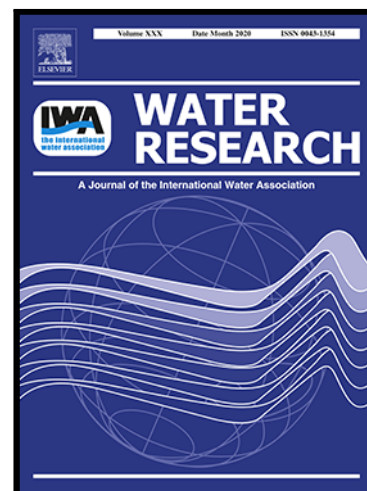


Journal Pre-proof

A modified robustness index for assessing operational performance of drinking water treatment plants: a comparative study within a new regulatory framework

Federica De Marines , Santo Fabio Corsino , Alida Cosenza ,
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Research highlights

- A novel robustness index for turbidity (TRI_{95B}) was proposed in this study
- A comprehensive comparison and validation against already existing TRIs was assessed
- TRI_{95B} showed better correspondence to the plant performances than others TRIs
- TRI_{95B} showed better compliance with the new regulation while considering the lower T_{goal}
- TRI_{95B} was able to identify failures at a lower discrepancy respect to the T_{goal}

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A modified robustness index for assessing operational performance of drinking water treatment plants: a comparative study within a new regulatory framework

Federica De Marines^{1*}, Santo Fabio Corsino¹, Alida Cosenza¹, Marco Capodici¹, Michele Torregrossa¹, Gaspare Viviani¹

¹Department of Engineering, University of Palermo, Viale delle Scienze, Edificio 8, 90128, Palermo, Italy

Corresponding Author: Federica De Marines (federica.demarines@unipa.it)

Abstract

Drinking water treatment plants (DWTPs) are facing emerging challenges affecting raw water quality. In addition, the new regulatory framework (EU 2184/2020) sets stricter limits for turbidity and percentile statistics for continuous compliance, demanding greater robustness of the treatment processes. To achieve this aim, this study proposes a turbidity robustness index (TRI), named TRI_{95B}, to be used as a warning tool for detecting deviations from water quality standards. TRI_{95B} has been compared with the TRIs existing in the literature. Furthermore, the TRI_{95B} validation has been performed by a three-year monitoring dataset of a full-scale DWTP. The proposed TRI_{95B} index has two key novelties compared to the existing indices required for adapting to the new drinking water regulation: i. introduces the 95th percentile as a statistical indicator; ii. considers an additional term that sets an alert when a threshold value is exceeded.

The comparison results suggest a better correspondence to the real plant performances of TRI_{95B} than the other TRIs. Indeed, both the sensitivity and specificity of TRI_{95B} were significantly higher than the other TRIs, indicating a better capacity to correctly classify both positive and negative cases. Moreover, while the previous TRIs identify a critical operating condition when the turbidity goal was significantly exceeded, TRI_{95B} highlights a failure condition at a lower discrepancy. Therefore, TRI_{95B} is also able to identify short-duration and low magnitude failures, thus coping with the purpose of the new regulation for drinking water.

Keywords: Drinking water treatment plant, robustness index, turbidity, drinking regulation.

Introduction

Drinking water treatment plants (DWTPs) provide an essential service to communities in developed countries. Indeed, ensuring a continuous supply of safe drinking water is crucial for safeguarding public health and sanitation. In recent years, the impacts of climate change have posed a significant challenge to such infrastructure, particularly with regards to the quality of raw water sources (Calero Preciado et al., 2021). Several studies in the scientific literature highlighted that for several years, the intensification of extreme climate events (including severe precipitation and drought) contributed to deteriorating the water quality in surface water bodies (Delpla et al., 2009; Yadava et al., 2023). Specifically, changes in precipitation patterns enhance the erosion and transport processes, leading to increased suspended and dissolved particles in surface waters (Skaland et al., 2022). Therefore, the turbidity in the influent raw water to DWTP increases, thus posing a significant operational challenge for maintaining high standards of treated water quality in compliance with regulatory requirements (Mi et al., 2019). Besides, predictions from various climate models suggest that raw water quality might deteriorate further in the future, thereby increasing challenges to DWTP (Quevedo-Castro et al., 2022).

Turbidity is an essential measurement in drinking water facilities as it can be used as a surrogate indicator of many parameters. Generally, a high level of turbidity is associated with an increased risk of *Cryptosporidium oocysts* and other microorganisms in drinking water (Hartshorn et al., 2015). In addition, elevated raw water turbidity caused by extreme rainfall has been associated with several waterborne diseases and gastrointestinal hospitalizations (De Roos et al., 2017; Delpla et al., 2009). Moreover, turbidity also serves as an indicator of organic matter, making it useful for evaluating the formation of disinfection by-products (Doménech et al., 2022; Pešić et al., 2020). The relationship with these parameters is of great importance, as turbidity is a parameter that can be continuously monitored with a very high analytical frequency. It is more easily controllable and can provide useful alerts even for other parameters that are monitored less frequently. Therefore, water utilities are expected to keep water turbidity levels in compliance with regulatory requirements to mitigate the risk of bacteriological failure and the formation of disinfection byproducts (DBPs).

In this scenario, the novel EU Directive 2020/2184 introduced significant steps forward to ensure the safety and quality of drinking water (Directive EU 2184/2020). One of the key focuses of Directive is the enhancement of the protection of public health through more stringent requirements for monitoring and controlling contaminants in drinking water. Within the Directive, turbidity is considered one of the key indicators of water quality, and specific limits and monitoring frequencies are established for its control. In more detail, turbidity at the water supply plant must be lower than 0.30 nephelometric turbidity units (NTU) in 95% of samples, and none must exceed 1 NTU. The new

limit imposed for turbidity by Directive represents a significant improvement compared to the previous regulation (Directive 98/83/EC) in which the indicative turbidity limit was 1 NTU. The introduction of 95% percentile statistics in the new Directive implies that a DWTP must be characterized by a certain degree of robustness.

The concept of robustness in DWTPs was already defined in previous literature (Hurst et al., 2004). The robustness of DWTPs measures their ability to provide excellent performance even under influent quality and quantity variation (Jung et al., 2019). Therefore, robustness is a measure of how the system copes with changes. Typically, DWTP operators and managers adopt statistical indicators (percentile, average, etc.) in view of aggregating and interpreting the huge amount of monitoring data with the final aim of supporting evidence-based decisions. To improve understanding of performance, turbidity robustness indices (TRIs) were proposed in past studies (Huck and Coffey, 2004); Li and Huck, 2008). Specifically, Huck and Coffey (Huck and Coffey, 2004) proposed a TRI based on the concepts of uniformity and overall performance against a goal. Thus, the TRI was composed of two terms that were aggregated by assigning an equal weight (0.5). Li and Huck (2008) improved the index of Huck and Coffey (2004) by introducing different weighting scores. However, this approach showed limitations in terms of the arbitrary assignments of weighting scores and the method complexity. Such limitations were partially overcome by the TRI proposed by Hartshorn (Hartshorn et al., 2015). The latter TRI introduced a novelty which is the concept of the percentage of time when the turbidity was below the goal value. In more detail, variability in performance was not considered when the turbidity was lower than the goal. Nevertheless, this method did not properly address performance variations. Moreover, Nemani et al. (2023) have recently observed that a low TRI value was obtained when the limit value was continuously exceeded, and the data distribution was quite uniform. Therefore, the existing TRIs fail as a tool indicating the risk (Nemani et al., 2023). Furthermore, the existing TRIs do not account for the requirements set by Directive EU 2184/2020 (the turbidity limit in 95% of the samples and the maximum limit of 1 NTU).

This study aims to propose a modified TRI (namely, TRI_{95B}) able to overcome the highlighted issues of the existing TRIs. TRI_{95B} was compared with those already available in the literature and validated by using a three-year monitoring dataset of a full-scale DWTP.

2. Materials and methods

2.1 Background to TRIs evaluation

To the best of the authors knowledge, three turbidity robustness indices are available in the literature (Tab. 1) proposed by Huck et al. (2001) (eq. 1), (Li and Huck, 2008) (eq. 2) and Hartshorn et al.

(2015) (eq. 3). According to previous studies, on the basis of the TRI value, six classes of system operation quality can be defined (Li and Huck, 2008) (Tab. 1).

[Tab. 1]

In the equations reported in Tab. 1, the first term represents the performance variability (T_{90}/T_{50}), whereas the second (T_{50}/T_{goal}) the compliance against the goal.

The terms “E”, “D” and “J” used as subscripts to distinguish the TRIs were referred to in a previous study (Hartshorn et al., 2015).

2.2 Development of the modified TRI

The proposed TRI, namely TRI_{95B} , is reported in Equation 4.

$$TRI_{95B} = \left\{ \left[B \times \left(1 - \frac{G\%}{100} \right) \times \frac{T_{95}}{T_{goal}} \right] + \left[B \times \frac{T_{50}}{T_{goal}} \times \frac{G\%}{100} \right] + \left[(1 - B) \left(\frac{T_{100}}{T_{max}} + 1 \right) \right] \right\} \times 100 \text{ [eq. 4]}$$

Symbols have the same meaning as already discussed. The main modifications to TRI_{95B} is the replacement of the 90th with the 95th percentile, as imposed by regulation. In fact, the new regulation requires the compliance with the turbidity reference value in 95% of samples. Therefore, the ratio T_{95}/T_{goal} represents the effectiveness of the process according to current regulation ($T_{goal} = 0.3$ NTU and compliance with the turbidity limit in 95% of the samples).

Additionally, the ratio T_{90}/T_{50} (representing the performance uniformity over a specific duration) was replaced by the ratio T_{50}/T_{goal} . This substitution was made to avoid that, being the time scale relatively short (one week), the extreme values of the distribution had too much influence in the calculation of the index. Nonetheless, the introduction of the 95th percentile allows considering the extreme values in the data distribution. Therefore, including T_{90}/T_{50} in the index as well would give excessive weight to the extreme values in the distribution, resulting in index with absolute values that are too high and not reflective of the plant's actual performance. Therefore, the term T_{50}/T_{goal} represents the new performance uniformity, more precisely indicating how the distribution aligns on average with the target value.

Furthermore, the term T_{100}/T_{max} has been added to TRI_{95B} . It signifies whether the highest measured turbidity value (T_{100}) during a run, excluding outliers, exceeded the threshold value set by the EU regulation ($T_{max} = 1$ NTU). Therefore, regardless of the data distribution, if the threshold value is exceeded by even a single data, the index must be able to signal an anomaly. To include this concept

into the index, a switch term (B) was introduced. The factor B is equal to 1 if the threshold value is never exceeded into the run, whereas it is equal to 0 if at least one data point exceeded 1 NTU. Therefore, if no data point exceeds 1 NTU, the B value is equal to 1, and the term T_{100}/T_{\max} is null. However, if even one data point exceeds 1 NTU, the B value is 0, and the TRI value depends only on T_{100}/T_{\max} . Consequently, when the T_{\max} is exceeded, since the regulation does not assign any weight to the data distribution during the run, both T_{50} and T_{95} were excluded from the index formulation. In this latter case, in view of ensuring that the value of the TRI is greater than 200 (thereby falling into the “severely upset” class), the term “+1” was added (Equation 4).

2.3 Full-scale plant description

The DWTP under study is located in Sicily (Italy). The DWTP treats surface water derived from a reservoir classified as A2 according to the Water Framework Directive (WFD) (Directive 2000/60/EC) and Legislative Decree 152/2006. In more detail, the decree (art. 80) classifies water into three categories (A1, A2, and A3) based on the assumed values of 46 parameters relating to physical, chemical and microbiological characteristics (Tab 1/A, Annex 2, part III). The plant consists of three lines operating in parallel, each having the same capacity of about 300 l/s. The three lines have a common pre-oxidation unit. Each line consists of a clariflocculation unit with sludge recirculation followed by a filtration unit (quartz sand filter). The coagulation-flocculation phase is carried out by adding aluminium sulphate polychloride as a coagulant agent and a cationic polyelectrolyte as a flocculant. The dosage of aluminium sulphate polychloride is automatically managed by a Supervisory Control and Data Acquisition (SCADA) system based on the continuous measurement of the raw water turbidity. The effluents from the three filtration units are mixed in a storage tank and subjected to final disinfection with chlorine dioxide and sodium hypochlorite. A hydraulic head dissipation tank is inserted upstream of each process line where raw water from the reservoir, filter backwash water, and supernatant from the sludge line are mixed. Turbidity is measured at various points in the plant by nephelometric online sensors (Ultraturb sc and 1720E by Hach Lange). The turbidity measured in the outlet of the load dissipation tank and in the outlet of the disinfection tank has been considered.

2.4 Data collection and analysis

Full-scale plant data were collected for 3 years (January 2020 – December 2023). The turbidity data were managed by a SCADA system that acquired the values measured by online sensors. These data were recorded by the SCADA within a 4-hour time interval. Consequently, each turbidity data point represented the average turbidity value measured over the previous 4 hours. TRI was calculated by

using one week of data (42 average data points) for each run and adopting the measurement of the outlet to the disinfection tank. All the TRIs were calculated both according to old ($T_{\text{goal}} < 1$ NTU) and new ($T_{\text{goal}} < 0.3$ NTU) regulations.

To evaluate the performances of TRIs, the sensibility and specificity of each of them were calculated. Specifically, the sensitivity was aimed at measuring the true positive rate, meaning the ability of TRIs to correctly identify the run during which the T_{goal} exceedance occurred (true positive - TP). Sensitivity was calculated as follows:

$$\text{Sensitivity} = \frac{\text{True positives}}{\text{True Positives} + \text{False Negatives}} \times 100 \quad [\text{eq. 5}]$$

On the other hand, specificity was aimed at measuring the ability of TRIs to correctly identify the runs during which the exceedance of the T_{goal} does not occur (True negative rate). Specificity was calculated as follows:

$$\text{Specificity} = \frac{\text{True negatives}}{\text{True Negatives} + \text{False Positives}} \times 100 \quad [\text{eq. 6}]$$

According to the mathematical significance of TRIs based on the values of T_{goal} and T_{90} (Tab. 1), for each run, the right TRI class was established. Then, true and false positives, as well as true and false negatives, were determined as follows:

- true positive (TP): the number of runs in which TRI fall into the slightly disturbed or superior classes and are correctly identified;
- false positive (FP): the number of runs in which TRI fall into the slightly disturbed or superior classes but are incorrectly identified;
- true negatives (TN): the number of runs in which TRI falls into the class stable or very stable and is correctly identified;
- false negative (FN): the number of runs in which TRI falls into the class stable or very stable but is incorrectly identified.

3. Results and discussion

3.1 Characteristics of raw water and compliance of treated water with regulations

Turbidity data collected from the SCADA system in the raw and the effluent disinfected water are reported in Figure 1.

[Fig.1]

The turbidity (maximum, mean, and median) over the three-year dataset available showed significant fluctuations (Fig. 1a). During 2021 and 2022, the maximum turbidity in raw water exceeded 50 NTU in several runs, while reaching a maximum above 450 NTU in one case. In 2023, the maximum values were below 50 NTU, except for two runs when turbidity was above 200 and 450 NTU. The mean and median of turbidity data were comparable, suggesting an approximately symmetric data distribution around a central value approximately equal to 18 NTU. As depicted in Figure 1b, the average turbidity in raw water ranged between 5 and 20 NTU for most of the three years, whereas turbidity values between 40 and 60 NTU were measured in the autumnal period, specifically between November and December. Thus, the DWTP was affected by turbidity fluctuations, especially during the rainy season. These types of fluctuations are likely due to the increase in solid transport due to erosion (Zeng et al., 2022) or sediment resuspension into the reservoir (Mi et al., 2019).

In Figure 1c, the trends of the maximum, 90th, and 95th percentiles, coupled with the median of the effluent turbidity data are depicted. The median turbidity showed a quite regular trend around 0.55 ± 0.15 NTU over the three-year period. On the contrary, 95th percentile and the maximum values showed a less regular trend, characterized by greater fluctuations. In particular, the 95th percentile was on average 0.81 ± 0.34 NTU, while the maximum was 1.01 ± 0.54 NTU. In any case the turbidity limit of 1 NTU (the indicative value of Directive 98/83/EC in force in Italy until March 5, 2023) was exceeded if one refers to the median of turbidity. Conversely, referring to the 95th and to the lower turbidity goal as required by the new regulation, several exceedances of the turbidity limit were observed. Based on the obtained results, it was clear that the 95th percentile of turbidity was more variable compared to the median. This result is mainly because the 95th percentile was more affected by extreme values and outliers than the median. This result has relevance, especially in cases of extreme turbidity values in the inlet raw water affecting the system's performance. Contrarily, both mean and median, although they are widely used to compare process performances, were characterized by a lower sensibility, thus not allowing us to consider effluent turbidity spiking (Upton et al., 2017). From this perspective, the new regulation introduced a more cautious approach, as it requires the water treatment process to be effective even in the case of turbidity short-term fluctuations. Overall, when considering the 95th percentile of turbidity as a reference parameter, the DWTP demonstrated a lower capacity to maintain a constant value in the effluent. This implies that the novelty introduced by the new regulation requires a thorough and accurate analysis of the plant's robustness.

3.2 Comparative assessment of TRIs in the framework of the old regulation

In this section, the results of the comparison between the proposed index and the literature indices are discussed. The turbidity robustness indexes available in the literature and the one proposed in this study were applied to the turbidity values dataset from the DWTP. The turbidity dataset referred to 156 weeks, although data were missing for 4 weeks (116th-120th) because of acquisition failure.

In a first stage of the study, these TRIs were calculated assuming a T_{goal} equal to 1 NTU (according to EU 2020/2184). For the calculation of TRI_{95B} , it was assumed that parameter B was equal to 1, since in old regulation any indication about a limit not to be exceeded was reported. Figure 2 shows the trends of the TRIs.

As reported in the previous section, the median of turbidity data in the effluent resulted below 1 NTU during the entire observation period. Therefore, any exceedance of the suggested threshold value for turbidity was observed when referring to T_{50} . In contrast, T_{95} exceeded the target in 20 weeks (< 15%).

[Fig. 2]

The TRIs resulted on average close to 92.5 ± 15 (TRI_{90E}), 64.3 ± 19 (TRI_{90D}), 58.4 ± 18 (TRI_{90J}), 57.8 ± 19 (TRI_{95B}). The TRI_{90E} proposed by Huck and Coffey (Huck and Coffey, 2004) showed the highest values, being approximately 25-30% higher than the others. Overall, all TRIs fell within the “very stable” and “stable” classes for over 90% of the runs, except for TRI_{90E} , which fell in the “slightly disturbed” class in 22% of runs (34 out of 156 weeks) (Tab. 2). Moreover, only TRI_{90E} and TRI_{90D} fell into classes higher than “moderately disturbed” for about 3 weeks, while in only one case there was an exceedance of the “upset” limit ($TRI > 160$). This indicated that both the 50th and 90th percentiles of turbidity were greater than the turbidity limit (1 NTU). Therefore, TRI_{90E} and TRI_{90D} suggested that the DWTP did not generate effluent water of the desired quality for a short duration during those weeks.

[Tab.2]

When defining the TRI_{90E} , the authors assumed that the turbidity variability in the effluent (T_{90}/T_{50}) had the same weight as achieving a precise target value (T_{50}/T_{goal}) (Huck and Coffey, 2004). As reported in previous studies, assigning equal weights to these terms made the robustness index less sensitive to the presence of extreme values that deviated significantly from the central value of the distribution (Hartshorn et al., 2015; Li and Huck, 2008). The novel TRI_{95B} was found to be very

consistent with TRI_{90J} . The TRI_{90J} was more affected by system performances, while the overall variance was given less consideration, especially in runs where the limit value was exceeded a few times. In fact, in this specific case, the percentage of time for which turbidity was found to be lower than the T_{goal} (G) was very high (>98%). Consequently, the weight of the first term of the TRI_{90J} and TRI_{95B} (i.e., T_{90}/T_{50} and T_{95}/T_{goal}) was very low. Therefore, the second term (T_{50}/T_{goal}) had a greater weight in the final value of these TRIs, which resulted in similar results. Certainly, this result was affected by the value of T_{goal} because a lower value could significantly change the weight attributed to the first term of the TRI.

3.3 Comparative assessment of TRIs in the framework of the EU 2020/2184

The TRIs were calculated referring to the EU 2020/2184, specifically reducing the T_{goal} to 0.30 NTU. The trends of the TRIs are shown in Figure 3, whereas the frequency of their occurrence within the robustness classes is reported in Table 3.

[Fig. 3]

In this case, the response of the TRIs was different than that obtained considering T_{goal} equal to 1 NTU. Specifically, TRI_{90E} and TRI_{90J} resulted quite low, with average values of 157 ± 29 and 129 ± 23 , respectively. Thus, according to the response provided by those TRIs, the plant fell mainly within the “slightly disturbed” and “moderately disturbed” classes (Table 3) despite the main statistical indicators of the effluent turbidity (median and T_{90}) consistently exceeded the 0.30 NTU limit.

[Tab.3]

The results provided by the TRI_{90E} indicated that the DWTP was affected by severe process instability. However, the absolute values of the index were generally low, and only a few runs indicated an “upset” class or higher. Similarly, regarding the TRI_{90J} this occurrence was even more evident. As reported in previous studies, TRI_{90J} was not a reliable indicator of performance against a target because it favoured variation rather than performance against a goal (Hartshorn et al., 2015; Nemani et al., 2023). Indeed, exceeding the T_{goal} resulted in “G” was zero during most of the runs. Consequently, the term containing T_{goal} was zero, and the robustness index depended only on the ratio T_{90}/T_{50} . Therefore, paradoxically, the value of this ratio was close to one, the corresponding value of TRI was low, despite the T_{goal} could be constantly exceeded in the long run. TRI_{90D} value was higher than that obtained by previous TRIs (180 ± 45). However, it still highlighted the same critical aspects

already discussed for the previous indices, mainly linked to the fact that the T_{goal} exceedance was not adequately identified by the TRI value. $\text{TRI}_{95\text{B}}$ resulted much higher compared to the other TRIs, averaging 228 ± 84 . Overall, $\text{TRI}_{95\text{B}}$ was the index that fell more frequently (101 out of 156 weeks) into the “severely upset” class (Tab. 3), indicating a significant exceedance of the maximum turbidity value at the DWTP outlet. Unlike the previous TRIs, $\text{TRI}_{95\text{B}}$ showed a close correspondence to the real trend of the effluent turbidity. Firstly, the use of the 95th percentile instead of the 90th percentile enabled to better consider more extreme values within the turbidity dataset. Consequently, this TRI was more sensitive to point out smaller variations in turbidity within the run. Additionally, by relating T_{95} to T_{goal} , a greater weight to process performance was given. Finally, the introduction of the B parameter clearly enabled to highlight occurrences when the effluent turbidity exceeded the maximum turbidity limit. This is a very important alert that the already existing TRIs did not allow to identify.

3.4 Reliability of TRIs

The investigated TRIs showed conflicting results, indicating the occurrence of different robustness classes. As previously demonstrated, the response of TRIs reported in the literature and the one proposed in this study became even more evident when the T_{goal} was decreased to 0.30 NTU. Figure 4 illustrates the cumulative distribution of the median, the 90th, the 95th and 100th percentiles of turbidity (Fig. 4a) and that of TRIs when considering a T_{goal} of 1 NTU (Fig. 4b) and 0.30 NTU (Fig. 4c).

[Fig. 4]

As previously stated, the T_{50} was less than 1 NTU for over 99% of runs, whereas the T_{90} was nearly 90% (Fig. 4a). Consistently, none of the TRIs exceeded the “upset” class (Fig. 4b). As mentioned earlier, among the TRIs, only $\text{TRI}_{90\text{E}}$ significantly deviated from the other robustness indices. Specifically, $\text{TRI}_{90\text{E}}$ was the only that indicated a significant exceedance (> 30%) of the “slightly disturbed” class. This result suggests that T_{50} was very close to T_{goal} and T_{90} exceeded this value for at least 30% of runs (Huck and Coffey, 2004). However, none of these conditions occurred, indicating that $\text{TRI}_{90\text{E}}$ was not able to accurately describe the real operating performance of the plant. On the other hand, the response of the other TRIs was more precise. Specifically, $\text{TRI}_{90\text{D}}$, $\text{TRI}_{90\text{I}}$, and $\text{TRI}_{95\text{B}}$ fell within the “very stable” and “stable” classes for approximately 45 and 50% of runs, indicating that the system ensured high-quality effluent in compliance with T_{goal} , for most of the observed period (> 96%). In fact, the T_{90} exceeds the T_{goal} only for a few runs. Accordingly, these TRIs indicated an exceedance of the “stable” class falling into the “slightly disturbed” class. These results enabled to

observe that when assigning fixed weights to the terms constituting the indices did not enable to consider the high variance of turbidity data, which increases especially if monitoring is continuous and consequently include possible hotspots (Nemani et al., 2023). Furthermore, in this case, the new TRI_{95B} did not provide significant new insights compared to those already present in the literature. This was likely due to the low discrepancy in turbidity data compared to the target value.

Indeed, the results changed drastically when considering a lower T_{goal} , thereby leading to an increase in the discrepancy between the measured turbidity data and the recommended value (0.30 NTU) (Fig. 4c). While the previous regulation did not explicitly refer to which statistical turbidity data had to be used for comparison with the recommended value, the new regulations unequivocally identify it as the T_{95} . From Figure 4a, it can be observed that T_{95} exceeded 0.30 NTU for over 95% of runs. Furthermore, even the maximum value of 1 NTU was exceeded for approximately 40% of runs. However, not all the TRIs provided results that clearly represented this performance. Indeed, according to Table 1, falling within the “upset” class should indicate that T_{90} was beyond 50% of T_{goal} . In contrast, TRI_{90J} fell into the “upset” or higher class only for 10% of runs, TRI_{90E} for about 45%, TRI_{90D} for about 70%, and TRI_{95B} for over 85%. Therefore, although the T_{goal} was exceeded for over 95% of runs, none of the old TRIs showed a realistic correlation to plant performance. Among all the robustness indices, only TRI_{95B} indicated a significant exceedance of T_{goal} . Furthermore, it fell within the “severely upset” class for over 70% of the runs, indicating a good correlation to the exceedance of the limit value of 1 NTU. Therefore, when considering a lower T_{goal} , the response of TRIs was significantly different, indicating that the oldest showed a lower correspondence with the actual conditions and performance of the plant compared to the new TRI_{95B}.

To better point out this aspect, the sensitivity and specificity of the TRIs were calculated, referring to both the old and the new regulations. It should be highlighted, that because when referring to the new regulation, TRIs never fell within the stable or very stable classes, it was assumed that the true positive values were the number of runs in which TRI fell into the upset or severely upset classes and were correctly identified, whereas the true negatives were assumed to be the number of runs in which TRI fell into a class lower than the upset. The achieved results are reported in Table 4.

[Tab. 4]

Referring to the old regulation, TRI_{90J} (71%) and TRI_{95B} (86%) showed a significantly higher sensitivity compared to the other TRIs, indicating a better capacity to detect true positive values. The specificity was comparable among all the TRIs (90%), apart from TRI_{90E}, which showed the lowest capacity to detect true negative values. When considering the T_{goal} of 0.30 NTU, the sensitivity of

the existing TRIs collapsed. Only the TRI_{95B} showed a very high sensitivity (> 95%), thus confirming that it can accurately identify the run during which the turbidity threshold is significantly exceeded and minimize the chances of missing any actual cases. This is particularly important because it can significantly impact treatment outcomes. Similarly, even the specificity of TRI_{95B} was significantly higher than the other TRIs (88%). Therefore, TRI_{95B} showed the highest capacity to minimize the chances of incorrectly identifying some runs as positive when they are not. It is worth noting that when referring to a lower T_{goal}, both the sensitivity and specificity of TRI_{95B} increased. Increasing both sensitivity and specificity indicated that the TRI_{95B} was very accurate if considering a more restrictive limit for turbidity. This improvement is crucial for enhancing the reliability and effectiveness of TRI, as it enables better water quality control.

To provide more insights about the response of the TRIs to the plant operating conditions, all the indices were related to the discrepancy between the T₉₅ in each run and the target turbidity of 0.30 NTU (Figure 5).

[Fig. 5]

TRI_{95B} fell within the “upset” class, starting from a discrepancy with T_{goal} lower than 0.30 NTU. On the other hand, the other TRIs indicated a predominantly “moderately disturbed” operating condition. The “upset” condition was reached by TRI_{90E} and TRI_{90D} only for discrepancy values greater than 0.6 NTU. This indicated that only when the effluent turbidity exceeded 0.9 NTU the old TRIs indicate that the system was unable to produce high-quality water for most of the run. Conversely, TRI_{95B} showed a nearly linear relationship with the turbidity goal discrepancy. This was certainly because the T₉₅/T_{goal} ratio increased as the discrepancy rose. Overall, TRI_{95B} was the only index to fall into the “upset” or higher class at lower discrepancy values.

The above results suggested that TRI_{95B} had greater accuracy and reliability toward the DWTP operations than the other indices. Indeed, TRI_{95B} was able to point out failures of plant operation even when the target turbidity was only slightly exceeded. Furthermore, considering the 95th percentile rather than the 90th allowed including extreme turbidity data within the run. Consequently, this was useful for identifying undesired process conditions even if they occur for a brief duration. Moreover, the introduction of the “B” term enabled to better highlight the occurrence of an extremely severe condition that is mandatory for the new regulation, thus providing additional reliability to the robustness index.

3.5 Overall considerations about TRIs and potential applications

This study showed that robustness indices represent a quantitative measure to assess how well a plant is performing in maintaining water quality standards while providing an early warning system by detecting deviations from desired water quality standards. The results reported in this study demonstrated that when considering the 95th percentile as a reference parameter for turbidity, the DWTP was not able to comply with the requirements of the new regulation. This suggested that a thorough and accurate analysis of the plant's robustness is required to provide high-quality water to consumers.

The TRIs already available in the literature and the one proposed in this study have demonstrated good reliability concerning the objectives set by the old regulations referring to water turbidity. Conversely, when considering a lower threshold, the old TRIs showed poor adaptability, while the new robustness index was proven to be more reliable.

Overall, TRI_{95B} showed a greater capability of synthetically and effectively describing the variability of plant performance, allowing highlighting process failures more accurately than the other TRIs. More specifically, the greater sensitivity shown by the TRI_{95B} i.e., the ability to identify failures even if they are of short duration and low magnitude, complies with the purpose of the new regulation for drinking water. The use of this TRI could represent a useful evaluation tool for DWTP managers to identify and address potential issues especially if they are associated with certain conditions (e.g., units' overload, significant variability of influent turbidity) (Zhang et al., 2012). The generalizability of the proposed index should be further investigated in other contexts (e.g. different dataset, different processes, different regulations). In this sense, future studies are recommended to increase the reliability of TRI_{95B}.

Such an approach can also be helpful in identifying process units that exhibit criticality and vulnerability to specific load conditions. In this sense, by monitoring TRI during time, operators could proactively manage risks associated with process upset, thus contributing to minimize process vulnerability. Future studies would be encouraged to put in relationship the TRI to plant's operational parameters or characteristics of the raw water (e.g., influent solids load, water temperature, turbidity fluctuations, etc.). Within this approach, using robustness indices could be helpful to predict how systems behave when subjected to different loads, environmental conditions, or operational disturbances. In this way, the application of the indices could highlight operational occurrences that stress specific process units, allowing the plant operator to mitigate or avoid process dysfunctions. In addition, the integration of robustness indices with predictive models could allow identifying failure units or processes and suggest preventive measures. This could enable operators to forecast the long-term stability and reliability of a drinking water treatment plant, which is crucial for providing safe water to population. Lastly, a further application of the TRI_{95B} could be to evaluate, on one hand, the

plant's response to intense short-duration events (e.g., turbidity peaks or short-term rainfall events), and on the other, seasonal variations and long-term trends. Certainly, the duration of the run should be appropriately chosen based on the objective of the study. Specifically, short-duration events will require shorter-duration runs; whereas analysing seasonal responses need for longer-duration runs and the availability of long-term datasets. Additionally, in a context of climate change, which leads to the occurrence of extreme and short-duration events, the index can be useful for assessing the potential vulnerability of the plant. In this regard, a useful approach could be to identify, through the index, a threshold value for a given event that leads to a robustness loss of the plant. All these gaps would require further investigation.

Conclusions

This study proposed a new turbidity robustness index, named TRI_{95B}. The proposed index has the ambitious goal of overcoming the limits of the existing indices in the literature. The proposed index has a more stable response when faced with a new regulation on DWTPs effluent quality (EU 2184/2020) that introduces statistical indicators to be compared with more stringent limits. Indeed, results showed that, compared to previous robustness indices, TRI_{95B} has higher accuracy and reliability when considering the requirements of the new regulation (turbidity < 0.30 NTU). TRI_{95B} also demonstrated better alignment with plant performance. When turbidity exceeded the T_{goal} within a run, TRI_{95B} fell within the “upset” class more frequently compared to other indices. Additionally, while other TRIs identified a critical condition (exceeding the threshold of the “upset” class) for high values of the discrepancy between the turbidity measured in the run and the target value, TRI_{95B} highlighted a failure condition for much lower values. Overall, robustness indices can be considered an excellent diagnostic tool to detect deviations from desired water quality standards and reduce DWTP vulnerability.

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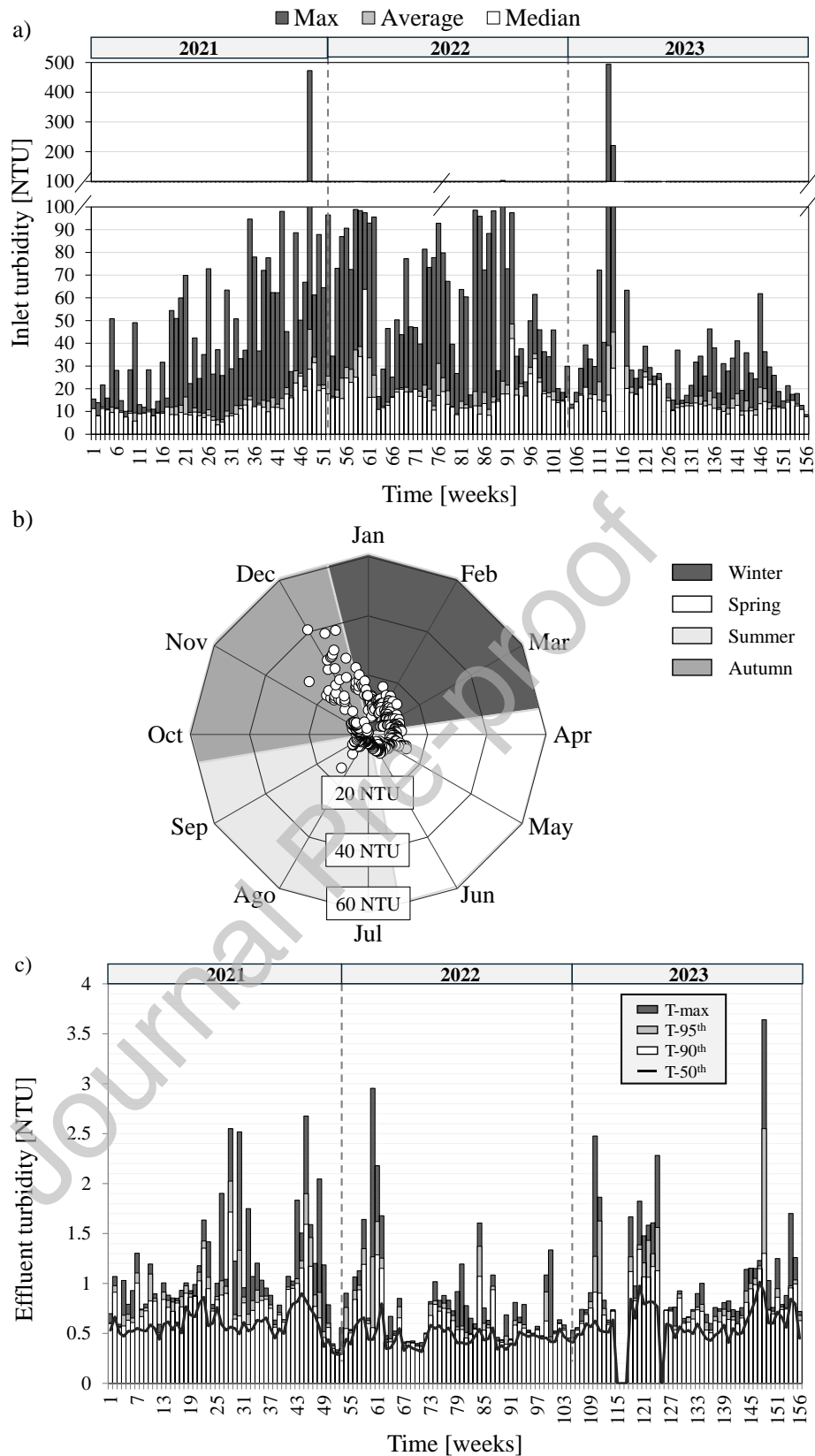


Fig. 1: Trends of the main statistics (mean, median, maximum) of turbidity data in influent water (a): seasonal variation of turbidity data (b); maximum, 90th, 95th percentiles and median of turbidity data measured at the outlet of the DWTP (data between weeks 116-120 and week 125 are missing).

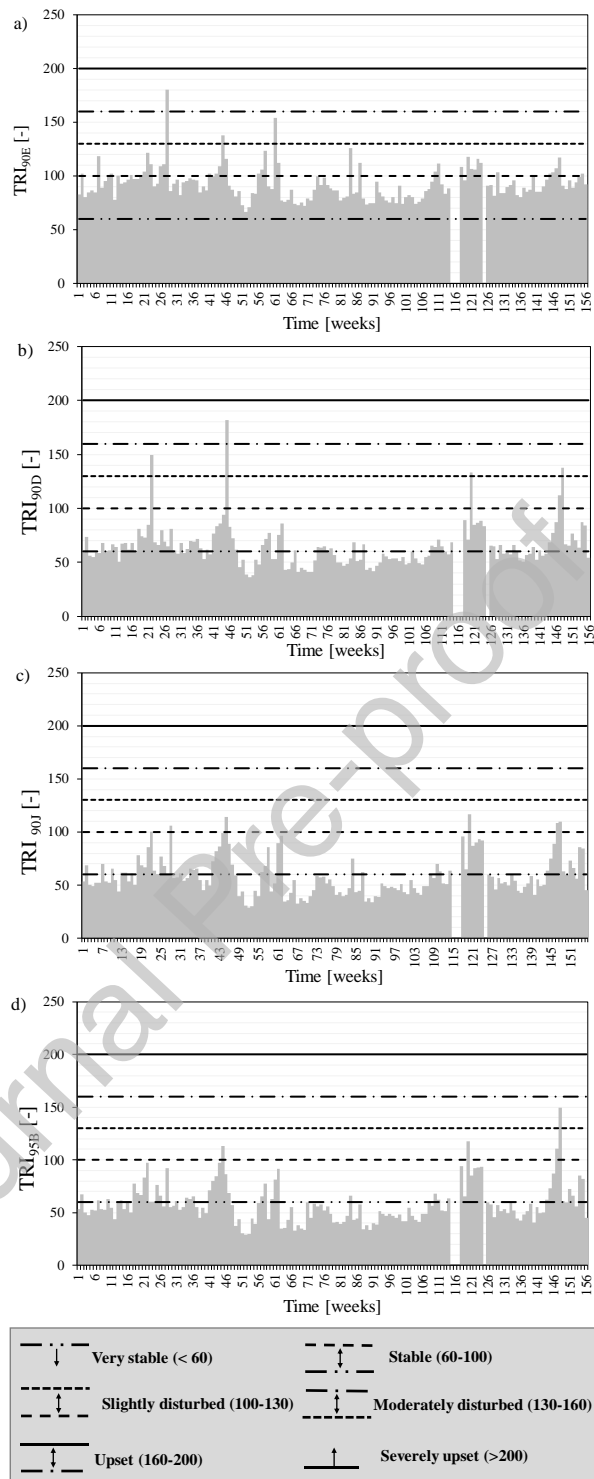


Figure 2: Trends of TRIs scores during the 2021-2023 period, assuming a T_{goal} of 1 NTU.

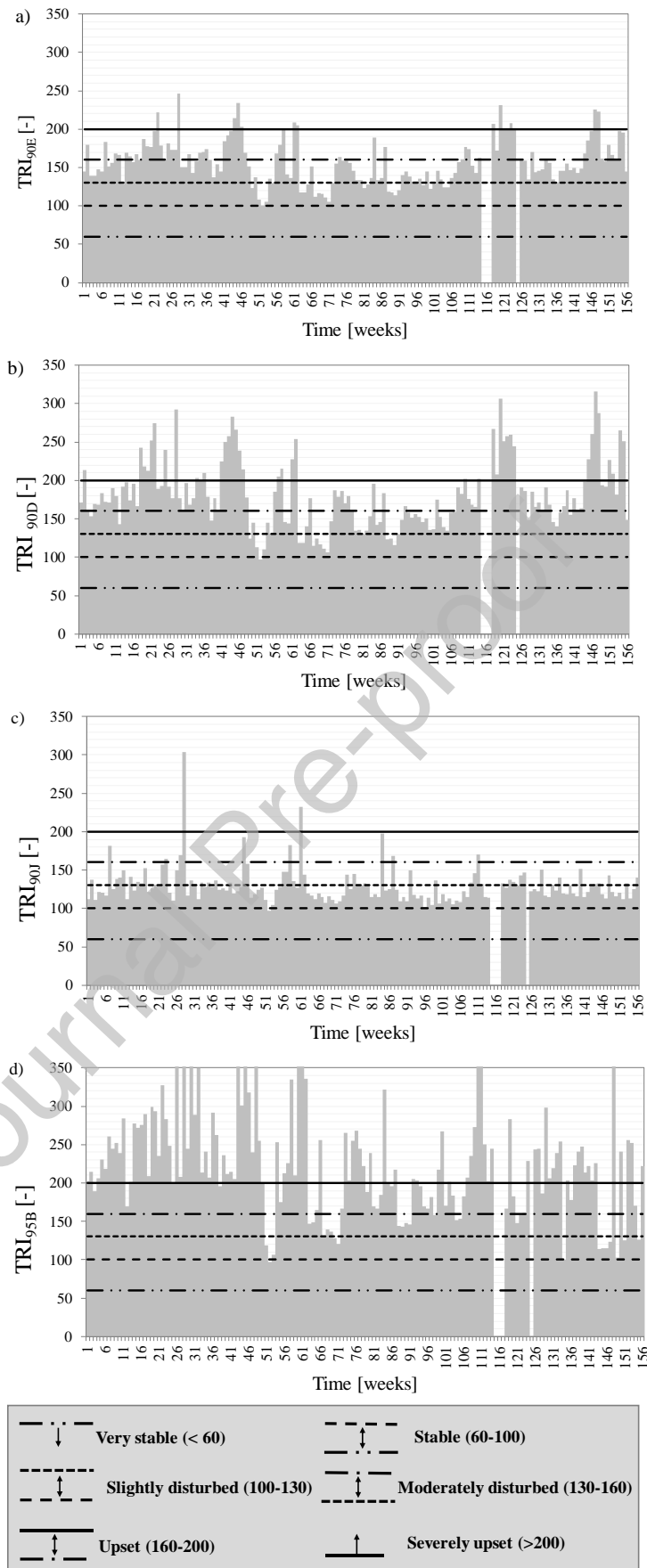


Figure 3: Trends of TRIs scores during the 2021-2023, period assuming a T_{goal} of 0.3 NTU.

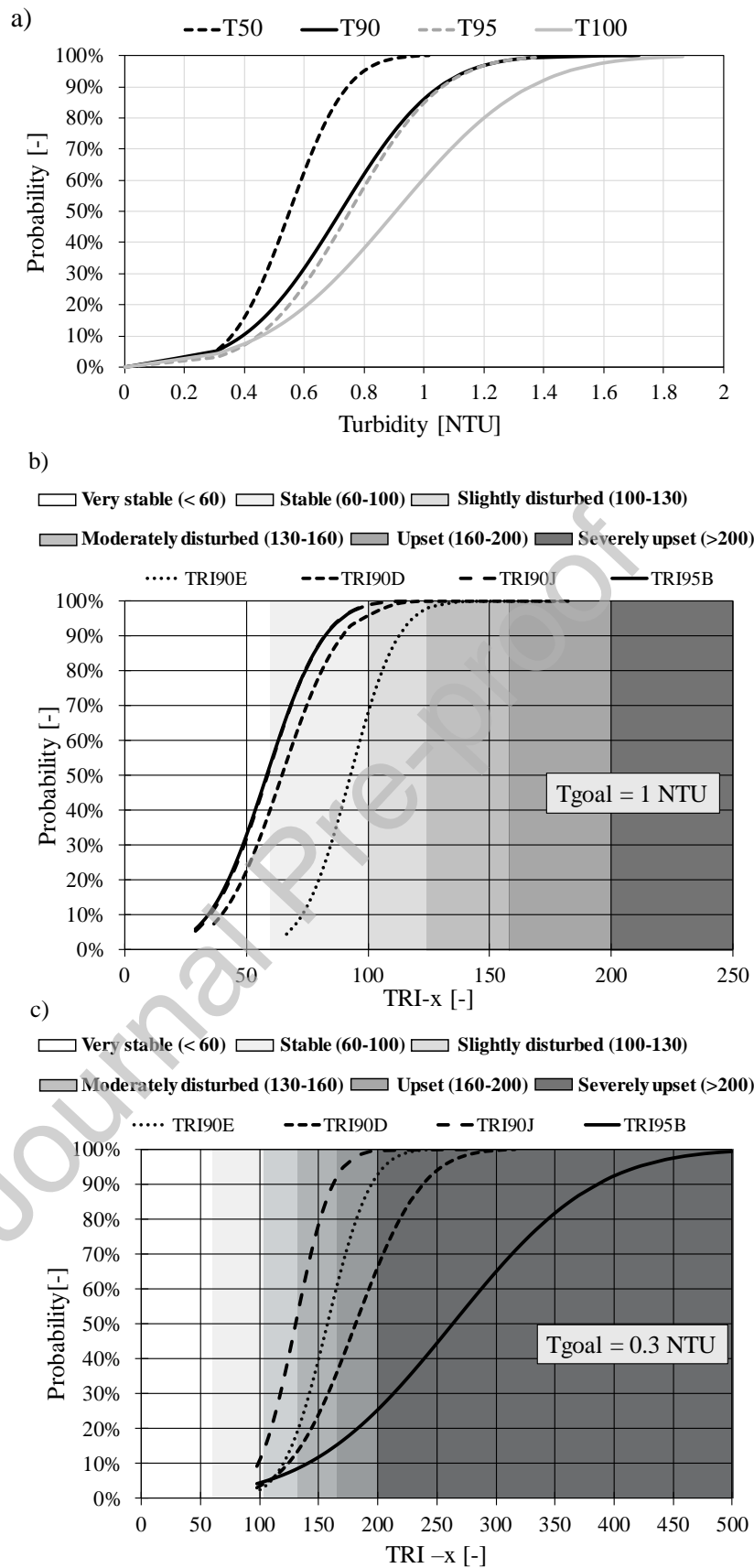


Figure 4: Cumulative distribution of T_{50} , T_{90} , T_{95} and T_{100} (a) and TRIs with T_{goal} of 1 NTU (b) and

0.30 NTU (c).

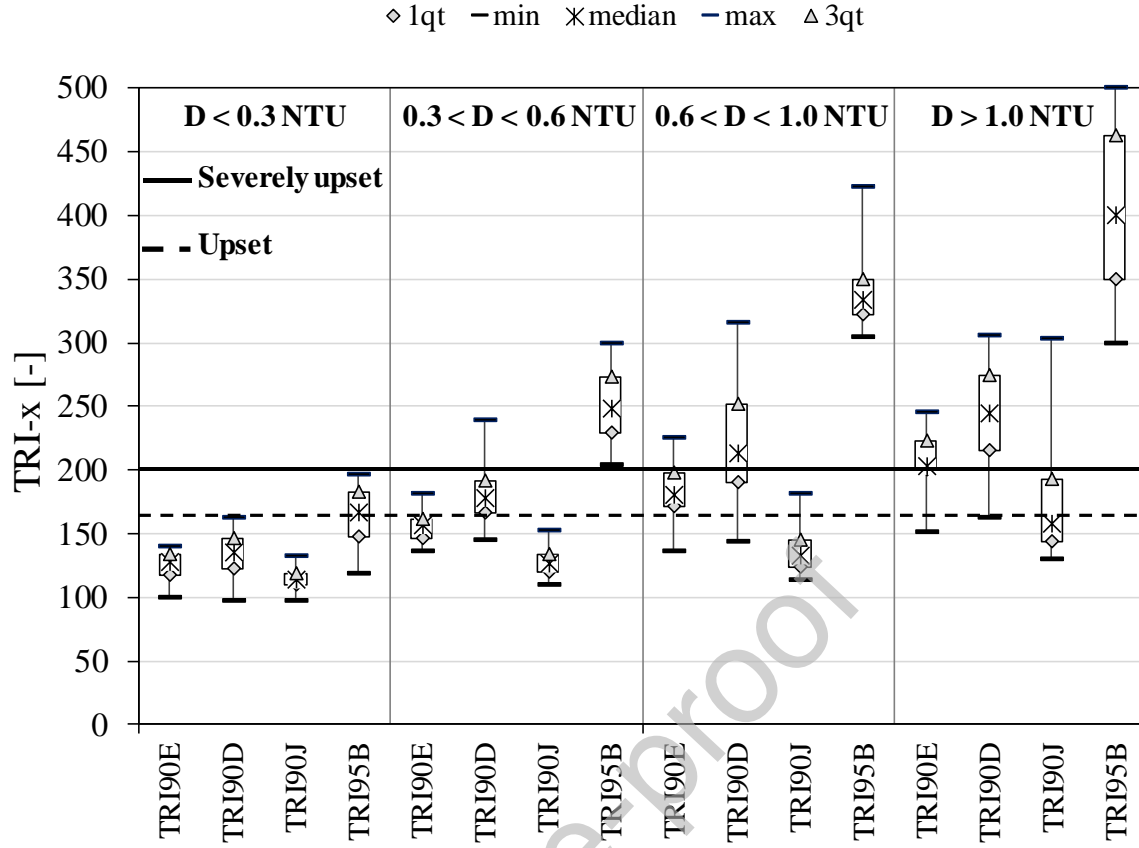


Figure 5: Boxplot of TRIs within different ranges of turbidity discrepancy.

Table 1: Existing TRIs in the literature; classification of system operation with robustness index value and mathematical significance

Eq.	Existing TRIs	Weight definition	Reference
[eq. 1]	$TRI_{90E} = \frac{1}{2} \left(\frac{T_{90}}{T_{50}} + \frac{T_{50}}{T_{goal}} \right)$	Weights are equal to 0.50	Huck et al. (2001)
[eq. 2]	$TRI_{90D} = \left(A_1 \frac{T_{90}}{T_{50}} + A_2 \frac{T_{50}}{T_{goal}} \right) \times 100$	$W = \left(\frac{T_{50}}{T_{goal}} + \frac{T_{60}}{T_{goal}} + \frac{T_{70}}{T_{goal}} + \frac{T_{80}}{T_{goal}} + \frac{T_{90}}{T_{goal}} \right) \times 10$ <p>$N = 50$</p> <p>$W \leq N \rightarrow \text{if } \frac{T_{90}}{T_{50}} \leq \frac{T_{50}}{T_{goal}} \rightarrow$ $\rightarrow A1 = 0.9; A2 = 0.1;$</p> <p>$W \leq N \rightarrow \text{if } \frac{T_{90}}{T_{50}} > \frac{T_{50}}{T_{goal}} \rightarrow$ $\rightarrow A1 = 0.1; A2 = 0.9;$</p> <p>$W > N \rightarrow \text{if } \frac{T_{90}}{T_{50}} \leq \frac{T_{50}}{T_{goal}} \rightarrow$ $\rightarrow A1 = 0.1; A2 = 0.9;$</p> <p>$W > N \rightarrow \text{if } \frac{T_{90}}{T_{50}} > \frac{T_{50}}{T_{goal}} \rightarrow$ $\rightarrow A1 = 0.9; A2 = 0.1$</p>	Li and Huck (2008)

[eq. 3]	$TRI_{90J} = \left\{ \left[\left(1 - \frac{G\%}{100} \right) \times \frac{T_{90}}{T_{50}} \right] + \left[\frac{T_{50}}{T_{goal}} \times \frac{G\%}{100} \right] \right\} \times 100$	G% is the percentage time below the turbidity goal within the run	Hartshorn et al. (2015)
Class	TRI values	Mathematical significance	
Very stable	<60	$T_{50} \ll T_{goal}$ and $T_{90} < 50\%$ of T_{goal}	
Stable	60–100	$T_{50} = 60\text{-}75\%$ of T_{goal} and $T_{90} \approx T_{goal}$	
Slightly disturbed	100–130	$T_{50} < T_{goal}$ and $T_{90} = 30\%$ over T_{goal}	
Moderately disturbed	130–160	$T_{50} = 20\%$ over T_{goal} and $T_{90} = 60\text{-}80\%$ over T_{goal}	
Upset	160–200	$T_{50}, T_{90} = 60\text{-}80\%$ over T_{goal}	
Severely upset	>200	$T_{50}, T_{90} = 100\%$ over T_{goal}	

Table 2: Occurrence of TRIs within a class of system operation quality ($T_{goal} = 1$ NTU)

TRI class	TRI _{90E}	TRI _{90D}	TRI _{90J}	TRI _{95B} (*)
Very stable	0	69	98	100
Stable	115	78	48	48
Slightly disturbed	34	1	6	3
Moderately disturbed	2	3	0	1
Upset	1	1	0	0
Severely upset	0	0	0	0
Not available	4	4	4	4
Total	156	156	156	156

Table 3: Occurrence of TRIs within a class of system operation quality ($T_{goal} = 0.3$ NTU)

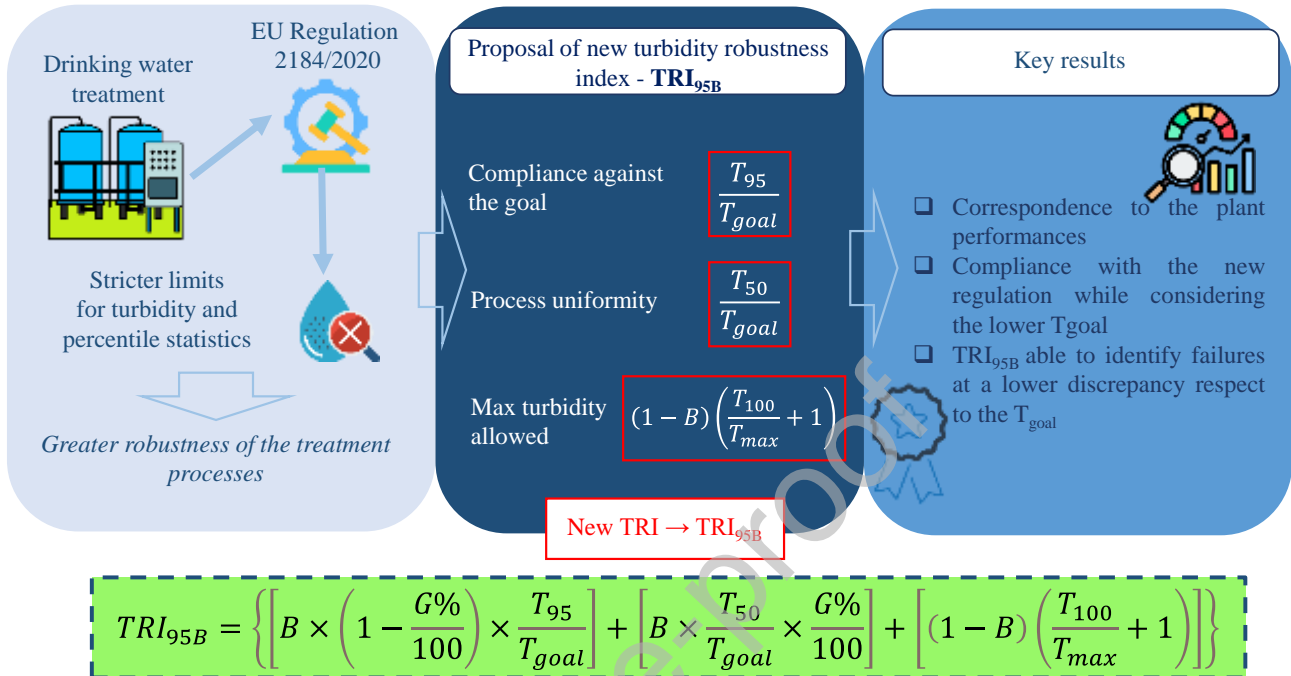
TRI class	TRI _{90E}	TRI _{90D}	TRI _{90J}	TRI _{95B}
Very stable	0	0	0	0
Stable	0	1	1	1
Slightly disturbed	25	15	91	12
Moderately disturbed	66	38	50	14
Upset	46	60	8	24
Severely upset	15	38	2	101
Not available	4	4	4	4
Total	156	156	156	156

Table 4: Results of sensitivity and specificity of TRIs referred to the old and new regulations

Directive 98/83/EC – Turbidity 1 NTU				
	TRI _{90E}	TRI _{90D}	TRI _{90J}	TRI _{95B}
Sensitivity [%]	29	43	71	86
Specificity [%]	21	87	92	88
Directive EU 2184/2020 – Turbidity 0.30 NTU				
Sensitivity [%]	11	29	1	97
Specificity [%]	35	59	41	91

Graphical Abstract

A modified robustness index for assessing operational performance of drinking water treatment plants: a comparative study within a new regulatory framework



Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: