

The wastewater treatment plant operation estimation through the use of the water quality index – the case study of WWTP-Montana, Bulgaria

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Wastewater treatment plants (WWTPs) are designed to treat the used water by improving its quality, so it is no longer harmful to the environment when discharged. The long-term mandatory monitoring of wastewater produces large amounts of data. It can be converted to a unitless number – the Water Quality Index (WQI) and used to assess the wastewater quality by checking compliance with the set regulations. It has gained increasing popularity among decision-makers, wastewater professionals, and environmental agencies.

Operation assessment of the WWTP-Montana for a period of 12 years (2011-2022) was performed using the Canadian Council of Ministers Water Quality Index (CCME WQI) calculation for the raw water (influent) and the treated water (effluent) of the WWTP and applying time series analysis of CCME WQI and water quality indicators – chemical oxygen demand (COD), biochemical oxygen demand after 5 days (BOD₅), total nitrogen (TN), total phosphorus (TP) and total suspended solids (TSS) in the influent. For the entire period, the calculated CCME WQI for the treated waters shows the perfect score of 100 (excellent water quality). The calculated CCME WQI at the inlet, on the other hand, classifies the raw water's quality as "poor" (64% of the CCME WQI values), "marginal" (32%) and "fair" (4%). The time series analysis reveal that higher water quality of the inlet wastewater is detected in summer (August) due to the lower concentrations of the five mandatory physicochemical indicators.

Keywords: CCME WQI, time series, WWTP, influent, effluent, discharge.

INTRODUCTION

Poor wastewater treatment worldwide (about 20% of the total water used) increases water pollution globally [1]. Wastewater treatment plants (WWTPs) are designed to treat the used water. Their primary role is to improve the discharged water quality, so it is of no harm to the environment. This objective is hard to achieve, as the treated effluents still contain a complex mixture of pollutants (e.g. suspended solids, nutrients, bacteria, microbes, etc.). Their environmental effects are often variable [2, 3]. The WWTPs discharge the treated water in the receiving surface water bodies and change, often negatively, their composition (elements' concentrations, salinity, pH, microbial community, etc.) – acting as point sources of contamination, or simply by means of dilution [4, 5]. To prevent breaking the environmental quality standards, thorough monitoring schemes of the effluent discharges and a detailed analysis of numerous different parameters are consequently needed to establish compliance [6].

To mitigate the interpretation of such huge datasets and to optimize the treatment processes, a unitless number – the Water Quality Index (WQI), was introduced as an assessment tool for wastewater quality [7]. It converts the monitoring results of all the monitored water quality parameters (chemical, physical and microbiological) into a single number (ranging from 1 to 100), which is then used to check compliance with the established water quality standards [8]. The calculated WQI value is used in the water quality estimation at a specific WWTP and time through the threshold values of the parameters in the strategic water quality documents [9, 10]. The higher the WQIs, the more efficient the treatment is. In contrast, the influents generally have low WQI values, which makes them harmful to the environment and, therefore necessitate treatment.

The Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) is currently one of the most widely used indices in water quality assessment [11-14]. There are many WQIs applied worldwide, but neither is universally accepted due to the difference in climate and land use. The main advantages of CCME WQI are its

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simplicity, flexibility to input water quality indicators and thresholds, and tolerance to missing data [15, 16]. Thus, the adoption of CCME WQI to different national environmental legislations could be easily performed. The data used in this study were collected from the WWTP of Montana town, Bulgaria. Therefore, the CCME WQI was calculated using the mandatory parameters established in Directive 91/271/EEC [17] and the national legislation [18].

The long-term mandatory monitoring programs of wastewaters produce a large amount of data [19]. There is a variety of statistical methods that could analyze water quality over time but they use a linear or monotonic trend assumption [20,21]. The STL method (Seasonal and Trend decomposition using Loess) deals with nonlinear and non-parametric data such as the changes in water quality. By the use of time series analysis, it is easy to identify trends in water quality changes [22]. Thus, it is used in decision-making for various hydrological processes and operational systems [23].

This study aims to assess the operation of the WWTP-Montana for a period of 12 years (2011-2022) – since it was put into operation in 2010. The assessment is performed by the following steps: (i) calculation of CCME WQI for the influent and effluent of the WWTP and (ii) time series analysis of CCME WQI and water quality indicators – chemical oxygen demand (COD), biochemical oxygen demand after 5 days (BOD₅), total nitrogen (TN), total phosphorus (TP) and total suspended solids (TSS) in the influent.

EXPERIMENTAL

Sampling

WWTP-Montana is designed to treat maximum 17 840 m³/d wastewaters of 98 618 population equivalent (p. e.) using tertiary treatment – with facilities for mechanical and biological treatment, nitrogen removal and chemical precipitation of phosphorus. The water quality parameters, monitored at the outlet of the treatment facility according to Directive 91/271/EEC [17] and Regulation 6 establishing emission standards for acceptable content of hazardous and dangerous substances in wastewater discharged into water bodies [18] are COD, BOD₅, TN, TP and TSS. Wastewater samples at the inlet and the outlet were collected daily from 01.01.2011 to 31.12.2022. The laboratory measurements were performed immediately after sampling at the laboratory on-site.

Chemical analysis

For the determination of the BOD₅, a standard methodology was used [24], based on the measurement of the dissolved oxygen in the sample on the first and on the fifth day. Between the measurements, the samples were stored in a thermostat at 20 ± 1 °C in the dark. All steps of the standard procedure were followed [24].

The methods for the spectrophotometric determination used cuvette tests LCK 1414 for COD, LCK 138 for TN and LCK 348 for TP, a portable spectrophotometer DR 3900 (Hach Lange GmbH, Berlin, Germany) and thermo-reactor LT 200 (Hach Lange GmbH, Berlin, Germany). The detailed procedure is described elsewhere [25]. The method validation, measurement uncertainty estimations and fitness for purpose have already been published [26].

The TSS concentrations were determined by air-pressured filtration of the water samples through glass-fiber filters, drying of the filter at 105 ± 2 °C and mass measurement of the retained particles onto the filter (1.5 μm) by an analytical balance [27].

Water quality index

The water quality index used in this study is the WQI developed by the CCME [28]. The CCME WQI is based on three factors characterizing the anthropogenic impact on the water quality:

- F₁ (Scope) – the percentage of water quality parameters, which do not meet the regulatory guideline values (“failed variables”) over the total number of variables included in the water quality assessment:

$$F_1 = \left(\frac{\text{Number of failed variables}}{\text{Total number of variables}} \right) \times 100$$

- F₂ (Frequency) – the percentage of measurements in which a water quality parameter exceeds the guideline values (“failed tests”) over the total number of tests (measurements):

$$F_2 = \left(\frac{\text{Number of failed tests}}{\text{Total number of tests}} \right) \times 100$$

- F₃ (Amplitude) – the extent of deviation of the “failed tests” values relative to the corresponding guideline values. The amplitude is calculated utilizing a three-step algorithm, at the beginning of which an assessment is made of the magnitude of the deviations (excursion) of the so-called “bad samples” relative to the corresponding maximum allowable concentrations:

$$\text{excursion}_i = \left(\frac{\text{Failed Test Value}_i}{\text{Objective}_j} \right) - 1,$$

where Failed Test Value_i is the value of the “bad” sample, and Objective_j is the reference value of the maximum allowable concentration for the corresponding water quality parameter. The normalized sum of deviations NSE is then calculated:

$$\text{NSE} = \sum_{i=1}^n \frac{\text{excursion}_i}{\text{Number of tests}}$$

Finally, the amplitude (F₃) is calculated using the formula:

$$F_3 = \left(\frac{\text{NSE}}{0.01\text{NSE} + 0.01} \right)$$

The calculation of CCME WQI is performed by aggregation of the obtained factors as follows:

$$\text{CCME WQI} = 100 - \left(\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732} \right)$$

The equation above gives a CCME WQI value between 0 and 100, with 0 being the “worst” and 100 – the “best” water quality. Within this range, the water quality is ranked into 5 categories: poor (0-44), marginal (45-64), fair (65-79), good (80-94) and excellent (95-100) [28].

Time series

Time series is a sequence of data with equal intervals over time, which could be defined as daily, weekly, monthly, yearly, etc. [23]. Time series data can show different patterns, so it is often useful to represent them by dividing a time series into three components – a trend component (a combination of the trend and cycle patterns), a seasonal component and a remainder component (containing anything else in the time series) [29]. In this study, additive decomposition was performed by the versatile and robust time series method STL [30-32].

A time series analyses of 6 parameters – CCME WQI and the monthly average values of the water quality indicators (COD, BOD₅, TN, TP and TSS) in the untreated (inlet) wastewater, were carried out. The total number of values for each one of the parameters used in this study was 137. An imputation (replacing NAs with reasonable values) by interpolation was performed for the missing data (7 for each one of the six parameters) [33]. All time series analyses were performed using R Statistical Software v4.4.1 [34].

RESULTS AND DISCUSSION

Sampling and basic statistics

Treated (outlet) and untreated (inlet) wastewater was collected from WWTP-Montana from 01.01.2011 to 31.12.2022. The results obtained for the five mandatory physicochemical indicators – COD, BOD₅, TN, TP and TSS were used for this study (Table 1). The water quality requirements for the WWTPs discharges are set the Directive 91/271/EEC [17] and in Regulation 6 [18]. No limits apply to the raw water at the inlet of the treatment plant.

Water quality index

The CCME WQIs for the inlet and the outlet of WWTP-Montana were calculated. The CCME WQI at the outlet of the treatment plant reveals the excellent performance of the treatment facility. No samples show exceedings of the regulatory permissible concentrations set in Directive 91/271/EEC [17]. For the entire period, the calculated CCME WQI shows the perfect score of 100 (excellent water quality). This finding is in line with observations for the mandatory monitoring in 2017 [35] and for random samplings in 2018 [25], 2019 [36] and 2020 [37], where no exceedings of the regulatory standards were identified. The concentrations of the monitored parameters show slight changes over the entire period – COD and TN show a marginal increase, whereas BOD₅, TP and TSS exhibit a marginal decrease (Fig. 1, Table 2).

The calculated CCME WQI at the inlet of the treatment plant classifies the water quality as poor (64% of the CCME WQI values) to marginal (32%), with a few exceptions (January 2011, July 2014, August 2014, September 2014, May 2015 and August 2015) of a fair (4%) water quality.

A closer look at the water quality at the inlet of the WWTP in terms of the concentrations of the monitored mandatory parameters reveals that in time the concentrations of COD (n = 4006), BOD₅ (n = 2852), TN (n = 4006) and TP (n = 4003) marginally increase, whereas the concentration of TSS (n = 2867) marginally decreases (Fig. 2, Table 2). These results lead to the conclusion that the decrease of the CCME WQI is due to a greater number of occurring excursions in the later years, rather than due to the change of the water composition at the inlet of the WWTP. Such findings confirm that the water quality in a municipality does not change significantly in time due to the same habits and way of life of the population.

Table 1. Basic statistics for the water quality parameters at the inlet and the outlet of WWTP-Montana.

	COD, mg/L O ₂	BOD ₅ , mg/L O ₂	TP, mg/L	TN, mg/L	TSS, mg/L
<i>Inlet permissible concentrations</i>	–	–	–	–	–
n	4006	2852	4003	4006	2867
mean	98.3	52.4	1.2	17.2	63.9
median	93.0	50.0	1.1	16.7	68.0
min	1.2	0.0	0.1	1.5	0.0
max	582.3	270.0	21.1	162.0	232.0
st. dev.	30.1	17.3	0.7	4.8	24.4
<i>Outlet permissible concentrations</i>	125	25	2	15	35
n	3900	2770	3898	3901	2771
mean	16.6	9.6	0.8	8.8	12.7
median	16.4	10.0	0.8	8.9	12.0
min	7.1	0	0.016	4.9	0
max	41.5	20.0	1.8	13.9	33.0
st. dev.	3.3	2.2	0.2	1.2	4.7

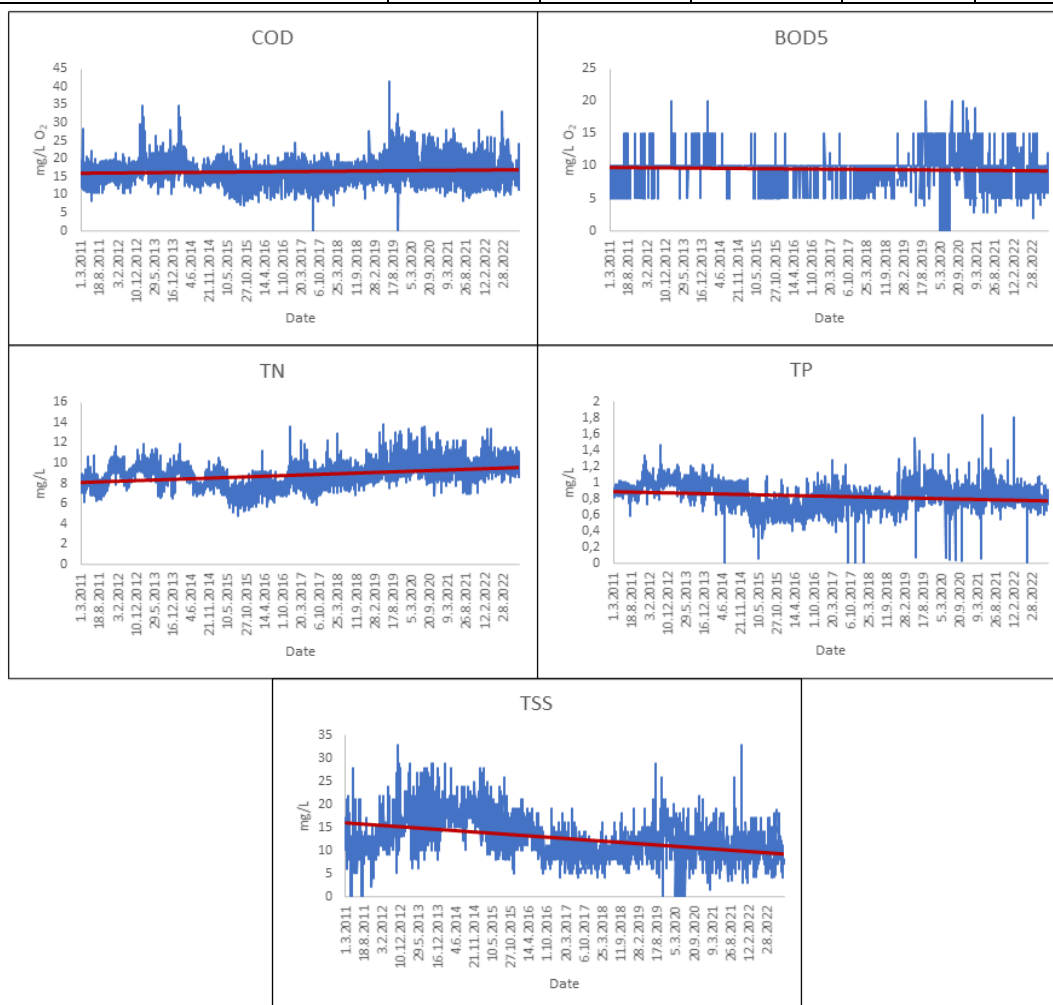


Fig. 1. Concentrations of COD, BOD₅, TN, TP and TSS (in blue) and the corresponding trend lines (in red) at the outlet of WWTP-Montana (2011-2022).

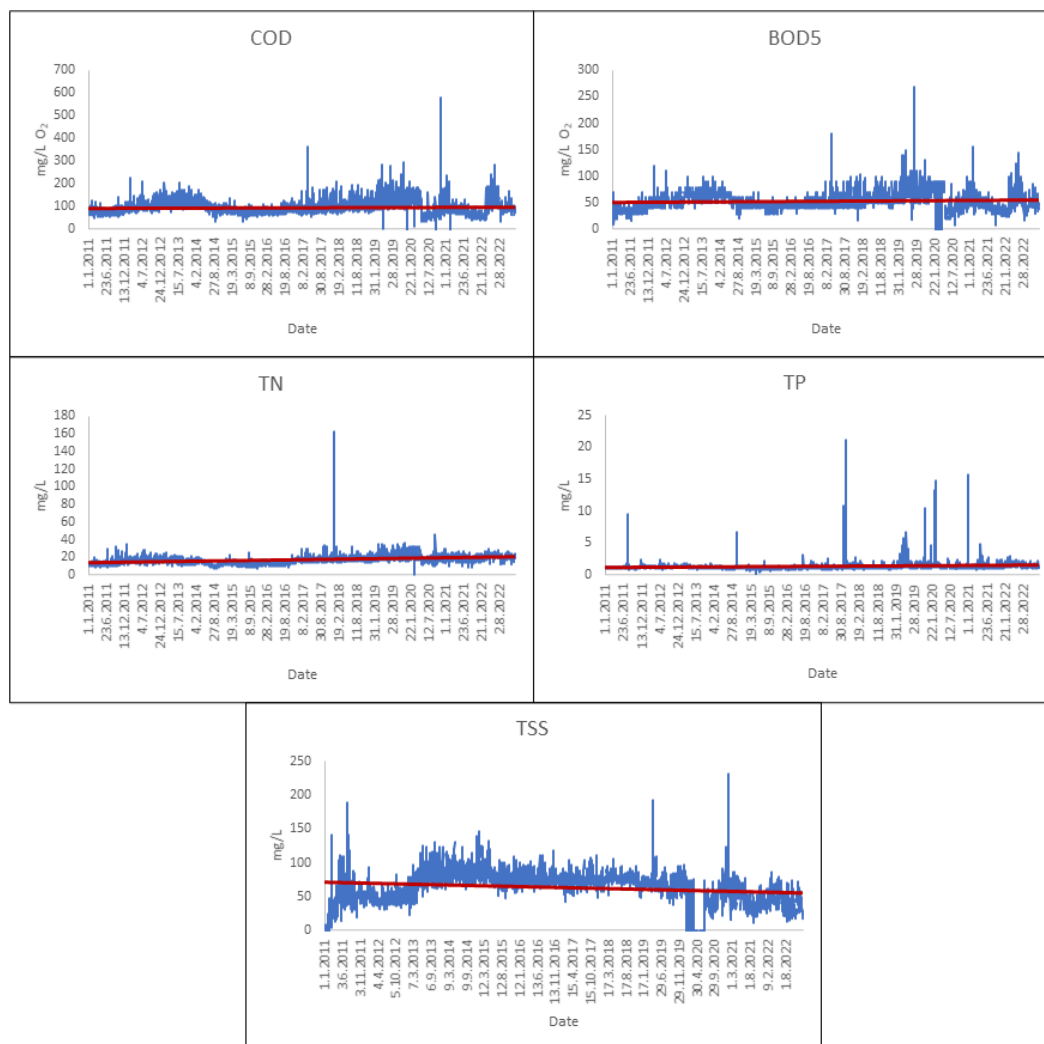


Fig. 2. Concentrations of COD, BOD₅, TN, TP and TSS (in blue) and the corresponding trend lines (in red) at the inlet of WWTP-Montana (2011-2022).

Table 2. Regression equations of the concentrations of the water quality parameters at the outlet and at the inlet of WWTP-Montana (See Figs. 1, 2).

Parameter	Outlet		Inlet	
	Regression equation	Coefficient of determination (R ²)	Regression equation	Coefficient of determination (R ²)
COD	$f(x)=0.0002x + 16.10$	0.0064	$f(x)=0.0003x + 97.71$	0.0001
BOD ₅	$f(x)= -0.0001x + 9.790$	0.0041	$f(x)=0.0013x + 49.69$	0.0086
TN	$f(x)=0.0004x + 8.097$	0.1223	$f(x)=0.0018x + 13.49$	0.2026
TP	$f(x)= -0.00003x + 0.8968$	0.0394	$f(x)=0.00005x + 1.078$	0.0194
TSS	$f(x)= -0.0017x + 16.01$	0.1666	$f(x)= -0.0039x + 71.94$	0.0363

Time series

Generally, there is a trend in the reduction of the CCME WQI at the inlet, meaning that the water quality worsens over time. It could be speculated that this is probably due to the increase in the industry in the Montana municipality in recent years, despite the constant population decline (by 14% for 2011-2021) [38]. As a first step of the time series analysis, the

data for each one of the water quality parameters was stored in a time series object in R with a frequency of 12 [39]. For the mandatory parameters, the inlet monthly concentrations were used. The additive decomposition of each time series object was performed by the STL method. The estimated components are presented in Figs. 3-8. Moreover, the calculated values of the seasonal components of each parameter are presented in Table 3. The higher

the observed monthly value, the higher the parameter's concentration. The highest values of the observed concentrations in the seasonal components are marked in red and bolded, and the lowest values are marked in green and italicized. In terms of the

CCME WQI, the higher the value, the better the water quality, so that the highest value is marked in green and italicized as the lowest are marked in red and bolded.

Table 3. Estimated values of the seasonal components of the water quality parameters at the inlet of WWTP-Montana.

	CCME WQI	COD	BOD ₅	TN	TP	TSS
January	-2.34	1.85	1.74	1.04	-0.01	6.48
February	-1.79	1.29	-0.01	0.74	0.11	-0.44
March	-3.38	4.80	1.78	0.88	0.00	0.80
April	-2.58	7.77	4.97	0.79	0.04	0.97
May	2.63	-2.99	-1.11	-0.35	0.01	-2.61
June	-1.53	0.48	0.15	-0.20	-0.03	-2.75
July	0.81	-3.39	-1.21	-0.64	<i>-0.08</i>	1.17
August	<i>5.66</i>	<i>-6.93</i>	<i>-3.18</i>	<i>-1.22</i>	<i>-0.05</i>	<i>-2.92</i>
September	2.13	-2.55	-1.77	-0.78	-0.02	<i>-3.64</i>
October	-1.14	-1.40	-1.03	-0.21	0.04	1.36
November	1.83	0.23	-1.29	-0.11	-0.02	2.08
December	-0.30	0.84	0.94	0.07	0.00	-0.50

Results obtained show 3 groups of parameters. For CCME WQI, COD, BOD₅ and TSS a pronounced seasonality is observed. A less pronounced seasonality is observed for TN and a lack of seasonality – for TP. The highest value for the CCME WQI (best water quality) and the lowest values for the mandatory parameters are observed in August. The reason for this is that the population of Montana usually is absent from the town, which also applies to the industry, both due to the holiday season. The time series plot of the CCME WQI is presented in Fig. 3. The seasonal component shows that the lowest values are observed in the spring months (the lowest in March) and the highest values are observed in August (the highest peak in the seasonal component), with lower peaks in May and in September. The trend component reveals that at the beginning of the studied period, the CCME WQI decreased, followed by an improvement during 2015, another decrease with the lowest wastewater quality during 2019 and a slight

increase afterwards.

The components of the COD and BOD₅ time series show similar behavior (Figs. 4, and 5). The seasonality is in contrast to the one observed in the CCME WQI time series – peaks are found in the spring (March and April), and the minimum – in August. The trend components of COD and BOD₅ are quite the opposite of the CCME WQI trend plot. One could see peaks during 2014 and 2019 when the worst water quality was observed.

The nutrients – TN and TP exhibit somewhat different behavior. For TN (Fig. 6), peaks are observed in the winter (January – April, with a maximum in January), and the lowest concentrations are observed in the summer (July – September, with a minimum in August). For TP (Fig. 7), a seasonality is difficult to observe. The trend components of the TN and TP time series are somewhat similar to those observed for COD and BOD₅ – the concentrations are highest in 2019 and lowest in 2015.

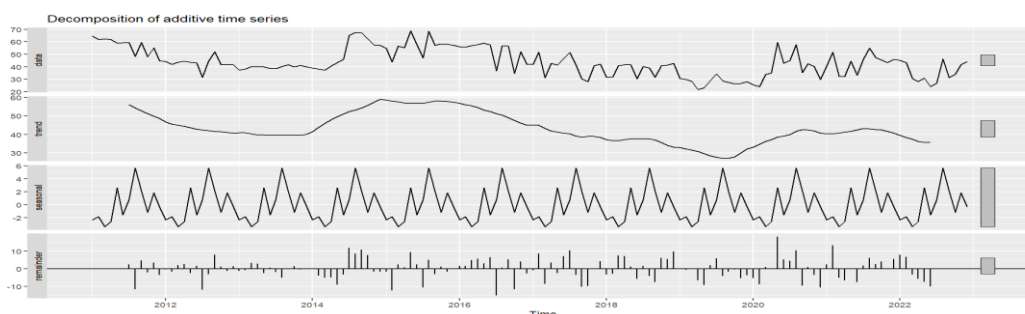


Fig. 3. Time series plot for the CCME WQI of the WWTP-Montana's inlet for 2011-2022.

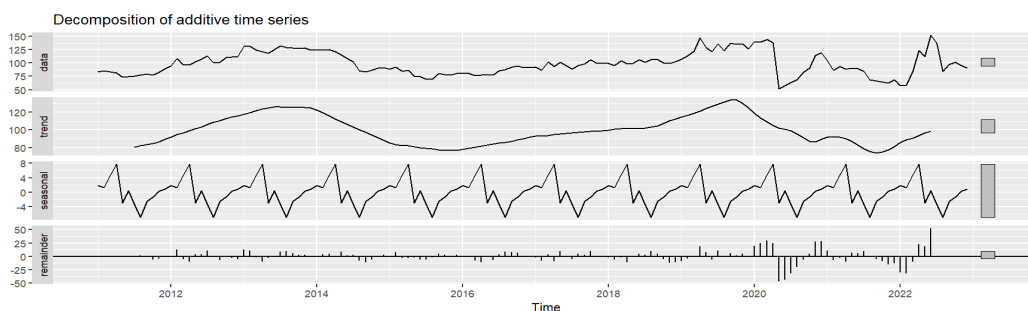


Fig. 4. Time series plots for COD in the WWTP-Montana’s inlet for 2011-2022.

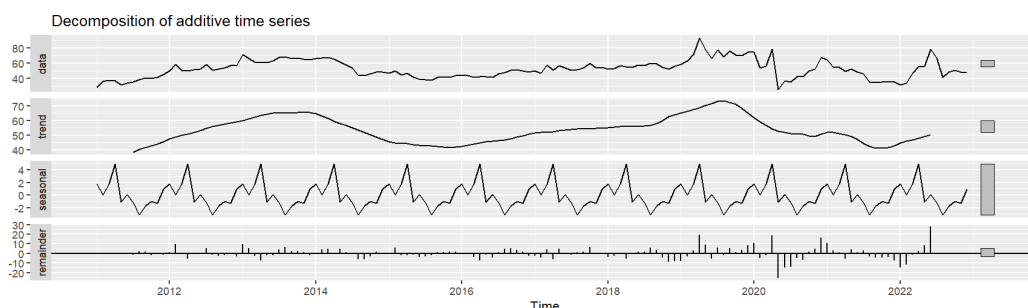


Fig. 5. Time series plots for BOD₅ in the WWTP-Montana’s inlet for 2011-2022.

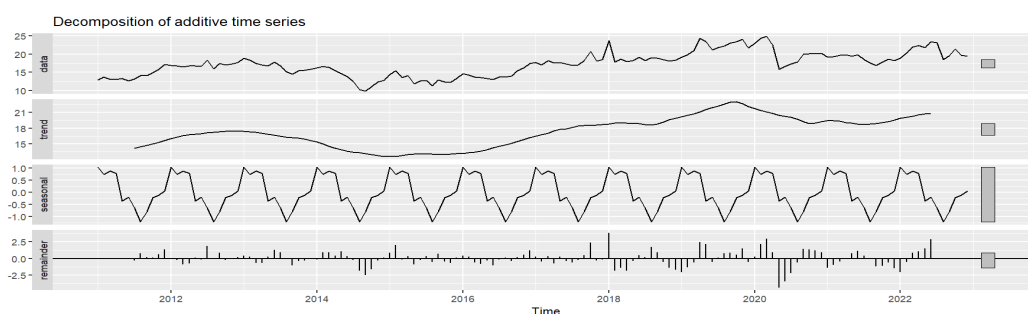


Fig. 6. Time series plots for TN in the WWTP-Montana’s inlet for 2011-2022.

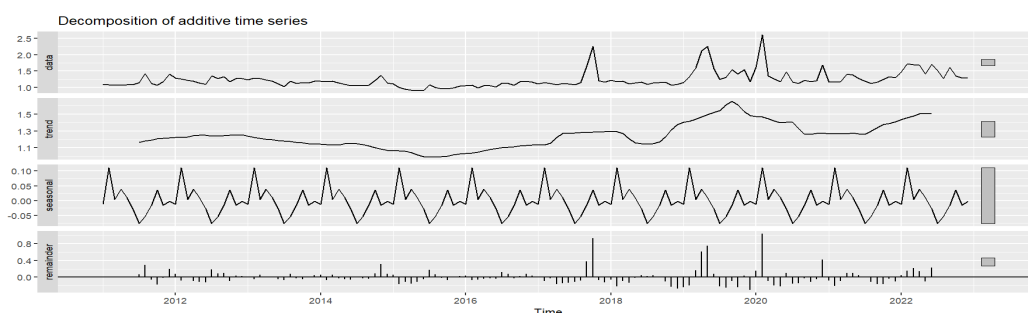


Fig. 7. Time series plots for TP in the WWTP-Montana’s inlet for 2011-2022.

The decomposition of the TSS time series is presented in Fig. 8. The seasonal component shows peaks in January and November and again the lowest concentrations are observed in August and September. As regards the trend component, there is no pronounced similarity with the other water quality parameters. Nevertheless, the TSS is

associated more with the TN and TP (Table 3), rather than COD and BOD₅, which confirms the previous finding for the source contributions to WWTP effluent loads for WWTP-Montana [35]. The maximum is observed for 2015, followed by a sharp decline in 2020.

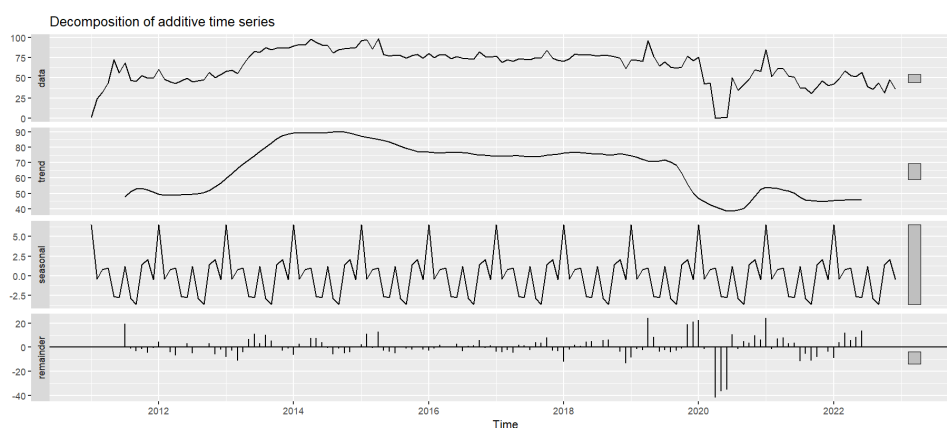


Fig. 8. Time series plots for TSS in the WWTP-Montana's inlet for 2011-2022.

CONCLUSION

The CCME WQI can be used as a reliable estimate for the operation of the WWTPs. The case study of WWTP-Montana shows the excellent performance of the treatment facility, which results in excellent water quality being discharged in the Ogosta River. The time series analyses reveal that higher water quality of the inlet wastewater is detected in summer (August) due to the lower concentrations of the five mandatory physicochemical indicators. Fair water quality is observed at the end of 2014 and 2015, marginal – especially during 2011, 2015, 2016 and 2021 and poor during the other years from the studied period with the lowest values of CCME WQI for 2019. The CCME WQI for the WWTP-Montana generally depends on the concentrations of COD and BOD₅, but not on the concentrations of TP and TN.

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