An Update of the Operational Quantitative Precipitation Estimation Algorithm in Southern Brazil Blending Dual Polarization Weather Radar Network with Rain gauges and Satellite Data - Preliminary Results

Parana Meteorological Service

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INTRODUCTION

Quantitative estimation of precipitation (QPE) of high resolution, accuracy, and real-time increases the potential of weather radars for many applications, such as flash flood forecasting and hydropower production and distribution management, agriculture, and other applications. Using polarimetric variables from dual-polarization weather radars has significantly improved quantitative precipitation estimation in many countries with diverse weather. In Brazil, in the past ten years, we have seen an increase in dual-polarization weather radar coverage, mostly S-Band and some X-Band, concentrated in the southern parts of the country, an area prone to severe weather with high precipitation and lightning due to mesoscale convective systems. This region's significant economic activity is agriculture and energy production, accounting for more than 33% of the hydro energy generation used in the country.

Therefore, the improvement of precipitation estimation is a necessary goal. Using weather radar's QPE depends on calibration, good fit with rain gauges and distrometers, good data filtering, target distance from the radar, orography (i.e., relative to the topography), and signal propagation, as well as other factors. A multi-sensor integration approach of remotely sensed precipitation estimation using weather satellites and weather radar with rain gauges improves the accuracy of hydrological models compared to a model using only rain gauge data.

A quantitative precipitation estimation algorithm called SIPREC (System for Integrated PRECipitation) [1] has been used operationally for over 15 years, combining data from different sources, such as weather radar, rain gauge, and satellite. Precipitation estimates are obtained through an automated precipitation classification scheme based on reflectivity structures. This approach aggregates data from rain gauges by interpolation while maintaining the spatial distribution of the radar or satellite measurement. Statistical results indicate that the method can reduce radar and satellite data errors. This method is an essential advantage in an operational environment since it does not require frequent processing to update the weights as in other known schemes.

However, this approach does not solve problems such as uncertainties related to Z-R estimation, spatial variability, and the one-hour temporal resolution. A recent significant rainfall event in Parana State (Figure 1), resulting in severe flooding (Figure 2), highlights the critical need for new tools that enhance accuracy.

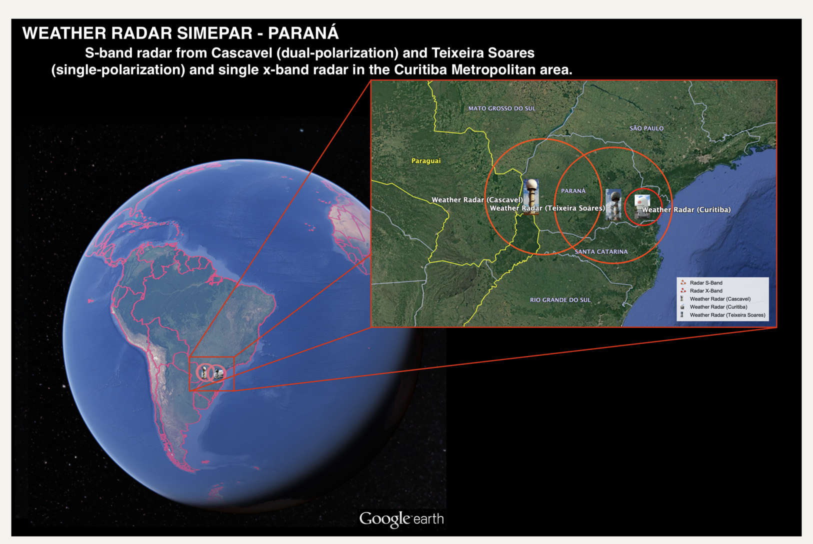

Figure 1: Weather radar network in Parana, Brazil.

Figure 2: Flooding in Francisco Beltrão on 11/Oct/22

OBJECTIVE

This study proposes the use of a machine learning architecture to implement an improved QPE model, using rain gauge, weather radar, and satellite, to generate a spatially and temporally consistent meteorological field.

DATA

- **MOSAIC WEATHER RADAR:** Z-R Precipitation estimates based in [2]
- **SATELLITE:** GPM/IMERG Precipitation estimates [3].
- **RAIN GAUGE:** Data from SIMEPAR rain gauge network.
- **PERIOD:** January 2018 to December 2022.

METHODOLOGY

To improve the SIPREC algorithm, we used machine learning classification and regression methods to address the problem of precipitation estimation using dual polarization variables and rain gauge. An enhanced satellite precipitation estimation using GOES-16 data also replaced the previous dataset, and a new quality control algorithm for the network of weather radars was also applied to the dataset.

Our proposed methodology for creating a new tool for quantitative rainfall estimation uses two machine learning algorithms, SVM (Support Vector Machine) [4] classification, and GBR (Gradient Boosting Regression) [5] modeling. To build a classification/regression model using machine learning algorithms and classify zero-inflated data - common in spatial precipitation datasets - we use the Support Vector Machine (SVM) algorithm to tell us whether the target is zero. The trained SVM model is then used as an input to the GBR model, which is trained with the corresponding observed outputs to find the best combination of model parameters to predict the unknown outputs (precipitation estimation).

Feature engineering involves selecting the rain gauge data using IDW (Inverse Distance Weighting Interpolation) based on its relevance to the interpolation problem and the weather radar mosaic using a Z-R disdrometric relationship [2] and the satellite precipitation estimation [3].

To evaluate the model's performance, we validated the trained GBR model using a separate dataset from the training set. The R2 (coefficient of determination) and RMSE (root-mean-square error) between the estimates and observations were calculated for the ML algorithms trained by the data set that did not include any station among those in the training set. The expected training and test data numbers are approximately 80% and 20%, respectively. Figure 3 depicts the flowchart of this new methodology, which we call SIPREC-ML.

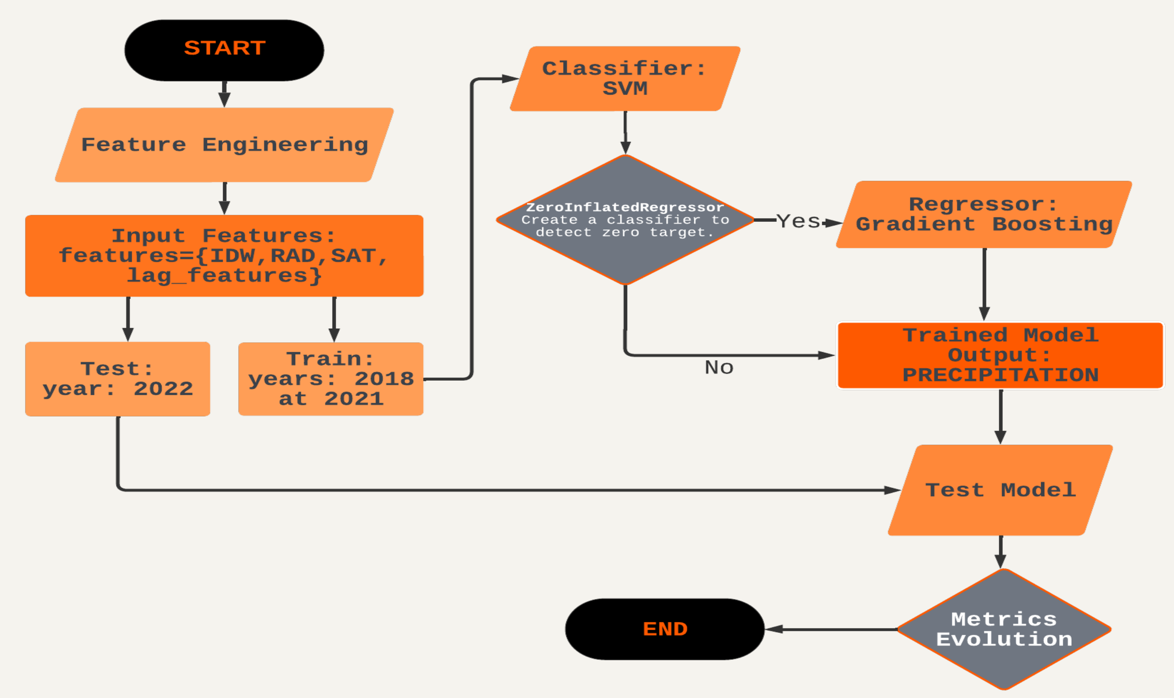

Figure 3: SIPREC-ML new flowchart.

PRELIMINARY RESULTS

The preliminary results showed excellent machine learning model performance for the SIPREC model compared to the older version, which uses Poisson's equation for data interpolation. Figure 4 and Table 1 present metrics evolutions and scatterplot test data of observed values against both models' estimates. SIPREC-ML shows superior temporal coherence, with an R2 of 0.93 versus 0.8 for the older SIPREC version. The SIPREC-ML reduced the errors of the estimates, showing an MSE of 0.21 versus 0.38 for the previous version of SIPREC.

Model	MSE	R2
SIPREC	0.38	0.8
SIPREC ML	0.21	0.93

Table 1: Evolution of SIPREC metrics from data test.

PRELIMINARY RESULTS

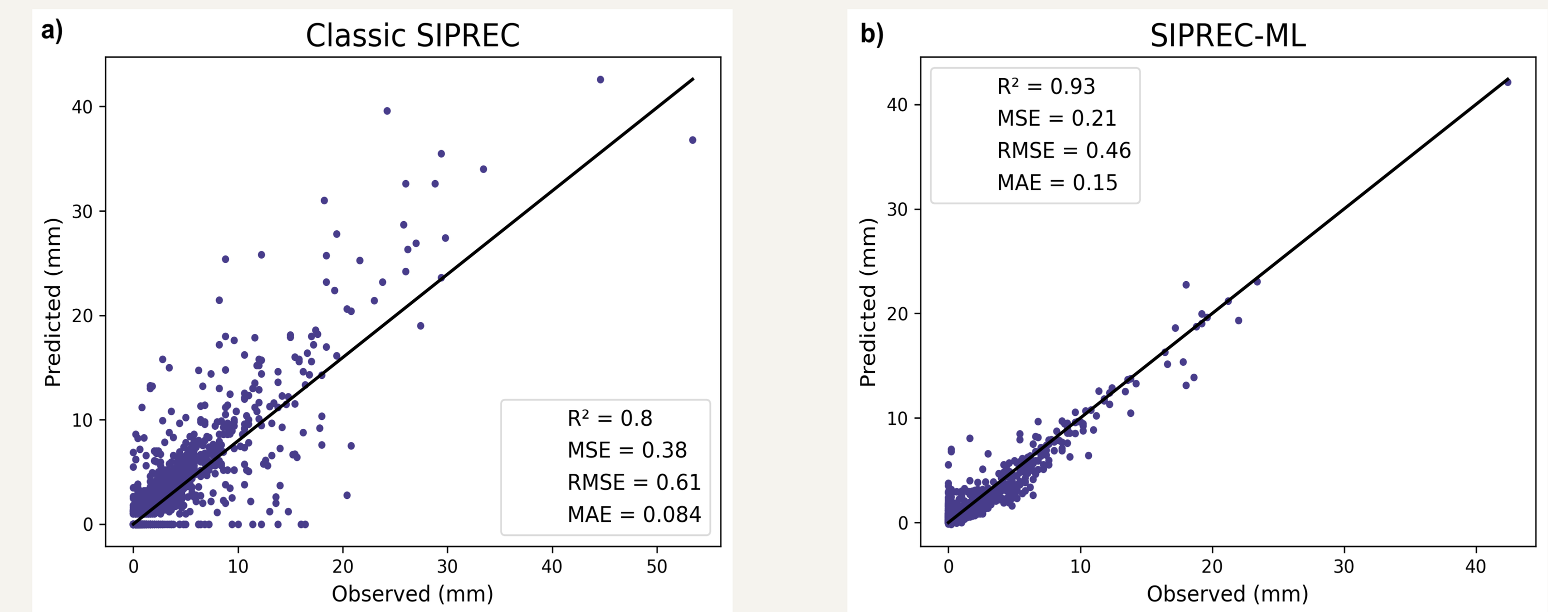

Figure 4: Scatter plot data test (a) SIPREC Poisson's model and (b) SIPREC ML model.

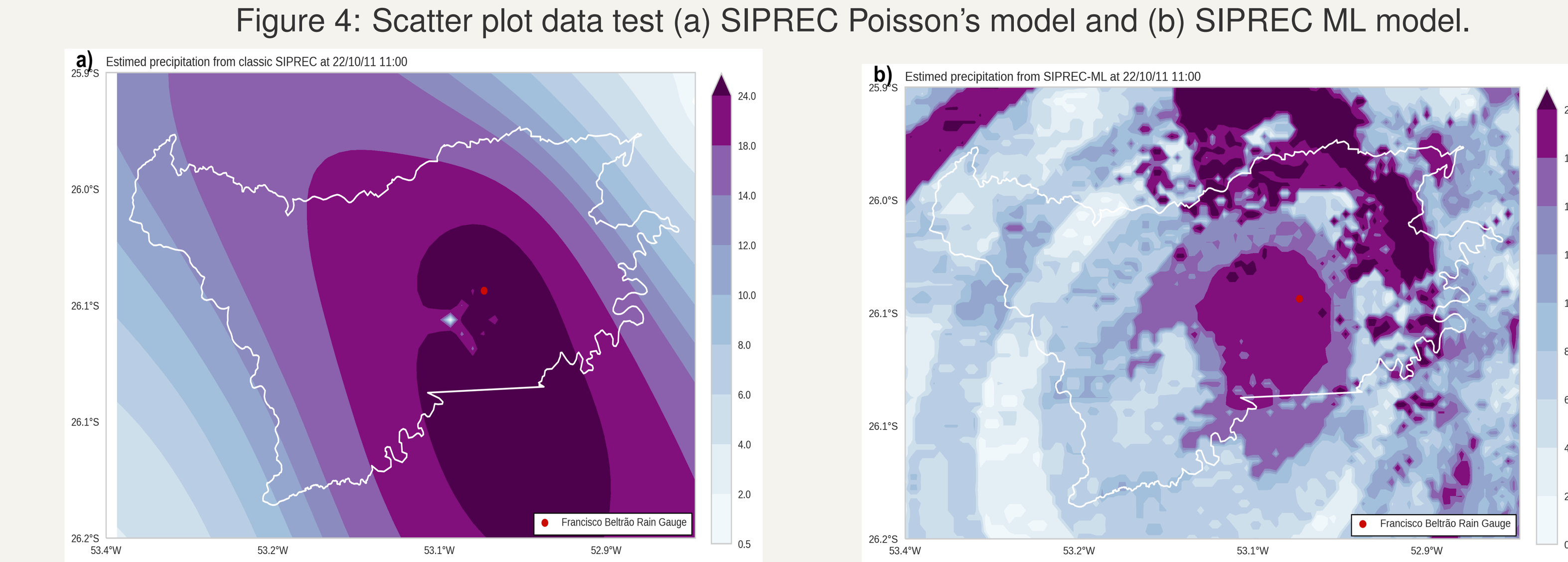

Figure 5: Models estimates precipitation for Francisco Beltrão at (a)SIPREC Poisson's model and (b)SIPREC ML model for 11 UTC on October 11, 2022 — Red Point Francisco Beltrão Rain Gauge.

Figure 5 compares the older version of SIPREC model and our proposed SIPREC-ML, for the event rainfall event on October 11, 2022, at 11 UTC, during which flooding occurred in the city of Francisco Beltrão. Our analysis revealed that the SIPREC ML data exhibited a more consistent behavior when compared to the radar and satellite data, providing a more realistic representation of the rainfall in the affected region.

We removed the Francisco Beltrão rain gauge during our training process and analyzed rainfall data. Our findings showed that the SIPREC ML rain gauge produced similar values to the Francisco Beltrão gauge, indicating the efficacy of our training approach. Additionally, the SIPREC Poisson data also a good approach extrapolated a rainfall grid with values ranging from 18 to 24 mm. Our findings also say the efficacy of our training approach. These results promise to improve rainfall prediction and flood risk assessment in urban areas and basins.

A performance evaluation study shows improvements in precipitation estimation, primarily when used in real-time in an operational environment. This paper presents the results of this evaluation, with applications in severe weather events with high precipitation in the area. Future research will present the long term evaluation, including impact of the weather radar and satellite precipitation estimations in the region.

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