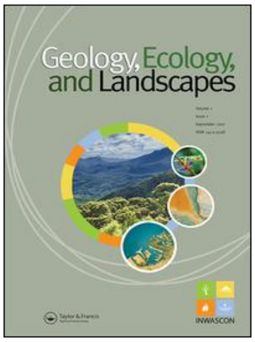

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RESEARCH ARTICLE

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Responses of stream water quality concentrations to vegetative cover variation in Muar River watershed

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ABSTRACT

Analysis of the historical land-cover of Muar River watershed has shown that forest and agriculture are the dominant land-covers over the last three decades. This information was used to evaluate the relationship between the vegetative landscape variation to stream water quality concentrations which was to provide an insight for management of water quality under humid tropical climate. Three out of the six water quality variables simulated using the hydrological simulation program FORTRAN (HSPF) model are sensitive to change in vegetative land-covers which include; biochemical oxygen demand (BOD), nitrate-nitrogen (NO_3-N), and orthophosphate (PO_4) concentrations. However, total suspended solids (TSS), dissolved oxygen (DO), and ammonia-nitrogen (NH_3-N) concentrations remain insensitive. Further analysis shows that patch density (PD) has a little impact on BOD, NO_3-N, and PO4 concentrations compared to edge density (ED), largest patch index (LPI), and landscape shape index (LSI) under varied landscape conditions. However, large ED, LPI, and LSI indices in both forest and agriculture will result to increase in BOD, NO_3-N, and PO_4 concentrations. Therefore, adequate knowledge of the responses of the water quality concentrations to landscape pattern and its dynamics can serve as an alternative solution to stream water quality deterioration in an abundant rainfall region.

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KEYWORDS
Landscape pattern; HSPF model; regression model; remote sensing; tropical climate

1. Introduction

The concentrations of water quality constituents in the runoff of a river determine the type and distribution of the aquatic ecosystem (Chen et al., 2016). Since correlation exists between pollution transport and vegetative cover (Mouri, Takizawa, & Oki, 2011), its wields a significant influence on runoff-pollution transportation processes. Harnessing the relationship between vegetative cover and stream concentrations is of practical significance for management of densely vegetative watershed in a tropical rainforest region (Uriarte, Yackulic, Lim, & Arce-Nazario, 2011). Several studies have shown that there is always a potential to improve water quality if the role of different combinations of vegetative cover conditions is known (Bu, Meng, Zhang, & Wan, 2014; Li, Gu, Liu, Han, & Zhang, 2008). To understand the responses of a watershed stream concentration from its vegetative cover, it is essential to observe the changes in their matric pattern due to regeneration or shift and furthermore recognize their roles on the accumulation, storage, and releases of pollutants. According to Zhou, Shangguan, and Zhao (2006), this approach is one of the most important techniques to improve water quality and prevent soil erosion. Hence, changes in vegetative cover indicate a change in some aspect of the river water quality (Jiang et al., 2014). It is known that NPS pollution accounts for the stream concentrations and plays a significant role in the water quality problems. Assessment of the stream water quality status became an important issue mainly due to anthropogenic activities resulting to different pollutants inflows.

Numerous indicators have been developed to show the impact of vegetative cover on water quality condition in a watershed (King et al., 2005; Miserendino et al., 2011; Zampella, Procopio, Lathrop, & Dow, 2007). Among them are spatio-temporal indicators, in which one may refer as long-term vegetation landscape pattern on NPS pollution. It shows the impact of vegetation cover on NPS loadings based on the spatial changes in vegetative cover within the watershed (Ouyang, Skidmore, Toxopeus, & Hao, 2010). However, it does not show the impact of the vegetative changes on the stream concentrations directly but rather illustrate how the spatial changes affect the transport of the NPS pollution loads. There is no argument regarding whether the changes in vegetative cover is the most important in influencing the water quality, if all other factors remaining constant. Hall et al. (2014) shows that vegetation cover status is a primary step in assessing stream

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degradation because it degrades first, followed by channel morphology, and eventually water quality.

Therefore, assessment of the spatial arrangement of vegetative cover landscape and their relationship to the stream concentrations will show the functionality of each matric to influence the assimilative capacity of a stream because of its vegetative landscape. Most of the assimilative capacity of a stream involves the relationships among vegetative cover that controlled the structure of the channel and floodplain (Ahearn et al., 2005). It is important to know the impact of the vegetative cover changes on the stream water quality condition that is blended with the landform and hydrology of the watershed because little is known on how vegetative cover influences stream nutrients fluctuation and ecosystem. Recent studies have attempted to show the relationship between landscape characteristics to water quality variables and how to utilize the outcome for future water resources management in an urbanized watershed scale (Shen, Hou, Li, & Aini, 2014). However, a single land-cover was used to demonstrate the impact of landscape matric to stream water quality concentration variables. In this study, we demonstrate how the historical pattern of the landscape matrix is related to six water quality variables. The specific objective of this paper is to utilize the historical land-cover data in evaluating the response of stream nutrient concentrations under varied spatial vegetative landscape configuration in Muar River watershed, and to show the relationship between changes in stream nutrients concentrations with vegetative landscape metric pattern changes.

2. Materials and methods

2.1. Study area

The Muar River watershed is a vegetative watershed located in between two states in the Malaysia peninsular: Johor and Negeri Sembilan. It sprays between 102°30′11.68″ E and 102°32′46.08″ E longitude and 2° 04′01.80″ N and 2°57′51.67″ N latitude (Figure 1) with a total drainage area of 6045 km^2. The rivers flow from southeast at the upstream to the southwest at the downstream and discharge into Malaka strait. Average annual rainfall is 2470 mm over a period of 1972 to 2017, while the mean air temperature is 25.6ºC. It falls in the region of abundant rainfall and seasons are differentiated by change in wind direction to either Southwest Monsoon from April to September, and the Northeast Monsoon from October to March. Local topography varies from 253 m of altitude to as low as 1 m above sea level. The current land cover of the watershed consists of 49.4% forest, 40.8% agriculture (which include 82% rubber, 15% oil palm, and other crops 3%), 8.2% urban, and 1.6% wetlands.

2.2. Study design

The study flow chart is illustrated in Figure 2. The first step was to produce four historical land-cover images utilizing remote sensing data obtained from United States Geological Survey (USGS) Global Visualization Viewer (https://glovis.usgs.gov). Then the watershed model of the study area was developed using HSPF model. The third step was to simulate each swapped land-covers maintaining the same calibration parameters and the water quality variables for

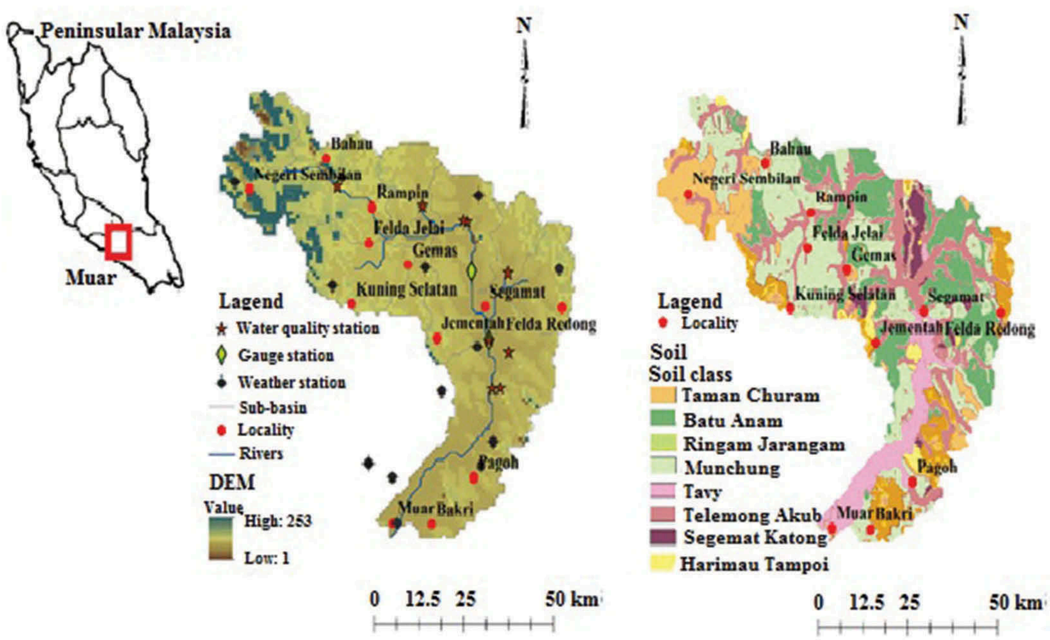

Figure 1. Map of the study area showing the location, soil property, and hydroclimatic station distribution.

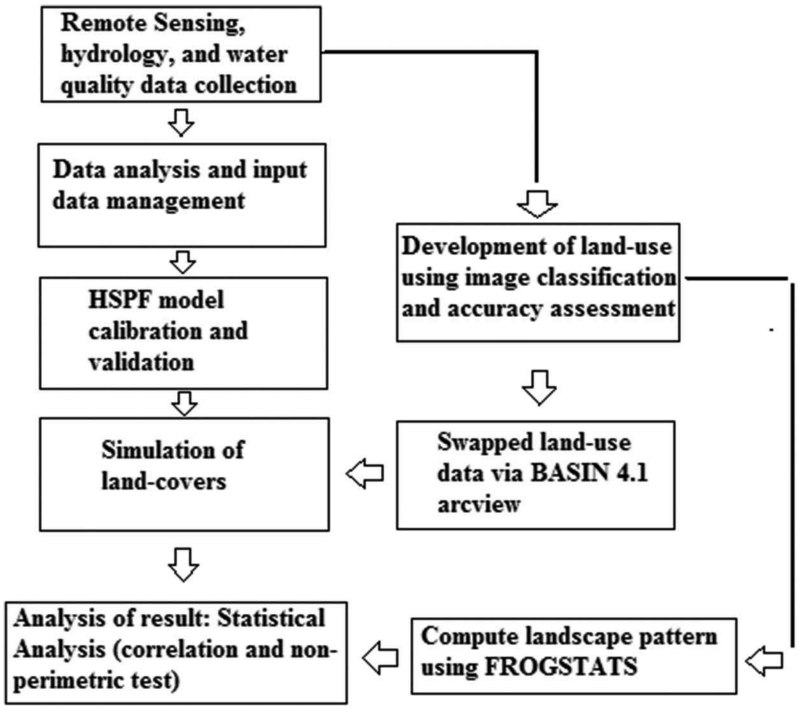

Figure 2. Methodology flow chart.

each simulation was obtained. In each result a statistical analysis was used to compare the water quality variables under the four land-cover conditions. Finally, the landscape matric patterns for the two-dominant vegetative cover (forest and agriculture) were computed using FRAGSTAT program and correlated with stream nutrients concentrations.

2.3. Input data and analysis

The weather data used in this study were obtained from Department of Irrigation and Drainage of Malaysia (DID), and they include precipitation and evaporation data while the remaining data such as wind speed, dew-point temperature, cloud cover, and solar radiation were obtained from Malaysia Meteorological Department (MMD). These data were used to build an input database for model runs. Hourly streamflows of the watershed were obtained from the DID, and monthly water quality data (total suspended solids––TSS, biochemical oxygen demand––BOD, dissolved oxygen––DO, ammonia nitrogen––NH_3-N, nitrate nitrogen––NO_3-N, orthophosphate––PO_4, and water temperature) from the Department of the Environment of Malaysia (DOE). The soil map of the study area was obtained from the Department of Agriculture and Fisheries (DOA). Elevation data from the Global Data Explorer (https://gdex.cr.usgs.gov/gdex/) were used for the watershed delineation and development of hydrological response units. The land-cover data were developed from remote-sensing data derived from the USGS Global Visualization Viewer. All the imageries were captured either by Landsat 4–5 (1988 and 1996 imageries), 7 (2009 imagery) and 8 OLI/TIRS (2016 imagery) operational land imager sensors and were used to produce historical land-cover data of the study area. The remote sensed data were analysed using geometric correction, image classification (utilizing 135 controlled points derived from the site-based maps and google earths), and accuracy assessment adopting the methodology used by Millard and Richardson (2015). Result of the accuracy assessment shows more than 82.7% precision and 84.1% sensitivity between the four land-covers produced for the year 1988, 1996, 2009, and 2016 (Figure 3). Analysis of the land-covers shows that the vegetative covers in the watershed do not change rapidly while forest and agriculture (oil palm and rubber) are the dominant land-cover class, although they tend to change their landscape configuration and structure over the years. For example, the forest land reduced from 71.2% in 1988 to 49.4% in 2016, but agriculture increased from 23.4% in 1988 to 40.8% in 2016.

2.4. Brief model description and set-up

HSPF is a dynamic model that performs a continuous simulation of hydrologic and water-quality processes using a set of modules organised in a hierarchical structure (Duda, Hummel, Donigian, & Imhoff, 2012). In this study, HSPF version 12.4 (Aqua-Terra, 2015) was used because the model framework consists of a top–down uniform data structures defined by a well programming pacts that are only used for a large-scale modelling efforts. Shenk, Wu,

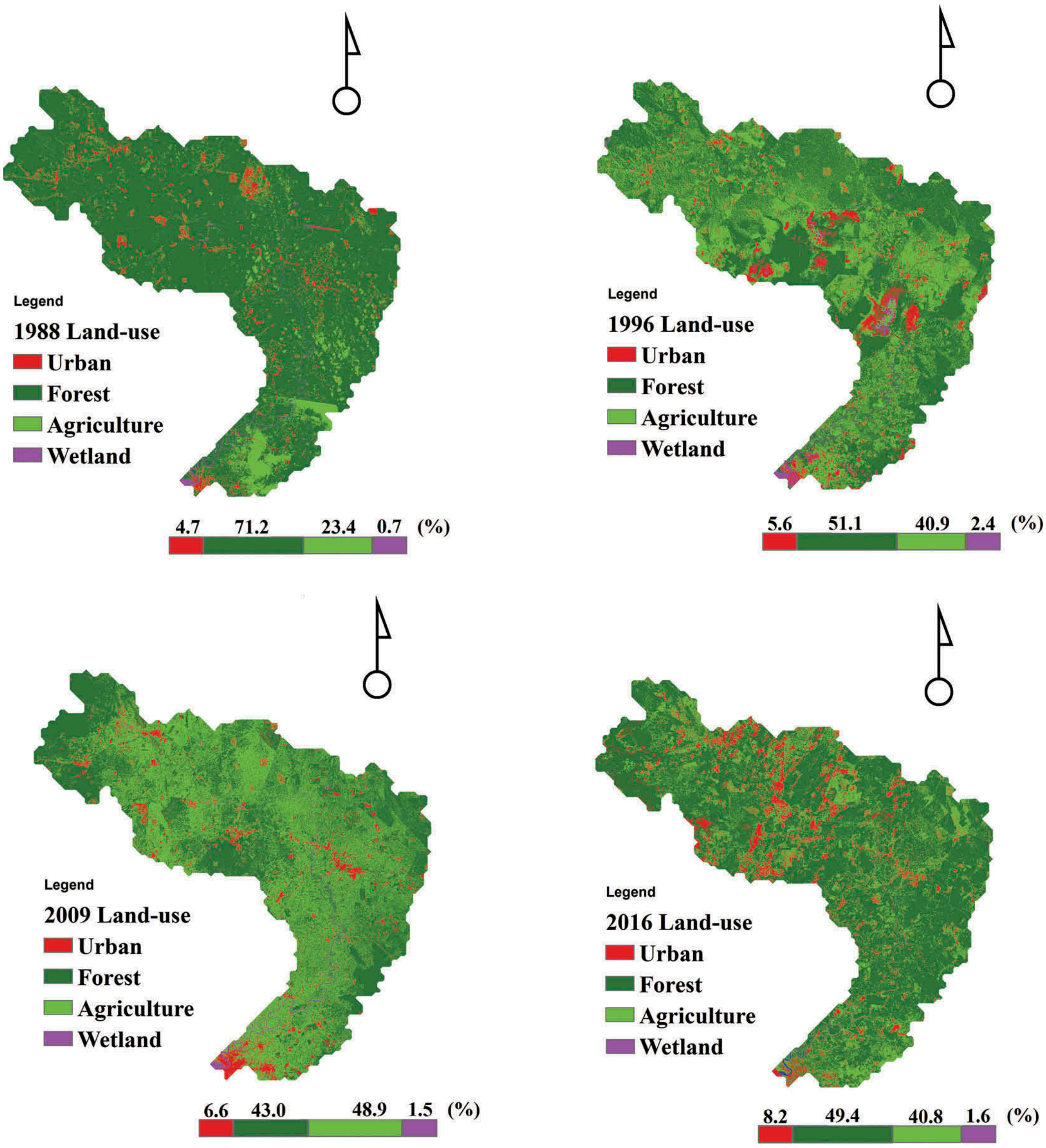

Figure 3. Land-covers of the Muar River watershed as derived from remote sensing data.

and Linker (2012) and Watts and Maidment (2007) explained the details of the model structure, configuration, and enhancement over the years. It utilized some add-in programmes that facilitate the modelling process, and the most important are the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS), weather data management utility (WDMUtil), and HSPEXP+ program.

BASIN Arcview version 4.1 was used to input spatial data (land use, elevation, and soil data) that define the physical structure of the watershed. This programme also interlinked other add-in programmes required to run HSPF such as Climate Assessment Tool (CAT) (Imhoff, Kittle, Gray, & Johnson, 2007) and WDMUtil.

We developed the hydrological model of the Muar River watershed using the measured streamflow data from 2014 to 2017 (4 years simulation). In addition, seven water quality variables were modelled which makes up of total suspended solid (TSS), water temperature (Tw), dissolved oxygen (DO), BOD, ammonia nitrogen (NH_3-N), nitrate nitrogen (NO_3-N), and orthophosphate (PO_4) were also calibrated and validated. The final modelling results comparing the observed and simulated values for both streamflow and water quality variables were represented using graphical plots. Model performance checks were conducted using the usual quantitative statistical test. These test are the coefficient of determination (R^2), Nash–Sutcliffe coefficient (NSE), and percentage bias (PBIAS) (Moriasi et al., 2007)).

2.5. Development and selection of landscape pattern indicators

Landscape pattern metrics show the measurements of landscape structure which can be used to define the spatial and temporal distribution of land-covers. However, researchers are sceptical on their relevance in on ecological processes and influence on the real landscape function (Kupfer, 2012). Yet a lot of studies have shown the correlation between landscape indices and ecological condition of an area, though some are considered as redundant and insignificant (Uuemaa, Antrop, Roosaare, Marja, & Mander, 2009). Therefore, in this study four landscape pattern indices were selected based on their proven correlation to water quality status of a watershed (Table 1). This is to ensure that less significant indices were removed and information redundancy are properly managed. The four land-covers produced (Figure 3) were prepared using ArcGIS *v* 10.3 and transferred in to FRAGSTATS software to calculate their landscape metrics (Feng & Liu, 2015).

2.6. Statistical analysis of the results

The changes in the stream water quality concentrations (TSS, DO, BOD, NH_3-N, NO_3-N, and PO_4-P) under the different vegetative landscape conditions were analysed using non-parametric test statistics as the simulated results are not normally distributed (Ghasemi & Zahediasl, 2012). For this study, the Jonckheere–Terpstra test was chosen because it tests the null hypothesis of no difference in response magnitude across scenarios against an ordered alternative, so that the response magnitude increases over a pre-specified ordering of the scenarios (Vock & Balakrishnan, 2011). Hence, it is used to determine whether there is a statistically significant relationship between the vegetative landscape changes and the simulated outputs of the stream water quality concentrations. We employed the hypothesis that the distributions of the stream water quality concentrations are the equal under each vegetative landscape considered (1988, 1996, 2009, and 2016 land-covers), and SPSS software was used for the analysis. However, in case of the null hypothesis is rejected, a *post hoc* analysis of the streams water quality data will be used to show how the water quality variables changes under each vegetative cover condition. The aim was to see to what extent the stream water quality concentrations vary and how their statistical values can be distinguished (Lunneborg, 2005). Furthermore, the water quality variables that significantly varied statistically due to the changes in the vegetative cover in Muar River watershed were selected.

The interaction between the statistically significant changes in water quality variables and the two vegetation landscapes metric indices were analysed using multiple linear regression. According to Shen et al. (2015), this method was long been used to relate water quality with landscape pattern metrics. The idea of correlating them is to understand how both the selected landscape metrics and stream water quality concentrations are related under densely vegetative settings that were derived from tropical rainforest.

3. Results

3.1. Model of Muar River watershed

The hydrological model of the watershed was developed by parameter adjustment based on the BASIN technical notes 6 and 8 (USEPA, 2015, 2000) and other relevant literatures. A sensitivity analysis of the hydrological and water quality parameters were done (Liu, Godrej, & Grizzard, 2011), and sensitive parameters were identified to reduce the uncertainty of the model results (Jia & Culver, 2008) prior to final calibration of the model. Afterward, the model results (Figure 4) show that it was able to capture the temporal variability of the streamflow under different flow conditions (PBIAS values for calibration and validation were −2.174 to −7.125, respectively). However, HSPF model is considered as one of the best model that simulates hydrological behaviour of a watershed relatively well when compared with other similar models (Singh, Knapp, Arnold, & Demissie, 2005; Xie & Lian, 2013). The statistical performance of the water quality model was satisfactory considering the amount of data used for the calibration and validation process (Fonseca, Botelho, Boaventura, & Vilar, 2014). In general, the model was able to capture the water quality processes in the watershed as the coefficient of determinant (R^2) and percentage

Table 1. Selected landscape metrics and their significance on water quality of a watershed.

Landscape index	Description	Influence on water quality variables
Patch density (PD)	Number of patches per unit area	It influences nonpoint source (NPS) nutrients load especially nitrogen or its constituents (Ouyang et al., 2010).
Largest patch index (LPI)	The sum of the landscape boundary divided by the square root of the total landscape area	Controls sediment flow and nutrients from NPS essentially under rainfall condition (Shen et al., 2015).
Edge density (ED)	Total length of all the edge segment per hectare for the considered landscape or class metric	It affects the distribution of NPS at the sub-catchment and influences the soluble nutrients elements in the stream (Ouyang et al., 2010; Shen et al., 2015).
Landscape shape index (LSI)	The area of the largest patch in the landscape divided by total landscape area	Significance to soluble phosphorus, dissolved oxygen under rainfall conditions (Bu et al., 2014)

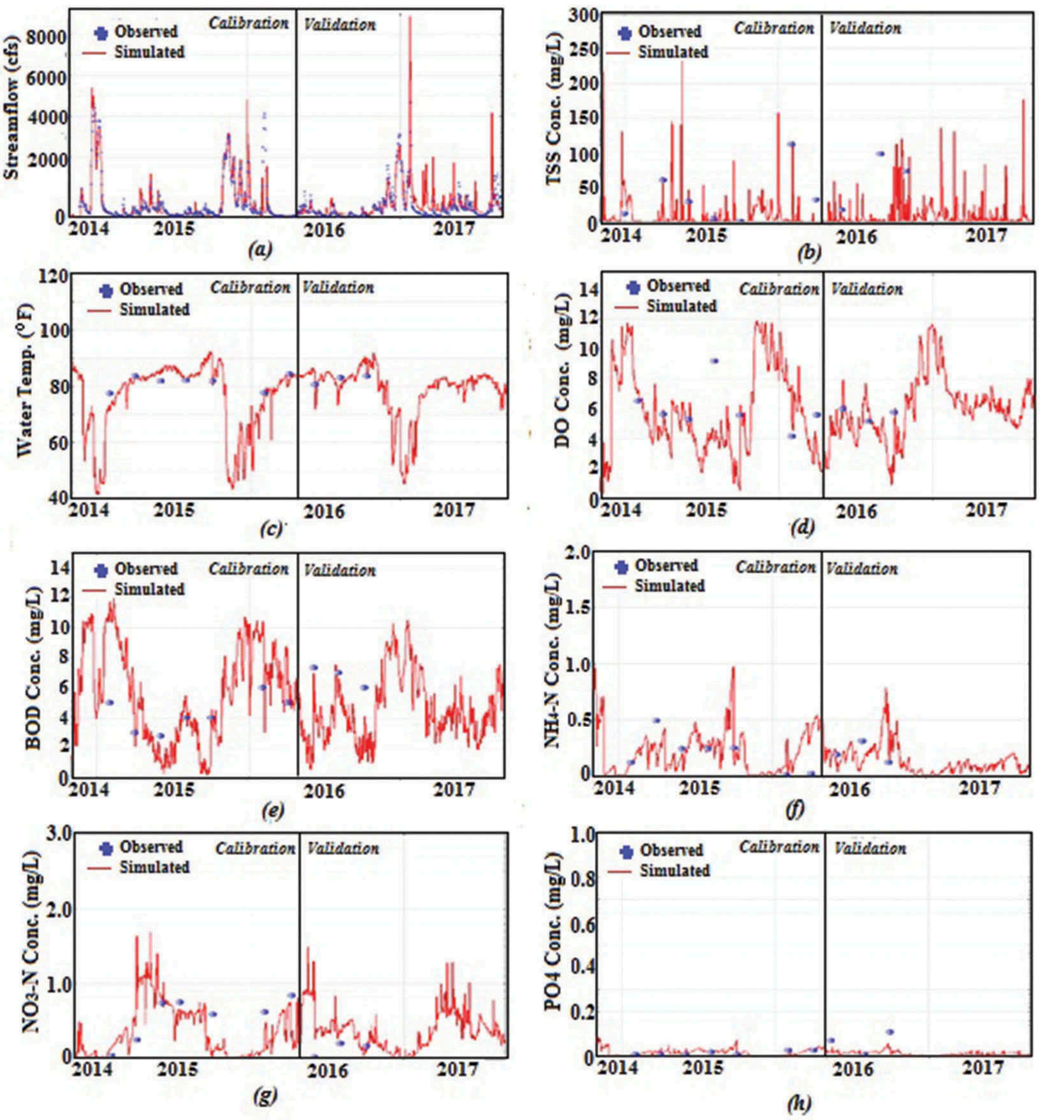

Figure 4. Graphical plots of model calibration and validation results: (a) streamflows, (b) total suspended sediment (TSS), (c) water temperature (T_w), (d) dissolved oxygen (DO), (e) biochemical oxygen demand (BOD), (f) ammonia nitrogen (NH_3-N), (g) nitrate nitrogen (NO_3-N), and (h) orthophosphate (PO_4).

bias (PBIAS) values for both calibration and validation fall within the range of 0.153 to 0.585 and −31.463 to 41.612, respectively (Figure 4 and Table 2).

Table 2. Statistical model performance result for Muar River watershed.

	Calibration		Validation	
Constituents	R^2	PBIAS	R^2	PBIAS
Streamflow	0.750	−2.174	0.645	−7.125
TSS	0.438	−2.941	0.316	8.584
T_w	0.512	11.402	0.499	26.622
DO	0.585	7.650	0.446	22.114
BOD	0.492	−3.035	0.385	−10.510
NH_3-N	0.370	−26.511	0.346	−31.463
NO_3-N	0.198	34.837	0.153	41.612
PO_4	0.472	−25.455	0.395	−16.259

3.2. *Description of vegetative landscape characteristics in the watershed*

It is a well-known fact that tropical humid climates influence rapid succession of pasture, plantations, and forest which result to changes in the ecosystem characteristics and vegetative patterns within a few years of regrowth (DeWalt, Maliakal, & Denslow, 2003). Therefore, it will result to varied metric pattern as the land-cover changes over the years. Our finding shows that the vegetative (both forest and agricultural) landscape areas consistently decrease and increase, respectively, except for the year 2016 which indicates an opposite result (Table 3). The reason for this inconsistency is that some of the agricultural areas (oil palm and rubber plantation) were mixed with secondary forest because of microclimatic influence (Hardwick et al., 2015) and poor maintenance or deserting the agricultural areas due to

Table 3. Landscape metric patterns of vegetative cover in Muar River watershed.

Landscape	Forest				Agriculture			
Years	1988	1996	2009	2016	1988	1996	2009	2016
Area (%)	71.2	51.1	43.0	49.4	23.4	40.9	48.9	40.8
Patch density (PD)	1.5	8.6	20.6	5.7	14.6	17.9	11.5	12.9
Largest patch index (LPI)	74.9	42.2	8.6	35.8	2.5	14.3	43.9	2.4
Edge density (ED)	57.5	136.8	157.7	97.7	64.9	141.9	164.7	114.1
Landscape shape index (LSI)	108.5	321.0	403.2	209.0	296.9	372.5	388.3	367.9

the shift in socioeconomic activities of the people (Siddiqui, 2012). Furthermore, the changes in the vegetative landscape pattern follow the variation in the landscape areas. The forest had a lower patch density (PD) when compared with agriculture from 1988 to 2016 except for the year 2009 which indicates higher PD for forest than agricultural landscape. But forest shows a higher large patch index (LPI) than agriculture, although the indices show a variability among the four-historical land-covers. Agriculture had a higher edge density (ED) than forest and increases steadily with increased landscape area except for the year 2016 which it decreases with decreased landscape area. Also, the landscape shape index (LSI) follows the same pattern with that of ED as shown in Table 3. In general, the results showed the direct links between the size of a vegetative landscape and their indices in the study area while their values depend on how they are spatially distributed.

3.3. Responses of stream water quality variables to changes in vegetative cover

The statistical analysis of the simulated water quality concentrations using Jonckheere–Terpstra non-parametric test shows that (Table 4) the water quality variables have different response to changes in vegetative landscape over the years in Muar River watershed. For example, TSS, DO, and NH_3-N concentrations do not significantly change over the four-historical vegetative landscape. A value of $p > 0.05$ indicates a rejection of the null hypothesis, thus implying that the concentrations of TSS, DO, and NH_3-N had no significant difference under varied vegetative covers in the watershed.

However, the other simulated water quality concentrations show different responses, with BOD, NO_3-N, and PO_4 varying as the vegetative landscape changes. The value of $p < 0.05$ affirms the null hypothesis and indicates that there is a difference between each stream water quality concentrations as the vegetative landscape varies. Further analysis of the statistical results using post-hoc test, shows that the outliers are more obvious for TSS, BOD, NH_3-N, and PO_4 as compared to DO and NO_3-N concentrations (Figure 5). The median values of BOD, NO_3-N, and PO_4 show a variability along the four vegetative landscapes. In each case, the statistical result shows that the changes in vegetative landscape in the watershed have different impacts on the water quality variables. The reasons for the varied responses are that each variable is controlled by different biochemical processes that are influenced by factors such as slope, soil type, weather conditions, etc. Our focus is only to evaluate how changes in vegetative covers affect the responses of different water quality variables if all other conditions are constant. In this regard, the water quality variables (BOD, NO_3-N, and PO_4) that respond to changes in vegetative landscape in the Muar River watershed are defined as sensitive water quality variables, while those (TSS, DO, and NH_3-N) that do not respond to the vegetative cover variability are referred to as insensitive water quality variables.

3.4. Interactions of the selected water quality variables with vegetative landscape metrics

We select the sensitive water quality variables that respond to vegetative cover variation in the watershed and further evaluate their interaction to

Table 4. Jonckheere–Terpstra test for stream concentrations under different land-use.

	Stream concentrations					
Statistical parameters	TSS	DO	BOD	NH_3-N	NO_3-N	PO_4
Number of levels in SCENARIOS	4	4	4	4	4	4
N	5304	5304	5304	5304	5304	5304
Observed J–T statistic	5,236,486	5,236,486	5,424,943	5,193,014	4,409,483	4,863,510.5
Mean J–T statistic	5,274,828	5,274,828	5,274,827.5	5,274,828	5,274,827.5	5,274,827.5
Std. deviation of J–T statistic	62,342.95	62,343.01	62,343.10	62,342.98	62,342.02	62,342.97
Std. J–T statistic	−0.615	−0.693	2.408	−1.312	−13.881	−6.598
P-values (two tailed)	0.539	0.488	0.016	0.189	0.000	0.000

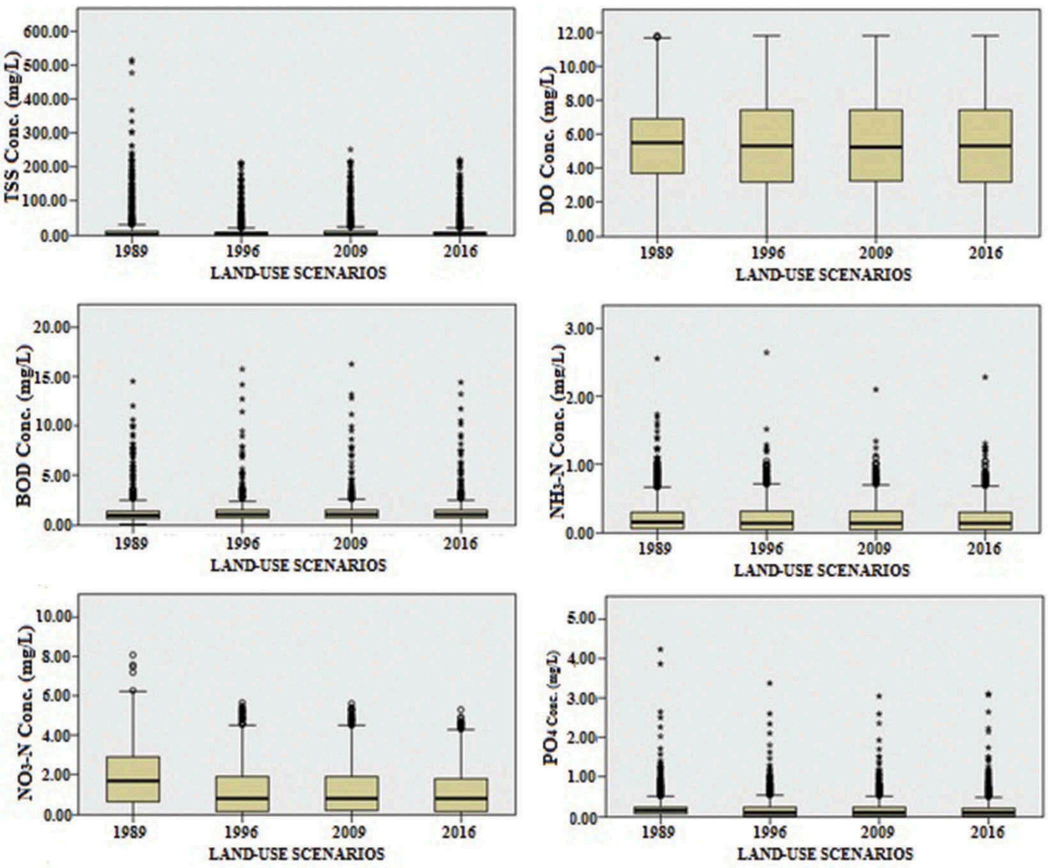

Figure 5. Box and whiskers distribution of the simulated water quality concentrations (in mg/L) under the four-historical land-covers.

the landscape pattern metrics. This is to evaluate how the identified sensitive water quality variables are correlated to the landscape pattern as the watershed vegetative land-cover changes over time.

3.4.1. Correlation between BOD and vegetative landscape metrics

The interaction between vegetation landscape indices and BOD concentrations from the correlation results are summarized in Table 5. All the correlating models show a negative correlation between variability of BOD concentrations with vegetative landscape indices except for forest LPI which shows a positive correlation with changes in BOD concentrations, meaning that forest was the major sources of BOD concentrations in the watershed. Its significance was further observed from the R^2 values of the correlation models derived between forest vegetation landscape indices and BOD concentrations. They all have a higher R^2 values when compared with agriculture landscapes metrics. Also, the results indicate that the flow of organic nutrients which determines the BOD level in the stream is mostly controlled by forest landscape, while the LSI is mostly significant followed by ED and then LPI index. For agriculture, it was observed that ED and LPI correlate well with BOD concentrations as compared with LSI, while PD shows the lowest R^2 value (Table 5). The results show that the movement of organic pollutants from agriculture landscape was resulted by the large ED and LPI landscape conditions and lower PD index. Low correlation between agriculture and PD shows that small amount of agriculture patches with large amount of agriculture edge and shape are linked to movement pf organic nutrients into the streams of Muar River watershed. In addition, since both forest and agriculture ED, LPI, and LSI landscape indices influence the movement of organic nutrients which results to changes in BOD concentrations. The likely alternative to control the flow of organic nutrient in the watershed is to reduce the edge and shape of the patches in both forest and agricultural vegetative land-cover while keeping the PD for agriculture unaltered.

Table 5. Correlation between vegetation landscape metrics with BOD concentrations.

Model	R^2	*p*-value	*F*-statistics
$BOD_{conc} = -0.002Forest_{PD}+1.195$	0.750	0.134	5.995
$BOD_{conc} = -0.00013Agric_{PD}+1.183$	0.011	0.968	0.002
$BOD_{conc} = 0.00014Forest_{LPI}+1.164$	0.525	0.275	2.210
$BOD_{conc} = -0.0012Agric_{LPI}+1.191$	0.765	0.125	6.515
$BOD_{conc} = -0.00032Forest_{ED}+1.217$	0.881	0.062	14.758
$BOD_{conc} = -0.00035Agric_{ED}+1.219$	0.800	0.106	7.988
$BOD_{conc} = -0.00011Forest_{LSI}+1.210$	0.903	0.049	18.717
$BOD_{conc} = -0.00027Agric_{LSI}+1.276$	0.519	0.280	2.156

PD, patch density; LPI, largest patch index; ED, edge density; LSI, landscape shape index.

3.4.2. Correlation between NO_3-N and vegetative landscape metrics

Analysis of the correlation of nitrate nitrogen (NO_3-N) with vegetative land-covers shows varied interactions between forest and agriculture (Table 6). The results show that both agriculture and forest landscape patterns are closely related to the changes in NO_3-N concentrations in the streams of Muar River watershed. However, only two out of the eight correlation models are positively correlated. Unlike BOD, the NO_3-N concentrations are more closely linked to agriculture landscape pattern indices than forest. The R^2 value of agriculture ED and LSI with NO3-N were higher than that of forest. It means that the significant changes in NO_3-N concentrations were influenced by the large edge and shape of the patches in agriculture landscape. On the other hand, based on the R^2 values the forest ED and LPI have more influence on NO_3-N variability than PD and LSI indices. It implies that higher ED and LPI values in forest landscape with higher values of ED and LSI in agriculture landscape areas will increase NO_3-N concentrations in the streams. The results indicate that the sources of NO_3-N concentrations from the two vegetative covers are produced under different landscape metric conditions. Based on the R^2 values in all the correlation models (Table 6), LPI index in agriculture is the major contributor to the changes in NO_3-N concentrations. To control the amount of NO_3-N concentrations that was derived from agriculture landscape, the edge and the shape of the patches might have to be reduced, while allowing the density and extend of the patches to increase. But for forest landscape areas, the reduction of the edge and extent of the patches might reduce the sources of NO3-N in the watershed by allowing ED and LSI to varied.

3.4.3. Correlation between PO_4 and vegetative landscape metrics

The results of the correlation models showed that the orthophosphate (PO_4) concentrations and landscape pattern varied under the two-vegetative land-covers (Table 7). In comparison, the regression equations between agriculture and forest landscape metrics with

Table 6. Correlation between vegetation landscape metrics with NO_3-N concentrations.

Model	R^2	p-value	F-statistics
$NO_3\text{-}N_{conc} = -0.027Forest_{PD}+1.636$	0.358	0.402	1.113
$NO_3\text{-}N_{conc} = 0.016Agric_{PD}+1.159$	0.014	0.881	0.029
$NO_3\text{-}N_{conc} = 0.012Forest_{LPI}+0.919$	0.705	0.160	4.776
$NO_3\text{-}N_{conc} = -0.008Agric_{LPI}+1.516$	0.182	0.573	0.446
$NO_3\text{-}N_{conc} = -0.007Forest_{ED}+2.152$	0.644	0.197	3.621
$NO_3\text{-}N_{conc} = -0.007Agric_{ED}+2.295$	0.734	0.143	5.526
$NO_3\text{-}N_{conc} = -0.002Forest_{LSI}+1.964$	0.579	0.239	2.746
$NO_3\text{-}N_{conc} = -0.009Agric_{LSI}+4.581$	0.941	0.030	31.771

PD, patch density; LPI, largest patch index; ED, edge density; LSI, landscape shape index.

Table 7. Correlation between vegetation landscape metrics with PO_4 concentrations.

Model	R^2	p-value	F-statistics
$PO_{4conc} = -0.002Forest_{PD}+0.206$	0.473	0.312	1.794
$PO_{4conc} = 0.001Agric_{PD}+0.176$	0.011	0.893	0.002
$PO_{4conc} = 0.001Forest_{LPI}+0.159$	0.772	0.122	6.759
$PO_{4conc} = -0.001Agric_{LPI}+0.199$	0.288	0.464	0.808
$PO_{4conc} = -0.00046Fores_{tED}+0.240$	0.775	0.120	6.873
$PO_{4conc} = -0.00049Agric_{ED}+0.249$	0.849	0.079	11.203
$PO_{4conc} = -0.00015Forest_{LSI}+0.228$	0.714	0.155	5.001
$PO_{4conc} = -0.00056Agric_{LSI}+0.389$	0.984	0.008	120.038

PD, patch density; LPI, largest patch index; ED, edge density; LSI, landscape shape index.

PO_4 concentration mostly indicate a negative correlation. Except for the correlation between PO_4 concentrations and agriculture ED and between PO_4 concentrations and forest LPI. In contrast, agriculture landscape is the major contributor of PO_4 concentrations in the watershed as compared with forest. The R^2 values are higher in agriculture than in the forest across the correlation models (Table 7). However, forest landscape also influences the movement of PO_4 pollution into the streams, as the R^2 values indicate. The ED and LSI indices were the main sources of PO_4 pollution in the agricultural area, while ED and LPI controls form forest areas. It indicates that ED influences PO_4 pollution in both the two-vegetative land-covers which was like the responses of NO_3-N concentrations. In both agriculture and forest landscape, the PD index shows the lowest R^2 values in correlation with PO_4 concentrations, meaning that the density of the patches in both land-covers has no significant on PO_4 pollutant flows in the watershed. The control of PO_4 concentrations in the streams of the watershed involved the reduction of forest and agriculture ED and LSI indices. Furthermore, if largest patch index (LPI) from forest is control, it might also reduce the amount of PO_4 pollution from nonpoint sources (NPS) areas which in turn will reduce PO_4 concentrations in the rivers.

4. Discussion

4.1. Variability of stream concentration to changes in vegetative cover

Different responses were observed for the stream water quality concentrations under varied vegetative covers. After statistical comparison of the stream water quality concentrations (Table 4), it shows that not all water quality variables change their status due to variation in the vegetative cover of their catchment area. As observed, three out of the six water quality variables produced different concentrations that are statistically significant. The temporal variation of some of the water quality variables indicates that vegetative land-covers have little influence on the water quality condition of the streams in Muar River watershed. Several studies have shown that the changes in stream water quality concentrations largely depend on the sources of pollution from the land-covers (Miserendino et al., 2011; Ngoye & Machiwa, 2004). Also, the vegetative distribution determines the hydrological behaviour of the watershed which controls the mechanism for pollution transport processes. In Muar River watershed, the major vegetative covers (agriculture and forest land-covers) were identified as the influential variables for stream water quality concentrations. The increase in agricultural areas was linked to increase in organic nutrients transport (Ouyang et al., 2010), which is similar to the results obtained in this study. Hence, the sensitivity of the BOD concentrations to vegetative land-cover variation in the watershed. Since the organic pollution in an aquatic system is measured using BOD level, and indicates the increase in the amount of bio-degradable organic matter in the streams which promote more of heterotrophic process in the water column that results in the depletion of DO concentrations (low DO responses to vegetative cover as shown in Table 4 and Figure 5) and the variability BOD levels (Singh, Basant, Malik, & Jain, 2009).

Although for NO_3-N and PO_4 concentrations, the changes in agriculture land area influence their high responses to change in vegetative land-cover. According to Yu, Xu, Wu, and Zuo (2016), agricultural land-cover affects the nutrient variables, implying that agricultural vegetative landscape had negative impact on stream water quality concentrations due to flow of nutrients from fertilization sources. Similar effects were noticed by the variability of NO_3-N and PO_4 concentrations in Muar River watershed. As the climatic conditions of the tropical watershed warrant abundant rainfall throughout the year (Makaremi, Salleh, Jaafar, & GhaffarianHoseini, 2012), the change in nitrate concentrations might influence it (Bussi, Janes, Whitehead, Dadson, & Holman, 2017), coupled with the expansion of agricultural areas in the watershed as noticed in Figure 3. The same condition applied to PO_4, as the vegetative land-cover varies, its concentrations changes (Figure 5), indicating the influence of the forest and agricultural land-covers on the soluble inorganic phosphorous transport into the streams (Vuorenmaa, Rekolainen, Lepistö, Kenttämies, & Kauppila, 2002). While for NH_3-N concentrations, it tends to remain unaltered (as shown by the outliers in Figure 5) despite the variability of nitrate and orthophosphate concentrations (as shown by the outliers in Figure 5). This might be connected to the sources of the pollution. Unlike NO_3-N and PO_4 pollutants, NH_3-N is a volatile substance that is converted either nitrate or nitrite via nitrification process (Bottomley et al., 2004) especially if the sources of the NH_3-N are limited to vegetative land-covers.

On the other hand, the increased inflow of organic pollution from the vegetative land-cover reduces the inflow of sediment due to the climatic condition (that promote rapid regrowth of pasture and intrusion of grasses in an exposed soil), and agricultural practices which reduced the soil exposure to direct runoff (Park & Cameron, 2008). The low responses of sediment concentrations (TSS) with change in vegetative covers affirm the earlier assertion that tropical rainforest discourages sediment export due to rapid vegetative cover regeneration (Chazdon, 2014), except under intensive agricultural practices (Guardiola-Claramonte et al., 2010) and deforestation (Ehigiator & Anyata, 2011). In our case, the vegetative cover in Muar River watershed do not experience aggressive deforestation neither much agricultural expansion except between the years of 1988 to 1996 (Figure 3). Yet, it does not alter the TSS concentrations when compared with the subsequent years (Table 4). However, the TSS of the year 1988 shows higher concentrations from the outliers (Figure 5), which indicates the influences of forest land-cover to TSS concentration than agriculture.

4.2. Significance of vegetative landscape matric to stream water quality concentrations

Landscape pattern metrics are considered as an indicator that shows the significance of spatial distribution of land-cover to stream water quality (Bu et al., 2014). Impacts of vegetation landscape pattern on stream water quality concentrations under varied vegetative land-cover conditions were highlighted in this study. The correlation between the landscape indices and the sensitive stream water quality variables (BOD, NO_3-N, and PO_4) under varied vegetative landscape shows that three out of the four indices considered have direct influences on the selected water quality concentrations in Muar River watershed. in which ED exerts much influence on the variability of BOD, NO_3-N, and PO_4 concentrations from the correlation results (Tables 5–7), followed by LSI and then LPI with PD showing the least impact in both the two-vegetative land-covers (agriculture and forest) contrary to other climatic regions that show the significant of PD on water quality of a watershed (Shen et al., 2015). However, these influences were more pronounce under agriculture than with forest landscape. As anticipated, agriculture landscape indices tend to have more effects on the BOD, NO_3-N, and PO_4 concentrations (Shen et al., 2015). Our findings suggest that decrease in ED in both forest and agriculture will reduce the stream water quality concentrations (BOD, NO_3-N, and PO_4). However, the correlation results show that increase in ED, LPI, and LSI will result to increase in BOD concentrations in the streams. The result indicates that less ED and LSI in both forest and agriculture will result to decrease in both NO_3-N and PO_4 concentrations. In general, ED and LSI had a better correlation under both forest and agriculture landscape with BOD, NO_3-N, and PO_4, implying that decreasing forest and agriculture edge and shape might decrease stream water quality concentrations. Understanding how the landscape pattern indicators are related to stream water quality provides an insight on the prevention measures to be taking in order to maintain the minimum water quality standard in a watershed scale (Ouyang et al., 2010; Turner & Rabalais, 2003). Some studies have recognized the significance of vegetation land-cover as a buffer in maintaining water quality standard in a watershed (Shi, Zhang, Li, Li, & Xu, 2017). Therefore, utilizing the relationship between the historical trends of vegetative landscape metrics with stream water quality concentrations will provide a resilience on the effects of pollution that are derived from NPS areas into stream.

5. Conclusion

Historical land-cover of the Muar River watershed was analysed using remote-sensing technique. The data show that vegetative landscape of the watershed changes over time with forest (both primary and secondary) and consistently remains the dominant land cover. The response of the stream water quality concentrations under varied historical vegetative land-covers in Muar River watershed indicates that the variability of the water quality concentrations largely depends on the sources of pollution and the dominant land-cover type. However, the landscape pattern metrics derived from historical land-covers show that the PD, LPI, ED, and LSI have varied influences on the stream water quality. Further analysis of the results shows that three out of the six water quality variables were identified as sensitive due to their responses to the historical land-covers. Correlating sensitive water quality variables with landscape pattern indicators shows that decrease in ED, LSI, and LPI in both agriculture and forest landscape might likely reduced the flow of the pollutants (BOD, NO_3-N, and PO_4) into the watershed streams. This study shows the influence of change in landscape pattern indictors (due to change in land-use) on the stream water quality concentrations, which will allow an effective water quality control that is significant to a sustainable natural ecosystem function.

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