IDENTIFYING THE SOURCE OF POLLUTANTS IN MALACCA RIVER USING GIS APPROACH

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Abstract. The study was conducted to determine the dominant source of pollutants in Malacca River using the combined methods of water sampling and GIS approach. The study was conducted in 9 sampling stations based on Malacca River sub-basins. The result of WQI indicated that station 4 and 5 are polluted; station 8 and 9 are clean; and other stations are slightly polluted. PCA identified several pollutant sources, namely agricultural, residential, industrial, animal husbandry activities, as well as sewage treatment plants. Applied GIS technique detected several areas as hotspots pollutants sources, namely agricultural activities in station 5; residential activities in station 1, 2, 5, 6, and 7; industrial activities in station 3, 4, 5, and 7; animal husbandry in station 5 and some scatterings in station 1 to 4; as well as sewage treatment plant in moderate hotspot area between station 5 and 6, respectively. Besides the recommendation to reduce the river water pollution through the control of pollutants source, this study provides crucial information for the identification of problematic areas and spatial database of Malacca River for better understanding and management of river water quality in the future, as well as a reference for future land use and urban design development purposes.
Keywords: *WQI, PCA, hotspot analysis, spatial database*

Introduction

River water pollution has received great attention in recent years and continues to receive serious concern throughout the world. Water quality deterioration is primarily connected to the subject of population growth and city expansion. This is a threatening factor to human and ecological health, drinking water availability, and furthermore to the economic development (Houser and Richardson, 2015; Morse and Wolheim, 2014; Li and Zhang, 2010). According to Iscen et al. (2008), surface water is easily exposed to pollution due to its - accessibility to wastewater disposal. Water quality impairment resulted from anthropogenic inputs (e.g. municipal and industrial wastewater discharges, agricultural runoff) and natural processes such as chemical weathering and soil erosion (Shin et al., 2013; Singh et al., 2011; Iscen et al., 2008), contributed to the input of non-point and point source pollutants of the river (Iscen et al., 2008). Therefore, water quality assessment with geographic information system (GIS) is an important tool in identifying possible pollutant sources with the aim to prevent and control water pollution; which is crucial for sustainable water resource use with respect to ecosystem health and social development (Iscen et al., 2008; Shrestha and Kazama, 2007; Zhang, 2006).

Malaysia as an ongoing developing country in South East Asia is facing major water quality problems (DOE, 2012). Human activities that generate economic benefit for the society has indirectly deteriorate the water quality of the river (Muyibi et al., 2008). Several studies focused on the assessment of water quality indicated that unsustainable development could result in environmental damage to surrounding areas, as well as to the biodiversity of benthic macroinvertebrates (Al-Shami et al., 2010). Specifically,

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researchers have identified that wastewater that were discharged from the manufacturing and agro-based industry, domestic sewage, animal husbandry, mining activity, and surface runoff originating from land clearing and earthwork activity; could lead to water resource pollution, especially in the river (DOE, 2012; Suratman et al., 2009; Deb et al., 2008; Ebrahimpour and Mushrifah, 2008; Muyibi et al., 2008).

This situation is no stranger to the state of Malacca, which has faced serious water pollution problems that led to the death of aquatic species along the Malacca River (Sinar Harian Online, 2016; Hua, 2015; Metro Online, 2015; Daneshmend et al., 2011). Malacca State was recognized by UNESCO as a World Heritage Site in 2008 (UNESCO, 2016) and since has become a world historical tourism center for the country. This establishment is important for the economic and population growth of Malacca State. Indirectly, Malacca River may not have been exposed to the issues of river water pollution in the past. Nevertheless, the increasing number of population, uncontrolled rapid development, and extreme land use has led to the 'disruption' of Malacca River. Besides water quality assessment and monitoring, an applied GIS through hotspot analysis would assist in determining the dominant source of pollution that has greater impact to Malacca River. GIS hotspot analysis is a method that has been frequently applied in various studies in the fields of diseases (Liu et al., 2006), mortality rates (Mclaughlin and Boscoe, 2007), environmental planning, as well as the environmental sciences (Ishioka et al., 2007). For instant, Liu et al. (2006) used GIS to assess and sample the pattern of heavy metal in paddy field; and Zhang (2006) used hotspot analysis of GIS approach to identify the pollutants in urban soils in Ireland.

Several GIS analysis methods have been proposed for hotspot analysis, such as spatial scan statistics (Ishioka et al., 2007), Tango' C index (Zhang and Lin, 2006; Tango, 1995), as well as Getis's G index (Getis and Ord, 1992). These methods are often used in the field of environmental sciences, planning, and management. Hotspot analysis which is extended from Moran's I index in spatial analysis, can be classified into two categories, namely global Moran's I (Oldland, 1998; Cliff and Ord, 1981) and local Moran's I index (Zhang et al., 2008; Mclaughlin and Boscoe, 2007; Getis and Ord, 1992). Unlike the particular analysis of Moran's I which only focuses on the detection of similar value clusterings, hotspot analysis technique using G-statistic has the ability to express the high/low value clusterings (Getis and Ord, 1992). This technique of hotspot analysis is applied to this study. The objectives of the study are (1) to identify water quality status and pollution sources using relationship elements of natural origins; and (2) to determine the dominant sources of pollutants through spatial pattern analysis.

Materials and Methods

Study Area

The state of Malacca is located in the southwest of Peninsular Malaysia with the geographical coordinates of 2°23'16.08"N to 2°24'52.27"N latitude and 102°10'36.45"E to 102°29'17.68"E longitude. Malacca is divided into three districts, namely Alor Gajah, Jasin, and Malacca Central. Total catchment area of Malacca is approximately around 670 km^2 with about 80 km distance of Malacca River. The basin is formed by 13 sub-basins namely Kampung Ampang Batu Gadek sub-basin, Kampung Balai sub-basin, Kampung Batu Berendam sub-basin, Kampung Buloh China sub-basin, Kampung Cheng sub-basin, Kampung Gadek sub-basin, Kampung Harmoni Belimbing Dalam sub-basin, Kampung Kelemak sub-basin, Kampung Panchor sub-basin,

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Kampung Pulau sub-basin, Kampung Sungai Petai sub-basin, Kampung Tamah Merah sub-basin, and Kampung Tualang sub-basin (*Figure 1*). Among the 13 sub-basins, only 7 sub-basins were selected, with 9 sampling stations located alongside Malacca River.

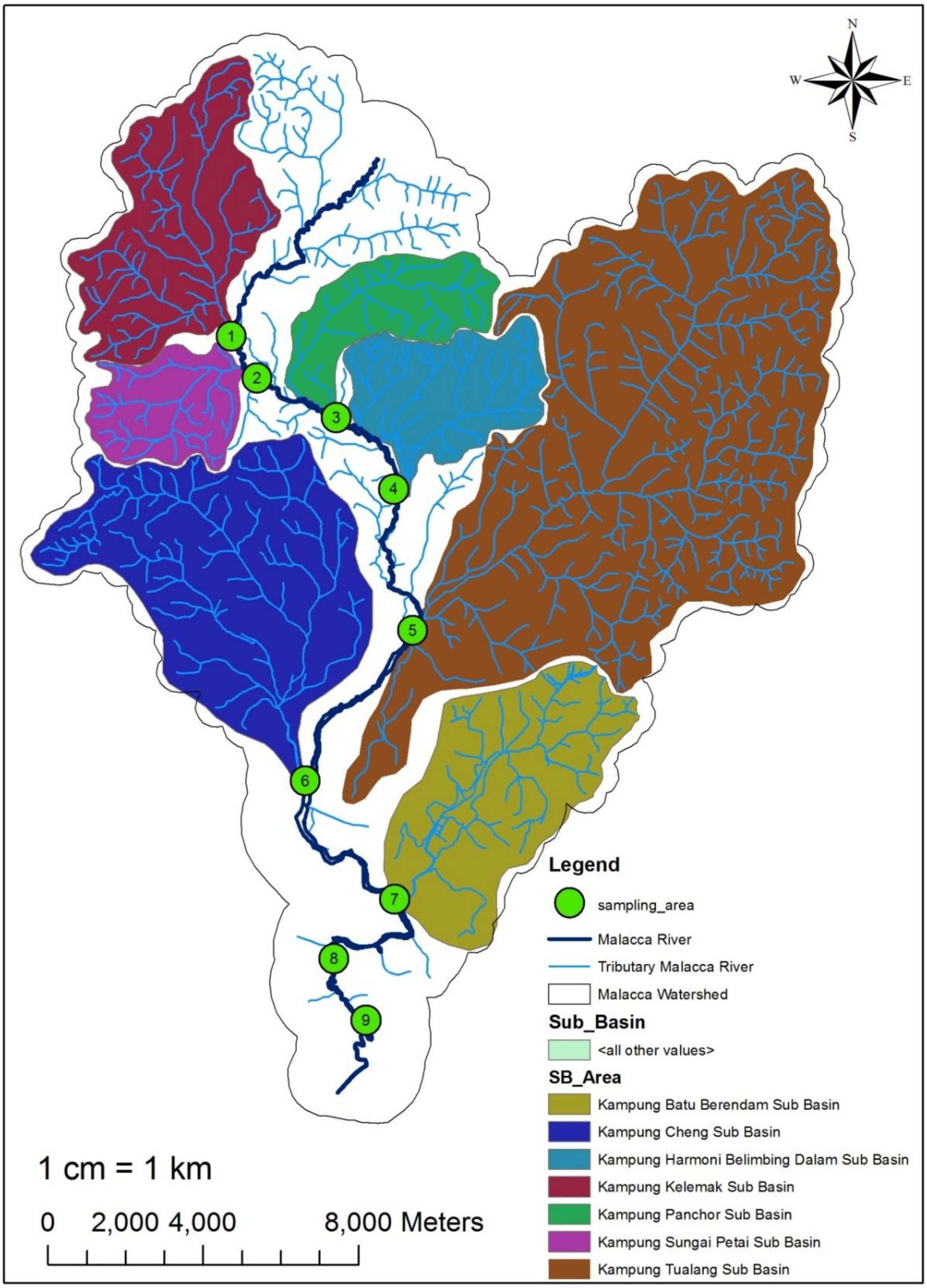

Figure 1. *Malacca River sub-basin and sampling area*

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Malacca River flows across Alor Gajah to the Malacca Central district before entering into the Straits of Malacca. Alongside Malacca River, there is a reservoir located between Alor Gajah and Malacca Central, namely Durian Tunggal Reservoir, with a catchment area of approximately 20 km^2 that act as a source of water supply for Malacca residents. The built-up area is mainly concentrated in the city center, Malacca Central, at a downstream area extending about 10 km to the west, 10 km to the east, and 20 km to the north. The urban land uses are primarily residential and commercial, while several industrial activities including high-technology and estates are located in the middle-stream and upstream areas. Most of the large-scale agricultural activities land use are located upstream.

Field Sampling

There were 9 sampling stations chosen alongside Malacca River. The locations were determined using a Global Positioning System (GPS) coordinates as shown in *Table 1* and the geographic coverage is as shown in *Figure 1*. The collection of water quality samples were carried out monthly from January to December 2015.

Table 1. *The latitude and longitude of sampling stations*

Station	Latitude	Longitude
S1	02°21’57.41”N	102°13’7.10”E
S2	02°21’30.16”N	102°13’18.20”E
S3	02°20’49.52”N	102°14’36.44”E
S4	02°19’41.70”N	102°15’27.30”E
S5	02°17’48.86”N	102°15’39.51”E
S6	02°15’46.55”N	102°14’10.72”E
S7	02°14’5.02”N	102°15’24.67”E
S8	02°13’14.33”N	102°14’35.01”E
S9	02°12’23.42”N	102°15’0.80”E

Source: Global Positioning System

The water samples were collected using ‘grab sampling’ technique in the polyethylene bottles without entrapping the air bubbles. Each bottle was labelled with the corresponding sampling station and kept at 4°C to minimize microbial activity in the water (APHA, 2005). The water samples were analyzed for physico-chemical parameters (i.e. pH, temperature, electrical conductivity (EC), salinity, turbidity, total suspended solid (TSS), dissolved solids (DS), dissolved oxygen (DO), biological oxygen demand (BOD), chemical oxygen demand (COD), and ammoniacal-nitrogen (NH_3-N), trace metals (i.e. mercury, cadmium, chromium, arsenic, zinc, lead and iron)) and biological parameters (i.e. Escherichia coliform and total coliform). Since water sample containing colloidal or suspended particulate material could interfere with the metal analysis, the samples were immediately filtered using 0.45 μm cellulose acetate membrane filter (Whatman Milipores, Clifton, NJ) at the laboratory. The purpose of this procedure was to prevent the occurrence of clogging during analysis with spectrometry instruments and to obtain the dissolved ions for metal analysis (APHA, 2005). Then, the samples were acidified with HNO_3 to $pH<2$ in order to prevent precipitation of the components for trace metal analysis and to retard any biological activities (APHA, 2005).

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Water Quality Analysis

The water samples were analyzed according to the procedure of APHA (2005), meaning that pH, turbidity, EC, TDS, salinity, and DO were measured on-site. SevenGo Duo pro probe (Mettler Toledo AG) was used for the measurement of pH values, while turbidity was tested using the Handled Turbidimeter Hach 2100. Orion Star Series Portable Meter was used to measure temperature, EC, DS, salinity, and DO. Meanwhile, NH3N was analyzed using a spectrophotometer at a specific wavelength using Hach Method 8038, COD was measured using APHA 5220B open reflux technique; BOD was measured using APHA 5210B (or Hach Method 8043); and TSS was measured using the APHA 2540D method. Both E-coli and total coliform were analyzed using Membrane Filtration method based on APHA 9221B, and trace metals were analyzed using inductive coupled plasma-mass spectrometry (ICP-MS, ELAN DRC-e 6100, Perkin Elmer). For quality assurance and quality control purposes, laboratory apparatus and polyethylene bottles were washed using 5% (v/v) of nitric acid and soaked overnight to remove contaminants and traces of cleaning reagent before the collection of water samples or conducting laboratory analysis.

Each sample was analyzed in triplicate before calculating the mean value, and standard deviation (SD) of less than 20% was used as an indicator of precision for each measured parameter. All the probe meters and instruments used were calibrated prior to analysis. In all cases, the standards and blank were treated in the same way as the representative river water samples to minimize matrix interference during analysis. The recovery of samples for all target elements fell within the standard requirements (90-110%).

Data Analysis

River water quality data were analyzed using Microsoft Excel and Statistical Package for Social Sciences version 19 (SPSS 19) for descriptive analysis, water quality index (WQI) and principal component analysis (PCA); to identify the water status and pollution source between elements of origin parameters, while ArcGIS version 9.3 was used to determine the dominant source of pollutants through spatial pattern analysis.

Water Quality Index (WQI)

Healthy river should have good water quality to assist with the survival of aquatic animals. The river health level is measured using WQI, which based on several parameters that need to be assessed and monitored. Different country uses different parameter to determine the WQI, whereas the Department of Environment (DOE) Malaysia using DO, BOD, COD, NH_3N, SS, and pH in determining the WQI. Generally, DO is use to measure the amount of oxygen available in water (Juahir et al., 2011); BOD determines the strength of pollutants in term of oxygen required to stabilize the wastes or measures biodegradable waste present in water (WSDE, 2002); COD measure the amount of organic and inorganic oxydizable compound in water (Davis and McCuen, 2005); SS determines the natural pollutants and causes of turbidity in water (Mathvi and Razazi, 2005); NH_3N determine the amount of ammonia exists in water that could cause eutrophication (Wang et al., 2010); and pH are to measure the acid strength in water (Davis and McCuen, 2005). Therefore, WQI for Malacca River are determined using formula that was developed by DOE (Eq.1), which consists of different sub-indexes (SIs) calculated according to the best-fit relationship (Eq.2-7):

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$$WQI = 0.22 * SI_{DO} + 0.19 * SI_{BOD} + 0.16 * SI_{COD} + 0.15 * SI_{AN} + 0.16 * SI_{SS} + 0.12 * SI_{pH} \quad \text{(Eq.1)}$$

where WQI is water quality index; SI_{DO} is sub-index of DO; SI_{BOD} is sub-index of BOD; SI_{COD} is sub-index of COD; SI_{AN} is sub-index of NH_3N; SI_{SS} is sub-index of SS; SI_{pH} is sub-index of pH. Meanwhile, the sub-indexes (SIs) formulation is as followed (Eq.2-7);
Best-fit equations for DO sub-index:

$$SI_{DO} = \begin{cases} 0 & \text{for DO} < 8 \\ 100 & \text{for DO} > 92 \\ -0.395 + 0.030DO^2 - 0.00020DO^3 & \text{for } 8 < DO < 92 \end{cases} \quad \text{(Eq.2)}$$

Best-fit equations for BOD sub-index:

$$SI_{BOD} = \begin{cases} 100.4 - 4.23BOD & \text{for BOD} < 5 \\ 108e^{-0.055BOD} - 0.1BOD & \text{for BOD} > 5 \end{cases} \quad \text{(Eq.3)}$$

Best-fit equations for COD sub-index:

$$SI_{COD} = \begin{cases} -1.33COD + 99.1 & \text{for COD} < 20 \\ 103e^{-0.0157COD} - 0.04COD & \text{for COD} > 20 \end{cases} \quad \text{(Eq.4)}$$

Best-fit equations for AN sub-index:

$$SI_{AN} = \begin{cases} 100.5 - 105AN & \text{for AN} < 0.3 \\ 94e^{-0.573AN} - 5|AN - 2| & \text{for } 0.3 < AN < 4 \\ 0 & \text{for AN} > 4 \end{cases} \quad \text{(Eq.5)}$$

Best-fit equations for SS sub-index:

$$SI_{SS} = \begin{cases} 97.5e^{-0.00676SS} + 0.05SS & \text{for SS} < 100 \\ 71e^{-0.0016SS} - 0.015SS & \text{for } 100 < SS < 1000 \\ 0 & \text{for SS} > 1000 \end{cases} \quad \text{(Eq.6)}$$

Best-fit equations for pH sub-index:

$$SI_{pH} = \begin{cases} 17.2 - 17.2pH + 5.02pH^2 & \text{for pH} < 5.5 \\ -242 + 95.5pH - 6.67pH^2 & \text{for } 5.5 < pH < 7 \\ -181 + 82.4pH - 6.05pH^2 & \text{for } 7 < pH < 8.75 \\ 536 - 77.0pH + 2.76pH^2 & \text{for pH} > 8.75 \end{cases} \quad \text{(Eq.7)}$$

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Principal Component Analysis (PCA)

Principal component analysis was designed to convert a large dataset of original correlated variables into a smaller set of new and uncorrelated variables (i.e. principal components). The data reduction process would provide the most meaningful parameter information that can describe a whole data set with minimum loss of original information (Iscen et al., 2008). The principal components are weighted linear combinations of original variables, with the first principal component representing the largest variability of the original data set, and the second component representing the next largest variance that is orthogonal to the first component (Deb et al., 2008). In other words, PCA can be explained as follows:

$$z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + \ldots + a_{im}x_{mj} \qquad \text{(Eq.8)}$$

Where *z* is the component score, *a* is the component loading, *x* is the measured value of the variable, *i* is the component number, *j* is the sample number, and *m* is the total number of variables. As stated above, the general procedures used in PCA are (1) the hypothesis in an original data group is then reduced to dominant components or factors (source of variation) that influence the observed data variance; and (2) the whole data set is extracted through eigenvalues and eigenvectors from the square matrix produced by multiplying the data matrix (Aris et al., 2013). In other words, the PCA will undergo varimax rotation to produce the principal components (PCs) before determining the eigenvalue. The eigenvalues of more than 1 are considered significant (Kim and Mueller, 1987) to measure a new group of variables, namely Varimax Factor (VFs). The VFs coefficients that recorded a correlation of greater than 0.75 are considered as ‘strong’, 0.75 to 0.50 as ‘moderate’ and 0.50 to 0.30 as ‘weak’ significant factor (Liu et al., 2006). However, only factor loadings above 0.6 were taken into account for this study. 20 parameter variables will undergo PCA to determine the source of pollutants before hotspot analysis for the dominant source of pollutants in Malacca River.

Spatial Pattern Clustering Through Hotspot Analysis

Hotspot analysis can be clustered (spatial clusters) or individual (spatial outliers). In this study, spatial cluster of pollution would be water quality with a high value of parameter surrounded by a high value of pollutant sources. Meanwhile, spatial outliers of pollution include water quality with a high value of parameter surrounded by a normal or low value of pollutants source. The concept of hotspot can be expressed as:

$$G(d) = \frac{\sum\sum w_{ij}(d)x_i x_j}{\sum\sum x_i x_j}\ , \quad i \neq j \qquad \text{(Eq.9)}$$

where x_i is the value at location *i*, x_j is the value at location *j* if *j* is within *d* of *i*, and w_{ij}(d) is the spatial weight based on the weighted distance (e.g. inverse distance) (Getis and Ord, 1992). The expected value of *G (d)* is:

$$E(G) = \frac{\sum\sum w_{ij}(d)}{n(n-1)} \qquad \text{(Eq.10)}$$

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where *E (G)* is typically a very small value when *n* is large. A high *G (d)* value suggest a clustering of high values, and a low *G (d)* value suggests a clustering of low values. *Z* scores are used to evaluate statistical significance for *G (d)*. In other words, high positive *Z* scores suggest the presence of a cluster of high values or a hotspot, while high negative of *Z* scores suggest the presence of a cluster of low value or a cold spot (*Figure 2*).

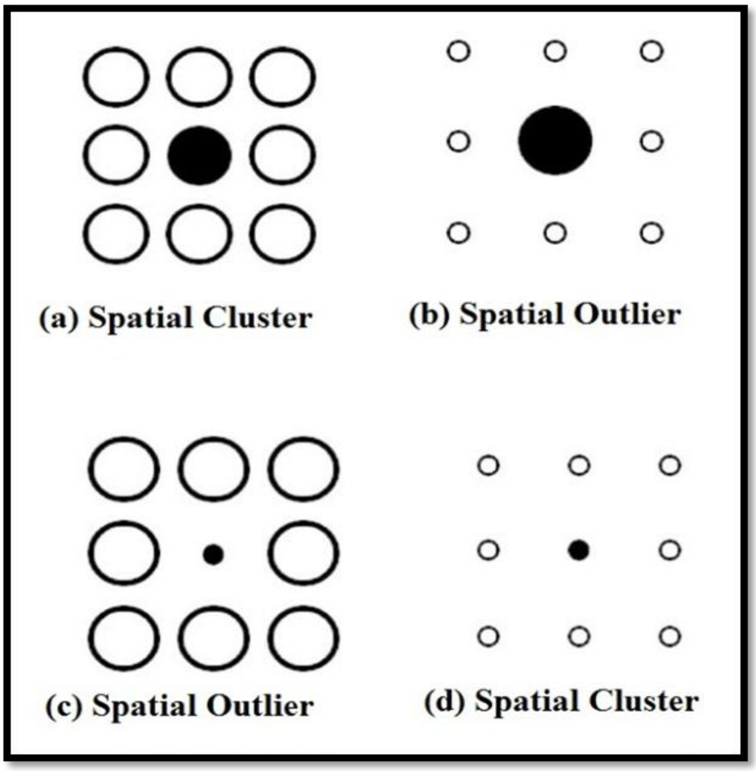

Figure 2. *The relationship of a location and its neighborhood; (a) and (b) are hotspot, (c) and (d) are cold spot*

Results and Discussion

Determination of Water Quality Status and WQI in the Malacca River

Water quality data of Malacca River (i.e. physico-chemical, biological, and trace element data) in comparison with the National Water Quality Standards (NWQS) (*Table 3* (i) and (ii) is as shown in *Table 4*. Based on *Table 4*, the result indicated that trace elements, together with pH and temperature, remained as class 1 in all sampling stations. Meanwhile, salinity in station 1 to 3 and station 7, together with turbidity in station 3, 8, and 9, was found to be in class 5. Only station 1 and 5 are in class 3 for turbidity, while other stations remained in class 2 and class 1 in terms of turbidity and salinity, respectively. Station 1 and 7 were found to be in class 5, station 2 and 3 to be in class 3, and station 4 to 6 were in class 1 for electrical conductivity and dissolved solids. However, only station 8 and 9 were in class 2 for electrical conductivity, while station 8 was within class 3 and station 9 was in class 1 for dissolved solids. For total suspended solids, most of the stations were classified as class 3, except for station 4, which was in class 4. BOD, COD, DO and NH_3N, in most of the water samples were classified as

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class 2 and class 3. However, station 2 and station 7 to 9 showed a class 4 BOD results. This includes NH_3N in station 1 to 3 and station 7 to 8 at class 4. Meanwhile, E. coli was classified as class 4 at station 3 and station 6 to 9, while the others were in class 5. Total coliform was found to be in class 5 for all sampling stations.

According to WQI (*Table 2*), majority of NH_3N and BOD parameters were in class 3, 4 or 5. Meanwhile, COD parameter from station 2 to 7 were in class 3, and others were in class 2. Both DO and TSS parameter showed that only several stations were in class 3. WQI trends showed that the water quality in Malacca River were declining from station 1 to station 7, which show that only station 4 and station 5 were polluted (class 4) while other stations were slightly polluted (class 3). Apart from that, station 8 and station 9 were still in clean condition, which is in class 2. Therefore, it can be said that all parameters value is affected (either decrease or increase) from the origins. These pollutants which came from human activities could cause problematical issues to the aquatic life in Malacca River.

Table 2. *WQI at sampling station in Malacca River sub-basin*

Water Quality Parameter	Unit	Water Sampling Station								
		S1	S2	S3	S4	S5	S6	S7	S8	S9
DO	mg/L	4.1	5.5	3.8	3.3	4.9	8.8	9.2	7.7	6.9
BOD	mg/L	5.0	6.0	2.0	4.0	4.0	7.0	6.0	5.0	2.0
COD	mg/L	22.0	77.0	61.0	53.0	47.0	38.0	29.0	13.0	21.0
AN	mg/L	1.4	0.8	2.6	4.8	7.2	3.3	0.7	1.8	2.1
TSS	mg/L	45	66	51	83	172	77	43	21	36
pH	-	6.5	6.3	6.4	6.4	6.8	6.5	6.6	6.3	5.8
Overall WQI		68	77	62	49	53	66	70	92	88
Class		III	III	III	IV	IV	III	III	II	II
Water Quality Status		Slightly Polluted	Slightly Polluted	Slightly Polluted	Polluted	Polluted	Slightly Polluted	Slightly Polluted	Clean	Clean

Table 3 (i). *National Water Quality Standards for Malaysia (adapted from Malaysian DOE, 2012)*

Category	Unit	Class					
		1	2A	2B	3	4	5
pH	-	6.5-8.5	6 – 9	6 – 9	5 – 9	5 – 9	-
Temp	°C	-	Normal+2°C	-	Normal+2°C	-	-
Sal	%	0.5	1	-	-	2	-
EC	µS/cm	1000	1000	-	-	6000	-
TSS	mg/L	25	50	50	150	300	300
DS	mg/L	500	1000	-	-	4000	-
Tur	NTU	5	50	50	-	-	-
BOD	mg/L	1	3	3	6	12	>12
COD	mg/L	10	25	25	50	100	>100
DO	mg/L	7	5 – 7	5 – 7	3 – 5	< 3	< 1
NH3N	mg/L	0.1	0.3	0.3	0.9	2.7	> 2.7
As	mg/L	-	0.05	0.05	0.4 (0.05)	0.1	-
Hg	mg/L	-	0.001	0.001	0.004(0.0001)	0.002	-
Cd	mg/L	-	0.01	0.01	0.01 (0.001)	0.01	-
Cr	mg/L	-	0.05	0.05	1.4 (0.05)	0.1	-
Pb	mg/L	-	0.05	0.05	0.02 (0.01)	5	-
Zn	mg/L	-	1	1	3.4	0.8	-
Fe	mg/L	-	1	1	1	1(leaf)5(others)	-
Total Coliform	count/100mL	100	5000	5000	5000(20000)	5000(20000)	> 50000
Ecoli	count/100mL	10	5000	5000	50000	50000	> 50000

Tur means Turbidity; DS means Dissolved Solid; Con means Electrical Conductivity; Sal means Salinity; Temp means Temperature; DO means Dissolved Oxygen; BOD means Biological Oxygen Demand; COD means Chemical Oxygen Demand; TSS means Total Suspended Solids; pH means Acidic or Basic water; NH_3N means Ammoniacal Nitrogen; E coli means *Escherichia* Coliform; Coli means Coliform; As means Arsenic; Hg means Mercury; Cd means Cadmium; Cr means Chromium; Pb means Lead; Zn means Zinc; Fe means Iron

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Table 3(ii). *Water Classes and Uses (adapted from Malaysian DOE, 2012)*

Class 1	Conservation of natural environment Water supply I – Practically no treatment necessary Fishery – Very sensitive aquatic species
Class 2A	Water supply II – Conventional treatment required Fishery II – Sensitive aquatic species
Class 2B	Recreational use with body contact
Class 3	Water supply III – Extensive treatment required Fishery III – Common of economic value and tolerant species; livestock drinking
Class 4	Irrigation
Class 5	None of the above

Identification of the Source of Pollutants

Based on the results of water quality status, it was found that parameters like E-coli, coliform, salinity, turbidity, NH_3N, and BOD were in the category of polluted conditions, while several parameters like EC, TSS, DS, COD, and DO were only slightly polluted. Other parameters remained as clean in Malacca River. Therefore, principal component analysis (PCA) was used to identify the source of pollutants that contributed to the pollution in Malacca River. As shown in *Table 5*, 7 PCs were obtained with eigenvalues more than 1, with 65% of total variance. The PC1 loadings with 14.7% of total variance have strong positive loadings on DS, EC, salinity and NH_3N. Physico-chemical parameters like DS, EC and salinity may be related to the erosion of riverbank due to dredging activities in the river and agricultural runoff from non-point source pollution (Juahir et al., 2011). The results were coupled with the NH_3N pollution together with salinity, highlighting the usage of pesticide for agricultural activities within oil palm and rubber plantations, and animal husbandry (chicken, cow, and goat) carried out within Malacca River basins. These activities contributed to the non-point sources of pollution that occured through surface runoff and water flows through the sub-basins before entering Malacca River. Additionally, PC2 loadings indicated a strong positive in terms of turbidity and TSS with total variance of 9.7%, which can be relate to interruption of human activities towards hydrologic modifications (such as dredging, water diversion, and channelization) that caused disruption in Malacca River (Daneshmand et al., 2011). Other activities like discharge from urban developments through land clearing (USGS, 2010) and surface runoff leading to erosion of road edges (Iscen et al., 2008) could also bring a small amount of pollution to the river.

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Table 4. *Mean (and standard deviation) values of water quality data along the Malacca River from in year 2015 (n=20)*

Category	Unit		S1	S2	S3	S4	S5	S6	S7	S8	S9
pH	-	Mean	6.50	6.43	6.46	6.46	6.55	6.49	6.64	6.40	6.33
		SD	0.34	0.28	0.31	0.43	0.21	0.31	0.35	0.34	0.47
Temp	°C	Mean	27.19	26.89	26.88	26.63	26.59	26.86	27.62	27.49	28.33
		SD	0.87	1.13	0.81	0.97	0.72	1.01	0.83	1.06	0.72
Sal	%	Mean	21.04	9.39	4.00	0.51	0.07	0.05	7.00	0.31	0.06
		SD	9.78	3.50	3.32	0.44	0.03	0.02	8.71	0.27	0.04
EC	µS/cm	Mean	16330.22	1403.73	1950.72	280.43	218.37	109.60	8173.90	1069.33	1093.83
		SD	12329.04	1067.37	1366.13	154.04	98.45	29.72	11118.65	459.17	630.46
TSS	mg/L	Mean	51.08	38.75	59.83	116.17	97.67	75.08	50.75	44.75	67.00
		SD	15.81	11.62	16.52	97.40	65.00	63.98	50.71	13.84	20.68
DS	mg/L	Mean	10444.61	1095.07	952.03	326.90	81.20	77.22	6257.26	505.89	223.00
		SD	7745.21	592.67	441.54	174.31	18.08	17.75	8716.84	214.39	136.15
Tur	NTU	Mean	116.70	73.61	584.57	99.86	121.18	84.85	63.62	297.77	209.71
		SD	67.18	29.59	494.93	70.09	65.26	30.01	47.17	128.61	276.70
BOD	mg/L	Mean	5.08	6.50	4.50	5.17	5.33	5.17	6.50	9.25	6.58
		SD	1.93	2.78	0.90	1.27	1.07	0.72	1.31	2.09	2.84
COD	mg/L	Mean	34.17	47.17	33.25	24.00	23.92	24.33	27.58	46.25	24.67
		SD	11.90	27.43	11.45	11.76	7.25	5.30	8.71	16.97	6.62
DO	mg/L	Mean	4.11	4.16	3.89	5.02	5.61	5.12	3.35	5.54	5.53
		SD	0.88	1.53	1.46	1.42	0.97	1.01	1.24	2.19	0.86
NH3N	mg/L	Mean	0.99	1.08	1.42	0.77	0.52	0.68	2.39	1.76	0.65
		SD	0.47	0.50	1.07	0.21	0.28	0.41	1.70	0.78	0.20
As	mg/L	Mean	0.0038	0.0040	0.0022	0.0026	0.0015	0.0022	0.0028	0.0037	0.0038
		SD	0.00426	0.00529	0.00147	0.00144	0.00080	0.00134	0.00119	0.00098	0.00204
Hg	mg/L	Mean	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003	0.0002	0.0002
		SD	0.00003	0.00009	0.00003	0.00000	0.00012	0.00000	0.00018	0.00000	0.00003
Cd	mg/L	Mean	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
		SD	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Cr	mg/L	Mean	0.0016	0.0023	0.0017	0.0012	0.0011	0.0011	0.0011	0.0033	0.0011
		SD	0.00151	0.00372	0.00161	0.00035	0.00029	0.00029	0.00029	0.00444	0.00029
Pb	mg/L	Mean	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
		SD	0.00000	0.00000	0.00000	0.00035	0.00000	0.00000	0.00000	0.00000	0.00000
Zn	mg/L	Mean	0.06	0.05	0.06	0.05	0.05	0.05	0.04	0.05	0.06
		SD	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02
Fe	mg/L	Mean	0.48	0.40	0.56	1.15	0.88	1.14	0.36	0.79	0.89
		SD	0.41	0.36	0.37	0.81	0.44	1.03	0.28	0.60	0.13
Total Coliform	count/100mL	Mean	698366.67	584866.67	701375.00	1005583.33	571808.33	656116.67	155958.33	117783.33	161558.33
		SD	510510.49	198044.61	448855.58	865227.40	340474.95	244295.76	107181.10	74326.53	94999.84
Ecoli	count/100mL	Mean	71275.00	63275.00	40358.33	17317.33	571808.33	20766.67	13745.00	14829.17	11455.83
		SD	33664.63	32261.69	43663.93	22922.74	340474.95	35458.43	6812.92	6701.57	7260.65

Tur means Turbidity; DS means Dissolved Solid; Con means Electrical Conductivity; Sal means Salinity; Temp means Temperature; DO means Dissolved Oxygen; BOD means Biological Oxygen Demand; COD means Chemical Oxygen Demand; TSS means Total Suspended Solids; pH means Acidic or Basic water; NH_3N means Ammoniacal Nitrogen; E coli means Escherichia Coliform; Coli means Coliform; As means Arsenic; Hg means Mercury; Cd means Cadmium; Cr means Chromium; Pb means Lead; Zn means Zinc; Fe means Iron; SD means Standard Deviation; S1 to S9 means Station 1 to Station 9

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On the other hand, PC3 loadings explained BOD loadings and COD loadings as moderately positive with 9.4% of total variance, which might be connected to anthropogenic activities and point source pollution like sewage treatment plants and industrial effluents (Juahir et al., 2011). Meanwhile, PC4 explaining E-coli loadings, coliform loadings, and pH loadings showed a moderate positive with 8.9% of total variance. The presence of E-coli and coliform indicated that animal husbandry, sewage treatment plant, and municipal wastes contributed to point source pollution in the river. This situation has caused the river water to absorb a large amount of oxygen and hence decreases the availability of DO, which indirectly underwent the anaerobic fermentation processes to produce ammonia and organic acid (Juahir et al., 2011). Consequently, acidic materials through hydrolysis have caused the water pH to decrease drastically. Next, PC5 explained moderate positive loadings on Zn and Fe with 8.4% of total variance. The Zn pollution can be linked to the large number of houses and building in the area that uses metallic roofs coated with Zn, which can mobilize into the atmosphere and waterways during acid rain or smog (Juahir et al., 2011), while Fe pollution can be attributed to metal group originating from industrial effluents (Aris et al., 2013). PC6 and PC7 loadings showed moderately positive Cr and Hg loadings having total variance of 7.4% and 6.4% respectively. Cr pollution can be linked to urban storm runoff (Juahir et al., 2011), and Hg pollution were suspected to link with plastic and chemical industrial wastewater (Papaioannou et al., 2010). Therefore, based on PCA analysis, 5 categories of pollutant sources were identified, namely agricultural activities, municipal and commercial residential activities, industrial activities, animal husbandry activities, as well as sewage treatment plant.

Classification of dominant pollutant sources

GIS Hotspot analysis was used to determine the dominant pollutant sources, which have been identified from PCA, namely agricultural, residential, industrial, and animal husbandry activities, as well as a sewage treatment plant, as shown in *Figure 3*. As described previously, Z score was used to evaluate the statistical significance for the variable in hotspot analysis. High positive Z scores suggest the presence of a cluster of high values or hotspots, while high negative Z scores suggest the presence of a cluster of low value or cold spot. For agricultural activity, the variable produced a general G-statistic of 0.0 and a Z score of 37.31, suggesting a spatial clustering of high value of 0.01 significant levels. Secondly, the residential variable has general G-statistic of 0.0 and a Z score of 74.72, with spatial clustering at a high value of 0.01 significant levels. Industrial variable indicated a general G-statistic of 0.0 and a Z score of 13.5 and suggested spatial clustering of high value of 0.01 significant levels., Animal husbandry activity showed general G-statistic of 0.0 with a Z score of -1.08, suggesting a spatial clustering of low values towards 0.10 significant levels. On the other hand, sewage treatment plant showed no value in general G-statistic and Z score, indicated that there are no significant level at the random value. Lastly, open space variable recorded a general G-statistic of 0.0 with a Z score of 28.73 indicating a high value of spatial clustering of 0.01 significant levels. All Z scores of selected variables were incorporated into GIS mapping to determine the dominant pollutant sources through hotspot analysis (*Figure 3*).

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Table 5. *Varimax rotation PCs for water quality in Malacca River basin*

Variables (Unit)	**Principle Components**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Turbidity (NTU)	-.104	.868	.016	.060	-.014	-.003	-.045
Dissolved Solid (mg/L)	.809	.027	.014	.076	-.128	.156	-.057
Electrical Conductivity (uS)	.859	.028	.003	.142	-.045	-.025	-.014
Salinity (ppt)	.808	-.075	-.212	-.124	.252	-.005	-.097
Temperature (°C)	.167	.171	-.204	-.384	.027	-.307	-.053
Dissolved Oxygen (mg/L)	-.367	-.283	.305	.415	.203	-.218	-.346
Biological Oxygen Demand (mg/L)	-.009	.049	.629	.095	.466	.334	.010
Chemical Oxygen Demand (mg/L)	-.056	.199	.609	.048	-.087	.022	-.070
Total Suspended Solid (mg/L)	-.193	.826	-.069	-.092	-.194	-.013	-.185
Acidity/Alkalinity (pH)	.081	.217	-.087	.745	-.201	.008	-.169
Ammociacal Nitrogen (mg/L)	.831	0.32	.011	.157	.128	-.010	.116
E-coli (cfu/100ml)	.533	-.048	-.124	.652	.359	-.108	.124
Coliform (cfu/100ml)	.027	.032	.293	.603	.096	-.192	-.221
Arsenic (mg/L)	.243	-.174	-.263	.011	.392	-.072	.047
Mercury (mg/L)	-.068	-.155	-.063	-.050	-.022	.065	.787
Chromium (mg/L)	.030	-.174	.037	.086	.322	.662	.267
Zinc (mg/L)	.146	.314	.014	-.091	.712	-.066	.156
Iron (mg/L)	-.114	-.258	-.051	-.068	.658	.028	.043
Initial Eigenvalue	2.650	1.751	1.692	1.609	1.517	1.336	1.157
% of Variance	14.723	9.729	9.398	8.939	8.427	7.422	6.430
Cumulative %	14.723	24.452	33.850	42.788	51.215	58.637	65.066

*The bold values are factor loadings above 0.60 that were taken after Varimax rotation are performed

Figure 3 (a) indicated the agricultural activities weighted concentration that concentrated in Kampung Tualang sub-basin (S5), which can be described as a hot spot area. The existence of a hot spot area in S5 sub-basin is due to the ease of access to water resources from Durian Tunggal Reservoirs. Indirectly, pesticide and chemical substances used for agricultural activities would enter surface runoff during the wet season. The water would flow into a nearby sub-basin before entering Malacca River. These processes contributed to the non-point source pollution. As shown in *Figure 3 (b)* residential activities shows that the high values are concentrated in Kampung Kelemak sub-basin (S1), Kampung Sungai Petai sub-basin (S2), Kampung Cheng sub-basin (S6), Kampung Batu Berendam sub-basin (S7), and a little bit at Kampung Tualang sub-basin (S5). There is also a highly weighted concentration located parallel to the Malacca River from S1 to S5. Only moderate values are shown along S6 to S9. Hence, residential activities showed that almost every sub basin is a hot spot area and hence it is a

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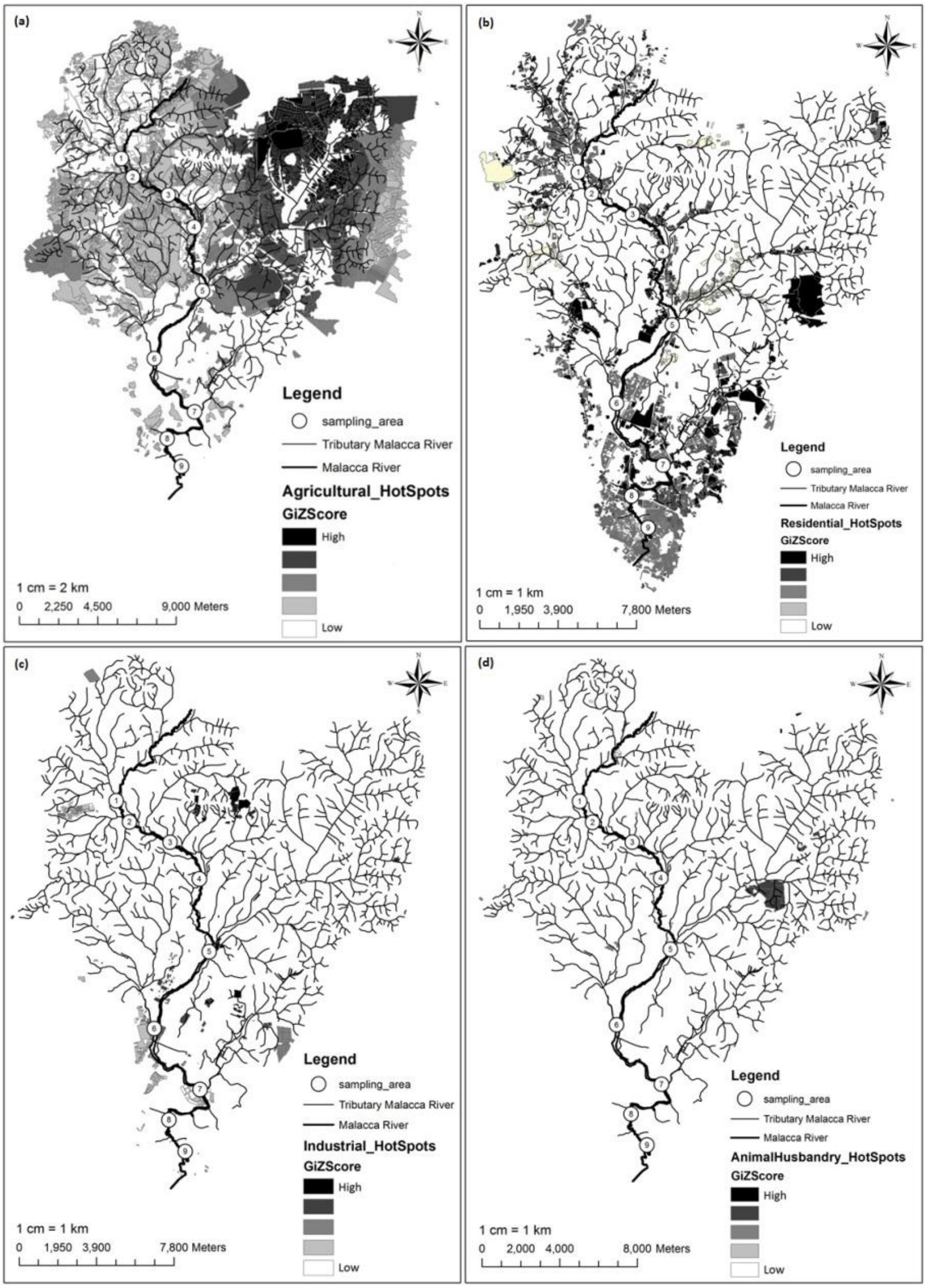
significant to contributor of pollution to the river. This situation may be related to the rapid and uncontrolled development, drastically increasing population, and unmanageable land clearing that brought pollution through wash water and cooking waste, municipal waste, and commercial waste as well as metallic roof pollution.



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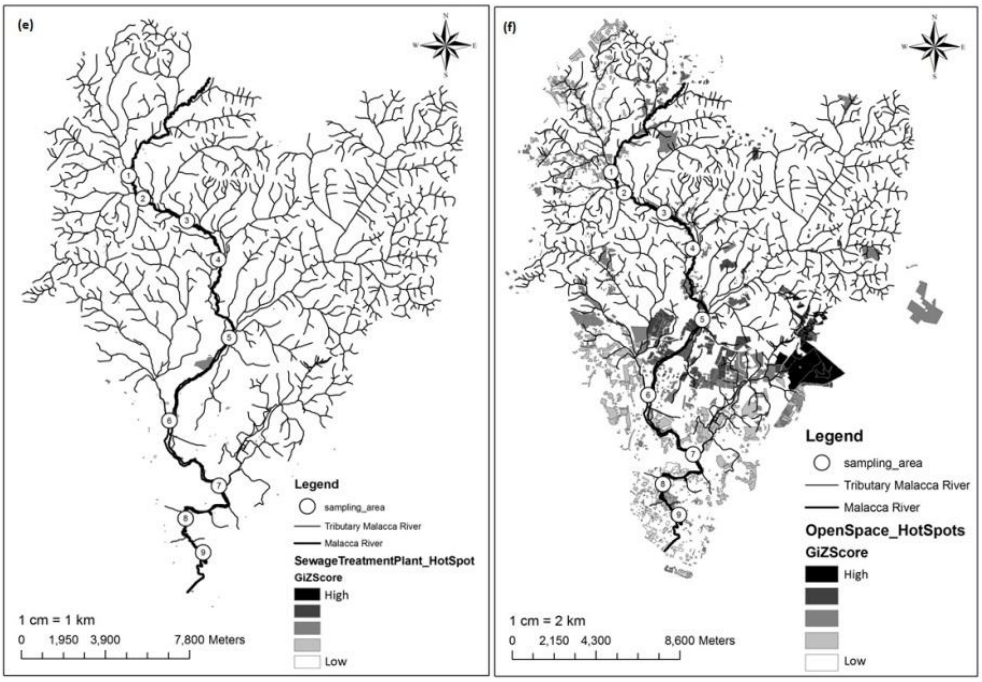

Figure 3. *Hotspot analysis of Pollutant Sources – (a) Agriculture; (b) Residential; (c) Industrial; (d) Animal Husbandry; (e) Sewage Treatment Plant; (f) Open Space*

Next, hot spot areas from industrial activities (*Figure 3 (c))* have been detected in Kampung Panchor sub-basin (S3), Harmoni Belimbing Dalam sub-basin (S4), Kampung Tualang sub-basin (S5), and Kampung Batu Berendam sub-basin (S7). High-technology and estate industries are the main contributors to point source pollution due to the direct discharge into sub basins before flowing into the main river. It is compulsory for industrial wastes to undergo treatment before being release onto surface water or in a river; however, certain industries refused to do so in order to save cost and time. Hence, these action increases the potential of hot spot area to pollute Malacca River sub-basins. Animal husbandry activities (refer to *Figure 3 (d))* shows a moderate hot spot area at Kampung Tualang sub-basin (S5) and several hot spots are scattered in sampling 1 to sampling 4 sub-basin, while the sewage treatment plant has a moderate hot spot area between S5 and S6 while others are scattered in S1 sub-basin and S6 to S9 sub-basins, respectively. Since animal husbandries are highlighted within a S5 sub-basin, this condition demonstrates that the activity is carried out in the area adjacent to Durian Tunggal Reservoirs as it is easier to obtain freshwater to feed the animals. However, unmanageable cleanliness within the farms led to animal feces flowing into the river through surface run-off, which contributed to the non-point source pollution. Sewage treatment plants that are scattered in downstream area can be clarified as low impact in terms of pollution in Malacca River, but they have a high chance to cause pollution if there is a malfunction that may lead to leakage (*Figure 3(e)).*

The open space variable shows a high value at Kampung Tualang sub-basin (S5) to act as a hot spot area, while moderate values were detected in S1 sub-basin and S6 to S8 sub-basins as shown in *Figure 3 (f).* Several moderate hot spot areas also exist along Malacca River, from sampling 1 to sampling 6. The main reason to have the open space variable in this study is to reduce river water pollution by controlling the pollutant source. This suggestion may be proposed to government sector agencies such as the

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Department of Environmental (DOE), Department of Irrigation and Drainage (JPS) and other departments that concerns with river water quality to build a monitoring system so that easi and frequent monitor of the water status could be done. At the same time, researchers and academicians may take the opportunity to develop studies on river water quality perspectives for a better environment.

Conclusion

This study has proven that PCA and GIS are remarkable and useful tools to discover the influential factors involved in Malacca River water quality. This study also revealed that sampling station 5 located in Kampung Tualang sub basin is considered to be the main area to cause pollution to the river through the dominant sources of pollutant from the agricultural, residential, industrial activities, and animal husbandry. Continuous exposure to pollutant sources concentration could pose a serious threat to the river's ecosystem in the present and future timeframe. Frequent assessment and monitoring is crucial for the continuous protection of Malacca River ecosystem. Therefore, this study does not only suggest the reduction of river water pollution by means of controlling the pollutant sources, but also by providing information which identifies the problematic areas for better management and understanding of the river water quality in the future. The study also provides a spatial database through GIS mapping for future reference for the development of proper land use and urban design procedures.

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