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Meteorological Parameter Prediction: A Comprehensive Review of Statistical, Machine Learning, and Deep Learning Approaches

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Abstract

Weather forecasting involves predicting atmospheric conditions for a specific location using various weather parameters. This is done by collecting data on the usual atmospheric conditions. However, reliable weather forecast remains a complex challenge for forecasters and analyzers. Weather data are critical across many sectors, including agriculture, tourism, airport operations, mining, and power generation. Traditional computational intelligence models have proven insufficient for delivering accurate predictions. Consequently, deep learning approaches are increasingly used to measure large data records, enabling more effective predictions by learning from historical data. The main component of the research includes the reviews of various statistical, machine learning, deep learning models, and hybrid models for meteorological parameter prediction. It evaluates their performance using different metrics. The proposed planning suggests that hybrid models offer superior prediction accuracy and recommends future research to explore their potential further. The intent of this research lies in its potential to improve weather forecasting accuracy.

Categories: Predictive Analytics, Deep Learning, Machine Learning (ML)
Keywords: meteorological parameters, weather forecasting, statistical models, machine learning models, deep learning models

Introduction And Background

Weather forecasting involves predicting atmospheric conditions (temperature, humidity, dew point, rainfall, pressure, wind direction, wind speed) through data analysis. Instruments like barometers, radar, and thermometers aid data collection. Accurate forecasts depend on factors like current weather observations, historical patterns, air and cloud movement tracking, and air pressure changes. Accurate atmospheric prediction is essential for safety and diverse sectors (occupation, journey, amusement). Agriculture benefits from informed decisions based on weather forecasts for enhanced crop yields [1]. Airports and naval operations depend on continuous weather updates for safe operations. Wind farms rely on accurate wind speed predictions for efficient turbine management during power generation. The mining industry requires precise weather information for monitoring the Earth’s crust and ensuring safety. Reliable weather forecasting is essential for tracking climate trends and providing timely environmental data for informed decision-making at various levels. Moreover, in precise cases, exact atmospheric predictions can help mitigate the impact of floods and droughts. Recent technologies like computational power, data bins, machine learning, and deep learning algorithms enable more precise climate predictions. Deep learning effectively extracts patterns from weather data. Various deep learning models have been developed for accurate weather forecasting. This paper reviews these models and their techniques. Traditional weather forecasting often involves a large team of meteorologists using a combination of techniques [2]. All the traditional weather forecasting models are discussed in Figure *1*. Persistence forecasting is a simple approach that uses current conditions to predict future values. The synoptic forecasting technique utilizes meteorological principles and observations to forecast future conditions. Statistical forecasting relies on historical weather data to predict future conditions based on statistical models. Computer forecasting uses complex computer models to simulate weather conditions and make predictions for the next few days. The following subsection highlights the key contributions of this work.

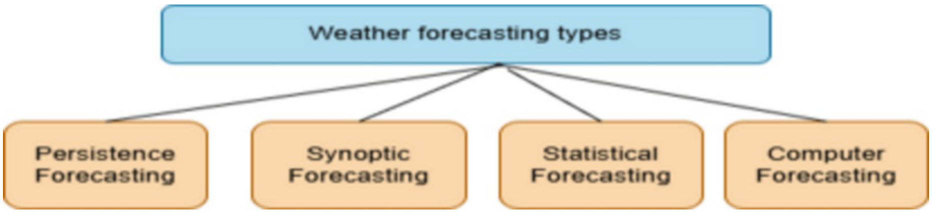

FIGURE 1: Weather forecasting types

Objectives

1. To investigate and compare various approaches, including statistical inference, machine learning, deep learning, and hybrid models, for different meteorological parameters prediction.

2. To evaluate the positive aspects along with the drawbacks of each approach.

3. To highlight the use of advanced techniques and hybrid approaches for improved atmospheric predictions.

4. Reviewing common performance metrics to evaluate each model enhances result comparability.

Organization

The remaining paper's structure is as follows: The Review section presents a comprehensive literature review of weather prediction models, including statistical, machine learning, deep learning, and hybrid approaches. It discusses the strengths and limitations of each model type and summarizes their performance based on relevant evaluation metrics. The Conclusions section summarizes the key findings and identifies promising future research directions for enhancing weather prediction accuracy.

Abbreviations used in this survey are presented in Table *1*.

Abbreviation	Definition
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
AR	Autoregressive
BiLSTM	Bidirectional long short-term memory
CNN	Convolutional neural network
DL	Deep learning
EEMD	Ensemble empirical mode decomposition
EMD	Empirical mode decomposition
FB	Fractional bias
GADTO	Generalized adaptive differential time optimization
GBR	Gradient boosting regression
GRU	Gated recurrent unit
LSSVM	Least squares support vector machine
LSTM	Long short-term memory
MA	Moving average
MAE	Mean absolute error
MAPE	Mean absolute percentage error

MBE	Mean bias error
ML	Machine learning
MLP	Multilayer perceptron
MLR	Multiple linear regression
MSE	Mean squared error
NARX	Nonlinear autoregressive exogenous model
NMAE	Normalized mean absolute error
NMSE	Normalized mean squared error
PE	Percentage error
RBF	Radial basis function
RF	Random forest
RMSE	Root mean squared error
RNN	Recurrent neural network
RSE	Residual standard error
SARIMA	Seasonal autoregressive integrated moving average
SARIMAX	Seasonal autoregressive integrated moving average with exogenous variables
SVR	Support vector regression
TM	Temperature
VAR	Vector autoregression
VARMA	Vector autoregressive moving average
VMA	Vector moving average
WS	Wind speed
XGBoost	Extreme gradient boosting

TABLE 1: Abbreviations

Review

Theoretical framework

This area provides an extensive review of literature related to weather forecasting techniques. Sabat et al. [3] focus on predicting essential meteorological parameters for Bengaluru City using statistical time series models aimed at enhancing weather forecast precision. In the study by Grigonytė and Butkevičiūtė [4], the ARIMA approach is applied to forecast limited WSs, optimized to improve accuracy, and the study suggests that combining ARIMA with other techniques could yield better results. In the study by Tektaş [5], a provisional analysis of the ANFIS and ARIMA approaches for weather prediction in Göztepe, İstanbul, finds ANFIS more accurate, thereby recommending it for practical forecasting applications. Elshewey et al. [6] introduce a hybrid approach that integrates wavelet decomposition with seasonal ARIMA and SARIMAX to forecast long-term temperatures in Delhi, showing superior performance over traditional models.

Dosdoğru and İpek [7] explore hybrid models that integrate XGBoost and ANNs to optimize WS predictions. Nagaraj and Kumar [8] tested various DL models such as LSTM, GRU, BiLSTM, and a CNN+LSTM combination for temperature and humidity predictions, with CNN+LSTM using the adaptive moment estimation (ADAM) optimizer emerging as the top performer. Barrera-Animas et al. [9] compare LSTM, BiLSTM, and XGBoost models for rainfall prediction, finding that BiLSTM yields the most promising outcomes.

Le et al. [10] propose a NARX approach to forecast daily rainfall in Hoa Binh City, leveraging meteorological data as input. Duhoon and Bhardwaj [11] seek to predict TM, WS, and rainfall through AI models and show that the MLP outperforms the RBF and systematic minimum optimization models for Delhi. Bochenek and Ustrnul [12] review various ML techniques, including DL, ANNs, backing vector machines, and XGBoost, concluding that ML is essential for future advancements in weather forecasting.

Ali et al. [13] propose a new optimization algorithm GADTO, for enhancing the BiLSTM model's accuracy in WS prediction, achieving a lower RMSE than other models. In the study by Alomar et al. [14], SVR, ARIMA, RF, and GBR are employed to predict air TM, with SVR delivering the most accurate daily and weekly forecasts. Nketiah et al. [15] examine RNNs and LSTM for atmospheric TM forecasting, revealing that LSTM performs better, especially with feature selection. Novitasari et al. [16] use ANFIS and SVR to predict various meteorological parameters, applying SVR specifically for rainfall forecasting.

Malik et al. [17] discuss the importance of accurate WS and solar radiation forecasts for renewable energy, comparing ANN algorithms, including Levenberg-Marquardt and Bayesian optimization methods, to boost accuracy. Finally, in the study by Endalie et al. [18], an LSTM model is developed to predict daily rainfall in Jimma, Ethiopia, showing high accuracy through RMSE, MAPE, and R^2, highlighting LSTM's potential for reliable rainfall predictions.

An overview of weather prediction modeling approaches

Figure *2* outlines the generic architecture for the atmospheric prediction model, encompassing data collection, data refinement, model identification, model fitting, validation, and result presentation. With the advent of technologies like internet of things, wireless sensor networks, and cloud computing, vast amounts of weather data are now accessible in diverse formats. However, this data often contains irrelevant and missing information. Data pre-processing techniques are crucial for improving data quality and preparing it for model fitting. Data refinement involves removing unwanted variations, null entries, and irregularities, which are often imputed using methods like mean, median, mode, or generative adversarial network. Model selection and training are crucial steps in any forecasting system. The choice of a suitable forecasting model, such as statistical, ML, or DL models, depends on the specific application domain and data characteristics. The selected model is trained on previous observations to learn structures and correlations. After training, the model's performance is checked using statistical metrics like MSE, RMSE, and MAE. Accurate weather forecasting is crucial for mitigating the impact of adverse weather events on social and economic activities. In recent years, several strategies have evolved to achieve this goal.

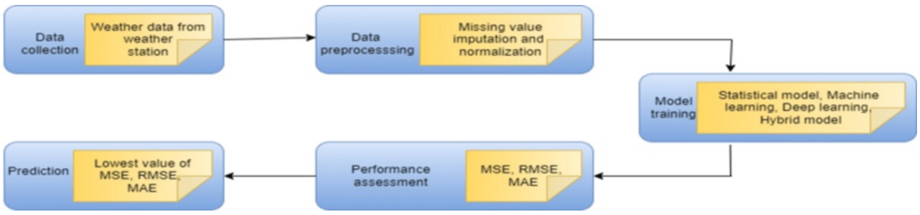

FIGURE 2: General framework for the weather prediction models

The following sections explore different categories of weather forecasting models presented in Figure *3*.

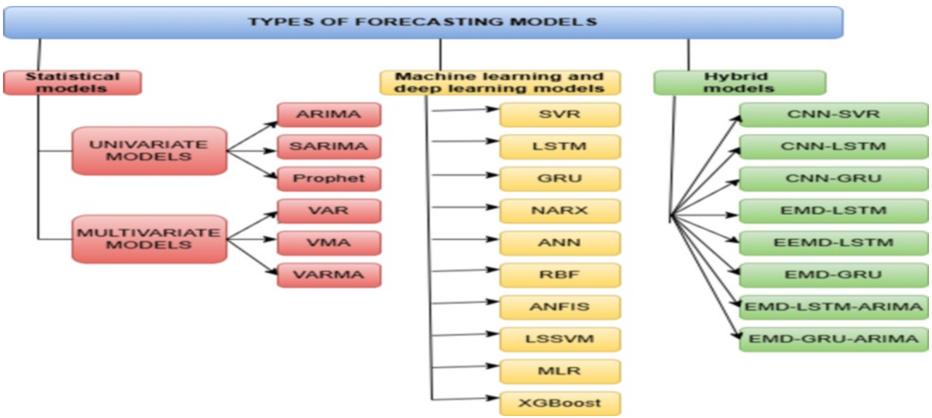

FIGURE 3: Types of predictive analytics models

Statistical models

Statistical models rely on previous observations to identify structures and correlations, and then use statistical techniques to make predictions. While effective for certain weather phenomena, analytical models may struggle to convey the intricacy and nonlinearity of weather patterns, especially during extreme events. Based on analyzing a number of meteorological parameters, the models are segmented into two divisions called univariate and multivariate models. The details of the above-mentioned models are as follows.

Univariate Statistical Model

Univariate time series models focus on forecasting the future values of a single variable using its previous observations. These models aim to capture temporal structures, including movements and seasonality. Common techniques employed in univariate models include autoregressive models, smoothing methods, and stochastic models.

ARIMA model: The traditional statistical model ARIMA (p, d, q) was created for past-series analysis. The numbers p, d, and q in this example indicate the number of AR, the MA, and the form of differencing needed to transform the nonstationary data to stationary data. Equation (1) represents the mathematical expression of the ARIMA model that utilizes lag polynomials:

$$\varphi_p(B)\,\phi_p(B^m)\,X_tY_t = \theta_q(B)\,\Theta_Q(B^m)^D\,\epsilon_t \qquad (1)$$

where

$$X_t = (1-B)^d\,(1-B^m)^D \qquad (2)$$

here, the terms (1-B),(1-B^m) are the non-seasonal and seasonal difference operators, and d and D are the rules, respectively.

Similarly, $\varphi_p(B)\,\phi_p(B^m)$ is defined as non-periodic and periodic AR polynomials of rule p, P, respectively. Further, $\theta_q(B)\,\Theta_Q(B^m)^D$ is defined as non-periodic and periodic MA polynomials of rule q, Q, respectively.

Finally, X_t and Y_t are the past series values at past t, and ϵ_t is the white noise process.

SARIMA model: SARIMA is an ARIMA approach with a periodic component. When past series data demonstrate seasonality, the SARIMA model is applied. The model is stated in Equation (3) with parameter values SARIMA ((p, d, q) (P, D, Q) m). The p, d, and q here are connected to the non-periodic ARIMA approach rule. Furthermore, P represents AR, D denotes periodic difference, Q denotes periodic MA, and m signifies the count of seasons:

$$\left(1-\sum_{j=1}^{p}\theta_j \mathrm{L}^j\right)(1-L)^d\,Y_t = \alpha + \left(1+\sum_{k=1}^{q}\theta_k \mathrm{L}^k\right)\epsilon_t \qquad (3)$$

L represents the decrease operator, θ represents the MA parameter, and ϵ_t represents the failure term. The rules q, d, and p denote the structure of ARIMA approach and are greater than or equal to zero. If d = 0, the ARIMA approach reduces to ARMA and has no differencing rule. d = 1 in the great majority of cases.

Prophet model: The Prophet approach, developed by Facebook, is planned for forecasting past batch data, especially those with daily observations containing seasonality, holidays, and trend changes. It effectively handles large datasets with missing data and outliers and is particularly adept at capturing seasonal effects. This makes it a valuable tool for a variety of past series forecasting tasks. The prophet model is stated in Equation (4):

$$y(m) = g(m) + s(m) + h(m) + \epsilon_m \qquad (4)$$

where $y(m)$ recorded value at time m, $g(m)$ movements function, $s(m)$ periodic component, $h(m)$ impact of vacation, and ϵ_m error term.

Strengths and Drawbacks of Statistical Univariate Models

1. Statistical models are often relatively simple to understand and implement.

2. They can be applied to datasets of moderate size, making them suitable for limited data scenarios.

3. Less accurate for capturing long-term trends and complex patterns.

4. Ignores external influences and is limited to analyzing single time series variables.

Multivariate Statistical Model

Multivariate time series models are designed to forecast multiple interrelated time series variables simultaneously. Unlike univariate models that focus on individual time series, multivariate models capture the dependencies and relationships between different variables. These models often extend traditional univariate techniques to accommodate the multivariate nature of the data.

VAR: The VAR model extend traditional univariate time series analysis by simultaneously forecasting multiple interdependent time series. They relate current values to past values of the variables, using an autoregressive component denoted by p.

The mathematical expression for the VAR approach of rule p is presented in Equation (5):

$$V_t = \mu + M_1 V_{t-1} + M_2 V_{t-2} + \cdots + M_p V_{t-p} + \epsilon_t \qquad (5)$$

where V_t is the (n × 1) magnitude of past batch at moment t, μ is the fixed value, and ϵ_t is the deviation term at moment t.

VMA: The VMA model analyzes multivariate time series data by representing the linear correlation between current values and past error terms. It is denoted by the moving average component q. The mathematical expression for a VMA(q) model is given in Equation (6):

$$V_t = \mu + R_1 \epsilon_{t-1} + \cdots + R_q \epsilon_{t-q} + \epsilon_t \qquad (6)$$

where V_t is the (n × 1) magnitude of past batch at moment t, μ is the fixed value, and ϵ_t is the deviation term at moment t.

VARMA: The VARMA model combines the AR and MA components of VAR and VMA models, respectively. The mathematical expression for a VARMA(p, q) model is given in Equation (7):

$$V_t = c + M_1 V_{t-1} + \cdots + M_p V_{t-p} + \epsilon_t + R_1 \epsilon_{t-1} + \cdots + R_q \epsilon_{t-q} \qquad (7)$$

where M_t represents the past value dependence, and R_t represents the error term dependence.

Table *2* summarizes the meteorological parameters such as TM, WS, and rainfall used in the statistical approaches. The effectiveness of these approaches is analyzed based on MSE, RMSE, and MAE. Table *3* presents the effectiveness evaluation metrics such as MSE, RMSE, and MAE for each meteorological parameter and for statistical models.

	Parameters			**Matrices**		
Models	Temperature	Wind speed	Rainfall	MSE	RMSE	MAE
ARIMA, SARIMA, Prophet, VAR, VMA, VARMA[3]	√	√		√	√	√
ARIMA [5]	√			√	√	√
ARIMA [19]			√		√	
ARIMA [4]		√		√	√	√
ARIMA [20]		√		√	√	√
ARIMA [21]			√		√	√

TABLE 2: Summary of variables utilized in statistical analysis

Parameters and references	MSE	RMSE	MAE
TM [3]	1.016	1.008	0.78
TM [3]	2.97	1.72	1.03
TM [3]	0.792	0.89	0.70
TM [3]	0.756	0.87	0.66
TM [3]	1.904	1.38	1.10
TM [3]	0.756	0.87	0.66
TM [5]	2.89	1.70	1.32
WS [3]	8.15	2.855	2.193
WS [3]	10.75	3.28	2.55
WS [3]	5.89	2.427	1.823
WS [3]	6.68	2.586	2.050
WS [3]	10.08	3.175	2.479
WS [3]	5.89	2.427	1.823
WS [4]	24.9	4.99	4.14
Rainfall [18]		0.057	
WS [19]	1.51	1.22	0.91
Rainfall [20]		91.49	65.02

TABLE 3: Error values for TM, WS, and rainfall for each model

Strengths and Drawbacks of Statistical Multivariate Models

1. Captures complex relationships and interdependencies between multiple variables.

2. Requires a large amount of data for training in multivariate models.

3. Complex to build and prone to issues like multicollinearity, exceeding, and model interpretability.

ML and DL models

ML and hierarchical learning models have emerged as powerful tools for weather forecasting. These methods, including cognitive frameworks, support vector machines, and ensemble methods, can learn complex patterns from large datasets, leading to more accurate and reliable predictions. Some common ML and DL models are discussed below.

MLR

Linear regression, both simple and multivariate, can be used for forecasting. Simple linear regression involves a single independent variable, while multivariate regression utilizes multiple independent variables. In this study, a MLR model was employed to predict daily rainfall using multiple environmental variables as input features. Multiple variable linear regression utilizes multiple independent parameters (X) to predict a single dependent parameter (Y). The mathematical expression of MLR is Equation (8):

$$Q_i = \beta_1 m_{i1} + \beta_2 m_{i2} + \beta_3 m_{i3} + \ldots + \beta_p m_{ip} + \epsilon_i = \mathbf{M}_i^T \boldsymbol{\beta} + \epsilon_i, \quad i = 1, 2, 3, \ldots, n \qquad (8)$$

here, Q_i is the dependent response for the i-th observation, $m_{i1}, m_{i2}, \ldots, m_{ip}$ are the independent variables or predictors for the i-th observation, ε_i is the residual for the i-th observation, $\mathbf{M}_i$ is the vector of predictors for the i-th observation, and $\beta_1, \beta_2, \beta_3, \ldots, \beta_p$ are the coefficients associated with each predictor.

RF

The RF regression is a forceful ML description for non-linear relationships. As an ensemble method, it constructs multiple decision trees during training and averages their predictions. The algorithm involves the following steps:

1. Randomly select a subset of data points from the training set.

2. Build a decision tree using the selected subset.

3. Repeat steps a and b to create N decision trees.

4. To predict a new data point, each tree makes a prediction, and the final prediction is the average of all these predictions.

The general mathematical expression of RF is Equation (9):

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tanh(W_h \cdot x_t + U_h \cdot (r_t \odot h_{t-1}) + b_h) \qquad (9)$$

here, h_t is the isolated state at past t, z_t is the revise gate at past t, h_{t-1} is the isolated state from the prior past step $t-1$, is the element-wise product, tanh is the hyperbolic tangent action,

W_h

is the poundage matrix, x_t is the charge vector at past t, U_h is the poundage grid, r_t is the readjust gate at past t, and b_h is the bias direction.

LSTM

The LSTM models carry out the vanishing gradient dispute in RNNs, enabling them to learn high-term dependencies in sequential data. LSTMs overcome this issue by using a recollection cell that can cache facts over long periods. This recollection cell is controlled by three gateways: the charge gateway, the forget gateway, and the gain gateway. These gateways regulate the flow of data into and out of the cell, allowing the grids to learn and retain deep-term dependencies.

1. Charge Gateway: This gateway controls the amount of new facts that enter the cell state.

2. Gain Gateway: This gateway regulates how much of the cell state is gain to the grid.

3. Forget Gateway: This gateway controls the amount of facts from the prior cell state that are forgotten.

GRU

The GRU addresses the vanishing gradient problem in RNNs, enabling them to learn long-term dependencies. GRUs use gating tools to switch the stream of facts through the grid, letting them capture deep-term dependencies more effectively.

SVR

The SVR is a powerful ML algorithm for regression assignments. It finds the optimal hyperplane to minimize prediction errors. SVR uses kernel actions to map facts into higher dimensions for linear separation. By adjusting the kernel parameters, SVR can effectively handle complex, nonlinear relationships. This makes it a suitable choice for weather forecasting, where the underlying patterns are often intricate and non-linear.

ANN

The ANNs are computational imitations inspired by biological neural nets. They provide a framework for various ML algorithms to process complex input data without requiring explicit programming. ANNs typically coincide with three main layers: input, hidden, and output layers. In this review, the rated conjugate pitch method was employed to study the neural nets, accelerating confluence by guiding the quest search in conjugate orders.

ANFIS

The ANFIS combines the learning capabilities of cognitive frameworks with the information depiction of fuzzy inference systems. It utilizes a layered architecture, with each layer performing specific functions.

ANFIS leverages gradient descent and chain rule for learning and optimization.

Table *4* lists the meteorological parameters such as TM, WS, and rainfall used in the machine ML and DL frameworks. Table *5* represents the performance evaluation metrics such as MSE, RMSE, and MAE for each parameter, ML, and DL framework.

	Parameters			**Matrices**		
Models	Temperature	Wind speed	Rainfall	MSE	RMSE	MAE
LSSVM [22]	√			√	√	√
MLR, XGBoost, RF [23]			√	√	√	√
NARX [10]			√	√	√	√
SMO, RBF, MLP [11]		√	√	√	√	√
BiLSTM [13]		√			√	√
RF, GBR, SVR [14]	√			√	√	√
SVR [16]			√	√	√	
MLP, ANFIS, BLSTM, LSTM [19]			√		√	
LSTM, GRU, BiLSTM [24]	√			√	√	
RF, GBT [25]	√				√	√
NARX [26]		√		√	√	√
LSTM [27]	√				√	
ANN, PSOANFIS, SVM [28]			√			√
LSTM [29]		√		√	√	√
LSTM, GRU [30]		√		√	√	√

TABLE 4: Summary of variables utilized in machine learning and deep learning analysis

GBR: gradient boosting regression; GBT: gradient boosting tree; SMO: systematic minimum optimization

Parameters and references	MSE	RMSE	MAE
TM [22]	2.43	1.56	1.25
TM [14]	3.24	1.8	1.3
TM [14]	12.96	3.6	2.8
TM [14]	13.69	3.7	2.8
TM [24]	1.037	1.018	0.791
TM [24]	1.135	1.065	0.811
TM [24]	1.274	1.128	0.853
TM [25]		0.016	0.021
TM [25]		0.017	0.022
TM [27]		0.082	
Rainfall [10]	28.83	5.37	3.02
Rainfall [11]	32.49	5.7	1.84
Rainfall [11]	92.16	9.6	4.0
Rainfall [11]	0.0256	0.16	0.14
Rainfall [16]	0.09	0.3	
Rainfall [19]		0.03	
Rainfall [19]		0.074	
Rainfall [19]		0.04	
Rainfall [19]		0.01	
Rainfall [28]			3.209
Rainfall [28]			3.281
Rainfall [28]			2.728
Rainfall [23]	74.13	8.61	4.97
Rainfall [23]	61.6	7.85	3.58
Rainfall [23]	77.7	8.82	4.49
WS [11]	3.42	1.85	1.43
WS [11]	3.72	1.93	1.44
WS [11]	0.014	0.12	0.18
WS [13]		0.012	0.007
WS [26]	5.01	2.248	1.751
WS [29]	0.739	0.86	0.67
WS [30]	0.098	0.314	0.256
WS [30]	0.1332	0.365	0.269

TABLE 5: Error values for TM, WS, and rainfall for each model

Strengths and Drawbacks of ML and DL Models

1. Ability to handle complex data patterns and high accuracy potential.

2. Automated feature extraction for nonlinear relationships.

3. Risk of overfitting and requires extensive parameter tuning.

4. High data requirements and interpretability challenges.

Hybrid models

Hybrid models combine statistical and ML techniques for improved forecasting accuracy. These models often integrate statistical models with DL techniques, such as combining ARIMA with LSTM or GRU. Hybrid models capture long-term trends and short-term fluctuations for accurate predictions. Hybrid models like EMD-LSTM, EEMD-LSTM, and EEMD-GRU are sophisticated methods for time series forecasting, especially for complex, non-linear data. EMD-LSTM decomposes time series using EMD before LSTM modeling. Then, it uses LSTM frameworks to predict each component, leading to more accurate forecasts. EEMD-LSTM refines this approach by employing EEMD to prevent mode mixing, resulting in more robust and reliable LSTM-based predictions. EEMD-GRU is similar to EEMD-LSTM but uses GRU instead of LSTM, offering a computationally efficient alternative while maintaining high prediction quality. These hybrid models are particularly valuable in areas such as weather forecasting, energy demand prediction, and financial market analysis, where time series data are often non-linear and non-stationary.

Table *6* summarizes the meteorological parameters such as TM, WS, and rainfall used in the hybrid models. The efficiency of these models is analyzed using MSE, RMSE, and MAE, as exhibited in Table *7*.

	Parameters			**Matrices**		
Models	Temperature	Wind speed	Rainfall	MSE	RMSE	MAE
CNN-LSTM [24]	√			√	√	√
CNN-BiLSTM [24]	√			√	√	√
CNN-GRU [24]	√			√	√	√
EMD–LSTM, EEMD–LSTM [29]		√		√	√	√
ANFIS-FFA [30]			√	√	√	√
EMD-LSTM, EMD-GRU [30]		√		√	√	√
EMD-LSTM-ARIMA, EMD-GRU-ARIMA [30]		√		√	√	√

TABLE 6: Summary of variables utilized in hybrid analysis

Parameters and references	MSE	RMSE	MAE
TM [24]	0.97	0.98	0.764
TM [24]	1.52	1.23	0.90
TM [24]	0.97	0.98	0.77
WS [29]	0.44	0.67	0.46
WS [29]	0.152	0.39	0.29
WS [30]	0.152	0.180	0.131
WS [30]	0.152	0.198	0.147
WS [30]	0.152	0.161	0.113
WS [30]	0.152	0.177	0.123
Rainfall [30]	0.073	0.272	0.133

TABLE 7: Error values for TM, WS, and rainfall for each model

Strengths and Drawbacks of Hybrid Models

1. Improved pattern capture and enhanced accuracy.

2. Increased complexity and computational cost.

3. A high volume of data requirements and difficulty in enhancing.

Measured parameters

Accurate measurements are crucial for the success of any forecasting model. Model performance can be evaluated using various metrics. Different models may use different metrics to evaluate performance. Performance metrics like NMSE, MBE, PE, FB, RSE, and NMAE are also essential for assessing meteorological model accuracy. These metrics provide crucial insights into model performance, helping identify systematic biases, quantify prediction errors, and assess the overall goodness-of-fit. By pinpointing model shortcomings and successes, researchers can enhance forecasts for critical parameters such as TM, WS, and rainfall. This has profound implications for sectors like agriculture, disaster response, and renewable energy.

MAE measures the average absolute difference between the predicted worth $\hat{a}_m$ and actual worth a_m. RMSE calculates the square root of the average squared differences, giving greater weight to larger errors. MSE calculates the average squared difference between predicted and real worth. MAPE evaluates the relative accuracy of predictions by calculating the average percentage difference between predicted and true worth. In all cases, lower values signify higher model accuracy. These error indicators are mathematically defined by Equations (10) through (19):

$$\mathrm{MAE} = \frac{1}{n}\sum_{m=1}^{n}|a_m - \hat{a}_m| \qquad (10)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{m=1}^{n}(a_m - \hat{a}_m)^2 \qquad (11)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{m=1}^{n}(a_m - \hat{a}_m)^2} \qquad (12)$$

$$\mathrm{NMSE} = \frac{\frac{1}{n}\sum_{m=1}^{n}(a_m - \bar{a})^2}{\frac{1}{n}\sum_{m=1}^{n}(a_m - \hat{a}_m)^2} \qquad (13)$$

$$\mathrm{RSE} = \sqrt{\frac{\sum_{m=1}^{n}(a_m - \hat{a}_m)^2}{n-k-1}} \qquad (14)$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(a_m - \hat{a}_m)^2}{\sum_{m=1}^{n}(a_m - \bar{a})^2} \qquad (15)$$

$$\mathrm{NMAE} = \frac{1}{n}\sum_{m=1}^{n}\frac{|a_m - \hat{a}_m|}{\text{Normalization Factor}} \qquad (16)$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{m=1}^{n}(\hat{a}_m - a_m) \qquad (17)$$

$$\mathrm{PE}_m = \frac{a_m - \hat{a}_m}{a_m} \times 100 \qquad (18)$$

$$\mathrm{FB} = \frac{2(\hat{a} - a)}{\hat{a} + a} \qquad (19)$$

here, $\hat{a}_m$ depicts the anticipated value, a_m depicts the true value, and n is the total number of data points. Among these metrics, MAE, MSE, and RMSE are considered negative indicators, meaning lower values signify better prediction accuracy.

Make sure to define the normalization factor clearly in your context, as it could vary (e.g., the mean of the actual values, a range, or a specific constant).

Research gaps and future research directions

1. Based on the analysis of the literature, several challenges have been identified in the field of weather forecasting. Addressing these challenges presents promising avenues for future research.

2. Data collection is crucial for forecasting, but the availability and quality of real-time weather facts remain challenging.

3. Most studies have used small datasets. Future research should focus on using large datasets and various techniques.

4. Significant research exists for TM, WS, and rainfall forecasting, but other parameters like pressure, wind direction, and dewpoint require further exploration.

5. Hybrid models show promise for future weather forecasting, potentially outperforming both statistical and ML models.

Summary of main research questions and claims

The main research questions addressed by this study are as follows:

1. What is the effectiveness of different models in predicting meteorological parameters?

2. How can the accuracy of meteorological parameter prediction be improved using various modeling approaches?

3. What is the impact of different modeling approaches on the accuracy of weather forecasting, as measured by RMSE, MAE, and MSE?

This study makes several key claims about meteorological parameter prediction:

1. Traditional statistical models exhibit limitations in accurately capturing complex patterns and non-linearities inherent in meteorological data.

2. ML and DL models demonstrate superior performance in capturing complex patterns and non-linearities in meteorological data, leading to more accurate predictions.

3. Hybrid models, combining the strengths of statistical, ML, and DL techniques, offer enhanced predictive

accuracy and robustness compared to individual models.

Conclusions

DL techniques have significantly improved the accuracy and effectiveness of weather forecasting and climate prediction. This survey delves into recent research in weather forecasting, providing a detailed analysis of various statistical models, ML models, DL models, and hybrid models, along with their applications in predicting specific weather parameters. The survey analyzes the performance of different techniques, highlighting the strengths and drawbacks of each method for weather forecasting. The models are assessed using various performance evaluation metrics for each parameter. Recent advancements in deep neural networks and hybrid models have shown promising results in enhancing prediction accuracy. This survey offers a large-scale overview of modern weather prediction models, their objectives, available datasets, and potential future research directions. It serves as a valuable resource for researchers interested in exploring the field of weather forecasting.

This research aligns with existing studies in the following ways: (i) It contributes to the growing field of ML and DL in meteorology. (ii) While traditional statistical methods have limitations, ML approaches offer improved accuracy but face challenges, such as overfitting. (iii) This study builds on previous research by reviewing and comparing statistical, ML, and hybrid models. (iv) It evaluates their performance using RMSE, MAE, and MSE, highlighting the advantages of hybrid models. (v) The findings contribute to the increasing interest in DL-based solutions for improved weather forecasting.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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References

1. Jaydev M, Kar R, Senapati BR, Nayak SK: Intelligent agro-industry for crop production considering soil properties and climatic variables to boost its efficiency. Machine Learning and Optimization for Engineering Design. Shastri AS, Shaw K, Singh M (ed): Springer, Singapore; 2023. 1:57-73. 10.1007/978-981-99-7456-6_5
2. Naveen L, Mohan HS: Atmospheric weather prediction using various machine learning techniques: a survey . 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Erode, India. 2019, 422-428. 10.1109/ICCMC.2019.8819643
3. Sabat NK, Nayak R, Srivastava H, Pati UC, Das SK: Prediction of meteorological parameters using statistical time series models: a case study. International Journal of Global Warming. 2023, 31:128-149. 10.1504/ijgw.2023.133547
4. Grigonytė E, Butkevičiūtė E: Short-term wind speed forecasting using ARIMA model. Energetika. 2016, 62:10.6001/energetika.v62i1-2.3313
5. Tektaş M: Weather forecasting using ANFIS and ARIMA models . Environmental Research, Engineering and Management. 2010, 51:5-10.
6. Elshewey AM, Shams MY, Elhady AM, Shohieb SM, Abdelhamid AA, Ibrahim A, Tarek Z: A novel WD-SARIMAX model for temperature forecasting using daily Delhi climate dataset. Sustainability. 2023, 15:757. 10.3390/su15010757
7. Dosdoğru AT, İpek AB: Hybrid boosting algorithms and artificial neural network for wind speed prediction . International Journal of Hydrogen Energy. 2022, 47:1449-1460. 10.1016/j.ijhydene.2021.10.154
8. Nagaraj R, Kumar LS: Univariate deep learning models for prediction of daily average temperature and

relative humidity: The case study of Chennai, India. Journal of Earth System Science. 2023, 132:100. 10.1007/s12040-023-02122-0

9. Barrera-Animas AY, Oyedele LO, Bilal M, Akinosho TD, Davila Delgado JM, Akanbi LA: Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting. Machine Learning with Applications. 2022, 7:100204. 10.1016/j.mlwa.2021.100204
10. Le VM, Pham BT, Le TT, Ly HB, Le LM: Daily rainfall prediction using nonlinear autoregressive neural network. Micro-Electronics and Telecommunication Engineering. Lecture Notes in Networks and Systems. Sharma DK, Balas VE, Son LH, Sharma R, Cengiz K (ed): Springer, Singapore; 2020. 106:213-221. 10.1007/978-981-15-2329-8_22
11. Duhoon V, Bhardwaj R: Artificial intelligence technique for weather parameter forecasting. 2021 International Conference on Computational Performance Evaluation (ComPE), Shillong, India. 2021, 98-102. 10.1109/ComPE53109.2021.9751934
12. Bochenek B, Ustrnul Z: Machine learning in weather prediction and climate analyses—applications and perspectives. Atmosphere. 2022, 13:180. 10.3390/atmos13020180
13. Alhussan AA, El-Kenawy E-SM, Abdelhamid AA, Ibrahim A, Eid MM, Khafaga DS: Wind speed forecasting using optimized bidirectional LSTM based on dipper throated and genetic optimization algorithms. Frontiers in Energy Research. 2023, 11:1172176. 10.3389/fenrg.2023.1172176
14. Alomar MK, Khaleel F, Aljumaily MM, et al.: Data-driven models for atmospheric air temperature forecasting at a continental climate region. PLoS ONE. 2022, 17:e0277079. 10.1371/journal.pone.0277079
15. Nketiah EA, Chenlong L, Yingchuan J, Aram SA: Recurrent neural network modeling of multivariate time series and its application in temperature forecasting. PLoS ONE. 2023, 18:e0285713. 10.1371/journal.pone.0285713
16. Novitasari DCR, Rohayani H, Suwanto, et al.: Weather parameters forecasting as variables for rainfall prediction using adaptive neuro fuzzy inference system (ANFIS) and support vector regression (SVR). Journal of Physics: Conference Series. 2020, 1501:012012. 10.1088/1742-6596/1501/1/012012
17. Malik P, Gehlot A, Singh R, Gupta LR, Thakur AK: A review on ANN based model for solar radiation and wind speed prediction with real-time data. Archives of Computational Methods in Engineering. 2022, 29:3183-3201. 10.1007/s11831-021-09687-3
18. Endalie D, Haile G, Taye W: Deep learning model for daily rainfall prediction: case study of Jimma, Ethiopia . Water Supply. 2022, 22:3448-3461. 10.2166/ws.2021.391
19. Cadenas E, Rivera W, Campos-Amezcua R, Heard C: Wind speed prediction using a univariate ARIMA model and a multivariate NARX model. Energies. 2016, 9:109. 10.3390/en9020109
20. Saikhu A, Arifin AZ, Fatichah C: Rainfall forecasting by using autoregressive integrated moving average, single input and multi input transfer function. 2017 11th International Conference on Information & Communication Technology and System (ICTS), Surabaya, Indonesia. 2017, 85-90. 10.1109/ICTS.2017.8265651
21. Adnan RM, Liang Z, Kuriqi A, Kisi O, Malik A, Li B, Mortazavizadeh F: Air temperature prediction using different machine learning models. Indonesian Journal of Electrical Engineering and Computer Science. 2021, 22:534-541. 10.11591/ijeecs.v22.i1.pp534-541
22. Liyew CM, Melese HA: Machine learning techniques to predict daily rainfall amount . Journal of Big Data. 2021, 8:153 . 10.1186/s40537-021-00545-4
23. Sabat NK, Pati UC, Das SK: ABTCN: an efficient hybrid deep learning approach for atmospheric temperature prediction. Environmental Science and Pollution Research. 2023, 30:125295-125312. 10.1007/s11356-023-27985-0
24. Hanoon MS, Ahmed AN, Zaini N, et al.: Developing machine learning algorithms for meteorological temperature and humidity forecasting at Terengganu state in Malaysia. Scientific Reports. 2021, 11:18935. 10.1038/s41598-021-96872-w
25. Zhao X, Liu J, Yu D, Chang J: One-day-ahead probabilistic wind speed forecast based on optimized numerical weather prediction data. Energy Conversion and Management. 2018, 164:560-569. 10.1016/j.enconman.2018.03.030
26. Salman AG, Heryadi Y, Abdurahman E, Suparta W: Single layer & multi-layer long short-term memory (LSTM) model with intermediate variables for weather forecasting. Procedia Computer Science. 2018, 135:89-98. 10.1016/j.procs.2018.08.153
27. Pham BT, Le LM, Le T-T, Thi Bui K-T, Le VM, Ly H-B, Prakash I: Development of advanced artificial intelligence models for daily rainfall prediction. Atmospheric Research. 2020, 237:104845. 10.1016/j.atmosres.2020.104845
28. Altan A, Karasu S, Zio E: A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer. Applied Soft Computing. 2021, 100:106996. 10.1016/j.asoc.2020.106996
29. Liu M-D, Ding L, Bai Y-L: Application of hybrid model based on empirical mode decomposition, novel recurrent neural networks and the ARIMA to wind speed prediction. Energy Conversion and Management. 2021, 233:113917. 10.1016/j.enconman.2021.113917
30. Yaseen ZM, Ghareb MI, Ebtehaj I, et al.: Rainfall pattern forecasting using novel hybrid intelligent model based ANFIS-FFA. Water Resources Management. 2018, 32:105-122. 10.1007/s11269-017-1797-0