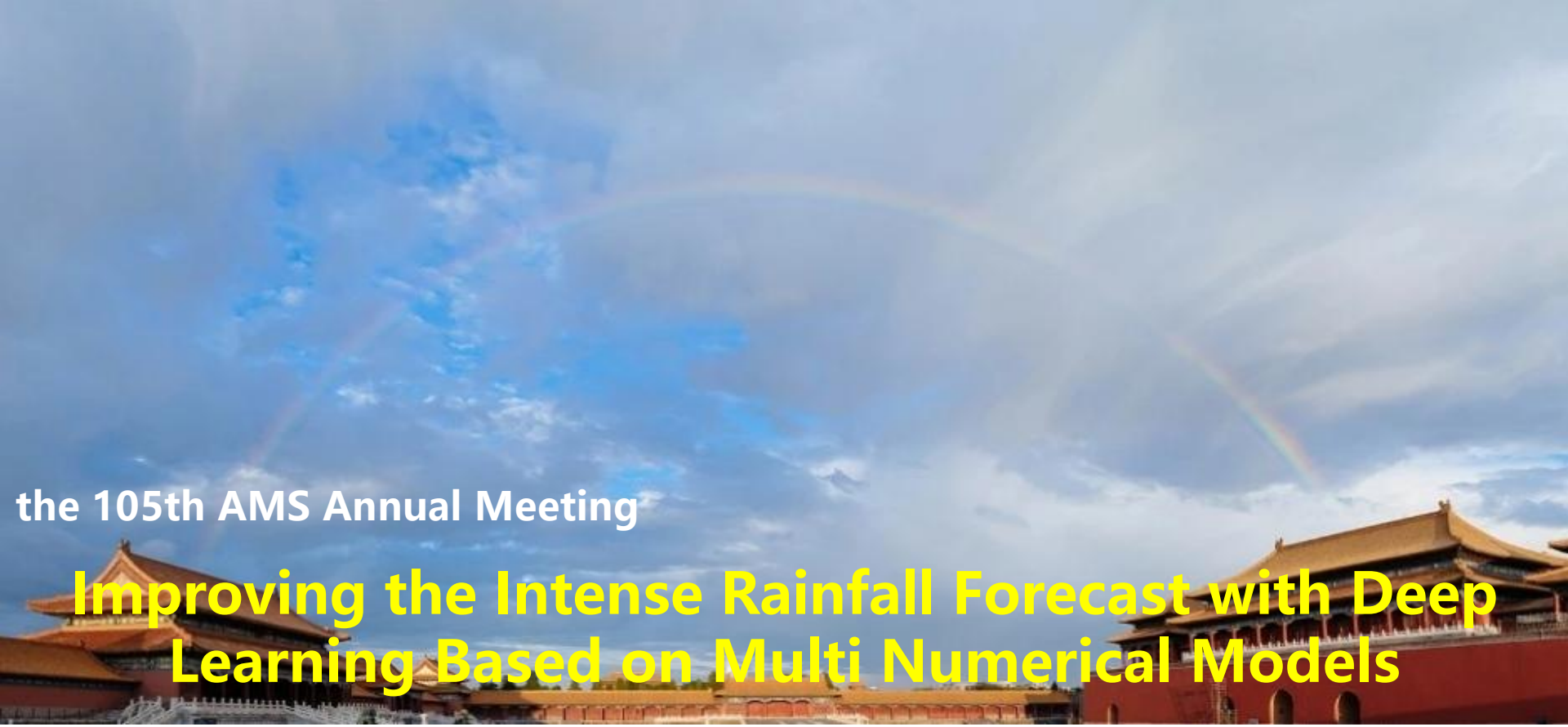


the 105th AMS Annual Meeting

Improving the Intense Rainfall Forecast with Deep Learning Based on Multi Numerical Models

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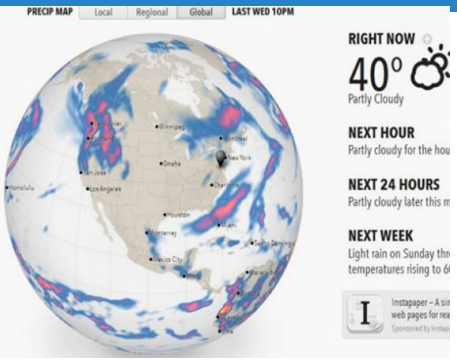
13 January 2025

New Orleans, Louisiana

Outline

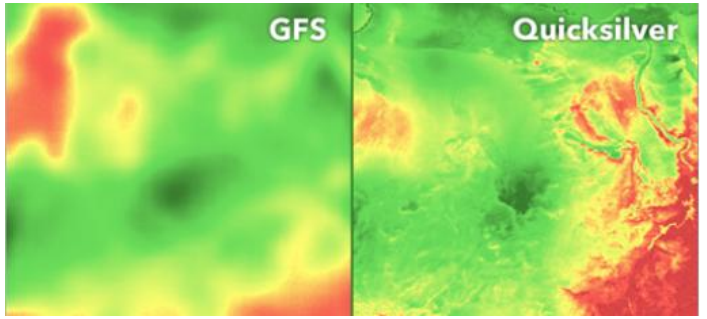
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2. Data and the Fusion Rain Network Design
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4. Conclusions

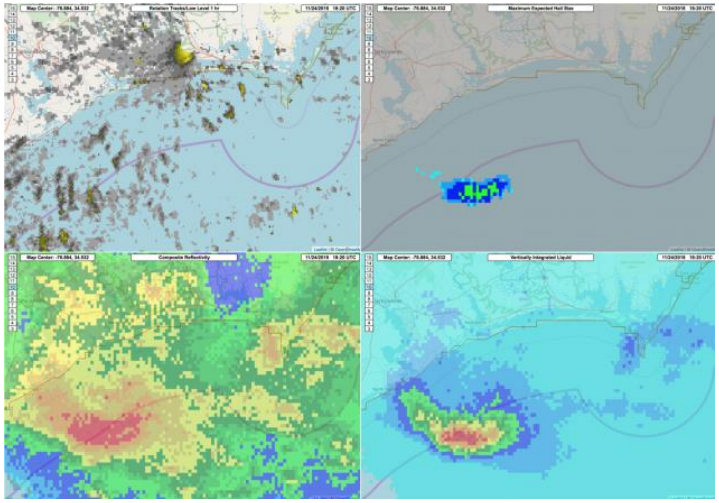
Using ML in Severe Weather



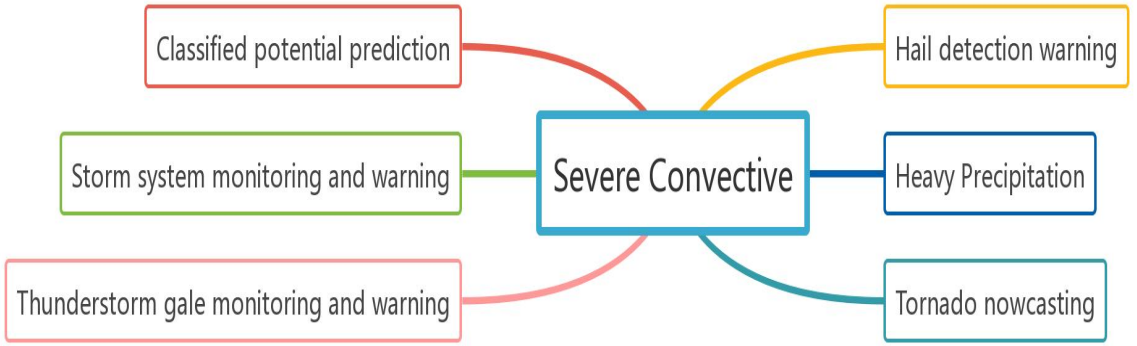
Dark Sky



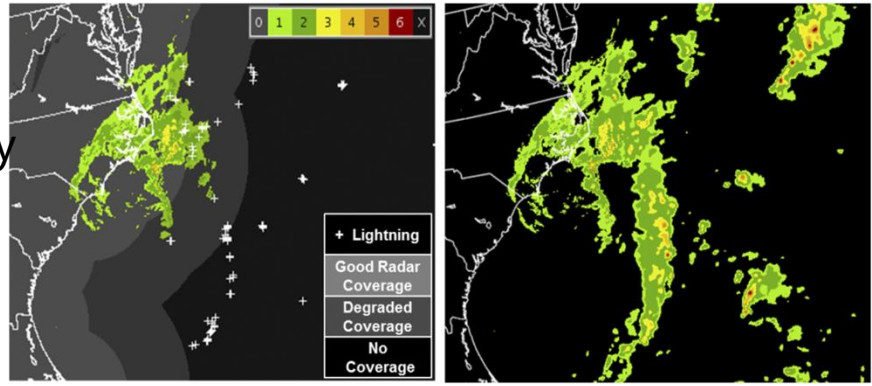




NOAA/CIMSS ProbSevere Model
Machin Learning based applications for environmental hazard detection and prediction



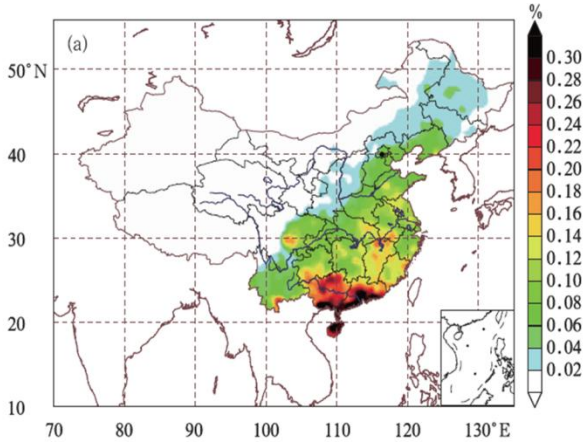
Creating Synthetic Radar Imagery Using Convolutional Neural Networks



Mark S. Veillette, etc. 2018

Severe weather –Intense Rainfall

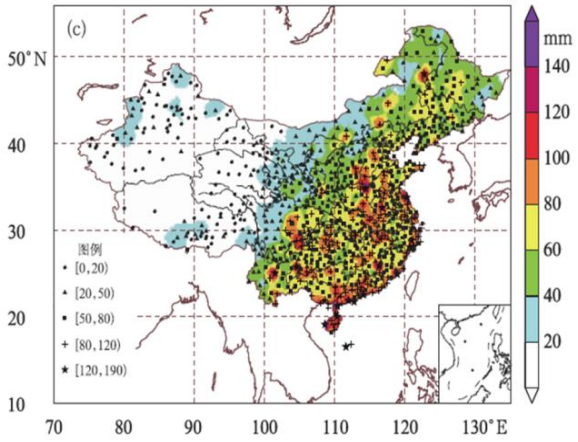
(Definition: Rain Rate>20mm/h or >50mm/3h)



Frequency distribution of intense rainfall in China

- Sudden
- Local
- Violet
- Fatal
- Difficult to forecast





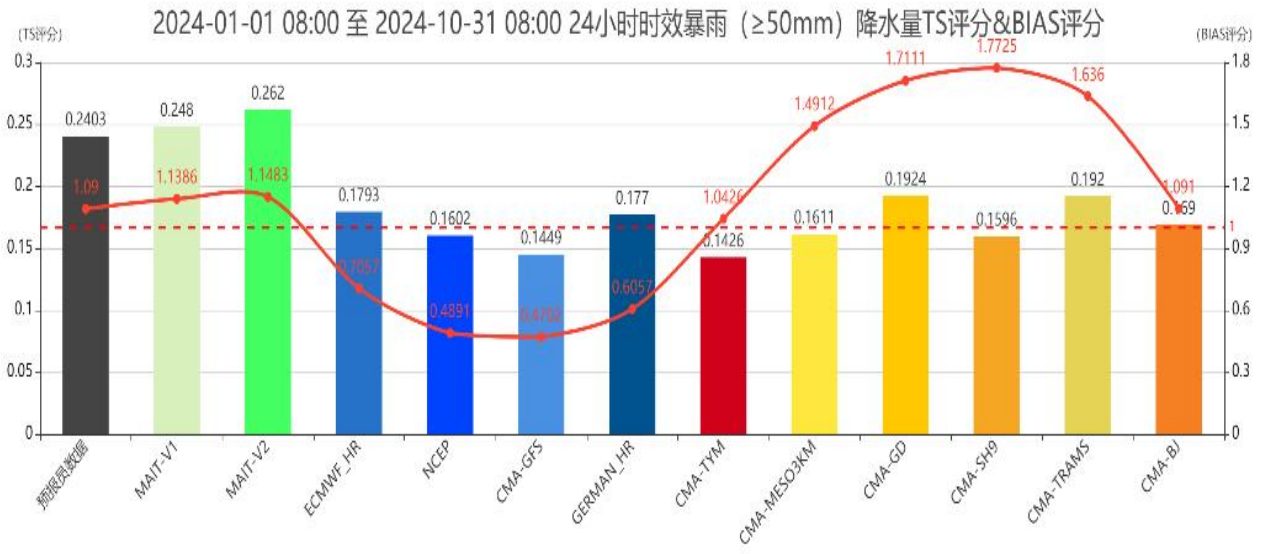
Distribution of maximum rainfall(mm) in a hour in China





Major Difficulties on heavy rain forecast

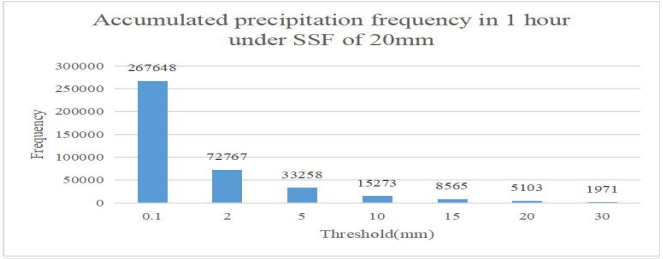
- Forecast Skill sharply reduced from light rain to heavy rain.
- It is difficult for any single model to outperform on all the rainstorms.
- Traditional correction methods generally gain improvement on light rain, but still suffers lower skill on heavy and extreme threshold.

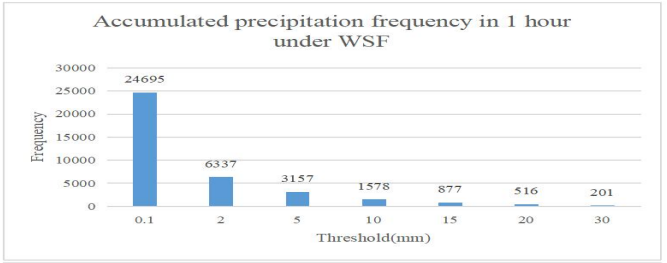


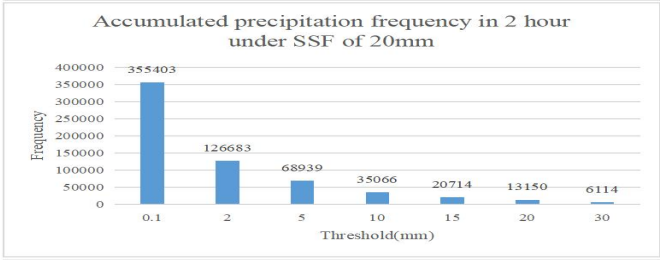
TS score and BIAS score of various mumerical models for rainstorm (>50mm/day) forecast in 2024.

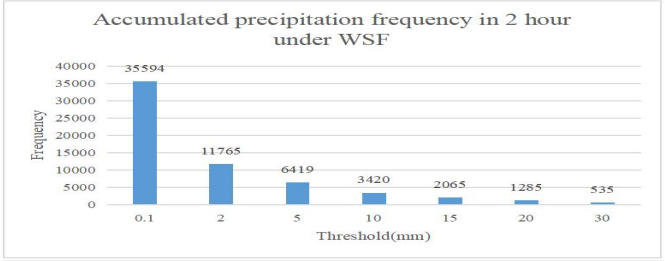
Major Difficulties on heavy rain forecast

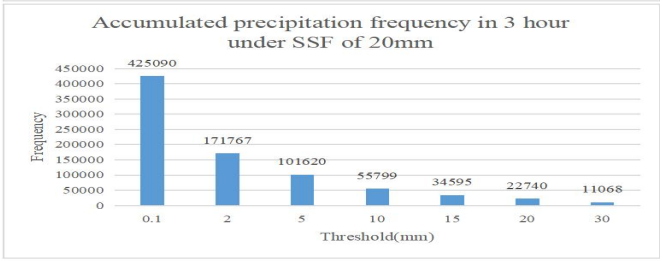
- Data-driven ML methods have achieved significant advancements in nowcasting recently, however longer lead-time precipitation forecasts still heavily depend on physical constraints.
- There is a significant class imbalance between heavy and light precipitation samples.

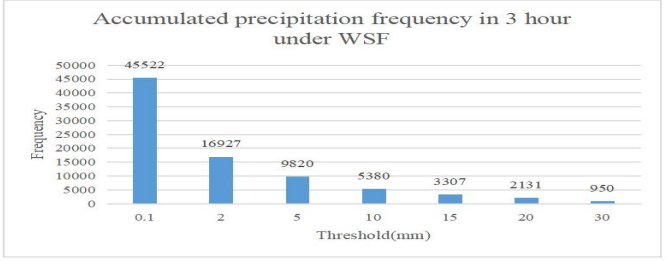






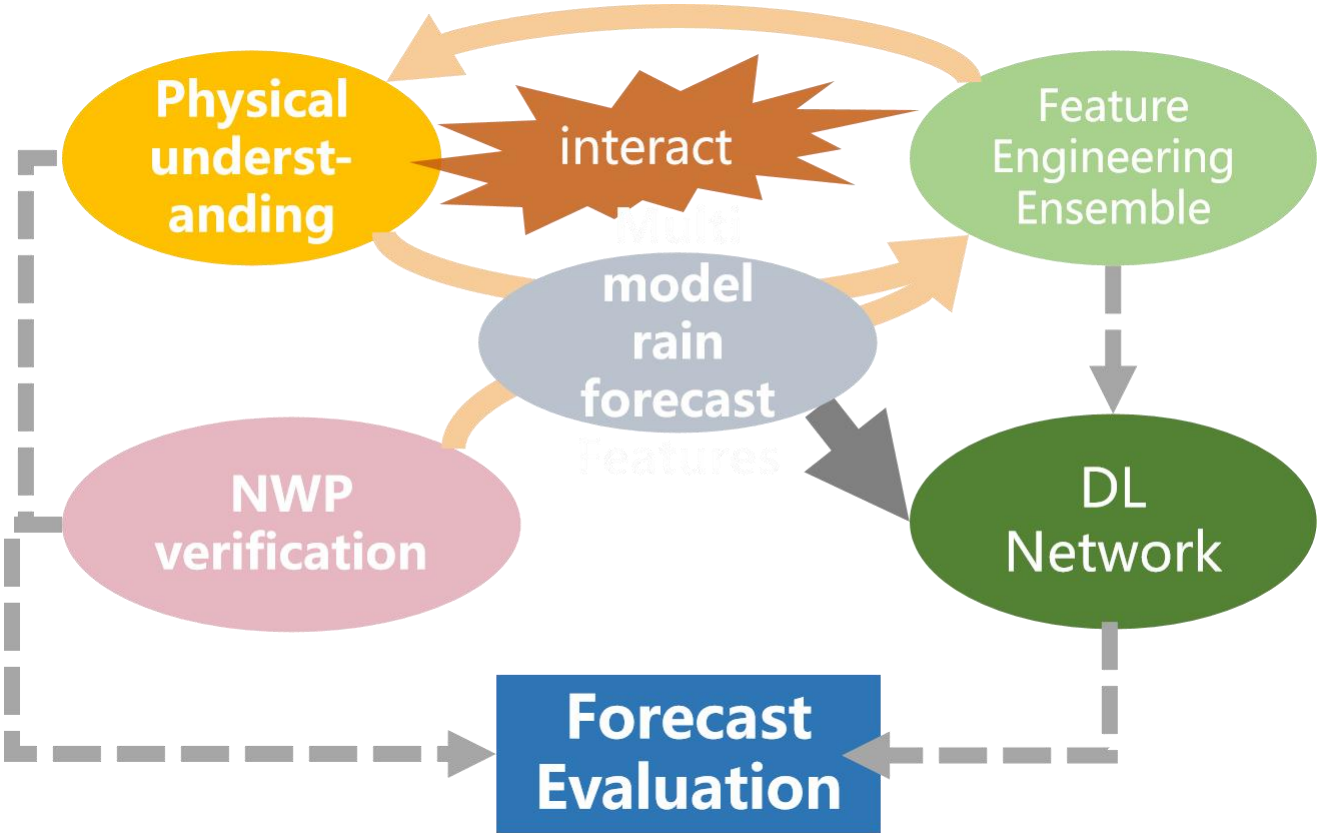






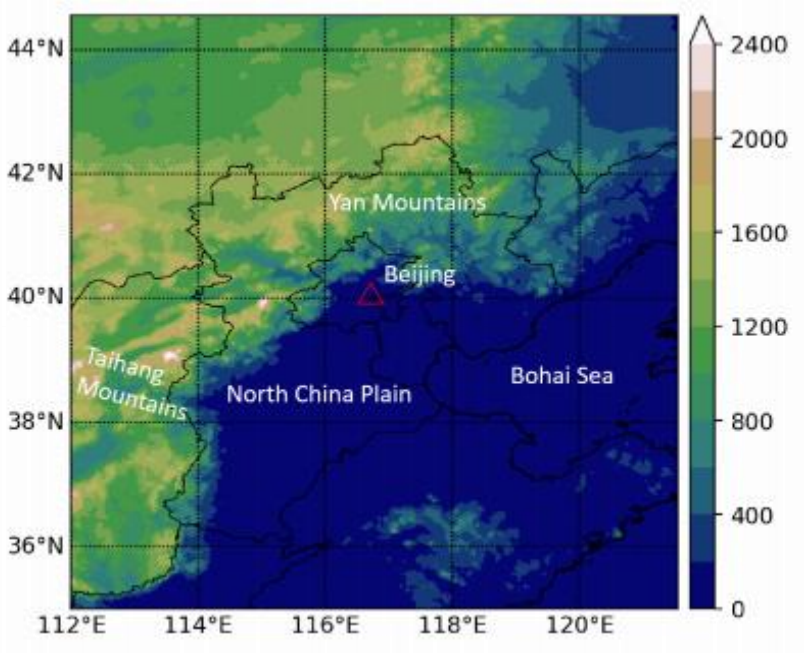
Aim：Improve Hour-scale Heavy Rain Forecast

a pivotal question: Can deep learning, with its nonlinear feature extraction capabilities, integrate the strengths of precipitation forecasts from models operating at varying scales?



2.1 Study area and Dataset

The target area is the expanded Beijing-Tianjin-Hebei region.



Study area and topographic elevation distribution (shaded, units: meters).

we employ the CMA Multi-source merged Precipitation Analysis System (CMPAS) as the observational data for precipitation, which integrates data from 7,768 ground-based automatic stations, satellites, and 8 radar observations in this area.

Table1： Introduction of the numerical models used

NWP data	ECMWF	CMA-SH9	CMA-3KM
cycle	00UTC/12UTC	00UTC/12UTC	00UTC/12UTC
lead time	10d	72h	36h
time resolution	3h	surface: 1h pressure: 3h	1h
spatial resolution	surface: 0.125° pressure: 0.25°	9km	0.03°
spatial range	Global	China	China

2.2 ML data

Dataset division and sample distribution

Leadtime/Sample		3	6	9	12	15	18	21	24	sum
Train	20190605 - 20191003 20200317 - 20200715	213	234	245	228	211	231	243	227	1832
Valid	20200716 - 20201001	79	76	79	81	79	78	82	83	637
Test1	20210701 - 20210831	124	124	124	124	124	124	124	124	992
Test2	20220701 - 20220831	124	124	124	124	124	124	124	124	992

Source	**Feature**
ECMWF	R3(T) 、R3(T-3)
CMA-SH9	R3(T) 、R3(T-3)
CMA-3KM	R3(T) 、R3(T-3)
META	Elevation、 Latitude、 Longitude
Time	cos(cycle)、 sin(cycle)、 cos(leadtime) 、sin(leadtime)

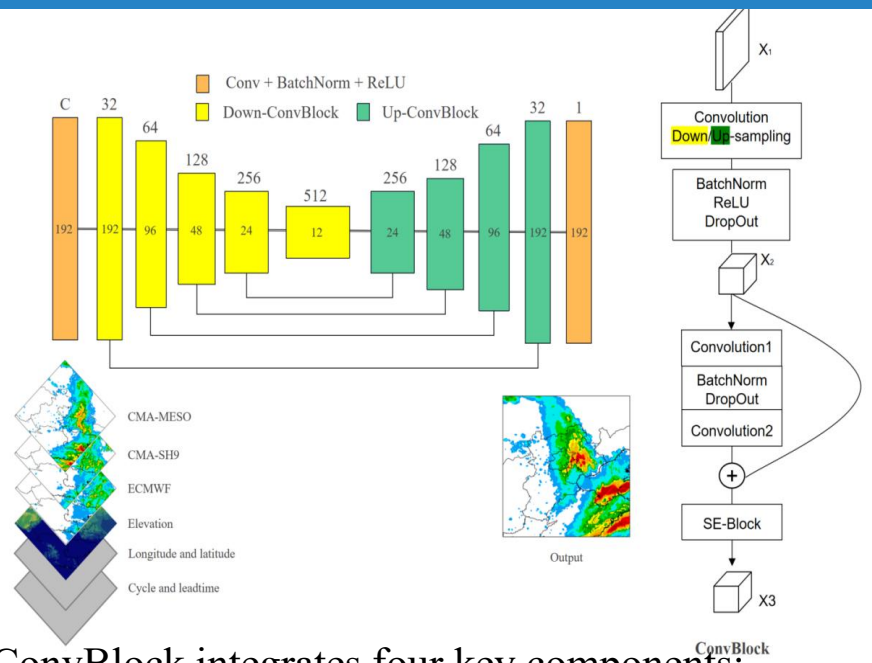
□ Evaluation metric

The metrics employed to assess model performance include Threat Score (TS), Probability of Detection (POD), False Alarm Rate (FAR), BIAS Score (BIAS) the Fraction Skill Score (FSS) is also employed for verification

2.3 Structure of the deep dearning model

The significant class imbalance between heavy and light precipitation samples is addressed through training sample selection, model architecture design, and loss function weighting.

- samples labeled Y (a 192×192 grid region) were discarded if fewer than 300 grid points recorded precipitation (P≥1 mm) in the training and validation datasets.
- The primary architecture of FRNet adopts an encoder-decoder framework inspired by U-Net. Skip connections link corresponding encoder and decoder layers.



Schematic Diagram of the Precipitation Deep Learning Correction Model-FRNet

$$\text{Loss} = L_{WMSE} + L_{WMAE}$$

$$L_{WMSE} = \sum_{i=1}^{192}\sum_{j=1}^{192} W_{i,j}(X_{i,j} - \widehat{X}_{i,j})^2$$

$$L_{WMAE} = \sum_{i=1}^{192}\sum_{j=1}^{192} W_{i,j}|X_{i,j} - \widehat{X}_{i,j}|^2$$

$$W_{i,j} = exp(ax_{i,j} + b)$$

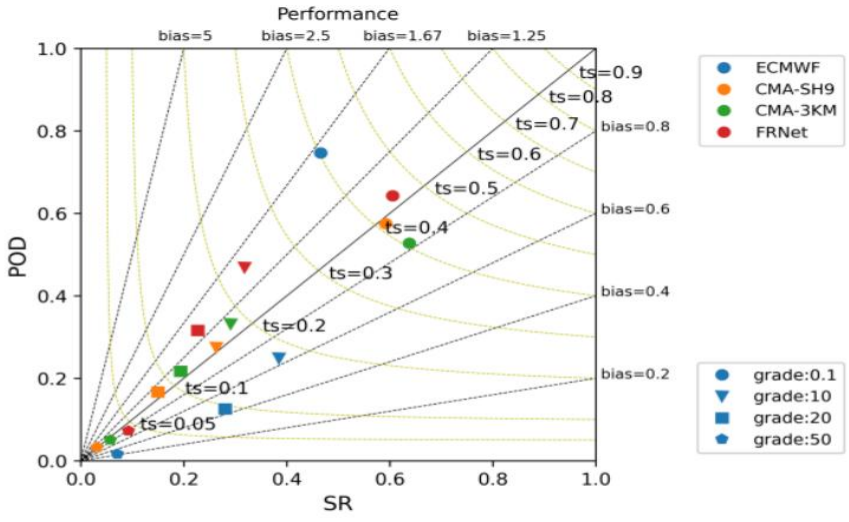
- Each ConvBlock integrates four key components: (a) Convolution operations. (b) Batch normalization , ReLU, and Dropout layers. (c) Residual connections, which comprise two convolutional layers and one BN+Dropout layer. (d) SE-Block : Squeeze-and-Excitation module).
- The loss function is a weighted combination of mean-squared error (MSE) and mean absolute error (MAE), and assigns greater weight to larger rainfall values (the weight is related to the normalized precipitation amount through an exponential relationship).

Outline

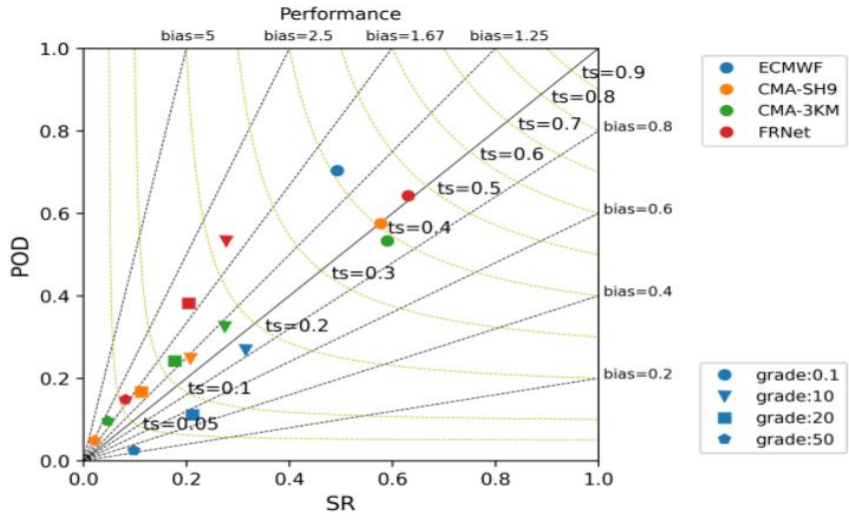
1. Background
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3.1 Statistical Evaluation Results

- FRNet consistent performance across both test datasets highlights its stability and robustness.
- It significantly enhances performance across all precipitation thresholds compared to the original numerical model forecasts. With greater gains observed at higher precipitation intensities, a 34%-61% increase of TS at 20mm and 54%-160% at 50mm.
- As to Bias scores, ECMWF's overestimation at light rain and underestimation at heavy rain are significant improved, but show an elevated BIAS (~1.4) for moderate rain.
- For POD and FAR, FRNet demonstrated a clear advantage, in particular at 50mm it obviously outperformed all numerical models



a. Year 2021



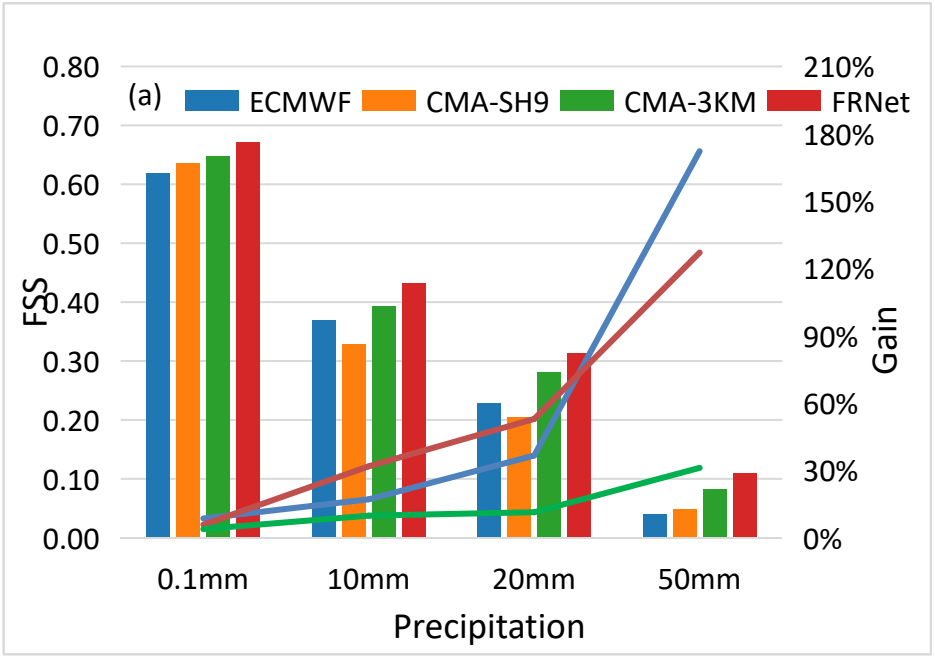
b. Year 2022

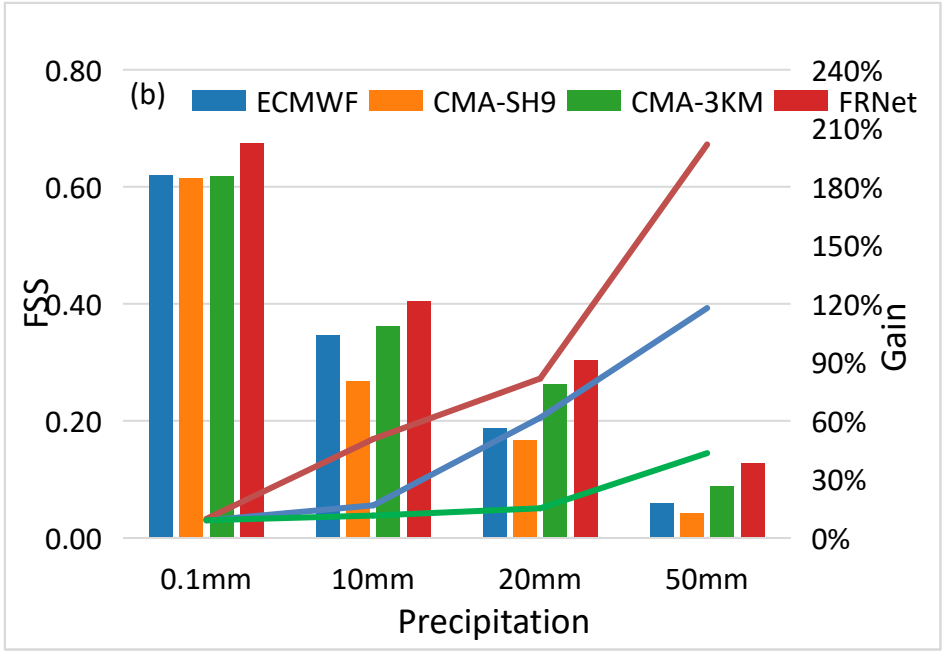
Fig. Comprehensive scoring of precipitation correction experiments on two test datasets

3.1 Statistical Evaluation Results

- Using a window size of 3 as an example, FRNet achieves an improvement rate of over 4%,10%, and 30% enhancement at the 0.1 mm ,10 mm and 20mm over numerical models. For precipitation exceeding 20 mm, FSS improvement rates increase sharply, for heavy precipitation of 50 mm, FRNet outperforms both ECMWF and CMA-SH9 by over 120% and CMA-3KM by over 20%.

- This statistical analysis highlights that FRNet not only excels in traditional point-to-point verification but also demonstrates significant advantages in forecasting convective structural patterns

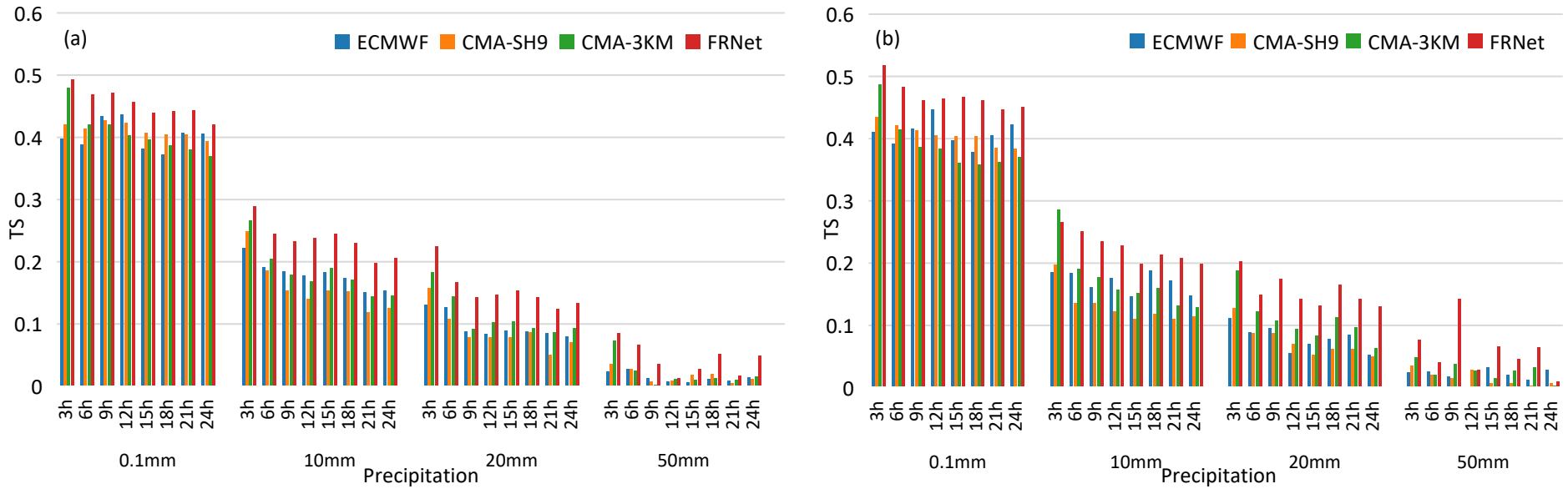




FSS scores (column) and improvement rates (curve) of precipitation correction experiments of FRNet and NWPs precipitation on the test sets in year (a) 2021 and (b) 2022.

3.1 Statistical Evaluation Results

- ECMWF shows strong forecasting capability for precipitation below 10 mm at lead times of 9 hours or more. For precipitation above 20 mm, particularly on heavy rainfall exceeding 50 mm the mesoscale model achieves much higher TS scores. While, FRNet significantly improves TS scores across all precipitation levels, including light, moderate, heavy, and torrential rain, compared to numerical models.
- In absolute terms, FRNet's 24-hour forecast performance matches the 6-hour forecast capability of numerical models, offering an "18-hour prediction time gain" over NWPs.



TS scores for various thresholds and lead times in the precipitation correction tests for (a) 2021 and (b) 2022, comparing the original numerical models with the FRNet.

Case 1. Systematic precipitation under the Influence of Subtropical High (July 27, 2022)

a widespread heavy precipitation event impacted most of North China, driven by the interaction between westerly cold air and the subtropical high. The rainband, oriented northeast to southwest.

the main rainband and slow eastward progression and split are reasonably predicted by models. However, the ECMWF overestimate the maximum intensity in central Hebei and underestimate the scattered secondary precipitation centers in the southern region. the mesoscale models performs vice versea.

The FRNet effectively integrated the strengths of global and mesoscale models. It adjusted the overall precipitation distribution eastward, mitigating the ECMWF model's overprediction in central Hebei and underprediction in the south.

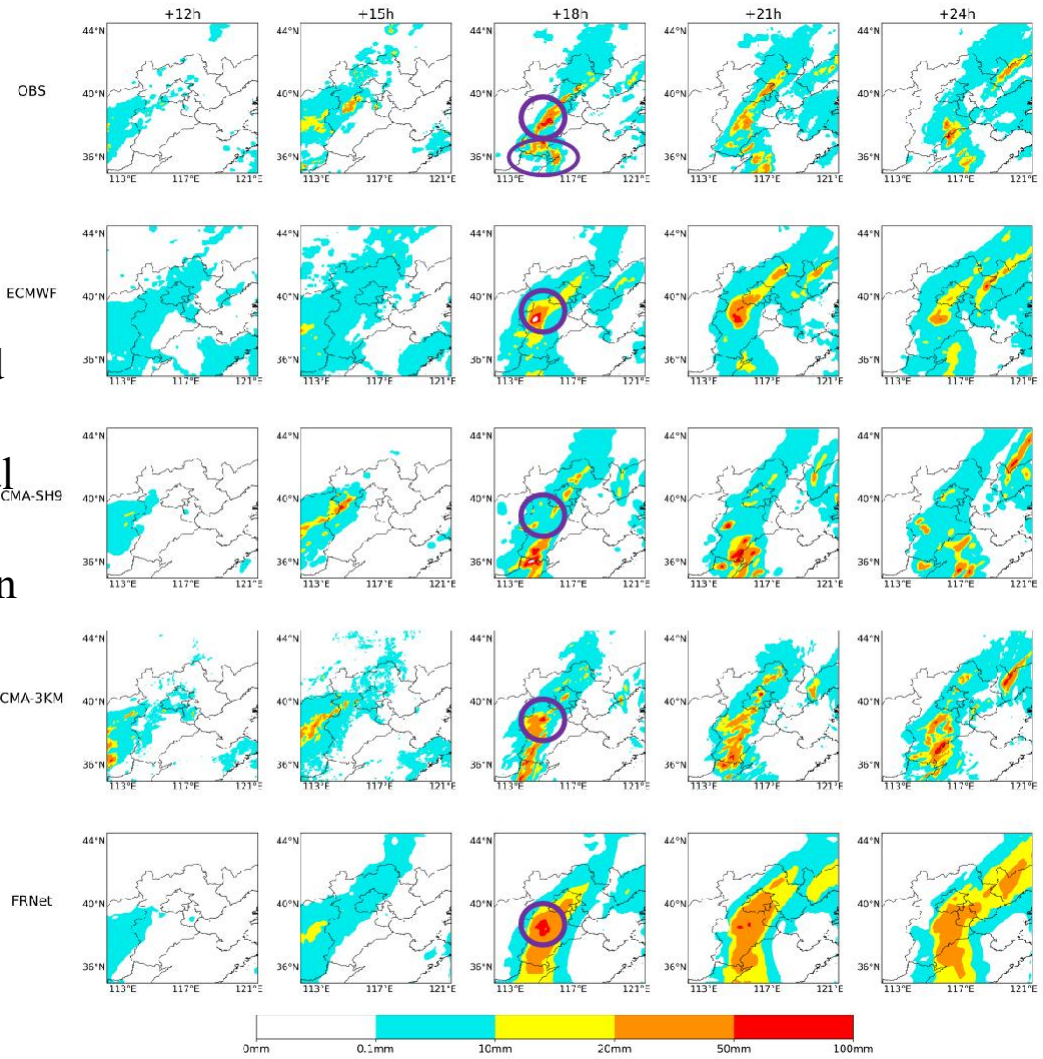
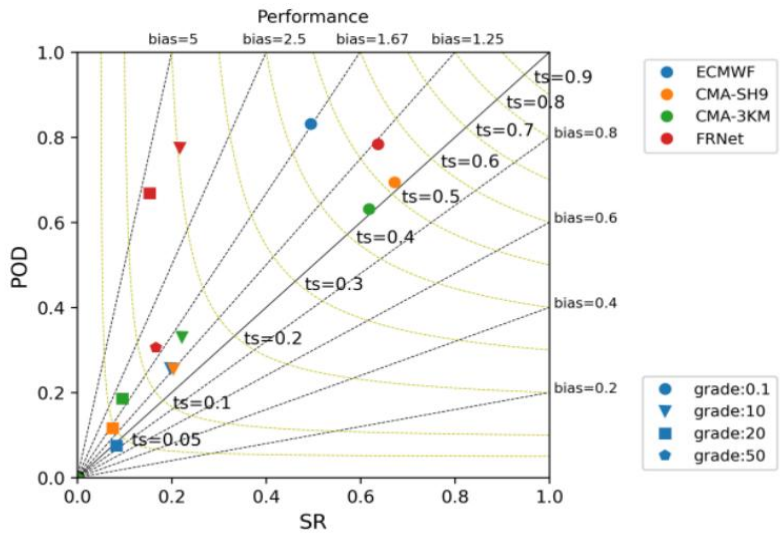
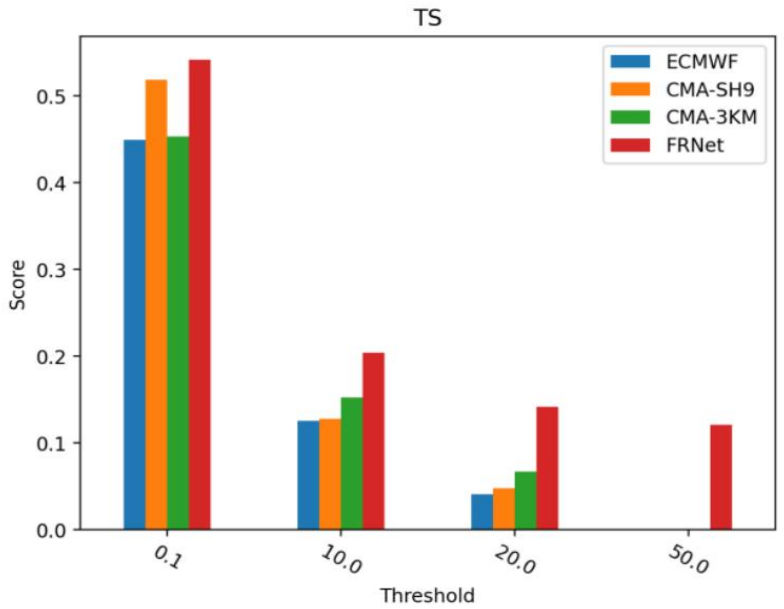


Fig. Precipitation distribution maps for the lead time 12 to 24 hours from 00 UTC on July 27, 2022

Case 1. Systematic precipitation under the Influence of Subtropical High (July 27, 2022)

- After correction by FRNet, the TS improved significantly, particularly for precipitation exceeding 20 mm. These improvements stemmed from enhanced accuracy in both spatial distribution and intensity, resulting in substantial gains for torrential rainfall forecasts.
- However,a notable bias in the deep learning correction scheme for moderate rainfall levels, where overestimation was observed.





Case 2. Severe Convective Precipitation Case (August 21, 2022)

This event exhibited both systematic and convective rainfall characteristics in the Beijing-Tianjin-Hebei region. The systemic precipitation located in the northern region is captured well by models .

As to the convective precipitation, the maximum hourly rainfall intensity reached 103.3 mm h^{-1} and hail was also reported in the warm sector of the subtropical high, which are great challenge for all the model forecasts.

ECMWF missed it, mesoscale models improved the intensity but significant positional deviations remained.

FRNet's correction integrated strengths from both global and mesoscale models, effectively capturing the position and movement of the main rainband while enhancing convective precipitation intensity near Cangzhou.

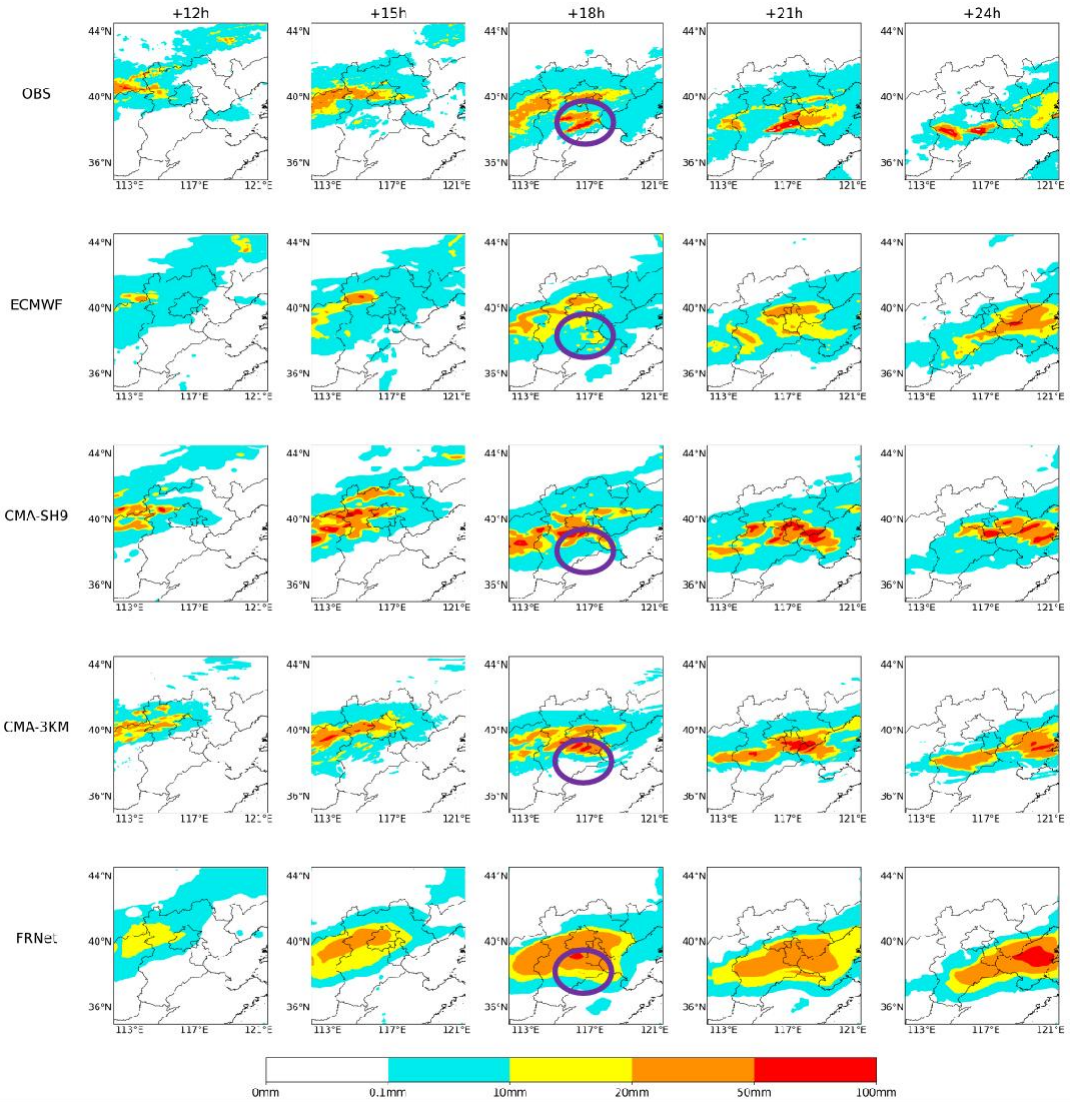
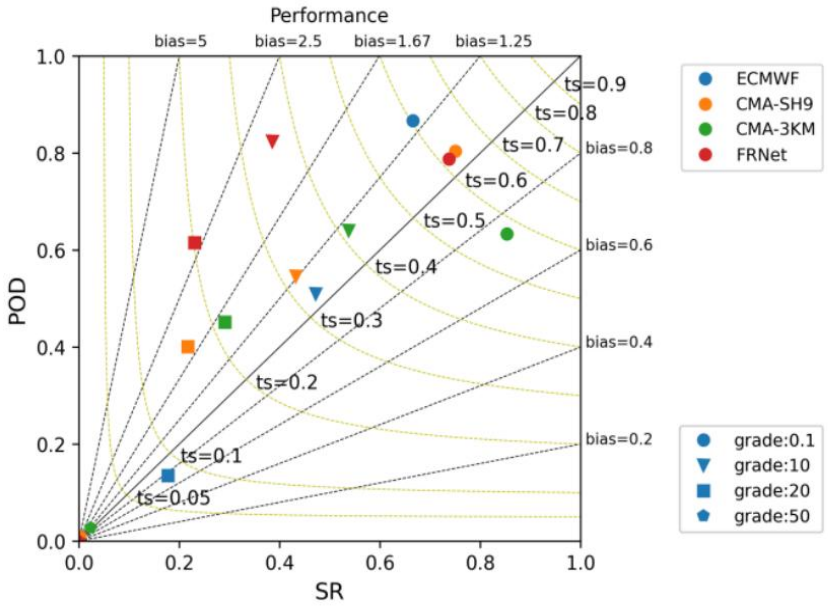


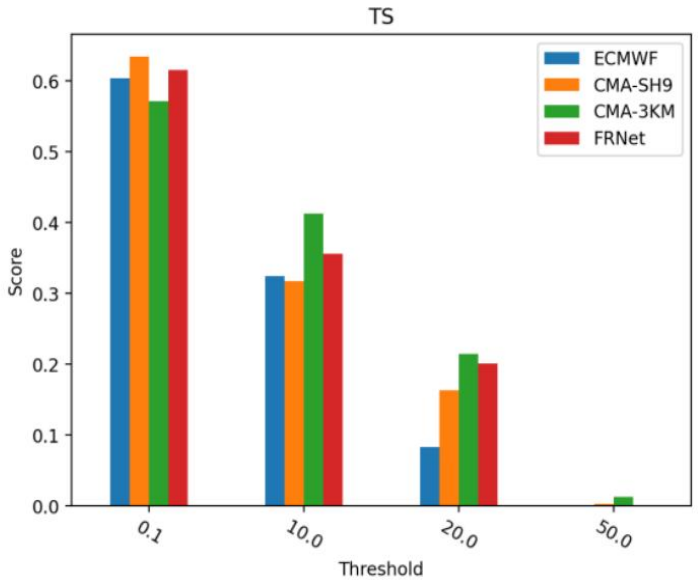
Fig. Precipitation distribution maps for the lead time 12 to 24 hours from 00 UTC on August 21, 2022

Case 2. Severe Convective Precipitation Case (August 21, 2022)

FRNet significantly improved scores for precipitation below 20 mm. However, due to overestimation in mesoscale models, FRNet's corrections became more pronounced and smoother, resulting in a Bias of 2.5 for 20 mm precipitation. For severe precipitation above 50 mm, FRNet's correction was less effective comparing to the CMA-3KM.

This suggests that when global models underestimate and mesoscale models overestimate, creating large discrepancies in local convective precipitation, FRNet's fine-tuning capability remains limited.



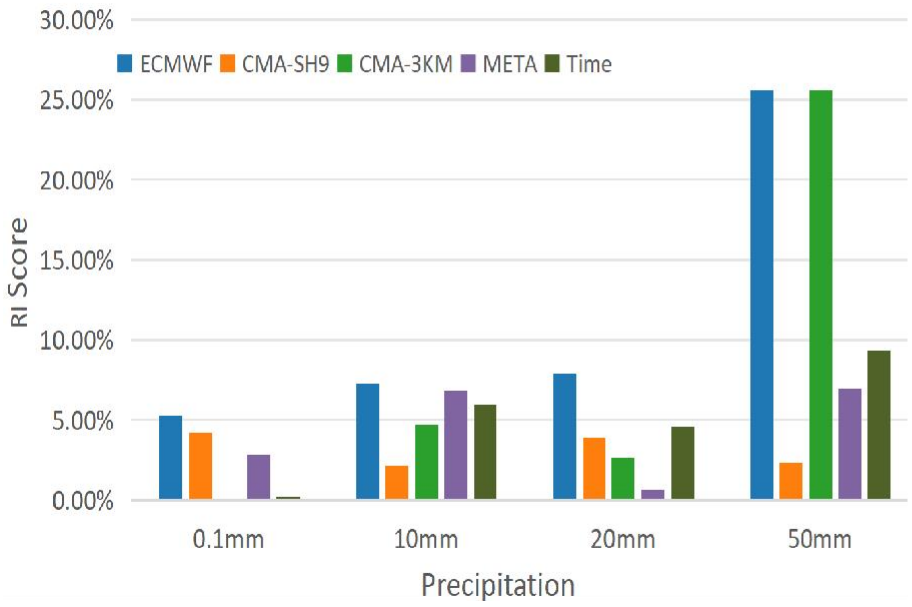


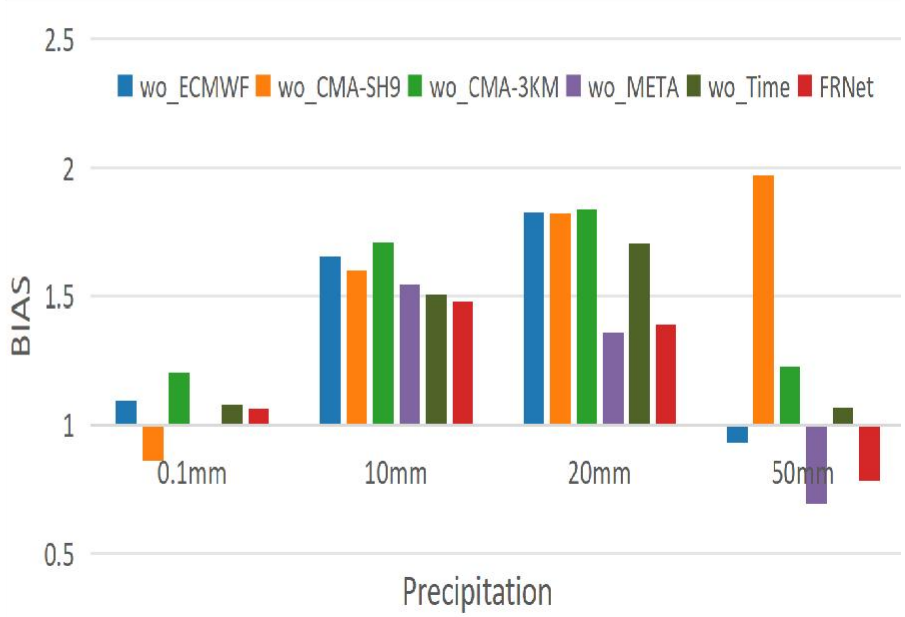
2.4 Ablation experiment

ECMWF, CMA-SH9, CMA-3KM, META, and Time all contribute positively across all precipitation intensities. The relative importance of these features varies by precipitation level, with their average contributions to TS improvement ranked as follows: ECMWF (11.51%), CMA-3KM (8.28%), Time (5.03%), META (4.34%), and CMA-SH9 (3.15%).

With a lower false alarm rate, ECMWF enhances reliability in heavy rainfall forecasts, enabling FRNet to correct systematic biases effectively. CMA-3KM's contribution at the 50 mm level stems from its high resolution, which improves the accuracy of intensity forecasts.

$$\text{Relative_Importance}(x) = (\text{TS}(\text{FRNet}) - \text{TS}(\text{wo_}x)) / \text{TS}(\text{FRNet})$$





Relative importance score (left) and Bias score (right) of the input features

2.6 Summary

A fusion rain network (FRNet) designed to improve intense rainfall forecasting by effectively integrating the strengths of multi-scale model rain features of 3-hour rainfall forecasts within a 24-hour lead time over North China in this study.

- Statistical assessments based on independent tests conducted for 2021 and 2022, reveal that the deep learning model significantly enhances forecast accuracy across various precipitation thresholds—ranging from light to torrential rain—across the lead times within the 24-hour period.

- Heavy rain case studies illustrate that FRNet effectively synthesizes the strengths of global models in predicting rain band location and movement, as well as mesoscale models in forecasting intensity and fine-scale structures. This integration results in a more comprehensive and precise adjustment of precipitation forecasts, offering superior guidance for intense rainfall events compared to any single numerical model.

- Machine learning ablation experiments confirm that the performance gains of FRNet are primarily driven by both the global and mesoscale model forecasts, complemented by geographic and temporal information.



Thanks for your attention!

Acknowledgments

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