# 2 Literature Review

## 2.1 Situation of water bodies in India

A report from Department of Jal Shakti. India possessed an abundance of water resources. However, India is gradually moving away from being a country with sufficient water due to rising population pressure and urbanization. It is currently supporting 18% of the world's population with only 4% of the world's water resources. As a result, importance of water resource management has grown significantly. The current state of our nation's water resources availability is a serious problem and a considerable concern.

Freshwater resources include water bodies as a vital component. There are a lot of bodies of water throughout the rural areas of India. These bodies of water have historically been crucial to the provision of drinking water, for home usage, for agricultural uses, etc. They were a vital contributor to the Minor Irrigation (MI) system for Indian agriculture. These bodies of water - whether they were created by nature or by humans - such as lakes, tanks, ponds, and other similar constructions have supported Indian agriculture over the years. Water bodies also play a significant role in metropolitan settings as a supply of drinking water, a way to absorb floodwater, and a pathway for ground water recharge. To conserve or restore these water bodies for healthy and sustainable development, it is crucial to examine where freshwater resources are located, how they are used, and how climate, technology, policy, and people may contribute.

24,24,540 water bodies were counted in the nation during the first census of water bodies (Jan 2023), of which ponds made up 59.5% (14,42,993), tanks 15.7% (3,81,805), and reservoirs 12.1% (2,92,280). The remaining 12.7% (3,07,462) were lakes and other water bodies, check dams, and percolation tanks, as well as water conservation schemes (Water bodies first census report by Govt. of India). Top five States in number of water bodies are mentioned in Figure 4.

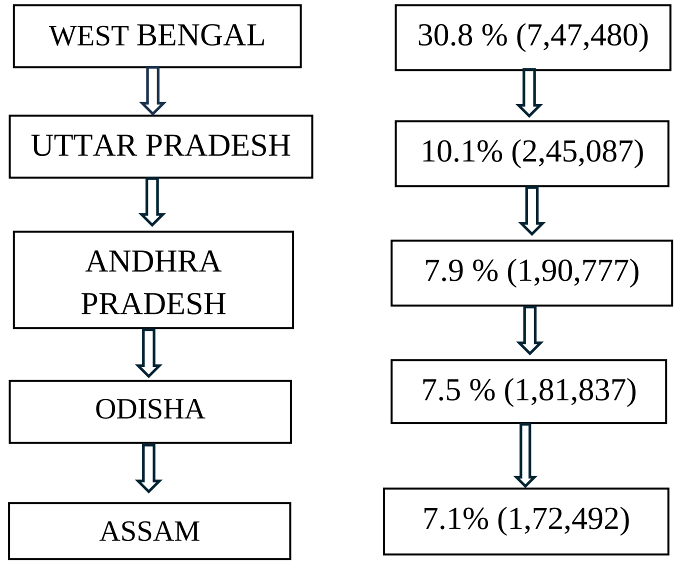


**Figure 4 Top five States in number of water bodies**

Source : Water bodies first census report- Department of Jal shakti

97.1% (23,55,055) of the 24,24,540 water bodies counted are in rural areas, and 2.9% (69,485) are in urban areas. The remaining 16.3% (3,94,500) of these water bodies are not in use or not functioning due to drying up, construction, siltation, damage beyond repair, salinity, industrial effluents, etc., while 83.7% (20,30,040) of them are "in use." Major water bodies are stated to be used for pisciculture out of all "in use" water bodies, followed by irrigation and ground water recharge. Private companies possess 55.2% (13,38,735) of the India's water bodies, while the government owns 44.8% (10,85,805) of them. 9.6% of all water bodies are found in tribal areas, 8.8% are in flood-prone areas, 7.2% are part of the Drought Prone Area Programme (DPAP), 2.0% are in Naxal-affected areas, and 0.7% are part of the Desert Development Programme (DDP), with the rest 71.7% being found in other places. 22% of water bodies are natural, while 78% are artificial. Most artificial water bodies are composed of dirt and cost up to Rs. 100,000 to create initially. 1.6% (38,496) of the total 24,24,540 water bodies are reportedly encroached upon. Ponds are the most encroached water bodies, followed by tanks. In the 24,516 water bodies whose encroachment regions may be evaluated, 62.8% of the water bodies are found to have less than 25% encroachment. Graph of spread of water bodies across country is given in Figure 5.

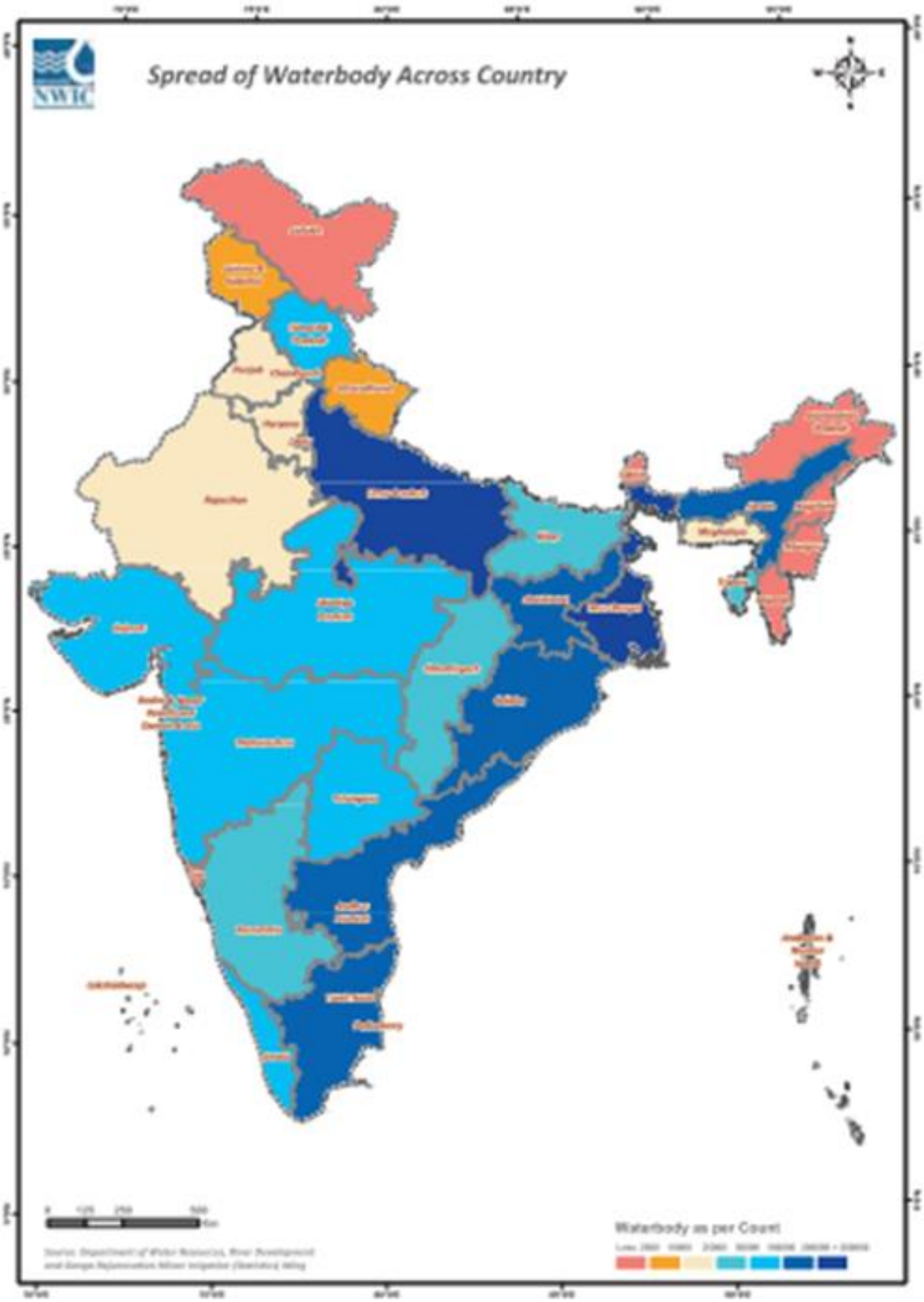


**Figure 5 Spread of water bodies across India**

Source : Water bodies first census report- Department of Jal shakti

## 2.2 Situation of water bodies in Gujarat

A report from Department of Jal Shakti :54,069 water bodies total, of which 98.3% (53,156) are in rural regions and the remaining 1.7% (913) are in urban areas, have been counted in one census (2023). 99.8% (53,979) of all water bodies are owned by the government; the remaining 0.2% (90) are privately owned. 60.7% (32,781) of the publicly held water bodies are owned by panchayats. 20% of water bodies (11,174) are found in tribal territories. 99.7% (53,903) of the water bodies are in use, whereas only 0.3% (166) of them aren't due to evaporation, siltation, damage beyond repair, or other factors. 50.1% (26,999) of the state's total water bodies are used for irrigation, while 43.9% (23,669) of them are utilized for pisciculture in Gujarat. There are 16,966 naturally occurring and 37,103 artificial water bodies. 95.3% (16,166) of the 16,966 natural water bodies are found in rural areas, compared to 4.7% (800) in urban areas. 99.7% (36,990) of the 37,103 man-made water bodies are found in rural areas, while 0.3% (113) are found in urban areas. According to criteria used to determine how much storage space was filled in the previous five years, out of 28,353 water bodies, 97.5% (27,643) are determined to be filled annually, and 2.5% (709) are typically filled. Distribution of various water bodies in Gujarat is presented pictorially in Figure 6 and the corresponding values are shown in Table 5.

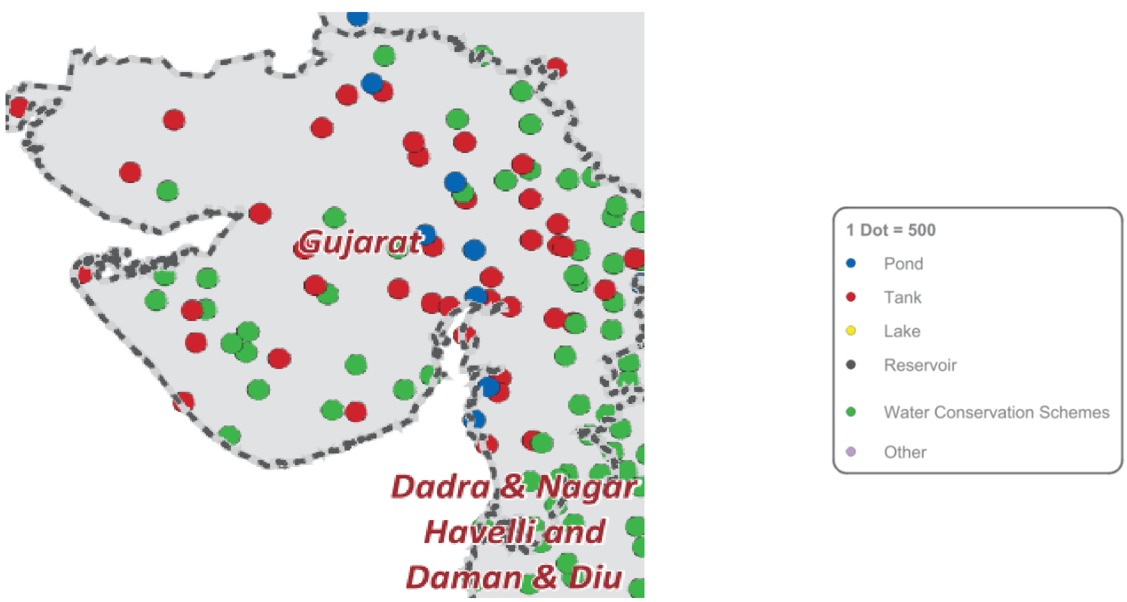


**Figure 6 Water bodies spread across Gujarat.**

Source : Water bodies first census report- Department of Jal shakti

**Table 5 Distribution of water bodies of Gujarat**

| S.No. | Parameter | Unit | Value | Percentage to Total* |
|---|---|---|---|---|
| **1** | **Total Number of Water Bodies** | **no.** | 54,069 | |
| | **Total Number of Water Bodies in Rural Areas** | **no.** | 53,156 | 98.31 |
| | **Total Number of Water Bodies in Urban Areas** | **no.** | 913 | 1.69 |
| **a** | **Total Number of Water Bodies by type** | **no.** | | |
| | Ponds | | 4,711 | 8.71 |
| | Tanks | | 22,963 | 42.47 |
| | Lakes | | 12 | 0.02 |
| | Reservoirs | | 667 | 1.23 |
| | Water Conservation Schemes/ Percolation tanks/ Check dams | | 25,667 | 47.47 |
| | Others | | 49 | 0.09 |
| **b** | **Water Bodies with Private Ownership** | **no.** | 90 | 0.17 |
| | **Water Bodies by area** | **no.** | | |
| | Drought Prone Area Programme (DPAP) | | 285 | 0.53 |
| | Tribal | | 11,174 | 20.67 |
| | Desert Development Programme (DDP) | | 2,323 | 4.30 |
| | Flood Prone | | 0 | 0.00 |
| | Others | | 40,287 | 74.51 |
| | Total | | 54,069 | 100.00 |
| **2** | **Water Bodies by type of use** | **no.** | | |
| | Irrigation | | 26,999 | 50.09 |
| | Industrial | | 0 | 0.00 |
| | Pisciculture | | 23,669 | 43.91 |
| | Domestic/ Drinking | | 149 | 0.28 |
| | Recreation | | 152 | 0.28 |
| | Religious | | 20 | 0.04 |
| | Ground Water recharge | | 2,889 | 5.36 |
| | Others | | 25 | 0.05 |
| | **Total** | | 53,903 | 100.00 |
| **3** | **Natural/ Man Made Water Bodies** | **no.** | | |
| | Natural | | 16,966 | 31.38 |
| | Man Made | | 37,103 | 68.62 |
| **4** | **Water Bodies Not in use due to reasons** | **no.** | | |
| | Dried up | | 3 | 1.81 |
| | Construction | | 5 | 3.01 |

| S.No. | Parameter | Unit | Value | Percentage to Total* |
|---|---|---|---|---|
| | Siltation | | 9 | 5.42 |
| | Destroyed beyond repair | | 0 | 0.00 |
| | Salinity | | 0 | 0.00 |
| | Due to industrial effluents | | 0 | 0.00 |
| | Others | | 149 | 89.76 |
| **5** | **Distribution of Water Bodies as per status of filling** | **no.** | | |
| | Filled up every year | | 27,643 | 97.50 |
| | Usually filled up | | 709 | 2.50 |
| | Rarely filled up | | 1 | 0.00 |
| | Never filled up | | 0 | 0.00 |
| | Total | | 28,353 | 100.00 |
| **6** | **Distribution of Water Bodies by number of city/ towns benefitted** | **no.** | | |
| | 1 | | 53,707 | 99.64 |
| | 2 to 5 | | 182 | 0.34 |
| | 6 to 10 | | 5 | 0.01 |
| | 11 to 20 | | 5 | 0.01 |
| | 21 to 50 | | 4 | 0.01 |
| | 50 to 500 | | 0 | 0.00 |
| | Total | | 53,903 | 100.00 |
| **7** | **Distribution of Water Bodies by Water Spread Area** | **Ha.** | | |
| | Less than 0.5 hectares | | 361 | 0.67 |
| | 0.5 hectares to 1.0 hectares | | 15,713 | 29.07 |
| | 1 hectare to 5 hectares | | 36,923 | 68.30 |
| | 5 hectares to 10 hectares | | 817 | 1.51 |
| | 10 hectares to 50 hectares | | 186 | 0.34 |
| | More than 50 hectares | | 57 | 0.11 |
| | Total | | 54,057 | 100.00 |
| **8** | **Distribution of Water Bodies by Storage Capacity (in Cu. Mtrs)** | **Cu. Mtrs** | | |
| | 0 to 100 | | 25,716 | 47.56 |
| | 100 to 1000 | | 34 | 0.06 |
| | 1000 to 10000 | | 8,122 | 15.02 |
| | More than 10000 | | 20,197 | 37.35 |
| | Total | | 54,069 | 100.00 |
| **9** | **Number of encroached water bodies** | **No.** | **22** | **0.04** |

## 2.3 Literature Assessment

One of the most crucial aspects of any regional hydrological variable is trend analysis, which considers geographical and temporal factors and provides results for current circumstances and predictions for future scenarios based on the examination of historical data.

The Kolong River in Assam has been polluted due to the construction of an embankment in 1964 to protect Nagaon town from floods. The river is now stagnant and polluted and is no longer a source of water for irrigation or navigation. The water quality index (WQI) indicated that the water quality was very poor to unsuitable at all seven sampling sites along the river and was worst during the monsoon season (Bora & Goswami, 2017).

Birawat et.al (2021) studied ten lakes in Bengaluru, India, to assess the impact of land use on water quality. The lakes were divided into three categories: rural, semi-urban, and urban, physicochemical analysis of the lake waters was conducted, and the water quality index was computed using the weighted arithmetic method and an overall index of pollution method. The results showed that urban lakes in Bengaluru had very poor water quality. This is likely due to several factors, including pollution from sewage and runoff from urban areas. Lakes in semi-urban watersheds are also at risk of deterioration, as these areas are rapidly developing. The study highlights the importance of protecting lakes from land use change and pollution. Lakes play an important role in the environment, providing habitat for aquatic life, filtering water, and storing floodwaters. Policymakers can utilize the study's data to create programs and regulations that safeguard lakes and water quality.

Three different water quality indices (WQIs) were used to assess the water quality of the river Ganga over a period of 11 years. These were the River Ganga Index by Ved Prakash, the weighted arithmetic index, and the WQI by the National Sanitation Foundation (NSF). The study found that the three indices showed variations in the water quality of the river Ganga over the 11-year period. The River Ganga Index by Ved Prakash classified the water quality as medium to good, the NSF Index classified the water quality as good, and the weighted arithmetic index classified the water quality as poor. The study suggested that the observed variations in the results of the three indices may be due to the different weights assigned to the physicochemical parameters in each index.

They also suggested that the weighted arithmetic index may be more sensitive to changes in water quality than the other two indices. Overall, the study suggests that the water quality of the river Ganga has remained relatively stable over the past 11 years, but that it is still not suitable for drinking or irrigation without prior treatment (Bhutiani et al., 2016).

A study of the water quality of Harni pond in Gujarat, India, during the summer, monsoon, and winter seasons of 2016-2017 used the Weighted arithmetic mean water quality index to assess the suitability of the water for drinking. It was found that the WQI of Harni pond was above 100 in all three seasons, which indicates that the water is unsafe for drinking. The highest WQI was found in the summer season, followed by the winter and monsoon seasons. The poor water quality of the pond was ascribed to several factors, including sewage pollution, agricultural runoff, and industrial effluent (Krupa & Parikh, 2018).

An ecosystem-specific water quality index (ES-WQI) has been developed for Lake Cajititlán in Mexico. The ES-WQI is a new tool that can be used to accurately track incremental improvements in water quality because of ongoing restoration projects. It also provides a baseline on which strategies must be implemented to improve the lake's physical, chemical, and biological characteristics to reach desirable water quality conditions. However, because the lake's water quality is not static, problems could arise when new monitoring data show that the parameters that were not originally incorporated in the ES-WQI was found to present detrimental effects on the lake's water. This is because the ES-WQI algorithm is based on historical data and multivariate statistical methods, and it may not be able to accurately reflect the water quality of the lake if new parameters are found to be important. ES-WQI should be updated periodically to include new parameters that are found to be important to the lake's ecosystem. The researchers also suggest that the ES-WQI can be used in conjunction with other water quality monitoring tools to get a more complete picture of the lake's water quality (Gradilla-Hernández et al., 2020).

For the Bulgarian rivers, four indices were calculated: the Water Quality Index - WQI, the Combinatorial Index of Water Pollution - CIP, the Index of Water Pollution - IWP, and the Index of Oxygen Balance in River Water - IOB: The rivers were the Vacha, the Lesnovska, and the Provadiyska. The findings indicated that all four indices approaches were effective for analysing the quality of river water, particularly in the context of anthropogenic impact. Uniform indicators can also be used to compare the water quality of different rivers and locations (Varbanov & Gartsiyanova, 2017).

A new Bathing Water Quality Index (BWQI) was reported. The BWQI is a predictive tool that considers the flushing time of a bathing area, the morphology of the area, the meteo marine conditions, and the physiological state of E. coli cells to assess the risk to human health. The BWQI ranges from 0 to 1, with higher values indicating better water quality. A BWQI of 0 indicates the worst possible water quality condition, while a BWQI of 1 indicates the best possible water quality condition. The BWQI was applied to the Santa Marinella bathing area in Italy. The results showed that the BWQI was lowest in the area most frequented by bathers, indicating a potential risk to human health. The study suggests that the BWQI is a low-cost and predictive tool that can be easily exported and applied to other semi-enclosed bathing areas. This makes it a valuable tool for environmentally sustainable and public health management (Bonamano et al., 2021).

The analysis of the WQI data reveals that surface water from the coastal south region to the north region of Gujarat was poor for drinking purposes. Kankal et al., (2012) studied quality of surface water in various sampling locations of Gujarat, India. The water quality index of the surface water ranged between 44-61, which indicates poor water quality. The high WQI values at some stations are due to higher values of fecal coliform, nitrate, total suspended solids, and BOD in the surface water. WQI can also be used to inform decision makers about how to manage water resources and protect public health.

Study of the water quality of a lake over a period of three months covering both dry and wet seasons was carried out on Lake Hawassa by Menberu et al., (2021). The study used three different water quality indices the assessment: the weighted arithmetic method, the modified Bascarón water quality index (MBWQI), and the Canadian Council of Ministers of the Environment (CCME) water quality index method. The study found that the water quality of the lake was unfit and bad as per the weighted arithmetic method and MBWQI methods, and marginal as per the CCME water quality index method. The study also found that the lake was under the hypertrophic stage, which is the most severe stage of eutrophication. Eutrophication is a process in which a water body becomes enriched with nutrients, such as nitrogen and phosphorus. This can lead to an overgrowth of algae and other aquatic plants, which can deplete oxygen levels in the water and make it uninhabitable for fish and other aquatic life. Studied Lake is unfit for all purposes and that mitigation measures are needed to control eutrophication and pollutant inflow.

Water quality of the Netravathi River in Karnataka, India was determined using two different water quality indices: the Bhargava WQI method and the Harmonic Mean WQI method. The study found that the water quality of the river varied from Excellent to Marginal range by Bhargava WQI method and Excellent to Poor range by Harmonic Mean WQI method. The authors concluded that the water quality of the river was deteriorating. The impact of human activity was severe on most of the parameters and that the main cause of deterioration in water quality was lack of proper sanitation, unprotected river sites, and high anthropogenic activities. Study suggests there is need to address the human-caused sources of pollution to improve the water quality of the river (Avvannavar & Shrihari, 2008).

A new water quality index called the Composite Water Quality Index (CWQI) was developed by Singh et al., (2019). A generalized index that can be used to classify both surface and groundwater into five categories: excellent, good, fair, poor, and polluted. The CWQI is calculated using a weighted average of 25 water quality parameters. The weights for each parameter were determined using the Saaty's Analytic Hierarchy Process (AHP) Multiple Criteria Decision Analysis (MCDA) tool. The AHP is a decision-making tool that allows for the incorporation of subjective judgments into a quantitative analysis. The CWQI has several advantages over other WQIs. First, it is a generalized index that can be used to assess the water quality of both surface and groundwater. Second, it uses a weighted average of water quality parameters, which gives more importance to parameters that are significant for water quality. Third, the weights for each parameter were determined using a quantitative method, which minimizes the subjectivity in assigning the parameter weights. CWQI can be used by water management authorities to identify areas where water quality is poor, track changes in water quality over time, evaluate the effectiveness of water pollution control measures, and make informed decisions about water resource management.

Simeonov et al., (2003) studied the use of multivariate statistical methods to analyses a large and complex dataset of surface water quality data from Northern Greece. The dataset included 27 parameters measured at 25 sampling sites monthly over a period of 3 years. Three different multivariate statistical methods were applied: cluster analysis (CA), principal component analysis (PCA), and multiple regression analysis on principal components (MRA-PC). The authors concluded that the use of multivariate statistical methods is essential for analyzing large and complex datasets of surface water quality data. It can be used to:

- Get better information about the quality of surface water.
- Design sampling and analytical protocols
- Develop effective pollution control and management strategies.

A study was conducted to monitor the water quality of the Arka River in Lebanon. The Arka River is the main inland water resource for human and agricultural needs in the Akkar region. The study assessed 19 physicochemical parameters and 4 microbiological parameters for 8 sampling locations along the river and for 7 sampling campaigns between March and July 2014. Daou et al., (2016) used principal component analysis (PCA) to evaluate the spatial and temporal variations in surface water quality. The first two principal components were characterized by mineral parameters and organic and bacteriological parameters, respectively. The parameters responsible for the variations were related not only to physicochemical parameters originating from soil leaching and intrusion of seawater, but also to organic and bacteriological parameters indicating anthropogenic pollution, especially for stations located in the Akkar flatland. Study found that anthropogenic pollution, especially from the flatland and the surrounding villages, is a major factor impacting water quality in the river.

Dalal et al., (2010) employed principal component analysis (PCA) for the interpretation of a large complex data matrix gathered from the Kandla Creek environmental monitoring program to determine the key sources contributing to water quality metrics. The authors state that PCA is a powerful tool for pattern recognition and that it can be used to derive better information about water quality and analytical protocols. They also suggest that it may be necessary to include certain new parameters in future monitoring studies and that it may be possible to eliminate some of the observed parameters.

Fan et al., (2010) used multivariate statistical methods, principal component analysis (PCA) and cluster analysis (CA), to assess water quality and identify pollution sources in the Pearl River Delta, China, to identify the parameters that were responsible for water quality variations in the three regions of the Delta: North River, East River, and West River. The identified parameters were - North River: organic related parameters (DO and $COD_{Mn}$), inorganic nutrients ($NH_3$-N and TP), and metal Hg; East River: organic related parameters ($BOD_5$) and inorganic nutrients ($NH_3$-N and TP); West River: organic related parameters ($COD_{Mn}$) and inorganic nutrients ($NH_3$-N and TP). From the study, it was concluded that the methods they used in their study can be a useful tool for assessing water quality and managing water resources in regions with many complex water quality datasets.

Kazi et al., (2009) reported use of multivariate statistical techniques, cluster analysis (CA) and principal component analysis (PCA), to assess water quality and identify pollution sources in Manchar Lake, Pakistan, for a period of one year. They then used PCA to identify the chemical correlations between the different water quality parameters. CA was used to classify the samples into clusters based on the PCA scores. Major causes of water quality deterioration were inflow of effluents from industrial, domestic, and agricultural sources into the lake and people living in boats and fishing.

Li et al., (2020) used the water quality index (WQI) method to assess the water quality of reservoirs in the lower reaches of the yellow river in China and compared the water quality of mountain and yellow river reservoirs. Water samples were collected from five reservoirs over a period of six years. Selected nine water variables were used in the WQI calculation using principal component analysis (PCA). The WQI values ranged from 17.8 to 77.8, indicating "good" to "very poor" water quality of the reservoirs. Mercury was the main contaminant in all five reservoirs, while total phosphorus (TP) and sulphate ($SO_4$) were other major contaminants in the mountain and Yellow River reservoirs, respectively. It was concluded that WQI is a helpful tool that can be used by the public and decision-makers to evaluate the water quality of drinking reservoirs in the lower reaches of the yellow river.

Barbulescu et al., (2021) investigated three aspects of the Brahmaputra river in India relating anthropogenic activities and environmental factors with water quality.

- Tested the hypothesis that there were monotonic trends in the eight water quality parameters that had been recorded at ten hydrological stations over a period of 17 years. They found that this hypothesis was rejected for all the parameters except for dissolved oxygen (DO), which showed a significant decreasing trend.
- Three water quality indices (WQIs) were used to assess the water quality of the Brahmaputra River: the CCME WQI, the British Columbia WQI, and a weighted index. They found that the water quality of the river was generally "good" to "very good" according to all three indices.
- A new algorithm to group the years and stations into clusters based on the computed WQIs was used. They found that there were two clusters for the spatially distributed data (i.e., data from all ten stations) and two clusters for the temporal-distributed data (i.e., data from all 17 years). The authors concluded that the procedure they proposed for determining the WQI temporal and regional evolution provided good results in terms of mean absolute error, root mean squared error (RMSE), and mean absolute percentage error (MAPE).

The primary tributary of the river Hindon that runs through important cities in western Uttar Pradesh, India, is the Kali River, which is a key supplier of surface water in the region. It runs throughout the urban and rural areas, carrying different levels of pollution. Singh et al., (2020) studied the spatial and temporal variations in river water quality of the river. Analysis of water samples collected from 17 sampling stations along the river stretch was done to determine the physicochemical variables and heavy metal concentrations. Physicochemical variables which were higher in summer than in winter are pH, electrical conductivity (EC), total dissolved solids (TDS), turbidity, biological oxygen demand (BOD), chemical oxygen demand (COD), chloride ($Cl^-$), sulphate ($SO_4^{2-}$), nitrate ($NO_3^-$) and phosphate ($PO_4^{3-}$). Multivariate statistical methods were used to assess the spatial and temporal variation in water quality and to identify current pollution sources. They found that the water was less polluted from sampling stations S1 to S8, but that downstream sampling sites were polluted. Pollution started at sampling station S9 and drastically increased at and beyond sampling station S13 due to effluents from industries and sugar mills in Muzaffarnagar. The authors concluded that the downstream region of the river needs to be cleaned to restore human health and flora and fauna in the river ecosystem.

The International Cooperative Programme Waters program monitors 189 surface water sites in 12 geographical regions in Europe and North America. From 1990 to 2001, sulphate concentrations decreased in all but one of the investigated regions. Nitrate increased in only one region and decreased in three North American regions. Improvements in alkalinity and pH were widely observed. The results from the International Cooperative Programme Waters program clearly show widespread improvement in surface water acid-base chemistry, in response to emissions controls programs and decreasing acidic deposition. Limited site-specific biological data suggest that continued improvement in the chemical status of acid-sensitive lakes and streams will lead to biological recovery in the future (Skjelkvåle et al., 2005).

Jaji et al., (2007) studied the water quality of the Ogun River in South-West, Nigeria. Water quality of the river was poor, with high concentrations of pollution indicators, nutrients, and trace metals above the acceptable limit set by the World Health Organization (WHO) for drinking water. The study collected water samples from 13 sites along the river course and analysed them for physico-chemical and bacteriological parameters as well as heavy metals. Parameters which were above the WHO limit are turbidity, phosphate, oil and grease, iron, and fecal coliform. The study concluded that the Ogun River was polluted along its course and that this pose a health risk to several rural communities which relied on the river primarily as their source of domestic water and recommended that a continuous pollution monitoring program be implemented for surface waters in Nigeria.

In the USA, of the 15 monitoring sites along the Delaware river and its tributaries that were investigated between 1980 and 2005, the water quality improved at 39%, remained the same at 51%, and declined at 10% of the stations. Although it has improved, the water quality is still fair to poor in the tidal estuary at Philadelphia and in the two biggest tributaries, the Lehigh and Schuylkill Rivers, where nitrogen and phosphorus levels exceed standards. The water quality was good in the freshwater Delaware River and tributaries upstream from Trenton (Kauffman et al., 2011).

The Yamuna River is a famous example of how urban waterways suffer greatly from pollution. Understanding how rivers respond to urbanization in terms of water quality is necessary for effective human intervention. To do this, time-series data from the Central Pollution Control Board

(CPCB) and the Central Water Commission (CWC) were examined. The dataset from 1978 to 2015 contained 44 parameters for 12 locations on Yamuna mainstream. Monsoon flows have been declining over the past two decades, according to statistical tests used to analyse patterns. In addition, rising non-monsoon flows from Delhi to Agra suggested that wastewater dumping into the river had a substantial impact on the river's overall flow. The river's groundwater characteristics, such as electrical conductivity, hardness, and sodium concentration, have been observed to rise with time. This proposes the usage of ground water that results in the conversion of residential wastewater, which then enters surface drains and degrades the Yamuna river's water quality. The Delhi to Agra stretch's dissolved oxygen (DO) and ammoniacal nitrogen (AN) concentrations do not sustain native aquatic life. This river stretch's total and fecal coliform concentrations are positively correlated, which suggests that household sewage predominates there. Decision-makers involved in river restoration and conservation activities can use Lokhande & Tare, (2021) analysis of the response of the riverine ecosystem to changing flow regimes and changes in river water quality as a guide.

Gomes & Wai, (2020) examined the 30-year temporal trends in Hong Kong water quality data. Urbanization had a relatively negative influence, as seen by the opposing trends for several water quality metrics and stream flow in catchments with developed area fractions of less than 40% and more than 70%. According to the study, contaminants entering streams from point sources were likely decreasing while those entering streams from catchment runoff were increasing. More research is required to determine the reasons for the rising trend in sediment supply. Maybe smaller-scale operations like cleaning roads and installing sediment traps in storm water networks should be subject to tougher environmental regulations. The increased sediment supply may result from less obvious sediment or unidentified sources (local and/or regional airborne particle transfer).

Despite an increase in anthropogenic effects from tourism and possibly from a long-distance transport of toxic elements from industrial enterprises in the Baikal region-Russia, the concentrations of major elements in the water from the Angara River source obtained in 2017–2018 suggest no increased water pollution. The maximum allowable concentrations of all ions and mineralization are not exceeded. The rigorous evaluation of the chemical and microbiological composition of water from the Angara River and lake Baikal requires ongoing monthly monitoring (Grebenshchikova et al., 2019).

Using a principal component analysis (PCA) and a water quality index multiplicative and weighted (WQI), Sedeño-Díaz & López-López (2007) evaluated geographical and long-term temporal trends in water quality for over 25 years. The WQI general rating scale was from 0-100, with 100 denoting the greatest level of water quality. WQI scores between 26.53 to 67.44 indicated Rio Lerma water should only be used for coarse fish and needs to be treated before being used for most industrial and agricultural purposes. Several indigenous fish species were observed to have disappeared, including two silverside food fishes that are extinct; and two others, one of which is a food fish, are endangered, and other three are threatened.

In the industrialized area of the Angul-Talcher region of Orissa (India), the water quality index (WQI) has been measured for several ponds of water. Water Quality Index was used to classify the appropriateness of pond water and to evaluate geographical and temporal fluctuation. The research area's pond water samples (n=14) were gathered from various sites. The monsoon season had a WQI score of 80 for the samples, whereas the summer had a score of 43. The increasing content of BOD and coliforms in the pond water has been revealed to be the primary cause of the higher value of WQI. According to the National Sanitation Foundation Water Quality Index (NSF-WQI), most of the water samples within the research region fell into the medium category (Reza & Singh, 2010).

The findings of a three-year monitoring study of surface water status in the Pannonian ecoregion for three distinct water types (4, 5B, and 5C) was reported and statistically analyzed using descriptive and multivariable analyses based on seven water quality indicators (pH, dissolved oxygen, biological oxygen demand (BOD), total organic carbon (TOC), nitrate, total nitrogen, and total phosphorus). Tomas et al., (2017) developed a modified water quality index (WQIM) for the Pannonian ecoregion. The applied analysis showed a substantial association between individual variables, BOD and TOC. WQI developed two linear prediction models (multivariable linear regression model (MLR) and piecewise linear regression model (PLR)) for assessing water quality in the Pannonian ecoregion. The indicator BOD was substituted by the indicator TOC in these linear models.

The standard steps in developing a WQI include parameter selection, weight assignment, the building of sub-index functions, and the final aggregation of weighted sub-index values. Tripathi & Singal, (2019) focused on the first phase, which is parameter selection. The findings of study were crucial in the future creation of the Ganga Water Quality Index. The initial available data for the current investigation was treated with Principal Component Analysis (PCA), which resulted in a decrease in the number of parameters from 28 to 9. This was done to make the process more viable and cost-effective by dramatically reducing the time, effort, and expense necessary to monitor samples for a wide range of parameters. The statistical approach used in WQI development makes it less biased and more impartial in character and serves as the foundation for the construction of a Ganga Water Quality Monitoring System Future GWQI.

Vasistha & Ganguly, (2020) evaluated the features of two lakes adjacent to each other to determine the lakes' status based on Designated Best Use (DBU) criteria for optimum usage and use. Furthermore, the research reports on the lake's characteristics for two seasons, with sampling conducted in August and October of 2019. Various water quality indices, including the National Sanitation Foundation Method (NSFWQI) and BIS 10500 (BISWQI), were used to calculate the indices. The research depicts both regional and temporal fluctuations in lake water quality. The overall water quality categorization for both lakes using the NSFWQI technique was good for both sample times. Similarly, using the BISWQI, the overall water quality was classified as excellent for both sample times. Furthermore, a novel technique to calculating water quality indexing is offered using a Modified Water Quality Index (MWQI), which employs the greatest number of criteria and so provides a means to eliminate ambiguity and glaring difficulties associated with WQI. Using this newly established MWQI, the water quality for both lakes was classified as excellent for samples obtained in August and October, respectively.

Voza & Vuković, (2018) constructed a model for defining and predicting temporal changes in water quality to optimize the processes of sampling, monitoring, and management. The patterns of historical variations in the Morava River Basin (Serbia) were detected using several multivariate statistical approaches. The findings of the cluster analysis are markers of the existence of three monitoring periods: low-water, transitional, and high-water periods, which correspond to fluctuations in water flow in the investigated river basin. The principal component/factor analysis was used to test the feasibility of decreasing the initial data set and identifying the primary pollution sources. The results showed that the natural component has the most effect in temporal groupings. A discriminant analysis (DA) was performed to identify the discriminating water quality factors. The DA enabled a considerable decrease in the data set by extracting two parameters.

Wang et al., (2022) developed a unique, cost-effective evaluation model for assessing river water quality utilizing data from 23 sample sites over a 1-year period in the Hong Kong water control zone of Tolo Harbour and Channel. First, using the Kruskal-Walli's test, hierarchical cluster analysis, and the water quality index (WQI), the spatio-temporal fluctuations of water quality parameters and the overall state of river water quality based on all 19 parameters were studied. The results showed that 99.27% of the water samples were determined to be in good or outstanding state of overall WQI, indicating that most water quality metrics and overall water quality status varied significantly over space but did not demonstrate noticeable seasonal changes. After that, utilizing Pearson's correlation analysis, factor analysis, and principal component analysis (PCA/FA), 8 parameters were found to have made the most impacts to water quality, the evaluation of overall water's state of quality. The results of linear regression analysis using the overall WQI as a benchmark showed that the best water quality assessment model, which can achieve the most accurate results with fewer parameters, was the cost-effective model built on $BOD_5$, COD, $NH_3$-N, $NO_{3-}$ N, $F^-$, TSS, and As.

A novel Quality Indicator (QI) and Water Quality Index (WQI) was developed by Lobato et al., (2015) taking into consideration the unique characteristics of the Amazon region, for the evaluation of the water quality of a hydroelectric plant reservoir in the Amazon area of Brazil. To choose the pertinent parameters to be used in the creation of both indices, factor analyses were used. The generated QI and WQI were then used to study the water quality at the reservoir after quality curves for each chosen parameter were created. The WQI was further helpful in identifying anthropogenic impacts in the area because water sampling stations suffering different anthropogenic impacts were classified differently, with poorer water quality, than stations near the dam and the environmental preservation area, which suffered significantly less anthropogenic impacts, and were categorised as presenting better water quality. The created indices are useful tools for identifying anthropogenic influences as well as for examining environmental conditions in regions with clearly defined hydrological cycles. The statistical methods used to create these indices may also be used to create other indices in various geographic locations, taking into consideration the unique characteristics of each location.

Das Kangabam et al., (2017) evaluate the water quality index (WQI) of Loktak lake, a significant wetland that has been under strain due to the expansion of human activity. The results indicate that nitrite concentrations are greater than allowed in all locations. To calculate the WQI and estimate the water potential for five sample locations, eleven parameters were used. Each parameter was given a relative weight between 1.46 and 4.09 based on how significant it was. Although the people who live inside the lake use it for drinking, the WQI values, which vary from 64 to 77, indicate that the water in Loktak lake is unfit for consumption by humans or animals. The lake must be managed properly, and implementing WQI will give the public and decision-makers a great tool for assessing the water quality of the lake and ensuring sustainable management.

Five stations along the stretch of the Benin River between Ajimele and Koko town in north central part of Delta State underwent water quality assessments from June to December 2011 to identify and pinpoint the origin of human activities influencing the river. On a monthly day excursion, twenty-four metrics have been tracked at five sample locations. Using parametric ANOVA and Duncan multiple range tests, inter-station comparisons and the locations of significant differences were conducted. The association between the water quality metrics and the state of the water quality were established using principal component analysis (PCA) and the water quality index (WQI). The first six PCA components accounted for 90.96% of the fluctuations that were detected and showed similarities between the sampling stations, showing a range of anthropogenic activities and pollution levels at the studied locations. Organic pollution, industrial effluent, soil erosion, nitrogen loading, and human activities, particularly at stations 4 and 5, have been identified as causes of variability in the sample stations. WQI for sample stations 1, 3, and 5 was extremely bad for drinking (201–300) and unacceptable (>301) for human consumptions. In the end, this investigation demonstrates the value of PCA and WQI in analyzing large datasets of surface water quality. It also makes a request to the state and federal ministries of the environment to address the issue of the Benin River's declining water quality by reducing organic pollution and effluent discharge into the river. It is strongly advised to monitor the quality of the water closely and consistently (Ayobahan et al., 2014).

Mustapha et al., (2014) assessed the regional variation of surface water quality and pollution source apportionment in Kano River, Nigeria, using statistical methods. The three major water pollution sites—high pollution sites, moderate pollution sites, and low pollution sites—were identified using principal component and factor analyses (PCA and FA), which helped to explain more than 65% of the variance in water quality. With just seven factors (DO, $BOD_5$, pH, $NH_3$, Cl, E. coli, and T. coli) for geographic variation, discriminant analysis produced a superior result with strong discriminatory capacity, pattern recognition, and significant data reduction, and it allowed for more than 90% accurate case assignment. The three components produced from PCA and FA were further subjected to one-way analysis of variance (one-way ANOVA) to assess the variation within and between the factors. The results revealed significant differences ($p < 0.05$) between the factors.

Using multivariate statistical approaches, including cluster analysis (CA), principal component analysis (PCA), factor analysis (FA), and discriminant analysis (DA), Phung et al., (2015) assessed temporal and geographic fluctuations in surface water quality. From 2008 to 2012, 38 distinct locations in Can Tho City, a Mekong Delta region of Vietnam, were used to monitor 11 water quality metrics. According to the varifactors from FA, the factors causing changes in water quality were related to sewage waste contamination by fecal coliform bacteria through sewer and septic systems, erosion from disturbed land, effluent inflow from sewage plants and industry, domestic wastewater discharges, industrial effluents, agricultural activities, and domestic wastewater. Nephelometric turbidity units (NTU), chemical oxygen demand (COD), and $NH_3$ were found to be the discriminating parameters in space, providing 67% correct assignment in spatial analysis; pH and $NO_2$ were found to be the discriminating parameters according to season, providing about 60% correct assignment. The results point to a potential updated sampling method that might decrease the quantity of sample locations and the indicator parameters in charge of significant fluctuations in water quality. Study illustrates the use of multivariate statistical techniques for assessing temporal and geographical changes in the assessment and management of water quality.

Nihalani & Meeruty, (2021) determined WQI for the year 2016 for surface water samples from Gujarat's rivers Mahi, Sabarmati, Narmada, and Tapi, utilizing a variety of physicochemical factors, including pH, electrical conductivity, DO, BOD, nitrate nitrogen, and total coliform. The WQI for the rivers Mahi and Sabarmati was determined to be between 30 and 50, the Narmada between 28 and 52, and the Tapi between 35 and 70. According to WQI, most of the surface water samples fall within the good to bad category. When compared to downstream, the quality of the river's water was better upstream. It may be assumed that industrial, urban runoff and sewage discharges were the main causes of the reduction in the quality of river water.

Gujarat's largest river, the Sabarmati, is used for drinking water and other domestic needs. It is subject to degradation since it also transports sewage and industrial pollutants from adjacent municipal corporations and industrial regions. As a result, continuous monitoring is required to maintain and restore the river's quality and quantity. Khatri et al., (2020) evaluated the river's pollution levels and the levels of several indicators in relation to drinking water regulations. Here, a total of 10 physicochemical characteristics were chosen, including conductivity, dissolved oxygen, BOD, turbidity, total dissolved solids, total alkalinity, and total hardness. Samples were taken between January 2015 and January 2016 at 11 locations along the Sabarmati river during the pre- and post-monsoon seasons. Additionally, to provide a general picture of pollution, the Weighted Arithmetic Water Quality Index (WAWQI) and Canadian Council of the Ministers of the Environment Water Quality Index (CCMEWQI) were used. To determine if there was a significant difference between the parameters in the pre- and post-monsoon seasons, Cohen's d test was used. It was discovered that the water quality by WAWQI was very contaminated and "unfit for drinking." While utilizing the CCMEWQI, it was discovered that the water quality varied from "Fair to marginal," according to WAWQI, it was also discovered that the water quality continued to decline during the post-monsoon season. All the metrics at various sites during pre- and post-monsoon season showed statistically significant changes. It may be inferred from the indicators and analysis that the river Sabarmati's water quality needs to be improved and that the necessary actions must be implemented.

Different human activities, such as the clearing of vegetation, industrial activity, encroachment, residential, and religious activities, provide ongoing pressure on the amount and quality of water. All these actions caused the water quality to decline. Most of these issues are in and around metropolitan regions. The water quality of the Godavari river in Nashik city has been thoroughly studied while taking this viewpoint into consideration. During the first week of June 2019, water samples were collected from 10 sampling stations. The standard approach has been used to examine physico-chemical parameters. The study was initiated to examine the water quality state of the Godavari river in terms of water quality index (WQI), and the Karl Pearson correlation matrix has been constructed for analyzing relationships between the water quality indicators. The study region's upper stream had an excellent water quality status generally (WQI 133.44), but as it entered the urban area, the water quality began to decline (WQI 35.01). Field observations show that a variety of human activities, including residential, industrial, and religious waste, were to blame for the diminishing water quality. The primary goal of the research was to examine the water quality index (WQI), along with corrective actions to lessen future degradation and related effects (Kharake & Raut, 2021).

Applying the newly developed water pollution index (WPI) approach to 368 groundwater samples (184 in each pre and post monsoon season) revealed the pollution load or water quality state of the Birbhum district of West Bengal, India. Groundwater quality is highly contaminated, according to WPI, which varied from 0.38 to 1.94 with a mean value of 0.831. Limits of agreement (LoA) and bias value (d) were used in the Bland-Altman analysis to verify the revised WPI. Compared to the current water quality indices, WPI matched the data extremely well in dictating its superior application and output in various water pollution investigations (Hossain & Patra, 2020).

Pristine water bodies in the Kashmir Himalayas are already showing signs of deterioration. Bhat et al., (2014) studied, the declining water quality of the Sukhnag stream, one of the main inflow streams to Lake Wular, and the data statistically analyzed. On 26 water quality measures, statistical methods including principal component analysis (PCA), regression analysis, and cluster analysis were used. 96% of the temporal and geographical variations in stream's water quality were recognized by PCA. The first component from the factor analysis accounted for 66% of the variation in velocity, total-P, $NO_3$-N, $Ca^{2+}$, $Na^+$, TS, TSS, and TDS combined. Sites IV and V and II and III have a 94% and 96% similarity, respectively, according to the Bray-Curtis cluster analysis. The seasonal similarity dendrogram revealed a maximum similarity of 97% between spring and autumn clusters and 82% between winter and summer clusters. The accumulation factor (AF) trend for nitrate, nitrite, and chloride indicated that downstream concentrations were roughly 2.0, 2.0, and 2.9 times larger than upstream values, respectively.

Filik Iscen et al., (2008) presented the use of several multivariate statistical methodologies for the interpretation of a complicated data matrix acquired from Uluabat lake, Turkey, surface water in 2004-2005. The dataset contains the analytical findings of a one-year study conducted at 12 sample points across the lake. Twelve metrics were examined monthly in the sample sites (excluding in December 2004, January, and February 2005, for a total of 1,296 observations). The results of the cluster analysis showed two distinct groups of similarities between the sampling locations, which were indicative of differing physicochemical characteristics and degrees of contamination in the investigated water system. The data structure was attributed to three latent components, which also account for 77.35% of the dataset's overall variation. The microbiological component, the first factor, accounted for 32.34% of the overall variation. The organic-nutrient factors were the second component, accounting for 25.46% of the variations, and the physicochemical factors, the third factor, accounting for 19.54%.

The North China Plain's largest shallow lake, Baiyangdian, is crucial for preserving ecological health in this densely populated area. An upgraded Water Quality Index approach and multivariate statistical techniques were used to analyse the temporal and geographical fluctuations of the lake's water quality and examine the primary determinants of these variations to investigate the effects of human activities on the lake's water quality. To assess the period from 2006 to 2016, data sets for 11 water quality metrics from six monitoring sites were used. The yearly WQI evaluation revealed that the lake's water quality has usually improved over the previous ten years. The six monitoring stations were separated into those in the western and eastern sections of the lake, and the twelve-month cycle was classified into dry and wet phases using cluster analysis. Using only two parameters (water temperature and fluoride) and six parameters (dissolved oxygen, ammonia nitrogen, total nitrogen, total phosphorus, anionic surfactant, and fecal coliform), respectively, discriminant analysis showed that 96.0% and 93.8% of the water quality data could be classified into the appropriate spatial and temporal clusters. The varifactors found using principal component analysis and factor analysis were similar for the two temporal clusters, and varifactors related to pollution explained more variance in the varifactors were different, indicating they are influenced by various anthropogenic activity types. According to a correlation study between lake water level and water quality, environmental water allocation to the lake often enhances water quality. These results offer a more detailed knowledge of the mechanisms that control water quality and may be useful for environmental management choices in Baiyangdian Lake and other large, shallow lakes in densely inhabited dryland areas (Han et al., 2020).

Data on the water quality of Manchar lake (Pakistan), collected during the 2005–2006 period with 36 parameters being monitored at five distinct locations, were subjected to multivariate statistical methods, cluster analysis (CA), and principal component analysis (PCA). To better understand water quality and to create a monitoring network, study was conducted to assesse and interprete large data sets on water quality and assigned contamination sources. By using PCA to analyse the chemical relationships, the samples were then categorized by CA using the PCA scores. Based on the similarity of their water quality, three major sample locations were identified: sites 1 and 2, site 4, and sites 3 and 5. The findings showed that input of effluent was one of the primary reasons of water quality decline. The findings showed that the main contributors to the decline in water quality at sites 2 and 3 were individuals living in boats and fishing, as well as wastewater from industrial, household, agricultural, and saline seeps that entered the lake at site 1 (Kazi et al., 2009).

Surface waters of Saraydüzü Dam lake, Sinop Province, Turkey for a year inside the limits of Sinop province were studied using WQI developed by Ramakrishnaiah. The WQI readings of the lake ranged from 17.62 to 29.88. In all months and at all stations, the prescribed limit values for water quality metrics were not exceeded. The Saraydüzü Dam lake water falls into the "very good" category for drinking water quality based on these criteria. The findings demonstrated that there were no nitrogen or phosphate imports that would have harmed the lake's ecosystem, and there were no low or inadequate levels of ambient oxygen brought on by excessive oxygen consumption during the organic matter's decomposition. Regarding SAR and salt percentage, irrigation water was determined to be of high quality; however, residual sodium carbonate was discovered to vary in quality throughout the year and wasn't always suitable for irrigation. Biological oxygen demand (BOD), total hardness (TH), total alkalinity (TA), calcium, nitrate, ammonium, mercury, and dissolved oxygen were the main variables responsible for the processes in the ecosystem, according to the results of factor analysis (FA). Other important variables include temperature, electrical conductivity, suspended solid matter (SSM), pH, total hardness (TH), and total alkalinity (TA) (Kükrer & Mutlu, 2019).

Between November 2015 and October 2016, research was conducted to examine the physicochemical characteristics of holy Prashar Lake. To assess the water quality of the lake, several analyses have been performed while keeping the study's objectives in mind. Water quality index was used to evaluate water quality on a seasonal basis. For the water quality measures, several statistical techniques like Pearson's correlation, cluster analysis, and principal component analysis were used. Depending on the season (winter > spring > autumn > summer > monsoon), WQI varied from 23 to 50. During the research period, a cluster analysis of similarity revealed a cluster spanning from 77 to 100% for the connection intensity between the seasons. Water temperature, conductivity, turbidity, BOD, TDS, hardness, calcium, phosphate, and sodium were all determined by PCA. The association intensity between the seasons was identified by cluster analysis of similarity as cluster ranging from 77 to 100% over the research period. During the summer and monsoon seasons, PCA found that water temperature, conductivity, turbidity, BOD, TDS, hardness, calcium, phosphate, sodium, and potassium were the primary characteristics that affected the water's quality. The results showed that overgrazing on the Prashar lake region and adjacent erosion were the primary causes of the water quality degradation during the monsoon season (Kumari & Sharma, 2019).

Principal component analysis (PCA) was used in a study to identify the primary and secondary monitoring stations for the Karoon river in Iran. Additionally, the link between the physical and chemical water quality measures was determined using canonical correlation analysis (CCA). Samples taken between 1999 and 2002 from 17 locations along the Karoon river were measured for 12 parameters. Four monitoring sites were eliminated because they provided insufficient information about how the water quality of the river varied annually. Further research revealed the significance of every aspect of water quality. The first four canonical correlations in CCA were respectively 0.993, 0.822, 0.785, and 0.660, indicating that EC and TDS were the two physical factors that dominated all canonical variates whereas ions and hardness received good marks from chemical parameters. The effectiveness of the PCA and CCA approaches were examined using basic regression and correlation techniques, respectively (Noori et al., 2010).

Studying and effectively managing water resources requires an understanding of the geographical and temporal variations in river water quality as well as a quantitative assessment of the trend of changes. The Water Pollution Index (WPI), the Daniel Trend Test, Cluster Analysis, and Discriminant Analysis were used as an integrated approach to quantitatively explore the spatial and temporal variations and the latent sources of water pollution in the Shanchong River basin, Northwest Basin of lake Fuxian, China. According to the findings, the primary trend of pollution was exacerbated during the changeover from the dry to the wet season. The Total Nitrogen Water

Pollution Index is the highest of all pollution metrics, while the Chemical Oxygen Demand (Chromium) is the lowest. The findings also reveal that farming operations along the Shanchong river, soil erosion and fish culture in the Shanchong river reservoir region, and domestic sewage from scattered rural residential areas are the primary causes of pollution. The study suggests that strategies to prevent water pollution in the Shanchong river basin should focus on non-point pollution control by using appropriate fertilizer formulas in farming, as well as soil and water conservation measures in the reservoir area and sewage purification from scattered villages (Wang et al., 2015).

The water level in Urmia lake located between the provinces of East Azerbaijan and West Azerbaijan in Iran has dropped dramatically in recent years, therefore monitoring the lake's water quality was critical from an environmental standpoint. The Mann-Kendall nonparametric test was used in the study to evaluate changes in qualitative characteristics of lake water (including electrical conductivity (EC), pH, total dissolved solids (TDS), and sodium adsorption ratio (SAR)) with variations in lake water level. Furthermore, the Pettitt test recognized abrupt change points in the time series of quality characteristics. During the period 2005-2015, samples were collected from five distinct sites and studied. The results indicated that the water level of Urmia lake had a substantial declining tendency and that, except for TDS, the other investigated quality indicators exhibited negative trends over the study period. It was discovered that the values of the Z statistic were greater in the eastern section of the lake than in the western half, and that the northern stations had a higher trend than those in the south of the bridge (Sattari et al., 2020).

Singh et al., (2004) detailed the use of several multivariate statistical approaches for the evaluation of temporal and geographical fluctuations and the interpretation of a sizable and intricate collection of water-quality data collected during monitoring of the Gomti river in Northern India. Different multivariate approaches, including cluster analysis, factor analysis/principal component analysis (FA/PCA), and discriminant analysis (DA), were used to handle the complicated data matrix (17,790 observations). With three distinct groupings of similarity between the sampling locations representing the various river system water-quality characteristics, cluster analysis (CA) produced positive findings. Six variables were found using FA/PCA, which are responsible for the data structure and account for 71% of the total variance of the data set. Gathered information allowed the grouping of the selected parameters into categories based on shared characteristics as well as an assessment of the contribution of each category to the overall variation in water quality. Significant data reduction was not, however, accomplished since it took 14 factors to account for 71% of the temporal and geographical variations in water quality. For data reduction and pattern recognition throughout both temporal and geographical analysis, discriminant analysis produced the best results. According to discriminant analysis, nine parameters allowed for 91% correct assignations in geographical analysis of three separate basin regions, while five parameters (pH, temperature, conductivity, total alkalinity, and magnesium) provided more than 88% of the proper assignations in temporal analysis. Thus, DA enabled the vast data set's dimensionality to be reduced, allowing the identification of a small number of indicator factors that explain significant differences in water quality. To improve the understanding of water quality and to create a monitoring network for efficient management of water resources, the study paper discusses the requirement and use of multivariate statistical approaches for the assessment and interpretation of huge complex data sets.

Water Quality Index (WQI) was developed to classify the Bhoj Wetland (Bada Talav + Chota Talav) lake water after analysis of the sampled lake water. WQI had an average value of 64.52 during premonsoon, 52.23 during monsoon, and 42.45 during post monsoon. Pre-monsoon samples often had a larger percentage of contaminated samples. Singh et al., (2015) used multivariate statistical methods for managing huge and complicated data sets to obtain more accurate data on the lake water quality. To analyze the latent structure of the data sets, factor analysis and principal component analysis were used. It was found that a total of four pre-monsoon, three monsoon, and three post-monsoon factors that account for the entire data structure. Pre-monsoon, monsoon, and post-monsoon data sets' cumulative percentage variances of 90.908, 89.078 and 85.456% have been explained by these variables, respectively. Following some degree of pollution from geogenic sources such rock weathering, the results of the overall investigation showed that agricultural runoff, waste dumping, leaching and irrigation with wastewater, land transformation in the surrounding regions were the primary causes of lake water contamination. Consequently, there is a pressing need for effective care and resource management.

The water quality dataset, which included 13 parameters at 18 sites of the Daliao river basin is located at eastern Liaoning Province - China from 2003 to 2005 (8424 observations), were analysed using multivariate statistical methods, such as cluster analysis (CA), discriminant analysis (DA), and principal component analysis (PCA), to obtain temporal and spatial variations and to identify potential pollution sources. Twelve months were divided into three periods (first, second, and third period) using hierarchical CA, and the 18 sample locations were divided into three groups (groups A, B, and C). Five parameters (DO, $NH_4$-N, Hg, volatile phenol, and E. coli) were found to correctly assign approximately 73.61% for the spatial variation analysis, while six significant parameters (temperature, pH, DO, $BOD_5$, volatile phenol, and E. coli) were identified by DA for distinguishing temporal or spatial groups. Sites experienced greater heavy metal pollution, organic pollution that consumes oxygen, and hazardous organic pollution during the first period than during the other two. During the first phase, oxygen-depleting organic pollution and hazardous organic pollution were the predominant problems at the sites in group B. The second period's pollution level fell somewhere between the first and second periods. For group C, the sites were most impacted by organic pollution that depleted oxygen during the third period and oil pollution that occurred during the first period. In the third period for group B, fecal contamination had the greatest impact on sites, showing the nature of non-point source pollution. Sites were also impacted by natural pollution in the second and third periods for group B and the second periods for group (Zhang et al., 2009).

Review of several lakes show the contribution of nitrogen enrichment in many. Longer growing seasons and changes in land use may result in greater fertilizer use, which might then drain into rivers, lakes, and other waterways, raising the danger of eutrophication and biodiversity loss. Heavy metals including Pb, Cr, Fe, and Hg, among others, are especially dangerous because they can contaminate water or induce chronic poisoning in aquatic organisms. In freshwater ecosystems across the world, harmful algal blooms are growing more frequent. In aquatic bodies, where it impacts the open-water, coastal, and benthic habitats, pollution by plastic trash is a growing environmental problem. Plastics are present in surface water at levels that are comparable to those found in locations where trash accumulates within marine gyres. The water quality of the lake has been analysed using a variety of techniques, including the Hyperion, water quality index, and hazard quotient. In addition to recycling nutrients in regulated urban agriculture, it is advised that pollution prevention and water reuse be implemented (Bhateria & Jain, 2016).

Patel et al., (2016) determined the pond quality by analysing the physicochemical characteristics of two ponds in Gujarat's Vadodara district over the course of a year. All the metrics were within the allowed ranges established by Indian norms, however the hardness readings for Alwa pond was a little bit higher than the ranges. The sulphates levels were greater in the summer, with readings of 287.73 mg/L at Limda and 172.08 mg/L at Alwa pond. Untreated residential waste discharge was identified as one of the main causes of the reduction in pond water quality. The research focused on the temporal variations in significant characteristics and how they relate to the pond's overall ecosystem. The article makes recommendations for future pond conservation measures.

From August 2002 to July 2004, fluctuations in various nutrient levels at Pandu lake-Andhra Pradesh were systematically investigated. Gross contamination results from the direct discharge of residential trash into Pandu lake from several locations of Bodhan town. The goal of the current inquiry was to determine the extent of sewage contamination by keeping track of important water quality indicators such dissolved oxygen, biological oxygen demand, alkalinity, calcium, nitrates, and phosphates, among others. Three distinct sampling stations provided monthly water samples. Low dissolved oxygen, high biological oxygen demand, increasing amounts of nitrates and phosphorus, and other findings indicated that the water body had transitioned from an oligotrophic to eutrophic state. The presence of phosphates was measured to be between 0.9 and 4.0 mg/L. Nitrate levels were found to be greater in Pandu lake and to be higher in the summer. An acceptable explanation was provided. Nitrate levels were observed to vary from 24.8 mg/L to 71.2 mg/L. Data on numerous chemical traits of Pandu lake varied depending on the location and the month. The lake appeared to be eutrophic throughout the year according to features including dissolved oxygen, biological oxygen demand, nitrates, phosphorus, and nutrient loading (Solanki et al., 2010).

Utilizing an appropriate WQI, a study evaluated the lake Manzala in northeastern Egypt water quality. Between August 2010 and August 2012, data for twelve water quality metrics were gathered from 11 lakeside sites and 4 drain outlet stations. The National Sanitation Foundation WQI and Lagoon WQI were employed as two WQIs, and a GIS tool was used to evaluate and spatially assign the lake's water quality characteristics. The findings show that the lake's water quality was critically low. According to L-WQI, the lake's eastern and southern regions have "Very Bad" water quality statuses, which are the worst off. While the lake's western region has the finest water quality, which L-WQI rates as "Good". Among the drains that were examined, the Bahr

Elbaqar drain has the poorest water quality status, "Very Bad," which has an impact on the lake's eastern region. According to both used indices, the lake's water quality was at its lowest in August 2011. The lake should be separated into distinct zones for fishing and other goals because of the lake's water quality parameters being assigned a geographical location. A quick plan for managing water quality should be implemented for the lake (Elshemy, 2016).

The five different water quality indices were taken into consideration for characterizing the coastal water quality at the Jawaharlal Nehru Port Trust in Bombay, India. They are the arithmetic water quality index, multiplicative water quality index, unweighted arithmetic water quality index, unweighted multiplicative water quality index, and Harkin's water quality index. The characteristics of the water quality indicators employed were dissolved oxygen, pH, biochemical oxygen demand, temperature, suspended solid, and turbidity. Aquatic life criteria and value function graphs for the variables were generated utilizing the harbor water quality standards. Unweighted arithmetic water quality index was discovered to be greater than weighted arithmetic water quality index, however unweighted multiplicative water quality index was shown to be lower. All the indices had strong correlations with one another, except for Harkin's water quality index. Compared to other WQIs, the Harkin's index was unique. The multiplicative water quality index was found to be the best water quality indicator for coastal waters after evaluation of other forms of indices (Gupta et al., 2003).

A study on the Polyphytos reservoir-Aliakmon river in Greece was conducted from June 2004 to May 2005 taking into consideration two WQIs i.e., The CCME (Canadian Council of Ministers of the Environment) and NSF (National Sanitation Foundation). Their effectiveness was compared, and a qualitative assessment of how well they convey a surface water body's quality was provided. Comparisons were made between the categorization findings and those attained by the EU's WFD-ECOFRAME technique. Conclusive findings were drawn and analysed based on the applicability and limitations of the evaluated indices. The NSF-WQI was more reliable index than the CCME-WQI, producing a categorization that was closer to that of the WFD-ECOFRAME method (Alexakis et al., 2016).

Using the National Sanitation Foundation Index (NSFWQI), Overall Index of Pollution (OIP), and multivariate methodologies, a study evaluated the surface water quality of the river Ganga in India. In the study, water samples from the Ganga river were taken at 20 different sampling sites for the analysis of 19 physico-chemical determinants for the year 2015–2016. To evaluate the water conditions for effective management of freshwater quality, multivariate approaches were used. The WQI results demonstrated that the medium and good categories of surface water quality differed at the chosen test sites. The six principal components that the PCA produced had significant influence on the hydrochemistry of river water (80.3%). Runoff from agricultural waste, untreated sewage, and several other human activities were shown to be the primary causes of the river Ganga's declining water quality. The use of strict laws and regulations is anticipated to safeguard freshwater resources for humans in the future by maintaining and protecting the freshwater resources against pollution (Matta et al., 2020).

Water quality indices commonly used in western nations, such as the National Sanitation Foundation Water Quality Index (NSFWQI) and the indigenous Vedprakash Water Quality Index (VWQI), cannot accurately reflect the water quality status of Indian rivers due to the higher levels of pollution in these rivers. The study used fuzzy modelling for assessing the water quality of Godavari river – 24 km stretch utilizing centroid, bisector, and mean of maximum (MOM) approaches for defuzzification, the fuzzy models were created utilizing triangular and trapezoidal membership functions. The triangle membership function fuzzy model using the bisector method of defuzzification was found to perform better than the triangular and trapezoidal membership function fuzzy model using the centroid and MOM method of defuzzification. The values of the fuzzy logic-based water quality index was contrasted with those of the NSFWQI and VWQI. As opposed to NSFWQI and VWQI, it was observed that the results of fuzzy-based water quality index were more indicative of the real river water quality state of Indian rivers. This is owing to the selected fuzzy logic approach's similar sensitivity to all parameters and ability to accurately reflect even a little change in any parameter's value, especially in cases when river segments with greater pollution levels (Nayak et al., 2020).

Mahananda river is a significant river in both India and Bangladesh because the populations of both nations make extensive use of the water. A study was conducted to assess the river's water quality and determine its suitability for drinking, industrial, agricultural, and other applications. Samples were taken in the pre- and post-monsoon seasons of 2016 from fourteen sampling points, and water quality index (WQI), agricultural, and industry-related indices were computed. Out of the fourteen sample stations, two were assigned a WQI score of "very bad," while the remaining two were given a score of "bad". Some sample sites had pH readings that were just a little bit higher than the permitted maximum limit. Two pre-monsoon season samples were assigned to the C2S1 category by United States Salinity Laboratory (USSL) diagram analysis, which denotes water with a medium salinity and low salt content. Four sample locations' magnesium hazard levels are above 50%, indicating that irrigation is not appropriate. However, there are several indices that permit the use of the water for irrigation, including sodium percent, residual sodium carbonate and residual sodium bicarbonate, Kelly's index, permeability index, and potential salinity. The water was classified as either moderately aggressive or non-aggressive based on the Langelier Saturation Index and aggressive index values. The water was classified as "aggressive" or "very aggressive" based on the Ryznar Stability Index values, making it unsuitable for industrial usage. Special attention should be paid to sampling sites S-1, S-2, S-8, and S-14 (Shil et al., 2019).

With the intention of evaluating changes in the Ganges river at several points in the Allahabad stretch, including that from the confluence with river Yamuna, the water quality index (WQI) of post-monsoon water samples was studied. Standard protocols were used to measure physical and chemical parameters including temperature, pH, electrical $Na^+$, $K^+$, conductivity (EC), dissolved oxygen (DO), total dissolved solids (TDS), main cations and anions, and alkalinity. The results were contrasted with the drinking guidelines provided by the World Health Organization (WHO) and Bureau of Indian Standards (BIS). A few parameters were chosen from the observed amounts to calculate the WQI for the differences in water quality at each designated sample location. The results revealed that the quality of the water at several of the locations had significantly declined. Water from the Ganges river near Allahabad had a WQI that varied from 86.20 to 157.69, which is of low quality. To uncover potential relationships between the observed water quality metrics, the Pearson's Correlation matrix was created. It has been demonstrated that the WQI may be a valuable instrument for determining the quality of the water and for forecasting trends in water quality variation at various points along the Ganges river (Sharma et al., 2014).

The Sen's Slope estimator and the Mann-Kendall Seasonal Test were used to conduct the trend investigation for Ebro River -Spain. The results showed parameter fluctuation over time, mostly because of the Ebro Basin's rising pH levels and declining phosphate content between 1981 and 2004. To identify the different sources of change in the water quality, exploratory data analysis was also done using display techniques (cluster analysis) and unsupervised pattern recognition (principal component analysis). Geologic, climatic, and human influences have all been identified thanks to PCA. The quality and hydrochemistry of river water was impacted by spatial and seasonal causes of variation (Bouza-Deaño et al., 2008).

The biggest freshwater lake of its kind in Northeastern India, Loktak lake, has been designated as a Ramsar Site because it supports a variety of species, including several that are vulnerable internationally. The lake helps with irrigation, electricity, and gives the nearby locals a living through fishing and farming. Due to recent fast urbanization, increased habitation, and other human activity, Loktak lake has become worse. So, research was conducted to evaluate the water quality and trends for the lake. Throughout a three-year period 2014–2016, the water quality of Loktak lake was evaluated monthly using a variety of water quality indices. To evaluate the lake's water quality trend, temporal distribution functions of the various water quality measures and indices were built. The lake's water quality was determined to be good overall throughout the year, with a little decline during the winter. However, lake’s water was quite murky and heavy in organic matter (Roy & Majumder, 2019).

A study was conducted on the physicochemical parameters of water quality of the sacred lake Nachiketa Tal in the Garhwal Himalaya. Seasonal variations in air temperature, water temperature, electrical conductivity, turbidity, salinity, TDS, dissolved oxygen, free $CO_2$, hardness, alkalinity, nitrates, phosphates, chlorides, calcium, and magnesium were measured at four sampling stations from May 2015 to April 2016. The statistical correlation and cluster analysis of Nachiketa Tal's different physicochemical properties were computed. During the monsoon season, the concentrations of nutrients, turbidity, electrical conductivity, and TDS increased while dissolved oxygen decreased at all sample stations, according to the findings of the study. As a result, the lake's water quality deteriorated throughout the monsoon season (Sharma & Tiwari, 2018).

Metal contamination in the Selenga river basin in Mongolia and Russia has attracted public attention in recent decades due to fast and intense development. Overall, a research found that heavy metal pollution in rivers was endangering the entire aquatic lotic system in the basin. The authors felt that there was an urgent need to define standard water quality norms for the waters of the Selenga river's transboundary system to monitor and implement effective water management measures (Nadmitov et al., 2015).

Weighted Arithmatic Mean Water quality index was established for Chandlodia lake in Ahmedabad, Gujarat, India, based on the examination of physico-chemical properties of water. Total dissolved solids, pH, alkalinity, total hardness, magnesium, calcium, and dissolved oxygen levels in several of the samples exceeded the acceptable limits set by Indian norms. Electrical conductivity, chloride, nitrate, and biological oxygen demand readings were found to be within acceptable ranges. Due to the presence of significant levels of contaminants, the completed WQI showed that the water quality was poor and not completely suitable for human consumption. Due to the lack of water filtration, the water was not considered suitable for public consumption or recycling. Research concluded that if the water quality of Chandlodia lake remains unchanged, the lake's ecology will be destroyed and suggested that Government agencies such as AUDA, AMC, and other civic organizations should take measures to prevent the discharge of residential trash straight into the lake or establish a water treatment system (Qureshimatva et al., 2015).

A new Water Quality Index (WQI) using Data Envelopment Analysis (DEA) was developed by Soltani et al., (2021). Rather than using subjective weights from a judgement procedure as DEA model inputs, more objective variables called "optimistic closeness values" that are correctly obtained from the observed values of the hydro chemical parameters were suggested. The suggested method was used to analyse the water quality of 47 dams in Algeria, which were specified by a dataset of ten hydro chemical parameters. The results of the DEA-based WQI application revealed that (i) 21.27%, 27.66%, 25.53%, 4.25% and 21.27% of the total dams are categorized as "Poor", "Marginal", "Medium", "Good" and "Excellent" water quality, respectively; (ii) the best water quality was found in "Kissir" and the worst one in "Bougara"; (iii) a priority scale on the hydro chemical parameters can be set for the treatment of water using the notion of slack value. Collectively, the new methodology has demonstrated its effectiveness not just for categorizing or rating locations based on water quality, but also as an alternative tool to help decision-makers manage water resources.

From April to December 2018, four sampling activities were carried out at 83 sites spanning the main rivers of the Lake Chaohu Basin (LCB) to investigate the critical parameters impacting its water quality. 15 physicochemical parameters were assessed, including turbidity (tur), dissolved oxygen (DO), ammonium ($NH_4$-N), nitrate ($NO_3$-N), and permanganate-COD ($COD_{Mn}$). The 15 environmental characteristics differed significantly on a regional level, and three significant groups (i.e., Groups I, II, and III) were identified using cluster analysis. A water quality index (WQI) based on these factors, which are routinely employed in WQI calculation, was utilized to assess water quality. In general, the water quality situation in LCB was classed as "moderate" (mean value of 69.1). Meanwhile, the status clearly differed between the three groups, with "good" in Group I and "moderate" in Groups II and III. WQI was highest in autumn, which was notably different from the other seasons. Regardless of select example rivers or the entire basin, the distribution of water quality was comparable with prior studies. Furthermore, a minimum water quality index (WQImin) comprising of five critical factors (tur, DO, $NH_4$-N, $NO_3$-N, and $COD_{Mn}$) did not differ significantly from the WQI based on all 15 parameters, and its percentage error was reasonably low (6.02%). WQImin was robust and potentially universal in determining river water quality assessment in both basins, thanks to its excellent application in the neighbouring Lake Taihu Basin (LTB). The discovery is likely to benefit low-cost and speedy water quality evaluation in surrounding basins. Furthermore, TN may not be suited for WQImin development in rivers, particularly in areas of very high concentration, resulting in an underestimation of water quality (Wu et al., 2021).

An approach based primarily on multivariate statistical methods and historical data distributions was used to develop an ecosystem-specific water quality index for the Santiago-Guadalajara River (SGR-WQI) in western Mexico. Despite the complexity of the suggested methodology for developing and calculating the SGR-WQI, application of the algorithm developed in the study offers stakeholders with a tool for explaining the wide variety of water quality data gathered through frequent monitoring campaigns. As a result, obtaining a value that can be used to steer public policy toward river rehabilitation is simple. The new SGR-WQI provides a baseline for defining the measures that must be implemented to improve the river's physical, chemical, and biological properties and achieve the desired condition. The WQI can also be used to objectively assess the improvement in river water quality because of the deployment of recovery techniques. The desirable water quality parameters must consider the river's multiple uses, such as agricultural irrigation and water supply for the GMA, as well as the requirement to support aquatic and terrestrial species biodiversity. The approach presented in work generates a WQI that is highly sensitive to parameter values that are outside of legal limitations. It also allows a WQI to distinguish between sampling points and seasons, clearly expressing temporal and spatial variability, and demonstrating the annual cycle and changes in water quality. To communicate the trends of the SGR-WQI to society and to serve as a tool for the administrators of this water resource to make more assertive decisions in its management, the creation of a friendly interface with an interactive menu is recommended as a strategy to inform the state about the evolution of the Santiago-Guadalajara River (Casillas García et al., 2021).

From 2015 to 2020, an Improved Water Pollution Index (IWPI) and multiple statistical methods were used to assess the overall water pollution situation and investigate spatiotemporal variations of seven physicochemical parameters at 20 sites within the Erdao Songhua River Basin (ESRB). The proposed IWPImin model, which employs the four critical parameters and their weights, has demonstrated excellent performance in water quality assessment, with the highest coefficient of determination (R2) and lowest Root Mean Square Error (RMSE) values of 0.996 and 0.51, respectively, and can be used to optimize water quality assessment strategies at a lower cost. For future management, the water quality of the middle and downstream should be carefully investigated, and the effects of point source and non-point source pollution in the ESRB should be properly controlled. During the period 2015-2020, the ESRB's water quality was assessed geographically and through annual and seasonal analyses, and it was determined to be "Good" (within the Class II criteria). However, there was an overall improvement in water quality during the observation period, with summer having the lowest water quality and winter having the best. The WPI values of TN and TP were frequently classified as Class II or worse, which had a negative impact on water bodies. The established IWPImin model included four critical parameters (PI, DO, $COD_{cr}$, and $BOD_5$) that contributed to model stability and performance. The model's performance was improved by incorporating weighting findings into the IWPI calculations; such a model improves the efficiency of water quality evaluation while saving money on parameter measurement (Wang et al., 2021).

The assessment of water quality parameters in the Godavari river was carried out to evaluate the water quality and the water quality index. The seasonal changes of WQI of the constructed Actual measured and Time series models are described in the work for the study period (2009-2012) and future period (2012-2015) of Rajahmundry and Dowlaiswaram water quality monitoring stations in Andhra Pradesh state, India. The weighted arithmetic mean WQI was calculated using the monthly values of eight water quality parameters: pH, Dissolved Oxygen, EC, TDS, Total Alkalinity, TH, Ca, and Mg. The statistical performance test results showed that the created models of respective stations performed very well, with MAE=4.97 & 3.41, RMSE=7.31 & 5.82, and MAPE=5.15% & 3.48%, respectively. It was discovered that fluctuations in DO levels generated large variances due to the high weightage factor. According to the current analysis, the future water quality of the Godavari at Rajahmundry and Dowlaiswaram stations will be excellent to good. WQI can successfully translate complex water quality data into information that the public and decision makers can comprehend and use (Akkaraboyina & Raju, 2012).

The water quality of streams in the Sapanca lake basin (Turkey) was studied using the Canadian Council of Ministers of the Environment Water Quality Index (CCME - WQI), the Oregon Water Quality Index (OWQI), and the National Sanitation Foundation Water Quality Index (NSF - WQI). The major reason is to assess how polluted streams are right now and to compare the top three worldwide WQIs using domestic data. In addition, a modified model based on the National Sanitation Foundation Water Quality Index (NSF-WQI) was developed. Temperature, pH, EC, DO, TDS, TSS, Ca, Mg, Cl, $SO_4$, orthophosphate-phosphorus (o-$PO_4$-P), nitrate ($NO_3$-N), nitrite ($NO_2$-N), $BOD_5$, and COD all have an impact on the modified WQI. Creating customized indices to achieve adequate results with a restricted number of parameters is very beneficial for saving the money required to measure many parameters. As a result, the goal of research is to reduce the number of pollutant parameters. WQImin (minimum) was created, taking temperature, pH, dissolved oxygen (DO), total suspended solid (TSS), and electrical conductivity (EC) into account. The same procedure was used with eutrophication parameters. WQIeut (eutrophication) is an alternative index constructed employing DO, o-$PO_4$-P, $NO_3$-N, $NO_2$-N, $BOD_5$, and COD parameters. The developed indices and the fifteen-parameter WQI had a good connection. Finally, the study discovered a eutrophication risk for Sapanca lake and the streams that feed it (Akkoyunlu & Akiner, 2012).

Chen et al., (2022) evaluated four typical urban rivers in Tanzania using the upper-urban-down gradient evaluation technique and analysed them using the NSF water quality index (WQI) and statistical methods to estimate the impact of urbanization on river water quality. The physicochemical indices monitored in these rivers revealed that the levels of those indicators of TN, TP, $PO_4$, $NH_4^+$, $COD_{Mn}$, and $NO_3$ were significantly accumulated in the lower reaches of the cities, indicating the life-type pollution features in such African urban waterways. The investigation yielded the following primary conclusions: According to the subjective WQI including sensory elements, the water quality of 30% of the tested river sections were medium to good. Furthermore, the river segments with noticeable water quality decrease were primarily limited to the metropolitan center area, and serious pollution of water bodies was directly associated to large cities, showing an increasing contamination tendency with the rapidly developing population. As a result, to assist in the formulation of water pollution control strategies in response to growing urbanization in African countries, it is required to establish an efficient and feasible technique of conducting timely monitoring of surface water quality.

The Nakdong River's hydro chemical and metal components are most likely sourced from industrial wastewater, irrigation activity, sediment loadings, and a minor seawater intrusion in South Korea. With a little time, difference, the temporal trends of pH, alkalinity, Cl, and hardness changes were highly comparable to those of TDS. TDS autocorrelation and spectral density were extremely comparable to pH, alkalinity, hardness, and Cl, although Fe, Mn, and turbidity showed different tendencies. PCA was performed on six significant PCs that accounted for 78% of the data variance. The variables having origins in geochemical conditions and anthropogenic sources were the two primary principal components. The results of the hydro chemical investigation can be used to make decisions about the protection, management, and conservation of the water quality of the river. It is envisaged that time series analysis and PCA will be used to improve water management and pollution control in the river and nearby deltaic zone (Sang Yong Chung et al., 2014).

A Water Quality Index (WQI) was constructed from nine physicochemical parameters to quantify the geographical and temporal variability of surface water quality of Chillán river (Central Chile). Modifications were made to the original WQI based on the results of a Principal Component Analysis (PCA) to lower the expenses involved with its deployment. The extended index utilized in the study is based on water quality data for the analysed watershed. When possible, additional metrics such as turbidity and, especially, microbiological data should be included. When developing parameter rating curves for a WQI, local background conditions can be considered. A specific WQI's applicability may be confined to the aquatic ecoregion/watershed for which it was designed. WQIs cannot be employed indefinitely without regard for their qualities and limits (Debels et al., 2005).

Luo et al., (2019) looked at the relationship between urbanization and water stress, as well as trends in BOD, TSS, and DO. Recently, Jakarta has seen fast population increase, water scarcity, flood risk, and land subsidence caused by groundwater overdraft. The study provides important information that resource managers can use to establish sustainable water conditions in Jakarta and beyond.

The findings of a rigorous one-year water quality investigation of the Pinios river are reported. Physicochemical parameters (pH, conductivity, and DO) showed no significant changes between sampling sites or dates. Nutrients (nitrogen and phosphorus compounds) displayed temporal fluctuations, which were most likely driven by seasonal differences in nutrient discharge from weather events. Heavy metals (Pb, Cd, Cr, Cu, Ni) were measured in the dissolved fraction, and the differences observed were related to the geology of the study area as well as the influence of anthropogenic sources. The statistical analysis of variance of the most relevant chemical parameters and heavy metals revealed considerable differences between sample times, but not between sampling sites (Fytianos et al., 2002).

Uddin et al., (2022) investigated the effectiveness of four statistical weighting methods in estimating weight values of water quality characteristics. In terms of contributing to uncertainty in the WQI model, the results showed that the rank sum method was more robust than other methods for estimating the weight value. The new research could help to reduce uncertainty and improve the performance of the WQI model. The investigation validated a recent study's finding that the weighting approach contributes to the uncertainty in the WQI model. As a result of the investigation, the weighting values had a marginally significant impact on producing uncertainty in the WQI model. As the study calculated less than 2% uncertainty in the weighting procedure, it may be held statistically accountable to predict weight values in the WQI model.

Water quality indices, multivariate statistical techniques such as CA, PCA, and machine learning based on physicochemical data are used in the study to describe the adequacy of surface water quality for aquatic usage in Qaroun lake, Egypt. According to the analytical data, the surface water in the investigated area of Qaroun lake was semi-saline, with trace element levels in the following order: Al > Ba > Fe > Ni > Cu > Zn > Pb > Mn > Cr > Cd. The surface water was highly impacted by Al, marginally by Cd and Cu, and only little by Zn. As a result of the widespread use of agricultural fertilizer and pesticides, industrial activities, and poor drainage networks, the surface water quality of the lake has degraded. In addition to the WQIs, which were validated by multivariate statistical analysis, industrial effluents and landfill leachates/municipal sewage were identified as the principal sources of trace element contamination in Qaroun lake. Therefore, utilization of physicochemical parameters and water quality indices supported by GIS techniques, multivariate modelling and machine learning was a useful and practical method for determining the quality of surface water and its progression (Gad et al., 2021).

To demarcate healthy and polluting areas, datasets were turned into simple maps using the Coastal Water Quality Index (CWQI) and a Geographical Information System (GIS)-based overlay mapping technique. Multiple parameter analyses found low water quality in Port Blair and Rangat bays. Poor water quality could be caused by anthropogenic activity. Chidiyatappu bay, on the other hand, has good water quality. In the open water, higher CWQI scores were perceived. However, reduced exploitation of coastal resources due to low anthropogenic activity resulted in a high-water quality score at Chidiyatappu bay. The research aims to combine the CWQI and a GIS-based mapping technique to produce a reliable, easy, and relevant output for water quality monitoring in a coastal context (Jha et al., 2015).

The utility of water quality indices as markers of water pollution for assessing spatial-temporal changes and classifying river water qualities was demonstrated. WQI (including 18 water quality parameters), WQImin and WQIm (considering five water quality parameters: temperature, pH, DO, EC, and TSS), and WQIDO (considering a single parameter, DO) were explored. Because of the low analytical cost, the water quality indices WQImin, WQIm, and WQIDO may be of relevance to underdeveloped countries. Water quality indices were utilized as a case study to analyze geographical and temporal changes in water quality in the Bagmati river basin (Nepal) from 1999 to 2003. The findings enabled to identify the substantial harmful effects of city urban activity on river water quality. The water quality index (WQI) in the studied portion of the river was 71 units (good) at the entry station and 47.6 units (poor) at the outlet station. During the study period, there was a substantial deterioration in water quality (mean WQI decrease=11.6%, p=0.042) in rural areas. A comparison investigation found that urban water quality was much worse than rural water quality. The investigation allowed to categorize the water quality stations into three categories: good water quality, medium water quality, and poor water quality. WQImin overestimated water quality, but with a similar trend as WQI, and was suitable for the periodic routine monitoring program. The association of WQI with WQImin and DO lead in the creation of two additional indices, WQIm and WQIDO, respectively. WQIm and WQIDO classifications of waters coincided in 90% and 93% of the samples, respectively (Kannel et al., 2007).

From 2008 to 2017, twelve hydro chemical indices wiz., (Mn, Cu, Zn, Hg, Pb, $NH_3$-N, COD-$_{Mn}$, DO, $BOD_5$, COD, TP, and TN) were collected using several analytical methodologies to better understand environmental status and ecological concerns of the Fenhe reservoir. Heavy metals' risks to human health and aquatic organisms were assessed. Heavy metals do not have a consistent geographical distribution. Biochemical factors and nutrients both pollute significantly in the midstream and downstream. High levels of contamination were indicated by hydro chemical indices in the midstream area. Water quality had improved downstream of the reservoir, however total nitrogen and total phosphorus levels have risen in recent years. According to the Canadian Council of Ministers of the Environment Water Quality Index, midstream water quality was generally low, with 80% of annual computations receiving a marginal grade. Cu and Zn posed significant ecological threats to aquatic creatures. Drinking water was generally safe for local inhabitants, but continuing monitoring is critical owing to ongoing concerns to water quality in these locations (Li et al., 2020).

To find trends in water quality happening across a rural-suburban-urban interface, temporal and spatial patterns of surface water quality were explored at 54 monitoring sites in the Wen-Rui Tang River watershed of eastern China. Parameters that were essential in measuring seasonal and regional fluctuations in water quality were identified using factor analysis. The most important parameters contributing to water quality variation were organic pollutants (dissolved oxygen (DO), chemical oxygen demand (manganese) ($COD_{Mn}$), and 5-day biochemical oxygen demand ($BOD_5$), nutrients (ammonia nitrogen ($NH_4^+$-N), total nitrogen (TN), total phosphorus (TP), and salt concentration (electrical conductivity (EC). The findings of the study contribute to current water quality remediation efforts by tracking trends in water quality across different land use zones (Mei et al., 2014).

Moskovchenko et al., (2009) studied the geographical and seasonal variations in water quality to assess the anthropogenic chemical inputs into the river system. Stream chemistry was examined in 24 sampling locations from January 2002 to December 2005. Pollution from non-point sources related with oil extraction was suggested by the spatial distribution of components in the Vatinsky Egan river basin. Data showed that ion concentrations in river waters were often inversely related to stream discharge. Salinity had the greatest geographical variance in hydrochemistry. Chloride had a broad and high concentration range. When compared to other West Siberian rivers, the Vatinsky Egan river had the most saline and regional effects further out in the watershed. The salinity of the river water rise dramatically as it flowed through the Samotlor oil field. Many Cl concentrations in the catchment's middle and lower reaches exceeded world average river values by one or more orders of magnitude. Total petroleum hydrocarbons (TPH) concentrations were over the acceptable water quality levels in 38% of sample occasions.

Two Water Quality Indices (National Science Foundation of the United States and Council of Ministers of Environment of Canada) were tested in the case of the Karun river system, Iran's most important river. These indices were generated using existing data, and their fluctuations were analyzed and compared in nine locations along the river across different time periods. The results demonstrated that the implementation of these reduced indices was satisfactory for the educational case study and could be duplicated in other Iranian areas (Mojahedi & Attari, 2009).

A modified nine-parameter Scottish WQI was used to assess the monthly water quality of the Douro river during a 10-year period (1992-2001), using a range of zero (lowest) to 100% (highest). The water's quality was at its lowest when it arrived in Portugal from Spain (WQI 47.3 - 0.7%); it steadily improved downstream, reaching a maximum of 61.7 - 0.7%. Overall, the three locations' water quality ranged from medium to bad. Although there was a seasonal decline in water quality from winter to summer, no statistical link between quality and discharge rate could be found. The occasional fall in quality was caused by a variety of factors depending on the location, including downstream Fecal coliform contamination and the topmost reservoir's high conductivity and low oxygen concentration. Due to the fact that two million people rely solely on the water from the last river location as their only source of drinking water, the study demonstrates the need to enforce the current international bilateral agreements and to put the European Water Quality Directive into practice in order to improve the quantity and quality of water received by the downstream country of a shared watershed (Bordalo et al., 2006).

Models in the multiplicative (MWQI) and additive (AWQI) categories were developed by the National Sanitation Foundation (NSF). The Canadian Water Quality Index (CCME WQI), sometimes known as the Canadian Water Quality Index (CWQI), was a measure of the water quality in Canada. For comparing the WQI models, Lumb et al., (2011) assessed the water quality data from thirty river sites located throughout the Canadian province of Ontario during the years 2002–2004 through 2006–2008 (three-year running averages) using NSF Indices, Oregon Water Quality Index (OWQI) AND CWQI. According to the study, AWQI and MWQI scores frequently tended to be higher than CWQI readings. As a result, compared to CWQI, the grades of the water quality for AWQI and MWQI were higher. In contrast, there was a greater and closer correlation between the OWQI and CWQI's scores for water quality. To grade the quality of water for aquatic uses, the CWQI formulation appeared to be the most severe overall, followed by the OWQI model.

By measuring physicochemical parameters and heavy metal concentrations at seventeen sampling stations (S1-S17) distributed throughout the river stretch, a study was carried out at Kali river to assess spatial and temporal variations in river water quality. Additionally, to identify current pollution sources, validate findings, and analyses spatial-temporal fluctuation in water quality, multivariate statistical approaches were applied. The Kali river was less contaminated, according to both the water quality index and the comprehensive pollution index. sites for downstream sampling were contaminated. The study recommends cleaning up the river's downstream area to improve both human health and the ecosystem's flora and wildlife (Singh et al., 2020).

Nguyen Van et al., (2022) studied a novel method of developing the Water Quality Index (WQI), which may be applied in real-world settings on a local or regional scale. The river was then subjected to the suggested index using quarterly data from the ten stations' monitoring of eleven parameters from 2017 to 2020. The WQI accurately reflected the state of the river's overall water quality, with 97.8% of its values falling into the excellent and good categories and 2.2% into the moderate category. The proposed WQI was found to be more appropriate for assessing river quality when compared to the WQIs adopted by the National Sanitation Foundation (NSF- WQI) and the Vietnam Environment Agency (VN-WQI) based on studies of river water quality. The development of the WQI utilizing the water quality monitoring data for the Huong river was suggested as a thorough and straightforward process. Based on the set of communality values for the eleven selected parameters, the multivariable approach (PCA) was used to establish relative weight (wi) for each water quality parameter objectively. Comparison between the river water quality ratings resulting from the suggested index (WQI), with the index NSF-WQI and index published by Vietnam Environment Agency (VN-WQI) in 2019 highlighted the varied classifications utilizing the three indices. The representative reflection of the real state of the river general water quality in terms of the WQI reveals that the WQI avoided ambiguity and eclipsing occurred to the VN-WQI. In addition to practical applications on a local or regional level, the proposed process and WQI could be employed for the river quality assessment in the years to come.

Radu et al., (2020) evaluated the Lower Danube river's water quality in line with the Water Framework Directive (Directive 2000/60/EC). Approximately 1500 samples from ten monitoring sites were collected and processed as part of the National Institute for Research and Development in Environmental Protection's (INCDPM) intensive monitoring programmed from 2011 to 2017, and the quality indicators specified in M.O. 161/2006 were analyzed in accordance with the applicable standards. The complicated set of data was subjected to multivariate statistical methods of water quality evaluation, and at the same time, the multiparametric quality index (ICPM), an index of worldwide comparative assessment of water quality over historical trends, was applied. The index was created by INCDPM. After the data were evaluated, the Lower Danube river's water quality was determined to be moderately polluted and to fall under Class III of surface water quality. According to the ecosystem approach, the levels of the monitored indicators did not match the Water Framework Directive's goal values.

By monitoring three sampling points within Sankey tank and Mallathahalli lake for a period of three months from March to May 2012, Ravikumar et al., (2013) examined the water quality index (WQI) in the surface water of the water bodies located in Bangalore Urban area. While electrical conductivity measurements placed Sankey tank and Mallathahalli lake waters, respectively, in the medium (C2) and high (C3) salinity categories, SAR readings suggested that both were good (S1) for irrigation. Sankey tank water is C2S1 (medium salinity-low sodium) type, whereas Mallathahalli lake water is C3S1 (high salinity-low sodium), according to a correlation between SAR and electrical conductivity. The water in Sankey tank and Mallathahalli lake was hard and very hard, respectively. Further evidence that tank water is of the good water class may be seen in the WQI values, which range from 50.34 to 63.38. Lake's water falls into the bad water category, with a WQI rating ranging from 111.69 to 137.09.

Rim-Rukeh et al., (2007) demonstrated that the physico-chemical parameters (pH, temperature, dissolved oxygen, total dissolved solids, electrical conductivity, sulphate, phosphate, zinc, lead, nickel, vanadium, and mercury) of river bodies in the Niger Delta region of Nigeria were within WHO standards for safe drinking water. Values for turbidity, BOD, nitrate, and iron were higher than allowed standards for drinking water quality. The water samples taken from the hand-dug wells met WHO guidelines for safe drinking water in terms of pH, temperature, dissolved oxygen, total dissolved solids, electrical conductivity, sulphate, phosphate, zinc, lead, nickel, vanadium, and mercury. The water samples had levels of turbidity, biochemical oxygen demand, nitrate, and iron that exceeded the standards for safe drinking water. Surface and ground water quality could significantly deteriorate because of the numerous petroleum-related facilities, operations, and other industrial activities in the delta. For development and monitoring reasons, it is important to define the baseline status of the surface and groundwater.

Numerous lakes in The Netherlands have their eutrophication factors subjected to a trend analysis. Data for 231 lakes total were available. Data on chlorophyll-a, total phosphorus, and total nitrogen were examined for the years 1980 through 1996. Chlorophyll a, total P, and total N concentrations dropped over the course of the summer in 65%, 73%, and 75% of the lakes with at least eight years of data between 1980 and 1996, respectively (Portielje & Van der Molen, 1998).

Utilizing six indicators of water quality, the water quality index (WQI) over the Sabarmati river basin stretch was determined using the weighted arithmetic approach. The investigation revealed that most of the indicators were severely impacted by human activity and sewage discharge in the river. The station in a very urban region, followed by the station in an urban area, and the station in a rural area, revealed the worst water quality. It was found that excessive anthropogenic activity, illegal sewage and industrial effluent discharge, poor sanitation, exposed river locations, and urban runoff were the main contributors to the decline in water quality. It is necessary to identify trends or changes in water quality over time and space, to gather data for designing tailored pollution prevention programmes, and to assess whether objectives like adherence to pollution laws or the implementation of efficient pollution control measures are being met (Shah & Joshi, 2017).

Pre-monsoon, monsoon, post-monsoon, and yearly surface water quality datasets for the upper Damodar river basin (DRB) for the years 2007 to 2010 were analysed. Six water quality indices (WQIs) were applied to each dataset to evaluate spatiotemporal variability and suitability for human use and aquatic life. These WQIs included two existing extended indices ($WQI_{obj}$ and $WQI_{sub}$) in addition to four newly designed simplified indices ($WQI_{m}$, $WQI_{min}$, $WQI_{DO}$, and $WQI_{pca}$). Results showed that at most sampling sites, which fall into the good to medium categories of water quality, developed indices exhibit, on average, similar spatiotemporal changes as compared to $WQI_{obj}$ at a reduced analytical cost. The study also discusses the necessity and value of developed indices over extended indices, particularly for developing nations. This is because monitoring costs and implementation costs are lower for developed methods than for extended methods, and generated maps may also help decision-making processes under various scenarios by taking spatial and temporal variability in DRB into account (Verma et al., 2019).

To determine the quality of water for public consumption and other home uses, the study set out to calculate water quality indices (WQIs) for six distinct Batlagundu, Dindigul District locations. It examines how environmental factors affect water quality. Twenty-four physico-chemical characteristics have been used in the work to determine five WQIs. Temperature, pH, sulphate, potassium, nitrate, phosphate, DO, BOD, and COD parameters all fell within BIS and WHO permissible limits, but others, including turbidity, total dissolved solids, electrical conductivity, total hardness, total alkalinity, calcium, magnesium, chloride, nitrite, fluoride, sodium, and iron, were found to be in excess. The results of WQIs showed that both anthropogenic and natural sources were responsible for the decline in water quality. According to the study mentioned above, the groundwater from the sampling sites previously mentioned was not suitable for human consumption but might be utilized for household purposes after being purified (Sarala Thambavani & Uma Mageswari, 2014).

Shin et al., (2013) determined the 15-year regional and temporal patterns connected to twenty water quality measures at urban New Jersey estuary. 12 sampling locations were decided namely 5 at Hackensack River, 2 at Cromakill Creek 1, at Penhorn Creek,1 at Sawmill Creek,1 at Berry’s Creek,1 at Mill Creek and 1 at Overpeck Creek.At five representative stations (sampling sites 1 to 5) along the river, there was no discernible improvement or deterioration in the river's water quality. Principal component analysis, CA, and stepwise regression were used to identify the sources of the pollution. The parameters of water quality that were examined here should be regarded as a reliable baseline study for comparisons in the evaluation of water quality. Long-term experimental research and integrated monitoring of physicochemical and biological characteristics are thus suggested to support more sustainable development with advantages to the economy and environment.

When compared to earlier studies, the condition of Sagar lake in India water has much higher levels of alkalinity, nitrate, and phosphate while having significantly lower levels of transparency, pH, total hardness, and chloride (Singh et al., 2009).

For Indian circumstances, a River Health Index (RHI) has been proposed and developed. For river water quality monitoring programmers, biological indicators including algae, macroinvertebrates, and fish are suggested to be added in addition to standard physico-chemical and nutritional parameters. Simple computations and the reporting of RHI value on a scale of 0 to 100 are two aspects of the suggested formulation that are innovative. Simple biotic indicators based on species identification and counting have been presented to make it simple enough for non-experts to perform. Based on a RHI score of = 20 or > 80, the River Health Level (RHL) can be categorized as "critical" or "excellent." RHI measurements can therefore be used to determine whether a river's sections are healthy or unhealthy. RHI 40 may be regarded as "poor," signaling the need for scientific intervention to enhance river health. It is being investigated whether to apply such a RHI formulation to the main Ganges River in India (Singh & Saxena, 2018).

To access the status and spatiotemporal patterns in water quality of seven selected (two natural and five constructed) wetlands in Punjab, several statistical approaches, and the water quality index (WQI) were used. The results showed that during the three study seasons (summer, monsoon, and winter) of the year 2019, the water quality in the chosen wetlands ranged from good to bad. Three kinds of wetlands with different water quality parameters and geographical patterns were found by principal component analysis. All examined water quality measures, except for pH, electrical conductivity, dissolved oxygen, biological oxygen requirement, and phosphate content, indicated temporal trends in water quality, according to analysis of variance. The understanding of the spatiotemporal trends in water quality has increased because of the comparison study, which will also be useful in the future for policymakers and other relevant authorities in designing improved water quality management plans for these wetlands (Singh et al., 2022).

It is extremely rare in literature to find a well-developed combination of irrigation water quality indexes (IWQIs) and entropy water quality indexes (EWQIs) for surface water appraisal in a polluted subtropical urban river. The National Sanitation Foundation Water Quality Index (NSFWQI) was used to create the IWQIs, which were then compared to the proposed EWQIs based on information entropy in the Dhaleshwari river, Bangladesh, to close the gap between the two. The datasets were subjected to principal component analysis (PCA), factor analysis (FA), Moran's spatial autocorrelation, and the random forest (RF) model. The resulting IWQIs, with IWQI-1 for the dry season and IWQI-2 for the rainy season, were further recommended. A similar tendency to the EWQIs was demonstrated and revealed poor to good quality water. The RF model's findings show that $NO_3^-$, $Mg^{2+}$, and Cr  are the main factors affecting surface water quality. For IWQImin-3, a substantial dispersion pattern was found during the wet season (Moran's I>0). Overall, IWQIs and EWQIs will produce cost-effective, entirely objective water quality control to create a scientific foundation for sustainable water management in the study basin (Siddique et al., 2022).

The degradation of surface water quality has impeded the long-term growth of China's economy, making surface water pollution a significant topic in recent years. Few research has looked at water pollution changes on a national level, but previous studies have examined regional variations in water pollution. A study summarized the geographical and temporal fluctuations in surface water quality in China over the B11th Five-Year Plan era by looking at 9 water quality metrics recorded at 422 sampling locations around the country. According to research, China's surface water quality is getting better. However, the continued decline in a number of sectors cannot be disregarded. Surface water quality was negatively impacted by human activities such as farming and over-urbanization. Although the surface water quality in the region has started to deteriorate, it was formerly considerably better in the upstream of major rivers in northwest China than in other places. Furthermore, southern China's surface water quality was superior to that of northern China (Sun et al., 2015).

To evaluate the geographical and temporal variability and to determine the level of water quality in the river Dongjiang, the water quality index (WQI) was produced. A modified WQI (designated as $WQI_{min}$) was established based on Principal Component Analysis (PCA) and correlation studies of the water parameters identified in dry and wet seasons during 2011–2012 to streamline the method and lower the analytical expenses of the water quality evaluation. $WQI_{min}$ obtained similar spatial changing trends and classifications of the water quality in comparison to the prior index. The results revealed excellent water quality in the tributary site close to the reservoir, good water quality in the river's upstream, and medium water quality in the river's downstream, which suggested that the urban wastewater from the river's deteriorating water quality was primarily caused by the growth of industry in the downstream and an increase in population. Additionally, WQImin was better able to capture the seasonal variations in water quality, which were slightly worse in the dry season than the wet season. The findings likewise support the need for ongoing surveillance to stop pollution brought on by human activity and business (Sun et al., 2016).

Pariyej lake's Water Quality Index was measured using Weighted arithmetic Mean Index to study the effects of industry, agriculture, and human activity. For the determination of W.Q.I. for the wet, winter, and summer seasons, physico-chemical parameters were tracked. The values of the parameters, including pH, Total Hardness, TDS, Calcium, Chloride, Nitrate, Sulphate, DO, and BOD, were within the permitted ranges. However, the levels of total alkalinity and magnesium were higher than those allowed by Indian Standards. The water quality index (W.Q.I.) values in the current inquiry, however, were reported to be less than 75 (67.20, 68.43, and 70.37) for distinct seasons, indicating that the water quality is subpar and not entirely suitable for human consumption (Thakor et al., 2011).

Concern over plastics in the form of fibers, pieces, or beads less than 5 mm is growing. A generic pollutant found in almost every environmental compartment, particularly in freshwater and marine environments, is microplastics. Not much study has been done on microplastic pollution in Indian aquatic systems, such as urban ponds. A study on Gotri pond in Vadodara was carried out by employing a conventional density separation technique, successful identification and separation of microplastics from water samples. According to the study, microplastic pollution in city ponds had been detected for the first time, with levels ranging from 0.010 mg to 0.039 mg per litters. FTIR spectroscopy was used to analyse the separated microplastics based on the material’s functional group identification (Chaudhari & Samnani,2023).