

Validation of Weather Radar-Based Rainfall Estimation to Support Flood Mitigation Strategies in the Bima Region

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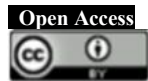
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Abstract

Flood is one of the most frequent hydrometeorological disasters in Bima, West Nusa Tenggara, Indonesia. Although the C-Band weather radar operated by the Meteorological, Climatological, and Geophysical Agency (BMKG) has been utilized for weather monitoring and early warning, the accuracy of its rainfall estimation products has not been comprehensively validated under the complex topographic conditions of the region. This study aims to evaluate the performance of four weather radar rainfall products, namely Constant Altitude Plan Position Indicator (CAPPI), Column Maximum (CMAX), Rain Tracking (RTR), and Surface Rainfall Intensity (SRI), by comparing radar-derived rainfall estimates with in-situ observations from Automatic Rain Gauge (ARG), Automatic Weather Station (AWS), and Automatic Agroclimate Weather Station (AAWS). The analysis was conducted across three radar distance zones (0–20 km, 20–50 km, and 100–150 km) to investigate the influence of radar range on rainfall estimation accuracy. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Receiver Operating Characteristic (ROC), and the Youden Index to determine the optimal rainfall and reflectivity thresholds for flood early warning. The results showed that CAPPI achieved the lowest RMSE (2.578 mm h⁻¹) within the 0–20 km zone, whereas CMAX provided the highest estimation accuracy at greater radar distances. ROC analysis further identified locally optimized rainfall warning thresholds ranging from 0.053 to 0.716 mm h⁻¹, depending on the radar distance zone, thereby improving the discrimination between flood and non-flood events. These findings contribute to improving radar-based rainfall estimation and support the development of a more reliable impact-based flood early warning system in tropical regions with complex terrain.

Keywords: Weather Radar; Rainfall Estimation; Flood Early Warning; Rainfall Validation; ROC Analysis; Bima.

1. Introduction

Hydrometeorological disasters have become the dominant type of disaster in Indonesia, accounting for approximately 99% of all disaster events in recent years, with floods representing the most frequent hazard (Badan Nasional Penanggulangan Bencana, 2024). Besides causing casualties, floods result in extensive damage to infrastructure, agriculture, and public facilities, leading to substantial economic losses and long-term disruption to regional development (Fitriyaningsih & Basani, 2019). The increasing frequency and intensity of flood events, exacerbated by climate variability, emphasize the

need for more effective disaster mitigation and early warning systems.

Accurate rainfall monitoring plays a critical role in flood mitigation because intense precipitation is the primary trigger of most flood events. Conventional rain gauges provide reliable point measurements but are often insufficient to capture the spatial variability of rainfall, particularly in regions with complex topography. Weather radar provides near real-time observations with high spatial and temporal resolution, enabling continuous monitoring of precipitation systems over large areas (Villarini & Krajewski, 2010; Wardoyo E., 2017). Consequently,

weather radar has become an essential component of modern flood early warning systems and Impact-Based Forecasting (IBF) (Sulistiyowati et al., 2020; World Meteorological Organization, 2021).

Radar-derived rainfall estimation is obtained by converting radar reflectivity (dBZ) into rainfall intensity through the reflectivity–rainfall (Z–R) relationship. However, radar observations are affected by several sources of uncertainty, including beam broadening, signal attenuation, terrain blocking, and increasing radar beam height with distance from the radar site. These factors may lead to substantial discrepancies between radar-derived rainfall estimates and ground observations. Therefore, validation against in-situ measurements is required before radar products can be reliably used for operational flood forecasting and the determination of rainfall thresholds for early warning systems (Villarini & Krajewski, 2010; World Meteorological Organization, 2021).

Bima City and Bima Regency, located in West Nusa Tenggara Province, are among the most flood-prone regions in eastern Indonesia. Flood events occur almost every year, with the highest frequency recorded in 2021, while severe flooding in 2023 and 2025 caused casualties, damaged transportation infrastructure, inundated residential areas and agricultural land, and generated considerable economic losses. The region is characterized by complex terrain consisting of mountainous areas, river basins, and coastal zones, creating additional challenges for weather radar observations because terrain obstruction may reduce radar measurement accuracy.

To improve weather monitoring, the Meteorological, Climatological, and Geophysical Agency (BMKG) operates a C-Band weather radar at Sultan Muhammad Salahuddin Meteorological Station in Bima. The radar generates several rainfall estimation products, including Column Maximum (CMAX), Constant Altitude Plan Position Indicator (CAPPI), Rain Tracking Radar (RTR), Surface Rainfall Intensity (SRI), and Precipitation Accumulation (PAC). Each product applies different algorithms to estimate rainfall and may exhibit different levels of accuracy depending on radar distance and local topographic conditions. PAC can be derived from several input products, including CMAX, CAPPI, RTR, SRI. Previous studies have demonstrated that radar rainfall estimation errors generally increase with distance from the radar due to beam broadening and increasing beam altitude (Villarini & Krajewski, 2010). Furthermore, mountainous terrain surrounding Bima may produce beam-blocking effects that reduce radar reflectivity and underestimate actual rainfall (Widomurti et al., 2020).

Despite the operational use of the C-Band weather radar in Bima since 2009, a comprehensive validation of multiple radar rainfall products across different radar distance zones has not yet been conducted. Previous studies in Indonesia have primarily focused on the general validation of weather radar products or the influence of terrain blocking on radar observations (Tondang et al., 2023; Widomurti et al., 2020). However, these studies did not

simultaneously compare the performance of multiple radar products, evaluate their accuracy under different radar distance zones, or translate the validation results into locally optimized rainfall thresholds for operational flood early warning systems. Consequently, the rainfall thresholds currently applied in operational forecasting have not been adequately validated for the local climatic and topographic conditions of the Bima region (World Meteorological Organization, 2021).

This study addresses these research gaps by performing a comprehensive validation of four weather radar rainfall products (CMAX, CAPPI, RTR, SRI) using ground observations collected from Automatic Rain Gauges (ARG), Automatic Weather Stations (AWS), and Automatic Agroclimate Weather Stations (AAWS). The validation is conducted within three radar distance zones (0–20 km, 20–50 km, and 100–150 km) using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Receiver Operating Characteristic (ROC) analysis, and the Youden Index to identify the optimal rainfall and reflectivity thresholds for flood early warning. The validated thresholds are subsequently integrated into a Radar-Based Early Warning System (Radar-EWS) framework through stakeholder consultation, providing scientific support for evidence-based flood mitigation and operational decision-making in tropical regions with complex terrain.

2. Material and Methods

2.1 Study Area

This study was conducted in Bima City and Bima Regency, West Nusa Tenggara Province, Indonesia, located on the eastern part of Sumbawa Island. The study area is characterized by complex topography comprising mountainous regions, river basins, coastal plains, and agricultural lands that are highly susceptible to flooding during the rainy season. The geographical location of the study area and the coverage of the Bima C-Band weather radar are presented in Figure 1.



Fig 1. Location of the study area showing Bima City, Bima Regency, and the coverage area of the Bima C-Band weather radar.

The Meteorological, Climatological, and Geophysical Agency (BMKG) operates a C-band weather radar at the Sultan Muhammad Salahuddin Meteorological Station, which has provided

continuous weather observations since 2009. The radar provides near real-time monitoring of precipitation systems over most parts of Bima City and

Bima Regency, supporting weather surveillance and flood early warning operations.

2.2 Research Design

This study employed a sequential explanatory mixed-methods design, in which quantitative analysis was conducted in the first stage, followed by qualitative analysis to support the interpretation and operational implementation of the quantitative findings. The quantitative component focused on validating weather radar rainfall products against ground-based rainfall observations and determining locally optimized rainfall thresholds for flood occurrence. Subsequently, the qualitative component was conducted through semi-structured interviews and Focus Group Discussions (FGDs) involving relevant stakeholders to evaluate the operational applicability of the proposed rainfall thresholds and to formulate a Radar-Based Flood Early Warning System (Radar-EWS) framework. This mixed-methods approach enables the integration of technical validation with institutional perspectives, thereby enhancing the applicability of the proposed framework for flood disaster mitigation (John W. Creswell & J. David Creswell, 2023).

The overall research workflow consisted of five sequential stages: (1) data collection, (2) preprocessing of radar and ground observation datasets, (3) validation of radar rainfall products using statistical performance metrics, (4) determination of optimal rainfall thresholds through Receiver Operating Characteristic (ROC) analysis, and (5) development of the Radar-EWS framework based on stakeholder consultation. The methodological framework adopted in this study is summarized in Figure 3.

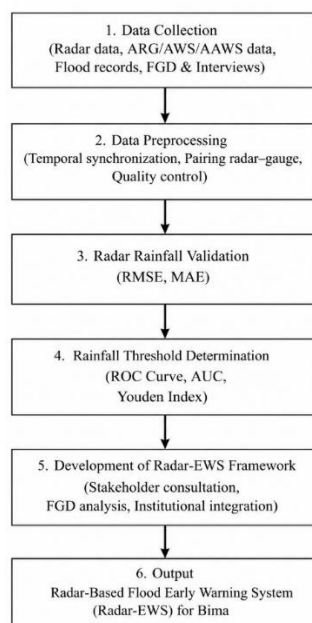


Fig 2. Overall research design adopted in this study.

2.3 Data Collection

Radar observations, ground-based rainfall measurements, flood records, and stakeholder consultation data were collected from multiple sources to support both the quantitative and qualitative components of this study. The quantitative analysis utilized weather radar products, rain gauge observations, and flood event records, whereas the qualitative analysis was based on interviews and Focus Group Discussions (FGDs) with relevant stakeholders. A summary of all datasets used in this study is presented in Table 1.

Table 1. Summary of datasets used in this study.

Data Category	Dataset	Source	Period
Primary	Semi-structured interviews	BMKG, BPBD, Local Government	2025
Primary	Focus Group Discussion (FGD)	BMKG, BPBD, local communities, academics, disaster volunteers	2025
Secondary	C-MAX radar product	BMKG	2021
Secondary	CAPPI radar product	BMKG	2021
Secondary	RTR radar product	BMKG	2021
Secondary	SRI radar product	BMKG	2021
Secondary	PAC radar product	BMKG	2021
Secondary	ARG rainfall observation	BMKG	2021

The year 2021 was selected as the analysis period for three main reasons. First, it recorded the highest flood frequency in Bima during the 2020–2024 period, providing an adequate number of flood events for statistical analyses, including ROC and rainfall threshold determination. Second, BMKG archives indicated that radar volume (.vol) files and rain gauge observations for 2021 had the highest data completeness, with more than 85% daily data availability. Third, using a complete calendar year allowed the analysis to represent all seasonal conditions, including the rainy season, transition periods, and the dry season, thereby improving the representativeness of the derived rainfall thresholds.

2.4 Data Preprocessing

Prior to the validation analysis, weather radar and ground-based rainfall datasets were preprocessed to ensure temporal consistency and data quality. Raw radar observations in .vol format obtained from the C-Band weather radar at BMKG Sultan Muhammad Salahuddin Meteorological Station were processed using Rainbow®5 software to generate five radar-derived rainfall products: Column

Maximum (CMAX), Constant Altitude Plan Position Indicator (CAPPI), Rain Tracking Radar (RTR), Surface Rainfall Intensity (SRI), and Precipitation Accumulation (PAC) (Wardoyo E., 2017). PAC was not evaluated as an independent rainfall product because it is a second-level radar product that requires another radar product as input. Since PAC can be generated from different input products, the best-performing product among CAPPI, CMAX, RTR, and SRI was identified for each distance zone and subsequently used to generate the corresponding PAC product.

Radar-derived rainfall estimates were subsequently extracted at the locations of Automatic Rain Gauges (ARG), Automatic Weather Stations (AWS), and Automatic Agroclimate Weather Stations (AAWS) using the geographic coordinates of each observation station. To ensure comparability, radar-derived rainfall data and ground observations were temporally synchronized based on the corresponding observation time. Only paired observations representing identical temporal intervals were retained for subsequent analyses.

Quality control procedures were then applied to remove incomplete records, duplicate observations, and unmatched radar–gauge pairs. Records containing missing rainfall values from either radar products or ground observations were excluded from the analysis. The resulting paired dataset was subsequently grouped according to three radar distance zones, namely 0–20 km, 20–50 km, and 100–150 km, to evaluate the influence of radar range on rainfall estimation accuracy (Villarini & Krajewski, 2010).

The preprocessed datasets were subsequently used as input for statistical validation and rainfall threshold determination.

2.5 Weather Radar Rainfall Products

Five weather radar rainfall products generated by the C-Band weather radar were evaluated in this study, namely Column Maximum (CMAX), Constant Altitude Plan Position Indicator (CAPPI), Rain Tracking Radar (RTR), Surface Rainfall Intensity (SRI), and Precipitation Accumulation (PAC). These products represent different algorithms for quantitative precipitation estimation (QPE) and provide complementary information on precipitation characteristics derived from radar reflectivity (Osman & Tahir, 2024). The characteristics and operational functions of each radar product are summarized in Table 2.

Table 2. Characteristics of weather radar rainfall products used in this study.

Product	Description	Primary application
CMAX	Maximum radar reflectivity within the vertical atmospheric column.	Identification of convective storm intensity and severe weather.
CAPPI	Radar reflectivity interpolated at a constant altitude above mean sea level.	Spatial comparison of precipitation and rainfall distribution.
RTR	Rainfall estimation based on tracking the movement of precipitation cells between successive radar scans.	Short-term rainfall accumulation estimation.
SRI	Near-surface rainfall intensity derived from radar reflectivity using the Z–R relationship.	Real-time rainfall intensity monitoring.
PAC	Accumulated rainfall over a specified time interval calculated from consecutive radar observations. In this study, PAC was generated using the best-performing radar product selected from CAPPI, CMAX, RTR, and SRI for each distance zone.	Hydrological analysis and flood monitoring.

Since each radar product applies a different rainfall estimation algorithm, their performance is expected to vary according to precipitation characteristics and radar observation distance. Therefore, all five products were independently validated against rainfall observations obtained from ARG, AWS, and AAWS stations to identify the most accurate product for flood early warning applications in the Bima region (Osman & Tahir, 2024).

2.6 Validation of Radar Rainfall Estimation

Radar-derived rainfall estimates were validated against in-situ rainfall observations obtained from ARG, AWS, and AAWS stations. The validation was performed separately for each radar rainfall product and radar distance zone to evaluate the influence of radar range on estimation accuracy (Tondang et al., 2023; Villarini & Krajewski, 2010).

Model performance was evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which quantify the differences between radar-derived rainfall estimates and ground observations (Chai & Draxler, 2014; Willmott & Matsuura, 2005).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (R_i - O_i)^2} \quad (1)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |R_i - O_i| \quad (2)$$

Lower RMSE and MAE values indicate better agreement between radar-derived rainfall estimates and observed rainfall.

2.7 Rainfall Threshold Determination

Following the validation of radar-derived rainfall estimates, Receiver Operating Characteristic (ROC) analysis was performed to determine the optimal rainfall and radar reflectivity thresholds associated with flood occurrence. ROC analysis is a widely used statistical method for evaluating the diagnostic performance of binary classification models by assessing the trade-off between sensitivity and specificity across different threshold values (Fawcett, 2006; Metz, 1978).

In this study, radar-derived rainfall estimates were classified into flood and non-flood events using historical flood occurrence records as the reference. The optimal threshold was identified using the Youden Index, which maximizes the combined sensitivity and specificity of the classifier. The Youden Index is expressed as

$$J = \text{Sensitivity} + \text{Specificity} - 1 \quad (3)$$

where Sensitivity represents the proportion of correctly identified flood events (true positive rate), whereas Specificity represents the proportion of correctly identified non-flood events (true negative rate). The threshold corresponding to the maximum Youden Index was selected as the optimal operational rainfall threshold.

To further evaluate the discrimination capability of each radar rainfall product, the Area Under the Receiver Operating Characteristic Curve (AUC) was calculated. AUC values range from 0.5 to 1.0, where values close to 1.0 indicate excellent discrimination between flood and non-flood events, whereas values near 0.5 indicate classification performance comparable to random guessing (Fawcett, 2006).

2.8 Development of Radar-Based Flood Early Warning Framework

The development of the Radar-Based Flood Early Warning System (Radar-EWS) was carried out by integrating the validated rainfall thresholds obtained from the quantitative analysis with qualitative information collected from relevant stakeholders. This mixed-method approach was adopted to ensure that the proposed framework was not only scientifically reliable but also operationally feasible within the existing disaster management system.

Following the determination of the optimal rainfall and radar reflectivity thresholds through ROC analysis, Focus Group Discussions (FGDs) and semi-structured interviews were conducted involving forecasters from the Meteorological, Climatological, and Geophysical Agency (BMKG), representatives of the Regional Disaster Management Agency (BPBD), local government officials, academics, and community representatives. These discussions aimed to evaluate the applicability of the proposed thresholds, identify

operational constraints, and formulate institutional response mechanisms for flood early warning.

The qualitative findings were analyzed using a thematic analysis approach to identify key issues related to warning dissemination, institutional coordination, decision-making processes, and community preparedness. The validated technical thresholds were subsequently integrated with stakeholder recommendations to develop a conceptual Radar-EWS framework that supports Impact-Based Forecasting (IBF) and evidence-based flood risk management (United Nations Office for Disaster Risk Reduction, 2022; World Meteorological Organization, 2021).

3. Result and Discussion

3.1 Characteristics of Radar Observation over the Study Area

To evaluate the influence of radar observation distance on rainfall estimation accuracy, rainfall observation stations were classified into three radar distance zones: 0–20 km, 20–50 km, and 100–150 km from the radar location. Figure 3 illustrates the spatial distribution of the Bima C-band weather radar together with Automatic Rain Gauges (ARG), Automatic Weather Stations (AWS), and Automatic Agroclimate Weather Stations (AAWS) used as reference observations in this study. The observation network covers most parts of Bima City and Bima Regency, providing representative rainfall measurements for validating radar-derived rainfall estimates under different radar observation distances.

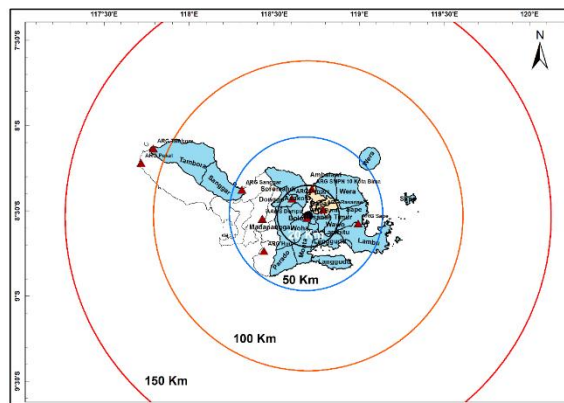


Fig 3. Spatial distribution of the Bima C-band weather radar, rainfall observation stations (ARG, AWS, and AAWS), and radar distance zones used for rainfall validation.

The rainfall observation stations are distributed across diverse physiographic settings, including coastal plains, river valleys, and mountainous regions. Such spatial variability is essential for evaluating radar performance because rainfall estimation accuracy is affected by radar observation geometry and local terrain conditions. Grouping the stations according to radar distance enables a systematic assessment of radar rainfall products under varying propagation conditions, where differences in beam height, beam broadening, and terrain obstruction may influence rainfall estimates.

Based on this observation network, the performance of four radar-derived rainfall products (CMAX, CAPPI, RTR, SRI) was evaluated separately within each radar distance zone. This zonal approach allows the identification of the most suitable radar rainfall product for different observation ranges and provides the basis for determining operational rainfall thresholds for flood early warning in the subsequent analyses.

3.2 Validation of Weather Radar Rainfall Products

3.2.1 Overall validation results

The performance of the five radar-derived rainfall products was evaluated by comparing radar-estimated rainfall with rainfall observations collected from Automatic Rain Gauges (ARG), Automatic Weather Stations (AWS), and Automatic Agroclimate Weather Stations (AAWS). Radar performance was assessed using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), where lower values

indicate better agreement between radar-derived and ground-observed rainfall. The validation was conducted separately for the three radar distance zones to investigate the influence of radar range on rainfall estimation accuracy.

Table 3 presents the validation results for the five radar rainfall products across the three radar distance zones. The results demonstrate substantial differences in estimation accuracy among the evaluated radar products. Within the near-distance zone (0–20 km), CAPPI produced the lowest RMSE (2.578 mm h⁻¹) and MAE (0.635 mm h⁻¹), indicating the closest agreement with rainfall observations. In contrast, CMAX consistently achieved the smallest estimation errors within the intermediate (20–50 km) and far-distance (100–150 km) zones, with RMSE values of 1.984 and 3.115 mm h⁻¹, respectively. These findings indicate that the optimal radar rainfall product varies according to radar observation distance rather than remaining consistent throughout the radar coverage area.

Table 3. Validation performance of four radar rainfall products based on RMSE and MAE within different radar distance zones.

Distance	Radar Product	N	MAE (mm/h)	RMSE (mm/h)	KW Test (H, p)	Notes
0–20 km	CMAX	216	0.881	2.567	H = 65.350	RMSE and MAE are higher than those of the best-performing product. The best-performing product in this zone, based on the lowest RMSE and MAE (Wilcoxon test. $p < 0.001$). The best-performing product in this zone, based on the lowest RMSE and MAE (Wilcoxon test. $p < 0.001$).
	SRI	216	0.672	2.633	p < 0.001	
	RTR	216	0.672	2.633	***	
	CAPPI 1km	216	0.635	2.578		
20–50 km	CMAX	336	0.566	1.984	H = 165.488	The best-performing product in this zone, based on the lowest RMSE and MAE (Wilcoxon test. $p < 0.001$). The best-performing product in this zone, based on the lowest RMSE and MAE (Wilcoxon test. $p < 0.001$).
	SRI	336	0.503	2.393	p < 0.001	
	RTR	336	0.502	2.393	***	
	CAPPI 1km	336	0.510	2.372		
100–150 km	CMAX	240	0.593	3.115	H = 82.979	The best-performing product in this zone, based on the lowest RMSE and MAE (Wilcoxon test. $p < 0.001$).
	SRI	240	0.531	3.134	p < 0.001	
	RTR	240	0.535	3.178	***	
	CAPPI 1km	240	0.531	3.134		

Overall, the validation results reveal that rainfall estimation performance is strongly influenced by radar distance. No individual radar product consistently outperformed the others across all observation zones, suggesting that distance-dependent product selection is more appropriate for operational quantitative precipitation estimation. The observed differences further indicate that local validation is essential before radar rainfall products are implemented for flood early warning applications.

3.2.2 Influence of radar distance

The validation results reveal a clear influence of radar observation distance on rainfall estimation

accuracy. As summarized in Table 3, the optimal radar rainfall product differed among the three distance zones, indicating that radar performance was not spatially uniform across the study area. CAPPI produced the most accurate rainfall estimates within the near-distance zone (0–20 km), whereas CMAX consistently outperformed the other products in the intermediate (20–50 km) and far-distance (100–150 km) zones.

The superior performance of CAPPI in the near-distance zone suggests that radar-derived rainfall estimates are more reliable when observations are acquired close to the radar site. Conversely, the improved performance of CMAX in the intermediate

and far-distance zones indicates that different quantitative precipitation estimation (QPE) algorithms respond differently to increasing radar observation distance. These findings demonstrate that no single radar product provides the highest accuracy throughout the entire radar coverage area.

The observed spatial variation highlights the importance of considering radar observation distance when selecting radar rainfall products for operational applications. Rather than applying a single rainfall product across the entire radar coverage, a distance-dependent approach can improve rainfall estimation accuracy and enhance the reliability of radar-based flood early warning systems.

3.2.3 Statistical comparison among radar products

The differences in rainfall estimation performance observed among the evaluated radar products were further assessed using non-parametric statistical analysis. Because the paired rainfall estimation errors did not satisfy the assumptions of normality, pairwise comparisons were performed using the Wilcoxon signed-rank test. The statistical comparison was conducted separately for each radar distance zone, and the results are summarized in Table 4.

Table 4. Pairwise statistical comparison of radar rainfall products using the Wilcoxon signed-rank test.

Radar distance zone	Product comparison	p-value	Significance	Interpretation
0–20 km	CMAX vs CAPPI	<0.001	***	CAPPI significantly outperformed CMAX.
	CMAX vs SRI	0.008	**	SRI significantly outperformed CMAX.
	CMAX vs RTR	0.01	*	RTR significantly outperformed CMAX.
	SRI vs RTR	0.634	ns	No significant difference.
20–50 km	CMAX vs CAPPI	<0.001	***	CMAX significantly outperformed CAPPI.
	CMAX vs SRI	<0.001	***	CMAX significantly outperformed SRI.
	CMAX vs RTR	<0.001	***	CMAX significantly outperformed RTR.
	SRI vs RTR	0.11	ns	No significant difference.
100–150 km	CMAX vs CAPPI	<0.001	***	CMAX significantly outperformed CAPPI.
	CMAX vs SRI	<0.001	***	CMAX significantly outperformed SRI.
	CMAX vs RTR	<0.001	***	CMAX significantly outperformed RTR.
	SRI vs RTR	0.754	ns	No significant difference.

3.3 Determination of Operational Rainfall Thresholds

3.3.1 ROC Analysis

Following the identification of the optimal radar rainfall products for each distance zone, Receiver Operating Characteristic (ROC) analysis was performed to determine rainfall thresholds associated with flood occurrence. ROC analysis evaluates the discrimination capability of radar-derived rainfall estimates by simultaneously considering sensitivity and specificity across different rainfall thresholds. The optimal threshold for each radar distance zone was determined using the Youden Index, which maximizes the combined true positive rate and true negative rate.

Figure 4 presents the ROC curves for the selected radar rainfall products within the three radar distance zones, while the corresponding optimal thresholds are summarized in Table 5. The ROC analysis demonstrated that the optimal rainfall thresholds differed among radar distance zones, reflecting the spatial variation in radar rainfall estimation performance. The near-distance zone (0–20 km) produced a substantially lower threshold than the intermediate-distance zone, indicating that rainfall observations close to the radar require different operational criteria from those located farther away.

Overall, the ROC results demonstrate that locally calibrated rainfall thresholds provide better discrimination of flood-producing rainfall events than a single threshold applied uniformly across the radar coverage area. These findings emphasize the importance of incorporating radar observation distance into operational rainfall threshold determination for flood early warning.

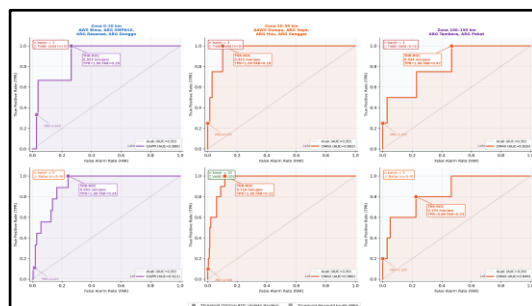


Fig 4. ROC (Receiver Operating Characteristic)

Table 5. ROC Result									
Zona	Product	n Flood	THR-ROC (mm/hour)	THR-P90 (mm/jam)	AUC	TP	FN	FP	TN
0–20 km	CAPPI 1km	9	0.053	2.223	0.911	9	0	50	157
20–50 km	CMAX	10	0.716	4.998	0.960	10	0	38	288
100–150 km	CMAX	5	0.154	1.507	0.846	4	1	53	182

3.3.2 Operational Interpretation

The operational rainfall thresholds derived from the ROC analysis are summarized in Table 6. The thresholds differ among radar distance zones, reflecting the spatial variability in radar rainfall estimation performance identified during the validation process. The near-distance zone (0–20 km), where

CAPPI demonstrated the highest accuracy, was characterized by a lower warning threshold (0.053 mm h⁻¹) and an alert threshold of 2.223 mm h⁻¹. In contrast, the intermediate (20–50 km) and far-distance (100–150 km) zones, where CMAX showed superior performance, required different threshold values to account for the variation in radar rainfall estimation accuracy.

Table 6. Operational rainfall thresholds for radar-based flood early warning across different radar distance zones.

Radar distance zone	Recommended radar product	ROC threshold (Warning) (mm h ⁻¹)	P90 threshold (Alert) (mm h ⁻¹)	Typical reflectivity (dBZ)	Operational interpretation
0–20 km	CAPPI	≥0.053	≥2.223	20–45	Suitable for near-range monitoring; lower rainfall threshold reflects higher radar sensitivity.
20–50 km	CMAX	≥0.716	≥4.998	20–45	Recommended for intermediate-range monitoring where CMAX provides the highest estimation accuracy.
100–150 km	CMAX	≥0.154	≥1.507	20–45	Applicable for far-range observations with locally calibrated operational thresholds.

The distance-specific thresholds provide a practical framework for operational radar rainfall monitoring by assigning the most appropriate radar product and rainfall threshold to each observation zone. The ROC-derived threshold represents the minimum rainfall intensity associated with potential flood occurrence and can therefore be used as the initial warning criterion, whereas the P90 threshold represents higher-intensity rainfall events that warrant increased operational attention. This two-level threshold system enables forecasters to distinguish between moderate rainfall events requiring enhanced monitoring and more extreme events with a higher likelihood of generating flood impacts.

Overall, the operational thresholds presented in Table 6 demonstrate that rainfall warning criteria should not be uniformly applied throughout the radar coverage area. Instead, integrating statistically validated radar products with distance-dependent rainfall thresholds provides a more robust basis for radar-based flood early warning and supports more reliable operational decision-making in the Bima region.

3.4 Development of Radar-Based Flood Early Warning Framework

3.4.1 Stakeholder Analysis

Following the quantitative validation of radar rainfall products, stakeholder consultation was conducted to evaluate the operational applicability of the proposed rainfall thresholds. The consultation involved representatives from the Meteorological, Climatological, and Geophysical Agency (BMKG), the Regional Disaster Management Agency (BPBD), local

government institutions, disaster response organizations, and academic institutions. The objective was to assess the practical relevance of radar-based rainfall thresholds for flood early warning and emergency response.

Table 7 summarizes the main findings obtained from stakeholder consultations. Overall, participants agreed that locally calibrated rainfall thresholds would improve the consistency of radar interpretation and support more effective operational decision-making. Stakeholders emphasized that warning criteria should account for spatial variations in radar performance and recommended integrating radar rainfall thresholds with existing flood monitoring procedures.

The consultation also highlighted several operational challenges, including differences in institutional interpretation of radar products, limited availability of standardized warning thresholds, and the need for improved coordination among forecasting and disaster management agencies. These findings indicate that technical validation alone is insufficient for operational implementation without institutional agreement on warning procedures.

Table 7. Summary of stakeholder perspectives on the implementation of radar-based flood early warning.

Theme	Stakeholder response	Implication
Radar accuracy	High agreement	Supports operational application
Local thresholds	Strong agreement	Improves warning consistency
Inter-agency coordination	Moderate agreement	Requires standardized procedures
Radar training	High agreement	Capacity building required

3.4.2 Governance Framework

Based on the quantitative validation results and stakeholder consultation, a radar-based flood early warning framework was developed to support operational decision-making in the Bima region. The framework integrates validated radar rainfall products, distance-dependent rainfall thresholds, and institutional response procedures into a unified operational workflow.

As illustrated in Figure 5, the framework consists of four sequential components. First, rainfall is continuously monitored using the BMKG C-band weather radar. Second, rainfall estimates are interpreted using the radar product identified as

optimal for each radar distance zone. Third, rainfall intensity is compared with locally calibrated operational thresholds derived from ROC analysis to determine the appropriate warning level. Finally, warning information is disseminated to disaster management agencies and local governments to support preparedness and emergency response.

The proposed framework provides a systematic approach for translating validated radar rainfall observations into operational flood warnings. By integrating technical validation with stakeholder consultation, the framework supports more consistent interpretation of radar information and facilitates evidence-based flood early warning in regions characterized by complex topography.

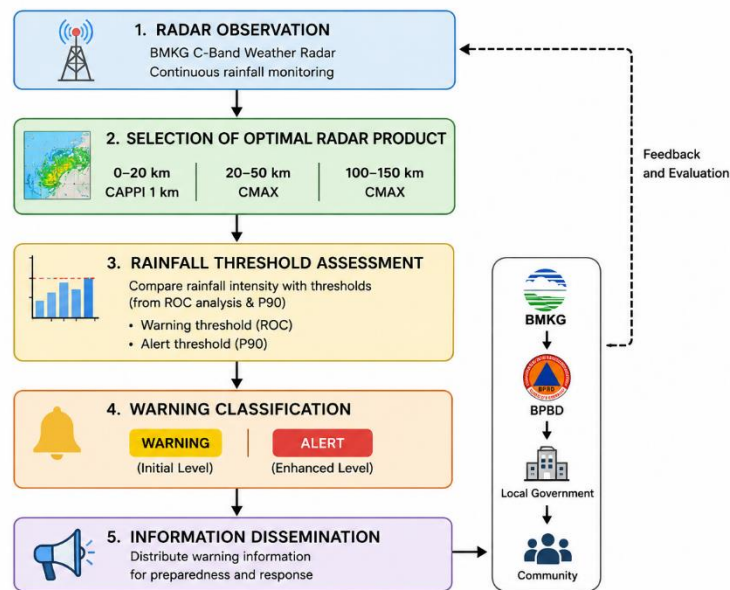


Fig 5. Proposed radar-based flood early warning framework developed from the validated radar rainfall products, distance-dependent rainfall thresholds, and stakeholder consultation.

3.5 Discussion

The results of this study demonstrate that radar observation distance significantly influences the accuracy of weather radar rainfall estimation. CAPPI produced the highest accuracy within the 0–20 km zone, whereas C-MAX consistently outperformed the remaining radar rainfall products in the intermediate (20–50 km) and far-distance (100–150 km) zones. These findings indicate that no single quantitative precipitation estimation (QPE) product can provide optimal performance across the entire radar coverage area, emphasizing the importance of distance-dependent radar product selection.

A comprehensive review conducted by Osman & Tahir (2024) analyzed weather radar QPE studies published between 2010 and 2023 and concluded that radar rainfall estimation accuracy is strongly affected by radar characteristics, precipitation type, terrain complexity, and the rainfall retrieval algorithm employed. The review further highlighted that most previous studies concentrated on algorithm

development and rainfall estimation accuracy, whereas relatively few translated validation results into operational flood warning criteria. The present study extends these previous efforts by combining radar product validation with ROC-based rainfall threshold determination and operational framework development, thereby bridging the gap between technical validation and practical implementation.

The influence of radar observation distance identified in this study is also consistent with the findings of (Villarini & Krajewski, 2010), who reported that rainfall estimation uncertainty generally increases with distance because radar beams become progressively higher and wider as they propagate away from the antenna. Their review identified beam broadening, beam overshooting, attenuation, and terrain blockage as the principal causes of radar rainfall errors. Similar conditions exist in the Bima region, where mountainous terrain surrounding the radar coverage area likely contributes to the variation in rainfall estimation accuracy observed among the evaluated radar

products. Consequently, the superior performance of CAPPI in the near-distance zone and CMAX at longer distances can be explained by differences in radar sampling geometry rather than algorithm performance alone.

A study by (Tahir et al. (2022) evaluated CAPPI-derived rainfall estimates for the Langat River Basin, Malaysia, and reported correlation coefficients ranging from 0.69 to 0.75 after local calibration of the Z–R relationship. The authors concluded that CAPPI provides reliable rainfall estimation when supported by regional calibration and local rainfall characteristics. These findings agree with the present study, where CAPPI achieved the best performance within the 0–20 km zone, suggesting that CAPPI is particularly effective for near-range rainfall monitoring when beam elevation remains relatively low.

Previous research in Indonesia by (Tondang et al. (2023) evaluated weather radar rainfall products against rain gauge observations in North Sumatra and demonstrated that radar-derived rainfall could provide acceptable rainfall estimates after local validation. However, the study evaluated radar products using general statistical indicators without explicitly considering radar observation distance or determining operational rainfall thresholds. Likewise, Widomurti et al. (2020) investigated the influence of terrain obstruction on weather radar observations in Bima and showed that terrain blockage substantially affected radar reflectivity in mountainous areas. Compared with these studies, the present research advances radar validation by simultaneously comparing multiple radar rainfall products across different distance zones and integrating the results into an operational threshold determination framework.

One of the major contributions of this study is the application of Receiver Operating Characteristic (ROC) analysis to convert radar rainfall validation results into operational rainfall thresholds. Previous radar validation studies have generally reported statistical indicators such as RMSE, MAE, correlation coefficients, or bias values without establishing rainfall thresholds that can be directly implemented in flood early warning systems. By maximizing the Youden Index, this study objectively determined rainfall thresholds that optimize the discrimination between flood and non-flood events for each radar distance zone. This approach enables the direct translation of radar validation results into operational decision-making criteria.

The proposed Radar-Based Flood Early Warning framework further distinguishes this study from previous investigations. Rather than stopping at rainfall validation, the framework integrates validated radar products, distance-dependent rainfall thresholds, and stakeholder consultation into a unified operational workflow. The World Meteorological Organization (World Meteorological Organization, 2021) emphasizes that effective impact-based forecasting requires not only accurate meteorological observations but also locally validated thresholds and institutional coordination for warning

dissemination. The framework developed in this study addresses these requirements and therefore provides a practical model for implementing radar-based flood early warning in tropical regions characterized by complex terrain.

Despite these contributions, several limitations remain. The analysis was based on observations from a single C-band weather radar and one year of rainfall records, which may not fully represent long-term climate variability. Furthermore, only conventional radar rainfall products were evaluated, whereas recent developments increasingly employ dual-polarization radar observations and machine learning techniques to improve quantitative precipitation estimation under complex precipitation conditions (Osman & Tahir, 2023). Future studies should therefore investigate the integration of dual-polarization variables, radar–gauge merging techniques, and artificial intelligence-based rainfall estimation to further enhance the robustness of radar-based flood early warning systems.

4. Conclusion

This study evaluated the performance of five weather radar rainfall products for flood early warning in Bima, Indonesia, by comparing radar-derived rainfall estimates with observations from ARG, AWS, and AAWS stations across three radar distance zones. The results demonstrate that radar observation distance significantly influences rainfall estimation accuracy. CAPPI produced the best performance within the 0–20 km zone, whereas CMAX consistently achieved the highest accuracy in the 20–50 km and 100–150 km zones. Statistical analyses confirmed that these differences were significant, indicating that the selection of radar rainfall products should consider radar observation distance rather than applying a single product throughout the radar coverage area.

Receiver Operating Characteristic (ROC) analysis successfully identified locally optimized rainfall thresholds for each radar distance zone. These thresholds provide an objective basis for operational flood early warning and demonstrate that distance-dependent warning criteria are more appropriate than a uniform rainfall threshold. The integration of validated radar products, locally calibrated rainfall thresholds, stakeholder consultation, and the proposed Radar-Based Flood Early Warning framework provides a practical approach for supporting operational decision-making in the Bima region.

Overall, this study contributes to the advancement of radar-based flood early warning by integrating quantitative radar validation with operational threshold determination and institutional implementation. The proposed framework offers a transferable methodology for other tropical regions with complex terrain where weather radar is increasingly used to support impact-based forecasting and disaster risk reduction.

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