Technology Review for Carbon Neutrality

Review

Global weather forecasting through deep learning: applications and challenges

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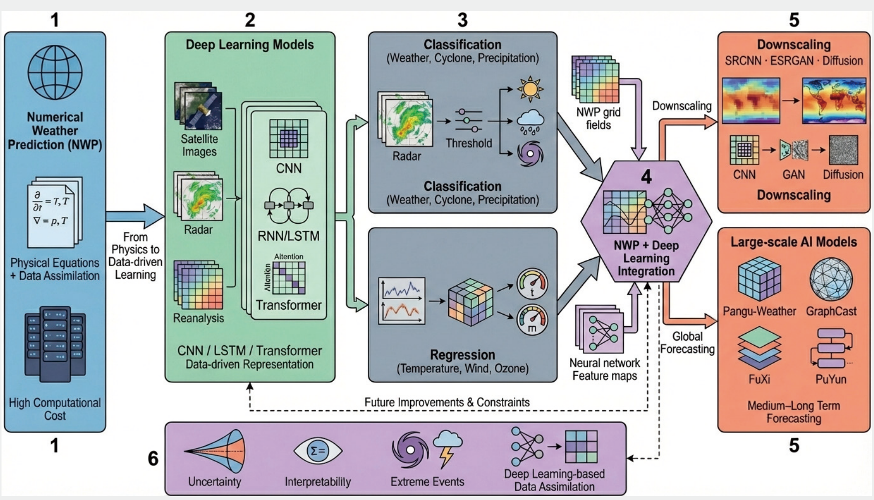
ABSTRACT

As climate mitigation and adaptation efforts are being implemented, precise and rapidly responsive weather forecasting with high spatio-temporal resolution has become paramount for optimizing the utilization of renewable energy resources, as well as making informed emergency response to extreme weather events. Conventional numerical weather prediction (NWP), based on solving complex physical equations, provides valuable forecasts for society but is computationally intensive and limited by model approximations. Recently, deep learning has emerged as a powerful complement to NWP, achieving notable gains in forecasting accuracy and computational efficiency. This review traces the evolution from NWP to data-driven deep learning approaches, highlighting the strengths of deep learning in short-term forecasts and its challenges in medium- and long-term forecasts, including model uncertainty and interpretability. It also reviews the potential of large-scale deep learning models in improving forecasting performance.



KEYWORDS

Weather forecasting; numerical weather prediction; deep learning; large-scale model

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1. Introduction

Weather forecasting is gaining ever stronger importance as society responds to climate change. On the adaptation side, with the increasing frequency of extreme weather events, precise weather forecasting plays a crucial role in mitigating the potential impacts of extreme weather events on life and property, supporting government agencies in making informed emergency decisions, and avoiding financial damages[1]. On the mitigation side, the advancement of renewable energy sources such as wind and solar is inherently variable and intermittent, contingent upon weather conditions at any given moment. Accurate weather forecasting plays a pivotal role in predicting wind speeds, solar irradiance levels, cloud cover, and other meteorological parameters that directly influence the output of wind turbines and solar panels. It is essential for ensuring a green and reliable power supply with high proportions of weather-dependent wind and solar energy.

Over the past few decades, traditional weather forecasting methods, particularly the numerical weather prediction (NWP) tool, have achieved remarkable success across various domains, such as daily weather forecasts, extreme disaster warnings, and climate change predictions. NWP explicitly encodes the physical laws governing atmospheric states into partial differential equations, which are subsequently solved via numerical simulations. Its predictive skill derives from the integration of physically based models, parameterizations of subgrid-scale processes, and assimilation of high-fidelity observational data. The accuracy of NWP has taken a qualitative leap forward in recent years due to continuous model enhancements, improved computing capabilities, and the establishment of a global collaborative observation network[2-4]. The integration of advanced data assimilation techniques and robust big data processing has further bolstered the real-time capability and responsiveness of these models[5].

Despite the substantial progress made by NWP models, the nonlinear, complex and variable nature of meteorological systems still presents considerable challenges in accurately capturing and simulating micro-scale meteorological phenomena. NWP often relies on intricate parameterization schemes, introducing a level of uncertainty that hinders the precise depiction of small-scale meteorology[6].

With the advent of highly efficient supercomputers equipped with graphics processing units (GPUs), the integration of deep learning technology has become feasible in the field of weather forecasting[7]. Deep learning, a subfield of machine learning, employs multi-layer neural networks to automatically learn hierarchical feature representations from data, thereby capturing highly complex and nonlinear relationships. Specifically, convolutional neural networks (CNNs) have been particularly effective in extracting spatial patterns, while recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are widely adopted for temporal sequence modeling. More recently, transformer-based models, powered by attention mechanisms, have achieved state-of-the-art performance across domains including natural language processing, computer vision, and geoscience. The scalability and representation capacity of transformers have also enabled the development of foundation models, or large-scale pre-trained models, which can be fine-tuned for diverse downstream tasks with unprecedented flexibility and accuracy[8]. These advancements provide the methodological basis for applying deep learning to weather and climate prediction, setting the stage for the emergence of large meteorological artificial intelligence (AI) models[9].

Unlike traditional numerical approaches, deep learning methods do not rely on intricate knowledge of physical processes. Instead, deep learning methods are data-driven and autonomously identify the implicate relationship between inputs and outputs and perform physical modeling based on available data. Such data-driven feature makes deep learning a particularly robust tool in handling intricate meteorological phenomena. It shows particular advantages in model uncertainty discovery, bias correction, and model process automation, thereby improving accuracy of real-time weather forecasts. As we see exponential growth in computational power and meteorological observation data, deep learning has become increasingly capable and well-suited for weather forecasting. It also opens avenues for new meteorological research[10].

This review examines the applications of deep learning in weather forecasting tasks including classification and regression. Our investigation will further extend to the methodological integration of NWP and deep learning, examining how deep learning facilitates meteorological downscaling (Fig. 1). Finally, we will look at the future impact of deep learning on the evolution of weather forecasting and its challenges[11,12].

2. Application of deep learning in weather forecasting

The primary objective of meteorological classification is to accurately categorize meteorological events ranging from clear skies and cloudy weather to overcast conditions[13]. Accurate meteorological classification is crucial for enhancing the quality of daily life, optimizing agricultural production, and fortifying disaster preparedness measures. On the other hand, the regression task focuses on predicting meteorological variables like temperature, humidity, and air pressure for future time periods, which is essential for facilitating informed decision-making, strategic planning, and resource allocation[14]. The tasks of weather forecasting align with classical deep learning problems of classification and regression.

2.1 Classification

Classification involves categorization of numerical values. Take precipitation as an example. The classification of precipitation depends on radar echo maps and the numerical values of gridded meteorological elements within a designated region. Precipitation occurs when the numerical values of grid points are greater than a predefined threshold, while precipitation is absent when values fall below this threshold[15]. Recent applications of deep learning methods in weather classification, cyclone classification, and rainfall classification are summarized in Table 1.

2.1.1 Weather classification

The weather classification task aims to categorize weather conditions into five distinct classes: overcast, foggy, rainy, sunny, and sunrise. Recent years have witnessed remarkable advancements in data-driven automatic weather classification research. A notable study by Gad et al.[16] compared classification performance among various machine learning models, including decision tree (CART), XGBoost, AdaBoost for classification tasks, and linear regression for regression tasks, using weather data from the National Climatic Data Center (NCDC) in the United States. They found that for classifying weather state labels, tree-based and boosting models provided superior accuracy, whereas for predicting numeric meteorological variables (e.g. temperature), simpler regression models achieved comparatively better performance under the R^2 metric. Image-based weather recognition also advanced considerably, largely due to the progress in computer vision techniques, particularly the application of deep Convolutional Neural Networks (CNNs). Xie et al.[17] accomplished unsupervised weather classification, marking a notable milestone by employing nearest neighbor clustering with semantic feature vectors. Sharma et al.[18] also achieved remarkable performance in weather classification, utilizing a CNN architecture and weather image data sourced from Kaggle. Another study by Yildirim et al.[19] employed CNNs for feature extraction and a Support Vector Machine (SVM) for classifying weather conditions into five distinct categories: overcast, foggy, rainy, sunny, and sunrise. This hybrid design leverages CNN's ability to extract high-level spatial features from weather images, while utilizing the strength of SVMs in handling classification boundaries with relatively small training data. However, such two-stage pipelines may suffer from increased computational complexity and lack of end-to-end optimization, which can limit scalability compared to fully deep learning-based approaches.

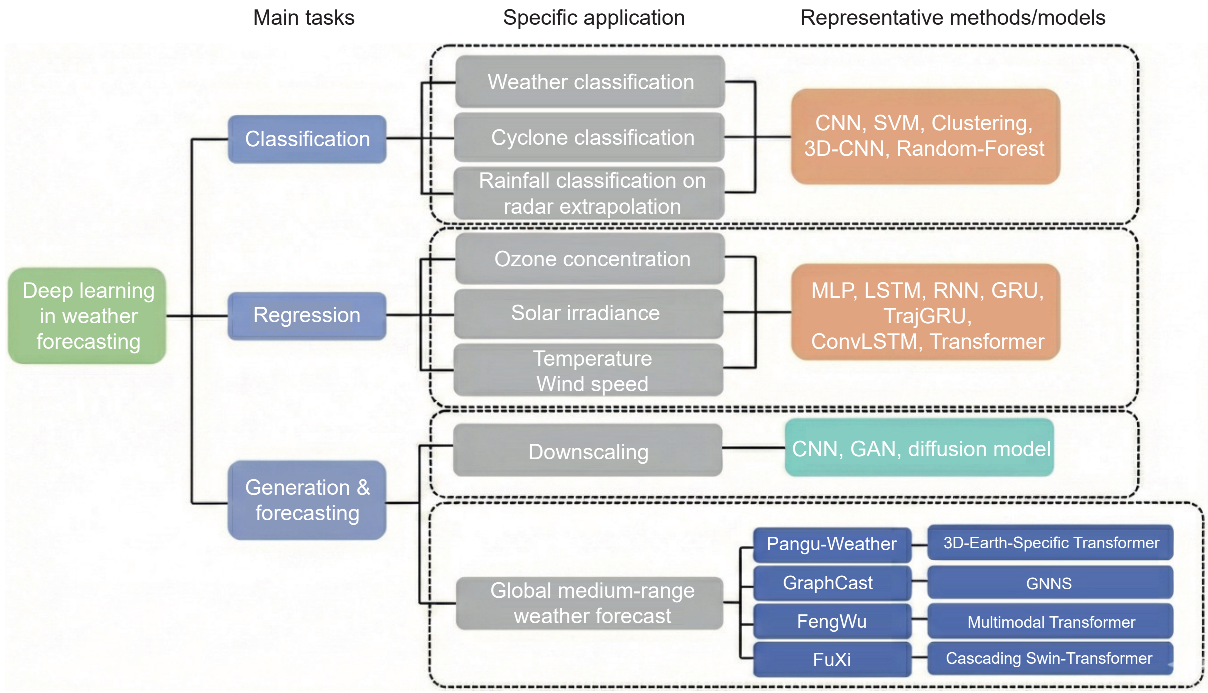

Fig. 1. Deep Learning in Weather Forecasting. NWP: Numerical Weather Prediction; CNN: Convolutional Neural Network; SVM: Support Vector Machine; MLP: Multilayer Perceptron; LSTM: Long Short-Term Memory; RNN: Recurrent Neural Network; GRU: Gated Recurrent Unit; GAN: Generative Adversarial Network.

Table 1. Meteorological classification research using deep learning methods.

Tasks	Deep learning algorithms	Main idea	Reference	Accuracy
Weather classification	Decision Tree XGBoost AdaBoost	Continuously improving predictive performance by building and combining tree models.	Gad et al.[16]	93%
	CNN Clustering	Unsupervised classification with semantic vectors	Xie et al.[17]	65%
	CNN	CNN architecture for weather images from Kaggle	Sharma et al.[18]	94%
	CNN SVM	CNN for feature extraction, SVM for weather type classification	Yildirim et al.[19]	96%
Cyclone classification	Ensemble learning	Ensemble approach with weak classifiers predicts cyclone from cloud images	Matsuoka et al.[22]	88%
	3D-CNN	Spatial features correlation with cyclone intensity changes	Wang et al.[23]	94%
	TCICENet	CNN cascade for cyclone intensity classification from satellite images	Zhang et al.[24]	81%
Rainfall classification on radar extrapolation	ANN	Precipitation recognition with ANN and random forest	Anand et al.[26]	68%
	CNN	Classification of cloud types in precipitation using radar data	Wang et al.[27]	—
	Random Forest CNN	Precipitation prediction from radar echoes with reduced errors	Arulraj et al.[28]	82%
	CNN	CNN model for squall line detection and classification	Xie et al.[31]	86%

Note: ANN: Artificial Neural Network; CNN: Convolutional Neural Network; SVM: Support Vector Machine.

2.1.2 Cyclone classification

Cyclones, characterized by intense rotating winds in the atmosphere, wield a profound impact on societal functioning and the economy. The accurate classification of cyclones is very important, and we can categorize them into extratropical cyclones and tropical cyclones based on their formation and activity ranges[20]. Tropical cyclones (TC) stand out as potent and highly destructive weather systems, further categorized by intensity into tropical depression, tropical storm, typhoon, severe typhoon, and super typhoon[21]. Recent advancements in deep learning technology have significantly contributed to the identification of tropical cyclones. Matsuoka et al.[22] introduced an ensemble learning approach to predict the occurrence of tropical cyclones, employing 10 weak classifiers. This method achieved a prediction accuracy ranging from 85.0% to 88.0% and successfully predicted tropical cyclone formations based solely on cloud images from the preceding 7 and 5 days. Zhang et al.[24] developed the Tropical Cyclone Intensity Classification and Estimation Network (TCICENet), employing a cascade of deep CNN using infrared geostationary satellite images from the Northwest Pacific basin.

2.1.3 Radar echo prediction for precipitation

Weather radar plays an important role in detecting precipitation through the transmission and reception of electromagnetic waves. Weather radar yields crucial echo data that serves as a cornerstone for predicting weather changes. Leveraging deep learning models, particularly based on CNN, to process radar echo data proves effective in identifying and classifying different precipitation conditions, thereby enhancing the utility of weather forecasting and extreme weather alerts[25].

Anand et al.[26] employed artificial neural networks (ANN) and the random forest algorithm to recognize precipitation. Their approach achieved a remarkable F1 score of 0.65 in distinguishing between precipitation and non-precipitation areas using microwave data, outperforming the traditional Goddard profiling (GPROF) algorithm, which yielded an F1 score of 0.59. Wang et al.[27] employed constant altitude plan position indicator (CAPPI) data inversion, zero-layer bright band identification, and developed a CNN model to differentiate stratiform and convective clouds within precipitation areas. Arulraj et al.[28] utilized random forest classifiers and CNN to independently define precipitation categories based on quantitative features extracted from ground radar echo data. This approach significantly reduced false alarms (77%) and missed detections (82%) in warm-season precipitation in the Southern Appalachian Mountains compared to the traditional Global Precipitation Measurement Ku-band precipitation radar (GPM Ku-PR) precipitation products[29,30]. Xie et al.[31] constructed a squall line dataset based on radar base data and trained a visual convolutional network with 16 hidden layers as the primary feature extraction network, achieving an area under the curve (AUC) of over 95%.

The integration of deep learning methodologies, especially CNN, into weather classification has demonstrated promising performance in recognizing diverse weather conditions. These advancements not only improve the accuracy of weather classification but also contribute to the broader understanding of meteorological patterns, thereby facilitating more intelligent decision-making processes. Despite these achievements, the performance of deep learning models depends on a substantial number of high-quality training samples. Currently, especially for extreme weather events such as squall lines, there is a relatively limited number of samples, limiting the model's generalization ability and accuracy. Enriching data for events like squall lines, encompassing pre-generation, pre-development, pre-disintegration, and pre-extinction phases, is imperative to enhance the timeliness and accuracy of predictions. Continuous efforts in data enrichment will improve the robustness and reliability of deep learning models in radar echo prediction for diverse weather conditions[32].

2.2 Regression

Meteorological regression tasks entail the prediction of numerical values associated with meteorological variables. Traditional weather forecasting methods depends on principles derived from atmospheric physics. Complementing these physical models are more accurate prediction solutions including statistical techniques such as multiple linear regression and ridge regression, time series forecasting techniques[33,34], and traditional machine learning approaches[35] such as support vector machines. More recently, deep learning models have made substantial progress in analyzing and predicting time series data. These models can capture complex spatiotemporal patterns and nonlinear relationships within meteorological data, thereby improving the accuracy of weather predictions[36-38] (Table 2).

The regression model proposed by Felix et al.[39] utilizes a multi-layer CNN structure to predict near-surface ozone concentration in Germany. This model outperforms previous meteorological models, especially in the initial two days, showcasing the advantages of deep learning in improving short-term forecasting. While CNNs are good at spatial information processing, RNNs often struggle with long-term dependencies due to the vanishing gradient problem[40]. This led to the development of LSTM and transformer, widely applied in time series prediction. Qing et al.[41] employed the LSTM model to devise a solar irradiance prediction scheme, demonstrating superior performance in predicting hourly solar irradiance. Similarly, Karevan et al.[42] proposed a Transductive LSTM model (T-LSTM), showcasing promising performance in weather forecasting by leveraging local information for time series prediction.

As RNN encodes temporal information and CNN encodes spatial information, and meteorological data possesses both temporal and spatial characteristics, more research is consequently combining the two solutions. Models that integrate multiple layers of convolution and recursive structures can automatically learn the spatiotemporal dependencies of meteorological data, forming spatiotemporal sequence predictions. Common models include Convolutional LSTM (ConvLSTM)[43] and trajectory gated recurrent unit (TrajGRU)[44]. ConvLSTM is a deep learning model that combines CNN and LSTM, specifically designed to process time series data and image sequences. It integrates CNN for learning spatial features and LSTM for learning temporal features, enabling the model to better understand and predict changes in spatiotemporal sequences, thereby providing a powerful strategy to improve prediction accuracy. Lin et al.[45] proposed the PredTemp model based on ConvLSTM for spatiotemporal temperature deviation prediction, using numerical weather forecast data for training and applying the predicted results to correct temperature predictions. The model proved to be very effective, particularly in improving temperature accuracy when adding precipitation elements. TrajGRU is a neural network model for handling spatiotemporal sequence data, primarily used for modeling and predicting trajectory data. This model combines the characteristics of LSTM and GRU to better capture long-term and short-term dependencies in spatiotemporal sequences. Zhang et al.[46] successfully improved wind speed predictions in NWP models, particularly in handling wind field predictions in the Northwest Pacific for different seasons and scales of 12–120 hours, while reducing training time and storage space requirements.

Transformer models[47] are highly suitable for weather forecasting applications due to their characteristics such as long-range modeling and global information retrieval. The Tensorial Encoder Transformer (TENT) model revolutionizes weather forecasting by leveraging tensorial attention to understand spatiotemporal weather patterns better. Through real-life data experiments, TENT surpasses conventional models, shedding light on key attributes for accurate predictions[48]. Bojesomo et al[49] proposed a new method for short-term weather forecasting using a modified U-Net model. By replacing convolution blocks with 3D shifted window transformers, it improves performance while reducing computational complexity. This study introduces a video transformer network for weather forecasting, addressing challenges in computational complexity and data requirements. Tested on Weather4Cast2021 data, the proposed model achieved competitive performance with MSE scores of 0.4750 with training data and 0.4420 during transfer learning. The postprocessing of ensemble weather forecasts was enhanced through the introduction of postprocessing of ensembles with transformers (PoET), leveraging hierarchical transformers. PoET directly improved ensemble members, irrespective of ensemble size, showing up to 20% improvement in skill for 2-m temperature and 2% for precipitation forecasts globally, outperforming simpler statistical methods[50].

3. Integration of deep learning into numerical weather prediction

While deep learning models excel in various aspects, their inability to determine the initial state necessitates the establishment of the zero field through numerical models. Additionally, the training data for these sophisticated deep learning models predominantly originates from reanalysis data—a process involving historical meteorological data and modern numerical weather forecast models. As illustrated in Fig. 2, rather than being viewed as competing approaches, NWP and deep learning are increasingly integrated. NWP provides physically consistent initial states of the atmosphere, while deep learning methods refine these outputs to correct systematic biases, enhance spatial resolution, and accelerate prediction speed.

Specifically, deep learning is integrated with NWP in two major developments: meteorological downscaling, and large-scale weather forecasting models (Table 3).

Table 2. Weather regression research using deep learning methods.

Tasks	Algorithms	Main idea	Reference
Ozone concentration	CNN	Use a multi-layer CNN structure	Felix et al.[39]
Solar irradiance	LSTM	LSTM effectively conveys and expresses information in lengthy time series	Qing et al.[41]
Temperature Wind speed	ConvLSTM	ConvLSTM combines CNN's learning of spatial features with LSTM's learning of temporal features	Lin et al.[45]
	TrajGRU	TrajGRU combines the characteristics of LSTM and GRU	Zhang et al.[46]
General weather patterns prediction Spatiotemporal weather pattern prediction	TENT	Leverage tensorial attention to understand spatiotemporal weather patterns better	Bilgin et al.[48]
	SwinUNet3D	Replace convolution blocks with 3D shifted window transformers	Bojesomo et al.[49]
	PoET	Introduce ensembles with transformers	Bouall et al.[50]

Note: CNN: Convolutional Neural Network; LSTM: Long Short-Term Memory; GRU: Gated Recurrent Unit; TENT: Tensorized Encoder Transformer; PoET: Post-processing Ensembles with Transformers.

Table 3. Research integrating deep learning with numerical weather prediction (NWP).

Tasks	Algorithms	Main idea	Reference
Meteorological downscaling	SRCNN	End-to-end mapping from low to high-resolution images	Dong et al.[54]
	ESRGAN	Optimized SRGAN for improved super-resolution image quality	Wang et al.[56]
	SRDiff	Generates high-quality images from noise using diffusion methods	Li et al.[58]
Large-scale weather forecasting models	Pangu-Weather	3D Swin Transformer for fast, accurate seven-day forecasts	Bi et al.[64]
	GraphCast	Uses GNNs for uniform global resolution and autoregressive fine-tuning	Lam et al.[67]
	FengWu	Multimodal network with a replay buffer strategy	Chen et al.[68]
	FuXi	Combines U-Transformer and cascading models	Chen et al.[69]

Note: SRCNN: Super-Resolution Convolutional Neural Network; ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks; SRDiff: Super-Resolution Diffusion Probabilistic Models; GNN: Graph Neural Network.

3.1 Meteorological downscaling

Downscaling serves as a transformative approach, converting the large-scale, low-resolution global climate models into high-resolution regional climate data. Fine-scale weather forecasts significantly contribute to enhancing the accuracy and adaptability of meteorological predictions to complex terrain, extreme weather events, as well as the specific needs of diverse industries and sectors such as agriculture, transportation and energy[51]. Traditional methods for downscaling are based on rules and professional knowledge. For example, statistical methods based on historical observational data; dynamical methods utilizing high-resolution numerical models to simulate meteorological processes; nested models coupling global and regional models[52]; data assimilation using observational data[53]. Innovative deep learning approaches have emerged as game-changers.

Dong et al.[54] introduced the Super-Resolution CNN (SRCNN), a fusion of sparse coding and CNN. This groundbreaking model achieves an end-to-end mapping of low-resolution images to high-resolution images, and swift practical online applicability. Generative adversarial networks (GAN), initially proposed by Goodfellow et al.[55] in 2014, found its way into the area of meteorological super-resolution in 2017. Wang et al.[56] proposed the enhanced super-resolution GAN (ESRGAN), which successfully improved the visual quality of single-image by optimizing the network architecture, adversarial loss, and perceptual loss of the SRGAN, and introducing technologies such as the Residual-in-Residual Dense Block (RRDB). The diffusion model[57] was first proposed in 2015 with the aim of eliminating the gaussian noise during training process and can be considered as a series of denoising autoencoders. In recent years, the diffusion model has been widely applied in the field of super-resolution. Li et al.[58] proposed the Super-Resolution with Diffusion (SRDiff) model, which, for the first time, optimizes the variational boundaries of data likelihood by introducing diffusion methods, gradually generating diverse and realistic super-resolution images from gaussian noise. This addresses problems in learning-driven single-image super-resolution (SISR) methods, such as excessive smoothing, pattern collapse, and large model storage space usage. It has the advantages of small model storage space usage and ease of training.

Deep learning models stand as powerful tools in the arsenal of meteorological advancements, particularly in the area of weather forecast downscaling. Their strength lies in their ability to effectively capture nonlinear relationships and the spatiotemporal evolution of meteorological variables, enable real-time updates, and model uncertainty, thereby enhancing local prediction accuracy. The integration of multimodal meteorological data, including satellite remote sensing, meteorological radar, and ground observation data, is seamlessly facilitated by deep learning, contributing to more comprehensive and accurate downscaled forecasts. Moreover, deep learning brings additional capabilities crucial for meteorological applications[59-61].

3.2 Large-scale weather forecasting models

Compared to NWP, which is physically grounded but computationally demanding[62], deep learning exhibits prowess in extracting insights from vast datasets while demanding relatively fewer computational resources for inference process. The advantages of deep learning in weather forecasting have been particularly proven in short-term predictions. Besides accuracy improvements, the faster inference process of deep learning methods makes minute-level weather forecasts feasible[63]. The capability of deep learning techniques has outperformed traditional interpolation techniques like optical flow in radar echo modeling[64].

In the area of medium-term and long-term forecasting or extreme weather event predictions, the previous deep learning methods show their advantages in prediction speed, but a lower resolution and accuracy of forecasting compared to numerical weather prediction methods. For example, those approaches often trained on low-resolution data, such as 5.625°, which neglect the complicate interaction between small-scale dynamics and large-scale weather patterns, as well as the impact of terrain characters on minute meteorological changes. Furthermore, those approaches fail in capturing the details of fine-scale structures.

But large-scale deep learning models break these limitations. They are equipped with ultra large-scale parameters and show advantages in tackling intricate prediction tasks with finesse, showcasing outstanding performance in the domain of medium- and long-term weather forecasting[65]. Many large-scale weather forecasting models are emerging that drive higher accuracy and speed in weather forecasting. Table 4 presents a comparison on forecasting accuracy of several weather forecasting models based on root mean square error (lower is better) for three atmospheric variables (Z500, T850, Q700) and two surface variables (T2M, WS10M) at forecasting lead times of 1 day and 7 days.

NVIDIA developed FourCastNet[66], which achieves high-resolution (0.25°) forecasts of surface wind and precipitation variables a week in advance within a mere 2 seconds. FourCast-Net boasts 8 times higher resolution than state-of-the-art deep learning based global weather models and outpaces numerical forecasting methods by a staggering 45,000 times. Leveraging the Adaptive Fourier Neural Operator (AFNO) to reduce computational complexity and developing a "pre-training + fine-tuning" paradigm extended to downstream tasks like precipitation forecasting, FourCastNet not only surpasses numerical models in forecast accuracy but does so at unprecedented speed.

Huawei's Pangu-Weather model[64] achieves exciting results in eclipsing traditional numerical models and FourCastNet. It can forecast upper-air meteorological variables (Z500, T850, T500, Q500, U500, V500), surface meteorological variables (T2M, U10, V10, WS10M), and tropical storm paths, all while operating at a speed 10,000 times faster. The Pangu-Weather model, featuring a 3D Swin Transformer as its backbone network, integrates high-dimensional information into a novel structure. This innovation allows the model to adeptly handle the intricate data related to atmospheric states at different pressure levels. Moreover, a hierarchical temporal aggregation strategy is adopted, which can leverage a greedy algorithm for time aggregation, selecting the optimal lead time for executing deep networks. This strategic approach mitigates error accumulation during the forecasting process, empowering the Pangu-Weather to predict weather for an impressive seven days or more with unparalleled accuracy.

In the vanguard of revolutionary weather forecasting, GraphCast[67], developed by DeepMind, stands out by predicting weather for the next 10 days in a mere 60 seconds, boasting exceptional accuracy. Compared to the European Centre for Medium-Range Weather Forecasts (ECMWF) deterministic operational forecast system (Integrated Forecasting System – High Resolution, IFS-HRES), it is more accurate in predicting 90% of atmospheric variables. In GraphCast, Encoder and Decoder based on graph neural networks (GNNs) are used to mapping the relationship between latitude-longitude grid data and "multi-mesh" representation, achieving uniform global spatial resolution. Deep GNNs enable efficient propagation of both local and long-range information across multiple scales, which achieves an effect similar to the global attention mechanism of Transformers. Additionally, a 12-step autoregressive fine-tuning strategy is employed to improve the accuracy of long-term forecasts.

FengWu[68] can generate high-precision global 10-day forecasts within a mere 30 seconds, tackling the interaction of atmospheric variables as a multi-task learning problem. Fengwu employs a multimodal neural network, automatically balancing weights to masterfully handle the representation and interaction of multiple atmospheric variables. Employing a replay buffer strategy optimizes multi-step prediction results, reducing autoregressive prediction errors and elevating the performance of long-term forecasts.

FuXi[69] achieves an ensemble average of the ECMWF Atmospheric Model Ensemble 15-day forecast on the evaluation set. Notably, its deterministic forecasts outshine those of the European Centre. FuXi relies on the U-Transformer structure and cascading models.

Figure 3 shows the architecture diagrams of these deep learning-based large-scale weather forecasting models.

Table 4. Comparison on forecasting accuracy of representative weather forecasting models.

Model	Forecast lead-time	Root mean square error (RMSE) for meteorological variables				
		Z500	T850	Q700	T2M	WS10M
Numerical weather prediction models						
IFS HRES	1 day	42	0.62	0.55	0.51	0.70
ERA5-Forecasts	1 day	43	0.59	0.53	0.71	0.65
IFS HRES	7 days	521	2.63	1.53	1.88	2.49
ERA5-Forecasts	7 days	534	2.68	1.59	2.06	2.52
Deep learning models						
Pangu-Weather	1 day	44	0.62	0.53	0.56	0.65
GraphCast	1 day	39	0.51	0.47	0.51	0.60
FengWu	1 day	39	0.64	-	0.60	-
FuXi	1 day	40	0.54	-	0.53	0.60
FourCastNet	1 day	81	0.82	-	0.94	
Pangu-Weather	7 days	501	2.51	1.47	1.97	2.37
GraphCast	7 days	467	2.33	1.30	1.81	2.30
FengWu	7 days	442	2.28	-	1.90	-
FuXi	7 days	433	2.14	-	1.65	2.47
FourCastNet	7 days	687	3.31	-	2.53	

Note: IFS HRES: Integrated Forecasting System High Resolution; ERA5-Forecasts: ECMWF Re-Analysis v5; Z500: Geopotential at 500 hPa; T850: Temperature at 850 hPa; Q700: Specific Humidity at 700 hPa; T2M: 2-Meter Temperature; WS10M: 10-Meter Wind Speed.

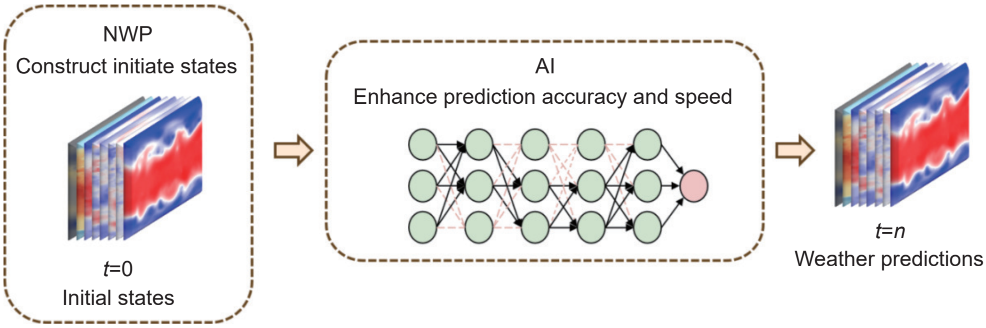

Fig. 2. NWP integration with deep learning for weather prediction. For the neuron network corresponding to the input, the neurons connected by solid lines are activated and play a dominant role in this prediction, whereas the neurons connected by dashed lines provide additional auxiliary information but do not take a leading role.

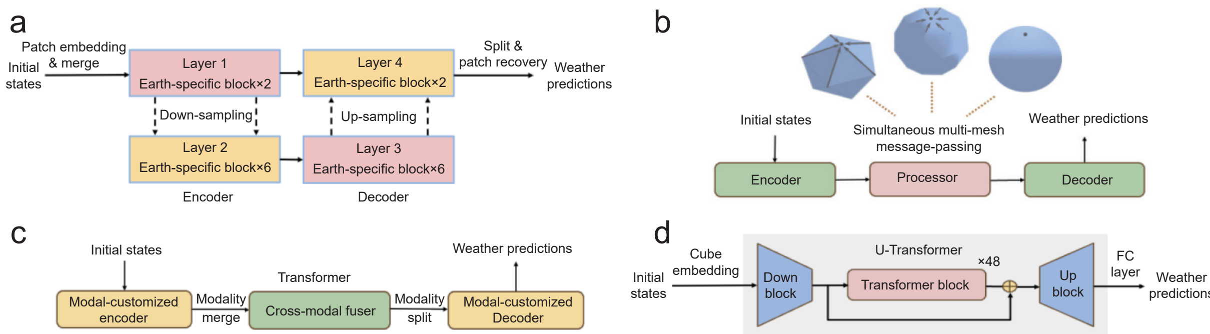

Fig. 3. Architecture diagram of several deep learning-based large-scale weather forecasting models. (a) Pangu-Weather. (b) GraphCast. (c) FengWu. (d) FuXi.

Breaking barriers in extreme weather prediction, NowcastNet[70] extends the near-term precipitation forecasts internationally to an impressive 3 hours, a notable advancement from the customary 1-hour using numerical methods. Tackling the limitations of forecasting extreme precipitation, NowcastNet outshines existing technologies across key indices like the Critical Success Index (CSI), power spectral density (PSD), and other crucial numerical indicators. NowcastNet lies an end-to-end modeling approach, seamlessly integrating deep learning with physical laws to comprehensively capture the intricate processes of precipitation. The model employs a mesoscale evolution network to adeptly model mesoscale precipitation processes, emphasizing significant physical properties such as convective motion. A neural evolution operator, based on the continuity equation (law of mass conservation), is ingeniously designed to simulate movements at a ten-kilometer scale in precipitation processes, minimizing cumulative forecast errors through meticulous backpropagation. Furthermore, the convective scale generation network comes into play, utilizing results from the mesoscale evolution network as conditions. It can capture convective generation and dissipation effects with a probabilistic generation model, focusing on kilometer-scale precipitation processes.

4. Challenges and outlook of deep learning in weather forecasting

Deep learning has made remarkable achievements in weather forecasting research, significantly enhancing the precision of meteorological forecasts, and serving as a vital component in the development of short-term power prediction and extreme event warning for power systems in the future. However, it must be acknowledged that applying deep learning to spatiotemporal data prediction encounters a set of challenges due to the high complexity of meteorological data, massive data volume, and diverse formats. These challenges include the quantification and handling of model uncertainty, the interpretability of deep learning models, extreme weather forecasting, and deep learning-based data assimilation.

4.1 Quantification and handling of uncertainty

Despite advanced sensing technologies being able to collect a large amount of Earth data, the processing and utilization of this data still face significant challenges. Data generated by different sensors differ in shape, content, and physical meaning, often accompanied by noise, uncertainty, and missing values. Future machine learning models will focus more on the assessment and management of uncertainty, using Monte Carlo methods and perturbed initial conditions based on ECMWF ensemble data assimilation to quantify uncertainty. Future research needs to supplement the uncertainty of initial conditions and consider model uncertainty to improve the accuracy and reliability of data-driven weather forecasts. For example, the Pangu-Weather performed poorly in analyzing the landing point of Typhoon Doksuri compared to numerical models, potentially due to the incomplete distribution similarity between reanalysis data and IFS zero-field data.

4.2 Interpretability

While deep learning models enhance weather forecasting accuracy, they face interpretability challenges as they may overfit data or fail to fully represent real physical processes[71]. Understanding the model's reasoning process is crucial for optimizing forecast models and ensuring their output aligns with the physical understanding of the Earth system. Traditional discussions of interpretability often stop at feature attribution or relevance propagation. However, future research should aim at physics-guided interpretability, where explanations are directly linked to conservation laws, energy transfer, or circulation regimes[72]. Moreover, with the rise of large-scale models, it is crucial to develop scalable interpretability frameworks that can capture reasoning not just at local patches but across global teleconnection patterns. Such advances would elevate interpretability from case studies toward systematic diagnostic tools for climate and weather research.

4.3 Forecasting of extreme weather

Against the backdrop of climate change, the frequency of extreme weather events is increasing, greatly affecting economic and social operations. Extreme weather remains the bottleneck of both deep learning and NWP approaches. Beyond conventional physical constraints, recent progress highlights two promising directions: (1) synthetic data generation using generative AI to augment rare extreme event samples, mitigating the long-tail data distribution problem; and (2) event-oriented hybrid models that couple deep learning's pattern recognition ability with targeted dynamical cores for specific hazards like tropical cyclones or squall lines. These novel directions go beyond existing over-smoothing solutions and could transform extreme event predictability.

4.4 Deep learning-based data assimilation

Data assimilation is a method used to integrate observations from different sources and numerical model outputs to improve the estimation of the current state of a system. This process aims to optimize the model's initial values to make them as consistent as possible with actual observations. Currently, the commonly used method for data assimilation is numerical modeling, which often requires running for several hours on a supercomputer cluster. With the improvement of global meteorological observation methods, the volume of observational data is increasing, and the temporal frequency of observational data is also rising. Numerical model-based data assimilation cannot quickly utilize the latest observational data to obtain initial background fields, while deep learning has computational speed that is unmatched by numerical models and can utilize the latest observational data for rolling updates. Future progress may lie in real-time rolling assimilation with streaming data (e.g., from satellites, radars, Internet-of-Things sensors), allowing models to continuously update states without the heavy batch-based cycles of numerical assimilation. Moreover, combining graph neural operators with deep learning assimilation could enable seamless integration of heterogeneous data sources, from reanalysis fields to crowd-sourced observations. Such innovations would move beyond incremental speed-ups toward a fundamentally new framework of adaptive assimilation.

5. Conclusion

In summary, this review highlights the transformative role of deep learning in advancing weather forecasting, particularly in enhancing short-term predictive accuracy and providing efficient computational alternatives to conventional numerical weather prediction (NWP). The evolution from physics-based NWP to data-driven deep learning approaches demonstrates significant progress in capturing complex spatiotemporal patterns, facilitating rapid and precise forecasts, and supporting critical applications such as renewable energy integration, extreme event warning, and climate adaptation. Moreover, the emergence of large-scale models exemplifies the growing potential of deep learning to complement, and in some cases surpass, traditional numerical models in specific forecasting tasks.

Nevertheless, several challenges remain on the path toward fully harnessing deep learning for meteorological prediction. Chief among them are the quantification and handling of model and data uncertainties, ensuring interpretability in ways consistent with physical laws, addressing the predictability limits of extreme weather, and developing deep learning-based frameworks for real-time data assimilation. Progress in these areas will require synergistic advances in both algorithmic innovation and the integration of diverse observational datasets. Promising directions include uncertainty-aware learning strategies, physics-guided interpretability frameworks, generative augmentation for rare events, and streaming assimilation systems that exploit the speed of deep learning.

Looking ahead, deep learning is expected to evolve into a foundational pillar of weather and climate prediction. By coupling the efficiency of data-driven models with the robustness of physical understanding, deep learning has the potential to reshape forecasting methodologies, enhance resilience to extreme weather, and accelerate the transition to a sustainable energy future. Addressing the open challenges discussed in this review will be essential for realizing this potential and ensuring that large-scale deep learning models become reliable, interpretable, and operationally deployable tools in the next generation of meteorological science.

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Author contribution statement

Bin Wang was responsible for the conceptualization and project administration. Shengchen Zhu was responsible for methodology design and formal analysis. Lianjun Wu and Yukai Liu contributed to the investigation, data curation, resources, visualization, and the writing of the original draft. Yinglan Liu contributed to the investigation, data curation, and resources. Wenshuo Liu contributed to the investigation, data curation, and resources. Xi Lu contributed to the conceptualization and methodology, and was involved in reviewing and editing the manuscript. Kebin He provided supervision of the manuscript. All authors have read and approved the final manuscript.

Data availability

Not applicable.

Use of AI statement

None.

Declaration of competing interest

Bin Wang, Shengchen Zhu, Lianjun Wu, Yukai Liu, Yinglan Liu, and Wenshuo Liu are the employees of Meta-Carbon Intelligent Technology Co., Ltd. All the other authors have no competing interests to declare that are relevant to the content of this article. The author Xi Lu is the Executive Editor-in-Chief of this journal. The author Kebin He is the Editor-in-Chief of this journal.

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