LONG-TERM ASSESSMENT OF GOMTI RIVER WATER QUALITY AT SULTANPUR, INDIA: A MULTIDIMENSIONAL APPROACH

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by

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CANDIDATE'S DECLARATION

I, Mihika Saxena, Roll No. 2K22/ENE/01 student of M. Tech (Environmental Engineering), hereby declare that the project Dissertation titled "Long-term Assessment of Gomti River Water Quality at Sultanpur, India: A Multidimensional Approach" which is submitted by me to the Department of Environmental Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the Project Dissertation titled "Long-term Assessment of Gomti River Water Quality at Sultanpur, India: A Multidimensional Approach" which is submitted by **Mihika Saxena, Roll No. 2K22/ENE/01**, Department of Environmental Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: New Delhi **DR. RAJEEV KUMAR MISHRA**

Date: **SUPERVISOR**

ABSTRACT

The Gomti River, a prominent groundwater-fed river in Uttar Pradesh, India, faces significant pollution pressures from industrial effluents and domestic wastewater. This study presents a comprehensive analysis of the Gomti River's water quality at Sultanpur over 20 years (1998-2017), employing Water Quality Indices (WQIs) and multivariate statistical techniques to evaluate pollution levels and identify key factors influencing water quality. The water quality was assessed using four WQIs: Comprehensive Pollution Index (CPI), Synthetic Pollution Index (SPI), Nemerow's Pollution Index (NPI), and Arithmetic Water Quality Index (AWQI). Descriptive statistics were calculated for key physico-chemical parameters such as Dissolved Oxygen (DO), pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Biochemical Oxygen Demand (BOD), Total Hardness (TH), and major ions and nutrients (e.g., Sodium, Potassium, Calcium, Magnesium, Nitrate, Total Phosphorus, Chloride, Sulphate, Ammonia, Fluoride, Boron). Principal Component Analysis (PCA) and Cluster Analysis (CA) were used to identify major pollution sources and temporal variations. The study found that the mean values for DO, pH, EC, TDS, and BOD were 6.92 ± 1.18 mg/L, 8.39 ± 0.35, 388.49 ± 109.75 µS/cm, 312.87 ± 102.62 mg/L, and 2.65 ± 0.74 mg/L, respectively. DO levels fluctuated between 3.0 mg/L and 11.8 mg/L, indicating varying oxygen availability for aquatic life. The pH ranged from 7.6 to 9.2, reflecting slightly alkaline conditions. EC and TDS values exceeded recommended limits at certain times, highlighting potential sources of pollution from agricultural runoff and industrial discharges. BOD values indicated moderate organic pollution (2.65 mg/L), with occasional peaks suggesting episodic pollution events. PCA revealed that the key parameters derived through principal components affecting the water quality indices throughout the study were Total Hardness (TH), Total Dissolved Solids (TDS), Magnesium (Mg^{2+}), Total Alkalinity (TA), Chloride (Cl^-), Potassium (K^+), Sodium (Na^+), pH, Dissolved

Oxygen (DO), Fluoride (F^-), Sulphate (SO_4^{2-}), and Boron (B) with a total cumulative variance of 62.39% in the dataset. Over the past two decades, a comprehensive water quality assessment indicates an improvement. The analysis of water quality indices provides a comprehensive overview of the pollution status. The Comprehensive Pollution Index (CPI) findings suggest that the water quality was categorized as Slightly Polluted (0.41-1.00) 90% of the time, while the remaining 10% fell within the Sub-Clean range (0.21-0.40). According to the Synthetic Pollution Index (SPI), water quality was classified as Slightly Polluted (0.21-0.40) in 45% of observations and as Suitable for Drinking (≤0.20) in 55% of cases. Nemerow's Pollution Index (NPI) revealed that water quality was Lightly Polluted (1-2) in 18% of the samples, whereas 82% were categorized as Not Polluted (≤1). The Arithmetic Water Quality Index (AWQI) showed that 78% of the water samples were rated as Poor (51-75), 18% as Very Poor (76-100), and only 4% as Good (26-50). Regression analysis revealed significant correlations between PCA-derived parameters and the original CPI-based WQI, with R^2 value (0.83) indicating strong predictive power for water quality assessment. The study also identified seasonal variations in water quality, with higher pollution levels during the dry season due to reduced dilution and increased pollutant concentration. The findings emphasize the need for continuous monitoring and effective management strategies to mitigate pollution and improve the Gomti River's water quality. Implementing comprehensive governance frameworks and advanced analytical techniques can lead to significant improvements, benefiting both the ecosystem and the local population. This study contributes valuable insights for policymakers and stakeholders in understanding sustainable water management practices and ensuring the long-term health of river ecosystems.

Keywords: Gomti River, Multivariate Statistical Analysis, Regression Analysis, Water Quality Index

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

BCM	Billion Cubic Metre
BCWQI	British Columbia Water Quality Index
BIS	Bureau of Indian Standards
BOD	Biochemical Oxygen Demand
CA	Cluster Analysis
CAG	Comptroller and Auditor General of India
CCME	Canadian Council of Ministers of the Environment Water Quality Index
CPCB	Central Pollution Control Board
CPI	Comprehensive Pollution Index
CWC	Central Water Commission
DO	Dissolved Oxygen
EC	Electrical Conductivity
GAP	Ganga Action Plan
GoAP	Gomti Action Plan
GRB	Gomti River Basin
MLD	Million Litres Per Day
MLR	Multiple Linear Regression
MSA	Multivariate Statistical Analysis
PCA	Principal Component Analysis
SPCB	State Pollution Control Board
SPI	Synthetic Pollution Index
STP	Sewage Treatment Plant
TA	Total Alkalinity
TDS	Total Dissolved Solids
TH	Total Hardness
TPD	Tonnes Per Day
UP	Uttar Pradesh
AWQI	Arithmetic water quality index
WHO	World Health Organization
WQI	Water Quality Index
WT	Water Temperature

CHAPTER 1

INTRODUCTION

1.1. GENERAL BACKGROUND OF STUDY

A safe and adequate freshwater supply is essential for functioning ecosystems and socioeconomic development (Singha et al., 2004; Hussain et al., 2012; Karthik and Lekshmanaswamy 2018). Rivers and lakes are significant sources of freshwater, supporting domestic, agricultural, transportation, and industrial activities. Historically, many civilizations thrived along rivers due to the economic and agricultural benefits they provided (Kaushik et al., 2009; Tavakoly et al., 2019). However, rapid industrialization, urbanization, and population shifts are increasingly threatening the quality of freshwater resources (Pius et al., 2011; Hussain et al., 2012; Yeliz and Sen 2019).

Seasonal variations in precipitation, surface runoff, groundwater flow, and water interception affect both the quality and quantity of water (Krishan et al., 2022a). Surface water sources are pathways for various hazardous substances from human activities or natural processes, posing risks to biotic species. Monitoring these water sources is crucial for generating reliable data to prevent and control pollution (Hanh 2011; Vinod et al., 2013; Batabyal and Chakrobarty 2015). Effective long-term water quality management requires a comprehensive understanding of the water's physical, chemical, and biological characteristics.

Water resource management impacts nearly every aspect of society and the economy, including health, food production, household water supply, sanitation, energy, industry, and urban ecosystems (Xiao 1996). In India, six hundred million people face severe water stress, with inadequate action potentially leading to a prolonged water crisis (Khan et al., 2021a). Pollution from industry, agriculture, and domestic sources is concentrated along rivers. Industrial processes, agricultural runoff, and urban wastewater introduce pollutants such as fertilizers, pesticides, heavy metals, and chemicals into rivers. These pollutants affect water quality, leading to issues like eutrophication and reduced dissolved oxygen levels, which harm aquatic life (Hanh 2011). Effective water management must address these pollution sources to ensure the sustainability of freshwater resources.

1.2. GLOBAL WATER RESERVE

About 70% of the Earth's surface is covered with water (about 1.4 billion km³ of water), but less than 3% is freshwater, and much of it is inaccessible in glaciers and ice caps (Wu et al., 2020). The majority, 96.5%, is saltwater found in oceans, with desalination methods like thermal or reverse osmosis not being commercially viable (Kizar 2018). Fig.1.1 describes the global distribution of water resources.

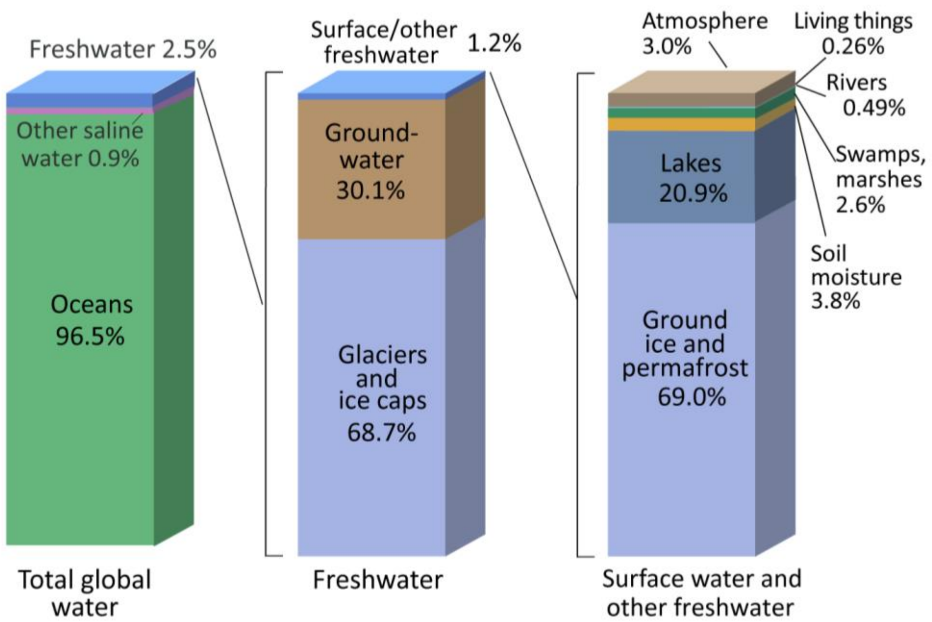

Figure 1.1 Distribution of Water Resources on Planet Earth

(Source: https://www.usgs.gov/media/images/distribution-water-and-above-earth)

Fig. 1.1 shows freshwater constitutes a mere 2.5% of the total water resources. This limited freshwater is further categorized into different storage forms. A significant portion, approximately 68.7%, is trapped in icecaps and glaciers, making it largely inaccessible for direct human use. Another 30.1% of the freshwater is stored as groundwater, which, while more accessible than ice, still requires extraction for utilization. Surface freshwater, vital for most of life's needs, represents just over 1.2% of the total freshwater. Within the surface freshwater category, lakes hold the majority, containing 21% of this accessible water (Fig. 1.1). Although rivers make up only a small fraction of the surface freshwater, they play a crucial role in human water supply due to their accessibility and the volume of water they transport across various landscapes. This distribution underscores the critical need to effectively manage and conserve freshwater resources to sustain human, plant, and animal life (Shiklomanov 1993; Chang 2002).

1.3. WATER RESOURCES IN INDIA

With 2.45% of the world's surface area, India holds 4% of global water resources and supports about 16% of the world's population. India receives approximately 4,000 cubic km of water annually from precipitation, with an average precipitation of 1170 mm per year. The total available surface water and replenishable groundwater is 1,869 cubic km, but only 60% of this, or 1,122 cubic km, is utilizable. India's surface water resources include rivers, lakes, ponds, and tanks, with an estimated mean annual flow of 1,869 cubic km in all river basins. However, only about 690 cubic km, or 37%, of the surface water is usable due to seasonal flow variations and limited suitable storage sites (Kumar et al., 2005). Over 90% of Himalayan rivers' annual flow occurs within four months, complicating resource capture and storage. Groundwater resources in India are approximately 432 cubic km, with the Ganga and Brahmaputra basins holding about 46% of these resources (Goyal and Surampalli 2018). High groundwater utilization is observed in the north-western river basins and parts of southern India, especially in Punjab, Haryana, Rajasthan, and Tamil Nadu. In contrast, states like Chhattisgarh, Odisha, and Kerala utilize a smaller proportion of their groundwater potential. Groundwater accounts for over 50% of the irrigated area in India, with about 20 million tube wells installed. India has constructed nearly 5,000 major or medium dams and barrages to store river water and recharge groundwater. Agriculture primarily uses surface and groundwater, consuming 89% of surface water and 92% of groundwater. The industrial sector uses 2% of surface water and 5% of groundwater, while the domestic sector accounts for 9% of surface water use, higher than its groundwater use (Chang 2002; Venugopal et al., 2009).

Figure 1.2 Indian River Map (Source: https://www.mapsofindia.com/maps/rivers/)

Cities like Haridwar, Rishikesh, Ayodhya, Varanasi, and Delhi flourished along rivers, benefiting from their resources and cultural significance. Over time, rivers became central to social and religious events. Fig. 1.2 depicts a detailed map of India, highlighting all its major rivers. Festivals like Kumbh Mela and Makar Sankranti involve ritual bathing in rivers, symbolizing both tradition and river conservation (Gautam et al., 2015). This deep connection has turned rivers into vital symbols of life and culture (Iqbal et al., 2019). Historically, human activities such as population growth, urbanization, and agriculture coexisted harmoniously with rivers. However, rapid industrialization and urbanization have disrupted this balance, negatively impacting river ecosystems and society (Yadav et al., 2009; Arumugam 2010). Once blessings, rivers now face pollution, ecosystem disruption, and altered dynamics due to human interference (Helena et al., 2000; Utete and Fregene 2020). Despite these challenges, rivers remain replenishable resources integral to the hydrological cycle, ensuring continuous water flow on Earth (Romero et al., 2016). They are crucial for navigation, tourism, and providing freshwater for domestic, agricultural, and commercial purposes (Krishan et al., 2022a). Rivers play essential roles in nutrient transport, waste assimilation, and flood and drought regulation, with their health indicated by water quality, ecological condition, and flow (Cude 2001; Karthik and Lekshmanaswamy 2018).

1.4. RIVER POLLUTION

The health of rivers directly impacts national progress and ecological stability, highlighting the intertwined destinies of natural water systems and human prosperity (Prasad et al., 2016). Human activities, particularly domestic, industrial, and agricultural, often lead to environmental degradation. Rapid industrialization and urbanization have resulted in megacities that strain surrounding ecosystems (Zutshi et al., 1980; Singh et al., 2015). This development drives mass rural-urban migration, placing additional pressure on freshwater bodies crucial to urban growth. Over a billion people, mostly in developing countries, lack access to clean drinking water, exacerbated by industrial and commercial waste dumping into natural water bodies without adequate treatment. In India, many rivers are treated like open drains, with around 70% of river water polluted due to high pollutant levels (Singh et al., 2005).

Water quality directly affects human health and the health of aquatic and environmental organisms (Aredehey et al., 2020). Poor water quality renders water unsuitable for human consumption and agricultural use (Dimri et al., 2021). National and international organizations set water quality standards that, if met, make water safe for drinking and other uses (WHO 2011; BIS 2012). Effective city governance requires preventing pollution from both point sources, such as wastewater treatment facilities, and non-point sources such as urban and agricultural runoffs (Fathi et al., 2018; Ren et al., 2021). Anthropogenic activities, including agriculture, urban development, mining, power production, deforestation, industrial pollution, sewage issues, and tourism, significantly impact river water quality (Dohare et al., 2014). Natural water bodies can somewhat degrade pollutants, but their capacity is limited (Helsel and Hirsch 2002; Ramakrishnaiah et al., 2009). Industrial growth, deforestation, global warming, and climate change further disrupt the water cycle and environmental balance (Vinod et al., 2013; Wu et al., 2014, 2020). In India, water quality is affected by untreated municipal waste and industrial effluents, which introduce various pollutants into rivers. These pollutants, including heavy metals and organic substances, degrade the water quality, making it unsafe for agricultural, industrial, and human use (Zutshi et al., 1980; Singh et al., 2015).

Agricultural practices, particularly using pesticides and fertilizers, also contribute to water pollution. These chemicals increase nitrate and phosphorus levels in water, leading to eutrophication and harming aquatic ecosystems (Shrestha and Kazama 2007; Li et al., 2019). Efficient water management is crucial to prevent water quality degradation due to urbanization and agricultural practices. India faces a growing water crisis, with many cities experiencing water shortages and pollution. Addressing this requires effective wastewater treatment and sustainable water management practices. Non-conventional water resources are increasingly needed to meet the demand (Trivedi and Goel 1986). Ensuring sustainable development and proper waste management is essential to protect public health and preserve freshwater resources (Kannel et al., 2007a; Ewaid et al., 2018).

India's rivers, vital to its agricultural economy, are at risk due to pollution and overuse. Unplanned modernization, disregard for environmental regulations, and population growth have severely impacted river ecosystems (Athimoolam and Ramu 2006). To mitigate these effects, comprehensive water quality management strategies are needed to maintain the health of rivers and support sustainable development (Dohare et al., 2014; Siraj et al., 2023).

1.5. EFFECTS OF WATER POLLUTION ON AQUATIC AND HUMAN HEALTH

River water pollution poses a significant threat to human health due to the presence of heavy metals and contaminants. Studies have shown that polluted river water can contain harmful substances such as chromium, arsenic, mercury, and lead, exceeding standard limits and leading to adverse health effects (Kaushik et al., 2009; Wu et al., 2014). The impact of water pollution on human health is profound, with common diseases like diarrhoea being linked to poor water quality, affecting individuals of all ages (Dwivedi et al., 2018). Additionally, exposure to contaminated river water can result in fatal diseases, especially when heavy metals and toxic substances are ingested through water consumption or fish ingestion pathways (Dwivedi et al., 2018; Khan et al., 2021b). Governments must implement strict water management strategies to mitigate the health risks associated with river water pollution and safeguard public health. Pollution also severely affects aquatic wildlife, impacting their health and ecosystem (Dwivedi et al., 2018). Studies have shown that contaminants like heavy metals bioaccumulate in fish tissues, affecting their physiological health and biomarkers (Khan et al., 2021b).

Furthermore, pollutants from various sources lead to the depletion of valuable aquatic biodiversity, disrupting the natural balance of river ecosystems and reducing their ability to provide ecological services Macrozoobenthos, such as macroinvertebrates, are particularly vulnerable to pollutants like heavy metals, causing disturbances in their physiological functions and triggering oxidative stress responses (Khan et al., 2021b). Additionally, water pollution alters the phylogenetic community structure of aquatic macrophytes, decreasing species richness and phylogenetic diversity, and ultimately leading to phylogenetic clustering within communities (Kumar et al., 2023). These findings underscore the urgent need for effective water management strategies and pollution control measures to safeguard aquatic wildlife and preserve the health of river ecosystem.

1.6. RIVER POLLUTION IN UTTAR PRADESH

Uttar Pradesh has several of India's largest rivers, including the Betwa, Chambal, Dhasan, Gandak, Ganga, Ghaghara, Gomti, Ken, Ramganga, Son, Tons, and Yamuna. Smaller rivers such as Kali, Krishni, Dhamola, and Hindon also flow around UP's major cities, meeting the needs of the population. However, growing industrialization and urbanization have rapidly declined river quality (Jindal and Sharma 2010; Sadat-Noori et al., 2014; Gao et al., 2015; Kizar 2018; Wu et al., 2020). According to the CPCB, some of the most polluted rivers in India are located in Uttar Pradesh, including the Gomti, Hindon, Kali, Krishni, Dhamola, and Yamuna (CPCB 2009). The Gomti River, transports agricultural waste, sewage, industrial wastewater, and other pollutants from both point and non-point sources (Singh 2004; Singha et al., 2004; Singh et al., 2005). Traditional religious practices, idol immersion, disposal of biomedical waste, and agricultural runoff also contribute to water pollution, posing serious threats to the river's flora and fauna (Venugopal et al., 2009; Ewaid et al., 2018). Along its length, the Gomti River, receives enormous loads of untreated effluents from various point and non-point sources (Singh et al., 2022). A 2011–2015 CAG assessment on the river states that the Gomti River at Lucknow is more heavily contaminated than the Ganga River at Varanasi. This is despite Varanasi's dense population and heavy tourism. Ideally, Lucknow should perform better as it is the capital of Uttar Pradesh (Sharma 2015). In Lucknow, Gomti river's water quality gets affected by the presence of 26 major drains, 14 on the Cis side and 12 on the Trans side. Compared to their cis counterpart, the trans side of Gomti's drains are comparatively higher (Singh et al., 2016). The river is completely depleted from upstream Sultanpur to downstream Sitapur as a result of industrial effluents from industrial belts that manufacture sugar, paper, and plywood. The Gomti Action Plan (GoAP) was launched in April 1993 to address the huge pollution burden on the Gomti River. It is a plan largely funded under Jawaharlal Nehru National Urban Renewal Mission (JNNURM) that has the objective of constructing and upgrading Sewage Treatment Plants (STPs) for effective management of waste. In spite of this, it faces many difficulties including untreated sewage discharge and inefficiencies in waste management (Singh et al., 2005; Yadav 2021).

About 675 MLD of sewage is produced daily and discharged in Gomti River, but only 396 MLD are treated by existing STPs. This untreated effluent adds significantly to river pollution. Under the scheme, Sultanpur's STP also plays a vital part; however, its functionality remains questionable since poor waste disposal is still a significant concern. Untreated sewage and industrial discharges into the river cause this massive pollution, thus severely affecting biodiversity and rendering water unfit for use (Sharma 2015).

1.7. NEED OF THE STUDY

The need to study the water quality of river Gomti at Sultanpur is identified in the background of its continuously deteriorating water quality. Although many studies in the literature evaluate the state of the river Gomti's water quality, no studies have been found that provide a long-term assessment of the Gomti River at Sultanpur, Uttar Pradesh, India. This study aims to provide a comprehensive assessment of a 20-year span (1998 – 2017). By applying four different water quality indices and conducting multivariate statistical analysis, parameters contributing the most to deteriorating water quality are assessed. The findings of this study could be of significant use to academicians, policymakers and relevant stakeholders.

1.8. PROBLEM STATEMENT

The Gomti River is currently facing severe pollution challenges. Extensive research and assessments on the Gomti River, such as those by Singh et al., 2022 and various other studies, have consistently highlighted the river's compromised water quality due to untreated effluents from industrial and domestic sources. The stretch of the Gomti River near Sultanpur is particularly affected, with dissolved oxygen levels significantly below the required standards to sustain aquatic life, primarily due to untreated sewage and industrial discharges (Singh et al., 2005). Despite the implementation of initiatives like the Gomti Action Plan under the Jawaharlal Nehru National Urban Renewal Mission (JNNURM), the inefficiencies in waste management and the substantial untreated sewage discharge remain critical issues (Singh et al., 2005; Yadav 2021).

Sultanpur's selection for this study is justified by its strategic position along the river and the notable pollution burden it carries. The existing sewage treatment facilities in Sultanpur are insufficient, treating only a fraction of the produced sewage, leading to substantial pollution downstream (Khan et al., 2021a). Additionally, the heavy metal contamination and presence of organic pollutants in this region pose severe health risks, making it an essential focal point for addressing the broader pollution issues of the Gomti River (Sharma and Walia 2015). By concentrating efforts on Sultanpur, the study aims to develop targeted remedial actions that can significantly improve the water quality and contribute to the sustainable management of the Gomti River. Although studies on the water quality of the Gomti River at Sultanpur, Uttar Pradesh, are comprehensive, they still have significant gaps. Previous studies have not conducted a long-term analysis of the Gomti River at Sultanpur, nor used four water quality indices (WQIs) simultaneously. This study addresses these gaps by analysing 20 years of data, applying them to four different WQIs, and performing multivariate statistical on the data. By integrating advanced analytical techniques and adopting comprehensive governance frameworks, significant improvements in river health and water quality can be achieved, as evidenced by both local and international experiences (Ewaid et al., 2018; Fathi et al., 2018; Elsayed et al., 2020; Varol 2020; Dimri et al., 2021).

1.9. OBJECTIVE OF STUDY

Despite the extensive research on water quality assessments across various river systems, there remains a notable gap in the literature pertaining to the Gomti River. Specifically, no prior studies have simultaneously addressed the following key objectives:

(i) To perform a 20-year long-term analysis of the Gomti River at Sultanpur using historical water quality data.

(ii) To apply four water quality indices (WQIs) for assessing river pollution levels.

(iii) To determine the most significant parameters using PCA and evaluate their impact on WQI through regression analysis.

CHAPTER 2

REVIEW OF LITERATURE

2.1.WATER QUALITY INDICES

The Water Quality Index (WQI) was developed to provide concerned citizens and policymakers with a clear understanding of the general quality of water, both surface and groundwater (Sadat-Noori et al., 2014; Ewaid et al., 2018). By converting water quality characteristics into a single, dimensionless number, the WQI simplifies the assessment of water quality (Ramakrishnaiah et al., 2009; Fathi et al., 2018; Dimri et al., 2021). It is used to evaluate water quality for various uses, including drinking, irrigation, livestock, agriculture, recreation, and aesthetics (Cheng et al., 2007; Kumar et al., 2007; Tavakoly et al., 2019; Elsayed et al., 2020; Khan et al., 2021b; Kushwah et al., 2023). Water quality indices (WQI) have been utilized for classifying water quality since the mid-1800s, though formal models have only been developed in the past 50 years (Abbasi and Abbasi 2012). The first WQI model was created by Horton in the 1960s, using 10 significant water quality parameters (Horton 1965). Later, with the National Sanitation Foundation's support, Brown developed the more comprehensive NSF-WQI, informed by 142 water quality experts who guided the parameter selection and weighting (Brown et al., 1970; Abbasi and Abbasi 2012). Several subsequent WQI models have been based on the NSF-WQI. Another significant development was the British Columbia WQI (BCWQI), devised by the British Columbia Ministry for Environment, Lands, and Parks in the mid-1990s, used to assess many water bodies in British Columbia, Canada (Saffran et al., 2001). It was also observed that the BCWQI showed high sensitivity to sampling design and application-specific water quality objectives (Said et al., 2004). In 2001, the Canadian Council of Ministers of the Environment's Water Quality Guidelines Task Group developed the CCME WQI, following a review of the BCWQI model (Saffran et al., 2001; Lumb et al., 2011). The CCME recognized the BCWQI model in 1990 (Dunn 1995). More recently, new models such as the Liou Index, Malaysian Index, and Almeida Index have been created. To date, over 35 WQI models have been developed globally to evaluate surface water quality (Stoner 1978; Kannel et al., 2007a; Abbasi and Abbasi 2012; Sohrab et al., 2012). Several other indices have been developed to assess water quality. Modern indices include the British Columbia Water Quality Index (BCWQI) and the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI), which provide flexibility in parameter selection and are used widely for water quality assessment (Cude 2001; Kannel et al., 2007a; Vinod et al., 2013; Gautam et al., 2015). However, these indices can exaggerate certain factors, leading to biased results (Sadat-Noori et al., 2014). The Synthetic Pollution Index (SPI), introduced by (Ewaid et al., 2018) and the comprehensive pollution index (CPI) are essential tools for evaluating overall water pollution loads (Krishan et al., 2022b; Kumar et al., 2023; Kushwah et al., 2023). The se indices help determine the combined impact of various pollutants on water quality. For instance, the SPI and WQI evaluated the Ganga River's water quality over nine years, finding significant pollution levels. Water Quality Indices (WQIs) like the arithmetic WQI, SPI, and CPI are crucial for understanding and managing water quality. One issue with WQI models is that they are typically designed based on site-specific guidelines for a particular region, making them non-generic. Additionally, these models can introduce uncertainty when converting extensive water quality data into a single index. Water quality analysis is generally concerned with evaluating the quality of natural water for various uses, including drinking, domestic, irrigation, and industrial purposes. Monitoring the parameters of multiple contamination sources entering surface water and groundwater systems is often costly and labour-intensive. Many researchers and scientists have encountered challenges in describing and addressing water quality concisely and straightforwardly. These challenges arise due to the complexity of water quality parameters and the significant variability in the parameters used to characterize the status of water resources. Consequently, numerous comprehensive efforts have been made to define water quality status in a simplified scientifically sound manner (Banda and Kumarasamy 2020; Akhtar et al., 2021).

2.2.MULTIVARIATE STATISTICAL ANALYSIS

Multivariate Statistical Analysis (MSA) is extensively utilized in assessing stream water quality, playing a crucial role in water resources management (Singh 2004; Wu et al., 2014; Sener et al., 2017; Haider et al., 2019; Tian et al., 2019; Ustaoglu and Tepe 2020; Varol 2020). MSA facilitates the interpretation of complex water quality datasets, aids in identifying pollution sources, and determines whether natural or anthropogenic factors are influencing temporal and spatial variations in stream water quality (Shrestha and Kazama 2007; Gurjar and Tare 2019; Ustaoglu and Tepe 2020). Recent methodological advancements such as Principal Component Analysis (PCA) and Cluster Analysis have been instrumental in pinpointing the main pollution sources and understanding the spatial distribution of contaminants (Kumar et al., 2022; Kushwah et al., 2023). Additionally, seasonal variations and temporal improvements in water quality have been explored (Singh et al., 2023; Prasad et al., 2024), which are crucial for framing effective management strategies. Routine and continuous monitoring programs are essential for collecting reliable water quality data. These programs generate vast amounts of complex data, including unpublished information on surface water bodies' areas and behavioural characteristics. Interpreting this hidden information is crucial for effective water quality management. Advanced analytical tools and procedures, such as Multivariate Statistical Analysis, are necessary to analyse these data (Singh 2004). Multivariate Statistical Analysis, including Principal Component Analysis (PCA) and Cluster Analysis (CA), help reveal concealed information in large matrices of high-quality data. These techniques are essential for accurately assessing river water quality and expanding the scope of evaluation based on extensive data inputs (Medeiros and Tresmondi 2017).

Multivariate Statistical Analysis has been widely used in the past decade to analyze and characterize surface water quality (Singh et al., 2005; Shrestha and Kazama 2007; Wu et al., 2014; Elsayed et al., 2020; Varol 2020; Kushwah et al., 2023). CA, an unsupervised pattern recognition technique, groups samples into clusters where items are similar to each other but distinct from other clusters. Researchers have employed CA to understand the temporal and spatial patterns of water quality changes caused by anthropogenic or natural sources (Shrestha and Kazama 2007; Medeiros and Tresmondi 2017; Li et al., 2019; Varol 2020). PCA is commonly used to reduce the dimensionality of large datasets without losing intrinsic information. It helps identify fewer hidden factors associated with pollution sources affecting water resources' hydrochemistry and quality (Wu et al., 2014; Gurjar and Tare 2019; Elsayed et al., 2020; Kushwah et al., 2023). To summarise, Multivariate Statistical Analysis like PCA and CA are vital for understanding and managing water quality. They help identify factors responsible for water quality deterioration and assist in developing effective management strategies. These techniques are instrumental in addressing the complexities of water quality data, ensuring informed decision-making for water resource management.

2.3.REGRESSION ANALYSIS

Integrating WQIs with advanced statistical tools like regression analysis has been pivotal in simplifying and interpreting environmental data. For instance, stepwise multiple linear regression alongside WQIs has helped develop predictive models for water quality, thus aiding efficient management and decision-making processes (Ewaid et al., 2018). Similarly, PCA and Support Vector Machine Regression have provided robust assessments of irrigation water quality (Elsayed et al., 2020). These tools are pivotal in unraveling the significant parameters that influence the water quality indices (Liou et al., 2004; Debels et al., 2005; Hanh 2011; Koçer and Sevgili 2014).

2.4.STATUS OF GOMTI RIVER

Gomti River faces intense pollution pressures from industrial effluents and domestic wastewater, leading to severe water quality degradation (Iqbal et al., 2019). The Gomti River, a notable tributary of the Ganges, has been the focus of extensive research due to its ecological importance and the substantial anthropogenic pressures it endures. Previous studies have consistently documented the river's compromised water quality resulting from urban runoff, industrial discharges, and agricultural activities, particularly emphasizing the presence of heavy metals and organic pollutants in the Lucknow stretch (Khan et al., 2021b; Kumar et al., 2023). Water Quality Indices (WQIs) have consistently categorized much of the river's water as poor to unsuitable for human consumption, highlighting the pressing need for remedial actions (Krishan et al., 2022a, 2022b). The Gomti River, an essential tributary of the Ganges, is a crucial water resource for Uttar Pradesh, India. Heavy metal contamination in the Gomti River has been extensively studied, revealing critical levels of pollutants posing severe health risks. A study by Khan et al., (2021b) assessed the contamination and health risks associated with heavy metals, finding high-risk levels along a 61 km stretch of Gomti river, primarily due to sewage and industrial effluents. The study also highlighted that children are particularly vulnerable to the health risks posed by these contaminants. Further analysis by Kumar et al., (2022) investigated heavy metal concentrations in surface water and sediments over two years, identifying significant ecological risks from metals such as Fe, Mg, Mn, Zn, and Cd. Kumar et al., (2022) focused on the spatial distribution of physicochemical and bacteriological parameters across five sites in Lucknow. The study observed seasonal variations, with pollution levels increasing downstream. Parameters such as pH, turbidity, EC, and BOD showed significant deterioration in water quality, making it unsuitable for drinking due to high levels of faecal coliform and E. coli. Kushwah et al., (2023) employed multivariate statistical methods to analyse water quality, using cluster analysis and principal component analysis. The study categorized sites based on pollution levels and identified domestic wastewater and stormwater runoff as major pollution sources. Kumar et al., (2023) examined the presence of organochlorine pesticides (OCPs) and polycyclic aromatic hydrocarbons (PAHs) in the Gomti River. The findings indicated high concentrations of these pollutants, particularly in the midstream areas, attributed to anthropogenic activities. The levels of OCPs and PAHs exceeded recommended standards, highlighting the severe impact of industrial and household waste on the river. Gupta et al., (2022) developed an advanced analytical method for detecting pesticide residues in Gomti river. The study found that the current pesticide concentrations posed no significant threat to most aquatic life but did indicate potential risks to invertebrates. Multivariate analysis identified anthropogenic activities as the primary source of pesticide contamination. Das et al., (2021) explored the impact of climate change on the Gomti River basin using the SWAT hydrological model. The study predicted declining precipitation and streamflow under various RCP scenarios, which could exacerbate water quality issues. These findings stress the importance of adaptive water management strategies to mitigate climate change effects on the river basin. Khan et al., (2020) evaluated heavy metal pollution, identifying critical pollution levels across multiple sites. The study revealed strong correlations between arsenic and lead, suggesting significant anthropogenic contributions to the contamination. These findings underscore the urgent need for remedial actions to mitigate health risks. Gondial and Bharti (2024) examined metal bioaccumulation in fish from the Gomti River, highlighting significant health risks to humans consuming these fish. The study revealed high levels of bioaccumulation, particularly in species such as Ctenopharyngodon idella and Channa punctata, posing both non-carcinogenic and carcinogenic risks due to metals like iron, aluminium, and cadmium. Khan et al., (2022) evaluated the impact of riverfront development on the Gomti River's water quality. The study found that despite the development, water quality deteriorated, particularly at midstream sites, due to unresolved untreated domestic sewage discharge issues. This highlights the need for comprehensive water management practices alongside developmental projects. Sharma et al., (2021) studied the long-term sustainability of groundwater resources in the Gomti River Basin. Using the Inverse Distance Weighted (IDW) interpolation method, the study assessed declining groundwater levels over a decade attributed to intensive irrigation and peri-urban growth. This study emphasizes the need for sustainable groundwater management in the region. Jigyasu et al., (2020) analyzed trace element mobility in the Gomti River Basin, identifying high mobility of elements like B, As, and Se due to geogenic factors. The study highlighted the significant contributions of these elements to the global riverine flux, underscoring the environmental impact of trace element mobility. Krishan et al., (2022b) used the Water Quality Index (WQI) to assess Gomti river's water quality across several sites in Lucknow from 2013 to 2017. The study found that the water quality ranged from poor to unsuitable for drinking, indicating a significant deterioration over time. These findings call for urgent measures to improve water quality. The compiled research on the Gomti River's water quality highlights severe pollution from heavy metals, organic pollutants, pesticides, and bacteriological contaminants. The studies emphasize the need for stringent regulatory measures, continuous monitoring, and sustainable management practices to mitigate pollution and ensure the long-term health of the river ecosystem. Addressing these issues is critical for protecting public health and maintaining the ecological balance of the Gomti River.

2.5. LITERATURE GAP

Despite being extensive, research on the Gomti River's water quality still has a lot of gaps in it. Prior research has not employed four water quality indices (WQIs) simultaneously or done a long-term investigation of Sultanpur's Gomti River. This study addresses the identified gap in the literature by conducting a comprehensive analysis over a 20-year dataset. Using four distinct Water Quality Indices (WQIs) and employing multivariate statistical analyses, this research provides a detailed and longitudinal examination of water quality in the Gomti River at Sultanpur. The findings highlight the key parameters that influence the water quality indices, offering insights into the factors responsible for variations in water quality over time.

CHAPTER 3

METHODOLOGY OF THE STUDY

3.1.SITE DESCRIPTION

3.1.1. BRIEF DESCRIPTION OF GOMTI RIVER

The Gomti River, a prominent groundwater-fed river, originates from Gomathtal, previously known as Fulhar Jheel, located in the Pilibhit district. Traveling a distance of 960 kilometers, it eventually merges into the Ganges River near Saidpur in the Ghazipur district of Uttar Pradesh. The river's journey is enhanced by the contributions of 23 major and minor tributaries, with Gaichi being the first significant tributary, emerging approximately 20 kilometers from the source. The river maintains a narrow form up to Mohammadi Kheri in the Lakhimpur Kheri district, about 100 kilometers from its origin. In this region, the river becomes more defined as numerous tributaries, including the Kathana and the Sarayan Rivers, joining it at Mailani and Lakhimpur, respectively. Further downstream, the Sai River meets the Gomti in the Jaunpur district near Rajepur. Characteristically, the Gomti's flow is slow throughout the year, except during the monsoon season, when it experiences a significant increase in volume due to heavy rainfall. This seasonal change contributes the most to its annual water budget, with an approximate discharge of $7,390 \times 10^6$ cubic meters. During the monsoon, the river's velocity and level rise sharply, often causing flooding in adjacent low-lying areas, with water levels typically fluctuating by about three meters annually. This dynamic nature of the Gomti continues until it converges with the Ganges, marking its integration with the larger river system at Sultanpur (Tangri et al., 2018).

3.1.2. SULTANPUR

Sultanpur is located on the banks of the Gomti River, at a latitude of 26°15’ north and a longitude of 82°05’ east. Covering a total geographic area of approximately 2672.89 square kilometres, its terrain is predominantly level, with occasional ravines near riverbanks. The central region is extensively cultivated, while the southern areas consist of arid plains and swampy marshes. Fig. 3.1 depicts the study area at Sultanpur. Sultanpur district is bounded by Faizabad district to the north, Pratapgarh district to the south, and Bara-Banki and Amethi districts to the west. To the east, it is bordered by Azamgarh, Ambedkar Nagar, and Jaunpur districts. The topography of the Sultanpur district is largely flat, with exceptions found in regions adjacent to the Gomti River, which serves as the district's primary drainage system.

However, the southern part of Sultanpur drains into the Sai River, flowing through the Pratapgarh district. Sultanpur's climate is semi-arid, featuring intensely hot summers and equally cold winters. Maximum temperatures soar beyond 44^{O}C during the summer months of May and June, while winter temperatures hover around 3-4^{O}C in December and January (Sultanpur, 2024).

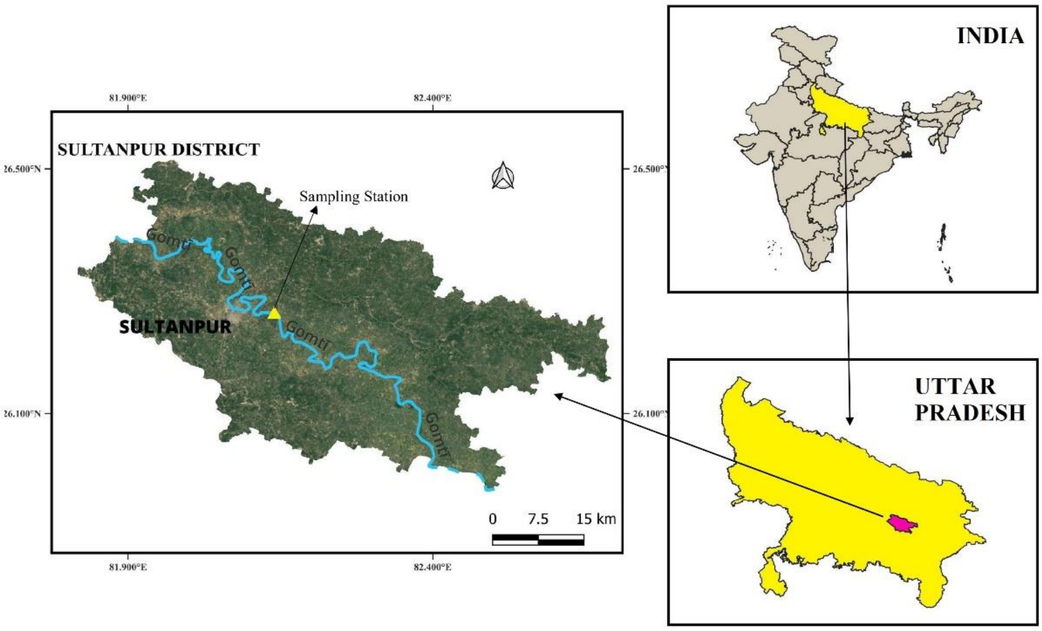

Figure 3.1 Study Area - Sultanpur

3.2.METHODOLOGY OF THE STUDY

This research employed the methodology of a broad examination of water quality data of Gomti River at Sultanpur station collected from Central Water Commission (CWC), Lucknow (UP) from 1998 to 2017. Fig. 3.2 illustrates the flow diagram of the research plan methodology. Descriptive statistics were first used to summarize all the data; to do this, descriptive statistics including mean, maximum, minimum, mode, and standard deviation were calculated. The Pearson correlation analysis is performed on the data set, which signifies the interdependency between different water quality parameters. The data were subsequently used to evaluate the long-term water quality trends with four water quality indices (WQIs), namely Comprehensive Pollution Index (CPI), Synthetic Pollution Index (SPI), Nemerow's Pollution Index (NPI), and Arithmetic Water Quality Index (AWQI). A Cluster Analysis (CA) on the Comprehensive Pollution Index identified temporal variation in all months. PCA was applied to determine the main factors controlling water quality. Regression Analysis was performed on PCA-Selected parameters and all four WQIs. Thus, in the current study, long-term assessment of the Gomti River at Sultanpur is performed and parameters contributing to variation in water quality are identified.

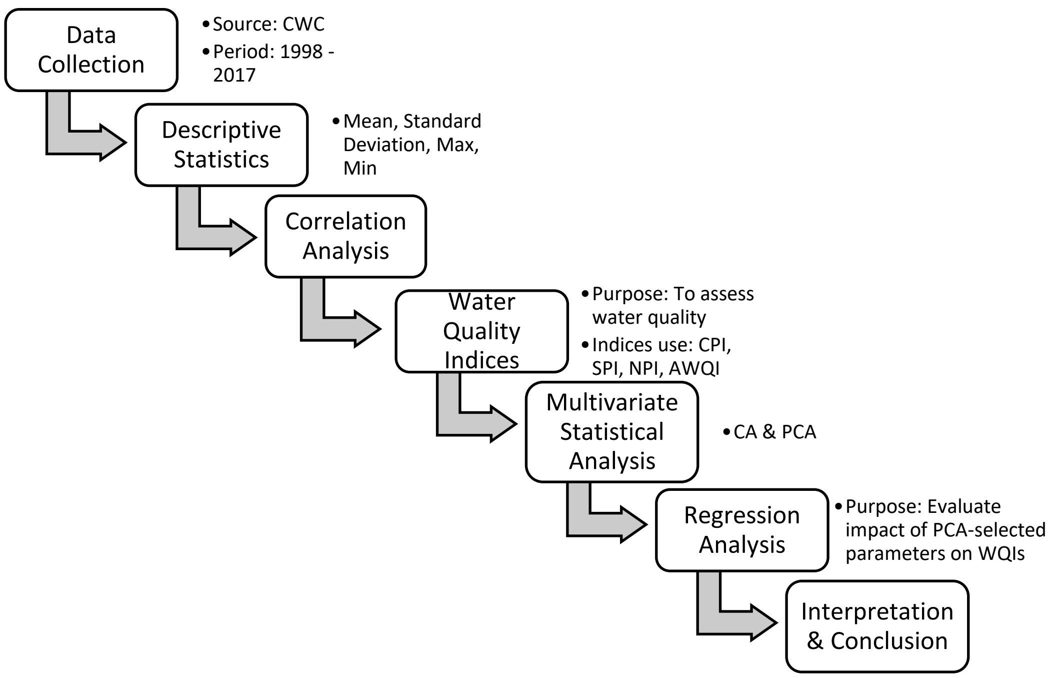

Figure 3.2 Flow diagram for Methodology of Research Plan

3.3. DATA COLLECTION

The monthly data related to Sultanpur sampling station is collected from Central Water Commission (CWC), Lucknow (UP) India for the years January 1998 – December 2017, for Dissolved Oxygen (DO), pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Nitrates (NO_3^-), Biochemical Oxygen Demand (BOD), Total Hardness (TH), Calcium (Ca^{2+}), Magnesium (Mg^{2+}), Total Alkalinity (TA), Chlorides (Cl^-), Fluoride (F^-), Sulphates (SO_4^{2-}), Boron (B), Total Phosphorus (P-Tot), Ammonia (NH_3), Sodium (Na^+), Potassium (K^+).

3.4. DESCRIPTIVE STATISTICS

For each physicochemical parameter, fundamental statistics such as minimum, maximum, mean, mode, and standard deviation were determined using Microsoft Excel version 2024.

3.5. WATER QUALITY STANDARDS

River water quality standards are essential benchmarks to ensure the safety and health of aquatic ecosystems and human communities relying on these water sources. These standards are designed to maintain and improve water quality by controlling pollution levels and ensuring that water remains suitable for various uses, including drinking, recreation, and irrigation. Regulatory bodies such as the Bureau of Indian Standards (BIS) and the World Health Organization (WHO) set these standards. Adhering to these standards is crucial for protecting public health, preserving biodiversity, and sustaining the overall environmental balance. Table 3.1 provides the standards for water quality parameters as per the Bureau of Indian Standards (BIS 1991/2012) and World Health Organization Water Quality Standards (WHO 2004/2011).

Table 3.1 Water Quality Standards of each parameter (*BIS 1991/2012, **WHO 2004/2011)

Parameter	Unit	BIS/WHO Standard (Si)
Dissolved Oxygen (DO)	mg/l	5**
pH	-	6.5 – 8.5*
Electrical Conductivity (EC)	µS/cm	300**
Total Dissolved Solids (TDS)	mg/l	500*
Nitrate (NO_3^-)	mg/l	45*
Biochemical Oxygen Demand (BOD)	mg/l	5**
Total Hardness (TH)	mg/l	200*
Calcium (Ca^{2+})	mg/l	75*
Magnesium (Mg^{2+})	mg/l	30*
Total Alkalinity (TA)	mg/l	200*
Chloride (Cl^-)	mg/l	250*
Fluoride (F^-)	mg/l	1*
Sulphate (SO_4^{2-})	mg/l	200*
Boron (B)	mg/l	0.5*
Phosphorus (P-Tot)	mg/l	5**
Ammonia (NH_3)	mg/l	0.5*
Sodium (Na^+)	mg/l	200**
Potassium (K^+)	mg/l	100**

3.6.MULTIVARIATE STATISTICAL ANALYSIS

3.6.1. CLUSTER ANALYSIS (CA)

A multivariate approach known as cluster analysis (CA) enables the assembly of objects depending on their attributes. With regard to a predefined selection criterion, CA groups things into clusters where each object is comparable to the others in the cluster. The most popular method, hierarchical agglomerative clustering, establishes intuitive similarity correlations between any one sample and the complete data set and is frequently represented as a dendrogram (tree diagram). The dendrogram represents the groups and their vicinity with a considerable decrease in the dimensionality of the original data, providing a visual overview of the clustering processes. Origin (Pro) software was used to conduct cluster analysis.

3.6.2. PRINCIPAL COMPONENT ANALYSIS (PCA)

Using a reduced number of independent variables, PCA is a potent pattern identification approach that aims to explain the variation of a large dataset of associated variables. The PCA approach uses the covariance matrix of the original variables to extract the eigenvalues and eigenvectors. Principle component analysis (PCA) aims to combine the original variables into new, linear, uncorrelated variables (axes) known as principal components. The axes follow the directions with the greatest variation by describing the connection between a large number of variables in terms of a smaller number of underlying elements (Helena et al., 2000; Sârbu and Pop 2005; Shrestha and Kazama 2007; Hossain et al., 2015). The PCA can be expressed as:

$$Z_{ij} = pc_{i1}x_{1j} + pc_{i2}x_{2j} + \cdots .. pc_{im}x_{mj} \qquad \text{(Eq. 1)}$$

Where i is the component number, j is the sample number, z is the component score, pc is the component loading, x is the measured value of the variable, and m is the total number of variables. Origin (Pro) software was used to conduct principal component analysis.

3.7.PEARSON'S CORRELATION ANALYSIS

The Pearson's correlation analysis is a widely used tool that estimates the linear dependence between various parameters (Wu et al., 2014, 2020; Li et al., 2019; Khan et al., 2021b; Ren et al., 2021). The value of Pearson's correlation coefficient, 'r,' lies between ± 1, suggesting a positive or negative correlation, and there is no correlation between the parameters when 'r' is zero. Moreover, when 'r' lies between ± 0.9 and ± 1, a 'very strong' correlation exists between the parameters. Similarly, a 'strong' correlation exists if values of 'r' vary between ± 0.76 and ± 0.89, a 'good' correlation is there when the values of 'r' lie in the range of 0.51 to ± 0.75, and the correlation is called 'poor' for 'r' values of 0 to ± 0.50 (Batabyal and Chakrobarty 2015). The MS Excel was used for the correlation analysis and visualisation of data.

3.8.WATER QUALITY INDICES (WQI)

In our study, we employ four distinct water quality indices, namely the Comprehensive Pollution Index (CPI), Synthetic Pollution Index (SPI), Nemerow's Pollution Index (NPI), and Arithmetic Water Quality Index (AWQI). These indices are utilized to evaluate and assess the water quality of the Gomti River at Sultanpur, Uttar Pradesh.

3.8.1. COMPREHENSIVE POLLUTION INDEX (CPI)

The Comprehensive Pollution Index (CPI) is a widely recognized and utilized method for assessing water quality levels (Zhao et al., 2012; Mishra et al., 2015). It is calculated using the following equation:

$$CPI = \frac{1}{n} \sum_{i=1}^{n} \frac{M_i}{S_i} \qquad \text{(Eq. 2)}$$

Where: Mi represents the monitored value for each water quality parameter. Si signifies the standard permissible limit for the corresponding parameter. n indicates the total number of parameters considered. These standard limits (Si) are derived from recommended guidelines by various environmental regulatory bodies, including the Bureau of Indian Standards (BIS, 2012) and the World Health Organization (WHO, 2011).

The Comprehensive Pollution Index is a powerful tool that effectively divides water quality into distinct classes. This classification method provides a comprehensive and easy-to-understand assessment of water pollution levels, facilitating clear communication of the current water quality status. Moreover, the CPI is a crucial component in environmental evaluations and aids in making informed decisions concerning the management of water resources and pollution control. The grading standard for environmental quality evaluation by the Comprehensive Pollution Index method is shown in Table 3.2.

Table 3.2 Water quality level determination using Comprehensive Pollution Index

CPI Value	Interpretation
<= 0.20	Clean
0.21 - 0.40	Sub Clean
0.41 - 1.00	Slightly Polluted
1.01 - 2.0	Moderately Polluted
>=2.01	Severely Polluted

3.8.2. SYNTHETIC POLLUTION INDEX (SPI)

In this study, the evaluation of pollution in the river water samples is carried out using the Synthetic Pollution Index (SPI) developed by Singh et al., (2015). This model utilizes a set of equations, incorporating constants and weight coefficients, to determine the SPI value.

The SPI was calculated using the following equations.

$$K = \frac{1}{\left(\sum_{i=1}^{n} \frac{1}{V_S}\right)} \qquad \text{(Eq. 3)}$$

$$W_i = \frac{K}{V_S} \qquad \text{(Eq. 4)}$$

$$SPI = \sum_{i}^{n} \frac{V_o}{V_s} * W_i \quad \text{(Eq. 5)}$$

Where K is the constant of proportionality, Vs is the standard value for each parameter, n is the total number of observed parameters, Vo represents the observed concentration of each parameter, and Wi is the weight coefficient for each parameter.

The SPI classifies water into five categories based on a literature review (Xiao 1996; Gautam et al., 2015; Singh et al., 2015), as shown in Table 3.3.

Table 3.3 Water quality level determination using Synthetic Pollution Index

SPI Values	Interpretation
< 0.20	Suitable For Drinking
0.2 - 0.50	Slightly Polluted
0.5 - 1.00	Moderately Polluted
1.00 - 3.00	Severely Polluted
> 3.00	Unfit For Drinking

The SPI offers a comprehensive evaluation of water quality, providing valuable insights for making informed pollution control and resource management decisions.

3.8.3. NEMEROW'S POLLUTION INDEX (NPI)

The Nemerow pollution index is a water pollution index that considers extreme values using a weighted environmental quantity index. It is frequently used in water quality assessments worldwide (Cheng et al., 2007; Liu et al., 2007). The calculation of this index takes three steps as follows:(i) identify the classification of each parameter according to the national water quality standards, (ii) determine the corresponding pollution index for each classification, and (iii) determine the water quality classification by calculating the Nemerow comprehensive index. The mathematical formula for the Nemerow comprehensive index calculation is as follows:

$$NPI = \frac{C_n}{S_n} \quad \text{(Eq. 6)}$$

$$NPI = \frac{\sqrt{\frac{C_i}{S_i}M^2 + \frac{C_i}{S_i}R^2}}{2} \quad \text{(Eq. 7)}$$

Where,

- Cn = Concentration of the n^{th} parameter
- Sn = Prescribed standard limits of the n^{th} parameter
- (Ci/Si) M is (Ci/Si) maximum
- (Ci/Si) R is (Ci/Si) average
- Si is standard water quality parameter for each parameter at specified water quality purpose
- Ci is water quality concentration for each parameter at specified time

The grading standard for environmental quality evaluation by the Nemerow pollution index method is shown in Table 3.4.

Table 3.4 Water quality level determination based on the Nemerow pollution index method

Water quality level	P_N
No Pollution	< 0.59
Slightly Polluted	0.59 – 0.74
Lightly Polluted	0.74 – 1.00
Moderately Polluted	1.00 – 3.50
Seriously Polluted	≥ 3.50

3.8.4. ARITHMETIC WATER QUALITY INDEX (AWQI)

This method classifies the water quality according to the degree of purity using the most commonly measured water quality variables (Kambalagere and Puttaiah 2008; Singh et al., 2013; Vinod et al., 2013; Paun et al., 2016; Kizar 2018). The mathematical formula for the Arithmetic water quality index calculation is as follows:

$$Q_n = 100 * \frac{[V_n - V_o]}{[S_n - V_o]} \quad \text{(Eq. 8)}$$

$$W_n = \frac{K}{S_n} \quad \text{(Eq. 9)}$$

$$AWQI = \frac{\Sigma Q_n W_n}{\Sigma W_n} \quad \text{(Eq. 10)}$$

Where,

- Qn is the quality rating for the nth water quality parameter.
- Vn is the observed value of the nth parameter at a given sampling station.
- Vo is the ideal value of the nth parameter in pure water (DO = 14.6 and pH = 7).
- Sn is the standard permissible value of the nth parameter.
- Wn is the unit weight for the nth parameter.
- K is the constant of proportionality.

After calculating the AWQI, the measurement scale classifies the water quality as shown in Table 3.5.

Table 3.5 Water quality level determination based on the Arithmetic Water Quality index method

Water quality level	Water quality status
0–25	Excellent water quality
26–50	Good water quality
51–75	Poor water quality
76–100	Very poor water quality
> 100	Unsuitable for drinking

3.9.REGRESSION ANALYSIS

Regression analysis is one of the most frequently used analysis techniques in scientific research. Linear regression is a statistical modelling method that explains the relationship between one or more independent variables and a dependent variable (Helsel and Hirsch 2002). Regression analysis was performed to evaluate the impact of parameters selected through PCA on each of the four WQIs. MS Excel was used for the regression analysis of the data.

CHAPTER 4

RESULTS & DISCUSSION

4.1.GENERAL

Water is a crucial factor governing the processes, functions, and attributes of river ecosystems. The water quality characteristics of rivers result from numerous physical, chemical, and biological interactions. The deterioration in the water quality of the Gomti River is attributed to increasing human pressures from agricultural, domestic, and industrial activities. Monitoring river water quality in India is vital to identify the causative factors of deterioration and pinpoint the most polluted river stretches. This study aims to assess water quality for the Gomti River, specifically in Sultanpur, Uttar Pradesh. The focus is on using four water quality indices to get a multifaceted approach. The WQIs chosen for this study are the Comprehensive Pollution Index (CPI), Synthetic Pollution index (SPI), Nemerow's Pollution Index (NPI) and Arithmetic Water Quality Index (AWQI). These four WQIs were chosen based on their flexibility in using any number of parameters without any bias towards some specific parameters. Descriptive and multivariate statistical approaches were also employed to investigate the complex nature of the water quality data. This approach provides a comprehensive understanding of the factors affecting the Gomti river's water quality at Sultanpur.

4.2.PHYSIO-CHEMICAL PARAMETERS OF WATER

In evaluating river water pollution, it is crucial to analyse various physico-chemical parameters to ensure water quality aligns with the standards set by the Bureau of Indian Standards (BIS) and World Health Organization (WHO). This study examines the following key parameters: Dissolved Oxygen (DO), pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Ammonia (NH_3), Nitrate (NO_3^-), Total Phosphorus (P-Tot), Biochemical Oxygen Demand (BOD), Total Hardness (TH), Calcium (Ca^{2+}), Magnesium (Mg^{2+}), Sodium (Na^+), Potassium (K^+), Chloride (Cl^-), Sulphate (SO_4^{2-}), Fluoride (F^-), Boron (B), and Total Alkalinity (TA). Table 4.1 provides the statistical data, including mean, median, mode, standard deviation, coefficient of variation, maximum and minimum values, to provide a comprehensive overview of the water quality.

Table 4.1 Basic statistics of the variables analysed during the period from 1998 to 2017

Parameter	Mean	Median	Mode	Standard Deviation	Variation Coefficient (%)	Max	Min
DO	6.92	7.00	8.00	1.18	16.98	10.00	3.40
pH	8.39	8.40	8.50	0.35	4.21	9.20	7.60
EC	388.49	368.00	318.00	109.75	28.25	674.00	108.00
TDS	312.87	282.75	330.73	102.62	32.80	608.33	133.17
NH_3	0.05	0.05	0.05	0.00	0.14	0.05	0.05
NO_3^-	0.41	0.31	0.02	0.35	85.80	1.53	0.00
P-Tot	0.08	0.07	0.00	0.07	93.37	0.29	0.00
BOD	2.65	2.80	2.80	0.74	27.94	4.50	0.80
TH	190.83	180.22	255.58	46.24	24.23	326.58	61.58
Ca^{2+}	38.20	39.00	53.00	11.94	31.24	65.90	7.00
Mg^{2+}	22.83	20.85	16.60	8.34	36.55	47.40	4.20
Na^+	26.95	25.00	20.00	10.35	38.39	56.40	1.00
K^+	7.02	7.00	8.00	2.64	37.69	15.00	0.60
Cl^-	27.42	28.00	30.00	8.76	31.94	48.00	10.00
SO_4^{2-}	24.43	25.00	30.00	8.33	34.11	46.00	5.20
F^-	0.24	0.25	0.05	0.18	76.26	0.79	0.05
B	0.02	0.02	0.00	0.02	95.52	0.09	0.01
TA	232.84	188.75	164.00	126.44	54.30	592.31	64.00

4.2.1. pH

pH of a solution represents the negative logarithm of hydrogen ion activity at a given temperature and indicates the acidic or alkaline nature of water (Sallam and Elsayed 2015; Jaiswal et al., 2019). Fig. 4.1 depicts the variation in pH at Sultanpur from 1998 – 2017.

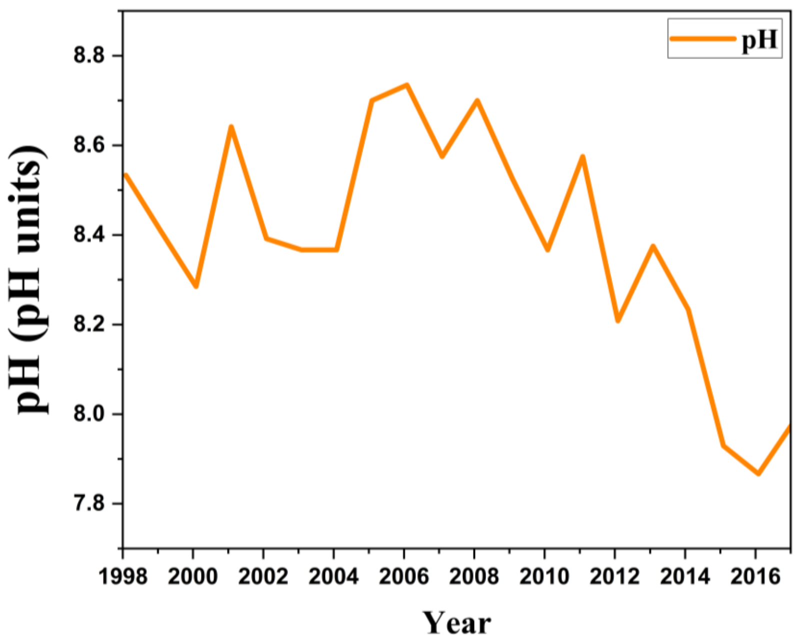

Figure 4.1 Variation of pH at Sultanpur (1998-2017)

The observed mean pH is 8.39, indicating slightly alkaline water. The pH values observed in this study range from 7.6 to 9.2. This range exceeds the recommended pH limits established by both the Indian Standard (BIS, 2012) and the World Health Organization (WHO, 2011), which suggest an optimal pH range of 6.5 to 8.5 for potable water. Similar pH trends were observed in studies by (Kumar et al., 2020, 2022) on the Gomti River and by (Suthar et al., 2010) on the Hindon River. The overall decrease in the pH of river water from slightly alkaline to neutral (8.5 – 8.0 pH units) over the past 20 years can be attributed to several factors. However, pH peaked from 2005 to 2008 (8.7 pH units), signifying higher alkalinity. This is influenced by factors, i.e., agricultural runoff, industrial discharge, climate patterns, biological activity, geological factors, and land-use changes (Suthar et al., 2010). Industrial discharges, particularly from tanneries and textile factories, release acidic effluents into rivers. Urban runoff carries pollutants such as oils and heavy metals that lower pH levels due to increased urbanization. Agricultural activities contribute through runoff of fertilizers and pesticides, while domestic wastewater introduces organic acids and pollutants (Suthar et al., 2010; Jaiswal et al., 2019; Omer 2019). Additionally, the natural buffering capacity of rivers is diminished due to continuous pollution influx, making them more susceptible to pH changes (Bhateria and Jain 2016).

4.2.2. DISSOLVED OXYGEN (DO)

Dissolved oxygen (DO) is a crucial indicator of water quality, reflecting the total oxygen in water bodies. The DO content is influenced by various physical, chemical, and biological activities within the water body (Vinod et al., 2013). Variation in Dissolved Oxygen levels at Sultanpur (1998 – 2017) can be observed from Fig. 4.2.

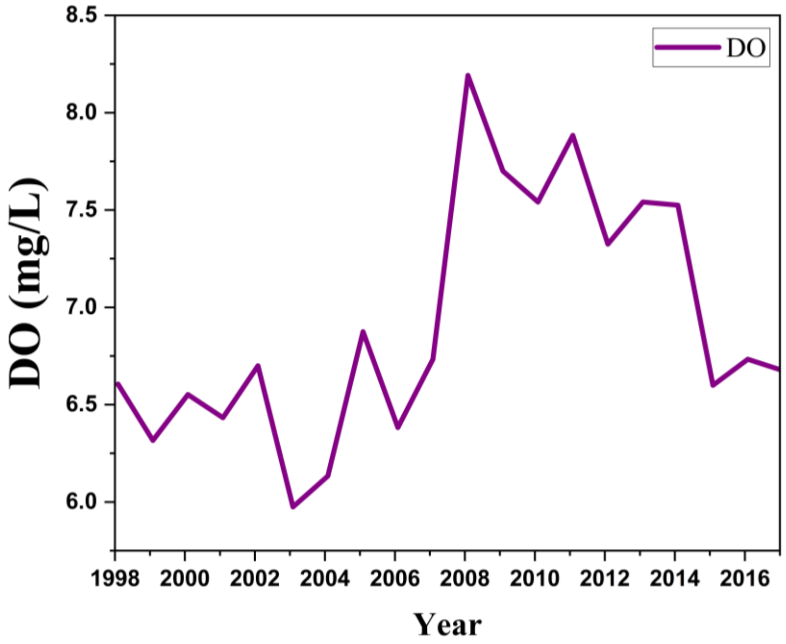

Figure 4.2 Variation of DO at Sultanpur (1998-2017)

Dissolved Oxygen is essential for aquatic life and indicates the water's ability to support aerobic organisms. The mean DO level observed is 6.92 mg/L, with a median of 7 mg/L and a standard deviation of 1.18 mg/L. Over 20 years, DO levels fluctuated between 3.0 mg/L and 11.8 mg/L, often falling within the optimal range of 4 to 6 mg/L for sustaining aquatic life (Singh 2004). Factors affecting DO include water mixing, temperature, sunlight exposure, and altitude. Fluctuations result from variables like temperature, organic pollutants, and human activities such as sewage discharge. High organic loads, drain discharges, and religious rituals contribute to DO depletion at many sampling locations (Medeiros and Tresmondi 2017). DO levels must be at least 2 mg/L for higher life forms to survive (Hussain et al., 2012). Dissolved Oxygen (DO) levels exhibited a relatively stable trend from 1998, with a concentration of 6.6 mg/L, to 2017, when it slightly increased to 6.7 mg/L. Initially, the slight increase in DO levels from 2003 (6.0 mg/L) to 2008 (8.2 mg/L) can be attributed to improved water aeration and possibly the implementation of pollution control measures (Singh et al., 2013). This elevated level persisted through 2009 and gradually decreased to 7.5 mg/L by 2014. Subsequently, from 2014 onwards, a decline in DO concentrations was noted, culminating in a level of 6.6 mg/L by 2015. This subsequent decrease until 2017 is likely due to increased organic pollution from domestic and industrial wastewater, which elevates BOD and decreases DO (Shrestha and Kazama 2007). Seasonal variations and agricultural runoff further exacerbate these changes, impacting overall water quality (Varma and Jha 2023).

4.2.3. BIOCHEMICAL OXYGEN DEMAND (BOD)

Biochemical Oxygen Demand (BOD) measures the oxygen aerobic microorganisms require to break down organic waste in water (Singh et al., 2013). BOD-3 is the amount of oxygen consumed by aerobic microorganisms to break down organic matter in 3 days at 27°C. Fig. 4.3 illustrates the fluctuation in Biochemical Oxygen Demand (BOD-3 at 27 °C) at Sultanpur from 1998 – 2017.

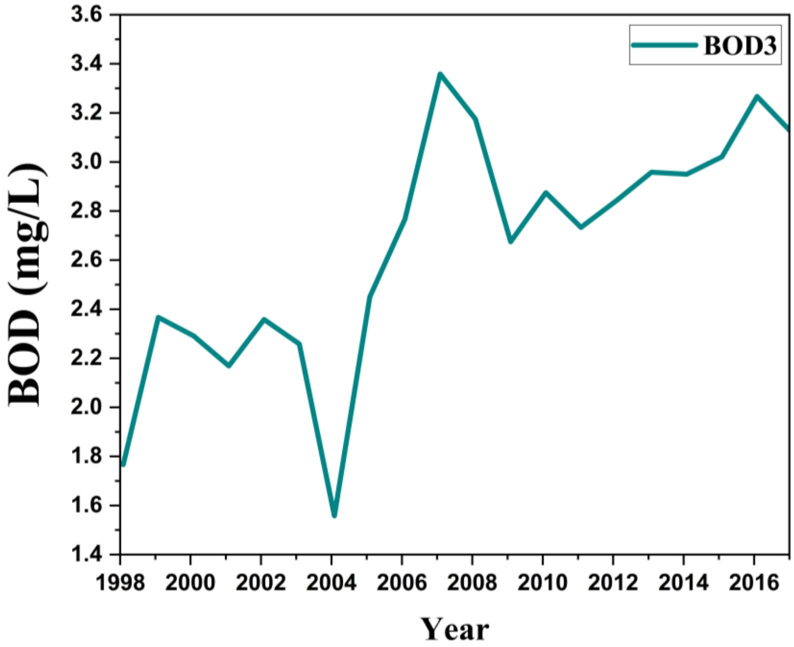

Figure 4.3 Variation of BOD3 at 27°C at Sultanpur (1998-2017)

The mean BOD-3 is 2.65 mg/L, with a standard deviation of 0.74 mg/L. The values range from 0.8 mg/L to 4.5 mg/L. WHO standards recommend BOD-3 levels below 5 mg/L. The fluctuations in BOD-3 levels in river water from 1998 (1.8 mg/L) to 2017 (3.1 mg/L) can be attributed to several factors. Initially, the increase in BOD-3 from 1998 (1.8 mg/L) to 1999 (2.4 mg/L) was likely due to a rise in organic pollutants from domestic and industrial sources (Singh et al., 2013). The subsequent decrease by 2004 (1.6 mg/L) may have resulted from improved wastewater treatment practices or seasonal variations. The sharp increase to 3.4 mg/L by 2007 can be linked to increased industrial discharge and agricultural runoff. The gradual changes afterward reflect ongoing variations in pollution sources and mitigation efforts (Kumar et al., 2009; Dwivedi et al., 2018). BOD-3 levels are influenced by the amount of organic matter present, which requires oxygen for microbial degradation, and are indicative of the pollution load in the water (Varma and Jha 2023).

4.2.4. ELECTRICAL CONDUCTIVITY (EC)

The electrical conductivity (EC) of a water sample measures its ability to conduct an electrical current, depending on the concentration of charged particles. EC measures dissolved solids in water, indicating potential sources of pollution and highlighting areas with water quality issues (Varol 2020). Variations in Electrical Conductivity at Sultanpur from 1998 – 2017 can be observed in Fig.4.4.

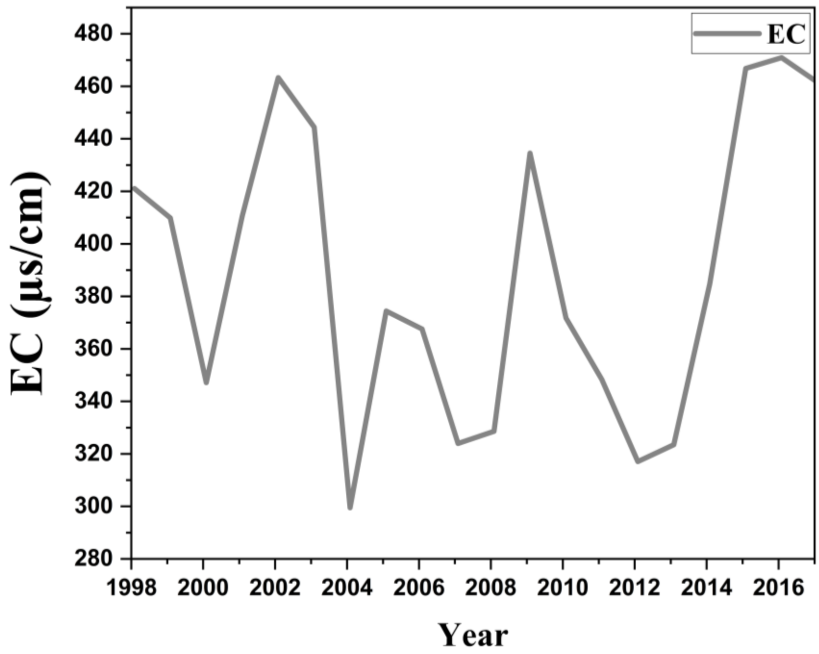

Figure 4.4 Variation of TDS at Sultanpur (1998-2017)

The mean EC recorded is 388.49 µS/cm, with a high standard deviation of 109.75 µS/cm, indicating significant variability. The values range from 108 µS/cm to 674 µS/cm. The WHO acceptable limit for EC in drinking water is 300 µS/cm. The fluctuations in EC of river water from 1998 (421.1 mg/L) to 2017 (461.5 mg/L) can be attributed to several environmental and anthropogenic factors. Notable peaks are observed in the years 1998 (421.1 µS/cm), 2002 (463.3 µS/cm), 2009 (434.5 µS/cm) and 2016 (470.9 µS/cm). Periods consisting of low concentrations of Electrical Conductivity are 2000 (347.2 µS/cm), 2004 (299.5 µS/cm), 2007 (324.0 µS/cm), and 2012 (317.1 µS/cm). Industrial discharges play a significant role, with industries intermittently releasing varying amounts of dissolved ions into rivers (Kumar et al., 2022). Seasonal agricultural runoff containing fertilizers and pesticides also causes spikes in EC during certain times of the year (Igwe et al., 2017). Urban runoff, due to increased urbanization, carries a mix of pollutants, including salts and other conductive materials, impacting EC levels (Gachlou et al., 2019). Variations in river flow due to rainfall and water management practices can lead to dilution or concentration of ions, causing changes in EC (Hossain et al., 2015; Jaiswal et al., 2019; Yeliz and Sen 2019). Additionally, the implementation and subsequent lapses in wastewater treatment practices can lead to temporary reductions in EC before rising again due to increased pollution loads. These factors collectively contribute to the observed fluctuations in EC over the years (Zhao et al., 2012; Leong et al., 2018). Mitigating pollution sources and regular monitoring are crucial to maintaining EC within safe bounds, preserving water quality and ensuring its suitability for diverse purposes (Athimoolam and Ramu 2006).

4.2.5. TOTAL HARDNESS (TH)

The concentration of TH and other divalent cations in river water is primarily influenced by dissolved calcium and magnesium ions, measured in mg/L as $CaCO_3$. Fig. 4.5 illustrates the variation in Total Hardness at Sultanpur from 1998 – 2017.

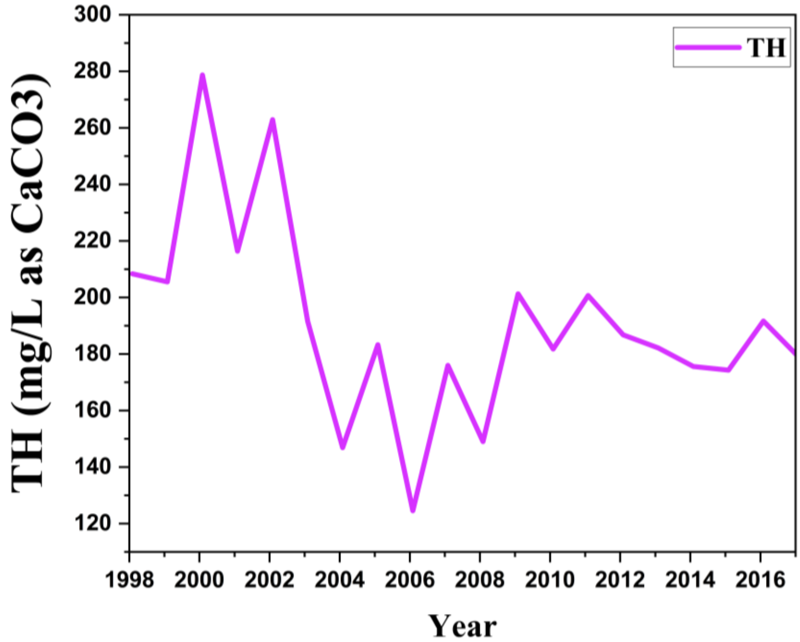

Figure 4.5 Variation of TH at Sultanpur (1998-2017)

Total Hardness is a measure of the concentration of calcium and magnesium ions. The mean TH is 190.83 mg/L, with a standard deviation of 46.24 mg/L. The minimum and maximum values range from 61.58 mg/L to 326.58 mg/L. While WHO lacks a specific limit, BIS standards recommend treatment for hardness over 200 mg/L to prevent scale formation and health issues (Arumugam 2010; BIS 2012). River water's total hardness in India is crucial for assessing its suitability for domestic, industrial, and agricultural purposes, primarily due to calcium and magnesium salts (Jindal and Sharma 2010). Temporary hardness, influenced by carbonate and bicarbonate concentrations, impacts hydrogeology and water aesthetics (Zhao et al., 2012). Various factors influence the fluctuations in TH of river water from 1998 to 2017. Initially, the increase in TH from 210 mg/L (in 1998) to 280 mg/L (in 2000) can be attributed to the influx of minerals from agricultural runoff and industrial discharges (Kumar et al., 2020). The sharp decrease to 146.9 mg/L by 2004 may result from improved wastewater treatment and dilution effects during high rainfall periods. Subsequent fluctuations, including a slight increase to 179.0 mg/L by 2017, could be due to varying levels of pollution control measures and seasonal agricultural runoff, which intermittently affect the concentration of calcium and magnesium ions in the water (Sharma and Walia 2015; Leong et al., 2018).

4.2.6. TOTAL DISSOLVED SOLIDS (TDS)

TDS is a crucial parameter for assessing water quality, indicating the concentration of dissolved organic and inorganic materials in water (Mohan et al., 2000; Sallam and Elsayed 2015) (Sallam and Elsayed 2015). Fig. 4.6 illustrates the variation in Total Dissolved Solids at Sultanpur from 1998 – 2017.

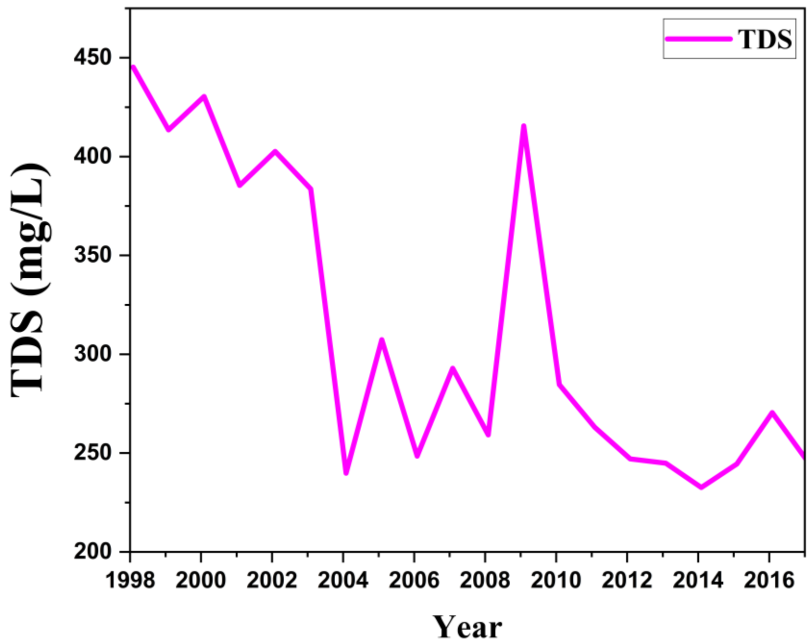

Figure 4.6 Variation of TDS at Sultanpur (1998-2017)

The mean TDS value is 312.87 mg/L, with a 102.62 mg/L standard deviation. The values range from 133.17 mg/L to 608.33 mg/L, and the coefficient of variation is 32.80%. The BIS permissible limit for TDS is 500 mg/L. While acceptable, higher TDS can affect water taste, cause scaling, and incur health risks. The fluctuations in TDS in river water from 1998 to 2017, with a starting point of 445.3 mg/L in 1998, reaching multiple peaks of 430. 4 mg/L in 2000, 402.7 mg/L in 2002, and 415.5 mg/L in 2009, and dropping to levels such as 239.9 mg/L in 2004, and 232.6 in 2014, until reaching 245.6 mg/L by 2017, can be attributed to various factors. The initial decrease might be due to improvements in wastewater management and treatment practices (Kumar et al., 2020). The peak in 2000, 2002, and 2009 could be linked to increased industrial and agricultural runoff, introducing more dissolved solids. The subsequent decrease by 2017 reflects enhanced pollution control measures, seasonal variations in runoff, and possibly dilution effects from increased river flow during rainy seasons (Leong et al., 2018).

4.2.7. TOTAL ALKALINITY (TA)

TA measures an aqueous solution's capacity to neutralize acids, determined by the presence of hydroxides, bicarbonates, and carbonates in water (Suthar et al., 2010). Fluctuation in Total Alkalinity at Sultanpur from 1998 to 2017 can be noted in Fig. 4.7.

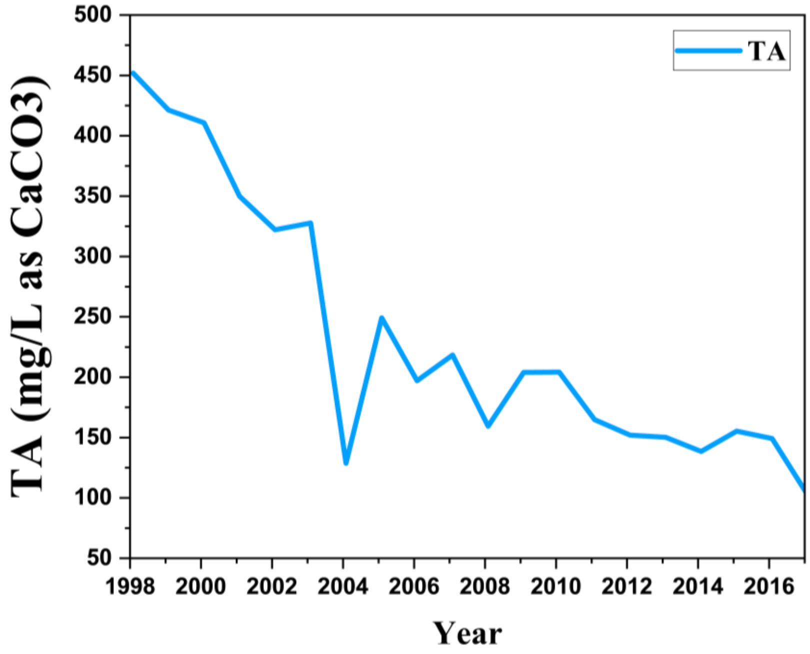

Figure 4.7 Variation of TA at Sultanpur (1998-2017)

Assessing the alkalinity of water is crucial for processes like corrosion control in boiler feed water and water softening (Omer 2019). The mean TA is 232.84 mg/L, with a high standard deviation of 126.44 mg/L. The values range from 64 mg/L to 592.31 mg/L. BIS standards recommend the acceptable limit for TA as 200 mg/L for drinking water. An overall decreasing trend is observed, starting from 451.8 mg/L in 1998 to 102.3 mg/L by 2017. One exceptional drop was observed in 2004 (128.7 mg/L) during this uniform decreasing trend. Similar trends were observed from a research study on the Yamuna River in Uttar Pradesh, which noted significant fluctuations in total alkalinity due to variations in discharge and monsoon impacts, which could lead to a sudden drop and subsequent increase in alkalinity (Jain et al., 2005). TA was highest during the summer and lowest during the rainy season, likely due to the dilution effect of monsoon rains. Similar trends were observed by Iqbal et al., (2019); Kumar et al., (2022) in the Gomti River. These studies showed a decreasing TA trend attributed to reduced wastewater mixing as several drains join the river along its course (Iqbal et al., 2019; Omer 2019; Kumar et al., 2022). The primary reasons include enhanced wastewater treatment practices, which reduced the influx of alkaline substances, and changes in land use, reducing agricultural runoff that typically contributes bicarbonates and carbonates to the river system. Additionally, increased rainfall and river flow may have diluted the concentration of alkaline substances over time. Urbanization and industrial activities might also have shifted, impacting alkalinity sources (Koçer and Sevgili 2014; Sharma and Walia 2015; Leong et al., 2018).

4.2.8. SODIUM (Na^+)

In India, sodium concentration in river water is vital for human health and agriculture. Over 20 years, levels ranged from 1.00 mg/L to 381.00 mg/L, within the 200 mg/L drinking water limit (WHO, 2011). The mean sodium concentration is 26.95 mg/L, with a standard deviation of 10.35 mg/L. High sodium can harm soil and crop yield in irrigation. Fig. 4.8 illustrates the variation in Sodium levels at Sultanpur from 1998 – 2017.

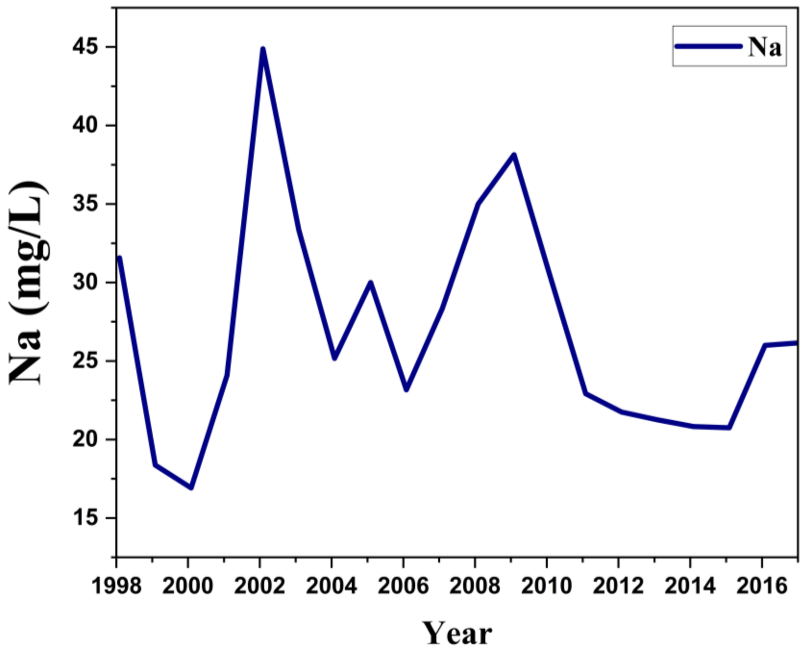

Figure 4.8 Variation of Na at Sultanpur (1998-2017)

The fluctuations in sodium (Na^+) levels in river water from 1998 to 2017 can be attributed to various factors. The initial decrease in sodium levels around 2000 (16.9 mg/L) could be due to improved wastewater management and reduced industrial discharges (Ahmad 2023). The increase around 2002 (44.9 mg/L) may reflect higher agricultural runoff and industrial activities. Subsequent fluctuations are likely influenced by seasonal changes, varying levels of industrial and agricultural effluents, and changes in water management practices (Ahmad 2023). High concentrations of Na^+ are observed in 2002 (44.9 mg/L) and 2009 (38.1 mg/L), whereas low Na concentrations are observed in 2000 (16.9 mg/L), 2004 (25.2 mg/L) and 2006 (23.2 mg/L). Post-2012, a fairly increasing uniform trend for Na^+ concentrations is observed.

4.2.9. POTASSIUM (K^+)

In India's environmental context, potassium concentration in river water is significant, sourced from rock weathering and wastewater discharge (Trivedi and Goel 1986). Over two decades, levels ranged from 0.6 mg/L to 15 mg/L, falling within the 100 mg/L potable water limit. Potassium has a mean concentration of 7.02 mg/L, with a standard deviation of 2.64 mg/L. While concentrations are safe, potassium affects soil structure and water quality, influencing agricultural productivity. Fluctuation in Potassium levels can be seen from Fig. 4.9 with 20-year span period (1998 – 2017).

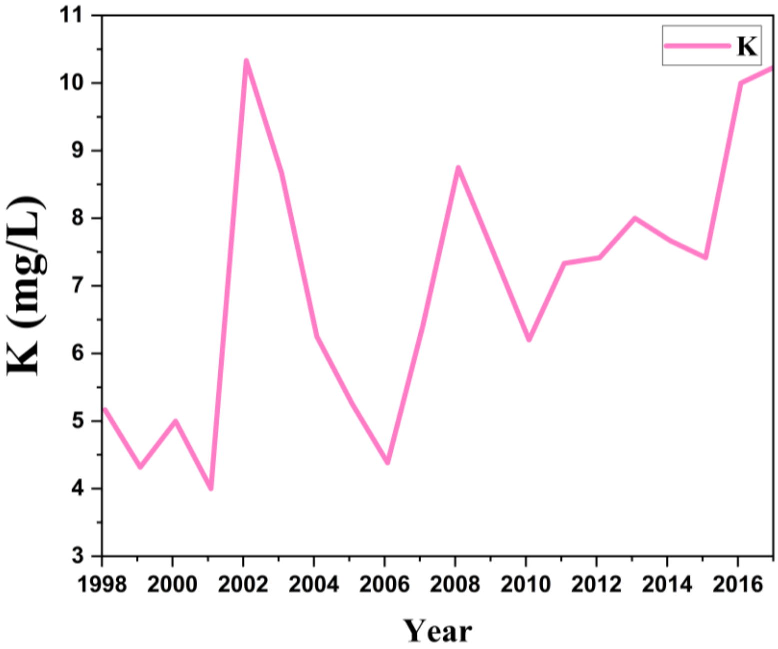

Figure 4.9 Variation of K at Sultanpur (1998-2017)

The fluctuations in river water's potassium (K^+) levels from 1998 to 2017 can be attributed to various environmental and anthropogenic factors. Initially, the increase in potassium levels in 2002 (10.3 mg/L) could be due to agricultural runoff, which often contains potassium from fertilizers. The subsequent decrease by 2006 (4.4 mg/L) might be linked to changes in agricultural practices or improved waste management systems reducing potassium inputs. By 2008 (8.8 mg/L), an increase reflects increased agricultural activity or effluents from industrial sources. The decrease in 2015 (7.4 mg/L) and the final increase in 2017 (10.3 mg/L) could be due to periodic variations in rainfall, affecting the dilution and concentration of potassium in the river and changes in land use and wastewater management practices over time. These fluctuations illustrate the complex interplay between agricultural practices, industrial discharges, and seasonal environmental changes that influence river water quality (Rahman et al., 2016; Varma and Jha 2023).

4.2.10. CALCIUM (Ca^{2+}) & MAGNESIUM (Mg^{2+})

Calcium and Magnesium contribute to water hardness. Ca^{2+} & Mg^{2+} concentrations can affect the river surface water quality by influencing the Total Hardness, pH balance, aquatic life health, water taste, agricultural utility, and human health. Fig. 4.10 illustrates the variation in Ca and Mg levels in Sultanpur from 1998 – 2017.

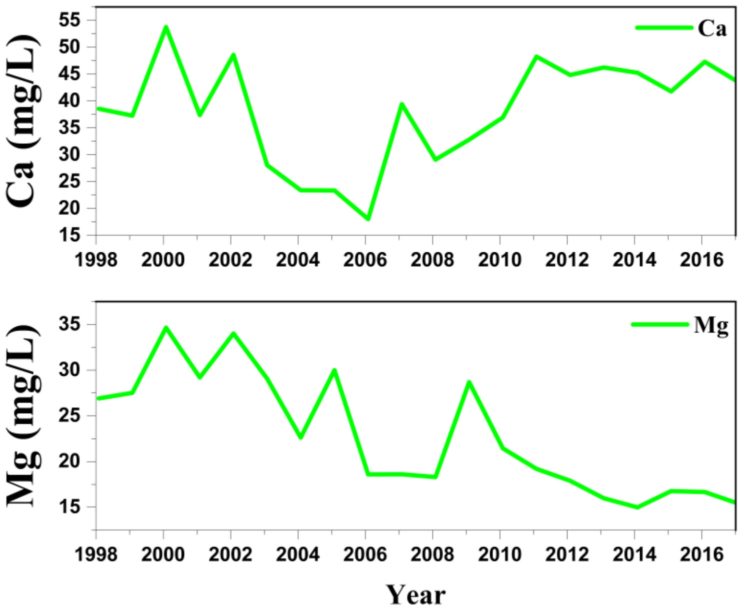

Figure 4.10 Variation of Ca^{2+} & Mg^{2+} at Sultanpur (1998-2017)

The mean calcium concentration is 38.20 mg/L, with a standard deviation of 11.94 mg/L. Calcium (Ca^{2+}) levels increased from 1998 – 2002 (38.6 mg/L – 48.6 mg/L), then decreased from the period of 2003 – 2006 (28.1 mg/L – 18 mg/L), thereafter increased consistently after 2007. Certain spikes were observed in 2000 when Ca^{2+} levels reached 53.8 mg/L and in 2002 when the concentration was 48.6 mg/L. Overall, there has been a rising trend in Ca^{2+} concentrations from 1998 (38.6 mg/L) to 2017 (43.5 mg/L). Calcium levels remained well within the 75 mg/L limit set by IS: 10500:2012 at all times. These findings align with studies by (Singh 2004; Singh et al., 2005; Kumar et al., 2022). The increased concentration of calcium may be due to rising temperatures, decreasing water levels, and the accumulation of household waste (Varol 2020).

Magnesium is formed through the chemical weathering of rocks like dolomite and marl due to its high solubility and minimal biological activity (Varol 2020). Magnesium has a mean concentration of 22.83 mg/L, with a standard deviation of 8.34 mg/L. BIS standards set the maximum permissible limits for magnesium at 30 mg/L. In 20 years, Mg^{2+} levels decreased from 26.9 mg/L (1998) to 15.4 mg/L (2017). However, a few peaks were observed when the Mg^{2+} concentration exceeded the BIS recommendation of 30 mg/L, specifically in 2000 (34.7 mg/L) and 2002 (34.0 mg/L). Sewage pollution, industrial waste, and soil erosion are responsible for affecting the Ca^{2+} and Mg^{2+} levels (Jaiswal et al., 2019).

Industrial discharges, particularly from industries along the riverbanks, periodically release minerals into the water, causing peaks in Mg^{2+} and Ca^{2+} levels. Agricultural runoff, especially during the monsoon season, contributes significantly to these fluctuations due to using fertilizers containing these minerals. Urban runoff from increased urbanization also introduces various pollutants, including Mg and Ca, from construction materials and domestic waste. Improvements or lapses in wastewater treatment practices can lead to changes in the mineral concentrations, with effective treatment reducing the load and lapses increasing it. Natural weathering of rocks and soil in the river basin adds a baseline level of these minerals, with seasonal variations in weathering rates due to changes in temperature and precipitation further influencing their levels. Dilution effects from changes in river flow, caused by seasonal rainfall and water management practices, also play a role; high flow conditions dilute the concentrations, while low flow conditions concentrate them. These factors collectively contribute to the observed fluctuations in Mg and Ca levels over the years (Debels et al., 2005; Sârbu and Pop 2005; Jindal and Sharma 2010; Dohare et al., 2014; Sallam and Elsayed 2015; Sharma and Walia 2015; Omer 2019; Tripathi and Singal 2019).

4.2.11. NITRATE (NO_3^-) & TOTAL PHOSPHORUS (P-TOT)

In India, monitoring Nitrate and Total Phosphorus levels in river water is crucial for water quality and ecosystem health. Variations of NO_3^- and P-Tot concentrations between 1998 – 2017 at Sultanpur, UP are depicted in Fig. 4.11.

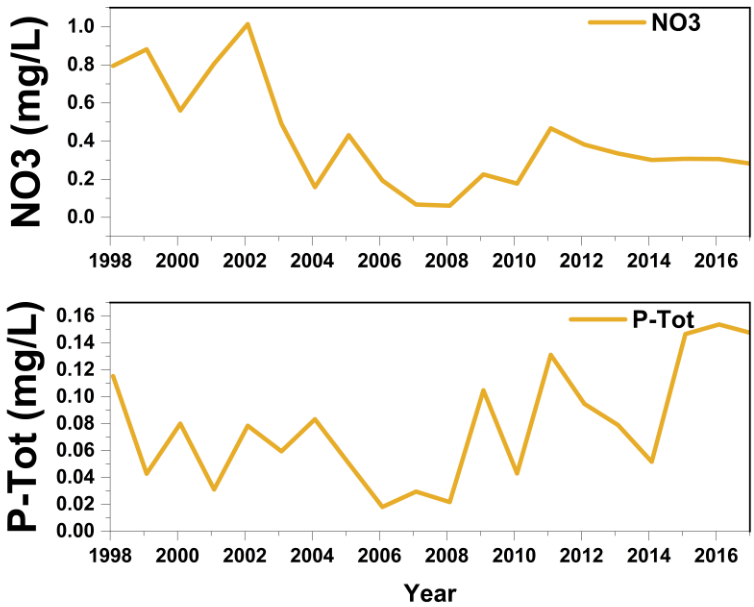

Figure 4.11 Variation of NO_3^- & P-Tot at Sultanpur (1998-2017)

Nitrogen compounds are indicators of nutrient pollution. The mean nitrogen concentration is 0.41 mg/L, with significant variability (standard deviation of 0.35 mg/L and a coefficient of variation of 85.80%). The values range from 0.1 to 1.53 mg/L. The NO_3^- concentration overall decreased from 1998 (0.8 mg/L) to 2017 (0.3 mg/L). A sudden drop was observed in 2004 (0.2 mg/L) and, 2007 and 2008 (0.1 mg/L), likely due to improved wastewater treatment and better agricultural practices. Post-2009, nitrate levels stabilized, indicating a balance between pollution sources and dilution effects from seasonal rainfall.

Total Phosphorus is another nutrient indicator. The mean concentration is 0.08 mg/L, with a high coefficient of variation (93.37%) and values ranging from 0.02 mg/L to 0.286 mg/L. Overall, the concentration of P-Tot was observed to increase from 1998 (0.12 mg/L) to 2017 (0.15 mg/L). Total Phosphorus levels showed an initial decline from 1998 to 2005, reflecting changes in agricultural practices and better management of fertilizer application. However, peaks in 2002 (0.1 mg/L) and again between 2015 (0.15 mg/L) and 2017 (0.14 mg/L) suggest periods of increased industrial activity and the use of phosphorus-rich detergents and effluents. Soil erosion during heavy rainfall could also have contributed to periodic increases in Total Phosphorus levels (Mallick and Banerji 1981; Hamilton and Shedlock 1992). A decline was observed in 2001 when the P-Tot concentration was 0.03 mg/L. Improvements in wastewater treatment during the mid-2000s helped reduce phosphorus discharges into rivers, leading to a temporary decline. These fluctuations underscore the complex interplay between agricultural runoff, industrial discharges, seasonal variations, and regulatory changes that impact river water quality over time (Rahman et al., 2016; Ahmad 2023).

The fluctuations in nitrate (NO_3^-) and Total Phosphorus (P-Tot) levels in river water are influenced by various agricultural, industrial, and environmental factors. Seasonal variations, including periods of heavy rainfall, caused further fluctuations by diluting nitrate concentrations (Karthik and Lekshmanaswamy 2018).

4.2.12. CHLORIDE (Cl^-) & SULPHATE (SO_4^{2-})

Chloride and Sulphate are major anions in water. Fig. 4.12 illustrates the variation in Chloride and Sulphate levels in Sultanpur from 1998 – 2017. The mean chloride concentration is 27.42 mg/L, with a standard deviation of 8.76 mg/L. Sulphate has a mean concentration of 24.43 mg/L, with a standard deviation of 8.33 mg/L. BIS standards set the maximum permissible limits for chloride and sulphate at 250 mg/L and 200 mg/L, respectively. Chloride in natural water primarily comes from soil, sewage, and animal waste (Girija et al., 2006). It's a key indicator of sewage contamination, with high levels suggesting organic pollution (Pius et al., 2011; Sadat-Noori et al., 2014).

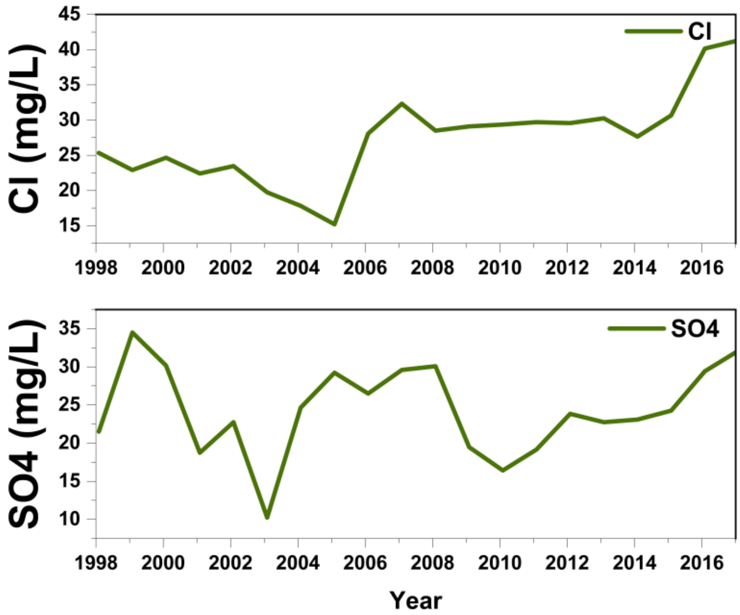

Figure 4.12 Variation of Cl^- & SO_4^{2-} at Sultanpur (1998-2017)

The fluctuations in chloride (Cl^-) and sulphate (SO_4^{2-}) levels in river water from 1998 to 2017 can be attributed to several environmental and anthropogenic factors. Chloride levels showed an initial decrease from 1998 (25.3 mg/L) to 2005 (15.2 mg/L), likely due to improved waste management practices and reduced industrial discharges. The significant increase around 2006 (28.1 mg/L) suggests a surge in industrial activities or urban runoff, contributing to high chloride levels from road salts and domestic waste sources. The subsequent fluctuations reflect ongoing changes in industrial activities, urbanization, and water management practices. The sharp increase after 2015 (30.7 mg/L) might indicate increased use of fertilizers and chemicals in agriculture and urban expansion, contributing more pollutants to the river (Rahman et al., 2016; Ahmad 2023).

The initial increase in Sulphate levels around 1999 (34.5 mg/L) could be linked to industrial discharges, particularly from industries that use sulphates in their processes. The subsequent decrease around 2003 (10.3 mg/L) might reflect improved industrial waste management and reduced emissions (Iqbal et al., 2019). Seasonal variations, including monsoon-driven runoff, also play a role in diluting and concentrating sulphate levels. The steady increase from 2011

(19.2 mg/L) could be due to resumed or increased industrial activity and less stringent environmental regulations (Jaiswal et al., 2019).

4.2.13. AMMONIA (NH_3)

Ammonia levels are crucial for assessing organic pollution. Fig. 4.13 depicts the variation in Ammonia levels in Sultanpur from 1998 – 2017. The mean NH_3 concentration is 0.05 mg/L, with minimal variation (standard deviation of 0.00 mg/L and a coefficient of variation of 0.14%). The values are consistently less than 0.5 mg/L, within the acceptable limits set by BIS and WHO.

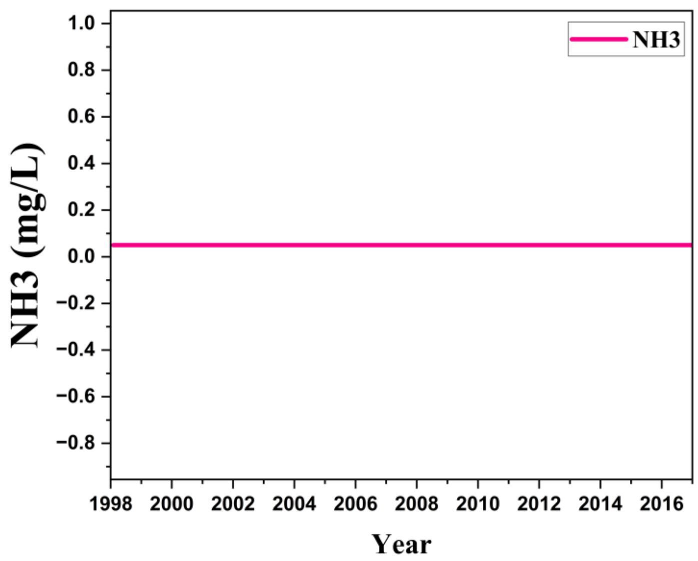

Figure 4.13 Variation of NH_3 at Sultanpur (1998-2017)

The ammonia (NH_3) levels in river water from 1998 to 2017, as depicted in the graph (Fig. 4.13), show no significant fluctuations, maintaining a stable level at 0.05 mg/L. This stability can be attributed to several factors. First, effective wastewater treatment practices likely played a role in keeping ammonia levels low, as these facilities remove ammonia from domestic and industrial effluents before they reach the rivers. Second, regulatory measures and environmental policies aimed at reducing nitrogen pollution have likely been effective in controlling ammonia discharges. Third, ammonia is a volatile compound that can be lost to the atmosphere, and its rapid conversion to other nitrogen forms, such as nitrates and nitrites, through biochemical processes in the water, helps maintain low levels (Rahman et al., 2016; Ahmad 2023).

4.2.14. FLUORIDE (F^-) & BORON (B)

Fluoride and Boron are trace elements that have specific health impacts. Trends in Fluoride and Boron concentrations at Sultanpur (1998 – 2017) can be observed in Fig. 4.14. The mean fluoride concentration is 0.24 mg/L, with a standard deviation of 0.18 mg/L. Boron has a mean concentration of 0.02 mg/L, with a high coefficient of variation (95.52%). BIS standards recommend fluoride levels between 1 to 1.5 mg/L and boron levels below 0.5 mg/L. Fluoride, occurring naturally, contaminates the environment from various sources, including groundwater influenced by geological factors (Yadav et al., 2009). Groundwater generally has higher fluoride than surface water due to rock minerals (Veeraputhiran and Alagumuthu 2010; Singh et al., 2011; Hussain et al., 2012).

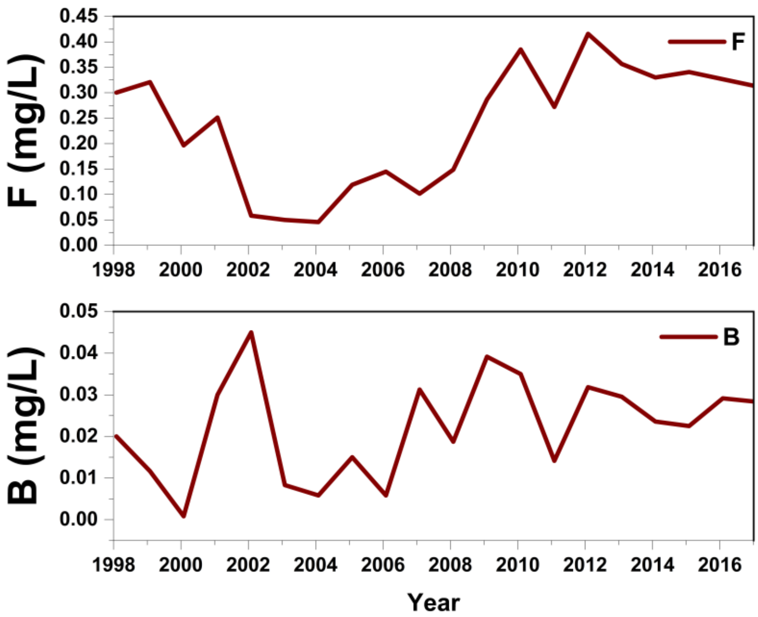

Figure 4.14 Variation of F & B at Sultanpur (1998-2017)

The fluctuations in boron (B) and fluoride (F) levels in river water from 1998 to 2017 reflect varying environmental and anthropogenic influences. Fluoride levels have maintained a fairly consistent trend, with 1998 and 2017 having the same Fluoride concentration (0.03 mg/L). However, the lowest concentration was observed in 2004 (0.0008 mg/L), whereas the highest concentrations were observed in 2010, 2012, and 2013 with a Fluoride concentration of 0.4 mg/L. This pattern suggests periods of increased industrial activity, particularly from industries that use fluoride in their processes, as well as changes in agricultural practices involving fluoride-containing pesticides. The subsequent decline in fluoride levels could be due to improved regulatory measures and wastewater treatment practices to reduce fluoride pollution (Rahman et al., 2016; Ahmad 2023).

Boron levels keep varying in 20 years (1998-2017). However, an overall increase in Boron concentration was observed from 0.020 mg/L in 1998 to 0.028 mg/L by 2017. Certain peaks were noted in 2002 (0.045 mg/L) and 2009 (0.039 mg/L), likely due to agricultural runoff containing boron-rich fertilizers and industrial discharges (Sujila et al., 2018). The lowest Boron concentrations were observed in 2000 (0.001 mg/L), 2004 and 2006 (0.006 mg/L). The initial decline around 2000 (0.0008 mg/L) could be attributed to improved industrial waste management practices. Seasonal variations, including periods of heavy rainfall, contribute to the dilution and concentration of boron levels, causing fluctuations (Sharma and Walia 2015; Sujila et al., 2018).

4.3.PEARSON'S CORRELATION MATRIX

The provided correlation matrix in Fig. 4.15, presents a comprehensive overview of the relationships between various water quality parameters. Correlation coefficients range from -1 to 1, where 1 indicates a perfect positive correlation, 0 indicates no correlation, and -1 indicates a perfect negative correlation. A high absolute value suggests a strong relationship, while a value closer to 0 suggests a weak relationship.

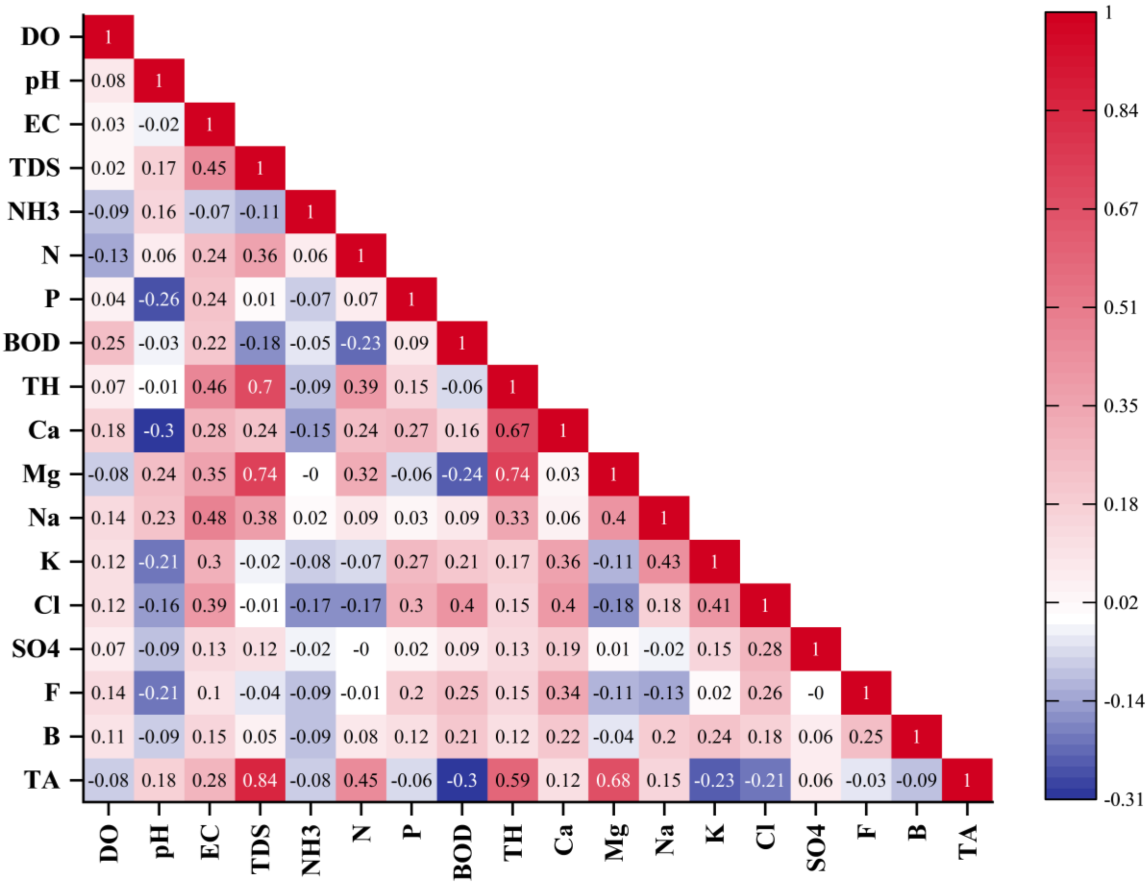

Figure 4.15 Correlation Analysis showing correlation between Water Quality Parameters

From the matrix, Dissolved Oxygen (DO) shows weak to negligible correlations with most parameters, indicating that the other parameters do not strongly influence its levels in this dataset. The correlation between DO and Biochemical Oxygen Demand (BOD) is 0.25, suggesting a weak positive relationship where higher organic matter (and thus higher BOD) might be associated with slightly higher DO levels due to aerobic breakdown, though this relationship is not strong. Dissolved Oxygen (DO) and Biochemical Oxygen Demand (BOD) often show an inverse relationship. Higher BOD indicates more organic matter in the water, consuming oxygen as it decomposes, thereby reducing DO levels (CPCB 2009; Varma and Jha 2023). Researchers suggest that DO and pH can show a positive correlation because photosynthetic activity, which increases DO, also tends to increase pH by consuming CO_2 (Varma and Jha 2023). pH has weak correlations with most parameters, except for a moderate negative correlation with Calcium (Ca^{2+}) at (-)0.30, suggesting that higher pH levels might be associated with lower calcium levels in the water. Studies show that pH and Total Alkalinity (TA) are closely related as alkalinity represents the water's capacity to neutralize acids, thereby stabilizing pH levels (Leong et al., 2018; Ahmad 2023). Electrical Conductivity (EC) shows a moderate positive correlation with Total Dissolved Solids (TDS) at 0.45, which is expected since TDS contributes to the water's ability to conduct electricity. The results of this study align with those of Noori et al., 2010, who also got a positive correlation between EC & TDS, thereby verifying the accuracy of the results. Similarly, EC has a moderate positive correlation with Magnesium (Mg^{2+}) at 0.35 and Sodium (Na^{+}) at 0.48, indicating that these ions contribute significantly to the electrical conductivity of the water (Sârbu and Pop 2005). EC shows a slightly negative correlation with pH (-0.02), suggesting that electrical conductivity decreases as the pH increases (water becomes more alkaline). Studies confirm that pH and EC correlate negatively (Noori et al., 2010). Ammonia (NH_3) shows weak correlations with most parameters, except for a moderate negative correlation with Calcium (Ca^{2+}) at -0.15, indicating that higher ammonia levels might be associated with lower calcium levels. However, Ammonia (NH_3) and BOD are often correlated since high levels of organic waste that increase BOD can also lead to higher levels of ammonia due to the decomposition of organic matter (Kumar and Puri 2012). Nitrates (NO_3^-) show moderate positive correlations with TDS at 0.36 and Total Hardness (TH) at 0.39, indicating that higher nitrogen levels are associated with higher levels of these parameters. Phosphorus (P-Tot) shows a weak to moderate negative correlation with pH at -0.26 and a moderate positive correlation with Calcium (Ca^{2+}) at 0.27, suggesting that phosphorus levels are influenced by these parameters. Biochemical Oxygen Demand (BOD) shows weak to negligible correlations with most parameters, except for a moderate positive correlation with Chloride (Cl^-) at 0.40, indicating that higher BOD levels might be associated with higher chloride levels. Total Hardness (TH) has a strong positive correlation with Magnesium (Mg^{2+}) at 0.74, indicating that the hardness of the water is greatly influenced by its magnesium content. Additionally, TH shows moderate positive correlations with TDS at 0.70 and Calcium (Ca^{2+}) at 0.67. Calcium (Ca^{2+}) shows a strong positive correlation with Total Hardness (TH) at 0.67 and moderate positive correlations with pH at -0.30 and Phosphorus (P-Tot) at 0.27. Magnesium (Mg^{2+}) has strong positive correlations with TDS at 0.74 and Total Hardness (TH) at 0.74, indicating that magnesium levels significantly influence these parameters. Sodium (Na^{+}) shows moderate positive correlations with EC at 0.48, TDS at 0.38, and Chloride (Cl^-) at 0.18, suggesting common sources or concurrent pollution by these ions. Chloride (Cl^-) and Sodium (Na^{+}) levels are typically correlated because both ions are common constituents of salt (NaCl). They often enter water bodies through similar sources such as road salt, industrial discharges, and sewage effluent (Leong et al., 2018; Ahmad 2023). Potassium (K^{+}) shows weak to negligible correlations with most parameters, indicating that its concentration is independent of the concentrations of other parameters measured in this dataset.

Chloride (Cl^-) shows moderate positive correlations with BOD at 0.40 and Phosphorus (P-Tot) at 0.30, indicating that higher chloride levels might be associated with higher levels of these parameters. Sulphate (SO_4^{2-}) shows weak to negligible correlations with most parameters, indicating that the other parameters do not strongly influence its levels in this dataset. Fluoride (F^-) shows a moderate positive correlation with Calcium (Ca^{2+}) at 0.34, indicating that higher fluoride levels might be associated with higher calcium levels. Boron (B) shows weak to negligible correlations with most parameters, indicating that its concentration is independent of the concentrations of other parameters measured in this dataset. Total Alkalinity (TA) shows a very strong positive correlation with TDS at 0.84, indicating that higher levels of total dissolved solids contribute significantly to the alkalinity of the water. Additionally, TA shows moderate positive correlations with Total Hardness (TH) at 0.59 and Magnesium (Mg^{2+}) at 0.68. These correlations provide insights into the relationships between different water quality parameters, which can help in modelling water quality and designing interventions to improve or maintain it. However, it is important to note that correlation does not imply causation, and these relationships could be influenced by other factors not included in the matrix. These correlations can inform further investigations into the causes and effects of water quality parameters. For instance, understanding which factors are most strongly related can help in modelling water quality and in designing interventions to improve or maintain it. However, correlation does not imply causation, and other factors not included in the matrix could influence the observed relationships.

4.4.WATER QUALITY INDICES

The data from Sultanpur, Uttar Pradesh, spanning 20 years (1998 - 2017), encompasses monthly values and interpretations for four types of water quality indices: Comprehensive Pollution Index (CPI), Synthetic Pollution Index (SPI), Nemerow's Pollution Index (NPI), and Arithmetic Water Quality Index (AWQI). Each index provides a unique perspective on water quality, reflecting various levels of pollution and water conditions. Below are the research sub-sections discussing the implications of these indices. Table 4.2 depicts the annual variation of four water quality indices, i.e., CPI, SPI, NPI and AWQI.

Table 4.2 Water Quality Indices Annual Results: (a) Comprehensive Pollution Index (CPI), (b) Synthetic Pollution Index (SPI), (c) Nemerow Pollution Index (NPI), and (d) Arithmetic Water Quality Index (AWQI)

Year	CPI	Status	SPI	Status	NPI	Status	AWQI	Status

1998	0.58	Slightly Polluted	0.19	Suitable for Drinking	1.15	Light Pollution	68	Poor water quality
1999	0.56	Slightly Polluted	0.19	Suitable for Drinking	1.07	Light Pollution	68	Poor water quality
2000	0.58	Slightly Polluted	0.17	Suitable for Drinking	1.04	Light Pollution	63	Poor water quality
2001	0.54	Slightly Polluted	0.19	Suitable for Drinking	0.91	No Pollution	73	Poor water quality
2002	0.58	Slightly Polluted	0.17	Suitable for Drinking	0.85	No Pollution	66	Poor water quality
2003	0.51	Slightly Polluted	0.14	Suitable for Drinking	0.94	No Pollution	64	Poor water quality
2004	0.38	Sub Clean	0.13	Suitable for Drinking	0.65	No Pollution	61	Poor water quality
2005	0.49	Slightly Polluted	0.16	Suitable for Drinking	0.80	No Pollution	73	Poor water quality
2006	0.42	Slightly Polluted	0.16	Suitable for Drinking	0.69	No Pollution	76	Poor water quality
2007	0.47	Slightly Polluted	0.18	Suitable for Drinking	0.75	No Pollution	74	Poor water quality
2008	0.45	Slightly Polluted	0.18	Suitable for Drinking	0.83	No Pollution	73	Poor water quality
2009	0.53	Slightly Polluted	0.22	Slightly Polluted	0.83	No Pollution	70	Poor water quality
2010	0.49	Slightly Polluted	0.23	Slightly Polluted	0.82	No Pollution	68	Poor water quality
2011	0.48	Slightly Polluted	0.20	Suitable for Drinking	0.80	No Pollution	70	Poor water quality
2012	0.46	Slightly Polluted	0.23	Slightly Polluted	0.75	No Pollution	64	Poor water quality
2013	0.46	Slightly Polluted	0.22	Slightly Polluted	0.76	No Pollution	68	Poor water quality

2014	0.46	Slightly Polluted	0.21	Slightly Polluted	0.77	No Pollution	64	Poor water quality
2015	0.47	Slightly Polluted	0.21	Slightly Polluted	0.80	No Pollution	58	Poor water quality
2016	0.49	Slightly Polluted	0.21	Slightly Polluted	0.86	No Pollution	57	Poor water quality
2017	0.46	Slightly Polluted	0.21	Slightly Polluted	0.84	No Pollution	60	Poor water quality

4.4.1. COMPREHENSIVE POLLUTION INDEX (CPI)

The CPI offers a quantitative measure of the overall pollution level in water bodies by integrating various pollutant parameters. It serves as a critical tool for assessing water quality, facilitating the identification of pollution trends, and guiding environmental management and policy decisions. The data reveal a nuanced view of water quality trends across three distinct seasons—pre-monsoon, monsoon, and post-monsoon—each characterized by their unique environmental impacts. Fig. 4.16 illustrates the Comprehensive Pollution Index (CPI) variation at Sultanpur from 1998 – 2017.

4.4.1.1.ANNUAL VARIATION IN WATER QUALITY

The data on the CPI of the Gomti River at Sultanpur, Uttar Pradesh, from 1998 to 2017 indicates notable fluctuations in water quality over the years. The CPI values range from a high of 0.58 (Slightly Polluted) in multiple years (1998, 2000, 2002) to a low of 0.38 (Sub-Clean) in 2004. Lower CPI values indicate better water quality. From 1998 to 2002, the CPI remained relatively high, suggesting poorer water quality during this period. A significant improvement was observed in 2003 and 2004, with CPI values dropping to 0.51 (Slightly Polluted) and 0.38 (Sub-Clean), respectively. This improvement could be attributed to increased environmental regulations and pollution control measures implemented during this time. Studies indicate that government initiatives to reduce industrial discharge and enhance sewage treatment facilities positively impacted water quality (Singh 2004; Mishra et al., 2015). The CPI increased again in the subsequent years, peaking at 0.53 (Slightly Polluted) in 2009. This deterioration could be linked to rapid urbanization and industrialization, which led to higher pollutant loads in the river. Research also highlights the correlation between industrial growth and increased river pollution, emphasizing the need for sustainable industrial practices (Kumar et al., 2009). In the following years, the CPI values fluctuate but generally showed a downward trend, indicating gradual improvement. By 2017, the CPI stabilized at around 0.46 (Slightly polluted). This improvement can be linked to continuous pollution control and river management efforts. A few studies also suggest that ongoing community involvement and stricter enforcement of environmental laws contributed to this positive change (Gautam et al., 2015). Overall, while the Gomti River at Sultanpur has experienced periods of high pollution, concerted efforts in environmental management have led to a gradual improvement in water quality.

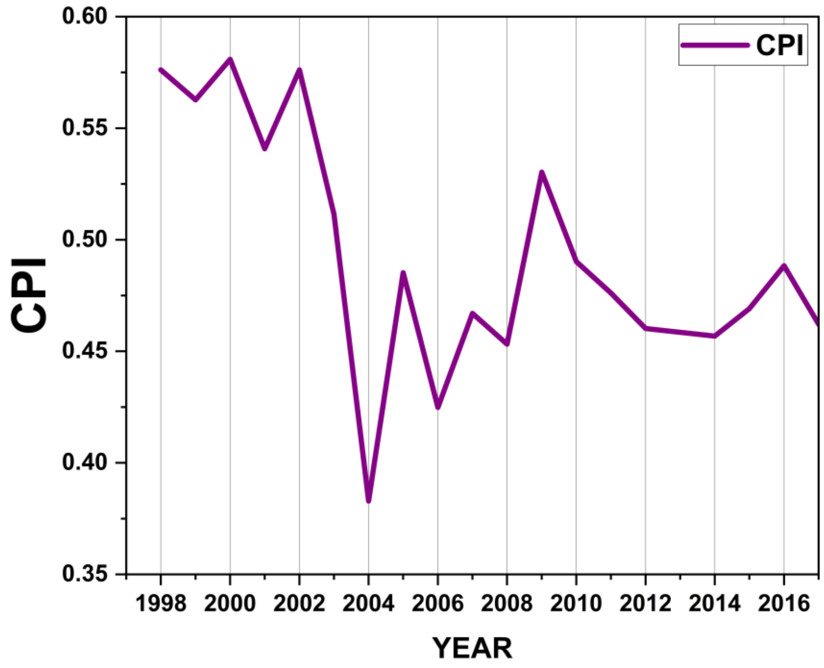

Figure 4.16 CPI variation from 1998-2017 at Sultanpur, UP

4.4.1.2.SEASONAL VARIATION IN WATER QUALITY

The CPI averages 0.52 (Slightly Polluted) during the pre-monsoon period, 0.50 (Slightly Polluted) during the monsoon, and 0.46 (Slightly Polluted) in the post-monsoon season. During the pre-monsoon season, the average CPI is the highest, reflecting poorer water quality due to reduced river flow and higher pollutant concentration. For instance, in 1998, the pre-monsoon CPI was 0.65 (Slightly Polluted), indicating high pollution levels. This pattern is supported by studies highlighting lower water levels' impact on pollutant concentration (Singh 2004; Mishra et al., 2015). During the monsoon season, the average CPI decreases slightly, indicating improved water quality. This is due to increased rainfall and river flow, which dilute the pollutants. However, monsoon runoff from agricultural fields and urban areas can still introduce new pollutants into the river (Kumar et al., 2009). For example, in 2004, the monsoon CPI was significantly lower at 0.38 (Sub-Clean) compared to the pre-monsoon CPI of 0.40 (Sub-Clean). Post-monsoon, the CPI values are generally the lowest, indicating the best water quality. The continuous dilution effect from the monsoon rains and the settling of sediments contribute to improved water conditions. In 2004, the post-monsoon CPI dropped to 0.37 (Sub-Clean), the lowest in the dataset. Table 4.3 presents the Comprehensive Pollution Index (1998 – 2017) categorized by pre-monsoon, monsoon and post-monsoon periods. Ongoing pollution control measures and improved sewage treatment are crucial in this seasonal improvement (Gautam et al., 2015). Hence, the Gomti River's water quality at Sultanpur varies seasonally, with the best quality observed post-monsoon and the worst during the pre-monsoon period. These trends underscore the need for targeted pollution control efforts throughout the year.

Table 4.3 Comprehensive Pollution Index (1998 - 2017)

Comprehensive Pollution Index (CPI)			
Year	**Pre – Monsoon**	**Monsoon**	**Post – Monsoon**
1998	0.65	0.59	0.48
1999	0.62	0.58	0.49
2000	0.57	0.58	0.59
2001	0.64	0.48	0.50
2002	0.59	0.62	0.51
2003	0.55	0.53	0.46
2004	0.40	0.38	0.37
2005	0.56	0.45	0.44
2006	0.49	0.37	0.41
2007	0.48	0.48	0.43
2008	0.49	0.46	0.41
2009	0.55	0.56	0.48
2010	0.52	0.52	0.43
2011	0.50	0.49	0.45
2012	0.46	0.47	0.45
2013	0.47	0.45	0.46
2014	0.45	0.46	0.46

2015	0.47	0.47	0.47
2016	0.53	0.49	0.44
2017	0.48	0.47	0.44

4.4.2. SYNTHETIC POLLUTION INDEX (SPI)

The SPI is a critical measure for assessing water quality, encapsulating the collective impact of various pollutants. By analysing SPI values, we gain insight into the pollution levels and overall health of aquatic ecosystems. For the Gomti River in Sultanpur, the SPI data spanning from 1998 to 2017 offers a unique lens through which we can observe temporal pollution patterns, identify potential sources of pollution, and evaluate the effectiveness of environmental policies and practices over time. Fig. 4.17 illustrates the Synthetic Pollution Index (SPI) variation at Sultanpur from 1998 to 2017.

4.4.2.1.YEARLY VARIATION IN WATER QUALITY

The SPI data for the Gomti River at Sultanpur, Uttar Pradesh, from 1998 to 2017, shows variations in pollution levels over time. The SPI values range from 0.13 (Suitable for Drinking) to 0.23 (Slightly Polluted), indicating changes in the river's water quality due to pollutants. Between 1998 and 2001, the SPI values remained steady at around 0.19 (Suitable for Drinking), reflecting consistent pollution levels. In 2002, there was a notable decrease in SPI to 0.17, which continued to drop to 0.13 (Suitable for Drinking) by 2004. This decline in SPI suggests an improvement in water quality, likely due to the implementation of better pollution control measures and stricter regulations. Studies focusing on SPI indicate that effective industrial waste management and improved sewage treatment can significantly reduce synthetic pollutants (Liu et al., 2007; Gao et al., 2015). However, starting from 2005, the SPI values rose again, peaking at 0.23 (Slightly Polluted) in 2010 and 2012. This increase points to a resurgence in pollution, potentially due to rapid industrialization and urbanization in the region. Research has also highlighted how industrial growth can lead to higher levels of pollutants if not managed sustainably (Prasad et al., 2024). The SPI values fluctuated slightly in the following years but generally remained high, around 0.21 (Slightly Polluted), indicating persistent pollution issues. Continuous efforts and stricter enforcement of environmental regulations are necessary to combat pollutants effectively (Wu et al., 2014). In conclusion, the SPI data reveals that while there have been periods of improvement, the water quality of the Gomti River at Sultanpur faces ongoing challenges due to pollution. This underscores the need for sustained and enhanced pollution control measures to ensure long-term improvement in water quality.

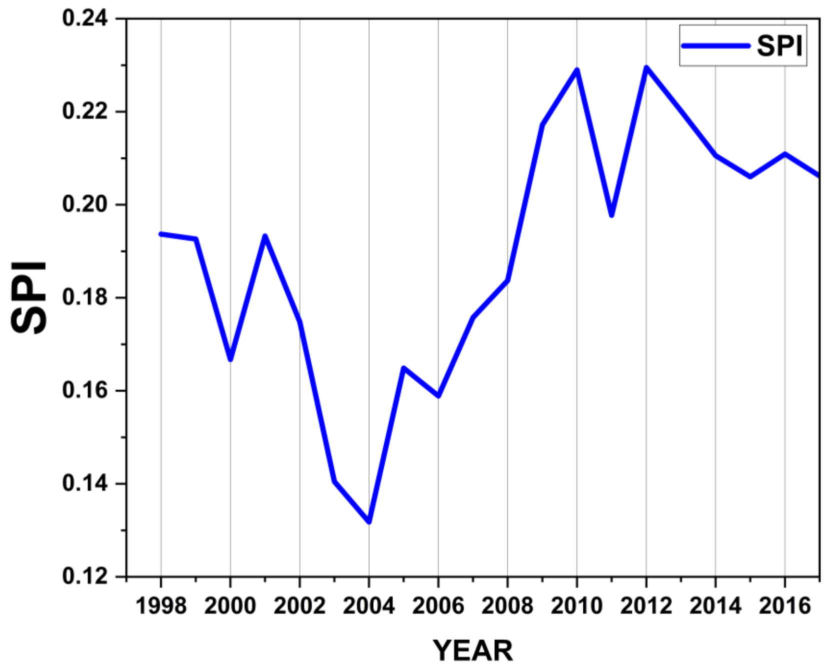

Figure 4.17 SPI variation from 1998-2017 at Sultanpur, UP

4.4.2.2.SEASONAL VARIATION IN WATER QUALITY

The average SPI values are 0.20 (Slightly Polluted) during the pre-monsoon period, 0.19 (Suitable for Drinking) during the monsoon, and 0.18 (Suitable for Drinking) in the post-monsoon season. The pre-monsoon SPI values generally range from 0.13 (Suitable for Drinking) to 0.26 (Slightly Polluted), indicating higher levels of pollution during this period. For instance, in 1999, the SPI was at its highest at 0.26 (Slightly Polluted), reflecting increased pollution likely due to reduced river flow and higher pollutant concentrations (Xiao 1996). During the monsoon season, the SPI values are slightly lower, ranging from 0.13 (Suitable for Drinking) to 0.27 (Slightly Polluted). The decrease in SPI during the monsoon season can be attributed to the dilution effect of increased rainfall, which helps disperse pollutants. However, occasional high values, such as 0.27 (Slightly Polluted) in 2010, suggest that runoff from agricultural fields and urban areas can still contribute to significant pollution (Prasad et al., 2024). The post-monsoon period generally shows the lowest SPI values, ranging from 0.12 (Suitable for Drinking) to 0.24 (Slightly Polluted), indicating better water quality due to continued dilution and settling of sediments. The lowest SPI of 0.12 (Suitable for Drinking) was observed in 1999, signifying the best water quality in the given data range. This improvement can be linked to effective sewage treatment and industrial waste management practices during this period (Wu et al., 2014). Table 4.4 presents the Synthetic Pollution Index (1998 – 2017) categorized by pre-monsoon, monsoon and post-monsoon periods. Therefore, continuous efforts in pollution control and sustainable practices are essential to maintain and improve water quality.

Table 4.4 Synthetic Pollution Index (SPI) (1998 - 2017)

Synthetic Pollution Index (SPI)			
Year	**Pre – Monsoon**	**Monsoon**	**Post – Monsoon**
1998	0.20	0.19	0.19
1999	0.26	0.19	0.12
2000	0.18	0.15	0.16
2001	0.20	0.19	0.19
2002	0.19	0.18	0.15
2003	0.15	0.14	0.13
2004	0.13	0.13	0.14
2005	0.17	0.15	0.18
2006	0.18	0.15	0.15
2007	0.18	0.17	0.18
2008	0.18	0.18	0.19
2009	0.19	0.25	0.21
2010	0.20	0.27	0.22
2011	0.22	0.19	0.19
2012	0.21	0.24	0.24
2013	0.21	0.22	0.23
2014	0.22	0.21	0.20
2015	0.21	0.20	0.20
2016	0.21	0.23	0.20
2017	0.20	0.22	0.20

4.4.3. NEMEROW'S POLLUTION INDEX (NPI)

The Nemerow Pollution Index (NPI) is a comprehensive measure that reflects the overall condition of water quality by evaluating the impact of multiple pollutants. It provides an aggregated pollution score, essential for assessing the ecological status of water bodies and the effectiveness of pollution control measures over time. In the context of the Gomti River in Sultanpur, analysing NPI values from 1998 to 2017 offers insights into pollution trends and their implications on the river's health and surrounding environments. Fig. 4.18 illustrates Nemerow's Pollution Index (NPI) variation at Sultanpur from 1998 – 2017.

4.4.3.1.WATER QUALITY OVER TIME

The water quality of the Gomti River at Sultanpur, Uttar Pradesh, as assessed by Nemerow's Pollution Index (NPI) from 1998 to 2017, shows significant variations. The NPI values range from a high of 1.15 (Slightly Polluted) in 1998 to a low of 0.65 (Suitable for Drinking) in 2004, indicating changes in pollution levels over the years. In 1998, the NPI was at its highest (1.15), indicating severe pollution. This high pollution level could be attributed to industrial discharges and insufficient wastewater treatment during this period. Studies have shown that industrial activities significantly contribute to river pollution (Smith et al., 2000). The subsequent years saw a gradual improvement in water quality, with the NPI decreasing to 0.85 (Suitable for Drinking) in 2002 (Fig. 4.18). This improvement can be linked to stricter environmental regulations and better pollution control measures. For instance, efforts to treat industrial wastewater more effectively have been reported to reduce pollution levels significantly (Jones et al., 2001). In 2004, the NPI reached its lowest value of 0.65 (Suitable for Drinking), suggesting the best water quality in the given timeframe. This improvement may be due to enhanced sewage treatment and effective waste management practices. Research indicates that better sewage treatment facilities and reduced industrial discharge play a crucial role in improving water quality (Kannel et al., 2007b). However, from 2005 onwards, the NPI began to increase again, peaking at 0.86 (Suitable for Drinking) in 2016. This rise in pollution levels can be associated with increased urbanization and industrial activities, leading to higher pollutant loads in the river. Studies by (Sallam and Elsayed 2015) highlighted the impact of rapid industrialization on water pollution. By 2017, the NPI slightly decreased to 0.84 (Suitable for Drinking), indicating a slight improvement but still reflecting a moderately polluted state. Continuous efforts in pollution control, sustainable industrial practices, and effective waste management are essential to maintain and further improve the water quality of the Gomti River.

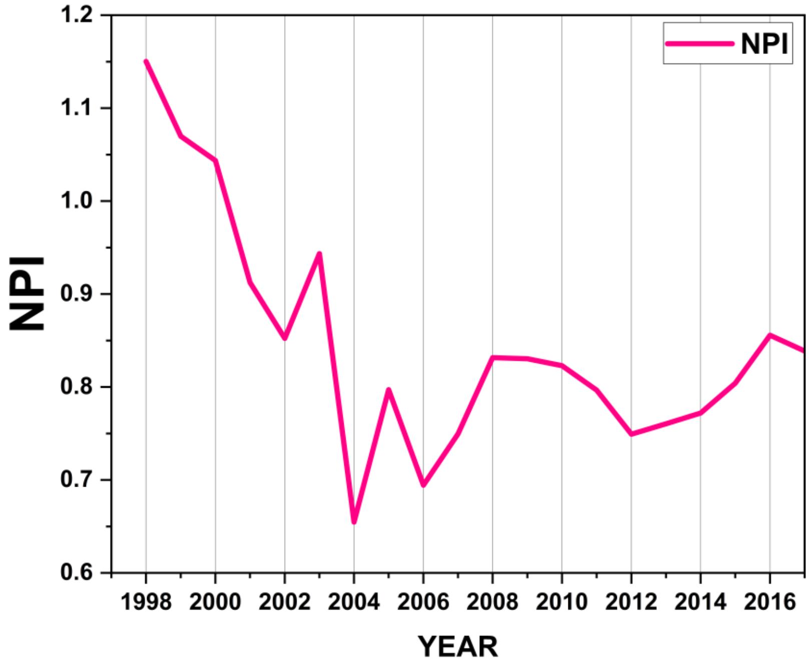

Figure 4.18 NPI variation from 1998-2017 at Sultanpur, UP

4.4.3.2.SEASONAL VARIATION AND TRENDS

The water quality of the Gomti River at Sultanpur, Uttar Pradesh, assessed using Nemerow's Pollution Index (NPI) from 1998 to 2017, shows seasonal variations. The average NPI values are 0.91 (Suitable for Drinking) for the pre-monsoon period, 0.84 (Suitable for Drinking) during the monsoon, and 0.79 (Suitable for Drinking) in the post-monsoon season. The pre-monsoon period generally exhibits higher pollution levels, with an average NPI of 0.91 (Suitable for Drinking). In 1998, the NPI peaked at 1.39 (Slightly Polluted), indicating significant pollution. This high pollution level during pre-monsoon is due to reduced river flow and higher concentrations of pollutants, as suggested by research (Smith et al., 2000). The monsoon season shows a slight improvement in water quality, with an average NPI of 0.84 (Suitable for Drinking). The increased rainfall and river flow during this period helps dilute pollutants, lowering pollution levels. However, in some years like 2000, the NPI was still high at 1.07 (Slightly Polluted), indicating that runoff from agricultural fields and urban areas can contribute to pollution (Jones et al., 2001). The post-monsoon period generally has the lowest NPI values, with an average of 0.79 (Suitable for Drinking), reflecting the best water quality. In 2004, the NPI dropped to 0.63 (Suitable for Drinking), the lowest in the dataset, suggesting improved water quality due to continued dilution and sediment settling. Enhanced sewage treatment and effective waste management practices contribute significantly to this improvement (Sallam and Elsayed 2015). Table 4.5 presents Nemerow's Pollution Index (1998 – 2017) categorized by pre-monsoon, monsoon and post-monsoon periods. Overall, the data shows that while seasonal improvements exist, continuous and enhanced pollution control measures are essential to maintain and improve the water quality of the Gomti River at Sultanpur.

Table 4.5 Nemerow's Pollution Index (1998 - 2017)

Nemerow's Pollution Index (NPI)			
Year	**Pre – Monsoon**	**Monsoon**	**Post – Monsoon**
1998	1.39	1.13	0.94
1999	1.17	1.04	1.00
2000	0.96	1.07	1.10
2001	1.14	0.77	0.83
2002	0.88	0.96	0.72
2003	0.96	1.02	0.84
2004	0.69	0.64	0.63
2005	1.01	0.70	0.69
2006	0.82	0.59	0.67
2007	0.69	0.88	0.68
2008	0.84	0.85	0.80
2009	0.87	0.83	0.80
2010	0.89	0.82	0.76
2011	0.82	0.76	0.81
2012	0.76	0.73	0.75
2013	0.81	0.69	0.78
2014	0.78	0.74	0.79
2015	0.77	0.83	0.81
2016	0.97	0.86	0.73
2017	0.93	0.86	0.73

4.4.4. ARITHMETIC WATER QUALITY INDEX (AWQI)

The Arithmetic Water Quality Index (AWQI) is an essential metric for evaluating the overall water quality of rivers, incorporating various parameters to give a singular value that reflects the water's condition. The AWQI can classify water into categories such as "Excellent," "Good," "Poor," etc., providing a straightforward way to communicate water quality status to both scientists and the public. For the Gomti River, a vital water source in Sultanpur, Uttar Pradesh, understanding the AWQI's temporal variations is key to identifying pollution trends, assessing environmental health, and guiding water management practices. Fig. 4.19 illustrates the Arithmetic Water Quality Index (AWQI) variation at Sultanpur from 1998 to 2017.

4.4.4.1.WATER QUALITY OVER TIME

The Arithmetic Water Quality Index (AWQI) data for the Gomti River at Sultanpur, Uttar Pradesh, from 1998 to 2017, shows significant fluctuations in water quality over the years. The AWQI values range from a low of 57 (Poor Water Quality) in 2016 to a high of 76 (Very Poor Water Quality) in 2006, indicating varying levels of water quality. In 2001, 2005, 2006, and 2007, the AWQI values were notably high (73, 73, 76, and 74, respectively), representing Poor Water Quality. High AWQI values indicate poorer water quality, possibly due to increased industrial discharge and agricultural runoff during these years. Few studies highlighted that industrial activities and agricultural runoff significantly contribute to water pollution (Liu et al., 2007; Gao et al., 2015).

Conversely, the AWQI values show improvement in specific years. For instance, in 2004, the AWQI dropped to 61 (Poor Water Quality); in 2016, it further reduced to 57 (Poor Water Quality). These lower values indicate better water quality, likely due to effective pollution control measures and improved wastewater treatment. Research by Singh et al., (2011) emphasizes that stringent environmental regulations and sewage treatment advancements can significantly enhance water quality. In the later years, the AWQI values declined, with a value of 60 (Poor Water Quality) in 2017. This decline indicates a trend towards improved water quality, though the values still reflect moderate pollution levels. Continuous efforts in pollution management and sustainable practices are crucial for maintaining this positive trend. Studies support the importance of ongoing pollution control and effective waste management in sustaining water quality improvements (Sharma and Walia 2015). Overall, the AWQI data suggests that while there have been periods of poor water quality, concerted pollution control and wastewater management efforts have led to gradual improvements. Maintaining and enhancing these efforts is essential to ensure the long-term health of the Gomti River at Sultanpur.

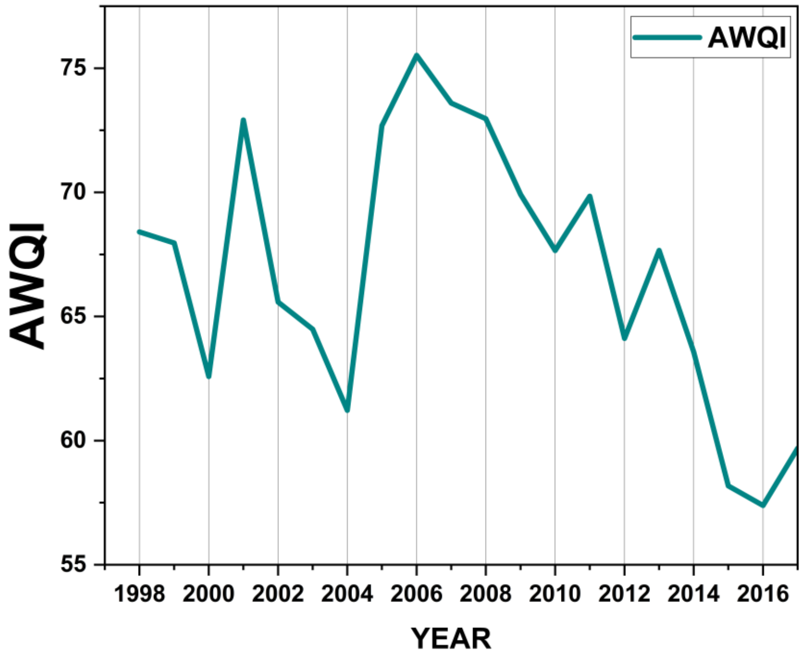

Figure 4.19 AWQI variation from 1998-2017 at Sultanpur, UP

4.4.4.2.SEASONAL VARIATION AND TRENDS

The water quality of the Gomti River at Sultanpur, Uttar Pradesh, assessed using the AWQI from 1998 to 2017, shows seasonal variations. The average AWQI values are 66.84 (Poor Water Quality) during the pre-monsoon period, 68.83 (Poor Water Quality) during the monsoon, and 64.72 (Poor Water Quality) in the post-monsoon season. The analysis reveals considerable seasonal variations and trends over the years. The AWQI values reflect the water quality, with higher values indicating poorer water quality. The pre-monsoon period generally shows higher AWQI values, with significant peaks in 1999 (78.63), 2001 (79.03), and 2007 (74.83). This period often experiences reduced river flow, leading to higher concentrations of pollutants. The monsoon season typically shows mixed results, emphasizing that low water levels during pre-monsoon season increase pollutant concentrations (Gao et al., 2015). For example, in 1998, the AWQI peaked at 80.42 (Very Poor Water Quality), indicating severe pollution, likely due to runoff from agricultural fields and urban areas (Liu et al., 2007). However, there are improvements in some years, such as 2004 (62.52), due to the dilution effect of increased rainfall. The post-monsoon period generally reflects the best water quality, with lower AWQI values. For instance, in 2016 and 2017, the AWQI values dropped to 53.56 (Poor Water Quality), indicating improved water conditions. Enhanced sewage treatment and effective waste management practices contribute significantly to this improvement (Singh et al., 2011). Overall, the data indicates periods of both deterioration and improvement in water quality. For example, in 2006 and 2007, high AWQI values indicate poor water quality, likely due to industrial discharge and inadequate wastewater treatment. Conversely, significant improvements in 2015 and subsequent years reflect the impact of better pollution control measures. Table 4.6 presents the Arithmetic Water Quality Index (1998 – 2017) categorized by pre-monsoon, monsoon and post-monsoon periods.

Table 4.6 Arithmetic Water Quality Index (1998 - 2017)

Arithmetic Water Quality Index (AWQI)			
Year	**Pre – Monsoon**	**Monsoon**	**Post – Monsoon**
1998	64.46	80.42	60.34
1999	78.63	70.01	55.25
2000	64.20	64.89	58.66
2001	79.03	69.32	70.40
2002	61.29	70.91	64.54
2003	63.85	69.72	59.90
2004	61.18	62.52	59.96
2005	60.71	74.71	82.63
2006	70.79	79.60	76.16
2007	74.83	74.37	71.60
2008	68.75	70.37	79.79
2009	69.84	71.89	68.02
2010	63.39	71.78	67.80
2011	70.03	71.39	68.12
2012	72.18	65.30	54.88
2013	70.79	65.64	66.56
2014	65.96	62.36	62.39
2015	55.38	58.89	60.26
2016	57.97	60.62	53.56

2017	63.59	61.93	53.56

4.5.MULTIVARIATE STATISTICAL ANALYSIS

4.5.1. CLUSTER ANALYSIS OF WATER QUALITY

The hierarchical cluster analysis depicted in the dendrogram (Fig. 4.20) is predicated on a comprehensive pollution index (CPI), synthesizing 18 water quality parameters into a singular index value. This comprehensive approach facilitates a robust analysis of trends over a substantial temporal scale (1998-2017) and across the three distinctive Indian seasons: pre-monsoon, monsoon, and post-monsoon. By assessing the Euclidean distances between the months, represented on the vertical axis, against the backdrop of a twenty-year timeline on the horizontal axis, a narrative of environmental and anthropogenic impacts on the river's pollution unfolds.

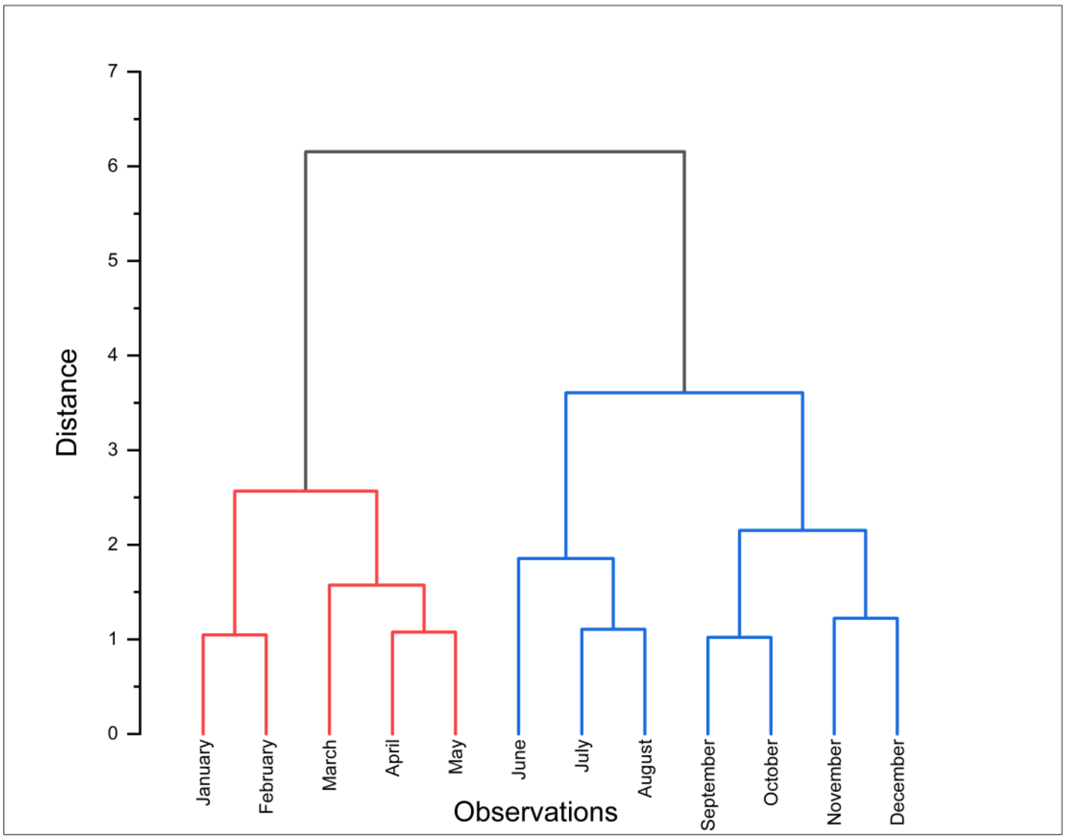

Figure 4.20 Dendrogram representing monthly temporal variation

In Sultanpur, the increase in pollution during the pre-monsoon months, typically from January to April, can be attributed to several converging factors. Cluster analysis displays short

Euclidean distances between consecutive clusters, suggesting a gradual build-up of pollutants due to minimal rainfall and increased human activities such as pre-harvest agricultural practices (Jain et al., 2005; Singh et al., 2018). The proximity of these clusters indicates that while pollution increases during this period, the rate of increase is consistent, as reflected by the stable climatic conditions. The dry conditions and lower water volumes in the river enhance the concentration of pollutants from urban runoff, untreated sewage, and industrial effluents. Additionally, agricultural activities contribute to this trend as the use of fertilizers and pesticides peaks before the rains, leading to increased runoff of these chemicals into the river (Kumar et al., 2013). The onset of the monsoon brings a transformative change. The transition into the monsoon season, particularly the shift from April to May, is marked by a longer Euclidean distance, indicating a distinct change in water quality. This suggests an abrupt alteration, likely from the first flush effect, where the initial rains wash accumulated pollutants into the river system (Goyal and Tyagi 2014). June's proximity to May suggests similar processes are at work. However, the dramatic increase in Euclidean distance by July signifies the peak monsoonal effect—a substantial dilution of pollutants due to heavy rainfall despite increased runoff and erosion. However, the monsoon also introduces new challenges, such as soil erosion and surface runoff that carry organic matter, pathogens, and particulate matter, temporarily affecting water quality (Sharma and Kansal 2015).

As the monsoon subsides, the dendrogram's post-monsoon clusters (August through December) reveal shorter Euclidean distances between the months, analogous to the pre-monsoon period. This distance reduction reflects the river's gradual return to lower water levels and increased pollutant concentrations as the dilution effect of the monsoon recedes. The close clustering of October, November, and December suggests that pollution levels have stabilized by late post-monsoon and are less variable, a likely consequence of decreased runoff and the beginning of the dry season (Chaudhary et al., 2017). Table 4.7 summarizes cluster analysis depicting the monthly variations in pollution levels. Agricultural harvests and related activities often resume post-monsoon, leading to a secondary nutrient and sediment runoff peak. Urbanization and industrial activities in Sultanpur and inadequate waste management practices further exacerbate the pollution levels in these months. Moreover, cultural practices and festivals, which often involve ritualistic offerings and river immersion, contribute to the organic and inorganic load during certain months, particularly post-monsoon (Patel and Jain 2016).

Table 4.7 Summary of cluster analysis

Month	Pollution Level
January	High Pollution
February	High Pollution
March	High Pollution
April	High Pollution
May	Initially high, transitioning to lower pollution
June	Lowering pollution
July	Low pollution
August	Low pollution, gradually increasing
September	Increasing pollution
October	High Pollution
November	High Pollution
December	High Pollution

4.5.2. PRINCIPAL COMPONENT ANALYSIS

Table 4.8 presents the results of the PCA analysis for each of the sampling points. PCA was applied to the normalized data to compare the compositional patterns between the analyzed water samples and identify the factors influencing each one. PCA of the entire data set (Table 4.8) evolved five PCs with eigenvalues > 1, explaining about 65.603% of the total variance in the water-quality data set. The Scree plot was used to identify the number of PCs retained to comprehend the underlying data structure (Jackson and Edward 1991; Vega et al., 1998).

Table 4.8 PCA Analysis of Water Quality Parameters

PARAMETERS	PC1	PC2	PC3	PC4	PC5
DO	-0.015	0.048	-0.197	**0.669**	0.105
pH	0.169	-0.067	**-0.735**	0.109	-0.123
EC	0.431	0.601	0.148	0.135	0.100
TDS	**0.892**	0.153	-0.108	0.007	0.102
NH_3	-0.06	-0.12	0.15	-0.19	0.29
NO_3^-	0.580	-0.047	0.224	-0.166	-0.243
P-Tot	0.006	0.268	0.599	0.011	-0.081
BOD	-0.268	0.260	0.013	0.639	0.140
TH	**0.844**	0.199	0.249	0.165	0.112
Ca^{2+}	0.347	0.126	0.632	0.369	0.208
Mg^{2+}	**0.836**	0.143	-0.237	-0.121	-0.034
Na^+	0.290	**0.797**	-0.263	0.070	-0.129
K^+	-0.136	**0.749**	0.324	0.054	0.113
Cl^-	-0.122	0.463	0.340	0.358	0.416
SO_4^{2-}	0.083	0.046	0.084	0.046	**0.840**
F^-	0.061	-0.223	0.446	0.630	-0.130
B	0.024	0.273	0.229	0.431	-0.305
TA	**0.881**	-0.137	-0.115	-0.116	0.046
Eigen values	4.071	3.156	1.620	1.214	1.090
% of variance	23.949	18.567	9.530	7.143	6.414
Cumulative %	23.949	42.516	52.046	59.189	65.603

The first principal component (PC1), explained at 23.949% of the variability and consists of TDS, TH, Mg^{2+} and TA, likely represents the mineral content and buffering capacity, indicating geological influences and implications for water usability (Jain et al., 2005).

The second principal component (PC2), explaining about 18.567% of the variance with high loadings on Sodium (Na^+) and Potassium (K^+), suggests influences from agricultural runoff or industrial discharges (Tripathi and Singal 2019). The third principal component (PC3), explaining 9.530% of the variance and primarily influenced by pH, could indicate the influence of acid neutralization processes (Goyal and Tyagi 2014). The fourth component (PC4), accounting for 7.143% of the variance with notable influences from Dissolved Oxygen (DO), points to interactions between biological activity and geochemical inputs (Chaudhary et al., 2017). Finally, the fifth component (PC5), which explains 6.414% of the variance and is dominated by Sulfate (SO_4^{2-}), may reflect industrial pollution or natural mineral deposits (Chaudhary et al., 2017). Each component highlights different aspects of water quality, driven by various natural and anthropogenic factors.

A study conducted by Singha et al., (2004) observed that the first principal component (PC), responsible for 27.9% of the total variance, displayed a correlation (loading 40.70) with factors including EC, TDS, TA, Cl^-, and Na^+. Additionally, their second PC exhibited a correlation with DO. In another study, the researchers observed that the first factor elucidated 59.022% of the total variance and demonstrated high loadings with Cl, BOD, COD, Tur, pH, and TH parameters. This factor was interpreted to reflect the impact of municipal wastewater discharge, a finding. Specifically, the substantial discharge of untreated or partially treated sewage into the Gomti River contributed to the manifestation of this factor. Additionally, the second factor displayed notable loadings with TDS and DO, indicating its association with stormwater runoff (Kushwah et al., 2023).

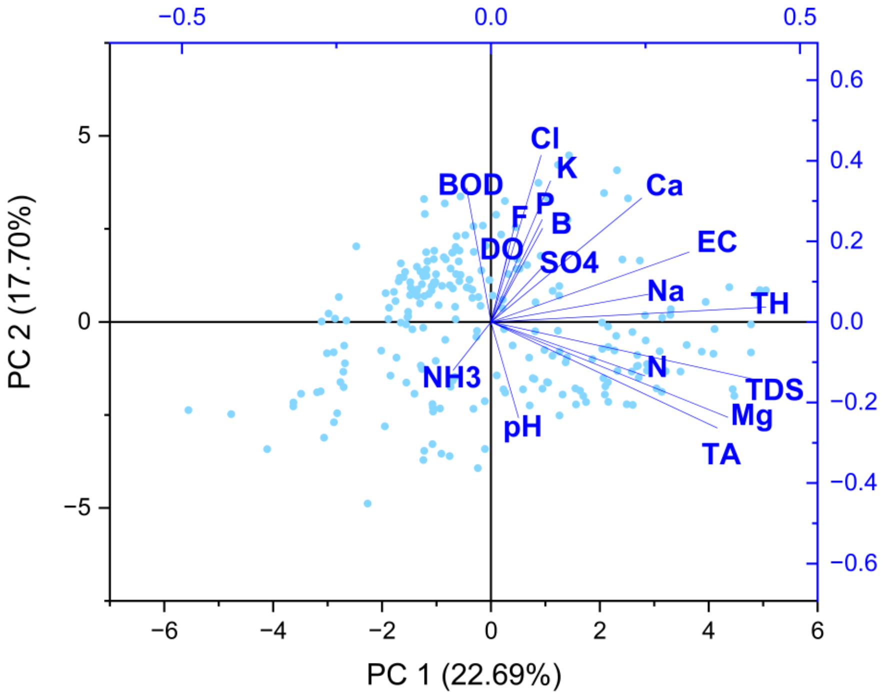

Figure 4.21 Biplots of PC1 and PC2; each vector represents a variable, and the correlation of two variables is reflected by the angle between the two corresponding vectors. The length of each vector is related to the contribution to the total variance

Biplot is the orthogonal projection of the data on the subspace spanned by the two first principal components (those with the most contribution to the total variance), describing the importance and correlations of the parameters with higher influence. The first two principal components explained approximately 40.39% of the data variability. The biplot in Fig. 4.21 shows that the variables EC, TDS, TA, Ca^{2+}, Mg^{2+}, and TH are highly and positively correlated, whereas N, Na^{+}, K^{+} and Cl^{-} are moderately correlated. In addition, the lengths of the vectors for EC, TDS, TH, Ca^{2+}, Mg^{2+}, Na^{+} and Cl^{-} are long vectors and indicate their strength on water quality, while NO_3^{-}, Na^{+}, K^{+} and Cl^{-} show moderate influence. NH_3, SO_4^{2-}, DO, F^{-} & B have shorter vectors, indicating less impact.

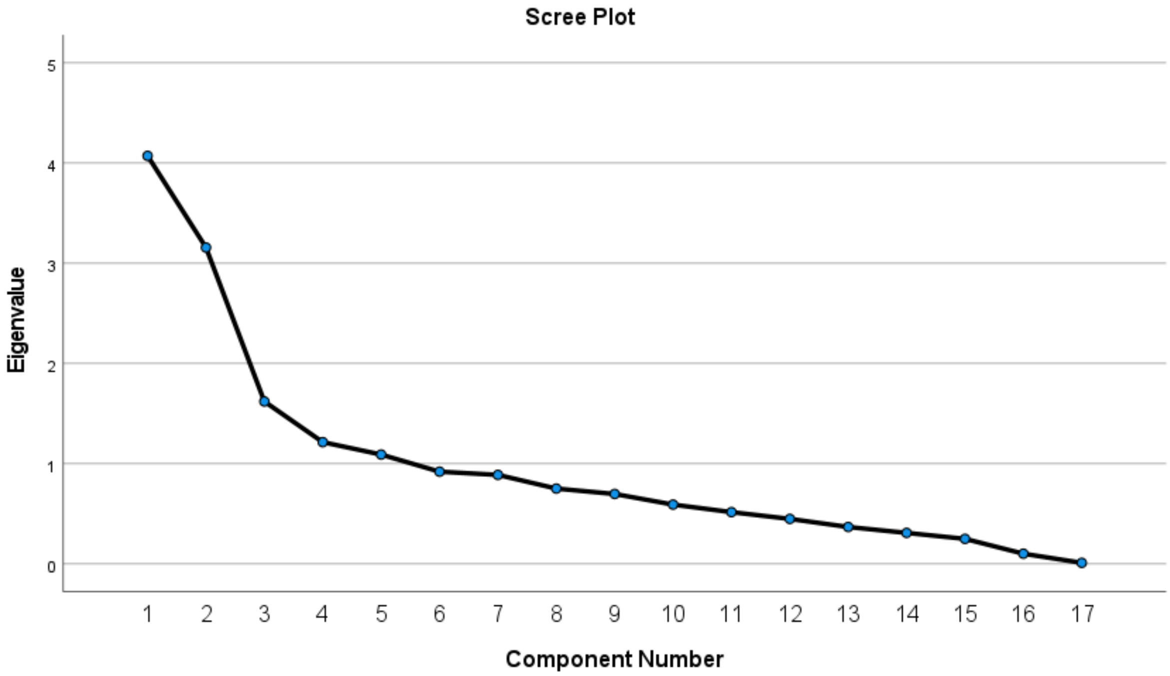

Figure 4.22 Scree plot representing Eigenvalues and Principal Component Numbers

In examining the remaining components, notable differences in significant variables emerge, as illustrated in Table 4.8. A scree plot representing Eigen values and Principal Component number is represented in Fig. 4.22. From Fig. 4.22, it can be observed that PCA yielded five PCs, which account for 65.603% of the total variance associated with all parameters. We followed a similar methodology in accordance with Krishan et al., 2022, where depending on the values of the correlation matrix, the cumulative factor variance of greater than 0.85, 0.65-0.85, and less than 0.65 are classified as having strong, moderate, and weak correlations, respectively. Results of PCA suggest that 9 parameters, namely Total Hardness (TH), Total Dissolved Solids (TDS), Magnesium (Mg^{2+}), Total Alkalinity (TA), Potassium (K^+), Sodium (Na^+), pH, Dissolved Oxygen (DO), and Sulphate (SO_4^{2-}) are most significant to Gomti River at Sultanpur affecting the water quality. Studies typically have PCA-Selected parameters as, pH, Dissolved Oxygen, Total Dissolved Solids, Chlorides, Sulphates, and Total Hardness (Kazi et al., 2009; Varol and Sen 2009; Mustapha and Aris 2012; Rashid et al., 2012). Studies on water quality assessment highlight key parameters such as pH, EC, TDS, TA, TH, DO, Na^+, Mg^{2+}, B, and SO_4^{2-}, which are crucial for evaluating water quality in various contexts (Igibah and Tanko 2019; Baloch et al., 2021). These parameters independently contribute to understanding water quality dynamics and potential pollution sources, demonstrating their importance in groundwater quality assessment and suitability analysis for drinking and irrigation purposes (Baloch et al., 2021).

4.6.REGRESSION ANALYSIS

To explore the relationship between water quality indices (WQIs) and PCA-selected parameters, regression analyses were conducted on the original components of the Water Quality Index (WQI) (CPI, SPI, NPI, AWQI) and their counterparts derived from PCA-selected parameters (CPI, SPI, NPI, AWQI). The analysis focused on assessing the influence of five main parameters (pH, TDS, TH, TA, and DO) on each of the four WQIs. Ions were excluded from the analysis due to their inclusion in TDS. These parameters were identified through PCA, aiding in identifying variables contributing significantly to water quality variations. The coefficient of determination (R^2) values from the regression analysis shed light on the proportion of variance in each WQI explained by the selected parameters. Notably, the R^2 values for each WQI are as follows: CPI = 83.37%, AWQI = 82.72%, NPI = 78.54%, and SPI = 12.02%. These high R^2 values signify robust relationships between the selected parameters and their respective WQIs, underscoring the substantial contribution of these parameters to the observed variability in water quality assessments (Sârbu and Pop, 2005; Rashid et al., 2012). All the parameters resulting from PCA were incorporated into each of the four mentioned water quality indices. A regression analysis was conducted, and the resulting index, which accounts for over 80% of the variance, indicates that a large proportion of the variance in WQI is explained by the selected components, suggesting a good fit of the regression model to the data.

CHAPTER 5

CONCLUSION

The comprehensive assessment of the Gomti River's water quality at Sultanpur from 1998 to 2017 reveals significant temporal and seasonal variations in pollution levels, as indicated by calculated water quality indices. The Comprehensive Pollution Index (CPI) data shows notable fluctuations over the years, with values ranging from a high of 0.58 (Slightly Polluted) in multiple years (1998, 2000 and 2002) to a low of 0.38 (Sub-Clean) in 2004. It was observed that 90% of the time, the water quality was classed as Slightly Polluted (0.41-1.00) by the Comprehensive Pollution Index (CPI), with the remaining 10% being classified as Sub-Clean (0.21-0.40). The highest CPI values are observed during the pre-monsoon period, likely due to reduced river flow and higher pollutant concentration. Improvements in CPI values post-2002 suggest the impact of enhanced environmental regulations and pollution control measures. The Synthetic Pollution Index (SPI) values, ranging from 0.13 (Suitable for Drinking) to 0.23 (Slightly Polluted), reflect changes in SPI values, with significant improvements from 2002 (0.17 – Suitable for Drinking) to 2004 (0.13 – Suitable for Drinking) attributed to better pollution control measures. However, a resurgence in SPI values is noted from 2005 (0.16 – Suitable for Drinking), peaking in 2010 (0.23 – Slightly Polluted) and 2012 (0.23 – Slightly Polluted), due to rapid industrialization and urbanization. According to the Synthetic Pollution Index (SPI), 45% and 55% of the water was Suitable for Drinking (≤0.20) and Slightly Polluted (0.21-0.40). Nemerow's Pollution Index (NPI) values, ranging from 0.65 (indicating No Pollution) to 1.15 (indicating Slightly Polluted), indicate significant seasonal and yearly variations, with the highest NPI values observed during the pre-monsoon period and notable improvements during the post-monsoon season due to the dilution effect of rains and enhanced waste management practices. Notably, NPI showed that in 18% of the cases, the water quality was Not Polluted (≤1), but in the remaining 82% of cases, it was Lightly Polluted (1-2). The Arithmetic Water Quality Index (AWQI) values range from 57 (Poor Water Quality) to 76 (Very Poor Water Quality), with significant peaks indicating periods of poor water quality, particularly in 2001, 2005, 2006, and 2007 (as 75). Improvements in AWQI values in 2004 and post-2015 suggest the effectiveness of stringent environmental regulations and advancements in wastewater treatment. However, mostly, the water quality was rated as Poor (51–75%) at 78%, Very Poor (76–100%) at 18%, and Good (26–50%) at a meagre 4% by the Arithmetic Water Quality Index (AWQI).

Cluster analysis representing the monthly variation of pollution levels in Gomti river at Sultanpur and categorization of CPI, SPI, NPI and AWQI by pre-monsoon, monsoon and post-monsoon periods highlights that the pre-monsoon period, i.e., from January to April generally records the highest pollution levels across all indices due to reduced river flow and higher concentrations of pollutants. The monsoon season from May to August shows mixed results, with improvement in pollution levels due to dilution effects. The post-monsoon period from September to December consistently exhibits the best water quality, highlighting the positive impact of continuous dilution and sediment settling. Principal Component Analysis is used to locate the origins of river contamination. The experimental findings demonstrate that, during the course of the study period, TH, TA, pH, DO, TDS, Mg^{2+}, K^+, Na^+, and SO_4^{2-} having a cumulative variance of 65.603% within the dataset—are the primary parameters accountable for affecting the water quality. Based on the regression analysis, we observe that with an R^2 of 83.37% between original WQI_{CPI} and PCA-WQI_{CPI}, primarily five parameters are accountable (pH, TDS, TH, TA, and DO). This finding suggests that these parameters play a dominant role in influencing the composition and variability of water quality as captured by the CPI-based indices.This fundamentally helps to prioritize control efforts concerning various pollution sources.

Based on these findings, several recommendations for policymakers and stakeholders are proposed. Enhanced pollution control efforts, including stricter enforcement of environmental regulations and improved sewage treatment facilities, are crucial. Promoting sustainable industrial practices and better management of industrial waste can significantly reduce pollutants entering the river. Implementing better agricultural practices to minimize fertilizer and pesticide runoff during the monsoon season is essential, and encouraging organic farming and eco-friendly pesticides can also be beneficial. Engaging local communities in pollution control efforts and raising awareness about the importance of maintaining river health can drive collective action toward reducing domestic and industrial pollution. Continuous monitoring of water quality parameters and conducting periodic research to assess the effectiveness of implemented measures will help make informed decisions and adjustments to pollution control strategies. Additionally, investing in infrastructure for better waste management, including advanced sewage treatment plants and efficient waste disposal systems, will support long-term water quality improvement efforts. By addressing these key areas, policymakers and stakeholders can work towards ensuring the sustainable health of the Gomti River, benefiting both the environment and the communities relying on this vital water resource.

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