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General capability of an adaptive learning model for dual-polarization radar rainfall mapping

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ABSTRACT

Radar quantitative precipitation estimation (QPE) plays an important role in water, weather, and climate research due to the advantages of radars in providing seamless scan of precipitation in both time and spatial domains. With the development of dual-polarization radar systems and the innovation of precipitation estimation algorithms based on deep learning, the accuracy of radar QPE has been significantly improved. However, the deep learning QPE models trained using local data may still be subject to degraded performance when applied in other regions. This paper quantifies the generalization capability of a deep learning QPE model trained using data in Florida, U.S. over other regions such as Oklahoma, U.S., which is characterized by different precipitation characteristics.

Index Terms—quantitative precipitation estimation, deep learning, weather radar

1. INTRODUCTION

Accurate estimation of surface precipitation at high spatiotemporal resolution is crucial for decision-making in severe weather and water resource management. Polarimetric weather radar, with its advantages of extensive area coverage and high spatiotemporal resolution, has become the primary operational instrument for Quantitative Precipitation Estimation (QPE) in many countries. Traditional parametric methods such as the radar reflectivity (Z) and rainfall rate (R) relationships rely on local raindrop size distributions (e.g., [1][2]), which often cannot capture the dynamic characteristics of precipitation processes and exhibit low generalizability.

With the development of artificial intelligence, particularly deep learning (DL) models, which have been utilized for classification and regression tasks, it has been demonstrated that DL can resolve the latent features contained in radar data and establish functional approximations between three-dimensional radar observations and surface precipitation measurements [3-5]. However, deep learning models exhibit strong regional characteristics, posing challenges to their general applicability across different precipitation regimes. This obstacle hinders the practical implementation of DL-based QPE networks. To study this issue, this article assesses the applicability and accuracy of an adaptive deep learning model trained in Florida, United States, in the Oklahoma region and attempts to optimize the deep learning model based on this assessment.

2. METHODOLOGY AND DEMONSTRATION STUDY

2.1 Deep learning QPE model

This article utilizes a deep learning framework based on ShuffleNet to quantify surface rainfall rates which framework shown in Figure 1. Within each range volume, the input data set for the deep learning system essentially constitutes a 9×9 matrix constructed from three matrices of different sizes. These three matrices include radar reflectivity, differential reflectivity, and specific differential phase observed from the two lowest scan elevation angles, as well as a 9×9 neighboring distance volume. Consequently, the input data can capture the physical and spatial patterns of the rainfall field, allowing the construction of a deep learning model to learn features from radar data and utilize the learned features for rainfall estimation.

The QPE system is trained using ground-based KMLB radar and rain gauge data in Florida, and the data were collected from 2017 to 2021. Based on the independent testing analysis, previous research has demonstrated the accuracy of this model [3,5].

2.2 Applicability of the Deep Learning Model

Given the prominent advantages of deep learning models in quantitatively estimating local precipitation, this research extends its focus to investigate the applicability and robustness of this model in different climatic and geographical conditions. Specifically, the study explores the performance of the deep learning model in Oklahoma, where the KTLX radar is deployed. This region presents a unique set of precipitation characteristics and challenges, providing a valuable opportunity to assess the generalizability and effectiveness of the deep learning approach across diverse environmental settings. This study aims to compare and validate the model's accuracy and reliability beyond its initial training region. By doing so, it contributes to broader applications in meteorological studies and operational weather forecasting.

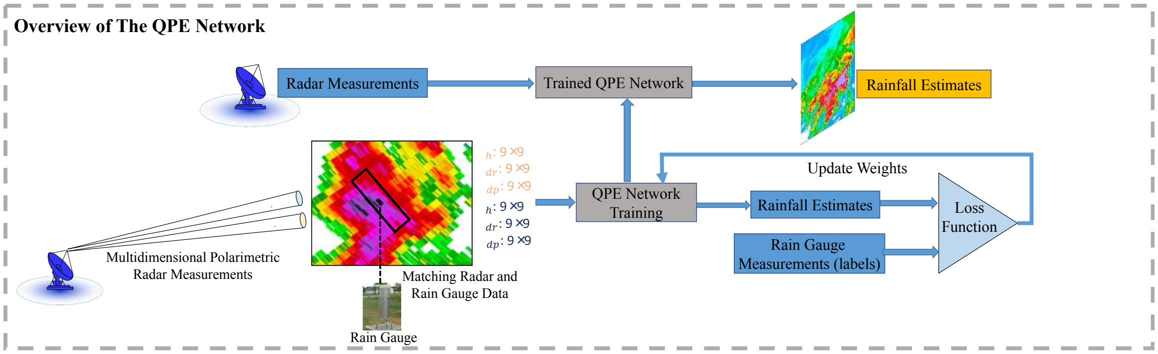

Fig. 1. Simplified diagram of the machine learning-based radar quantitative precipitation estimation (QPE) model.

Figure 2 details the application study domain. The black dot represents the KTLX WSR-88D radar station, the primary source of radar data for the study. The blue dots indicate the rain gauge stations from the NOAA Meteorological Assimilation Data Ingest System (MADIS), located within a 200-kilometer radius of the KTLX radar station. The red dots denote the local rain gauges in the Little Washita River Basin (LWRB). These local gauges are particularly significant as they serve as ground truth references, offering high-accuracy precipitation data essential for evaluating the performance of the QPE algorithms derived from the radar data in this specific region.

Fig. 2. Location of the KTLX WSR-88D (black dot) in Oklahoma City, OK, USA. The red dots indicate rain gauges over the Little Washita River basin and the blue dots represent MADIS rain gauges within 200-km from the radar station.

3. RESULTS AND DISCUSSION

In order to evaluate the performance of the machine learning system, the following scores are calculated, including bias ratio (BIAS_Ratio), Pearson's correlation coefficient (CORR), normalized standard error (NSE), root mean square error (RMSE), and mean absolute error (MAE).

$$\text{BIAS\_Ratio} = \frac{\sum_{n=1}^{N} R_n}{\sum_{n=1}^{N} G_n} \tag{1a}$$

$$\text{CORR} = \frac{\sum_{n=1}^{N}(R_n-\overline{R_n})(G_n-\overline{G_n})}{\sqrt{\sum_{n=1}^{N}(R_n-\overline{R_n})^2}\sqrt{\sum_{n=1}^{N}(G_n-\overline{G_n})^2}} \tag{1b}$$

$$\text{NSE} = \frac{\sum_{n=1}^{N}|R_n-G_n|}{\sum_{n=1}^{N} G_n} \tag{1c}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(R_n-G_n)^2} \tag{1d}$$

$$\text{MAE} = \frac{1}{N}\sum_{n=1}^{N}|R_n-G_n| \tag{1e}$$

where R_n and G_n stand for the radar rainfall estimate and gauge rainfall record (mm/hr) at sample time n; $\overline{R_n}$ and $\overline{G_n}$ denote the mean of radar and gauge rainfall estimates; N stands for the total number of samples.

To validate the effectiveness of the quantitative precipitation estimation (QPE) model for the Florida region, several traditional radar QPE algorithms (2a, 2b, 2c) were introduced for comparison, and quantitative evaluation metrics were used to analyze all algorithms.

$$Z_h = 300R^{1.4} \tag{2a}$$

$$Z_h = 200R^{1.6} \tag{2b}$$

$$R(Z_h, Z_{dr}) = (1.42 \times 10^{-2})Z_h^{0.770}Z_{drl}^{-1.67} \tag{2c}$$

where Z is in units of $\mathrm{mm}^6\mathrm{m}^{-3}$ and R denotes the rainfall rate in $\mathrm{mm/h}$.

In addition, this article evaluates the general applicability of the deep learning algorithm by comparing it with two operational precipitation estimation products. The rainfall accumulations from 2200 UTC on August 31 to 0400 UTC on September 1, 2020, are depicted in Figure 3, which showcases the performance of various radar rainfall algorithms. Figure 3(a) represents the convective $Z-R$ relation precipitation estimation, while Figure 3(b) shows the stratiform $Z-R$ relation precipitation estimation. Figure 3(c) illustrates the WSR-88D dual-polarization algorithm's precipitation estimation. Figures 3(e) and 3(f) present the MRMS Radar-Only and MRMS Gauge-Corrected product precipitation estimations, respectively.

Notably, Figure 3(d) highlights the deep learning algorithm's precipitation estimation, which stands out due to its superior performance in capturing detailed spatial patterns of rainfall distribution. The deep learning model demonstrates a remarkable ability to accurately reflect variations in precipitation intensity and distribution, surpassing the other algorithms in both precision and detail. This enhanced capability to capture fine-scale details sets the deep learning approach apart.

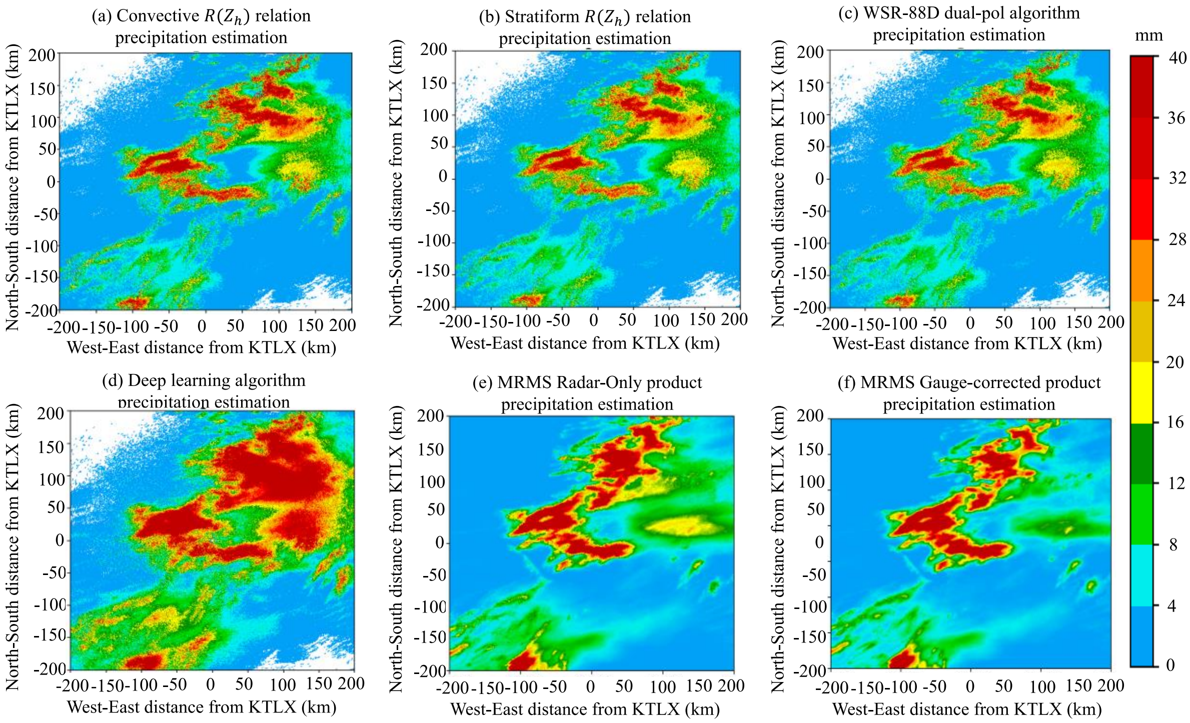

Fig. 3. Rainfall accumulations from 2200UTC, Aug 31, to 0400UTC, Sep 1, 2020, based on different radar rainfall algorithms: (a) convective *Z-R* relation; (b) stratiform *Z-R* relation; (c) WSR-88D dual-pol algorithm; (d) deep learning model proposed in this study; (e) operational product from MRMS (radar-only); (f) operational product from MRMS (gauge-corrected).

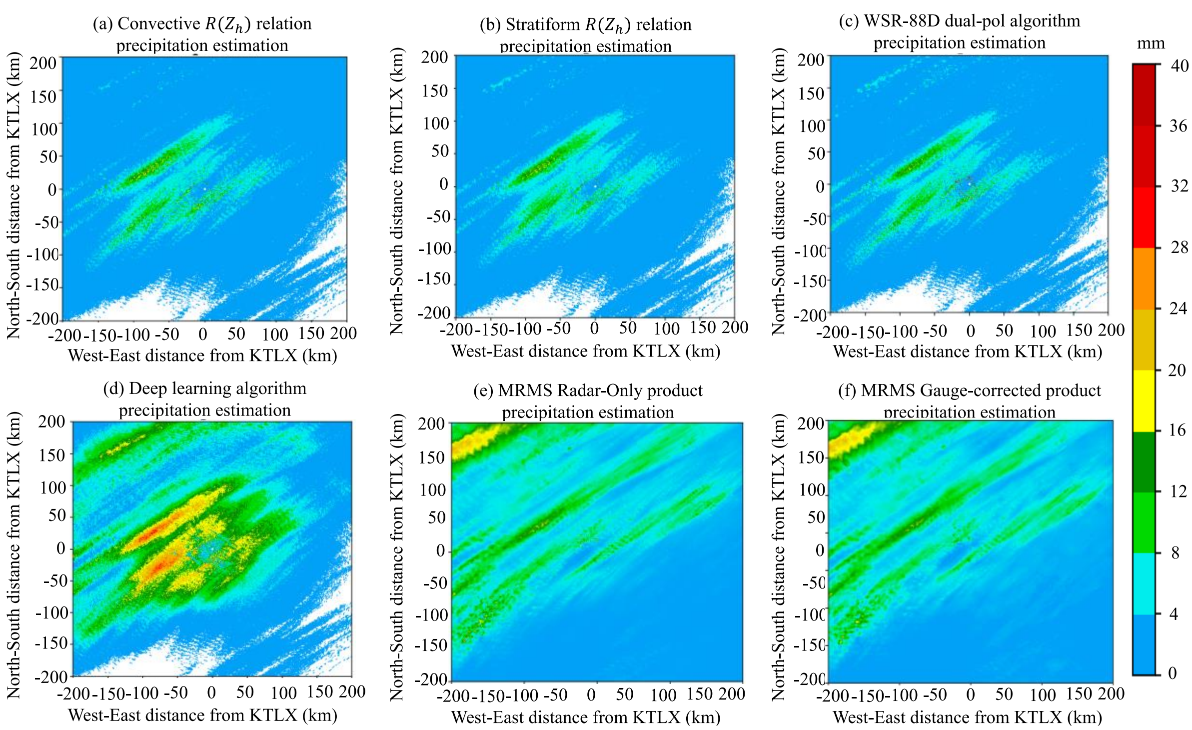

Fig. 4. Rainfall accumulations from 0600UTC to 1200UTC, Oct 26, 2020, based on different radar rainfall algorithms: (a) convective *Z-R* relation; (b) stratiform *Z-R* relation; (c) WSR-88D dual-pol algorithm; (d) deep learning model proposed in this study; (e) operational product from MRMS (radar-only); (f) operational product from MRMS (gauge-corrected).

In addition to this heavy precipitation event, Fig. 4 presents a case study during a light precipitation case. In cases of lower precipitation intensity, the deep learning model (Figure 4(d)) provides more accurate and detailed rainfall estimations compared to both the traditional radar methods (Figures 4(a)-(c)) and the MRMS products (Figures 4(e)-(f)). This demonstrates the deep learning model's superior capability in capturing the nuances of light precipitation events, making it a more reliable option in such scenarios.

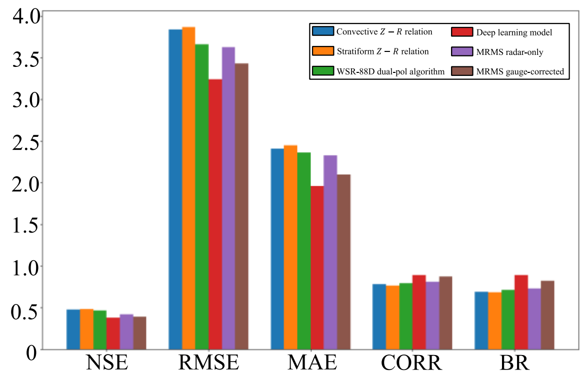

Fig. 5. The average performance of evaluation scores for three precipitation events in 2020.

Figure 5 illustrates the average performance of evaluation scores for three precipitation events on May 15, August 31, and October 26, 2020. Notably, the deep learning model demonstrates superior performance compared to traditional radar rainfall algorithms. The deep learning model achieves lower RMSE and MAE values, indicating its higher accuracy in estimating precipitation. Additionally, the deep learning model exhibits a comparable correlation coefficient (CORR) and bias ratio (BR), further highlighting its robustness in capturing the spatial and temporal variability of rainfall. These results underscore the deep learning model's ability to deliver more precise and reliable precipitation estimates, making it a valuable tool for meteorological applications.

4. SUMMARY AND CONCLUSION

This paper dives into the feasibility of deep learning in polarimetric radar-based quantitative precipitation estimation methods and its applicability in different precipitation regimes. The model was trained using dual-polarization radar observations and rain gauge data collected in Florida from 2019 to 2021.

To validate the model's performance in other regions, the study focuses on an area within a 200-kilometer radius of the KTLX radar in Oklahoma. By analyzing three precipitation events that occurred in 2020, the study compares the performance of the deep learning model using radar data against rain gauge data provided by the LWRB and MADIS networks. Both qualitative analysis of rainfall accumulation cases and quantitative error evaluations reveal that, despite being trained with data from Florida, the model can still accurately and effectively estimate precipitation in Oklahoma. The study demonstrates that the deep learning model not only exhibits high accuracy in quantitative precipitation estimation but also shows strong generalization capability across different regions.

5. ACKNOWLEDGMENT

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