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A Dual Neural Network Framework for Correcting X-Band Radar Reflectivity and Estimating Rainfall Using GPM DPR and Rain Gauge Observations in Cyprus †

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Abstract

Ground-based weather radars are essential to better understand precipitation systems, to improve the Quantitative Precipitation Estimation (QPE), and to subsequently provide input to hydrological models. However, reflectivity measured by radars is typically affected by various sources of uncertainty, including attenuation and calibration errors. Due to these limitations, the two ground-based X-band weather radars of Cyprus, namely, at Rizoelia (LCA) and Nata (PFO), have not yet been employed for QPE. This study presents a dual neural network framework with the ultimate goal of converting the ground-based radar raw reflectivity to rainfall rate, using satellite and in situ observations. The two ground-based radars are aligned with GPM DPR using the volume-matching method. Preliminary results demonstrate the feasibility of converting raw ground-based radar reflectivity to rainfall estimates using neural networks trained with spaceborne and in situ observations.

Keywords: radar calibration; attenuation correction; neural networks; GPM DPR; rainfall estimation; ground-based radar; Quantitative Precipitation Estimation (QPE)

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1. Introduction

Polarimetric weather radars provide enhanced insights into precipitation characteristics by enabling the estimation parameters such as the mean particle size, the hydrometeor type, and the drop shape. Traditional Z–R relationships rely on empirical assumptions and often face challenges in capturing the spatial and temporal complexities of precipitation. Thus, the conversion of radar reflectivity to rain rate at the surface presents a timeless challenge in radar meteorology. In response, machine learning offers a data-driven alternative that has proven potential in improving the accuracy and adaptability of rainfall retrieval.

In recent years, neural networks have gained attraction in improving rainfall estimation from radar data, due to their various advantages over traditional Z–R relationships. Xiao et al. [1] developed a three-layer perceptron using both horizontal (Zh) and differential reflectivity (ZDR), which resulted in more accurate results that employing Zh alone. With regard to rainfall prediction, Teschl et al. [2] applied a back-propagation neural network (BPNN) using vertical reflectivity (Zv) profiles and precipitation height to predict rainfall 5 min ahead. Recent advancements introduced enhanced architectures like convolutional neural networks (CNNs) [3–5]. Zhang et al. [3] applied a 1D CNN for real-time precipitation estimation using both radar and meteorological data.

This work proposes a dual neural network framework to convert ground-based radar reflectivity into rainfall rates, combining satellite and in situ data with radar observations that are aligned to GPM DPR.

2. Materials and Methods

This study uses data from the Cyprus radar network, which includes two ground-based X-band dual-polarization radars operated by the Cyprus Department of Meteorology. The stations are located in Rizoelia (LCA) and Nata (PFO). The radar reflectivity measurements are calibrated using data from the GPM DPR Ku-band (GPM Ku). Additionally, rainfall observations from 37 automatic weather stations (AWS) equipped with tipping bucket rain gauges (pulse data) were used (see Figure 1). The rainfall data were provided as timestamped events marking a fixed rainfall depth. These timestamps were converted from local time to UTC, and rainfall intensity (mm/h) was calculated by dividing the tip volume by the time difference between events, and subsequently multiplying by 3600. Events with implausibly long time gaps or unrealistically high intensities were excluded to ensure data quality.

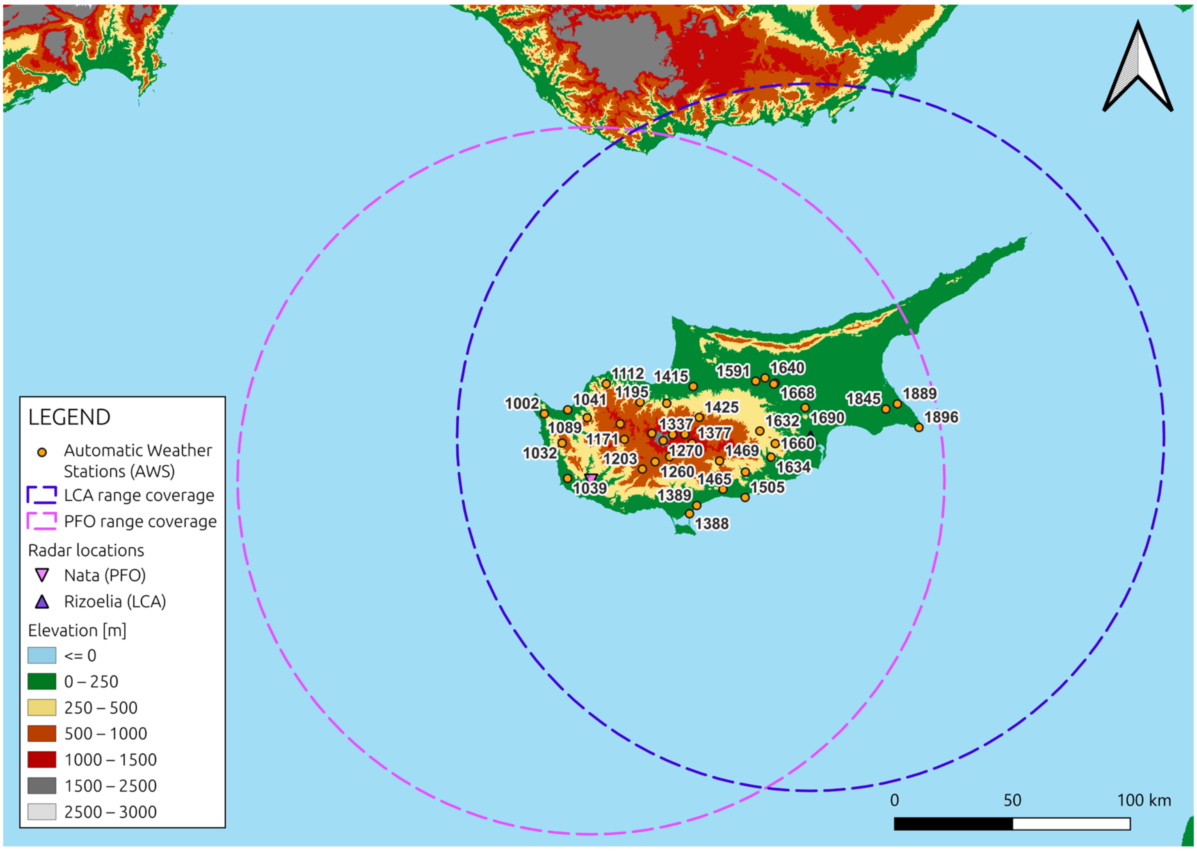

Figure 1. Geographical location of the 37 Automatic Weather Stations (AWS) with respect to the radar locations and their spatial coverage.

The methodology of this study is based on a dual-stage framework designed to convert ground radar reflectivity measurements into near-surface rainfall rates. In the first stage, a feedforward neural network is used to correct the ground radar reflectivity using volume-matched reflectivity from the GPM Ku-band. In the second stage, a separate neural network model estimates near-surface rainfall rates based on the corrected reflectivity data and corresponding pulse rainfall measurements.

The first step in developing the neural network framework was to define the input and output vectors. For the first network (Stage 1), the input vector included the volume-matched raw ground reflectivity, the corresponding range to the radar, the Path-Integrated Reflectivity (PIR), and the GPM overpass time. The output vector consisted of the volume-matched GPM Ku reflectivity. The corrected ground reflectivity produced by this first network was then used as an input in the second network (Stage 2) to estimate near-surface rainfall rates using pulse data.

3. Results

The analysis of the results focuses on the hydrological year 2019–2020, identified as a stable calibration period for both the LCA and PFO radars. In the first stage of the framework, the neural network model for the LCA radar demonstrated strong and consistent performance across the training, validation, and test sets, showing high agreement with the target values and minimal bias. In contrast, the model for the PFO radar showed moderately lower performance, with a slightly weaker fit and a consistent tendency to slightly underestimate reflectivity values. Despite these differences, both models delivered acceptable results for the purposes of reflectivity correction.

Figures 2 and 3 illustrate the performance of the neural network models for LCA and PFO radars, respectively. For the LCA radar, the neural network consistently underestimated rainfall rates in both training and test sets, failing to predict values above approximately 5 mm/h, indicating a limitation in capturing higher rainfall intensities. Similarly, for the PFO radar, the neural network also showed a tendency to underestimate, particularly struggling with low-intensity events, as it did not predict rainfall rates below about 1.5 mm/h.

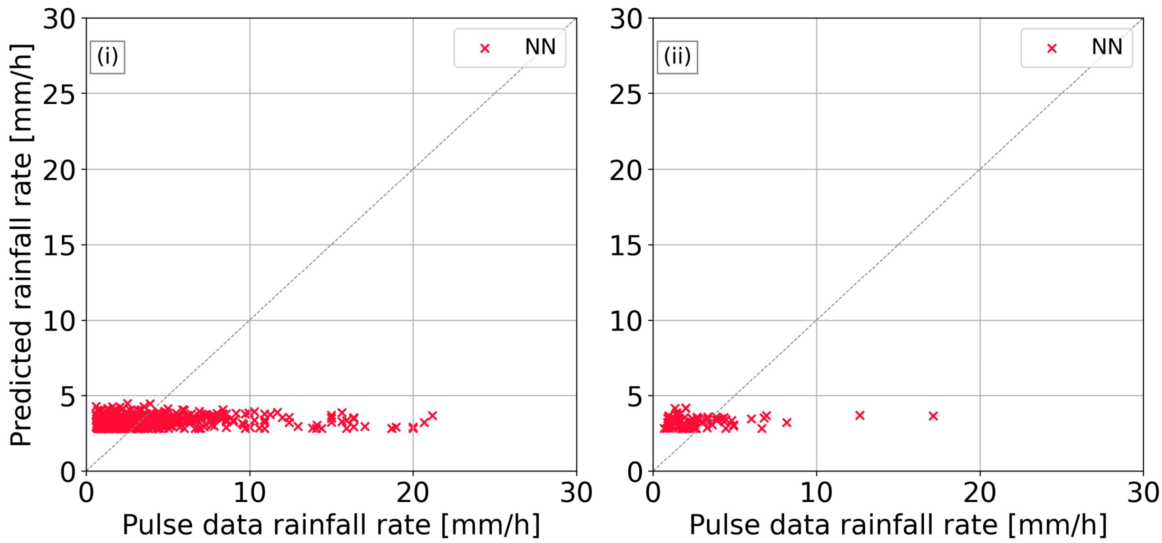

Figure 2. Scatter plots comparing predicted rainfall rates [mm/h] from the neural network models with the pulse data rainfall rates [mm/h] for the LCA radar. Plot (**i**) on the left represents the training dataset, while plot (**ii**) on the right shows the test dataset.

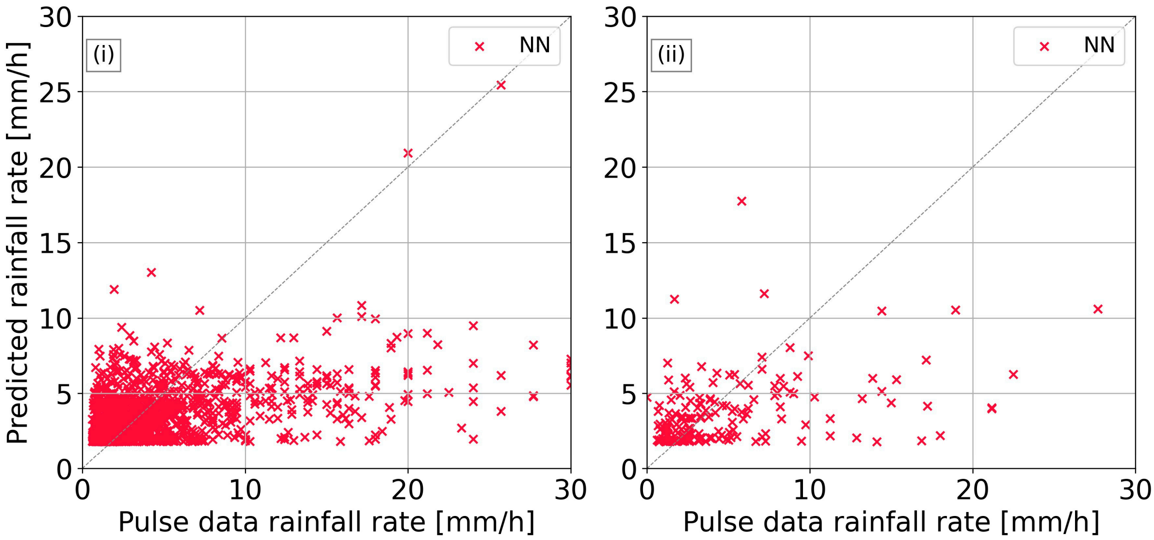

Figure 3. Scatter plots comparing predicted rainfall rates [mm/h] from the neural network models with the pulse data rainfall rates [mm/h] for the PFO radar. Plot (**i**) on the left represents the training dataset, while plot (**ii**) on the right shows the test dataset.

4. Discussion and Conclusions

The first stage of the dual-stage framework, which corrected ground radar reflectivity using volume-matched GPM Ku data, proved effective and improved the quality of radar inputs, offering a potential alternative to traditional calibration methods. However, the second stage, which estimated rainfall rates from the corrected reflectivity using pulse data, faced significant limitations. One key challenge was the continued underestimation in the corrected reflectivity values, which likely contributed to the underprediction of rainfall rates by the neural network model. Additionally, the pulse-derived rainfall rates, being indirect estimates from tipping bucket gauges, introduced further uncertainty into model training and performance.

Despite the above-described limitations, the results highlight the potential of data-driven approaches for radar rainfall estimation. The effective performance of the first stage demonstrates that neural networks can play a valuable role in enhancing radar reflectivity quality. Building on this foundation, future research should explore more advanced or alternative AI models to improve radar rainfall rate estimations, particularly those capable of capturing extreme and low-intensity events more accurately. Incorporating additional meteorological variables and using more directly comparable training data (e.g., disdrometer measurements) could further enhance model reliability and performance, supporting the development of more accurate AI-based precipitation estimation frameworks.

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Conflicts of Interest: The authors declare no conflicts of interest.

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