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Case Report

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A Neuro-Symbolic Dashboard for Climate-Resilient Water Quality Monitoring

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Abstract

Climate change is increasingly affecting the quality of freshwater resources, making real-time monitoring and intelligent analysis of water parameters essential for environmental protection and sustainable resource management. In this paper, we present a neuro-symbolic dashboard for climate-resilient water quality monitoring, developed within the Tech4You project (Technologies for Climate Change Adaptation and Quality of Life Improvement) in Southern Italy. Our system combines neural network-based prediction (Long Short-Term Memory networks) with logic-driven data exploration and interactive web-based forms, providing domain experts with a unified platform for data analysis, anomaly detection, and hypothesis formulation. We demonstrate the system through a case study at the Fitterizzi monitoring station in the province of Cosenza, where multisensory buoys continuously record physicochemical and meteorological parameters. Raw sensor data is preprocessed and cleaned using standard data science libraries, and missing values are predicted using LSTM models trained on multivariate time series. The processed data is then explored through an interactive dashboard that integrates time series charts, scatter plots, box plots, radar charts, and sortable tables, all configurable by operators via dynamic web forms. A multi-site comparison between Fitterizzi and San Nicola further validates the approach, revealing common trends and site-specific deviations. Our results show that the neuro-symbolic approach, combining AI prediction with rule-based reasoning and interactive visualization, provides a practical and flexible tool for environmental monitoring and decision support under changing climatic conditions.

Keywords: water quality monitoring, climate change adaptation, neuro-symbolic systems, LSTM, interactive dashboards, environmental data analysis

1 Introduction

Climate change is exerting increasing pressure on freshwater ecosystems worldwide, altering hydrological cycles, intensifying extreme weather events, and degrading water quality in rivers, lakes, and coastal areas [1, 2]. As temperatures rise and precipitation patterns shift, water bodies are subject to more frequent episodes of elevated turbidity, nutrient loading, and altered chemical equilibria, posing risks to both ecological health and human water supply [3]. In this context, continuous monitoring of physico-chemical water quality parameters has become a critical component of environmental management and climate adaptation strategies.

Modern monitoring infrastructures, such as multiparameter buoys equipped with in-situ sensors, enable the collection of high-frequency, multi-dimensional data on parameters including pH, dissolved oxygen, conductivity, turbidity, and nutrient concentrations, alongside meteorological variables such as rainfall, atmospheric pressure, and humidity. However, the sheer volume and complexity of these data streams present significant challenges for interpretation and decision-making.

We present a neuro-symbolic dashboard for water quality monitoring offering static and real time visualizations of sensor readings and the ability to perform intelligent reasoning over the data, detect complex anomalies based on domain knowledge, or allow operators to dynamically reconfigure analysis parameters. The application was developed within the Tech4You project (Technologies for Climate Change Adaptation and Quality of Life Improvement; https://ecs-tech4you.it/). The system integrates three complementary components:

1. *Neural network-based prediction*, using Long Short-Term Memory (LSTM) networks [4] to forecast missing or future sensor values based on multivariate time-series data, ensuring data continuity even during sensor failures.
2. *Logic-driven data exploration*, using rule-based reasoning to declaratively specify conditions of interest (e.g., threshold violations, co-occurring parameter deviations) and to filter, transform, and structure data for visualization.
3. *Interactive operator-facing forms*, using dynamic web-based interfaces that allow domain experts to select parameters, define alert thresholds, and configure visualizations in real time.

The logic-driven data exploration and interactive forms are implemented using ASP Chef [5–7], a web-based tool for building declarative data processing pipelines with integrated visualization capabilities. ASP Chef leverages Answer Set Programming (ASP) [8] as its reasoning engine and supports modern JavaScript visualization libraries (including Tabulator, and vis.js) for rendering interactive charts, tables, and network diagrams. The interactive forms are powered by SurveyJS [9], a JSON-configurable form library that enables operators to parameterize the analysis dynamically.

This paper presents a case study at the Fitterizzi monitoring station in the province of Cosenza, Southern Italy, where the system has been tested to support the analysis of data collected by multisensory buoys. We demonstrate how the dashboard enables effective visual exploration of parameter trends, detection of critical values, multi-site comparison, and interactive hypothesis formulation by domain experts.

The remainder of this paper is organized as follows. Section 2 describes the study area, monitoring infrastructure, and data characteristics. Section 3 presents the methodology, including data preprocessing, LSTM-based prediction and dashboard architecture. Section 4 presents the interactive data exploration through the interactive dashboard. Section 5 reviews related work. Section 6 concludes the paper and outlines future directions.

2 Study Area and Data

The monitoring station is located at the Fitterizzi gauge (183 m a.s.l.) in the upper Turbolo Creek catchment, a small (7 km^2) headwater basin in the province of Cosenza, Calabria (southern Italy) [10]. The catchment extends from 183 to 1,005 m a.s.l. and is characterized by crystalline-metamorphic formations of the Calabrian Coastal Range, which promote groundwater recharge and sustain a nearly perennial streamflow regime. The area is considered particularly vulnerable to drought conditions, with climate projections indicating increasing drying trends in the region. The Fitterizzi station was selected within the Tech4You project due to its representative hydrological setting and the availability of co-located meteorological observations.

2.1 Monitoring Infrastructure

Data were collected using multiparameter buoys equipped with in-situ probes that continuously record a comprehensive set of physicochemical water quality parameters, including:

- ammonia (NH_3), nitrate ions (NO_3^-), and ammonium ions (NH_4^+) as indicators of nutrient loading;
- fluorescent dissolved organic matter (fDOM) as a proxy for organic pollution;
- specific conductance (SpCond), salinity (Sal), and total dissolved solids (TDS) as measures of ionic composition;
- dissolved oxygen (DO) and redox potential (ORP) as indicators of water chemistry and biological activity;
- pH and temperature (T) as fundamental physicochemical parameters;
- turbidity as an indicator of suspended particulate matter.

In addition, meteorological and hydrological observations were available for the same monitoring period from a co-located weather station, including rainfall, atmospheric pressure, hydrometric level, and humidity. This multi-source dataset enables rich, multi-dimensional analysis and allows the investigation of relationships between environmental conditions and water quality metrics.

2.2 Data Characteristics and Quality Issues

The raw dataset consists of two files: a CSV file containing sensor data and an Excel (XLSX) file containing meteorological and hydrological observations. Summary statistics for both datasets are reported in Tables 1 and 2. Several data quality issues were identified during initial inspection:

Table 1: Summary of descriptive statistics for sensor parameters.

Parameter	count	mean	std	min	25%	50%	75%	max
NH_3 mg/L	21100	0.009	0.005	0	0.01	0.01	0.01	0.03
Cond μS/cm	41285	412.28	50.90	3.90	369.20	418.90	453.70	530.20
fDOM QSU	41285	20.25	8.55	−6.83	14.31	19.52	23.98	117.86
NH_4^+ mV	21100	−57.98	9.95	−74.90	−66.60	−57.20	−52.20	−23.20
NO_3^- mV	11277	−127.08	348.83	−607.70	−607.70	127.70	140.60	607.80
ORP mV	38395	−18.35	389.66	−636.0	−447.10	310.10	333.70	383.10
Sal psu	41285	0.24	0.03	0.0	0.23	0.25	0.26	0.33
TDS mg/L	41285	330.03	39.70	2.0	312.0	332.0	353.0	442.0
Turbidity FNU	41285	55.36	308.68	−0.20	2.95	5.25	10.70	6176.52
pH	38395	9.04	0.91	5.80	8.28	8.37	10.07	10.17
Temp °C	41285	15.37	4.54	5.95	11.68	14.58	19.02	26.79

Table 2: Summary of descriptive statistics for meteorological parameters.

Parameter	count	mean	std	min	25%	50%	75%	max
Rain mm	8736	0.14	0.85	0	0	0	0	31.0
Water Level m	8736	0.39	0.07	0.26	0.34	0.38	0.42	1.06
Pressure hPa	8736	995.33	6.17	976.2	992.1	995.33	998.4	1013.7
Solar Rad. W/m^2	8736	188.78	284.48	0	0	0	323	1117
Humidity %	8736	73.38	22.07	14	56.0	75.0	96.0	100.0
Wind Speed m/s	8736	3.46	2.85	0	1.6	2.3	4.4	22.7

1. *Missing values*: Not all sensor variables have the same number of observations, resulting in significant gaps in the data (Figure 1).
2. *Extreme or anomalous values*: Some parameters (e.g., NO_3^- and fDOM) exhibit extreme or unexpected negative values, suggesting calibration problems or sensor malfunctions.
3. *Temporal misalignment*: The observation periods of the two data sources do not overlap entirely.
4. *Irregular sampling*: While meteorological data are collected at a regular hourly frequency ($\Delta T = 1\,\text{h}$), the sensor data have irregular time intervals between readings.

3 Methodology

3.1 Data Preprocessing

Given the data quality issues identified in Section 2.2, a preprocessing pipeline was implemented using standard Python data science libraries (Pandas [11] and NumPy) to prepare the data for analysis and modeling. The main steps were as follows:

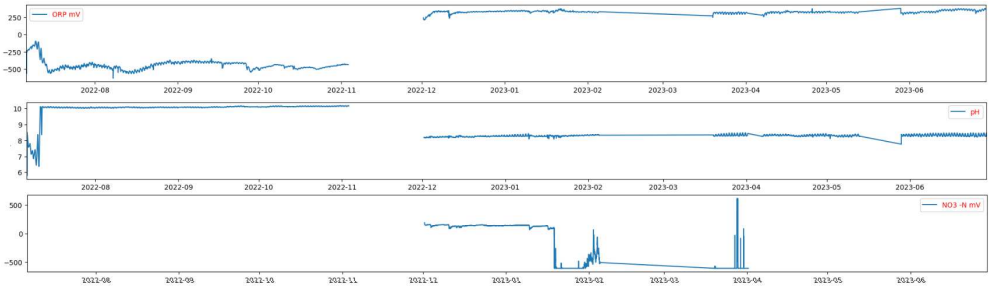


Fig. 1: Time series of selected variables showing missing values as gaps in the data, illustrating the challenges of sensor malfunctions and irregular data collection.

1. *Resampling*: Since the sensor data have irregular time intervals, they were resampled to a fixed 1-hour frequency ($\Delta T = 1\,\mathrm{h}$) to match the meteorological data and to enable standard time-series analysis.
2. *Temporal alignment*: Both datasets were filtered to include only the overlapping observation period, and then merged into a single unified dataset.
3. *Missing value handling*: Remaining missing values were addressed through interpolation and, where applicable, through LSTM-based prediction (Section 3.2).
4. *Outlier filtering*: Extreme values attributable to sensor malfunctions (e.g., large negative readings for NO_3^- and fDOM) were flagged and excluded from downstream analysis.

3.2 Time-Series Prediction with LSTM

Given the presence of sensor failures and persistent missing values for some variables, we employed time-series forecasting to predict missing values and maintain data continuity. The approach leverages readings from other sensors that remain operational to predict values for a target variable.

We implemented a prediction model using a Long Short-Term Memory (LSTM) network [4], a specialized type of recurrent neural network designed to capture long-term dependencies in sequential data through memory cells and gating mechanisms (input, output, and forget gates), as illustrated in Figure 2.

The model architecture consists of:

- an LSTM layer with 64 neurons to capture temporal patterns and long-range dependencies;
- a dropout layer with a rate of 0.5 to prevent overfitting during training;
- two dense (fully connected) layers, the first with 10 neurons, to produce the final prediction.

We demonstrate the approach by predicting pH values based on observations from the previous 12 hours. The model was trained for 80 epochs using the Mean Squared Error (MSE) as the loss function and the Adam optimizer with a learning rate of 0.01. All model definition, training, and evaluation were implemented using TensorFlow [12].

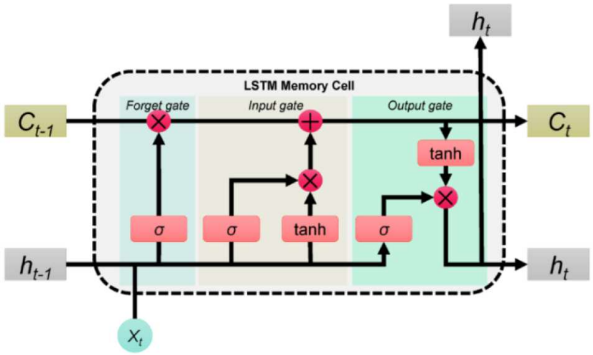


Fig. 2: Architecture of an LSTM cell, showing the input, forget, and output gates that regulate information flow through the memory cell.

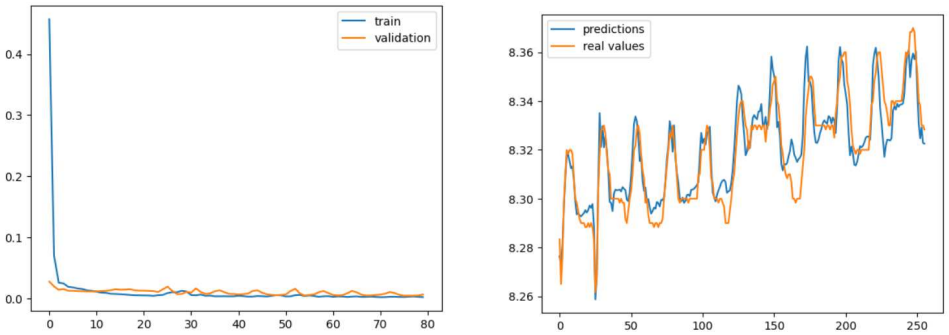


Fig. 3: Left: training and validation loss curves (MSE) across epochs, showing convergence. Right: model performance on the test dataset, comparing predicted and actual pH values (RMSE = 0.014).

The training and validation loss curves are shown in Figure 3 (left), demonstrating stable convergence. The model achieves a Root Mean Squared Error (RMSE) of 0.014 on the test dataset (Figure 3, right), indicating high accuracy in predicting pH values from the multivariate sensor readings.

3.3 Dashboard Architecture

The monitoring dashboard is implemented as a standalone web application that serves as the central hub for data exploration and decision support. It integrates static and real time visualizations of processed sensor data with links to interactive, logic-driven analysis recipes hosted on the ASP Chef platform [5, 6].

The architecture comprises three layers:

1. *Data processing layer*: Python scripts handle data ingestion, preprocessing (Section 3.1), and LSTM-based prediction (Section 3.2). Cleaned data is exported in formats suitable for both static visualization and logic-based analysis.

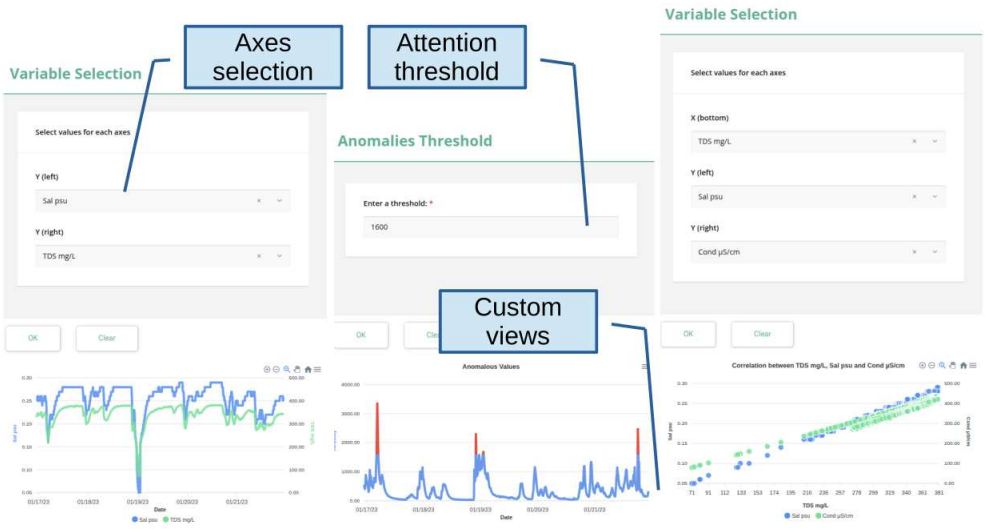


Fig. 4: Interactive configuration of data visualization using web forms. Three panels show different configuration stages: (left) selection of two water quality parameters to compare over time; (center) definition of an attention threshold for anomaly highlighting; (right) selection of two parameters to compare against a control variable. Corresponding charts update in real time based on operator selections.

2. *Logic and visualization layer*: Processed data is loaded into ASP Chef recipes, where rule-based programs filter, aggregate, and transform the data according to domain-specific conditions (e.g., threshold violations, multi-parameter correlations). The results are rendered using integrated JavaScript visualization libraries:
   - *Chart.js* for time series, scatter plots, box plots, and radar charts;
   - *Tabulator* for interactive, sortable, and filterable data tables;
   - *vis.js* for network diagrams showing parameter correlations or logical dependencies.
3. *Interactive configuration layer*: Dynamic web forms, powered by SurveyJS [9], allow operators to configure the analysis without modifying the input data.

A key feature of the dashboard is the ability for domain experts to dynamically configure data analysis and visualization through interactive web forms. Rather than requiring users to edit analysis parameters directly in configuration files or code, the system provides intuitive form-based interfaces (Figure 4) where operators can:

- select which sensor parameters (e.g., conductivity, pH, turbidity) to visualize and compare;
- define attention thresholds to highlight anomalous readings (e.g., turbidity values exceeding 1600 FNU);
- choose pairs of variables to explore correlations against a control parameter;

Datetime	Cond	fDOM Q...	ORP mV	Sal psu	TDS mg/L	Turbidity	pH	Temp °C
2023-01-17 00:10:00...	377.5	20.3	333.3	0.25	341	556.91	8.29	10.369
2023-01-17 00:20:00...	369	26.39	333.1	0.25	333	398.02	8.29	10.335
2023-01-17 00:30:00...	371	25.89	332.1	0.25	335	398.5	8.3	10.345
2023-01-17 00:40:00...	379.3	19.87	332.3	0.26	342	549.96	8.3	10.366
2023-01-17 00:50:00...	384.8	13.14	333	0.26	347	885.06	8.29	10.389
2023-01-17 01:00:00...	381.5	14.74	333.8	0.26	344	802.13	8.29	10.402
2023-01-17 01:10:00...	379.9	17.15	334	0.26	342	649.36	8.29	10.398
2023-01-17 01:20:00...	377.4	16.97	334.2	0.25	340	682.28	8.29	10.389
2023-01-17 01:30:00...	375.4	18.5	334.6	0.25	338	572.62	8.28	10.397

Fig. 5: Interactive tabular view of the Fitterizzi dataset, supporting sorting, filtering, and pagination for detailed data inspection.

- configure the time range and aggregation level for the analysis.

These inputs are captured as structured JSON objects and automatically incorporated into the data processing pipeline. The rule-based reasoning engine interprets the operator's configuration at runtime, adapting both the filtering logic and the visualization output accordingly. This design eliminates the need for operators to interact with any programming language or to understand the underlying data processing pipeline, making the system accessible to field technicians and environmental managers.

4 Exploratory Data Analysis

The dashboard provides a suite of interactive visualizations for exploring the Fitterizzi dataset. Figure 4 also presents three representative analyses generated through the system, displaying the time series of conductivity and pH over a selected period (November 2023), which allow operators to visually identify common trends and temporal variations; shows turbidity measurements with anomalous values highlighted above a threshold defined by the operator through the interactive form interface (Section 3.3); and presents a scatter plot revealing the expected linear relationship between conductivity, salinity, and TDS, confirming the physicochemical consistency of the measurements and serving as a data quality check.

The interactive table view (Figure 5) provides an additional modality for data inspection, allowing operators to sort, filter, and browse the dataset with pagination, which is particularly useful for identifying specific events or time periods of interest.

4.1 Multi-Site Comparison

To validate the generalizability of the monitoring approach and to identify site-specific deviations, we compared the Fitterizzi dataset with data collected at a second monitoring station in San Nicola, also located in the province of Cosenza. This comparison enables the detection of common regional trends as well as location-specific anomalies that may require targeted intervention.

	Place	Cond	fDOM Q...	ORP mV	Sal psu	TDS mg...	Turbidity	pH	Temp °C
min (2 items)									
min	San Nicola	225.2	-1.44	279.9	0.16	220	21.09	7.66	6.38
min	Fitterizzi	78.8	0.9	313	0.05	71	26.94	8.08	5.96
25% (2 items)									
25%	San Nicola	242.65	-1.21	302.8	0.17	227	64.57	7.68	8.63
25%	Fitterizzi	350.75	15.34	329.4	0.24	323	89.08	8.25	8.99
50% (2 items)									
50%	San Nicola	261.2	-1.1	326.7	0.17	234	66.07	7.83	10.28
50%	Fitterizzi	382.9	27.06	341.3	0.26	350	200.91	8.28	10.51
75% (2 items)									
75%	San Nicola	345.9	9.25	341.95	0.23	306	90.11	8.39	10.95
75%	Fitterizzi	420.1	35.61	354.1	0.28	373	494.21	8.29	11.28
max (2 items)									
max	San Nicola	364.7	14.49	372	0.25	331	4406.08	8.43	11.84
max	Fitterizzi	437	45.97	377.8	0.29	382	3348.47	8.34	12.28

(a) Comparison of quartile values for selected parameters between Fitterizzi and San Nicola.

Place	Week Mean Values							
	Cond	fDOM QSU	ORP mV	Sal psu	TDS mg/L	Turbidity	pH	Temp °C
Fitterizzi	374.93	25.69	342.45	0.25	339.64	354.52	8.27	10.15
San Nicola	284.79	3.16	324.38	0.19	259.58	226.43	8.01	9.84

(b) Comparison of weekly mean values for selected parameters between the two monitoring stations.

Fig. 6: Tabular comparison of aggregated water quality statistics between Fitterizzi and San Nicola, grouped by quartile (a) and weekly mean (b).

Figure 6 presents tabular comparisons of quartile and weekly mean values between the two sites, grouped by location to facilitate side-by-side inspection. Figure 7 provides graphical summaries: the radar chart (left) highlights that Fitterizzi generally exhibits higher mean values for most parameters, while the box plots (right) reveal extremely low minimum values for conductivity and TDS at one site, which are likely attributable to sensor malfunctions rather than genuine environmental conditions. These findings demonstrate how the dashboard can serve as a tool for both inter-site comparison and data quality assurance.

4.2 Interactive Dashboard

The standalone dashboard web application consolidates all of the visualizations and interactive tools described above into a unified interface as shown in Figure 8. Operators access the dashboard through a web browser and can navigate between different analysis views, including time series exploration, anomaly detection, multi-site comparison, and tabular data inspection (Figure 8a). Each view provides links to the corresponding interactive ASP Chef recipes, where operators can further customize the analysis using the form-based configuration interface (Figure 8b).

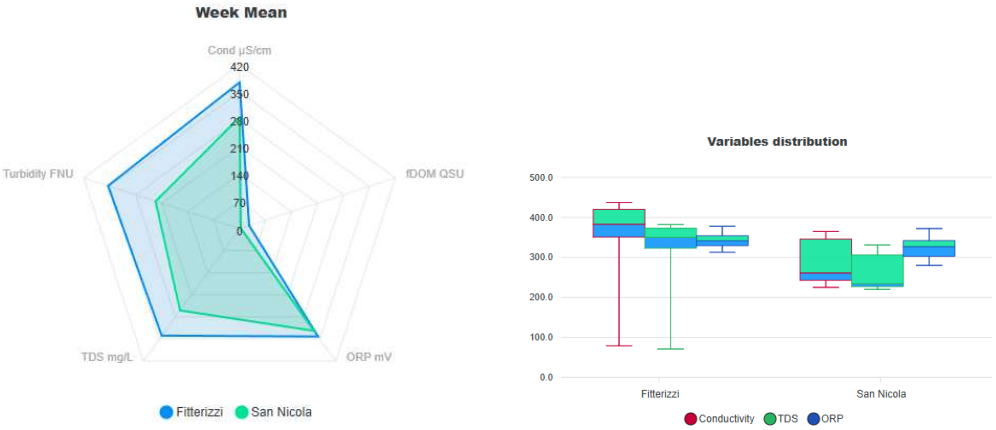


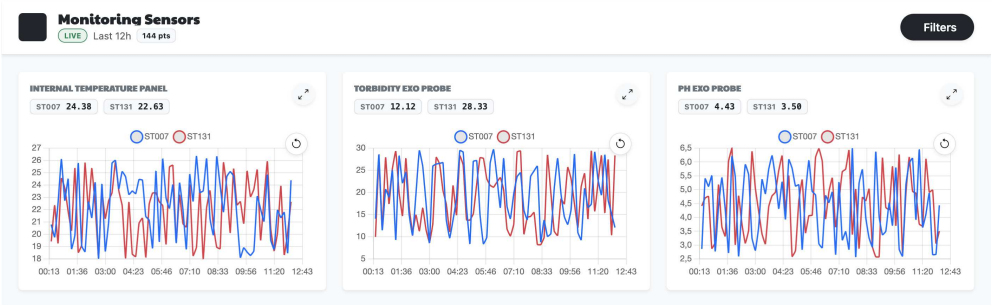
Fig. 7: Left: radar chart comparing mean weekly values of selected parameters across the two monitoring stations. Right: box plots showing the distribution of conductivity and TDS, revealing extremely low minimum values at one site that may indicate sensor malfunctions.

The neuro-symbolic approach presented in this work offers several advantages over purely data-driven dashboards for environmental monitoring:

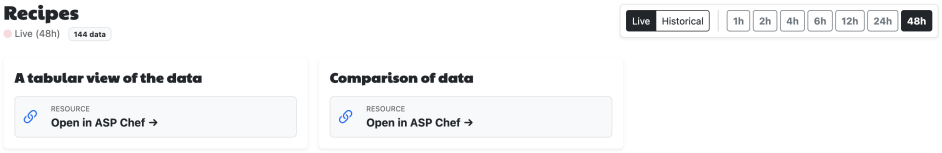
- *Data continuity*: The LSTM-based prediction component ensures that the monitoring system can maintain continuous data streams even during sensor outages, providing operators with complete time series for analysis.
- *Intelligent filtering*: The rule-based reasoning layer enables the specification of domain-specific conditions (such as threshold violations, joint parameter deviations, or temporal patterns) in a declarative manner, without requiring custom code for each new analysis scenario.
- *Interactive configurability*: The form-based interface allows non-technical users to adjust analysis parameters, select variables of interest, and define alert conditions in real time, fostering a tighter feedback loop between data exploration and domain expertise.
- *Multi-site scalability*: The same pipeline architecture can be applied to additional monitoring stations with minimal adaptation, as demonstrated by the Fitterizzi–San Nicola comparison.

5 Related Work

Machine learning techniques have been widely applied to water quality prediction and monitoring. Traditional approaches based on Random Forest, Decision Trees, Support Vector Regression, and Gradient Boosting Regression have demonstrated effectiveness for estimating key water quality indicators from environmental sensor data [13–15]. These models typically rely on handcrafted features and require careful preprocessing and domain knowledge. Deep learning approaches have shown strong performance in capturing non-linear patterns and temporal dependencies in water



(a) Dashboard charts updated in real time of all the sensors. The user can filter for specified temporal ranges using historical measures, filters can be used to select the charts to be shown.



(b) ASP Chef recipe section in which the user selects the data temporal range and visualization type to be shown in the recipe itself.

Fig. 8: Platform interfaces for real-time sensor monitoring and customized data visualization.

quality data. LSTM-based models have been successfully applied to forecast pH and water temperature in mariculture environments [16], and recurrent neural networks have been used for water quality assessment in complex coastal lagoons [17] and river systems [18]. Hybrid architectures combining Convolutional Neural Networks (CNNs) with LSTM layers have enabled simultaneous prediction of multiple water quality indicators [19].

However, most existing systems focus exclusively on prediction accuracy and lack integrated support for interactive data exploration, operator-driven configuration, or declarative rule-based reasoning. Our approach complements the prediction capabilities of LSTM networks with a logic-driven analysis layer and interactive web-based forms, providing a more comprehensive tool for operational monitoring and decision support.

In a broader context of environmental monitoring dashboards, several commercial platforms provide web-based visualization of sensor data, including WISKI, Aquarius, and HydroVu. The dashboard presented in this work is fully open source and built on a composable, logic-driven architecture, allowing the analysis pipeline, visualization types, and data sources to be freely extended and customized by the adopting community.

6 Conclusion

In this work, we presented a neuro-symbolic dashboard for climate-resilient water quality monitoring, developed within the Tech4You project and demonstrated through a case study at the Fitterizzi monitoring station in Southern Italy. The system integrates LSTM-based time-series prediction for ensuring data continuity during sensor failures, rule-based reasoning for intelligent data filtering and anomaly detection, and interactive web-based forms for operator-driven configuration of analysis parameters and visualizations.

The results demonstrate that the approach provides practical value for environmental monitoring: the LSTM model achieves high accuracy in predicting pH values from correlated sensor readings; the interactive visualizations enable effective exploration of temporal trends, inter-parameter correlations, and multi-site comparisons; and the form-based configuration interface makes the system accessible to domain experts.

The multi-site comparison between Fitterizzi and San Nicola illustrates the scalability of the approach, revealing both common regional patterns and site-specific deviations that inform targeted monitoring strategies.

As a direction for future work, we envision the integration of weather and climate forecast data into the dashboard, enabling proactive rather than reactive monitoring. By coupling real-time sensor readings with short-term weather predictions (e.g., heavy rainfall forecasts), the system could anticipate episodes of elevated turbidity or nutrient runoff before they occur, providing early warning capabilities to environmental managers and policymakers. Additionally, we plan to support for additional monitoring stations across the Calabria region, and the incorporation of more advanced predictive models for multi-parameter forecasting.

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Ethics, Consent to Participate, and Consent to Publish declarations. Not applicable.

Data availability statement. The data analyzed during the current study is available in the Zenodo repository: 10.5281/zenodo.21627482.

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