Enhanced Adaptive Learning Model for Accurate Dual-Polarization Radar Rainfall Mapping

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***Abstract*—This study investigates the generalization capability of a deep learning model for dual-polarization radar-based quantitative precipitation estimation (QPE). The model is built upon a ShuffleNet architecture and trained using an extensive dataset, including radar reflectivity, differential reflectivity, and specific differential phase, from the KMLB radar in Florida covering the years from 2017 to 2021. Rain gauge data was also incorporated to enhance accuracy in estimating surface rainfall rates. Although the model demonstrates great performance in Florida, its adaptability was assessed by testing it in two contrasting regions: Oklahoma and California. Oklahoma, with its complex weather systems influenced by topography and the nearby Gulf of Mexico and Rocky Mountains, presents unique challenges for QPE models. Similarly, California's diverse precipitation patterns, ranging from coastal rain events to mountainous snowfall, offer another rigorous testing environment. The model's performance in these regions was validated against high-precision rain gauge measurements, providing key insights into its strengths and limitations. The results indicate that while the model performs well in its training region, accuracy challenges arise when applied to areas with differing climatic conditions, highlighting the need for adaptive learning techniques or region-specific model adjustments to improve QPE performance across diverse environments.**

I. Introduction

One of the persistent challenges in radar-based quantitative precipitation estimation (QPE) lies in applying radar rainfall relations developed in specific regions to areas with varying weather and geographical conditions. The traditional parametric approaches may face limitations in capturing local precipitation dynamics when used in regions outside their training environment [1] [2].

Deep learning has shown great promise in overcoming these challenges by detecting complex patterns in large datasets, leading to more accurate QPE models. However, even the most sophisticated deep learning models struggle with generalization when applied to regions with distinct climatic patterns and topographies. This limitation highlights the need for adaptive QPE models capable of maintaining high performance across diverse regions [3] [4] [5].

This study addresses model generalization by evaluating a deep learning-based QPE model trained with radar data from Florida, a region characterized by frequent convective storms and coastal precipitation. The model's performance is assessed in two distinct precipitation regimes: Oklahoma and California. By exploring the model's adaptability, this study emphasizes the importance of region-specific modifications and adaptive learning techniques to improve the reliability of QPE models in operational settings.

II. Methodology and Demonstration Studies

A. Deep learning QPE model

This study employs a deep learning framework based on ShuffleNet to estimate surface rainfall rates. The model processes radar observations within each range volume, structured into a 9×9 matrix that integrates three key radar variables: reflectivity (Z), differential reflectivity (Z_{dr}), and specific differential phase (K_{dp}). These variables are extracted from the two lowest scan elevation angles, while a 9×9 neighboring distance volume is also included to capture spatial patterns in the precipitation field. This combination enables the model to learn both physical and spatial features of rainfall.

The model is trained using data from the KMLB radar in Florida, along with rain gauge measurements collected from 2017 to 2021. The integration of radar variables and ground-based rain gauge data helps the model learn the relationship between radar observations and surface rainfall rates, improving the estimation accuracy across various precipitation scenarios [5].

B. Suitability of the Deep Learning Model

In this study, the deep learning QPE model, trained with radar and rain gauge data from Florida (Fig. 1(d)), is applied to two distinct regions: California (Fig. 1(b)) and Oklahoma (Fig. 1(c)). The figure illustrates the test locations, where stars indicate radar sites and colored dots represent rain gauge stations. California uses the KMUX radar (green star) with rain gauge data from Valley Water (red dots), while Oklahoma utilizes the KTLX radar (blue star) and rain gauge data from the NOAA MADIS and LWRB networks (green dots). These setups help assess the model's generalization across different precipitation regimes and provide valuable insights into its performance in varying climatic conditions.

III. Results and Evaluation

Fig. 2 compares the performance of six precipitation estimation models across three regions—Florida, Oklahoma, and California—using five key metrics: mean absolute error (MAE), root mean squared error (RMSE), correlation coefficient (CORR), normalized standard error (NSE), and BIAS Ratio (BR). The models evaluated are Convective Z-R relation, Stratiform Z-R relation, WSR-88D dual-pol algorithm, deep learning model, MRMS radar-only, and MRMS gauge-corrected.

The deep learning model consistently outperforms other models across all regions. It achieves the highest Correlation Coefficient (CORR), indicating its ability to accurately capture

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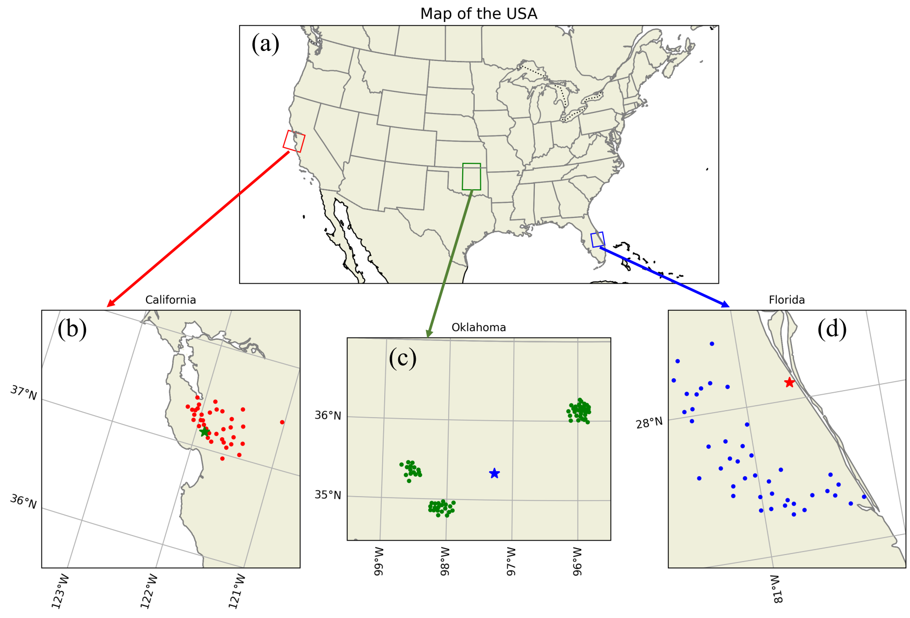

Fig. 1. Geographical representation of the test regions used to evaluate the deep learning-based QPE model trained on Florida data. The top panel(a) shows the locations of the three regions: California (red box), Oklahoma (green box), and Florida (blue box). The bottom panels depict zoomed-in views of each region with rain gauge stations (colored dots) and radar locations (stars). California(b) uses the KMUX radar and Valley Water rain gauges, Oklahoma(c) utilizes the KTLX radar and NOAA MADIS and LWRB rain gauges, and Florida(d)is represented with the KMLB radar and its associated rain gauge network.

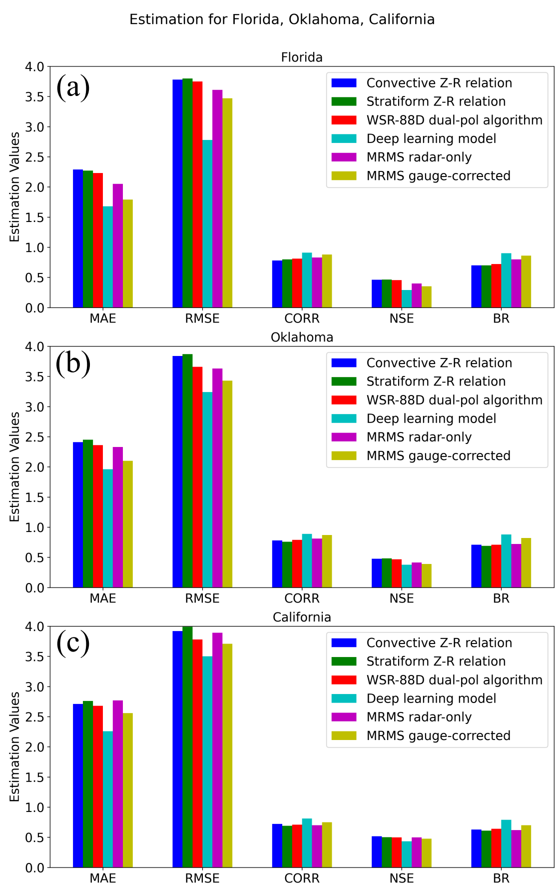

Fig. 2. Model performance comparison across (a) Florida, (b) Oklahoma, and (c) California using estimation metrics (MAE, RMSE, CORR, NSE, BR).

precipitation patterns. The model also delivers competitive results in MAE and RMSE, with low error rates in its predictions. Its performance remains robust across regions with varying weather conditions, including California, which is known for its complex terrain and precipitation patterns.

Overall, the deep learning model demonstrates strong predictive accuracy and adaptability, making it the most reliable option for precipitation estimation. Its consistent performance across all regions and metrics highlights its effectiveness in handling diverse climate challenges.

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