Demo: Where does *that* even come from?! Localizing Water Pollution through IoT and Modeling

Julia Steiwer
ComNets, Universität Bremen
Bremen, Germany
julia.steiwer@comnets.uni-bremen.de

Anna Förster
ComNets, Universität Bremen
Bremen, Germany
afoerster@comnets.uni-bremen.de

Abstract

This paper presents the development of an IoT-based system for detecting, localizing, and predicting point sources of water pollution. Despite global efforts like the UN's Agenda 2030, water pollution persists, impacting billions and causing preventable deaths. Our system aims to classify pollution types, localize sources, and predict its spread, contributing to better water management and early warning systems. The system's core is a sensor node that measures key water quality indicators, with plans to expand. Initial field tests show promising detection, but further validation is needed for reliable localization and prediction.

CCS Concepts

• Computing methodologies → Modeling and simulation; **• Computer systems organization → Sensor networks**; **• Hardware → Sensor applications and deployments**.

Keywords

IoT, Modeling, Simulation, Sensors, Water Pollution, Point Sources

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1 Introduction

In 2010, the UN recognized the human right to water and sanitation [2], yet 2 billion people still lack access to clean water, leading to 1 million preventable deaths annually from diarrhea [6]. Pollution stems from natural and human sources, including wastewater, agriculture, runoff, and atmospheric deposition [3], with contamination from point (e.g., sewage) and non-point (e.g., runoff) sources, including transboundary pollution [1]. Early detection and localization are crucial to mitigate impacts on human and environmental health. We are developing an IoT-based system for detecting, localizing, and predicting water pollution.

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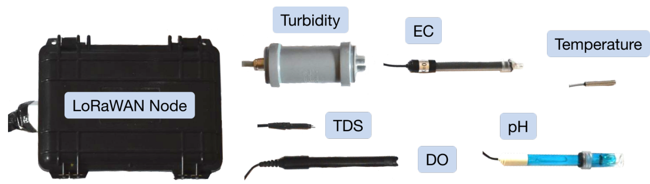

Figure 1: Monitoring node with sensors.

2 Research Questions

Our research aims to address key questions on water pollution through system implementation and modeling in fluvial systems. While contamination detection and classification are well-studied, localization and prediction remain less explored. The primary research questions are: (1) How does a self-made sensor system compare to high-end solutions in contamination detection? (2) Can pollution sources be reliably localized with a confidence of γ%? (3) Is it possible to predict pollution along a fluvial system using in-situ sensors, satellite imagery, and system data? (4) What sensor density and essential sensors are required for accurate localization and prediction?

3 Methodology

3.1 Node Specifications

The system's core is a sensor node comprising six sensors and a LoRaWAN communication unit (Fig. 1), based on the MoleNet wireless underground sensor network (WUSN) platform [7]. The prototype for water quality monitoring measures the parameters temperature, pH, dissolved oxygen (DO), electrical conductivity (EC), total dissolved solids (TDS), and turbidity. The sensors were selected for their low cost and microcontroller compatibility, making the node affordable ($500 per unit). LoRaWAN was chosen for its low power consumption and long transmission range, suitable for both urban and rural environments. Data is transmitted to TheThingsNetwork (TTN) via LoRaWAN and retrieved through a webhook for display on ThingSpeak. The system runs on a Heltec WiFi LoRa 32 (V3) board with an SX1262 LoRa chip and is powered by a 2200 mAh battery with optional solar charging for extended runtime. Deep sleep minimizes energy consumption between measurements. Field tests have been conducted at the wastewater treatment plant (WWTP) of the Hospital for Tropical Medicine in Bangkok (TH) and the author's garden ponds in Melle (DE).

The system can detect parameter changes and certain pollutants, but extended testing is required to validate its long-term accuracy. The sensor suite must be expanded to include key water quality indicators like nutrients and pathogens. To enhance monitoring, we

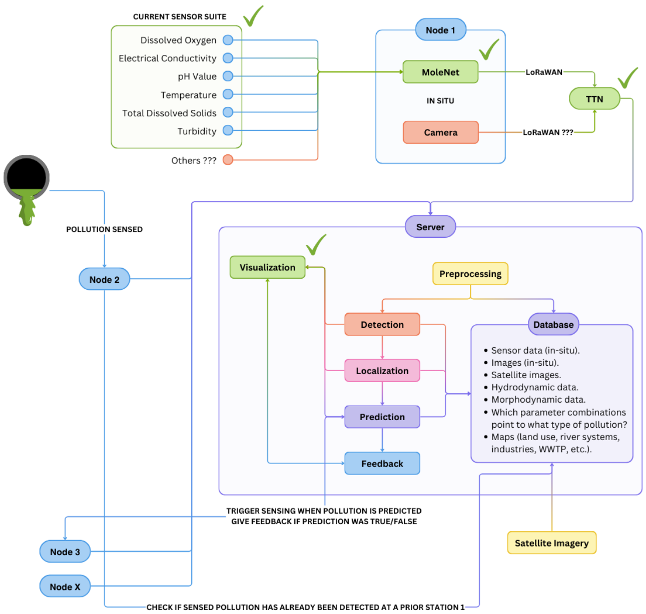

Figure 2: System plan for localizing and predicting pollution.

plan to integrate in-situ sensors with camera and satellite imagery. Near-infrared satellite images will allow large-scale assessment of chlorophyll content, improving spatial resolution and enabling detection of harmful algal blooms (HABs). Webcam images will help capture surface phenomena, such as plant cover, water discoloration, or nearby pollution sources, that sensors may miss.

3.2 Localization and Prediction System

Data-driven rules are needed to classify pollution types and identify sources within a fluvial system. Using historical datasets and limnological insights, we aim to develop a simple classifier. For example, stable temperature and pH with a drop in DO and an increase in EC and turbidity may indicate nutrient-rich manure, while simultaneous pH and EC changes point to industrial discharge [4].

A basic model will first be used to localize pollution sources. At the Aller-Weser confluence (DE) (Fig. 3), for instance, without hydrodynamic data, pollution detected at point C has an equal chance of originating from either point A (Weser) or B (Aller). Factoring in flow rates (MQ), however, increases the likelihood that the pollution at C came from the Weser, as it contributes more water after the outfall (198 m^3/s at Dörverden[1] before and 317 m^3/s at Intschede[2] after the outfall). Further refinement considers pollution type; higher levels of heavy metals like Pb, Cd, Zn, and Hg suggest the Aller as the source, given its connection to former mining regions [5].

Accurate source identification requires extensive knowledge of the fluvial system, considering parameters like hydromorphodynamics, land use, and environmental factors. If few parameters suffice for high accuracy, a simple model may be used; otherwise, machine learning may be employed. However, gathering sufficient high-quality data is challenging. Relying solely on in-situ monitoring is impractical, so the system requires an extensive database integrating global datasets and image data for large-scale events.

[1]Dörverden level: https://t1p.de/weser_pegel_doerverden
[2]Intschede level: https://t1p.de/weser_pegel_intschede

Figure 3: Satellite view of the Aller outfall, DE. The orange dots denote potential measurement stations. Station A is located in the Weser river (left) while station B is located in the Aller river (right), both before the outfall. Station C is located in the Weser river after the outfall. In our example of a trivial model, pollution is detected in C and we aim to assess the likelihood that it could have also been detected in either A or B.

Once pollution classification and localization are reliable, the system will aim to predict downstream pollution. By analyzing upstream conditions at station A and internal and external factors, predictions can determine whether pollution at station C will dissipate, remain below critical thresholds, or increase. To validate predictions, station A will trigger a call to action for station C when pollution is expected, critical for integrating an early-warning system and preventing false alarms.

Simulations will be used to test localization and prediction models, followed by system optimization to find the minimum number of nodes required to create a cost-effective grid with a confidence level of γ%, as deploying sensors everywhere is not economic.

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