Journal of Electrical Engineering and Computer (JEECOM)
Vol. 8, No. 1 (2026), DOI: 10.33650/jeecom.v8i1.13750
p-ISSN: 2715-0410; e-ISSN: 2715-6427

Development Of An IoT-Based Irrigation Water Quality Monitoring System Using The CCME WQI Method for Agricultural Modernization

Brigitha Raco [1*], Ryan L. Singgeta[2], Eiren Koribu [3]
[1,3] Civil Enginnering, Universitas Katolik De La Salle, Manado, Indonesia
[2] Electrical Enginnering, Universitas Katolik De La Salle, Manado, Indonesia

Article Info

Article history:

Received Desember 18, 2025
Revised April 9, 2026
Accepted April 24, 2026

Keywords:

Water Quality
Irrigation
Sensor
IoT
CCME WQI

ABSTRACT

The degradation of irrigation water quality presents a critical challenge for sustainable agriculture, particularly under increasing hydrometeorological pressure. This study developed an Internet of Things (IoT)–based monitoring system and applied the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) to evaluate temporal variations in irrigation water quality.

The system integrates pH, water temperature, total dissolved solids (TDS), and turbidity sensors with an ESP32 microcontroller, enabling real-time data transmission to a cloud-based platform. Water quality assessment was conducted from August to December using CCME WQI, with objectives defined based on national regulations and internationally recognized guidelines.

The results reveal a progressive decline in irrigation water quality throughout the monitoring period. CCME WQI values decreased from 70.24 (*Fair*) in August to 32.28 (*Poor*) in December, indicating increasing frequency and severity of guideline exceedances. Turbidity was identified as the dominant contributor to water quality degradation, particularly during rainfall events, followed by episodicpH reductions and diurnal temperature variability. In contrast, TDS remained stable and consistently below threshold values.

The integration of high-resolution IoT monitoring with the CCME WQI framework provides a reliable and objective approach for continuous irrigation water quality assessment. This method effectively captures temporal dynamics and supports early identification of critical degradation periods, offering a practical basis for adaptive irrigation water management.

Corresponding Author:
Brigitha Raco,
Universitas Katolik De La Salle, Kombos Kairagi 1 Manado 95115- Indonesia
Email: braco@unikadelasalle.ac.id

1. INTRODUCTION

Agricultural modernization aimed at strengthening national food security increasingly necessitates water-efficient, data-driven and responsive to climatic variability. In Indonesia, these priorities are embedded in national policy frameworks, including Law No 18/2012 on Food and the National Medium-Term Development Plan (RPJMN) 2020-2024, which explicity position irrigation modernization as a strategic development agenda [1], [2]. Within irrigated paddy system, irrigation-water quality constitutes not merely an environmental parameter but a critical technical determinat of system perfomance, influencing crop productivity, soil-plant interactions, and the operational reliability of irrigation conveyance systems. Established FAO guidelines indicates that parameters such as salinity, total dissolved solid (TDS), electrical conductivity, specific-iom toxicity and infiltratrion constrainsts can directly affect irrigation suitability and long-term soil health, thereby necessitating systematic monitoring and adaptive management[3].

In Indonesia, irrigation-water quality assessment must be explicitly aligned with regulatory thresholds defined under Government Regulation (PP) No. 22/2021 to ensure consistency between observed condition and designated water-use standards [4]. However, desIPte this regulatory and operational importance, irrigation-water quality monitoring remains constrained by the limited temporal resolution of conventional approaches. Periodic field sampling and lapboratory-based analyses are inherently discontinuous, rendering them inadequate for capturing raIPd hydrometeorological-driven fluctuations, such as rainfall-induced turbidity spikes, sediment transport dynamics and short-term physicochemical variability [5]. These limitations are particularly critical in troIPcal irrigation systems, where water quality is strongly influenced by episodicclimatic events.

Recent advances in Internet of Things (IoT)-based monitoring systems have enabled high-frequency, real-time acquisition of multi-parameter water quality data, including pH, temperature, TDS and turbidity, thereby significantly improving temporal resolution and responsiveness in environmental monitoring [6], [7]. Concurrently, composite water quality indices such as the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) have been widely adopted to transfrom, multidimensional datasets into a single, interpretable metric for management and policy applications [8], [9]. Comparative evaluations, including the analysis of the Cikakembang River, demonstrate that CCME WQI exhibits superior sensitivy in representing both the frequency and magnitude of deviations from water quality objectives, particularly through its incorporation of the amplitude component (F3), compared to methods such as STORET and Pollution Index [10].

Notwithstanding these advancements, the integration between real-time monitoring technologies and standardized, regulation-based assessments frameworks remains limited. Existing IoT-based studies predominantly focus on data acquisition and transmission, with insufficient linkage to regulatory benchmarking and decision-oriented evaluation. Conversely, applications of CCME WQI are largely based on discrete or offline datasets, thereby limiting their ability to capture dynamic temporal variability inherent in irrigation systems. Furthermore, there is a lack of comprehensive implementation that combines real-time IoT sensing, validated sensor calibration and CCME WQI computation within irrigation canals, explicitly benchmarked against national regulatory standards. This gap is further compounded by limited investigations into irrigation water quality dyanmics under hydrometeorological variability, whicj plays a dominat role in determining water quality conditions in troIPcal agrivultural environments.

The absence of such integration has practical implications, as current approaches do not adequately support the operational requirements of modern irrigation systems, including precision irrigation schedulling, early detection of water quality deterioration, and risk-informed management under climate variability. Integrating real-time IoT monitoring with CCME-WQI provides methodological pathways to transfrom high-frequency sensor data into actionable decision indicators, enabling improved irrigation performance, reduced risk of water quality-induced crop stress, and enchanced system resilience under changing climatic conditions [6], [11].

2. METHOD

This study was conducted through sequential stages as illustrated in the research flowchart in Figure 1, starting from literature review and ending with conclusions. The methodology integrates hardware development, software implementation, and irrigation water quality assessment using the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI). This research builds upon a previous study that implemented an IoT-based irrigation water quality monitoring system combined with the STORET method and the Pollution Index (IP). In that earlier study, STORET and IP were applied as baseline assessment tools based on discrete compliance scores and pollution levels. However, their limitations in handling continuous, high-resolution datasets highlight the need for a more comprehensive index capable of capturing the scope, frequency, and magnitude of water quality violations simultaneously. Therefore, CCME WQI was adopted as a more robust framework for integrating real-time IoT-based monitoring data [12]. The literature review focused on three main aspects: (1) irrigation water quality standards, (2) IoT-based water quality monitoring systems, and (3) water quality indices, particularly CCME WQI. FAO guidelines were used as a reference for irrigation water quality and its impact on agricultural productivity [3]. The theoretical framework and formulation of CCME WQI were adopted from official CCME publications and peer-reviewed studies [13], [14], while IoT-related literature was used to define a reliable real-time monitoring architecture [15].

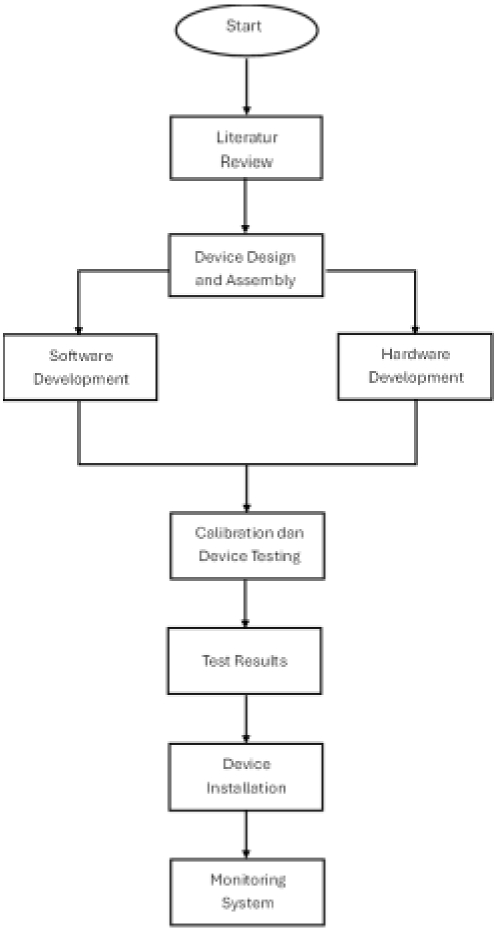

Figure 1. Research Methodology Flowchart

As illustrated in Figure 2, the hardware system was designed as an integrated IoT sensor-node architecture consisting of multiple water quality sensors, including pH, total dissolved solids (TDS)/electrical conductivity, water temperature, and turbidity sensors, connected to an ESP32 microcontroller. This configuration follows the standard IoT paradigm, in which sensors acquire environmental data, the microcontroller processes the data, and communication modules transmit information to a remote server [7], [15]. The integration of sensing elements, communication modules, and local display components (LCD 16×2) within a single monitoring unit ensures compactness, operational robustness, and suitability for field deployment in irrigation environments. This architecture enables synchronized multi-parameter acquisition and real-time data transmission, forming a complete end-to-end monitoring system.

The software component was developed to manage sensor data acquisition, preprocessing, and transmission to a cloud-based database. The ESP32 firmware was programmed to read sensor outputs at predefined intervals, convert raw signals into engineering units, and transmit the data in near real time. On the server side, data are stored and visualized in graphical and tabular formats, enabling continuous observation and interpretation of irrigation water quality dynamics. This integrated workflow establishes a direct linkage between field-scale sensing and decision-oriented data analysis, consistent with best practices in IoT-based environmental monitoring systems.

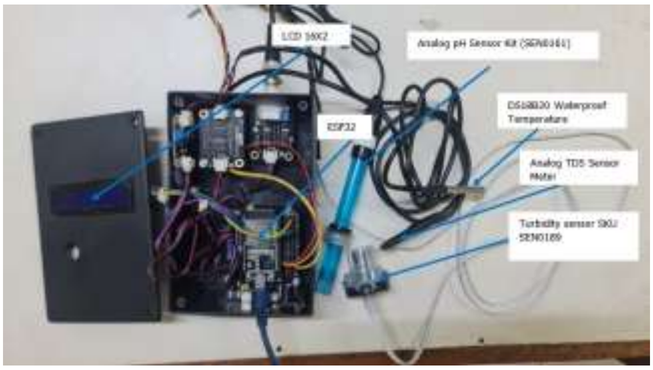

Figure 2. Box Monitoring

Prior to field deployment, all sensors were calibrated as shown in Figure 3, using standard reference solutions under controlled conditions. Calibration is essential to minimize systematic errors, improve measurement accuracy, and ensure signal stability. The calibration process was conducted iteratively, and whenever unstable readings or significant deviations were observed, corrective actions were applied to both hardware and firmware components. This procedure aligns with quality assurance principles in environmental sensor networks, where calibration is a critical step in ensuring data reliability and comparability [7]. The inclusion of validated calibration is particularly important because CCME WQI computation is highly sensitive to threshold exceedances, which may be influenced by measurement uncertainty.

Figure 3. Calibration Sensor

After successful calibration and system testing, the monitoring unit was installed in an irrigation canal at the Tara-Tara II agricultural area. Sensors were positioned to represent the main irrigation flow, ensuring that the collected data reflect actual water quality conditions within the system. As presented in Figure 4, the system continuously monitored water quality parameters and transmitted the data to a cloud-based platform for real-time visualization. The dashboard interface enabled time-series representation of each parameter, allowing raIPd identification of fluctuations, anomalies, and potential exceedances of water quality standards. This real-time capability significantly enhances temporal resolution compared to conventional periodic sampling and supports timely detection of hydrometeorological-driven variations in water quality.

The definition of water quality objectives constitutes a critical step in the application of CCME WQI, as all index components; Scope (F1), Frequency (F2), and Amplitude (F3) are calculated based on compliance with predefined standards. In this study, water quality objectives were primarily derived from Government Regulation of the Republic of Indonesia No. 22 of 2021, particularly Annex VI concerning surface water quality standards [4]. For parameters not explicitly specified for irrigation purposes, such as turbidity and electrical conductivity, threshold values were supplemented using internationally recognized FAO guidelines and relevant scientific literature [3], [8]. This approach is consistent with CCME recommendations, which allow the use of national regulations, international guidelines, or scientifically accepted thresholds, provided that they are applied consistently [8]. The continuously acquired IoT-based data were organized as time-series datasets and grouped according to monitoring periods. Each observation was evaluated against the defined water quality objectives to determine compliance or non-compliance.

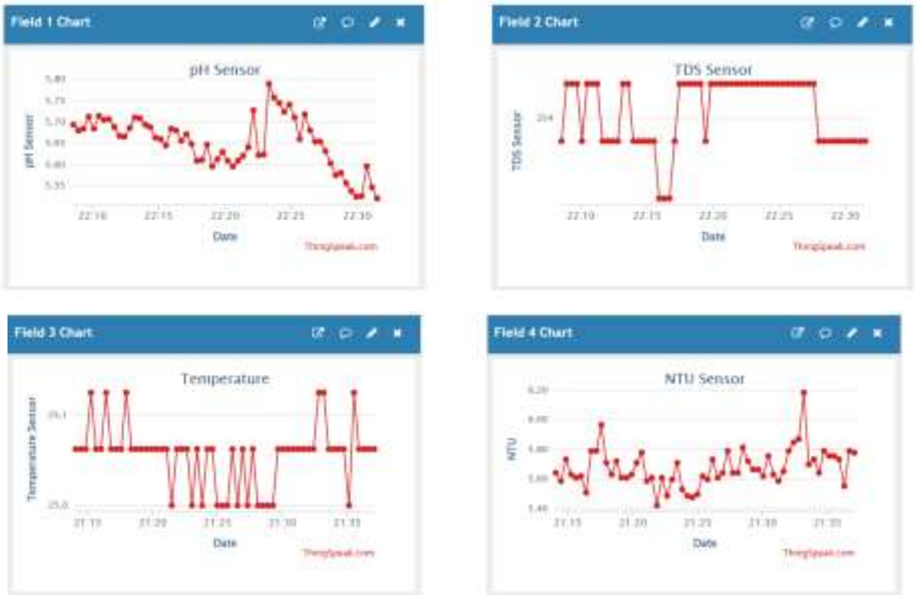

Figure 4. IoT-Based Data Recording Display

The Scope (F1) represents the percentage of parameters that failed to meet the objectives, the Frequency (F2) represents the percentage of individual tests that exceeded the standards, and the Amplitude (F3) quantifies the magnitude of deviation from the objectives. These components were computed following the standard CCME WQI formulation [13], [14] and subsequently combined to produce a single index value ranging from 0 (worst) to 100 (best), classified into five categories: Excellent, Good, Fair, Marginal, and Poor.

The integration of real-time IoT monitoring with CCME WQI computation enables a continuous, objective, and quantitative assessment of irrigation water quality. This approach is particularly effective in capturing short-term fluctuations and cumulative impacts driven by hydrometeorological variability, such as rainfall-induced sediment transport. Methodologically, the proposed system represents an end-to-end integration of calibrated multi-parameter sensing, real-time data transmission, cloud-based visualization, and regulation-based CCME WQI evaluation, thereby addressing the limitations of conventional monitoring approaches and providing a robust framework for data-driven irrigation water management. This analysis represents the initial stage of the CCME Water Quality (CCME WQ) assessment, aimed at determining the status of each water quality parameter based on Annex VI of Government Regulation of the Republic of Indonesia No. 22 of 2021 on Environmental Protection and Management in Table 1.

Water quality parameters monitored using the IoT system include pH, water temperature, total dissolved solids (TDS)/electrical conductivity, and turbidity. The pH and temperature measurements were directly benchmarked against the national surface water quality standards relevant to irrigation use. For TDS/electrical conductivity and turbidity, which are not fully specified for irrigation purposes in the national regulation, interpretation was supported by internationally recognized FAO irrigation water quality guidelines, as widely adopted in peer-reviewed studies [11][3].

This approach is consistent with CCME recommendations, which allow water quality objectives to be based on national regulations, international guidelines, or scientifically accepted standards, provided that they are relevant and applied consistently [8]. Accordingly, each IoT-derived measurement was assessed against clearly defined and scientifically defensible thresholds in the CCME WQI computation. Continuously acquired IoT-based water quality data were organized as time series and grouped according to monitoring periods. Each parameter value was evaluated against the defined water quality objectives to determine compliance or non-compliance.

Table 1. Water Quality Standards for Physical and Chemical Parameters Used in This Study Based on Government Regulation (PP) No. 82 of 2001

No	Parameter	Unit	Class I	Class II	Class III	Class IV	Remarks
1	Temperature	°C	Dev.3	Dev.3	Dev.3	Dev.5	Deviation from ambient air temperature above the water surface
2	TDS	Mg/L	1.000	1.000	1.000	2.000	
3	Acidity (pH)		6 - 9	6 - 9	6 - 9	5 – 9	If natural conditions fall outside this range, the standard is determined based on natural background conditions

The turbidity standard for irrigation water is not explicitly specified in Government Regulation of the Republic of Indonesia (PP) No. 22 of 2021 in Table 2; therefore, it is also derived from various scientific studies on the use of water for agricultural purposes that evaluate turbidity levels.

Table 2. Turbidity Water Quality Standards to Be Used in This Study

Parameter	Value	Suitability for Irrigation and Remarks	Reference Source
Turbidity (NTU)	< 50	Very good. Does not interfere with irrigation systems; sedimentation is very low.	FAO (Ayers & Westcot, 1985); EPA (2012)
	50-100	Suitable for surface irrigation; low clogging risk; commonly observed in stable open earthen channels.	WHO (2017); EPA (2012)
	100-250	Moderately turbid water; beginning to cause sedimentation; may interfere with pressurized irrigation systems; indicates mild erosion.	Gholami et al., 2019; Hillel (2004)
	250-500	High sedimentation; affects channel conveyance capacity; sediment control measures (e.g., settling basins) are required.	Sheridan (1978); EPA (2012)
	>500	Not suitable for use without treatment; indicates severe erosion; carries sediment-bound pathogens and contaminants.	Borah & Bera (2004); WHO (2017)

Adopted standard values were used as irrigation water turbidity thresholds for water quality assessment in this study using the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI). The CCME WQI is a composite index developed to transform multidimensional water quality data into a single, interpretable metric suitable for water resource management and policy applications. The index was nationally standardized by the Canadian Council of Ministers of the Environment in 2001 and has since been widely applied for surface water quality assessment across different environmental settings.

A key strength of the CCME WQI is its flexibility in accommodating varying water quality parameters, regulatory objectives, and monitoring periods, making it suitable for both temporal trend analysis and spatial comparison of water quality, provided consistent objectives are applied. The index integrates three components: Scope (F1), Frequency (F2), and Amplitude (F3), which collectively quantify the extent, occurrence, and magnitude of deviations from water quality objectives.

The CCME WQI has been extensively applied worldwide, including in Indonesia, for assessing surface and irrigation water quality under diverse hydrological and environmental conditions. The Scope (F1) represents the percentage of water quality variables that fail to meet the established objectives at least once during the monitoring period as in (1):

$$F1 = \left[\frac{Number\ of\ failed\ variables}{Total\ number\ of\ variables}\right] \times 100 \tag{1}$$

where $N_f$is the number of failed variables and $N_v$is the total number of measured variables.
The Frequency (F2) represents the percentage of individual tests that fail to meet the objectives as in (2):

$$F2 = \left[\frac{Number\ of\ failed\ test}{Total\ number\ of\ test}\right] \times 100 \tag{2}$$

where $N_{tf}$is the number of failed tests and $N_t$is the total number of tests.

The Amplitude (F3) quantifies the magnitude of deviation from the objectives. For each failed test, an excursion is calculated as in (3):

$$excursion = \left[\frac{Failed\ test\ value_i}{Objective}\right] - 1 \tag{3}$$

$$excursion = \left[\frac{Objective}{Failed\ test\ value_i}\right] - 1$$

where $C_i$is the measured concentration and $O_i$is the corresponding water quality objective.
The normalized sum of excursions (nse) is computed as in (4):

$$\frac{\sum_{i=1}^{n} Excursion_i}{\#of\ test} \tag{4}$$

The Amplitude factor (F3) is then calculated using an asymptotic scaling function, as in (5) :

$$F3 = \left[\frac{nse}{0.01nse + 0.01}\right] \tag{5}$$

Finally, the CCME WQI score is obtained as in (6):

$$CCME\ WQI = 100 - \left[\frac{\sqrt{F1 + F2 + F3}}{1.732}\right] \tag{6}$$

The CCME WQI ranges from 0 (worst) to 100 (best) and is classified into five quality categories: Excellent (95–100), Good (80–94), Fair (65–79), Marginal (45–64), and Poor (0–44) [16].

3. RESULTS AND DISCUSSION

Based on daily observations with morning–afternoon–evening–night resolution, the pH, TDS, temperature, and turbidity parameters in Figure 5, do not act independently but instead interact in determining the overall status of irrigation water quality. Among these parameters, turbidity is the most responsive to hydrometeorological dynamics, particularly during rainfall periods, and frequently emerges as the primary contributor to the Frequency (F2) and Amplitude (F3) components of the CCME WQI. Persistently elevated turbidity values are strongly correlated with increased excursion amplitudes, indicating substantial deviations from established water quality standards.

The pH parameter exhibits episodic fluctuations, especially during nighttime and early morning periods, occasionally falling below the minimum guideline threshold. From a scientific perspective, low pH conditions are commonly associated with elevated concentrations of suspended organic matter and intensified microbial resIPration processes, which are often concurrent with high turbidity levels. Water temperature demonstrates pronounced diurnal variability, characterized by lower values during night–morning intervals and higher values during daytime periods. Temperature exceedances contribute to failed tests; however, their amplitude is generally smaller than that observed for turbidity-related violations. In contrast, Total Dissolved Solids (TDS) remain relatively stable throughout the monitoring period and consistently below the regulatory threshold, resulting in a negligible contribution to the overall decline in CCME WQI values. These interactions collectively confirm that the deterioration of irrigation water quality is not driven by a single parameter but rather by the combined effects of exceedance frequency (F2) and deviation magnitude (F3), with turbidity acting as the dominant factor, followed by pH and temperature[17].

The temporal variation of irrigation water quality from August to December in Table 3, was evaluated using the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI). The results reveal a consistent and progressive degradation of water quality throughout the monitoring period, reflecting increasing environmental pressure on the irrigation system. In August, the CCME WQI value reached 70.24, corresponding to the Fair category. This condition indicates that irrigation water quality was generally protected, with only occasional deviations from the guideline values. The relatively low F1 (50) suggests that only half of the evaluated parameters exceeded the guideline limits during the month, while the low F2 (12.50) and F3 (0.84) values indicate limited frequency and low magnitude of exceedances.

Figure 5. Graph of pH, Temperature, TDS and turbidity parameter values during the monitoring period (morning, afternoon, evening, night)

Table 3. CCME WQI Result

Month	F1	F2	F3	CCME WQI	Status
Agustus	50.00	12.50	0.84	70.24	Fair
September	75.00	12.08	3.35	56.10	Poor
Oktober	75.00	25.00	4.85	54.27	Poor
November	75.00	23.75	12.31	54.03	Poor
Desember	75.00	89.29	12.66	32.28	Poor

According to CCME guidelines, such conditions are characteristic of water bodies experiencing minor and infrequent disturbances [1]. A marked decline in water quality was observed in September, when the CCME WQI decreased to 56.10, falling into the Poor category. This deterioration coincided with an increase in F1 to 75, indicating that most of the monitored parameters violated guideline values at least once during the month. Although the frequency of exceedances (F2 = 12.08) remained relatively low, the increase in F3 (3.35) reflects greater deviation from acceptable limits, suggesting the onset of more severe water quality stress. The degradation trend continued in October, with the CCME WQI further declining to 54.27. Unlike September, this reduction was primarily driven by a substantial increase in F2 (25.00), indicating more frequent guideline exceedances. The persistence of high F1 (75) values confirms that the deterioration affected multiple parameters simultaneously. Such a pattern is indicative of a transition from episodic disturbances to recurrent water quality impairment, as highlighted in previous CCME WQI applications. In November, the CCME WQI remained relatively stable at 54.03, still classified as Poor, but with a notable increase in F3 to 12.31. This rise in amplitude suggests that although the number of exceedances did not increase significantly, the severity of the violations intensified. High turbidity values and recurring low pH events contributed substantially to this increase, reflecting intensified sediment input and altered physicochemical conditions. High F3 values are widely recognized as a critical indicator of water quality stress because they represent deviations far beyond guideline thresholds. The most critical condition was recorded in December, when the CCME WQI dropped sharply to 32.28, approaching the lower bound of the Poor category. This severe decline was driven by an exceptionally high F2 value (89.29), indicating that nearly all measurements exceeded guideline values, combined with a persistently high F3 (12.66). These results indicate both frequent and severe water quality violations, rendering the irrigation water unsuitable without appropriate management intervention. Overall, the temporal pattern demonstrates a clear seasonal signal, with water quality progressively deteriorating from the dry to the wet season. The increasing dominance of turbidity, accompanied by episodiclow pH and suboptimal temperature conditions, suggests strong links to rainfall-induced surface runoff, soil erosion, and sediment transport into the irrigation channels. Similar seasonal degradation patterns have been reported in irrigation and river systems in troIPcal regions, where hydrometeorological variability exerts strong control over water quality dynamics. The findings confirm that the CCME WQI is highly sensitive to temporal variations in irrigation water quality and effectively captures both the frequency and magnitude of guideline exceedances. Moreover, the integration of IoT-based high-frequency monitoring with CCME WQI provides a robust framework for identifying critical periods of water quality degradation and supports adaptive irrigation water management strategies.

4. CONCLUSION

This study successfully developed and implemented an IoT-based irrigation water quality monitoring system integrated with the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) to evaluate temporal variations in irrigation water quality. The integration of real-time sensor data (pH, temperature, TDS, and turbidity) with the CCME WQI framework proved effective in transforming high-frequency, multidimensional measurements into a single, interpretable index that supports continuous water quality assessment and management.

The results demonstrate a clear temporal degradation of irrigation water quality from August to December, indicating increasing environmental pressure on the irrigation system. The CCME WQI values revealed a transition from Fair conditions in August to persistently Poor conditions in subsequent months, with the most critical deterioration observed in December. This decline was primarily driven by increased frequency (F2) and magnitude (F3) of guideline exceedances, with turbidity identified as the dominant contributing parameter under rainfall-driven hydrometeorological conditions, while episodiclow pH and diurnal temperature variations provided secondary contributions. In contrast, TDS remained relatively stable and consistently below regulatory thresholds, indicating a limited role in the observed degradation.

The interaction among hydrometeorological dynamics, sediment input, and physicochemical processes underscores that irrigation water quality deterioration is governed by the combined effects of exceedance frequency and deviation magnitude across multiple parameters, rather than by a single controlling variable. These findings are consistent with the conceptual basis of the CCME WQI and confirm its sensitivity in capturing both short-term fluctuations and cumulative impacts in irrigation systems.

Importantly, this study reaffirms its novelty by demonstrating an end-to-end integration of real-time IoT-based multi-parameter sensing with CCME WQI computation explicitly benchmarked against national regulatory standards and supported by validated sensor calibration. Unlike previous approaches that rely on offline datasets or focus solely on data acquisition, this study operationalizes CCME WQI within a real-time monitoring framework, enabling continuous, regulation-based evaluation of irrigation water quality under dynamic hydrometeorological conditions. From an applied perspective, this integrated framework provides a robust basis for precision irrigation management by enabling early detection of water quality deterioration, reducing the risk of irrigation failure associated with poor water conditions, and supporting adaptive responses to climate variability. Therefore, the proposed system represents a scalable, data-driven approach that enhances the resilience and sustainability of irrigation systems.

Overall, the study confirms that the integration of IoT-based high-resolution monitoring with real-time CCME WQI computation constitutes a novel, objective, and decision-oriented methodology for irrigation water quality management. Future research should focus on extending the monitoring duration, incorporating additional water quality parameters (e.g., nutrients and biological indicators), and linking water quality dynamics with crop response to further advance precision irrigation and sustainable agricultural water management.

ACKNOWLEDGEMENTS

The author sincerely expresses gratitude for the financial support provided through the Research Grant under the PDP (Penelitian Dosen Pemula) scheme for the Fiscal Year 2025, funded by the Ministry of Higher Education, Science, and Technology (Kemenristekdikti), Republic of Indonesia. This research was carried out under Contract Agreement No. 137/C3/DT.05.00/PL/2025; 855/LL16/AL.04/2025; and 0034/KPDP/LPPM/VI/2025. The author also wishes to acknowledge the Research and Community Service Institute (LPPM) of Universitas Katolik De La Salle Manado (UKDLSM), for administering this research scheme and providing valuable guidance, as well as all parties who have extended their support throughout the implementation of this study.

REFERENCES

[1] Government of Indonesia, "Law No. 18/2012 on Food," Jakarta, 2012.
[2] Ministry of National Development Planning (Bappenas), "Rencana Pembangunan Jangka Menengah Nasional (RPJMN) 2020-2024."
[3] R.S. Ayers and D.W. Westcot, *Water Quality for Agriculture*, vol. 29 Rev.1. Rome, Italy: Food and agriculture organization of the United Nations, 1985.
[4] Government of Indonesia, *PP No. 22/2021 on Environmental Protection and Management*. Jakarta, Indonesia, 2021.
[5] S. Behmel, M. Damour, R. Ludwig, and M. J. Rodriguez, "Water quality monitoring strategies — A review and future perspectives," *Science of the Total Environment*, vol. 571, pp. 1312–1329, Nov. 2016, doi: 10.1016/j.scitotenv.2016.06.235.
[6] S. Promput, S. Maithomklang, and C. Panya-isara, "Design and Analysis Performance of IoT-Based Water Quality Monitoring System using LoRa Technology," *TEM Journal*, vol. 12, no. 1, pp. 29–35, Feb. 2023, doi: 10.18421/TEM121-04.
[7] J. A. Stankovic, "Research directions for the internet of things," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 3–9, Feb. 2014, doi: 10.1109/JIOT.2014.2312291.
[8] Canadian Council of Ministers of the Enviroment, "CCME Water Quality Index 1.0 : Technical Report," Canada, 2001.
[9] A. A. Khan, R. Paterson, and H. Khan, "Modification and application of the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI)," *Ecol. Indic.*, vol. 5, no. 1, pp. 1–11, 2005, doi: 10.1016/j.ecolind.2004.02.002.
[10] F. Fitriana, D. Yudianto, and Y. C. Seo, "Analysis of Cikakembang River Water Quality Using the Pollution Index, STORET, and CCME-WQI Methods," *Jurnal Presipitasi: Media Komunikasi dan Pengembangan Teknik Lingkungan*, vol. 22, no. 2, pp. 485–496, 2025, doi: 10.14710/presipitasi.v22i2.485-496.
[11] FAO, "Water Quality for Agriculture, FAO Irrigation and Drainage," Rome, 29AD.
[12] B. Raco and R. L. Singgeta, "Analisis Kualitas Air Irigasi Dengan Metode Storet Dan Metode Indeks Pencemaranan (IP) Pada Monitoring System Berbasis IoT," *Rang Teknik Journal*, vol. 8, no. 1, 2025, doi: 10.31869/rtj.v8i1.6151.
[13] B. Neary, D. Williamson, M. Environment, and R. Wright, "Ccme Water Quality Index 1.0 Technical Report," *Canadian Environmental Quality Guidelines Canadian Council of Ministers of the Environment*, 2001.
[14] "Canadian Water Quality Guidelines for the Protection of Aquatic Life: CCME Water Quality Index User's Manual.," 2017. [Online]. Available: http://www.ccme.ca/en/resources/canadian_environmental_quality_guidelines/calculators.html.
[15] V. Bhatnagar, G. Singh, G. Kumar, and R. Gupta, "Internet Of Things In Smart Agriculture: Applications And Open Challenges," *International Journal of Students' Research in Technology & Management*, vol. 8, no. 1, pp. 11–17, Jan. 2020, doi: 10.18510/ijsrtm.2020.812.
[16] Y. Romdania, A. Herison, G. E. Susilo, and E. Novilyansa, "Kajian Penggunaan Metode IP, STORET, dan CCME WQI Dalam Menentukan Status Kualitas Air," *Spatial Wahana Komunikasi Dan Informasi Geografis*, vol. 18, no. 2, Sep. 2018.
[17] Canadian Council of Ministers of the Environment (CCME)., *Canadian water quality guidelines for the protection of aquatic life: turbidity. In: Canadian environmental quality guidelines.* Ottawa: CCME, 2002.