INTISARI

Estimasi curah hujan berbasis radar (*Quantitative Precipitation Estimation*/QPE) memiliki keunggulan dalam hal cakupan spasial luas, tetapi masih dipengaruhi oleh bias. Penelitian ini bertujuan meningkatkan akurasi QPE melalui penggabungan data radar dan penakar hujan dengan tiga metode, yakni *Local Bias* (LB), *Kriging with External Drift* (KED), dan *Bayesian* (BAY). Data yang digunakan berupa rekaman radar cuaca Pangkalan Bun periode Maret hingga Agustus 2024 dan penakar hujan otomatis yang tersebar di wilayah cakupan radar. Tahap pra-pemrosesan radar mencakup koreksi *clutter* dan atenuasi, dilanjutkan evaluasi QPE, serta penerapan metode *merging* dengan validasi menggunakan metrik korelasi, *Root Mean Square Error* (RMSE), *Mean Absolute Error* (MAE), *Structure-Amplitude-Location* (SAL), serta matriks kontingensi untuk menilai kinerja deteksi hujan. Hasil menunjukkan QPE radar cenderung *overestimate* dengan korelasi 0,59 dan RMSE 8,47. Penerapan teknik *merging* memperbaiki akurasi QPE, dimana LB meningkatkan korelasi menjadi 0,64 dengan penurunan RMSE 9%, KED menghasilkan korelasi tertinggi 0,65, sementara BAY menurunkan RMSE terbesar hingga 7,65 (10%) dengan MAE terendah. Analisis spasial menunjukkan LB paling konservatif dalam mempertahankan pola radar, KED memperluas distribusi hujan, sementara BAY memiliki kecenderungan mereduksi puncak intensitas. Pada musim hujan yang didominasi oleh hujan meluas dan berdurasi panjang, seluruh metode lebih stabil, sedangkan pada musim kemarau BAY menunjukkan hasil lebih unggul. Performa *merging* relatif baik pada hujan ringan–sedang, tetapi pada hujan lebat masih terdapat kelemahan baik dalam deteksi maupun estimasi. Distribusi jaringan penakar terbukti berperan penting dalam menekan kesalahan estimasi. Keseluruhan hasil memperlihatkan bahwa integrasi radar dan penakar dapat meningkatkan akurasi QPE radar, dengan efektivitas bergantung pada distribusi penakar, musim, dan intensitas hujan.

Kata kunci: Radar cuaca, *Quantitative Precipitation Estimation*, *merging*, *Local Bias, Kriging with External Drift, Bayesian*

ABSTRACT

Radar-based Quantitative Precipitation Estimation (QPE) offers advantages in terms of wide spatial coverage, but remains affected by systematic biases. This study aims to enhance QPE accuracy through the integration of radar and rain gauge data using three methods: Local Bias (LB), Kriging with External Drift (KED), and Bayesian (BAY). The dataset comprises weather radar records from Pangkalan Bun (March to August 2024) and automatic rain gauges distributed across the radar coverage area. Radar preprocessing included clutter and attenuation correction, followed by QPE evaluation and merging, validated using correlation, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Structure-Amplitude-Location (SAL), and contingency metrics. Results indicate that raw radar QPE tends to overestimate rainfall, with a correlation of 0.59 and RMSE of 8.47. The merging techniques successfully improved QPE accuracy. LB increased the correlation to 0.64 with a 9% RMSE reduction, KED achieved the highest correlation at 0.65, while BAY provided the largest RMSE reduction to 7.65 (10%) with the lowest MAE. Spatial analysis revealed that LB preserved radar patterns with minimal adjustment, KED expanded rainfall distribution, while BAY reduced peak intensities. During the rainy season, which is dominated by widespread and persistent rainfall, all methods show more stable performance, whereas during the dry season, the BAY method performs better. Performance by intensity indicated improvements for light–moderate rainfall, but moderate–heavy rainfall remained challenging for all methods. Gauge density analysis confirmed that a denser and well-distributed network significantly reduces errors. This study confirms that integrating radar and gauge data can enhance QPE accuracy, with effectiveness depending on gauge distribution, season, and rainfall intensity.

Keywords: *Weather radar, Quantitative Precipitation Estimation, merging, Local Bias, Kriging with External Drift, Bayesian*