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Pollutant load estimation and load reduction target (LRT) projection for total maximum daily load (TMD) allocation on tropical rivers

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ABSTRACT

Pollutant load may be defined as the mass of a substance that passes a particular point of a river in a specified amount of time. Meanwhile, estimation of pollutant loading and identification of their sources is crucial to environmental management and planning. For the first time (in this study), Flow rate measurement was used to estimate daily pollutant loading from Intermittent water quality concentration data, using a 2-dymensional Water Quality Analyser (WQA). Subsequently, Total Maximum Daily Load (TMDL) was determined using the Load duration approach, while Load Reduction Targets were projected for the future, the using regression option of trend analysis available in the WQA. Out of the ten parameters used for the study, BOD, NH_3, and TSS have been identified as the most critical pollutants in the area, which require average load reduction of 3898.88 kg^{-day}, 1053.28 kg^{-day}, and 444,716.50 kg^{-day} respectively, to achieve water quality class II, until 2030. Moreover, the study reveals that the load reduction target for BOD and TSS would decrease in the future, while that of NH_3 increases ($p < 0.001$). This is even as significant variability also exists for the projected load reduction target over the months throughout the projected period ($p < 0.01$). It was concluded that WQA provides a cost and time effective, and a reliable means for estimation of Pollutant load and projection of Load Reduction Target. The study recommends source identification for the critical pollutants into the river and allocation of TMDLs using the dynamic flow approach.

1. Introduction

Pollutant load may be defined as the mass of a substance that passes a particular point of a river (such as a monitoring station or a watershed outlet) in a specified amount of time (e.g., daily, annually, etc. (Meals et al., 2013). According to (Han et al., 2021) an accurate accounting of the load of pollutants entering the water body can judge and predict the current and future trends of water pollution, thus providing a scientific basis for government decision-making and management, and providing data support for water resources protection and water pollution prevention. Meanwhile, estimation of pollutant loading and identification of their sources is crucial to environmental management and planning (Zhang et al., 2011; Zhao et al., 2015).

Pollutant load have been used to ascertain the amount of pollutant a particular water body can accept before becoming impaired for a given standard; this is term as the Total Maximum Daily Load, which is key to water resource management (Hunter and Kang, 2016). It has also been used to ascertain the amount of pollutant flow needed to be reduced from pollutant sources for the purpose of water quality restoration and quality assurance. This is term as load reduction target, which is necessary for the implementation of TMDL. These can be achieve using "load duration approach" (Yan et al., 2019), where average Daily Loads (DL) are compared with the flow conditions and water quality standards to develop the Total Maximum Daily Loads (TMDL).

The fundamental data requirements for pollutant load estimation include flow and pollutant concentration. However, unlike taking flow measurements, it is rather difficult and economically intensive to take water samples and laboratory analysis for several water quality

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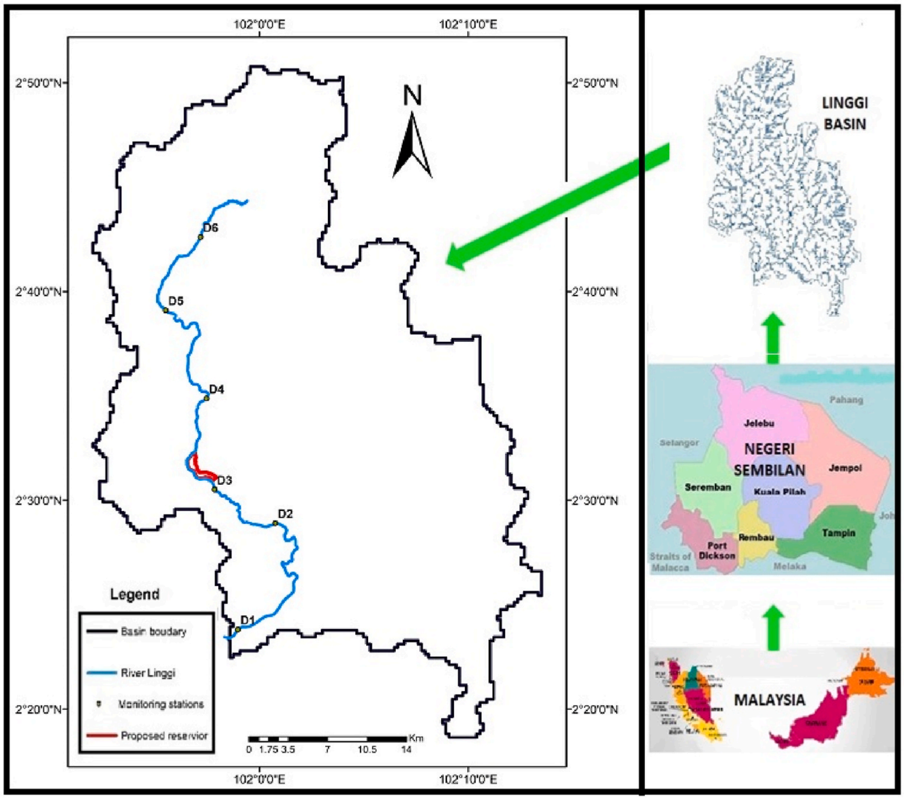

Fig. 1. Study area.

parameters daily, as required for the calculation of pollutant loads. To overcome this limitation, this study used Water Quality Analyser (WQA) to estimate pollutant loads from regular flow and intermitted concentration data. The result was used to project the load reduction target for critical pollutants to support the future implementation of TMDL for rivers in the tropical rainforest. Tropical rainforests are the wet areas around the equator.

Effort is currently underway under the Malaysian Vision Valley (MVV) Development Plan, to establish an additional water treatment plant lower course of the River Linggi, Malaysia, with a view to ensure sustainable water quantity supply to the city of Port Dickson until 2030 (RPM Engineers, 2021). However, the Linggi basin has been identified as one of the most polluted river basins in the country (Nather Khan and Begham, 2012; Semblian, 2014). Therefore, this study used the Linggi basin as a case study, with a view to providing data support for the present and future implementation of TMDL for the MVD and overall water resource management across the basin and other rivers in the tropical rainforest.

2. Materials and methods

2.1. Study area

With about 1298 km^2 for its total drainage area, Sungai Linggi runs

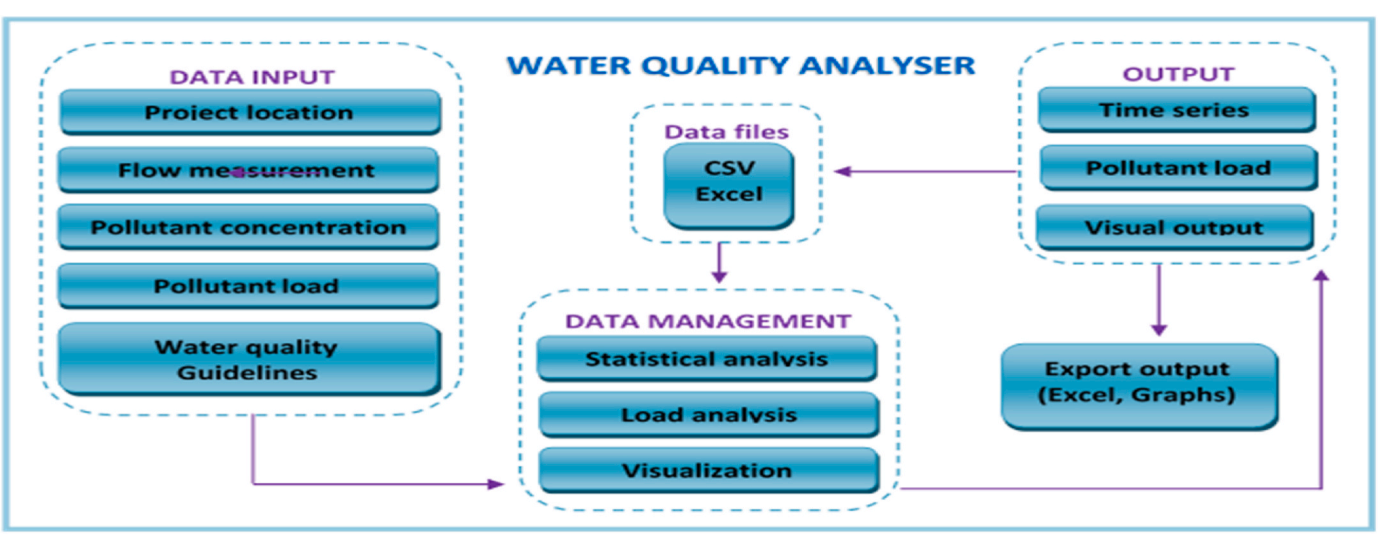

Fig. 2. Simplified architectural design of the Water Quality Analyser (WQA).

through about 75 km across inter-state basin boundary covering part of Negeri Sembilan and Melaka before drains into Straits of Malacca in the southwest direction. It passes through Seremban town and several industrial estates before discharging into the Straits of Melaka (Fig. 1). This contributes to the status of the river basin as one of the most polluted river basins in Malaysia. (Nather Khan and Begham, 2012; Semblian, 2014). Hence, the river was classified as class III, which means it water required extensive treatment for water resources (Elias et al., 2018). Yet the river is among the most important rivers in the Malaysian peninsular (Daneshmand et al., 2011), for the provision of domestic water (Semblian, 2014) and other ecosystem services (E.S.S., 2021). River Linggi provides 60% drinking water requirement to Seremban, which is the capital city for the state of Sembilan. The river also provides 100% drinking water requirement to the town of Port Dickson, which is the second largest town in the state (Semblian, 2014). Based on the 2020 population census data, the two cities have a population of around, 692,283, and 128,689 respectively.

With an average daily high temperature between 25 and 35 °C and average monthly rainfall between 2 and 12 mm day−1 throughout the year (Abdul Zali et al., 2021). The climate of the Linggi basin is classified with the remaining watershed in the Malaysian peninsular as the tropical rainforest (Hazir et al., 2020). Tropical rainforest are the wet areas around the equator that are characterized by higher rainfall and high-level biodiversity (Bradford and Murphy, 2019). Similar climate zones are found in Australia, Bangladesh, Bolivia, Brazil, Indonesia, Peru, and may countries of the world (Doblas et al., 2020), covering about one-third of the world's surface (Tawer et al., 2021). The outcome of this study therefore would have a wide geographical application.

2.2. Model calibration

In order to estimate the pollutant loads using the WQA, water quality data and flow/discharge (Q) measurements were obtained from the Department of Environment (DOE), Malaysia and the Department of Irrigation and Drainage (DID), Malaysia respectively for the period from 2017 to 2019, However, the water quality data was intermitted, containing around five observations for each year. This underscore the advantage of WQA for its ability to estimate the pollutant from an intermitted record.

Water Quality Analyser (WQA) (Fig. 2) is an integrated collection of analysis and assessment tools for time series data. It is capable of conduction several pollutant loads analysis (TPL, EMC, TDL, etc.) as well as providing estimation of the pollutant load for non-sample periods. Where the input data is usually in Excel format the output include visual image and excel spreadsheet, but where the visual images can also be selected and export as numerical values, for further analysis. For the first time, this study used the WQA to project the pollutant load for a tropical river, using continuous flow data and intermitted concentration record. Although the WQA is a new methodology collection, the incorporated tools are not new. Example, the trend analysis tool is a commonly used technique to determine a trend for hydrologic time series data (Arslan et al., 2020).

Fundamentally, the WQA comprises of four modules, which include Data management and visualization, Loads Tool, Trend Tool, as well as the eGuides and Guidelines tool.

The Data Management and Visualization module functions as the central hub of data flow and visualization, which is designed to import, store, export and visualize water quality data. It consists of data files, a visual charts and processing tools. Each processing tool provides feedback about the state of a time series data and a set of recommended actions to perform on the data.

The load estimation module makes assumptions about the behavior of pollutant concentrations in-stream during times when water quality isn't sampled. This task is based on nine of the most common methods for long-term load calculation. It can also calculate event mean concentration (EMC) using four methods for estimating loads from storm events.

The trend tool is a major enhancement of the original trend tool for Catchment Hydrology developed by the CRC. Based on feedback from CRC partners the current version consists of 13 statistical test which include: Spearman's Rho, Linear Regression, Distribution-Free CUSUM, Cumulative Deviation, Worsley Likelihood Ratio, Rank-Sum, Student's t, Median Crossing, Turning Points, Rank Difference, Autocorrelation, and Seasonal Mann-Kendall.

The eGuides consists of some of commonly referred to water quality guidelines against which health can be tested. However, Local guidelines can be incorporated through the Guidelines tool. The guidelines tool is a statistical tool developed to store relevant guideline values in a searchable database for later recall. It is also used to test new datasets against the stored guideline values to provide a statistically sound indication of the water health. The tool can also assist in setting up new water quality targets.

2.3. Techniques of pollutant load estimate and analysis

Averaging technique of the WQA (Fig. 2) was used to estimate the pollutant load, where the continuous flow record and the intermitted water quality monitoring data were used as input. Averaging approaches use some form of average in the calculation of the loads, which involves multiplying the average concentration for a period by the mean daily flow for each day in the time, to obtain a succession of estimated daily loads. Thus (Thomas et al., 2022):

$$Loading\ (Kg / day) = C_i\ (m / L) \times Q_i\left(m^3 / s\right)$$

Subsequently, the average daily concentration of un-sampled days is determined through linear interpolation between the sampled concentrations.

For the first time this study used the WQA to estimate pollutant load. Alternative techniques for load estimation (available within the WQA) include ratio, rating curve techniques, and catchment model. However, where Ration method has Beale ration as the only option, rating curve techniques and catchment model are less versatile and lack universality. On the other hand, the averaging techniques has numerous options, which include Flow weighted concentration, linear interpolation of concentration, Flow stratified sampling, among others. Hence, it is more versatile and universal.

2.4. Techniques of TMDL calculation and projection of LRT

Total maximum Daily Load (TMDL) concept lies in assessment of the maximum pollutant load a water body can accept before becoming impaired (Hunter and Kang, 2016). In this study, TMDL was calculated using Load duration approach, Thus: TMDL (Kg/day) = WQS × flow (m^3/s) * unit conversion factor (EPA, 2007).

Where: WQS is the maximum limit of concentrations for respective parameters in the Water Quality Standard. In this case, the National Water Quality Standard for Malaysia (NWQSM) (DOE, 2023) was used. 86.4 is the unit conversion factor (Yan et al., 2019; Chen et al., 2022) also used mathematical optimization method to developed TMDL.

The difference between the TMDLs at different class of water quality standard and pollutant loads were taken as the load reduction target. However, this was with consideration to Margin of Safety (MoS), which according to the review of MoS conducted by (Nunoo et al., 2020), is mostly 10%. However, (Adnan et al., 2022) used 15%, but in this study the 10% MoS was used. Thus:

TMDL = WLA + LA + MoS (Adnan et al., 2022; EPA, 2022).

Where: WLA = Waste Load Allocation (kg/day) (from point source).

LA = Load Allocation (Kg/day) (from non-point source).

MoS = Margin of Safety.

Within the WQA, regression option of the trend analysis was employed for the projection the load reduction targets. Thus:

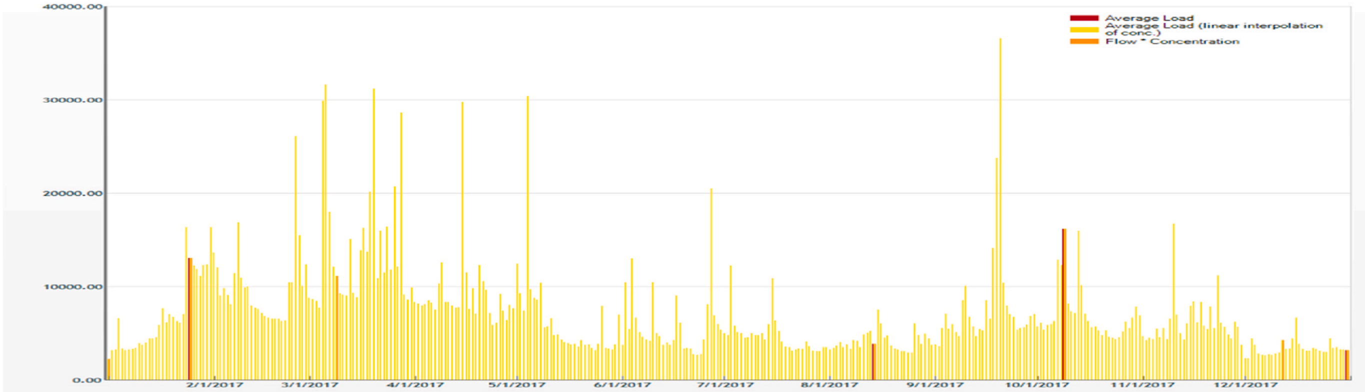

Fig. 3. Daily load for BOD for DOE 01 in 2017.

$$b = \frac{\sum_{i=1}^{n} (x_i - \widetilde{x}) (y_i - \widetilde{y})}{\sum_{i=1}^{n} (x_i - \widetilde{x})^2}$$

$$Intercept : \overline{y} \,.\, b\overline{x}$$

$$\sigma = \sqrt{\frac{12\sum_{i=1}^{n}(y_i - \ \alpha - bx_i)^2}{n(n-2)\ (n^2-1)}}$$

The test statistic $s = {}^{b}\!/_{\sigma}$

The test statistic 'S' follows a Student-t distribution where df = n-2. The beta coefficient "S" was used for the future projection.

Other alternative tools for trend analysis within the WQA include Mann-Kendall, Spearman's Rho, and Seasonal Kendall, which are non-parametric tests. Therefore having satisfied the requirements of the parametric test, the data was subjected to the parametric test for the trend analysis.

2.5. Variability test for the load reduction target (LRT)

Analysis of Variance (ANOVA) was used to examine the monthly dynamics for the projected load reduction target. This is with the view to determine the appropriate technique for the TMDL implementation in the area (Zainudin et al., 2019).

3. Results and discussion

3.1. Daily load (DL)

Pollutant loads were estimated for six heavy metals (Cr, Cd, Fe, Hg, Pb, Zn) and four (BOD, COD, NH_3, TSS) out of the six water quality parameters contained in the Malaysian Water Quality Index (DOE, 2023; Karim and Kamsani, 2020); except for DO and pH, which doesn't support pollutant load calculation. The load was estimated for the six DOE monitoring stations (Fig. 1) for the three years period (2017–2019). One sample graph output (for BOD, station 1, 2017) is shown on Fig. 3, while the remaining 179 graphs were presented in Appendix 1).

Subsequently, the estimated daily loads were used for the determination of TMDL and Load reduction targets, using the Load duration approach (EPA, 2007; Yan et al., 2019). Thus.

3.2. Total maximum daily load (TMDL) and load reduction target (LRT)

The foundation of water resource management embodied in the TMDL concept, which lies in assessment of the maximum pollutant load a water body can accept before becoming impaired (Hunter and Kang, 2016) for a particular use at a particular standard; and establishing the amount of pollutant allowed into the river for a particular standard to be maintained (Adnan et al., 2022). Typically a TMDL is developed for each pollutant/waterbody (EPA, 2022). Therefore, Fig. 4 show the TMDL at varying flow conditions and the average daily loads, for River Linggi, for

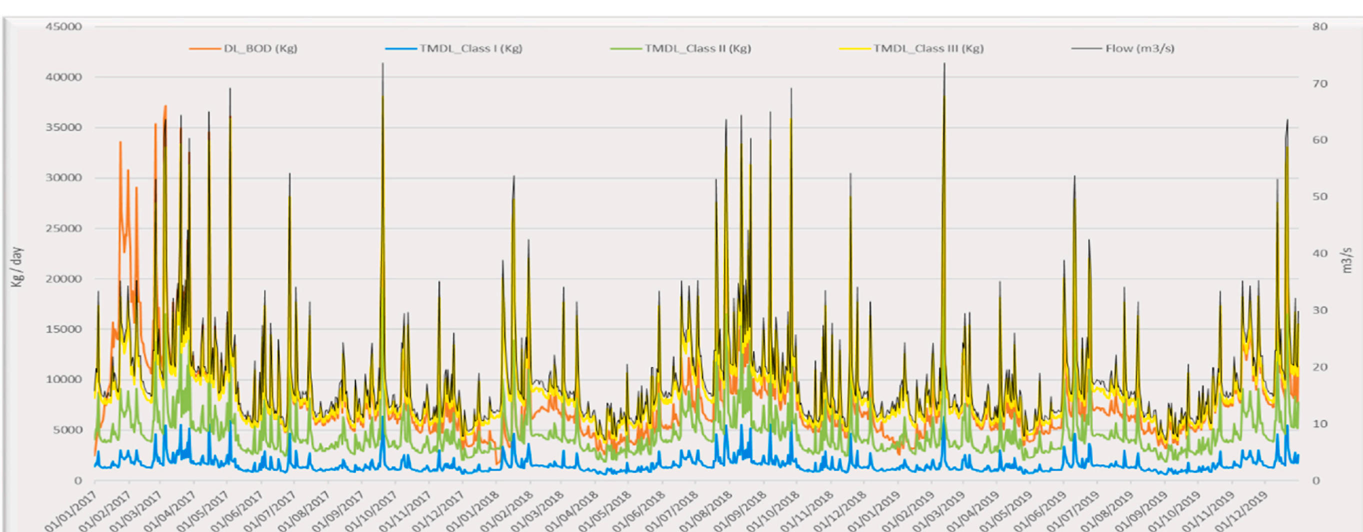

Fig. 4. DL_{BOD} and TMDL at varying flow conditions.

BOD, while the remaining (COD, NH_3, SS, Cd, Cr^{+3}, Fe^{+2}, Hg, Pb, and Zn) were compressed in Appendix 2. Thus.

3.2.1. TMDL and LRT for BOD

Based on the information on Fig. 4 and Appendix 2a, the DL_{BOD} ranged (811.91–110,920.91 kg^{-day}) at varying flow condition. However, a potential outlier has been observed in the month of February 2017, which need to be investigated. Moreover, the river suffered several accidental pollution from pipelines of sewage treatment plant in recent years (E.S.S., 2021) On the other hand, $TMDL_I$, $TMDL_{II}$, and $TMDL_{III}$ for the BOD, ranged (374.73–6567.87 kg^{-day}), (1124.18–19,703.61 kg^{-day}) and (2248.35–39,407.21 kg^{-day}) respectively.

The average DL_{BOD} (8203.16 kg^{-day}) is greater than the average $TMDL_I$ (1552.24 kg^{-day}) and $TMDL_{II}$ (4656.72 kg^{-day}), but less than the average $TMDL_{III}$ (9313.44 kg^{-day}) Appendix 3a). This means the BOD load into the river already exceeded the Assimilation Capacity of the river for the water quality class I and II, by an average of 6650.92 kg^{-day} and 3544.44 kg^{-day} respectively. Hence, the river is within the WQ-class III given it present BOD load, and should not receive BOD addition of more than 1110.28 kg^{-day} to remain within its present status (class III).

Moreover, an average BOD load reduction target of not less than 3544.44 kg^{-day} would be needed for the river to be restored to water quality class II. However, restoration should also take cognisance of the margin of 10% safety (MoS) (Nunoo et al., 2020).

Therefore the restoration target for BOD = 3544.44 + *(3544.44 x 0.1) = 3898*.88 kg^{-day}

3.2.2. TMDL and LRT for COD

DL_{COD} ranged from a minimum of 2841.68 kg^{-day} to the maximum of 225,436.47 kg^{-day} at varying flow conditions. The $TMDL_I$, $TMDL_{II}$, and $TMDL_{III}$ on the other hand, ranged from minimum of 3747.26, 9368.14, and 18,736.27 kg^{-day} respectively to maximum of 65,678.69, 164,196.72, and 328,393.44 kg^{-day} respectively (Appendix 2b).

The average DL_{COD} (27,120.93 kg^{-day}) was less than $TMDL_{II}$ (38,805.99 kg^{-day}) and $TMDL_{III}$ (77,611.98 kg^{-day}), but greater than the average $TMDL_I$ (15,522.40 kg^{-day}) Appendix 3b). Therefore, the COD load into the river was within the water quality class II, as its exceeded the river assimilation capacity of class I, by an average of 11,598.53 kg^{-day}. Hence, the river requires no restoration as per COD. Moreover, an average addition of 11,685.06 kg^{-day} of COD load into the river could deteriorate the COD status of the river to WQ-class III.

3.2.3. TMDL and LRT for NH_3

DL_{NH3} ranged 5.49–20,523.19 kg^{-day} as it responds to different flow conditions, while $TMDL_I$, $TMDL_{II}$, and $TMDL_{III}$ ranged 47.47–656.79 kg^{-day}, 112.42–1970.36 kg^{-day}, and 337.25–5911.03 kg^{-day} respectively (Appendix 2c). However, (Abdulkareem et al., 2018) reported an estimated average annual TSS load from non-point sources in Kelantan River basin, between 1984 and 2013, at 656 Kg.

Unlike the case of BOD and COD, the average DL_{NH3} (1423.20 kg^{-day}) was greater than the average $TMDL_I$ (155.22 kg^{-day}), $TMDL_{II}$ (465.67 kg^{-day}), and $TMDL_{III}$ (1397.53 kg^{-day}) Appendix 3c). This means the NH_3 load was within water quality class IV, as it exceeded the Load assimilation capacity of the river for the water quality class I, II, and III by 1267.98 kg^{-day} 957.53 kg^{-day} and 26.19 kg^{-day} respectively. NH3 was since identified with, TSS, as "the primary causes for water quality impairment in Linggi River" (Daneshmand et al., 2011). Similarly (E.S.S., 2021) predicted future deterioration of NH_4 for the river.

Going by the above result, an average reduction of NH_3 load allocation of 957.53 kg^{-day} from any source or combination of sources would be needed to restore the river to water quality class II, while a little average reduction of 26.19 kg^{-day} could restore it to water quality class III.

Therefore restoration target to water quality class II for NH_3 = *957.53 + (957.53 x 0.1) = 1053*.28 kg^{-day}

3.2.4. TMDL and LRT for TSS

DL_{SS}, $TMDL_I$, $TMDL_{II}$, and $TMDL_{III}$ ranged 655.83–31,691,520.69 kg^{-day}, 9368.14–164,196.72 kg^{-day}, 18736.29–328,393.44 kg^{-day}, and 56,208.87–985,180.32 kg^{-day} respectively (Appendix 2d). (Abdulkareem et al., 2018) estimated an annual TSS load from non-point sources in Kelantan River basin, between 1984 and 2013, at 1,581,167 Kg.

Of all the WQI parameters used for this study, SS seems to be the most critical, as the average DL_{SS} (481,899.71 kg^{-day}) is greater than the average $TMDL_I$ (38,805.99 kg^{-day}), $TMDL_{II}$ 77611.98 kg^{-day}), and even the $TMDL_{III}$ (232,853.95 kg^{-day}) Appendix 3d). This means the SS load into the river exceeded its assimilation capacity by 443,093.72 kg^{-day}, 404,287.73 kg^{-day}, and 249,063.76 kg^{-day} for the water quality class I, II, and III respectively. Therefore, any effort to restore the river to water quality class II must include reduction of SS load allocation by an average of 404,287.73 kg^{-day}. As mentioned earlier, (Daneshmand et al., 2011) reported that SS was among the primary cause of pollution in Linggi River.

Considering the 10% MoS (Nunoo et al., 2020) the load reduction requirement for restoration to class II = 404,287.73 + *(*404,287.73 *x 0.1) = 444,716*.50 kg^{-day}

Therefore, an average load reduction of 249,063.76 kg^{-day} + MoS could only restore the river to water quality class III as per TSS.

3.2.5. TMDL and LRT for cd

The DL_{Cd} ranged 0.37 kg^{-day} to 6.57 kg^{-day} at varying flow conditions (Appendix 2e); which was less than the $TMDL_{II}$ (3.75–65.68 kg^{-day}). Moreover, the mean DL_{Cd} (1.51 kg^{-day}) was less than that of the $TMDL_{II}$ (15.52), but greater than the $TMDL_I$ (0.00 kg^{-day}) Appendix 3e); which means the water quality status of the river as per Cd, is class II. It also means the stream can assimilate an average addition of Cd load up to 14.01 kg^{-day} and remain within the water quality class II.

3.2.6. TMDL and LRT for Cr^{+2}

Although it shows less variability as compere to DL_{Cd}, DL_{Cr} range from a minimum of 0.37 kg^{-day} to the maximum of 18.29 kg^{-day}, which was less than the range of $TMDL_{II}$ (1878–328.37 kg^{-day}) Appendix 2f) throughout the year. Hence, the average DL_{Cr} (1.66 kg^{-day}) was greater than the average $TMDL_I$ (0.00 kg^{-day}), but by far, less than the average $TMDL_{II}$ (77.61 kg^{-day}) Appendix 3f). This means the stream can assimilate an average daily load addition of 75.96 kg^{-day} of Cr and remain in water quality class II.

3.2.7. TMDL and LRT for Fe^{+2}

Daily load for Fe^{+2} ranged 4.06–7655.18 kg^{-day}, while that of the $TMDL_{II}$ ranged 374.73–6567.87 kg^{-day} (Appendix 2g). Moreover, the average DL_{Fe} (572.69 kg^{-day}) was greater than the average $TMDL_I$ (0.00 kg^{-day}), but less than the average $TMDL_{II}$ (1552.24 kg^{-day}) Appendix 3g). This mean the river can still assimilate an average Fe addition of 979.55 kg^{-day} within its current class II status for Fe^{+2}. Occasionally however, DL_{Fe} hike to exceed the assimilation capacity at class II (Appendix 2g), yet the average stood within the class II.

3.2.8. TMDL and LRT for hg

Like the case of Fe^{+2}, DL_{Hg} also exceeds the simulation capacity of the river for water quality class II in some occasions. However, the range of the DL_{Hg} (0.11–6.57 kg^{-day}) was largely within the class II, as when compared to $TMDL_{II}$ range (0.37–6.57 kg^{-day}) Appendix 2h). Moreover, the mean DL_{Hg} (1.31 kg^{-day}) was less than the mean $TMDL_{II}$ (1.55) (Appendix 3h), but less than the average $TMDL_I$ (0.00 kg^{-day}), which means in the average, the river can receive an additional Hg load of about 0.24 kg^{-day} and remain in the same class II status for the Hg.

3.2.9. TMDL and LRT for pb

Except on one occasion, the daily pollutant loads for Pb (0.41–577.26 kg^{-day}) were less than the $TMDL_{II}$ for the Pb (18.74–328.39 kg^{-day}) throughout the period in review (Appendix 2i).

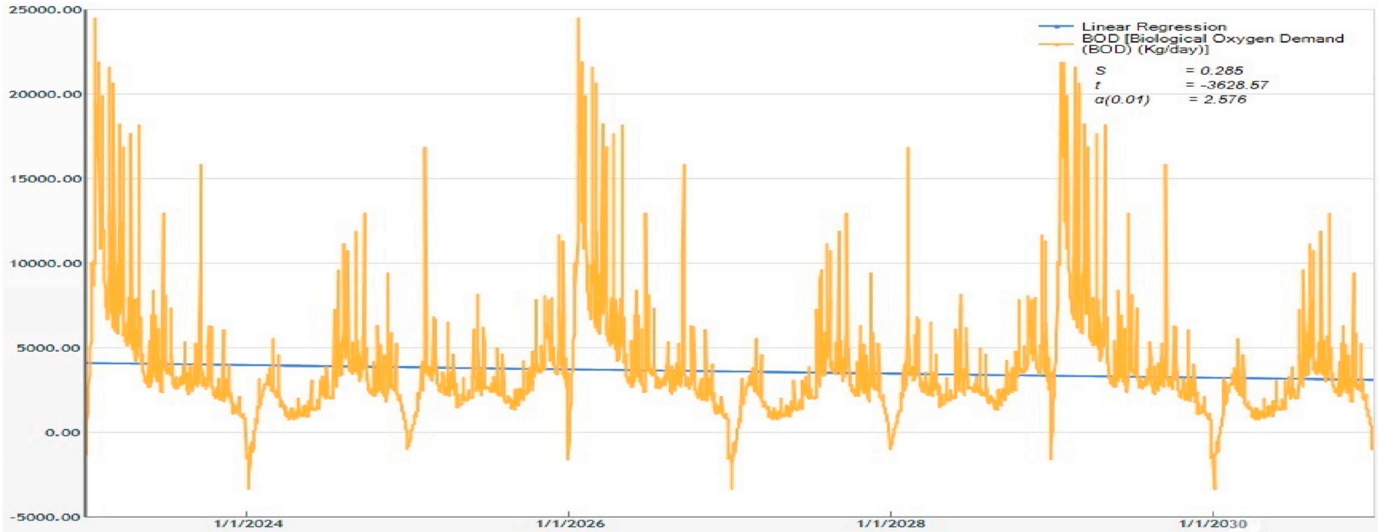

Fig. 5. Projected load reduction target to water quality class II for BOD until 2030.

Therefore the average DL_{Pb} (13.10 kg^{-day}) was also greater than the average $TMDL_{I}$ (0.00 kg^{-day}), less than the average $TMDL_{II}$ (77.61 kg^{-day}) (Appendix 3i), which means the river can assimilate and average addition of up to 64.51 kg^{-day} and remain in water quality class II as per Pb.

3.2.10. TMDL and LRT for zn

Daily pollutant load for Zn ranged from 1.82 to 429.23 kg^{-day} (Appendix 2j) as it fluctuates based on the flow rate over time. This was less than the $TMDL_{II}$, which ranged from 1873.63 to 32,839.34 kg^{-day}. Which means the daily loads of Zn were within the river assimilation capacity for water quality class II, throughout the three-year period used for this study. Similarly, the average DL_{Zn} (39.95 kg^{-day}) was greater than the average $TMDL_{I}$ (0.00 kg^{-day}), but less than the $TMDL_{II}$ (7761.20 kg^{-day}) Appendix 3j). This means the river was on water quality class II, and can assimilate an additional Zn load up to 8705.33 kg^{-day} and remain within the same water quality class II for Zn.

3.3. Critical pollutants and the variabilities of their LRT

The forgoing results affirmed the previous findings that TSS and NH_3 were the most critical pollutant in the study area (river Linggi) (Daneshmand et al., 2011; E.S.S., 2021). The river therefore fall under water quality class IV as per the pollutant load analysis and TMDL for the two parameters. The next were COD and BOD, which fall under water quality class II and III respectively. Except for Hg, which in some occasions exceed the water quality class II, on the average, all the heavy metals used for the load analysis fall within the water quality class II, including the Hg. This coincides with the study conducted by (Razak et al., 2021), which also put the river status at class II for most of the heavy metals, using concentration values.

Therefore, the river required restoration only for TSS, NH_3 and TSS, but need no restoration for COD and heavy metals. Hence, this study identified TSS, NH_3, and BOD as most critical pollutant in the Linggi basin in the order of priority. Therefore, future projection of load reduction target and TMDL allocation would be based on the three critical parameters.

Moreover, the ANOVA used revealed a significant temporal variability for the pollutant loads and the corresponding assimilation capacities over the months of a year, throughout the three years period used for the study (Appendix 4). Therefore dynamic flow approach (Zainudin et al., 2019) would be the best alternative for the implementation TMDL allocation for the river. Hence, the TMDL allocation

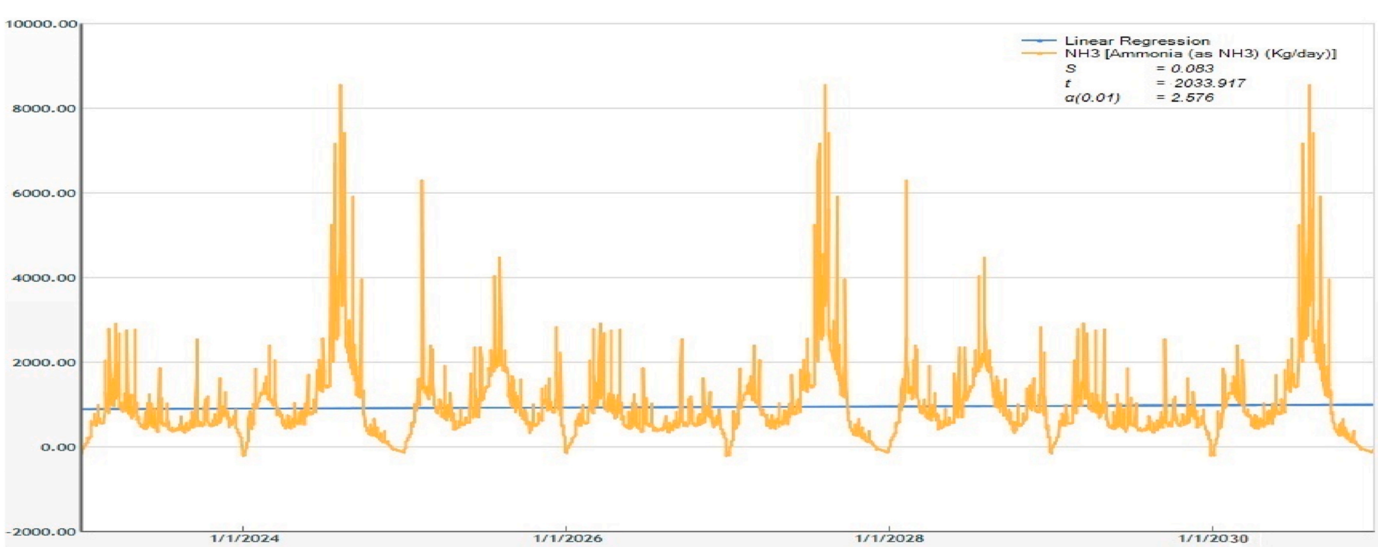

Fig. 6. Projected load reduction target to water quality class II for NH_3 until 2030.

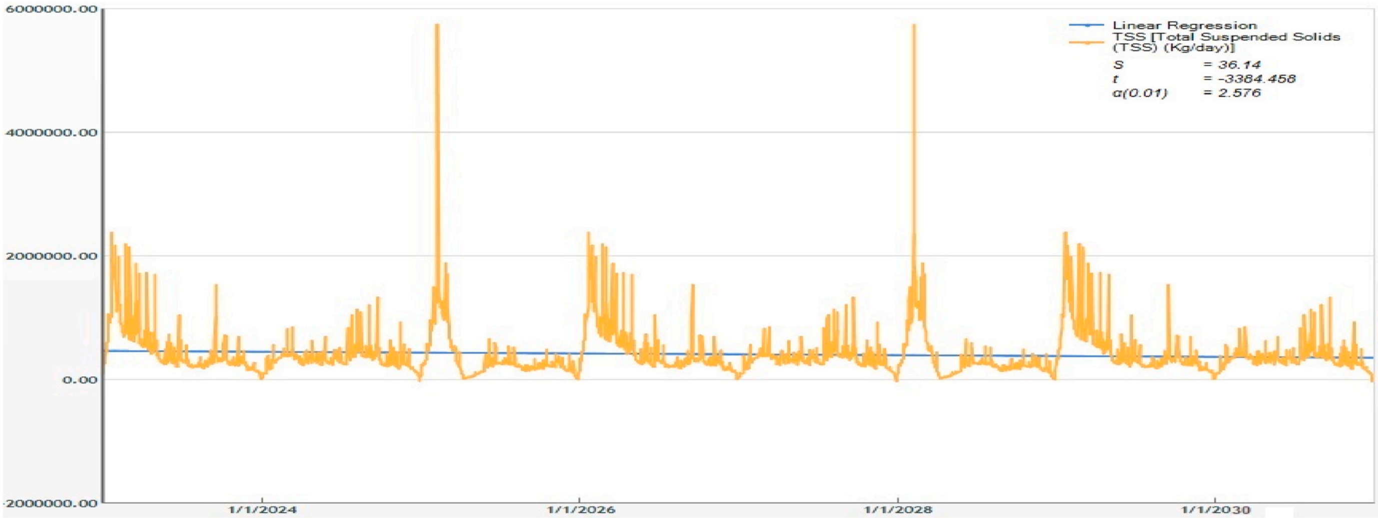

Fig. 7. Projected load reduction target to water quality class II for TSS until 2030.

Table 1
Variabilities of projected load reduction target over the months.

ANOVA		Sum of Squares	df	Mean Square	F	Sig.
Load reduction target for BOD	Between Groups	2,864,509,754.048	11	260409977.641	27.412	0.000
	Within Groups	27,644,126,366.208	2910	9,499,699.782		
	Total	30,508,636,120.256	2921			
Load reduction target for NH3	Between Groups	639869373.485	11	58,169,943.044	99.631	0.000
	Within Groups	1,699,021,163.257	2910	583,856.070		
	Total	2,338,890,536.741	2921			
Load reduction target for TSS	Between Groups	114838873224116.700	11	10439897565828.791	100.063	0.000
	Within Groups	303611023511062.600	2910	104333685055.348		
	Total	418449896735179.300	2921			

implementation should be on monthly basis.

For example, the load reduction target for BOD to water quality class range from minimum of 2637.81 Kg^{-day} (+MoS) being an average for the month of May, to a Maximum of 6096.68 Kg^{-day} (+MoS) being the average for the month of February. However, due to potential outlier observed for the month of February (Fig. 3), the nearest maximum value was upheld, which is 4947.04 Kg^{-day}, which was the average for the month of March. It should be recalled at this juncture that the average load reduction target for BOD to the water quality class to was 3544.44 Kg^{-day} + the 10% MoS.

Similarly, the load reduction target for NH_3 to the water quality class II ranged from 324.49 Kg^{-day} to 1963.81 Kg^{-day} (+MoS) being averages for the months of January and August respectively. On the other hand, the load reduction target to water quality class II range from 284,653.15 to 1,001,816.27 Kg^{-day} (+MoS) being averages for the months of November and February respectively.

3.4. Trend analysis for the projection of the load reduction target (LRT)

Prior to the TMDL allocation, and bearing in mind, the need to provide data support for the Malaysian Vision Valley (MVV) Development Plan for 2030. The Water Quality Analyser (WQA) was used to project the load reduction targets for the critical pollutants (BOD, NH_3, and TSS) until 2023. This is with a view to provide framework for future implementation of TMDL in the study area. Appendix 5 summarized the results of the projection while Figs. 5–7 provides the details.

Trend analysis conducted reveal a decresing trends of load reduction target for BOD ($S = 0.29$; $t = -3628.57$ ($df = 6558$) $\alpha = 0.01$). Therefore the result was used to project the future load reduction target (Fig. 4).

The average restoration target projected, varried among the years, which range from 2467.94 Kg^{-day} + MoS (for the year 2026) to 5124.87 Kg^{-day} + MoS (for the year 2023), while the average for the projected load for the eight years is 3618.59 Kg^{-day} + MoS (Appenedix 5a). Significant variabilities also exist over the mounts for each of the years ($F = 27.41$ ($df = 11, 2910$)$p = 0.01$) (Table 1), where the month of January 2024, 2027 and 2030 would require no load reduction, while other mouth would require the load reduction that range from <1000 Kg^{-day} + MoS to > 10,000 Kg^{-day} + MoS (Fig. 5). This is even as the lowest averages would be obtained in the months of Janauary and December, while the highest averages would be obtained in the mouths of February to March. This futher underscore the need for the adoption of dynamic flow approach (Zainudin et al., 2019) for the implementation of TMDL in the study area.

Unlike the case of BOD, the trend analysis conducted for the load reduction target for NH_3 reveal an incresing trends ($S = 0.083$; $t = 2033.92$ ($df = 6558$) $\alpha = 0.01$). Hence the result was used to project the future load reduction target for the NH_3 (Fig. 6).

Like the case of BOD, the lowest average of the load reduction target for NH_3 would be obtained in the months of December and January, while the month of August would have the highest average load reduction target (1939.00 kg^{-day} + MoS (Appendix 5b). Moreover, the river would require no restoration to the water quality class II in the month of December 2024, 2027, and 2030. Hence, the ANOVA used revealed a significant variabilities ($F = 99.63$ ($df = 11, 2910$)$p = 0.01$) among the months throughout the projected period (Table 1). Therefore dynamic flow approach (Zainudin et al., 2019) would be recommended for the implementation of TMDL as per NH_3.

Similar to BOD, the trend analysis conducted for TSS also reveal a decresing trends ($S = 36.14$; $t = -3384.46$ ($df = 6558$) $\alpha = 0.01$), which was used to project the future load reduction target (Fig. 7).

Although the outcome indicated the need for load reduction throughout the projected period (Appendix 5c), significant variabilities

Table 2
Result validation.

Parameter (kg/day)	Field data (Avr.) (Mg/L)	Water Quality class	DL (Avr.)	TMDL (Avr.) WQ class I	TMDL (Avr.) WQ class II	TMDL (Avr.) WQ class III
BOD	5.7	III	8203.16	1552.24	9646.72	9313.44
COD	18.33	II	27,120.93	15,522.40	38,805.99	77,611.98
NH3	0.92	IV	1423.20	155.22	465.67	1397.53
SS	328		481,899.71	38,805.99	77,611.98	232,853.95
Cd	<0.001	II	1.51	0.00	15.52	–
Cr	<0.001		1.66	0.00	77.61	–
Fe	0.42		572.69	0.00	1552.24	–
Hg	<0.001		1.31	0.00	1.55	–
Pb	0.0087		13.10	0.00	77.61	–
Zn	0.029		39.95	0.00	7761.20	–

exist over the months (F = 100.06 (df = 11, 2910)p = 0.01) (Table 1), where the months of December (148,933.50 Kg^{-day} + MoS) and February (924,446.67 Kg^{-day} + MoS) would have the minimum and maximum load reduction targets respectively. As mention earlier, the implication of this finding is that the dynamic flow approach (Zainudin et al., 2019) would be recommended for the implementation of TMDL in the study area.

Load reduction targets for the three critical pollutants (BOD, NH_3, and TSS) exhibit significant temporal variabilities over the months of the years throughout the predicted period (F = 27.41 (df = 11, 2910)p = 0.01), (F = 99.63 (df = 11, 2910)p = 0.01), and (F = 100.06 (df = 11, 2910)p = 0.01) respectively (Table 1). Therefore, dynamic flow approach (Zainudin et al., 2019) is recommended for the implementation of TMDL in the study area. Previous studies (Adnan et al., 2022) often used only flow variabilities (High – low flows) to explain the variation in pollutant load for TMDL implementation. This will further require flow measurements for the TMDL implementation. This study therefore came up with a framework that will assist the water managers in the TMDL implementation on monthly basis, without relying on additional measurement of flow conditions.

4. Result validation

The result of the projected pollutant loadings coincides with that of the water quality classification from the field data. Where the average BOD (5.7 mg/L) was classified into the water quality class III. COD (18.33 mg/L), Cd (<0.001 mg/L), Cr (<0.001 m/L), Fe (0.42 mg/L), Hg (<0.001 mg/L), Pb (0.0087 mg/L), and Zn (0.029) were classified into water quality class II; while NH_3 (0.92 mg/L) and SS (295 mg/L) above class III respectively (Table 2).

This also shows that the water quality classification could be obtain from the projected result of the pollutant load. It also justifies the reliability of the Water Quality analyser (WQA) and Load duration approach for the estimation of pollutant load and the Total Maximum Daily Load (TMDL) respectively.

5. Conclusions

Having estimated the pollutant loads and projected the load reduction targets using WQA, it was found that.

i. The WQA provides a cost and time effective, and a reliable tool for the projection of pollutant loads for tropical rivers.
ii. BOD load into the river exceeded its assimilation capacity for water quality class II, while NH_3 and SS loads exceeded the assimilation capacity of the river for water quality class III respectively. However, COD, Cd, Cr, Fe, Hg, Pb, and Zn were within the assimilation capacity for the water quality class II.
iii. This study identified TSS, NH_3, and BOD as most critical pollutant in the Linggi basin in the order of priority.
iv. Restoration of the river to water quality class II for the critical pollutants (BOD, NH_3, and SS) would require load reduction target of 3898.88 kg^{-day}, 1053.28 kg^{-day}, and 444,716.50 kg^{-day} respectively.
v. Although the river require no restoration for COD and heavy metals, load addition of more than 11,685.06 kg^{-day}, 14.01 kg^{-day}, 75.96 kg^{-day}, 979.55 kg^{-day}, 0.24 kg^{-day}, and 64.51 kg^{-day}, and 8705.33 kg^{-day} would deteriorate the water quality of the river to class III for the COD, Cd, Cr, Fe, Hg, Pb, and Zn respectively.
vi. Load reduction target for BOD and TSS would decrease towards the future, while that of NH_3 increases.
vii. Significant variability exists for the projected load reduction target over the months throughout the projected period.

6. Recommendations
   i. The basin need restoration from excessive BOD loads and more critical, the NH_3 and SS loads. This should be achieve through TMDL allocation, after identification of respective pollutant sources.
   ii. Implementation of the TMDL allocation should take into cognizance, the temporal variation of the load reduction targets. Hence the dynamic flow approach (Zainudin et al., 2019) is recommended for the implementation of TMDL for the tropical rainforest areas.

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CRediT authorship contribution statement

Nura Bello: Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Nor Rohaizah Jamil:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition. **Looi Ley Juen:** Supervision, Methodology, Formal analysis. **Yap Ng Keng:** Supervision, Software.

Declaration of competing interest

Both authors agreed of the outcome of the review with no competing of interest, and there is no conflict of interest with any organization or person.

Data availability

The authors do not have permission to share data.

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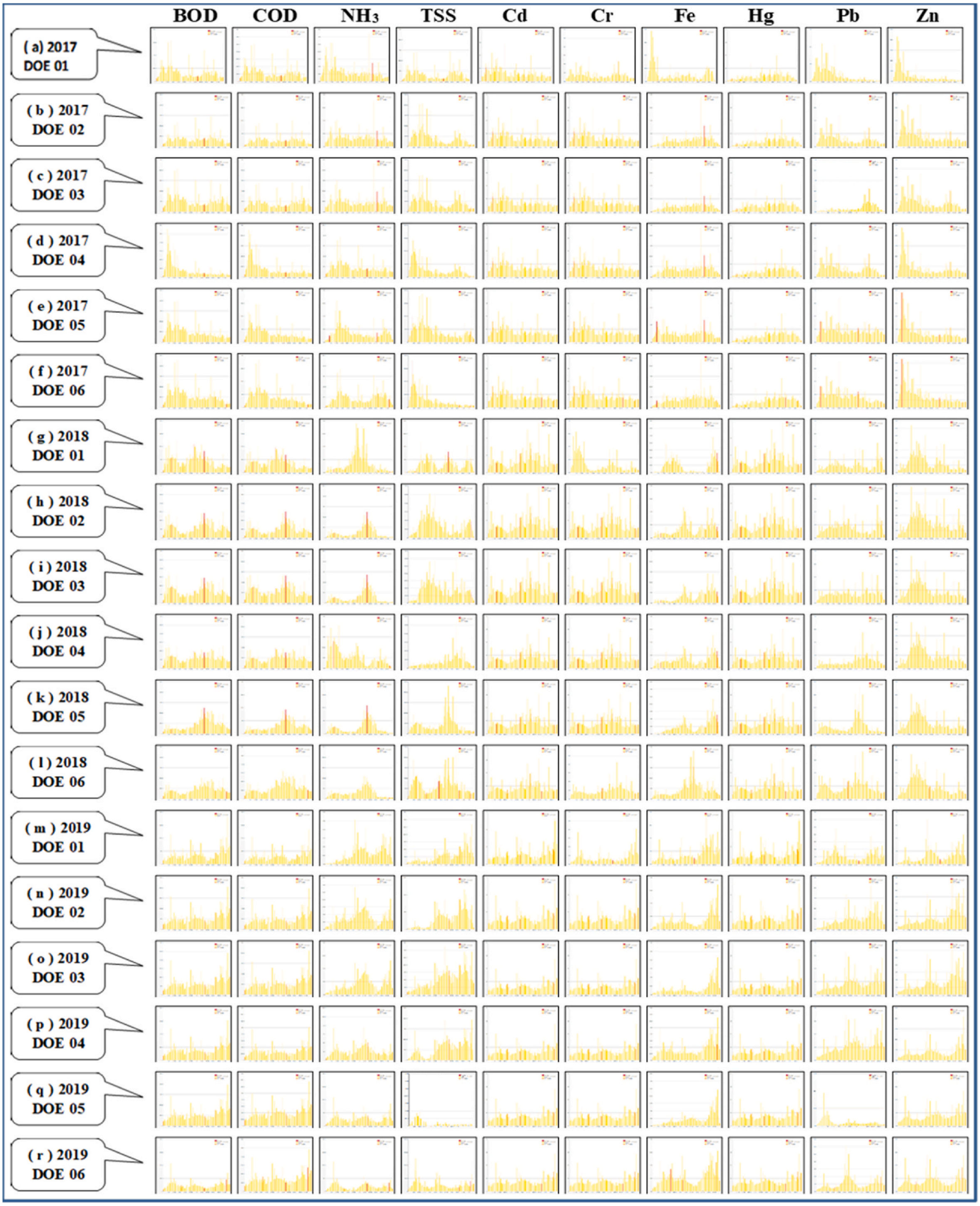
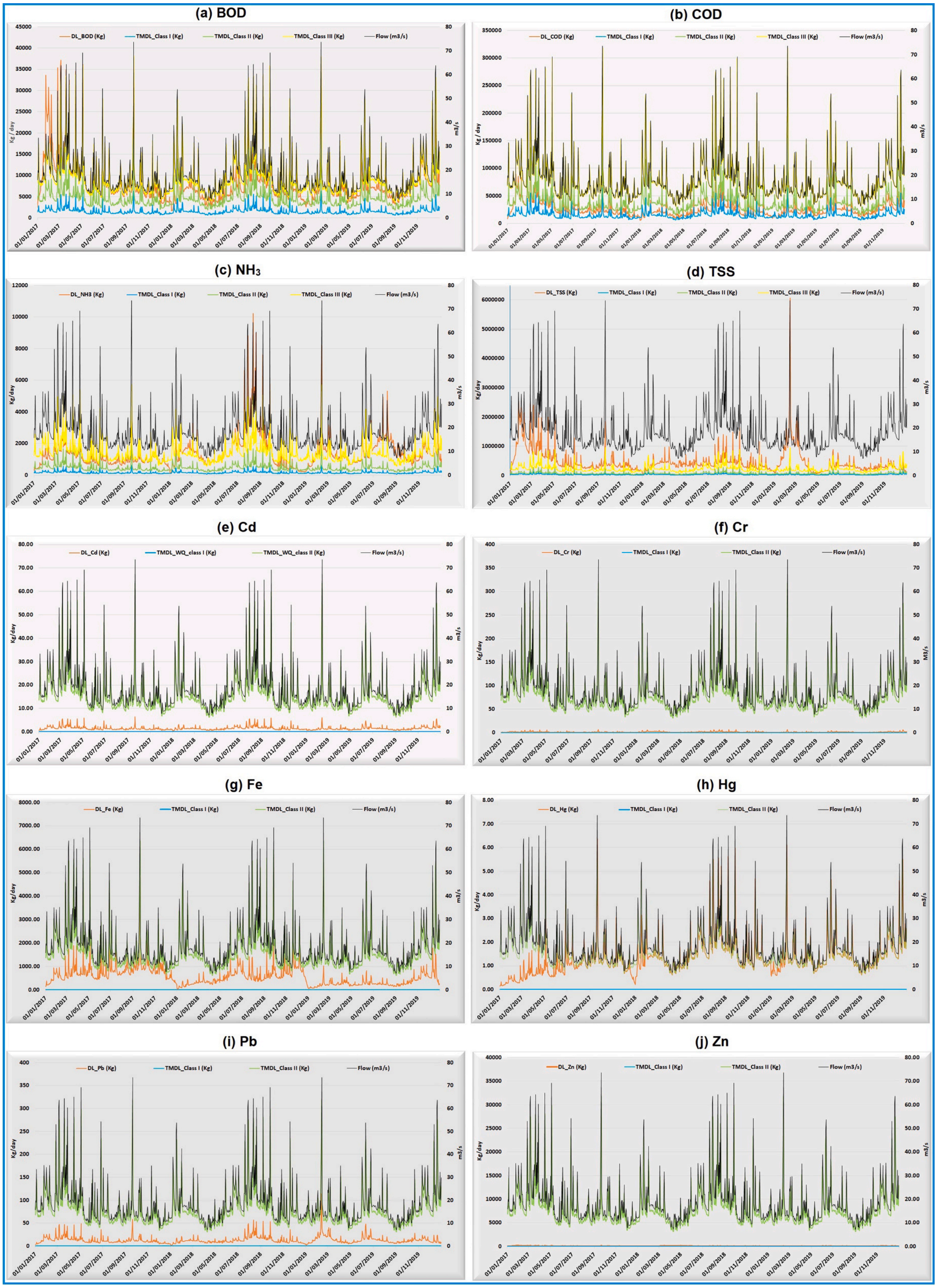
Appendix 1. Daily Load



Appendix 2. Daily loads and TMDLs at varying flow conditions and time_2017–2019



Appendix 3. Average DLs and TMDLs_2017–2019

Appendix 4. Variabilities of pollutant loads over the months of the year_2017–2019

ANOVA		Sum of Squares	df	Mean Square	F	Sig.
BOD	Between Groups	10,866,489,694.872	11	987862699.534	22.346	0.000
	Within Groups	289910708515.277	6558	44,207,183.366		
	Total	300777198210.149	6569			

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ANOVA		Sum of Squares	df	Mean Square	F	Sig.
COD	Between Groups	98,236,106,007.962	11	8,930,555,091.633	22.970	0.000
	Within Groups	2549645956940.689	6558	388784073.946		
	Total	2647882062948.650	6569			
NH3	Between Groups	1,592,201,629.648	11	144745602.695	67.415	0.000
	Within Groups	14,080,524,255.818	6558	2,147,075.977		
	Total	15,672,725,885.466	6569			
TSS	Between Groups	317638601431217.500	11	28876236493747.047	39.928	0.000
	Within Groups	4742741439591170.000	6558	723199365597.922		
	Total	5060380041022388.000	6569			
Cd	Between Groups	239.884	11	21.808	35.441	0.000
	Within Groups	4035.339	6558	0.615		
	Total	4275.223	6569			
Cr	Between Groups	405.479	11	36.862	29.270	0.000
	Within Groups	8259.009	6558	1.259		
	Total	8664.488	6569			
Fe	Between Groups	173319633.206	11	15,756,330.291	62.123	0.000
	Within Groups	1,663,300,987.970	6558	253,629.306		
	Total	1,836,620,621.176	6569			
Hg	Between Groups	497.819	11	45.256	86.628	0.000
	Within Groups	3426.026	6558	0.522		
	Total	3923.845	6569			
Pb	Between Groups	63,704.231	11	5791.294	18.477	0.000
	Within Groups	2,055,467.202	6558	313.429		
	Total	2,119,171.433	6569			
Zn	Between Groups	492,942.835	11	44,812.985	48.940	0.000
	Within Groups	6,004,965.178	6558	915.670		
	Total	6,497,908.013	6569			

Appendix 5. Projected load reduction target to water quality class II (Kg^{-day})

(a) BOD

Year/month	2023	2024	2025	2026	2027	2028	2029	2030	Average
Jan.	9133.76	−257.27	879.81	9699.28	−156.32	879.53	10,120.25	−57.27	**3780.22**
Feb.	10,877.51	2656.12	4521.31	10,553.59	2691.99	4600.00	10,353.08	2828.15	**6135.22**
March	9270.37	2121.39	3101.07	9215.85	2121.11	2976.44	9167.64	1971.78	**4993.21**
April	6160.23	1062.86	2671.23	6182.57	1062.58	2626.41	6172.72	1067.70	**3375.79**
May	4371.68	1344.30	2310.68	4396.04	1344.01	2387.29	4360.58	1352.29	**2733.36**
June	4317.57	1979.46	3468.03	4207.17	1979.18	3423.04	4344.11	2062.91	**3222.68**
July	3588.97	3424.90	2591.56	3562.65	3424.62	2579.68	3397.48	3407.94	**3247.22**
Aug.	3121.24	4971.90	1984.87	3108.86	4971.62	1968.59	3119.89	4985.29	**3529.03**
Sept.	4139.38	4583.65	2321.91	4153.01	4583.37	2351.75	4126.17	4573.49	**3854.09**
Oct.	3045.57	2950.88	3690.77	3014.52	2950.59	3767.99	2995.49	2929.80	**3168.20**
Nov.	2421.70	3036.10	5264.02	2393.76	3035.82	5215.61	2384.68	3028.32	**3347.50**
Dec.	1050.50	1607.00	4419.76	967.38	1606.72	4281.85	867.85	1491.69	**2036.59**
Average	**5124.87**	**2456.77**	**3102.08**	**5121.22**	**2467.94**	**3088.18**	**5117.50**	**2470.17**	**3618.59**

(b) NH_3

Year/Month	2023	2024	2025	2026	2027	2028	2029	2030	Average
Jan.	226.08	422.79	492.78	250.99	458.51	492.86	270.89	493.57	**388.56**
Feb.	731.67	1222.53	1697.78	739.17	1233.73	1722.12	751.22	1286.60	**1173.10**
March	1425.59	1005.71	1035.61	1427.24	1005.80	986.69	1428.36	944.54	**1157.44**
April	979.95	574.08	750.90	982.47	574.16	736.41	980.11	577.11	**769.40**
May	679.62	748.39	642.55	682.11	748.47	664.93	676.02	754.47	**699.57**
June	640.94	1205.94	1151.11	624.02	1206.02	1157.15	642.50	1265.98	**986.71**
July	510.17	2482.54	1801.95	505.81	2482.63	1827.50	481.87	2482.24	**1571.84**
Aug.	440.98	3498.41	1867.40	440.84	3498.50	1839.36	444.31	3482.19	**1939.00**
Sept.	685.45	1791.23	1014.49	690.45	1791.31	994.78	689.33	1750.79	**1175.98**
Oct.	640.88	404.60	541.46	640.52	404.68	546.73	642.43	386.33	**525.95**
Nov.	759.99	141.02	990.20	758.30	141.11	991.12	763.43	132.97	**584.77**
Dec.	440.36	−76.20	913.63	419.25	−76.12	883.56	391.87	−78.36	**352.25**
Average	**680.14**	**1118.42**	**1074.99**	**680.10**	**1122.40**	**1070.27**	**680.19**	**1123.20**	**943.71**

(c) TSS

Year/Month	2023	2024	2025	2026	2027	2028	2029	2030	Average
Jan.	981,665.52	184,846.87	499,100.22	1,030,949.60	193,289.46	499,064.08	1,066,748.87	201,575.92	**582,155.07**
Feb.	1,107,098.47	359,035.55	1,520,279.05	1,075,847.65	362,088.60	1,532,936.64	1,056,561.68	381,725.73	**924,446.67**
March	961,649.59	414,072.66	632,077.59	955,540.95	414,036.52	578,728.25	950,012.59	395,421.35	**662,692.44**
April	608,455.58	337,707.49	70,497.86	609,386.07	337,671.35	64,249.08	607,331.25	340,278.14	**371,947.10**
May	408,888.79	344,458.14	119,011.58	409,533.26	344,422.00	126,429.61	405,290.80	342,953.66	**312,623.48**
June	368,885.97	318,563.67	306,297.85	358,434.31	318,527.53	305,851.23	368,036.77	326,103.23	**333,837.57**
July	280,406.05	401,751.50	275,140.25	277,516.68	401,715.36	274,809.15	263,769.80	396,859.85	**321,496.08**

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(c) TSS

Year/Month	2023	2024	2025	2026	2027	2028	2029	2030	Average
Aug.	231,572.62	511,204.71	221,035.75	231,540.78	511,168.57	218,303.11	233,590.03	511,917.07	**333,791.58**
Sept.	396,128.39	467,054.38	193,316.07	399,572.78	467,018.24	193,964.35	399,472.64	465,886.94	**372,801.72**
Oct.	347,793.50	294,466.71	234,621.33	344,999.34	294,430.57	237,496.15	343,433.56	292,018.89	**298,657.51**
Nov.	290,399.70	290,919.93	256,545.25	287,638.78	290,883.79	252,002.03	286,999.45	289,679.57	**280,633.56**
Dec.	149,289.24	165,995.76	134,059.28	144,875.07	165,959.62	133,837.30	138,337.60	159,114.09	**148,933.50**
Average	**511,019.45**	**340,839.78**	**371,831.84**	**510,486.27**	**341,767.64**	**368,139.25**	**509,965.42**	**341,961.20**	**412,001.36**

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