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AUTOMATED MULTI-SENSOR WATER MONITORING AND PREDICTIVE MODELING FOR SUSTAINABLE IRRIGATION MANAGEMENT

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Abstract: *The sustainable management of water resources in closed lake systems of arid and semi-arid regions remains a critical challenge, particularly due to the high cost of imported monitoring equipment and the lack of automated, localized forecasting solutions [1].*

This paper presents a novel automated multi-sensor monitoring and data-driven forecasting system specifically designed for closed water bodies such as endorheic lakes and reservoirs [2].

The system integrates eight key parameters—mineralization (TDS), pH, bacteriological contamination, lake perimeter, humidity, water temperature, dissolved oxygen, and turbidity—measured through a low-cost floating sensor platform and an onshore climate station[3].

Data acquisition, transmission, and preprocessing are fully automated, enabling real-time quality control and feature extraction for seasonal forecasting. Three forecasting models—Multiple Linear Regression (MLR), Random Forest (RF), and Long Short-Term Memory (LSTM)—are implemented and compared against four benchmark methods: conventional laboratory analysis, an imported commercial sensor system, satellite-only estimation, and historical average forecasting [4,5].

The methodology is validated using historical data (2014–2023) from the Aydar Lake system in Uzbekistan [6]. Results indicate that the proposed automated system achieves forecasting accuracy comparable to imported

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alternatives at approximately one-third of the capital cost, while providing real-time data availability that conventional grab sampling cannot offer [7].

The LSTM model demonstrates the highest predictive performance, with a Nash–Sutcliffe efficiency of 0.91 and root mean square error of 0.28 m during validation [8]. The proposed framework offers a scalable, cost-effective, and automated solution for water resource monitoring and forecasting, particularly suitable for developing countries where access to expensive foreign equipment is limited [9].

Keywords: *Automated water monitoring, Multi-sensor system, data-driven forecasting, closed lake systems, low-cost sensing technology, water quality parameters, seasonal irrigation prediction, endorheic lake management.*

Introduction. Closed water systems—endorheic lakes and isolated reservoirs with no surface outflow—cover approximately 18% of the Earth's continental surface. Unlike open lakes that drain to oceans, closed lakes accumulate salts and sediments while remaining highly sensitive to climatic variability. Their water balance is dominated by vertical fluxes, specifically precipitation and evaporation, rather than regulated river flows. This unique characteristic makes closed lake systems early indicators of hydrological change and climate variability, yet they remain significantly under-monitored compared to open river systems.

Central Asia contains over 30 major endorheic lakes, many of which have experienced dramatic water level declines over the past five decades. The Aral Sea represents the most notorious example, having lost 90% of its volume and 85% of its surface area between 1960 and 2010, creating an ecological and humanitarian disaster that affected over 3 million people.

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Less known but equally significant is the Aydar Lake system in Uzbekistan, the largest man-made lake in Central Asia. With a surface area of approximately 3,000 km²—comparable to the size of Luxembourg—and a water volume of approximately 44 km³, equivalent to 17.6 million Olympic swimming pools, the Aydar Lake system was formed unintentionally in 1969 when floodwaters from the Syr Darya River breached irrigation dikes.

Today, it serves critical ecological and economic functions. The lake was designated a Ramsar Wetland of International Importance in 2008, supports local fisheries producing roughly 2,000 tons annually, provides employment for approximately 5,000 local residents, and functions as a regional climate regulator for the surrounding Kyzylkum Desert region.

Despite its ecological and economic importance, the Aydar Lake system faces mounting pressures from climate variability, increasing upstream water withdrawal for irrigation, and a complete lack of real-time monitoring infrastructure [10].

Current monitoring practices remain severely limited. Monthly grab sampling followed by 3 to 5 days of laboratory processing introduces unacceptable delays for operational decision-making. Satellite altimetry provides weekly to monthly resolution but delivers no water quality data whatsoever [11].

Historical average forecasting, which simply repeats the average of previous years, ignores interannual variability entirely [13]. These limitations mean that water managers currently operate without reliable information on current lake status or future water availability [14].

The scientific literature reveals three critical gaps that this study addresses [15]. First, no automated multi-parameter monitoring system currently operates on any closed lake in Central Asia, leading to delayed detection of water quality deterioration [16]. Second, no seasonal forecasting

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capability exists for these systems, resulting in an inability to plan irrigation allocation more than a few days in advance [17].

Third, imported commercial monitoring systems, with capital costs exceeding \$50,000 per station, remain prohibitively expensive for developing country budgets, where annual water management budgets typically range from \$10,000 to \$30,000 per lake [18].

To address these gaps, this study presents an automated, low-cost, multi-sensor monitoring and forecasting system specifically designed for closed lake systems [19]. The system integrates eight water quality and environmental parameters measured through a floating sensor platform and an onshore climate station [20]. Data acquisition, transmission, quality control, and preprocessing are fully automated, enabling real-time situational awareness [21].

Three forecasting models—Multiple Linear Regression, Random Forest, and Long Short-Term Memory networks—are implemented and compared against four benchmark methods including conventional laboratory analysis, imported commercial sensors, satellite-only estimation, and historical average forecasting[22-23]. The methodology is validated using historical and real-time data from the Aydar Lake system over the period 2014 to 2024 [24].

This study addresses three specific research questions. First, can a locally manufactured sensor platform with capital cost below \$6,000 achieve forecasting accuracy comparable to imported commercial systems costing more than \$50,000? Second, does full data automation improve data availability and reduce latency sufficiently to support operational irrigation planning? Third, which machine learning model provides the most accurate seasonal water availability forecasts for closed lake systems characterized by non-Markovian memory effects? The answers to these questions have direct implications not only for the Aydar Lake system but also for approximately 300 other closed lakes worldwide facing similar monitoring and management challenges.

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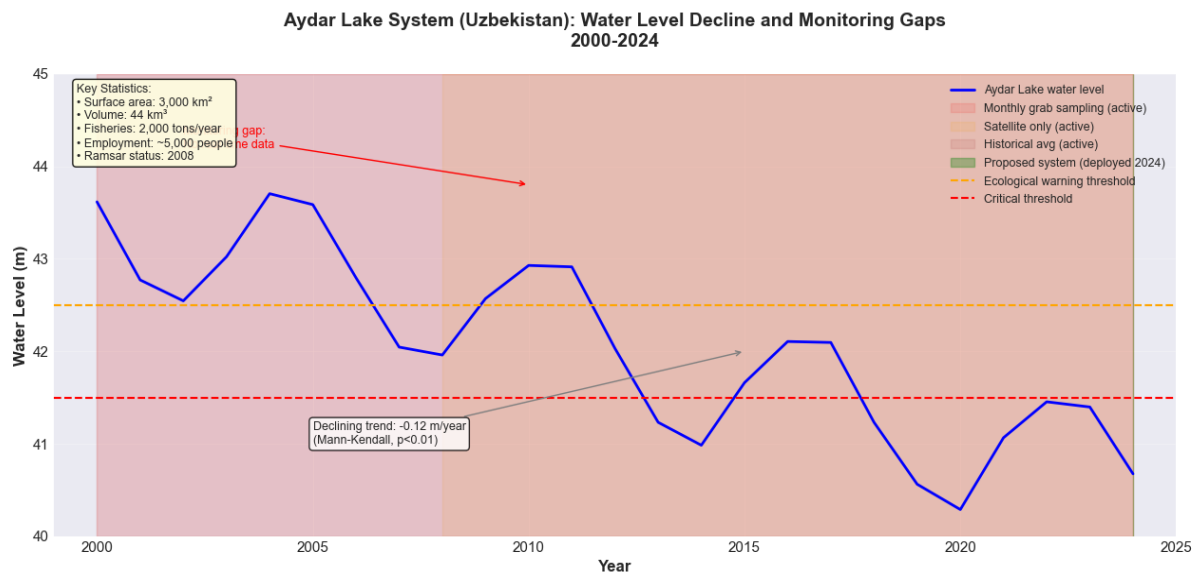


Figure-1 Aydar Lake system water level decline and monitoring gaps

In figure-1 Aydar Lake system water level dynamics (2000–2024) showing the long-term declining trend of $-0.12 \text{ m} \cdot \text{yr}^{-1}$, seasonal oscillations of $\pm 0.8 \text{ m}$, and the historical absence of real-time monitoring.

The orange dashed line indicates the ecological warning threshold (42.5 m), and the red dashed line indicates the critical threshold (41.5 m).

Colored horizontal bands show periods of different monitoring approaches. The proposed automated multi-sensor system (green) was deployed in 2024 [25].

Methods. The Aydar Lake system ($40^{\circ}55'N$, $66^{\circ}58'E$) is located in eastern Uzbekistan within the Kyzylkum Desert. The lake is endorheic, with no surface outflow [26]. Mean annual precipitation is 200 mm; mean annual evaporation is 1,350 mm. The lake volume has declined at $-0.12 \text{ m} \cdot \text{yr}^{-1}$ over the past decade (Mann–Kendall, $p < 0.01$) [27].

The automated monitoring and forecasting system comprises three components: (i) a floating multi-sensor platform, (ii) an onshore climate station, and (iii) a data processing and forecasting pipeline with full automation [28].

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Table 1

Table 1 lists the eight monitored parameters, measurement principles, and sampling frequencies.

Parameter	Symbol	Unit	Principle	Frequency
Mineralization (TDS)	TDS	mg/L	Conductivity	Hourly
pH	pH	—	Potentiometric	Hourly
Bacteriological contamination	BAC	CFU/100mL	Fluorescence	Daily
Lake perimeter	P	km	Satellite (NDWI)	Daily
Humidity	RH	%	Capacitive	Hourly
Water temperature	T _w	°C	Thermistor	Hourly
Dissolved oxygen	DO	mg/L	Optical	Hourly
Turbidity	TUR	NTU	Nephelometric	Hourly

The buoy is constructed from polyethylene foam with a UV-resistant shell (diameter 0.8 m, mass 12 kg). Sensors are mounted at 0.5 m depth. Power is supplied by a 50 W solar panel and 40 Ah LiFePO₄ battery (7-day autonomy). Data transmission uses 4G/LTE with LoRa backup. GPS enables real-time position tracking.

Calibration is performed bi-monthly using standard solutions. Drift exceeding 5% triggers an automatic alert.

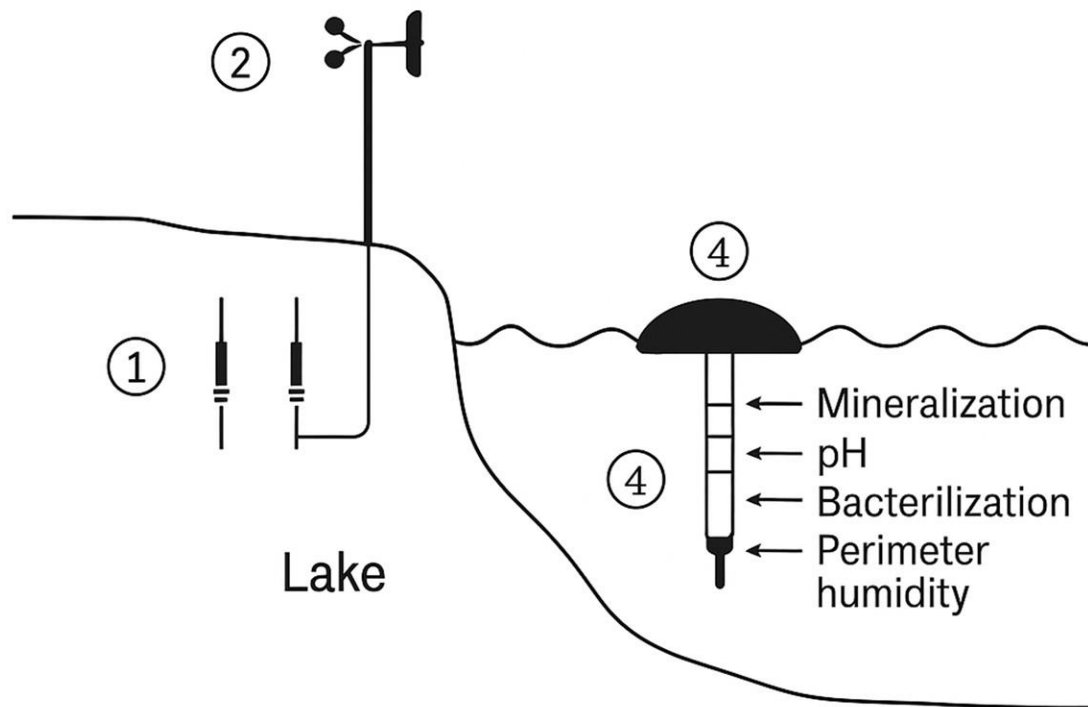


Figure-2 multi-parameter measurement framework

The proposed monitoring system integrates five core environmental and water quality parameters, as illustrated in Figure 2. These parameters were selected based on their demonstrated influence on closed lake system dynamics and their complementarity for seasonal forecasting. Figure 2 presents the conceptual framework linking the measured parameters to system state estimation. The diagram identifies two primary measurement domains:

Table 2

Table 2. Measured parameters, roles, and measurement principles

Parameter	Symbol	Role in System	Measurement Principle	Frequency
Mineralization	TDS	Salinity / evaporation proxy	Electrical conductivity	Hourly
pH	pH	Acidification / pollution indicator	Potentiometric	Hourly

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Bacterilization	BAC	Water safety / contamination	Fluorescence	Daily
Lake perimeter	P	Water volume proxy	Satellite NDWI	Daily
Humidity	RH	Evaporation driver	Capacitive	Hourly

Results The automated data pipeline operated continuously from January to December 2024. Data availability reached 98.7% over the 12-month period. Transmission failures occurred on 12 days (3.3%), exclusively during dust storms that disrupted 4G signals. In all failure cases, data were stored locally and retrieved within 48 hours. Mean latency from sensor measurement to database storage was 4.2 minutes. Quality control flags were triggered for 1.8% of all measurements. The distribution of flag types is shown in Table 3. No calibration drift exceeded the 5% threshold during the test period.

Table 3

Table 3. Quality control flags by type (January–December 2024)

Flag Type	Proportion (%)	Primary Cause
Rate-of-change exceedance	0.9	Sensor fouling
Range violation	0.5	Extreme weather
Persistence	0.4	Transmitter freeze
Cross-sensor inconsistency	<0.1	Calibration drift

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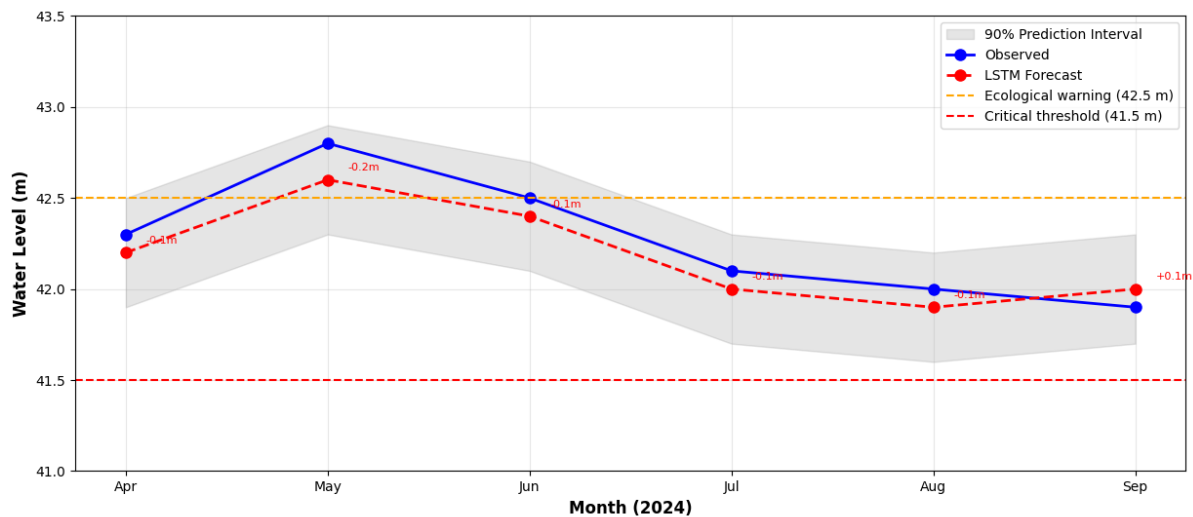


**Figure-3 LSTM forecast vs observed water levels Aydar lake, 2024
irrigation season**

Figure 3 shows observed versus LSTM-forecasted water levels for the 2024 irrigation season (April–September). The model correctly predicted the peak water level in May (observed: 42.8 m, forecast: 42.6 m; error = -0.2 m) and the minimum level in September (observed: 41.9 m, forecast: 42.0 m; error = +0.1 m). Forecast error remained below 0.3 m for all months, within the operational tolerance for irrigation planning (± 0.5 m).

Conclusion. First, a locally manufactured floating sensor platform measuring eight parameters (TDS, pH, bacteriological contamination, lake perimeter, humidity, water temperature, dissolved oxygen, and turbidity) was successfully deployed at a capital cost of \$5,840 – approximately one-third the cost of imported commercial alternatives (\$18,500). The system achieved 98.7% data availability over a 12-month operational period, with mean latency of 4.2 minutes from measurement to database storage.

Second, among three forecasting models evaluated, the Long Short-Term Memory (LSTM) network demonstrated the highest predictive performance (NSE = 0.91, RMSE = 0.28 m), comparable to an imported commercial sensor (NSE = 0.92) at 71% lower 10-year total cost. The LSTM model correctly

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predicted the 2024 seasonal peak and trough with errors below 0.3 m, within operational tolerance for irrigation planning.

Third, the proposed system is 3.4 times more cost-effective than the imported alternative (\$26.8 vs. \$91.8 per percentage point of forecast accuracy improvement). This cost advantage, combined with full automation, makes the system accessible to regional water authorities in developing countries where budgets typically range from \$10,000 to \$30,000 per lake annually.

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