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Deep Learning for Polarimetric Radar Quantitative Precipitation Estimation: Model Interpretation and Explainability

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***Abstract*—Real-time and accurate precipitation estimation is critical for environmental protection and water resources management. Compared to traditional methods, i.e., radar reflectivity (Z) and rainfall rate (R) relations, relying on local raindrop size distributions, the deep learning model can fit the functional relationship between radar observations and rainfall rate measurements. However, the black-box nature of deep learning models makes it difficult to explain the physical mechanisms behind their results. To address this problem, this study proposes DQPENet, a deep learning model for polarimetric radar QPE utilizing dense blocks. We employ a permutation test to understand the relative importance of different radar data input variables. Additionally, we propose a regression importance value (RIV) method for the precipitation estimation task to visualize feature importance regions. Our experimental results show that radar reflectivity and specific differential phase at the lowest elevation angle are the two most important observables for the model's precipitation estimation. Furthermore, we find that radar data closer to the rain gauge are more influential on the model's results, indicating that the deep learning model is able to capture the underlying physical mechanism of atmospheric data.**

***Index Terms*—Dual-polarization, quantitative precipitation estimation, deep learning, permutation test, regression importance value**

I. Introduction

In the field of atmospheric science, the task of quantitative precipitation estimation (QPE) is crucial. It aims to provide accurate and timely estimates of rainfall rate and amount, as well as precipitation distribution, on a global and regional scale. Traditionally, the relationship between radar reflectivity (Z) and precipitation intensity (R), also known as Z-R relations, has been the main basis for radar data retrieval of precipitation [1–3]. Nevertheless, these conventional parametric relations are sophisticated to be derived and do not incorporate the spatial information of precipitation from radar observations.

With the development of deep learning (DL) technology, various DL models are used for classification or regression tasks, and have achieved impressive performances [4–6]. Studies have proved that it is feasible to estimate ground precipitation rate from polarimetric radar measurements using deep learning networks, so deep learning methods exhibit great potential in QPE tasks [7]. However, due to the black-box nature of the model, we cannot understand the basis of the model decisions, resulting in a lack of physical interpretability of the model results [8].

In recent years, research on the interpretability of DL models has yielded some achievements. It attempts to mine the underlying physical mechanisms captured by DL models, and reveal the reasons for the model results [9–11]. In this paper, we first proposed a DQPENet model for precipitation estimation. Then, we designed a regressor importance value (RIV) method to visualize the features that have the greatest impact on the model's results. Additionally, we introduce a permutation test method to rank the importance of features. The feasibility of applying interpretation techniques to the QPE task is demonstrated using the Weather Surveillance Radar - 1988 Doppler (WSR-88D) observations near Melbourne (KMLB), Florida, USA.

II. Dataset and Methodology

Figure 1 illustrates the pipeline of our DL model interpretation technology framework for QPE. In the first module, we introduce the study domain and the data set.

A. Datasets

In this article, our study domain is located in the city of Melbourne on the Florida peninsula. Dual-polarization radar data are collected from KMLB Weather Surveillance Radar - 1988 Doppler (WSR-88D) near Melbourne, Florida. We use three polarimetric observables, i.e., reflectivity (Z), differential reflectivity (Z_{dr}) and specific differential phase (K_{dp}) as the inputs for the model. The ground truth for the model is obtained from rain gauge data collected by the South Florida Water Management District (SFWMD) rain gauge network. Only radar observations and rain gauge data within 150km from the KMLB radar station are selected as the dataset to ensure data quality. The above radar and rain gauge data from 2016-2019 are used in this study, where the data from 2016-2018 as training and validation data, and the data from 2019 as testing data.

B. Overview of DQPENet

The concept of the DQPENet essentially consists of two main components: dense blocks and transition layers. The

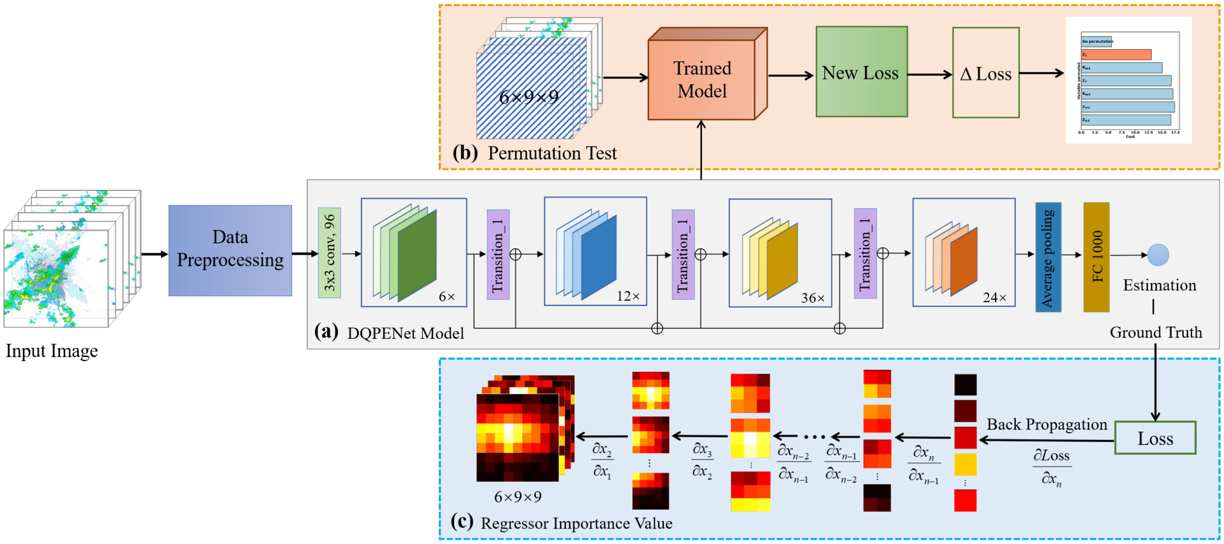

Fig. 1. Flowchart of the deep learning interpretation technology for polarimetric radar QPE: (a) DQPENet module; (b) permutation test; (c) regression importance value.

radar data are fed into a 3×3 convolution layer, followed by four dense blocks and three transition layers. In the end, the precipitation intensity is obtained through an adaptive average pooling layer and a fully connected layer. Each dense block is composed of several bottleneck layers, and each bottleneck layer has a batch normalization, ReLU and convolution sub-layers, i.e., BN-ReLU-Conv(1×1), followed by a BN-ReLU-Conv(3×3) set of layers. The four dense blocks contain 6, 12, 36 and 24 bottleneck layers respectively. The transition layers have the same internal structure, consisting of a BN layer and a 1×1 Conv layer, followed by an average pooling layer with stride 2. The input of the model is (6, 9, 9) containing the 3D radar data of the above 3 variables in a 9×9 pixel window at two elevation angles. The total number of samples in our dataset is 101337, including training, validation, and testing data.

III. Interpretation Methods

A. Permutation Test

The permutation test quantifies the importance of each variable to the precipitation estimation results. When disrupting the matrix of a variable, the method ranks it by quantifying whether the model loss has increased or decreased, i.e., the more the loss has increased, the more important the variable is [12]. This algorithm consists of N steps, where N stands for the total number of variables. At the end of each step, the most important variable is permanently permuted. In this paper, we rank the following six variables: Z_1, Z_{dr1}, K_{dp1}, Z_2, Z_{dr2}, K_{dp2}, where 1 and 2 represent the lowest and the second lowest elevation angles respectively.

B. Regressor Importance Value

In this paper, we design an RIV method that can be used for regression tasks and apply it to precipitation estimation. Specifically, through the backpropagation process, RIV optimizes the model parameters and calculates the gradient information (i.e., the importance value, I_v) of each input pixel through the chain rule, and visualizes the value of I_v. RIV is defined by:

$$I_v = \frac{\partial L}{\partial \theta^{i,j}}|_{\theta^{i,j}=\theta_0^{i,j}} \tag{1}$$

where L is the mean square error (MSE) between the precipitation estimates and rain gauge observations, i and j are the horizontal and vertical coordinates of each grid point respectively, $\theta^{i,j}$ is one scale regressor at one grid point, $\theta_0^{i,j}$ is the value of $\theta^{i,j}$ in a testing sample. This method does not need to increase the complexity of the model and can calculate the importance value of all pixels, so the RIV result has the same dimensions as the input radar data. I_v can be regarded as the correlation between L and $\theta^{i,j}$, and reflects the degree of $\theta^{i,j}$ influence on the loss function, which can explain the reason why the model makes this decision.

IV. Results and Analysis

A. Example Estimation Products

To compare the performance of the DQPENet model in precipitation estimation, this paper adopts two commonly used traditional Z-R relations, as follows:

$$R(Z) = 1.70 \times 10^{-2} \times Z^{0.714} \tag{2}$$

$$R(Z, Z_{dr}) = 1.42 \times 10^{-2} \times Z^{0.770} \times (10^{\frac{Z_{dr}}{10}})^{-1.670} \tag{3}$$

where R stands for the rainfall rate in mm/h. In this article, the precipitation intensity over an hour is accumulated to obtain the hourly radar precipitation amount. In order to quantify the performance of the DQPENet model, five evaluation metrics are computed, including root mean absolute error (MAE), mean square error (RMSE), deviation (BIAS), the correlation coefficient (CC), and normalized standard error (NSE).

TABLE I: Evaluation results of hourly rainfall estimates from three QPE methods

Model	MAE (mm)	RMSE (mm)	CC (ratio)	NSE (%)	BIAS (ratio)
DQPENet	**1.58**	**2.68**	**0.92**	**26**	**0.91**
$R_(Z)$	3.26	5.07	0.76	54	0.54
$R(Z, Z_{dr})$	3.34	5.15	0.78	55	0.49

Table I shows the MAE, RMSE, CC, NSE and BIAS ratio values of the three QPE methods. It can be seen that DQPENet achieves superior estimation performance than the other two methods, it has MAE of 1.58 mm, RMSE of 2.68 mm, NSE of 26%, correlation of 0.92, and bias of 0.91 for hourly rainfall estimates.

B. Results of Interpretable Methods

Figure 2 shows the results of the permutation test for the DQPENet model, the more important features are above, and the less important features are below. It can be seen that the most important feature is Z_1, i.e., the radar reflectivity of the lowest elevation angle, followed by K_{dp1}. In fact, K_{dp1} is less susceptible to radar observation bias and hail, and is more accurate than estimates obtained by using Z and Z_{dr} in heavy precipitation, so the relationship between K_{dp1} and R is closer to linear [13]. This also indicates that the heavy precipitation data have a strong influence on the estimated results.

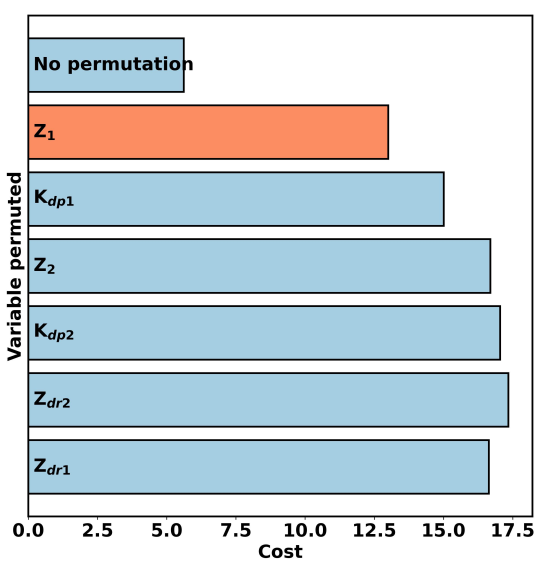

Fig. 2. Results of permutation test for DQPENet, based on 24493 testing examples. The most important variables are in orange.

Figure 3 shows the result of RIV, where subplots (a) and (c) are one sample of the input model at four different times for light and high rainfall rates respectively, i.e., images of size 9 $\times$ 9. Fig. 3(b) and (d) are RIV visualizations of each variable corresponding to the one sample, with the color guide being values of importance, the larger the value and the brighter the color, the more important it is to the model results. As can be seen from Fig. 3, the highlighted areas of all variables are in the center, this is because the center points of radar samples correspond to the rain gauge measurements, so the data at the center point and its surroundings have the strongest correlation with the rain gauge data, and are more important for the estimation of precipitation. Combined with the result of the permutation test in Fig. 2, the two variables Z_1 and K_{dp1} are the most important for the model result, so the highlighted areas of these two variables in Fig. 3 are the most obvious.

V. Conclusion

In this paper, we discuss the feasibility of applying interpretability methods to QPE tasks, including the permutation test and regression importance values. First, we transform the task of estimating precipitation into a regression problem and design a DQPENet model using dense blocks. Then, through the permutation test, the importance of model input variables is sorted, among which Z_1 and K_{dp1} are the most important for precipitation estimation. According to the back-propagation of the loss function and the change of the model gradient, the RIV method visualizes the areas of samples that have the greatest impact on the model results. From the visualization results of RIV, it can be concluded that the radar data with a stronger association with rain gauge data are more important to the precipitation estimation. The experimental results can provide further guidance on how to select observed variables from radar data as model inputs for precipitation estimation and verify whether the deep learning model results are plausible.

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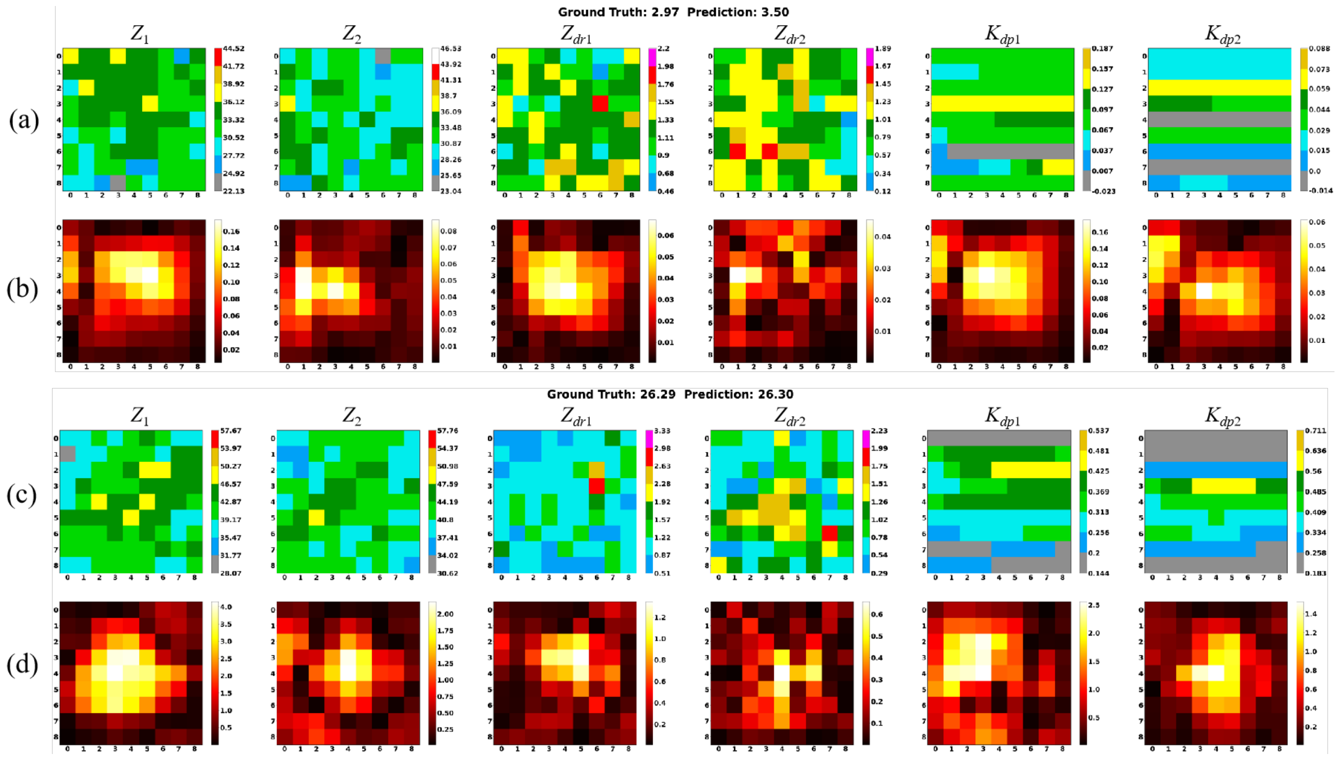

Fig. 3. The comparison of RIV in the different thresholds.Regression importance value results for one sample of the precipitation case at 13:00 UTC on 24 January 2019. The first row is the original images input to the model, and the second row is the corresponding RIV visualization.

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