Data Fusion Optimization and Contribution Assessment of Dual-Polarization Radar Data in Short-Term Forecasting of Convective Precipitation

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China's complex geographical environment frequently leads to severe convective weather events, including thunderstorms, hail, and tornadoes, posing significant threats to the economy and public safety. Upgraded Doppler weather radar systems now provide a broader range of parameters, enhancing short-term quantitative precipitation estimation. Leveraging the Conv-LSTM method, these systems capture spatiotemporal characteristics and relationships among multiple parameters within radar echo images, enabling precise short-term forecasting of convective weather precipitation. The integration of advanced equipment and technology has yielded breakthroughs in quantitative precipitation forecasting for short-term convective events.To fully utilize Doppler weather radar parameters and select the most effective ones for precipitation estimation, an evaluation and optimization of the current convolutional neural network is essential. Our approach enhances the neural network structure by incorporating a self-attention mechanism layer to assess individual parameter contributions. This ensures that the most informative parameters receive greater importance in the forecasting process. Additionally, we introduce a dynamic allocation layer that prioritizes parameters with higher weightings for subsequent predictions.The study results reveal that within the self-attention layer, the KDP parameter exhibits the highest composite weight, underscoring its significance. When compared to the conventional ConvLSTM algorithm, our improved algorithm, which dynamically selects parameters after discerning different precipitation phases, consistently yields superior estimation performance. These findings provide a viable assessment strategy and optimization approach for the application of Doppler weather radar parameters in the estimation of precipitation during severe convective weather events.

CCS CONCEPTS • Computing methodologies~Approximate dynamic programming methods • Computing methodologies~Perceptron algorithm •Applied computing~Forecasting

Additional Keywords and Phrases: ConvLSTM, Dual-Polarization Radar, Data fusion, Evaluation model, Self-attention mechanism

1 INTRODUCTION

China, with its diverse climatic zones, exhibits a vast array of complex weather patterns. Hazardous weather types each have unique attributes, with severe convective weather events like heavy rain and hailstorms being particularly sudden, localized, short-lived, and destructive. These events contribute significantly to economic damages and safety risks. From 2001 to 2007, direct economic losses from these events averaged 11 billion yuan annually, amounting to 6%-15% of total meteorological disaster losses[1]. Given the nature of such weather, short-term forecasting remains a daunting task in meteorology. Advancements in technology are vital for improving predictions.

Historically, equipment like radars, automatic stations, satellites, and GPS/MET have been paramount in severe convective weather forecasting. These tools, combined with storm identification and numerical forecasting methods, help predict future precipitation. However, these approaches have their limitations. While techniques like the TITAN and SCIT algorithms showed early promise, they are constrained by linear extrapolation and data quality[8,9]. Current forecasting trends lean towards providing probabilistic data, which challenges deterministic predictions[10].

Fine numerical weather forecasting technology has been an important development direction for severe convective weather forecasting in recent years. However, the assimilation of conventional weather observation data and the complexity of the model are approaching their limits. For instance, models with sufficiently fine horizontal grid spacing can produce more accurate high-impact weather forecast results[4]. The Rapid Update Cycle (RUC) in the United States can provide high spatiotemporal resolution mesoscale weather analysis products and short-term numerical forecast products. The rapid update numerical weather prediction system (NWP) is now capable of leveraging the latest weather observation data to guide forecasts within 48 hours[5,6,7]. However, research results from NIGEL M. Roberts and colleagues indicate that NWP models with grid spacing as low as 1km are the most mature at all scales. As the scale decreases, errors grow rapidly, and combined with the pre-existing errors at larger scales, this could limit the usability of the model[11].

In recent years, with the accumulation of big data and the rapid advancement of computer technology, artificial intelligence and deep learning techniques have begun to emerge in the field of meteorological forecasting. Unlike traditional forecasting methods based on empirical relationships, deep learning methods are entirely data-driven. Theoretically, their performance improves with the increase in training data volume, making them particularly suitable for short-term forecasting tasks with large volumes of radar observation data. In May 2023, the "Short-Term Forecasting of Severe Convection" innovation team of the China Meteorological Administration released the short-term monitoring and early warning system based on multi-source data - SWAN3.0. This system integrates deep learning technology and successfully completes tasks like extrapolating radar precipitation, analyzing potential tornado risks, and graded forecasting of thunderstorm winds. It provides minute-level near-term precipitation forecasts updated every 6 minutes for the next 3 hours for the Asian Games venues[2,3]. Xingjian Shi's team proposed describing short-term precipitation forecasting as a spatiotemporal sequence prediction problem. In their end-to-end trainable forecast model, predictions are made through multiple stacked ConvLSTM layers. Experimental results on radar echo datasets show that the ConvLSTM model consistently outperforms the state-of-the-art ROVER algorithm[12].

Moreover, Doppler weather radars have played a crucial role in predicting storm patterns. The introduction of dual-polarization technology has significantly enhanced short-term severe convective weather forecasting[13]. Building on this, this paper utilizes the ConvLSTM model to analyze dual-polarization radar data for near-term severe weather predictions, aiming for superior forecasting accuracy.

2 PRELIMINARIES

2.1 The Underutilization of Dual-Polarization Radar Parameters

The dual-polarization Doppler radar emits electromagnetic waves both vertically and horizontally, capturing data from two separate channels. This advanced radar not only measures traditional metrics like reflectivity, spectral width, and radial velocity, but it also gauges the innate horizontal and vertical reflectivities. This enhanced capability allows it to determine differential propagation phase shift, correlation coefficients, and differential reflectivity factors. The definitions of these parameters are as follows:

$$
\begin{aligned}
Z_H &= \frac{16\pi^2}{9|K|^2}\int D^6 \cdot \left|\frac{m^2-1}{4\pi+(m^2-1)P}\right| N(D)dD \\
Z_V &= \frac{16\pi^2}{9|K|^2}\int D^6 \cdot \left|\frac{m^2-1}{4\pi+(m^2-1)P'}\right| N(D)dD \\
Z_{DR} &= 10\log_{10}(Z_H/Z_V) \\
K_{DP} &= \frac{2\pi}{k_0}\cdot R_e\int [f_H(D)-f_V(D)]\, N(D)dD
\end{aligned}
\tag{1}
$$

Where $|K|^2$ represents the dielectric constant of the particle, D is the precipitation particle's equivalent diameter, m is the complex refractive index of water, $N(D)$ signifies the distribution of the droplet spectrum, referring to the concentration of rain droplets.. P、P' are geometric factors, while R_e represents the real part of a complex number. Z_H and Z_V reflect the size and concentration of rain droplets under a certain droplet spectrum and can be used to determine the size and type of precipitation particles.The larger the volume of the precipitation particles, the higher their reflectivity. It primarily displays the size of precipitation particles in the observation area; the closer the shape of the precipitation particle is to a sphere, the value approaches 0. It represents the phase difference between horizontal and vertical echoes due to precipitation particles over a set distance. It mainly reveals the liquid water content during undiluted precipitation, with its value being nearly directly related to the rate of precipitation.

Radar precipitation estimation typically relies on the relational method. The core idea behind this is the positive correlation between the radar reflectivity factor and the actual precipitation rate. By establishing an empirical relationship between these two, once the radar measures the reflectivity factor of precipitation, this relationship can be employed to calculate the precipitation rate. By accumulating these rates over a specific time period, we can estimate the total precipitation for that duration.

The inherent attributes of dual-polarization radar include a description of the phase state of precipitation particles. When it comes to estimating precipitation volume and identifying precipitation particles, this method offers significant improvements over traditional radars. However, experiments on precipitation estimation by Zhang Yu and others have shown considerable differences in the results of different algorithms[14]. This can be attributed to the changes in the size and phase state of precipitation particles during convective weather processes. If parameters cannot accurately describe precipitation, it directly affects the accuracy of precipitation estimation. This study's comparative results also indicate that introducing any one of the three variables alone would result in an underestimation of precipitation volume. A potential improvement might be to identify and categorize precipitation particles before implementing the estimation or to ascertain the development process of the convective system.

The CSU-HIDRO method provides a classification framework for precipitation estimation. As illustrated in Figure 1, this method employs fuzzy logic to categorize hydrometeors. Based on different types of precipitation, the method primarily classifies precipitation into three main categories: liquid precipitation, ice crystals, and mixed-type precipitation. Depending on specific threshold values, the appropriate precipitation rate calculation formula is selected to accurately estimate the different types of precipitation, as detailed in the equation :

$$\begin{gathered} R(Z_H) = a_1 Z_H^{b_1} \\ R(K_{DP}) = a_2 K_{DP}^{b_2} \\ R(Z_H, Z_{DR}) = a_3 Z_{H^3}^{b_3} 10^{c_3 Z_{DR}} \\ R(K_{DP}, Z_{DR}) = a_4 (K_{DP})^{b_4} 10^{c_4 Z_{DR}} \end{gathered} \tag{2}$$

Where a_1,a_2,a_3,a_4,b_1,b_2,b_3,b_4,c_3,c_4 are fitting parameters, and represents a dimensionless value.

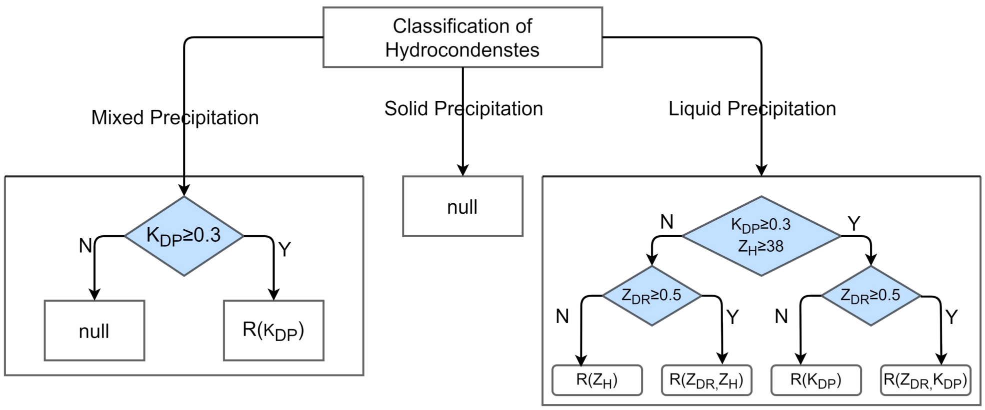

Figure1 Schematic Diagram of the CSU-HIDRO Method

Building upon this foundation, the role of machine learning becomes increasingly significant. Machine learning's capability to discern complex patterns in large datasets can be leveraged to address the challenges presented by dual-polarization radar data. By integrating machine learning, particularly deep learning techniques, into the analysis of radar data, we can further refine the categorization process and improve precipitation estimation accuracy. Machine learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are adept at interpreting complex weather data, potentially leading to a more nuanced understanding of precipitation types and volumes.

Moreover, the use of machine learning in analyzing dual-polarization radar data helps in identifying subtle signatures of severe weather phenomena, often overlooked by conventional methods. This integration not only enhances the accuracy of short-term forecasting of convective precipitation but also addresses the high dimensionality and noisy nature of radar data, which are significant hurdles in traditional analysis techniques. Thus, the fusion of advanced radar technologies with sophisticated machine learning models marks a promising direction for future meteorological research, setting new benchmarks in precipitation estimation and weather prediction accuracy.

2.2 The flaws of the ConvLSTM structure

From the lens of machine learning, using radar observations to forecast precipitation aligns with the spatiotemporal sequence prediction paradigm. Radar data is presented as two-dimensional echo maps marked with timestamps, capturing between 6 to 10 frames hourly. The objective of short-term forecasting is to project the next 6-60 frames. Segmenting each radar echo frame into an MxN grid, representing precipitation points, allows for the depiction of any spatiotemporal sequence of these points as a tensor. Given a series of such tensors, the challenge lies in predicting a subsequent sequence of length m based on n previous observations.

The ConvLSTM model, combining convolutional processes with recurrent neural networks, has demonstrated its effectiveness in extracting spatiotemporal features for such predictions. However, despite its capabilities, the ConvLSTM architecture has intrinsic limitations. One critical issue is its struggle to dynamically adjust its learned weights in response to evolving prediction factors within channels. This limitation can result in a significant loss of spatiotemporal details, leading to inaccuracies in predicting intense convective precipitation and underutilizing the potential of dual-polarization radar data.

To address these challenges, integrating advanced machine learning techniques into the ConvLSTM framework can be highly beneficial. One approach is to enhance the model's ability to adapt to changing data patterns. This can be achieved by incorporating attention mechanisms, particularly self-attention, which allows the model to weigh the importance of different parts of the input sequence differently. By doing so, the model can focus more on the significant features relevant to the current prediction task, thereby improving its responsiveness to changes in weather patterns.

Furthermore, introducing regularization techniques such as dropout or batch normalization within the ConvLSTM structure can help mitigate overfitting and improve the model's generalization capabilities. This is particularly important when dealing with the high variability and noise inherent in radar data.

Another promising direction is the exploration of hybrid models that combine ConvLSTM with other neural network architectures. For instance, integrating ConvLSTM with Generative Adversarial Networks (GANs) or Autoencoders can enable the model to learn more complex representations of spatiotemporal data. Such hybrid models can better capture the intricate dynamics of convective weather systems, offering a more robust framework for precipitation forecasting.

3 METHODOLOGY

3.1 Self-attention mechanism

In the realm of natural language processing (NLP), conventional convolutional models grapple with the loss of information when navigating lengthy sequences. This limitation becomes glaring when inputs and outputs share a non-linear relationship. Depending solely on a fixed-length state vector falls short in capturing the essence of current feature details (like dual-polarization parameters) throughout the spatiotemporal network in relation to the precipitation evolution.

Initially designed for computer vision tasks such as image recognition and tracking, the attention mechanism's distinct focus model was later repurposed for NLP. The mechanism assigns importance weights to the features of an input sequence, emulating the relevance of current features in a broader context. These weights hinge on the affinity between feature data in both input and output. By integrating the attention mechanism, the model computes an "attention score" for every feature detail, indicating the radar parameters' importance in the input vis-a-vis the output prediction. Notably, these scores advise the model to prioritize parameters with higher scores. They also serve as a yardstick to gauge the contribution of each dual-polarization parameter towards the rainfall quantity (R) forecast.

We added an attention layer before the decision layer of the original prediction model. This discerning layer is geared towards comprehending the correlation between feature data and end results.

$$s_i = \mathrm{MLP}(h_i, \tilde{y}) = v^{T} \tanh (W_1 h_i + W_2 \tilde{y}) \quad (3)$$

Where $\mathrm{MLP}(*)$ is the perceptual layer, and $\tanh(*)$ is the activation function. h_i is the intermediate layer state of the features after encoding and recognition through ConvLSTM. $\tilde{y}$ is the target output to be decoded by ConvLSTM. v、W are the parameters to be learned and trained.

The attention layer will apply a degree of focus to each feature factor, normalizing their relevance to obtain the weight value assigned to each feature.

$$a_i = \mathrm{softmax}\ (s_i) \frac{\exp s_i}{\sum_{j-1}^{m} s_j} \quad (4)$$

Where s_i is the degree of attention obtained after learning the input features, $\mathrm{softmax}\ (*)$ represents the normalization process; and a_i is the attention weight, satisfying $a_i \in [0,1]$.

3.2 Probabilistic Assessment Method

In the paper, three key metrics — CSI (Critical Success Index), POD (Probability of Detection), and FAR (False Alarm Ratio) — are employed to gauge the proficiency of the CIUNet model in predicting the CI probability. These metrics serve as pivotal indicators in assessing the contribution of dual-polarization radar parameters. The formulation for CSI, POD, and FAR is provided below:

$$\begin{aligned} \mathrm{CSI} &= \frac{TP}{TP+FP+FN} \\ \mathrm{POD} &= \frac{TP}{TP+FN} \\ \mathrm{FAR} &= \frac{FP}{TP+FP} \end{aligned} \quad (5)$$

Wherein, TP (True Positive) denotes the number of grids where both the prediction and observation meet the given CI probability threshold; FP (False Positive) signifies the number of grids where the prediction meets the given probability threshold, but the observation does not; FN (False Negative) is indicative of the grid count where the observation surpasses the threshold, but the prediction falls short. The resultant values for CSI, POD, and FAR are confined within the interval $[0,1]$.

3.3 Data Fusion Strategy

In the paper, we introduced a dynamic weight parameter determination technique rooted in radar image recognition of precipitation particles and the classification standards set by the CSU-HIDRO method. By leveraging the outcomes of precipitation particle categorization, the dynamic layer autonomously zeroes in on the heftiest weight from the assimilated parameters for precipitation approximation, thereby amplifying estimation precision. The methodology is elucidated below:

Initially, we calculate the total number of non-zero values within the grid in the K_{DP}, Z_H and Z_{DR}, as well as the total number of grids in the K_{DP},$Z_H$andZ_{DR} that exceed the reference value. The initial weights for the three types of dual-polarization radar data are set to $l_{K_{DP}}$, l_{Z_H} and $l_{Z_{DR}}$. Assuming the data is spread out linearly, we calculate the rainfall amount R based on K_{DP}, Z_H and Z_{DR}. The likelihood of leveraging each modality in the CSU-HIDRO method is formulated as:

$$
\begin{aligned}
P_{K_{DP}} &= \frac{n_{K_{DP}}}{N_{K_{DP}}} \\
P_{Z_H} &= \frac{n_{Z_H}}{N_{Z_H}} \\
P_{Z_{DR}} &= \frac{n_{Z_{DR}}}{N_{Z_{DR}}} \\
P_{R(K_{DP})} &= P_{K_{DP}}
\end{aligned} \tag{6}
$$

Next, We transform the likelihood of each modality's employment into the frequency of usage for K_{DP}, Z_H and Z_{DR}. A heightened frequency denotes a more pronounced contribution of the respective data towards forecasting the rainfall amount R. Consequently, the foundational weight parameters for K_{DP}, Z_H and Z_{DR} are abstracted as:

$$
\begin{aligned}
l_{Z_{DR}} &= P_{R(K_{DP},Z_{DR})} + P_{R(Z_H,Z_{DR})} \\
l_{Z_H} &= P_{R(Z_H)} + P_{R(Z_H,Z_{DR})} \\
l_{K_{DP}} &= P_{R(K_{DP})} + P_{R(K_{DP},Z_{DR})}
\end{aligned} \tag{7}
$$

Normalize the weight parameters:

$$
\begin{aligned}
\tau_0 &= l_{K_{DP}} + l_{Z_H} + l_{Z_{DR}} \\
w_{Z_H} &= \frac{l_{Z_H}}{\tau_0} \\
w_{Z_{DR}} &= \frac{l_{Z_{DR}}}{\tau_0} \\
w_{K_{DP}} &= \frac{l_{K_{DP}}}{\tau_0}
\end{aligned} \tag{8}
$$

With the dynamically curated weight determination formula in place, we set the batch_size to 10. Throughout each forward propagation cycle, the channel weights are refreshed.

This dynamic approach ensures that the model continually refines its weighting strategy, aligning more closely with real-world data, and delivering enhanced precipitation estimates.The schematic diagram of this model is as follows:

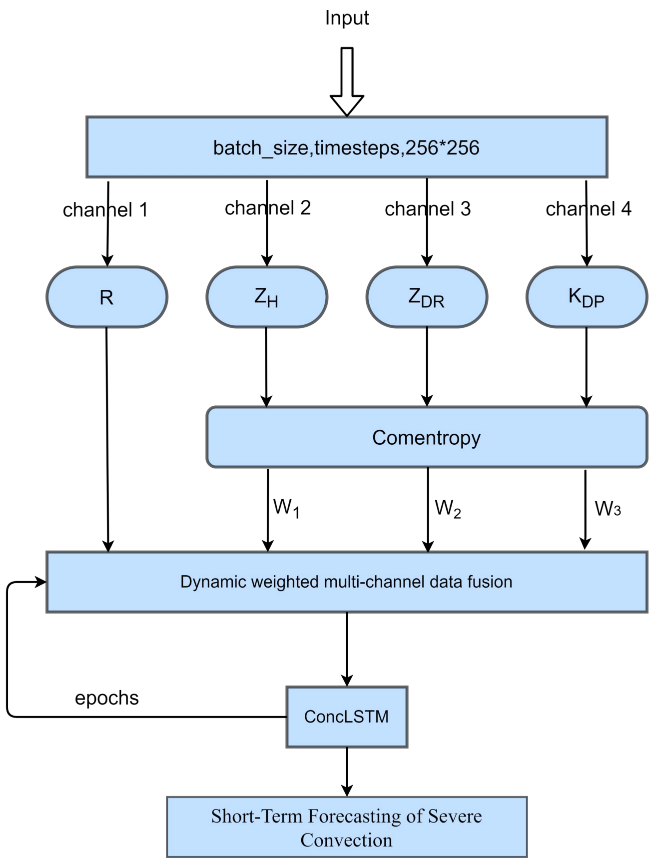

Figure2 Flowchart of Dynamic Weighted Multi-Channel Data Fusion Algorithm

4 EXPERIMENT

4.1 Dataset

For the research outlined in this study, we sourced observational data from the advanced CINRAD/SAD dual-polarimetric radar, focusing on readings from the Southwest region spanning from 2021 through June 2022. The raw dual-polarization radar data is structured in VolumeScan cycles. Each of these cycles houses a collection of ElevationAngle scans, and further breaking down, each ElevationAngle scan is composed of numerous Radials, with each Radial containing an array of RangeGates. Traditionally, this type of data is preserved in binary format, encapsulating the quartet of parameters crucial for our experimental endeavor.

To prepare this raw radar data for our investigative purposes, we embarked on an intricate data preprocessing journey. This procedure integrated several pivotal steps: transitioning the data format, transforming geographic coordinates, ensuring data quality, precipitation rate computation, and synchronizing the timestamps. Post these refining steps, our data emerged as a chronologically curated set, where a cluster of 10 frames corresponded to one observational hour.

It is important to note that the observational data utilized in this study is not publicly available and is subject to certain restrictions. Access to the data was granted under a specific data-sharing agreement and research collaboration with the Southwest Air Traffic Management Bureau Meteorological Service Center. Due to the sensitive nature of the data and the agreements in place, we are unable to provide direct access to the dataset or publicly share it..

For the core of our study, we meticulously sifted through the data to retain only those observations pertinent to the specific region under consideration and instances of pronounced convective meteorological phenomena. Our analytical lens was trained on capturing the spatiotemporal evolution during the inception, zenith, and waning stages of convective weather. Harnessing the power of the ASUSESC8000-E11P GPU, we utilized the PyTorch framework for all computational methods.

Segmenting our historical data repository, we allocated 60% to training, 20% to both validation and testing. The training phase was rigorously conducted on the designated training set and continuously calibrated against the validation subset to guard against overfitting. Any gaps or missing data points were seamlessly bridged by averaging values from the four proximate, non-missing grid points. Further refining, non-overlapping sequence chunks were carved out using a window spanning 20 units and a stride length of 10.

This meticulous data acquisition and preparation regime fortified the integrity and relevance of our radar dataset, culminating in a robust spatiotemporal modeling framework for predicting convective weather patterns.

4.2 Experimental results and analysis

To ascertain the significance of dual-polarization radar data in forecasting intense convective rainfall on a short-term basis, our study embarked on four distinct comparative experimental analyses. Initially, we earmarked strong convective rainfall datasets, identified through specific file names, aligning them with the designated experiments: $\mathrm{Base}\ \_\mathrm{Z_H}$, $\mathrm{Base}\ \_\mathrm{Z_{DR}}$, $\mathrm{Base}\ \_\mathrm{K_{DP}}$, and $\mathrm{Base}\ \_\mathrm{K_{DP}}, \mathrm{Z_{DR}}, \mathrm{Z_H}$. In our inaugural experimental series, either $\mathrm{K_{DP}}$、 $\mathrm{Z_H}$ and $\mathrm{Z_{DR}}$was incrementally incorporated as a predictive element into a novel channel, keeping all other training parameters static. This approach birthed three separate comparative experiments. Following this, experiments $\mathrm{Base}\ \_\mathrm{Z_H}$, $\mathrm{Base}\ \_\mathrm{Z_{DR}}$, and $\mathrm{Base}\ \_\mathrm{K_{DP}}$ were amalgamated, each manifesting as its distinct predictive variable within the model. The significance of $\mathrm{Base}\ \_\mathrm{Z_H}$, $\mathrm{Base}\ \_\mathrm{Z_{DR}}$, and $\mathrm{Base}\ \_\mathrm{K_{DP}}$ was appraised via an attention mechanism.

For the evaluations, we anchored our threshold probability at 10%, with the findings detailed in Table1.

Table1 Assessment Results of Radar Parameter Contribution

Experiment	CSI	POD	FAR
Base	0.539	0.731	0.253
$\mathrm{Base}\ \_\mathrm{Z_H}$	0.615	0.769	0.222
$\mathrm{Base}\ \_\mathrm{Z_{DR}}$	0.621	0.762	0.226
$\mathrm{Base}\ \_\mathrm{K_{DP}}$	0.657	0.771	0.210
$\mathrm{Base}\ \_\mathrm{K_{DP}}, \mathrm{Z_{DR}}, \mathrm{Z_H}$	0.684	0.795	0.203

From the table, it's evident that the $\mathrm{Base}\_\ \mathrm{K_{DP}}, \mathrm{Z_{DR}}, \mathrm{Z_H}$ the best predictive results, while the baseline experiment performed the poorest. This suggests the substantial contribution of dual-polarization radar data in the near-term forecasting of strong convective precipitation. Within this dataset, the predictive performance of

$\mathrm{Base\ \_K_{DP}}$ closely follows that of $\mathrm{Base\_K_{DP}, Z_{DR}, Z_H}$, indicating that it offers the most significant contribution to precipitation quantity forecasting.

This variance in prediction performance can be attributed to the evolving nature of convective weather. In the early stages of its development, when precipitation is relatively weak($\mathrm{Z_H} < 35\mathrm{dBZ}$), it's highly susceptible to noise interference, resulting in a diminished contribution from certain strategies. During these periods, choosing the likes of $\mathrm{Z_H}$ and $\mathrm{Z_{DR}}$ as primary predictive factors is more appropriate. Conversely, in the early stages with stronger precipitation($\mathrm{Z_H} \geq 35\mathrm{dBZ}$), the contribution of $\mathrm{K_{DP}}$ is more significant. As convective weather matures, and precipitation particles become larger and more uniformly distributed, algorithms using all three parameters yield the best results.

This differentiation in parameter contribution underscores the need for dynamic weighting. A crucial step is to utilize data inputted into the network during each training iteration to calculate dynamic weights for the parameters. These weights are adjusted based on the current type of precipitation particle, and the weighted features are then inputted into the model for training. The evaluation metrics used are CSI (Critical Success Index), POD (Probability of Detection), and FAR (False Alarm Ratio).

Table2 Assessment Metrics Results for the Dynamic Weighted Multi-channel Fusion Model

Experiment	CSI	POD	FAR
Dynamic_w	0.792	0.831	0.187

In the evaluation results of the dynamic weight model, both CSI and POD increased, indicating an improved prediction accuracy by 10.8% with the enhanced model. Additionally, we calculated the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) for both the original ConvLSTM model and the dynamically weighted multi-channel fusion improvement model:

Table 3 Comparison of MSE and RMSE Before and After Model Improvement

Model	MSE	RMSE
ConvLSTM	7.70	2.55
Dynamic_ConvLSTM	6.95	2.27

The reduced values for both metrics demonstrate the dynamic weighting's capability to adjust radar parameter participation and enhance contribution, achieving an excellent data fusion result.

5 CONCLUSION

In experiments confined to single-site observations, the strategy that amalgamating all factors emerged as the dominant contributor throughout the entire convective rainfall trajectory. The predictions birthed from this holistic approach mirrored the actual rainfall metrics harvested from rain gauges with uncanny accuracy. Contrarily, predictions hewn from the other duo of strategies were largely in tandem with each other. However, a common thread binding all three strategies was a subtle but consistent underestimation of the precipitation values. This nuance underscores a vital inference: in regions grappling with resource limitations or devoid of a sprawling meteorological infrastructure, dual-polarization radar data can be a pivotal asset in prognosticating the quantum of intense convective rainfall.

A side-by-side juxtaposition with control channel experiments illuminated a clear portrait: the dynamic weighted multi-channel data amalgamation methodology palpably bolstered the precision of ConvLSTM models in forecasting. This enhancement was especially palpable against the canvas of evolving meteorological patterns and the kaleidoscope of precipitation particle distributions. Further, the research punctuated the indispensability of meticulous parameter recalibration, championing it as a groundbreaking approach to enhance the model's spatiotemporal resilience. Such a transformation primes the model to adeptly navigate the turbulence of abrupt and geographically confined convective meteorological phenomena. This revelation carries profound implications for bolstering the tenacity and agility of weather prediction algorithms, more so in the crucible of meteorological extremities.

Conclusively, this investigative odyssey underscores the transformative potential that dual-polarization radar holds in refining the quality of meteorological services. By amplifying the preemptive alert mechanisms and disaster response blueprints, dual-polarization radar seeds a paradigm of offering meteorological insights with heightened reliability to the masses. This evolution doesn't just elevate societal safety benchmarks but also sows the seeds for novel avenues of exploration and innovation in the meteorological domain. In essence, the insights harvested from this study are pivotal cornerstones in the journey of advancing meteorological science and elevating the efficacy and caliber of meteorological services.

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Leilei Deng	master student	Aircraft wake evolution law study	
Zhiyuan Chen	master student	Numerical simulation of aircraft wake turbulence	
Xianbiao Kang	Associate Professor	Meteorological evolutionary forecasts	

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