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Hydrochemical indices as a proxy for assessing land-use impacts on water resources: a sustainable management perspective and case study of Can Tho City, Vietnam

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Abstract

Can Tho City is experiencing water stress driven by rapid global changes. This study assesses the spatiotemporal variation in surface water quality (SWQ) through a multivariate statistical approach to provide evidence-based scientific information supporting sustainable water resource management and contributing to achieving the city's sustainable development goals (SDGs). The complex SWQ dataset with 14 monthly-measured parameters at 73 sampling sites throughout the city was collected and analyzed. The obtained results indicated that average concentrations of biochemical oxygen demand, chemical oxygen

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demand (COD), dissolved oxygen (DO), total coliform, turbidity, total suspended solids, and phosphate (PO_4^{3-}) exceeded the permissible national levels. Spatially, cluster analysis had divided the city's river basin into three different zones (mixed urban-industrial, agricultural, and mixed urban–rural zones). The key sources of SWQ pollution in these three zones were individually identified by principal component/factor analysis (PCA/FA), which were mainly related to domestic wastewater, industrial effluents, farming runoff, soil erosion, upstream sediment flows, and severe droughts. Discriminant analysis also explored that COD, DO, turbidity, nitrate (NO_3^-), and PO_4^{3-} were the key parameters discriminating SWQ in the city among seasons and land-use zones. The temporally analyzed results from weighted arithmetic water quality index (WAWQI) estimation revealed the deterioration of SWQ conditions, whereby the total polluted monitoring sites of the city increased from 29% in 2013 to 51% in 2019. The key drivers of this deterioration were the expansion in built-up and industrial land areas, farming runoff, and droughts.

Graphical abstract

Hydrochemical indices as a proxy for assessing land use land cover impacts on water resources: a sustainable management perspective with a case study from Can Tho
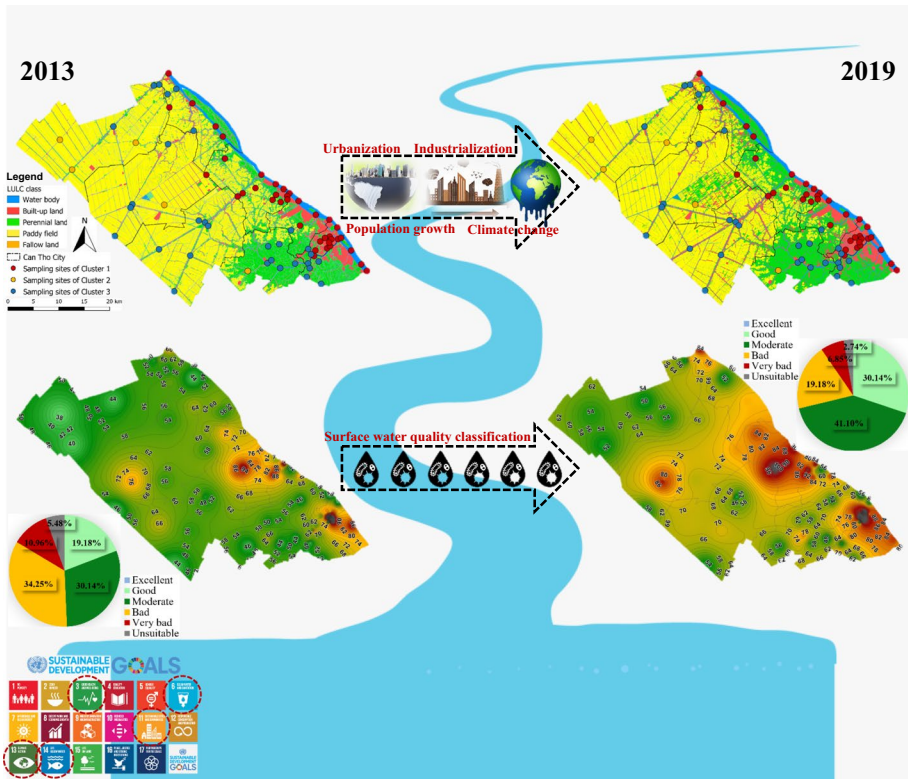
Keywords Surface water quality · Spatiotemporal variations · Multivariate statistical approach · Water quality index · Can Tho City · Vietnam

1 Introduction

Water resources have become a focal point for the sustainable development of human societies globally (Guppy et al. 2019), particularly in developing regions that often face a scarcity of clean water (Saraswat et al. 2017; Duc et al. 2021). Thus, the implementation of integrated water resource management (IWRM) to support easy access to safe water for the entire population is recommended in SDG 6 (UN 2015; Benson et al. 2020). However, in many countries of Southeast Asia (SEA), including Vietnam, this complex task is often affected by various challenges because of rapid industrial growth, urbanization (Hoekstra et al. 2018; Duc et al. 2021), unsustainable agricultural practices (Mallick et al. 2021), irregular land use (Kumar et al. 2019b; Duc et al. 2021), poor governance, and climate change (Wilderer 2007; Colloff et al. 2019; Li et al. 2021).

Vietnam, a rapidly developing country, actively engages in achieving SDGs using 115 national targets (Duc et al. 2021). In 2016, the rate of nationwide households with access to clean water reached 93.4%, and the target of 100% could be met by 2030. However, the nation's current wastewater treatment systems have not kept pace with demand due to rapid development of urban and industrial areas. Currently, only 12% of generated wastewater is treated in the country (MOPI 2018). According to the WB (2019), water stress will be widespread by 2030 (affecting 11 out of 16 national river basins) due to increasing water demand. Thus, the national targets set for 2030 may require further adoption of IWRM, which significantly supports achieving not only SDG 6 but also SDGs 3, 6, 11, 12, 13, and 14, as shown in Fig. 1 (Nilsson 2016; Guppy et al. 2019; UN 2019; Benson et al. 2020; Fonseca et al. 2020; Stibbe and Prescott 2020; ISC 2021).

In Vietnam, Can Tho City is a major dynamically developing economic center. This city is making great efforts to achieve its SDGs, and the City Resilience Strategy for 2030 has been planned in 2016 describing these efforts. Based on the city's SDG targets, this
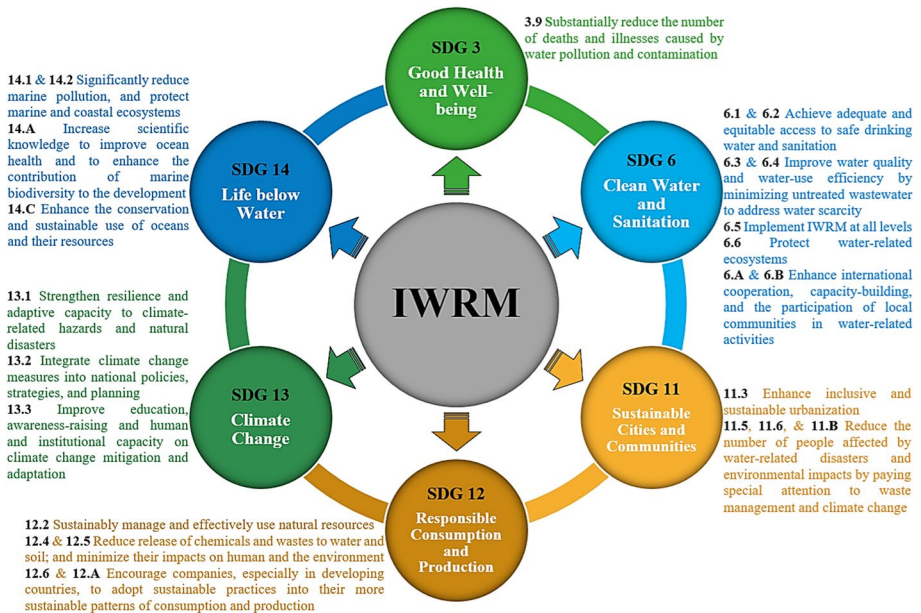

Fig. 1 Linkages among IWRM, key water-related SDGs, and their main targets

strategy has clearly identified future opportunities and challenges in the categories of health and well-being, economy and society, infrastructure and environment, and governance. Moreover, specific immediate and long-term actions have been planned to support the development of Can Tho as a green, sustainable, and proactive river city (CTCPC 2019a). However, in the recent past, the city has witnessed rapid and unplanned industrial urbanization accompanied by land-use changes, leading to multiple water-related stresses including recurring seasonal flooding, extreme droughts, and severe water pollution (Duc et al. 2021). The situation has worsened due to the absence of water governance and infrastructure (Trung et al. 2019; Duc et al. 2021). Untreated wastewater is directly discharged into the city's river network, causing contamination with various pollutants and exceeding the desirable Class A1 rating of the National Technical Regulation on Surface Water Quality (NTRSWQ) (Duc et al. 2021). Despite this critical situation, no comprehensive evaluation of SWQ in the city is yet available.

Considering these specific conditions, a comprehensive analysis and report of spatiotemporal variation in SWQ in Can Tho City is essential for decision-makers to develop robust IWRM plans, thereby supporting to achieve several SDGs in the city. Basically, the IWRM approach uses nexus approach (linkage between water-land-climate-agriculture-industry) in a more coordinated way in order to cater socioeconomic development in more sustainable way (GWP and INBO 2009; Katusiime and Schütt 2020). In addition, this also facilitates science-policy integration by translating these scientific results into appropriate policy actions and effectively mitigating water quality degradation in the city (Katyaini and Barua 2016). This interface is a social process linking scientists and other actors in the policy process and allowing for exchanges, co-evolution, and joint construction of knowledge to enrich decision-making (Wesselink et al. 2013; Ramachandran et al. 2014; Katyaini and Barua 2016). According to Hecker et al. (2018) and Roque et al. (2022), different transdisciplinary scientific approaches like citizen science, community-based participatory research, participatory mapping, participatory modeling, and projecting plausible future scenarios are being used in different combinations to empower different beneficiaries/stakeholders, increasing knowledge exchange benefits and uptake of results, and hence improving the decision-making process.

In recent years, sophisticated data-driven analytical approaches, fuzzy theory, and hydrological and geochemical models have been widely adopted as reliable tools to improve complex water quality assessments in rapidly developing cities like Can Tho. Selection of the optimal tool for water quality assessment depends on data availability, calculation time, intended output variables, and typical water quality characteristics in case study areas (Mishra et al. 2017; Duc et al. 2021). Some tools that are commonly used by surface water researchers around the world include the fuzzy analytic hierarchy process (Fuzzy-AHP), storm water management model (SWMM), system dynamic model (VENSIM), river basin simulation model (RIBASIM), water evaluation and planning (WEAP), water balance model (WBalMo), soil and water assessment tool (SWAT), hydrologic engineering center river analysis system (HEC-RAS), and MIKE (Singh et al. 2014; Kumar et al. 2017a, 2019a; Mishra et al. 2017; Minh et al. 2019a; Angello et al. 2020; Duc et al. 2021). However, most of these tools are data intensive and relatively complex to operate, which limits their usability for the overall evaluation of SWQ in data-deficient regions (Kumar et al. 2017a, b, 2019a; Duc et al. 2021). To address these problems, multivariate statistical techniques such as correlation analysis, CA, PCA/FA, DA, regression analysis (RA), and the use of water quality indexes (WQIs) have been extensively applied in recent water quality-related studies such as Singh et al. (2011, 2017), Avtar et al. (2013), Kumar et al. (2017b), Mallick et al. (2018),

Dashora et al. (2022). These tools are useful and reliable for modeling and interpretation of complex datasets of water quality to clarify variation and identify hydrological processes responsible for sophisticated water quality changes. For Vietnam, previous studies (Phung et al. 2015; Ngoc et al. 2017; Minh et al. 2019b, 2020; Duc et al. 2021) have utilized CA, PCA/FA, and DA to evaluate partly variations in water quality in Can Tho, Vung Tau, and An Giang Cities. For other countries, water quality changes in Khambhat (India), Limpopo (South Africa), and Sylhet Cities (Bangladesh) have also been assessed, respectively, by Kumar et al. (2019b), Molekoa et al. (2019), and Kadir et al. (2021) using similar statistical techniques. However, none of these studies have evaluated variation in water quality jointly over a long period of time, identified the correlated relationships among key drivers (e.g., land-use and policy changes) and variation in water quality, assessed overall water quality using integrated mathematical tools (e.g., WQIs and integrated pollution indexes), or proposed specific potential solutions for improving water quality in the studied areas.

It is also noteworthy that although the cities included in the above-mentioned studies and Can Tho have common characteristics such as a tropical and monsoonal climate (characterized in both Can Tho, Vung Tau, An Giang, Khambhat, and Sylhet), abundant water resources (Can Tho, An Giang, and Sylhet), poor water infrastructures and governance (all cities), and rapid population growth and urbanization (Can Tho, Vung Tau, Khambhat, and Sylhet); these cities are still distinguished from Can Tho by water quality features. For instance, only agricultural activity is mainly responsible for water quality variations in An Giang and Khambhat (Kumar et al. 2019b; Minh et al. 2019b, 2020), urbanization is the key driver merely controlling water quality in Sylhet (Kadir et al. 2021), mining activity is the single factor to water quality degradation in Limpopo (Molekoa et al. 2019), and only industrialization and saline water intrusion are responsible for water pollution in Vung Tau (Ngoc et al. 2017); while a more complicated situation can be found in Can Tho, where water quality is cumulatively influenced by diverse and complex factors including not only population growth, industrial urbanization, agriculture, climate change, but also water use-related activities in the upper regions (CTCPC 2019b; DONRE 2020a). A study by Duc et al. (2021) assessing the water quality status of a part of Can Tho City's river network (only SWQ variation along the Hau River) has also reflected this complicated situation.

Based on these knowledge gaps as well as the current status of SWQ and progress toward SDGs in Can Tho City, the present study comprehensively evaluates the spatiotemporal SWQ variation in the data-scarce river network of Can Tho City during rapid land-use changes from 2013 to 2019 using an integrated approach of multivariate statistical techniques and WAWQI estimation. The specific key objectives of this study are as follows: to evaluate the spatiotemporal variation and classifications of SWQ in the city's various zones, to trace the key drivers of such variation, and to propose potential mitigation measures for sustainable future management of river water in the city. Noticeably, this study provides useful baseline information for local policy planners and technical staff to enhance their capacity and understanding of applying multivariate analytical techniques for monitoring and evaluating water quality at their respective watershed levels. Furthermore, the results will also aid policymakers in designing management policies on time to achieve SDGs, particularly SDGs 6 (clean water and sanitation), 3 (human well-being), 11 (sustainable cities), 12 (effective natural resource consumption), 13 (climate change mitigation), and 14 (river ecosystem conservation), allowing those policymakers to be actively involved in helping their regions reach these global targets.

2 Study area

Can Tho City (9º55′08″N–10º19′38″N and 105º13′38″E–105º50′35″E) is the main regional urban center located in the middle of the Vietnamese Mekong Delta (VMD), Vietnam (CTCPC 2020) (Fig. 2). Comprising five urban and four rural districts, it covers nearly 1440 km² (around 80% of which for agricultural production) (CTCSO 2020a).
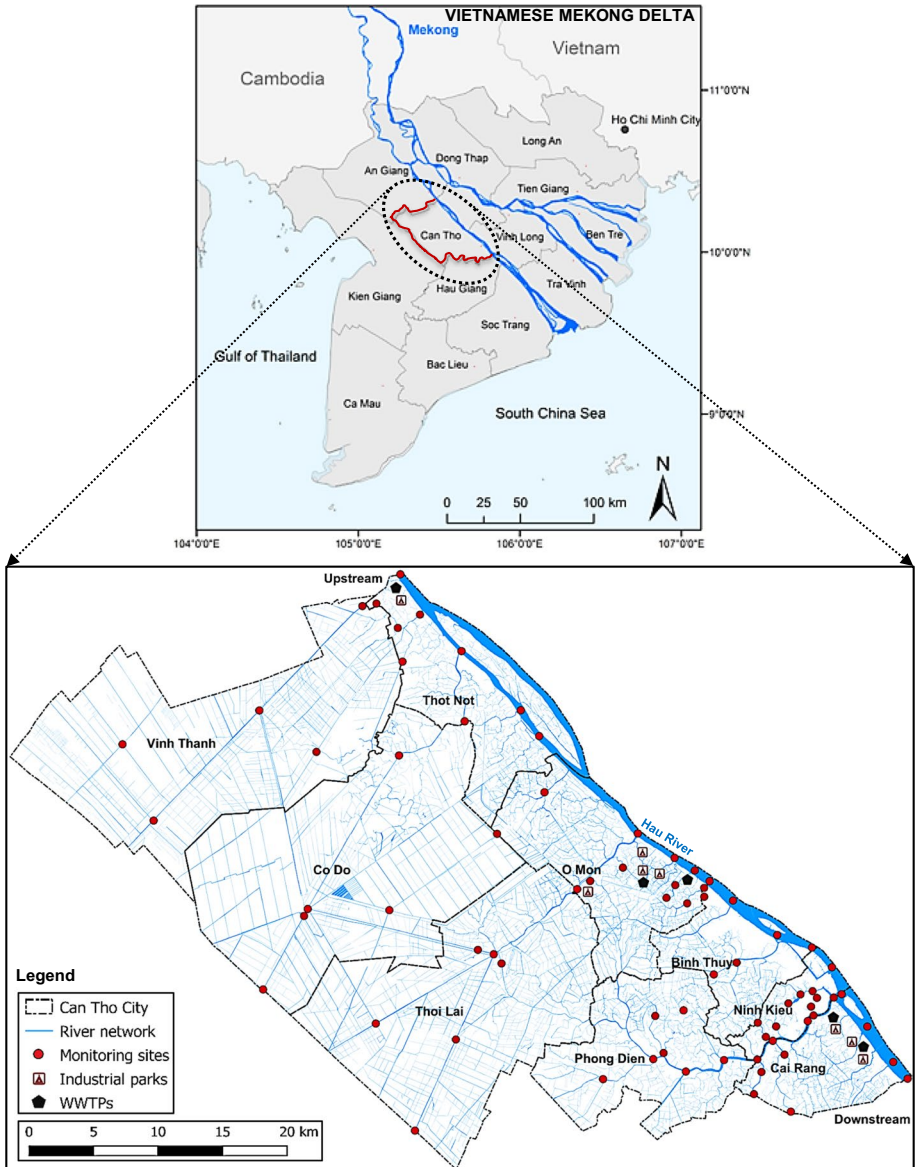

Fig. 2 Study area with its river network, 73 SWQ monitoring sites, industrial parks, and locations of wastewater treatment plants (WWTPs)

Noticeably, these urban districts (Ninh Kieu, Cai Rang, Binh Thuy, O Mon and Thot Not) are all located along nearly 60 km of the Hau River, one of the main tributaries of the Mekong River and key sources of water supply for the city (Duc et al. 2021). Being as a fourth most populous city in Vietnam, its population is projected to be 2.1 million by 2030 (UN DESA 2019; Duc et al. 2021). Table 2 of Appendix 2 shows the area, population, and SWQ monitoring network of the city.

Can Tho is located in a tropical and monsoonal climate with two distinctive seasons, i.e., wet (May to November) and dry (December to April) (Fig. 15 of Appendix 1), causing the seasonal SWQ variation in the city. Its average annual humidity and rainfall are 83% and 1650 mm (90% of which is being received in the wet season), respectively. Remarkably, the city has a dense waterway of more than 3405 km (Konings 2012). Despite its water abundance, the city recently faces clean water shortages in the dry season (Neumann et al. 2011; Duc et al. 2021). Besides, the growth of point pollution sources has increasingly become a matter of concern for SWQ management for the city. On the other hand, only four industrial (the total daily treatment capacity: 14,500 m^3) and one domestic WWTPs (30.000 m^3) are currently functional in the city. These five plants are located in the most industrialized (Thot Not, O Mon, and Cai Rang) and populous districts (Ninh Kieu) (Fig. 2) to mainly treat wastewater discharged from the eight largest industrial parks and nearly 62.800 out of 359.400 households of the city. However, these WWTPs are able to cater only 20 and 60% of total domestic and industrial wastewater generated in the city (DOC 2019; CTCPC 2019b; CTCSO 2020a). Noticeably, the local master plans are currently focusing on sustaining rapid industrial urbanization and achieving ambient SWQ of Class A1 (Duc et al. 2021).

3 Methodology

3.1 Monitored parameters and analytical methods

In all, 14 SWQ parameters (Table 2 of Appendix 2) were recorded monthly in 2013–2019 at 73 sampling sites that were recorded using Global Positioning System (GPS III, Garmin). At each sampling site, the collection of water samples was implemented monthly on the day of the lowest tide. On this day, two samples were, respectively, collected at the times of the highest and lowest water levels in clean polypropylene bottles. They were then brought to the laboratory in ice chests; stored below 4°C in Lovibond ET618-4 incubator (Germany) to minimize chemical alterations; and classified for anion, cation, and trace metal analyses. Before being analyzed, these collected samples were filtered through 0.45 μm Millipore membrane filters. Further, they were acidified by 1% HNO_3 (Ultra pure, Merck) for cation analysis, while HBO_3 acid was also used as a preservative for nitrate analysis (DONRE 2020a).

According to DONRE (2020a), in situ measurement of pH was done using LAQUA PH210 handheld meter (Japan) with a precision of 1%. Anions (F^-, NO_2^-, NO_3^-, and PO_4^{3-}) were analyzed by DIONEX ICS-90 (USA) ion chromatograph with an error percentage of less than 2% using duplicates, while cations and trace metals (NH_4^+, Cr^+, and Fe) were, respectively, determined by Jenway 6505 UV/Vis (UK) and Shimadzu AA-6800 atomic absorption (Japan) spectrophotometers with a precision of less than 1% using duplicates. For analyzing the remaining parameters, HACH DR-6000 spectrophotometer (USA) (analyzing DO, COD, and TSS), Lovibond BOD-OxiDirect sensor

system (Germany) (analyzing BOD), 0.45 μm Millipore membrane filters (analyzing TC), and Secchi disks (analyzing Turbidity) were utilized. For each instrument, after the analysis of every five samples, one replicate was used to check its accuracy. Regarding sampling, preservation, transportation, and especially analytical methods (Table 2 of Appendix 2) were strictly conducted according to the guidelines of the NTRSWQ in Vietnam (MONRE 2015; DONRE 2020a).

First, to identify key spatiotemporal characteristics, correlations, similarities, and dissimilarities among these analyzed parameters, the Statistical Package for the Social Sciences (SPSS) was applied for correlation analysis, CA, PCA/FA, and DA. Then, annual WAWQI values were estimated to assess spatiotemporal variation in SWQ in the city. Finally, the correlations between these WAWQI values and annual land-use changes were analyzed using RA to trace the key drivers responsible for the city's SWQ changes. For the validation process of these analyzed results, land-use maps, field survey data, and reports were collected from the city's departments and utilized to give fair ideas how land-use patterns and their changes had a significant correlation with SWQ evolution in the study area. The research methodology is briefly illustrated in Fig. 3.

STEP 1 - Descriptive statistics and correlation analysis using SPSS software → an overal assessment of SWQ, polluted parameters and their key relationships

STEP 2 - Cluster analysis (CA) using the Ward's method → spatial clusters and the distribution of monitoring sites based on similar SWQ characteristics

STEP 4 - Principal component/factor analysis (PCA/FA) using the Varimax matrix → diverse pollution sources responsible for the spatial SWQ variations in each cluster

STEP 3 - Discriminant analysis (DA) → the most spatially discriminant and significant SWQ parameters among identified clusters

STEP 5 - CA, DA, WAWQI calculation using the Horton method, map generation, and dicussion on annual levels of SWQ parameters → the seasonal and temporal SWQ classification and variations

STEP 6 - LULC and WAWQI analysis using regression analysis (RA) → key driving forces responsible for the spatio-temporal variations of SWQ
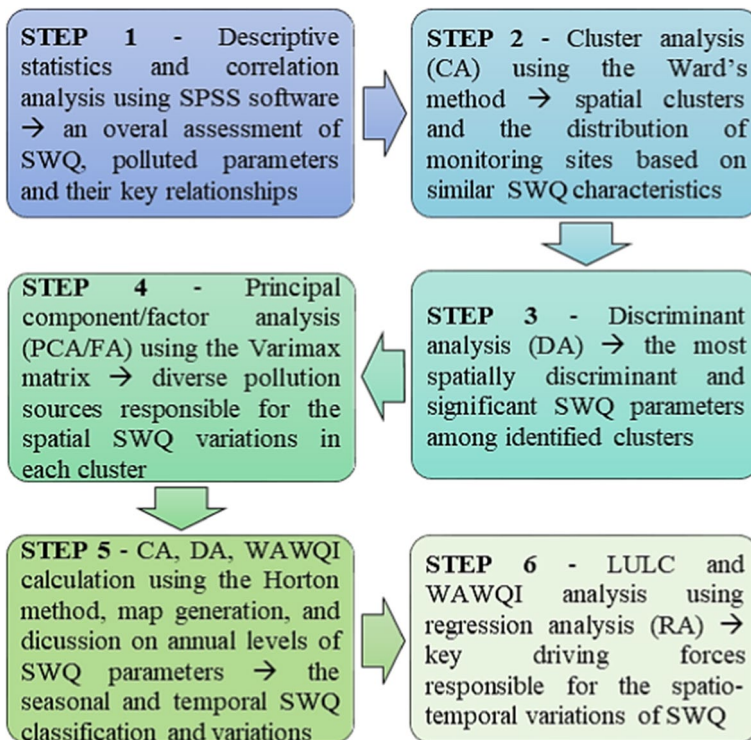
Fig. 3 Flowchart of the research methodology

3.2 Statistical analysis

3.2.1 Descriptive statistics and correlation analysis

The descriptive statistics of 14 SWQ parameters were determined to assess the overall SWQ of the city. The mean parameter values for each season and the whole year (2013–2019) were calculated for comparison with each other and with the permissible limit of Class A1, as well as to identify important pollution parameters for further analysis. These selected parameters were subjected to a correlation analysis using Spearman's rank coefficient to explore significant relationships between their concentrations and potential sources.

3.2.2 Cluster, discriminant, and principal component/factor analyses

Since Can Tho has diverse characteristics of water, land use, and climate; CA was utilized to examine the spatial and seasonal variation in the city's SWQ. Using Ward's method of agglomerative hierarchical clustering, comparisons among 73 sampling sites and 12 months were conducted, respectively. Based on their similarity of SWQ characteristics, spatial and seasonal clusters were identified (Singh et al. 2004, 2017; Minh et al. 2019b) by measuring linkage distances between them and determining D_{link}/D_{max}—the ratio of the linkage distance of the identified cluster to the maximal linkage distance (Simeonov et al. 2004; Duan et al. 2016).

To determine the optimal parameters for further exploring the spatial and seasonal SWQ variations, DA was applied for the identified clusters. This analysis constructs discriminant functions (DFs) using the stepwise method with the F test of Wilks' lambda mode to identify the most discriminant parameters for these variations (Duan et al. 2016). In this stepwise method, parameters are gradually input (the forward mode) and then removed (the reverse mode) to examine the corresponding changes of F and lambda values, thereby identifying these spatially and seasonally discriminant parameters (Abdullah 2019; IBM 2020; Minh et al. 2020).

Next, the PCA/FA technique was separately applied to spatial clusters to investigate their possible pollutant sources by transforming SWQ parameters into new principal components (PCs). PCA begins with the extraction of eigenvectors and eigenvalues (> 1.0), in which the highest values indicate the most significant PCs (Mazlum et al. 1999; Jolliffe 2002). PCs are obtained by multiplying an eigenvector with the correlated parameters. Then, FA reduces the contributions of less-significant parameters and generates new groups of factors (Fs) (Zhang et al. 2011; Avtar et al. 2013; Duan et al. 2016). The most significant parameters are represented by Fs' absolutely high loadings (> 0.5) and considered helpful for interpretation. Absolute loadings > 0.75 and > 0.5 are, respectively, designated 'strong' and 'moderate' (Liu et al. 2003; Avtar et al. 2011).

3.3 Weighted arithmetic water quality index

WAWQI offers a simple and reliable tool for evaluating overall water quality. This tool combines physicochemical and biological parameters into single values that can be compared to the appropriate regulatory standards (Kizar 2018; Minh et al. 2020). Annual WAWQI values were calculated by aggregating all 14 SWQ parameters. These index values were compared to

the allowable standards for drinking water as recommended by the National Guideline for the Calculation of the Water Quality Index (NGCWQI) (MONRE 2019) and World Health Organization (WHO) (WHO 2017) guidelines to explore spatiotemporal variation in SWQ in the city. Water quality status was evaluated as summarized in Table 3 of Appendix 2. The WAWQI was estimated using the Horton method (Eq. (1)) (Horton 1965; Kachroud et al. 2019).

$$\text{WAWQI}_i = \frac{\sum_{i=1}^{n} Q_i * W_i}{\sum_{i=1}^{n} W_i} \tag{1}$$

where Q_i is a quality rating of the nth parameter, $Q_i = [(V_i - V_{di})/(S_i - V_{di})]*100$ in which V_i is the estimated value of the nth parameter, V_{di} is the ideal value in the pure water of the nth parameter ($V_{di} = 0$, except $pH = 7$ and $DO = 14.6$ mg/L), S_i is the permissible limit of the nth parameter, and W_i is the unit weight of nth parameter, defined as $W_i = K/S_i$ in which K is a proportionality constant, $K = 1/\sum_{i=1}^{n}(1/S_i)$.

To illustrate the variation in SWQ, contour maps of WAWQI were generated using the inverse distance-weighted (IDW) interpolation technique. This technique estimates values at locations other than the measured sampling points characterized by local influences. The strongest influences are always found near observation points (Kumar et al. 2019b).

3.4 Land-use changes

To quantify land-use changes during the study period, annual land-use maps and areas were collected from the city's Department of Natural Resources and Environment (DONRE 2020b) and Central Statistics Office (CSO) (CTCSO 2020a, b, c) and then used as the primary input for the processes of analysis and validation. According to DONRE (2020b), Landsat-5 Thematic Mapper (TM) satellite datasets and topographic maps were used to prepare these city's land-use maps using an unsupervised classification technique in Erdas Imagine 9.0. For example, to prepare the 2013 and 2019 land-use maps, the satellite images, respectively, acquired on 24 December 2013 and 21 December 2019 were downloaded from the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/) for referencing and processing (DONRE 2020b). Apart from using these freely available satellite datasets, field surveys of land-use changes were also annually conducted by the city's DONRE and CSO to provide more detailed statistics on the annual changes of each land-use category in the city (CTCSO 2020b; DONRE 2020b). Based on the collected datasets, five major land-use categories in the city were classified, namely water bodies, built-up land, perennial land, paddy fields, and fallow land (CTCSO 2020a, b; DONRE 2020b). The annual areas of these different land-use classes and average WAWQI values were analyzed using RA to determine their correlations and identify the key factors responsible for the city's spatiotemporal variation in SWQ. The coefficient of determination (R^2) and significance test (P-value) were used to verify the applicability of RA (Udovicic et al. 2007; Sarstedt et al. 2017).

4 Results and discussion

4.1 Overall assessment of SWQ

A statistical summary of the huge SWQ dataset used in this study is provided in Table 3 of Appendix 2. As indicated, compared to the permissible limits of Class A1, the annual

mean levels of BOD, COD, DO, TC, turbidity, TSS, and PO_4^{3-} during the research period were unacceptable for residential use. Thus, these SWQ factors were considered the primary parameters and used for further analyses. In addition, NO_3^- was included because it sporadically exceeds the desirable concentration due to intensive agricultural activities (Minh et al. 2020; Singh et al. 2021) in the city (CTCSO 2020a).

The results of correlation analysis are shown in Table 1. They indicate strong and moderate positive correlations among BOD, COD, TC, turbidity, and TSS, suggesting common sources of point pollution such as poor management of domestic and industrial wastewater, urban drainage, and septic systems. Moreover, TC in the river can be attributed to farming activities involving the excess application of microbial mineralization and feedlot runoff (Phung et al. 2015; Duan et al. 2016; CPI 2017). Excess soil erosion and sediment flows are seasonal drivers of high turbidity and TSS in surface water (Rina et al. 2013; Abd Wahab et al. 2018; Leigh et al. 2019; Duc et al. 2021). A moderate positive correlation was observed between NO_3^- and PO_4^{3-}, suggesting a common cause, most likely agricultural runoff polluted with inorganic fertilizers containing nitrogen and phosphorus (Kumar et al. 2010, 2016, 2019b, 2020a; Minh et al. 2020; Singh et al. 2021). In addition, heavy rainfall and soil erosion during floods can transport nitrogen and phosphorus from adjacent agricultural lands into water bodies (WRWC 2018; Alewell et al. 2020; Duc et al. 2021). On the other hand, inverse associations were found for DO with COD, BOD, turbidity, and TSS. The intensity of these are indicators of both organic and inorganic pollutants in the aquatic environment that decompose and deplete DO. A negative association between TC and NO_3^- was found. A possible reason is that during the wet season, when water is turbid and DO is low, coliform bacteria rely on NO_3^- as an oxygen source, leading to an increase in coliform bacteria and a decrease in NO_3^- concentration.

4.2 Spatial variation in SWQ

4.2.1 Spatial distribution of monitoring sites

In the spatial CA process, an agglomeration schedule and dendrogram were generated, shown in Fig. 16 of Appendix 1 and Fig. 4, respectively. The optimal number of clusters was three, which is consistent with the result obtained from the dendrogram based on $(D_{link}/D_{max}) *100 < 10$. For better visualizing and especially validating these obtained

Table 1 Correlation matrix of eight SWQ parameters in Can Tho City

Parameters	BOD$_5$ (20°C)	COD	DO	TC	Turbidity	TSS	NO$_3^-$	PO$_4^{3-}$
BOD$_5$ (20°C)	1							
COD	0.894	1						
DO	−0.89	−0.887	1					
TC	0.738	0.797	−0.779	1				
Turbidity	0.564	0.634	−0.687	0.789	1			
TSS	0.836	0.841	−0.881	0.748	0.745	1		
NO$_3^-$	−0.743	−0.751	0.658	−0.726	−0.522	−0.642	1	
PO$_4^{3-}$	−0.260	−0.307	0.241	−0.383	−0.226	−0.184	0.512	1
Note: Correlation coefficients range from -1 (red) to 1 (green)								
-1 [gradient scale] **1**								

results, the SWQ monitoring sites in these three clusters are shown on the city's 2019 land-use map (Fig. 5). As shown, Cluster 1 was the largest, comprising 38 sites. Aside from CD1, all of them were located in mixed urban-industrial zones of five urban districts along the Hau River, which are dominated by residential, commercial, and industrial uses. Cluster 2 included only five sites in agricultural zones of rural districts, including Co Do, Phong Dien, and Vinh Thanh, where a strong reliance on farming practices was observed. The 30 remaining sites belonged to Cluster 3, representing mixed urban–rural areas in rural and partly urban districts. Notably, despite being occupied by agricultural land, most of these sites were closely surrounded by rural residential areas and market areas with relatively high population density. Based on the validation process, it can be seen that the results obtained from CA are highly associated with the land-use patterns in the city.

4.2.2 Spatial variation in SWQ

To further explore spatial variation in SWQ among clusters, DA was performed. In Appendix 2, Table 4 lists the calculated F and Wilks' lambda values, and Table 5 shows the final results. DO, NO_3^-, COD, and PO_4^{3-} were the most significant SWQ parameters for discriminating spatially among clusters. Box and whisker plots indicating the average levels of these parameters are shown in Fig. 6. While COD dominated Cluster 1 in both concentration and range, a contrasting pattern was observed in Clusters 2 and 3, in which DO had its first and second highest levels, respectively. Similarly, Cluster 2 clearly showed the highest levels of NO_3^- and PO_4^{3-}. Remarkably, Cluster 3 showed moderate levels of all parameters. To clarify these patterns, mean levels of BOD, TC, turbidity, and TSS are also provided in Table 6 (Appendix 2). Cluster 1 had the highest levels of these parameters, followed by Clusters 3 and 2, respectively.

4.2.3 Determination of pollution sources

The PCA/FA technique was employed to identify potential SWQ pollution sources for each cluster. Figure 17 of Appendix 1 shows eigenvalues (> 1), and Fig. 7 and Table 7 of Appendix 2 provide the loadings of SWQ parameters corresponding to factors in each spatial
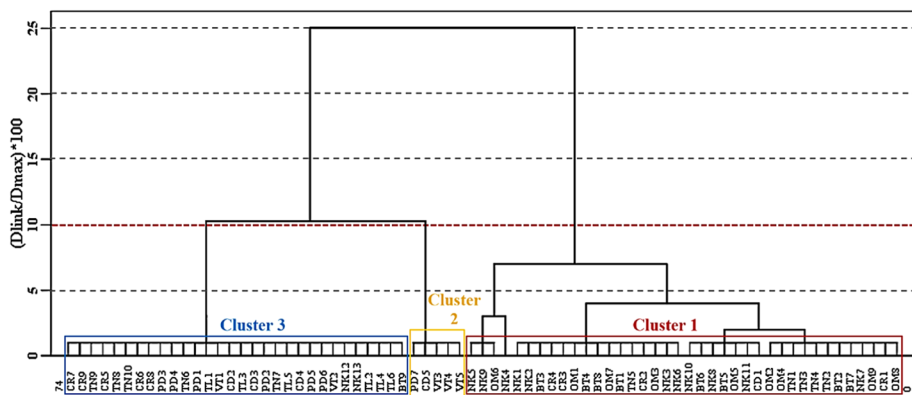

Fig. 4 Dendrogram illustrating the spatial clustering of 73 monitoring sites according to their SWQ characteristics
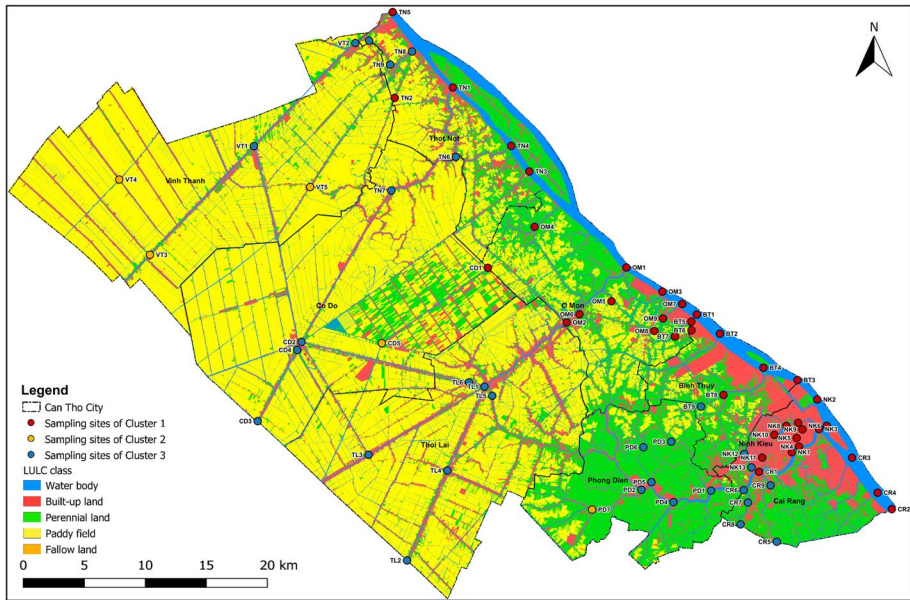
Fig. 5 The three spatial clusters and associated SWQ sampling sites on the 2019 land-use map of Can Tho City

cluster. Clusters 1, 2, and 3 each had three PCs, explaining 80.46, 89.52, and 70.37%, respectively, of the total variance in the SWQ dataset.

For Cluster 1, factor 1 was the most significant factor, explaining nearly 52% of the dataset variance. This factor showed strong and moderate COD, BOD, and DO loadings. As noted above, these parameters indicate the dominance of point pollution sources associated with anthropogenic activities, such as wastewater discharge from industrial urbanization zones. Two less-significant factors, namely, 2 (15.63%) and 3 (12.95%), exhibited high and moderate loadings for NO_3^-, PO_4^{3-}, TC, turbidity, and TSS. These results demonstrate impacts of both urban drainage and farming runoff on SWQ. For Cluster 2, the two most significant factors were 1 and 2, with a cumulative variance of 72.89%, which had high loadings for NO_3^-, PO_4^{3-}, DO, turbidity, and TSS. These factors are indicative of agricultural practices, such as large inputs of inorganic fertilizers and disturbed soil erosion. Factor 3 (16.63%) indicated strong loadings for BOD and TC, suggesting influences from urban activities. For Cluster 3, factors 1 (33.65%) and 2 (23.55%) had high loadings for BOD, COD, DO, TC, turbidity, and NO_3^-, indicating diverse drivers (e.g., residential, industrial, and agricultural sources) of variation in SWQ. Factor 3 (13.17%) showed moderate loadings for TSS and PO_4^{3-}, representing both urban and agricultural activities.

Generally, the PCA/FA findings were consistent with those obtained from spatial CA and DA as well as the city's land-use patterns mapped in Fig. 5. The most significant factor of Cluster 1 strongly indicated that SWQ in Thot Not, O Mon, Binh Thuy, Ninh Kieu, and Cai Rang urban districts were mainly influenced by industrial and urban processes, while agricultural practices were mostly responsible for the SWQ status of Cluster 2 (Vinh Thanh and parts of Co Do and Phong Dien rural districts). Notably, both farming and urbanization were key drivers of SWQ in Cluster 3 (parts of Cai Rang and Thot Not urban districts, and most of Phong Dien, Thoi Lai, and Co Do rural ones).
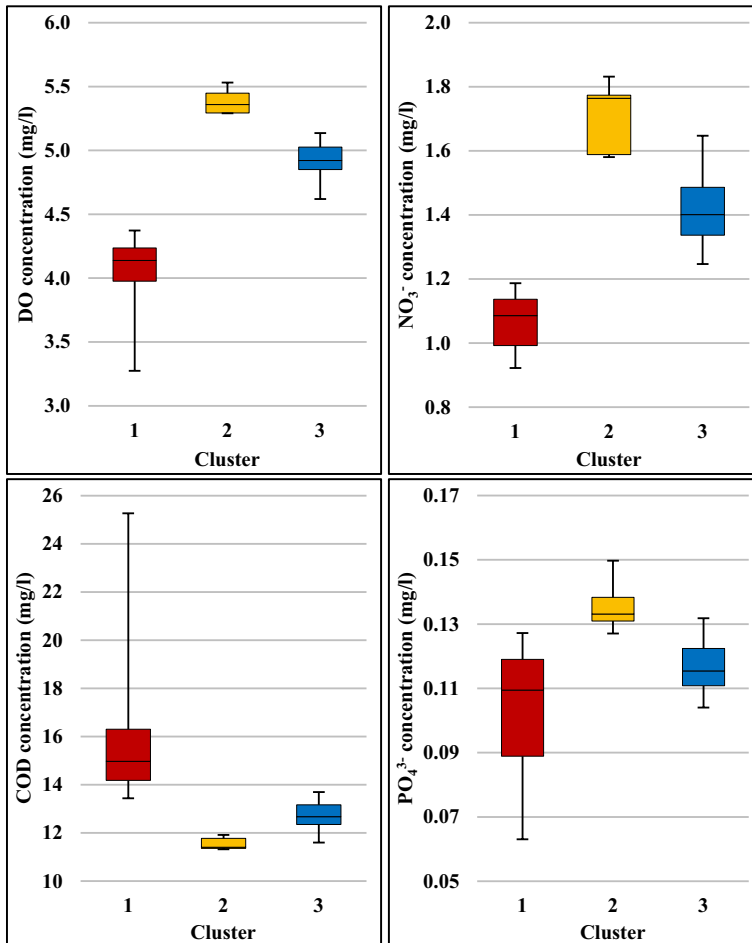
Fig. 6 Mean levels of the most spatially discriminant SWQ parameters

4.3 Seasonal and temporal variation in SWQ

4.3.1 Seasonal distribution of SWQ

In the seasonal CA process, SWQ characteristics during all 12 months were grouped into two clusters (Fig. 16b of Appendix 1) at (D_{link}/D_{max}) *100 < 5 (Fig. 8). The city's annual SWQ and hydro-meteorological reports were used to reference and validate this seasonal clustering result. Consequently, this result is consistent with the city's tropical monsoonal climate, which shows distinct alternation between the dry and wet seasons. Cluster 1 included January, February, March, April, and December and corresponded closely to the dry season in the city, characterized by periods of low flow and drought (Fig. 15 of
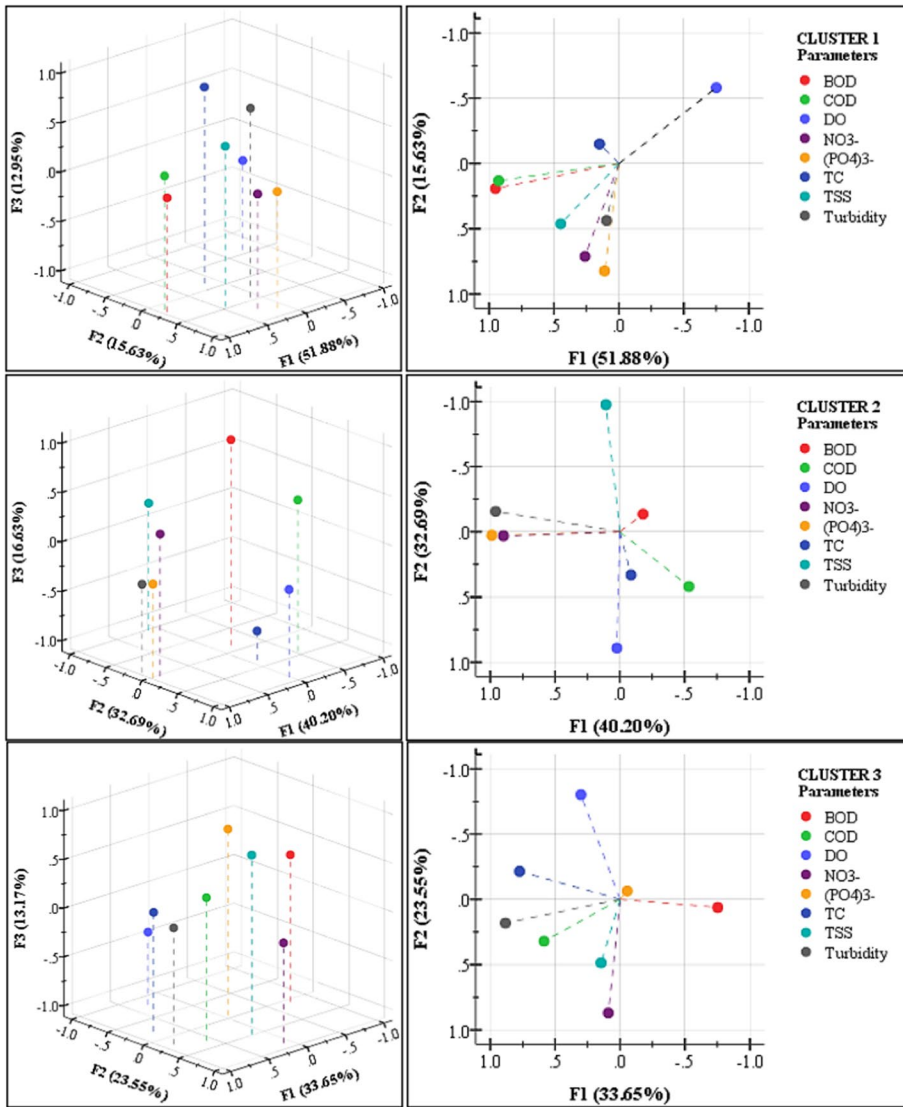
Fig. 7 3D and 2D scatter plots showing SWQ parameter loadings for the PCs of spatial clusters

Appendix 1). Cluster 2 contained the remaining months, reflecting the wet season with periods of high flow, rain, and flooding. A statistical summary of seasonal mean concentrations of SWQ parameter is provided in Table 3 of Appendix 2. As indicated, the mean levels of pH, BOD, COD, TC, fluoride (F^-), chromium (Cr_6^+), and iron (Fe) were higher in the dry season than the monsoon season, while the opposite trend was observed for the seven remaining parameters. This variation may have arisen from diverse impacts of the local climatic (dry and wet seasons) and hydrological conditions (low- and high-flow periods).

Fig. 8 Dendrogram illustrating seasonal clustering of 12 months according to their SWQ characteristics

4.3.2 Seasonal variation in SWQ

As analyzed (using DA) and shown in Tables 4 and 5 of Appendix 2, DO, turbidity, PO_4^{3-}, and COD were the most significant SWQ paramet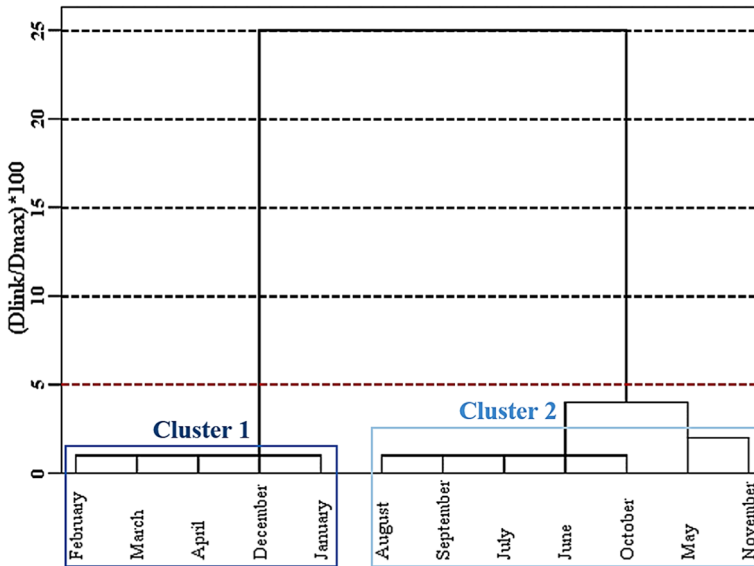ers for discriminating between the dry (Cluster 1) and wet (Cluster 2) seasons. Their average levels are compared in Fig. 9. The average DO level was much lower in the dry season than during the wet season due to the local climatic diversity. DO concentrations are partially controlled by water temperature (Chen et al. 2015). Thus, the warmer river water present during the city's dry period (Tam et al. 2022) becomes saturated with oxygen more easily and can hold less DO (Shrestha and Kazama 2007; FED 2014; Duan et al. 2016). This lower DO level was also driven by the higher levels of COD (Fig. 9) and BOD (Table 3 of Appendix 2) in the dry season, representing organic and inorganic matter in the water that requires oxygen for decomposition. Notably, lower water levels combined with a direct discharge of domestic, industrial, and farming wastewater into water bodies may be responsible for the high levels of COD and BOD pollution in the city during the dry season.

During the wet season, high turbidity and PO_4^{3-} levels were observed, brought by the transboundary nature of the river systems (Minh et al. 2019b). As part of the VMD's downstream area, the city receives large amounts of alluvial flows carrying nutrients (phosphorus and nitrogen) due to erosion of disturbed soil and agricultural activities in the upstream areas (e.g., An Giang, an intensively agricultural province; Fig. 2) during the rainy and flooding periods (Minh et al. 2019b, 2020; Duc et al. 2021). In addition, the high levels of turbidity, PO_4^{3-}, TSS, and NO_3^- during the wet season were driven by high local runoff of inorganic fertilizers, anaerobic wastewaters, and urban activities in the city (Phung et al. 2015; Tam et al. 2022).
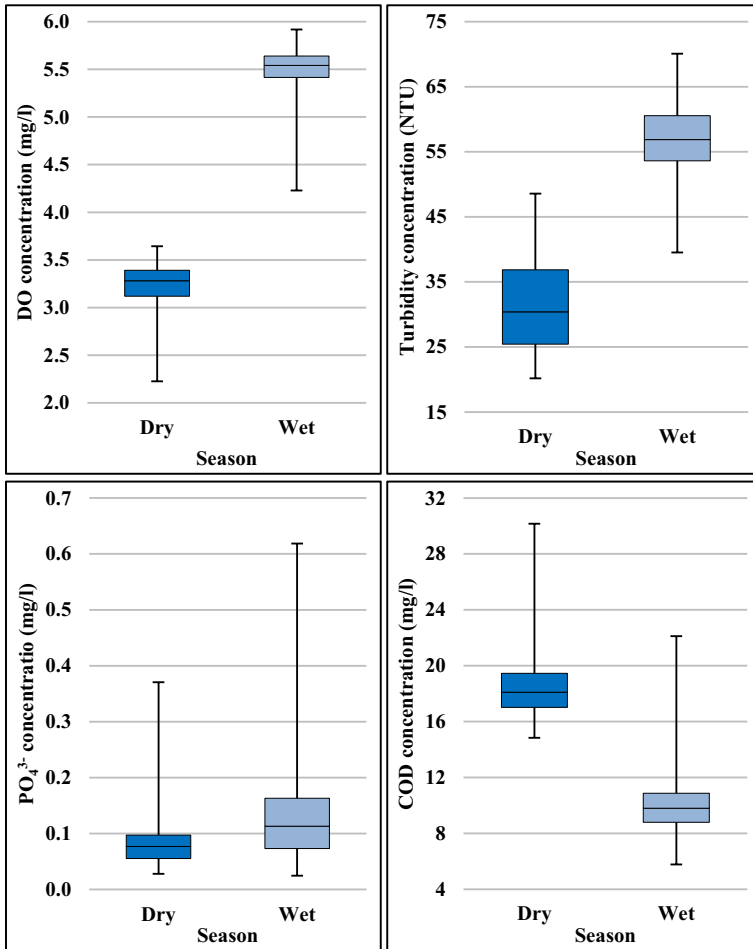
Fig. 9 Mean levels of the most important SWQ parameters for discriminating between the dry and wet seasons

4.3.3 Temporal classification of SWQ

For temporal SWQ classification, annual WAWQI values were calculated and compared (Tables 8 and 9 of Appendix 2). Higher levels of SWQ parameters would cause higher index values. The WAWQI values and their distributions on contour maps in 2013 and 2019 are shown in Figs. 10 and 11, respectively. The estimated mean index values in 2013 and 2019 were 62 and 72, respectively. Most of the indexes were higher in 2019 than in 2013, with 66 indexes (2019) compared to 7 (2013). In 2013, SWQ at 26.03% of all sites was bad or very bad for domestic usage. These sites were mainly located in the most populous and industrialized districts, particularly Ninh Kieu (NK8 and NK9 at Bung Xang and Xang Thoi lakes), Cai Rang (CR1–CR4 in the Hung Phu industrial zone), O Mon (OM1, OM2, and OM4–OM9 at O Mon market and in the Tra Noc industrial park), and Thot Not (TN5 in the Thot Not industrial zone) (Fig. 10). Only 2.74% of all sites (NK4 and NK5,
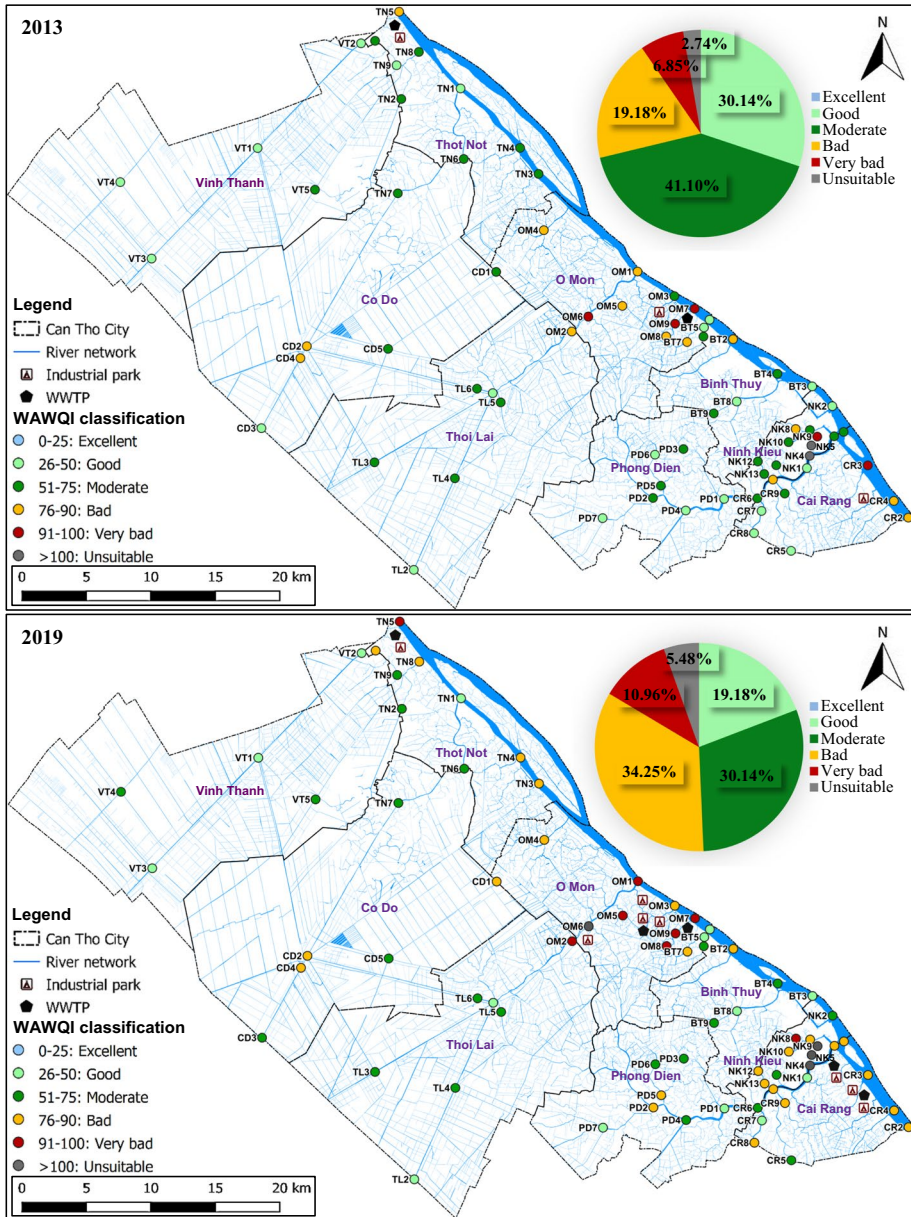
Fig. 10 Temporal variation and statistical classifications of SWQ in 2013 and 2019

along the highly polluted Tham Tuong canal) had intensively polluted and unusable water. Notably, the remaining sites (over 71%) showed good or moderate SWQ status.

In 2019, the total proportion of sites classified with bad and very bad SWQ conditions was higher than 45%, predominantly located in urban zones along the Hau River. Notably, the number of sites with unsuitable status was double that at 5.48% compared
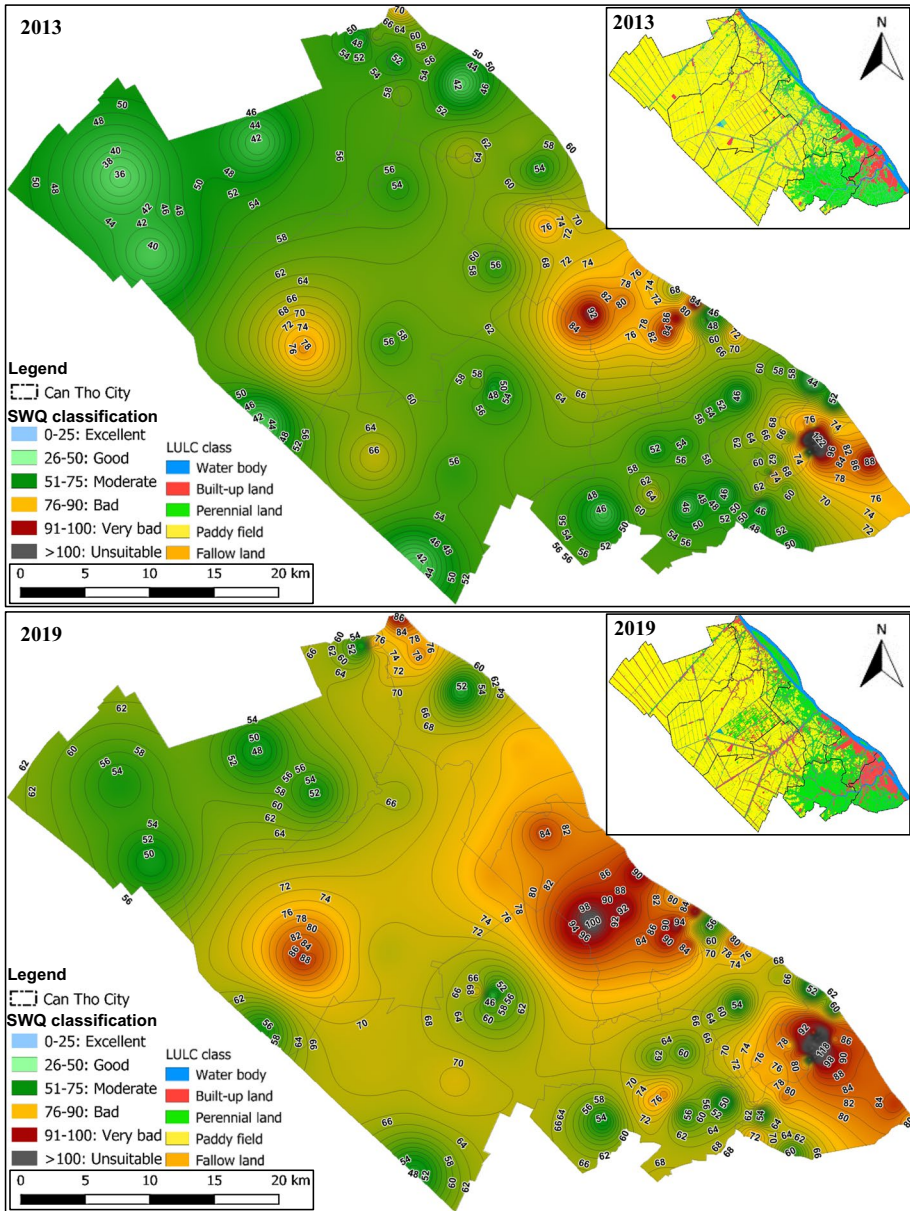
Fig. 11 Spatiotemporal distributions of WAWQI values and corresponding land-use maps in 2013 and 2019

to 2013. This shift was mainly due to the considerable growth of industrial parks (five new large parks including O Mon, Northern O Mon, Tra Noc 2, and Hung Phu 2A and 2B) and WWTPs in urban districts along the Hau River (Fig. 11)) during the period of 2014–2018 (MOC 2011; VNGO 2015; CTCPC 2019b; MOPI 2020). Only 49.32%

of the total water samples were suitable for daily consumption, mostly from Thoi Lai, Phong Dien, and Vinh Thanh districts. The unacceptable SWQ at CD1, CD2, CD4, PD2, and PD5 was dominant, as large rural residential areas and local food production facilities surround these sites.

As mentioned above, spatiotemporal distributions of WAWQI values shown in contour maps (Fig. 11) were validated using 2013 and 2019 land-use maps. As validated, the results obtained from WAWQI calculation were highly consistent with the classification of spatial SWQ clusters and the city's land-use characteristics. The majority of polluted sites with high WAWQI values (from 75 to over 100) in both 2013 and 2019 belonged to Cluster 1, which is dominated by residential, commercial, and industrial lands along the Hau River and canals. Moderate SWQ status with tolerable index values ranging from 50 to 75 was recorded at most of the monitoring locations in Cluster 3, while SWQ at all sites of Cluster 2 (mainly large areas of agricultural land in rural districts) was generally acceptable for human consumption, as demonstrated by low WAWQI values ranging from 35 to 50.

4.3.4 Temporal variation in SWQ

Overall, compared to 2013, SWQ in 2019 indicated degradation, particularly in urban districts and along major rivers due to intensive industrial urbanization beginning in 2014. For clarity, the annual levels of the four most spatially discriminant SWQ parameters are analyzed and discussed (Fig. 12); and annual SWQ-related and land-use reports collected from the city's departments were thoroughly referenced to validate and better support this analysis and discussion. A negative correlation was found between COD and DO levels during the study period. Increasing trends occurred in COD levels, particularly from 2015 to 2019, and these trends were attributed to industrial urbanization beginning at the end of 2014. Notably, although a series of canal rehabilitation and industrial WWTP projects were conducted from mid-2013 to the end of 2016 in pollution hotspots (i.e., Tham Tuong, Cai Khe, Ngong, Sang Trang, and Cay Me canals), these projects were efficient only temporarily and locally around selected sites. In addition, 100-year droughts in 2015 and 2016 (Guo et al. 2017) contributed to increasing COD levels over this 4-year period.

A very slight increase in 2017, followed by a decrease in 2018, was observed in the COD levels of Clusters 1 and 3. The success of recent projects (i.e., the first domestic and new industrial WWTPs in urban districts) in early 2018 was considered the key driver of this decline. However, the expansion of human settlement in rural areas caused the COD loading of Cluster 2 to increase slightly. Since 2018, inadequate wastewater management infrastructure and the rapid emergence of new trading centers, residential areas, and local markets have occurred (DONRE 2019, 2020a; MONRE 2020), driving increased COD pollution for all clusters in 2019. NO_3^- and PO_4^{3-} levels showed downward trends during the study period, driven by the shrinking of agricultural land area in 2013–2016 and severe droughts in 2015–2016. The expansion of urbanized and industrialized areas was the main contributor to the reduction in agricultural land, thereby causing decreases in NO_3^- and PO_4^{3-} levels.

4.4 Correlation between SWQ and land-use variation

Using RA, the correlated linkages between annual changes in WAWQI values and land-use areas were determined (Fig. 14) to provide clear quantitative evidence of the key
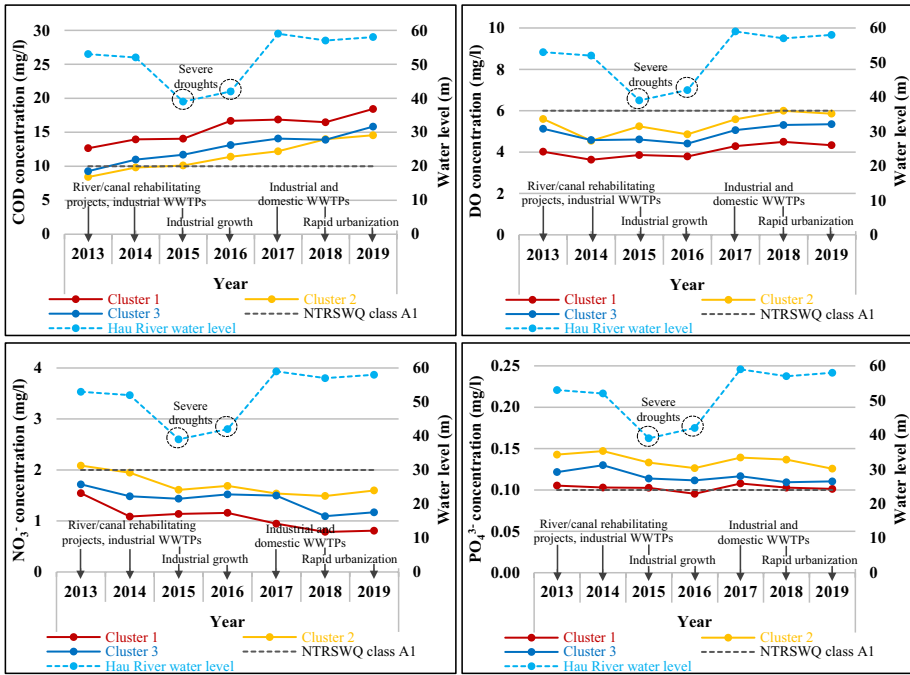
Fig. 12 Variation in annual COD, DO, NO_3^-, and PO_4^{3-} levels in each cluster during the study period

drivers of SWQ degradation in Can Tho City. The collected land-use dataset indicated the dominance of agricultural land, followed by built-up, water bodies, and fallow land (Fig. 13). The average annual WAWQI values and areas of various land-use classes are summarized in Table 10 of Appendix 2 (CTCSO 2020a, b, c; DONRE 2020b).

Upward trends were observed in the areas of annual built-up land and water bodies. Built-up land covered 182.21 km² in 2013, which soared to 217.68 km² in 2019, while water bodies experienced an increase from 75.13 to 86.44 km². While rapid industrialization (during 2014–2016) and urbanization (2018–2019) led to the expansion of the built-up land area, rehabilitation of a series of canals and lakes (2013–2015) resulted in the growth
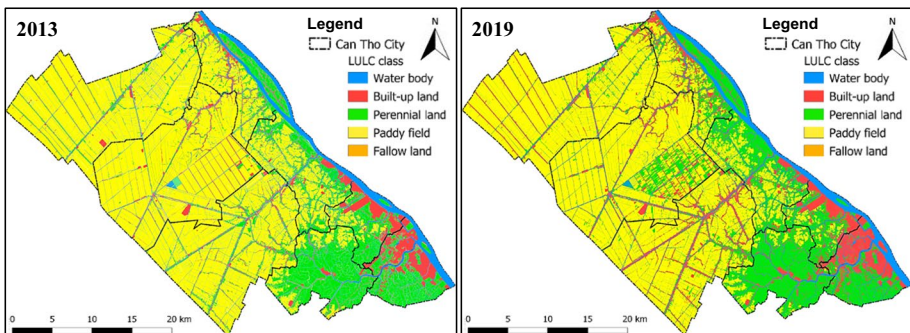
Fig. 13 Land-use maps of the study area in 2013 and 2019
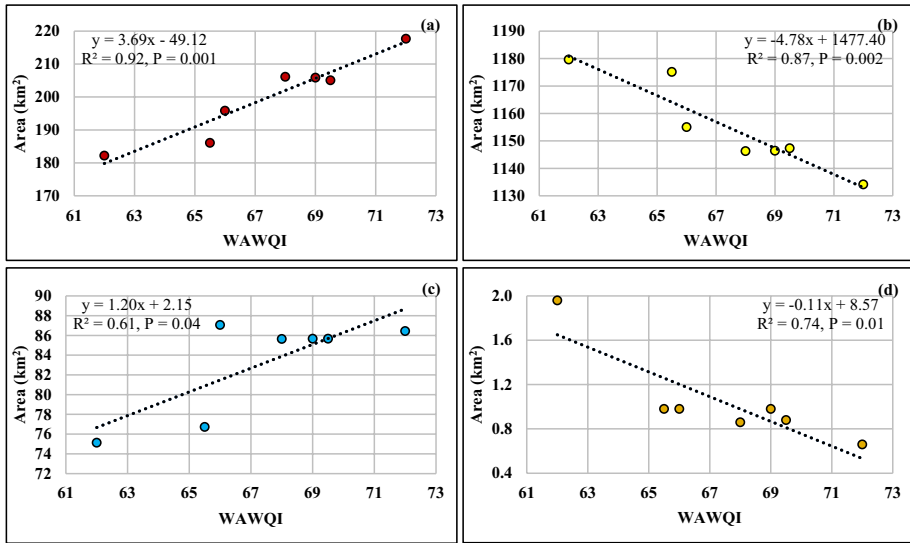
Fig. 14 Correlated relationships between average annual WAWQI values and areas of built-up land **a**, agricultural land **b**, water bodies **c**, and fallow land **d** during the study period

of water bodies (CTCPC 2016; CTODA 2016a, b). The opposite trends were observed for agricultural and fallow land, which decreased from 1,179.66 to 1,134.18 km^2 and from 1.96 to 0.66 km^2, respectively. Notably, paddy field area showed the largest decrease from 2013 to 2019, from 941.54 to 867.72 km^2, mainly due to urbanization of rural areas and severe droughts (2015–2016) (Sebastian et al. 2016; CTCSO 2020b). Mean annual WAWQI values showed an increasing trend from 2013 to 2019, except for a slight drop in 2018, attributable to the introduction of new domestic and industrial WWTPs in early 2018.

As illustrated in Fig. 14a, a strong positive correlation ($R^2 = 0.92$ and $P = 0.001$) between WAWQI values and built-up land area was observed, revealing that as the city became increasingly urbanized and industrialized, its SWQ progressively worsened. By contrast, Fig. 14a and d shows strong and moderate negative correlations between WAWQI values and agricultural and fallow land areas. These correlations indicate that as the areas of agricultural and fallow lands decreased, a corresponding increase in WAWQI was observed, indicating declining SWQ. From 2013 to 2019, large areas of agricultural (45.48 km^2) and fallow (1.3 km^2) lands along major rivers and canals were cleared to allow for industrial urbanization processes, which were noted above as key drivers of increasingly serious pollution and declining SWQ in the city.

The variation in the area of water bodies was positively correlated with changes in WAWQI values (Fig. 14c), indicating that SWQ of the city was increasingly polluted despite an increase in water area between 2013 and 2019. However, the strength of this correlation was only moderate, with $R^2 = 0.61$ and $P = 0.04$. Although the expansion of water surface area mainly from 2013 (75.13 km^2) to 2015 (87.06 km^2) due to canal rehabilitation projects was temporarily and locally effective at improving SWQ in heavily polluted hotspots, particularly in 2017 and 2018, pollution of river water remains a concerning issue in many zones throughout the study area. It is noteworthy that these findings and

interpretation are also consistent with local SWQ-related and land-use reports mentioned above (CTCPC 2016, 2019b; DONRE 2020a). In general, our findings confirm that SWQ in the city is controlled by multiple driving forces, among which urbanization and industrialization are the main factors.

5 Proposed countermeasures

5.1 Specific measures

The analyzed results indicated the city's SWQ, especially in urban districts, polluted by diverse pollution sources, was not suitable for human consumption, with upward trends in both annual WAWQIs and concentrations of most SWQ parameters over the research period. These concentrations were constantly higher than the permissible limits of Class A1 prescribed as a key target in the city's master plans. Therefore, some specific solutions are proposed as follows.

Firstly, the identification of water resources with poor quality in the city should be entailed with the estimation of specific pollutant loads discharged into the city's water bodies from various possible sources. This provides the Can Tho policy-makers guidance to design optimal solutions toward achieving the SWQ Class A1 in particular and improving IWRM in general. A reliable science-based tool (well adopted in different locations around the world) (Zaidi and deMonsabert 2015; Vallero 2016; Camacho et al. 2018; Sang-Cheol and Jihyung 2018; MDEP 2022), the total maximum daily load (TMDL) approach is applied. The TMDL will calculate the highest load of each pollutant (discharged from either point or non-point pollution sources in the city) that a water body can assimilate and still meet the city's SWQ of Class A1 (Camacho et al. 2018; Sang-Cheol and Jihyung 2018). Noticeably, seasonal variation in pollutant loads in the city can also be calculated (AMTC 2017; MDEP 2022). According to Vallero (2016), AMTC (2017), and MDEP (2022), five steps should be implemented in the TMDL process in the city: (1) Selection of pollutants (i.e., eight polluted SWQ parameters (Table 3 of Appendix 2)) in need of consideration, (2) Estimation of the water body assimilative capacity (i.e., permissible limits set by Class A1 (Table 3 of Appendix 2)), (3) Estimation of the each parameter's loading from all pollution sources to the water body, (4) Analysis of the each parameter's current load and determination of needed reductions to meet permissible limits of Class A1, and (5) Allocation, including a margin of safety, of the allowable load among the different pollution sources in a manner that SWQ of Class A1 will be achieved. TMDL estimation's inputs include land use, SWQ parameters, modeling techniques, calculation methods, and other relevant evidence (i.e., outcomes obtained from this study) (AMTC 2017). In the city, five urban districts along the Hau River should be prioritized to be a pilot for TMDL estimation, since their SWQ recorded at many sampling sites of Cluster 1 has shown the most extreme degradation due to cumulative effects from more drivers (population growth, industrial urbanization, upstream flows, climate change, and even policy changes) than that in other areas of the city. Moreover, Can Tho City is characterized by poor stakeholder engagement in its water governance (Trung et al. 2019; Duc et al. 2021), so active public involvement is strongly advisable. Locals are typically more aware of their water usage and

watershed than state agencies; hence, their involvement will be valuable for the successful TMDL implementation in the city. Specifically, their activities include providing datasets and information to the state agencies, checking and giving feedback on the impaired water list, reviewing and giving comments on draft reports, and assisting the general development of TMDL.

Secondly, based on TMDL generated results, advanced hydrological models should be applied to predict the fate and transport of different pollutants and identify technological measures for achieving SWQ of Class A1. Based on the city's SWQ characteristics, the study suggests some advanced models comprising SWMM (applied for assessing SWQ pollution caused by flood and urban drainage in four urban and flooded districts Ninh Kieu, Cai Rang, Binh Thuy, and O Mon), VENSIM (for identifying effects of population, water demand, and wastewater growth on SWQ in the whole city), WEAP (for evaluating effectiveness of the current and planned WWTPs along the Hau River, hence proposing more cutting-edge treatment technology and optimal treatment capacity for these WWTPs), and an integrated hydrological model SWAT-MODFLOW (for examining agricultural impacts on both groundwater and SWQ in the city's intensively agricultural districts Vinh Thanh, Co Do, and Thoi Lai where groundwater overexploitation is very prominent). Moreover, due to the highly accurate capability to capture the spatiotemporal variations in the hydro-meteorological variables and represent the dynamics of the hydrologic processes in large water bodies like Can Tho City's river network (Kumar and Reshmidevi 2013; García et al. 2016; Wang and Xie 2018; GWSP 2019), remote sensing (RS) techniques with the support of a geographic information system (GIS) are strongly proposed as a practical tool to improve the SWQ in the city. According to Kumar and Reshmidevi (2013) and INBO and IOwater (2018), these techniques have significantly changed the SWQ assessment and management methodologies by providing complementary datasets needed to confront key water-related challenges. Specifically, all eight polluted SWQ parameters in the city can be assessed and estimated by near real-time monitoring and measuring variations in the water's optical properties caused by the contaminants' presence (Kumar and Reshmidevi 2013). Furthermore, the repercussions of management policies, land-use practices, point and non-point source pollution, upstream flow, and climate change (i.e., flood and drought events) that are characterized as threats to the city's SWQ can be visualized and assessed by RS and GIS application (Kumar and Reshmidevi 2013; INBO and IOwater 2018; Wang and Xie 2018; GWSP 2019). Especially, integrated use of these state–of–the–art models, techniques, and approaches for estimating the dynamics of SWQ evolution will be significantly useful in supporting the city to achieve its target SWQ of Class A1.

Thirdly, technical approaches are still prominent practice in Can Tho City's SWQ management with an emphasis on structural solutions such as canal/lake rehabilitation and WWTP application (CTCPC 2019b; Trung et al. 2019; CTCSO 2020a; Duc et al. 2021). These approaches may work in times but expose unintended consequences in the long run. Thus, these should be combined with socio-hydrology, an integrated approach to manage and allocate water resources by involving all actors and stakeholders, and considering how water resources link different sectors of society (Di Baldassarre et al. 2015, 2019; Pande and Savenije 2016; Kumar et al. 2020b). It can develop a generalizable understanding of the interaction and feedback between technical, natural, and social processes (Di Baldassarre et al. 2019; Kumar et al. 2020b), effectively improving SWQ management practice for the longer term. Therefore, this combination of an

advanced socio-hydrology approach and the implementation of short-term technological solutions (i.e., the application of models, techniques, approaches, and WWTPs) will not only assist the city to comprehensively address SWQ-related problems in achieving ambient SWQ of Class A1 but also maintain it in the distant future. Additionally, stakeholders should be strongly involved in making and implementing other water policies, strategies, and master plans in the city thanks to the application of the science-policy interface and participatory approaches mentioned in the previous part.

5.2 General measures

Industrial urbanization is considered an inevitable environmental change in developing cities such as Can Tho. According to the current and future master plans, the city's government is continuously investing in industrial urbanization projects to achieve comprehensive development goals by 2030. These plans suggest structural measures (particularly building of WWTPs) as prioritized environmental projects to improve future SWQ (CTCPC 2019a; Duc et al. 2021). However, in accordance with previous research (Duc et al. 2021), the present study indicated that although the development of WWPTs was effective at mitigating SWQ pollution, it is not feasible as a standalone solution for improving SWQ to reach the desirable Class A1 rating in the future while undergoing rapid industrial urbanization. Moreover, the implementation of structural measures may have negative repercussions such as financial burden, land appropriation in urbanized centers, and disturbance to local ecosystems. Therefore, a hybrid solution should be considered for the management of domestic and industrial wastewater (Duc et al. 2021), wherein WWTP construction is combined with other options, particularly green infrastructure or nature-based solutions such as constructed wetlands, rain gardens, vegetated swales and median strips, bioswales, porous pavement, and enhancement of riparian buffers and floodplains; such a hybrid approach can be more environmentally sustainable and cost-effective than other methods (Lee et al. 2016; Esmail and Suleiman 2020; Duc et al. 2021). Nevertheless, technical, economic, and socio-ecological evaluation of green infrastructure methods is beyond the scope of this study and is recommended as a subject for future research.

In addition, as industrial urbanization was considered the main driver of future SWQ pollution in the city, strict but technically feasible policies and regulations should be established to restrict effluent concentration and the volume of wastewater discharged from the city's households industrial plants into water bodies. These policies and regulations should focus on solutions ranging from the promotion of decentralized WWTPs, adoption of industrial symbiosis and sustainability-oriented hybrid solutions, and application of green technologies (e.g., absorbent gardens, green rooftops, roadside plantings, and storm water tree trenches) for wastewater treatment and sustainable resource management (Lee et al. 2016; Esmail and Suleiman 2020). Furthermore, the city's government should consider the concepts of the circular economy, sustainable, cleaner production, and Industry 4.0 standards in the future (Wyes 2018). In particular, circular economy practices are considered one of the most important methods for increasing sustainable manufacturing (Gupta et al. 2021; Shayganmehr et al. 2021; Satyro et al. 2021), followed by the practices of cleaner production and Industry 4.0 standards (Satyro et al. 2023). Supply chain traceability and

information, reuse and recycling infrastructure, and promotion of a natural and clean environment are potential practices through which manufacturing organizations and cities can enhance their sustainability (Wyes 2018; Gupta et al. 2021; Satyro et al. 2021, 2023). However, a robust scientific understanding of their economic and environmental benefits should be achieved before prioritizing and practicing these concepts at the local level.

6 Conclusions and future work

Using a multivariate analytical approach, this study successfully obtained an overall picture of spatiotemporal variation in SWQ in Can Tho City during the period of 2013–2019. In this period, BOD, COD, DO, TC, turbidity, TSS, and PO_4^{3-} levels exceeded the permissible values for Class A1 and the water was unacceptable for residential use. Based on CA, the city's SWQ and river network can be divided into two seasonal clusters (dry and wet seasons) and three spatial zones (urban-industrial, agricultural, and mixed urban–rural zones), and PCA successfully identified key SWQ pollution sources for these groups, including point (industrial and household activities), non-point (surface runoff from agricultural fields), and mixed sources (industrial, household and agricultural runoff). According to DA, COD, DO, turbidity, PO_4^{3-}, and NO_3^- were the most important SWQ parameters for discriminating between spatial zones and seasonal clusters. The city's river water was markedly more polluted during the dry season, with higher COD, BOD, and TC concentrations, while the opposite trend was found in the wet season, with higher levels of turbidity, TSS, PO_4^{3-}, and NO_3^-. Spatially, SWQ status was bad or unsuitable for domestic usage in most urban districts, while rural districts generally showed moderate or good levels, indicating usable water. Temporally, SWQ was clearly worse in 2019 than in 2013, mainly due to increased built-up land area and severe droughts. The greatest negative changes in SWQ were observed in five urban districts along the Hau River and its major diversions.

In addition to the construction of WWTPs, applying the robust models, tools, and approaches proposed in this study to assess, analyze, and predict SWQ can support revision of the city's policies and master plans toward achieving the target SWQ of Class A1 as well as SDGs. Besides, to develop Can Tho into a green, sustainable, and proactive river city, as planned in its 2030 resilience strategy, the study also suggests cleaner solutions for the city, comprising sustainability-oriented hybrid, green infrastructure, clean technological, and nature-based solutions to improve the city's IWRM in a timely manner. However, to successfully implement this 2030 strategy, consensus and close collaboration among key stakeholders across all levels is strongly promoted by applying diverse participatory approaches to the implementation process of water policies, master plans, research, and solutions in the city.

Appendix 1

See Figs. 15, 16 and 17.
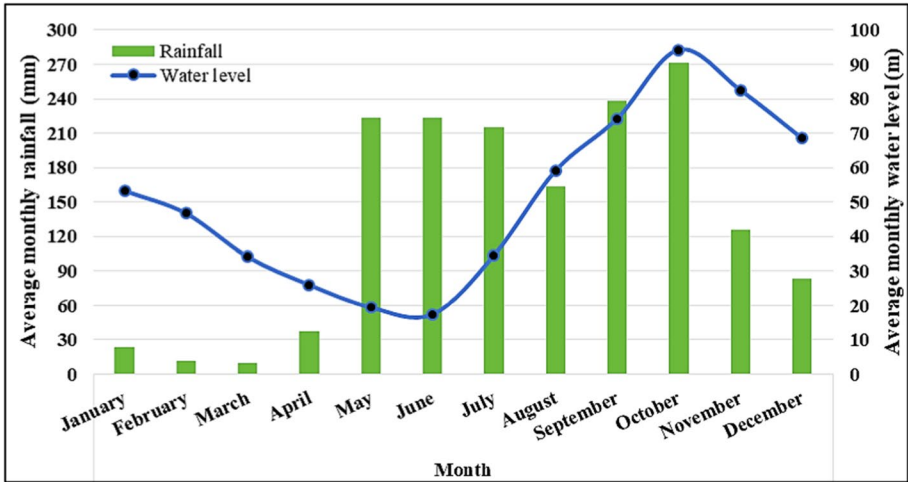
Fig. 15 The average monthly rainfall and Hau River water level in the city for the period of 2013–2019
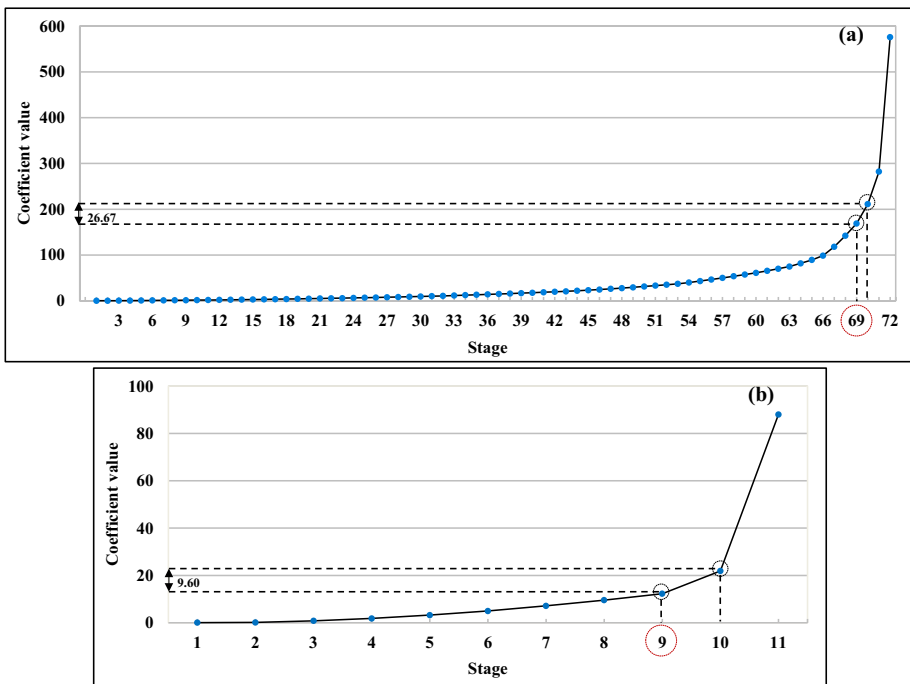
Fig. 16 The change of agglomeration coefficient values during the stages of the spatial and seasonal CA processes. The clustering was ideally stopped after the 69th (for spatial CA) and 9th (for seasonal CA) stages that showed the first noticeable increase in coefficient values of 26.67 and 9.60, respectively. Therefore, the optimal number of spatial and seasonal clusters was three (72nd stage–69th stage = 3) and two (11th stage–9th stage = 2), respectively
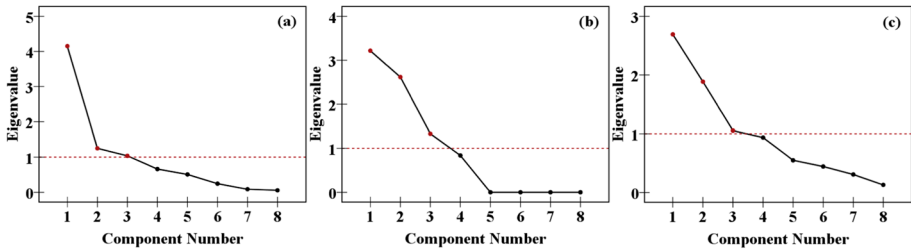
Fig. 17 The scree plots showing eigenvalues (> 1) for Clusters 1 (**a**), 2 (**b**), and 3 (**c**)

Appendix 2

See Tables 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12.

Table 2 The area and population characteristics in 2019, and the SWQ monitoring network of nine districts in the study area

No.	Districts		Area (km^2)	Population (people)	Rate of the total pop. (%)	Rate of urban/rural residence (%)	SWQ monitoring network	
	Name	Type					Number of sampling sites	Code
1	Thot Not	Urban	121	155,360	12.58	65.75	10	TN1-TN10
2	O Mon		132	128,677	10.42		9	OM1-OM9
3	Binh Thuy		71	142,164	11.51		9	BT1-BT9
4	Ninh Kieu		29	280,494	22.71		13	NK1-NK13
5	Cai Rang		67	105,393	8.53		9	CR1-CR9
6	Vinh Thanh	Rural	307	98,399	7.97	34.25	5	VT1-VT5
7	Co Do		320	116,576	9.44		5	CD1-CD5
8	Thoi Lai		267	109,684	8.88		6	TL1-TL6
9	Phong Dien		125	98,424	7.96		7	PD1-PD7
Total	**9 (urban: 5, rural: 4)**		**1,439**	**1,235,171**	**100**	**100**	**73**	**73**

Table 3 The SWQ parameters monitored and their analytical methods used for the period of 2013–2019 in the city's river network

No.	Parameters (abbreviations)	Units	Analytical methods
1	Potential of hydrogen (pH)	–	Potentiometric determination by glass electrode
2	Biochemical oxygen demand (BOD_5 (20 °C))	mg/l	Determination by a closed system with respirometric BOD tests
3	Chemical oxygen demand (COD)	mg/l	Colorimetry using potassium dichromate digestion solution
4	Dissolved oxygen (DO)	mg/l	Colorimetry using indigo carmine method with hydrazine and sodium hydrosulfite
5	Total coliform (TC)	CFU/100 ml	Membrane filtration
6	Total suspended solids (TSS)	mg/l	Photometric determination calibrated by gravimetric method (dried at 103–105 °C)
7	Turbidity	NTU	20-cm-diameter Secchi depth measurement
8	Fluoride (F^-)	mg/l	Ion chromatography using suppressed conductivity detection
9	Nitrite (NO_2^-)	mg/l	Ion chromatography using suppressed conductivity detection
10	Nitrate (NO_3^-)	mg/l	Ion chromatography using suppressed conductivity detection
11	Phosphate (PO_4^{3-})	mg/l	Ion chromatography with ammonium molybdate and ascorbic acid
12	Ammonium (NH_4^+)	mg/l	Spectrophotometry using indophenol method with phenol and hypochlorite
13	Chromium (Cr_6^+)	mg/l	Spectrophotometry using graphite furnace atomic absorption
14	Iron (Fe)	mg/l	Spectrophotometry using flame atomic absorption

CFU colony-forming units; *NTU* nephelometric turbidity units

Table 4 Water quality classification (with corresponding colors) for human consumption using the WAWQI values as recommended by the NGCWQI and WHO guidelines

WAWQI ranges	Water quality classification
0 – 25	Excellent
26 – 50	Good
51 – 75	Moderate
76 – 90	Bad
91 – 100	Very bad
Above 100	Unsuitable for drinking

Table 5 Statistically seasonal and whole year summary of SWQ parameters' mean concentrations in the study area for the period of 2013–2019

No.	Parameters	Units	Dry season				Wet season				Whole year				Permissible limits set by the NTRSWQ			
															A		B	
			Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	A1	A2	B1	B2
1	pH	–	7.13	7.34	**7.24**	0.04	6.99	7.47	**7.23**	0.06	7.10	7.38	**7.23**	0.04	6–8.5	6–8.5	5.5–9	5.5–9
2	BOD_5 (20 °C)	mg/l	7.87	18.94	**10.40**	1.79	4.66	15.40	**7.14**	1.60	5.85	18.38	**8.60**	2.09	4	6	15	25
3	COD	mg/l	14.85	30.16	**18.61**	2.59	5.78	22.11	**10.16**	2.36	11.32	25.27	**14.12**	2.31	10	15	30	50
4	DO	mg/l	2.23	3.64	**3.21**	0.27	4.23	5.92	**5.47**	0.29	3.27	5.53	**4.50**	0.52	≥6	≥5	≥4	≥2
5	TC	CFU/100 ml	2,581	8,432	**3,960**	809	1,047	5,554	**2,501**	875	1,579	8,005	**3,192**	935	2,500	5,000	7,500	10,000
6	Turbidity	NTU	20.19	48.58	**30.89**	6.75	39.52	70.07	**56.20**	6.15	25.85	60.17	**39.22**	7.82	5	5	–	–
7	TSS	mg/l	24.96	76.80	**38.11**	8.12	50.61	83.70	**60.87**	6.53	37.21	69.99	**50.40**	8.40	20	30	50	100
8	F^-	mg/l	0.04	0.59	**0.14**	0.08	0.02	0.25	**0.10**	0.04	0.04	0.34	**0.12**	0.05	1	1.5	1.5	2
9	NO_2^-	mg/l	0.01	0.04	**0.02**	0.01	0.01	0.07	**0.03**	0.02	0.02	0.04	**0.03**	0.005	0.05	0.05	0.05	0.05
10	NO_3^-	mg/l	0.73	1.57	**1.05**	0.20	1.04	2.02	**1.41**	0.23	0.92	1.83	**1.25**	0.23	2	5	10	15
11	PO_4^{3-}	mg/l	0.028	0.371	**0.086**	0.056	0.025	0.619	**0.130**	0.089	0.06	0.15	**0.11**	0.02	0.1	0.2	0.3	0.5
12	NH_4^+	mg/l	0.10	0.37	**0.20**	0.06	0.10	0.68	**0.23**	0.08	0.11	0.67	**0.22**	0.10	0.3	0.3	0.9	0.9
13	Cr_6^+	mg/l	0.0030	0.0131	**0.0062**	0.0021	0.0001	0.0170	**0.0039**	0.0031	0.0014	0.0115	**0.0050**	0.0020	0.01	0.02	0.04	0.05
14	Fe	mg/l	0.21	0.81	**0.34**	0.09	0.17	0.56	**0.29**	0.07	0.20	0.63	**0.32**	0.07	0.5	1	1.5	2

Min. Minimum; *Max.* Maximum; *SD* Standard deviation; *A1* For residential use and other purposes; *A2* For residential use with proper treatment, preservation of aquatic plants or other purposes; *B1* For irrigation or other purposes requiring the similar quality of water or other purposes; and B2—For water transport and other purposes requiring low quality

Table 6 The F and Wilks' lambda values calculated for testing in the entering and removing models of DA to explore the most spatial and seasonal discriminant SWQ variables

Steps	Variables	F to Enter/Remove	Wilks' lambda	Steps	Variables	F to Enter/Remove	Wilks' lambda
Spatial variables							
Entering model							
0	BOD_5 (20 °C)	49.077	0.416	2	BOD (20 °C)	7.829	0.033
	COD	29.577	0.542		**COD**	**13.428**	**0.029**
	DO	**187.722**	**0.157**		TC	0.228	0.040
	TC	24.403	0.589		Turbidity	0.116	0.041
	Turbidity	22.020	0.614		TSS	0.653	0.040
	TSS	54.536	0.391		PO_4^{3-}	4.704	0.036
	NO_3^-	184.494	0.159	3	BOD (20 °C)	0.849	0.028
	PO_4^{3-}	13.969	0.715		TC	2.536	0.027
1	BOD (20 °C)	4.179	0.140		Turbidity	0.117	0.029
	COD	8.881	0.125		TSS	0.918	0.028
	TC	1.459	0.151		PO_4^{3-}	**5.190**	**0.025**
	Turbidity	0.211	0.156	4	BOD (20 °C)	0.739	0.025
	TSS	0.775	0.154		TC	2.110	0.024
	NO_3^-	**98.892**	**0.041**		Turbidity	0.414	0.025
	PO_4^{3-}	21.060	0.098		TSS	0.549	0.025
Removing model							
1	DO	187.722	–	4	DO	122.119	0.117
2	DO	100.854	0.159		NO_3^-	70.739	0.078
	NO_3^-	98.892	0.157		COD	13.911	0.036
3	DO	105.444	0.119		PO_4^{3-}	5.190	0.029
	NO_3^-	111.836	0.125				
	COD	13.428	0.041				
Seasonal variables							

Table 6 (continued)

Steps	Variables	F to Enter/Remove	Wilks' lambda	Steps	Variables	F to Enter/Remove	Wilks' lambda
Entering model							
0	BOD_5 (20 °C)	56.991	0.149	2	BOD (20 °C)	0.531	0.004
	COD	649.239	0.015		COD	0.095	0.004
	DO	**1244.243**	**0.008**		TC	0.107	0.004
	TC	20.198	0.331		TSS	0.011	0.004
	Turbidity	24.448	0.290		NO_3^-	0.082	0.004
	TSS	215.741	0.044		**PO_4^{3-}**	**4.492**	**0.003**
	NO_3^-	29.523	0.253	3	BOD (20 °C)	0.046	0.002
	PO_4^{3-}	1.131	0.898		**COD**	**4.255**	**0.002**
1	BOD (20 °C)	0.926	0.007		TC	0.039	0.002
	COD	2.136	0.006		TSS	1.440	0.002
	TC	1.315	0.007		NO_3^-	1.462	0.002
	Turbidity	**9.347**	**0.004**	4	BOD (20 °C)	1.809	0.001
	TSS	0.672	0.007		TC	0.030	0.002
	NO_3^-	6.505	0.005		TSS	1.139	0.001
	PO_4^{3-}	1.428	0.007		NO_3^-	0.045	0.002
Removing model							
1	DO	1244.243	–	4	DO	17.346	0.005
2	DO	659.013	0.290		Turbidity	6.365	0.003
	Turbidity	9.347	0.008		PO_4^{3-}	10.368	0.004
3	DO	839.356	0.265		COD	4.255	0.003
	Turbidity	13.979	0.007				
	PO_4^{3-}	4.492	0.004				

Table 7 The most discriminant variables of the spatial and seasonal SWQ variation in the study area

Steps	Variables entered/ removed [a][b]	Wilks' lambda	Exact F	P value
Spatial variables				
1	DO	0.157[*]	187.722	0.000
2	NO_3^-	0.041[*]	136.628	0.000
3	COD	0.029[*]	110.125	0.000
4	PO_4^{3-}	0.025[*]	88.706	0.000
Seasonal variables				
1	DO	0.008[*]	1244.243	0.000
2	Turbidity	0.004[*]	1146.079	0.000
3	PO_4^{3-}	0.003[*]	1062.018	0.000
4	COD	0.002[*]	1121.684	0.000

Significance levels are denoted as follows: [*]$P < 0.001$. A Wilks' lambda value of 1 indicates that the means of SWQ parameters between clusters were not different, and a value of 0 shows that the means of SWQ parameters between clusters were totally different

[a]Minimum partial F to Enter is 3.84; and b. Maximum partial F to Remove is 2.71

Table 8 The average concentration of critical SWQ parameters for the period of 2013–2019 according to spatially different clusters

No.	Parameters	Units	Mean concentration		
			Cluster 1	Cluster 2	Cluster 3
1	BOD_5 (20 °C)	mg/l	10.10	6.13	7.10
2	TC	CFU/100 ml	3,740	2,000	2,697
3	Turbidity	NTU	43.65	29.47	35.22
4	TSS	mg/l	56.49	38.56	44.67

Table 9 The multivariate FA scores (> 0.5) of eight experimental variables according to spatial clusters

Parameters	Cluster 1			Cluster 2			Cluster 3		
	F1	F2	F3	F1	F2	F3	F1	F2	F3
BOD_5 (20 °C)	0.951					0.973	−0.753		
COD	0.927			−0.533			0.585		
DO	−0.751				0.892			−0.802	
TC			0.877			−0.816	0.774		
Turbidity			0.806	0.959			0.883		
TSS			0.515		−0.977				0.730
NO_3^-		0.712		0.898				0.871	
PO_4^{3-}		0.824		0.988					0.801
Eigenvalue	4.150	1.250	1.036	3.216	2.615	1.331	2.692	1.884	1.053
Percentage of variance (%)	51.88	15.63	12.95	40.20	32.69	16.63	33.65	23.55	13.17
Cumulative percentage (%)	51.88	67.51	80.46	40.20	72.89	89.52	33.65	57.20	70.37

Table 10 The WAWQI values calculated for SWQ classification (with corresponding colors) at 73 sampling sites throughout the study area in the years 2013 and 2019

No.	Codes	Years		No.	Codes	Years		No.	Codes	Years	
		2013	2019			2013	2019			2013	2019
1	TN1	37	45	26	BT7	76	86	51	VT1	40	47
2	TN2	59	68	27	BT8	40	47	52	VT2	47	48
3	TN3	52	76	28	BT9	52	63	53	VT3	38	48
4	TN4	62	76	29	NK1	36	44	54	VT4	35	52
5	TN5	76	92	30	NK2	40	51	55	VT5	55	51
6	TN6	65	72	31	NK3	73	82	56	CD1	54	78
7	TN7	53	65	32	NK4	126	122	57	CD2	76	82
8	TN8	59	79	33	NK5	153	128	58	CD3	38	51
9	TN9	49	73	34	NK6	74	84	59	CD4	79	89
10	TN10	59	77	35	NK7	72	85	60	CD5	55	68
11	OM1	78	92	36	NK8	76	92	61	TL1	47	44
12	OM2	85	91	37	NK9	91	151	62	TL2	37	47
13	OM3	64	78	38	NK10	61	76	63	TL3	68	69
14	OM4	77	85	39	NK11	59	74	64	TL4	54	71
15	OM5	81	94	40	NK12	59	77	65	TL5	53	59
16	OM6	96	107	41	NK13	57	77	66	TL6	59	69
17	OM7	96	93	42	CR1	80	77	67	PD1	41	41
18	OM8	90	91	43	CR2	76	79	68	PD2	67	77
19	OM9	91	95	44	CR3	92	83	69	PD3	52	56
20	BT1	37	46	45	CR4	76	86	70	PD4	40	52
21	BT2	76	84	46	CR5	45	53	71	PD5	58	79
22	BT3	30	34	47	CR6	63	74	72	PD6	49	59
23	BT4	57	66	48	CR7	41	47	73	PD7	41	49
24	BT5	43	46	49	CR8	44	77	**Min/Max**		**30/164**	**34/151**
25	BT6	57	61	50	CR9	59	81	**Mean ± SD**		**62 ± 23**	**72 ± 21**

Table 11 The calculated annual WAWQI values at 73 sampling sites throughout the study area during the research period of 2013–2019

No.	Codes	2013	2014	2015	2016	2017	2018	2019	No	Codes	2013	2014	2015	2016	2017	2018	2019
1	TN1	37	89	80	58	50	69	45	38	NK10	61	173	78	105	107	96	76
2	TN2	59	82	74	92	76	68	68	39	NK11	59	63	76	94	69	74	74
3	TN3	52	46	69	50	98	100	76	40	NK12	59	73	52	79	51	68	77
4	TN4	62	52	67	76	76	79	76	41	NK13	57	54	61	102	40	59	77
5	TN5	76	60	49	99	77	61	92	42	CR1	80	72	54	56	77	80	77
6	TN6	65	90	54	54	51	53	72	43	CR2	76	54	77	73	75	82	79
7	TN7	53	46	66	54	51	45	65	44	CR3	92	51	76	106	76	68	83
8	TN8	59	54	29	83	85	80	79	45	CR4	76	51	64	72	51	53	86
9	TN9	49	52	34	35	87	80	73	46	CR5	45	31	72	79	60	50	53
10	TN10	59	39	45	77	71	76	77	47	CR6	63	35	41	47	73	79	74
11	OM1	78	78	75	91	94	98	92	48	CR7	41	46	39	54	89	80	47
12	OM2	85	76	101	106	92	98	91	49	CR8	44	41	71	52	85	81	77
13	OM3	64	42	56	69	54	62	78	50	CR9	59	70	40	39	88	82	81
14	OM4	77	58	61	53	56	80	85	51	VT1	40	32	60	54	74	64	47
15	OM5	81	46	60	68	95	82	94	52	VT2	47	74	42	47	72	58	48
16	OM6	96	147	81	139	107	98	107	53	VT3	38	32	55	28	49	55	48
17	OM7	96	53	75	50	73	90	93	54	VT4	35	30	42	32	33	36	52
18	OM8	90	88	73	54	64	75	91	55	VT5	55	49	30	43	49	33	51
19	OM9	91	141	62	60	79	72	95	56	CD1	54	130	52	64	51	49	78
20	BT1	37	61	53	59	60	58	46	57	CD2	76	46	75	84	88	68	82
21	BT2	76	52	95	74	76	70	84	58	CD3	38	44	75	77	47	55	51
22	BT3	30	64	195	66	76	71	34	59	CD4	79	56	33	64	64	60	89
23	BT4	57	64	109	58	80	71	66	60	CD5	55	31	61	38	31	32	68
24	BT5	43	78	77	132	88	91	46	61	TL1	47	54	68	51	54	51	44
25	BT6	57	58	65	93	91	94	61	62	TL2	37	64	63	55	42	39	47

Table 11 (continued)

No.	Codes	Years						
		2013	2014	2015	2016	2017	2018	2019
26	BT7	76	44	67	79	68	78	86
27	BT8	40	55	54	49	60	55	47
28	BT9	52	47	33	76	51	54	63
29	NK1	36	53	71	71	58	60	44
30	NK2	40	55	74	70	60	68	51
31	NK3	73	49	81	48	62	64	82
32	NK4	126	89	84	131	126	98	122
33	NK5	153	185	80	99	104	96	128
34	NK6	74	108	57	67	84	80	84
35	NK7	72	106	130	110	84	80	85
36	NK8	76	120	111	103	68	95	92
37	NK9	91	177	156	114	89	84	151

No	Codes	Years						
		2013	2014	2015	2016	2017	2018	2019
63	TL3	68	45	62	57	45	52	69
64	TL4	54	131	41	33	77	55	71
65	TL5	53	39	71	46	74	52	59
66	TL6	59	54	33	40	72	67	69
67	PD1	41	29	41	64	51	47	41
68	PD2	67	39	42	62	51	45	77
69	PD3	52	31	51	55	73	61	56
70	PD4	40	39	59	64	51	55	52
71	PD5	58	36	36	51	73	63	79
72	PD6	49	57	55	54	51	57	59
73	PD7	41	31	64	38	33	34	49
Mean		**62**	**65.5**	**66**	**69**	**69.5**	**68**	**72**

Table 12 The average annual WAWQI values for all sampling sites and areas of four different land-use categories between 2013 and 2019 in the study area

Land-use categories	Area (km^2)							Overall trend
	2013	2014	2015	2016	2017	2018	2019	
Built-up land	182.21	186.09	195.86	205.89	205.07	206.15	217.68	Increased
Agricultural land	1,179.66	1,175.16	1,155.06	1,146.42	1,147.34	1,146.31	1,134.18	Decreased
Water bodies	75.13	76.73	87.06	85.67	85.67	85.64	86.44	Increased
Fallow land	1.96	0.98	0.98	0.98	0.88	0.86	0.66	Decreased
Total	**1438.96**	**1438.96**	**1438.96**	**1438.96**	**1438.96**	**1438.96**	**1438.96**	Unchanged
WAWQI	**Value**							
All sampling sites	62	65.5	66	69	69.5	68	72	Increased

Data availability The authors confirm that the secondary dataset supporting the findings of this study are available within the article and its supplementary materials. The primary dataset that support the findings of this study are available from the corresponding author upon reasonable request. This primary dataset are not publicly available due to restrictions (e.g., the most of the primary dataset is related to the case study's development policies and master plans, and it belongs to the cities' governmental organizations).

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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