AI-Powered Rainfall Forecasting: Progress, Challenges, Future Directions

Leiming Ma

Shanghai Typhoon Institute, 166 Puxi Rd., Shanghai, China, 200030

Fudan University，2005 Songhu Rd., Shanghai，China，200438

E-mail: malm@typhoon.org.cn

Abstract

Rainfall forecasting holds significant importance across a wide range of sectors, including disaster prevention, energy planning and agriculture. In the past decade, artificial intelligence(AI) has emerged as a revolutionary approach, aiming to overcome the long-standing limitations of traditional numerical weather prediction (NWP) models and statistical downscaling models (SDMs) for rainfall forecasting. This chapter briefly introduces the remarkable progress made in AI-based rainfall forecasting. It mainly focuses on three major aspects: physical-constrained machine learning (ML), multi-modal data fusion, and extreme event prediction. AI-based models can be used to resolve the subgrid-scale parameterization problems (e.g., convective parameterization) that troubled NWP models for a long time. For instance, DeepMind's GraphCast employs dynamic graph neural networks to generate a high-resolution global forecast. Making 10-day forecasts with GraphCast takes less than a minute on a single Google TPU v4 machine. Regarding multi-modal data fusion, systems such as National Oceanic and Atmospheric Administration (NOAA) Multi-Radar Multi-Sensor(MRMS) combine various data sources and significantly improves the accuracy of forecasts. For the extreme rainfall prediction, the application of adversarial training and attention mechanisms has also led to improvements. The review finally suggests the future research directions. It emphasizes how AI is updating rainfall forecasting technology, enabling it to better meet the challenges posed by a changing climate.

Keywords: Rainfall, Forecast, Artificial Intelligence, Numerical Prediction, Model

1. Introduction

It is well known that rainfall forecasting lies at the center of meteorological science, posing important influence over various aspects of human life and the environment. It serves as the basis for disaster management, guiding flood prevention measures. In agriculture, it also helps farmers determine optimal planting schedules. For the energy sector, especially hydropower, accurate precipitation forecasts are crucial for energy production planning.

In the past decade, the rainfall forecasting technology has undergone a revolutionary transformation, thanks to the rapid advances of artificial intelligence (AI)[6, 9, 23]. Among the various AI approaches, convolutional neural networks (CNNs) have been extensively utilized for spatial modeling in computer vision and geoscientific domains, while recurrent neural networks (RNNs) excel in handling time series data sets by recursively feeding their outputs as subsequent inputs. Shi et al. (2015) [22] pioneered the integration of Convolutional Long Short - Term

Memory (ConvLSTM) to combine the strengths of CNNs and RNNs for precipitation nowcasting in Hong Kong. This innovation entailed substituting convolutional operations for the fully connected operations in the basic LSTM architecture.

In a prior research[5], we introduced a novel star - shaped bridge architecture and employed a specialized multi - sigmoid loss function, which we consider a differentiable critical success index (CSI). Some studies have also employed CNNs for nowcasting. For instance, U - Net[20] uses a seminal network architecture, featuring a symmetric pathway, bridged by skip connections. The U - Net based model has been widely used in recent nowcasting studies [1,10,11], owing to its simpler form compared to RNN - fused models and its effective multi - scale processing architecture. AI has emerged as a powerful solution to overcome the long-standing limitations of traditional numerical weather prediction (NWP) and statistical downscaling models (SDMs). A decade ago, NWP and SDMs are the major techniques for rainfall forecasting. NWP models, such as the renowned ECMWF Integrated Forecasting System (IFS), were built upon fundamental fluid equations, attempting to capture the movement of air masses, heat and moisture transfer, and the development of weather systems. However, the atmosphere is an extremely complex and multi-scale chaotic system. NWP models then faced substantial obstacles when dealing with these chaotic processes, including turbulence, cloud microphysics, and small-scale convective cells. Parameterization on these processes introduced uncertainties, leading to error of forecasts, particularly in regions with complex terrain. On the other hand, SDMs downscale large-scale climate projections to local scales by establishing statistical relationships between large-scale climate variables and local precipitation. SDMs were computationally more efficient compared to NWP models and were useful for generating long-term climate projections at a regional level. They suffered from a lack of physical consistency due to the assumptions on stationary relationships between large-scale and local variables, which often did not hold true in the real world.

One of the most persistent challenges in NWP models is the parameterization of unresolved processes. Convection. The Kain-Fritsch parameterization, widely used in the Weather Research and Forecasting (WRF) model, has been found to misinterpret convective initiation, particularly in high-elevation regions. Turbulence is another area where NWP models struggle. Eddy viscosity closures, used to parameterize the effects of turbulence, often underestimate momentum transfer in unstable boundary layers. In these layers, the rapid mixing of air due to turbulence plays a crucial role in heat, moisture, and momentum transfer. Incorrect parameterization of turbulence can lead to errors in predicting the development of low-level jets, which significantly influence precipitation patterns. SDMs also face significant challenges when dealing with regional climate heterogeneity. These models assume that the statistical relationships between large-scale variables and local precipitation remain constant over time. However, in reality, climate change has led to non-stationary relationships, especially in regions where the influence of large-scale climate modes is complex. For instance, the changing nature of ENSO events, along with the emergence of new climate patterns, has led to a breakdown in the traditional statistical relationships assumed by SDMs, which can have serious consequences for water resource management, agricultural planning, and disaster prevention. The accuracy of precipitation forecasting is also seriously hampered by data scarcity and multi-source discrepancies. It is well known that the scarcity of data in ocean can lead to large error in predicting the development and movement of tropical cyclones.

2. Recent advances of AI for rainfall forecast

Since 2020, AI, especially deep learning (DL), has emerged as a revolutionary technology in the field of precipitation forecasting (Figure 1). AI's ability to handle large volumes of data, learn complex patterns, and adapt to changing conditions has made it a rule-changer in addressing the limitations of traditional forecasting methods.

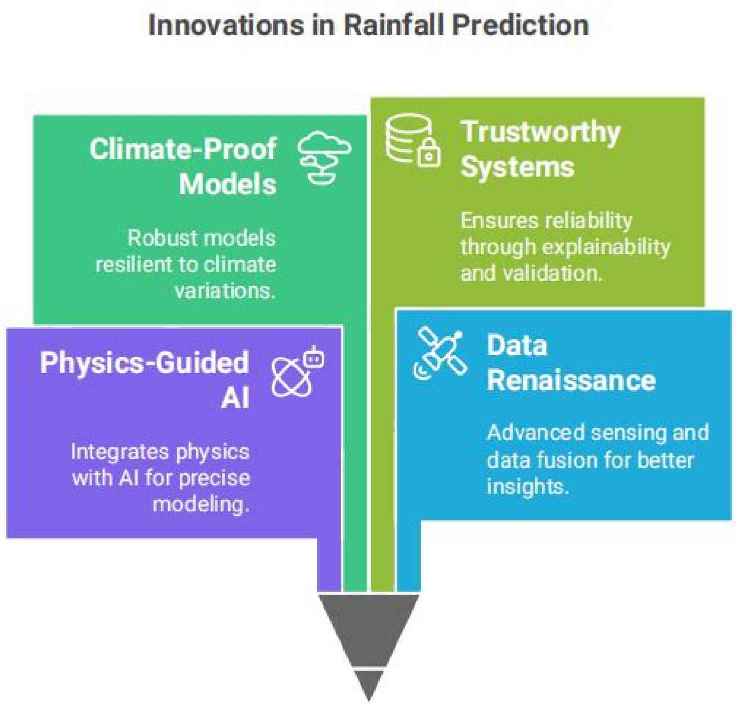

Figure 1 Recent Innovations in Rainfall Prediction equipped with AI techniques

2.1 Multi - Modal Data Fusion

Data - driven models that integrate information from multi - source data have the potential to yield more accurate inferences[3]. With the rapid increase in the availability of observations rich in spatial and temporal structures, manually extracting useful information becomes impracticable. In contrast, AI nowcasting techniques with inputs from diverse data sources, known as multi - modal learning[3], can autonomously learn abstract representations of the interactions among multiple inputs. These characteristics render AI based multi - modal learning an especially attractive approach for enhancing the performance of nowcasting[19, 21].

Significant progress has been achieved in generating gridded nowcasts from diverse input sources. For instance, Zhou et al. (2020)[26] successfully integrated meteorological satellite observations, weather radar network data, and lightning location system information for lightning nowcasting. Pan et al. (2021)[16] further explored the microphysics of convective storms by merging polarimetric radar variables, such as ZDR and KDP. Leinonen et al. (2022)[12] introduced a deep learning model capable of utilizing multiple data sources and adapting to different hazard types. However, due to the design of the model structure, they lack the ability to handle unaligned heterogeneous data, which is a common scenario in meteorological operations due to differences in data - generating infrastructure. Cao et al. (2025)[4] generalized the paradigm of multi - modal learning for nowcasting. They fully leverage the high flexibility offered by the Vision - Transformer (VIT) architecture[13,14, 25], which provides capabilities for pre - training and transfer learning[15].

2.2 Physics-Constrained ML

Models like NowcastNet and GraphCast have been at the forefront of integrating physical constraints with ML. NowcastNet, a nonlinear nowcasting model designed for extreme precipitation that unifies physical-evolution schemes and conditional-learning methods into a neural-network framework with end-to-end forecast error optimization. On the basis of radar observations from the USA and China, the model produces physically plausible precipitation nowcasts with sharp multiscale patterns over regions of 2,048 km × 2,048 km and with lead times of up to 3 h.

GraphCast is another weather forecasting system based on machine learning and Graph Neural Networks (GNNs), which are a particularly useful architecture for processing spatially structured data. GraphCast makes forecasts at the high resolution of 0.25 degrees longitude/latitude (28km x 28km at the equator). That's more than a million grid points covering the entire Earth's surface. At each grid point the model predicts five Earth-surface variables, including temperature, wind speed and direction, and mean sea-level pressure, and six atmospheric variables at each of 37 levels of altitude, including specific humidity, wind speed and direction, and temperature. While GraphCast's training was computationally intensive, the resulting forecasting model is highly efficient. Making 10-day forecasts with GraphCast takes less than a minute on a single Google TPU v4 machine. For comparison, a 10-day forecast using global numerical model, can take hours of computation in a supercomputer with hundreds of machines.

2.3 Rainfall Forecasting

ECMWF has launched the AI-based weather forecasting system AIFS. By integrating machine learning and AI technologies, AIFS has achieved a significant improvement in forecasting speed. In terms of several key indicators, the forecasting accuracy of AIFS is 20% higher than that of the current state-of-the-art numerical models, which helps improve the accuracy of precipitation forecasting. NASA has launched the "TROPICS" constellation of cube satellites. The mission aims to observe the formation and development of tropical cyclones and provide data for improving tropical cyclone forecasts. This can help improve the accuracy of precipitation forecasting in tropical cyclone-affected areas. The GenCast model developed by Google DeepMind has an accuracy that exceeds the ENS integrated model of the European Centre for Medium-Range Weather Forecasts. GenCast has learned 40 years of meteorological data up to 2018 and predicts the weather trend in 2019. The results show that among the more than 1300 indicators predicted by GenCast, about 97% of the prediction results are better than those of ENS, which performs well in precipitation forecasting. Microsoft Research, in collaboration with the

University of Cambridge, has developed the Aardvark Weather system. It completely abandons physical simulations and instead uses deep learning technology to generate high-precision predictions with extremely low computational costs. Microsoft also focuses on local short-term weather forecasting. Its AI model updates precipitation predictions every two minutes, combining radar and satellite data to provide high-precision immediate forecasts.

3. Challenges in AI rainfall forecasting

AI-based rainfall forecasting, despite its great promise, confronts significant challenges in physical understanding, data management, model performance, and interpretability. Overcoming these challenges demands joint efforts from the international meteorological community. This includes further research in AI-meteorology integration, improved data collection and management strategies, and the development of more interpretable and robust AI models.

3.1 Inadequate Physical Understanding and Representation

3.1.1 Limited integration of Physical Laws

AI models, especially those based on deep learning, often lack a complete and accurate integration of the fundamental physical laws that govern precipitation processes. Traditional NWP models rely on equations like the Navier-Stokes equations for fluid dynamics and thermodynamics principles to simulate the atmosphere. In contrast, AI models might learn patterns from historical data without directly applying these laws. For example, neural network-based precipitation forecasting models, due to the absence of explicit physical constraints, have produced unrealistic predictions of rainfall intensity and distribution in complex terrains. In mountainous regions, where the orographic effect is crucial for precipitation formation, these models failed to accurately capture the interaction between the terrain and the atmosphere, resulting in significant forecast errors.

3.1.2 Deficiency in Representing Sub-grid Scale Processes

Convective rainfall is usually influenced by sub-grid scale processes, such as cloud microphysics, turbulence, and small-scale convective cells. These processes occur at scales smaller than the grid resolution of most weather models, and both NWP and AI-based models struggle to represent them accurately. AI models often find it challenging to simulate the initiation and development of convective rainfall system, which is highly dependent on sub-grid scale processes. The nonlinear nature of these processes makes it difficult for AI models to learn and replicate them from data alone.

3.2 Data-oriented Challenges

3.2.1 Incomplete and Noisy Data

The quality of input data is of great importance for accurate AI-based rainfall forecasting. In many parts of the world, especially remote regions, data collection is sparse and incomplete. Observations over ocean are far less dense compared to land-based ones. For instance, the scarcity of data in the ocean can lead to inaccuracies in predicting the development and movement of tropical cyclones, which are major precipitation contributors. Additionally, noisy precipitation data from rain gauges and radar systems have led to significant errors in training AI models, resulting in poor forecasting performance. AI models rely on large amounts of historical data to learn patterns and make predictions. However, long-term and high-resolution rainfall data is usually inadequate. In some regions, the historical record of precipitation data may only span a few decades, which may not be sufficient for the model to capture long-term trends and their impact on precipitation. High-resolution data that can correctly represent the extreme features of local rainfall events, is also quite limited. It's impossible for AI models trained on low-resolution data to accurately predict the location and intensity of small-scale, high-impact rainfall events.

3.2.2 Data Heterogeneity

Precipitation forecasting often requires integrating data from multiple sources, such as weather radars, satellites, rain gauges, and numerical weather prediction models. Each data source has its own characteristics, e.g., different spatial and temporal resolutions, measurement uncertainties, and data formats. Weather radar data provides high-resolution information about precipitation in the short-term but has limitations in detecting light precipitation and is affected by beam blockage in complex terrains. Satellite-based precipitation estimates offer global coverage but may have lower spatial resolution and higher uncertainties. Integrating these diverse data sources in a way that maximizes their complementary information and minimizes the negative impacts of their differences is a significant challenge.

The lack of unified data standards and pre-processing methods across different data providers and research groups is another aspect of data heterogeneity. Different data sources may use different type of measurement and data quality control procedures. The pre-processing steps, such as data filtering, interpolation, and normalization, can also vary widely. Inconsistent data standards and pre-processing methods were major barriers to the effective use of data in improving precipitation forecasts.

3.3 Model-related Challenges

3.3.1 Limitation of Training Data

AI models, particularly deep neural networks, are prone to overfitting, especially when the training data is limited or the model is too complex. A neural network model trained on rainfall data from a specific region performed well on the training dataset but failed to accurately predict rainfall in other regions or under different weather conditions, highlighting the overfitting problem in these models.

The ability of AI models to generalize to changing conditions is also a concern. Climate change is altering the frequency, intensity, and patterns of rainfall events. However, many AI models are trained on historical data that may not fully represent future climate scenarios. As a result, these models may fail to accurately predict precipitation under new climate conditions. An analysis of the performance of AI models in predicting extreme precipitation events found that models trained on pre-climate-change data had poor performance in predicting the more intense and frequent extreme precipitation events expected in the future due to climate change.

3.3.2 Model Explainability

Most AI models used in precipitation forecasting, such as deep neural networks, are often regarded as black - box models. While they can produce accurate predictions, it is difficult to understand how the model arrives at those predictions. Understanding the physical processes is crucial for validating and improving rainfall forecasts. However, when an AI model predicts a heavy precipitation event, it is not clear which input variables or model components contributed most to that prediction. This lack of interpretability makes it challenging for forecasters to trust and use these models in operational forecasting (Figure 2).

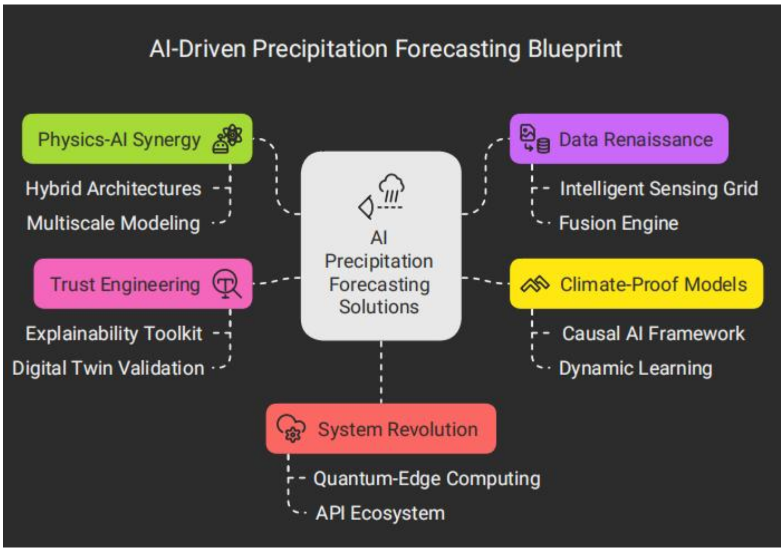

Figure 2 Current Challenges for AI-driven Precipitation Forecast

4. Directions for Technical solutions

The challenges in AI-based rainfall/precipitation forecasting can be addressed through a combination of technical solutions. These solutions require collaborative efforts from the meteorological, data science, and AI research communities to ensure that AI can fully take effects in this field.

4.1 Solutions for Physical Understanding and Representation

To address the limited incorporation of physical laws in AI models, a promising approach is to develop physics-informed neural networks (PINNs). PINNs embed physical equations, such as the Navier-Stokes equations for fluid dynamics relevant to atmospheric processes, directly into the neural network structure. For example, Raissi et al. (2019)[18] proposed a method where the residuals of the governing physical equations are added as additional loss terms during the neural network training process. This forces the model to respect physical constraints while learning from data. In the context of precipitation forecasting, this could help the model better predict precipitation intensity and distribution in complex terrains by accurately representing the interaction between the terrain and the atmosphere. Another way is to use knowledge distillation techniques. Knowledge from traditional NWP models can be transferred to more lightweight neural networks. The physical constraints, such as temperature lapse rate and energy conservation principles, are distilled into the neural network. To better represent sub-grid scale processes, hierarchical neural network architectures can be employed.. Hess et al. (2022)[8] proposed a framework based on physically constrained generative adversarial networks (GAN) to improve local distributions and spatial structure simultaneously. Their method outperforms existing ones in correcting local distributions and leads to strongly improved spatial patterns, especially regarding the intermittency of daily precipitation. Enforcing a physical constraint to preserve global precipitation sums, the GAN can generalize to future climate scenarios unseen during training.

4.2 Solutions for Data-related Challenges

To handle noisy data, advanced data cleaning algorithms can be used. For example, median filtering and wavelet-based denoising techniques can be applied to rainfall data from rain gauges and radar systems. Qiu and Yuan (2023)[17] demonstrated that wavelet-based denoising can effectively remove noise from radar-derived precipitation data. To obtain long-term data, efforts can be made to combine historical datasets from multiple sources. For example, historical weather station data, satellite-based precipitation records, and reanalysis datasets can be integrated. The Climate Forecast System Reanalysis (CFSR) and the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis datasets can be merged with local weather observation data to create more comprehensive long-term datasets. For high-resolution data, new sensor technologies and data fusion methods can be explored. For instance, the development of next-generation weather radars with higher resolutions and more frequent updates can provide more detailed precipitation information. Additionally, data fusion techniques can combine data from multiple sensors to generate high-resolution precipitation datasets. To integrate multiple data sources with different characteristics, multi-modal neural network architectures can be used. For example, a convolutional neural network (CNN)-based model can be designed to process satellite infrared imagery, radar reflectivity data[4], and ground-based precipitation measurements simultaneously. The CNN layers can be tailored to the specific characteristics of each data source, such as using different kernel sizes and activation functions for satellite and radar data. As for pre-processing, a library that provides standardized data filtering, interpolation, and normalization procedures can be made available to the research community.

4.3 Solutions for Model-related Challenges

To prevent overfitting, regularization techniques can be applied. L1 and L2 regularization, as described by Gupta et al. (2018)[7], add penalty terms to the loss function of the neural network. These penalty terms encourage the model to keep its weights small, preventing it from learning the idiosyncrasies of the training data. In precipitation forecasting, this can help the model focus on the general patterns and physical relationships in the data. For example, when training a neural network on precipitation data from a specific region, L2 regularization can ensure that the model does not over-adapt to the local data and can still perform well in other regions or under different weather conditions. To improve generalization to unseen or changing conditions, a pre-trained AI model on a large - scale global precipitation dataset can be fine-tuned on local data with specific climate characteristics. As demonstrated by Yosinski et al. (2014)[24], transfer learning allows the model to leverage the knowledge learned from the global datasets and adapt it to the local or changing climate conditions. Generative models can also be used to augment the training data to include scenarios similar to those expected under changing conditions. By training AI models on this augmented dataset, the models can be better prepared to predict precipitation under new and unseen climate conditions.

To make AI models more interpretable, Bach et al. (2015)[2] introduced layer - wise relevance propagation (LRP), which calculates the contribution of each input feature to the final output of the neural network. LRP can be applied to a deep neural network to understand which input variables (such as temperature, humidity, and wind speed) are most important for rainfall forecasting. Another approach is to use attention mechanism in rainfall forecasting model. By analyzing the attention maps, meteorologists can gain insights into which regions or features in the precipitation - related data the model is paying the most attention to, making the model's decision - making process more interpretable.

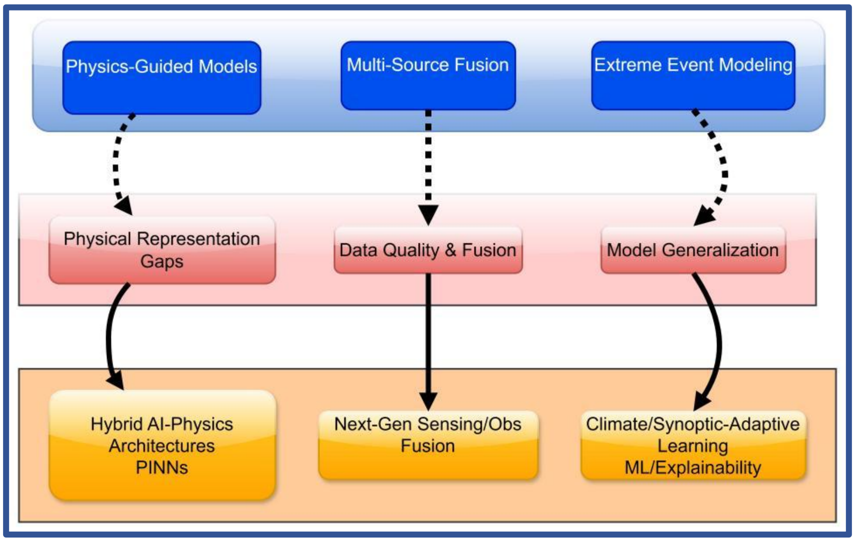

Figure 3 Future Solutions for AI Rainfall Prediction (the dashed arrows indicate current targets of AI prediction techniques; the solid arrows show the future direction for the solution of AI rainfall prediction problem)

5. Conclusion and Discussion

This chapter briefly introduces the remarkable progress made in AI rainfall forecasting in the past decade. Physics - constrained ML models like NowcastNet and GraphCast have successfully introduced physical equations into deep-learning architectures. NowcastNet, by embedding Navier - Stokes residuals, has curbed errors in complex terrains. GraphCast, with its dynamic graph neural networks, has achieved high - resolution global forecasts and outperformed traditional NWP in extreme event detection. Multi-modal data fusion system such as NOAA's MRMS significantly elevated precipitation forecasting accuracy. They amalgamate diverse data sources, such as satellite, radar (Figure 4), and ground-based measurements, to capture multi-scale dynamics, extend warning lead times, and cut down false alarms. Extreme event modeling has also advanced, with GANs and attention -

based models becoming better at predicting rare and high-impact precipitation events. AI has the potential to revolutionize rainfall forecasting, which is of great importance for disaster management.

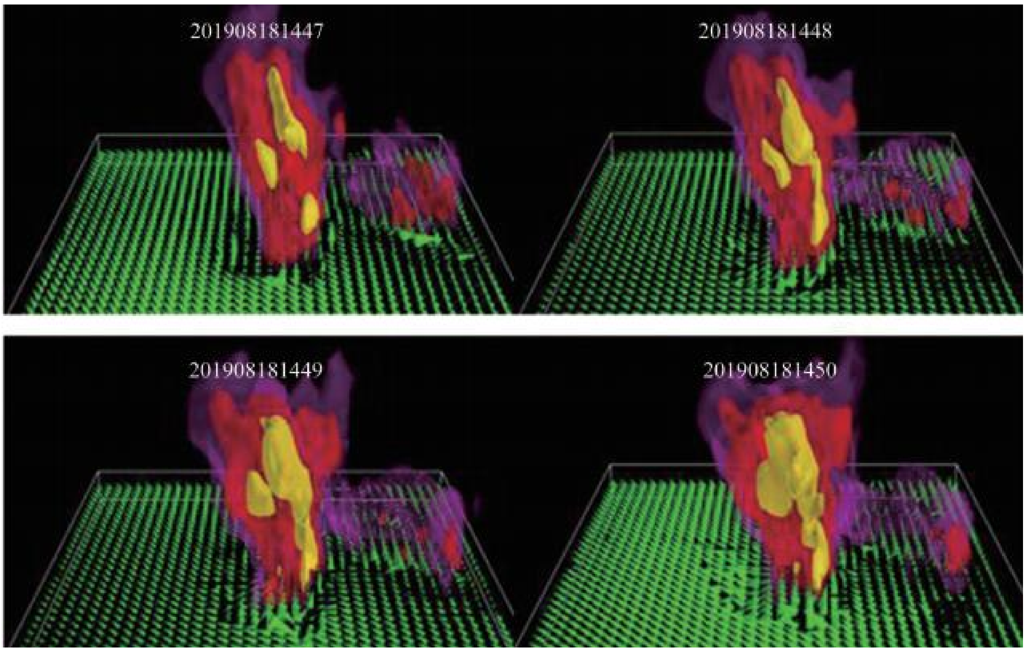

Figure 4 The 3-D hail storm structure observed by X-band radar at time interval of 1 minute (Cited from Ma et al., 2023[27])

However, despite these advancements, AI rainfall forecasting still grapples with significant challenges. Inadequate physical understanding and representation in AI models can lead to unrealistic predictions, particularly in complex terrains. Data - related issues, such as incomplete and noisy data, data heterogeneity, and integration problems, pose difficulties to accurate forecasting. Model - related challenges, including overfitting, poor generalization to changing climate conditions, and lack of interpretability, limit the trust and adoption of AI models in operational forecasting.

In this consideration, this review suggests that future research should be focused on further integrating physical principles into AI models. Advanced physics-informed neural networks and knowledge distillation techniques should be valuable for improving the physical consistency of AI models. In terms of data, efforts should be directed towards improving data quality, quantity, and integration.

For model-related aspects, research should aim to create more explainable AI models. Relevance propagation and attention mechanisms can be further refined to offer more in-depth insights into model structure. Additionally, enhancing the generalization ability of AI models to changing climate conditions through transfer learning and data augmentation can also be considered.

By addressing these challenges through continuous research and development, AI can provide more accurate, reliable, and interpretable precipitation forecasts. This will not only benefit the scientific community but also have far-reaching implications for various sectors, including disaster management, agriculture, and renewable energy, helping to build more resilient societies in the face of climate variability.

Conflict of Interest

The authors declare no conflict of interest." or delete this entire section

References

[1] Agrawal, S., Barrington, L., Bromberg, C., Burge, J., Gazen, C., & Hickey, J. (2019). Machine learning for precipitation nowcasting from radar images. arXiv preprint arXiv:1912.12132.

[2] Bach, S., Binder, A., Montavon, G., Klauschen, F., Müller, K. - R., & Samek, W. (2015). On pixel - wise explanations for non - linear classifier decisions by layer - wise relevance propagation. PloS one, 10(7), e0130140.

[3] Baltrušaitis, T., Ahuja, C., & Morency, L. - P. (2018). Multimodal machine learning: A survey and taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(2), 423–443. https://doi.org/10.1109/tpami.2018.2798607

[4] Cao, Y., Chen, L., Wu, J., & Feng, J. (2025). Enhancing nowcasting with multi - resolution inputs using deep learning: Exploring model decision mechanisms. Geophysical Research Letters, 52, e2024GL113699. https://doi.org/10.1029/2024GL113699

[5] Chen, L., Cao, Y., Ma, L., & Zhang, J. (2020). A deep learning - based methodology for precipitation nowcasting with radar. Earth and Space Science, 7(2), e2019EA000812. https://doi.org/10.1029/2019ea000812

[6] Geng, L., Geng, H., Min, J., Zhuang, X., & Zheng, Y. (2022). Af - srnet: Quantitative precipitation forecasting model based on attention fusion mechanism and residual spatiotemporal feature extraction. Remote Sensing, 14(20), 5106. https://doi.org/10.3390/rs14205106

[7] Gupta, S., Gupta, R., Ojha, M., Singh, K.P. (2018). A Comparative Analysis of Various Regularization Techniques to Solve Overfitting Problem in Artificial Neural Network. In: Panda, B., Sharma, S., Roy, N. (eds) Data Science and Analytics. REDSET 2017. Communications in Computer and Information Science, vol 799. Springer, Singapore. https://doi.org/10.1007/978-981-10-8527-7_30

[8] Hess, P., Drüke, M., Petri, S. et al (2022). Physically constrained generative adversarial networks for improving precipitation fields from Earth system models. Nat Mach Intell 4, 828–839. https://doi.org/10.1038/s42256-022-00540-1

[9] Kaae Sønderby, C., Espeholt, L., Heek, J., Dehghani, M., Oliver, A., Salimans, T., et al. (2020). Metnet: A neural weather model for precipitation forecasting. arXiv e - prints, arXiv–2003.

[10] Kim, Y., & Hong, S. (2021). Very short - term rainfall prediction using ground radar observations and conditional generative adversarial networks. IEEE Transactions on Geoscience and Remote Sensing, 60, 1–8. https://doi.org/10.1109/tgrs.2021.3108812

[11] Ko, J., Lee, K., Hwang, H., Oh, S. - G., Son, S. - W., & Shin, K. (2022). Effective training strategies for deep - learning - based precipitation nowcasting and estimation. Computers and Geosciences, 161, 105072. https://doi.org/10.1016/j.cageo.2022.105072

[12] Leinonen, J., Hamann, U., & Germann, U. (2022). Seamless lightning nowcasting with recurrent - convolutional deep learning. Artificial Intelligence for the Earth Systems, 1(4), e220043. https://doi.org/10.1175/aies - d - 22 - 0043.1

[13] Liu, Y., Hu, T., Zhang, H., Wu, H., Wang, S., Ma, L., & Long, M. (2023). itransformer: Inverted transformers are effective for time series forecasting. arXiv preprint arXiv:2310.06625.

[14] Lu, K., Grover, A., Abbeel, P., & Mordatch, I. (2022). Frozen pretrained transformers as universal computation engines. Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 36(7), 7628–7636). https://doi.org/10.1609/aaai.v36i7.20729

[15] Nguyen, T., Brandstetter, J., Kapoor, A., Gupta, J. K., & Grover, A. (2023). Climax: A foundation model for weather and climate. arXiv preprint, arXiv:2301.10343.

[16] Pan, X., Lu, Y., Zhao, K., Huang, H., Wang, M., & Chen, H. (2021). Improving nowcasting of convective development by incorporating polarimetric radar variables into a deep - learning model. Geophysical Research Letters, 48(21), e2021GL095302. https://doi.org/10.1029/2021gl095302

[17] Qiu F., Yuan K., 2023: Denoising complex background radar signals based on wavelet decomposition thresholding. Applied Mathematics and Nonlinear Sciences, 9(1). DOI: 10.2478/amns.2023.2.00535

[18] Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics – informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686 – 707.

[19] Reichstein, M., Camps - Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat (2019). Deep learning and process understanding for data - driven earth system science. Nature, 566(7743), 195–204. https://doi.org/10.1038/s41586 - 019 - 0912 - 1

[20] Ronneberger, O., Fischer, P., & Brox, T. (2015). U - net: Convolutional networks for biomedical image segmentation. Medical image computing and computer - assisted intervention–miccai 2015: 18th international conference, munich, germany, october 5 - 9, 2015, proceedings, Part III(Vol. 18, 234–241). https://doi.org/10.1007/978 - 3 - 319 - 24574 - 4_28

[21] Rothfusz, L. P., Schneider, R., Novak, D., Klockow - McClain, K., Gerard, A. E., Karstens, C., et al. (2018). Facets: A proposed next - generation paradigm for high - impact weather forecasting. Bulletin of the American Meteorological Society, 99(10), 2025–2043. https://doi.org/10.1175/bams - d - 16 - 0100.1

[22] Shi, X., Chen, Z., Wang, H., Yeung, D. - Y., Wong, W. - K., & Woo, W. - c. (2015). Convolutional LSTM network: A machine learning approach for precipitation nowcasting. Advances in Neural Information Processing Systems, 28.

[23] Weyn, J. A., Durran, D. R., & Caruana, R. (2020). Improving data - driven global weather prediction using deep convolutional neural networks on a cubed sphere. Journal of Advances in Modeling Earth Systems, 12(9), e2020MS002109. https://doi.org/10.1029/2020ms002109

[24] Yosinski, J., Clune, J., Bengio, Y., & Lipson, H. (2014). How transferable are features in deep neural networks? In Advances in neural information processing systems 27, pp. 3320 – 3328.

[25] Yuan, Y., & Lin, L. (2020). Self - supervised pretraining of transformers for satellite image time series classification. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 474–487. https://doi.org/10.1109/jstars.2020.3036602

[26] Zhou, K., Zheng, Y., Dong, W., & Wang, T. (2020). A deep learning network for cloud - to - ground lightning nowcasting with multisource data. Journal of Atmospheric and Oceanic Technology, 37(5), 927–942. https://doi.org/10.1175/jtech - d - 19 - 0146.1

[27] MA, L.， Lin, H， Chu, H., et al. (2023). Research progress of Shanghai operational intelligent forecast technologies on severe convection. Advances in Earth Science，38（2）：111-124. DOI：10.11867/j.issn.1001-8166.2023.003