



A Spatially Coherent Hybrid Machine Learning Approach for Improving Radar Quantitative Precipitation Estimation

Sungho Jung¹ and Yoon-Seop Chang²

¹Electronics and Telecommunications Research Institute, Daejeon, Republic of Korea (jungsh@etri.re.kr)

²Electronics and Telecommunications Research Institute, Daejeon, Republic of Korea (ychang76@etri.re.kr)

Accurate high-resolution quantitative precipitation estimation (QPE) using weather radar is essential for hydrological simulation and forecasting under increasing climate crisis. Although empirical Z-R relationships are widely used, their rainfall type-specific and regionally constrained nature limits generalization across diverse precipitation regimes. Data-driven machine learning offers a promising alternative, yet conventional regression-based approaches frequently struggle to preserve the spatial structure of radar imagery due to residual estimation artifacts.

To address these limitations, this study aims to develop a spatially coherent hybrid machine learning framework for radar QPE over South Korea, integrating three core methodological components. First, Gaussian Mixture Model (GMM) soft clustering is applied using radar reflectivity, terrain attributes, and Z-R derived variables, mitigating the boundary discontinuities inherent to hard-clustering approaches through probabilistic regime assignment. Second, cluster-specific Extreme Gradient Boosting (XGBoost) regressors trained with posterior probabilities as sample weights are merged through probability-weighted blending, enabling nonlinear Z-R mapping across heterogeneous precipitation regimes. Third, a binary mask derived from raw radar reflectivity thresholding is multiplied element-wise against the blended output, eliminating residual estimates over non-precipitating regions and restoring the spatial footprint of the original radar observation. For model training, we utilize Hybrid Surface Rainfall (HSR) composite reflectivity, Automated Synoptic Observing System (ASOS) rain gauges, and terrain data. The dense Automatic Weather Station (AWS) network serves as a robust independent validation set, ensuring spatial reliability across varied topography and rainfall intensities.

The framework is designed to capture nonlinear precipitation patterns across convective, orographic, and frontal regimes. Also, this approach minimizes the spatial uncertainty common in ML-based QPE outputs. The resulting framework maintains numerical continuity, contributing to the enhanced reliability of real-time hydrometeorological modeling and early warning operations.

This work was supported by Electronics and Telecommunications Research Institute (ETRI) grant funded by the Korean government [26ZR1300, Development of Technology for the Urban Extreme Rainfall Response Platform].