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Fuzzy logic control implementation for flow regulation in stormwater urban reservoirs

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ABSTRACT

The uncertainty surrounding climate change and urban expansion adds pressure to urban drainage systems by increasing rainfall frequency and elevating peak runoff rates. To reduce urban flooding, stormwater infrastructure can be managed in real-time by retrofitting it with sensors and controllable gates, facilitating dynamic adjustments across entire watersheds during rainfall events and enhancing the resilience of these structures. In this study, we introduce a Fuzzy Logic Control (FLC) implementation for five online stormwater reservoirs located in the Aricanduva basin (São Paulo, Brazil), using experience-based rules aimed at promoting intelligent flood mitigation decision-making, as the first steps to implementing real-time control systems. A 2D hydrodynamic model was employed to apply FLC in the five reservoirs, and their effectiveness in reducing flood effects was evaluated using a 25-year design storm hydrograph. The findings indicate that the FLC implementation decreases peak flow by 38.15%, 20.60%, 14.40%, and 12.04% in the Aricanduva I, Limoeiro, Caguaçu, and Aricanduva III reservoirs, respectively. However, for the Aricanduva II reservoir, the peak flow increases by 2.11%. In contrast, the accumulated volume flooding reduction values were 1.20%, 0.60%, and 0.58% in the Aricanduva I, Limoeiro, and Aricanduva III reservoirs, respectively, while the values were -5.83% and -2.11% for the Caguaçu and Aricanduva II reservoirs, respectively. This approach allows for the assessment of which reservoirs with FLC implementation could effectively assist flood risk managers in reducing urban flooding, particularly in data-scarce watersheds. This research aligns with the Sustainable Development Goals (SDGs) 6, 9, 11, and 13 by improving resilient urban drainage systems, alleviating climate-related flood risks, safeguarding water ecosystems, and integrating smart technologies for adaptive infrastructure.

KEYWORDS: Fuzzy Logic Control (FLC); Flood control; Stormwater management reservoirs; Urban flooding.

1 INTRODUCTION

The rapid growth of megacities with an intense densification and verticalization, the aging infrastructure and along with the increasing frequency and intensity of extreme weather events, presents significant challenges to become cities resilient to urban floods. Urban flood risk management focuses on developing strategies to mitigate the impacts of climate change, particularly the damages resulting from flooding caused by the overflow of urban rivers or canals. Building a resilient city entails the capacity to adapt to such hazards, thereby reducing human and economic losses while leveraging natural advantages for sustainable urban development (Nkwunonwo et al., 2020).

There are modeling approaches to simulate the complex non-linear dynamics of urban floods and assess their impacts or the effectiveness of the measures against them. Some of them are focus on the optimal operation of the detention or retention urban reservoirs by implementing Real-time control (RTC) strategies on outlet devices (e.g., pump systems, orifices, gates) (Qi et al., 2021; Li, 2020).

Despite its significant potential benefits, the implementation of RTC strategies in urban drainage systems remains limited to only a few cities worldwide (Lund et al., 2018). Additionally, existing studies have largely been conducted in catchments with high-quality and detailed data on urban drainage networks, including high-resolution flow and water level time series (Mounce et al., 2020; Li, 2020), or with a suitable sensor distribution (Bartos and Kerkez, 2021). Such data availability is relatively rare in urban basins of less developed countries, highlighting a critical gap in knowledge and practice (Sánchez, 2025).

This study aims to reduce a crucial knowledge gap by providing the first steps of the implementation of Fuzzy Logic Control (FLC) as a RTC flood risk reduction measure. Specifically, it investigates that manually configuration of a Fuzzy Interference System (FIS) for each outlet device of multiple urban reservoirs can reduce peak flow and the accumulated flooding volume. The configuration of each FIS was done by a rule-based method that take into account the constructive characteristics of the reservoir. After that, it was compared the flow rates of a rainfall-runoff simulation with a design precipitation of 25-year return period of the baseline and FLC implementation scenario by using two indexes.

This control approach is planned to be applied in an urban basin with poorly gauged characteristics, serving as a proof of concept for the practical application of a fuzzy real-time control in outlet devices of reservoirs with monitoring limitations. Overall, this analysis represents the initial steps toward evaluating the potential of the FLC control implementation as a reactive control strategy and contributes to the broader discussion on urban flood risk management in less developed countries.

2 MATERIALS AND METHODS

This study implemented a reproducible framework to address the implementation of a flow control strategy with data scarcity conditions in an urban watershed, by using the open source hydrodynamic-hydrological model HydroPol2D (Gomes Jr et al., 2023) with a FAIR data principles approach (Wilkinson et al., 2016).

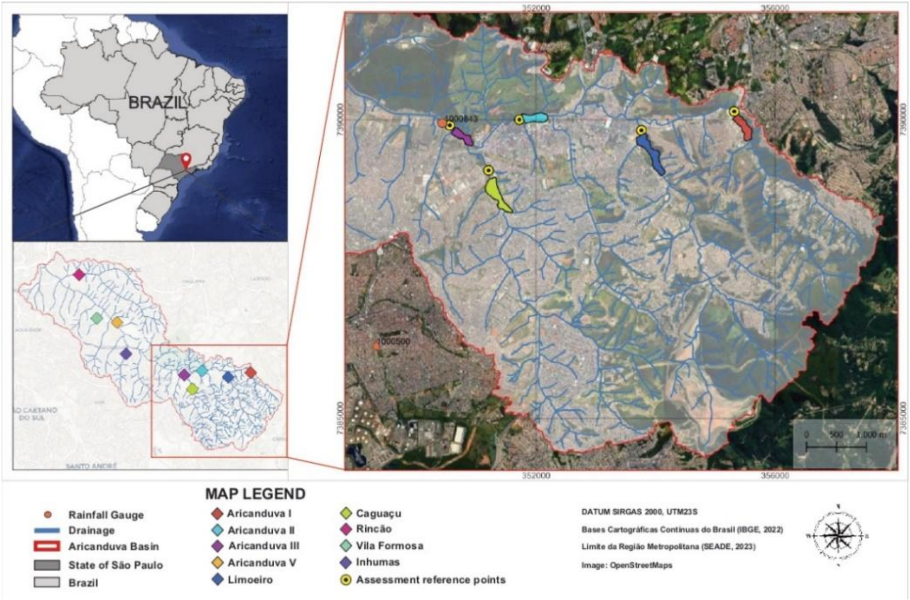

Figure 1: Location of the analysed reservoirs in the study. Taken from Sánchez (2025).

We chose the upstream online reservoirs of the Aricanduva watershed to implement the controllers. This watershed is one of the largest within the São Paulo Metropolitan Area (SPMA), located in the eastern part of the city and encompasses approximately 100 km^2, where multiple studies had assessed its vulnerability to floods (Sanchez, 2025). The online reservoirs where the FLC is implemented are Limoeiro, Caguaçu, and Aricanduva I, Aricanduva II, and Acricanduva III (Figure 1).

To evaluate FLC performance for each stormwater reservoir, we simulated hydrographs generated by the SCS Unit Hydrographs Runoff Method based on each reservoir's drainage area characteristics. Then, we compared the baseline scenario (without FLC implementation) with the control scenario (with FLC implementation) by using the Accumulated Flooding Volume Reduction (AFVR) (Li, 2020) and the Peak Flow Reduction (PFR) indexes.

2.1 Fuzzy Logic Control implementation

The stormwater reservoirs analysed have culverts and spillways as outlet devices. These structures were modeled through rating curves as a function of the water level (Gomes Jr et al., 2024). However, if the culvert and the spillway are retrofitted with a vertically controllable device that modifies the cross-sectional area, the sluice fate equation with discharge to the atmosphere, can be applied (Sánchez, 2025). Thus, these devices have the dual functionality of culvert /spillway or gated culvert/gated spillway (Sánchez, 2025).

The development of a fuzzy controller involves the building of a Fuzzy Interference System. The FIS is established with two components: the controller membership function parameters (CMFPs) and the fuzzy control rules (FCRs) (Li, 2020). The CMPs implemented for controlling the gated culvert and the gated spillway of the reservoirs are defined for two input variables and one output variable. The first input variable is the water level (WL) at the current time and the second input variable is the water level variation (WLV) between the control intervals.

The WL has three membership functions (MFs) in the gated culvert case and four in the gated spillway case. On the other hand, The WLV has five MFs in the gated culvert and two in the gated spillway case. Lastly the output variable is the Gate Opening (GO), selected to characterize gate openness, defined with five MFs ranging from 0% to 100% in increments of 25%. This output variable is the same for both outlet devices.

The FCRs are based on CMFP values and establish an effective IF-THEN statement by defining the degree of relationship between the input and output MFs. Table 1 shows the inputs MFs and summarizes a total of fifteen FCRs for each reservoir in the gated culvert case. Table 2 shows the input MFs and summarizes eight FCRs for each reservoir in gated spillway case. The defuzzification method chose was Mean of Maxima (MOM), that is the commonly used in the creation of FISs. Taking into account the established rules and the method of defuzzification can be generated an output surface, which describes all possible combinations of WL and WLV across the range, as well as their relation with GO.

Table 1 Title of the Table

Reservoirs	Water Level (WL)	Water Level Variation (WLV)				
		N. High (NH)	N. Low (NL)	Zero (Z)	P. Low (PL)	P. High (PH)
Aricanduva I	Low (L)	Open 25	Open 25	Open 100	Open 50	Open 50
	Medium (M)	Open 25	Open 25	Open 100	Open 50	Open 75
	High (H)	Open 75	Open 75	Open 100	Open 100	Open 100
Limoeiro	Low (L)	Open 25	Open 25	Open 25	Open 50	Open 50
	Medium (M)	Open 25	Open 25	Open 50	Open 75	Open 75
	High (H)	Open 50	Open 50	Open 75	Open 100	Open 100
Caguaçu	Low (L)	Open 25	Open 25	Open 25	Open 50	Open 50
	Medium (M)	Open 25	Open 25	Open 25	Open 75	Open 75
	High (H)	Open 25	Open 50	Open 50	Open 100	Open 100
Aricanduva II	Low (L)	Open 25	Open 25	Open 25	Open 50	Open 50
	Medium (M)	Open 25	Open 25	Open 25	Open 75	Open 75

	High (H)	Open 50	Open 50	Open 50	Open 100	Open 100
Aricanduva III	Low (L)	Open 25	Open 25	Open 25	Open 50	Open 50
	Medium (M)	Open 25	Open 25	Open 25	Open 75	Open 75
	High (H)	Open 25	Open 50	Open 50	Open 100	Open 100

Table 2 Title of the Table

Reservoirs	Water Level Variation (WLV)	Water Level (WL)			
		Low (L)	M. Low (ML)	M. High (MH)	High (H)
Aricanduva I	Negative (N)	Open 0	Open 0	Open 25	Open 25
	High (H)	Open 0	Open 0	Open 25	Open 50
Limoeiro	Negative (N)	Open 0	Open 0	Open 25	Open 25
	High (H)	Open 0	Open 25	Open 25	Open 50
Caguaçu	Negative (N)	Open 0	Open 25	Open 25	Open 25
	High (H)	Open 0	Open 25	Open 25	Open 50
Aricanduva II	Negative (N)	Open 0	Open 0	Open 0	Open 25
	High (H)	Open 0	Open 25	Open 25	Open 50
Aricanduva III	Negative (N)	Open 0	Open 0	Open 25	Open 25
	High (H)	Open 0	Open 25	Open 25	Open 50

This study used a coupled hydrological-hydrodynamic model, called HydroPol2D (Gomes Jr et al., 2023), of the Aricanduva river Basin previously calibrated (Sánchez, 2025) for the implementation of this controller. The model is an open code source based on MATLAB programming language, providing the possibility to modify their modules and the implementation of the FLC by creating ".fis files". Therefore, for our approach the process begins with HydroPol2D's hydrological-hydraulic solver. Then, as we established a control interval of five minutes, during the simulation time every five minutes is done the FIS evaluation using the current state conditions of WL and WLV. Later, the output generated by the FIS is defuzzified into gate openness and will adjust the boundary internal conditions of the gated culvert and spillway. This looping mechanism is to represent the conditions of an RTC simulation.

2.2 Simulated hydrographs

The inflow hydrographs for each reservoir were determined by using the SCS Unit Hydrograph Method. The curve number were calculated by weighting the land use land cover areas form Brown et al. (2022) and considering references to the curve number from HEC-HMS within each drainage area. The time of concentration was estimated by using both the California (USBR) and Kiprich methods. The duration of the event between reservoirs varies and a time step of 10 minutes was determined.

Storm events were modeled by using an alternating block method derived from the equation of the intensity-duration-frequency (IDF) curve (Equation 1) obtained from the Aricanduva River Watershed Notebook (FCTH, 2022). The rain was characterized by a duration of 2 hours and a 25-year return period.

$$I_{t_d,t_r} = 32.77(t_d + 20)^{-0.878} + 16.1(t_d + 30)^{-0.9306}\left\{-0.4692 - 0.8474\, ln\left[ln\left(\frac{Tr}{Tr-1}\right)\right]\right\} \quad (1)$$

Where I_{t_d,t_r} is the intensity of the rain [mm / min] for a duration of the rain t_d [minutes] in the return period Tr [years].

2.3 Indexes for flooding severity assessment

We considered the Accumulated Flooding Volume Reduction (Li, 2020) and the Peak Flow Reduction as indexes to describe the changes in severity of the flooding approximately 100 meters downstream of the reservoir. The equation for calculating AFVR under the 25-year hydrograph scenario is formulated in Equation 2. PFR index shows the reduction in the maximum flow downstream of the reservoir under the 25-year hydrograph scenario. This index is determined by the Equation 3.

$$AFVR = \int_{t_0}^{t_n} \frac{Q_{b,i} - Q_{o,i}}{Q_{b,i}} \, d_t \qquad (2)$$

$$PFR = \frac{Q_{b,max} - Q_{o,max}}{Q_{b,max}} \, . 100\% \qquad (3)$$

Where $Q_{o,i}$ is the downstream flow rate in the control scenario, $Q_{b,i}$is the downstream flow rate in the base scenario, t_o is the start time of the simulation, $t_n$is the end time of the simulation, $Q_{o,max}$ is the maximum downstream flow rate during the control scenario, and $Q_{b,max}$ is the downstream flow rate during the base scenario.

3 RESULTS

This study developed individual simulations for each reservoir to establish control rules to reduce peak flows. Figure 2 compared the hydrographs for the Aricanduva I reservoir between the baseline and the FLC implementation scenario, using the outflow hydrographs generated with a 25-yeat design storm as inflow (dark blue line). The baseline scenario (red line) shows the performance of the outlet devices without FLC implementation. The reservoir delayed and reduced the inflow peak, and both outlet devices generate a peak flow with a rapid recession limb.

In contrast, the FLC implementation scenario (teal line) demonstrated how controllers further reduce the peak flow with gradual discharge. This behavior resulted from control rules for the gated spillway that increase the reservoir storage capacity, using the orifice condition in the gated culvert and its discharge capacity to increase the upstream energy head at the outlet device. This condition is verified in the right subplot, which shows the opening states of the gated culvert (green line) and gated spillway (purple line); the latter remains closed throughout the event.

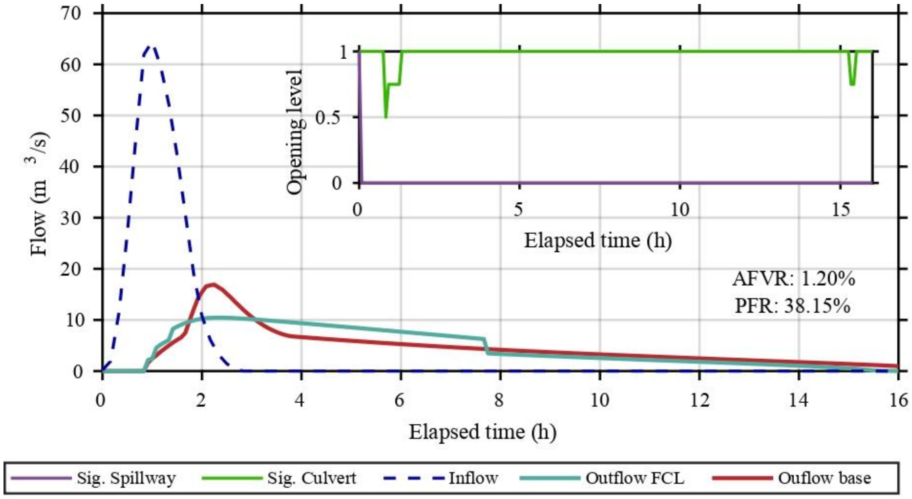

Figure 2: Hydrographs comparison between the baseline scenario (red line) and FLC application scenario (teal line) of the Aricanduva I reservoir at 100 meters downstream from the weir produced by the inflow (dark blue line). Taken from Sánchez (2025).

The PFR values in this study were 38.15%, 20.60%, 14.40% and 8.30% for the Aricanduva I, Limoeiro, Caguaçu, and Aricanduva III reservoirs, respectively. These values indicated a reduction in peak flow discharge in all reservoirs except Aricanduva II (Figure 3), which shows a 2.11% inverse in peak flow, due to aspects of the FLC configuration in this reservoir. First, we established rules for the gated spillway to increase reservoir storage capacity up to a specified level, utilizing the gated culvert condition to maximize discharge capacity during the hydrograph's rising limb. Consequently, the increased upstream energy head and adaptable cross-section culvert size enhanced the discharge in this structure.

Second, we implemented gate openings with steps of 25% to establish minimal rules in FISs, then for Aricanduva II's gated spillway, once discharge begins, sufficiently high upstream energy head accumulates to increase the discharge through this structure. Consequently, the flow was raising at the assessment point. After testing various MF configurations, the Aricanduva II reservoir did not show any improvement with the controller application.

The AFVR values were 1.20%, 0.60%, 8.30%, and 0.58% for the Aricanduva I, Limoeiro, Aricanduva II, and Aricanduva III reservoirs, respectively. These results indicated that the implementation of FLC slightly outperforms the baseline scenario in reducing flood volume. In contrast, the Caguaçu reservoir showed an AFVR value of -5.83%, indicating poor performance in reducing flood volume.

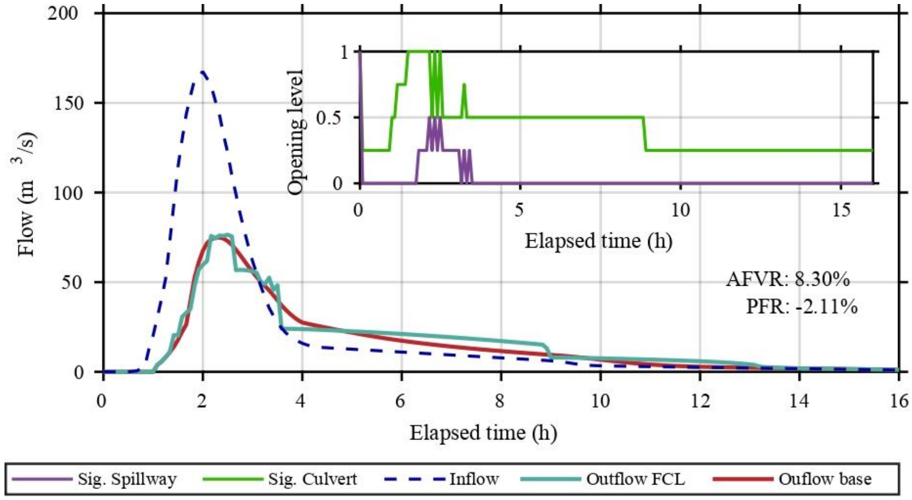

Figure 2: Hydrographs comparison between the baseline scenario (red line) and FLC application scenario (teal line) of the Aricanduva II reservoir at 100 meters downstream from the weir produced by the inflow (dark blue line). Taken from Sánchez (2025).

4 DISCUSSION

In this study, we assessed a fuzzy logic control strategy with rule-based membership functions for online stormwater reservoirs located in the watershed upstream area to reduce flooding flow. For that purpose, we evaluated each FLC's performance using AFVR and PFR metrics. This is a decentralized analysis for each reservoir that helps to determine whether FLC implementation can reduce the watershed flood impacts. Moreover, this framework was adopted due to the insufficient records of precipitation, water level, and discharge near the online reservoirs analysed.

Consequently, we found that FLC implementation in the outlet devices of the Aricanduva II reservoir (Figure 3), with established membership functions and rules, was ineffective in reducing the flood impacts. Furthermore, AFVR values were lower than those reported in previous studies using data-driven strategies with genetic algorithms (GA) (Li, 2020; Talei et al., 2010). This discrepancy may be due to some predetermined control rules that do not match optimal measurements and limited sluice gate opening ranges that cause significant flow variation.

Nevertheless, FLC can be tuned in various ways, with different and multiple membership functions or rules that could be explored to enhance the reservoir operation. Several studies have focused on developing accurate and optimal fuzzy interference systems using appropriate tuning methods (Li, 2020; Mounce et al.,2020; Ostojin et al., 2011; Talei et al., 2010). Future research could apply these tuning methods to improve FLC in stormwater reservoirs by using these individual hydrodynamic models for and employing data-driven, stochastic, and heuristic algorithms under various precipitation regimes (e.g., multiple design storms with return periods using non-stationary IDF curves or climate change scenarios).

4.1 Uncertainties and limitations

Although the effectiveness of the implementation of FLC as a flood control strategy is implemented individually in each reservoir, it is important to recognize that certain uncertainties and limitations inherent to the hydrodynamic model and the used approach also influence this analysis. The precision of the modelling results remains dependent on the quality of the input data, the methodologies used, and the assumptions made throughout the process.

In this study, only the outlet devices that regulate the outflow of the reservoir was explicitly modeled, with limited data available on the structures, constraining comprehensive representation. For example, some reservoirs present energy dissipators or culverts in some of their entrance that could not be represented in the model due to lack of information. These data limitations, along with uncertainties in the DEM generated form LiDAR processing and the assumption of static initial conditions prior to flood events contribute to the overall uncertainty in the simulation outcomes.

Other limitation is that FLC performance heavily depends on the quality of fuzzy control rules and membership functions, which are often designed empirically or based on limited data. Although subjective rule definition may capture complex hydrological dynamics, as observed in four of the face addressed reservoirs, this approach may also result in suboptimal gate operations. Future studies could incorporate metaheuristic optimization algorithms to automate rule tuning and MFs parameterization, thus reducing subjectively and improving adaptability.

Furthermore, the practical effectiveness of this controller in real-world scenarios warrants further validation, potentially through predictive fuzzy logic controllers that incorporate probabilistic rainfall forecasts and ensemble modelling to quantify uncertainty (Sun et al., 2024; Amitaba et al., 2024).

5 CONCLUSION

This study proposes the first steps to apply a fuzzy logic control tool based on fuzzy logic theory on outlet devices of stormwater reservoirs to reduce downstream flooding volume in poorly gauged urban watershed. The results demonstrate that upstream stormwater reservoirs can be controlled by using FLC to leverage their hydraulic characteristics and reduce the peak flow and the accumulated flooding volume for lowering flood impacts in downstream. Additionally, this framework of control simulation tool opens the possibility to integrate various metaheuristic and stochastic algorithms to enhance the FLC performance.

The main contributions of this study are: (i) The simulation of a RTC strategy incorporating FLC into rainfall-runoff model to increase the resilience of the reservoirs. (ii) The development of a framework to establish a FISs using a manually rule based method for each reservoir. (iii) The implementation of the AFVR and the PFR indexes can assess the effectiveness of FLC implementation in the outlet devices and assist in the assessment of the membership functions and the fuzzy control rules.

This study demonstrates the potential benefits of implementing FLC into urban flood control structures, especially in stormwater reservoirs with data scarcity. However, several uncertainties and limitations remain, including model assumptions, the data limitations, and the sensitivity of FLC input inaccuracies. Future research should focus on integrating advanced optimization algorithms and robust filtering methods into the established framework to enhance system reliability and performance. Finally, the implemented approach allows the assessment of which reservoirs with FLC implementation could effectively reduce urban flooding impacts, particularly in data-scarce watersheds.

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REFERENCES

AMITABA, I.W., JUWONO, P.T., LIMANTARA, L.M., ASMARANTO, R. (2024). Real time operation simulation model with early release reservoir storage. Journal of Human, Earth, and Future 5, 574–590

BARTOS, M., KERKEZ, B. (2021). Pipedream: An interactive digital twin model for natural and urban drainage systems. Environmental Modelling & Software 144, 105120.

BROWN, C.F., BRUMBY, S.P., GUZDER-WILLIAMS, B., BIRCH, T., HYDE, S.B., MAZZARIELLO, J., CZERWINSKI, W., PASQUARELLA, V.J., HAERTEL, R., ILYUSHCHENKO, S., ET AL. (2022). Dynamic world, near real-time global 10 m land use land cover mapping. Scientific Data 9, 251

FCTH, (2022). Caderno de bacio hidrogr´agica - Bacia do Rio Aricanduva. 2 ed., Prefeitura do Munic´ıpio de São Paulo Secretaria Municipal de Infraestrutura Urbana e Obra. Web-1

GOMES, M. N. et al. (2023) HydroPol2D — Distributed hydrodynamic and water quality model: Challenges and opportunities in poorly-gauged catchments. Journal of Hydrology, v. 625, p. 129982.

GOMES, M. N., Jr et al. (2024) Spatio-Temporal performance of 2D local inertial hydrodynamic models for urban drainage and Dam-Break applications. SSRN.

LI, J. (2020). A data-driven improved fuzzy logic control optimization-simulation tool for reducing flooding volume at downstream urban drainage systems. The Science of the Total Environment, v. 732, p. 138931.

LUND, N.S.V., FALK, A.K.V., BORUP, M., MADSEN, H., STEEN MIKKELSEN, P. (2018). Model predictive control of urban drainage systems: A review and perspective towards smart real-time water management. Critical reviews in environmental science and technology 48, 279–339.

MOUNCE, S. R. et al. (2019) Optimisation of a fuzzy logic-based local real-time control system for mitigation of sewer flooding using genetic algorithms. Journal of Hydroinformatics, v. 22, n. 2, p. 281–295.

NKWUNONWO, U. C.; WHITWORTH, M.; BAILY, B. (2020) A review of the current status of flood modelling for urban flood risk management in the developing countries. Scientific African, v. 7, p. e00269.

OSTOJIN, S., MOUNCE, S., BOXALL, J. (2011). An artificial intelligence approach for optimizing pumping in sewer systems. Journal of hydroinformatics 13, 295–306

QI, W. et al. (2021) A review on applications of urban flood models in flood mitigation strategies. Natural Hazards, v. 108, n. 1, p. 31–62.

SÁNCHEZ, M. H. (2025) A novel framework for flood Vulnerability Assessment and FuzzyControlled Reservoir Optimization in Data-Scarce Urban Watersheds. Dissertation (Master of Science)—[s.l.] São Carlos School of Engineering, University of São Paulo. Web-2.

SUN, L., XIA, J., SHE, D., DING, W., JIANG, J., LIU, B., ZHAO, F. (2024). A predictive fuzzy logic and rule-based control approach for practical real-time operation of urban stormwater storage system. Water Research 266, 122437.850

TALEI, A., CHUA, L.H.C., QUEK, C. (2010). A novel application of a neuro-fuzzy computational technique in event-based rainfall–runoff modeling. Expert Systems with Applications 37, 7456–7468

Web sites:
Web-1:
https://www.prefeitura.sp.gov.br/cidade/secretarias/upload/obras/cadernos_de_drenagem/CBH_2022_Aricanduva_ed2.pdf.
Web-2: https://teses.usp.br/index.php?option=com_jumi&fileid=38&Itemid=183&id=77AD002BD8E7