Unreliable Results of a Commercial Real-Time Water Quality Sensor in Identifying Fecal Contamination of Drinking Water

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Abstract

Low-cost technologies are increasingly being explored and marketed as capable of filling gaps in global water quality monitoring (WQM), especially in resource-limited settings. This study evaluates a commercially available, low-cost triboelectric-based sensor that is marketed for real-time detection of *E. coli* in drinking and environmental waters. A result of 0 indicates contaminated water, whereas a result of 99 indicates "safe" water. A total of 199 water samples were prepared by serial dilution of raw wastewater influent into deionized water to produce a range of *E. coli* concentrations from <1 to >100 CFU/100 mL in evaluating the triboelectric sensor. Sensor readings were collected using three settings on each of five devices, generating nearly 9,000 individual readings to compare against Membrane Filtration taken in triplicate as the true *E. coli* concentration. Spearman's rank correlation revealed no statistical significance between the sensor score and *E. coli* concentrations ($\rho = -0.1493$, $p = 0.0603$). When sensor readings were taken in aggregate, a moderate predictive capacity was observed as a presence/absence classification (AUC = 0.77), though this requires 15 measurements per sample, which is beyond the guidelines of the technology. The sensor frequently misclassified both known-negative and known-positive samples, with a high rate (64%) of score clustering at the extremes (0 or 99). These findings indicate that the sensor in its current form is not suitable for public health evaluation of microbial contamination in drinking water. The lack of predictive ability, which contradicts the marketed capacities and user expectations, is likely not unique to the evaluated sensor. This study highlights the importance of rigorous validation of novel WQM technologies before deployment to identify the appropriate application of sensors, which may remain beneficial, even if not for immediate public health use.

Introduction

Importance is being placed on novel and low-cost methods to monitor water quality to fill gaps in Water Quality Monitoring (WQM) capacity(1–7). Fit-for-purpose technologies are needed in rural and remote regions, or in resource-limited areas where standard methods and laboratories are not financially feasible(8,9). While investment is needed to improve infrastructure and WQM capacity globally, a temporary solution may be to increase the use of low-cost, novel technologies. These novel technologies include marketed and laboratory-prototype level methods that may be simpler and cheaper than their standard method counterparts(10). Novel technologies may not meet regulatory-level monitoring needs regarding the accuracy of measurements but may be fit for the purpose of identifying risks to human health at a low cost.

One proposed technology, a commercial real-time water quality sensor, denoted as "sensor" throughout, has been identified from past market and literature searches as a novel and marketed technology for measuring a variety of contaminants in water. Marketing material for the sensor suggests that it is capable of measuring *E. coli* and potentially other fecal pathogens, with anecdotal evidence also supporting this claim. This technology works by measuring triboelectric effects in a water sample. Triboelectric effects, or surface electrification, can occur when objects move across one another and create a buildup of static electricity on one surface(11). One phenomenon related to triboelectric effects is the measurement of static electricity buildup on the surface of a pipe with moving fluids. Some studies have shown that triboelectric effects can be used for measuring specific chemicals in water(12–14), though it is unclear whether such technologies can effectively measure pathogens in water, which are of concern to human health. No prior peer-reviewed studies have evaluated the performance of this sensor for specific contaminants. This study seeks to evaluate the sensor's ability to measure *E. coli* levels in drinking water.

Methods

Methods: Measurements

Samples representing contaminated drinking water supplies (n=199) were prepared by spiking serial dilutions of wastewater influent from the Orange Water and Sewer Authority (OWASA) into de-ionized (DI) water. Dilution factors of wastewater influent ranged from 10^{-9} to 10^{-4}, which produced a range of fecal contamination from <1 to 1,000 CFU/100 mL *E. coli*. The 1000-mL stock solutions of *E. coli* were used to take measurements with the sensor.

Sensor measurements were taken as per vendor recommendations by pouring 100 mL of well-mixed stock solution into a thin-walled plastic cup and gently swirling the 100 mL sample. The sensor is then turned on by holding the appropriate test button (Tap, Bottle, or Environment), 2 to 3 inches from the wall of the cup. In one motion, the sensor was brought towards the cup to about half an inch above the water level, and the button was then released. All measurements produced a water quality score from 0-99 (0 representing the worst water quality), which were stored on the technology's mobile app, connected via Bluetooth. Each test button was tested in triplicate per sample (n=199) using a new cup across five separate Lishtot TestDrop Pro sensors using each of the three sensor settings, generating nearly 9000 readings. Laboratory blanks and raw mixed influent were also tested on the sensor as known negative and known positive readings.

The sensor was evaluated against the standard method of Membrane Filtration (MF) on MI agar. A 100-mL sample was taken by pipette and passed through filter paper, and then transferred to MI agar as per the EPA method 1604(15). MF measurements were completed in triplicate for each stock solution.

Methods: Analysis

The sensor was evaluated for its ability to accurately predict the WHO *E. coli* risk category (Very low risk as <1 CFU/100 mL, Low risk as 1-<10 CFU/100 mL, Moderate risk as 10-<100 CFU/100 mL, and High risk as ≥100 CFU/100 mL *E. coli*)(16) for the stock solution. The true *E. coli* concentration was taken as the arithmetic average of the triplicate membrane filtration readings(17). MF readings were compared against the average of the triplicate measurements for each sensor button on each device to determine suitability for predicting *E. coli* and the broader risk categories.

Analysis of the data was completed using Python. Analysis includes jitter plots, boxplots for each device and button, and non-parametric evaluation using Spearman's Rank-Order Correlation.

Results

The n = 199 stock solutions varied in *E. coli* concentration from non-detect to "too numerous to count" (TNTC), with concentration distribution shown in Table 1 below. The sensor measurements ranged from 0 to 100 and are shown separately by each device and button type (Tap, Bottle, Environment) in the jitter plot in Figure 1, with sensor score on the Y-axis. Across all five devices (L1 to L5), approximately 24% and 40% of sensor scores returned >=99 and 0, respectively. This is shown by the concentration of points at the poles of the jitter plot. For raw influent (n = 23 samples, x = 1035 observations), 35% measurements resulted in readings of >=99, implying no contamination. All measurement data are available in Table S1.

Table 1. Distribution of Stock Samples Spiked with Wastewater Influent

WHO Risk Category	*E. coli* Range [CFU/100-mL]	Number of Stock Samples
De-Ionized (Blank)	Non-detect	22
Very Low Risk (spiked)	Non-detect	24
Low Risk	Detect-<10	61
Moderate Risk	10-<100	28
High Risk	>100-TNTC	39
Raw Wastewater	TNTC	23

Fig. 1: Jitter plot of the (unaveraged) sensor scores for each device (L1-L5) for each button type (Tap, Bottle, Environment), showing no difference in distribution

Tests to determine the correlation between sensor reading and *E. coli* concentration did not result in any predictive power between the variables with an R^2 value greater than 0.2, suggesting low correlation.

Given the possible non-parametric distribution of the data, Spearman's Rank evaluation was used to determine any correlation between the sensor score and *E. coli* concentration, shown in Figure 2. Spearman's rank correlation coefficient, or Spearman's Rho (ρ), is -0.1493, showing that the strength of association between the rank of average E. coli count and the rank of sensor score is very weak. The p-value of this correlation, or the chance that the correlation happened only due to chance, was 0.0603. Since the p-value is greater than a 0.05 significance level (α), we do not have enough evidence to reject the null hypothesis of no correlation. Observations for samples with <1 CFU/100 mL *E. coli* showed a wide distribution across all sensor score rankings, implying limited effectiveness of predictive capacity. A Spearman's Rank evaluation removing these results indicates a Spearman's Rho (ρ) of 0.0473 with a p-value of 0.6202, seen in Figure S1.

Fig. 2: Spearman's Rank Correlation between averaged E. coli concentration and averaged sensor reading

Further evaluation of the sensor scores as a Presence/Absence test was conducted with a classification test. This was indicated by a Presence/Absence cutoff of any *E. coli* detected with the sensor readings being the aggregate average score for each button across the 5 devices (n = 15 measurements). The results in Figure 3 below show that the "Bottled Water" option has an Area Under the Curve (AUC) of 0.63, implying a weak predictive capacity. A further analysis of each device and button combination results in a minimum and maximum AUC of 0.35 and 0.65 for a single device-button combination, respectively, as seen in Figure S2.

Fig. 3: Area Under the Curve measures for E. coli contamination, with Presence/Absence classification for aggregated sensor readings by button

Discussion

The sensor scores do not appear to have a significant link to *E. coli* concentrations and are a poor predictor of *E. coli* risk categories. The high number of readings at the measurement extremes of 0 and >=99, which represented approximately 64% of all measurements, may lead to significant misinterpretation of water quality. This includes misclassifying both DI-blanks and raw wastewater influent as contaminated and clean, respectively. The lack of correlation in ranked data, shown by Spearman's Rank evaluation, shows that the device is a poor predictor of *E. coli*.

There is limited evidence that repeated measurements across many devices may result in an improved predictive ability for the Presence/Absence of *E. coli*. However, the distribution of AUC scores ranged from 0.35 to 0.65, indicating a lack of predictive power. The distribution of AUC scores, including 0.5, equivalent to random categorizing, implies the sensors inability to categorize waters as "safe". The sensor is therefore an inappropriate instrument for public health evaluation of potential drinking water for microbial contamination. At the time of this publication, no other peer-reviewed studies evaluating the sensor have been identified. Past anecdotal evidence suggests that other laboratories and organizations have seen success with the sensor. One grey literature source suggests a presence/absence prediction rate of 76% for measuring fecal contaminants, though this source seemed to suggest inconsistent readings within replicate samples(18). This internal inconsistency appears similar to the observations of the current study.

Triboelectric effects have been used to directly measure some chemical compounds, such as mercury(19) and catechin(20) in agitated water systems. The success of triboelectric effect measurements for chemical contaminants may depend on selective surfaces, where surface electrification will occur more in the presence of the target compound. The unique signal generated by a spike in the target compound may distinguish the sample from one with other contaminants. As such, triboelectric meters may be best suited for evaluating the presence of specific contaminants. This may not be easily transferable to a non-selective measurement, as with the sensor, where no selective materials are used and where all contaminants are measured at once. The triboelectric effect does not appear to be fit for the purpose of measuring *E. coli* in drinking water contaminated by human feces.

It is possible that the amount of signal electrification of the plastic surface generated by the microorganisms in diluted sewage is not sufficiently distinguished from background triboelectric effects, which are seen even in DI water. Triboelectric forces in water are measured in flow-through systems elsewhere, regardless of chemical content(21). It is possible that the act of swirling the sample by hand does not allow for adequate buildup of surface electrification, or that the presence of microorganisms does not create a unique electrification profile. A flow-through version of this sensor technology does exist from the same company, though it was outside the scope of this study.

Conclusion

In its current form, the sensor does not seem to be a beneficial tool in filling the capacity gap for Water Quality Monitoring. This work has served to highlight the need for evaluation of novel technologies related to low-cost water quality monitoring. The sector must find and implement solutions that adequately meet the health and safety needs of populations while remaining economically viable. Such solutions may rely on novel technologies, which should be properly evaluated before implementation. It may be useful to replicate this effort with other products and marketed WQM tests.

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Supporting Information:

S1 Table: Sensor Test Scores and E coli measurements

S2: Appendix: Performance of Sensor excluding <1 CFU/100mL Values

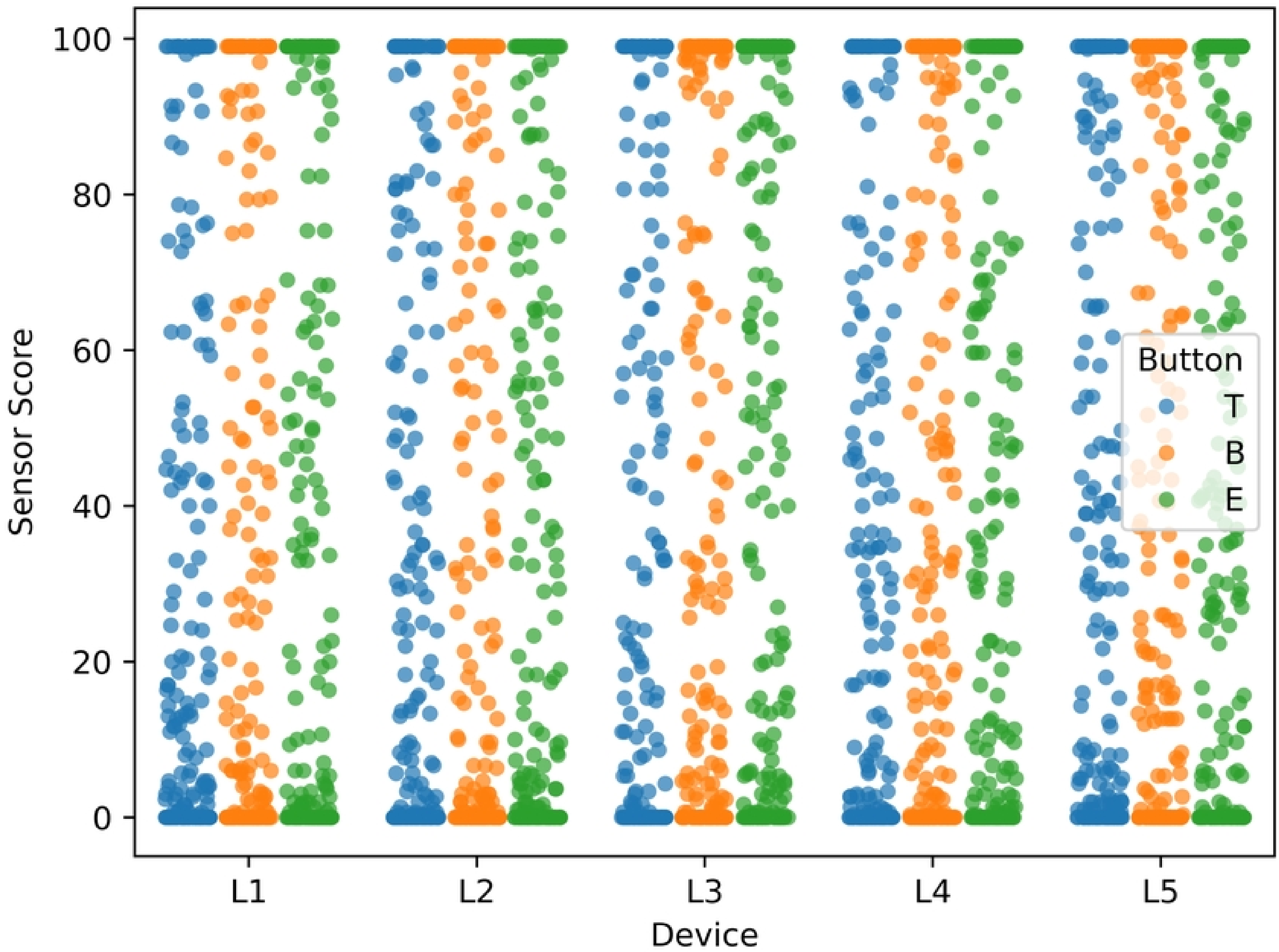

Fig. 1

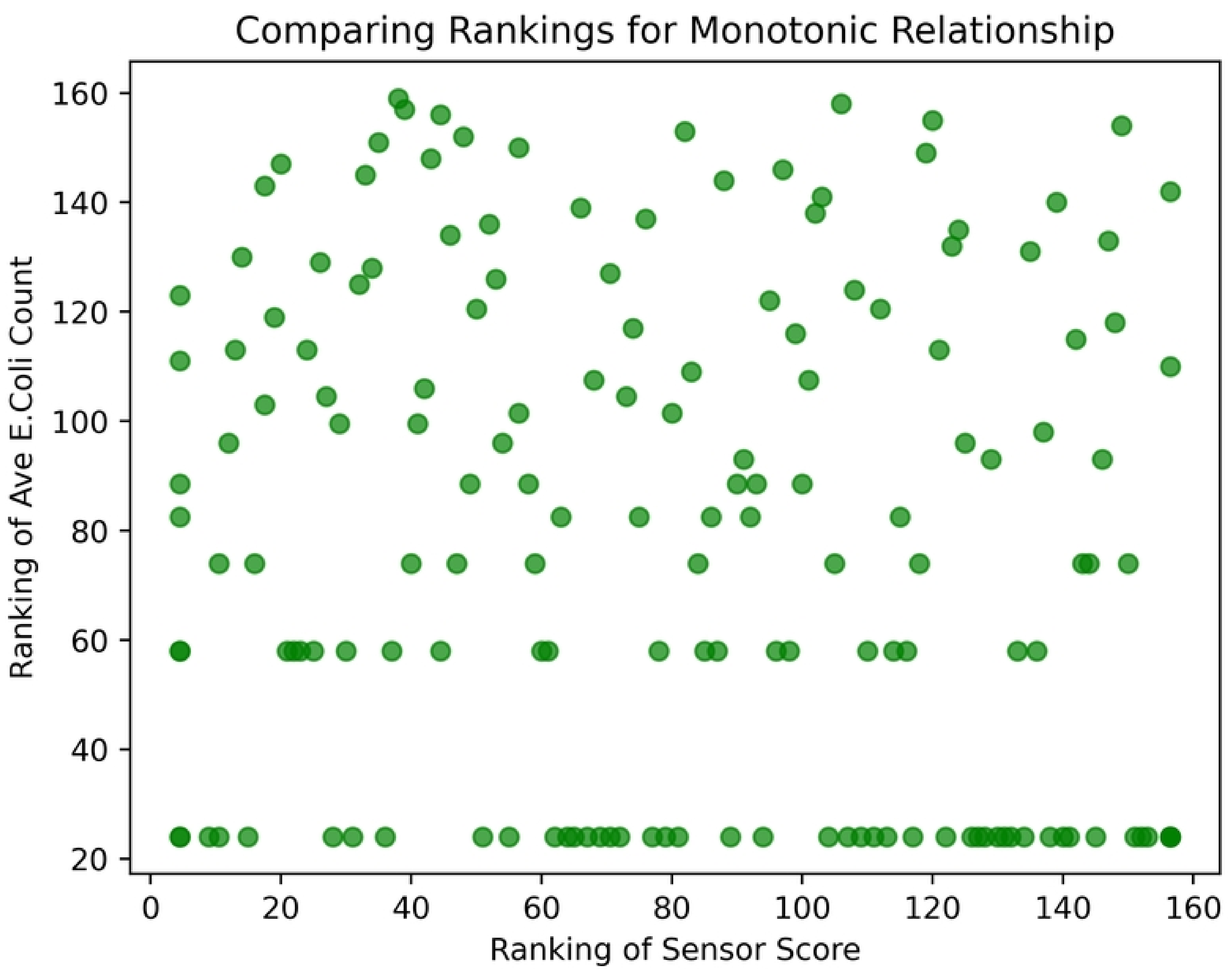
Comparing Rankings for Monotonic Relationship
Ranking of Ave E.Coli Count
Ranking of Sensor Score
160
140
120
100
80
60
40
20
0
20
40
60
80
100
120
140
160

Fig. 2

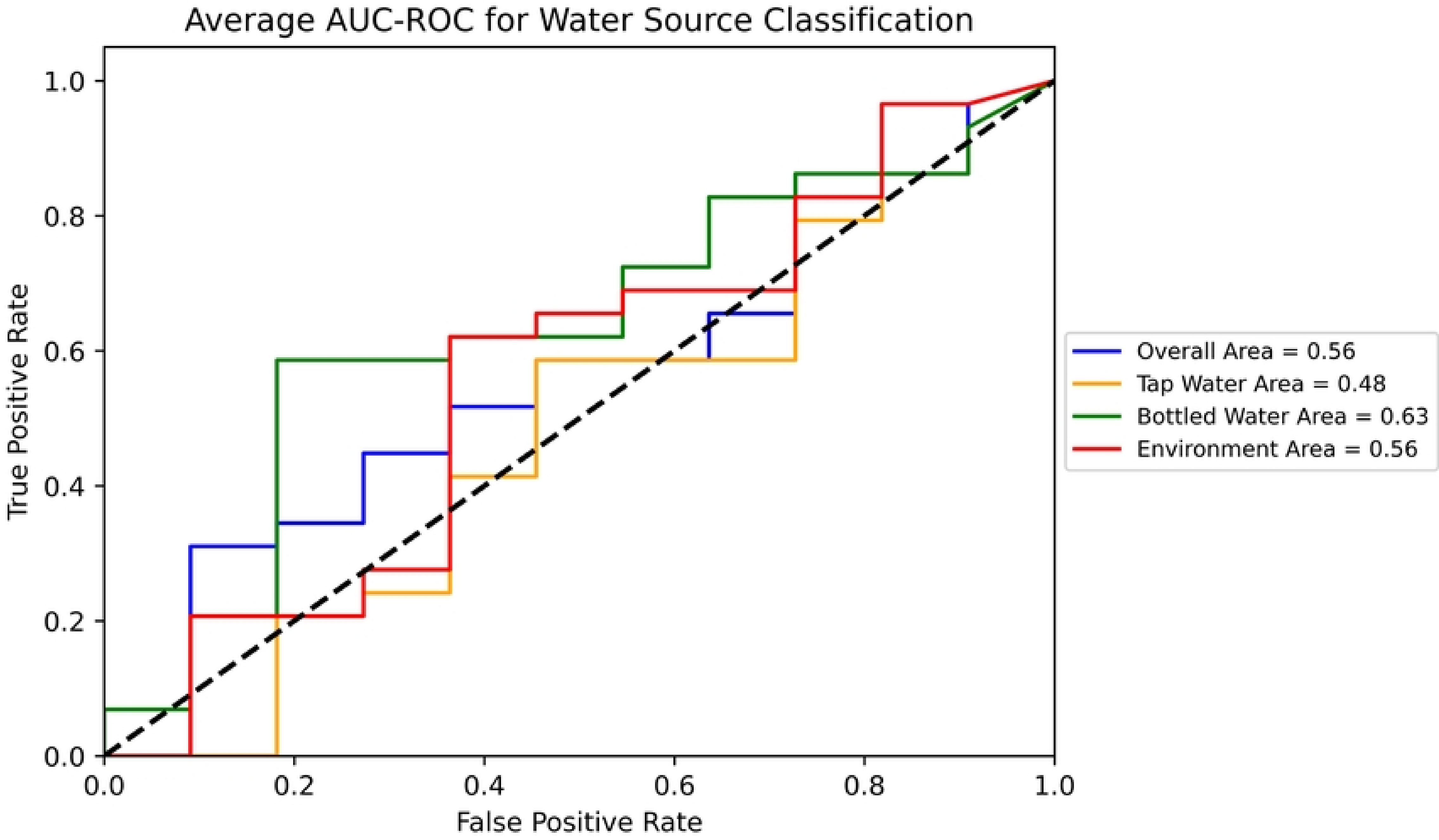
Average AUC-ROC for Water Source Classification
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Overall Area = 0.56
Tap Water Area = 0.48
Bottled Water Area = 0.63
Environment Area = 0.56

Fig. 3