

Community-Based Flood Early Warning System in the Pacora River Basin, Panama

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Abstract

Recurrent flooding in the Pacora River basin (east of Panama City) exposes structural and social vulnerabilities that traditional warning systems, based solely on precipitation, fail to mitigate effectively owing to high false-positive rates and insufficient lead times. This study presents the design, implementation and retrospective evaluation of the Community-Based Flood Early Warning System (SATCOI, for its acronym in Spanish), a hybrid architecture that integrates distributed hydrologic-hydraulic modelling (QSWAT/HEC-RAS 2D), IoT telemetry via LoRaWAN and an operational strategy of dynamic thresholds. The contribution is methodological and proof-of-concept in scope: it formulates and tests a “2-of-3” decision rule in which multiscale rainfall, river stage and 30-min rate of rise are combined, with the rainfall stream modulated by a bounded categorical Antecedent Precipitation Index (API-72, $k = 0.85$; maximum 10% threshold reduction). Within a 25-case retrospective inventory (2018-2024), SATCOI indicated—in-sample, not as prospective skill—a 77.8% reduction in false positives (from 60% to 13.3%) relative to a static P24h threshold and eliminated false negatives; the alert lead time is reported as a reconstructed sensor-model latency (1.5 ± 0.5 h to 4.8 ± 1.2 h), distinct from the 4 - 6 h upstream sensing window that is a design expectation of gauge placement. Rainfall thresholds derive from IDF/Gumbel design rainfall, which does not by itself establish a stage-discharge relation at Carriazo; stage and rate-of-rise triggers are model-informed, obtained from HEC-RAS 2D stage hydrographs referenced to a common verified datum, pending paired hydro-metric validation. A +4% wet-side precipitation sensitivity test, informed by CMIP6-derived national projections for eastern Panama, projects an approximate 12% expansion of the 100-year floodplain by 2050, interpreted as a sce-

nario-based sensitivity indicator rather than a deterministic SSP5-8.5 forecast. Participatory validation with more than 200 purposively sampled participants yielded descriptive process indicators (>70% stated confidence; 20-min mean drill response), not representative estimates of basin-wide behaviour. SATCOI provides a potentially replicable framework for humid-tropical risk management, indicating that integrating data science, low-cost technology and multi-level governance supports climate resilience subject to local recalibration and prospective validation.

Keywords

Flood Early Warning System, Hydrological-Hydraulic Modeling, IoT/LoRaWAN, Community-Based Disaster Risk Reduction, Panama

1. Introduction

Floods are among the most recurrent hazards in Panama, and their impacts reflect the interaction of hydroclimatic extremes, rapid land-use change, exposure and local vulnerability [1] [2]. Flood early warning systems that combine monitoring, numerical modelling and preparedness can improve anticipation and support more timely action [3] [4], and community participation is central to warning-response effectiveness and long-term system sustainability [5] [6]. Although such systems have been implemented internationally, few studies provide a *quantitatively testable* linkage among physically based rainfall-runoff-inundation modelling, low-cost IoT telemetry, antecedent-moisture modulation and event-based retrospective verification in a humid tropical basin; in Panama, still fewer integrate these technical and social components within a single operational architecture. The contribution of this study is therefore methodological and operational rather than merely descriptive: it formulates and retrospectively evaluates a hybrid “2-of-3” decision rule modulated by a bounded Antecedent Precipitation Index (API-72), and it makes explicit the data, modelling and governance conditions required to translate model outputs into community-actionable thresholds. This contribution is not limited to Panama; it provides a transferable protocol whose numerical parameters must be locally recalibrated.

Panama’s National Water Security Plan 2015-2050 provides the national framework for preventive management of water-related risks [7]. The National Policy for Integrated Disaster Risk Management 2022-2030 likewise emphasizes interinstitutional coordination, social participation, and the strengthening of local capacities [8]. Together, these instruments provide the policy basis for a community-based flood early warning system in the Pacora River basin.

The Pacora River basin, located east of Panama City, constitutes an instructive case of flood vulnerability. The analytical basin boundary used for hydrologic and hydraulic modelling is approximately 388 km² (Figure 1); the alternative value reported in preliminary descriptions corresponds to an earlier delineation of the

basin, and all model results in this study refer to the modelling boundary stated above. The basin intersects primarily the townships of Pacora (45.63%), San Martín (37.66%) and Las Garzas (12.85%). Its risk profile combines high mean annual precipitation (approximately 2616 mm), deforestation, inappropriate agricultural land use, unplanned urban expansion, steep upper-basin slopes and occupation of low-gradient flood-prone areas [2].

Hydroclimatic analyses confirm marked spatial gradients: annual precipitation exceeding 3000 mm in La Chapa, River Village, and San Miguel contrasts with 2210–2500 mm in Pacora and Las Garzas. Maximum temperatures approach 30°C in the lower basin and decrease with elevation. The rainy season contributes approximately 82%–90% of annual precipitation, promoting rapid runoff from the headwaters toward low-lying plains. Combined with the basin's morphometry (Gravelius compactness coefficient $K_c = 1.80$; mean slope = 17.57%), these conditions favor recurrent flooding in sectors such as La Mireya and Cabra [9].

Plutonic formations predominate in the upper basin (57%), whereas sedimentary deposits of sandstone and shale occur in the lower basin around Las Garzas, Utivé, and Hacienda La Mesa (36%). In combination with poorly drained clayey soils, these lower-basin conditions favor water accumulation during flood events [2].

Participatory activities in Pacora, Las Garzas, and San Martín identified recurrent inundation locations, communication gaps, and the upstream-to-downstream warning role. These qualitative observations are not population estimates.

Land-use dynamics also exacerbate flood risk. Broadleaf secondary forest (44.8%) remains concentrated in the upper basin, whereas pasture (33.1%) and urban development (4.2%) predominate in parts of the middle and lower basin [2]. Project vulnerability workshops conducted in Pacora, Las Garzas, and San Martín revealed marked disparities: downstream communities reported low adaptive capacity and largely reactive protocols, whereas upstream communities recognized their strategic role in warning downstream populations. The survey figures reported there (90% of participants able to identify flood-prone areas, 47% reporting communication gaps with authorities) are descriptive results of the territorial diagnosis (Section 2.1); they characterize baseline risk perception and are distinct from the participatory validation of warning thresholds reported in Sections 2.6 and 3.5.

Updated national climate-change scenarios reported in Panama's Fourth National Communication project increases in maximum and minimum temperatures and spatially variable precipitation changes for 2030, 2050, and 2070. By 2050, maximum temperature is projected to increase by approximately 0.90°C–1.50°C and minimum temperature by 1.18°C–1.37°C, while annual precipitation may change from –2.82% to +4.38% [10]. These ranges are treated throughout as sensitivity bounds rather than as a uniform increase in extreme rainfall; the +4% wet-side multiplier used in the hydraulic sensitivity tests (Sections 2.7 and 3.6) is the rounded upper bound of this 4NC range for eastern Panama, not a determin-

istic projection of a single CMIP6 pathway.

On this basis, the present study is positioned as a critical methodological review and proof-of-concept analysis rather than as an empirical derivation of an operational rating curve. Three scope statements govern the reading of the results. First, the rainfall thresholds derive from the intensity-duration-frequency (IDF) curves and the Gumbel/GEV frequency analysis of Section 2.2, which characterize *design rainfall only*; they do not, by themselves, establish a stage-discharge relationship at the Carriazo control section, and the stage and rate-of-rise thresholds are instead *model-informed* triggers obtained from HEC-RAS 2D simulated stage hydrographs at Carriazo (Section 2.3.2), referenced to a common verified datum. Second, the hydraulic scenarios reported are 10-, 50- and 100-year return periods, and the API-72 modulation is a *bounded categorical* adjustment capped at a 10% threshold reduction (Section 2.5). Third, the performance metrics are computed on a 25-case retrospective inventory that also informed threshold inspection, and are therefore reported as *in-sample retrospective diagnostics*, not as prospective forecast skill (Sections 2.5.2 and 3.4). The transferable element is the methodological architecture and the validation protocol, not the numerical thresholds.

We address these scope-bounded contributions through three guiding questions. **Q1)** To what extent does the integration of QSWAT-HEC-RAS 2D modeling and IoT telemetry improve *reconstructed* warning latency and in-sample reliability relative to a rainfall-only static threshold? **Q2)** How do model-informed operational thresholds change when antecedent moisture (API-72, bounded categorical) and a +4% precipitation sensitivity test are considered, and what additional hydrometric evidence is required before any discharge-based interpretation? **Q3)** Which governance conditions promote community adoption and long-term sustainability, and how should the resulting social indicators be interpreted methodologically? These questions are examined through a data-model-operations architecture designed for quantitative, in-sample assessment and for participatory validation under explicitly stated limitations.

Figure 1 presents a hydrographic map and the territorial context of the Pacora River basin, showing the analytical modelling boundary used for QSWAT and HEC-RAS. (drainage area 388 km²; the 367.47 km² value reported in earlier descriptions corresponds to a previous delineation). The map displays the river network and its hydrographic sub-basins (Cabobré-Utívé, upper, middle and lower reaches, Río Indio and Río Tataré), the protected areas overlapping the basin (Parque Nacional Chagres, Reserva Hidrológica Cuenca Alta del Río Pacora, Refugio de Vida Silvestre Humedal de Bahía de Panamá, Zona de Protección Hidrológica Tapagra and Área Silvestre Narganá), and the political division at the corregimiento level. It also locates the three automatic SATCOI monitoring stations that constitute the community early-warning network, distinguished from the IMHPA National Meteorological Station Network, which is plotted by observation type (automatic and conventional). The map is referenced to WGS 84/UTM zone 17N at 1:50,000, consistent with the common verified datum used for stage observa-

tions (Sections 2.3.2 and 2.5). Compiled by CATHALAC from STRI, SINIA Panamá and Esri Panamá sources.

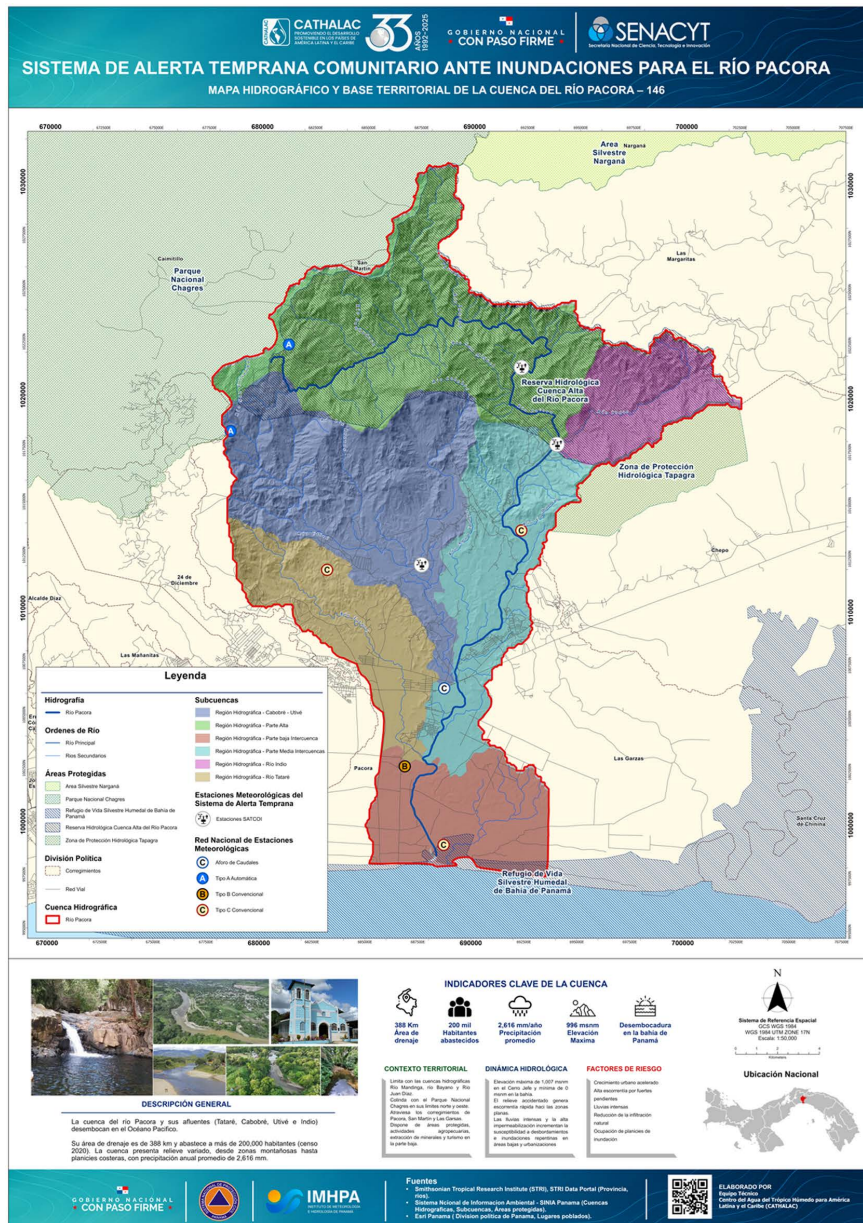


Figure 1. Hydrography, modelling boundary, and SATCOI monitoring network in the Pacora River basin, Panama. Map prepared by CATHALAC using datasets from STRI, SINIA Panamá, and Esri Panamá, together with SATCOI project GIS layers; complete data-source credits are provided within the map.

2. Methodology

The design and implementation of SATCOI followed an integrated methodology linking technical and social components. The methodology comprised seven areas: territorial and social diagnosis; hydroclimatic and statistical analysis; hydrologic and hydraulic modeling; design and installation of the IoT system and Lo-

RaWAN connectivity; an operational strategy for defining thresholds; community participation and governance; and integration of future climate scenarios.

Each area involved a combination of secondary-data compilation, field studies, interviews, community workshops, and technical tests (**Figure 2**). Technical and social components were kept methodologically distinct: the territorial and participatory activities provide descriptive process evidence, whereas the hydrologic-hydraulic modeling and the 25-case inventory provide in-sample technical diagnostics (Sections 3.4 and 4.4).

2.1. Territorial and Social Diagnosis and Climate Change

The initial diagnosis considered biophysical, socioeconomic, and environmental variables, including land use, forest cover, slope, geology, population density, and social vulnerability. Community participation comprised vulnerability and risk workshops, structured perception questionnaires, and validation exercises conducted in 2024 and 2025 in Pacora, Las Garzas, and San Martín. Participants were selected purposively and included community members, local leaders, women, youth, and institutional representatives; more than 200 people participated in total. Responses were analyzed in aggregate to identify risk perceptions, communication gaps, critical locations, and governance requirements. No individually identifiable information was retained. These data constitute a descriptive territorial diagnosis based on non-probability sampling; they are not a statistically representative survey of the basin population and are distinct from the participatory validation of warning thresholds reported in Sections 2.6 and 3.5.



Figure 2. Integrated methodology for the Pacora River early warning system.

Future climate scenarios from Panama's Fourth National Communication on Climate Change (4NC) and the Interactive Climate Risk Platform were incorporated to adjust thresholds and anticipate changes in precipitation and temperature patterns. At the regional scale, 4NC scenarios indicate possible precipitation de-

creases in western Panama and possible increases in the eastern region. For basins in eastern Panama, including Pacora, these changes imply that torrential rainfall episodes may become more frequent and intense (**Table 1**). The scenario labels in **Table 1** identify the CMIP6 ensembles underlying the 4NC products; they are not used to attribute any single result deterministically to SSP2-4.5 or SSP5-8.5. The +4% wet-side multiplier used in the hydraulic sensitivity tests (Sections 2.7 and 3.6) is the rounded upper bound of the 2050 annual-precipitation range for eastern Panama.

Table 1. Climate-change projections relevant to the Pacora River basin.

Variable/ Horizon	2050 (National- Regional)	2070 (National- Regional)	Methodological notes
Maximum temperature (Tmax)	+0.90°C to +1.5°C	↑ an increasing trend	CMIP6; downscaling to approximately 1 km; 2002-2022 reference period; SSP2-4.5/SSP5-8.5
Minimum temperature (Tmin)	+1.18°C to +1.37°C	↑ increasing trend	Higher nighttime temperatures; heat stress; reduced soil cooling
Annual precipitation	−2.82% to +4.38%	−4.04% to +6.87%	Possible increase in eastern Panama and decrease in western Panama
Sea-level rise	2050 scenarios	—	Tide-gauge and satellite bases

Note. Scenario labels identify source ensembles for the 4NC products and do not imply deterministic attribution of SATCOI results to a single pathway. The +4% wet-side sensitivity multiplier used in hydraulic re-simulation is the rounded upper bound of the 2050 annual-precipitation range for eastern Panama.

2.2. Hydroclimatic Analysis and Statistical Modeling

The hydroclimatic analysis characterized precipitation, temperature, and antecedent moisture conditions in the Pacora River basin using station observations and gridded products. CHIRPS v2.0 [11], ERA5-Land [12], and Global Weather Model data were evaluated against available IMHPA observations. Record screening included temporal-consistency checks, missing-data assessment, outlier detection, and comparison of overlapping station and gridded series.

Extreme rainfall was estimated using the Gumbel and Generalized Extreme Value distributions fitted by maximum likelihood. Model selection was guided by the Akaike and Bayesian information criteria, and the analysis followed established extreme-value principles [13] [14]. Intensity-duration-frequency curves and alternating-block design hyetographs were derived for selected return periods. CHIRPS and ERA5-Land were used only after bias evaluation against station observations. The fitted distributions provided rainfall-depth estimates for a range of return periods; the 10-, 50-, and 100-year values were used for the hydraulic

scenarios reported in Sections 2.3 and 3.2. The 100 year, 24 h design rainfall was approximately 280 mm in the fitted series. Alternating-block hyetographs generated from the IDF curves served as hydrologic-model inputs by distributing design rainfall over time.

These extreme-value products characterize design rainfall only. They do not, by themselves, establish a stage-discharge relationship at the Carriazo control section. Conversion of a rainfall return level into river stage or discharge requires the coupled QSWAT-HEC-RAS modeling chain described in Section 2.3, or an independently calibrated rating curve based on paired discharge-stage observations. The present analysis does not derive an empirical rating curve at Carriazo; this limitation is carried forward to Sections 2.3.2, 2.5, and 4.4.

The 72-h Antecedent Precipitation Index (API-72) quantifies soil-moisture conditions before a rainfall event and is calculated recursively as:

$$API_t = P_t + k \cdot API_{t-1}$$

where

- API_t is the Antecedent Precipitation Index at time t (mm);
- P_t is the observed hourly precipitation at time t (mm);
- k is a dimensionless decay coefficient ($0 < k < 1$). For the Pacora basin, $k = 0.85$ was calibrated empirically by maximizing the correlation with local soil-moisture observations.
- API_{t-1} is the index value at the preceding time step.

The index accumulates precipitation over 72 h with exponential decay and represents short-term soil-moisture memory, following the general use of antecedent wetness indicators in rainfall-runoff modeling [15]. Values were normalized using seasonal quartiles, with thresholds of 0.33 (dry), 0.66 (intermediate), and >0.66 (wet or saturated) to classify antecedent conditions. These classes were used with the bounded categorical modulation specified in Section 2.5.1 ($f_{API} = 1.00, 0.95$, and 0.90 for dry, intermediate, and wet conditions, respectively; maximum 10% threshold reduction). No continuous API reduction was adopted operationally.

Spatial and seasonal patterns. Maps of annual precipitation, wet- and dry-season rainfall, maximum temperature (approximately 30°C in the lowlands), and soil moisture reveal a pronounced north-south gradient. Mountain headwaters (La Chapa, San Miguel, and River Village) receive more than 3,000 mm annually, compared with 2200 - 2500 mm in the lower-basin sectors of Pacora and Las Garzas. The wet season accounts for 82% - 90% of total precipitation, with June peaks exceeding 800 mm and coinciding with high relative humidity and saturated soils in the lowlands.

Hydroclimatic projections from the Fourth National Communication [10] and the Interactive Climate Risk Platform [16] were treated as sensitivity bounds rather than as a uniform increase in extreme rainfall throughout the basin. The +4% wet-side multiplier used in the hydraulic tests corresponds to the rounded upper bound of the 2050 4NC range for eastern Panama; the lower bound was interpreted as a dry/neutral sensitivity case. This procedure represents a scenario-

based sensitivity test and not a new probabilistic IDF analysis for future climate.

The extreme-value analysis is a first-order frequency approximation. Uncertainty arising from model selection (Gumbel vs GEV), limited record length, possible non-stationarity, dependence among annual maxima, and the absence of full confidence propagation is acknowledged in Section 4.4 and is inherited by the downstream QSWAT-HEC-RAS chain and the model-informed thresholds.

The principal implication for SATCOI is that hydroclimatic conditions favor rapid runoff and prolonged accumulation in low-lying areas. These findings informed (i) QSWAT calibration for runoff generation; (ii) definition of the HEC-RAS 2D floodplain scenario for the 10-, 50-, and 100-year return periods; (iii) candidate dynamic warning thresholds (P1h, P3h, P6h, P12h, and P24h); and (iv) the design of drills and evacuation protocols in critical communities.

2.3. Hydrologic and Hydraulic Modeling

Hydrologic and hydraulic modeling was central to the design of SATCOI. QSWAT, the QGIS interface for the Soil and Water Assessment Tool, was coupled with HEC-RAS 2D to represent runoff generation, flow concentration, and flood-wave propagation throughout the basin [17] [18].

QSWAT was calibrated using historical precipitation and available discharge information documented in Section 2.3.1. The basin was divided into subbasins and hydrologic response units to represent variations in topography, land use, and soil type. Calibrated parameters included curve number, hydraulic conductivity, and vegetation-cover factors; parameter adjustment and uncertainty analysis used SUFI-2 principles [17]-[19].

HEC-RAS 2D was implemented to delineate flood extent and water levels under peak discharges associated with 10-, 50-, and 100-year return periods. ALOS-PAL-SAR topography was locally refined with available LiDAR data in critical flood zones. Modeling procedures followed published hydrologic and HEC-RAS guidance [19] [20].

Simulations used a 10 - 20 m polygonal mesh, refined to 5 m in urban channels. A variable computational time step of 1 - 5 s was applied to maintain a Courant number below 0.8 and support numerical stability under transient flood-wave conditions [20].

HEC-RAS outputs delineated floodplain extent and relative depth and identified critical sectors such as La Mireya, Las Garzas and Cabobré. Stage time series at the Carriazo control section were post-processed for each design return period to extract maximum stage and the maximum 30-min rate of rise; these model-derived metrics were used to define the stage and rate-of-rise triggers derived in Section 2.3.2. Because no paired observed discharge-stage dataset was available at Carriazo, these triggers are model-informed operational values and not empirically calibrated rating-curve coefficients. Model results were therefore used to derive, rather than to empirically calibrate, operational warning thresholds. HEC-RAS hydraulic scenario maps were prepared for the 10-, 50- and 100-year design

events; the broader hydrologic frequency analysis also included 2-, 5- and 500-year events, which are not presented as floodplain maps in the hydraulic-scenario figures of Section 3.2.

Simulated results were compared with observed evidence and established rain-fall-runoff modeling practice [21]. The integrated workflow provides the technical basis for SATCOI's operational application while retaining explicit limitations related to the availability of continuous streamflow observations and event-scale hydrometric validation (Sections 2.3.1 and 4.4).

2.3.1. Hydrologic Model Configuration and Calibration (QSWAT)

Hydrologic simulation was performed using QSWAT 1.6 coupled with SWAT. The basin was discretized into subbasins and hydrologic response units. Inputs included CHIRPS v2.0, ERA5-Land, and a 12.5 m ALOS-PALSAR digital elevation model locally refined with LiDAR data [11] [12] [17] [18].

Streamflow data provenance. Discharge information was used at two distinct levels. Monthly observed discharge records from IMHPA were available for the calibration and validation period shown in **Figure 3** and were used to assess model performance at the monthly scale. Continuous event-scale discharge observations were not available at the Carriazo control section for the full study period; consequently, the design-return-period hydrographs transferred to HEC-RAS were QSWAT-simulated and are model-derived. These values were not treated as independent observations. Missing or incomplete records were excluded from event-scale diagnostics rather than interpolated. This provenance distinction is why the operational stage and rate-of-rise thresholds are described as model-informed triggers (Sections 2.3.2 and 2.5), not an empirically calibrated rating-curve coefficients.

Table 2 summarizes the 15 most sensitive hydrological parameters identified through global sensitivity analysis, their initial calibration ranges, final optimized values, and parameter-significance metrics. The prioritized parameters reflect dominant processes in humid tropical basins: infiltration limited by clayey soils (CN2, SOL_K), moisture retention in the soil profile (SOL_AWC, EPCO), and subsurface flow dynamics (GW_DELAY, ALPHA_BF). The t-statistics and p-values in **Table 2** refer to parameter significance within the SUFI-2 calibration ensemble and are not inferential statistical tests of warning-system performance.

Regarding the adjustments made in SWAT-CUP:

- **r_**: Relative adjustment (multiplicative); final value = initial value $\times$ (1 + calibrated value). Example: Initial CN2 = 70 $\times$ (1 + 0.15) = 80.5.
- **a_**: Absolute adjustment (additive); final value = initial value + calibrated value.
- **v_**: Direct replacement; the calibrated value completely replaces the initial value.

With the calibrated parameterization, QSWAT showed satisfactory performance during calibration (NSE = 0.78; R^2 = 0.82) and validation (NSE = 0.75; R^2 = 0.79), meeting commonly applied performance criteria for watershed simulations [22].

Figure 3 presents the observed and simulated hydrographs and includes the 95PPU uncertainty band calculated via SUFI-2. These monthly aggregates confirm that the model reproduces the principal temporal dynamics of streamflow, but they do not, by themselves, establish event-scale forecast skill.

Event-scale diagnostics. Because continuous event-scale discharge observations were limited, peak-discharge and peak-timing errors were not computed for all cases in the retrospective inventory. Therefore, the alert lead time reported in Section 3.4 is interpreted as a reconstructed sensor-model latency within the retrospective inventory, not as verified forecast skill. Prospective evaluation with observed event hydrographs is required before operational forecasting claims can be made.

Figure 3 QSWAT calibration and validation hydrographs with the 95PPU uncertainty band for the Pacora River basin (1984–2022). The upper panel shows monthly precipitation used as hydroclimatic context, while the lower panel compares observed and QSWAT-simulated streamflow at the monthly scale. The shaded band represents the 95% prediction uncertainty derived using SUFI-2/SWAT-CUP. The vertical dotted line separates calibration (1984–2010) from validation (2011–2022). Insets summarize NSE, R^2 , PBIAS, p-factor, and r-factor. Monthly goodness-of-fit does not by itself establish event-scale peak timing or magnitude accuracy (see Section 2.3.1).

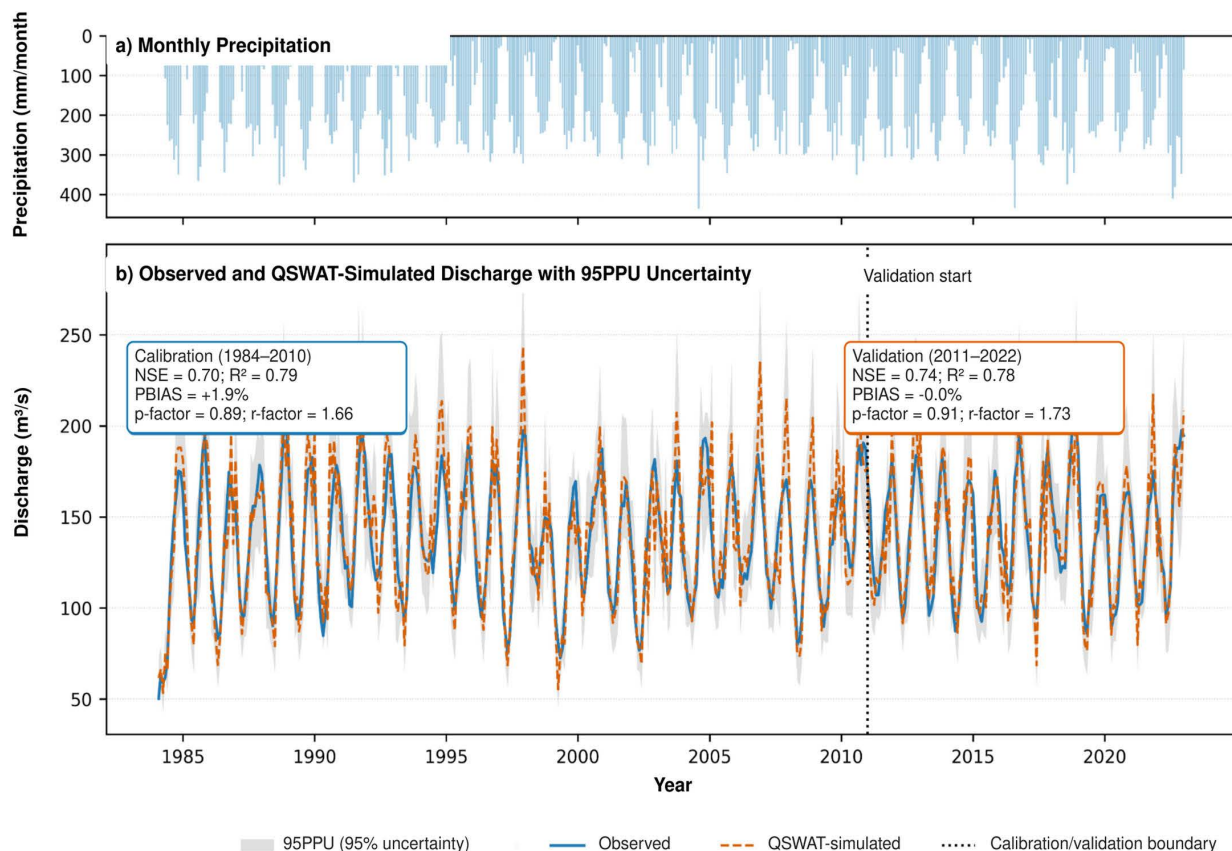


Figure 3. QSWAT calibration and validation hydrographs with the 95PPU uncertainty band for the Pacora River basin (1984–2022).

Table 2. Sensitive hydrologic parameters calibrated in SWAT-CUP for the Pacora River basin.

Parameter Name	Physical Description	Initial Range	Final Calibrated Value	Adjustment Type	t-stat (p-value)	Justification for the Basin
r_CN2.mgt	SCS Curve Number (condition II)	−0.20 to +0.20	+0.15	Relative	8.42 (<0.001)	Poorly drained clayey soils increase surface runoff; the positive adjustment reflects lower infiltration than standard values.
r_SOL_AWC.sol	Available water capacity of the soil (mm H ₂ O/mm soil)	0.10 to 0.30	0.22	Relative	6.18 (<0.001)	Clay-loam textures in the lower basin retain more moisture than sandy soils, which is vital for modeling API-72.
r_ESCO.hru	Soil evaporation compensation factor	0.80 to 1.00	0.92	Relative	4.33 (0.002)	High relative humidity and vegetation cover reduce direct evaporation; a high value reflects humid tropical conditions.
a_GW_DELAY.gw	Deep aquifer recharge delay (days)	100 to 300	185	Absolute	−3.87 (0.004)	Plutonic formations in headwaters allow moderate recharge; sediments in lower areas delay subsurface flow.
r_ALPHA_BF.gw	Baseflow alpha factor (days ^{−1})	0.01 to 0.10	0.04	Relative	−5.21 (<0.001)	Rapid basin response to rainfall events; a low value indicates a significant contribution of surface flow vs. baseflow.
v_CH_N2.rte	Manning's coefficient for the main channel	0.010 to 0.050	0.025	Replacement	3.95 (0.003)	Channel with a gravel/rock bed and scattered riparian vegetation; intermediate resistance between a concrete channel and a dense natural channel.
r_SURLAG.bsn	Surface runoff lag coefficient	1.0 to 24.0	4.2	Relative	2.88 (0.012)	Steep slopes in headwaters favor rapid concentration; a low value accelerates the arrival of runoff to the channel.
r_CANMX.hru	Maximum canopy storage (mm)	0.5 to 5.0	2.8	Relative	−2.14 (0.045)	Secondary forest and pasture cover intercepts precipitation; the moderate value reflects seasonal tropical vegetation.
a_SOL_K.sol	Saturated hydraulic conductivity (mm/h)	5.0 to 150.0	42.5	Absolute	−4.67 (0.001)	Poorly drained clayey soils in the lower basin reduce permeability; the value was calibrated against the basin response and mapped soil classes.
r_EPCO.hru	Plant uptake compensation factor	0.01 to 1.00	0.78	Relative	3.12 (0.008)	Tropical vegetation has high water use efficiency; a high value allows moisture extraction from deep soil layers.

Continued

v_CH_K2.rte	Effective hydraulic conductivity in main-channel alluvium (mm/h)	0.01 to 500.0	85.0	Replacement	2.45 (0.028)	Channel with mobile sediments and vegetation on the margins; intermediate conductivity allows moderate lateral infiltration.
r_REVAPM N.gw	Threshold depth of water in the shallow aquifer for revap (mm)	0.0 to 500.0	180.0	Relative	-1.89 (0.078)	A shallow water table in floodplains favors direct evaporation from the aquifer in the dry season.
r_GWQMN. gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0.0 to 5000.0	1200.0	Relative	4.01 (0.003)	Shallow aquifers in low areas contribute rapidly to baseflow after rainfall events.
r_RCHRG_ DP.gw	Deep aquifer percolation fraction	0.0 to 1.0	0.12	Relative	-3.34 (0.006)	Predominance of lateral subsurface flow vs. deep vertical recharge in mountainous tropical basins.
r_LAT_SEE P.lat	Lateral flow travel time (fraction)	0.0 to 1.0	0.35	Relative	2.76 (0.015)	Steep slopes and medium-texture soils favor lateral subsurface flow toward the channel.

Note. t-statistics and p-values refer to parameter significance within the SUFI-2 calibration ensemble and are not inferential tests of warning-system performance or forecast skill.

2.3.2. Two-Dimensional Hydraulic Model Configuration and Calibration (HEC-RAS)

Flood-wave propagation was simulated with the HEC-RAS 6.4 two-dimensional module by solving the full Saint-Venant equations. The topographic base used a hybrid DEM (ALOS-PALSAR + LiDAR). The two-dimensional computational mesh had a resolution of 5×5 m in urban channels and 10 - 20 m across the rural floodplain. Breaklines were incorporated along embankments and channel banks.

Flow resistance was parameterized with land-use-specific Manning roughness coefficients (n), calibrated against historical high-water marks and reported in **Table 3**. Initial values were based on Chow [23], Arcement and Schneider [24] and the HEC-RAS technical reference [25], with local adjustment for humid-tropical conditions. For mixed-cover cells, a weighted coefficient was assigned according to the dominant cover fraction. Bridges and culverts were represented using the HEC-RAS two-dimensional bridge tools, while road embankments were incorporated as breaklines rather than represented solely through increased roughness.

Boundary conditions:

- Upstream: peak-discharge hydrographs derived from QSWAT for 10-, 50-, and 100-year return periods. These hydrographs are model-derived (Section 2.3.1) and were not treated as independently observed discharges.

- Downstream: normal-depth condition.
- Numerical scheme: full momentum for extreme events, maintaining a CFL < 0.8.

Spatial validation and achieved fit. Calibration and validation used an iterative procedure that compared the simulated flood extent with (i) post-event Sentinel-2 flood polygons for the 2010 and 2021 events, (ii) 14 high-water marks collected with differential GPS (± 0.03 m vertical accuracy), and (iii) 8 community-reported maximum-level records from residential structures in La Mireya, Las Garzas and Cabobré; all stage references were tied to a common verified datum, and the community-reported records were used as complementary evidence alongside the instrumental DGPS marks, not as independent measurements. Spatial fit was evaluated with the Fagan index (*sensu* Horritt and Bates [26]), computed as $F = (A_{\text{obs}} \cap A_{\text{sim}}) / (A_{\text{obs}} \cup A_{\text{sim}})$, where A_{obs} and A_{sim} denote the observed and simulated inundated areas, respectively. The achieved indices were $F = 0.79$ for the 2010 event and $F = 0.81$ for the 2021 event, both exceeding the $F > 0.75$ satisfactory-calibration criterion. This spatial agreement confirms that the calibrated model reproduces the areal extent of past floods; it does not, however, constitute a paired discharge-stage rating curve at Carriazo, and the stage and rate-of-rise triggers derived below therefore remain model-informed (Section 2.5).

Derivation of model-informed stage and rate-of-rise triggers. To link hydraulic simulations with operational thresholds, stage time series were extracted at the Carriazo control section for each 10-, 50-, and 100-year design event. From these simulated hydrographs, two metrics were computed: maximum stage and maximum 30 min rate of rise. The stage thresholds in **Table 4** were assigned by relating these model-derived metrics to observed inundation impacts at critical receptors, including access roads, dwellings, and community infrastructure documented in the territorial diagnosis and historical events. The rate-of-rise threshold was computed over the same 30 min window used in the operational rule. The 30 min interval is the rate-of-rise calculation window and is not an alert-persistence duration; alert activation persistence is defined separately as 10 min in Section 2.5.1. Because no paired observed discharge-stage dataset was available at Carriazo, these values are model-derived operational triggers, not empirical rating-curve coefficients.

Uncertainty associated with flow resistance was quantified through local sensitivity analysis by varying the Manning coefficients by $\pm 10\%$ relative to the calibrated values. The model was substantially more sensitive to variations in the main channel, where a ± 0.005 change in n produced $\pm 8\%$ changes in maximum inundation depth, than across the floodplain, where a ± 0.010 change altered depth by only $\pm 3\%$ at critical control points. This sensitivity analysis is a local model-perturbation test and not an inferential statistical test of system performance.

Table 3. Land-use-specific Manning roughness coefficients (n) assigned in the HEC-RAS 2D model for the Pacora River basin.

Land use/cover	Initial literature value (n)	Final calibration range	Adopted optimum	Physical rationale	Source/method
Main channel (rock/concrete bed)	0.035	0.032 - 0.038	0.034	Highly irregular bed with boulders and coarse sediment; form resistance dominates	Chow [23]; calibration against high-water marks
Secondary channel (fine sediment)	0.040	0.038 - 0.045	0.041	Sand/silt bed with scattered riparian vegetation; combined grain and form resistance	Arcement & Schneider [24]
Dense secondary forest (headwaters)	0.070	0.065 - 0.075	0.068	High resistance from trunks, foliage, and understory vegetation; obstructed flow	Chow [23]; validation with Sentinel-2 imagery
Pasture/rainfed agriculture	0.045	0.040 - 0.050	0.044	Seasonal herbaceous vegetation; moderate resistance varying with phenological cycle	Chow [23] and Arcement and Schneider [24]; seasonal adjustment
Residential urban area	0.015	0.013 - 0.018	0.016	Predominantly paved surfaces; localized obstacles (buildings and walls) represented as equivalent roughness	Arcement & Schneider [24]; LiDAR-based calibration
Dense urban area (central Pacora)	0.018	0.016 - 0.022	0.019	Higher obstacle density, narrow streets, and artificial drainage restrict flow	Calibration against the 2010 and 2021 historical events
Mangrove/coastal wetland	0.080	0.075 - 0.090	0.082	Dense roots and emergent vegetation create very high overland-flow resistance	Mazda et al. [27]; field validation
Low-gradient clayey soils (La Mireya and Las Garzas)	0.050	0.045 - 0.060	0.053	Fine texture, poor drainage, water accumulation, viscosity, and microtopography increase resistance	Calibration against high-water marks and mapped soil classes
Floodplain expansion areas (unvegetated)	0.035	0.030 - 0.040	0.036	Relatively smooth recent sediments; low resistance except during high-energy events	HEC-RAS 2D calibration and flood marks
Transportation infrastructure (embankments and bridges)	0.020*	0.018 - 0.025*	0.022*	Paved surface modeled as a breakline with equivalent roughness to represent an obstruction	U.S. Army Corps of Engineers [20]; geometric parameterization

* Values applied to 2D cells intersected by linear infrastructure; physical obstruction is represented by breaklines rather than by roughness alone.

2.4. Design and Installation of the IoT Monitoring System

The monitoring system comprised ultrasonic water-level sensors, automatic weather

stations and solar-powered rain gauges connected through LoRaWAN gateways; the level sensors were referenced to a common verified datum (Section 2.3.2). Strategic sites were selected at Carriazo and Cabobré. Field-connectivity tests identified Carriazo as the principal upstream point, providing an estimated 4 - 6 h upstream sensing window before flood-wave arrival in the lower basin. This window is a design expectation governed by flood-wave travel time between the upstream gauge and the exposed downstream reaches; it is not a measured forecast lead time and was **not** derived from paired observed flood hydrographs (the reconstructed in-sample alert lead time is reported and qualified separately in Section 3.4). Equipment specifications, calibration records and maintenance tolerances are documented separately from the effective field performance reported in Section 3.3, so that manufacturer tolerances are not conflated with observed telemetry reliability.

The monitoring architecture is consistent with Panama's policy emphasis on improving hydrometeorological information and preparedness for climate-related risks [10].

The system was designed as an IoT network of low-power sensors capable of transmitting real-time data through the LoRaWAN protocol. The network architecture was designed for low-connectivity conditions and included redundant gateways linked to a cloud-based data-management platform. A compact weather station recorded precipitation, temperature, humidity, and wind speed and direction. Solar panels and backup batteries provided 5 - 7 days of autonomy.

The selection of sensor locations reflected the results of the hydrologic modeling, prioritizing upstream locations such as La Chapa and Carriazo to maximize the upstream detection lead within the sensing window (Section 3.3), and downstream locations such as the urban areas of Pacora and Cabobré to monitor the hydraulic response in densely populated areas. This siting criterion concerns the *technical detection* of the approaching flood wave and is distinct from the *community response time* assessed through drills in Sections 2.6 and 3.5.

Software-layer quality assurance and quality control (QA/QC) protocols used a 5-min moving-median filter to remove isolated spikes (outliers) caused by turbulence or temporary obstruction of the ultrasonic sensor. A simple exponential-smoothing algorithm was then applied to stabilize the rate of rise ($\Delta h/\Delta t$) and prevent erroneous warning activation in the multiscale logic. These QA/QC filters operate on the raw signal and are **distinct from** the 10 min activation-persistence window and the 30 min rate-of-rise calculation window defined in Section 2.5.1; they do not constitute alert persistence, and neither the 5 min filter nor the 10 min confirmation window is a warning lead time.

The implementation follows established IoT-based flood-monitoring approaches by combining low-power sensing, real-time data transmission and remote visualization [28]-[30]. SATCOI extends these elements with an auditable multisource decision rule (**Figure 4**) and community-centered warning procedures; the stage and rate-of-rise triggers it relies on are model-informed values derived from local

hydrologic-hydraulic modelling (Sections 2.3.2 and 2.5), not empirically calibrated rating-curve coefficients, and they require paired hydrometric verification at Carriazo before any discharge-based interpretation (Sections 2.3.1 and 4.4).

2.5. Operational Strategy: Dynamic Thresholds and Hybrid Decision Logic

The operational strategy of SATCOI integrates three information streams—multiscale rainfall, hydrometric stage, and the rate of stage rise—combined through a hybrid decision rule and modulated by antecedent moisture. To avoid conflating the configuration proposed for future operational testing with the configuration that produced the retrospective skill metrics reported in Section 3.4, this section is organized into three explicitly separated blocks. *Block A* defines the proposed operating specification for prospective testing. *Block B* states which of those settings were actually used to reconstruct the 25-case retrospective inventory and labels the resulting metrics as in-sample diagnostics. *Block C* documents preliminary sensitivity adjustments that were explored but **not** adopted operationally, and that are superseded by Block A. Throughout, the notation matches **Figure 4**.

A foundational clarification governs all three blocks. Rainfall thresholds are derived from the intensity-duration-frequency (IDF) curves and the Gumbel/GEV frequency analysis of Section 2.2; these statistical products characterize the distribution of design rainfall only. They do not, by themselves, establish a stage-discharge relationship at the Carriazo control section. Conversion of a rainfall return level into a river stage or a rate of rise requires the coupled QSWAT-HEC-RAS 2D modelling chain of Section 2.3, or an independently calibrated rating curve based on paired discharge-stage observations. Accordingly, the precipitation indicator in the decision rule is fed by IDF/Gumbel design rainfall, whereas the stage and rate-of-rise indicators are fed by HEC-RAS 2D simulated stage hydrographs extracted at Carriazo (Section 2.3.2), referenced to a common verified datum. No quantile of the virtual-point or rainfall frequency analysis is interpreted as a discharge.

2.5.1. Block A—Proposed Operating Specification for Prospective Testing

API modulation (bounded categorical). Critical rainfall thresholds are adjusted by a bounded categorical factor that depends on the antecedent-moisture class of the 72-h API (Section 2.2):

$$P_{\text{adj},N,d} = P_{\text{base},N,d} \times f_{\text{API}}$$

where $P_{\text{base},N,d}$ is the base rainfall threshold for alert level N and accumulation window d ($d \in \{1, 3, 6, 12, 24 \text{ h}\}$), and f_{API} takes the values 1.00, 0.95 and 0.90 for the dry, intermediate and wet/saturated classes, respectively. The maximum operational reduction of rainfall thresholds is therefore 10%. This bounded categorical rule is the proposed setting for prospective testing; it deliberately replaces the larger and continuous reductions described in Block C, which were not adopted.

Two-of-three decision rule. At alert level N, three binary indicators are evaluated from the three streams:

- $C_{P,N} = 1[P_{\text{obs},d} > P_{\text{adj},N,d}]$ (precipitation condition),
- $C_{H,N} = 1[h_t > N_{h,\text{crit},N}]$ (hydrometric stage condition, with h_t the stage from the level sensor referred to the common verified datum and $N_{h,\text{crit},N}$ the stage threshold for level N),
- $C_{R,N} = 1[\Delta h_{30} > \Delta h_{\text{crit},N}]$ (rate-of-rise condition, with $\Delta h_{30} = h_t - h_{\{t-30 \text{ min}\}}$ the stage change over a 30-min window).

A raw warning state is activated when at least two indicators are simultaneously active:

$$A_N^{\text{raw}}(t) = 1 \text{ if } C_{P,N} + C_{H,N} + C_{R,N} \geq 2; \text{ otherwise } 0.$$

Activation persistence and deactivation hysteresis. The raw vote is converted into the operational alert state $A_{N(t)}$ only after it is maintained for a 10 min activation-persistence window; shorter fluctuations are treated as sensor noise and do not raise an alert. Deactivation uses hysteresis to prevent oscillation: the alert at level N is cleared only after the stage falls 0.10 m below the applicable activation threshold, *i.e.* when $h_t < N_{h,\text{crit},N} - 0.10$ m. The 30 min interval is the rate-of-rise calculation window and is **not** an alert-persistence duration; the 10 min interval is the activation-persistence duration and is **not** a warning lead time. Neither interval is interpreted as forecast skill. The thresholds entering $C_{H,N}$ and $C_{R,N}$ are model-derived operational triggers obtained from HEC-RAS 2D stage hydrographs at Carriazo and linked to observed inundation impacts at critical receptors (Section 2.3.2); they are not empirical rating-curve coefficients, because no paired observed discharge-stage dataset was available at Carriazo to calibrate one.

Figure 4 presents this proposed operating specification as three parallel pathways (precipitation, hydrometric, rate-of-rise) feeding the two-of-three vote, the activation confirmation, the alert state and the deactivation hysteresis, together with the traceability fields required to audit any future run (API method, cut-offs and factors, thresholds, units and datum, persistence and hysteresis, and input timestamps and alert state).

2.5.2. Block B—Configuration Underlying the Retrospective 25-Case Inventory

The retrospective evaluation reported in Section 3.4 was reconstructed using the same bounded categorical API factors of Block A ($f_{\text{API}} = 1.00/0.95/0.90$; maximum 10% reduction). No continuous API reduction and no Block C adjustment was applied in that reconstruction. The precipitation thresholds of the inventory derive from the IDF/Gumbel design rainfall of Section 2.2; the stage and rate-of-rise thresholds derive from the HEC-RAS 2D simulations of Section 2.3.2; the API-72 classes derive from the seasonal-quartile normalization of Section 2.2.

Because the same 25-case inventory (10 observed flood events and 15 rainfall-without-flood events, 2018-2024) was inspected both during threshold categorization and during performance evaluation, the metrics of **Table 5** are reported as

in-sample retrospective diagnostics, not as independent prospective skill. A temporally held-out evaluation (for example, threshold inspection on an earlier sub-period and verification on a later sub-period) is recommended before any operational skill claim is made. Within this in-sample dataset, the two-of-three logic with the Block A API modulation reduced false positives from 9 to 2 (a 77.8% relative reduction against the static P24h reference) and eliminated false negatives; these values describe discrimination in the evaluation dataset and are not extrapolated to future performance.

2.5.3. Block C—Exploratory Adjustments Not Adopted Operationally

Two preliminary formulations were explored during system design but are **not** part of the operating specification of Block A and were **not** used in the retrospective reconstruction of Block B. They are retained here only for transparency and are superseded by the bounded 10% categorical rule.

(i) An unbounded categorical factor with a deeper wet-class reduction, $\alpha(S1) = 1.0$, $\alpha(S2) = 0.9$, $\alpha(S3) = 0.75$, implying up to a 25% threshold reduction. This was rejected because the 25% wet-class step increased the likelihood of missed detections under moderately wet but non-flood-producing conditions.

(ii) A continuous moisture-dependent adjustment of static Gumbel thresholds,

$$\text{Threshold}_{\text{dynamic}} = P_{\text{static}} \times [1 - \alpha_w \cdot (\text{API}_{72}/\text{API}_{\text{max}})],$$

with window-specific sensitivity coefficients (e.g. $\alpha_{1h} = 0.15$ and $\alpha_{24h} = 0.30$, implying reductions of up to 30%) and API_{max} the historical saturation limit defined by the upper seasonal quartile. This continuous form was rejected for operational use because it is not traceable to a verified rating curve at Carriazo and because its reduction magnitude exceeded the bounded categorical cap adopted in Block A.

Consequently, every operational and retrospective statement in this manuscript refers to Block A (prospective specification) or Block B (retrospective reconstruction); Block C values appear nowhere in **Table 4**, **Table 5** or Section 3.4.

Figure 4 Proposed operating specification for prospective testing (Block A), shown as three parallel indicator pathways—precipitation (multiscale rainfall modulated by the bounded categorical API-72 factor $f_{\text{API}} = 1.00/0.95/0.90$), hydrometric stage (referred to a common verified datum), and 30 min rate of rise—feeding a two-of-three majority vote, a 10 min activation confirmation, the alert state (Yellow/Orange/Red) and a 0.10 m deactivation hysteresis. The 30 min interval is the rate-of-rise calculation window and the 10 min interval is the activation-persistence duration; neither is a warning lead time. Candidate settings are distinct from the configuration underlying the retrospective 25-case inventory (Block B); exploratory adjustments not adopted operationally are documented in Block C. Traceability fields (API method, cut-offs and factors, thresholds, units and datum, persistence and hysteresis, inputs, timestamps and alert state) are archived for audit. Rainfall thresholds derive from IDF/Gumbel design rainfall; stage and rate-of-rise thresholds derive from HEC-RAS 2D simulated stage hydrographs at Carriazo and are not established by the Gumbel/GEV frequency analysis alone.

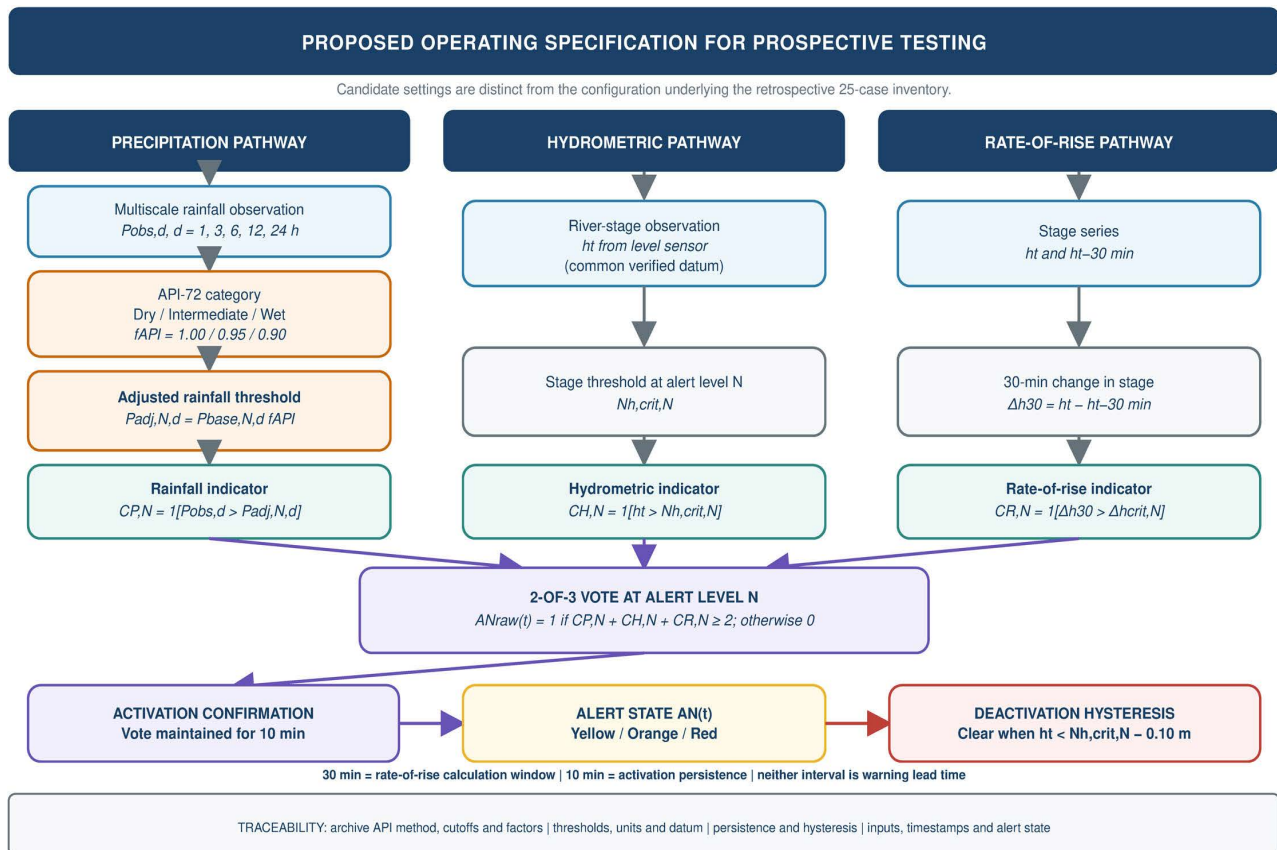


Figure 4. Summarizes the proposed decision flow. The 10 min persistence requirement is a design setting, whereas the 30 min interval is the window used to calculate stage rise; neither interval is a measured warning lead time.

2.6. Community Participation and Governance

Long-term effectiveness of community-based early warning systems depends on inclusive governance, shared institutional responsibilities, and sustained local capacity. Evidence from Panama and international practice indicates that linking scientific information with community participation strengthens water-risk planning and local ownership of warning procedures [5] [6] [31] [32].

Participatory-validation methods. Social validation used purposive (non-probability) sampling of community leaders, community-board (*juntas comunales*) members, women, youth and representatives of exposed households in Pacora, Las Garzas and San Martín, yielding more than 200 participants across 2024-2025. Activities followed a standardized protocol: (i) participatory mapping of historical flood points; (ii) presentation of the model-derived thresholds of Section 2.5; (iii) a pre-tested rated-scale questionnaire capturing perceived usefulness, trust relative to conventional warning sources, and intended response; and (iv) timed evacuation drills. Response time was measured from the warning signal (mobile message) to arrival at the predefined assembly point, using drill logs and observer timestamps; the mean of two drills is reported in Section 3.5. Questionnaire items were administered and stored in aggregate; no individually identifiable responses were retained. Demographic variables summarized descriptively were sex distribution,

age groups, community and local role. The principal biases are non-random sampling, social-desirability bias, and hypothetical bias in stated confidence and intended behaviour; drill conditions also differ from real emergencies. Accordingly, all social figures are reported as descriptive process indicators, not as statistically representative estimates of basin-wide behaviour nor as causal evidence of changed trust or compliance.

SATCOI was designed with a strong emphasis on community participation. Local risk management committees were established, evacuation drills were conducted, and response protocols were developed. Alliances were formed with national institutions, such as SINAPROC (National Civil Protection System of Panama), IMHPA (Institute of Meteorology and Hydrology of Panama), and local governments, to ensure the system's sustainability and institutional support. Project workshops involved representatives from Pacora, Las Garzas and San Martín, with substantial participation by women and community boards, and identified recurrent flood locations (La Mireya, Cabra, Hugo Spadafora, Las Tecas) while documenting existing protocols, resources and risk perceptions. Most communities hold flood information, though it is often neither systematized nor digitized; existing protocols are primarily reactive and lack clear assignment of responsibilities.

According to Mitre (2025), basin-governance relies heavily on local community boards, supported by agencies such as SINAPROC, the Red Cross, the Fire Department, the National Police, and health centers, but these partnerships, tend to be sporadic rather than governed by formalized protocols.

SATCOI promotes a horizontal governance model in which upstream communities in San Martín act as local sentinels communicating with downstream populations in Pacora and Las Garzas; the proposed SAT Network brings together community leaders, women, youth, technical institutions, and local authorities. This design is consistent with community-based preparedness and knowledge-integration principles reported in the literature [5] [6] [31] [32].

2.7. Integration of Climate-Change Scenarios into Early Warning System Modeling and Design

The SATCOI framework incorporated climate-change information from Panama's Fourth National Communication [10] and the Interactive Climate Risk Platform [16]. The source products draw on CMIP6 ensembles downscaled for SSP2-4.5 and SSP5-8.5; these scenario labels are reported here only because they are the ensembles underlying the 4NC products, not because any single result below is attributable to one pathway. Projections for 2030, 2050 and 2070 were used to define sensitivity tests, not deterministic forecasts for the Pacora basin.

For eastern Panama, including the Pacora basin (modelling boundary [388 km²]; see Section 1 and **Figure 1**), the 2050 4NC projections indicate a +0.90°C to +1.5°C increase in maximum temperature, a +1.18°C to +1.37°C increase in minimum temperature, and an annual-precipitation change spanning -2.82% to

+4.38% (**Table 1**). These ranges were treated as sensitivity bounds rather than as a uniform basin-wide increase in extreme rainfall.

a) Hydrologic and hydraulic modeling. Projected precipitation changes were applied as sensitivity multipliers to the locally fitted IDF curves for 10-, 50-, and 100-year return periods, and the resulting design storms were propagated through QSWAT and HEC-RAS 2D to estimate possible changes in peak discharge and flood extent [10]. The +4% multiplier adopted for the wet-side test is a rounded upper-bound value consistent with the +4.38% top of the 4NC 2050 range for eastern Panama; it is not a deterministic SSP5-8.5 projection. The lower bound (−2.82%) was interpreted as a dry/neutral sensitivity case, so that the analysis brackets both wet and dry plausible futures rather than assuming monotonic intensification.

Operational thresholds. Precipitation thresholds (P1h - P24h) were adjusted arithmetically in the sensitivity tests (e.g. a +4% annual-precipitation anomaly produced order-of-magnitude adjustments of $\approx +5$ mm for P1h and +15 mm for P24h at the orange level). This arithmetic modulation is a preliminary screening step and does not replace full threshold re-derivation; operational re-calibration under future climates requires re-running the IDF/Gumbel analysis and the QSWAT-HEC-RAS chain on projected series, which is recommended as future work.

b) API-72 and antecedent moisture. Wetter projected antecedent conditions were explored by increasing the frequency of the wet API-72 class in sensitivity tests; the operational threshold reduction remained capped at the bounded 10% of Section 2.5.1 to avoid excessive sensitivity to index uncertainty. No continuous API reduction (Section 2.5.3) was used.

c) Governance and community participation. Workshops communicated the range and uncertainty of the climate projections and discussed how changing hydroclimatic conditions could affect evacuation decisions; participant responses were treated as primary project data and as stated preferences, not as verified behaviour.

Integrating climate-change sensitivity tests strengthens SATCOI's adaptive capacity and is consistent with climate-resilient disaster-risk reduction principles [10] [33].

3. Results

SATCOI results are presented in five evidentiary dimensions: hydroclimatic characterization, hydrologic and hydraulic design analysis, monitoring-system design, retrospective in-sample assessment of the decision rule, and descriptive participatory findings. Climate information is discussed separately as context and future work rather than as a completed scenario experiment.

3.1. Hydroclimatic Characterization

Hydroclimatic analysis of the Pacora River basin identified spatial and temporal

gradients that contribute to its high flood susceptibility. Spatially, CHIRPS satellite records (1991-2020) and the IMHPA series indicate mean annual precipitation exceeding 3,000 mm in mountainous headwaters such as La Chapa, San Miguel, and River Village, decreasing to 2200 - 2500 mm/year in lower-basin sectors such as Pacora and Las Garzas. This north-south gradient, intensified by topography and forest cover, generates substantial contrasts in runoff generation.

The temporal distribution shows that the rainy season accounts for 82% - 90% of annual precipitation, with critical June peaks of as much as 800 mm per month. These structural conditions justify adaptive thresholds because soils remain saturated for much of the year, increasing the likelihood of flash floods during intense rainfall. Temperature records indicate maximum values near 36 °C in the lower basin, decreasing gradually toward higher elevations and affecting evapotranspiration and soil-water retention.

Moisture conditions and soil properties increase vulnerability in La Mireya, Cabra, and Las Garzas, where poorly drained clayey textures occur on gentle slopes. National climate-risk information also identifies the southern basin as an area where multiple hazards converge [16]. Overall, the hydroclimatic characterization supports the use of multiscale thresholds and an adaptive community-based early warning system.

3.2. Hydrologic and Hydraulic Modeling

Hydrologic and hydraulic modeling integrated QSWAT discharge estimates with HEC-RAS 2D flood-propagation analysis. QSWAT was calibrated using CHIRPS v2.0 and ERA5-Land precipitation datasets together with the available discharge information (Section 2.3.1). The design peak discharge reported below, and the scenario differences derived from it, are model-derived: the $\approx 350 \text{ m}^3/\text{s}$ value for the 100-year event is a QSWAT-simulated design discharge propagated through HEC-RAS 2D, not an independently observed measurement. Propagating the +4% wet-side precipitation multiplier (Section 2.7) through the same chain yielded a 5% - 8% increase in design peak discharge; this is a model-based scenario difference, not an inferential statistical test, and no p-value is attached to it [10] [17] [20].

Figure 5 shows the intensity-duration-frequency (IDF) curve fitted for the Pacora River basin using the Gumbel extreme-value distribution applied to the historical rainfall series. Rainfall depth increases progressively with return period, reaching approximately 280 mm in 24 h for the 100-year event. This curve informs the precipitation thresholds of the early warning system only. Consistent with Section 2.5, the Gumbel/IDF frequency analysis does not, by itself, establish a stage-discharge relationship at the Carriazo control section; the stage and rate-of-rise thresholds are derived instead from the HEC-RAS 2D simulated stage hydrographs extracted at Carriazo (Section 2.3.2). The curve therefore indicates that extreme precipitation associated with the 50- and 100-year return periods poses a significant overflow risk downstream in the lower basin, which—together with the hydraulic results below—forms the basis for defining the multisource thresholds

of SATCOL.

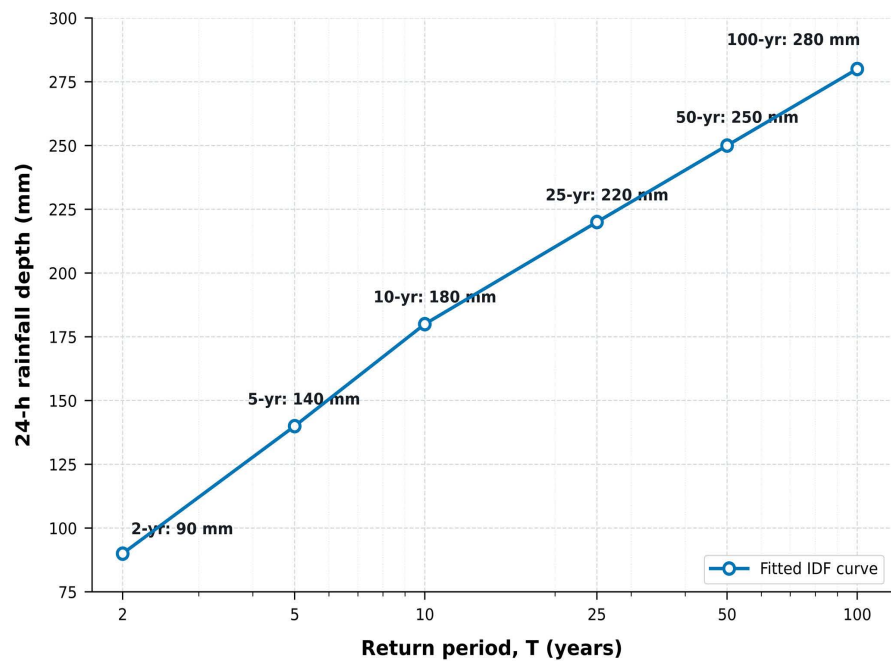


Figure 5. Fitted IDF curve for the Pacora River Basin based on 24 h rainfall depths.

The hydraulic analysis used HEC-RAS 2D with a 12.5-m ALOS-PALSAR digital elevation model refined by LiDAR in critical flood zones to improve topographic accuracy. Scenarios with return periods of 10, 50, and 100 years were simulated, and floodplains primarily affecting La Mireya, Las Garzas, Hugo Spadafora, and the urban area of Pacora were identified (**Figure 6**). For the 100-year event, the present inundated area is approximately 9 km²; hydraulic re-simulation under the +4% sensitivity test projects an expansion to ≈10.1 km² (≈+12%), with relative inundation depths ranging from 1 to 3 m. As noted in Section 3.6, this +12% figure is a scenario-based sensitivity indicator obtained by re-running the hydraulic model with the +4%-scaled design storm, and is not a deterministic SSP5-8.5 forecast.

Model calibration and validation followed established hydrologic and hydraulic procedures [17] [20]. The quantitative spatial evidence is the Fagan-index comparison of simulated extents against post-event Sentinel-2 flood polygons and differential-GPS high-water marks described in Section 2.3.2; the participatory comparison with recurrent-flood areas reported by residents provided an additional qualitative line of evidence but did not replace that quantitative spatial validation, nor does it constitute event-scale forecast skill (Section 2.3.1).

Taken together, the modeling confirms that the Pacora River basin faces high hydrologic risk, aggravated by the projected precipitation sensitivity tested here and by unplanned downstream urban expansion, supporting the need for a multisource early warning system whose thresholds are model-informed rather than empirically calibrated from paired discharge-stage observations at Carriazo.

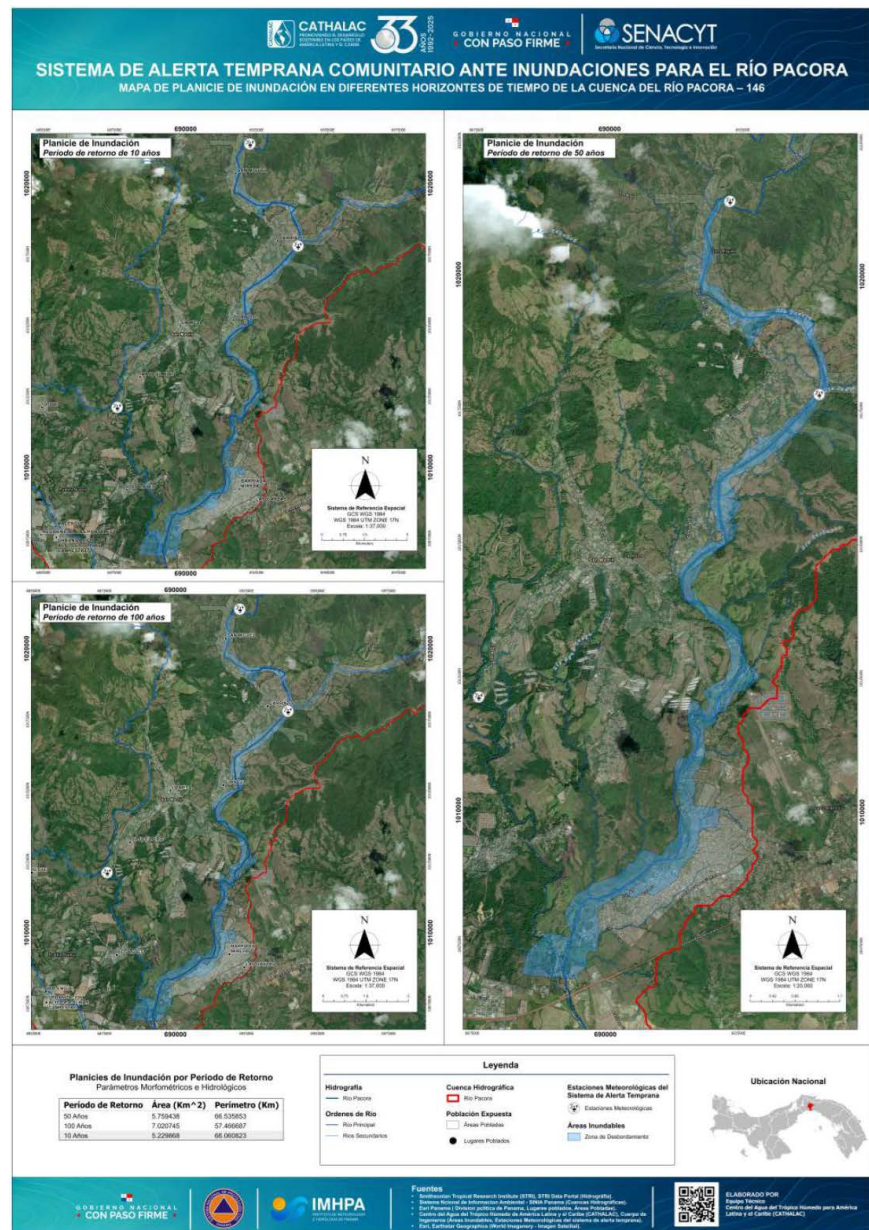


Figure 6. Simulated inundation extents for the 10-, 50-, and 100-year design events in the Pacora River basin, Panama. Map prepared by CATHALAC from HEC-RAS 2D simulations using the ALOS-PALSAR digital elevation model, LiDAR refinements, and the hydrographic and contextual datasets described in Sections 2.3 and 2.3.2; complete data and basemap credits are provided within the map.

Rainfall depth increases with return period and reaches approximately 280 mm in 24 h for the 100-year event. The curve informs precipitation thresholds only; stage and rate-of-rise thresholds derive from HEC-RAS 2D stage hydrographs at Carriazo (Sections 2.3.2 and 2.5).

3.3. IoT Monitoring System

Installation of the IoT-based monitoring system in the Pacora River basin incor-

porated real-time sensors and transmission protocols adapted to low-connectivity conditions. The network was designed for redundancy, low power consumption, and expansion and included two principal nodes at Carriazo and Cabobré. These sites were selected according to hydrologic conditions and population exposure to improve early detection of critical hydrometeorological events.

The node design integrates water-level and rainfall sensing, solar power and LoRaWAN transmission to a gateway and visualization platform. Sensor accuracy, datum stability and communication continuity require documented field checks before being used to quantify operational reliability.

Field tests achieved a successful event-transmission rate of 92%, and the deployed network provided effective spatial coverage of approximately 92% in the critical monitoring areas; these are field-diagnostic metrics of telemetry reliability and sensor siting, not measures of hydrologic forecast skill. Connectivity limitations persisted in forested terrain, particularly around Carriazo, and were mitigated in the design by higher-gain antennas and relay protocols to improve network robustness. To maintain warning continuity during technological failure, redundant notification procedures—mobile messaging and direct community communication—were incorporated into the operating protocol, consistent with the governance and digital-divide considerations of Sections 2.6 and 4.4.

The IoT implementation delivered a mean data-transmission latency of approximately 2 min from sensor to the central dashboard. This latency is the time for information to reach operators and communities; it is not a hydrologic lead time. The 4 - 6 h upstream sensing window associated with the Carriazo node is a design expectation driven by the placement of the gauge relative to flood-wave travel time (Section 2.4), not a capacity created by the telemetry itself: the IoT contribution is to monitor that window in near real time at ~2 min latency, so that the model-informed thresholds of Section 2.5 can be evaluated as conditions develop. The reconstructed in-sample alert lead time for the evaluated events (4.8 ± 1.2 h, against a reconstructed traditional baseline of 1.5 ± 0.5 h) is reported and qualified in Section 3.4 as a sensor-model latency within the retrospective inventory, not as verified forecast skill; prospective validation with observed hydrographs (Section 2.3.1) is required before any operational forecasting claim is made. Scenario-based changes in design peak discharge under the +4% precipitation sensitivity (5% - 8%) are documented in Section 3.6 and are model-based scenario differences, not inferential statistical results; they are not attributed to the monitoring system and no p-value is associated with them here.

Community-facing validation of the monitoring design—perceived usefulness, trust relative to conventional warning sources, and drill-based response time—is reported separately in Sections 2.6 and 3.5, where the corresponding figures are presented as descriptive process indicators from purposively sampled participatory activities rather than as causal evidence of technological-social integration. The technical design of the IoT layer was intended to be compatible with those community protocols, but the social outcomes are assessed independently of the telemetry metrics above.

3.4. Operational Validation of the Dynamic Threshold Strategy

Activation thresholds translated hydroclimatic modeling results into real-time operating parameters. The strategy combined precipitation at multiple accumulation periods (P1h, P3h, P6h, P12h and P24h) with river level and the 30 min rate of rise. Under the two-out-of-three rule, a warning is issued only when at least two variables exceed their predefined thresholds and the resulting vote is maintained for the 10 min activation-persistence window (Section 2.5.1). The 30 min interval is the rate-of-rise calculation window and is not an alert-persistence duration; neither the 10 min nor the 30 min interval is a warning lead time. This rule was developed and evaluated as part of the present study to reduce sensitivity to isolated sensor noise and to localized rainfall that does not produce significant flooding.

Thresholds were defined using the calibrated IDF curves, Gumbel design rainfall and QSWAT/HEC-RAS simulations, with antecedent wetness represented by API-72. During wetter antecedent conditions, rainfall thresholds were reduced by the bounded categorical factor of Section 2.5.1 (maximum 10%); during dry conditions they were left at the base value. These adjustments, and the fact that the same 25-case inventory was inspected both during threshold categorization and during performance evaluation, mean that the metrics below are in-sample retrospective diagnostics, not independent prospective skill (see Section 2.5.2).

Activation thresholds were established for three warning levels (yellow, orange, and red) by combining precipitation, river level, and the rate of rise. **Table 4** summarizes these values.

Table 4. Warning activation thresholds combining precipitation, level, and rate of rise.

Level	Distance D_thr (m)	Equivalent stage h_eq (m)	$\Delta h/30$ min (m)	P1h (mm)	P3h (mm)	P6h (mm)	P12h (mm)	P24h (mm)	Peak intensity (10 - 15 min) (mm/h)
Yellow	3.82	1.38	0.25	53.2	70.0	83.2	99.0	117.69	300
Orange	3.46	1.75	0.40	56.5	86.9	111.8	138.6	155.59	450
Red	3.24	1.96	0.60	71.8	102.1	126.7	155.1	180.69	700

Source: Authors' calculations. Note: The stage-rise window is 30 min and the proposed activation persistence is 10 min. Sensor-distance and stage values require a common verified datum.

Operational Performance Validation

SATCOI performance was evaluated retrospectively using 25 significant hydro-meteorological cases from 2018-2024: 10 observed flood cases and 15 rainfall cases without observed flooding. Reference classifications triangulated official SINAP-ROC reports, Sentinel-2 imagery, and community records. Because the same inventory informed threshold inspection and performance evaluation, all metrics are reported as in-sample diagnostics; a temporally held-out evaluation (e.g. threshold inspection on an earlier sub-period and verification on a later sub-period) is

recommended before any operational skill claim.

Reduction in False Positives

For the 15 rainfall cases without observed flooding, the traditional static P24h threshold produced 9 false positives (60.0%), whereas SATCOI produced 2 (13.3%). This corresponds to a 77.8% relative reduction. The result applies to the defined retrospective dataset and is not be generalized beyond the evaluation period. The importance of controlling false alarms is consistent with prior early warning research [34].

Reconstructed Lead Time

Within the retrospective inventory, the integration of real-time IoT sensors and model-informed thresholds increased the reconstructed alert lead time from 1.5 ± 0.5 h (traditional, empirical observation and manual reports) to 4.8 ± 1.2 h for events with recurrence below 50 years, and up to 6.2 h for extreme events—a net gain of +3.3 h ($\approx 220\%$). This value is a reconstructed sensor-model latency for the evaluated cases, not a verified forecast-skill metric; it is distinct from the 4 - 6 h upstream sensing window that is a *design expectation* of the Carriazo placement (Sections 2.4 and 3.3). Prospective validation with observed hydrographs is required to convert the former into demonstrated skill.

Overall Performance Metrics

Table 5 synthesizes descriptive performance metrics for the 25-case in-sample retrospective inventory. No inferential significance test was applied.

Within the 25-case inventory, SATCOI classified all 10 flood cases as alerts and produced no false negatives, whereas the static-threshold reference missed 2 of the 10 cases. These figures describe only the evaluated inventory. These arithmetic summaries do not independently verify the case classifications or the operating configuration, and do not constitute an out-of-sample test.

Table 5. Performance metrics of SATCOI compared with the traditional system. Descriptive in-sample performance metrics of SATCOI and the static-threshold reference.

Metric	Traditional System	SATCOI (two-out-of-three + API-72)
Events evaluated, N	25	25
Observed flood events	10	10
Observed non-flood events	15	15
True positives (TP)	8	10
False positives (FP)	9	2
False negatives (FN)	2	0
True negatives (TN)	6	13
Sensitivity (recall)	80.0%	100.0%
Precision (PPV)	47.1%	83.3%

Continued

Specificity	40.0%	86.7%
Accuracy	56.0%	92.0%
F1-score	59.3%	90.9%
False-positive rate	60.0%	13.3%
False-negative rate	20.0%	0.0%
Relative reduction in false positives	—	77.8%

Note. Performance metrics were calculated from a single validation inventory of 25 significant hydrometeorological events during 2018–2024, comprising 10 observed flood events and 15 rainfall events without observed flooding. The reference classification was established by triangulating official SINAPROC reports, Sentinel-2 imagery, and community records. The traditional system produced TP = 8, FP = 9, FN = 2, and TN = 6; SATCOI produced TP = 10, FP = 2, FN = 0, and TN = 13. Sensitivity was calculated as $TP/(TP + FN)$, precision as $TP/(TP + FP)$, specificity as $TN/(TN + FP)$, accuracy as $(TP + TN)/N$, and F1-score as $2 \times (\text{precision} \times \text{sensitivity})/(\text{precision} + \text{sensitivity})$. The relative reduction in false positives was $[(9 - 2)/9] \times 100 = 77.8\%$.

Within the retrospective inventory, precision increased from 47.1% to 83.3%, specificity from 40.0% to 86.7%, and accuracy from 56.0% to 92.0%. These are descriptive differences from paired classifications of the same 25 cases; no out-of-sample inference is made.

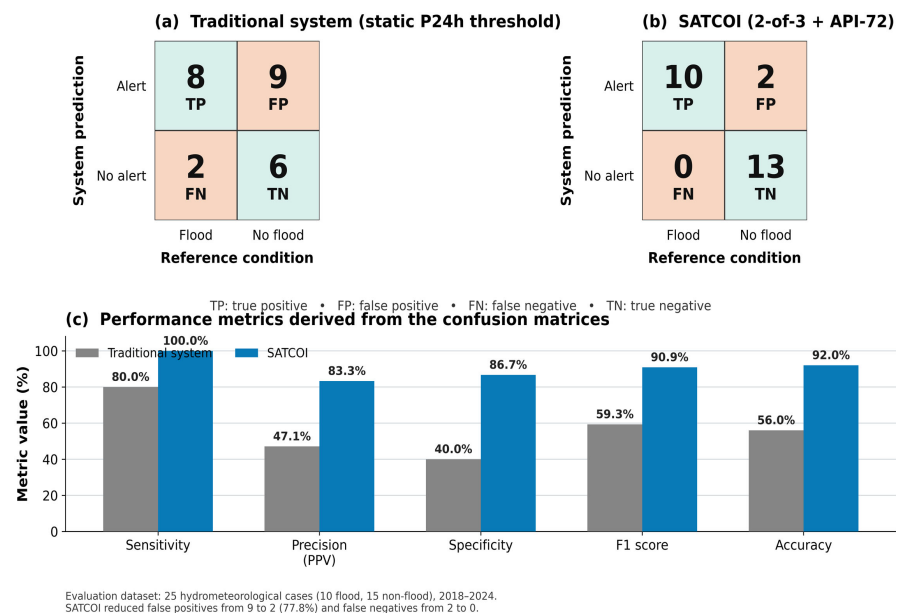


Figure 7. Comparative operational performance of the traditional flood-warning system and SATCOI in the Pacora River basin. The confusion matrices and derived performance metrics are based on 25 hydrometeorological cases recorded between 2018 and 2024. SATCOI reduced the number of false positives from 9 to 2 and eliminated false negatives, thereby increasing overall accuracy from 56.0% to 92.0%.

Figure 7 presents the comparative operational performance of the traditional warning system and SATCOI using three complementary panels. Panel (a) shows the confusion matrix for the traditional system, which correctly identified 8 flood events but generated 9 false positives, missed 2 events, and correctly classified 6 non-flood cases. Panel (b) presents the SATCOI confusion matrix, with 10 true positives, 2 false positives, no false negatives, and 13 true negatives. Panel (c) compares the performance metrics derived from these matrices. Relative to the traditional system, SATCOI increased sensitivity from 80.0% to 100.0%, precision from 47.1% to 83.3%, specificity from 40.0% to 86.7%, F1 score from 59.3% to 90.9%, and overall accuracy from 56.0% to 92.0%. Within the 25-case evaluation dataset, the hybrid 2-of-3 decision logic combined with API-72 reduced false positives by 77.8% and eliminated false negatives. No inferential significance is assigned to these differences.

Discussion of Operational Validation

Evaluation using simulations and observed-event reconstructions indicated that the 10-min activation-persistence window and the 0.10-m deactivation hysteresis (Section 2.5.1) improved operational stability by reducing rapid alert-state transitions during intermittent rainfall and keeping warnings active until conditions showed a sustained decline, thereby limiting contradictory public messages.

Within the same 25-case in-sample inventory, the two-of-three rule with API-72 reduced false positives from 9 to 2 and false negatives from 2 to 0 relative to the static P24h threshold. These descriptive differences suggest improved discrimination in this inventory; they do not establish out-of-sample effectiveness.

The integration of technically defined thresholds, operational safeguards and participatory validation provides a promising basis for strengthening warning reliability and community confidence; however, changes in public trust and response behavior must be assessed separately through surveys, drills and response-time records (Section 3.5). Subject to local calibration, institutional coordination and community validation, the SATCOI approach offers a potentially transferable methodological framework for other humid-tropical basins.

3.5. Community Validation

SATCOI was evaluated through the participatory workshops and drills of Section 2.6, conducted in 2024-2025 in Pacora, Las Garzas and San Martín, with more than 200 participants (community leaders, community-board members, women, youth and local authorities). Activities enabled participants to assess the relevance of proposed thresholds, warning messages and response protocols.

More than 70% of participants reported greater confidence in SATCOI than in the conventional warning sources considered in the questionnaire, and 65% indicated willingness to follow early-evacuation protocols based on issued warnings; drills produced a mean community response time of 20 min. These percentages and the response time are descriptive indicators of stated perception and drill performance among purposively sampled participants; they do not constitute a probability sample of the basin population, an independent estimate of behavioral

compliance, or causal evidence of changed public trust. Community participation is widely recognized as central to flood early-warning effectiveness [5] [6] [35].

The activities identified practical gaps—strengthening evacuation routes, digitizing historical flood records and improving inclusion of older adults and persons with disabilities. Incorporating local testimony aligned the technical design with residents' empirical knowledge and confirmed agreement between modelled high-risk zones and historically affected areas, which strengthens SATCOI's sustainability by ensuring technical criteria address actual community perceptions and needs. Social indicators should continue to be monitored independently of the technical performance metrics of Section 3.4.

3.6. Climate Change Scenarios

Climate-scenario sensitivity tests evaluated SATCOI under projected 2050 conditions [10]. Applying the +4% wet-side sensitivity multiplier (the rounded upper bound of the 4NC 2050 range for eastern Panama; Section 2.7) to the fitted 100-year, 24 h rainfall depth increased the design value from ≈ 280 to ≈ 291 mm, and QSWAT/HEC-RAS re-simulation produced a corresponding 5% - 8% increase in peak discharge. Floodplain re-simulation under the same +4% design storm projects an expansion of as much as 12% in inundated area for the 100-year scenario (≈ 9 km² to ≈ 10.1 km²), particularly in La Mireya and Las Garzas, with relative depths of 1 - 3 m. This 12% figure is therefore a scenario-based sensitivity indicator obtained by hydraulic re-simulation under the +4% multiplier, not a deterministic SSP5-8.5 forecast; dry or neutral cases within the 4NC range would imply smaller or negligible expansion, though they do not remove the need for periodic recalibration because land-use change and localized convective extremes may remain dominant drivers.

Separately, the operational thresholds P1h - P24h were adjusted arithmetically in the sensitivity tests (e.g. P24h red threshold 180 $\rightarrow$ 195 mm; 30 min rate-of-rise threshold 0.60 $\rightarrow$ 0.65 m). These arithmetic adjustments are scenario assumptions and preliminary screening values that require periodic recalibration with new observations and, ultimately, full re-derivation through the modelling chain (Section 2.7, point 2); they are not validated future thresholds.

The simulations indicate that the two-out-of-three framework with dynamically modulated thresholds can preserve a 4 - 6 h upstream sensing window (design expectation, Section 2.4) under the tested scenarios. Workshop participants supported conservative warning procedures under more extreme conditions; this is a stated preference, not verified evacuation behavior. The sensitivity results are consistent with national projections of higher temperatures and spatially variable precipitation by mid-century [10], and support periodic stress testing of SATCOI as climate risks evolve [33].

4. Discussion

4.1. Scientific Contribution: Adaptive Hybrid Decision Logic

The principal scientific contribution is not the isolated use of hydrologic-hydrau-

lic modelling, IoT telemetry, antecedent-moisture indices or community participation—each established in the flood early-warning literature—but their operational coupling through a single testable decision rule and a documented retrospective inventory. SATCOI formulates and evaluates a hybrid “2-of-3” rule combining multiscale rainfall, river stage and 30 min rate of rise, with the rainfall stream modulated by a *bounded categorical* API-72 factor (maximum 10% reduction; Section 2.5.1), confirmed over a 10 min activation-persistence window and released through a 0.10 m deactivation hysteresis. This coupling converts the system from a monitoring infrastructure into a hypothesis-testing framework for reducing false positives while preserving detection, and makes explicit the data, modelling and governance conditions required to translate model outputs into community-actionable thresholds. The transferable element is therefore the methodological architecture and the validation protocol, not the numerical thresholds, which require local recalibration.

Two qualifications govern interpretation. First, the contribution is inferential and methodological, not an empirical rating curve: rainfall thresholds derive from the IDF/Gumbel-GEV frequency analysis of Section 2.2, which characterizes design rainfall only and does not, by itself, establish a stage-discharge relationship at Carriazo; the stage and rate-of-rise thresholds are *model-informed* triggers obtained from HEC-RAS 2D simulated stage hydrographs at Carriazo (Section 2.3.2), referenced to a common verified datum and linked to observed inundation impacts, not empirically calibrated coefficients, because no paired discharge-stage dataset was available. Second, the headline figures are in-sample retrospective diagnostics, not prospective skill: the same 25-case inventory was used both to inspect threshold categories and to evaluate performance (Section 2.5.2), so the 77.8% false-positive reduction and the elimination of false negatives describe discrimination in the evaluation cohort and are not extrapolated; a temporally held-out evaluation is required before any operational skill claim. Finally, the extreme-value statistics inherit uncertainty from model selection, record length, possible non-stationarity and dependence among annual maxima (Section 2.2), which propagates through the QSWAT-HEC-RAS chain to the thresholds. Together these boundaries delimit what SATCOI currently supports—reconnaissance-level hazard screening and threshold prioritization—from what it does not yet support, namely operationally validated discharge forecasting.

4.2. International Comparison

Compared with warning approaches that rely mainly on human observers, radio communication or a single static rainfall threshold, SATCOI automates monitoring through IoT and LoRaWAN while retaining community participation. Its distinctive operational element is the combination of a bounded API-72 modulation with three independent criteria (precipitation, stage and rate of rise) under a 2-of-3 vote with explicit persistence and hysteresis—a combination that, to our knowledge, has not been quantitatively evaluated against a documented multi-

event inventory in a humid tropical basin of this scale. The comparison in **Table 6** should be read as a *feature-level* contrast with representative conventional designs, not as a benchmark against any single published system; the “Operational Distinction” column states the *intended* advantage, whose realized magnitude in SATCOI is the in-sample result of Section 3.4. The transferability of the approach depends on local hydrologic calibration, communications coverage, institutional capacity and community validation [3] [5] [6] [35]; the numerical thresholds are site-specific and must be re-derived elsewhere through the same QSWAT-HEC-RAS chain and the same validation protocol.

Table 6. International comparison of SATCOI and conventional early warning systems (feature-level contrast; “Operational Distinction” states the intended advantage, evaluated in-sample in Section 3.4).

Characteristic	Selected Conventional Approaches	SATCOI (Panama)	Operational Distinction
Transmission	GSM/SMS or VHF radio	LoRaWAN + IoT	Autonomy, low cost, and rural coverage; ~2 min data latency (Section 3.3), not a hydrologic lead time
Logic	Single static rainfall threshold	Hybrid (2-of-3 + API) Hybrid 2-of-3 + bounded API-72 (max 10%)	Reduces false alarms from sensor noise or localized rainfall; in-sample 77.8% FP reduction (Section 3.4)
Modeling	Empirical or rainfall-only	QSWAT + HEC-RAS 2D (model-informed; pending paired hydrometric validation at Carriazo)	Physically informed threshold basis requiring paired hydrometric validation
Governance	Vertical (agency-to-community)	Horizontal (upstream communities as local sentinels)	Empowers upstream communities; social outcomes are descriptive process indicators (Sections 2.6, 3.5)

4.3. Public-Policy Implications

1) Institutionalization. Community-based early warning systems should be recognized as critical national infrastructure supported by recurrent budgets, rather than as project-funded pilots whose sensors and batteries lapse when a grant ends.

2) Multilevel governance. Formal shared-responsibility agreements are needed under which communities maintain field equipment and SINAPROC/IMHPA manage data, calibration and threshold review, converting the currently sporadic partnerships described in Section 2.6 into standing protocols.

3) Climate-aware land-use regulation. New development should be restricted in areas projected to enter the floodplain under the +4% wet-side sensitivity test (Sections 2.7 and 3.6). This is a planning tool derived from a scenario-based sensitivity indicator—not a deterministic SSP5-8.5 flood map—and should be paired with periodic re-derivation of the design storms as observations accumulate.

4) Scalability. The open architecture (open-source modelling stack + LoRaWAN) can be replicated in other priority basins, provided that the local QSWAT-HEC-RAS chain, the IDF/Gumbel rainfall analysis and the validation protocol are re-run and the bounded API-72 factors are recalibrated to local antecedent-moisture

statistics.

4.4. Limitations

This study has several limitations that delimit the present status of SATCOI and the strength of its inferences.

1) Hydrometric provenance and absent rating curve. The hydrologic forcing includes model-derived (QSWAT-simulated) discharge wherever continuous observed gauging was unavailable at Carriazo (Section 2.3.1); the stage and rate-of-rise thresholds of **Table 4** are therefore *model-informed* triggers referenced to a common verified datum, not empirically calibrated rating-curve coefficients, and the Gumbel/GEV analysis establishes design rainfall only (Section 2.5). Paired discharge-stage observations, or a site-specific hydraulic model validated against them, are required before any discharge-based interpretation.

2) In-sample evaluation and reconstructed lead time. The 25-case inventory informed both threshold categorization and performance computation, so the **Table 5** metrics are in-sample diagnostics, not prospective skill (Sections 2.5.2, 3.4); the reported lead time (4.8 ± 1.2 h against a reconstructed traditional baseline of 1.5 ± 0.5 h) is a sensor-model latency for the evaluated cases, distinct from the 4 - 6 h upstream sensing window that is a *design expectation* of the Carriazo placement (Sections 2.4, 3.3), and neither is verified forecast skill.

3) Event-scale and inferential gaps. Monthly goodness-of-fit ($NSE \approx 0.75 - 0.78$; Section 2.3.1) does not by itself establish event-scale peak timing or magnitude accuracy; no inferential test, ensemble, replicate set or confidence interval underlies the comparison beyond the descriptive paired check of Section 3.4, so no statistical significance is claimed and the 5% - 8% peak-discharge change under the +4% multiplier is a model-based scenario difference (Sections 3.3, 3.6).

4) Extreme-value and climate representation. The design rainfall inherits Gumbel/GEV uncertainty (model selection, record length, non-stationarity, dependence; Section 2.2), and the +4% multiplier is a rounded upper bound of the 4NC 2050 range for eastern Panama (-2.82% to $+4.38\%$; Sections 2.7, 3.6), so the +12% floodplain expansion is a scenario-based sensitivity indicator from hydraulic re-simulation, not a deterministic projection, while arithmetic threshold adjustments remain preliminary screening values requiring full re-derivation.

5) Social evidence. Participatory indicators (>200 participants; >70% stated confidence; 65% stated willingness; 20 min mean drill response) derive from purposive, non-probability sampling with social-desirability and hypothetical bias and from drill conditions differing from real emergencies (Sections 2.6, 3.5); they are descriptive process metrics, not representative estimates of basin-wide behaviour or causal evidence of changed trust.

6) Data, sustainability and inclusion. CHIRPS and ERA5-Land may underestimate localized convective extremes (Section 2.2); battery and sensor maintenance in a corrosive tropical environment is financially challenging; digital warnings must be complemented by physical sirens for older adults and vulnerable groups;

and connectivity constraints in forested terrain around Carriazo remain a recurrent engineering challenge addressed through higher-gain antennas, relay protocols and redundant notification pathways [3] [35].

Collectively, these limitations indicate that SATCOI integrates modelling, IoT monitoring and community participation in a single operational architecture and offers an adaptable framework for other humid-tropical basins, but is not yet a validated operational forecasting system—a transition requiring paired hydro-metric data at Carriazo, held-out validation, uncertainty propagation and sustained funding.

5. Conclusions and Recommendations

The Pacora River Community-Based Flood Early Warning System shows that hydrologic-hydraulic modelling, real-time IoT monitoring and participatory governance can be integrated into a coherent operational architecture for local flood-risk management. This architectural integration, however, is not equivalent to a validated operational forecasting system: the present status of SATCOI is that of a model-informed, retrospectively screened decision framework whose operational skill remains contingent on prospective, temporally held-out and paired-hydro-metric validation (Section 4.4).

Within the 25-case retrospective inventory (10 observed flood events and 15 rainfall-without-flood events, 2018-2024), the two-out-of-three rule with the bounded categorical API-72 modulation reduced false positives by 77.8% relative to a static P24h threshold and eliminated false negatives. Because the same inventory informed both threshold categorization and performance evaluation, these values are in-sample retrospective diagnostics that indicate improved discrimination within the evaluation cohort; they are not extrapolated to future performance, and a held-out evaluation is required before any broader skill claim (Sections 2.5.2, 3.4, 4.1).

SATCOI increased the reconstructed warning lead time from approximately 1 - 2 h to 4 - 6 h through upstream sensing and model-informed thresholds. More than 70% of workshop participants reported greater confidence in SATCOI than in the conventional warning sources considered, and drills produced a mean response time of approximately 20 min. These social indicators should continue to be monitored independently of technical performance metrics.

Within the same inventory, the reconstructed alert lead time increased from 1.5 ± 0.5 h (traditional, empirical observation and manual reports) to 4.8 ± 1.2 h for events with recurrence below 50 years, and up to 6.2 h for extreme events. This figure is a reconstructed sensor-model latency, not a verified forecast-skill metric; it is distinct from the 4 - 6 h upstream sensing window, which is a design expectation of the Carriazo placement governed by flood-wave travel time (Sections 2.4, 3.3, 4.4). On the social side, more than 70% of workshop participants reported greater confidence in SATCOI than in the conventional warning sources considered, and drills produced a mean response time of approximately 20 min; these

are descriptive process indicators from purposively sampled participatory activities, not representative estimates of basin-wide behaviour or causal evidence of changed trust, and they should continue to be monitored independently of the technical performance metrics (Sections 2.6, 3.5).

Climate-scenario sensitivity tests indicate that the area inundated by the 100-year event could expand by as much as 12% by 2050. This value derives from a +4% wet-side sensitivity multiplier—the rounded upper bound of the 4NC 2050 range for eastern Panama—obtained by hydraulic re-simulation, and is therefore a scenario-based sensitivity indicator, not a deterministic SSP5-8.5 projection (Sections 2.7, 3.6, 4.4). The result supports periodic re-derivation of rainfall analyses, hydraulic models and operational thresholds through the full QSWAT-HEC-RAS chain, rather than treating the current configuration as fixed or relying on arithmetic threshold adjustment alone.

To consolidate and scale SATCOI, the system should be integrated into national operating protocols and official communication channels, with stable maintenance arrangements, routine recalibration and clearly assigned institutional responsibilities. Future development may evaluate intelligent forecasting methods, but any artificial-intelligence component should be trained and validated with basin-specific observations before operational use [4].

SATCOI therefore provides a potentially transferable framework for humid-tropical basins, subject to local hydrologic calibration—including re-running the IDF/Gumbel and QSWAT-HEC-RAS chain and obtaining paired discharge-stage observations at the relevant control section—prospective and held-out performance assessment, communications testing, and sustained community and institutional participation (Sections 4.2, 4.4).

Recommendations:

- Scale the SATCOI experience to other vulnerable watersheds, both urban and rural, incorporating site-specific adjustments to thresholds and re-running the local hydrologic-hydraulic chain (IDF/Gumbel, QSWAT and HEC-RAS 2D) to improve applicability and accuracy.
- Ensure sustainable financing through national budgetary mechanisms, international grants, and public-community partnerships, guaranteeing the continuous operation of the system and its long-term viability.
- Institutionalize governance through formal shared-responsibility agreements between SINAPROC, IMHPA, MiAmbiente, Community Boards, and community organizations, consolidating a co-responsibility model that reinforces stakeholder commitment.
- Expand and densify the sensor network, prioritizing critical and upstream locations, to improve spatial coverage, data latency and the representativeness of the upstream sensing window (Section 2.4); note that hydrologic lead time is governed by flood-wave travel time and is not extended by adding sensors alone (Sections 3.3, 4.4).
- Implement continuous training programs aimed at communities, local leaders,

and technical personnel to reinforce social appropriation and basic maintenance capacities, fostering the system's sustainability.

- Integrate SATCOI into national risk management and water security policies, articulating it with the National Water Security Plan 2015-2050 and the National Climate Change Strategy, recognizing it as a key adaptation instrument.
- Promote social and gender inclusion by strengthening the active participation of women, youth, and vulnerable groups within the early warning system's operations committees.
- Foster Nature-based Solutions (NbS), such as the restoration of riparian forests and mangroves, to complement SATCOI's function by reducing peak flows and improving ecological resilience.
- Prioritize the periodic update of climate scenarios and hydrological models to anticipate future changes, systematically adjusting early warning strategies through full re-derivation of rainfall, stage and rate-of-rise thresholds via the modelling chain rather than arithmetic adjustment alone, and thus ensuring long-term sustainability and effectiveness (Sections 2.7, 3.6, 4.4).

In conclusion, SATCOI offers an operational basis for flood-risk reduction and climate adaptation in the Pacora River basin by connecting scientific analysis, monitoring technology, institutional coordination, and community participation. Its long-term value will depend on maintaining the observational network, documenting warning outcomes, and revising thresholds as new evidence becomes available.

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Author Contributions

Conceptualization, F.P.T., O.S. and T.M.; methodology, F.P.T., O.S., O.A., D.M. and O.P.; software and modeling, O.S., O.A., D.M. and O.P.; validation, F.P.T., O.A., L.V., E.Y., and T.M.; formal analysis, F.P.T., O.A., T.M. and O.P.; investigation, all authors; resources, F.P.T., L.V. and E.Y.; data curation, E.Y., O.S., and O.A.; community engagement, T.M., L.V., D.M. and O.A.; visualization, O.A.,

T.M. and F.P.T.; writing—original draft, F.P.T., O.A. and T.M.; writing—review and editing, all authors; supervision, F.P.T.; project administration, F.P.T. and T.M.; funding acquisition, F.P.T. All authors have read and agreed to the submitted version of the manuscript.

Data Availability Statement

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request. Raw hydrometeorological records supplied by IMHPA are subject to the data provider's access conditions and cannot be redistributed by the authors. Aggregated, non-identifiable workshop data and model outputs may be made available subject to institutional and ethical restrictions.

Ethics Approval and Consent to Participate

The Pacora River Community-Based Flood Early Warning System protocol was reviewed by the Bioethics Committee for Research of The Panama Clinic, Panama, which approved an exemption from ethics review because the protocol was determined not to require ethical review under the Committee's applicable procedures (exemption reference: CA-CBI-TPC-024; 28 July 2023). The workshops, interviews, and surveys conducted with community members were non-interventional activities undertaken for community participation and project validation. All participants were informed of the purpose of the activities and the voluntary nature of their participation, and informed consent was obtained prior to participation. No personally identifiable information is reported in this manuscript, and the information collected was anonymized and handled confidentially for the purposes of system development, validation, and evaluation.

Consent for Publication

Not applicable, provided that the manuscript and figures contain no identifiable personal information or recognizable participant images.

Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) solely for English-language editing, editorial quality control, and bibliographic cross-checking. All scientific content, analyses, interpretations, and references were reviewed and verified by the authors, who take full responsibility for the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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