

A Survey on Global Weather Forecasting: Models, Techniques, and Emerging Trends

M. Narender¹, Mosleh Mahmoud Khyyat²

¹ Lincoln University College, Petaling Jaya, Selangor Darul Ehsan-47301, Malaysia,

² Information Systems and Technology College of Computer Science and Engineering, University of Jeddah.

Email: pdf.narender@lincoln.edu.my, mkhayyat@uj.edu.sa

Abstract: The forecasting of global weather patterns assists in predicting qualitative and quantitative atmospheric variables such as temperature, humidity, atmospheric pressure, precipitation, wind speed, and clouds movement. Accurate weather forecasting plays a crucial role in agriculture, transportation, disaster management, and environmental monitoring. Recent advances in numerical weather prediction, satellite observations, artificial intelligence, and high-performance computing have significantly improved forecasting capabilities. This survey reviews recent developments in global weather forecasting, emphasizing machine learning, deep learning, probabilistic forecasting, ensemble forecasting, graph neural networks, Fourier neural operators, and federated learning approaches. The study highlights major achievements, limitations, and future research directions toward scalable, privacy-preserving, and highly accurate weather forecasting systems.

Keywords: Global Weather Forecasting; Numerical Weather Prediction; Deep Learning; Federated Learning; Climate Modelling; Spatio-Temporal Models.

1. Introduction

Weather forecasting is the scientific process of predicting atmospheric conditions at a given location and time. It utilizes observations collected from satellites, weather stations, ocean buoys, radar systems, and remote sensing platforms to estimate future atmospheric states. Global weather forecasting extends this process to continental and planetary scales, requiring the integration of vast amounts of heterogeneous data.

The World Meteorological Organization (WMO) coordinates international efforts in weather observation and forecasting. Despite significant advances, forecasting systems continue to face several challenges, including incomplete measurements, noisy observations, computational complexity, and spatio-temporal variability of atmospheric phenomena.

Traditional numerical weather prediction (NWP) models provide reliable forecasts but often require enormous computational resources and long execution times. Consequently, researchers have increasingly adopted machine learning (ML), deep learning (DL), and federated learning (FL) techniques to improve forecasting efficiency and accuracy.

2. Related Work

Federated Learning has emerged as a promising paradigm for distributed weather forecasting. Lee et al. [1] proposed a Temperature Scaling (TS) technique that improves local training performance and model convergence in federated learning systems. Although originally developed for generic FL applications, the approach shows potential for geographically distributed weather forecasting networks.

Bonev et al. [2] introduced FourCastNet 3, which integrates geometric probabilistic learning for scalable probabilistic weather prediction. Their model effectively captures uncertainty while maintaining high forecasting accuracy.

Abouomar et al. [3] proposed a hierarchical federated learning framework for smart agricultural systems. The architecture preserves data privacy and supports decentralized learning, making it suitable for weather forecasting applications involving geographically distributed data sources. Vicino et al. [4] explored federated learning for distributed weather forecasting, their work demonstrated that collaborative forecasting can be achieved without sharing raw data among participating organizations.

Forecast accuracy remains a central challenge in weather prediction. Subich et al. [5] addressed the double-penalty problem in data-driven forecasting by introducing a modified spherical harmonic loss function that improves spatial consistency and forecast accuracy. Andrae et al. [6] investigated diffusion models for ensemble weather forecasting, their results shown that diffusion-based approaches can generate realistic probabilistic forecasts and effectively capture forecast uncertainty.

Mahesh et al. [7] developed large-scale ensemble forecasting systems using Spherical Fourier Neural Operators (SFNOs), this approach efficiently generates massive ensembles and supports global weather forecasting applications. Mahesh et al. [8] further analyzed SFNO-based hindcast ensembles and demonstrated improved uncertainty quantification and atmospheric variability representation.

Price et al. [9] highlighted the growing interest in probabilistic weather forecasting using machine learning techniques, their results indicated that ML-based probabilistic forecasts can achieve competitive accuracy while significantly reducing computational costs. Karbauer et al. [10] proposed a parsimonious deep learning framework based on HEALPix meshes, this method improves computational efficiency while maintaining forecasting skill at global scales.

Watt-Meyer et al. [11] introduced ACE, a learned atmospheric model capable of fast and accurate climate prediction, their work demonstrated that data-driven approaches can effectively model large-scale atmospheric dynamics. Pathak et al. [12] developed FourCastNet using Adaptive Fourier Neural Operators (AFNOs), enabling high-resolution weather forecasting with significantly faster inference than traditional NWP systems.

Bi et al. [13] proposed Pangu-Weather, a three-dimensional deep learning system that delivers highly accurate global weather forecasts with remarkable computational efficiency. Lam et al. [14] introduced GraphCast, which employs graph neural networks to model atmospheric dynamics, their results shown superior forecasting performance across multiple weather variables. Kurth et al. [15] enhanced FourCastNet through optimized AFNO architectures, accelerating forecasting workflows and improving operational feasibility.

Overall, the literature review demonstrates a transition from physics-based forecasting towards AI-driven, probabilistic, and distributed forecasting paradigms. Emerging technologies such as graph neural networks, Fourier neural operators, diffusion models, ensemble learning, and federated learning continue to reshape modern weather forecasting systems.

Table 1. Comparative Analysis of Global Weather Forecasting Literature

Ref.	Paper	Approach	Merits	Demerits
[1]	Lee et al. (2025)	Temperature Scaling for Federated Learning	Improves local convergence and generalization; privacy-preserving	Communication overhead; not specifically designed for weather forecasting
[2]	Bonev et al. (2025)	FourCastNet 3 with Geometric Probabilistic Learning	Scalable probabilistic forecasting; uncertainty estimation	Requires large-scale training data and computational resources
[3]	Abouomar et al. (2025)	Hierarchical Federated Learning	Preserves privacy; supports distributed systems	Complex coordination and communication latency
[4]	Vicino et al. (2025)	Federated Learning for Distributed Weather Forecasting	Collaborative forecasting without data sharing	Model heterogeneity and non-IID data issues
[5]	Subich et al. (2025)	Modified Spherical Harmonic Loss Function	Improves spatial consistency and forecasting accuracy	Increased computational complexity
[6]	Andrae et al. (2024)	Diffusion Models for Ensemble Forecasting	Realistic probabilistic forecasts	High training cost and slower inference
[7]	Mahesh et al. (2024)	SFNO for Large Ensembles	Efficient large-scale forecasting	Requires substantial computational infrastructure
[8]	Mahesh et al. (2024)	SFNO Hindcast Ensemble Analysis	Improved uncertainty quantification	Computationally expensive
[9]	Price et al. (2024)	ML-Based Probabilistic Forecasting	Reduced computational cost	Dependence on historical training data
[10]	Karbauer et al. (2024)	HEALPix Mesh-Based Deep Learning	Computational efficiency	Loss of fine-scale atmospheric details
[11]	Watt-Meyer et al. (2023)	ACE Atmospheric Model	Fast climate prediction	Limited physical interpretability
[12]	Pathak et al. (2022)	FourCastNet using AFNO	High-resolution forecasting	Heavy dependence on training data
[13]	Bi et al. (2022)	Pangu-Weather	Highly accurate global forecasts	Large model size and training complexity
[14]	Lam et al. (2022)	GraphCast	Effective spatial relationship modeling	Complex graph construction
[15]	Kurth et al. (2022)	Optimized FourCastNet with AFNO	Accelerated forecasting	Reduced explainability

Table 2. Research Gap Analysis in Global Weather Forecasting

Research Area	Identified Gap	Impact on Forecasting	Future Research Direction
Federated Learning for Weather Forecasting	Limited large-scale deployment of federated frameworks in operational weather forecasting systems	Restricts privacy-preserving collaboration among meteorological agencies	Develop scalable and communication-efficient federated weather forecasting architectures
Probabilistic Forecasting	Difficulty in accurately quantifying uncertainty for extreme weather events	Reduced reliability in risk assessment and disaster management	Advanced uncertainty-aware and generative forecasting models
Ensemble Forecasting	High computational cost associated with large ensemble generation	Limits real-time forecasting and resource-constrained deployments	Lightweight ensemble generation and efficient neural operator designs
Deep Learning-based Forecasting	Heavy dependence on large datasets and high-performance computing resources	Increases training cost and limits accessibility for smaller organizations	Model compression, pruning, and efficient training strategies
Explainability and Interpretability	Most AI models function as black-box systems with limited interpretability	Reduces trust among meteorologists and operational forecasters	Integration of Explainable AI (XAI) techniques into forecasting models
Physics-Aware Forecasting	Insufficient incorporation of atmospheric physics constraints into AI models	May generate physically inconsistent predictions	Development of physics-informed and hybrid AI–NWP frameworks
Extreme Weather Prediction	Limited accuracy for rare and high-impact weather events such as cyclones, floods, and heatwaves	Affects disaster preparedness and mitigation strategies	Specialized architectures for extreme event forecasting
Distributed Meteorological Data Processing	Heterogeneous and non-IID data across distributed weather stations remain inadequately addressed	Degrades model convergence and forecasting performance	Robust federated aggregation and domain adaptation techniques
Real-Time Forecasting	Balancing forecast accuracy, uncertainty estimation, and inference speed remains challenging	Limits operational deployment of advanced forecasting systems	Fast probabilistic forecasting and efficient inference mechanisms
Unified Weather-Climate Modeling	Separate treatment of weather and climate prediction tasks	Reduces long-term forecasting consistency and scalability	Foundation models capable of supporting both weather and climate forecasting
Data Availability and Standardization	Lack of globally standardized datasets for training and	Makes fair comparison among	Creation of open, standardized, and

	benchmarking AI weather models	forecasting models difficult	globally representative benchmark datasets
Sustainability and Energy Efficiency	Large AI models consume significant computational power and energy	Increases operational costs and environmental impact	Green AI and energy-efficient forecasting architectures

3. Conclusion

Weather forecasting has undergone a significant transformation through the integration of artificial intelligence, machine learning, and distributed learning technologies. Recent developments in probabilistic forecasting, graph neural networks, Fourier neural operators, and federated learning have demonstrated substantial improvements in forecasting accuracy, efficiency, and scalability. Despite these advances, challenges remain in uncertainty quantification, model interpretability, privacy preservation, and computational efficiency. Future research should focus on hybrid physics-informed AI models, privacy-preserving distributed learning frameworks, and scalable ensemble forecasting architectures to support next-generation weather and climate prediction systems.

References

1. K. Lee et al., "Improving Local Training in Federated Learning via Temperature Scaling," *Advanced Engineering Informatics*, vol. 71, pt. A, Art. no. 104283, 2026.
2. B. Bonev et al., "FourCastNet 3: A Geometric Approach to Probabilistic Machine-Learning Weather Forecasting at Scale," arXiv preprint, 2025.
3. A. Abouomar et al., "Hierarchical Federated Learning for Smart Agricultural Systems," arXiv preprint, 2025.
4. D. Vicino et al., "Federated Learning for Distributed Weather Forecasting," *CEUR Workshop Proceedings*, 2025.
5. C. Subich et al., "Fixing the Double Penalty in Data-Driven Weather Forecasting Through a Modified Spherical Harmonic Loss Function," 2025.
6. M. Andrae et al., "Continuous Ensemble Weather Forecasting with Diffusion Models," 2024.
7. A. Mahesh et al., "Design of Ensemble Weather Forecasts using Spherical Fourier Neural Operators," 2024.
8. A. Mahesh et al., "Properties of a Huge Ensemble of Hindcasts Generated with Spherical Fourier Neural Operators," 2024.
9. I. Price et al., "Probabilistic Weather Forecasting with Machine Learning," *Nature*, vol. 624, 2024.
10. M. Karbauer et al., "Advancing Parsimonious Deep Learning Weather Forecasting Using the HEALPix Mesh," *Journal of Advances in Modeling Earth Systems*, vol. 16, 2024.
11. O. Watt-Meyer et al., "ACE: A Fast, Skillful Learned Global Atmospheric Model for Climate Prediction," 2023.
12. J. Pathak et al., "FourCastNet: A Global Data-Driven High-Resolution Weather Model Using Adaptive Fourier Neural Operators," 2022.
13. K. Bi et al., "Pangu-Weather: A 3D High-Resolution Model for Fast and Accurate Global Weather Forecasting," 2022.
14. R. Lam et al., "GraphCast: Learning Skillful Medium-Range Global Weather Forecasting," 2022.
15. T. Kurth et al., "FourCastNet: Accelerating Global High-Resolution Weather Forecasting Using Adaptive Fourier Neural Operators," 2022.