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Assessment of the impacts of landscape patterns on water quality in Trondheim rivers and Fjord, Norway

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ABSTRACT

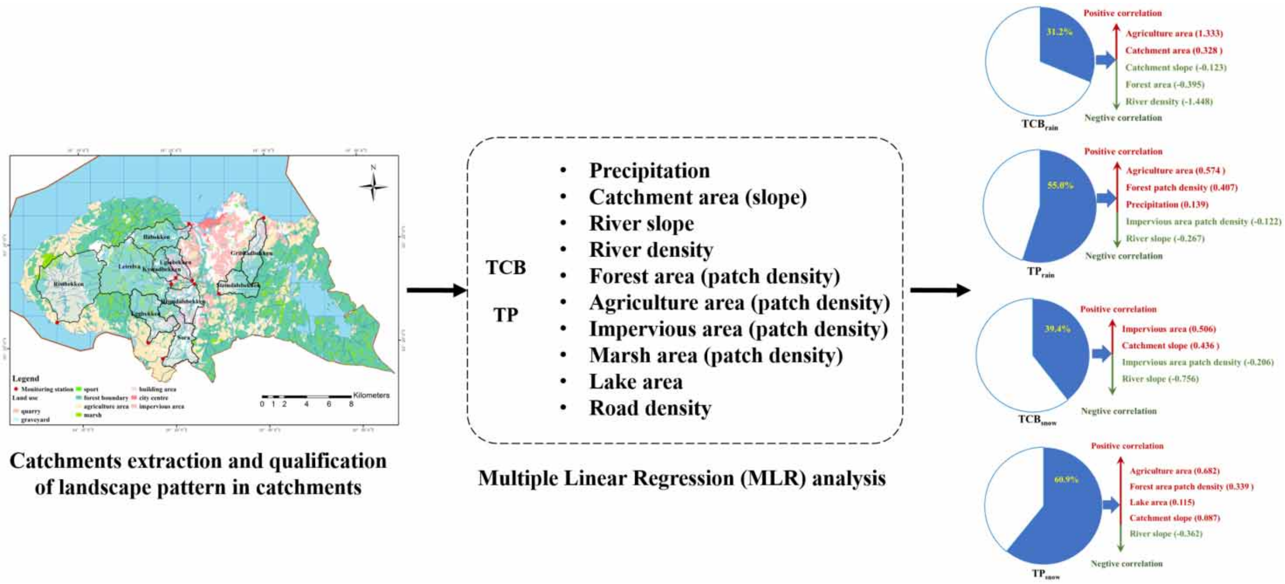
Due to the impacts of hydrological and ecological processes on water quality, discharges from upstream catchments have induced significant pollution to the recipients. This study aims to investigate the possible pollution sources from catchments with different types of land use and landscape patterns and develop the relationships between water quality and the catchment hydro-geological and environmental variables. Data from 10 monitoring sites in Trondheim formulated the basis of the case study. Thermotolerant coliform bacteria (TCB) and total phosphorus (TP) were applied as main indicators to represent the water quality in the recipient rivers, streams and in Trondheim Fjord. Based on the GIS-oriented spatial analysis, 15 hydro-geographical and landscape parameters were selected as explanatory variables. Multiple linear regression (MLR) models were developed at catchment and river reach scales to study correlations between the explanatory variables and the response variables, TCB and TP, in rain and snow seasons. The study showed that the spatial landscape patterns resulted in differences in the concentrations of TCB and TP in the recipients. The agricultural land was shown to be the main pollution source, leading to a higher concentration of TP in streams. Buildings, roads, and other impervious areas have induced an increase in both TCB and TP. In contrast, the forest areas, lakes, river density and steep river slopes were shown to have capacity to filter incoming P-rich runoff, thus prevent pollutant conveyance and accumulation in recipients.

Key words: landscape pattern, GIS, MLR model, thermotolerant coliform bacteria (TCB) and total phosphorus (TP), water quality

HIGHLIGHTS

- A GIS-based topographical and landscape analysis was performed.
- The composition and configuration of the landscape were analysed. Fifteen indicators were selected as explanatory variables.
- MLR models were developed to study the relations between landscape variables and water quality indicator TCB and TP.
- The agricultural land was shown to be the main pollution source.
- TP is more sensitive to land use and landscape patterns than TCB.

GRAPHICAL ABSTRACT



INTRODUCTION

Land use types and landscape patterns in the upstream catchments have an important impact on the water quality in the downstream recipients (Hunsaker & Levine 1995; Shiels 2010; Glavan *et al.* 2012; Łowicki 2012; Bechmann 2014; Billmire & Koziol 2018; Wu & Lu 2021). Xiao *et al.* (2016) found that landscape composition and configuration metrics at different seasons and scales affect the water quality (e.g., pH, DO, BOD, NH_3), regardless of flow conditions. A number of other investigations also found close relationships between land use patterns in the catchment area and water quality indicators (Boyer *et al.* 2002; Schröder *et al.* 2004; Dow *et al.* 2006; Linard 2013; Bartsch *et al.* 2014; Maguire *et al.* 2019).

The alternation in land use from natural areas with high vegetation coverage to partially developed rural or highly developed urban areas has been identified as one of the main causes affecting the quality of runoff and waterflow in rivers and recipients, which also affects the ecological conditions of the catchments (Raymond *et al.* 2017). The impacts of agricultural land use on water quality have been studied extensively in many countries. The study on an agricultural catchment in Poland showed that the structure of the land cover of the catchment has a strong impact on water quality in downstream recipients (Łowicki 2012). A recent, up-to-date EC compendium reports that agriculture is responsible for an average of 77% of the total load of nitrogen into the EU environment, and 36% of EU rivers and 32% of lakes were reported as eutrophic in the late 2010 s (EC 2021).

Because landscapes are spatially heterogeneous areas, or environmental mosaics, the structure and the function of the landscape are themselves scale dependent. The relationships between land use variables and the water quality indicators were studied at different scales (Schröder *et al.* 2004; Dow *et al.* 2006; Linard 2013; Wu & Lu 2021). Particularly, Allan (2004) introduced a multiscale investigation approach to evaluate the relationship between the stream condition and land use in the three scales: the river reach, a buffer of a defined width along the entire upstream and the entire catchment upstream of a site.

In Norway, monitoring of water quality in the rivers and water bodies in relation to environmental standards have been required since the implementation of the EU Water Framework Directive (WFD) in 2007 EC (2000). Based on water quality requirements and environmental standards in Trondheim, action-oriented monitoring has been carried out since 1995 (Nøst 2009). According to the reports of Nøst listed in the references, thermotolerant coliform bacteria (TCB) and total phosphorus (TP) have been selected as the most central target parameters, indicating contamination discharges from municipal sewer systems, construction wastes and rural activity.

The point source pollution TCB from the sewer systems to the River Nidelva and Leirelva in Trondheim were analysed (e.g. Bruaset *et al.* 2010; Sivertsen & Barrio 2018), which have shown with a reduction of 6% in TCB in the water from River

Nidelva, a reduction of 0.8% TCB in the water from the River Leirelva during 2010–2016. Chang *et al.* (2014) studied the nonpoint source pollution and the correlations between water quality and landscape patterns. However, the study of Chang *et al.* was insufficient to provide comprehensive and profound understanding of the scale effect of the analysis, the seasonal sensitivity and how the landscape patterns affect the water quality in recipients. Therefore, the main purposes of this study were to (**a**) investigate the impacts of land use patterns on water quality in cold climate, (**b**) understand the scale effect and the seasonal sensitivity in regard to source pollutant from landscape patterns and (**c**) provide scientific background information for municipal water management, pollution control and mitigation at catchment and river scales.

METHOD AND MATERIALS

Study area

Trondheim is situated in the middle of Norway, by the mouth of the River Nidelva on the south shore of Trondheim Fjord. Several river tributaries and streams merge first into the River Nidelva and then into Trondheim Fjord. Trondheim has a predominantly hemiboreal oceanic climate, with a humid continental and subarctic climate, mean monthly minimum temperatures of −4.10 °C in February and maximum temperatures of 19.40 °C in July (seklima.met.no). The city center, a commercial and densely populated residential area, is in the low-lying areas besides the River Nidelva and near Trondheim Fjord (Figure 1).

Data acquisition

Precipitation

Six pluviometer stations have been operating in Trondheim since 1960. In this study, precipitation data from three of the stations at Risvollan, Voll and Leinstrand were collected from the Norwegian Centre for Climate Services (seklima.met.no). Precipitation data was provided in the Appendix 1 of the supplementary materials.

Topography and land use

Topographic data with 25-m spatial resolution was applied to delineate the elevation ranges, generate the digital elevation model (DEM), river systems and catchments of the study area (Figure 2). Land use information with 25-m spatial resolution

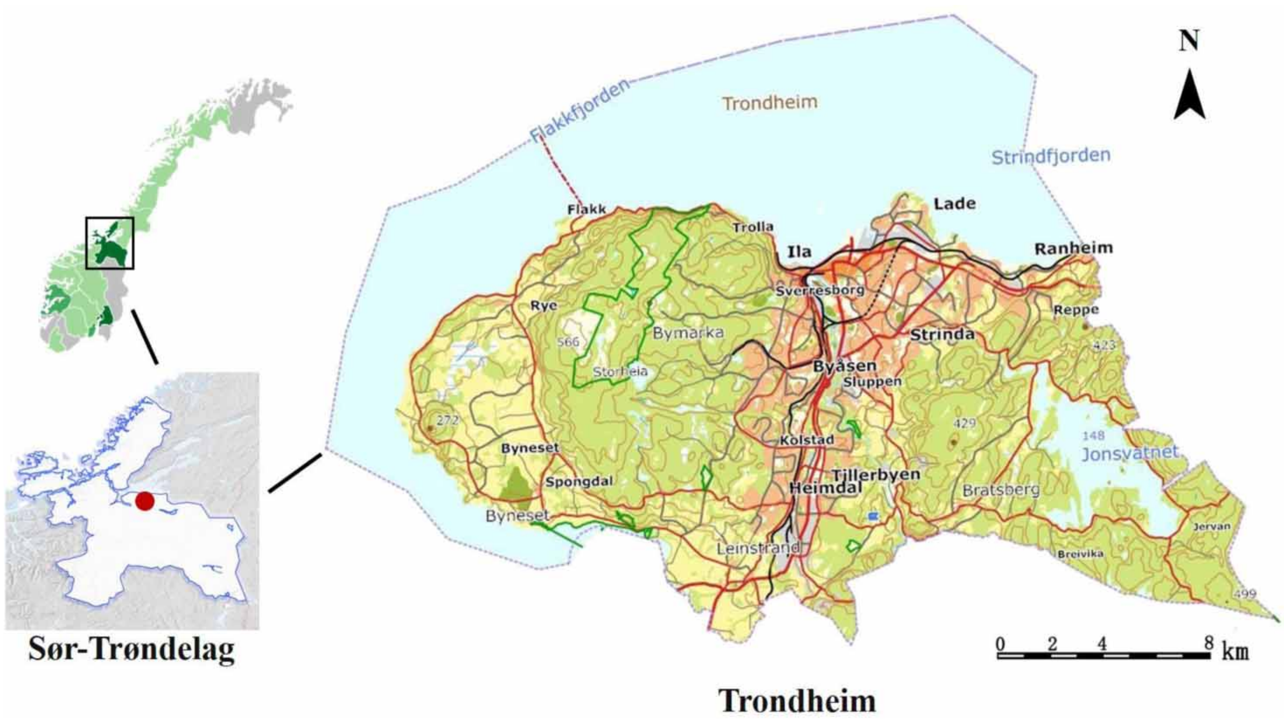


Figure 1 | Map of Trondheim.

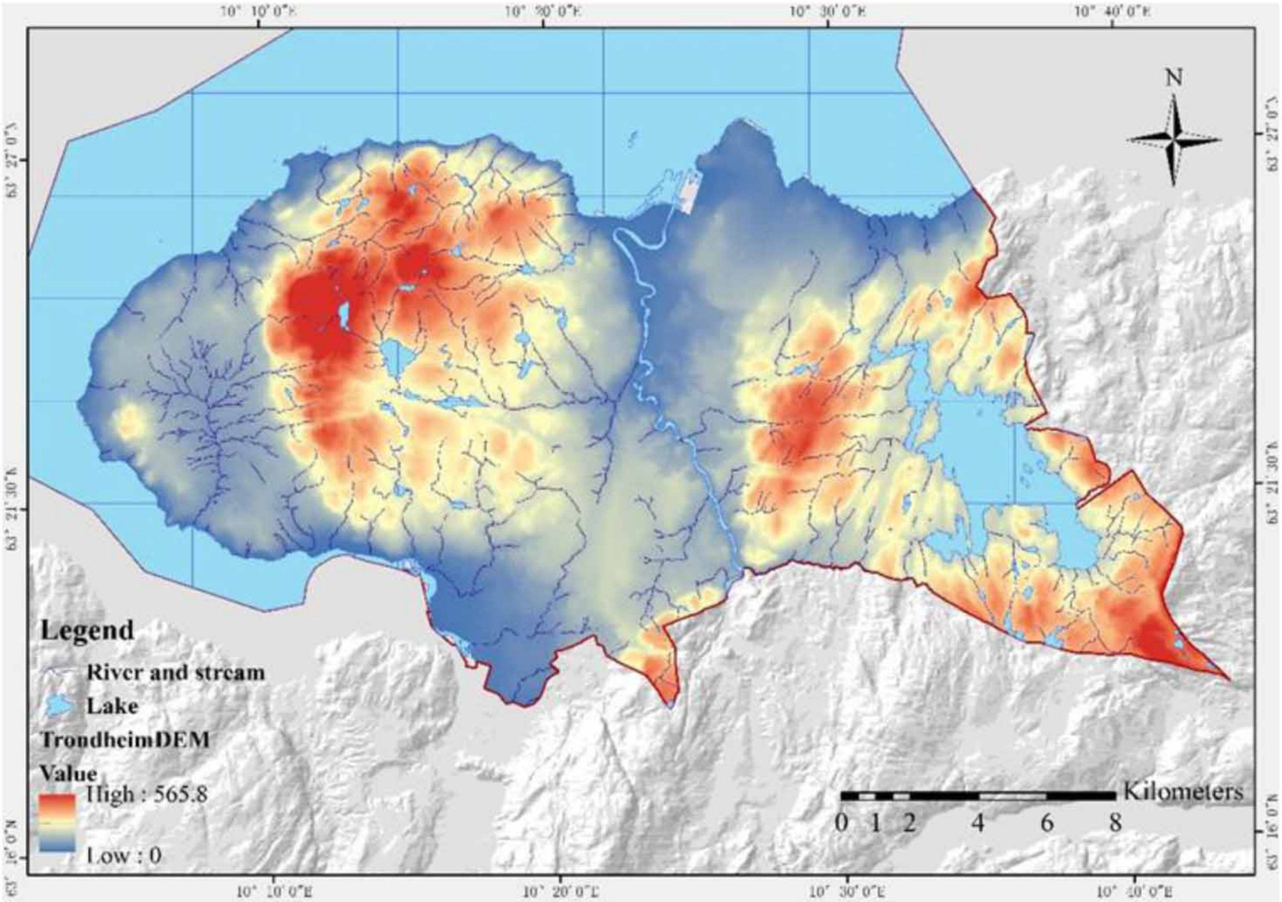


Figure 2 | DEM of Trondheim and topographic features.

at level 2010 is presented in Figure 3. Despite the development and increase of urbanization in the whole study area is not so significant as it is in the city centres, there are still some changes in the land use classification from 2011 to 2020, according to the Statistics Norway (SSB) (https://www.ssb.no/). Considering the small changes of land use in the whole catchment versus the rapid development in cities, it is assumed that the land use and landscape patterns of the study catchment have no changes in this study.

Water quality

To ensure good water quality and good ecological condition of the rivers and water bodies in Trondheim, a monitoring programme has been established since 1995 to provide a background of the water quality condition in rivers and water bodies, and to provide a basis for assessing and prioritizing measures to reduce pollution and improve the aquatic environment and to monitor and control the effects of implemented measures (Nøst 2002). TCB and TP are the two important parameters monitored in the long term by the water administrator in Trondheim, which are used to represent the water quality and the pollution discharges from municipal sewers, road runoff and construction wastes and pollutant from the entire catchment with different land use types and activities.

Since 1995, 30 monitoring stations have been established along the rivers and streams. TCB and TP are long-term monitoring parameters by municipality, representing the pollution from municipal sewers and the rest areas of the catchment with different land uses. Considering features of topography, land use and variation of water quality, 10 monitoring river stations with monthly measured concentrations of TCB and TP from 2009 to 2020 were selected for the following analysis (Figure 4). The data are presented in the municipal annual reports (Nøst, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021).

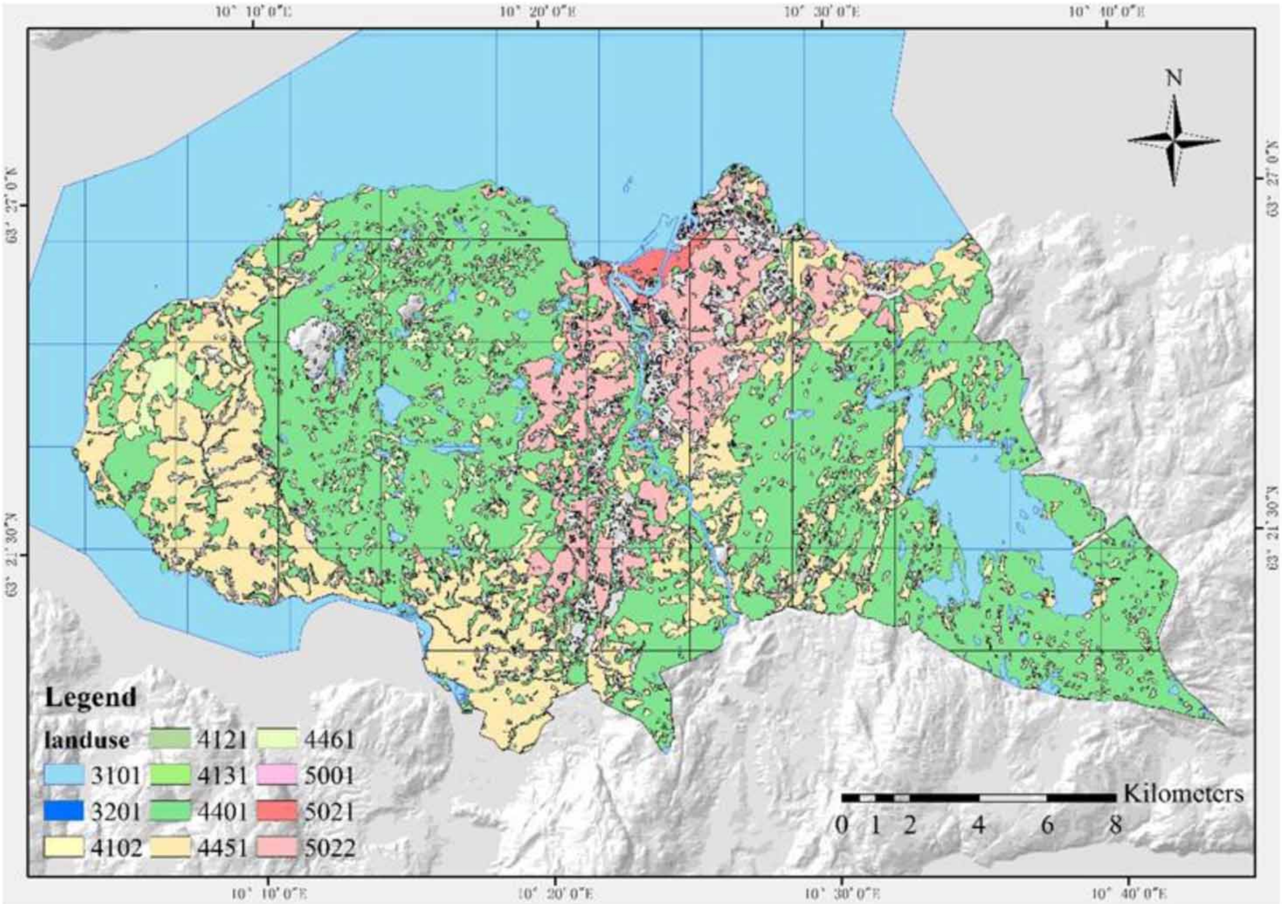


Figure 3 | Map of land use categories of the study area. *Interpretation of the geodata codes and the different land use types in Figure 2: 3101-lake; 3201-stream; 4102-quarry; 4121-graveyard; 4131-sport; 4401-forest boundary; 4451-agricultural area; 4461-marsh; 5001-building area; 5021-city centre; 5022-impervious area.

More information of the river systems, catchment information and monitoring data and TCB and TP are described in the Appendix 2 of the supplementary material of paper.

According to selected data, high or extremely high concentrations of TCB and TP have been measured in several stations from time to time, particularly in the last 5 to 6 years. The internal and external assessment reports showed that the extremely high pollution was caused by sewer leakages, wrong sewer connection and combined sewer overflow discharges (CSOs) during heavy or extreme precipitation periods (Sivertsen & Barrio 2018; Nøst 2019, 2020). We also found that the measured concentrations of TCB and TP do not always correspond to the time of precipitation, according to the measured data; thus, other pollution sources should be investigated.

Methods

Considering the analysis of nonpoint source pollution was affected by diverse aspects, such as landscape patterns, hydro-geo-topographical, environmental features, land use types and associated activities, this study developed an innovative and holistic approach of GIS in combination with landscape pattern analysis and water quality regression analysis.

Geospatial and topographical analysis

Since landscape is a spatially heterogeneous area and environmental mosaics, the structures and functions of landscape are thus scale dependent. Therefore, it is essential to conduct multiscale analyses to explore relationships between land use and water quality. The spatial and geomorphological characteristics, such as catchment area and average slope, land use categories and their percentage, river density, average slope, lake area, road area and road density, and river slope and river

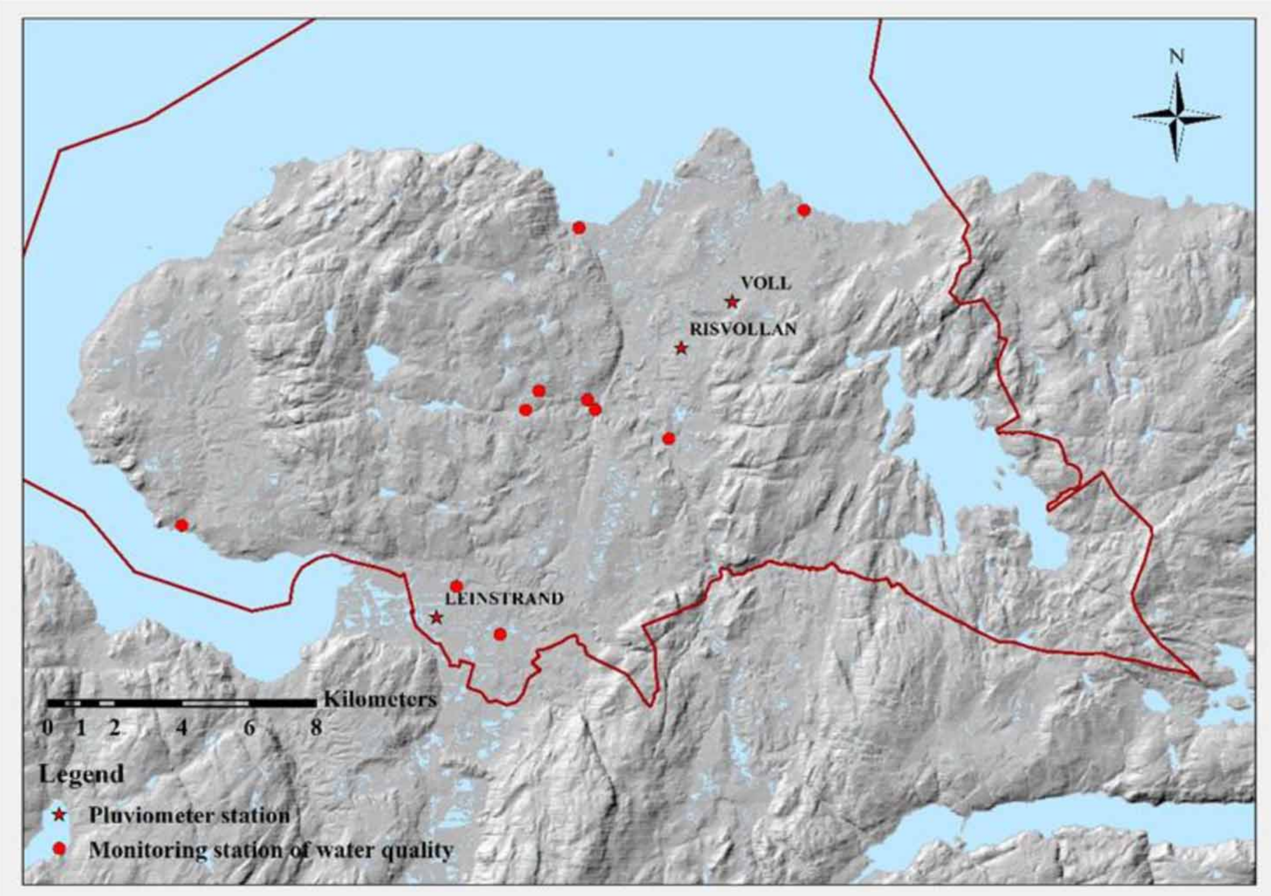


Figure 4 | Map of the water quality measuring stations along the rivers and streams in Trondheim (Nøst 2020) and the three climate stations in the study catchment.

density, were considered important environmental variables that affect water quality through the transportation and concentration of pollutants.

Using the 10 monitoring stations as discharge outlets, catchments were delineated using ArcHydro Tool in ArcGIS, with size varying from 3.8 to 28 km^2 (Figure 5). The catchments represent different land use conditions. The geo-hydrological features of river density, river slope, catchment area and catchment slope in each catchment were calculated. Table 1 is a summary of the information about the rivers and streams, including the catchments and land use compositions and the measuring information. Five of the catchments are dominated by forest (>50%), one by urban land use, with buildings and a high percentage of impervious areas, one by agricultural activities, and three are hybrids, with forest, urban or agriculture and other land use types.

Scale and landscape patterns analysis

To investigate the effects of landscape patterns on water quality, two spatial scales were defined in this study: (a) the catchment scale, representing the upstream area of the monitoring sites, and (b) river reach scale, a buffer zone of 200 metres in width on each bank of the streams and one kilometre in length upstream of the monitoring sites.

Landscape patterns of the two scales were calculated by GIS analysis of the land use in the study area. According to the geodata codes illustrated in Figure 3, the land use of the study area was categorized into five main types: forest, marsh, lake, agriculture and impervious area. The impervious area includes residential, commercial and public building areas, roads and other paved areas. Landscape metrics reflecting the composition and the configuration were analysed by a software tool, FRAGSTATS (McGarigal & Marks 1995). PLAND and PD are the two terms representing the landscape patterns, where

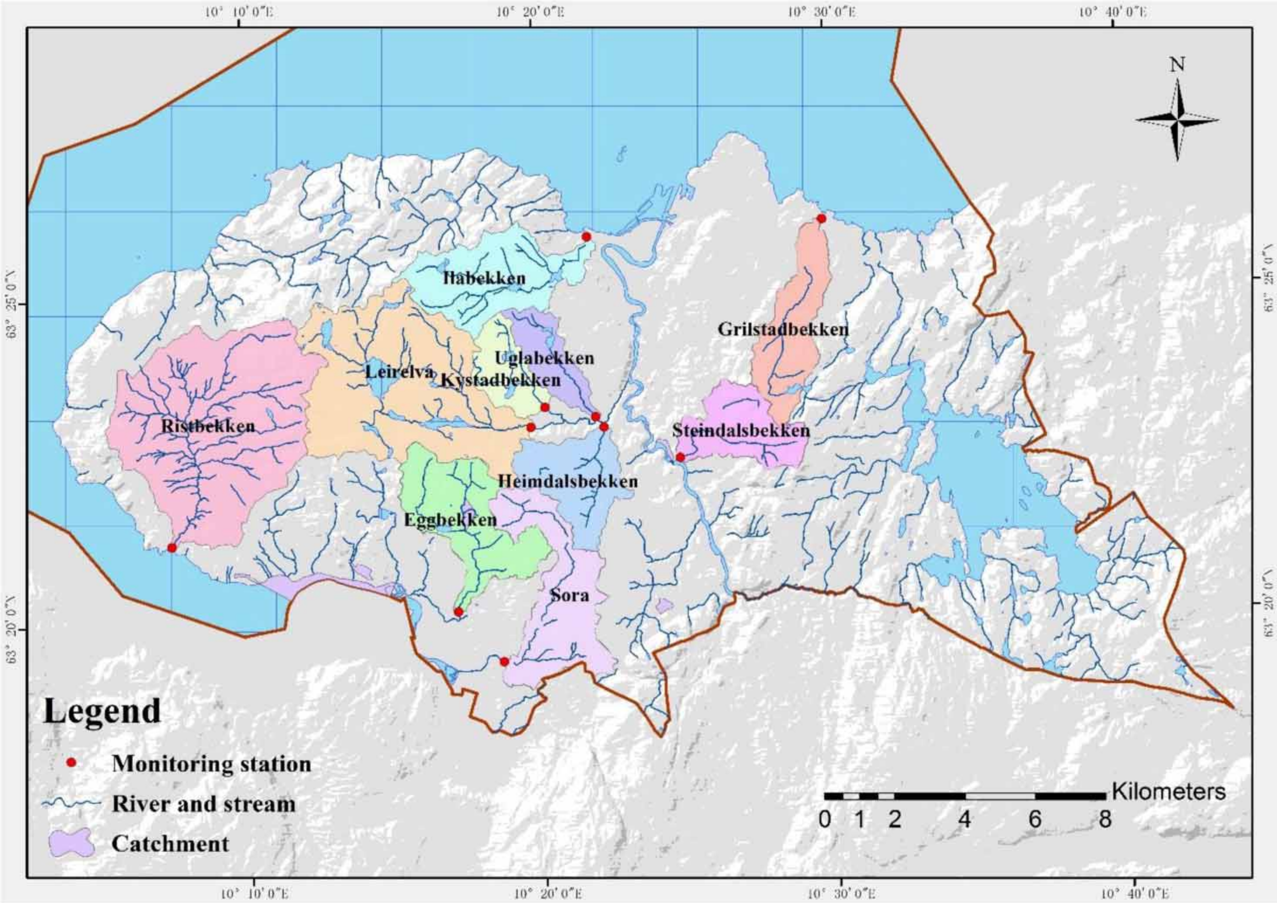


Figure 5 | Water quality monitoring stations and corresponding catchments.

PLAND, presenting the percentage of different land use types, is a measure of the landscape composition, called patch type. PD represents the number of patches of a certain patch type, which reflects the extent of landscape fragmentation.

Temporal scales of the analysis

Both rainfall and snowfall are recorded several months every year in Trondheim, as well as hybrid rain and snow in winter and spring. Since the processes of surface runoff and flow transport in the snow season are different from those in the rain season, the impacts of the landscape variables on water quality indicators were assessed separately for the two seasons. The rain season is defined from May to October and the snow season from November to April the following year.

MLR analysis

Explanatory variables

To determine the most suitable regression models, a stepwise linear method with a variable significance cut-off of 0.05 was used to select the explanatory variables, which include landscape pattern indicators, precipitation and geo-morphological metrics. The selected explanatory variables for the MLR model analysis are given in Table 2.

Response variables

TCB and TP are the two indicators that were measured to represent water quality in rivers and streams, and Trondheim Fjord, which are used response variables for the MLR analysis.

Development of MLR models

MLR models were developed to express the impacts of the explanatory variables on the two water quality indicators, called response variables. To minimize the disparity between the variables expressed by different measurement units, the explanatory

Table 1 | Summary of river and streams, catchment area, land use, monitoring stations and parameters and monitoring periods

River and streams	Catchment size	Land use	Connecting rivers and recipients	Monitoring stations
Leirelva	28 km^2	Forest (70%) Marsh (16%) Rest (14%)	Nidelva	Station No. 2 at Leirelva outlet. Measuring going on since 1995. Data available since 2009.
Uglabekken	3.8 km^2	Urban (53%) Forest (31%) Rest (16%)	Leirelva	Station No. 13 at Uglabekken outlet since 1997 (TCB) and 2001 (TP). Data available since 2001.
Heimdalsbekken	3.9 km^2	Forest (30%) Building (33%) Rest (37%)	Leirelva	Station No. 12 at Heimdalsbekken outlet since 1997 (TCB) and 2001 (TP). Data available since 2001.
Kystadbekken	3.8 km^2	Forest (64%) Building (16%) Rest (20%)	Leirelva	Station No. 14 at Kystadbekken outlet since 1997 (TCB) and 2001 (TP). Data available since 2001.
Steindalsbekken	5.9 km^2	Forest (57%) Agriculture (33%) Rest (10%)	Nidelva	Station No. 17. Measuring and data available since 2009 for TCB and TP.
Søra	10.2 km ^{2}	Forest (34%) Agriculture (30%) Rest (36%)	River Gaula and Trondheim Fjord at Bysenet	Station No. 5 (Søra station 1) 1997–2016; Søra station No. 3–4 since 2017. Data available since 2001 for TCB and TP.
Eggbekken	10.2 km^2	Forest (58%) Agriculture (21%) Rest (10%)	River Gaula and Trondheim Fjord at Bysenet	Station No. 20 at Eggbekken outlet. TCB measurement from 1997 and TP 2001. Data available since 2001.
Ristbekken	27.9 km^2	Agriculture (50%) Forest (37%) Rest (13%)	Drain to Trondheim Fjord.	Station No. 21 outlet of Ristbekken at Mølla. Data available since 2009 for TCB and TP.
Grilstadbekken	7.7 km^2	Forest (44%) Agriculture (23%) Building (20%) Rest (13%)	Fjord from east part of the city	Station No. 23 at outlet of the river since 2000 for TCB and TP. Data available since 2001.
Ilabekken	9.4 km^2	Forest (74%) Marsh (11%) Rest (15%)	Trondheim Fjord from west of the city	Station No. 27 at Ilabekken outlet since 2001. Data available since 2009 for TCB and TP

variables were standardized into units of standard deviation, by subtracting the values from their mean and dividing by their standard deviation. Based on the function expressed by Equation (1), these standardized values were then regressed against a denary or natural logarithm of TCB and TP of the two seasons, which are assumed to have normal distributions.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \tag{1}$$

where y represents the response variable (TCB or TP), x_k represents the explanatory variables, β_k is the slope coefficient for the k_{th} explanatory variables and β_0 for the intercept.

Fitness assessment

R^2 was used to express the variance of the response variables predicted from the explanatory variables.

$$R^2 = SSR/SST = 1 - SSE/SST \tag{2}$$

where R^2 is the coefficient of determination, *SSR* presents the sum of squared differences of the predicted response variable values and the mean of the response variable. *SST* is the sum of squared differences of each of the individual values and the mean of the response variable. *SSE* is the sum of squared differences of the predicted values and observed data.

Table 2 | Explanatory variables for MLR model analyses

Explanatory variables	Unit	Abbreviation	Catchment scale	Reach scale
1. Percentage of lake area	%	lpland	√	√
2. Percentage of forest area	%	fpland	√	√
3. Patch density of forest	number per 100 hectares	fpd	√	√
4. Percentage of agriculture area	%	agpland	√	√
5. Patch density of agriculture area	number per 100 hectares	agpd	√	√
6. Percentage of impervious area	%	impland	√	√
7. Patch density of impervious area	number per 100 hectares	impd	√	√
8. Percentage of marsh area	%	mpland	√	√
9. Patch density of marsh area	number per 100 hectares	mpd	√	√
10. Precipitation	mm	prec	√	√
11. River slope	%	rivslp	√	√
12. Road density	%	roden	√	√
13. Catchment area	km^2	area	√	–
14. River density	km/km^2	rivden	√	–
15. Mean slope of catchment	Degree	catslp	√	–

R^2 is a coefficient of determination, representing the 'goodness of fit', and is used to measure the variability of the response variables obtained from the regression model.

Adjusted R^2 is the adjusted value of the coefficient of determination, represented by the number of explanatory variables included in the MLR model.

Adjusted R^2 is the adjusted value of R^2 calculated by Equation (3).

$$Adjusted\ R^2 = 1 - (1 - R^2)[(n - 1)/(n - k - 1)] \tag{3}$$

where n is the total number of water samples, k is the number of explanatory variables in the developed regression model equations. Adjusted R^2 is used to measure how the calculated response variables fit to the observed values.

In this study, data from 10 monitoring sites (see Figure 4) are used for regression analysis, with each site having the monthly water quality monitoring data of TCB and TP from 2009 to 2020.

RESULTS AND DISCUSSION

Regression analysis

MLR models were developed to establish the relations of landscape variables and the TCB and TP values at the catchment and river reach scales and for the rain and snow seasons, respectively. Table 3 is a summary of the correlation coefficient of the selected explanatory variables with the response variables, TCB and TP.

Catchment scale models

According to Table 3, the five most relevant explanatory variables (fpland, agpland, area, catslp and rivden) were selected to predict TCB, and five variables (fpd, agpland, impd, prec and rivslp) were selected for TP in the rain season, expressed by

Table 3 | Summary of the MLR analysis results

	Correlation coefficients							
	TCB				TP			
	Rain season		Snow season		Rain season		Snow season	
Explanatory Variables	Catchment scale	Reach scale	Catchment scale	Reach scale	Catchment scale	Reach scale	Catchment scale	Reach scale
lpland		−0.303				−0.241	0.115	−0.166
fpland	−0.395							
fpd					0.407	0.211	0.339	0.336
agpland	0.328	0.286			0.574	0.930	0.682	0.657
agpd								0.157
impland		0.592	0.506					
impd			−0.206	0.127	−0.122	0.388		0.358
mpland				0.249				0.175
mpd				−0.606				
area	1.333							
prec					0.139	0.132		
catslp	−0.123		0.436				0.087	
rivslp		−0.679	−0.756	−0.732	−0.267	−0.290	−0.362	−0.166
roden				0.273		0.308		
rivden	−1.448						0.036	

TCB_r and TP_r in Equations (4) and (5), respectively, where r means rain season.

$$\lg(TCB_r) = -0.395Zfpland + 0.328Zagpland + 1.333Zarea - 1.448Zrivden - 0.123Zcatslp \tag{4}$$

$$\lg(TP_r) = 0.407Zfpd + 0.574Zagpland - 0.122Zimpd + 0.139Zprec - 0.267Zrivslp \tag{5}$$

where Z is the standardized values of the explanatory variables.

Four explanatory variables (impland, impd, catslp and rivslp) were selected to measure the impacts of landscape on TCB and five explanatory variables (fpd, agpland, lpland, catslp, and rivslp) were selected for TP in the snow season, expressed by TCB_s and TP_s in Equations (6) and (7), where the subscript s means the snow season.

$$\ln(TCB_s) = 0.506Zimpland - 0.206Zimpd + 0.436Zcatslp - 0.756Zrivslp \tag{6}$$

$$\ln(TP_s) = 0.339Zfpd + 0.682Zagpland + 0.115Zlpland - 0.362Zrivslp + 0.087Zcatslp \tag{7}$$

where Z represents the standardized values of the explanatory variables.

At catchment scale, the adjusted R^2 of the observed versus the predicted value was 0.312 for TCB and 0.55 for TP, and the residual standard error of the models was 0.60 for TCB and 0.26 for TP in the rain model. The adjusted R^2 was 0.394 for TCB and 0.609 for TP, and the residual standard errors of the models were 1.39 for the TCB and 0.60 for the TP in the snow model (Figure 6 and Table 4). The variation in the two estimated indicators in the snow model is greater than in the rain model.

Reach scale models

According to the MLR analysis at reach scale (Table 3), four explanatory variables were selected to predict TCB and seven for TP, respectively, for the rain season, expressed by TCB_r and TP_r. The equations are expressed in Equations (8) and (9).

$$\ln(TCB_r) = 0.286Zagpland + 0.592Zimpland - 0.303Zlpland - 0.679Zrivslp \tag{8}$$

$$\ln(TP_r) = 0.211Zfpd + 0.930Zagpland + 0.388Zimpd - 0.241Zlpland - 0.290Zrivslp + 0.308Zroden + 0.132Zprec \tag{9}$$

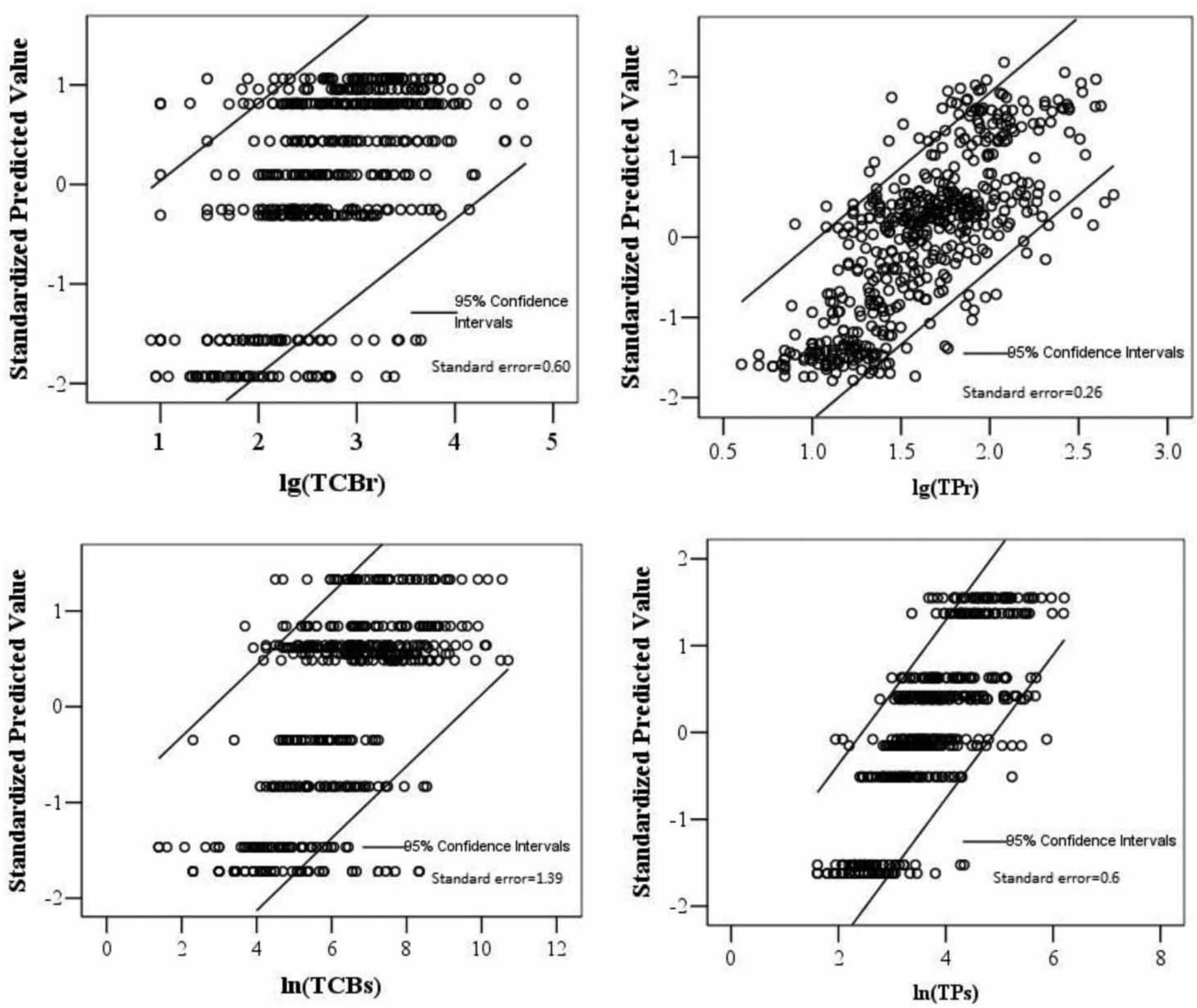


Figure 6 | Relations between the logarithms of monthly measured water quality indicators (TCB and TP) and the standardized predicted values at catchment scale.

Table 4 | Summary of *Adjusted R^2* and the residual standard error for TCB and TP

	TCB				TP			
	Catchment scale		Reach scale		Catchment scale		Reach scale	
	Rain	Snow	Rain	Snow	Rain	Snow	Rain	Snow
Adjusted R^2	0.312	0.394	0.318	0.456	0.55	0.609	0.534	0.593
Residual standardized error	0.60	1.39	1.40	0.50	0.26	0.60	0.29	0.26

where Z represents the standardized values of the explanatory variables.

Five explanatory variables were selected to predict TCB and seven for TP in the snow season, expressed by TCBs and TPs respectively at reach scale. The relations are expressed by Equations (10) and (11).

$$\ln(TCB_s) = 0.249Zmpland - 0.606Zmpd + 0.127Zimpd - 0.732Zrivslp + 0.273Zroden \quad (10)$$

$$\lg(TP_s) = 0.336Zfpd + 0.657Zagpland + 0.157Zagpd + 0.175Zmpland + 0.358Zspd - 0.166Zlpland - 0.190Zrivslp \quad (11)$$

Similarly, Z represents the standardized values of the explanatory variables.

At reach scale, the adjusted R^2 and the residual standard error of the models were, respectively, 0.318 and 1.4 for TCB and 0.534 and 0.29 for TP, in the rain model, as well as 0.456 and 0.5 for TCB and 0.593 and 0.26 for TP, in the snow model (Figure 7 and Table 4). Compared to the analysis at the catchment scale, the variation in TCB and TP in the rain model is greater than that in the snow model for river reach scale analysis.

Residual analysis

Residual analyses were conducted to verify whether the conditions for a linear model of each response variables have been met. The residual plots, which measure the strength of the difference between observed and predicted values, are presented in Figures 8 and 9. Through residual analysis showing in Figures 8 and 9, T test was used to identify outliers and assess the equal variance assumption. The results showed that the differences of data sets are in range of −3.5 to 3.5, except for the very few outliers, which validate the regression model, i.e., the results are reasonable and acceptable.

DISCUSSION

Scale and seasonal effects on TCB

According to the catchment scale analysis for the rain season (Table 3), for TCB, the explanatory variable with the largest regression coefficient is the total catchment area (1.33), which can be explained by several reasons. Firstly, the point-oriented pollution discharges, such as sewage leakage, CSOs during heavy rain events and other pollutant discharge incidents were not included in the landscape pattern analysis, which were estimated the main causes of high TCB concentration from the catchment (Nøst 2015, 2016, 2017, 2018, 2019, 2020; Sivertsen & Barrio 2018). The analysis and assessment results correspond to other international literature (e.g. Swann 2016; Jennings *et al.* 2018).

In the snow season, the percentage of the impervious area is the main contributor to TCB concentration (0.506). In contrast to pollution discharges, the impacts of river slope were negative (−0.756 and −0.732 at the catchment and reach scales, respectively). River density makes the largest negative contribution to TCB concentration (−1.448). It is consequently concluded that river systems with higher drainage capacity play a positive role in the dilution and purification of the discharges from the upstream catchments and, thus, play a role in mitigating the TCB concentration.

Scale and seasonal effects on TP

The results in Table 3 indicate that a higher percentage of agricultural area leads to a higher concentration of TP in streams; this is one of the most dominant pollutant sources to recipients, similar finding has been presented in the European Commission report (EC 2021). The analysis results also showed that the coverage of forest land with less fragmented areas plays a significant role in preventing pollutants being flushed into the streams, at catchment scale in the rain season (0.93), which corresponds to the results obtained by Osborne & Kovacic (1993) of the ability of forested areas to filter incoming P-rich runoff. Further, precipitation has a positive impact on TP yield, appearing only in the rainy season. The results also showed that river slope can reduce the TP concentration in both seasons and at both scales. A higher percentage of impervious areas in riparian regions caused an increase of pollution in both seasons. In the rain season, a higher density of road in a riparian area of 200-metre width resulted in a higher concentration of TCB (snow season) and TP (rain season). It is, thus, concluded that roads that are far away from riparian areas or low road density in riparian areas can help to improve the water quality of the rivers. Otherwise, mitigation measures should be taken to prevent pollution discharges from roads.

Comparison and the effects of other variables and the effects in rain and snow seasons

According to the selected explanatory variables and the MLR model analysis, the spatial impact of the landscape patterns on TP is more sensitive than on TCB, which is reasonable and corresponds with our knowledge and experience that high and extremely high TCB concentrations observed and were caused by point pollution incidents (e.g. Nøst 2019, 2020), also corresponded to other published conclusions (e.g. Wu & Lu 2021).

The MLR model analysis at catchment and river reach levels did not result in a clear distinction of TCB and TP yield in the rain and snow seasons. Both TCB and TP are sensitive to intense or extreme storm events than to the relatively static landscape patterns.

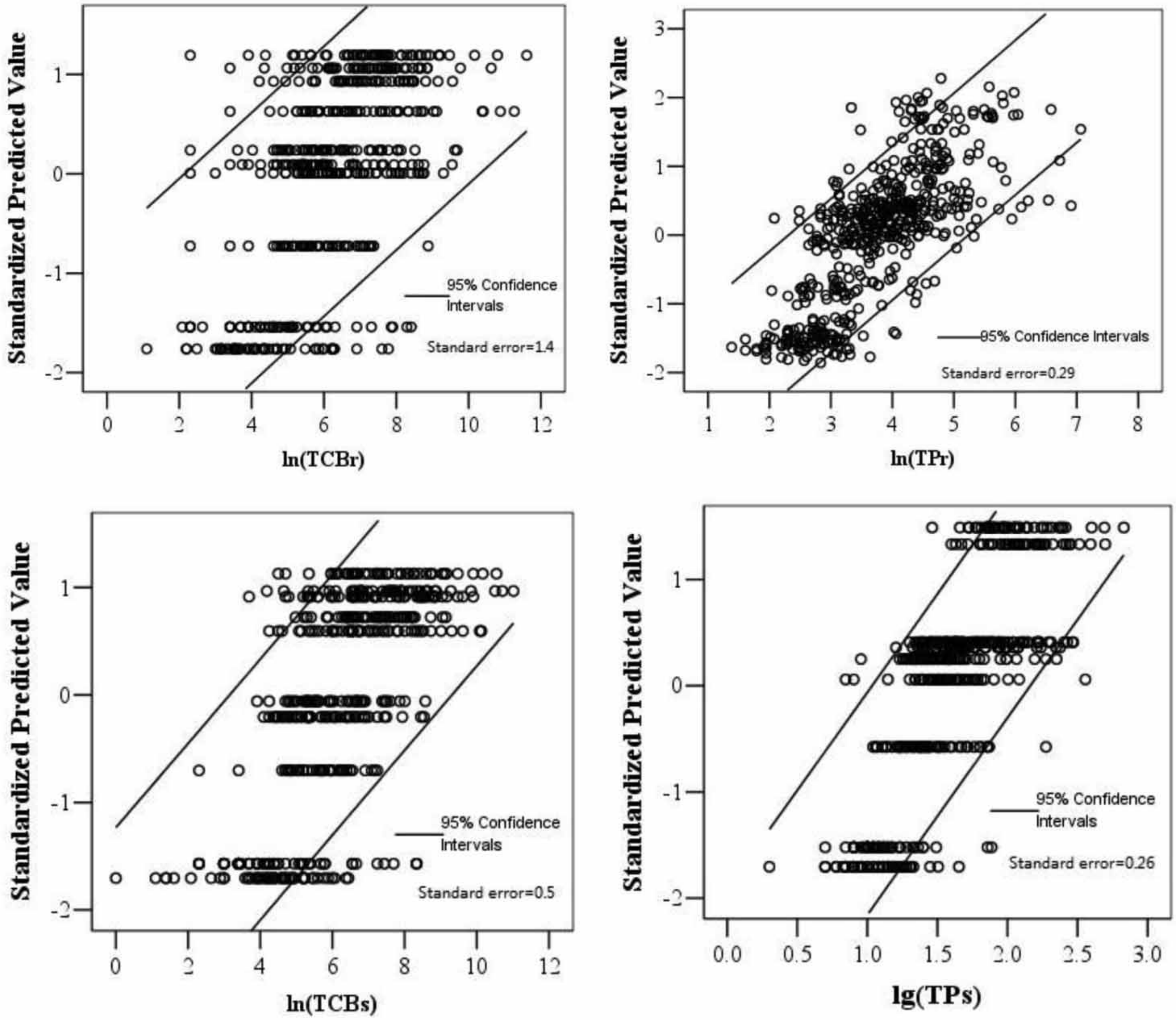


Figure 7 | Logarithm of observed TCB and TP versus standardized predicted value for rain and snow seasons at reach scale.

Future research

The highest concentrations of TCB and TP have been observed in recent years, during highly intense and extreme precipitation events, which cannot be represented by the monthly precipitation and detected by monthly measurements. Therefore, high resolution data, such as hourly and daily precipitation, should be used for the analysis; and immediate discharge measurements of TCB and TP should be taken right after the extreme events. Further, quantitative analysis such as sewer models should be run to predict the sewer overflow, particularly the CSOs, during intense or extreme precipitation events.

Due to the complexity of the nonpoint pollution sources, data expressing the geological conditions, such as soil types and erosions, the use of pesticides and nutrients, and wastes from livestock, should be considered as important information for non-point pollution assessment in the future.

The regression analysis in this paper provided a moderate correlation between the landscape indices, geographical features and water quality indicators presented by TCB and TP. Further, the MLR equations in both seasons and at the two scales do reveal some responses of TCB and TP with the selected explanatory parameters, which declared a need to test several other pollution indicators when attempting to develop satisfactory relations between landscape variables and water quality

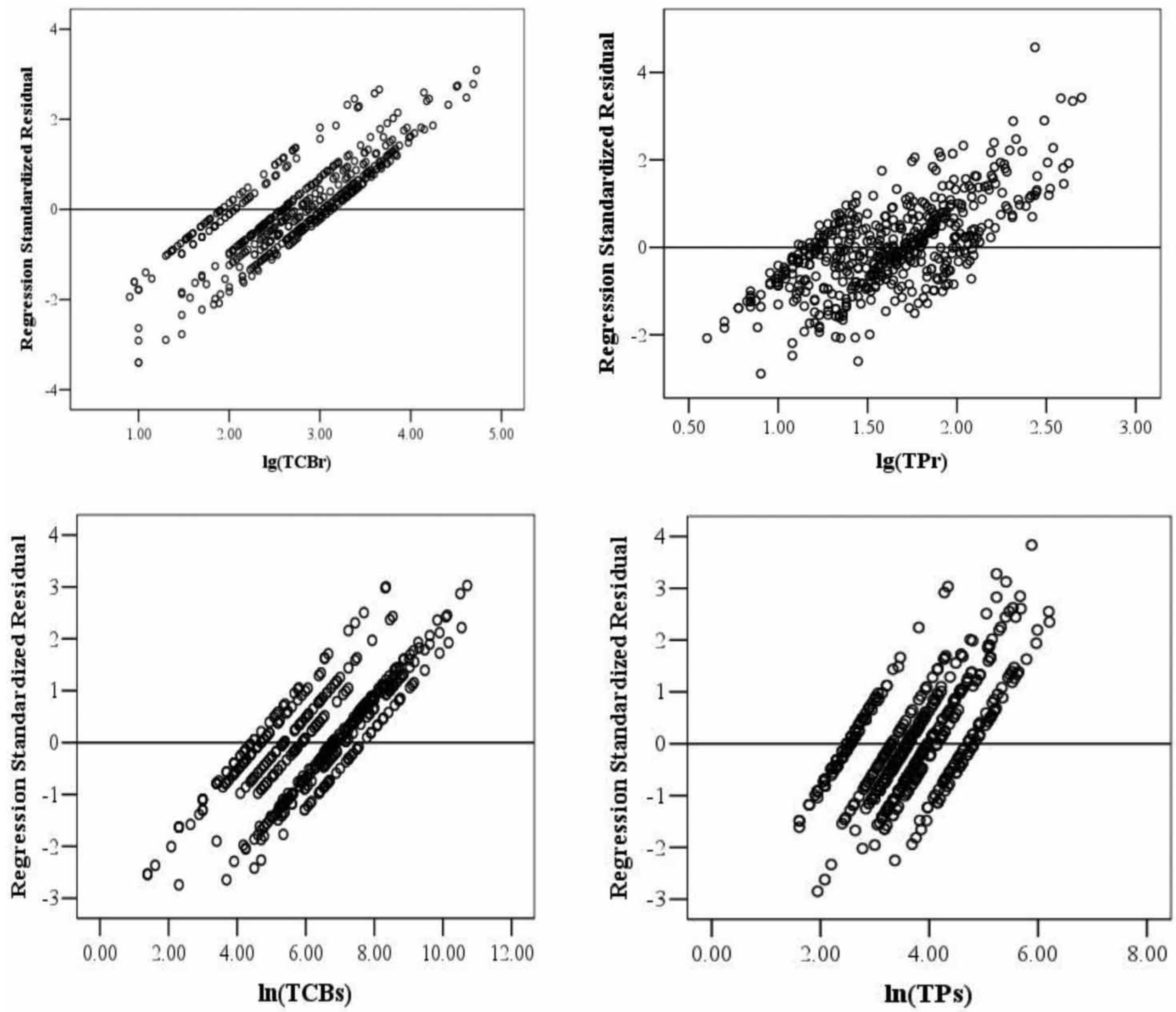


Figure 8 | Standardized residuals between observed and predicted TCB and TP at catchment scale.

indicators. Further, for water quality variables, several other pollution indicators, in addition to TCB and TP may be observed, increasing also monitoring frequency during the extreme events.

CONCLUSIONS

The regression analyses resulted in relatively higher correlation coefficients of the explanatory variables with TP than with TCB, which means the impact of land use and landscape patterns on TP is more sensitive than that on TCB. Secondly, farmland has the highest positive correlations with water quality indicators, TCB and TP, meaning that agricultural activities and livestock may be the main pollution sources to the rivers and streams downstream, particularly the concentration of TP. In addition, positive effects on TCB were found in building areas, roads and other impervious areas.

Furthermore, features of forest area, catchment slope, river density and slope have ability to absorb at least part of the incoming TCB and TP. The larger the percentage of forest areas, the stronger the ability to prevent the pollutant transportation from sources.

The research presented in this study has opened the new possibility of applying MLR model to quantify the relations between the explanatory variables with the water quality indicators. When the MLR model equations have been properly calibrated and verified, they can be used to predict the concentrations of the TCB and TP under different climate and land use

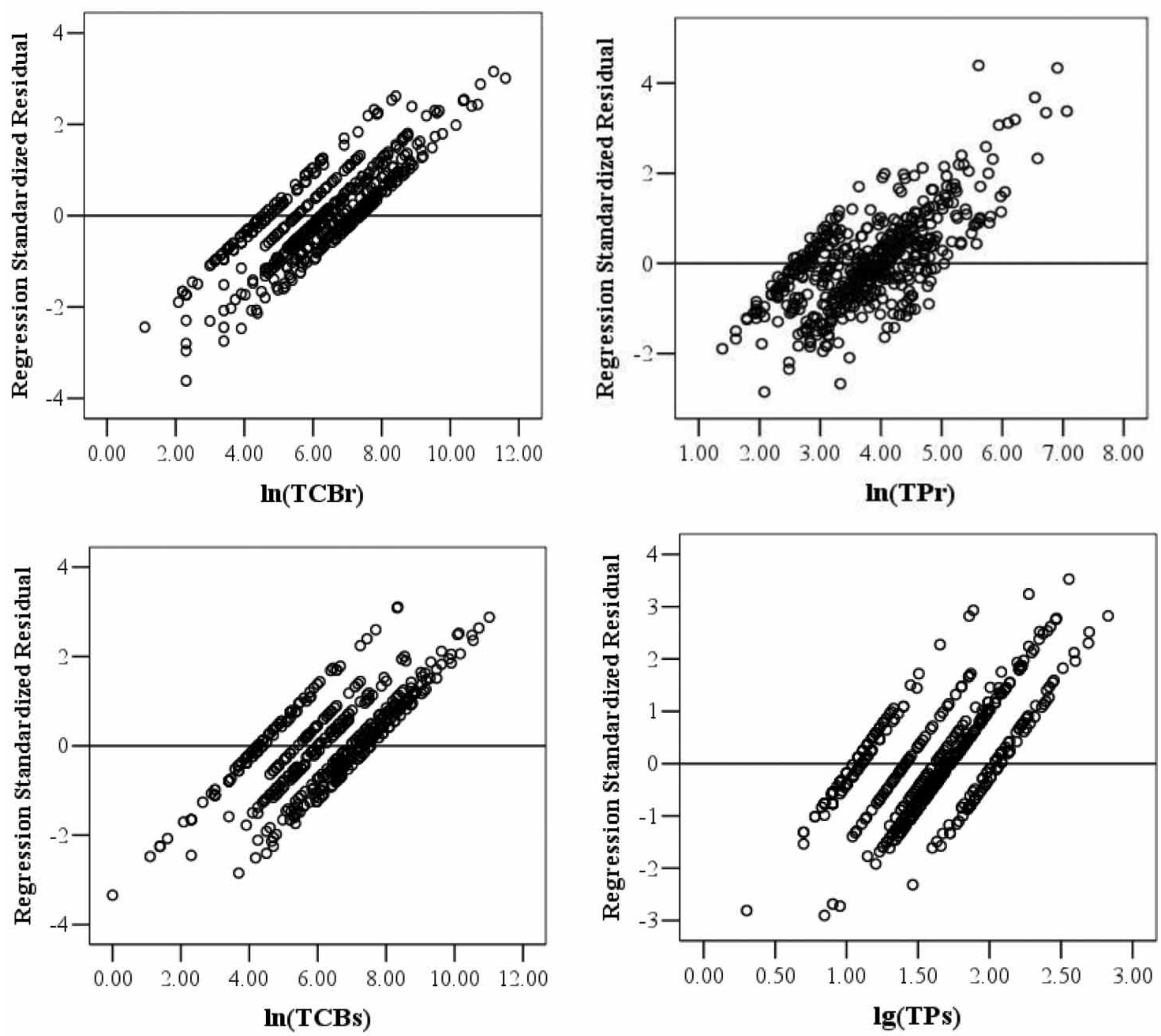


Figure 9 | Standardized residuals between observed and predicted TCB and TP at reach scale.

scenarios, which requires also great need of the spatial and temporal data on catchment geographical features and landscape patterns. The advanced studies would provide scientific background information for urban and rural development and catchment water management.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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