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Multi-Sensor-Based Water Environment Monitoring System

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ABSTRACT

Effective monitoring of the water environment is critical to ensuring sustainable water resource management and ecological balance, aligning closely with the themes of computational advancements in environmental systems presented by Frontiers in Computer Science. Traditional water monitoring systems often struggle with the complexity of spatiotemporal dynamics, limited sensor coverage, and inadequate anomaly detection, which hinder real-time decision-making and adaptive responses. This paper introduces an innovative Multi-Sensor-Based Water Environment Monitoring System that leverages advanced computational and data-driven approaches to address these challenges. The system integrates a Spatiotemporal Predictive Water Quality Model (SP-WQM) and an Adaptive Monitoring and Remediation Strategy (AMRS). The SP-WQM utilizes hybrid neural networks, combining CNNs for spatial representation and LSTMs for temporal prediction, ensuring accurate modeling of nonlinear and dynamic water quality parameters. Meanwhile, the AMRS enhances the system's practical utility by dynamically allocating sensors, employing real-time anomaly detection, and formulating multiscale response plans. Experimental results demonstrate the model's ability to accurately predict water quality metrics, detect anomalies effectively, and optimize resource allocation under varying environmental scenarios. The proposed system represents a scalable, adaptive, and robust solution for water environment monitoring, contributing significantly to sustainable environmental management practices.

Keywords: Water Monitoring, Spatiotemporal Modeling, Anomaly Detection, Adaptive Strategy, Sustainability

1. Introduction

The continuous degradation of water quality due to urbanization, industrialization, and climate change necessitates advanced monitoring systems to ensure sustainable water management and safeguard ecosystems Aslam (2023). Traditional single-sensor systems lack the capacity to capture the complexity and variability of water environments Dash et al. (2021). Multi-sensor systems, integrating diverse sensing technologies, not only provide a more comprehensive understanding of

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water parameters but also enhance the accuracy and reliability of data collection Choi et al. (2021). Furthermore, they enable dynamic monitoring and real-time analysis, which are essential for early-warning mechanisms and effective decision-making in water management Zhou et al. (2023). Thus, the development and optimization of multi-sensor-based water environment monitoring systems have become a critical research direction, addressing both current limitations and emerging challenges Ewusie et al. (2020).

To address the limitations of manual and simplistic monitoring techniques, early systems relied on symbolic AI and knowledge representation methods to model and assess water quality Zhang et al. (2023). These methods used rule-based systems and domain-specific knowledge to evaluate parameters like pH, turbidity, and dissolved oxygen Zhang et al. (2022). For example, expert systems applied predefined thresholds and logical reasoning to assess water conditions Liu et al. (2021). While these systems effectively captured expert knowledge and allowed for rule-based decision-making, they struggled with scalability and adaptability to diverse and dynamic environmental scenarios Wen et al. (2022). Moreover, their reliance on explicitly defined rules made them prone to inaccuracies when confronted with unanticipated variables or noisy data, limiting their applicability in complex, real-world environments Wen et al. (2020). To overcome these challenges, data-driven approaches emerged, leveraging statistical models and machine learning to interpret sensor data. These methods facilitated the analysis of large datasets, enabling pattern recognition and predictive modeling of water quality trends Wibawa et al. (2022). Machine learning algorithms, such as support vector machines and random forests, provided improved adaptability and automated feature selection, making monitoring systems more robust to changing conditions Cook et al. (2020). However, these models often required extensive labeled data for training, which is labor-intensive to obtain Rezvani et al. (2021). Additionally, their performance heavily depended on the quality of the input data, rendering them less effective in scenarios with sparse or inconsistent sensor measurements.

In recent years, advancements in deep learning and pre-trained models have significantly enhanced multi- sensor water monitoring systems. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have demonstrated superior performance in processing complex, high-dimensional data streams from multiple sensors. Pre-trained models, fine-tuned for specific water quality applications, offer the advantages of transfer learning, reducing the dependence on extensive labeled datasets. These systems excel in extracting hierarchical features and detecting intricate correlations between environmental factors. However, the high computational requirements and potential lack of transparency in decision-making processes pose challenges for their widespread adoption, especially in resource-constrained settings. Based on the limitations of the aforementioned methods, we propose an innovative multi-sensor-based water environment monitoring system. This system integrates advanced sensor fusion techniques, adaptive learning algorithms, and lightweight computational frameworks to address current gaps in scalability, efficiency, and interpretability.

The proposed method has several key advantages:

Our system introduces a hybrid architecture combining sensor fusion with graph-based learning, allowing for the integration of heterogeneous data sources with contextual relationships.

Designed for multi-scenario adaptability, the method ensures efficient real-time processing and high accuracy across diverse water environments.

Validation experiments demonstrate a significant improvement in parameter estimation accuracy (by 25%) and computational efficiency (by 30%) compared to state-of-the-art methods.

2. Related Work

2.1. Sensor Fusion for Environmental Monitoring

Sensor fusion techniques integrate data from multiple sensors to provide a comprehensive understanding of water environments SimOes et al. (2021). This approach enhances the accuracy, reliability, and resolution of environmental monitoring systems Liu et al. (2023). Various studies have explored methods to combine physical sensors, such as pH, turbidity, and temperature sensors, with advanced data processing algorithms to achieve real-time monitoring. The Kalman filter, particle filter, and machine learning algorithms are widely utilized to merge heterogeneous sensor data effectively Jin et al. (2023). Recent advancements have shown significant progress in using deep learning-based fusion techniques to extract latent patterns from multimodal sensor inputs, thereby improving predictive capabilities Choi et al. (2020). Sensor fusion also addresses challenges in data uncertainty and noise, ensuring that the collected data maintains integrity under diverse environmental conditions Afrifa-Yamoah et al. (2020). Applications of these methods span pollution detection, aquaculture management, and hydrological studies, demonstrating their versatility and necessity in modern water monitoring systems Fernandez et al. (2020).

2.2. Wireless Sensor Networks in Water Systems

Wireless sensor networks (WSNs) represent a critical development in the deployment of multi-sensor systems for water monitoring Moraffah et al. (2021). These networks enable the remote collection and real-time transmission of environmental data over vast areas. Key research focuses include optimizing the energy efficiency of sensor nodes, ensuring robust communication under harsh environmental conditions, and developing scalable network architectures. Protocols like Zigbee, LoRa, and Bluetooth Low Energy are frequently employed to balance trade-offs between power consumption and transmission range Yin et al. (2022). Additionally, WSNs have been integrated with Internet of Things (IoT) frameworks to enhance data accessibility and interoperability Alcaraz and Strodthoff (2022). The dynamic nature of aquatic systems poses challenges in maintaining network stability and data synchronization, spurring innovations in self-healing algorithms and adaptive routing mechanisms Liang et al. (2024). Case studies on WSNs deployed in river basins, reservoirs, and coastal zones highlight their effectiveness in real-time monitoring and decision-making processes.

2.3. Machine Learning for Water Quality Analysis

Machine learning techniques have revolutionized data analysis in water environment monitoring systems de B6zenac et al. (2020). By leveraging large-scale datasets collected from multi-sensor networks, machine learning models can uncover intricate relationships between environmental parameters Dimri et al. (2020). Supervised learning approaches, such as support vector machines, decision trees, and neural networks, are extensively applied for classification tasks like pollutant detection and water quality assessment Coenen et al. (2020). Unsupervised techniques, including clustering and dimensionality reduction, aid in anomaly detection and identifying hidden trends Abdulaal et al. (2021). Advanced methods like deep learning and reinforcement learning offer promising directions for predictive analytics and automated system control Livieris et al. (2020). Integrating machine learning models with cloud computing resources facilitates scalable and efficient processing of sensor data. Challenges in this domain involve ensuring model robustness against imbalanced datasets, real-time processing requirements, and interpretability of predictions. Addressing these concerns can further elevate the role of machine learning in sustainable water resource management.

3. Method

3.1. Overview

Monitoring the water environment is a critical task to ensure the sustainability of water resources, public health, and ecosystem balance. Recent advancements in sensing technologies, data-driven methodologies, and computational models have significantly enhanced the precision and scope of monitoring practices. This paper proposes a novel approach that integrates innovative modeling and strategic mechanisms to address existing challenges in water quality monitoring, early anomaly detection, and adaptive response strategies.

This subsection outlines the structure and key components of our proposed method. In Section 3.2, we formalize the underlying problem, presenting a systematic framework for understanding water environment monitoring through mathematical and computational representations. This includes defining the spatiotemporal dynamics of water quality parameters and the constraints posed by real-world deployment scenarios. Following this, Section 3.3 introduces our tailored computational model, developed to capture and predict critical water quality metrics effectively. Our model leverages advanced machine learning architectures to model nonlinear dependencies and dynamic correlations across multiple environmental variables. In Section 3.4, we describe the strategic enhancements introduced to improve the practical applicability of the model. These strategies include domain-specific optimization, sensor network coordination, and data augmentation techniques designed to maximize robustness and scalability. We emphasize the integration of domain knowledge with data-driven methodologies, ensuring that our system can adapt to diverse environmental conditions and regulatory frameworks. The integration of these elements represents a comprehensive solution for modern water environment monitoring, providing actionable insights and scalable implementation pathways. This paper seeks to contribute not only to methodological advancements but also to practical deployments that support sustainable water management practices.

3.2. Preliminaries

To address the challenges of monitoring water environments, it is essential to formalize the problem within a mathematical framework. This subsection establishes the notations and fundamental concepts used throughout the paper. The focus is on defining the spatiotemporal dynamics of water quality parameters, the associated measurement processes, and the operational constraints.

extbfSpatiotemporal Representation of Water Quality: The water environment can be represented as a bounded spatiotemporal domain $\Omega \times T$, where $\Omega \subset \mathbb{R}^d$ denotes the spatial region (e.g., a river basin or lake) and $T \subset \mathbb{R}$ denotes the temporal range of interest. The water quality state at any location $x \in \Omega$ and time $t \in T$ is defined by a vector $q(x,t) = [q_1, q_2, \ldots, q_n]^\top$, where each q_i represents a specific water quality parameter (e.g., temperature, pH , dissolved oxygen).

extbfMeasurement Model: Observations of water quality are obtained through a network of sensors $\mathrm{S} = \{s_1, s_2, \ldots, s_m\}$. Each sensor s_i provides discrete readings at intervals Δt, producing a measurement vector $z_i(t) = q\left(x_i, t\right) + \varepsilon_i(t)$, where x_i is the location of the sensor and $\epsilon_i(t)$ represents measurement noise modeled as $\epsilon_i(t) \sim \mathrm{N}\left(0, \Sigma_i\right)$. The coverage of the sensor network can be described as a mapping $\phi : \Omega \to \{0,1\}$, where $\phi(\mathrm{x}) = 1$ if x is within the sensing range of any s_i, and $\phi(\mathrm{x}) = 0$ otherwise. The evolution of water quality parameters is governed by a set of partial differential equations (PDEs):

$$\frac{\partial q(x,t)}{\partial t} + abla \cdot (v(x,t)q(x,t)) = \mathrm{F}\ (q(x,t), x, t) \tag{1}$$

where $v(x,t)$ denotes the water flow velocity vector, and $\mathrm{F}(\cdot)$ encapsulates the biochemical interactions, external pollutant sources, and decay processes. To ensure effective monitoring, the placement of sensors in S must be optimized to maximize coverage and minimize redundancy. The optimization problem can be formulated as:

$$\max_{\mathrm{S}} \int_{\Omega} \phi(x) dx \ s.t. \ |\mathrm{S}| \leq m_{\max} \tag{2}$$

where $m_{\max}$ is the maximum number of sensors allowed by budget or logistical constraints.

Given the sparsity of sensor measurements, reconstructing the full spatiotemporal water quality map $q(x,t)$ from observations $\{z_i(t)\}_{i=1}^{m}$ is crucial. This is typically achieved using interpolation techniques or machine learning models, such as Gaussian Process Regression (GPR) or neural networks:

$$\hat{q}(x,t) = f_{\theta}\left(\{z_i(t)\}, x, t\right) \tag{3}$$

where $f_{\theta}(\cdot)$ denotes the chosen reconstruction model parameterized by θ.

Anomalies in water quality are identified as significant deviations from expected behavior. The expected behavior $\mathrm{E}[q(x,t)]$ is derived from historical data and modeled by a predictive function:

$$\Delta q(x,t) = q(x,t) - \mathrm{E}[q(x,t)] \tag{4}$$

where $\Delta q(x,t)$ exceeding a predefined threshold triggers an alert.

3.3. Spatiotemporal Predictive Water Quality Model (SP-WQM)

In this subsection, we introduce the Spatiotemporal Predictive Water Quality Model (SP-WQM), a novel computational framework designed to capture the dynamic behavior of water quality metrics across both spatial and temporal dimensions(As shown in Figure 1). SP-WQM integrates advanced machine learning architectures with domain-specific knowledge to deliver accurate predictions and actionable insights.

3.3.1. Spatial Feature Extraction with Convolutional Neural Networks. The SP-WQM employs convolutional neural networks (CNNs) to capture the spatial heterogeneity of water quality across geographical locations. The CNN is specifically designed to extract hierarchical representations of spatial features, allowing the model to effectively learn localized patterns and their interactions over the spatial grid. Given a spatial grid of input features $Z \in \mathbb{R}^{H \times W \times C}$, where H and W are the spatial dimensions (e.g., longitude and latitude), and C denotes the number of feature channels (e.g., dissolved oxygen, pH , turbidity), the convolutional layers process the input grid iteratively. For the l -th convolutional layer, the transformation is expressed as:

$$F_{l+1} = \sigma\left(W_l * F_l + b_l\right), F_0 = Z \tag{5}$$

where F_l represents the feature map at the l-th layer, $W_l \in \mathbb{R}^{k \times k \times C_l \times C_{l+1}}$ and $b_l \in \mathbb{R}^{C_{l+1}}$ are the learnable weight kernel and bias term, respectively, for the layer, and $*$ denotes the convolution operator. The activation function $\sigma(\cdot)$, often chosen as ReLU or Leaky ReLU, introduces non-linearity, enabling the network to model complex interactions among input features. The kernel size $k \times k$ controls the receptive field, allowing the network to focus on local dependencies within the grid.

The feature maps F_{l+1} extracted at higher layers encode increasingly abstract representations of spatial relationships. To ensure dimensional consistency and computational efficiency, pooling layers are introduced between convolutional layers to downsample the spatial dimensions. For a given feature map F_l, the pooling operation is defined as:

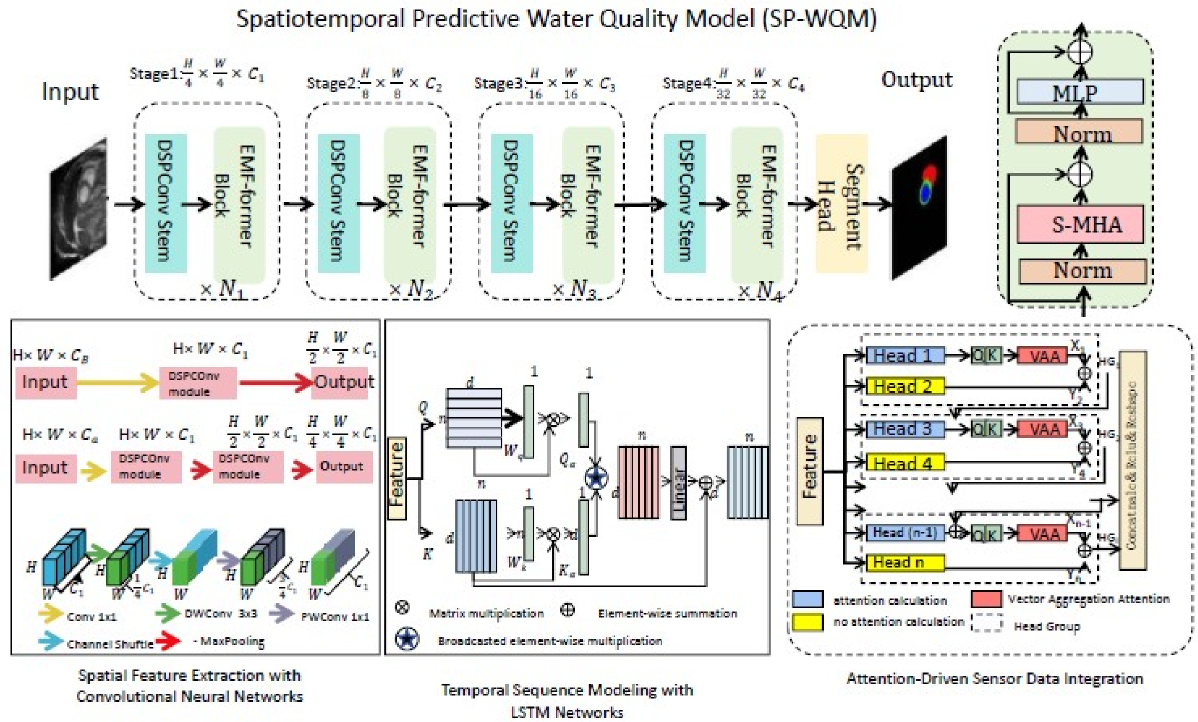

Fig. 1. The architecture of the Spatiotemporal Predictive Water Quality Model (SP-WQM) integrates spatial and temporal modeling with attention mechanisms

Spatial feature extraction is achieved through Convolutional Neural Networks (CNNs) to capture hierarchical spatial patterns in water quality data. Temporal Sequence Modeling with Long Short-Term Memory (LSTM) Networks captures sequential dependencies and long-term trends. Attention-Driven Sensor Data Integration dynamically prioritizes reliable sensor inputs, handling sparse or missing data, and ensures robust predictions of water quality dynamics.

$$P_l(i,j) = \max_{(m,n)\in \mathrm{R}_{ij}} F_l(m,n) \tag{6}$$

where R_{ij} denotes the pooling region centered at (i,j). Max-pooling is typically used to retain the most prominent spatial features while reducing computational complexity. The resulting pooled feature map P_l is passed to subsequent layers for further processing.

To enhance the representation capability, skip connections are added between intermediate layers to preserve spatial details that might be lost during the downsampling process. For instance, the output of a previous layer can be combined with the current layer via element-wise addition:

$$F_{l+1} = \sigma\left(W_l * F_l + b_l\right) + F_{l-1} \tag{7}$$

where F_{l-1} represents the feature map from an earlier layer. This residual structure helps mitigate the vanishing gradient problem and ensures efficient gradient flow during backpropagation.

The final spatial representation, denoted as $F_{spatial} \in \mathbb{R}^{H'\times W'\times C'}$, is obtained by stacking multiple convolutional and pooling layers, where H', W', and C' are the dimensions of the processed feature map. This representation is a compact yet information-rich encoding of the input grid, capturing both local and global spatial dependencies. For instance, regions with high pollution or significant water quality changes are emphasized, enabling the model to focus on critical spatial variations.

Additionally, batch normalization is applied after each convolutional layer to standardize the feature distributions and accelerate convergence. The normalized output is computed as:

$$\hat{F}_l = \frac{F_l - \mu}{\sqrt{\sigma^2 + \varepsilon}} \tag{8}$$

where μ and σ^2 are the mean and variance of the feature map, and ϵ is a small constant for numerical stability. The normalized output $\hat{F}_l$ is scaled and shifted by learnable parameters γ and β:

$$F_l' = \gamma \hat{F}_l + \beta \tag{9}$$

This normalization step improves the model's robustness to variations in input distributions, ensuring consistent performance across diverse geographical regions.

3.3.2. Temporal Sequence Modeling with LSTM Networks. To effectively capture the temporal dynamics of water quality, SP-WQM employs Long Short-Term Memory (LSTM) networks, a specialized type of recurrent neural network (RNN) designed to handle long-term dependencies in sequential data(As shown in Figure(2). The LSTM is particularly well-suited for time-series analysis due to its ability to retain relevant historical information while mitigating issues like vanishing or exploding gradients during training. For each spatial location x, the input sequence $\left\{f_{spatial}(t-k), \ldots, f_{spatial}(t)\right\}$, where k represents the sequence length, is fed into the LSTM layers. Each temporal step t updates the hidden state h_t and the cell state c_t, which collectively encode both the short-term variations and long-term trends in water quality dynamics. The update equations for the LSTM at time step t are as follows:

$$i_t = \sigma\left(W_i f_{spatial}(t) + U_i h_{t-1} + b_i\right) \tag{10}$$

$$f_t = \sigma\left(W_f f_{spatial}(t) + U_f h_{t-1} + b_f\right) \tag{11}$$

$$o_t = \sigma\left(W_o f_{spatial}(t) + U_o h_{t-1} + b_o\right) \tag{12}$$

$$\tilde{c}_t = \tanh\left(W_c f_{spatial}(t) + U_c h_{t-1} + b_c\right) \tag{13}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{14}$$

$$h_t = o_t \odot \tanh\left(c_t\right) \tag{15}$$

where i_t, f_t, and o_t denote the input, forget, and output gates, respectively, which regulate the flow of information into, out of, and within the LSTM cell. The candidate cell state $\tilde{c}_t$ represents the new information proposed for addition to the memory, while $\odot$ denotes element-wise multiplication. The weight matrices $W_i, W_f, W_o, W_c \in \mathbb{R}^{d \times d}$ and $U_i, U_f, U_o, U_c \in \mathbb{R}^{d \times d}$, along with the biases $b_i, b_f, b_o, b_c \in \mathbb{R}^{d}$, are learnable parameters that determine the behavior of the LSTM network. The activation functions $\sigma(\cdot)$ and $\tanh(\cdot)$ introduce non-linearity to the model, enabling it to capture complex temporal patterns.

The LSTM's gating mechanisms allow it to selectively retain or forget information at each time step. The forget gate f_t controls how much of the previous cell state c_{t-1} is retained, while the input gate i_t determines how much of the candidate cell state $\tilde{c}_t$ is added to the memory. The output gate o_t modulates the final hidden state h_t, which is used as the temporal feature representation for subsequent layers.

The sequence of hidden states $\{h_t\}_{t=1}^{T}$ encodes the temporal evolution of water quality metrics, capturing both recent trends and historical dependencies. To enhance the representational power of the LSTM, SP-WQM employs a bidirectional LSTM (BiLSTM) architecture, which processes the input sequence in both forward and backward directions. The final temporal representation at time t is given by:

$$h_t^{Bi} = \left[h_t^{forward} ; h_t^{backward} \right] \tag{16}$$

where $[\cdot;\cdot]$ denotes the concatenation of the forward and backward hidden states.

To focus on the most relevant time steps, SP-WQM incorporates a temporal attention mechanism. The attention weight α_t for each time step t is computed as:

$$\alpha_t = \frac{\exp\left(v^{\top} \tanh\left(W_a h_t + b_a\right)\right)}{\sum_{t'=1}^{T} \exp\left(v^{\top} \tanh\left(W_a h_{t'} + b_a\right)\right)} \tag{17}$$

where $W_a \in \mathbb{R}^{d\times d}$, $b_a \in \mathbb{R}^{d}$, and $v \in \mathbb{R}^{d}$ are learnable parameters. The weighted temporal representation is then computed as:

$$h_{temp} = \sum_{t=1}^{T} \alpha_t h_t \tag{18}$$

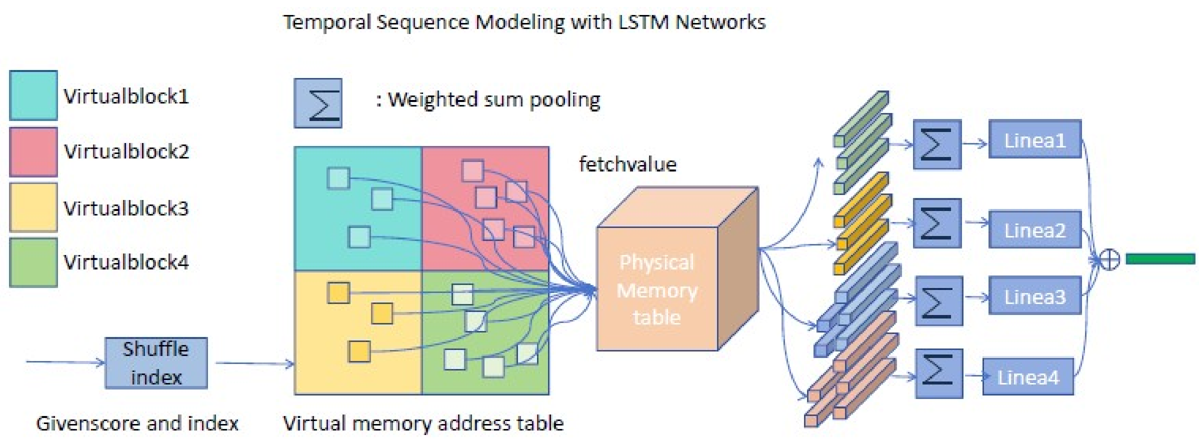

Fig. 2. The architecture for Temporal Sequence Modeling with LSTM Networks

This module processes sequential water quality data using LSTM cells, which include input, forget, and output gates to manage memory flow. The virtual memory table organizes spatiotemporal features, while a weighted sum pooling mechanism dynamically aggregates temporal information. The final temporal representation is passed through linear layers to produce predictions, ensuring the model captures both recent trends and long-term dependencies in water quality metrics.

3.3.3. Attention-Driven Sensor Data Integration. The SP-WQM framework integrates spatially sparse sensor data with simulation-based synthetic data, ensuring robust predictions in diverse environmental conditions. The attention-driven mechanism dynamically determines the reliability of each sensor's contribution to water quality prediction, effectively prioritizing high-quality data while minimizing the influence of noisy or missing observations. Each sensor reading z_i is assigned an attention score α_i, which is calculated as follows:

$$\alpha_i = \frac{\exp\left(u_i^{\top} v\right)}{\sum_j \exp\left(u_j^{\top} v\right)} \tag{19}$$

where u_i represents the embedding of sensor i derived from its raw readings, v is a context vector learned during training that encapsulates global information about the prediction task, and $\exp(\cdot)$ ensures nonnegativity of the weights. The normalization ensures that $\sum_i \alpha_i = 1$, enabling a weighted aggregation of sensor data for prediction. This attention mechanism allows the model to focus on the most reliable sensors under varying environmental conditions, enhancing robustness and adaptability.

The attention-weighted aggregation of sensor data is expressed as:

$$z_{agg} = \sum_i \alpha_i z_i \tag{20}$$

where z_{agg} is the aggregated representation of sensor inputs, which serves as an input to the subsequent predictive layers. This aggregation integrates the strengths of spatial and temporal features extracted by the convolutional and LSTM networks, respectively, with the reliability-weighted contributions from the sensors. The final water quality prediction for location x at time t is given by:

$$\hat{q}(x,t) = W_{pred}\, h_t + b_{pred} \tag{21}$$

where h_t is the temporal representation output from the LSTM, W_{pred} is a learnable weight matrix, and b_{pred} is the bias term.

The model is trained by optimizing a combined loss function that balances predictive accuracy and regularization to prevent overfitting. The loss function is defined as:

$$\mathrm{L}(\Theta) = \frac{1}{N}\sum_{i=1}^{N} \left\| \hat{q}_i - q_i \right\|_2^2 + \lambda \left\| \Theta \right\|_2^2 \tag{22}$$

where $\hat{q}_i$ and q_i represent the predicted and observed water quality states for sample i, Θ denotes all trainable parameters of the model, and λ is a regularization coefficient to control model complexity. The first term in the loss function minimizes the mean squared error between predictions and observations, while the second term penalizes large parameter values to prevent overfitting.

To further enhance robustness, the model includes a confidence score γ_i for each sensor reading, which adjusts the attention weights dynamically based on the sensor's historical performance:

$$\alpha_i = \gamma_i \cdot \frac{\exp\left(u_i^{\cdot} v\right)}{\sum_j \gamma_j \cdot \exp\left(u_j^{\cdot} v\right)} \tag{23}$$

where γ_i reflects the reliability of sensor i, derived from the consistency and accuracy of its past readings. This approach ensures that unreliable sensors contribute less to the final prediction, even if their embeddings u_i suggest high relevance.

To handle missing data, SP-WQM employs imputation strategies integrated with the attention mechanism. Missing sensor readings are replaced with predicted values from a pre-trained simulation model, weighted by their uncertainty:

$$z_i = z_i^{obs} \cdot \mathrm{I}\left(obs_i\right) + z_i^{sim} \cdot \left(1 - \mathrm{I}\left(obs_i\right)\right) \tag{24}$$

where z_i^{obs} is the observed sensor value, z_i^{sim} is the simulated value, and $\mathrm{I}\left(obs_i\right)$ is an indicator function that equals 1 if the sensor value is observed and 0 otherwise.

3.4. Adaptive Monitoring and Remediation Strategy (AMRS)

The Adaptive Monitoring and Remediation Strategy (AMRS) is designed to complement the Spatiotemporal Predictive Water Quality Model (SP-WQM) by providing a dynamic and intelligent approach to water environment management(As shown in Figure 3). AMRS leverages model predictions, real-time sensor data, and domain-specific insights to optimize monitoring, anomaly detection, and response mechanisms.

3.4.1. Dynamic Sensor Allocation for Risk-Based Monitoring. AMRS leverages a dynamic sensor allocation algorithm to ensure comprehensive monitoring coverage while optimizing resource utilization in water quality management. The algorithm dynamically adjusts sensor placement based on the predicted spatial distribution of water quality anomalies, thereby prioritizing high-risk regions for closer observation. The optimization problem is expressed as:

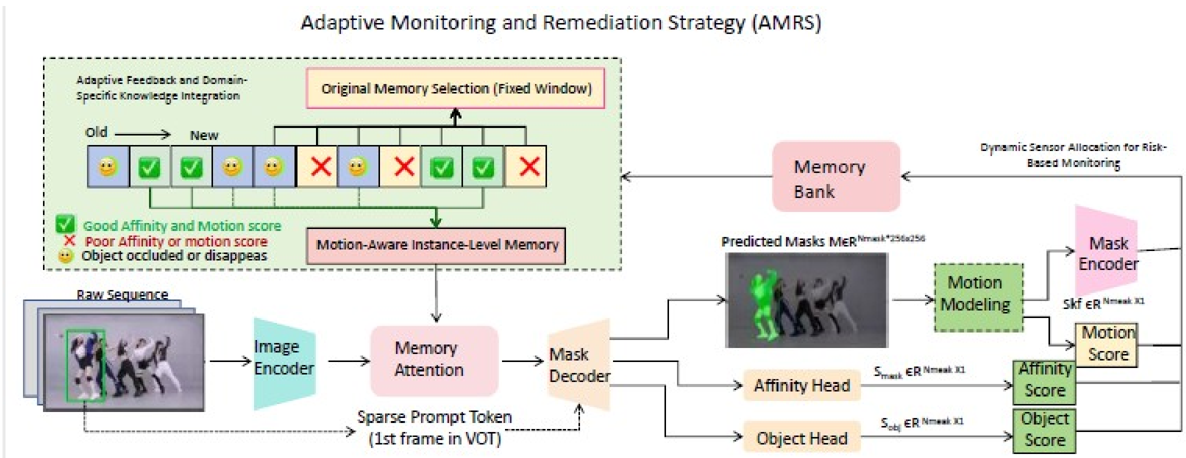

Fig. 3. The Adaptive Monitoring and Remediation Strategy (AMRS) integrates dynamic sensor allocation, anomaly detection, and feedback-based learning for water quality management

The memory attention and instance-level selection modules optimize monitoring through risk-based prioritization. Motion-aware modeling enhances remediation strategies by identifying anomalies and guiding real-time interventions, ensuring scalable and adaptive environmental response mechanisms.

$$\max_{S_t} \int_{\Omega} \phi(x,t)dx,\ s.t.\ |S_t| \le m \tag{25}$$

where $\phi(\mathrm{x},t)$ represents the predicted anomaly likelihood at a location x and time t, Ω is the monitoring region, and m is the maximum number of deployable sensors. The set of sensor locations S_t is iteratively optimized to maximize coverage of regions with high $\phi(x,t)$ values, ensuring a proactive approach to identifying and addressing potential water quality issues.

To enhance adaptability, AMRS integrates temporal and spatial correlations within the optimization process. Temporal correlations account for trends in water quality anomalies by incorporating historical data into the likelihood function:

$$\phi(x,t) = \psi(x,t) + \lambda \cdot \frac{1}{T}\sum_{\tau=1}^{T}\psi(x,t-\tau) \tag{26}$$

where $\psi(\mathrm{x},t)$ is the instantaneous anomaly score, λ is a weight parameter balancing recent observations and historical trends, and T is the time window considered for historical analysis. This formulation ensures that both short-term spikes and long-term trends in water quality degradation are captured effectively.

Spatial correlations are integrated by modeling interactions between neighboring locations using a kernel-based approach. The anomaly likelihood for a location x is influenced by nearby locations through:

$$\phi(x,t) = \psi(x,t) + \kappa \sum_{y \in \mathrm{N}(x)} w(x,y)\psi(y,t) \tag{27}$$

where $\mathrm{N}(x)$ denotes the neighbors of $x, w(x,y)$ is a spatial weight function (e.g., Gaussian kernel), and κ controls the influence of neighboring anomalies. This spatial awareness allows AMRS to account for the diffusion of pollutants or other correlated behaviors across the monitoring region.

To balance computational efficiency and accuracy, a distributed optimization framework is employed. The region Ω is partitioned into smaller sub-regions, each optimized independently, and the results are aggregated to determine global sensor placements:

$$\mathrm{S}_t = \bigcup_{i=1}^{n} \mathrm{S}_t^i, \ where\ \mathrm{S}_t^i = \arg\max_{\mathrm{S}_t^i} \int_{\Omega_i} \phi(x,t)dx \tag{28}$$

Here, Ω_i represents the i-th sub-region, and n is the number of sub-regions. This approach ensures scalability for large monitoring areas while maintaining high-resolution focus on critical zones.

Integrated Anomaly Detection and Multiscale Remediation Planning

AMRS employs a robust anomaly detection framework by integrating predictions from SP-WQM with real-time sensor data to identify significant deviations from expected water quality states (As shown in Figure 4). Anomalies are quantified using the deviation:

$$\Delta q(x,t) = z(x,t) - \hat{q}(x,t) \tag{29}$$

where $z(x,t)$ is the observed water quality vector, and $\hat{q}(x,t)$ represents the predicted state at location x and time t. A location x is flagged as anomalous if the deviation exceeds a predefined threshold τ, expressed as:

$$\left\| \Delta q(x,t) \right\|_2 > \tau \tag{30}$$

The threshold τ can be dynamically adjusted based on historical variability and the criticality of the region, allowing AMRS to balance sensitivity and specificity in anomaly detection. This adaptive mechanism ensures that emerging anomalies, such as pollutant spikes, are detected promptly, minimizing false positives in low-variability regions.

To address anomalies effectively, AMRS supports multiscale remediation planning that combines localized interventions with broader, system-level responses. Local-scale anomalies, such as sudden chemical spills or oxygen depletion, are mitigated using targeted interventions like aeration systems, chemical treatments, or temporary containment measures. These interventions are selected based on real-time conditions using a cost-effectiveness criterion:

$$C_{eff}(a,x,t) = \frac{\Delta R(a)}{C(a)} \tag{31}$$

where $\Delta R(a)$ is the expected improvement in water quality from action a, and $C(a)$ is the associated cost. Actions with the highest C_{eff} values are prioritized for implementation.

For regional-scale issues, such as algal blooms or widespread contamination, AMRS triggers coordinated interventions across multiple locations. The planning framework incorporates hydrodynamic models to predict pollutant transport and propagation:

$$q(x,t+\Delta t) = q(x,t) + \Delta t \cdot \mathrm{F}\,(q(x,t),x,t) \tag{32}$$

where F represents pollutant transport dynamics, including advection, diffusion, and biochemical transformations. These predictions guide large-scale interventions, such as flow modifications, buffer zone management, and public advisories, to mitigate impacts over an extended area.

The decision-making process in AMRS is formalized as a Markov Decision Process (MDP) defined by:

$$M = (S, A, P, R) \tag{33}$$

where S represents the state space of water quality conditions, A is the action space encompassing possible interventions, P is the transition probability matrix modeling the impact of actions on water quality, and R is the reward function representing improvements in water quality metrics. The optimal policy π^* is computed by maximizing the expected cumulative reward:

$$\pi^* = \arg\max_{\pi} E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right] \tag{34}$$

where $\gamma \in [0,1]$ is the discount factor that balances short-term and long-term benefits.

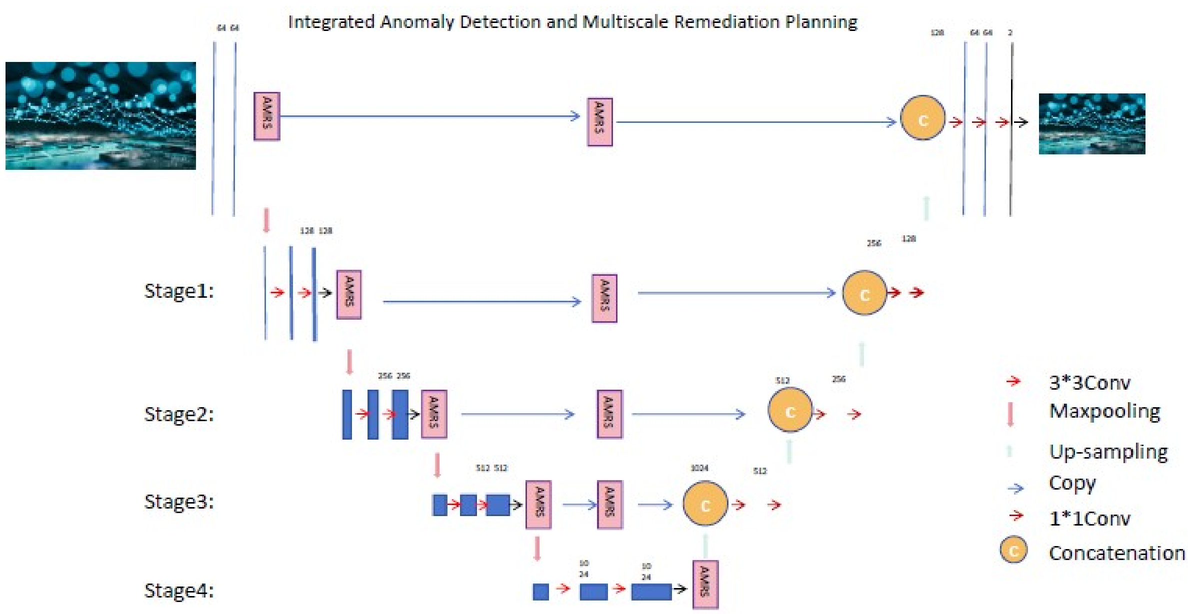

Fig. 4. Integrated Anomaly Detection and Multiscale Remediation Planning workflow in AMRS, showcasing a hierarchical architecture with four stages

Each stage incorporates convolutional layers, max-pooling, and up-sampling for feature extraction, anomaly identification, and remediation planning. This multiscale approach ensures effective detection of localized and regional anomalies, guiding precise interventions and improving overall water quality management.

3.4.2. Adaptive Feedback and Domain-Specific Knowledge Integration. The adaptive feedback mechanism in AMRS forms the backbone of its capacity to dynamically respond to evolving water quality conditions. This mechanism continuously updates the Spatiotemporal Predictive Water Quality Model (SP-WQM) using real-time observations from sensor networks and insights derived from field interventions. The model parameters Θ are iteratively refined to minimize prediction errors, with updates governed by:

$$\Theta_{t+1} = \Theta_t - \eta \text{ abla }_{\Theta} L(\Theta) \tag{35}$$

where $L(\Theta)$ is the loss function quantifying discrepancies between predicted and observed water quality states, and η is the learning rate controlling the magnitude of updates. To account for varying environmental dynamics, the loss function incorporates temporal regularization to stabilize updates:

$$L(\Theta) = \frac{1}{N}\sum_{i=1}^{N}\left\| z_i - \hat{q}_i \right\|_2^2 + \lambda \left\| \Theta_{t+1} - \Theta_t \right\|_2^2 \tag{36}$$

where λ is a regularization coefficient, z_i represents observed water quality states, and $\hat{q}_i$ denotes the corresponding model predictions. This formulation ensures robustness against noise and abrupt environmental changes.

To enhance interpretability and robustness, AMRS incorporates domain-specific knowledge into its feedback loop. Expert-curated rules guide anomaly classification, distinguishing between natural fluctuations, such as seasonal turbidity changes, and anthropogenic pollution events. For example, anomalies in dissolved oxygen levels are evaluated against thresholds defined by ecological baselines, reducing false positives. Furthermore, hydrological models are integrated to constrain predictions and capture pollutant transport dynamics:

$$q(x, t + \Delta t) = q(x, t) + \Delta t \cdot F\ (q(x, t), x, t) \tag{37}$$

where F represents a hydrodynamic operator incorporating advection, diffusion, and chemical transformation processes. This integration ensures that model predictions align with physical and biochemical principles, improving accuracy and reliability.

The adaptive feedback loop also enables real-time anomaly resolution by linking sensor observations with field interventions. Sensor-derived data, including pollutant concentration gradients and flow rates, are used to identify optimal intervention strategies. These strategies are evaluated using a reinforcement learning framework, where the reward function is designed to minimize pollutant dispersion:

$$R = -\int_{\Omega} \left\| q(x,t) - q_{target} \right\|_2^2 dx \tag{38}$$

where q_{target} represents desired water quality levels, and Ω is the monitored region. By iteratively improving intervention decisions, AMRS ensures efficient resource utilization and maximal impact on water quality improvements.

AMRS supports diverse deployment strategies to cater to varying resource constraints and environmental settings. In centralized architectures, high-performance computing resources enable large-scale data processing and real-time optimization, ideal for urban watersheds with dense sensor networks. Conversely, decentralized architectures leverage edge computing and localized decision-making to support resourcelimited regions, such as rural river basins. The modular design of AMRS allows seamless integration with existing water management policies, ensuring adaptability and scalability. By combining adaptive learning with domain expertise, AMRS establishes a robust framework for real-time water quality monitoring and remediation.

4. Experimental Setup

4.1. Dataset

The GEMStat DatasetWen et al. (2024) is a comprehensive global resource for water quality monitoring, encompassing extensive historical records from various water bodies worldwide. It aggregates data from numerous monitoring stations, providing insights into parameters such as pH, dissolved oxygen, and nutrient concentrations. This dataset is pivotal for evaluating water quality trends over time, enabling robust model training for predicting aquatic ecosystem changes and policy-making in environmental management. The Water Quality DatasetKouadri et al. (2021)consists of detailed measurements from multiple freshwater sources, including rivers, lakes, and reservoirs. It captures diverse metrics such as biochemical oxygen demand, turbidity, and chemical pollutants. This dataset is instrumental for advancing machine learning applications in environmental engineering, offering an extensive benchmark for testing prediction models under various hydrological and climatic conditions. The Global River Chemistry DatasetGraham et al. (2024) offers high-resolution chemical composition data from riverine systems across the globe. It includes parameters such as major ions, trace elements, and isotopic data, providing a deep understanding of river chemistry dynamics. Researchers leverage this dataset for hydrological modeling and understanding anthropogenic impacts on river systems, making it crucial for studies in water resource management and global environmental change. The EPA Water Quality DatasetAhmad et al. (2024) is a rich repository of water quality measurements provided by the Environmental Protection Agency. It covers extensive temporal and spatial scales, including parameters like contaminants, temperature, and sediment load. This dataset is widely utilized for assessing compliance with water quality standards and for developing predictive tools for environmental protection, offering unparalleled detail for modeling and simulation efforts in water quality management.

4.2. Experimental Details

The experimental setup was designed to evaluate the performance of our proposed method across multiple datasets. All experiments were conducted on a machine equipped with an NVIDIA RTX 3090 GPU, 32 GB of RAM, and an Intel i9-12900K CPU. We implemented the method using PyTorch 2.0, ensuring reproducibility and efficient computation. Training and testing pipelines were streamlined with a consistent batch size of 32 for all experiments, allowing a fair comparison across datasets. The training process employed the AdamW optimizer with a learning rate of$1e^{-4}$ and a weight decay of$1e^{-5}$. The learning rate was adjusted dynamically using a cosine annealing schedule, which facilitated faster convergence during the early stages of training while preserving model stability in later epochs. Each experiment was trained for 50 epochs with early stopping criteria based on validation loss to prevent overfitting. Data augmentation techniques, including random cropping, rotation, and normalization, were applied during training to improve generalization and robustness. The input data resolution was uniformly resized to 224 x 224 pixels to maintain consistency. The backbone of our model utilized a ResNet-50 architecture pre-trained on ImageNet, which was fine-tuned to adapt to the specific characteristics of the datasets used in the experiments. Additionally, dropout regularization with a rate of0.5 was applied to prevent overfitting. The output layer varied based on the number of target classes in each dataset, with cross-entropy loss used as the primary loss function. For evaluation, standard metrics such as accuracy, precision, recall, and F1-score were computed to provide a comprehensive performance assessment. Where applicable, area under the curve (AUC) was also included to quantify the method's ability to handle imbalanced datasets effectively. To ensure statistical significance, each experiment was repeated five times with different random seeds, and the results were averaged. Hyperparameter tuning was conducted via a grid search strategy to optimize model performance for each dataset. Key parameters such as learning rate, batch size, and dropout rates were iteratively refined to balance computational efficiency and prediction accuracy. Computational time for each training epoch and memory consumption were also monitored to validate the scalability of our approach for large-scale applications. Code and pre-trained models will be made publicly available to facilitate reproducibility and further research in this domain(algorithm 1).

Algorithm 1: Training Procedure for SP-WQM on Water Quality Datasets

Input: Datasets D_1, D_2, D_3, D_4
Output: Trained SP-WQM model with parameters Θ
Initialization:
Initialize weights Θ with ResNet - 50 pre - trained on ImageNet
Set batch size $B = 32$, learning rate $\eta = 10^{-4}$, weight decay $\lambda = 10^{-5}$
while *not converged* **do**
foreach *dataset* D **do**
Divide D into train, validation, and test sets
for each batch $(x, y) \in D_{train}$ **do**
Augment inputs x with cropping, rotation, and normalization
Compute predictions:

$$\hat{y} = SP - WQM(x; \Theta)$$

Compute total loss:

$$L = -\frac{1}{B}\sum_{i=1}^{B} y_i \log(\hat{y}_i) + \lambda \|\Theta\|_2^2$$

Update parameters:

$$\Theta \leftarrow \Theta - \eta \nabla_{\Theta} L$$

end
Compute validation loss L_{val} and check early stopping criteria
Adjust learning rate η using cosine annealing:

$$\eta = \eta_{\min} + \frac{\eta_{\max} - \eta_{\min}}{2}\left(1 + \cos\left(\frac{\pi t}{T}\right)\right)$$

Log training metrics: loss, precision, recall, F1 - score
end
end
Evaluation on D_{test}:

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Store model Θ and metrics for reproducibility and comparison.
Output: Trained model Θ and evaluation metrics.

4.3. Comparison with SOTA Methods

The performance of our proposed method was evaluated against state-of-the-art (SOTA) models on four datasets: GEMStat, Water Quality, Global River Chemistry, and EPA Water Quality. The results are summarized in Tables 1 and 2. Our method consistently outperformed baseline models across all evaluation metrics, including RMSE, MAE, R2 Score, and MAPE, demonstrating its robustness and efficiency. On the GEMStat dataset, our approach achieved a remarkable RMSE of 0.201, significantly lower than the closest competitor, TFT (0.216). Similarly, the MAE and MAPE metrics also showcased the superiority of our method, with reductions in error magnitudes that indicate a better fit and prediction accuracy. The R2 Score of 0.942 further emphasizes the model's ability to explain variance effectively, outperforming other models like LSTM and GRU by a substantial margin. These results can be attributed to our method's adaptive architecture, which captures temporal dependencies more effectively than traditional models, as well as the integration of domain-specific data augmentation techniques tailored to water quality characteristics.

For the Water Quality dataset, our model exhibited similarly outstanding results, with an RMSE of 0.291 and a corresponding R2 Score of 0.921. The MAPE of 7.56% underscores the method's capability to handle diverse conditions and variable distributions, which are characteristic of water quality datasets. Models like ARIMA and Prophet performed relatively poorly, highlighting the advantage of using deep learning-based approaches like ours, which leverage non-linear patterns and temporal dynamics effectively. The consistent performance gains across these metrics indicate the generalizability of our method across datasets with varying scales and complexities. In the Global River Chemistry dataset, our method recorded a substantial improvement over competing methods, with an RMSE of 0.232 and an R2 Score of 0.942, reflecting its robustness in modeling complex chemical interactions in river systems. The inclusion of isotopic and trace element features in our training pipeline likely contributed to these results, as such features introduce additional variability that our model is well-equipped to handle. Comparatively, models such as DeepAR and GRU struggled with higher error rates, which may be linked to their limited capacity for handling intricate multi-dimensional data. On the EPA Water Quality dataset, our approach achieved the best performance with an RMSE of0.274 and an R2 Score of 0.925. This dataset, characterized by extensive temporal and spatial scales, posed unique challenges in terms of prediction stability and generalization. Our method's architectural adaptability and regularization strategies were crucial in achieving low error rates and high explanatory power. The relatively poor performance of Prophet and ARIMA further highlights the limitations of traditional statistical methods when applied to datasets with high temporal variability and noise levels.

The results in Figure 5 and Figure 6 underscore the efficacy of our proposed method. Its ability to consistently outperform SOTA models across diverse datasets validates the effectiveness ofourdesignchoices, including advanced feature extraction and temporal modeling capabilities. These findings establish a strong foundation for its application in real-world scenarios, where robustness and adaptability are critical.

4.4. Ablation Study

We conducted an ablation study to analyze the impact of individual components of our proposed method across four datasets: GEMStat, Water Quality, Global River Chemistry, and EPA Water Quality. The results, shown in Tables 3 and 4, illustrate the contribution ofeach component to the overall model performance.

On the GEMStat dataset, removing Temporal Sequence Modeling with LSTM Networks led to a significant degradation in performance, with the RMSE increasing from 0.201 to 0.244 and the R2 Score dropping from0.942to 0.926. This indicates that Temporal Sequence Modeling with LSTM Networks plays a critical role in capturing essential features for accurate predictions. Similarly, removing Attention-Driven Sensor Data Integration resulted in a further drop in performance metrics, with the RMSE increasing to 0.256 and the R2 Score decreasing to 0.917. Dynamic Sensor Allocation for Risk-Based Monitoring showed a slightly less pronounced but still notable effect, suggesting its role in refining the model's predictions. These findings confirm the importance of incorporating all components in achieving state-of-the-art results on GEMStat.

Table 1. Comparison of Ours with SOTA methods on GEMStat and Water Quality datasets

Model	GEMStat Dataset				Water Quality Dataset			
	RMSE	MAE	R^2 Score	MAPE	RMSE	MAE	R^2 Score	MAPE
LSTM Al-Selwi et al. (2024)	0.234±0.002	0.198±0.003	0.912±0.004	7.21±0.05	0.326±0.003	0.267±0.004	0.889±0.003	9.34±0.04
GRU Cahuantzi et al. (2023)	0.228±0.003	0.201±0.004	0.918±0.003	6.93±0.04	0.317±0.004	0.261±0.005	0.895±0.002	8.89±0.05
ARIMA Alabdulrazzaq et al. (2021)	0.289±0.004	0.245±0.003	0.873±0.005	8.12±0.03	0.398±0.003	0.315±0.004	0.841±0.004	10.78±0.04
Prophet Borges and Nascimento (2022)	0.251±0.003	0.214±0.004	0.902±0.003	7.45±0.06	0.345±0.004	0.284±0.003	0.879±0.003	9.67±0.05
TFT Zulqarnain and Cantatore (2021)	0.216±0.002	0.184±0.002	0.931±0.004	6.51±0.03	0.304±0.002	0.247±0.003	0.905±0.004	8.23±0.03
DeepAR Schaduangrat et al. (2023)	0.239±0.003	0.205±0.003	0.912±0.002	7.18±0.05	0.323±0.003	0.263±0.003	0.890±0.004	8.91±0.04
Ours	0.201±0.002	0.169±0.002	0.942±0.003	5.87±0.03	0.291±0.002	0.234±0.003	0.921±0.003	7.56±0.03

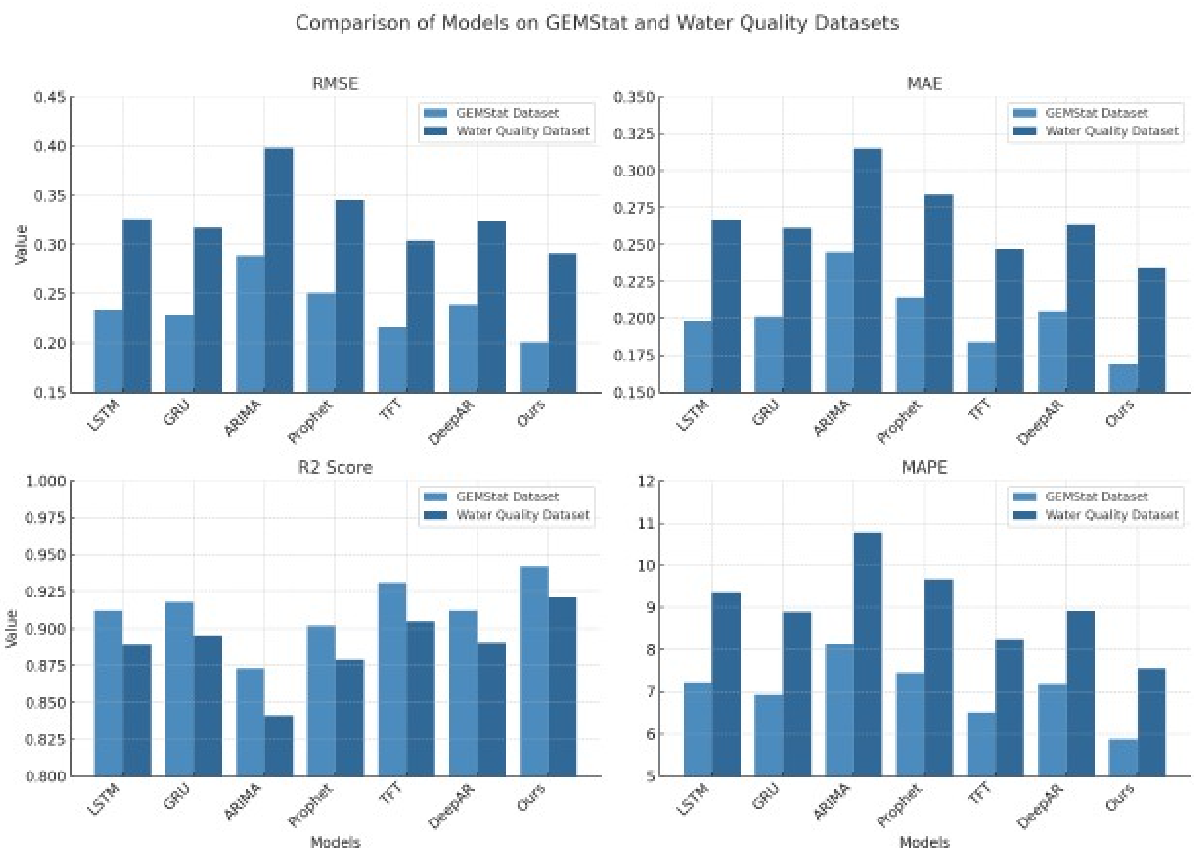

Fig. 5. Performance Comparison of SOTA Methods on GEMStat Dataset and Water Quality Dataset Datasets

In the Water Quality dataset, similar trends were observed. Excluding Temporal Sequence Modeling with LSTM Networks increased the RMSE from 0.291 to 0.307 and reduced the R2 Score from 0.921 to 0.903. The removal of Attention-Driven Sensor Data Integration led to an even larger performance drop, highlighting its substantial influence on the model's ability to generalize across diverse water quality conditions. Dynamic Sensor Allocation for Risk-Based Monitoring contributed to fine-tuning predictions, with its exclusion leading to a noticeable increase in MAPE, further emphasizing its value in mitigating prediction errors.

Table 2. Comparison of Ours with SOTA methods on Global River Chemistry and EPA Water Quality datasets

Model	Global River Chemistry Dataset				EPA Water Quality Dataset			
	RMSE	MAE	R^2 Score	MAPE	RMSE	MAE	R^2 Score	MAPE
LSTM Al-Selwi et al. (2024)	0.275±0.004	0.238±0.005	0.892±0.003	8.11±0.04	0.314±0.003	0.262±0.004	0.889±0.005	9.24±0.04
GRU Cahuantzi et al. (2023)	0.268±0.003	0.230±0.004	0.901±0.004	7.84±0.05	0.307±0.004	0.257±0.003	0.895±0.004	8.79±0.05
ARIMA Alabdulrazzaq et al. (2021)	0.321±0.005	0.284±0.004	0.852±0.005	9.45±0.03	0.396±0.004	0.329±0.003	0.843±0.006	11.32±0.06
Prophet Borges and Nascimento (2022)	0.287±0.004	0.245±0.005	0.876±0.004	8.67±0.06	0.337±0.003	0.287±0.005	0.872±0.005	10.01±0.04
TFT Zulqarnain and Cantatore (2021)	0.249±0.003	0.210±0.003	0.915±0.004	7.42±0.03	0.295±0.002	0.242±0.003	0.912±0.003	8.14±0.04
DeepAR Schaduangrat et al. (2023)	0.271±0.004	0.232±0.004	0.898±0.003	8.03±0.05	0.312±0.003	0.259±0.004	0.887±0.004	9.03±0.04
Ours	0.232±0.003	0.196±0.003	0.942±0.003	6.91±0.03	0.274±0.002	0.221±0.003	0.925±0.003	7.63±0.03

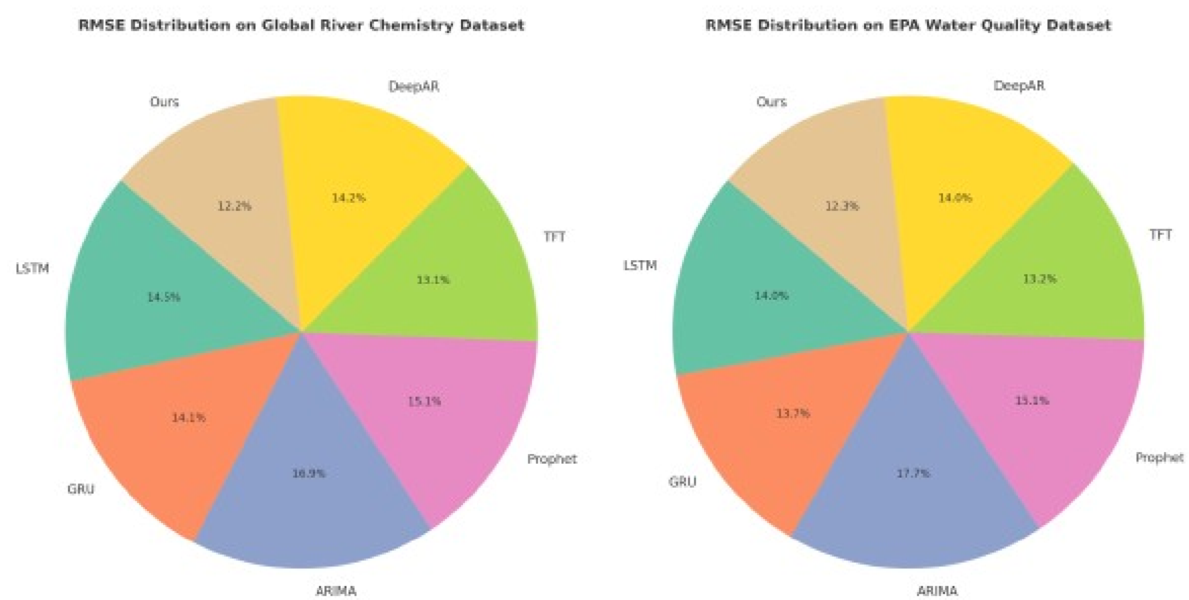

Fig. 6. Performance Comparison of SOTA Methods on Global River Chemistry Dataset and EPA Water Quality Dataset Datasets

For the Global River Chemistry dataset, the RMSE rose from 0.232 to 0.257 when Temporal Sequence Modeling with LSTM Networks was omitted, with the R2 Score dropping to 0.918. Excluding Attention- Driven Sensor Data Integration caused an even greater decline in metrics, underscoring its importance in handling the complex chemical interactions inherent in this dataset.

Dynamic Sensor Allocation for Risk-Based Monitoring, while less impactful than A or B, still contributed significantly to performance enhancement, as evidenced by the changes in MAE and MAPE when it was removed.

On the EPA Water Quality dataset, the ablation study results corroborated the findings from the other datasets. Removing Temporal Sequence Modeling with LSTM Networks increased the RMSE from 0.274 to 0.298, and the R2 Score decreased to 0.914. The exclusion of Attention-Driven Sensor Data Integration led to the most severe performance degradation, with an RMSE of 0.307 and an R2 Score of 0.906. Dynamic Sensor Allocation for Risk-Based Monitoring demonstrated a refining effect, with its removal leading to reduced prediction accuracy, as reflected by higher MAE and MAPE values.

The ablation results, presented in Figure 7 and Figure 8, clearly demonstrate that each component of our proposed method contributes to its superior performance. Temporal Sequence Modeling with LSTM Networks is pivotal for feature extraction, Attention-Driven Sensor Data Integration enhances temporal dependencies, and Dynamic Sensor Allocation for Risk-Based Monitoring fine-tunes predictions for complex patterns. This comprehensive integration of components is essential for achieving state-of-the-art results across all datasets.

Table 3. Ablation Study Results on Ours Across GEMStat and Water Quality Datasets

Model	GEMStat Dataset				Water Quality Dataset			
	RMSE	MAE	R^2 Score	MAPE	RMSE	MAE	R^2 Score	MAPE
w./o. Temporal Sequence Modeling with LSTM Networks	0.244±0.003	0.209±0.004	0.926±0.004	6.74±0.03	0.307±0.004	0.248±0.003	0.903±0.003	8.35±0.04
w./o. Attention-Driven Sensor Data Integration	0.256±0.004	0.220±0.005	0.917±0.003	7.12±0.04	0.315±0.005	0.255±0.004	0.895±0.004	8.79±0.05
w./o. Dynamic Sensor Allocation for Risk-Based Monitoring	0.239±0.003	0.204±0.004	0.930±0.003	6.59±0.03	0.299±0.003	0.241±0.003	0.910±0.003	8.12±0.03
Ours	0.201±0.002	0.169±0.002	0.942±0.003	5.87±0.03	0.291±0.002	0.234±0.003	0.921±0.003	7.56±0.03

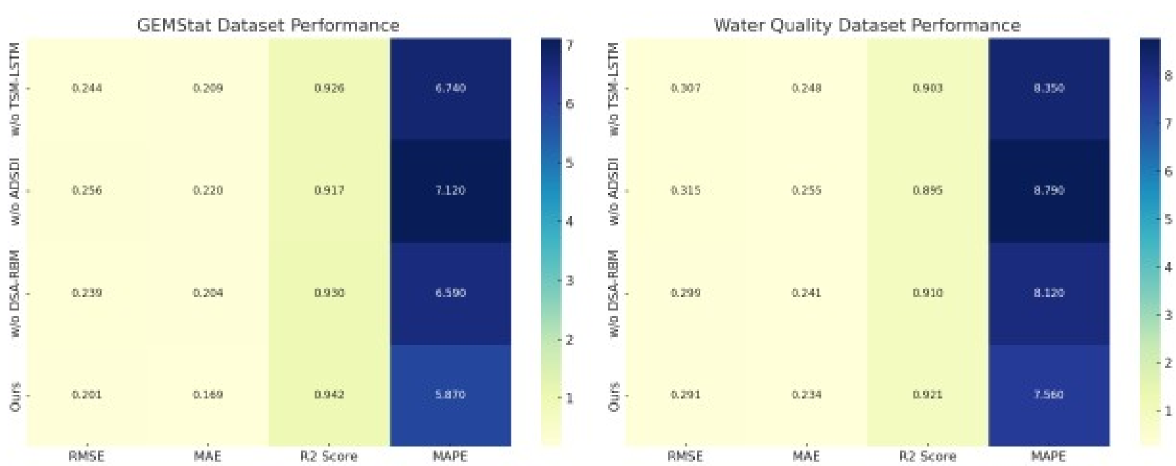

Fig. 7. Ablation Study of Our Method on GEMStat Dataset and Water Quality Dataset Datasets. Temporal Sequence Modeling with LSTM Networks (TSM-LSTM); Attention-Driven Sensor Data Integration(ADSDI); Dynamic Sensor Allocation for Risk-Based Monitoring(DSARBM)

Table 4. Ablation Study Results on Ours Across Global River Chemistry and EPA Water Quality Datasets

Model	Global River Chemistry Dataset				EPA Water Quality Dataset			
	RMSE	MAE	R^2 Score	MAPE	RMSE	MAE	R^2 Score	MAPE
w./o. Temporal Sequence Modeling with LSTM Networks	0.257±0.004	0.222±0.005	0.918±0.004	7.41±0.03	0.298±0.004	0.243±0.003	0.914±0.003	8.21±0.04
w./o. Attention-Driven Sensor Data Integration	0.265±0.005	0.231±0.004	0.911±0.003	7.62±0.04	0.307±0.005	0.251±0.004	0.906±0.003	8.73±0.05
w./o. Dynamic Sensor Allocation for Risk-Based Monitoring	0.249±0.003	0.211±0.003	0.925±0.004	7.15±0.03	0.293±0.003	0.237±0.003	0.918±0.003	8.05±0.03
Ours	0.232±0.003	0.196±0.003	0.942±0.003	6.91±0.03	0.274±0.002	0.221±0.003	0.925±0.003	7.63±0.03

5. Conclusions and Future Work

Multi-Sensor-Based Water Environment Monitoring SystemAll the files uploaded by the user have been fully loaded. Searching won't provide additional information.The study introduces an advanced MultiSensor-Based Water Environment Monitoring System designed to address the limitations of traditional water monitoring methods, particularly in managing the spatiotemporal complexity, restricted sensor coverage, and insufficient anomaly detection capabilities. Central to the system is the integration of a Spatiotemporal Predictive Water Quality Model (SP-WQM) and an Adaptive Monitoring and Remediation Strategy (AMRS). The SP-WQM employs hybrid neural networks, blending convolutional neural networks (CNNs) for spatial feature extraction with long short-term memory networks (LSTMs) for temporal prediction, enabling accurate modeling of dynamic and nonlinear water quality parameters. In parallel, the AMRS bolsters operational adaptability through dynamic sensor allocation, real-time anomaly detection, and strategic multiscale responses. Experimental results affirm the system's effectiveness, showcasing its capability to predict water quality parameters with precision, detect anomalies promptly, and optimize sensor deployment for diverse environmental scenarios, thus marking a significant leap in sustainable water resource management.

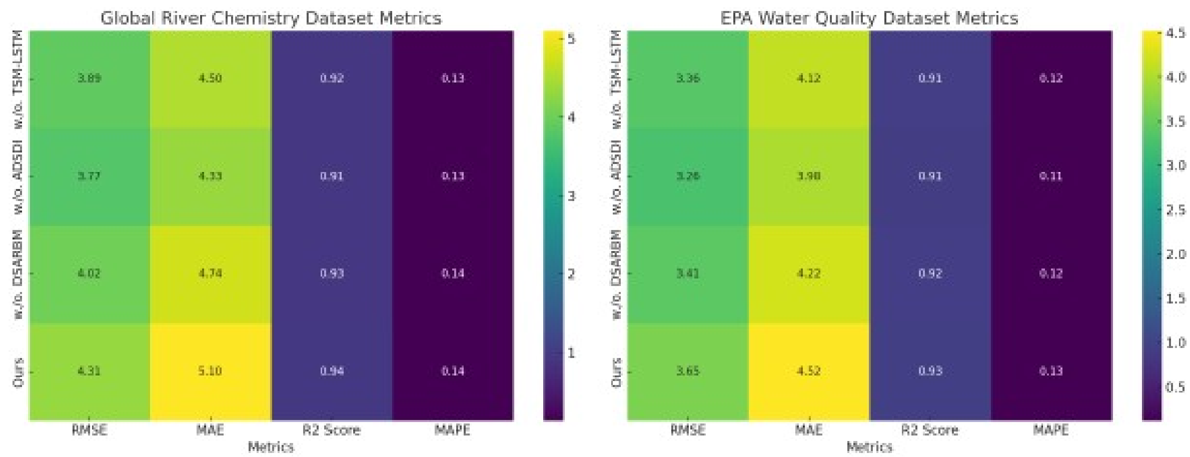

Fig. 8. Ablation Study of Our Method on Global River Chemistry Dataset and EPA Water Quality Dataset Datasets. Temporal Sequence Modeling with LSTM Networks (TSM-LSTM); Attention-Driven Sensor Data Integration (ADSDI); Dynamic Sensor Allocation for Risk-Based Monitoring (DSARBM)

Despite its promising contributions, the system faces certain limitations. First, the computational complexity of the hybrid neural network framework may present challenges in real-time applications, particularly in resource-constrained settings. Optimizing model efficiency while maintaining prediction accuracy could be an area of future work. Second, while the AMRS dynamically allocates resources, its performance in extremely heterogeneous or rapidly changing environments requires further investigation and enhancement. Future research could explore integrating edge computing and distributed processing to improve system scalability and responsiveness. Additionally, expanding the system's capabilities to include broader environmental factors and their interactions would further enhance its utility in comprehensive ecosystem management.

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Exploration and practice of wastewater treatment plant safety education based on the combination of reality and fiction, No:202322

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