ASSESSMENT OF EUTROPHICATION STATUS OF SELECTED LAKES OF DHAKA CITY USING GIS AND MACHINE LEARNING ALGORITHM

MD MUNTASIR MAMUN

M.Sc. ENGINEERING THESIS

DEPARTMENT OF CIVIL ENGINEERING
MILITARY INSTITUTE OF SCIENCE AND TECHNOLOGY
DHAKA, BANGLADESH

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Civil Engineering

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DECLARATION

I hereby declare that the study reported in this thesis entitled as above is my own original work and has not been submitted before anywhere for any degree or other purposes. Further I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged and/or cited in the reference section.

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A Thesis

By

Md Muntasir Mamun

DEDICATION

Dedicated to my all family members

ACKNOWLEDGEMENT

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ABSTRACT

Eutrophication in Lakes are caused by the confluence of numerous nutrients (nitrogen, phosphorus etc), temperature, sunshine, dissolved oxygen, land use/land cover, socio-economic condition, and other biophysical processes. Excess nutrients lead to algal blooms, which in turn cause fish mortality, abnormal lake conditions, and an overall disruption of the aquatic ecosystem. Dhaka city's lakes were seen decline in water quality because of excessive urbanization, uncontrolled sewerage disposal that led to Eutrophication. This research set out to evaluate the current and prospective eutrophication levels in five selected lakes in Dhaka city, Bangladesh namely Uttara, Mirpur, Baridhara, Gulshan and Hatirjheel areas. Primary water quality data were measured form collected water samples and secondary satellite imagery data were used to evaluate Trophic State Index (TSI). Calculated TSI from water quality parameters (Chl-a test & TN test) were used to compare and validate the TSI value computed from NDCI. Subsequently, Artificial Neural Network (ANN) model of machine learning algorithm was developed incorporating land use land cover (LULC) and different normalized satellite indices using 1990, 2000 and 2010 imagery that predicted the NDCI of 2021. Predicted NDCI of 2021 was validated using TSI calculated from primary data. ANN model was trained to predict the NDCI value for 2030 and 2040 to evaluate the TSI.

From Carlson's trophic state equation, TSI for Chl-a were calculated as 81.64, 82, 88.61, 88.44 and 90.99, and TSI for TN were found to be 98.53, 94.46, 102.19, 92.42 and 98.39 indicating "Hypertrophic" state for all five lakes. Calculated NDCI and corresponding TSI value from satellite imagery showed 84 to 95 percent similarity with the field measurement TSI values for 2021. Individual calculated TSI from NDCI of 1990 and 2000 imagery revealed "Supertrophic" and 2010 and 2021 imagery showed "Hypertrophic" state for all five lakes indicating lakes are in declined condition. Trained ANN model from 1990, 2000 and 2010 predicted TSI value of 2021 with 81 percent accuracy. This calibrated model further predicted NDCI and corresponding TSI for 2030 as 82.85, 82.28, 84.11, 76.38 & 79.22 and for 2040 as 87, 85.85, 88.07, 79.92 & 84.56 for all five lakes. These predicted results indicate all lakes are "Hypertrophic" condition with higher TSI values. Therefore, these lake water quality monitoring and subsequently proper management should be ensured immediately.

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LIST OF ACRONYMS

WQ	:	Water Quality
DO	:	Dissolved Oxygen
BOD	:	Biological Oxygen Demand
COD	:	Chemical Oxygen Demand
TP	:	Total Phosphorus
TN	:	Total Nitrogen
Chl-a	:	Chlorophyll-a
TSI	:	Trophic State Index
TLI	:	Trophic Level Index
EI	:	Eutrophication Index
RS	:	Remote Sensing
GIS	:	Geographic Information System
RS & GIS	:	Remote Sensing and Geographic Information System
USGS	:	United States Geological Survey
LU/LC	:	Land Use and Land Cover
NDBI	:	Normalized Difference Built-up Index
NDVI	:	Normalized Difference Vegetation Index
NDWI	:	Normalized Difference Water Index
NDTI	:	Normalized Difference Turbidity Index
NDCI	:	Normalized Difference Chlorophyll Index
ANN	:	Artificial Neural Network

CHAPTER 1
INTRODUCTION

1.1 Background

Water is necessary for life and plays an important role in the ecosystem of the earth. It is one of the most important, scarce, valuable, and nonrenewable natural resources on the planet (Jayalakshmi and Velappan, 2015). The growing demand for fresh water and limits on the development of water resources emphasize the significance of protecting current water resources now more than ever (McIntosh and Pontius, 2017). Bangladesh, one of the world's most densely populated countries, has significant water pollution and scarcity (Hasan et al. 2019). Biochemical compounds and heavy metals have increased in water as a result of both industrial and human waste, posing a serious hazard to the aquatic system and public health (Zhou et al. 2018). Fertilizers and pesticides used in agriculture damage groundwater aquifers and contribute to the deterioration of surface water quality (Rahman and Hossain, 2008). Clean water and sanitation, one of the Sustainable Development Goals (SDGs) has been set for implementing integrated water resource management by 2030. Eutrophication is one of the most important problems that impact the quality of water in reservoirs in the global management of surface water resources such as ponds, lakes, canals or even rivers (Sechi and Sulis, 2009).

Lakes are very important for any city. Proper lake function can ease the impact of floods and droughts by storing large amounts of water and releasing it during shortages. Lakes also work to replenish groundwater, positively influence water quality of downstream watercourses, and preserve the biodiversity and habitat of the area. Lakes can provide prime opportunities for recreation, tourism, and residential living. Lakes have historical and traditional values. Lakes of a city can balance aquatic ecosystem and help to support social economic needs. Therefore, preserving lakes inside any city would ensure sustainable development.

By 2030, Dhaka, the capital of Bangladesh, is expected to be the sixth-largest megacity in the world. Due to the unplanned expansion of Dhaka city, this has resulted in deterioration of water quality over the time (Bashar and Fung, 2020). Dhaka is situated in the country's geographic center. It is located in the Ganges and Brahmaputra rivers' large deltaic zone. Lake water usage and quality deterioration have increased rapidly in Dhaka

City. Unplanned urbanization and industrialization are contributing to major environmental degradation. The lake must be developed with care in order to support ecological processes that replenish the groundwater, preserve aquatic life, maintain ecological balance, and create recreational areas around the lake. For the sake of the ecosystem, protecting the lake from pollution should be a top priority (Jan-E-Alam et al. 2017). Out of 360 sqkm land area of Dhaka city, major lakes like Dhanmondi (0.39 sqkm), Ramna (0.25 sqkm), Crescent (0.31 sqkm), Baridhara-Gulshan (2.02 sqkm), Gulshan-Banani (1.61 sqkm) and Uttara (1.86 sqkm) cover around 6.44 sqkm only (Islam, et al. 2012). Whereas a city should have at least 10% (which is 36 sqkm for Dhaka city) water bodies of its land area (Karim et al. 2015).

Physical, chemical, and biological qualities of water are affected by industrial and domestic pollution. The urban run-off, sewage discharge, waste disposal contribute much to water contamination, which will eventually affect humanity. These lakes flow through the heart of Dhaka, getting contaminated by industrial effluents, municipal wastes, sewage, and other toxic substances, posing several health and economic concerns, particularly for the poor and slum inhabitants. Therefore water quality of various lakes of Dhaka city is deteriorating due to the unplanned and excessive urbanization, unauthorized sewerage connection etc. The water of Gulshan Lake has been contaminated by sewage from the Badda, Baridhara, Gulshan, and Banani residential districts, as well as harmful discharges from neighboring enterprises. Lake water chemistry varies seasonally due to pollution and water level, affecting biodiversity (flora and fauna) and ecological stability (Razzak et al. 2013). Water quality of Dhanmondi, Gulshan and other lakes are not suitable for aquatic lives due to the unfavorable environmental condition. To restore the health of both lakes, strict rules must be implemented; illegal encroachment and garbage dumping must be stopped by enforcing existing laws and regulations (Islam et al. 2014).

Figure 1.1: Fish Mortality in Baridhara-Gulshan Lake Area (September 2021)

Dhanmondi Lake's trophic status was recently assessed to be hypertrophic with rapidly declining water quality. Many pollutants enter the Banani lake from residential areas, including human excreta, cow manure, and waste from shops and restaurants, as well as dust from aerial sources (Khondaker et al. 1994). Illegal connections of domestic and industrial wastewaters to the storm sewer network are common in Dhaka, and this has a negative impact on Hatirjheel Lake pollution. Hatirjheel has always been a virtual wasteland, contributing to the decline of water quality in the Begunbari Khal-Balu-Sitalakhya river system (Alam, 2011). Total nitrogen (TN) and total phosphorus (TP) concentration in lake water is a powerful predictor of a variety of measures of lake water quality and ecosystem composition. As lakes age and sediment fills in, eutrophication occurs gradually over decades (Siddika et al. 2015). Excess nitrogen can hasten the eutrophication process, which is the gradual enrichment of natural nutrients in streams, and lakes that causes algae blooms in ponds, lakes, and reservoirs. Algae deplete the DO in the water as they grow and decay. Nutrient overproduction can result in a range of issues, ranging from anoxic waters (due to decomposition) to toxic algal blooms (eutrophication), all of which reduce aquatic diversity and cause habitat damage (Rahman and Hossain, 2008).

Systematic water quality monitoring, risk assessment and preventative measures are very important to address Lake Eutrophication (Liu et al. 2019). Outbreak of algae depends on the interaction of a wide range of biophysical processes and socio-economic factors including nutrients, temperature, sunlight, dissolved oxygen, land use changes etc (Rafiee and Jahangiri-Rad, 2015). Algal blooms are caused by excessive nutrients which cause fish mortality, unusual lake condition and finally aquatic ecosystem imbalance (Srisuksomwong and Pekkoh, 2020). Trophic State Index (TSI), Trophic Level Index (TLI), Eutrophication Index (EI) etc can be derived from the Water Quality Indicators (WQIs) such as Chlorophyll-a concentration (main indicator), Total Nitrogen (TN) which are widely used to assess and predict lake eutrophication status (Xu, Tao, Dawson and Li, 2001). Water quality monitoring in surface waters is critical for obtaining quantitative data on the water's features. The cost and time involved in testing and monitoring water quality in situ might be excessively expensive and time consuming. Satellite photography is an alternate way for monitoring water quality. Several water quality measures have been monitored using remote sensing techniques and capabilities throughout the last few decades. Different satellite sensors have been utilized for water body monitoring depending on the study region (Yigit et al. 2019). No single variable is representative of the lake eutrophication status due to their multidimensional nature. GIS can integrate the lake eutrophication assessment process with multidimensional spatial analysis with the help of satellite/drone images and thematic maps (Huo et al. 2013). GIS is the most appropriate tool for such a geo-spatial assessment and visualization, as it is for many other environmental management tasks. Maps built with sampling water quality data and associated GIS tools can aid decision makers and the general public in comprehending the current situation (Rahman and Hossain, 2008). Future prediction of eutrophication is complex because of the spatial and temporal distributions of lakes that are affected by various climatic, geographical and ecological factors. Machine Learning is able to predict effectively the non-linear relationships among variables that are characteristics of ecosystem. This is also capable of simulating trends of algal growth dynamics and predicting chlorophyll status based on water quality monitoring data (Xu et al. 2001).

Over the last few decades, eutrophication has become a severe problem for aquatic ecosystems, owing to excess nutrients connected with industrial activity. Lake restoration programs strive to return lakes' water quality to, or close to, its natural state (Rabalais et al. 2002). Lake trophic status has become a significant tool for lake managers and researchers. The trophic condition of a lake serves as a proxy for its production, water quality, biological integrity, and compliance with designated usage criteria. Lake water quality affects recreation, habitat and species richness, as well as property and ecological benefits. As a result, monitoring water quality is critical for managing eutrophication and lake productivity (Nojavan et al. 2019). Lake's transition from oligotrophy to eutrophication is a gradual process. The transition from one life stage to the next is based on variations in the amount of nutrient influx and the lake's productivity. The rate of natural processes can be greatly altered by cultural eutrophication, and the life expectancy of the afflicted aquatic body can be significantly reduced. This can be avoided if appropriate conservation measures are implemented (Devi Prasad and Siddaraju, 2012).

In the current study, trophic status of the reservoir and its temporal and spatial variations through physic-chemical analysis of water were determined along with the calculation of indices (Esfandi et al. 2018). Different species have the potential to live in water bodies with varying levels of dissolved oxygen. Eutrophication is a phenomenon in which excess nutrients (nitrogen and phosphorus compounds) in a water body induce algae to bloom, lowering the water quality of the water body (Viet et al. 2016). Cyanobacteria are responsible for a variety of problems with water quality, including the possible generation of toxins and taste-and-odor compounds. A "bloom" is defined as high concentrations of algal cells with a "pea soup" appearance when dense algae populations form, turning water a green or greenish brown tint. Near the surface, dense blooms may resemble a layer of green paint. Algal blooms in the dam environment pose a threat to both recreational and economic activities. Algal blooms arise when a set of favorable environmental conditions exist. These blooms frequently cause dam water to discolor, as well as dissolved oxygen loss, fish mortality, and possibly shellfish poisoning. Dam ecosystems are highly dynamic and complicated systems (Rafiee and Jahangiri-Rad, 2015). When a body of water becomes eutrophicated, it loses its fundamental functions and, as a result, has an impact on the economy and society's long-term sustainability. As a result, solving water eutrophication and restoring the diverse functions of the water system have become major concerns for environmental biologists in recent years (Yang et al. 2008).

1.2 Objectives

This study targeted lakes of Dhaka city to asses and predict eutrophication status in order to achieve "clean water and sanitation", one of the 17 sustainable development goals. In doing so, specific objectives were set to meet the overall objective.

The specific objectives are as follows:

i) To assess eutrophication status of five selected lakes of Dhaka city using remote sensing and GIS.

ii) To predict the future eutrophication status of those lakes using Machine Learning algorithm.

1.3 Scope

Eutrophication is one the major problems of the surface water which is identified by the many researchers around the world. Many studies and researches have been carried out in many developed countries. Very few researches have been found in Bangladesh, but eutrophication is a slow process which is affecting aquatic ecosystem. As a result, it is a less focused area of environmental engineering which should be taken care soon. Therefore, this research focus on to assess eutrophication status from past to present and predict future status.

In doing so, five major lakes of Dhaka city including Uttara, Mirpur, Baridhara, Gulshan and Hatirjheel areas were selected as study area for this research. Initially, satellite images of Landsat data series TM 4-5/OLI-8 (30 meters spatial resolution) of 1990, 2000, 2010 and 2021 were downloaded. These image data were analyzed and Land Use/Land Cover (LU/LC) was classified, and NDVI (vegetation index), NDBI (built-up index), NDWI (water index) and NDCI (chlorophyll index) have been developed of the five selected lakes using RS (remote sensing) and GIS software (ArcGIS). TSI was developed using NDCI values of the lakes.

Chlorophyll-a concentration (main indicator of eutrophication), TN (another indicator of eutrophication), phosphate, dissolved oxygen (DO), Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), pH, Turbidity, Colour, TDS test have been carried out for the five selected lakes with seasonal variations (September to December 2021). TSI was calculated using chlorophyll and TN test data. TSI for Chlorophyll and TN test data (2021) were calibrated with the TSI for NDCI data (2021).

Finally, prediction model was developed to simulate with the help of Artificial Neural Network (ANN) of machine learning using MOLUSCE plug-in of Q-GIS software. LU/LC, NDVI, NDBI, NDWI, NDCI, Water Body were used as input data. Prediction maps of eutrophication status of 2030 and 2040 for the five selected lakes of the Dhaka city were developed.

1.4 Limiting Factors

Limiting factors in this study are given below:

i) Only five lakes of Dhaka city were selected for this study.
ii) Satellite images have been downloaded from landsat-5 TM and Landsat-8 OLI which are 30m resolution.

1.5 Thesis Structure

This paper is structured into following chapters:

Chapter 1: This is the introductory chapter of the thesis paper.

Chapter 2: This chapter summarized the related literatures starting from the history of lakes of Dhaka city followed by water quality parameters and present lake condition. Thereafter lake eutrophication and trophic state index (TSI) followed by RS & GIS technique to identify Chlorophyll-a concentration in the lake water. Finally, adopt machine learning algorithm (Artificial Neural Network-ANN) to predict future eutrophication state of the selected lakes of Dhaka city.

Chapter 3: This chapter discussed about the detail methodology of the thesis.

Chapter 4: This chapter discussed about the data collection. Satellite images were downloaded from the Landsat 4-5 TM and OLI-8 for the image analysis using ArcGIS software. Water samples were collected from the selected lakes for chlorophyll-a concentration calculation to develop TSI. Finally, ANN model was applied to predict eutrophication status in 2030 and 2040.

Chapter 5: This chapter showed and discussed all results found after testing water sample data, different indices of image analysis and predicted eutrophication status of 2030 and 2040.

Chapter 6: Concluding remarks and few recommendations were suggested in this chapter.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This chapter will discuss elaborately literatures related to eutrophication, water quality, estimation of chlorophyll concentration using remote sensing and geographic information system (RS & GIS), trophic state index (TSI) and finally prediction method using machine learning algorithm (Artificial Neural Network-ANN).

2.2 Eutrophication

Eutrophication is currently recognized by the whole scientific community as the greatest threat to water quality (Opiyo et al. 2019). Eutrophication is currently the largest threat to the world's water bodies, and this scenario is expected to persist for at least the next decade (Downing, 2014). The Greek term "Trophi" means "food" or "nutrition," whereas the phrases "oligo," "meso," "eu," and "hyper" denote "rare," "moderate," "abundant," and "excessive," respectively. As a result, biologists have coined the terms oligotrophic, mesotrophic, eutrophic, and hypertrophic to represent the varied nutritional levels of a marine or freshwater habitat. "Eutrophication" is defined as "the accelerated growth of algae on higher forms of plant life caused by the enrichment of water with nutrients, particularly nitrogen and/or phosphorus compounds, causing an undesirable disturbance to the balance of organisms present in the water as well as the water's quality" (Klein and Perera, 2002).

The most common cause of eutrophication is anthropogenic pollution of water with excessive nutrients. This has the effect of rapidly increasing biomass, which can have both beneficial and bad consequences (Davis and Shaw, 2009). Excessive plant and algal growth indicate eutrophication, which is caused by increased availability of one or more limiting growth sources for photosynthesis, such as sunshine, carbon dioxide, and nitrogen fertilizers (Schindler, 2006). Eutrophication occurs naturally over centuries which are known as natural eutrophication. Human activities have accelerated the rate and extent of eutrophication, which is known as cultural eutrophication (Walter et al.

2001). The most visible consequence of cultural eutrophication is the formation of dense blooms of toxic, foul-smelling phytoplankton, which lower water clarity and degrade water quality (Lehtiniemi et al. 2005). When dense algal blooms die, microbial breakdown depletes dissolved oxygen, resulting in a hypoxic or anoxic 'dead zone' where most species are unable to survive. During the summer, dead zones can be observed in many freshwater lakes (Arend et al. 2011).

Bloom is a greenish floating waste produced by cyanobacteria on the surface of a water body that pollutes the water and is linked to respiratory and skin irritation issues (Morris and Monier, 2003). When algae and zooplankton die and descend to the bottom of a water body, bacteria decompose them, lowering the concentration of dissolved oxygen in the water body to levels that may not be enough to support fish existence (Nishimura et al. 2002). Algae can produce poisons and cause organic substances in water to degrade into poisonous fumes, poisoning fish and seashells (Carmichael, 2001). Furthermore, eutrophication-related high rates of photosynthesis can deplete dissolved inorganic carbon and elevate pH to dangerously high levels during the day (Turner and Chislock, 2010). Eutrophication is the sum of the effects of excessive phytoplankton growth leading to imbalanced primary and secondary productivity and a faster rate of succession from existence to higher serial stage (Khan and Ansari, 2005).

Water is not a commodity like any other, but rather a cultural property that must be defended and preserved, especially in the face of a global shortage of drinking water and a rise in demand. The eutrophication process is a complex subject that will necessitate the collaboration of scientists, policymakers, and citizens (Scannone, 2016). Eutrophication was recognized as a pollution problem in many European and North American lakes and reservoirs in the mid-nineteenth century (Davis and Shaw, 2009). Comprehensive guidelines for assessing eutrophication should be developed by taking into account a variety of factors in conjunction with the development of the economy and society (Yang et al. 2008). Controlling and managing cultural eutrophication is a difficult task that will involve the collaboration of scientists, policymakers, and citizens to limit nutrient inputs, create effective, long-term biomanipulation techniques, and restore aquatic communities (Chislock et al. 2013). Non-linear mathematical model can be utilized to investigate eutrophication of a lake caused by an excessive supply of nutrients (Misra, 2007).

2.3 Water Quality (WQ) Assessment Using RS & GIS

Water quality is described in terms of its physical, chemical, and biological aspects and assessed as a water quality index (WQI) to determine whether or not it is potable. The Water Quality Index (WQI) is a single number that indicates the total water quality at a given place based on a number of water quality criteria (Jayalakshmi and Velappan, 2015). For any intended purpose, the WQI specifies the quality of water in terms of an index number. Chlorophyll-a, water clarity, turbidity, and suspended particle matter (SPM) are the most important markers of water quality (Kabbara et al. 2008). Researchers identified that in eutrophicated water bodies, DO concentration is unstable. Generally, the physical and chemical evaluation parameters were used to assess water eutrophication, mainly nutrient concentration (N and P), algal chlorophyll, water transparency and dissolved oxygen (Cheng and Li, 2006). Detailed water quality metrics such as suspended sediments, water clarity, chlorophyll-a, and turbidity can be assessed using Landsat data series (Buhan et al. 2016).

Globally, Remote Sensing (RS) and Geographic Information Systems (GIS) are extensively employed to monitor water quality. The advancement of GIS and spatial analysis allows us to integrate laboratory data with geographic data, as well as simulate the geographical distributions of water quality parameters with more rigor and accuracy (Mouna et al. 2011). Reflectance spectroscopy is a rapidly developing technology that can be used to extract valuable information about surface materials with only a few in-situ measurements. Hyperspectral images, on the other hand, enable for better detection of chlorophyll and thus algae due to the narrow spectral bands collected between 450 and 600 nm which is time saving technology (Rostom et al. 2017).

Optical RS technologies have proven to be beneficial and successful in estimating and mapping water quality elements such as dissolved organic matter, chlorophyll, and total suspended matter concentrations (Fichot et al. 2016). Suspended sediments boost the brightness emitted by surface water in the visible and near infrared (NIR) portions of the electromagnetic spectrum, making spectral fingerprints in the visible and NIR bands promising and practicable for detecting water contaminants (Wen and Yang, 2011). Because of the significant absorption of the red and blue wavelengths and the reflection of the green wavelengths, the human eye perceives healthy vegetation as green. There is less adsorption in the red and blue regions, and the quantity of reflection in the red wave band increases when the plant is stressed, which inhibits normal growth and chlorophyll production (Abou El-Magd and El-Zeiny, 2014). Many researchers use the visible and near infrared bands of the solar spectrum (mostly from blue to near infrared region) in their studies to obtain robust correlations between water column reflection (in some cases emission) and physical and biogeochemical constituents, such as transparency, chlorophyll concentration (phytoplankton), organic matters, and mineral suspended sediments in various waterbodies (El-Din et al. 2013).

Although in-situ measurement of water quality indicators, including physical, chemical, and biological qualities; provides excellent accuracy, but it is a labor-intensive and time-consuming operation (Duan et al. 2013). Laboratory examination, in order to determine reservoir eutrophic conditions, can be used for assessment of current year. The reservoir's eutrophication zone maps can be created using ArcGIS and the traditional Kriging method (Esfandi et al. 2018). One of the most prominent supervised classification methods for remote sensing image data is maximum likelihood. This approach is based on the likelihood of a pixel belonging to a specific class. The basic idea implies that all classes have the same probabilities and that the input bands have normal distributions. The ArcGIS program is an effective tool for mapping the spatial distribution of physicochemical characteristics (Al-Dahhan et al. 2019). Several researchers used remote sensing technology to classify and analyze the trophic status of lakes. A geographic information system (GIS) can be used to execute a variety of basic spatial analysis functions (Xu et al. 2001).

2.4 Eutrophication Estimation Using RS & GIS

Chlorophyll-a is the most important indication of trophic status. It mostly reflects green; it absorbs the majority of energy from violet-blue and orange-red light wavelengths, which cause chlorophyll to appear green. Obviously, adding chl-b to the mix in addition to chl-a increases spectrum absorption. Low light circumstances favor the synthesis of chl-b to chl-a molecules in a higher ratio, boosting photosynthetic output. The absorption spectrum of both the Chlorophyll-a and Chlorophyll-b pigments are shown in Figure 2.1 (Schlichter et al. 1997).

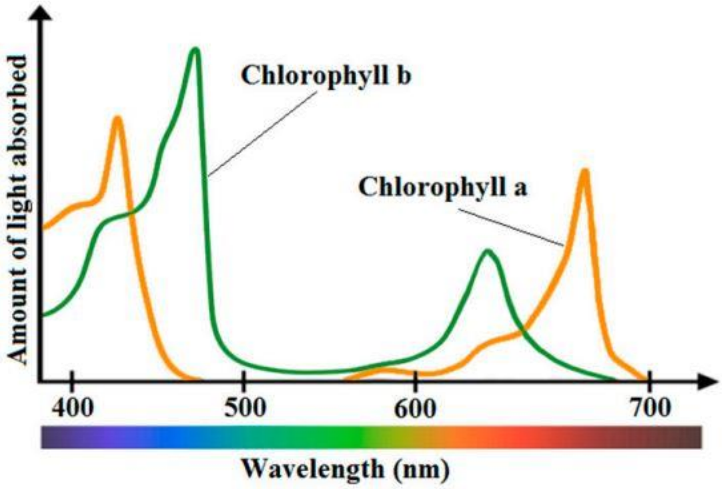

Figure 2.1: Absorption Spectrum of Chl-a and Chl-b Pigment (Schlichter et al. 1997)

Plants use chlorophyll pigments (chlorophyll a and chlorophyll b) to absorb light energy for photosynthesis, and these vital pigments are present in the highest concentrations in healthy leaf material (Croft et al. 2017). The use of chlorophyll as an eutrophication indicator should be seen in the context of a more comprehensive understanding of eutrophication (Doering et al. 2006). Planktonic algae proliferation is a major cause of aquatic life loss and harm to aquatic ecosystems and water functioning in lakes (Li et al. 2017). The radiometric and limnological data collected after each field campaign was combined into a single dataset that was used to calibrate the methods (Augusto-Silva et al. 2014). Moderate resolution data from Sentinel-1, Landsat-8 and Sentinel-2 can be used for water body extraction and water quality monitoring, and MODIS (Moderate Resolution Imaging Spectroradiometer) can be employed for water quality evaluation (Politi and Prairie, 2018).

The use of remote sensing techniques in the estimation and development of maps of chl-a levels are found to be a useful tool for monitoring and assessing water quality in both marine and fresh waterways (Buditama et al. 2017). Several techniques for chl-a mapping have been devised and tested in marine environments, estuaries, and freshwater masses (Kaymaz, 2018). Currently, satellite photos are being employed in the field of research. The accuracy of the results obtained from satellite photos should be checked by comparing them to the laboratory results (Şeyma and Ersin, 2018). Many satellite borne sensors have improved capabilities with respect to spectral, radiometric, temporal, and spatial resolutions, data from satellite sensors may provide better information on chl-a variability than conventional field monitoring (Tyler et al. 2016). Before employing satellite datasets, it is necessary to do a detailed examination of the local correlations between in situ-measured chl-a and spectral bands of airborne or handheld sensors for a geographic and/or seasonal region (Xie et al. 2015). Researcher examined the performance of several algorithms based on spectral bands to estimate chl-a in a shallow, turbid, productive tropical estuarine-lagoon system using in situ reflectance spectra (Lins et al. 2017).

Water remote sensing is based on the observation of the water colour from a distance, without taking water samples (Hussein and Assaf, 2020). As a result, the use of satellite remote sensing techniques, defined as a technique for estimating geophysical parameters from electromagnetic energy reflected or emitted from the earth, based on water's optical properties (Pielke Sr, 2013). Remote sensing techniques have been widely used to measure the qualitative parameters of water bodies. There can be eleven water-quality parameters (WQP) measured by remote sensing techniques. These parameters are chlorophyll-a (chl-a), coloured dissolved organic matters (CDOM), Secchi disk depth (SDD), turbidity, total suspended sediments (TSS), water temperature (WT), total phosphorus (TP), sea surface salinity (SSS), dissolved oxygen (DO), biochemical oxygen demand (BOD), and chemical oxygen demand (COD). Chlorophyll absorbs most of violet-blue and orange-red wavelengths, reflects green, and decreases short wavelengths' response (particularly blue band wavelengths) (Gholizadeh et al. 2016). In order to validate satellite imagery analysis, evenly distributed in situ data collections over the lake should be calibrated (Zhang et al. 2009).

Chlorophyll a (chl a) is a pigment found in phytoplankton and is one of the Water Framework Directive (WFD)'s primary metrics for determining the trophic state of water (Matthews, 2011). Furthermore, chlorophyll is a key indication of phytoplankton biomass and can be used to assess water clarity (Salem et al. 2017). Phytoplankton blooms are natural occurrences in the water environment that demonstrate how a water ecosystem functions normally (Carstensen et al. 2015). Toxic cyanobacteria blooms or excessive blooms produced by human impact, on the other hand, cause environmental issues that affect inland waters directly by lowering water quality and indirectly by restricting the use of drinking water, fishing, and swimming (Ansper and Alikas, 2018).

RS is increasingly being employed to monitor and map Harmful Algal Blooms (HABs) in aquatic systems, because it can collect synoptic data over many spatial and temporal dimensions (Kutser et al. 2020). It has been demonstrated that satellite and airborne optical remote sensing can estimate concentrations of, and changes in, parameters such as chlorophyll-a (Chl-a), phycocyanin, and turbidity, which are common indicators used to estimate the presence and intensity of HABs (Kudela et al. 2015). Satellite and airborne optical remote sensing have been shown to estimate concentrations and changes in parameters such as chlorophyll-a (Chl-a), phycocyanin, and turbidity, which are commonly employed to measure the presence and intensity of HABs (Mchau et al. 2019). Ideally, the water quality sampling can be planned in advance to take place on a cloud-free day coincident with satellite overpass. However, in reality, many water quality samples do not exactly match cloud-free satellite observations in time due to survey logistics constraints and the uncertainty of weather conditions (Wang et al. 2020). Blue to green spectral bands are favorable for determining Chl-a concentrations in clear (oligotrophic) water conditions, whereas red and near-infrared bands are preferred in high-biomass and turbid coastal and inland waters (Moses et al. 2009).

Algal blooms, which are frequently triggered by eutrophication in freshwater, are linked to chl-a concentrations since it is required for photosynthesis (Lim and Choi, 2015). Increasing chl-a concentration produces a decrease in spectral sensitivity at short wavelengths, especially in the blue band, according to many studies (Brivio et al. 2001). To quantify chl-a, various visual spectral bands and their ratios are commonly used. In the remotely detected signal, spectral band ratios can diminish irradiance, atmospheric, and air-water surface impacts (Lillesand, et al. 2014). The spectral areas 630–645 nm, 660–670 nm, 680–687 nm, and 700–735 nm were discovered to be prospective regions where the first derivatives might be utilized to estimate chlorophyll content (Han and Jordan, 2005). Researcher discovered that the reflectance curve and baseline from 672 to 742 nm (CHRIS spectral Bands 8–12) have the strongest correlation and sensitivity to chl-a concentration fluctuations (Mannheim et al. 2004).

Landsat-8 OLI bands to assess chl-a concentration and used Band 2, Band 5, and a ratio of Band 2/Band 4 can be used (Kim et al. 2014). Researcher also introduced the Normalized Difference Chlorophyll Index (NDCI) to forecast chl-a concentration (Mishra and Mishra, 2012). Maximum chlorophyll index (MCI) was used to exploit the height of the measurements in a certain spectral band above a baseline which passes through three bands B4 (665 nm), B5 (705 nm), and B6 (740 nm) (Alikas et al. 2010). Three different remotely sensed indices can be used to represent three different water quality parameters; maximum chlorophyll index (MCI), green normalized difference vegetation index (GNDVI), and normalized difference turbidity index (NDTI) (Elhag et al. 2019). While satellite data allows for repeated land surface measurements, NDVI is known to be saturated at high biomass and is not sensitive enough to leaf chlorophyll content to give an early warning of chlorophyll loss in broadleaf species (Morley et al. 2020). Normalized Difference Water Index (NDWI) has been widely used for water bodies extraction (McFeeters, 1996). Normalized Difference Chlorophyll Index (NDCI), but instead of red, uses the red-edge band. Normalized Difference Turbidity Index (NDTI) uses red and green reflectance for estimating the turbidity in water bodies. However, the same index has been used for chlorophyll-a estimation (Watanabe et al. 2017).

2.5 Calculation of Trophic State Index (TSI)

The higher the concentration of chlorophyll-a, the worse the water quality, and hence it can be used as a primary indication of water body trophic state (Hosmani, 2010). The trophic status of aquatic ecosystems is determined by nutrient dynamics (Jekatierynczuk-Rudczyk et al. 2014). The trophic condition must be assessed before conservation and management measures can be developed (Sharma et al. 2010). Various researchers have classified lakes using a variety of approaches and indexes. The Trophic Status Index (TSI) is a widely used metric for determining the trophic state or overall health of a lake. As Carlson's Trophic State index needs minimum data and easy to understand, it is ideal for volunteer water conservation program and to educate the common man regarding the threats to the water bodies like lakes and conservation strategies that can be adopted (Devi Prasad and Siddaraju, 2012). Trophic state can be utilized as a public communication tool as well as a management tool to give scientific agreement on eutrophication and lake character. Given its wide relevance and extensive history, it's critical to examine and update the methods for calculating trophic state on a regular basis (Farnaz et al. 2019). It is debatable whether production refers to the rate of phytoplankton growth (productivity) or algal weight or biomass (production), but because biomass is easier to quantify and can be immediately translated into many of the lake management issues, researchers focus on biomass (Carlson and Simpson, 1996).

Many research focused on predicting Chl-a concentrations and identifying key factors that support their production, such as temperature, water retention time, water level, photoperiod, macrophyte presence, and zooplankton herbivory (Yang et al. 2008). Researchers have used the equation of TSI of Carlson to estimate and classify the degree of eutrophication uses three limnological parameters, such as Chl a (µg/L) (Cuevas Madrid et al. 2020). The TSI model was created by Carlson for lakes with few rooted aquatic plants and low non-algal turbidity which is useful for the researchers. At the same time, landsat satellite imagery with 30-meter spatial resolution (freely available) is cost effective and available throughout the late summer season, allowing for TSI calculation (Fuller and Jodoin, 2016). TSI is a numeric index of lake trophic state on a scale from 1 to 100, where a higher number indicates greater nutrient enrichment (Vollenweider et al. 1998).

There are many types of TSI mentioned as follows:

i) TRIX Index: This index represents the linear combination of the logarithm of four state variables such as Chl-a, DO, N, TP.

ii) Carlson's Trophic State Index (TSI): The concept of trophic status is based on the fact that changes in nutrient levels.

iii) Trophic Diatom Indices: The diatom trophic indices describe diatom distribution in relationship to either “dissolved” (orthophosphate) or “total” phosphorus, that are mostly closely correlated with the nitrogen concentration in the water.

iv) Benthic Trophic State Index: The benthic TSI is determined by comparing the rates of sediment–water oxygen exchange in opaque (dark) and transparent (light) chambers incubated at or near room temperature.

v) Oligochaete Trophic Index: The association of oligochaetes with organic enrichment of water was used to develop the “oligochaete trophic index.”

vi) Trophic Level Index (TLI): Four parameters are combined to construct the TLI. These are concentrations of total nitrogen, total phosphorus, and chlorophyll a, and transparency.

vii) Trophic Index of Macrophytes: Concentrations of soluble reactive phosphorus in both the water body and sediment pore water were assigned to macrophyte species and related to their phosphorus demand.

viii) Infaunal Trophic Index: The method is based on categorizing macroinvertebrate species into one of four groups based on the sort of food they consume and where they get it.

ix) Marine Trophic Index: The trophic level of a consumer is calculated by adding one level to the mean trophic level of its prey.

x) Index of Trophic Completeness: The ITC is a trophic completeness measure based on freshwater macroinvertebrate communities.

Above indices were used by many researchers many a times in different studies (Pavluk and Bij, 2013).

Trophic Level Index (TLI) can be calculated using following equations:

$$TLI\ (Chl\text{-}a) = 10\ [2.5 + 1.086\ \ln(Chla)]$$

$$TLI\ (TP) = 10\ [9.436 + 1.624\ \ln(TP)]$$

$$TLI\ (TN) = 10\ [5.453 + 1.694\ \ln(TN)]$$

$$TLI\ (SD) = 10\ [5.118 - 1.94\ \ln(SD)]$$

$$TLI\ (COD) = 10\ [0.109 + 2.661\ \ln(COD)]$$

Researchers used Chl-a, TP, TN, SD and COD, and identified high levels of TN and TP resulted in noticeable eutrophication of the lakes during the summer (Liu, Zhang, Sun, Wu and Chen, 2019).

Carlson developed Trophic State Indices as follows:

$$TSI(SD) = 60 - 14.41\ \ln(SD)$$

$$TSI(Chl\text{-}a) = 9.81\ \ln(Chl) + 30.6$$

$$TSI(TP) = 14.42\ \ln(TP) + 4.15$$

$$TSI(TN) = 54.45 + 14.43\ \ln(TN)$$

Chlorophyll can be utilized as the major index because it is a direct estimator of algal weight. Total phosphorus and Secchi depth should only be used to estimate trophic state if chlorophyll readings are unavailable since they have interferences and are not completely related to algal biomass. Trophic state categorization is the classification of a waterbody's current status along a trophic state axis (Carlson, 2007).

2.6 Machine Learning Algorithm-Artificial Neural Network (ANN)

Different ANNs have been investigated for water quality prediction because of their capacity to learn the temporal dynamics of a system with less input data and efficiency in handling nonlinear problems (He et al. 2014). Various methodologies, ranging from regression-based methods such as linear and multilinear regression to watershed models, can be used to investigate the effects of LULC on water quality and quantity. Several researches have been conducted to better understand the relationship between LULC and river water quality (Ouma et al. 2020). ANN, one of the branches of Machine Learning Algorithm, is a type of information processing model inspired by organic nerve systems. The paradigm's structure is the most important factor. It consists of a huge number of highly interconnected processing neurons that work together to solve problems. In ANN applications, back-propagation is a typical learning algorithm (i.e., BP-ANN). The weights in the network are determined using a gradient descent approach. There are three or more layers in an ANN: an input layer, hidden layer(s), and output layer. The input layer contains input nodes (neurons), which are the network's input variables. The hidden layer normally contains a series of nodes associated with a transfer function, while the output layer contains the system's desired output. Weights connect each layer of the network, which must be determined using a learning method (Huo et al. 2014).

ANN can use known input data without making any assumptions. The ANN creates a mapping of input and output variables that can then be used to anticipate desired outcomes based on appropriate inputs. By selecting a sufficient set of linking weights and transfer functions, a multi-layer neural network may approximate any smooth, measurable function between input and output vectors. The back propagation neural network (BPNN) can be utilized for prediction based on the classification results (Fu et al. 2010). One of the most important responsibilities of an ANN is to identify the model input variables that have a substantial impact on the output variable (s). In general, input variables are chosen based on priority knowledge of causal variables, time series plot inspections, and statistical analysis of probable inputs and outputs (Palani et al. 2008). The ANN model incorporates a number of extremely flexible function approximations that can be applied to a variety of water resource applications. The ANN model has been validated in limnological, river, and coastal systems by many researchers (Zhang et al. 2015).

Where domain knowledge of ecosystem processes is insufficient, ANNs have the ability to identify helpful models. A typical neural network is made up of several pieces known as neurons or nodes. Direct communication links connect each neuron to other neurons, and each link has a weight associated with it. (Mozejko and Gniot, 2008). Because of the training to learn the association with data, a back-propagation neural network is suitable for predicting. There were three layers in the model: input, hidden, and output. Iteration was used to determine the number of hidden layers, which took into account a mean squared error value and a correlation coefficient (Srisuksomwong and Pekkoh, 2020). The use of water quality indicators (WQIs) to anticipate eutrophication levels in lake waters is common. However, there are two factors that make prediction problematic. On the one hand, diverse climatic, geographical, and ecological factors have influenced the spatial and temporal distributions. The indications, on the other hand, are interdependent and linked, adding to the complexity of prediction (Huo et al. 2013).

Environmental monitoring, ecological sustainability, and human health all rely on accurate water quality predictions. Furthermore, for early control of intelligent aquaculture in the future, forecasting future changes in water quality is a requirement (Fijani et al. 2019). Traditional methodologies are unable to match the demands of researchers as data volume grows. ANN models, often known as data-driven models, have progressed as computing capacity has increased (Chen et al. 2020). ANN models work even when the underlying relationships of the collected data are difficult to articulate. Furthermore, as compared to traditional techniques, ANN requires fewer prior assumptions and can achieve higher accuracy (Li et al. 2019). In addition, because of their similarities to the brain nervous system, ANN is well suited to handling non-linear and unpredictable issues and become a hotspot in water quality research (Zhang et al. 2017). Water quality is crucial in any aquatic system because it can influence aquatic creature growth and represent the extent of pollution (Han et al. 2012). Water quality prediction is the process of predicting how water quality will change over time (Chen et al. 2018). ANN can be used to predict Chlorophyll-a (Chl-a) levels in the environment of dams. In terms of minimizing the effects of dam algal blooms, this predictive technology allows for proactive rather than reactive management regimens (Rafiee and Jahangiri-Rad, 2015).

2.7 Important Findings from Literature Review

Different types of eutrophication status were identified in lakes along with causes, effects and future consequences. Various types of water quality parameters and trophic status with their relation were also found. Trophic State Index (TSI), Eutrophication Index (EI), and Trophic Level Index (TLI) are used to classify lake trophic status and TSI is selected by many researchers. Carlson's TSI equations were found to calculate trophic status. Using different RS sensors, algal bloom is identified and Chl-a concentration is calculated. It was mentioned in many papers that Chl-a concentration is a prime indicator and TN is also an indicator to get an idea on the algal bloom quantity. From the satellite imagery, different type of indices such as NDVI, NDBI, NDWI and NDCI are calculayed and LU/LC is classified. GIS can integrate all field and satellite data effectively for better analysis. ANN model is widely used in all over the globe for future prediction. In this area of study, many research papers found in developed countries whereas very few research papers found in Bangladesh. Therefore, eutrophication is less focused in Bangladesh. Due to the less priority, water bodies in Bangladesh are not taken care properly. As a result, aquatic ecosystem of Dhaka city is already in danger as population density and all kind of pollution are highest here. It is now time demanding matter to focus on this issue in Bangladesh especially in Dhaka.

2.7.1 There are many sensors available around the globe. Researchers use limited sensors for the specific purpose. For the water quality assessment, available satellite sensors are as shown in Table 2.1.

Table 2.1: Sensors Used in Water Quality Assessment (Gholizadeh et al. 2016).

Category	Satellite-Sensor	Spatial Resolution (meter)	Revisit Interval (day)
High Resolution	Digital Globe World View-1	0.5 m	1.7
	Digital Globe World View-2	1.85-0.46 m	1.1
	NOAA World View-3	1.24-3.7-0.31 m	1-1.45
	Digital Globe Quickbird	2.62-0.65 m	2.5
	GeoEye-1	1.65-0.41 m	3
	SPOT-5 HRG	2.5-5-10-20 m	2-3
Moderate Resolution	Landsat-8 OLI/TIRS	30-15-100 m	16
	Landsat-7 ETM+	30-15-60 m	16
	Landsat-5 TM	30-120 m	16
	Landsat-5 MSS	80 m	18
Regional Global Resolution	Terra MODIS	250-500-1000 m	1-2
	Envisat-1 MERIS	300-1200 m	Daily

2.7.2 Spectral bands and their ratio are utilized for measuring specific index to identify desired signature. Different combinations of bands indicate various type of ground and water body condition. To calculate various indices, available band combination are shown in Table 2.2

Table 2.2: Spectral Bands with Ratio to measure Chl-a (Gholizadeh et al. 2016).

Band Combination	Sensor
Ration between Green and Red	Landsat 5-TM, Landsat 5-MSS, Landsat 7-ETM+, SPOT, IRS-LISS-III
Ration between Near Infrared (NIR) and Red	Landsat 5-TM, HICO, PROBA-CHRIS, MODIS, MERIS, AISA
Ration between Green and Blue	Landsat 5-TM, Landsat 7-ETM+, MERIS, PROBA-CHRIS, EO-1 Hyperin
Ration between Blue and Red	Landsat 5-TM, Landsat 7-ETM+

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This chapter explains in details the methodology and the key issues in implementation of the research including study area. Two types of data have been collected namely water sample from the selected lakes as primary data and satellite imagery downloaded from the freely available website as secondary data.

3.2 Selection of Study Area

Dhaka is the capital of Bangladesh. Dhaka City is densely populated in the world (8th largest megacity). Geographically Dhaka is located between 23˚40´ and 23˚54´ North latitudes and 90˚20´ and 90˚28´ East longitudes (as shown in Figure 3.1).

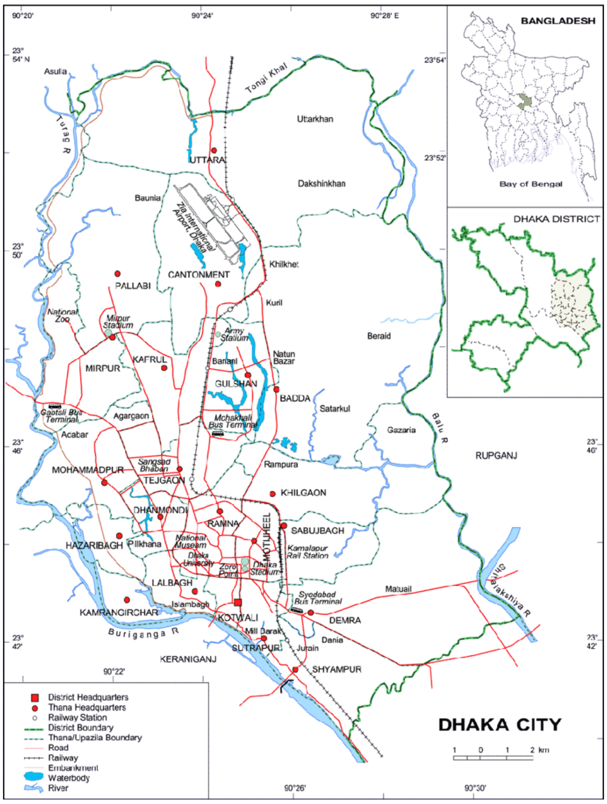

Figure 3.1: Basic Topographic Features of the Dhaka City (Ishtiaque et al. 2014)

Five major lakes of Dhaka City Corporation including Uttara, Mirpur Gulshan, Baridhara and Hatirjheel area were selected as study area of this research. All five lakes fall under Dhaka North City Corporation (DNCC). These areas were selected because of varying urbanization pattern and locations. Average length and width of the Uttara, Mirpur Baridhara, Gulshan and Hatirjheel lakes are 6100 feet by 300 feet, 4600 feet by 700 feet, 5995 feet by 400 feet, 7100 feet by 500 feet and 11,850 feet by 550 feet respectively.

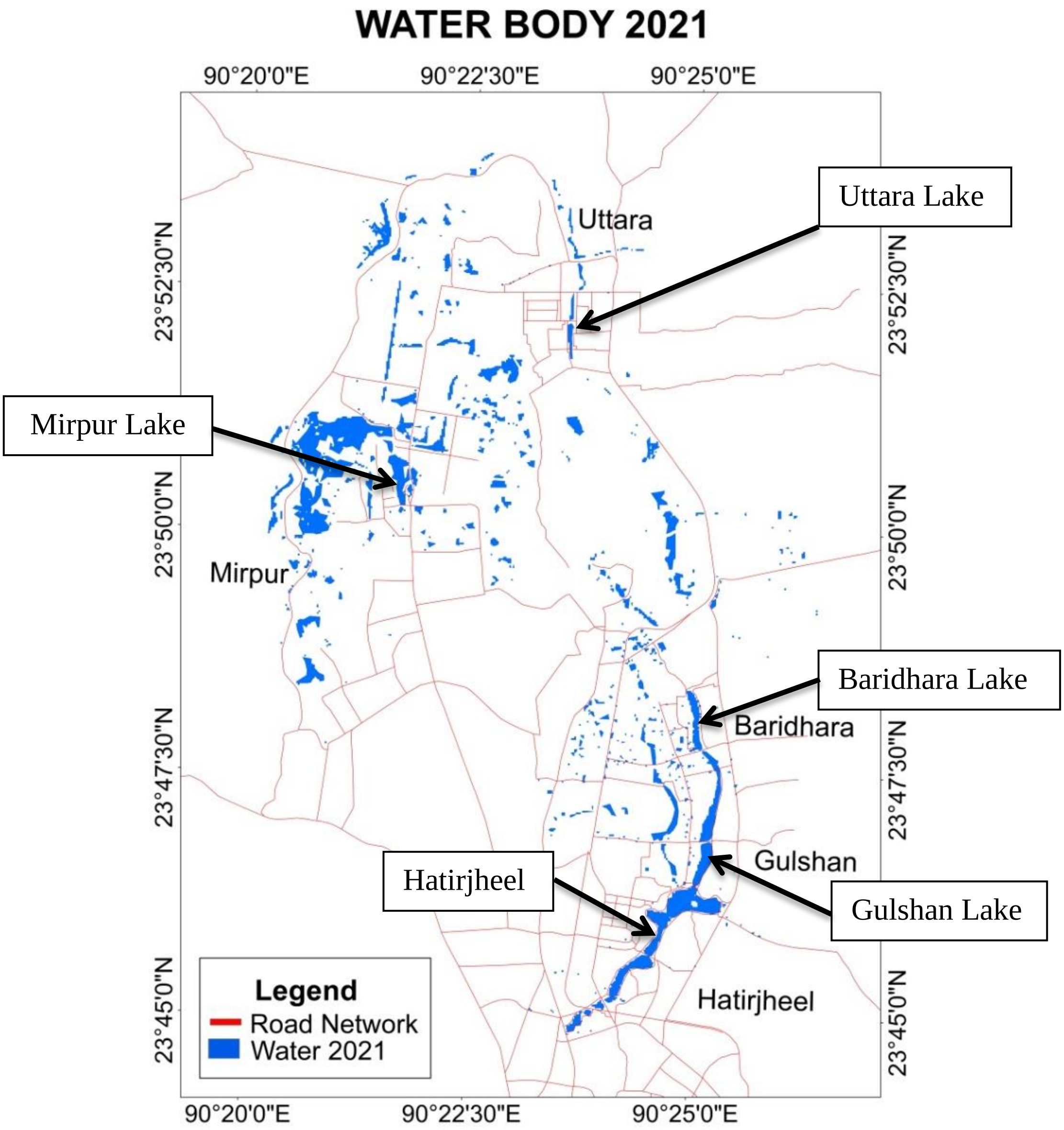

Figure 3.2: Five Selected Lakes of Dhaka City

3.3 Research Conceptual Design

Research is conceptualized as follows:

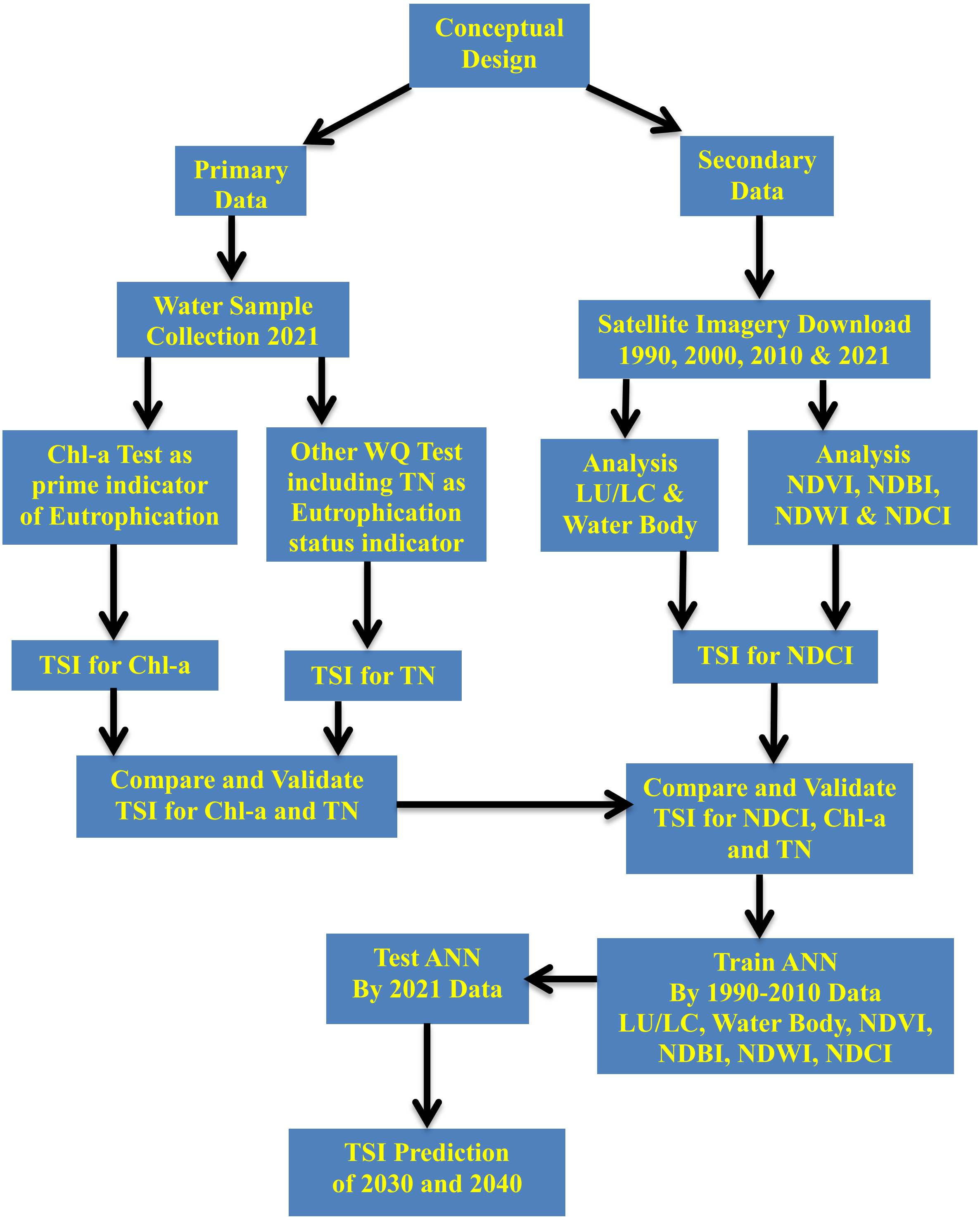

Figure 3.3: Research Flow Chart

3.4 Testing of Water Quality Parameters

Spectrophotometry was used to test Chlorophyl-a concentration, TN, Phosphate, COD and water colour. DO meter used to test DO and BOD. pH meter was used to test pH. Turbidity meter was used to test turbidity. EC meter was used to test TDS

3.5 Calculation of Trophic State Index (TSI) for Chl-a and TN

Trophic State Index (TSI) was calculated from Chlorophyll-a concentration and Total Nitrogen (TN) which are obtained from water sample data of 2021 using widely used and recommended Carlson's equation (Carlson, 2007).

TSI (Chl-a)=9.81xLn(Chl-a)+30.6----------------------------------(3.1)

Where Chl-a is measured in micro-gram per litre and corresponding value of TSI denote whether eutrophic or not.

TSI (TN) = 54.45 + 14.43 ln(TN)------------------------------------(3.2)

Where TN is measured in mg/L and corresponding value of TSI denote whether eutrophic or not.

The final value obtained from the equation indicates the Trophic Status with an index ranging from 0-100. TSI value 0-40 indicates Oligotrophic aquatic ecosystem (Low ecological productivity), 40-50 indicates mesotrophic (Moderate ecological productivity), 50-70 indicates eutrophic (High ecological productivity) and 70-100 indicates hypereutrophic (highest ecological productivity). Chlorophyll-a is reflective of high phytoplankton abundance in the water (Opiyo et al. 2019).

Water sample test data were calculated by using equation 3.1 and 3.2 to find out TSI values. These values were plotted in the following table 3.1 to identify trophic status.

Table 3.1: Carlson's Trophic State Index (TSI)

TSI	Trophic Status	Remarks
0-40	Oligotrophic	Less nutrients
40-50	Mesotrophic	Moderate nutrients
50-70	Eutrophic	Abundant of nutrients
70-100	Hypertrophic	Excess of nutrients

3.6 Calculation of Various Indices

Four indices were calculated using following formulas:

NDVI: The formula of estimating NDVI from Landsat images is stated below (Yuan and Bauer, 2007):

$$NDVI = \frac{R_{NIR} - R_{red}}{R_{NIR} + R_{red}} \quad \text{------------------------(3.3)}$$

Where R_{NIR} and R_{red} denote the spectral reflectances in the red and near-infrared bands of the TM and OLI, respectively. This NDVI equation produces values between 1 and 1, with positive values representing vegetated areas and negative values representing non-vegetated surface features such as water, barren, clouds, built-up area, and snow.

NDBI: NDBI can be calculated by following formula (He et al. 2010).

$$NDBI = \frac{R_{SWIR} - R_{NIR}}{R_{SWIR} + R_{NIR}} \quad \text{------------------------(3.4)}$$

Where, R_{NIR} is the near Infrared band of Landsat TM and OLI and R_{SWIR} is the short-wave Infrared (SWIR) for Landsat TM and short-wave Infrared (SWIR) 1 for Landsat OLI.

Additionally, the NDBI value ranges from -1 to +1. The negative number of NDBI corresponds to water bodies, whereas the positive value corresponds to built-up regions. Vegetation has a low NDBI value (Macarof and Statescu, 2017).

NDWI: Gao (1996) developed the NDWI and the generic formula for estimating the NDWI is specified below (Jackson et al., 2004):

$$NDWI = \frac{R_{NIR} - R_{SWIR}}{R_{NIR} + R_{SWIR}} \qquad \text{-------------------------(3.5)}$$

Where, RNIR is the near Infrared band of Landsat TM and OLI and RSWIR is the short-wave Infrared (SWIR) for Landsat TM and short-wave Infrared (SWIR) 1 for Landsat OLI.

NDCI: The formula of extracting NDCI for the water is stated below (Buma and Lee, 2020).

$$NDCI = \frac{Band_{T4,O5} - Band_{T3,O4}}{Band_{T4,O5} + Band_{T3,O4}} \qquad \text{-------------------------(3.6)}$$

Hence, $Band_{T4}$ or $Band_{O5}$ are the NIR bands, and $Band_{T3}$ and $Band_{O4}$ are the red bands of Landsat TM and OLI correspondingly.

3.7 Calculation of TSI for NDCI

TSI was calculated from NDCI values using graphical representation (box method) as shown figure 3.4. Basing on the NDCI values, corresponding TSI values as follows:

TSI (Oligophic)= 00 to 40 and Equivalent NDCI= -0.2 to -0.17

TSI (Mesotrophic)= 40 to 50 and Equivalent NDCI= -0.17 to -0.10

TSI (Eutrophic)= 50 to 70 and Equivalent NDCI= -0.10 to 0.0

TSI (Supertrophic)= 70 to 100 and Equivalent NDCI= -0.9 to 0.12

TSI (Hypertrophic)= 70 to 100 and Equivalent NDCI=0.12 and above

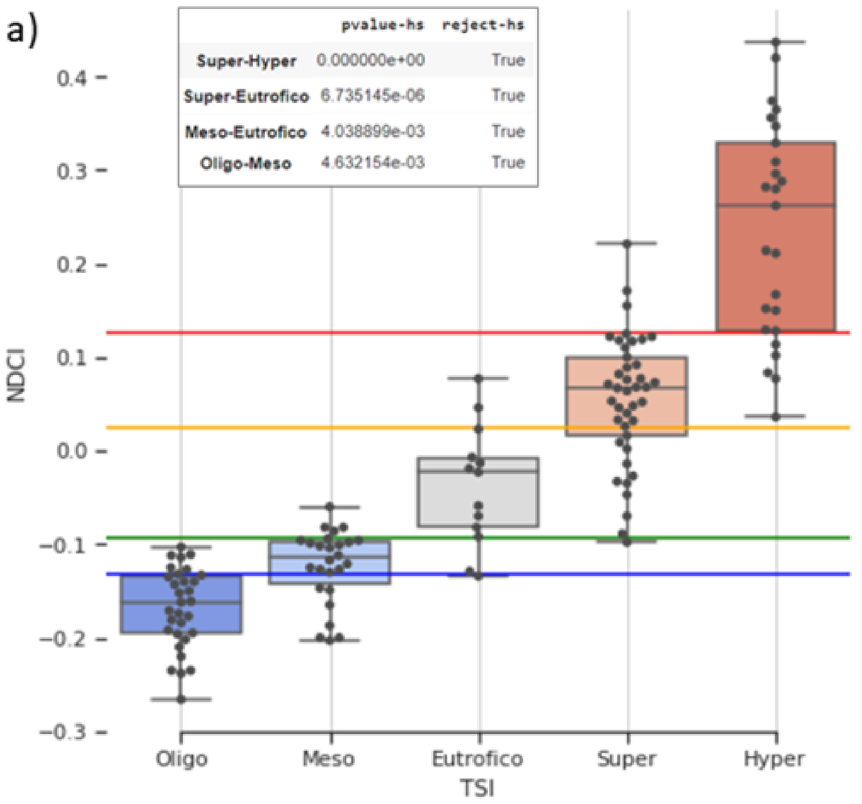

Figure 3.4: Eutrophication Status and Corresponding NDCI (Lobo et al. 2021)

3.8 Calibration and Validation: Water Sampling and Satellite Data

TSI calculated by Chl-a and TN of water sample data were calibrated and validated with the same time (November 2021) TSI calculated by NDCI values which were analyzed using satellite imagery.

3.9 Prediction of Eutrophication Status

ANN Model was developed using six input data (LU/LC, NDVI, NDCI, NDBI, NDWI, and Area of Water Body). To run this prediction model, Q-GIS 2.18 (Molusc Plugin) was used. Training model was developed using the year of 1990, 2000 and 2010 datasets. Thereafter, test output of 2021 was developed to validate training model. Finally, Prediction of eutrophication status was developed in 2030 and 2040.

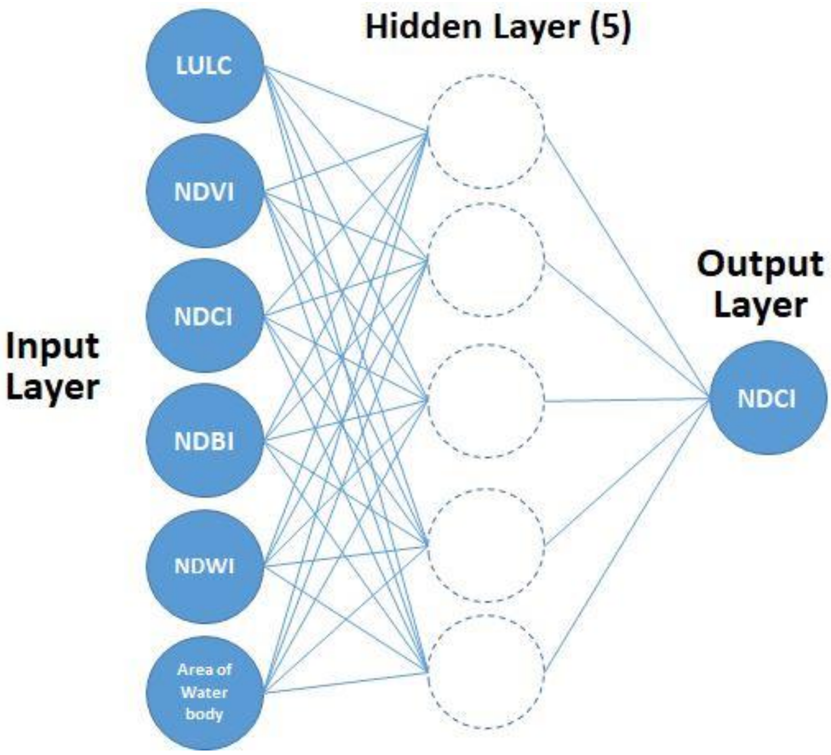

Figure 3.5: ANN Model Developed for Future Prediction of Eutrophication

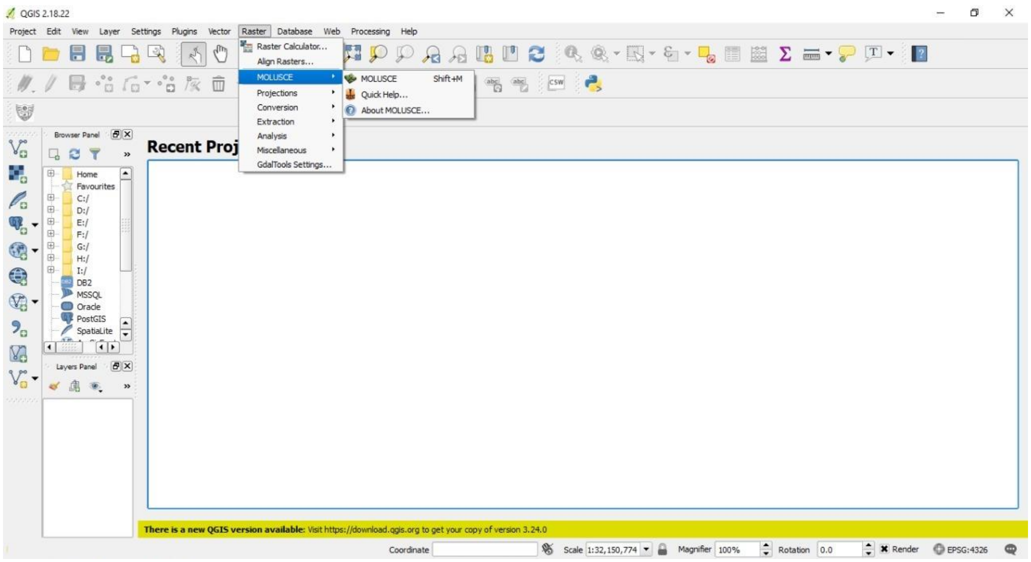

Figure 3.6: QGIS Molusce Plug-in Interface

CHAPTER 4
DATA COLLECTION

4.1 Water Sampling Locations

Water sampling locations were selected in three different points for better results from the same lake as shown in figure 4.1.

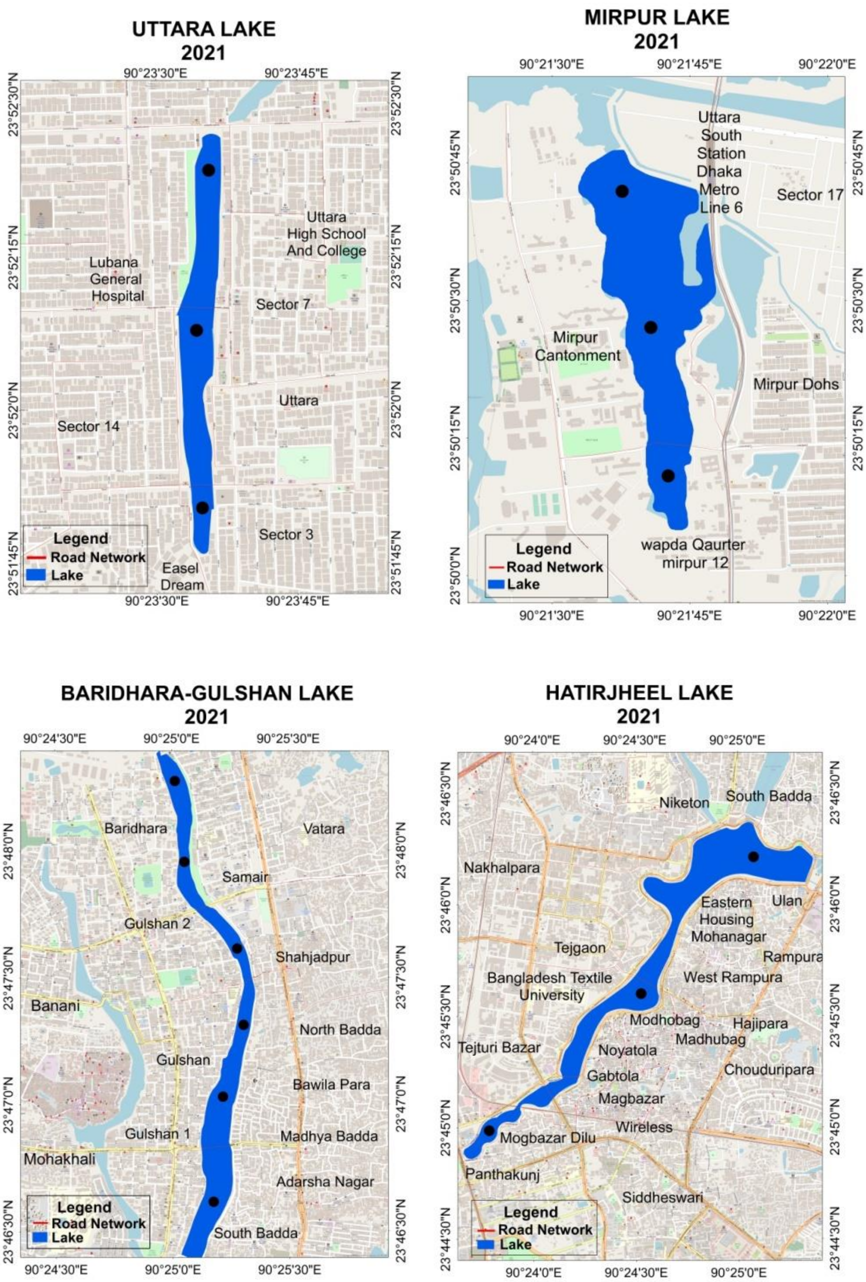

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Figure 4.1: Water Sampling Points of Five Selected Lakes

4.2 Water Sample Collection

For this study, water samples were collected from five selected lakes of Dhaka city namely Uttara, Mirpur, Baridhara, Gulshan and Hatirjheel areas. Water samples were collected in three different date (25 September, 13 November and 19 December 2021) considering the date of satellite imagery data. Satellite imagery download was planned on 1st week of November of 1990, 2000, 2010 and 2021. Therefore, before and after satellite imagery download dates were selected for water sampling to find out average values. Water samples have been collected in between 08:00 am to 12:30 pm from the top layer (maximum 0.20 metre) of the lakes (Queensland, 2019). All samples were tested on the same day at Botany Lab of University of Dhaka and Environment lab of MIST.

Figure 4.2: Collection of Water Sample from the Five Selected Lakes

Botany Lab of University of Dhaka was used to test Chlorophyll-a concentration (prime indicator of eutrophication) of the collected water samples.

Figure 4.3: Chlorophyll-a Test at Botany Lab, University of Dhaka

Environment Lab of MIST was used to test various water quality parameters such as Total Nitrogen-TN (one of the main indicators of eutrophication), phosphate, DO, BOD, COD, Turbidity, Colour, pH and TDS of the collected water samples to identify any variation of water quality due to the eutrophication.

4.3 Identification of Sources of Pollution

Sources of pollution were identified by conducting physical survey using handheld Global Positioning System (GPS). Many points were found where different types of sewerage connection coming from residential areas, hospitals/clinics, restaurants etc.

Figure 4.4: Identification of Sources of Pollution Using Handheld GPS

4.4 Satellite Imagery Collection

For this study, satellite imagery was downloaded from USGS website (freely available) with cloud cover less than 10%, temporal resolution 16 days and spatial resolution 30m. 1^{st} week of November 1990, 2000, 20210 and 2021 were selected and downloaded for this analysis to get better image quality. In doing so, Landsat 4-5 TM image data were downloaded for the year of 1990, 2000 and 2010, and Landsat 8 OLI image data was downloaded for the year of 2021.

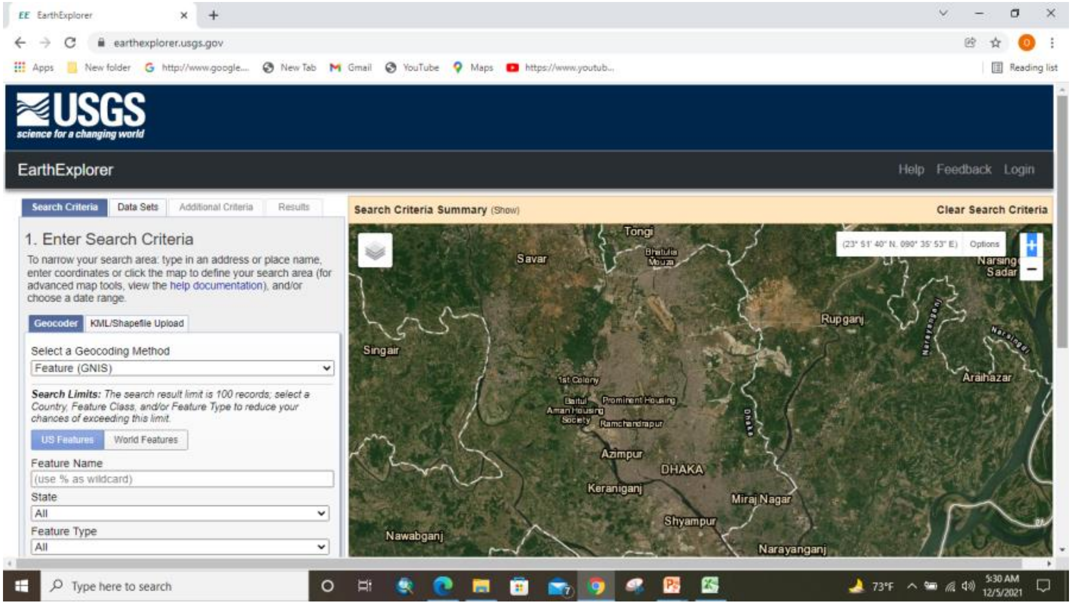

Figure 4.5: USGS Website Interface

Technical specification of Landsat 4-5 TM bands is shown in table 4.1 (Gholizadeh et al. 2016).

Table 4.1: Technical Specification of Landsat 4-5 TM Bands

Band	Wavelength	Useful for mapping
Band 1 – blue	0.45-0.52	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 2 – green	0.52-0.60	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 3 – red	0.63-0.69	Discriminates vegetation slopes
Band 4 - Near Infrared	0.77-0.90	Emphasizes biomass content and shorelines
Band 5 - Short-wave Infrared	1.55-1.75	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 6 - Thermal Infrared	10.40-12.50	Thermal mapping and estimated soil moisture
Band 7 - Short-wave Infrared	2.09-2.35	Hydrothermally altered rocks associated with mineral deposits

Technical specification of Landsat 8 OLI bands is shown in table 4.2 (Gholizadeh et al. 2016).

Table 4.2: Technical Specification of Landsat-8 OLI Bands

Band	Wavelength	Useful for mapping
Band 1 - coastal aerosol	0.43-0.45	Coastal and aerosol studies
Band 2 – blue	0.45-0.51	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 3 – green	0.53-0.59	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 4 – red	0.64-0.67	Discriminates vegetation slopes
Band 5 - Near Infrared (NIR)	0.85-0.88	Emphasizes biomass content and shorelines
Band 6 - Short-wave Infrared (SWIR) 1	1.57-1.65	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.11-2.29	Improved moisture content of soil and vegetation; penetrates thin clouds
Band 8 – Panchromatic	0.50-0.68	15 meter resolution, sharper image definition
Band 9 – Cirrus	1.36-1.38	Improved detection of cirrus cloud contamination
Band 10 - TIRS 1	10.60-11.19	100 meter resolution, thermal mapping and estimated soil moisture
Band 11 - TIRS 2	11.50-12.51	100 meter resolution, improved thermal mapping and estimated soil moisture

4.5 Satellite Imagery Processing

Raw images were processed using ArcGIS 10.3. Image pre-processing (radiometric correction) and multispectral band combination were applied.

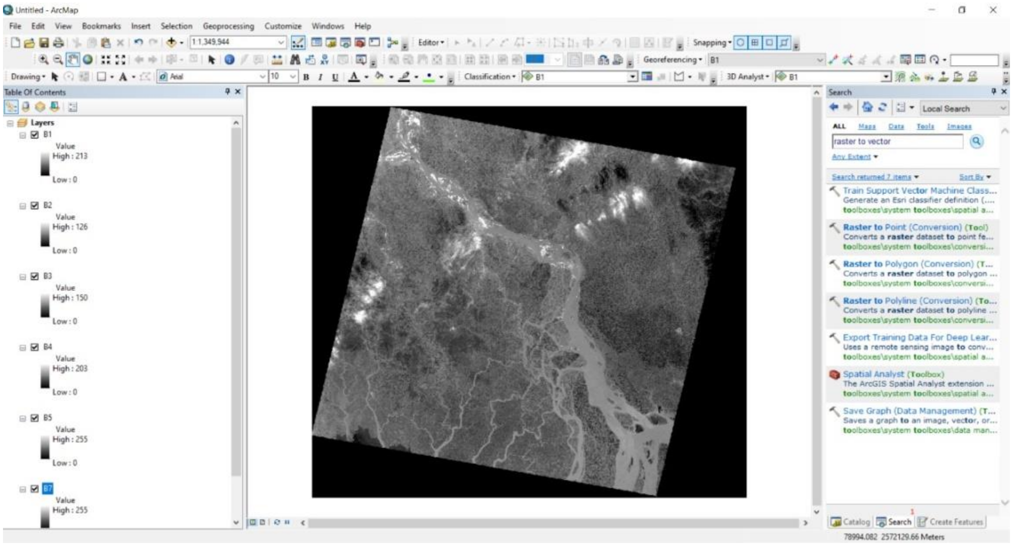

Figure 4.6: Image Processing Using ArcGIS Software

Area of interest was extracted for analysis. Considering influenced areas around the five selected lakes, latitude 23˚43´ to 23˚54´ and longitude 90˚20´ to 90˚27´ was extracted from the downloaded satellite imagery. Extracted area (as shown in figure 3.7) is approximately 82 sqkm around the five selected lakes

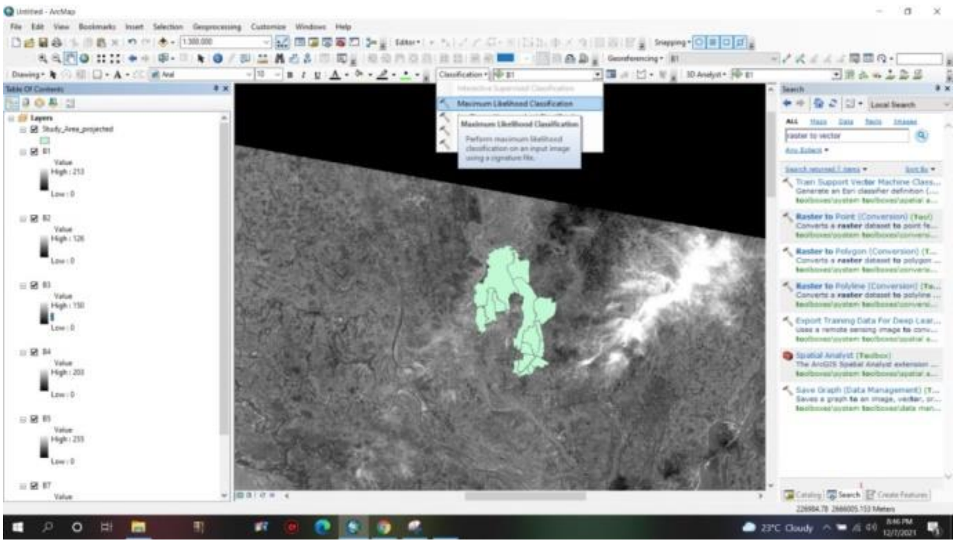

Figure 4.7: Satellite Imagery Coverage Areas of Five Selected Lakes

Water bodies, built-up areas, vegetation cover and barren lands were categorized for LU/LC. In doing so, Maximum Likelihood Supervised Classification (MLSC) of ArcGIS was applied.

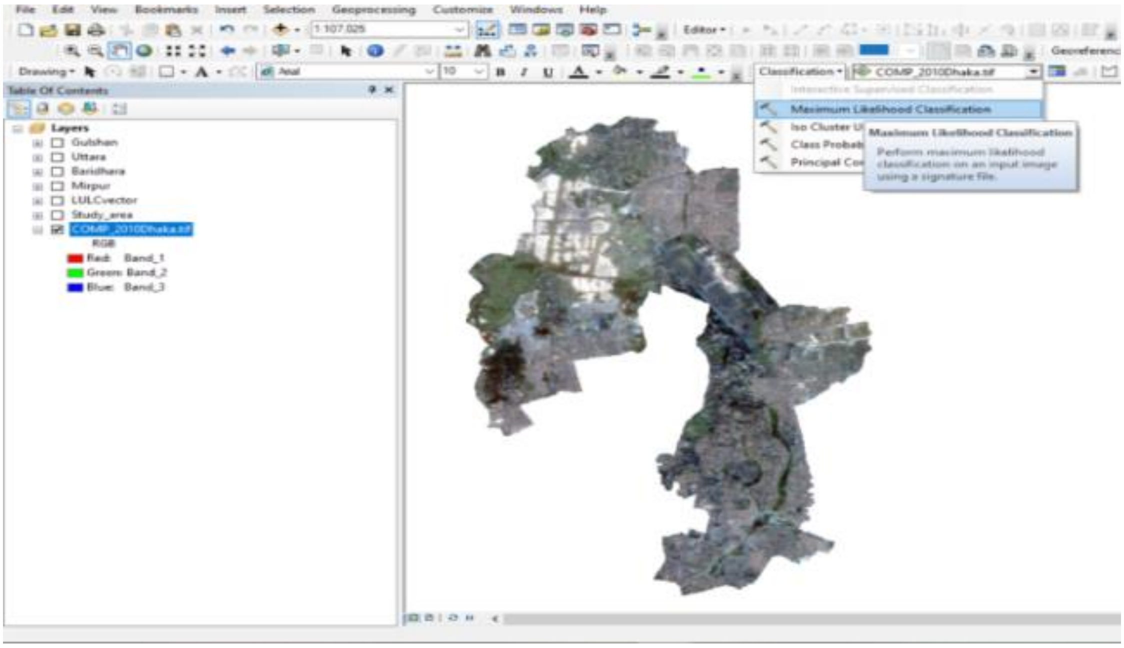

Figure 4.8: Image Classification Using ArcGIS Software

CHAPTER 5
RESULTS AND DISCUSSIONS

5.1 Introduction

This chapter provides the outcomes of water sampling (2021) results, identification of sources of pollution, satellite imagery analysis in the year of 1990, 2000, 2010 and 2021, and finally prediction of eutrophication in the year of 2030 and 2040 were shown here chronologically.

5.2 Eutrophication Status: Basing on Water Quality Parameters

Chl-a concentration test results in different dates are shown in table 5.1. Average chl-a concentration were calculated from three samples of each lake, TSI were calculated using equation 3.1, and results are shown in table 5.1.

Table 5.1: TSI for Chlorophyll-a (Chl-a) Concentration

Lake	Chl-a: 1st Sampling 25/09/21	Average (μg/L)	TSI Chl-a	Chl-a: 2nd Sampling 13/11/21	Average (μg/L)	TSI Chl-a	Chl-a: 3rd Sampling 19/12/21	Average (μg/L)	TSI Chl-a
Uttara-1	288.89	209.17	**83.02**	322.04	162.6	**80.55**	239.16	176.81	**81.36**
Uttara-2	134.38			76.96			105.37		
Uttara-3	204.24			88.8			185.89		
Mirpur-1	139.7	154.68	**80.06**	132.61	206.01	**82.87**	271.14	210.78	**83.09**
Mirpur-2	130.2			339.8			172.9		
Mirpur-3	194.15			145.63			188.3		
Baridhara-1	420.32	487.08	**91.31**	200.1	340.18	**87.79**	254.56	306.26	**86.75**
Baridhara-2	670.33			368.22			329.15		
Baridhara-3	370.59			452.23			335.07		
Gulshan-1	631.64	581.3	**93.04**	394.27	257.32	**85.05**	301.92	322.06	**87.25**
Gulshan-2	542.27			284.16			344.54		
Gulshan-3	570			93.54			319.68		
Hatirjheel-1	548.75			510.21			468.59		
Hatirjheel-2	480.55	508.94	**91.74**	450.15	478.85	**91.14**	410.43	431.45	**90.11**
Hatirjheel-3	497.52			476.2			415.33		

TN test results in different dates are shown in table 5.2. Average TN was calculated from three samples of each lake, TSI were calculated using equation 3.2, and results are shown in table 5.2.

Table 5.2: TSI for Total Nitrogen (TN)

Lake	TN: 1st Sampling 25/09/21	Average (mg/L)	**TSI (TN)**	TN: 2nd Sampling 13/11/21	Average (mg/L)	**TSI (TN)**	TN: 3rd Sampling 19/12/21	Average (mg/L)	**TSI (TN)**
Uttara-1	15.2			16.9			24.7		
Uttara-2	18.6	17.2	**95.50**	20.5	19.5	**97.31**	28.8	28.5	**102.78**
Uttara-3	17.8			21.1			32		
Mirpur-1	13.1			14.3			20.7	20.0	
Mirpur-2	13.9	13.63	**92.14**	14.4	15.06	**93.58**	18.9		**97.68**
Mirpur-3	13.9			16.5			20.4		
Baridhara-1	19.7			24.4			27.1		
Baridhara-2	22.7	21.23	**98.54**	28.6	26.7	**101.84**	36.3	36.13	**106.21**
Baridhara-3	21.3			27.1			45		
Gulshan-1	10.8			12.4			19.7		
Gulshan-2	9.9	10.9	**88.91**	11.3	12.43	**90.81**	22.2	19.83	**97.55**
Gulshan-3	12			13.6			17.6		
Hatirjheel-1	18.3			19.5			22.77		
Hatirjheel-2	19.1	19.2	**97.08**	21.8	21.44	**98.68**	23.34	22.55	**99.41**
Hatirjheel-3	20.2			23.02			21.56		

According to the Carlson's Trophic State Index (table 3.1), all the values of TSI (Chl-a) and TSI (TN) fall within the range of 70-100 which indicate **"Hypertrophic"** condition for five selected lakes (Uttara, Mirpur, Baridhara, Gulshan and Hatirjheel areas) in the year of 2021 (September to December).

Figure 5.1 is showing, TSI (Chl-a) values of 1st, 2nd and 3rd sampling were found almost same pattern. Average TSI (Chl-a) values of Hatirjheel and Baridhara-Gulshan lakes are higher than the Mirpur and Uttara lakes.

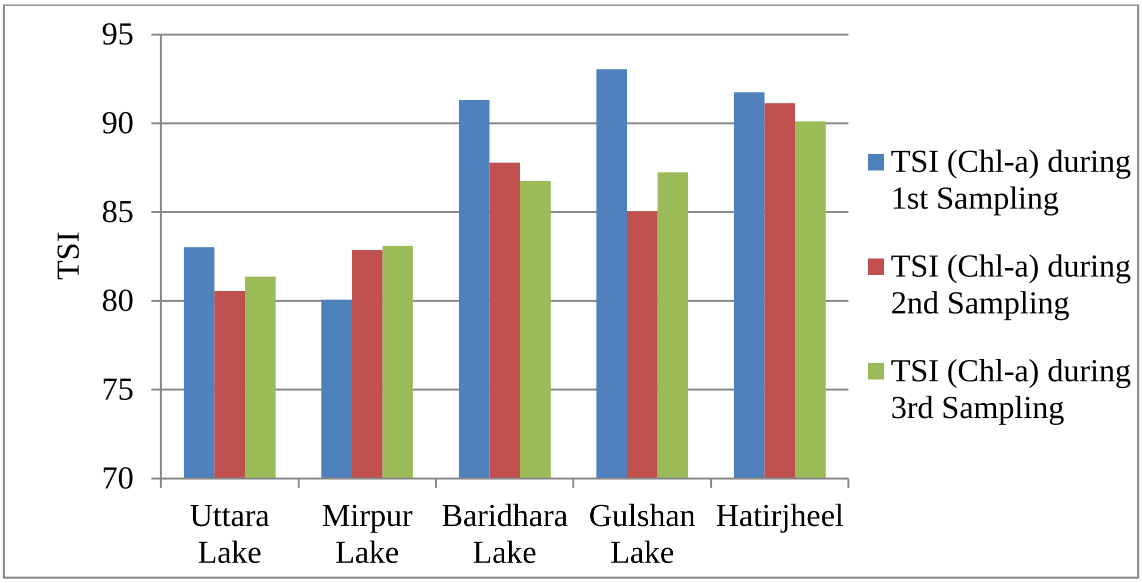

Figure 5.1: TSI (Chl-a) in Different Lakes

Figure 5.2 is showing, TSI (TN) values 1st, 2nd and 3rd sampling were found almost same pattern. Average TSI (TN) values of Uttara and Baridhara lakes are higher than the Mirpur, Gulshan and Hatirjheel lakes.

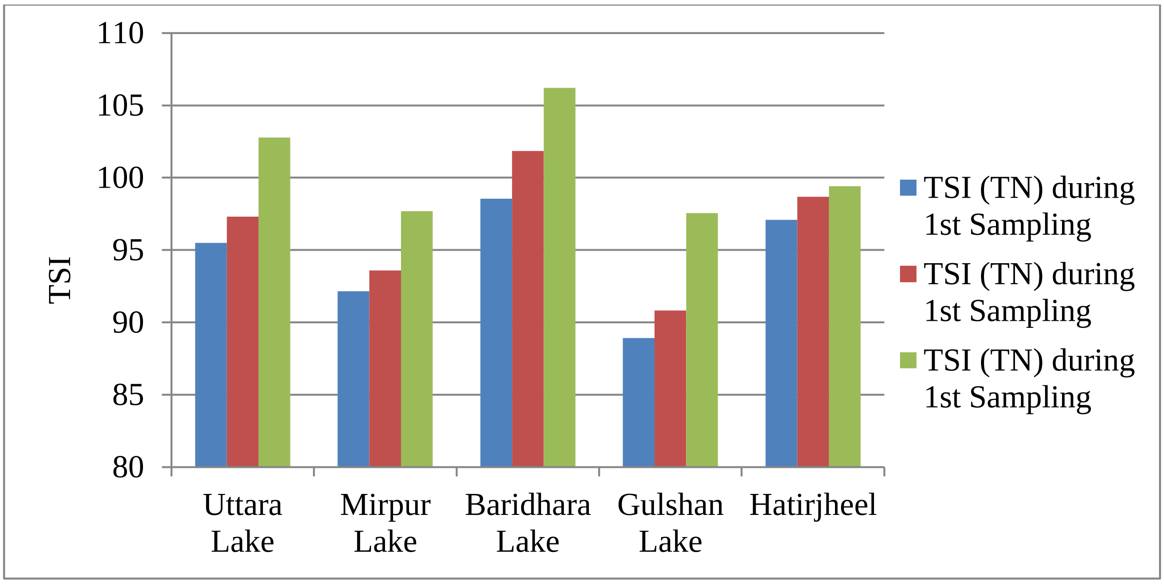

Figure 5.2: TSI (TN) in Different Lakes

Water quality parameters (phosphate, dissolved oxygen, BOD, COD, pH, colour, turbidity and TDS) were tested during 1st sampling on 25 September 2021. Average values were calculated from the results of three sample data. Test results are summarized in table 5.3.

Table 5.3: Water Quality (WQ) Parameters-1st Sampling

Lake	PO_4^{3-} mg/L	DO mg/L	BOD mg/L	COD mg/L	pH	Colour Pt/Co	Turbidity NTU	TDS mg/L
Uttara-1	3.1	4.39	12.9	46	7.11	95	27.3	238
Uttara-2	3.2	3.91	12	40	7.26	83	21.5	168
Uttara-3	3.6	4.31	13.8	39	7.36	88	23.6	157.9
Average	**3.3**	**4.20**	**12.9**	**41.66**	**7.24**	**88.67**	**24.13**	**187.97**
Mirpur-1	2.7	1.72	19.5	70	7.4	99	20.1	158.1
Mirpur-2	3.2	1.21	18.6	69	7.56	92	17.5	138.4
Mirpur-3	2.9	4.5	18	76	7.43	115	18.6	176.8
Average	**2.93**	**2.47**	**18.7**	**71.66**	**7.46**	**102**	**18.73**	**157.77**
Baridhara-1	3.7	4.45	11.7	52	7.09	130	23.6	232
Baridhara-2	3.3	2.03	10.5	47	7.16	125	21.5	242
Baridhara-3	3.1	3.21	9.6	46	7.21	120	25.5	229
Average	**3.36**	**3.23**	**10.6**	**48.33**	**7.15**	**125**	**23.53**	**234.33**
Gulshan-1	2.4	3.1	15.9	56	7.09	84	21.6	220
Gulshan-2	2.2	2.49	16.8	60	7.13	97	18.3	223
Gulshan-3	2.6	2.56	15	52	7.08	122	22.6	251
Average	**2.4**	**2.71**	**15.9**	**56**	**7.1**	**101**	**20.83**	**231.33**
Hatirjheel-1	2.8	2.99	13.9	51	7.13	90	20.5	218
Hatirjheel-2	3.0	2.78	14.8	57	7.07	96	19.4	223
Hatirjheel-3	2.9	3.2	13.1	49	7.11	123	21.9	246
Average	**2.9**	**2.99**	**13.93**	**52.33**	**7.10**	**104**	**21.34**	**220.45**

Water quality parameters (phosphate, dissolved oxygen, BOD, COD, pH, colour, turbidity and TDS) were tested during 2nd sampling on 13 November 2021. Average values were calculated from the results of three sample data. Test results are summarized in table 5.4.

Table 5.4: Water Quality (WQ) Parameters-2nd Sampling

Lake	PO_4^{3-} mg/L	DO mg/L	BOD mg/L	COD mg/L	pH	Colour Pt/Co	Turbidity NTU	TDS mg/L
Uttara-1	7.9	3.18	17.4	56	6.68	88	37.5	242
Uttara-2	10.5	3.23	16.8	62	6.72	78	23.1	209
Uttara-3	9.6	3.94	17.4	71	6.75	86	26.3	185
Average	**9.33**	**3.45**	**17.2**	**63**	**6.72**	**84**	**28.96**	**212**
Mirpur-1	5.3	1.62	24.6	83	6.64	92	21.9	157.7
Mirpur-2	5.1	1.26	25.8	80	6.69	88	23.6	150.7
Mirpur-3	5.6	3.12	23.4	89	6.6	120	22.2	201
Average	**5.33**	**2**	**24.6**	**84**	**6.64**	**100**	**22.56**	**169.8**
Baridhara-1	8.9	1.1	29.4	84	6.5	121	26.3	277
Baridhara-2	11.2	1.92	30.6	71	6.54	126	24.6	264
Baridhara-3	9	2.33	28.8	85	6.62	111	31.5	255
Average	**9.7**	**1.78**	**29.6**	**80**	**6.55**	**119.3**	**27.46**	**265.33**
Gulshan-1	4.2	2.21	22.8	72	6.36	78	23.1	268
Gulshan-2	5.1	2.11	20.4	70	6.22	92	22.6	336
Gulshan-3	4.6	2.12	25.2	65	6.48	112	26.3	265
Average	**4.63**	**2.14**	**22.8**	**69**	**6.35**	**94**	**24**	**289.67**
Hatirjheel-1	6.55	2.82	25.34	74	6.66	95	25.97	257.7
Hatirjheel-2	6.76	2.29	26.96	75	6.48	115	25.87	250.7
Hatirjheel-3	6.89	2.45	25.78	78	6.83	97	24.42	217
Average	**6.73**	**2.52**	**26.02**	**75.67**	**6.65**	**102.33**	**25.42**	**241.8**

Water quality parameters (phosphate, dissolved oxygen, BOD, COD, pH, colour, turbidity and TDS) were tested during 3rd sampling on 19 December 2021. Average values were calculated from the results of three sample data. Test results are summarized in table 5.5.

Table 5.5: Water Quality (WQ) Parameters-3rd Sampling (19 December 2021)

Lake	PO_4^{3-} mg/L	DO mg/L	BOD mg/L	COD mg/L	pH	Colour Pt/Co	Turbidity NTU	TDS mg/L
Uttara-1	8.6	2.18	23	61	7.44	99	33.5	198.5
Uttara-2	9.9	2.92	28	72	7.36	81	22.2	174.4
Uttara-3	9.2	2.65	18	80	7.3	75	24.44	170.7
Average	**9.23**	**2.58**	**23**	**71**	**7.37**	**85**	**26.7133**	**181.2**
Mirpur-1	7.2	1.51	31	81	8.13	89	18.5	103.8
Mirpur-2	8.5	1.15	33	96	7.82	100	21.44	124.6
Mirpur-3	6.2	2.16	29	101	7.65	110	20.87	145.8
Average	**7.3**	**1.60**	**31**	**92.67**	**7.87**	**99.67**	**20.27**	**124.73**
Baridhara-1	12.2	1.11	34	101	7.11	130	24.77	181.2
Baridhara-2	13.1	1.65	39	96	7.08	142	21.56	200
Baridhara-3	9.6	1.82	32	105	7.15	156	27.34	243
Average	**11.63**	**1.52**	**35**	**100.6**	**7.11**	**142.7**	**24.5567**	**208.07**
Gulshan-1	9.2	2.01	25	76	7.85	70	21.22	206
Gulshan-2	8.5	2.05	23	83	7.25	83	19.76	222
Gulshan-3	8.1	1.92	26	78	7.3	116	23.41	203
Average	**8.6**	**1.99**	**24.67**	**79**	**7.47**	**89.67**	**21.4633**	**210.33**
Hatirjheel-1	9.82	1.71	35	89	7.09	105	22.45	183.42
Hatirjheel-2	8.44	1.85	32	102	7.67	120	22.15	164.17
Hatirjheel-3	9.02	1.68	31	92	7.32	115	21.94	195.35
Average	**9.09**	**1.74**	**32.66**	**94.33**	**7.36**	**113.33**	**22.18**	**180.98**

Phosphate values (PO_4^{3-}) of five selected lakes were found 3.3, 2.93, 3.36, 2.4 and 2.9 (1st sampling), 9.33, 5.33, 9.7, 4.63 and 6.73 (2nd sampling), and 9.23, 7.3, 11.63, 8.6 & 9.09 (3rd sampling) respectively as shown in figure 5.3. Baridhara lake was found highest.

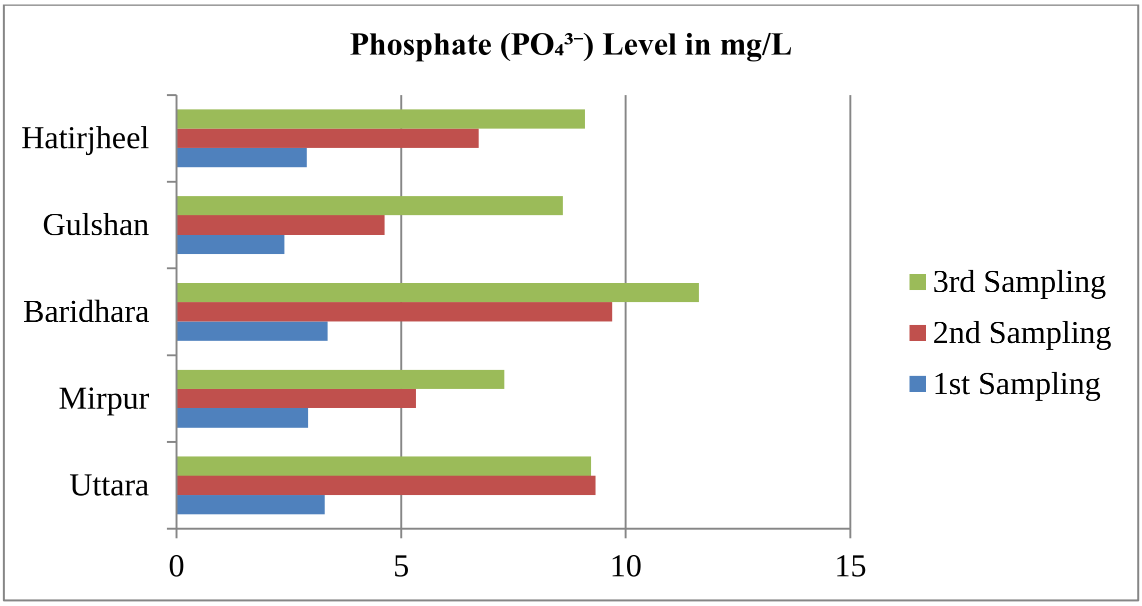

Figure 5.3: Phosphate Values in Different Lakes

DO values of five selected lakes were found 4.20, 2.47, 3.23, 2.71 and 2.99 (1st sampling), 3.45, 2, 1.78, 2.14 and 2.52 (2nd sampling), and 2.58, 1.6, 1.52, 1.99 and 1.74 (3rd sampling) respectively as shown in figure 5.4. Uttara lake was found highest.

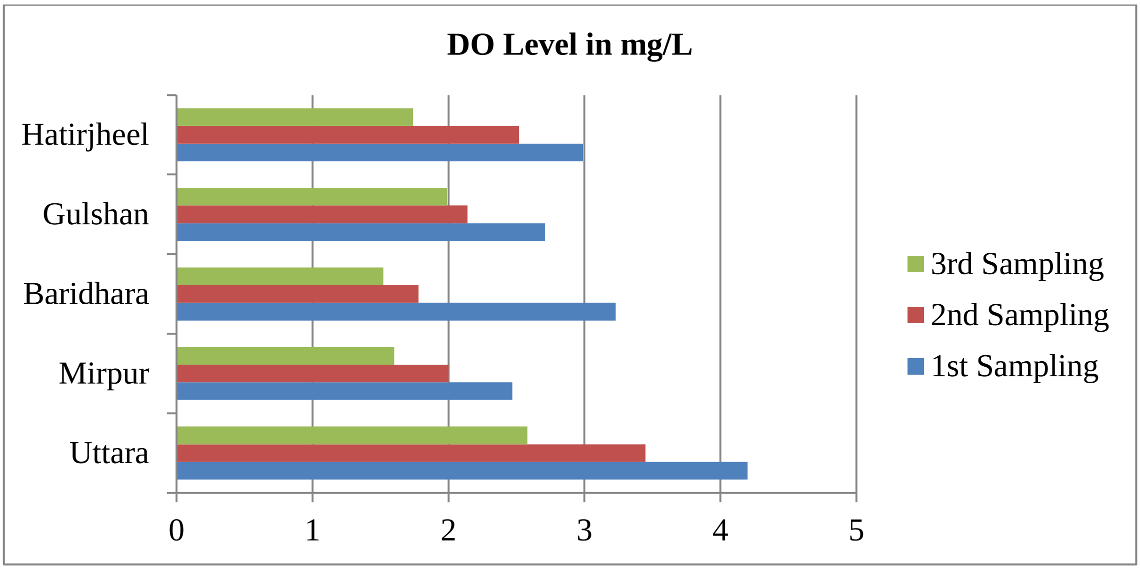

Figure 5.4: DO Values in Different Lakes

BOD values of five selected lakes were found 12.9, 18.7, 10.6, 15.9 and 13.93 (1st sampling), 17.2, 24.6, 29.6, 22.8 and 26.02 (2nd sampling), and 23, 31, 35, 24.67 and 32.66 (3rd sampling) respectively as shown in figure 5.5. Baridhara lake found highest.

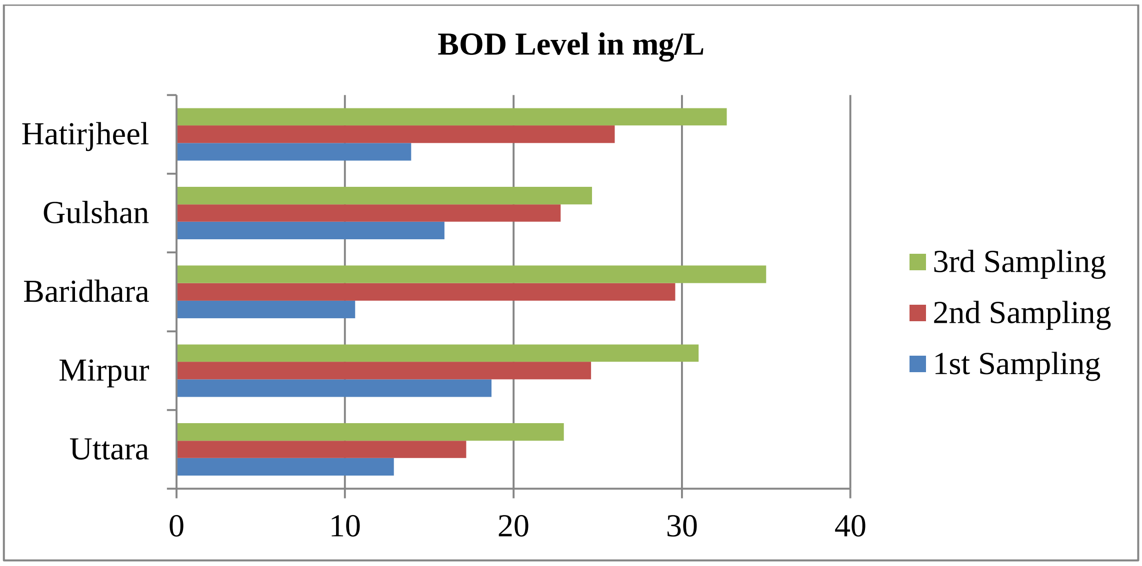

Figure 5.5: BOD Values in Different Lakes

COD values of five selected lakes were found 41.67, 71.67, 48.33, 56 and 52.33 (1st sampling), 63, 84, 80, 69 and 75.67 (2nd sampling), and 71, 92.67, 100.6, 79 and 95.33 (3rd sampling) respectively as shown in figure 5.6. Mirpur lake was found highest.

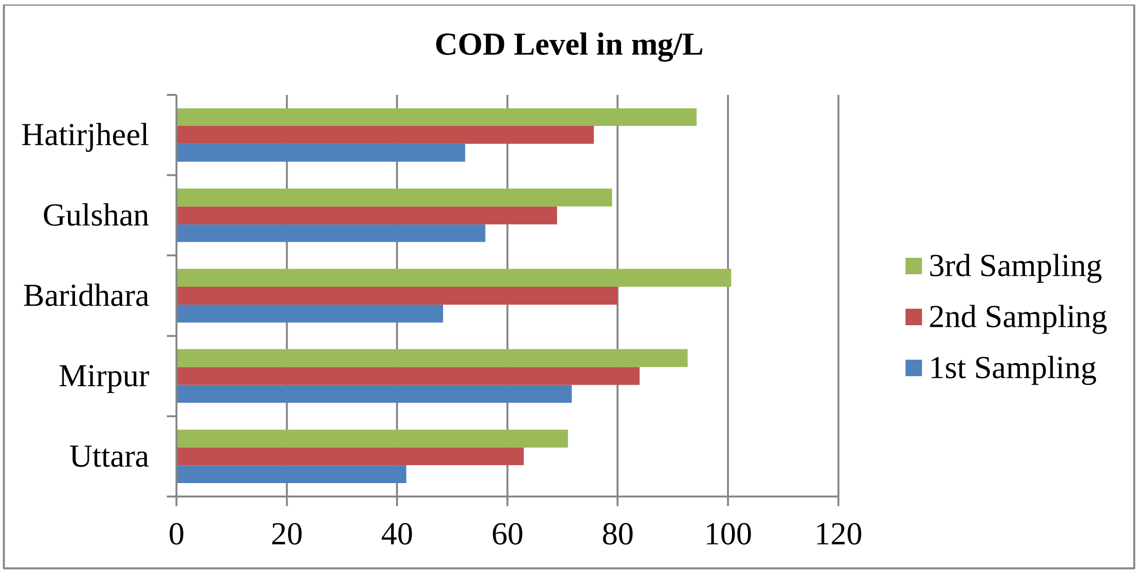

Figure 5.6: COD Values in Different Lakes

pH values of five selected lakes were found 7.24, 7.46, 7.15, 7.1 and 7.1 (1st sampling), 6.72, 6.64, 6.5, 6.35 and 6.65 (2nd sampling), and 7.37, 7.87, 7.11, 7.47 and 7.36 (3rd sampling) respectively as shown in figure 5.7. Mirpur lake was found highest.

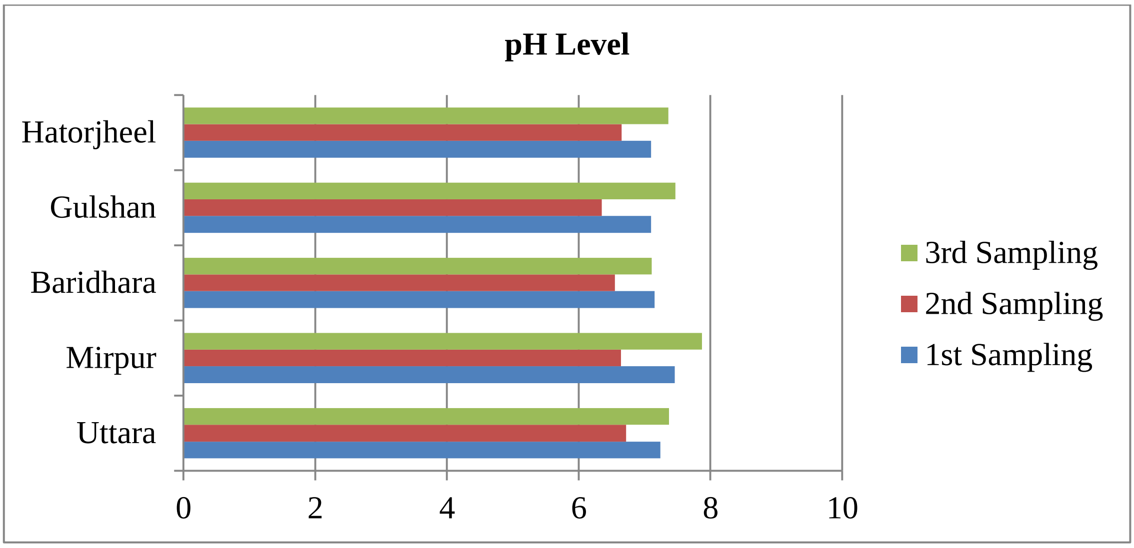

Figure 5.7: pH Values in Different Lakes

Water colour values of five selected lakes were found 88.67, 102, 125, 101 and 104 (1st sampling), 84, 100, 119.3, 94 and 102.33 (2nd sampling), and 85, 99.67, 142.7, 89.67 and 113.33 (3rd sampling) respectively as shown in figure 5.8. Baridhara lake was found highest.

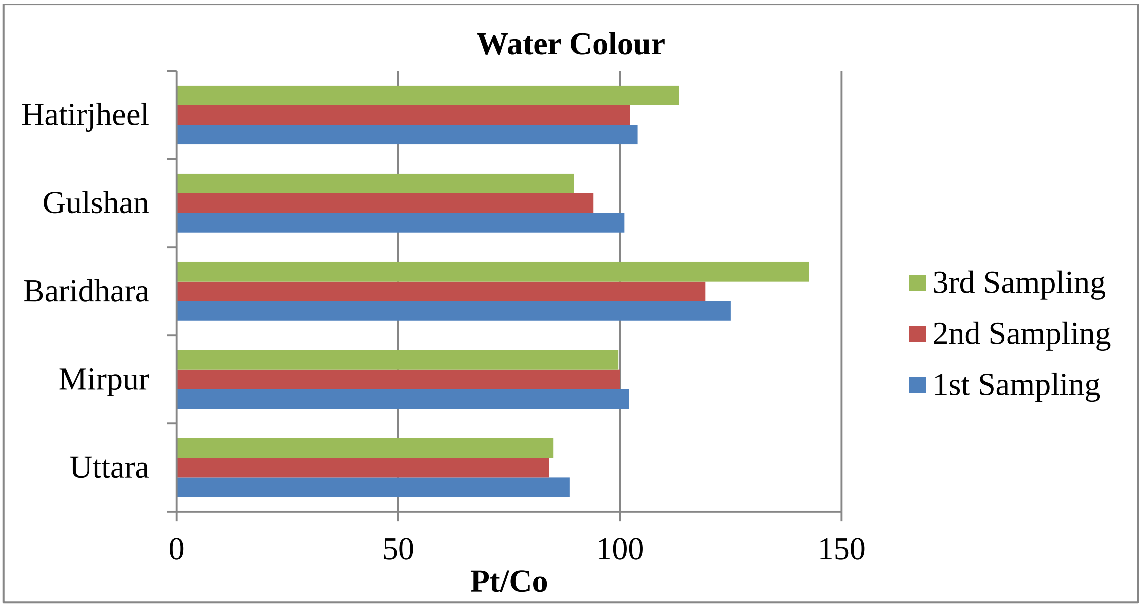

Figure 5.8: Water Colour Values in Different Lakes

Turbidity of five selected lakes were found 24.13, 18.73, 23.53, 20.83 and 21.34 (1st sampling), 28.97, 22.57, 27.47, 24 and 25.42 (2nd sampling), and 26.71, 20.27, 24.55, 21.46 and 22.18 (3rd sampling) respectively as shown in figure 5.9. Uttara lake was found highest.

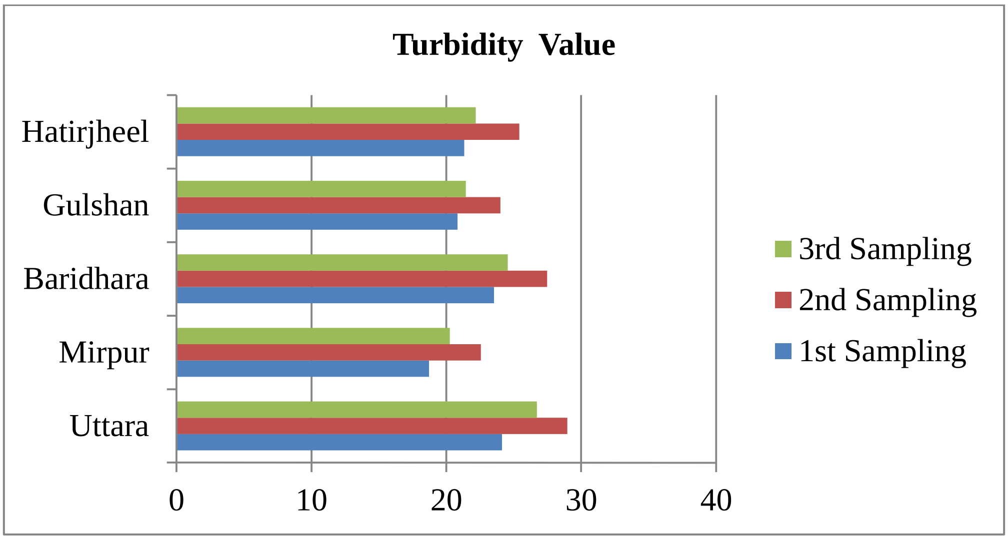

Figure 5.9: Turbidity Values in Different Lakes

TDS values of five selected lakes were found 187.97, 157.77, 234.33, 234.33 and 220.45 (1st sampling), 212, 169.8, 265.33, 289.67 and 241.8 (2nd sampling), and 181.2, 124.73, 208.07, 210.33 and 180.98 (3rd sampling) respectively as shown in figure 5.10. Gulshan lake was found highest.

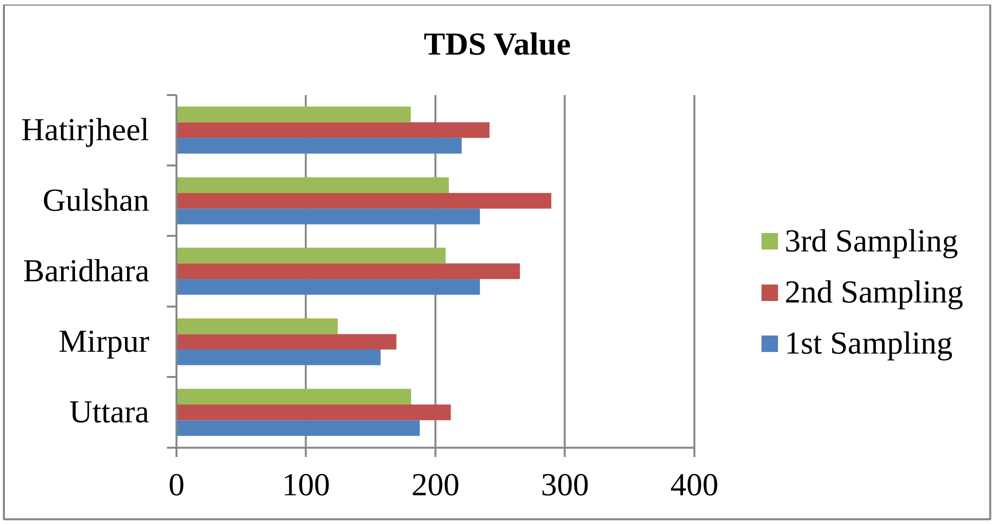

Figure 5.10: TDS Values in Different Lakes

5.3 Sources of Pollution

Ground survey was carried out along the both sides of the five selected lakes using handheld GPS to identify sources of pollution. Many point sources were found around the lakes. Sources of pollution are shown in figure 5.11. Uttara, Gulshan-Baridhara and Hatirjheel areas were found more sources of pollution than Mirpur area due to the urbanization development.

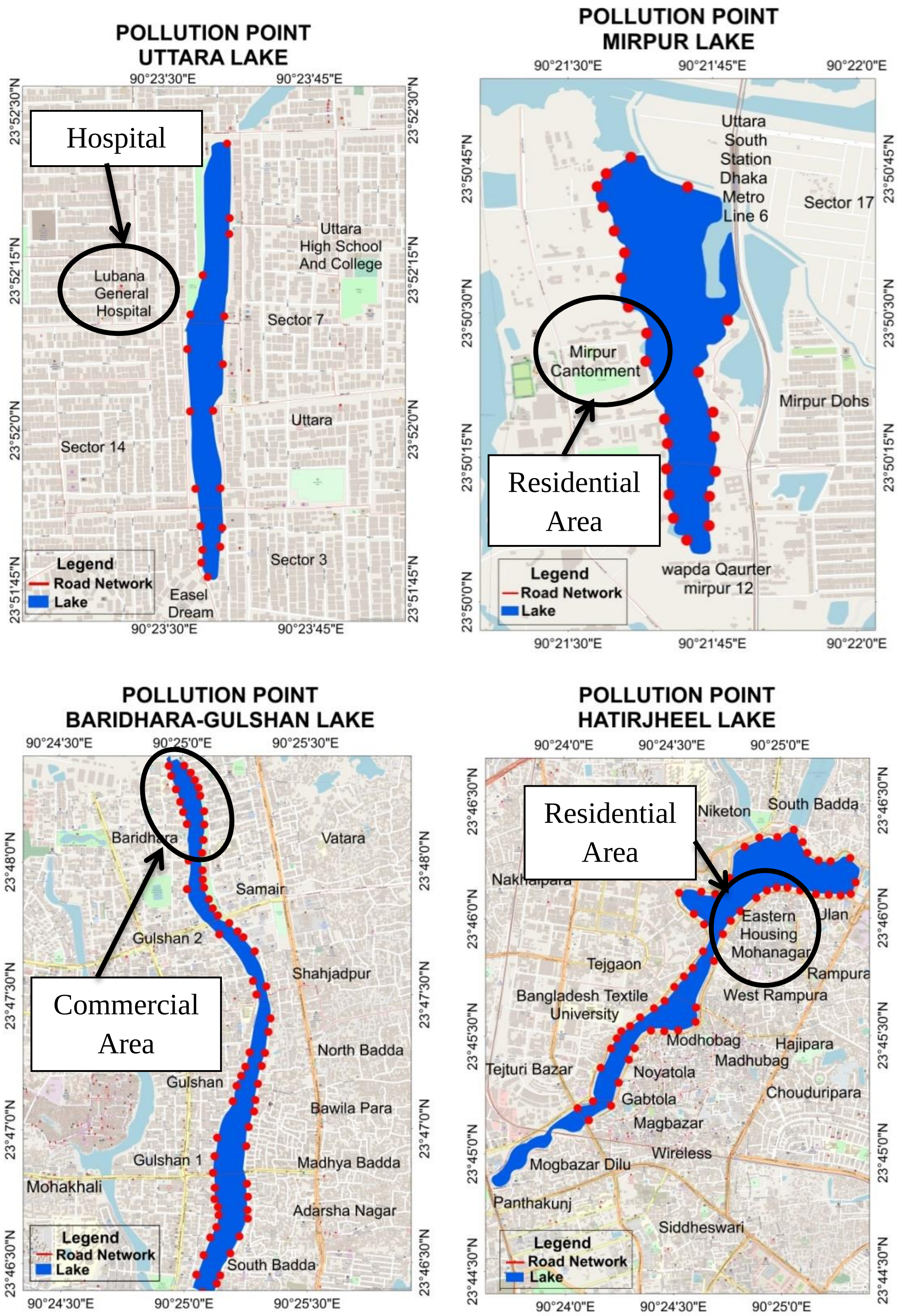

Figure 5.11: Sources of Pollution in Different Lakes (Red Dots)

5.4 Eutrophication Status: Basing on Satellite Imagery Analysis

Satellite images were downloaded in the year of 1990, 2000, 2010, and 2021 and processed using ArcGIS software. Land use/land cover (LU/LC) was analyzed using Maximum Likelihood Supervised Classification (MLSC) tool. Calculated areas are shown in table 5.6. Total area in every year was found almost similar.

Table 5.6: LU/LC Change Pattern in Different Year (areas in sqkm)

LU/LC	1990	2000	2010	2021
Urban Area	22.17	26.72	35.35	38.81
Vegetation	24.78	22.46	20.84	17.34
Barren Land	12.46	18.39	13.28	19.67
Water Body	22.59	14.53	12.54	6.28
Total area	82	82.1	82.01	82.1

Here to be mentioned that urban areas were increased from 22.17 to 38.81 sqkm (75% increased). Vegetation covers were reduced from 24.78 to 17.34 sqkm (30% reduced). Barren lands were increased from 12.46 to 19.67 sqkm (57.86% increased). Change in water bodies of the influenced area were reduced significantly from 22.59 to 6.28 sqkm (72.2% reduced) as shown in figure 5.6. These changes of LU/LC pattern directly influencing/affecting algal content in lake. Specifically, increased numbers of urban areas are main sources of sewerage discharge (mainly nitrogen) in to the lakes.

Figure 5.12 and 5.13 are showing LU/LC and water bodies change pattern respectively. LU/LC changed in respect to reduced water body. LU/LC and water body pattern changed significantly over the time (1990 to 2021). NDVI, NDBI, NDWI and NDCI were calculated using equation 3.3 to 3.6 respectively and shown in figure 5.14 to 5.17 respectively. NDVI, NDBI, NDWI and NDCI pattern changed due to the change of LU/LC and water body pattern.

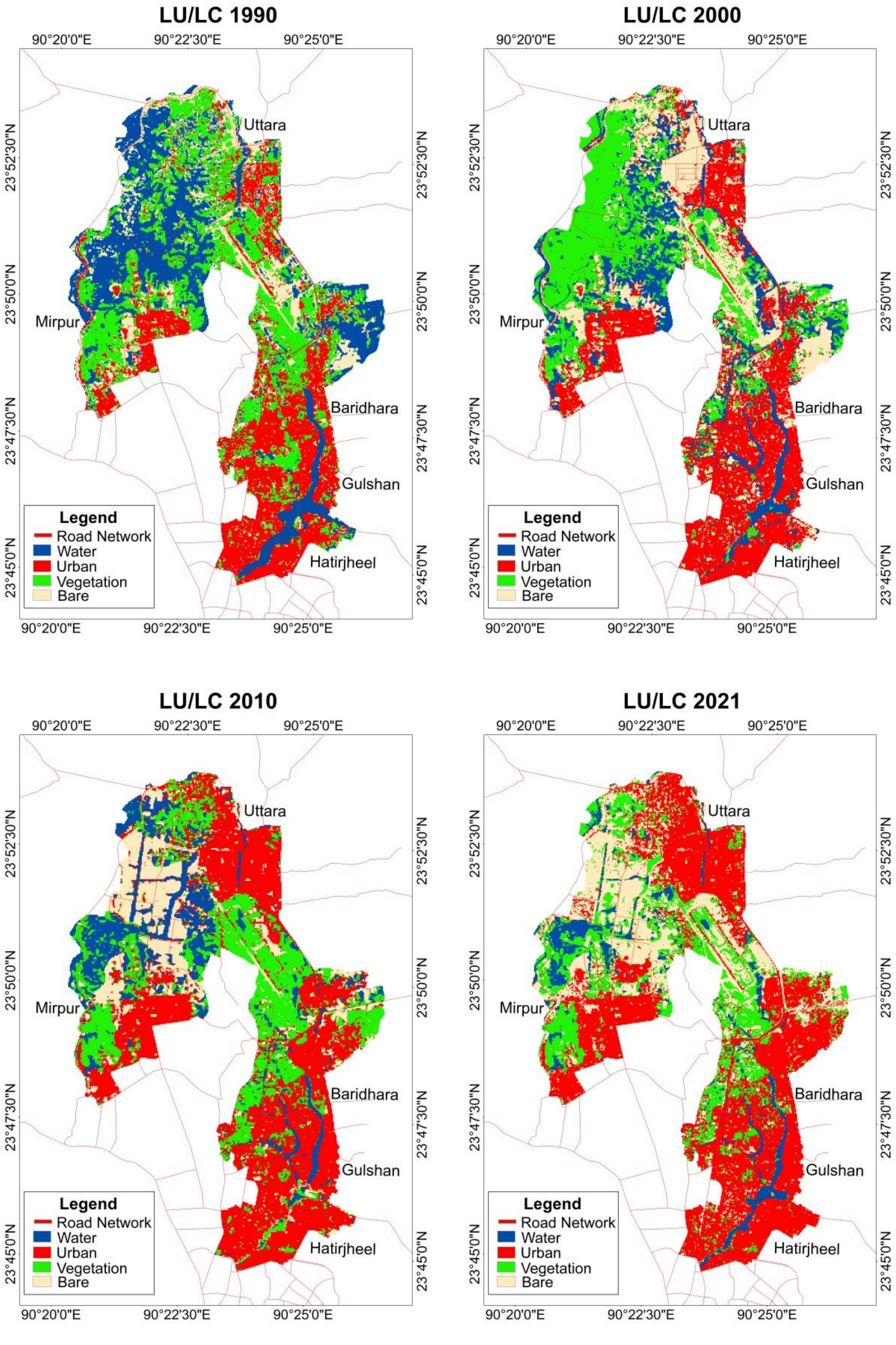

Figure 5.12: LU/LC Change Pattern in the Year of 1990, 2000, 2010 and 2021

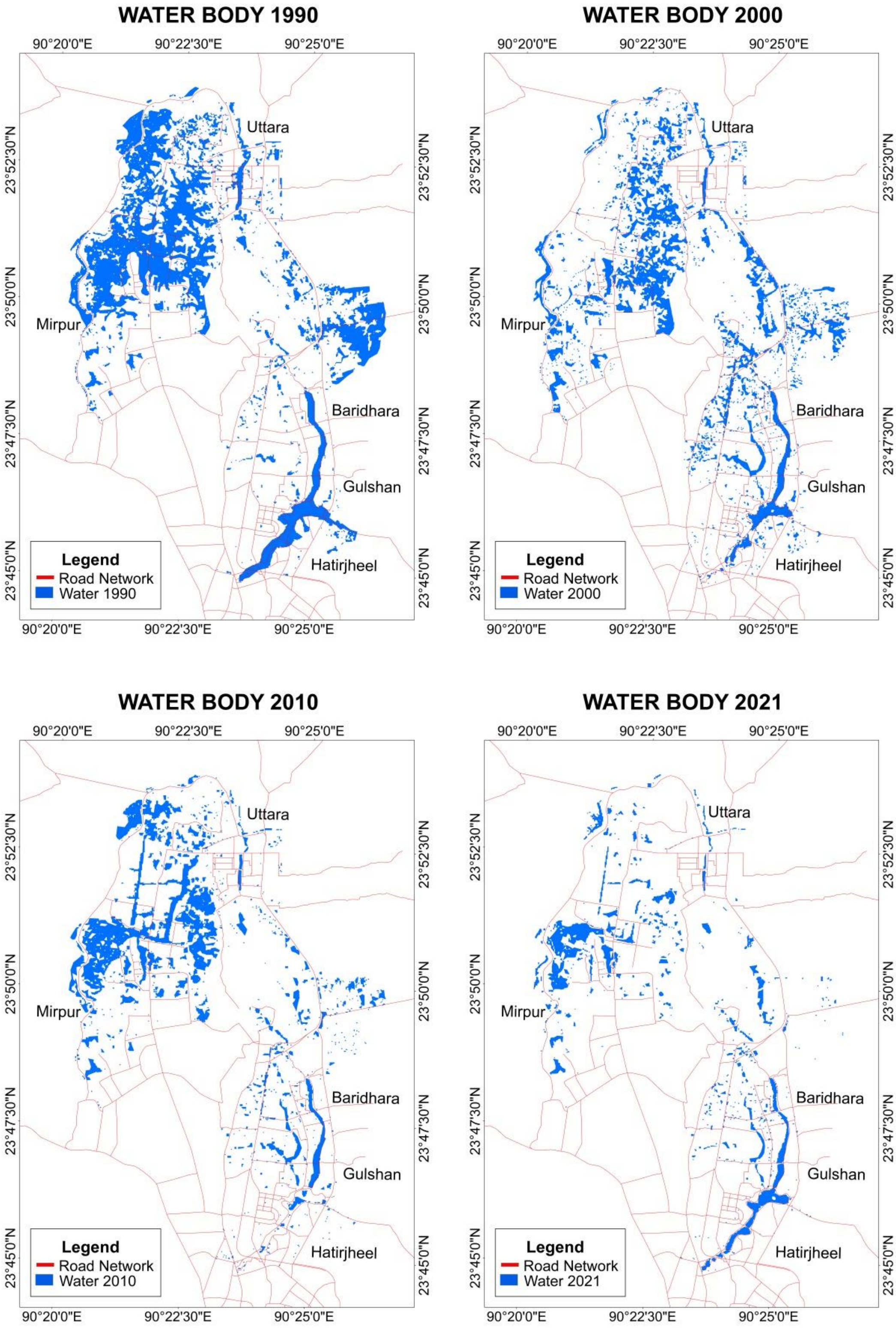

Figure 5.13: Water Body Change Pattern in the Year of 1990, 2000, 2010 and 2021

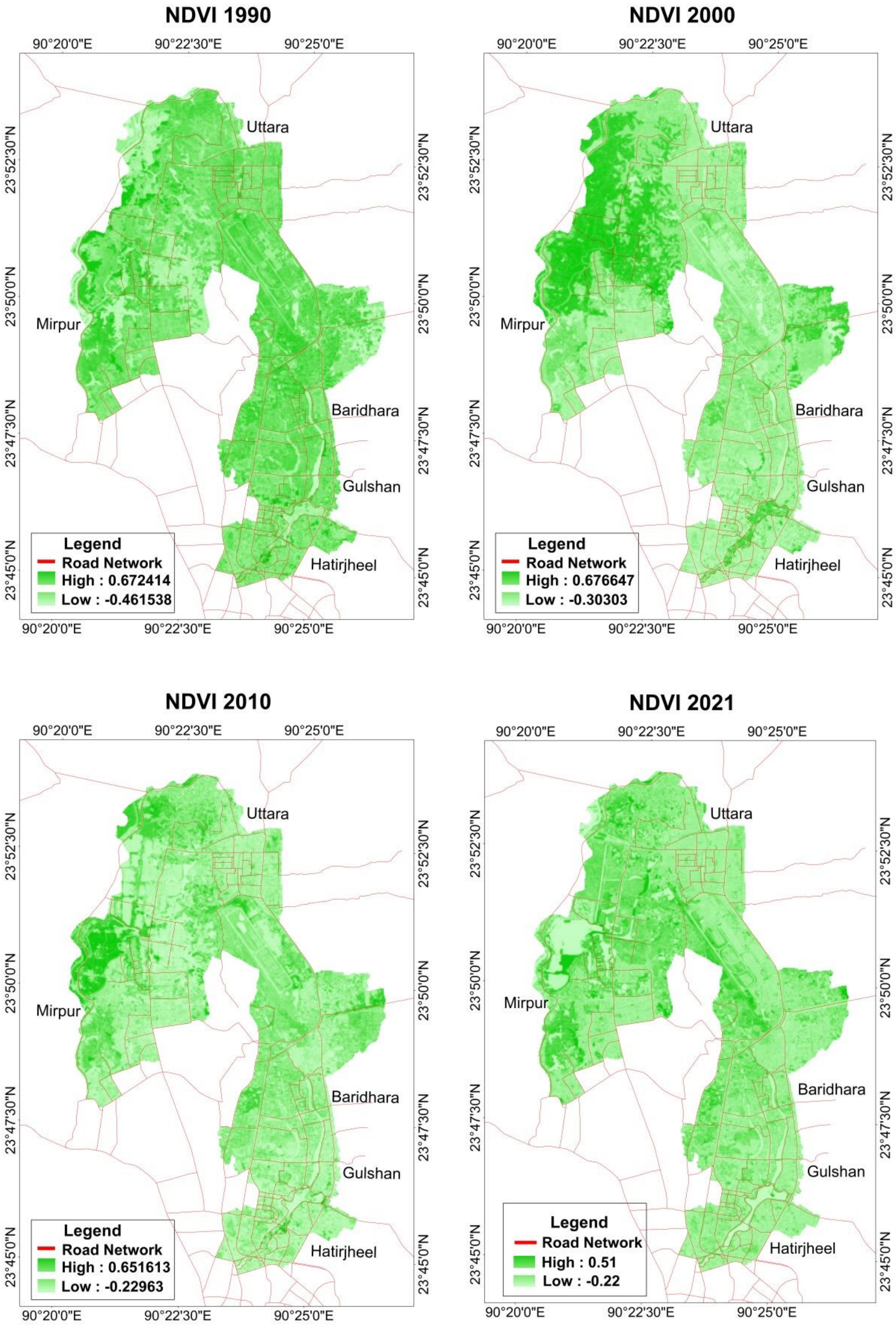

Figure 5.14: NDVI Change Pattern in the Year of 1990, 2000, 2010 and 2021

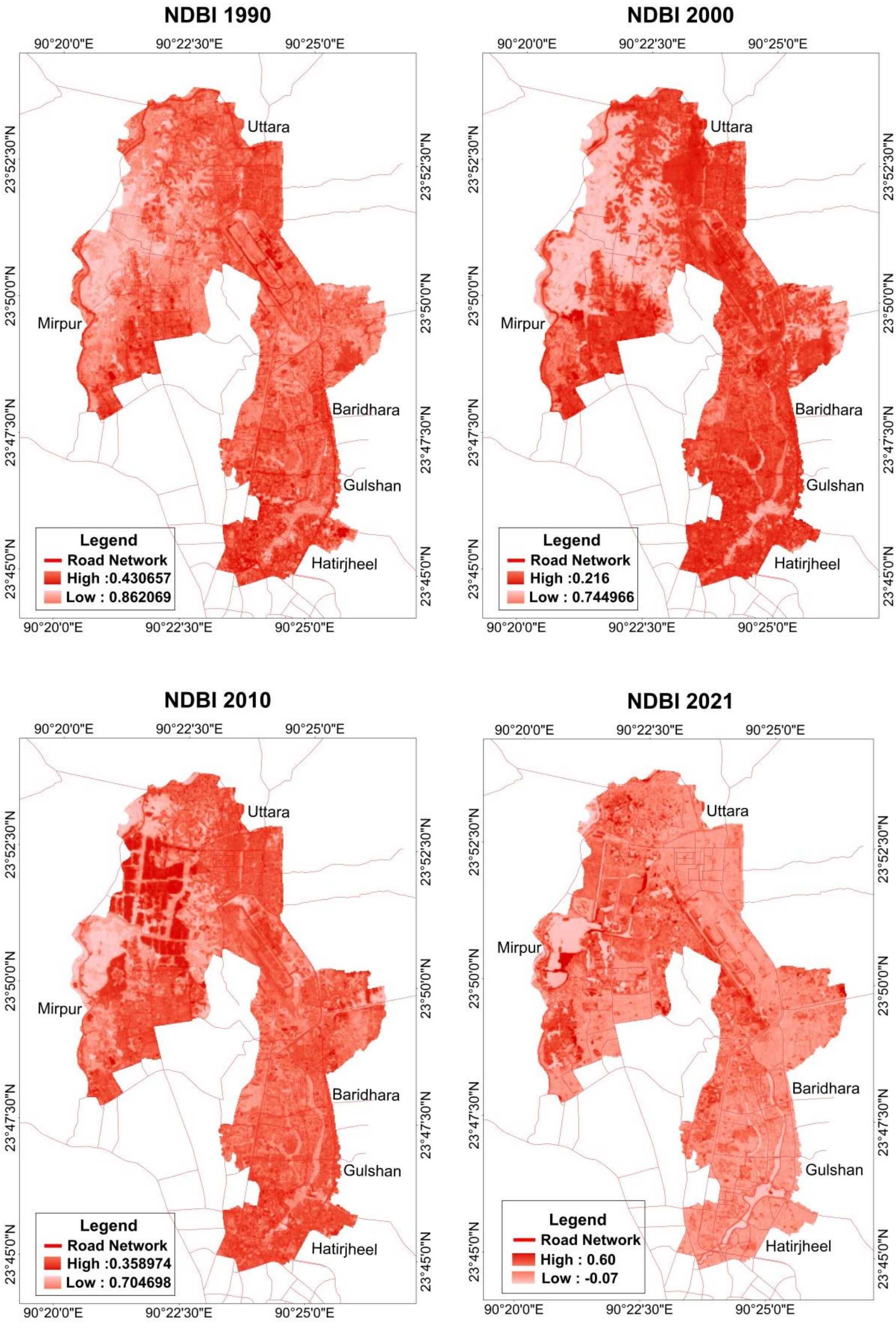

Figure 5.15: NDBI Change Pattern in the Year of 1990, 2000, 2010 and 2021

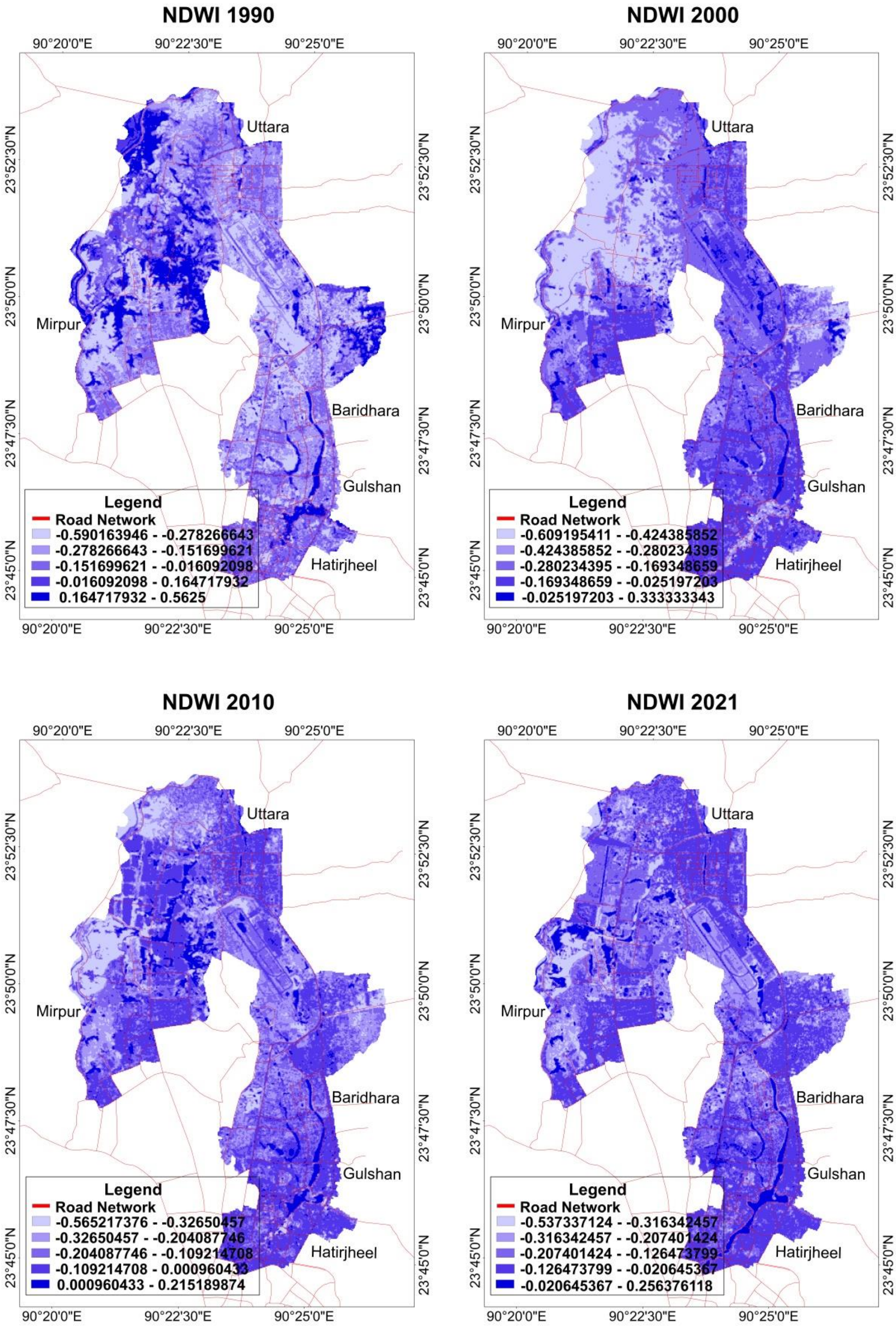

Figure 5.16: NDWI Change Pattern in the Year of 1990, 2000, 2010 and 2021

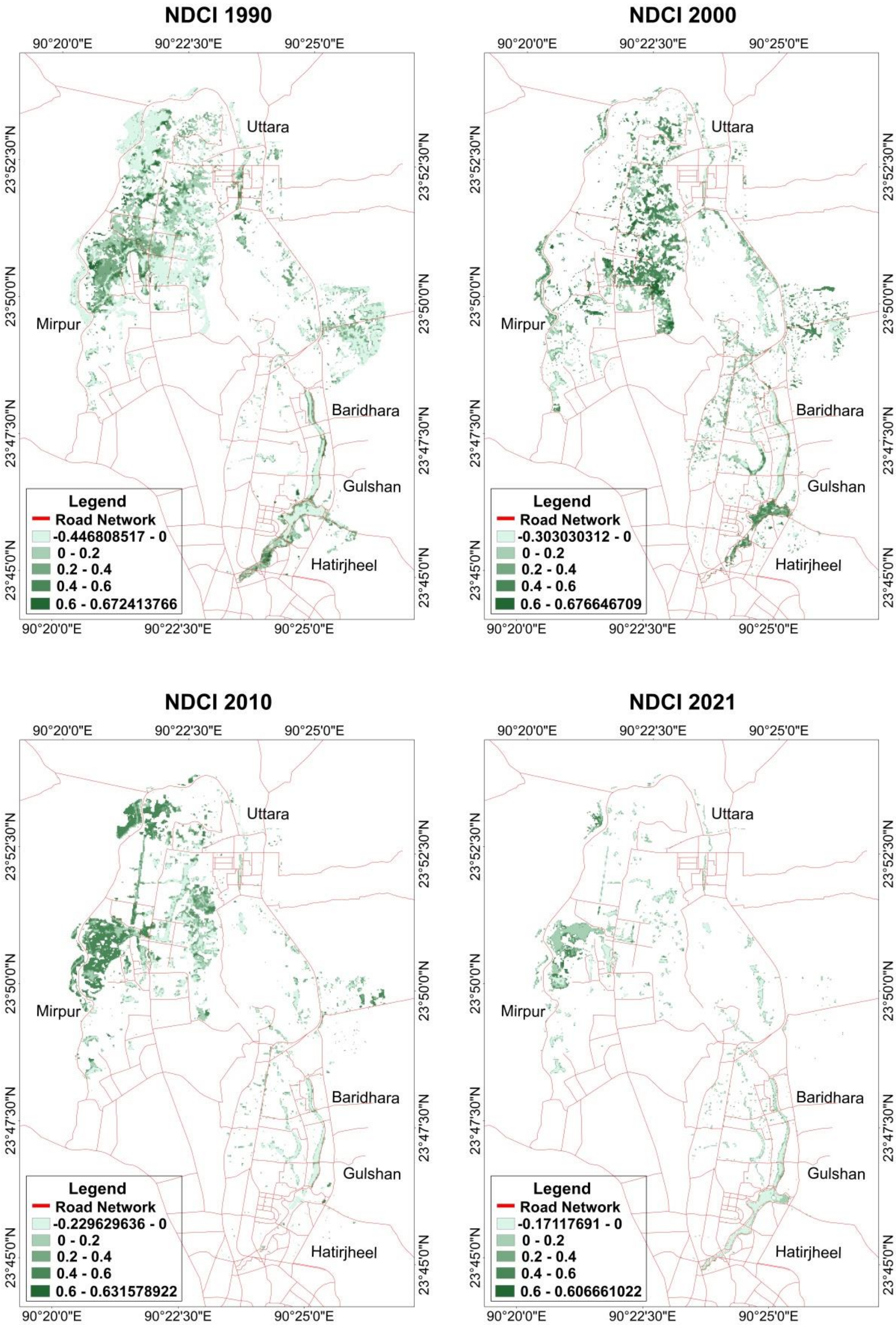

Figure 5.17: NDCI Change Pattern in the Year of 1990, 2000, 2010 and 2021

5.5 NDCI Values and Corresponding Trophic Status

Table 5.7 summarized and compared average TSI for NDCI which was calculated using figure 3.4 (box method) and figure 5.17 (satellite imagery analysis). Average TSI for Chl-a derived from table 5.1 and average TSI for TN derived from table 5.2.

Table 5.7: Comparison Between TSI (NDCI) Vs TSI (Chl-a) Vs TSI (TN)

Lake	Average TSI (NDCI) November 2021	Average TSI (Chl-a) November 2021	Average TSI (TN) November 2021
Uttara	78.28	81.64	98.53
Mirpur	77.42	82.01	94.46
Baridhara	79.57	88.61	102.19
Gulshan	72.71	88.44	92.42
Hatirjheel	76.71	90.99	98.39

According to the Carlson's Trophic State Index (table 3.1), all TSI values were found within the range of **Hypertrophic** state (TSI 70 to 100) for all five selected lakes in the year of 2021. All results are shown in figure 5.18 and found nearly similar.

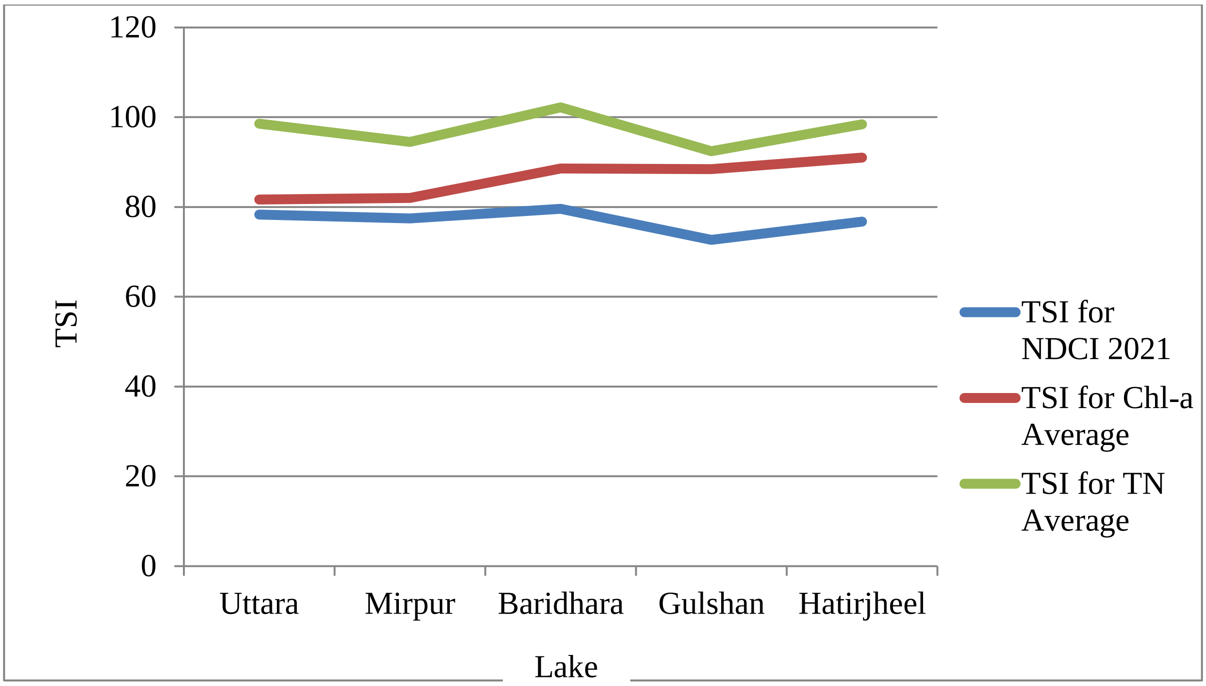

Figure 5.18: Comparison Between TSI

NDCI change pattern for the five selected lakes were developed by analyzing satellite imagery of different years and shown in figure 5.17. Average NDCI values were calculated and derived from the figure 5.17 and shown in table 5.8.

Table 5.8: Average NDCI Values of Different Lakes

Lake	**Year-1990**	**Year-2000**	**Year-2010**	**Year-2021**
Uttara	0.088	0.105	0.153	0.178
Mirpur	0.086	0.108	0.150	0.172
Baridhara	0.102	0.112	0.166	0.187
Gulshan	0.066	0.082	0.117	0.139
Hatirjheel	0.076	0.093	0.148	0.167

Using figure 3.4 and table 5.8, it can be summarized that in the year of 1990, average NDCI value indicates TSI value within the range of **“Supertrophic”** for all the lakes. In the year of 2000, average NDCI value indicates TSI value within the range of **“Supertrophic”** for all the lakes too. In in the year of 2010, average NDCI value indicates TSI value within the range of **“Hypertrophic”** for all the lakes except Gulshan lake which is **“Supertrophic”**. In the year of 2021, average NDCI value indicates TSI value within the range of **“Hypertrophic”** for all the five lakes. These are shown in figure 5.18 to 5.21.

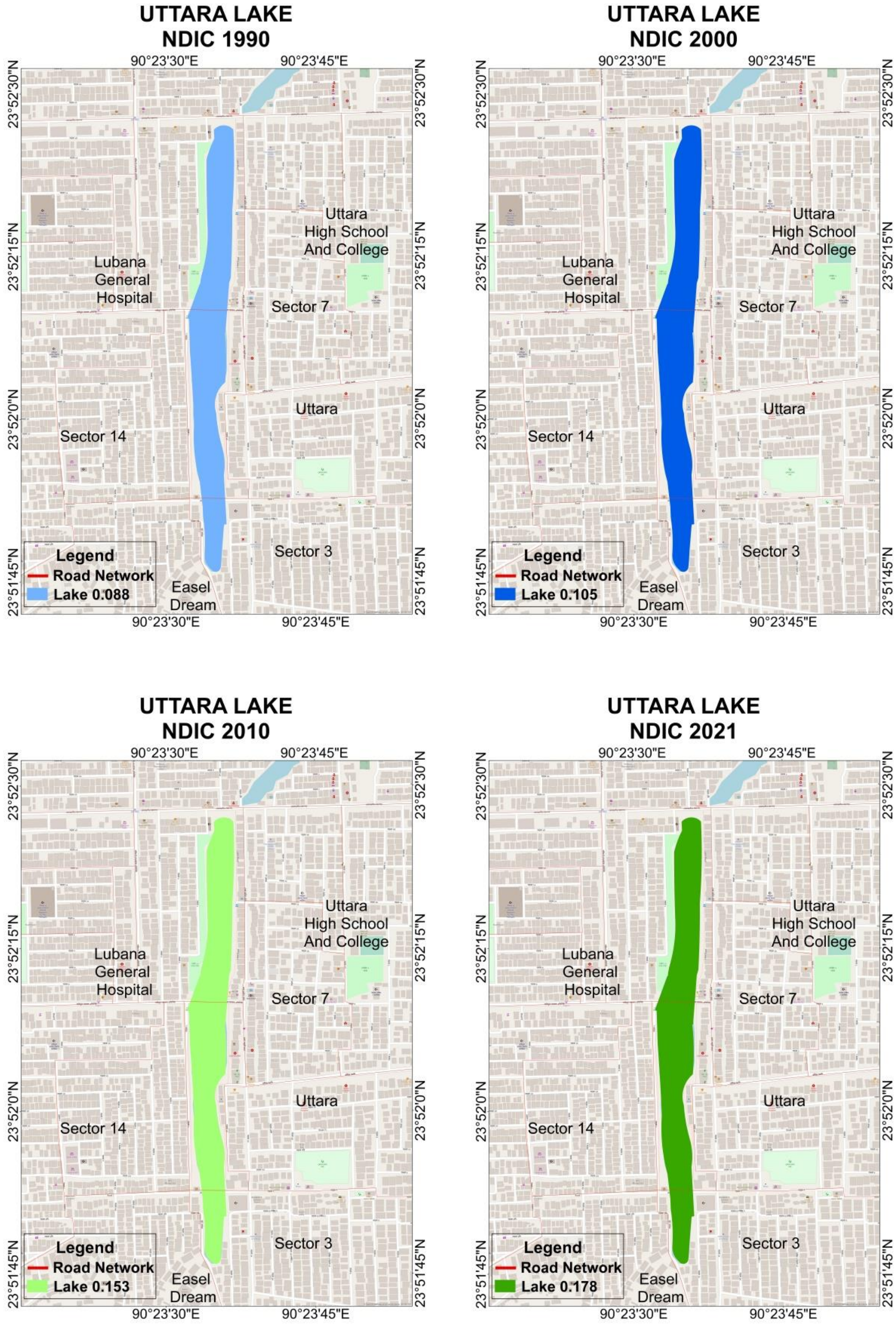

Figure 5.19: NDCI Maps of Uttara Lake in 1990, 2000, 2010 and 2021

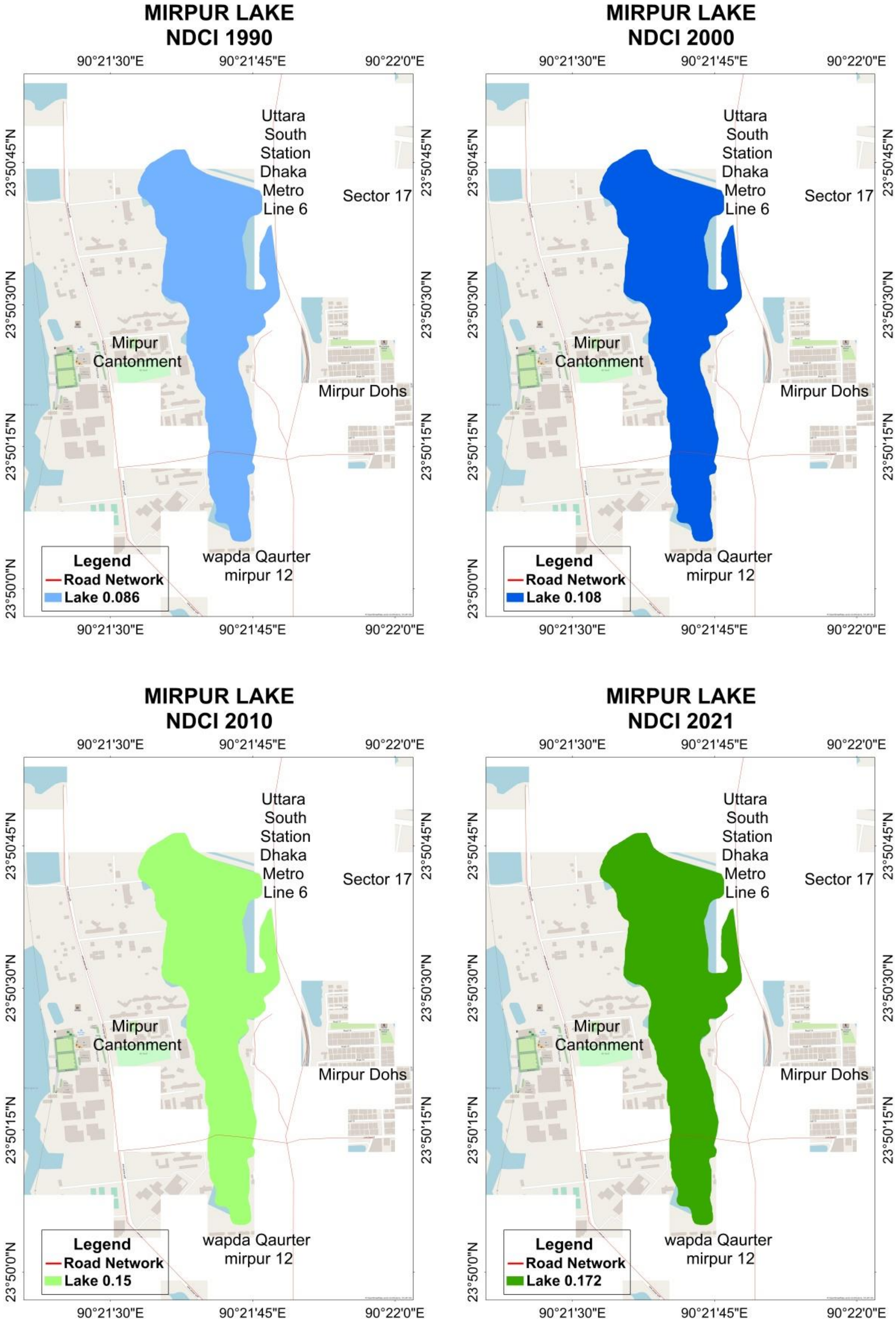

Figure 5.20: NDCI Maps of Mipur Lake in 1990, 2000, 2010 and 2021

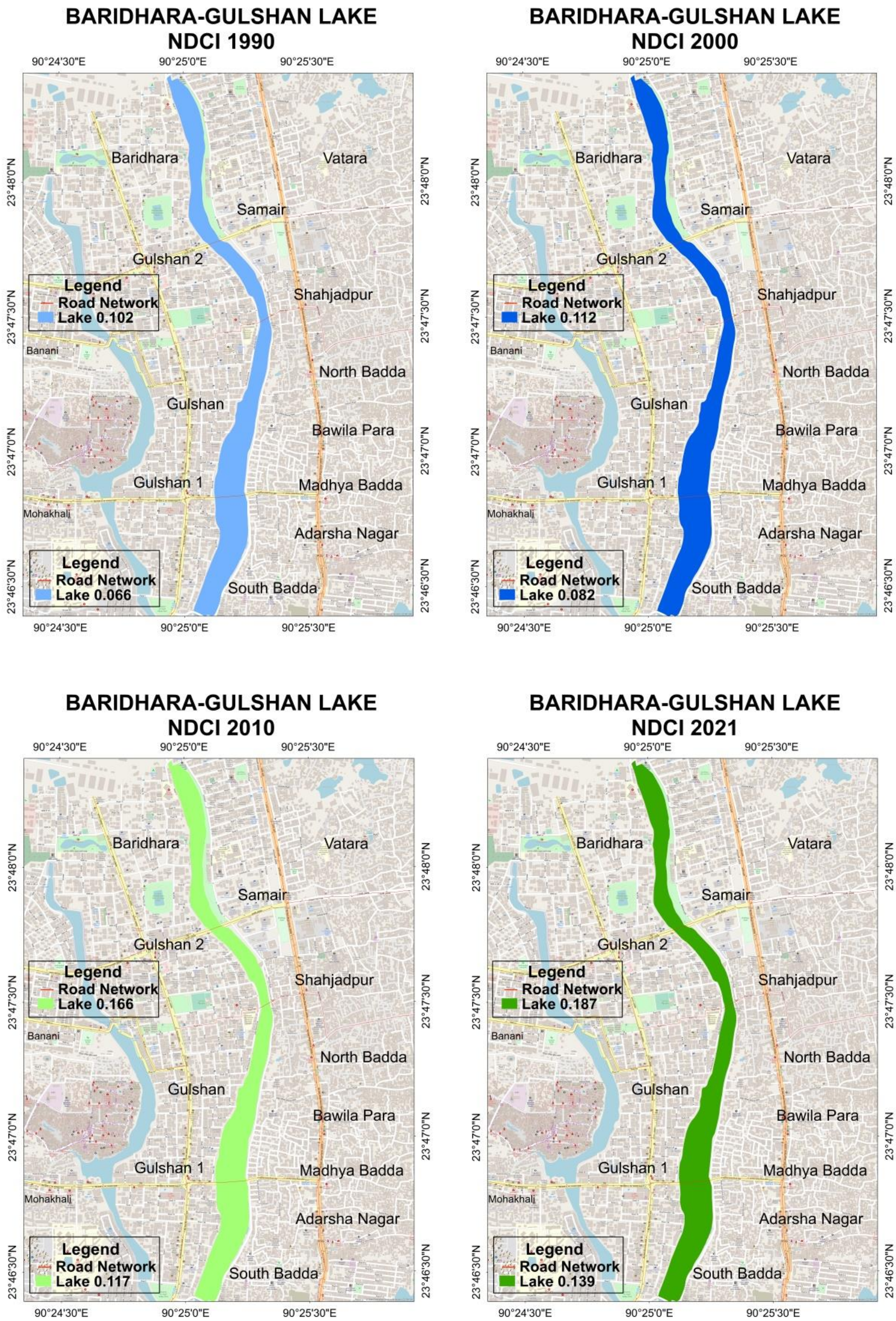

Figure 5.21: NDCI Maps of Baridhara-Gulshan Lake in 1990, 2000, 2010 and 2021

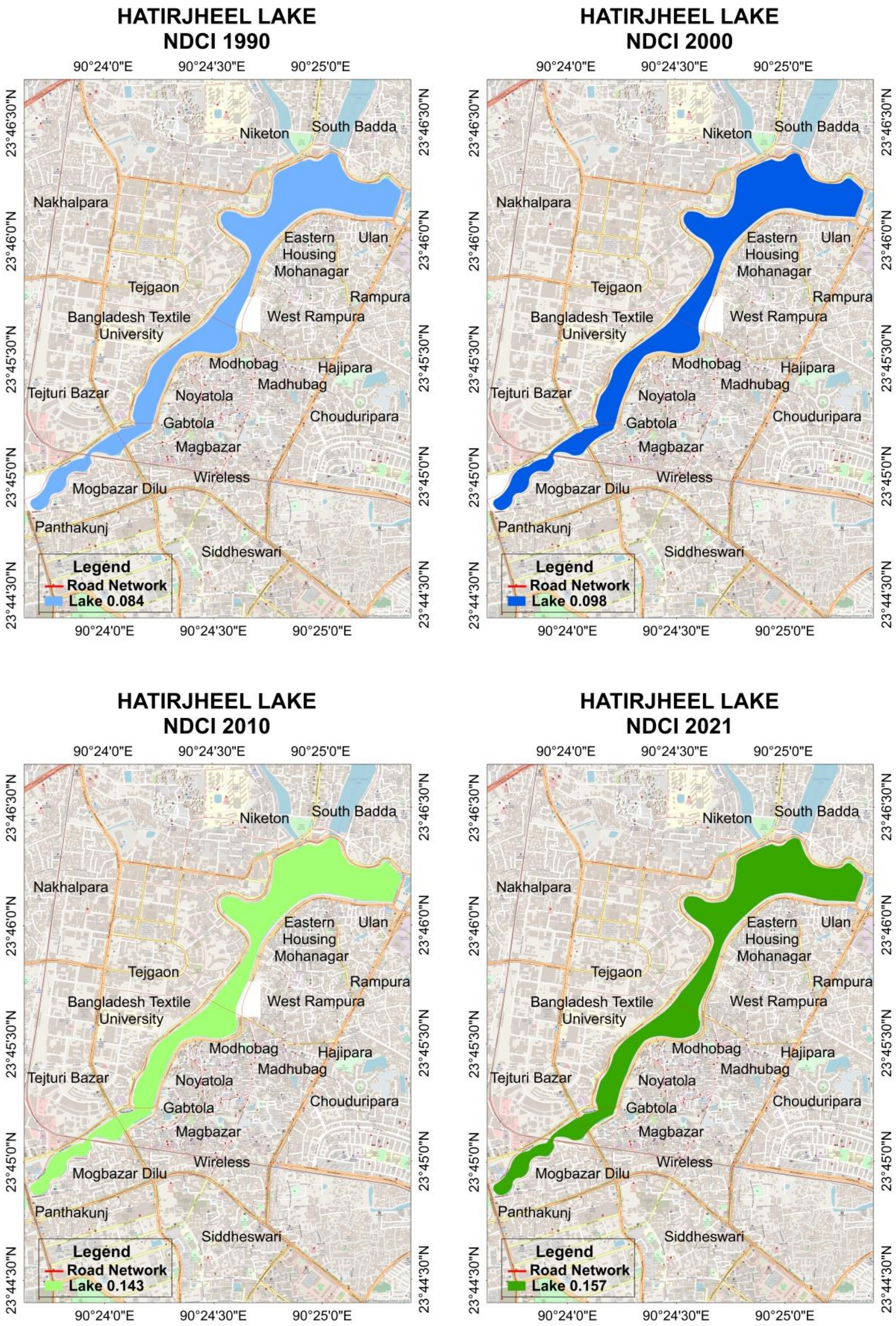

Figure 5.22: NDCI Maps of Hatirjheel in 1990, 2000, 2010 and 2021

5.6 ANN Model Validation

Using ANN model (figure 3.6), trained NDCI values were derived for the year of 2021. Model was found 81% accurate as shown in table 5.9. Trained vs expected NDCI values are shown in figure 5.22.

Table 5.9: Chi-Square Test for Goodness of Model Fitting

Lake	**1990 (NDCI)**	**2000 (NDCI)**	**2010 (NDCI)**	**2021 (NDCI) Expected**	**2021 (NDCI) Trained**	**χ2**	**p**
Uttara	0.088	0.105	0.153	0.178	0.185	0.97	81%
Mirpur	0.086	0.108	0.150	0.172	0.182		
Baridhara	0.102	0.112	0.166	0.187	0.196		
Gulshan	0.066	0.082	0.117	0.139	0.143		
Hatirjheel	0.076	0.093	0.148	0.167	0.171		

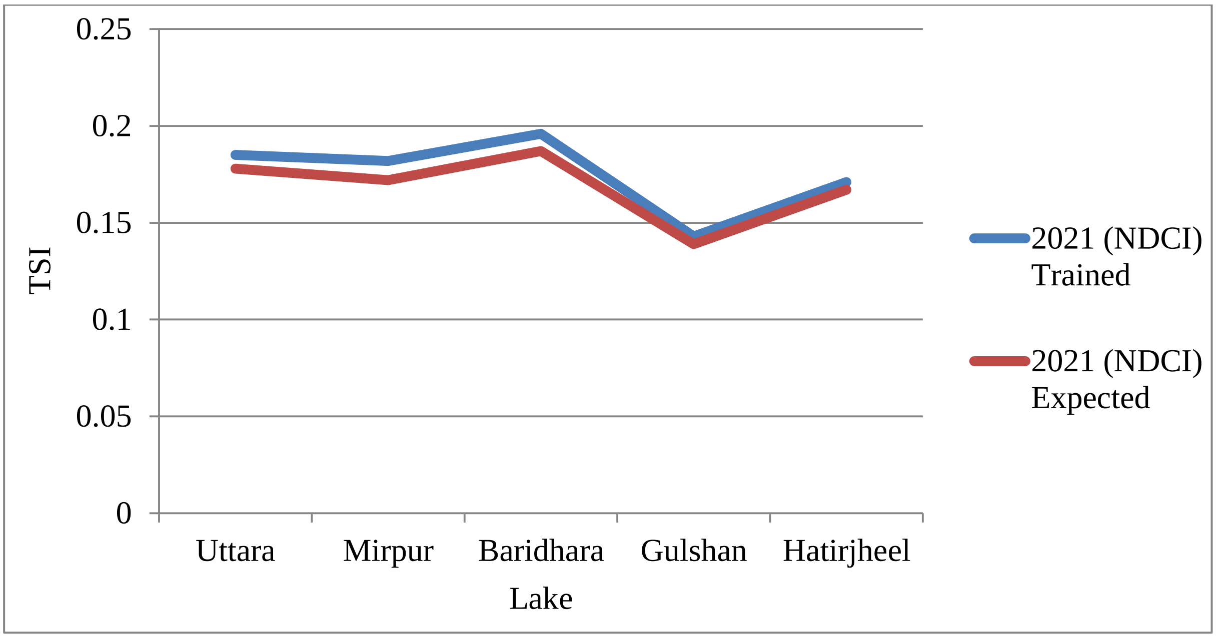

Figure 5.23: Trained Vs Expected NDCI Values

5.7 Prediction Maps in the Year of 2030 and 2040

After training model validation, prediction of NDCI values were developed using ANN model (figure 3.6) for the year of 2030 and 2040. Table 5.10 is showing predicted NDCI values and figure 5.23 to 5.26 are showing predicted NDCI maps for five selected lakes of 2030 and 2040.

Table 5.10: NDCI Prediction for the Year of 2030 and 2040

Lake	1990	2000	2010	2021	2030	2040
Uttara	0.088	0.105	0.153	0.178	0.21 **(TSI=82.85)** Hypertrophic	0.239 **(TSI=87)** Hypertrophic
Mirpur	0.086	0.108	0.15	0.172	0.20 **(TSI=82.28)** Hypertrophic	0.231 **(TSI=85.85)** Hypertrophic
Baridhara	0.102	0.112	0.166	0.187	0.218 **(TSI=84.11)** Hypertrophic	0.246 **(TSI=88.07)** Hypertrophic
Gulshan	0.066	0.082	0.117	0.139	0.164 **(TSI=76.38)** Hypertrophic	0.189 **(TSI=79.92)** Hypertrophic
Hatirjheel	0.084	0.098	0.143	0.157	0.183 **(TSI=79.22)** Hypertrophic	0.217 **(TSI=84.56)** Hypertrophic

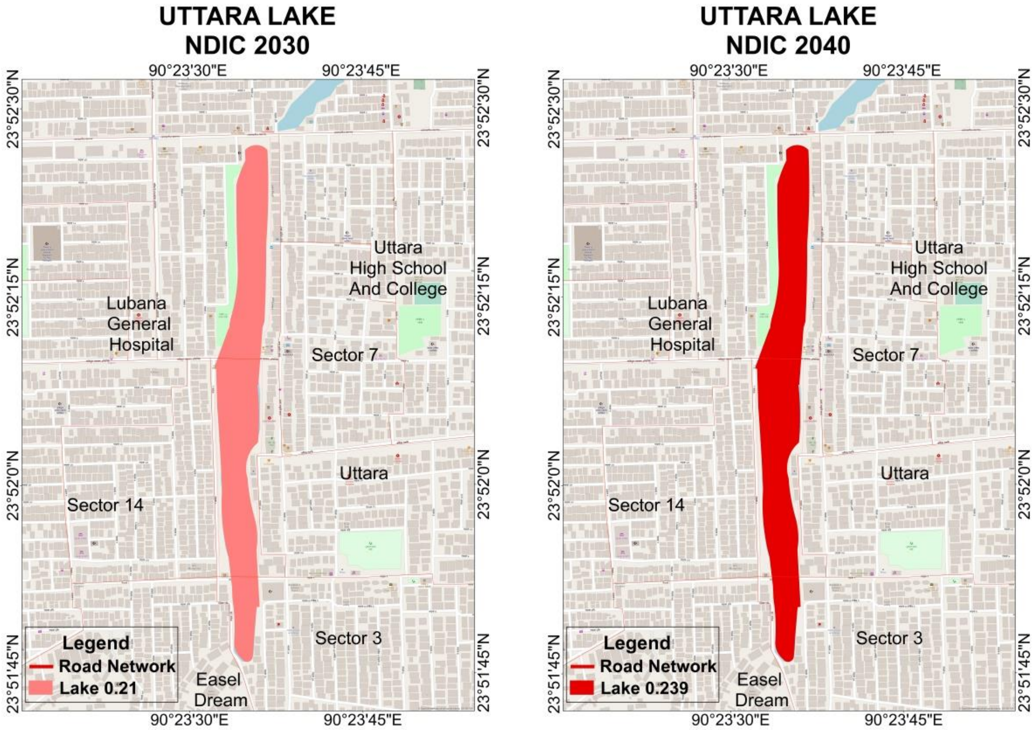

Figure 5.24: Predicted NDCI Maps of 2030 and 2040 of Uttara Lake

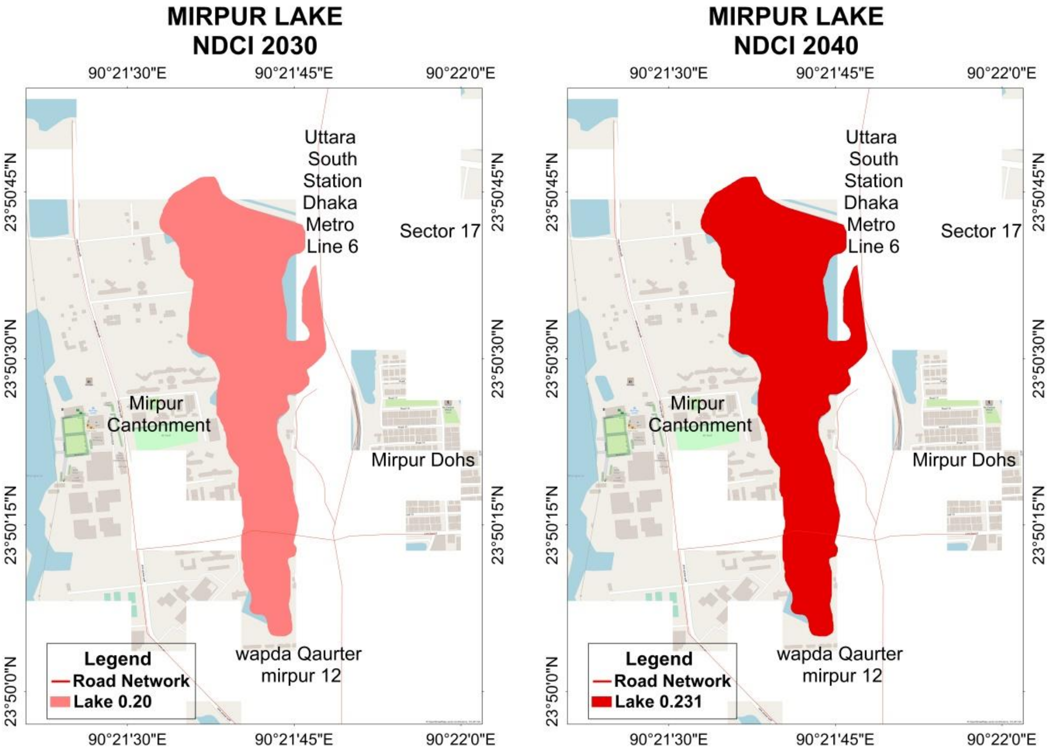

Figure 5.25: Predicted NDCI Maps of 2030 and 2040 of Mirpur Lake

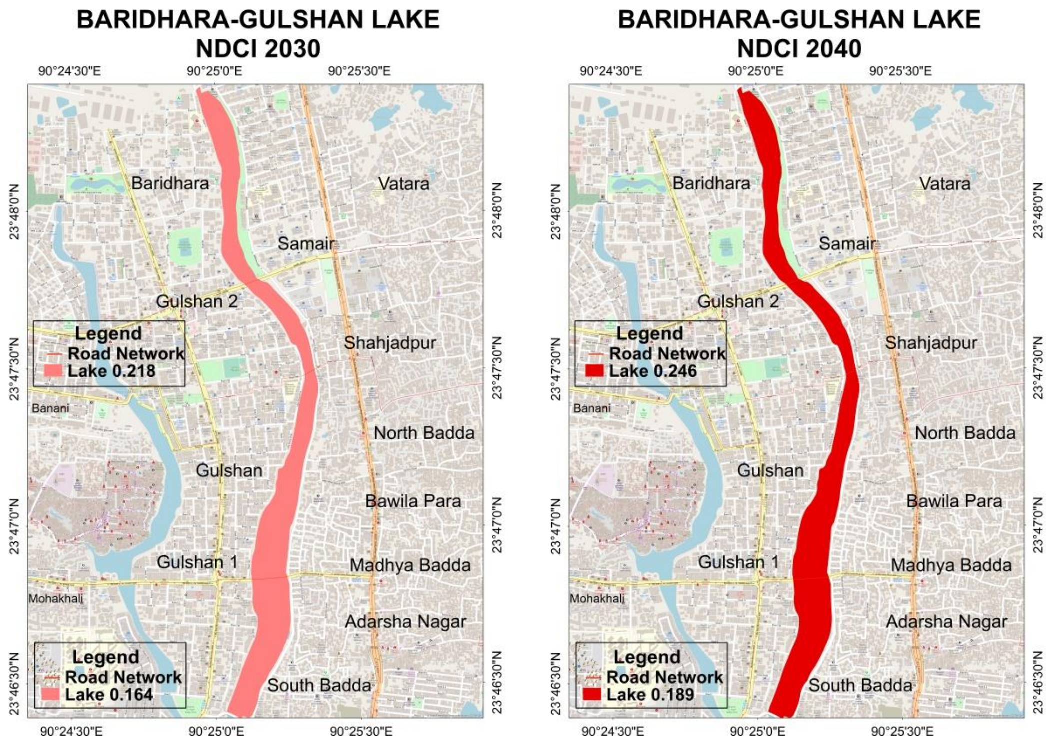

Figure 5.26: Predicted NDCI Maps of 2030 and 2040 of Baridhara-Gulshan Lake

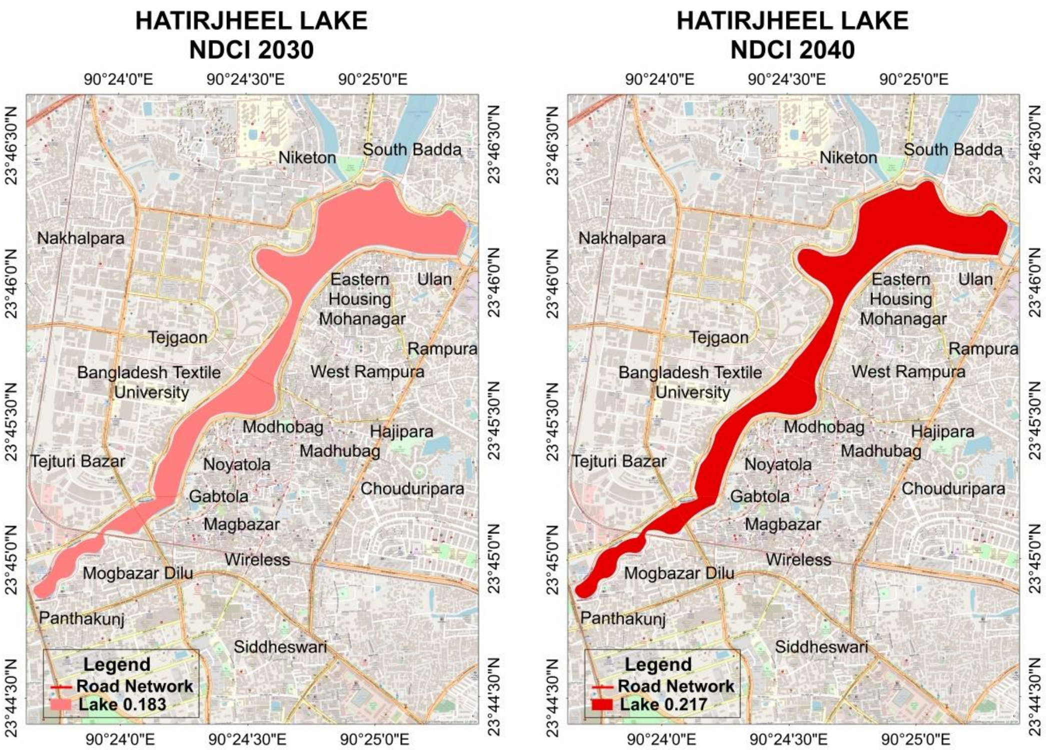

Figure 5.27: Predicted NDCI Maps of 2030 and 2040 of Hatirjheel

5.8 Discussions

Chl-a concentration for Uttara lake was found 162.6 to 209.17 ug/L and corresponding TSI values 80.55 to 83.02. On the other hand, TN for Uttara lake was found 17.2 to 28.5 mg/L and corresponding TSI values 95.5 to 102.78. Chl-a concentration for Mirpur lake was found 154.68 to 210.78 ug/L and corresponding TSI values 80.06 to 83.09. On the other hand, TN for Mirpur lake was found 13.63 to 20 mg/L and corresponding TSI values 92.14 to 97.68. Chl-a concentration for Baridhara lake was found 306.26 to 487.08 ug/L and corresponding TSI values 88.75 to 91.31. On the other hand, TN for Baridhara lake was found 21.23 to 36.13 mg/L and corresponding TSI values 98.54 to 106.21. Chl-a concentration for Gulshan lake was found 257.32 to 581.3 ug/L and corresponding TSI values 85.05 to 93.04. On the other hand, TN for Gulshan lake was found 10.9 to 19.83 mg/L and corresponding TSI values 88.91 to 97.55. Chl-a concentration for Hatirjheel was found 431.45 to 508.94 ug/L and corresponding TSI values 90.11 to 91.74. On the other hand, TN for Hatirjheel was found 19.2 to 22.55 mg/L and corresponding TSI values 97.08 to 99.41.

Waters with high levels of nutrients from fertilizers, septic systems, sewage treatment plants and urban runoff may have high concentrations of chlorophyll a and excess amounts of algae. Chlorophyll-a is considered a direct effect or primary symptom of eutrophication. Monitoring chlorophyll levels is a direct way of tracking algal growth. Surface waters that have high chlorophyll conditions are typically high in nutrients, generally phosphorus and nitrogen. These nutrients cause the algae to grow or bloom. Chlorophyll-a is the pigment that makes plants and algae green. This pigment allows plants and algae to photosynthesize. In photosynthesis, plants use the sun's energy to convert carbon dioxide and water into oxygen and cellular material.

As all the water samples were tested after summer and rainy seasons, algae grow to higher concentrations. Due to the raining more nutrients get washed into the lake and fueling an algal bloom. As the algal concentration increases the water transparency decreases. This means that less light can penetrate through the water so the algae are only at the very top of the lake where there is enough light for photosynthesis.

According to the Chl-a concentration test results, all lakes have significant amount of chlorophyll. However, Baridhara-Gulshan lakes and Hatirjheel were found higher TSI values than Uttara and Mirpur lakes. According to the TN test results, all lakes have significant amount of TN. However, Uttara lake, Baridhara lake and Hatirjheel were found higher TSI values than Mirpur and Gulshan lakes. According to the Carlson's Trophic State Index, TSI value 70-100 indicates **"Hypertrophic"** condition (Carlson, 2007). It was found that TSI values are higher than 70 which indicate **"Hypertrophic"** condition for all five selected lakes.

Phosphate values for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 3.3 to 9.3 mg/L, 2.93 to 7.3 mg/L, 3.36 to 11.63 mg/L, 2.4 to 8.6 mg/L and 2.9 to 9.09 mg/L respectively. **Uttara lake was found higher phosphate value than the other lakes.** Too much phosphorus can cause increased growth of algae and large aquatic plants, which can result in decreased levels of dissolved oxygen which is indicator of eutrophication. High levels of phosphorus can also lead to algae blooms that produce algal toxins which can be harmful to human and animal health. High concentrations of phosphorus result from surface runoff of urban areas and lawns, leaking septic systems or discharges from sewage treatment plants. Phosphorus is an essential element for plant life, but when there is too much of it in water, it can speed up eutrophication (a reduction in dissolved oxygen in water bodies caused by an increase of mineral and organic nutrients) of rivers and lakes.

DO values for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 2.58 to 4.2 mg/L, 1.6 to 2.47 mg/L, 1.52 to 3.23 mg/L, 1.99 to 2.71 mg/L and 1.74 to 2.99 mg/L respectively. **Baridhara lake was found higher DO value than the other lakes.** When dissolved oxygen becomes too low, fish and other aquatic organisms cannot survive. The colder water is the more oxygen it can hold. As the water becomes warmer, less oxygen can be dissolved in the water. Dissolved oxygen (DO) is a measure of how much oxygen is dissolved in the water - the amount of oxygen available to living aquatic organisms. Low dissolved oxygen (DO) primarily results from excessive algae growth caused by phosphorus. Nitrogen is another nutrient that can contribute to algae growth. As the algae die and decompose, the process consumes dissolved oxygen.

BOD values for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 12.9 to 23 mg/L, 18.7 to 31 mg/L, 10.6 to 35 mg/L, 15.9 to 24.67 mg/L and 13.93 to 32.66 mg/L respectively. **Baridhara lake was found higher BOD value than the other lakes.** The BOD is an important parameter for assessing water quality. It deals with the amount of oxygen consumption (mg O2 L− 1) by aerobic biological organisms to oxidize organic compounds. Sewage with high BOD can cause a decrease in oxygen of receiving waters, which in turn can cause the death of some organism. BOD directly affects the amount of dissolved oxygen in rivers and streams. The greater the BOD, the more rapidly oxygen is depleted in the stream. This means less oxygen is available to higher forms of aquatic life. High BOD is harmful to ecosystems as fish and other aquatic life may suffocate in oxygen-depleted waters. Furthermore, it is important that wastewater treatment processes are designed to handle the high organic matter loading present in wastewaters.

COD values for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 41.67 to 71 mg/L, 71.67 to 92.67 mg/L, 48.33 to 100.6 mg/L, 56 to 79 mg/L and 52.33 to 95.33 mg/L respectively. **Baridhara lake was found higher COD value than the other lakes.** High COD indicates presence of all forms of organic matter, both biodegradable and non-biodegradable and hence the degree of pollution in waters. This makes COD useful as an indicator of organic pollution in surface waters. High levels of wastewater COD indicate concentrations of organics that can deplete dissolved oxygen in the water, leading to negative environmental and regulatory consequences. To help determine the impact and ultimately limit the amount of organic pollution in water, oxygen demand is an essential measurement. When the COD levels are higher, there is a greater demand for oxygen. This means that there is likely more oxidizable organic material in water with high COD levels. This also means that there are reduced Dissolved Oxygen (DO) concentrations in wastewater with high COD levels.

pH level for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 6.72 to 7.37, 6.64 to 7.87, 6.5 to 7.11, 6.35 to 7.47 and 6.65 to 7.36 respectively. **Mirpur lake was found higher pH level than the other lakes.** High pH causes a bitter taste, water pipes and water-using appliances become encrusted with deposits, and it depresses the effectiveness of the disinfection of chlorine, thereby causing the need for additional chlorine when pH is high. Low-pH water will corrode or dissolve metals and other substances. When the pH of water becomes greater than 8.5, water taste can become more bitter. This elevated pH can also lead to calcium and magnesium carbonate building up in your pipes. While this higher pH doesn't pose any health risks, it can cause skin to become dry, itchy and irritated. pH is an important quantity that reflects the chemical conditions of a solution. The pH can control the availability of nutrients, biological functions, microbial activity, and the behavior of chemicals.

Water colour values for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 84 to 88.67, 99.67 to 102, 119.3 to 142.7, 89.67 to 101 and 102.33 to 113.33 Pt-Co respectively. **Baridhara lake was found higher water colour value than the other lakes.** Highly colored water has significant effects on aquatic plants and algal growth. Light is very critical for the growth of aquatic plants and colored water can limit the penetration of light. Thus a highly colored body of water could not sustain aquatic life which could lead to the long term impairment of the ecosystem.

Turbidity values for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 24.13 to 28.97, 18.73 to 22.57, 23.53 to 27.47, 20.83 to 24 and 21.34 to 25.42 NTU respectively. **Uttara lake was found higher turbidity value than the other lakes.** Material that causes water to be turbid include clay, silt, very tiny inorganic and organic matter, algae, dissolved colored organic compounds, and plankton and other microscopic organisms. Excess turbidity can cause heavy metals to be added to the water supply. These metals may include lead, mercury, and cadmium, which are toxic to humans. Turbidity can harm aquatic life by reducing the food supply, degrading spawning beds and affecting the function of fish gills.

TDS values for Uttara lake, Mirpur lake, Baridhara lake, Gulshan lake and Hatirjheel were found 181.2 to 212, 124.73 to 169.8, 208.07 to 265.33, 210.33 to 289.67 and 180.38 to 241.8 respectively. **Gulshan lake was found higher TDS value than the other lakes.**

In bodies of water, like rivers, higher levels of total dissolved solids often harm aquatic species. The TDS changes the mineral content of the water, which is important to survival of many animals. Also, dissolved salt can dehydrate the skin of aquatic animals, which can be fatal. Even if the high amount is due to the presence of beneficial minerals, increased levels of TDS can give water a bitter, metallic, or salty taste, along with discoloring the water and creating an unpleasant odor.

Visible indications of eutrophication are high turbidity caused by algal blooms, dense macrophyte growth, mass development of harmful cyanobacteria (blue green algae), reduced species diversity, oxygen depletion, formation of hydrogen sulfide, fish kills, and smell nuisance. Oxygen depletion, or hypoxia, is a common consequence of eutrophication, both in fresh water and seawater. The direct effects of hypoxia include fish kills, especially the death of fish that need high levels of dissolved oxygen. Eutrophication leads to an increased algal growth (because the level of nutrients increases). It can lead to a shift in species composition to fast growing algae species (including toxic species) and a shift from long lived macroalgae to more nuisance species. In all the cases, five selected lakes were found imbalance water quality. However, Baridhara lake was found most severe condition over other lakes. Sources of pollution were identified around the all lakes. It was observed that sewerage connections from residential areas, hospitals/clinics, restaurants/shops etc were found around the five selected lakes. These sewerage connections are the sources of nitrogen and phosphorus. Mirpur lake area is comparatively less populated area. As a result, less numbers of pollution points were found around this lake.

LU/LC change pattern is directly influencing/affecting algal content in lake. Specifically, increased numbers of urban areas are main sources of sewerage discharge (main sources of nitrogen) into the lakes. Satellite imagery analysis was carried out in the year of 1990. 2000, 2010 and 2021. It was found that urban area increased from 22.17 to 38.81 sqkm (75% increased) over the specified time. On the other hand, vegetation cover was reduced from 24.78 to 17.34 sqkm (30% reduced). Barren land was increased from 12.46 to 19.67 sqkm (57.86% increased). Change in water body of the influenced area was reduced significantly from 22.59 to 6.28 sqkm (72.2% reduced). These all factors directly influence the lake water quality.

NDVI analysis in different year shows that healthy vegetation cover reduced significantly over the time. At the same time, NDBI analysis in different year shows that build up area coverage increased significantly. NDWI analysis pattern indicates that significant change in water index all over the study area. At the same time, NDCI analysis shows that chlorophyll index all over the water content areas. Average value for each lake was measured from this index and TSI was calculated using Eutrophication Status Vs NDCI figure (Lobo et al. 2021). In the year of 1990, it was found that all five major lakes are within the range of **"Supertrophic".** In the year of 2000, it was also found that all five major lakes are within the range of **"Supertrophic".** In the year of 2010, on the other hand, all five major lakes are within the range of **"Hypertrophic"** except Gulshan lake**.** In the year of 2021, it was identified that all five major lakes are within the range of **"Hypertrophic".** By 31 years, all lakes changed to next higher trophic state i.e. **"Supertrophic" to "Hypertrophic".** Therefore, lakes were previously in relatively good condition, presently condition deteriorated and in future it will be more unusable.

ANN model was applied using MOLUSC Plug-in of QGIS software. LU/LC, water body, NDVI, NDBI, NDWI and NDCI values were used as input data as these all directly influence lake water quality. For the training model, input data were used from the year of 1990, 2000 and 2010. From the ANN model, expected NDCI values for the year of 2021 were found 81% similar to the predicted value. After training data validation, ANN model was applied and predicted NDCI values for the year of 2030 and 2040 found. All five lakes were found **"Hypertrophic"** condition and NDCI values are increasing. As a result, TSI values are also increasing.

This study assessed initially different water quality parameters including chl-a and TN in the year of 2021 (September to December). This assessment will help any other research related to the water quality investigation. As it has also measured eutrophication status therefore this can also help to further assessment on eutrophication. As this study assessed and analyzed satellite imagery of 1990, 2000, 2010 and 2021 therefore these data can also be used for previous assessment related to this. Satellite imagery analysis mainly focused on chlorophyll assessment and find out trophic state of selected lakes. As a result, it can also help to study on this issue further. This whole study can help decision makers to plan and execute lake management related issues. With the help of this study, Clean water and sanitation can be ensured. Lake management will be improved and lake water quality can be monitored. Public health issues will be addressed and recreational facilities can be developed. Finally, lake ecosystem and ecological balance can be ensured to meet the one of the SDGs mentioned by the United Nations.

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

6.1.1 The study was carried out in five selected lakes of Dhaka city in Uttara, Mirpur, Baridhara, Gulshan and Hatirjheel areas. The study focused to assess previous and present eutrophication status using satellite imagery covering the year 1990, 2000, 2010 and 2021. Water quality parameters of selected lakes were tested in the year of 2021. Thereafter, satellite imagery analysis and present water quality data were calibrated. Using previous and present lake water quality data, future eutrophication status in the year of 2030 and 2040 was predicted using ANN model. Following observations were found from this study:

i) Chlorophyll-a concentration ranges between 154.68 µg/l (Mirpur) to 581.3 µg/l (Gulshan) and corresponding TSI ranges from 80.06 to 93.04. Calculated TN also indicate the similar phenomenon for these lakes and TN value ranges between 10.9 mg/L (Gulshan) to 36.13 mg/L (Baridhara) and corresponding TSI ranges from 88.91 to 106.21. Both results indicate the "**Hypertrophic"** condition for all lakes in 2021 (November to December).

ii) Phosphate values (PO_4^{3-}) of five selected lakes were found 2.4 to 9.33 mg/L. DO values were found 1.52 to 4.20 mg/L. BOD values were found 10.6 to 32.66 mg/L. COD values were found 41.67 to 100.6 mg/L. pH level were found 6.35 to 7.87 (within the range). Water colour values were found 84 to 142.7 Pt-Co. Turbidity values were found 18.73 to 27.47 NTU. TDS values were found 124.73 to 289.67. All water quality parameters were found imbalanced condition.

iii) Sources of pollution were identified around the five selected lakes which are discharging different types of waste directly from residential areas, hospitals/clinics, restaurants/shops and other facilities. Therefore, all WQ parameters were found imbalanced.

iv) From the LU/LC classification, urban area was increased from 22.17 to 38.81 sqkm (75% increased); vegetation cover was reduced from 24.78 to 17.34 sqkm (30% reduced); barren land was increased from 12.46 to 19.67 sqkm (57.86% increased); and water body was reduced significantly from 22.59 to 6.28 sqkm (72.2% reduced).

v) In the year of 1990, average NDCI value indicates TSI value within the range of **“Supertrophic”** for all the lakes. In the year of 2000, average NDCI value indicates TSI value within the range of **“Supertrophic”** for all the lakes too. In in the year of 2010, average NDCI value indicates TSI value within the range of **“Hypertrophic”** for all the lakes except Gulshan lake which is **“Supertrophic”**. In the year of 2021, average NDCI value indicates TSI value within the range of **“Hypertrophic”** for all the five lakes. NDCI values varied from 0.066 (Gulshan lake) to 0.187 (Baridhara Lake) over the year (1990 to 2021) which indicate trophic status **“Supertrophic to Hypertrophic”** condition by 31 years.

vi) ANN model was developed and applied using MOLUSC Plug-in of QGIS software. LU/LC, water body, NDVI, NDBI, NDWI and NDCI values were used as input data. For the training model, input data were used from the year of 1990 to 2010. From the ANN model, NDCI values for the year of 2021 were found 0.185, 0.182, 0.196, 0.143 and 0.171 where tested results are almost similar (81%) to the predicted trained data.

vii) After training data validation, ANN model was applied using LU/LC, water body, NDVI, NDBI, NDWI and NDCI values as input data. Predicted NDCI (TSI value) values for the year of 2030 and 2040 were found 0.21 (82.85), 0.2 (82.28), 0.218 (84.11), 0.164 (76.38) & 0.183 (79.22) and 0.239 (87), 0.231 (85.85), 0.246 (88.07), 0.189 (79.92) & 0.217 (84.56) for Uttara, Mirpur, Baridhara, Gulshan and Hatirjheel areas respectively. It is to be mentioned that all five lakes were predicted as **“Hypertrophic”** with more TSI values**.**

6.1.2 This study will be beneficial for the decision makers to carry out lake monitoring and management. This study identified lake eutrophication from the previous data and calibrated with the present data. As this study predicted future eutrophication status therefore it can help to develop policies and action plan by which all lakes can be monitored and managed effectively and efficiently. Subsequently lake water quality can be improved, ecological balance can be ensured, recreational facilities can be developed, and water can be stored to meet future demand.

6.2 Recommendations and Further Study

The topic of Eutrophication status in Dhaka city's lakes explored here within the limited time and resource. On the other hand, this topic is so wide and there is plenty of opportunities for future study in terms of seasonal variation, iterative monitoring, introducing other important parameters (Total Phosphate), comparing with drone imagery etc. Based on the findings of the study and experienced gathered during the research work following recommendations are made that need to be explored in the future:

i) All lakes of Dhaka city are in deteriorating condition and need to have special attention by the authority. Therefore, an organized and active Lake Committee / Institute may be formed to recover and regular monitoring of these lakes condition.

ii) Every lake has its unique characteristics which contributed by its surrounding LULC pattern. Therefore, identifying of pollution sources and implementation of treatment plants may be introduced where findings of similar study results may be used.

iii) A numerical model can be developed for these lakes which will be used to assess the lake's present condition and, will predict future status also by incorporating regular monitoring information.

iv) An integrated study may be conducted in future by considering all the lakes and surrounding water bodies where seasonal and in-depth data may be used for better projection of lake condition.

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