

Article

Extreme Hydrological Events and Land Cover Impacts on Water Resources in Haiti: Remote Sensing and Modeling Tools Can Improve Adaptation Planning

Jeldane Joseph ¹, Suranjana Chatterjee ¹ , Joseph J. Molnar ² and Frances O'Donnell ^{1,*} 

¹ Department of Civil and Environmental Engineering, Auburn University, Auburn, AL 36849, USA; jzj0148@auburn.edu (J.J.); szc0228@auburn.edu (S.C.)

² Department of Agricultural Economics and Rural Sociology, Auburn University, Auburn, AL 36849, USA; molnajj@auburn.edu

* Correspondence: fco0002@auburn.edu

Abstract

Populations in areas with limited hydrological data face ongoing challenges related to water supply and management, with climate change increasing the risks of floods and droughts. New remote sensing and modeling tools can improve land and water management in these regions, especially when combined with limited ground measurements and local knowledge of extreme events. This study examined hydrological extremes and land cover change impacts in the Grande Rivière du Nord watershed, Haiti, using satellite and model-based data. Precipitation extremes were obtained from the Global Precipitation Measurement Integrated Multi-satellite Retrievals for GPM (GPM IMERG; 2000–2025), and streamflow data were sourced from the Group on Earth Observation Global Water Sustainability (GEOGLOWS) system and bias-corrected with a small historical hydrologic database. Annual maximum series were created and fitted with Gumbel, Lognormal, and Generalized Extreme Value (GEV) distributions using the L-moment method. Goodness-of-fit tests identified the best models, and precipitation amounts for return periods of 2–100 years were estimated. The precipitation maxima aligned with locally reported extreme events, and GEV provided the best overall fit. Using the bias-corrected streamflow, a hydrologic model was calibrated and validated and then applied to land cover change scenarios. Simulations suggest that moderate land-use change can increase peak flows beyond channel capacity, raising flood risk and informing adaptation planning in northern Haiti, which has limited data.

Keywords: GPM IMERG; remote sensing; extreme value analysis; hydrologic modeling; flood risk; Haiti



Academic Editors: Hao Chen,
Linjing Qiu and Wenbin Ding

Received: 16 January 2026

Revised: 24 February 2026

Accepted: 25 February 2026

Published: 3 March 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The lack of reliable and accessible hydrometeorological data remains a major obstacle in designing and implementing effective water management solutions in developing countries. In this context, remote sensing and other large-scale data products have emerged as valuable approaches to address data gaps by providing information on rainfall patterns, soil moisture, surface water dynamics, and land-use change, thus supporting monitoring and early-warning systems for floods and droughts [1,2]. Earlier projections suggested that by 2020, the number of water-scarce countries could approach approximately 35, and

that by 2025, one-third of the developing world's population might face severe water shortages [1]. Consistent with these concerns, 2020 estimates indicated that more than 2 billion people lacked safely managed drinking-water services globally [3,4]. In data-scarce settings, remote sensing products offer a cost-effective and scalable way to support water resource planning and disaster risk reduction.

Haiti ranks as the fourth most vulnerable country to the impacts of climate change [5]. This high level of vulnerability reflects a combination of environmental, geographic, social, and institutional factors [5]. The country is located in the hurricane belt, while its mountainous terrain increases the risk of landslides and flash floods during heavy rainfall [6,7]. Additionally, extensive deforestation has occurred, mainly caused by the population's reliance on charcoal for cooking, with estimates indicating that less than 2% of the original forest remains. This degradation weakens slope stability, causes erosion, and reduces infiltration [8,9]. Over the past twenty years, Haiti has faced more than 30 major storms and 40 flood events, impacting over 3.5 million people [10]. Past hurricanes caused severe flooding, loss of life, and displacement of thousands of residents [6]. Climate projections indicate that, by 2100, average surface temperatures could rise by 1.2–2.3 °C, with about a 5% decrease in rainfall and sea levels increasing by up to 0.6 m compared to the 1986–2005 baseline period [5].

Extreme events associated with climate change are already worsening Haiti's water crisis [11]. Despite having an estimated 2.76 billion cubic meters of renewable groundwater annually and total reserves exceeding 56 billion cubic meters [12], the country ranks among the lowest in water availability worldwide [13,14]. This is due to weak infrastructure, uneven water distribution, population growth, and unsustainable resource use [14]. Hurricanes and other extreme events worsen these issues by damaging water and sanitation systems and contaminating surface and groundwater sources, which increases pressure on limited supplies and raises the risk of disease outbreaks [15]. To address some of these challenges, national agencies such as the Direction Nationale de l'Eau Potable et de l'Assainissement collaborate with non-governmental organizations to finance and implement water infrastructure initiatives [8]. However, current systems are still inadequate to satisfy the population's needs. In many regions, households travel long distances to fetch water, which places a heavy burden on already vulnerable communities [9]. The Haitian government must prioritize building resilience in water systems, especially as climate change continues to disrupt infrastructure and livelihoods [16]. Strengthening resilience involves not only enhancing physical infrastructure but also adapting institutional and community-level responses [17]. Integrated strategies such as Integrated Water Resources Management (IWRM); improved water, sanitation, and hygiene projects; community involvement; and investment in education are all crucial components [18].

These efforts rely on accurate hydrologic and climatological data. Several studies have utilized remote sensing in Haiti across different contexts, including flood risk assessment, drought monitoring, and population mapping [19,20]. However, these efforts are still limited by validation and accuracy challenges due to the ongoing lack of ground-based observations that can be addressed by improved integration of different data product types. Building on this foundation, the present study uses a novel combination of satellite-based precipitation data from Global Precipitation Measurement Integrated Multi-satellite Retrievals for GPM Integrated Water Resources Management (GPM IMERG) and simulated streamflow from the Group on Earth Observation Global Water Sustainability (GE-OGLOWS) European Centre for Medium-Range Weather Forecasts (ECMWF) Streamflow Service with one of the few ground-informed historical streamflow datasets available for Haiti (Simbi) [21]. This integrated approach of remote sensing and data analysis supports hydrological analysis in the Grande Rivière du Nord (GRN) watershed, where gauging

infrastructure is limited but flood hazards are prevalent. By leveraging the high temporal and spatial resolution of GPM IMERG and using Simbi to enhance the reliability of GEOGLOWS) estimates, the study aims to improve on previous studies to produce more robust assessments of extreme precipitation and streamflow behavior in northern Haiti.

Within this framework, this study aims to enhance water resilience in northern Haiti by improving water resource management and flood risk mitigation in the context of climate change. Specifically, it investigates hydrological trends and patterns in the GRN watershed to better understand how climate variability and change affect water resources. It also develops and demonstrates methods for using remote sensing as an alternative approach for hydrological analysis in the Northern Corridor of Haiti, considering the country's limited ground-based data. Additionally, the project creates hydrological modeling scenarios using available data to assess how land-use changes and urbanization affect streamflow patterns and flood risks in the GRN watershed.

2. Materials and Methods

2.1. Study Area

This study examines the GRN watershed (Figure 1), located in Haiti's North and Northeast departments. It is one of the country's largest basins, covering approximately 663 km² [22]. The river begins in the Vallières mountain range and flows northwest toward the Atlantic Ocean, passing through 18 communes, including Baho, Grande Rivière du Nord, Quartier-Morin, Limonade, and parts of Cap-Haïtien and Dondon [22].

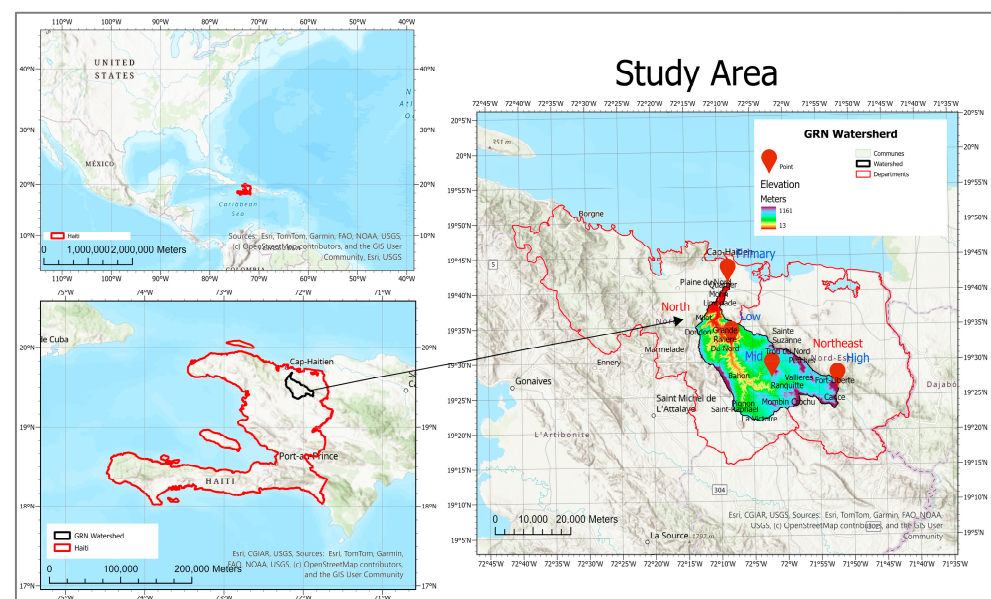


Figure 1. Grande Rivière du Nord (GRN) watershed digital elevation model (DEM) and Global Precipitation Measurement Integrated Multi-satellite Retrievals (GPM IMERG) extraction points: one primary point for the full IDF analysis and three elevation zone points for the 2007 sensitivity check.

The watershed shows significant spatial and temporal variation in rainfall. The average annual precipitation is approximately 1440 mm, but more than 60% of the basin receives over 1500 mm, and some mountainous regions like Vallières can reach up to 2347 mm [22]. During the rainy season in northern Haiti, daily rainfall exceeding 40 mm is common [23], indicating that short-duration, high-intensity rainfall is a regular aspect of the regional climate. Runoff accounts for about 66% of annual rainfall, and a 1999 US Army Corps study reported an average discharge of 7.66 cubic meters per second (cm) at the river mouth [24].

The topography features low mountains, intermediate hills, and rocky massifs. Soils are mainly clay and clay-loam (Hydrologic Soil Group C), and slopes in much of the basin

range from 3% to 12% in incline, leading to quick runoff and erosion. Downstream towns like Limonade and Quartier-Morin are densely populated, with over 50% of the land having slopes under 12% incline, which slows drainage and increases the risk of flooding and sediment buildup [22].

The region features a tropical climate, with average monthly temperatures ranging from 24 °C to 27.6 °C and a mean relative humidity of approximately 76% [22]. Local vegetation includes fruit and medicinal trees such as *Citrus* spp., *Psidium guajava*, and *Ricinus communis*. Due to its socio-environmental significance, high rainfall variability, and exposure to hydrological hazards, the GRN watershed serves as a representative case for evaluating climate-driven water challenges in northern Haiti.

2.2. Intensity–Duration–Frequency Analysis

The analysis methods used in this study are outlined in Figure 2. A hydrological analysis was performed to characterize historical patterns of extreme hydrological events and evaluate their implications for water resilience in the region. Gridded precipitation data were sourced from NASA Earthdata, specifically the GPM IMERG Version 07B product (GPM_3IMERGHHL.07B). IMERG offers half-hourly precipitation estimates at a spatial resolution of $0.1^\circ \times 0.1^\circ$ (about 10 km $\times$ 10 km) spanning the period of 2000–2025. This product was selected because its fine temporal resolution allows for analysis of low-duration, high-intensity rainfall and because it has been found to perform well in the Caribbean region [25–27]. In particular, a study in Southwestern Haiti compared IMERG to gauge data and found generally good performance [25].

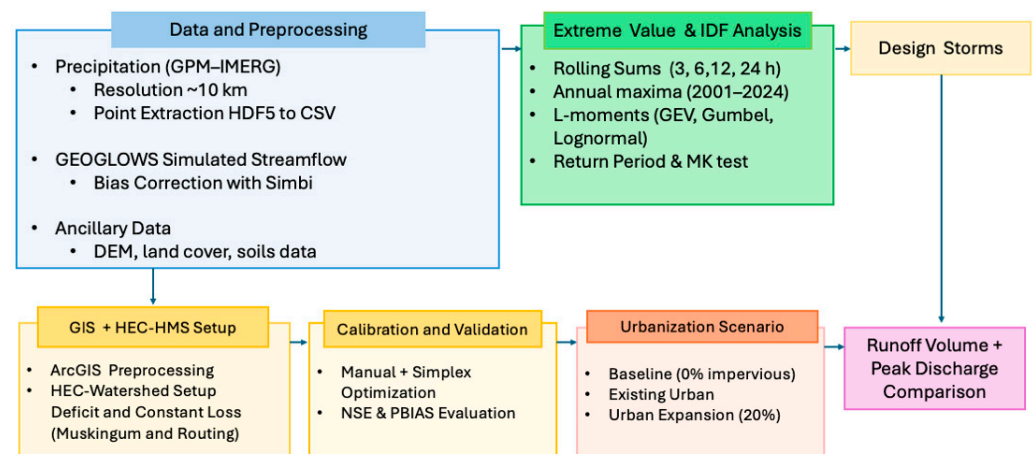


Figure 2. Study workflow and analysis steps.

The raw data, available in HDF5 format, were extracted at the primary location used for the full-period intensity–duration–frequency (IDF) analysis within the watershed (19.6856° N, -72.1435° W) (Figure 1). This location was selected within the basin, near the available hydrometric observational station used in the Simbi dataset, to maintain spatial consistency between the precipitation forcing location and the streamflow reference area.

Temporal aggregation from 30 min data to 3, 6, 12, and 24 h was performed using rolling (moving) sums evaluated every 30 min (6, 12, 24, and 48 consecutive intervals, respectively). Annual maximum precipitation series were then derived for each duration by selecting the largest rolling accumulation within each calendar year, allowing overlapping windows while applying consistent criteria across the full record. Incomplete years (2000 and 2025) were excluded to ensure consistency across the analysis period. Therefore, all annual-maximum-based analyses were conducted for the 2001–2024 period. The processed dataset contained no missing values. Using Microsoft Excel, annual maximum precipitation values were identified for each duration to support the IDF analysis.

Because convective rainfall can be spatially heterogeneous over mountainous terrain, a targeted sensitivity check was performed for 2007 (a representative extreme year) using additional IMERG extraction points distributed across elevation zones within the watershed (Figure 1). Specifically, precipitation was also extracted at three supplementary locations representing high (1161 m), mid (471 m), and low (90 m) elevation zones (Table 1), and the resulting annual maxima and short-duration extremes were compared to quantify the influence of within-basin pixel selection on IDF-relevant statistics. The comparison indicates that the mid-elevation point is very similar to the primary point for longer durations (approximately 4% difference for 6–24 h), whereas larger differences occur for 3 h and at the high-elevation location, consistent with localized convective rainfall.

Table 1. Location, elevation, and 2007 maximum 3 to 24 h precipitation totals (mm) at the primary extraction point and low-, mid-, and high-elevation sensitivity points.

Point	Lat	Lon	Elevation (m)	Max 3 h	Max 6 h	Max 12 h	Max 24 h
Primary	19.6856	72.1435	17	76	116	116	116
Low	19.5359	72.1367	90	57	89	90	101
Mid	19.4594	72.0358	471	57	111	111	112
High	19.4328	71.8711	1161	40	55	56	60

The L-moment method [28] was used to fit Gumbel, Generalized Extreme Value (GEV), and Lognormal distributions, with parameters estimated using probability-weighted moments (PWM). The goodness of fit was evaluated by plotting the fitted and empirical cumulative distribution functions (CDFs) and calculating the root-mean-square error (RMSE), mean absolute error (MAE), and probability plot correlation coefficient (PPCC) for each distribution and duration in R. Exceedance probabilities for a threshold x^* were calculated as

$$EP(x^*) = 1 - F_X(x^*) \quad (1)$$

where F_X is the fitted CDF. The return period was derived as

$$T(x^*) = \frac{1}{EP(x^*)} \quad (2)$$

Finally, a Mann–Kendall test was conducted to evaluate trends in the frequency of annual maximum precipitation over the study period. It employed R version 4.2.1 (R Foundation for Statistical Computing, Vienna, Austria) and the Kendall package [29].

2.3. Hydrological Modeling

Hydrological modeling was conducted using Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) to assess the impacts of urbanization on the GRN watershed. A 30 m resolution digital elevation model (DEM) was acquired from the United States Geological Survey. Watershed boundaries and river flow data for Haiti were included. All spatial datasets were preprocessed in ArcGIS Pro version 3.5.0 (ESRI, Redlands, CA, USA) and projected to UTM WGS 84 Zone 18N to ensure proper alignment and overlay. Because datasets had different native resolutions (e.g., 30 m DEM, 10 m land cover, and generalized soil mapping), raster-derived variables were summarized at the subbasin scale using area-weighted zonal statistics to derive subbasin-level model inputs consistent with the HEC-HMS modeling unit.

Land cover data were obtained from the European Space Agency [30], World Resources Institute Google Dynamic World V1 [31], and ESRI Sentinel-2 Land-Cover [32]. All land cover datasets had a spatial resolution of 10 m; however, ESRI Sentinel-2 was used to

derive subbasin land cover fractions for curve number estimation, while the other products were used for cross-checking built-up patterns. Soil data were sourced from the Food and Agriculture Organization (FAO; Table 2).

Table 2. Soil data and loss parameters for model input.

Subbasin	Soil Texture	Dominant Soil Series ¹	Depth (mm)	Maximum Deficit (mm)
1	Clay Loam	Bd	1200	384
2	Clay Loam	Nd	2000	640
3	Clay Loam	Ne	2500	800
4	Clay Loam	Bd/Nd	1600	512
7	Clay Loam	Bd	1200	384
10	Clay Loam	Bd	1200	384
17	Clay Loam	Bd	1200	384
19	Clay Loam	Bd	1200	384
20	Clay Loam	Ne	2500	800

¹ Soil unit symbols follow the Food and Agriculture Organization (FAO) legend from the Soil Map of the World: Bd = Dystric Cambisols; Nd = Dystric Nitisols; Ne = Eutric Nitisols.

In HEC-HMS, the DEM was used to delineate subbasins (Figure 3), identify the main channel and tributaries, and define flow paths within the watershed. Routing was simulated using the Muskingum method with initial parameters of $K = 0.5$ and $X = 0.25$. Lag time was calculated as 0.6 times the time of concentration following the TR-55 guidelines. Infiltration losses were modeled with the deficit and constant loss method, starting with an initial deficit of 50.8 mm, based on the HEC-HMS User's Manual.

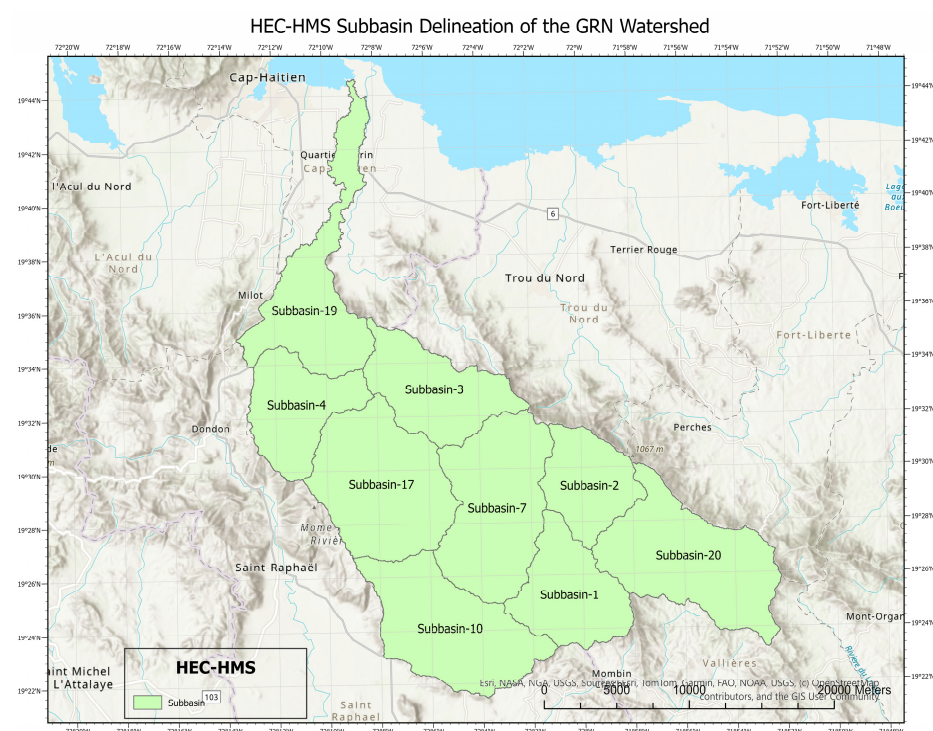


Figure 3. Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) delineation of the Grande Rivière du Nord (GRN) watershed into nine subbasins.

Maximum deficit and constant loss rate values were derived from soil texture. For clay-loam soils, porosity (0.47), wilting point (0.15), field capacity (0.45), and constant infiltration rate ($2.45 \times 10^{-4} \text{ cm day}^{-1}$) were obtained from [33]. These values were used to calculate model parameters according to HEC-HMS documentation.

Precipitation was input as a specified hyetograph; reference evapotranspiration was set at 8 mm per day according to FAO Penman–Monteith under tropical conditions. The canopy method used was Simple with a maximum storage capacity of 2.5 mm. The precipitation series was based on daily data aggregated from 30 min GPM data, covering 31 August 2007 to 1 January 2008. Discharge was specified in cm at a 1-day interval for the calibration period from 1 May to 31 December 2007. The year 2007 was chosen due to its high annual precipitation within the 2000–2025 period and significant flooding in Haiti’s north and northeast regions.

2.4. HEC-HMS Model Calibration and Validation

HEC-HMS was calibrated manually (loss module: infiltration and antecedent storage) and then automatically (Simplex, peak-weighted RMSE). Manual calibration was used only to adjust the initial loss settings (based on soil texture values reported in [33]) that initially prevented runoff generation, after which parameters were optimized automatically within predefined bounds. Automatically calibrated parameters included the deficit and constant loss terms from 0.04 to 8 mm/h, the Muskingum-K parameter from 0.016 to 2, and the X parameter from 0.01 to 0.50, calibrated individually for each subbasin and reach, respectively. GEOGLOWS streamflow was bias-corrected using a distribution-based quantile mapping approach with Simbi as the reference [21]: probability distributions were fit to the full GEOGLOWS and Simbi flow series, and each GEOGLOWS value was mapped to the corresponding percentile of the Simbi distribution. Using GEOGLOWS corrected streamflow, performance was assessed with Nash–Sutcliffe Efficiency (NSE) and Percent Bias (PBIAS) and interpreted relative to benchmarks in [34].

The model was validated for the 1 May–31 December 2019 period as an independent, data-complete period outside the calibration window.

2.5. Urbanization Scenario

Following calibration and validation, we developed scenarios to assess urbanization impacts on runoff and peak discharge. A pre-urbanization baseline (no impervious area) served as a reference. The Existing Urban scenario applied current subbasin imperviousness from ESRI land cover (Table 3). Imperviousness was calculated using ArcGIS Pro for each subbasin as the percentage of area classified as built-up in the land cover dataset. This was calculated as the area of built-up pixels within the subbasin divided by the total subbasin area and multiplied by 100. It is used here as a proxy for impervious cover and then assigned as the impervious fraction in HEC-HMS. The Urban Expansion scenario set imperviousness to 20% as a hypothetical development scenario to evaluate runoff sensitivity to increased housing and infrastructure rather than as a precise forecast. Scenarios were compared to the baseline using design storms generated in HEC-HMS (Frequency Storm), with rainfall depths from 3 h and 24 h IDF curves. Storm durations matched IDF durations, with 5 min hyetograph increments centered at 50% of the duration. The storms assumed uniform spatial distribution and no area reduction.

Table 3. Impervious surface percentages by subbasin in existing conditions.

Subbasin	Impervious Surface (%)
1	5.55
2	5.85
3	5.02
4	5.81
7	5.30

Table 3. Cont.

Subbasin	Impervious Surface (%)
10	6.02
17	6.92
19	14.94
20	5.51

3. Results

3.1. Analysis of Precipitation and Streamflow Trends

The analysis of annual maximum rainfall for 3, 6, 12, and 24 h periods reveals significant year-to-year variability in the GRN watershed. Figure 4 shows that the highest values occur in 2007, 2008, 2012, and 2016, aligning with major hydrometeorological events reported for northern Haiti. Annual totals also reach peaks in 2007 (2127 mm) and 2016 (2152 mm) (Figure 5). Conversely, the 2002–2003 and 2020–2021 periods are characterized by relatively low rainfall, with 2020 identified as one of the driest recent years in Haiti.

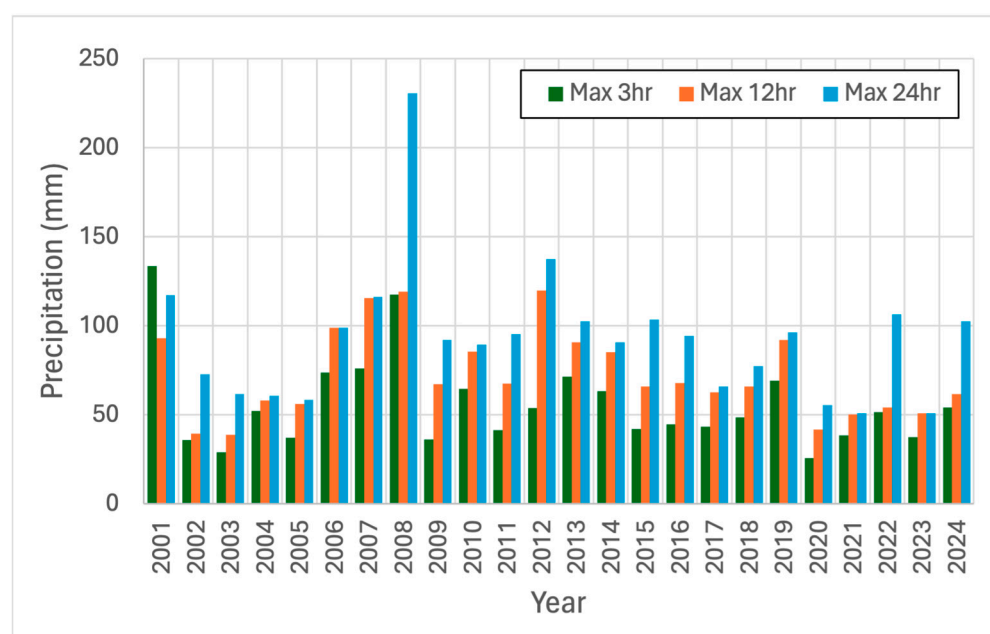


Figure 4. Annual maximum precipitation (mm) for 3 h, 6 h, 12 h, and 24 h durations in the (Grande Rivière du Nord) GRN watershed from 2001 to 2024.

The Mann–Kendall test ($\tau = 0.0362$, p -value = 0.823) shows no significant trend in the annual maximum precipitation series. L-moments were used to estimate the parameters of the Gumbel, Lognormal, and GEV distributions for the four durations. Goodness-of-fit metrics (PPCC, RMSE, and MAE) (Table 4), along with visual inspection (Figure 6), indicate that all three models fit the empirical data reasonably well and result in very similar curves, with the GEV distribution providing the best overall fit, especially for low and extreme values.

Design rainfall depths derived from the GEV distribution for return periods of 2, 5, 10, 20, 50, and 100 years are summarized in Table 5. As expected, rainfall depths increase with both return period and event duration. For example, 10-year rainfall ranges from 79 mm (3 h) to 137 mm (24 h), while 100-year rainfall ranges from 123 mm (3 h) to 213 mm (24 h). These estimates form the basis for the IDF curves and the design of hydraulic structures and flood management measures in the GRN watershed.

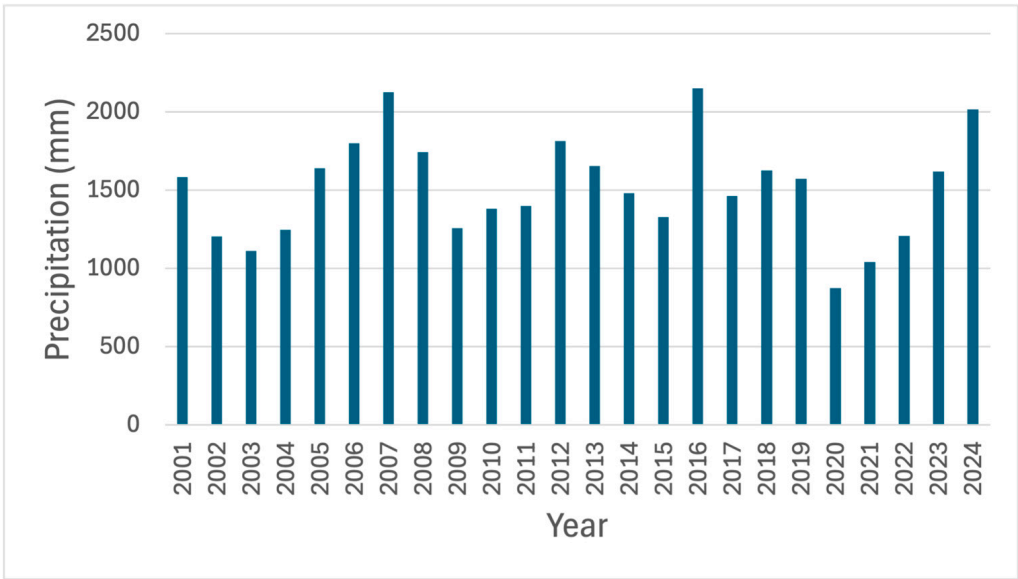


Figure 5. Total annual precipitation (mm) from 2001 to 2024 in the GRN watershed.

Table 4. Distribution fit statistics (probability plot correlation coefficient (PPCC), root mean square error (RMSE), and mean absolute error (MAE)) for Gumbel, Lognormal, and Generalized Extreme Value (GEV) models across 3–24 h precipitation durations.

Duration Period	Distribution	RMSE	MAE	PPCC
3 h	Gumbel	1.06	0.99	0.92
3 h	Lognormal	1.06	0.99	0.92
3 h	GEV	1.06	0.99	0.91
12 h	Lognormal	1.05	0.99	0.97
12 h	Gumbel	1.05	0.99	0.97
12 h	GEV	1.05	0.99	0.98
6 h	Gumbel	1.05	0.99	0.98
6 h	Lognormal	1.05	0.99	0.97
6 h	GEV	1.05	0.99	0.97
24 h	Gumbel	1.07	0.99	0.86
24 h	Lognormal	1.07	0.99	0.86
24 h	GEV	1.07	0.99	0.85

Table 5. Design rainfall depths by duration and return period predicted by the GEV distribution for the GRN watershed.

Return Period (Years)	3 h Precip (mm)	6 h Precip (mm)	12 h Precip (mm)	24 h Precip (mm)
2	49	61	69	86
5	66	83	92	116
10	79	99	107	137
20	92	115	120	159
50	109	137	138	189
100	123	155	151	213

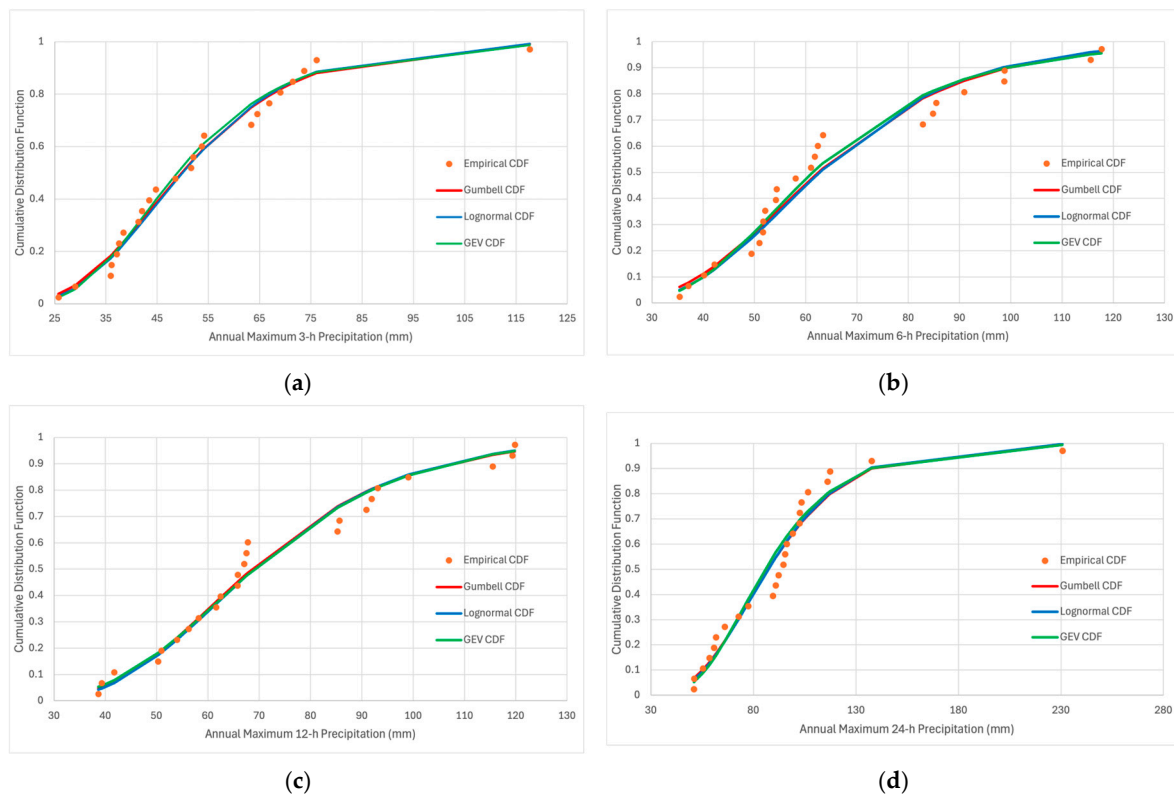


Figure 6. Cumulative distribution function comparison for (a) 3 h, (b) 6 h, (c) 12 h, and (d) 24 h maximum precipitation using empirical data and fitted distributions.

3.2. HEC-HMS (Watershed Modeling)

The initial, uncalibrated model failed to produce any runoff, with a bias of 100% and an NSE of -0.332 . This was due to an excessively high constant infiltration rate for clay loam soil, which caused all rainfall to infiltrate. After manually calibrating by adjusting a scaling factor for the maximum deficit, the constant rate, and setting the initial deficit to 5 mm, the runoff volume aligned well with observations (PBIAS = -0.11% , Very Good; [34]). However, peak discharges were still overestimated by about 64%, and flood peaks occurred at incorrect times, leading to a very low NSE of -0.846 .

An automatic calibration using an Optimization Trial to calibrate Muskingum K and X and the constant infiltration rate further improved performance. The simulated runoff volume was 459 mm compared to the GEOGLOWS value of 500.6 mm (PBIAS = -8.42% , Good), with the peak flow error decreasing to -59 cm and NSE increasing to 0.445. In addition, the simulated peak occurred on 6 October 2007 compared to 11 October 2007 in the GEOGLOWS series (peak timing error = -5 days), indicating the model peak was early. Although this NSE remains below the Satisfactory threshold ($\text{NSE} \geq 0.50$), it clearly shows improvement. Visually, the model captured flows more realistically during early June, late July, and the September–November period, although some differences in peak magnitude and timing still exist (Figure 7). These remaining errors likely reflect limitations in the calibration and validation process. Limited ground-based data were available in this region. Therefore, a degree of uncertainty is embedded in the remote sensing-based precipitation inputs, the GEOGLOWS product in place of gauge-based stream flow data, and gridded land cover and soils data.

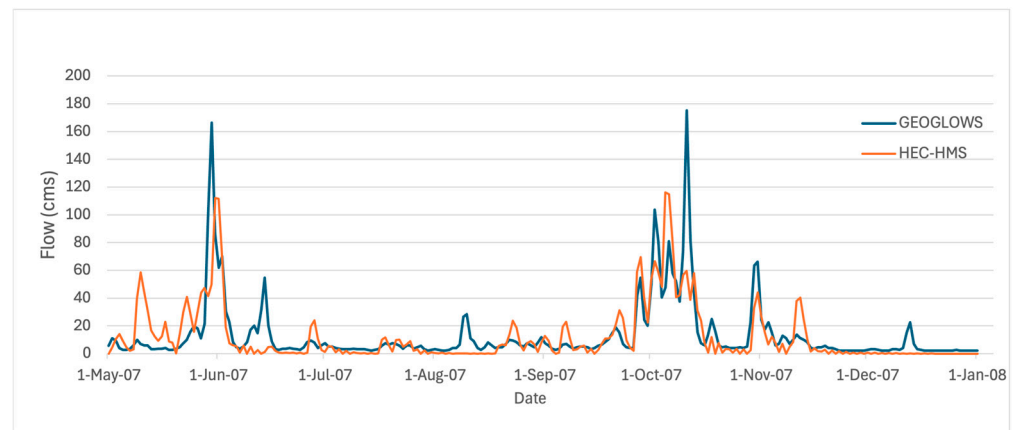


Figure 7. Group on Earth Observation Global Water Sustainability (GEOGLOWS) vs. Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) simulated streamflow for the model calibration period after manual and auto calibration in the period of May–December 2007.

The 2019 validation (Figure 8) further emphasizes the need for model improvement. Visually, the model performed well during certain periods, especially in June and October, where simulated flows closely matched GEOGLOWS values. However, it either underestimated or overestimated flows in other months, notably in August and December. Quantitatively, the simulated peak discharge differed from observations by around 23% and the total runoff volume by about 11%. The PBIAS value remained within the good performance category, indicating a reasonable estimate of overall runoff volume, but the NSE stayed below 0.50, confirming that the model's overall accuracy is still unsatisfactory.

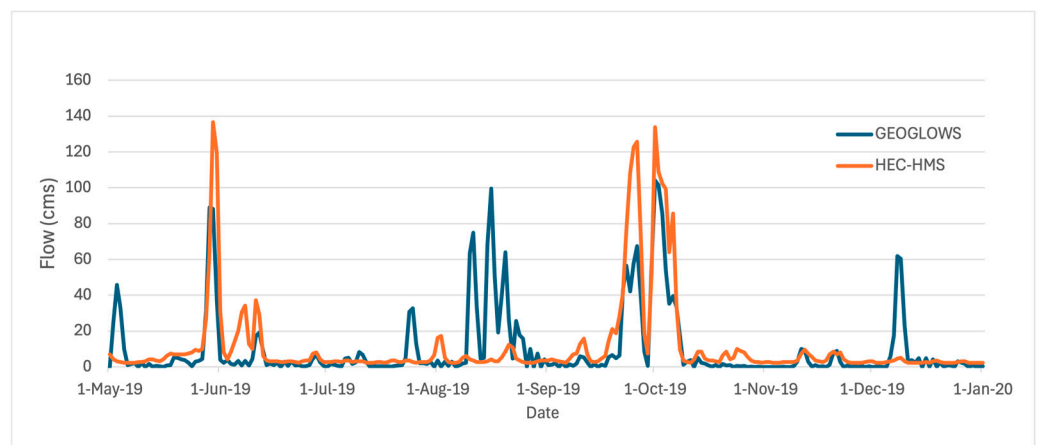


Figure 8. Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) vs. Group on Earth Observation Global Water Sustainability (GEOGLOWS) streamflow for the model validation period of May–December 2019.

Although the NSE remains below the recommended threshold, the model offers a reasonable approximation of runoff behavior, especially for volume estimation, with PBIAS in the Good category. Considering this and its ability to capture several key streamflow events, the calibrated model was deemed suitable for scenario-based analysis of urbanization effects. Despite the limitations in model performance, we feel that these results are useful for planning-level analyses but would not be appropriate for infrastructure design.

3.3. Urbanization Scenarios

The comparison between the non-urbanized baseline (0% impervious surface) and the current urban condition shows a significant increase in both peak discharge and runoff

volume after impervious surfaces are introduced (Figure 9). Peak flow rose from 116 to 126 cm, representing an approximate 8.6% increase, while runoff volume grew from 459 mm to 522 mm, representing a more notable 13.7% rise. In some parts of the hydrograph, streamflow peaks become sharper, especially the highest peaks, while the timing stays nearly the same. These findings clearly indicate that even with existing urban conditions, urbanization greatly enhances the watershed's hydrological response.

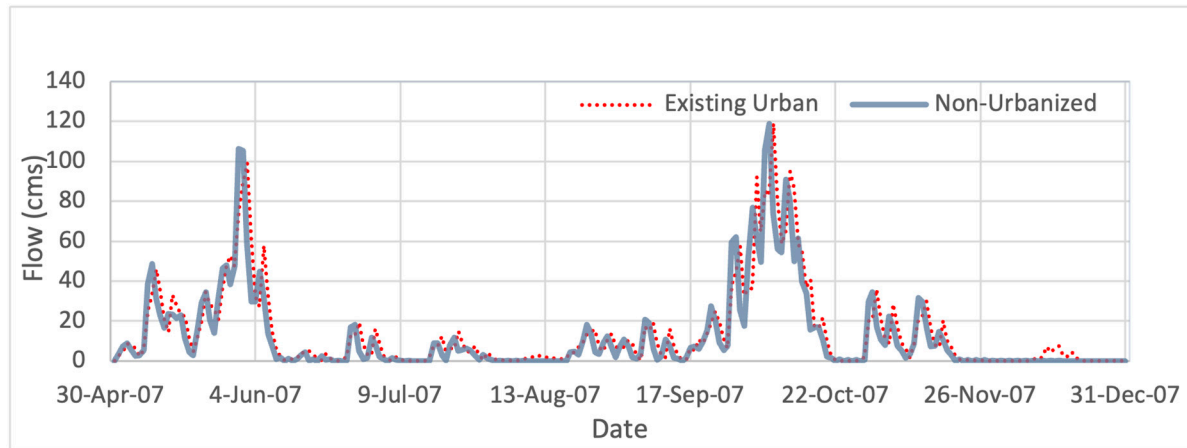


Figure 9. Comparison of peak discharge between non-urbanized and existing urban conditions for measured precipitation during the model calibration period.

The 20% impervious-surface expansion scenario further intensified the impacts of urbanization (Figure 10). The simulated runoff volume rose by approximately 64%, from 459 mm to 755 mm, while peak discharge grew by about 45%, from 116 cm to 169 cm. This escalation is clearly visible in the comparative hydrographs, with sharper and more distinct peak flows throughout the simulation period. In December, for example, an additional flow of roughly 60 cm was produced, highlighting the basin's sensitivity to increased imperviousness. Peak timing also shifts slightly earlier, indicating a faster runoff response due to decreased infiltration.

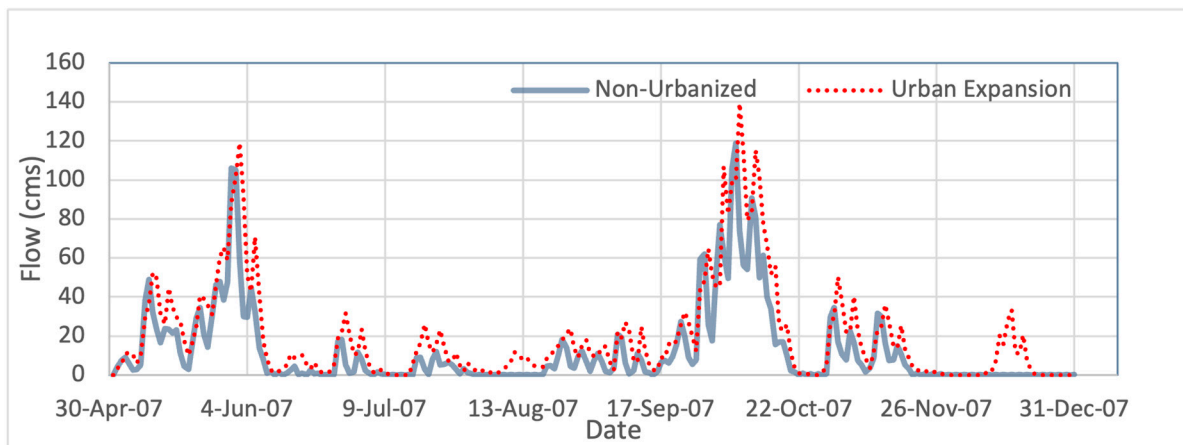


Figure 10. Comparison of peak discharge between non-urbanized and urban expansion conditions for measured precipitation during the model calibration period.

The results (Tables 6 and 7, Figures 11 and 12) clearly show a progressive increase in peak discharge as urbanization advances across all return periods. For example, during a 2-year rainfall event with a 24 h duration, peak discharge rises from 181 cm in the non-urbanized scenario to 198 cm under current urban conditions, and further to 259 cm in the urban expansion scenario. This trend also applies to more extreme events; for a 100-year

return period, peak discharge increases from 543 cm in the non-urbanized scenario to 718 cm under the urban expansion scenario.

Table 6. Peak discharge in cubic meters per second (cm) simulated from design storms under different urbanization scenarios (3 h duration) of hydrological response.

3 h Design Storm Peak Discharge			
Return Period (Years)	Non-Urban (cm)	Existing Urban (cm)	Expansion Urban (cm)
2	386	398	440
5	597	609	652
10	760	772	815
100	1313	1335	1368

Table 7. Peak discharge in cubic meters per second (cm) simulated from design storms under different urbanization scenarios (24 h duration).

24 h Design Storm Peak Discharge			
Return Period (Years)	Non-Urban (cm)	Existing Urban (cm)	Expansion Urban (cm)
2	181	198	259
5	249	272	354
10	298	325	422
100	543	581	718

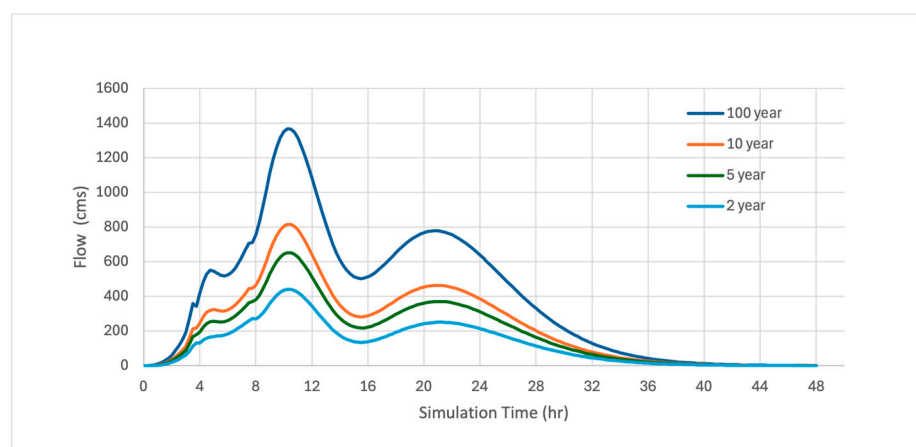


Figure 11. Simulated streamflow in cubic meters per second (cm) for design storms under the urban expansion scenario (3 h duration).

For a 3 h period, the 5-year rainfall event (66 mm) under non-urbanized conditions produces a peak discharge of 597 cm, slightly exceeding the river's maximum capacity of 585 cm reported for the MARNDR watershed diagnostic report [22]. Although the Mann–Kendall test did not identify a statistically significant trend in the precipitation time series, several years (2006, 2007, 2008, 2013, and 2019) recorded maximum 3 h rainfall values that meet or surpass this threshold. The exceedance probability for rainfall intensities between 60 and 70 mm over 3 h, which lead to such peak discharges, ranges from 0.3 to 0.1, suggesting that events of this magnitude are likely to occur approximately every 3 to 10 years.

Overall, these findings demonstrate that even moderate urbanization significantly enhances the basin's hydrological response, leading to peak flows that can surpass the

river's channel capacity and increasing the risk of damaging floods under current and future conditions.

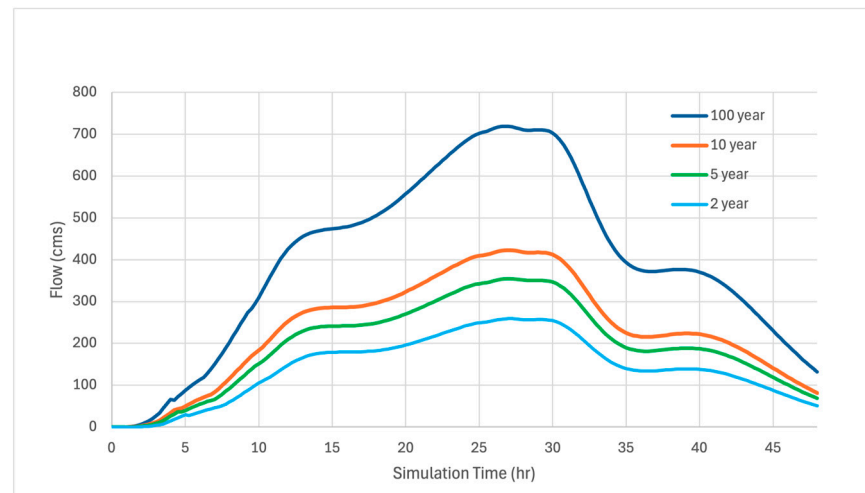


Figure 12. Simulated streamflow in cubic meters per second (cm) for design storms under the urban expansion scenario (24 h duration).

To better demonstrate how storm duration affects flood response, hydrographs were created for multiple return periods under 3 h and 24 h durations in the urban expansion scenario. The results (Figures 10 and 11) show that shorter-duration storms consistently produce sharper and more intense peaks than longer-duration events. For example, the 3 h 100-year storm resulted in a highly concentrated hydrograph with two distinct, steep peaks exceeding 1300 cm, while the 24 h 100-year event produced a wider, flatter peak that rose more gradually and reached about 700 cm. In several cases, the 3 h hydrographs also showed secondary peaks or delayed declines, indicating differences in runoff timing among subbasins and sensitivity to routing configurations.

4. Discussion

The annual maxima series reveal that extreme rainfall in the GRN watershed varies greatly from year to year and is closely linked to major hydrometeorological events. Clusters of high annual maxima and totals in 2007, 2008, 2012, and 2016 align with documented floods and tropical cyclones affecting northern Haiti, including the 2007 floods; hurricanes Fay, Gustav, Hanna, and Ike in 2008; hurricanes Isaac and Sandy in 2012; and Hurricane Matthew in 2016 [1,35–37]. These years stand in stark contrast to dry periods like 2002–2003 and 2020–2021, confirming that the watershed experiences both flood and drought conditions within the same multi-decadal span.

The drought years demonstrate that low annual rainfall does not prevent the occurrence of short, intense events. For instance, in 2020, total yearly precipitation was among the lowest on record, yet a 24 h accumulation of 51 mm still surpassed the 40 mm daily threshold commonly seen during Haiti's rainy season. Coupled with the basin's complex topography, showing steeper slopes upstream and gentler slopes downstream in areas like Limonade and Quartier Morin, such events can still cause localized flooding even in relatively dry years. This pattern supports national assessments [22,38] that highlight the north and northeast as simultaneously vulnerable to both drought and flooding.

Despite this significant interannual variability, the Mann–Kendall test did not identify a statistically significant trend in either annual maximum or total precipitation. This aligns with other studies in Haiti, such as [39] in the Gonaïves watershed, where extreme precipitation series also appeared roughly stationary over the analyzed period. However, the lack of a detected trend should not be mistaken for a lack of risk: the occurrence of very

wet years, along with the concentration of intense storms in specific periods, shows that extreme events remain a persistent threat even without a clear upward or downward trend.

A key limitation of this analysis is the nature of the precipitation data. Several studies have shown that satellite products such as TRMM tend to underestimate intense rainfall during extreme events [39,40], whereas GPM IMERG generally performs better when bias-corrected with ground observations. In this study, GPM IMERG was used without gauge-based bias correction due to the lack of reliable long-term rain gauge data in the watershed. In addition, GPM IMERG spatial resolution ($\sim 10 \text{ km} \times 10 \text{ km}$) is relatively coarse compared with the watershed's complex topography and the localized nature of convective storms. Consequently, short-duration extremes may be under- or over-represented at the basin scale, particularly in mountainous subareas, which introduces additional uncertainty in annual maxima, IDF estimates, and simulated peak flows [41–43]. As a result, the design rainfall estimates and derived return periods may be affected by systematic biases that cannot be fully quantified. However, a previous study that evaluated GPM IMERG against gauge data in Southwestern Haiti found that much of the error in the data could be attributed to no rain and light rain days [25], which are not factored into IDF analysis.

The comparison with the le Ministère de l'Agriculture, des Ressources naturelles et du Développement rural (MARNDR) [22] diagnostic further highlights these uncertainties. For a 10-year return period, MARNDR estimated daily rainfall of about 120 mm, while this study estimates around 137 mm for a similar period. This difference may result from a combination of factors, including potential climate changes in recent decades, methodological differences in estimation techniques, and residual biases in satellite-only data. Nonetheless, both studies agree that design storms in the GRN are intense and capable of producing high flood peaks.

The modeling results for the GRN watershed align with findings from other Haitian basins and emphasize concerns about flood vulnerability. Ref. [7] showed that flood mitigation infrastructure in Cap-Haïtien is inadequate even for events with return periods as short as five years, while [39] reported high rainfall intensities over a wide range of return periods in the Gonaïves watershed. Combined with the current simulations, these studies indicate that in Haiti, even relatively common storms can produce flows that surpass channel and infrastructure capacities, especially where drainage and protective structures are under designed or poorly maintained.

The urban and urban expansion scenarios show how land-use change increases this hazard. Short-duration, high-intensity storms consistently produce sharper and higher peaks than longer-duration events with the same return period. While studies on urbanization effects in this region are limited, our results align well with a study in Colombia that projected increases in peak flow of 22–101% [44] and a study in Puerto Rico that found increases of around 65% in daily streamflow [45]. In an urbanizing basin with limited infiltration capacity, these brief bursts of intense rainfall are especially effective at triggering rapid runoff and potential flash floods, leaving little time for warning or emergency response.

Meanwhile, several features of the simulated hydrographs highlight model and data limitations. Secondary peaks and delayed recessions indicate that the current Muskingum K–X routing does not fully represent spatial variability in travel times and storage throughout the river network. The 2019 validation also reveals uncertainty in the reference datasets. In late August, HEC-HMS overestimated flows, while GPM IMERG successfully captured Hurricane Dorian rainfall, but GEOGLOWS failed to show a matching peak. This aligns with known tendencies of ERA5 (which supports GEOGLOWS) to smooth or underestimate extremes in tropical, mountainous regions. These issues suggest that part of the difference

between simulated and GEOGLOWS flows originates from both the benchmark streamflow product and the rainfall–runoff model.

Overall, these findings suggest that satellite-based products like GPM IMERG can offer useful initial estimates of extreme precipitation and, when combined with hydrological modeling, provide valuable insights into how urbanization affects flood response in data-scarce basins like northern Haiti. Simultaneously, uncertainties stemming from the lack of bias correction, limited in situ observations, and model data mismatches may affect the magnitude of estimated annual maxima, IDF values, and simulated peak flows; therefore, absolute design values and return periods should be interpreted with appropriate caution. These uncertainties underscore the need to improve precipitation and streamflow monitoring and to strengthen flood management strategies, including upgraded infrastructure, improved urban drainage, and watershed-scale measures to reduce runoff and build climate resilience.

5. Conclusions

This study aimed to improve water resilience in Haiti by analyzing extreme rainfall and assessing how urbanization alters the hydrological behavior of the GRN watershed. In the context of climate change, rapid land-use change, and limited ground-based data, it showed that satellite products and hydrological modeling can help fill critical information gaps for flood risk assessment.

The IDF analysis based on GPM IMERG V07 data revealed strong interannual variability and highlighted that a few years concentrated the most extreme events, often coinciding with documented floods in northern Haiti. Design storm simulations further showed that even under non-urbanized conditions, short-duration, high-intensity storms can generate peak discharges that exceed the river's capacity, underscoring the need to explicitly account for such events in risk management.

Using HEC-HMS with GEOGLOWS streamflow corrected by the Simbi database, the modeling scenarios demonstrated that increasing impervious surfaces leads to higher runoff volumes, higher peak flows, and modest shifts in flood timing. Even moderate urban expansion produced noticeable changes, indicating that future urban growth could substantially amplify hydrological risks if not accompanied by appropriate drainage and land-use planning.

Despite limitations related to the lack of ground-based precipitation data and the inability to fully correct satellite biases, the overall consistency between simulated results and reported flood events supports the relevance of combining remote sensing and hydrological models in data-scarce environments such as northern Haiti. More broadly, the findings highlight the need to strengthen drainage infrastructure, integrate watershed-scale tools into planning, and promote more sustainable urbanization as key levers for enhancing Haiti's climate resilience.

Author Contributions: Conceptualization, J.J., J.J.M. and F.O.; Methodology, J.J. and F.O.; Validation, J.J. and F.O.; Formal Analysis, J.J. and S.C.; Investigation, J.J. and F.O.; Resources, J.J.M. and F.O.; Data Curation, J.J.; Writing—Original Draft Preparation, J.J. and S.C.; Writing—Review and Editing, J.J.M. and F.O.; Visualization, J.J. and F.O.; Supervision, J.J.M. and F.O.; Project Administration, J.J.M. and F.O.; Funding Acquisition, J.J.M. and F.O. All authors have read and agreed to the published version of the manuscript.

Funding: Financial support for this work was provided by Auburn University and the Pan-American Development Foundation (PADF), Prime Award Number 72052118IO00004.

Data Availability Statement: Publicly available datasets were used in this study. GPM IMERG precipitation data are accessible from NASA Earthdata; GEOGLOWS streamflow data are obtainable

from the GEOGLOWS portal; and the Simbi streamflow dataset is available online. The derived datasets created during the current study (e.g., annual maxima series, fitted distribution parameters, and model inputs/outputs) are accessible from the corresponding author upon reasonable request.

Acknowledgments: The authors have reviewed and edited the output and take full responsibility for the content of this publication. The authors gratefully acknowledge Auburn University’s Department of Civil and Environmental Engineering and the Université d’État d’Haïti, Campus Henri Christophe de Limonade, for their institutional support. The authors thank Xing Fang, Mikerly Mistral Joseph, and Abraham Alvares for their assistance with data processing and for providing constructive feedback on the analysis. The authors used Grammarly (version 2025) to check and improve the grammar, spelling, and clarity of the manuscript. All authors reviewed and revised the text, taking full responsibility for the final content.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CDF	Cumulative Distribution Function
cms	Cubic Meters per Second
DEM	Digital Elevation Model
GEOGLOWS	Group on Earth Observation Global Water Sustainability
GPM IMERG	Global Precipitation Measurement Integrated Multi-satellite Retrievals for GPM
FAO	Food and Agriculture Organization
GEV	Generalized Extreme Value
GRN	Grande Rivière du Nord
HEC-HMS	Hydrologic Engineering Center-Hydrologic Modeling System
IDF	Intensity–Duration–Frequency
MAE	Mean Absolute Error
MARNDR	Le Ministère de l’Agriculture, des Ressources naturelles et du Développement rural
NSE	Nash–Sutcliffe Efficiency
PBIAS	Percent Bias
PPCC	Probability Plot Coefficient
PWM	Probability-Weighted Moments
RMSE	Root-Mean-Square Error

References

1. Bozza, A.; Durand, A.; Confortola, G.; Soncini, A.; Allenbach, B.; Bocchiola, D. Potential of Remote Sensing and Open Street Data for Flood Mapping in Poorly Gauged Areas: A Case Study in Gonaïves, Haiti. *Appl. Geomat.* **2016**, *8*, 117–131. [[CrossRef](#)]
2. Sheffield, J.; Wood, E.F.; Pan, M.; Beck, H.; Coccia, G.; Serrat-Capdevila, A.; Verbist, K. Satellite Remote Sensing for Water Resources Management: Potential for Supporting Sustainable Development in Data-Poor Regions. *Water Resour. Res.* **2018**, *54*, 9724–9758. [[CrossRef](#)]
3. Vairavamoorthy, K.; Gorantiwar, S.D.; Pathirana, A. Managing Urban Water Supplies in Developing Countries—Climate Change and Water Scarcity Scenarios. *Phys. Chem. Earth Parts A/B/C* **2008**, *33*, 330–339. [[CrossRef](#)]
4. Hope, R. Four Billion People Lack Safe Water. *Science* **2024**, *385*, 708–709. [[CrossRef](#)] [[PubMed](#)]
5. Tiepolo, M.; Bacci, M. Tracking Climate Change Vulnerability at Municipal Level in Rural Haiti Using Open Data. In *Renewing Local Planning to Face Climate Change in the Tropics*; Tiepolo, M., Pezzoli, A., Tarchiani, V., Eds.; Green Energy and Technology; Springer International Publishing: Cham, Switzerland, 2017; pp. 103–131.
6. Felima, C.A. Haiti’s Disproportionate Casualties after Environmental Disasters: Analyzing Human Vulnerabilities and the Impacts of Natural Hazards. *J. Haitian Stud.* **2009**, *15*, 6–28.
7. Jean Louis, M.; Crosato, A.; Mosselman, E.; Maskey, S. Effects of Urbanization and Deforestation on Flooding: Case Study of Cap-Haïtien City, Haiti. *J. Flood Risk Manag.* **2024**, *17*, e13020. [[CrossRef](#)]
8. Gelting, R.; Bliss, K.; Patrick, M.; Lockhart, G.; Handzel, T. Water, Sanitation and Hygiene in Haiti: Past, Present, and Future. *Am. J. Trop. Med. Hyg.* **2013**, *89*, 665–670. [[CrossRef](#)] [[PubMed](#)]

9. Sturmer, K. Water Scarcity and Sanitation in Haiti: The Problem and Solution. 2017. Available online: https://www.worldfoodprize.org/documents/filelibrary/youth_programs/2017_gyi_papers/group_13/Sturmer_Katie_2017_GYI_At_Large_Pa_FBE48B73D8F20.pdf (accessed on 1 November 2024).
10. Glas, H.; De Maeyer, P.; Merisier, S.; Deruyter, G. Development of a Low-cost Methodology for Data Acquisition and Flood Risk Assessment in the Floodplain of the River Moustiques in Haiti. *J. Flood Risk Manag.* **2020**, *13*, e12608. [\[CrossRef\]](#)
11. Varma, M.K.; Satterthwaite, M.L.; Klasing, A.M.; Shoranick, T.; Jean, J.; Barry, D.; Fawzi, M.C.S.; McKeever, J.; Lyon, E. Wòch Nan Soley: The Denial of the Right to Water in Haiti. *Health Hum. Rights* **2008**, *10*, 67. [\[CrossRef\]](#)
12. Adamson, J.K.; Jean-Baptiste, G.; Miner, W.J. Summary of Groundwater Resources in Haiti. In *Geological Society of America Special Papers*; Geological Society of America: Washington, DC, USA, 2016; Volume 520, pp. 137–158.
13. Lungová, K. Access to Drinking Water and Community Development in Northwestern Haiti. *Dev. Environ. Foresight* **2015**, *1*, 44–61.
14. Stoa, R.B. Water Governance in Haiti: An Assessment of Laws and Institutional Capacities. *Tulane Environ. Law J.* **2017**, *29*, 243–246.
15. START Center; Sankar-Gorton, L.; Lubeck-Schricker, M.; Hossain, R.; Iwu, C.D.; Hess, J.; Levin, C. The Impact of Climate Change on Public Health in Humanitarian Settings. *Gates Open Res.* **2024**, *8*, 71.
16. Mondestin, S. *Renforcer La Résilience de l'eau Dans Les Communautés Urbaines Rurales: Grands Besoins et Grands Défis*; US-AID/WATSAN: Washington, DC, USA; UEH: Port-au-Prince, Haiti, 2022.
17. Huffman, E. *Water Resources Management: Sector Results Profile*; World Bank: Washington, DC, USA, 2014.
18. Rahaman, M.M.; Varis, O. Integrated Water Resources Management: Evolution, Prospects and Future Challenges. *Sustain. Sci. Pract. Policy* **2005**, *1*, 15–21. [\[CrossRef\]](#)
19. Azar, D.; Graesser, J.; Engstrom, R.; Comenetz, J.; Leddy, R.M.; Schechtman, N.G.; Andrews, T. Spatial Refinement of Census Population Distribution Using Remotely Sensed Estimates of Impervious Surfaces in Haiti. *Int. J. Remote Sens.* **2010**, *31*, 5635–5655. [\[CrossRef\]](#)
20. Heimhuber, V.; Hannemann, J.-C.; Rieger, W. Flood Risk Management in Remote and Impoverished Areas—A Case Study of Onaville, Haiti. *Water* **2015**, *7*, 3832–3860. [\[CrossRef\]](#)
21. Bathelemy, R.; Brigode, P.; Andréassian, V.; Perrin, C.; Moron, V.; Gaucherel, C.; Tric, E.; Boisson, D. Simbi: Historical Hydro-Meteorological Time Series and Signatures for 24 Catchments in Haiti. *Earth Syst. Sci. Data* **2024**, *16*, 2073–2098. [\[CrossRef\]](#)
22. MARNDR. *Rapport Final Du Diagnostic Du Bassin Versant Grande Rivière Du Nord*; Ministère de l'Agriculture, des Ressources Naturelles et du Développement Rural: Port-au-Prince, Haiti, 2011.
23. Cohen, M.J.; Singh, B. *Climate Change Resilience: The Case of Haiti*; Oxfam International: Boston, MA, USA, 2014.
24. Waite Roebuck, L.; Markley, B.; Knowles, R.B.; Buckalew, J.O. *Water Resources Assessment of Haiti*; US Army Corps of Engineers Mobile District and Topographic Engineering Center: Mobile, AL, USA, 1999.
25. Pierre, M.A.C.; Taner, S.Ç. Assessment of Different Satellite-Based Precipitation Products Over Southwestern Haiti. *CJOS* **2025**, *55*, 414–441. [\[CrossRef\]](#)
26. Bathelemy, R.; Brigode, P.; Boisson, D.; Tric, E. Rainfall in the Greater and Lesser Antilles: Performance of Five Gridded Datasets on a Daily Timescale. *J. Hydrol. Reg. Stud.* **2022**, *43*, 101203. [\[CrossRef\]](#)
27. Horta, I.T.L.G.; Bortolozzo, L.A.P.; Pacheco, R.; Quevedo, F.F.M.; Tech, A.R.B. Daily Rainfall Data Validation: IMERG, CHIRPS, and Gauges. *Statistics* **2023**, *7*, 9.
28. Hosking, J.R.M. L-Moments: Analysis and Estimation of Distributions Using Linear Combinations of Order Statistics. *J. R. Stat. Soc. Ser. B Stat. Methodol.* **1990**, *52*, 105–124. [\[CrossRef\]](#)
29. McLeod, A.I. Kendall: Kendall Rank Correlation and Mann–Kendall Trend Test, CRAN-R Project. 2022. Available online: <https://CRAN.R-project.org/package=Kendall> (accessed on 24 February 2026).
30. Dingman, S.L.; Dingman, S.L. *Physical Hydrology*, 3rd ed.; Waveland Press, Inc.: Long Grove, IL, USA, 2015.
31. Zanaga, D.; Van De Kerchove, R.; Daems, D.; De Keersmaecker, W.; Brockmann, C.; Kirches, G.; Wevers, J.; Cartus, O.; Santoro, M.; Fritz, S.; et al. ESA WorldCover 10 m 2021 V200 2022. Available online: <https://pure.iiasa.ac.at/id/eprint/18478/> (accessed on 24 February 2026).
32. Brown, C.F.; Brumby, S.P.; Guzder-Williams, B.; Birch, T.; Hyde, S.B.; Mazzariello, J.; Czerwinski, W.; Pasquarella, V.J.; Haertel, R.; Ilyushchenko, S.; et al. Dynamic World, Near Real-Time Global 10 m Land Use Land Cover Mapping. *Sci. Data* **2022**, *9*, 251. [\[CrossRef\]](#)
33. Karra, K.; Kontgis, C.; Statman-Weil, Z.; Mazzariello, J.C.; Mathis, M.; Brumby, S.P. Global Land Use/Land Cover with Sentinel 2 and Deep Learning. In Proceedings of the 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 11–16 July 2021; pp. 4704–4707.
34. Moriasi, D.N.; Gitau, M.W.; Pai, N.; Daggupati, P. Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Trans. ASABE* **2015**, *58*, 1763–1785. [\[CrossRef\]](#)
35. Hirsch, N. Atlantique Nord 2007: Dean Frappe La Martinique. *La Météorologie* **2008**, *62*, 68–72. [\[CrossRef\]](#)

36. Alan, F. *Shocks and Poverty in Haiti*; World Bank: Washington, DC, USA, 2014.
37. Index, Global Hunger Indice de la Faim Dans le Monde. 2013. Available online: <https://reliefweb.int/report/world/2013-global-hunger-index-challenge-hunger-building-resilience-achieve-food-and> (accessed on 24 February 2026).
38. PANA. *Programme Changements Climatiques République d'Haïti*; PANA: Cancun, Mexico, 2006.
39. Ilorme, F.; Griffis, V.W.; Watkins, D.W. Regional Rainfall Frequency and Ungauged Basin Analysis for Flood Risk Assessment in Haiti. *J. Hydrol. Eng.* **2014**, *19*, 123–132. [[CrossRef](#)]
40. Kyaw, A.K.; Shahid, S.; Wang, X. Remote Sensing for Development of Rainfall Intensity–Duration–Frequency Curves at Ungauged Locations of Yangon, Myanmar. *Water* **2022**, *14*, 1699. [[CrossRef](#)]
41. Fang, J.; Yang, W.; Luan, Y.; Du, J.; Lin, A.; Zhao, L. Evaluation of the TRMM 3B42 and GPM IMERG Products for Extreme Precipitation Analysis over China. *Atmos. Res.* **2019**, *223*, 24–38. [[CrossRef](#)]
42. Venkatesh, K.; Maheswaran, R.; Devacharan, J. Framework for Developing IDF Curves Using Satellite Precipitation: A Case Study Using GPM-IMERG V6 Data. *Earth Sci. Inform.* **2022**, *15*, 671–687. [[CrossRef](#)]
43. Wang, Z.; Zhong, R.; Lai, C.; Chen, J. Evaluation of the GPM IMERG Satellite-Based Precipitation Products and the Hydrological Utility. *Atmos. Res.* **2017**, *196*, 151–163. [[CrossRef](#)]
44. González-Álvarez, Á.; Herrera-Piñeres, M.; Vilorio-Marimón, O.M. Sensitivity of Peak Flow Response to Imperviousness Increase in a Tropical Caribbean Ungauged Urban Catchment. *Urban Water J.* **2022**, *19*, 509–519. [[CrossRef](#)]
45. Wu, W.; Hall, C.A.S.; Scatena, F.N. Modelling the Impact of Recent Land-cover Changes on the Stream Flows in Northeastern Puerto Rico. *Hydrol. Process.* **2007**, *21*, 2944–2956. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.