Urban Flood Prediction Using Products based on Weather Radar Data

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ABSTRACT

Urban floods generate economic and social impacts. Due to the characteristics of urban basins, intense rainfall causes flash floods and the spatial variability of rainfall leads to very diverse responses from the basin in terms of flooding. Urban flooding forecasting is usually carried out based on precipitation forecasts and hydrological and hydrodynamic modeling. However, the urban basin specificities mean that common weather forecasts do not meet the temporal and spatial scales required for accurate flash flood prediction. To solve this problem, a more precise precipitation forecast is needed, with higher spatial and temporal resolution. Nowcasting based on radar data can address these issues. In this context, this study aimed to evaluate the accuracy of urban flooding forecasting based on hydrological and hydrodynamic modeling using precipitation estimation from a meteorological radar as the model's input data. Simulations were performed for a calibrated model in the Storm Water Management Model (SWMM) software for the

Monjolinho watershed in São Carlos, São Paulo, Brazil. Precipitation estimates from the meteorological radar operated by the Institute of Meteorological Research at São Paulo State University (IPMet/UNESP), located in Bauru, São Paulo, Brazil, were used. The evaluation was conducted based on the simulation results of the intense rainfall event that occurred on December 28, 2022. The simulation results were compared to the water level data measured by a water level gauge. For the analyzed event, an accurate estimation of the time to peak was observed; however, the peak water level was underestimated when radar-derived data were used as model input. This finding indicates the potential of radar data as input for urban flood forecasting models. Hence, it is recommended that the Z–R relationship is calibrated to better represent precipitation values observed at the ground level.

KEYWORDS: precipitation estimation, urban flood forecasting, hydrological modeling, meteorological radar

1 INTRODUCTION

The global population is still growing and is expected to continue doing so until 2054, likely reaching its maximum by the end of this century (United Nations, 2018). In addition, by 2021, the urban population already accounted for 57% of the world's population, and global urban growth has been projected to reach 68% of the total population by 2050 (UN-Habitat, 2024). In Latin America, the accelerated expansion of urbanized areas, the lack of adequate planning, and the neglect of ecological aspects in public policies intensify the impacts of extreme rainfall events (Coates and Nygren, 2020). In view of future projections, it is therefore critically important to enhance the predictability of extreme flood events, with the greatest possible lead time, in urban centers where the largest populations are and will continue to be concentrated, with the most severe impacts disproportionately affecting populations with fewer financial resources.

In this context, hydrological modeling emerges as an important and robust tool for simulating and forecasting floods resulting from extreme precipitation events, thereby minimizing impacts on property and human life. In general, data used in hydrological process modeling are based on information from rain gauges, general circulation models of the atmosphere, the Weather Research and Forecasting (WRF) model, meteorological radars, and meteorological satellite imagery (Silva et al., 2023). One of the main challenges in hydrological modeling concerns rainfalls' spatial variability assimilation, which is often addressed through interpolation. In many cases, rainfall interpolation using classical methods is the only alternative for estimating precipitation in areas without adequate instrumental coverage or where acceptable-quality measurements are unavailable; however, such approaches often result in low-accuracy information (Hu et al., 2019). In contrast, meteorological radar is generally considered one of the most effective instruments from this perspective.

Sokol et al. (2021) emphasize that rain gauges remain the most widely used instruments for point-scale field measurements of precipitation intensity and duration. However, these devices exhibit limited accuracy in estimating precipitation over complex terrain - such as mountainous regions - due to their sparse spatial distribution. In contrast, weather radars are remote sensing instruments extensively employed in hydrology and meteorology, precisely because they provide precipitation estimates over specific areas with high temporal and spatial resolution. According to Sokol et al. (2021), the use of radar-derived rainfall data in hydrological modeling emerged in response to the need for accurately capturing the spatial structure of precipitation fields and for investigating the potential of such data to generate short-term quantitative forecasts.

The inherent differences between weather radars and rain gauges hinder direct comparisons between data obtained from these two types of instruments (Sokol et al., 2021). Costabile et al. (2026) modeled a rainfall event that occurred in Crotone, Italy, on November 21, 2020, using both rain gauge and radar data, and concluded that simulations based solely on rain gauges often overestimate peak values, whereas radar-based simulations yielded more accurate results. Conversely, Shehu and Haberlandt (2021) underscore the importance of integrating rain gauge and radar data for nowcasting applications in urban hydrology. Their findings indicate that, among simulations using raw radar data, rain gauge data alone, and a combination of both, only the combined approach exhibited a certain degree of predictability (up to 20 minutes).

Weather radars, however, are not exempt from errors. The main categories of errors affecting weather radars include: (i) hardware-related errors: electronic instability, antenna accuracy, and signal processing quality; (ii) radar beam geometry and scanning strategy: increasing distance from the radar site, beam broadening, and greater spacing between consecutive beams; (iii) data contaminated by echoes from non-meteorological targets, such as tall buildings or electromagnetic interference; (iv) terrain obstructions; (v) signal attenuation due to rainfall; and (vi) anomalous propagation of the radar beam caused by specific atmospheric temperature gradients. Such errors can be mitigated through the application of dedicated quality control techniques (Sokol et al., 2021).

In recent years, substantial progress has been made in the quality control of radar data, driven notably by advancements in programming techniques and image processing - such as Machine Learning (ML), Deep Learning (DL), Neural Networks, and Artificial Intelligence (AI) - as well as by improvements in error and uncertainty correction methods - such as water vapor correction techniques and the assimilation of Doppler radial velocity into Numerical Weather Prediction (NWP) models - and by the evolution of new technologies - including Synthetic Aperture Radar (SAR) and Dual-Polarization (dual-pol) radars (Sokol et al., 2021; Dandekar et al., 2025; Misra et al., 2025). These advances have enabled the application of radar data for diverse purposes, including hydrological modeling, urban flood risk modeling and management, and flood inundation mapping (Sokol et al., 2021; Li et al., 2020; Costabile et al., 2026; Dandekar et al., 2025; Misra et al., 2025). In hydrological modeling, however, it is essential to account for uncertainties arising from initial conditions - such as soil moisture - and from the radar estimates themselves - including incorrect calibration, sample representativeness, non-meteorological echoes, and uncertainties in Z-R relationships (Sokol et al., 2021; Li et al., 2020).

Sokol et al. (2021) assert that, despite all the advancements in rainfall measurement techniques and technologies and the development of urban rain gauge networks, obtaining rainfall data tailored to urban hydrology remains challenging. This is due to the fact that such applications demand greater spatial and temporal precision than is typically required for rural catchments.

Currently, the most widely used meteorological radars are Doppler radars, which operate across different frequency ranges (bands). A meteorological radar functions by emitting electromagnetic pulses that interact with hydrometeors, such as raindrops, snow, or ice. When this interaction occurs, part of the electromagnetic energy is scattered back to the radar as an echo. Based on the characteristics of this echo, it is possible to estimate hydrometeors location and intensity (Doviak and Zrnić, 1993). An S-band radar operates at frequencies between 2 and 4 GHz, which are less susceptible to attenuation compared to radars operating at other bands (such as C or X). This attenuation occurs due to the presence of gases, aerosols, and hydrometeors along the propagation path between the radar and the target. S-band radar is particularly effective for monitoring rainfall over long distances, up to 450 km; however, due to the curvature of the Earth, precipitation volumes are typically estimated within a radius of up to 240 km.

Accordingly, the present study aims to evaluate the response of a previously calibrated hydrological and hydraulic model using both rain gauge data and radar-derived rainfall estimates, in order to assess the spatial and temporal applicability of radar-estimated precipitation for water level estimation in urban rivers. The modeling results are compared with water level gauge data located in the urban area of São Carlos, São Paulo State, Brazil. The analysis had a particular emphasis on extreme events that have occurred in the region.

2 MATERIALS AND METHODS

2.1 Study Area

The Monjolinho watershed is located in the central portion of São Paulo State, Brazil, with its drainage area encompassing the municipalities of Ibaté and São Carlos. A large portion of the urbanized area of São Carlos is drained by the Monjolinho River, as well as by tributaries such as the Mineirinho

Stream, Tijuco Preto Stream, and the Gregório Stream. Owing to the municipality's accelerated urban expansion, an increase in flood events has been observed during periods of high rainfall accumulation, particularly along reaches of the Monjolinho River and the Gregório Stream (Lima and Amorim, 2014), which are located within the urbanized area of the Monjolinho River basin (Figure 1).

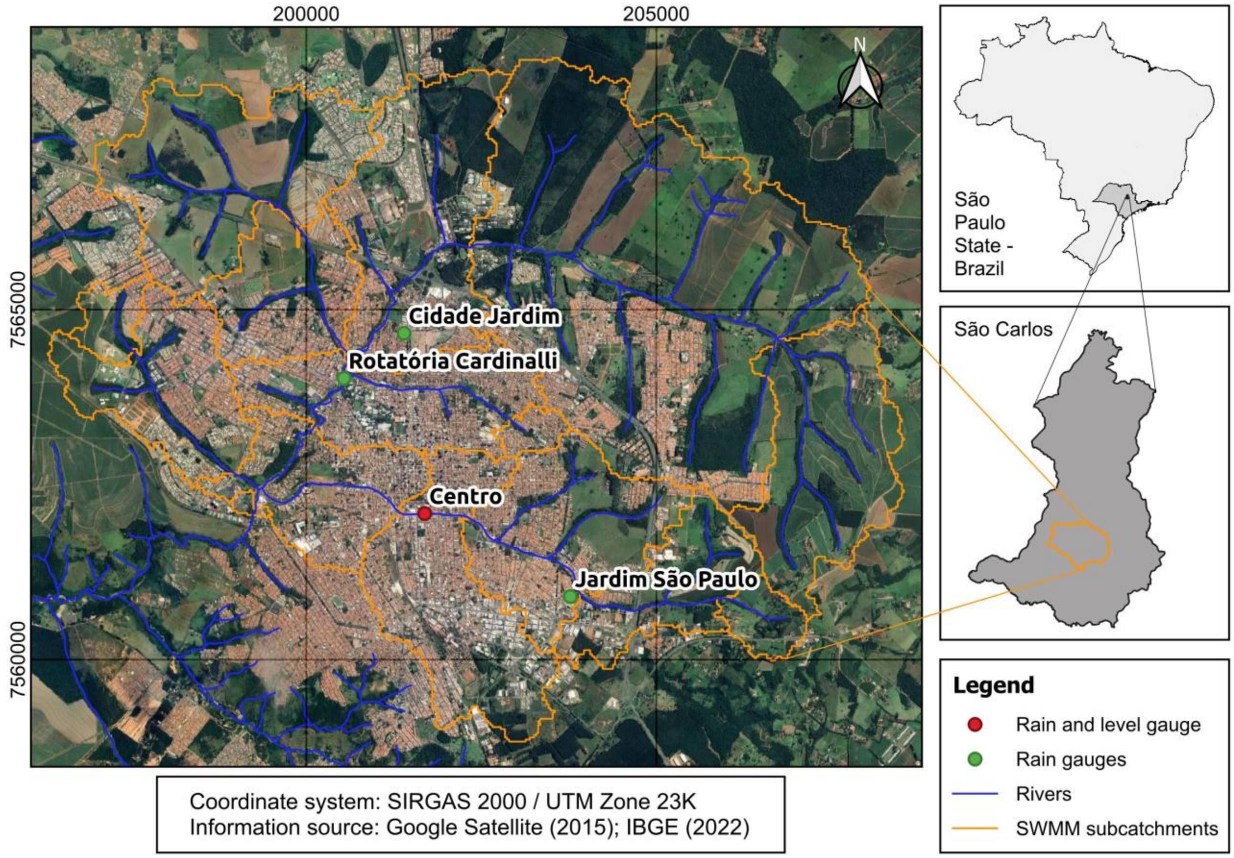

Figure 1: Study area, modeling subcatchments, and level and precipitation gauges' location

2.2 Pluviometric Data

Precipitation estimates from the meteorological radar operated by the Bauru Center for Meteorology, affiliated with the São Paulo State University (IPMet/UNESP), were used in this study. Accumulated rainfall estimates from this radar are generated based on a set of volumetric scanning tasks performed every 7.5 minutes. This set consists of fourteen complete antenna rotations in azimuth, each at a distinct elevation angle, ranging from 0.3° to 45°. Upon completion of the fourteen scans, all volumes are combined to generate the CAPPI (Constant Altitude Plan Position Indicator) product. Due to the beamwidth of the transmitted signal, which for IPMet radars is approximately 2°, spatial resolution decreases with increasing distance from the radar. Nevertheless, the CAPPI product is interpolated onto a regular grid with a spatial resolution of 750 × 750 m.

As reference data, rainfall measurements were collected from two gauges operated by the National Centre for Monitoring and Alerting Natural Disasters (CEMADEN) and from two additional gauges operated by the Municipality of São Carlos (PMSC), in partnership with the Federal University of São Carlos (UFSCar). These gauges provide the only rainfall observations in the region with a 10-minute temporal resolution, which is more suitable for the travel times of flood waves within the study watershed. Data from the four available surrounding gauges were interpolated using the inverse distance weighting (IDW) method to obtain a representative hyetograph for each subcatchment used in the modeling.

The simulations were performed for an intense rainfall event that occurred on December 28, 2022. This event was selected because it is one of the few for which data from both selected precipitation estimation sources are available, as well as water level observations within the study basin, enabling comparison with the modeling results. These water level data were obtained from a water level gauge associated with the aforementioned PMSC rain gauges. The locations of the gauges used in this study are shown in Figure 1.

2.3 Hydrological Model

The Storm Water Management Model (SWMM) is a widely used software for hydrological and hydraulic modeling in urban areas. It enables the simulation of rainfall–runoff transformation in watersheds and can be applied to single-event or long-term simulations, including analyses of both the quantity and quality of surface runoff in micro- and macrodrainage systems. SWMM integrates hydrological and hydraulic components: the surface runoff module is conceptual and concentrated at the subcatchment scale. The hydraulic module adopts a physically distributed approach to model flows and water levels, solving the full one-dimensional (1D) Saint-Venant equations. This integration allows for the assessment of system behavior from runoff generation to its conveyance through drainage networks (James et al., 2010; Perin et al., 2020).

Recognized for its flexibility and robustness, SWMM is widely applied in urban planning and water resources management studies and is considered one of the most commonly used tools for urban stormwater management (Gao et al., 2023; Tamm et al., 2023). Furthermore, its ability to analyze water quality scenarios and to accommodate different watershed configurations makes it an essential tool for environmental impact assessments and for mitigating risks associated with climate change.

For these reasons, SWMM was selected for this study. It was previously calibrated and validated by Fava (2019) based on the subcatchments delineation shown in Figure 1. The calibration followed a multi-event and multi-site approach, developed for a highly urbanized watershed with limited hydrological data. To optimize parameters related to the watershed of interest, an automated tool based on genetic algorithms was employed, considering the absence of discharge measurements and the availability of only water level data. Despite the limitations of using water level data to fully represent the hydrological response of the basin, the model demonstrated consistent performance.

3 RESULTS AND DISCUSSION

Figure 2 illustrates the spatial and temporal distribution of rainfall estimated by the IPMet meteorological radar. Figure 3 presents the hyetograph of the average precipitation within the watershed, obtained through interpolation of rainfall data from CEMADEN and PMSC gauges. The values are similar to those observed in the radar-based estimates, with the identification of three distinct precipitation periods over the analyzed interval, indicating good agreement between the data sources. Nevertheless, it is possible to note that the gauges-based hyetograph showed a greater accumulated precipitation each time step.

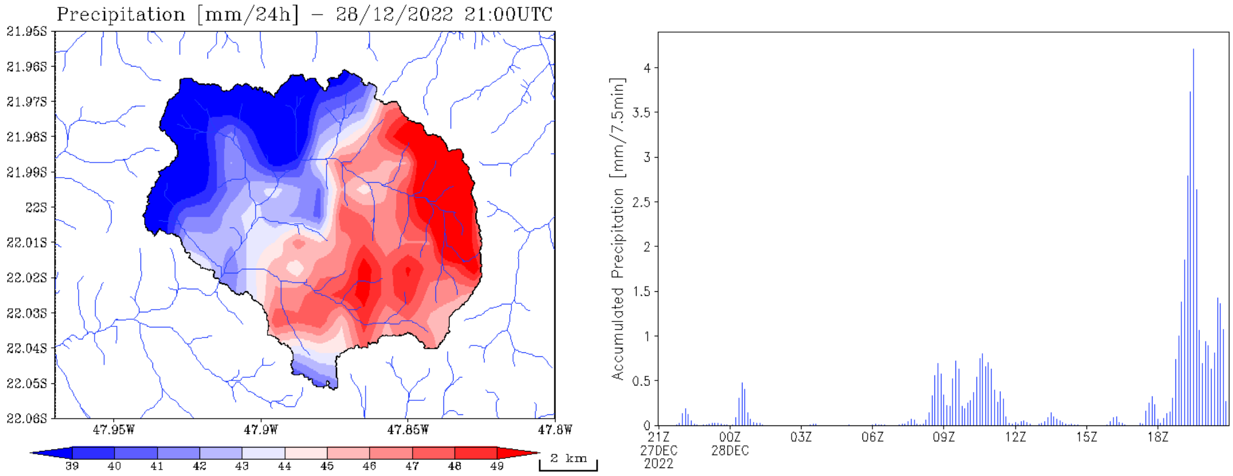

Figure 2: Estimated precipitation based on the meteorological radar for the event of December 28, 2022. The left figure shows the accumulated precipitation in 24 hours, and the right figure shows the average hyetograph for the catchment based on the radar estimates

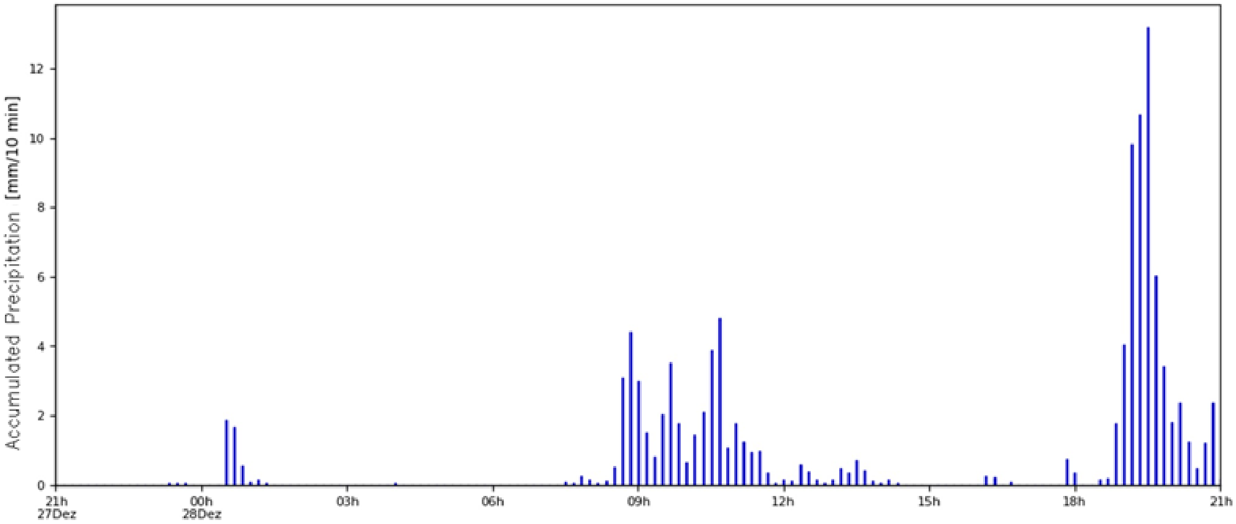

Figure 3: Average hyetograph for the catchment based on the rain gauges for the event of December 28, 2022

Analysis of the results generated by the SWMM model (Figure 4) indicates that both data sources – radar- and rain gauges–based rainfall – produced simulations that could predict the in situ water level observations. The simulation driven by radar products, although underestimating water level values, successfully reproduced the increase in peak stage at the same time it was observed. The simulation based on rainfall interpolated from rain gauges data resulted in the smallest error compared to the observed values, which is consistent with the high sensor density within a relatively small area.

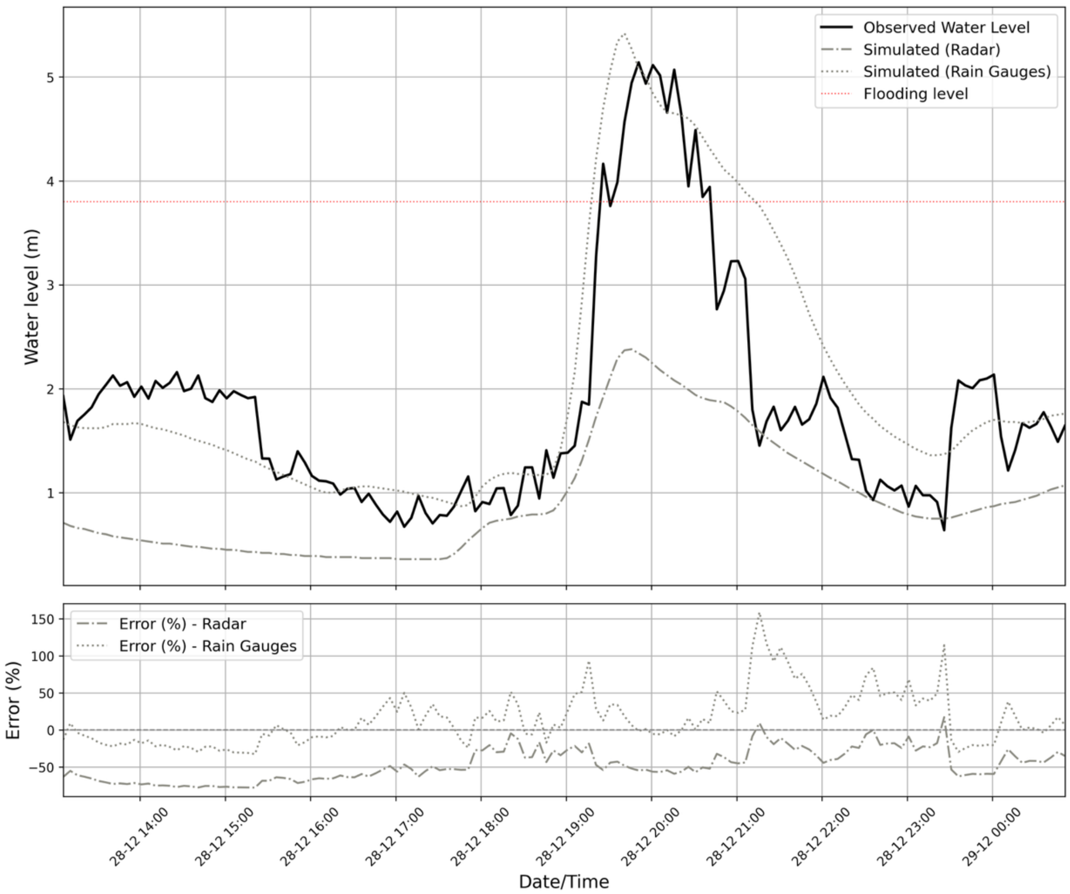

Figure 4: Observed and simulated water levels and respective errors for the event of December 28, 2022

The underestimated water level values generated using radar-derived rainfall, when compared to observations, can be explained by a possible underestimation of rainfall by the radar. This underestimation becomes evident when comparing the hyetographs presented in Figures 2 and 3. Rainfall estimation relies on the relationship between the reflectivity of electromagnetic waves and the effective precipitation rate (the Z–R relationship), which may be inadequate and lead to precipitation underestimation for the analyzed case. Although several Z–R relationships have been proposed in the literature, an accurate estimation of rainfall volume ideally requires that this relationship be locally derived, using reflectivity and observed rainfall at the site of interest. In this study, the Z–R relationship proposed by R. V. Calheiros (Emídio and Landim, 2008), with parameters a = 32 and b = 1.65, was adopted.

The results obtained from rainfall interpolation using data from CEMADEN and PMSC rain gauges showed good performance, adequately reproducing the observed hydrograph in terms of both magnitude and time to peak of the water level. However, the limited spatial distribution of measurement instruments may account for potential discrepancies, which highlights the importance of evaluating alternative sources of precipitation estimates. Radar products, for instance, provide greater spatial representativeness of rainfall distribution and can complement rain gauges data. It is noteworthy that both precipitation estimation approaches could provide suitable inputs for the hydrological model, as they produced water level time series similar to the observed data, indicating their potential applicability under conditions of rain gauge data scarcity or inconsistency. In this context, integrating different precipitation estimation sources may enhance the precision and accuracy of hydrological simulations, particularly in regions with limited rainfall monitoring networks, as is the case in Brazil and many parts of the world. In light of these considerations, future studies are essential to further explore this integration and to develop more robust and reliable approaches for urban floods forecasting.

4 CONCLUSION

Simulations driven by radar-derived rainfall data showed a reasonable agreement with observations, with the timing of the simulated peak water level being consistent with the observed peak. Simulations based on rain gauges data yielded better overall results; however, such data are not always available with adequate spatial distribution and temporal resolution. The scarcity of rain gauges data reinforces radar products' advantage, which provide greater spatial representativeness and can replace or complement local measurements in data-limited contexts. Based on the presented results, future analyses may focus on the integration of the products used to drive the hydrological model, aiming to increase information redundancy. Thus, this study presents a promising scenario for the application of advanced forecasting and disaster management techniques, particularly in regions with insufficient monitoring infrastructure.

The results also highlight the strong capability of SWMM to simulate both the timing and the magnitude of peak water levels using either radar- or rain gauge-based rainfall inputs. This demonstrates the potential for integrating the employed tools by leveraging their complementarity to enhance redundancy and reliability in early warning and nowcasting systems. However, it should be noted that the hydrological model was calibrated using rain gauges data without directly incorporating spatially distributed products such as radar rainfall estimates, which may have influenced the model performance when radar-based estimates were used as inputs.

Given the good performance in reproducing the time to peak of the water level using radar precipitation estimates, despite the underestimation of the peak magnitude, there is a clear need to calibrate radar estimations in order to derive a new, locally representative Z–R relationship for the study area. The Z–R relationship proposed by R. V. Calheiros (Emídio and Landim, 2008), being relatively old, may no longer adequately represent rainfall volumes based on reflectivity, as the radar system may have undergone changes over time, such as variations in transmitted power or attenuation due to residue accumulation on the radome, among other factors. Therefore, in light of the obtained results, the continuation of the research is of fundamental importance.

5 ACKNOWLEDGEMENTS

This research was supported by the Coordination for the Improvement of Higher Education Personnel (CAPES), Finance Code 001, and by the National Council for Scientific and Technological Development (CNPq), through the project "Advances in Nowcasting Tools Applied to Urban Flooding" (grant no. 446043/2023-0) and the project "Multi-scale Forecasting of Extreme Meteorological Events for Hydrological Applications" (grant no. 446029/2023-8).

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