Evaluation of machine learning based Quantitative Precipitation Estimation

EunYeol Kim[1] , V. Chandrasekar[1]

Introduction

Quantitative precipitation estimation (QPE) is an important research field in remote sensing. However, wide spatial and temporal variability of precipitation is a huge challenge for accurate QPE. The radar based rainfall estimation has been widely studied in physical relation between radar reflectivity and rainfall rate. In recent years, machine learning based QPE has been studied for accurate rainfall estimation [1]. The machine learning based QPE requires accurate measurements from ground rain gauges to use it as a ground truth. However, the resolution of measurements from rain gauges are varying in temporal and spatial resolution. In this paper, the evaluation of machine learning technique for QPE from different temporal gauge measurements is discussed. The KMLB Next Generation Radar (NEXRAD) is S-band radar collecting the data every 5 minutes temporal resolution in Florida. 39 rain gauges are present in 100km range from KMLB radar and measuring the rainfall every 1 minute temporal resolution. The difference in spatial and temporal domain between gauge data and radar data are matched to train the machine learning models. The in-situ ground measurements are used as a ground truth. Dual polarized radar moments, reflectivity (Z), differential reflectivity (Z_{dr}) and specific differential phase shift (K_{DP})[2] are used to train machine learning based QPE. Combination of U-net architecture and regression deep neural network is presented for QPE and evaluated using the metrics.

1. Description and Data

- Rain gauge data collected for TRMM, GPM and Florida KMLB S band NEXRAD radar data are used to train machine learning model
- 39 rain gauges within 100km from KMLB radar were used (shown in figure 1)
- August 2015, November 2016 are used as training (75%), validation (25%) data and August, September 2017 are used for test data
- Radar data observed from Plan Position Indicator scan was aligned to the gauge location
- 7x7 range gates from the radar data closest to the gauge location was used (shown in figure 2)
- Reflectivity (Z), differential reflectivity (Z_{dr}) and specific differential phase shift (K_{dp}) from lowest two elevation angles (0.5°, 1.0°) are used
- 1 minute rainfall rate of machine learning based QPE, Deep Neural Network (DNN) model using vertical profile of radar moments [1] and National Weather Service (NWS) Z-R equation are evaluated

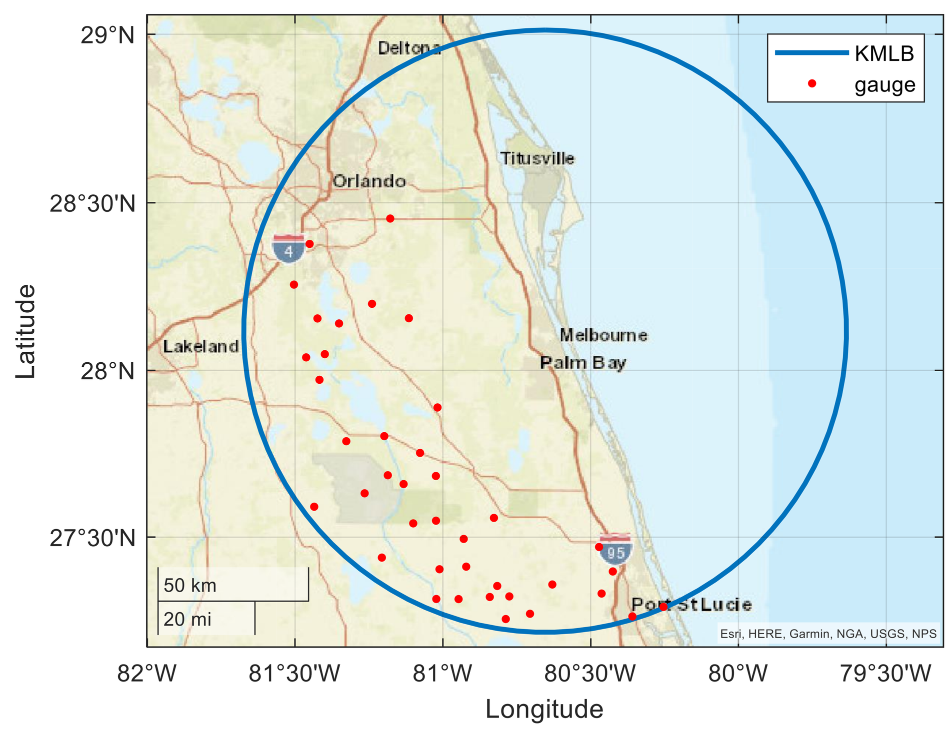

Figure 1. Map of KMLB radar and rain gauges

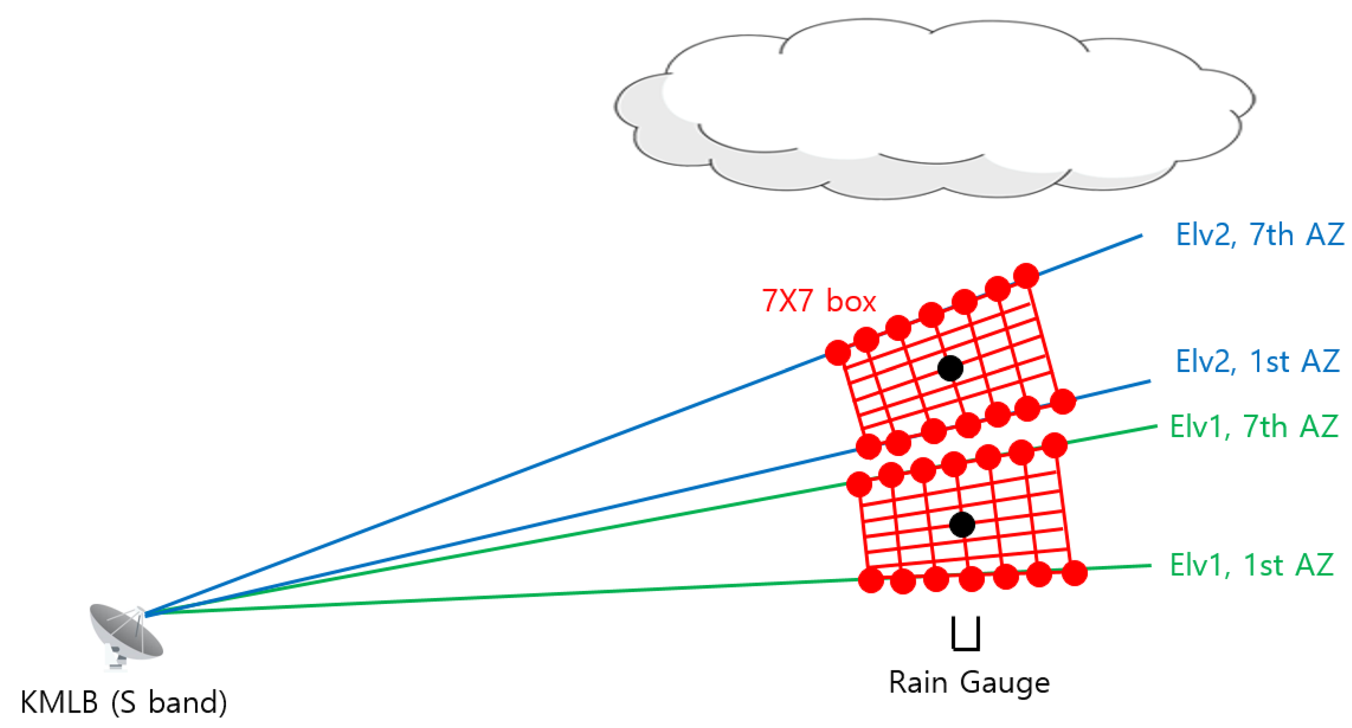

Figure 2. Diagram of spatial alignment

2. Evaluation of machine learning based QPE

- Machine learning model is structured with combination of U-net architecture and regression deep neural network models
- 7x7 square shape radar moments of Z, Z_{dr}, K_{dp} are used to train the machine learning model

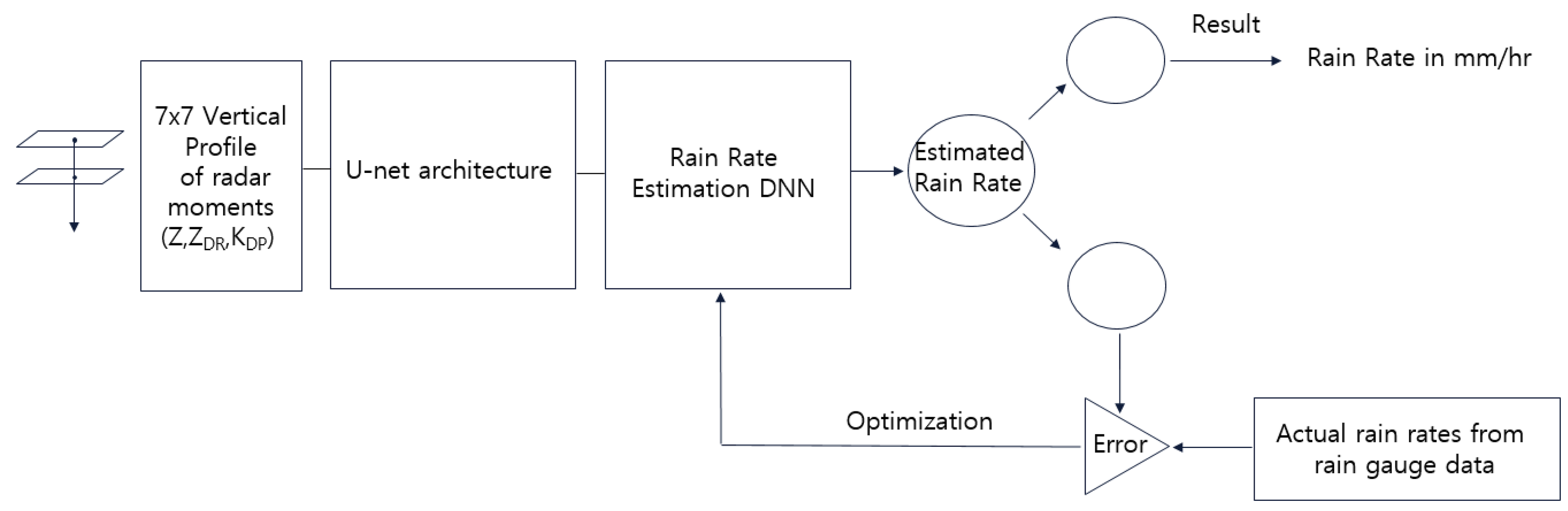

Figure 3. Flowchart of machine learning based QPE

1 minute rainfall rate QPE Evaluation

Evaluation metrics used

$$\text{Mean Absolute Error (MAE)} = \frac{1}{N}\sum_{i=1}^{N}|Actual_i - Estimate_i|$$

N : total number of samples
i : samples

$$\text{Normalized Mean Absolute Error (NMAE)} = \frac{MAE}{\text{mean(Actual)}}$$

$$\text{Correlation (CORR)} = \frac{\sum_{i=1}^{N}(Actual_i - mean(Actual_i)) * (Estimate_i - mean(Estimate_i))}{\sqrt{\sum_{i=1}^{N}(Actual_i - mean(Actual_i))^2} * \sqrt{\sum_{i=1}^{N}(Estimate_i - mean(Estimate_i))^2}}$$

	MAE	NMAE	CORR
U-net Train	5.13	0.46	0.82
U-net Validation	5.29	0.46	0.82
U-net Test	5.12	0.50	0.76
DNN Test[1]	5.71	0.55	0.73
NWS Z-R Test	6.67	0.65	0.67

Table 1. Evaluation of machine learning model and NWS Z-R equation

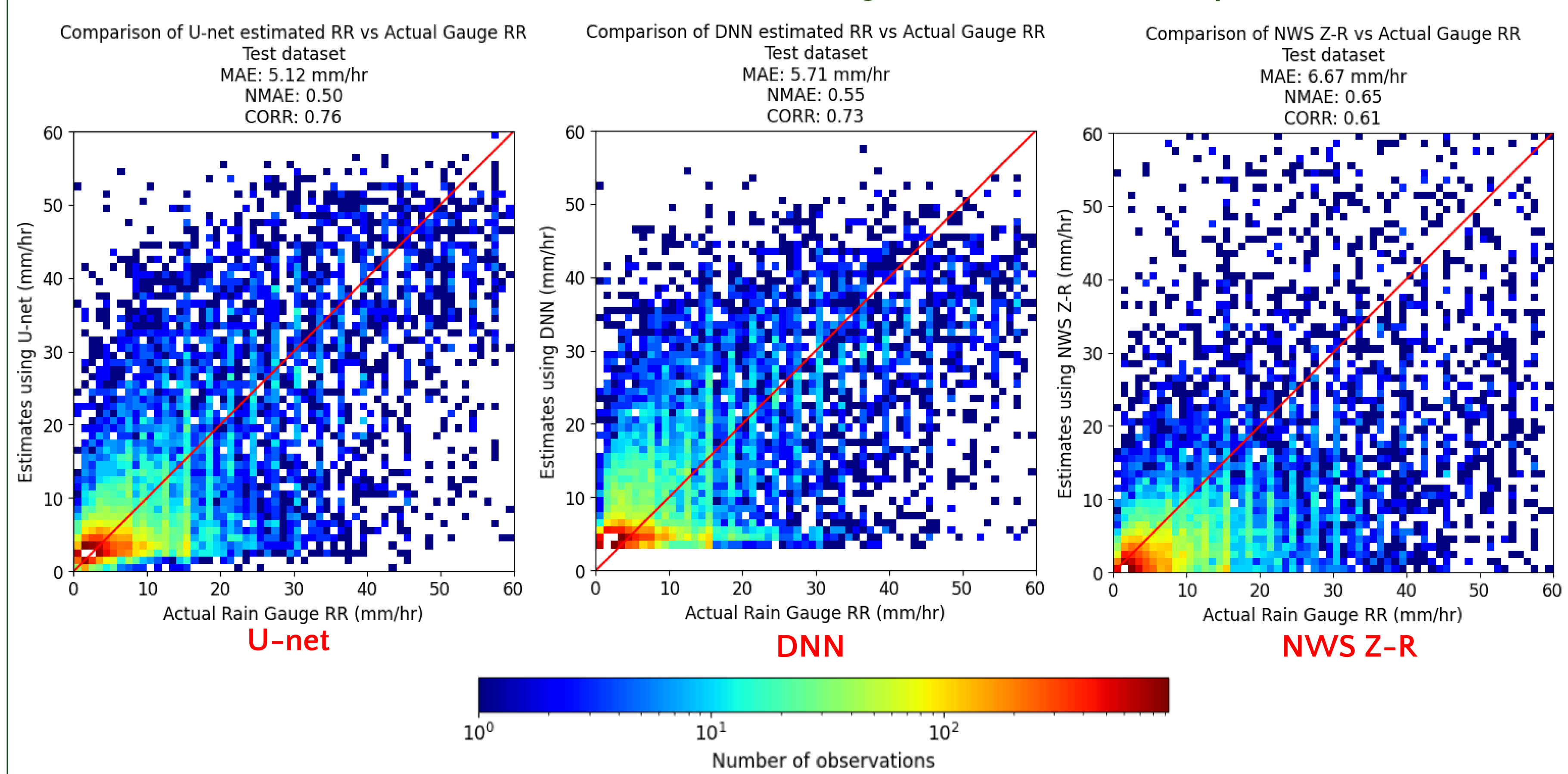

Figure 4. Scatter plot of machine learning models and Z-R equation on August, September 2017 test data

3. Summary

- Combination of U-net architecture and regression deep neural network machine learning model QPE outperforms National Weather Service Z-R equation

4. Reference

[1] EunYeol Kim, V.Chandrasekar, Chandrasekar Radhakrishnan, Luca Delle Monache, and Duncan Axisa, "Radar Based Quantitative Precipitation Estimation Using Deep Learning over the UAE region", 104th American Meteorological Society Annual Meeting, 2024
[2] Chen, H., V. Chandrasekar, and R. Bechini, 2017: An Improved Dual-Polarization Radar Rainfall Algorithm (DROPS2.0): Application in NASA IFloodS Field Campaign. J. Hydrometeor., 18, 917–937, https://doi.org/10.1175/JHM-D-16-0124.1.

5. Acknowledgement

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[1]Colorado State University Contact: eunyeol.kim@colostate.edu, chandra@colostate.edu