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A Combined Modeling Framework for Accurate Thunderstorm Forecasting in Low-Risk Areas of Bangladesh

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Abstract

Thunderstorms can devastate buildings, crops and human life even in "low risk" areas like Sitakunda, Bangladesh. This conundrum underscores the need for timely and accurate forecasting to safeguard vulnerable, resource-poor populations. But traditional models often struggle to account for the nonlinear and seasonality of thunderstorms, and little research has been done on predicting the daily occurrence of thunderstorms in low-risk regions. This research seeks to enhance thunderstorm frequency forecasting by extensively evaluating and comparing statistical, machine learning, and deep learning approaches (ETS, ARIMA, STL-ETS, STL-ARIMA, NNAR, TBATS, Prophet, GARCH, SVM, and LSTM). An innovatively combined model is also developed. Applying daily thunderstorm counts from Sitakunda (1981-2023) and forecasting three years ahead (2024–2026), and measuring performance using RMSE and MAE, the findings show the combination model achieves the lowest prediction errors and most reliable forecasts. Although Prophet and SVM show comparable results, GARCH has the lowest RMSE (1.3137). By contrast, LSTM and NNAR exhibit larger errors, suggesting that they struggle to model the unpredictable nature of thunderstorms. These results demonstrate the benefits of combination forecasting in improving thunderstorm predictions for low-risk areas. Incorporation of these models into early warning systems and local governance can enhance preparedness, minimize disruptions and injuries, and foster resilience to thunderstorm risks in the long term.

Keywords: Thunderstorm, Time Series Analysis, Machine Learning, Deep Learning, Combination Forecasting Model.

1. Introduction

Thunderstorms, also known as electrical or lightning storms, are characterized by lightning and the accompanying acoustic waves in the Earth's atmosphere. Less severe variants are commonly referred to as thundershowers [1]. A disaster is generally defined as an event causing substantial

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damage or loss to individuals or property [2]. Therefore, even extreme atmospheric events such as storms or earthquakes are not considered disasters unless they affect human populations or infrastructure [3]. While all thunderstorms contain lightning by nature, predicting whether a given storm will produce hazardous convective weather (HCW), including tornadoes, strong winds, large hail, or heavy rain, remains challenging [4]. This difficulty is compounded by the fact that severe thunderstorms are exceedingly rare and often go unreported due to the lack of reliable observation systems, making the development of precise climatologies particularly difficult [5]. Globally, more than 16 million thunderstorms occur each year, with approximately 2,000 storms active at any given time [6].

In Bangladesh, significant local convective storms occur every year from March to May during the pre-monsoon season, resulting in fatalities and property destruction [7]. Between 2011 and 2020, lightning strikes claimed the lives of 2,164 people, nearly four deaths per week in Bangladesh, according to the country's disaster management department[8]. However, a Bangladeshi NGO reports at least a thousand more lightning-related fatalities between 2010 and 2021, underscoring the severe and under-acknowledged impact of these events[8].

To address these challenges, modern forecasting methods have increasingly turned to machine learning (ML) and deep learning (DL) techniques. Complex non-linear patterns that are usually overlooked by conventional statistical models like ARIMA, ETS, TBATS, GARCH, and STL can be captured by models like Long Short-Term Memory (LSTM), Neural Network Autoregression (NNAR), and Support Vector Machines (SVM) [9]. A promising strategy involves combination forecasting, which combines multiple models to improve predictive performance [10]. This strategy makes use of the advantages of statistical and data-driven approaches to identify complex seasonal and temporal patterns. Empirical research continuously demonstrates that ensemble models frequently perform more accurately and reliably than the best single-model forecasts.

Even with these developments, it is still very difficult to predict daily thunderstorm activity in climatologically complicated areas like Sitakund, Bangladesh. During the pre-monsoon months (March to May), the area frequently suffers strong local convective storms that cause fatalities and property damage[7]. The study's dataset, which includes daily recordings spanning around 43 years (1981–2023), presents both analytical potential and difficulties[11]. Managing such a large dataset necessitates careful model selection and data preprocessing to guarantee that pertinent trends are recorded while limiting the impact of out-of-date or irrelevant patterns[12].

Sitakund was selected as a representative low-risk region because it provides a controlled environment for evaluating forecasting models without the confounding effects of hazard frequency. High-risk regions often suffer from sparse or inconsistent observational records due to damage, reporting gaps, and rapid storm evolution, which can bias model training and validation. By focusing on Sitakund, where thunderstorms occur regularly but with relatively lower severity, we ensure data continuity across four decades and create a robust testing ground for developing transferable forecasting frameworks. This approach aligns with recent applied forecasting studies in Bangladesh that emphasize model validation in diverse climatological contexts before scaling to high-risk zones [13–15].

Using historical meteorological data from 1981 to 2023, this study attempts to develop and evaluate a combination forecasting model that uses time series, deep learning, and machine learning techniques for accurate daily thunderstorm forecasting in Bangladesh's low-risk (Sitakund) regions. Sitakund, which is in Bangladesh's Chittagong District, is well known for its varied topography, which includes hills, forests, and coastal regions [16]. Because of its tropical monsoon environment, Sitakund is vulnerable to weather phenomena, including thunderstorms and heavy rains, which have an impact on infrastructure and local livelihoods [17].

The primary objective is to develop a robust combination model that blends traditional time series models (e.g., ARIMA and ETS) with state-of-the-art machine learning techniques (e.g., LSTM and SVM) to forecast daily thunderstorms effectively. The proposed model will be compared with existing forecasting techniques across parallel districts in Bangladesh to handle both linear seasonality and complex non-linear correlations in thunderstorm data. Ultimately, this research aims to provide accurate and actionable thunderstorm forecasts to assist disaster management officials in resource allocation and proactive decision-making. Additionally, this study will propose new strategies and policies tailored to Bangladesh's unique meteorological challenges, thereby enhancing disaster preparedness and long-term resilience.

2. Methods and Materials

Data source

According to the study, Sitakund is a low-risk area for convective weather events in Bangladesh since it has a comparatively lower frequency of thunderstorms during the pre-monsoon season[18]. Figure 1 displays comparable information. Hence, the daily thunderstorm data for Sitakund Station were collected for this study from the Bangladesh Meteorological Department (BMD)[19]. The data comprises 15,705 observations from January 1981 to December 2023 after adjusting for all missing values. We therefore intend to forecast thunderstorm frequency in Sitakund based on the daily thunderstorm frequency data from Sitakund Station. The Sitakund sub-district in southeast Bangladesh is depicted in Figure 2, emphasizing both its administrative borders and its significance to the local thunderstorm climate. Figure 3 illustrates the overall architecture of the proposed combination forecasting model, which integrates GARCH, SVR, and LSTM methods.

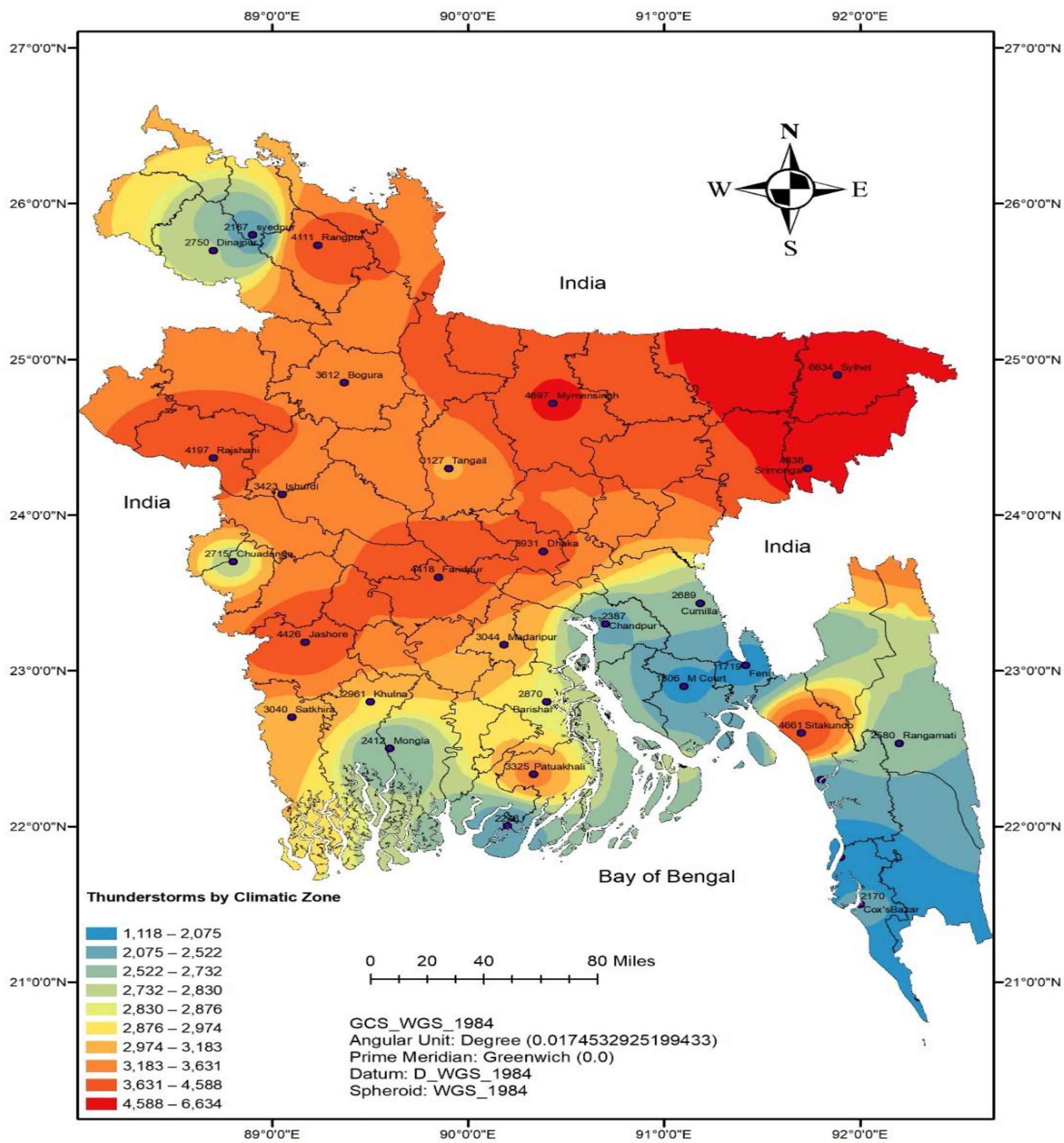

Figure 1: Map of Bangladesh's lowest thunderstorms by climatic zone, showing the locations of meteorological stations and the study area.

The challenges and unique characteristics of thunderstorm forecasting are carefully considered in planning every stage of this study, including data collection, preprocessing, model building, and performance evaluation. Because thunderstorm data contains both linear and non-linear trends over a long period (1981–2023), our methodology combines machine learning and deep learning techniques. By using both advanced deep learning models like LSTM and more traditional models like ARIMA, ETS, TBATS, SVR, NNAR, GARCH, Prophet, and STL, the study aims to create a reliable combination model that can adapt to the particular meteorological features of high-risk areas. The methodology is designed to systematically address data issues such as feature scaling, seasonal decomposition, and missing values to produce a high-quality dataset that improves model performance. This section will also discuss the training and validation processes, how to compare and understand model outputs, and metrics like RMSE, MAE, MASE, and ACF1 that are used to evaluate model correctness [20].

Study Design

In terms of prediction accuracy, the suggested model performs better than the current combined models found in the literature [13–15].

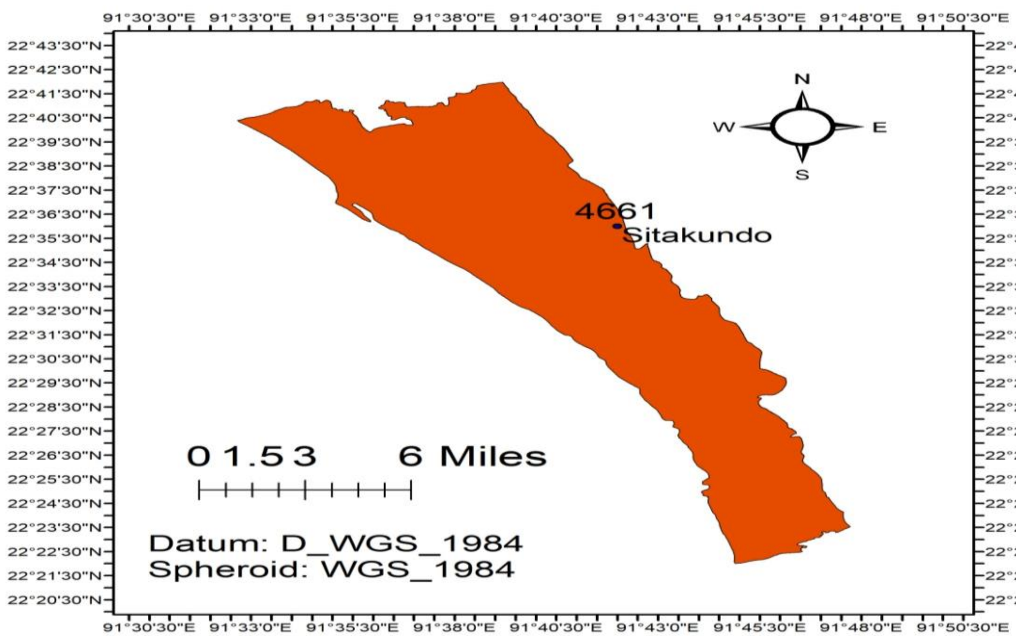

Figure 2: Geographical Location of Sitakund sub-district within Southeastern Bangladesh: Topographic and Administrative Features Relevant to Thunderstorm Climatology.

30% (4,712 observations) of the data were set aside for testing, while 70% (10,993 observations) of the data were used to train the models. The R and Python programming languages, which provide a complete environment for statistical modeling, data preprocessing, and visualization, were used for all of the studies in this study.

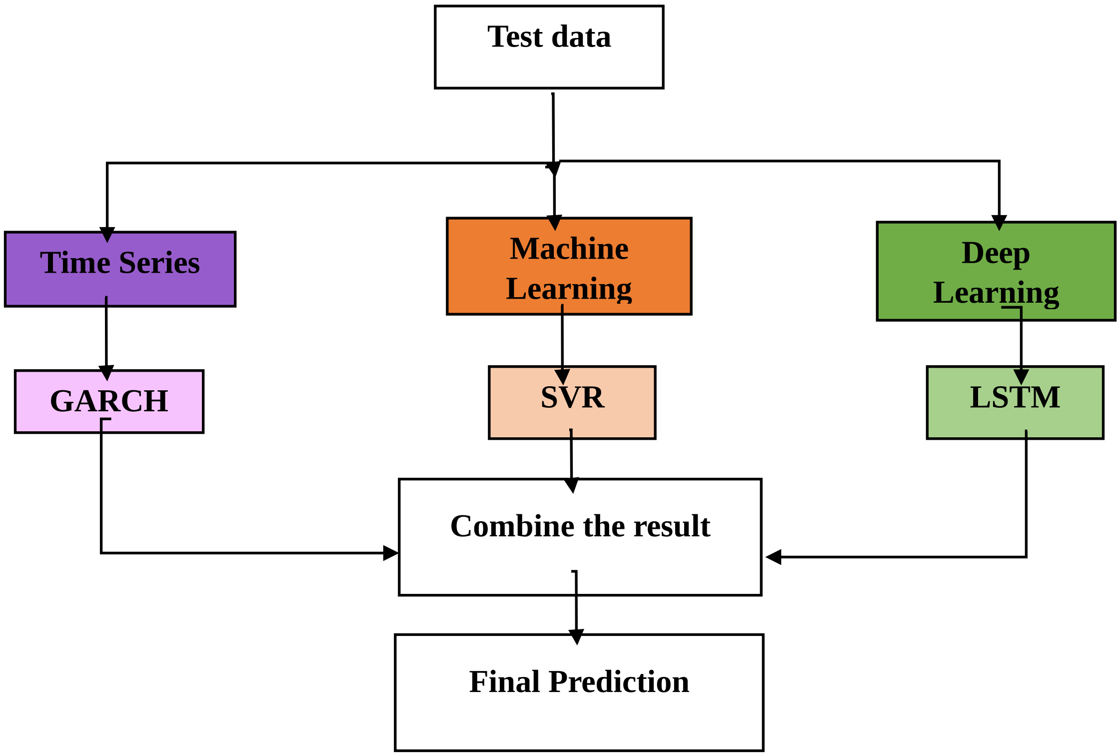

Figure 3: Proposed Structure for a Combined Statistical and Machine Learning Model

ARIMA model

A statistical analysis model called an autoregressive integrated moving average, or ARIMA, makes use of time series data to either forecast future trends or gain a deeper understanding of the data set[21]. Every element in ARIMA has a standard notation and operates as a parameter. A common notation for ARIMA models would be ARIMA with p, d, and q, in which the parameters are replaced with integer values to denote the kind of ARIMA model being used. The parameters are defined as [22].

> *p*: the number of lag observations in the model, also known as the lag order.
>
> *d*: the number of times the raw observations are differenced; also known as the degree of differencing.
>
> *q*: the size of the moving average window, also known as the order of the moving average.

One particularly promising linear forecasting model is ARIMA. Rendering the series stationary is the first step in the ARIMA forecasting process. This may entail applying nonlinear transformations such as logarithms or deflation and differencing it a total of 'd' times. A linear combination of 'p' past observations and 'q' errors can be used to represent the series once it has been made stationary.

$$Y_t+\phi_1 Y_{t\text{-}1}+\ldots+\phi_i Y_{t\text{-}p}=Z_t+\hat{\theta}_1 Z_{t\text{-}1}+\hat{\theta}_j Z+\varepsilon_t, \tag{1}$$

where $\{Z_t\}$ ~ WN $(0,\hat{\sigma}^2)$. $Y_t \wedge \varepsilon_t$ represents time series values. φ_i $(i=1,2,\ldots,p)$ $are\ autoregressive\ (AR)$ coefficients and θ_j $(j=1,2,\ldots,q)$ are moving average (MA) coefficients. The ARIMA (p, d, q) model involves three non-negative whole numbers, p, d, and q, which determine the order of the model. Some specific instances of the ARIMA model, such as AR(p) and MA(q), can be derived by appropriately setting one or more of these values to zero. These variations are represented as ARIMA (p, 0, 0) and ARIMA (0, 0, q), respectively. Furthermore, by adjusting the values of p, d, and q, various ARIMA models can be created. When dealing with a particular time series dataset, the selection of the simplest ARIMA model, along with its specific parameter values, is crucial in ensuring the model's effectiveness[23].

ETS model

The ETS model can be used to forecast univariate time series data by taking into consideration the seasonal and trend components[24]. The model under discussion is very flexible and can generate seasonal components for a variety of characteristics and patterns[25]. The three main characteristics of the model in question are error, trend, and seasonal components. There are four possible values for each parameter: Z is auto, M is multiplicative, N is none, and A is additive. ETS (A, M, N) thus signifies the following: no seasonality, multiplicative for trend, and additive for error[26].

STL decomposition

Decomposition techniques are crucial tools in time series analysis that help uncover the underlying components in observable data, such as trend, seasonality, and irregular fluctuations[27]. Unlike the traditional approach, SEATS (Seasonal Extraction in ARIMA Time Series) and X11, STL can handle any type of seasonality, which means it can handle daily and sub-daily series data in addition to monthly and quarterly data[28,29]. The daily thunderstorm occurrence data, which shows intricate seasonal patterns with weekly, monthly, and annual changes, provides the basis for thunderstorm forecasting. To successfully separate and model these patterns, we used the STL technique for seasonal adjustment in our ML-based combination model.

TBATS model

The TBATS considers trends, seasonal components, ARMA errors, Box-Cox transformation, and trigonometric seasonality $(\omega,\{p,q\},\varphi,\{<m_1,k_1>,<m_2,k_2>,\ldots,<m_T,k_T>\})$ model, which was first presented in 2011.

Where ω is a Box-Cox transformation, p, q are ARMA parameters, φ is a damping parameter, $m_{1,\dots,}m_T$ are seasonal periods, $k_{1,\dots,}k_T$ are the number of Fourier series pairs. The model can be written as

$$
\begin{aligned}
y_t^{(\omega)} &= l_{t-1} + \varphi b_{t-1} + \sum_{i=1}^{T} s_{t-1}^{(i)} + \alpha d_t \\
b_t &= b_{t-1} + \beta d_t \\
s_t^{(i)} &= \sum_{j=1}^{k_i} s_{j,t}^{(i)} \\
s_{j,t}^{(i)} &= s_{j,t-1}^{(i)} cos\lambda_j^{(i)} + s_{j,t-1}^{*} sin\lambda_j^{(i)} + \gamma_1^{(i)} d_t \\
s_{j,t}^{*(i)} &= -s_{j,t-1}^{(i)} sin\lambda_j^{(i)} + s_{j,t-1}^{*} cos\lambda_j^{(i)} + \gamma_2^{(i)} d_t \\
\lambda_j^{(i)} &= \frac{2\pi j}{m_i},
\end{aligned}
\tag{2}
$$

where, i = 1, …., T, d_t is an ARMA (p, q) process, $\alpha, \beta, \gamma_1 \wedge \gamma_2$ are smoothing parameters, l_0 is an initial level, and b_0 is a slope value [30].

Prophet model

The Prophet approach for time series data forecasting was created by Facebook's Core Data Science team. Prophet aims to forecast "at scale," meaning that it aspires to be the automated forecasting tool that facilitates the tuning of time series methods and enables analysts with varying backgrounds or those with little to no forecasting experience to provide precise forecasts [31]. According to Facebook, Prophet performs best with time series that have significant seasonal impacts and multiple seasons of historical data, and it is resistant to outliers and trend changes. Despite not having seasonality, our data does well in this case. Prophet performs admirably in this regard. Analysts don't have to worry about their data not being suitable for PROPHET forecasting because Prophet is autonomous and can handle time series data with large fluctuations [32]. The following equation is:

$$y(t) = c(t) + s(t) + h(t) + x(t) \tag{3}$$

GARCH model

GARCH models are primarily used to determine the conditional variances and volatilities of financial time-series data. The amount of historical data required for a reliable volatility estimate is still substantial, even after these volatilities are used to value the options as usual[33]. Therefore, it is sufficient to estimate the discrete-time GARCH parameters for the available data frequency when estimating a continuous-time GARCH process. Models with an autoregressive component are also subject to the analysis[34].

NNAR model

NNAR models represent intricate nonlinear relationships and functional forms and can be thought of as a network of neurons or nodes. The neurons in a basic neural network framework are arranged in two layers: (i) the top layer identifies the predictions, and (ii) the bottom layer identifies the original time series. The final model is comparable to a straightforward linear regression and only turns nonlinear when an intermediary layer containing "hidden neurons" is added[35]. which uses the lag values of the time series as inputs and is a feed-forward neural network with a single hidden layer. It is known as the NNAR $(p, P, k)_m$ model, in which m is the duration of the seasonal period, k is the number of nodes in the hidden layer, p is the number of input lags, and P is the seasonal lags. The following is the formula for the NNAR $(p, P, k)_m$ model[35].

$$y_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, y_{t-m}, y_{t-2m}, \ldots, y_{t-Pm}) + \varepsilon_t, \tag{4}$$

this case, f stands for the neural network with a single layer of k hidden nodes, and ε_t is the residual series.

SVR model

Support Vector Regression (SVR), a powerful type of supervised machine learning designed specifically for regression applications, is derived from Support Vector Machines (SVM). SVR demonstrates remarkable proficiency in effectively handling complex, non-linear patterns frequently observed in time series data. Predictions that depart more than ε units from the intended output are penalized by the algorithm's ε-insensitive loss function[36]. Additionally, it can generate projections for future periods that are more stable and exhibit resistance to outliers[37].

LSTM model

Long-term dependencies are captured by LSTM, which performs exceptionally well in sequence prediction tasks. Order dependence makes it perfect for speech recognition, machine translation, and time series. Because it can store knowledge of past states, capture historical information of time series, and mitigate issues of recurrent networks like vanishing and exploding gradients, the Long Short-Term Memory (LSTM) network is favored over other prediction models. To achieve satisfactory prediction performance, LSTM can extract the dynamic and nonlinear characteristics of process data[38]. The equations for an LSTM cell's forward pass with a forget gate in the compact form are:[39,40]

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$

$$O_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \quad (5)$$

$$C_t = f_t . C_{t-1} + i_t . \sigma_c (W_c x_t + U_c h_{t-1} + b_c)$$

$$h_t = O_t . \sigma_h (c_t).$$

Evaluation metrics

The difference between a predicted and actual value is called a residual. Consequently, the forecast error for the relevant time frame

$$e_t = Y_t - \hat{Y}_t \quad (6)$$

Where Y is the actual value for time t, E_t is the forecast error at period t, and is the forecast value for time t. Averaging certain functions of the difference between actual values, also known as residuals, is the most popular method used to describe the errors produced by a particular forecasting system. Forecasting performance is evaluated using a range of forecasting error measures, some of which are as follows:

The root mean squared error (RMSE) is calculated from the following equation,

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}} \quad (7)$$

The mean absolute error (MAE) is calculated from the following equation

$$\text{MAE} = \frac{\sum_{t=1}^{n} |e_t|}{n} \quad (8)$$

MAPE indicates how large the forecast errors are in comparison to the series' actual values. MAPE can be calculated using,

$$\text{MAPE} = \frac{\sum_{t=1}^{n} |\frac{e_t}{Y_t}|}{n} \quad (9)$$

Where n is the number of observations of time series, $e_t = Y_t - \hat{Y}_t$; e_t = the forecast error at period t, Y_t = the actual value in period t and $\hat{Y}_t$= forecast value for period t [30].

The accuracy of forecasts is gauged by the mean absolute scaled error or MASE. MASE is calculated from the following [41] equation,$\hat{y}_i$

$$\text{MASE} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{|y_i - \hat{y}_i|}{\frac{1}{n-m} \sum_{j=m+1}^{n} |y_j - \hat{y}_{j-m}|} \right) \quad (10)$$

ACF1: Error autocorrelation at lag 1. It measures the degree to which the current value of a time series has been impacted by its historical values [42].

3. Results and Analysis

Data description

This section employs a variety of graphs, including time plots and seasonal subseries plots, for distinct objectives. Table 1 summarizes the distribution of daily thunderstorm counts in Sitakunda over 1981–2023. The dataset comprises 15,705 observations, with a mean of 0.388 events per day. The high skewness (4.2032) and kurtosis (22.5760) indicate that thunderstorms are rare but occasionally extreme, reflecting the sporadic nature of severe weather in this low-risk region. These plots make it easier for us to describe a time series' different characteristics. A thorough examination of each component separately is made easier by this split. The graphic displays (Figure 4) the number of thunderstorms each year (1981–2023), which ranges from 0 to 15. There is no discernible long-term trend in thunderstorm activity, which peaks in the late 1990s and early 2000s. Additive seasonality is suggested by regular seasonal patterns and considerable interannual variability. Figure 5 displays the Sitakund time series dataset's STL (Seasonal-Trend decomposition using LOESS) decomposition, which tracks daily thunderstorms over time. The data is divided into four parts by the time series decomposition: the Original (blue), which shows all variations; Trend (green), which shows a long-term upward trajectory from 1980 to 2020; Seasonal (purple), which highlights periodic patterns; and Random (orange), which represents erratic fluctuations.

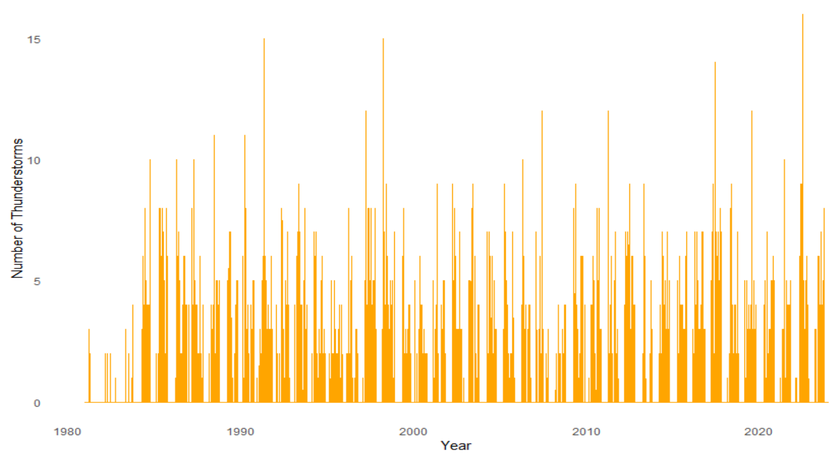

Figure 4: Time series plot displays the number of thunderstorms over time from 1981 to 2023 for the Sitakund Data.

Table 1. Descriptive statistics of daily thunderstorm counts in Sitakunda (1981–2023).

Count	Minimum	Maximum	Mean	Median	SD	Skewness	Kurtosis
15705	0	16	0.388	0	1.2235	4.2032	22.576

Figure 5: Decomposition plot of the Sitakund dataset for January 1981 to December 2023.

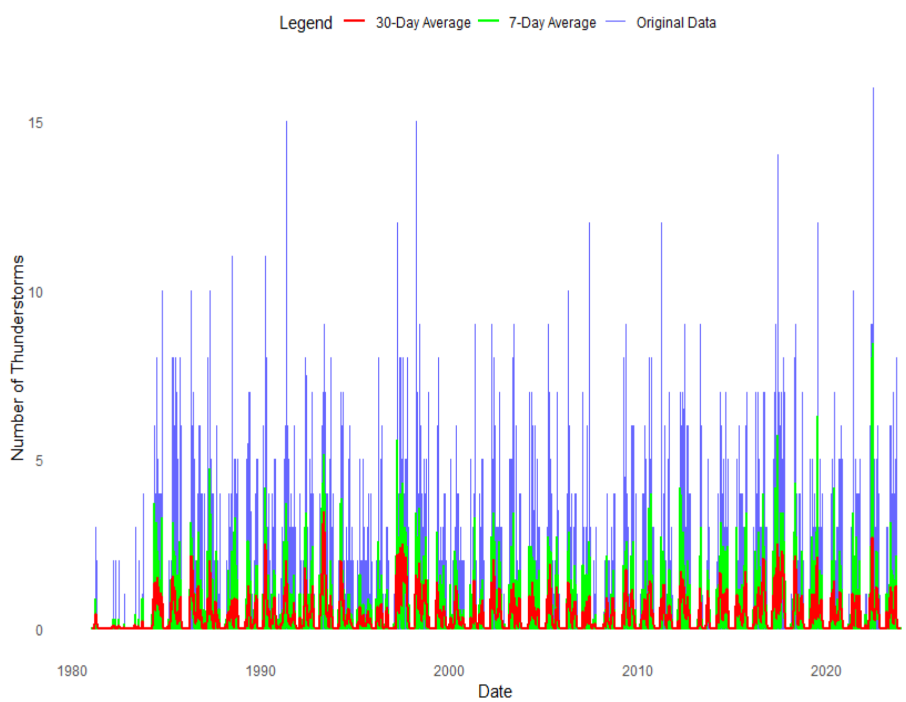

Figure 6: Temporal Trends in Thunderstorms of the Sitakund dataset for January 1981 to December 2023.

The original data and smoothed trends, the 7-Day Average for short-term trends, and the 30-Day Average for long-term trends are displayed alongside the thunderstorm counts (1981–2023) plot. Significant activity is indicated by peaks, and trends and variability are made clearer by smoothing (Figure 6). A distinct seasonal tendency is seen in Figure 7, which displays monthly thunderstorm numbers from 1981 to 2023. While December and January have the least amount of activity, May has the highest number of thunderstorms, with counts as high as 15 and greater variability.

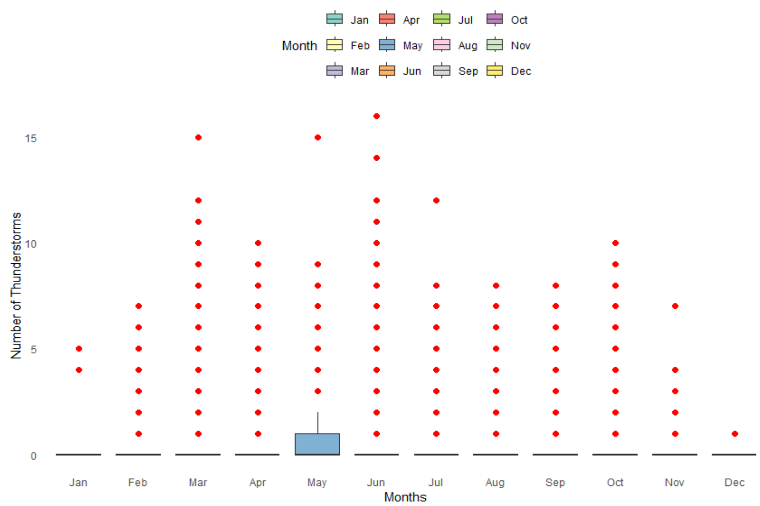

Figure 7: The box plot illustrates the distribution of monthly thunderstorm frequency in Sitakund from January 1981 to December 2023.

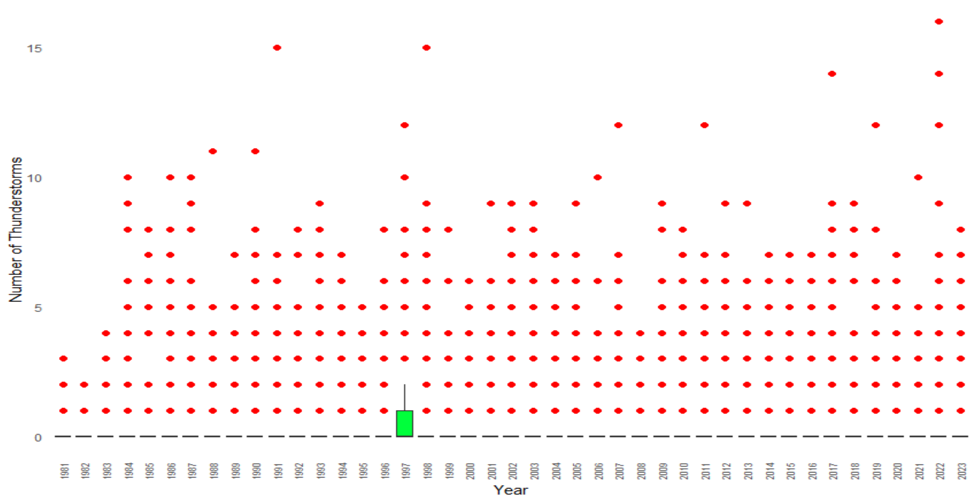

Figure 8: The box plot illustrates the distribution of yearly thunderstorm frequency in Sitakund from January 1981 to December 2023.

Red dots indicate yearly thunderstorm frequencies (0–15), while Figure 8 displays annual thunderstorm counts (1981–2023). Although there is no discernible long-term trend, it does emphasize periods of increased activity and notable interannual variability. A one-year box plot shows higher volatility during that period. According to Table 2, Several time-series models are compared based on RMSE, MAE, MASE, ACF1, and MAPE. GARCH achieves the lowest RMSE (1.3137) and performs best overall, indicating high accuracy. Prophet is the second-best model with a competitive RMSE (1.3476) and balanced performance across metrics. Combination models also perform effectively by integrating the strengths of various approaches. NNAR exhibits the highest RMSE (2.2024) and MAE (2.0904), indicating a poor fit for the data. Models like TBATS and STL-based methods provide reasonable accuracy and handle seasonality well, striking a balance between simplicity and performance.

Table 2: Forecasting accuracy measures of different models for the Sitakund dataset.

Model	**RMSE**	**MAE**	**MASE**	**ACF1**
ETS	1.3898	**0.4537**	**0.5807**	0.4019
ARIMA	1.3823	0.4698	0.6013	0.4019
STL+ETS	1.4002	0.6945	0.8179	0.4178
STL+ARIMA	1.3867	0.7188	0.8425	0.4178
NNAR	2.2024	2.0904	2.6758	0.4088
TBATS	1.3586	0.7400	0.8451	0.4402
Prophet	1.3476	0.6783	0.7850	0.4240
GARCH	**1.3137**	0.7355	0.9418	**0.4013**
SVR	1.3550	0.5371	0.6875	**0.4018**
LSTM	1.4793	0.8064	1.6137	0.4322
Combination (GARCH+SVR+LSTM)	**1.3438**	**0.6838**	**NA**	**0.4107**

Figure 9 displays daily thunderstorms across several decades, with colored lines representing forecasts from GARCH, LSTM, SVM, and a combination model, and black bars representing observed data. Compared to separate models, the combination model (red) produces projections that are smoother and more accurate, better capturing trends and variability, particularly in later years, demonstrating its capacity to manage complicated data.

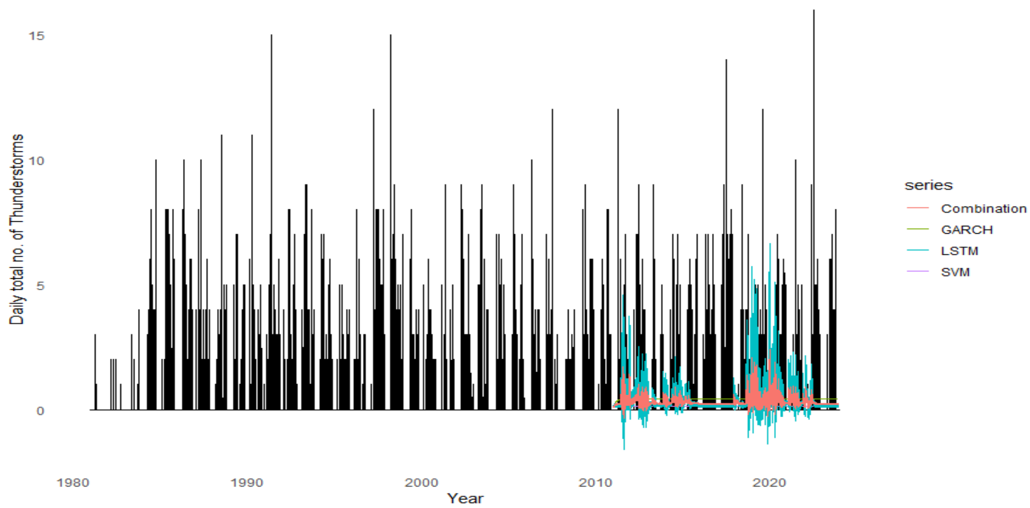

Figure 9: Forecasted daily thunderstorm trend of the Combination-GARCH-LSTM-SVM model.

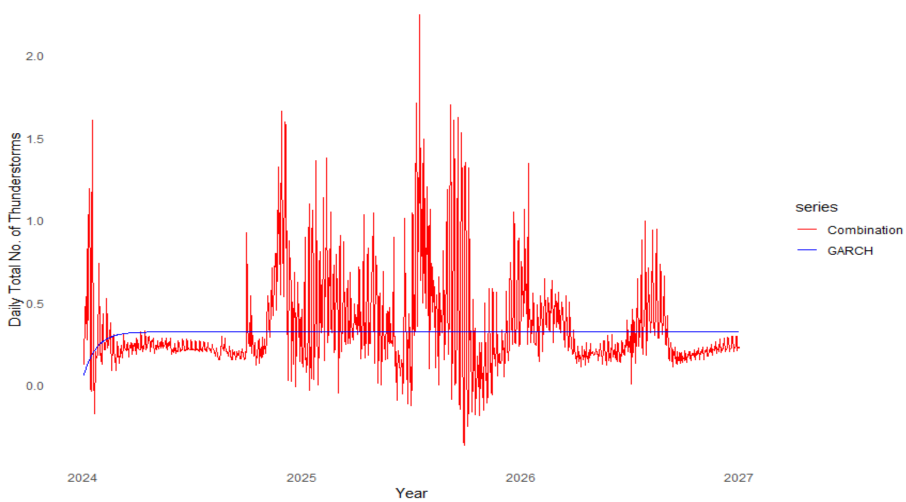

Figure 10: Forecasted plot of Thunderstorm days from January 2024 to December 2026 in Sitakund using the Combination and GARCH model based on the entire dataset.

Table 3: Forecasted Thunderstorm days in Sitakund from January 2026 to December 2026.

Date	Combination	GARCH	Date	Combination	GARCH
1/6/2026	1	0			
1/12/2026	1	0	8/7/2026	1	0
7/20/2026	1	0	8/8/2026	1	0
7/31/2026	1	0	8/14/2026	1	0
8/1/2026	1	0	8/20/2026	1	0

In Figure 10, according to the graphic, for Sitakund, the "Combination" model forecasts more consistently and steadily than the "GARCH" model, which shows higher unpredictability. Because of its smoother trend and fewer sharp changes, which suggest better management of noise and outliers in the data, the "Combination" model might be seen as more trustworthy for future forecasts. Table 3 reveals the performance of the "Combination" model over the "GARCH" model.

4. Discussion

Table 3 shows the resumption of data with records in January to December of 2026. The absence of forecasts from February to June, however, indicates a protracted period of filtered redundancy or atmospheric stability. July and August see a resurgence in forecasting activity, especially in late July and early August, which could be related to changes in the seasonal weather patterns or heightened volatility risk. There are no entries for the year's last quarter, which runs from September to December 2026, indicating that things will remain calm for a long time to come. ETS, ARIMA, STL+ETS, STL+ARIMA, NNAR, TBATS, Prophet, GARCH, SVR, LSTM, and a combination model were among the time-series, machine learning, and deep-learning forecasting models that were assessed in the study. The GARCH model first showed the best performance with an RMSE of 1.3137, followed closely by TBATS and Prophet based on the RMSE, MAE, and other accuracy criteria (Table 2). The forecast plots show that GARCH's forecast was unable to catch substantial fluctuations in the thunderstorm data (Figure 10), despite achieving the lowest RMSE of 1.3137. With an RMSE of 1.3438, the combination model performed well, proving its capacity to provide stability over the prediction period while balancing bias and variation.

The increasingly deadly nature of thunderstorms in Bangladesh is evident in the updated statistics. At least 74 people, among them 35 farmers, were killed by lightning strikes between April and May 8, 2025, as 43 of these deaths occurred within eight days of the beginning of May[43]. On a single day, 11 were killed, and 9 were wounded. In the previous ten years through 2021, there were more than 2,800 people killed by lightning strikes throughout the country[43,44]. On the other hand, the Ministry of Disaster Management and Relief and the Disaster Forum said at least 3,162 people died of lightning strikes between 2011 and 2021[45]. After more than 200 people were killed in May 2016, Bangladesh officially classified lightning strikes as a natural disaster[45].

The escalating impacts of climate change are the main cause of this concerning trend, according to experts. Bangladesh, a low-lying delta country encircled by the Bay of Bengal, is increasingly vulnerable to more frequent and fatal lightning strikes, highlighting the critical need for enhanced mitigation techniques and early warning systems[46]. Storms killed around 15,000 people worldwide in 2023, the third-highest number since 1990 reports. In 1991, storm events claimed the lives of about 146 thousand people globally, the greatest annual death toll from storms in the previous three decades[47]. One of the deadliest storms of the century struck Bangladesh that year when a huge cyclone struck. Storm-related fatalities were also exceptionally high in 2008, primarily as a result of a cyclone that struck Myanmar in May[47]. Hybrid machine learning techniques have improved thunderstorm modeling globally. In China's flood-prone areas, ensemble models that integrate GARCH, LSTM, and ARIMA have shown increased accuracy in predicting weather volatility[48].

Through a variety of initiatives, such as ads and training courses, the government is aggressively educating the people about the dangers of lightning and thunderstorms[49]. The building of cyclone shelters is one of the government's efforts to fortify the infrastructure against the effects of lightning and thunderstorms[50]. Future research should extend the current univariate forecasting framework to incorporate multivariate time-series modeling with key atmospheric drivers such as pressure, humidity, sea surface temperature (SST), and wind shear to better capture the complex dynamics preceding thunderstorm events. Advanced ensemble strategies, including weighted averaging, stacking, or boosting, should also be explored to improve forecast reliability beyond the simple averaging used in this study. Methodological innovations from adjacent fields offer valuable insights; for instance, hybrid modeling approaches combining statistical and machine learning techniques have been successfully applied to predict complex environmental phenomena [15]. Such an integrated approach would align with Bangladesh's national priority of mitigating lightning-related fatalities, which have claimed over 3,000 lives in the last decade.

Our model has limitations such as overfitting and underfitting. While underfitting can overlook subtle indicators of storm activity, resulting in missed forecasts, overfitting may cause the model to learn noise instead of true thunderstorm patterns. Moreover, a simple averaging was used to develop the ensemble combination model, which cannot best capture the contribution of each model. Future research of Sitakund must consider multivariate time series modeling using more atmospheric parameters that comprise pressure, humidity, sea surface temperature (SST), and wind shear. The state-of-the-art ensemble learning methods, including weighted averaging, stacking, or boosting, must also be looked into to enhance the reliability of the forecast.

5. Conclusion

Even in Bangladesh's low-risk regions, this study emphasizes how crucial precise thunderstorm forecasting is to controlling public health hazards and improving readiness for disasters. The suggested approach outperforms individual models in capturing intricate patterns and seasonal variations by combining machine learning and deep learning models. Additionally, proactive decision-making, effective resource allocation, and public safety education can be supported by incorporating sophisticated forecasting tools into local governing systems. These results highlight the potential of combination models as accurate weather prediction tools and their function in building resilience in communities that are at risk.

Declarations

This manuscript is an original work and has not been published previously, nor is it under consideration for publication elsewhere, in whole or in part, in any language.

Availability of Data and Materials

The data used in this study were provided by the Climate Division of the Bangladesh Meteorological Department. Access to the data may be subject to the agency's data sharing policies and is available from the corresponding author upon reasonable request.

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Author contributions:

S.A. contributed to processing, analyzing data, interpreting the results, editing, and drafting the manuscript. M.M.H.K.'s main contributions were pre-processing the data and analyzing the findings. R.R. conceptualized the research idea and design and supervised the study. Every author has approved the final version.

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