Enhanced Nowcasting Through a Novel Radar Echo Extrapolation Algorithm: Integrating Recurrent Convolutional Neural Networks with Optical Flow Methods

Xugang LI[1,2], Zhiyuan SHU[2], Shaoyu HOU[1,2,3*], Feng LV[1,2], Wuyi WANG[1,2], Rong MAI[1,2], Haipeng ZHU[2]

1. Xingtai Atmospheric Environment Field Scientific Test Base of CMA, Xingtai 054000, China; 2. Hebei Provincial Weather Modification Center, Shijiazhuang 051432, China; 3. China Meteorological Administration Xiong'an Atmospheric Boundary Layer Key Laboratory, Xiong'an New Area 071000, China

Abstract This study proposes a novel radar echo extrapolation algorithm, OF-ConvGRU, which integrates Optical Flow (OF) and Convolutional Gated Recurrent Unit (ConvGRU) methods for improved nowcasting. Using the Standardized Radar Dataset of the Guangdong - Hong Kong - Macao Greater Bay Area, the performance of OF-ConvGRU was evaluated against OF and ConvGRU methods. Threat Score (TS) and Bias Score (BIAS) were employed to assess extrapolation accuracy across various echo intensities (20 -50 dBz) and weather phenomena. Results demonstrate that OF-ConvGRU significantly enhances prediction accuracy for moderate-intensity echoes (30 -40 dBz), effectively combining OF's precise motion estimation with ConvGRU's nonlinear learning capabilities. However, challenges persist in low-intensity (20 dBz) and high-intensity (50 dBz) echo predictions. The study reveals distinct advantages of each method in specific contexts, highlighting the importance of multi-method approaches in operational nowcasting. OF-ConvGRU shows promise in balancing short-term accuracy with long-term stability, particularly for complex weather systems.

Key words Radar echo extrapolation; Nowcasting; Optical flow; Deep learning

DOI 10.19547/j.issn2152 -3940.2025.03.011

The United Nations World Water Development Report highlights the significant impact of extreme precipitation events on these sectors, emphasizing the need for robust infrastructure and reliable forecasting and warning systems[1]. Consequently, improving nowcasting accuracy has become an urgent research priority in meteorology and hydrology.

Radar echo extrapolation, a key method for short-term precipitation forecasting, can be conceptualized as the estimation and prediction of temporal trends in image sequences. Algorithmically, radar echo extrapolation methods can be categorized into traditional approaches and deep learning-based techniques. Traditional methods include cross-correlation techniques[2-3], optical flow methods[4-5], and centroid tracking algorithms[6-7]. However, These methods often struggle with rapidly evolving local convective weather systems, where echo development violates conservation assumptions, leading to deteriorating forecast accuracy over time.

RNNs, known for their memory capabilities[8], have been enhanced with Gated Recurrent Units (GRU) to address long-term dependency issues[9]. Ballas[10] further developed the Convolutional GRU (ConvGRU), replacing fully connected layers with convolutional layers and expanding input and hidden states spatially. This modification allows spatial feature information to flow between RNN nodes as three-dimensional tensors, significantly enhancing radar echo extrapolation capabilities. Shi[11] pioneered the ConvLSTM model to learn spatiotemporal evolution features between images. Subsequent improvements led to the development of Encoder - Forecaster (EF) structures with ConvGRU and TrajGRU[12], addressing spatial structure representation challenges in traditional LSTM models for radar echo extrapolation. Among these methods, the ConvGRU approach has demonstrated significant potential for practical applications[13].

This study proposes a novel approach, OF-ConvGRU, which integrates Optical Flow (OF) extrapolation results as input for ConvGRU, aiming to provide more accurate echo evolution information. The findings are expected to offer new insights for improving short-term forecast precision, thereby providing more reliable support for ecosystem management and water resource allocation decisions.

1 Materials and methods

1.1 Data source The Standardized Radar Dataset of the Guangdong - Hong Kong - Macao Greater Bay Area, developed by the Shenzhen Meteorological Bureau, was utilized in this study. It comprises a single vertical layer at an altitude of 2.5 km with a horizontal resolution of approximately 1 km, covering an area of about 255 km^2. Each sample contains 41 time steps spanning a total duration of 240 minutes with 6-minute intervals. After data screening, 16 550 valid samples were retained, of which 11 585 were allocated to the training set, 4 965 to the validation set, and 1 655 to the test set.

1.2 Research methods Radar echo extrapolation was per-

Received: April 10, 2025　　Accepted: May 29, 2025

Supported by Scientific Research and Development Project of Hebei Meteorological Bureau (23ky08).

* Corresponding author.

formed using three methods: Convolutional Gated Recurrent Unit (ConvGRU), Optical Flow (OF), and a hybrid approach combining the two (OF-ConvGRU). OF and ConvGRU served as baseline methods for comparison with OF-ConvGRU. The extrapolation results of these three methods were quantitatively evaluated using Threat Score (TS) and Bias Score (BIAS), enabling a comprehensive analysis of their performance strengths and limitations.

1.3 The OF-ConvGRU method As illustrated in Fig. 1, the model employs a coupling mechanism that utilizes OF extrapolation results as frame-by-frame inputs for the ConvGRU. This approach more directly reflects improvements compared to simple superposition. Specifically, OF extrapolation results at time T replace the 0 dBz echo predicted by ConvGRU, while OF predictions for strong echoes above 40 dBz substitute the corresponding ConvGRU results to mitigate ConvGRU's intensity attenuation issue. This coupling strategy is denoted by the " + " symbol in the figure and can be expressed as follows:

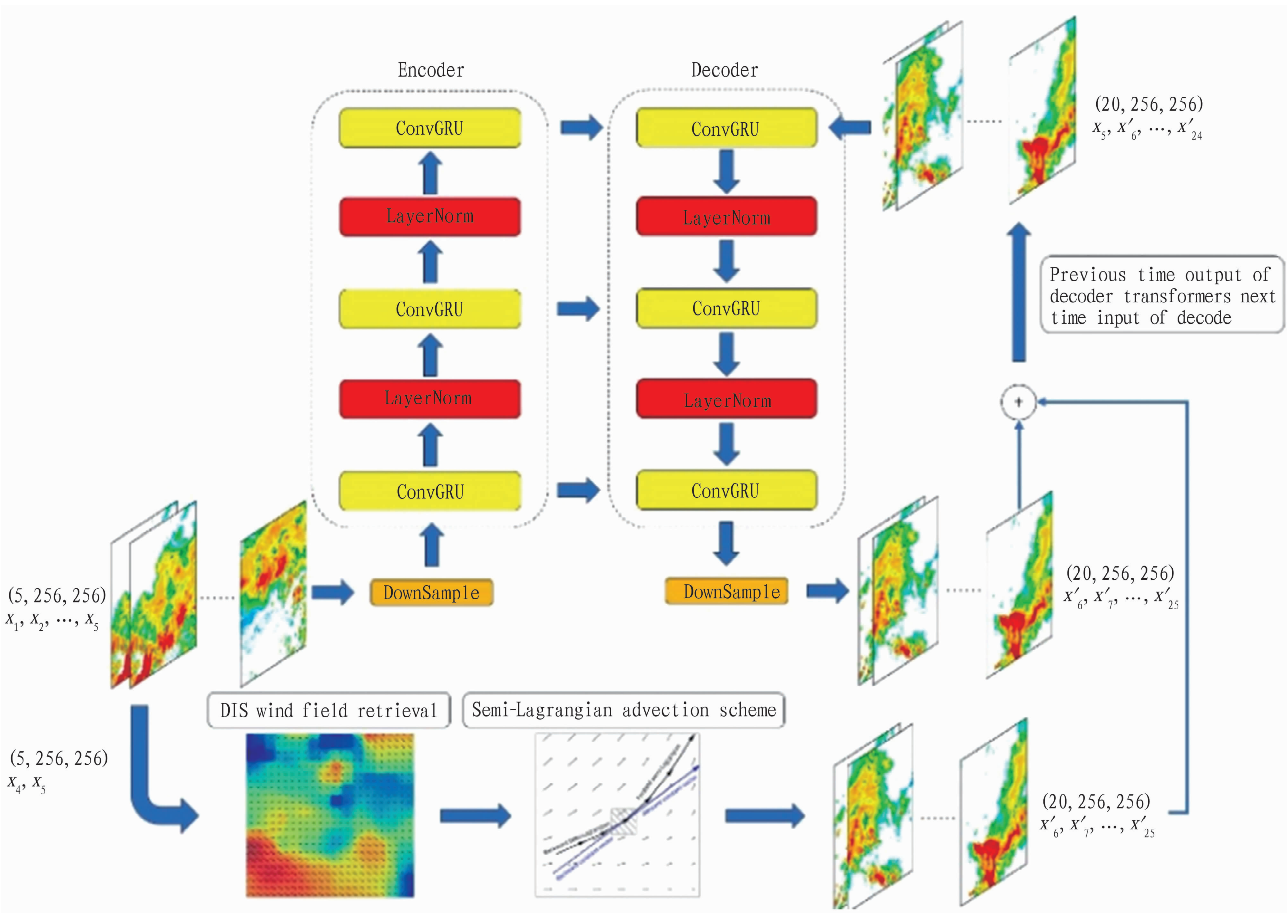

Fig. 1 Schematic diagram of the OF-ConvGRU model architecture

$$\begin{cases} Input_{ConvGRU,\,T+1} = Output_{ConvGRU,\,T} \\ Input_{ConvGRU,\,T+1} = Output_{OF,\,T}[\,(Output_{ConvGRU,\,T}=0)\ \cap\ (Output_{OF,\,T}>40\ dBz)\,] \end{cases} \tag{1}$$

where $Input_{ConvGRU,\,T+1}$ represents the input of ConvGRU at time $T+1$, $Output_{ConvGRU,\,T}$ and $Output_{OF,\,T}$ represent the output of ConvGRU and OF at time T, respectively. $\cap$ represents intersection.

Prior to model training, the radar echo dataset underwent normalization preprocessing to the [0, 1] interval to optimize network performance. The training process utilized the Adam optimizer with an initial learning rate of 0.001. Considering the varying importance of predicting different echo intensities, a weighted root mean square error (WMSE) was selected as the loss function calculated as shown in the equation (2). This design aims to enable the model to capture strong echo features more accurately, thereby enhancing prediction precision.

$$w\,(dBz) = \begin{cases} 1,\ dBz < 20 \\ 2,\ 20 \leqslant dBz < 25 \\ 3,\ 25 \leqslant dBz < 30 \\ 4,\ 30 \leqslant dBz < 40 \\ 5,\ dBz \geqslant 40 \end{cases} \tag{2}$$

2 Results and analysis

2.1 Extrapolation of squall line echoes Squall lines are intense mesoscale convective systems featuring linearly arranged thunderstorms. Fig. 2 illustrates that the squall line is moving towards the lower right, consistent with the echo evolution observed over the past 30 min (Fig. 3). Apart from the areas in the lower left and upper right corners of the image, there are extensive regions with low or no velocity. This results in small OF-extrapolated echo displacement vectors and a merging of extrapolated echoes. However, the actual echo movement is towards the upper-right direction. Consequently, the displacement vector calculated by the SLAS shows significant deviation from the observed movement.

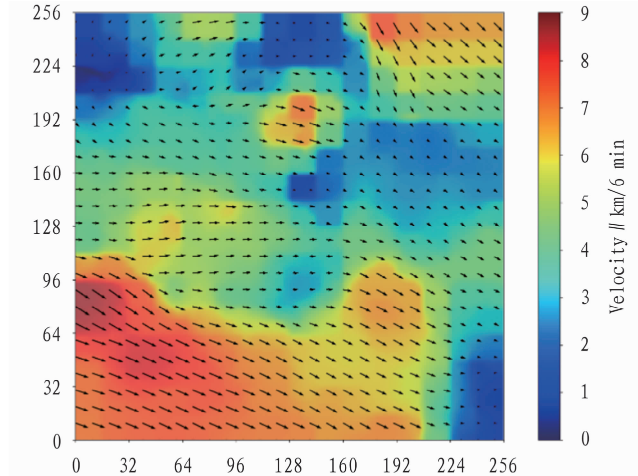

Fig. 2 The displacement vector inversion based on the optical flow (OF) method

Fig. 4 presents a comparison of observed results with extrapolations from three methods at 30, 60, 90, and 120 min forecast lead times. OF-ConvGRU demonstrates superior overall performance, maintaining the general echo structure while effectively capturing the evolution of strong echo regions. In contrast, ConvGRU,

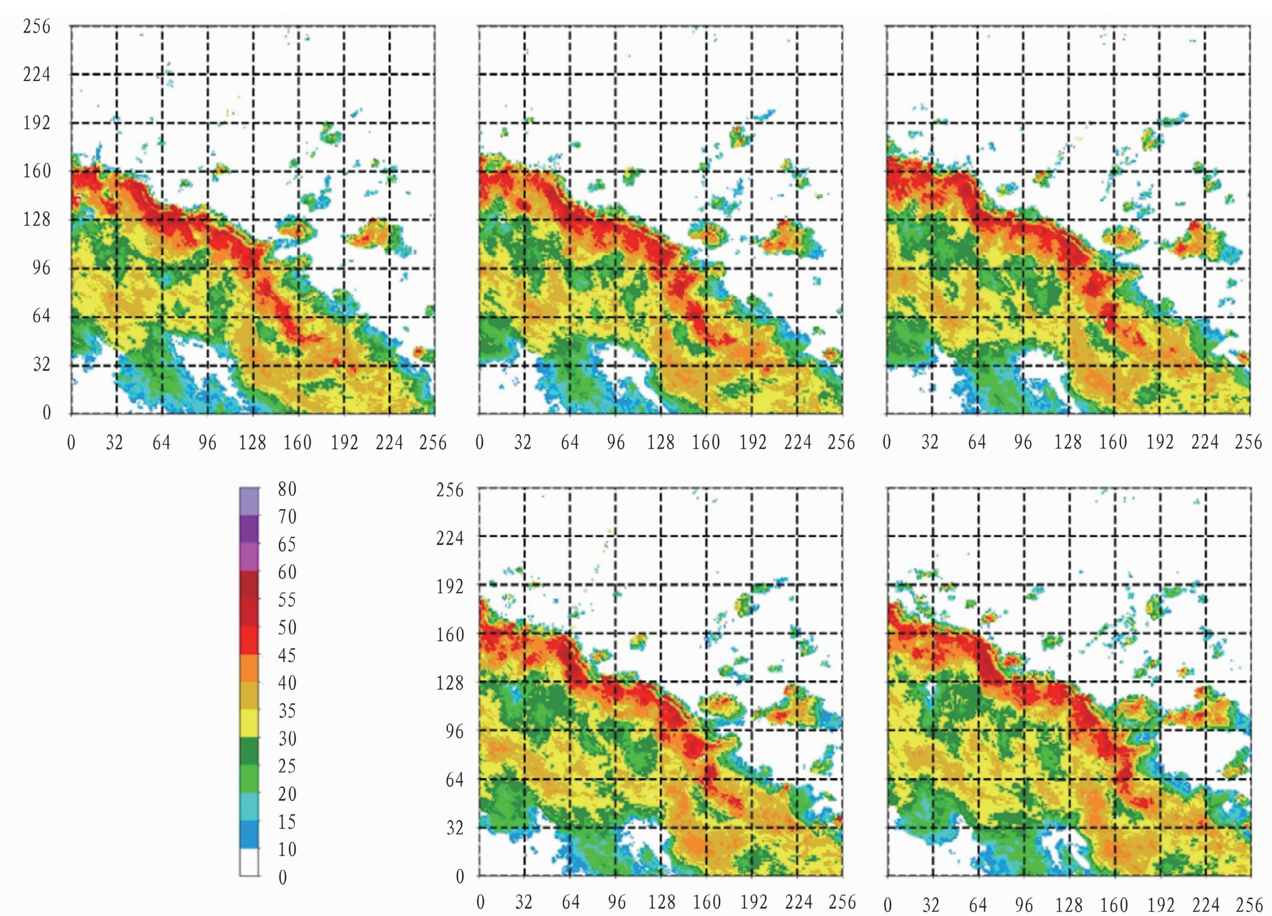

Fig. 3 Five frames of radar echo observation images in the first 30 min

while preserving the approximate echo morphology in short-term forecasts, exhibits significant intensity attenuation and structural blurring as forecast time increases. The OF method excels inmaintaining echo intensity and detail but shows notable deviations in predicting echo movement and morphological changes, particularly in longer-term forecasts. Notably, OF-ConvGRU maintains the overall echo structure and intensity distribution well even at 120 min, indicating its potential for extended forecasts. However, all methods still have room for improvement in predicting small-scale features and precisely locating strong echo regions.

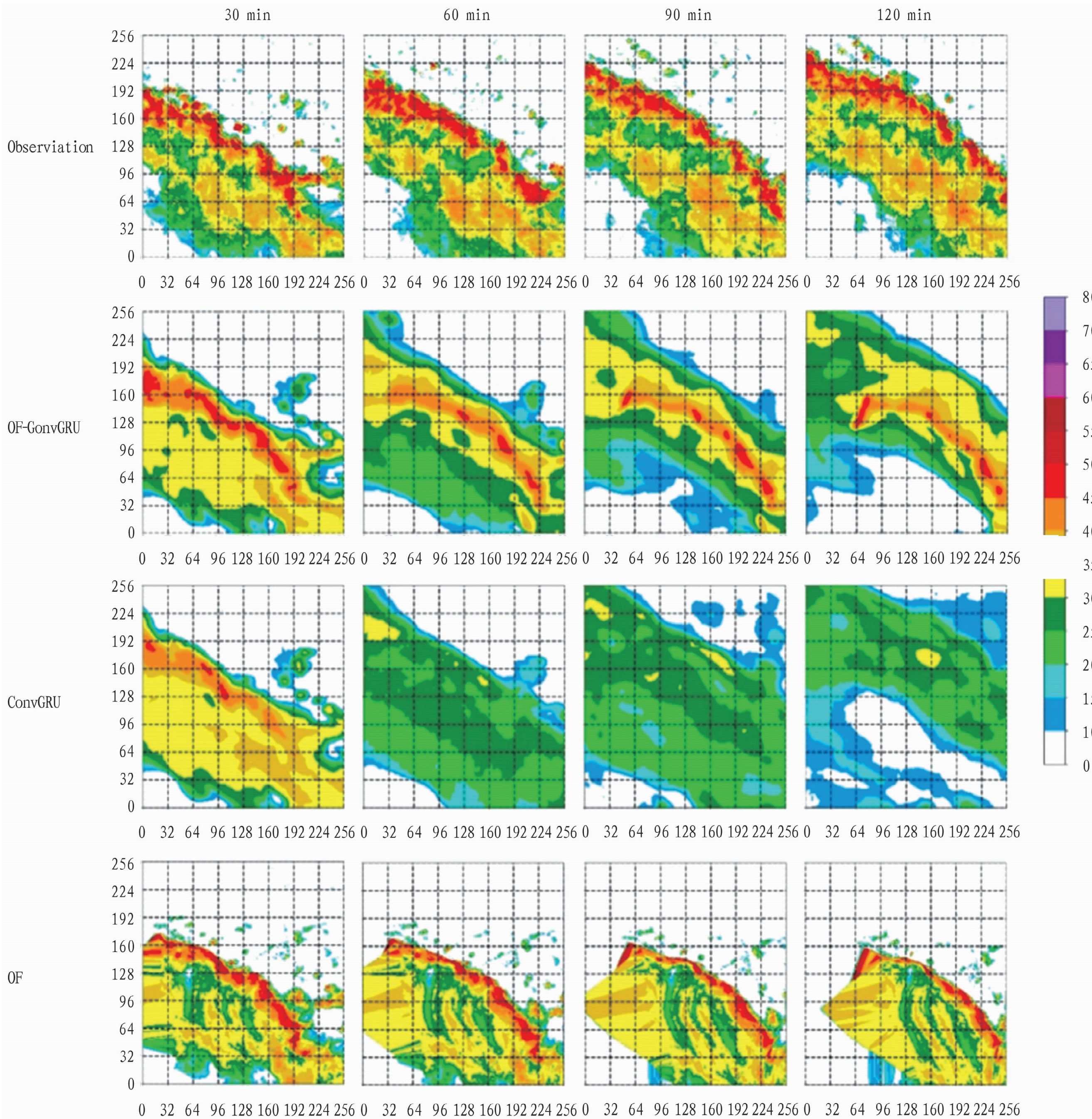

Fig. 4 The extrapolated echoes of the three algorithms for a squall line process

Fig. 5 illustrates the performance of OF, ConvGRU, and OF-ConvGRU methods in squall line forecasting. At 20 and 30 dBz thresholds, OF-ConvGRU demonstrates the highest and most stable TS scores with optimal BIAS, indicating superior performance in capturing the overall squall line structure, likely due to its integration of OF's precise motion estimation and ConvGRU's nonlinear evolution prediction capabilities. At 40 dBz, OF excels in short-term forecasts, while OF-ConvGRU shows greater long-term stability, reflecting OF's advantage in maintaining strong echo structures and OF-ConvGRU's ability to predict sustained evolution. At 50 dBz, all methods show significant degradation, especially long-term, highlighting the challenge of predicting extremely strong convective regions within rapidly evolving squall lines. Overall, OF-ConvGRU exhibits the best comprehensive performance, particularly in capturing overall structure and evolution, though all methods face challenges in predicting long-term evolution of extremely strong convective cores.

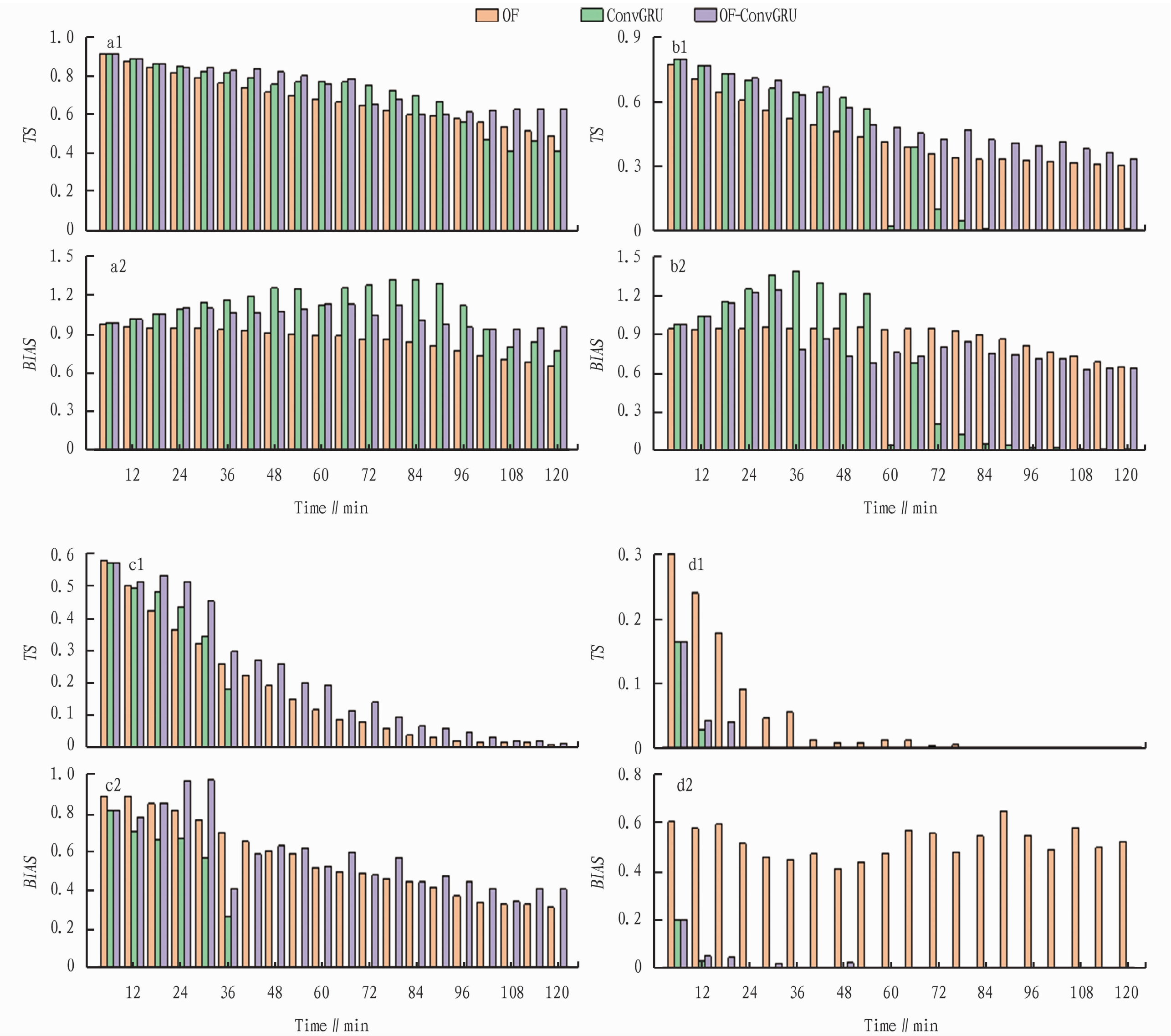

Fig. 5 Variations of evaluation scores on the extrapolation results of the three algorithms for a squall line process under the thresholds of 20 dBz (a), 30 dBz (b), 40 dBz (c) and 50 dBz (d)

3 Conclusion and discussion

Based on the comprehensive analysis of the OF-ConvGRU method and its comparison with OF and ConvGRU approaches, the following conclusions can be drawn:

(1) The OF-ConvGRU model demonstrates superior performance in nowcasting complex weather systems, particularly for moderate-intensity echoes (30 – 40 dBz). It effectively combines the strengths of optical flow's precise motion estimation and ConvGRU's nonlinear learning capabilities, resulting in more accurate predictions of overall echo structure and evolution. This is evidenced by higher and more stable Threat Scores (TS) across various weather phenomena, including squall lines and scattered severe convection.

(2) While OF-ConvGRU shows significant improvements, it still faces challenges in certain scenarios. For low-intensity echoes (20 dBz), it tends to produce false alarms, and for high-intensity echoes (50 dBz), it lacks effective quantitative extrapolation. These limitations suggest that further refinement of the model is necessary to enhance its performance across the full spectrum of echo intensities, particularly for extreme weather events.

(3) The comparative analysis reveals that each method (OF, ConvGRU, and OF-ConvGRU) has distinct advantages in specific contexts. OF excels in maintaining echo intensity and fine-scale structures, especially for short-term forecasts of strong echoes. ConvGRU shows promise in capturing overall echo morphology but suffers from intensity attenuation over time. OF-ConvGRU balances these strengths, offering more stable long-term predictions and better representation of echo evolution. This underscores the

importance of considering multiple approaches in operational nowcasting to address the diverse characteristics of different weather systems.

References

[1] POINTET T. The United Nations world water development report 2022 on groundwater[R]. LHB. 2022, 108(1): 2090867.
[2] WANG G, WONG W, LIU L, *et al.* Application of multi-scale tracking radar echoes scheme in quantitative precipitation nowcasting[J]. Advances in Atmospheric Sciences, 2013, 30: 448 –460.
[3] MECKLENBURG S, JOSS J, SCHMID W. Improving the nowcasting of precipitation in an Alpine region with an enhanced radar echo tracking algorithm[J]. Journal of Hydrology, 2000, 239(1 –4): 46 –68.
[4] ZHU J, DAI J. A rain-type adaptive optical flow method and its application in tropical cyclone rainfall nowcasting[J]. Frontiers of Earth Science, 2022, 16(2): 248 –264.
[5] BECHINI R, CHANDRASEKAR V. An enhanced optical flow technique for radar nowcasting of precipitation and winds[J]. Journal of Atmospheric and Oceanic Technology, 2017, 34(12): 2637 –2658.
[6] CRANE RK. Automatic cell detection and tracking[J]. IEEE Transactions on Geoscience Electronics, 1979, 17(4): 250 –262.
[7] JOHNSON JT, MACKEEN PL, WITT A, *et al.* The storm cell identification and tracking algorithm: An enhanced WSR-88D algorithm[J]. Weather and Forecasting, 1998, 13(2): 263 –276.
[8] HOCHREITER S, SCHMIDHUBER J. Long short-term memory[J]. Neural Computation, 1997, 9(8): 1735 –1780.
[9] CHO K, MERRIENBOER BV, GÜLÇEHRE Ç, *et al.* Learning phrase representations using RNN encoder-decoder for statistical machine translation// Conference on Empirical Methods in Natural Language Processing [C]. Association for Computational Linguistics, 2014.
[10] BALLAS N, YAO L, PAL C, *et al.* Delving deeper into convolutional networks for learning video representations, arXiv preprint arXiv:1511.06432[Z]. 2015.
[11] SHI X, CHEN Z, WANG H, *et al.* Convolutional LSTM network: A machine learning approach for precipitation nowcasting// Advances in Neural Information Processing Systems[M]. MIT Press, 2015.
[12] SHI X, GAO Z, LAUSEN L, *et al.* Deep learning for precipitation nowcasting: A benchmark and a new model// Advances in Neural Information Processing Systems[M]. MIT Press, 2017.
[13] ZHANG Z, LUO L, CHEN L, *et al.* Applicability of convolutional gated recurrent unit neural network and optical flow method in nowcasting[J]. Meteorological Monthly, 2022, 48(11): 1361 –1372.

About the Databases of Meteorological and Environmental Research