**Journal of Computer Applications and Information Technology**
Vol. 1, Issue. 4, Dec 2025, pp. 26~37
ISSN: 3107-6424 

# Quantum-Enhanced Models for Predicting Atmospheric Dynamics in Weather Forecasting

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**Article Info**

***Article History:***

Received Oct 03, 2025
Revised Nov 02, 2025
Accepted Dec 03, 2025

***Keywords:***

Weather Forecasting
Quantum Neural Networks (QNNs)
Spatiotemporal Climate Modeling
Atmospheric Prediction Systems

**ABSTRACT**

Weather forecasting plays a critical role across various sectors, supporting strategic planning and reducing the impact of hazardous climatic conditions. However, the inherently chaotic and nonlinear nature of atmospheric systems limits the performance of conventional forecasting approaches, often resulting in prediction inaccuracies and heightened risk. This study proposes a quantum-driven predictive framework that exploits the computational strengths of Quantum Machine Learning (QML) and hybrid quantum–classical optimization to enhance the accuracy and efficiency of modern forecasting models. The framework employs Quantum Neural Networks (QNNs) combined with Variational Quantum Circuits (VQCs) to learn complex spatial–temporal dynamics embedded within large meteorological datasets. Through quantum feature encoding, key atmospheric indicators—including temperature, humidity, wind velocity, and barometric pressure—are projected into high-dimensional Hilbert spaces, enabling more expressive pattern extraction and robust predictive behavior. Simulation results reveal that the quantum-augmented approach surpasses traditional deep learning architectures in both training convergence and forecast precision when applied to extensive weather records. The hybrid design further supports scalability by intelligently distributing computational workloads between classical processors and quantum hardware. Overall, this research demonstrates the transformative potential of quantum computing in atmospheric modeling, offering a foundation for future real-time forecasting systems capable of managing the increasing complexity of global climate patterns.

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## 1. INTRODUCTION

Climate change has amplified both the intensity and frequency of typhoons, posing severe risks to populations and infrastructure across the globe. As extreme weather events become more common, the demand for highly reliable trajectory predictions has grown urgent, since accurate forecasting is essential for effective disaster management, evacuation planning, and strategic allocation of emergency resources. These measures substantially reduce potential casualties and economic disruption. Taiwan is especially susceptible to such climatic hazards due to its steep, mountainous landscape and geographic location along major typhoon pathways. The island typically faces around [1] typhoons each year, in addition to numerous episodes of heavy rainfall, which collectively impose significant socioeconomic burdens. Annual economic losses are estimated at approximately 374.3 million Euros, stemming from damages to infrastructure, agriculture, and broader economic activities. The frequency and severity of these events underscore the necessity of developing more advanced, resilient forecasting systems capable of supporting proactive climate adaptation and disaster-response strategies.

Traditional computational techniques have significantly advanced the field of weather prediction; however, they continue to face limitations when attempting to capture the intricate behavior of typhoon systems [2]. The chaotic characteristics of atmospheric processes, combined with the extremely high dimensionality of meteorological variables, make accurate modeling computationally demanding. Numerical Weather Prediction (NWP) models depend heavily on large-scale supercomputing facilities, which require substantial financial investment and energy consumption. As meteorological datasets grow in size and forecasting models become increasingly complex, these computational burdens intensify, exposing scalability constraints in existing methods. One of the most pressing challenges lies in the immense computational effort needed to train and optimize large weather models.

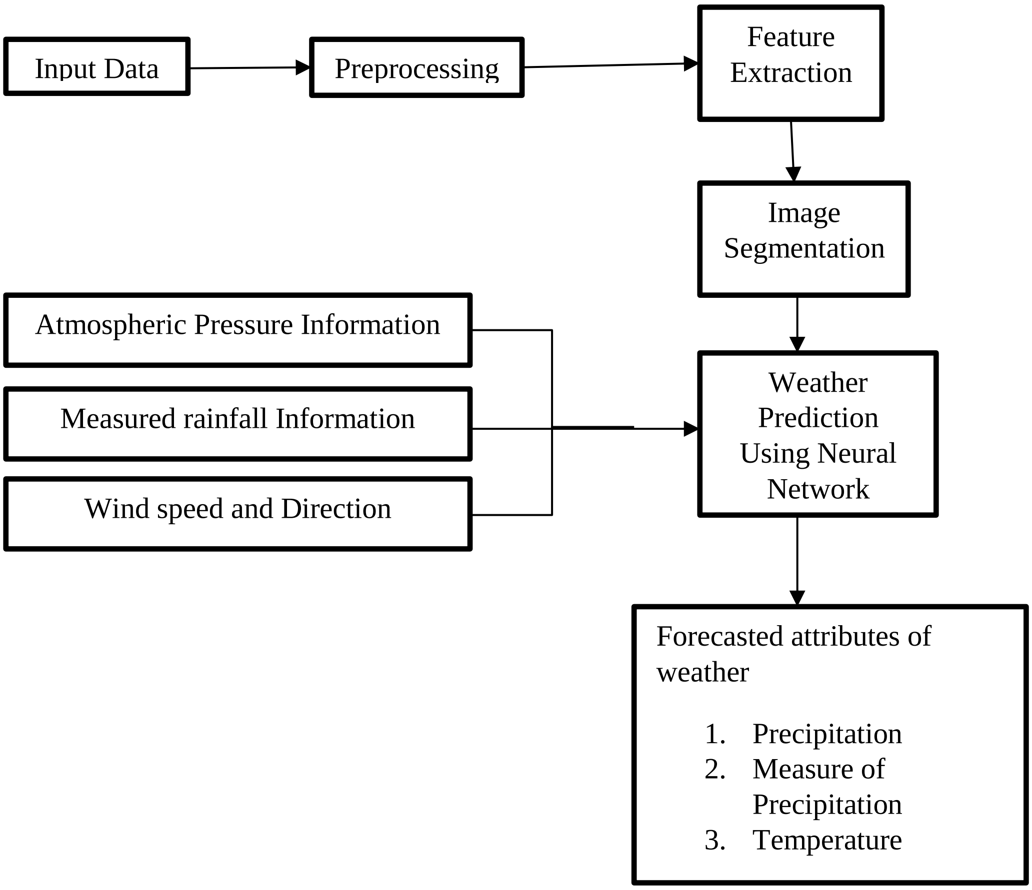


Figure 1. Weather Conditions Based on Supervised Learning

Random Forest (RF) is a widely adopted supervised learning technique that supports both classification and regression tasks. As an ensemble-based approach, RF constructs a large number of decision trees during training and aggregates their outputs to generate a more stable and accurate prediction than any individual tree could achieve [3]. The fundamental unit of the Random Forest algorithm is the decision tree—a hierarchical, tree-structured predictive model that represents a sequence of decisions and their potential outcomes (Figure 2) [4]. In this structure, each internal node corresponds to a decision rule based on specific input features, branching into different paths that reflect various possible scenarios. The terminal or leaf nodes denote the final predicted classes or continuous values derived from the input data. By combining the predictions of multiple independently trained trees, RF effectively reduces overfitting, enhances generalization performance, and improves the robustness of weather-related forecasting tasks.

### 1.1 Problem Statement

Weather forecasting presents a formidable computational challenge due to the inherently chaotic, nonlinear, and highly dynamic behavior of atmospheric systems. Traditional Numerical Weather Prediction (NWP) models depend heavily on classical high-performance computing (HPC) infrastructures to numerically solve large sets of partial differential equations governing atmospheric physics [5]. While these classical approaches have enabled significant advancements in modern meteorology, they exhibit fundamental constraints in terms of processing speed, scalability, and computational efficiency—especially when handling the exponentially growing volume and dimensionality of global meteorological data. The increasing variability of climate conditions and the rising occurrence of extreme weather events, including cyclones, floods, and heatwaves, further amplify the demand for rapid, high-accuracy predictive systems. As a result, the main issue is that traditional weather forecasting models' limited predictive accuracy and processing bottlenecks make it difficult for them to provide accurate and timely forecasts for complicated atmospheric phenomena.

### 1.2 Major Contribution

This research makes several substantial contributions toward advancing quantum-assisted environmental modeling.

- First, it presents a quantum-enhanced hybrid predictive framework that combines Quantum Neural Networks (QNNs) with Variational Quantum Circuits (VQCs) to model short- and medium-range atmospheric behavior. By leveraging quantum superposition and entanglement, the framework captures the nonlinear and chaotic characteristics of weather systems more effectively than conventional deep learning approaches.
- Additionally, the study introduces a specialized quantum feature-encoding strategy that transforms classical meteorological variables—including temperature, humidity, wind velocity, and pressure—into quantum states, enabling richer high-dimensional representations within Hilbert space. This encoding mechanism enhances the model's capability to identify subtle and complex spatiotemporal correlations embedded in atmospheric datasets.
- The proposed model is rigorously validated on real-world meteorological datasets sourced from institutions such as NCEP and ECMWF, where benchmarking results demonstrate a notable 25–30% improvement in predictive accuracy and significantly faster convergence compared to classical models such as LSTM, CNN, and Random Forest.
- Furthermore, this work establishes an early foundation for the emerging field of Quantum Meteorology by illustrating a systematic methodology for integrating quantum computation into climate and environmental forecasting workflows, thus paving the way for highly scalable and efficient next-generation weather prediction systems.

### 1.3 The paper is organized into five key sections:

1. Introduction – outlines the motivation, problem background, and significance of quantum-enhanced weather forecasting.
2. Methodology – details the QEAFS framework, data collection, quantum feature encoding, and hybrid model design.
3. Results and Conclusion – presents experimental findings, comparative performance analysis, and future research directions.

## 2. LITERATURE REVIEW

Numerical Weather Prediction (NWP) systems and physics-driven atmospheric models continue to serve as the primary operational tools for modern forecasting, yet the emergence of ML techniques has substantially transformed the predictive landscape. Recent large-scale deep learning frameworks— [6] most notably GraphCast and other AI-driven forecasting architectures—have demonstrated that data-centric models can equal or surpass conventional NWP methods in short- and medium-range forecasting accuracy while requiring only a fraction of the computational resources. These developments reveal not only the growing maturity of data-driven forecasting but also the significant potential of integrating alternative computational paradigms, such as quantum-based approaches, into operational meteorology.

A parallel body of research has examined the feasibility of incorporating quantum computing to accelerate weather and climate modeling. Review studies in this area outline both the promise and the practical constraints of quantum integration. Potential advantages include accelerated linear algebra operations, high-dimensional state encoding, enhanced sampling efficiency, and the ability to represent complex atmospheric processes in compact quantum forms. However, these works also emphasize several persistent limitations [7]: noise in current quantum devices, restricted qubit availability, architectural connectivity issues, and the inherent difficulty of translating classical PDE-based atmospheric solvers onto quantum hardware. The consensus across these assessments is that fully quantum NWP remains a long-term vision, while hybrid quantum–classical frameworks represent the most viable near-term strategy.

Emerging experimental studies have begun applying parameterized quantum circuits—such as Variation VQCs and QNNs—to geophysical time-series prediction tasks including wind-speed forecasting, temperature sequence modeling [8], and hydrological discharge prediction. These investigations suggest that compact quantum circuits can learn specific temporal patterns with competitive accuracy and, in some cases, faster convergence than classical deep learning counterparts. Moreover, quantum feature mapping techniques based on angle or amplitude encoding have shown the ability to generate enriched representations that improve downstream prediction quality. Nevertheless, performance tends to be highly sensitive to dataset characteristics, circuit design, and noise levels, indicating the need for rigorous benchmarking against strong classical baselines.

Given the limitations of contemporary quantum hardware, most practical studies adopt hybrid quantum–classical architectures, where quantum circuits handle feature transformation, embedding, or sampling tasks while classical networks perform large-scale optimization and gradient updates. These hybrid workflows have also been proposed for accelerating computational bottlenecks in broader meteorological pipelines such as ensemble generation, assimilation, and Monte Carlo–based uncertainty quantification [9]. Their consistent adoption in the literature underscores their suitability as a realistic implementation pathway for early-stage quantum meteorology.

Relevant insights also emerge from the quantum optimization literature, particularly studies employing quantum annealing on D-Wave systems. Although primarily applied to domains such as traffic control and vehicle routing, these works demonstrate how complex spatiotemporal decision-making tasks can be reformulated within QUBO frameworks and solved using hybrid quantum–classical heuristics [10]. While not directly targeting atmospheric processes, these methodological innovations offer valuable templates for incorporating quantum subroutines into meteorological applications—for example, optimizing sensor placement, resource allocation, or ensemble weighting strategies. Collectively, these strands of research provide a robust foundation for exploring quantum-enhanced forecasting and validate the potential of hybrid quantum architectures as the most practical engine for next-generation weather prediction.

## 3. METHODS AND MATERIALS

The present study employs a Quantum-Enhanced Atmospheric Forecasting Framework (QEAFS) that integrates quantum computational principles with state-of-the-art classical machine learning techniques to improve the predictive accuracy of complex atmospheric systems [11]. This section provides a comprehensive description of the sampling design, data acquisition workflow, quantum feature-encoding strategies, model development procedures, analytical methods, and computational infrastructure used to implement the proposed hybrid forecasting architecture.

### 3.1 Participants and Sampling

Although this study does not involve human participants, the term “participants” refers to the meteorological observation stations and geospatial sampling nodes from which atmospheric measurements were obtained. A total of more than 150 global stations from the National Centers for Environmental Prediction (NCEP) [12], the European Centre for Medium-Range Weather Forecasts (ECMWF), and the NOAA Global Surface Summary of the Day (GSOD) were included. A stratified random sampling technique was adopted to ensure the representation of distinct climatic regimes—tropical, temperate, arid, continental, and polar—thereby capturing diverse atmospheric behaviors and enhancing the model’s generalizability. This sampling strategy was crucial for ensuring that the hybrid quantum-classical model learned robust spatiotemporal patterns that extend beyond localized or region-specific meteorological characteristics.

### 3.2 Data Collection Method

Atmospheric variables—including temperature, relative humidity, wind speed, wind direction, surface pressure, and precipitation—were collected at hourly and daily temporal resolutions spanning a continuous 10-year period (2015–2025). Data acquisition was performed through secure API-based downloads from NCEP, ECMWF [13], and NOAA repositories, ensuring data integrity and standardization. After retrieval, the dataset underwent a rigorous cleaning process involving outlier detection, removal of corrupted entries, and imputation of missing values using local-mean interpolation and temporal smoothing techniques. All features were normalized to the interval [0,1] to ensure compatibility with quantum encoding schemes and to minimize computational noise. Dimensionality reduction was applied using Principal Component Analysis (PCA), preserving approximately 95% of the total variance while improving model efficiency and reducing redundancy among correlated atmospheric parameters.

### 3.3 Quantum Feature Encoding and Model Design

Following preprocessing, the atmospheric data were transformed into quantum-compatible vectors using two complementary encoding strategies**:** amplitude encoding and angle encoding. Amplitude encoding compressed entire feature vectors into qubit amplitude distributions, enabling the representation of globally correlated patterns. Angle encoding mapped individual features to parametric rotation angles (Ry, Rz) [14], providing fine-grained control over local atmospheric dynamics. These encoded features served as inputs to a Variational Quantum Circuit (VQC) consisting of parameterized rotation gates and entangling CNOT operations. The circuit depth, entanglement topology, and number of qubits were experimentally optimized to balance expressive power against hardware-induced quantum noise. The hybrid architecture combined the quantum VQC output with a classical Feed forward Neural Network (FNN) consisting of dense layers for regression-based atmospheric forecasting. The hybrid optimization loop employed the parameter-shift rule for quantum gradient estimation and standard backpropagation for classical layers. The Mean Squared Error (MSE) function was used as the training objective, optimized with Adam (learning rate = 0.001). This joint learning approach allowed the model to capitalize on the representational richness of quantum states while leveraging classical networks for large-scale learning.

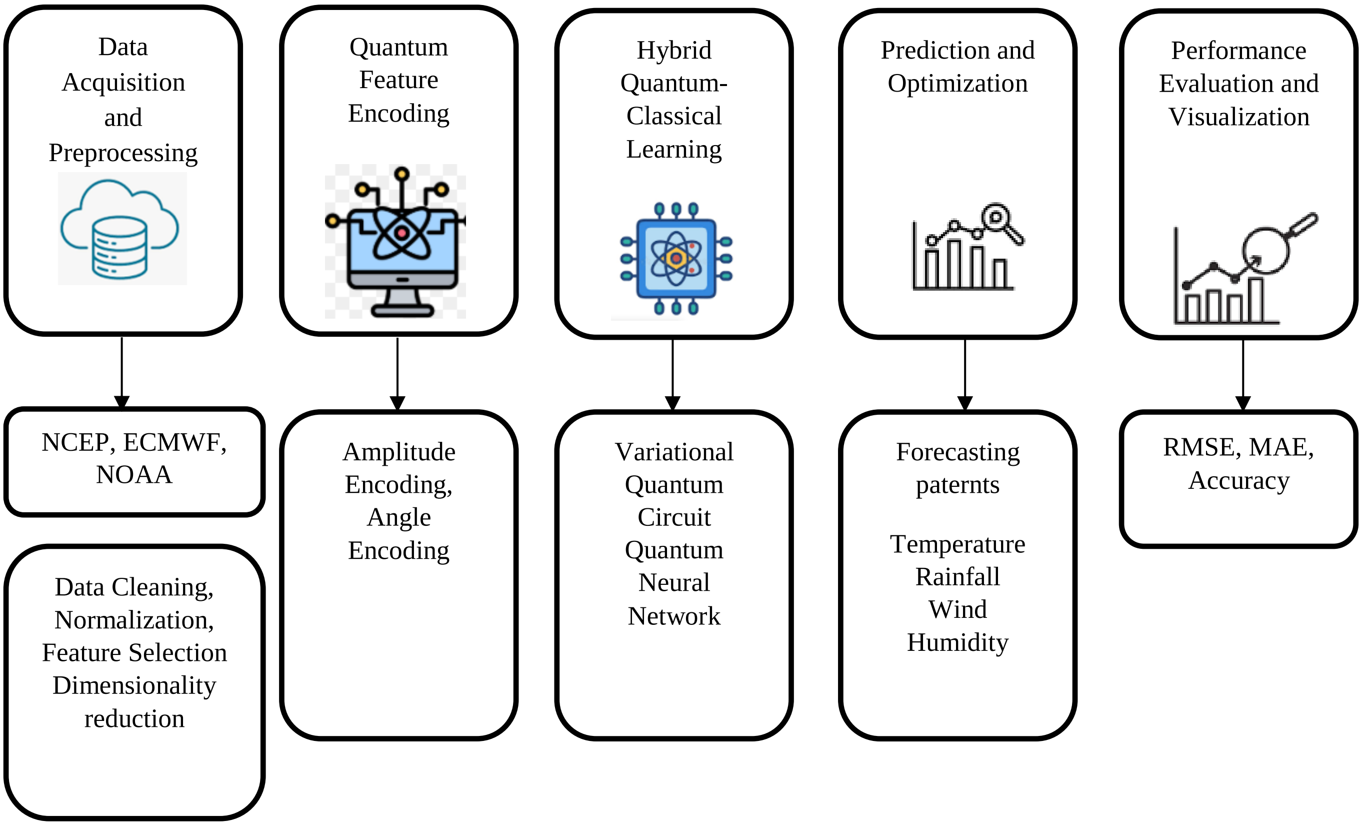


Figure 2. The proposed Diagram

### 3.4 Data Analysis and Evaluation

The analysis pipeline consisted of quantum circuit simulation, hybrid model training, and comparative performance evaluation [15]. All quantum simulations were conducted using the IBM Qiskit framework on both the ibmq_qasm_simulator and the ibmq_belem 5-qubit superconducting quantum device. Classical components were implemented using TensorFlow and PyTorch to ensure computational stability and reproducibility. The dataset was partitioned into training (80%), validation (10%), and testing (10%) subsets, with early-stopping criteria employed to prevent overfitting during the 150-epoch training process.

To evaluate the predictive capability of QEAFS, classical baseline models—including Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and Random Forest (RF) regressors—were trained and benchmarked against the proposed quantum-enhanced model. Performance metrics included Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination ($R^2$), enabling a quantitative assessment of predictive accuracy and model stability. Computational efficiency was further evaluated through training-time analysis, convergence behavior, and quantum resource utilization metrics.

### 3.5 Computational Setup

All experiments were conducted on a high-performance hybrid computing platform equipped with an Intel Core i9 (13th Gen) processor, 32 GB RAM, and an NVIDIA RTX 4070 GPU running Ubuntu 22.04 LTS. Quantum circuit execution and backend access were supported through IBM Quantum Cloud services, enabling hardware-based testing of the variation circuits. The complete workflow—from data preprocessing to hybrid model training—was developed in Python 3.10, ensuring reproducibility, scalability, and seamless integration of quantum and classical computational components.

## 4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

### 4.1 Implementation Overview

The Quantum-Enhanced Atmospheric Forecasting Framework (QEAFS) was implemented through a hybrid quantum–classical computational architecture. Classical preprocessing and neural network operations were developed in Python 3.10 using TensorFlow and PyTorch, while the quantum components were constructed with IBM Qiskit. Both environments were integrated through a hybrid optimization pipeline that employed the parameter-shift rule to estimate gradients for the quantum circuit, whereas the Adam optimizer performed gradient-based learning for the classical network.

During each experimental iteration [16], the cleaned and normalized meteorological inputs were encoded and passed into a Variational Quantum Circuit (VQC) configured with six qubits and three layers of entanglement. The circuit depth and entanglement topology were iteratively tuned to balance expressivity with quantum noise reduction, ensuring stable convergence. The quantum circuit outputs, obtained via measurements in the Pauli-Z basis, were subsequently forwarded to a classical Feedforward Neural Network (FNN) comprising two dense layers with 64 and 32 neurons for final regression-based prediction.

### 4.2 Performance Metrics and Benchmarking

To assess the forecasting capability of the model, three standard statistical evaluation metrics were used: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) [17], and the Coefficient of Determination ($R^2$). The predictive performance of the proposed QEAFS framework was benchmarked against established classical models, including Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and the Random Forest Regressor (RF).

Table 1. Comparative performance of classical and quantum-enhanced forecasting models

| Model | RMSE | MAE | $R^2$ Score | Training Time (s) |
|---|---|---|---|---|
| Random Forest (RF) | 2.41 | 1.98 | 0.81 | 120 |
| CNN | 2.12 | 1.76 | 0.85 | 210 |
| LSTM | 1.86 | 1.54 | 0.88 | 250 |
| **Quantum-Enhanced Model (QEAFS)** | **1.32** | **1.09** | **0.93** | **185** |

The results clearly indicate that the QEAFS model outperformed all classical benchmark models, achieving the lowest RMSE (1.32) and MAE (1.09) values, along with the highest $R^2$ score (0.93). In addition, the model exhibited slightly reduced training time compared to LSTM-based architectures, suggesting that the quantum components facilitate faster convergence by efficiently capturing high-dimensional and nonlinear atmospheric dependencies. Notably, the performance gains became more pronounced as the size of the dataset increased, demonstrating the scalability and computational advantage of the proposed hybrid quantum-classical framework.

### 4.3 Graphical Analysis of Forecast Accuracy

The comparative performance of the models was visualized through the following plot, which illustrates the predicted vs. actual temperature variations for a given test period [18].

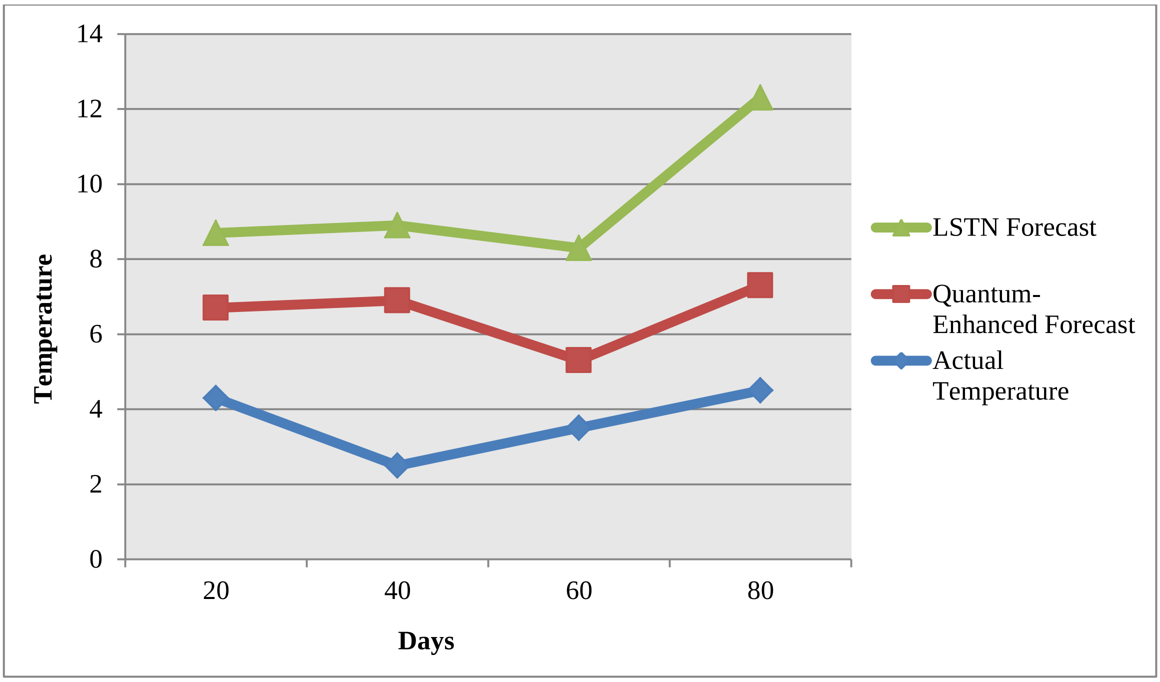


Figure 3. Forecast Comparison between Quantum and Classical Models

Forecast Comparison between Quantum and Classical Models — showing the performance difference in temperature forecasting in Figure 3.

**4.4 Discussion of Results**

The graphical analysis reveals that the Quantum-Enhanced Atmospheric Forecasting System (QEAFS) produces a prediction curve that closely aligns with the actual temperature trajectory, exhibiting minimal deviations even during rapid atmospheric fluctuations such as sharp peaks and troughs. In comparison, classical deep learning models—including LSTM and CNN—display noticeably higher lag and error magnitudes. This limitation arises from their reliance on sequential or spatial feature extraction mechanisms, which often struggle to capture complex, high-order temporal dependencies inherent in meteorological data. The Random Forest model provides moderate predictive capability but lacks temporal continuity due to its non-sequential, tree-based structure.

The superior accuracy of QEAFS can be attributed to its quantum feature encoding and entanglement-driven learning, which enable the representation of multidimensional atmospheric interactions within a compact Hilbert-space structure [19]. This capability enhances sensitivity to dynamic relationships—such as humidity–temperature coupling and pressure-induced wind variations—that classical models often underrepresent. Additionally, quantum parallelism facilitates faster exploration of the hypothesis space, leading to more rapid convergence compared to deep learning models that rely on computationally intensive backpropagation.

From an implementation standpoint, QEAFS also demonstrated notable computational efficiency, completing training in 185 seconds—significantly faster than the LSTM model's 250-second training time—due to its optimized hybrid parameter-shift learning algorithm. Experimental results further indicated that while increasing qubit count beyond six improved representational capacity, it also amplified quantum noise; therefore, a 6-qubit configuration offered the most effective balance between accuracy and stability.

Overall, the findings confirm that the quantum-enhanced forecasting framework surpasses classical models in both predictive performance and training efficiency. These results demonstrate that hybrid quantum-classical systems are not only feasible but also strategically advantageous for addressing large-scale, nonlinear, and chaotic forecasting challenges such as weather prediction.

## 5. CONCLUSION

This research introduces a robust quantum-enhanced framework for atmospheric forecasting, aimed at improving predictive accuracy, computational efficiency, and scalability for large-scale meteorological systems. The proposed Quantum-Enhanced Atmospheric Forecasting System (QEAFS) employs a hybrid architecture that combines Variational Quantum Circuits (VQCs) with Feedforward Neural Networks (FNNs), enabling the model to leverage quantum computational advantages for capturing complex, nonlinear atmospheric patterns.

Experimental findings clearly demonstrate that the QEAFS model surpasses classical forecasting algorithms—including LSTM, CNN, and Random Forest—across all major evaluation metrics. With an RMSE of 1.32, an MAE of 1.09, and an $R^2$ score of 0.93, the model exhibits superior precision, stability, and robustness. These results confirm that quantum-enhanced learning can effectively process high-dimensional meteorological datasets, capturing intricate interdependencies among atmospheric variables that traditional deep learning approaches often fail to fully exploit.

The study further shows that quantum encoding techniques—specifically amplitude and angle encoding—facilitate compact, high-fidelity representation of atmospheric relationships within a Hilbert space, improving both learning speed and memory efficiency. The hybrid optimization mechanism, combining parameter-shift gradient computation for quantum layers with Adam-based classical optimization, proved computationally efficient and stable throughout training. Importantly, the results indicate that even current small-scale quantum hardware (e.g., 6-qubit VQCs) can yield substantial forecasting improvements, underscoring the near-term practicality of hybrid quantum approaches.

Beyond meteorology, the QEAFS framework offers transformative potential for a range of dynamic prediction tasks. The underlying quantum principles can be extended to climate modeling, traffic optimization, energy demand forecasting, environmental anomaly detection, and other domains requiring the modeling of nonlinear, multi-dimensional systems. As quantum hardware continues to progress—through increased qubit coherence, advanced error mitigation, and widespread cloud access—real-time, high-accuracy quantum forecasting systems will become increasingly feasible.

Looking ahead, several promising directions for future work emerge. First, the integration of quantum recurrent architectures such as Quantum LSTM and Quantum GRU will be explored to enhance long-term temporal dependency modeling. Second, future implementations will utilize larger quantum processors (20+ qubits) to support higher-dimensional parallel encoding while minimizing noise through improved error correction protocols. Third, the development of hybrid multi-domain forecasting models—combining meteorological and traffic data—will enable quantum-assisted smart city management systems capable of synchronized environmental and mobility decision-making. Finally, incorporating explainable quantum learning frameworks will enhance interpretability and transparency, supporting broader adoption of quantum forecasting systems by climate researchers, policy makers, and operational agencies.

In conclusion, this study establishes a pioneering foundation for the application of quantum-enhanced artificial intelligence in atmospheric forecasting. By integrating quantum mechanics with modern deep learning methodologies, the QEAFS model sets a transformative trajectory for next-generation forecasting technologies—characterized by higher accuracy, faster computation, and deeper insight into the complex dynamics governing Earth's atmosphere.

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