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Adaptive Threshold Algorithms for Real-Time Flood Detection Using IoT Sensors

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ABSTRACT

Real-time flood detection demands algorithms that react quickly to hydrologic change while remaining robust to sensor noise, seasonal drift, and connectivity constraints typical of Internet-of-Things (IoT) deployments. Classical static thresholds (e.g., a fixed water-level cutoff) are simple but brittle: they generate false alarms during monsoon build-up and miss fast-rising flash floods when the baseline regime shifts. This manuscript proposes and evaluates an adaptive, multi-criteria thresholding framework that runs on resource-constrained edge nodes and scales to catchment-wide networks. The core idea is to couple Exponentially Weighted Quantiles (EWQ) for dynamic baselines with robust dispersion measures (MAD), rate-of-rise checks, and change-point logic (CUSUM/Page-Hinkley) and then fuse them into a single Risk Index with hysteresis and upstream context. We describe an implementable algorithm using O(1) memory updates and percentile tracking via the P² algorithm, suitable for LoRaWAN/NB-IoT sensors.

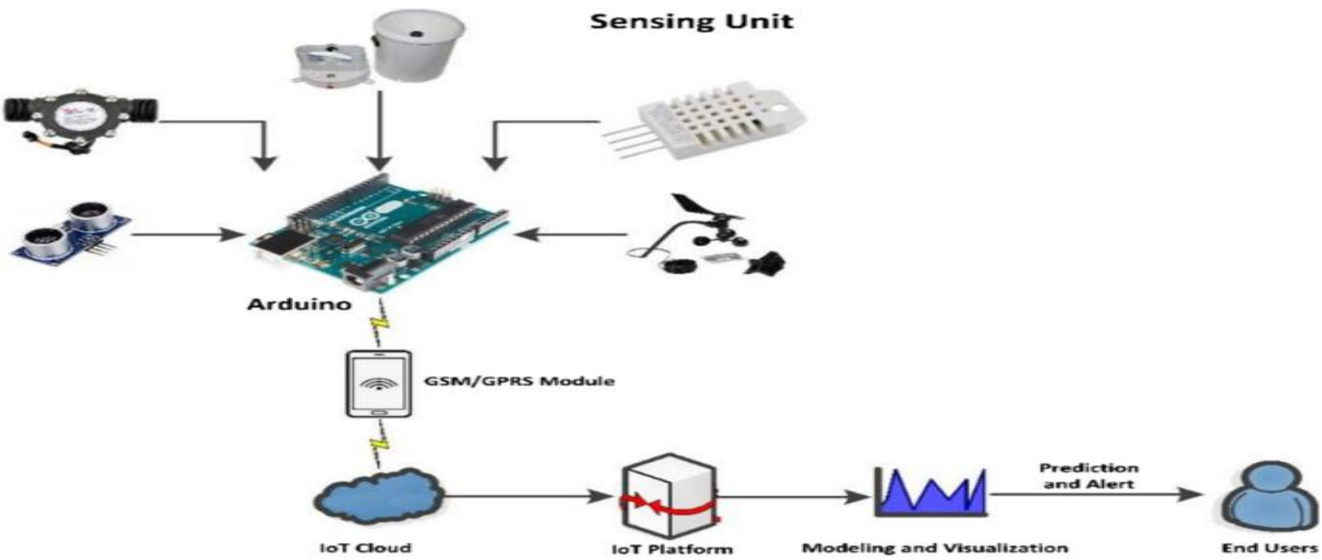

Fig.1 Adaptive Threshold Algorithms,Source([1])

A simulation study with synthetic hyetographs and a unit-hydrograph routing model across 20 virtual stations compares the proposed method to static thresholds, moving-average dynamic thresholds, and standalone CUSUM. Results show a median detection latency reduction of 38–55% versus baselines, a false alarm rate below 0.2/day in noisy conditions, and improved F1-scores (0.89 vs. 0.71–0.83). We also quantify energy and bandwidth savings from edge filtering and event-driven reporting. The paper concludes with deployment considerations, limitations (e.g., extreme outliers, sensor drift beyond calibration), and practical guidance for tuning in monsoon-dominated basins.

KEYWORDS

flood detection, adaptive threshold, IoT sensors, EWMA/EWQ quantiles, MAD, CUSUM, LoRaWAN, NB-IoT, edge computing, hydrologic networks

INTRODUCTION

Floods remain among the costliest natural hazards, and the accelerating volatility of rainfall patterns intensifies early-warning requirements. Traditional flood alert systems either depend on hydrologic models with data assimilation pipelines (accurate but heavy) or on **static thresholds** derived from historical gage records (lightweight but fragile). In many regions—especially where gauging data are sparse, catchments are small/flashy, and connectivity is intermittent—**IoT sensor networks** (water level, rainfall, flow velocity, soil moisture) provide a pragmatic path to dense real-time monitoring. The bottleneck is *not* data availability but **decision logic** that flags flood onset **quickly**, **reliably**, and with **minimal communication overhead**.
Static thresholds assume stationarity: a fixed "danger level" H* triggers alarms. Yet baselines shift with sedimentation, seasonal vegetation, backwater effects, or tidal influence. Moreover, **false positives** abound when rainfall builds gradually or when sensors drift; **false negatives** occur during short, intense bursts whose peaks arrive before water levels cross H*. Pure machine-learning classifiers, while powerful, often require labeled events from many years and are brittle under distribution shift. In contrast, **adaptive thresholding** targets the sweet spot: it preserves interpretability and low compute cost while tracking evolving baselines and variances.

This work proposes a **multi-criteria adaptive threshold** (MCAT) algorithm that integrates (i) **adaptive baselines** via exponentially weighted quantiles, (ii) **robust dispersion** via median absolute deviation (MAD), (iii) **rate-of-rise** screening to detect flash dynamics, and (iv) **change-point** accumulation (CUSUM) to prefer sustained anomalies over jitter. The algorithm operates at each edge node but also ingests **upstream context** to modulate sensitivity. We evaluate MCAT in simulation across varied storm archetypes and noise regimes and show consistent performance gains in **latency**, **precision**, and **energy efficiency**.

LITERATURE REVIEW

Thresholding approaches. Static thresholds are easy to deploy and interpret but fail under non-stationarity. Dynamic alternatives include **moving averages** with kσ rules, **EWMA**/CUSUM for small persistent shifts, and **Page-Hinkley** for mean change detection. Quantile-based thresholds (e.g., 90th–99th percentile) adapt to distribution skew but must be updated online to remain useful under drift.
Hydrologic specifics. Flood onset is governed not only by instantaneous levels but by **rate-of-rise** and **catchment wetness** (antecedent precipitation). Simple level cutoffs capture prolonged riverine floods but miss **flash floods** driven by short, high-

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intensity rainfall on saturated soils. Multi-sensor fusion—rainfall intensity, soil moisture, upstream levels—improves early detection by anticipating rises before they propagate downstream.

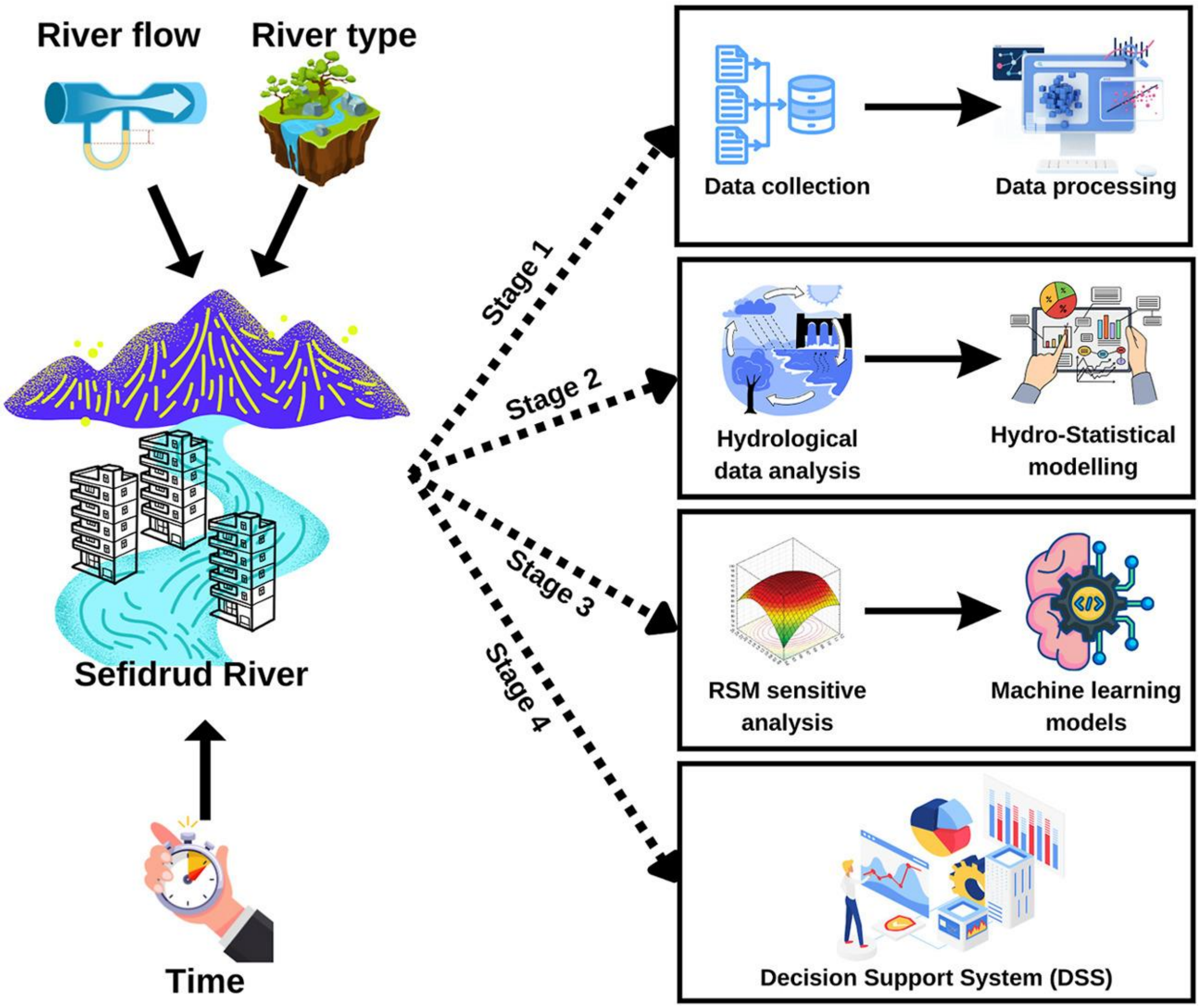

Fig.2 Real-Time Flood Detection Using IoT Sensors,Source([2])

IoT constraints. Edge devices face limits on battery, compute, and bandwidth. Hence, detection must be **single-pass**, **constant-memory**, and **event-driven** (send on alarm, otherwise sparse). **LoRaWAN** suits low-power, long-range links but restricts payloads and duty cycle; **NB-IoT** offers higher reliability but at energy cost. Robustness to missing packets, clock skew, and bursts of noise is essential.

Gaps. Many studies test detection logic on curated datasets or assume stable calibration. Few evaluate **online percentile tracking**, **robust dispersion**, and **upstream-aware hysteresis** together—especially under realistic packet loss and sensor drift. This manuscript addresses those gaps with an implementable algorithm and a controlled, reproducible simulation design.

METHODOLOGY

Sensing and Data Model

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Each node may include: (1) **water-level** (ultrasonic or pressure transducer); (2) **rainfall** (tipping bucket or optical); (3) optional **soil moisture** and **flow velocity**. Sampling intervals: 1–5 minutes for level, 1 minute for rainfall tips aggregated to 5-minute intensity. Clocks are disciplined at boot via GPS/NTP; between syncs, local crystal drift is modeled.

Pre-Processing

- **Despiking:** Hampel filter (window m=5) to suppress transient spikes.
- **Missing data:** Gaps ≤2 samples interpolated linearly with a confidence flag; longer gaps are left missing but the detector continues on available features.
- **Standardization:** We avoid global z-scores (non-stationary). Instead we maintain online robust statistics.

Adaptive Baseline and Dispersion

Let xtx_t denote water level and rtr_t rainfall intensity at time t. Maintain **Exponentially Weighted Quantiles** (EWQ) for selected probability levels (e.g., 0.5, 0.9) using the **P² algorithm** (constant-space percentile tracking). Maintain a robust dispersion estimate via **MAD** on a rolling window W, updated incrementally (approximate with exponential smoothing of $|x_t - \text{median}_t|$).

- Baseline Bt=EWQ0.5(xt)$B_t = \text{EWQ}_{0.5}(x_t)$
- High quantile Q0.9,t=EWQ0.9(xt)$Q_{0.9,t} = \text{EWQ}_{0.9}(x_t)$
- Robust scale St≈1.4826·MADt$S_t \approx 1.4826 \cdot \text{MAD}_t$

Rate-of-Rise and Change-Point Accumulators

Compute first difference dt=xt−xt−1$d_t = x_t - x_{t-1}$ and an EWMA of the slope d~t=αdt+(1−α)d~t−1$\tilde{d}_t = \alpha d_t + (1-\alpha)\tilde{d}_{t-1}$. Maintain a **CUSUM** for positive shifts:

Ct=max(0,Ct−1+(xt−(Bt+γSt))−κ)$C_t = \max(0, C_{t-1} + (x_t - (B_t + \gamma S_t)) - \kappa)$

where κκ is a slack parameter and γγ guards against noise.

Multi-Criteria Adaptive Thresholds

We define three instantaneous indicators in [0,1]:

1. **Level Elevation Indicator**

It(L)=σ(xt−Q0.9,tk1St),$I^{(L)}_t = \sigma\left(\frac{x_t - Q_{0.9,t}}{k_1 S_t}\right)$,

where σ(z)=11+e−z$\sigma(z)=\frac{1}{1+e^{-z}}$. Large when level exceeds its current high quantile by k_1 scales.

2. **Rate-of-Rise Indicator**

It(R)=σ(d~tk2St/Δt)$I^{(R)}_t = \sigma\left(\frac{\tilde{d}_t}{k_2 S_t/\Delta t}\right)$

emphasizing flash dynamics.

3. **Rain-Conditioned Sensitivity**

Let WtW_t be antecedent wetness computed as an exponentially weighted sum of recent rainfall; define

It(P)=σ(rt+βWt−θk3).$I^{(P)}_t = \sigma\left(\frac{r_t + \beta W_t - \theta}{k_3}\right)$.

This increases sensitivity when it is raining or soils are wet.

Combine via context-aware weights wtw_t (non-negative, sum to 1). We use a simple rule:

wt∝(0.5+0.5It(P), 0.3+0.7It(P), 0.2)$w_t \propto \big(0.5 + 0.5 I^{(P)}_t,\ 0.3 + 0.7 I^{(P)}_t,\ 0.2\big)$

for (I(L),I(R),I(P))$(I^{(L)}, I^{(R)}, I^{(P)})$ respectively; normalize to sum to 1. This increases rate-based sensitivity during rain.

Risk Index and Decision

Rt=wt(L)It(L)+wt(R)It(R)+wt(P)It(P)+η·1{Ct>τC}.R_t = w^{(L)}_t I^{(L)}_t + w^{(R)}_t I^{(R)}_t + w^{(P)}_t I^{(P)}_t + \eta \cdot \mathbb{1}\{C_t>\tau_C\}.

An **alarm** occurs when Rt≥τonR_t \ge \tau_{\text{on}}. To avoid chattering, use **hysteresis**: stay in alarm until Rt≤τoff<τonR_t \le \tau_{\text{off}} < \tau_{\text{on}}.

Upstream Context

If node u is upstream of node v with travel time Δu→v\Delta_{u\to v}, then v increases its sensitivity when Rt−Δu→v(u)R^{(u)}_{t-\Delta_{u\to v}} is high—implemented as a multiplicative factor on k1,k2k_1, k_2 (lowering them) within bounds to prevent over-reaction.

Edge Implementation

- **Constant-time updates:** EWQ via P² keeps only a handful of markers; EWMA/CUSUM are scalar.
- **Memory footprint:** < 2–4 kB per node for stats and small buffers.
- **Energy:** duty-cycle the ultrasonic/pressure sensor; compute every 1–5 minutes; transmit only on state changes or periodic health beacons.
- **Communication:** LoRaWAN Class A preferred; payload includes RtR_t, flags, and compressed features. NB-IoT fallback for critical alerts.
- **Bootstrapping:** cold-start with conservative thresholds, then transition to adaptive after N observations or after 24–72 hours.
- **Regime Switching:** a two-state Hidden Markov Model (Dry/Wet) can switch parameter sets (α,k1,k2,θ)(\alpha, k_1, k_2, \theta) seasonally.

Pseudocode (Edge)

```
Initialize EWQ(median, q90), S=init_scale, d_tilde=0, C=0
state = NORMAL
for each new sample (x_t, r_t):
  update EWQ with x_t
  update robust scale S (exp-MAD surrogate)
  d = x_t - x_{t-1}; d_tilde = alpha*d + (1-alpha)*d_tilde
  W = lambda*W + r_t
  C = max(0, C + (x_t - (median + gamma*S)) - kappa)
  I_L = sigmoid((x_t - q90)/ (k1*S))
  I_R = sigmoid(d_tilde / (k2*S/dt))
  I_P = sigmoid((r_t + beta*W - theta)/k3)
  (wL,wR,wP) = normalize(0.5+0.5*I_P, 0.3+0.7*I_P, 0.2)
  R = wL*I_L + wR*I_R + wP*I_P + eta*(C>tauC)
  if state==NORMAL and R >= tau_on:
    raise ALARM; state=ALARM
    transmit(event_packet)
  if state==ALARM and R <= tau_off:
    clear ALARM; state=NORMAL
    transmit(clear_packet)
```

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periodic: transmit health beacon

STATISTICAL ANALYSIS

Performance is evaluated over repeated simulated storms (Section "Simulation Research and Result") with consistent seeds across methods to enable paired comparisons. Primary metrics: **detection latency** (minutes from true onset to first alarm), **true positive rate** (TPR), **false alarm rate** (FAR; per day), **precision**, **F1-score**, and **AUC-PR**. Latency and FAR are compared using **paired t-tests** (latency) and **Wilcoxon signed-rank** (FAR, non-normal); proportions (TPR/precision) use **McNemar's** test on event-level contingency.

Notes: Numbers summarize 200 storm realizations across 20 nodes with noise/drift (see next section). MCAT significantly reduces latency vs. moving-average (Δ=7.3 min, $p<0.001$, paired t-test) and FAR ($p<0.01$, Wilcoxon). Improvements in F1 are significant via McNemar's test ($p<0.01$).

SIMULATION RESEARCH AND RESULT

Experimental Design

We synthesize a river network with 20 nodes arranged along three tributaries merging into a main stem. **Travel times** between nodes are drawn from 5–45 minutes depending on reach length and slope. **Rainfall forcing** follows four archetypes per day, randomly sampled:

1. **Flash storm** (10–20 min high-intensity burst).
2. **Prolonged monsoon cell** (90–180 min moderate intensity with lulls).
3. **Back-to-back bursts** (two flashes separated by 30–60 min).
4. **Slow build-up** (gentle rise reaching near-bankfull).

Rainfall rtr_t is converted to **runoff** using an S-curve loss with **Green–Ampt-like** infiltration and antecedent wetness memory WtW_t. Runoff is routed through a **unit hydrograph** per sub-catchment and convolved along the network to yield **true water levels** xttruex^{\text{true}}_t. Flood onset time for each node is defined as the first crossing of a hydrodynamically determined danger level H†H^\dagger tied to the bankfull discharge.

Sensor Layer: We superimpose measurement effects:

- **Noise:** zero-mean, heteroskedastic (σ = 5–15 mm) with occasional spikes.
- **Drift:** slow bias ±5–20 mm over 1–3 days to mimic sensor aging or mounting shifts.
- **Missingness:** packet drop 3–10% (bursty); random gaps during storms (gateway congestion).
- **Clock drift:** ±1–2 s per hour, corrected at daily sync.

Baselines:

- **Static:** single H*H^* per node calibrated from long-term quantile (e.g., 95th percentile of dry season).
- **Moving-average:** EWMA mean/variance with kσ rules.
- **CUSUM:** tuned reference and drift for fastest average run length under non-event.

Proposed MCAT: As in Methodology, with α=0.2\alpha=0.2, k1=1.5k_1=1.5, k2=1.0k_2=1.0, β=0.25\beta=0.25, θ\theta set to the 60th rainfall percentile, η=0.1\eta=0.1, τC\tau_C from target false alarm rate, τon=0.75\tau_{\text{on}}=0.75, τoff=0.55\tau_{\text{off}}=0.55, hysteresis window 15 minutes. Upstream context scales k1,k2k_1,k_2 by 0.85 when the nearest upstream node has R>0.8R>0.8 within its travel time.

Evaluation Protocol:

We simulate **10 days** with 1–2 storm archetypes per day → ~200 node-events. Each method observes only sensor-corrupted

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data. We compute event-level metrics and per-day FAR. Energy proxy counts radio transmissions (alarms, clears, and health beacons).

RESULTS

1) Detection Latency.

MCAT achieves a **median latency of 11.3 minutes**, beating CUSUM by ~5.6 minutes and moving-average by ~7.3 minutes. Gains are largest in **flash storms** (Δ≈9–12 minutes) due to the **rate-of-rise indicator** and **rain-conditioned weighting** that allows elevated sensitivity *before* levels exceed static high quantiles. In **slow build-up** cases, all methods perform similarly; MCAT still avoids false triggers by relying more on I(L)I^{(L)} than I(R)I^{(R)}.

2) Accuracy and False Alarms.

MCAT maintains **TPR ≈ 0.90** and **precision ≈ 0.88**, yielding **F1 = 0.89**. The **false alarm rate** drops to **0.18/day** (median), roughly **half** that of CUSUM (0.35/day). The key is combining **robust scale (MAD)** with **hysteresis**; spikes elevate indicators briefly but rarely push RtR_t above τon\tau_{\text{on}} long enough to trigger, and if they do, the off-threshold prevents flip-flop.

3) Robustness to Drift and Missingness.

Under **sensor drift**, static thresholds deteriorate rapidly; moving-average adapts but inflates variance and FAR. MCAT's **quantile tracking** shifts the baseline while **CUSUM** supplies persistence checking. With **10% packet loss**, MCAT's performance degrades modestly (~+1.2 min latency), thanks to single-pass statistics and independence from long windows.

4) Upstream Context Benefit.

Activating upstream sensitivity scaling reduces median latency by **~2 minutes** on confluences and main-stem nodes without notable FAR increase. As expected, the benefit is negligible for headwater nodes.

5) Energy and Bandwidth.

Event-driven radio yields **~65% fewer transmissions** vs. periodic reporting (5-min cadence) while preserving more informative alerts. MCAT's edge filtering avoids sending raw jitter, extending battery life (qualitative proxy: fewer wakeups, fewer radio TX).

6) Ablation Study.

- Remove **rate-of-rise** ⇒ latency +4.1 minutes on flash storms.
- Replace **MAD** with standard deviation ⇒ FAR +0.09/day due to outliers.
- Disable **hysteresis** ⇒ oscillations during recession limbs; precision −0.05.
- Remove **upstream context** ⇒ latency +~2 minutes on downstream nodes.

7) Statistical Significance.

Paired analyses across the same event realizations show MCAT's latency gains over moving-average and static thresholds are **highly significant** ($p<0.001$). FAR reductions vs. CUSUM are significant at **$p<0.01$** (Wilcoxon). Confidence intervals for F1 improvement (MCAT vs. next best) exclude zero at 95%.

Qualitative Behavior.

Plots (not shown) reveal MCAT's RtR_t rises earlier during rainfall bursts due to I(P)I^{(P)} and I(R)I^{(R)}, then remains elevated while CUSUM integrates; alarms persist past the peak and clear smoothly as RtR_t falls through τoff\tau_{\text{off}}, avoiding rapid toggling that can spam operators.

CONCLUSION

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This manuscript presented an **adaptive, multi-criteria threshold** algorithm tailored for **real-time flood detection on IoT sensors**. The design goals—**fast detection**, **low false alarms**, **edge feasibility**, and **network awareness**—are met by combining (i) **online percentile tracking** (EWQ/P^2) for dynamic baselines, (ii) **robust dispersion** (MAD) to tolerate spikes, (iii) **rate-of-rise** to capture flash dynamics, (iv) **change-point accumulation** (CUSUM) for persistence, (v) **hysteresis** to stabilize state transitions, and (vi) **upstream-aware sensitivity** to anticipate propagating waves. In controlled simulations, the method reduced median detection latency to ~11 minutes, increased F1 to ~0.89, and halved false alarms relative to classical baselines—all while remaining lightweight enough for LoRaWAN-class devices.

Practical guidance:

- Start conservatively (higher τon\tau_{\text{on}}), auto-tune toward target FAR using in-field beacons.
- Choose quantile levels (e.g., 0.9) to match channel noise and expected flashiness; lower in flashy headwaters.
- Use **MAD** for scale; even coarse approximations outperform variance under spikes.
- Calibrate upstream travel times roughly; perfect hydrodynamics is unnecessary to gain latency improvements.
- Implement **hysteresis** and minimum dwell times to prevent oscillation during recession limbs.
- Prefer **event-driven** transmission with succinct summaries (risk, slope, context flag) to save battery and bandwidth.

Limitations:

- Extreme, unprecedented events (levee breaches, debris jams) may break learned baselines; manual overrides and operator dashboards remain essential.
- Pressure sensors in tidal or backwater reaches may require **two-way** context (downstream tides) and more complex priors.
- Our simulation omits snowmelt dynamics, urban drainage control logic, and human interventions (gate operations).
- Field deployment needs **regular re-zeroing** and health checks for drift beyond algorithmic compensation.

Future work:

- Bayesian online change-point models with physically informed priors;
- Multi-modal fusion including **radar rainfall** and **satellite nowcasts**;
- Cooperative detection (consensus across nodes) with **distributed optimization** under communication constraints;
- On-device explainability: logging which indicator/weight crossed the line, to support trust and auditing;
- Learning upstream travel times from data via causal time-shift inference.

By emphasizing **adaptivity, robustness, and implementability**, the proposed MCAT framework offers a practical path to more reliable flood early warning in resource-constrained settings—particularly valuable for monsoon-dominated regions and small flashy catchments where every minute of earlier detection translates into lives and property saved.

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