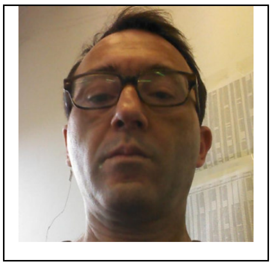
Nowcasting Techniques for Short-Term Weather Forecasts Using Radar Data

Alessandro Mazza [1,2], Andrea Antonini [2], Alberto Ortolani [1,2], Samantha Melani [1,2],

[1] CNR IBE, Via Madonna del Piano 10, Sesto Fiorentino (FI) 50019, Italy
[2] LaMMA Consortium, via Madonna del Piano 10, Sesto Fiorentino (FI) 50019, Italy;



Alessandro Mazza

1 Introduction

Short-term weather forecasts using radar measurements predict precipitation within minutes to a few hours, aiding various fields such as severe weather monitoring, airport operations, and planning of sporting events. Radar forecasts are especially crucial during severe weather conditions like storms, as they provide real-time data that enhances weather alert systems and emergency preparedness.

In airports, accurate precipitation forecasting is vital for air traffic management, flight safety, and scheduling. Similarly, for outdoor sports events, reliable forecasts ensure the safety of participants and spectators by enabling informed decisions about schedule adjustments.

This study implemented a precipitation nowcasting procedure in the Tuscany region to provide accurate forecasts over various areas. The method chosen aims to be compatible with cost-effective hardware without sacrificing performance. While recent advancements in machine learning, especially deep neural networks, have improved nowcasting, their computational demands are high. Therefore, a deterministic nowcasting method was selected for this study, as it balances quality and computational efficiency.

The chosen method, described by Ayzel et al. [1], was applied to data from the radar network of the Italian Civil Protection in Tuscany, covering all precipitation phenomena from January 1, 2022, to December 31, 2023. The study aimed to determine the impact of area size on forecast quality, assessed through Critical Success Index (CSI) and Mean Absolute Error (MAE). The analysis revealed that nowcasting quality depends on the persistence of rainfall intensity and is generally better for stratiform than convective phenomena due to the latter's variability.

The paper is structured as follows: Section 2 describes the nowcasting technique and chosen procedure, introduces evaluation indices, and details the radar network. Section 3 presents the dataset. Section 4 presents the results and analysis of the nowcasting procedure. Section 5 concludes the study.

2 Methodology

2.1 The nowcasting technique

Nowcasting techniques for precipitation using radar measurements can be categorized into three groups based on the hypothesis of the precipitation field characteristics: climatology-based forecasts, recent observation-based predictions, and Lagrangian methods. Lagrangian methods, which assume the persistence of precipitation intensity and movement, are particularly accurate. They involve two phases: tracking the precipitation velocity field from consecutive radar images and predicting the rainfall field using this velocity data.

This study implemented four radar-based nowcasting procedures within a Lagrangian framework [1], divided into two categories: "sparse" and "dense." The sparse group identifies features for tracking using either the two most recent radar images (SparseSD) or the 24 most recent images (Sparse). The dense group employs the Dense Inverse Search algorithm (DIS) for pixel velocity estimation, with procedures differing in extrapolation methods: constant vector advection (Dense) and Lagrangian advection (DenseRotation). DenseRotation, which predicts rotational motions, was found to be the most accurate despite its higher computational demands. Due to the hardware capabilities available for this study, DenseRotation was adopted for its superior predictive accuracy.

All procedures are available in the Python library raynimotion; the source code and the documentation can be found in a GitHub repository (https://rainymotion.readthedocs.io).

2.2 Evaluation Method

To assess the accuracy of precipitation nowcasting, we used two indices: the Critical Success Index (CSI) and the Mean Absolute Error (MAE).

Critical Success Index (CSI):

$$CSI = \frac{hits}{hits + false\ alarms + misses}, \quad (1)$$

 corresponding author email:

Where hits are the correct predictions, false alarms the incorrect predictions, and misses the missed event. A threshold of 1 mm/h for rain rate was used, based on studies by Bowler and Foresti [2,3]. CSI evaluates predictive accuracy, where a value of one indicates perfect predictions. It captures the temporal evolution of the weather phenomenon effectively.

Mean Absolute Error (MAE):

$$MAE = \sum_{i=1}^{N} \frac{|M_i - P_i|}{N}, \tag{2}$$

Where M_i and P_i are the measured and predicted rain rates for the i-th pixel, and N is the total number of pixels. MAE measures the average error between the predictions and actual measurements, providing a straightforward quantitative assessment of forecast accuracy.

3 Dataset

The dataset is the radar measurements within the Tuscany region of civil protection [4]. The measurements have been acquired from January 1, 2022, to December 31, 2023 and The SRI (Surface Rainfall Intensity) product was utilized.

4 Results

To assess the influence of area size on nowcasting accuracy, the procedure was applied to areas of 1, 1.5, and 2 degrees on each side, centered at coordinates 43.75 North, 11.25 East. We analyzed all precipitation phenomena with an average rain rate (Avg_RR that is the average of the rain rate on the pixels of the image) greater than 0.5 mm/h at peak intensity. These included both convective (intense, localized rainfall) and stratiform (less intense, widespread rainfall) phenomena, covering the entire duration from start to end, including low-intensity moments.

The analysis demonstrated that nowcasting is more reliable when the mean precipitation value varies less, as the model assumes the persistence of the rainfall regime. When this assumption holds (e.g., Figure 1 shows good persistence for about 70 minutes), nowcasting remains consistent. Conversely, if the rainfall regime is not persistent (e.g., Figure 2), nowcasting quality deteriorates rapidly.

Stein and Hewson [5,6] proposed the deterministic limit as a criterion for determining whether the nowcasting was sufficiently reliable, which is a threshold CSI value of 0.5, corresponding to a 50 percent hit rate of all cases. We observed that a CSI value greater than or equal to 0.5 corresponds to a nowcasting that is sufficiently accurate for our purposes; therefore, we adopted this criterion. The maximum acceptable values for MAE, consistent with satisfactory nowcasting, were established in accordance with a CSI value of 0.5.

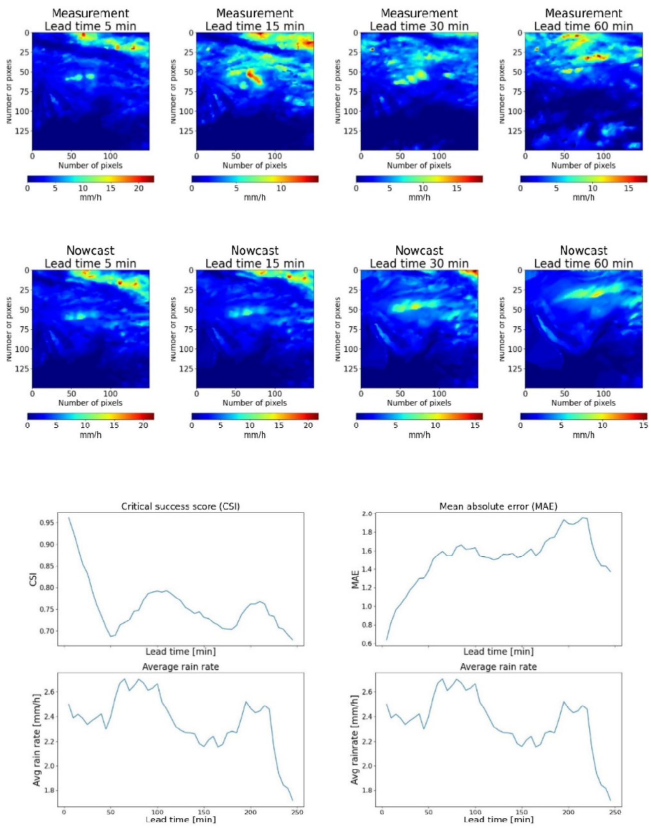


***Figure 1**: An example of precipitation nowcasting. It displays the measurements and their corresponding nowcasting, the trend of CSI and MAE and the average rain rate.*

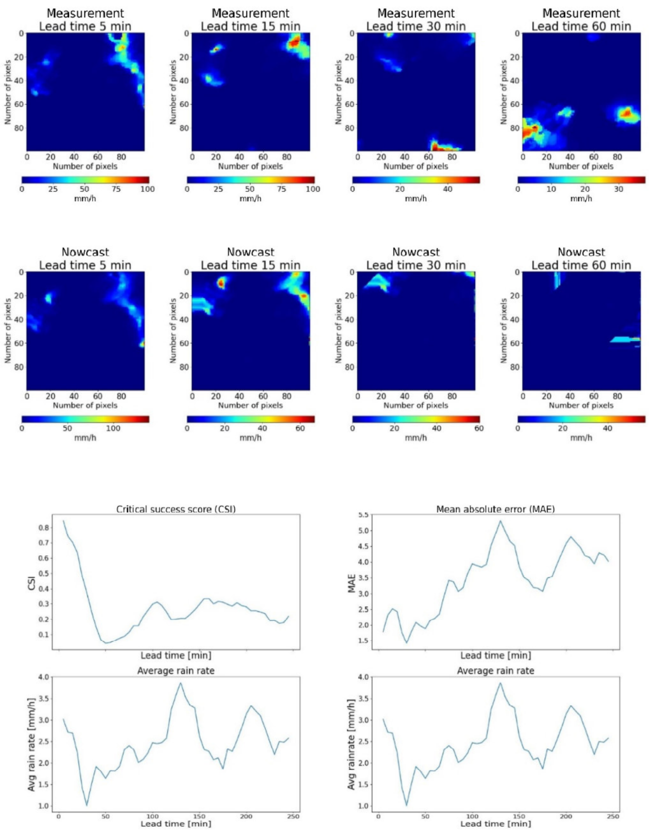


***Figure 2**: An example of precipitation nowcasting. It displays the measurements and their corresponding nowcasting, the trend of CSI and MAE and the average rain rate.*

4.1 Dependence of nowcasting quality on lead time using all data

The analysis of nowcasting quality over time showed that its accuracy declines as lead time increases. Higher average rain rates correspond to higher acceptable threshold values for MAE, as relative errors decrease (Figure 3). The quality of nowcasting was found to be roughly independent of the area size.

For modest rainfall regimes (0-0.3 mm/h), sufficient quality is maintained for lead times up to 20 minutes. For slightly more consistent rainfall (0.3-0.6 mm/h), it extends to about 40 minutes. For substantial rainfall (0.6-1 mm/h), it reaches approximately 70 minutes. For very heavy rainfall (>1 mm/h), it extends up to 105 minutes.

The corresponding MAE thresholds are: 0.15 for 0-0.3 mm/h, 0.5 for 0.3-0.6 mm/h, 0.95 for 0.6-1 mm/h, 1.68 for >1 mm/h.

4.2 Dependence of nowcasting quality on lead time for singular phenomena

In our analysis of individual phenomena, we focused on the dependency of CSI and MAE on lead time for all average rain rate values due to the limited availability of measurements. Figure 4 illustrate nowcasting for a stratiform and a convective phenomena. The results show that nowcasting performs better for stratiform phenomena compared to convective ones. This difference is due to the significant spatiotemporal variability of convective phenomena, making them harder to track. The maximum acceptable lead time for stratiform phenomena exceeds 100 minutes, while for convective phenomena, it is less than 50 minutes. Additionally, the maximum lead time varies with area size for stratiform phenomena but remains constant for convective ones. This variation is due to the nature of the phenomena: stratiform phenomena cover larger areas, so changes in area size significantly affect precipitation patterns, whereas convective phenomena affect smaller areas, resulting in similar patterns regardless of area size changes.

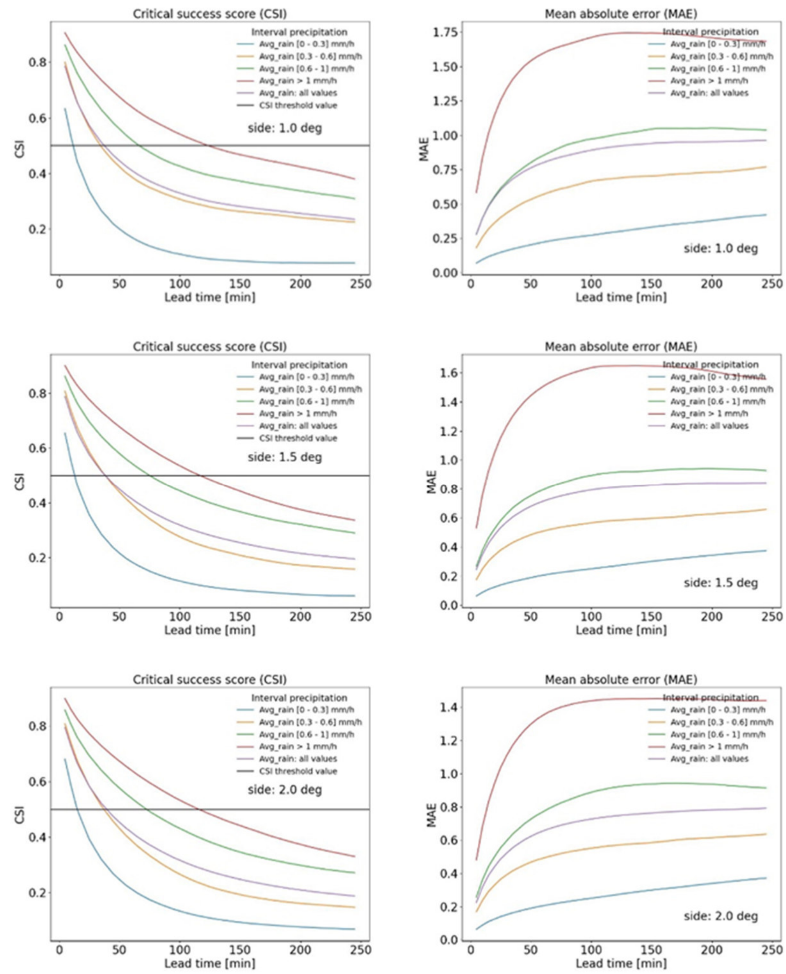


***Figure 3**: CSI and MAE are shown as a function of lead time for different intervals of average precipitation. The 0.5 CSI threshold has been indicated. The figure specifies the side of the surface area.*

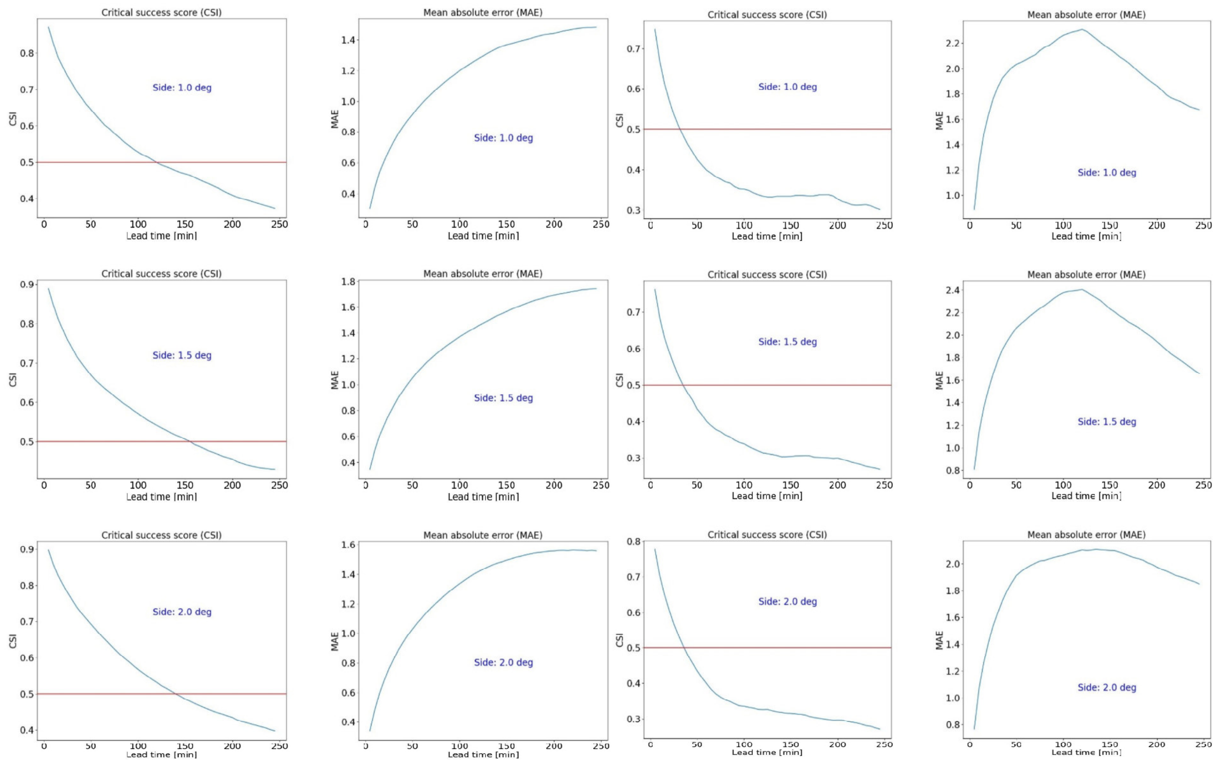


***Figure 4**: CSI and MAE are shown as a function of lead time for different intervals of average precipitation. The 0.5 CSI threshold has been indicated. The figure specifies the side of the surface area. On the left the stratiform phenomenon, on the right the convective one.*

5 Conclusion

The application of nowcasting techniques to 24 months of precipitation phenomena revealed that:

- Nowcasting performs better when the intensity of precipitation remains constant during the considered time interval.
- The quality of nowcasting is high for substantial precipitation. The higher the average rain rate in the considered region, the longer the time interval for which nowcasting is sufficiently accurate. For low precipitation, nowcasting is less reliable, but since such phenomena are of little interest for our purposes, this issue is of minor relevance.
- The quality of nowcasting, analyzed across all measurements within the considered period, is generally independent of the size of the area under consideration. Some variability is observed for individual stratiform phenomena, but this is entirely random.
- The quality of nowcasting for stratiform phenomena is better than that experienced for convective phenomena due to their greater variability

6 Acknowledgements

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7 References

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