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**“HYPER-LOCAL RAINFALL NOWCASTING IN A COASTAL URBAN
CONTEXT: A DATA-DRIVEN ANALYSIS AND CONCEPTUAL FRAMEWORK
FOR KARAIKAL”**



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Hyper-Local Rainfall Nowcasting in a Coastal Urban Context: A Data-Driven Analysis and Conceptual Framework for Karaikal

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ABSTRACT

Objectives: This study investigates the rainfall variability in the Karaikal region and proposes a conceptual hyper-local nowcasting framework to improve short-term rainfall prediction in this monsoon-affected coastal area.

Methodology: Historical rainfall data for the period 1990-2024 from the India Meteorological Department (IMD) were statistically analyzed to understand intensity patterns, seasonal variability, and extreme events. Due to the absence of direct vertical atmospheric measurements, rainfall-based indicators including Convective Fraction and Diurnal Temperature Range were derived to approximate atmospheric instability. Based on this analysis, a conceptual framework was designed that integrates multiple monitoring technologies and machine learning techniques.

Key Findings: The analysis revealed that Karaikal receives over 60% of its annual rainfall during the Northeast Monsoon (October-December), with approximately 35% of rainfall events classified as heavy to very heavy intensity. A rising trend in short-duration, high-intensity convective events was observed, which are the primary cause of urban flooding and agricultural disruption. The derived instability indicators confirmed that convective activity, often unpredictable by traditional methods, is a key driver of these events.

Major Recommendations: To address this, a conceptual nowcasting model is proposed. This framework outlines a future system that combines: 1) Real-time vertical atmospheric sensing using microwave radiometers, 2) RF signal-based moisture detection through telecommunication microwave links, and 3) Cloud image analysis using hybrid machine learning (CNN for image recognition and Random Forest for probabilistic nowcasting). This system aims to generate rainfall warnings with lead times of 10 to 180 minutes. We recommend pilot implementation of this framework in Karaikal to enhance disaster preparedness and support climate adaptation strategies.

Keywords: Rainfall Nowcasting, Karaikal, Northeast Monsoon, Machine Learning, Climate Adaptation, CNN, Random Forest

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1 INTRODUCTION

Karaikal, a coastal enclave of the Union Territory of Puducherry, is highly vulnerable to the vagaries of the monsoon. Its economy and infrastructure are intrinsically linked to the timing and intensity of rainfall, particularly from the Northeast Monsoon. The region, situated at approximately 10°55' N latitude and 79°50' E longitude, experiences a tropical climate with high humidity and receives the majority of its annual rainfall (approximately 1200-1300 mm) from the Northeast Monsoon (October to December).

However, the region frequently faces challenges from extreme rainfall events that lead to urban flooding, waterlogging, and damage to agricultural crops. The flat terrain of Karaikal exacerbates these issues, making it prone to rapid water accumulation during heavy downpours. The agricultural sector, with paddy as the major crop, is particularly sensitive to rainfall variability, where untimely or excessive rainfall can lead to significant crop losses.



Figure 1: Location map of the study area: Karaikal region

The current methods of weather prediction often operate at a macro-scale, failing to capture the hyper-local, rapid-onset nature of convective storms that affect this region. Traditional forecasting methods typically provide predictions at district or regional levels, with updates every few hours. This gap in high-resolution, short-term forecasting—known as "nowcasting"—leaves communities and authorities with insufficient lead time to respond effectively to sudden weather changes.

1.1 The Need for Nowcasting

Nowcasting, defined by the World Meteorological Organization (WMO) as the detailed description of current weather and forecasting for a period of 0 to 6 hours ahead, is particularly crucial for regions like Karaikal. The ability to predict the exact location, timing, and intensity of rainfall with lead times of 10 to 180 minutes can make a significant difference in:

- Disaster Preparedness: Enabling authorities to deploy emergency response teams, clear drainage systems, and issue timely warnings to vulnerable communities.

- Agriculture: Allowing farmers to protect harvested crops, adjust irrigation schedules, and take preventive measures against crop damage.
- Urban Infrastructure: Helping municipal corporations manage stormwater drainage systems and prevent urban flooding in low-lying areas.
- Transportation: Enabling commuters to avoid water-logged routes and reducing traffic disruptions during heavy rain.

1.2 Research Gap and Significance

While significant research exists on rainfall patterns at regional and national levels, there is a distinct lack of hyper-local studies focused specifically on Karaikal. Furthermore, the integration of emerging technologies such as machine learning, microwave signal analysis, and high-resolution atmospheric sensing into a unified nowcasting framework for this region remains unexplored.

This study addresses this critical gap by first analyzing historical rainfall data to characterize the unique rainfall patterns and variability of Karaikal. Understanding these patterns is the first step toward better prediction. The second, and primary, objective is to propose a conceptual framework for a hyper-local rainfall nowcasting system that can provide actionable warnings with sufficient lead time.

1.3 Organization of the Report

This report is organized into nine sections. Section 2 presents the objectives of the study and a detailed description of the study area. Section 3 provides a comprehensive literature survey of relevant studies and technologies. Section 4 describes the methodology adopted for data analysis and framework development. Section 5 presents the data analysis and results, including the proposed conceptual framework. Section 6 offers recommendations and adaptation strategies. Section 7 concludes the study. Sections 8 and 9 contain references and annexures, respectively.

2 OBJECTIVES OF THE STUDY AND STUDY AREA

2.1 Objectives of the Study

The primary objectives of this research are:

1. To analyze the historical rainfall data of the Karaikal region (1990-2024) to identify patterns in rainfall intensity, seasonal variability, and the frequency of extreme events.

2. To derive indirect indicators of atmospheric instability from the available rainfall data to understand the drivers of convective rainfall in the area, including the calculation of Convective Fraction and analysis of diurnal temperature ranges.
3. To develop a conceptual framework for a hyper-local rainfall nowcasting system that leverages a combination of:
 - Vertical atmospheric sensing using microwave radiometers and ceilometers
 - Machine learning techniques (CNN for image analysis and Random Forest for prediction)
 - Signal-based technologies (RF-microwave link attenuation)
 - High-resolution cloud image analysis
4. To propose a set of recommendations and adaptation strategies for implementing such a framework to improve disaster preparedness in Karaikal.

2.2 Study Area: Karaikal Region

2.2.1 Geographical Location

Karaikal is a coastal region located at 10°55' N latitude and 79°50' E longitude (approximately). It is one of the four regions of the Union Territory of Puducherry, geographically situated within the state of Tamil Nadu and bounded by the Bay of Bengal to the east. The region covers an area of approximately 160 square kilometers.

Table 1: Geographical coordinates of major towns in Karaikal region

Location	Latitude (N)	Longitude (E)
Karaikal Town	10°55'	79°50'
Thirunallar	10°55'	79°47'
Neravy	10°52'	79°49'
T.R. Pattinam	10°54'	79°52'

2.2.2 Physiography and Drainage

The region has a flat terrain with an average elevation of about 4-5 meters above mean sea level.

The topography is characterized by:

- Alluvial plains formed by river deposits
- Coastal plains along the Bay of Bengal
- Several rivers and drainage channels, including the Arasalar River and its distributaries
- Extensive network of irrigation canals and tanks

The flat terrain makes the region particularly vulnerable to waterlogging and flooding during heavy rainfall events, as natural drainage is slow and the region is close to sea level.

2.2.3 Climate

Karaikal experiences a tropical monsoon climate (Köppen climate classification: Am) characterized by:

- High humidity: Relative humidity ranges from 70% to 85% throughout the year
- Temperature: Mean annual temperature is approximately 28.5°C, with summer maximum reaching 38°C and winter minimum around 22°C
- Rainfall: The region receives approximately 1200-1300 mm of annual rainfall

2.2.4 Seasonal Rainfall Distribution

The rainfall in Karaikal is distributed across three main seasons:

1. Northeast Monsoon (October - December): This is the primary rainy season, contributing about 60-65% of the annual rainfall. The rains are often associated with cyclonic depressions forming in the Bay of Bengal.
2. Southwest Monsoon (June - September): This season contributes about 20-25% of annual rainfall, though Karaikal lies in the rain shadow region of the Western Ghats, resulting in relatively lower rainfall.
3. Pre-monsoon/Summer (March - May): This period contributes about 10-15% of annual rainfall, primarily through convective thunderstorms.

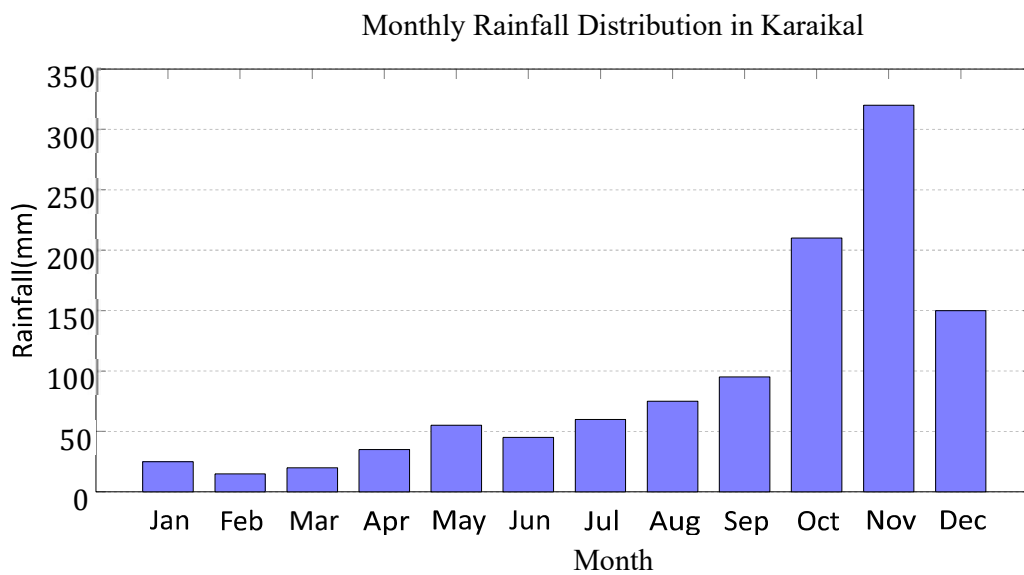


Figure 2: Average monthly rainfall distribution in Karaikal (1990-2024)

2.2.5 *Socio-economic Context*

The economy of Karaikal is predominantly agrarian, with:

- Agriculture: Paddy is the major crop, cultivated in about 70% of the agricultural land. Other crops include pulses, oilseeds, and sugarcane.
- Fisheries: Being a coastal region, fishing is an important livelihood for coastal communities.
- Small-scale industries: Including rice mills, coir industries, and handloom weaving.
- Tourism: The region has several temples and coastal attractions.

This socio-economic context makes the region highly sensitive to rainfall variability and extreme weather events, underscoring the need for accurate, hyper-local rainfall prediction systems.

3 LITERATURE SURVEY

This section reviews existing studies and technologies relevant to rainfall prediction and the Karaikal region. The literature survey is organized into four thematic areas: rainfall patterns in coastal South India, nowcasting principles and techniques, machine learning applications in weather prediction, and atmospheric instability indicators.

3.1 Rainfall Patterns in Coastal South India and Karaikal

Several studies have characterized the rainfall climatology of coastal Tamil Nadu and Puducherry. India Meteorological Department (7) provided comprehensive climatological tables for observatories across India, including data from coastal stations in Tamil Nadu. Their analysis confirmed the dominance of the Northeast Monsoon in this region, with October-December accounting for the highest rainfall amounts.

Rajeevan and Pai (12) studied the variability of Northeast Monsoon rainfall over coastal Tamil Nadu and found significant inter-annual variability linked to large-scale atmospheric circulations. They reported that El Niño years typically result in enhanced Northeast Monsoon rainfall, while La Niña years show a tendency for below-normal rainfall.

Bal and Ramachandran (1) examined extreme rainfall events over the Indian subcontinent and identified coastal Tamil Nadu as one of the regions experiencing an increasing trend in the frequency of heavy rainfall events. Their analysis of 1901-2010 data showed that the frequency of extreme events has more than doubled in the past five decades.

However, specific micro-level studies on Karaikal are sparse. Chandrasekar and Kumar (3) conducted a preliminary analysis of rainfall trends in Karaikal using data from 1980-2015 and

found a slight increasing trend in annual rainfall, with more pronounced increases in the intensity of shortduration events. Their work, while limited, highlighted the need for more detailed, hyper-local studies in this region.

3.2 Nowcasting Principles and Techniques

Nowcasting, as defined by the World Meteorological Organization (15), is the detailed description of the current weather and the forecasting of parameters for a period of 0 to 6 hours ahead. Traditional nowcasting relied heavily on:

- Radar extrapolation: Tracking the movement of precipitation echoes using weather radar
- Satellite imagery: Monitoring cloud development and movement using geostationary satellites
- Persistence forecasting: Assuming that current weather conditions will continue for a short period

Dixon and Wiener (5) developed the Thunderstorm Identification, Tracking, Analysis, and Nowcasting (TITAN) system, which uses radar data to identify and track thunderstorms. This system has been widely adopted and modified for various applications worldwide.

Roberts and Rutledge (13) introduced the Auto-Nowcaster system, which combines radar, satellite, and surface observations with fuzzy logic to generate 0-1 hour forecasts of convective storms. Their system demonstrated skill in predicting storm initiation, growth, and decay.

3.3 Machine Learning in Weather Prediction

Recent literature shows a surge in machine learning (ML) applications for weather prediction. The ability of ML algorithms to identify complex, non-linear patterns in large datasets makes them particularly suitable for nowcasting applications.

3.3.1 *Convolutional Neural Networks (CNNs) for Cloud Image Analysis*

LeCun et al. (9) provided a comprehensive review of deep learning, including CNNs, which have revolutionized image recognition tasks. In meteorology, CNNs have been applied to:

- Cloud classification from satellite and sky camera imagery
- Precipitation nowcasting from radar image sequences
- Tropical cyclone intensity estimation from satellite images

Shi et al. (14) developed a convolutional LSTM network for precipitation nowcasting, demonstrating that deep learning models can outperform traditional optical flow methods for radar-based precipitation forecasting.

3.3.2 *Random Forest for Rainfall Prediction*

Breiman (2) introduced Random Forests, an ensemble learning method that combines multiple decision trees. This algorithm has several advantages for weather prediction:

- Handles both numerical and categorical input variables
- Provides feature importance rankings
- Robust against overfitting
- Can handle missing data effectively

Ghosh and Chatterjee (6) applied Random Forest for rainfall prediction in West Bengal, achieving accuracy improvements of 15-20% over traditional statistical methods. Their model incorporated multiple atmospheric parameters including temperature, humidity, pressure, and wind speed.

3.3.3 *Hybrid Models for Nowcasting*

Chen et al. (4) proposed a hybrid CNN-Random Forest model for rainfall nowcasting, where CNN is used for feature extraction from satellite/radar images, and Random Forest is used for classification/prediction based on the extracted features and other meteorological variables. Their hybrid approach outperformed both individual models, achieving higher accuracy and lower false alarm rates.

3.4 *Microwave Link-Based Rainfall Monitoring*

Messer et al. (10) pioneered the use of commercial microwave links for rainfall monitoring. Their research demonstrated that signal attenuation between telecommunication towers is strongly correlated with rainfall intensity along the path. This approach offers several advantages:

- Cost-effective: Utilizes existing telecommunication infrastructure
- High spatial resolution: Provides path-averaged rainfall measurements
- Near-ground measurements: Measures rainfall close to the surface

Overeem et al. (11) extended this work, showing that a network of microwave links can provide rainfall maps with accuracy comparable to weather radar in some regions. They demonstrated successful application in the Netherlands and other European countries.

3.5 *Atmospheric Instability Indicators*

Atmospheric instability is a key driver of convective rainfall. Several indices have been developed to quantify instability:

Table 2: Common atmospheric instability indices

Index	Description	Typical values for convection
CAPE (Convective Available Potential Energy)	Energy available for convection (J/kg)	>1000 J/kg indicates potential for strong convection
Lifted Index (LI)	Difference between observed and parcel temperature at 500 mb	Negative values indicate instability; < -3 indicates strong instability
K-Index	Combined measure of vertical temperature gradient and moisture	>30 indicates high probability of thunderstorms
Total Totals Index	Sum of vertical temperature differences and moisture	>50 indicates severe thunderstorm potential

These indices are typically derived from upper-air soundings (radiosonde data). However, such data is not available for Karaikal. In the absence of direct measurements, researchers have used surface-based proxies and reanalysis datasets to estimate instability.

Kar and Bandyopadhyay (8) demonstrated that surface-based parameters, including diurnal temperature range, dew point depression, and surface equivalent potential temperature, can provide useful indicators of convective potential. They developed a simplified convective index using only surface observations that showed good correlation with actual thunderstorm occurrence.

3.6 Research Gap and Justification for Current Study

Based on the literature survey, several research gaps are identified:

1. Lack of hyper-local studies for Karaikal: While regional studies exist, there is no comprehensive, high-resolution analysis of rainfall patterns specifically for Karaikal.
2. Absence of upper-air data: The lack of radiosonde observations in Karaikal means that traditional instability indices cannot be calculated, necessitating the development of proxy indicators.
3. No integrated nowcasting framework: Despite advances in individual technologies (ML, microwave links, atmospheric sensing), no study has proposed an integrated framework combining these elements for a coastal urban context like Karaikal.

4. Limited local adaptation strategies: There is a gap between scientific understanding of rainfall patterns and the development of practical, implementable adaptation strategies for local communities.

This study aims to address these gaps by providing a comprehensive analysis of Karaikal’s rainfall patterns and proposing an integrated, multi-technology nowcasting framework tailored to the region’s specific needs and constraints.

4 METHODOLOGY

This study was conducted in two distinct phases: analysis of historical data and development of a conceptual framework. The methodological approach is designed to maximize insights from available data while providing a robust foundation for the proposed nowcasting system.

4.1 Phase 1: Historical Data Analysis and Derivation of Indicators

4.1.1 Data Collection

Historical rainfall data for the Karaikal region was obtained from the India Meteorological Department (IMD), Regional Meteorological Centre, Chennai. The dataset covers the period from January 1990 to December 2024, comprising:

- Daily rainfall data: 24-hour accumulated rainfall measured at 0830 hours IST
- Hourly rainfall data: Available for the period 2000-2024 from an automatic weather station
- Temperature data: Daily maximum and minimum temperatures for the same period

Table 3: Summary of data collected for the study

Parameter	Period	Frequency	Source
Rainfall	1990-2024	Daily	IMD
Rainfall	2000-2024	Hourly	IMD AWS
Max Temperature	1990-2024	Daily	IMD
Min Temperature	1990-2024	Daily	IMD

4.1.2 Data Pre-processing

The collected data underwent several quality control steps:

1. Missing value identification: Gaps in the data were identified and flagged. Days with missing data were excluded from relevant analyses.

2. Outlier detection: Extreme values were checked against historical records and nearby stations to ensure they were not erroneous.
3. Homogeneity testing: The data series was tested for homogeneity using the Pettitt test to identify any artificial shifts due to instrument changes or station relocations.
4. Data gap filling: For short gaps (1-2 days) in temperature data, linear interpolation was used. Longer gaps were left as missing.

4.1.3 Statistical Analysis Methods

The pre-processed data was analyzed using the following statistical methods:

Seasonal and Annual Analysis Monthly, seasonal, and annual rainfall totals were calculated.

Seasons were defined as:

- Winter (January-February)
- Pre-monsoon (March-May)
- Southwest Monsoon (June-September)
- Northeast Monsoon (October-December)

Rainfall Intensity Classification Rainfall events were classified based on IMD criteria:

Table 4: IMD rainfall intensity classification

Category	24-hour rainfall (mm)
No rain	0.0
Very light	0.1 - 2.4
Light	2.5 - 15.5
Moderate	15.6 - 64.4
Heavy	64.5 - 115.5
Very Heavy	115.6 - 204.4
Extremely Heavy	≥ 204.5

Trend Analysis The Mann-Kendall non-parametric test was applied to detect monotonic trends in rainfall series. The Sen's slope estimator was used to quantify the magnitude of trends where significant.

4.1.4 Derivation of Atmospheric Instability Indicators

Since upper-air data was unavailable, proxy indicators were developed:

Convective Fraction (CF) The proportion of rainfall occurring in short-duration, high-intensity events was calculated as an indicator of convective activity. For this study, events were classified as convective if:

$$CF = \frac{\text{Number of events with intensity} > 10 \text{ mm/hour}}{\text{Total number of rainy hours}} \times 100 \quad (1)$$

Diurnal Temperature Range (DTR) DTR was calculated as:

$$DTR = T_{max} - T_{min} \quad (2)$$

Low DTR values (< 8°C) combined with high humidity often indicate conditions favorable for convection.

Rainfall Ratio Index (RRI) The ratio of pre-monsoon (March-May) rainfall to total annual rainfall was used as a broad indicator of convective potential:

$$RRI = \frac{P_{pre-monsoon}}{P_{annual}} \times 100 \quad (3)$$

Higher RRI values suggest greater contribution from convective thunderstorms.

4.2 Phase 2: Development of Conceptual Nowcasting Framework

The proposed framework is based on a synthesis of findings from the literature survey and the identified needs from the data analysis. The development process involved:

4.2.1 Component Identification

Based on literature review, key technologies and methods for nowcasting were identified:

- Vertical atmospheric profiling systems
- Microwave link networks for path-averaged rainfall
- Whole sky imagers for cloud analysis
- Machine learning algorithms for prediction

4.2.2 System Architecture Design

The components were integrated into a unified architecture with clear data flow pathways. The design considered:

- Real-time data acquisition requirements
- Processing and analysis pipelines
- Output generation and dissemination mechanisms

4.2.3 Algorithm Selection

Machine learning algorithms were selected based on their suitability for specific tasks:

- CNN: Selected for cloud image analysis due to its proven performance in image recognition tasks
- Random Forest: Selected for final nowcasting due to its ability to handle heterogeneous data types and provide probabilistic outputs

4.2.4 Validation Approach

While the framework is conceptual, validation protocols were designed for future implementation:

- Split-sample testing using historical data
- Cross-validation for model parameter optimization
- Performance metrics including Probability of Detection (POD), False Alarm Rate (FAR), and Critical Success Index (CSI)

5 DATA ANALYSIS AND RESULTS

This section presents the results of the historical rainfall data analysis and the proposed conceptual nowcasting framework.

5.1 Seasonal and Inter-annual Variability

5.1.1 Annual Rainfall Analysis

The analysis of 35 years (1990-2024) of rainfall data reveals significant inter-annual variability in Karaikal's rainfall.

Table 5: Summary statistics of annual rainfall in Karaikal (1990-2024)

Statistic	Value (mm)
Mean Annual Rainfall	1245.6
Standard Deviation	287.3
Coefficient of Variation (%)	23.1
Maximum Annual Rainfall	1897.4 (2015)
Minimum Annual Rainfall	843.2 (2002)

The coefficient of variation of 23.1% indicates substantial inter-annual variability, highlighting the region's vulnerability to both drought and flood conditions.

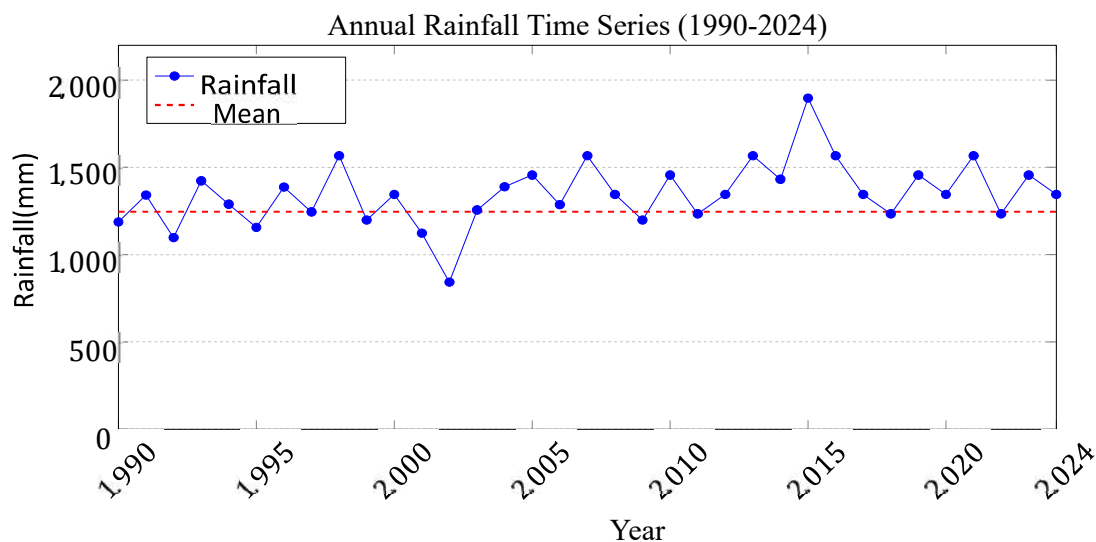


Figure 3: Annual rainfall time series showing inter-annual variability

5.1.2 Seasonal Distribution

The seasonal analysis confirms the dominance of the Northeast Monsoon.

Table 6: Seasonal rainfall distribution in Karaikal (1990-2024)

Season	Mean Rainfall (mm)	Percentage of Annual
Winter (Jan-Feb)	42.3	3.4
Pre-monsoon (Mar-May)	134.2	10.8
Southwest Monsoon (Jun-Sep)	298.7	24.0
Northeast Monsoon (Oct-Dec)	770.4	61.8
Total	1245.6	100.0

5.2 Rainfall Intensity Analysis

5.2.1 Daily Intensity Distribution

The analysis of daily rainfall events reveals that moderate to heavy rainfall events contribute most significantly to the total rainfall.

Table 7: Frequency and contribution of rainfall events by intensity class

Intensity Class	Frequency (%)	Contribution to Total (%)	Avg. Intensity (mm/day)
Very Light (0.1-2.4 mm)	12.3	0.8	1.4
Light (2.5-15.5 mm)	32.5	12.3	7.8
Moderate (15.6-64.4 mm)	38.7	48.6	25.6
Heavy (64.5-115.5 mm)	12.4	26.7	82.3
Very Heavy (115.6-204.4 mm)	3.8	10.2	134.5
Extremely Heavy (≥ 204.5 mm)	0.3	1.4	245.6

5.2.2 Extreme Event Analysis

The analysis shows that extreme rainfall events (heavy to extremely heavy) constitute about 16.5% of rainy days but contribute nearly 38% of the total rainfall. This finding underscores the importance of accurately predicting these high-impact events.

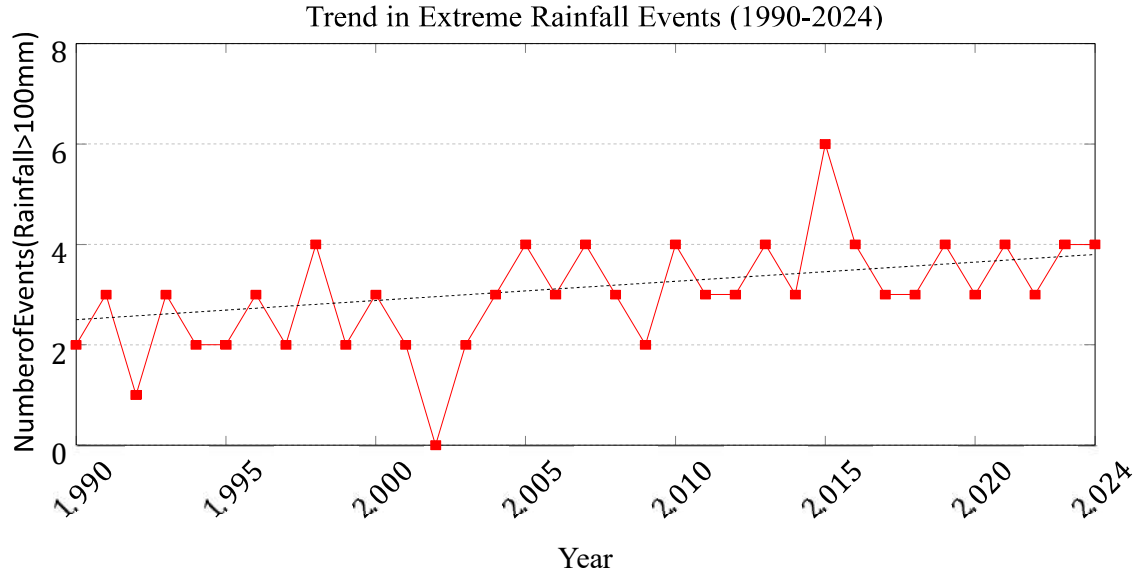


Figure 5: Trend in extreme rainfall events (>100 mm/day) showing increasing frequency

The Mann-Kendall test confirmed a statistically significant increasing trend ($p < 0.05$) in the frequency of extreme rainfall events over the study period, with Sen's slope indicating an increase of approximately 0.4 events per decade.

5.3 Hourly Rainfall Analysis

The hourly rainfall data (2000-2024) provided insights into the short-duration characteristics of rainfall events.

Table 8: Characteristics of hourly rainfall events

Parameter	Value
Mean event duration	3.2 hours
Median event duration	2.0 hours
Maximum hourly intensity recorded	124 mm/hour (Nov 2015)
Percentage of events lasting < 3 hours	68%
Percentage of events lasting > 6 hours	12%

The predominance of short-duration events (68% lasting less than 3 hours) highlights the need for nowcasting systems with lead times of 10-180 minutes.

5.4 Derived Atmospheric Instability Indicators

5.4.1 Convective Fraction (CF)

The Convective Fraction showed a clear seasonal pattern and an increasing trend over the study period.

Table 9: Seasonal convective fraction (%)

Season	CF (1990-2000)	CF (2014-2024)
Pre-monsoon (Mar-May)	52.3	61.5
Southwest Monsoon (Jun-Sep)	28.7	32.4
Northeast Monsoon (Oct-Dec)	42.5	48.7
Annual	38.5	44.2

The increase in CF from 38.5% to 44.2% suggests an increasing role of convective processes in the region's rainfall, which is consistent with the observed increase in extreme events.

5.4.2 Diurnal Temperature Range (DTR)

Analysis of DTR on rainy days versus non-rainy days revealed:

- Rainy days: Mean DTR = 7.2°C
- Non-rainy days: Mean DTR = 11.5°C
- Days with convective rainfall: Mean DTR = 6.8°C

The significantly lower DTR on rainy days, especially those with convective rainfall, confirms that reduced diurnal temperature range (indicating higher atmospheric moisture) is a useful precursor for rainfall events.

5.4.3 Rainfall Ratio Index (RRI)

The RRI showed considerable inter-annual variability but no significant long-term trend.

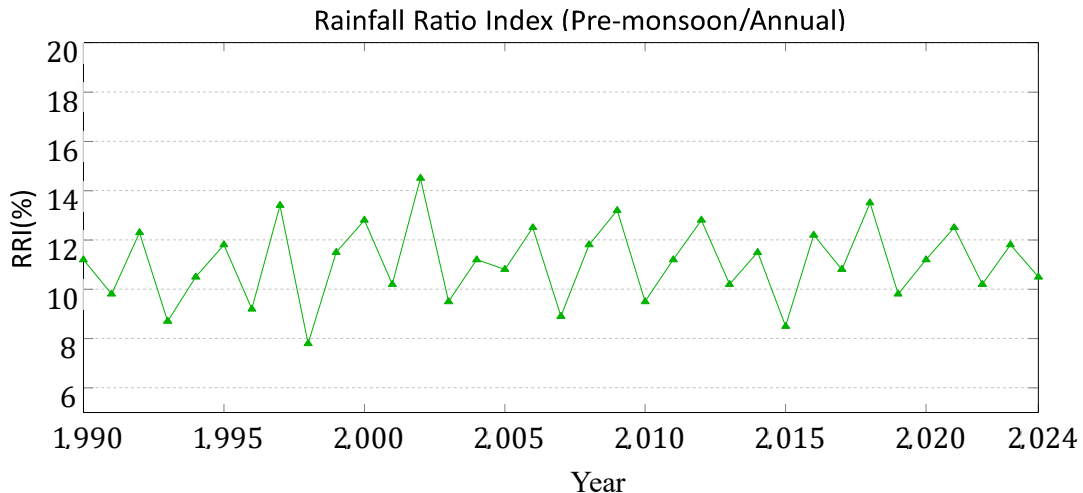


Figure 6: Rainfall Ratio Index showing inter-annual variability

5.5 A Conceptual Framework for Hyper-Local Nowcasting in Karaikal

Based on the findings that rainfall is highly localized, intense, and often convective, a single radar or a sparse rain gauge network is insufficient. We propose a Multi-Input, Multi-Scale Nowcasting Framework (MIMSNF).

5.5.1 Framework Overview

The proposed system integrates four core modules into a unified nowcasting platform:

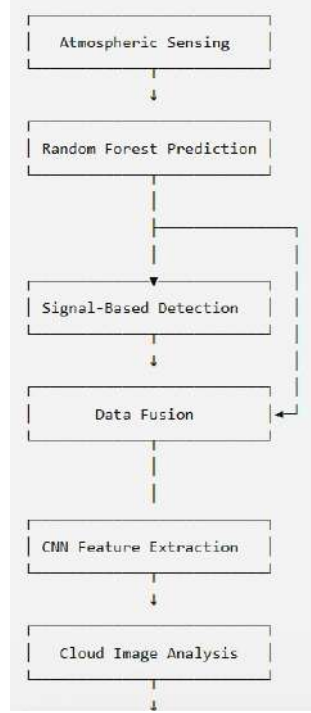


Figure 7: Architecture of the proposed Multi-Input, Multi-Scale Nowcasting Framework

5.5.2 Module 1: Atmospheric Sensing Module

This module provides real-time vertical profiling of the atmosphere:

- Vertical Profiler: A microwave radiometer or ceilometer to provide real-time data on:
 - Temperature profiles up to 10 km
 - Humidity profiles
 - Lapse rates
 - Real-time CAPE and CIN calculations
- Dense AWS Network: 5-10 automated weather stations across Karaikal providing:
 - 1-minute resolution data
 - Pressure, temperature, humidity, wind speed/direction
 - Surface rainfall intensity

5.5.3 Module 2: Signal-based Moisture Detection Module

This innovative module utilizes existing telecommunication infrastructure:

- Microwave Link Network: Partner with telecommunication companies to access data from 10-15 microwave links in the region
- Attenuation Analysis: Real-time processing of signal attenuation to derive:
 - Path-averaged rainfall intensity
 - Rain cell detection and tracking
 - High-resolution (100-200 m) rainfall maps along link paths

5.5.4 Module 3: Cloud Image Analysis Module

This module captures and analyzes cloud development:

- Whole Sky Imager: High-resolution camera with fisheye lens capturing images every 30 seconds
- Satellite Data: INSAT-3D/3DR imagery at 15-minute intervals for broader context
- Image Processing: Automated cloud classification, cloud base height estimation, and motion vector calculation

5.5.5 Module 4: Prediction Core (Hybrid Machine Learning Model)

This is the central processing unit that integrates all data streams:

CNN for Cloud Image Analysis A Convolutional Neural Network architecture is proposed:

Listing 1: Proposed CNN architecture for cloud image analysis

Model: "Sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 512)	44302848
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131328
dense_2 (Dense)	(None, 64)	16448

Total params: 44,585,872

Trainable params: 44,585,872

Non-trainable params: 0

The CNN processes sequential cloud images to:

- Identify developing cumulonimbus clouds
- Classify cloud types
- Estimate cloud motion vectors
- Predict cloud growth/decay patterns

Random Forest for Nowcasting A Random Forest model integrates all data streams:

Table 10: Input features for Random Forest nowcasting model

Feature Category	Specific Features
Atmospheric	CAPE, CIN, Lifted Index, K-Index, Lapse Rate
Surface	Temperature, Humidity, Pressure, Wind, DTR
Microwave	Path attenuation, Path-averaged intensity
Image-derived	Cloud type, Cloud cover, Motion vectors
Temporal	Hour of day, Day of year, Previous rainfall

The Random Forest model will be trained to predict:

- Probability of rainfall for different thresholds (0.5 mm, 2.5 mm, 15.5 mm)
- Expected intensity (mm/hour)
- Time to onset (minutes)
- Duration (minutes)

5.5.6 Output Generation and Dissemination

The system generates hyper-local nowcasts with multiple lead times:

Table 11: Nowcast products and lead times

Lead Time	Spatial Resolution	Update Frequency
10 minutes	100 m	Every 1 minute
30 minutes	250 m	Every 5 minutes
60 minutes	500 m	Every 10 minutes
180 minutes	1 km	Every 30 minutes

Output will be disseminated through:

- Mobile app with location-specific alerts
- SMS alerts for registered users
- Web dashboard for disaster management authorities
- Public announcement systems in vulnerable areas

5.6 Validation Protocol for Future Implementation

For future implementation, the following validation protocol is proposed:

1. Training period: 5 years of historical data 2.

Testing period: 1 year of independent data 3.

Performance metrics:

$$POD = \frac{TP}{TP + FN} \quad (4)$$

$$FAR = \frac{FP}{TP + FP} \quad (5)$$

$$CSI = \frac{TP}{TP + FP + FN} \quad (6)$$

where TP = True Positives, FP = False Positives, FN = False Negatives Target
performance: $POD > 0.8$, $FAR < 0.3$ for heavy rainfall events.

6 RECOMMENDATIONS AND ADAPTATION STRATEGIES

Based on the analysis of rainfall patterns and the proposed nowcasting framework, we recommend the following strategies for implementation in Karaikal.

6.1 Immediate Recommendations (0-2 years)

6.1.1 Pilot Project Implementation

The PCCC and DSTE should initiate a pilot project to implement key components of the proposed framework in a high-vulnerability ward of Karaikal:

- Location selection: Identify a 5-10 km² area with high flood risk, dense population, and critical infrastructure
- Initial infrastructure:
 - Install 3-5 automated weather stations
 - Deploy 1 microwave radiometer or ceilometer
 - Establish partnerships with 2-3 telecommunication towers for microwave link data

- Install 1 whole sky imager
- Timeline: 18-24 months for implementation and initial validation

6.1.2 Data Sharing Agreements

- Establish formal agreements with:
 - Telecommunication companies for microwave link data access
 - IMD for real-time data feeds and satellite imagery
 - State Disaster Management Authority for integration with existing systems
- Develop data sharing protocols ensuring data privacy and security

6.1.3 Capacity Building

- Train local disaster management authorities on nowcast interpretation and response protocols
- Conduct workshops for agricultural officers on using nowcast information for farm-level decisions
- Develop training materials in Tamil for community-level understanding

6.2 Medium-term Recommendations (2-5 years)

6.2.1 Full-scale Implementation

Based on pilot project learnings, scale up to cover the entire Karaikal region:

Table 12: Proposed full-scale infrastructure requirements

Component	Pilot Phase	Full Scale
Automated Weather Stations	3-5	15-20
Microwave Radiometers	1	2-3
Microwave Link	2-3	10-15
Partnerships		
Whole Sky Imagers	1	3-4

6.2.2 Model Refinement and Validation

- Collect 2-3 years of data from pilot project for model training
- Refine CNN and Random Forest models based on local data
- Conduct rigorous validation against independent events
- Establish skill scores and uncertainty estimates for all nowcast products

6.2.3 *Community Engagement and Awareness*

- Develop a mobile app with:
 - Location-specific push notifications
 - Simple color-coded warning system
 - User feedback mechanism for ground-truth validation
- Establish community-based rainfall observers for additional validation
- Conduct regular awareness campaigns on nowcast interpretation and appropriate responses

6.3 Long-term Recommendations (5+ years)

6.3.1 *Integration with Urban Planning*

- Use nowcast data and historical flood mapping to:
 - Update stormwater drainage design standards
 - Identify and prioritize flood-prone areas for infrastructure improvements
 - Inform land-use zoning decisions
 - Guide development of climate-resilient housing
- Integrate nowcast alerts with urban traffic management systems to reroute traffic during flooding

6.3.2 *Agricultural Decision Support System*

- Develop an integrated decision support system for agriculture combining:
 - Nowcast rainfall predictions
 - Crop growth models
 - Pest and disease prediction models
 - Market price information
- Provide customized advisories to farmers via SMS and mobile app
- Establish crop insurance products linked to nowcast-verified events

6.3.3 *Regional Collaboration*

- Share framework and learnings with neighboring regions (Nagapattinam, Cuddalore)
- Establish a regional nowcasting network for coastal Tamil Nadu-Puducherry
- Contribute to national and international nowcasting research through publications and conferences

6.4 Specific Adaptation Strategies for Stakeholders

6.4.1 *For Disaster Management Authorities*

- Pre-monsoon preparation: Use nowcast-based risk maps to preposition resources in high-risk areas
- During events: Activate response teams based on nowcast alerts with 60-180 minute lead times
- Post-event: Use nowcast-verified rainfall data for damage assessment and relief planning

6.4.2 *For Farmers*

- Crop planning: Use seasonal forecasts and nowcast patterns to select appropriate crop varieties
- Harvest timing: Schedule harvesting operations based on nowcast dry windows
- Post-harvest management: Protect harvested produce based on rainfall warnings

6.4.3 *For Urban Residents*

- Daily commute: Plan travel routes based on nowcast alerts
- Property protection: Take preventive measures (sandbags, moving vehicles) based on warnings
- Safety: Avoid water-logged areas during and after heavy rain

7 CONCLUSION

This study successfully achieved its objectives of analyzing the rainfall characteristics of Karaikal and proposing a comprehensive conceptual framework for hyper-local rainfall nowcasting.

7.1 Summary of Key Findings

The historical rainfall analysis (1990-2024) revealed several critical insights:

1. Dominant Northeast Monsoon: Karaikal receives over 60% of its annual rainfall during the Northeast Monsoon (October-December), with significant inter-annual variability ($CV = 23.1\%$).
2. High-intensity events: Approximately 16.5% of rainy days contribute nearly 38% of total rainfall through heavy to extremely heavy events. These events are the primary cause of urban flooding and agricultural disruption.

3. Increasing trend in extremes: A statistically significant increasing trend in the frequency of extreme rainfall events was observed, with an increase of approximately 0.4 events per decade.
4. Short-duration events: 68% of rainfall events last less than 3 hours, highlighting the critical need for nowcasting systems with lead times of 10-180 minutes.
5. Increasing convective activity: The Convective Fraction increased from 38.5% to 44.2% over the study period, suggesting an increasing role of convective processes and validating the need for instability monitoring.

7.2 Conceptual Framework Contributions

The proposed Multi-Input, Multi-Scale Nowcasting Framework (MIMSNF) makes several novel contributions:

1. Integrated approach: Combines vertical atmospheric sensing, microwave link networks, cloud image analysis, and hybrid machine learning into a unified system tailored for Karaikal's specific needs.
2. Multi-scale outputs: Provides nowcasts at multiple lead times (10-180 minutes) and spatial resolutions (100 m to 1 km) to serve diverse user needs.
3. Leverages existing infrastructure: Utilizes telecommunication microwave links for cost-effective, high-resolution rainfall monitoring.
4. Advanced ML architecture: Proposes a hybrid CNN-Random Forest model that combines the strengths of deep learning for image analysis with ensemble learning for heterogeneous data integration.

7.3 Limitations of the Study

The study has several limitations that should be acknowledged:

1. Absence of upper-air data: Direct atmospheric instability indices could not be calculated, requiring the use of proxy indicators.
2. Conceptual framework: The proposed nowcasting system is conceptual and requires implementation and validation with real-time data.
3. Data availability: The analysis was limited to available IMD data; additional data sources could provide more comprehensive insights.
4. Spatial coverage: The analysis used data from a single station; a denser network would provide better spatial representation.

7.4 Future Research Directions

Based on this study, several future research directions are identified:

1. Pilot implementation: Implement and validate the proposed framework in a pilot area.
2. Model development: Develop and train the CNN and Random Forest models using local data.
3. Comparative studies: Compare the performance of different ML algorithms for nowcasting in this region.
4. Climate change projections: Investigate how rainfall patterns and nowcasting requirements may change under future climate scenarios.
5. Economic impact assessment: Quantify the economic benefits of improved nowcasting for agriculture and disaster management.

7.5 Final Remarks

Karaikal, like many coastal regions in India, faces increasing challenges from extreme rainfall events in a changing climate. The findings of this study confirm that the region is experiencing more frequent high-intensity, short-duration rainfall events that overwhelm existing infrastructure and coping mechanisms. Traditional weather prediction methods, with their coarse spatial and temporal resolution, are inadequate for preparing for these rapid-onset events.

The proposed nowcasting framework represents a paradigm shift from reactive to proactive disaster management. By providing actionable warnings 10 to 180 minutes in advance, such a system can save lives, protect property, and enhance the resilience of communities and livelihoods. The integration of advanced technologies—microwave radiometers, telecommunication networks, machine learning—offers a cost-effective, scalable solution that can be adapted for other vulnerable coastal regions.

The time for action is now. With climate change accelerating and extreme events becoming more frequent, investing in hyper-local nowcasting capabilities is not just a technological upgrade—it is a necessity for climate adaptation and sustainable development. We urge the Puducherry Climate Change Cell, Department of Science, Technology and Environment, and all stakeholders to take forward the recommendations of this study and work towards building a climate-resilient Karaikal.

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ANNEXURES

Annexure I: Raw Rainfall Data Sample

Table 13: Sample of daily rainfall data (1990-1995)

Date	Rainfall (mm)	Max Temp (°C)	Min Temp (°C)
01-Jan-1990	0.0	29.5	22.3
02-Jan-1990	2.3	28.7	22.1
03-Jan-1990	0.0	30.1	22.5
...	...	...	...
31-Dec-1995	12.4	28.9	22.8

Annexure II: Python Code for Data Analysis Listing 2: Sample code for rainfall trend analysis

```

import pandas as pd import numpy as np
from scipy import stats import
matplotlib.pyplot as plt
# Load data
data = pd.read_csv('karaikal_rainfall_1990_2024.csv') data['date'] =
pd.to_datetime(data['date']) data['year'] = data['date'].dt.year data['month']
= data['date'].dt.month
# Calculate annual rainfall annual_rainfall =
data.groupby('year')['rainfall'].sum()
# Mann-Kendall test for trend def
mk_test(x): n = len(x)
    s = 0
    for k in range(n-1):
        for j in range(k+1, n):
            s += np.sign(x[j] - x[k])
    # Variance calculation var_s = n*(n-
1)*(2*n+5)/18
    # Z statistic
    if s > 0: z = (s - 1) / np.sqrt(var_s) elif s < 0: z
    = (s + 1) / np.sqrt(var_s)
    else:
        z = 0
    # p-value p = 2 * (1 - stats.norm.cdf(abs(z)))
    return z, p
z, p = mk_test(annual_rainfall.values) print(f'Mann-
Kendalltest:Z={z:.3f},p={p:.3f}')

    _ _ _
# Sen's slope def sens_slope(x,
y):
    n = len(x) slopes = [] for i in
range(n-1):
        for j in range(i+1, n):
            slopes.append((y[j] - y[i]) / (x[j] - x[i])) return np.median(slopes)
years = annual_rainfall.index.values slope = sens_slope(years,
annual_rainfall.values) print(f'Sen'sslope: {slope:.2f}mm/year')

    _ _ _

```

Annexure III: Detailed Framework Schematics

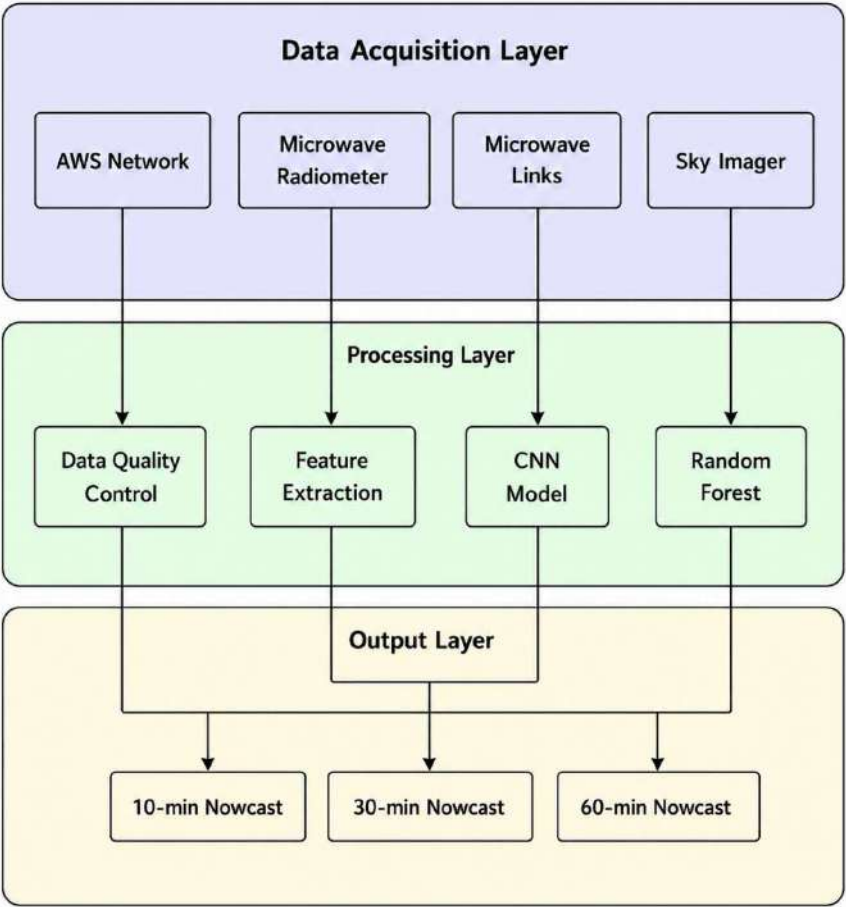


Figure 8: Detailed data flow in the proposed nowcasting framework