

Article

Reservoir Inflow Risk-Window Early Warning Informed by Monitoring and Routing-Decay Modeling

Boming Wang ¹, Junfeng Mo ², Ersong Wang ³, Zuolun Li ³ and Yongwei Gong ^{1,*} 

¹ Key Laboratory of Urban Stormwater System and Water Environment, Ministry of Education, Beijing University of Civil Engineering and Architecture, Beijing 100044, China; wangboming0122@163.com

² Shanghai Municipal Engineering Design Institute (Group) Co., Ltd., Shanghai 200092, China; mojunfeng@smedi.com

³ Beijing Energy Conservation & Sustainable Urban and Rural Development Provincial and Ministry Co-Construction Collaboration Innovation Center, School of Environment and Energy Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China; wangersong@126.com (E.W.); lizhuolungk@163.com (Z.L.)

* Correspondence: gongyongwei@bucea.edu.cn

Abstract

Against the backdrop of multi-source water transfers and increasingly frequent extreme rainfall, short-term deterioration of reservoir inflow water quality has become a key risk to intake safety, treatment operations, and urban water-supply security. Traditional assessments based on static thresholds and annual or seasonal averages often fail to identify high-risk periods at the event scale. Using continuous online monitoring data from 2021 to 2024 for the inflow of Yuqiao Reservoir, Tianjin, China, this study developed a month-specific dynamic-threshold framework and green/yellow/red risk windows and integrated a reach-wise river–reservoir routing scheme; a two-box decay model; and a three-class risk trigger into a unified analytical framework for long-term background characterization, event propagation analysis, source-contribution interpretation, and early-warning evaluation. Results show that the permanganate index (COD_{Mn}) exhibits an overall stable-to-declining background with pronounced wet-season pulses, whereas total nitrogen (TN) and total phosphorus (TP) remain at moderate-to-high levels, with yellow/red risk windows clustering markedly in the wet season. In typical red and yellow events, nitrogen contributions from upstream control sections progressively accumulate toward the reservoir inlet along the river–reservoir cascade system, whereas in some events the residual contribution from unmonitored near-inlet inflows becomes dominant. The COD_{Mn} -based three-class trigger achieves an overall accuracy of approximately 71.5% and shows comparatively strong identification of yellow-level risk, while remaining conservative for red-level alarms. These findings indicate that coupling month-specific dynamic thresholds with event-scale routing-decay analysis and trigger-based classification can support inflow monitoring, intake-risk early warning, and coordinated operation of key upstream reaches and near-reservoir control zones in water-transfer–reservoir integrated systems.



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Keywords: inflow water quality risk; dynamic thresholds; core warning window; two-box routing-decay model; relative source contributions

1. Introduction

Reservoir-type drinking-water sources are a critical component of urban source-water security, and short-term deterioration of inflow water quality can directly affect intake

safety, coagulant dosing, and operational scheduling decisions. Under intensified watershed development, aggravated non-point source pollution, and increasingly frequent extreme rainfall, reservoir inflows are more prone to short-duration high-concentration episodes dominated by organic matter and nutrients. Related studies have shown that even when annual or seasonal average water quality meets standards, event-period “risk windows” can still exert substantial impacts on plant operation and downstream water supply [1–6]. Overall, urban drinking-water sources face multiple compounding pressures, whereas current monitoring and assessment still rely mainly on long-term metrics such as annual/seasonal averages, compliance rates, or exceedance days. This results in a clear deficiency in identifying and quantifying event-scale risks at hourly-to-daily timescales [7–9], making it urgent to strengthen early warning of inflow “risk windows” under the constraint of routine and publicly available monitoring.

Comparative studies between urban and non-urban catchments indicate that under storm conditions, flow pathways and land use patterns can significantly influence downstream river reaches and reservoir inflow water quality [10,11]. Storm events can rapidly deteriorate source-water quality by importing elevated loads of nutrients and organic matter, underscoring the need for event-scale monitoring and early-warning models for drinking-water safety [12,13]. In typical drinking-water reservoirs, flood runoff and water-level fluctuations can further alter thermal stratification and the composition of dissolved organic matter, leading to staged increases in nutrients and color and markedly elevating the pressure on coagulation and disinfection processes [1,2,14,15]. These findings suggest that inflow water quality risk is characterized by event-driven behavior and strong upstream–downstream coupling. Without event-scale identification of “when, what processes, and along which pathways” lead to the opening of risk windows, it is difficult to implement timely and targeted scheduling and emergency treatment measures.

To characterize multi-parameter water-quality status and associated risks, a range of methods has been proposed domestically and internationally, including water quality indices (WQI/WQI_{min}), water-quality deterioration rates, and probability-distribution and frequency analyses. These methods integrate concentrations of multiple pollutants into comparable grades or risk classes and have been applied to assess spatiotemporal patterns of water-quality evolution and health risks at large-reservoir and watershed scales [16–19]. Extensive engineering practice and cascade-reservoir studies show that large-scale water-transfer projects and joint operation of reservoir groups can modify hydrodynamic conditions and nutrient-transport processes at the inlet and within the reservoir, thereby affecting water quality in receiving areas and downstream risks [20–23]. Hydrodynamic regulation plays an important controlling role in the spatial distribution of nutrients and trace metals within reservoirs and downstream [19,24–27]. While these studies help depict long-term spatiotemporal differences and overall risk levels, they often rely on fixed thresholds or static classification standards, making it difficult to reflect the degree of “relative abnormality” under different seasons and hydrological scenarios [8,9]. Moreover, they frequently focus on single stations or a small number of sections, lacking characterization of upstream event propagation and attenuation along river–reservoir systems [3,26,28]. Their outputs also tend to remain at the level of “risk grade identification,” with limited linkage to concrete decision-making steps such as plant scheduling and early warning triggering [19,22,29].

With the proliferation of online monitoring and public data platforms, an increasing number of studies have used high-frequency water-quality time series to develop machine-learning or deep-learning models that predict future changes in key indicators and provide exceedance warnings [7,13,30]. Building on this, some studies have introduced seasonal or quantile-based dynamic thresholds and event-level indicators to enhance the identifi-

cation of short-duration risk processes [8,9] and have employed simplified routing-decay models in typical water-transfer projects and multi-reservoir–river cascade systems to analyze upstream event lag times, load reductions, and contributions from control sections [24,26,28]. However, such data-driven or mechanistically simplified approaches still generally depend on numerous parameters and have limited physical interpretability, with insufficient consideration of hydrodynamic processes between upstream and the reservoir inlet, pollutant-load decay, and event-propagation lag times [9,31]. Early warning studies oriented toward drinking-water plant scheduling often focus on single-point exceedance prediction or empirical threshold triggering, and systematic exploration of an integrated framework of “multi-section along the pathway + event windows + interpretable trigger rules” remains limited [9,31].

To address these gaps, this paper develops an inflow water-quality early warning framework centered on drinking-water intake safety by combining publicly available on-line monitoring data, month-specific dynamic thresholds, and a simplified routing-decay mechanism from the perspective of event-scale risk windows. Taking Tianjin’s Yuqiao Reservoir and its upstream multi-reservoir–river cascade system as the study area, we use continuous online water-quality and hydrological records from 2021 to 2024, which represent the currently available continuous monitoring period with sufficient cross-station comparability for event-scale analysis and framework evaluation, to (i) construct month-specific dynamic thresholds and descriptive risk-window overlays at the inlet, (ii) perform event-scale upstream-to-inlet routing-decay simulation and load decomposition, and (iii) develop a monthly quantile-based risk trigger and three-class early-warning classification for operational scheduling. Through empirical analyses of typical red/yellow events, this study aims—under the constraint of relying only on routine and publicly available monitoring—to organically link dynamic risk identification, the mechanism of upstream event propagation, and executable inlet early warning rules, thereby providing a transferable technical pathway for risk management of drinking-water sources in river–reservoir cascade systems.

2. Materials and Methods

2.1. Study Area and Data

Yuqiao Reservoir is located in the lower reaches of the Luan River system within the Haihe River Basin. It serves as the core surface-water source for Tianjin’s centralized water-supply system and as an important regulating reservoir, providing long-term water supply to the urban core and surrounding areas through the Luan River Water Diversion Project. The study area is characterized by higher elevations in the north and lower elevations in the south, transitioning from low-to-middle mountains and hills in the north to an alluvial–proluvial plain in the south. Land use exhibits an overall gradient of “upstream ecological source area–midstream agricultural area–downstream urban area”: the upstream mountainous region is dominated by forests and grasslands, the midstream comprises valley farmland and rural settlements, and the downstream coastal plain and Tianjin urban area contain concentrated impervious surfaces. Together, these features provide diverse pollution sources and hydrological backgrounds that influence inflow water quality. Tianjin has established a multi-source joint water-supply pattern relying on the Luan River diversion and the Middle Route of the South-to-North Water Diversion Project. This study focuses on the serial Luan River–Yuqiao Reservoir system: Panjiakou and Daheiting are upstream controlling reservoirs; Guojiatun, Xinglongzhuang, Shangbancheng Bridge, and Wulongji are mainstem monitoring stations; Lihe Bridge and Guohe Bridge are located in the near-reservoir river reaches; and the Yuqiao inlet represents the water quality conditions at the intake (Figure 1). Previous studies have shown that since the 1990s, under the

combined effects of sustained nutrient inputs and altered hydrodynamic conditions, Yuqiao Reservoir has been at the transition margin from eutrophic to hypereutrophic status. Multi-year chlorophyll-a concentrations have remained high, and cyanobacterial blooms have occurred repeatedly, imposing persistent pressure on drinking-water quality and supply security in Tianjin [32,33].

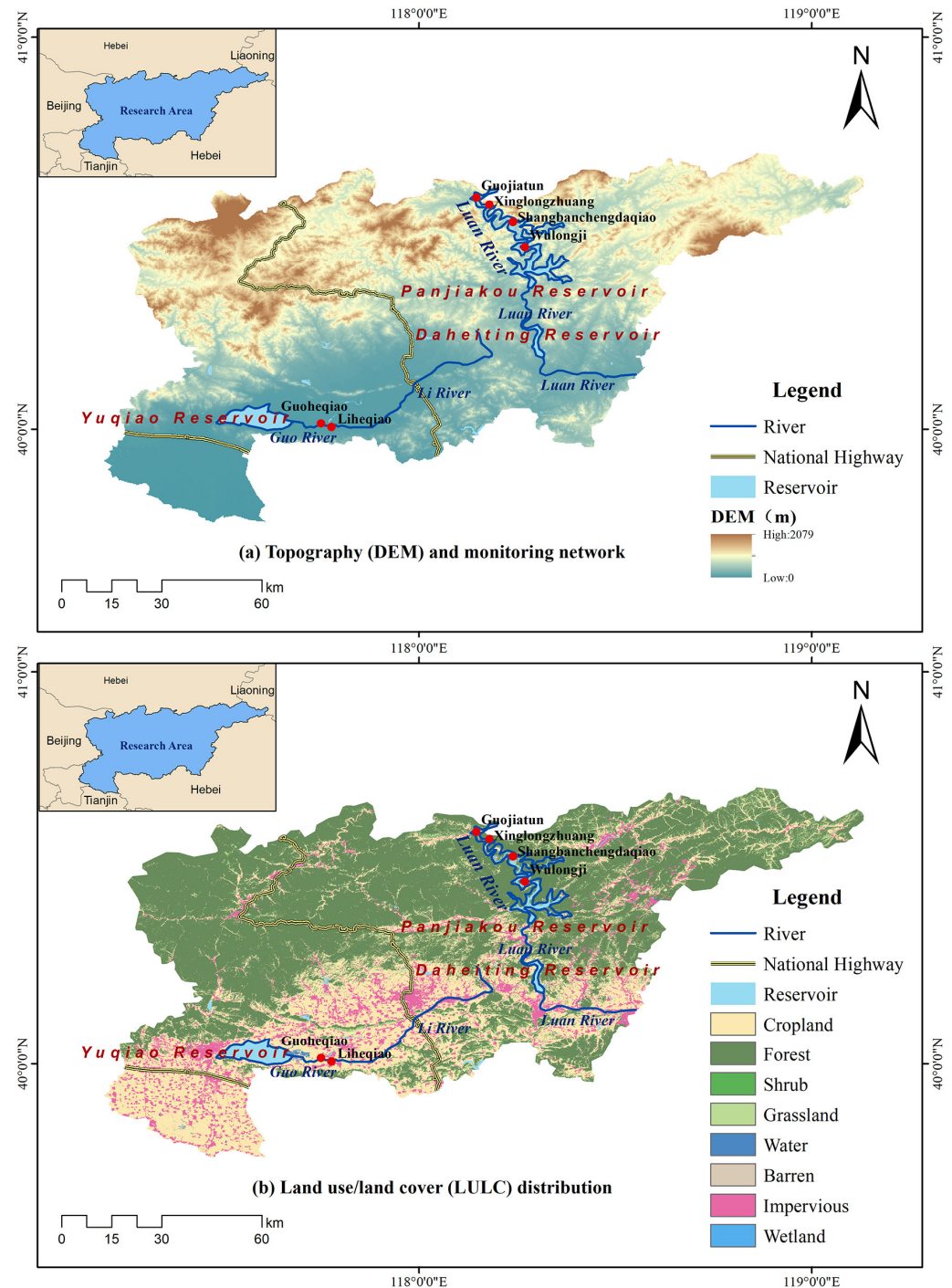


Figure 1. Study area and monitoring network of the Yuqiao–Luanhe cascade system. (a) Digital elevation model (DEM) with the monitoring sites and major rivers/reservoirs. (b) Land use/land cover (LULC) map of the basin.

Hydrological and storage data were obtained from the National Water and Rain Information Platform, covering hourly or 15 min records of discharge, water level, and storage for key controlling reservoirs (e.g., Panjiakou and Daheiting) and major hydrological

stations (e.g., Guojiatun, Wulongji, Lihe Bridge, and Guohe Bridge). Water-quality data were sourced from the National Real-Time Publication System for Automatic Surface-Water Quality Monitoring, including 4-hourly automatic monitoring time series of TN, TP, $\text{NH}_3\text{-N}$, COD_{Mn} , turbidity, and related indicators at the upstream control sections and the Yuqiao inlet. Online monitoring data from 2021 to 2024 were used because this period represents the currently available continuous monitoring interval with relatively consistent multi-station coverage and cross-station comparability for the event-scale analyses conducted in this study. The selected period covers different inflow regimes and hydrological year types and is sufficient to support seasonal threshold construction, typical-event identification, routing-decay analysis, and preliminary trigger evaluation. However, it is not intended to support strong long-term climatological inference, and the related limitation is further discussed in Section 4.2. After quality control and gap filling, the available water-quality and hydrological inputs were standardized to a common 4-hourly time base in the main preprocessing stage. This 4-hourly dataset was used as the preprocessed input basis for subsequent event-scale analyses, whereas additional hourly resampling was introduced only within stage B for transport simulation, hydraulic mixing, ETA alignment, and trigger evaluation. Detailed data sources and preprocessing procedures are provided in Section 2.2.

2.2. Research Framework, Data Preprocessing, and Dynamic-Threshold System

To enable identification and early warning of reservoir inflow water quality risk windows using only routine online monitoring data, this study develops an integrated workflow of “data preprocessing-dynamic thresholds and risk windows-routing-decay and load decomposition-risk trigger” (Figure 2). First, multi-station online water-quality and hydrological records from 2021 to 2024 are subjected to quality control and time harmonization to generate baseline time series for long-term background characterization and event identification (stage 0). Second, a month-specific quantile-based threshold system is constructed at the inlet for indicators such as COD_{Mn} , and hourly concentrations are classified into green/yellow/red categories to provide unified decision boundaries for subsequent event identification and risk statistics. Third, based on event-scale risk windows and the upstream-to-inlet pathway, a two-box routing-decay model is established, and scenario simulations are performed to further decompose the inflow event loads of indicators such as TN during typical events. Finally, using inlet event features under different decay scenarios, the dynamic thresholds are combined to build a three-class (green/yellow/red) risk trigger, and warning performance is evaluated using a confusion matrix (see Section 2.3 for the implementation of Stages A–C).

Within this framework, data preprocessing and dynamic-threshold construction provide the key foundation linking “long-term background-event identification-trigger-based classification”. Prior to inflow-risk analysis, water-quality and hydrological datasets must be placed on a unified time base, outliers removed, and a dynamic-threshold system suitable for event identification established. In the main preprocessing stage, the available water-quality and hydrological records were quality-controlled, gap-filled as needed, and aligned to a common 4-hourly time base. This 4-hourly dataset was used for baseline characterization and stage A event identification. For stage B only, the 4-hourly inputs were further converted to an hourly time axis to support transport simulation, hydraulic mixing, ETA alignment, and trigger evaluation. Specifically, water-quality series were reindexed to an hourly timeline and interpolated in time, whereas discharge series were resampled to hourly resolution using the configured forward-fill scheme. Accordingly, the operational time axis in stage B was hourly, while the upstream preprocessed inputs remained at 4 h resolution.

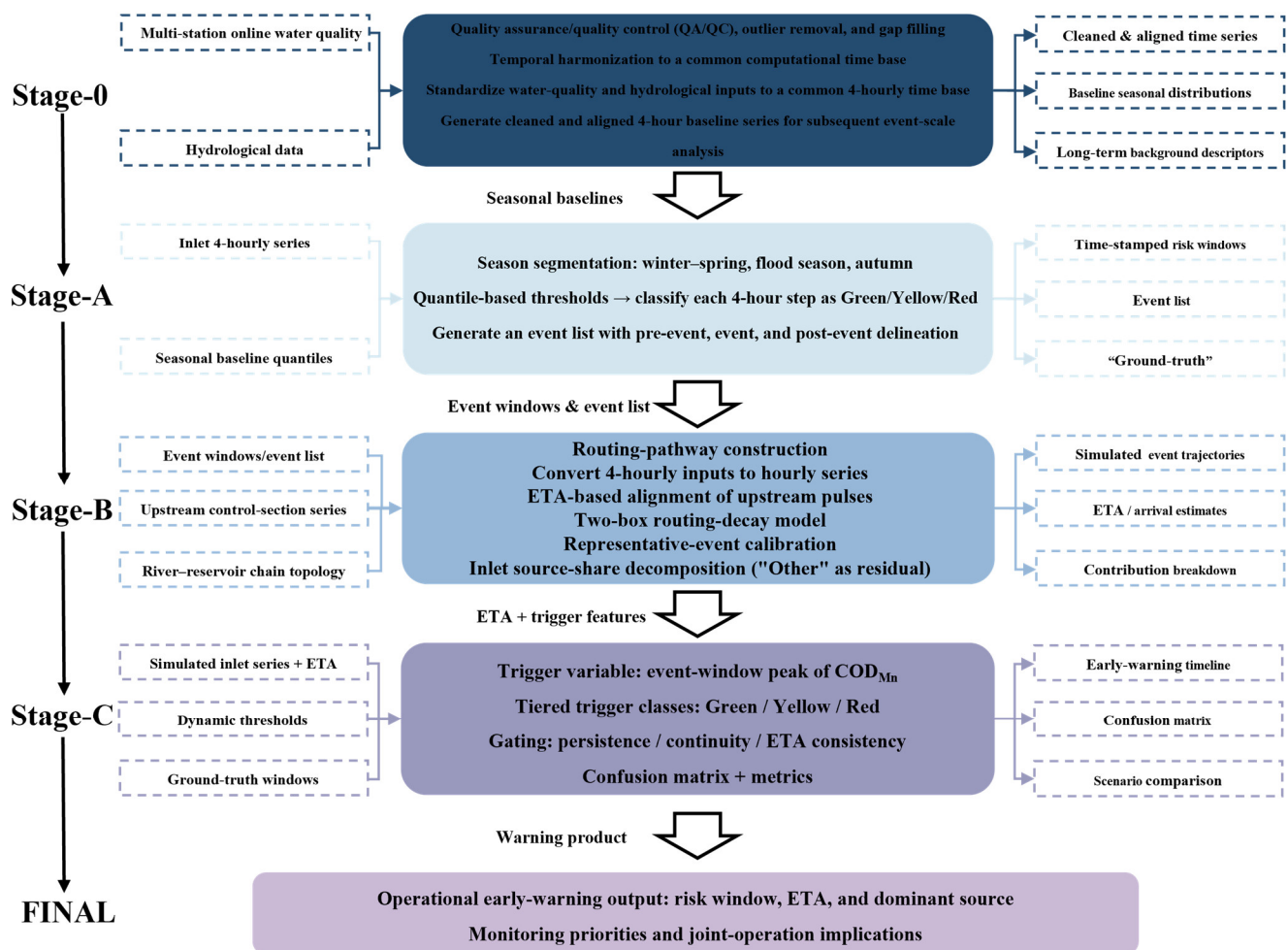


Figure 2. Method flowchart.

Given the pronounced temporal variation of source-water quality, this study distinguishes between descriptive monthly threshold overlays and formal monthly trigger thresholds. For the operational trigger, a month-of-year quantile table is defined at the inlet station for COD_{Mn} , in which q_{low} , q_{mid} , and q_{high} correspond to the 25th, 50th, and 75th percentiles, respectively. These month-specific thresholds are used to define trigger classes as green for $C_{\text{mid}} < q_{\text{low}}$, yellow for $q_{\text{mid}} \leq C_{\text{mid}} < q_{\text{high}}$, and red for $C_{\text{mid}} \geq q_{\text{high}}$, while values within $q_{\text{low}} < C_{\text{mid}} < q_{\text{mid}}$ are treated as non-trigger transition intervals rather than as a formal warning class. This monthly quantile-based scheme is used as the method of record for operational triggering because it provides an explicit and reproducible set of boundaries for subsequent trigger construction, window aggregation, and performance evaluation. In parallel, the long-term overview plots in Figures 3 and 4 display month-specific q_{mid} and q_{high} overlays to visualize the median background level and an upper monthly reference line at the inlet.

The month-specific thresholds serve two related but distinct purposes in this study. First, the descriptive $q_{\text{mid}}/q_{\text{high}}$ overlays shown in Figures 3 and 4 are used to visualize long-term background variation and to support interpretation of inlet risk-window patterns across years. Second, the monthly quantile table ($q_{\text{low}}/q_{\text{mid}}/q_{\text{high}}$) provides the formal boundaries for the operational three-class trigger, such that model-derived event features can be compared against explicit monthly thresholds to build the confusion matrix and evaluate warning performance. Consequently, under the constraint of relying only

on publicly available online monitoring, the framework remains interpretable while still capturing short-duration high-risk processes at the reservoir inlet.

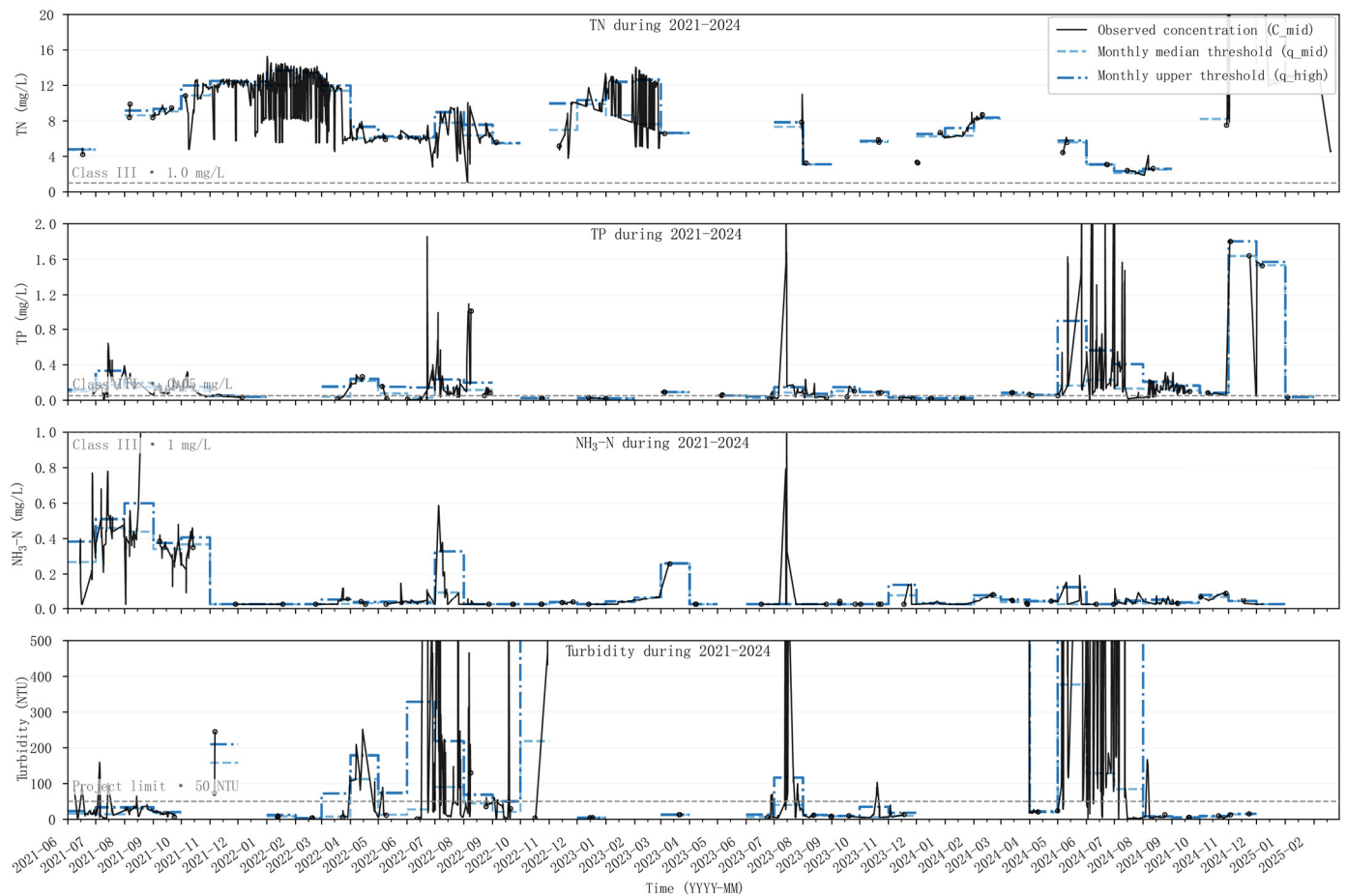


Figure 3. Long-term evolution of multiple water-quality indicators at the Yuqiao Reservoir inlet (2021–2024), with descriptive month-specific q_{mid}/q_{high} threshold overlays for long-term interpretation.

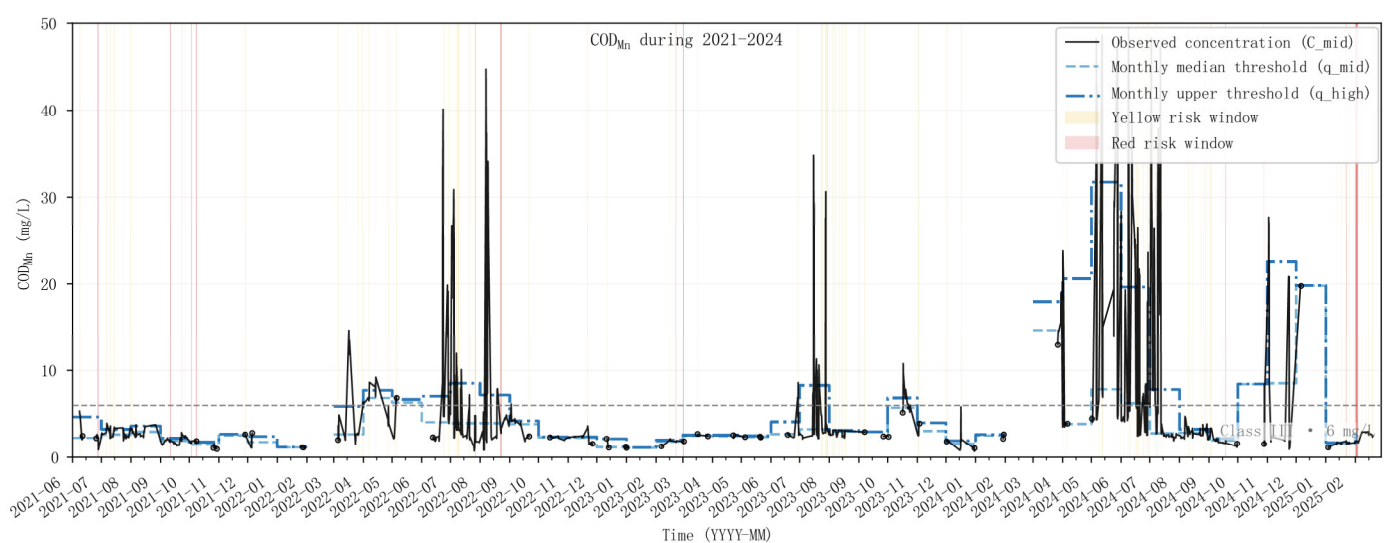


Figure 4. Long-term COD_{Mn} time series at the Yuqiao Reservoir inlet (2021–2024), with descriptive month-specific q_{mid}/q_{high} threshold overlays and the corresponding risk-window visualization.

2.3. Integrated Event-Scale Workflow for Event Identification, Routing-Decay, and Trigger-Based Classification (Stages A–C)

2.3.1. Overview of the Integrated Event-Scale Workflow

Building on the dynamic-threshold system, this study integrates event identification, upstream-to-inlet routing-decay simulation, and trigger-based three-class early-warning classification into a reproducible event-scale analytical workflow (stages A–C), forming a closed loop of “risk-window identification, event-propagation interpretation, and warning-performance evaluation”.

2.3.2. Event Identification and Delineation of Risk Windows (Stage A)

Based on the month-specific inlet threshold references described in Section 2.2, a 4-hourly COD_{Mn} sequence is screened to delineate elevated inlet periods and corresponding event windows. In this stage, q_{mid} and q_{high} are used as month-specific reference levels for descriptive inlet event-window interpretation, while the formal three-class operational trigger is introduced later through the tuned monthly quantile table in stage B/stage C. When COD_{Mn} remains elevated for a number of consecutive time steps and satisfies criteria such as a minimum duration and merging of brief dropouts, the corresponding period is delineated as a yellow or red event window for subsequent routing-decay and trigger analyses. Meanwhile, the responses of TN, TP, and other indicators within the same period are recorded to enhance the robustness of event identification. Each event is further partitioned into three stages—pre-event, event period, and post-event—representing pollutant accumulation, peak exposure, and recession/attenuation, respectively, thereby providing event-scale risk-window boundaries for load estimation and warning evaluation. By combining the peak timings of TN and COD_{Mn} at upstream control sections, an ETA (estimated time of arrival) window corresponding to the inlet event is constructed to align upstream stations with the inlet in time, providing complete event-scale inputs for subsequent routing-decay calculations and trigger-based classification.

2.3.3. Two-Box Routing-Decay Model and Source Decomposition of Event Loads (Stage B)

To characterize, at the event scale, the transport and attenuation of upstream pollution pulses toward the reservoir inlet, each “upstream control section-inlet” pathway is simplified into a two-box model with a unified structure. The model consists of a fast box and a slow box representing short- and long-residence water bodies, respectively, and each box follows first-order mixing and decay processes. The corresponding conceptual mass-balance relationships are summarized in Equations (1) and (2), which describe the pathway-scale two-compartment representation used here to interpret transport, attenuation, and outlet response:

$$C_1^{t+\Delta t} = C_1^t + \frac{\Delta t}{\tau_1} (C_{in}^t - C_1^t) - k_1 \Delta t C_1^t \quad (1)$$

$$C_{out}^t = C_2^t \quad (2)$$

In these equations, C_1^t and C_2^t denote the representative concentrations in the fast and slow boxes at time step t , respectively; C_{in}^t is the pathway input concentration; C_{out}^t is the pathway outlet concentration; τ_1 and τ_2 are the characteristic residence times of the fast and slow boxes; k_1 and k_2 are first-order decay coefficients; and Δt is the computational time step. These equations are used here as a conceptual two-compartment representation of pathway attenuation and outlet response. In the implemented stage B workflow, the propagated front concentration was evaluated on an hourly time axis and then transformed into low-, mid-, and high-decay trajectories, which provide the practical basis for the inlet concentration series used in subsequent triggering and event-window analysis. In this stage,

the concentration inputs were obtained by converting the preprocessed 4-hourly water-quality series to an hourly time axis through time-based interpolation, while discharge was converted from 4-hourly to hourly resolution through forward fill under the current configuration. This hourly treatment was introduced to provide a common operational time base for routing, mixing, and event-window trigger extraction, rather than to reconstruct true sub-hour dynamics.

Key conceptual parameters of the two-box representation include the characteristic residence times τ_1 and τ_2 and the decay-related coefficients k_1 and k_2 , which jointly control pathway retention, attenuation strength, and outlet response. One representative red event and one representative yellow event in 2023 were selected. Under the constraint of the ETA window, the observed inlet TN hydrograph was used as the calibration target. Event-based calibration was then performed so that the simulated process matches observations as closely as possible in terms of peak magnitude, arrival time, and tail recession/attenuation. A chained river–reservoir cascade system was then constructed along “Guojiatun → Xinglongzhuang → Shangbancheng Bridge → Wulongji → Panjiakou → Daheiting → Lihe Bridge → Guohe Bridge → inlet”, where the output of each upstream unit serves as the input to the next, thereby maintaining consistent parameter interpretation along the entire pathway.

Within each red/yellow event window, the contribution of each upstream station to the inlet TN event load is calculated using the concentration series output by the two-box model together with the corresponding discharge. The event-window TN load attributed to the i -th explicit upstream pathway is defined by Equation (3):

$$L_i = \sum_{t=t_s}^{t_e} C_{i,\text{out}}(t) Q_{\text{int}}(t) \Delta t \quad (3)$$

where L_i denotes the event-window TN load attributed to the i -th explicit upstream pathway at the reservoir inlet, $C_{i,\text{out}}^t$ is the corresponding outlet concentration of that pathway, Q_{int}^t is the inlet flow used in the event-window load accounting, and Δt is the time-step length. Here, Equation (3) is used as an event-scale accounting relation to summarize pathway-specific inlet load contributions.

The total inlet TN event load can be expressed as the sum of loads from all explicit upstream pathways and the residual intermediate inflow term (Equation (4)):

$$L_{\text{inlet}} = \sum_i L_i + \text{Other} \quad (4)$$

where L_{inlet} denotes the total inlet TN event load over the event window, and “other” represents the residual contribution from intermediate inflows not covered by the chained pathway, such as near-reservoir channels, shoreline discharges, and unmonitored tributaries. In the present manuscript, Equation (4) serves as a bookkeeping relation for total event-load partitioning rather than as a direct exported model state. The relative contribution of each explicit upstream pathway is then quantified by Equation (5) to compare pathway dominance in controlling TN loads during the event period:

$$\text{Contribution Rate}_i = \frac{L_i}{\sum_j L_j} \quad (5)$$

In Equation (5), $\text{Contribution Rate}_i$ denotes the relative share of the i -th pathway within the explicitly represented upstream contributions. This expression is used as a normalized event-scale indicator for source apportionment and comparison across pathways. To facilitate event-load estimation when only summary statistics are required, the event-window mean concentration and mean discharge of the i -th upstream section are defined

by Equation (6), and the corresponding event load can be approximated by Equation (7). These expressions provide a summary-statistic approximation for event-scale interpretation rather than the unique operational computation route of the implemented code.

$$\bar{C}_i = \frac{1}{t_e - t_s} \sum_{t=t_s}^{t_e} C_{i,\text{up}}(t), \bar{Q}_i = \frac{1}{t_e - t_s} \sum_{t=t_s}^{t_e} Q_{i,\text{up}}(t) \quad (6)$$

$$L_{i,\text{up}} \approx \bar{C}_i \bar{Q}_i (t_e - t_s) \quad (7)$$

In these equations, $\bar{C}_i$ and $\bar{Q}_i$ denote the event-window mean concentration and mean discharge of the i -th upstream section, respectively, and T_e denotes the event duration. Equation (7) thus provides an event-mean approximation of upstream load magnitude when a compact window-scale summary is preferred. On this basis, the magnitude of Other during the event can be obtained using Equation (4) or, equivalently, Equation (8) and—together with station-wise contribution ratios—is used to analyze the dominance of different pathways in controlling TN loads during the event period. Equation (8) therefore provides a residual representation of non-explicit sources in the event-load accounting framework:

$$\text{Other} = L_{\text{inlet}} - \sum_i L_i \quad (8)$$

To examine the influence of attenuation strength on event propagation, three scenarios—weak, moderate, and strong decay—are constructed by perturbing a pathway-scale inlet load retention indicator across pathways, as summarized in Equation (9). This quantity is used here as a scenario-oriented comparative indicator rather than as a directly exported model state variable:

$$\alpha_i = \frac{L_i}{L_{i,\text{up}}} \quad (9)$$

In Equation (9), α_i denotes the apparent event-window retention ratio of pathway i , expressed as the ratio between the inlet-attributed load and the corresponding upstream event load. It is introduced here to motivate comparative weak, moderate, and strong decay scenarios in a compact form. Three groups of inlet event concentration and load trajectories are then generated. Under each scenario, features such as peak concentration and event duration within the event window are extracted as inputs to the stage C risk trigger and are used to compare the identification capability and robustness of the three-class classification under different decay scenarios.

2.3.4. Risk Trigger, Three-Class Classification, and Performance Evaluation (Stage C)

Building on the event windows identified in stage A and the scenario simulations in stage B, this study establishes a three-class classification system for inflow water quality risk, with risk levels defined as green (low risk), yellow (moderate risk), and red (high risk). On the observation side, 4-hourly concentrations at the inlet station are evaluated against the monthly quantile table used in the tuned operational trigger, in which q_{low} , q_{mid} , and q_{high} correspond to the 25th, 50th, and 75th percentiles, respectively. On the model side, event-window peak concentrations (or representative summary statistics) extracted from the simulated inlet trajectories under different decay scenarios are used as the single trigger variable input to the classification module. These simulated inlet trajectories were evaluated on the stage B hourly time axis derived from the original 4-hourly inputs. Thus, the trigger operated on an hourly resampled event-scale sequence rather than on direct hourly observations.

The risk trigger operates with monthly tiered thresholds coupled with gating conditions. Specifically, a trigger value is classified as green when $C_{\text{mid}} < q_{\text{low}}$, as yellow

when $q_{\text{mid}} \leq C_{\text{mid}} < q_{\text{high}}$, and as red when $C_{\text{mid}} \geq q_{\text{high}}$. Values within $q_{\text{low}} < C_{\text{mid}} < q_{\text{mid}}$ are treated as non-trigger transition intervals rather than as a formal warning class. When gate requirements—such as minimum persistence duration, temporal continuity, or ETA consistency—are not satisfied, the output is kept as green to suppress spurious activations induced by noise. At the event scale, the model-derived three-class sequence is compared against the observation-based ground truth to construct a confusion matrix, and metrics including overall accuracy, red/yellow recall, and the green $\rightarrow$ red false-alarm rate are calculated. These indicators are used to evaluate the comprehensive performance of the trigger in both identifying high-risk events and controlling false alarms (see Section 3.4 for detailed results).

To make the event-window and trigger definitions explicit, the main rule-level criteria used in this study are summarized in Table 1.

Table 1. Summary of event-window and trigger-rule definitions.

Item	Definition or Rule Used in This Study
Risk classes	Green, yellow, and red represent low-, moderate-, and high-risk states, respectively.
Trigger thresholds	Green: $C_{\text{mid}} < q_{\text{low}}$; yellow: $q_{\text{mid}} \leq C_{\text{mid}} < q_{\text{high}}$; red: $C_{\text{mid}} \geq q_{\text{high}}$.
Transition interval	$q_{\text{low}} < C_{\text{mid}} < q_{\text{mid}}$ is treated as a non-trigger transition interval rather than as a formal warning class.
Event window	A risk window is delineated when elevated COD_{Mn} conditions persist across consecutive time steps and satisfy continuity criteria.
Short-dropout merging	Brief interruptions within an otherwise continuous elevated period are merged to avoid artificial fragmentation of one event.
Event stages	Each event is divided into pre-event, event period, and post-event stages, representing antecedent accumulation, peak exposure, and recession/attenuation.
ETA consistency	Upstream peaks are aligned with the inlet event window using the estimated time of arrival (ETA) constraint.
Gate condition	If persistence, continuity, or ETA consistency requirements are not satisfied, the trigger output is kept as green.
Short-sample seasons	Seasons with markedly short sample lengths are retained only for qualitative reference and excluded from cross-year quantitative comparison.

3. Results

3.1. Long-Term Evolution of Inflow Water Quality and Seasonal Risk Background

3.1.1. Long-Term Multi-Indicator Evolution and Overview of Risk Exposure at the Inlet

From 2021 to 2024, COD_{Mn} , TN, TP, $\text{NH}_3\text{-N}$, and turbidity at the Yuqiao Reservoir inlet generally remained around—or slightly below—the Class III limits of China’s Surface Water Environmental Quality Standard but exhibited pronounced pulses during the flood season and in certain years (Figure 3) [34]. Among these indicators, COD_{Mn} was further used as the representative indicator for risk-window characterization, and its long-term dynamics are shown separately in Figure 4. COD_{Mn} was relatively stable in 2021–2022, whereas it exceeded 3 mg/L multiple times during wet periods in 2023–2024. TN, TP, and turbidity often increased synchronously during rainstorms or during water-transfer releases, while $\text{NH}_3\text{-N}$ was more sensitive to local inflows and temperature variations. Yellow/red risk windows were mainly concentrated in June–September, whereas the dry season was dominated by green windows or short yellow windows, indicating that high-risk exposure is closely associated with storm runoff and upstream inflow processes.

Our results indicate that inflow water quality during 2021–2024 was overall relatively stable during normal-flow periods, whereas short-duration pulse-type deterioration occurred more readily during the flood season. In particular, TN, TP, and turbidity often rose in concert during rainstorms or water-transfer releases, suggesting that storm runoff and hydrodynamic processes may jointly amplify inflow risk exposure. This pattern is

consistent with reports from other drinking-water reservoirs showing that organic matter, nutrients, and turbidity increase markedly with rainfall during the flood season [15,27]. In addition, our results suggest that nutrient inputs, transparency changes, and hydraulic conditions jointly contribute to the formation and amplification of risk windows, which agrees with conclusions from multivariate statistical analyses indicating that reservoir trophic status is jointly controlled by “nutrients-transparency-hydraulic conditions” [35].

In Figures 3 and 4, the blue q_{mid} and q_{high} step lines are shown as descriptive month-specific threshold overlays to visualize the monthly median background and an upper monthly reference level at the inlet. They are used for long-term interpretation and are not necessarily numerically identical to the tuned monthly trigger table adopted for operational classification.

3.1.2. Seasonal Patterns and Year-to-Year Variation in COD_{Mn} Risk Windows During 2021–2024

Seasonal statistics within the 2021–2024 study period (Figure 4; Table 2) indicate that COD_{Mn} yellow/red risk windows were most prevalent in summer and, in some years, also extended into parts of autumn and winter, whereas spring generally exhibited lower risk. In most years, the proportion of red windows in summer and autumn approached or exceeded 40%. In autumn 2023, there were almost no green windows, and TN and TP increased markedly; in spring 2024, the proportion of red windows was close to 60%, suggesting relatively sustained exposure to organic matter during the flood season and during certain non-flood periods within the present observation window. Seasons with markedly short sample lengths were retained for qualitative reference but were not included in cross-year quantitative comparison, in order to avoid unstable proportional statistics caused by limited temporal coverage.

Table 2. Seasonal proportions of COD_{Mn} risk windows at the Yuqiao Reservoir inlet from 2021 to 2024.

Year	Season	Total Hours	Green Window Proportion (%)	Yellow Window Proportion (%)	Red Window Proportion (%)
2021	Summer	1735	52.2	26.2	21.6
2021	Autumn	1040	78.8	21.2	0
2021	Winter	215	58.1	0	41.9
2022	Spring	890	29.8	50	20.2
2022	Summer	3595	35.3	20.7	43.9
2022	Autumn	635	32.3	25.2	42.5
2022	Winter	285	61.4	31.6	7
2023	Spring	375	92	8	0
2023	Summer	2165	28.2	48	23.8
2023	Autumn	685	0	42.3	57.7
2023	Winter	375	32	38.7	29.3
2024	Spring	955	12.6	27.7	59.7
2024	Summer	3370	30.6	31.3	38.1
2024	Autumn	1045	50.7	15.3	34
2024	Winter	835	17.4	38.3	44.3

Overall, the 2021–2024 records suggest a descriptive temporal pattern of high-risk COD_{Mn} exposure characterized by flood-season clustering, with anomalous autumn–winter prominence in certain years, which may reflect the combined influence of storm runoff and operational scheduling changes on elevated organic matter exposure during specific periods. This observation is broadly consistent with findings from other domestic reservoirs that rainfall runoff amplifies the transport of organic matter and nutrients and elevates risks to drinking-water sources [15,27], and it provides a temporal background for the subsequent mechanism-oriented analyses based on typical events.

3.2. Seasonal Risk Windows and Typical Red/Yellow Event Processes

3.2.1. Overview of Typical Red/Yellow Events

To compare red/yellow events under different causal backgrounds, this section selects one COD_{Mn} red event during 3–7 February 2023 and one COD_{Mn} yellow event during 17–22 February 2023, representing two typical scenarios: (i) winter low temperature with inflow dominated by upstream releases and (ii) an early-spring transition period with continuous water-transfer releases superimposed on local rainfall. The corresponding COD_{Mn} and TN trajectories and the delineation of risk windows are shown in Figures 5 and 6.

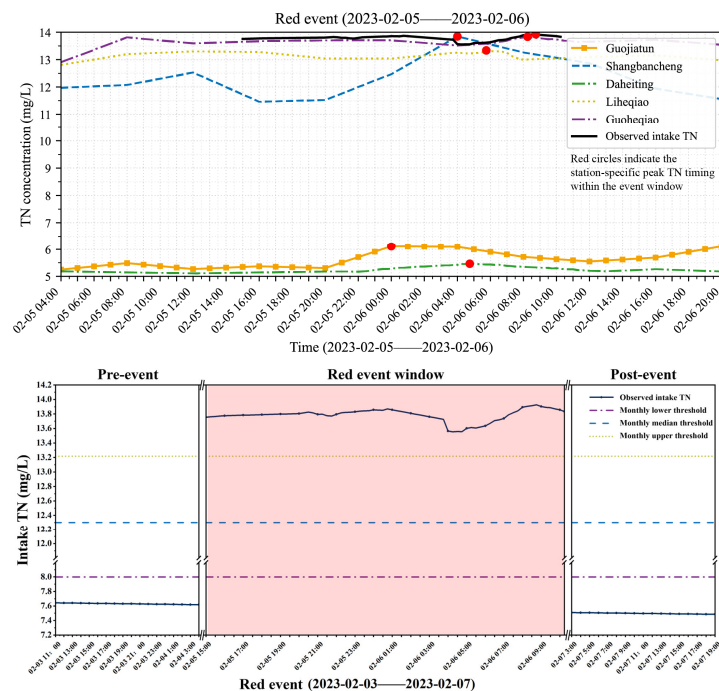


Figure 5. Typical red event: TN concentration dynamics from upstream control stations to the intake and the corresponding risk window. **Upper:** TN dynamics across upstream sections. **Lower:** intake TN with the shaded red risk window and pre-event references.

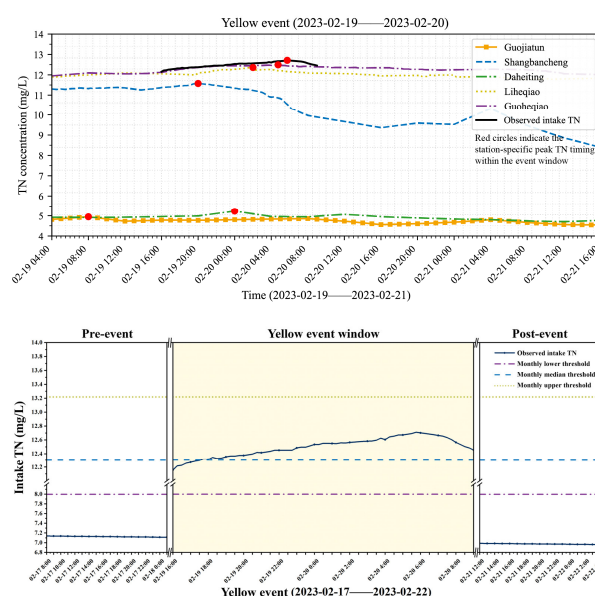


Figure 6. Typical yellow event: TN concentration dynamics from upstream control stations to the intake and the corresponding risk window. **Upper:** TN dynamics across upstream sections. **Lower:** intake TN with the shaded yellow risk window and pre-event references.

3.2.2. Process Characteristics of the Typical Red Event

During the red event (Figure 5), TN at the inlet station remains at a relatively stable background level prior to the event; after entering the red window, it rapidly jumps within several hours and exceeds the red threshold, forming a high-level plateau that persists for 1–2 d, and then gradually recedes to near the pre-event level. Along the pathway, TN peaks occur sequentially at Guojiatun, Shangbancheng Bridge, Daheiting, Lihe Bridge, and Guohe Bridge. The inter-station time lags are broadly consistent with the magnitude of delays estimated based on ETA, indicating that this red event propagates stepwise from upstream to downstream along the river–reservoir cascade system. The superposition of a strong upstream pulse and local accumulation in the middle and lower reaches jointly produces a long-duration, high-concentration red risk window at the inlet. The “sequential peak progression + high-level plateau” pattern observed in this study is consistent with high-frequency monitoring evidence showing lagged transport of nutrients and particulates during storm runoff and a pronounced event contribution [36,37].

3.2.3. Process Characteristics of the Typical Yellow Event

During the yellow event (Figure 6), TN at the inlet station gradually rises from a relatively low background and reaches its peak in the middle-to-late part of the yellow window. Concentrations are mostly distributed around the yellow threshold and only briefly approach the red threshold. After the event ends, TN returns more rapidly, exhibiting an overall moderate-risk process characterized by “gradual rise-moderate plateau-rapid recovery”. Along the pathway, TN peaks also progress from upstream to downstream; however, increases at upstream stations such as Guojiatun and Shangbancheng Bridge are limited, whereas mid- and downstream stations such as Guohe Bridge maintain elevated TN background levels during the window and contribute more prominently to the inlet TN rise. This reflects a superimposed process of “sustained high background in the middle and lower reaches + moderate upstream disturbance”. The longitudinal differences and downstream amplification observed in this study suggest that downstream reservoirs/reaches may significantly modulate upstream pollution pulses; this interpretation is consistent with observational and modeling evidence from cascaded reservoir–river systems [38].

Synthesizing the two typical events, within the same chained water-transfer system, red events tend to manifest as a strong upstream pulse superimposed on elevated conditions in the middle and lower reaches, resulting in a high-level, persistent plateau-type red window at the inlet; yellow events primarily reflect mild disturbances superimposed on an already high background in the middle and lower reaches, with inlet TN remaining at a moderate level. These process characteristics provide event-scale evidence for the subsequent interpretation of relative source contributions to inflow red/yellow events across control sections.

3.3. Upstream-to-Inlet Routing-Decay and Relative Source Contribution Analysis During Typical Events

This section uses the red and yellow core warning windows in February 2023 as representative cases. Based on the two-box routing results, event-window relative source contribution indices were estimated for COD_{Mn} , TN, TP, $\text{NH}_3\text{-N}$, and turbidity (NTU) and were grouped into five source categories: the four displayed control sections Guojiatun, Shangbancheng Bridge, Lihe Bridge, and Guohe Bridge and “Other” (Figure 7). During the study period, these four stations provided relatively complete online water-quality records suitable for event-scale comparison. “Other” denotes the aggregated contribution from unmonitored or non-explicit inflow sources not separately represented by the four displayed control sections, including near-reservoir tributaries, local channels, shoreline discharges,

and other ungauged inputs. For concentration-based indicators, the contribution indices are used to compare relative event-window source shares; for turbidity (NTU), they should be interpreted as relative turbidity contribution indices rather than strict mass loads.

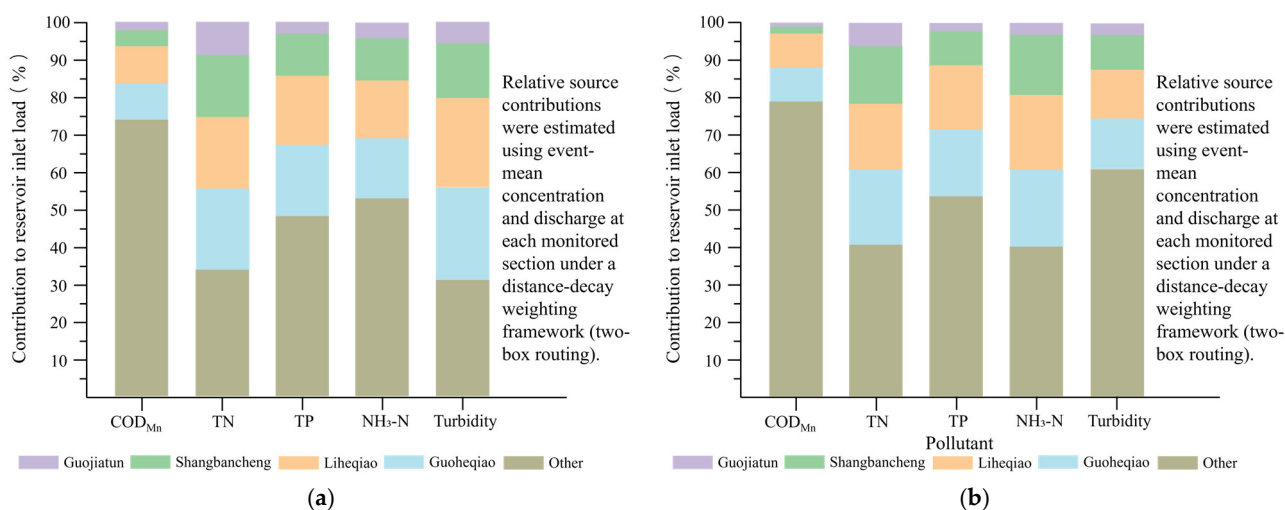


Figure 7. Relative source contribution indices for COD_{Mn}, TN, TP, NH₃-N, and turbidity (NTU) during (a) the red warning event (5–6 February 2023) and (b) the yellow warning event (19–20 February 2023). “Other” denotes the aggregated contribution from unmonitored or non-explicit inflow sources not separately represented by the four displayed control sections. For turbidity (NTU), the plotted values are interpreted as relative turbidity contribution indices rather than strict mass loads.

For the red warning event on 5–6 February (Figure 7a), the relative contribution indices of COD_{Mn} and turbidity (NTU) are clearly dominated by “Other”, and the combined contribution of the four displayed stations accounts for only a secondary share. This indicates that during this high-risk episode, organic matter and suspended particles are more strongly controlled by background conditions and local inputs in the near-inlet zone. The combined contribution of the four displayed stations to TN, TP, and NH₃-N is at a moderate level and generally exhibits a longitudinal accumulation pattern of “lowest at Guojiatun, intermediate at Shangbancheng Bridge, and highest at Lihe Bridge and Guohe Bridge”. This reflects the progressive superposition of nutrient loads along the chained system and the formation of a high-contribution zone immediately upstream of the reservoir inlet, whereas “Other” mainly amplifies event peaks for turbidity and, to some extent, selected nutrient-related indicators.

For the yellow warning event on 19–20 February (Figure 7b), the source structure of each indicator is overall similar to that of the red event: TN, TP, and NH₃-N are still dominated by Lihe Bridge and Guohe Bridge, followed by Shangbancheng Bridge, with Guojiatun contributing the least. This indicates that the along-path transport pattern of nutrient-related contribution indices is broadly consistent between the two event types. Compared with the red event, however, the share of “Other” for COD_{Mn} further increases in the yellow event, while the combined contribution of the four stations to turbidity (NTU) decreases. This suggests that under moderate-risk conditions, organic matter and turbidity contributions depend more heavily on local processes in the near-inlet zone and unmonitored side branches, rather than on concentrated upstream pulse transport.

Synthesizing the two events indicates the following. On one hand, the chained upstream reservoir group and control sections provide a consistent explanation of nutrient-related contribution indices such as TN, TP, and NH₃-N, underscoring the dominant role of upstream river reaches and reservoir groups in shaping event-period nutrient inflow patterns. On the other hand, the persistently high share of “Other” for COD_{Mn} and turbidity

(NTU) highlights that unmonitored convergence near the inlet, local discharges, and short-range wind-wave resuspension may be key contributors to event peaks of organic matter and turbidity.

Although turbidity and TP often increase together during storm-driven inflows, their source-contribution structures may differ. In the two winter/early-spring events examined here, TP was more associated with nutrient transport along the monitored upstream river-reservoir chain, whereas turbidity was more sensitive to near-inlet local inputs, shoreline disturbance, and short-range resuspension. Therefore, the dominance of “Other” for turbidity does not contradict the co-occurrence of TP and turbidity increases but indicates that nutrient-related indicators and suspended-particle signals may have different source structures within the same event window.

Overall, our results indicate that the chained upstream reservoir group and control sections consistently explain nutrient-related contribution patterns (TN, TP, and $\text{NH}_3\text{-N}$), whereas event peaks of COD_{Mn} and turbidity (NTU) are more readily amplified by near-inlet local processes such as unmonitored convergence, local discharges, and short-range wind-wave resuspension. This suggests a dual structure in which upstream reservoirs dominate nutrient-related contributions, while near-reservoir local processes amplify organic matter and turbidity signals. Similar source-sink co-driving mechanisms have been reported for drinking-water sources, where upstream agricultural non-point inputs and near-reservoir urban/point-source inputs jointly affect reservoir nutrient and organic loads [3,39]. In comparison, the amplification by near-inlet local processes is more pronounced within the high-risk event windows identified in this study.

3.4. Performance Evaluation of the Three-Class Risk Trigger

The reference risk classes are determined offline based on inlet-station COD_{Mn} under the monthly quantile-based trigger framework and event-window setting described above. In contrast, the trigger performs green/yellow/red classification independently for the full period 2021–2024 on the stage B hourly time axis using the COD_{Mn} scenarios produced by the two-box model; the two procedures are implemented independently. The resulting confusion matrix (Figure 8) shows an overall classification accuracy of approximately 71.5%. This value was calculated as the ratio of correctly classified samples to the total number of samples, i.e., $(12,530 + 6595 + 35)/26,795 = 71.5\%$. Among the three classes, yellow achieves the highest recall, indicating that most moderate-risk periods can be detected by the trigger. Green has a moderate identification rate, with only a small proportion misclassified as yellow or red. By contrast, the detection rate for red is noticeably low, suggesting an overall conservative configuration that “prefers assigning yellow or green and reports red less frequently”.

The confusion-matrix results further indicate that the trigger yields high recall for the yellow class but relatively low detection for the red class, reflecting an output tendency that prioritizes “reducing severe-level false alarms while ensuring reminders for moderate risk”. This suggests that threshold-based early warning involves a trade-off between “high-risk detection” and “false-alarm control”: a higher red threshold and stringent ETA/discharge gating can suppress frequent red alarms under low-to-moderate pollution levels, whereas the consecutive-exceedance criterion makes the yellow class more sensitive to COD_{Mn} increases. Similar trade-offs and configuration tendencies have been discussed in related threshold-based early warning studies [40,41]. For benchmarking, we further compare our trigger performance with previous water-quality early warning research. Existing studies have reported overall accuracies of 80–95% for multi-indicator early warning models based on Bayesian networks or mobile monitoring platforms, while their recognition capability can likewise be imbalanced across risk levels [9,42]. Compared with these studies, the overall accuracy of the present system is at a medium level for threshold-based early

warning. Its strength lies in the high recall for yellow, whereas the low detection rate for red indicates that the current trigger rules remain conservative for severe risk. To improve recognition of severe events while controlling false alarms, related studies suggest optimizing the red threshold and gating conditions or introducing multi-source trigger fusion methods [9,42].

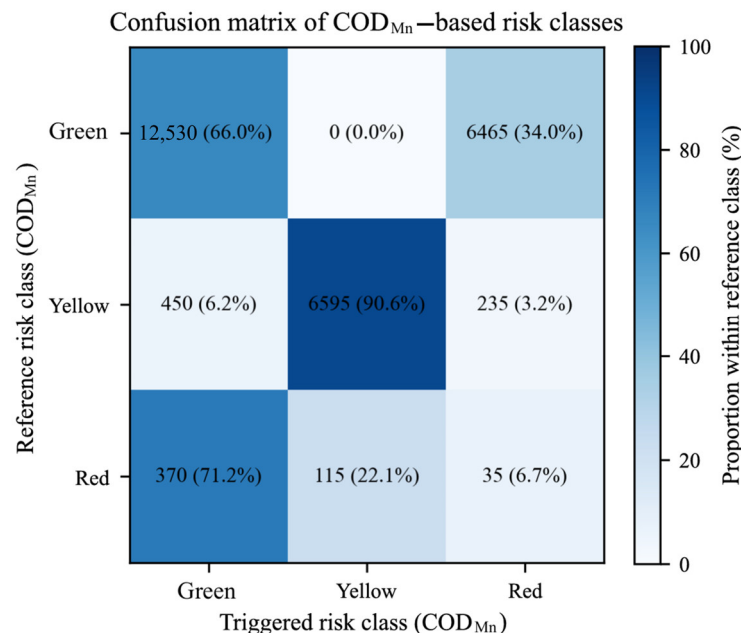


Figure 8. Confusion matrix of COD_{Mn}-based risk classes at the inlet. Cell values indicate sample counts, and percentages indicate row-wise proportions within each reference class.

4. Discussion

4.1. Methodological Advantages and Application Potential

Under the constraint of limited monitoring stations, the integrated framework proposed in this study—“dynamic risk windows + routing-decay + trigger”—can achieve event-scale risk classification using only routine online data from the inlet and a small number of upstream control sections, without building a full-basin hydrodynamic-water-quality model. Related studies have also indicated that for a river–reservoir cascade system with relatively weak monitoring networks but a need to safeguard drinking-water security, it is feasible to support early warning decisions using simplified mechanisms or interpretable rules [41,43]. Compared with assessment approaches based on static thresholds or annual/seasonal averages, our framework emphasizes an “inlet-centered, upstream-tracing” logic, enabling rapid preliminary screening of high-risk periods and key inflow pathways and providing targeted support for subsequently deploying refined water-quality models and intensified monitoring under a limited number of typical scenarios. Similar tiered application strategies have been adopted in related studies and have been shown to have practical value [43]. Therefore, this framework can serve as a first-layer tool in a “coarse screening first, refined calculation later” strategy, improving the foresight of inflow-risk identification and operational decision-making under controllable cost.

4.2. Model Assumptions and Uncertainty

At the data and threshold levels, the monthly quantile-based trigger thresholds were constructed based on online monitoring and routine hydrological data from 2021 to 2024. They may not fully cover extremely wet/dry years or abnormal operational scenarios. Accordingly, the present dataset is intended to support event-scale framework development

and preliminary evaluation rather than strong long-term climatological generalization. Moreover, inlet COD_{Mn} is used as the representative indicator for the three-class risk definition, whereas TN, TP, $\text{NH}_3\text{-N}$, and turbidity (NTU) are used only in relative source contribution analysis for typical events, which may underestimate the risk of special events dominated by nutrients or turbidity. In addition, discharge at some upstream control sections relies on estimation, which can introduce systematic errors in the magnitude of inflow loads and amplify the uncertainty of threshold partitioning. Because the original water-quality and discharge inputs were available at 4 h resolution, the hourly series used in stage B were obtained by temporal resampling rather than direct hourly observation. Specifically, concentration was interpolated in time, whereas discharge was forward-filled between adjacent 4 h records. This treatment may smooth sub-hour peaks and introduce approximation in event timing and peak magnitude. Therefore, the stage B hourly series should be interpreted as an event-scale analytical approximation rather than a reconstruction of true sub-hour dynamics.

Regarding the routing model, the two-box model simplifies the complex river-reservoir system into two serial compartments and assumes that parameters remain broadly stable before and after the event within the same ETA window. It does not explicitly represent in-reservoir stratification, localized inflows, or multi-path transport processes. Parameters are primarily calibrated using a limited number of typical events; extrapolating them to other years and event types may introduce bias, and further validation on a larger and more diverse set of events is needed.

For early warning classification, our results indicate that under the current samples, the risk trigger shows a relatively low detection rate for the red class but a very small false-alarm rate, implying an overall conservative triggering behavior. Therefore, its generalizability to longer time series and other drinking-water sources still needs to be tested. In particular, expanding monitoring datasets to cover more hydrological years and event types, and incorporating multi-source information and probabilistic frameworks on this basis, would improve robustness and uncertainty characterization. Similar improvement directions and evaluation strategies have also been proposed in related studies [41].

4.3. Management Implications and Future Research Directions

From a management perspective, the month-specific dynamic threshold framework and the resulting risk-window patterns derived from publicly available monitoring data can directly indicate “which years and which periods” have more concentrated high inflow risks. For Yuqiao Reservoir, COD_{Mn} yellow/red risk windows shifted markedly toward autumn and winter in 2023 and were accompanied by elevated TN and TP levels. This suggests that under the coexistence of intensive water transfers and complex hydrological conditions, autumn and winter should be treated as priority periods for inflow water-quality assurance, during which intensified monitoring and relatively conservative water-quantity scheduling should be arranged. The relative source contribution analysis indicates that upstream control sections such as Guojiatun, Shangbancheng Bridge, and Guohe Bridge account for most of the TN-related contribution during typical red/yellow events, whereas Lihe Bridge contributes relatively less. Meanwhile, “Other” in the near-inlet zone still occupies a high share for COD_{Mn} and the relative turbidity contribution index. In terms of management, it is therefore necessary, on one hand, to reduce transferable nitrogen loads through watershed non-point source control and discharge restrictions at key control sections and, on the other hand, to investigate outfalls and tributaries near the reservoir inlet that are not covered by routine monitoring, so as to prevent short-term organic matter and turbidity pulses from being amplified under high water levels or water-transfer operating conditions. This distinction also implies that TP control should focus more on upstream nutrient-transfer

pathways, whereas turbidity control requires additional attention to near-inlet ungauged inflows, shoreline disturbances, and local resuspension processes.

Future work can, on one hand, test the robustness of the “dynamic risk windows + routing-decay” framework across more years and events and evaluate its warning and response value by incorporating external information such as operating records and complaint incidents. On the other hand, the method can be extended to other multi-source water-transfer reservoirs or reservoir inlets, and the portability of risk classification and triggering strategies can be assessed under different monitoring densities and operational patterns. This would provide a foundation for coupling with more refined water-quality models or real-time operational optimization.

5. Conclusions

Based on publicly available water-quality and hydrological data from 2021 to 2024, this study established an integrated framework of “month-specific dynamic thresholds-event/risk windows-two-box routing-decay-risk trigger” to characterize inflow water quality risks in a river–reservoir cascade system from three perspectives: long-term exposure, event-scale source contributions, and early warning performance.

Green/yellow/red windows derived from dynamic thresholds indicate that high risks of inflow COD_{Mn} and major nutrients are mainly concentrated in the wet season, while in a few years, continuous yellow/red windows also occur in autumn and winter, highlighting pronounced seasonal clustering and interannual variability in inflow water quality.

The ETA-constrained two-box routing-decay model satisfactorily reproduces the chained propagation of typical events along the “upstream reservoirs-bridge stations-reservoir inlet” pathway. Overall, red events can be summarized as “a strong upstream pulse superimposed on an elevated middle-lower reach background,” whereas yellow events are characterized by “persistently high middle-lower reach background with moderate upstream disturbances”.

Relative source contribution analysis shows that upstream control sections such as Guojiatun, Shangbancheng Bridge, Lihe Bridge, and Guohe Bridge dominate nutrient-related contribution patterns (e.g., TN). In contrast, COD_{Mn} and the relative turbidity contribution index are, in many events, largely associated with “Other,” which comprises unmonitored or non-explicit inflow sources near the inlet and surrounding reservoir zone, indicating that local inputs may play a prominent role in shaping high-risk windows.

The COD_{Mn} -based three-class risk trigger achieves acceptable overall accuracy, performs well in identifying yellow-level risk, and is conservative for red-level risk with a low false-alarm rate. It can serve as a “coarse screening first, refined calculation later” inflow early warning tool, providing a basis for tiered response and subsequent fine-scale simulations in multi-reservoir-water-transfer systems.

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