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Seasonal effect of agricultural pollutants on coastline environment: a case study of the southern estuarine water ecosystem of the boseong county Korea

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The untreated disposal of wastewater in the coastal environment leads to growth of harmful algal blooms which risks the coastal ecology and human health. The harmful algal bloom can destroy aquatic natural life by reducing dissolved oxygen concentration. This study aimed to evaluate the eutrophication status at the Boseong county, Beolgyo village estuary, considering different water quality parameters. Furthermore, this study also investigated the effect of land use activates the estuarine water environment. The date of the acquisition for the Landsat 8 high-resolution satellite images were four different events i.e., 11th March, 2019, 15th June, 2019, 19th September, 2019, and 8th December, 2019 in four different seasons such as Spring, Summer, Fall, and Winter respectively for selected study region. Land use and land cover were extracted on the basis of accuracy's percentage and the Kappa coefficient. Concentrations of water quality parameters such as Chlorophyll-a (Chl-a), Total Phosphorous (TP), Transparency of Sechi Depth (TSD) were extracted using Carlson Trophic State Index (CTSI). The study found that the overall value of the CTSI is classified under the medium eutrophication state in summer and autumn season (CTSI~60-70). While it falls in the light eutrophic state in winter and spring seasons (CTSI~50-60). The value of TSI for all studied nutrients is the higher nearby cropping area as well as land settlements. The spatial variation of the trophic index in the study region aided strong evidence to be detected over the area's adjutant to agrarian farming and urban habitats. The study concludes that the TSI could be used as a simple management tool to classify individual water ecosystems into broad classification that represent their water quality health.
Keywords: Landsat-8, chlorophyll-a, eutrophication, total phosphorous, algal bloom, CTSI

INTRODUCTION

Better water quality is crucial for the aquaculture industry and fisheries. It is also significant for convenience use: beaches, swimming, surfing, etc. and is critical for the coastal environment. With the increasing population and industrial development alongside coastal areas, coastal water ecosystem has become vulnerable to diverse pollutants (Iqbal *et al*., 2018a ; Iqbal *et al*., 2018b). By direct disposal of raw debris, residential garbage and toxic agrochemical discharge from neighborhoods disturbing the nearby status of water quality, aquaculture and tour industry. Moreover, in a bigger scenario as a whole this condition is hazardous and updraft costal biodiversity (Kim *et al*., 2013). The coastal regions are the most populated parts of the ecosphere and are therefore stalwartly pretentious by humans, leading to disagreeable ecological variations that may change the environments, such as eutrophication (Iqbal *et al*., 2019; Agwanda, and Iqbal 2019). Monitoring the water quality is very important from the perceptions of the coastal water resource management and utilization (Agwanda, and Iqbal 2019). Globally, towards many highly populous coastal zones, enormous input of industrial, agricultural and sewage discharges have huge impressions by changing the pollutants characteristics, generation of harmful algal blooms disturbing biodiversity, recreational activities, tourism, fisheries, and other activities

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(Shoaib *et al*., 2019; Malik *et al*., 2020). Eutrophication from pollution load and agricultural discharges have been worsened coastal water globally, usually demonstrated as augmented prime production in the dynamic surface layers leading to increase in algal masses and red tides. The concentration of nitrogen, phosphorous and chlorophyll is a sign of algal masses in the fresh and saline waters (Kim *et al*., 2013; Iqbal *et al*., 2019), and applied as an indicators of fresh water ecology to evaluate deviations in water-quality in respond to eutrophic status (Yu *et al*.,2010). The seasonal variation eutrophication in estuarine regions of coastal areas are deliberated disagreeable, and numerous local as well as universal treaties to contest the contrary effects on the environments have been established (Bertani *et al*., 2017; Saputra *et al*., 2017).

The western coast of South Korea is categorized by light water depths, wide-ranging tides, largo tidal currents, and numerous constituents from the local environment, toughing the quantification of water quality variables such as Chl-a, TSD, and TP concentrations (Choi *et al*., 2011). Furthermore, numerous public buildings built sideways the west coast throughout the previous few years have expressively altered aquatic ecosystems, causing high dynamic variation of the coastal water quality (Choi *et al*., 2011). Because land use alteration via anthropogenic activities, such as urbanization or industrial development cause huge discharge of waste disposal which enters nearby water bodies and effected its water quality dynamics. Carlson Trophic State Index (CTSI) is one of the most widely used trophic state index. Trophic state indexes have been proposed to quantify the degree of eutrophication in systems. Among them, Carlson (1977) formulated a quantitative index to measure the degree of eutrophication in lakes based on TP, CHL-a, and TSD. According to Carlson and others, limnologists broadly agree that TP is the best predictor of algal growth, Chl-a is the most accurate indicator of algal biomass, and TSD is the best measure of water clarity in water bodies. Carlson's trophic state index can help to clarify reservoir ecology, and it offers a worthwhile tool for management of water bodies. It is used to quantify the eutrophication status of water bodies. It helps to categorize the water bodies and offers a worthwhile tool for management of water bodies. The index is well-defined as the over-all mass of nutrients in the considered water system. Carlson, (1977) proposed and formulated an index method for classifying the health of water ecosystem known as CTSI. The CTSI method can be formulated based on averaging the trophic states of two or more than two water quality parameters such as transparency of TSD, Chl-a, and T-P (Carlson,1977; Patra *et al*., 2017; Saputra *et al*., 2017). The following study used three parameters for evaluating of the eutrophication status of the coastline region of Boseong County Korea.

Traditionally, Nitrogen, Phosphorous and chlorophyll a concentration, have been observed by defining concentration from distinct *in situ* water samples composed from diverse depths at static points. While these small ships and boat based sample collection deliver facts about the limited horizontal and vertical dissemination of phytoplankton biomasses, these extents offer some degree of facts on the spatial temporal variation of eutrophication status (Salehi *et al.,* 2020). The point based manual samples collection signify only a small fraction of the total water body, and with a large spatiotemporal variations in the variables such as plenty of phytoplankton in the ocean, it is nearly impossible to have a complete valuation by assessing eutrophication status based on field scale observations (Kim *et al*., 2013; Saputra *et al*., 2017).

The traditional method is laborious and time consuming and very difficult to provide spatial scale variation of large area coverage and have drawbacks due to economic cost and high man-power. The traditional water quality monitoring relies on manual field sampling and laboratory analysis of chlorophyll-*a* (Chl-*a*) concentration, which is resources intensive and time consuming (Yu *et al*.,2010; Bertani *et al*., 2017; Gittings *et al*., 2017; Anttila *et al*., 2018). So, manual based water quality sampling and evaluating is difficult job by using ships or boat due to having high spatial inconsistency. Infrequent studies of coastal environment do not provide the complete understanding of growth of harmful algae and eutrophication state (Gittings *et al*., 2017; Park *et al*., 2017; Anttila *et al*., 2018; Otvaviani *et al*., 2018). In order to comprehend the production of harmful algae, growth of red tides, and water quality status, researcher is utilizing remote sensing technique to deal the spatial temporal variation of water quality on the greater coverage of water ecosystem such as open ocean and coastal environment (Kim *et al*., 2017; Ottaviani *et al*., 2018). Remote sensing (RS) application offer a cost-effective and appropriate technique to perceive the Globe, particularly the large scale spatial extent of dissimilarities of natural spectacles (Otvaviani *et al*., 2018). RS applications have also been useful to observe spatial and temporal variation of eutrophic status in order to develop the comprehending of coastal and ocean water quality, prime creation, seasonal unevenness etc. (Anttila *et al*., 2018). However, RS exposure is constrained by dualistic prime aspects: (a) Glint of sun which cause unclear value of bright pixel failed to echo the qualitative characteristics of water bodies (Kim *et al*., 2017; Gittings *et al*., 2017), and, subsequently, RS facts at the sun glint localities should be barred. (b) While cloud blockage between satellite and earth surface also not provide complete and clear information (Ottaviani *et al*., 2018), therefore, cloud free images and direly required. The core aim of the study is to investigate the eutrophication status, land use and land cover mapping and exploring their potential impacts on coastal water quality. Previously, no scientific findings were presents on the southern estuarine water ecosystem of the Boseong County, Korea. The detailed objectives of this study were to (1) extract land use land cover characteristics of the study area, (2) to determine the concentration of Chl-a, TP, and TSD, and (3) seasonal based spatial variation of TSI values.

MATERIALS AND METHODS

***Study Area*:** This study was carried out in the region of the southern estuarine water ecosystem of the Boseong county South Korea. The study region was situated within the southern costal side of Jeollanam-do (latitude 34°50'–34°55'N, longitude 127°20' –127°30'E), which is the complex manmade and natural region (Fig. 1). Jeollanam-do province is a province the southwest of South Korea. The province was formed in 1986 from the southern half of Joella province. Its large parts consist of mountains forest such as Jonje Mountain and Mangil-Bong. The Boseong River passes the center of the county. The climate of the county is moderate. The average annual temperature is 12.7℃. While temperate in winter drop up to -0.5℃ and the average temperature increased in summer is 27.8℃. The mean annual precipitation is 1450mm.

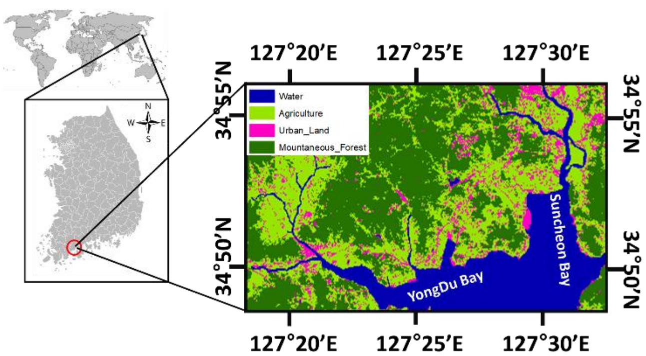

Figure 1. Description of the study area and land cover characteristics

***Remotely Sensed Data*:** The high-resolution satellite imageryLandsat-8 seasonal based cloud free scenes were collected for the selected study region. The cloud free Landsat 8 images were downloaded from the USGS GLOVIS website (https://glovis.usgs.gov). The study is comprised by two tiles having path 115 and 116 and row number is same as 36. The Landsat-8 was launched in 2013. It is one the mission of Landsat satellite program. The Landsat 8 have a temporal resolution of 16 days while its spatial resolution is 30 m.

The Digital numbers (DN) were converted into reflectance and radiances. ENVI Classic 5.3 was used for the preprocessing of the data. ENVI built in Band math is used for the radiometric calibration and radiance calculations while FLAASH module is used for the atmospheric correction. Land use and land cover extracted on the bases of accuracy's percentage and Kappa coefficient. The accuracy is a measure of the degree of closeness of a measured or calculated value to its actual value. Its range from 0 to 100 in percentage. Higher values indicates the classification was more realistic than classified by chance alone. The Kappa coefficient is a statistical measure of inter-rater reliability or agreement that is used to assess qualitative forms and determine agreement between two raters. A Kappa coefficient equal to 1 means perfect agreement where as a value close to zero means that the agreement is no better than would be expected by chance. The four-major land feature extracted were, urban settlement, mountainous forest, crops and water bodies.

The preprocessing of the Landsat-8 data stage consists of all the operation and processes, which convert raw data into a useable form for further scientific analysis and pre-processing attempts to compensate the systematic errors through correction. Moreover, systematic and radiometric corrections have been done for DN. The Landsat-8 data using ENVI software were converted for surface reflectance by the top-of-atmosphere is recommended for land surface mapping calibration, because the following method does not require advanced knowledge of sample collection in the field. The nearest neighboring method was applied to the realm of the original value of the pixels in the resampled imageries.

Furthermore, the radiometric correction is also applied to sort out and correct the digital numbers of the images. Remote sensing sensor accounts the intensity of the electromagnetic radiation in the form of digital numbers (DN). These DN are converted into more readable and meaningful formats like reflectance and radiance. Nowadays many remote sensing software packages already included image preprocessing tools. In this study, DN values of the images directly converted to reflectance using ENVI software, while the FLAASH Module in the ENVI has corrected the atmospheric correction.

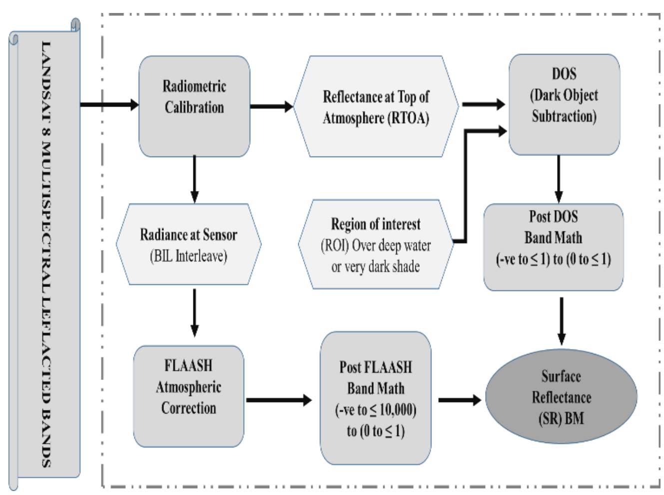

Figure 2. The preprocessing process of the Landsat 8 images

***Water Quality Assessment*:** The water quality parameter concentrations such as Chl-a, (TP), and TSD were extracted using different algorithms. The study used the algorithm proposed by Ren *et al*. (2018) for the TSD that is:

$$TSD = 1.7351 \times \mathrm{e}\left(-2.141 \times \frac{B4}{B3}\right)$$

For the calculation of Chl-a, algorithm proposed by Nazeer *et al*. (2016) for complex coastal water was used.

$$Chl\_a = 1.31 + 0.64 \times (B4)/(B2)^2$$

For the estimation of TP, the band ratio model proposed by Wu *et al*. (2013) was employed.

$$\ln(TP) = -21.45\left(\frac{B4}{B3}\right) - 14.42\left(\frac{B2}{B4}\right) + 42.99(B2) + 27.1$$

Here B2, B3, and B4 are the blue, green and red band value of the Landsat 8 OLI bands. One of the ways to illustrate the health of the coastal ecosystem is the by using TP, Chl-a, and TSD data to calculate the Trophic State Index (Carlson 1977). This index value classifies the state of coastal ecosystem using their scale value from 0-100.

***Trophic State Classification*:** The most applied index-based eutrophication classification of aquatic bodies is the CTSI (Carlson, 1977). CTSI evaluate the eutrophication state or photosynthetic pigments of the water bodies by utilizing but not limited the Chl-a, TSD and TP. The CTSI has a continuous scale ranging from 0 to 100 to present the eutrophication stage of the water ecosystem based on either transparency or nutrient concentration. A CTSI score less than 30 termed as ultraoligotrophic condition, whereas values range from 60-70 is assigned as the heavy eutrophic state (Carlson,1977, Patra *et al*., 2017; Saputra *et al*., 2017). The following formulae used to calculate the TSI and CTSI based on water quality parameters concentrations that are given below (Carlson, 1977).

$$TSI(Chl) = 9.81 \times \ln\left[Chl(\mu g/\mathrm{L})\right] + 30.6$$

$$TSI(TP) = 14.42 \times \ln\left[TP(\mu g/\mathrm{L})\right] + 4.15$$

$$TSI(SDT) = 60 - 14.42 \times \ln\left[SDT(m)\right]$$

Carlson's Trophic State Index (CTSI)

$$(CTSI) = \frac{TSI(Chl) + TSI(TP) + TSI(SDT)}{3}$$

***Statistical Analysis*:** The applied algorithm accuracy was assessed based on the following three statistical estimators. The first statistical estimator used in the study is confident of determination (R^2), which assess the relative deviation of the applied model result with ground-based observation or other existing models.

$$R^2 = \frac{\left\{\sum_{i=1}^{N}\left(M1_i - \overline{M1_i}\right)\left(M2_i - \overline{M2_i}\right)\right\}^2}{\sum_{i=1}^{N}\left(M1_i - \overline{M1_i}\right)^2\left(M2_i - \overline{M2_i}\right)^2}$$

The second statistical estimators used in the following study is Bias, which is determined by determined by adding the difference between applied models finding with other similar existing models results.

$$Bias = \frac{\sum_{i=1}^{N}(M1_i - M2_i)}{\sum_{i=1}^{N} M1_i} \times 100$$

The third statistical estimators used in the following study is the root mean square error (RMSE), which is rooted mean of two corresponding modeling results for relative error estimation.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M1_i - M2_i)^2}$$

Here M1 is the results of the applied model and M2 is the other existing model used for the accuracy assessment of the applied algorithm.

RESULTS

The land use land cover of coastal region Boseong County is shown in fig 3. Due to the spatial landscape of the chosen study region, the general classes named urban settlement,

Table 1. The spatial resolution of the Landsat 8 band designations.

	Bands	Wavelength (micrometers)	Resolution (meters)
Landsat 8 Operational Land lmager (OLI) and Thermal Infrared Sensor (TIRS) Launched February 11, 2013	Band 1 - Coastal aerosol	0.43 - 0.45	30
	Band 2 – Blue	0.45 - 0.51	30
	Band 3 – Green	0.53 - 0.59	30
	Band 4 – Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - SWIR 1	1.57 - 1.65	30
	Band 7 - SWIR 2	2.11 - 2.29	30
	Band 8 – Panchromatic	0.50 - 0.68	15
	Band 9 – Cirrus	1.36 - 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100

Source (https://www.usgs.gov/media/images/landsat-8-band-designations) mountainous forest, water, and agricultural farms were considered as LULC feature classes. About 60 % of the study region is covered by the mountainous forest. Whereas, fig. 3 shows the spatial distribution of trophic index value over the entire study region in all seasons. The study found that the overall value of the CTSI is classified under the medium eutrophication state in summer and autumn season (Table 2). While, it falls in the light eutrophic state in winter and spring seasons (Table 2). Fig. 4 shows that the value of TSI (TSD) in all seasons is higher than the other parameters.

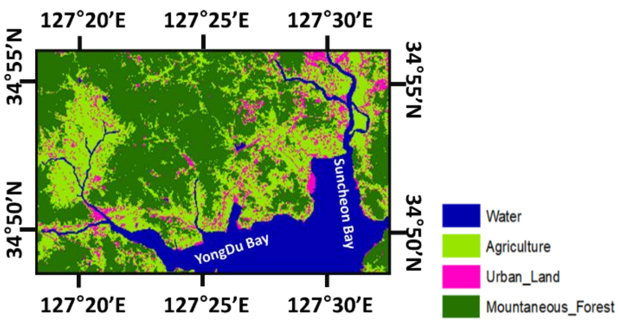

Figure 3. Land use Landcover information of the southern estuarine water ecosystem of the Boseong county republic of Korea

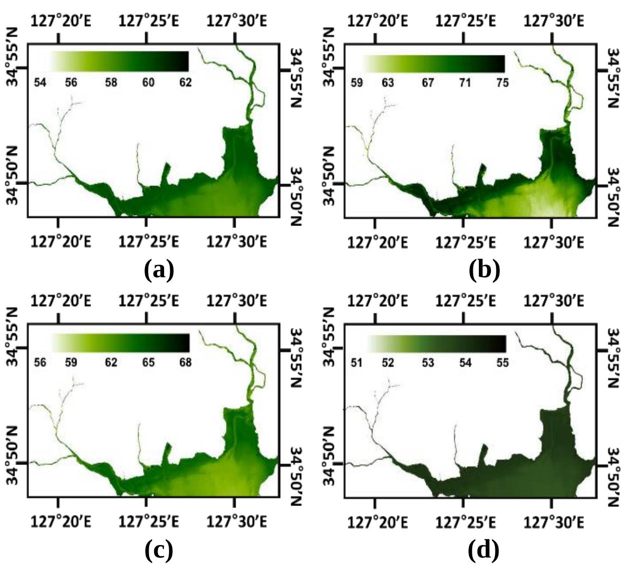

Figure 4. Spatial maps of Trophic state classifications for a) spring season, b) summer season, c) autumn season, and d) winter season

Assessment of the Land-Cover Classification: Accuracy assessment report of Landsat-8 scenes are shown in the Table 3. The figure 2 shows that the eastern side of the coastal water is connected with the agricultural land and urban settlement. After extracting the LULC classified image, accuracy assessment was performed using 100 random sampling points. By means of the randomly selected sample assessment, the classified image presented the higher value of Kappa coefficient and overall accuracy about 83 % (Table. 4). The exact area of water body was classified by using the technique of land-use land-cover classification system. From these accuracy assessments, it can be deduced that high-resolution image can be best suited for water body detection and the further assessment of the water body.

Table 2. Carlson Trophic Index classification (Carlson, 1977).

Index Value	Trophic Status	Explanation
<30	Ultraoligotrophic	The nutrients quantity is negligible. The waterbody is clean.
30-40	Oligotrophic	The nutrients quantity in water body is low.
40-50	Mesotrophic	Moderate nutrients concentration.
50-60	Light Eutrophic	The nutrients concentration is high. Declining in water purity.
60-70	Medium Eutrophic	The concentration of the pollutants is high.
70-80	Heavy Eutrophic	The nutrients concentration is high causing algal blooms.
>80	Hyper Eutrophic	The nutrients concentration is very high. Algal clamping is developed. Most of the aquatic life including fish can't survive.

Accuracy Assessment of the Employed Models: The statistical analysis assessment (Table 4) shows that models used in this study are reliable to investigate the trophic state of the coastal water by using satellite imagery. The statistical analysis show that the result is well agreed with other regional/world-wide algorithms. The values show that the result has a high value of correlation coefficient, low bias, and the low RMSE value for Chl-a, TSD, and TP for case of summer season. These results are also parallel on other seasons. Hence, this study can be reliable in monitoring and classifying the water quality status of the selected coastal zone. Based on trophic state index and statistical assessment, the following study can be applied in classifying and management of the water quality status of the selected coastal zone.

Table 3. The accuracy assessment approach between observed and land cover dataset.

Class	User accuracy	Producer accuracy
Water	79%	92.31%
Urban	71%	77.79%
Mountainous forest	88%	78.23%
Crop	89%	81.92%
Overall accuracy	83%	
Kappa coefficient	0.79	

Table 4. Statistical comparisons of used algorithm in this study with other regional/world-wide algorithms.

Algorithms	R	Bias	RMSE
Chl-a (µg/L) (Watanabe *et al.*, 2015)	0.96	0.11	0.24
TSD (m) (Kloiber *et al.*, 2002)	0.81	0.06	0.03
TP (µg/L) (Zhang *et al.*, 2017)	0.89	0.13	0.16

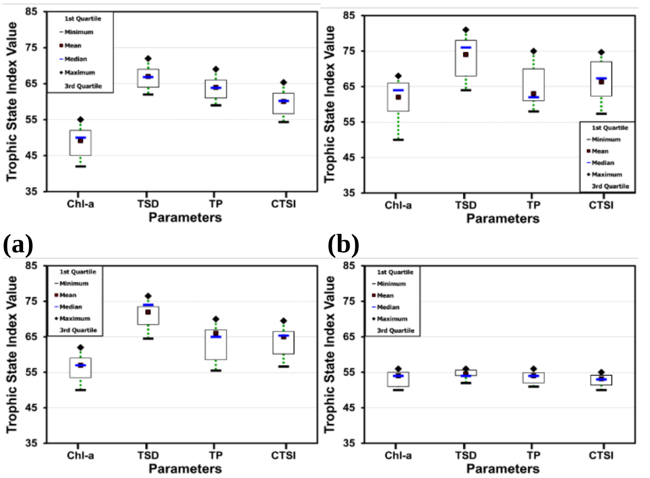

Figure 5. Graphical representation the trophic status of water quality parameters with box and whisker plots a) spring season, b) summer season.

DISCUSSION

The impact of land use land cover on the spatial variation also supported by many previous studies of where anthropogenic activities and land cover alteration plays a significant role in the spatial variation of surface water quality (Rizvi *et al.*, 2021; Shehab *et al.*, 2021; Salehi *et al.*, 2020; Manbohi *et al.*, 2020; Gu *et al.*, 2019). Jung *et al.*, 2021 also highlights the potential impact of human factors on the variation of the surface water quality. The higher value of TSI (TSD) indicates that there is also presence of the suspended solids or other organic particles which reduced the water clarity (Mamun and An, 2017).

Eutrophication in the coastal estuarine zone is a main ecological concern globally. In the coastal zone of the southern sea, eutrophication affects not only the coastal waters but also the open seas. Numerous strategy contexts aim to hamper its advancement but eutrophication related water-quality parameters, such as TSD, Chl-a, and other nutrients concentrations, still show contradictory spatial trends in several coastal and marine environments. In this research, we have explored the linkages of agricultural pollutants discharge on the eutrophication status of coastal environment and their various anthropogenic, climatic and seasonal discharge drivers on the estuarine coastal waters (Gu *et al.,* 2019; Wang *et al.*, 2019; Liu *et al.*, 2019).

We observed that it is essential to differentiate more and less effected zones of the coastal waters, based on their spatial variation of the eutrophication with the estuarine environment, to internment altered eutrophication dynamics. Spatial variation in eutrophication conditions associate best with variation in effluent discharge in climatic and seasonal drivers, like water temperature and seasonal variation in precipitation, respectively. In the estuarine waters, prime indications are more assorted, with significant effects from anthropogenic load and agricultural nutrient discharges.

Very few analogous researches from other areas evaluating the spatial variation in eutrophication status have been available. Study of Murray *et al.,* (2019), which analyzed a consistent valuation basis for the third time and determines that the spatial variation of 'problematic zones' in relations to eutrophication has declined. Analyzing the effects of nutrient augmentation in 54 estuaries of the United States (Bricker *et al.,* 2008) determines that situations were projected to be deteriorate, due to surges in anthropogenic and agricultural loads with amassed population.

In coastal estuarine environments disposed to high nutrient and agricultural pollutants loads, assessment of eutrophication status can be considered equivalent to an 'ecological status' assessment. This kind of spatial variation Valuations can provide an ancillary sign of whether situations are refining in coastal zones (Iqbal *et al.,* 2019). The seasonal based assessments used for the valuation development for the estuarine water are more appropriate and operative for necessities of the sustainable coastal water monitoring, fortification and management. As such, our fallouts encounter any coastal front paradigm and highlight a necessity for rigorous confined local-catchment and seasonal dealings for healthy eutrophication management of the coastal waters (Kolada, 2021; Murray *et al.,* 2019; Agwanda, and Iqbal 2019).

The value of CTSI for all studied parameters is the higher besides cropping area as well as urban settlements. The spatial variation of the TSI in the study region aided strong evidences to be detected over the area's adjutant to agrarian farming and urban habitants (Gittings *et al.,* 2017). The study suggests that coastal eutrophication advanced due to which the nutrients from human and natural activities transport occurs resulting in the deterioration of the water quality. Water treatment plant essential to be installed in order to control eutrophication disparity in the coastline ecosystem at the pollution entrance point. The spatial variation of the designed TSI is a suitable means to detect sources of sediment transport in the costal ecosystem (Opiyo *et al.,* 2019; Yu *et al.,* 2010; Bertani *et al.,* 2017).

***Conclusions*:** The spatial variation of the trophic index in the study region aided strong evidences to be detected over the areas adjacent to agrarian farming and urban habitants. The study suggests that coastal eutrophication advanced due to which the nutrients transport from human and natural activities occurs resulting in the deterioration of the water quality. Furthermore, higher values of TSI in summer season indicated high temperature and high rainfall also incorporated in worsening the coastal water quality. The Water treatment plant is essential to be installed in order to control eutrophication disparity in the coastline ecosystem at the pollution entrance point. The Spatial variation of the designed TSI is a suitable means to detect sources of debris composites in the water ecosystem. Lastly, the study concludes that the TSI could be used as a simple management tool to classify individual water ecosystems into broad categories that mirror their water quality status.

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Conflicts of Interes**t:** The authors declare no conflict of interest.

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