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RESEARCH ARTICLE

Land use-based assessment of surface-water quality using indices approaches

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ABSTRACT
This study assessed land-use impacts on surface-water quality and explored relationships between water indexes with water parameters. Twenty-seven water samples, collected from canals located in agricultural, industrial, and residential areas, were analyzed for 22 parameters. Water quality index (WQI), heavy metal pollution index (HPI), and metal quality index (MQI) results showed poor to very poor water quality across all land uses. Agriculture had the highest WQI (39), followed by residential (12) and industrial areas (7). Industrial areas exhibited the highest HPI and MQI, indicating higher heavy metal pollution in the areas. Stepwise multiple regression analysis revealed a significant correlation between WQI and electrical conductivity and chemical oxygen demand (COD), explaining 71% of WQI variance. Discriminant analysis differentiated the three land uses with 100% accuracy using turbidity, COD, biochemical oxygen demand, Mg, and, Na. Tailored management strategies should be developed for each land-used type to improve water quality in urban areas.

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KEYWORDS
Water quality index; heavy metal pollution index; metal quality index; surface water quality; land uses

1. Introduction

Surface water, an important component of a natural ecosystem, is highly susceptible to deterioration and pollution from various sources, such as domestic, industrial, and agricultural activities that discharge wastewater and pollutants (Iloms et al. 2020, Naidoo and Olaniran 2014). This pollution can have a significant impact on human health, aquatic species, vegetation, and finally, aquatic biodiversity (M. K. Hasan, Shahriar, and Jim 2019; Inyinbor et al. 2018; Sun et al. 2019). Generally, surface water quality could be governed by a combination of anthropogenic activities and natural processes, which exhibited increasing impacts in recent years (Uddin et al. 2022). Natural processes, such as the rock weathering, erosion, and precipitation, may influence surface water over a large area, while anthropogenic impacts could be site-specific, varying with local pollution sources (Ding et al. 2015; Hamid, Bhat, and Jehangir 2019; P. Kumar, Matta, and Kumar 2024). Anthropogenic activities such as land-use types may alter surface water quality differently (Cheng et al. 2022) by discharging wastewater/runoff from residential, industrial, and agricultural areas (land-use types) into connected water bodies (Moriken, Jamil, and Abdullah 2019).

Among the three land-use types – agricultural, residential, and industrial – agricultural activities are known to cause widespread impacts over a large area (nonpoint source pollution) (Dowd-Uribe, Press, and Los Huertos 2008) and can be found in any country throughout the world States (Giri and Qiu 2016; Liu et al. 2021; US-EPA 2009). Agricultural activities can influence the quality of surface water bodies through the erosion and/or leaching of field-applied inorganic fertilizers, pesticides, and animal manures to surrounding water bodies (Giri and Qiu 2016). In addition, mechanical manipulation on the crop fields, such as plowing and harrowing, may speed up the deterioration of nearby surface water bodies by facilitating on-field runoff or erosion. Another land-use type that can significantly affect surface water quality is residential activities, which may discharge untreated domestic and municipal wastewater, polluting the surrounding surface water bodies. Domestic/municipal wastewater is often characterized by high levels of organic matter (biochemical oxygen demand (BOD_5) and chemical oxygen demand (COD)), ortho – phosphorus, and ammonium ion (NH_4^+), originating from toilets, kitchens, and washing (Butler, Friedler, and Gatt 1995). As a result, surface water bodies receiving such discharge may become contaminated with excessive levels of dissolved nutrients and organic matter (Mu et al. 2023). Moreover, the surface water in urban areas can be polluted by industrial activities, which discharge wastewater with varying characteristics depending on the industry, for example, chemical production, food processing, and the textile industry (Ching and Redzwan 2017; Tariq, Ali, and Shah 2005). A common feature of industrial wastewater is its high concentration of heavy metals (Azimi et al. 2017). Consequently, the heavy-metal concentration of cultivated land was found to be significantly affected by surrounding land-use types and industries (Li et al. 2017). Similarly, high heavy-metal concentrations have been observed in surface water bodies located in or near the industrial region of central India (Tiwari et al. 2015). These findings indicate that anthropogenic land-use types can release wastewater containing divese pollutants, polluting the nearby surface water bodies.

Residential and agricultural activities have been identified as significant contributors to surface water pollution, often resulting in elevated levels of organic carbon,

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nitrogen (N), phosphorus (P) nutrients, and microorganisms (Butler, Friedler, and Gatt 1995; Yang et al. 2022). The assessment of these parameters can be achieved through the water quality index (WQI), which integrates multiple physical, chemical, and biological parameters into a single numerical value. Numerous studies have employed various WQI models such as the NSF-WQI (Uddin, Nash, and Olbert 2021), CCME-WQI, WA-WQI (Hyarat and Al Kuisi 2021), RMS-WQI (Gani et al. 2023; Sajib et al. 2024), and principal component analysis/factor analysis-based WQI models (T. V. Le, Do, and Nguyen 2023). These models employ distinct computational methods and incorporate diverse water quality parameters (Uddin, Nash, and Olbert 2021). Despite the diversity of WQI models, they share a common purpose of assessing surface water quality by classifying it into different grades, ranging from excellent to poor quality (Uddin, Diganta, et al. 2023; Uddin, Rahman, et al. 2023). Conversely, industrial production has been found to contribute to heavy metal pollution in nearby water bodies. Surface water polluted with heavy metals can be assessed using specific indices such as the heavy metal pollution index (HPI) (Badeenezhad et al. 2023), the hazard index (HI) (Uddin et al. 2024), and the metal quality index (MQI) (H. Singh et al. 2023). These indices help quantify and determine the extent of water quality (WQI) or metal contamination (HPI and MQI) in surface water bodies associated with different land-use types.

Based on these findings, it can be hypothesized that water bodies receiving industrial wastewater may exhibit higher heavy metal concentrations than those receiving other types of wastewater. Additionally, water bodies receiving discharges from residential areas may face pollution from various physicochemical properties, while those receiving runoff or eroded materials from agricultural areas may have elevated nutrient and organic matter levels. These hypotheses suggest that surface water bodies receiving discharges from different land-use types should have distinct characteristics, which need more studies to be specifically examined.

Therefore, Ho Chi Minh City was chosen as a case study to examine the impacts of land-use types on surface water quality and analyze relationships between water indexes and land-use types, as well as water quality parameters in the city's canals. Previous studies have examined the water quality of larger water systems, such as the Saigon River and its tributaries in Ho Chi Minh City (T. N. Nguyen, Ha, and Sthiannopkao 2011; H. D. Nguyen et al. 2019; A. D. Pham 2017; V. Tran et al. 2016). However, smaller water systems, such as canals that connect pollution sources to the Saigon River and its tributaries have received less attention. Additionally, given that the main objective of this study is to assess the impact of various land-use types on surface water systems, small canals serve as ideal target water bodies. In larger rivers like the Saigon River, water quality may be affected by multiple pollution sources, making it challenging to accurately determine the specific impacts of the three land-use types. By focusing on smaller canals, it becomes easier to understand and measure the direct influence of land-use activities on surrounding water systems.

2. Materials and methods

2.1. Study area

Ho Chi Minh City (Figure 1), a densely populated and rapidly growing megacity in Vietnam, faces significant pollution challenges in its surface water system. The City is an economic and political center in southern Vietnam with a fast growth rate recently. The population of the City was around 8.9 million inhabitants (as of January 2019), growing at a rate of 2.2% per year for the last 10 years (T. Tran 2019). The City is situated on a relatively flat topography with a dense hydrological waterway network (700 km in length). The City comprises 24 administrative districts with a total area of 2095 km^2. The tropical climatic regime of the studied area is distinguished by two different seasons, the rainy season from May to October and the dry season from December to April (van Emmerik et al. 2018). The annual rainfall of Ho Chi Minh City is around 1868 mm more concentrated in the rainy season, and the average temperature is 27.4°C. Three primary land-use types – agricultural, residential, and industrial – have been identified as the main sources of pollution in the City's water bodies (Van Leeuwen, Dan, and Dieperink 2015), which are the focus in the current study.

2.2. Experimental factor and setup

The effects of three land uses including agricultural, industrial, and residential areas on surface water quality were examined in the current study. The three land uses were chosen for the current study because they occupy a large proportion of the city's land area and may have the greatest impact on the city's surface water system. The agricultural area occupies 111 836 ha equal to 53.4% of the total area, followed by residential (29 351 ha equal to 14%) and industrial area (9 484 ha equal to 4.5%) (Ho Chi Minh City Statistical Office 2021). The great differences in properties/characteristics of these land uses would lead to significant changes in surface water quality as these pollution sources can discharge various wastes to the vicinity. The canals and sampling sites for water sampling were randomly selected within these land uses, making the current experiment set up as a completely randomized design with nine replicates (see the following section).

2.3. Sampling and chemical analysis

Surface water samples were taken from canals in Ho Chi Minh City for the current study (Figure 1). Twenty-seven canals distributed across three land-use types (agricultural, industrial, and residential) were examined and selected to take surface water samples (Figure 1). The selection process was carried out in two distinct steps. Firstly, a comprehensive survey was conducted to ascertain the general landscape of the target canals in relation to their predominant land use types. This involved the examination of satellite images, Google Maps images, and on-site surveys to evaluate the primary land use influences. In the second step, specific canals were identified to represent three land use types to perform water sampling for the research. This methodical approach ensured a well-informed selection of sampling sites for a more accurate assessment of

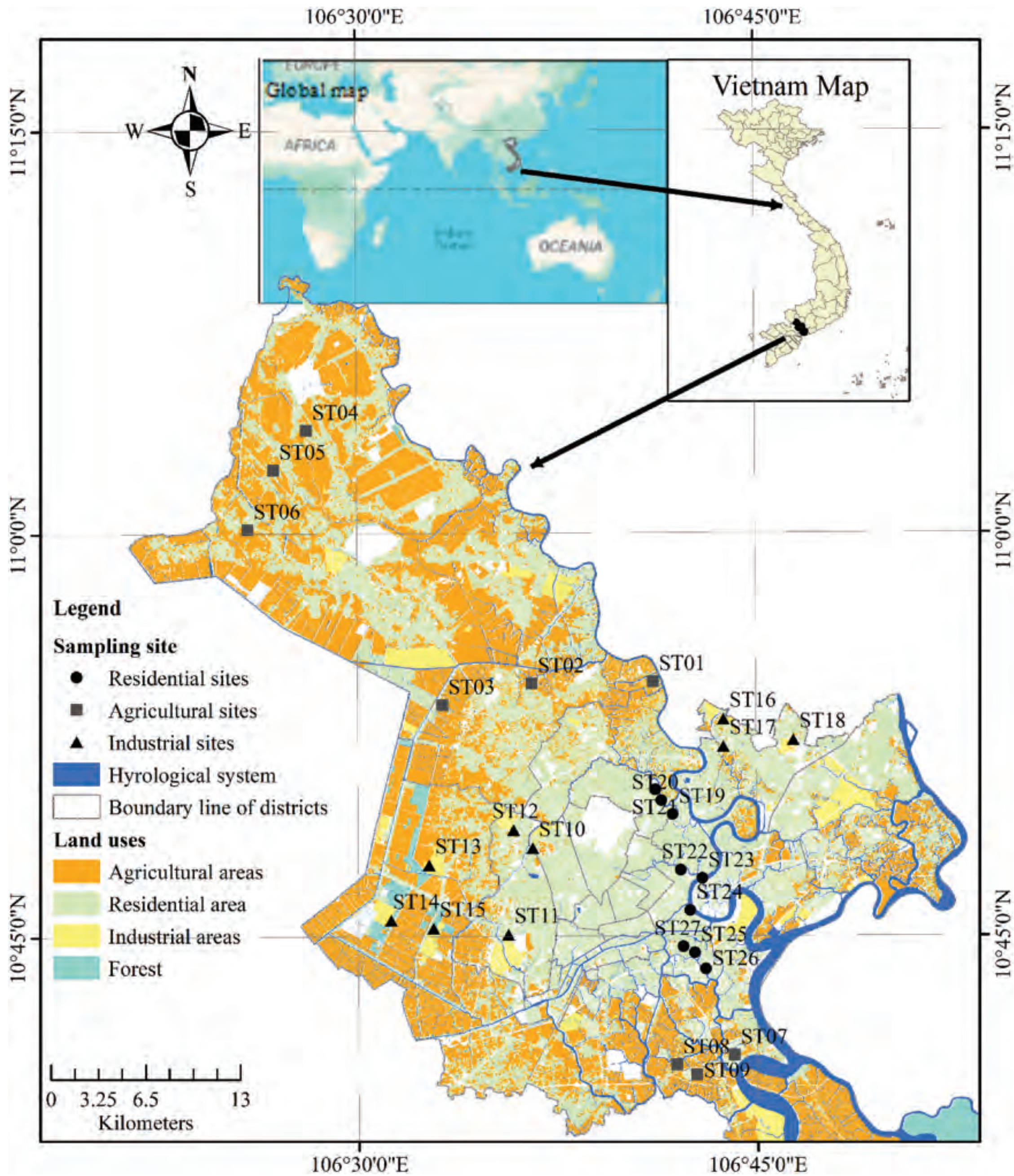

Figure 1. Map of studied areas and sampling sites.

water quality across various land uses. On each selected canal, one surface water sample was taken for analysis. The surface water samples were taken from these canals because we focused on small canals, connecting pollution sources to the Saison River and its tributaries, which were frequently studied.

To avoid the dilution effect of rainfall, which may diminish the magnitude of water parameters (Aigberua 2017; Edokpayi et al. 2017), we conducted sampling during the dry season, in March 2019. On the day of sampling, a Van Dorn water sampler was used to collect the surface water samples from the 0–50 cm water layer. For each sample, eight sub-samples were obtained from both sides of a pre-selected canal and pooled into a 40-liter bucket. Subsequently, around 5 liters of water from this bucket were transferred to a plastic bottle with a firm cap. The filled bottles were immediately stored in an ice box at 4°C and transported to the laboratory for chemical analyses.

On-site measurements were conducted on the remaining water in the bucket for temperature, pH, electrical conductivity (EC), dissolved oxygen (DO), and turbidity. These parameters were measured using appropriate instruments: a thermometer for temperature, a pH meter for pH levels, an EC meter for electrical conductivity, a portable DO meter for dissolved oxygen, and a Hach DR/2010 spectrophotometer for turbidity. The taken-water samples were analyzed for chemical, biological, and metal concentrations in the laboratory. The measured chemical and biological parameters included biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), ammonium (NH_4^+), phosphate

Table 1. Elements and associated maximum permissible limit (MPL) used for HPI and MQI estimation.

Element	MPL (mg L^{-1})	Reference
Ca	400	Goher et al.(2014)
Mg	60	Goher et al. (2014)
Na	919	Goher et al. (2014)
Al	5	FAO (1992)
Fe	1.5	MONRE (2015)
Mn	0.5	MONRE (2015)
Cd	0.01	FAO (1992); MONRE (2015)
Sr	400*	
Zn	1.5	MONRE (2015)
Pb	0.05	MONRE (2015)

(*) Qi et al. (2015) found that the increased application rate of Sr, up to 3026 mg kg^{-1} of stable Sr to the soil, did not induce any significant toxic effect on the growth of 26 cultivars of three crop species, oats, wheat, and barley. Nevertheless, because chemical properties and then environmental behaviors of Sr are similar to those of Ca (Nedobukh and Semenishchev 2019), we used the MPL of 400 mg L^{-1} of Ca for Sr in the current study.

(PO_4^{3-}), total suspended solids (TSS), and coliform bacteria (Coliform). These analyses followed procedures outlined in the National Technical Regulation on surface water quality (2008). For metal analysis, the remaining water in each sample was filtered through Whatman No.42 filter paper and acidified to pH < 2 using concentrated nitrite acid before measurements. The concentration of metals (K, Mg, Na, Ca, Al, Fe, Mn, Cd, Sr, Zn, and Pb) in the acidified filtrates was determined using inductively coupled plasma-optical emission spectrometry (ICP-OES), following the procedure established by Giri and Singh (2013).

2.4. Calculation and statistical analyses

This study measured 10 physical, chemical, and biological water parameters, which exhibit variation across multiple dimensions due to individual parameter fluctuation and different land uses. To unify the sources of variation, the water quality index is used and calculated based on these 10 parameters. The WQI utilizes aggregation techniques to effectively synthesize comprehensive water quality data into a single numerical value to provide an overall assessment of water quality (Ruth Olubukola Ajoke, Emmanuel Edet, and Oko Emmanuel 2021; Uddin, Nash, and Olbert 2021). While WQI may have several limitations, such as ambiguity and eclipsing (Gupta and Gupta 2021) and uncertainties (Uddin et al. 2022; Uddin, Nash, and Olbert 2021), it has gained popularity since its inception in the 1960s due to its adaptable structure, holistic view, comparison, and user-friendly approach (Gupta and Gupta 2021; Uddin, Nash, and Olbert 2021). The water quality index (WQI) was calculated based on the method by MONRE (2010) and was described by H. Pham et al. (2017) in Equation (1). There are many models developed to compute WQI (A. Kumar, Matta, and Bhatnagar 2021; Uddin, Nash, and Olbert 2021), but the model established by the Vietnamese Ministry of Natural Resources and Environment (MONRE) is used as it provides a context-specific assessment framework calibrated to local environmental conditions and aligned with national standards. This model ensures reliable water quality evaluation within the Vietnamese regulatory context and supports evidence-based decision-making. In brief, it is computed using 10 water parameters, including COD, BOD_5, NH_4^+, PO_4^{3-}, turbidity, TSS, coliform, DO, pH, and temperature with different weightage associated with these parameters.

$$WQI = \frac{SI_{(T,pH)}}{100}\left[\frac{1}{5}\sum_i^5 SI_i \; X \frac{1}{2}\sum_e^2 SI_e \; XSI_c\right]^{1/3} \quad (1)$$

Where $SI_{(T,pH)}$ is a sub-index of temperature and pH, SI_i is a sub-index of five water parameters (DO, BOD_5, COD, N-NH_4, P-PO_4), SI_e is a sub-index of TSS and turbidity, and SI_c is a sub-index of coliform. Further details on the calculation and interpretation of these sub-indices can be found in MONRE (2010).

The heavy metal pollution index (HPI) was computed, following Equation (2) by Mohan, Nithila, and Reddy (1996) and Pal et al. (2017).

$$HPI = \frac{\sum_{i=1}^n w_i q_i}{\sum_{i=1}^n w_i} \quad (2)$$

where $w_i = 1/s_i$; s_i= maximum permissible limit for irrigation water (Table 1); n is the number of parameters analyzed; q_i is the sub-index of the i^{th} parameter and equal $\frac{m_i}{s_i}x100$; m_i is the measured value of the heavy metal. For the current study, five heavy metals, including Fe, Mn, Cd, Zn, and Pb were used for HPI estimation. These trace elements are referred to as heavy metals in many other studies (M. Bhuyan et al. 2017; M. S. Bhuyan et al. 2019; M. Hasan et al. 2022; T. V. Le and Nguyen 2023) because their automatic densities are higher than 4000 kg m^3 (Vardhan, Kumar, and Panda 2019). The HPI is an essential indicator for assessing heavy metal contamination in water. An HPI value below 100 signifies non-contaminated water, whereas values above 100 suggest the presence of heavy metal contamination (Badeenezhad et al. 2023).

The metal quality index (MQI) was calculated through Equation (3) (Pal et al. 2017).

$$MQI = \sum_{i=1}^n \frac{m_i}{s_i} \quad (3)$$

Where m_i and s_i are similar to the HPI equation. For the current study, all metals used for HPI estimation plus Al, Sr, Na, Ca, and Mg concentrations were included to estimate MQI. Potassium concentration in the water was not taken for the MQI estimation because its maximum concentration in the water may not cause serious effects on plants (WHO 2018). A MQI value exceeding 1 acts as a cautionary threshold (Pal et al. 2017), suggesting potential issues related to metal presence in the water, and prompting the necessity for additional assessment or mitigation strategies.

Multivariate analysis (discriminant analysis, DA) and multiple regression analysis (stepwise regression analysis) were conducted to examine the relationship between land use with water parameters and between the three indexes (WQI, HPI, and MQI) with water parameters. DA can be applied to classify samples into different groups, using linear combinations of different variables. Two different modes, standard and stepwise, are commonly used to build the discriminant functions representing important variables of individual groups (K. P. Singh et al. 2004). In the current study, DA was carried out to establish discriminant functions of the water parameters to discriminate three land uses. Both standard and stepwise methods were used to build full and reduced discriminant functions, respectively, following the procedure by Hajigholizadeh and Melesse (2017). In addition, simple regression analysis was conducted to examine the inter-correlations among the 22 water parameters.

To compare the physicochemical properties and metal concentrations of surface water across three land uses in the current study, a one-way Analysis of Variance (ANOVA) was conducted, using a completely randomized design. The overall ANOVA model was $\gamma_{ij} = \mu + \alpha_j + \in_{ij}$, where γ_{ik} is the observed response variable; μ is overall population mean; α_j is the fixed effect of the jth land-use; and $\in_{ij}$ is the random error terms with mean zero and having a normal distribution (Ott and Longnecker 2011). When ANOVA indicated significant difference at $p \leq 0.05$, Tukey's honest significant difference test was used to compare means between individual parameters.

2.5. Uncertainty statements

Uncertainty emerges when the employed methods are incapable of accurately capturing the true quality of surface water. In this study, 22 water parameters were examined, which were subsequently utilized to compute three indices: WQI, HPI, and MQI. The study proceeded through four steps: (1) the selection of canals representing three land-use types (agricultural, residential, and industrial); (2) field surveys and water sampling conducted according to established standard procedures; (3) analysis of 22 parameters from 27 water samples collected; and (4) computation of the WQI, HPI, and MQI indices. Each of these steps entails varying degrees of uncertainty, which are discussed by (Uddin et al. 2022, 2024; Uddin, Nash, and Olbert 2021). Moreover, the WQI method also contains two main uncertainties, including ambiguity and eclipsing, contributing to reducing the reliability of a study, which is discussed in Sajib et al. (2023)

To mitigate uncertainty, several techniques were employed in this study. The selection of appropriate canals relied on the analysis of satellite images, Google Maps images, and on-site surveys. Water samples were collected thrice for each land-use type, and five sub-samples were pooled to form one composite water sample. The chemical analysis of water samples was duplicated, and the average was taken. Metal content analysis was implemented following standard procedures with a standard curve accuracy exceeding 99%. Analysis of Variance (ANOVA) using a completely randomized design with nine replicates, and the computation of root mean squared error (RMSE) parameters (Uddin et al. 2022) were also employed to minimize uncertainty and enhance the accuracy of the research findings.

3. Results

3.1. Physiochemical and biological properties of surface water

Of the 22 water parameters measured in the current study, temperature, coliform density, and the concentration of PO_4^{3-}, Al, Mn, and Pb were not significantly different across the three land uses. The temperature of the surface water varied from 30.1 to 35.5°C; the PO_4^{3-} concentration ranged from 0.02 to 2.19 (mg L^{-1}); coliform ranged from 390 to 240,000 (MPN 100^{-1} mL); Al ranged from 0.3 to 0.4 (mg L^{-1}); Mn ranged from 0.01 to 0.98 (mg L^{-1}), and Pb ranged from 0.004 to 0.013 (mg L^{-1}).

Figure 2 shows that the pH, DO, turbidity, and EC of surface water were significantly different between the three land uses. The pH was significantly higher in the agricultural area (7.5) than in the industrial area (6.9) and was within the permissible range (5.5–9). The DO concentration was much higher in the agricultural area (4.3) and lower in the industrial area (1.7) and residential area (2.3 mg L^{-1}). The DO concentration in the agricultural area exceeded the minimum permissible limit (MiPL, 4 mg L^{-1}), while that in the other two areas was lower than the limit. Turbidity in all three land uses exceeded the maximum permissible limit (MPL) and was highest in the industrial area. EC was highest in the residential area (4237) and low in agricultural (660) and industrial (1170 µS cm^1) areas. BOD_5, COD, NH_4^+, and TSS of surface water were significantly different among the three land uses (Figure 3). All four parameters were significantly higher in the industrial area ($BOD_5 = 44.3$; COD = 102, $NH_4^+ = 11.7$, and TSS = 80 mg L^{-1}) than in the others (13.7, 32.2, 2.3, and 79 for the agricultural area, and 22.3, 76.8, 8.5, and 51.4 for the residential area, respectively). The level of these parameters of three land uses was much higher than the associated MPLs, 15 (BOD_5), 30 (COD), 0.9 (NH_4^+), and 50 (mg L^{-1}, TSS). The correlation coefficients among these water parameters showed that temperature was significantly correlated with only pH, while pH was well correlated with DO, Na, and Fe, and DO has a strong relationship with 9 water parameters (Suplementary Table S1). Other water parameters such as turbidity, EC, COD, BOD_5, $N\text{-}NH_4$, and $P\text{-}PO_4$ exhibited significant connections with various other water parameters.

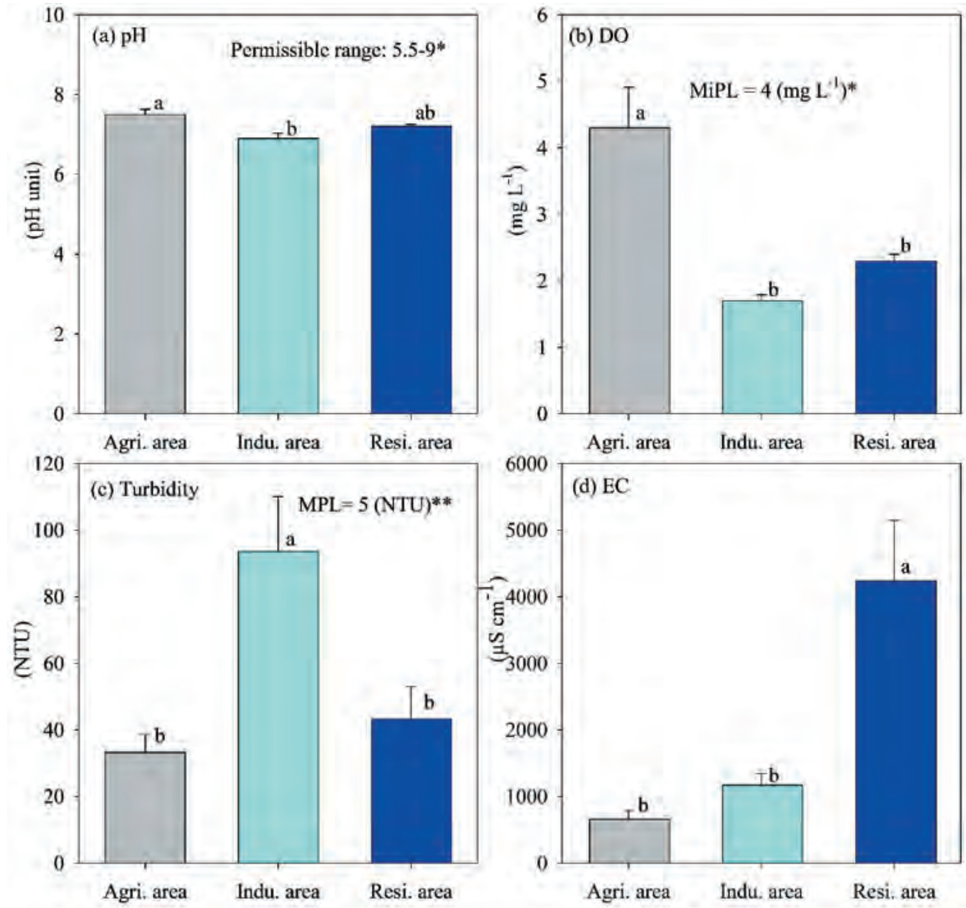

Figure 2. pH, DO, Turbidity, and EC of surface water collected from three studied land-uses. Within a panel, bars attached with the same letter are not significantly different from the other. Error bars indicate standard error. MPL = maximum permissible limit, MiPL = minimum permissible limit. Agri, indu, and Resi = agricultural, industrial, and residential, respectively. *, ** are Vietnam national standard values for surface water used for irrigation (MONRE 2015) and (Qcvn 2009), respectively.

3.2. Metal concentration

The concentration of base metals, such as Mg, Ca, K, and Na in surface water varied significantly among the three land uses (Figure 4). The residential area had the highest concentration of Mg (56), Ca (6.3), and K (91.2, mg L^{-1}) in surface water, while the industrial area had Na concentration (97 mg L^{-1}) in surface water significantly higher than the agricultural area (60) and residential area (65 mg L^{-1}). The concentration of Mg, Ca, and Na in surface water was lower than the maximum permissible limit. Figure 5 showed that surface water from the industrial area had a concentration of Fe (531.4), Cd (0.11), and Zn (81.8, μg L^{-1}) significantly higher than that from the other two land uses (320.7, 0.08, and 31.6 for the agricultural area, and 124.1, 0.08, and 4.49 for the residential area, respectively). The residential area had a Sr concentration (998) of surface water significantly higher than the agricultural area (7.3) and industrial area (162 μg L^{-1}).

3.3. Index results

Figure 6 shows that the agricultural area had significantly higher WQI (39) than the other two areas (7 and 12 for industrial and residential areas, respectively). Surface water in the agricultural area was classified into the poor class and that in the other two areas was into the very poor category. The HPI (Figure 7a) and MQI (Figure 7b) were significantly different among the three land uses. The industrial area had much greater HPI (4.7) and MQI (1.14) than the agricultural area (3.7 and 0.75, respectively). Meanwhile, the residential area showed the HPI (4.1) and MQI (0.91) values that were in between the other two areas. The HPI values for the three land uses were much lower than the critical value (100). The value of MQI in the industrial area was higher than the critical value (1) but these in the agricultural and residential areas were lower than the critical value.

3.4. Relationship between indices and land use

Table 2 shows that among the 11 physical, chemical, and biological parameters of surface water, EC and COD were strongly correlated with WQI with slopes of −0.003 and −0.217, respectively. The two parameters explained 21.42 and 50.12% of the total variance of the WQI, respectively. HPI was significantly linked with Fe, Mn, Cd, Zn, and Pb, with slopes of 0.4, 3.2, 7988, 0.4, and 322, respectively. These parameters explained 1.47, 15.13, 3.47, 0.02, and 79.89 of the total variance of HPI, respectively. MQI was significantly correlated with Mg, Ca, Na, Al, Fe, Mn, Zn, and Pb with slopes of 0.004, 0.003, 0.001, 0.2, 0.7, 2, 0.7, and 20.2, respectively. Fe and Mn were the two

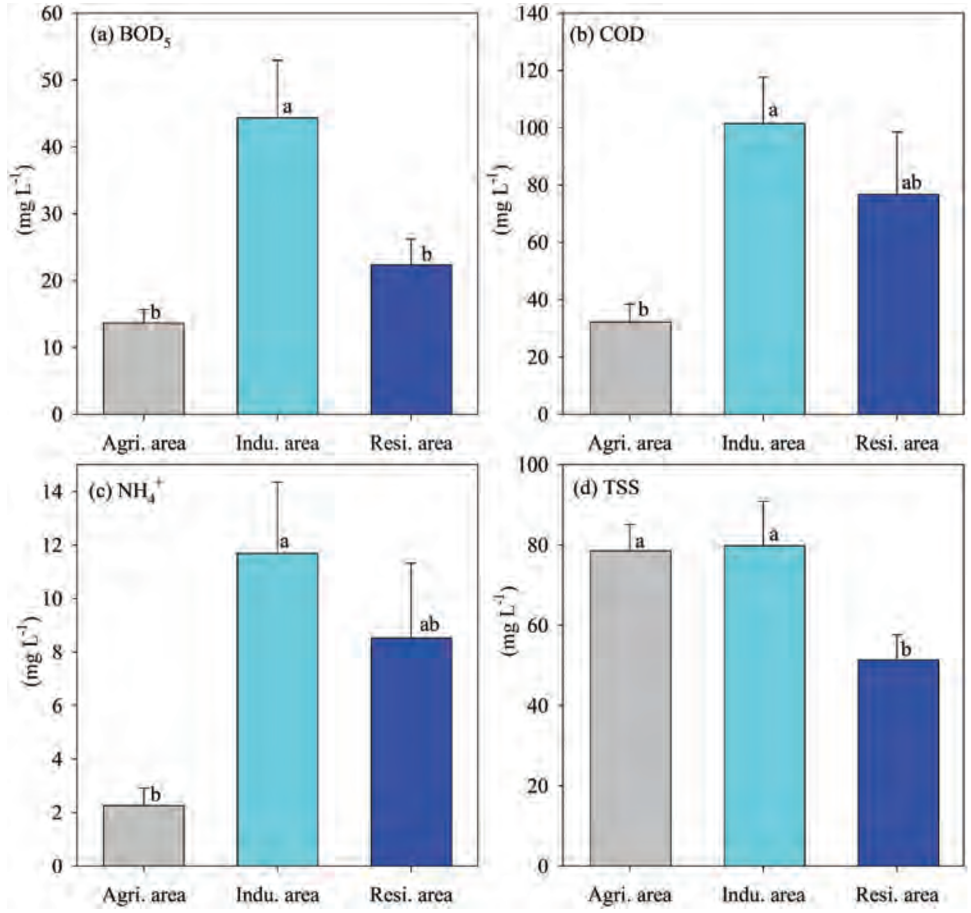

Figure 3. BOD_5, COD, NH_4^+, and TSS concentrations of surface water collected from three studied areas. Within a panel, bars attached with the same letter are not significantly different from the other. Error bars indicate standard error. MPL = maximum permissible limit. * is Vietnam national standard values for surface water used for irrigation (MONRE 2015).

most important parameters that explained the greatest proportion of the overall variation of MQI, with explaining percentages of 30.46 and 64.59%, respectively.

Tables 3 and 4 show the discriminant-function coefficients and classification matrix of three land uses obtained using discriminant analysis (DA) applied over the whole data set. Three land uses were used as a grouping variable to establish two discriminant functions, which explained 100% of the total variance of three land uses for two methods (standard and stepwise). Wilks' Lambda for both functions was lower than 0.05, indicating that the two functions were significant. The standard method used all 22 analyzed water parameters to construct the classification functions, while the stepwise method reduced the whole dataset to 5 parameters, including turbidity, COD, BOD_5, Mg, and Na. The coefficient of the classification function of Coliform was Zero, while that of Cd was the highest in absolute value. The two methods predicted 100% of cases correctively for each of the three land uses (Table 4).

4. Discussion

Despite falling within the poor quality classification, WQI values in agricultural areas were significantly higher than those in other land-use zones (Figure 6), suggesting that industrial and residential activities may contribute more significantly to the pollution of surrounding water bodies through the release of untreated wastewater or effluent in the present study. Both residential and industrial areas exhibited comparable and low WQI values, falling into the 'very poor' classification. Research has identified residential and industrial activities as the primary factors contributing to water degradation in urban environments (Moriken, Jamil, and Abdullah 2019). Similarly, urbanization has been recognized as a major influence on surface water quality deterioration in South Korea (Lee et al. 2009). The similarity in WQI between residential and industrial areas observed in the current study could be explained by the characteristics of wastewater from these two land uses. While residential areas often discharge wastewater with high concentrations of nutrients and organic matter (Nofiana Raharjo, Istirokhatun, and Susanto 2019), certain industries such as food processing companies may release effluents that also contain high levels of nutrients and organic matter (Dindaş et al. 2018; Noukeu et al. 2016). Ho Chi Minh City hosts various industries, including food processing, wood processing, chemical, beverage, garment and textile dyeing, footwear, mechanical and manufacturing engineering, electronics, pharmaceutical, and rubber plastics. Notably, Ho Chi Minh City has not yet fully implemented a centralized wastewater treatment system. As a result, wastewater from these areas may be released into

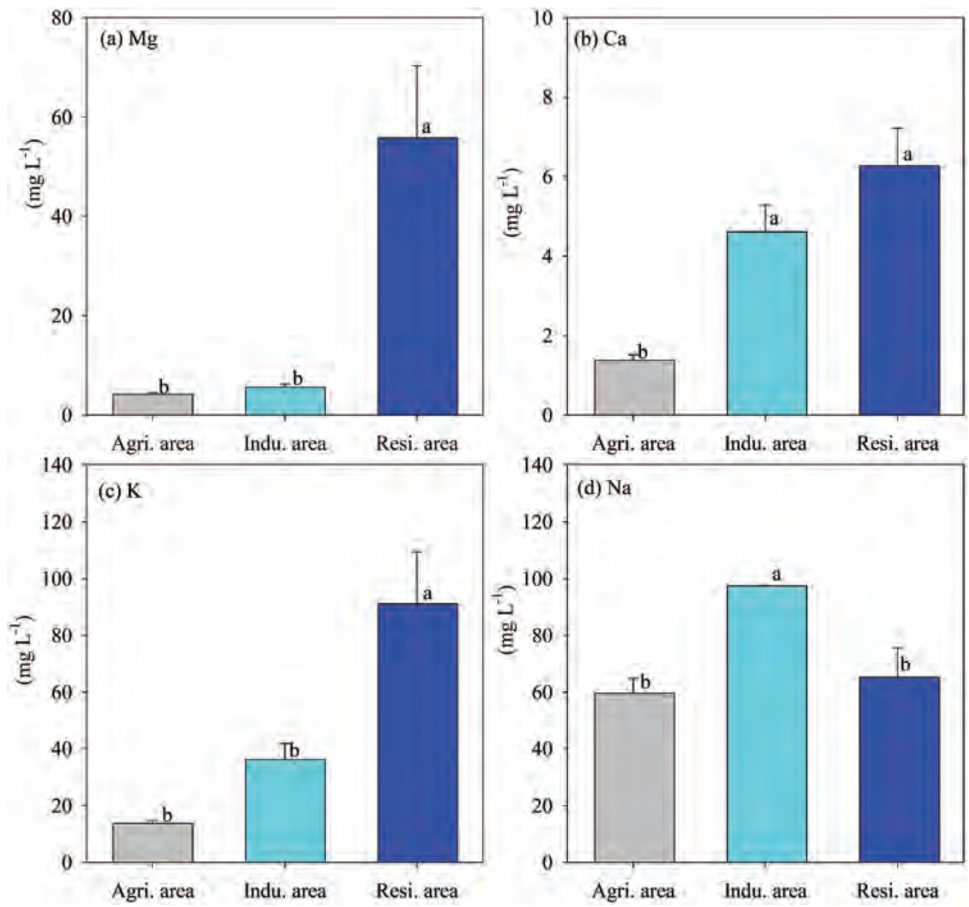

Figure 4. Mg, Ca, K, and Na concentrations of surface water collected from three studied land uses. Within a panel, bars attached with the same letter are not significantly different from the other. Error bars indicate standard error. * is derived from table 1.

the environment after passing through household-level wastewater systems or discharged directly into the surface water system without adequate treatment. This insufficient management of residential and industrial wastewater has contributed to the decline in water quality observed in the surrounding canals, as demonstrated in Figure 6.

Agricultural activities in Ho Chi Minh City, which are mostly involved in the production of paddy rice, vegetables, flowers, and bonsai, are the primary cause of pollution for surface water in the vicinities. Agricultural pollution is often characterized by a high content of nutrients (particularly N, P), and some heavy metals, as well as organic matter (Moriken, Jamil, and Abdullah 2019), decreasing the quality of water bodies receiving surface runoff from agricultural fields. Compared to the maximum permissible limits, surface water from the agricultural area exhibited greater concentrations of COD, NH_4^+, TSS, and coliform, indicating that water quality in the area was in poor condition (Figure 6). Compared to the other land uses, surface water in the agricultural area had higher concentrations of DO and lower values of turbidity, EC, BOD_5, COD, NH_4^+ (Figures 2 and 3), resulting in relatively higher WQI.

Heavy metal pollution (HPI) and metal quality (MQI) computed for the 27 sampling sites showed statistically significant differences across the three land uses (Figures 7(a,b)). The industrial area had the highest HPI and MQI values, suggesting that the water bodies surrounding this area were more polluted with heavy metal than those surrounding other areas. Similarly, anthropogenic activities in the industrial area were identified as the primary contributor to raising the metal content of the surface area near the pollution sources (Charles et al. 2018). Ghorbani, Hafezi Moghadas, and Kashi (2015) found that soils collected from or surrounding industrial land had a greater heavy-metal concentration than those collected from agricultural and natural land uses, implying that water bodies located on or near the industrial area could be more contaminated with heavy metals than other water bodies. In particular, the characteristics of wastewater discharged from the industrial area vary with the types of enterprises (Tariq, Ali, and Shah 2005). The current study found that surface water from the industrial area had the highest concentration of Na, Fe, Cd and Zn (Figures 4(d), 5(a–d)). Industrial activities are the main sources of metals for various environmental components (Azimi et al. 2017). Some food-processing facilities such as seafood plants may discharge wastewater with a high salt concentration (Ching and Redzwan 2017). A traditional method of applying salt, typically sodium chloride, to preserve seafood and aquacultural products before processing could be the main cause of increased Na concentration in the water bodies surrounding the industrial area (Figure 4d). This observation supports the hypothesis that food-processing enterprises may be the main cause of low WQI (Figure 6) owing to the discharge of wastewater with high COD and nutrient concentrations.

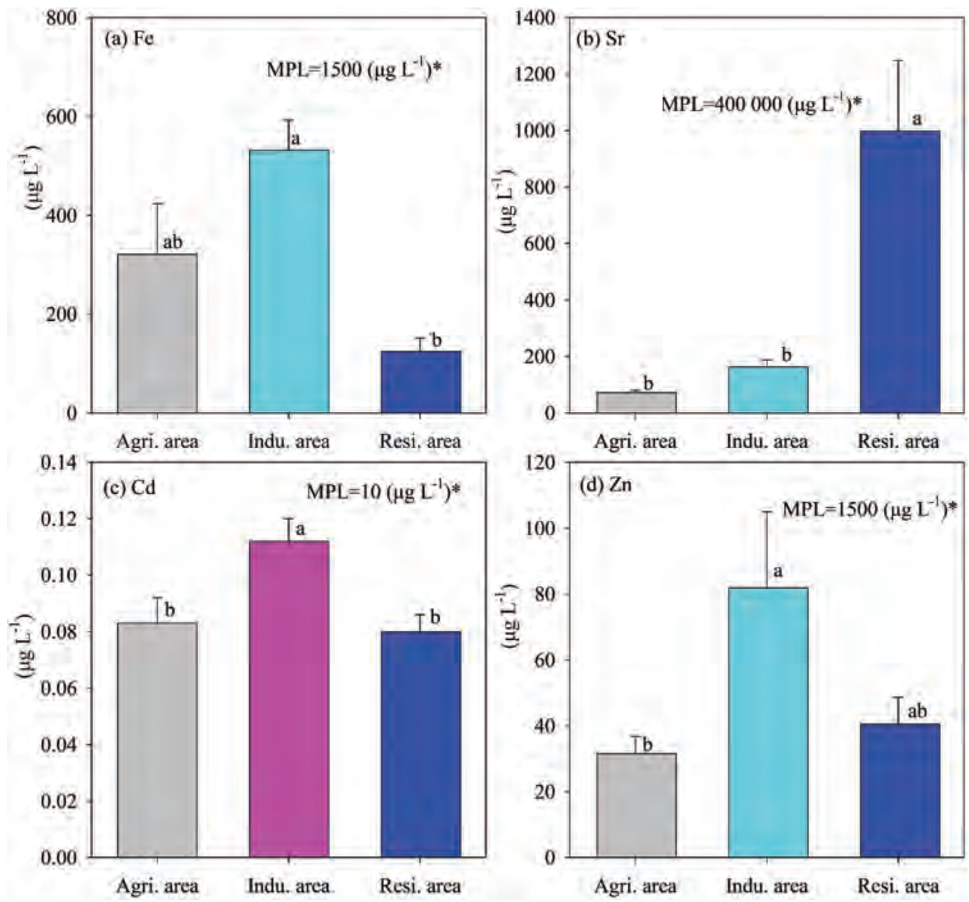

Figure 5. Fe, Sr, Cd, and Zn concentration of surface water collected from three studied land uses. Within a panel, bars attached with the same letter are not significantly different from the other. Error bars indicate standard error. * is derived from table 1.

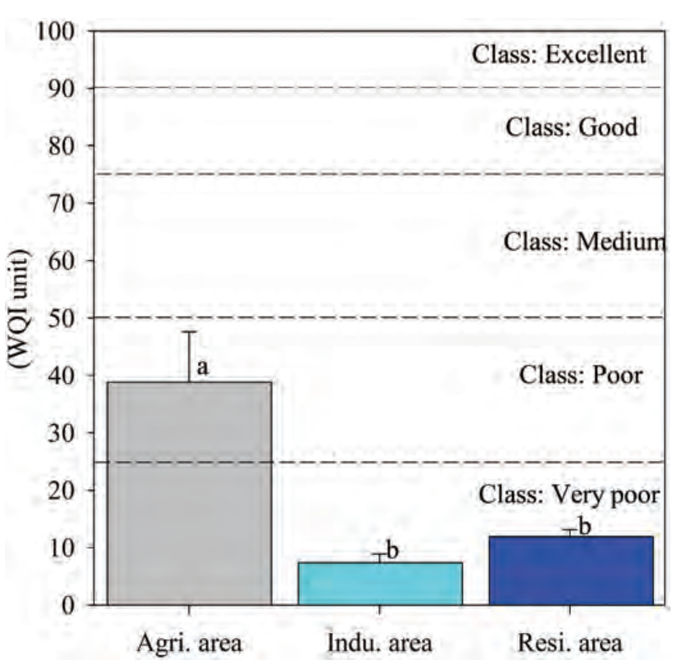

Figure 6. WQI of three studied land uses. Note: the bars attached with the same letter are not significantly different from the other. Error bars indicate standard error. Agri. Area, Indu. Area, and res. Area are these three land uses of agricultural, industry, and residential areas, respectively.

It is also worth noting that water collected from the residential areas contained the highest concentration of base metals, including Mg, Ca, K, and Sr (Figures 4a–c, and 5b). Domestic wastewater with a high concentration of base metals, such as Na, K, Ca, and Mg (Cruz et al. 2018) could be the cause for the finding. Especially, the use of soap and detergent, both compounds of potassium salts, for washing and bathing may lead to greywater with a great K content, which could be accountable for the finding. Domestic wastewater contained the highest content of alkaline metals (FAO (1992); V. Kumar and Chopra 2012), leading to a higher concentration of some base metals in residential areas than in the other areas, as shown in Figures 4 (a–c), and 5(b). In the case of Sr, limited studies were conducted to examine the main source of this element. Sr is a silver-gray alkaline metal that naturally occurs in the earth's mantle as a mixture of four stable isotopes (Sr-84, Sr-86, SR-87, and Sr-88) (Burger and Lichtscheidl-Schultz 2018). Because Sr naturally coexists with other base metals such as Ca and Mg (Ying 2015), its concentration was found to be significantly higher in areas having the greatest concentration of Mg and Ca, such as the residential area in the current study. This indicated that these alkaline metals (Mg, Ca, and Sr) could be derived from similar sources, the domestic wastewater discharged from the residential areas.

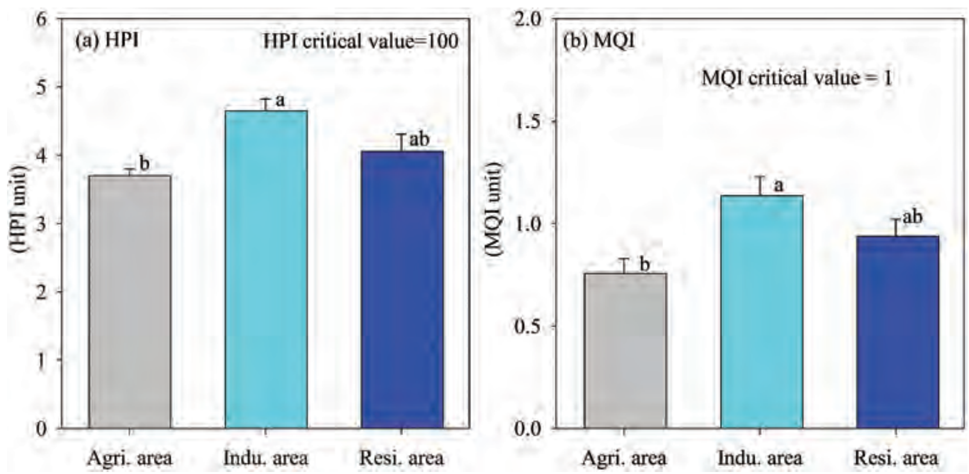

Figure 7. HPI (a) and MQI (b) of surface water collected from the three land uses. Within a panel, bars attached with the same letter are not significantly different from the other. Error bars indicate standard error. Agri. Area, Indu. Area, and res. Area are these three land uses of agricultural, industry, and residential areas, respectively.

Table 2. The slope, probability, and contributive percentage of different water parameters from stepwise multiple regression analysis of WQI, HPI, and MQI with water quality parameters. Bold numbers indicated the relationship between the indexes with the parameters is significant with Pro>F lower than 0.05.

	WQI				HPI			MQI		
Parameters	Slope	Pro>F	%	Parameters	Slope	Pro>F	%	Slope	Pro>F	%
Temperature	0.0	0.62	1.04	K	0.0	0.53	0.00	0.0	0.49	0.00
pH	0.0	0.21	7.42	Mg	0.0	0.49	0.00	**0.004**	**0.00**	**0.59**
DO	0.0	0.59	1.22	Ca	0.0	0.83	0.00	**0.003**	**0.00**	**0.03**
Turbidity	0.0	0.14	8.64	Na	0.0	0.11	0.01	**0.001**	**0.00**	**0.56**
EC	**−0.003**	**0.03**	**21.42**	Al	0.0	0.54	0.00	**0.2**	**0.00**	**0.11**
COD	**−0.217**	**0.00**	**50.11**	Fe	**0.4**	**0.00**	**1.47**	**0.7**	**0.00**	**30.46**
BOD_5	0.0	0.70	0.62	Mn	**3.2**	**0.00**	**15.13**	**2.0**	**0.00**	**64.57**
NH_4^+	0.0	0.31	4.25	Cd	**7988.6**	**0.00**	**3.47**	0.0	0.25	0.00
PO_4^{3-}	0.0	0.54	1.59	Sr	0.0	0.48	0.00	0.0	0.70	0.00
TSS	0.0	0.35	3.63	Zn	**0.4**	**0.03**	**0.02**	**0.7**	**0.00**	**1.01**
Coliform	0.0	0.91	0.06	Pb	**322.2**	**0.00**	**79.89**	**20.2**	**0.00**	**2.67**

Table 3. Classification-function coefficients for discriminant analysis of three land-uses. Note: two discriminant functions were established, explaining 100% of the total variance of three land-uses and Wilks' lambda of each function was lower than 0.05 for two methods.

	Standard method			Stepwise method		
Parameters	Agricultural	Industrial	Residential	Agricultural	Industrial	Residential
Temperature	180.4	143.2	168.6			
pH	1274.0	829.8	1079.6			
DO	31.2	−36.1	−7.8			
Turbidity	14.0	3.9	8.5	0.09	0.18	0.08
EC	−0.1	0.0	0.0			
COD	7.2	17.9	15.4	0.06	0.08	0.36
BOD_5	−23.9	−21.3	−25.2	−0.11	−0.07	−0.63
NH_4^+	33.8	−37.6	−10.2			
PO_4^{3-}	−1185.4	−1004.3	−1174.2			
TSS	−3.6	−1.0	−2.5			
Coliform	0.0	0.0	0.0			
K	18.8	3.5	10.4			
Mg	24.0	15.4	19.8	0.62	1.04	1.35
Ca	−374.4	−46.0	−193.3			
Na	22.0	16.1	20.6	0.75	1.24	1.32
Al	1324.1	2881.7	2552.0			
Fe	−707.7	−701.3	−798.3			
Mn	−2905.7	−230.7	−1411.4			
Cd	−7355294.3	−4747608.9	−6492705.6			
Zn	−3875.2	3466.4	882.8			
Pb	−250005.1	27370.3	−87080.9			
Constant	−6893.6	−6346.3	−7444.0	−26.44	−75.46	−90.21

Table 4. Classification matrix for discriminant analysis of three land-uses.

		Land-uses assigned by DA			
Land-use	% correct	Agricultural	Industrial	Residential	Total
Standard method					
Agricultural	100	9	0	0	9
Industrial	100	0	9	0	9
Residential	100	0	0	9	9
Total	100	9	9	9	27
Stepwise method					
Agricultural	100	9	0	0	9
Industrial	100	0	9	0	9
Residential	100	0	0	9	9
Total	100	9	9	9	27

Two water parameters, electrical conductivity (EC) and chemical oxygen demand (COD), demonstrated significant differences among the three land-use types. EC values were highest in residential areas (Figure 2d), indicating elevated levels of dissolved ions in canals derived from residential land use. On the other hand, COD values were highest in industrial areas (Figure 3b), suggesting increased levels of organic compounds in surface water originated from industrial land use. The stepwise multiple regression analysis showed that WQI was strongly dependent on these two parameters, EC and COD, which together explained 71.5% of the total variance of the WQI (Table 2). These findings indicate that the chemical properties of surface water (for example, EC and COD) were the most important in determining the WQI of the three land uses in the current study. Because the HPI was computed using the concentration of Fe, Mn, Cd, Zn, and Pb, the index was strongly correlated with all these metals. Surface water from the current study was contaminated with heavy metals in the following order: Fe>Mn>Zn>Pb>Cd. The MQI was uncorrelated with K, Cd, and Sr (through stepwise regression analysis). These indicated that heavy metals such as Fe, Mn, Zn, and Pb were important in determining the metal indexes.

Discriminant analysis (DA) was carried out helping in grouping water samples sharing common features (Bhat and Pandit 2014). In the current study, standard DA showed that one hundred percent of cases were correctly predicted for each of the three land uses (Table 4), indicating that individual land use had distinctive features, which could be used to separate and assign the water samples into different land uses. The finding also suggests that the physical, chemical, biological, and metallic properties of surface water were largely dependent on and different across the three land uses. Those types of lands discharged low-quality wastewater differently, polluting the receiving surface-water bodies. On the other hand, the stepwise method of DA extracted five water parameters, including turbidity, COD, BOD_5, Mg, and Na, which could be used to predict the membership of surface water in each of the three land uses with an accuracy of up to 100% of correct cases. ANOVA showed that these five parameters were significantly different among the three land uses. These findings indicate that the distinctive features of the three land uses in terms of surface water quality in the current study can be represented by these five parameters. Standard and stepwise methods of DA were also used to detect water parameters significantly contributing to the separation of water samples based on different groups in a water pollution assessment-based study in Tay Ninh province, a nearby province of Ho Chi Minh City (T. T. H. Le et al. 2017). Although their results differed greatly from those in the current study due to differences in the measured dataset, DA is proven to be helpful in both studies.

5. Conclusions and implementation

The surface water quality across the study area ranged from poor and very poor, with distinct variation among the three land-use types. Agricultural areas exhibited relatively better water quality, followed by residential and industrial areas. Industrial areas showed significantly higher heavy metal index (HPI) and metal quality index (MQI) values than agricultural areas, indicating that the water bodies surrounding the industrial areas were more polluted with heavy metals. The strong correlation of water quality index (WQI) with electrical conductivity (EC) and chemical oxygen demand (COD), along with the association of HPI and MQI with Fe, Mn, Zn, and Pb suggest that these physical, chemical, and metal parameters were crucial in defining the water quality of the study area. Moreover, the land-use impacts on surface water quality could be effectively distinguished with 100% accuracy, using five water parameters, which were turbidity, COD, BOD_5, Mg, and Na. However, the study had notable limitations, including a relatively small sample size and lack of seasonal variation data. Addressing these limitations in future research would enhance our understanding of the complex relationship between land use and surface water quality, enabling the development of targeted management strategies to enhance water quality in Ho Chi Minh City.

Disclosure statement

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Data availability statement

Data available on request due to privacy/ethical restrictions

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