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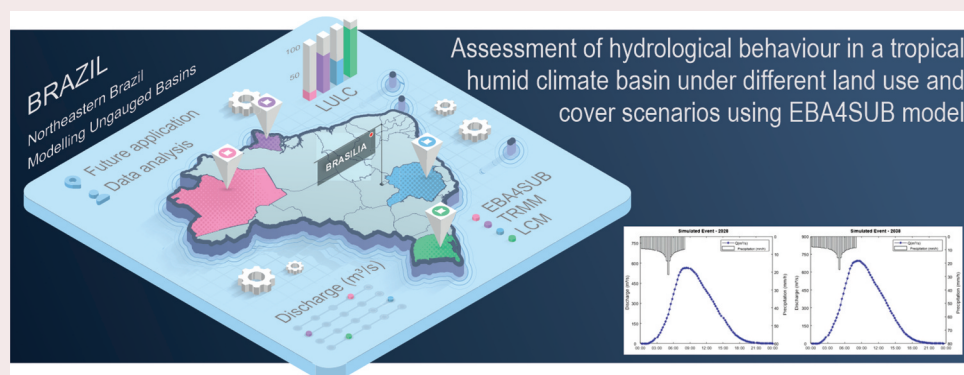
Assessment of hydrological behaviour in a tropical humid climate basin under different land use and cover scenarios using EBA4SUB model

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ABSTRACT

Coastal areas in Brazil are vital for economic and environmental sustainability but are increasingly affected by urbanization and agricultural expansion, altering hydrological dynamics. This study evaluates the hydrological behaviour of the Cupissura River basin, a tropical humid basin, under different land use and cover scenarios. Surface and peak flows were estimated using the Event-Based Approach for Small and Ungauged Basins (EBA4SUB) model, supported by TRMM satellite and CEMADEN rain gauge observations. Land use projections for 2028 and 2038 were simulated with the Land Change Modeler based on maps from 1998, 2006, and 2018, achieving an accuracy of kappa = 0.79. Simulated peak discharges increased from 63.3 m³/s (1998) to 131.5 m³/s (2006), reaching 694.8 m³/s by 2038 under projected land use. These demonstrate the model's reliability and applicability for ungauged tropical basins, providing valuable insights for sustainable water resource management in coastal regions subject to climate and land use pressures.



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1 Introduction

Brazil's coastal zone holds particular importance from both economic and environmental perspectives (Haddad and Araújo 2025, Patrizzi *et al.* 2025). It concentrates a large share of the national population (Pardal *et al.* 2024), hosts major industrial activities, active ports, and key tourist destinations, and faces increasing pressure on water resources due to rising demand (Feitosa *et al.* 2023). In this context, understanding the dynamics and challenges of the Brazilian coast is essential for promoting sustainable development, safeguarding this natural and economic heritage, and ensuring the responsible management of coastal watersheds (Rocha *et al.* 2024).

Coastal zones in Brazil face complex challenges arising from the interaction between freshwater and saltwater systems,

combined with pressures from urbanization, industrial expansion, port operations, and coastal tourism (Massei *et al.* 2023, García-Londoño and Roldán-Clarà 2025). Lacerda *et al.* (2021) analysed urban forest loss using a GIS-based approach and integrated urban planning tools, showing that the most significant landscape transformations involved declines in arboreal and shrub vegetation and the expansion of built-up areas. Rocha *et al.* (2024) assessed urban forest decline and predicted future urban expansion using modelling and spatial analysis techniques, demonstrating a consistent trend towards increased transitions from vegetation to urbanized areas by 2040. In light of the impacts associated with vegetation loss driven by anthropogenic pressure and urban expansion, De Sousa *et al.* (2023) proposed a methodology to assess urban

sprawl and land degradation through orbital imagery, river water quality data, and land surface temperature. Their approach proved effective for evaluating land use and land cover changes and associated environmental impacts.

According to Zou *et al.* (2023), an integrated and coordinated management approach in coastal basins is essential to conserve water resources, mitigate the impacts of extreme events such as floods and storms, and protect fragile and highly exposed coastal ecosystems. Zhang *et al.* (2025) emphasise the need to account for land use and land cover changes when developing management strategies for these basins. In recent years, several studies have explored different approaches to these challenges. In this context, the implementation of integrated coastal zone management policies involving multiple sectors and stakeholders has proven effective for addressing coastal issues holistically, thereby promoting a sustainable balance between development and environmental conservation (Wang *et al.* 2024).

The coastal watersheds of northeastern Brazil are particularly important for regional water security, as they serve as key sources of water supply for large urban centres (Costa *et al.* 2024). Dantas *et al.* (2020) emphasise that the intense development occurring in these basins – whether through the construction of water-supply reservoirs or the expansion of urban areas – requires careful planning that considers environmental constraints and the capacity of local soils to support different land uses. With the exponential increase in water demand driven by anthropogenic pressures, hydrological monitoring becomes even more essential for the planning, use, and conservation of water resources (Vaz *et al.* 2025). However, information on the spatial distribution, quantity, quality, and future variability of these resources remains limited. Hydrological time series are available only for a small number of small and medium-sized watersheds, with few exceptions documented in the literature (Brasil Neto *et al.* 2021).

Despite the recognized importance of coastal watersheds for regional water security, hydrological monitoring in these areas remains limited, hindering the accurate assessment of rainfall–runoff processes and their response to land use dynamics. This data scarcity constrains the capacity to model hydrological behaviour and to design effective management strategies. Therefore, the development and application of robust conceptual models capable of simulating surface and peak flows in ungauged tropical basins under varying land use conditions are essential for sustainable water planning.

In order to overcome this lack of data, the development of hydrological models capable of simulating and quantifying rainfall–runoff processes represents a promising alternative. Numerous models are available in the literature, and the choice of the most suitable one depends on its robustness, accuracy, consistency, and ease of parameterization. Recently, a conceptual rainfall–runoff model for ungauged catchments was developed by Petroselli (2020), named the *Event-Based Approach for Small and Ungauged Basins (EBA4SUB)*. This model differs from traditional continuous or semi-distributed models due to its event-based structure, minimal calibration requirements, and ability to perform effectively in data-scarce basins. EBA4SUB integrates physically-based and empirical components to estimate rainfall excess and surface runoff,

using parameters derived from topography, land use, and soil data rather than long hydrometric series. These characteristics make it particularly suitable for small tropical basins with limited hydrological observations.

At the same time, the coupling of hydrological modelling with land use and land cover forecasting presents strong potential for simulating future scenarios (Chim *et al.* 2021, Silva *et al.* 2022a, Ait El Haj *et al.* 2023). Spatial dynamic modelling of land use and its temporal evolution has been extensively applied in environmental studies. Several approaches exist, including agent-based models, cellular automata, hybrid systems, and spatial statistical models. Among these, the Land Change Modeler (LCM) has gained increasing attention for its capacity to predict land use changes and assess associated environmental impacts, particularly in the context of land use planning (Sharma *et al.* 2018, Sari *et al.* 2023). The LCM was selected for this study due to its accessibility and relatively short learning curve.

Considering the gap in streamflow data and the need for hydrological predictive tools, this study focuses on analysing the hydrological behaviour of a particular basin while accounting for land use and land cover transformations driven by both natural and anthropogenic factors. Recently selected for the expansion of the João Pessoa water supply system, the Cupissura River Basin is of particular importance for the surrounding rural population. The general objective of this study is to estimate the hydrological response of a tropical humid basin under different land use and land cover scenarios. The specific objectives are to: (i) estimate surface runoff and peak flows for different return periods from a conceptual model for ungauged basins; (ii) identify land use evolution through the analysis of land cover time series for 1998, 2006 and 2018; (iii) simulate future land use and land cover scenarios for 2028 and 2038; and (iv) estimate and assess surface runoff under these future scenarios.

The novelty of this study lies in the integrated application of the EBA4SUB rainfall–runoff model and the LCM within a tropical humid coastal basin in northeastern Brazil. Although these models have been applied individually in different regions worldwide, their combined implementation in a small, data-scarce tropical basin undergoing rapid land use change is unprecedented in the Brazilian context. This approach enables a spatially explicit assessment of how projected land use dynamics influence surface and peak flows, addressing the scarcity of hydrological data in coastal catchments and providing a transferable framework for sustainable water resource management under similar tropical conditions.

2 Materials and methods

2.1 Study area

The research was conducted in the Cupissura River Basin, located in the southeastern region of the state of Paraíba, between the municipalities of Caaporã and Itambé. The basin lies between the geographic coordinates 7°23'51"S to 7°29'45"S latitude and 34°53'19"W to 35°06'38"W longitude, covering an area of approximately 110 km² (Fig. 1). The region is situated along the northeastern Brazilian coast and is characterized by

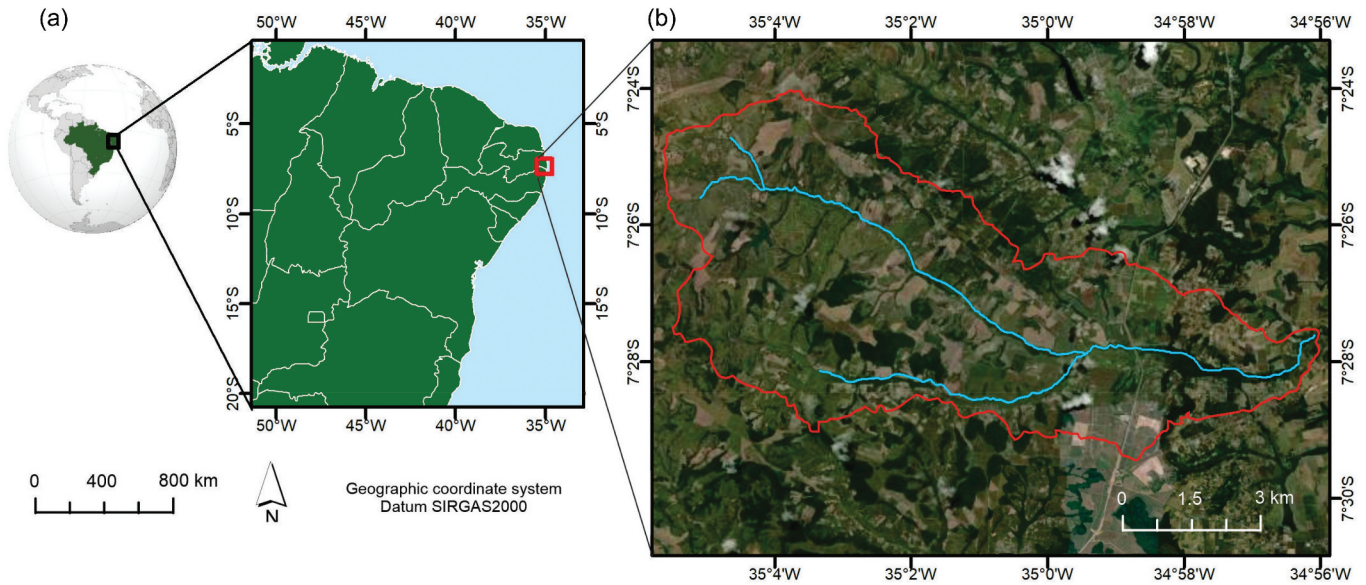


Figure 1. Location of the Cupissura River Basin in northeastern Brazil. Panel (a) shows the location of the Abiaí-Papocas watershed within the states of Paraíba and Pernambuco. Panel (b) presents the Cupissura sub-basin, highlighting the main hydrographic features, including the Cupissura and Muzumba streams.

sedimentary geology, with a predominance of rocks belonging to the Barreiras Formation (Lima *et al.* 2024). The geomorphology is composed mainly of low-altitude terrain, ranging from 0 to 200 m above sea level, and includes a coastal plain interspersed with isolated hills and low ridges (Alves *et al.* 2022). The native vegetation is predominantly Atlantic Forest, featuring lowland rainforest, mangroves, and coastal sandbank ecosystems (Sousa *et al.* 2023). The climate is classified as tropical humid, with rainfall occurring throughout the year and a mean annual temperature of approximately 26°C. The rainy season extends from April to July, whereas the driest months occur between September and December (Silva *et al.* 2022b).

2.2 Datasets

2.2.1 Satellite images

For hydrological modelling, a digital elevation model (DEM) was obtained from the United States Geological Survey (USGS) portal (<https://earthexplorer.usgs.gov/>). This DEM was generated from data acquired by the Shuttle Radar Topography Mission (SRTM) and has a spatial resolution of 30 m. Land use and land cover scenarios in the Cupissura River basin were analysed through the production and interpretation of thematic maps derived from Landsat satellite imagery, also with a spatial resolution of 30 m. Image selection considered minimal cloud cover and temporal consistency among acquisition dates to ensure reliable multitemporal comparison. The images were acquired from orbit 214, point 65, via the USGS catalogue, corresponding to Landsat-5 (TM sensor; 14 June 1998, and 26 August 2006) and Landsat-8 (OLI/TIRS sensor; 27 August 2018), and were downloaded from the USGS GloVis portal (<https://glovis.usgs.gov/app>).

2.2.2 Precipitation data

Two rainfall datasets were employed in this study. The first consisted of satellite-based precipitation data obtained from

Table 1. Information on the rainfall datasets used in the study.

Station code	Latitude	Longitude	Source
260765301A	−7.42	−35.12	CEMADEN
260765302A	−7.52	−35.08	CEMADEN
250300101A	−7.52	−34.92	CEMADEN
TRMM1	−7.37	−35.12	TRMM
TRMM2	−7.37	−34.87	TRMM

the Tropical Rainfall Measuring Mission (TRMM) (Huffman *et al.* 1997). Specifically, the TRMM 3B42V7 product, provided by the US National Aeronautics and Space Administration (NASA), was used, offering a spatial resolution of $0.25^\circ \times 0.25^\circ$ (approximately 25 km) and a temporal resolution of 3 h, sourced from the NASA portal (<https://www.earthdata.nasa.gov/data/platforms/space-based-platforms/trmm/data-access-tools>). Within the Cupissura River sub-basin, two TRMM 3B42V7 grid cells were utilized to extract rainfall data for the years 1998 and 2006. The second dataset comprised rain gauge observations obtained from the platform of the National Centre for Monitoring and Early Warning of Natural Disasters (CEMADEN). Rainfall occurrence or absence was recorded at hourly and sub-hourly intervals throughout 2018 using automatic rain gauges. These measurements were aggregated into 3 h intervals to match the temporal resolution of the TRMM dataset. A total of three stations were used for the study area, all located near the zone of influence of the Cupissura River Basin, as shown in Table 1.

2.3 Methodology

The procedures and methodologies adopted for data acquisition, processing, and analysis are described below and summarised in the flowchart presented in Fig. 2. The workflow integrates land use modelling through the LCM and hydrological modelling using the EBA4SUB framework. The input datasets include historical land use maps, a DEM, and precipitation data obtained from both satellite sources (TRMM)

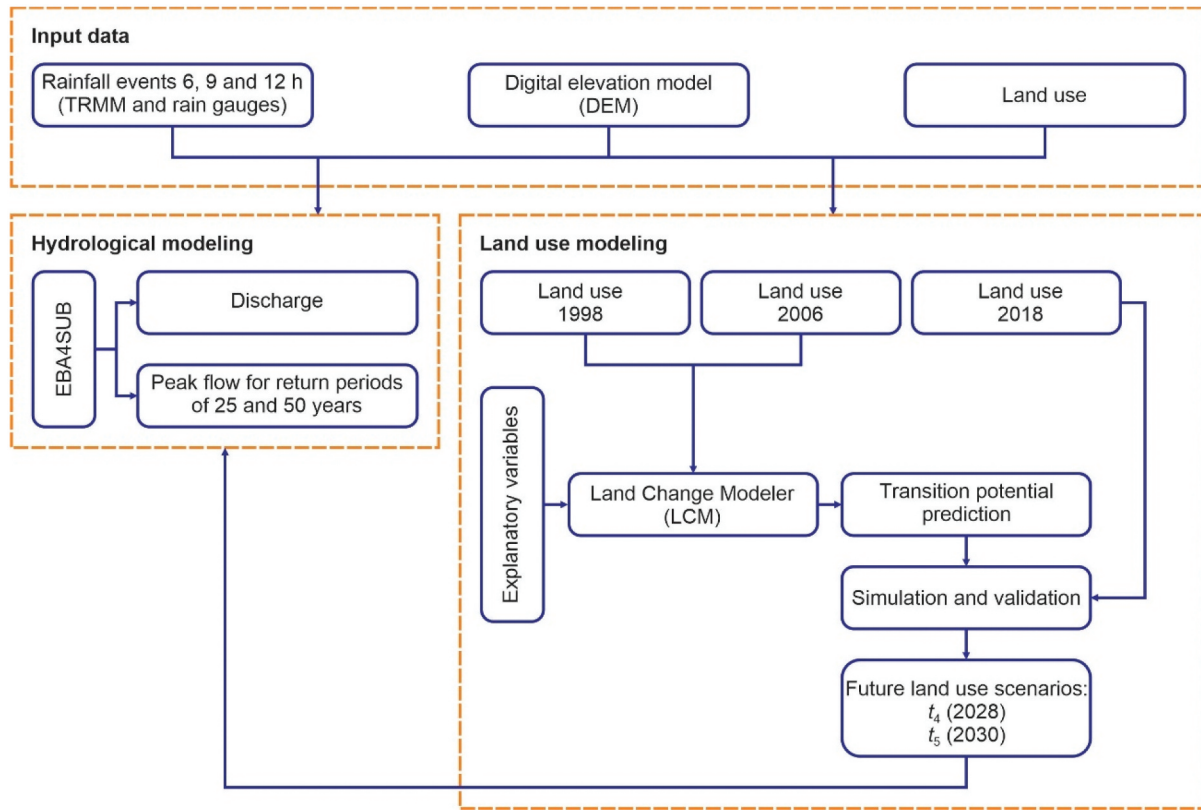


Figure 2. Workflow illustrating the methodology used for land use forecasting and hydrological modelling. The process integrates satellite and field data, land use dynamics (1998–2018), land use simulation (2028–2038), and the application of the Event-Based Approach for Small and Ungauged Basins (EBA4SUB) model to estimate discharge and peak flow under current and projected scenarios.

and rain gauges. The methodology comprises: (i) assessing land use changes; (ii) predicting future land use scenarios for 2028 and 2038; and (iii) simulating surface runoff and peak discharges for different rainfall events and return periods.

2.3.1 Land use and land cover segmentation and classification

Land use and land cover classification was based on satellite images for the years 1998, 2006, and 2018, which were georeferenced using SPRING software version 5.4.3 (Câmara *et al.* 1996). Georeferencing was performed with 25 ground control points per image, resulting in a root mean square error of less than one pixel (0.76 pixels for 1998 and 2006; 0.78 pixels for 2018). The adopted projection system was Universal Transverse Mercator (UTM), SIRGAS 2000 datum, zone 25 South.

Following georeferencing, image segmentation was carried out in SPRING using a method based on similarity and area parameters set to 5 and 30 pixels, respectively. The images were then classified using the band compositions 5(R), 4(G), 3(B) for 1998 and 2006, and 6(R), 5(G), 4(B) for 2018, through a supervised classification approach employing the Bhattacharyya classifier with a 99.9% acceptance threshold (Cunha *et al.* 2022). This classifier is a parametric supervised method that evaluates statistical separability between spectral classes using the Bhattacharyya distance, which quantifies the degree of overlap between class probability distributions in multispectral space. Greater Bhattacharyya distances indicate stronger class separability and improved classification accuracy. This method has proven effective in tropical regions of

Brazil for distinguishing heterogeneous surface patterns, particularly where spectral confusion occurs among vegetation, agricultural, and urban classes (Sampath and Radhakrishnan 2024, Jalali Mojahed *et al.* 2025).

In this study, the land use and cover classes defined were: urban infrastructure, forest formation, crop mosaic, agriculture and pasture mosaic, sugar cane, and water. To verify classification uncertainties, Google Earth Pro version 7.3.3 was used, supporting the resolution of potential land use conflicts.

2.3.2 Intensity–duration–frequency

The intensity–duration–frequency (IDF) curve derived from rain gauge stations was used to estimate flow rates for return periods of 25 and 50 years, applying the following empirical equation:

$$i = \frac{973.248 T_r^{0.207}}{(t + 10.327)^{0.751}} \quad (1)$$

where i is the average maximum precipitation intensity (mm/h), T_r is the return period (years), and t is the rainfall duration (minutes). This equation was adapted from empirical relationships established for the State of Paraíba, Brazil, based on historical rainfall records and fitted through non-linear regression models. The parameters were derived from probability distributions applied to disaggregated daily rainfall series and validated with high coefficients of determination ($R^2 > 0.99$) across most stations (Campos *et al.* 2017).

Table 2. Characteristics of the selected rainfall events used for hydrological simulation.

Event	Duration (h)	Precipitation (mm)	Date	Start time
1	6	66.97	19/07/1998	04:30
2		98.81	11/06/2006	19:30
3		100.61	13/04/2018	04:30
4	9	68.13	16/06/1998	19:30
5		110.02	23–24/05/2006	22:30
6		78.04	09/05/2018	07:30
7	12	77.87	09/07/1998	13:30
8		67.03	09/04/2006	01:30
9		67.65	11/04/2018	01:30

2.3.3 Events

Considering the spatial and temporal distribution of the rainfall network in the basin, represented by TRMM data and rain gauge stations, the Thiessen method was used to calculate the average precipitation for the selected events, ensuring a uniform spatial representation. Thus, precipitation was computed as a weighted average, where P_i is the precipitation recorded at station i and A_i is its associated area of influence:

$$P_{\text{med}} = \frac{\sum_{i=1}^n P_i A_i}{A} \quad (2)$$

where P_{med} is the average precipitation in the basin (mm), P_i is the precipitation at station i (mm), A_i is the area of the respective Thiessen polygon within the basin (km^2), and A is the total basin area (km^2).

The calculation of average precipitation was carried out for the analysed time series, in which the mean hourly precipitation over 3 h intervals was obtained for each study year. This procedure enabled the identification and selection of rainfall events. For the present study, events with durations of 6, 9, and 12 were selected, as shown in Table 2. These event durations share the same cumulative rainfall excess and the same initial abstraction value derived from the CN method, but differ in their physically-based temporal distribution. Such durations are typical for the region, as reported by Das Neves Almeida *et al.* (2025).

2.4 Hydrological behaviour: description of the EBA4SUB model

The EBA4SUB model was developed by Grimaldi and Petroselli (2015). In this study, the model was used to determine the design hydrograph for an ungauged watershed, enabling the estimation of gross precipitation, excess rainfall, peak discharge, and hydrographs associated with specific return periods. The model is recommended for basins with an area smaller than 500 km^2 , where rainfall can be assumed to be spatially homogeneous.

The model consists of three main stages: (a) estimation of gross precipitation, (b) determination of excess rainfall, and (c) rainfall–runoff transformation. The input data include rainfall events, land use, topography (DEM), and soil properties. In stage (a), the analyst may use observed rainfall data recorded at rain gauge stations or precipitation derived from synthetic hyetographs and their respective IDF curves. In this study, measured rainfall data from rain gauges were used, together

with the Chicago hyetograph, for which the following equations were applied to estimate gross precipitation:

$$i(t, T_r) = a(T_r) n(T_r) \left(\frac{t_p - t}{r_c} \right)^{n-1} \text{ for } t \leq t_p \quad (3)$$

$$i(t, T_r) = a(T_r) n(T_r) \left(\frac{t - t_p}{1 - r_c} \right)^{n-1} \text{ for } t > t_p \quad (4)$$

where i is the precipitation intensity (mm/h), t is time (h), T_r is the return period (years), a and n are the IDF coefficients, t_p is the peak time, and r_c is the ratio between the peak time and the total rainfall duration.

The time of concentration (T_c) was estimated using the Giandotti formula (Equation 5), derived from the DEM:

$$T_c = \frac{4\sqrt{A} + 1.5L}{\sqrt{H}} \quad (5)$$

The lag time (T_L) was assumed as $T_L = 0.6T_c$, following Grimaldi *et al.* (2010, 2012). The area reduction factor proposed by Leclerc and Schaake (1972) was applied to adjust the accumulated precipitation:

$$ARF = \frac{AR}{PR} = 1 - e^{(-1,1,t^{0.25})} + e^{(-1,1,t^{0.25}-0,0259A)} \quad (6)$$

where A_R is the accumulated areal precipitation (mm), P_R is the point rainfall (mm), t is the rainfall duration (h), and A is the basin area (km^2).

In stage (b), excess rainfall was estimated using the curve number (CN) for Green-Ampt (CN4GA) method (Grimaldi *et al.* 2013), which combines the empirical SCS-CN method for estimating cumulative excess rainfall with a physically-based Green-Ampt infiltration formulation:

$$P_e = \frac{(P - I_a)^2}{P - I_a + S} \text{ if } P > I_a = \lambda S \quad (7)$$

$$P_e = 0 \text{ if } P < I_a \quad (8)$$

where P_e is the accumulated excess rainfall, P is the accumulated gross precipitation, I_a is the initial abstraction, λ is the initial abstraction coefficient (0.2 in this study), and S is the potential maximum retention related to the CN value.

$$q_0(t) = K_s \left(1 + \frac{\Delta\theta\Delta H}{I(t)} \right) \text{ for } t > t_p \quad (9)$$

$$q_0(t) = i(t) \text{ for } t < t_p \quad (10)$$

where q_0 is the infiltration rate (mm/h), $i(t)$ is the gross rainfall intensity (mm/h), $I(t)$ is the cumulative infiltration (mm), K_s is the saturated hydraulic conductivity, t_p is the reflection time, ΔH is the wetting front suction head (mm), and $\Delta\theta$ is the soil moisture content deficit.

The CN4GA method combines the empirical SCS-CN approach with the physically-based Green-Ampt infiltration model (Grimaldi *et al.* 2013). In this hybrid formulation, the total rainfall excess estimated by the SCS-CN method is temporally distributed according to the Green-Ampt equation, providing a more realistic representation of infiltration

and surface runoff dynamics. The Green-Ampt component incorporates soil hydraulic properties such as saturated hydraulic conductivity (K_s), wetting front suction head (ΔH), and soil moisture deficit ($\Delta\theta$), whereas the SCS-CN component supplies the cumulative runoff volume based on land use, soil type, and antecedent moisture conditions. This integration preserves the simplicity of the SCS-CN method while enhancing its physical consistency and temporal resolution, particularly for event-based simulations in ungauged basins.

Thus, the CN4GA method enables the accumulated excess rainfall estimated using the SCS-CN method to be temporally distributed with finer resolution according to the Green-Ampt formulation, a physically-based infiltration equation. In stage (c), the transformation of excess precipitation into surface runoff was performed using the width-function-based instantaneous unit hydrograph (WFIUH-1par) method (Grimaldi *et al.* 2012a). This approach derives the unit hydrograph directly from the geomorphological structure of the basin, quantified through the distribution of flow paths extracted from the DEM. The “1par” formulation indicates that the hydrograph is parameterised by a single velocity parameter, assumed constant for channel cells and for hillslope cells. Each grid cell’s travel time to the basin outlet is computed from its flow path length and local slope, enabling a physically-based representation of the basin’s hydrological response without the need for empirical calibration – an essential characteristic for ungauged basins. The WFIUH is defined as:

$$WFIUH(t) = \frac{L_c(x)}{v_c(x)} + \frac{L_h(x)}{v_h(x)} \quad (11)$$

where L_c and L_h are the drainage path lengths within channel and hillslope cells, respectively, for a given DEM cell x , and v_c and v_h are the assumed velocities in the channel and hillslope.

Finally, the design hydrograph is obtained by performing the integral convolution between the WFIUH and the excess precipitation determined by the CN4GA method:

$$q(t) = A \int_0^t WFIUH(t-r) * P_n(\tau) d\tau \quad (12)$$

where A is the contributing area of the basin (km^2), t is the rainfall duration (h), τ is the time increment (h), and $P_n(\tau)$ is the excess precipitation (mm).

Because the Cupissura River basin is ungauged, no stream-flow measurements or historical discharge records are available for direct validation of the simulated hydrographs. The use of EBA4SUB is therefore particularly appropriate, as the model was explicitly developed for small ungauged basins and has been extensively validated in previous applications where observed discharge data were available. Its parameterization structure reduces subjective choices and ensures internal consistency of the hydrological response.

To enhance confidence in the model outputs under data-scarce conditions, supplementary verification procedures were adopted, including: (i) cross-checking rainfall events between TRMM and CEMADEN datasets; (ii) assessing the coherence between simulated hydrograph dynamics and changes in

infiltration capacity driven by land cover; and (iii) comparing the magnitude and temporal pattern of simulated hydrographs with results documented for similar tropical humid basins. These procedures support the reliability of the model simulations in the absence of direct hydrometric measurements.

2.5 Future spatial dynamic modelling

The change in land use and cover was modelled using the LCM module in the IDRISI TerrSet software (Clark Labs). The LCM is a spatial dynamic framework designed to simulate historical land use trends, identify their key drivers, and project future spatial configurations as well as associated environmental consequences (Eastman 2009).

The years 2028 and 2038 were selected as target years to represent short- and medium-term planning horizons, approximately 10 and 20 years beyond the most recent observed dataset (2018). These time frames align with planning cycles commonly adopted by Brazilian environmental and water resource management agencies, which frequently rely on decadal projections to assess land use and hydrological dynamics. Furthermore, a 10-year interval provides a balance between realistic model predictability and the ability to capture gradual anthropogenic and climatic transformations in the basin.

Predictions of future scenarios for 2028 and 2038 comprise three main steps: (1) change analysis: transitions between land cover classes are identified; (2) transition potential modelling: the likelihood of change between classes is estimated, and the most relevant transitions are incorporated into a sub-model; (3) change prediction: future scenarios are generated using historical change rates between t_1 and t_2 coupled with the transition potential model.

The approach used to model land use and land cover (LULC) for t_4 (2028) and t_5 (2038) involves three processes: transition potential prediction, simulation, and validation. The input dataset includes: (i) LULC for t_1 (1998); (ii) LULC for t_2 (2006); (iii) explanatory variables; and (iv) LULC for t_3 (2018), which is used to validate the simulation for that period. This section provides a clear and structured explanation of how the LCM was employed to forecast land use and cover changes, ensuring that the steps and methodology are accessible to readers familiar with spatial dynamic modelling.

2.5.1 Transition potential prediction

The transition potential prediction stage consists of the following steps: analysis of changes in land use structure, identification of transitions, and testing and selection of explanatory variables (Dantas *et al.* 2025). The selection of the explanatory variable was performed using Cramer’s V test, followed by transition potential modelling for the period t_3 (2018) using a multi-layer perceptron neural network (MLP-NN) (Gowri and Manjula 2025, Ismael and Kumar 2025).

2.5.2 Evaluation of land cover changes

The evaluation of land cover changes was performed using raster maps of land use and cover for t_1 (1998) and t_2 (2006). The analysis was based on a pixel-by-pixel comparison

between the two maps to identify transitions among land use classes. This procedure generated a change detection matrix, from which the areas of gain, loss, and persistence were quantified for each class.

Subsequently, gain–loss charts were produced to visualise the magnitude and direction of land use transformations, enabling the identification of dominant transition processes (e.g. forest to agriculture, agriculture to urban). The analysis was conducted within the LCM environment, which automatically computes these statistics and provides a spatially explicit representation of change trajectories. This evaluation facilitated the identification of the most dynamic land cover categories and supported the formulation of hypotheses regarding the factors driving the spatial patterns of change in the Cupissura River Basin.

2.5.3 Identification of transitions between land use and cover categories

The analysis of land use and land cover changes for t_1 (1998), t_2 (2006), and t_3 (2018) enabled the identification of the most relevant transitions for constructing the transition sub-model in the LCM. The selected transitions were defined based on the observed reduction in agriculture–pasture mosaic and the expansion of forested areas, urban infrastructure, and sugarcane fields. The key transitions incorporated into the model were (a) crop mosaic to agriculture and pasture mosaic; (b) agriculture and pasture mosaic to forest formation; (c) agriculture and pasture mosaic to urban infrastructure; and (d) agriculture and pasture mosaic to sugarcane.

2.5.4 Testing and selection of explanatory variables

After defining the transitions of interest, the explanatory variables were tested and selected for input and calibration of the transition potential sub-model using Cramer's V test. This test evaluates the strength of association between each explanatory variable and the identified transitions.

$$V = \sqrt{\frac{X^2}{n(q-1)}} \quad (13)$$

where V is Cramer's V index; X^2 is the Chi-square statistic ($(O - E)^2/E$); O is the observed frequency for a category; E is the expected frequency in the corresponding category; n is the sample size; and q is the smaller of the number of rows or columns in the land cover matrix.

According to Eastman (2016), high Cramer's V values indicate strong association and good explanatory potential, with values above 0.15 supporting the inclusion of the variable in the transition potential sub-model. The explanatory variables tested included distance from watercourses, distance from urban areas, distance from forested areas, distance from crop areas, distance from sugarcane fields, slope, and altitude. Distances were computed using the *Distance* command in the IDRISI TerrSet software, while slope and altitude were derived from the DEM. In some cases, a natural logarithmic transformation was applied to linearize the explanatory variables.

2.5.5 Transition potential modelling

The modelling of the transition potential was performed using an MLP-NN. This technique constructs relationships between the explanatory variables and the model's input layers through a network of artificial neurons. The MLP-NN was implemented in the LCM environment, initially considering all variables in automatic mode. The maximum number of iterations was set to 10 000, and an accuracy threshold greater than 80% was adopted. After several training cycles, this level of accuracy was achieved. Once processing was completed, the software generated a report indicating the variables effectively used in the model.

2.5.6 Simulation and validation of future land use scenarios

Markov chains. With the transition potential model defined, the simulation of land use for the period t_3 (2018) was carried out using the Markov chains (MC) technique integrated into the LCM. This technique predicts the transition matrix of land cover changes based on the probability of class transitions from one period to another.

Validation of the land use and cover simulation. The validation of the LCM output was performed by comparing the simulated land use and cover map for t_3 (2018) with the observed reference map. Agreement between the two maps was quantified using the kappa coefficient, which indicates the degree of simulation accuracy relative to the reference, accounting for agreement in both the number of land use classes and their spatial distribution. Validation was conducted in the *Validate* module of IDRISI TerrSet, which also provides additional accuracy indices such as K_{no}, K_{standard}, K_{location}, and K_{locationStrata}, allowing for a more detailed evaluation of model performance.

The kappa index ranges from -1 to 1 , with values interpreted as follows: (a) kappa = 1: perfect agreement; (b) kappa > 0.8: substantial agreement; (c) $0.6 < \text{kappa} < 0.8$: moderate agreement; (d) $0.4 < \text{kappa} < 0.6$: weak agreement; (e) kappa < 0.4: poor or non-significant agreement; and (f) kappa = 0: agreement equivalent to that expected by chance. The general formula for calculating the kappa coefficient is:

$$\text{Kappa} = \frac{P_0 - P_e}{1 - P_e} \quad (14)$$

where P_0 is the observed proportion and P_e is the expected proportion.

Simulation of land use and cover for t_4 (2028) and t_5 (2038). The simulation of future land cover for t_4 (2028) and t_5 (2038) was performed based on the transition trends identified in previous periods (t_1 , t_2 , and t_3). The modelling was implemented in the LCM, enabling the projection of future scenarios and the assessment of potential changes in the study area.

3 Results and discussion

3.1 Changes in land use and cover

Land use changes in the Cupissura River sub-basin were analysed through supervised classification, resulting in thematic maps for the years 1998, 2006, and 2018. In 1998, the

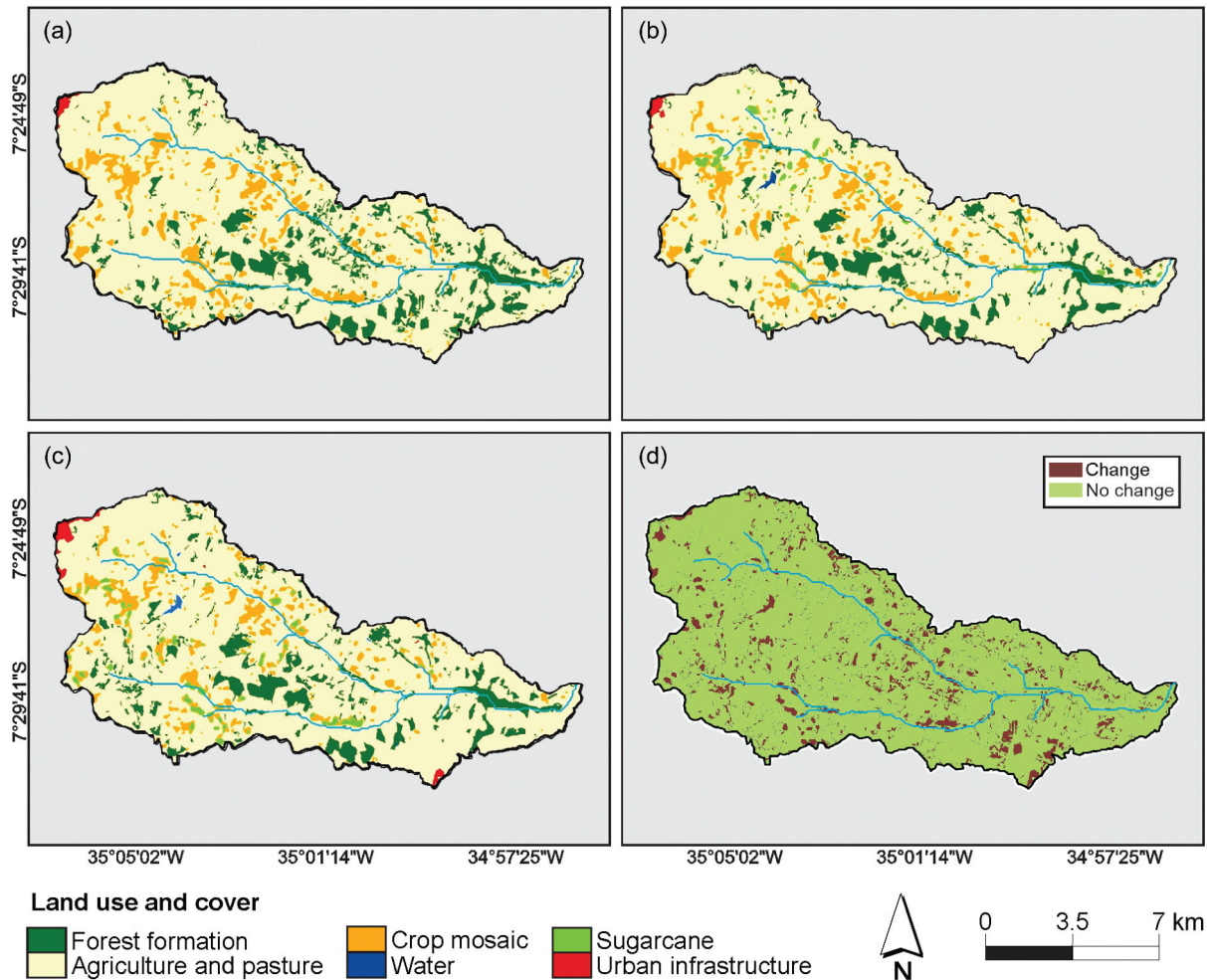


Figure 3. Land use and land cover maps of the Cupissura River sub-basin for the years (a) 1998, (b) 2006, and (c) 2018; and (d) spatial distribution of land use and cover changes between 1998 and 2018, highlighting areas of change and no change.

agriculture and pasture mosaic dominated the sub-basin, covering 78.27% of the total area (Fig. 3a; Table 3). Other land use classes included crop mosaic (9.23%), forest formation (12.20%), and sugarcane (0.01%), while urban infrastructure occupied only 0.31 km², representing a marginal proportion of the total basin area.

Figure 3 illustrates the spatial distribution of land use and land cover in 1998, 2006, and 2018. In 1998 (Fig. 3a), forest formation was concentrated primarily along the northern and eastern margins of the basin. By 2006 (Fig. 3b), substantial conversion of these areas to agriculture and pasture mosaic had occurred, accompanied by a spatial consolidation of agricultural dominance in the central basin. By 2018 (Fig. 3c), a limited reversion of agriculture

and pasture mosaic to small patches of forest formation was observed near basin margins. The expansion of the urban infrastructure remained modest across all three time periods. These spatial patterns complement the temporal changes quantified in Table 3.

Since the 1980s, coastal basins in northeastern Brazil have undergone accelerated urban expansion, driven by private investment and reinforced by public policies encouraging housing developments and agricultural growth (Beuchle *et al.* 2015). The results of this study align with the findings of Santos *et al.* (2021) and Ramos Filho *et al.* (2025), which reported progressive forest cover losses in northeastern Brazilian basins.

In 2006, the agriculture and pasture mosaic increased to 80.60% (Fig. 3b; Table 3), while the crop mosaic and forest

Table 3. Changes in land use and cover in the Cupissura River sub-basin for the years 1998, 2006, and 2018.

Land use	Area 1998 (km ²)	Percentage (%)	Area 2006 (km ²)	Percentage (%)	Area 2018 (km ²)	Percentage (%)
Forest formation	14.40	11.42	11.59	9.19	10.55	8.36
Agriculture and pasture	86.03	68.21	88.59	70.24	86.97	68.95
Crop mosaic	10.85	8.60	8.44	6.69	8.51	6.74
Water	0.01	0.01	0.16	0.13	0.19	0.15
Sugarcane	14.52	11.51	16.98	13.46	19.06	15.11
Urban infrastructure	0.31	0.25	0.37	0.29	0.86	0.68
Total	126.13	100.00	126.13	100.00	126.13	100.00

formation declined to 7.68% and 9.60%, respectively. Sugarcane cultivation expanded to 1.65% of the area, accompanied by a modest increase in urban infrastructure to 0.36 km². The reduction in forest formation – from 13.40 km² in 1998 to 10.55 km² in 2006 – indicates intensified agricultural activities and the expansion of sugarcane cultivation across the sub-basin.

By 2018, forest formation showed partial recovery, totalling 11.59 km², although still representing a reduction of approximately 13.50% compared with 1998 (Fig. 3c). Agriculture and pasture mosaic and sugarcane fields reached 86.97 and 1.78 km², respectively, reinforcing the trend of agricultural consolidation in the region. These findings demonstrate the dynamic nature of land use transformations in the Cupissura River sub-basin, marked by the sustained predominance of agricultural activities, expansion of sugarcane cultivation, and gradual decline in forested areas. Although urban infrastructure expanded over time, it continues to occupy a relatively small fraction of the total basin area.

3.2 Application of the EBA4SUB model

The WFIUH methodology was applied to characterise the shape of the design hydrograph for the Cupissura River sub-basin (Fig. 4). The results indicate that 2018 exhibited the highest peak in the WFIUH function, associated with an increased CN, which suggests reduced infiltration capacity and greater propensity for surface runoff. Although the timing of the hydrograph peak (T_c) remains approximately constant across the three years, the magnitude differs, with 2018 presenting the most pronounced peak. This behaviour reflects the influence of land use changes on runoff generation rather than on flow routing or travel time. Figure 5 shows the simulated hydrographs for three representative storm durations (6, 9, and 12 h) for the years 1998, 2006, and 2018.

For the 12 h events, the flows were more moderate, with 61.98 m³/s in 2006 and 56.77 m³/s in 2018, while the highest

flow was observed in 1998 (81.84 m³/s). These variations reflect the hydrological response of the sub-basin to different land use conditions over time. The time series of peak discharges clearly shows temporal variability: peak flows nearly doubled between 1998 and 2006. This is illustrated by the highest simulated peak flow across all events in 2006 (131.47 m³/s for the 9 h rainfall event). This increase may be attributed to a combination of higher rainfall intensities in 2006 and the enhanced propensity of the watershed to generate surface runoff as a result of land use changes. In 2018, the hydrographs exhibit slightly lower peaks for comparable rainfall magnitudes, which may indicate partial reforestation and/or increased surface retention capacity within the basin. The hydrograph shapes also suggest changes in basin response time: the sharper rising limbs observed in 2006 and 2018 point to a greater propensity for rapid runoff concentration compared with 1998.

The results obtained are promising and consistent with those reported by Grimaldi and Petroselli (2015), Piscopia *et al.* (2015), and Petroselli and Grimaldi (2018), who applied the EBA4SUB model in Italian sub-basins ranging in size from 8 to 441 km² under different climatic regimes. In these studies, model outputs were compared with observed discharge data. Petroselli *et al.* (2019) analysed storm durations equal to the time of concentration (approximately 5 h) and documented potential overestimation of flood volumes when 24 h alternating block hyetographs are used in hydrograph modelling. Młyński *et al.* (2020) evaluated the performance of EBA4SUB in estimating design peak flows for specific return periods in catchments of the upper Vistula River basin. Their findings indicate that EBA4SUB is a viable alternative for flood estimation in ungauged basins, although peak discharges for high return periods may reach nearly twice the values obtained using other methods.

Figure 6 presents the simulated design hydrographs derived from IDF curves for 25- and 50-year return periods. The difference in peak flow magnitude is substantial, increasing from 199.08 m³/s ($T = 25$ years) to 274.22 m³/s ($T = 50$ years), representing a 37.8% increase. This sensitivity to extreme rainfall demonstrates the marked and abrupt rising limb associated with the 50-year event, which indicates a faster hydrological response and higher flow intensity due to reduced lag time during intense storms. These findings have direct implications for flood hazard planning, including sizing detention basins, culverts, and emergency spillways. They underscore the importance of using IDF curves in predicting flooded areas and volumes in the sub-basin.

Although no observed streamflow dataset exists for the Cupissura River basin, preventing a conventional calibration–validation procedure, the hydrological responses simulated by EBA4SUB were consistent with the expected effects of land cover changes on infiltration dynamics and peak flow generation. The behaviour of the model aligns with documented applications in ungauged tropical basins, where EBA4SUB has demonstrated robust performance without requiring empirical calibration. These consistencies support the suitability of the model for the present study and reinforce the reliability of the hydrological interpretations under the different land use scenarios.

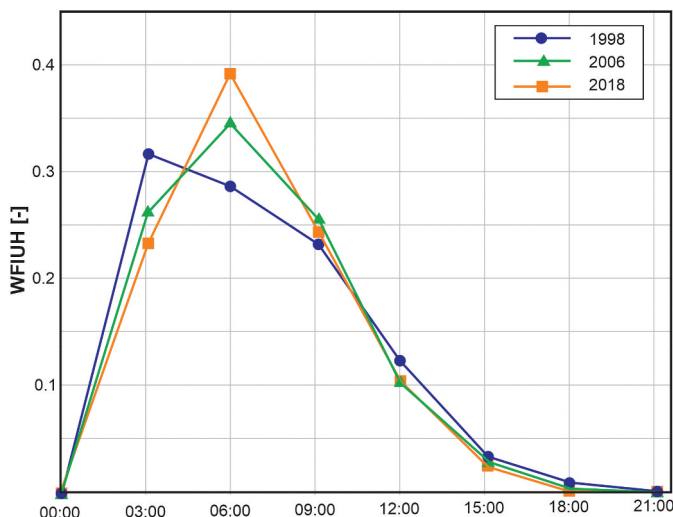


Figure 4. Width-function-based instantaneous unit hydrograph (WFIUH) for the studied years.

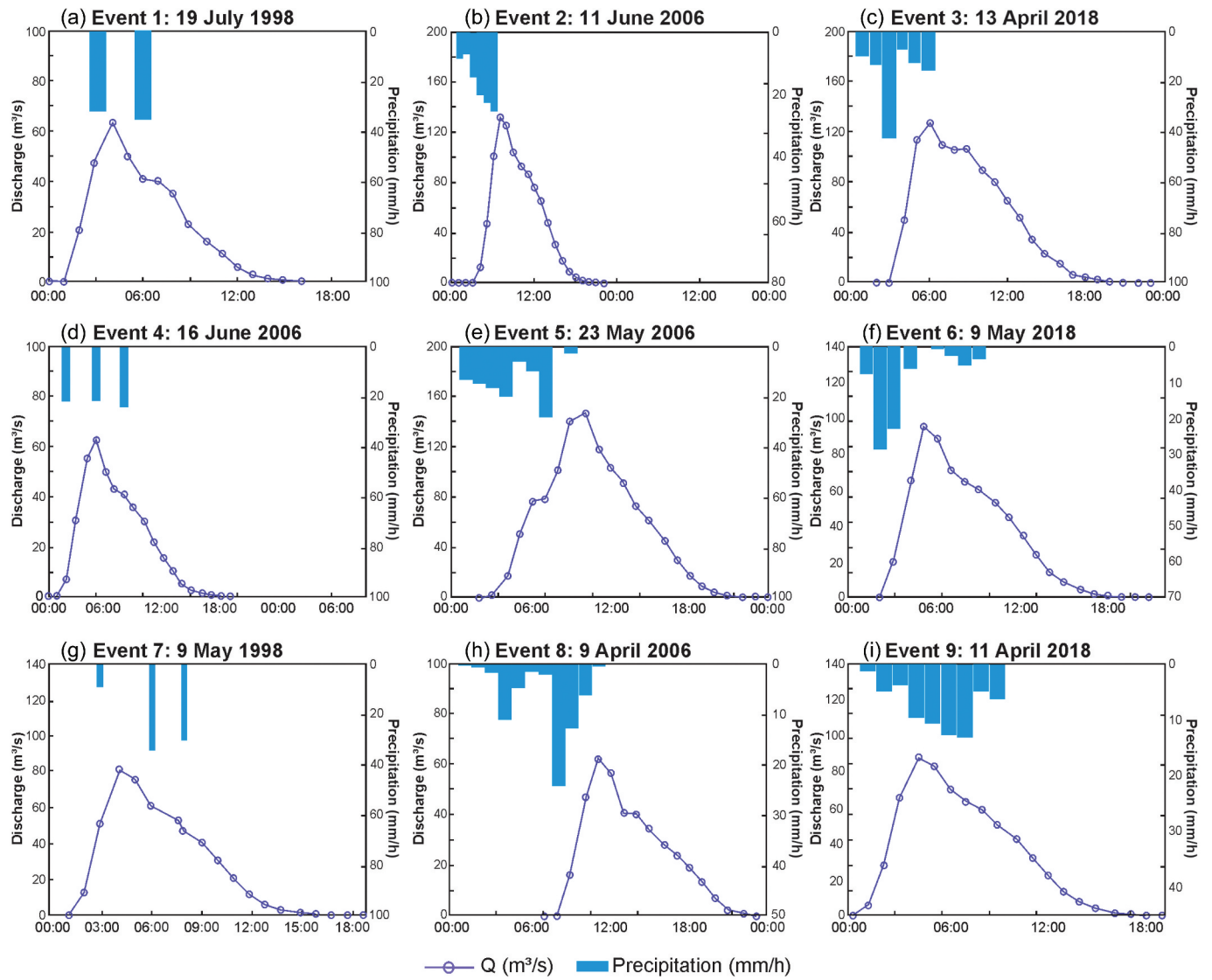


Figure 5. Observed gross precipitation and modelled discharge in EBA4SUB for events with a 6 h duration (a–c), for events with a 9 h duration (d–f), and for events with a 12 h duration (g–i).

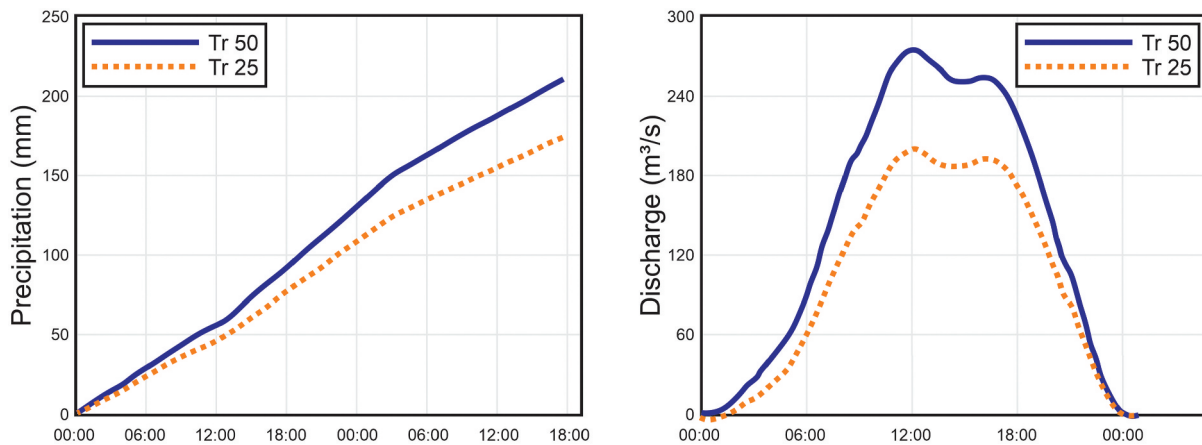


Figure 6. Observed gross precipitation and modelled discharge based on intensity–duration–frequency (IDF) curves for 25- and 50-year return periods.

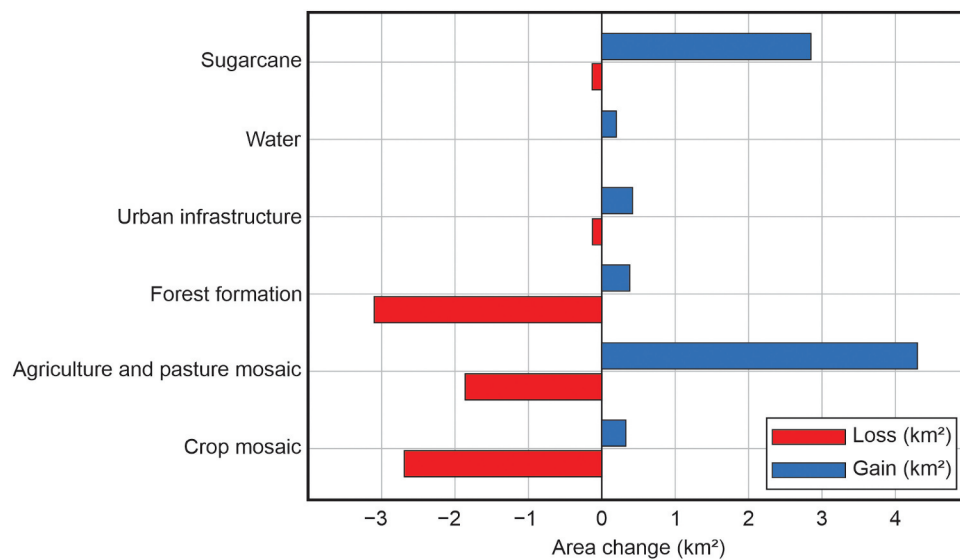


Figure 7. Gains and losses in square kilometres (km²) by land use category in the Cupissura River sub-basin.

3.3 Modelling future land use and cover scenarios

3.3.1 Analysis of land use and cover changes

The analysis of land use changes between t_1 (1998) and t_2 (2006) was performed using the LCM, resulting in Fig. 7, which illustrates the gains and losses in area for each land use category. Figure 7 also includes an additional layer showing the net difference between total gains and total losses for each land use/cover class during this period. Beyond the patterns visible through the visual inspection of Fig. 3, the most substantial decrease (in absolute terms) occurred in the forest formation class. The agriculture/pasture mosaic exhibits a net increase (with gains exceeding losses), yet it is the only class that also presents negative values within its internal transitions, which may suggest intra-category shifts possibly linked to agricultural intensification. The considerable gain in sugarcane area likely reflects economic incentives driving land conversion towards monoculture. Collectively, these processes indicate growing anthropogenic pressure on natural land cover and highlight the progressive transformation of the basin's land system.

3.3.2 Explanatory variables selected after Cramer's V test

Explanatory variables with Cramer's V values above 0.15 were selected (Table 4). Altitude, slope, and distance from water bodies all presented a Cramer's V value of 0.8824. Proximity to urban infrastructure and to sugarcane fields also exerted a notable influence on land use transitions. The MLP-NN was used to predict land use transitions and achieved an accuracy of 90.20% after 10 000 iterations.

Table 4. Explanatory variables and Cramer's V test results.

Explanatory variable	Transformation	Cramer's V
Altitude	Natural log	0.8824
Slope	Natural log	0.8824
Distance from water	Natural log	0.8824
Distance from urban infrastructure	Natural log	0.6764
Distance from forest formation	Natural log	0.7118
Distance from crop mosaic	Natural log	0.6000
Distance from sugarcane	Natural log	0.6765

3.3.3 Transition probability matrix between t_1 (1998) and t_2 (2006)

Table 5 shows the transition matrix of land use and cover between 1998 and 2006, indicating percentages of change and persistence. The analysis revealed high stability coefficients for the agriculture and pasture mosaic (0.9519) and urban infrastructure (0.9139). In contrast, forest formation (0.5209) and sugarcane (0.0007) exhibited low stability, suggesting greater susceptibility to land use changes.

3.3.4 Validation of land use and cover simulation for 2018

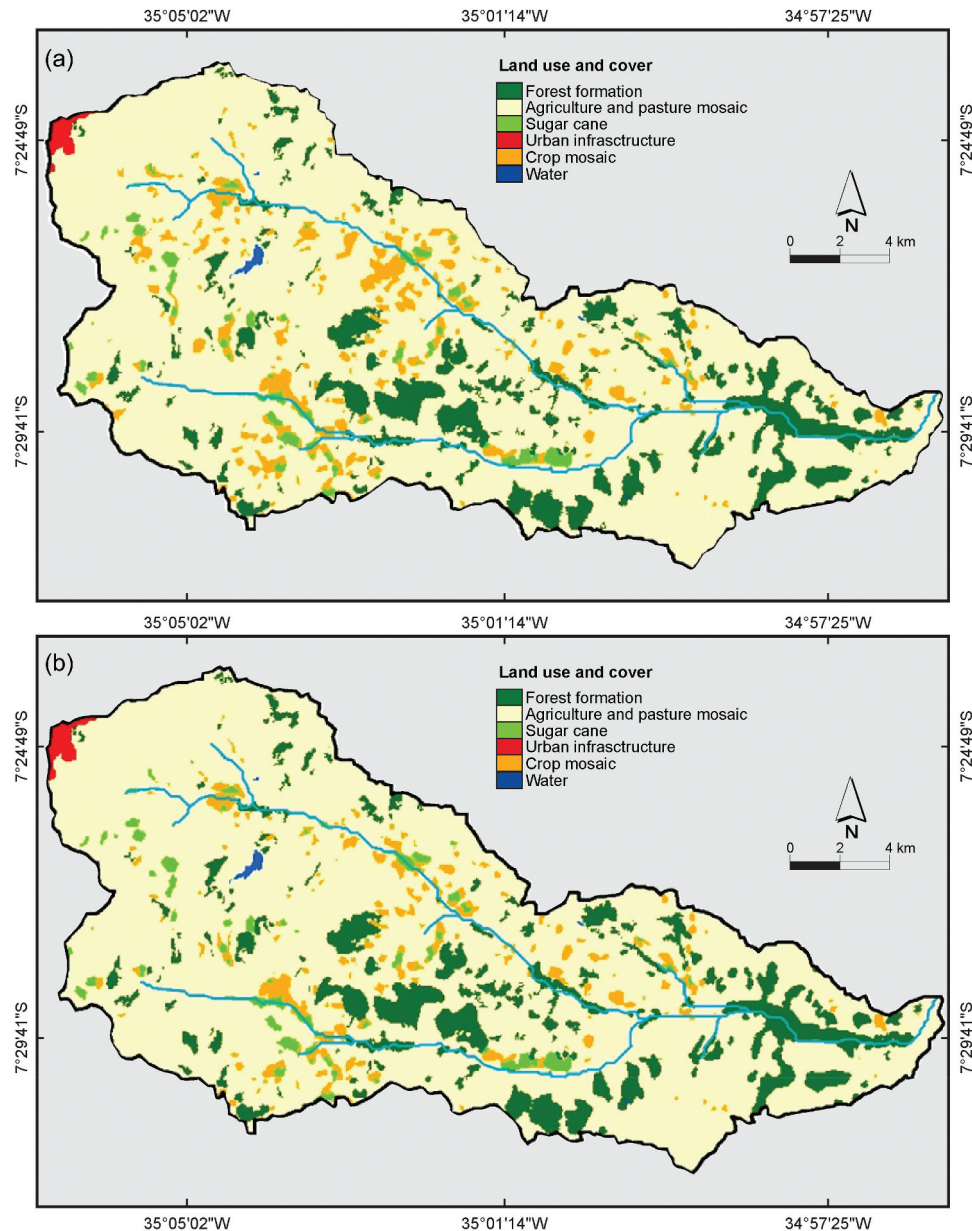
Validation of the LCM simulation for 2018 demonstrated strong agreement between the observed and simulated maps, with a kappa coefficient of 0.7866. This level of concordance indicates that the model effectively reproduces the spatial distribution of land use classes in the study area. Additional kappa indices also exceeded 0.7866, confirming the robustness and reliability of the simulation.

3.3.5 Simulated land use and cover scenarios for t_4 (2028) and t_5 (2038)

Figure 8a presents the simulated land use and cover maps for t_4 (2028). The projected scenario for 2028 indicates that the agriculture and pasture mosaic will continue to dominate the sub-basin, occupying 88.71% of the area, followed by forest formation (13.75%) and crop mosaic (4.64%). Urban infrastructure remains spatially limited, and sugarcane shows a slightly expansion. Figure 8b illustrates the land use and cover projection for t_5 (2038). The scenario reveals a slight decrease in the agriculture and pasture mosaic (89.237%) – following a minor increase in 2028 – accompanied by an increase in forest formation (14.317%) and sugarcane (2.171%). The agriculture and pasture mosaic remains the dominant class across all future periods. The modest rise in forest formation appears primarily along fragmented patches at the basin margins, likely reflecting model sensitivity to

Table 5. Land use and land cover transition matrix between 1998 and 2006, showing change and persistence percentages.

Land use	Crop mosaic	Agriculture and pasture	Forest formation	Urban infrastructure	Water	Sugarcane
Crop mosaic	0.6202	0.2401	0.0013	0.0000	0.0001	0.1383
Agriculture and pasture	0.0144	0.9519	0.0274	0.0012	0.0028	0.0022
Forest formation	0.0036	0.4744	0.5209	0.0001	0.0004	0.0005
Urban infrastructure	0.0003	0.0851	0.0006	0.9139	0.0000	0.0000
Water	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Sugarcane	0.0065	0.9784	0.0129	0.0005	0.0011	0.0007

**Figure 8.** Simulated land use and cover maps for (a) t_4 – 2028, and (b) t_5 – 2038.

restoration or conservation areas. Sugarcane exhibits increasing spatial continuity, whereas urban infrastructure remains geographically constrained.

3.4 Simulation of surface runoff for rainfall events using IDF curves in future scenarios

Figure 9 presents the simulated hydrographs under future land use and cover scenarios for 2028 and 2038. Rainfall

events for both scenarios were simulated using IDF curves derived from rain gauge data corresponding to return periods of 25 and 50 years. The Chicago hyetograph method was applied to generate the temporal distribution of rainfall. The total rainfall depth was kept constant across scenarios to isolate the hydrological influence of land use and cover changes simulated by the LCM. Thus, variations in peak discharge between 2028 and 2038 primarily reflect differences in infiltration capacity, imperviousness, and surface

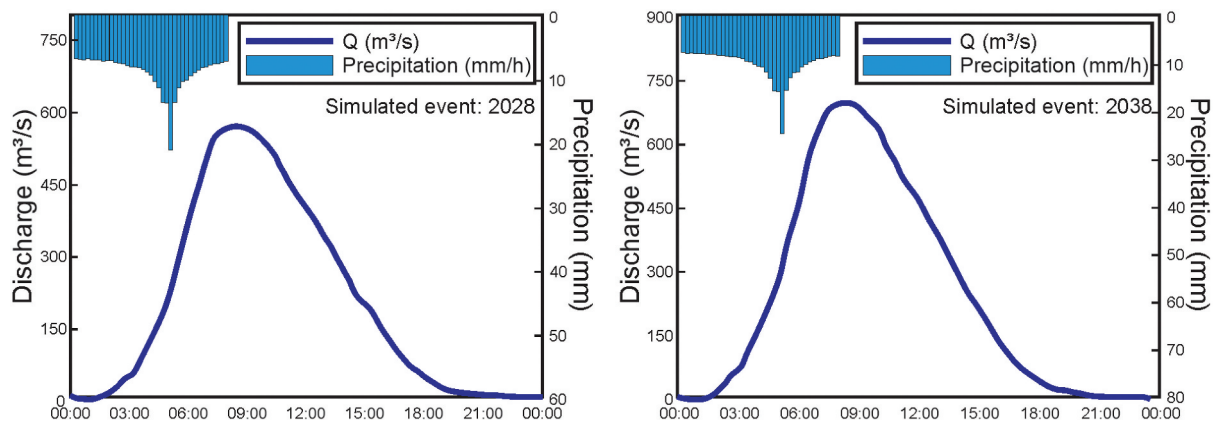


Figure 9. Simulated flows for future land use scenarios.

roughness resulting from evolving land cover patterns. A substantial increase in peak discharge is observed across the two scenarios. The peak flow in 2028 was estimated at $563.82 \text{ m}^3/\text{s}$, while in 2038 it reached $694.80 \text{ m}^3/\text{s}$, representing an increase of 23.2% over a 10-year period. This rise in peak flow highlights the combined effect of extreme rainfall intensities derived from IDF curves and the reduced infiltration potential caused by land cover changes, including increased imperviousness and the intensification of agricultural land use. The hydrographs exhibit shorter time-to-peak responses, indicating a declining capacity of the basin to buffer rainfall inputs under future land use configurations.

The analysis suggests that both extreme rainfall events and land cover changes are key drivers of flow variability. These results are critical for the design of hydraulic structures and for water resource management within the basin, emphasizing the need to integrate climatic and land use factors into future simulations and planning strategies.

4 Conclusions

The analysis of land use and cover changes in the Cupissura River sub-basin revealed the predominance of agricultural activities, particularly the mosaic of agriculture and pasture. A marked decline in forest cover was observed over the study period, likely associated with the expansion of sugarcane cultivation and increases in agricultural and pasture areas. These findings underscore the need to balance economic development with environmental protection and highlight the importance of adopting sustainable land management practices to prevent further degradation of biodiversity and natural resources.

Continued monitoring of land use and cover dynamics is recommended to assess the effectiveness of implemented measures and to identify emerging trends and pressures. Raising awareness among local communities regarding responsible natural resource use remains essential for ensuring long-term regional sustainability.

Hydrological simulations showed that although the general shape of the hydrographs was consistent among events, peak discharges varied due to differences in basin response linked to CN values. Peak flow estimates also differed considerably

across return periods, reflecting potential implications for flood extent and storage volumes within the sub-basin.

LCM modelling indicated substantial losses of forest formation and agricultural–pasture mosaic classes between 1998 and 2006. Topographic factors, proximity to watercourses, and distances to urban infrastructure, forested areas, and sugarcane fields were identified as key drivers of these transitions. The 2018 prediction exhibited high accuracy, reinforcing the reliability of the modelling framework.

The results provide important insights for water resource management and the planning of hydraulic infrastructure such as dams, bridges, and canals. The study clearly demonstrates that variations in land use and cover exert a significant influence on peak flows, a critical parameter for the design and sizing of such structures.

Finally, conclusions emphasise the need to consider uncertainty in future projections and to adopt integrated and efficient water resource planning strategies to ensure the sustainability of watershed management in tropical humid regions exposed to ongoing land use change.

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Data availability

Data will be made available on request.

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