

Article

A Reference-Value-Based Drinking-Water Quality Deterioration Index for Sustainable Monitoring of Water Supply Network Points

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Abstract

Drinking-water management requires tools that can support the interpretation of multi-parameter monitoring data beyond binary compliance assessment. The novelty of this study lies in adapting a reference-value-based deterioration logic to treated drinking water monitored at network points and combining it with parameter eligibility rules, treatment of results below LoQ, contribution analysis, and sensitivity testing. This study proposes the Drinking-Water Quality Deterioration Index (DWQDI) as a simple, transparent tool for screening reference-value-based water-quality deterioration signals in chemical and physicochemical monitoring data from water supply network points. This index is based on the ratio of concentration to a reference value and was developed for treated drinking water monitored in the distribution network; it expresses reference-value proximity within monitored samples rather than temporal change in water quality. It does not replace formal compliance assessment or health risk assessment but rather provides a complementary tool for sustainable and risk-oriented monitoring. The proposed index was applied to an extended chemical monitoring dataset comprising 25 drinking-water samples collected from 16 anonymized network locations between 2021 and 2026. The dataset included 59 chemical and physicochemical parameters, and a significant proportion of results were below the analytical limits of quantification. Baseline DWQDI values ranged from 0.030 to 0.147, with all samples classified as having very low deterioration. Despite the absence of deterioration due to exceedances, the index differentiated samples and identified the main factors contributing to the deterioration signal. The permanganate index, Total THM, and nickel accounted for most of the total normalized load. The proposed index can help water utilities identify network samples, locations, and parameters requiring further diagnostic investigation and can be implemented in other water supply systems using routinely available monitoring data.



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1. Introduction

Ensuring the safety of water intended for human consumption remains one of the fundamental tasks of water supply systems. However, in recent years, the approach towards drinking-water safety in Europe has shifted significantly from traditional compliance monitoring towards risk-based management. The Directive (EU) 2020/2184 requires the

entire water supply chain to be taken into account, from the catchment and abstraction area, through treatment, storage and distribution, right up to the point of compliance [1]. The transposition of these requirements into Polish law has introduced a clear distinction between compliance monitoring and operational monitoring and has emphasized the importance of representative sampling points within the water supply network [2,3]. This shift is consistent with international water safety planning and risk management guidance for drinking-water supplies [4–6].

In water management practice, water quality monitoring results are often interpreted primarily in binary terms: as either compliant or non-compliant with a parametric value. While such an interpretation is necessary from a legal perspective, it is not always sufficient for the management of a water supply network. Water that meets the formal requirements may still show variations between points in the network, across years or between groups of parameters. These differences may result, among other things, from retention time, hydraulic conditions, the depletion of the disinfectant, the presence of disinfection by-product precursors, pipe materials, deposits or local operational conditions [7–16]. For this reason, tools are needed that do not replace compliance assessments but help to better interpret monitoring data falling below the parametric values.

Various water quality indices have been widely used for the synthetic assessment of water quality, including the classic WQI, indices based on the weighting of parameters, multi-criteria methods, and indicators relating concentrations to limit values [17–29]. A majority of these methods were developed for surface water, groundwater, catchment areas, or the general classification of water resource quality. Their direct application to treated water at points in the water supply network is limited. Tap water requires a different interpretation from natural waters, as it is assessed against parametric values, often contains many results below the limit of quantification, and some parameters are grouped, such as total trihalomethanes, total pesticides, or polycyclic aromatic hydrocarbons [1–3,14–16].

Conceptually, DWQDI differs from conventional WQI-type indices [17–29] in its assessment object, input logic and interpretation. It is not intended to classify water resources or produce a general water-quality grade. Instead, it uses drinking-water parametric values as parameter-specific reference points to quantify reference-value-based deterioration signals in treated water at network monitoring points. The method is unweighted by design, avoids simultaneous use of aggregate and compound-level parameters, explicitly accounts for values reported below LoQ, and separates sample ranking from parameter contribution. Therefore, the arithmetic mean used in DWQDI is only the aggregation step of a network-point-oriented procedure, not the full methodological contribution of the index.

There is therefore a gap between the formal assessment of compliance and the practical need to compare network points on the basis of multi-parameter monitoring data. In particular, there is a lack of a simple, auditable and transferable indicator for selected chemical and physicochemical monitoring data that would show reference-value-based deterioration signals at network points, while remaining consistent with the logic of the reference values used in the regulations. This indicator should be applicable to typical laboratory data, without the need for a hydraulic model, detailed infrastructure data, exposure data or toxicological parameters. It should also allow for the transparent treatment of results reported as below the limit of quantification [30–33].

The aim of this study was to develop and apply the Drinking-Water Quality Deterioration Index, referred to as DWQDI, to interpret monitoring data from points in the water supply network. The index is based on the relationship between the measured concentration of a parameter and an adopted reference value. It was intended as a tool to support sustainable and risk-oriented monitoring, rather than as a tool for formal compliance assessment, health risk assessment or temporal degradation analysis.

The specific objectives were to define the DWQDI calculation procedure, apply it to an anonymized monitoring dataset from water supply network points, identify the parameters contributing most strongly to the deterioration signal, and test the stability of sample ranking under alternative treatments of values below LoQ.

The scientific contribution of this study does not lie in introducing a new mathematical normalization formula, but in adapting a reference-value-based deterioration logic to treated drinking water monitored at network points and embedding it in a transparent procedure that includes parameter eligibility, treatment of results below LoQ, contribution analysis, and sensitivity testing. In this study, deterioration is therefore understood as a reference-value-based screening signal, not as demonstrated temporal degradation of water quality.

Three research assumptions were adopted. Firstly, monitoring data that meet quality requirements may still show measurable differences in the degree of relative deterioration in water quality between network samples. Secondly, the aggregated signal of quality deterioration may be governed by a small group of parameters, such as indicators of organic matter, disinfection by-products, or selected metals. Thirdly, the ranking of samples obtained using the DWQDI should remain stable regardless of how results below the limit of quantification are treated.

The proposed approach was applied to an extended chemical monitoring dataset comprising 25 drinking-water samples collected from 16 anonymized water supply network locations between 2021 and 2026. The analysis included parameter selection, unit harmonization, assignment of reference values, treatment of left-censored data, calculation of DWQDI, parameter contribution analysis, and sensitivity testing. This approach made it possible to assess whether a simple monitoring-based indicator can support the interpretation of drinking-water quality in distribution networks and identify samples, locations, or parameters requiring further diagnostic attention.

2. Materials and Methods

2.1. Study Design and Regulatory Context

This study was designed as a methodological and empirical assessment of drinking-water quality deterioration at monitoring points within a municipal water supply network. The proposed Drinking-Water Quality Deterioration Index, hereafter referred to as DWQDI, was developed to support the interpretation of selected chemical and physicochemical monitoring data collected at the distribution stage of a water supply system. Data preparation, calculations, all analyses and graphical presentation of the results, including Figures, were performed using Microsoft Excel for Microsoft 365 (Microsoft Corporation, Redmond, WA, USA). The index expresses measured concentrations in relation to parameter-specific reference values and provides a comparable measure of reference-value proximity across network samples and monitoring locations.

DWQDI was not intended to replace legal compliance assessment, regulatory monitoring programs or quantitative health risk assessment. Compliance with drinking-water requirements remains determined by the applicable sampling procedures, analytical methods, parametric values and decisions of the competent authority. The role of DWQDI is different. It provides an additional interpretive layer that helps identify network points and parameters for which measured values are closer to reference levels, even when no formal exceedance is observed.

The methodological position of the index reflects the current shift in European drinking-water regulation from a mainly compliance-based approach towards risk-based water safety management. Directive (EU) 2020/2184 requires a risk-based approach covering the whole supply chain, including abstraction areas, treatment, storage, and distribution

up to the point of compliance [1]. In the Polish legal framework, this approach is reflected in the distinction between compliance monitoring and operational monitoring, and in the obligation to designate representative sampling points in the water supply network [2]. The current Polish drinking-water quality regulation provides the parametric values and analytical requirements used as reference points in the present study [3]. All historical samples were retrospectively normalized using this common set of reference values to ensure consistent comparison across the complete dataset. These calculations do not constitute retrospective legal compliance assessments.

The index focuses on water supply network points rather than abstraction areas, treatment plant performance or internal building installations. Treatment plant outlet data may be used as background information, but the main DWQDI assessment is based on samples collected within the distribution network. This distinction is important because the index is intended to support sustainable monitoring of the network stage, where water quality may be affected by distribution conditions, residence time, disinfectant decay, pipe materials, deposits and other system-specific factors.

The general position of DWQDI within risk-based drinking-water monitoring is presented in Figure 1.

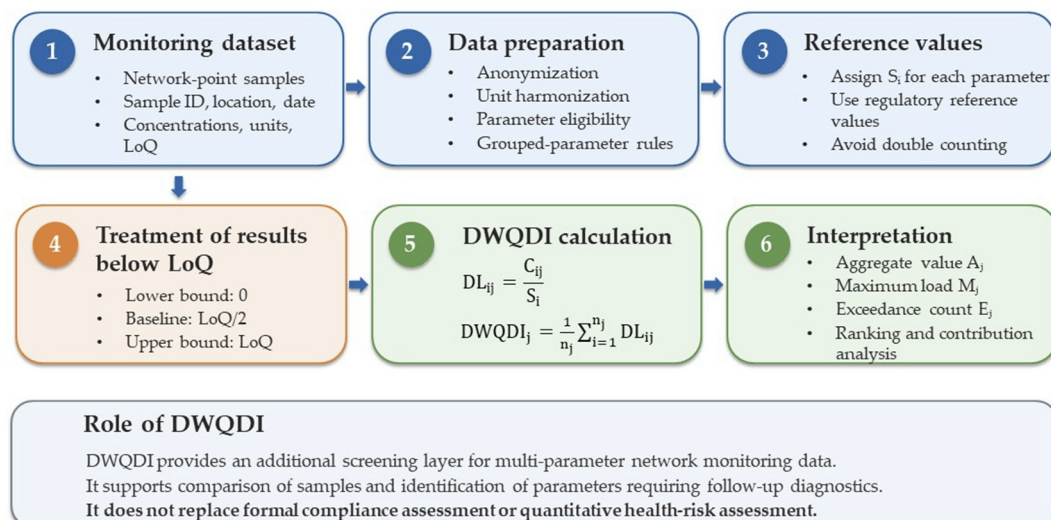


Figure 1. Conceptual workflow of DWQDI for sustainable monitoring of water supply network points.

DWQDI uses harmonized monitoring data and reference values to quantify reference-value-based deterioration signals at water supply network points.

2.2. Monitoring Dataset and Network-Point Selection

The empirical part of the study was based on an extended chemical monitoring dataset collected from a municipal water supply network. The dataset included 25 drinking-water samples collected between March 2021 and May 2026 from 16 network monitoring locations. Some locations were sampled more than once, whereas others were represented by a single observation. For this reason, the primary DWQDI calculations were carried out at the sample level. A location-level aggregation equation is provided as an optional extension, but the empirical interpretation remained sample-based because the monitoring design was unbalanced.

To maintain confidentiality and avoid disclosing sensitive information on water supply infrastructure, the original sampling locations were anonymized. Network monitoring locations were coded as N1 to N16, and individual samples were coded as S1 to S25.

The anonymization procedure did not affect the analytical results, sampling dates, or the assignment of samples to monitoring locations.

The dataset comprised 59 chemical and physicochemical parameters. These included metals and metalloids, volatile organic compounds, pesticides, disinfection by-products, polycyclic aromatic hydrocarbons, organic matter indicators and selected operationally relevant parameters. The monitoring results were reported either as quantified concentrations or as values below the analytical quantification limit. Since a large part of the dataset consisted of left-censored observations, these results were retained in the analysis and treated according to the procedure described in Section 2.5.

Before the calculation of DWQDI, the dataset was reviewed for completeness, consistency of units, and suitability of individual parameters for index calculation. Parameters were included in the main index only when their analytical unit was unambiguous, a numerical reference value was available, and their inclusion did not lead to double counting of the same chemical group. For grouped parameters, aggregate values were preferred in the main DWQDI calculation when this was consistent with the regulatory reference value. This rule was applied in particular to total trihalomethanes, total polycyclic aromatic hydrocarbons and pesticide-related parameters.

Treatment plant outlet data were not included in the main DWQDI ranking and were not used to calculate changes between treatment and distribution. They were treated only as general background information on treated water quality. This separation was necessary because the available records did not provide paired treatment-plant-outlet and network observations, and the purpose of the study was to compare monitoring samples at network points rather than to quantify temporal or spatial changes across the treatment-distribution boundary. The available retrospective monitoring records did not include complete metadata on flushing or stagnation conditions, detailed sampling point type, analytical equipment, quality-control records, or parameter-specific expanded uncertainty. Therefore, metal-related signals, especially nickel and copper, were interpreted only as sample-level screening signals and were not attributed directly to the distribution network, internal installation, or sampling procedure.

The parameters considered for DWQDI calculation are presented in Table 1.

Table 1. Parameters considered for DWQDI calculation and reference values.

Parameter	Calculation Unit	Reference Value (S_i)	Use in DWQDI	Comment
Total THM	µg/L	100 µg/L	main	Main DBP parameter; individual THM species used only diagnostically
Total PAHs	µg/L	0.10 µg/L	main	Aggregate PAH parameter; values below LoQ treated according to Section 2.5
Boron	mg/L	1.5 mg/L	main	Direct ratio calculation
Copper	mg/L	2.0 mg/L	main	Direct ratio calculation
Nickel	µg/L	20 µg/L	main	Direct ratio calculation
Chromium	µg/L	50 µg/L	main	Current value: 25 µg/L discussed as future stricter value
Permanganate index	mg/L O ₂	5.0 mg/L O ₂	main	Indicator of oxidisable organic matter
Sodium	mg/L	200 mg/L	conditional	Indicator parameter; optional operational variant
Silver	mg/L	0.010 mg/L	conditional	Relevant if silver-containing materials or disinfection are applicable
Pesticides	µg/L	0.10 or 0.50 µg/L	conditional	Individual and total pesticide values not used together
Trichloromethane	µg/L	30 µg/L	diagnostic	Not included together with Total THM
Bromodichloromethane	µg/L	15 µg/L	diagnostic	Not included together with Total THM
Tetrachloromethane	µg/L	not assigned	diagnostic	Excluded from main DWQDI unless a reference value is adopted
TOC	mg/L	not assigned	diagnostic	No fixed numerical parametric value
Magnesium	mg/L	7–125 mg/L	diagnostic	Range parameter; not used in simple (C_i/S_i) calculation

S_i denotes the reference value adopted for parameter i . Parameters classified as “main” were included in the baseline DWQDI calculation. Parameters classified as “conditional” may be included only in a clearly defined variant of the index. Parameters classified as “diagnostic” were retained for interpretation but were not included in the main DWQDI calculation. Total THM was used instead of individual THM species to avoid double counting of disinfection by-products. Reference values are based on the current Polish drinking-water quality regulation implementing Directive (EU) 2020/2184 [3].

2.3. Parameter Eligibility, Grouped Parameters and Unit Harmonization

The calculation of DWQDI required prior verification of parameter eligibility. A parameter was included in the main index only when three conditions were met. First, the analytical unit had to be confirmed. Second, a numerical reference value had to be available. Third, the inclusion of the parameter could not duplicate another aggregate parameter representing the same chemical group.

The baseline DWQDI was restricted to parameters that were quantified at least once, with the exception of Total PAHs, which were retained as a regulated aggregate group because the reported LoQ was low relative to the reference value. This rule was used for the present empirical application and should not be interpreted as allowing direct comparison between datasets calculated from different analytical packages. For comparative applications, the eligible parameter set should be defined before calculation and kept constant across compared samples or systems. Additional groups, such as metals, disinfection by-products or indicator parameters, may also be reported as separate modules. Parameters reported exclusively below LoQ and not used in the baseline index were retained in the dataset but excluded from the main calculation to avoid dilution of the index by uniformly non-quantified screening parameters.

For grouped parameters, aggregate values were preferred in the main DWQDI calculation. Total THM was included as the main disinfection by-product indicator because this parameter has a regulatory reference value and represents the combined concentration of regulated THM compounds. Individual THM species, including trichloromethane and bromodichloromethane, were retained for diagnostic interpretation of the THM profile, but they were not included together with Total THM in the main index calculation.

The same principle was applied to polycyclic aromatic hydrocarbons and pesticides. If an aggregate value was available and corresponded to a regulatory reference value, the aggregate parameter was used in the main calculation. Individual compounds belonging to the same group were retained for supporting interpretation unless a separate compound-level analysis was required.

Parameters with recommended ranges rather than single upper reference values were not included in the main ratio-based DWQDI. This applied, for example, to magnesium. Such parameters were retained for descriptive interpretation because a simple concentration-to-reference ratio would not adequately represent their regulatory or health-related meaning. Therefore, the baseline DWQDI should be interpreted as an index for selected chemical and physicochemical parameters with one-sided upper reference values, not as a general index for all drinking-water quality parameters.

2.4. Development of the Drinking-Water Quality Deterioration Index

DWQDI was based on the relationship between a measured concentration and the adopted reference value for the same parameter. First, a parameter-level deterioration load was calculated for each eligible parameter in each sample (Equation (1)).

$$DL_{ij} = \frac{C_{ij}}{S_i} \quad (1)$$

where

DL_{ij} —the normalized concentration-to-reference ratio of parameter i in sample j ;
 C_{ij} —the harmonized concentration of parameter i measured or substituted in sample j ;
 S_i —the adopted reference value for parameter i ;
 i —the parameter index;
 j —the sample index.

A value of DL_{ij} below 1.00 means that the concentration of a given parameter is below the adopted reference value. A value equal to or greater than 1.00 means that the concentration reaches or exceeds the adopted reference value. In this study, DL_{ij} was interpreted as a relative deterioration signal, not as a direct measure of health risk.

The aggregation step was deliberately kept as an unweighted arithmetic mean to maintain auditability and avoid introducing subjective parameter weights. This choice does not imply that all parameters have the same health or regulatory significance; it only means that DWQDI was designed as a screening-level proximity indicator rather than a weighted health-risk or compliance-severity index. This differs from many WQI formulations, in which normalized subindices are combined with assigned weights to obtain a general water-quality class. In DWQDI, the arithmetic mean is used only to summarize eligible deterioration loads after the rules for parameter inclusion, grouped parameters, and left-censored data are applied.

Similar WQI-type and drinking-water index approaches from the consulted literature [17–29] were considered as methodological background, but they were not directly adopted because they differ from DWQDI in assessment object, weighting assumptions, treatment of grouped parameters, or handling of values reported below LoQ.

The sample-level DWQDI was calculated as the arithmetic mean of deterioration loads for all eligible parameters included in a given sample. To calculate the DWQDI, Equation (2) can be used:

$$DWQDI_j = \frac{1}{n_j} \sum_{i=1}^{n_j} DL_{ij} \quad (2)$$

where

$DWQDI_j$ —the Drinking-Water Quality Deterioration Index for sample j ;

n_j —the number of eligible parameters included in the calculation for sample j ;

DL_{ij} —the normalized concentration-to-reference ratio of parameter i in sample j .

Where more than one sample was available for a given monitoring location, a location-level DWQDI can be calculated as the mean of sample-level DWQDI values assigned to that location according to Equation (3).

$$DWQDI_{N_k} = \frac{1}{m_k} \sum_{j=1}^{m_k} DWQDI_j \quad (3)$$

where

$DWQDI_{N_k}$ —the mean DWQDI for monitoring location N_k ;

$DWQDI_j$ —the DWQDI value for sample j collected at monitoring location N_k ;

m_k —the number of samples collected at monitoring location N_k ;

N_k —the anonymized monitoring location.

This aggregation was used only where repeated samples were available. The main analysis remained sample-based because the dataset was not balanced across all monitoring locations.

2.5. Treatment of Left-Censored Results

A substantial part of the dataset consisted of results reported below the analytical quantification limit. These values were treated as left-censored observations. They were not removed from the dataset because their exclusion would artificially reduce the number of parameters included in the calculation and could bias the interpretation of samples with many non-quantified results [30–33].

Three substitution scenarios were used to assess the influence of left-censored observations on DWQDI. The middle-bound scenario was adopted as the baseline calculation. The

lower-bound and upper-bound scenarios were used for sensitivity analysis and presented in Table 2.

Table 2. Treatment of left-censored values in DWQDI calculation.

Scenario	Substitution Rule	Role in the Study	Interpretation
Lower-bound	0	sensitivity analysis	optimistic assumption
Middle-bound	LoQ/2	baseline calculation	intermediate assumption
Upper-bound	LoQ	sensitivity analysis	conservative assumption

LoQ denotes the analytical quantification limit reported for a given parameter in a given sample. The middle-bound scenario was used as a baseline reference scenario for reporting a single set of DWQDI values, but it was not interpreted as the statistically best estimate of the true concentration. The lower-bound and upper-bound scenarios were used as sensitivity bounds to assess the influence of non-quantified results on DWQDI values and sample ranking.

For each result reported as below LoQ, the concentration used in the baseline calculation was assigned according to Equation (4):

$$C_{ij} = \frac{LoQ_{ij}}{2} \quad (4)$$

where

C_{ij} —the harmonized concentration of parameter i measured or substituted in sample j ;

LoQ_{ij} —the analytical quantification limit reported for parameter i in sample j .

The use of the middle-bound scenario avoided both complete removal of non-quantified results and the conservative assumption that all values below LoQ were equal to LoQ. The lower-bound and upper-bound scenarios were then used to test whether the ranking of samples and the interpretation of dominant parameters were stable under different assumptions.

In addition, the analytical quantification limits were compared with the adopted reference values where possible. This step was included because the interpretation of a non-quantified result depends on whether the quantification limit is sufficiently low in relation to the reference value. When the LoQ is high relative to the reference value, a result reported as below LoQ provides weaker information on the actual deterioration level.

2.6. DWQDI Interpretation Classes

The interpretation of DWQDI was based on three complementary quantities. The aggregate value A_j corresponds to the sample level DWQDI and describes the average proximity of all eligible parameters to their adopted reference values. The maximum parameter level load $M_j = \max(DL_{ij})$ identifies the parameter closest to, or exceeding, its reference value. The exceedance count $E_j = \sum I(DL_{ij} \geq 1)$ indicates the number of parameters reaching or exceeding the adopted reference value, where I is equal to one when the condition is met and 0 otherwise. Therefore, the aggregate DWQDI value should not be interpreted alone, but together with M_j and E_j .

The interpretive bands for A_j were not statistically optimized and were not derived from the distribution of the analyzed dataset. This was intentional because the dataset was limited and all samples were compliant; deriving threshold values from these observations would make the bands system-specific and would reduce transferability. The thresholds of 0.30 and 0.60 were adopted to remain consistent with the regulatory monitoring logic based on 30 percent and 60 percent of parametric values [2,3]. The intervals 0.60–0.80 and

0.80–1.00 were introduced as operational warning bands to distinguish values above the low-proximity range from values approaching the adopted reference value. The value 1.00 was retained as a high aggregate warning level. These bands should be interpreted as screening bands for A_j , not as legal decision rules or as classifications of individual parameter-level loads. The interpretation of DWQDI is presented in Table 3.

Table 3. Interpretive bands for the aggregate DWQDI value A_j .

A_j	Class	Interpretation
<0.30	very low average reference proximity	Average normalized load remains far below adopted reference values
0.30 to <0.60	low average reference proximity	Average normalized load is elevated but remains below 60 percent of reference values
0.60 to <0.80	moderate warning	Average value exceeds the low-proximity range and requires closer interpretation together with M_j and E_j
0.80 to <1.00	high warning	Average value is close to adopted reference values and requires diagnostic interpretation
≥ 1.00	high aggregate warning	Average value equals or exceeds 1.00; individual exceedances are reported separately through E_j

The bands refer only to the aggregate DWQDI value A_j . Individual parameter-level loads are interpreted separately using M_j and E_j . The bands were used for screening and ranking only. They do not replace compliance assessment, risk assessment or decisions of the competent authority. If $E_j > 0$, the sample should be flagged as containing one or more parameters reaching or exceeding the adopted reference value, irrespective of the aggregate DWQDI value.

The interpretation of DWQDI was deliberately conservative. A low DWQDI value does not mean that monitoring is unnecessary, and a high DWQDI value does not automatically mean that the water is unsafe. The index indicates relative deterioration in relation to adopted reference values. Formal conclusions on drinking-water compliance and consumer safety remain outside the scope of the index.

2.7. Sensitivity Analysis and Parameter Contribution

Sensitivity analysis was performed as a deterministic robustness assessment of the uncertainty components that could be evaluated from the available monitoring dataset. Two aspects were considered: the treatment of results reported below LoQ and the influence of parameter selection. The baseline calculation used the middle-bound substitution scenario, in which values reported below LoQ were replaced by $\text{LoQ}/2$. Two additional scenarios were tested: a lower-bound scenario, in which values below LoQ were replaced by zero, and an upper-bound scenario, in which they were replaced by LoQ. Parameter selection was assessed using the leave-one-parameter-out procedure described below. Sample-ranking stability was evaluated using Spearman's rank correlation coefficient calculated for the 25 samples. Analytical measurement uncertainty and sampling variability were not quantified because the dataset did not include replicate analyses, duplicate samples, parameter-specific expanded uncertainty values, or a balanced repeated sampling design.

The influence of individual parameters was evaluated using a leave-one-parameter-out procedure. In this procedure, DWQDI was recalculated after removing one parameter from the eligible parameter set using Equation (5):

$$DWQDI_{j,-k} = \frac{1}{n_j - 1} \sum_{\substack{i=1 \\ i \neq k}}^{n_j} DL_{ij} \quad (5)$$

where

$DWQDI_{j,-k}$ —the DWQDI value for sample j after removing parameter k ;

n_j —the number of eligible parameters originally included in sample j ;
 k —the parameter removed from the calculation.

This analysis was used to identify whether the ranking of samples was controlled by one dominant parameter or by a broader group of parameters. Particular attention was paid to Total THM because disinfection by-products are legally regulated and may represent a relevant distribution-stage deterioration signal.

Parameter contribution was also calculated for each sample. The contribution of parameter i to the total deterioration signal in sample j was calculated from Equation (6):

$$PC_{ij} = \frac{DL_{ij}}{\sum_{i=1}^{n_j} DL_{ij}} \cdot 100 \quad (6)$$

where

PC_{ij} —the percentage contribution of parameter i to the total deterioration in sample j ;
 DL_{ij} —the normalized concentration-to-reference ratio of parameter i in sample j ;
 n_j —the number of eligible parameters included in the calculation for sample j ;
 i —the parameter index;
 j —the sample index.

Parameter contributions were aggregated across all samples as the sum of parameter-level loads for a given parameter divided by the sum of all parameter-level loads in the dataset.

The contribution analysis was used to distinguish samples influenced mainly by one parameter group from samples showing a broader deterioration pattern. DWQDI was calculated as an unweighted index; no parameter weights were applied in the baseline calculation or in the sensitivity analysis.

3. Results

3.1. Structure of the Monitoring Dataset and Detection Pattern

The results should be interpreted in view of the dataset structure. The dataset comprised 25 samples from 16 anonymized network monitoring locations, and because the sampling design was unbalanced, the main interpretation was performed at the sample level. The parameters presented in Table 4 were selected because they were either included in the baseline DWQDI calculation or were relevant for interpreting the chemical profile of the monitoring dataset. The selection was based on four criteria: availability of a numerical reference value, relevance to drinking-water quality regulation, occurrence of quantified results in the dataset, and usefulness for interpreting distribution-stage deterioration. Parameters that were reported exclusively below LoQ were retained when they represented regulated aggregate groups and could be handled through the left-censored data procedure.

The detection pattern of the parameters most relevant to DWQDI interpretation is summarized in Table 4.

LoQ denotes the analytical quantification limit. Observed ranges were calculated only from quantified results. For parameters reported exclusively below LoQ, the reported LoQ value is shown instead of a numerical range. Parameters included in this table were selected either because they entered the baseline DWQDI calculation or because they supported diagnostic interpretation of the monitoring dataset.

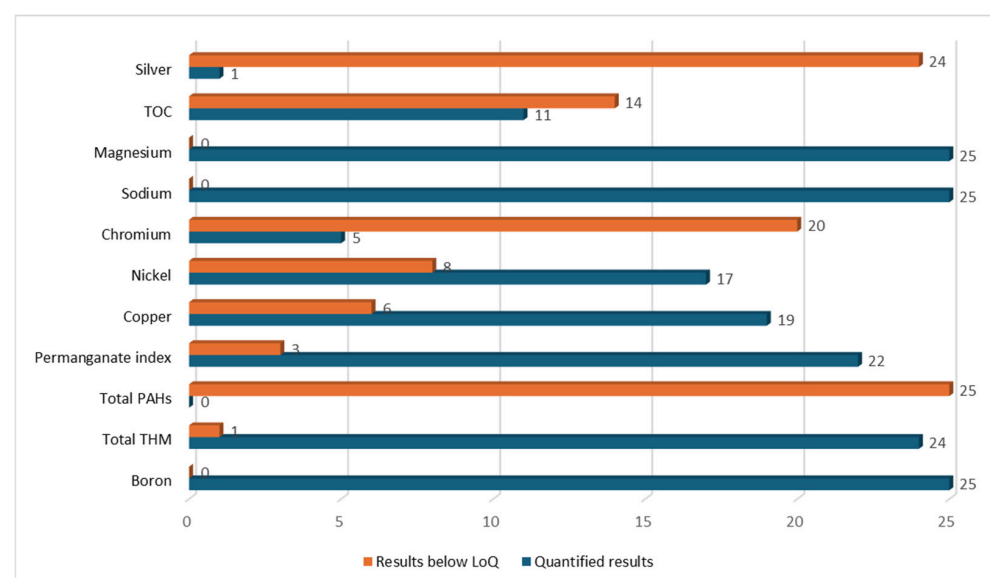
Table 4. Detection frequency and observed ranges of parameters relevant to DWQDI interpretation.

Parameter	Unit	Quantified Results	Results Below LoQ	Observed Range	Reason for Inclusion
Boron	mg/L	25/25	0/25	0.033–0.13	Regulated chemical parameter, quantified in all samples
Total THM	µg/L	24/25	1/25	1.2–26	Regulated DBP group and key distribution-stage indicator
Total PAHs	µg/L	0/25	25/25	<0.005	Regulated aggregate parameter, included through left-censored data treatment
Permanganate index	mg/L O ₂	22/25	3/25	0.51–2.5	Indicator of oxidisable organic matter and water-quality change
Copper	mg/L	19/25	6/25	0.00094–0.0051	Regulated metal, relevant to materials and distribution systems
Nickel	µg/L	17/25	8/25	0.61–9.1	Regulated metal with visible contribution to DWQDI
Chromium	µg/L	5/25	20/25	0.54–1.0	Regulated chemical parameter, included despite low detection frequency
Sodium	mg/L	25/25	0/25	9.8–32	Indicator parameter, used for operational interpretation
Magnesium	mg/L	25/25	0/25	10–22	Diagnostic parameter with recommended range, not used in baseline DWQDI
TOC	mg/L	11/25	14/25	2.0–4.2	Diagnostic organic matter indicator without fixed numerical parametric value
Silver	mg/L	1/25	24/25	0.0012	Conditional parameter, relevant only where silver-containing materials or treatment apply

The most frequently quantified parameters were boron, Total THM, permanganate index, copper, and nickel. Total THM was quantified in almost all samples and showed a clear distribution-stage relevance. The maximum observed Total THM concentration was 26 µg/L, which remained below the adopted reference value of 100 µg/L. The permanganate index reached 2.5 mg/L O₂, corresponding to one half of the adopted reference value. Nickel reached a maximum concentration of 9.1 µg/L, which was also below the adopted reference value but had a visible influence on the index in selected samples.

Total PAHs were not quantified in any sample, but the reported LoQ was low in relation to the adopted reference value. In the monitoring dataset, Total PAHs were reported as an aggregate laboratory result and were not reconstructed from individual PAH components. Therefore, Total PAHs were retained in the baseline DWQDI calculation through the middle-bound substitution scenario. Since the same LoQ was reported in all samples, this parameter affected the absolute index value but did not differentiate the ranking of samples. Its inclusion therefore improved regulatory coverage of the baseline parameter set, but it should not be interpreted as evidence of differences between network samples.

Figure 2 presents the number of quantified results and results reported below LoQ for each parameter listed in Table 4.

**Figure 2.** Detection pattern of parameters relevant to DWQDI interpretation.

3.2. Parameter-Level Deterioration Loads

Parameter-level deterioration loads were calculated as ratios between harmonized concentrations and adopted reference values. All parameter-level loads remained below 1.00, which means that none of the parameters included in the baseline DWQDI reached or exceeded its adopted reference value.

The highest parameter-level deterioration loads were observed for the permanganate index, nickel, and Total THM. The permanganate index reached a maximum DL_{ij} of 0.500, nickel reached 0.455, and Total THM reached 0.260. These parameters were therefore the main drivers of the relative deterioration signal. Boron contributed more moderately, with a maximum DL_{ij} of 0.087. Total PAHs contributed a constant baseline load of 0.025 because all values were reported below the same LoQ and were substituted using the middle-bound scenario. Chromium and copper had very low deterioration loads.

Figure 3 presents deterioration loads for the parameters included in the baseline DWQDI calculation. Samples are ordered according to decreasing DWQDI values.

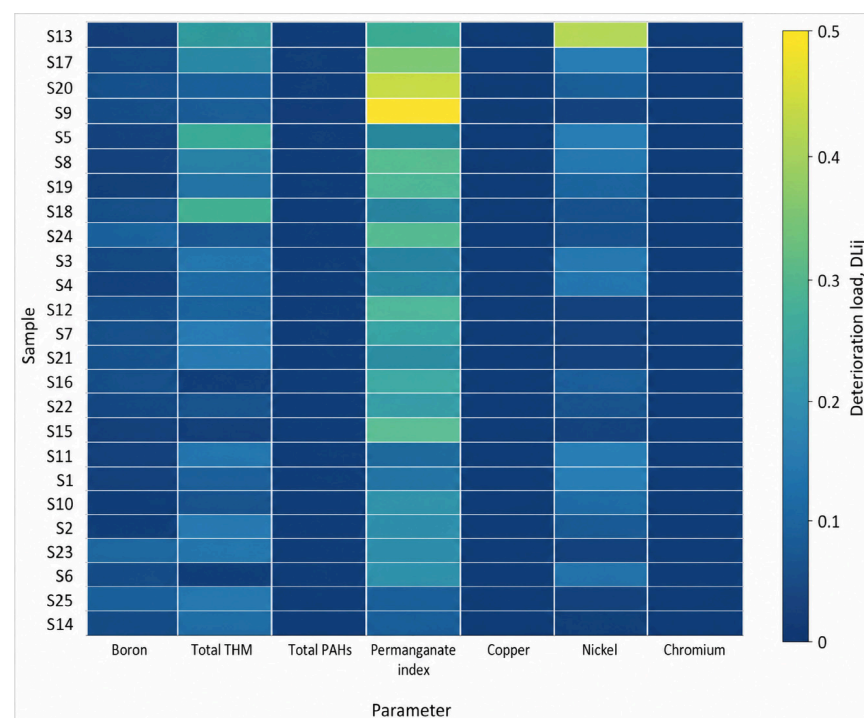


Figure 3. Parameter-level normalized concentration to reference ratios for the DWQDI calculation.

Figure 3 presents parameter-level normalized concentration ratios for parameters included in the baseline DWQDI calculation. Samples are ordered according to decreasing DWQDI values. Lighter cells indicate higher normalized concentration-to-reference ratios.

The map shows that no parameter reached or exceeded its adopted reference value, but selected samples had visible reference-value-based deterioration signals. This distinction is important because the purpose of DWQDI is not only to identify exceedances, but also to compare network samples in terms of their proximity to adopted reference values.

3.3. Worked Example of DWQDI Calculation

To illustrate how the index was calculated, one sample with the highest baseline DWQDI value was selected as a worked example. The sample was coded as S13 and belonged to anonymized monitoring location N3. The calculation was performed using the baseline left-censored data scenario, in which values reported below LoQ were replaced by $LoQ/2$.

The parameter-level deterioration loads for sample S13 are shown in Table 5.

Table 5. Worked example of DWQDI calculation for sample S13.

Parameter	Concentration Used in Calculation C_{ij}	Reference Value S_i	Normalized Concentration-to-Reference Ratio DL_{ij}
Boron	0.094 mg/L	1.5 mg/L	0.0627
Total THM	20 µg/L	100 µg/L	0.2000
Total PAHs	0.0025 µg/L	0.10 µg/L	0.0250
Permanganate index	1.4 mg/L O ₂	5.0 mg/L O ₂	0.2800
Copper	0.00094 mg/L	2.0 mg/L	0.0005
Nickel	9.1 µg/L	20 µg/L	0.4550
Chromium	0.25 µg/L	50 µg/L	0.0050

The sum of the seven normalized concentration-to-reference ratios for sample S13 was 1.0282. Therefore, the DWQDI value was calculated as

$$DWQDI_{S13} = \frac{1.0282}{7} = 0.1469$$

where

$DWQDI_{S13}$ —the Drinking-Water Quality Deterioration Index calculated for sample S13;
 n —the number of eligible parameters included in the calculation ($n = 7$).

The highest normalized concentration to reference ratio in sample S13 was obtained for nickel, followed by the permanganate index and Total THM. This means that the relatively high DWQDI value for this sample was not caused by a regulatory exceedance, but by the combined effect of several parameters approaching their reference values to different degrees. The sample remained within the very low deterioration class because the final DWQDI value was below 0.30.

3.4. DWQDI Values and Ranking of Network Samples

Baseline DWQDI values were calculated using the middle-bound treatment for values below LoQ. The index values ranged from 0.030 to 0.147, with a mean value of 0.064. All samples were classified as representing very low deterioration according to the interpretation classes defined in Table 3.

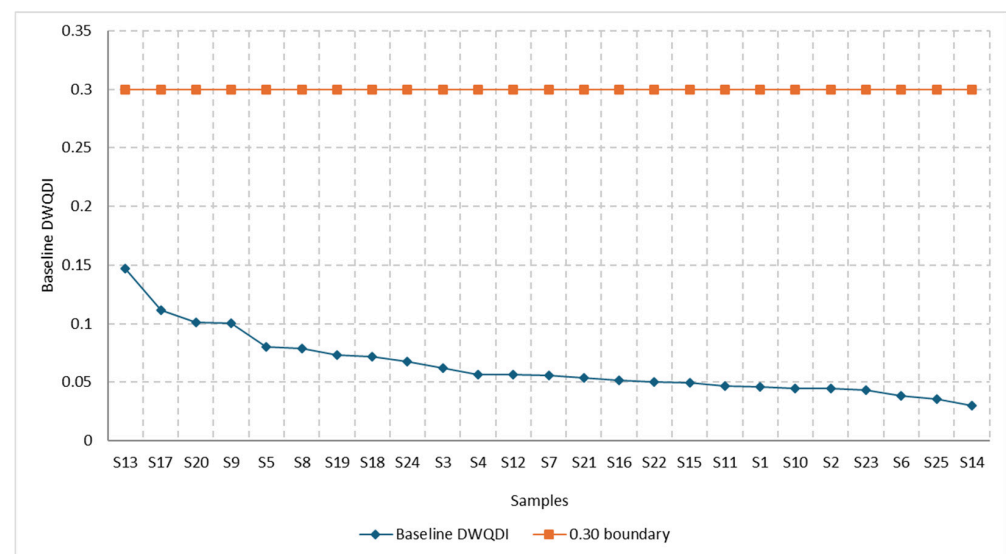
The aggregate DWQDI values were interpreted together with the maximum parameter-level load M_j and the exceedance count E_j . In the analyzed dataset, $E_j = 0$ for all samples, which means that no individual parameter reached or exceeded its adopted reference value. The highest M_j value was 0.500 for sample S9, whereas its aggregate DWQDI value was 0.101, confirming that the aggregate index and maximum parameter-level load provide complementary information.

Although all DWQDI values remained below 0.30, the index differentiated the network samples. The highest DWQDI value was obtained for sample S13, followed by S17, S20 and S9. The highest-ranked samples were influenced mainly by nickel, the permanganate index, and Total THM.

The DWQDI calculation results are shown in Table 6, and the complete ranking of all network samples is presented in Figure 4.

Table 6. Highest aggregate DWQDI values among network samples with maximum parameter-level loads.

Rank	Sample	Location Code	Year	DWQDI _{Aj}	Class	Dominant Parameter	Maximum DL _{ij} M _j
1	S13	N3	2023	0.147	very low deterioration	Nickel	0.455
2	S17	N10	2024	0.112	very low deterioration	Permanganate index	0.460
3	S20	N10	2025	0.101	very low deterioration	Permanganate index	0.480
4	S9	N5	2022	0.101	very low deterioration	Permanganate index	0.500
5	S5	N5	2021	0.080	very low deterioration	Total THM	0.200
6	S8	N4	2022	0.079	very low deterioration	Permanganate index	0.260
7	S19	N11	2024	0.073	very low deterioration	Permanganate index	0.260
8	S18	N4	2024	0.072	very low deterioration	Total THM	0.260
9	S24	N15	2025	0.067	very low deterioration	Permanganate index	0.260
10	S3	N3	2021	0.062	very low deterioration	Total THM	0.120

**Figure 4.** Ranking of network samples according to baseline DWQDI.

Samples are ordered from the highest to the lowest DWQDI value. The dashed line indicates the boundary between very low and low deterioration.

The ranking confirmed that the analyzed samples were far from the adopted reference values when considered as aggregated DWQDI scores. However, the index still provided useful differentiation among network samples. This differentiation was driven by selected parameters rather than by uniform deterioration across all analyzed substances.

3.5. Contribution of Parameters to DWQDI

The contribution analysis showed that the baseline DWQDI was controlled mainly by the permanganate index, Total THM, and nickel. Across all samples, the permanganate index accounted for 45.0 percent of the total deterioration signal. Total THM accounted for 20.7 percent and nickel for 15.7 percent. Boron contributed 11.3 percent, whereas Total PAHs contributed 5.6 percent. Chromium and copper had minor contributions, below 2 percent and below 1 percent, respectively.

Figure 5 presents the percentage contribution of each parameter included in the baseline DWQDI calculation.

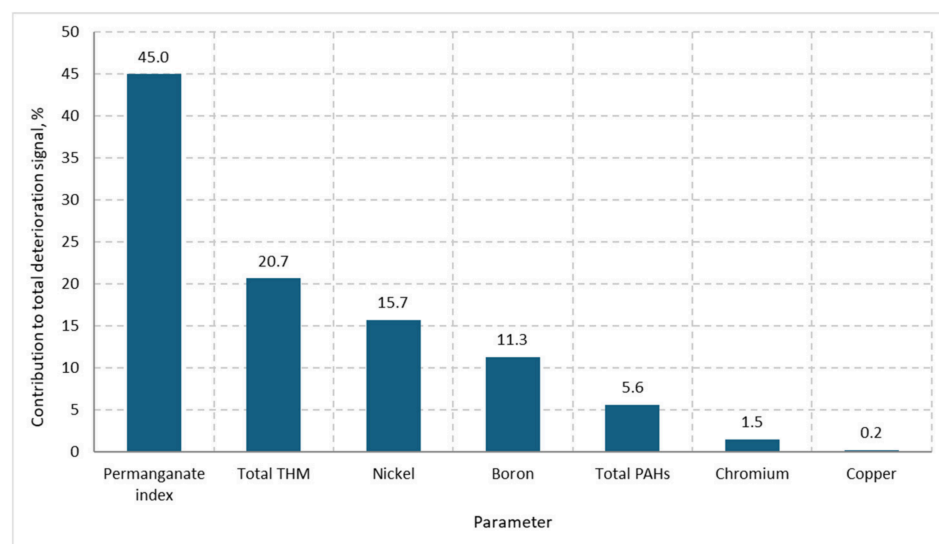


Figure 5. Contribution of parameters to the total DWQDI signal.

The contribution pattern indicates that DWQDI was not controlled by a single parameter in all samples. In some samples, the highest contribution came from the permanganate index, while in others Total THM or nickel was dominant. Total PAHs contributed to the index because they were included through the left-censored data procedure, but they did not differentiate samples because all results were below the same LoQ.

3.6. Sensitivity to the Treatment of Left-Censored Results

The sensitivity analysis showed that DWQDI values were only moderately affected by the treatment of results reported below LoQ. Under the lower-bound scenario, DWQDI values ranged from 0.017 to 0.143, with a mean value of 0.058. Under the baseline middle-bound scenario, the range was 0.030 to 0.147, with a mean value of 0.064. Under the upper-bound scenario, the range was 0.043 to 0.151, with a mean value of 0.069. The sensitivity analysis is presented in Table 7.

Table 7. Sensitivity of DWQDI to the treatment of results below LoQ.

Scenario	Substitution Rule	Minimum DWQDI	Mean DWQDI	Maximum DWQDI	Rank Correlation with Baseline (n = 25)
Lower-bound	0	0.017	0.058	0.143	0.992
Middle-bound	LoQ/2	0.030	0.064	0.147	1.000
Upper-bound	LoQ	0.043	0.069	0.151	0.991
Chromium future value variant	LoQ/2	0.031	0.065	0.148	0.998

The middle-bound scenario was used as the baseline calculation. The chromium future value variant used 25 µg/L instead of 50 µg/L as the reference value for chromium.

The rank correlations between the baseline scenario and the lower-bound and upper-bound scenarios were above 0.99. This indicates that the sample ranking was stable despite changes in the treatment of left-censored values. The top-ranked sample remained S13 under all substitution scenarios. Samples S17, S20 and S9 also remained among the highest-ranked samples, although their internal order changed slightly between scenarios.

The alternative chromium reference value had a very small effect on DWQDI. This was expected because chromium concentrations were low in relation to both the current and future reference values. The ranking under the future chromium value variant was therefore almost identical to the baseline ranking.

Figure 6 presents scenario-based sensitivity to the treatment of values below LoQ rather than a full analytical uncertainty range. Because the monitoring dataset did not include replicate measurements or parameter-specific expanded uncertainty values, uncertainty intervals for the main DWQDI contributors could not be estimated in this study.

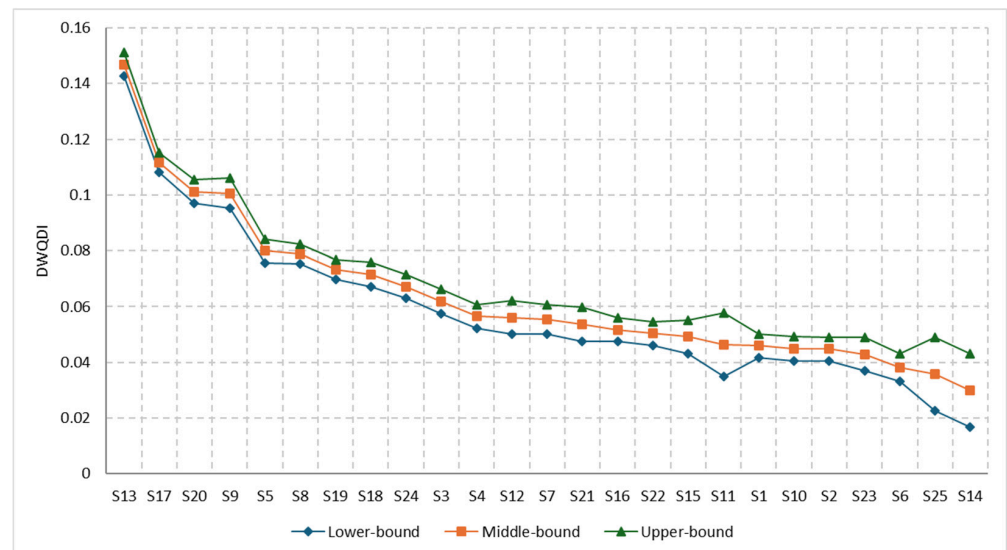


Figure 6. Sensitivity of DWQDI to the treatment of values below LoQ. Samples are ordered according to the baseline DWQDI ranking.

The leave-one-parameter-out analysis confirmed that the permanganate index, Total THM, and nickel had the strongest influence on the interpretation of results. Removing the permanganate index changed the sample ranking most strongly, with a rank correlation of 0.730 compared with the baseline ranking. Removing Total THM and nickel also affected the ranking, with rank correlations of 0.851 and 0.912, respectively. Removing parameters with low or constant contributions, such as copper, chromium, or Total PAHs, did not materially change the ranking.

4. Discussion

4.1. DWQDI as a Complementary Tool for Interpreting Compliant Monitoring Data

The results support the working assumption that drinking-water monitoring data can reveal relative quality deterioration even when no regulatory exceedance is observed. All analyzed samples remained within the very low deterioration class, yet DWQDI differentiated the network samples and identified those in which selected parameters were closer to their adopted reference values. Thus, higher DWQDI values indicate higher proximity to adopted reference values, not proof of temporal degradation of water quality in the network. Because the arithmetic mean is compensatory, DWQDI should be interpreted together with the maximum parameter-level load M_j , the exceedance count E_j , the dominant parameter, and the contribution analysis.

This role is consistent with the general purpose of water quality indices, which convert multi-parameter datasets into more interpretable forms [17–23]. However, DWQDI differs from many WQI-type and WPI-type approaches because it was designed for treated drinking water at network monitoring points, not for raw water, rivers, groundwater or general water-resource classification [24–29].

The highest DWQDI value was obtained for sample S13, mainly due to nickel, the permanganate index and Total THM. This did not indicate non-compliance, but it showed a stronger relative deterioration signal than in other samples. The unweighted structure

of DWQDI was appropriate because it kept the calculation directly traceable to measured concentrations and reference values.

4.2. Regulatory and Operational Relevance of the Observed Deterioration Pattern

DWQDI should be interpreted in the context of the current shift towards risk-based drinking-water management. Directive (EU) 2020/2184 requires a risk-based approach across the supply chain, while the Polish legal framework distinguishes compliance monitoring from operational monitoring and requires representative sampling points within the water supply network [1–3]. In this setting, DWQDI provides an additional screening layer that helps interpret monitoring data before more formal risk assessment or corrective decisions are considered.

The thresholds of 0.30 and 0.60 were used only as interpretive bands for the aggregate value A_j , not as legal decision rules. In the analyzed dataset, all aggregate DWQDI values were below 0.30, but selected individual parameter-level loads were higher, especially for the permanganate index, Total THM, and nickel. Therefore, A_j was interpreted together with M_j and E_j . Since $E_j = 0$ for all samples, no exceedance flag was present in the analyzed dataset.

The main contributors to DWQDI were technically meaningful, and their interpretation is consistent with previous studies on distribution-system water quality, disinfection by-products, infrastructure reliability and biological stability [7–16,34–46]. References addressing water infrastructure reliability and risk-oriented management [34–39] were retained to support the broader operational-management context of DWQDI, not as direct validation of the chemical index. The permanganate index reflected oxidizable organic matter and may indicate changes in the organic matrix of treated water. Total THM represented regulated disinfection by-products relevant to distribution-stage water quality. Nickel may be associated with source-water composition, materials, or local distribution conditions. Total PAHs were retained through the left-censored data procedure because their LoQ was low relative to the reference value. Since they were below the same LoQ in all samples, they affected the absolute DWQDI value but not the sample ranking.

4.3. Transferability, Robustness and Future Development

The proposed method is transferable as a procedure rather than as a fixed parameter list. It requires only routinely available monitoring information: sample date, monitoring point, concentration, unit, reference value and LoQ. It does not require hydraulic modeling, detailed asset data, exposure assumptions or toxicological dose–response parameters.

The presented dataset should therefore be treated as an empirical demonstration rather than a universal benchmark. In applications outside the present regulatory context, the eligible parameter set and reference values should be adapted to the applicable national or regional drinking-water quality requirements. Direct comparison between utilities or countries should therefore be made only for the same predefined parameter set or for clearly declared parameter modules.

The sensitivity analysis showed that the interpretation was robust with respect to the treatment of values below LoQ. DWQDI values changed slightly between the lower-bound, middle-bound and upper-bound scenarios, but the sample ranking remained stable. This is important because extended drinking-water screening datasets often contain many left-censored results.

From a sustainable water management perspective, DWQDI can support more than routine interpretation of monitoring results. By identifying network samples, locations and parameters with relatively higher deterioration signals, the index may help utilities prioritize diagnostic sampling, plan targeted operational checks and allocate laboratory

resources more efficiently. Even when all samples remain within the lowest interpretive band, the ranking may still indicate which samples or parameters should be considered first for follow-up diagnostic sampling or routine operational review. In the longer term, repeated DWQDI application may support infrastructure management by indicating parts of the distribution network where water quality is more sensitive to operational or material-related conditions. This role is consistent with recent data-driven approaches to sustainable water resources management, where classification and monitoring-based assessment are used to support interpretation and management decisions.

The study has limitations. The dataset was relatively small and unevenly distributed across monitoring locations, so the results should be interpreted primarily at the sample level. In addition, the dataset did not allow paired outlet-network or repeated same-point change analysis, so temporal deterioration could not be quantified. The available routine monitoring records did not include replicate analyses, duplicate samples, parameter-specific measurement uncertainty or a balanced sampling design. Therefore, analytical measurement uncertainty and sampling variability could not be quantified in the present application. Several operationally important parameters, including nitrate, iron, manganese, pH, turbidity, conductivity, free chlorine and temperature, were not available at this stage. Their absence limits the interpretation of operational processes such as disinfectant decay, corrosion-related changes, particulate release and temperature-related water-quality variation. Future extensions would require separate normalization functions for parameters with lower limits, recommended ranges, zero-tolerance criteria or qualitative interpretation. Future applications should test DWQDI on larger and more balanced datasets, include laboratory uncertainty and repeated sampling where available, compare it with selected WQI or WPI approaches [17–29], and link it with further risk-oriented tools for water infrastructure reliability [34–39], water resources and water-quality management [40–47]. Such comparison would require a separate methodological design because existing indices differ in parameter sets, weighting assumptions, and interpretation scales.

5. Conclusions

This study developed and applied the Drinking-Water Quality Deterioration Index as a monitoring-based tool for interpreting multi-parameter drinking-water quality data from water supply network points. The novelty of the work lies in adapting a reference-value-based deterioration approach to treated drinking water monitored within the distribution network and combining it with parameter eligibility rules, treatment of values below LoQ, contribution analysis and sensitivity testing. The main objectives were achieved by defining the DWQDI calculation procedure, applying it to an anonymized monitoring dataset, identifying the dominant contributors to the deterioration signal and testing the stability of sample ranking. The index should be interpreted as a reference-value-based screening indicator, not as evidence of temporal deterioration between treatment plant outlet and network points or between successive samples.

Application of DWQDI to 25 network samples showed that all samples remained within the very low average reference-proximity class and that no exceedances were observed. Nevertheless, the index differentiated samples and identified the main contributors to the deterioration signal, mainly the permanganate index, Total THM and nickel.

The comparison of lower-bound, middle-bound and upper-bound substitution scenarios showed that the treatment of results below LoQ had only a limited effect on DWQDI values and did not materially change sample ranking. This supports the robustness of the index for extended drinking-water screening datasets containing many non-quantified results.

DWQDI is applicable as a procedure to other water supply networks for selected chemical and physicochemical parameters with numerical upper reference values, because

it requires routinely available monitoring data, reference values and quantification limits. Future applications should test the index on larger datasets, include additional operational parameters and link DWQDI with more detailed risk-oriented assessments where needed.

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Conflicts of Interest: The author declares no conflicts of interest.

References

1. European Parliament and Council. Directive (EU) 2020/2184 of the European Parliament and of the Council of 16 December 2020 on the Quality of Water Intended for Human Consumption (Recast). *Off. J. Eur. Union* **2020**, *L 435*, 1–62. Available online: <https://eur-lex.europa.eu/eli/dir/2020/2184/oj/eng> (accessed on 9 July 2026).
2. Ustawa z Dnia 13 Marca 2026 r. o Zmianie Ustawy o Zbiorowym Zaopatrzeniu w Wodę i Zbiorowym Odprowadzaniu Ścieków Oraz Niektórych Innych Ustaw. *Dz.U.* 2026, Poz. 605. Available online: <https://isap.sejm.gov.pl/isap.nsf/DocDetails.xsp?id=WDU20260000605> (accessed on 9 July 2026).
3. Rozporządzenie Ministra Zdrowia z Dnia 22 Maja 2026 r. w Sprawie Jakości Wody Przeznaczonej do Spożycia Przez Ludzi. *Dz.U.* 2026, Poz. 748. Available online: <https://isap.sejm.gov.pl/isap.nsf/DocDetails.xsp?id=WDU20260000748> (accessed on 9 July 2026).
4. World Health Organization. *Guidelines for Drinking-Water Quality: Fourth Edition Incorporating the First, Second and Third Addenda*; World Health Organization: Geneva, Switzerland, 2026. Available online: <https://www.who.int/publications/i/item/9789240121225> (accessed on 9 July 2026).
5. World Health Organization. *International Water Association. Water Safety Plan Manual: Step-by-Step Risk Management for Drinking-Water Suppliers*, 2nd ed.; World Health Organization: Geneva, Switzerland, 2023. Available online: <https://www.who.int/publications/i/item/9789240067691> (accessed on 9 July 2026).
6. EN 15975-2:2013; Security of Drinking Water Supply—Guidelines for Risk and Crisis Management—Part 2: Risk Management. European Committee for Standardization (CEN): Brussels, Belgium, 2013.
7. National Research Council. *Drinking Water Distribution Systems: Assessing and Reducing Risks*; National Academies Press: Washington, DC, USA, 2006. [CrossRef] [PubMed]
8. Liu, G.; Zhang, Y.; Knibbe, W.-J.; Feng, C.; Liu, W.; Medema, G.; van der Meer, W. Potential impacts of changing supply-water quality on drinking water distribution: A review. *Water Res.* **2017**, *116*, 135–148. [CrossRef] [PubMed]
9. Li, R.A.; McDonald, J.A.; Sathasivan, A.; Khan, S.J. Disinfectant residual stability leading to disinfectant decay and by-product formation in drinking water distribution systems: A systematic review. *Water Res.* **2019**, *153*, 335–348. [CrossRef] [PubMed]
10. Prest, E.I.; Hammes, F.; van Loosdrecht, M.C.M.; Vrouwenvelder, J.S. Biological stability of drinking water: Controlling factors, methods, and challenges. *Front. Microbiol.* **2016**, *7*, 45. [CrossRef] [PubMed]
11. Learbuch, K.L.G.; Smidt, H.; van der Wielen, P.W.J.J. Water and biofilm in drinking water distribution systems in the Netherlands. *Sci. Total Environ.* **2022**, *831*, 154940. [CrossRef] [PubMed]
12. Weston, S.L.; Scheili, A.; Behmel, S.; Rodriguez, M.J. Water quality in drinking water distribution systems: Research trends through the 21st century. *Environ. Sci. Water Res. Technol.* **2022**, *8*, 3054–3064. [CrossRef]
13. Gillespie, S.; Lipphaus, P.; Green, J.; Parsons, S.; Weir, P.; Juskowiak, K.; Jefferson, B.; Jarvis, P.; Nocker, A. Assessing microbiological water quality in drinking water distribution systems with disinfectant residual using flow cytometry. *Water Res.* **2014**, *65*, 224–234. [CrossRef] [PubMed]
14. Richardson, S.D.; Plewa, M.J.; Wagner, E.D.; Schoeny, R.; DeMarini, D.M. Occurrence, genotoxicity, and carcinogenicity of regulated and emerging disinfection by-products in drinking water: A review and roadmap for research. *Mutat. Res. Rev. Mutat. Res.* **2007**, *636*, 178–242. [CrossRef] [PubMed]
15. Krasner, S.W.; Weinberg, H.S.; Richardson, S.D.; Pastor, S.J.; Chinn, R.; Scilimenti, M.J.; Onstad, G.D.; Thruston, A.D., Jr. Occurrence of a new generation of disinfection byproducts. *Environ. Sci. Technol.* **2006**, *40*, 7175–7185. [CrossRef] [PubMed]

16. Chowdhury, S.; Champagne, P.; McLellan, P.J. Models for predicting disinfection byproduct formation in drinking waters: A chronological review. *Sci. Total Environ.* **2009**, *407*, 4189–4206. [[CrossRef](#)] [[PubMed](#)]
17. Horton, R.K. An index number system for rating water quality. *J. Water Pollut. Control Fed.* **1965**, *37*, 300–306.
18. Brown, R.M.; McClelland, N.I.; Deininger, R.A.; Tozer, R.G. A water quality index—Do we dare? *Water Sew. Work.* **1970**, *117*, 339–343.
19. Pesce, S.F.; Wunderlin, D.A. Use of water quality indices to verify the impact of Córdoba City (Argentina) on Suquía River. *Water Res.* **2000**, *34*, 2915–2926. [[CrossRef](#)]
20. Tyagi, S.; Sharma, B.; Singh, P.; Dobhal, R. Water quality assessment in terms of water quality index. *Am. J. Water Res.* **2013**, *1*, 34–38. [[CrossRef](#)]
21. Lumb, A.; Sharma, T.C.; Bibeault, J.-F. A review of genesis and evolution of Water Quality Index (WQI) and some future directions. *Water Qual. Expo. Health* **2011**, *3*, 11–24. [[CrossRef](#)]
22. Sutadian, A.D.; Muttill, N.; Yilmaz, A.G.; Perera, B.J.C. Development of river water quality indices—A review. *Environ. Monit. Assess.* **2016**, *188*, 58. [[CrossRef](#)] [[PubMed](#)]
23. Uddin, M.G.; Nash, S.; Olbert, A.I. A review of water quality index models and their use for assessing surface water quality. *Ecol. Indic.* **2021**, *122*, 107218. [[CrossRef](#)]
24. Chidiac, S.; El Najjar, P.; Ouaini, N.; El Rayess, Y.; El Azzi, D. A comprehensive review of water quality indices (WQIs): History, models, attempts and perspectives. *Rev. Environ. Sci. Biotechnol.* **2023**, *22*, 349–395. [[CrossRef](#)] [[PubMed](#)]
25. Hossain, M.; Patra, P.K. Water pollution index—A new integrated approach to rank water quality. *Ecol. Indic.* **2020**, *117*, 106668. [[CrossRef](#)]
26. Hurley, T.; Sadiq, R.; Mazumder, A. Adaptation and evaluation of the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) for use as an effective tool to characterize drinking source water quality. *Water Res.* **2012**, *46*, 3544–3552. [[CrossRef](#)] [[PubMed](#)]
27. Scheili, A.; Rodriguez, M.J.; Sadiq, R. Development, application, and sensitivity analysis of a water quality index for drinking water management in small systems. *Environ. Monit. Assess.* **2015**, *187*, 685. [[CrossRef](#)] [[PubMed](#)]
28. Klamt, R.A.; da Costa, A.B.; Gaedke, M.A.; Lobo, E.A. Drinking water quality indices: A systematic review. *Ambient. Água* **2021**, *16*, e2630. [[CrossRef](#)]
29. Han, X.; Liu, X.; Gao, D.; Ma, B.; Gao, X.; Cheng, M. Costs and benefits of the development methods of drinking water quality index: A systematic review. *Ecol. Indic.* **2022**, *144*, 109501. [[CrossRef](#)]
30. Helsel, D.R. *Nondetects and Data Analysis: Statistics for Censored Environmental Data*; Wiley: Hoboken, NJ, USA, 2005.
31. Helsel, D.R. *Statistics for Censored Environmental Data Using Minitab® and R*, 2nd ed.; Wiley: Hoboken, NJ, USA, 2012. [[CrossRef](#)]
32. Antweiler, R.C.; Taylor, H.E. Evaluation of statistical treatments of left-censored environmental data using coincident uncensored data sets: I. Summary statistics. *Environ. Sci. Technol.* **2008**, *42*, 3732–3738. [[CrossRef](#)] [[PubMed](#)]
33. Antweiler, R.C. Evaluation of statistical treatments of left-censored environmental data using coincident uncensored data sets: II. Group comparisons. *Environ. Sci. Technol.* **2015**, *49*, 13439–13446. [[CrossRef](#)] [[PubMed](#)]
34. Żywiec, J.; Szpak, D.; Wartalska, K.; Grzegorzec, M. The Impact of Climate Change on the Failure of Water Supply Infrastructure: A Bibliometric Analysis of the Current State of Knowledge. *Water* **2024**, *16*, 1043. [[CrossRef](#)]
35. Pietrucha-Urbanik, K.; Studziński, A. Data-Driven Assessment of Seasonal Impacts on Sewer Network Failures. *Sustainability* **2025**, *17*, 11226. [[CrossRef](#)]
36. Boryczko, K.; Rak, J. Method for Assessment of Water Supply Diversification. *Resources* **2020**, *9*, 87. [[CrossRef](#)]
37. Boryczko, K.; Ważna, N.; Kawalerski, M. Blackout and Crisis Water Supply: Diversification of Water Intakes. *Water* **2024**, *16*, 3370. [[CrossRef](#)]
38. Boryczko, K.; Bartoszek, L.; Koszelnik, P.; Rak, J. A new concept for risk analysis relating to the degradation of water reservoirs. *Environ. Sci. Pollut. Res.* **2018**, *25*, 25591–25599. [[CrossRef](#)] [[PubMed](#)]
39. Boryczko, K.; Szpak, D.; Żywiec, J.; Tchórzewska-Cieślak, B. The Use of a Fault Tree Analysis (FTA) in the Operator Reliability Assessment of the Critical Infrastructure on the Example of Water Supply System. *Energies* **2022**, *15*, 4416. [[CrossRef](#)]
40. Domoń, A.; Papciak, D.; Tchórzewska-Cieślak, B. Influence of Water Treatment Technology on the Stability of Tap Water. *Water* **2023**, *15*, 911. [[CrossRef](#)]
41. Papciak, D.; Domoń, A.; Zdeb, M.; Tchórzewska-Cieślak, B.; Konkol, J.; Socho, E. Mechanism of Biofilm Formation on Installation Materials and Its Impact on the Quality of Tap Water. *Water* **2022**, *14*, 2401. [[CrossRef](#)]
42. Domoń, A.; Papciak, D.; Tchórzewska-Cieślak, B.; Pietrucha-Urbanik, K. Biostability of Tap Water—A Qualitative Analysis of Health Risk in the Example of Groundwater Treatment (Semi-Technical Scale). *Water* **2018**, *10*, 1764. [[CrossRef](#)]
43. Zamorska, J. Biological Stability of Water after the Biofiltration Process. *J. Ecol. Eng.* **2018**, *19*, 234–239. [[CrossRef](#)] [[PubMed](#)]
44. Babiarz, B.; Puszkarewicz, A. Selected Causes of Exploitation Problems Caused by Secondary Contamination of Drinking Tap Water. *Tech. Trans.* **2018**, *3*, 131–140. [[CrossRef](#)]

45. Papciak, D.; Tchórzewska-Cieślak, B.; Domoń, A.; Wojtuś, A.; Żywiec, J. Effect of PVC installation on quality and stability of tap water. *Desalin. Water Treat.* **2020**, *186*, 297–308. [[CrossRef](#)]
46. Żywiec, J.; Tchórzewska-Cieślak, B.; Papciak, D.; Domoń, A. Changes of microbiological parameters of water in domestic distribution system in terms of water supply safety. *Desalin. Water Treat.* **2021**, *226*, 37–51. [[CrossRef](#)]
47. Biedunkova, O.; Kuznietsov, P.; Tsos, O.; Karaim, O. Hydrochemical Typology of Natural Lakes in the Polissia Region Based on Self-Organizing Maps: Implications for Sustainable Water Resources Management. *Water* **2026**, *18*, 926. [[CrossRef](#)]

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