right)^2 \right] \right\} + \gamma(0)$$

Here h is such that $0 \leq h \leq L$ and C_0 is the difference between the sill $C1$ and ‘nugget’ $\gamma(0)$. The value x_0 at the estimated location (i.e. unobserved location) can be calculated by using a weighted average of the observed rainfall values x_i at locations around it. Optimal weights are those that produce minimum variance and they can be obtained by solving a set of simultaneous equations. A spatial interpolation program, Easy Kriging 2.1 (EasyKrig2.1 2000), was used to model the semivariance and kriging. Each time step (a week) in rainfall data represents a separate set of data for kriging. In this work, semivariogram parameters were estimated only for 4 cases using mean seasonal values. Initially, the parameters were estimated by inspection of the shape of the semivariogram. Then, the cross-validation criteria were applied to ensure the correct range that produces a minimum residual error for each parameter. The best sets of parameters for L , $\gamma(0)$ and $C1$ were obtained by performing a least square fit. Data records at the estimation point were not used in the estimation of parameters.

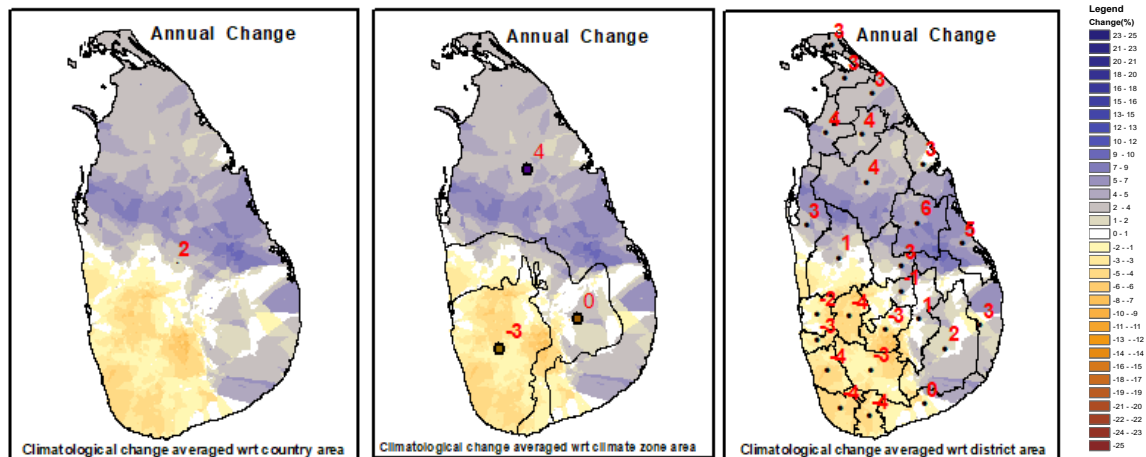
3. Results and Discussion

3.1 Changes of Annual Rainfall of the country, with the Climatic Zones & with the districts.



Map 2

Map 3



Map 4

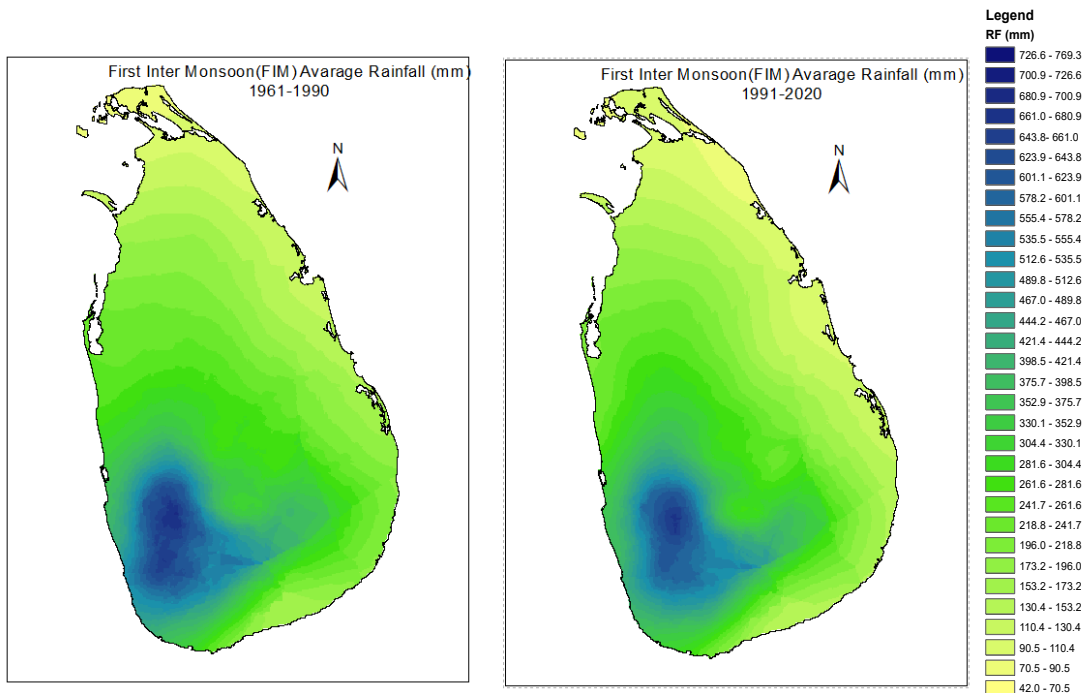
Map 5

Map 6

Map 2 & Map 3 represent the annual average rainfall depth in Sri Lanka over the last two 30-year periods from 1961 to 1990 and 1991 to 2020 while Map 4, Map 5 & Map 6 represent climatological change over the last two 30-year periods with respect to the country area, climate zone area & district area. As presented in Map 4 & Map 5, a considerable part of the wet zone shows a 3 % negative change of rainfall over the last 30 years. The western slopes of the central highlands show a significant negative change of rainfall compared to the other parts of the island. (Map 5) The Intermediate Zone shows a decreasing of rainfall mainly in the south western part of central highland while the eastern slopes of

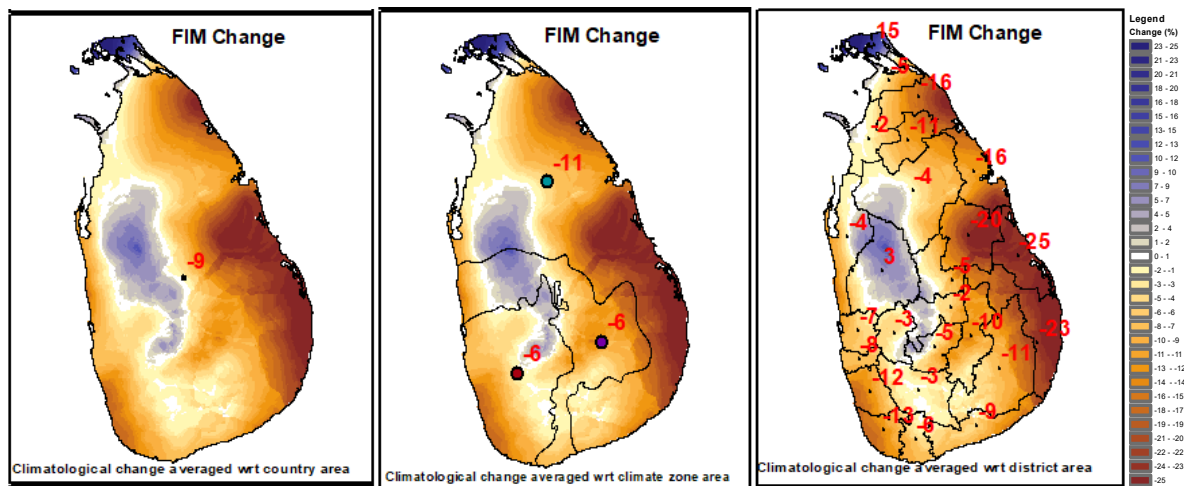
the central highlands show positive change. Map 5 & Map 6 shows the Variation of Annual Rainfall of the country, with respect to the Climatic Zone area & with respect to the districts area. Most parts of the Dry Zone show 4 % positive change of rainfall. This indicates in what way the rainfall in the country changed over the last 30-year period with comparing to the 30-year period of 1961 to 1990.

3.2 Changes of First Inter Monsoonal (FIM) Rainfall of the country, with the Climatic Zones & the districts.



Map 7

Map 8



Map 9

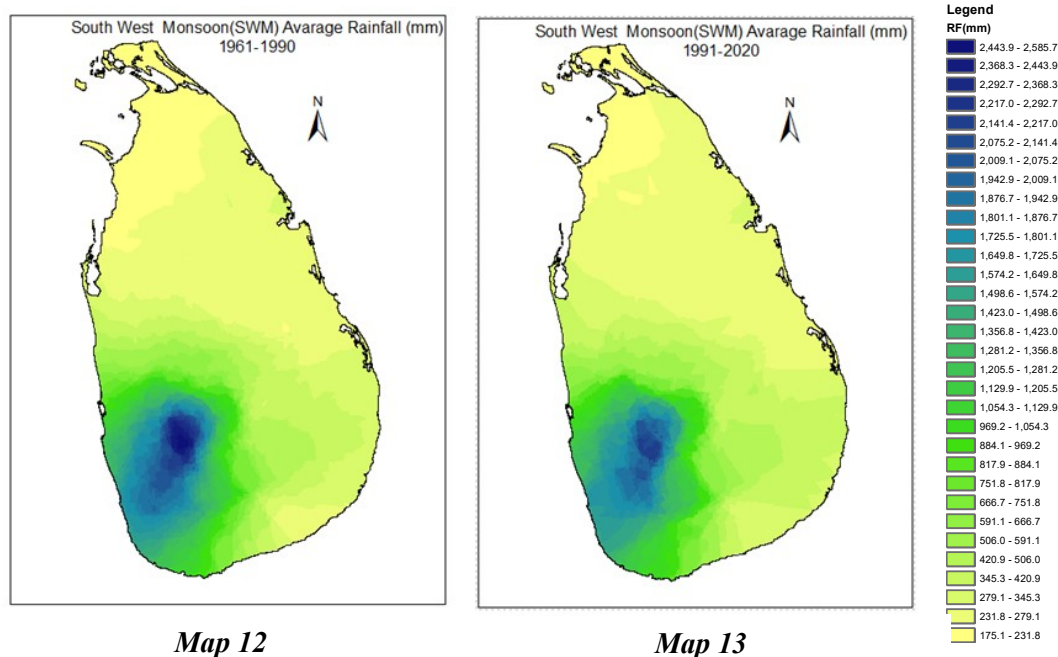
Map 10

Map 11

Map 7 & Map 8 represent the average rainfall of the first inter monsoon (FIM) in Sri Lanka over the last two 30-year periods from 1961 to 1990 and 1991 to 2020 while map 9, map 10 & map 11 represent

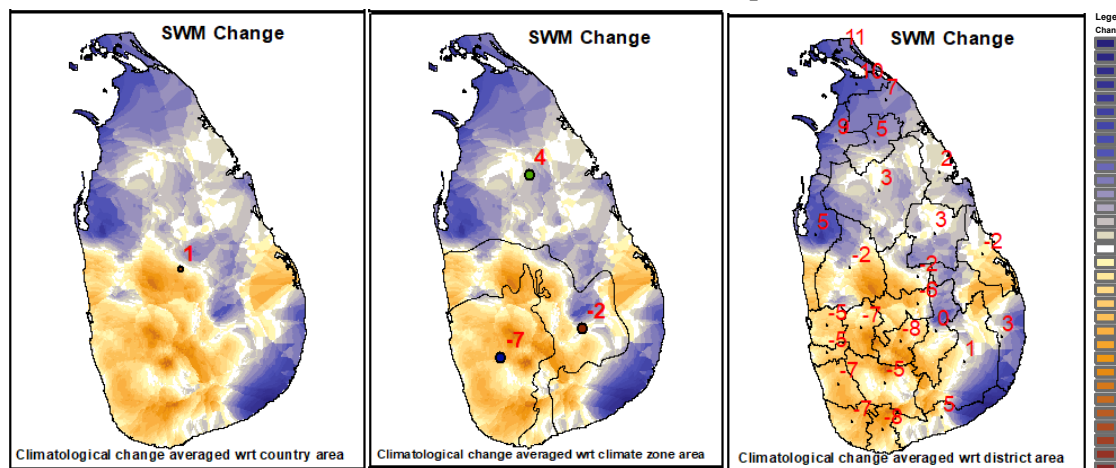
the changes over the last two 30 years with respect to the country area, climate zone area & district area. Average rainfall has changed negatively during the First-Inter Monsoon at most of the area. FIM average rainfall has changed with negative value of 9 % with respect to country a and has decreased 6 % with respect to wet zone & intermediate zone and highest decreasing value of 11 % represent the dry zone. Batticaloa district represent the highest negative value of 25 % while Kurunegala district represent the only positive value of 3%.

3.3 Changes of South West Monsoonal (SWM) Rainfall of the country, with the Climatic Zones & with the districts.



Map 12

Map 13



Map 14

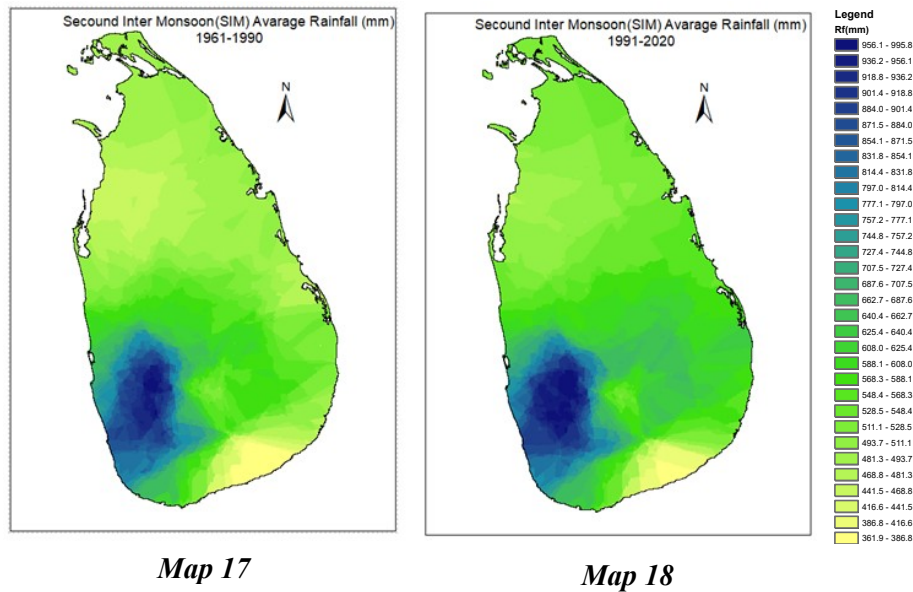
Map 15

Map 16

Map 12 & Map 13 represent the average rainfall of the South West monsoon (SWM) in Sri Lanka over the last two 30-year periods from 1961 to 1990 and 1991 to 2020 while map 14, map 15 & map 16 represent the changes over the last two 30 years with respect to the country area, climate zone area & district area. Map 14 shows the rainfall records of the Southwest Monsoon season a negative change in

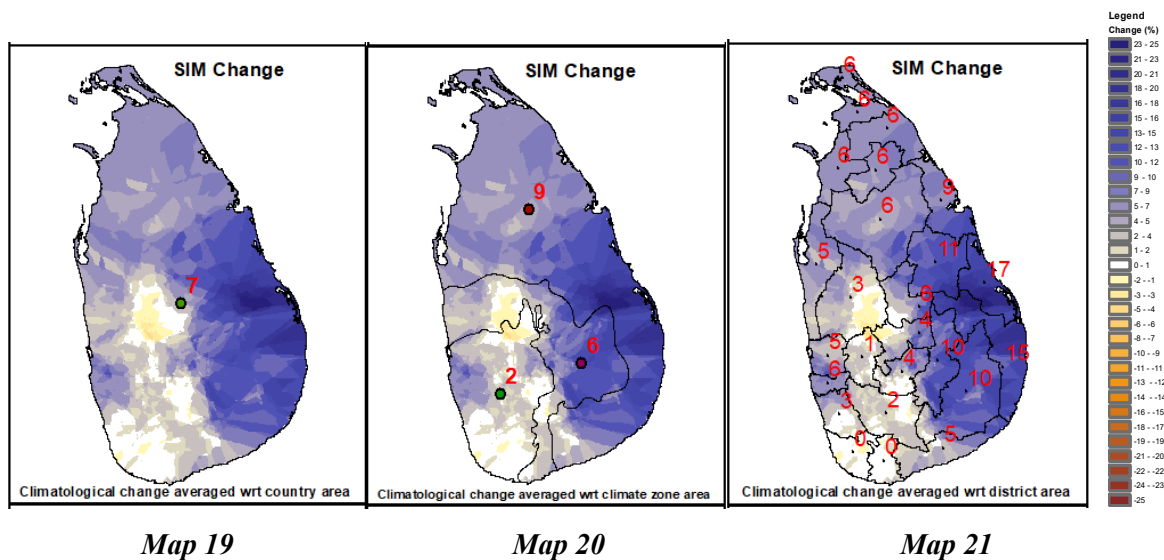
Wet Zone & Intermediate Zones of the country while positive change in Dry Zone. Southwest Monsoon season is the season which receives the highest rainfall over the southwest part of the island (Map 12 & Map 13), since it shows the 7 % negative change of over the wet zone (Map 15).

3.4 Change of Second Inter Monsoonal (SIM) Rainfall of the country, with the Climatic Zones & the districts



Map 17

Map 18



Map 19

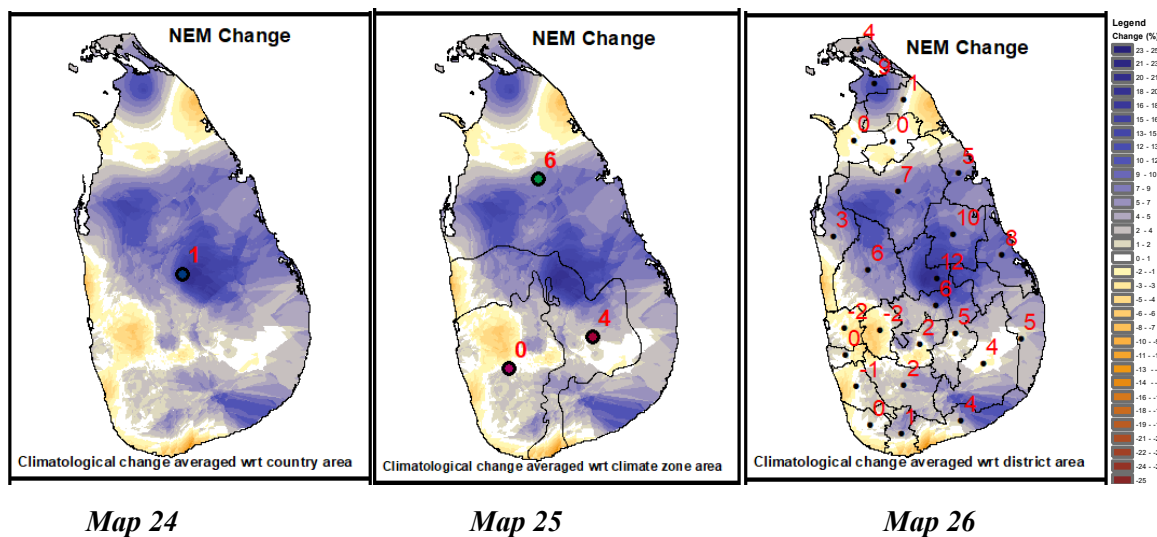
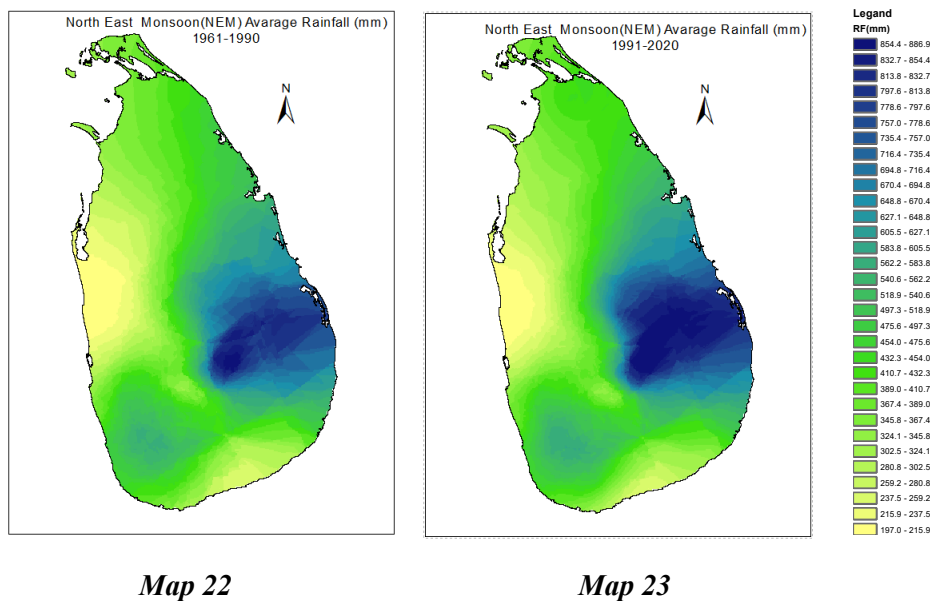
Map 20

Map 21

Map 17 & Map 18 represent the average rainfall of the Second Inter Monsoon (SIM) in Sri Lanka over the last two 30-year periods from 1961 to 1990 and 1991 to 2020 while map 19, map 20 & map 21 represent the change over the last two 30 years with respect to the country area, climate zone area &

district area. All three maps from Map 19 to Map 21 clearly show a positive change of average rainfall of Second Inter Monsoonal Rainfall of the country. The rainfall in the all three climatic zones have shown a positive change while dry zone represents highest value of 9 % positive Change. Thus, the above changes are to be studied further will be advantage to identify the changing climate and its effects to the agriculture and other economic activities of the country.

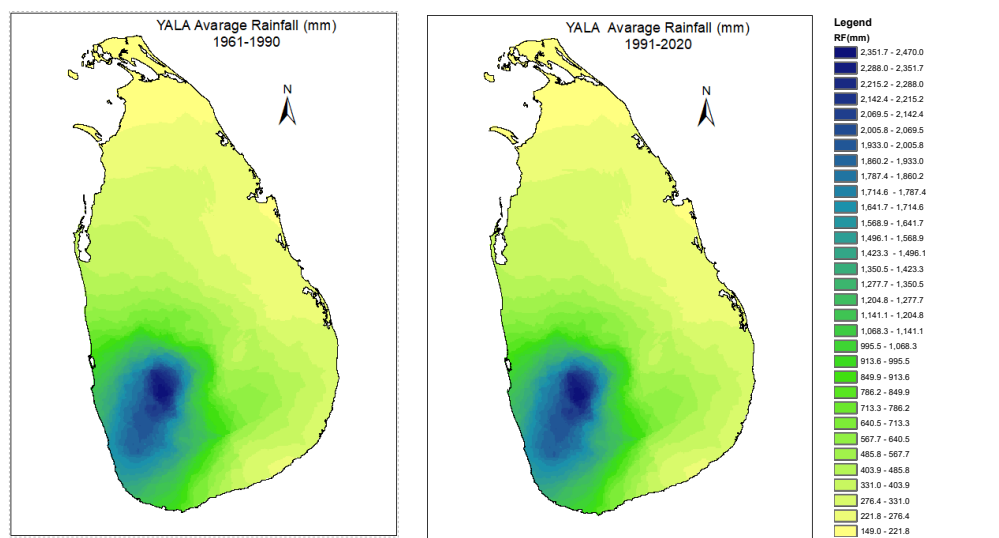
3.5 Changes of North East Monsoonal (NEM) Rainfall of the country, with the Climatic Zones & the districts



Map 22 & Map 23 represent the average rainfall of the North East Monsoon (NEM) in Sri Lanka over the last two 30-year periods from 1961 to 1990 and 1991 to 2020 while map 24, map 25 & map 26

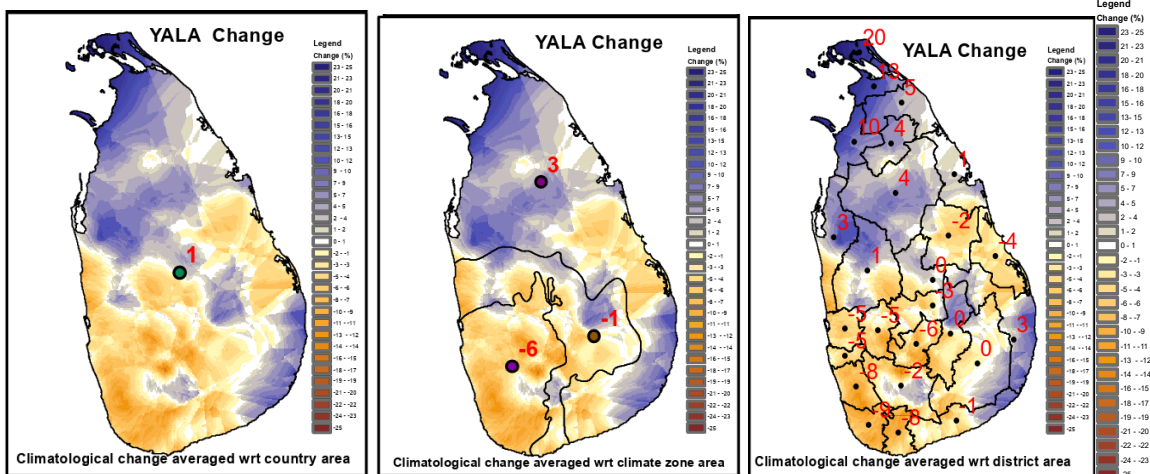
represent the change over the last two 30 years with respect to the country area, climate zone area & district area. Compared with the rainfall changes during the Northeast Monsoon over the south western area in Sri Lanka which lies on the leeward side of the Northeast Monsoon (NEM) reported less rainfall change. According to Map 25, it shows 0 % in Wet Zone. It means that the said the changes of rainy season is not effective over that geographical area. However, the average rainfall records during North East Monsoon (NEM) season indicate a positive change in North East and Eastern parts of the country. According to Map 25 it shows 4 % in Intermediate Zone and 6 % in Dry Zone.

3.6 Change of YALA seasons Rainfall of the country, with the Climatic Zones & with the districts



Map 27

Map 28



Map 29

Map 30

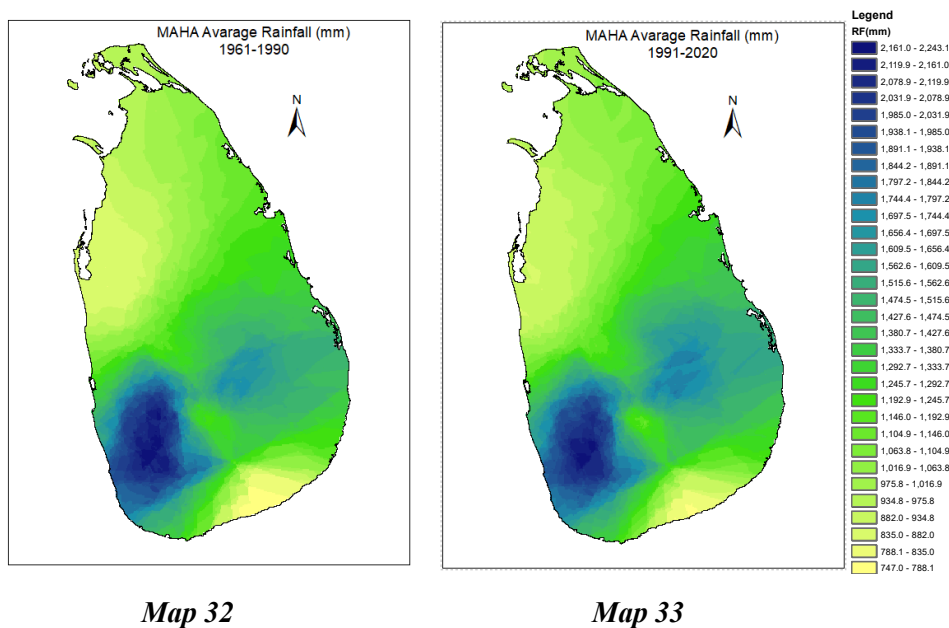
Map 31

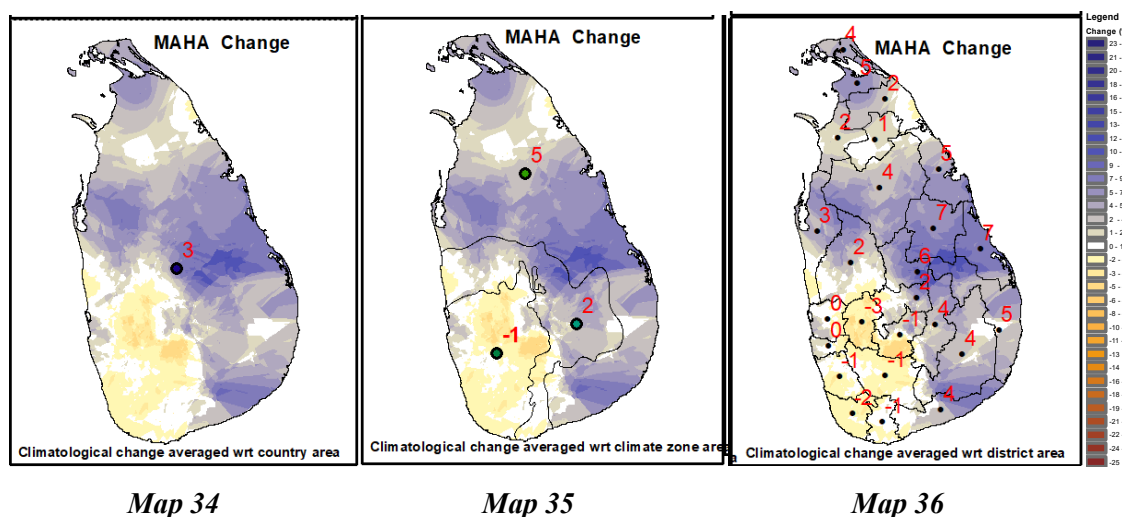
Map 27 & Map 28 represent the average rainfall of the Yala season in Sri Lanka over the last two 30-year periods from 1961 to 1990 and 1991 to 2020 while map 29, map 30 & map 31 represent the change over the last two 30 years with respect to the country area, climate zone area & district area. In this

study during YALA season (FIM + SWM) 6 % negative rainfall change is observed at wet zone and 1 % negative rainfall change is observed at Intermediate zone while a 3% positive of rainfall change is observed in dry zone. (map 29 to Map 30).

Paddy is cultivated in twenty-five districts in Sri Lanka; Rain fed lowland rice is grown in river deltas and coastal areas, using abandoned fields that are flooded with rainwater for at least part of the cropping season and in the rain fed upland environment rice is grown in valleys and mountains which is known as terraced cultivation. Upland environments are highly heterogeneous, with climates ranging from humid to sub humid, soils from relatively fertile to highly infertile, and topography from flat to steeply sloping. Paddy rice or 'rough rice' is produced to varying extents in all twenty-five districts of the nine provinces in Sri Lanka during both 'Yala' and 'Maha' cultivation seasons. Thus, those changes of rainfall during Yala season may affect to above agricultural activities and are to be studied further will be advantage to identify the changing climate and its effects to the agriculture and other economic activities of the country.

3.7 Change of MAHA seasons Rainfall of the country, with the Climatic Zones & with the districts





Map 32 & Map 33 represent the average rainfall of the MAHA season in Sri Lanka over the last two 30-year periods from 1961 to 1990 and 1991 to 2020 while map 29, map 30 & map 31 represent the change over the last two 30 years with respect to the country area, climate zone area & district area. MAHA season (SIM + NEM; major cultivating season; September to March). In Maha season (SIM + NEM), the average rainfall is higher compared to YALA season. Map 34 shows the change of average rainfall over the last two 30 years with respect to the country area indicates positive change by 3 %. Map35 shows that considerable part of the wet zone shows a 1 % negative rainfall change over the last 30 years and most parts of the Intermediate Zone and Dry Zone shows a 5 % positive change of average rainfall. Effect of these changes are to be studied further if it is favourable to this agricultural season.

4. Conclusion:

The study reveals that the slight upward change shown in spatial rainfall distribution in Sri Lanka. In-depth, the dry zone of Sri Lanka has shown a 4 % positive change in annual rainfall while the Wet zone has shown a relatively negative change of (-3 %), specifically in the western hill slopes in the last 30-year period of 1991 to 2020 concerning the 30 years of 1961-1990 due to variations of climate change. However, the positive change in rainfall during the SIM has shown some significant scattered distribution over the entire country. The same variations have shown positive changes in rainfall during NEM & SWM times, particularly toward the eastern parts of the country.

In contrast, study manuscripts indicate decreasing change only during the period of FIM over the country. Thus, increasing rainfall changes have shown during SWM, SIM and NEM as well as annually over most probably in the country's Agricultural, Hydro Power & other hydro meteorology-related areas.

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Heavy Rainfall during the First Week of June 2024 in Sri Lanka: A Case Study

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ABSTRACT

This case study examines why the extreme rainfall event of 1–2 June 2024 over Sri Lanka was substantially underestimated by operational numerical weather prediction models, despite the presence of favorable large-scale southwest monsoon conditions. The study addresses the key question of which mesoscale and synoptic-scale atmospheric processes contributed to the observed rainfall intensity and why these processes were inadequately represented in forecast guidance. Several locations, including Ehaliyagoda in the Sabaragamuwa Province, recorded more than 400 mm of rainfall within 24 hours, far exceeding model-predicted amounts. Using high-resolution local rainfall observations, satellite-derived products, and a comparative evaluation of multiple operational forecasts (IMD, NCMRWF, NCEP, and ECMWF), the analysis focuses on multi-level wind circulations, low-level convergence, atmospheric instability, and enhanced precipitable water vapor. Results show that the interaction between localized mesoscale wind convergence and an exceptionally moisture-rich environment played a decisive role in convective intensification, leading to extreme short-duration rainfall. These critical mesoscale features were poorly resolved or underestimated by most operational models, contributing to the forecast failure. The event affected more than 235,000 people and caused widespread damage to housing and infrastructure. The findings highlight fundamental limitations of current forecasting systems in capturing short-duration, high-impact rainfall events over Sri Lanka and underscore the need for improved mesoscale diagnostics, real-time monitoring, and region-specific forecasting strategies to strengthen early warning and disaster preparedness.

Keywords: Extreme Rainfall in Sri Lanka, 1 June 2024

1. Introduction

Sri Lanka is a tropical island located in the Indian Ocean, characterized by complex terrain with a prominent central highland region rising to elevations above 1,900 m (Fig. 1). The central highlands consist of peaks, ridges, plateaus, and valleys that exert strong control on regional atmospheric flow and rainfall distribution through orographic lifting and flow blocking. As a result, rainfall exhibits pronounced spatial variability across relatively short distances, particularly between the windward and leeward sides of the island.

The country's rainfall regime is governed primarily by the southwest and northeast monsoons, inter-monsoonal convection, and occasional synoptic-scale systems such as low-pressure areas, depressions, and tropical cyclones over the Bay of Bengal. Orographic enhancement during the southwest monsoon is especially important, as moist southwesterly winds interact with the central highlands, producing intense rainfall over the western, southern, and central regions. Rainfall is the most critical climatic variable for Sri Lanka, strongly influencing agriculture, hydropower generation, and disaster risk. Previous studies have documented the increasing frequency and intensity of short-duration extreme

rainfall events over Sri Lanka and highlighted the role of mesoscale processes and moisture availability in amplifying rainfall extremes (Pathmarajah, 2018; Thevakaran et al., 2019; Sanjeevani & Manawadu, 2017).

Sri Lanka experiences four distinct climatic seasons, comprising two monsoon and two inter-monsoon periods. The southwest monsoon (May–September), contributes the 30% of annual rainfall and is frequently associated with short-duration, high-intensity rainfall events and localized flooding. Understanding the interaction between large-scale monsoon flow, mesoscale circulation, and topography (Fig. 1) is therefore essential for analyzing extreme rainfall events such as the June 2024 case was examined in this study.



Figure 1: Topography of Sri Lanka showing the central highlands and major physiographic regions.

Markedly high rainfall was recorded during the first week of June 2024. The observed rainfall distribution on 01 June 2024 (Fig. 2) and 02 June 2024 (Fig. 3) were presented in the Figures below. Ehaliyagoda, located in the Sabaragamuwa Province of Sri Lanka, recorded more than 400 mm of rainfall within a 24-hour period on 01 June 2024, making it the focal point of this case study.

The extreme rainfall event of had severe socio-economic impacts in Sri Lanka. More than 235,000 people were affected, with 37 fatalities and numerous injuries reported. Housing damage was extensive, including over 60,000 houses in Ratnapura, more than 32,000 in Kalutara, and over 22,000 in Matara, underscoring the vulnerability of these districts to short-duration, high-intensity rainfall events.

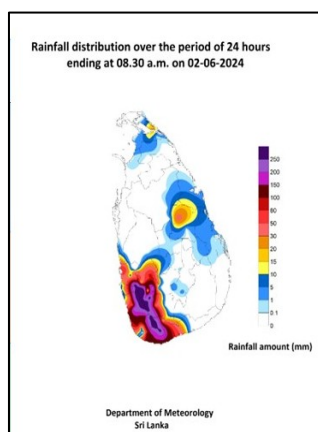


Figure 2: Daily total rainfall on 1st June 2024

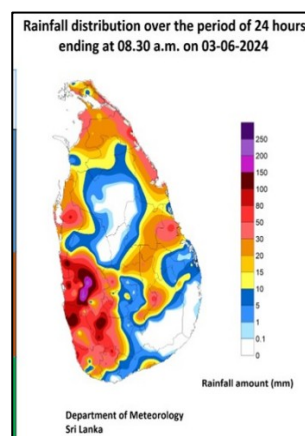


Figure 3: Daily total rainfall on 2nd June 2024

2. Data and Methodology

Accurate forecasting of the selected high rainfall event required the integration of multiple datasets and analytical techniques. This section describes the sources of data used and the methodology adopted for the analysis.

2.1 Data Sources

To ensure a comprehensive assessment, both observational and model-based datasets were utilized. The data sources are categorized as follows:

2.1.1 Local Observations

Ground-based meteorological observations from the Sri Lanka Department of Meteorology were employed. These included rainfall data, surface temperature, relative humidity, wind speed and direction, and pressure values obtained from the national network of weather stations. These datasets provided the baseline information for validating forecast outputs.

2.1.2 Numerical Weather Prediction (NWP) Outputs

Operational model forecasts generated by the Sri Lanka Department of Meteorology were analyzed. These NWP products formed the first layer of forecast guidance and were compared against international models for consistency and accuracy.

2.1.3 Global and Regional Model Data

To supplement local forecasts, model outputs from the following agencies were used:

Indian Meteorological Department (IMD): Provided regional-scale forecasts over South Asia, primarily based on the IMD–WRF and GFS systems, with typical horizontal resolutions of ~12 km (regional WRF) and ~25 km (global GFS).

National Centers for Environmental Prediction (NCEP): Provided global operational forecast and reanalysis products, including GFS and reanalysis datasets, with a typical horizontal resolution of ~0.25° (~25 km) for operational forecasts.

European Centre for Medium-Range Weather Forecasts (ECMWF): Supplied high-resolution deterministic and ensemble forecast products with advanced data assimilation systems, featuring a horizontal resolution of approximately 9 km for the deterministic (HRES) and ~18 km for the ensemble forecasts (ENS).

These datasets were particularly valuable in capturing large-scale synoptic conditions influencing rainfall over Sri Lanka.

2.1.4 Satellite Data

Satellite imagery was employed for real-time monitoring and analysis of convective systems, cloud patterns, and storm development. The following platforms were utilized:

- INSAT (India): Provided geostationary observations of cloud cover, convection, and precipitation over the South Asian region.
- Himawari (Japan Meteorological Agency): Supplied high-frequency, high-resolution imagery for monitoring mesoscale convective activity.
- Windy: Used as a supplementary visualization tool for interpreting global model outputs and satellite-based weather products.

2.2 Methodology

The methodology followed a structured approach combining observational validation and multi-model comparison:

1. Event Identification: The high rainfall event was first identified through local observation records and preliminary operational forecasts.
2. Data Collection: Observational, model-based, and satellite datasets corresponding to the event period were collected.
3. Model Comparison: Forecast outputs from multiple agencies were compared to assess similarities and discrepancies in rainfall prediction, synoptic features, and convective activity.
4. Satellite Validation: Satellite imagery was used to verify the spatial distribution of cloud clusters, convective systems, and rainfall occurrence.
5. Integration and Analysis: Observational data were integrated with model outputs and satellite products to evaluate forecast accuracy and identify key atmospheric drivers behind the event.
6. In addition to synoptic and mesoscale factors, large-scale atmospheric drivers were analyzed to understand their possible influence on rainfall variability during the event. Two important indices were considered: the Oceanic Niño Index (ONI) and the Madden–Julian Oscillation (MJO).

3. Results

3.1 Rainfall forecasts

None of the operational numerical weather prediction (NWP) models adequately captured the observed extreme rainfall over the affected area, highlighting notable limitations in forecast skill. The 24-hour forecasts initialized at 00 UTC on 31 May 2024 from IMD, ECMWF, NCEP, and other global models, as well as the corresponding 48-hour forecasts, significantly underestimated the rainfall, with predicted

values remaining below 100 mm. Similar underestimation was observed in the forecasts initialized at 12 UTC on 31 May and 00 UTC on 01 June 2024. Across all forecast runs, the models consistently failed to resolve the localized intensity and spatial extent of the event, suggesting challenges in simulating mesoscale convective processes and orographic enhancement within the region. The forecasted rainfall comparisons are presented in the Figures below (Fig. 4(a) to Fig. 5(l)).

24 hours and 48 hours based on 00 UTC 31 May (IMD)

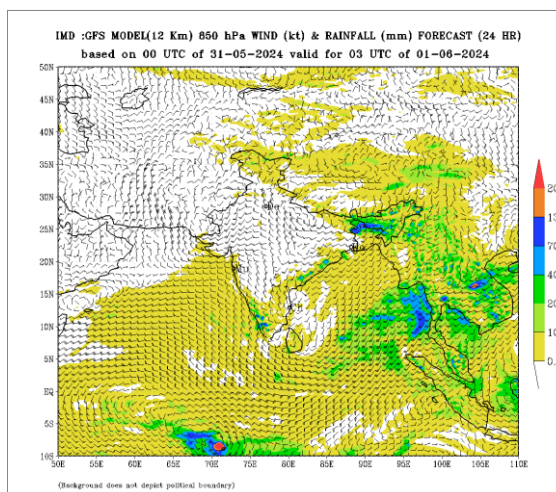


Figure 4(a) : 24-hour rainfall forecasts based on 00 UTC 31 May from IMD

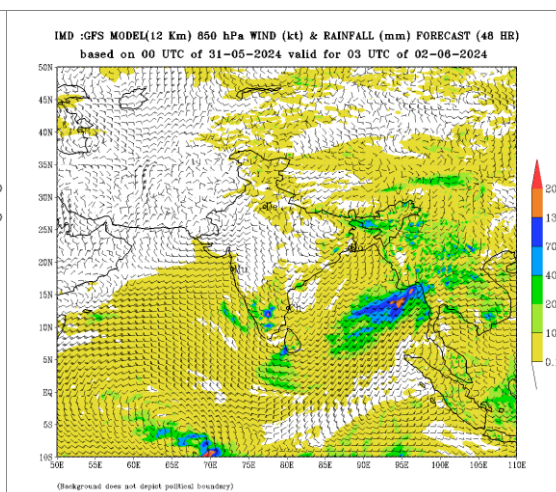


Figure 4(b) : 48-hour rainfall forecasts based on 00 UTC 31 May from IMD

Rainfall forecasts for 24 hours and 48 hours based on 00 UTC 31 May (ECMWF)

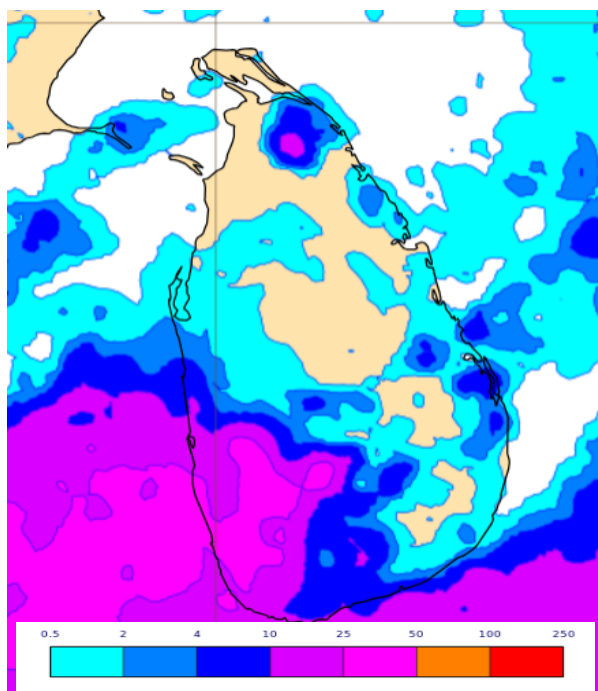


Figure 5(a) : 24 hour rainfall forecasts based on 00 UTC 31 May from ECMWF

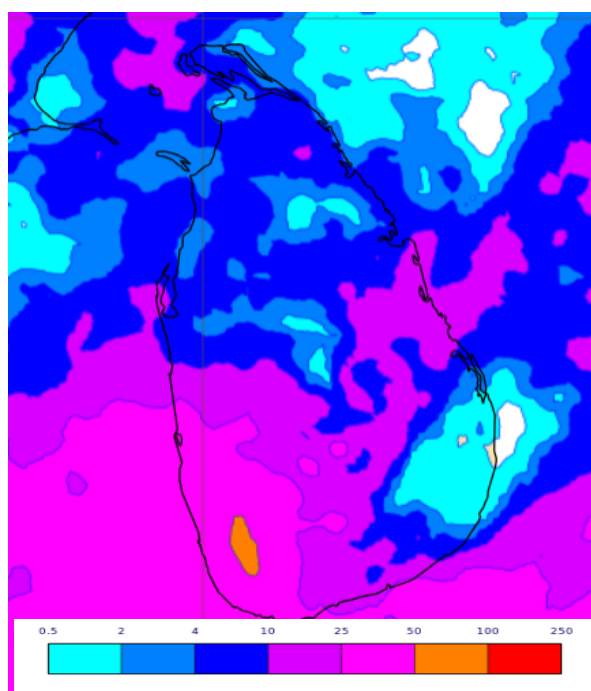


Figure 5(b) : 48-hour rainfall forecasts based on 00 UTC 31 May from ECMWF

Rainfall forecasts for 24 hours and 48 hours based on 12 UTC 31 May (ECMWF)

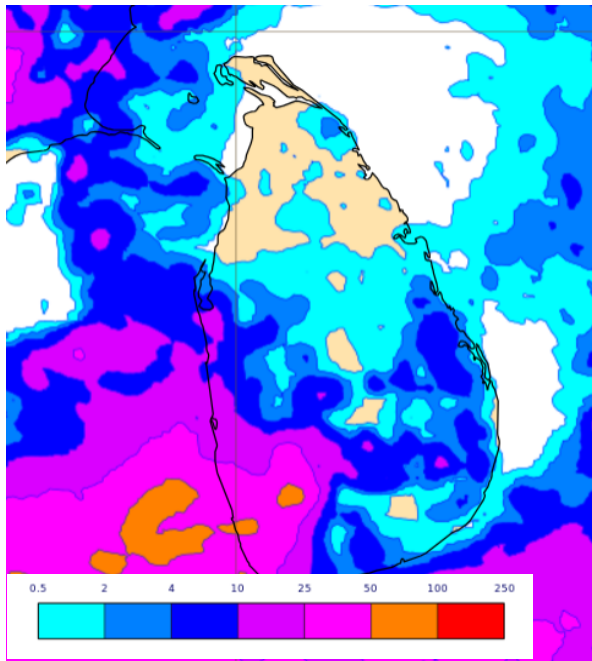


Figure 5(c) : 24 hour rainfall forecasts based on 12 UTC 31 May from ECMWF

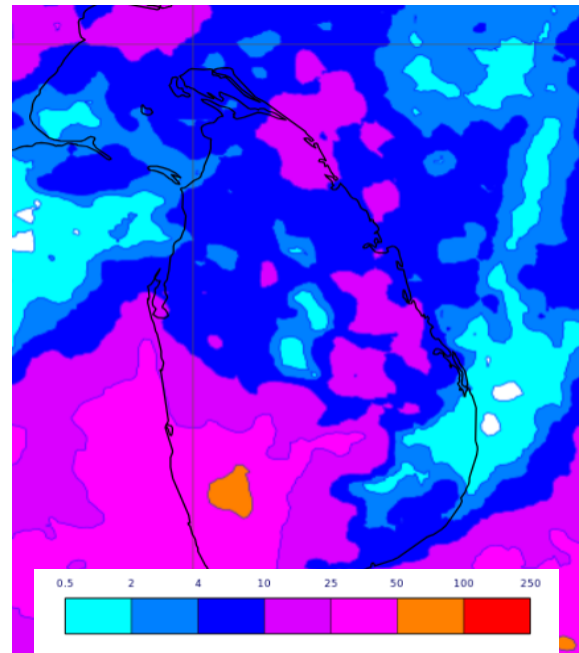


Figure 5(d) : 48 hour rainfall forecasts based on 12 UTC 31 May from ECMWF

Rainfall forecasts for 24 hours and 48 hours based on 00 UTC 01 June (ECMWF)

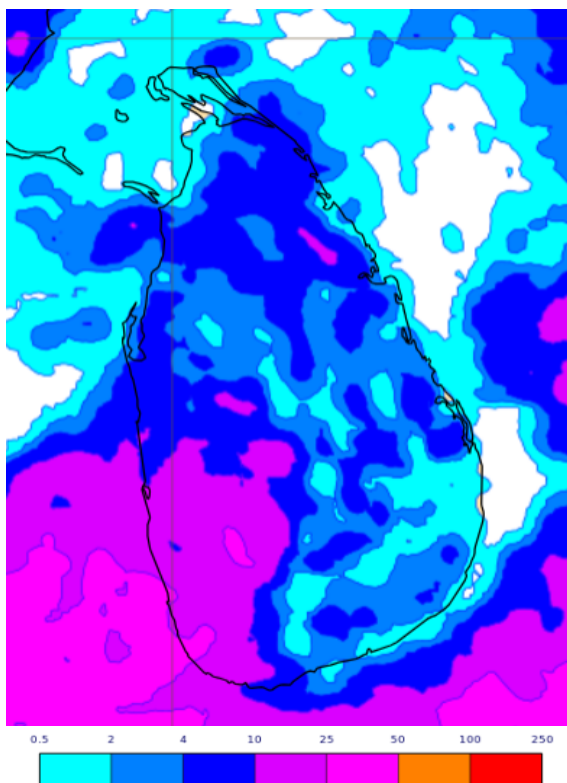


Figure 5(e) : 24-hour rainfall forecasts based on 00 UTC 01 June from ECMWF

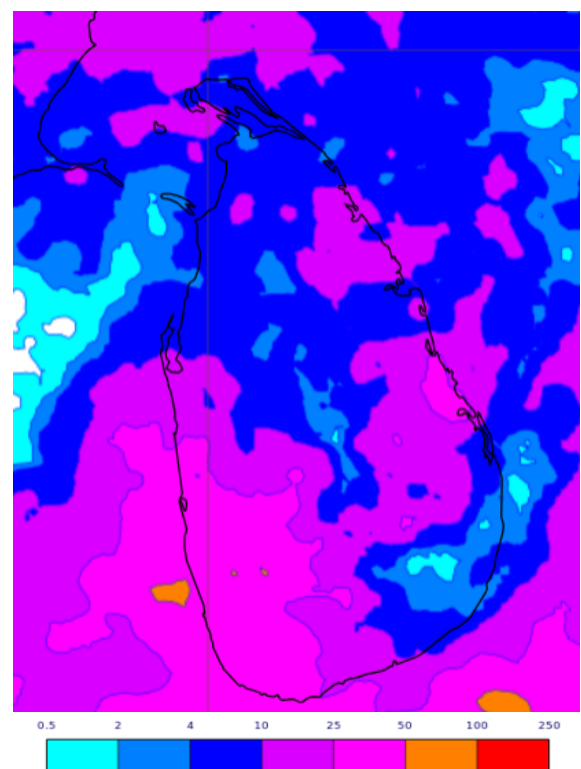


Figure 5(f) : 48-hour rainfall forecasts based on 00 UTC 01 June from ECMWF

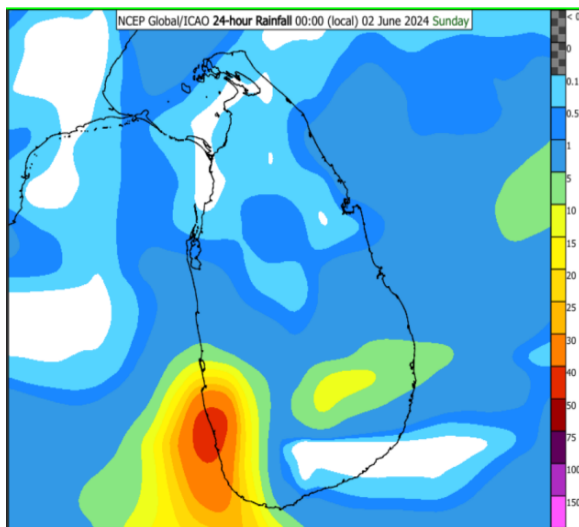
Rainfall forecasts for 24 hours and 48 hours based on 00 UTC 31 May (NCEP)

Figure 5(g) : 24 hour rainfall forecasts based on 00 UTC 31 May from NCEP

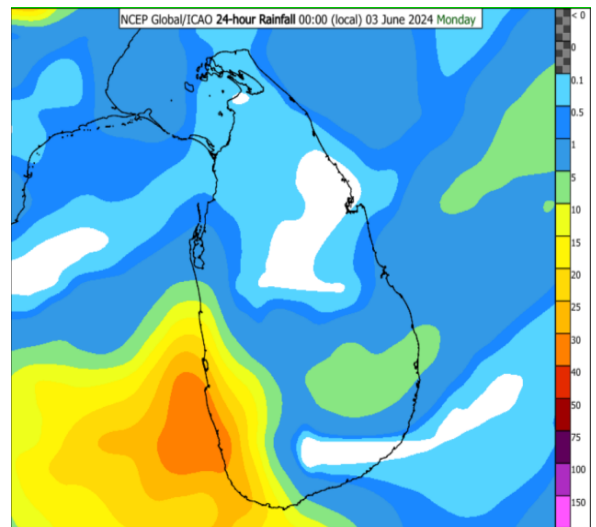


Figure 5(h) : 48 hour rainfall forecasts based on 00 UTC 31 May from NCEP

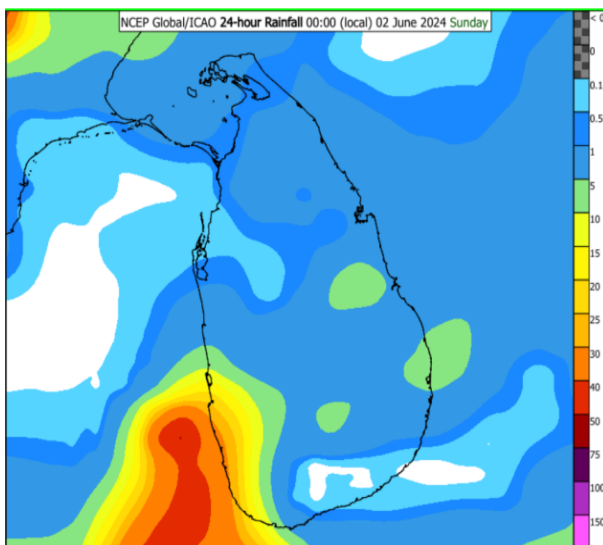
Rainfall forecasts for 24 hours and 48 hours based on 12 UTC 31 May (NCEP)

Figure 5(i) : 24 hour rainfall forecasts based on 12 UTC 31 May from NCEP

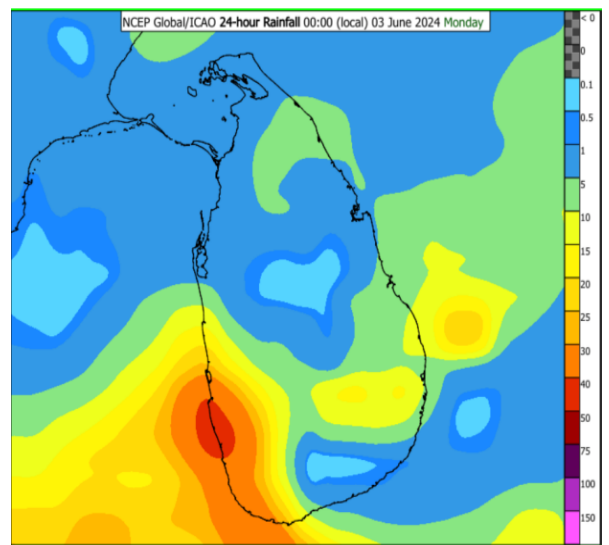


Figure 5(j) : 48 hour rainfall forecasts based on 12 UTC 31 May from NCEP

Rainfall forecasts for 24 hours and 48 hours based on 12 UTC 31 May (NCEP)

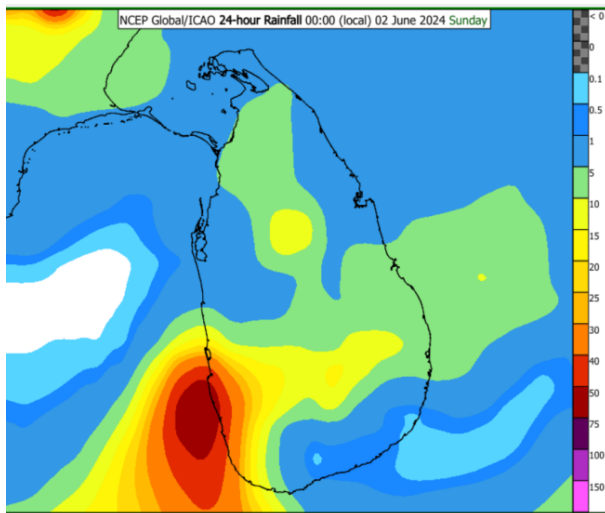


Figure 5(k) : 24 hour rainfall forecasts based on 00 UTC 01 June from NCEP

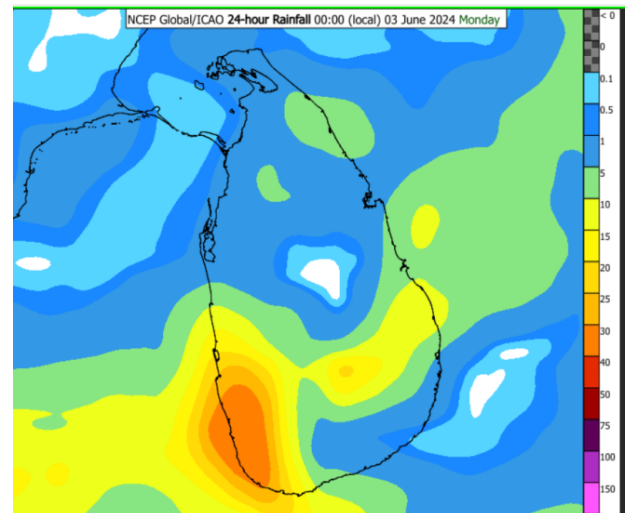


Figure 5(l) : 48 hour rainfall forecasts based on 00 UTC 01 June from NCEP

Extreme Rainfall Forecasts by ECMWF

The ECMWF Extreme Forecast Index (EFI) also unable to capture this event, indicating that even advanced probabilistic forecasting tools were unable to anticipate the extreme rainfall over the affected region (Fig.6 (a), (b) and (c)).

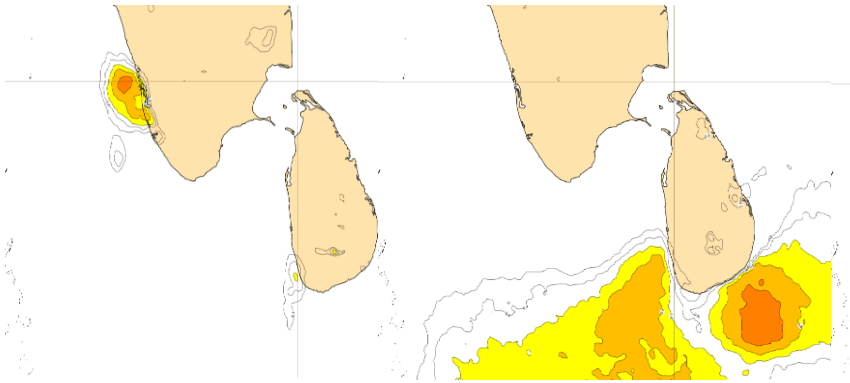


Figure 6(a) : Extream rainfall foresact indx from ECMWF for 31 May 2024

Figure 6(b) : Extream rainfall foresact indx from ECMWF for 01 June 2024

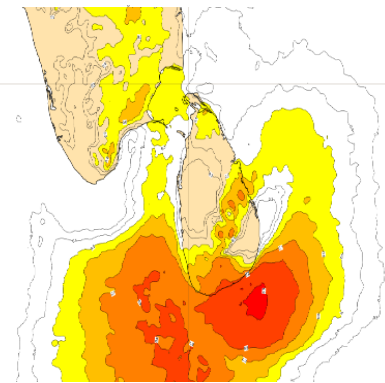


Figure 6(c) : Extream rainfall foresact indx from ECMWF for 02 June 2024

3.2 Wind Analysis (IMD charts)

Analysis of IMD wind charts based on 00 UTC 31 May 2024 at 850 hPa, 700 hPa, and 500 hPa levels did not indicate a strong synoptic-scale signal typically associated with extreme rainfall.

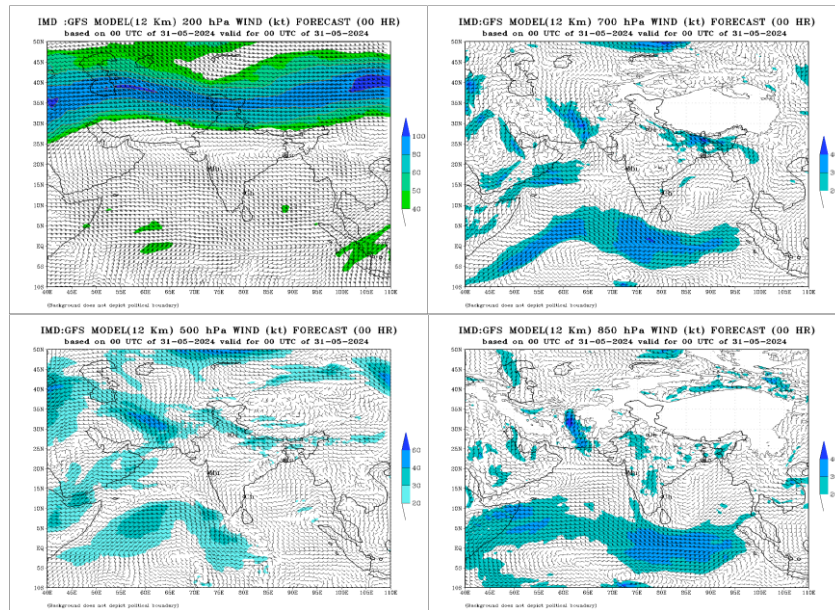


Figure 7: IMD wind pattern charts at 850 mb, 700 mb, 500mb and 200 mb levels and vertical cross-section showing small cyclonic circulations on 00 UTC 31 May.

However, subtle indications of unstable and weakly organized wind flow were present, suggesting a potential for localized convective development (Fig. 7).

24 Hours wind forecast based on 00 UTC 31 May using IMD charts

Wind patterns at the 850 hPa, 700 hPa, and 500 hPa levels indicated unstable flow conditions with weak cyclonic circulations discernible across these layers (Fig. 8). Such features are conducive to convective development and locally enhanced rainfall potential. The vertical cross-section at 00 UTC on 31 May further illustrates the presence of these small-scale cyclonic circulations.

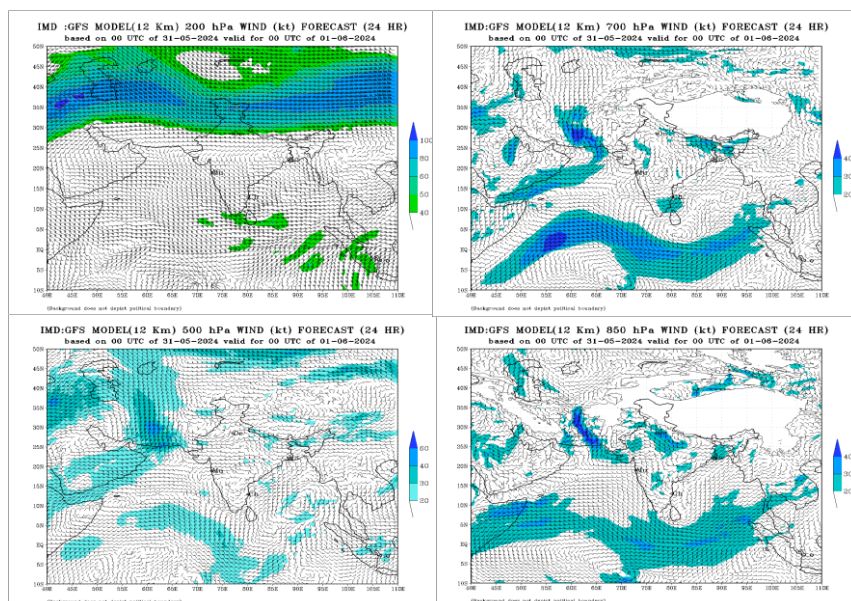


Figure 5: 24 hour wind forecasts based on 00 UTC 31 May from IMD

Dynamical Forcing Analysis (source: <https://tropic.ssec.wisc.edu>)

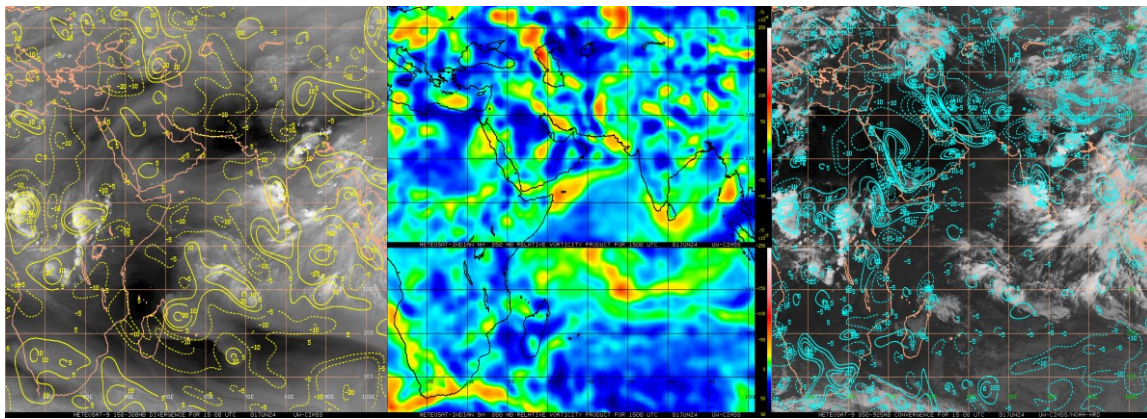


Figure. 9(a) 850-925 mb convergence Figure. 9(b) 850 mb relative vorticity Figure. 9(c) 150-300 mb divergence

On 01 June 2024, the dynamical environment over the study region exhibited conditions highly favorable for deep convection. At the lower troposphere (850–925 hPa), marked convergence was present (Fig. 9(a)), indicating the accumulation of moist air near the surface and its subsequent upward forcing. This was further supported by the presence of positive relative vorticity (Fig. 9(b)), consistent with cyclonic circulation and enhanced vertical motion often associated with low-pressure disturbances or trough-like features. In the upper troposphere (150–300 hPa), significant divergence was observed (Fig. 9(c)), providing an efficient exhaust mechanism for rising parcels and reducing static stability aloft. The simultaneous occurrence of low-level convergence, cyclonic vorticity, and upper-level divergence represents the classic vertical structure conducive to the initiation and maintenance of organized convection. These dynamical factors together would have contributed to enhanced upward motion, cloud development, and the potential for heavy rainfall over the region.

Precipitable Water Vapor

Predictable water vapor (PWV) estimates indicated above-average atmospheric moisture over Sri Lanka during this period (Fig. 10), creating a moisture-rich environment that favored the development of the intense rainfall event.

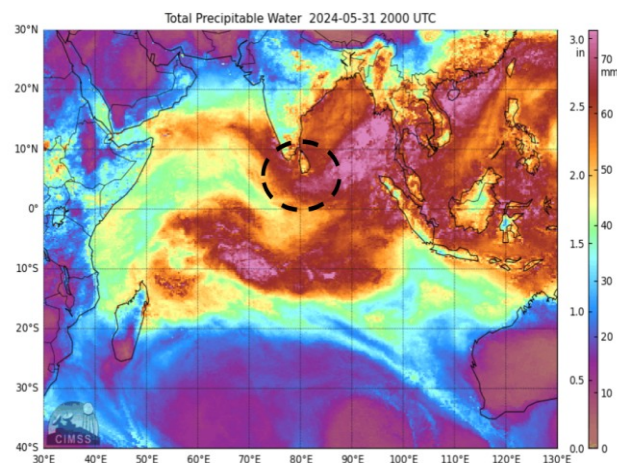


Figure 10: Total Precipitable Water

(source: https://tropic.ssec.wisc.edu/real-time/mimic_tpw/global/main.html)

3.3 Large-scale intraseasonal influences

3.3.1 Oceanic Niño Index (ONI)

The ONI, which measures sea surface temperature anomalies in the equatorial Pacific, is a widely used indicator of El Niño–Southern Oscillation (ENSO) phases. During the period of study, ONI values ranged between 0.0 and +0.4, which is classified as a neutral phase. This indicates that neither El Niño nor La Niña conditions were present. Consequently, the influence of ENSO-related teleconnections on rainfall over Sri Lanka during this event was expected to be minimal. The neutral state implies that local and regional atmospheric conditions, rather than Pacific Ocean forcing, played the primary role in driving the observed rainfall. (source: <https://www.cpc.ncep.noaa.gov/>)

3.3.2 Madden–Julian Oscillation (MJO)

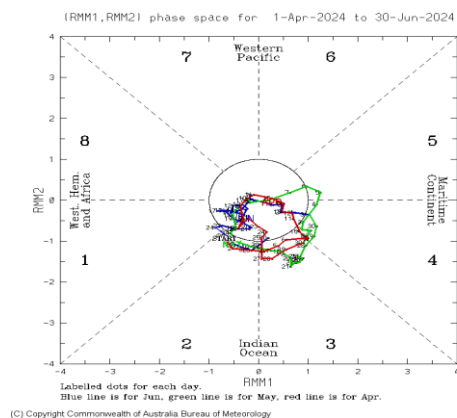


Figure. 11: MJO from 01 April to 30 June

The MJO is an intraseasonal tropical disturbance characterized by eastward-moving convective and circulation anomalies. Its different phases modulate rainfall patterns across the tropics. During the analyzed period, the MJO was located in Phase 4 (Fig. 11), which typically enhances convection over the Maritime Continent but exerts limited direct influence on Sri Lanka. As a result, the MJO did not significantly support or amplify rainfall during this event. (source: <https://cpc.ncep.noaa.gov/>)

4. Conclusion

The extreme rainfall event over Ehaliyagoda on 01 June 2024 was primarily driven by local and mesoscale factors rather than large-scale climate drivers, as both ENSO and MJO were in near-neutral phases during this period. The persistent southwesterly wind flow transported abundant moisture toward the region, while the area's geographical setting—low-lying terrain adjacent to steep orographic slopes—enhanced orographic lifting. Analysis of the vertical cross-section at 00 UTC on 31 May

revealed small-scale cyclonic circulations, which, combined with above-average precipitable water vapor, created favorable conditions for convective activity. vertical alignment of dynamical features enhanced upward motion and moisture transport, ultimately favoring the development of deep clouds and heavy rainfall over the region. These local and mesoscale interactions collectively produced the unusually high rainfall observed in the affected area.

5. Discussion

Complexity of Sri Lanka's terrain adds challenges through orographic effects enhancing localized rainfall. Ehaliyagoda, located in the Sabaragamuwa Province of Sri Lanka at the foothills of the central highlands, recorded more than 400 mm of rainfall within a 24-hour period on 01 June 2024. Its geographical setting, characterized by low-lying terrain adjacent to steep orographic slopes, makes the area highly susceptible to rainfall enhancement under the influence of moisture-laden southwesterly winds. Sabaragamuwa Province, particularly the Ratnapura and Kegalle districts, lies within the wet zone of Sri Lanka and is among the regions most exposed to the Southwest Monsoon. Orographic lifting along the central highlands significantly amplifies rainfall, often leading to localized extremes. Historical evidence further highlights the province's vulnerability to high-impact weather events such as floods and landslides, emphasizing the importance of investigating this extreme event.

- Localized small-scale cyclonic wind circulations at multiple levels contributed critically to the heavy rainfall but were not captured adequately by operational models.
- High atmospheric moisture combined with unstable winds produced favorable conditions for extreme rainfall.
- The alignment of low-level convergence, cyclonic vorticity, and upper-level divergence on 01 June 2024 created a highly supportive environment for organized convection.
- Model limitations are primarily due to insufficient resolution and inadequate data assimilation.
- Improving model resolution and integrating better observational data are essential for improved forecasting and disaster mitigation.
- Despite the underestimation by numerical models, forecasters at the National Meteorological Centre were able to predict rainfall exceeding 150 mm for the affected area based on their expertise and practical knowledge of local weather patterns. This highlights that reliance solely on model outputs is often insufficient for accurately forecasting tropical weather, where mesoscale and local factors can dominate extreme rainfall events.

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Projected Changes in Temperature and Precipitation over Sri Lanka under CMIP6 Shared Socioeconomic Pathways

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ABSTRACT

Sri Lanka, an island nation in the northern Indian Ocean, is characterized by a tropical climate with pronounced spatial and seasonal variability. Understanding how rainfall and temperature may change under future climate conditions is critical for national climate assessments and long-term planning. This study presents a comprehensive assessment of projected changes in precipitation and temperature over Sri Lanka using a multi-model ensemble of 25 downscaled and bias-corrected high-resolution global climate models from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Projections are examined under intermediate (SSP2–4.5) and high (SSP5–8.5) emission scenarios, with ERA5 reanalysis data used as the observational reference. Results indicate a long-term increase in annual rainfall across Sri Lanka, with stronger and more spatially extensive wetting under the high-emissions pathway. Seasonal analysis reveals intensified rainfall during the Northeast and Southwest Monsoons, contrasted by persistent drying during the First Inter-Monsoon, highlighting a clear redistribution of rainfall across seasons. Temperature projections show robust and sustained warming across all regions and seasons, with stronger increases under SSP5–8.5 and pronounced divergence between scenarios toward mid- and late-century. Warming is spatially coherent, with enhanced increases over inland and lowland regions, indicating a fundamental shift in the national thermal regime. Overall, the projections suggest that Sri Lanka's future climate will be characterized by intensified monsoonal rainfall, increased seasonal contrasts, and sustained warming, with outcomes strongly dependent on future emission pathways. These findings provide a robust, CMIP6-consistent scientific basis for national climate change assessments and sector-relevant climate interpretation in Sri Lanka.

1. Introduction

Sri Lanka's climate is shaped by its tropical maritime setting and the strong seasonal influence of two monsoon systems, which generate pronounced spatial and temporal variability in rainfall and temperature across the island. The Southwest Monsoon (May–September) brings substantial precipitation to the western, southern, and windward slopes of the central highlands, while the Northeast Monsoon (December–February) predominantly influences the northern and eastern regions (Department of Meteorology, Sri Lanka, 2020). The inter-monsoon periods produce additional convective instability, often triggering thunderstorms and localized extreme rainfall events. Although temperatures are high throughout the year, topographic contrasts particularly in the central highlands moderate thermal conditions and create distinct agro-ecological and climatological zones (Herath & Ratnayake, 2004; Zubair *et al.*, 2015). This diverse climate system supports agriculture, ecosystems, and livelihoods but also increases the country's vulnerability to floods, droughts, landslides, storm surges, and heat stress (UNDP, 2016; Rathnayake *et al.*, 2020).

Growing evidence indicates that climate variability and long-term climate change are already influencing rainfall patterns, monsoon behaviour, and temperature extremes, as highlighted in the IPCC Sixth Assessment Report (2021) and other regional climate assessments. Local analyses show trends of increasing temperature, intensifying extreme rainfall events, and shifts in monsoon onset timing (Zubair & Ropelewski, 2006; De Costa, 2008). Studies using observational records and regional model simulations have also reported spatially heterogeneous rainfall trends, with some regions experiencing significant declines in the Southwest Monsoon and others showing heightened inter-annual variability (Ranmuthugala *et al.*, 2019; Premalal *et al.*, 2020). These observed changes underline the need for robust future climate projections tailored to Sri Lanka.

Climate change impact studies depend heavily on future projections derived from global climate models (GCMs). Due to their coarse spatial resolution, GCM outputs require downscaling either through empirical statistical approaches or regional climate modelling to provide finer resolution information suitable for national scale assessment. Downscaled projections for Sri Lanka have been widely used to investigate future rainfall regimes, temperature extremes, crop yields, hydrology, water resources, and disaster risks (Zubair *et al.*, 2005; Eriyagama *et al.*, 2010; Rathnayake, Chandrasekara, 2021 & Samaraweera *et al.*, 2024). These projections play a critical role in supporting climate-resilient planning and adaptation policies.

The number and diversity of Global Climate Models (GCMs) have expanded substantially across successive phases of the Coupled Model Intercomparison Project (CMIP). CMIP3, which informed the IPCC Fourth Assessment Report, comprised 25 models (Meehl *et al.*, 2007; IPCC, 2007), while CMIP5 increased this ensemble to 61 models (Taylor *et al.*, 2012; IPCC, 2013). The latest CMIP6 generation incorporates improved representations of radiative forcing, internal climate variability, and large-scale circulation processes, including monsoon dynamics, providing a more robust basis for climate projections over South Asia (Eyring *et al.*, 2016; Lee *et al.*, 2021; IPCC, 2023). For Sri Lanka, where rainfall is strongly modulated by the Southwest Monsoon (May–September) and Northeast Monsoon (December–February), localized CMIP6-based projections are therefore essential for assessing future changes in seasonal rainfall regimes, temperature extremes, sea-level rise, and the frequency of climate-induced hazards.

Despite these advances, the rapidly growing number of available GCMs, together with multiple ensemble members for individual models, results in an extremely large pool of simulations. Given practical constraints in computational capacity and analytical resources, climate impact and adaptation studies rarely employ the full CMIP ensemble. Consequently, most studies rely on a single model or a carefully selected subset of models. Selecting an ensemble that both realistically represents the SWM–NEM rainfall characteristics and adequately samples projection uncertainty remains a key challenge for

small-island, monsoon-dominated environments such as Sri Lanka, where complex topography and land–sea interactions strongly influence rainfall variability.

Uncertainty in climate projections arises from interacting sources, including assumptions regarding future greenhouse gas emission pathways, differences in climate model formulation, internal climate variability, and the choice of downscaling techniques. In monsoon-influenced regions, precipitation projections exhibit substantially greater uncertainty than temperature projections, as natural variability and inter-model differences in simulating convection and circulation can dominate seasonal rainfall responses, particularly at local scales (Climate Change 2021: The Physical Science Basis; Assessment of Climate Change over the Indian Region). Darshika *et al.* (2018) applied a multi-model ensemble approach and reported increasing rainfall over southwestern Sri Lanka with decreasing tendencies over the northeastern region. Given advances in CMIP6 model physics and improved representation of monsoon processes, this study reassesses regional rainfall responses using a refined ensemble framework, yielding updated projections for both monsoon seasons.

In this context, the primary objective of this study is to develop CMIP6-based climate change projections for Sri Lanka using a multi-model ensemble approach. An initial pool of 25 CMIP6 Global Climate Models was evaluated, from which six models were selected based on their ability to represent key regional climate characteristics and monsoon-driven rainfall variability. The resulting six-model ensemble was used to generate robust projections of future changes in rainfall and temperature regimes, while accounting for inter-model uncertainty relevant to national-scale impact and adaptation planning.

2. Data

As shown in Table 1, ERA5 reanalysis products were employed as the observational reference dataset for this analysis. Evaluation against available in-situ observations indicates only minor deviations, with slightly larger differences over the central highlands. Importantly, ERA5 provides spatially complete, quality-controlled precipitation and temperature fields with no missing values during the reference period (1995–2014). In contrast, in-situ rainfall records across Sri Lanka contain some data gaps, and long-term temperature observations are available from only 18 stations, which is insufficient to construct a reliable national-scale gridded dataset, particularly in regions of complex topography. Consequently, the entire analysis was conducted using ERA5 daily data at a 25×25 km resolution, providing a consistent and practical basis for evaluating CMIP6 model performance at annual and seasonal scales, while acknowledging the inherent limitations of reanalysis products.

On selecting climate projection data, a thorough review is suggested to ensure access to future climate datasets with adequate horizontal resolution for assessing sectoral impacts in any target area. The NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) provide a valuable

resource in this regard. This dataset includes future climate scenarios from 25 global climate models (GCMs) under two shared socio-economic pathways (SSP2-4.5 and SSP5-8.5), at a spatial resolution of $25 \times 25 \text{ km}^2$. Such characteristics make NEX-GDDP-CMIP6 particularly suitable as a starting point for regional-scale analyses.

Table 1: Data and their sources

Data	Spatiotemporal resolution	Duration	Source
Precipitation Minimum temperature Maximum temperature	Point/Daily	1980 – 2014	DoM
Precipitation Minimum temperature Maximum temperature	$25 \times 25 \text{ km/Daily}$	1995 – 2014	ERA5 https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form
GCMs data	$25 \times 25 \text{ km/Daily}$	1981 – 2100	NEX-GDDP-CMIP6 https://ds.nccs.nasa.gov/thredds/ncss/AMES/NEX/GDDP-CMIP6

Table 2: Data Field Description for NEX-GDDP

CMIP6 models included	25 GCMs UKESM1-0-LL, TaiESM1, NorESM2-MM, NorESM2-LM, MRI-ESM2-0, MPI-ESM1-2-LR, MPI-ESM1-2-HR, MIROC6, MIROC-ES2L, KACE-1-0-G, IPSL-CM6A-LR, INM-CM5-0, INM-CM4-8, GISS-E2-1-G, GFDL-ESM4, FGOALS-g3, EC-Earth3-Veg-LR, EC-Earth3, CanESM5, CNRM-ESM2-1, CNRM-CM6-1, CMCC-ESM2, BCC-CSM2-MR, ACCESS-ESM1-5, ACCESS-CM2
SSP scenarios	SSP2-4.5 and SSP5-8.5
Temporal resolution	Daily from 1950-01-01 to 2100-12-31 from 1950 through 2014 (“Retrospective Run”) and from 2015 to 2100 (“Prospective Run”)
Spatial Resolution	0.25 degrees x 0.25 degrees
Climate Variables	Precipitation, Maximum and Minimum Temperature
Dataset Projection and Datum	Geographic, WGS84

3. Approach and Methodology

This section provides an in-depth explanation of the approach and methodology applied in this analysis.

3.1 Preprocessing ERA5 Data

Following the retrieval of precipitation, maximum temperature, and minimum temperature datasets from the ERA5 repository, preprocessing was conducted to ensure consistency with the General Circulation Model (GCM) datasets in terms of units, spatial and temporal resolution, and spatial domain. Precipitation values provided in meters (m) by ERA5 were converted to millimeters (mm) by multiplying by 1000. Similarly, temperature values expressed in Kelvin (K) were converted to degrees

Celsius (°C) by subtracting 273.15. To harmonize the spatial domain, bilinear interpolation was applied, thereby aligning the ERA5 data with the resolution and coverage of the GCM datasets.

3.2 Preprocessing GCM Data

Precipitation and temperature datasets were obtained from the NEX-GDDP-CMIP6 repository. Precipitation values, originally expressed in kgm-1s-1, were converted to millimeters (mm), while temperature values in Kelvin were converted to degrees Celsius. The processed datasets were further constrained to the period 1995–2014 to facilitate climatological analysis and the selection of suitable GCMs.

3.3 Model Performance Evaluation

Not all CMIP6 GCMs are directly applicable to the Sri Lankan context due to regional climatic specificities and performance limitations. Therefore, a subset of GCMs was identified from the available CMIP6 ensemble based on a structured evaluation framework. The selection process aimed to exclude models with the least realistic representation of local climate while retaining those capable of capturing the maximum possible range of projected changes. At the same time, satisfactory performance across multiple evaluation metrics was required to ensure robustness.

Accordingly, the following approach was adopted:

- **Performance-based screening:** Models were first assessed against statistical metrics and climate indices to evaluate their ability to reproduce observed climatological patterns.
- **Range-of-change consideration:** From the screened models, those representing diverse trajectories of precipitation and temperature change were prioritized to capture the breadth of plausible futures.
- **Balanced selection:** The final subset was chosen to balance realism with diversity, ensuring that the selected GCMs both perform satisfactorily and reflect the maximum possible range of climate variability relevant to Sri Lanka.

This procedure yielded a set of plausible GCMs tailored to the country context, which were subsequently used for detailed climate impact analysis.

ERA5 and historical GCM datasets were regridded to a common spatial resolution of 25 km and daily as well as aggregated monthly timescales data prepared for the period 1995–2014. This harmonization ensured comparability across datasets during the evaluation process. Model performance was assessed using several statistical metrics, as defined in Equations (1)–(4). These metrics were applied to both

precipitation and temperature variables to comprehensively evaluate the ability of the GCMs to reproduce observed climatological patterns. The evaluation was conducted at both annual and seasonal scales, with particular emphasis on the Southwest Monsoon, Northeast Monsoon, and the two Inter-monsoon periods, thereby capturing the dominant climatic regimes over Sri Lanka.

$TSS = \frac{(1+R_m)^4}{4(SDR_m+1/SDR_m)^2}$	(1)
$RSR = \sqrt{\frac{\sum_{m=1}^n (sim_m - obs_m)^2}{\sum_{m=1}^n (obs_m - \overline{obs_m})^2}}$	(2)
$RSQUARE = \frac{[\sum_{m=1}^n (obs_m - \overline{obs_m}) (sim_m - \overline{sim_m})]^2}{\sum_{m=1}^n (obs_m - \overline{obs_m})^2 * \sum_{m=1}^n (sim_m - \overline{sim_m})^2}$	(3)
$PBIAS = \frac{\sum_{m=1}^n sim_m - \sum_{m=1}^n obs_m}{\sum_{m=1}^n obs_m} * 100\%$	(4)

Where TSS, RSR, RSQUARE and PBIAS Taylor skill score, root mean square error to standard deviation, coefficient of determination and percentage bias (Misra V et al., 2018 and Noska R et al., 2016). Obs and Sim represent observed and GCM values. Subscript m represents monthly value. R is the correlation between observed and GCM monthly rainfall while SDR is the ratio between standard deviation of simulated and observed monthly rainfall.

In addition to the standard performance metrics, four climate indices were computed to strengthen the evaluation process by capturing aspects of climate extremes. Consecutive Dry Days (CDD) quantify the maximum number of consecutive days with negligible precipitation, providing insight into drought persistence. R95PTOT represents the proportion of total precipitation contributed by very wet days, defined as those exceeding the 95th percentile of daily rainfall, thereby highlighting the intensity of extreme precipitation events. TN10P measures the percentage of cold nights relative to the 10th percentile of the reference period, serving as an indicator of changes in lower-tail temperature extremes. Conversely, TX90P denotes the percentage of very warm days relative to the 90th percentile of the reference period, reflecting the frequency of upper-tail temperature extremes. Together, these indices complement the conventional evaluation metrics by offering a more comprehensive assessment of the models' ability to reproduce both mean climate conditions and extremes.

To rank GCMs, Compromise Programming was employed, as illustrated in Equation (5) (Raju et al., 2017). In this framework, f_j denotes the normalized value of metric j for a given climate model, f_j^* represents the normalized ideal value of metric j, w_j is the weight assigned to metric j, n is the total number of metrics considered, and p is the power factor. For this study, equal weights were assigned to

all metrics ($w_j=1/n$), and a power factor of $p=2$ was adopted, corresponding to the squared Euclidean distance.

$$L_p = \left[\sum_{j=1}^n w_j^p |f_j^* - f_j| \right]^{1/p} \quad (5)$$

The resulting compromise measure, L_p , provides a quantitative assessment of model performance, with smaller values of L_p indicating closer proximity to the ideal solution and, therefore, better performance. Based on this ranking procedure, the six best-performing GCMs were identified and selected for subsequent analysis.

To further verify the selected models, we evaluated the spread of GCMs, a Skill Test was applied using scatter plots. The Skill Test involved calculating the change in annual mean temperature (dT) and the percentage change in annual precipitation ($dP\%$) for each CMIP6 model available in the NEX dataset under the SSP2-4.5 and SSP5-8.5 scenarios. These values were plotted in scatter plots at the national scale, thereby illustrating the distribution of model projections for the 2030s, 2050s, and 2080s.

Future scenarios were defined as follows:

- 2040s: average over 2031–2050
- 2060s: average over 2051–2070
- 2080s: average over 2071–2090

All projections were compared against the baseline climate (rainfall and mean temperature) for the period 1995–2014. The Skill Test was conducted for both annual and seasonal scales, covering the Southwest Monsoon, Northeast Monsoon, and the two Inter-monsoon periods.

Models falling within the 10th and 90th percentiles of dT and $dP\%$ during the 2030s, 2050s, and 2080s under both SSP scenarios were identified as the best-performing models. These models were subsequently verified the selected models.

3.4 Downscaling of Selected GCMs

The coarse spatial resolution of the NEX-GDDP dataset ($25 \times 25 \text{ km}^2$) limits its applicability for detailed national- and local-scale climate change analyses. Comprehensive assessments of local climate impacts such as changes in extremes, agricultural productivity, and water resource availability require high-resolution climate variables that cannot be directly obtained from coarse-resolution projections (Komurcu *et al.*, 2018). To address this limitation, a statistical downscaling and spatial redistribution

approach was employed to generate datasets at a resolution of $1 \times 1 \text{ km}^2$ for subsequent impact studies in the target areas.

For temperature, a robust regression approach (Evans and Ram, 2016) was applied. In this method, coarse-resolution temperature data served as the dependent variable, while a high-resolution Digital Elevation Model (DEM; $1 \times 1 \text{ km}^2$) was used as the independent variable to construct a bivariate (or multivariate) regression model. This approach has demonstrated consistent success in downscaling temperature data, as robust regression techniques are well-suited for handling large sample sizes without introducing significant bias. The GTOPO30 global DEM, with a horizontal grid spacing of 30 arc seconds (approximately 1 km), was used as input for the downscaling process. Derived from multiple raster and vector sources of topographic information, GTOPO30 is distributed in tiles to facilitate ease of use. Downscaling was implemented using functions available in the *spatialEco* R package (version 1.0-0).

For precipitation, establishing a direct statistical relationship with elevation proved challenging. Therefore, a bilinear resampling method was adopted to convert precipitation data from $25 \times 25 \text{ km}^2$ to $1 \times 1 \text{ km}^2$ resolution for improving the spatial redistribution. The ERA5 precipitation dataset was used as the reference surface to guide the resampling process, ensuring that the downscaled precipitation fields approximate observed spatial patterns while preserving the original GCM structure.

The downscaling procedures were applied to selected GCMs representing plausible extreme conditions. The resulting $1 \times 1 \text{ km}^2$ datasets provided the basis for developing future climate projections and assessing potential risks in the country. This approach preserves large-scale precipitation signals while enhancing spatial detail for national-scale assessment, rather than generating new local-scale rainfall variability.

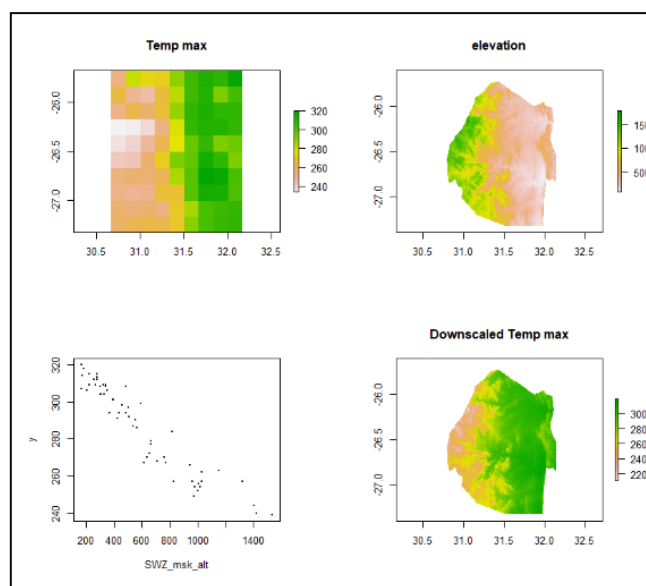


Figure 1: Downscaling temperature data to $1 \times 1 \text{ km}^2$ resolution using T_{max} and GTOPO 30 DEM data in *spatialEco* 1.0-0 R package

3.5 Development of Future Scenarios and Identification of Hotspots for Sri Lanka

Once the subset of plausible GCMs was selected, ensemble mean projections were developed to construct future scenarios and identify potential climate hotspots across Sri Lanka. The following steps were undertaken:

1. Development of future climate datasets:

Future rainfall, maximum temperature, and minimum temperature were generated for three time slices 2040s, 2060s, and 2080s at annual, SWM season, NEM season and two inter-monsoon season scales. Each time slice was represented by a 20-year average (e.g., 2031–2050 for the 2040s, 2051–2070 for the 2060s, and 2071–2090 for the 2080s).

2. Estimation of climate change signals:

Future climate change was quantified by calculating the difference between projected future climate and the baseline climate (1995–2014) for rainfall, maximum temperature, and minimum temperature. This was performed for annual and seasonal scales.

3. Identification of climate hotspots:

Hotspots were identified by screening the 20-year datasets/maps for each time slice. Specifically, maximum rainfall, maximum of maximum temperature, and minimum of minimum temperature were extracted for each grid cell across the study area. This enabled the detection of spatial locations most vulnerable to extreme changes in rainfall and temperature at annual and seasonal scales.

3.6 Software Utilized

Throughout the analysis, we employed state-of-the-art open-source software developed by internationally recognized institutions. The software tools utilized are outlined below.

Table 3: Summary of software utilized during the assignment.

Software	Purpose	Developer
Climate Data Operators (CDO) in Windows Subsystem for Linux (WSL) with Ubuntu 20.04.4 LTS distribution	To access, modify and analyze gridded timeseries climate data.	Max Planck Institute for Meteorology
Python programming language	To execute the GCM selection process, Map generation, etc.	
R programming language	To execute the downscaling approach	
Panoply	To visualize gridded timeseries climate data.	NASA's Goddard Institute for Space Studies (GISS)
Excel, Word, PowerPoint	To conduct general purpose office works	Microsoft Corporation Inc.

4. Results and Discussion

To identify CMIP6 models with balanced performance across climatology, monsoon seasonality, and climate extremes, a multi-criteria ranking based on Compromise Programming was applied, and the resulting model rankings are shown in Figure 2.

Ranked GCMs for Annual & CI			Ranked GCMs for Annual, CI & SW			Ranked GCMs for Annual, CI, SW & NE		
GCM	L _p	Rank	GCM	L _p	Rank	GCM	L _p	Rank
CNRM-CM6-1	0.381556	1	CNRM-CM6-1	0.399588	1	CNRM-CM6-1	0.381669	1
MPI-ESM1-2-LR	0.417642	2	CNRM-ESM2-1	0.417608	2	CNRM-ESM2-1	0.392158	2
CNRM-ESM2-1	0.418839	3	MIROC-ES2L	0.432432	3	UKESM1-0-LL	0.405598	3
MIROC-ES2L	0.422002	4	UKESM1-0-LL	0.435593	4	ACCESS-CM2	0.411454	4
EC-Earth3-Veg-LR	0.450931	5	ACCESS-CM2	0.439293	5	MIROC-ES2L	0.41297	5
ACCESS-CM2	0.470153	6	EC-Earth3-Veg-LR	0.446681	6	GISS-E2-1-G	0.428529	6
UKESM1-0-LL	0.48123	7	GISS-E2-1-G	0.46467	7	NorESM2-LM	0.444376	7
GISS-E2-1-G	0.487188	8	INM-CM5-0	0.472948	8	INM-CM5-0	0.445668	8
NorESM2-LM	0.490222	9	NorESM2-LM	0.485976	9	MPI-ESM1-2-LR	0.44846	9
IPSL-CM6A-LR	0.498362	10	CanESM5	0.486992	10	EC-Earth3-Veg-LR	0.455548	10
MPI-ESM1-2-HR	0.505498	11	MPI-ESM1-2-LR	0.489177	11	NorESM2-MM	0.469008	11
MRI-ESM2-0	0.509588	12	MRI-ESM2-0	0.505345	12	CanESM5	0.472197	12
CanESM5	0.51017	13	MPI-ESM1-2-HR	0.505434	13	FGOALS-g3	0.478093	13
INM-CM5-0	0.515496	14	INM-CM4-8	0.505909	14	MRI-ESM2-0	0.479621	14
MIROC6	0.534286	15	FGOALS-g3	0.509675	15	INM-CM4-8	0.479915	15
GFDL-ESM4	0.536097	16	CMCC-ESM2	0.513882	16	CMCC-ESM2	0.487282	16
NorESM2-MM	0.53785	17	NorESM2-MM	0.514491	17	MPI-ESM1-2-HR	0.489579	17
ACCESS-ESM1-5	0.538585	18	GFDL-ESM4	0.519938	18	GFDL-ESM4	0.505638	18
CMCC-ESM2	0.53958	19	KACE-1-0-G	0.527911	19	MIROC6	0.508182	19
INM-CM4-8	0.554038	20	IPSL-CM6A-LR	0.532849	20	ACCESS-ESM1-5	0.516637	20
EC-Earth3	0.558315	21	ACCESS-ESM1-5	0.545459	21	IPSL-CM6A-LR	0.517221	21
FGOALS-g3	0.566212	22	BCC-CSM2-MR	0.55316	22	BCC-CSM2-MR	0.531451	22
BCC-CSM2-MR	0.59552	23	MIROC6	0.571831	23	EC-Earth3	0.560015	23
KACE-1-0-G	0.614287	24	EC-Earth3	0.583755	24	KACE-1-0-G	0.567891	24
TaiESM1	0.729316	25	TaiESM1	0.700271	25	TaiESM1	0.697336	25

Figure 2: Performance-based ranking of 25 CMIP6 global climate models (GCMs) for Sri Lanka derived using

Compromise Programming (L_p metric). Models are ranked according to their distance from the ideal solution based on multiple performance metrics (Taylor Skill Score, RMSE–standard deviation ratio, coefficient of determination, and percentage bias) applied to (a) annual climatology and climate indices, (b) annual climatology, climate indices, and Southwest monsoon (SWM) performance, and (c) annual climatology, climate indices, and both Southwest and Northeast monsoon (NEM) performance. Lower L_p values indicate better overall model performance.

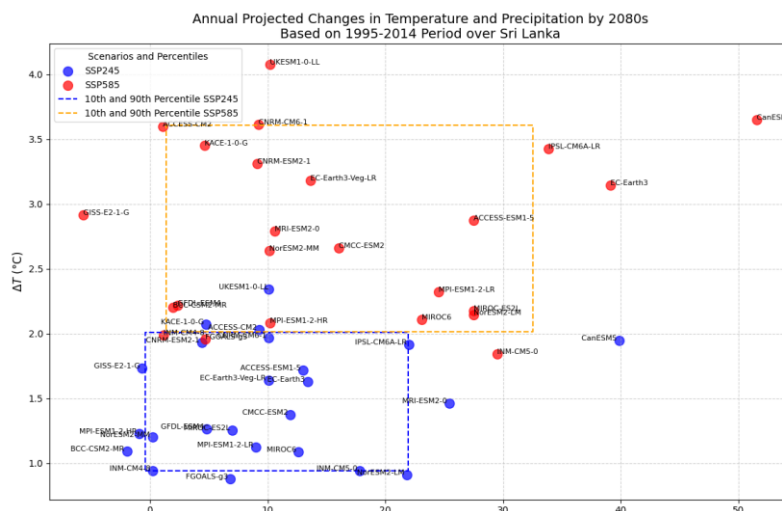


Figure 3: Presents the scatter plot of the Skill Test for the 2080s, illustrating the methodology and the spread of GCM projections

Figure 3 projected annual mean changes in temperature (ΔT , °C) and precipitation (ΔP , %) over Sri Lanka for the 2080s (2071–2090) relative to the 1995–2014 baseline under SSP2-4.5 (blue) and SSP5-8.5 (red) scenarios. Each point represents an individual CMIP6 GCM. Dashed boxes indicate the 10th–90th percentile ranges of the ensemble for temperature and precipitation under each scenario, highlighting the spread and central tendency of projected climate change signals.

The ensemble projections indicate a robust warming signal over Sri Lanka by the late 21st century under both emission scenarios, with all models projecting positive temperature changes. Under SSP2-4.5, annual mean warming is generally constrained within a narrower range, whereas SSP5-8.5 exhibits substantially higher warming and increased inter-model spread. Precipitation projections show greater variability than temperature, particularly under SSP5-8.5, with models indicating both moderate and pronounced increases in annual rainfall. The 10th–90th percentile ranges highlight a clear scenario-dependent divergence, with stronger warming and wetter conditions becoming increasingly likely under higher forcing, while temperature projections remain more tightly clustered than precipitation across the ensemble.

A two-stage selection strategy combining Compromise Programming–based performance ranking and consistency within ensemble projection space was used to identify robust CMIP6 models for Sri Lanka. Models exhibiting balanced skill across climatology, monsoon seasonality, and climate extremes, while also representing the central tendency of late-century temperature and precipitation projections, were retained.

Accordingly, the final ensemble comprises CNRM-CM6-1, CNRM-ESM2-1, EC-Earth3-Veg-LR, ACCESS-CM2, MPI-ESM1-2-LR, and MIROC-ES2L, which collectively demonstrate balanced performance across climatology, monsoon seasonality, and climate extremes.

Table 4. CMIP6 global climate models selected for ensemble projections over Sri Lanka based on integrated performance ranking and projection consistency.

No.	CMIP6 Model	Modelling Centre
1	CNRM-CM6-1	CNRM–CERFACS, France
2	CNRM-ESM2-1	CNRM–CERFACS, France
3	EC-Earth3-Veg-LR	EC-Earth Consortium (Europe)
4	ACCESS-CM2	CSIRO–Bureau of Meteorology, Australia
5	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (MPI-M), Germany
6	MIROC-ES2L	MIROC Consortium, Japan

Projected changes in temperature and precipitation over Sri Lanka were analyzed using a six-member CMIP6 multi-model ensemble under SSP2-4.5 and SSP5-8.5 scenarios, relative to the 1995–2014 baseline. Results are presented for the 2040s, 2060s, and 2080s, emphasizing ensemble mean responses and associated inter-model uncertainty.

4.1 Projected Changes in Rainfall

4.1.1 Projected changes in annual rainfall over Sri Lanka

PROJECTED CHANGE IN ANNUAL TOTAL PRECIPITATION (RELATIVE TO 1995–2014 BASELINE)

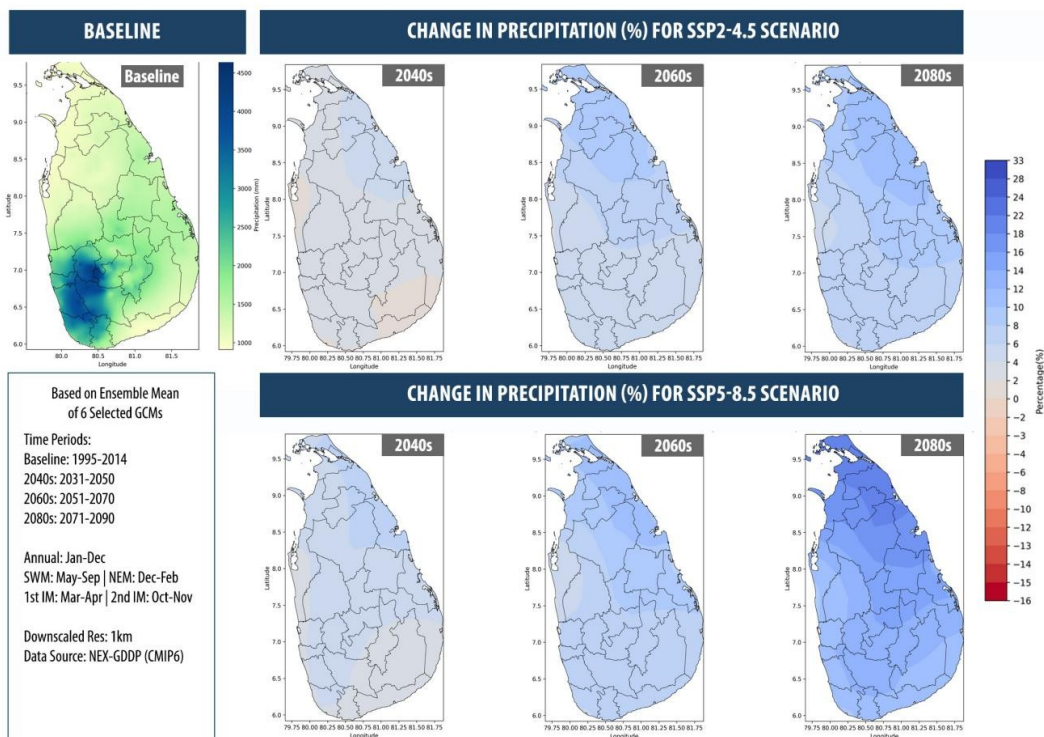


Figure 4: Projected change in annual total precipitation (%) in Sri Lanka relative to the 1995–2014 baseline, using the ensemble mean of six CMIP6 GCMs. Percentage changes are presented for SSP2-4.5 and SSP5-8.5 for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090).

Annual rainfall projections indicate a clear long-term shift toward wetter conditions across Sri Lanka, with the strength and spatial coherence of change increasing through the century and varying by emission pathway. Under the intermediate-emissions scenario, changes are modest in the near term and become more evident toward mid- and late-century, particularly over the Northern, North-Central, and Eastern regions. In contrast, the high-emissions scenario shows earlier, stronger, and more widespread wetting, with island-wide increases intensifying toward the end of the century. Overall, the results indicate enhanced annual rainfall across Sri Lanka under future climate change, with substantially greater increases under higher warming levels.

Table 5: shows projected percentage changes in mean rainfall over Sri Lanka under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods.

Scenario	Time slice	Projected rainfall change
SSP2-4.5	2040s (2031–2050)	(1 – 5) % increase
	2060s (2051–2070)	(3 – 10) % increase
	2080s (2071–2090)	(4 – 12) % increase
SSP5-8.5	2040s (2031–2050)	(2 – 7) % increase
	2060s (2051–2070)	(3 – 11) % increase
	2080s (2071–2090)	(7 – 20) % increase

4.1.2 Projected change in rainfall during North East monsoon (December to February)

PROJECTED CHANGE IN NORTH-EAST MONSOON SEASON TOTAL PRECIPITATION
(RELATIVE TO 1995–2014 BASELINE)

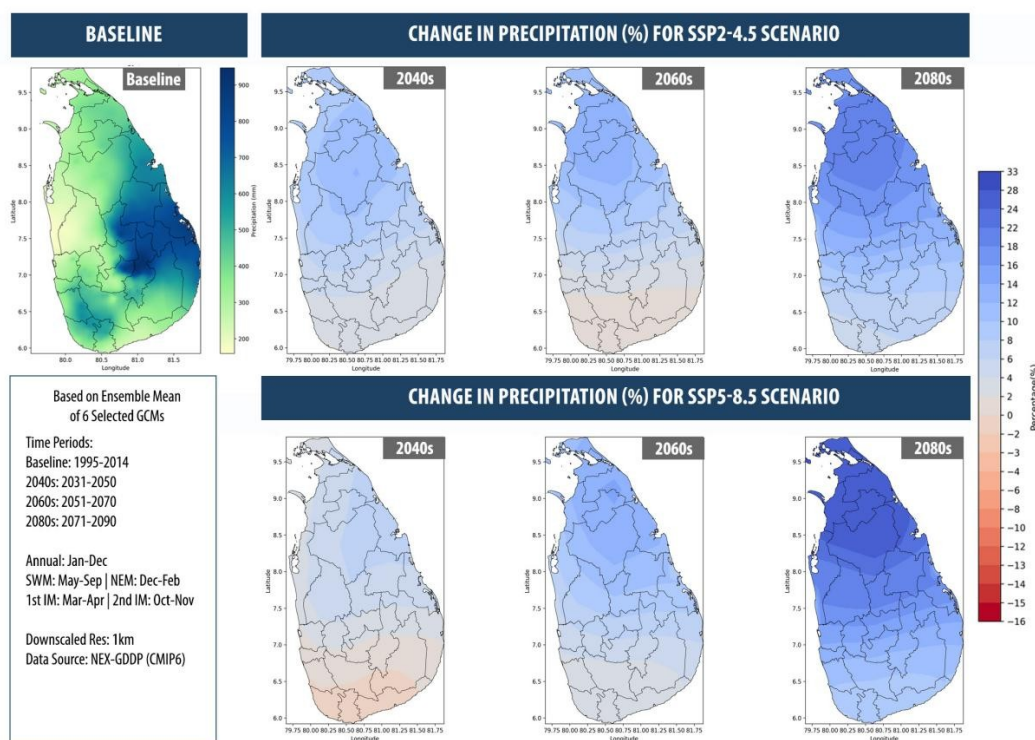


Figure 5: Projected change in North-East Monsoon (NE: December-February) total precipitation in Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 GCMs. Maps show percentage change under SSP2-4.5 and SSP5-8.5 for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090).

Multi-model ensemble projections indicate a robust increase in Northeast Monsoon (NEM) rainfall across Sri Lanka during the 21st century, with stronger wetting under higher emission scenarios. Rainfall increases intensify toward mid- and late-century, particularly over the Northern, Eastern, and Central regions, with the high-emissions pathway exhibiting larger and more spatially coherent changes. Any localized near-term drying in southern districts weakens over time as the island-wide wetting signal becomes dominant, indicating high confidence in increasing NEM rainfall under future climate change.

Table 6: shows projected percentage changes in mean rainfall over Sri Lanka under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods.

Scenario	Time slice	Projected rainfall change
SSP2-4.5	2040s (2031–2050)	(2–12) % increase
	2060s (2051–2070)	(2–13) % increase
	2080s (2071–2090)	(4–19) % increase
SSP5-8.5	2040s (2031–2050)	(1-7) % increase
	2060s (2051–2070)	(2-14) % increase
	2080s (2071–2090)	(7–28) % increase

4.1.3 Projected changes in rainfall during First Inter-monsoon (March- April)

PROJECTED CHANGE IN FIRST INTER-MONSOON SEASON TOTAL PRECIPITATION
(RELATIVE TO 1995-2014 BASELINE)

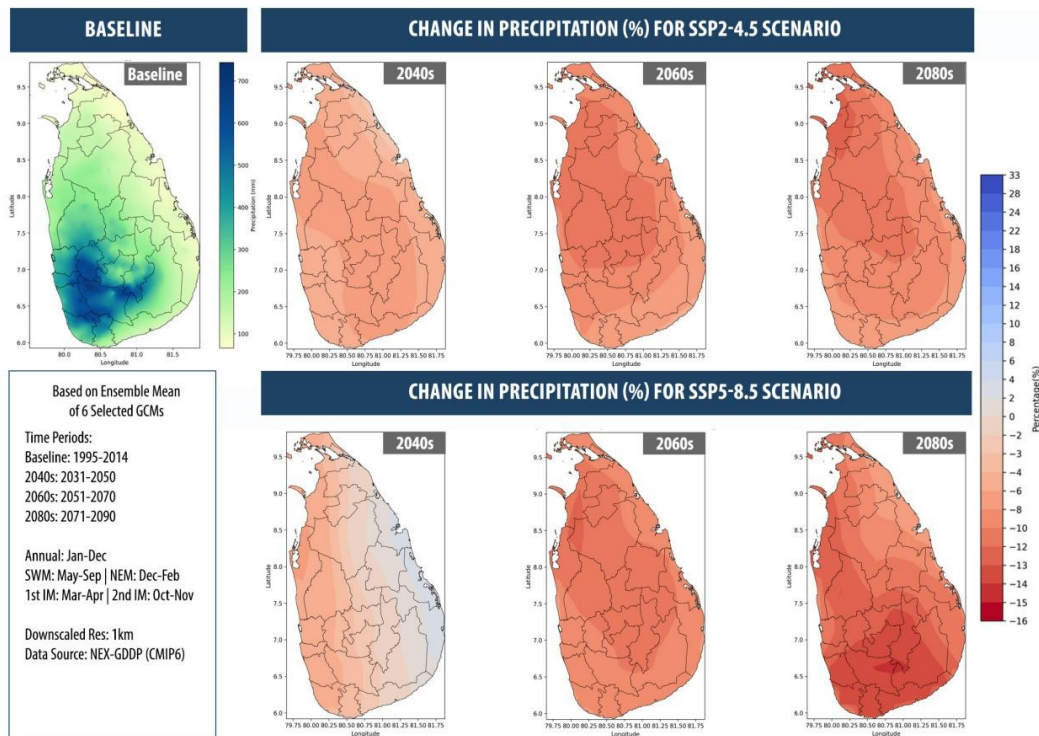


Figure 6: Projected change in First Inter-Monsoon (FIM: March–April) total precipitation in Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 GCMs. Maps show percentage change under SSP2-4.5 and SSP5-8.5 for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090).

Projections for the First Inter-Monsoon (FIM) season indicate a robust and regionally consistent drying signal across Sri Lanka throughout the 21st century, with drying intensifying under higher emission scenarios. Both intermediate and high-emission pathways show widespread rainfall reductions, with the strongest declines evident over the western, southern, and central regions.

Table 7: shows projected percentage changes in mean rainfall over Sri Lanka under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods.

Scenario	Time slice	Projected rainfall change
SSP2-4.5	2040s (2031–2050)	(2 - 8) % decrease
	2060s (2051–2070)	(5 - 11) % decrease
	2080s (2071–2090)	(5- 13) % decrease
SSP5-8.5	2040s (2031–2050)	(3 - 7) % decrease
	2060s (2051–2070)	(6 - 12) % decrease
	2080s (2071–2090)	(6 - 14) % decrease

4.1.4 Projected change in Southwest monsoon rainfall (May to September)

PROJECTED CHANGE IN SOUTH-WEST MONSOON SEASON TOTAL PRECIPITATION
(RELATIVE TO 1995-2014 BASELINE)

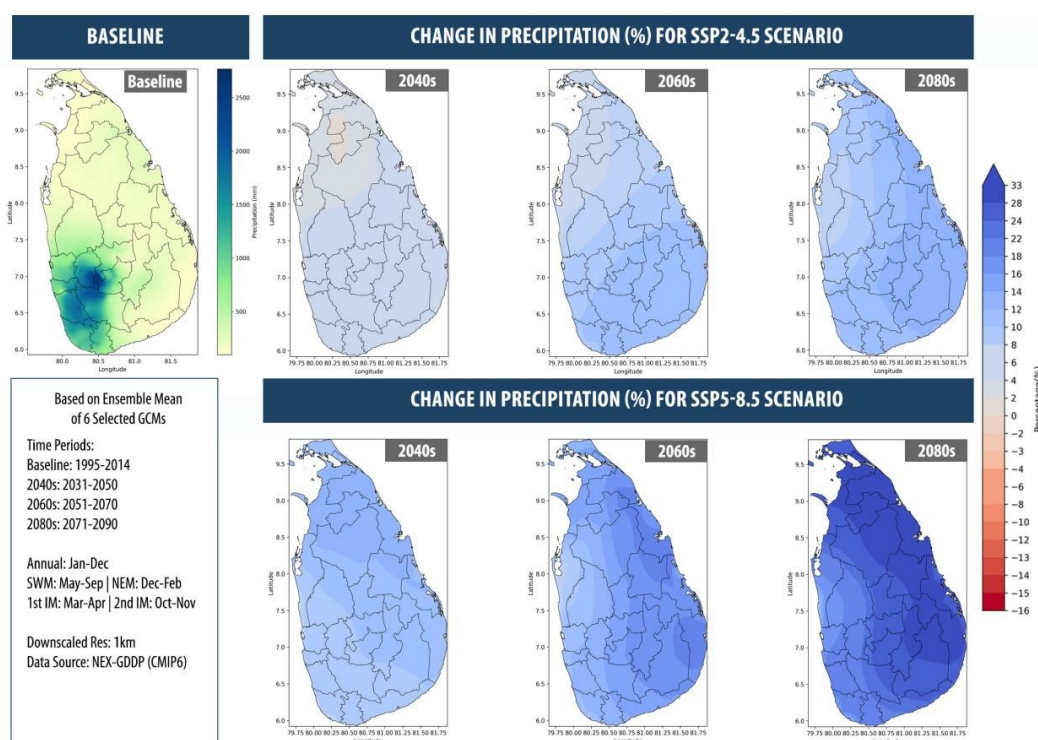


Figure 7: Projected change in Southwest Monsoon (SWM: May-September) total rainfall in Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 GCMs. Maps show percentage change under SSP2-4.5(upper) and SSP5-8.5(lower) for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090).

Under the intermediate-emissions scenario (SSP2–4.5), near-term changes (2040s) are modest and spatially heterogeneous, indicating a weak but emerging signal. By mid- to late-century (2060s–2080s), a clearer and more spatially coherent increase in rainfall is evident, over the Northern, North-Central, and Eastern regions. In contrast, the high-emissions scenario (SSP5–8.5) shows larger and more widespread increases across all periods, with island-wide positive anomalies apparent as early as the 2040s. Southern and southwestern regions exhibit comparatively moderate changes but maintain a consistent upward trend.

Table 8: shows projected percentage changes in mean rainfall over Sri Lanka under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods.

Scenario	Time slice	Projected rainfall change (%)
SSP2-4.5	2040s (2031–2050)	(1 – 6) % increase
	2060s (2051–2070)	(4– 12) % increase
	2080s (2071–2090)	(5 – 14) % increase
SSP5-8.5	2040s (2031–2050)	(6 – 14) % increase
	2060s (2051–2070)	(6 – 19) % increase
	2080s (2071–2090)	(10 – 34) % increase

4.1.5 Projected changes in Rainfall during Second inter-monsoon season (October to November)

PROJECTED CHANGE IN SECOND INTER-MONSOON SEASON TOTAL PRECIPITATION (RELATIVE TO 1995–2014 BASELINE)

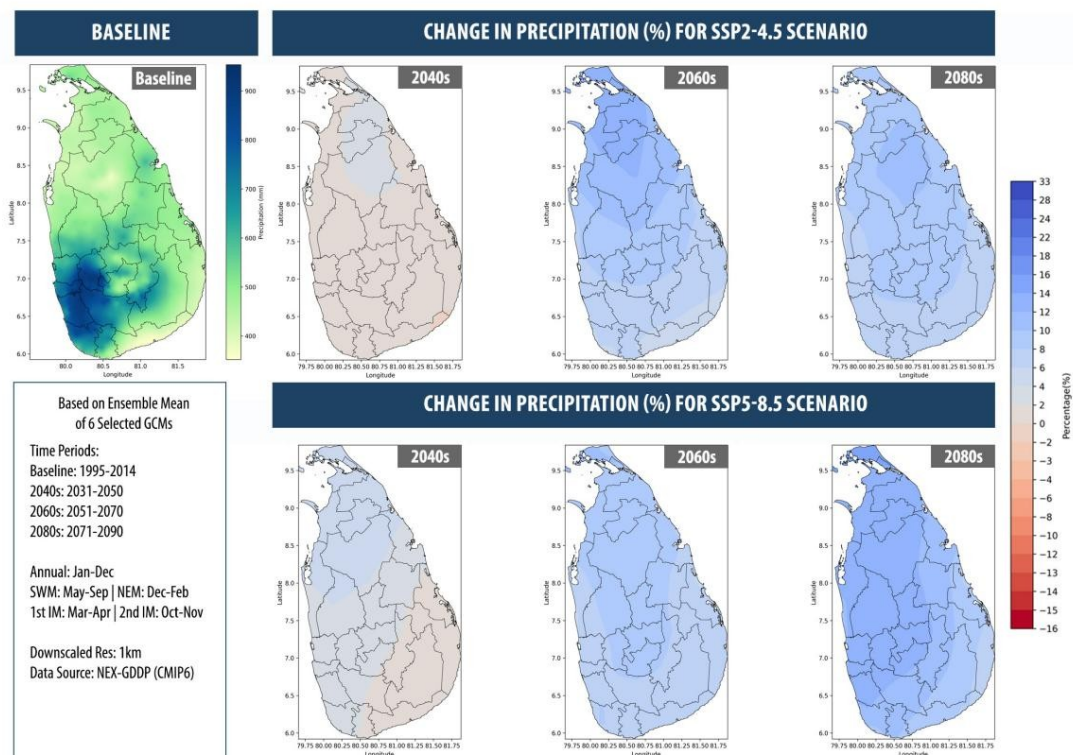


Figure 8: Projected change in Second Inter-Monsoon (SIM: October–November) total precipitation in Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 GCMs. Maps show percentage change under SSP2-4.5 and SSP5-8.5 for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090).

Under the intermediate-emissions scenario, projected changes in Second Inter-Monsoon rainfall remain weak (–2% – + 3%) in the near term, indicating largely near-neutral conditions. A transition toward wetter conditions emerges by mid-century, with positive anomalies becoming more broad-scale signal, particularly over the central highlands and western and eastern regions. By late century, this wetting

signal strengthens across most districts, suggesting a moderate intensification of inter-monsoon rainfall. In contrast, the high-emissions scenario exhibits a stronger and more persistent wetting signal throughout the century. Rainfall increases are already evident in the near term, expand spatially by mid-century, and become widespread and pronounced by late century, indicating a substantially intensified SIM rainfall regime under higher warming levels.

Table 9: shows projected percentage changes in mean rainfall over Sri Lanka under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected rainfall change (%)
SSP2-4.5	2040s (2031–2050)	-2 % decrease – 3 % increase
	2060s (2051–2070)	5 – 13 % increase
	2080s (2071–2090)	5 – 11 % increase
SSP5-8.5	2040s (2031–2050)	3 – 6 % increase
	2060s (2051–2070)	5 – 11 % increase
	2080s (2071–2090)	5– 16 % increase

4.2 Projected Changes in Temperature

4.2.1 Projected changes in annual mean maximum temperature (°C) over Sri Lanka

PROJECTED CHANGE IN ANNUAL MEAN MAXIMUM TEMPERATURE (RELATIVE TO 1995-2014 BASELINE)

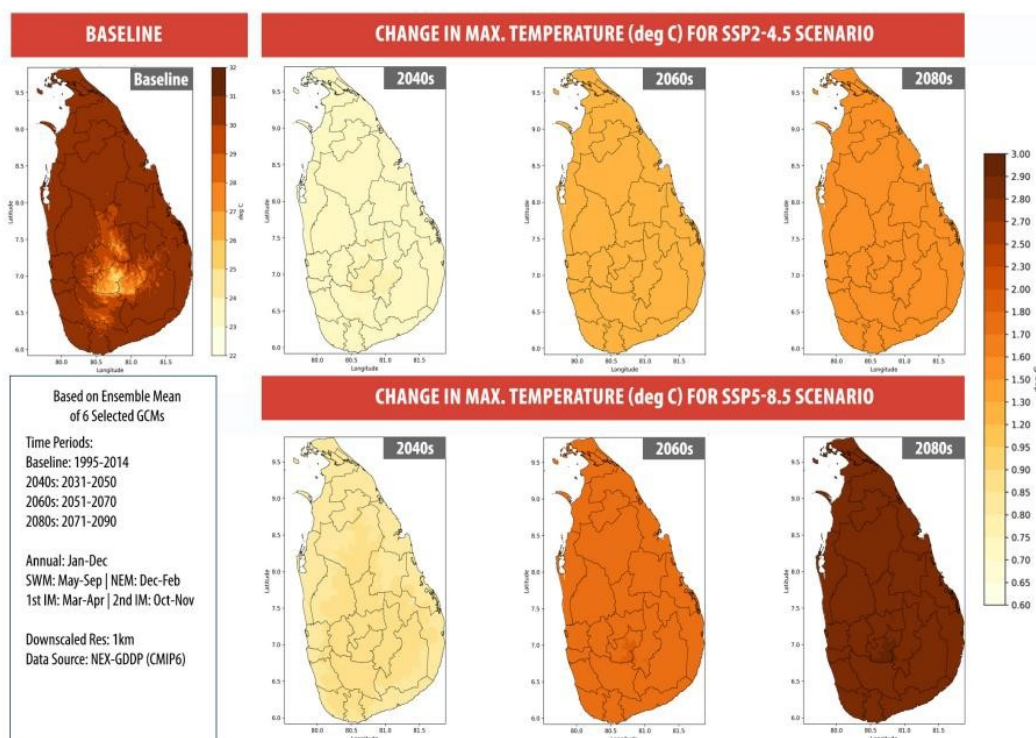


Figure 9: Projected changes in annual mean maximum temperature (°C) over Sri Lanka relative to 1995–2014, based on the ensemble mean of six CMIP6 models. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom).

Under the SSP2-4.5 scenario, a consistent warming signal is projected across the entire island in all future periods. Comparison between scenarios highlights a clear divergence toward the latter half of the century. While both scenarios project robust and broad-scale warming, the magnitude of increase under SSP5-8.5 is markedly higher than under SSP2-4.5, particularly in the late-century period.

Table 10: shows projected changes in mean maximum temperature over Sri Lanka under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected change in mean maximum Temperature (Tmax) (°C)
SSP2-4.5	2040s (2031–2050)	0.7 – 0.8 increase
	2060s (2051–2070)	1.2 – 1.3 increase
	2080s (2071–2090)	1.5 – 1.6 increase
SSP5-8.5	2040s (2031–2050)	0.8 – 0.9 increase
	2060s (2051–2070)	1.7 – 1.8 increase
	2080s (2071–2090)	2.8 – 3.0 increase

4.2.2 Projected change in annual mean minimum temperatures (Tmin)

PROJECTED CHANGE IN ANNUAL MEAN MINIMUM TEMPERATURE (RELATIVE TO 1995-2014 BASELINE)

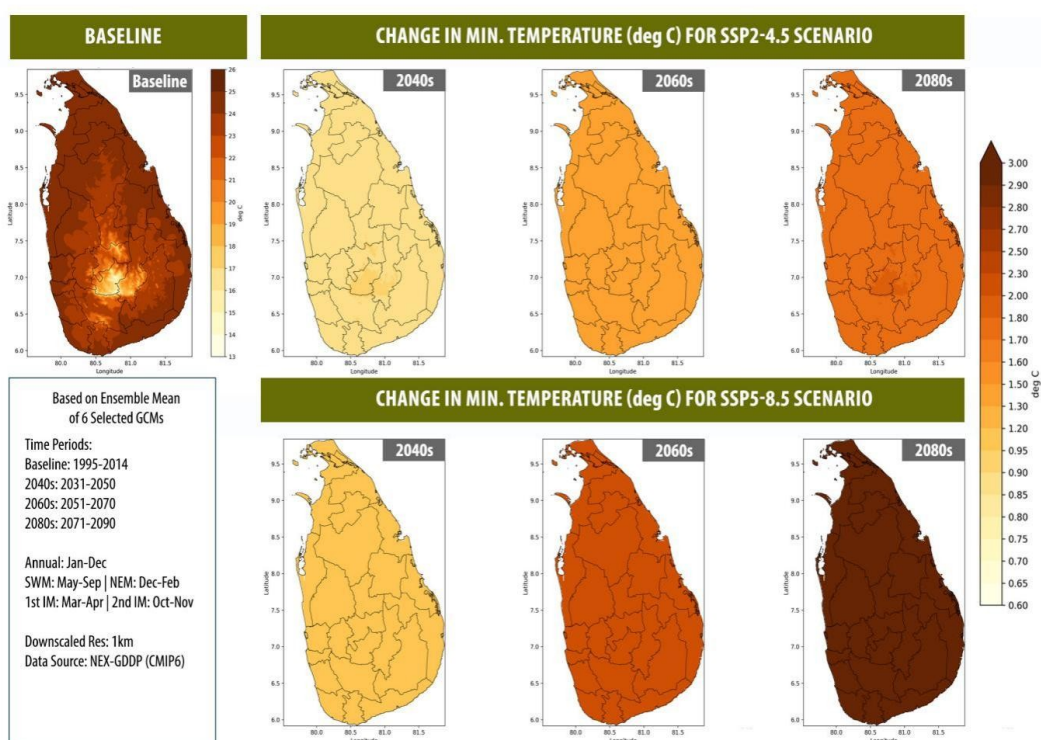


Figure 10: Projected changes in annual mean minimum temperature (°C) over Sri Lanka relative to 1995–2014, based on the ensemble mean of six CMIP6 models. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom).

Results show a progressive increase in minimum temperature under both emission scenarios, with pronounced divergence emerging after mid-century. Spatial patterns indicate enhanced warming over inland regions, suggesting the development of temperature hotspots. While projections remain similar through the 2040s, differences between scenarios become substantial toward late century, highlighting the increasing influence of emission pathways on long-term temperature outcomes.

Table 11: shows projected changes in mean minimum temperature over Sri Lanka under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected change in mean minimum Temperature (Tmin) (°C)
SSP2-4.5	2040s (2031–2050)	0.8 – 0.9 increase
	2060s (2051–2070)	1.4 – 1.5 increase
	2080s (2071–2090)	1.7 – 1.8 increase
SSP5-8.5	2040s (2031–2050)	1.1 – 1.2 increase
	2060s (2051–2070)	2.0 – 2.2 increase
	2080s (2071–2090)	3.2 – 3.5 increase

4.2.3 Projected change in Mean Maximum Temperatures during North East monsoon season (December to February)

PROJECTED CHANGE IN NORTH-EAST MONSOON SEASON MEAN MAXIMUM TEMPERATURE
(RELATIVE TO 1995–2014 BASELINE)

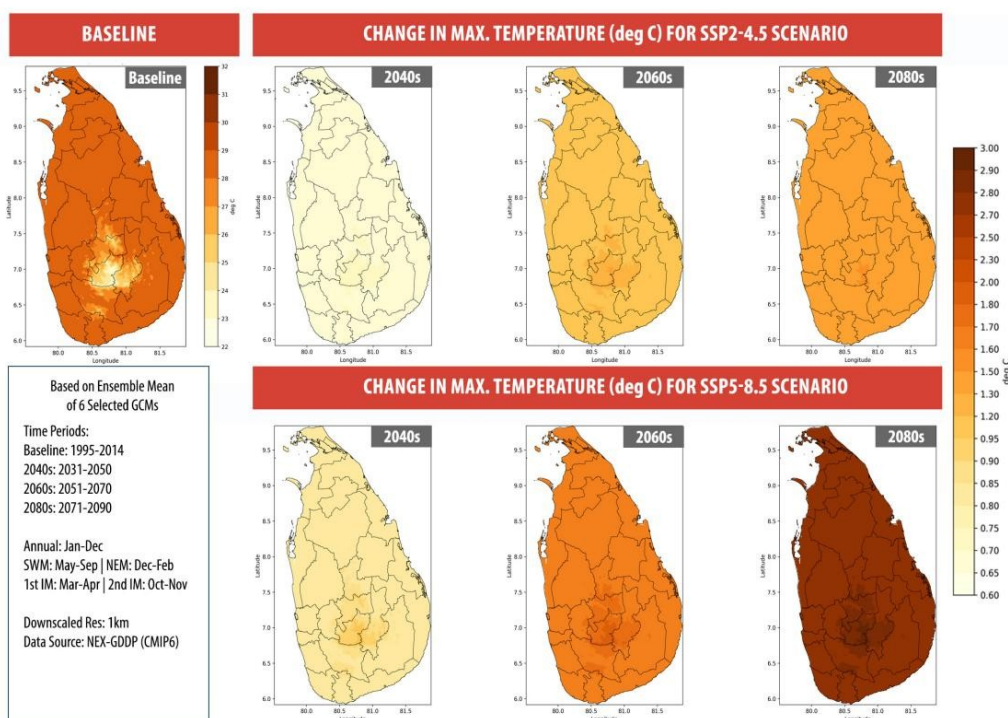


Figure 11: Projected change in mean maximum temperature (°C) over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models during North-East Monsoon (December–February) season. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios.

Mean maximum temperature during the North-East Monsoon season is projected to increase across all regions of Sri Lanka under both SSP2-4.5 and SSP5-8.5 scenarios, relative to the 1995–2014 baseline. The warming signal intensifies with time and shows a coherent spatial pattern, indicating a robust response to increasing greenhouse gas forcing.

Table 12: shows projected changes in mean maximum temperature over Sri Lanka during NE monsoon under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected change in mean maximum Temperatures(T_{max} °C)
SSP2-4.5	2040s (2031–2050)	0.7 – 0.8 increase
	2060s (2051–2070)	1.2 – 1.3 increase
	2080s (2071–2090)	1.4 – 1.6 increase
SSP5-8.5	2040s (2031–2050)	0.8 – 1.0 increase
	2060s (2051–2070)	1.6 – 1.9 increase
	2080s (2071–2090)	2.7 – 3.0 increase

4.2.4 Projected change in Mean Minimum Temperatures during North East monsoon (December to February)

PROJECTED CHANGE IN NORTH-EAST MONSOON SEASON MEAN MINIMUM TEMPERATURE (RELATIVE TO 1995-2014 BASELINE)

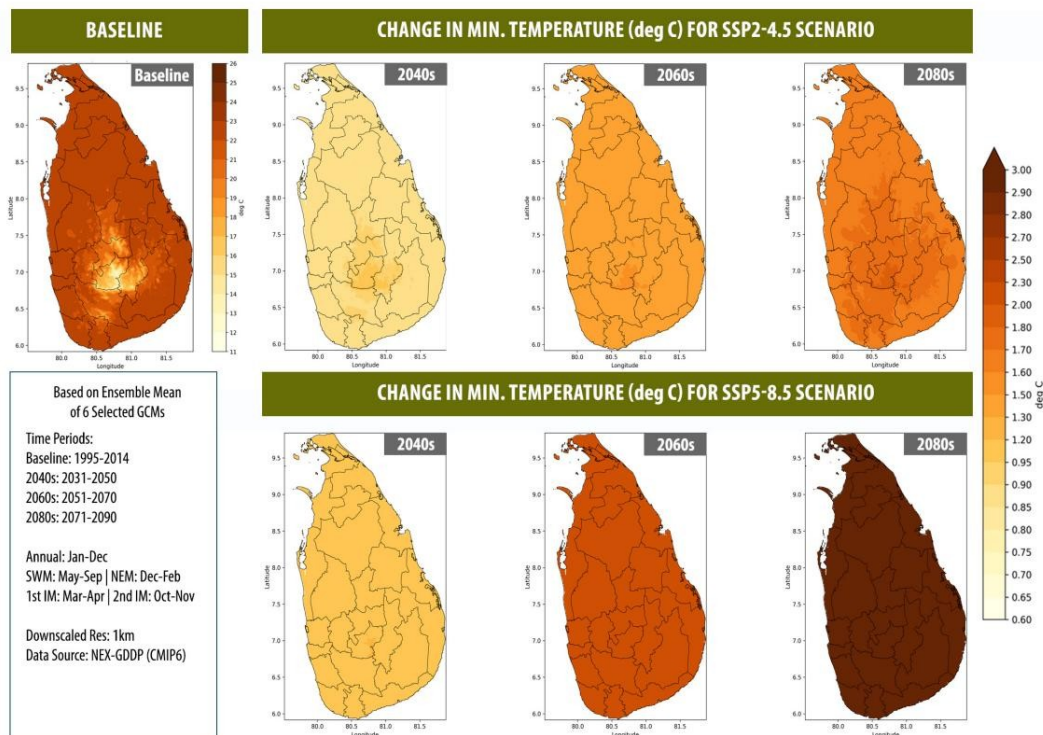


Figure 12: Projected change in mean minimum temperature (°C) over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models during North-East Monsoon (December–February) season. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios.

Mean minimum temperature during the North-East Monsoon season is projected to increase across Sri Lanka under both SSP2-4.5 and SSP5-8.5 scenarios, relative to the 1995–2014 baseline. The warming signal is spatially coherent and strengthens markedly from the 2040s to the 2080s, indicating a robust increase in night-time temperatures during the monsoon season.

Table 13. shows projected changes in mean minimum temperature over Sri Lanka during NE monsoon under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected change in mean minimum Temperatures (Tmin) (°C)
SSP2-4.5	2040s (2031–2050)	0.9 – 1.0 increase
	2060s (2051–2070)	1.4 – 1.6 increase
	2080s (2071–2090)	1.7 – 1.9 increase
SSP5-8.5	2040s (2031–2050)	1.1 – 1.3 increase
	2060s (2051–2070)	2.0 – 2.3 increase
	2080s (2071–2090)	3.2 – 3.7 increase

4.2.5 Projected change in Mean Maximum Temperatures during First Inter-monsoon (March–April)

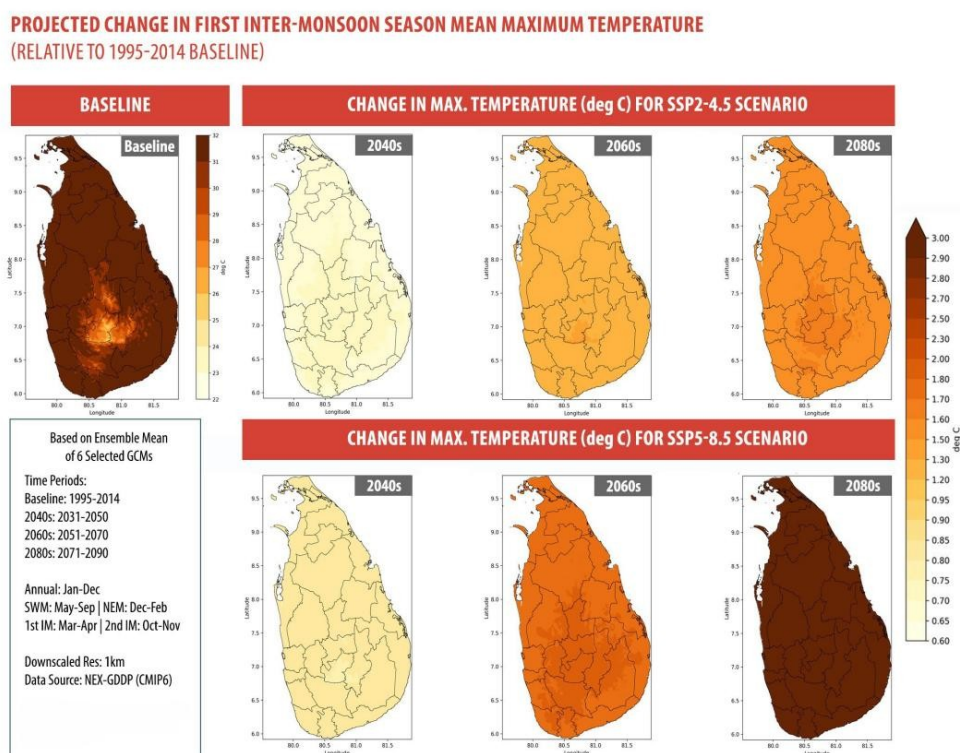


Figure 13: Projected change in mean maximum temperature (°C) over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models during first inter-monsoon (March–April) season. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios.

Relative to the 1995–2014 baseline, ensemble mean projections indicate a clear and progressive increase in first inter-monsoon (March–April) mean maximum temperature across Sri Lanka under both

SSP2-4.5 and SSP5-8.5 scenarios. Under the intermediate SSP2-4.5 pathway, warming is modest by the 2040s, intensifies by the 2060s, and becomes more pronounced by the 2080s, with spatially coherent increases across the island. The high-emissions SSP5-8.5 scenario exhibits a similar temporal evolution but with substantially greater magnitude, particularly from the mid-century onward. By the 2080s, widespread and strong warming dominates all regions, indicating a robust signal that exceeds near-term variability.

Table 14: shows projected changes in mean maximum temperature over Sri Lanka during first inter-monsoon under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected change in mean maximum Temperatures((Tax) °C)
SSP2-4.5	2040s (2031–2050)	0.7 – 0.8 increase
	2060s (2051–2070)	1.2 - 1.4 increase
	2080s (2071–2090)	1.6 –1.7 increase
SSP5-8.5	2040s (2031–2050)	0.7 – 0.8 increase
	2060s (2051–2070)	1.8 – 2.0 increase
	2080s (2071–2090)	3.0 –3.1 increase

4.2.6 Projected change in Mean Minimum Temperatures during First Inter-monsoon (March–April)

PROJECTED CHANGE IN FIRST INTER-MONSOON SEASON MEAN MINIMUM TEMPERATURE
(RELATIVE TO 1995–2014 BASELINE)

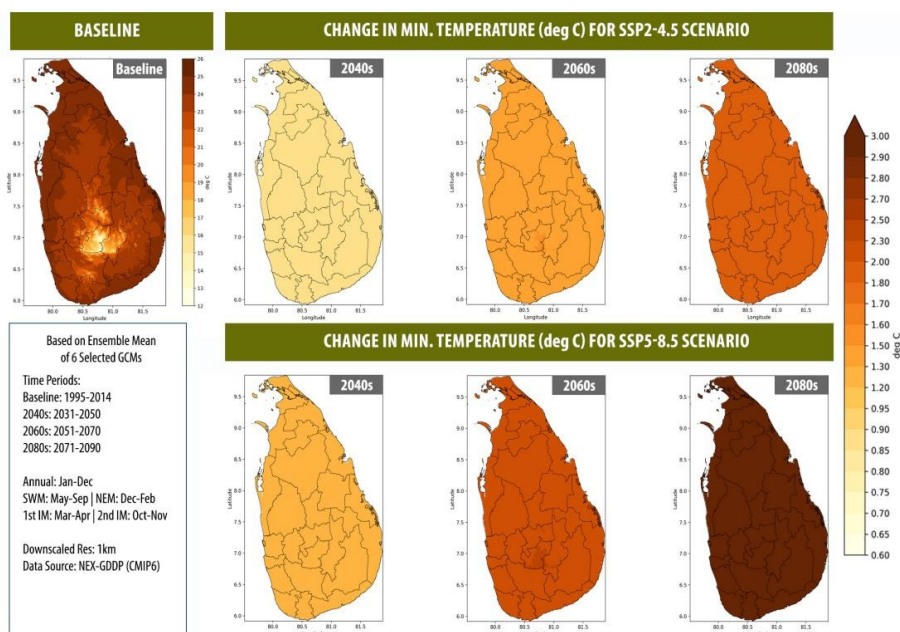


Figure 14: Projected change in mean minimum temperature (°C) in First-Inter Monsoon (December–February) season over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios.

Ensemble mean projections indicate a consistent and spatially coherent increase in first inter-monsoon (March–April) mean minimum temperature across Sri Lanka relative to the 1995–2014 baseline under both SSP2-4.5 and SSP5-8.5 scenarios. Under SSP2-4.5, warming is relatively modest in the 2040s but strengthens by the 2060s and becomes more pronounced by the 2080s, with widespread increases evident across all climatic regions. The SSP5-8.5 scenario exhibits a substantially stronger warming signal, with accelerated increases emerging by mid-century and intensifying markedly toward the late century. By the 2080s, near-uniform and high-magnitude warming dominates the island, indicating a robust increase in nighttime temperatures.

Table 15: shows projected changes in mean minimum temperature over Sri Lanka during First inter-monsoon under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected change in mean minimum) Temperature (Tmin) (°C)
SSP2-4.5	2040s (2031–2050)	0.85 – 0.87 increase
	2060s (2051–2070)	1.48 – 1.5 increase
	2080s (2071–2090)	1.86 – 1.89 increase
SSP5-8.5	2040s (2031–2050)	1.24 – 1.3 increase
	2060s (2051–2070)	2.22 – 2.36 increase
	2080s (2071–2090)	3.48 – 3.64 increase

4.2.7 Projected change of Mean Maximum Temperatures during Southwest monsoon (May to September)

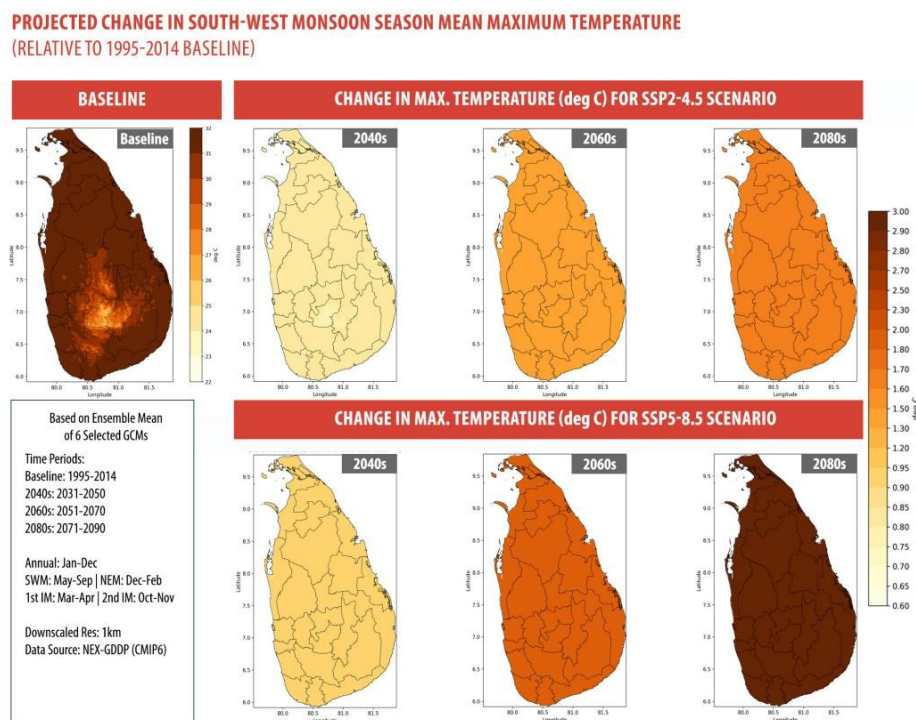


Figure 15 Projected change in mean maximum temperature (°C) in Southwest monsoon (May–September) season over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios

Relative to the 1995–2014 baseline, ensemble mean projections indicate a robust and progressive increase in south-west monsoon (May–September) mean maximum temperature across Sri Lanka under both SSP2-4.5 and SSP5-8.5 scenarios. Under the intermediate emissions pathway (SSP2-4.5), warming is relatively limited in the 2040s but intensifies by the 2060s and becomes widespread by the 2080s, with coherent increases evident across all regions. The high-emissions SSP5-8.5 scenario exhibits a markedly stronger warming signal, with substantial temperature increases emerging by mid-century and amplifying sharply toward the late century. By the 2080s, strong and spatially uniform warming dominates the island, indicating a pronounced increase in daytime temperatures during the monsoon period.

Table 16: shows projected changes in mean minimum temperature over Sri Lanka during Southwest monsoon under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected change in mean maximum (Tmax) Temperature (°C)
SSP2-4.5	2040s (2031–2050)	0.86 – 0.87 increase
	2060s (2051–2070)	1.38 – 1.4 increase
	2080s (2071–2090)	1.76 – 1.77 increase
SSP5-8.5	2040s (2031–2050)	1.04 – 1.1 increase
	2060s (2051–2070)	1.98 – 2.09 increase
	2080s (2071–2090)	3.12 – 3.27 increase

4.2.8 Projected change of Mean Minimum Temperatures during Southwest monsoon (May to September)

The ensemble means projections show a consistent increase in South-West Monsoon (SWM) season mean minimum temperature across Sri Lanka under both SSP2-4.5 and SSP5-8.5 scenarios relative to the 1995–2014 baseline (Figure 16). Under SSP2-4.5, modest warming is evident by the 2040s, strengthening further in the 2060s and 2080s, with broadly uniform increases across the island and slightly higher warming over lowland regions compared to the central highlands. In contrast, SSP5-8.5 exhibits stronger and more widespread warming at all future time slices, with the magnitude of increase intensifying markedly toward the late century. By the 2080s, much of the island is characterized by high levels of warming, indicating a dominant and spatially coherent climate change signal.

**PROJECTED CHANGE IN SOUTH-WEST MONSOON SEASON MEAN MINIMUM TEMPERATURE
(RELATIVE TO 1995-2014 BASELINE)**

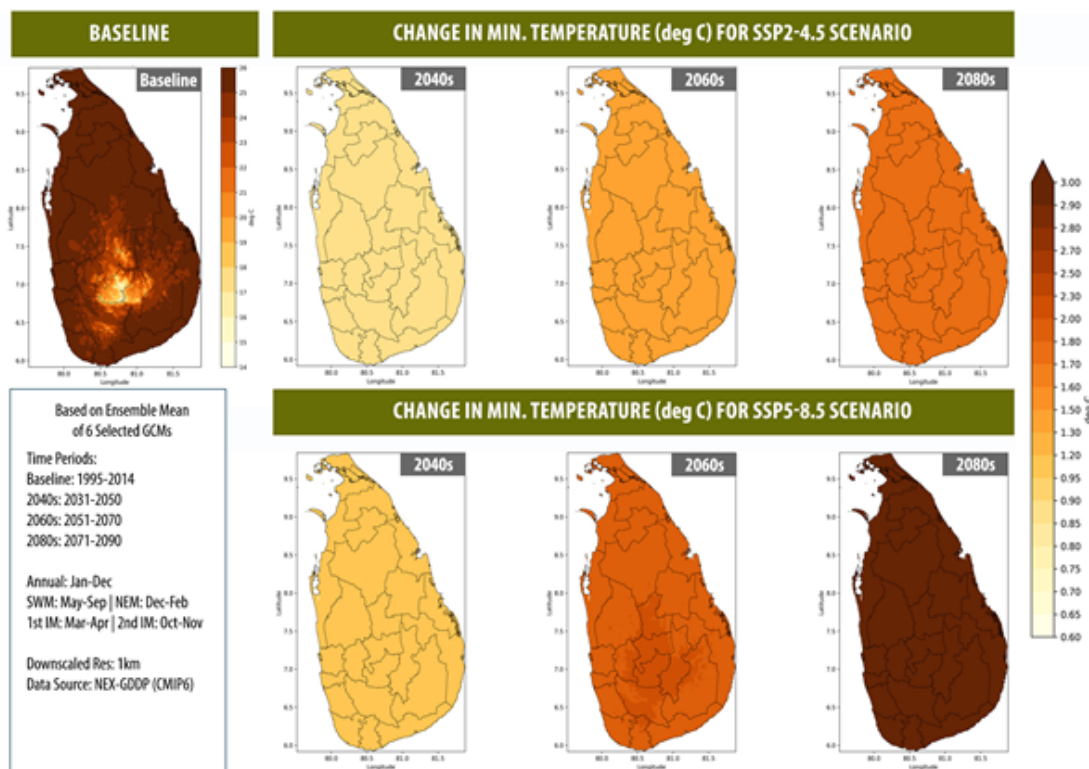


Figure 16: Projected change in Southwest monsoon (May–September) season mean minimum temperature ($^{\circ}\text{C}$) over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios

Table 17: shows projected changes in mean minimum temperature over Sri Lanka during Southwest monsoon under SSP2-4.5 and SSP5-8.5 for mid- and late-century periods

Scenario	Time slice	Projected mean minimum Temperature (Tmin) ($^{\circ}\text{C}$)
SSP2-4.5	2040s (2031–2050)	0.86 – 0.87 increase
	2060s (2051–2070)	1.38 – 1.4 increase
	2080s (2071–2090)	1.76 – 1.77 increase
SSP5-8.5	2040s (2031–2050)	1.04 – 1.1 increase
	2060s (2051–2070)	1.98 – 2.09 increase
	2080s (2071–2090)	3.12 – 3.27 increase

4.2.9 Projected change of Mean Maximum Temperatures during Second inter- monsoon (October–November)

PROJECTED CHANGE IN SECOND INTER-MONSOON SEASON MEAN MAXIMUM TEMPERATURE (RELATIVE TO 1995–2014 BASELINE)

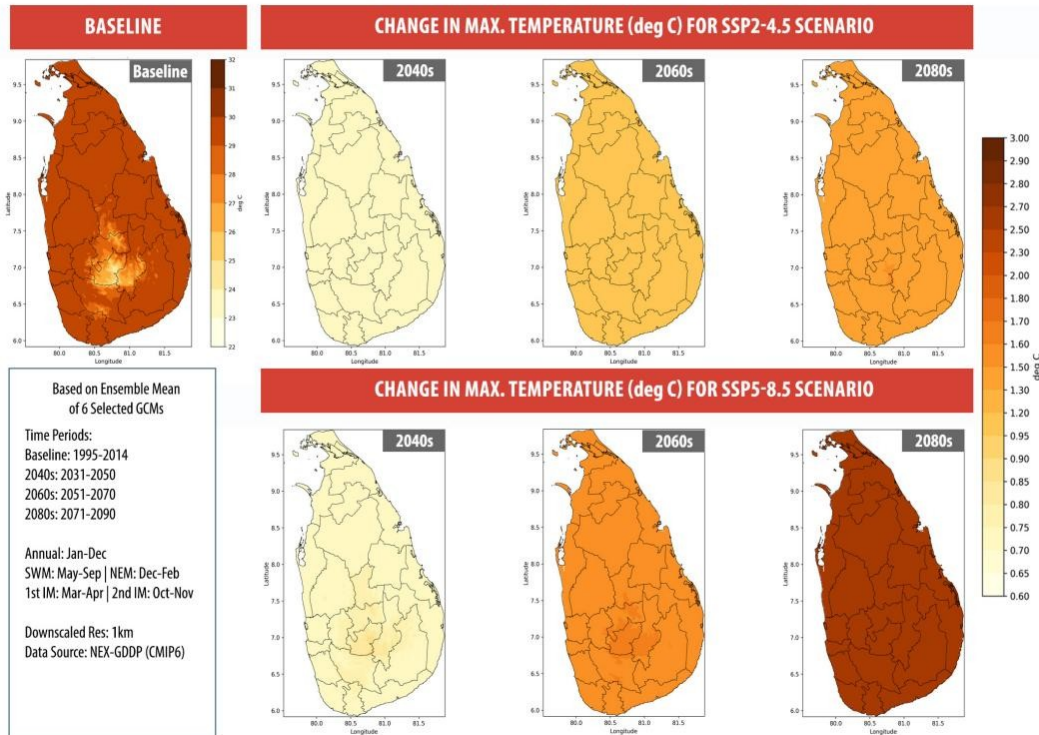


Figure 17: Projected change in mean maximum temperature ($^{\circ}\text{C}$) in Second Inter-monsoon (October–November) season over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios

The ensemble means projections indicate a systematic increase in Second Inter-Monsoon (SIM) season mean maximum temperature across Sri Lanka under both SSP2-4.5 and SSP5-8.5 scenarios relative to the 1995–2014 baseline. Under SSP2-4.5, warming is modest in the 2040s, becomes more pronounced by the 2060s, and strengthens further by the 2080s, with largely uniform spatial patterns and slightly higher warming over inland and northern regions. Under SSP5-8.5, temperature increases are consistently larger at all time horizons, with a marked intensification toward the late century. By the 2080s, widespread high-magnitude warming dominates across the island, indicating a strong and spatially coherent forced climate signal.

Table 18: Projected changes in SIM-season mean maximum temperature (°C) over Sri Lanka

Scenario	Time slice	Projected change in mean maximum Temperature (Tmax) (°C)
SSP2-4.5	2040s (2031–2050)	0.7 – 0.74 increase
	2060s (2051–2070)	1.1 – 1.2 increase
	2080s (2071–2090)	1.4 – 1.5 increase
SSP5-8.5	2040s (2031–2050)	0.7 – 0.9 increase
	2060s (2051–2070)	1.6 – 1.7 increase
	2080s (2071–2090)	2.6– 2.7 increase

4.2.10 Projected change of Mean Minimum Temperatures during Second inter-monsoon season (October–November)

PROJECTED CHANGE IN SECOND INTER-MONSOON SEASON MEAN MINIMUM TEMPERATURE (RELATIVE TO 1995–2014 BASELINE)

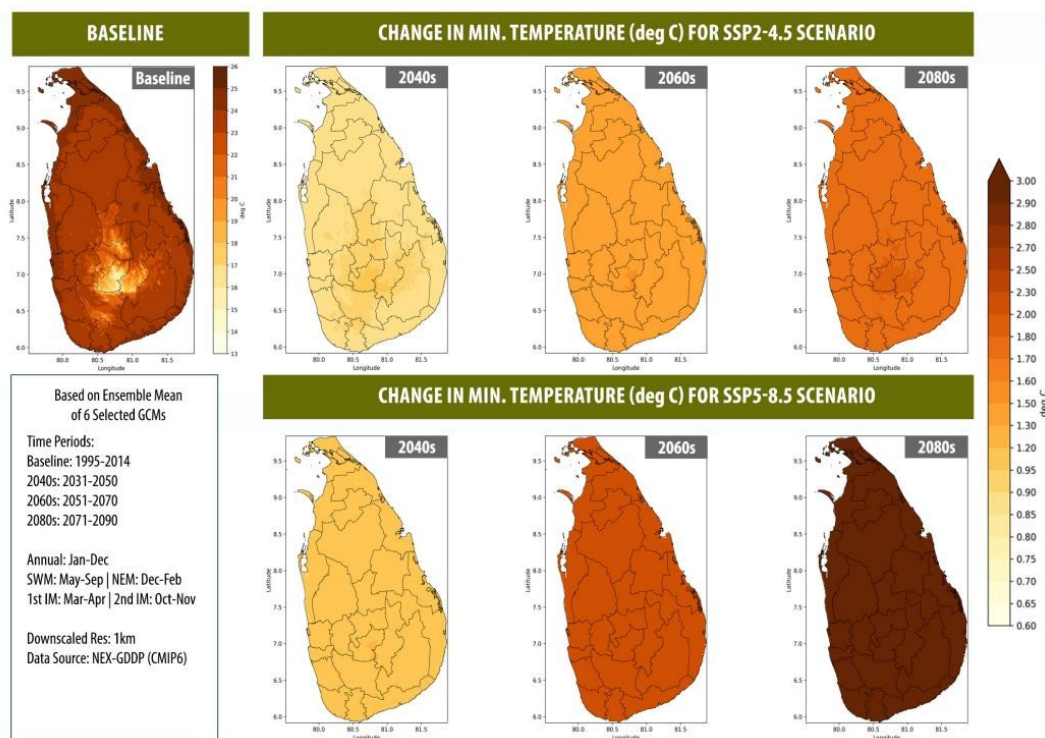


Figure 18: Projected change in mean minimum temperature (°C) in Second Inter-monsoon (October–November) season over Sri Lanka relative to the 1995–2014 baseline, based on the ensemble mean of six CMIP6 models. Projections are shown for the 2040s (2031–2050), 2060s (2051–2070), and 2080s (2071–2090) under SSP2-4.5 (top) and SSP5-8.5 (bottom) scenarios

The ensemble mean projections indicate a consistent and island-wide increase in SIM-season mean minimum temperature over Sri Lanka under both SSP2-4.5 and SSP5-8.5 scenarios relative to the 1995–2014 baseline. Under SSP2-4.5, modest warming is evident by the 2040s, with a further strengthening in the 2060s and 2080s. The spatial pattern is relatively uniform, with slightly lower warming over parts of the central highlands compared to surrounding lowland regions. In contrast, SSP5-8.5 shows

substantially stronger warming at all future time horizons, with a pronounced intensification toward the late century. By the 2080s, widespread high-magnitude increases in minimum temperature dominate across the island, indicating a strong and spatially coherent climate change signal.

Table 19: Projected changes in SIM-season mean minimum temperature (°C) over Sri Lanka

Scenario	Time slice	Projected change in mean minimum Temperature (Tmin)(°C)
SSP2-4.5	2040s (2031–2050)	0.9 – 1.1 increase
	2060s (2051–2070)	1.4 – 1.5 increase
	2080s (2071–2090)	1.7 – 2.0 increase
SSP5-8.5	2040s (2031–2050)	0.7 – 0.9 increase
	2060s (2051–2070)	2.0 – 2.2 increase
	2080s (2071–2090)	3.1 – 3.5 increase

5. Discussion

The climate projections indicate a clear tendency toward increased rainfall across Sri Lanka during the 21st century, with both the magnitude and spatial coherence of change strengthening over time and varying by emission pathway. At the annual scale, rainfall increases are evident under both SSP2-4.5 and SSP5-8.5 scenarios, with relatively modest changes in the near term and more pronounced wetting toward mid- and late-century. The stronger and more widespread increases under the high-emissions pathway underscore the sensitivity of Sri Lanka's rainfall regime to higher levels of global warming.

Seasonal analysis reveals pronounced contrasts across the monsoon cycle, highlighting the importance of sub-annual assessment. The Northeast and Southwest Monsoons exhibit robust and spatially coherent increases in rainfall, with confidence strengthening toward the end of the century, indicating an overall intensification of monsoon-related moisture transport. In contrast, the First Inter-Monsoon consistently displays a drying tendency across both emission scenarios. This persistent drying likely reflects the sensitivity of transition-season rainfall to changes in atmospheric stability and large-scale circulation. Unlike the primary monsoon seasons, First Inter-Monsoon rainfall is largely driven by localized convection, which may be suppressed under warming due to increased mid-tropospheric stability and reduced pre-monsoon ascent. The coexistence of enhanced monsoonal rainfall and inter-monsoon drying therefore points to a redistribution of rainfall across seasons rather than a uniform wetting response.

Projected changes in the Second Inter-Monsoon further support this interpretation, with rainfall transitioning from near-neutral conditions in the near term toward moderate and more spatially coherent

increases later in the century, particularly under the high-emissions pathway. Together, these seasonal patterns indicate increasing seasonal contrast, characterized by strengthened monsoonal rainfall and altered transition-season precipitation.

The projected strengthening of monsoonal rainfall, combined with widespread warming, is consistent with a globally recognized feature of climate change, whereby a warmer atmosphere enhances moisture availability and increases the likelihood of heavy precipitation events, as assessed in IPCC reports.

Projected temperature changes further confirm the presence of a strong forced climate signal across Sri Lanka. Both mean maximum and minimum temperatures increase consistently under all emission scenarios, with limited divergence in the near term and substantially stronger separation emerging after mid-century. Warming is most pronounced over inland and lowland regions, indicating the development of temperature hotspots, while the high-emissions pathway produces markedly greater and more spatially uniform warming, particularly for minimum temperatures. The widespread rise in night-time temperatures points to a fundamental shift in the national thermal regime, with implications for background climate conditions rather than isolated extremes.

Taken together, the combined rainfall and temperature projections depict a future climate characterized by intensified monsoonal rainfall, increased seasonal redistribution of precipitation, and sustained warming across all regions of Sri Lanka. The growing divergence between emission pathways beyond the mid-21st century highlights the critical role of future greenhouse gas trajectories in shaping national-scale hydroclimatic outcomes, with higher emissions amplifying both the magnitude and spatial coherence of projected changes.

Although rainfall extremes are not explicitly analysed in this study, the simulated changes in mean rainfall and temperature are consistent with conditions conducive to more frequent heavy rainfall events, highlighting the value of complementary analyses focused on precipitation extremes.

These projected shifts in rainfall and temperature regimes have direct implications for the livelihoods and well-being of Sri Lankan communities, given the country's strong dependence on climate-sensitive sectors. Enhanced annual and Northeast Monsoon rainfall, particularly over the Northern, North-Central, and Eastern regions, may improve water availability but also increase the risk of flooding, soil erosion, and infrastructure damage, especially in low-lying and poorly drained areas. In contrast, the persistent drying projected during the First Inter-Monsoon season could exacerbate short-term water stress, disrupt agricultural calendars, and increase vulnerability among rain-fed farming systems. The concurrent intensification of wet-season rainfall and inter-seasonal drying suggests a future marked by heightened rainfall variability, increasing exposure to both flood- and drought-related risks. Together,

these findings underscore the importance of adaptive water management, climate-resilient agricultural practices, and enhanced seasonal preparedness to mitigate climate-related risks under future warming.

6. Conclusion

This study provides a comprehensive assessment of projected rainfall and temperature changes over Sri Lanka under intermediate and high greenhouse gas emission scenarios. The six-member ensemble, consisting of CNRM-CM6-1, CNRM-ESM2-1, EC-Earth3-Veg-LR, ACCESS-CM2, MPI-ESM1-2-LR, and MIROC-ES2L, provides a robust and internally consistent basis for future climate projections over Sri Lanka. The results indicate a long-term increase in annual rainfall, with stronger and more spatially extensive wetting under higher emission pathways. Seasonal analysis shows that this increase is driven primarily by intensified Northeast and Southwest Monsoon rainfall, while the First Inter-Monsoon consistently exhibits drying across scenarios, highlighting a clear redistribution of rainfall across the year.

Temperature projections indicate substantial and sustained warming across all seasons throughout the 21st century, with the magnitude of change strongly dependent on future emission pathways. While near-term warming is comparable between scenarios, pronounced divergence emerges toward mid- and late-century, reflecting the increasing influence of greenhouse gas forcing. The widespread warming of both daytime and night-time temperatures across the island signifies a fundamental shift in Sri Lanka's thermal regime under climate change. Together, these rainfall and temperature projections provide a robust scientific foundation for national climate change assessments and enhance understanding of how Sri Lanka's climate system may evolve under future CMIP6 scenarios.

Projections presented here are subject to multiple sources of uncertainty. Confidence is high in the direction and magnitude of future temperature increases across Sri Lanka, as warming is consistent across models and scenarios. Confidence is medium in projected changes in seasonal mean precipitation, reflecting substantial inter-model spread and sensitivity to monsoon dynamics. Use of ERA5 as a reanalysis reference introduces low to medium confidence in model performance assessment for precipitation, particularly over complex terrain. Scenario uncertainty increases toward late century, with larger divergence between SSP2-4.5 and SSP5-8.5. High-resolution precipitation outputs should therefore be interpreted with medium confidence as spatial refinements of large-scale signals rather than precise local projections.

Previous studies based on CMIP5 projections generally suggested a weakening or reduction of Northeast Monsoon rainfall over Sri Lanka in future periods (Dharshika et al., 2018). In contrast, the present CMIP6-based analysis indicates a consistent increase in Northeast Monsoon rainfall across

future time horizons, with strengthening signals toward mid- and late-century. This difference likely reflects advances in CMIP6 model physics, including improved representation of aerosol forcing, large-scale circulation, and monsoon processes, which are particularly critical for the Northeast Monsoon system. The convergence of multiple CMIP6 models toward an increasing Northeast Monsoon rainfall signal, together with performance-based model selection, enhances confidence in the robustness of these projections. The performance-based CMIP6 ensemble developed in this study provides a reproducible framework that can be readily extended to sector-specific impact assessments and future updates as newer model generations become available.

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Impact of El Niño Southern Oscillation on the Southwest Monsoon Rainfall over Sri Lanka in the Decaying Period of El Niño

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ABSTRACT

Sri Lanka experiences monsoonal climates with four seasons. The southwest monsoon (SWM) is the longest rainfall season, lasting five months (May–September). Previous work by Ranaweera and Kamae (2024) demonstrated a significant influence of the El Niño–Southern Oscillation (ENSO) on first inter-monsoon (FIM) rainfall in Sri Lanka during the decaying phase of El Niño; however, the corresponding impact on SWM rainfall has not yet been examined. This study investigates the influence of ENSO during the decaying phase of El Niño on SWM seasonal rainfall over Sri Lanka. Rainfall observations from 75 meteorological stations operated by the Department of Meteorology for the period 1975–2019 were analyzed together with Japanese 55-year Reanalysis (JRA-55) data and COBE sea surface temperature (SST) datasets. The analysis reveals a significant positive correlation between SWM rainfall at most stations, excluding a few located in the central highlands, and the preceding year's November, December, and January Niño3.4 index (NDJ ENSO). Rainfall patterns associated with historical super and strong El Niño events during 1975–2019 were further examined. One out of three super El Niño events and both strong El Niño events exhibited rainfall anomaly patterns consistent with the identified positive relationship. Enhanced moisture transport associated with strong monsoonal wind flow was identified as the primary mechanism driving the observed positive rainfall anomalies. In contrast, the 1983 and 2016 El Niño events displayed considerable spatial variability in SWM rainfall, with no coherent distribution pattern, likely due to the influence of additional atmospheric and regional factors. These findings address an important research gap and provide insights that may contribute to improving seasonal rainfall forecasts for Sri Lanka.

1. Introduction

El Niño–Southern Oscillation (ENSO) is the most energetic mode of interannual climate variability in the global climate system, arising from coupled ocean–atmosphere interactions in the tropical Pacific Ocean (McPhaden et al. 2020). During El Niño events, positive sea surface temperature (SST) anomalies develop in the eastern equatorial Pacific Ocean east of the international dateline (Ueda 2014). El Niño events typically recur at intervals of approximately two to seven years (McPhaden et al. 2006). According to Xie et al. (2009), the El Niño lifecycle consists of three stages: development during boreal summer, a peak in early boreal winter, and decay during the subsequent spring. El Niño is associated with increased atmospheric pressure over the western Pacific and reduced atmospheric pressure over the eastern Pacific, leading to weakened equatorial trade winds. Through the Bjerknes feedback mechanism, weakened trade winds and elevated SSTs reinforce each other, amplifying the El Niño signal (McPhaden et al. 2006). Previous studies have identified a delayed influence of El Niño on the Indian Ocean following its peak phase (Xie et al. 2009, 2016). This delayed response is explained by the Indo-western Pacific Ocean Capacitor (IPOC) mode. During December–February, El Niño induces westward-propagating oceanic Rossby waves in the South Indian Ocean, leading to SST warming in

the southwestern Indian Ocean. This warming generates an antisymmetric wind pattern over the tropical Indian Ocean during March–May. Subsequently, the excitation of a tropospheric Kelvin wave propagating into the western Pacific triggers a second warming phase in the Indian Ocean. These processes modulate large-scale atmospheric circulation patterns, including anomalous anticyclones and the Pacific–Japan/East Asia teleconnection. The IPOC mode is sustained from boreal spring to summer through wind–evaporation–SST feedbacks and inter-basin interactions, driven by both thermodynamic processes (e.g., anomalous surface heat fluxes and radiative effects) and dynamic processes such as oceanic Rossby waves (Kosaka et al. 2021).

Sri Lanka is an island nation located in the tropical Indian Ocean, with a total land area of approximately 65,610 km². The spatial distribution of rainfall observation stations and topography is shown in Figure 1. The central region of the southern half of the island is characterized by mountainous terrain exceeding 2,500 m in elevation. Annual rainfall across Sri Lanka exhibits substantial spatial variability, ranging from approximately 900 mm to over 5,000 mm. Based on annual rainfall totals, the country is classified into three climatic zones: the dry zone (annual rainfall < 1,750 mm), intermediate zone (1,750–2,500 mm), and wet zone (> 2,500 mm). Seasonal climate variability in Sri Lanka is primarily governed by the latitudinal migration of the Intertropical Convergence Zone (ITCZ). As a result of this seasonal shift, Sri Lanka experiences a monsoonal climate with four distinct rainfall seasons. In addition, large-scale atmospheric variability associated with the Indian and Pacific Oceans plays an important role in modulating local weather conditions (Jayawardene et al. 2005). The southwest monsoon (SWM) is one of the most prominent of the four rainfall seasons in Sri Lanka, accounting for approximately 30% of the country's annual rainfall. The SWM extends from May to September and has the longest duration among the seasonal rainfall regimes (Punyawardena 2008). Rainfall during May, June, and September contributes substantially to total SWM precipitation, with the southwestern region of the island receiving the highest rainfall amounts. Among the four seasons, the SWM is particularly susceptible to natural hazards associated with extreme rainfall, especially during monsoon onset. Floods, landslides, slope failures, coastal inundation, and climate-sensitive disease outbreaks such as dengue fever frequently occur during this season, predominantly affecting the densely populated southwestern part of the island.

Several previous studies have examined the concurrent influence of ENSO on Sri Lanka's seasonal rainfall during the developing phase of El Niño (Abeysekera et al. 2019; Hapuarachchi et al. 2015; Premalal 2013; Punyawardena and Cherry 1999; Suppiah 1989, 1996, 1997). However, these studies did not explicitly investigate the underlying meteorological mechanisms responsible for ENSO-related rainfall variability. Moreover, despite the recognized importance of the IPOC mechanism in the Indian Ocean, its influence on Sri Lanka's seasonal rainfall has not been systematically examined. Recently, Ranaweera and Kamae (2024) demonstrated, for the first time, a significant impact of ENSO during the decaying phase of El Niño on First Inter-Monsoon

(FIM) rainfall in Sri Lanka, and identified the associated meteorological drivers. Nevertheless, the influence of ENSO during the decaying phase on SWM rainfall remains unexplored. Following the peak of El Niño, basin-wide warming of the Indian Ocean develops, and surrounding regions become increasingly influenced by IPOC-related processes. Given Sri Lanka's geographic location within the Indian Ocean, the island is likely to be sensitive to these delayed ENSO effects. Therefore, a comprehensive understanding of ENSO impacts on Sri Lanka's seasonal rainfall requires explicit consideration of the decaying phase of El Niño (Ranaweera and Kamae 2024). Recent studies also suggest that Indian Ocean warming can significantly modulate Sri Lanka's rainfall variability (Kajakokulan et al. 2023). Furthermore, an increasing frequency of El Niño events has been reported in recent decades (Wang et al. 2019), highlighting the growing importance of understanding ENSO-related climate impacts.

This study investigates the influence of ENSO during the decaying phase of El Niño on SWM rainfall over Sri Lanka. The findings aim to improve the understanding of large-scale climate controls on SWM variability and to contribute to more reliable seasonal rainfall forecasting. Improved seasonal forecasts are essential for effective disaster risk reduction, water resource management, and agricultural planning, thereby supporting sustainable development efforts in Sri Lanka.

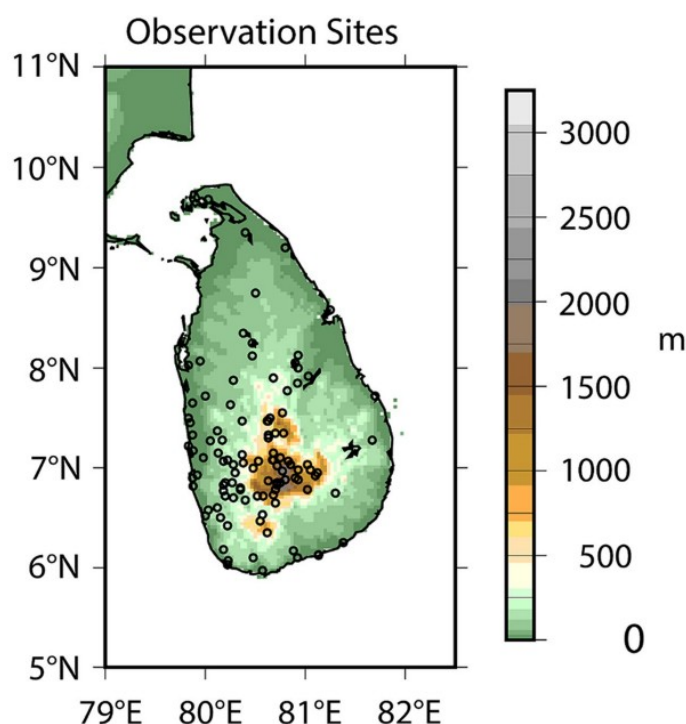


Figure 1. The rainfall observation sites and topography map of Sri Lanka (Ranaweera and Kamae 2024).

2. Materials and Methods

Two types of Observational data and one reanalysis dataset were used for the study. Department of Meteorology (DOM), Sri Lanka, provided the rainfall observational data. SST data from the COBE-SST2 (Hirahara et al. 2014) data set with a spatial resolution of $1.0^{\circ} \times 1.0^{\circ}$ is used. Atmospheric circulation patterns were investigated by using Japanese 55-year Reanalysis (JRA 55) data (Kobayashi et al. 2015) at $1.25^{\circ} \times 1.25^{\circ}$ spatial resolution.

According to the definition introduced by the National Oceanic and Atmospheric Administration (NOAA) of the United States Climate Prediction Centre, El Niño events were identified according to the Oceanic Niño Index in the Niño 3.4 region. Therefore, five consecutive over-lapping 3-month periods at or above the $+ 0.5$ K anomaly (Kousky and Higgins 2007) in the Niño 3.4 region were identified as warm El Niño events. The events are further categorized according to the NOAA classification as; strong El Niño events (SST anomaly between 1.5-1.9 K); and super El Niño events (SST anomaly greater than or equal to 2.0 K). Table 1 shows the Super and strong El Niño events recorded in the period between 1975 and 2019.

The study was done for the May-September season in the following year of El Niño events. The SST anomalies in the Eastern Pacific started to develop from June to August and reached a peak in December. Then in the following year April, it starts to decay rapidly. This study focused on the SWM seasons in the decaying period of El Niño events. By using the COBE-SST2 dataset, SST patterns were investigated for all super and strong El Niño events shown in Table 1.

When selecting the study period, IPOC conditions were considered the main factor as same as in our previous study. The El Niño-induced Indian Ocean warming persists through the following year's summer, consistent with IPOC only after the 1970s (Xie et al. 2010). According to Xie et al. (2016), a high correlation between summer North Indian Ocean SST and preceding winter ENSO can be seen in the mid-1970s. Moreover, researchers identified that the high correlation of the atmospheric anomalies in the Indo-tropical North Pacific with ENSO is due to the high variance of ENSO after the 1970s (Kubota et al. 2015). Therefore, the study period 1975-2019 was selected according to the above factors.

Table 1. Super and strong El Niño events in the period between 1975-2019.

Strong El Niño	Super El Niño
1987-1988	1982-1983
1991-1992	1997-1998
	2015-2016

Weather station's monthly and daily observational rainfall data from 220 stations were obtained from the DOM Sri Lanka to identify the rainfall patterns. During the study, it was highly concerned about the quality and accuracy of the data. The stations were eliminated where missing values were more than three months. The number of missing values was high in the SWM season due to the seasonal flooding and related disasters that occurred at the beginning of the SWM seasons. Therefore, the number of stations that have a complete data set for the SWM season was 78. Each station's rainfall data time series plots were investigated to identify unnatural rainfall values. Identified unnatural values were corrected by checking the nearby rainfall station's daily records. The rainfall and extreme event record books of the DOM were also investigated for data validation. The selected stations and locations show in table 2. The correlation between each station's seasonal rainfall for SWM and the preceding year's November, December, and January Niño3.4 SST anomaly (NDJ ENSO) has been investigated. Then the rainfall anomalies for SWM in the decaying period of El Niño events were calculated for each super and strong El Niño event recorded between 1975 and 2019.

The atmospheric behaviors that caused the impact were examined by using JRA 55 data from 1975. Spatial patterns of temporal regression coefficients of geopotential height, horizontal wind, sea surface pressure, and anomalous water vapor transport in SWM in the decaying period of El Niño were investigated with NDJ ENSO for the period 1975-2019.

The sea level pressure parameter of the surface analysis fields (anl_surfl25) was used to analyze the Sea surface pressure. Geopotential height and u-component and v-component horizontal winds were taken from the isobaric analysis field (anl_p125). Zonal and meridional water vapor flux parameters of the total column analysis field (anl_column125) were analyzed to investigate water vapor transportation. The analysis was done for each super and strong El Niño event recorded between 1975 and 2019.

Table 2. Selected 78 meteorological stations and their locations.

Station	Lat(⁰ N)	Lon(⁰ E)	Station	lat	lon
Anuradhapura	80.38	8.35	Angoda Mental Hospital	79.92	6.93
Badulla	81.05	6.98	Detanagalla	80.68	6.73
Batticaloa	81.70	7.72	Geekiyanakanda Estate	80.12	6.60
Campion Estate	80.70	6.78	Depedena Group	80.55	6.47
Colombo	79.87	6.90	Galatura Estate	80.28	6.70
Crystal Hill Estate	80.65	7.50	Katugastota	80.63	7.33
Galle	80.22	6.03	Maha Illuppallama	80.47	8.12
Hambantota	81.13	6.12	Welimada Group	80.90	6.90
Helbodde Estate	80.67	7.08	Katunayaka	79.88	7.17
Helbodde North	80.68	7.08	Ratmalana	79.88	6.82
Holmwood Estate	80.72	6.85	Ledgerwatte Estate	81.02	7.03
Hope Estate	80.75	7.10	Pasyala	80.13	7.15
Kurunegala	80.37	7.47	Andigama Farm	80.12	7.37
Nuwara Eliya	80.77	6.97	Rayigama	80.18	6.77
Puttalam	79.83	8.03	Sirikandura Estate	80.15	6.50
Alupolla Group	80.58	6.72	Pelawatte	80.22	6.42
Ambepussa Govt Farm	80.17	7.28	Okkampitiya	81.30	6.75
Amparai Tank	81.67	7.28	Illukkumbura	80.77	7.55
Annfield Estate	80.63	6.87	Kekenadura (Matara)	80.57	5.97
Balangoda Post Office	80.70	6.65	Bopatthalawa	80.72	6.83
Duckwari Estate	80.78	7.35	Liddesdale Estate	80.85	7.03
Eheliyagoda S.P.	80.27	6.85	Lunuwila (Bandirippuwa)	79.87	7.33
Galphele Wattedgama	80.7	7.35	Kalatuwawa	80.20	6.85
Henarathgoda Bot Grdns	79.98	7.10	Pussella S.P.	80.35	6.80
Kandy-Kings Pavilion	80.63	7.30	Jaffna	80.03	9.68
Kekenadura (Matara)	80.57	5.97	Anningkanda Estate	80.62	6.35
Kenilworth (Strathellie)	80.48	7.00	Baddegama Estate	80.18	6.18
Labuduwa	80.23	6.07	Vincit Estate	80.22	7.08
Labugama Tank	80.18	6.83	Vavuniya	80.50	8.75
Liddesdale Estate	80.85	7.03	Lower Spring Valley	81.10	6.92
Matale-P.W.D.	80.62	7.47	Angunakolapelessa	80.88	6.17
Nachchaduwa	80.47	8.25	Maha Lewaya (Hambantota)	81.13	6.13
Negombo	79.83	7.22	Wariyapola Exptl.Station	80.25	7.63
New Forest	80.68	7.15	Polontalawa	80.00	7.72
Ratnapura	80.40	6.68	Clyde Estate	80.03	6.58
Rayigama	80.18	6.77	Anningkanda Estate	80.62	6.35
Sirikandura Estate	80.15	6.50	Palugaswewa Estate	79.87	7.65
Trincomalee	81.25	8.58	Hapugastenna Estate	80.52	6.72
Angoda Mental Hospital	79.92	6.93	Debedde Estate	81.12	6.95

3. Results

Sea surface temperature (SST) patterns associated with all super and strong El Niño events that occurred between 1975 and 2019 were examined. Figure 2 illustrates the SST anomaly patterns during October–December (OND) of each El Niño year, together with the corresponding SST patterns for the subsequent May–September period. As shown in Figure 2 C, D, G, H, and K, the eastern Pacific Ocean exhibits a gradual decay of positive SST anomalies during the May–September season.

Pronounced positive SST anomalies were observed in the eastern Pacific (160° – 80° W) during OND 1982 and 1997 (Figure 2A, B). In contrast, during OND 2015, the strongest warming was concentrated in the central Pacific (170° – 90° W; Figure 2F). Notably, the 2015 El Niño event was also characterized by widespread positive SST anomalies across the Indian Ocean basin (Figure 2F). During OND 1997, the Indian Ocean exhibited an SST anomaly pattern resembling the Indian Ocean Dipole (IOD) mode. Compared with the super El Niño events, the strong El Niño events of 1987 and 1991 displayed relatively weaker positive SST anomalies in the eastern Pacific during OND (Figure 2E, I). Nevertheless, a similar SST anomaly configuration was evident over the central equatorial Pacific during the 1987, 1991, and 2015 events, with peak SST anomalies located in the central Pacific.

In contrast, notable differences in Indian Ocean SST patterns around Sri Lanka are evident between the 1987 and 1991 events. During OND 1987, a positive IOD-like pattern is apparent, with relatively strong positive SST anomalies over the region (Figure 2E). In the subsequent May–September period following each El Niño event, SST anomalies in the eastern equatorial Pacific exhibit a pronounced weakening, as shown in Figure 2 C, D, G, H, and K. Although Indian Ocean warming persists during these periods, SST patterns resembling negative IOD events are evident in the Indian Ocean during the May–September seasons following the 1997 and 2015 El Niño events. Furthermore, SST anomaly patterns indicative of the development of La Niña conditions emerge in the eastern Pacific during these periods.

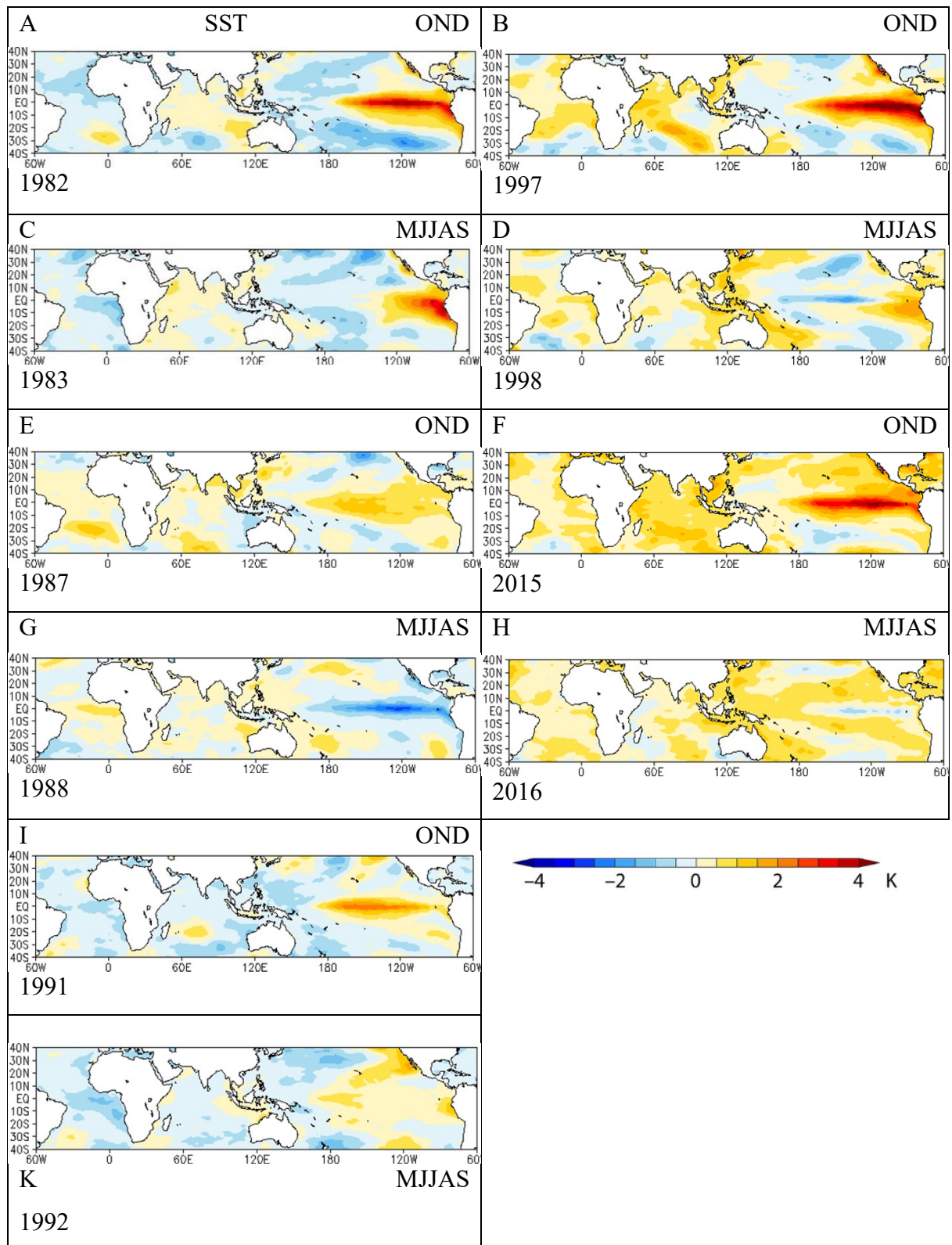


Figure 2. SST anomaly patterns in super and strong El Niño years and the following year, May-September (A, E, I, B, F), SST patterns for OND 1982, 1987, 1991, 1997, and 2015, respectively. (C, G, K, D, H) The SST patterns in the following year, May-September.

The correlation coefficient between stations' seasonal rainfall in the SWM season and NDJ ENSO for the period 1975-2019 has been plotted to investigate the relationship between stations' seasonal rainfall and NDJ ENSO. Figure 3 shows the correlation coefficient between stations' seasonal rainfall in the SWM season and NDJ ENSO for the period 1975-2019. A positive correlation (0.0-0.6) between stations' SWM season rainfall and NDJ ENSO can be identified in this season, except for nine stations in central hilly areas, where a small negative correlation can be observed, as seen in Figure 3.

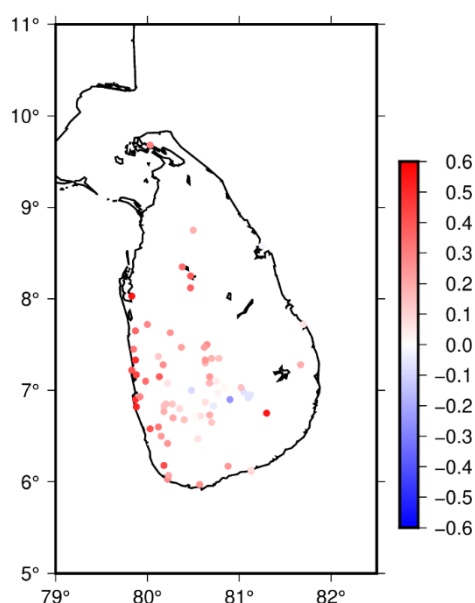


Figure 3. Correlation between stations' seasonal rainfall in SWM and the preceding year's NDJ ENSO index for the period 1975-2019.

To identify the potential behavior of atmospheric variables that contributed to the above positive correlation pattern, horizontal wind anomaly, geopotential height anomaly, mean sea level Pressure anomaly, and vertically integrated water vapor flux associated with NDJ ENSO were plotted. The large-scale fields of regression coefficient of May to September geopotential height and 850 hPa wind onto the preceding year NDJ ENSO for 1958-2021 are shown in Figure 4A. The local regression coefficients over Sri Lanka are shown in Figure 4B.

An anomalous subtropical high in the tropical Northwestern Pacific and easterly wind anomaly in the northern Indian Ocean, and meridional anti-symmetric wind pattern with anomalous easterlies over the Arabian Sea can be identified in Figure 4A, which is consistent with the delayed ENSO impacts explained by Xie et al. (2009, 2016). Moreover, anomalous wind patterns that extended to the BOB, accompanied by easterly wind anomalies disturbed by the monsoonal winds coming from the southwestern Indian Ocean regions, can be observed in this season. Antisymmetric wind patterns can be seen in Figure 4B over the Sri Lanka area. Figure 4C shows the large-scale field of May to September mean-sea level Pressure regression coefficient onto the preceding year NDJ ENSO for 1958-2021. Figure 4E shows the large-scale field of May to September vertically integrated water vapor flux onto the preceding year NDJ ENSO for 1958-2021.

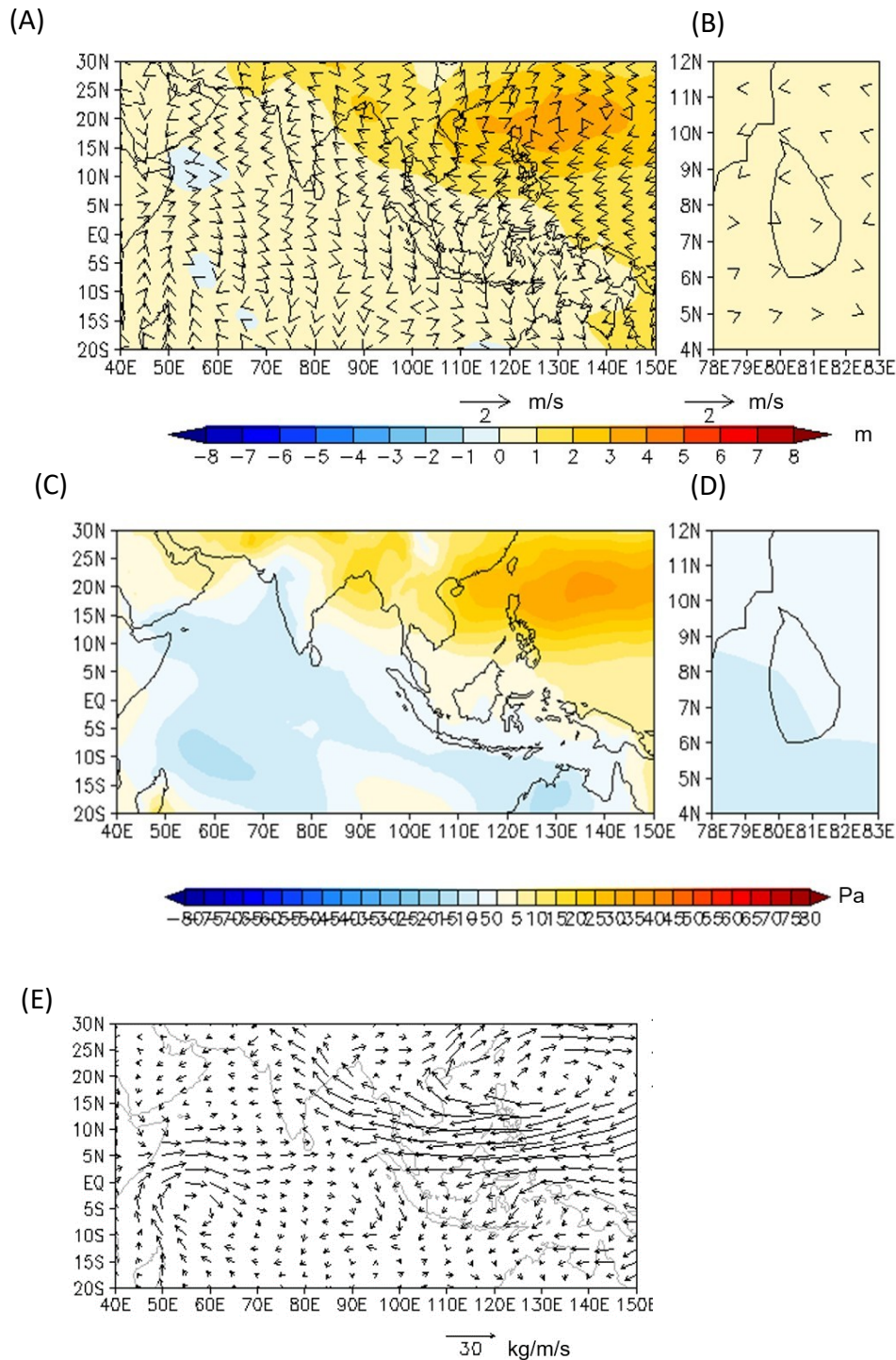


Figure 4. (A, B) Spatial patterns of temporal regression coefficients of geopotential height (m; shading) and horizontal wind (m/s; vectors) at 850 hPa level between May and September onto NDJ Niño3.4 for 1958–2021 over (A) the western Pacific and Indian Ocean, and (B) Sri Lanka. (C, D) Spatial patterns of temporal regression coefficients of sea level pressure (hPa; shading) between May and September onto NDJ Niño3.4 for 1958–2021 over (C) the western Pacific and Indian Ocean, and (D) Sri Lanka. (E) Spatial patterns of temporal regression coefficients of vertically integrated water vapor flux ($\text{kg m}^{-1} \text{s}^{-1}$) between May and September onto NDJ Niño3.4 for 1958–2021 over the western Pacific and Indian Ocean. Only regression coefficients of geopotential height significant at the 95% confidence level are shown.

Ranaweera and Kamae (2024) reported high-pressure anomalies over the western equatorial Pacific Ocean and the Bay of Bengal (BOB) during the FIM season. For the SWM season, a weakened high-

pressure system in the western equatorial Pacific and a northward shifted high-pressure area over the BOB are evident (Figure 4c). Additionally, moisture transport from the western and southwestern Indian Ocean toward Sri Lanka is observed during the SWM season (Figure 4e). This moisture transport, driven by strong monsoonal winds with high water vapor content, contributes to enhanced precipitation across the country (Figure 3), particularly over the western and southwestern regions.

Thereafter, seasonal rainfall anomalies during each SWM season in the decaying period of super and strong El Niño events from 1975 to 2019 were investigated to identify the consistency of the positive correlation pattern. The seasonal rainfall anomalies in each station in SWM during the decaying period of each super and strong El Niño event between 1975 and 2019 are shown in Figure 5.

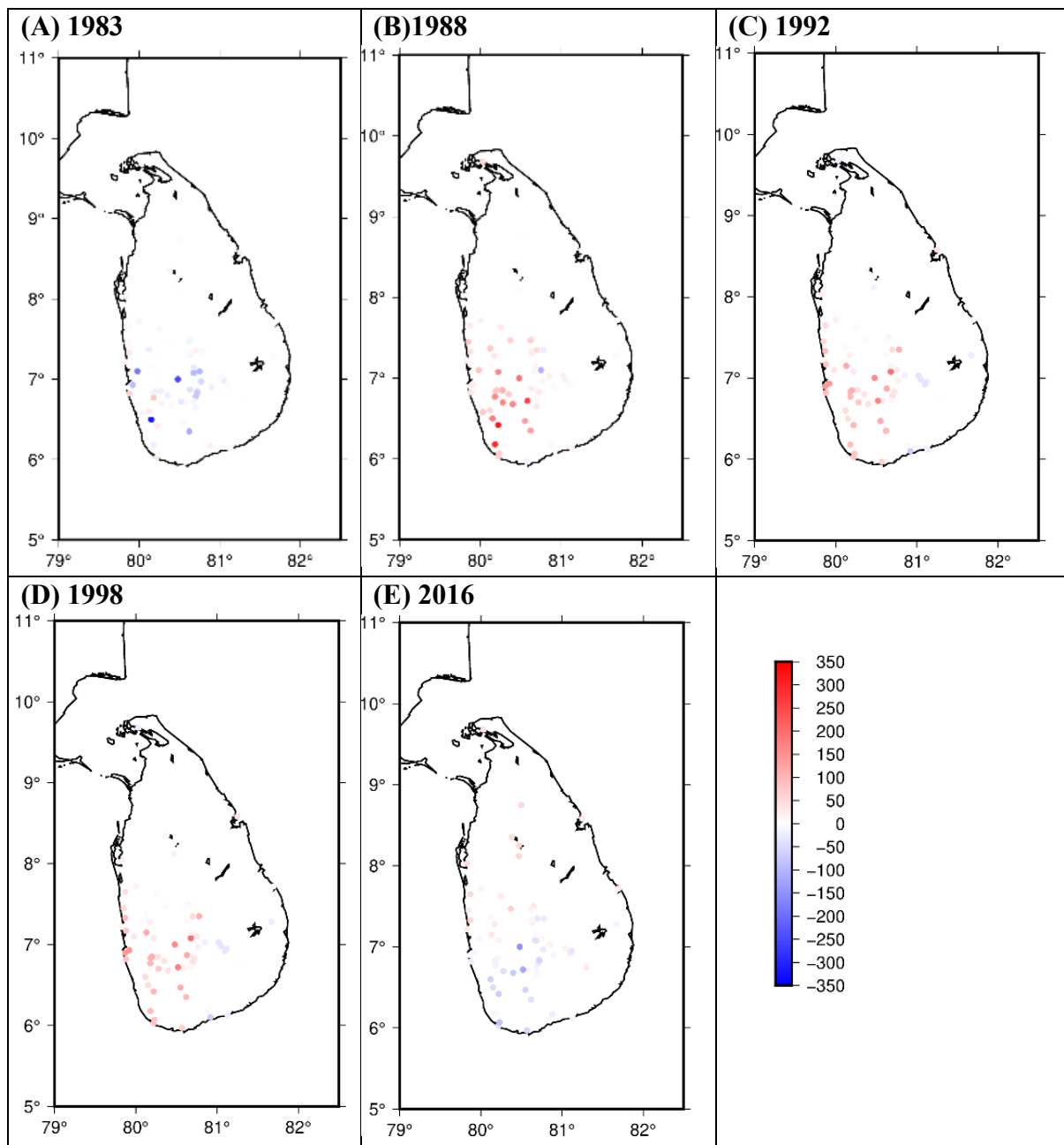


Figure 5: Rainfall anomaly (mm) in May-September (SWM season) in the decaying period of each super and strong El Niño event between 1975- 2021 (A) 1983, (B) 1988, (C) 1992, (D) 1998, (E) 2016.

A positive rainfall anomaly was identified in the SWM in the decaying period of the super El Niño event in 1997 and the strong El Niño events in 1987 and 1991; the percentage of stations with positive rainfall anomaly was 78%, 87%, and 72% respectively, as seen in Figures 5D, B, and C. In contrast, this positive seasonal rainfall anomaly pattern cannot be identified in the SWM in the decaying period of the super El Niño events in 1982 and 2015. SWM seasons in 1983 and 2015 show negative rainfall anomalies at 65% and 55% of stations. Therefore, the rainfall anomaly patterns were not consistent with the Positive correlation pattern explained in Figure 3.

Thereafter, investigated the atmospheric parameters to examine possible factors contributing to this contrast in rainfall anomaly patterns in the SWM in 1983 and 2016. Figure 6 illustrates the behavior of atmospheric parameters in May-September 1983 and 2016.

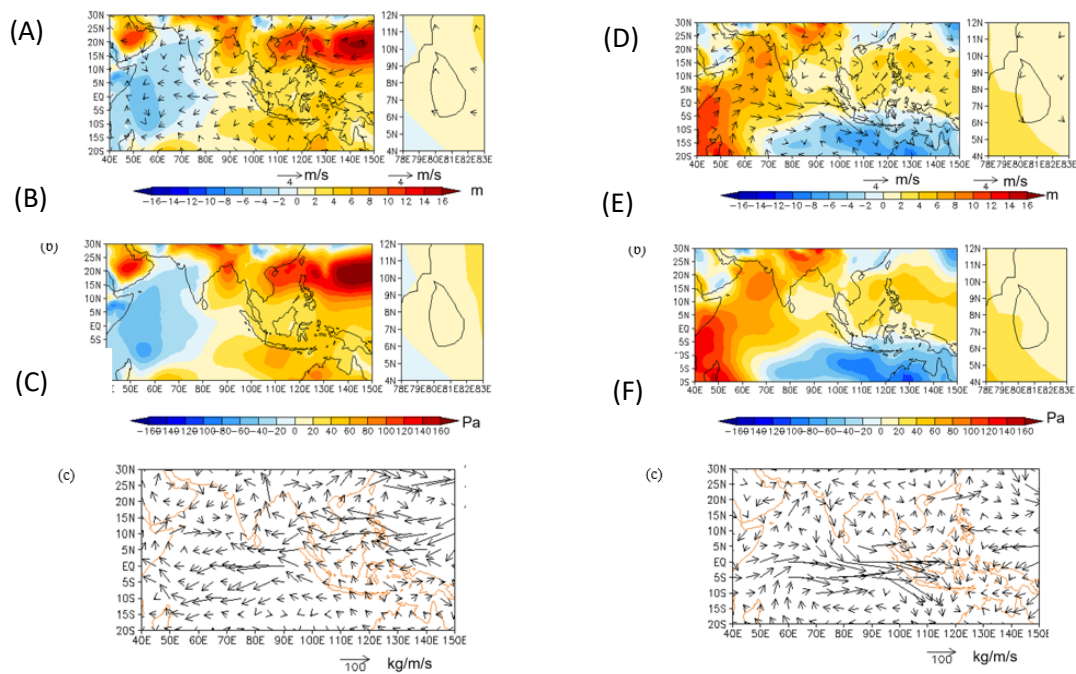


Figure 6. The behavior of atmospheric parameters in May-September in the decaying period of the 1982 and 2015 events. (A) Geopotential height (m; shading) and horizontal wind (m/s; vectors) anomalies at 850 hPa level, (B) Sea level pressure anomalies (Pa), and (C) vertically integrated water vapor flux [kg/m/s] anomalies between May and September 1983. (D) Geopotential height (m; shading) and horizontal wind (m/s; vectors) anomalies at 850 hPa level, (E) Sea level pressure anomalies (Pa), and (F) vertically integrated water vapor flux [kg/m/s] anomalies between May-September 2016.

Anti-symmetric wind patterns with anomalous easterlies over the Arabian Sea which can be observed in Figure 4A were not clear in 1983 and 2016 (see Figure 6 A, D).

Furthermore, the pressure anomaly pattern was found over the Western North Pacific in Figure 6 A, and E consistent with Figure 4B. Moreover, Figure 4C clearly shows water vapor transportation from the western and southwestern Ocean areas to the country. This pattern cannot be identified in the SWM in 1983 and 2016 as seen in Figure 6C, F.

4. Discussion and Conclusion

The study findings show a positive correlation between stations' rainfall and the preceding year's NDJ ENSO index for the SWM season in most stations, except in the few stations in the central hilly areas. Stations in the western and southwestern parts of the country show a significant positive correlation, particularly due to the water vapor being transported from the western and southwestern Ocean areas to the country, accompanied by the monsoonal strong wind flow with a high moisture content in the SWM season. The SWM seasons in the decaying period of all strong El Niño events and one of the three super El Niño events provide further evidence for the above finding. In contrast, the SWM season in the decaying period of the super El Niño event in 1982 and the strong El Niño event in 2016 shows negative rainfall anomaly at 65% and 55% of the stations, respectively. The possible atmospheric factors were investigated, and the discussion on the contrast finding is as follows.

The SWM season is mainly influenced by large-scale factors; it mainly depends on the strength of the Indian Summer monsoon. During the years with weak monsoon conditions, Sri Lanka experienced less rainfall than Normal monsoon years, particularly in the southwestern quarter of the island.

The strength, lifetime, and transition of ENSO show asymmetries in recent decades (Stein et al 2010). A rapid transition to La Niña events can be identified in 1997-1998 and 2015-2016 super El Niño events (Naoi et al 2020). Moreover, the transition of the El Niño to La Niña events was in the SWM season between May and September. La Niña events strongly affect the Walker circulation through strong trade winds due to upwelling in the eastern Pacific. The impact of it may extend to other areas of the world, including the Sri Lankan region. The influence of El Niño on Walker circulation through the latent heating can differ due to the position of the warmest SST anomaly (Weng et al. 2009, Blamey et al 2018). Furthermore, slightly different peak periods of each event can be identified as another possible factor for the different impacts on seasonal rainfall in Sri Lanka. Moreover, the type of El Niño may also cause different impacts on different areas of the world.

To investigate the impact of IOD on the contrasting results, the IOD index for the SWM season in the decaying period of the super and strong El Niño events between 1975 and 2019 was investigated.

Average IOD index values were negative in 1988, 1992, 1998, and 2016. From those four years, three years show positive rainfall anomaly at a high percentage of stations. However, the year 2016 shows contrasting results with a smaller percentage of stations at 45%. In the year 1983 average IOD index values were positive, and the number of stations that showed positive rainfall anomaly was low (see Table 03) at 35%.

Moreover, in 1983, SST in the Indian Ocean was relatively low compared to other super El Niño events. Therefore, when considering the factors mentioned above, it becomes evident that a reliable and consistent relationship between negative or positive average IOD and seasonal rainfall anomaly patterns in the SWM season in the decaying period of the El Niño events cannot be identified.

Table 3. Average IOD index values and the percentage of stations show a positive anomaly for the SWM season in the decaying period of each El Niño event.

Year	Average IOD index for May-September	The percentage of stations shows a positive anomaly
1983	0.2226	35 %
1988	-0.3236	87 %
1992	-0.698	71 %
1998	-0.2348	78 %
2016	-0.439	45 %

Then investigated the possible impact of the Madden-Julian Oscillation (MJO) on the contrasting result. When MJO is in phases 5, 6, 7, or 8, the SWM seasonal rainfall is suppressed in Sri Lanka (Jayawardhana et al 2020). In 2016, MJO was in Phase 8 in the first week of June, it was in Phase 6 in the middle two weeks of August, and it was in Phase 5 in the last two weeks of September. Such conditions may have contributed to suppressed rainfall in the SWM season in the year 2016. In contrast, in the SWM season 1983, MJO was not in phases 5,6,7, or 8 except from May 21st to 25th when it was in phase 5. Therefore, the clear contribution of MJO to the rainfall reduction of the SWM season in the decaying period of the super El Niño event in 1982 cannot be identified.

Some previous researchers found that the SWM seasonal rainfall is negatively correlated with SST in the Arabian Sea and the Central BOB. They further found that the changes in the parameters such as moisture, moisture transport, and zonal wind over the Arabian Sea caused a decrease in the SWM rainfall in Sri Lanka (Shelton et al 2022). All events from 1997 exhibit comparatively high SST anomalies in the Indian Ocean and Arabian Sea regions, particularly during the decaying period of those events in the SWM. Therefore, the Indian Ocean and Arabian Sea warming may also have an impact on the decrease in the seasonal rainfall in the SWM season in Sri Lanka in the decaying period of El Niño events. However, there was no consistency in rainfall patterns in the SWM season in the decaying period of El Niño events.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Assessment of Climate Extreme Indices Across Sri Lanka (1975–2024)

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ABSTRACT

This study presents a comprehensive assessment of climate extremes across Sri Lanka based on 50 years (1975–2024) of daily precipitation and minimum and maximum temperature observations from 18 meteorological stations. Using 22 standardized indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) and the Expert Team on Sector-Specific Climate Indices (ET-SCI), trends were evaluated using the non-parametric Mann–Kendall test and Sen’s slope estimator. Results reveal a coherent and asymmetric warming signal, characterized by stronger and more spatially consistent increases in minimum temperatures than maximum temperatures, leading to a widespread decline in the diurnal temperature range. Frequency based temperature indices indicate a marked reduction in cool days and nights and a robust increase in warm days and, particularly, warm nights across all climatic zones, while trends in the most extreme hot and cold events remain spatially heterogeneous. Rainfall persistence indices show mostly weak and non-significant trends, indicating limited long-term change in wet and dry spell duration. In contrast, threshold and intensity based rainfall indices exhibit predominantly increasing trends at selected locations, reflecting a rise in the frequency and average intensity of moderate to heavy rainfall events. However, the most extreme rainfall indices display no consistent island wide signal. Overall, the findings highlight dominant night-time warming and localized intensification of rainfall as the most robust signals of recent climate change in Sri Lanka.

Key words: Sri Lanka, Climate Extreme indices, Climpack software, Temperature, Precipitation

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) highlights in its Sixth Assessment Report (AR6, 2023) that human-induced warming has already altered the frequency and intensity of climate extremes, including heatwaves, heavy precipitation, droughts, and tropical cyclones. These changes are projected to intensify as global temperatures continue to rise, increasing the likelihood of unprecedented and compound extreme events. Understanding how such extremes evolve at regional and local scales is therefore critical for assessing vulnerability and informing effective adaptation planning.

Sri Lanka is situated within the South Asian monsoon region, one of the world’s most climate-sensitive areas. Regional climate variability is strongly influenced by large-scale atmospheric–oceanic drivers such as the South Asian Monsoon, the Indian Ocean Dipole (IOD), and the El Niño–Southern Oscillation (ENSO), all of which modulate rainfall distribution, drought occurrence, and extreme precipitation episodes across the island. In recent decades, South Asia has experienced intensified heatwaves, erratic monsoons, and more frequent heavy rainfall events, consistent with broader warming

trends reported by the IPCC. These regional-scale climate dynamics directly shape Sri Lanka's hydroclimatic variability and contribute to the increasing uncertainty in seasonal rainfall patterns.

The island's climate is fundamentally governed by a tropical, monsoonal regime, which creates distinct regional variations in precipitation. Rainfall is primarily driven by the Southwest Monsoon (SWM) (May–September) and the Northeast Monsoon (NEM) (December–February), which define the Wet and Dry Zones, respectively. Two inter-monsoon periods, particularly the second (October–November), contribute significantly to the annual total, resulting in a highly dynamic and spatially varied monthly rainfall regime.

Sri Lanka's tropical location in the Indian Ocean and its monsoon-governed climate make it highly sensitive to these regional influences. While its geographical position supports diverse ecosystems and socio-economic development, it simultaneously exposes the country to climate induced hazards such as floods, droughts, strong winds, and extreme rainfall events, that account for nearly 96% of recorded natural disasters (Eriyagama & Smakhtin, 2010). Additional vulnerabilities arise from the nation's limited land area, high population density, and dependence on climate-sensitive sectors (Esham & Garforth, 2013; IPCC, 2021; World Bank, 2020). The Global Climate Risk Index (2018) identifies Sri Lanka among the most climate-vulnerable countries globally.

Observed climatic changes reinforce these concerns. Temperature records indicate an increase of approximately 0.8°C since the early 20th century (Carbon Brief, 2018), consistent with national reports showing a warming rate of about 0.16°C per decade since the 1960s (Esham & Garforth, 2013). Long-term rainfall trends reveal a decline of about 7% in annual precipitation, with marked reductions during the northeast monsoon and second inter-monsoon seasons (Eriyagama & Smakhtin, 2010). Meanwhile, less consecutive dry days, is observed western coastal areas and reductions in consecutive wet days in Nuwaraeliya and Rathnapura, and spatially heterogeneous trends in extreme rainfall (Jayawardena et al., 2018) suggest growing irregularity and intensification of hydroclimatic extremes. These patterns are further modulated by ENSO, which can enhance northeast monsoon rainfall in the northern and eastern dry regions (Zubair & Ropelewski, 2006). Sri Lanka's tropical monsoonal climate exhibits strong spatial and temporal variability, making the country highly sensitive to changes in climate extremes. Previous studies (Premal and Punyawardena, 2009; Abeysekera *et al.*, 2020) provide consistent evidence of a warming trend, with significant increases in mean, maximum, and minimum temperatures, alongside declining cold days and nights and increasing warm days and nights. These results indicate a robust intensification of the national temperature regime. In contrast, extreme rainfall trends remain spatially heterogeneous, with limited island-wide signals but emerging increases in heavy rainfall intensity, particularly in the Dry Zone.

Despite a growing body of evidence, comprehensive and up-to-date assessments of climate extremes in Sri Lanka using standardized indices remain limited, particularly beyond 2015. The Expert Team on Climate Change Detection and Indices (ETCCDI) framework provides a robust and internationally comparable basis for evaluating changes in extreme temperature and precipitation, while sector-specific indices developed under the Expert Team on Sector-Specific Climate Indices (ET-SCI) enable targeted assessments of climate-sensitive extremes. Accordingly, this study undertakes a detailed evaluation of ETCCDI and ET-SCI-based indices for the 50-year period 1975–2024 to improve understanding of evolving hydroclimatic extremes across Sri Lanka. Whereas earlier assessments have relied on shorter observational records (e.g. 34 years in Jayawardena et al.2018), the present analysis adopts a longer-term perspective consistent with the multi-decadal analytical framework recommended in the IPCC Sixth Assessment Report (WG I).

2. Data and Methodology

2.1 Study area

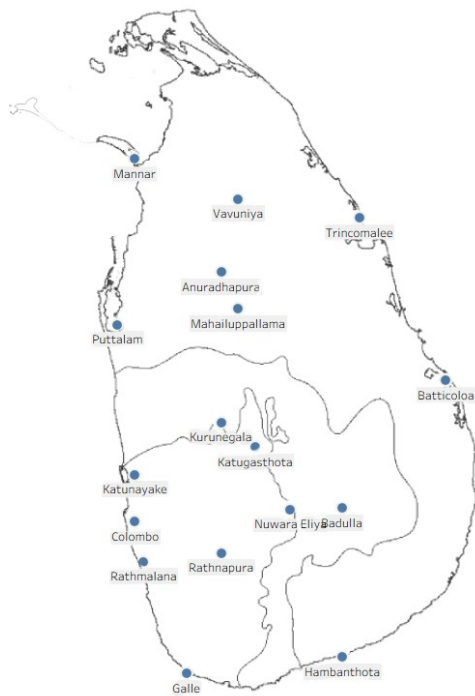
Sri Lanka is a tropical island located in the northern Indian Ocean (5°–10° N, 79°–82° E) with a complex climate shaped by the Southwest (May–September) and Northeast (December–February) monsoons, separated by two inter-monsoon seasons. Strong spatial variability in rainfall and temperature arises from the interaction of monsoonal circulation with topography, particularly the central highlands, resulting in distinct wet, intermediate, and dry climatic zones.

2.2 Data Sources and Tools

The Department of Meteorology, Sri Lanka, operates 24 principal meteorological stations nationwide. For this study, 18 stations (Figure 01) were selected based on the continuity and completeness of their daily temperature and precipitation records, each providing a minimum of 50 years of data. This selection aligns with World Meteorological Organization (WMO) recommendations, which suggest a minimum 30-year record for robust climatological assessments and reliable trend detection (WMO, 2017). The selected stations provide representative coverage of Sri Lanka's wet, intermediate, and dry agro-climatic zones, ensuring both spatial and temporal reliability.

Table 1: List of meteorological stations and their corresponding geographic coordinates used for the long-term temperature and precipitation analysis.

	Name	Latitude(⁰N)	Longitude(⁰E)		Name	Latitude(⁰N)	Longitude(⁰E)
1	Anuradhapura	8.33	80.38	10	Katunayake	7.17	79.88
2	Badulla	6.98	81.05	11	Kurunagala	7.47	80.35
3	Bandarawela	6.82	80.97	12	Maha Illuppallama	8.12	80.47
4	Batticaloa	7.71	81.70	13	Mannar	8.98	79.90
5	Colombo	6.90	79.87	14	Nuwara Eliya	6.97	80.77
6	Galle	6.03	80.22	15	Puttalam	8.03	79.83
7	Hambanthota	6.12	81.13	16	Rathnapura	6.72	80.38
8	Katugasthota	7.33	80.63	17	Trincomalee	8.58	81.25
9	Vavuniya	8.75	80.50	18	Rathmalana	6.67	79.95



The stations were chosen based on the completeness and continuity of their daily temperature and precipitation records for the period 1975–2024. The selection ensures representative coverage across the island's three main agro-climatic zones (Wet, Intermediate, and Dry), which is critical for assessing the spatial variability of climate extremes.

Figure 1: Geographical distribution of the 18 meteorological stations selected for the study across Sri Lanka.

The daily maximum temperature (Tmax), minimum temperature (Tmin), and precipitation records from these stations were analyzed using Climpack, which is the standardized software developed by the WMO and ETCCDI for calculating climate extreme indices. The software ensures methodological consistency, international comparability, and enhanced computational performance, while incorporating improved quality-control procedures and a wide range of index outputs. Using Climpack, temperature and precipitation extremes were assessed for the period 1975–2024, offering a 50-year data set suitable for evaluating long-term trends and spatial variability in climatic extremes across Sri Lanka.

2.3 Extreme Climate Indices

This study examines variations in the frequency and intensity of climate extremes using 22 indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) and Expert Team on Sector Specific Climate Indices (ET-SCI) (Table 2 and 3). All of these indices were calculated using the Climpack-v2 software using daily observational minimum and maximum temperatures and rainfall records (Alexander and Herold, 2015). This software's documentation may be found at (https://infoasis.shinyapps.io/climpack/w_82bbdb27/user_guide/Climpack_user_guide.htm). The indices are classified as intensity

indices, duration indices, absolute threshold indices and relative threshold indices. These indices ensure international comparability and consistency with previous regional and global studies (Alexander et al., 2006; Zhang et al., 2011). Applying this globally recognized frameworks to the Sri Lankan context enables a robust assessment of the spatial and temporal evolution of climate extremes across the island's diverse climatic zones.

This approach ensures consistency and comparability with previous regional and global climate assessments. Long-term trends in the indices were evaluated using the non parametric Mann–Kendall test, with trend magnitudes quantified using Sen's slope estimator. Statistical significance was assessed at the 5% confidence level ($p < 0.05$). All visualizations were produced using Tableau software.

Table 2: Precipitation extreme indices

Index code	Name	Definition	ET/ ETCCDI	Units
PRCPTOT	Wet day precipitation	Annual total precipitation on wet days	ETCCDI	mm
SDII	Simple Daily Intensity Index	Simple precipitation intensity index	ETCCDI	mm/day
CDD	Consecutive Dry Days	Maximum length of dry spell (Max no. of days with $P < 1\text{mm}$)	ETCCDI	Days
CWD	Consecutive Wet Days	Maximum length of wet spell (Max no. of days with $P \geq 1\text{mm}$)	ETCCDI	Days
R10mm	Precipitation days	Annual count of days when $\text{PRCP} \geq 10\text{mm}$	ETCCDI	Days
R20mm	Precipitation days	Annual count of days when $\text{PRCP} \geq 20\text{ mm}$	ETCCDI	Days
R30mm	Precipitation days	Annual count of days when $\text{PRCP} \geq 30\text{ mm}$	ETCCDI	Days
R95p	Very wet day precipitation	Annual total precipitation when $\text{PRCP} > 95\text{th percentile of daily precipitation}$	ETCCDI	mm
R99p	Extremely wet days	Annual total Precipitation when $\text{PRCP} > 99\text{th percentile of Daily precipitation}$	ETCCDI	mm
RX1day	Maximum 1-day precipitation	Annual Maximum 1-day precipitation	ETCCDI	mm
RX5Day	Maximum 5-day precipitation	Annual maximum consecutive 5-day precipitation	ETCCDI	mm

Table 3: Temperature extreme indices

Index code	Name	Definition	ET/ETCCDI	Units
TXm	Mean TX	Mean Daily Maximum Temperatures	ET-SCI	°C
TNm	Mean TN	Mean Daily Minimum Temperatures	ET-SCI	°C
DTR	Daily temperature range	DTR Daily temperature range Monthly mean difference between TX and TN	ETCCDI	°C
TXx	Hottest day	Monthly maximum value of daily maximum temperature	ETCCDI	°C
TNx	Hottest night	Monthly maximum value of daily minimum temperature	ETCCDI	°C
TXn	Coolest day	Annual highest TN Monthly minimum value of daily maximum temperature	ETCCDI	°C
TNn	Coolest night	Monthly minimum value of daily minimum temperature	ETCCDI	°C
TN10p	Cold nights	Percentage of days when TN < 10th percentile	ETCCDI	%
TN90p	Warm nights	Percentage of days when TN > 90th percentile	ETCCDI	%
TX10p	Cold days	Percentage of days when TX < 10th percentile	ETCCDI	%
TX90p	Warm days	Percentage of days when TX > 90th percentile	ETCCDI	%

3. Results

Analysis of ten precipitation-related climate extreme indices reveals distinct spatial and temporal patterns across Sri Lanka, highlighting both region-specific and island-wide signals of change. Trend directions are denoted by triangle shapes (▲ increase, ▼ decrease), while statistical significance is represented by color coding (red for statistically significant, green for non significant trends. Significant changes at the 5% level).

3.1 Change in precipitation related indices during 1975-2024

3.1.1 Wet and Dry Spell Duration (CWD and CDD).

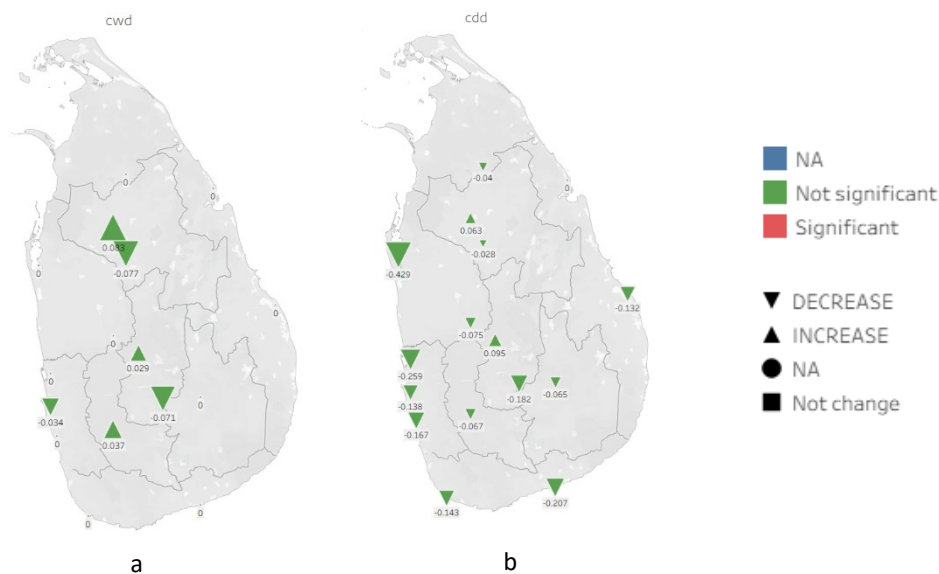


Figure 2: Spatial distribution of long-term trends in Consecutive Wet Days (CWD:(a)) and Consecutive Dry Days (CDD:(b)) across Sri Lanka during 1975-2024.

The Consecutive Wet Days (CWD) index shows mostly weak and non-significant trends across Sri Lanka, indicating little change in the persistence of wet spells. In contrast, the Consecutive Dry Days (CDD) index displays predominantly decreasing trends but not significant, over most stations, suggesting a reduction in the duration of prolonged dry spells across many regions.

3.1.2 Heavy and Very Heavy Rainfall Days (R10mm, R20mm, R30mm).

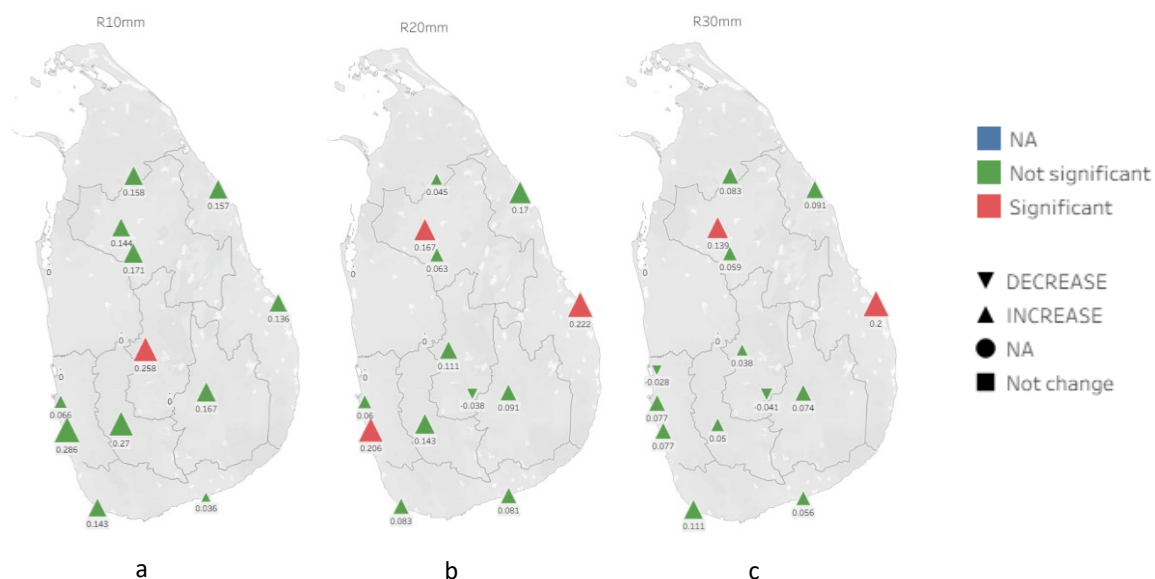


Figure 3: Spatial distribution of trends in the frequency of rainfall events exceeding 10 mm, 20 mm, and 30 mm across Sri Lanka during 1975-2024.

Figure 3 represents map of the trends for number of days with precipitation equal to or greater than 10 mm (a), 20 mm (b) and 30 mm (c) rainfall in Sri Lanka. The R10mm, R20mm, and R30mm indices are dominated by increasing trend across Sri Lanka; however, Anuradhapura and Batticaloa show a significantly increasing trend in number of days with precipitation equal to or greater than 20 mm and 30 mm rainfall. R10mm shows a statistically significant increasing trend at Rathmalana, indicating a rise in the frequency of days with rainfall ≥ 10 mm at this station.

3.1.3 Extremely Wet Days and Precipitation Totals (R95p, R99p, PRCPTOT).

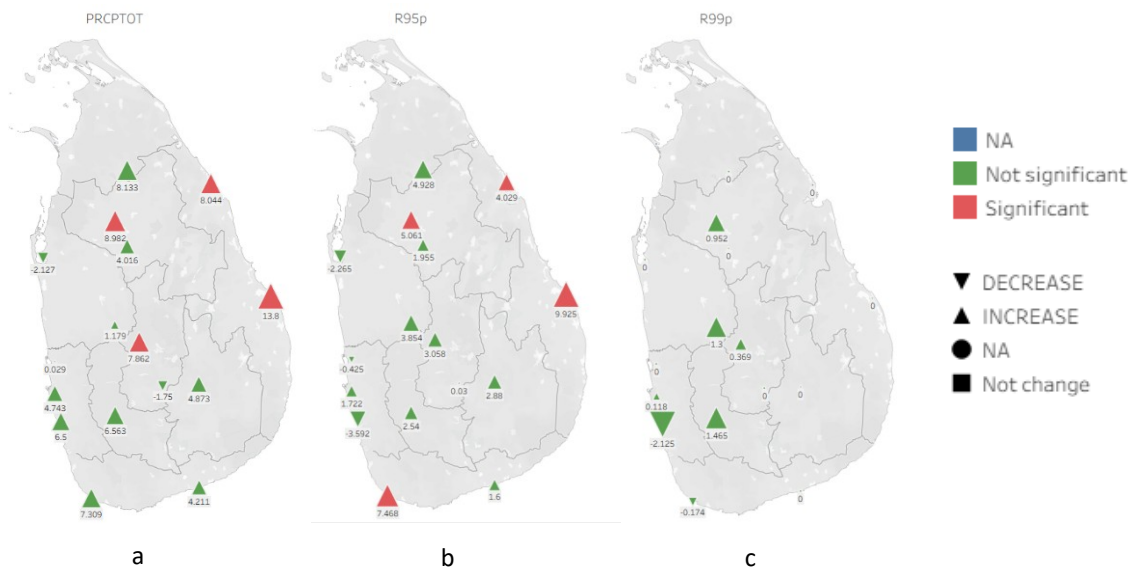


Figure 4: Spatial patterns of trends in annual total precipitation (PRCPTOT-(a)), very wet day precipitation (R95p;(b)), and extremely wet day precipitation (R99p: (c) across Sri Lanka during 1975-2024.

Figure 4, the extremely wet day precipitation (R95p) index, shows increasing trends over most places with statistically significant increasing trends at Anuradhapura, Batticaloa, Trincomalee and Galle indicating localized intensification of very wet days. In contrast, extremely wet day precipitation (R99p) trends are increase but non-significant across Sri Lanka, suggesting no robust long-term change in the most extreme rainfall events. The PRCPTOT index exhibits mostly increasing trend with isolated significant increases at Anuradhapura, Batticaloa, Trincomalee and Kurunegala stations, confirming strong spatial heterogeneity in total annual rainfall changes rather than an island-wide trend.

3.1.4 Rainfall Intensity and Maximum Daily Events (SDII, RX1day and RX5day).

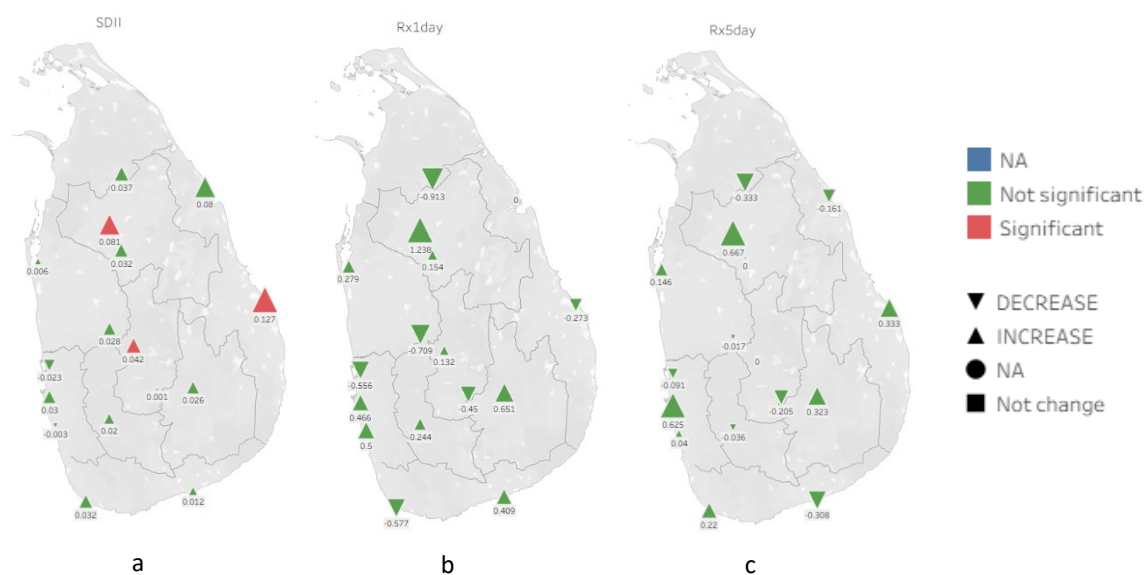


Figure 5: Spatial distribution of trends in the Simple Daily Intensity Index (SDII), maximum 1-day precipitation (RX1 Day) and maximum 5 day consecutive precipitation (RX5 Day) across Sri Lanka during 1975-2024.

The simple daily intensity index (SDII) indicates predominantly increasing trends, though only the Anuradhapura, Batticaloa and Katugastota exhibit a statistically significant rise (Figure 5). This confirms intensification of average rainfall on wet days in that area. By contrast, the annual maximum 1-day precipitation (RX1day) and annual maximum consecutive 5-day precipitation (RX5Days) show spatially inconsistent increases and decreases, with no statistically significant trends across the island. This suggests that while mean rainfall intensities are rising in some regions, the magnitude of the single heaviest annual rainfall event and remains highly variable and not systematically changing.

3.2 Change in Temperature related indices during 1975-2024

3.2.1 DTR (Trend in Diurnal Temperature Range)

The spatial distribution of Diurnal Temperature Range (DTR) trends indicates a predominantly declining tendency across most meteorological stations, suggesting a general narrowing of the difference between daily maximum and minimum temperatures over the study period (Figure 6). Negative DTR trends are particularly evident in the Northwestern, western, southwestern, and Northcentral regions, including stations such as Colombo, Katunayake, Puttalam, Galle, and Anuradhapura where the magnitude of decrease is relatively stronger. In contrast, a few inland and southeastern stations (e.g., Rathnapura and Hambantota) exhibit weak positive or near-zero DTR trends, indicating localized deviations from the national pattern. However, these increases are generally small and spatially isolated, suggesting that they do not dominate the overall signal.

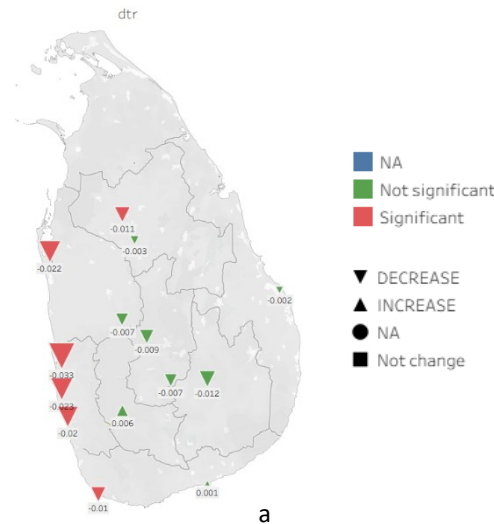


Figure 6: Spatial distribution of long-term trends in Diurnal Temperature Range (DTR) across Sri Lanka derived from daily temperature data during 1975-2024.

3.2.2 Trends in Mean daily Maximum (TXm) and mean daily Minimum (TNm) Temperatures

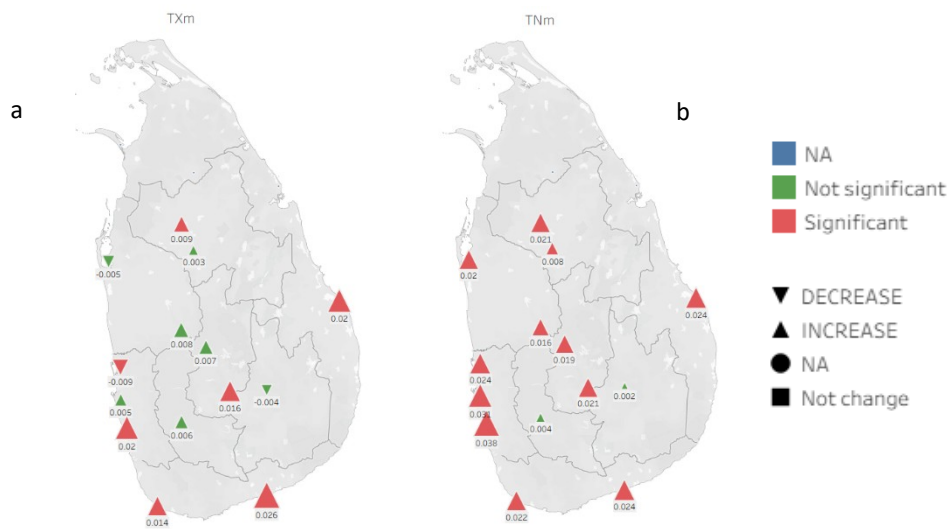


Figure 7: Spatial distribution of long-term trends in monthly maximum temperature (TXm; (a) and monthly minimum temperature (TNm; (b) across Sri Lanka during 1975-2024.

The spatial patterns of mean daily maximum (TXm) temperature and Mean Daily Minimum temperatures (TNm) reveal a coherent warming signal across Sri Lanka, with stronger and more spatially consistent increases in TNm compared to TXm (Figure 7). Most stations show positive TNm trends, particularly in the western, southern, and central regions, indicating a pronounced rise in nighttime temperatures. The magnitude and consistency of TNm warming suggest that nighttime temperatures are increasing more rapidly than daytime temperatures across much of the island. In contrast, TXm trends are generally positive but more heterogeneous, with moderate increases evident at several coastal and lowland stations (e.g., eastern and southern coasts), while central highland locations exhibit weaker or

near-zero trends, reflecting elevation-related moderation of daytime warming. The disparity between TXm and TNm trends highlights an asymmetric warming pattern, which is consistent with the observed reduction in diurnal temperature range (DTR) and underscores the dominance of nighttime warming in shaping recent temperature changes.

3.2.3 Hottest day (TXx) and Hottest Night (TNx)

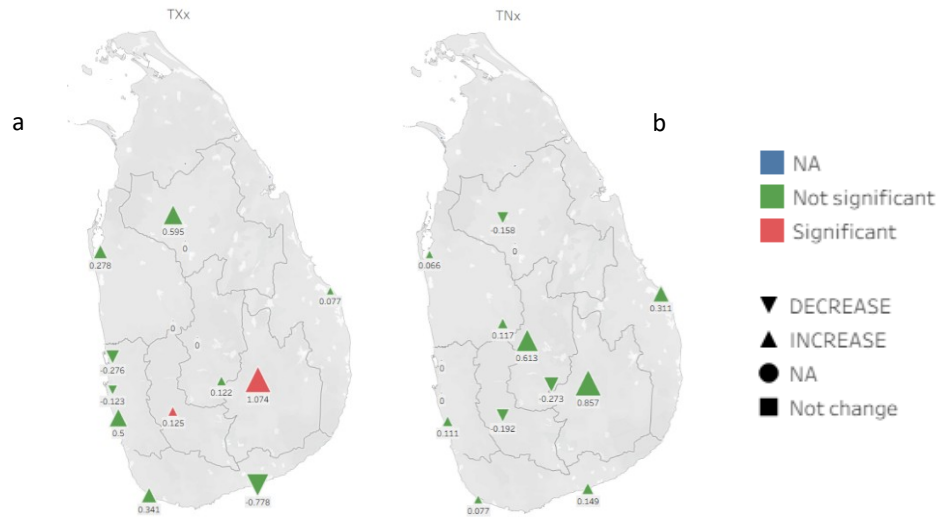


Figure 8: Spatial distribution of trends in temperature extremes across Sri Lanka, showing changes in maximum of Maximum Temperature-Hottest day (TXx) and Maximum of minimum temperature-Hottest night (TNx) during 1975-2024.

TXx exhibits predominantly increasing but statistically non-significant trends across most stations, indicating a general intensification of extreme daytime temperatures. A statistically significant increase is observed at Rathnapura and Badulla, highlighting localized amplification of hot extremes in the eastern region. TNx shows mixed but mainly non significant trends, with weak increases and decreases distributed spatially, suggesting no coherent national scale trend in extreme night-time temperatures.

3.2.4 TXn -coldest day (Trend in Minimum of Maximum Temperature) and TNn -coldest night (Trend in Minimum of Minimum Temperature)

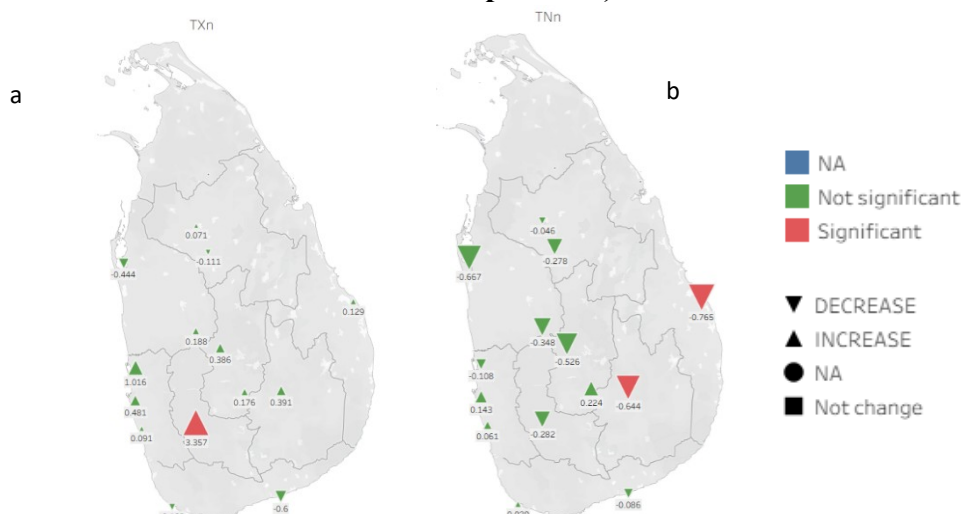


Figure 9: Spatial patterns of trends in temperature extremes over Sri Lanka, showing changes in annual minimum of daily maximum temperature-coldest day (TXn:(a)) and annual minimum of daily minimum temperature-coldest night (TNn:(b)) during 1975-2024.

Coldest day (TXn) shows predominantly increasing but statistically non significant trends across most stations, indicating a gradual rise in cool day temperatures without strong spatial coherence. A statistically significant increase at Rathnapura suggests localized cooling of daytime cold day streams. Coldest Night (TNn) displays decreasing with statistically significant at Batticaloa and Badulla, indicating a strengthening of cold night extremes in parts of the eastern region, while other stations show weak and non-significant changes.

3.2.5 Trend in Cold days (TX10p) and Trend in Warm days (TX90p)

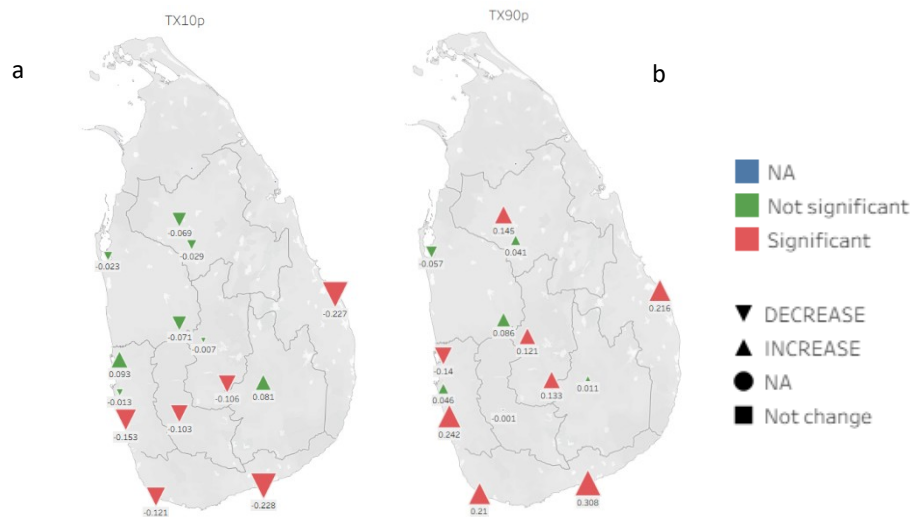


Figure 10: Spatial distribution of long-term trends in cold days (TX10p: (a)) and warm Days (TX90p: (b)) across Sri Lanka during 1975-2024.

Long term trend in cold days (TX10p) shows predominantly decreasing trends across Sri Lanka, indicating a general reduction in the frequency of cool days. Statistically significant decreases are evident at 1/3 of stations highlighting a marked decline in cool daytime extremes in the eastern and southern coastal regions (Figure 10). Warm days (TX90p) exhibits mainly increasing trends, with statistically significant increases at around 50% of stations, reflecting a robust intensification of warm-day extremes across all three climatic Zones of the country.

3.2.6 Trend in Cool Nights (TN10p) and Trend in Warm Nights (TN90p)

Figure 11, Trend in Cool nights (TN10p), exhibits predominantly decreasing trends across Sri Lanka, indicating a reduction in the frequency of cool nights. Statistically significant decreases are observed at Anuradhapura, highlighting a weakening of cold night extremes in the north-central region, while most other stations show non-significant declines.

Trend in warm nights (TN90p) shows widespread increasing trends, with statistically significant increases at 10 out of 18 stations, reflecting a robust intensification of warm night extremes across dry, intermediate, and wet zones of the country.

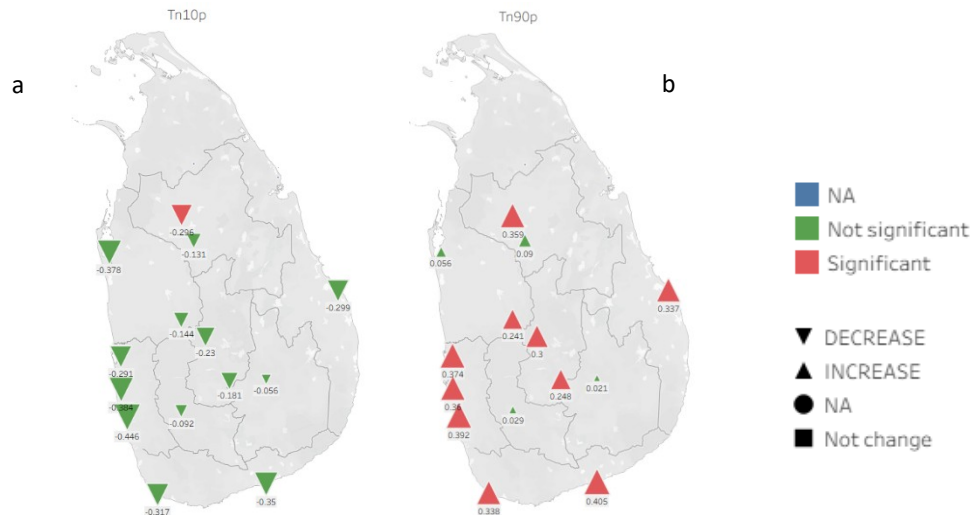


Figure 11: Spatial distribution of long-term trends in the percentage of cool nights (TN10p:(a)) and warm nights (TN90p:(b)) across Sri Lanka during 1975-2024.

3.2.7. Seasonal Trends in Diurnal Temperature Range during Yala and Maha Cultivation Seasons

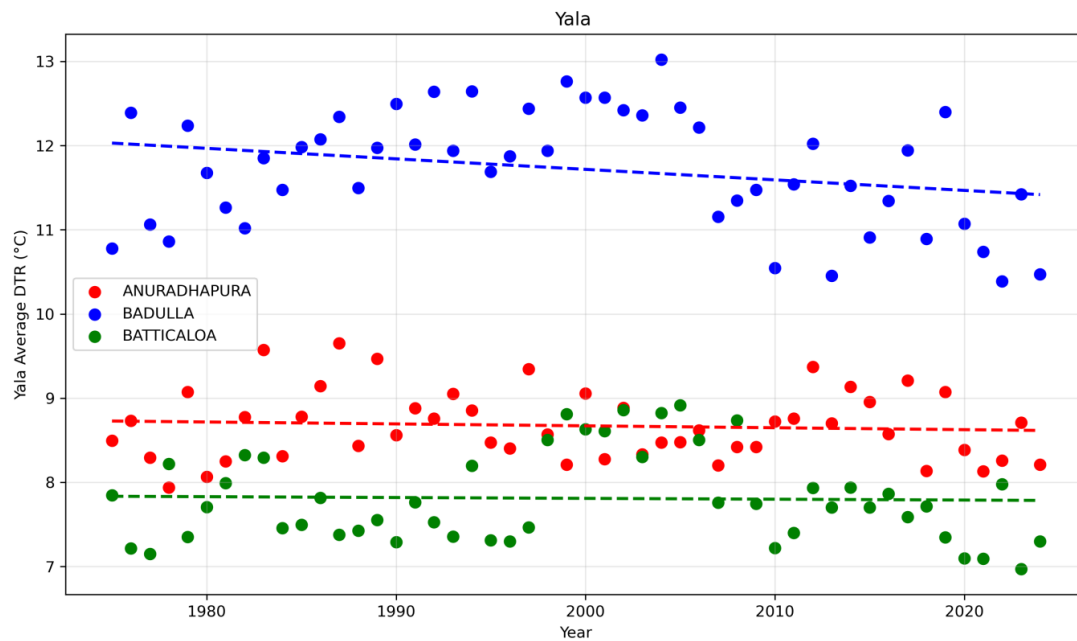


Figure 12: Interannual variability and long-term trends in seasonal mean diurnal temperature range (DTR, °C) during the Yala season at Anuradhapura, Badulla, and Batticaloa for the period 1975–2024. Dots represent seasonal mean DTR values, and dashed lines indicate linear trend estimates for each station.

Seasonal analysis of the diurnal temperature range (DTR) indicates a consistent declining tendency during Yala season, reflecting a narrowing gap between daytime and nighttime temperatures. DTR decreases modestly at Badulla, while weaker declines are evident at Anuradhapura and Batticaloa.

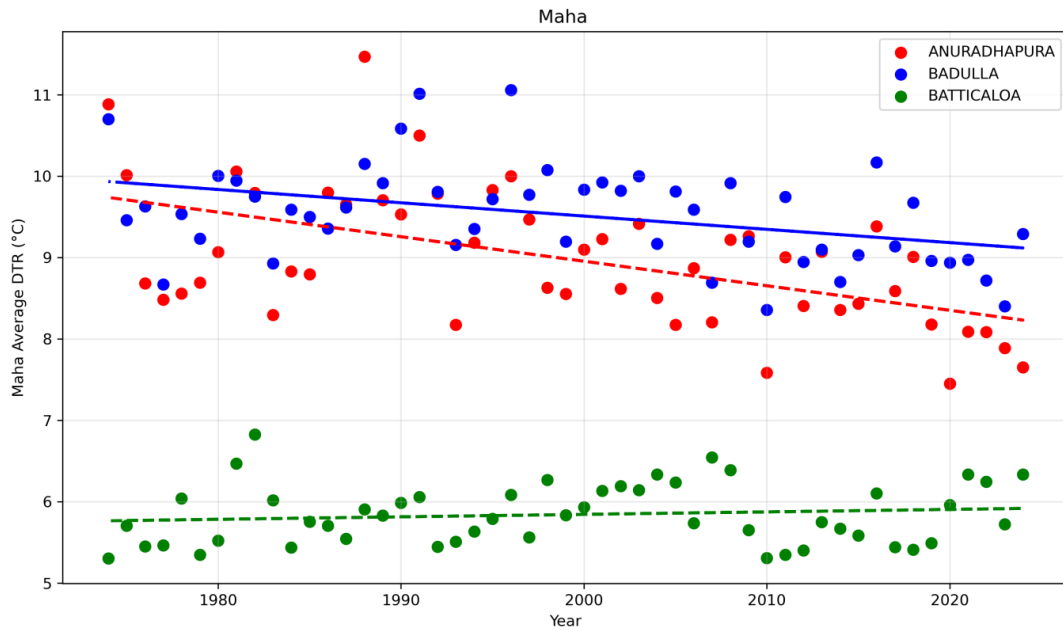


Figure 13: Interannual variability and long-term trends in seasonal mean diurnal temperature range (DTR, °C) during the Maha season at Anuradhapura, Badulla, and Batticaloa for the period 1975–2024. Dots represent seasonal mean DTR values, and dashed lines indicate linear trend estimates for each station.

Diurnal temperature range (DTR) in Maha season also indicates a consistent declining tendency, reflecting a narrowing gap between daytime and nighttime temperatures with a more pronounced decline in DTR at Anuradhapura and Badulla, whereas Batticaloa exhibits a weak increasing or near stable tendency. Overall, the seasonal patterns indicate that DTR reduction is stronger during the Maha season, particularly at inland stations, highlighting enhanced night-time warming relative to daytime temperatures.

4. Discussion

Rainfall extreme indices over Sri Lanka reveal a clearer signal in intensity and threshold based indices than in persistence based measures. CWD shows mostly weak and non significant trends, while CDD exhibits predominantly decreasing but non significant trends, indicating limited long-term change in wet or dry spell persistence. In contrast, R10mm, R20mm, and R30mm display widespread increasing tendencies, with statistically significant increases at Anuradhapura and Batticaloa for heavier rainfall thresholds and at Rathmalana for R10mm, highlighting localized increases in the frequency of moderate to heavy rainfall events. Extreme rainfall intensity indices further support this pattern. R95p, PRCPTOT, and SDII show predominantly increasing trends, with significant intensification at Anuradhapura, Batticaloa, Trincomalee, Galle, and Katugastota, indicating enhanced rainfall amounts and higher mean intensity on wet days in selected regions. By contrast, R99p, RX1day, and RX5day exhibit spatially inconsistent and statistically non significant trends, suggesting that while rainfall

frequency and average intensity are increasing, the magnitude of the most extreme annual rainfall events remains highly variable and without a robust long-term signal.

Temperature extreme indices show a coherent warming signal across Sri Lanka, dominated by night-time warming. The Diurnal Temperature Range (DTR) exhibits predominantly decreasing trends, especially across western, northwestern, southwestern, and north-central regions including Colombo, Katunayake, Puttalam, Galle, and Anuradhapura, indicating a systematic narrowing of the difference between daytime and nighttime temperatures. This pattern is driven by stronger and more spatially consistent increases in TNm compared to TXm, while weaker TXm trends in the central highlands reflect elevation related moderation of daytime warming. Extreme and frequency based indices further confirm this asymmetric warming. TXx shows generally increasing but mostly non significant trends, with localized significant increases at Ratnapura and Badulla, while TNx exhibits no coherent island-wide signal. Cold extremes show mixed responses, with TXn increasing weakly and TNn decreasing significantly at Batticaloa and Badulla. The widespread decline in TX10p and TN10p, together with significant increases in TX90p and particularly TN90p, indicates a robust reduction in cool extremes and a strong intensification of warm night extremes across all climatic zones. The consistent decline in diurnal temperature range during both Yala and Maha seasons, with a stronger reduction in Maha, indicates enhanced night-time warming relative to daytime temperatures, particularly at inland locations. This dominance of night-time warming is consistent with global scale observations reported in IPCC AR6 WG I, which highlight asymmetric warming driven by minimum temperature increases.

5. Conclusion

This study provides the most up-to-date and long-term assessment of climate extremes across Sri Lanka using standardized ETCCDI and ET-SCI indices over a 50-year period (1975–2024). Rainfall extremes are characterized by increasing frequency and average intensity of moderate to heavy rainfall events at selected locations, rather than systematic changes in rainfall persistence or the magnitude of the most extreme single-event precipitation. The absence of coherent trends in consecutive wet and dry days, as well as in annual maximum rainfall events, underscores the continued dominance of natural variability at the highest extremes, despite emerging signals of localized intensification.

Temperature extremes exhibit a more spatially coherent and robust signal, dominated by asymmetric warming driven by rapidly increasing night-time temperatures. The widespread decline in diurnal temperature range, together with significant increases in warm nights and reductions in cool days and nights, indicates a fundamental shift in the thermal regime of Sri Lanka. While trends in the most extreme hot and cold events remain spatially heterogeneous, enhanced night-time warming represents the most consistent and climatically significant signal over the past five decades. These findings emphasize the importance of sustained monitoring of climate extremes using standardized indices to

support climate-risk assessment, early warning systems, and sector-specific adaptation planning across Sri Lanka.

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