



Influence of land use and land cover datasets on dam-break modeling in the semiarid region of Brazil

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Abstract

Accurate estimation of Manning's roughness coefficient is critical for reliable hydraulic modeling of dam-break floods. However, for this type of accident, the lack of historical flood data makes the definition of Manning's roughness coefficient challenging. This study utilizes high-resolution land use and land cover (LULC) data to determine Manning's roughness coefficient values for application in dam-breaking studies. This study assesses the influence of a regional high-resolution LULC dataset (MapBiomias) and two high-resolution LULC datasets (Dynamic World and ESRI 10 m Annual) on hydraulic parameters related to flood wave propagation and flood hazard assessment. The simulations indicated substantial variations in flood behavior across the Dynamic World generated predominant regions with elevated Manning values, resulting in expanded flood zones and heightened flow attenuation simulations. Conversely, the ESRI 10 m Annual exhibited predominant regions of lower roughness, leading to simulations with diminished flood areas, reduced propagation times, and decreased attenuation of peak flows. Compared with the other LULC datasets, MapBiomias demonstrated a balanced representation of the Manning coefficient's domains and yielded intermediate outcomes. These discrepancies highlight the challenges associated with accurately determining Manning's values to ensure precise outcomes in flood modeling. The quality of this modeling is critical for identifying risks, formulating emergency responses, and implementing effective mitigation strategies in downstream regions.

Keywords Hydraulic modeling · Dam break · Manning's roughness · LULC · Flood hazard assessment

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1 Introduction

Dam-formed reservoirs provide many benefits, including supplying water for human and animal consumption, controlling floods, irrigating crops, generating hydroelectric power, facilitating navigation, and providing spaces for recreational activities.

Notwithstanding the implementation of rigorous safety protocols and the application of advanced engineering principles in the design and construction of dams, the intrinsic risk associated with these structures persists. Consequently, accidents may occur due to natural disasters, human error, or deterioration of a dam's structural integrity due to aging (Viseu and de Almeida 2009).

Dams pose a technological hazard (UNDRR 2020), characterizing the risk of accidents that could threaten downstream valleys, endangering populations, infrastructure, and environmentally sensitive areas (Hariri-Ardebili 2018).

In this context, conducting a flood hazard assessment is of fundamental importance for developing prevention and mitigation strategies that aim to reduce the impact of water-related disasters on populations and improve living conditions in downstream areas (Aureli et al. 2024).

Understanding peak depth and discharge data, especially during critical flood events, is crucial for designing structures and protecting lives and properties (Rashid and Chaudhry 1995). The severity of fatalities and property damage in a dam failure depends on several factors, including hydraulic data such as flow velocity, water depth, and the time available for response following the accident (ICOLD 2018).

These output data are usually estimated via numerical models (Werner 2001). However, owing to the inherent variability in the models and the parameters employed, significant uncertainties are associated with the resulting estimates (Ballesteros et al. 2011; Merwade et al. 2008).

Numerical models can estimate the flow rate, velocity, water depth, flood wave propagation time (t), and combination of depth and velocity, which are employed to quantify the intensity of flooding and its downstream impacts (DHS 2011).

The depth and velocity relationship is a reference for evaluating flood hazards. This relationship is often applied in curves to assess the vulnerability and severity of flooding on people, vehicles, and buildings (Smith et al. 2014; USBR 1988; Viseu 2006).

Flood maps are important for assessing consequences, planning mitigation strategies, and preparing emergency action plans (EAPs). They represent the results of hydrodynamic simulations obtained through numerical models (Costabile et al. 2020).

The outcomes predicted by numerical models are inherently prone to significant uncertainty, mainly due to the intrinsic variability of results and the underlying parameters (Ballesteros et al. 2011).

The primary sources of uncertainty and error often originate from the input data utilized in these models (Garrote et al. 2021). The accuracy and reliability of hydraulic model results are contingent upon the quality of digital elevation models (DEMs) and the appropriate selection of Manning's roughness coefficient (Lim and Brandt 2019; Yalcin 2020).

Consequently, calibration of the models using data from historical events represents a method of eliminating these uncertainties (Merwade et al. 2008; Papaioannou et al. 2016).

Several studies have focused on the calibration of models, particularly on the roughness coefficient, as it directly influences the dynamics of water flow and the extent of the flooded area (Horritt and Bates 2002).

The performance of two-dimensional models is sensitive to the values assigned to roughness (Liu et al. 2019), which demonstrates that the accurate definition of roughness coefficients in open channel flow simulations is crucial when seeking results that are more closely aligned with reality (Ballesteros et al. 2011).

The scarcity of observational depth and velocity data for high-flow events renders model calibration technically challenging (Merwade et al. 2008). Furthermore, studies on hypothetical dam failures frequently lack prior information on previous floods of comparable magnitude, further complicating the Manning coefficient's calibration (Almeida et al. 2024; Bharath et al. 2021).

Owing to the magnitude of dam failure studies, calibrating Manning values is difficult. A potential solution involves the use of land cover maps to enhance roughness parameterization. For example, as illustrated in the study of inundation flood events by Pinos and Timbe (2019), land cover data proved to be a valuable resource for refining flood modeling.

Previous studies often adopt a uniform Manning's roughness value applicable to both the channel and the floodplain. For instance, Lim and Brandt (2019) employed this approach in their research. Furthermore, the assumption of uniform roughness across the entire floodplain and a single roughness value for the channel is common in many studies, as highlighted by Dimitriadis et al. (2016) and Horritt and Bates (2002).

In a flood inundation study conducted on four reaches, using a single Manning's value for the floodplain resulted in flood areas comparable to or even more accurate than those obtained with spatially distributed roughness (Liu et al. 2019). Another study applied variable Manning coefficients based on land use and land cover to a hypothetical dam-break scenario, resulting in smaller inundation areas than those in a scenario with a uniform Manning value (Almeida et al. 2024).

In recent years, global land use and land cover (LULC) datasets have demonstrated potential utility in studies of dam breaks. Pandey et al. (2024) employed the ESRI land cover map to define spatially varying Manning's roughness values. Silva and Eleutério (2023) also utilized Landsat 5 imagery combined with reference data from the Natural Resources Conservation Service (NRCS) to assign Manning's coefficients.

LULC data facilitate the assignment of spatially variable roughness values within the floodplain, reflecting differences in surface characteristics. As demonstrated by the study conducted by Soliman et al. (2022), which used the LULC 2020-ESRI dataset for 2D flood modeling, this approach can be a viable alternative to the National Land Cover Database (USA).

Advances in remote sensing and data processing have enhanced the quality of LULC products, facilitating the generation of LULC maps with enhanced spatial and temporal detail, which can be employed in diverse research endeavors (Wang et al. 2023; Xu et al. 2024).

Although several studies have examined the influence of Manning's coefficient in flood modeling, research on the use of different LULC databases in dam failure scenarios remains limited—particularly in data-scarce environments such as semiarid regions. This study addresses this gap by conducting a comparative analysis of three high-resolution LULC databases and their impacts on dam failure modeling.

The datasets analyzed include MapBiomas (MapBiomas Project 2024), the Dynamic World (Brown et al. 2022), and ESRI Land Cover (Karra et al. 2021), which were used to simulate hypothetical dam failures in four dams located in Brazil. The region is characterized by a semiarid climate and intermittent river flow, adding complexity to the hydraulic modeling process.

This study explores how LULC data can be used to determine Manning's roughness values in dam break assessments. It also evaluates the effects of using LULC datasets on key hydraulic factors, such as peak flow, time to peak, water depth, areas at risk of flooding, and the number of affected buildings. Furthermore, the behavior of floods can be assessed by evaluating the velocity and attenuation of flood waves, contingent on the LULC dataset utilized.

Therefore, this study aims to provide a deeper understanding of how LULC data are used in dam failure simulations to generate flood maps, analyze consequences, manage risks, and respond to emergencies.

2 Methodology

2.1 Case study

The case study comprises four dams that form part of the São Francisco River Integration Project (PISF), a significant water infrastructure project in Brazil, Table 1. This project aims to guarantee water security for human consumption and agricultural and industrial activities in the northern and northeast regions of Brazil.

These reservoirs are integrated with canal structures and pumping stations, guaranteeing uninterrupted water transportation through canals. Furthermore, these structures can compensate during periods of pump system shutdown, thereby maintaining the water supply.

The dams in the study are in the semiarid region of Brazil, specifically in Pernambuco. This region has a semi-arid climate with low and irregular rainfall. Another important characteristic is that the rivers downstream of the dams are intermittent, not having a continuous flow, and are directly dependent on periods of rainfall for their flow. Figure 1 presents the geographic locations of the four dams selected for the case study.

The downstream distances employed in the simulations were determined based on the dam size and the geomorphological characteristics of the downstream valleys.

The simulations were conducted at the following distances: 20.01 km for the Barro Branco dam, 22.90 km for the Copiti dam, 44.40 km for the Negreiros dam, and 74.48 km for the Milagres dam. The downstream length for the Barro Branco dam was contingent upon determining significant flow values, whereas for the Copiti, Negreiros, and Milagre dams, the distance of analysis extended to the entrance of reservoirs downstream.

Table 1 Dams selected for the case study

Dam	Latitude	Longitude	Height (m)	Reservoir volume (hm ³)	Type of dam
Copiti	-8.259	-37.711	17.2	6.33	Embankment
Barro Branco	-8.030	-37.259	12.6	0.27	Embankment
Negreiros	-8.095	-39.174	36.6	23.61	Concrete
Milagres	-7.924	-39.080	39.0	91.79	Embankment

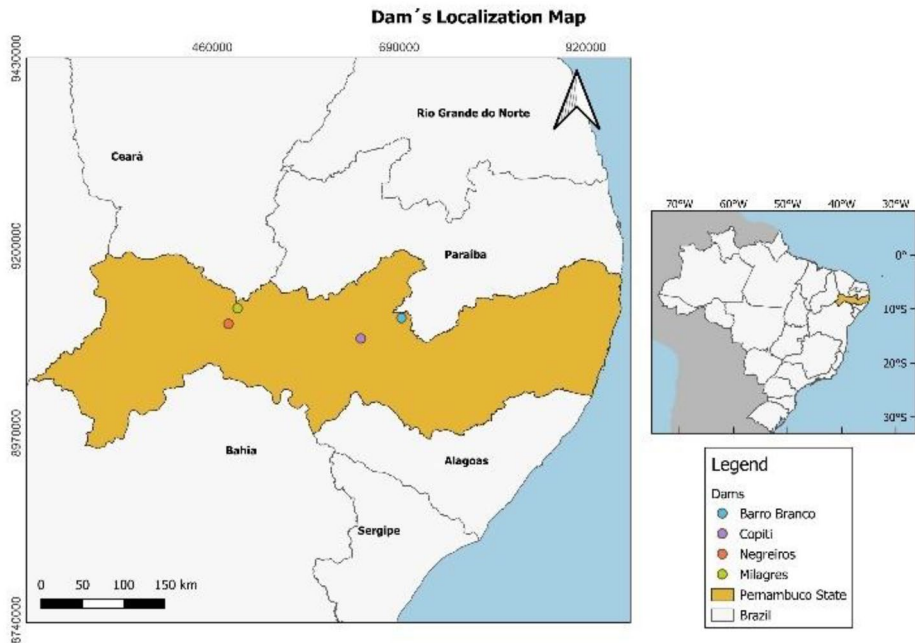


Fig. 1 Dam's Localization Map

The Pernambuco region uses the PE3D digital terrain model, with a spatial resolution ranging from 0.5 to 1 m (PERNAMBUCO 2016). This model provides a highly accurate representation of topography and is employed extensively in various applications, including urban planning, environmental management, and water resource studies.

2.2 Land use and land cover

This study utilized three high-resolution LULC datasets: the Dynamic World Global 10 m resolution near real-time land cover dataset, the MapBiomias 10 m collection BETA dataset, and the ESRI 10 m annual land cover dataset, which were selected for their high resolution and comprehensive temporal coverage. These datasets facilitated a detailed analysis of Manning's roughness coefficient variation, as illustrated in Fig. 2.

The MapBiomias 10 m collection BETA dataset is a high-resolution (10 m) LULC dataset that provides annual maps from 2016 to 2022. It utilizes Sentinel-2 imagery and offers detailed LULC classifications (MapBiomias Project 2024).

The ESRI 10 m annual land cover dataset provides annual global maps of LULC from 2017 to 2023 via ESA Sentinel-2 imagery at a 10 m resolution. These maps are produced by the Impact Observatory, which leverages billions of human-labeled pixels to train a deep learning model for land classification (Karra et al. 2021).

The Dynamic World is a 10 m resolution near-real-time LULC dataset that provides class probabilities and labels for nine classes. This dataset uses Sentinel-2 LIC imagery and updates with new data every 2–5 days, depending on latitude. Predictions are generated only

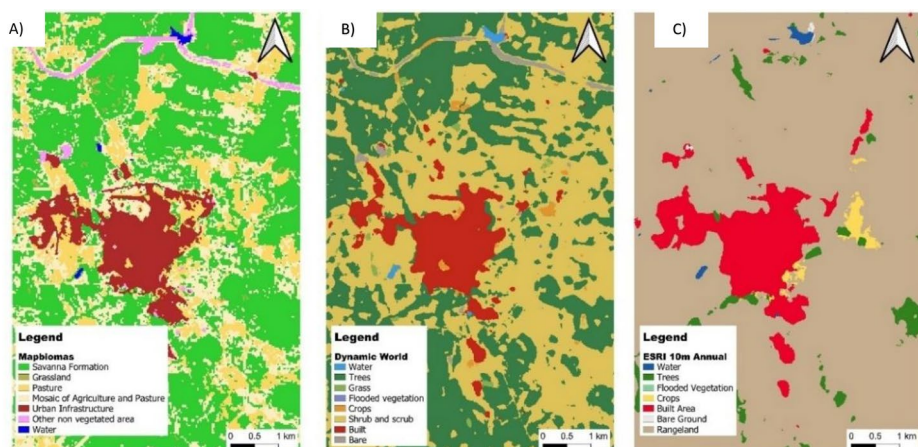


Fig. 2 LULC datasets: A) MapBiomos, B) Dynamic World, and C) ESRI 10 m Annual Land Cover

Table 2 Manning coefficient adopted for each LULC class

Class	Manning (MapBiomos) ($s/m^{1/3}$)	Manning (Dynamic World) ($s/m^{1/3}$)	Manning (ESRI) ($s/m^{1/3}$)
NoData	0.06	0.06	0.06
Water	0.038	0.038	0.038
Trees/Forest	0.08	0.08	0.08
Flooded Vegetation	-	0.05	0.05
Pasture/Mosaico of agriculture and pasture	0.04	0.04	0.04
Crops	0.04	0.04	0.04
Shrub and Scrub	-	0.08	-
Savanna	0.08	-	-
Built Area/Urban	0.08 a 0.1	0.08 a 0.1	0.08 a 0.1
Bare Ground	-	0.03	0.03
Non-Vegetated Area	0.08	-	-
Rangeland	-	-	0.04

for images with less than 35% cloud coverage, and cloud and shadow removal techniques are applied. (Brown et al. 2022).

Each cell of the 2D computational domain received Manning's n values based on land cover classifications from the respective LULC datasets. According to the literature, each land cover class was associated with a representative roughness value (Chow 1959), as shown in Table 2. These spatially distributed values were incorporated through the RAS Mapper interface, ensuring that each cell's resistance to flow reflects the local land cover characteristics.

The LULC datasets used in this study differ in classification schemes due to the distinct methodologies applied during their development. Manning's roughness coefficients were

assigned based on each dataset's specific land use classes. Classes with identical or hydrologically similar characteristics were grouped and assigned the same Manning coefficient to ensure consistency across datasets. This approach aimed to standardize surface roughness representation by applying uniform runoff resistance values to comparable land cover types, regardless of the data source.

2.3 Dam break simulation

The two-dimensional unsteady flow in the HEC-RAS model is solved via the mass conservation Eq. (1) and the momentum conservation equations along the x - and y -axes (2 and 3) of Saint-Venant (USACE 2023).

$$\frac{\partial H}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial y} = q \quad (1)$$

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} = -g \frac{\partial H}{\partial x} + v_t \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) - S_{fx}u + fv \quad (2)$$

$$\frac{\partial v}{\partial t} + u \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} = -g \frac{\partial H}{\partial y} + v_t \left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right) - S_{fy}v + fu \quad (3)$$

where H is the water surface elevation (m); u and v are the velocity components in the x and y directions (m/s), respectively; t is time (s); h is the water depth (m); q is a lateral flow term ($\text{m}^3/\text{s}/\text{m}^2$); g is the gravitational acceleration (m/s^2); v_t is the turbulent viscosity coefficient (m^2/s); S_{fx} and S_{fy} are the resistance gradients in the x and y directions, respectively; and f is the Coriolis parameter.

The HEC-RAS 2D allows the default Manning's n value for the entire 2D flow area to be defined. Additionally, it allows for the specification of Manning's roughness coefficient via a land cover layer in the RAS Mapper. In this case, a spatially variable land-use classification table associated with Manning's n values can be added, which serves as a reference for the base values in areas where polygons are defined. Importantly, for any area within the 2D flow area not covered by this layer, the default Manning's n value is applied to that portion of the flow area.

The diffusion-wave equation (DWE) approach was selected for its simplicity and speed. It discards inertial terms, resulting in more straightforward and expedient equations. This approach exhibits high stability and allows for larger time steps, making it particularly advantageous for initial model configurations and rapid preliminary estimations. Additionally, the DWE can be utilized to assess the extent of rapid flooding.

The simulations considered the piping failure mode. For the concrete dam, the breach parameters were defined based on the ranges suggested by the Federal Emergency Management Agency (FEMA) (FEMA 2013).

Froehlich's equations were used to define breach parameters in embankment dams. The equations are defined as follows (Froehlich 1995):

$$t_f = 0.00254 V_w^{0.53} h_b^{-0.9} \quad (4)$$

$$B_{ave} = 0,1803k_0V_w^{0,32}h_b^{0,19} \quad (5)$$

where B_{ave} is the average breach width (m); t_f is the breach formation time (hours or seconds); k_0 is a constant (1,4 - Overtopping or 1,0 - Piping); V_w is the volume of water in the reservoir (m³); and h_b is the height of the water above the breach (m).

Three simulations were carried out for each dam, considering the same dam failure conditions and the same digital terrain model (DTM). The simulations differed only according to the distinct LULC datasets.

The analysis process begins by importing the DTM and LULC data into RAS-MAPPER, where they are processed to generate the spatial information required for subsequent modeling steps. Manning's roughness values are assigned on the basis of the LULC characteristics (Table 2). These values are crucial for accurately representing the terrain's resistance to flow. The 2D computational mesh and the geometry of the dam are subsequently defined, allowing for a detailed representation of the downstream valley.

Once the computational domain is set, the breach parameters, including the dimensions and failure time, are configured. These parameters are critical for simulating the failure scenario. After these parameters are defined, the simulations are executed for each LULC dataset.

The simulation results provide a comprehensive view of the flood. These results include the dam break hydrograph and its propagation along the downstream valley in the analyses, providing data such as flow rate (Q), time (t), and depth (h) and enabling the generation of hydrodynamic risk (R_H) maps.

2.4 Potential downstream impacts

The intensity of the flood flow due to dam failure was classified according to the criteria established by Viseu (2006) for the hazard level to buildings on the basis of dynamic risk (R_H), which considers the product of flood velocity (U , m/s) and water depth (h , m), as detailed in Table 3.

Google's Open Buildings dataset was employed to estimate the potential downstream population at risk in the event of a hypothetical dam failure. This dataset comprises the contours of approximately 1.8 billion buildings extracted from 50 cm high-resolution satellite imagery, covering vast regions across Africa, Latin America, the Caribbean, South Asia, and Southeast Asia (Sirko et al. 2021).

The data are in polygon format with an attribute table that includes latitude, longitude, area (in square meters), and a confidence interval ranging from 0.65 to 1.00. This study considers only polygons with a confidence interval of 0.70 or greater. Despite inherent limitations, the Open Buildings dataset is crucial for preliminary flood impact assessments. This method facilitates the estimation of building density and spatial distribution, offering significant support for early-stage hazard analyses.

Table 3 Flow hazard levels for buildings

Level	Class	Class N°	Dynamic Risk (m ² /s)
Reduced	Green	1	$R_H \leq 3$
Medium	Yellow	2	$3 < R_H \leq 5$
Important	Orange	3	$5 < R_H \leq 7$
Very Important	Red	4	$R_H > 7$

The downstream impact analysis integrated Open Buildings data with a dynamic risk classification system based on predefined hazard levels. The entire processing workflow was conducted within the Google Earth Engine (GEE) platform. As illustrated in Fig. 3, the methodology involves classifying and quantifying affected buildings, following the structured flowchart. This process incorporates risk maps generated by HEC-RAS and ultimately categorizes buildings according to flood hazard levels.

3 Results and discussion

3.1 LULC for manning's roughness coefficient

For each LULC dataset, the most recent data were used: MapBiomass Collection 2022 and ESRI 10 m Annual Land Cover Collection 2023. In the case of Dynamic World, data availability depends on cloud cover in satellite images. Figure 4 presents the available dataset for the Negreiros Dam, highlighting the limitations caused by cloud cover.

Therefore, each study area was selected from images from 2023 with adequate information and low cloud cover. Table 4 shows the corresponding Dynamic World collection date for each dam.

Fig. 3 Flowchart of the Classification and Quantification Process for Buildings Affected by Hypothetical Dam Failure

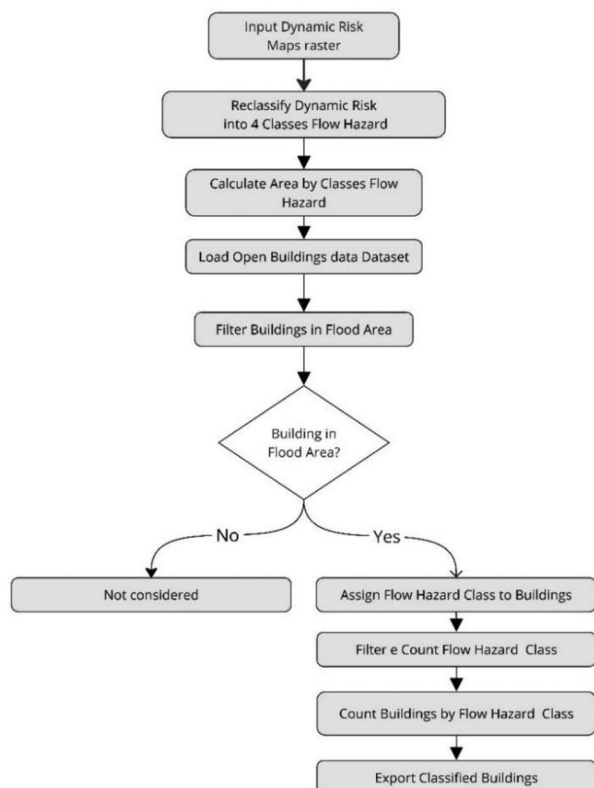


Fig. 4 Land Use and Land Cover Map for the Negreiros Dam Area Using Dynamic World Dataset



Table 4 Collection dates of dynamic world images for each dam in 2023

Dam	Dates Image
Copiti	11/2023
Barro Branco	07/2023
Mialgres	11/2023
Negreiros	11/2023

For each study area, Manning's values were defined according to different land cover types based on the Manning's values presented in Table 2. Figures 5 and 6 show the spatial distributions of Manning's roughness coefficients in the study regions derived from high-resolution LULC data: (A) MapBiomias 10 m collection BETA, (B) Dynamic World, and (C) ESRI 10 m Annual Land Cover.

The breach parameters for embankment dams were determined based on the empirical formulations proposed by Froehlich (1995), while for the concrete dam, FEMA-recommended values were adopted. These parameters were subsequently incorporated into the HEC-RAS model, which simulated the breach hydrographs and provided the peak flow (Q_{peak}) and time to peak (t_{peak}) values presented in Table 5.

The results are structured around three central themes: flood area, flow attenuation, and time-to-peak. These parameters enable a broader comparison of the performance of different LULC datasets and their impact on hydraulic response across dams of various sizes and breach characteristics.

3.1.1 Total flooded area and manning's influence

Table 6 shows the flood area values and the percentage difference between them. Compared with the results of the Dynamic World and ESRI datasets, MapBiomias presented intermediate area values. Consequently, this dataset is the baseline for comparing flood areas.

Compared with MapBiomias, flood areas modeled via the Dynamic World dataset resulted in larger values, ranging from 1.1 to 8.4%. The results highlight the tendency of the Dynamic World dataset to produce larger flood areas, which can be attributed to its higher

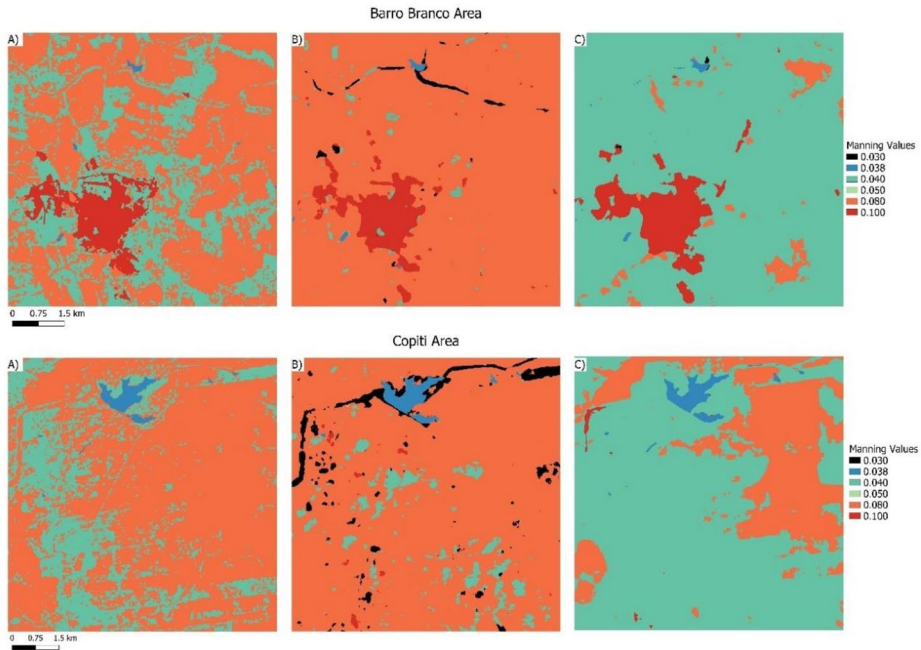


Fig. 5 Maps of Manning's roughness coefficients for the Barro Branco and Copiti areas: **A)** MapBiomass 10 m Collection BETA, **B)** Dynamic World, and **C)** ESRI 10 m Annual Land Cover

Manning coefficient of roughness values, representing surfaces with greater resistance to flow. This resistance causes the hydrograph to propagate more slowly, increasing lateral dispersion and expanding flooded areas.

In contrast, the ESRI dataset exhibited negative discrepancies compared with MapBiomass, with variations from -0.5% to -2.9% . These findings indicate that the lower Manning's roughness coefficient values of the ESRI dataset result in faster and more concentrated runoff within the channel, limiting the lateral spread of water and reducing the predicted flood areas.

These differences are likely due to variations in the land use classification and Manning's roughness coefficients adopted for each dataset, which directly affect the flood modeling results. To illustrate this, Fig. 7 summarizes the percentage distribution of Manning's values in the areas affected by flooding for the four dams under the three distinct land use datasets.

The selection of Manning values, combined with specific land characteristics, resulted in Dynamic World dynamic world datasets exhibiting most of the areas with the highest Manning values ($0.08 \text{ s/m}^{1/3}$). This high resistance to water flow was influenced primarily by areas classified as shrubs and scrubs. In contrast, the ESRI annual 10 m datasets exhibited significant areas with the lowest Manning values ($0.04 \text{ s/m}^{1/3}$), mainly because the areas classified as pasture.

The simulations with MapBiomass revealed an intermediate distribution of Manning area values between Dynamic World and ESRI. This distribution was influenced primarily by land uses classified as pasture or mosaic agriculture and pasture ($0.04 \text{ s/m}^{1/3}$) and Brazilian Cerrado (Savanna) ($0.08 \text{ s/m}^{1/3}$).

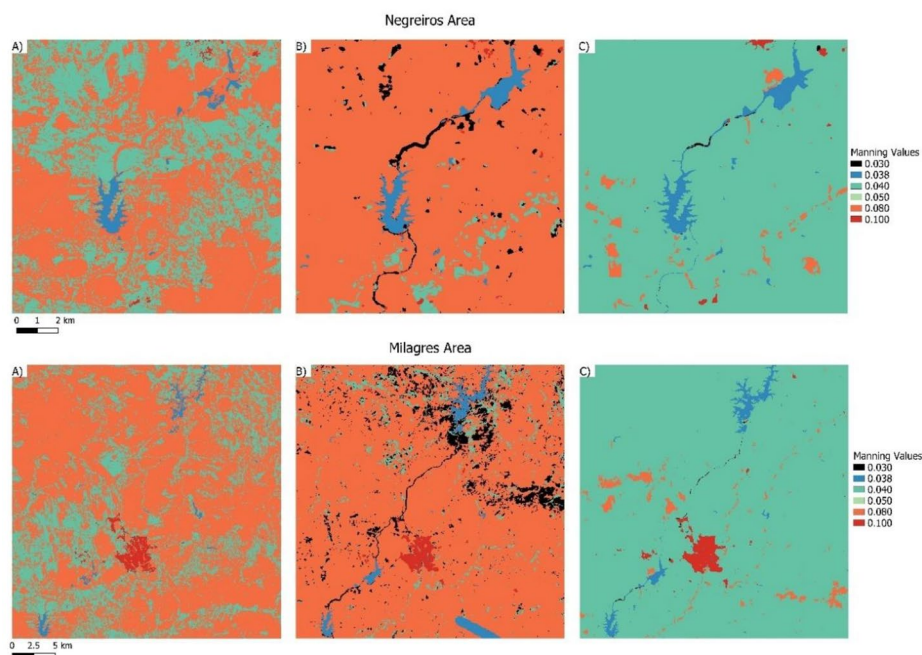


Fig. 6 Maps of Manning's roughness coefficients for the Negreiros and Milagres areas: **A)** MapBiomass 10 m Collection BETA, **B)** Dynamic World, and **C)** ESRI 10 m Annual Land Cover

Table 5 Estimated breach parameters for the dams

Dam	Breach Bottom Width (m)	Side slopes (H: V)	t_f (h)	Q_{peak} (m ³ /s)	t_{peak} (m)
Barro Branco	4	0.9	0.19	576.94	12
Copiti	33	0.9	0.83	1830.68	51
Negreiros	16	0	0.30	4067.50	19
Milagres	94	0.9	1.93	19116.41	117

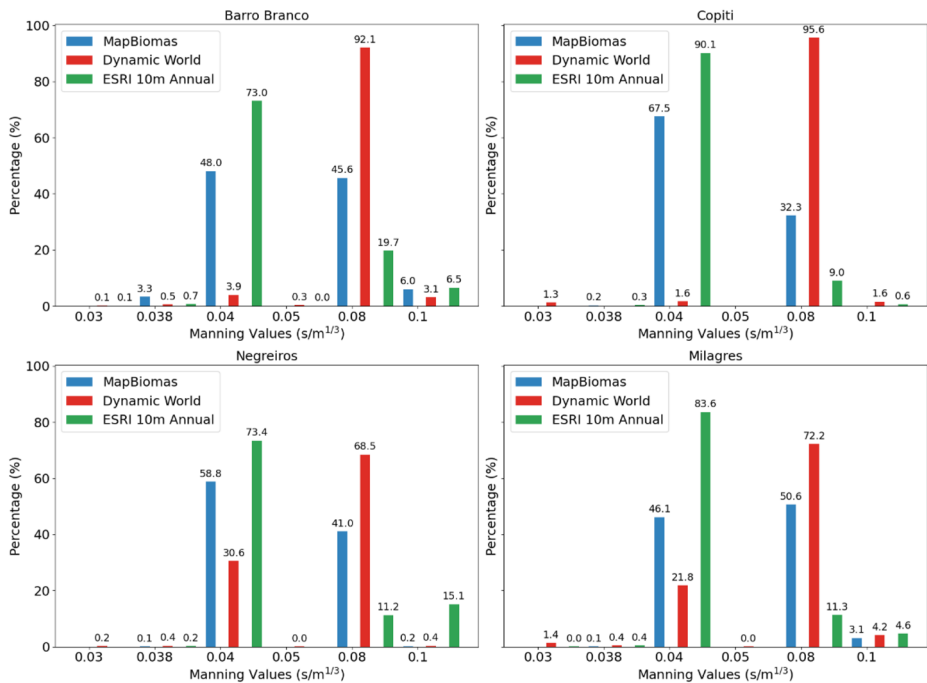
3.1.2 Hydrograph propagation

The analysis examines hydrograph propagation via cross-sectional values determined by the downstream distances from each dam. Figures 8, 9, 10 and 11 illustrate the changes in the normalized flow rate over time for different dam failure simulations, highlighting the differences due to the LULC datasets. The peak flow Q at each analysis point was represented as a proportion of the peak flow at the dam Q_{peak} , resulting in a dimensionless flow (Q/Q_{peak}).

The simulation results for each dam exhibited distinct behaviors that were directly related to their characteristics, such as reservoir volume and breach parameters. The Barro Branco Dam, the smaller dam, demonstrated the most significant attenuation of the flood wave. At 5 km downstream, the normalized flow rate decreased significantly to value between 0.36 and 0.50. By 20 km, the flood wave had virtually dissipated, which reflected the limited hydraulic energy generated by its small reservoir.

Table 6 Total flooded area for each dam derived from various LULC datasets

DAM	LULC Dataset	Flood area total (ha)	Difference (%)
Barro Branco	Mapbiomas	356.93	-
	Dynamic World	360.93	1.1%
	ESRI	355.13	-0.5%
Copiti	Mapbiomas	816.57	0.0%
	Dynamic World	885.27	8.4%
	ESRI	792.58	-2.9%
Negreiros	Mapbiomas	1982.35	-
	Dynamic World	2016.01	1.7%
	ESRI	1937.51	-2.3%
Milagres	Mapbiomas	4927.35	-
	Dynamic World	5027.31	2.0%
	ESRI	4802.06	-0.4%


Fig. 7 Distribution of Manning Values in Flooded Areas for Each Dam and LULC dataset

The Copiti Dam exhibited normalized flow rate values between 0.86 and 0.94 at 5 km, with a more pronounced reduction observed at 20 km, where values declined to between 0.32 and 0.53. Other distances were excluded from the analysis because of the presence of a downstream reservoir, which could influence the results by introducing backwater effects.

The Negreiros Dam exhibited higher normalized flow rates of 0.92 to 0.96 at 5 km, with values between 0.58 and 0.69 at 20 km, indicating moderate flood wave attenuation. A new

Fig. 8 Barro Branco dam normalized hydrograph:-(MB: Map-Biomas; DW: Dynamic World; ESRI: ESRI 10 m Annual)

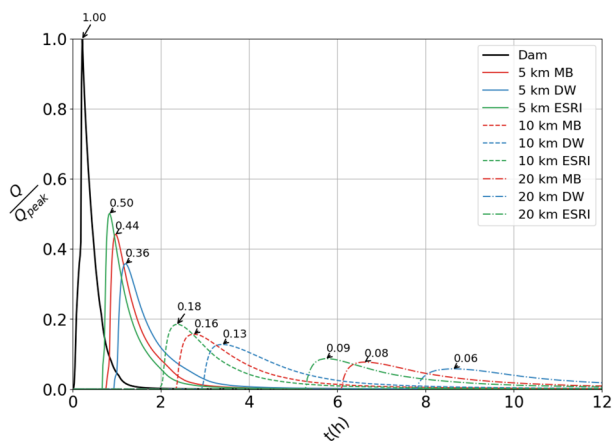


Fig. 9 Copiti dam normalized hydrographs: (MB: MapBiomas; DW: Dynamic World; ESRI: ESRI 10 m Annual)

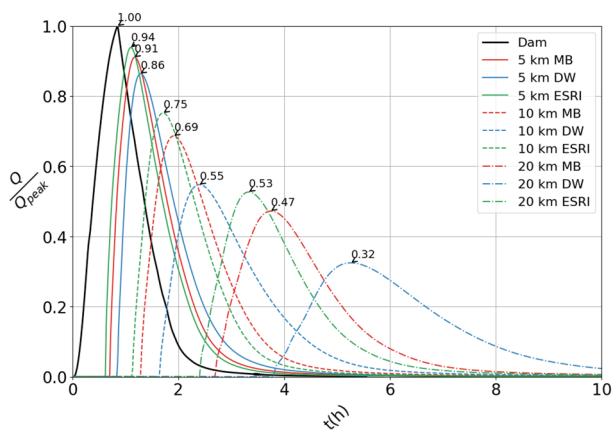


Fig. 10 Negreiros dam normalized hydrographs: (MB: Map-Biomas; DW: Dynamic World; ESRI: ESRI 10 m Annual)

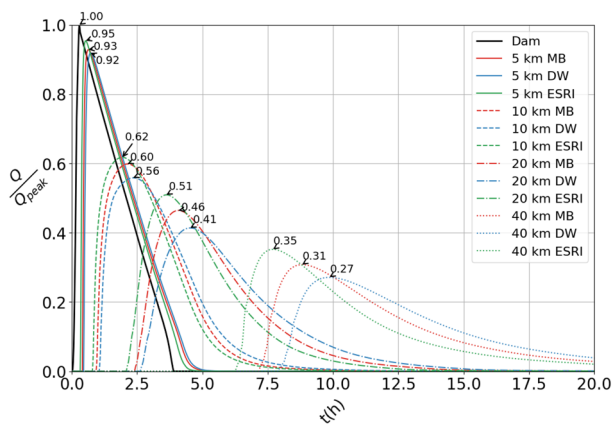
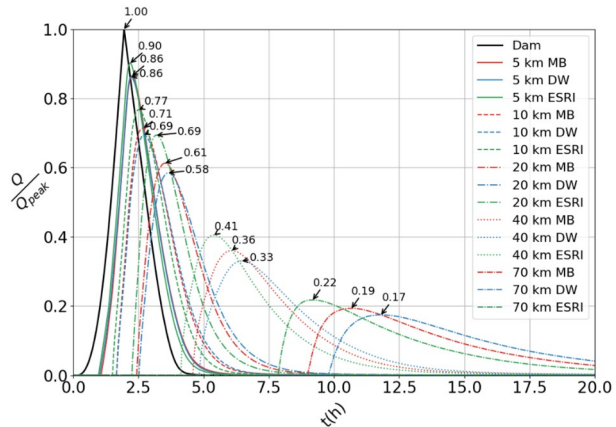


Fig. 11 Milagres dam normalized hydrographs: (MB: MapBiomass; DW: Dynamic World; ESRI: ESRI 10 m Annual)



analysis point was introduced at 40 km, where the normalized flow rates decreased further to values between 0.25 and 0.35.

In contrast, larger dams such as Milagres Dam exhibited more sustained and pronounced flood wave propagation. At 5 km, the normalized flow rate ranged from 0.86 to 0.90, suggesting that the flow persisted longer. Even at 20 km, the flow remained considerable, with normalized values between 0.58 and 0.69. Additional analysis points were introduced at 40 km and 70 km, where the flow rates decreased to 0.33 and 0.41 and 0.17 and 0.22, respectively.

The variations in Manning roughness significantly affected the energy dissipation and flow propagation velocity. Each LULC dataset showed different effects on peak flow attenuation and wave propagation velocity, which is essential for understanding flood risks and emergency response needs.

Simulations using ESRI data, characterized by the lowest Manning coefficients, resulted in minimal peak flow attenuation, leading to higher peak flows and shorter travel times. These simulation scenarios imply that flood waves maintain much of their initial energy, making rapid emergency responses essential for downstream communities.

Conversely, simulations using Dynamic World data with the highest Manning coefficients revealed lower peak flows and longer travel times. The Dynamic World simulation reveals a longer peak flow time and implies a longer flood duration. The MapBiomass data generally produced intermediate results between those of the ESRI and Dynamic World, providing a balance in peak flow and propagation velocity.

As the distance to the dam increases, the discrepancies in the simulation results become more pronounced. Manning's roughness had less impact at shorter distances, resulting in lower energy dissipation. However, the roughness effect at greater distances becomes more significant, leading to greater divergence between peak flows and hydrograph travel times in the different simulations.

The divergence between the values increases in all the dams and becomes more evident at distances greater than 20 km. In the case of the Copiti dam, there is a more pronounced discrepancy between the peak time and the flow value resulting from the Dynamic World simulation than from the other LULC types.

3.1.3 Water level

Table 7 summarizes the water levels at varying distances from the dams for different LULC datasets. Assessing water levels across multiple LULC datasets helps clarify the influence of land use and land cover on hydraulic modeling results. The results reveal discrepancies at shorter distances, which gradually decrease over longer distances, highlighting the localized impact of LULC on flood wave behavior.

The results demonstrate that surface roughness has flood propagation and water depth, especially in the early stages of the flood wave. While flow depth is typically a function of both discharge and terrain characteristics, higher roughness values increase flow resistance, causing greater water depths even under lower flow rates. For example, simulations using the Dynamic World dataset—representing higher surface resistance—produced higher water levels at 5 km downstream. However, these differences diminished downstream as depth values converged across all LULC datasets.

3.2 Potential downstream impacts

The analysis revealed differences in hydraulic parameter values due to the variability in Manning's coefficients across different LULC datasets. These variations directly influence the hydraulic behavior along the valley, affecting both the flow resistance and flood wave propagation speed.

Understanding how these differences impact the assessment of downstream effects and the effectiveness of emergency actions is crucial for minimizing damage in extreme events. To address this, a complementary analysis evaluated response zones, flow hazard levels, and the number of affected buildings, considering variations in Manning's coefficient and LULC dataset characteristics.

Table 7 Water level for different LULC datasets according to distance: (MB: mapbiomas; DW: dynamic world; ESRI: ESRI 10 m Annual)

Dam	Distance (km)	MB (m)	DW (m)	ESRI (m)
Barro Branco	5	559.16	559.3	559.11
	10	542.64	542.62	542.61
	20	520.13	519.95	520.22
Copiti	5	475.21	476.43	475.08
	10	464.91	464.72	464.26
	20	442.82	443.09	442.92
Negreiros	5	416.84	417.11	415.63
	10	398.89	398.9	398.66
	20	390.64	390.92	390.83
	40	370.22	370.18	370.21
Milagres	5	463.52	463.81	462.03
	10	453.88	454.66	453.42
	20	437.91	438.01	436.41
	40	404.09	404.37	404.27
	70	373.52	373.7	373.7

3.2.1 Flood wave extent across LULC datasets

The propagation time of a flood wave is critical in determining the time available for issuing warnings and implementing emergency actions, such as evacuations. Specific time intervals were delineated to analyze the evolution of the flood and the influence of Manning's coefficient values.

The 0.5-hour interval is particularly important for identifying areas near the dam requiring immediate action, such as issuing automatic warnings and implementing immediate evacuation procedures. The 1.0- and 2.0-hour intervals encompass the progression of the wave to areas situated at a slightly greater distance, where a more extensive window of opportunity exists to implement mitigation actions. Figure 12 illustrates how the different LULC datasets affect the extent of flood propagation at different time intervals (0.5, 1.0, and 2.0 h) for the four dams analyzed.

The dam size and the type of material are critical factors in the dynamics of a flood wave resulting from a breach. They directly influence propagation in terms of flow and time. Concrete dams, such as the Negreiros dam, fail more suddenly, resulting in a more intense flood wave with a greater range in the initial times analyzed.

In contrast, the Milagres dam, embankment dam, and largest infrastructure analyzed had a slower initial propagation due to the longer breach formation time, as shown in Table 5. This situation caused shorter distances in the first time intervals (0.5 h and 1.0 h), even compared with those of smaller embankment dams such as those of Barro Branco and Copiti.

The different roughness values assigned to the LULC types in each dataset significantly impacted the distances traveled by the flood wave. The results consistently show that simulations using the ESRI 10 m Annual dataset produced the greatest propagation distances across all the dams and time intervals. In contrast, simulations with the Dynamic World

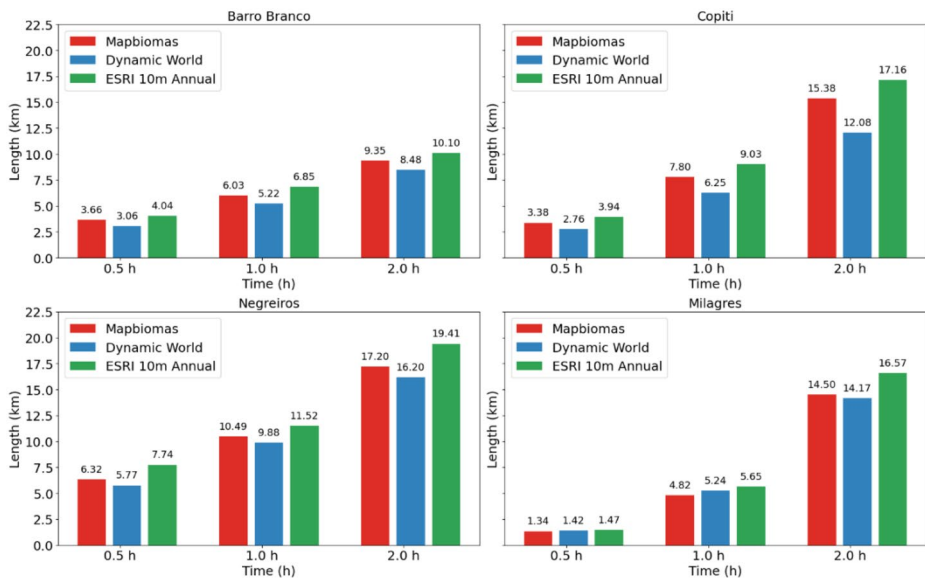


Fig. 12 Flood Wave Propagation for Different LULC Datasets at 0.5, 1.0, and 2.0-Hour Intervals for the Barro Branco, Copiti, Negreiros, and Milagres Dams

dataset tend to yield the shortest distances, which is attributed to the higher Manning values that increase resistance to flow. The MapBiomass results typically fall between these extremes, except for the Milagres dam at 0.5 h and 1.0 h, which has the shortest distances.

The estimated distances demonstrate considerable discrepancies between the simulations. For example, at the 0.5 h time interval, the divergence between the ESRI and Dynamic World simulations reaches 32.0% for the Barro Branco dam, 42.8% for the Copiti dam, and 34.1% for the Negreiros dam.

As the time intervals increase, no observable pattern emerges regarding the discrepancies between the simulations. In certain instances, the discrepancies between the datasets appear to increase over time. For example, in the case of the Milagres dam, the discrepancy between the ESRI and Dynamic World datasets increases from 3.5% at 0.5 h to 7.8% at 1.0 h and then to 17.0% at 2.0 h.

Similarly, the discrepancy between ESRI and MapBiomass also increases from 3.5% at 0.5 h to 7.8% at 1.0 h and then to 17.0% at 2.0 h, demonstrating an expanding divergence in the estimated propagation distances.

The converse is also true in other cases, namely, the discrepancies decrease over time. For example, in the Negreiros dam, the discrepancy between the ESRI and Dynamic World is 34.1% at 0.5 h, 16.6% at 1.0 h, and 19.8% at 2.0 h. A comparable pattern is observed in the discrepancy between the ESRI 10 m Annual and MapBiomass, which decreases from 22.5% at 0.5 h to 9.8% at 1.0 h and then stabilizes at 12.8% at 2.0 h.

For the Barro Branco dam, the discrepancy between the ESRI 10 m Annual and Dynamic World datasets decreases from 32.0% at 0.5 h to 31.2% at 1.0 h and finally to 19.1% at 2.0 h. Similarly, the discrepancy between the ESRI and MapBiomass decreases from 32.0% at 0.5 h to 31.2% at 1.0 h and finally to 19.1% at 2.0 h.

The Copiti Dam represents a notable case, exhibiting the most significant discrepancies among the analyzed scenarios over time. For example, the divergence between the ESRI 10 m Annual and Dynamic World data reaches 42.8% at 0.5 h, marginally increased to 44.4% at 1.0 h, and stabilized at 42.0% at 2.0 h.

The results indicate that the observed discrepancies are closely tied to Manning's roughness coefficients assigned to the downstream region. In the simulation using ESRI 10 m Annual data, 90.1% of the inundated area has a roughness value of 0.04, reflecting lower resistance to flow. Conversely, in the simulation based on Dynamic World data, 95.6% of the inundated area is associated with a significantly higher roughness value of 0.08, indicating increased resistance to water flow. The absence of an observable pattern indicates that spatially distributed roughness as a function of land use and land cover statistics (LULCSs) can represent characteristics throughout the analysis region and influence the results of hydraulic modeling. For example, the distances used to define warning areas.

The analysis of these differences between simulations demonstrates the significance of terrain roughness in flood models. Simulations with elevated roughness values, such as those in the Dynamic World, could reduce the efficacy of early warning mechanisms. Conversely, the ESRI scenarios underscore the necessity for more resilient risk management strategies to guarantee a prompt and effective response.

3.2.2 Flow hazard areas

The simulations demonstrate that the dimensions of the dams and the Manning coefficients directly influence the size of the flood areas, as illustrated in Fig. 13. This figure presents the proportion of flood hazard areas categorized into four classes, as defined in Table 3: Class 1 (green) represents reduced hazard, Class 2 (yellow) indicates medium hazard, Class 3 (orange) corresponds to important hazard, and Class 4 (red) denotes very important hazard.

The classification of areas on the basis of flow hazard is directly related to dam size, resulting in a greater proportion of low-hazard zones in smaller dams. For example, the Barro Branco dam, the smallest, predominantly features low-risk areas, with 94.7–96.3% of its extent classified as Class 1, whereas higher-risk zones, Classes 3 and 4, account for only 1.6–2.3%.

In contrast, larger dams significantly increase in high-hazard areas. A clear example is the Milagres dam, where Class 1 areas constitute only 43.3–48.9%, whereas Class 4 zones dominate, ranging from 36.9 to 43.9%. This pattern highlights the direct correlation between dam size and the concentration of high-hazard areas.

The analysis demonstrated the existence of disparate trends between the datasets. The simulations conducted with the Dynamic World dataset generated a more expansive total flooded area, with a greater proportion of low-hazard areas classified as Class 1. In con-

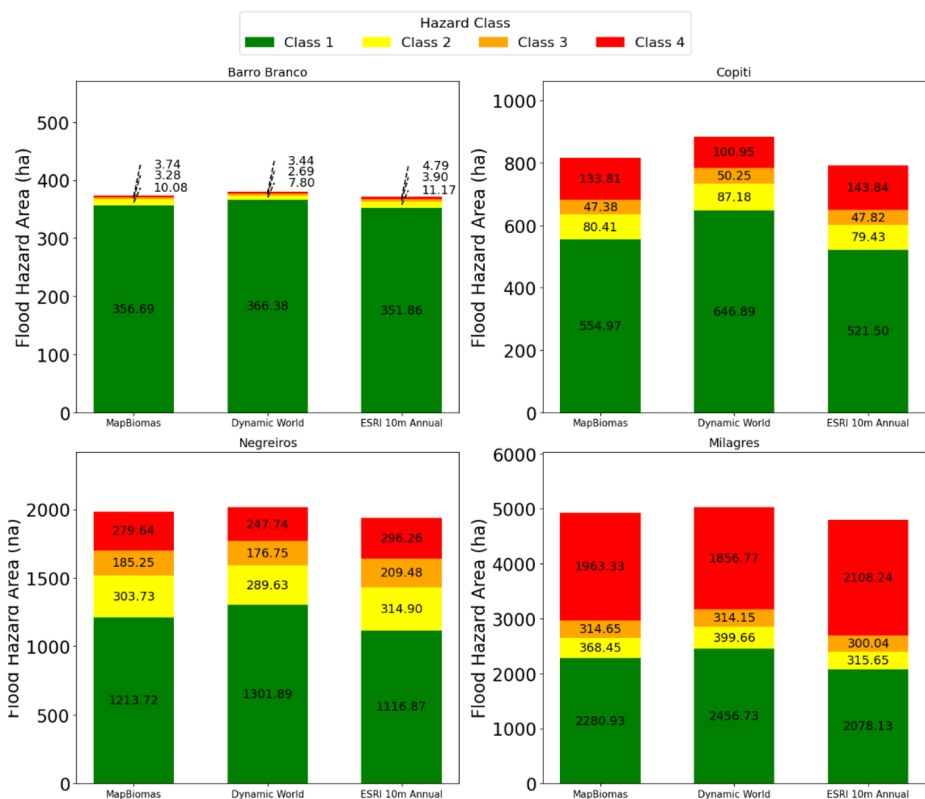


Fig. 13 Distribution of Flow Hazard Area for Different LULC Datasets and Dams

trast, simulations using the ESRI dataset produced smaller total flooded areas and lower proportions of Class 1 areas. However, these scenarios consistently demonstrated a higher concentration of high-hazard zones classified as “Very Important” (Class 4) in all cases and as “Important” (Class 3) in many cases.

The simulations demonstrate that the dimensions of the dams and the Manning coefficients directly influence the size of the flood areas. The definition of the Manning values associated with the LULC datasets also influences the dynamic risk values, which affect the classification of the areas in terms of the flow hazard level.

3.2.3 Buildings affected

The next logical step was identifying and analyzing the buildings within the designated hazard zones. These buildings were then classified on the basis of the hazard level of their respective locations, establishing a clear connection between the hazard area results and the detailed analysis of the impacted structures, Fig. 14.

In all the simulations, most buildings in the flood zones were classified as Class 1, indicating reduced hazard levels. However, simulations involving the Negreiros and Milagres dams uniquely identified buildings within Class 3 and 4 zones, indicating higher hazard levels.

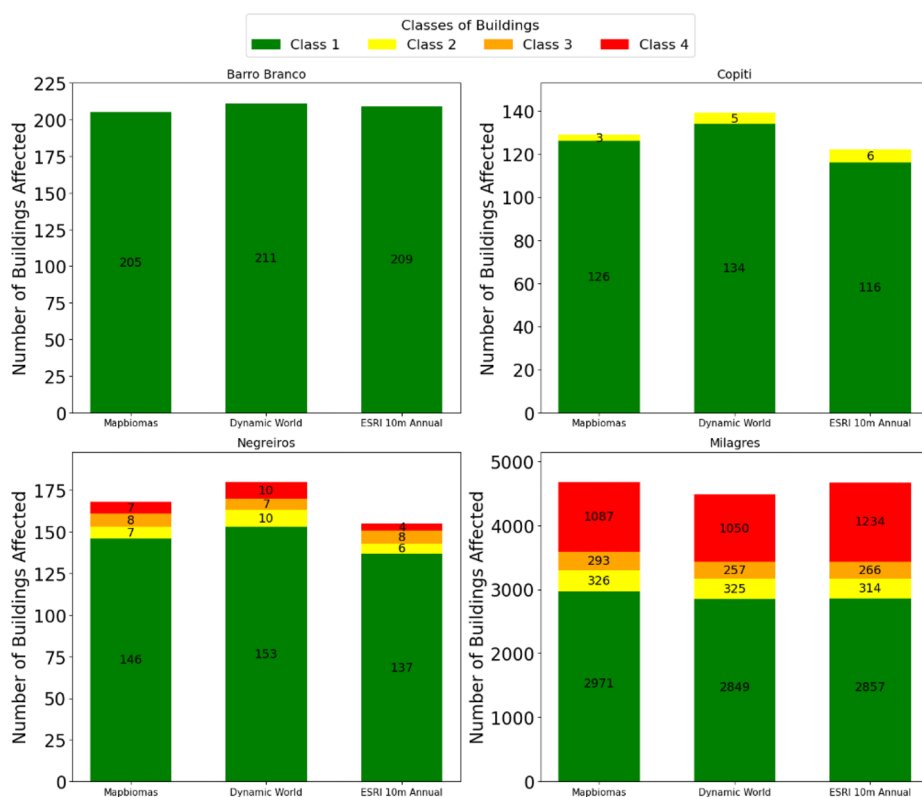


Fig. 14 Distribution of Affected Buildings by Flow Hazard Level for Different LULC Datasets

For the Barro Branco, Copiti, and Negreiros dams, the Dynamic World dataset resulted in the highest number of potentially affected buildings, which may be attributed to the larger total flood area predicted by this dataset.

In the case of the Negreiros dam, the simulation conducted with the Dynamic World dataset identified 10 buildings in Class 3 and 7 buildings in Class 4, representing the highest number across all simulations.

Notably, the MapBiomas dataset exhibited fewer buildings in Classes 3 and 4. Although the ESRI 10 m Annual dataset encompassed larger areas classified as Class 4, it recorded the lowest number of affected buildings compared with the other two simulations. For the Barro Branco, Copiti, and Negreiros dams, the Dynamic World dataset predicted the largest number of potentially affected buildings, likely because of the greater total flood area in this scenario.

The only exception was the Milagres dam, where the simulation with the ESRI 10 m Annual dataset resulted in the highest number of affected buildings, including those in the Class 4 area. Specifically, 1234 buildings were identified in Class 4 under the ESRI dataset, compared with 1087 in MapBiomas and 1050 in Dynamic World. Notably, the Dynamic World simulations presented the lowest number of buildings classified as Class 1 in this dam.

Despite its smaller size, the Barro Branco Dam affects a relatively high number of buildings compared to the other dams, mainly due to its proximity to Sertânia, a city located just downstream. In contrast, Copiti Dam impacts an area with a smaller urban center, resulting in fewer affected buildings (Fig. 15).

However, Negreiros Dam is situated in an area without any major downstream towns, with only scattered buildings along its area of influence, resulting in a lower overall impact. In the case of Milagres Dam, which is the largest dam studied, the downstream area includes the city of Salgueiro. Owing to the proximity of these urban centers, many buildings are affected (Fig. 16).

4 Conclusions

This study proposed evaluating high-resolution LULC datasets as a data source for determining Manning's roughness coefficient values for dam break inundation simulations. The analysis incorporated the global datasets Dynamic World and ESRI 10 m Annual and the regional MapBiomas dataset.

The results highlight the influence of LULC characteristics and Manning's roughness coefficients on flood wave behavior, significantly impacting parameters such as time to peak, depth, peak flow, and flood risk area. These parameters are crucial for understanding the magnitude and intensity of downstream impacts, which are essential for effective risk management and emergency response planning.

Manning values also significantly impact dynamic risk classification, categorizing areas based on their hazard levels. The simulations with higher Manning coefficients resulted in more flood area extension and a more significant proportion of low- and moderate-hazard areas (classes 1 and 2). On the other hand, scenarios with lower Manning values showed a predominance of high- and very high-hazard areas (classes 3 and 4), indicating more critical risks but less a flood area extended.

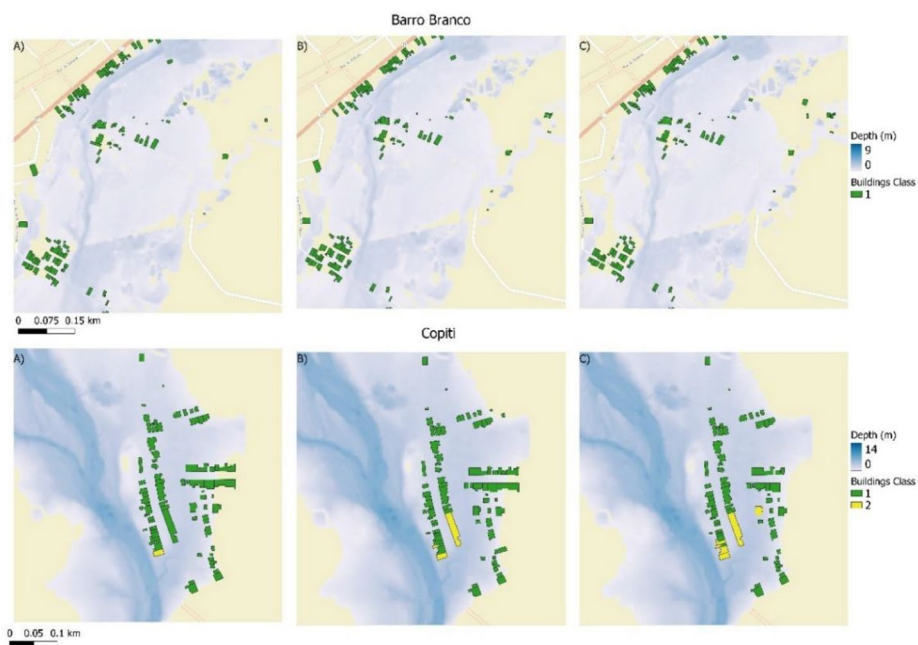


Fig. 15 The classification of affected buildings and flood depth for the Barro Branco and Copiti: (A) MapBiomias, (B) Dynamic World and (C) ESRI 10 m Annual

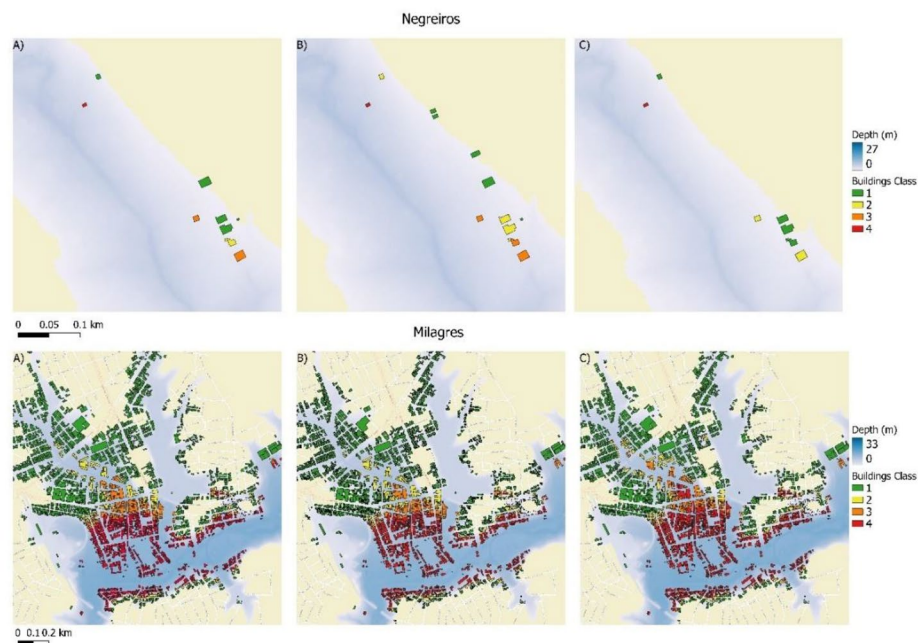


Fig. 16 The classification of affected buildings and flood depth for the Negreiros and Milagres: (A) MapBiomias, (B) Dynamic World and (C) ESRI 10 m Annual

LULC datasets, as demonstrated in this study, are promising tools for estimating Manning's values in dam-break flood studies, particularly in cases where calibration data are insufficient (Almeida et al. 2024; Bharath et al. 2021). These datasets enable the selection of region-specific Manning values, improving the accuracy of simulations and enhancing downstream impact assessments and contingency planning.

LULC data updated regularly also captures changes in downstream conditions over time, enabling periodic reviews of impact studies and emergency response plans. Global LULC systems such as the dynamic world and ESRI provide valuable data for analyzing extreme floods or dam failures, especially in data-scarce regions.

However, high-resolution regional datasets such as MapBiomas offer a distinct advantage by better representing local land-use characteristics, which can improve the definition of roughness values and flood simulation results.

Integrating high-resolution LULC data from advanced remote sensing presents new opportunities for dam failure studies, particularly in determining roughness coefficients while considering seasonal variations.

Since Dynamic World provides near real-time data, future research could investigate how seasonal variations in land use within the downstream valley affect dam-break simulations throughout the year. This approach would account for periodic roughness and land cover changes, leading to more precise damage assessments and adaptive emergency planning across seasons.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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