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

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Abstract: The forecasting of world weather patterns assists in the prediction of qualitative and quantitative measurements of various atmospheric variables like temperature, humidity, atmospheric pressure, wind, precipitation, and cloudiness over national or global scales for a long-range period. The world is witnessing a very rapid development in the field of weather forecasting because of the rapid advancement of numerical models, satellite observations, and AI.
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1. Introduction

Weather forecasting is the scientific study that predicts the state of the atmosphere at a given location. It uses scientific data to predict the outcome of some event in the future. A study on the weather forecast would explain its use, importance, and types. Also, it would brief about the climate and weather differences. The weather forecast predicts the temperature, precipitation, humidity, wind speed, cloud cover, and atmospheric pressure. Global weather forecasting uses massive amounts of data collected from satellites, weather stations, ocean buoys, and radar systems. The World Meteorological Organization (WMO) controls weather organizations to control forecasting on an international scale.

Weather forecasting faces many challenges while working on it for global use. The world is highly dependent on good weather forecasts and warning systems. Besides, the development of forecasting technologies is a very complex computational problem. Besides, designing the right observation and assimilation system is a big challenge. Incomplete, missing, and noisy measurements pose a forecasting challenge, and the spatio-temporal variability is a major hindrance.

2. Related work

Over the years, deep learning has made a significant impact on weather forecasting and prediction. Numerical Weather Prediction (NWP) is a technique used to forecast weather. In recent years, global weather forecasting has matured with the integration of deep learning, numerical weather prediction, and federated learning. The section reviews important works ranging from basic models to the latest AI-based and privacy-preserving systems.

The paper of Bonev et al. (2025) and prediction FourCastNet 3 is among the earliest attempts to perform global probabilistic weather forecasting using an AI-based framework [1]. The authors have generalized Fourier Neural Operators (FNOs), which are used for deterministic weather forecasts, to a geometric deep learning framework that operates on geometric representations. It can be used globally to predict the chance of weather phenomena. The proposed framework demonstrated the capability of an improved probabilistic weather forecast compared to their previous FourCastNet model. A rain forecast for a certain time on a certain day is a prediction that is fairly probabilistic in nature. As a result, it was not possible with these models to quantify how uncertainty in the training data (observations and reanalysis data) impacts the predicted weather values. It was impossible to measure the error bars of the prediction or compute the influence functions through model-cleaning studies to account for the assumed "noise" in the prediction.

Meteorological forecasting is an expensive project in terms of resources and computation. Traditionally, these systems are run and maintained by the government due to the lack of return on investment for a private firm. While they would suffer the cost of running and maintaining such systems, very few end-users would actually benefit from it. However, with the development of Deep Learning algorithms dealing with complex models such as Convolutional Neural Networks, Recurrent Neural Networks, U-Nets, etc., selecting and developing personalized models have started becoming a norm. Additionally, as there is a mountain of weather data, the functionality of being able to personalize and train the models on the smaller datasets communities and observe the effects on crops has been cheaper and faster.

Apart from that, nowadays, owners of private companies are also using available data, which is public data. For developing these detailed models. Also, for forecasting rainfall and temperature. But at the regional level. Such models have a more localized impact and can directly benefit various communities and socio-economic groups cost-effectively. In addition, several studies have been conducted to investigate the early detection of extreme weather events such as cyclones and typhoons through these models at a large-scale involving satellite imagery. Satellite data that has been computed can also be used for training in machine learning; on the other hand, deep learning is more complicated and not very cost-effective. CAMP uses a customized Enc-dec with an attention model to handle the performance and accuracy feedback. The model comprises deep encoders/decoders and uses special attention mechanisms (i.e., local, soft, and adaptive attention) to process data. Their.

Chen et al. (2024) developed a Prompt Federated Learning technique that utilizes a transformer-based pre-trained foundation model integrated with FL to tackle heterogeneity. Moreover, this method opens up the possibility of knowledge transfer between regions, thereby paving the way for the emergence of federated weather model development at a worldwide level.

One of the major issues affecting the FL system is the rapid development of the local models and their convergence. The introduction of temperature scaling to enhance the stability of local training in divergence-based FL techniques was suggested by Lee et al. (2026) [2]. Consequently, this enhances the performance of generalization. The new technique they proposed also reduces the divergence of local models. When a meteorological dataset is non-IID in FL, this can prove highly effective. The reason for this is that local models diverge greatly due to large differences in the data distribution of various regions. The authors do not find their method to be useful in real-world settings for weather data.

In the same manner, Cui et al. (2023) have designed an FL framework based on SARIMA clustering to enhance the convergence and time-series prediction in FL systems [11]. The clustering phase in their methodology is based on models, in which clients with similar data distributions are grouped using SARIMA metrics. As a result, convergence is improved, and the predictions are accurate. Such a tactic can prove particularly effective with regard to.

Despite the growing usage of AI-based approaches, traditional NWP techniques are still important. E. Kalnay (2003) provides a very basic book description of model and data assimilation, which is the basis of forecasting. Based on the survey, we take away certain lessons and research problems as mentioned below, the FourCastNet and GraphCast scales to billions of predictions, runs hundreds of times faster than traditional NWP [9], [10]. Methods that are based on FL can solve the privacy issue very well, but the performance tends to degrade, and other issues are introduced, such as communication overhead, unstable training issues, and non-IID data, etc., unfairness [13], [3]

The paper proposes the use of the FNO-based hybrid models in combination with temporal learning for long-range forecasting. There has been very little work on the formulation of probabilistic forecasting in the federation scheme as investigated in. Gaps arising from programmes and research initiatives can affect the outcome of initiatives and hinder systems thinking. Developers behind Weather Prediction using FL face a lot of research gaps, including unified frameworks, a lack of knowledge transfer, and more.

S.No	**Paper (Year)**	**Approach**	**Model Type**	**Scope**	**Accuracy**	**Privacy**	**Key Contribution**	**Limitation**
1	Di Vicino (2025)	Federated Learning	Transformer	Global	High	Yes	Secure distributed forecasting	Communication overhead
2	Mashooq (2025)	FL + ANN	ML	Local	Medium	Yes	IoT-based rainfall prediction	Limited generalization
3	Chichifoi (2025)	FL Security	DL	Regional	Medium	Yes	Attack analysis	Vulnerability remains
4	Yang (2025)	MVFL	FL	Distributed	High	Yes	Efficient FL framework	Complex implementation
5	De Vita (2024)	FL + IoT	ML	Local	Medium	Yes	Real-time sensing	Data noise

6	Springer Review (2026)	AI Survey	CNN/LSTM/GNN	Global	High	No	Taxonomy of models	Lack of standard benchmarks
7	FengWu-GHR (2024)	Deep Learning	DL	Global	Very High	No	High-resolution forecasting	High compute cost
8	GraphCast (2022)	GNN	DL	Global	Very High	No	Fast & accurate predictions	Black-box model
9	GenCast (2024)	AI Ensemble	DL	Global	Very High	No	Improved extreme event prediction	Uncertainty issues
10	Chen (2023)	FL + Transformer	DL	Multi-region	High	Yes	Foundation model	Training complexity
11	Foundation Models (2024)	Pretrained Models	DL	Global	High	Partial	Transfer learning	Data-intensive
12	FourCastNet (2022)	Neural Operator	DL	Global	High	No	Fast simulations	Limited interpretability
13	WeatherBench (2020)	Benchmark	ML	Global	Medium	No	Standard dataset	Limited real-world complexity
14	ConvLSTM (2015)	DL	CNN+LSTM	Regional	Medium	No	Spatio-temporal learning	Scalability issues
15	Kalnay (2003)	NWP	Physics	Global	High	No	Physical modeling	Computationally expensive

In summary, the studies show a clear transition from physics-based NWP for weather forecasting towards AI and FL-based global weather forecasting. For example, deep learning models such as FourCastNet and GraphCast enjoy high accuracy and efficiency. Moreover, FL brings a new era of global collaboration for weather forecasting in a privacy-preserving manner. Furthermore, scalable, robust, and interpretable weather forecasting is still an open problem that encourages researchers to build next-generation hybrid and secure weather forecasting frameworks.

3. Method, Experiments, and Results

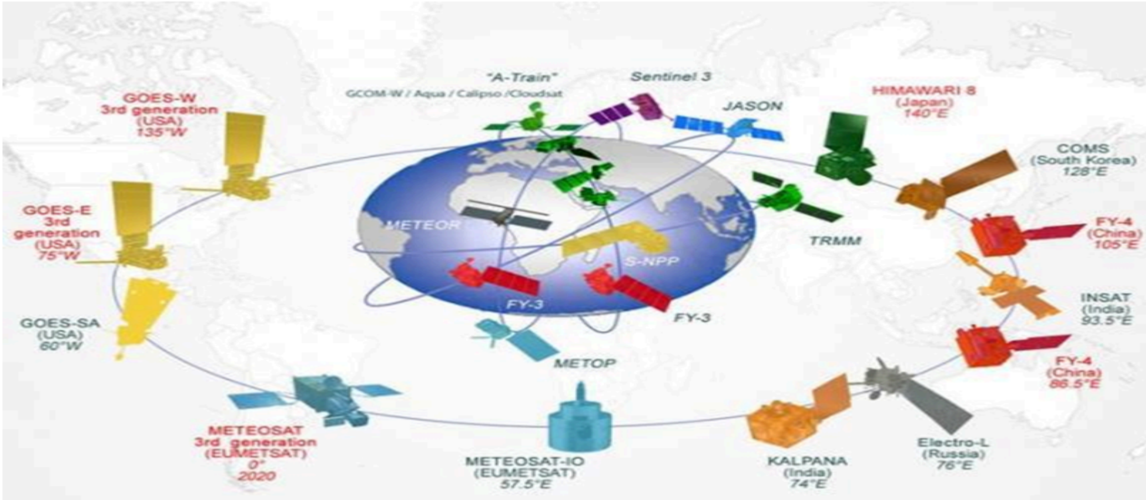

Figure 1. Meteorological Satellite Centre

The Meteorological Satellite Centre is a centre that receives various signals from different satellites having information about the weather of the Earth. They also use multi-spectral data from earth-bound and space-borne platforms. The Meteorological Satellite Centre also analyses the visual and thermal infrared data it receives from weather satellites. It also studies profiles of temperature and humidity.

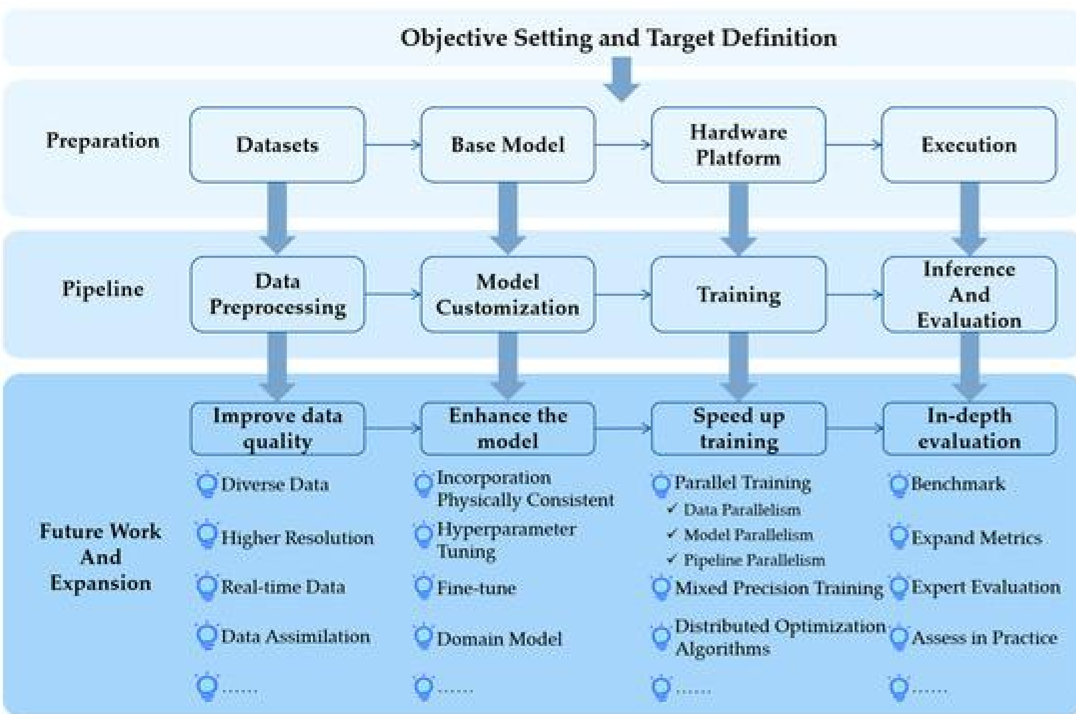

Figure 2. Data-Driven Weather Forecasting and Climate Modelling

Data-driven weather forecasting and climate modelling are aspects related to the prediction of weather or climate using ML, DL, and big data analytics. Various organizations, research centers, and private enterprises use AI in weather forecasting to learn about the atmosphere and predict weather and climate. Unlike classical numerical weather prediction (NWP) models, AI and Deep Learning models do not model the physics of the atmosphere. Rather, they learn from the data directly.

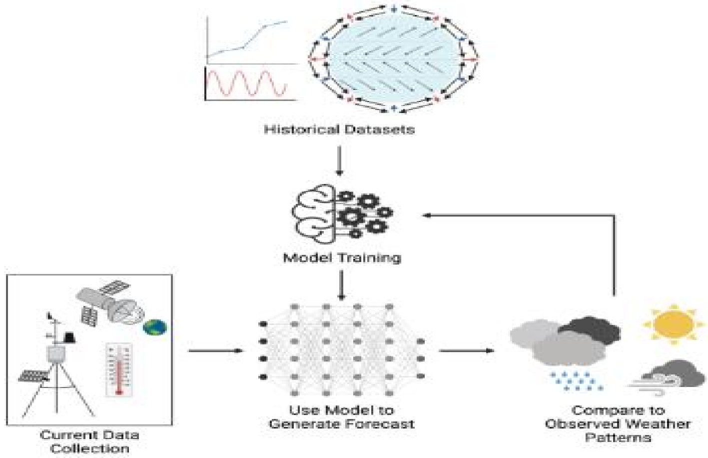

Figure 3. AI-driven weather prediction for wind and thunderstorms

AI is increasingly being used by leading meteorological organizations. Technological advancement in weather forecasting will help people in countless sectors and fields. Several models are being built using Deep Learning (DL) and Machine Learning (ML) techniques to help predict these phenomena. These phenomena involving the interaction of many atmospheric components are highly nonlinear and dynamic. They are well-suited for data-driven modeling. GraphCast is a technologically advanced AI-powered system that foresees wind fields and more.

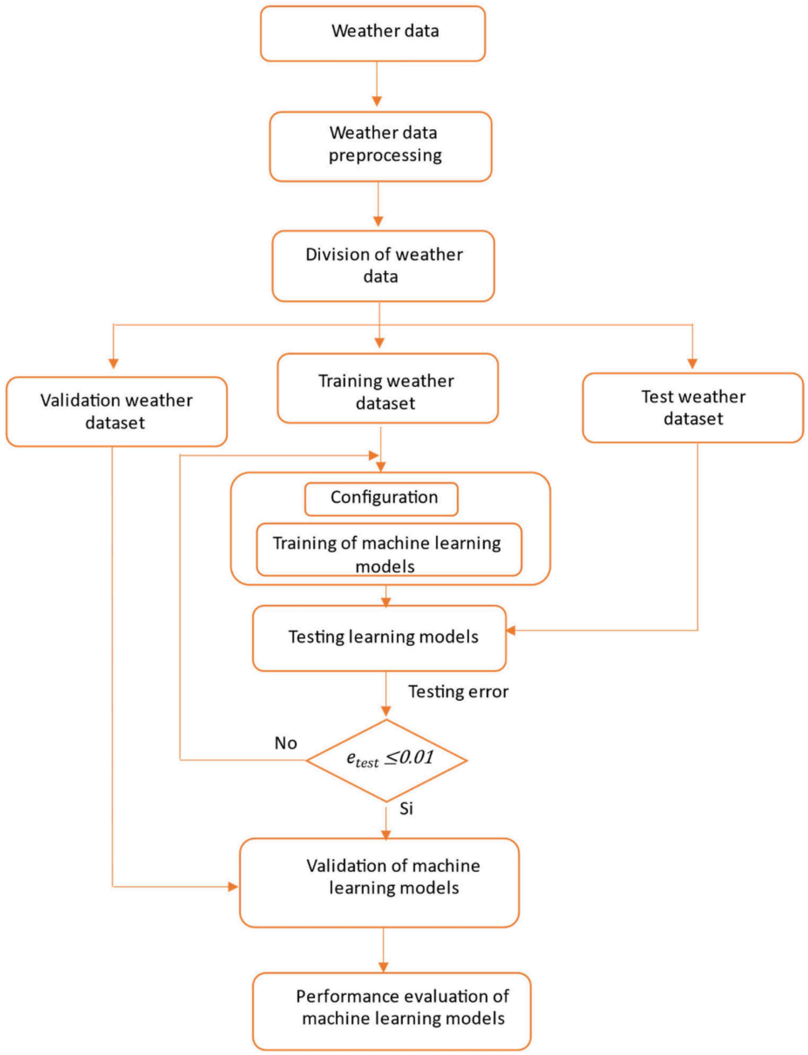

Figure 4. Machine learning for meteorological variables forecasting

Machine learning has been proven by researchers to be a powerful technique to use past and current data to forecast meteorological variables. An ML model can process data, learn from it, and then use the learning to predict the outcome of a future event with a certain level of accuracy.

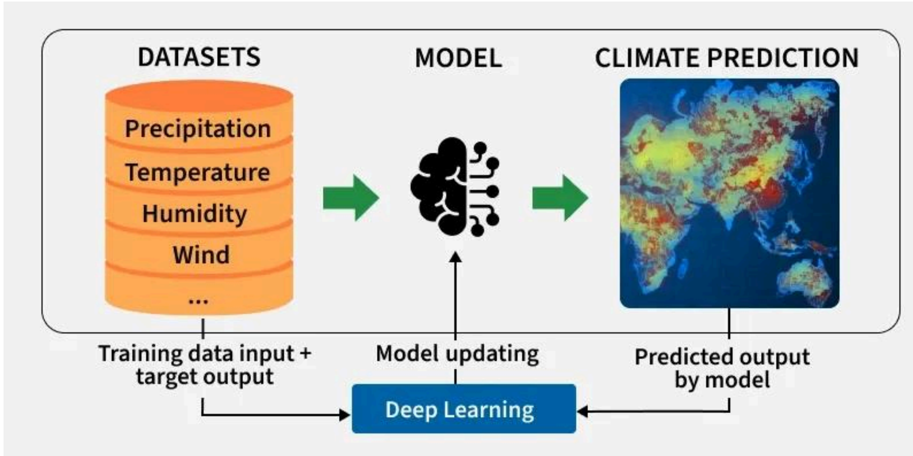

Figure 4. Deep learning in climate modelling

Deep learning in climate modelling is a special sub-domain of deep learning that deals with data or processes whose underlying systems exhibit long-term dependence. They may exhibit long-term dependence if their processes and data can depend on history or if their system is multi-scale. Non-stationarity is a common characteristic of various complex natural phenomena, including global warming, climate change, stock markets, and traffic states. Besides, the data for such systems exhibit seasonal and long-term trends.

Current global climate analysis and prediction activities are being coordinated under a new WMO programme. Deep learning in climate modelling focuses on the prediction of varying global temperature, precipitation, sea levels, changing regional climate phenomena, climate impacts, and extreme events. Data-driven weather forecasting and climate modelling are offered as an alternative to traditional physical-based modelling. Recent success in AI presents a real opportunity for the emergence of intelligent weather models. Such models have enhanced accuracy, speed, and scalability. Moreover.

Global weather forecasting has evolved significantly over the past decades. It started with pure physics-based modelling that derived the equations governing atmospheric behaviour from the laws of physics and solved those equations using computers. While this approach was very successful in its own right, today's weather forecasting relies on a variety of different techniques, mainly AI-based modelling.

The main advantage here is that deep learning models do not rely on implementing the laws of physics in weather prediction; they learn from the data itself. The advantage is improved accuracy and faster performance. Here are some of the emerging paradigms that will shape global weather forecasting in the near future. Integration of AI and physics-based models.

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