Pivotal asservation of Water Quality in Kuwait territorial waters availed in conjunction with machine learning techniques and satellite imagery

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Abstract

Seawater pollution has been identified as being the most serious menace to both humankind and aquatic ecosystems. Any regulation or policy ought to be preceded by seawater evaluations. The conventional techniques for determining the quality of saltwater have been demonstrated to be laborious and expensive. On the contrary, using in-situ measurements, earth observation data from satellites can provide thorough, swiftly, and affordable information about water bodies. As a result, this research proposes an alternative strategy for identifying water quality index (WQI) utilizing machine learning techniques that simulate seawater characteristics using in-situ measurements and remotely sensed data. Fuzzy logic was utilized to estimate WQI in terms of six parameters which are chlorophyll, pH, dissolved oxygen (DO), conductivity, salinity, and turbidity. Data records of these parameters were collected over a year (2016-2017) from 15 buoy stations deployed in Kuwait's territorial waters, five of which were in Kuwait Bay.

Additionally, two different machine learning techniques were used to correlate spectral bands from Landsat-8 with in-situ measurements, which are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). An appropriate estimate of WQI in Kuwaiti territorial seas was determined by fuzzy logic. Furthermore, it was discovered that GA outperformed PSO in its capacity to observe WQI over the Bay of Kuwait. Based on spatial mapping, it was revealed that there is a pressure on Kuwait bay due to the concentration of anthropogenic activities. For further studies, it is recommended to apply other methods to estimate WQI and compare the results to fuzzy logic results.

Key words: Kuwait Bay, WQI, GA, PSO, fuzzy logic, Landsat-8, spatial mapping.

1. Introduction

Human waste has a wide range of environmental effects when urbanization grows in intensity in nations with dense populations. Severe environmental risks, especially for aquatic life, are associated with the unauthorized discharge of wastewater into the ocean. By contracting an infection from eating tainted seafood, people may also be affected by unlawful sewage effluent indirectly (Banana et al., 2016). Sewage discharges have been identified as a major contributor to coastal contamination in the Arabian Gulf countries (Mamoon et al., 2015).

It is essential to evaluate the ocean's water quality before executing a seawater protection strategy. The quality of the water cannot be accurately described by a single criterion. In order to assess the quality of the water, various physical and chemical saltwater parameters have been found. The Water Quality Index (WQI) can be used to gauge a water body's total water quality (Kachroud et al., 2019).

The assessment of WQI has been the focus of thousands of approaches since its founding in 1965. The most recent method for evaluating WQI is fuzzy logic (Icaga, 2007). The concentration levels that are either very close to or very distant from the limits are grouped together in conventional ways of categorizing water quality measures using an unambiguous set. The distinctions between the classes of parameters may therefore be misleading. Contrary, when assessing the quality of water using fuzzy logic, the standard quality classes are converted into continuous form. The sum of the concentration values of the various quality metrics is then subjected to fuzzy rules. Finally, a WQI estimate is produced by De-fuzzifying the addition of concentration values (Icaga, 2006).

When compared to alternatives including remote sensing technologies, traditional, time-consuming, and expensive laboratory analysis is used to measure and analyse water quality variables needed to calculate WQI. In addition to the expanding use of technology, new techniques for assessing water quality are being developed. These include remote sensing and geographic information systems (GIS), which use satellite data to determine the quality of the water. These methods work on increasing the accuracy of the observed data and decrease time and cost (Abdelmalik, 2018).

2. Objectives

This paper mainly aims to evaluate water quality index (WQI) of the study region using fuzzy logic as well as assessing the spatial and seasonal variation of WQI. In addition to using machine learning techniques specifically, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to correlate between in-situ measurements and spectral bands to ascertain the coefficients of each band and develop a reliable equation that estimates WQI in the Bay of Kuwait.

3. Data and methods

3.1 Study Region

The data was collected from 15 monitoring buoy stations deployed in Kuwait's waters. five buoy stations are in Kuwait Bay, and the other monitoring stations are in the Arabian Gulf as presented in Figure 1, stations names are provided in Table 1. As indicated in Figure 1, the current investigation was carried out within Kuwait's territorial seas. Kuwait's territorial waters encompass an area of around 8000 km^2, and they are separated into three distinct areas: Kuwait Bay, Southern Waters, and Northern Waters (Al-bannai, 2021). The most important subregion is Kuwait Bay, which is a shallow water tongue that spans 750 km^2.

Table 1 Monitoring stations

Station No.	Station	Station No.	Station	Station No.	Station
St-1	Southeast of Ras Al-Khaid	**St-2**	Khor Boubyan	**St-3**	Khor AlSabiya Entrance
St-4	Northeast of Ras Ajuzha	**St-5**	Northeast of Doha Port	**St-6**	Northeast of Doha Port 2
St-7	West of Doha Port	**St-8**	West of AlAkaz	**St-9**	Southeast of Al-Beda'a
St-10	Ahmadi Port	**St-11**	Southeast of Abdullah Port	**St-12**	Northeast of Kubbar Island
St-13	Southest of Qaruh Island	**St-14**	Northeast of Um AlMaradim Island	**St-15**	Southeast of Mina Az-Zour

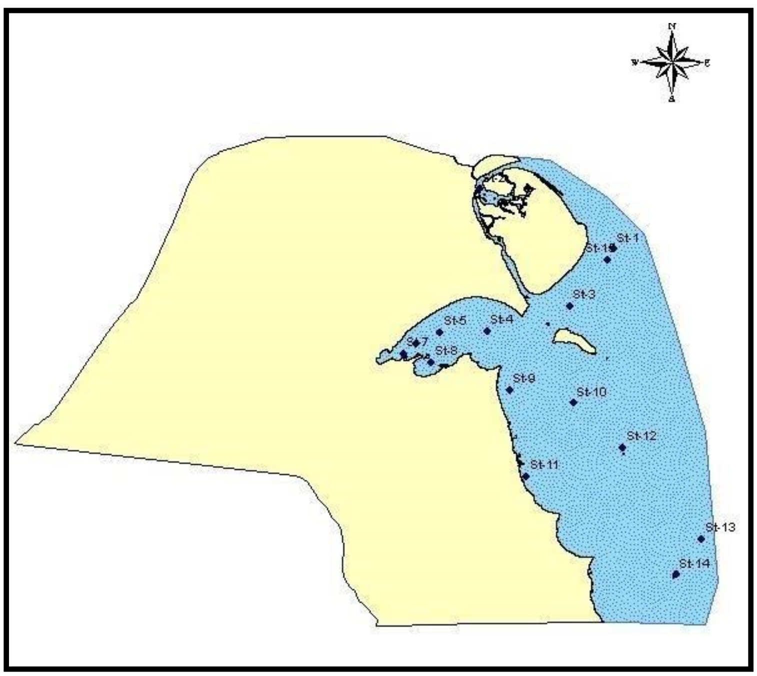


Figure 1. Kuwait map showing study region.

3.2 Data Collection

The seawater quality parameters data set obtained from Kuwait Environmental Public Authority (KEPA) was recorded over a year (2016–2017). The measured parameters were recorded every 24 hours including six parameters which are provided in Table2.

Table 2 Seawater quality parameters

Parameter	Unit	Importance in marine ecosystem
pH	-	It indicates the relative acidity or alkalinity of water
Turbidity	NTU	It is defined by the quantity of light scattering generated by suspended matter in water
Chlorophyll	Ug/L	It is a critical chemical property for photosynthesis
Conductivity	mS/cm	It is a significant indicator of ocean electromagnetic properties
Dissolved Oxygen	mg/L	It facilitates the respiration of aquatic organisms and aids in the breakdown of organic materials
Salinity	%	It quantifies the amount of salt in seawater.

3.3 Landsat-8 Image Processing

Landsat-8 images were collected from Earth Explorer website The outcomes have been made accessible for identifying, and the one that is clear of clouds and debris is preferable. As a result, it is strongly advised that satellite image acquisition occur on the same day as in-situ sample collection to decrease errors and provide more accurate calibration of the algorithms used to assess water quality (Bonansea et al., 2015). For this study, a total of ten cloud-free scenes of Landsat-8 over the study period, covering all Kuwait Bay stations and all seasons of the year. Only six of them were suitable for utilization and the other four were disregarded.

Atmospheric Calibration of images has been performed on ENVI 5.2 software, to remove atmospheric influences and translate radiometric readings into radiation. While Radiometric calibration was performed to convert the digital numbers of remotely sensed satellite images to absolute values per unit wavelength or reflectance (Chavez, 1996). Five bands were used in this study which are provided in Table 3. Bands pixel values are required for the machine learning techniques which use the correlation spectral bands (pixel values) and in-situ data.

Table 3 Landsat-8 Bands combination (USGS, 2019)

Sensor	Spectral Band	Use Area	Wavelength (µm)	Resolution
OLI	Band 1	Coastal/Aerosol	0.433 - 0.453	30 m
OLI	Band 2	Blue	0.450 - 0.515	30 m
OLI	Band 3	Green	0.525 - 0.600	30 m
OLI	Band 4	Red	0.630 – 0.680	30 m
OLI	Band 5	Near Infrared (NIR)	0.845 – 0.885	30

3.4 Estimating WQI using Fuzzy Logic

Fuzzy logic was used to calculate WQI of water bodies in Kuwait according to seasonal variations. The process of developing WQI using Fuzzy Interface System (FIS) transforms the output set to a crisp one. The selection of seawater parameters serves as the foundation for WQI development. In addition, six characteristics were used to assess the water quality of 15 stations. According to the KEPA data that is currently accessible, from December 2016 to December 2017. The one-year analysis was divided into four seasons: winter, spring, summer, and autumn. The included parameters and their ranges are presented in Table 4.

Table 3
Parameters used in determining WQI using fuzzy logic.

Parameter	Range	Indication	Reference
pH	0-6.5	Acidic	(Husada & Nurhidayat, 2020)
	6.5-8	Neutral	
	8-14	Alkaline	
DO (mg/L)	<4	Unaccepted	(Vigueras-Velázquez et al.,2020)*
	4-8	Normal	
Turbidity (NTU)	<15	Good	Azisa et al. (2015)
	15-25	Fairly turbid	
	25-35	Rather turbid	
	35-50	Turbid	
	>50	Very turbid	
Chlorophyll (Ug/L)	<3	Excellent	Lin & Huang (2015)*
	3-10	Average	
	>10	Poor	
Salinity (%)	<33	Low	KEPA
	33-45	Excellent	
	>45	High	
Conductivity	**(mS/cm)** 30 to 60	Normal	Zheng et al. (2018)

*Some modifications were made (merging some ranges together) to meet the standard criteria of the parameter by KEPA.

WQI was added as an output and its classes are presented in Table 5, according to the Canadian Council of Ministries of the Environment (CCME) method (CCME, 2001). 24 rules were constructed based on global criteria and according to the available data ranges to develop WQI. Then, these 24 rules were successfully used in the rule base step according to Mamdani fuzzy inference. For the computation of the fuzzy rule, the minimum operator “and” was used to ensure having all parameters within the specified ranges. Finally, WQI was developed.

Table 5: Water quality categories per CCME approach (CCME, 2001).

Class No.	WQI	Quality Class	Description
1	<44	Poor	Water quality is almost always threatened or harmed; conditions are frequently.
2			45-64 Bad Water quality is typically protected, but it is periodically threatened or harmed; conditions occasionally deviate from natural or optimal levels.
3	65-79	Marginal	Water quality is typically protected, but it is periodically threatened or harmed; conditions occasionally deviate from natural or optimal levels.
4	80-94	Good	Water quality is preserved with only minimum risk or impairment; conditions rarely deviate from natural or optimal levels.
5	95-100	Excellent	Water quality is preserved with virtually little threat or impairment; circumstances are astonishingly close to natural or pristine levels.

3.5 Machine Learning Techniques

In this research, two machine learning techniques were adopted to correlate spectral bands with in-situ measurements, which are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Both techniques are considered as optimization techniques. In this case, both are solving an unconstrained, single objective optimization problem. Moreover, the main objective of these techniques is to discover the optimum coefficient for each band that lessen the absolute difference between bands and the in-situ measurement of WQI. Each station has its own objective function, where it includes WQI measured over several days, in addition to spectral bands retrieved from images collected on the same days as WQI was measured. The developed equation will be used later to measure WQI over the same station. In details, each station will have a single equation that is used to measure WQI during any season. The validity of the resultant equation will be evaluated using statistical tests. For both techniques, the objective function used is presented by the following equation:

$$f = \left|\left(\sum_{i=1}^{5} coeffiecient * b_i\right) - \sum_{day=1}^{n}(in\ situ\ mesurement)\right| \tag{1}$$

Where b is the pixel value of each band, which was obtained from ArcMap, n is the number of days included in the equation and it is also equal to the number of images collected for the same station, while coefficient is the number to be obtained by the machine learning techniques. The following equations were used in PSO (Eberhart & Kennedy, 1995).

$$V(t+1) + w * V(t) + c_1 * rand * (X_{pbest} - X(t)) + c_2 * rand * (X_{gbest} - X(t)) \tag{2}$$

$$X(t+1) = X(t) + V(t+1) \tag{3}$$

Where:

V(t): Velocity of the particle at time t
X(t): Particle position at time t

w: Inertia weight c_{1}: personal

factor. c_{2}: global factor.

rand: uniformly distributed random number between 0 and 1

X_{pbest}: Particle's personal best position

X_{gbest}: Particle's global best position

3.6 Spatial Mapping

Spatial mapping of WQI over stations during the four seasons were generated using ArcMap 10.8.2 software. Spatial mapping can help in visualizing the spatial distribution of WQI in all regions of Kuwait waters. Additionally, the most affected regions can be pointed out from the developed maps.

3.7 Goodness of fit measures

Model evaluation is a crucial aspect in the development of a system model. Goodness of fit is being measured by several tests to evaluate the validity of the model. Four statistical tests were applied to assess the validation of PSO and GA equations. The applied statistical tests are: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of determination (R^2). Where MSE estimates how close a regression line is to a group of data points. A smaller MSE indicates that the data points are dispersed closely around its mean (Gupta, 2023). On the other hand, RMSE measures the average differences between estimated values by a model and the actual ones. The lower the RMSE value, the better the model is. A perfect model would have an RMSE value of 0 (Moody, 2019). Additionally, R^2 represents the variance proportion for a dependent variable which is explained by an independent variable in a regression model, the closer R^2 to 1, the better the model. While MAE measures the errors between estimated values and observed ones, the model shows more accuracy as MAE gets closer to 0 (Hiregoudar, 2020).

The previous statistical tests are given by the following equations:

$$MSE = \sum_{i=1}^{n} \frac{(\hat{y}-y_i)^2}{n} \quad (4)$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}-y_i)^2}{n}} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{6}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{7}$$

Where:

$\hat{y}_i$: is the predicted value. y_i: is the observed value. n: number of observations. $\bar{y}$: the mean of observed values.

4. Results and discussion

4.1 WQI over seasons

Six criteria related to saltwater quality constitute the water quality index. As a result, any of them changing will affect the total quality of seawater. The variation in WQI over stations in the winter is illustrated in Figure 2. It is clear that station 2 (Khor Bobyan), with its 22% WQI, undesirable water, had the lowest WQI. It is noticed that 60% of Kuwait Bay stations had bad water quality while the remaining 40% had marginal water quality. Maximum observed WQI was 72% which is marginal WQI. The high inflow of freshwater from Shat Al-Arab during winter to Kuwait waters also contribute to decrease the WQI in some stations in Kuwait marine.

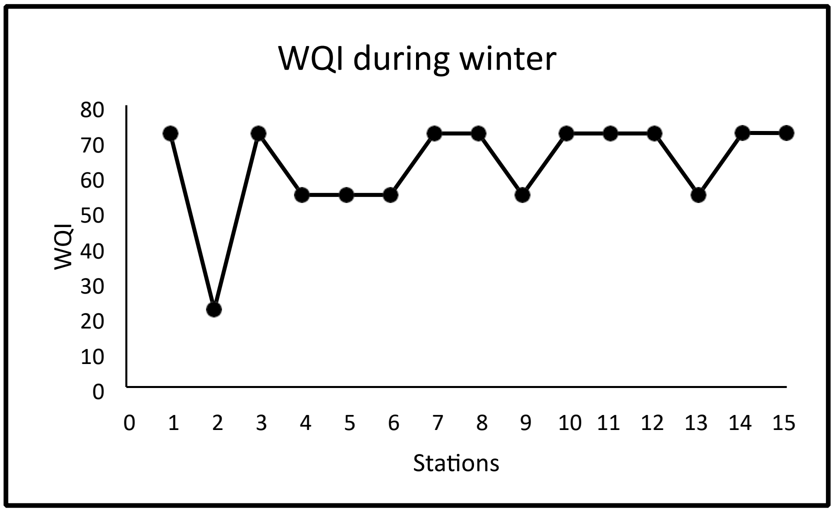


Figure 4. Variation of WQI in winter over stations

Figure 3 reveals that stations 1, 2, and 3 established no improvement and no degradation in WQI. 80% of the stations in Kuwait Bay had poor WQI. The West of Doha Port displayed a 20% decrease in WQI, placing it in the poor category rather than the marginal one observed during winter. WQI in Ahmadi Port also decreased to be in the bad range. An 18% improvement in WQI in Southeast of Qaruh Island was observed. The last five stations had the same trend of WQI.

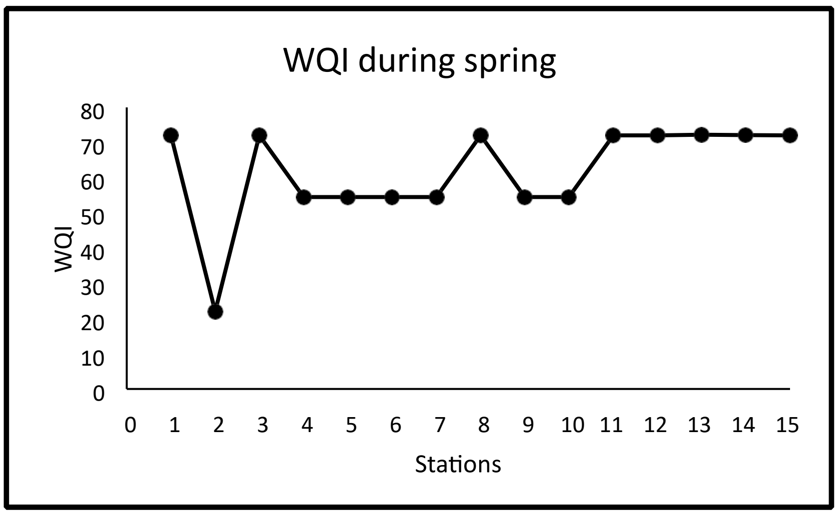


Figure 3. Variation of WQI in spring over stations

As shown in Figure 4 summer season indicated an elevation in WQI in some stations namely Southeast of Ras Al-Khaid, Khor Boubyan and Khor Alsabiya Entrance stations. On the other hand, Kuwait bay showed constant WQI in its all stations which is considered as bad water quality. Furthermore, it is examined as the lowest detected WQI compared to other Kuwait territorial waters. Which is justified by the concentration of anthropogenic activities along the bay of Kuwait Al-Abdulghani et. al (2013). Other stations emphasized no variation in WQI. Regarding stations where WQI has been changed, these changes can be related to the inflow from sat Al-Arab river. Al-Mutairi et. al (2014) mentioned that inflow from Shat Al-Arab plays a role in fluctuating seawater quality in Kuwait marine. Additionally, during summer season the discharge from Shat Al-Arab reaches its lowest levels which lessen the amount of nutrients that plays a role in deteriorating seawater quality in Kuwait waters (Devlin et al., 2015).

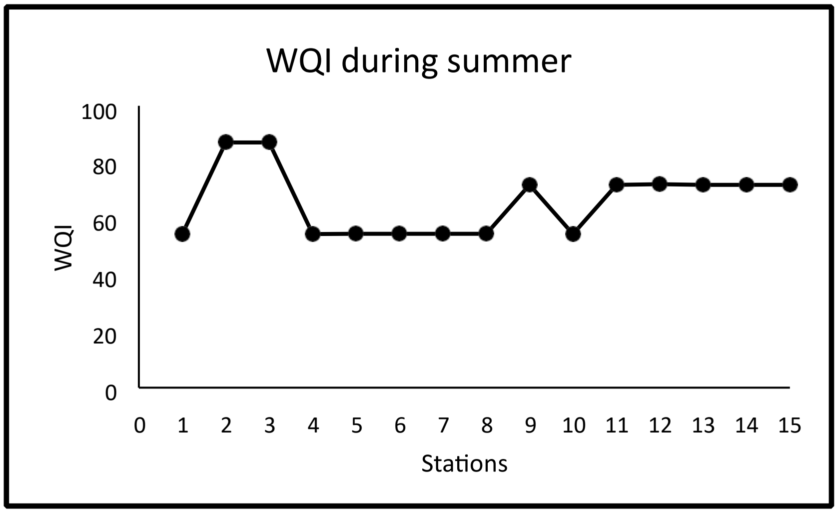


Figure 4. Variation of WQI in summer over stations

Figure 5 delineates the variation of WQI among stations in autumn season. Compared to summer season, Ras Al-Khaid WQI changed to be poor water quality. Water quality in Khor Boubyan and Khor Alsabiya Entrance stations also decreased. Conversely, Northeast of Ras Ajuzha showed an improvement in WQI. Whereas other Kuwait bay stations did not depict any variation. A significant upsurge in WQI in Station 11 was noticed while other stations clarified no variation in WQI compared to summer season. During Autumn season water circulation is low since there is no significant input from Shat Al-Arab river (Devlin. et al,2015) Which contributes to the deteriorating WQI in some stations.

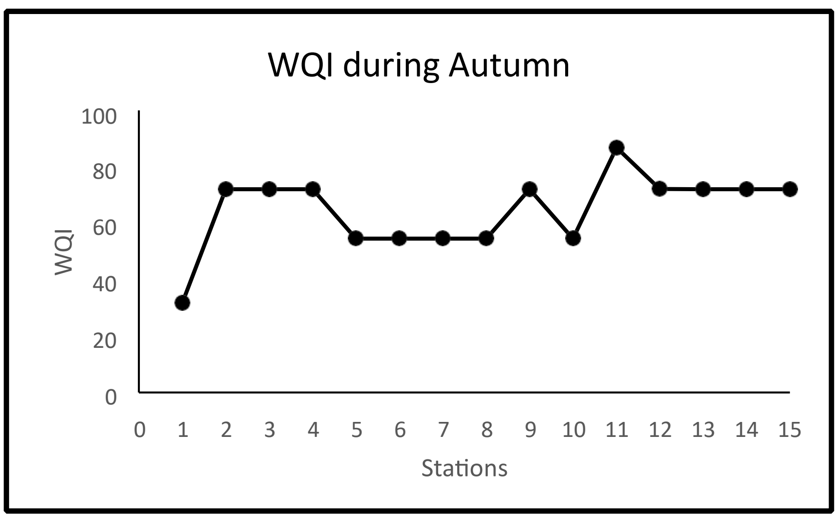
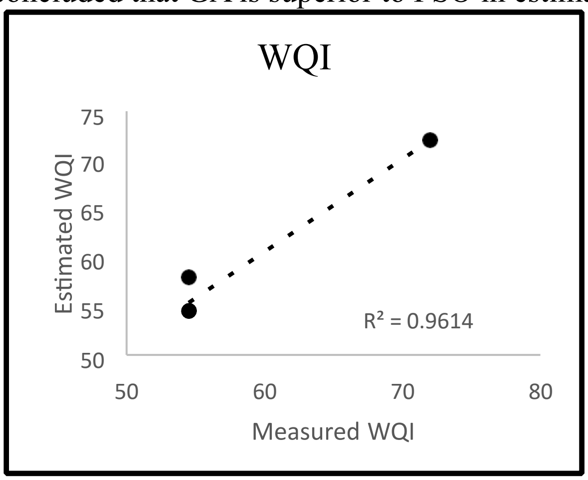


Figure 5. Variation of WQI in autumn over stations

4.2 Goodness of fit measures

Estimated WQI from the resultant equations of GA and PSO are plotted versus measured WQI and presented in Figures 6 and 7, respectively. Regarding WQI estimated using GA equation, R^2 ranges from 0.7084 (West of Doha Port station) to 0.9998 (Northeast of Doha Port). Indicating strong reliability of the resultant equations from GA. Whereas WQI estimated using PSO equations, the resultant R^2 ranges from 0.5517 (West of Doha Port) to 0.8623 (West of AlAkaz). MSE of the resultant equations by GA ranged from 0.0128 (Northeast of Doha Port) to 33.43 (West of Doha Port). While it ranged from 34.75 (Northeast of Doha Port 2) to 316.09 (Northeast of Doha Port) using PSO. The best estimated RMSE of GA equations was 0.113 (Northeast of Doha Port), while the worst was 5.78 (West of Doha Port). Regarding PSO equations, minimum RMSE was 5.77 (West of Alakaz) while the maximum was (17.78) (Northeast of Doha Port). Moreover, the results showed that MAE for GA was in the range from 0.0529 (Northeast of Doha Port) to 4.08 (West of Doha Port). On the other hand, MAE estimates using PSO ranged from 3.36 (Northeast of Doha Port 2) to 11.38 (Northeast of Ras Ajuzha). According to the previous values, it can be concluded that GA is superior to PSO in estimating WQI among Kuwait bay stations.



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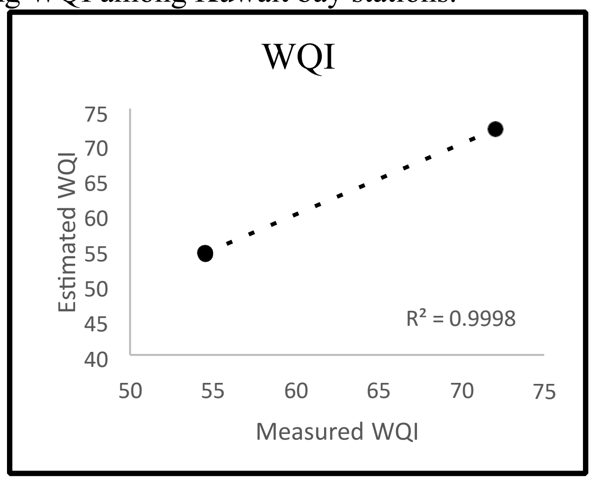

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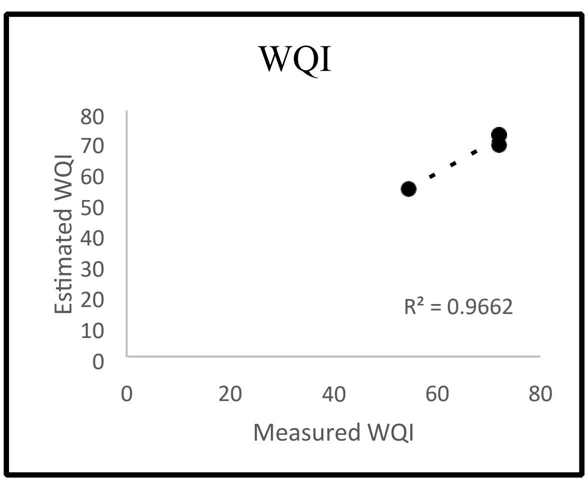

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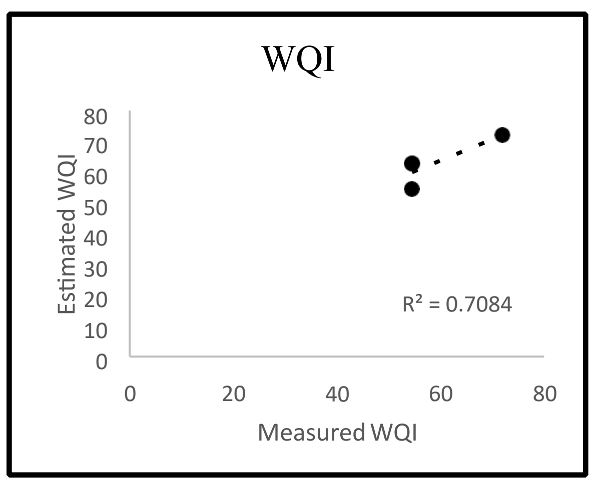

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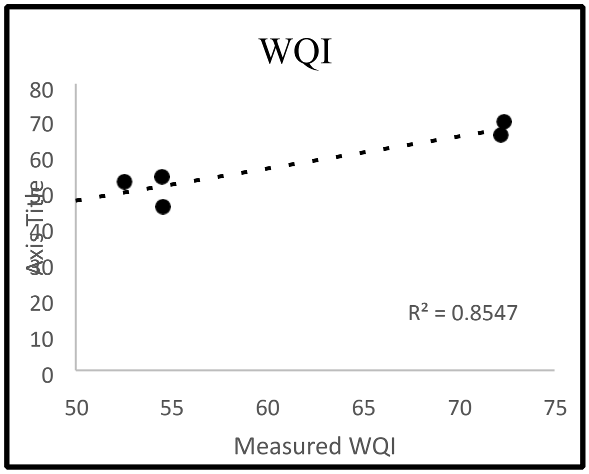
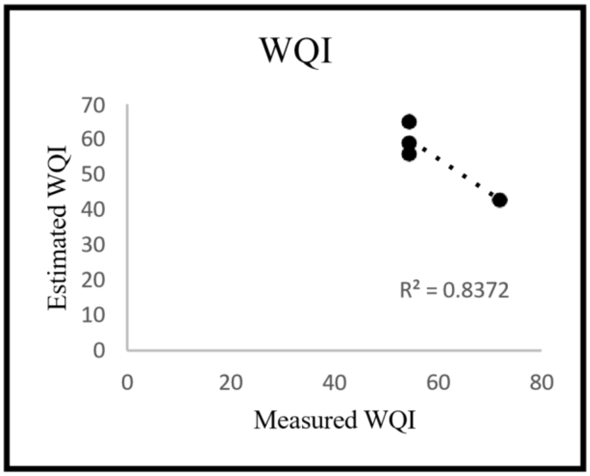


(e)

Figure 6. Comparison between measured WQI and calculated WQI over stations using GA: (a): station 4, (b): station 5, (c): station 6, (d): station 7, (e): station 8



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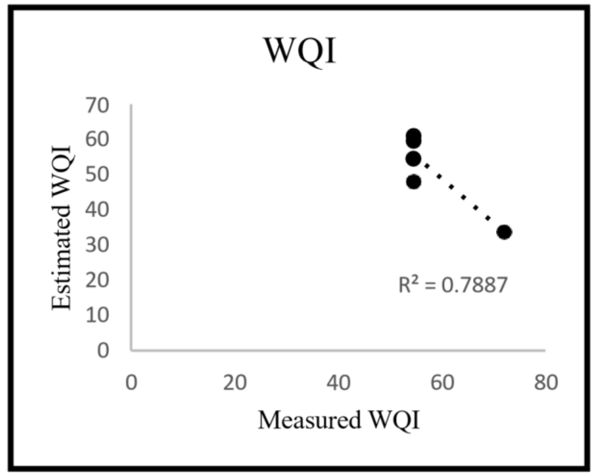

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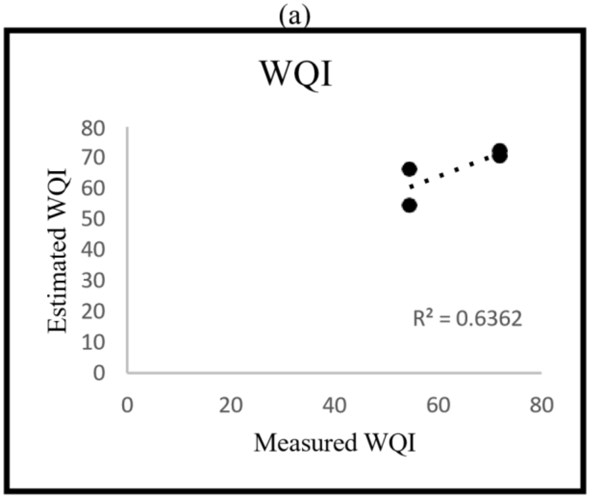

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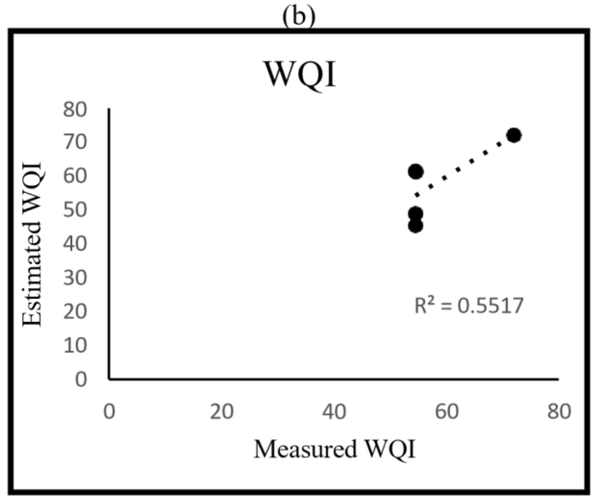

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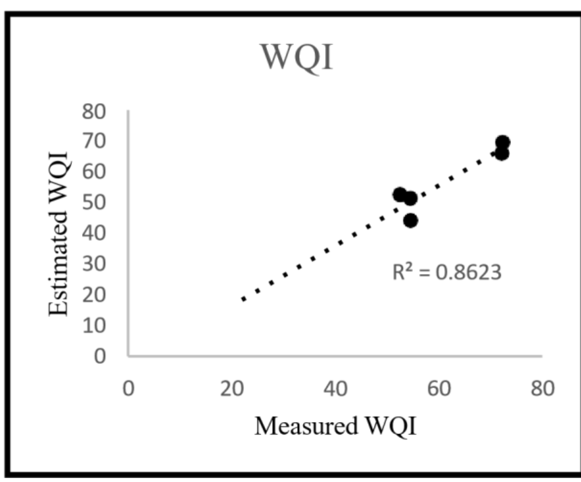


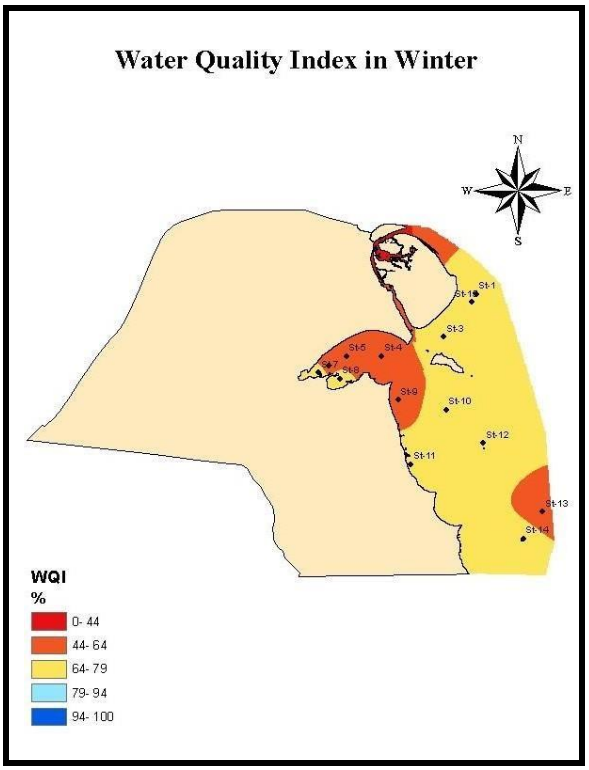
(e)

Figure 7. Comparison between measured WQI and calculated WQI over stations using PSO: (a): station 4, (b): station 5, (c): station 6, (d): station 7, (e): station 8

4.3 Spatial mapping

The following figures represent the spatial mapping of WQI over the four seasons in Kuwait. Generally, Kuwait bay's WQI was worse than other territorial waters except for Khor

Boubyan in winter and spring at which the lowest WQI was detected. The discharge from Shat Al-Arab River plays a significant role in changing WQI in Kuwait. It results in an increase in freshwater into Kuwait which mixes with Kuwait waters and increases water circulation there. Conversely, it holds sediments and other nutrients which tend to increase the water quality in Kuwait. In winter and spring WQI is lower close to the outfall's locations. The dark colors in the Kuwait bay indicates less quality of water there particularly close to AlDoha power and desalination plants. Moreover, it can be referred to the concentrated man-made activities there, especially Shuwaikh power plant. It is obvious that the water quality in the Arabian gulf is much better due to the higher water mixing and circulation compared to the bay of Kuwait (Al-Mutairi & Al-Battay, 2014). According to these figures, WQI at any location in Kuwait waters can be detected.



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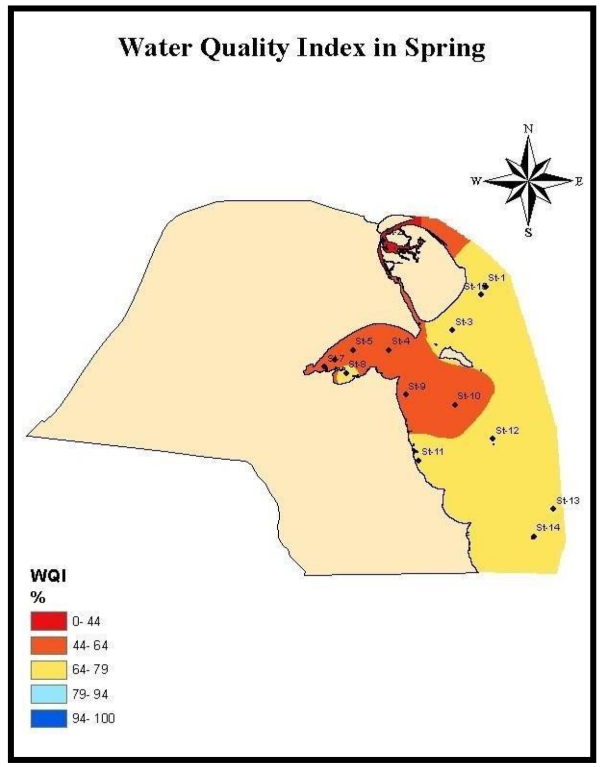

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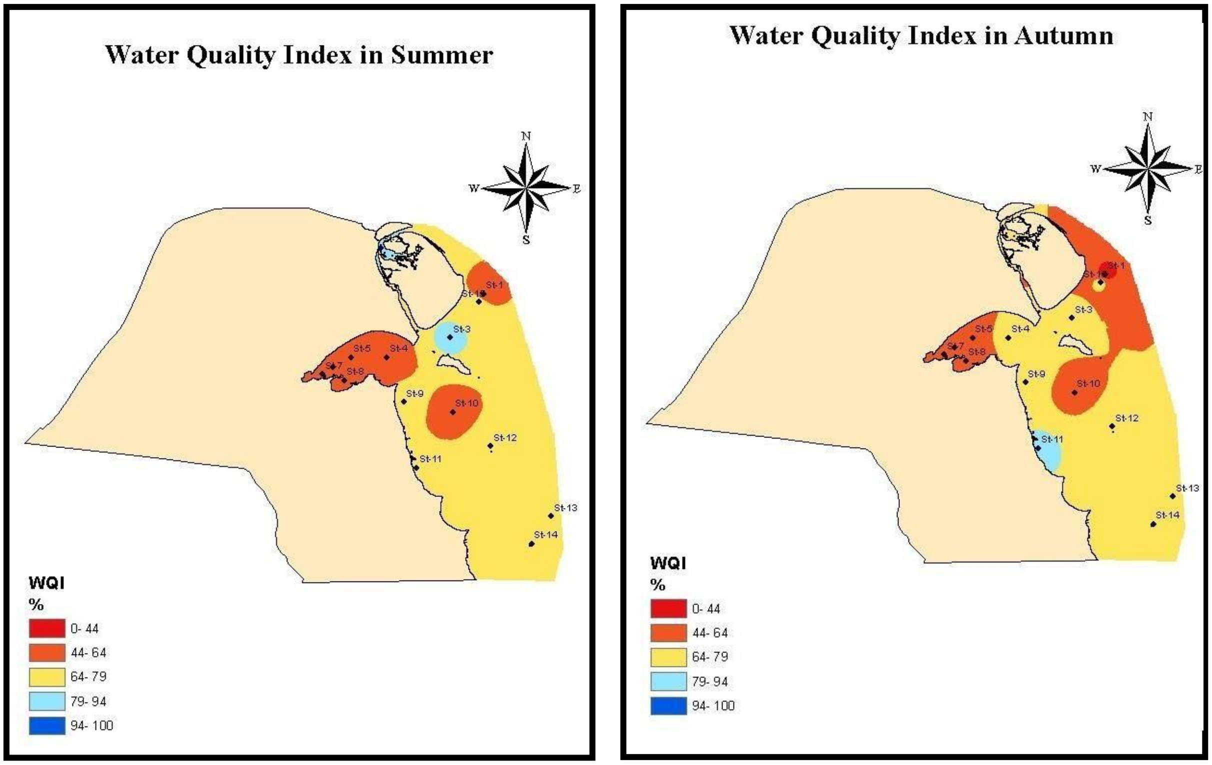

(c) (d)

Figure 8. WQI over stations along the four seasons: (a):winter, (b):spring, (c):summer, (d) autumn

5. Conclusion

Water quality features provide the base for analysing the suitability of water for different uses and improve the current conditions. In order to detect WQI, this paper introduces dynamical models and model-based data assimilation (optimization) techniques, which simulate WQI using in-situ measurements and remotely sensed data. In addition to estimate WQI using non-traditional method which is fuzzy logic. Two other machine learning techniques were employed, which are GA and PSO to correlate between spectral bands and in-situ measurements, to develop a sustainable equation that can be used for each station to estimate WQI along any season. The study was implemented in Kuwait, data was collected from 15 buoy stations deployed in Kuwait territorial waters, five stations of them are in Kuwait Bay. WQI was assessed upon fuzzy logic, it varied from 22% in winter to 87% in autumn. GA and PSO showed good results in estimating WQI based on Landsat-8 bands and in-situ measurements in five stations in Kuwait bay. For WQI R^2 ranged from 0.7084 to 0.9988 and from 0.5517 to 0.8623 using GA and PSO, respectively. MAE of WQI using GA equation was in the range from 0.0529 to 4.0 while it was in the range of 3.36 to 11.38 using PSO equation. It can be concluded that the GA showed higher efficiency than PSO in detecting all parameters. Using spatial mapping techniques, it was demonstrated in this research that WQI may be discovered across the ocean, regardless of the presence of buoy stations. The pressure on Kuwait Bay was seen on the maps since it is suffering more than other Kuwaiti territorial seas. Furthermore, this can be justified that by the anthropogenic activities that have impact on the Bay's marine, the loads from Shat Al-Arab River, as well as the wastewater discharge. In conclusion, it is recommended to apply these machine learning techniques and include more stations in further studies.

6. Acknowledgement

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