

**DEVELOPMENT OF EARLY WARNING FOR EXTREME
RAINFALL IN SURABAYA AND ITS SURROUNDINGS USING
DUAL-POLARIZATION WEATHER RADAR ENHANCED BY
ARTIFICIAL INTELLIGENCE**

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**APPLIED CLIMATOLOGY STUDY PROGRAM
FACULTY OF MATHEMATICS AND NATURAL SCIENCES
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Bogor, August 2026

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RINGKASAN

ALI WARDHANA. Pengembangan Peringatan Dini Curah Hujan Ekstrem di Surabaya dan Sekitarnya melalui Radar Cuaca Dual Polar diperkuat Kecerdasan Buatan. Dibimbing oleh RIZALDI BOER, BAMBANG DWI DASANTO, DANANG EKO NURYANTO, dan I PUTU SANTIKAYASA

Estimasi Curah Hujan Kuantitatif (Quantitative Precipitation Estimation/QPE) yang Akurat sangat penting untuk mitigasi bencana hidrometeorologi, khususnya banjir perkotaan di wilayah metropolitan seperti Surabaya. Curah hujan di wilayah ini menunjukkan variabilitas spasial dan temporal yang signifikan karena sistem konvektif tropis yang kompleks. Meskipun radar cuaca dual-polarisasi pita C memberikan pengamatan resolusi tinggi, kinerja operasionalnya seringkali terganggu oleh pelemahan sinyal, kontaminasi *ground clutter* dan ketidakcukupan hubungan curah hujan radar empiris konvensional dalam menangkap karakteristik mikrofisika nonlinier dari curah hujan tropis. Untuk mengatasi tantangan ini, penelitian ini mengembangkan kerangka kerja validasi terintegrasi untuk estimasi curah hujan menggunakan radar cuaca dual-polarisasi pita C dan pengamatan Stasiun Cuaca Otomatis (Automated Weather Station/AWS). Kerangka kerja ini selanjutnya ditingkatkan melalui teknik pembelajaran mesin dan pembelajaran mendalam untuk mendukung peringatan dini operasional cuaca ekstrem di wilayah metropolitan Surabaya.

Metodologi penelitian dilakukan dalam beberapa tahap. Awalnya, tinjauan literatur sistematis dilakukan untuk mengevaluasi kondisi terkini metode estimasi curah hujan berbasis pembelajaran mesin dan pembelajaran mendalam. Selanjutnya, prosedur kontrol kualitas fisik yang kuat dikembangkan. Kerangka kerja Bayesian Dual-Polarization Dual-Scan (DPDS) yang baru diusulkan untuk mengurangi kontaminasi *ground clutter* dengan mengintegrasikan deskriptor polarimetrik dengan informasi koherensi temporal. Atenuasi sinyal diatasi dengan membandingkan teknik koreksi berbasis fase, yaitu metode Linear PhiDP dan ZPHI. Setelah pra-pemrosesan radar, kerangka kerja fusi data multi-sensor dibentuk dengan menyinkronkan variabel polarimetrik yang berasal dari radar dengan pengamatan meteorologi permukaan dari Stasiun AWS, termasuk suhu udara, kelembaban relatif, tekanan atmosfer, dan kecepatan angin. Akhirnya, model Random Forest (RF), Extreme Gradient Boosting (XGBoost), dan 1D-Convolutional Neural Network–Long digunakan. dikembangkan dan divalidasi secara independen selama peristiwa banjir ekstrem di Jawa Timur dari tanggal 14–23 Maret 2026.

Temuan menunjukkan bahwa kontrol kualitas fisik berfungsi sebagai prasyarat yang sangat diperlukan untuk estimasi curah hujan berbasis radar. Namun, hal itu sendiri masih kurang untuk mencapai estimasi curah hujan kuantitatif yang tepat. Kerangka kerja DPDS yang diusulkan secara efektif membedakan gema meteorologi dari gema non-meteorologi, sehingga secara signifikan mengurangi kontaminasi kekacauan perkotaan dan meningkatkan keandalan data radar. Meskipun koreksi atenuasi berhasil memulihkan struktur reflektivitas di belakang inti konvektif yang intens, analisis statistik menunjukkan bahwa pemilihan metode koreksi atenuasi berbasis fase hanya memiliki dampak terbatas pada akurasi estimasi curah hujan akhir. Sebaliknya, kinerja estimasi curah hujan terutama diatur

oleh pemilihan hubungan curah hujan radar Z-R. Bahkan hubungan empiris yang dikalibrasi secara lokal yang paling mahir secara konsisten meremehkan curah hujan konvektif ekstrem, menggarisbawahi keterbatasan formulasi parametrik tetap di lingkungan maritim tropis.

Transisi dari pendekatan empiris ke pendekatan berbasis data Algoritma secara signifikan meningkatkan kinerja estimasi curah hujan. Analisis *feature importance* mengungkapkan bahwa reflektivitas horizontal dekat permukaan yang dikoreksi adalah prediktor utama intensitas curah hujan. Penggabungan variabel meteorologi permukaan, khususnya kecepatan angin, secara signifikan meningkatkan akurasi estimasi dengan menyelesaikan proses atmosfer di bawah awan seperti penguapan dan *wind shear*. Di antara model yang dievaluasi, model RF yang mengintegrasikan radar dan variabel meteorologi menunjukkan kinerja yang paling kuat dan andal secara operasional selama validasi independen. Model ini mencapai kesalahan estimasi terendah (RMSE = 1,20 mm/6-menit; MAE = 0,41 mm/6-menit), koefisien korelasi tertinggi (CC = 0,58), dan koefisien determinasi tertinggi ($R^2 = 0,32$) selama peristiwa banjir Maret 2026. Lebih lanjut, model ini secara konsisten menghasilkan Indeks CSI tertinggi di berbagai ambang batas curah hujan, dari ringan hingga ekstrem. Sebaliknya, arsitektur 1D-CNN-LSTM menunjukkan kemampuan terbatas dalam merepresentasikan rentang dinamis penuh curah hujan tropis ekstrem, terutama karena representasi temporal satu dimensi tidak mampu menggambarkan morfologi spasial dan kompleksitas struktural sistem badai konvektif secara memadai.

Penelitian ini menjelaskan bahwa estimasi curah hujan tropis yang andal tidak dapat dicapai hanya melalui persamaan radar empiris atau pengamatan sensor tunggal. Integrasi pengamatan radar cuaca polarisasi ganda dengan pengukuran meteorologi permukaan, menggunakan kerangka kerja pembelajaran mesin yang dioptimalkan seperti RF memberikan solusi yang terukur, akurat, dan layak secara operasional untuk estimasi curah hujan kuantitatif di lingkungan tropis. Temuan ini mendukung pergeseran paradigma dari estimasi curah hujan radar konvensional ke kerangka kerja berbasis kecerdasan buatan terintegrasi untuk aplikasi hidrometeorologi operasional. Akibatnya, disarankan agar lembaga meteorologi operasional mengadopsi kerangka kerja pembelajaran mesin radar-meteorologi gabungan bersamaan dengan ambang batas intensitas curah hujan 6 menit yang distandarisasi untuk meningkatkan sistem peringatan dini secara real-time. Penelitian masa depan harus fokus pada arsitektur pembelajaran mendalam multidimensi yang memanfaatkan representasi tensor spasial dengan lebih baik untuk menangkap struktur spasial rumit dari curah hujan konvektif tropis.

Kata kunci: Koreksi atenuasi, Polarisasi ganda, Pembelajaran mesin, Estimasi curah hujan kuantitatif, Radar cuaca

SUMMARY

ALI WARDHANA. Development of Early Warning for Extreme Rainfall in Surabaya and Its Surroundings using Dual-Polarization Weather Radar Enhanced by Artificial Intelligence. Supervised by RIZALDI BOER, BAMBANG DWI DASANTO, DANANG EKO NURYANTO, and I PUTU SANTIKAYASA

Precise Quantitative Precipitation Estimation (QPE) is crucial for mitigating hydrometeorological disasters, particularly urban flooding in metropolitan areas such as Surabaya. Rainfall in this region exhibits significant spatial and temporal variability due to complex tropical convective systems. While C-band dual-polarization weather radar provides high-resolution observations, its operational performance is often compromised by severe signal attenuation, ground clutter contamination, and the inadequacy of conventional empirical radar rainfall relationships in capturing the nonlinear microphysical characteristics of tropical precipitation. To overcome these challenges, this study developed an integrated validation framework for rainfall estimation utilizing C-band dual-polarization weather radar and Automated Weather Station (AWS) observations. This framework was further enhanced through Machine Learning (ML) and Deep Learning (DL) techniques to support operational extreme rainfall early warning in the Surabaya metropolitan region.

The research methodology was conducted in several stages. Initially, a systematic literature review was conducted to evaluate the current state of ML and DL-based rainfall estimation methods. Subsequently, robust physical quality-control procedures were developed. A novel Bayesian Dual-Polarization Dual-Scan (DPDS) framework was proposed to mitigate ground clutter contamination by integrating polarimetric descriptors with temporal coherence information. Signal attenuation was addressed by comparing phase-based correction techniques, namely Linear PhiDP and ZPHI methods. Following radar preprocessing, a multi-sensor data fusion framework was established by synchronizing radar-derived polarimetric variables with surface meteorological observations from the Advanced Weather Stations (AWS), including air temperature, relative humidity, atmospheric pressure, and wind speed. Finally, Random Forest (RF), Extreme Gradient Boosting (XGBoost), and a one-dimensional Convolutional Neural Network–Long Short-Term Memory (1D-CNN-LSTM) model were developed and independently validated during an extreme flood event in East Java from March 14–23, 2026.

The findings reveal that physical quality control serves as an indispensable prerequisite for radar-based rainfall estimation. Yet, it falls short of achieving precise quantitative precipitation estimation (QPE) on its own. The proposed DPDS framework effectively differentiated meteorological echoes from non-meteorological echoes, thereby significantly mitigating urban clutter contamination and enhancing radar data reliability. While attenuation correction successfully recovered reflectivity structures behind intense convective cores, statistical analyses indicated that selecting phase-based attenuation correction methods had only a limited impact on final rainfall estimation accuracy. Instead, rainfall estimation performance was primarily governed by the selection of radar rainfall relationships. Even the most proficient locally calibrated empirical relationships

consistently underestimated extreme convective rainfall, underscoring the limitations of fixed parametric formulations in tropical maritime environments.

The transition from empirical approaches to data-driven algorithms significantly improved rainfall estimation performance. Feature importance analyses revealed that attenuation-corrected near-surface horizontal reflectivity was the primary predictor of rainfall intensity. The incorporation of surface meteorological variables, particularly wind speed, significantly improved estimation accuracy by resolving below-cloud atmospheric processes such as evaporation and wind shear. Among the evaluated models, the Random Forest model integrating radar and meteorological variables exhibited the most robust, operationally reliable performance during independent validation. This model achieved the lowest estimation errors (RMSE = 1.20 mm/6-min; MAE = 0.41 mm/6-min), the highest correlation coefficient (CC = 0.58), and the highest coefficient of determination ($R^2 = 0.32$) during the March 2026 flood event. Furthermore, it consistently produced the highest Critical Success Index (CSI) across multiple rainfall thresholds, from light to extreme. In contrast, the 1D-CNN-LSTM architecture demonstrated limited capability in representing the full dynamic range of extreme tropical rainfall, primarily because its one-dimensional temporal representation was unable to adequately characterize the spatial morphology and structural complexity of convective storm systems.

In summary, this study elucidates that reliable tropical rainfall estimation cannot be achieved solely through empirical radar equations or single-sensor observations. The integration of dual-polarization weather radar observations with surface meteorological measurements, employing optimized ML frameworks such as Random Forest, provides a scalable, accurate, and operationally viable solution for quantitative precipitation estimation in tropical environments. These findings advocate a paradigm shift from conventional radar rainfall estimation to integrated, artificial intelligence-based frameworks for operational hydrometeorological applications. Consequently, it is recommended that operational meteorological agencies adopt combined radar-meteorological ML frameworks in conjunction with standardized 6-minute rainfall intensity thresholds to enhance real-time flash flood early warning systems. Future research should focus on multidimensional DL architectures that leverage spatial tensor representations better to capture the intricate spatial structures of tropical convective precipitation.

Keywords: Attenuation correction, Dual-polarization, Machine Learning, Quantitative precipitation estimation, Weather radar

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PREFACE

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Bogor, August 2026

Ali Wardhana

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