

Identification of Atmospheric Dynamics of a Tropical Hail Event and Application of Radar Reflectivity Nowcasting Using a UNet-ConvLSTM2D Deep Learning Model

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Abstract:

Hail is a small-scale hydrometeorological phenomenon threatening disaster-prone regions of Indonesia, yet understanding of its atmospheric dynamics and deep learning-based radar nowcasting remain limited. This study characterizes the atmospheric conditions of the Depok City hailstorm on 28 October 2024 and evaluates a hybrid UNet-ConvLSTM2D model in predicting radar reflectivity. The study employed Column Maximum (CMAX) radar reflectivity data in PNG and VOL formats from the Soekarno-Hatta Class I Meteorological Station, cloud-top temperature and Cloud Convective Overlay data from Himawari-9 satellite imagery, and ERA5 reanalysis data on storm thermodynamic and kinematic conditions, while radar data from January 2023 to October 2024 were used for model training and validation. Model performance was assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), Structural Similarity Index (SSIM), Critical Success Index (CSI), and Heidke Skill Score (HSS) across five reflectivity thresholds. Results show maximum radar reflectivity exceeding 55 dBZ at 08.18 UTC and 08.42 UTC, cloud-top temperatures of approximately -61°C to -73°C, and Convective Available Potential Energy (CAPE) of 524-590 J/kg with weak vertical wind shear of 2.4-2.8 m/s from ERA5, confirming a moderately unstable tropical convective environment. Prediction results yielded average values of 184.5897 for MSE, 9.7081 for MAE, and 0.3956 for SSIM, with CSI decreasing from 0.588 to 0.284 and HSS from 0.637 to 0.057 as lead time increased from 8 to 56 minutes. These findings are expected to enhance understanding of the atmospheric dynamics contributing to hail and support wider deep learning-based nowcasting for early warning in tropical Indonesia.

1. Introduction

Indonesia is among the countries most vulnerable to hydrometeorological disasters, as reflected by the fluctuating yet generally increasing frequency of such events across different regions (Aeni & Anwar, 2024; Yanfatriani dkk., 2024). These disasters affect a substantially larger number of people than geological hazards, making hydrometeorological disasters a primary focus of national disaster mitigation policies (Rosyida & Nurmasari, 2019). Their impacts extend across multiple sectors, including disruptions to ground transportation networks and aviation operations, as demonstrated by flight diversions at Soekarno-Hatta International Airport caused by significant weather phenomena (Adzan dkk., 2025; Dave dkk., 2021). These conditions highlight that localized and mesoscale severe weather events, including short-lived convective phenomena such as hail, can produce impacts disproportionate to their brief duration.

From a physical perspective, hail forms through vigorous convection within Cumulonimbus clouds, where strong updrafts enable ice particles to undergo repeated cycles of freezing and accretion before eventually falling to the surface once their weight exceeds the lifting capacity of the updraft (Fadholi, 2012). This process is governed by the interaction of multiple atmospheric variables, including thermodynamic variables such as instability energy and convective inhibition, as well as kinematic

variables such as vertical wind shear and storm relative helicity, which collectively determine the potential, intensity, and type of hail-producing convective storms. A comprehensive understanding of these meteorological variables is therefore a fundamental step that must precede the development of any prediction system, given that hail is a highly nonlinear phenomenon that evolves over extremely limited spatial and temporal scales and cannot be adequately explained using a single type of observational data.

To achieve this comprehensive understanding, the present study examines atmospheric conditions during the hail event using three complementary types of observational data, namely weather radar, satellite imagery, and atmospheric reanalysis. Weather radar provides three-dimensional information on precipitation clouds based on the physical principle of microwave backscattering by hydrometeors (Kou dkk., 2023; Thomas dkk., 2020). Satellite imagery provides information on cloud-top temperature and the spatial distribution of convective clouds (Ariwibowo & Anang Ahmad Khairin Nur, 2018; Rumapea dkk., 2022). Atmospheric reanalysis data, meanwhile, provide thermodynamic and kinematic characteristics of the storm environment that cannot be directly obtained from radar or satellite observations alone. The combination of these three data sources enables a more comprehensive identification of the variables that play a significant role in hail formation than would be possible using a single data source.

Once this understanding of the variables governing hail formation is established, the subsequent challenge lies in detecting and predicting its occurrence rapidly, given that hail-producing convective cells typically persist for only tens of minutes to a few hours, with the critical phase of core intensification preceding hail-fall commonly developing and dissipating within about 10 to 30 minutes (Wapler, 2017). This characteristic underlies the need for high-resolution weather monitoring systems to support very short-term prediction, or nowcasting. Among the available observational data, weather radar was selected as the primary data source for the prediction stage because it directly captures the dynamics of convective systems at a substantially higher temporal resolution than other observation systems, including satellite imagery (Sokol dkk., 2021), making it more representative for monitoring rapid changes in small-scale convective systems such as hail.

In Indonesia, the Meteorology, Climatology, and Geophysics Agency (BMKG) has implemented radar echo extrapolation for nowcasting through the Short-Term Ensemble Prediction System (STEPS), which demonstrated satisfactory forecasting performance for short lead times using C-band radar observations in Pangkalan Bun (Ali & Sa'adah, 2021). However, optical flow-based methods such as STEPS fundamentally rely on the assumption of smooth and quasi-linear motion fields (Ayzel dkk., 2019; Woo & Wong, 2017), an assumption that becomes a significant limitation when applied to convective systems characterized by rapid growth and dissipation, as commonly observed in severe convective weather such as hail. This limitation has driven a paradigm shift toward deep learning approaches capable of learning nonlinear atmospheric dynamics directly from spatiotemporal data (S. Wang dkk., 2020).

The development of deep learning architectures for radar nowcasting began with ConvLSTM, which established the foundation for modeling spatio-temporal sequential data (Shi dkk., 2015a). This framework was subsequently extended through benchmark evaluations and the introduction of TrajGRU to address limitations in motion representation (Shi dkk., 2017). More recent developments, including PFST-LSTM with pseudoflow prediction (Luo dkk., 2020), ConvLSTM integrated with SmaAT-UNet (Liao dkk., 2024), and ConvLSTM2D for radar echo extrapolation (Naz dkk., 2024), have progressively improved the preservation of spatial details while reducing blurry predictions at longer lead times. The latest advancement, the hybrid UNet–ConvLSTM2D architecture, has been reported to outperform previous models by achieving higher Critical Success Index (CSI) and Heidke Skill Score (HSS) values,

lower Mean Squared Error (MSE), and improved computational efficiency (Naz dkk., 2025a). However, this architecture, like most of its predecessors, has thus far been developed and validated only on radar data from mid and high latitude regions, and its applicability to tropical convective systems, including hail-producing cases in Indonesia, where convective dynamics evolve more rapidly, has not yet been examined.

Despite these advances, nearly all existing deep learning studies on radar nowcasting have been developed and validated using weather radar data from mid and high latitude regions, where atmospheric convective dynamics differ substantially from those in tropical environments. Meanwhile, comprehensive understanding of the meteorological variables responsible for hail occurrence, as well as the application of comparable prediction models using Indonesian weather radar data, remains extremely limited. This geographical and methodological gap underscores the need for the present study, both to comprehensively examine the meteorological variables involved in hail occurrence and to evaluate the feasibility of deep learning-based nowcasting using radar data, as an initial step toward supporting BMKG's early warning system for mitigating hail and other hydrometeorological disasters in tropical Indonesia.

2. Method

2.1. Study Area

This study focuses on Depok City as the primary study area, located at geographical coordinates of 6.402905° S and 106.778419° E, as shown in Figure 2. Depok was selected because it forms part of the Jabodetabek metropolitan region that has repeatedly experienced hail events and significant convective weather phenomena, while also facing increasing vulnerability to hydrometeorological disasters amid rapid urbanization in Indonesia (Aeni & Anwar, 2024; Ariwibowo & Anang Ahmad Khairin Nur, 2018). Depok also lies within the observational coverage of the Tangerang C-band weather radar (6.171433° S, 106.646622° E), which provides a coverage radius of approximately 200 km, and radar observations from this station were accordingly used as the primary data source for this research.

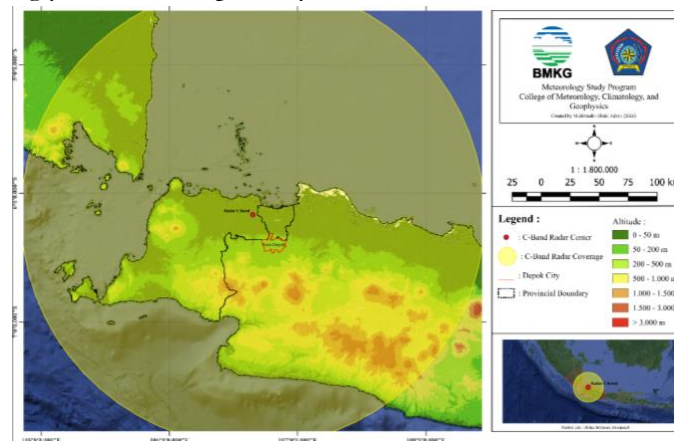


Figure 1. Research map.

2.2. Research Data

This study employed radar, satellite, and reanalysis data to characterize the hail event and support model development. Weather radar data were obtained from the Soekarno–Hatta Class I Meteorological Station in the form of Column Maximum (CMAX) reflectivity products, comprising PNG-format images at 4084×4084 pixel resolution and 8-minute temporal resolution spanning January 2023 to October 2024, used

for training, validation, and testing of the UNet-ConvLSTM2D model, with the testing subset specifically corresponding to the period during which the hail event occurred, and VOL-format products acquired specifically for 28 October 2024, used to identify the hail event through vertical reflectivity analysis. Himawari-9 satellite data included Band 13 for retrieving Cloud Top Temperature (CTT) and Bands 8, 13, and 15 for generating Cloud Convective Overlays (CCO) using the Split Window at Equation (1) and Dual Channel Difference at Equation (2) methods (Djazim Syaifullah dkk., 2016; Rumapea dkk., 2022). ERA5 reanalysis data from the Copernicus Climate Data Store (CDS) provided temperature (T), specific humidity (q), zonal and meridional wind components (u, v), 2 m temperature (T2m), 2 m dew point temperature (D2m), surface pressure (SP), 10 m wind components (U10, V10), geopotential (z), CAPE, CIN, KI, TT, and Zero Degree Level (ZDL), from which dew point temperature (Td), height above ground level (AGL), LCL, LFC, EL, CCL, Deep-Layer Shear (0–6 km), SRH (0–3 km), and BRN were subsequently derived.

$$IR - IR2 \leq 2 \quad (1)$$

$$IR - WV \leq 3 \quad (2)$$

2.3. Preprocessing, Processing, and the UNet-ConvLSTM2D Architecture to prediction

The preprocessing stage began with filtering the CMAX PNG radar sequences, where only complete sequences consisting of 14 consecutive images at 8-minute intervals without missing frames were retained. Each image was subsequently cropped from 4,084 x 4,084 pixels to 256 x 256 pixels and further downsampled to 64 x 64 pixels to reduce computational load during model development while preserving the echo movement in each frame, including single-cell echoes, so that they remain observable (Calota dkk., 2023; Kim & Ushio, 2022). The radar reflectivity data were then converted from RGB reflectivity values (0–70 dBZ) to 8-bit grayscale values (0–255) using Equation (3), followed by normalization to the range of 0–1 (x') using Equation (4). The resulting dataset was divided into 2,730 sequences (80%) for training and 683 sequences (20%) for validation, while the hail-event dataset identified from the CMAX VOL product using the RainDART application was reserved as the testing dataset.

During the processing stage, the UNet-ConvLSTM2D model was trained using input tensors of shape (B, 7, 64, 64, 1). The input sequences were first processed by an encoder consisting of three ConvLSTM blocks with 64, 128, and 256 filters, respectively, interleaved with MaxPool3D layers that progressively reduced the spatial resolution from 64×64 to 16×16 . The encoded features were then compressed within the bottleneck using a TakeLastFrame operation followed by a ConvLSTM unit, whose internal computations involve the hidden state $H_t^{(1)}$, cell state $C_t^{(1)}$, and the input $i_t^{(1)}$ /forget $f_t^{(1)}$ /output $o_t^{(1)}$ gates, as formulated in Equations (5)–(9) (Shi dkk., 2015a). Finally, the decoder autoregressively reconstructed the encoded representations into seven predicted frames through Conv3DTranspose layers with skip connections, followed by a Conv3D layer, producing an output tensor of shape (B, 7, 64, 64, 1) representing the radar reflectivity nowcasting results.

$$Grayscale(0 - 255) = \frac{dBZ}{70} \times 255 \quad (3)$$

$$x' = \frac{x - 0}{255 - 0} \quad (4)$$

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \circ C_{t-1} + b_i) \quad (5)$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \circ C_{t-1} + b_f) \quad (6)$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \quad (7)$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_o) \quad (8)$$

$$H_t = o_t \circ \tanh(C_t) \quad (9)$$

2.4. Model Evaluation of Radar Reflectivity Predictions Against Radar Observations

The performance of the UNet–ConvLSTM2D model was evaluated by comparing predicted radar reflectivity against actual radar observations from the CMAX PNG testing dataset during the hail event, which was identified from the CMAX VOL product using the RainDART application. This evaluation emphasized how closely the model's predictions matched the observed radar reflectivity, assessed through binary classification metrics, pixel-based metrics, and spatial visual analysis. Radar reflectivity pixels were classified at five thresholds (5, 10, 20, 30, and 40 dBZ) into the contingency table categories TP, TN, FN, and FP shown in Table 1 (Naz dkk., 2024; Tan dkk., 2020). These contingency statistics were subsequently used to calculate the Critical Success Index (CSI) Equation (10) (Chen dkk., 2020; Piran dkk., 2024) and the Heidke Skill Score (HSS) Equation (11), which quantify the model's rainfall detection performance. Pixel-based evaluation was conducted using the Mean Squared Error (MSE) as the loss function Equation (12) (Shi dkk., 2015a; Zhang dkk., 2023), the Mean Absolute Error (MAE), which is more robust to outliers Equation (13) (Zhang dkk., 2023), and the Structural Similarity Index (SSIM) to assess structural similarity between the predicted and observed radar reflectivity fields in terms of luminance, contrast, and structural information Equation (14) (Luo dkk., 2020; Naz dkk., 2024). Spatial visual evaluation was performed using difference maps to identify the spatial distribution of prediction bias, where overestimation and underestimation relative to the observed radar reflectivity fields were represented by red and blue, respectively (Naz dkk., 2025a).

Table 1. *Confusion matrix table*

Confusion Matrix		Observation	
Prediction		Positive	Negative
		True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

$$CSI = \frac{TP}{TP + FN + FP} \quad (10)$$

$$HSS = \frac{2(TP \times TN - FN \times FP)}{(TP + FN)(FN + TN) + (TP + FP)(FP + TN)} \quad (11)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (12)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (13)$$

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (14)$$

3. Result

3.1. Hail Event Identification Using Weather Radar Data

Weather radar data constitute one of the meteorological instruments capable of capturing the spatial distribution of precipitation at a relatively detailed resolution and in near real-time. Figure 3 presents the

CMAX (Column Maximum) product for the period 07:46–08:50 UTC, extracted from altitude layers between 4.5 km and 15 km. The lower boundary of 4.5 km was selected to capture the maximum reflectivity above the standard freezing level in the Jabodetabek region (Ariwibowo & Anang Ahmad Khairin Nur, 2018). Based on this product, a radar echo entering the Depok City area was first identified between 08:02 and 08:10 UTC, indicating the growth phase of the convective system. In addition, a region of maximum reflectivity exceeding 55 dBZ was identified at 08:18 and 08:42 UTC, as marked by the black boxes in the figure.

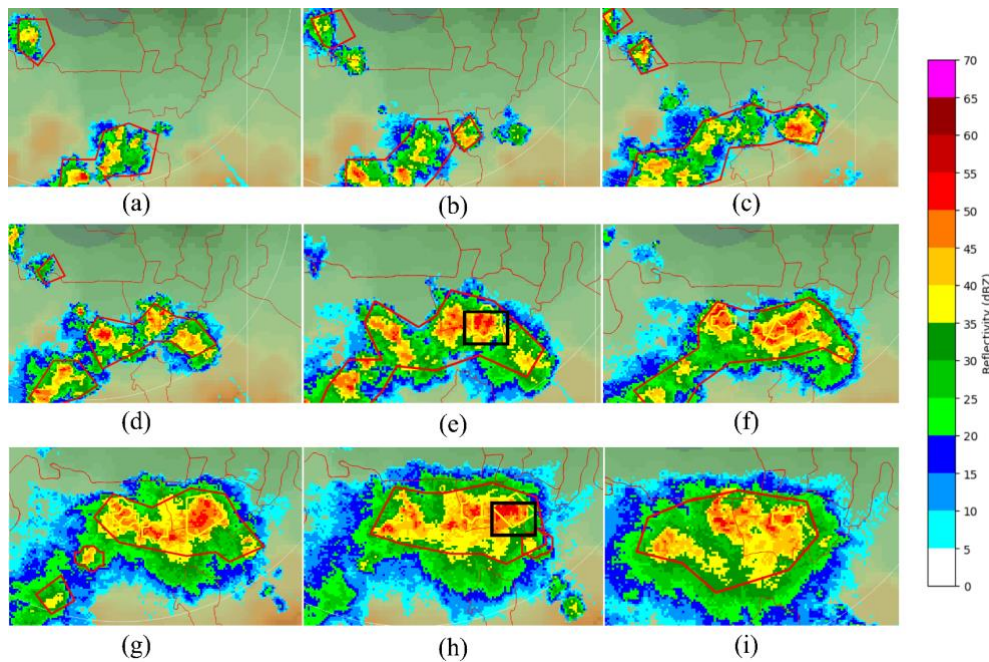


Figure 3. *Maximum reflectivity visualization at altitudes of 4.5–15 km at (a) 07:46, (b) 07:54, (c) 08:02, (d) 08:10, (e) 08:18, (f) 08:26, (g) 08:34, (h) 08:42, and (i) 08:50 WIB, with the black boxes indicating areas of reflectivity >55 dBZ.*

Physically, hail forms when strong updrafts within convective clouds lift water droplets above the freezing level (the altitude at which air temperature falls below 0°C), causing the droplets to become supercooled water that subsequently interacts with ice nuclei and freezes (Dennis & Kumjian, 2017). Repeated cycles of updraft and downdraft promote hailstone growth through successive accretion processes, progressively increasing the particle's diameter and mass until it becomes sufficiently heavy to overcome the upward air motion and fall to the surface as hail. Based on a radiosonde observational study conducted in the vicinity of Depok City, the freezing level altitude was estimated to range between 4.7 km and 4.9 km above mean sea level (Ariwibowo & Anang Ahmad Khairin Nur, 2018).

Hail events can be identified by examining the maximum radar reflectivity above the freezing level. Reflectivity values exceeding 55 dBZ at these altitudes indicate the presence of large ice particles, which can only develop through repeated accretion processes within vigorous convective clouds (Mason, 1972; Prasetyo dkk., 2022). As shown in Figure 4, particularly through the VCUT (vertical cut) product, maximum reflectivity values exceeding 55 dBZ above the freezing level were observed at 08:18 UTC at point A (106.802, -6.427) and at 08:42 UTC at point B (106.810, -6.420). These observations indicate that the convective system had reached its mature stage, characterized by strong updrafts continuing to lift hydrometeors while downdrafts developed concurrently within the storm (Byers & Braham, 1949; D.

Wang dkk., 2022). Under these conditions, hailstones continued to grow through repeated vertical transport before ultimately falling to the surface as hail.

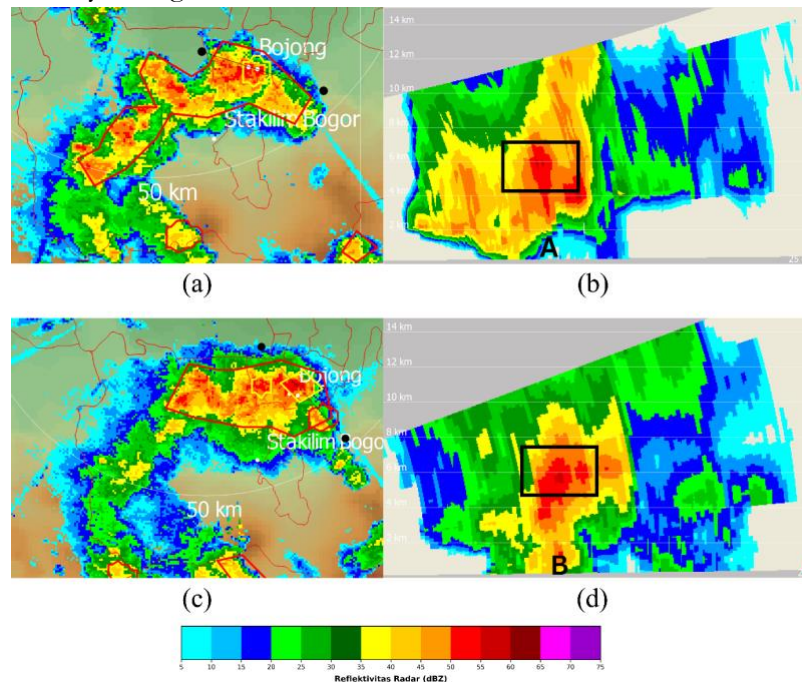


Figure 4. Visualization of maximum reflectivity (>55 dBZ) above the freezing level over Depok City at Point A (08:18 UTC) using (a) CMAX and (b) VCUT (vertical cut), and at Point B (08:42 UTC) using (c) CMAX and (d) VCUT (vertical cut), with black boxes indicating areas of reflectivity exceeding 55 dBZ.

3.2. Hail Identification Using Himawari-9 Satellite Data

Based on the Himawari-9 Band 13 brightness temperature time series in Figure 5, both observation points (Point A and Point B) initially exhibited relatively warm cloud-top temperatures ranging from 20°C to 2°C between 07:00 and 07:40 UTC, followed by a sharp decrease between 07:40 and 08:40 UTC. At 08:18 UTC, marked by the orange line, Point A had reached a cloud-top temperature of approximately -61°C , coinciding with the observed occurrence of hail at that location. Meanwhile, at 08:42 UTC, marked by the black line, Point B recorded a cloud-top temperature of approximately -71°C , close to its minimum value of -72.3°C , coinciding with the observed occurrence of hail at that location. At the same time, Point A had likewise recorded a value of approximately -71°C , close to its own minimum cloud-top temperature of -73.3°C . Following 08:42 UTC, cloud-top temperatures at both points remained relatively stable until 09:00 UTC, after which a gradual warming trend was observed through 10:00 UTC, with Point B exhibiting a brief decrease at 09:50 UTC before resuming its warming trend.

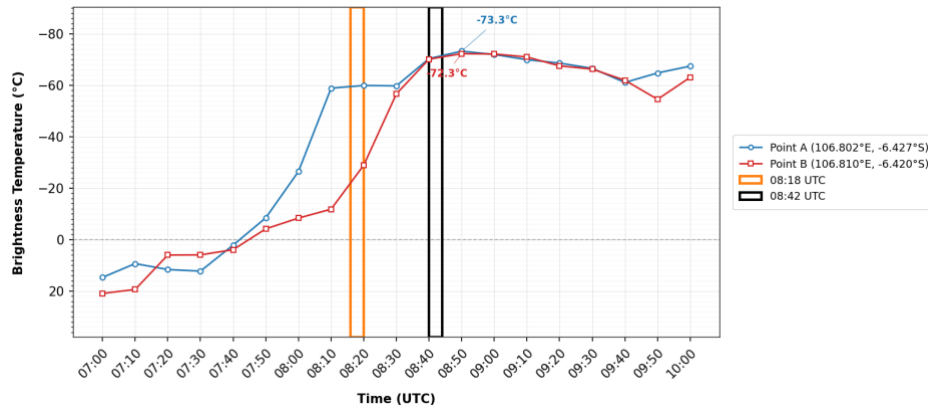


Figure 5. Time series of cloud-top temperature with the orange box indicating the hail event at Point A (08:18 UTC) and the black box indicating the hail event at Point B (08:42 UTC).

Figure 6 presents the results of the Cloud Convective Overlay (CCO) analysis derived from Himawari-9 imagery at 08:20 UTC and 08:40 UTC, illustrating the spatial distribution of Cumulonimbus (CB) cloud coverage in the vicinity of Point A and Point B. At 08:20 UTC, both observation points remained outside the boundary of the CB cloud polygon, which was at that time concentrated in the southwestern portion of the domain, indicating that neither point was yet enveloped by the convective system. By 08:40 UTC, however, the CB cloud coverage had expanded substantially toward the northeast, extending across the entire domain surrounding Depok City and encompassing both Point A and Point B within the CB cloud area.

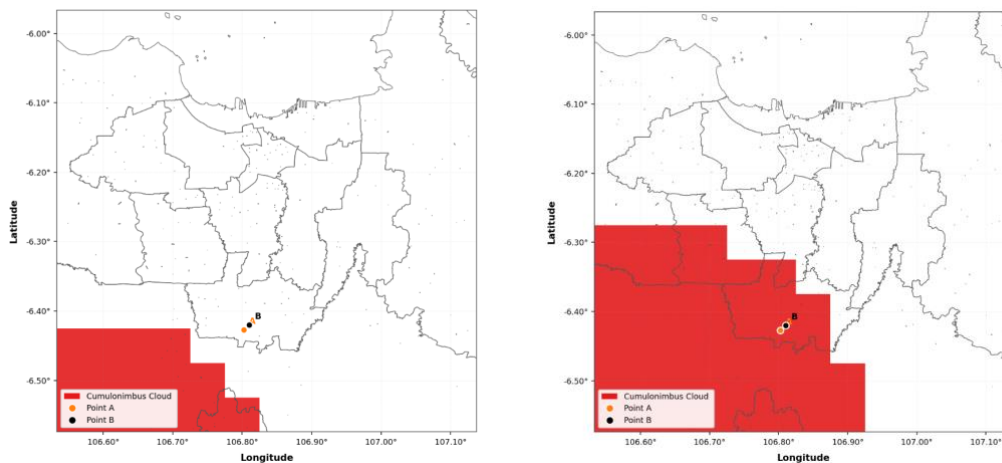


Figure 6. Distribution of cumulonimbus clouds (red) at (a) 08:20 UTC and (b) 08:40 UTC.

3.3. Hail Identification Using ECMWF Data

Figure 7 and Table 2 present the atmospheric thermodynamic profiles (Skew-T Log-P) derived from ERA5 reanalysis at 08.00 UTC and 09.00 UTC, representing atmospheric conditions before and after the hail event, respectively. At 08.00 UTC, CAPE was recorded at 524 J/kg and CIN at 3 J/kg, with a KI of 34.9 and a TT' of 44.6, whereas at 09.00 UTC, CAPE increased to 590 J/kg and CIN to 20 J/kg, with a KI of 33.6 and TT' remaining at 44.6. In addition, the Deep-Layer Shear (DLS 0-6 km) increased from 2.4 m/s at 08.00 UTC to 2.8 m/s at 09.00 UTC, while the Storm Relative Helicity (SRH 0-3 km) decreased from 47.7 m²/s² to 35.4 m²/s², and the Bulk Richardson Number (BRN) decreased from 179.7 to 150.2 over the same period. With respect to the key parcel-lifting levels, the Lifting Condensation Level (LCL) was recorded at 0.90 km at 08.00 UTC and decreased to 0.76 km at 09.00 UTC. The Convective

Condensation Level (CCL) similarly decreased from 1.27 km to 1.21 km, and the Level of Free Convection (LFC) decreased from 1.65 km to 1.62 km, while the Equilibrium Level (EL) was recorded at 13.07 km and 13.13 km at 08.00 UTC and 09.00 UTC, respectively.

Table 2. *Values of Atmospheric Thermodynamic Profile Parameters.*

No.	Parameters	08.00 UTC	09.00 UTC	Unit
1	CAPE	524	590	J/kg
2	CIN	3	20	J/kg
3	KI	34.9	33.6	K
4	TT	44.6	44.6	K
5	DLS (0–6 km)	2.4	2.8	m/s
6	SRH (0–3 km)	47.7	35.4	m ² /s ²
7	BRN	179.7	150.2	
8	LCL	0.90	0.76	km
9	CCL	1.27	1.21	km
10	LFC	1.65	1.62	km
11	EL	13.07	13.13	km

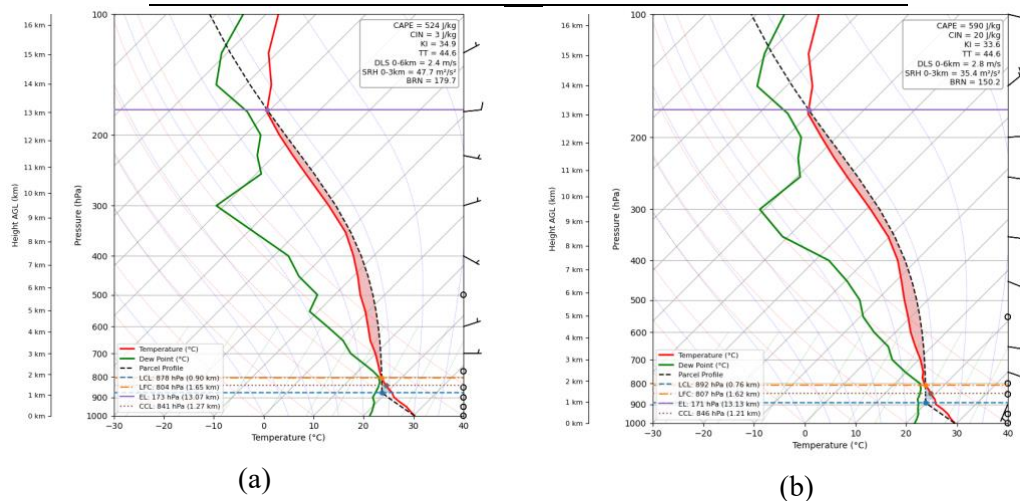


Figure 7. *Atmospheric thermodynamic profiles before the hail event at (a) 08:00 UTC and after the hail event at (b) 09:00 UTC.*

3.4. Radar Reflectivity Predictions During the Hail Event Compared with Radar Observations

Within the black boxes marking the time of the hail occurrence, namely at $t + 8$ min (08.18 UTC) and $t + 32$ min (08.42 UTC) in Figure 8, the UNet-ConvLSTM2D model was able to capture the overall shape and spatial pattern of the radar echo, closely resembling the corresponding ground truth observations at the same location. At $t + 8$ min, the model predicted the presence of a high-reflectivity core (yellow-orange, approximately 40–45 dBZ) at a position relatively consistent with the pattern shown in the observed image, although the maximum observed reflectivity exceeding 55 dBZ was not reproduced. At $t + 32$ min, the model was still able to reproduce the general shape of the echo within the black box area, although the predicted reflectivity intensity, dominated by green values (approximately 25–30 dBZ), appeared lower than the observed intensity, which showed orange-red values exceeding 55 dBZ.

Based on the difference maps presented in Figure 8 for both time steps, the black box area at $t + 8$ min was dominated by white to light blue values, indicating that the model prediction was relatively close to the observed values during that period. At $t + 32$ min, however, a more distinct blue signature was evident within the black box, indicating that the predicted values were lower than the observed values

at the location of the hail occurrence (underestimation). Overall, despite differences in intensity at both hail occurrence times, the model remained capable of capturing the large-scale echo pattern surrounding the event location, as illustrated in Figure 8 (Ravuri dkk., 2021).

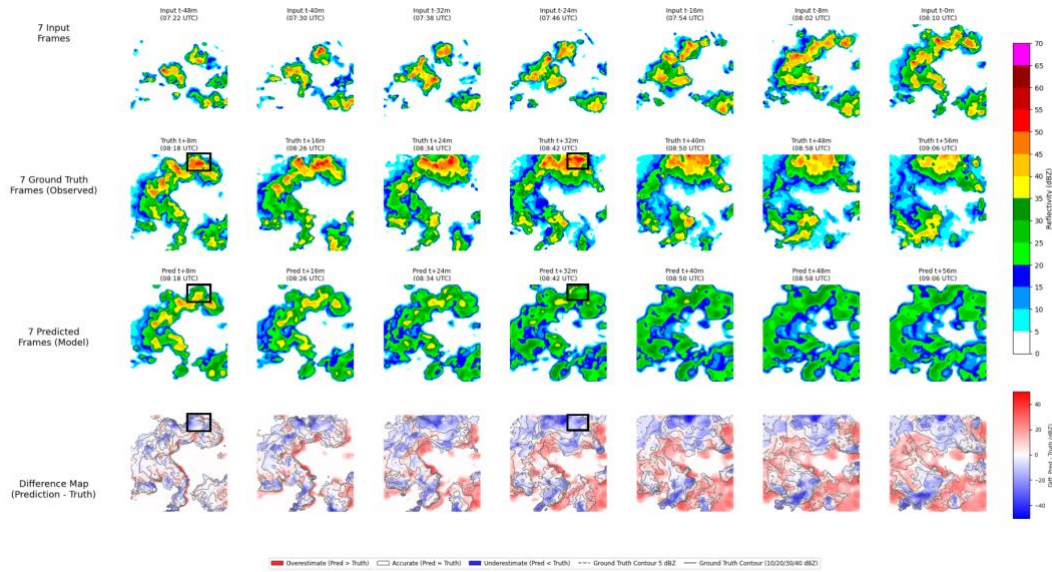


Figure 8. Comparison of radar-based hail predictions and observations from 08:18 to 09:06 UTC, with the black boxes highlighting the predicted and observed hail events at 08:18 and 08:42 UTC.

3.5. Pixel-Based Evaluation of Radar Predictions versus Observations Using MSE, MAE, and SSIM

Based on the pixel-based evaluation results presented in Figure 9, the model achieved average values of 184.5897 for Mean Squared Error (MSE), 9.7081 for Mean Absolute Error (MAE), and 0.3956 for the Structural Similarity Index (SSIM). Both MSE and MAE exhibited an increasing trend with forecast lead time, rising from 67.2978 and 4.6776, respectively, at $t + 8$ min to peak values of 254.3733 and 12.5811 at $t + 48$ min, followed by a slight decrease at $t + 56$ min. In contrast, the SSIM values showed a continuous decline from 0.6220 at $t + 8$ min to 0.2694 at $t + 56$ min, indicating a progressive reduction in structural similarity between the predicted and observed radar reflectivity fields as the lead time increased. At $t + 8$ min to $t + 24$ min, both MSE (67.2978, 117.6453, and 167.2361) and MAE (4.6776, 6.9207, and 8.8888) remained below their respective overall average values of 184.5897 and 9.7081, while SSIM at these lead times (0.6220, 0.5110, and 0.4313) remained above its overall average of 0.3956. From $t + 32$ min onward, MSE and MAE exceeded their respective averages, while SSIM fell below its average.

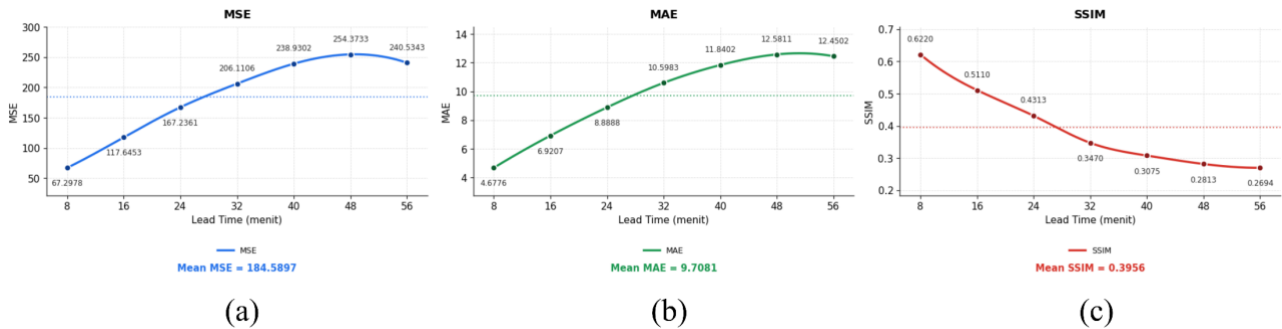


Figure 9. Graph showing the evaluation of hail event predictions using (a) MSE, (b) MAE, and (c) SSIM from 08:18 to 09:06 UTC.

3.6. Evaluation of Reflectivity Threshold Predictions Against Observations Across Lead Times Using CSI and HSS

As shown in Figure 10, the average Critical Success Index (CSI) and Heidke Skill Score (HSS) decreased markedly during the early forecast period (8–24 min) and then declined more gradually toward the longest lead time (56 min). Specifically, the average CSI decreased from 0.588 to 0.284, while the average HSS dropped from 0.637 to 0.057. These results indicate that the model's ability to correctly detect precipitation events (true positives, TP) progressively deteriorated with increasing lead time, accompanied by an increase in both false alarms (FP) and missed detections (FN). A consistent pattern was observed across all reflectivity thresholds. Lower thresholds (5 and 10 dBZ) consistently produced the highest CSI and HSS values throughout the forecasting period, whereas higher thresholds (30 and 40 dBZ) yielded substantially lower scores, approaching zero at longer lead times. These findings indicate that the model becomes increasingly challenged in predicting heavy to extreme precipitation compared with light to moderate precipitation. This is reflected in the average CSI (0.5977, 0.5651, 0.4243, 0.2290, 0.0504) and HSS (0.3021, 0.3593, 0.3504, 0.2610, 0.0725) values for the 5, 10, 20, 30, and 40 dBZ thresholds, respectively, indicating that the model becomes increasingly challenged in predicting heavy to extreme precipitation compared with light to moderate precipitation.

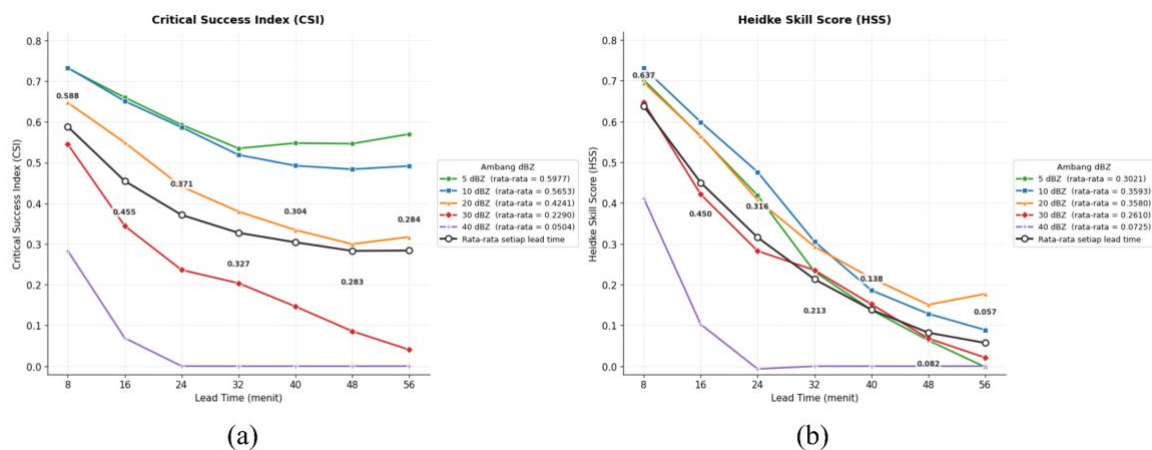


Figure 10. Multi-threshold reflectivity evaluation graph of hail events using (a) CSI and (b) HSS from 08:18 to 09:06 UTC.

4. Discussion

4.1. Atmospheric Conditions Associated with the Hail Event Based on Radar, Satellite, and ECMWF Data

The combined observations from weather radar, Himawari-9 satellite imagery, and ECMWF reanalysis provide a consistent physical interpretation of the convective environment associated with the hail event. The radar observations indicate the development of a strong convective core with enhanced reflectivity extending above the freezing level, which is physically consistent with hail-producing convection because hydrometeors can undergo repeated cycles of vertical transport, freezing, and accretion within vigorous updrafts. Previous radar-based research has similarly associated strong reflectivity above the freezing level with the presence of large ice particles within convective clouds, particularly when accompanied by characteristic signatures of intense convection (Prasetyo dkk., 2022). The Himawari-9 observations provide complementary evidence through the development of very cold cloud tops, indicating substantial

vertical growth of the convective cloud. Similar cloud-top evolution has been documented in other severe convective events in Indonesia and supports the interpretation of deep cumulonimbus development associated with strong updraft activity (Diniyati dkk., 2021; Frystine dkk., 2022; Rumapea dkk., 2022). The atmospheric profile further indicates that the storm developed in an environment characterized by sufficient instability, limited convective inhibition, and relatively weak vertical wind shear. This combination suggests that the development of the convective system was supported primarily by buoyancy and moisture availability rather than strong dynamical organization associated with highly sheared environments. Such characteristics are consistent with previous descriptions of hail-producing convection in tropical maritime environments, where strong convective development can occur under comparatively weak vertical shear (Prasetyo dkk., 2022; Sari & Lasher-Trapp, 2025). The spatial expansion of the cumulonimbus cloud identified by the Cloud Convective Overlay also complements the radar observations by illustrating the progressive development of the cloud shield around the event area. Together, the three datasets indicate that the hail event resulted from the interaction of thermodynamic instability, deep cloud development, and hydrometeor growth within a rapidly evolving convective system rather than from a single atmospheric factor.

4.2. Model Performance Against Radar Observations Across Lead Times and Reflectivity Thresholds

The comparison between predicted and observed radar fields indicates that the model is able to reproduce the general spatial organization of the convective system, particularly during the earlier stages of prediction. The correspondence becomes weaker as the forecast horizon increases, with localized convective structures being more difficult to preserve than broader and more coherent echo patterns. This behavior can be interpreted in relation to the nonlinear evolution of convective systems, where echo structures are continuously modified by the growth and decay of convective cells, hydrometeor development, and interactions among neighboring cells. Previous radar nowcasting studies have similarly shown that prediction correspondence tends to deteriorate as the forecast horizon increases, particularly for rapidly evolving precipitation systems (Ayzel dkk., 2020; Naz dkk., 2025a). Thus, the observed degradation is not necessarily indicative of a specific deficiency of the proposed architecture, but reflects the increasing uncertainty associated with the future state of a nonlinear atmospheric system.

A similar pattern emerges when the predictions are considered across different reflectivity intensities. The model is more consistent in representing the broader low to moderate reflectivity structures, while highly intense convective regions are more difficult to reproduce, particularly as prediction uncertainty increases. This behavior can be related to the uneven distribution of reflectivity intensities in radar observations, where intense convective structures occupy a relatively limited portion of the observed field. The use of Mean Squared Error as the training objective can further favor predictions that remain close to the dominant distribution of the target field, producing smoother representations and reducing the magnitude of localized extremes when several future states are plausible (Naz dkk., 2025a; Shi dkk., 2015b; Zhang dkk., 2023). Previous studies have reported comparable difficulties in maintaining high intensity precipitation structures during radar nowcasting, supporting the interpretation that the reduced representation of convective extremes is associated with both the statistical characteristics of the data and the nonlinear nature of storm evolution (Ayzel dkk., 2020; Naz dkk., 2025a; Shi dkk., 2015b; Trebing dkk., 2021).

The combined behavior across forecast horizon and reflectivity intensity indicates that the principal challenge is not simply the displacement of the storm system, but the representation of its rapidly changing internal structure. Large scale and relatively persistent features provide stronger spatial and

temporal continuity for the model to learn, whereas localized intense cores are more sensitive to small scale atmospheric processes that evolve rapidly and are therefore less predictable. This distinction is particularly important for hail producing convection because the most intense regions of a storm are closely related to the development and growth of hydrometeors. The results therefore suggest that future improvements in radar nowcasting should place greater emphasis on preserving localized convective structures while retaining the broader spatial organization of the storm. Such improvements may involve alternative objective functions or modeling strategies that better represent extreme reflectivity and the uncertainty associated with rapidly evolving convection (Naz dkk., 2025b; Rahimi dkk., 2024; Zhang dkk., 2023).

4.3. *Implications*

The findings of this study have broader implications for the application of computational methods in atmospheric physics. Radar reflectivity can be interpreted not only as an observational product, but also as a spatio-temporal representation of the evolving physical state of a convective system. Changes in the radar echo field contain information about the development, movement, intensification, and decay of hydrometeor populations. By learning these evolving patterns, the deep learning framework provides a computational representation of atmospheric dynamics that complements conventional observational analysis. The integration of spatial feature extraction with temporal modeling is particularly relevant for convective systems because their evolution involves both the organization of individual cells and the temporal interaction among these structures.

From the perspective of physics, this study contributes by connecting atmospheric observation, remote sensing, and computational modeling within a unified framework for investigating nonlinear atmospheric phenomena. Radar observations provide information on hydrometeor distribution, satellite observations describe the evolution of the cloud structure, and atmospheric reanalysis provides the broader thermodynamic and kinematic context. Their integration allows the convective system to be interpreted as a coupled physical process rather than as a collection of independent variables. At the same time, the difficulty in preserving localized intense structures demonstrates that data-driven models remain constrained by the nonlinear nature and predictability limits of the atmosphere. These findings provide a basis for further development of radar nowcasting methods that can better preserve convective extremes while maintaining a physically meaningful representation of storm evolution.

5. Conclusion

Analysis of the three observational datasets confirms the physical characteristics of the hailstorm event in Depok City on 28 October 2024. Radar data show reflectivity exceeding 55 dBZ above the freezing level at 08.18 UTC at Point A and 08.42 UTC at Point B, consistent with cloud-top temperatures derived from Himawari-9 imagery reaching approximately -61°C to -73°C at both points. ERA5 reanalysis data indicate a moderately unstable tropical maritime environment, characterized by CAPE of 524-590 J/kg, CIN of 3-20 J/kg, persistently weak vertical wind shear of 2.4-2.8 m/s, and low LCL, CCL, and LFC heights of 0.76-1.65 km, reflecting a relatively moist near-surface layer. Together, these three datasets confirm a convective core with very cold cloud tops and weak vertical shear, a combination typical of hail-producing environments in tropical maritime regions. Radar prediction evaluation yielded average values of 184.5897 for MSE, 9.7081 for MAE, and 0.3956 for SSIM, with CSI decreasing from 0.588 to 0.284 and HSS from 0.637 to 0.057 as lead time increased from 8 to 56 minutes, demonstrating that the hybrid UNet-ConvLSTM2D model performed well at short lead times but degraded at longer lead times

and higher reflectivity thresholds. These findings are expected to strengthen understanding of the atmospheric dynamics underlying hail occurrence and to support the development of deep learning-based nowcasting for early warning of hydrometeorological hazards in Indonesia.

Authors Contribution

Muhizzadin Abdul Adzan: Data curation, Software, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. **Deni Septiadi:** Data curation, Validation, Supervision, Writing – review & editing. **Adi Mulsandi:** Methodology, Validation, Writing – review & editing. **Latifah Nurul Qomariyatuzzamzami:** Methodology, Validation, Writing – review & editing.

Ethical statement

This study is based on weather radar observations and computational modeling and does not involve human participants or animals. Therefore, formal ethical approval was not required. The radar data used in this study were obtained from the Soekarno–Hatta Class I Meteorological Station, BMKG, for research purposes. No personal or sensitive data were collected, processed, or analyzed.

Declaration of AI Use

The authors used ChatGPT (OpenAI) to assist in improving the clarity, coherence, and academic writing of the manuscript. DeepL was used to translate the original manuscript from Indonesian into English, ensuring clear, accurate, and well-structured language. Grammarly was used for English grammar, spelling, punctuation, and style checking. In addition, Claude (Anthropic) was used to assist in organizing the conceptual framework and improving the logical flow of the manuscript. All AI-assisted outputs were carefully reviewed, verified, and revised by the authors. The authors take full responsibility for the accuracy, originality, scientific content, and integrity of the final manuscript.

Conflict of Interest

The authors declare that there are no financial or non-financial conflicts of interest that could have influenced the work reported in this manuscript. All authors have reviewed and approved this statement.

Supplementary Materials and Data Availability

The weather radar datasets used in this study were obtained from the Soekarno–Hatta Class I Meteorological Station, BMKG, and are not publicly available due to institutional data access policies. Data may be made available by the corresponding author upon reasonable request and subject to permission from BMKG. No additional supplementary materials are associated with this manuscript.

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