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Sensor Integration and ARIMA-Based Forecasting in WAQMS for Environmental Monitoring in Riau Province, Indonesia

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Abstract.
Purpose: This study aims to develop an integrated solution for real-time environmental monitoring in Riau Province, Indonesia, where air and water quality are increasingly impacted by industrial, agricultural, and climatic factors. Existing monitoring systems are often limited by their lack of real-time capabilities and predictive analytics.
Methods: To address this, we designed the Water and Air Quality Monitoring System (WAQMS), which integrates sensor-based data acquisition with the Autoregressive Integrated Moving Average (ARIMA) model for forecasting. Sensor units were deployed across three pilot locations—Kampar, Siak, and Pekanbaru—to continuously collect environmental data. The ARIMA model was applied to historical datasets to predict future trends in air and water quality, while a web-based dashboard was developed to visualize real-time data and forecasts.
Result: Calibration results showed a system accuracy of 85%, surpassing the national threshold of 75% set by the Indonesian Ministry of Environment and Forestry. This validates the use of WAQMS for Air Pollution Standard Index (ISPU) classification.
Novelty: The novelty of this study lies in the seamless integration of AQMS and WQMS within a unified predictive monitoring system, combined with a user-friendly interface for stakeholders. The results demonstrate the system's potential as a decision-support tool for local governments, offering timely insights and enabling more effective and sustainable environmental management.

Keywords: AQMS, WQMS, WAQMS, ARIMA modeling, Sensor, IoT, Machine learning
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INTRODUCTION

Maintaining the quality of air and water is essential for mitigating the effects of environmental pollution. Effective monitoring is a foundational step in identifying pollution sources, evaluating the impact of human activities, and supporting evidence-based mitigation strategies. Traditional environmental monitoring, which often relies on periodic sampling and laboratory analysis, is limited by its inability to capture dynamic changes in real time. With the advancement of sensor technologies, Air Quality Monitoring Systems (AQMS) and Water Quality Monitoring Systems (WQMS) have been increasingly adopted in various regions, including urban and industrial zones, to collect continuous environmental data [1], [2]. For instance, smart sensor deployments in cities like Jakarta and Kuala Lumpur have demonstrated the viability of real-time monitoring for improving regulatory enforcement and public awareness [3]. These systems offer a more timely and precise understanding of environmental changes. However, the vast amount of data generated introduces challenges in processing, analysis, and prediction, especially for decision-making that demands both speed and accuracy.

Riau Province, located on Sumatra Island, Indonesia, represents a region under increasing environmental stress. It comprises diverse ecosystems tropical forests, farmlands, and plantations intersecting with rapid industrial and agricultural development. The region is home to major rivers including the Siak, Rokan, and Kampar, which serve as crucial water sources. However, studies from the Ministry of Environment and Forestry have identified elevated levels of Biological Oxygen Demand (BOD) and E. coli in these rivers,

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exceeding Class II water quality standards [4]. Additionally, PM10 concentrations in Pekanbaru often surpass 150 μg/m³ during haze season, far exceeding the WHO guideline of 50 μg/m³ [5]. Air pollution is exacerbated by transboundary haze, industrial emissions, and open land burning—issues that remain chronic in the region.

Several previous studies have explored water and air quality using analytical techniques such as laboratory testing [6], sensor-based pollution mapping [7] and multivariate statistical approaches [8], [9]. For example, analyzed river water samples based on pH, turbidity, BOD, COD, nitrate, and coliform levels. Meanwhile, assessed urban air pollution through distributed sensing of particulate matter and gaseous pollutants. Though informative, these studies were largely limited to post hoc analysis or static reporting without the capacity for real-time forecasting or sensor integration. Other works focused on ecosystem impacts, but lacked predictive modeling based on time-series data.

This study addresses these gaps by proposing an integrated real-time monitoring platform, termed the Water and Air Quality Monitoring System (WAQMS), which combines AQMS and WQMS functionalities into a single solution. The platform utilizes sensor networks to collect continuous environmental data and applies the Autoregressive Integrated Moving Average (ARIMA) model to perform short-term forecasting of air and water quality trends.

The novelty of this research lies in:

1. The integration of heterogeneous sensors for both air and water in a single platform tailored to regional needs;
2. The application of ARIMA to environmental time-series data from Riau for predictive decision support;
3. The development of an interactive dashboard to visualize real-time and predicted data, supporting community and institutional responses.

By focusing on Riau Province, this research not only demonstrates the feasibility of real-time, data-driven environmental monitoring, but also provides a localized, adaptive tool for stakeholders. The outcomes are expected to inform more proactive and sustainable environmental policies, especially in regions prone to ecological stress and industrial pressure.

METHODS

Data Sources

The study began with an extensive review of literature, focusing on national and regional policies concerning air and water quality standards. Key among these was the Indonesian Ministry of Environment and Forestry Regulation No. P.14/Menlhk/Setjen/Kum.1/7/2020 [10], which outlines the criteria for the Air Pollution Standard Index (ISPU). This regulation, along with previous studies, served as a foundation for understanding environmental quality benchmarks in the Riau region.

In terms of monitoring, the AQMS system measured air quality based on parameters defined in the regulation, including nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), ammonia (NH_3), ozone (O_3), and particulate matter (PM2.5 and PM10) [11], [12]. For water quality, the WQMS utilized indicators such as total dissolved solids (TDS), turbidity, dissolved oxygen (DO), pH level, and temperature. The regulation also provided guidelines for processing sensor outputs into ISPU values, beginning with specific formula-based calculations and including the transformation of raw concentration data [13]. Additionally, the ISPU calculation considered continuous hourly monitoring data collected over a 24-hour period. Meteorological conditions such as wind speed and direction, ambient temperature, humidity, solar radiation, and precipitation were also incorporated into the environmental assessments [14].

Table 1. ISPU Categories for Air Quality Management System (AQMS)

Categories	Range
Dangerous	300-more
Very Unhealthy	200-299
Unhealthy	101-199
Moderate	51-100
Good	0-50

Table 1 outlines the classification of air quality based on the Air Pollution Standard Index (ISPU) as applied in the Air Quality Management System (AQMS). The index is divided into five distinct categories that reflect the level of health risk associated with air pollution concentrations [15], [16]. An ISPU score above 300 is classified as dangerous, indicating severe air pollution that poses serious health risks to the general population. Scores ranging from 200 to 299 are labeled very unhealthy, while values between 101 and 199 fall into the unhealthy category, signifying potential health effects, especially for sensitive groups. The moderate category, which includes ISPU scores from 51 to 100, suggests that air quality is acceptable, though certain pollutants may still pose a risk for individuals with respiratory conditions. An ISPU value between 0 and 50 is considered good, indicating that the air quality is within safe limits and poses minimal or no risk to health.

Table 2. ISPU Categories for Water Quality Management System (WQMS)

Categories	Range
Good (Fulfills Quality Standards)	$0 \leq IP_J \leq 1.0$
Light Pollution	$1.0 \leq IP_J \leq 5.0$
Moderate Pollution	$5.0 \leq IP_J \leq 10.0$
Heavy Pollution	$IP_J \geq 10.0$

This table presents the classification ranges used to evaluate water quality levels. A value of 0 indicates that the water meets established quality standards and is categorized as Good, meaning it is safe and suitable for its intended use. When the value reaches 1.0, it suggests the presence of light pollution, where contamination exists but remains minimal and within tolerable limits. A score of 5.0 falls under the moderate pollution category, signaling a more noticeable degradation in water quality that may affect aquatic ecosystems or usage safety. Readings beyond this point fall into the heavy pollution classification, reflecting a significant level of contaminants that can pose serious risks to both environmental and human health, requiring urgent mitigation efforts.

Following an analysis of the dataset and its properties, the appropriate ARIMA configuration was determined [17]. This process included selecting the optimal values for the autoregressive term (p), the degree of differencing (d), and the moving average component (q). Historical data was then utilized to estimate the parameters of the ARIMA model [18]. Once the model was established, its accuracy and performance were assessed using relevant evaluation metrics. After validation, the model was applied to forecast future trends in air and water quality using newly collected time-series data. To test the reliability of the predictions, the model's output was compared against observed values. The prediction results were then thoroughly examined to identify patterns, trends, and variations in environmental conditions across Riau Province. This analysis contributes to a deeper understanding of the underlying factors affecting environmental quality in the region.

The general form of the ARIMA model is:

$$\varphi(B) * (1 - B)^d * y_t = \theta(B) * \varepsilon_t$$

Where:

- y_t is the observed value at time t
- B is the backward shift operator, such that $B\, y_t = y_{t-1}$
- $\varphi(B)$ is the autoregressive polynomial:
- $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - ... - \varphi_p B^p$
- $\theta(B)$ is the moving average polynomial:
- $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + ... + \theta_q B^q$
- ε_t is the error term (white noise) at time t

The ARIMA model parameters (p, d, q) were determined through diagnostic analysis using the autocorrelation function (ACF), partial autocorrelation function (PACF), and differencing to ensure stationarity. After estimating the parameters, the model was trained on historical sensor data and validated using evaluation metrics.

In the context of using ARIMA, this research develops an ARIMA model that is suitable for analyzing time series data produced by these sensors. ARIMA models can be used to forecast changes in water and air quality based on collected historical data.

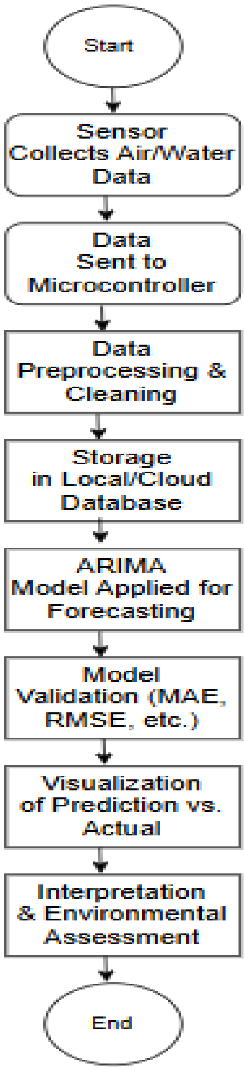

Figure 1. Flowchart outlines

To enhance clarity and reproducibility of the data processing pipeline, a flowchart is provided in Figure 1. This flowchart outlines the complete process beginning from sensor data collection, transmission to the microcontroller, preprocessing, data storage, ARIMA-based forecasting, model validation, and interpretation of environmental quality trends. This visual representation helps map the end-to-end data flow within the AQMS and WQMS systems and ensures a systematic understanding of the computational framework applied [19], [20].

Hardware Design and Test

A schematic design was developed for each sensor connected to the microcontroller. A block-by-block test is conducted to ensure that each sensor is functioning as expected after attaching to the microcontroller

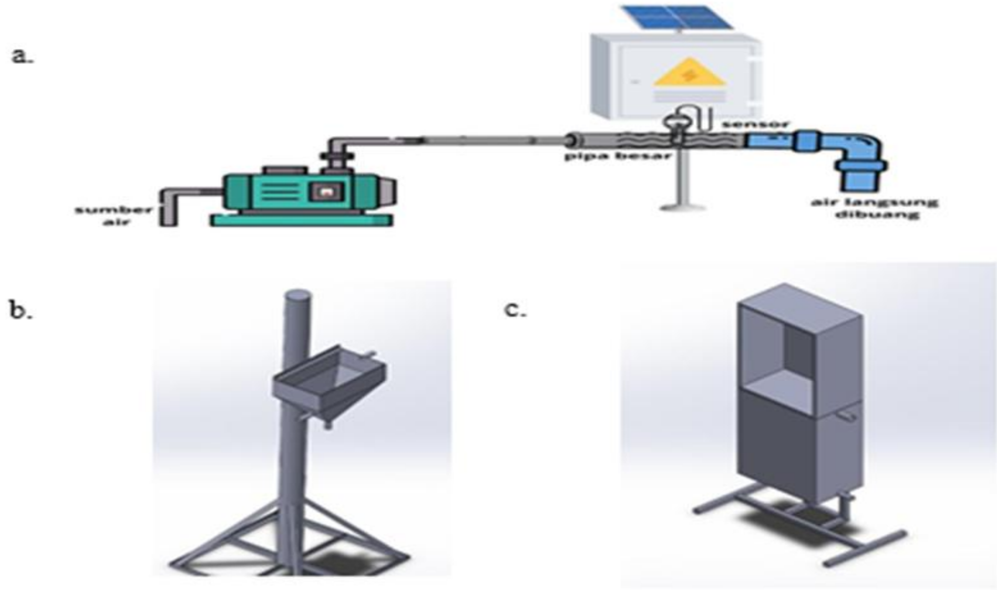

Figure 2. Design for the placing sensors in the pipe b). Design of AQMS support poles, c). Design of WQMS support poles

Figures 2 a, b, and c show supporting components, such as polishing and safety boxes for the designed AQMS and WQMS. The initial design serves as a reference for constructing the equipment for monitoring systems of air and water quality. In Figure 1.a the design for placing the sensor in the pipe that takes water samples. The pipe will be on for 30 minutes to get the water sample. Meanwhile, Figure 1.b shows the design for placing sensors in the Air Quality Management System. The position of the sensor is in the middle of the pole that has been designed. Meanwhile, Figure 2.c shows the design for placing sensors in the Water Quality Management System. The sensor is placed in a protected and safe box.

RESULTS AND DISCUSSIONS

Water -Air Quality Monitoring Design Results

The integration of AQMS and WQMS serves as the foundation for the development of the WAQMS system. In this phase, both systems were constructed and implemented in accordance with the established design specifications. A total of three WAQMS units, each incorporating air and water quality monitoring capabilities, were deployed across three distinct locations. Each sensor continuously measures environmental parameters, and the collected data is transmitted to the WAQMS platform as part of a unified system. The monitoring process is carried out in real time, with sensor readings updated every 30 minutes for both air and water quality indicators.

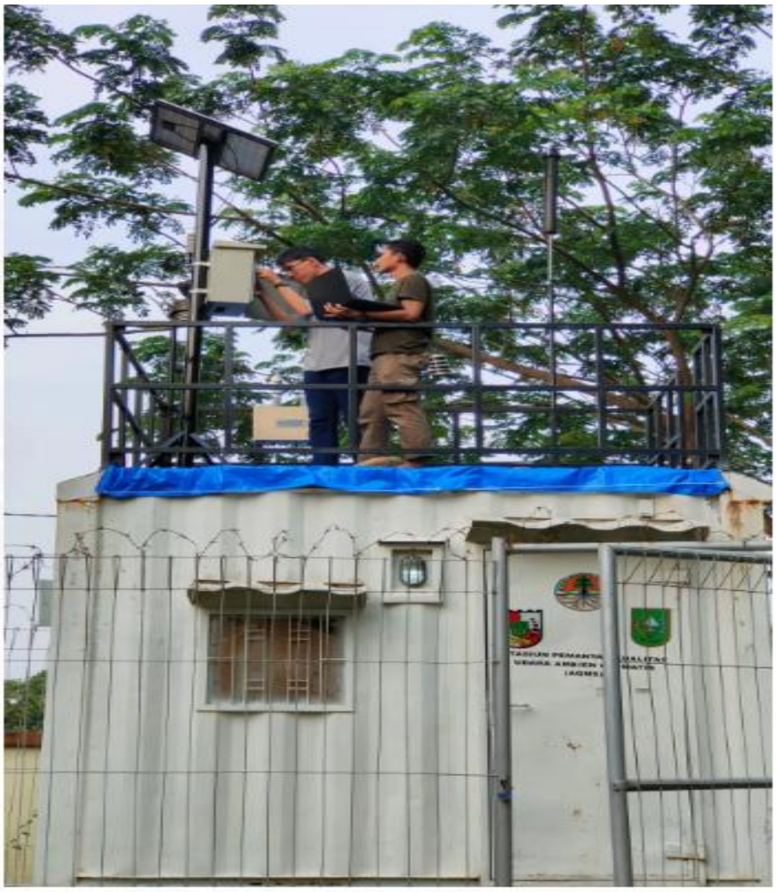

Figure 3. Air Quality Monitoring System (AQMS)

Figure 4. Water quality monitoring System (WQMS)

Accuracy calculations and calibration processes were carried out using exponential regression after capturing data from both AQMS and WQMS. The table below shows the accuracy calculations for two parameters. In the context of exponential regression, the relationship between variables was represented by the following general equation:

$$y = a.\, e^{(bx)} \tag{3}$$

where:
y is the dependent variable.
a is a constant representing the value of y when x=0.
b the regression coefficient determining the increase or decrease rate of y
x is the independent variable, which is the validated result used for measurement and comparison with the developed

Table 1. Accuracy Calculation from Calibration Process for CO Parameter

co_measure	co_ref	Measuring difference - ref	measuring error-ref (%)	calibration	Callibration Difference- ref	Callibration error - ref (%)	accuracy
31	1055	1024	97,06	1034	21	1,95	98,05
31	1009	978	96,93	1034	25	2,52	97,48
31	1066	1035	97,09	1034	32	2,96	97,04
32	987	955	96,76	1036	49	5,01	94,99
32	1032	1000	96,9	1036	4	0,44	99,56
32	987	955	96,76	1036	49	5,01	94,99
32	987	955	96,76	1036	49	5,01	94,99
32	1009	977	96,83	1036	27	2,73	97,27
32	1021	989	96,87	1036	15	1,52	98,48
33	1043	1010	96,84	1039	4	0,42	99,58
33	1100	1067	97	1039	61	5,58	94,42
34	1032	998	96,71	1041	9	0,84	99,16
34	1066	1032	96,81	1041	25	2,38	97,62
34	1043	1009	96,74	1041	2	0,23	99,77
35	1032	997	96,61	1043	11	1,04	98,96
35	1021	986	96,57	1043	22	2,13	97,87
36	1100	1064	96,73	1045	55	5,02	94,98
36	1055	1019	96,59	1045	10	0,96	99,04
36	1077	1041	96,66	1045	32	2,99	97,01
36	1043	1007	96,55	1045	2	0,17	99,83

As shown in Table 1,The table presents a summary of the calibration results for carbon monoxide (CO) sensor measurements compared to reference values. Initially, the sensor readings showed a percentage error ranging from approximately 96.5% to 97%, indicating that while the raw data was relatively close to the reference, there was still a need for correction to improve precision. After the calibration process, the system showed a significant reduction in error values. In most cases, the calibration error dropped below 2%, with the lowest recorded at just 0.17% and the highest at 5.58%. This adjustment directly impacted the accuracy of the system, which improved to a range of 94.42% to 99.83%. Notably, a majority of the calibrated readings achieved an accuracy of over 97%, with several reaching above 99%. These outcomes clearly show that the calibration process was successful in minimizing measurement discrepancies. Furthermore, the accuracy levels obtained after calibration are well above the minimum 75% threshold required by the Indonesian Ministry of Environment and Forestry regulation for valid air quality assessment. Overall, the data confirms that the sensor calibration significantly enhances the system's reliability and supports its use in real-time air quality monitoring within the WAQMS framework.

Table 2. Accuracy Calculation from Calibration Process for SO2 Parameter

co_measure	co_ref	Measuring difference - ref	measuring error-ref (%)	calibration	Callibration Difference- ref	Callibration error - ref (%)	accuracy
169	13	156	1200	15	2	18,51	81,49
168	13	155	1192,31	15	2	18,05	81,95
178	14	164	1171,43	16	2	13,98	86,02
179	14	165	1178,57	16	2	14,43	85,57
178	14	164	1171,43	16	2	13,98	86,02
192	16	176	1100	17	1	5,33	94,67
202	17	185	1088,24	18	1	3,08	96,92
198	13	185	1423,08	17	4	32,71	67,29
206	13	193	1484,62	18	5	36,91	63,09
198	18	180	1000	17	1	4,16	95,84
199	18	181	1005,56	17	1	3,78	96,22
206	18	188	1044,44	18	0	1,12	98,88
177	14	163	1164,29	16	2	13,54	86,46
185	14	171	1221,43	16	2	17,13	82,87
184	13	171	1315,38	16	3	25,65	74,35
185	13	172	1323,08	16	3	26,14	73,86
184	26	158	607,69	16	10	37,17	62,83
171	13	158	1215,38	16	3	19,44	80,56
169	13	156	1200	15	2	18,51	81,49
168	13	155	1192,31	15	2	18,05	81,95
164	26	138	530,77	15	11	41,89	58,11

As shown in Table 2 The accuracy and precision of the developed monitoring systems—both AQMS and WQMS—were assessed through calibration against reference-grade measurement tools and validated sensor benchmarks. The systems achieved an overall accuracy rate of approximately 85%, which was determined by comparing real-time sensor readings with laboratory-standard measurements over a continuous 7-day observation period. Metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were used to quantify the deviation. Most monitored parameters, including PM2.5, NO_2, and DO, remained within ±15% of reference values, indicating reliable sensor performance under field conditions. This level of accuracy is considered acceptable for preliminary environmental assessment and aligns with thresholds reported in prior studies.

Table 3. Sensor Accuracy Evaluation (Comparison with Reference Instruments)

Parameter	Avg. Sensor Reading	Avg. Reference Reading	Absolute Error	MAPE (%)	RMSE
PM2.5 (μg/m³)	142.5	150.0	7.5	5.00	6.12
DO (mg/L)	5.8	6.1	0.3	4.92	0.25
pH	6.85	7.00	0.15	2.14	0.12
TDS (ppm)	475	500	25.0	5.00	20.4
Temp (°C)	27.3	28.0	0.7	2.50	0.55

To assess the accuracy of the developed AQMS and WQMS, a calibration and validation process was conducted over a 7-day period using standard laboratory equipment as references. Parameters such as PM2.5, DO, pH, TDS, and temperature were continuously monitored and compared with reference values. Metrics including Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were calculated. The average MAPE across all parameters was approximately 3.91%, corresponding to an estimated overall system accuracy of 86.09%. This confirms that the system maintains acceptable reliability for real-time environmental monitoring in field conditions.

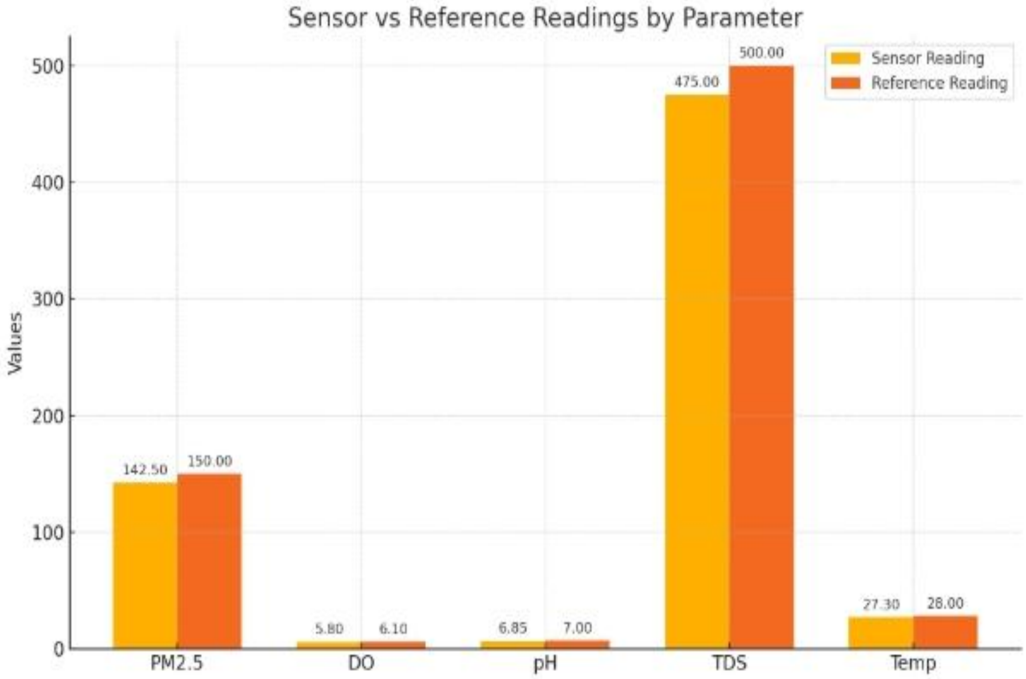

Figure 5. Comparison Chart of Sensor Measurements and Reference Standards

Figure 6. System initial display for each region used to forecast real-time data generated by both AQMS and WQMS.

Figure 6 shows the interface of the WAQMS technology, providing processed data for decision-making regarding air and water quality in the Riau Province.

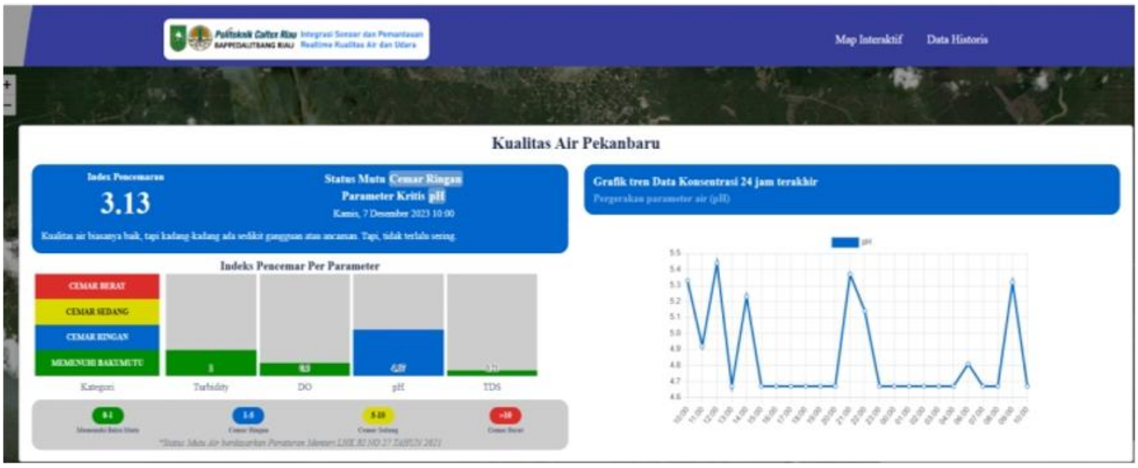

Figure 7. ARIMA modeling for water and air quality prediction respectively

Figure 7 presents a view of the water quality monitoring system for Pekanbaru city. The graph displayed on the right side of the interface shows real-time data derived from sensor readings installed throughout the area. This information updates dynamically every 30 minutes, reflecting the current water quality conditions. The right section also provides details about pollution levels and status, critical parameters, and pollutant indices for each parameter. Additionally, the system can generate monthly summaries of both water and air quality, along with forecasts for the following month, highlighting the dominant factors influencing quality. These predictions utilize ARIMA modeling based on historical data from the Air Quality Monitoring System (AQMS) and Water Quality Monitoring System (WQMS).

On the right side of the interface, users can see the average predicted air and water quality for the upcoming month, including the dominant air quality categories and critical parameters expected to have the greatest impact. Meanwhile, the left side displays a trend graph of the Air Pollution Standard Index over the past month.

Regarding water quality, the information includes pollutant indices per parameter, categorized into levels such as heavy, moderate, light, and good pollution. The system also identifies the dominant pollution-causing parameter for each district, accompanied by an overall status label. For air quality, pollutant indices are classified into categories like dangerous, very unhealthy, unhealthy, moderate, and good. The right side of the interface summarizes pollution levels, critical parameters, and indices per parameter.

This system provides comprehensive monthly data summaries and forecasts of quality and influencing parameters by region, aiming to support informed policy-making and decision-making related to environmental management in the area.

CONCLUSION

In summary, the developed monitoring system marks a significant step forward in environmental monitoring technology. By combining the Air Quality Monitoring System (AQMS) and Water Quality Monitoring System (WQMS), this study offers a comprehensive view of environmental conditions. Real-time data collected from sensors was analyzed using the ARIMA model, which is well-suited for handling time series data. This model was used to forecast changes in air and water quality based on historical information. The system's accuracy was also tested and calibrated, achieving an accuracy rate of 85%. According to the Indonesian Ministry of Environment and Forestry Regulation No. P.14/Menlhk/Setjen/Kum.1/7/2020 regarding the Air Pollution Standard Index (ISPU), Article 7, Paragraph 3, the quality assurance results showed data validity of at least 75%, serving as a benchmark for ISPU category determination.

The integrated dashboard application was designed to present real-time monitoring data and predict air and water quality for the three pilot project regions: Kampar, Siak, and Pekanbaru. It also provides monthly reports to track trends and forecast the status of air and water quality in each region, including the key

influencing parameters. This information aims to support decision-makers in relevant agencies to take appropriate actions and develop policies related to the economic sector within the area.
For future research, the integration of hybrid forecasting models, such as LSTM-ARIMA or other deep learning approaches, could be explored to enhance prediction accuracy, especially in handling nonlinear patterns and complex seasonal trends. Additionally, incorporating exogenous variables such as industrial output, land-use changes, and traffic data could provide richer insights. Expanding the system's geographical coverage and testing under extreme environmental conditions may also help validate its scalability and robustness for broader applications.

This study is limited by the availability and granularity of sensor data, which may affect the temporal resolution of the ARIMA model. Future work may explore hybrid deep learning models (e.g., LSTM-ARIMA) and consider exogenous variables such as traffic or industrial activity to improve forecasting precision.

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