Global J. Environ. Sci. Manage. 13(1): 01-26, Winter 2027, Serial #49

Global Journal of Environmental Science and Management
(GJESM)

Homepage: https://www.gjesm.net/

Podcasts

ORIGINAL RESEARCH ARTICLE

Integration of the online river water quality monitoring management framework based on inclusive governance

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ARTICLE INFO

Article History:
Received 09 April 2026
Revised 13 June 2026
Accepted 15 July 2026

Keywords:
Data quality
Inclusive governance
Multi-stakeholder collaboration
Online river water quality monitoring
System performance

ABSTRACT

BACKGROUND AND OBJECTIVES: Online river water quality monitoring systems are increasingly used to support pollution control. Nonetheless, the efficacy of these systems remains constrained by key technical and organizational challenges, namely high data variability, sensor instability, restricted interoperability, and decentralized institutional governance. These challenges reduce the trustworthiness of online data for evidence-based pollution control policy and decision-making. The study objectives were to develop an integrated framework to improve data quality, system performance, and coordination in the governance of online river water quality monitoring river water quality monitoring in watersheds across Indonesia.

METHODS: A transdisciplinary methodological approach was applied by combining 1) Integrated data quality management to assess data completeness, accuracy, validity span and stability; 2) Key performance indicators measured by the analytical hierarchy process to evaluate the performance of online river water quality monitoring systems; and 3) Soft systems methodology to build a governance-oriented conceptual model through rich descriptions, root definitions, conceptual models and evaluation of the 3Es (efficacy, efficiency and effectiveness). This study analyzed environmental data collected between 2023 and 2025 from four monitoring stations representing the upstream and downstream reaches of the Ciliwung and Cisadane Rivers. To complement these quantitative findings, semi-structured interviews were conducted with a broad range of stakeholders, including government agencies, vendors, academics, researchers, the media, community-based non-governmental organizations, and local communities residing near the four stations.

FINDINGS: An analysis of data quality demonstrated robust completeness (99–100 percent), highly variable non-zero completeness across all stations, high validity across the range for dissolved oxygen, hydrogen potential, and temperature (greater than 95 percent), and large fluctuations in stability at stations affected by tidal and sediment dynamics. The system performance index was 61.18 percent. Synthesizing soft systems methodology highlighted key operational barriers, such as fragmented roles, low trust towards online data, and lack of community participation. Consequently, this study developed an online river water quality monitoring management framework designed to prioritize digital interoperability, transparency, accountability, and multi-stakeholder governance.

CONCLUSION: The inclusive governance-based online river water quality monitoring framework provides an empirically informed conceptual framework for organizing data-quality, performance, and governance improvements, improved collaboration among government agencies. Subject to contextual adaptation and prospective validation, this framework offers valuable insights for management design in other watersheds, ultimately contributing to the advancement of digital environmental governance in developing nations.

DOI:10. 22034.gjesm.2027.01.01

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NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
81	10	6

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Note: Discussion period for this manuscript open until March 01, 2027 on GJESM website at the “Show Article”.

INTRODUCTION

Rivers play a vital role in supporting ecological processes, socio-economic activities, and providing essential services such as domestic water supply, fisheries, agriculture, and recreation (Singh *et al.,* 2020; Debnath *et al.,* 2021). Fluvial systems have experienced progressive environmental degradation, driven primarily by rapid urbanization and industrial expansion (Kumar *et al*., 2017; Chen *et al*., 2022). This phenomenon is seen in many developing countries, including Indonesia. Carvalho *et al*. (2019) and UNEP (2021) emphasized that monitoring river water quality is important for understanding pollutant behavior, identifying pollution sources, and supporting effective environmental management and intervention strategies. In recent years, river water quality monitoring has transitioned from labor-intensive manual sampling protocols toward automated, real-time data acquisition leveraging Internet of Things (IoT)-enabled (Zhang *et al*., 2020; Singh *et al*., 2022). Sustainable development goal 6.3 (SDG 6.3) is to improve water quality by reducing pollution and treating wastewater (Kremere *et al*., 2019). Recently, the advancement of sensor technology has enabled the development of online river water quality monitoring systems that are always on and can sense critical parameters such as dissolved oxygen (DO), chemical oxygen demand (COD), biochemical oxygen demand (BOD), potential of hydrogen (pH), turbidity, temperature, conductivity and nutrient concentrations (Farouk *et al*., 2023; Rajendran *et al*., 2025). To enhance the national environmental monitoring network, the Ministry of Environment (KLH) has established online river water quality monitoring (ORWQM) as a core strategic initiative. The number of ORWQM stations in Indonesia has continued to increase from 2015 to 2024, reaching 347 stations in different watersheds (KLHK, 2024). Institutionally, ORWQM can be a national strategic instrument for KLH and local governments to achieve the SDG 6.3 target on water pollution control. ORWQM assessments should focus on three key areas: data quality, system performance and inclusive governance. Ultimately, the proposed framework provides a conceptual basis to validate ORWQM data integrity, evaluate system performance across multidimensional indicators, and design highly adaptive, transparent, and participatory governance models. The literature on stakeholder engagement in water management suggests that effective participation relies on clarity of purpose, transparency, accountability, capacity, access to information, and ongoing evaluation (Akhmouch and Clavreul, 2016). Soft Systems Methodology (SSM) is used to develop a governance model that clarifies actor roles, institutional fragmentation, levels of trust in online data, and the need for multi-stakeholder coordination. Existing research demonstrates that poor-quality environmental data—specifically when inaccurate, incomplete, unstable, or invalid—compromises the integrity of monitoring programs and obstructs evidence-based policy formulation (Wang and Strong, 1996; Batini and Scannapieco, 2016). In Indonesia, inconsistent sensor data and missing values are frequently reported, limiting the use of online measurements for modeling, pollution law enforcement, early warning system (EWS), and compliance reporting (Wahyono and Yudo, 2022; Yudo *et al.,* 2023; Yudo *et al*., 2026). In tandem with data-related limitations, institutional and governance bottlenecks pose formidable obstacles to the enduring viability of the ORWQM system. Different government agencies, such as KLH, the Watershed Management Agency (BPDAS), the River Basin Organization (BBWS), the Environment Agency (DLH) at the provincial and district levels, and local government, have overlapping mandates in water resource management. Institutional fragmentation, coupled with the absence of both formal coordination mechanisms and an integrated data sharing framework hinder the efficiency and accountability of the monitoring system

(OECD, 2015; World Bank, 2017). Experiences from other countries suggest that the monitoring systems are more likely to have a positive impact on policy if they are supported by open data initiatives, community engagement and multi-stakeholder management (Gupta *et al*., 2020; Dong *et al*., 2023; Domínguez-Rendón *et al*., 2024). In Indonesia, citizen participation in river management remains limited. Furthermore, monitoring data are frequently not effectively disseminated to local communities or river-centric non-governmental organizations (NGOs), thereby hindering collaborative surveillance and timely pollution response efforts (Shao and Bishop, 2021; Basuki *et al*., 2024; Sulistiyowati and Uyun, 2024). Prior research has predominantly concentrated on isolated technical dimensions, such as enhancing sensor accuracy and developing predictive water quality models, or has alternatively focused on formal governance frameworks for pollution control (Ratolojanahary *et al*., 2019; Talagala *et al*., 2019; Zhou, 2020; Cao *et al*., 2022). Several studies highlight the importance of integrated, multi-stakeholder watershed governance (Behmel *et al.,* 2018; Lim *et al.,* 2022). Existing ORWQM assessments generally address sensor performance, data analytics, and institutional governance separately, leaving a gap in explaining how data-quality problems affect system performance and translate into governance actions. To bridge this critical literature gap, this study establishes a comprehensive socio-technical framework that systematically couples TDQM–ODQEM data-quality diagnosis, key performance indicator (KPI) – analytic hierarchy process (AHP) performance prioritization, and SSM-based governance redesign. Its novelty lies in a traceable pathway from identifying whether online data are complete, valid, stable, and usable, to prioritizing performance constraints and converting them into governance activities, clearer institutional roles, and coordination mechanisms. Consequently, the proposed framework consolidates diagnostic, evaluative, and participatory functions into a unified managerial logic, offering strong potential to facilitate evidence-based pollution-control decisions upon prospective implementation and empirical evaluation. This study aims to determine the extent to which the community understands the functions and benefits of the ORWQM stations, as well as their concerns about the condition of the surrounding river water quality. Furthermore, the study evaluates community willingness and capacity to participate in environmental monitoring, while identifying key systemic barriers, such as institutional distrust, constrained digital literacy, and information asymmetry—that may compromise the efficacy of ORWQM governance. This survey aims to measure the extent to which community perceptions are based on subjective data obtained quantitatively through a questionnaire instrument. This study was carried out at the Graduate School of Sustainable Development, Universitas Indonesia, Jakarta, Indonesia, in 2025.

MATERIALS AND METHODS

The study area

This study used four ORWQM stations as samples. The two stations are located on the Ciliwung River (Manggarai and Kelapa Dua) and the two stations are located on the Cisadane River (Empang Dam and Kali Sabi). The four monitoring stations were purposively selected to ensure river-basin representation, ORWQM data availability, and relevance to regional pollution-control efforts. The Ciliwung and Cisadane Rivers were chosen because they are strategic rivers in the Jakarta, Bogor, Depok, Tangerang and Bekasi areas and are part of priority watersheds (Yulianto *et al*., 2021). Differences among Manggarai, Kelapa Dua, Empang Dam, and Kali Sabi are interpreted in terms of station locations, hydrodynamic conditions, sediment influences, urban/industrial pressures, sensor behavior, and institutional maintenance contexts. Alternative explanations, including stable environmental conditions, sensor resolution, communication disruptions, and operational downtime, are considered to avoid over-attribution of patterns to

a single cause. According Wahjono (2016), the technology of ORWQM has been applied to priority watersheds, namely Ciliwung and Cisadane rivers. The four monitoring stations used in this study were Manggarai, Kelapa Dua, Empang Dam, and Kali Sabi, chosen because they represent the spatial variation and pollution levels in the Ciliwung and Cisadane Rivers. Manggarai Station monitors the lower reaches of the Ciliwung River in the densely populated metropolitan area of Jakarta, while Kelapa Dua Station captures the transitional middle to lower reaches, which are significantly influenced by residential development and land-use alterations. In the Cisadane River, Empang Dam Station represents the upper reaches of the system, while Kali Sabi Station represents the lower reaches, which are affected by domestic, urban, and industrial activities. Fig. 1 illustrates the spatial distribution of the four monitoring stations across the Jakarta, Tangerang, Bogor, and Depok areas on Java Island, while Table 1 details their respective physical addresses and geographic coordinates. ORWQM stations are installed along riverbanks in several watersheds in the upper, middle, and lower reaches of rivers (Fig. 2a). This system plays a crucial role in water resource management (Tsatsaros *et al.,* 2021; Rodriguez *et al.,* 2021), environmental protection, and data-driven decision-making. This system can strengthen oversight, policy evaluation, and inter-agency coordination in river water quality management (Saleh and Stanley, 2023). From a technical perspective, each ORWQM station features an identical hardware configuration (Fig. 2b), comprising sensors, data loggers, batteries, solar cells, modems, and pumps (Wahyono *et al.,* 2026). Some of the data logger functions include: setting the time interval for sending data to the data center via global system for mobile communications, sending data to be displayed on a running text, displaying data on a liquid crystal display (LCD) screen, setting periodic sensor cleaning, setting the pump interval for taking water samples from the river, and setting battery charging (Fig. 2c). Data collection was executed utilizing two multiparameter sensors: the first is a physicochemical sensor that measures 11 parameters, namely electrical conductivity, salinity, total dissolved solids (TDS), DO, temperature, pH, turbidity, nitrate, ammonia, oxidation reduction potential (ORP), and depth. The second is an organic sensor that measures 3 parameters: BOD, COD, and total suspended solids (TSS). This system works by periodically measuring 14 water quality parameters, archiving the logged data locally, and transmitting it at scheduled intervals to a centralized data center.

The data sources

This study used three primary data sources. First, ORWQM data (2023–2025) at four ORWQM stations in the Ciliwung–Cisadane region (Manggarai, Kelapa Dua, Empang Dam, and Kali Sabi) covering 11 water quality parameters (COD, BOD, TSS, DO, pH, nitrate, ammonia, temperature, conductivity, TDS, and turbidity). With data transmission configured at hourly intervals, each station typically registers a minimum of 24 records per day. Consequently, assuming continuous sensor operation, a single station is projected to accumulate approximately 8,760 records annually. One data record consists of 17 columns or fields: Station ID, Date, Time, and several water quality parameters. Second, semi-structured interviews were conducted with 27 cross-sectoral stakeholders, including government representatives, academics/researchers, private vendors, NGOs, media, and station operators. Third, the study gathered empirical data on local residents' perceptions within the immediate vicinity of the four monitoring stations through structured questionnaire surveys.

The methods used

This study uses three stages of analysis, namely: 1) Data quality evaluation with a combined approach of total data quality management (TDQM) and online data quality evaluation model (ODQEM) for performance improvement.

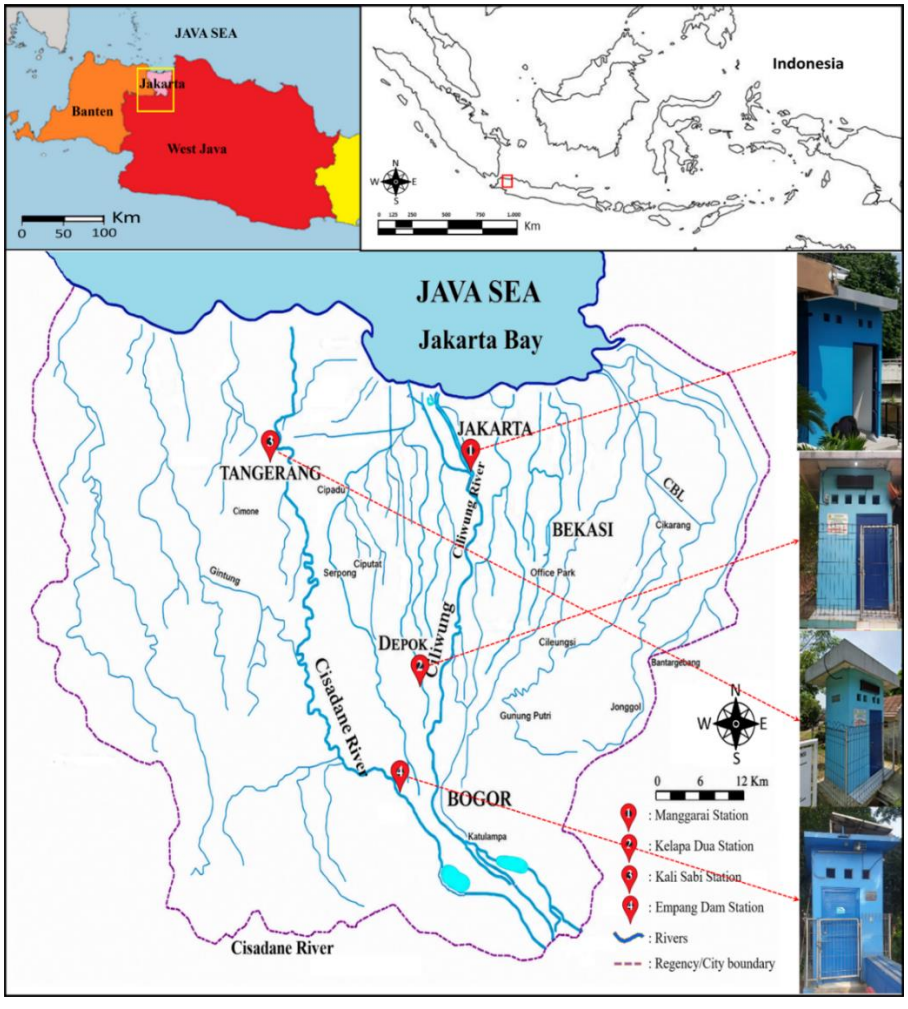

Fig. 1: Geographical location of four stations in the Jakarta, Tangerang, Bogor, and Depok areas on Java Island, Indonesia

Table 1: Location of four ORWQM stations on the Ciliwung River and Cisadane River

No.	Station Name	River	Address	Coordinate	
				Latitude	Longitudes
1	Manggarai	Ciliwung	Tambak Street, RT.07/ RW.04, Pegangsaan, Menteng District, Central Jakarta, DKI Jakarta	-6.20784	106.84851
2	Kelapa Dua	Ciliwung	Arus Alley, RT.07/ RW.01, Srengseng Sawah, Jagakarsa District, South Jakarta, DKI Jakarta.	-6.35264	106.83564
3	Empang Dam	Cisadane	Sedane Street, RT.05/ RW.06, Paledang, Bogor City, West Java Province	-6.60777	106.79288
4	Kali Sabi	Cisadane tributary	Moh. Toha Street, RT.01/ RW.01, Periuk, Periuk District, Tangerang City, Banten, Province	-6.16079	106.62772

TDQM provides a conceptual framework through general data quality dimensions, namely completeness, validity, accuracy, and uniqueness (Wang and Strong, 1996; Wang, 1998). This framework is then adapted with ODQEM technical indicators, namely completeness index (CI), range validity (RV), stability index (SI), accuracy vs lab, and uniqueness (duplicate check); 2) System performance evaluation with a combined method of KPI and AHP. To evaluate the ORWQM system,

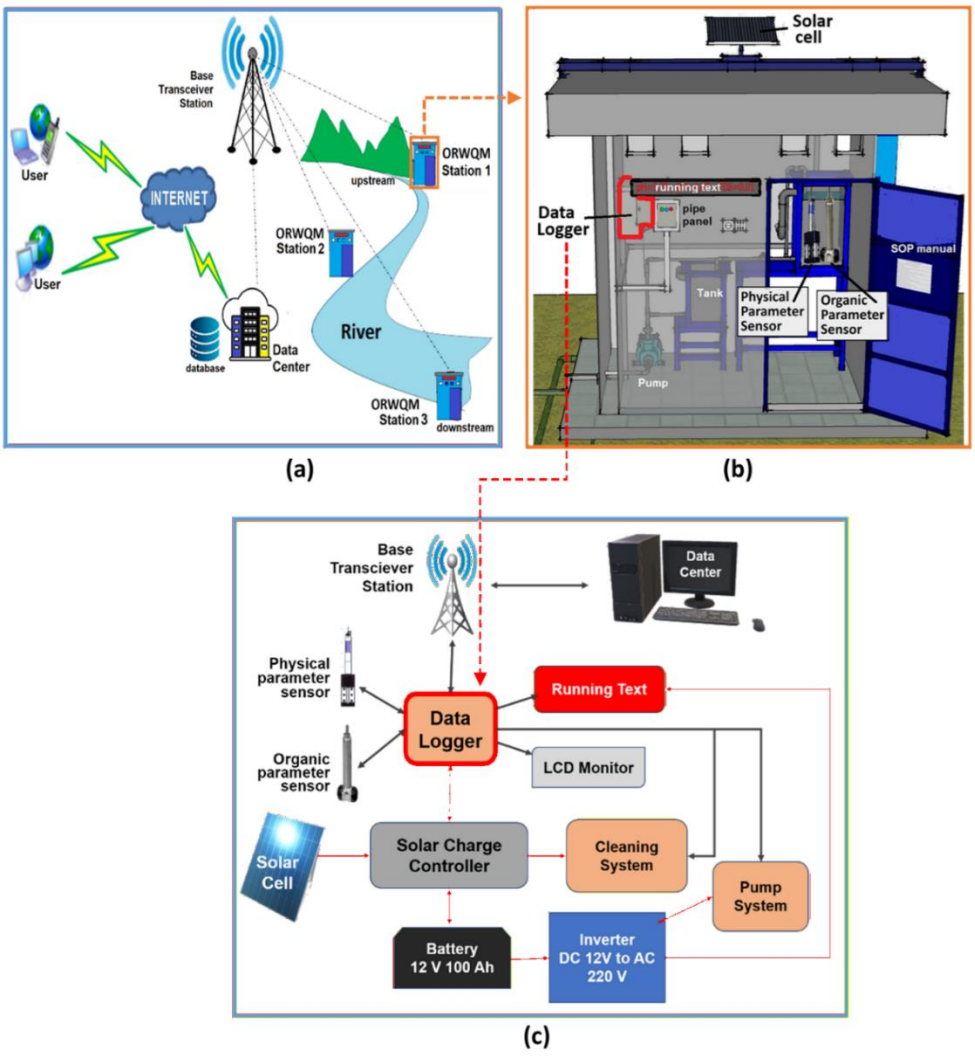

Fig. 2: Diagram of the ORWQM station: (a) Connection system; (b) Station components; and (c) Flow diagram (Modified from Wahyono *et al.,* 2026)

performance assessments are executed by synthesizing the AHP-derived priority weight (Saaty, 1990) with the actual performance scores of each individual KPI (Lo-Iacono-Ferreira *et al.,* 2018; Mamun *et al.,* 2019); 3) Designing a conceptual governance model using the SSM approach. In creating this conceptual model, three SSM components serve as the basis and must be followed: Root definition, Do P, by doing Q, to achieve R (PQR formula), and customers, actors, transformation, worldview, owners, environment (CATWOE). Success indicators are operationalized and evaluated through the '3E' framework, comprising efficacy, efficiency, and effectiveness. This SSM phase analyzes the overall picture, CATWOE analysis, and conceptual modeling to define institutional roles, stakeholder interactions, operational challenges, and governance gaps. Methodologically, this study contributes an integrative mechanism that systematically bridges three established approaches. TDQM-ODQEM generates diagnostic indicators of data usability, then KPI-AHP transforms these indicators and system concerns

derived from stakeholders into weighted priorities, and finally SSM transforms the prioritized issues into root definitions, CATWOE elements, conceptual activities, and governance improvements. This constructs a methodological bridge between quantitative data-quality assessments and qualitative governance redesign, integrating the two by systematically feeding the analytical outputs of each stage as explicit inputs into the next.

Data quality evaluation

The first stage of this research was to analyze data quality at the four stations by evaluating core dimensions adapted from the TDQM (Wang and Strong, 1996; Batini and Scannapieco, 2016). This research used a combined approach between the TDQM and the proposed ODQEM water quality evaluation model. The TDQM provides a conceptual framework through general data quality dimensions: completeness, validity, accuracy, and uniqueness (Wang and Strong, 1996; Wang, 1998). This framework was then adapted to the context of sensor-based ORWQM using the ODQEM technical indicators: CI, RV, SI, accuracy vs lab, and uniqueness (duplicate check). The following formulas are used to calculate each dimension of CI, RV, SI, and accuracy compared to the Lab. The completeness analysis evaluates two core dimensions: structural completeness (the presence of expected time-stamped records) and functional completeness (the proportion of analytically viable, non-zero values). The CI dimension refers to the quantity of available data compared to the total observation time, using Eq. 1 (Egidio *et al.*, 2022; Teh *et al.*, 2020):

$$CI = \frac{N_{\text{valid}}}{N_{\text{expected}}} \times 100\% \quad (1)$$

The more complete the data recorded and stored by the online sensor system, the higher the CI value, approaching 100 percent (%). Low values, on the other hand, indicate missing data, transmission interference, or inactive sensors. RV dimensions account for the percentage of measurements falling within the regulatory ranges, specifically those satisfying water quality standards, using Eq. 2 (Wagner *et al.*, 2006):

$$RV = \frac{N_{\text{in-range}}}{N_{\text{valid}}} \times 100\% \quad (2)$$

As detailed in Table 2, the permissible value ranges are derived from Indonesian regulatory standards: Ministry of Environment and Forestry No. 2 of 2022 and No. 492 of 2016 (KLHK, 2016; PerMen, 2022), as well as the Regulation of the Ministry of Health of the Republic of Indonesia No. 492 of 2010 (Menkes, 2010). High RV with ≥ 90% = the majority of data is realistic, and the sensor is functioning normally. Medium RV (70–90%) = some data points are 'out of range,' possibly due to sensor interference or extreme river conditions. Low RV (< 70%) = the sensor may have a problem (fouling, drift, loss of calibration). RV has been widely used to evaluate the quality of environmental sensor data. Measurement accuracy was evaluated by comparing the online sensor data with laboratory analyses, utilizing the mean absolute error (MAE), using Eq. 3 (Zhang and Thorbun, 2022):

$$MAE = \frac{1}{n}\sum | S_i - L_i | \quad (3)$$

where S_i is the sensor measurement, and L_i is the corresponding laboratory reference value. In the initial analysis, the absolute percentage error was calculated for each sensor-laboratory observation pair and subsequently converted it into a relative accuracy score using Eq. 4 (Hyndman and Koehler, 2006):

$$APE_i = (|S_i - L_i| \,/\, |L_i|) \times 100\%; \text{ and } RAS_i = 100\% - APE_i \quad (4)$$

Percentage-based error measures are commonly used as unit-free measures of relative deviation,

Table 2: Acceptable range for each water quality parameter (PerMen, 2022; Menkes, 2010; KLHK, 2016)

Parameter	Range
BOD	0.1 - 60 milligrams per liter (mg/L)
COD	0.1 - 500 mg/L
Temperature	0° C – 50 degree Clesius (°C)
DO	0 - 15 mg/L; or 0 - 200%
pH	0 - 14 units
Nitrate	0 - 50 mg/L
Nitrite	0 – 10 mg/L
TSS	0 - 500 mg/L
TDS /conductivity/salinity	0 - 100,000 microSiemens per centimeter (µS/cm) or 0 - 100 mS/cm
Turbidity	0 - 1000 nephelometric turbidity unit (NTU)
Ammonia	0 - 100 mg/L as N /0 – 10 mg/L
Depth (pressure)	0 - 10 m or more

although they require caution when reference values are zero or close to zero (Hyndman and Koehler, 2006). The RAS used in this study is an interpretative transformation of APE and is not presented as a conventional statistical agreement metric. In alignment with recent studies on high-frequency river monitoring, evaluating measurement accuracy is essential for validating ORWQM system outputs (Wagner *et al*., 2006; Pellerin *et al.,* 2016). Stability is used as a diagnostic indicator to flag potential flatline behavior. Flatline events are initially identified when identical values persist for three or more consecutive records (QARTOD). This threshold is used as an initial screening rule, not as evidence of sensor failure. Signal flatlining may occur if the sensor experiences sediment-induced fouling, calibration drift, or physical degradation. This indicator has been widely used to evaluate the quality of environmental sensor data, using Eq. 5 (Adu-Manu *et al*., 2017; Zhang *et al.,* 2022):

$$SI = \frac{Number\ of\ flatline\ segments}{Total\ segments} \times 100\% \qquad (5)$$

SI value:

a) A high SI (>90%) indicates stable, reasonable data quality and can be used immediately.
b) A moderate SI (70–90%) indicates quite stable conditions with minor anomalies and needs to be verified by field samples.
c) A low SI (50–70%) indicates unstable data; sensor checks and comparison with manual data are necessary.
d) A very low SI (<50%) indicates very unstable data; sensor maintenance and data imputation are required.

Uniqueness measures the degree to which a dataset is free from duplicate or redundant entries, calculated as the ratio of unique data points to the total number of observations. Uniqueness in ORWQM is determined by the timestamp, which is the time information attached to each time series data point, and each measurement must be unique, by using Eq. 6 (Ehrlinger and Wöß, 2022):

$$Uq = \frac{Number\ of\ unique\ values}{Total\ values} \times 100\% \qquad (6)$$

Uq value of 100% indicates all unique data, and a value <100% indicates redundancy.

System performance evaluation

The next step is to evaluate the performance of the ORWQM system using KPI and AHP instruments. The KPI method is a set of indicators that focus on the performance aspects most critical to the organization's current and future success (Parmenter, 2020). According to Lo-Iacono-Ferreira *et al*. (2018), a KPI serves as an index to quantify critical factors related to established objectives, thereby evaluating organizational performance toward those goals. AHP is a procedure for ranking decision alternatives when decision-makers have multiple

objectives or criteria to consider (Saaty, 1990). The following is the equations for the consistency index (CI) and consistency ratio (CR), according to Saaty (1990):

$$CI = \frac{\lambda_{max} - n}{(n-1)} \quad (7)$$

$$CR = \frac{CI}{RI} \quad (8)$$

The steps involved in evaluating the performance of the ORWQM system (Fig. 3) are: a) Establishing KPIs representing five aspects of the system: technical, institutional, social, economic, and environmental; b) Assign priority weights to each indicator based on the perceptions of experts and stakeholders; c) Collect actual data to measure the actual score of each indicator based on field data and supporting documents; d) Change all measurement results to a 0–1 scale (low–very low) for cross-dimensional comparison. To reconcile the heterogeneous measurement units across indicators—ranging from percentages and ratios to qualitative perceptual scales—raw scores are normalized utilizing both quantitative and qualitative criteria; e) The AHP weight of each indicator is multiplied by its normalized actual score to obtain the indicator's contribution value, using Eq. 9 (Hwang and Yoon, 1981; Triantaphyllou, 2000; Saaty, 2008):

$$I_i = W_i \times S_i \quad (9)$$

Where: I_i = indicator contribution; W_i = AHP weight; S_i = actual score

f) The contribution values of all indicators are then summed to obtain the overall system performance index (PI), using the weighted sum, using Eq. 10 (Hwang and Yoon, 1981; Triantaphyllou, 2000):

$$PI = \sum_{i=1}^{n} (w_i \times S_i) \quad (10)$$

g) The final phase entails interpreting the index results and assessing individual indicator contributions to formulate actionable recommendations for system enhancements. Table 3 the system PI index assessment shows KPI scores based on system performance categories, from low to excellent. This methodology aligns with established guidelines for constructing composite indicators, which mandate explicit and transparent justification for all normalization, weighting, aggregation, and interpretation design choices (OECD, 2008). Given that composite index classification is often sensitive to threshold selection, a sensitivity analysis utilizing alternative category thresholds was performed. The ORWQM performance index remained within a reasonable range under plausible alternatives, indicating that the primary interpretation is robust. However, the numerical scores and the contribution of weighted indicators were emphasized over the categorical labels.

Soft systems methodology

The SSM stages in this study follow the Hardjosoekarto (2012) approach, which is used to understand and address complex, unstructured, multi-stakeholder problem situations. This approach represents an action-oriented investigative framework for addressing adverse conditions, wherein participants systematically analyze the situation to design and implement targeted interventions (Checkland and Poulter, 2020). To navigate unstructured and highly complex situations involving multiple stakeholders with competing priorities, this study utilized the SSM process (Fig. 4) as a diagnostic tool to identify key issues. Semi-structured interviews were conducted with 27 stakeholders representing government agencies, local environmental organizations, academics / researchers, vendors, operators, NGOs, media, and the public. Participants were selected using purposive sampling based on their active involvement in ORWQM planning, operations, data utilization, policy implementation, or

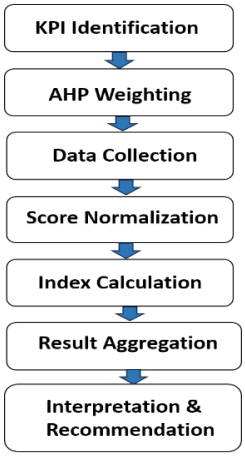

Fig. 3: KPI measurement stages using the AHP method

Table 3: System PI index scoring

Category	KPI value Range	Interpretation
Excellent	≥ 80%	Effective system, high synergy between technical and institutional aspects
Good	65%–79%	System is fairly stable, institutional/social improvements are still needed
Fair	50%–64%	Moderate performance, needs improved coordination and funding support
Low	< 50%	System not yet functioning optimally, fundamental technical and policy issues

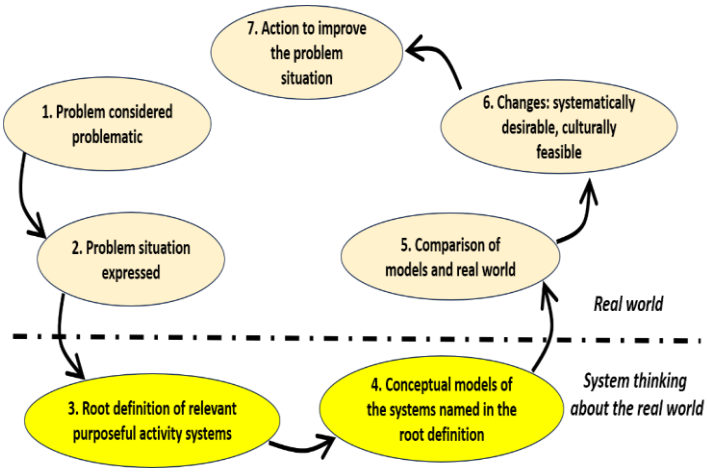

Fig. 4: Steps of SSM (Hardjosoekarto, 2012)

community advocacy. Discussions were guided by a thematic protocol covering operational challenges, data quality, system performance, institutional coordination, public accessibility, and future governance pathways. Specifically, interview transcripts were divided into meaningful statement units, coded, and grouped into recurring themes related to data quality, technical reliability, institutional coordination, financing, public transparency, stakeholder participation, and pollution response. These themes were then used to build a rich picture, formulate the root definition and PQR, identify CATWOE elements, define governance and operational gaps, and develop activities included in the conceptual model. Guided by this foundational understanding, key root definitions designed was developed to model the desired human activity

system. Then, a conceptual model is developed and validated with CATWOE analysis to ensure the clarity of its elements: Customers, Actors, Transformation, Weltanschauung, Owners, and Environmental constraints. The success of the model is assessed based on the 3E principle of efficacy, efficiency, and effectiveness. The next step is the comparison of the conceptual model with the actual conditions to find out gaps, areas for improvement, and potential for intervention. Within the SSM framework, validating social acceptability is essential; this entails assessing whether the system's actors perceive the proposed model as plausible, realistic, and actionable. Through this process, key informants provide insights into the feasibility of model implementation, potential institutional barriers, and the possibility of strengthening inter-institutional coordination mechanisms.

RESULTS AND DISCUSSION

Data quality analysis

Data quality was evaluated across four stations for 2023–2025 using CI, RV and SI accuracy against laboratory measurements, and uniqueness. The findings demonstrate a clear divergence between data availability and actual analytical usability. The United States Geological Survey (USGS) guidance for continuous water quality monitors also states that continuous monitoring data must undergo site selection, field operations, calibration, computation, correction, review, and reporting before it can be used to interpret water quality (Wagner *et al*., 2006). The completeness index (CI) analysis demonstrates near-perfect structural completeness across all four monitoring stations, with values ranging from 99% to 100%. Manggarai had the strongest overall completeness non-zero, with most parameters exceeding 90%, whereas Empang Dam showed substantial gaps for DO (50.5%), pH (59.0%), nitrate (48.0%), and salinity (1.1%) (Fig. 5). These results are also consistent with the study of Behmel *et al*. (2018) who indicated the importance of real-time data reliability to support water quality management. While the Kelapa Dua station exhibited parameter-specific data deficiencies, most notably for TSS and salinity, while Kali Sabi station demonstrated high completeness for nitrate, TDS, salinity, and conductivity, despite suffering from sparse ammonia coverage. Thus, the principal finding is not simply that some stations transmitted more data, but that apparently continuous records could still contain parameter-level failures. These findings underscore the necessity of evaluating completeness in conjunction with validity, stability, and reference measurements rather than conflating mere data availability with data reliability (Wagner *et al*., 2006; Bushnell *et al*., 2020). A comparison across monitoring sites reveals that the Empang Dam station exhibits exceptionally high data completeness (excluding zero-value entries) for key environmental parameters. This means that the Manggarai system can transmit data continuously, and generate data which is easier to use for analysis. This supports the need to interpret completeness together with validity, stability, and reference measurements rather than treating data availability as evidence of reliability (Wagner *et al*., 2006; Bushnell *et al*., 2020: Rozemeijer *et al*., 2025). While these data gaps are likely attributable to sensor malfunctions, operational constraints, maintenance issues, or data-processing errors, the lack of diagnostic records precludes a definitive attribution of their precise causes. Kelapa Dua showed intermediate performance, with relatively good completeness for pH, nitrate, temperature, and turbidity but poorer results for TSS and salinity, indicating parameter-specific rather than system-wide problems. Kali Sabi performed relatively well for nitrate, TDS, salinity, and conductivity but poorly for ammonia. These differences show that key parameters such as DO, pH, turbidity, conductivity/TDS, and temperature respond differently to field conditions and system limitations (Rojas *et al*., 2021).

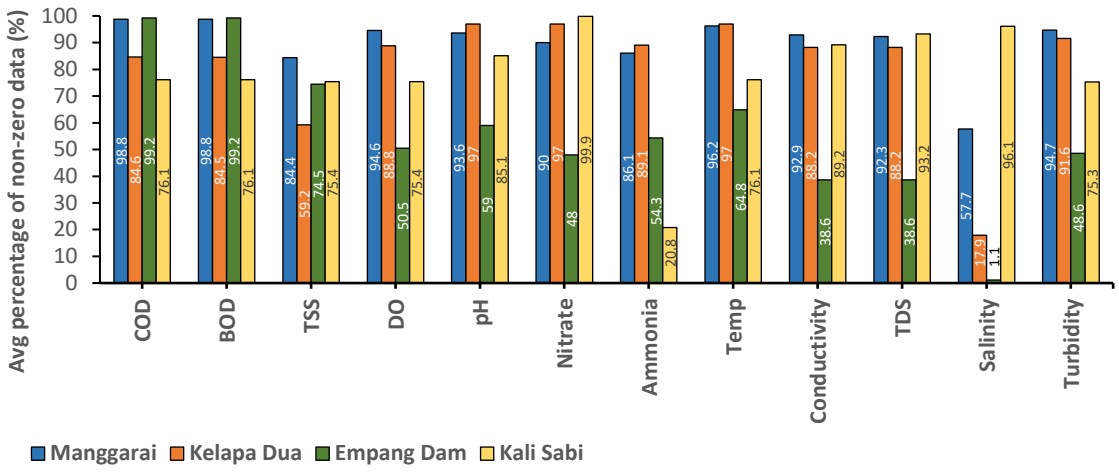

Fig. 5: Percentage of non-zero complete data at the four stations

Range validity

The results of the RV analysis corroborate the idea that data quality of ORWQM cannot be determined only on data completeness. Across nearly all monitored parameters, including TSS, DO, pH, ammonia, temperature, salinity and turbidity, the Manggarai station consistently exhibited elevated RV values. However, the lower RV values for conductivity and TDS suggest that the sensors based on electrodes could be subject to interference. This finding aligns with established continuous monitoring protocols, which emphasize specific conductance as a critical parameter requiring systematic calibration, monitoring, and correction due to its high susceptibility to sensor drift and biofouling (Wagner *et al.*, 2006). The Kelapa Dua Station had a serious problem with nitrate, unlike the Manggarai Station, which had a much smaller RV value than the other measures (Fig. 6). This indicates that the nitrate sensor itself may be problematic, such as interference with the sensor, detection limits or installation problems, despite good performance of the other metrics. These findings align with the high-frequency monitoring study by Rozemeijer *et al.* (2025), which demonstrated that nutrient sensors demand more stringent maintenance and calibration due to their susceptibility to intricate measurement methodologies and fluctuating environmental conditions. At the Empang Dam, the RV values were more consistent than at Kelapa Dua and Kali Sabi. The majority of parameters were inside the valid range, although the total data was not zero, and the stability level was low. Kali Sabi showed the most substantial validity problems for COD, BOD and conductivity measurements. The low validity of COD and BOD is important as they are the major indicators of organic pollution load. The real-time variations in the organic pollution load cannot be reliably captured by the system due to the inherent measurement limitations of COD and BOD proxies. Consequently, readings exceeding these operational thresholds are typically attributable to sensor error, drift, or extreme hydrological conditions. Observations exceeding regulatory water quality thresholds are not automatically considered invalid. If the observations remain within the instrument's physical and specific measurement range, they are still considered valid because they may represent a true pollution event. Regulatory violations are assessed separately as environmental compliance issues, not as data validity filters, requiring further investigation and appropriate management responses when necessary.

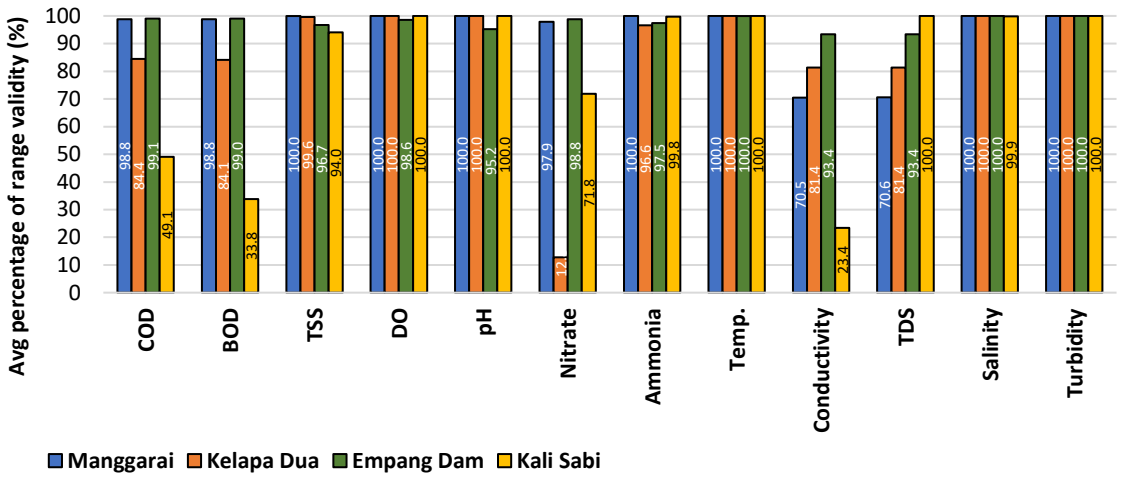

Fig. 6: Percentage of range validity data at the four stations

Stability index (SI)

The SI results reveal marked differences in temporal behavior among stations (Fig. 7) Manggarai was the most stable for COD, BOD, DO, pH, and turbidity, but ammonia, conductivity, TDS, and salinity remained less reliable. Kelapa Dua station exhibited moderate-to-high parameter stability overall, it demonstrated reduced performance regarding TSS and DO. Conversely, the Empang Dam station displayed the most widespread instability, most notably for DO, pH, and nitrate, while the Kali Sabi station was characterized by pronounced fluctuations in pH and temperature. This is in agreement with Shaughnessy *et al*. (2019), who pointed out that data from continuous monitoring of water quality often needs to be fixed to account for sensor drift and fouling before it can be analyzed fully. Rinn *et al*. (2025) confirmed fouling and drift to be especially problematic for nutrient and electrochemical sensors. These results are in line with those of Wagner *et al*. (2006), which showed that the ORWQM system is sensitive to field disturbances, such as sensor contamination, response shifts, calibration errors, and operational disruptions, which can all affect the stability and reliability of the data. Importantly, SI values serve as diagnostic indicators requiring secondary validation, rather than functioning as definitive metrics of operational failure.

Accuracy

Accuracy was assessed by comparing sensor data with manual measurements reported by KLH, although the limited number of paired observations restricts the robustness of the results. At Manggarai Station, pH and temperature demonstrated the highest alignment with reference values, yielding relative accuracy scores of approximately 88–99% alongside minimal absolute errors. These percentages represent relative accuracy, not MAE. Future studies should use more frequent, synchronized sensor and laboratory measurements across different seasons and hydrological conditions. Consistent with USGS guidance, continuous sensor data should also undergo field verification, cleaning, calibration, correction, and quality review before being used for water-quality interpretation (Wagner *et al.*, 2006). A comparison of online sensor data and manual reference measurements at the Kelapa Dua station reveals persistent, moderate-to-high deviations (ranging from 12% to 85%) across key water quality parameters, including COD, BOD, TSS, pH, temperature, and TDS. Such practice is common in ORWQM as data

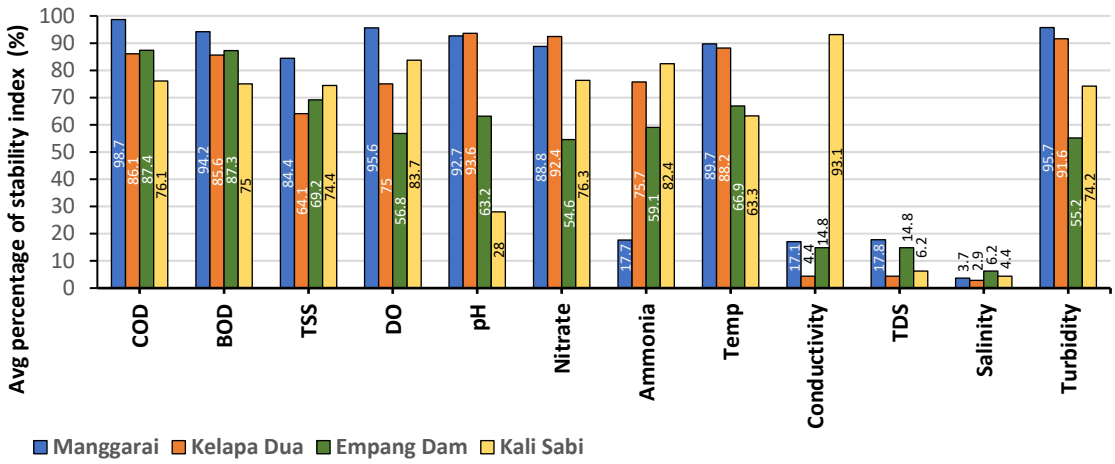

Fig. 7: Percentage of stability Index at the four stations

masking does not work when sensors are tuned off or connection drops out (Teh *et al.*, 2020). The relative accuracy scores at Kali Sabi Station show a wide range in sensor data accuracy over the test period, likely due to sensor instability and technical issues related to the field. Studies on IoT-based water quality monitoring suggest that while real-time systems can improve monitoring efficiency, the accuracy largely relies on the quality of sensors, the design of the system, and the validation of data using reference measurements (Budiarti *et al.*, 2019). The limitations of sparse manual calibration data highlight the need for future studies to employ high-frequency, synchronized sensor and laboratory monitoring across a broader range of seasonal and hydrological regimes. The data-quality metrics identify anomalies but cannot confirm their causes because diagnostic, maintenance, power, communication, and field records were incomplete. Thus, technical failures are treated as plausible explanations alongside environmental variability, sensor resolution, sampling differences, laboratory uncertainty, and data processing. Station-specific discrepancies are likely attributable to interacting environmental, technical, and operational dynamics; consequently, the analysis prioritizes localized, parameter-specific patterns over simple metrics of data availability.

Evaluation of system performance

System performance was assessed through 20 KPIs covering technical, institutional, social, economic, and environmental dimensions (Fig. 8). The indicators were derived from literature and policy review, stakeholder interviews, and empirical findings from the four stations. This structure shifts the assessment from a narrow evaluation of sensor operation to an evaluation of whether the monitoring system can produce credible information, sustain operations, coordinate institutional action, engage users, and contribute to pollution control. Accordingly, technical QA/QC is evaluated as merely one dimension of system performance, rather than being disproportionately cited as the primary driver of operational limitations. A clear process is required for the high frequency water quality detection in terms of data collection, sensor selection, sensor condition maintenance, sensor calibration and data processing

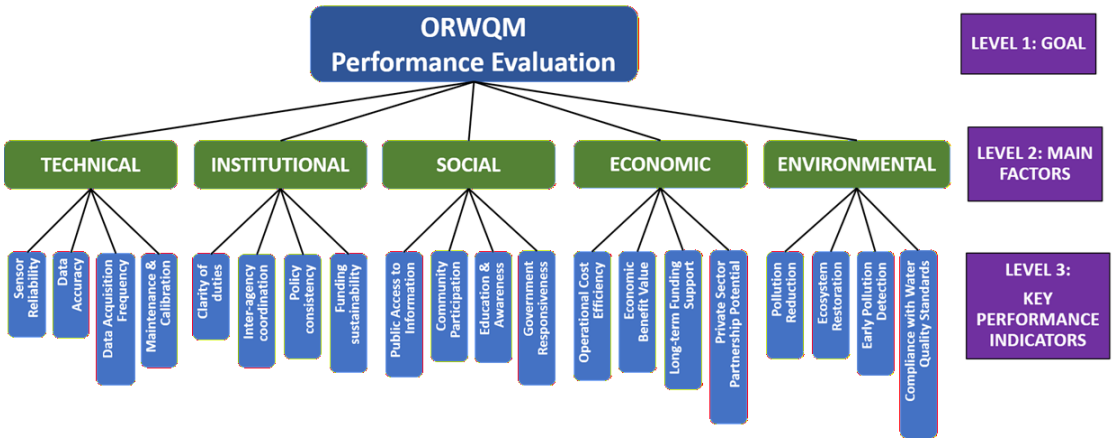

Fig. 8: Hierarchy of ORWQM system performance

(Rozemeijer *et al*., 2025). Calibration, sensor checks, metadata, and quality control are also emphasized to ensure data reliability, as in real-time quality assurance/quality control (QA/QC) systems such as quality assurance/quality control of real-time oceanographic data (QARTOD) (Bushnell *et al*., 2020). Technical indicators include sensor reliability, data accuracy, frequency of data collection, and maintenance and calibration. These four are critical for sensor monitoring reliant systems because water quality instrumentation is highly susceptible to calibration drift, telemetry failures, biofouling, and measurement inaccuracies in the absence of routine maintenance. Reliable real-time data are used worldwide to ensure and control quality, to carry out calibration checks and to validate the data against reference standards or field measurements (Wagner *et al*., 2000). Institutional indicators include unambiguous duties, inter-agency coordination, policy consistency and sustainable funding. These are critical because the success of an ORWQM system depends to a large extent on the relationships between the technical operators, data owners, decision makers and pollution response units. This is consistent with the Organization for Economic Co-operation and Development (OECD) principles on water governance, which designate role clarity, policy coherence, data sharing, financial sustainability, and stakeholder engagement as the structural pillars of effective water resource management (OECD, 2015). Other important social indicators include public access to information, community involvement, education and awareness, and government responsiveness. United Nation-Water (UN-Water) underscores that data transparency and public involvement are vital for water quality improvement, noting that citizen science simultaneously enhances community capacity and strengthens environmental monitoring efforts (UN-Water, 2011; Domínguez-Rendón *et al*., 2024).

Priority weight analysis using the AHP method

The results of the AHP analysis involving 15 sources from various stakeholders showed that environmental variables received the highest weight (0.3174), institutional variables were the second priority (0.208), and technical variables were the third priority (0.2000). The economic dimension (0.1520) underscored the critical importance of cost efficiency and long-term financial sustainability. Similarly, the social dimension (0.1226) yielded a significant contribution, albeit with a marginally lower overall weight. Based on the variable weights above, the maximum eigenvalue is λ_{max} = 5.4199. Based on formula (6) with five factors and the λ_{max} value, a value of 0.01049 was obtained. The random index

(RI) value obtained from the table provided by Saaty (2004) was 1.12 for 7 variables. The consistency ratio (CR) value calculated based on Eq. 8 was 0.00937 or 0.937%, which is much lower than the 10% threshold, indicating acceptable consistency, so the weights given are appropriate for performance assessment. The trend suggests that the experts attach more importance to environmental performance than tool functionality. They say that real-time monitoring should help to detect pollution early, improve the response, and comply with the standards. Water quality data is vital for facilitating early warning systems and rapid response protocols, thereby mitigating both environmental and health risks (UNEP, 2024). The relative significance of environmental parameters in AHP results supports the use of ORWQM as a pollution control tool, rather than a data logging system. The results of the aggregation of the expert pairwise comparison assessments are presented in Table 4.

Priority indicators of each dimension

In terms of technical aspects, data accuracy was the most weighted aspect (42.1%) followed by sensor maintenance and calibration (25.4%), sensor reliability (21.1%) and data collection frequency (11.4%). Findings indicate that experts prioritize the quality and reliability of transmitted data over its sheer volume. This preference aligns with international real-time monitoring standards, which identify calibration, sensor inspection and quality control protocols as essential prerequisites for valid data analysis and decision making (Bushnell *et al*., 2020; Rozemeijer *et al*., 2025). High-frequency data do not inherently reflect high quality or strong performance, particularly when compromised by anomalies, systematic shifts, or a lack of reference validation. Institutionally, policy consistency ranked highest (35.4%), followed by funding sustainability (30.8%), inter-agency coordination (20.3%), and task clarity (13.4%), supporting OECD principles on coherent policies, clear roles, adequate funding, and effective evaluation. Social priorities were education and awareness (35.0%), public participation (26.3%), government responsiveness (24.6%), and information access (14.0%). Despite receiving the lowest weight, public accessibility remains vital for ensuring transparency and facilitating collective action (Domínguez-Rendón *et al*., 2024). Economically, long-term funding (36.1%) was prioritized over economic benefits (30.0%), private partnerships (21.1%), and cost efficiency (12.9%), indicating that sustainable financing should cover capital, operational, and maintenance needs without weakening system functions. Environmentally, compliance with water quality standards ranked highest (29.0%), followed by pollution reduction (28.0%), early detection (22.9%), and ecosystem restoration (20.3%), confirming ORWQM's role in supporting water quality management.

Overall indicator weight priorities

The indicators with the highest global weights were compliance with quality standards (9.2%), pollution reduction (8.9%), data accuracy (8.4%), policy consistency (7.4%), and early pollution detection (7.3%). These priorities establish a logical framework wherein empirical accuracy and coherent policy design collectively facilitate early anomaly detection, regulatory compliance, and subsequent pollution mitigation. The model therefore extends beyond monitoring inputs and processes by linking ORWQM performance to environmental outcomes and response-based action. This supports the use of integrated dashboards, data validation, pollution-response SOPs, and cross-agency reporting mechanisms for timely decision making, effective stakeholder coordination, and continuous improvement. Despite receiving lower weights in the evaluation, public information accessibility and operational cost-efficiency remain indispensable supporting conditions for fostering transparency, accountability, stakeholder acceptance, and long-term system sustainability across diverse institutional, environmental, governance, and community implementation contexts.

Table 4: Geometric mean of pairwise comparisons

Indicators	Technical	Institutional	Social	Economic	Environmental
Technical	1	0.9130	1.7286	1.2080	0.6919
Institutional	1.0953	1	2.4042	1.3638	0.5490
Social	0.5785	0.4159	1	0.7408	0.4693
Economic	0.8278	0.7333	1.3498	1	0.4219
Environmental	1.4453	1.8215	2.1307	2.3700	1

System performance index (PI)

The actual scores of the 20 indicators were assessed on a 0–100 scale, converted to performance scores of 1–4, and multiplied by their respective global AHP weights. The weighted indicator scores were then aggregated to obtain the overall ORWQM system performance index (PI). The resulting PI was 2.447 on a 0–4 scale, equivalent to 61.181%, placing the system in the "adequate" category. This result indicates that the system is operational but still requires improvement to achieve a higher level of effectiveness. The index should be interpreted as a diagnostic measure of the gap between indicator priorities and actual operational performance rather than as a stand-alone value (Nardo *et al*., 2005; OECD, 2008). At the aspect level, the technical aspect achieved the highest performance index (2.847), followed by the institutional (2.797), economic (2.576), environmental (2.527), and social aspects (1.380). Thus, technical and institutional performance was relatively stronger, while the social aspect showed the largest performance gap. However, the environmental and economic aspects contributed the most to the overall PI, with weighted scores of 0.714 and 0.701, respectively, because of their higher aspect weights. These findings confirm that the overall index reflects both the relative importance and actual performance of the technical, institutional, social, economic, and environmental dimensions (Vilanova *et al*., 2015; Sakai, 2024). Tables 5 and 6 present the indicator-level calculations and their aggregation into the overall System PI. Collectively, these dimensions yield an overall System PI of 2.447 on a 0–4 scale, corresponding to an efficiency level of 61.181%.

Studies on the implementation of the OECD water governance indicator framework at the local level have also shown that problems are often located not only in regulations or institutions but also in the implementation of operational instruments (Akhmouch and Clavreul, 2016; OECD, 2018). Within the ORWQM framework, the utility of dashboard data is maximized when coupled with defined operational pathways, including field verification, early warning notifications, systematic incident reporting and rapid responses to localized pollution sources. The lowest score was in the social aspect with an index of 1.380. This value shows that the benefits of the system have not yet been fully reached the community; users of information and actors in environmental monitoring. Citizen science initiatives in water quality monitoring have been shown to build community capacity and raise ecological literacy; however, their ability to drive governance accountability is highly contingent upon robust information accessibility and prompt regulatory action (Tsatsaros *et al*., 2021; Domínguez-Rendón *et al*., 2024) and these results are in line with that literature. The low social index indicates the need to transform the dashboard from a data platform into a tool for risk communication, environmental education, a complaint channel and a collaborative medium between the government, river communities, schools, universities and environmental NGOs. Despite secure long-term economic benefits and funding, cost-efficiency and private-sector synergy require further cultivation. This is consistent with OECD guidelines asserting that sound financing and budgeting are fundamental to the sustainable governance of water policies and the lifecycle

Table 5: AHP weight and performance score of the ORWQM indicators

Aspect	Indicator	Local weight	Global weight	Actual score	Performance score (1–4)	Weighted score
Technical	Sensor reliability	0.209	0.034	82	3	0.102
Technical	Data accuracy	0.419	0.068	78	3	0.204
Technical	Data acquisition frequency	0.11	0.018	95	4	0.071
Technical	Maintenance and calibration	0.263	0.043	65	2	0.085
Institutional	Clarity of duties	0.134	0.017	75	3	0.051
Institutional	Inter-agency coordination	0.203	0.026	65	2	0.052
Institutional	Policy consistency	0.354	0.045	75	3	0.135
Institutional	Funding sustainability	0.308	0.039	80	3	0.117
Social	Public access to information	0.139	0.022	60	2	0.044
Social	Community participation	0.255	0.04	55	1	0.04
Social	Education and awareness	0.365	0.057	50	1	0.057
Social	Government responsiveness	0.241	0.038	65	2	0.075
Economic	Operational cost efficiency	0.194	0.053	70	2	0.106
Economic	Economic benefit value	0.297	0.081	75	3	0.243
Economic	Long-term funding support	0.279	0.076	75	3	0.228
Economic	Private-sector partnership potential	0.229	0.062	65	2	0.125
Environmental	Pollution reduction	0.262	0.074	70	2	0.148
Environmental	Ecosystem restoration	0.211	0.06	65	2	0.12
Environmental	Early pollution detection	0.244	0.069	75	3	0.207
Environmental	Compliance with water-quality standards	0.283	0.08	78	3	0.24

Table 6: Aspect-level performance and overall ORWQM system PI

Aspect	Aspect weight	Weighted aspect score	Aspect performance index (0-4)
Technical	0,162	0,462	2,847
Institutional	0,127	0,355	2,797
Social	0,157	0,216	1,380
Economic	0,272	0,701	2,576
Environmental	0,283	0,714	2,527
System PI (0–4)	1,000		2,447
System PI (%)			61,181

management of infrastructure (OECD, 2018). Strengths are early detection and compliance with quality standards in the environmental sector but ecosystem restoration and pollution reduction need to be more integrated with source control programmes. Studies on real-time monitoring show that ORWQM systems can aid in early warning and rapid action against pollution concerns (Hou *et al*., 2014; Zhang *et al*., 2020; Saleh and Stanley, 2023). In summary, performance evaluation results highlight five overarching priorities for system improvement: (1) improving the quality of QA/QC, calibration and sensor maintenance; (2) aligning policies and division of tasks between agencies; (3) ensuring funding for long-term operations and maintenance; (4) expanding public access, data literacy and community engagement; and (5) integrating ORWQM data with oversight mechanisms, law enforcement and ecosystem restoration.

Conceptual model design of inclusive governance-based ORWQM

The conceptual model design was developed using SSM through field observations, surveys of communities living around the stations and semi-structured interviews with 23 informants representing government, community, academics / researchers, vendors, NGOs/river communities and the media. The SSM findings revealed three main challenges in managing ORWQM. Primarily, data quality requires further refinement; while sensors deliver continuous real-time streams, a subset of the generated data fails to satisfy established validity criteria. Calibration,

validation, technical interpretation, QA and QC are required. Second, the response to the pollution indication is not uniform and the rapid action procedures, field verification and source tracing are not always timely. Third, collaboration remains absent in governance because coordination among KLH, DLH, BBWS, vendors, academics, communities, and the media has not been integrated into a mechanism to ensure system sustainability. This directly contradicts QARTOD guidelines, which stress that rigorous quality control testing, sensor management, and the active involvement of qualified scientific, technical, and data management personnel are essential to ensure sensor data integrity in decision-making processes (Bushnell *et al.,* 2020). Based on the results of the rich picture (Fig. 9) and CATWOE analysis, a root definition was obtained that describes a human activity system involving the KLH, the DLH, BBWS, academics, vendors, the public, river communities, and the media to transform ORWQM sensor data into valid, easily accessible, and actionable water quality information to strengthen river water pollution control in a fast, transparent, collaborative, and sustainable manner. refines the overarching root definition into three constituent sub-root definitions, specifically focusing on strengthening national governance, maximizing technical system and rapid response capabilities, and fostering public participation and empowerment. The overall formulation is reduced to three interrelated conceptual models. The first conceptual model focuses on improving national governance and policy frameworks to address fragmented authority, inadequate inter-agency coordination, and inconsistent data standards and SOPs. Here, the KLH is the national policy maker and data manager. The DLH implements and uses regional data, the BBWS coordinates river and infrastructure management, and the National Development Planning Agency (BAPPENAS) supports funding and integration in development plans. This methodology aligns with the OECD (2015) framework, which conceptualizes water governance as a multi-level system integrating policies, institutions, instruments, financing, and accountability mechanisms. The second conceptual model is on the effectiveness of technical systems, maintenance and rapid response to link the real-time data and pollution control measures. The third conceptual model highlights community empowerment and multi-stakeholder collaboration, which enables data transparency and social support to sustain the system. Surveys near ORWQM stations demonstrate that broad public support coexists with limited community understanding of station functions, with most residents receiving only direct water quality data. A study by Domínguez-Rendón *et al*. (2024) found that community participation in water quality monitoring can empower community organizations or NGOs to improve data collection and reporting, environmental literacy, and bridge the gap between policymakers and citizens affected by pollution. These three models together form an inclusive governance-based ORWQM management framework (Fig. 10). This framework uses data quality analysis as a technical diagnosis, KPI-AHP results as the basis for prioritizing performance improvements, and SSM as the basis for developing practical institutional changes through collaborative stakeholder engagement processes. The workflow systematically advances from data quality validation to a KPI-AHP-based performance evaluation, culminating in conceptual modeling and the subsequent execution of the inclusive governance framework. This approach extends previous studies (Behmel *et al*., 2016; Li *et al*., 2018; Faybishenko *et al*., 2022; Mansouri *et al*., 2023) which primarily focused on the technical aspects of tools and data collection, emphasizing the importance of good data, responsive systems, well-coordinated institutions, and public engagement. This integration is expected to lead to evidence-based ORWQM management, efficient pollution control, river ecosystem protection, and adaptive, accountable, and sustainable governance. The proposed model

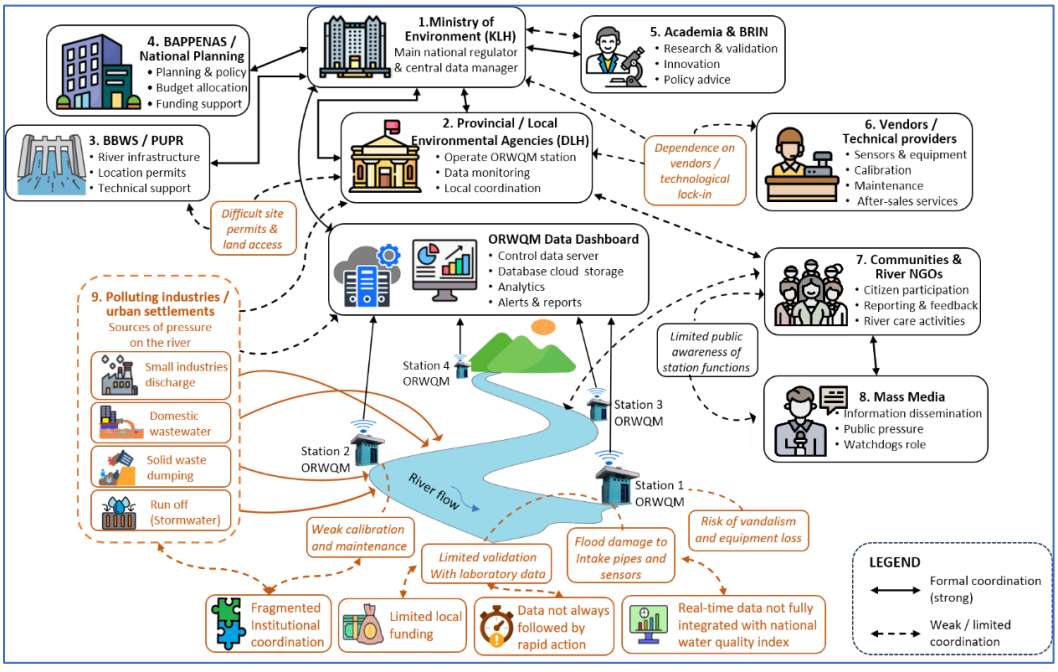

Fig. 9: Rich picture

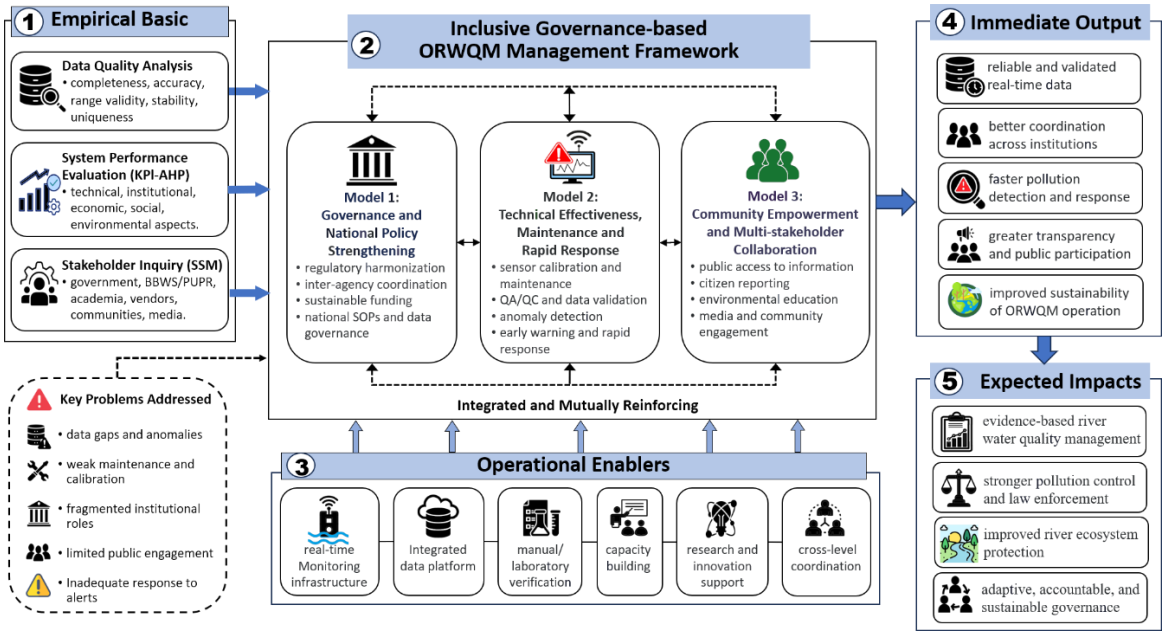

Fig. 10: Integrated ORWQM management framework based on inclusive governance

contends that the policy utility of real-time data is strictly contingent upon satisfying three core criteria: technical validity, institutional responsiveness, and public accessibility. Data without validation and calibration is vulnerable to misinterpretation. In the absence of SOPs for rapid response, the collected data risk becoming merely passive digital archives rather than tools for active

intervention. Systems lose social legitimacy without transparency and public participation. The inclusive governance-based ORWQM framework bridges technical data analytics, KPI-AHP-derived improvement priorities, and the overarching demand for a transparent, adaptive, and sustainable river management paradigm. This proposed ORWQM framework based on inclusive governance serves as a bridge between the results of technical data analysis, improvement priorities through KPI-AHP, and the need for a more transparent, adaptive, and sustainable river management model.

Limitations and future research

This study has several limitations that should be considered when interpreting the findings. First, the four ORWQM stations were purposively selected to represent contrasting upstream–downstream and urban–industrial gradients across the Ciliwung and Cisadane watersheds. Consequently, the findings offer analytical transferability rather than statistical generalizability to the broader network of ORWQM stations in Indonesia. Second, variable data coverage across stations and a modest number of paired validation samples limits the evaluation of long-term sensor reliability. This constraint risks failing to account for parameter-specific bias, sensor calibration drift, or temporal and environmental discrepancies during sample collection. Third, the KPI–AHP results depend on expert judgment and may be influenced by the composition and perspectives of the expert panel, while the composite PI may vary under alternative normalization, weighting, and aggregation procedures. Fourth, stakeholder recruitment was purposive, and the community survey relied on self-reported data, the study is subject to potential selection, recall, and social desirability biases. Fifth, the SSM findings are context-specific because they reflect the institutional arrangements, stakeholder relationships, and governance conditions of the two studied watersheds. Finally, a key limitation of this study is that the proposed framework has yet to undergo prospective evaluation through longitudinal implementation or external validation across alternative watersheds. Future research should therefore expand the number and diversity of stations, increase the frequency of laboratory comparisons, examine alternative index-construction scenarios, include broader stakeholder groups, and evaluate the framework prospectively across different watershed contexts.

CONCLUSION

This multiple case study aims to understand the ORWQM conditions at four stations with different upstream-downstream characteristics, urbanization, and industrial influences in the Ciliwung-Cisadane watershed. Therefore, the performance results at each station cannot be statistically generalized to all ORWQM stations in Indonesia. This study proposes an inclusive governance-based ORWQM management framework that systematically integrates data quality evaluation, system performance assessment, and multi-stakeholder governance. The results reveal that successful ORWQM implementation requires more than technological infrastructure and real-time data; it demands rigorous data quality, operational dependability, robust institutional coordination, long-term financial viability, data transparency, and stakeholder engagement. Thus, ORWQM needs to be understood as a socio-technical system that connects data, institutions, decision-making, and pollution control. Data quality evaluation indicates that data completeness at the four stations is generally high, but some data still require validation due to zero values, negative anomalies, low validity ranges, and uneven stability. These conditions are potentially attributable to environmental influences and technical anomalies, such as biofouling, sensor drift, power instability, or data transmission failures. These findings emphasize that completeness alone is insufficient to describe data quality, as numerically complete data can be pseudo-

complete if they are not valid, stable, or accurate. The system evaluation results indicate that the ORWQM composite PI falls within the 'good' threshold; however, the underlying weighting framework heavily prioritizes institutional aspects, followed by technical and economic considerations. This indicates that performance improvements are not solely achieved through sensor device improvements but also require institutional strengthening, clarity of authority, coordination between actors, improved operating procedures, data interoperability, follow-up mechanisms, and sustainable maintenance funding. The SSM synthesis yielded a conceptual model of ORWQM governance that integrates policies, real-time monitoring systems, early warning, rapid response, and public participation. This model fortifies the cooperative capacity of pentahelix stakeholders encompassing government bodies, academia, private sector vendors, the public or NGOs, and the media to promote transparency, accountability, mutual oversight, and rapid response to potential pollution indications. Converting raw data into validated and accessible information is expected to support more coordinated decision-making, although this benefit was not tested in this study. The main contribution of this study lies in the development of a conceptual framework that synthesizes data quality, system performance, and inclusive governance into a unified ORWQM management model. While this framework possesses the potential to facilitate early detection, rapid incident response, regulatory compliance, inter-institutional coordination, and evidence-based policymaking, its operational effectiveness, feasibility, and implementation outcomes remain unexamined under diverse environmental and institutional conditions through practical field applications. Application to other watersheds requires further adaptation and validation based on local hydrological conditions, monitoring infrastructure, data availability, institutional capacity, regulations, and stakeholder characteristics.

AUTHOR CONTRIBUTIONS

S. Yudo, the corresponding author, conducted the investigation, comprehensive analysis, literature review, and manuscript preparation. D.N. Martono conducted the selection and review of the methodology used. D. Sutjiningsih were involved in the conceptualization and review of the manuscript; B. Kurniawan supervised the writing process. All authors read and approved the final manuscript.

ACKNOWLEDGEMENT

This study was supported by internal funding [No. 3/III.5/HK/2025] from the Research Organization for Life Sciences and Environmental, National Research and Innovation Agency, Indonesia

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy, have been completely observed by the authors.

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POSTIVE AI STATEMENT

During the preparation of this work, the author(s) have used Artificial Intelligence (AI), Grammarly, in order to correct grammatical errors, suggest corrections, and reduce typos. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

ABBREVIATIONS

%	Percent
3E	Efficacy, efficiency, effectiveness
°C	Degree Celcius
AHP	Analytic hierarchy process
BAPPENAS	Badan Perencanaan Pembangunan Nasional (National Development Planning Agency)
BBWS	Balai Besar Wilayah Sungai (River Basin Organization)
BOD	*Biochemical oxygen demand*
BPDAS	Balai Pengelola Daerah Aliran Sungai (Watersheds Management Center)
CATWOE	Customers, actors,
CI	Completeness index
COD	Chemical oxygen demand
CR	Consistency ratio
DAS	Daerah aliran sungai
DLH	Dinas Lingkungan Hidup
DO	*Dissolved oxygen*
EWS	Early warning system
KLH	Kementerian Lingkungan Hidup
KLHK	Kementerian Lingkungan Hidup dan Kehutanan (Ministry of Environment and Forestry)
KPI	Key performance indicator
LCD	Liquid crystal display
MAE	Mean absolute error
mg/L	Milligram per liter
µS/cm	MicroSiemens per centimeter
NGOs	Non-governmental organizations
O&M	Operation and maintenance
NTU	Nephelometric turbidity unit
ODQEM	Online data quality evaluation management
OECD	Organization for economic co-operation and development
ORP	Oxidation reduction potential
ORWQM	Online river water quality monitoring
pH	Potential of hydrogen
PI	Performance index
PQR	P (What) Q (How) R (Why)
QA/QC	Quality assurance/quality control
QARTOD	Quality assurance/quality control of real-time oceanographic data
RV	Range validity
SDGs	Sustainable development goals
SI	Stability index
SOP	Standard operating procedure
SSM	Soft systems methodology
TDQM	Total data quality management
TDS	Total dissolved solids
TSS	Total suspended solids
UN	United nation
UNEP	United Nations Environment Programme
UQ	Uniqueness
USGS	United States Geological Survey
WHO	World Health Organization

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HOW TO CITE THIS ARTICLE:
Yudo, S.; Martono, D.N.; Sutjiningsih, D.; Kurniawan, B., (2026). Integration of the online river water quality monitoring management framework based on inclusive governance. Global J. Environ. Sci. Manage., 13(1): 01-26.

DOI: 10.22034/gjesm.2027.01.01
URL: https://www.gjesm.net/article_735445.html