EXPLORING URBAN FLOOD VULNERABILITY

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RESUMO – As mudanças climáticas devem aumentar a frequência e intensidade de eventos extremos de precipitação, enquanto o crescimento urbano em superfícies impermeáveis e da população pode elevar o impacto de inundações. Este estudo avalia os impactos das inundações utilizando curvas não estacionárias de intensidade-duração-frequência (IDF) na bacia urbana do Rio Aricanduva em São Paulo, Brasil. Dados censitários do IBGE foram usados para analisar a densidade populacional e de domicílios, e o modelo HydroPol2D simulou as inundações com precipitações de projeto de Huff para períodos de retorno de 2 a 100 anos. Os resultados evidenciam que a bacia é suscetível a inundações em todos os cenários. Sob um período de retorno de 2 anos, cerca de 22.782 pessoas (1,66%) seriam afetadas; sob 100 anos, esse número sobe para 48.344 (3,53%). Os impactos nos domicílios seguem padrão semelhante, de 8.813 (1,54%) no cenário de 2 anos a 18.708 (3,26%) no de 100 anos, com base nas condições de densidade de 2022. Esses resultados confirmam a vulnerabilidade da bacia às inundações nas condições atuais, podendo ajudar modelagens e avaliações de impacto em bacias urbanas com escassez de dados, apoiando estratégias de prevenção e controle alinhadas aos ODS 6, 9, 11 e 13.

Palavras-Chave – Inundações urbanas; Avaliação da vulnerabilidade às inundações; Modelagem hidrológica-hidrodinâmica.

ABSTRACT– Climate change is projected to increase the frequency and intensity of extreme precipitation events, while urban growth in impervious surfaces and population may heighten the impact of flooding. This study evaluates flood impacts using non-stationary intensity-duration-frequency (IDF) curves in the urban basin of the Aricanduva River in São Paulo, Brazil. Census data from IBGE was used to analyze population and household density, and the HydroPol2D model simulated flooding using Huff design precipitation for return periods of 2 to 100 years. Results show that the basin is susceptible to flooding across all scenarios. Under a 2-year return period, approximately 22,782 people (1.66%) would be affected; under a 100-year return period, this number rises to 48,344 (3.53%). Household impacts follow a similar pattern, from 8,813 (1.54%) in the 2-year scenario to 18,708 (3.26%) in the 100-year scenario, based on 2022 density conditions. These findings confirm the basin's vulnerability to flooding under current conditions, and can support flood modeling and impact assessments in data-scarce urban watersheds, aiding prevention and control strategies aligned with SDGs 6, 9, 11, and 13.

Key-words – Urban flooding; Flood vulnerability assessment; Hydrological-hydrodynamic modeling.

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1. INTRODUCTION

Flash floods are a natural hazards, characterized by sudden inundation following intense, short-duration rainfall events. These floods typically develop within minutes to hours, leaving little time for warning or response, and are especially prevalent in low-lying or poorly drained urban areas. The primary drivers of flash floods include extreme precipitation, geomorphological factors such as slope and soil type, and anthropogenic influences like deforestation and land use change.

Urban areas are particularly vulnerable to flash floods due to the proliferation of impervious surfaces (Reddi *et al.* 2019). Rapid population growth and unplanned urban expansion often lead to changes on natural drainage channels and the construction of inadequate or poorly maintained drainage infrastructure, further exacerbating flood risk. Additionally, socioeconomic factors such as poverty, informal settlements, and limited risk awareness compound the vulnerability of urban populations, particularly in developing regions (Giri *et al.*, 2021).

Moreover, urban drainage systems, often designed based on outdated rainfall data, are frequently overwhelmed by the combined effects of urban growth and climate-induced increases in rainfall intensity (Brodie & Dunn, 2010). Poor urban planning, including construction in near to flood prone zones and insufficient maintenance of drainage infrastructure, further amplifies flood risk and impact severity (Salazar-Briones *et al*., 2020). These challenges are particularly severe in developing countries, where rapid urbanization outpaces infrastructure development and governance capacity.

There are several flood risk management strategies to address the hazard of urban flash floods. One of them is the hydrological and hydraulic modeling, used to simulate runoff processes and flood propagation in urban catchments, supporting risk quantification and infrastructure design. While hydrological models are efficient and hydraulic models provide detailed spatial representations, it may oversimplify urban process and may require high-quality data and computational resources (Alejandro *et al.*, 2019). Other strategy can be classified as GIS-Based Multiciteria Decision Analysis, that integrates spatial data on rainfall, land use, drainage, vulnerability, and other socioeconomic data to map flood risk and prioritize mitigation actions. Generally, the framework in this strategy integrates analytical hierarchical process (AHP) and machine learning (ML) approaches (Nachappa *et al.*, 2020). Recently, with the support of the computational power and advanced in ML techniques, the uses of remote sensing imagery and real-time monitoring arose as approaches to capture the complexity of urban flash floods dynamics. With the advances in satellite and Unmanned Aerial Vehicle (UAV) imagery, rapid and accurate flood extent mapping is enabled, even in data-scare environments (Mohamadiazar *et al*., 2024). On the other hand, with the real-time monitoring, rainfall threshold analysis, and IoT sensor networks support timely alerts (Early Warning Systems), reducing mortality and economic losses (Qatrinnada *et al.*, 2024).

Despite these advances, there are gaps remained in the urban flash flood impacts, particularly in developing countries. For example, many urban areas in developing countries lack high-resolution, reliable hydrological, topographical, and socio-economic data, limiting the calibration and validation of flood models and risk assessments (Surminski & Oramas-Dorta, 2013) disabling the methodological adaption from advances models developed in high resource settings. Other example is that vulnerable population are of the underrepresented in risk assessment and resilience planning, leading to inequitable outcomes and persistent risk (Barankin *et al.*, 2021) usually, accompanied by weak institutional frameworks and limited stakeholder engagement.

This study aims to reduce a crucial knowledge gap by exploring a framework for assessing flood vulnerability in urban watersheds using public available data, open-source model, and census data under non-satationary Intensity-Duration-Frequency (IDF) curves for 2-, 5-, 10-, 25-, 50-, 100-year return periods simulations. The study area was the Aricanduva River Basin, located in São Paulo city, Brazil. The results showing a vulnerability across the watershed in all the simulated events, justifying further studies to enhance flood resilience.

2. MATERIALS AND METHODS

The implemented framework used in this study to address flood vulnerability in an urban watershed is represented in the Figure 1, and is divided in two phases. The first is the flood maps generation and the second is the flood impact analysis with demographic and socio-economic data.

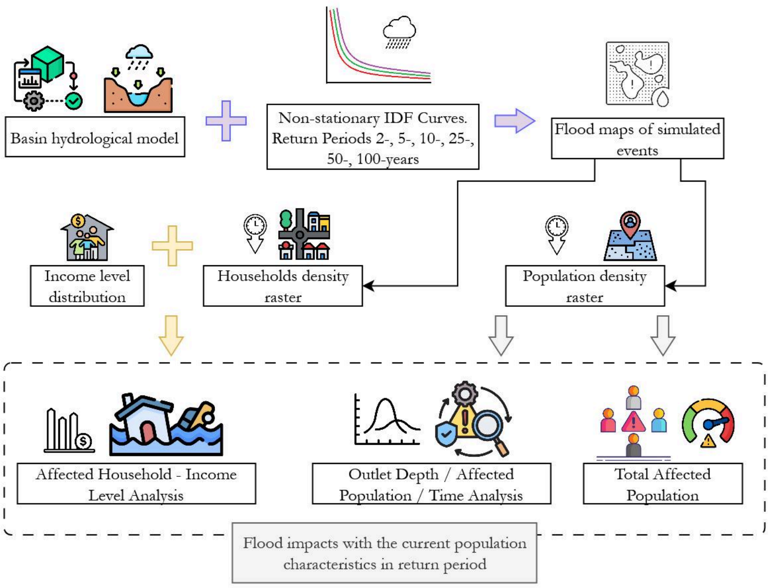

Figure 1 – Methodological framework.

2.1. Flood Maps Generation

For the generation of the flood maps, we used the coupled hydrological-hydrodynamic model called HydroPol2D (Gomes *et al*. 2023, Gomes *et al*. 2024). The key parameters of the model are: manning coefficient (η); hydraulic conductivity of saturated soil (k_{sat}); average matrix water potential at the wetting front (Ψ); and soil moisture (Δθ). The Aricanduva watershed's model was calibrated and validated in Sánchez (2025) by using 12 flood events monitored by 15 SAISP (Sistema de Alerta a Inundações de São Paulo) gauges.

The simulated events were design storms with a second quartile Huff distribution for the return periods of 2-, 5-, 10-, 25, 50-, and 100-years and an event duration of 360 minutes. We used the IDF curves developed by Silva (2022) for the city of São Paulo, Brazil, for the construction of these design storms.

2.2. Flood Impact Analyses

We used the methodology applied in Sánchez (2025) to assess the impact of the simulated events. The evaluation encompasses socio-economic impacts, with the premise that any flood depth exceeding 0.5 meters can adversely affect the inhabitants of the inundated area. The impact assessments are categorized into three analyses: Total Affected Population (TAP), Affected Population During the Event (APDE), and Affected Households by Income Level (AHIL). The input data for the analyses are the flood maps (generated by the simulations), the demographic density map (IBGE, 2022), the household density map (IBGE, 2022), and household income census data (IBGE, 2010).

TAP is obtained by overlaying the maximum flood map with the demographic density map. APDE is obtained by overlaying the flood maps of each 10-minute timestep with the demographic density map; it reflects the basin-wide affected population at each time interval compared with water depths at reference points. The reference points used in this study were the rainfall gauge 1000843 and the watershed's Outlet (Figure 2). Finally, the AHIL is obtained by overlaying the maximum flood map with the household density map and spatialized household income census data.

2.3. Study Area

The study area was the Aricanduva Basin (Figure 2), covering around 100 km² in the eastern São Paulo Metropolitan Area (SPMA), faces frequent flooding along its main river, particularly during intense rainfall events due to heavy urbanization, reduced soil permeability, and high slope areas (Simas *et al*., 2017).

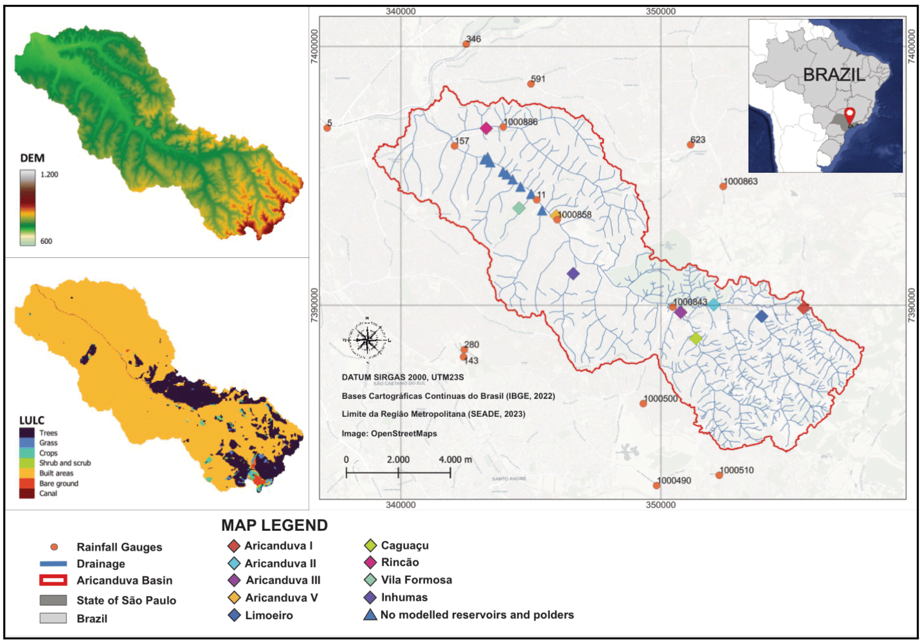

Figure 2 – Aricanduva River Basin, São Paulo - Brazil. Taken from Sánchez (2025).

3. RESULTS

The Total Affected Population versus design rainfall for 2-, 5-, 10-, 25-, 50-, and 100-year return periods is presented in Figure 3.

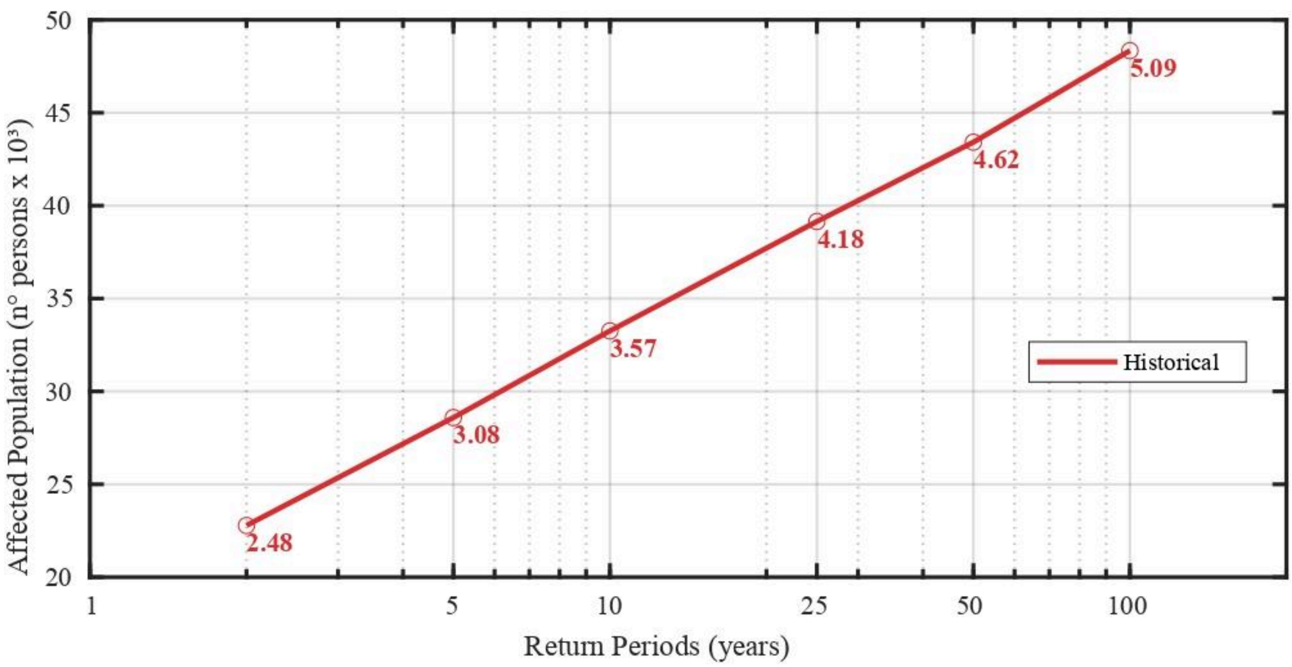

Figure 3 – Total Affected Population through the simulated events

This figure summarizes the total impact of each simulated event. The markers represent the inundated area in km² of each simulation. For 2-, 5-, 10-, 25-, 50-, 100-year simulations, the TAP was 1.66%, 2.09%, 2.43%, 2.86%, 3.17%, and 3.53%, respectively, from the total inhabitants within the Aricanduva watershed. It was noticeable an inverse relation between the affected population and the frequency of the events, due to the increase of total inundated area across the simulated scenarios.

The Affected Population During Event analysis for 2-, 5-, 10-, 25-, 50-, and 100-year return periods in two reference points is presented in Figure 4. Y-axis represents the affected population in all the watershed at that time; the Inverted-Y-axis represents the water depth normalized by the drainage area of each reference point; and the X-axis represents the elapsed time.

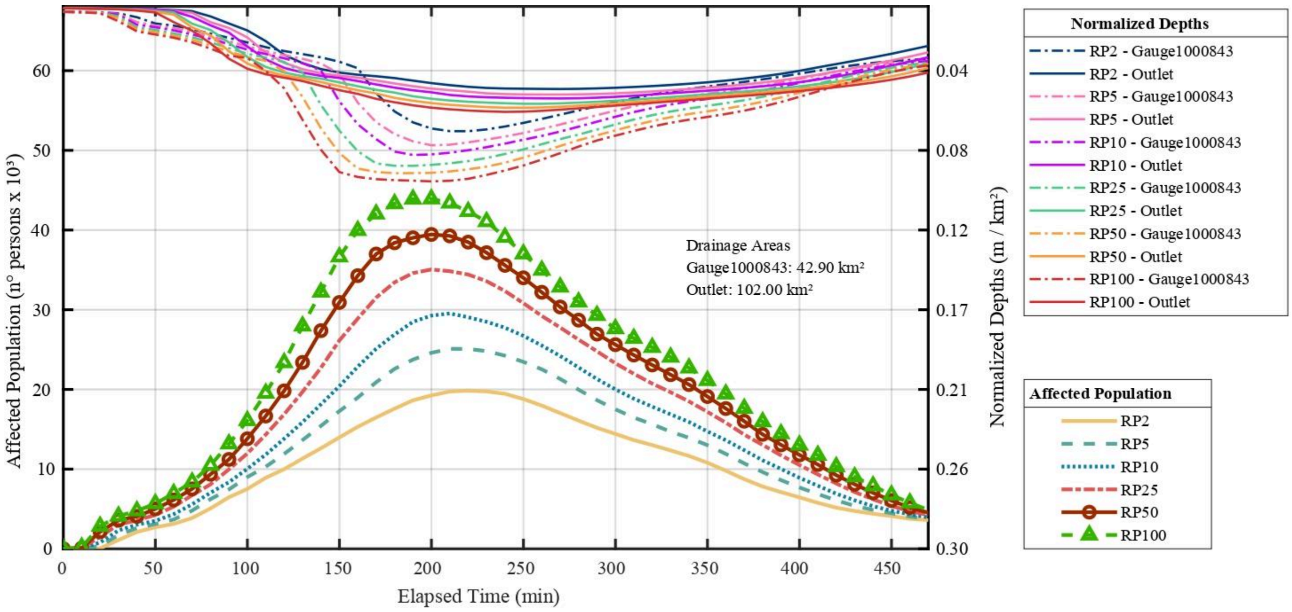

Figure 4 – Affected Population During Event analysis through the simulated events

The reference points were the Rainfall Gauge-1000843, located at the upstream zone, and the Aricanduva watershed's outlet. Taking the 2-year return period simulation as a reference, with an impact peak of 19,847 affected people, the increments of the impact peaks in the 5-, 10-, 25-, 50-, and 100-year return period simulations were 26.44%, 48.81%, 76.62%, 98.77%, and 121.25%, respectively. Regarding the increments of the depth peaks in the Rainfall Gauge-1000843, with a 2.99 meters as a reference from the 2-year return period simulation, were 11.37%, 19.06%, 27.76%, 33.78%, and 40.13%, respectively. Lastly, the depth peaks' increments at the watershed's Outlet, with a 4.71 meters as a reference from the 2-year return period simulation, were 6.58%, 11.25%, 17.83%, 22.50%, and 27.39%, respectively. Moreover, the lag-time between the depth peaks and the impact peaks had an increasing tendency in the upstream zone and remains relatively constant in the watershed's outlet. This analysis can help to evaluate the effectivity of structural flood control strategies to mitigate the impacts in different points of the watershed.

The Affected Households by Income Level analysis for 2-, 5-, 10-, 25-, 50-, and 100-year return periods is presented in Figure 5.

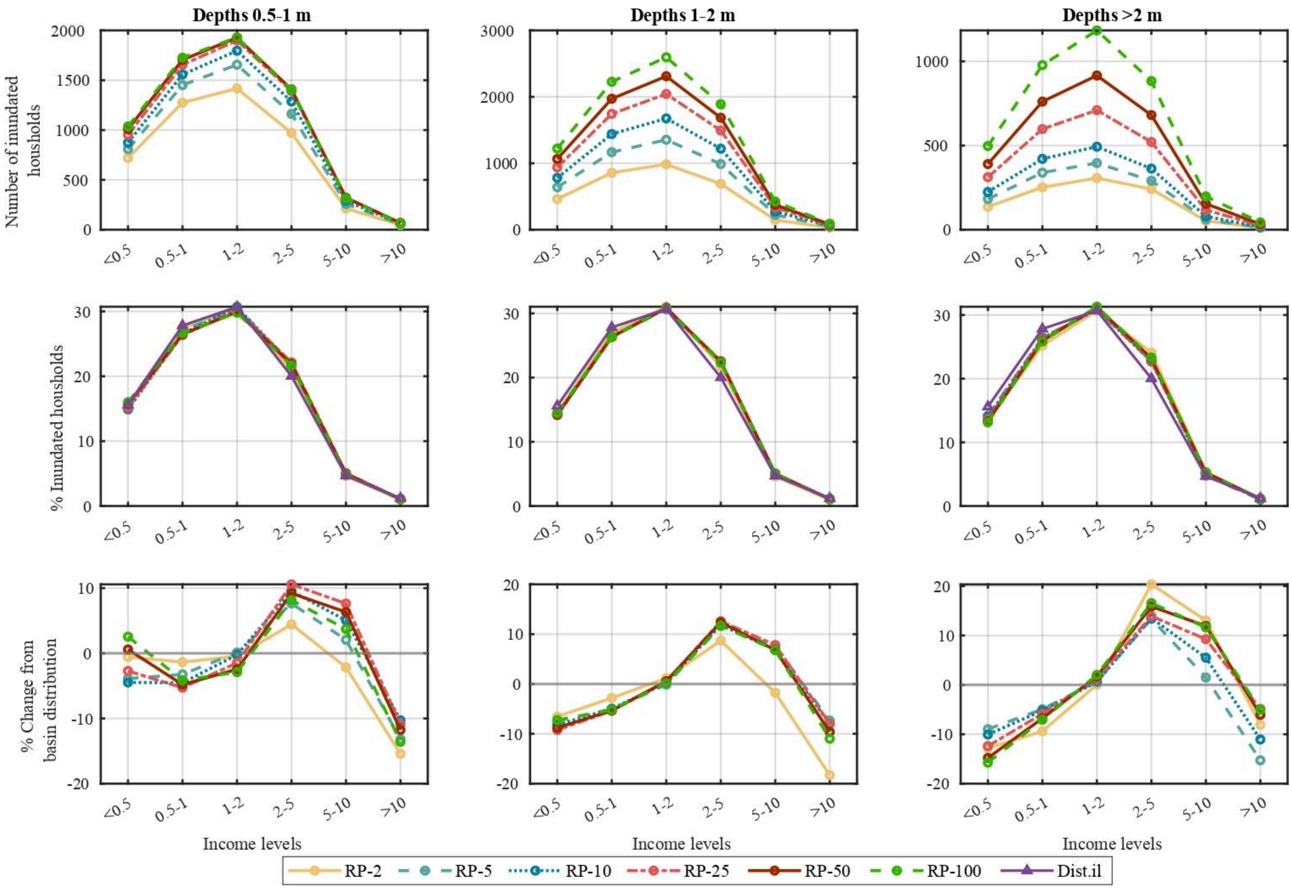

Figure 5 – Affected Households by Income Level analysis through the simulated events

The first row, which represents the number of affected households, presented a peak in the 1-2 Minimum Wage (MW) income level group in all the flood depths. In the second row, which represents the normalization of the affected houses by the total affected houses in each simulation, we noticed a similar distribution of the impact across all return periods. However, in the third row, which represents the percentage of change per income level, we could visualize the next main findings: (i) The 1-2 MW income level group was nearly to zero in all the flood depths. (ii) The flood depth categories 0.5-1 m and >2 m presented variability in the income level groups across the simulated scenarios. (iii) Nevertheless, in these flood depths, the <0.5, 0.5-1, and >10 MW income level groups had a tendency to be proportionally less affected by floods, and the 2-5 and 5-10 MW income level groups had a tendency to be proportionally more affected by floods.

4. DISCUSSION AND CONCLUSION

This study presents a method to evaluate flooding impacts on populations and estimates the impacts on households by income level. We employed a coupled hydrodynamic-hydrological model to simulate flood dynamics and demographic census data to assess the flood vulnerability in the study area. The Aricanduva watershed , a densely populated urban area in the eastern part of the city of São Paulo, Brazil, served as the study area to illustrate the model’s efficacy and the vulnerability assessment process. This analysis examined flood impacts across recurrence intervals using non-stationary IDF curve parameters extracted from historical data of the city of São Paulo.

Findings indicate that the Aricanduva watershed's flood vulnerability under current demographic and climate conditions. For example, in this study area that has a population of 1'369.994 people, a 2-year return period simulation showed 1.66% of the population being affected by the flood. That value increased to 2.86% for a 25-year simulation, and reached 3.53% for a 100-year simulation.

On the other hand, in the case of the 573.649 households presented in the Aricanduva watershed, the 2-year return period simulation impacted 1.54% of households, 2.65% under the 25-year simulation, and 3.26% under the 100-year simulation. Regarding the affected houses by income level groups analysis, the income level groups that had a tendency to be proportionally less affected by floods were the households that received <0.5, 0.5-1, and >10 Minimum Wage. On the other hand, the income level groups with 2-5 and 5-10 Minimum Wage had a tendency to be proportionally more affected by floods. The income level group that received 1-2 Minimum Wage had a neutral proportionality. This analysis can help to develop public policies that want to mitigate the flood impact through reallocation or non-structural measures based on taxes or insurance.

Furthermore, it is important to recognize that the reliability of this flood risk analysis depends on the quality of the input data, the modeling assumptions, and the methodological choices adopted. Regarding the hydrological model's input data, DEM errors inherited from LiDAR processing may over- or underestimate flood extents, and the use of static initial conditions (soil moisture, water depths) across all scenarios may introduce irregularities in the simulated flows. Regarding the non-stationary IDF curves of Silva (2022), while methodologically advanced, they are based only on time-based covariates and do not capture urbanization or microclimate effects that represent sub-hourly rainfall.

In terms of methodological constraints, key hydraulic structures (eight polders and the Tobão reservoir) were excluded due to data scarcity, which may underestimate the basin's flood regulation capacity. Additionally, the socioeconomic data were also a source of uncertainty, as household income was taken from the static 2010 census, which does not reflect subsequent variability, particularly among lower-income groups, that may be present in the 2022 census.

Finally, the proposed framework quantifies only direct impacts (i.e., residents in areas with flood depths ≥0.5 m) captured through a street-level rainfall-runoff model. Marginal impacts, such as business interruption, indirect tangible losses, infrastructure damage, and intangible effects, were not quantified, meaning our estimates likely represent an underestimate of the total flood impact.

Future studies should expand the scope by integrating land cover changes, demographic projections, and climate change projections (e.g., CMIP6) or broader socioeconomic impacts to enhance comprehensive flood risk management. Moreover, integrating this flood vulnerability framework with the determination of critical watershed infrastructure flood vulnerability (such as service networks, critical buildings, and mobility routes) and the incorporation of parameters of historically inundated areas would be a benefit for enhancing the comprehension of flood risks in urban watersheds.

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