

Article

Radar–Rain Gauge Merging for High-Spatiotemporal-Resolution Rainfall Estimation Using Radial Basis Function Interpolation

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Abstract: This study introduces methods for generating fused precipitation data by applying radial basis function (RBF) interpolation, which integrates radar reflectivity-based data with ground-based precipitation gauge measurements. Rain gauges provide direct point rainfall measurements near the ground, while radars capture the spatial variability of precipitation. However, radar-based estimates, particularly for extreme rainfall events, often lack accuracy due to their indirect derivation from radar reflectivity. The study aims to produce high-resolution gridded ground precipitation data by merging radar rainfall estimates with the precise rain gauge measurements. Rain gauge data were sourced from automated synoptic observing systems (ASOSs) and automatic weather systems (AWSs), while radar data, based on hybrid surface rainfall (HSR) composites, were all provided by the Korea Meteorological Administration (KMA). Although RBF interpolation is a well-established technique, its application to the merging of radar and rain gauge data is unprecedented. To validate the accuracy of the proposed method, it was compared with traditional approaches, including the mean field bias (MFB) adjustment method, and kriging-based methods such as regression kriging (RK) and kriging with external drift (KED). Leave-one-out cross-validation (LOOCV) was performed to assess errors by analyzing overall error statistics, spatial errors, and errors in rainfall intensity data. The results showed that the RBF-based method outperformed the others in terms of accuracy.

Keywords: radar–rain gauge merging; spatial interpolation; radial basis function; kriging; kriging with external drift



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1. Introduction

Obtaining accurate precipitation data is essential for various applications, including hydrological modeling, flood forecasting, water resource management, agricultural planning, and climate research [1–4]. Understanding precipitation patterns is crucial, especially in regions prone to extreme weather events, where accurate data can significantly improve disaster preparedness and mitigation efforts [5–8]. However, accurately measuring rainfall remains a significant challenge due to the inherent limitations of individual observational systems.

Ground-based rain gauges are highly accurate for measuring rainfall at specific locations, making them a widely used tool for precipitation measurement. However, the sparse spatial distribution of rain gauges, particularly in mountainous or remote areas, limits their ability to represent the spatial variability of precipitation. These coverage

gaps can lead to considerable errors when analyzing or modeling precipitation over larger areas [9–12]. In contrast, weather radars provide broad spatial coverage and near-real-time monitoring, making them indispensable for understanding precipitation patterns over large areas. Radars detect precipitation indirectly through measurements of reflectivity, which is then converted into rainfall intensity using empirical relationships such as the R-Z relationship [13]. Despite these advantages, radar data often suffer from inaccuracies caused by beam attenuation, ground clutter, and uncertainties in reflectivity-to-rainfall conversion, particularly during extreme rainfall events or in complex terrains [14–18].

To overcome these challenges, radar–rain gauge fusion has emerged as a promising approach, combining the strengths of each measurement system. Radar–rain gauge fusion leverages the spatial coverage of radar data and the ground-level accuracy of rain gauge measurements to produce more reliable precipitation datasets. Numerous studies have demonstrated that radar–gauge fusion provides superior rainfall estimates compared to using radar or rain gauge data alone [19–21]. These improvements are evident even in large-scale studies conducted at relatively low spatial and temporal resolutions [22–26].

Among the most common approaches, the mean field bias (MFB) adjustment method reduces systematic radar errors by applying gauge-derived bias correction. This method assumes that the bias between radar and gauge measurements is consistent over a given region and time, allowing for a simple yet effective correction of radar precipitation estimates [24,27–29]. However, MFB often fails to capture local variability as it applies a global correction across the entire domain.

Kriging with external drift (KED) and regression kriging (RK) are geostatistical approaches that leverage additional explanatory variables to enhance spatial interpolation. KED incorporates external data, such as radar reflectivity, as a secondary variable to model spatial trends in precipitation, while still relying on rain gauge measurements for calibration. This method allows for more flexible and localized interpolation, accommodating spatially varying relationships between radar and gauge data [30,31]. One limitation of KED is its reliance on a strong correlation between the primary and secondary variables, which may not always hold under complex atmospheric conditions or extreme rainfall events [32–34]. Similarly, RK combines regression analysis with kriging by first modeling the relationship between radar reflectivity and rain gauge measurements through linear regression and then interpolating the regression residuals using kriging. This two-step process allows RK to capture both global trends and localized variability in precipitation [35,36]. Traditional methods such as MFB, KED, and RK have significantly contributed to improving rainfall estimation. However, challenges persist in achieving accurate and efficient rainfall estimation, particularly in urban and hydrologically sensitive areas where fine-scale spatial and temporal resolution is essential [37–39]. These limitations underscore the need to explore alternative approaches that can complement or enhance existing techniques.

Radial basis function (RBF) interpolation, known for its flexibility and ability to model nonlinear spatial relationships, has been effectively applied in various scientific fields [40,41]. However, its application in radar–rain gauge fusion remains relatively underexplored. In this study, we propose a novel approach that applies the well-known RBF interpolation method to integrate radar and rain gauge data for generating high-resolution gridded precipitation datasets. The radar data are derived from hybrid surface rainfall (HSR) composite reflectivity [42], while the rain gauge data are based on 1 min measurements collected by automated synoptic observing systems (ASOSs) and automatic weather systems (AWSs). High-resolution rain gauge data are crucial for accurately estimating extreme rainfall events, which are vital in urban drainage system design and climate model validation [43].

To validate the proposed approach, we conducted a comprehensive comparison with traditional methods, including MFB adjustment, RK, and KED. Using leave-one-out cross-validation (LOOCV), we evaluated the overall accuracy, spatial error distribution, and performance across different rainfall intensities.

2. Study Region and Data

2.1. Study Region

The study area covers South Korea. In Figure 1a, the black solid line marks the perimeter of the radar composite area produced in real time by the Korea Meteorological Administration (KMA), with a spatial resolution of 500 m and dimensions of 2305 by 2881 pixels. The region outlined in blue indicates the fusion domain of the KMA radar composite and rain gauges, which is the primary focus of this study. This area has a spatial resolution of 1 km and dimensions of 960 by 960 pixels. In Figure 1b, the area outlined in purple represents the region containing ground rain gauges, which is used for verification and data output testing.

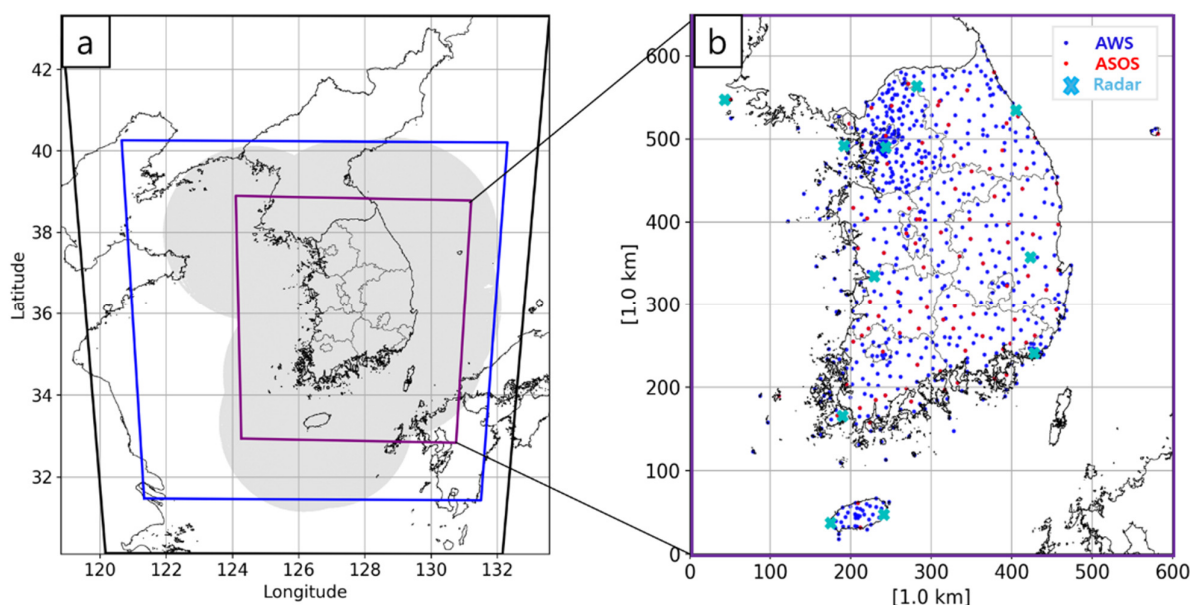


Figure 1. (a) The original HSR area (black line) and the fusion area (blue line) with 1 km resolution of 960 by 960 pixels. The gray-shaded region represents the HSR radar composite area, while the area inside the purple line indicates the verification region. (b) A zoomed-in view of the verification region, showing the locations of the automatic weather systems (AWSs), automated synoptic observing systems (ASOSs), and weather radar.

2.2. Radar and Rain Gauge Data

2.2.1. Weather Radar Data

The KMA enhances the accuracy of radar-based precipitation estimates using the HSR synthesis technique. This method integrates reflectivity data from multiple radars, selecting the lowest elevation angle unaffected by terrain blockage to minimize the effects of ground clutter and non-meteorological echoes [42]. Before HSR synthesis, radar data undergo a quality control process using the Clutter Elimination Algorithm for Non-precipitation Echo of Radar data (CLEANER) algorithm [44], which eliminates ground clutter and anomalous propagation echoes, and corrects radial velocity folding in Doppler radar data. Operational since March 2018, the HSR technique relies on CLEANER-processed data as a preprocessing step, ensuring accurate and reliable precipitation measurements. This HSR composite data are derived from 11 KMA weather radars, comprising 10 S-band radars and 1 C-band radar.

Between 2014 and 2019, the KMA upgraded all radars, except the one at Incheon Airport, from single-polarization to dual-polarization systems. In August 2022, the Incheon Airport radar was also replaced with a dual-polarization radar. The composite data are based on reflectivity, and the Marshall–Palmer R-Z relation, where $Z = 200R^{1.6}$ [45], was applied to convert the reflectivity values into rainfall estimates.

2.2.2. Rain Gauge Data

The KMA operates two types of automatic weather observation systems, automated synoptic observing systems (ASOSs) and automatic weather systems (AWSs), categorized based on their purpose. AWS stations are strategically installed in remote areas, such as mountains and islands, where human observation is challenging. These stations facilitate real-time monitoring of localized severe weather phenomena, including heavy rainfall, hail, thunderstorms, and gusty winds. The meteorological data collected from these networks are essential as initial inputs for numerical weather prediction models. AWS stations measure fundamental meteorological parameters such as temperature, wind direction, wind speed, precipitation, and the presence of rainfall. Some selected AWS sites also provide additional measurements of pressure and humidity. The rain gauges used at AWS stations employ a tipping-bucket mechanism with a resolution of 0.5 mm per minute.

AWSs were first introduced in South Korea in the late 1980s and expanded nationwide during the 1990s to support disaster management and localized weather forecasting. Over the years, AWS maintenance has been focused on enhancing data reliability, including regular calibration of sensors and system updates to integrate advanced telemetry and remote diagnostics.

In contrast, ASOS stations are primarily located at regional offices, weather stations, and observation posts, where they conduct comprehensive weather observations and contribute data to international meteorological networks. Beyond the basic measurements conducted by AWSs, ASOS stations capture additional parameters, including sunshine duration, solar radiation, surface temperature, ground temperature, and soil temperature. The rain gauges at ASOS stations use a weighing mechanism, which offers a higher resolution of 0.1 mm per minute, providing greater accuracy compared to AWS stations. First implemented in the late 1970s, ASOSs serve as the national standard for weather observation in South Korea, adhering to World Meteorological Organization (WMO) standards. Maintenance of ASOS stations includes periodic replacement of high-precision instruments, routine on-site inspections, and adherence to international calibration protocols. With approximately 100 stations, ASOSs support long-term climate studies and high-accuracy data collection.

Both ASOSs and AWSs collect data at one-minute intervals, ensuring high temporal resolution, with a network density of approximately one station per 13 square kilometers. To ensure the reliability and accuracy of the data collected from AWSs and ASOSs, the KMA implements comprehensive quality assurance and quality control procedures. These procedures include regular maintenance, calibration, and systematic management of maintenance logs, encompassing sensor replacements, system upgrades, and corrective actions for identified issues. This rigorous approach ensures the provision of high-quality meteorological data essential for weather forecasting, climate monitoring, and various research applications. As of 1 September 2023, a total of 98 ASOS and 554 AWS stations are in operation across South Korea. The spatial distribution of these stations, along with radar sites, is shown in Figure 1b.

2.3. Events Description

In 2022, South Korea experienced significant rainfall variability and extreme weather events compared to the average. During the summer and autumn, the country faced multiple instances of heavy rainfall and typhoons, with some regions recording unprecedented precipitation levels.

This analysis focuses on six rainfall events from 2022, selected based on periods when rainfall was recorded at three or more gauge stations. The selection criteria required that the average 10 min accumulated rainfall intensity at these points consistently exceeded 3.0 mm h^{-1} . The characteristics of these events are detailed in Table 1, presented in chronological order. Maximum and average intensity values were derived from rain gauge measurements, with intensity converted to an hourly rate based on 10 min cumulative rainfall data.

Table 1. Characteristics of the six analyzed events in 2022. The time is LST.

Case Identifier	1	2	3	4	5	6
Start [day/month time]	29/06 15:00	23/07 15:00	08/08 09:00	15/08 17:00	05/09 04:00	03/10 17:00
End [day/month time]	30/06 20:00	24/07 07:00	10/08 09:00	16/08 09:00	06/09 09:00	04/10 10:00
Duration [h]	29	18	48	16	29	17
Maximum intensity at a station [mm h^{-1}]	153.6	150.0	168.0	138.0	138.0	105.0
* Average rainfall intensity at all stations [mm h^{-1}]	2.3	1.3	2.1	0.8	4.4	2.2

* The average rainfall intensity was calculated, including values of 0.0 mm h^{-1} .

Figure 2a–f display radar precipitation images for each case, illustrating the total accumulated rainfall over the durations specified in Table 1. Among these periods, the fifth case recorded the highest average rainfall intensity as measured by rain gauges, while the third case exhibited the peak maximum rainfall intensity. A brief description of the six cases from 2022 is as follows.

Case 1: On 29–30 June, intense rainfall affected South Korea's central region, especially Seoul, Gyeonggi, and Gangwon, where rainfall rates exceeded 30–50 mm per hour, with some areas receiving up to 80 mm per hour. The monsoon front, which remained stationary over the region, caused over 200 mm of rainfall in some areas, unusually high for late June.

Case 2: From 23–24 July, the reactivation of the monsoon front brought sustained rainfall to central South Korea, with localized heavy rainfall exceeding 50 mm per hour due to atmospheric instability.

Case 3: From 8–10 August, the Seoul metropolitan area experienced record-breaking rainfall, reaching up to 141.5 mm per hour and totaling over 500 mm. This extreme event, driven by strong atmospheric instability and moisture influx, caused significant flooding, particularly in Gangnam. This represents one of the highest hourly rainfall rates recorded in Seoul since the 1920s.

Case 4: On 15–16 August, the reactivated monsoon front brought intense rainfall to Seoul and Gangwon, with rates exceeding 50 mm per hour. This added to the already saturated soils from earlier rains, leading to flooding and landslides.

Case 5: Typhoon 'Hinnamnor' caused severe rainfall and strong winds in southern South Korea from 5–6 September, with some areas experiencing rainfall rates up to 100 mm per hour, resulting in river overflow, flooding, and landslides.

Case 6: From 3–4 October, a low-pressure system brought concentrated heavy rainfall to the central region, particularly Seoul, Gyeonggi, and Gangwon, with rainfall rates of 30–50 mm per hour, leading to flooding and inundation in low-lying areas.

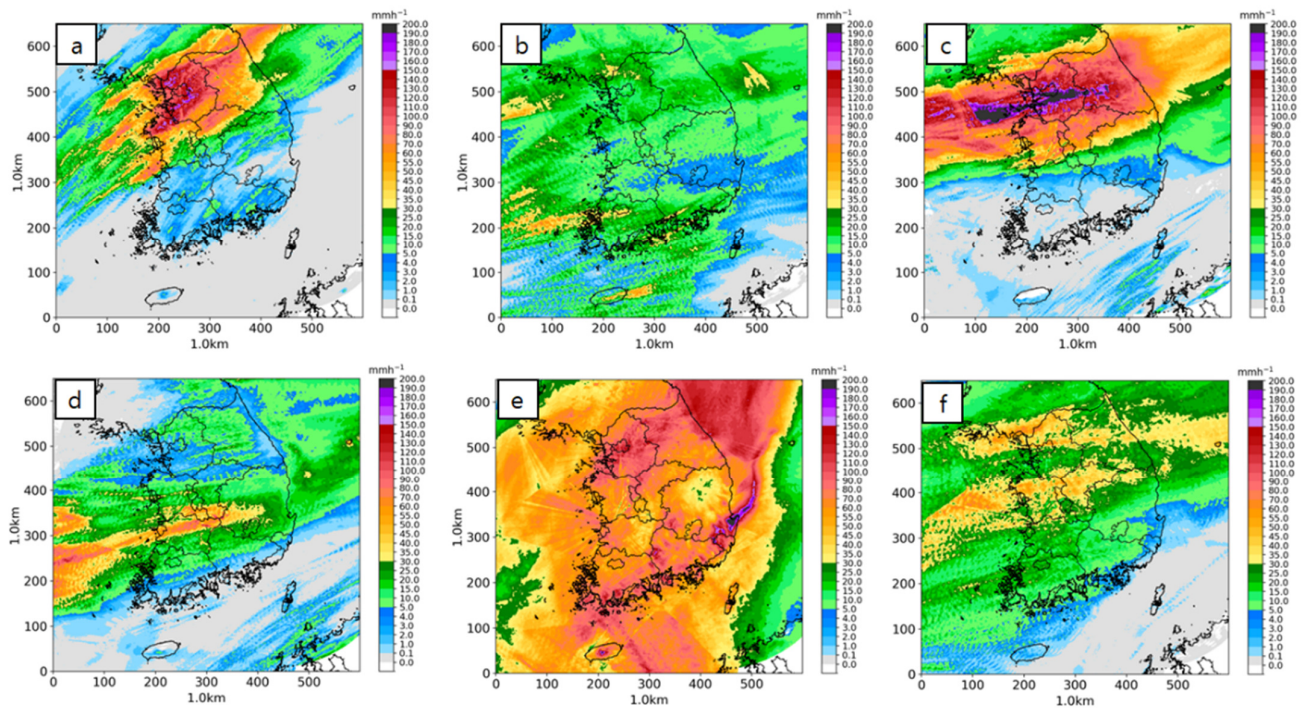


Figure 2. Radar precipitation images of total accumulated rainfall for each case over the periods specified in Table 1: (a) case 1 (29 h), (b) case 2 (18 h), (c) case 3 (48 h), (d) case 4 (16 h), (e) case 5 (29 h), and (f) case 6 (17 h).

3. Methodology

3.1. Overall Algorithm for Generating Merged Precipitation

The method for generating a radar–rain gauge fusion rainfall field aimed to accurately represent the spatial and temporal distribution of rainfall by combining the high spatial resolution of radar data with the ground-truth accuracy of rain gauge measurements. This approach is designed to ensure consistency between the two data sources, correct inherent biases and errors, and maintain high spatial and temporal resolution. Additionally, it seeks to be scalable to various regions, support near-real-time processing, and operate robustly under different weather conditions to ensure reliable performance across diverse rainfall intensities and types [42,46].

To address terrain-induced radar reflectivity errors, this study utilizes data generated through the HSR compositing method, which selects reflectivity values from the lowest elevation angles unaffected by ground clutter and beam blockage, thereby improving the accuracy of radar rainfall estimation in complex terrains. To validate the proposed radar–rain gauge merging methods, we compared their accuracy with existing approaches, including the mean field bias (MFB) adjustment method and two kriging-based interpolation methods, using the same dataset.

The overall algorithm for generating radar–rain gauge merged precipitation data consists of the following steps: (1) aligning 10 min rain gauge data with radar timestamps and calculating the accumulated rain rate; (2) resampling radar data from 0.5 km to 1 km and estimating precipitation using the R-Z relationship; and (3) generating radar–rain gauge merged precipitation fields at the desired resolution of 1 km spatially and 10 min temporally (see Figure 3). To standardize the minimum estimated precipitation value at 0.1 mm h^{-1} , all calculated precipitation amounts less than or equal to 0.1 mm h^{-1} were set to zero.

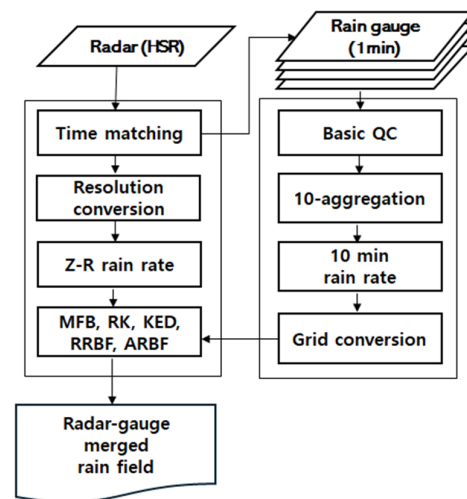


Figure 3. Flowchart of the algorithm for generating a precipitation field using the radar–rain gauge merging method.

3.1.1. Rain Gauge Alignment and 10 min Accumulation

In this study, we utilized 10 min accumulated rain gauge data, which we converted into hourly intensity before merging with radar data. Since the data are stored as daily cumulative values at 1 min intervals, direct 10 min or 1 min accumulation values are not available. To calculate the 10 min accumulated rainfall using daily cumulative data stored at 1 min intervals, we collected a total of 11 cumulative data points at 1 min intervals, including the value at the end of the 10 min accumulation period. Using these accumulative values, we derived 10 one-minute rainfall amounts by subtracting the previous minute's data from the next minute's data. The average of these 10 values was then converted into hourly rainfall intensity to represent rain gauge precipitation.

While one might consider selecting data at 10 min intervals and subtracting consecutive values to compute 10 min accumulated rainfall, this approach can be problematic. Cumulative values often reset to zero at midnight—and occasionally at other times—leading to potential inaccuracies. Therefore, to ensure a comprehensive and accurate analysis, we opted to utilize all data within each 10 min period.

The daily cumulative data provided by the KMA denote missing values as '–99'. When calculating 1 min cumulative rainfall, if either of two consecutive data points is negative or if the 1 min cumulative rainfall exceeds 8 mm (equivalent to 480 mm h^{-1}), we mark these values as 'NaN' (not a number). This threshold is based on extreme climatic values observed during the summer season in Korea (see [47]). In such cases, the affected data points are treated as 'NaN' among the total of 10 one-minute data points within the 10 min interval. We consider the 10 min average valid only if at least 6 out of these 10 values (60%) are not 'NaN'. When subtracting consecutive values from 11 data points at 1 min intervals, a single '–99' entry can result in two 'nan' values if used with adjacent time points. Therefore, even with up to 2 problematic data points among the 11, we can still obtain at least 6 valid 1 min cumulative data points, allowing us to compute a reliable 10 min average. This quality control process is conducted during the generation of 10 min data, and only the data that pass this process are subsequently used, without generating separate flags. As a result, the rain gauge data used at 10 min intervals may not be consistently continuous.

Producing rain gauge data with a 10 min accumulation instead of the conventional 1 h accumulation offers several advantages. This shorter time accumulation provides higher temporal resolution, allowing for more accurate capture of short-term rainfall variations [43,48]. It also aligns more effectively with the high-frequency updates of radar

data, improving synchronization and accuracy in the merging process. Furthermore, the 10 min interval enables faster real-time analysis and enhances the detection of brief, intense rainfall events that might otherwise be averaged out over a longer accumulation period.

The time difference between ground rain gauge measurements and radar-derived rainfall estimates arises from several factors. Radar detects precipitation at higher altitudes, resulting in a lag as rain takes time to reach the ground. Additionally, variations in fall velocity, radar scan intervals, and the influence of terrain can all contribute to discrepancies between the timing of radar-detected rainfall and ground measurements [49].

The timestamp of the HSR composite radar field corresponds to the start time of each radar's scan. Individual radars used in the composite data complete their scans within 5 min, and the quality control and compositing process are also completed within this timeframe. Although radar data are produced at 5 min intervals, this study utilizes radar data at 10 min intervals so they can be merged with 10 min rain gauge intensities.

To determine the optimal synchronization time for merging radar and rain gauge data, we adjusted the endpoint of the rain gauge accumulation period and compared the correlation coefficient (COR) and normalized mean absolute error (NMAE) between radar-derived rainfall (ZR) and 10 min rain gauge intensities, as shown in Figure 4. Detailed definitions of COR and NMAE are provided in Section 3.3. The test case, detailed in Table 1, spans from August 8 to 10 2022. Figure 4 indicates that setting the rain gauge endpoint to 7 or 8 min after the radar timestamp yields the lowest NMAE and highest COR values.

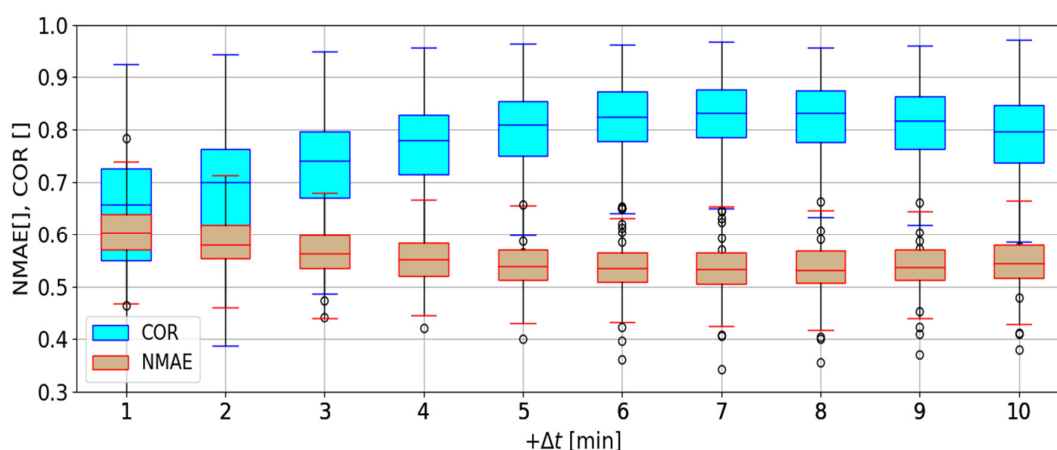


Figure 4. Box plots for COR and NMAE values based on the rain gauge accumulation end time relative to the radar timestamp (case 3: 8 August 2022, 09:00, to 10 August 2022, 09:00, LST).

As a result, this study adopts 10 min accumulated rain gauge data with the end time set to 8 min after the radar timestamp. For instance, if the radar timestamp is 8:00 AM, the corresponding rain gauge data spans from 7:58 to 8:08 AM. In Figure 4, only precipitation values exceeding 0.5 mm h^{-1} at both radar and rain gauge locations were included in the comparison to ensure consistency. This threshold was selected because the ASOS rain gauge records precipitation in increments of 0.1 mm per minute, leading to a minimum detectable 10 min accumulation of 0.1 mm. When converted to an hourly rate, this corresponds to 0.6 mm h^{-1} . Therefore, to effectively assess the agreement between radar and rain gauge measurements, we considered values exceeding 0.5 mm h^{-1} .

3.1.2. Radar Resampling and Precipitation Estimation

The raw radar composite obtained from the KMA has a spatial resolution of 0.5 km and covers a significantly larger area than the radar composite domain illustrated in Figure 1a. The area targeted for generating the radar–rain gauge merged field corresponds

to the KMA's wind synthesis system using Doppler measurements (WISSDOM) production domain [50]. To process the data, values within a radius of approximately 0.5 km (about 4 pixels) of each pixel in this domain are averaged. For efficient resolution conversion, a lookup table is pre-generated and reused throughout the process. The radar data, resampled to a 1 km resolution, are then converted into radar precipitation using the R–Z relationship (see Table 2).

Table 2. Estimation methods.

Name	Short Name	Rain Gauges	Radar	Remark
R–Z relation	ZR	No	Yes	$Z = aR^b$ ($a = 200$, $b = 1.6$)
Mean field bias adjustment	MFB	Yes	Yes	$\hat{R}_{MFB}(z, t) = c(t)R(z, t)$
Regression kriging	RK	Yes	Yes	$\hat{R}_{RK}(z, t) = \hat{\epsilon}_{OK}(z, t) + \hat{G}(z, t)$
Kriging with external drift	KED	Yes	Yes	$\hat{R}_{KED}(z, t) = \sum_{i=1}^N w_i^{KED}(t)G(z_i, t)$
Regression RBF	RRBF	Yes	Yes	$\hat{R}_{RBF}(z, t) = \hat{\epsilon}_{RBF}(z, t) + c(t)R(z, t)$
Augmented RBF	ARBF	Yes	Yes	$\hat{R}_{ARBF}(z, t) = \sum_{i=1}^N w_i^{ARBF}(t)\phi(z - z_i) + a(t)R(z, t)$

3.1.3. Generation of Radar–Rain Gauge Merged Precipitation Field

The 10 min accumulated rainfall intensity from each rain gauge location is merged with the 1 km resolution radar precipitation data generated earlier to create the radar–rain gauge precipitation field, using estimation methods described in the following section.

3.2. Estimation Methods

Six estimation methods, including the two proposed in this study, are evaluated for their performance in precipitation estimation using radar data. Table 2 summarizes these methods: the first two rely solely on radar-based techniques, the third and fourth utilize well-known kriging-based radar–rain gauge merging methods, and the fifth and sixth are the RBF-based interpolation techniques introduced in this study.

3.2.1. Radar-Based Methods

The first method uses the R–Z relationship, which relates radar reflectivity (Z) to rain gauge precipitation (R). In this study, we use the Marshall–Palmer equation [45], expressed as $Z = 200R^{1.6}$.

The second method, known as the mean field bias (MFB) adjustment, developed by Smith and Krajewski [12,51], involves correcting radar rainfall estimates using rain gauge data. The MFB adjustment method assumes that radar estimates are influenced by a single uniform multiplicative error. In this study, the MFB factor, $c(t)$, is estimated at each time step as the ratio of the sum of the 10 min accumulated rain gauge intensities to the corresponding radar R–Z rainfall estimates at the same locations:

$$c(t) = \frac{\sum G(z_i, t)}{\sum R(z_i, t)}, \quad (1)$$

where $G(z_i, t)$ and $R(z_i, t)$ represent the rain rates measured by rain gauge and radar at location z_i and time t , respectively. From the MFB-adjusted rainfall estimates at time t , $\hat{R}_{MFB}(z, t)$ is then obtained by multiplying the radar rainfall field by $c(t)$, as shown below:

$$\hat{R}_{MFB}(z, t) = c(t)R(z, t), \quad (2)$$

where $\hat{R}_{MFB}(z, t)$ is the estimation of rain rate at location z and time t .

3.2.2. Kriging-Based Methods

The kriging-based methods used for rain gauge and radar precipitation merging in this study are RK and KED. The RK method employed in this study follows a three-step process that combines regression with kriging:

1. Residual Calculation: Consider a linear regression, $G(z_i, t) = \alpha(t)R(z_i, t) + \epsilon(z_i, t)$. Residuals are computed using the following equation:

$$\hat{\epsilon}(z_i, t) = G(z_i, t) - \hat{G}(z_i, t), \quad i = 1, \dots, N \quad (3)$$

where N is the number of paired rain gauge and radar observations at the same locations and $\hat{G}(z_i, t) = \hat{\alpha}(t)R(z_i, t)$ is the fitted value derived from the regression model, where $\hat{\alpha}(t)$ is the estimated regression coefficient. The decision to use a single parameter was driven by the goal of ensuring that the trend reflects zero precipitation in areas where the radar estimates reported no precipitation.

2. Residual Interpolation: The residuals $\hat{\epsilon}(z_i, t)$ are interpolated using the ordinary kriging (OK) method to obtain the interpolated residuals $\hat{\epsilon}_{OK}(z, t)$ at unsampled location z .
3. Final Estimate: The final rainfall estimate is obtained by adding the estimated trend $\hat{G}(z, t)$ to the interpolated residual:

$$\hat{R}_{RK}(z, t) = \hat{\epsilon}_{OK}(z, t) + \hat{G}(z, t). \quad (4)$$

The interpolation residuals $\hat{\epsilon}_{OK}(z, t)$ at the specific location z are a linear combination of the residuals $\epsilon(z_i, t)$ and weights $w_i(t)$ at the corresponding location s_i .

$$\hat{\epsilon}_{OK}(z, t) = \sum_{i=1}^N w_i^{OK}(t) \epsilon(z_i, t) \quad (5)$$

subject to the constraint $\sum_{i=1}^N w_i^{OK}(t) = 1$.

KED directly incorporates external variables (secondary variables) into the kriging process. In this case, radar data are used as external variables. The KED predictor is expressed as a linear combination of observations:

$$\hat{R}_{KED}(z, t) = \sum_{i=1}^N w_i^{KED}(t) G(z_i, t) \quad (6)$$

where $\hat{R}_{KED}(z, t)$ is the estimated rain rate at location z and $w_i^{KED}(t)$ are the weights. These weights satisfy the following constraints: $\sum_{j=1}^N w_j^{KED}(t) = 1$ and $\sum_{j=1}^N w_j^{KED}(t) R(z_j, t) = R(z, t)$. The weights are determined by solving a system of linear equations derived from the covariance matrix of residuals and the extended vector of covariances at z . This process accounts for the external drift term, which uses radar data to improve interpolation accuracy by incorporating spatial trends directly into the kriging procedure.

3.2.3. Radial Basis Function-Based Methods

The RBF-based interpolation methods proposed in this study are the regression (or residual) RBF (RRBF) interpolation and the augmented RBF (ARBF) interpolation. The RRBF interpolation method is conceptually similar to the RK method. However, instead of using OK for residual interpolation, as shown in Equation (4), and regression modeling, the RBF interpolation and MFB are employed. The RRBF interpolation assumes that

$$G_{RRBF}(z_i, t) = \epsilon_{RBF}(z_i, t) + c(t)R(z_i, t) \quad (7)$$

Here, the residual $e_{RBF}(z, t)$ at location z is estimated using the linear equation:

$$\hat{e}_{RBF}(z, t) = \sum_{i=1}^N w_i^{RBF}(t) \phi(|z - z_i|), \quad (8)$$

where $r_i = |z - z_i|$ is the distance between the interpolated point z and the center z_i of each radial basis function ϕ , and w_i is the coefficient or the weight corresponding to $\phi(r_i)$. In this method, each station point is used as a center for the RBF.

The ARBF interpolation method differs from RRBf and RK in that it is computed in a single step, similar to KED. The ARBF interpolation equation is as follows (see [52]):

$$\hat{R}_{ARBF}(z, t) = \sum_{i=1}^N w_i^{ARBF}(t) \phi(|z - z_i|) + a(t)R(z, t) \quad (9)$$

where $a(t)R(z, t)$ represents the polynomial term added to the standard RBF interpolation equation where $R(z, t)$ can be the radar precipitation value at location z . To solve this equation for the $N + 1$ unknowns $[w_1^{ARBF}(t), \dots, w_N^{ARBF}(t), a(t)]$, an additional condition is required:

$$\sum_{i=1}^N w_i^{ARBF}(t) R(z_i, t) = 0. \quad (10)$$

For the basis $\phi(r)$, the following exponential function is used ([53]):

$$\phi_i(r) = \exp\left(-\frac{r}{s}\right) \quad (11)$$

where s is the shape parameter, which determines the radius of influence during interpolation. In this study, we selected the shape parameter $s = 6$ km based on empirical testing to achieve optimal interpolation performance. A larger s value results in a broader area of influence, while a smaller s value creates a more localized influence area. To determine the appropriate value of s , we conducted both quantitative evaluations, analyzing changes in LOOCV errors relative to variations in s , and qualitative assessments, considering the natural appearance of the precipitation field. Although the LOOCV evaluation results are not included in the main text, we employed an approach similar to that presented in Appendix A of [53] to identify the optimal s .

3.3. Validation Methods

The performance of each method was evaluated using leave-one-out cross-validation (LOOCV). This approach involves estimating rainfall at each rain gauge location by excluding the observation at the interpolation point and using the remaining data for prediction. The procedure is repeated for every location and method. The accuracy of the estimations for all locations at each time step is then assessed using statistical skill scores, which provide a quantitative measure of model performance. In this study, the skill scores employed include the correlation coefficient (COR), mean bias error (MBE), and mean absolute error (MAE). These metrics are calculated as follows:

- Correlation coefficient (COR): Pearson's correlation coefficient measures the strength and direction of the linear relationship between the predicted (y_i) and observed (x_i) values:

$$COR = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}},$$

where N represents the number of observation points, $\bar{x}$ is the mean of all x_i values, and $\bar{y}$ is the mean of all y_i values.

- Mean bias error (MBE): This metric quantifies the average bias of predictions compared to observations:

$$\frac{1}{N} \sum_{i=1}^N (y_i - x_i).$$

- Mean absolute error (MAE): MAE measures the average magnitude of errors between predictions and observations, ignoring their direction:

$$\frac{1}{N} \sum_{i=1}^N |y_i - x_i|.$$

To account for significant variations in errors due to differing rainfall intensities, normalized metrics such as normalized mean bias error (NMBE) and normalized mean absolute error (NMAE) are also used. These normalized metrics are derived by dividing MBE or MAE by the mean value of the observed rain gauge data $\bar{x}$. These metrics ensure a fair comparison of performance across varying rainfall intensities.

4. Results

The six methods described in Section 3 and summarized in Table 2 were applied to the rainfall events listed in Table 1. To evaluate the performance of each method, both quantitative and visual analysis were conducted. The quantitative assessment primarily involved the use of LOOCV, allowing for a comparison of the overall accuracy, spatial errors, and errors associated with varying rainfall intensities across all cases. The visual analysis focused on comparing the temporal continuity and smoothing effects observed in the generated precipitation images.

4.1. Quantitative Error Analysis

4.1.1. Total Error by Methodology

To evaluate the performance of all methods, a comparison was conducted among radar-based rainfall field generation methods (ZR and MFB), kriging-based radar–gauge merging methods (RK and KED), and RBF-based radar–gauge merging methods (RRBF and ARBF). For radar-based rainfall fields, the grid point values corresponding to the rain gauge locations were directly compared to the gauge observations. For kriging-based and RBF-based merging methods, the rainfall intensity values at the rain gauge locations were compared with the corresponding LOOCV estimates.

Figure 5 presents scatter plots comparing observed rain gauge values with the estimated values (for ZR and MFB) or LOOCV values (for RK, KED, RRBF, and ARBF) at the corresponding locations for the six methodologies. The discontinuities observed along the x -axis in the scatter plots arise from differences in the observational resolutions of AWSs and ASOSs, which are 0.5 mm per minute and 0.1 mm per minute, respectively. When the 10 min cumulative values are converted to hourly rainfall intensities, the minimum observational resolutions become 3.0 mm and 0.6 mm, respectively, leading to significant differences in the data.

Based on the analysis of Figure 5, the R-Z method demonstrates the lowest correlation coefficient (COR) with the rain gauge data, indicating relatively poor performance in aligning with observed values. It also exhibits a tendency to underestimate rainfall compared to the gauge observations. In contrast, the MFB method, which incorporates adjustments using rain gauge data, shows a slight improvement in COR and reductions in both the mean bias error (MBE) and mean absolute error (MAE) compared to the R-Z method.

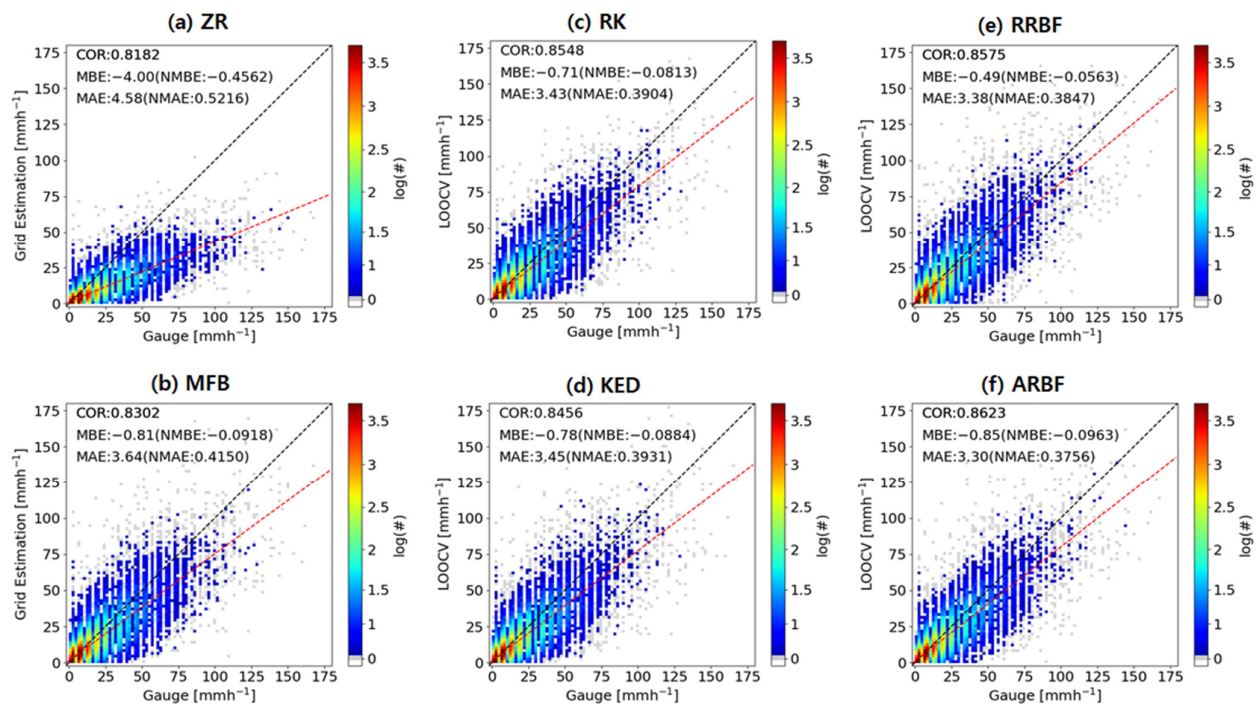


Figure 5. Scatter plots of rain gauge values versus estimated values or leave-one-out cross-validation (LOOCV) values for all cases by method: (a) radar precipitation obtained by R-Z relation (ZR), (b) mean field bias (MFB) adjustment, (c) regression kriging (RK), (d) kriging with external drift (KED) (e) regression radial basis function (RRBF), and (f) augmented radial basis function (ARBF). The comparison is conducted using 10 min average rainfall intensity.

Both the RK and KED methods produce similar results, with lower errors than the MFB method. However, RK slightly outperforms KED, achieving a marginally higher COR and slightly smaller MBE and MAE values. The RBF-based methods demonstrate even smaller MAE values compared to both RK and KED. Among these, the ARBF method achieves the smallest MAE across all approaches, indicating its strong alignment with gauge observations. Furthermore, the RRBf method stands out for having the smallest MBE among all the methods, reflecting its minimal bias in the estimated rainfall values.

The 10 min cumulative rainfall data are more sensitive to short-term changes in precipitation compared to the 1 h cumulative rainfall, enabling a higher temporal and spatial resolution in merging. However, the shorter accumulation period may lead to increased data noise or errors in the rain gauge observations. To compare the rainfall intensity using the one-hour cumulative data for each method, we used the average of six 10 min interval data points for each observation point. Figure 6 shows the results of the analysis performed in the same manner as Figure 5, but using the 60 min values for comparison. In the 60 min average values, similar to the 10 min averages, the ARBF method shows the highest correlation coefficient and the smallest MAE, while RRBf exhibits the smallest bias value. In Figures 5 and 6, comparisons are made at locations where the rain gauge data are at least 0.1 mmh^{-1} , and all estimated precipitation values below 0.1 mmh^{-1} are treated as ‘no rain’.

The bar graphs in Figure 7 compare the performance of six methods based on three metrics, COR, NMBE, and NMAE, for both 10 min and 60 min averages. ARBF and RRBf consistently show the highest COR values, with ARBF slightly outperforming RRBf. Both methods also exhibit the lowest NMBE, indicating minimal bias. In terms of NMAE, ARBF has the smallest value, followed by RRBf, indicating the best accuracy. Overall, ARBF and RRBf perform the best, especially when using 60 min averaged data, reducing noise and improving accuracy.

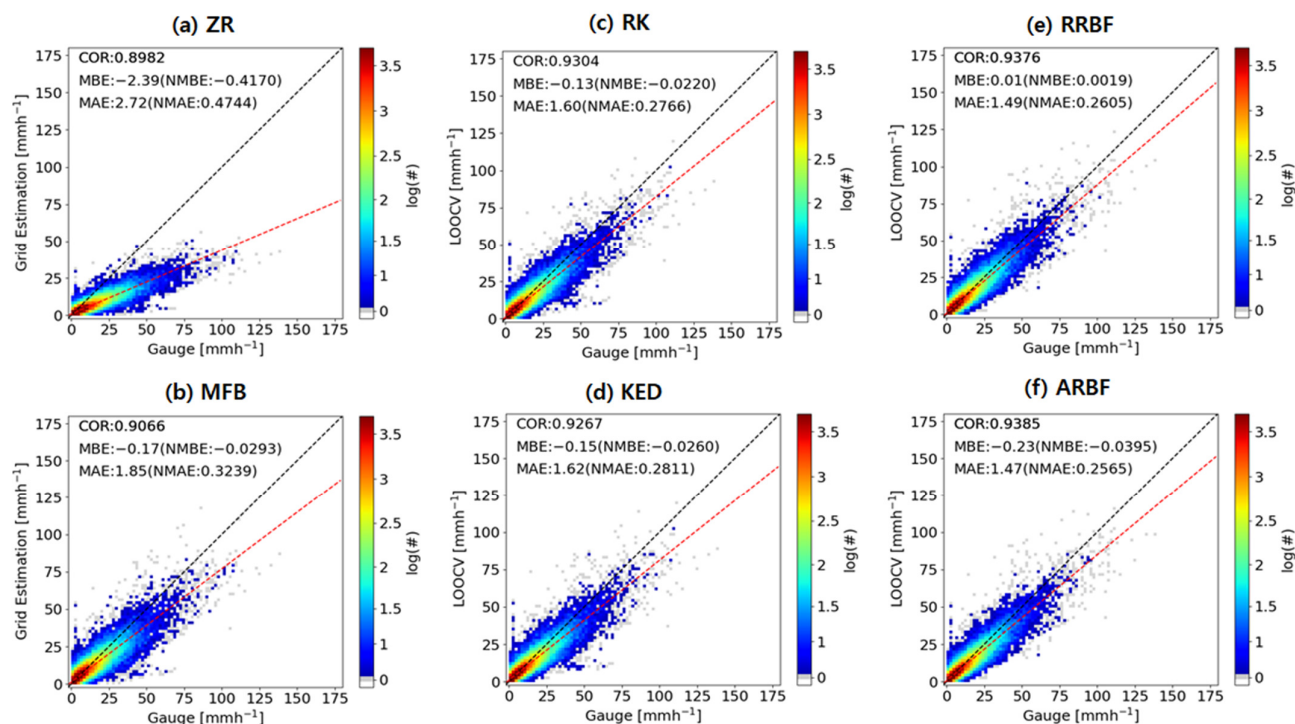


Figure 6. As with Figure 5, the comparison is conducted using 60 min average rainfall intensity.

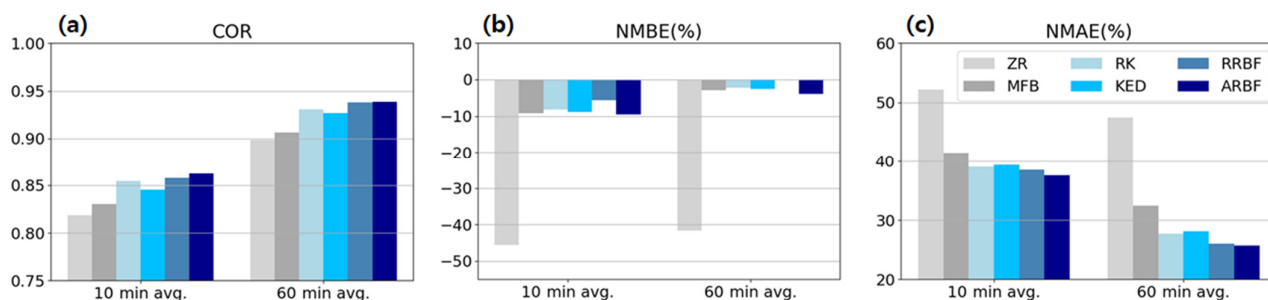


Figure 7. Comparison of the performance of six methods (ZR, MFB, RK, KED, RRBF, and ARBF) based on three statistical metrics, (a) correlation coefficient (COR), (b) normalized mean bias error (NMBE), and (c) normalized mean absolute error (NMAE), for both 10 min and 60 min average rainfall data.

4.1.2. Errors Based on Rain Intensity

To understand the characteristics of each method, we analyzed the errors based on various rainfall intensities using LOOCV values. Figure 8a,b display the NMBE and NMAE values, respectively, for each method based on gauge-based rainfall intensity, excluding ZR precipitation. ZR precipitation exhibits relatively large NMBE and NMAE values compared to the other methods, making it unsuitable for inclusion in the same figures.

In Figure 8a, the NMBE shows a trend of increasing negative bias as the rainfall intensity increased. Overall, MFB exhibits the largest negative bias, whereas RRBF exhibits the smallest bias across all rainfall intensities. Between approximately 25 mmh⁻¹ and 80 mmh⁻¹, ARBF shows a smaller bias than RK. However, at rainfall intensities above 80 mmh⁻¹, RK outperforms ARBF.

Figure 8b provides important error information for each method. MFB shows the highest error across all rainfall intensities. For rainfall intensities below 40 mmh⁻¹, ARBF exhibits the smallest error, whereas for intensities above 40 mmh⁻¹, RRBF achieves the lowest error. The error trends observed in Figure 8b explain why ARBF generally yielded

the smallest NMAE values in Figure 5. Since low-intensity rainfall occurs more frequently, methods with smaller errors in low-intensity rainfall tend to perform better overall. However, considering the overall error patterns in Figure 8b, RRBf appears to deliver the best performance. It is important to note that higher normalized errors at lower rainfall intensities are commonly observed in precipitation estimation studies, as minor discrepancies between observed and estimated values become more significant when actual rainfall amounts are low [54].

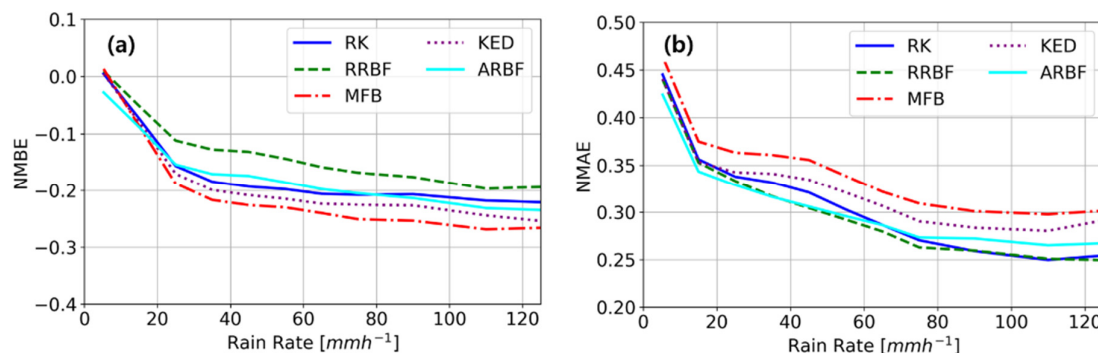


Figure 8. (a) Normalized mean bias error (NMBE) and (b) normalized mean absolute error (NMAE) values for each method as a function of rainfall intensity.

4.1.3. Error Distribution by Spatial Location

By analyzing the average LOOCV at rain gauge locations, it is possible to identify the site-specific characteristics. Locations with significant discrepancies between ZR precipitation and rain gauge measurements may indicate substantial differences between the radar and gauge data. These discrepancies could result from issues such as inaccuracies in the radar composite field or problematic rain gauges that were not adequately filtered out during quality control. Furthermore, locations with persistently large LOOCV errors—regardless of differences with ZR precipitation—may signal significant discrepancies in rainfall estimates relative to radar data or large variability between neighboring rain gauge measurements, which can influence gridded estimates due to the surrounding gauges' impact.

Figure 9 visualizes the bias between the 10 min rainfall intensity at each rain gauge location and the LOOCV values of each method in Table 2. For the analysis, all six cases from Table 1 were used. In this figure, the numbers in the lower right corner of each panel indicate the minimum and maximum average values calculated for each point.

For ZR and MFB, estimated values corresponding to the grid points closest to the rain gauge locations were used instead of LOOCV values. The darker blue dots represent areas where the estimated or LOOCV values consistently underestimate precipitation. Figure 9a (ZR) indicates that radar precipitation estimates are lower than those from the rain gauges in most locations. The comparison of rain gauge and radar precipitation provides valuable insights into the characteristics of the radar composite field and the specific features of the rain gauge locations. For instance, in Figure 9b, the MBE values for MFB, adjusted based on the rainfall ratio between radar and gauges, generally show a reduction in the bias of ZR precipitation. However, precipitation in the central region of Jeju Island continues to be underestimated. Figure 9c,d show that this issue remains even when using kriging-based methods.

The underestimation of radar precipitation on Jeju Island is likely due to the use of high-altitude reflectivity values to avoid topographic echoes from Hallasan Mountain. This issue highlights the radar's HSR synthesis strategy, which relies on the lowest altitude data unaffected by topographic clutter or other interferences [42,55]. Both kriging-based

and RBF-based precipitation estimation methods prove effective in narrowing the bias range compared to ZR or MFB methods. The most significant improvement is seen in the Hallasan region of Jeju Island (highlighted by the red dashed circle), where the RBF-based merging method provides precipitation estimates that align more closely with rain gauge measurements around Hallasan Mountain than the kriging-based methods (see Figure 9c–f).

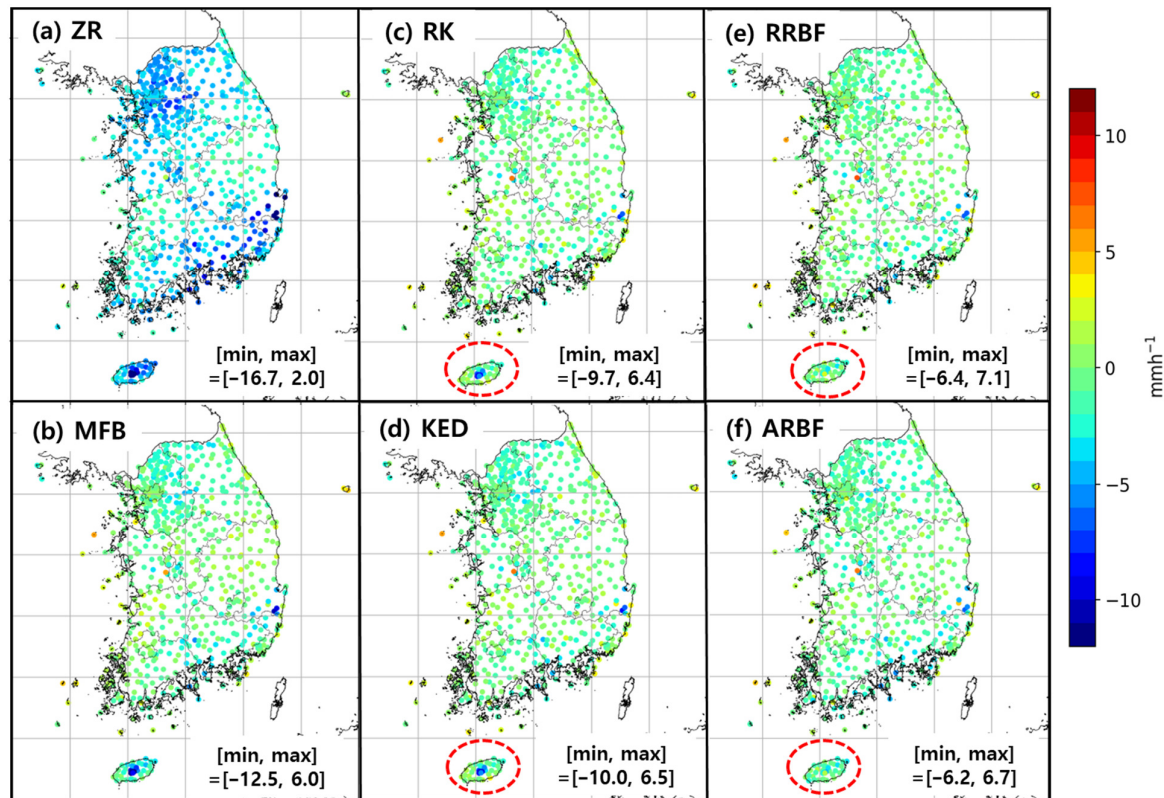


Figure 9. Spatial distribution of MBE at each gauge point, categorized by method: (a) ZR, (b) MFB, (c) RK, (d) KED, (e) RRBf, and (f) ARBF. The red dashed circle represents the region of Jeju Island, which includes Hallasan, the highest mountain in South Korea.

It should be noted that Figures 5–9 were analyzed using only the data from each gauge where the rainfall exceeded 0.1 mmh^{-1} . As a result, the number of data points used for each location in Figure 9 may vary.

4.2. Analysis of Precipitation Field

4.2.1. Smoothing Effects on Rainfall Fields

The smoothing effect in rainfall images reduces data noise and effectively captures overall patterns but can obscure localized variations, particularly in regions with high rainfall variability or rapid intensity changes. While smoothing is useful for identifying broad trends, it limits the accuracy of localized rainfall, especially when dealing with short-time-interval data. Kriging-based methods, such as KED, tend to smooth spatial variability by averaging localized patterns, which can result in a loss of detail in areas with significant rainfall variability [39,56].

Figure 10a–g, respectively, present the 10 min accumulated rainfall intensity observed by rain gauges and the estimated precipitation results obtained using six different methods—ZR, MFB, RK, KED, RRBf, and ARBF—at 22:50 LST on 29 June 2022. In Figure 10b,c, which show radar-based estimation methods, the ZR method estimates a maximum rainfall intensity of 103.6 mmh^{-1} , with significant rainfall observed in the northwestern regions.

However, this method appears to underestimate peak rainfall values compared to other approaches. Figure 10c shows a similar pattern to ZR but with higher maximum values of 131.8 mmh^{-1} . Figure 10d,e illustrate kriging-based methods. The RK method provides a clear overall pattern but exhibits excessive smoothing, particularly in areas of strong rainfall near the center, reaching a maximum intensity of 125.1 mmh^{-1} . In Figure 10e, the KED method also shows smoothing in heavy-rainfall regions, particularly around the center, with a maximum of 123.9 mmh^{-1} . Figure 10f,g represent RBF-based estimation methods. The RRBF method captures the rainfall distribution with less smoothing and achieves a higher maximum intensity of 127.0 mmh^{-1} , better preserving localized variations. The ARBF method shows a more defined rainfall distribution with relatively less smoothing and a maximum intensity of 119.6 mmh^{-1} .

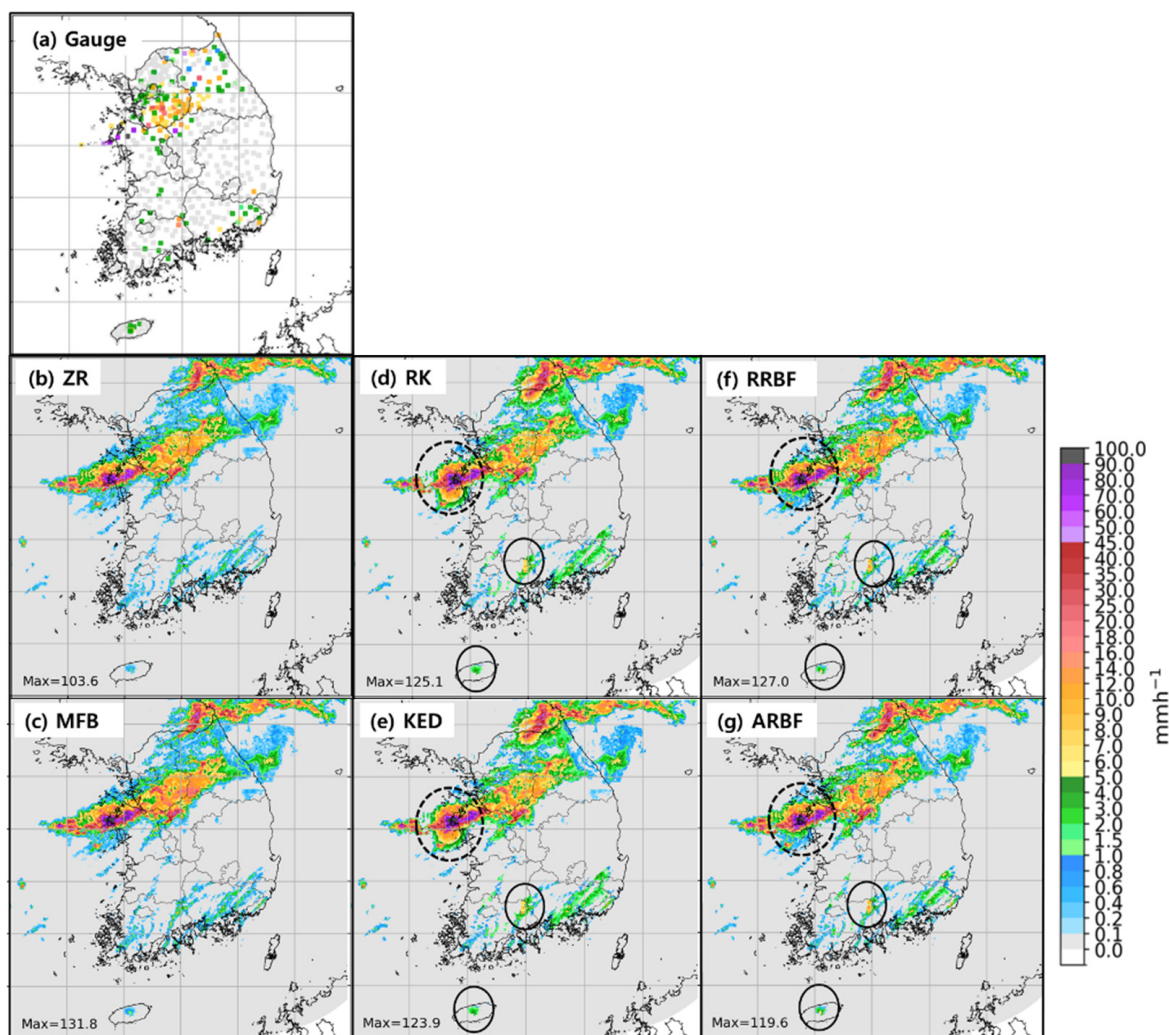


Figure 10. For 29 June 2022, at 22:50 LST, examples of precipitation images by method: (a) rain gauge 10 min accumulated rainfall intensity, (b) ZR, (c) RK, (d) RRBF, (e) MFB, (f) KED, and (g) ARBF. In the kriging- and RBF-based images, the black dashed circle indicates the location of the strongest rainfall for comparison. The two black solid circles represent the regions where the mountains Jirisan and Hallasan are located, respectively.

Notably, the kriging-based methods, RK and KED, tend to overly smooth intense precipitation areas, potentially obscuring sharp gradients, which may reduce accuracy in representing localized heavy rainfall. Overall, while ZR underestimates rainfall peaks, RK, RRBF, and ARBF effectively capture localized heavy rainfall with better accuracy. MFB

provides the highest estimation of rainfall intensity, whereas KR and KED tend to smooth out the variability.

Upon analyzing the precipitation images in Figure 10, we observed that the integration of radar and rain gauge data effectively compensates for the underestimation of precipitation in mountainous regions caused by HSR synthesis. Specifically, in the vicinity of Jirisan, the ZR and MFB methods displayed precipitation in yellow at gauge locations, which was not evident in the radar data alone. However, in the rain gauge-integrated images (d)–(g), the precipitation near Jirisan is distinctly represented in yellow (within the black circle on land). Similarly, the precipitation over Hallasan in Jeju Island shows a slight increase in intensity due to the incorporation of rain gauge data. These findings indicate that the fusion of radar and rain gauge data effectively addresses the limitations of radar observations in complex terrains, leading to a more accurate representation of precipitation distribution.

4.2.2. Temporal Continuity of Precipitation Fields

In this section, we analyze the temporal variations in gridded rainfall data generated at 10 min intervals from 00:00 to 03:00 LST on 24 July 2022, to examine the continuity of rainfall fields over time. Figure 11 presents the average rainfall values exceeding 5 mmh^{-1} for each time slot, generated using the ZR, MFB, RK, KED, RRBF, and ARBF methods. Notably, ZR exhibits generally lower average values and a smoother curve compared to the other methods. RK, KED, and ARBF display similar patterns, while RRBF shows a pattern akin to MFB. All methods, except ZR, demonstrate a tendency for average rainfall to decrease at 01:30, with RK, KED, and ARBF exhibiting the most significant changes. This time-series analysis of average values enables a quantitative assessment of the temporal continuity of the generated rainfall fields.

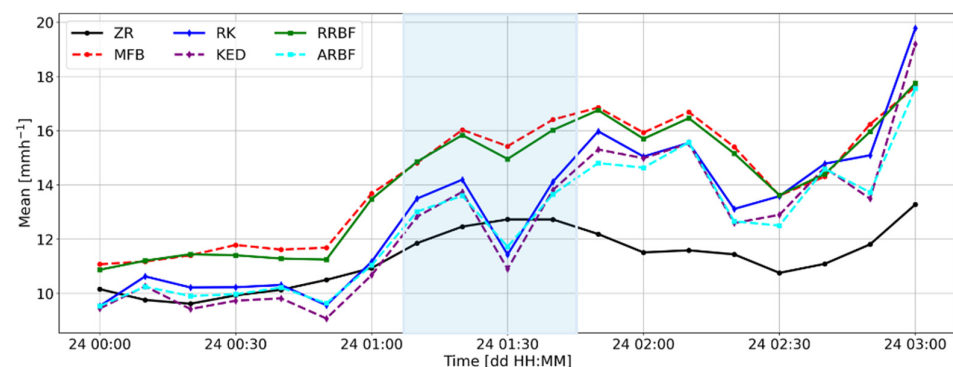


Figure 11. Time series of average rainfall rates exceeding 5 mm h^{-1} , generated using ZR, MFB, RK, KED, RRBF, and ARBF methods, from 00:00 to 03:00 LST on 24 July 2022.

Figure 12 illustrates the rainfall field images generated by each method from 01:10 to 03:00 (shaded in light blue in Figure 11). At 01:30, where a decrease in average rainfall is observed, the images reveal that RK and KED methods show an increase in rainfall between 1 mmh^{-1} and 5 mmh^{-1} , while rainfall values exceeding 5 mmh^{-1} decrease. This discontinuity stems from the nature of the kriging interpolation technique, which optimizes spatial variability independently at each time step by generating separate variograms. As a result, rainfall patterns may not remain consistent over consecutive time steps, leading to abrupt changes. For instance, the RK method shows sharp variations in regions with high rainfall intensity, highlighting a lack of temporal smoothness. Similarly, the KED method exhibits irregular shifts or variations in areas of heavy rainfall across time intervals, resulting in temporal discontinuity. In contrast, the RBF-based RRBF method produces rainfall fields that are much more temporally continuous, similar to the MFB method. The RRBF method maintains the spatial structure while providing temporally smooth and

coherent rainfall patterns, ensuring that changes across time steps appear more natural. This difference stems from the RBF interpolation technique, which uses a globally continuous function to estimate rainfall values. Unlike kriging methods, RBF methods employ a single shape parameter for interpolation, allowing smoother transitions between time steps.

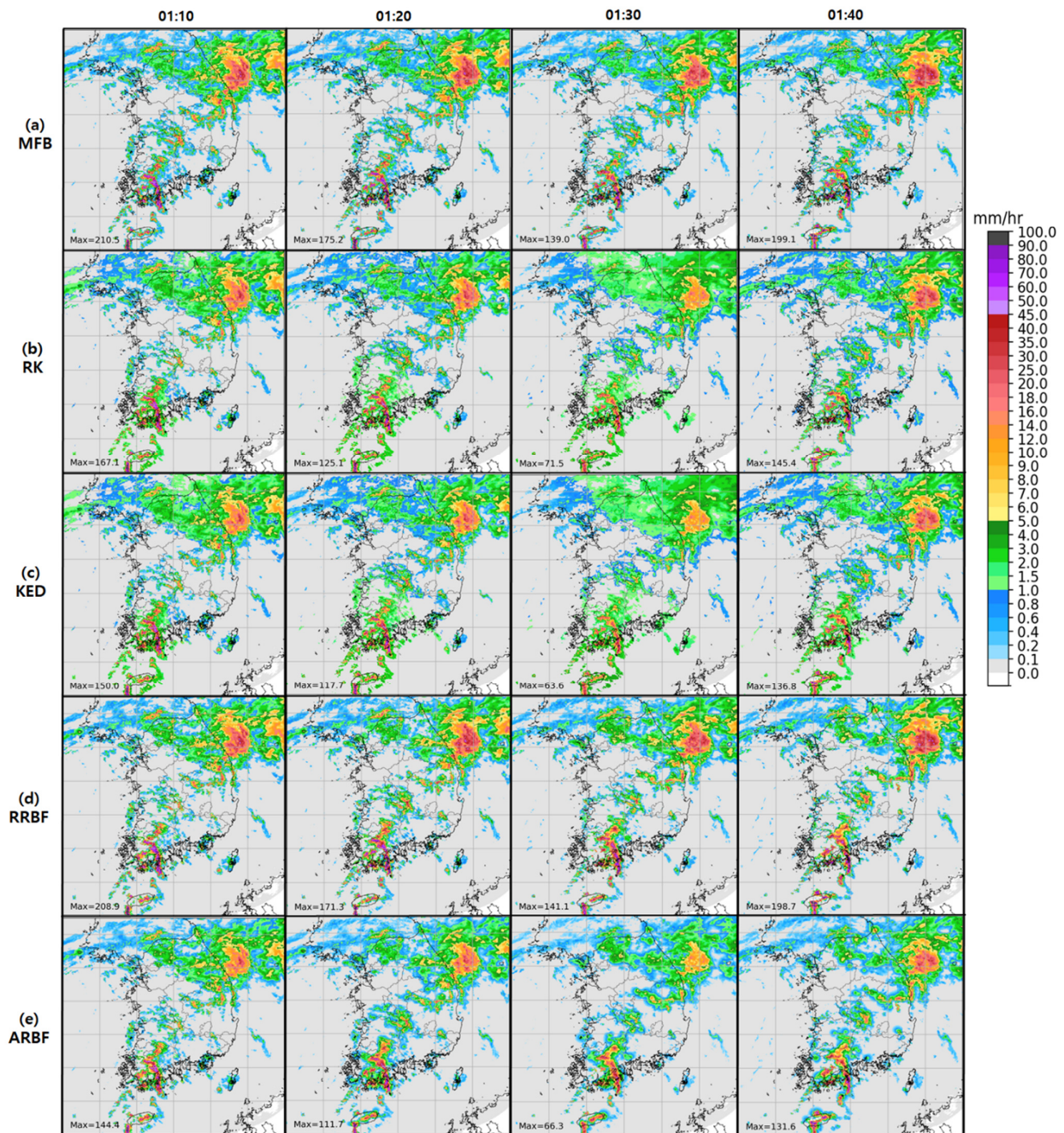


Figure 12. Example of gridded filed images over time for each method: (a) MFB, (b) RK, (c) KED, (d) RRBf, and (e) ARBF. The time is from 1:10 to 1:40 LST on 24 July 2022.

In conclusion, while kriging-based methods such as RK and KED excel in spatial interpolation, they can introduce temporal discontinuities that disrupt the consistency of rainfall patterns. In contrast, RBF-based methods like ARBF and RRBf offer more natural and continuous temporal variations. Although RRBf exhibits slight discontinuities compared to ZR, these can be mitigated by calculating the ratio of the two values, 'c', using sufficient data over intervals longer than 10 min, such as one hour, during rain gauge

integration. This approach is expected to effectively address the minor discontinuities observed in RRBF.

5. Discussion

In this study, we utilized quality-controlled radar reflectivity composite data officially provided by the KMA. Each of the 11 radars underwent rigorous quality control processes, including simulated shielding rates based on terrain echo classification and topographic maps, minimizing the effects of terrain. To mitigate terrain-induced distortions such as echoes and radar beam blockage, the HSR synthesis method was employed. This method prioritizes the selection of the lowest elevation reflectivity values unaffected by terrain shielding. However, in regions with significant beam blockage, the HSR approach increases the elevation angle, which may lead to lower reflectivity values. This limitation was addressed through radar–rain gauge integration in specific areas, such as Hallasan Mountain on Jeju Island, as shown in Figures 9 and 10. By integrating radar and rain gauge data, we aimed to reduce radar reflectivity distortions caused by terrain and enhance reliability across diverse rainfall intensities and types.

To capture South Korea’s unique geographic characteristics—marked by high spatiotemporal variability due to its mountainous terrain and surrounding oceans—we adopted a 10 min temporal resolution for radar and rain gauge fusion. This short accumulation interval offers higher sensitivity to short-term rainfall variations than a 1 h interval, enabling the creation of high-resolution spatiotemporal rainfall datasets. However, this shorter timeframe can amplify noise or errors from rain gauges, as confirmed by error distribution comparisons in 10 min and 60 min rainfall scatter plots.

Rain gauge data, serving as approximations of ground truth in radar–rain gauge fusion, are critically dependent on their accuracy and quality control. Basic quality control processes, such as removing missing data and filtering out values exceeding physical limits, were applied in this study. However, outliers observed in the 60 min scatter plots and spatial evaluations suggest that more advanced quality control methods could significantly enhance fusion accuracy. These outliers were often linked to gauge observation errors or discrepancies in radar reflectivity, particularly during events such as snowfall or hail. Such discrepancies emphasize the need for robust methodologies to address these challenges.

Additionally, scenarios with minimal rainfall or limited comparison points—such as during the development of small-scale convective cells—pose specific challenges for radar–rain gauge fusion. In such cases, the reliability of the parameter ‘ c ’, which represents the ratio of radar rain rate to rain gauge values calculated every 10 min, may decrease. Temporal discontinuities can arise, as highlighted in Figure 12, particularly when the number of valid comparison points is limited. Developing methods for selecting and calibrating parameter ‘ c ’ under these conditions is a critical area for improvement in our research.

6. Conclusions

In this study, we developed the algorithms to integrate spatially high-resolution radar data (time: 5 min; spatial resolution: 0.5 km) and rainfall gauge data collected at 1 min intervals. The proposed algorithms convert the rainfall gauge data into 10 min cumulative values and generate precipitation field data at a 1 km resolution, also at 10 min intervals. We found that the RBF-based techniques are suitable for real-time integration of radar and rainfall gauge measurements, allowing for the generation of near-real-time rainfall fields. While the RBF-based methods are well established, the use of regression residuals and augmented RBF for radar–rain gauge integration is one of the first applications of this kind.

The proposed methods were compared with widely used techniques such as MFB, RK, and KED, using 10 min interval data generated in the same manner. The methods were ap-

plied to six rainfall cases in South Korea in 2022, with ZR and MFB being evaluated through direct comparisons at gauge locations, and the remaining methods assessed using leave-one-out cross validation (LOOCV) for overall error comparisons. In addition to overall error analysis, we examined errors related to rainfall intensity and spatial variations across rainfall gauge sites, with the RRBf method demonstrating the best overall performance.

Finally, the generated images revealed excessive smoothing in kriging-based methods during periods of intense rainfall, especially in certain regions. Temporal discontinuities were also observed in some time intervals in kriging methods. These discontinuities were almost absent in RRBf, which demonstrated better performance in quantitative error analysis. Therefore, it is expected that with further examination of additional cases and addressing specific issues, these methods will become promising solutions for the real-time integration of radar and rainfall gauge data.

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