

Beyond water quality: Integrating antimicrobial resistance into urban river water health assessment for one health governance

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Beyond water quality: Integrating antimicrobial resistance into urban river water health assessment for one health governance

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Abstract

Untreated sewage and industrial discharges are degrading urban rivers, reducing the availability of safe water and increasing environmental and public-health risks. Conventional water-quality assessment frameworks support regulatory monitoring but do not explicitly account for environmental antimicrobial resistance (AMR), that limit their capacity to inform risk-based urban water governance within One Health and sustainable development. To address this gap, we developed a hierarchical decision-support framework that integrates conventional water quality parameters (WQPs) and AMR into a Cumulative Water Health Index (CWHI). The CWHI combines a conventional Water Quality Index (WQI) with a novel AMR Burden Index (ABI) that translates heterogeneous environmental data into interpretable risk classes for surveillance and management. The framework was applied to the anthropogenic impacted Musi River, India, using 20 samples collected from ten locations during wet and dry seasons. The assessment included 20 WQPs, 11 antibiotic resistance genes, anthropogenic pollution indicator of mobile genetic element *intI1*, and antibiotic concentrations. CWHI classified all evaluated sites as "Critical", while ABI values were predominantly "Moderate" to "High" along the urban river stretch. This indicates substantial AMR-related risks despite spatial variation in water quality. No significant seasonal shifts in index classifications were observed. Thus, by integrating WQPs with AMR, the proposed framework provides a transparent and actionable tool for AMR-informed river assessment, surveillance prioritization, and risk-based urban water governance. It also provides an operational link between AMR surveillance and the UN-SDGs 6 on clean water and sanitation and SDG 11 on sustainable cities and communities, while advancing the One Health objectives of SDG 3.

Keywords: *AMR; Fuzzy logic; Risk Assessment; Sewage Pollution; Water Quality Parameters; Policy Support Framework*

1. Introduction

Cities experiencing water stress are under increasing pressure to ensure clean water for growing urban populations, a challenge exacerbated by the accelerated degradation of surface-water systems. Rivers are still an important part of urban water infrastructure in rapidly urbanizing areas, but are being impaired by untreated sewage, industrial effluents, and stormwater runoff (Williams et al. 2019; Pereda et al. 2021). River deterioration is no longer an environmental concern only, but rather also a matter of sustainable urban water management, public health protection, and long-term urban resilience. One emerging challenge that remains largely absent from routine river health assessments is environmental antimicrobial resistance (AMR) (Keenum et al. 2026). Sewage-impacted rivers have become major reservoirs and transmission pathways for antibiotic resistance genes (ARGs), antibiotic-resistant bacteria (ARBs), mobile genetic elements (MGEs), and antibiotic residues, creating environmental conditions. They facilitate the persistence and dissemination of AMR in water bodies (Singh et al. 2019; Sabri et al. 2020). Since these pathways interconnect human, animal, and ecosystem health, AMR has become a central One Health concern with implications that extend beyond water pollution alone (Graham et al. 2019; Franklin et al. 2024). Despite growing recognition of these interconnected risks, AMR indicators are not yet incorporated into routine river monitoring/assessment programs or water governance frameworks. This greatly limits their capacity to inform environmental decision-making.

Most regulatory river-health assessments continue to rely on physicochemical water-quality parameters and microbial indicators that are integrated into Water Quality Indices (WQIs) to classify water suitability (Wu et al. 2018; Chidiac et al. 2023). Although these indices provide valuable support for environmental monitoring and regulatory compliance, they do not account for AMR-related hazards such as ARGs, anthropogenic pollution markers (e.g., *intI1*), or antibiotic selection pressure (Grenni 2022). Consequently, rivers classified as having acceptable physicochemical quality may still pose substantial public-health and environmental risks due to their role in maintaining and disseminating AMR (Jiang et al. 2021; Prasad et al. 2024). This knowledge gap creates a policy challenge, as conventional water-quality assessment may underestimate environmental risks and provide an incomplete basis for water-use planning, surveillance prioritization, and river management.

Decision-support approaches capable of integrating diverse environmental information into transparent and interpretable assessments are therefore needed. Fuzzy logic inference systems have been widely used in water-quality assessments because they accommodate uncertainty, represent gradual environmental transitions, and incorporate expert knowledge through explicit

rule-based reasoning (Zadeh 1965). Hierarchical fuzzy architectures further improve interpretability by reducing rule complexity while preserving interactions among environmental variables (Liou et al. 2003; Ocampo-Duque et al. 2006; Icaga 2007) . However, existing applications remain largely restricted to conventional physicochemical water quality (Gharibi et al. 2012; Ji et al. 2015; Ding et al. 2017), and no practical framework has integrated conventional water-quality indicators and environmental AMR into a single cumulative assessment capable of supporting environmental decision-making and urban water governance.

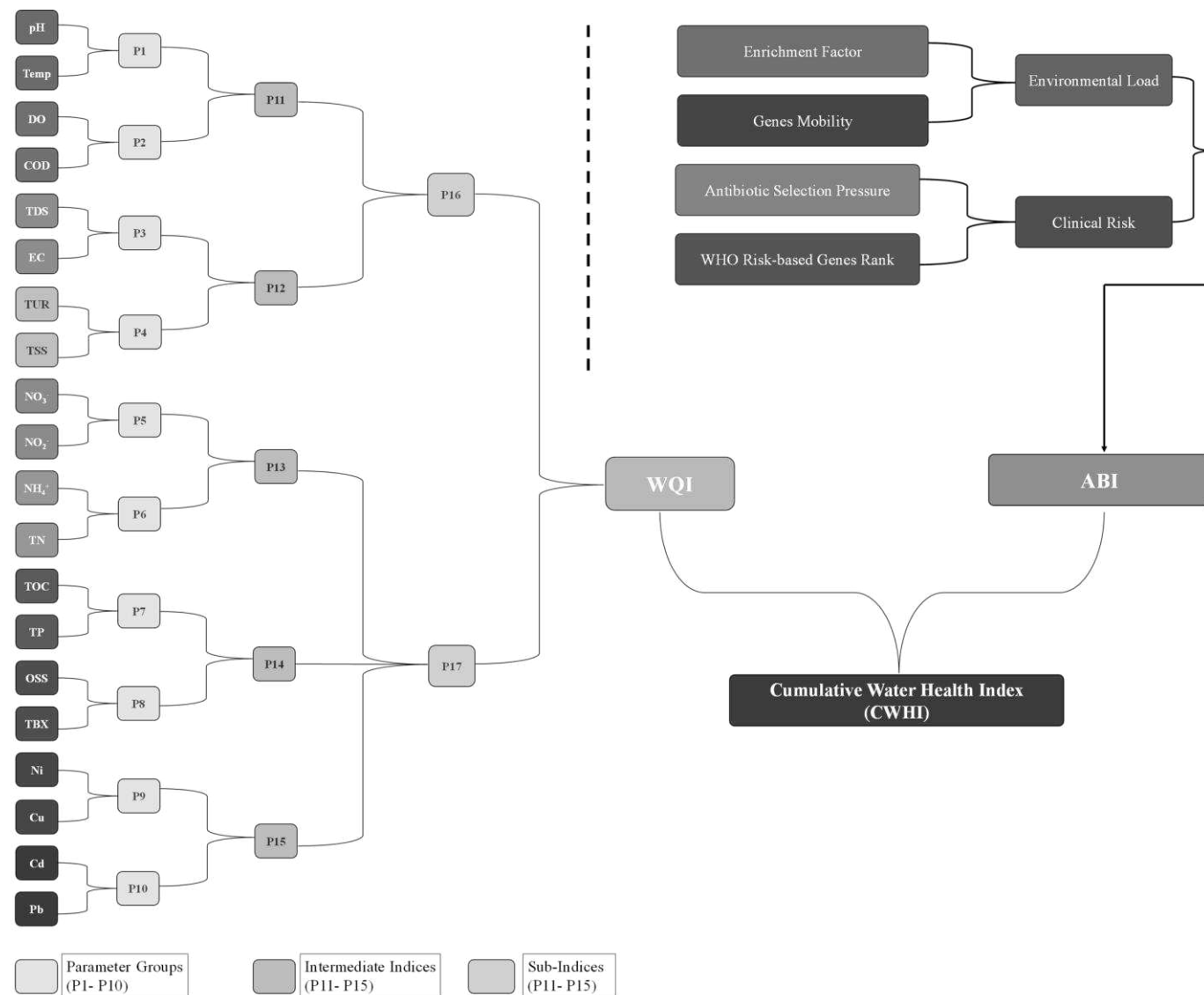
This study addresses this gap by developing a hierarchical decision-support framework that integrates conventional water quality and environmental AMR into a Cumulative Water Health Index (CWHI). The framework combines a Water Quality Index (WQI) with a novel AMR Burden Index (ABI) to produce an interpretable assessment of cumulative river health risks. Using the sewage-impacted Musi River in India as a real-time demonstration case, this study (i) develop an integrated assessment framework for cumulative water-health evaluation; (ii) evaluate its robustness through scenario, sensitivity, and uncertainty analyses; (iii) demonstrate its application in a sewage-impacted urban river; and (iv) examine its potential to support AMR-informed river assessment, surveillance prioritization, and risk-based urban water governance.

2. Methods

2.1 Fuzzy Logic Framework

The three-stage hierarchical Mamdani fuzzy inference framework integrates conventional WQPs and AMR burden into a cumulative surface-water health indicator (**Figure 1**).

The framework consists of sequential modules in which Stage 1 computes Water Quality Index (WQI), Stage 2 computes an AMR Burden Index (ABI), and Stage 3 combines both outputs to derive a cumulative surface-water health index (CWHI). Each module was implemented as an independent Mamdani fuzzy inference system (MFIS) (Mamdani 1974) using centroid defuzzification (Mahapatra et al. 2011). Five linguistic classes: Very Poor (VP), Poor (P), Moderate (M), Good (G), and Very Good (VG) were used to characterize all input and output variables that were mapped onto a shared universe of discourse. This standardized structure allows a smooth data flow between modules, and each intermediate output serves as a direct crisp input for the next stage system after defuzzification. Hierarchical design has been preferred over single flat architecture because it reduces the rules complexity while maintaining non-linear interaction between variables.



Temp = Temperature; DO = Dissolved Oxygen; COD = Chemical Oxygen Demand; TDS = Total Dissolved Solids; EC = Electrical Conductivity; TUR = Turbidity; TSS = Total Suspended Solids; NO₃⁻ = Nitrate; NO₂⁻ = Nitrite; NH₄⁺ = Ammonium; TN = Total Nitrogen; TOC = Total Organic Carbon; TP = Total Phosphorus; OSS = Heterotrophic Bacteria; TBX = *E. coli*; Ni = Nickel; Cu = Copper; Cd = Cadmium; Pb = Lead; WQI = Water Quality Index; ABI = AMR Burden Index

Figure 1. Schematic diagram of the Cumulative Water Health Index (CWHI) framework by integrating Water Quality Index (WQI), and AMR Burden Index (ABI).

Table 1. Fuzzy classifications and Linguistic terms used in the model for the WQI

Group	Variables	Units	MF Range	VP (a=b, c, d)	P (a, b, c)	M (a, b, c)	G (a, b, c)	VG (a, b, c=d)
1	DO	mg/L	0–16	0, 1.5, 3	2.5, 3.75, 5	4.5, 6.0, 7.5	7, 8.5, 10	9.5, 12.75, 16
	COD	mg/L	0-500	0, 7.5, 15	10, 30, 50	40, 80, 120	100, 175, 250	200, 350, 500
2	pH	—	0-14	0, 4.25, 5	5, 5.75, 6.5	6, 7.25, 8.5	8, 8.5, 9	9.5, 11.75, 14
	Temperature	°C	0-40	0, 10, 20	18, 21.5, 25	23, 26.5, 30	28, 31.5, 35	33, 36.5, 40
3	TDS	mg/L	0-2000	0, 75, 150	100, 200, 300	250, 425, 600	500, 850, 1200	1000, 1500, 2000
	EC	μS/cm	0-3000	0, 325, 650	500, 850, 1200	1000, 1500, 2000	1800, 2200, 2600	2400, 2700, 3000
4	Turbidity	NTU	0-250	0, 2.5, 5	4, 7.5, 11	9, 29.5, 50	40, 85, 130	100, 175, 250
	TSS	mg/L	0-350	0, 12.5, 25	15, 32.5, 50	40, 70, 100	80, 140, 200	160, 255, 350
5	Nitrate	mg/L	0-60	0, 2.5, 5	4, 7, 10	8, 11.5, 15	12, 18.5, 25	20, 40, 60
	Nitrite	mg/L	0-5	0, 0.1, 0.2	0.15, 0.33, 0.5	0.4, 0.7, 1	0.8, 1.65, 2.5	2, 3.5, 5
6	Ammonium	mg/L	0-300	0, 0.25, 0.5	0.4, 0.95, 1.5	1.2, 3.1, 5	4, 12, 20	15, 157.5, 300
	TN	mg/L	0-60	0, 1, 2	1.5, 3.75, 6	4.5, 8.25, 12	10, 17.5, 25	20, 40, 60
7	TP	mg/L	0-60	0, 0.05, 0.1	0.08, 0.29, 0.5	0.4, 1.2, 2	1.5, 5.75, 10	7, 33.5, 60
	TOC	mg/L	0-40	0, 1, 2	1.5, 3.25, 5	4, 8, 12	9, 14.5, 20	16, 28, 40
8	TBX	CFU/ml	0-10	0, 0.5, 1	0.5, 1.5, 2.5	2, 3.5, 5	4, 5.5, 7	6, 8, 10
	OSS	CFU/ml	0-10	0, 0.5, 1	0.5, 1.5, 2.5	2, 3.5, 5	4, 5.5, 7	6, 8, 10
9	Cu	μg/L	0-100	0, 2.5, 5	4, 9.5, 15	12, 21, 30	25, 42.5, 60	50, 75, 100
	Ni	μg/L	0-100	0, 5, 10	8, 16.5, 25	20, 35, 50	45, 62.5, 80	70, 85, 100
10	Pb	μg/L	0-30	0, 1, 2	1.5, 3.25, 5	4, 7, 10	8, 13, 18	14, 22, 30
	Cd	μg/L	0-50	0, 0.4, 0.8	0.6, 1.55, 2.5	2, 5, 8	7, 16, 25	20, 35, 50
Output	Fuzzy Index	—	0 - 100	0, 10, 20	15, 25, 35	30, 40, 50	45, 57.5, 70	65, 82.5, 100

2.2 Membership Function and linguistic classes

The complete pipeline contains 11 sub-systems, 550 rules for the WQI module, 25 ARG-level rules per ARG in the AMR module, and 25 rules for the final fusion system. Each WQP input was assigned a universe of discourse spanning its ecologically relevant range, bounded by the stringent regulatory threshold at the lower end and the maximum expected concentration for severely polluted urban rivers at the upper end. Membership Function (MF) breakpoints were defined from WHO drinking water guidelines (WHO 2011), Bureau of Indian Standards IS:10500 (BIS 2012), and the Central Pollution Control Board (CPCB) designated best-use classifications for Class D/E rivers (**Supplementary Table SA**). The 20 physicochemical parameters and their corresponding MF configurations are summarized in **Table 1**. Each input and output variable represented five fuzzy membership functions corresponding to the linguistic classes VP, P, M, G, and VG, show a spectrum from extremely good to severely degraded WQ (**Figure 2**), following the works of (Mahapatra et al. 2011) and (Gharibi et al. 2012). Without adding unnecessary rule-based complexity, the five-class scheme offers enough resolution to identify ecologically significant quality gradients (Golshan et al. 2020).

Triangular membership functions were assigned to the intermediate classes to capture gradual transitions between states, while trapezoidal membership functions were assigned to the boundary classes to better represent open-ended extreme conditions (**Supplementary information 1**). This combination was chosen to strike a balance between computational ease, interpretability, and sensitivity.

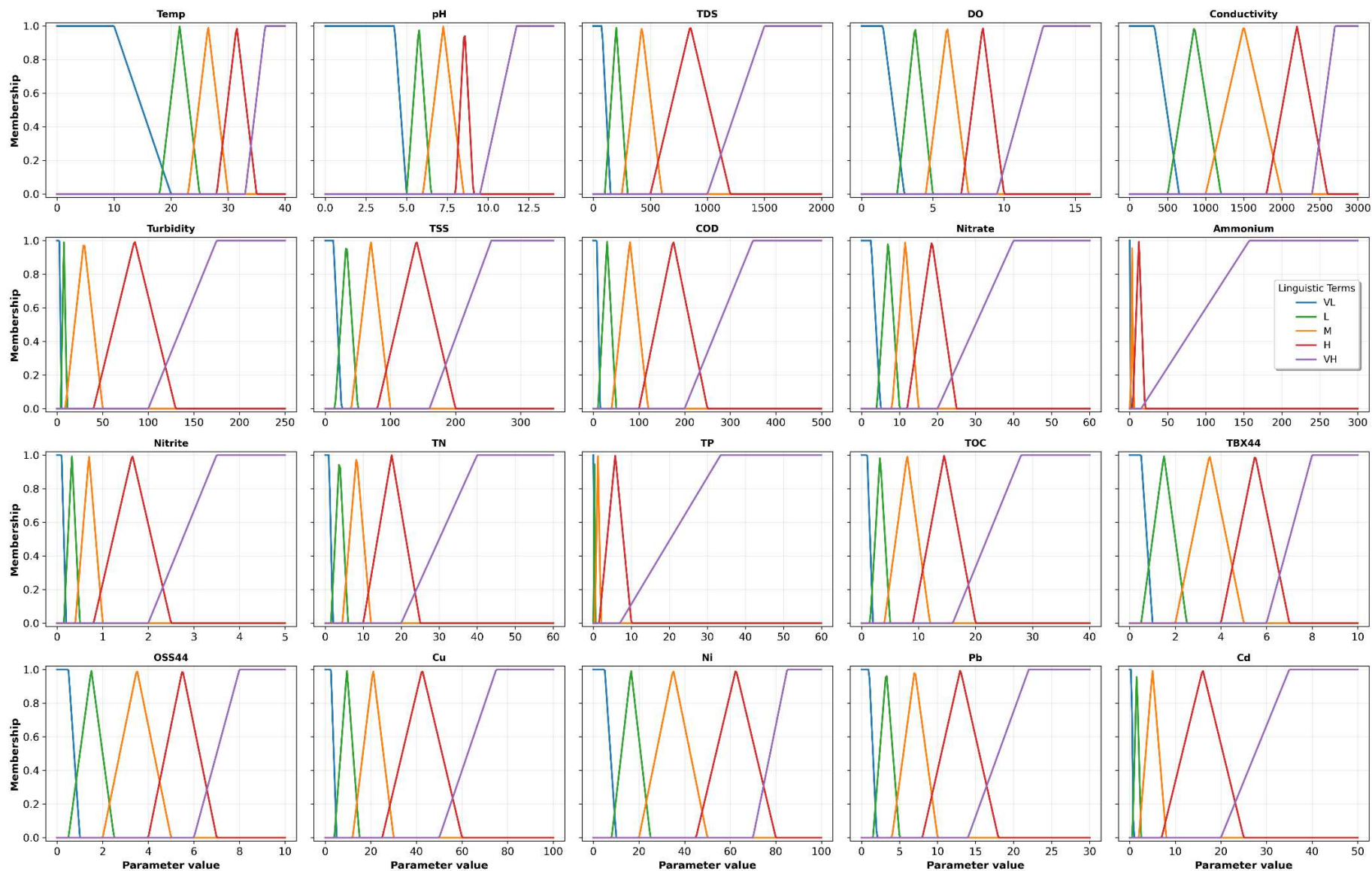


Figure 2. WQI Input Membership Functions (Triangular and Trapezoidal Partitioning). Panel plot displaying fuzzy membership functions for 20 water quality parameters (Temp, pH, TDS, DO, Conductivity, Turbidity, TSS, COD, Nitrate, Ammonium, Nitrite, TN, TP, TOC, TBX, OSS, Cu, Ni, Pb, Cd) across five linguistic terms: Very Low (VL; blue), Low (L; green), Medium (M; orange), High (H; red), and Very High (VH; purple). Interior terms (L, M, H) use triangular membership functions; boundary terms (VL, VH) employ trapezoidal shapes.

2.3 Fuzzy inference rule-base construction

A fuzzy “AND” operator and a collection of rule aggregation tables that converted combinations of antecedent linguistic states into consequent output classes were used to construct the inference structure of the hierarchical MFIS (Ross 2010; Gharibi et al. 2012). The rule base was created to maintain interpretability while enabling ecologically significant interactions among variables to be represented within a consistent decision-support structure because the proposed framework integrates heterogeneous WQP and AMR-related indicators.

Five input linguistic states for pollutant concentrations are as follows Very high (VH), High (H), Moderate (M), Low (L), and Very Low (VL) and five output linguistic states for water quality: Very Poor (VP), Poor (P), Moderate (M), Good (G), and Excellent (E) are defined by the framework. The final WQI classes are reported as Critical (0–20), Poor (20–40), Moderate (40–60), Good (60–80), and Excellent (80–100). The logical relationships between the system's input and output subsets are established by inference rules. A series of if-then rules that produce new output subsets are used to formalize these relationships. The antecedent (the “if” part) and consequent (“then” part) are the two main parts of every rule. The rule base can be expressed for any two-input subsystem as explained in the respective module’s **Supplementary Information 2**.

2.4 Module Development

2.4.1 Stage 1 WQP Module

WQPs module was designed to include an extended 20 WQPs into a single WQI through a hierarchical cascade of fuzzy subsystems, structurally adapted and modified from (Mahapatra et al. 2011) and (Gharibi et al. 2012). The parameters were first grouped into ten pairwise subsystems with different levels, representing major dimensions of river-water quality, including oxygen-substrate dynamics, acid-base reflux, thermal stress, ionic pollution, particulate load, inorganic nitrogen, ammoniacal nitrogen, nutrient–organic coupling, bacterial load, and metal contamination. The detailed rule based WQP construction and hierarchical framework are described in **Supplementary Information A**.

2.4.2 Stage 2 AMR burden module

The AMR burden module was developed to quantify AMR burden using four complementary components: (i) ARG enrichment, (ii) mobility potential, (iii) antibiotic selection pressure and

(iv) WHO informed AMR priority risk score (Zhang et al. 2021; Sati et al. 2025). This four-dimensional framework (**Supplementary Tables S2**) was designed to account not only for ARG abundance, but also for the ecological potential for dissemination and the clinical significance of resistance determinants in aquatic environments. The framework integrates WHO priority pathogen relevance and ESKAPE-associated (Martínez et al. 2014; WHO 2019) AMR considerations alongside predicted no-effect concentration for resistance selection ($PNEC_{res}$) (Bengtsson-Palme and Larsson 2016; Kneis et al. 2025) based antibiotic selection pressure thresholds to represent environmentally relevant resistance-selection dynamics in sewage-impacted river systems. The rationale for selecting the factors, rule based construction and fusion table framework are described in **Supplementary Information B**.

Enrichment Factor: ARG enrichment EF_{ARG_i} was calculated as the copy-number of each ARG normalized to the *16S rRNA* gene copy number, expressed as a ratio to the corresponding value in the reference site (**equation 1**):

$$EF_{ARG_i} = \frac{ARG_i}{16S\ rRNA} \quad (1)$$

Similarly, for mobility gene *intI1*, enrichment factor EF_{intI1_k} is calculated using **equation 2**:

$$EF_{intI1_k} = \frac{intI1_k}{16S\ rRNA} \quad (2)$$

Where ARG_i is the absolute copy number of the *i*-th ARG; *16S rRNA* is the copy number of the total bacterial community biomass gene in the same sample. Similarly, $intI1_k$ denotes the copy number of the *k*-th sample of class 1 integron integrase MGE marker gene.

Here, normalization to *16S rRNA* gene copies accounts for variation in total bacterial biomass between samples, ensuring that enrichment reflects the proportion of the bacterial community carrying each ARG rather than absolute abundance. The upstream site was selected as the reference baseline as it represents the least anthropogenically impacted condition in the transect.

Mobility and intI1 Integration: Mobility score ($MobRaw_i$) representing the potential for ARG dissemination through horizontal gene transfer (HGT) was computed as a composite of ARG enrichment and *intI1* abundance limited to a maximum of 10 (**equation 3**):

$$MobRaw_i = EF_{ARG_i} \times \min(EF_{intI1_k}, 10) \quad (3)$$

The mobility score was then percentile-normalized against the dataset distribution (Q_{50} , Q_{75} , Q_{90} , Q_{95} breakpoints) to produce a calibrated mobility score as in **equation 4**:

$$Mob_i = \begin{cases} \frac{MobRaw_i}{q_{50}} \times 25, & MobRaw_i \leq q_{50} \\ 25 + \frac{MobRaw_i - q_{50}}{q_{75} - q_{50}} \times 25, & q_{50} < MobRaw_i \leq q_{75} \\ 50 + \frac{MobRaw_i - q_{75}}{q_{90} - q_{75}} \times 25, & q_{75} < MobRaw_i \leq q_{90} \\ 75 + \frac{MobRaw_i - q_{90}}{q_{95} - q_{90}} \times 15, & q_{90} < MobRaw_i \leq q_{95} \\ \min\left(100, 90 + \frac{MobRaw_i - q_{95}}{q_{95}} \times 10\right), & MobRaw_i > q_{95} \end{cases} \quad (4)$$

Antibiotic Selection Pressure: Antibiotic selection pressure ($AbxPress_{ij}$) was computed as the ratio of measured concentration to the ($PNEC_{res}$), as proposed by Bengtsson-Palme et al. (Bengtsson-Palme and Larsson 2016) (**equation 5**)

$$AbxPress_{ij} = \max\left(0, \frac{C_{ij}}{PNEC_{res,j}} \times 100, 100\right) \quad (5)$$

Where C_{ij} is the measured environmental concentration of antibiotic j associated with ARG i ; $PNEC_{res,j}$ is the PNEC value of antibiotic j . *clip* constrains the resulting score to the range $[0, 100]$, where 0 indicates no selection pressure and 100 indicates pressure at or exceeding the PNEC threshold; and $AbxPress_{ij} \in [0, 100]$ is the resultant selection pressure score expressed as a percentage. If an ARG is linked to more than one measured antibiotic, antibiotic selection pressure ($AbxPress_i$) scores are averaged (**equation 6**)

$$AbxPress_i = \frac{1}{m} \sum_{j=1}^m AbxPress_{ij} \quad (6)$$

$PNEC_{res,j}$ values were also sourced from the EnviResist database (Kneis et al. 2025) and presented in the **Supplementary Table S5** which provides ecologically derived thresholds for resistance selection based on minimum selective concentration studies. For ARGs associated with directly measured antibiotics (Tier 1: $qnrS \leftrightarrow CIP/NOR$, $ermF \leftrightarrow ERY/AZM$, and $sulI/sul2 \leftrightarrow TMP$), measured concentrations were applied directly (**Supplementary Table S6**). For ARGs whose corresponding antibiotics were not measured (Tier 2: all *tet* genes, *blaNDM*, *blaCTX-M*, and *aph3-Ib*), seasonal PEC/PNEC ratios (**equation 7**) derived from dry- and wet-season monitoring data for urban rivers were used as fallback values (**equation 8**; **Supplementary Table S7**) for selection pressure. These ratios were transformed using a sigmoid function with $k = 0.05$, where k is a slope parameter controlling the steepness of the response curve.

$$Ratio = \frac{PEC}{PNEC} \quad (7)$$

$$AbxPress_i^{fallback} = \frac{100}{1 + \exp[-k(Ratio - 100)]} \quad (8)$$

ARG risk: Each ARG was processed through two parallel Mamdani fuzzy inference subsystems (**Figure 1**). This subsystem is an environmental-load fuzzy system using *EF* and *Mob* (**equation 9**), and a clinical-risk fuzzy system using an internal ARG priority score, based on WHO bacterial priority categories and related clinical relevance (Sati et al. 2025) together with antibiotic selection pressure (**equation 10**).

$$EnvLoad_i = F_{env}(EF_i, Mob_i) \quad (9)$$

$$ClinRisk_i = F_{clin}(WHO_i, AbxPress_i) \quad (10)$$

The final per-ARG risk score was obtained by integrating these outputs using weights based on metadata-derived ranking scores adapted from environmental AMR risk frameworks (**equation 11**) (Zhang et al. 2021; Shuai et al. 2024; Jiang et al. 2024). For critical-priority ARGs (WHO-informed rank ≥ 70 ; **Supplementary Table S6**) (Martínez et al. 2014), environmental load received higher weight because the environmental spread of last-resort resistance determinants represents a substantial public health concern even at low clinical pressure. For high and medium-priority ARGs, lesser weight was assigned to the clinical risk component (Zhang et al. 2022; Prasad et al. 2024), reflecting their broader occurrence and stronger dependence on ongoing selection pressure. Hence, the final ARG-specific risk score ($ARGRisk_i$) is computed as a weighted (w_{env}) combination of environmental load ($EnvLoad_i$) and clinical risk ($ClinRisk_i$), with $w_{env} = 0.55$ for critical-tier ARGs and $w_{env} = 0.45$ for the remaining ARGs.

$$ARGRisk_i = w_{env} EnvLoad_i + (1 - w_{env}) ClinRisk_i \quad (11)$$

ARGs grouped into critical, high, and medium tier scores (*TierScore*), with critical defined as rank greater than or equal to 70, high as 50-69, and medium as below 50, was computed using **equation 12**. Within each tier, the script applies a top two weighted score, giving 70% weight to the highest-risk ARG and 30% to the second-highest ARG. The maximum-based aggregation is consistent with risk assessment conventions for systems where any single catastrophic failure can constitute an unacceptable hazard, regardless of the status of other components.

$$TierScore = \begin{cases} 0, & n = 0 \\ v_1, & n = 1 \\ 0.70 v_1 + 0.30 v_2, & n \geq 2 \end{cases} \quad (12)$$

where v_1 and v_2 are the largest and second-largest ARG risk scores in that tier.

Final AMR Burden Index: The AMR Burden Index (ABI) was computed as a weighted sum of the three tier scores and then clipped to 0–100 (**equation 13**):

$$ABI = \max(0.50 Tier_{critical} + 0.30 Tier_{high} + 0.20 Tier_{medium}, 0, 100) \quad (13)$$

The distinct fuzzy universes for these ABI inputs are described as: EF is fuzzified on a 0–1000 range using the linguistic breaks (**Supplementary Table S2**), whereas mobility, risk rank, and antibiotic pressure are all handled on 0–100 scales. The final ABI output is further classified as: Very Low Risk (< 20), Low Risk (18–40), Moderate Risk (38–60), High Risk (58–80), Very High Risk (≥ 80).

2.4.3 Stage 3 Cumulative Water Health Module

The cumulative surface-water health index is produced by the Cumulative Water Health Module, which uses a two-input Mamdani fuzzy inference system to combine the WQI and ABI outputs. The fusion rule base was created with two principles: first, poor performance in both dimensions should result in a highly degraded cumulative water quality; second, an increased AMR burden should raise overall risk even when WQPs appear to be less affected. To support river surveillance and water-use management, the CWHI outputs were categorized into five interpretative classes: Critical (0–20), Poor (20–40), Moderate (40–60), Good (60–80), and Excellent (80–100). By integrating WQI and ABI within the same framework, the model provides a more comprehensive representation of surface-water health in sewage-impacted urban rivers (**Supplementary Table S8**).

2.5 Defuzzification

Defuzzification was used to convert the aggregated fuzzy output of each inference stage into a single crisp value for subsequent analysis and index computation (Ross 2010). In the developed model, all modules used centroid defuzzification to convert aggregated fuzzy outputs into crisp scores using **equation 17**:

$$z^* = \frac{\int_z z \cdot \mu_{agg}(z) dz}{\int_z \mu_{agg}(z) dz} \quad (17)$$

Where z^* is the defuzzified crisp output value, z denotes the output variable, and $\mu_{agg}(z)$ represents the aggregated MF of the fuzzy output set.

All universes of discourse were discretized to 200 equally spaced points for numerical integration, providing sufficient resolution for centroid estimation without excessive computational overhead. This method was selected because it preserves contributions from the

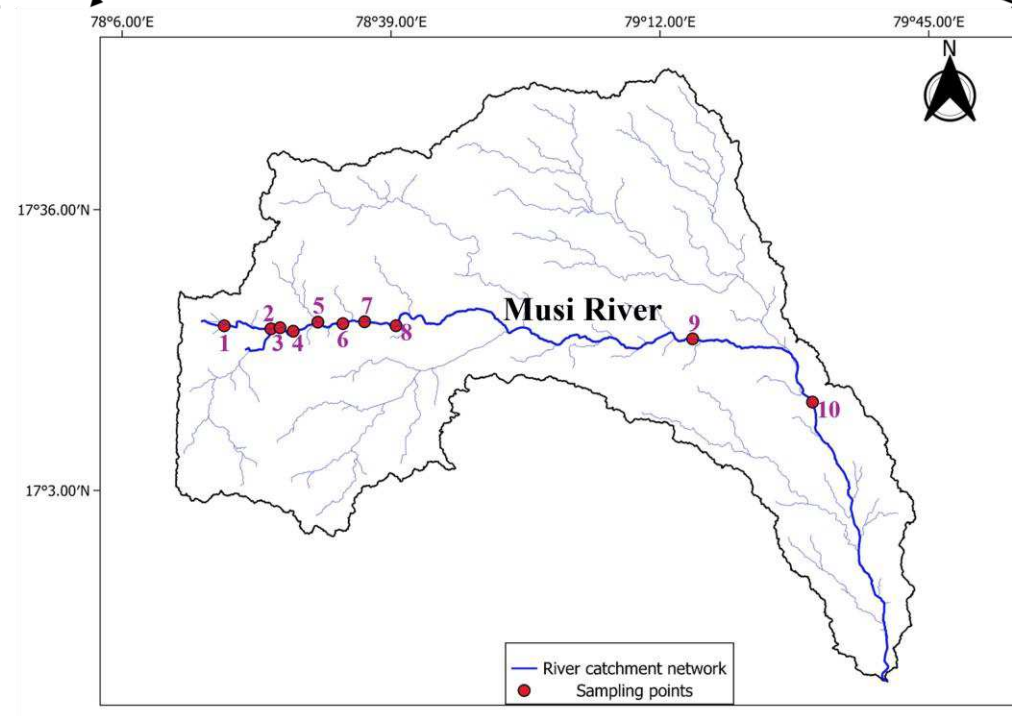
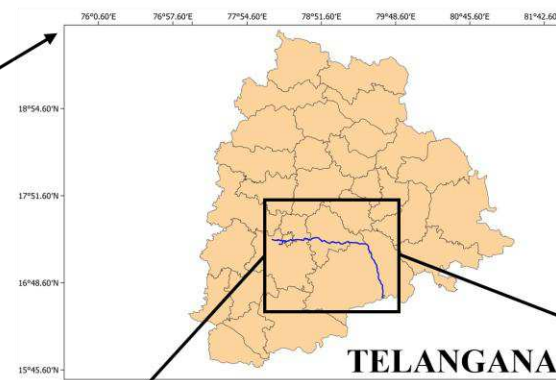
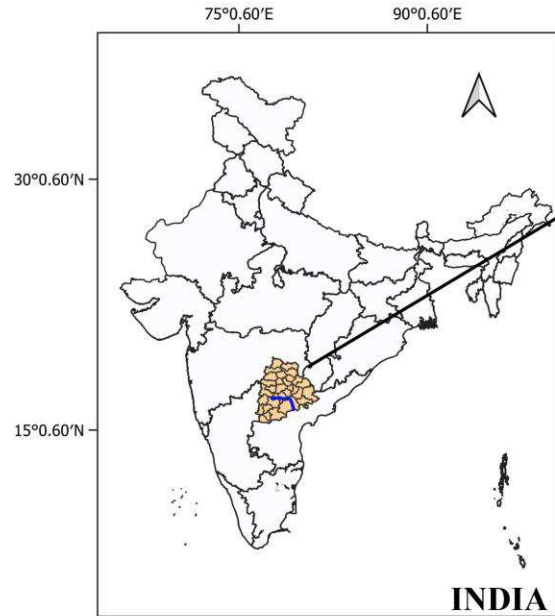
full output membership distribution and is widely used in environmental applications of fuzzy inference systems (Mahapatra et al. 2011; Gharibi et al. 2012).

2.6 Model framework validation, sensitivity and uncertainty analysis

All framework computations and simulations were performed in Python 3.12. Model performance was evaluated through a combination of internal validation, sensitivity analysis, and uncertainty analysis. Internal validation examined the logical consistency of the hierarchical fuzzy framework using idealized WQI–ABI combinations covering the full range of environmental conditions (**Supplementary Table S8**). Framework behavior was further assessed using rule-based diagnostics, response surface evaluation, and fusion-space analysis. Sensitivity analysis was performed by using one-at-a-time perturbations ($\pm 10\%$) under four representative decision regions (low-risk, transition, high-risk, and boundary) and a global grid-based assessment across the WQI–ABI decision space (Pianosi et al. 2016). Model uncertainty was quantified using Monte Carlo propagation (5,000 iterations) (Seifi et al. 2020), from which the mean response, standard deviation, 95% confidence intervals, and coefficient of variation were calculated to evaluate output stability.

2.7 Study area and framework application

The Musi River, one of India's most sewage-impacted urban rivers, was selected as the demonstration case (**Figure 3**) for the proposed framework. Flowing through Hyderabad, the river receives untreated sewage and wastewater discharges that generate pronounced spatial gradients in WQ and AMR, making it well suited for evaluating integrated water-health assessment under urban conditions. Previous studies have documented substantial deterioration in physicochemical water quality, antibiotic occurrence, and AMR determinants along the river continuum (Gothwal and Shashidhar 2017; Sonkar et al. 2026).



Sampling point	Location
1	Osman Sagar (OS)
2	Bapughat Bridge (BGB)
3	Somi Reddy Nagar (SRN)
4	Puranapul (PP)
5	Golnaka Bridge (GNB)
6	Nagole Bridge (NGB)
7	Peerzadiguda (PZ)
8	Pratap Singaram Bridge (PSB)
9	Nagaram Bridge (NRB)
10	Musi Reservoir (MR)

Figure 3. Location of the study area and 10 sampling sites along the Musi River, Telangana, India. The black polygon represents the catchment boundary, blue lines represent the river and associated drainage network, and red circles denote sampling sites. Coordinate annotations are expressed as latitude and longitude in degrees and minutes.

The framework was applied using a spatially resolved dataset from our previously published field investigations (Sonkar et al. 2026) . Sampling sites represented upstream, urban, and downstream reaches of the river. The dataset included 20 physicochemical water-quality parameters, microbial indicators, ARGs, the anthropogenic pollution marker/MGE (*intI1*), and antibiotic concentrations required to derive the ABI. These data were used to evaluate the spatial and seasonal performance of the proposed CWHI and to demonstrate its potential for AMR-informed river assessment and urban water governance.

3. Results & Discussion

3.1 Conceptual validation of the model framework

The controlled 5×5 fusion-space analysis demonstrated coherent cumulative behaviour of the hierarchical fuzzy framework across all idealized scenarios (**Figure 4; Supplementary Table S10**). The CWHI outputs generated consistent classifications across the full WQI–ABI decision space. Regardless of ABI classification, the resulting CWHI remained in the Critical category under WQI = VP, with values consistently observed at 8.3. Conversely, lower cumulative water-health classifications were obtained when elevated ABI classes were combined with moderate-to-good WQI classifications. For example, under Good WQI conditions, scenarios classified with ABI = VL produced a Good CWHI classification (70.0), whereas scenarios classified with ABI = VH produced a Critical CWHI classification (8.39). Likewise, under Excellent WQI conditions, scenarios classified with ABI = VL and ABI = L produced Excellent CWHI classifications (91.6), whereas scenarios classified with ABI = H produced a Poor CWHI classification (30.0). These classifications show that the framework prevented low AMR burden from concealing seriously degraded water-quality conditions while also preventing favourable water-quality conditions from fully compensating for elevated AMR burden. Additionally, different cumulative water-health classifications were produced by intermediate combinations. ABI classes of M provided Poor classifications (30.0), ABI = H and VH produced a Critical classification (8.39), and ABI = VH produced a Critical classification (8.39), while situations classified with ABI = VL produced a Moderate CWHI classification (50.0) under Moderate WQI conditions. These results show the fuzzy rule structure's cumulative penalization of rising AMR burden.

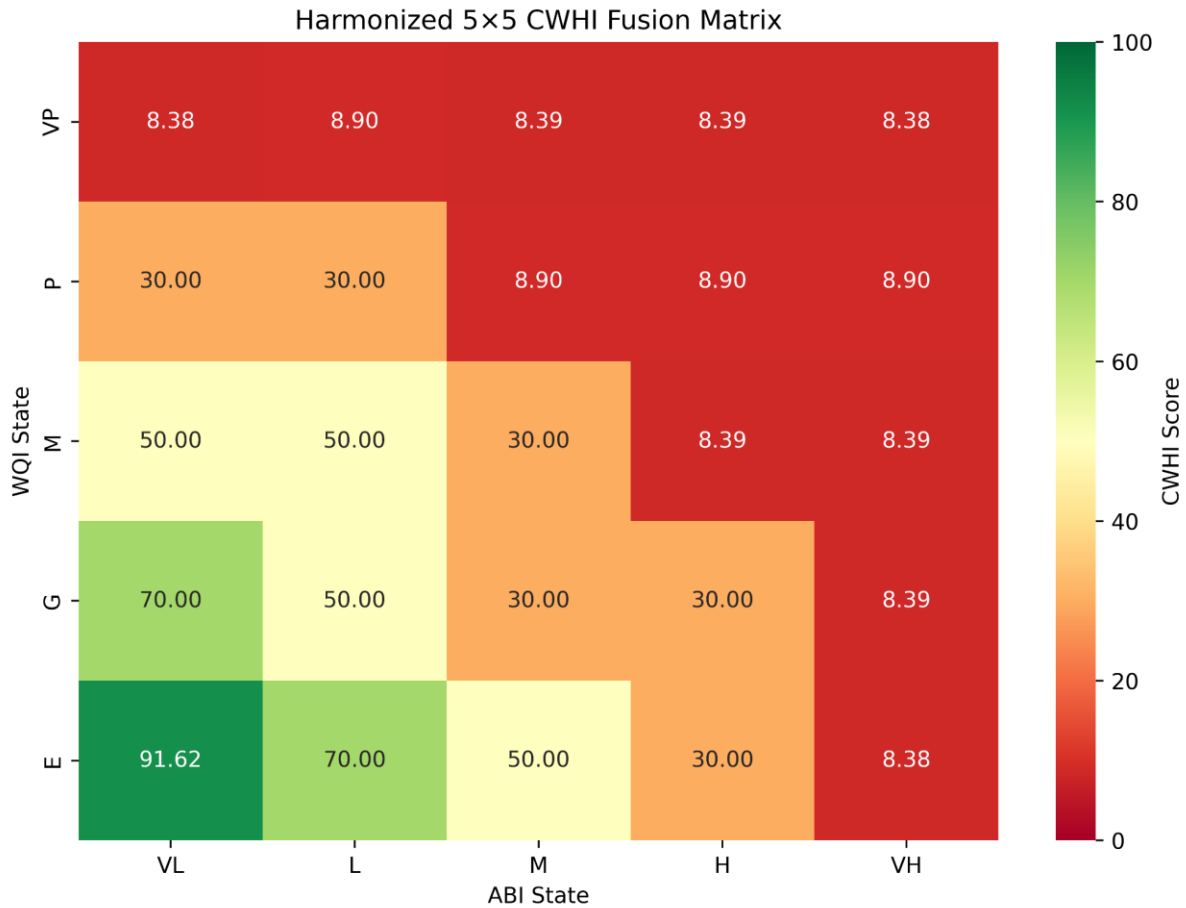


Figure 4. The inferential structure of the fuzzy framework across idealized WQI-ABI class combinations is displayed in a heatmap of the 5x5 CWHI fusion matrix.

The fusion matrix heatmap further illustrated the inferential structure of the model across the full WQI-ABI decision space (**Figure 5**). Along with nearby inferential domains linked to overlapping membership regions, distinct plateau regions belonging to stable fuzzy classes were found. Mamdani-based fuzzy systems that use centroid defuzzification and overlapping membership functions exhibit these response patterns (Gharibi et al. 2012).

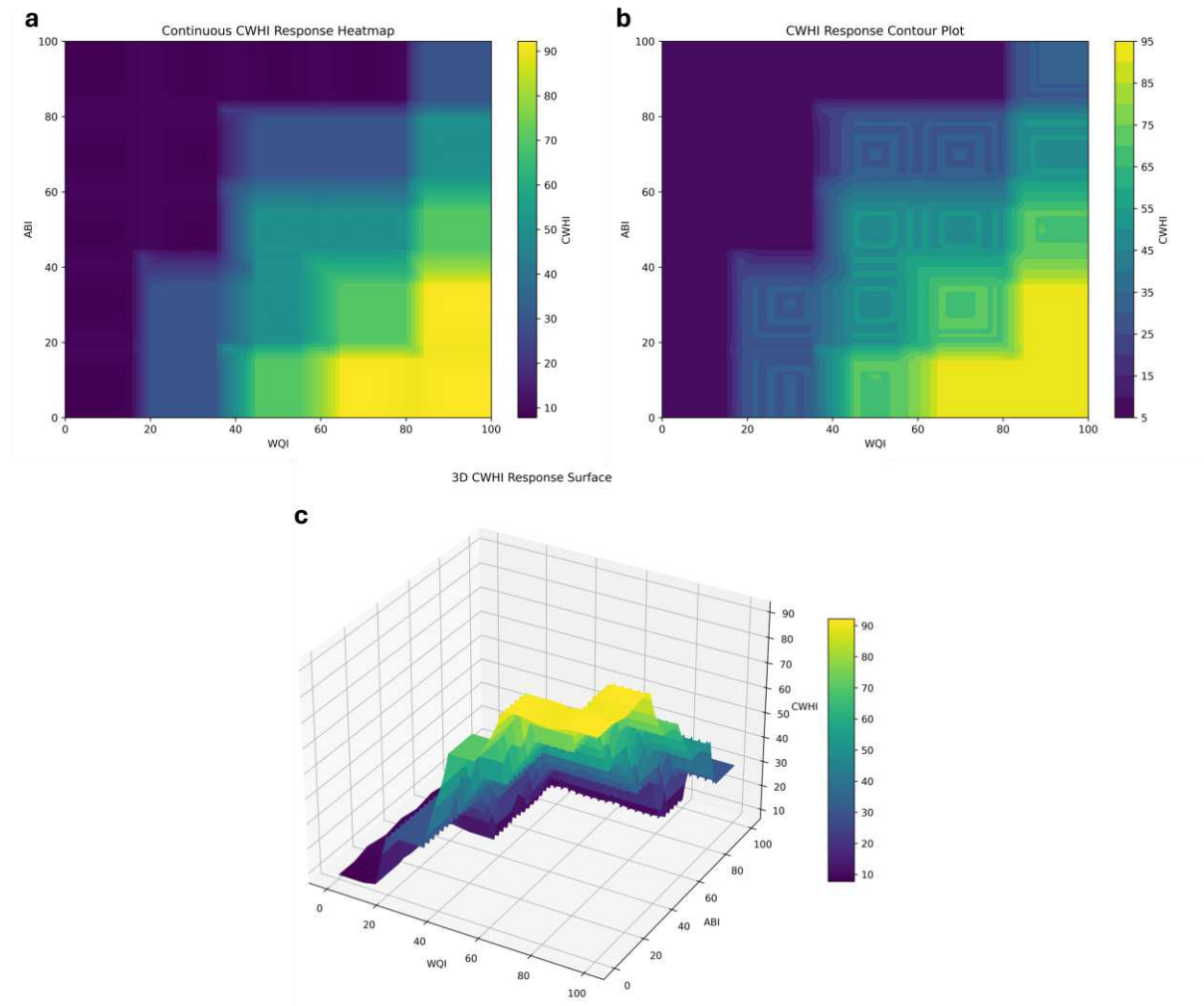


Figure 5. Facet plot of CWHI response to WQI and ABI: (a) continuous heatmap, (b) contour showing rule transitions, (c) 3D response surface (CWHI 0–100).

Continuous response-surface analysis further illustrated the nonlinear inferential structure of CWHI across the complete WQI–ABI domain. The generated heatmap and contour plots (**Figure 5a & 5b**) showed distinct response regions associated with different combinations of WQI and ABI classifications. Multiple rule activation domains were represented by the response surface, which was made up of stable fuzzy plateau regions divided by intermediate overlap zones. The contour structure provided additional evidence of spatial variation in inferential responsiveness throughout the decision space. Stronger response gradients were seen close to intermediate overlap zones, while relatively stable regions were seen under extreme low-risk and high-risk situations. In areas where several fuzzy rules were initiated at once, moderate WQI and ABI combinations demonstrated relatively higher local responsiveness.

Non-compensatory nature of the framework is evident from 3-D response surface (**Figure 5c**). The higher values of CWHI are primarily obtained due to good WQI and lower classes of ABI. Even in presence of good WQI conditions, incorporation of higher ABI classes leads to reduction in overall classifications of water-health. Poor conditions for WQI still resulted in minimal CWHI in all ABI states. In the response surface, there were also regions that are flat, which meant that slight variations around those areas brought about minimal changes in the defuzzified CWHI outcomes. Stable inference zones resulting from overlapping linguistic classes are represented by these regions.

3.2 Sensitivity analysis

Both multi-region sensitivity analysis and single point OAT perturbation were used to assess how sensitive the CWHI framework was to variations in WQI and ABI inputs. The single-point OAT analysis, conducted at a base operating point of $WQI = ABI = 50$ ($CWHI_{base} = 30.00$), revealed near-zero local sensitivity for both inputs under $\pm 10\%$ perturbation (**Supplementary Table S11**). A 10% increase in ABI produced a marginal CWHI decline of -0.116 (sensitivity index = -0.039), while perturbations of the WQI at this location produced no measurable change. These results are attributable to the base point lying within a plateau region of the Mamdani output surface and do not indicate insensitivity of the model at large.

The multi-region sensitivity analysis demonstrated that model responsiveness is markedly region dependent. Results from four representative operating zones are summarized in **Table 2**. Under low-risk conditions ($WQI = 80$; $ABI = 20$), the framework exhibited greater sensitivity to WQI perturbation (sensitivity coefficient = 1.49) than to ABI perturbation (0.59). This indicates the expected behavior in upper-quality zones, where declines in WQ have a quite larger effect on CWHI than small increases in AMR burden.

In contrast, the transition-region scenario ($WQI = 50$; $ABI = 50$) displayed almost no local sensitivity for both WQI and ABI inputs. This behavior indicated a stable fuzzy plateau region where any disturbances stayed within the same inferential domain, leading to only slight changes in the defuzzified CWHI output. Under high-risk conditions ($WQI = 20$; $ABI = 80$), WQI sensitivity was effectively zero while ABI sensitivity remained measurable at 0.671. This is consistent with the framework's conservative penalization structure in which advanced deterioration along both axes leaves the system within a flat Critical plateau that is reachable only via ABI variation. Conversely, the boundary-zone scenario ($WQI = 40$; $ABI = 60$) demonstrated that the ABI sensitivity was elevated (4.997 versus 0.588 for WQI). This pattern

indicates that in transitional regions of the decision space, where conditions are moderately degraded, the CWHI output is considerably more sensitive to changes in AMR burden than to equivalent changes in physicochemical quality. Overall, these results indicate that sensitivity behavior within the framework was spatially heterogeneous and strongly dependent on local inferential regions rather than being globally uniform across the entire decision space.

Table 2. Local sensitivity of CWHI using $\pm 10\%$ perturbation in WQI and ABI.

Region	Base WQI	Base ABI	Base CWHI	Δ CWHI WQI	Δ CWHI ABI	Sensitivity WQI	Sensitivity ABI
Low Risk	80	20	60.253	9.987	4.748	1.658	0.788
Transition	50	50	30.000	0.000	0.058	0.000	0.019
High Risk	20	80	10.509	0.000	0.705	0.000	0.671
Boundary	40	60	20.018	1.177	10.003	0.588	4.997

Global grid-based sensitivity analysis over a uniform 101×101 input grid (step size = 1.0) yielded mean WQI and ABI gradients of 0.436 and 0.458, respectively (**Supplementary Table S12**). Median gradients for both variables were near zero (WQI: 2.13×10^{-14} ; ABI: 2.84×10^{-14}), indicating that large portions of the decision space are occupied by flat plateau regions (**Supplementary Figures S1**) and that active sensitivity is concentrated in relatively narrow transition bands rather than uniformly distributed. Overall, both WQI and ABI contributed to the integrated response structure, although local responsiveness varied across different regions of the decision space.

3.3 Uncertainty analysis

Stability analysis for CWHI against stochastic variations in WQI and ABI input data using Monte Carlo method ($N = 5,000$ simulations) was done by sampling WQI and ABI independently according to normal distributions with mean = 50 and SD = 5. The CWHI values obtained through simulation produced an average value of 29.14 (SD = 3.08, CV = 10.55%) and a 95% CI of [19.72, 30.00]. These summary statistics are reported in **Table 3**.

Table 3. Monte Carlo uncertainty analysis summary ($N = 5,000$ iterations; base point WQI = ABI = 50, SD = 5)

Statistic	Value
Mean CWHI	29.14
Standard Deviation	3.08
95% CI Lower	19.72

95% CI Upper	30.00
Coefficient of Variation (%)	10.55

The average simulated value of the CWHI (29.14) was relatively close to the deterministic baseline (30.00) for the chosen parameters. It implies low levels of systematic bias from stochastic variations of the inputs. The coefficient variation of 10.55% corresponds to an intermediate degree of relative uncertainty and is compatible with the close to constant behavior seen in sensitivity analysis. As for the confidence limits, the upper bound approaches closer to the deterministic CWHI value (30.00) and with lower bound 19.72 create the asymmetric shape of the fuzzy output surface in this bounded area (**Supplementary Figure S2**). More specifically, this asymmetry aligns with the CWHI fusion rule table's conservative, risk-penalizing aggregation logic. The observed uncertainty characteristics confirm that the framework maintains a stable central estimate while retaining sufficient responsiveness to directional shifts in input conditions.

3.4 Real scenario application of the hierarchical fuzzy framework

3.4.1 Site-wise WQ classification alongside river

Implementation of the hierarchical fuzzy approach to Musi River data indicated physicochemical pollution at all selected sites. The generated values for WQI ranged between 7.78 and 27.34, indicating that all sites were either classified as Critical or Poor water quality category. Musi Reservoir (MR) recorded WQI values of 27.33 (wet) and 27.35 (dry), both of which were classed as Poor, whereas Osman Sagar (OS) produced the highest WQI in both datasets (wet: 27.33; dry: 27.33). All remaining sites such as BGB, SRN, PP, GNB, NGB, PZ, PSB, and NRB, produced WQI values between 7.78 and 7.90 and were classified as Critical in both datasets (Table 4). From the results, it is evident that the analyzed sites are affected by high WQ deterioration based on the fuzzy water quality module employed. In addition, the small variation in WQI among these urban and wastewater-influenced sites implies that the environments have similar degrees of pollution regardless of differences in anthropogenic impact. The entire urban stretch is still near the lower end of the WQI output space, which is consistent with the untreated municipal sewage (de Medeiros et al. 2017; Sonkar et al. 2026), industrial effluents (Lübbert et al. 2017), and hospital effluents (Al Salah et al. 2020). Seasonal fluctuation within the examined dataset did not significantly change the overall WQ risk classification of the evaluated sites, as evidenced by the lack of WQI class transitions between wet and dry datasets (Supplementary Table S13). This stability is in line with the framework

design, which uses overlapping fuzzy membership structures instead of sudden threshold-based transitions to control inferential outputs.

Examination of the intermediate group scores provides further mechanistic context (**Figure 6**). Gr14 (TP–TOC sub-index) remained at low across all urban sites in both datasets (wet city mean: 7.95; dry city mean: 8.24), identifying organic carbon and phosphorus loading as the dominant constraint on WQI classification. Simultaneously, Gr5 (Nitrate–Nitrite) reached the system maximum (91.6) at urban sites in the dry dataset, reflecting extreme nitrogenous enrichment under reduced dilution conditions. The conservative rule structure of the hierarchical fusion, where the weaker sub-index governs the output, ensures that simultaneous impairment across multiple parameter groups as observed here, produces consistently Critical WQI classifications regardless of the marginal condition of any individual parameter.



Figure 6. Heatmap of intermediate fuzzy group scores (Gr1–Gr17) across Musi River sampling sites during the (a) dry and (b) wet season. The panel summarizes the internal hierarchical response of the WQI framework and highlights parameter groups contributing most strongly to degraded site-level classification.

3.4.2 AMR burden characterization across evaluated sites

The ABI outputs demonstrated substantial variation in AMR-associated risk across the evaluated site (**Table 5**). ABI values ranged from 37.41 to 65.89, covering, Low, Moderate, and High AMR risk classifications depending on the ARG composition, mobility potential, clinical relevance weighting, and antibiotic selection pressure associated with each site. The lowest ABI was observed at OS during the wet period (ABI = 37.41), and the highest at BGB during the dry period (ABI = 65.89). Several wastewater-impacted site units, including SRN (wet: 65.00; dry: 61.02), PZ (wet: 63.93), and NRB (wet: 64.54), consistently produced ABI values exceeding 60, indicating substantial AMR burden within the urban stretch. In the wet dataset, three sites were classified as High, five as Moderate, and two as Low, whereas in the dry dataset, four sites were classified as High, six as Moderate. It reflects an increase in AMR-associated risk across sites under dry-period conditions. This shift is attributable to an increase in clinical risk scores across sites (mean: wet 56.9 → dry 74.2) consistent with higher concentration of clinically relevant ARG pools when flow is reduced, rather than a structural change in the model's behavior.

The ARG-specific outputs further demonstrated that the dominant resistance drivers varied across site units (**Figure 7**). *sull* (sulfonamide resistance) was the top driver at 11 of 20 site-season dataset combinations, followed by *ermF* (4), *bla_{CTX-M}* (2), *bla_{NDM}* (2), and *qnrS* (1). The prevalence of *sull* is consistent with its physical association with *intI1*, which mediates HGT and co-resistance acquisition (Zheng et al. 2025). The occurrence of *bla_{NDM}* as the top driver at OS (dry) and MR (wet), both low-burden sites with dominance ratios near 0.16–0.19, reflects the ABI's clinical-priority weighting. Even where total ARG abundance is low, the presence of a Critical Priority carbapenem resistance determinant (**Supplementary Table S6**) generates a disproportionate clinical risk output, which is the intended behavior of the clinical risk component.

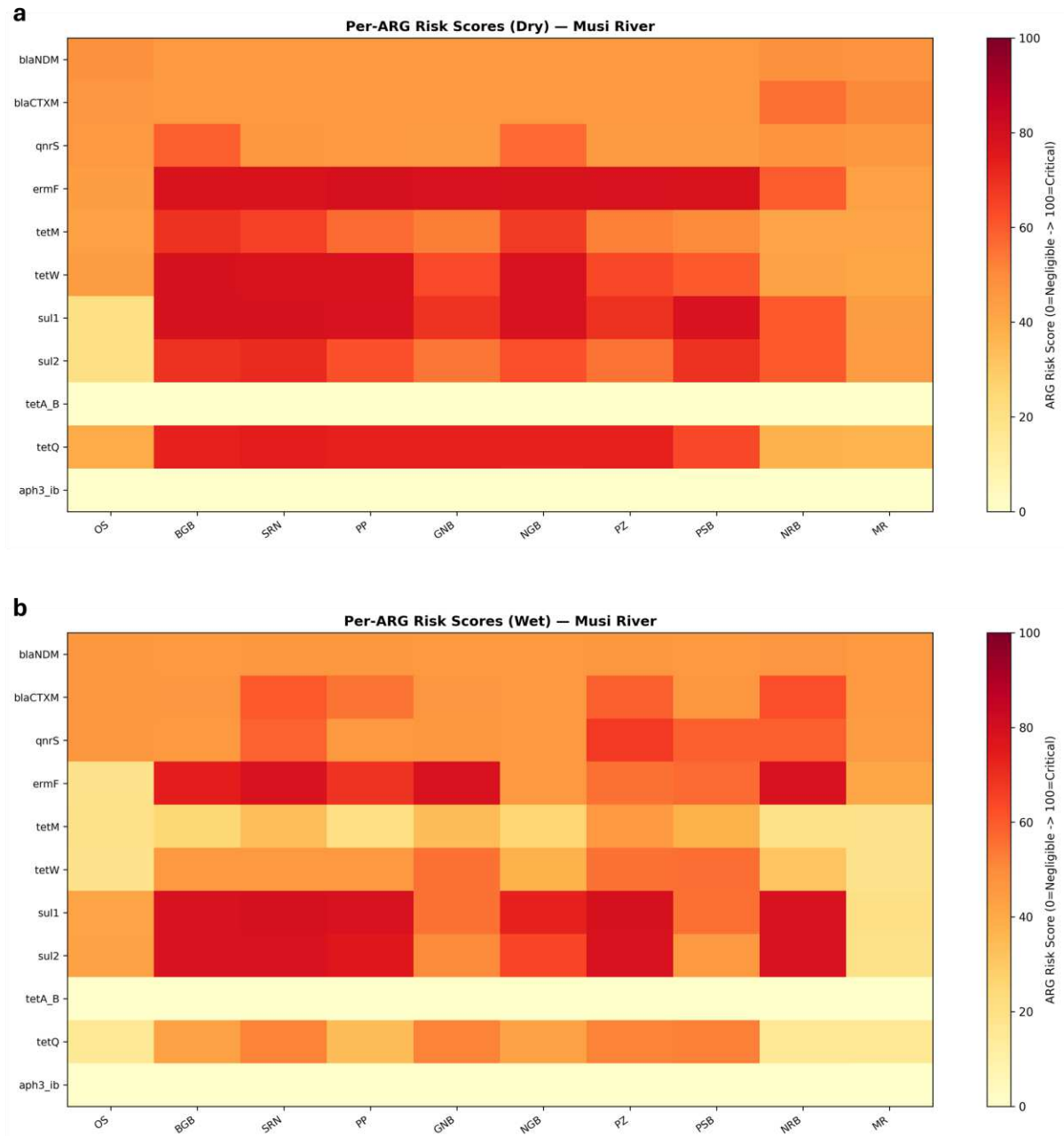


Figure 7. Heatmap of per-ARG risk scores across Musi River sampling sites during the (a) dry and (b) wet season. The panel highlights site-specific contributions of individual resistance determinants to the inferred AMR burden and enables identification of dominant ARG drivers under both seasons.

The occurrence of multiple clinically relevant ARG classes within the evaluated sites supports the rationale for integrating enrichment factors, mobility potential, clinical relevance, and antibiotic selection pressure within AMR burden framework rather than relying on ARG abundance measurements alone. The inclusion of a $PNEC_{res}$ (Bengtsson-Palme and Larsson 2016; Kneis et al. 2025) based antibiotic selection pressure component (**Supplementary Table**

S5 and S7) additionally enabled the model to account for environmentally relevant resistance-selection conditions. Fluoroquinolone, macrolide, and trimethoprim associated selection pressures contributed substantially to the inferred AMR burden across several urban sites, particularly at locations where ARG co-occurred with elevated integron-associated mobility potential, as evidenced by strong positive correlations between *intI1* and *tetW* (0.87), *tetQ* (0.87), and *sulI* (0.55) across the dataset (**Supplementary Table S14.**).

Despite variation in ABI magnitude among sites, the robustness of ABI outputs was computed and yielded CV values below 5% for 16 of 20 site–dataset combinations (classified robust). (**Supplementary Information D, Supplementary Table S15**). This indicates stable inferential behavior of the AMR module under moderate parameter uncertainty. The four exceptions, OS (dry; CV: 0.163), NRB (dry; CV: 0.117), and MR (wet; CV: 0.071; dry; CV: 0.075), are located at the low-burden extremes of the evaluated sites, where lower baseline ARG concentrations render relative scores more sensitive to normalization reference selection, particularly under the pooled-reference scenario C (**Supplementary Information D**). These results suggest that reference pool composition should be carefully taken into account when applying the framework to reaches that comprise background-condition locations and that ABI-based categorization is resilient at sites with prolonged ARG loading.

Table 4. Site-specific WQI scores and fuzzy classification for both wet and dry season sampling locations.

Season	Location	Stretch	WQI	WQI Class
Wet	Osman Sagar (OS)	Upstream	27.334	Poor
Wet	Bapughat Bridge (BGB)	Urban	7.826	Critical
Wet	Somi Reddy Nagar (SRN)	Urban	7.852	Critical
Wet	Puranapul (PP)	Urban	7.826	Critical
Wet	Golnaka Bridge (GNB)	Urban	7.826	Critical
Wet	Nagole Bridge (NGB)	Urban	7.852	Critical
Wet	Peerzadiguda (PZ)	Urban	7.852	Critical
Wet	Pratap Singaram Bridge (PSB)	Urban	7.852	Critical
Wet	Nagaram Bridge (NRB)	Semi-urban	7.826	Critical
Wet	Musi Reservoir (MR)	Downstream	27.334	Poor
Dry	Osman Sagar (OS)	Upstream	27.333	Poor
Dry	Bapughat Bridge (BGB)	Urban	7.852	Critical
Dry	Somi Reddy Nagar (SRN)	Urban	7.852	Critical
Dry	Puranapul (PP)	Urban	7.852	Critical
Dry	Golnaka Bridge (GNB)	Urban	7.778	Critical
Dry	Nagole Bridge (NGB)	Urban	7.904	Critical
Dry	Peerzadiguda (PZ)	Urban	7.852	Critical
Dry	Pratap Singaram Bridge (PSB)	Urban	7.904	Critical
Dry	Nagaram Bridge (NRB)	Semi-urban	7.859	Critical
Dry	Musi Reservoir (MR)	Downstream	27.345	Poor

Table 5. Site-wise ABI scores and corresponding fuzzy risk classifications for Musi River during wet and dry seasons.

Season	Location	Stretch	AMR Index	AMR Class	Top Driver ARG	Env load	Clin risk
Wet	OS	Upstream	37.414	Low	<i>blaCTX-M</i>	9.192	56.954
Wet	BGB	Urban	56.639	Moderate	<i>sulI</i>	49.877	61.554
Wet	SRN	Urban	64.996	High	<i>sulI</i>	60.870	61.498
Wet	PP	Urban	57.969	Moderate	<i>sulI</i>	46.502	61.498
Wet	GNB	Urban	53.812	Moderate	<i>ermF</i>	56.504	52.377
Wet	NGB	Urban	48.840	Moderate	<i>sulI</i>	41.425	57.010
Wet	PZ	Urban	63.928	High	<i>sulI</i>	67.580	57.010
Wet	PSB	Urban	53.818	Moderate	<i>qnrS</i>	59.190	47.761
Wet	NRB	Semi-urban	64.538	High	<i>sulI</i>	45.119	61.626
Wet	MR	Downstream	37.170	Low	<i>blaNDM</i>	8.739	52.248
Dry	OS	Upstream	45.428	Moderate	<i>blaNDM</i>	12.398	65.759
Dry	BGB	Urban	65.891	High	<i>sulI</i>	61.018	75.137
Dry	SRN	Urban	61.024	High	<i>sulI</i>	58.159	75.137
Dry	PP	Urban	60.210	High	<i>ermF</i>	53.447	75.137
Dry	GNB	Urban	58.411	Moderate	<i>ermF</i>	44.546	75.137
Dry	NGB	Urban	64.804	High	<i>sulI</i>	58.184	75.137
Dry	PZ	Urban	58.396	Moderate	<i>ermF</i>	44.740	75.137
Dry	PSB	Urban	58.842	Moderate	<i>sulI</i>	46.550	75.065
Dry	NRB	Semi-urban	54.974	Moderate	<i>sulI</i>	25.317	75.008
Dry	MR	Downstream	46.521	Moderate	<i>blaCTX-M</i>	11.728	75.008

3.4.3 Integrated Cumulative Water-Health Classification

Integration of WQI and ABI through the hierarchical fusion framework produced CWHI values ranging from 8.52 to 19.75 across all evaluated sites and sampling seasons (Table 6). All CWHI outputs fell within the Critical class, indicating that no evaluated site attained a composite water-health status above the lowest risk tier. During the wet season, OS site had the highest CWHI value (CWHI = 19.05), which is associated with the dataset's highest WQI (27.33; Poor class) and lowest ABI (37.41; Low class). Even at the Low ABI class, the AMR burden component continued to provide enough cumulative risk within the fusion structure, thus even with these relatively improved WQ individual index values, the cumulative categorization remained Critical. This outcome is in line with the ideal fusion matrix, where the combination of Poor WQI and Low-to-Moderate ABI translates into a CWHI range around 8.9 to 30.0 (scenarios S6-S8, Supplementary Table S10), and with Moderate ABI ensures that the Critical class remains valid.

The lowest CWHI values observed in the dataset were at sites with both severely degraded WQI and high ABI. BGB during the dry period (WQI = 7.85 and ABI = 65.89, High class), yielded CWHI = 9.00 with comparable outputs were observed at SRN in the wet period (WQI = 7.85; ABI = 65.00; CWHI = 9.15), PP in the dry period (WQI = 7.85; ABI = 60.21; CWHI = 9.99), and NRB in the wet period (WQI = 7.83; ABI = 64.54; CWHI = 9.23). These results confirm that simultaneous WQ degradation and elevated AMR burden consistently constrained CWHI classification to the lowest range of the Critical class.

The distribution of CWHI outputs across sites and seasons reflects the non-compensatory aggregation logic of the fusion framework, in which improvement in one domain does not proportionally offset elevated risk in the complementary domain. As demonstrated by the validated ideal matrix, a site with Excellent WQI and High ABI returns a Poor CWHI (S24: CWHI = 30.0), while a site with Good WQI and Very High ABI returns a Critical CWHI (S20: CWHI = 8.39). The only pathway to a Safe classification (CWHI > 80) requires Excellent WQI simultaneously with Very Low ABI (S21: CWHI = 91.62), a condition unattained at any evaluated site in the present dataset. This behavior is environmentally relevant for sewage-impacted urban waters, where conventional WQ assessment alone may underestimate broader public-health risks associated with AMR dissemination (Sabri et al. 2020; Prasad et al. 2024; Sonkar et al. 2026). The framework thus provides an integrated decision-support approach capable of simultaneously evaluating physicochemical impairment and AMR-associated

burden within individual site units, consistent with its intended function as a site-level risk classification tool.

Table 6. Site-wise integrated CWHI results for Musi River sampling locations during wet and dry seasons.

Location	Season	Stretch	CWHI	CWHI Class
OS	Wet	Upstream	19.051	Critical
BGB	Wet	Urban	9.428	Critical
SRN	Wet	Urban	9.149	Critical
PP	Wet	Urban	9.663	Critical
GNB	Wet	Urban	8.953	Critical
NGB	Wet	Urban	8.522	Critical
PZ	Wet	Urban	9.330	Critical
PSB	Wet	Urban	8.954	Critical
NRB	Wet	Semi-urban	9.226	Critical
MR	Wet	Downstream	19.747	Critical
OS	Dry	Upstream	8.989	Critical
BGB	Dry	Urban	9.001	Critical
SRN	Dry	Urban	9.845	Critical
PP	Dry	Urban	9.995	Critical
GNB	Dry	Urban	9.742	Critical
NGB	Dry	Urban	9.181	Critical
PZ	Dry	Urban	9.740	Critical
PSB	Dry	Urban	9.821	Critical
NRB	Dry	Semi-urban	9.144	Critical
MR	Dry	Downstream	8.835	Critical

3.5 Policy implications for AMR-informed urban water governance

3.5.1 Integrating AMR into water-use classification

Conventional water-use classification frameworks, including the Central Pollution Control Board Designated Best Use criteria (CPCB 2019) in India, primarily rely on physicochemical and microbiological indicators to determine the suitability of surface waters for different uses. These frameworks provide an important regulatory basis for water-resource management, but do not explicitly consider environmental AMR, including ARGs, MGEs, or antibiotic residues. Consequently, compliance with conventional water-quality standards does not necessarily indicate low AMR risk (Berendonk et al. 2015; Manaia et al. 2015).

The proposed CWHI addresses this gap by introducing AMR as an additional decision layer within existing water-use classification systems. Notably, rather than replacing current regulatory classifications, the CWHI serves as a precautionary overlay that integrates WQPs and AMR burden into a cumulative risk-based assessment. The current application of the framework to the River Musi showed that all urban sites were classified as Critical, and indicates the reliance on WQPs alone may underestimate cumulative one health risks in sewage-impacted rivers (Berglund et al. 2015; Van Boeckel et al. 2019; Chopyk et al. 2020; Prasad et al. 2024).

Accordingly, the proposed classification adopts a non-compensatory approach in which elevated AMR-burden restricts permissible water uses even when conventional water-quality are within regulatory limits. Such a framework provides a more precautionary basis for decisions on irrigation reuse, industrial abstraction, ecological restoration, and recreational water use (as described in Table 7), particularly in water-stressed urban regions where wastewater-impacted rivers are increasingly important water resources.

Table 7. Use based classification for frequency of AMR monitoring in surface-water based on the developed CWHI framework.

CWHI Class	Score Range	Permissible Water Uses	AMR Requirement	Monitoring
Safe	> 80	All uses include direct human contact, drinking source, aquaculture, and animal propagation, and irrigation of edible crops.	Routine surveillance	annual AMR
Good	60–80	Outdoor bathing; drinking after conventional treatment operations, supervised aquaculture, animal propagation, and irrigation of edible crops.	Biannual integron monitoring	AMR and
Moderate	40–60	Restricted irrigation and limited non-potable reuse following risk evaluation; caution for aquaculture and livestock exposure	Quarterly mobility-marker profiling	ARG and
Poor	20–40	Restricted industrial reuse and controlled non-food-crop applications following treatment; unsuitable for direct human-contact uses	Monthly assessment and discharge monitoring	AMR hotspot
Critical	< 20	Unsuitable for direct reuse, irrigation of edible crops, recreation, or ecological exposure pathways without advanced treatment and containment measures.	Continuous wastewater and point-source discharge locations	or high-frequency surveillance at

3.5.2 Risk-based environmental decision-making

Beyond water-use classification, the CWHI provides a practical decision-support tool by translating complex physicochemical water quality and AMR information into transparent and interpretable risk categories. As a precautionary, risk-tiered overlay to the existing CPCB classification system, it incorporates AMR into water-use decisions by adopting the more conservative assessment of either conventional water quality or AMR burden (Table 7). This non-compensatory approach recognizes that improvements in physicochemical water quality

cannot offset elevated AMR burden, providing a more precautionary basis for One Health-oriented urban water governance.

The integrated assessment enables regulators to identify priority monitoring locations, evaluate spatial patterns of cumulative river-health risks, and prioritize surveillance where conventional water-quality assessment alone may underestimate environmental hazards. In particular, locations with elevated ARG abundance and *intI1* indicate greater potential for HGT and environmental dissemination of AMR. As *intI1* is increasingly recognized as an anthropogenic pollution marker, its inclusion in routine monitoring provides a practical and cost-effective means of strengthening AMR surveillance alongside conventional water-quality program.

CWHI also provides a consistent metric for evaluating the effectiveness of management interventions, including wastewater treatment plant upgrades, decentralized sanitation systems, pollution-source control, and river-restoration program. By enabling comparisons of cumulative river-health risks across locations and over time, the framework supports adaptive environmental management, evidence-based resource allocation, and communication among environmental managers, public health agencies, and other stakeholders. Furthermore, the framework complements existing initiatives, including India's National Action Plan (Ministry of Health and Population 2020) on AMR and the WHO One Health approach (Graham et al. 2019), by providing an operational mechanism for incorporating environmental AMR into routine environmental decision-making (Berendonk et al. 2015).

3.5.3 Policy implementation

For urban-water governance, the CWHI framework serves as a useful decision-support tool, especially in areas with growing AMR pressure, limited wastewater treatment capacity, and rapid urbanization (Berglund et al. 2015; Hendriksen et al. 2019). First, it creates targeted monitoring possible. Areas with high ABI and strong co-occurrence of ARGs with *intI1* have a higher potential for horizontal gene transfer and should be monitored more closely (Quintela-Baluja et al. 2021). Within current regulatory systems, the use of *intI1* as HGT-based indicator offers an affordable method for routine surveillance (Gillings et al. 2015). Second, the framework can be used to communicate both water-consumption and risk. The CWHI score reduces the complexity of AMR information into one easy-to-understand class and makes the output more palatable to policy makers. The framework is also aligned with the operational needs identified in the WHO GLASS guidance (WHO 2025) and the National AMR Action Plan framework (Ministry of Health and Population 2020). In addition, using WQ and AMR

loads in the calculation of the CWHI class, it provides a unified way to assess the surface water-health risk metrics. These metrics may be employed for intervention's effectiveness such as WWTP upgrades, decentralized systems, and pollution control measures (Sonkar et al. 2025; Kumar et al. 2026).

In the short-term implementation, the existing river-monitoring programs can be expanded to include a limited set of environmental AMR indicators, such as representative ARGs, *intI1*, and antibiotic residues, alongside the conventional WQP. This would provide a more comprehensive evidence base for assessing cumulative water-health risks without requiring fundamental changes to current monitoring infrastructure. Over the course of the period, the CWHI could be integrated into regulatory reporting as a complementary decision-support metric for prioritizing surveillance, evaluating wastewater-treatment performance. For long-term implementation, monitoring should focus on strengthening upstream source control and reducing environmental selection pressure (Hocquet et al. 2016; Gothwal and Shashidhar 2017) through improved wastewater treatment, advanced treatment of hospital and pharmaceutical effluents, and the wider adoption of nature-based treatment systems. Future regulatory frameworks could incorporate AMR-informed assessment into water-use planning to ensure that the decisions reflect both conventional water quality and the environmental potential for resistance dissemination. Such an approach would support more resilient urban water governance in rapidly urbanizing, water-stressed regions (Bougnom and Piddock 2017; WHO 2018) while contributing to national and global strategies to mitigate AMR.

4. Limitations and future scope

The developed model framework is intended as a decision-support tool rather than a predictive model. The performance of the proposed model depends on the availability of representative water-quality and AMR datasets and may require local calibration before application across different environmental or regulatory settings. The current model implementation integrated the reported ARGs, *intI1*, and antibiotic concentrations to classify AMR burden. However, it does not explicitly incorporate pathogen infectivity, exposure pathways, or quantitative human-health risk. Future research should focus on integrating the model with metagenomic surveillance and quantitative microbial risk assessment to adapt this framework for routine monitoring, regulatory assessment, and AMR-informed water governance.

5. Conclusion

This study developed an integrated decision-support framework that combines conventional WQ and environmental AMR into a CWHI for urban rivers. It provides a more comprehensive assessment of surface-water health than conventional water-quality indices alone. The framework application to the Musi River demonstrated its ability to translate complex environmental information into transparent risk categories. As AMR becomes an increasingly important challenge for urban water management, considering AMR in routine river health assessments can strengthen One Health-based governance and provide a practical evidence base for risk-informed policies in sewage-impacted and water-stressed regions.

CRedit authorship contribution statement

Arun Kashyap: Conceptualization, Methodology, Software, Formal analysis, Validation, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization. **Vikas Sonkar:** Data Curation, Writing – review & editing, Investigation. **Shashidhar Thatikonda:** Supervision, Methodology, Conceptualization, Writing – review & editing, Validation, Visualization.

Data availability

All data, including the additional figures and necessary tables are made available as part of supplementary information.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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