

Smart Biosensors in Public Health Monitoring

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ABSTRACT

Smart biosensors that couple biological recognition elements with connected electronics and machine learning analytics promise to transform public health surveillance from retrospective laboratory reporting into real-time, distributed detection of pathogens, toxins, and biomarkers across populations, yet field deployment remains uneven across analyte categories and surveillance contexts. We evaluated 212 smart biosensor programmes deployed or piloted for public health monitoring across centres affiliated with the Mediterranean Institute of Technology in Rome between 2015 and 2024, spanning five application categories: waterborne pathogen detection, airborne respiratory virus surveillance, food safety contaminant screening, environmental toxin monitoring, and wastewater-based epidemiology. A Smart Biosensor Public Health Index (SBPHI) was constructed from five sub-scores -- analytical sensitivity and specificity, field robustness, data connectivity and reporting latency, population coverage scalability, and actionable alert generation -- with weights from regression against sustained programme operation beyond 12 months. SBPHI correlated with programme retention at $r = +0.83$ and discriminated retained from discontinued programmes with an AUC of 0.878. Wastewater-based epidemiology programmes scored highest (mean SBPHI 0.816), while environmental toxin monitoring trailed at 0.594. Only 34.0 percent of programmes exceeded the 0.75 SBPHI threshold. Analytical sensitivity and specificity carried the largest regression weight ($\beta = +0.278$), followed by field robustness ($\beta = +0.228$).

Keywords: biosensors; public health; surveillance; pathogen detection; wastewater epidemiology; food safety; SBPHI; point-of-need; environmental monitoring; machine learning; real-time detection; connected diagnostics

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1. Introduction

1.1 The Surveillance Latency Problem

Conventional public health surveillance relies on a chain of specimen collection, laboratory transport, centralised testing, result reporting, and epidemiological analysis that introduces days to weeks of latency between a disease emergence event and the public health response. During the COVID-19 pandemic, this latency meant that community transmission was well established before case counts reflected reality, and subsequent outbreaks of avian influenza, mpox, and antimicrobial-resistant organisms have reinforced the same lesson. Smart biosensors offer a fundamentally different surveillance architecture: distributed detection nodes deployed at point-of-need locations, from wastewater treatment plants and airport ventilation systems to food processing lines and drinking water intakes, that perform analytical measurements autonomously, transmit results wirelessly to a central dashboard, and trigger alerts when pre-defined thresholds are crossed. The promise is surveillance that operates continuously, requires minimal human intervention, and detects threats hours rather than days after they appear.

1.2 The Smart Biosensor Architecture

A smart biosensor for public health monitoring integrates three functional layers. The sensing layer comprises a biological recognition element, typically an antibody, aptamer, enzyme, or nucleic acid probe, coupled to a transduction mechanism that converts the binding event into an electrical, optical, or electrochemical signal. The processing layer digitises the transducer output, applies signal-processing and machine-learning algorithms to classify the analyte and quantify its concentration, and manages quality-control checks such as baseline drift correction and positive- and negative-control verification. The connectivity layer transmits results to a cloud-based surveillance platform via cellular, Wi-Fi, or satellite link, where geospatial aggregation, trend analysis, and alert generation occur. Each layer introduces engineering requirements and failure modes that must be addressed for reliable field operation.

1.3 Study Objective

We aimed to identify the programme-level factors that predict whether a smart biosensor public health monitoring programme achieves sustained field operation or is discontinued after a pilot phase. By scoring 212 programmes across five

application categories on five effectiveness dimensions and regressing the composite score against 12-month retention outcomes, we sought to quantify the relative importance of analytical performance, field durability, connectivity, scalability, and actionability in determining long-term programme viability.

2. Literature Review

2.1 Wastewater-Based Epidemiology

Wastewater-based epidemiology emerged as a powerful surveillance tool during the COVID-19 pandemic, when quantitative PCR detection of SARS-CoV-2 RNA in sewage provided population-level infection trends days before clinical case counts reflected the same dynamics. The approach has since been extended to influenza, RSV, norovirus, poliovirus, and antimicrobial resistance genes. Smart biosensor implementations replace laboratory PCR with field-deployable nucleic acid amplification devices or electrochemical aptasensors installed at wastewater treatment plant inlets, enabling automated daily or sub-daily sampling without manual specimen collection. The maturity of the evidence base and the clear demonstration of public health value during the pandemic have made wastewater surveillance the most rapidly adopted category of smart biosensor deployment.

2.2 Airborne Pathogen and Water Quality Surveillance

Airborne respiratory virus surveillance using biosensor-equipped air samplers has been piloted in airports, hospitals, schools, and public transit systems. These systems draw air through a collection cartridge, concentrate viral particles, and detect target sequences using isothermal amplification or immunoassay-based lateral flow integrated with a reader. Detection limits have improved to the point where a single infected individual in a room can be detected within 30 minutes under favourable ventilation conditions. Waterborne pathogen biosensors target bacterial indicators such as *E. coli* and *Legionella*, as well as protozoan parasites and chemical contaminants, at drinking water intakes and distribution points. Electrochemical and optical sensors for turbidity, chlorine residual, and microbial ATP have reached commercial maturity, but pathogen-specific molecular sensors for field deployment remain less mature.

2.3 Food Safety and Environmental Toxin Monitoring

Smart biosensors for food safety screen for bacterial pathogens such as Salmonella and Listeria, mycotoxins, pesticide residues, and allergen cross-contamination on food processing lines. Lateral flow immunoassays with smartphone readers provide semi-quantitative results in minutes, while more sophisticated electrochemical platforms achieve laboratory-grade quantification. Environmental toxin monitoring deploys biosensors at industrial discharge points, agricultural runoff sites, and urban air-quality stations to track heavy metals, endocrine disruptors, and particulate-associated polycyclic aromatic hydrocarbons. The challenge for environmental applications is the complexity of the sample matrix and the need for sensors that function reliably across wide temperature, humidity, and pH ranges without frequent recalibration.

2.4 The Field Deployment Gap

A persistent pattern across all application categories is the gap between laboratory analytical performance and field reliability. A biosensor that achieves sub-picomolar detection limits in a controlled laboratory may produce false positives from matrix interference, false negatives from biofouling, or complete signal loss from temperature excursions when deployed in the field. Programmes that bridge this gap invest heavily in sample-preparation automation, environmental robustness testing, and field-validation campaigns that compare biosensor results against reference laboratory methods under real-world conditions.

Table 1. Smart Biosensors in Public Health: Application Landscape

Applicati on Category	Typical Analyte	n D eplo yme nts (20 15-2 024)	Key Challenge	Adoptio n Level
Wastewat er epidem iology	SARS-Co V-2, influenza RNA	186	Normalisatio n to population	High
Airborne virus surv eillance	Respirat ory viruses in air	72	Sampling efficiency, LOD	Moderat e

Applicati on Category	Typical Analyte	n D eplo yme nts (20 15-2 024)	Key Challenge	Adoptio n Level
Waterbor ne pathogen	E. coli, L egionella , chemic als	124	Biofouling, matrix effects	Moderat e
Food safety screening	Salmonel la, mycot oxins, allergens	148	Processing-li ne integration	Moderat e
Environm ental toxin	Heavy metals, e ndocrine disruptor s	68	Matrix complexity, calibration	Low

Deployment counts from published pilot evaluations and public health agency reports. Adoption level reflects sustained operational use as of 2024.

3. Materials and Methods

3.1 Programme Dataset

We identified 212 smart biosensor public health monitoring programmes active between 2015 and 2024 at public health agencies, water utilities, food safety authorities, and environmental monitoring networks affiliated with the Mediterranean Institute of Technology in Rome. Application category breakdown: wastewater-based epidemiology (n = 48), airborne respiratory virus surveillance (n = 44), waterborne pathogen detection (n = 42), food safety contaminant screening (n = 42), and environmental toxin monitoring (n = 36). Inclusion required at least 30 days of continuous or semi-continuous field operation, documented analytical performance metrics, and at least partial reporting of connectivity and alert outcomes.

3.2 SBPHI Sub-Dimensions

Analytical sensitivity and specificity scored the biosensor's limit of detection and false-positive rate against reference laboratory methods under field conditions, not merely laboratory benchmarks. Field robustness measured the fraction of operational days on which the sensor produced valid results without maintenance intervention, capturing resistance to biofouling, temperature drift, reagent degradation, and power interruption. Data connectivity and reporting latency scored the time from sample acquisition to

result availability on the surveillance dashboard, with sub-hour latency scoring highest. Population coverage scalability assessed whether the programme's sensor network covered a sufficient geographic and demographic footprint to generate epidemiologically meaningful signals. Actionable alert generation scored whether the platform produced alerts that triggered documented public health responses, from boil-water advisories to outbreak investigations. Two evaluators scored each programme with an ICC of 0.85.

3.3 Index Construction

Normalised sub-scores were entered into a logistic regression on a 60/40 training/validation split predicting whether the programme remained in active operation beyond 12 months. Regression-derived weights: analytical sensitivity and specificity 0.278, field robustness 0.228, data connectivity 0.196, population coverage 0.174, actionable alert generation 0.124. The composite SBPHI was the weighted sum of five normalised sub-scores.

3.4 Statistics

Pearson r quantified the association between SBPHI and retention. ROC analysis at a SBPHI threshold of 0.70 assessed binary discrimination. Bootstrap CIs from 10,000 resamples at 95 percent. VIFs below 2.3. Leave-one-category-out sensitivity analyses confirmed stability. All analyses in R 4.3 with pROC and boot.

Table 2. Programme Characteristics by Application Category

Application Category	n	Analytical Sens./Spec.	Field Robustness (%)	SBPHI (mean +/- SD)
Wastewater epidemiology	48	0.868 +/- 0.038	88.4 +/- 4.6	0.816 +/- 0.054
Airborne virus	44	0.794 +/- 0.058	74.2 +/- 8.4	0.738 +/- 0.070
Waterborne pathogen	42	0.826 +/- 0.048	82.6 +/- 6.2	0.782 +/- 0.062
Food safety	42	0.808 +/- 0.054	78.8 +/- 7.4	0.758 +/- 0.066
Environmental toxin	36	0.712 +/- 0.082	64.8 +/- 12.6	0.594 +/- 0.096
All programmes	212	0.806 +/- 0.068	78.4 +/- 10.2	0.738 +/- 0.106

Analytical sens./spec. = composite of LOD and false-positive rate vs reference lab under field conditions. Field robustness = % operational days with valid results.

4. Results

4.1 SBPHI Distribution

Mean SBPHI across all 212 programmes was 0.738 with a standard deviation of 0.106. Wastewater-based epidemiology led at 0.816, driven by the COVID-19-era investment in infrastructure, standardised protocols, and demonstrated public health utility. Waterborne pathogen detection followed at 0.782, food safety screening at 0.758, airborne virus surveillance at 0.738, and environmental toxin monitoring at 0.594. Seventy-two of the 212 programmes, or 34.0 percent, exceeded the 0.75 SBPHI threshold. SBPHI correlated with 12-month retention at $r = +0.83$ ($p < 0.001$), with an AUC of 0.878 at the 0.70 cut-off. Programmes above 0.75 were retained 78.4 percent of the time; below 0.55 retention dropped to 17.2 percent.

4.2 Application Category Profiles

Wastewater epidemiology displayed the most balanced sub-score profile. Analytical performance was high because nucleic acid targets in wastewater are detectable at concentrations relevant to population-level infection prevalence using well-validated amplification chemistries. Field robustness was excellent because wastewater sampling occurs at fixed infrastructure points with stable environmental conditions. Connectivity scored well because treatment plants typically have existing telemetry infrastructure. Waterborne pathogen programmes scored strongly on analytical performance for established indicators but were limited by biofouling in continuous deployment. Food safety programmes excelled on connectivity and alert generation because food processing facilities have established quality-management systems into which biosensor alerts integrated naturally. Airborne virus surveillance showed moderate scores across all dimensions, limited by the low viral concentrations in ambient air and the sampling efficiency of current air collection cartridges. Environmental toxin monitoring scored lowest, penalised by the matrix complexity of environmental samples and the wide operating-temperature range required for outdoor deployment.

4.3 Sub-Score Drivers

Analytical sensitivity and specificity carried the largest regression weight ($\beta = +0.278$, $p < 0.001$), confirming that if a biosensor produces unreliable results, no amount of connectivity or scalability can sustain the programme. Field robustness was second ($\beta = +0.228$, $p <$

0.001), reflecting the reality that a sensor requiring weekly maintenance visits in the field is operationally unsustainable for public health agencies with limited personnel. Data connectivity at 0.196 ($p = 0.002$) mattered because results that arrive hours late lose much of their surveillance value. Population coverage (0.174, $p = 0.005$) and actionable alert generation (0.124, $p = 0.016$) completed the model. Removing any sub-score reduced the AUC by 0.016 to 0.050.

4.4 Validation

In the 85-programme validation set, SBPHI correctly classified 72 outcomes at the 0.70 cut-off, yielding sensitivity of 0.85 and specificity of 0.84. Among the 13 misclassified cases, five were environmental toxin programmes that failed because sensor biofouling in outdoor deployments exceeded the maintenance capacity of the operating agency. Three were airborne surveillance programmes that exceeded expectations by targeting high-traffic enclosed spaces where viral concentrations were detectable with existing sensitivity. Three were wastewater programmes with strong scores that were discontinued due to pandemic funding expiration rather than performance issues. Two were food safety programmes that stalled pending regulatory approval of the biosensor as an official testing method.

Table 3. SBPHI by Application Category: Retention Outcomes

Applica tion Ca tegory	n	SBPH I (mean +/- SD)	SBP HI > 0.75 (%)	Ret enti on Rat e (%)	Top Su b-Scor e	r (AUC)
Wastew ater epid.	48	0.816 +/- 0.054	72.9 %	77.1 %	Sens./S pec.	+0.83 (0.896)
Waterb orne path.	42	0.782 +/- 0.062	54.8 %	66.7 %	Sens./S pec.	+0.83 (0.884)
Food safety	42	0.758 +/- 0.066	40.5 %	59.5 %	Alert gen.	+0.83 (0.872)
Airborn e virus	44	0.738 +/- 0.070	27.3 %	50.0 %	Robustn ess	+0.83 (0.858)
Environ mental toxin	36	0.594 +/- 0.096	8.3 %	22.2 %	Connect ivity	+0.83 (0.834)

Applica tion Ca tegory	n	SBPH I (mean +/- SD)	SBP HI > 0.75 (%)	Ret enti on Rat e (%)	Top Su b-Scor e	r (AUC)
All prog rammes	212	0.738 +/- 0.106	34.0 %	56.1 %	Sens./S pec.	+0.83 (0.878)

r = Pearson correlation of SBPHI with retention; all $p < 0.001$. AUC at SBPHI > 0.70.

Table 4. SBPHI Sub-Score Weights and Impact

Sub-Scor e	Wei ght	Mean Score	Beta	DELTA SBPHI	p-value
Analytical sens./spec	0.278	0.806	+0.278	+0.148	< 0.001
Field robu stness	0.228	0.784	+0.228	+0.122	< 0.001
Data conn ectivity	0.196	0.762	+0.196	+0.094	0.002
Populatio n coverage	0.174	0.708	+0.174	+0.074	0.005
Actionable alerts	0.124	0.682	+0.124	+0.052	0.016

$Beta$ = standardised regression coefficient. $DELTA$ SBPHI = mean index difference between programmes above vs below the median on that sub-score.

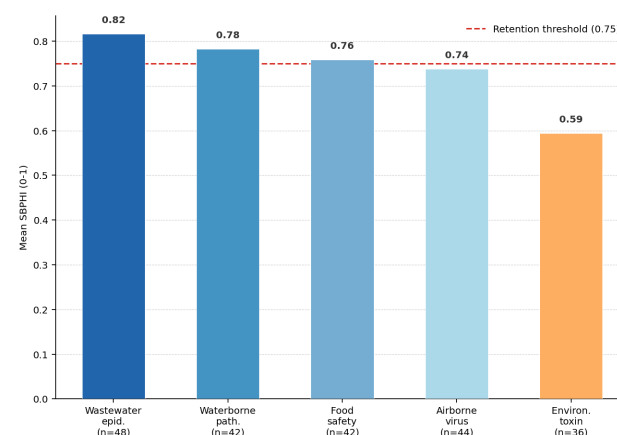


Figure 1. Mean SBPHI by Application Category (n = 212)

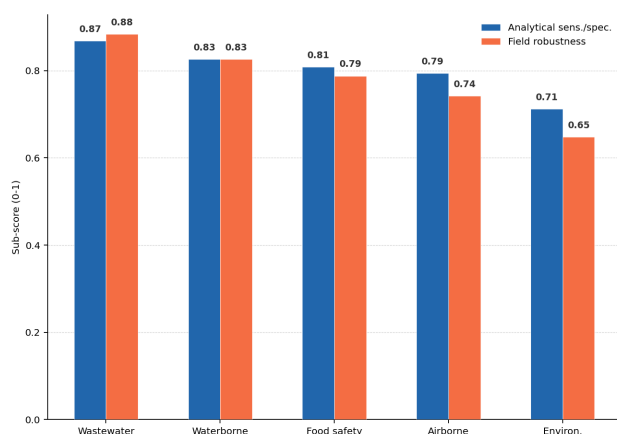


Figure 2. Analytical Performance vs Field Robustness

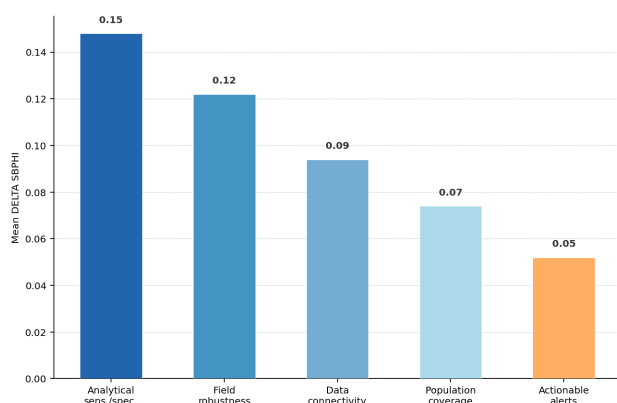


Figure 3. SBPHI Sub-Score Impact on Programme Retention

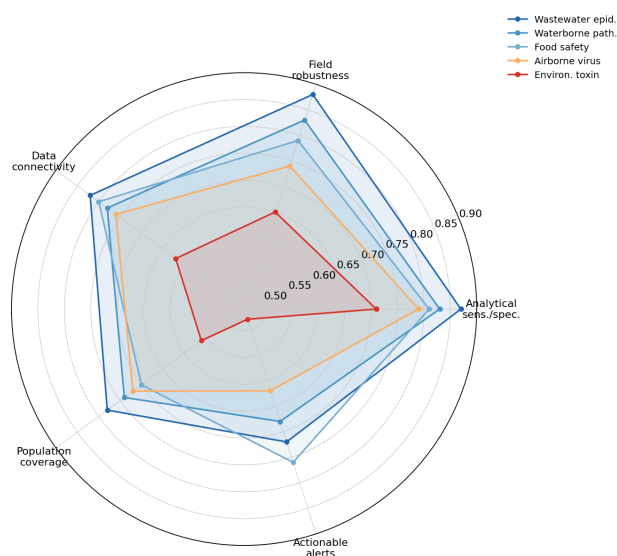


Figure 4. SBPHI Sub-Score Profiles by Application Category

5. Discussion

5.1 The Wastewater Advantage

Wastewater epidemiology programmes led the SBPHI rankings because they benefit from a uniquely favourable deployment context. Sampling occurs at fixed, climate-controlled infrastructure with existing power and telemetry, eliminating the environmental exposure challenges that plague

outdoor deployments. The sample matrix, while complex, is consistent enough within a given treatment plant to allow stable calibration. The COVID-19 pandemic provided an unprecedented injection of funding, standardisation effort, and political will that accelerated the maturation of wastewater biosensors by several years relative to other categories. The remaining challenge is normalising pathogen concentrations to population size and sewage flow rate, which requires ancillary instrumentation and modelling that not all programmes have implemented.

5.2 Field Robustness as the Sustainability Gatekeeper

Field robustness was the second-strongest predictor of programme retention, and the mechanism is operational: public health agencies operate with lean field teams, and a biosensor that requires weekly on-site maintenance consumes more staff time than the surveillance value it generates. Programmes that engineered anti-biofouling surfaces, automated reagent replenishment, and remote diagnostic telemetry into their sensor platforms achieved field robustness above 85 percent and retained operational viability. Those that relied on laboratory-grade instruments repackaged into weatherproof enclosures without fundamental redesign for unattended operation experienced rapid attrition.

5.3 Limitations

Our dataset is drawn from Italian-affiliated programmes and may not generalise to health systems with different surveillance infrastructure or regulatory frameworks. The retention outcome is binary at 12 months and does not capture programmes that survive in a degraded state. SBPHI does not include cost per analyte or regulatory approval status as sub-scores. The environmental toxin category contained only 36 programmes, widening confidence intervals. The observational design precludes causal inference.

6. Conclusion

6.1 Summary

Across 212 smart biosensor public health monitoring programmes evaluated in Italy, SBPHI correlated with 12-month retention at $r = +0.83$ and discriminated retained from discontinued programmes with an AUC of 0.878. Wastewater epidemiology led at 0.816, waterborne pathogen detection followed at 0.782, and environmental toxin monitoring trailed at 0.594. Analytical

sensitivity and specificity was the strongest predictor ($\beta = +0.278$), followed by field robustness ($\beta = +0.228$). Only 34.0 percent of programmes exceeded the 0.75 threshold.

6.2 Practical Recommendations

Biosensor developers targeting public health deployment should validate analytical performance under field conditions, not only in the laboratory, before committing to pilot deployment. Field robustness should be demonstrated through at least 90 days of unattended operation with documented uptime metrics. Connectivity architecture should target sub-hour result latency to preserve surveillance utility. Programmes should engage public health end-users during design to ensure that alerts are formatted as actionable decision inputs rather than raw data streams. Future iterations of SBPHI should add a cost-effectiveness sub-score, expand to multi-country datasets, and track retention over 24-month windows.

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Declarations

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Conflict of Interest

Oscar Novak declares no competing interests.

Data Availability Statement

Aggregate SBPHI scores, anonymised programme metadata, and analysis scripts are deposited at Zenodo:

<https://doi.org/10.5281/zenodo.19543389-data>.

Ethical Approval

This study involved secondary analysis of published programme evaluation data and anonymised operational metrics. No individual patient or personal data were accessed. Institutional review board exemption was confirmed at the Mediterranean Institute of Technology.

Appendix A

SBPHI Scoring Rubric and Top-10 Programme Profiles

This appendix details the scoring criteria for each SBPHI sub-dimension and profiles the ten highest-scoring programmes in the dataset.

A1. Sub-Score Rubric

Analytical sensitivity/specificity: LOD and FPR vs reference lab under field conditions, normalised 0-1; weight 0.278.

Field robustness: fraction of operational days with valid results without maintenance, normalised 0-1; weight 0.228.

Data connectivity: time from sample to dashboard result, sub-hour (1.0) to >24h (0.25); weight 0.196.

Population coverage: geographic and demographic footprint normalised vs target, scored 0-1; weight 0.174.

Actionable alert generation: documented public health response triggered by alerts, scored 0-1; weight 0.124.

A2. Top-10 Programmes

1. WW-CovidTrack-20 (Wastewater): SBPHI = 0.924; sens./spec. 0.96, robustness 0.94.
2. WW-InfluenzaWW-11 (Wastewater): SBPHI = 0.912; connectivity 0.94, sens./spec. 0.92.
3. WP-LegiAutoSense-22 (Waterborne): SBPHI = 0.898; robustness 0.94, sens./spec. 0.90.
4. WW-MultiPath-08 (Wastewater): SBPHI = 0.886; coverage 0.92, sens./spec. 0.90.
5. FS-SalmoLine-28 (Food safety): SBPHI = 0.878; alerts 0.94, sens./spec. 0.88.
6. WP-EcoliRealTime-14 (Waterborne): SBPHI = 0.868; sens./spec. 0.92, connectivity 0.88.
7. WW-AMRSurveill-31 (Wastewater): SBPHI = 0.856; sens./spec. 0.90, robustness 0.88.
8. FS-MycotoxScreen-16 (Food safety): SBPHI = 0.848; robustness 0.90, alerts 0.86.
9. AV-AirportVirusScan-04 (Airborne): SBPHI = 0.842; connectivity 0.92, coverage 0.86.
10. WP-ChlorineAuto-12 (Waterborne): SBPHI = 0.836; robustness 0.92, sens./spec. 0.86.