Performance of Nowcasting Algorithms for Ground-based Radar Precipitation Estimates during Cloud Seeding Period in Northern Thailand

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Abstract

Nowcasting typically refers to the prediction of weather conditions on very short time scales, ranging from a few minutes up to two hours. This approach leverages real-time remote sensing data, such as ground-based weather radar imagery, along with extrapolation techniques to provide highly accurate and timely weather forecasts. Beyond its benefits to meteorology and hydrology, nowcasting is also crucial for weather modification operations. In Thailand, cloud seeding plays a significant role in enhancing rainfall to meet the demands of agriculture and reservoir management, as well as in mitigating natural disasters. This research aims to assess the skill of nowcasting based on convective and stratiform events, which are systematically selected from rainfall characteristics and spatial patterns. Our focus area is located in the northern part of Thailand, where an S-band ground-based weather radar is operated by the Department of Royal Rainmaking and Agricultural Aviation, installed at Omkoi district, Chiang Mai. The radar observes every six minutes for volume scanning in 14 elevation angles covering an effective radius of 240 kilometers. This provides data for weather monitoring, a critical process for detecting seedable clouds. In the prediction process, radar reflectivity is firstly converted to rain rate using the Z-R relationship. Subsequently, three algorithms from the Rainymotion open-source projects —Eulerian Persistence, Sparse, and DenseRotation—are employed as prediction models to compare nowcasted rainfall for the next hours. Finally, to evaluate nowcasting performance, evaluation metrics such as mean absolute error (MAE) and critical success index (CSI) are calculated. The results show that the Sparse model offers the most accurate numerical predictions, especially for longer lead times, as indicated by lower MAE. Meanwhile, the DenseRotation model is the most effective at predicting rainfall events across different intensities and time frames, as reflected by its high CSI scores. This study highlights the value of nowcasting models, such as DenseRotation, in improving decision-making for weather modification operations.

Keywords: Nowcasting, Weather Radar, Radar Nowcasting, Precipitation Nowcasting, Cloud Seeding

1. Introduction

Nowcasting refers to the prediction of short-term events, typically spanning a time frame of minutes to a few hours. This involves using real-time data to forecast immediate changes in weather conditions, such as rain, thunderstorms, or temperature shifts. The importance of nowcasting lies in its ability to provide timely and highly localized predictions. Unlike longer-term forecasts, nowcasting focuses on rapid changes in conditions, making it invaluable in scenarios where real-time decision-making is critical. In weather forecasting, for instance, nowcasting can help authorities issue timely alerts to reduce damage from sudden storms or floods. Similarly, in cloud seeding, nowcasting allows rainmakers to determine the most opportune moments and locations for weather modification operations.

Cloud seeding is an advanced weather modification technique aimed at artificially inducing or enhancing precipitation, often used to combat droughts or mitigate other disasters: hail, wildfires, air pollution. In Thailand, cloud seeding has been a key component of the country's water management strategy, especially given the nation's frequent droughts and agricultural dependence on consistent rainfall. The approach to cloud seeding was initiated by His Majesty King Bhumibol Adulyadej in the 1950s. The process begins with identifying suitable clouds through extensive weather monitoring, including the use of radar systems and weather satellites. Once the target clouds are located, aircraft are deployed to disperse chemicals like sodium chloride, calcium chloride, and urea into the clouds depending on the seeding methods. However, before taking off, scientists must predict the target coordinates and submit the flight plan to air traffic control at least 1 hour in advance. Therefore, short-term forecasts become important and significantly affect the success of the operation."

Currently, there are various nowcasting techniques, ranging from traditional methods using image processing techniques such as optical flow (eg., Ayzel et al., 2019), to machine learning techniques (eg., Ayzel et al., 2020) and even large artificial intelligence models (eg., Ravuri et al., 2021). However, when exploring suitable nowcasting techniques, it is crucial to experiment with benchmark methods to establish a foundational reference for further development. Therefore, for this experiment, we chose the nowcasting technique from the open-source project “rainymotion”, proposed by Ayzel et al. (2019), which serves as an open benchmark for radar-based precipitation nowcasting. Radar data was obtained from the Department of Royal Rainmaking and Agricultural Aviation’s radar stations. Evaluation events were selected based on rain intensity measurements from the Hydro Informatics Institute

(Public Organization)'s rain gauges. Finally, the results will be assessed using the mean absolute error (MAE) and the critical success index (CSI).

2. Methods and Data

2.1 Study Area

In this study, the research area is in the upper northern region of Thailand, which is significant due to the high diversity of weather modification missions in the area. These missions include rainmaking to support agricultural areas, reservoirs, mitigating the severity of hailstorms, reducing the impacts of wildfires and haze, and air pollution. The Omkoi weather radar station, operated by the Department of Royal Rainmaking and Agricultural Aviation, located in Omkoi District, Chiang Mai Province (Latitude: 17.7982, Longitude: 98.4323, Altitude: 1,173 meters), is responsible for monitoring the weather conditions and cloud formations in this region. The radar extent coverage 240 kilometers around the station. Additionally, there are 170 rain gauges located within the radar's detection range, as shown in Figure 1.

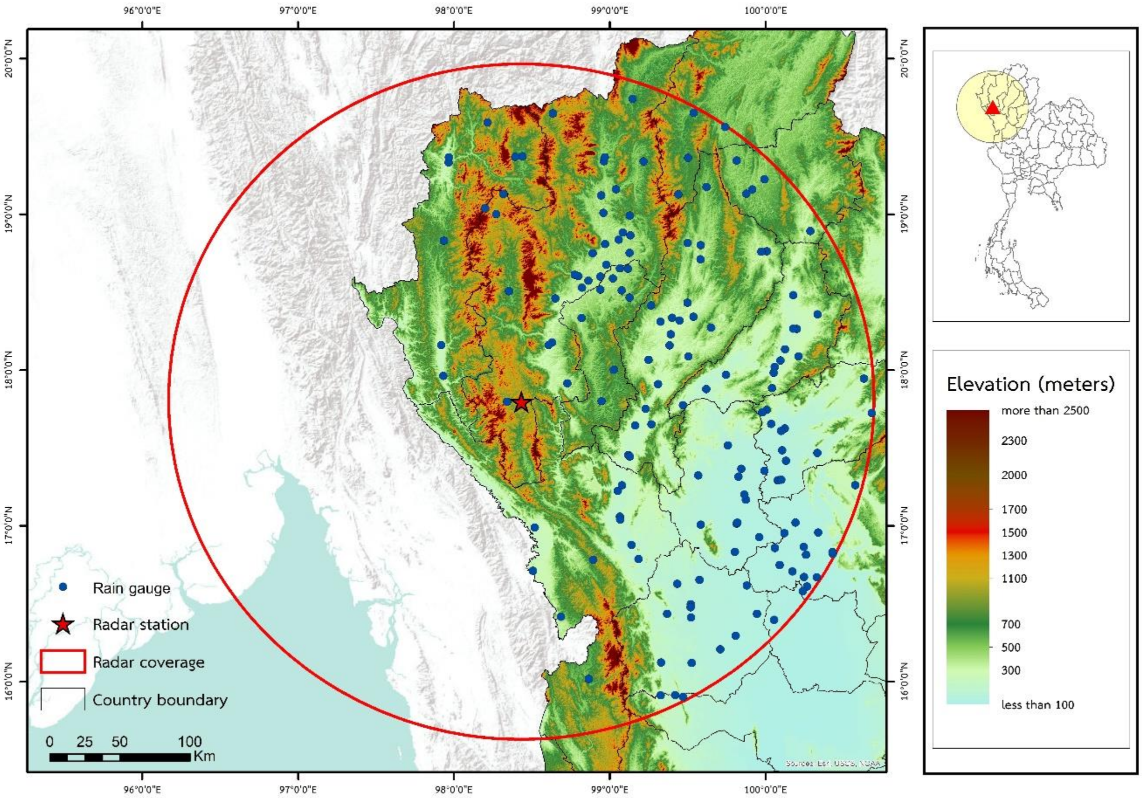

Figure 1: Map of study area. The map displays the scanning coverage of the Omkoi weather radar station, which has a radius of 240 kilometers.

2.2 Radar Data

The Omkoi weather radar is S-band dual polarization doppler radar, operating in VCP 11 mode. In this experiment, we used raw radar data during January to December 2018 and processed these to rain rate. The corrected reflectivity data that passed quality control process from the station will be converted into CAPPI images at a height of 2.5 kilometers. After that, corrected reflectivity greater than 53 dBZ, typically indicative of hail (Fulton et al., 1998), will be filtered out, and values below 15 dBZ, considered signal noise (Chantraket et al., 2016a; 2016b; 2022; Mapiam et al., 2009), will be removed.

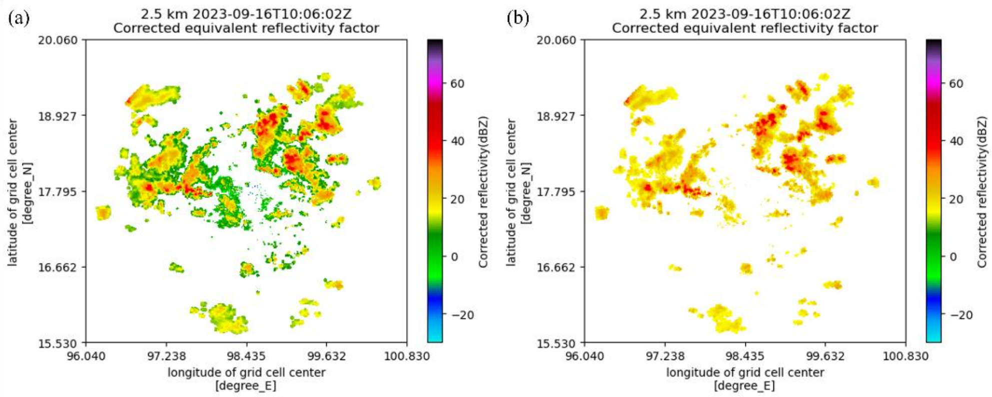

Figure 2: Corrected reflectivity (a) before filtering and (b) after filtering.

Rainfall intensity estimates will be derived using the ZR relationship equation, specifically the Marshall-Palmer relationship, which is applicable to the selected events, encompassing both stratiform and convective precipitation (Mahavik et al., 2021).

$$Z = 200R^{1.6}$$

Spatial and temporal resolution of the radar-based precipitation product is 1x1 km and 6 min, respectively. The entire radar data processing was performed using the Py-ART library, developed by Helmus and Collis (2016).

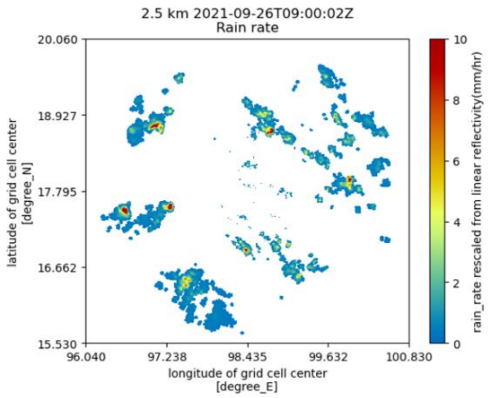

Figure 3: Example radar-based precipitation product.

2.3 Evaluation Events

To classify rainfall events, the criteria from Tokay and Short (1996) were adopted. The thresholds for the stratiform rain type were set at 1, 2, and 5 mm/h for very light, light, and moderate rain, respectively. In contrast, the convective rain type includes 10, 20, and more than 20 mm/h for heavy, very heavy, and extreme rainfall, respectively. Subsequently, the selection process was conducted in conjunction with the radar data completeness on the dates of the selected events based-on daytime of seeding operation, starting from 00Z to 12Z.

Table 1: Summary of selected events

	Date	Time (UTC)	Duration (hours)	Maximum rain (mm/h)	Rain category	Rain type
1	2021-05-07	07:00 – 08:00	1	1	Very light	Stratiform
2	2021-05-11	04:00 – 12:00	8	1.8	Light	
3	2021-05-14	07:00 – 12:00	5	2.4	Moderate	
4	2021-04-20	06:00 – 12:00	6	8	Heavy	Convective
5	2021-09-26	00:00 – 12:00	12	19.4	Very Heavy	
6	2021-10-30	00:00 – 12:00	12	32.6	Extreme	

2.4 Nowcasting Algorithms

In this research, two nowcasting algorithms from the rainymotion open-source project were employed: Sparse and DenseRotation. These algorithms are widely recognized for their efficiency in radar-based precipitation nowcasting, leveraging optical flow methods to track and extrapolate over short periods. Eulerian persistence was used as the benchmark for this experiment.

The Sparse algorithm, core idea behind this group of methods is to identify distinct features in a radar image suitable for tracking. A feature is defined as a sharp gradient point of rainfall intensity, often referred to as a corner. This method is more universal and less arbitrary than traditional approaches, which track storm cells as contiguous objects. Unlike classical methods, this approach focuses on the gradient sharpness in the neighborhood of a cell, eliminating the need to define arbitrary or scale-dependent precipitation features. Within this framework, two models were developed that differ slightly in terms of tracking and extrapolation techniques. In this study, for sparse group we selected Sparse model that utilizes the 24 most recent radar images, focusing only on features that remain persistent throughout the entire 24-time steps, then extrapolation by linear regression technique.

The DenseRotation algorithm, The Dense group of models uses the Dense Inverse Search (DIS) algorithm by default. DIS estimates the velocity of each image pixel by analyzing two consecutive radar images. It was chosen as the default for motion field retrieval due to its superior accuracy and computational efficiency compared to other optical flow algorithms. The main difference between the two approaches is that the semi-Lagrangian extrapolation scheme enables the representation of large-scale rotational movements while assuming that the motion field remains constant.

The Eulerian persistence model is a simple benchmark that assumes the precipitation field remains unchanged over any lead time. Despite its simplicity, this model is quite effective for very short lead times. Additionally, its performance during verification serves as a good indicator of how quickly temporal correlations decay in different weather events.

2.5 Evaluation Metric

The performance of the nowcasting algorithms is evaluated using two key metrics: Mean Absolute Error (MAE) and Critical Success Index (CSI). These metrics assess the accuracy and reliability of the nowcasted compared to actual data.

Mean Absolute Error (MAE) measures the average magnitude of the errors between the nowcasted and observed rainfall intensities. It is calculated by taking the absolute differences between the predicted and actual values and then averaging these differences over the entire dataset. The formula for MAE is:

$$MAE = \frac{\sum_{i=1}^{n} |nowcasted_i - observed_i|}{n}$$

Critical Success Index (CSI), also known as the Threat Score, evaluates the proportion of correctly predicted precipitation events relative to the total number of observed events. It is calculated by comparing the nowcasted precipitation events to the observed events, considering both true positives and false positives and negatives. The formula for CSI is:

$$CSI = \frac{hits}{hits + false\ alarms + misses}$$

For the CSI calculation, the rain rate thresholds from the studies of Bower et al. (2006) and Foresti et al. (2016) were adopted: 0.125, 0.25, 0.5, 1, and 5 mm/h.

3. Result and Discussion

During the nowcasting process, each selected event was analyzed using the Sparse, DenseRotation, and Persistence models, generating predictions up to 1 hour ahead, divided into 10 lead times at 6-minute intervals. The forecast results were compared with the actual observations at each corresponding time interval. Subsequently, the performance was evaluated and reported using the Mean Absolute Error (MAE) as a continuous score (where a lower value indicates better performance) and the Critical Success Index (CSI) as a categorical score (where a higher value indicates better performance). An example of radar-based precipitation nowcast is shown in Fig. 4.

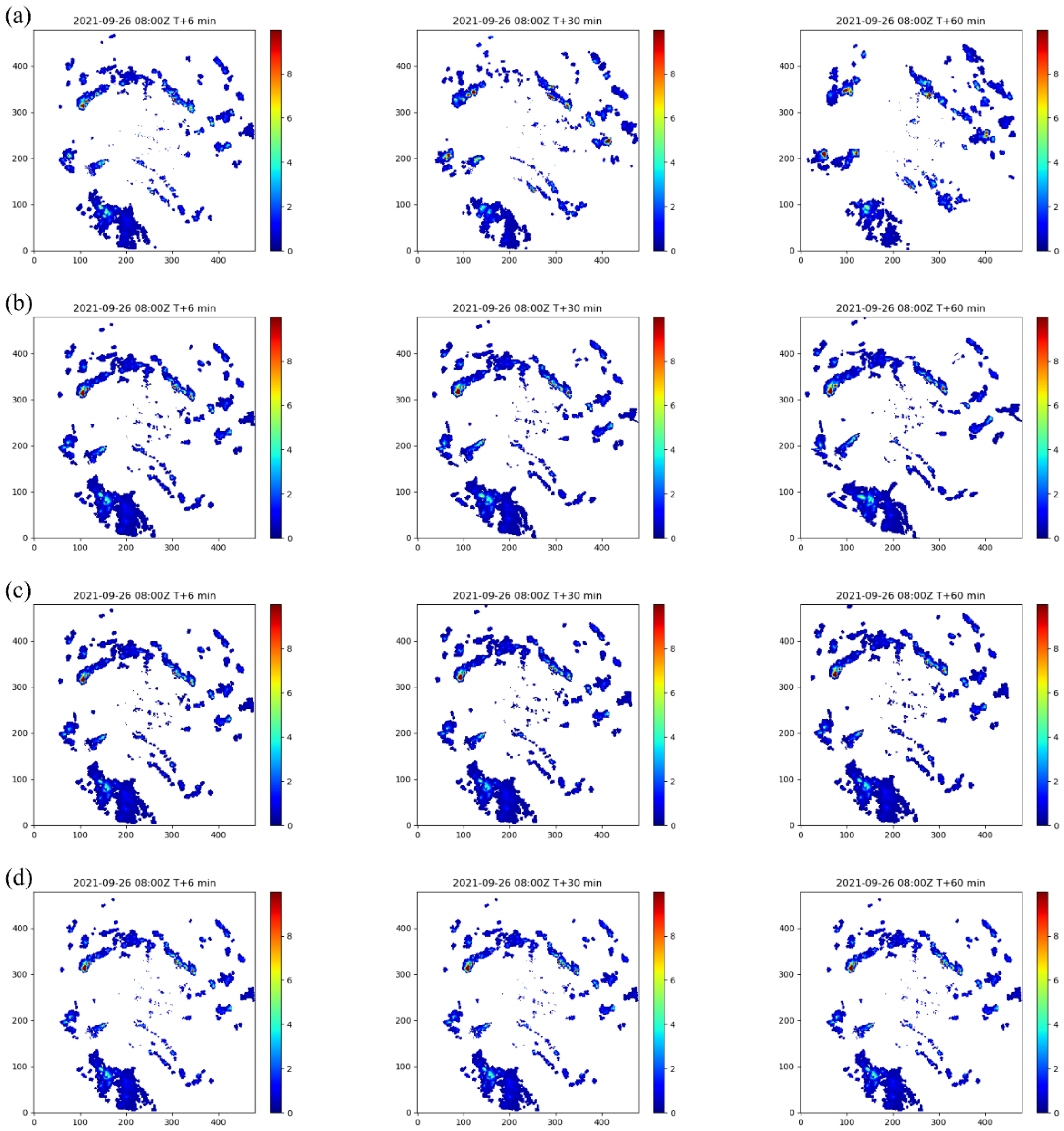

Figure 4: Example radar-based precipitation nowcasting (a) ground truth, (b) DenseRotation, (c) Sparse and (d) Persistence.

The MAE results are displayed for various lead times, ranging from 0 to 60 minutes as shown in Fig. 5. Firstly, the Sparse model consistently demonstrates the lowest MAE values, indicating better performance in predicting rainfall intensity compared to the other models, particularly for longer lead times. The DenseRotation model performs comparably to the Sparse model, often showing slightly higher MAE values but still outperforming the Persistence model in most cases. Overall, the MAE results suggest that the Sparse model is the most accurate for nowcasting precipitation over both short and longer lead times, while DenseRotation offers reasonable performance. The Persistence model is less effective as the lead time increases.

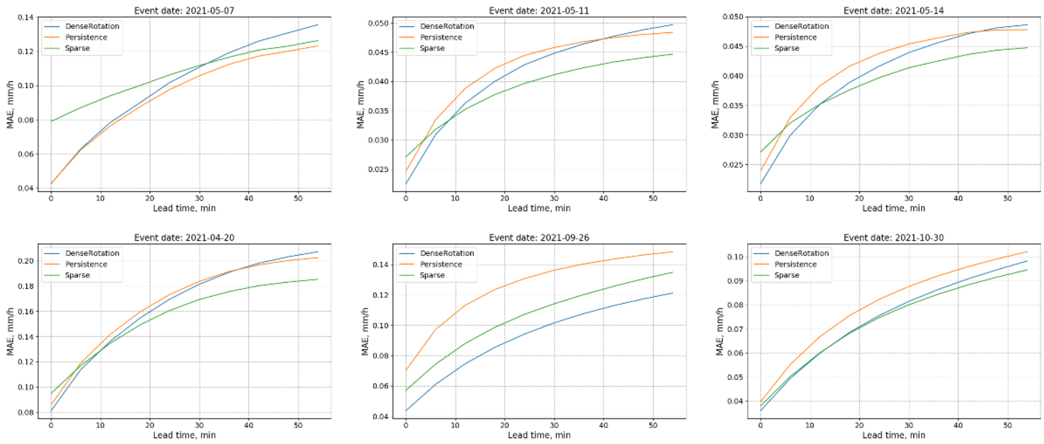

Figure 5: Mean Absolute Error (MAE) of different nowcasting models.

Meanwhile, based on the performance evaluation using the CSI, the DenseRotation model demonstrated better effectiveness than the other models in all events. For example, Fig. 6. Show the CSI on event date: 14 May 2021 as a representative of the stratiform group. The figure shows the DenseRotation model consistently outperforms the Persistence and Sparse models across all thresholds and lead times, indicating higher effectiveness in predicting rainfall events.

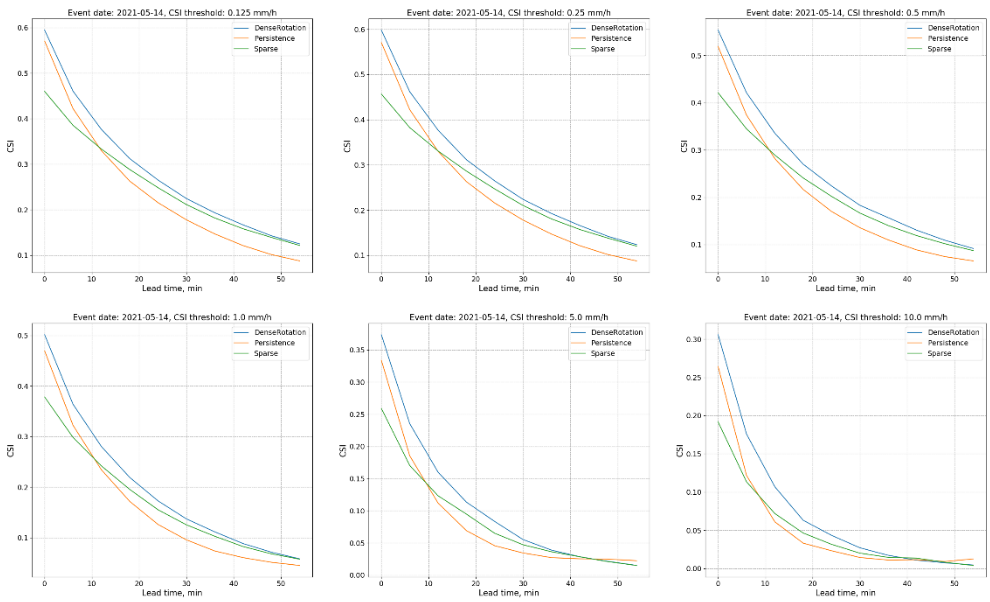

Figure 6: Critical Success Index (CSI) for the event date: 14 May 2021.

Next, Fig. 7, the analysis results for the case of the convective rainfall event on 20 April 2021, which experienced heavy rainfall, revealed that: the DenseRotation model consistently achieves higher CSI scores than the Sparse and Persistence models across all rainfall thresholds and lead times, indicating its superior ability to predict rainfall events. To confirm that, the case of the very heavy rainfall on 26 September 2021 which has longer duration (12 hours) was shown in Fig. 8.

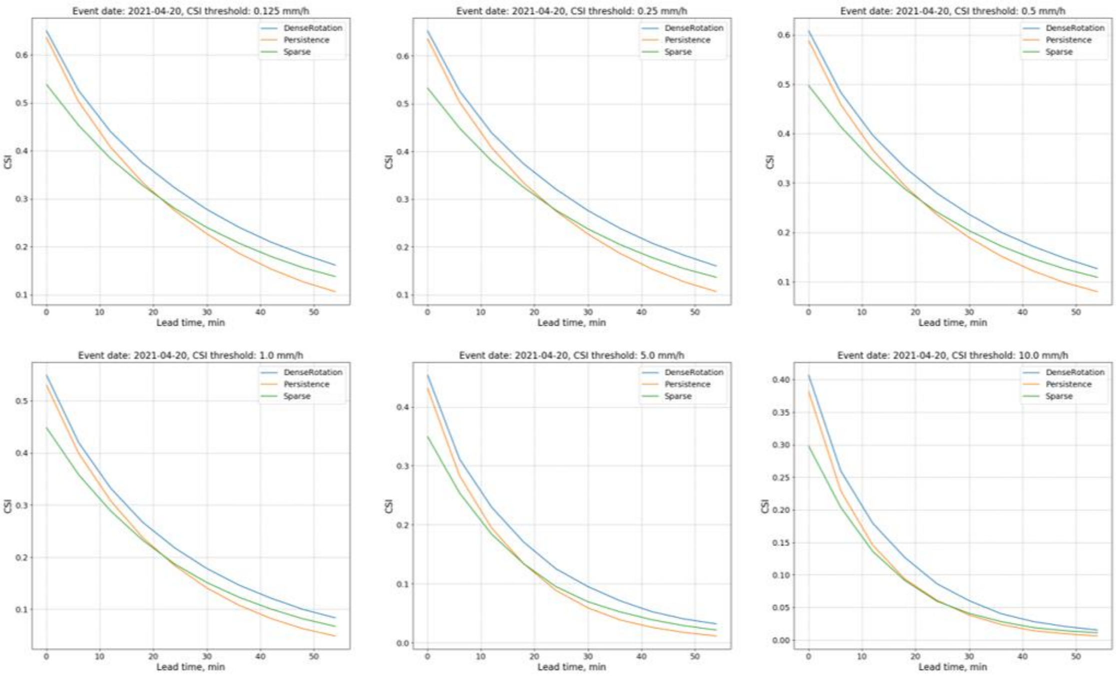

Figure 7: Critical Success Index (CSI) for the event date: 20 April 2021.

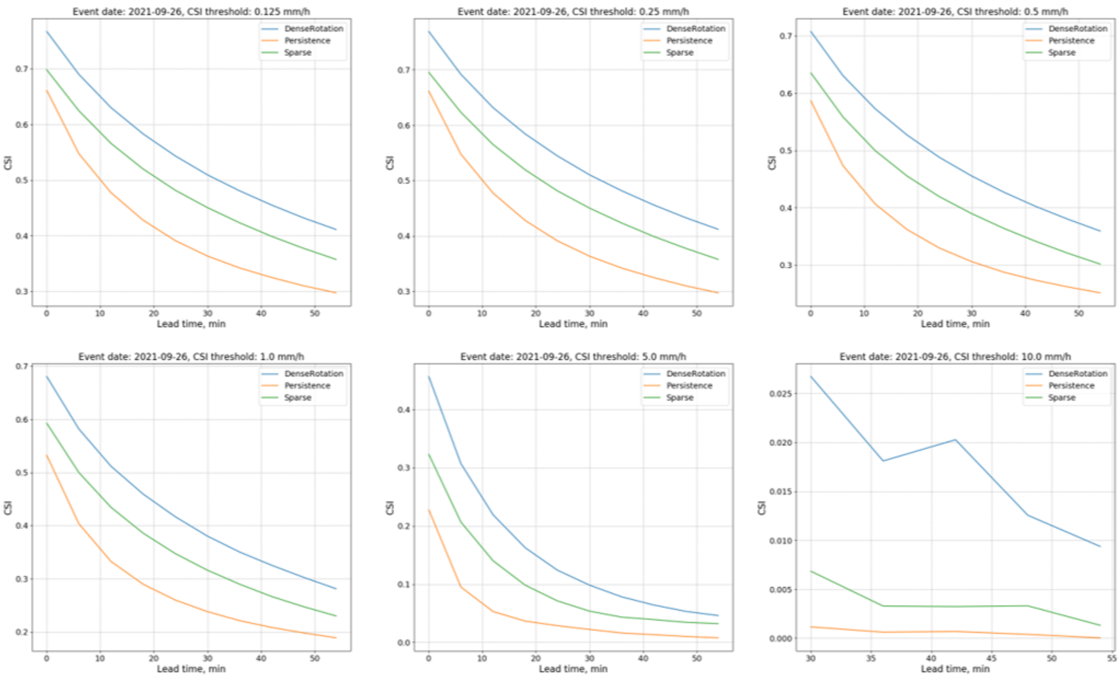

Figure 8: Critical Success Index (CSI) for the event date: 26 September 2021.

Notably, at the highest threshold (10 mm/h), the DenseRotation model exhibits significant variability in CSI values, indicating potential challenges in forecasting extreme rainfall events accurately at longer lead times. Overall, from CSI results, the DenseRotation model demonstrates the best performance across most thresholds and lead times, reaffirming its robustness for nowcasting precipitation events, while, from MAE, the Sparse model is the most accurate if numerical accuracy is desired.

4. Conclusion

This research demonstrates the effectiveness of nowcasting algorithms for radar-based precipitation estimation during cloud seeding operations in Northern Thailand. By employing the Sparse, DenseRotation, and Persistence models, we were able to evaluate their performance in predicting rainfall for different types of events, including both stratiform and convective rainfall.

The results indicate that the Sparse model provides the most accurate numerical predictions in terms of Mean Absolute Error (MAE), particularly over longer lead times. On the other hand, the DenseRotation model consistently achieved the highest scores in terms of the Critical Success Index (CSI), suggesting its superior effectiveness in forecasting rainfall events across various intensity thresholds and lead times. The Persistence model, while useful for very short lead times, showed comparatively lower performance in both MAE and CSI metrics, underscoring the limitations of simpler models in complex weather conditions.

Overall, this study highlights the value of advanced nowcasting models like DenseRotation for real-time decision-making in weather modification operations. It also emphasizes the importance of using a combination of different evaluation metrics, such as MAE and CSI, to comprehensively assess model performance. Future work could focus on further refining these models and incorporating additional data sources to enhance their accuracy and reliability, particularly for extreme weather events.

These findings will contribute to developing more robust cloud monitoring systems and optimizing weather modification activities in Thailand, ultimately supporting agriculture, water resource management, and disaster mitigation efforts.

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