MODIFIED PROJECT REPORT

ON

“WATER QUALITY MODELLING OF A LAKE SYSTEM: A CASE STUDY”

COLLEGE OF ENGINEERING TRIVANDRUM
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PROJECT DETAILS

1. **Name and Address of the principal Investigator**	: Dr. Swarna Latha K Associate Professor Department of Civil Engineering College of Engineering Trivandrum
2. **Project Details**	
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ABBREVATIONS

ABC	Akkulam Boat Club
AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
APHA	American Public Health Association
AV	Akkulam Veli
BOD	Biological Oxygen Demand
BSWQI	British Columbia Water Quality Index
CFU	Colony Forming Unit
CHL a	Chlorophyll a
COD	Chemical Oxygen Demand
CPCB	Central Pollution Control Board
CTSI	Carlson's Trophic State Index
DEP	Department of Environmental Protection
DN	Digital Number
DO	Dissolved Oxygen
DOQQs	Digital Ortho Quarter Quads
EDTA	Ethylene Diamine Tetra acetic Acid
EIC	English Indian Clay
ERDAS	Earth Resource Development Assessment System
ESRI	Environmental System Research Institute
ETM+	Enhanced Thematic Mapper plus
FC	Fecal Coliform

GIS	Geographic Information System
GPS	Global Positioning System
GUI	Graphical User Interface
HCL	Hydrochloric Acid
IMD	Indian Meteorological Department
IRS	Indian Remote Sensing Satellite
ISRO	Indian Space Research Organization
LISS III	Linear Imaging Self Scanning Sensor III
LU/LC	Land Use/Land Cover
MPN	Most Probable Number
MSE	Mean Square Error
NE	North East
NIR	Near Infrared
NRSC	National Remote Sensing Centre
NSFWQI	National Sanitation Foundation Water Quality Index
NTU	Nephelometric Turbidity Unit
NWI	National Wetland Inventory
OLI	Operational Land Image
ORP	Oxidation Reduction Potential
PEDA	Pensacola Estuarine Drainage Area
RS	Remote Sensing
SDD	Secchi Disk Depth
SIFFS	South Indian Federation of Fisheries Society
SPSS	Statistical Package for the Social Science
SW	South West

SWIR	Short Wave Infrared
TI	Trophic Index
TIRS	Thermal Infrered Sensor
TM	Thematic Mapper
TSI	Trophic State Index
USEPA	United State Environmental Protection Agency
USGS	United State Geological Survey
VSSC	Vikram Sarabhai Space Centre
WQ	Water Quality
WQI	Water Quality Index

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Surface water is an essential natural resource for human survival and to the health of ecosystem. Water resources comprise of coastal water and fresh water such as lakes, rivers and groundwater. The total amount of water on the earth is about 1.35 billion cubic kilometres. Over 97% of this quantity is in the ocean as salt water. The Earth's fresh water amounts to only 37 million cubic kilometres, of which 80% occurs in polar ice caps and glaciers. In reality, very little water is readily available for human consumption.

In the past few decades, the increasing anthropogenic activities especially urbanisation, rise in population, and industrial pollution affected quality of our water resources. This global issue is happening throughout the world. Water pollution is the contamination of water bodies (e.g. lakes, rivers, oceans, and aquifers). Water pollution occurs when pollutants are directly or indirectly discharged into water bodies without adequate treatment to remove harmful compounds. Water pollution affects plants and organisms living in water bodies. When pollutants enter into a water body, the quality of water deteriorates, affecting aquatic ecosystem. In almost all cases, the effect is damaging not only to individual species, but also to the natural biological communities. The nutrients from the agricultural fields, sewage from the human settlements and industrial units drain in to reservoirs and lakes. It contributes to the increasing level of suspended particles, algae growth, and colouring of water and reduces dissolved oxygen level that deplete the quality of water and causes threat to the aquatic system.

An analysis of the nature and rates of environmental change over recent decades are essential for a proper understanding of why present environmental problems have arisen. It is also necessary to allow formulation of accurate preductive models of environmental change. In this respect, information on the existing land use/land cover pattern, its spatial distribution and changes in the land use pattern is a pre-requisite for planning, utilisation and formulation of policies and programmes for making any micro and macro-level developmental plan(Musthafaet al.,(2005).

Land has been going through tremendous transformations due to sprawls, industrialization and urbanization. The changes in land use affect the ecosystem in terms of land cover, land quality and capability, weather and climate, quantity of land that can be sustained and in short the whole population and socio-economic determinants(Charles., 2011).

Land use change detection using remote sensing data and analysis using GIS has been applied to both rural and urban areas. The method is very efficient for assessing the change or degrading trends of a region (Musthafa et al., 2005). Change detection involves the use of satellite imageries of the study area, from which land use maps can be generated by visual interpretation or digital image processing.

Water quality is a general descriptor of water properties in terms of physical, chemical, thermal, and/or biological characteristics. It is difficult to define a single water quality standard to meet all uses and user needs. For example, physical, chemical, and biological parameters of water that are suitable for human consumption are different from those parameters of water suitable for irrigating a crop. Water quality is affected by materials delivered to a water body from either point or nonpoint sources. To handle this problem, it is necessary to carry out water quality assessment, planning, and management, in which water quality monitoring plays an important role.

With the development of remote sensing (RS) techniques, water quality monitoring based on RS methods becomes accessible and very efficient. As the pollutants scatter and absorb the incoming solar radiation, the water quality is significantly correlated with the water column's optical characteristics, such as colour and transparency, which can be obtained from RS data. Therefore, investigators suggest that optical data can provide an alternative means for obtaining relatively low-cost, simultaneous information on surface water quality conditions from numerous lakes, coastal, and oceanic areas (Akbar et al., 2007). Although the methods to retrieve water quality from RS data might not be as precise as traditional methods, they are time and cost efficient over the large area and can provide the opportunity for regular observation of even very remote regions. Therefore, remote sensing techniques have been widely used in estimating the pollution situation of surface water.

The present study mainly focuses on Akkulam-Veli lake which is the only one urban lake in Thiruvananthapuram which is under severe deterioration. This study incorporates the application of remote sensing and GIS in water quality. Water quality is predicted from different type of satellite imagery namely IRS-LISS III and Landsat. Different water quality models have been developed for the prediction of different water quality parameters. The studies on modelling of lake system in Kerala using artificial intelligence are very rare. The artificial intelligence has the superiority of modelling complex relationship between water quality parameters and it has also been used for the prediction of water quality. The other aspects like variation of water quality parameters and index were also studied for the lake system.

1.2 OBJECTIVES OF THE STUDY

- To collect data for assessing the present status of water quality of the Akkulam-Veli Lake and to arrive eutrophication status of the existing lake system and to conduct trend analysis for major water quality parameters
- To develop regression model to predict water quality parameters from satellite imagery data and use the model for prediction.
- To make a comparison between eutophic status of the lake and that predicted using regression model developed using satellite imagery combined with trend analysis
- To assess the water quality using water quality index
- To develop models for Water Quality Index using regression, ANN and ANFIS and thereby predicting the water quality of the lake system
- To develop models for DO for the lake system using ANN and ANFIS

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

The review of literature includes the studies conducted mainly in different lake systems focusing on various water quality parameters and its standards, Eutrophication status, land use change analysis, regression analysis, water quality index for various lakes and different water quality modelling and the validation.

Yang and Liu, (2005) had made the land-use and land cover change mapping in an estuarine watershed using satellite imagery and GIS**.** The authors were involved in an interdisciplinary effort to develop environmental indicators for an estuarine ecosystem assessment in the Gulf of Mexico region. This project started with developing a method to use RS and GIS to monitor land Use/cover in the Pensacola estuarine drainage area (PEDA), Florida. Once this method was developed, they applied it to PEDA and analyzed the results. Landsat TM and ETM+ were used as the primary data, followed by USGS DOQQs, digital topographical maps, ESRI 2002 roads and political boundaries, National Wetland Inventory (NWI), HUCs, Florida DEP land-use maps and USGS land use/cover maps (both complied with Anderson classifications). The researchers found this to be an accurate, detailed method to distinguish land use/cover changes.

Water quality index serves as a single number to indicate the overall water quality. Even though many water quality index determination methods are available, National Sanitation Foundation Water Quality Index (NSFWQI) with modified weights by Central Pollution Control Board is used for the surface waters in India. NSFWQI was used by **Sharma et al.,(2008)** for studying the pollution potential of Yamuna river. This paper deals with the water quality profile of North India's Yamuna river using physico-chemical and bacteriological parameters that converge into a single value NSF WQI and the water quality map was developed. The paper suggests water quality map as a useful tool to conserve and improve the health of the water body.

Weiqi et al., (2008) made a Remote Sensing approach to monitor the water quality in slightly polluted inland water body. They established a water quality retrieval model and analyzed the eight common concerned water quality variables. The variables are algae content, turbidity, concentration of COD, Total Nitrate, Ammonia nitrate, Nitrate Nitrogen, Total phosphorous and Dissolved Phosphorous. Image used for this study is Landsat 5. Multiple regression is carried out to find out the relation between the reflectance values and the water quality parameters.

The depleted dissolved oxygen indicates the level of organic pollution, **Singh et al., (2009)** conducted studies on the training, validation and application of artificial neural network (ANN) models for computing the dissolved oxygen (DO) and biochemical oxygen demand (BOD) levels in the Gomti River (India). Two ANN models with feed-forward network with back propagation learning algorithm were used for the development of model. The model computed values of DO and BOD by ANN were in close agreement with their respective measured values in the river water. The study proposed neural networks as effective tool for the computation of water quality.

Gazzaz et al., (2012) in their paper described design and application of neural network model for computing the Water Quality Index (WQI). WQI predictions of this model had significant, positive, very high correlation with the measured WQI values. The generated model is capable of providing highly accurate forecasts of the WQI for any monitoring site and period of time for which WQ data are available. Findings from this study emphasize that the ANN enables easy modelling of the WQI and allows for identification of the comparative importance and contribution of input WQ variables to the model predictions.

Kanagalakshmi et al., (2012) made a study on impact of land use on environmental quality due to urbanization. From this study they concluded that the changes of Land Use and Land Cover modify the physical parameter of earth surface and thus affecting material and energy interchanges between land and atmosphere. Agricultural land used as an urban area have significant (-ve) effects on the environmental quality as they generate environmental problems such as impact of the water cycle, impact on the ground (or) surface water, discharge of water pollutants, emission of air pollutant, and soil degradation etc.

Bhattacharya and Poonam, (2013) studied about various water quality indices (WQI) used in the surface water quality assessment. There are numerous WQI specific for any region because many National and International agencies define water quality criteria for various uses considering various parameters in water quality assessment and pollution control. Different WQI such as NSFWQI, CCME WQI and WQI are frequently used for water quality assessment. Their background and application area has been mentioned in this study. As per their study CCME and BCWQI are the most efficient for low parameter values. General WQI is an efficient one but parameters selection is difficult and need more attention depending on the source and time. Smith's index gives a better aggregation of datasets. The main drawback of NSFQI is the eclipsing effect. Due to this affect one or more parameters which have values above permissible limit are masked if rest of the parameters are within the limits. Indices are very helpful tool to represent water quality in a simple and understandable manner.

Christiana and Diofantos, (2013)used archived satellite images, for finding out the spatial and temporal variations of water quality in the outlet and intlet areas of Asprokremmos Dam. They could find out that the highest values of water quality parameters correspond to the inlet area where the outfall of the Xeros River exists. It is the area where the water flows into the Dam carrying clay and suspended solids from the Xeros River resulting in increased values of turbidity accompanied with high reflectance values. They could also install an innovative, energy-autonomous floating sensor platform (buoy) which is in the Asprokremmos Dam and is used to transfer turbidity data wireless. This can assist further to test and calibrate their developed equation as well as to provide alert to the Cyprus Water Development Department if turbidity values unusually increased.

Sheela et al.,(2013) made an attempt to quickly assess the pollution status in a vast area (Akkulam-Veli Lake, Kerala, India) directly from the satellite imagery (IRS P6- LISSIII) using NSFWQI. It is also attempted to calculate the pH, dissolved oxygen (DO), biochemical oxygen demand (BOD) and fecal coliforms (FC) in the Lake system. Regression equations were developed for the prediction of NSFWQI, pH, DO, BOD and FC from radiance values in green, red, NIR and SWIR bands of satellite imagery. The study reveals that the simple regression equation formed by the ratio of radiance in the green and the red bands, which yields a strong correlation coefficient for the prediction of NSFWQI. For the prediction of DO, the best equation is the simple regression equation formed by the ratio of radiance in green and red bands. For BOD, multiple regression equation was formed by the radiance in the red and SWIR bands. The best equation for predicting pH is the regression equation with the ratio of green and red bands. But for faecal coliform, multiple regression equation on formed by the ratio of radiance in the green and SWIR bands.

In recent years, several researches have been conducted on water quality forecast models. Artificial Intelligence (AI) such as Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) has become gradually popular for prediction and forecasting in a number of areas like water resources and environmental science. Several studies has been conducted in forecasting the water quality using artificial intelligence since a large number of factors affecting the water quality have a complicated non-linear relation with the variables. **Zhen Ma et al., (2014)** used a back propagation neural network model to predict the water quality in shrimp tanks. The computed results for water quality showed good agreement with the experimental values. The results revealed that the ANN model efficiently predicts the water quality in shrimp tanks and proves that ANN model can preserve nonlinear characteristics between input and output variables, which are superior to traditional statistical models.

CHAPTER 3

BACKGROUND STUDY

3.1 GENERAL

This chapter deals with the theory behind each process involved in the study. The eutrophication process, land use analysis, water quality assessment using water quality index and various water quality modelling were incorporated.

3.2 EUTROPHICATION AND TROPHIC STATE INDEX

Eutrophication is an enrichment of water by nutrient that causes structural changes to the ecosystem such as increased production of algae and aquatic plants, depletion of fish species, general deterioration of water quality and other effects that reduce and preclude use.

The quantity of nitrogen, phosphorus, and other biologically useful nutrients is the primary determinant on Trophic State Index (TSI). Nutrients such as Nitrogen and Phosphorus tend to be limiting resources in standing water bodies, so increased concentration tends to result in increased plant growth, followed by corollary increase in subsequent trophic levels. Consequently, water body's trophic index may sometimes be used to make a rough estimate of its biological condition. Although the term "Trophic Index" is commonly applied to lakes, any surface water body may be indexed.

Carlson's index is one of the more commonly used trophic indices and is the trophic index used by the United States Environmental Protection Agency. Both natural and anthropogenic factors can influence a lake or other water body's Trophic Index. A water body situated in a nutrient-rich region with high Net Primary Productivity may be naturally eutrophic. Nutrients carried into water bodies from non-point sources such as agricultural runoff, residential areas increase the algal biomass, and can easily convert oligotrophic lake to hypereutrophic.

A lake is usually classified as being in one of the three possible classes, oligotrophic, mesotrophic or eutrophic. Lakes with extreme trophic indices may also be considered hyper oligotrophic or hypereutrophic. Oligotrophic lakes generally host very little or no aquatic vegetation and are relatively clear, while eutrophic lakes tend to host large quantities of organisms, including algal blooms. Each trophic class supports different types of fish and other organisms, as well. If the algal biomass in a lake or other water body reaches too high a concentration (say >80 TSI), massive fish die-offs may occur as decomposing biomass deoxygenates the water. Table 3.1 below demonstrates how the index values translate into trophic classes.

Table 3.1: Lake Trophic State and Classification Range for Trophic State Index

(Source: Carlson and Simpson 1996)

Trophic State Index	Sechhi Disk Depth (SDD) in m	Trophic Class
<30-40	>8-4	Oligotrophic
40-50	4-2	Mesotrophic
50-70	2-0.5	Eutrophic
70-100+	0.5-<0.25	Hypereutrophic

3.3 LAND USE MAP

Land use involves the management and modification of natural environment or wilderness into built environment such as settlements and semi-natural habitats such as arable fields, pastures, and managed woods. It also has been defined as "the total of arrangements, activities, and inputs that people undertake in a certain land cover type. Land Use/Land Cover data refers to data that is a result of classifying raw satellite data into "land use and land cover" (lulc) categories based on the return value of the satellite image.

Land use map is prepared by conducting supervised classification. In supervised classification the user or image analyst “supervises” the pixel classification process. The user specifies the various pixels values or spectral signatures that should be associated with each class. This is done by selecting representative sample sites of known cover type called Training Sites or Areas**.** The computer algorithm then uses the spectral signatures from these training areas to classify the whole image. Ideally the classes should not overlap or should only minimally overlap with other classes.

3.4WATER QUALITY

The quality of water resource refers to the chemical, physical, biological, and radiological characteristics of water. Water quality is one of the main characteristics of a water body affecting its suitability for use. It is a measure of the condition of water relative to the requirements of one or more biotic species and or to any human need or purpose. For conforming the good quality of water resource large number of physico-chemical and biological parameters are to be studied in detail and must be found in normal range. In any rational formulation and deciding quality of water resource an adequate knowledge of existing nature of physico-chemical parameter, magnitude and source of any pollution load must be known for which monitoring of physico-chemical parameters and pollutants is essential.

Assessment of water resource quality from any region largely depends on the nature and extent of the industrial, agricultural and other anthropogenic activities in the nearby areas. Escalated anthropogenic activities have caused many-fold increase in the organic pollution load of the surface water bodies in India.

3.5WATER QUALITY INDEX

Water quality index (WQI) provides a single number that expresses overall water quality based on several water quality parameters. The objective of water quality index is to turn complex water quality data into information that is understandable and usable by public. Water quality index provide information on a rating scale from zero to hundred. Higher value of WQI indicates better quality of water and lower value shows poor water quality.

WQI is used as a management tool in water quality assessment. A single number cannot tell the whole story of water quality; there are many other water quality parameters that are not included in the index. A water quality index based on some very important parameters can provide simple indicator of water quality. Generally, water quality indices incorporate data from multiple water quality parameters in to a mathematical equation that rates the health of a water body with number.

3.6WATER QUALITY MODELLING

Water quality modelling is the basis of water pollution control. Monitoring and assessing the quality of surface waters are critical for managing and improving its quality. Models are used to predict trends in water quality based on current water conditions, including pollutant concentrations.

Several deterministic and stochastic water quality models have been developed to manage best practices for conserving water quality. Most of these models are very complex and require a significant amount of field data to support the analysis. Furthermore, many statistically based water quality models assume the relationship between the response and prediction variables are linear and normally distributed. As water quality can be affected by many factors, traditional data processing methods are no longer sufficient for analysis as many factors exhibit complex nonlinear relationships to water quality forecast variables. Therefore, utilizing a statistical approach usually does not provide high precision.

Although, parametric statistical and deterministic models have been the traditional approaches for modelling the water quality but these require vast information on various hydrological sub processes in order to arrive the end results. In recent years, several researches have been conducted on water quality forecast models. However, since a large number of factors affecting the water quality have a complicated non-linear relation with the variables; traditional data processing methods are no longer good enough for solving the problem.

3.6.1 Artificial Neural Network (ANN)

Artificial neural network is an information processing technique that is inspired by the way biological nervous systems, such as the brain, process information. ANN can show a surprising number of human brain's characteristics, e.g., learning from experience and generalizing from previous sample to solve new problems.

The artificial neural networks is capable of imitating the basic characteristics of the human brain such as self-adaptability, self-organization and error tolerant and has been widely adopted for model identification, analysis and forecast, system recognition and design optimization. Unlike many statistically based water quality models, which assume a linear relationship between response and prediction variables and their normal distribution, ANNs are able to map the non-linear relationships that are characteristics of aquatic eco-systems.

The ANN approach has several advantages over traditional phenomenological or semi-empirical models, since they require known input data set without any assumptions. The ANN develops a mapping of the input and output variables, which can subsequently be used to predict desired output as a function of suitable inputs (Aslan, M, 2008). A typical ANN model is shown in figure 3.1.

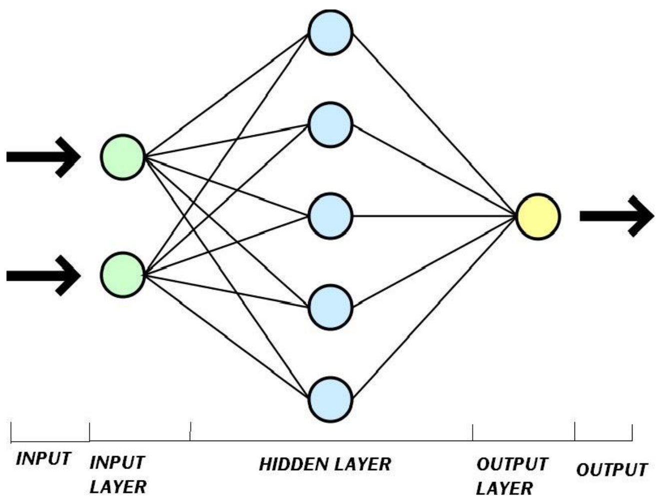


Figure3.1: Typical Model of an Artificial Neural Network
(Source: Huiqun et al., 2008)

An ANN must have at least three layers. The first layer is the input layer in which the input data is introduced to the model. The second layer is the hidden layer which processes the input data in the input layer. In hidden layer, activation function is applied on neurons. The number of hidden layer might be more than one. Finally the output layer is the component of the network that contains the output data of the model (Huiqun et al.,2014).

3.6.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The fuzzy system and neural networks are complementary technologies. The most important reason for combining fuzzy systems with neural networks is to use learning capability of neural network. While the learning capability is an advantage from the view point of a fuzzy system, from the viewpoint of a neural network there are additional advantages to a combined system. Because a neuron-fuzzy system is based on linguistic rules, we can easily integrate prior knowledge in to the system, and this can substantially shorten the learning process(Aslan M, 2008).

Fuzzy logic system models a system with the help of a fuzzy rule or rules. Fuzzy rules are the expressions that state the relationship between the system's inputs and outputs depending on the linguistic variables and in the form of if-then statements.

One of the popular integrated systems is an ANFIS (Adaptive Neuro- Fuzzy Inference System), which is about taking a fuzzy inference system and back propagation algorithm. ANFIS technique is a network structure consisting of a number of nodes connected through directional links. Each node has a node function with adjustable or fixed parameters. Learning or training phase of network is a process to determine parameter value to sufficiently fit the training data.

In ANFIS, the output of each rule can be a linear combination of input variables plus a constant term or can be only a constant term. The final output is the weighted average of each rule's output (Aslan M, 2008). Basic structure of ANFIS is shown in figure 3.2.

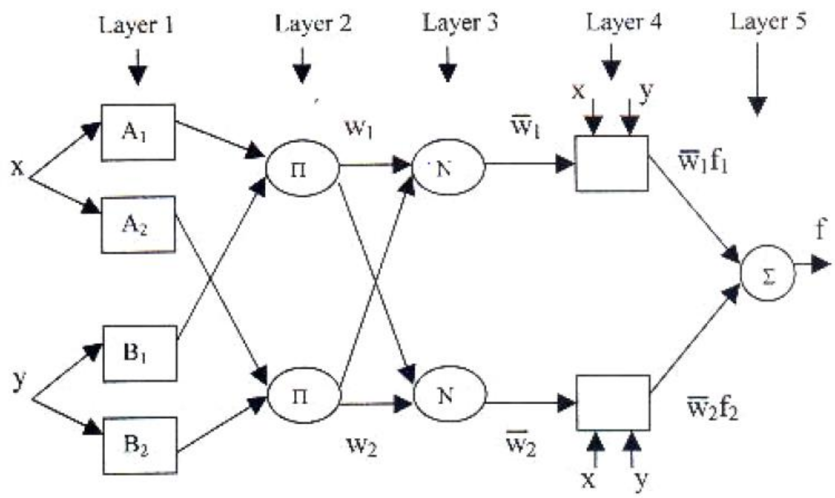


Figure 3.2:Basic ANFIS Structure

(Source: Aslan, 2008)

CHAPTER 4

STUDY AREA AND DATA COLLECTION

4.1 GENERAL

In this study Akkulam Veli lake is selected as study area. It is one of the urban tropical lake in south India and is a well-known tourist place. This chapter deals with the salient features of the study area and data required in this study. Data collection includes water samples which are collected from the 16 sampling stations and satellite imagery of different years.

4.2 AKKULAM – VELI LAKE

Akkulam Veli (AV) Lake is brackish water located at the 5 km of north-western portion of the Thiruvananthapuram city along the south west coast of India, and is partially divided into two by a bund formed lengthwise. It is about 75 ha (63.6 ha of Akkulam and 12 ha of Veli) with depth ranging from 2.25 m to 3.75 m. The Lake is situated between 8^0 31’14” and 8^0 31’52” N latitudes and 76^0 53’ 12" and 76^0 54’ 6" E longitudes. The lake is under environmental degradation because of the high pollution load of the Thiruvananthapuram city reaching the lake through Kannamoold drain in the upstream of the Akkulam lake and due to the joining of TS Canal in the upstream of Veli lake and thereby causing hyper eutrophication in the lake system. The location map of Akkulam Veli Lake is given in figure 4.1.

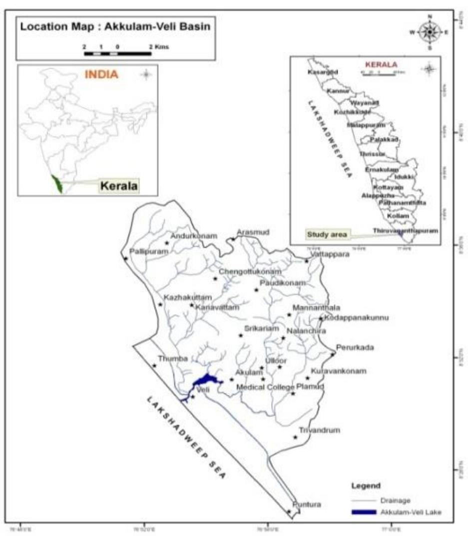


Figure 4.1: Location Map of Akkulam – Veli Lake

(Source: Sheela et al., 2013)

4.2.1Morphometry of Akkulam – Veli Lake

The knowledge of the morphological characteristics of a lake is important because the shape of the water body affects the physical, chemical, and biological properties of the ecosystem (Bezerra-Neto et aI., 2010). These dimensions influence the lake's water quality and productivity levels (WOW, 2004).The morphological features of the AV lake are given in table 4.1.

Table 4.1: Morphological Features of Akkulam Veli Lake

(Source: Sheela.,2011)

Sl. No	Item	Unit	Value
1	Elevation		Around Mean Sea Level
2	Lake Area	km^2	0.76
3	Maximum Length	km	3.2
4	Maximum Width	m	525
5	Mean Width	m	250
6	Maximum Depth	m	5.7
7	Minimum Depth	m	0.22
8	Mean Depth	m	0.9
9	Shore Length	km	7
10	Volume	m^3	373,927.41
11	Watershed Area	km^2	143.9
12	Watershed to lake Surface Area		189.34

Lake surface area is used to predict the potential effects of wind on a lake and it also influences the dilution capacity of the lake system. The lakes with greater surface area are subjected to larger waves during windy conditions and the larger waves have the ability to mix water at greater depths. Lakes with greater surface area have a greater dilution capacity than lakes with as smaller surface area(Sheela A.M., 2011). For the AV Lake, the surface area is very small (0.76 km^2) and smaller waves are generated during windy conditions. These waves have the ability to mix water at smaller depths only. Hence, resuspension of sediments due to wind action is not prominent. Further as the lake surface area is small, less water is available to dilute the contaminants entering the lake and hence the dilution capacity is very low for the AV Lake.

The maximum length is important because it can influence the depth at which waves can mix water and bottom sediments in a lake (Lakewatch, 2001). AV lake has a maximum length of 3.2 km and a maximum width of 0.52 km with a mean depth of 0.9m (Table 4.1).As the maximum length of the lake is small, waves are prevented from becoming very large and mixing of water is reduced. The narrow shape in some portion of the Veli Lake also restricts the formation of wind induced wave action.

The depth of the lake is important as it indicates productivity in a lake system (Lakewatch, 2001). Shallow lakes are more productive than deeper lakes. For the AV lake, almost the entire area has depth less than 4.57 m and falls under shallow lake category. The mean depth of the Akkulam Lake is 0.34 m and that of the Veli lake is 1.3 m. This shows that the Akkulam lake is more shallower than that in the Veli lake. The bund in between the two lakes is responsible for the partial obstruction to the flow from the Akkulam lake to the Veli lake causing siltation in the former.

The maximum depth of a lake influences the movement of fine organic sediments found at the bottom of a lake. The maximum depth observed is 5.7 m in the downstream portion of the Veli lake.

Shoreline length is the linear measurement of a water body's entire perimeter, at a given water level (Lakewatch, 2001). It provides a measurement of the actual amount of interface between a water body and the surrounding land. Shoreline development refers to the length of a lake's shoreline relative to a circle of the same area. For the AV lake, the shoreline length is 7 km and the shoreline development is 2.3 i.e. the interface between the lake and the surrounding land is more. Hence, the buffer zone around the lake shall be notified and steps shall be taken for shoreline planting to prevent soil erosion.

The total lake volume influences lake's dilution capacity (WOW, 2004). The volume of water available in the entire AV lake is 373,927.4 m^3 (Table 4.1). The volume of water in the Akkulam lake is 155,663.6 m3 and that in the Veli lake is 218,263.8 m3. Since the lake volume is very small, the dilution capacity of the lake is also very little. The dilution capacity of the Veli lake is more when compared with that of the Akkulam lake.

Bathymetric maps can be used to describe a lake's physical features. The bathymetry map als o shows the location of bund located in between the Akkulam and Veli lake in figure 4.2.

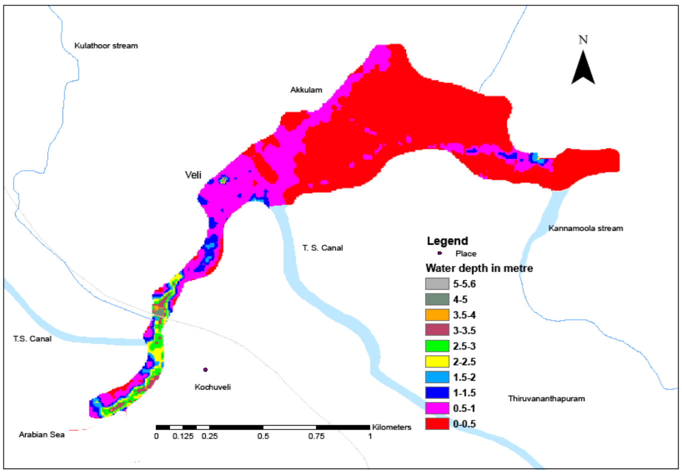


Figure 4.2: Bathymetry Map of Akkulam – Veli Lake (Sheela et al., 2011)

(Source: Hydrographic survey in November, 2007, Department of Harbour, Kerala)

From the bathymetry map it can be seen that a major portion of the Akkulam lake has depth less than 0.5m and in its downstream portion, the depth is in between 0.5 m and 1m. The existence of bund can be observed between the Akkulam and the Veli lake. Then up to the middle portion of the Veli Lake, the depth is in between 0.5 and 1m.

4.2.2 Administrative Division

A major portion of the Thiruvananthapuram Taluk and some portion of the Nedumangad Taluk, lie in the AV lake basin. The basin consists of a major portion of the Thiruvananthapuram Corporation area (54 wards), the entire area of the panchayaths of Kazhakuttom(17 wards), Kudappanakkunnu (27 wards) and Sreekaryam (22 wards), and some portion of the panchayaths of Andoorkkonam (10 wards), Pothankode (12 wards) Vembayam (12 wards), and a few wards in the Karakulam. The administrative divisions of the Akkulam Veli lake is shown in figure 4.3.

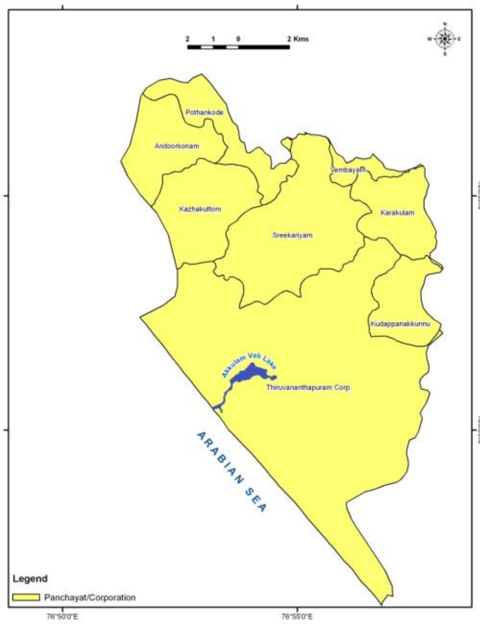


Figure 4.3: Administrative Divisions of the Akkulam – Veli Lake

(Source: Sheela et al., 2011)

4.2.3 Climate

The AV lake basin enjoys a tropical humid climate (Arunkumar, 2007). The area experiences two monsoons, the SW monsoon and NE monsoon. Based on the monsoonal cycle, the year has been divided into three seasons namely premonsoon PRM (February - May),monsoon -MON (June - September) and postmonsoon (October January). The climatic parameters include rainfall, temperature, wind and humidity.

4.2.4 Physiography

The AV lake is situated in the coastal area of Thiruvananthapuram district. The entire area of the basin (143.9 sq.km) lies in the lowland (<7.5 m) midlands (between75 m & 7.5 m) and some portion in the high lands (> 75 m).

4.2.5Drainage

The major streams that drain into the AV lake include the Kannamoola stream and the Kulathur stream. The Kannamoola stream is formed by the confluence of the Ulloor stream, Pattom stream and the Amayizhanchan canal near Pattoor. The Ulloor stream originates from Vattappara and Arasumud area and flows through Paudikonam, Ulloor and Kesavadasapuram and joins the Pattom stream near Pattoor. The Pattom stream originates from the Kudappanakunnu- Mannanthala area and flows through Kuravankonam, Plamood, and Gowreeshapattom and meets the Ulloor stream and the Amayizhanchan canal at Pattoor.

The Amayizhanchan canal starts from Vellayambalam (backwash of filters from the water treatment plant of Kerala Water Authority) and passes through Thampanoor, East Fort, Vanchiyoor and Pattoor i.e. through the midst of the Thiruvananthapuram city. Thus the Pattom stream, Ulloor stream and Amayizhanchan canal join to form Kannamoola stream and it then flow through Kannamoola, and joins with the upstream portion of the Akkulam lake. Medical College channel joins the Kannamoola stream before it joins with the Akkulam lake.

The Kulathur stream starts from the Andoorkkonam, Pallippuram and Chengottukonam area, and it joins the Veli lake on its northern shore. It passes through Kazhakuttom, Kariavattom and Pangappara, and brings in substantial quantities of fresh water to the lake during SW and NE monsoon. The TS canal connects the lake with two estuaries, namely, the Kadinamkulam lake in the north and the Poonthura lake in the south. The drainage map of Akkulam Veli lake is shown in figure 4.4.

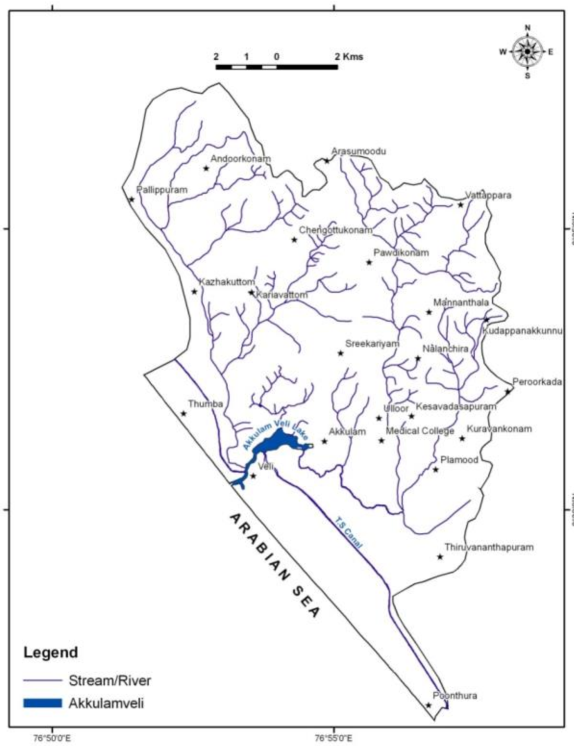


Figure 4.4: Drainage Map of Akkulam – Veli Lake

(Source: Sheela et al., 2011)

4.2.6 Drainage Basin

The Akkulam-Veli lake basin consists of six sub-basins, namely, the Amayizhanchan basin, Pattom basin, Ulloor Basin, Medical College basin, Kulathur basin and the TS canal basin (Figure 4.5).Among these, Ulloor basin (19.71%), the Pattom basin (10.8%), the Amayizhanchan basin (6.11%) and the Medical College basin (5.65%) together constitute the Kannamoola basin and it is the largest basin (42.27%) in the AV lake basin. The entire area of the Amayizhanchan basin covers the commercial/agglomerated settlement area of the Thiruvananthapuram Corporation. The commercial centers like Thampanoor, Statue, Palayam, and East Fort lie in this basin. When the Amayizhanchan canal passes through this urban area, it is being fouled by sewage and garbage and becomes a dirty gutter. The overflow from the sewerage system in the Thiruvananthapuram city as well as from the settlements and commercial establishments situated on either sides of the canal are the main sources of pollution in this area.

The stagnation of waste water makes the situation pathetic. Thiscontaminated canal is one of the main reasons for the deterioration of water quality of the AV lake. In the Medical College basin, Medical College is the main source of pollution. In the Pattom basin, the important places are Kudappanakunnu, Mannanthala, Peroorkada, Kuravankonam, and Plamood. The important places situated in the Ulloor basin are Arasmud, Vattappara, Ulloor, and Kesavadasapuram.

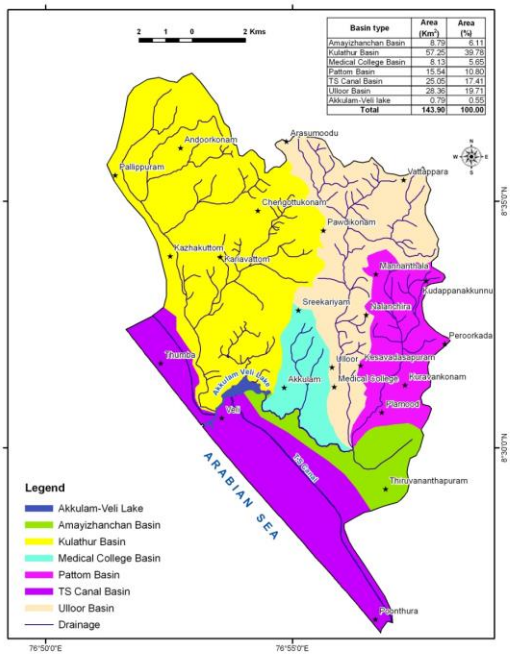


Figure 4.5: Sub Drainage Basin Map of Akkulam – Veli Lake

(Source: Sheela., 2011)

The TS canal basin (17.41%) covers thickly populated coastal areas of Thiruvananthapuram city. The places namely Valiyathura, Shangumugham, and Thumba are located in this basin. Improper sanitation facilities in the area are the main reason for degradation of water quality of TS Canal. Domestic waste water including sewage generated in the Thiurvananthapuram city also reaches the T S Canal. The major portion of the Kulathur basin (39.79%) comes under the rural area. Andoorkonam, Pallipuram, Chengottukonam, Kazhakuttom, and Kariavattom are the main places located in this basin. Kulathur stream after passing through this area meets the Veli lake.

4.3 DATA COLLECTION

Water samples were collected from 16 sampling stations from June 2012 to May 2014 and were analysed in the laboratory. Satellite imagery for the years 2007, 2011 and 2013 were purchased from NRSC, Hyderabad. The satellite images namely Landsat 8 and IRS P6 LISS 3 were used in this study.

4.3.1 Sampling Stations in the Study Area

Sixteen sampling stations were selected in the AV Lake covering both Akkulam and Veli. The sampling stations were selected such that they are well distributed in the lake and they assist in accounting major pollution sources. Stations 1 to 12 are in Veli Lake and 13 to 16 are in Akkulam lake. The locations of these 16 sampling stations are taken with the help of Handheld GPS. Details of sampling stations are shown in table 4.2.Some portion of the lake was covered with water hyacinth and the data of those stations were not used for the study of modelling purpose.

Figure 4.6 shows the location of sampling stations and figure 4.7 shows the images of some sampling stations collected at the time of data collection.

Table 4.2: Details of Sampling Stations

Sl No	Station No	Longitude	Latitude	Station description
1	S1	76°53’20”	8°30’25”	Near Sea
2	S2	76°53’13”	8°30’32”	Veli Boat Club
3	S3	76°53’20”	8°30’36”	Bridge Near VSSC
4	S4	76°53’24”	8°30’39”	SIFFS
5	S5	76°53’24”	8°30’56”	Bridge Near Kulathoor Stream
6	S6	76°53’31”	8°30’50”	Opposite Toddy Bar

7	S7	76°53’34”	8°30’57”	Opposite English Indian Clay
8	S8	76°53’34”	8°31’04”	Opposite English Indian Outlet
9	S9	76°53’31”	8°31’00”	Backside of ISRO
10	S10	76°53’38”	8°31’08”	T S Canal Junction
11	S11	76°53’44”	8°31’00”	Inside T S Canal
12	S12	76°53’43”	8°31’12”	Opposite Artech Flat
13	S13	76°53’52”	8°31’12”	Opposite Trap Akkulam
14	S14	76°54’0”	8°31’20”	Opposite PTC Tower
15	S15	76°54’11”	8°31’20”	Between Akkulam Boat club and PTC Towers
16	S16	76°54’19”	8°31’11”	Akkulam Boat Club

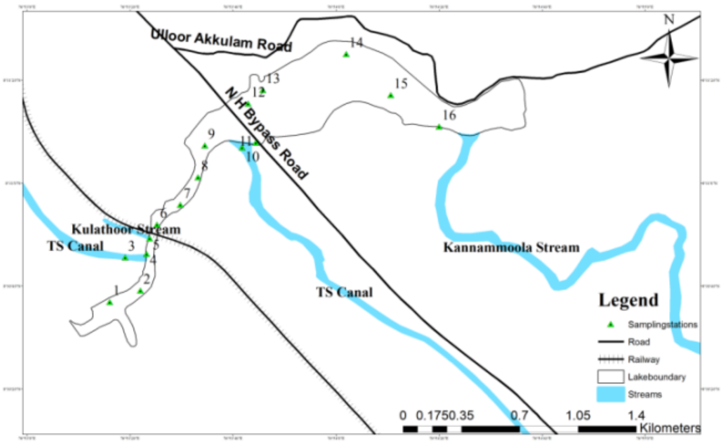


Figure4.6: Location of Sampling Stations

Station S1: Near Sea **Station S2:Veli Boat Club**

Station S3: Bridge near VSSC

Station S4: Near SIFF

Station S5: Bridge near Kulathoor

Station S6: Opposite Toddy Bar

Station S7: Opposite EI Clay

Station S8: Opposite EI Outlet

Station S9: Backside of ISRO

Station S10: T. S Canal Junction

Station S11: Inside T. S Canal

Figure 4.7: Images of Sampling Stations

4.3.2 Satellite Data

Satellite images used in the study are Landsat 8 image on 29-04-2013 and LISS III images of 7th February 2013, 3rd March 2013, 2nd March 2011 and 12th December 2007.

Table 4.3: Details of Satellite Data

No.	Satellite	Sensor	Date of acquisition
1	Landsat 8	OLI/TRS	29-04-2013
2	IRS P6	LISS III	07-02-2013
3	IRS P6	LISS III	03-03-2013
4	IRS P6	LISS III	02-03-2011
5	IRS P6	LISS III	12-12-2007

The satellite-based spectral radiance acquired by spectral bands of blue, green, red, near NIR and SWIR were used to quantify water quality variables of interest. Landsat 8 image is acquired from www.glcf.org and images from www.bhuvan.nrsc.gov.in.The details of the data are shown in the Table 4.3.

4.3.3 Rainfall Data

The rainfall data for Thiruvananthapuram city for the year 2012 and 2013 was collected from Indian Meteorological Department (IMD).

CHAPTER 5

METHODOLOGY

5.1 GENERAL

The detailed methodology adopted for this study is disused in this chapter.

5.2 TROPHIC STATE INDEX

The quantities of nitrogen, phosphorus, and other biologically useful nutrients are the primary determinants of Trophic State Index (TSI) in a water body. Carlson's index is one of the more commonly used trophic indices and is the trophic index used by the United States Environmental Protection Agency. The Trophic State is defined as the total weight of biomass in a given water body at the time of measurement. Because they are of public concern, the Carlson index uses the algal biomass as an objective classifier of a lake or other water body's trophic status. According to the US EPA, the Carlson Index should only be used with lakes that have relatively a few rooted plants and non-algal turbidity sources.

Three independent variables can be used to calculate the Carlson Index: chlorophyll pigments, total phosphorus and Secchi depth. Of these three, chlorophyll will probably yield the most accurate measures, as it is the most accurate predictor of biomass.

The formulas for calculating the TSI values for Secchi disk, TP, and chlorophyll a are as follows:

$$TSI\ (SD)\ =\ 60 - 14.41\ ln(SD) \tag{5.1}$$

$$TSI\ (Chl\ a)\ =\ 9.81\ ln(Chl\ a) + 30.6 \tag{5.2}$$

$$TSI\ (TP)\ =\ 14.42\ ln(TP) + 4.15 \tag{5.3}$$

Where,TP and Chlorophyll-a in micrograms per litre, SD transparency in meters.

5.2.1 Carlson's Trophic State Index

Carlson Trophic State Index (CTSI) gives an idea about the eutrophication status of a lake wherein eutrophication is a major threat to the existence of the lake. Carlson (1977) developed a numerical trophic state index for lakes that incorporates most lakes in a scale of 0 to 100.Some shallow urban lakes suffer from an overgrowth of emergent and/or submergent aquatic weeds, not algae. In these lakes, control of algal biomass might not be the primary concern. Regional variations often constrain the trophic state target for an individual lake. So for this study, TSI is calculated as per the CTSI equation and also using the Modified equation by Sheela et al., specifically for the Akkulam- Veli lake. As per this model TP is not a limiting nutrient in the lake system. So, trophic state index based on TP is not included in the model. (Sheela et al., 2010)

The modified CTSI for the AV Lake is as follows:

$$TSI - SDD = 10 * \{5.143 - \left(\frac{\ln SDD}{\ln 1.309}\right)\} \tag{5.4}$$

$$TSI - Chl\ a = 10 * \{5.143 - (-0.713\ - 0.259\left(\frac{\ln Chl\ a}{\ln 1.309}\right))\} \tag{5.5}$$

Where

SDD	Secchi disk depth (in m)
Chl– a	Concentration of chlorophyll- a in milligrams per cubic meter
TSI –SDD	Trophic State Index based on Secchi disk transparency
TSI- Chl a	Trophic State Index based on Chlorophyll

5.3LAND USE CHANGE ANALYSIS

Land use map is prepared by conducting supervised classification on LISS III imagery of the study area. For that satellite images for different time periods were collected and study area extracted in Arc GIS platform using watershed boundary which is digitized from the toposheet. Image pre-processing is done in ERDAS Imagine software. Then supervised classification performed by collecting training areas for each land use class identified. Based on the training samples collected, classification was done. Google Earth was used to verify the classification accuracy. Classification accuracy is found out based on it. Finally, the land use maps were prepared for different time period and identified the change in area for each land use classes.

In this process the user selects pixels that represent patterns the user recognizes or that the user can identify with the help from other sources. Knowledge of the data, the classes desired, and the algorithm to be used is required before the beginning of selecting training samples.

By identifying patterns in the imagery, the user can train the computer system to identify pixels with similar characteristics. By setting priorities to the classes, the user supervises the classification of pixels as they are assigned to a class value. If the classification is accurate then each resulting class corresponds to a pattern that the user originally identified. A typical supervised classification can be summarised into three steps ie, training stage, classification stage, and output stage.

In training stage the user identifies the representative training areas and develops a numerical description of the spectral attributes of each land cover type of interest in the scene. Training requires close interaction between the image analyst and the image data. And in classification stage each pixel in the image dataset is categorized into the land cover class it closely resembles. The file thus obtained is in digital format and is converted into thematic maps in output stage. Here each category is assigned a colour.

After that Accuracy assessment is carried out with the aid of Google earth imagery. For that 90 sample points were selected from Google earth image. Their Latitude and longitude were noted. Then export those data into shape file. And then check whether those points are correctly placed above the same classes in the land use map. Mismatches should be noted down to prepare accuracy assessment matrix. Using this matrix it is possible to calculate producer’s accuracy, user’s accuracy and over all accuracy.

5.4WATER QUALITY ANALYSIS FROM SATELLITE IMAGERY

Satellite imageries can be utilized for water quality monitoring. And it is a quick and cost effective method. So in order to review the capabilities of Remote Sensing this objective is included in this study. This objective has mainly 2 goals. One is for preparing a model for analysing the various water quality variables using Landsat 8 imagery of 2013 and using this model an attempt is made to predict the spatial extend of each parameter.

Next goal is to prepare model for National sanitation Federation Water Quality Index (NSFWQI) and Carlson's Trophic State Index (CTSI) using LISS III imagery of 2013 and predicted the values of NSFWQI & TSI for the year 2011and then compare those values. The detailed methodology is explained in the following section and the flow chart is shown in figure 5.1.

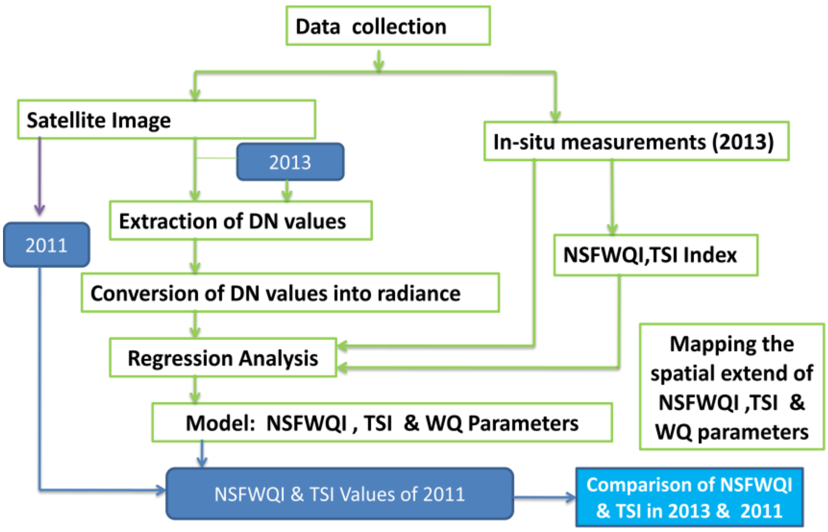


Figure 5.1: Methodology for Water Quality Analysis from Satellite Imagery

5.4.1 Conversion of DN to Radiance

Before carrying out atmospheric correction, the digital number values in the satellite image bands were converted from digital number to unit less planetary reflection values as described below. This conversion is necessary for studies regarding reflectance of lake surfaces because the raw digital numbers of a Landsat image are not only dependent on the reflectance characteristics of the specific scene, but also contain noise and digital number value offsets that are a result of the viewing geometry of the satellite, the angle of the sun's incoming radiation, atmospheric depth due to viewing angle and the design characteristics of the sensor. Conversion of the data to radiance removes the voltage bias and gains from the satellite sensor using the following formula:

$$\text{Pixel Radiance} = \text{Gain} * DN + \text{Bias} \tag{5.6}$$

Where

$$\text{Bias} = L_{min}$$

$$\text{Gain} = (L_{max} - L_{min}) / (Q_{cal\,max} - Q_{cal\,min}) \tag{5.7}$$

L_{min} is spectral radiance at the sensor's aperture in watts/(m2*ster*µm)

L_{max} is the spectral radiance scaled to Q CAL max in watts/(m2*ster*µm)

5.4.2 Extracting Pixel Values

After delineating the water body and converting the DN value into radiance, extract the values in each band of the sensor corresponding to the sample locations. This was done in ERDAS imagine 11. The shape file of the site was superimposed on the image and the raster image corresponding to the boundary shape file was clipped. This clipped image was used to extract pixel values. It is done by using Inquire tool in ERDAS Imagine. Figure 5.2 shows the Inquire window and the way in which pixel values are obtained from ERDAS imagine.

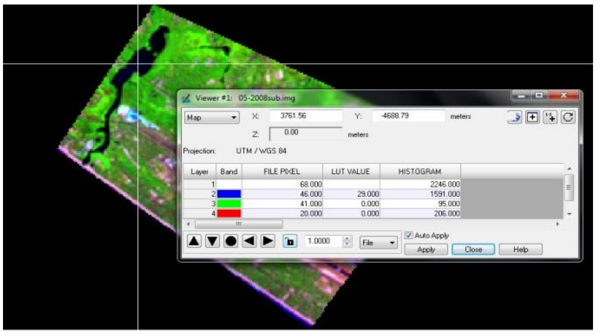


Figure 5.2: Inquire windows in ERDAS Imagine 11.

5.4.3 Estimation of Water Quality Variables from Satellite Data

The ground measured data was divided into two groups comprising of 80% and 20% of the data respectively. The satellite data was used to quantify relationship of variables with bands or bands ratio using 80% of ground measured data. Thus, models with most suitable bands or bands ratio to estimate each variable from satellite data was obtained. These models were used to predict water quality variables at any location of surface water sources. The models will be validated using the remaining 20% ground measured data.The following equation was used to establish the relationships between water quality parameters and the reflectance from different bands (Eran, 2007).

$$\mathbf{WQ_k = a + b * x_{1k} + c * x_{2k} + d * x_{3k} + e * x_{4k}} \qquad (5.8)$$

Where

WQ_k is the water quality parameter (chlorophyll- a, SSM...etc.), measured at station k,

k is the measurement station number, k=1, ...,6

x_l is the pixel reflectance at station k at a particular band l=1, ..., 4 a, b, c, d, e are the model coefficients

The model coefficient for each parameter in the equation was found by Regression Analysis. This was done by using SPSS Statistics 19. SPSS Statistics is a software package used for statistical analysis. It can be used effectively for statistical analysis, data mining, text analytics, data collection, collaboration and Deployment. In this case, the water quality parameter was taken as the dependent variable and the reflectance values from the four bands at sample locations were taken as the independent variables. Regression analysis was done in SPSS 19 and the output was saved. The output includes Anova table, model coefficients, R-square values etc. The values of model coefficients with least standard error were found by considering various combinations of the data. These coefficients were then substituted in the general equation. Then the parameter value corresponding to the rest of the 20% of the values were found and was compared with the actual value. The values obtained were comparable with that of the actual values and so, the model can be further used to predict the parameter value in any other location within the lake boundary.

Water quality levels depend on more than 30 variables, and the main ones of these are different for different waters and can change from place to place. Thus, it is difficult to develop a common algorithm which is valid for assessment of all kinds of waters. The water-leaving radiance detected by satellite sensors is the collective radiance contributed by all components in the water. The spectral properties of pollutants and nutrients and their influences on water-leaving radiance are not well known. In this study, regression analysis was used to determine the water quality parameters of Akkulam lake. Satellite images acquired near the time of the in situ measurements at eight stations at various parts of the lake were input into regression formulae to predict each water quality parameter. The model obtained for the water quality parameters (Nitrate, SDD, Chlorophylla, BOD, DO, pH, Turbidity and NSFWQI,TSI Chla, TSI SDD) are given in the table 5.1.

Table 5.1: Model Equations

Parameter	Model
Nitrate	$Y = 0.005\ R_r - 0.118\ R_b - 0.157\ R_{NIR} - 0.117\ R_{SWIR} - 8.487$
SDD	$Y = 1.43 - 0.068\ R_{NIR} + 0.059\ R_{SWIR} - 0.0786\ R_{r/g} - 0.376\ R_{b/r}$
Turbidity	$Y = 0.560\ R_r + 1.252\ Rg + 2.553\ Rb - 2.913\ R_{NIR} - 3.327\ R_{SWIR} - 71.257$
Chlorophyll a	$Y = 7.649 - 0.029\ R_b - 0.105\ R_{NIR} + 0.141\ R_{SWIR} + 1.22\ R_{b/r} - 1.212\ R_{r/g} - 6.863\ R_{b/g}$
BOD	$Y = 25.608 - 0.151\ R_{NIR} - 0.388\ R_r + 0.428\ R_{SWIR} + 5.155\ R_{r/NIR}$
DO	$Y = 2.562 - 0.539\ R_{NIR} + 0.3\ R_{SWIR} - 0.059\ R_g + 0.234\ R_b - 0.031\ R_r$
pH	$Y = 12.549 - 1.069\ R_{NIR} + 0.061\ R_g - 0.105\ R_r + 0.905\ R_{SWIR}$
NSFWQI	$-11.467-1.341_{NIR}+1.89_{swir}-0.146_{g}+0.175_{r}$
TSI CHL a	$78.048-0.318_{NIR}+0.368_{SWIR+}14.207_{b/r}+4.816_{r/g}-32.672_{b/g}-0.098_{b}$

5.5 REGRESSION ANALYSIS BETWEEN LAND USE AND WATER QUALITY

The regression analysis is carried out to establish the relation between the water quality parameters and the land use type. For this basin wise land use is considered. Water quality parameters of stations where the upstream joins with the lake were also used for the regression analysis. And the over-all procedure of this phase can be represented by the flow diagram in figure 5.3.

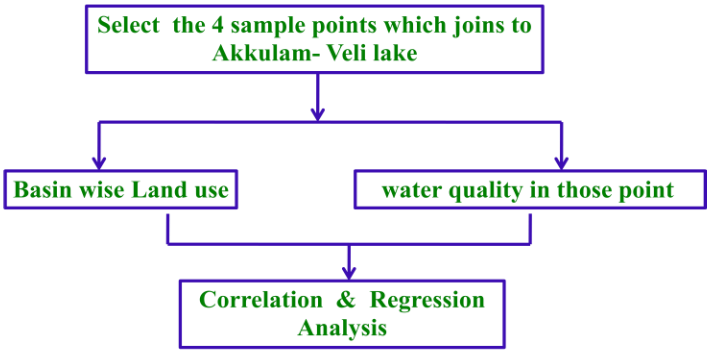


Figure 5.3: Flow Diagram for Regression between Land Use and Water Quality

5.6WATER QUALITY PARAMETERS

The various physicochemical and biological parameters were analysed using standard methods (APHA, 2005).The parameters studied include temperature, depth, secchi disk depth(SDD), pH, turbidity, electrical conductivity, oxidation-reduction potential, salinity, total solids, total dissolved solids, total suspended solids, total alkalinity, carbonate, bicarbonate, total hardness, calcium, magnesium, sodium, potassium, sulphate, nitrate, phosphate, chloride, dissolved oxygen, biochemical oxygen demand, chlorophyll a, pheophytin and faecal coliform. Summary of various procedures for the estimation of physico-chemical parameters are shown in table 5.2.

Table 5.2: Method of Determination of Water Quality Parameters

Sl no	Parameters	Methodology
1	Temperature	Mercury thermometer
2	Secchi disk depth	Secchi disk
3	Ph	PHmeter
4	Turbidity	Digital Nephelo turbidity meter

5	Electrical conductivity	Conductivity meter
6	ORP	Water analyser
7	Salinity	Water analyser
8	Total solids	Gravimetric method
9	Total dissolved solids	Gravimetric method
10	Total suspended solids	Gravimetric method
11	Total alkalinity	Titration with 0.02N HCl using methyl orange indicator
12	Carbonate	Titrimetric method
13	Bicarbonate	Titrimetric method
14	Total hardness	EDTA method
15	Calcium	EDTA method
16	Magnesium	EDTA method
17	Sodium	Flame photometer
18	Potassium	Flame photometer
19	Sulphate	Spectrophotometric method
20	Nitrate	Spectrophotometric method
21	Phosphate	Spectrophotometric method
22	Chloride	Argentometric method
23	Dissolved oxygen	Winkler's Iodometric method
24	Biochemical oxygen demand	Difference of the oxygen content
25	Chlorophyll a	Spectrophotometric method
26	Pheophytin	Spectrophotometric method
27	Faecal coliform	Most Probable Number (MPN) method

5.7 WATER QUALITY INDEX

Water quality index (WQI) provides a single number that expresses overall water quality based on several water quality parameters. The objective of water quality index is to turn complex water quality data into information that is understandable and usable by public. Water quality index provide information on a rating scale from zero to hundred. Higher value of WQI indicates better quality of water and lower value shows poor water quality.

WQI is used as a management tool in water quality assessment. A single number cannot tell the whole story of water quality; there are many other water quality parameters that are not included in the index. A water quality index based on some very important parameters can provide simple indicator of water quality. Generally, water quality indices incorporate data from multiple water quality parameters in to a mathematical equation that rates the health of a water body with number.Water quality index (WQI) expresses overall water quality based on several water quality parameters. In this study, National Sanitation Foundation formula (NSF) was used to calculate the water quality index.

$$NSFWQI = \sum W_i I_i \quad (5.9)$$

Where

W_i = weight associated with i^{th} water quality parameter

I_i = sub index for i^{th} water quality parameter

In NSFWQI four parameters were considered for calculation of WQI. They were pH, DO, BOD and faecal coliform. To calculate the WQI, the raw analytical results for each parameter, having different unit of measurement, were first transformed into non-dimensional sub-index values (Sharma et al., 2008).The sub index equations associated with each parameter is shown in table 5.3.

Table 5.3: Sub index Equations for Water Quality Parameters (NSF WQI) (Source: Sharma, et al. 2008)

Water Quality Parameters	Range Applicable	Equation
DO (Percent Saturation)	0 - 40% saturation 40+ - 100% saturation100+ - 140% saturation>140%	IDO = 0.18 + 0.66 X (%sat DO) IDO = -13.55 + 1.17 X (%sat DO) IDO = 163.34 - 0.62 X (%sat DO) IDO = 50
BOD(mg/l)	0 – 10 10+ - 30 > 30	IBOD = 96.67 - 7.0 X (BOD) IBOD = 38.9 -1.23 X (BOD) IBOD = 2
pH	2-5 5+ - 7.3 7.3+ - 10 10+ - 12 < 2 or >12	IpH = 16.1 + 7.35 X (pH) IpH = - 142.67+33.5 X (pH) IpH = 316.96 - 29.85 X (pH) IpH = 96.17 - 8.0 X (pH) IpH = 0

Faecal Coliform (CFU/100ml)	$1\text{-}10^3$ $10^3\text{-}10^5$ $>10^5$	IFC = 97.2 - 26.6log(FC) IFC = 42.33 – 7.75log(FC) IFC = 2

These sub-indices were multiplied by weight and then combined to give a single water quality index rating value ranging from 0 to 100.For the surface waters in India the NSF WQI is being used with a slight modification in weights by Central Pollution Control Board (CPCB, 2001).The original and modified weights by CPCB are shown in table 5.4.

Table 5.4: Original and Modified Weights for the computation of NSF WQI (Source: Sharma,et al. 2008)

Water quality parameter	Original Weights from NSF WQI	Modified weights by CPCB
DO	0.17	0.31
BOD	0.1	0.19
pH	0.12	0.22
Fecal coliform	0.15	0.28
Total	0.54	1.00

The various levels of water quality according to NSFWQI are shown in table 5.5.

Table 5.5: WQI and status of water quality (Source: Sharma, et al. 2008)

NSF WQI	Description	Class	Color Code	Remarks
63-100	Good to Excellent	A	Blue	Non polluted
51-62	Medium to Good	B	Green	Non polluted
38-50	Bad	C	Yellow	Polluted
<38	Bad to very bad	D or E	Red	Heavily polluted

5.8 WATER QUALITY MODELLING

Water quality modelling is the basis of water pollution control. Monitoring and assessing the quality of surface waters are critical for managing and improving its quality. Models are used to predict trends in water quality based on current water conditions, including pollutant concentrations.

5.8.1 Regression Modelling

Statistical regression models were developed for WQI and DO. The statistical tool SPSS v20 was used for model development. The dependent variable was regressed against independent variable. To determine the straight linear relationship the following multiple linear equations was used.

$$Y=a + b_1X_1 + b_2X_2 \quad (5.10)$$

Where,

X is the independent variable,

Y is the dependent variable

a and b are regression coefficients.

To study the non-linear relation logarithmic linear equation was used. The best model was selected on the basis of regression coefficient, R^2.

5.8.1.1 Goodness of fit of the model

The model's goodness of fit against experimental data has been tested using Chi-squared test.16 set of data has been used for chi square test.

$$\chi^2 = (O-E)^2 / E \quad (5.11)$$

Where,

O is the Observed data set

E is the Experimental data set

Assuming 5% confidence, if χ^2 values obtained from Chi squared distribution table is greater than the sum of χ^2 values obtained for the data set calculated using (5.11). This indicates that the predicted values do fit with the observed data using regression model.

5.8.2 Artificial Neural Network (ANN)

ANN model was developed for the prediction of WQI and DO. Back-propagation is a training method used for prediction problems associated with input/output pairs. The input parameters were selected based on different input trails. MATLAB Neural Network Toolbox was used. In this study, back-propagation algorithm was used for training the ANN. MATLAB v 2013 was used for developing models.

5.8.2.1 Data Grouping

For the modelling total available data is splitting in to two sets. 80% of data was used for training and 20% for testing.

5.8.2.2 Data normalization

All the water quality variables and WQI were normalized into representative range of values (a, b) for the computation using ANN. In this study, the range selected was 0 and 1.

Normalization to the range (a, b)

$$X_S = \left[(b-a) * \frac{(X_0 - X_{min})/}{(X_{max} - X_{min})} \right] + a \qquad (5.12)$$

Where,

X_S is the normalized observation

$X_o$is the raw observation

X_{min} is the minimum value of parameter

X_{max} is the maximum value of parameter

5.8.2.3 Input Parameter Selection

- WQI model - The inputs for water quality index models were pH, DO, BOD, total solids and chlorophyll a based on different trails.
- DO model - The input variables for the model were temperature, pH, electrical conductivity, turbidity, hardness and chlorophyll a.

5.8.2.4 Development of Model

In the development of model, the network architecture was designed. The number of inputs for WQI was fixed as 5 and 6 for DO model. The number of hidden neurons was fixed by trial and error method. During the training of different transfer like tansig, purelin were checked. The training function used was trainlm. The best architecture with least Mean Square Error (MSE) was selected after training and that architecture was used for testing the model.

5.8.2.5 Sensitivity analysis

A sensitivity analysis was carried out to evaluate the relative importance of each of the inputs in prediction of the WQI. Sensitivity analysis refers to assessment of the importance of predictors in the fitted models. This analysis ranks the predictor variables according to the deterioration in model performance that occurs if a variable is removed from the model. Ultimately, it identifies the variables that can be ignored safely in subsequent analyses as well as the essential variables which must be retained (Nabeel et al., 2012).

In this study, sensitivity analysis was based on examining the effects of the input variables on the dependent variable following the 'leave-one-out' method which corresponds to assessing changes in the network error that will be obtained if each input variable is removed at a time.

5.8.3 Modelling with ANFIS

The models for DO and WQI were developed with Adaptive Neuro fuzzy Interference system. For modelling with ANFIS, the MATLAB v 2013A, ANFIS Graphical User Interface was used. The inputs and output were same as used in ANN modelling. The training dataset which contains input and desired output set was loaded to train the FIS. An initial FIS structure was developed using grid partition method. In FIS, the data was trained for different input and output membership functions. The input membership functions trained were trimf, trapmf, gbellmf, gaussmf, gauss2mf,pimf, dsigmf, psigmf and the output membership functions were linear and constant, the data was trained for different combinations of input and output membership functions. The learning algorithm selected was hybrid and back propagation.

The number of epochs was set between 70 and 90 and the error tolerance was set to zero as the stopping criteria for training. The membership function and the learning algorithm which gave least error were used for testing the model. For testing the best model a program was used. The predicted and observed values were correlated. The performance of ANN and ANFIS models were compared with the regression models.

5.9 VALIDATION OF THE DEVELOPED MODELS

All the models developed in regression, ANN and ANFIS were validated. For the validation of models water quality data of February 2015 was used. The water samples were collected from the same16 sampling stations during the month of February 2015. The samples were analysed for different water quality parameters like temperature, pH, electrical conductivity, Oxidation-reduction potential, dissolved oxygen, biochemical oxygen demand, total solids, hardness, potassium, faecal coliform, pheophytin and chlorophyll a using standard methods APHA.

5.10 MODEL PERFORMANCE EVALUATION

To know the reliability of the model, the performance evaluation of the models were done. The performance of the models developed was analysed using different model performance criteria. The following model performance criteria were used.

a) Index of Agreement

Index of Agreement (d) is the degree to which values are accurately predicted. The Index of Agreement varies from 0 to 1. A value of 1 indicates prefect agreement between observed and predicted observations while 0 denotes complete disagreement.

$$d = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}\left[\left|P_i - \overline{O}\right| - \left|O_i - \overline{O}\right|\right]^2} \quad (5.13)$$

Where,

N - Number of data points

O_i - observation data points

P_i - predicted data points

$\overline{O}$ - mean of the observed data points.

b) Correlation Coefficient

It is the degree to which the fluctuations in observed concentrations are followed by fluctuations in predicted concentration .The value varies between -1 and +1, where -1 indicates negative correlation and +1 indicates positive correlation.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 GENERAL

This chapter deals with the results obtained from the study conducted. In the present study mainly focuses on the eutrophication condition of the lake which is estimated from TSI -SDD, analysis of land use change for different years from satellite imageries with the help of satellite imagery

The water quality of the AV lake was also studied with the help of Water Quality Index. The models for WQI and DO were prepared using regression models, ANN and ANFIS and results were compared. The detailed results are discussed in the following headings.

6.2 EUTROPHICATION STATUS OF AKKULAM - VELI LAKE

Eutrophication is a serious environmental problem since it results in a deterioration of water quality. TSI-SDD is calculated using the equation 5.4 for all the three years. Figure 6.1, figure 6.2 and figure 6.3 show the monthly variation of TSI-SDD for 2012, 2013 and 2014 and values range from 83.86 – 99.03, 78.68 – 106.01 and 90.41 – 111.20 respectively.Eutrophication in the lake is more during 2014. In all these three years the observed TSI-SDD value is above 70. Hence the trophic state of the entire AV lake falls in the 'hyper-eutrophic' condition. One of the main reasons for the hyper eutrophication is the discharge of turbid urban waste water especially from Kannamoola drain, which passes through the Thiruvananthapuram city before joining the upstream part of the Akkulam lake.

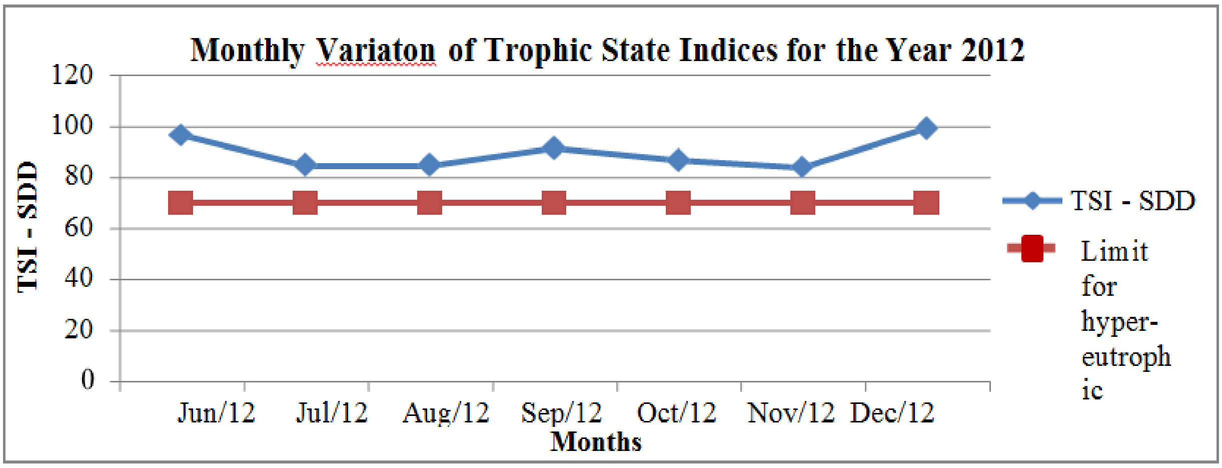


Figure 6.1: Monthly Variation of Trophic State Indices for the Year 2012

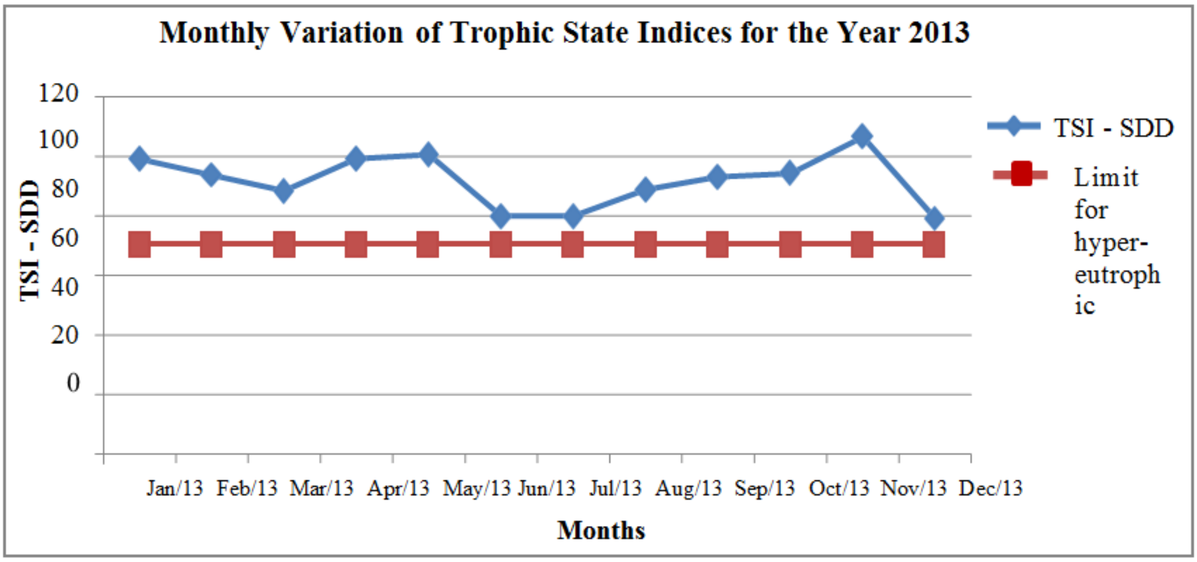


Figure 6.2: Monthly Variation of Trophic State Indices for the Year 2013

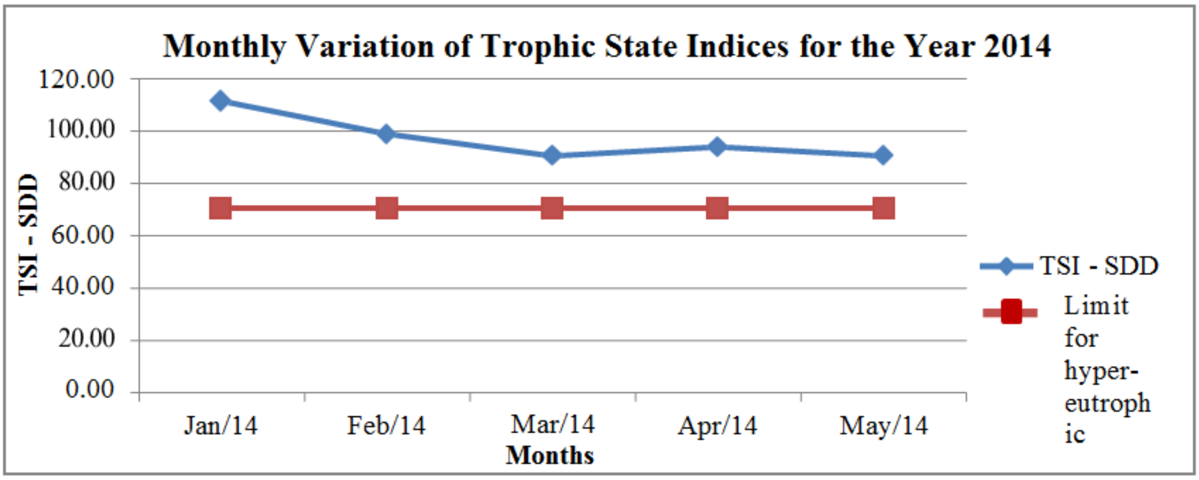


Figure 6.3: Monthly Variation of Trophic State Indices for the Year 2014

6.3 ANALYSIS OF LANDUSE CHANGE

There is a great change in built up area within this small time period. ie.13.6587 % of the land changed into built up area. And with that there is a reduction of -13.2757 % in Vegetation cover. The Percentage changes of different land Use classes in different years are given in table 6.1and the graphical representation is shown in figure 6.5.This shows the fast growing trend of the area, and this will surely lead to the increase in water pollution. There is only a slight change in Barren/ sandy area and also in water body. Figure 6.4 shows the Land Use map of 2007, 2011 and 2013.

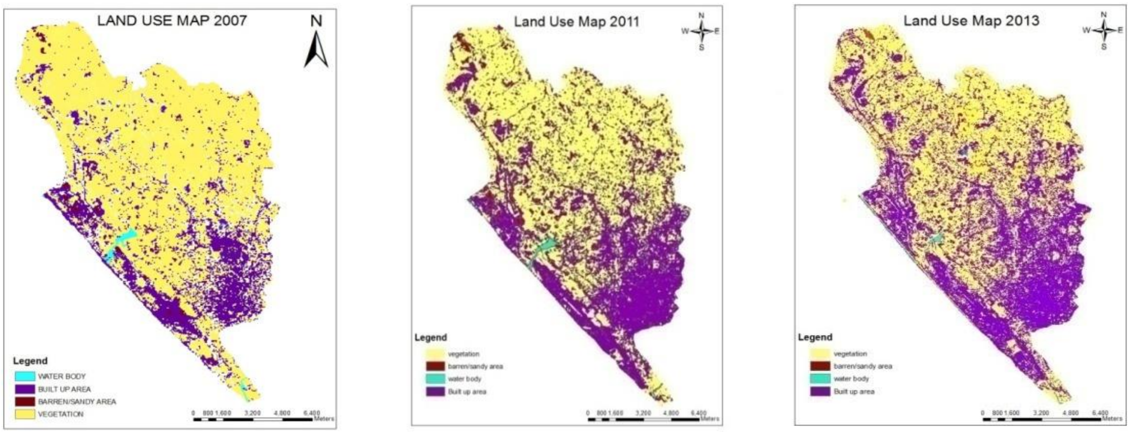


Figure 6.4: Land Use map of 2007, 2011 and 2013

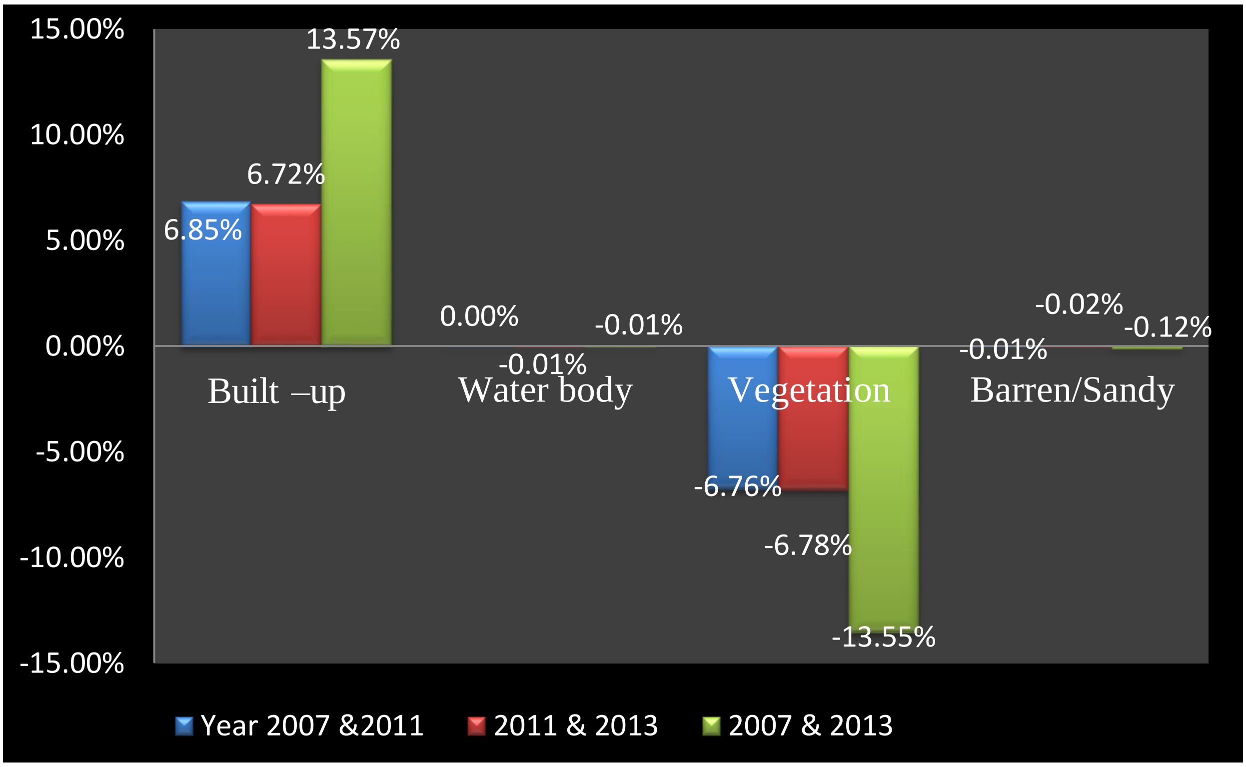


Figure 6.5: Graphical Representation of Percentage Changes in the Different Land Use Classes in Different Years

Table 6.1: Percentage changes of different land Use classes in different years

Land Use Type	**Year 2007 & 2011**	**Year 2011 & 2013**	**Year 2007 &2013**
Built –up	6.85%	6.72 %	13.57 %
Water body	0.001 %	-0.01 %	-0.01 %
Vegetation	-6.76 %	-6.78 %	-13.551%
Barren land/Sandy area	-0.006 %	-0.018 %	-0.12%

The decrease in vegetation and increase in built up area are approximately same as shown in Table 6.1. This shows that vegetated area is getting converted to built-up area and urbanisation is fast progressing in the city. With growing urbanisation, the waste management sector has not yet improved to cope up with increasing solid/liquid wastes produced. Therefore the urban effluents in treated, partially treated and untreated form are reaching the lake through the urban drains. Other than these, factors such as soil erosion and wastes from construction and operations in built up area in the lake basin are all happening in and around the lake catchment and are found to be responsible for continuously polluting the lake.

6.4 WATER QUALITY ANALYSIS USING SATELLITE IMAGERY

The models were developed for the water quality parameters (Nitrate, SDD, Chlorophyll a, BOD, DO, pH, Turbidity, NSFWQI, TSI Chla, TSI SDD using the corresponding value of water quality parameters and then also validated with the corresponding measured values of those parameters in each sample location. Error percentage method is used for that. The following tables (table 6.2 to 6.5) show the measured and predicted values of those parameters and its error percentage. Table contains the predicted values of each parameter obtained from Landsat 8 imagery. Table 6.6 contains values of NSFWQI and TSI index of 2013 obtained from LISS III imagery. Table 6.7 contains values of NSFWQI and TSI index of 2011 obtained from the LISS III imagery using regression model prepared from 2013 water quality data and 2013 imagery.

The models prepared show an error percentage of less than 10. The predicted and measured values didn't show much variation. Models prepared from Landsat 8 shows more accurate values than LISS III imagery. It is due to the presence of Blue band in Landsat 8 imagery. And blue band has high influence in analysing the water quality. Figure 6.6 and figure 6.7 show the spatial extend of NSFWQI from LISS III 2013 and LISS III 2011.Similarly figure 6.8 and figure 6.9 show the spatial extend of Trophic State Index from LISS III 2013 and LISS III 2011.

A comparison of these values is carried out to find out variation in the water quality in the lake. And it shows most of the regions considered as medium category as became changed to 'Bad' category. Likewise Lake changed from Eutrophic state to hypereutrophic. So this study reveals that degradation occurred for water quality from 2011 to 2013. This study reveals remote sensing is very useful in quick assessment of water quality and to find-out the historic conditions of the lake.

Table 6.2: Values of Predicted and Measured Nitrate and SDD

Station	Nitrate (mg/l)		SDD (m)	
	Measured	Predicted	Predicted	Measured
Veli Boat Club	1.8	1.7	0.30	0.3
VSSC Bridge	1.6	1.5	0.2	0.2
SIFFS	1.5	1.5	0.35	0.35
Near railway bridge, Kulathur	1.4	1.5	0.2	0.3
Opposite Toddy bar	1.4	1.4	0.3	0.3
Opposite English Indian Clay	1.3	1.2	0.3	0.35
EI outlet	1.2	1.4	0.3	0.3
Backside of ISRO	1.1	1.2	0.23	0.25
TS Canal junction	1	1	0.2	0.35
Inxside TS Canal	1	1.2	0.16	0.2
Opposite Artech Flat	0.9	1	0.15	0.2
Near Trap Akkulam	1.2	1.1	0.2	0.2
Opposite PTC Tower	2	2	0.15	0.15
Between ABC and PTC Tower	2	1.9	0.2	0.2
Percentage Error	**2.03 %**		**0.8 %**	

Table 6.3: Values of Predicted and Measured values of Chlorophyll a and BOD

Station	Chlorophyll a (microgram/l)		Turbidity (NTU)	
	Measured	Predicted	Predicted	Measured
Veli Boat Club	1.3	1.4	20	22
VSSC Bridge	1.2	1.3	21	20

SIFFS	2.0	1.1	15	18
Near railway bridge, Kulathur	2.0	2.0	21	23
Opposite Toddy bar	1.5	1.8	19	22
Opposite English Indian Clay	1.5	1.5	18	21
EI outlet	1.4	1.5	27	28
Backside of ISRO	1.5	1.7	20	23
TS Canal junction	0.8	1.5	25	22
Inxside TS Canal	1.4	0.8	25	23
Opposite Artech Flat	1.2	1.4	22	24
Near Trap Akkulam	1.1	1.3	23	21
Opposite PTC Tower	1.9	1.3	22	24
Between ABC and PTC Tower	1.2	1.5	20	24
Percentage Error	**7.9 %**		**3.12 %**	

Table 6.4: Values of Predicted and Measured BOD and DO

Station	BOD (mg/l)		DO (mg/l)	
	Measured	predicted	Measured	Predicted
Veli Boat Club	2.5	2.5	5.7	4.8
VSSC Bridge	4	4	5.4	5.3
SIFFS	11	13	4.8	3.7

Near railway bridge, Kulathur	18	12	3.8	4.0
Opposite Toddy bar	8	11	4.2	4.3
Opposite English Indian Clay	9	10	5.4	5.4
EI outlet	13	14	3.9	3.9
Backside of ISRO	14	11	3.6	3.8
TS Canal junction	13	16	3.9	3.3
Inxside TS Canal	12	10	4.4	4.0
Opposite Artech Flat	12	12	4	4.0
Near Trap Akkulam	18	14	3.4	3.4
Opposite PTC Tower	25	20	3.6	3.7
Between ABC and PTC Tower	28	36	3.5	3.2
Percentage Error	**2.5 %**		**0.8 %**	

Table 6.5: NSFWQI and TSIChl a Calculation from LANDSAT 8 imagery(2013)

Station	TSI Chl a		NSFWQI	
	Measured	Predicted	Predicted	Measured
Veli Boat Club	61.2	61.3	57	58
VSSC Bridge	61.3	61.1	46	48

SIFFS	63.1	63.3	42	44
Near railway bridge, Kulathur	63.0	63.1	47	48
Opposite Toddy bar	62.6	62.2	50	50
Opposite English Indian Clay	61.9	61.8	45	42
EI outlet	61.5	62.3	42	42
Backside of ISRO	61.8	61.7	39	41
TS Canal junction	59.0	59.4	47	48
Inxside TS Canal	61.9	62.4	48	47
Opposite Artech Flat	60.7	60.8	41	43
Near Trap Akkulam	60.1	61.2	42	41
Opposite PTC Tower	62.8	61.5	40	39
Between ABC and PTC Tower	60.8	60.6	40	39
Percentage Error	**0.2 %**		**0.8 %**	

Table 6.6: NSFWQI and CTSI Calculations from LISS III imagery (2013)

CTSI Measured	CTSI Predicted	Status of the Lake	NSFWQI Measured	NSFWQI Predicted	Status of the Lake
96	98	Hypereutrophic	52	52	Medium
97	92	Hypereutrophic	55	50	Medium

96	93	Hypereutrophic	65	45	Medium
100	92	Hypereutrophic	47	47	Bad
105	94	Hypereutrophic	64	55	Medium
86	80	Hypereutrophic	60	46	Medium
94	92	Hypereutrophic	61	59	Medium
100	98	Hypereutrophic	61	50	Medium
77	80	Hypereutrophic	54	54	Medium
80	93	Hypereutrophic	46	53	Bad
67	83	Hypereutrophic	52	49	Medium
88	82	Hypereutrophic	39	40	Bad
80	89	Hypereutrophic	36	47	Bad
74	81	Hypereutrophic	37	39	Bad
90	97	Hypereutrophic	41	48	Bad
Percentage Error = 2.2 %			**Error Percentage = 4.72 %**		

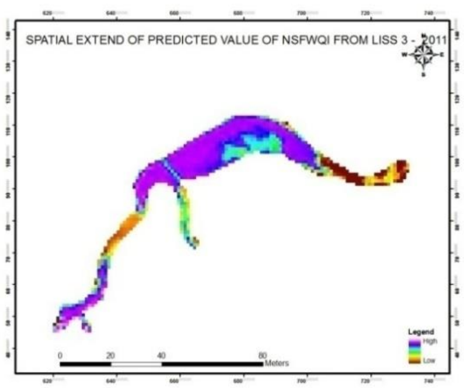


Figure 6.6: Spatial Extend of NSFWQI

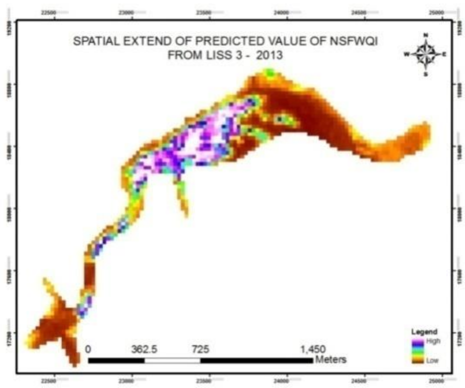
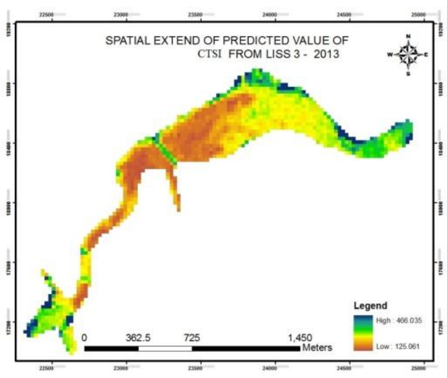


Figure 6.7: Spatial Extend of NSFWQI from LISS III (2011)



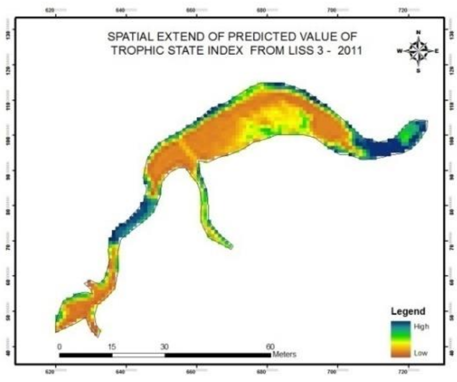


Figure 6.8: Spatial Extend of NSFWQI from LISS III (2011)

Figure 6.9: Spatial Extend of Trophic State Index

Table 6.7: Predicted and measured Values of NSFWQI and CTSI Values from LISS III (2011)

STATION	CTSI from LISS III (2011)		NSFWQI from LISS III (2011)	
	Predicted	**Status**	**Predicted**	**Status**
Veli Boat Club	63	Eutrophic	51	Medium
VSSC Bridge	61	Eutrophic	55	Medium
SIFFS	62	Eutrophic	67	Good
Near railway bridge, Kulathur	63	Eutrophic	49	Bad
Opposite Toddy bar	218	Hypereutrophic	65	Good
Opposite English Indian Clay	218	Hypereutrophic	61	Good
EI outlet	101	Hypereutrophic	61	Good
Backside of ISRO	101	Hypereutrophic	72	Good

TS Canal junction	64	Eutrophic	54	Medium
Inxside TS Canal	89	Hypereutrophic	52	Medium
Opposite Artech Flat	65	Eutrophic	39	Bad
Near Trap Akkulam	66	Eutrophic	36	Bad
Opposite PTC Tower	62	Eutrophic	37	Bad
Between ABC and PTC Tower	59	Eutrophic	41	Bad
Akkulam Boat Club	62	Eutrophic	47	Bad

6.5 REGRESSION BETWEEN LAND USE AND WATER QUALITY

Regression analysis is carried out between the water quality of the sampling stations where upstream joins the lake and the land use in those basin for which the water quality data is selected. From this analysis it is clear that the change in land use is posing adverse effects on the water quality of lake.

Table 6.8: Regression between Land Use and Water quality

Water quality Parameter	Equation
Turbidity	5.369+0.8234Built-up Area -0.037 Vegetation
Phosphate	-0.037+0.036 Built-up Area - 0.002 Vegetation
Nitrate	0.548+0.006 Built-up Area - 0.004 Vegetation
pH	6.426-0.022 Builtup
FC	7324.79+303.8 Built-up Area -30.84 Vegetation
SDD	0.493-0.025 built up+0.006 Vegetation
Chl a	2.424+0.103 builtup-0.009 Vegetation
BOD	-44.797+5.677Builtup-0.408 vegetation

The decrease (%) in vegetation and increase in built up area are approximately same as shown in Figure 6.5. This shows that vegetated area is getting converted to built-up area. Urbanisation is fast progressing in this area, but at the same time urban wastewater effluents in treated/partially treated and untreated form are reaching the lake through the urban drains. Other than these, factors such as soil erosion and wastes due to construction and operations in built up area in the lake basin are all happening and are found to be responsible for pollution of lake.

Conductivity, Phosphate, FC, TDS, and Nitrate is positively correlated with built up area and Vegetation is negatively related to Phosphate, nitrate, & turbidity. So when vegetation decreases phosphate, turbidity & nitrate increases. There is change in land use from vegetation to builtup and thereby causing increase in phosphate, turbidity and nitrate. Increase in built up area decreases DO and increases BOD. Increase in built up area increases FC and pH. Increase in built up area thereby increases BOD, FC and pH and decreases DO and thereby leading todecrease in NSFWQI in the lake. SDD, decreases with increase in built up area. Chla increases with increase in built-up area. Nutrients like phosphorous and Nitrate increase with increase in built-up which leads hypereutrophic condition in lake.

6.6 SPATIAL VARIATION OF WATER QUALITY PARAMETERS USING REMOTE SENSING AND GIS

In this study variation of some important water quality parameters such as SDD, pH, BOD, DO, Hardness, and Turbidity of Akkulam Veli lake are modelled using geospatial technology.

6.6.1 Secchi Disk Depth (SDD)

If SDD <0.5 is termed as hypereutrophic condition. Figure 6.10 shows the spatial variation of SDD in monsoon season for the year 2012. In post monsoon season of 2012 the entire lake under hypereutrophic condition except in near sea region as shown in figure 6.11.

The spatial variation of SDD for pre monsoon season of 2013 is shown in figure 6.12. From this figure it is clear that the entire lake is under hypereutrophic condition. In monsoon (figure 6.13) and post monsoon season (figure 6.14) of 2013 only a small portion of Veli lake is under eutrophic state and other portions are in hypereutrophic condition.

In 2014 the Akkulam Veli lake is under hypereutrophic condition as shown in figure 6.15.

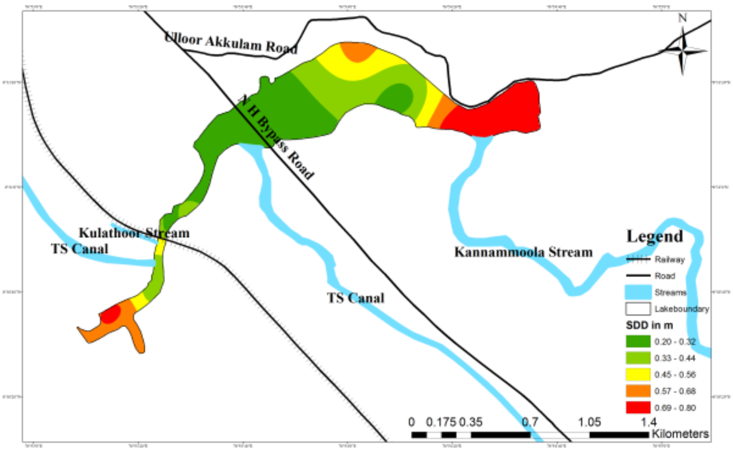


Figure 6.10: Spatial Variation of SDD in Monsoon season for the Year 2012

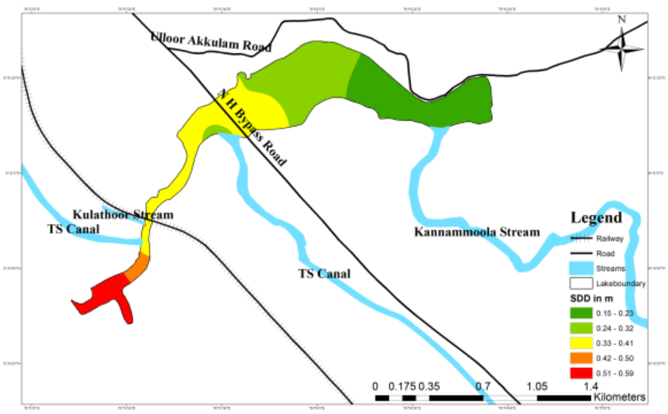


Figure6.11: Spatial Variation of SDD in Post Monsoon season for the Year 2012

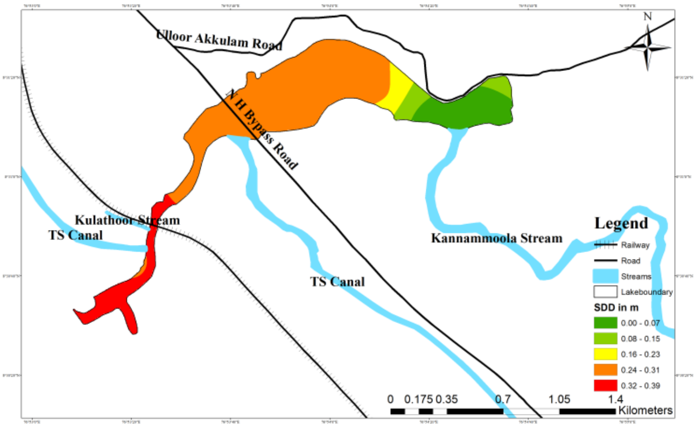


Figure 6.12: Spatial Variation of SDD in Pre Monsoon season for the Year 2013

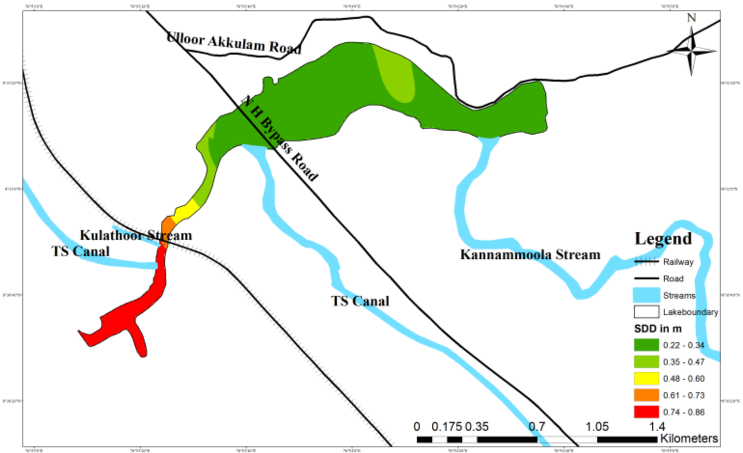


Figure6.13: Spatial Variation of SDD in Monsoon season for the Year 2013

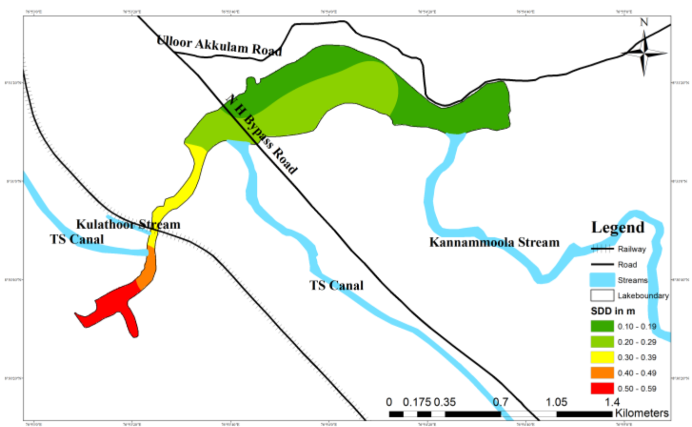


Figure6.14: Spatial Variation of SDD in Post Monsoon season for the Year 2013

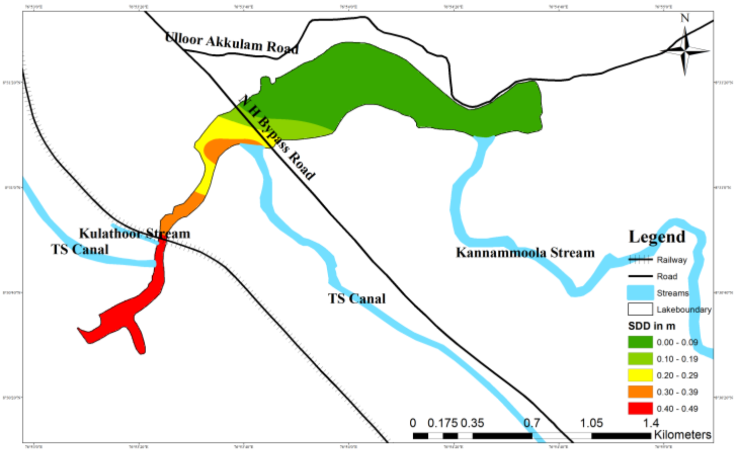


Figure6.15: Spatial Variation of SDD in Pre Monsoon season for the Year 2014

6.6.2pH

The spatial distribution of pH for various seasons in 2012, 2013 and 2014 years were shown in following figures. In 2012 pH value ranges from 6.68 - 7.62 in monsoon (figure 6.16) and 7.49 - 8.12 in post monsoon seasons(figure 6.17). In 2013 the values ranges from 0 - 7.34 for pre monsoon(figure 6.18), 7.04 - 7.83 for monsoon(figure 6.19) and 7.77 - 8.41 for post monsoon season(figure 6.20).

Similarly in 2014 the pH value ranges from 6.57 - 9.46 in pre monsoon season(figure 6.21). In all these maps the highest values were shown in red colour and lowest values were shown in green colour. In 2012 the highest pH value was obtained in Akkulam lake. In 2013 the highest value is obtained in Veli lake and a small portion of the Akkulam lake.

Veli lake is situated on the sea ward side and Akkulam lake is situated on the landward side. Veli lake is separated from nearby sea by a sand bar. However, during monsoon and post monsoon seasons, sand bar opens and flushing of lake with sea water happens occasionally. Tidal influence also is affecting the lake. This may be the reason for the rise in pH, especially in the Velis side of lak.

The limit for pH prescribed by the Ministry of Environment and Forests is between 6.5 and 8.5. In monsoon and post monsoon season of the year 2012, the pH value was more than the lower limit of 6.5 and the water quality conforms to the standards with respect to pH.

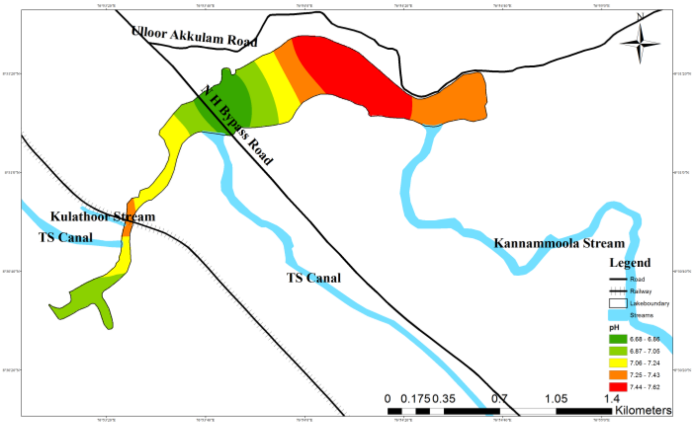


Figure6.16: Spatial Variation of pH in Monsoon season for the Year 2012

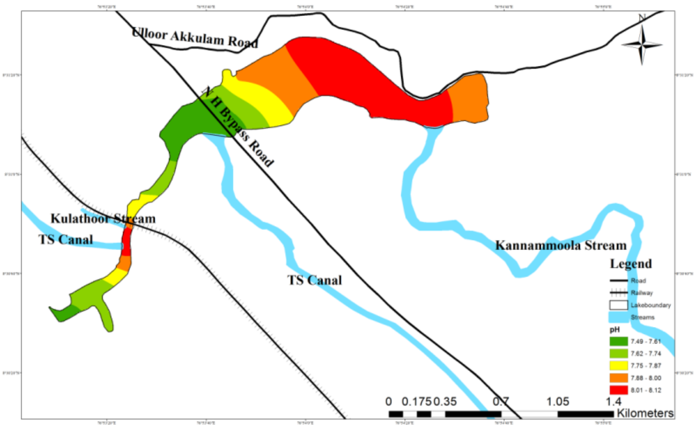


Figure6.17: Spatial Variation of pH in Post Monsoon season for the Year 2012

In 2013 the pH value of monsoon and post monsoon season was obtained as more than the lower limit of 6.5 and below the upper limit. So in these two seasons, pH conforms to the standards. But in pre monsoon season, pH was below the lower limit and upper limit. pH below 6.5 may cause corrosion.

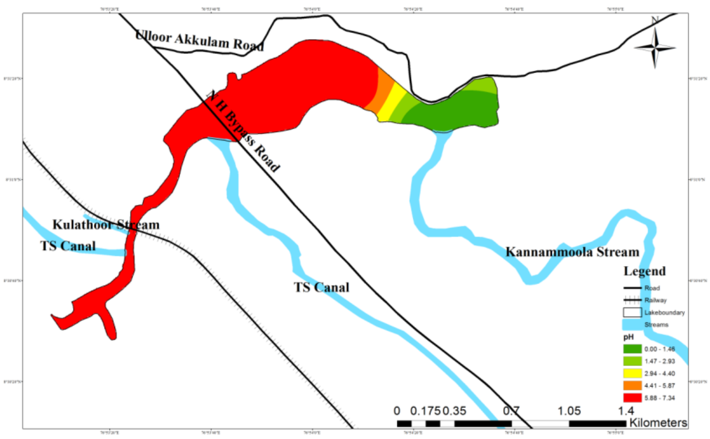


Figure6.18: Spatial Variation of pH in Pre Monsoon season for the Year 2013

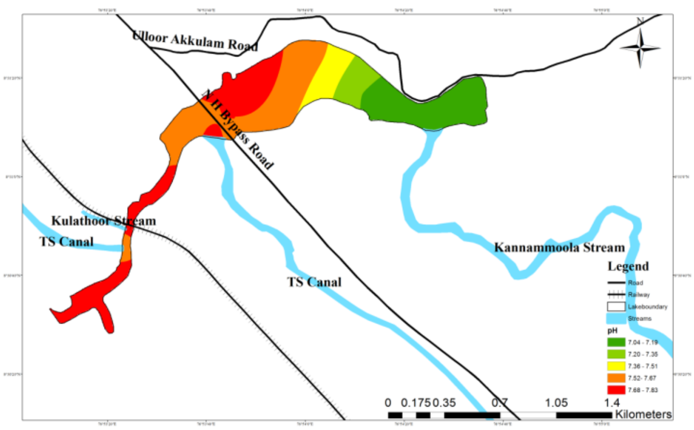


Figure6.19: Spatial Variation of pH in Monsoon season for the Year 2013

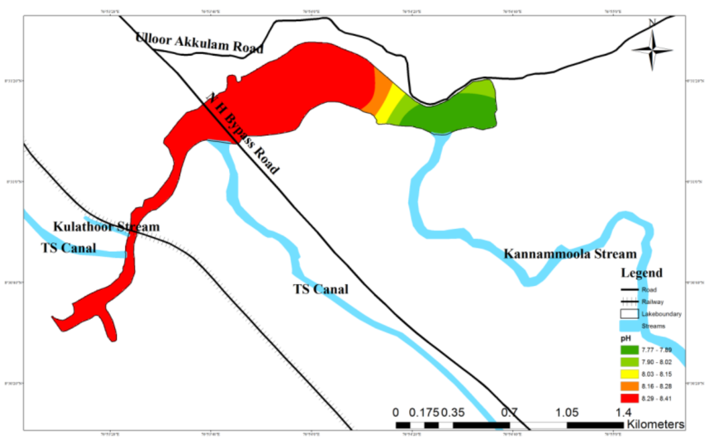


Figure6.20: Spatial Variation of pH in Post Monsoon season for the Year 2013

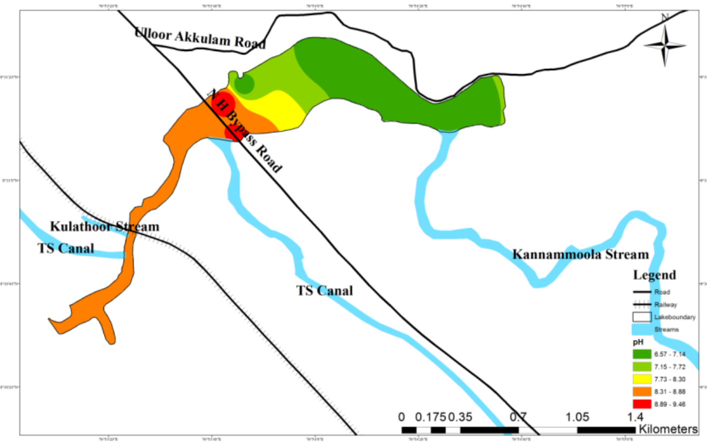


Figure6.21: Spatial Variation of pH in Pre Monsoon season for the Year 2014

6.6.3 Biochemical Oxygen Demand (BOD)

Biochemical Oxygen Demand is one of the important chemical parameters in water quality analysis. It is used as the index of organic pollution of waste water that can be decomposed by bacteria under aerobic condition. As per the limit prescribed by the MoEF, the maximum limit for BOD value is 3 mg/L.

Figure 6.22 and Figure 6.23 show the spatial variation of BOD in monsoon season and post monsoon season for the year 2012 and it ranges from 8.40 - 53.69 and 4.36 -50.20.

Figure 6.24, figure 6.25 and figure 6.26show the spatial variation of BOD in 2013. The BOD value ranges from 4.10 – 35.34 in pre monsoon, 4.90 – 37.19 in monsoon and 8.76 – 27.80 in post monsoon.

Similarly in 2014 BOD ranges from 12.02 – 56.01in pre monsoon season as shown in figure 6.27. The value of BOD is above the limiting standard of 3 mg/L in all the seasons. So both Akkulam and Veli lake do not conform to the water quality standards. In all the seasons the highest BOD value was obtained in Akkulam lake except pre monsoon season for the year 2014.

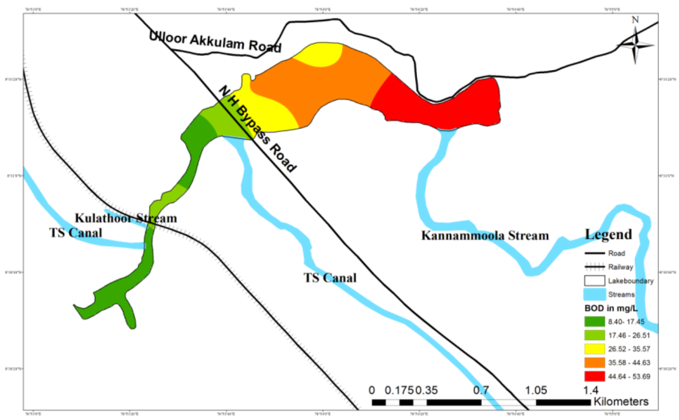


Figure6.22: Spatial Variation of BOD in Monsoon season for the Year 2012

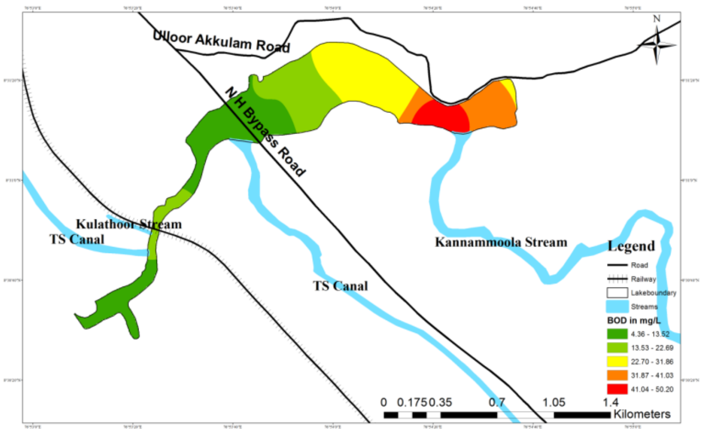


Figure6.23: Spatial Variation of BOD in Post Monsoon season for the Year 2012

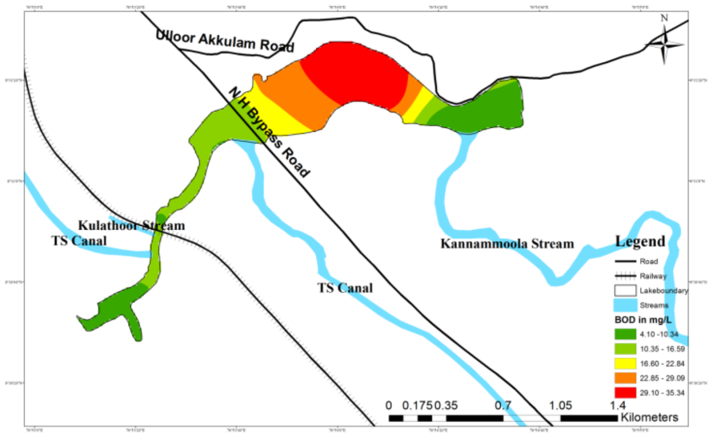


Figure6.24: Spatial Variation of BOD in Pre Monsoon season for the Year 2013

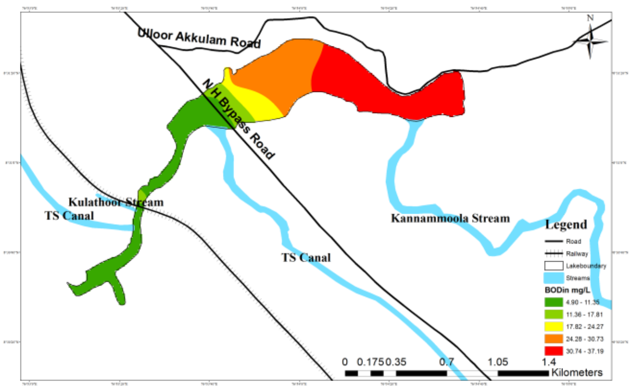


Figure6.25: Spatial Variation of BOD in Monsoon season for the Year 2013

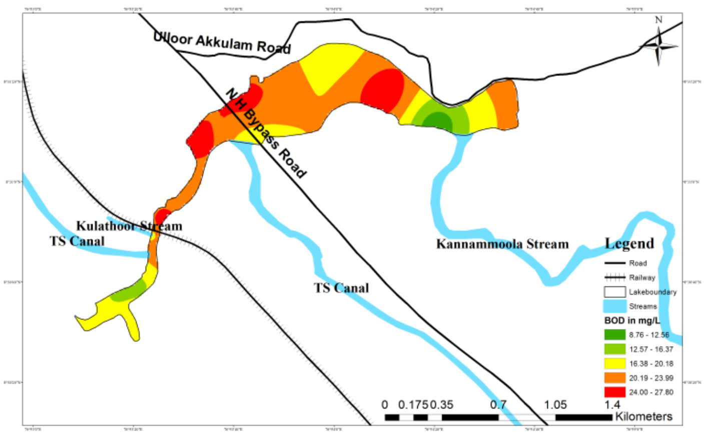


Figure6.26: Spatial Variation of BOD in Post Monsoon season for the Year 2013

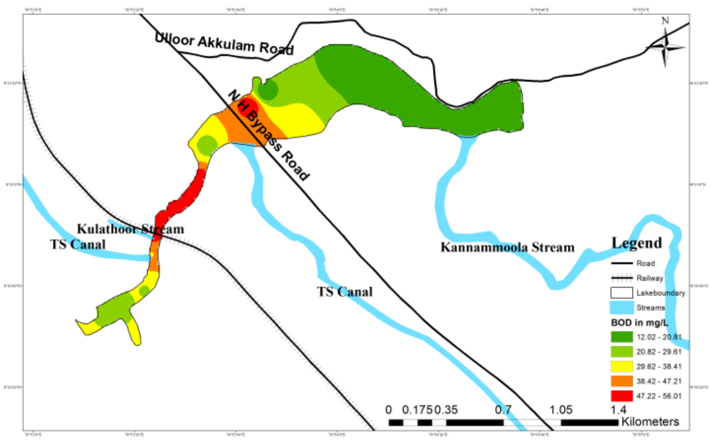


Figure6.27: Spatial Variation of BOD in Pre Monsoon season for the Year 2014

6.6.4 Dissolved Oxygen (DO)

Oxygen dissolved in water is a very important parameter in water analysis as it serves as an indicator of the physical, chemical and biological activities of the water body. The presence of oxygen is essential for the survival of aquatic life in water and it is considered to be the major limiting factor in water bodies with organic materials. According to Ministry of Environment and Forests the minimum concentration of dissolved oxygen prescribed is 5 mg/L.

The spatial variation of dissolved oxygen for monsoon and post monsoon season for the year 2012 is shown in figure 6.28 and figure 6.29. The DO values range from 0 - 5.79 in monsoon season and 0 – 6.89 in post monsoon season. In these two seasons only a small portion of Veli lake conforms to the water quality standard of DO.

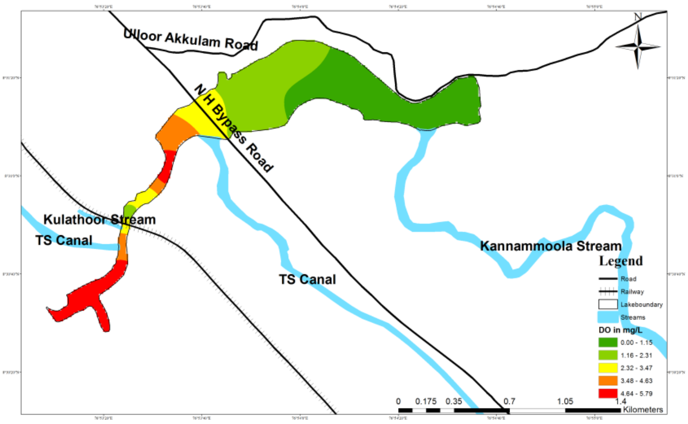


Figure6.28: Spatial Variation of DO in Monsoon season for the Year 2012

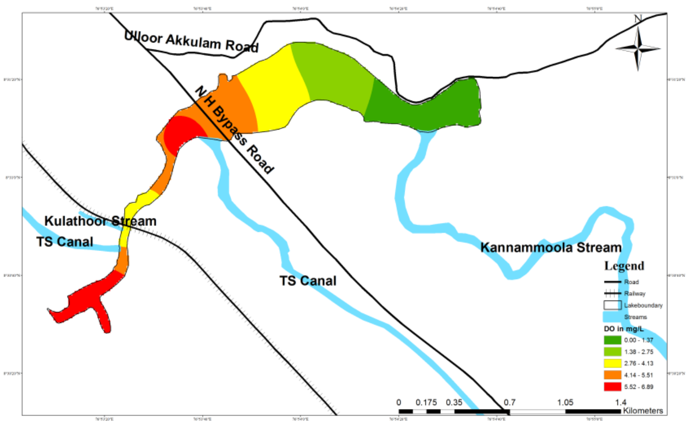


Figure6.29: Spatial Variation of DO in Post Monsoon season for the Year 2012

In 2013 DO values ranged from 0 – 6.44, 1.55 – 6.54 and 2.67 – 4.66 during pre monsoon (figure 6.30), monsoon (figure 6.31) and post monsoon (figure 6.32) seasons respectively. In Pre monsoon and monsoon only a small portion of Veli lake conforms to the water quality standard of DO. In all the years Akkulam lake does not conform to the water quality standard of DO. Figure 6.33 shows spatial variation of DO for the year 2014.

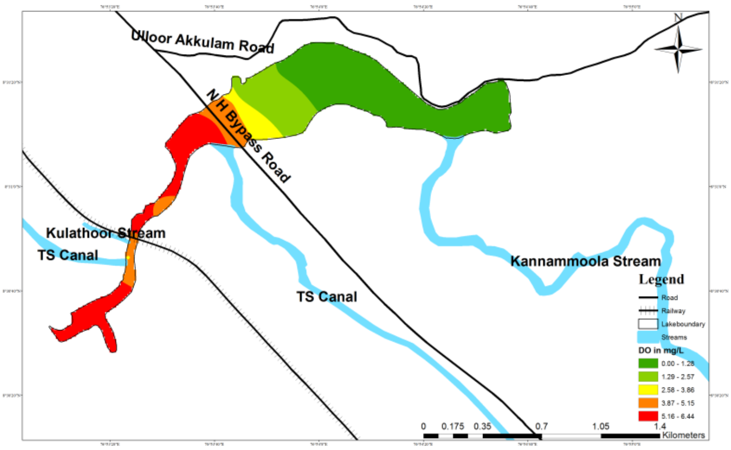


Figure6.30: Spatial Variation of DO in Pre Monsoon season for the Year 2013

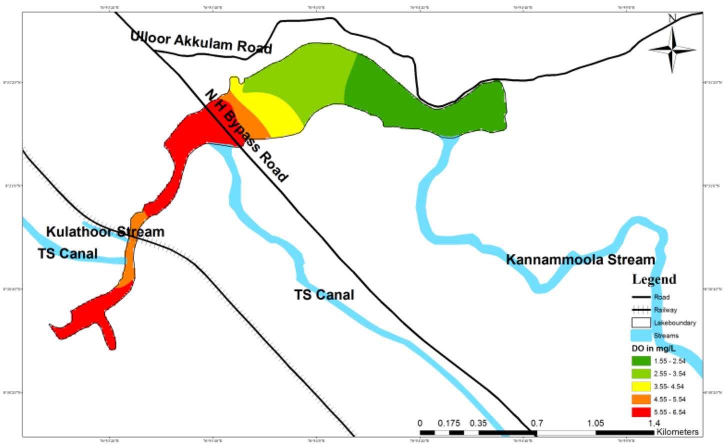


Figure6.31: Spatial Variation of DO in Monsoon season for the Year 2013

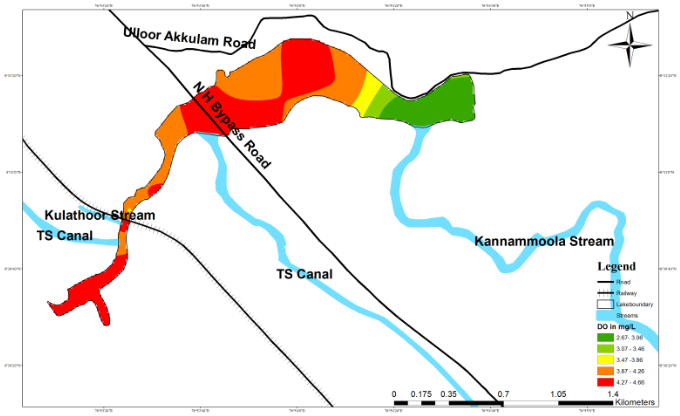


Figure6.32: Spatial Variation of DO in Post Monsoon season for the Year 2013

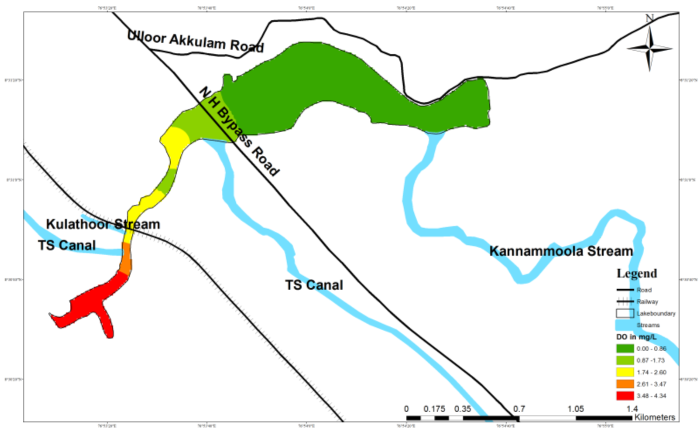


Figure6.33: Spatial Variation of DO in Pre Monsoon season for the Year 2014

There is variation in DO and BOD along the longitudinal direction of lake since the lake is receiving pollutants from point and diffused sources. The portion of the lake near to the sea (Veli side) is having low BOD and high DO whereas high BOD and low DO values on the eastern side (Akkulam side). Low DO values in the Akkulam side are due to the effect of discharge of wastewater carrying drains joining the lake in this area i.e the Kannamoola drain joining the Akkulam lake in its upstream portion. The lake slowly recovers and due to the occasional flushing due to sea water on the Veli side, this region is having comparatively higher values of DO.

6.6.5 Total Hardness

Hardness is an important parameter in decreasing the toxic effect of poisonous element. Hardness below 300mg/L is considered as potable but, beyond this limit cause scale formation.

The hardness value ranges from 88.75 – 185.04 in monsoon season (figure 6.34) and 79.5 – 173.54 in post monsoon season (figure 6.35) for the year 2012, the lake is under moderately hard condition in 2012.

In 2013 the value fluctuates from 0.00 – 189.54 in pre monsoon (figure 6.36), 74.66 – 195.50 in monsoon season (figure 6.37) and 0.00 – 197.54 in post monsoon season (figure 6.38). In 2014 the value ranges from 0.00 – 197.04 in monsoon season (figure 6.39).

In all the years the highest hardness value was observed in Veli lake. This is the site which is the mixing point of Veli lake with sea water. Also in all the years hardness value is below 300 mg/L.

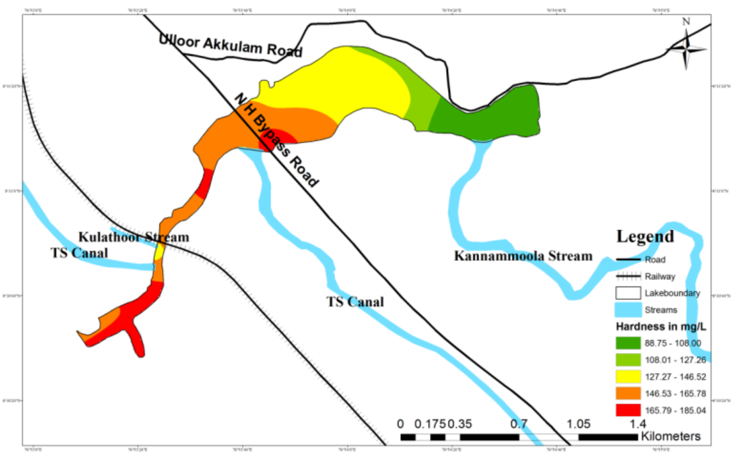


Figure6.34: Spatial Variation of Hardness in Monsoon season for the Year 2012

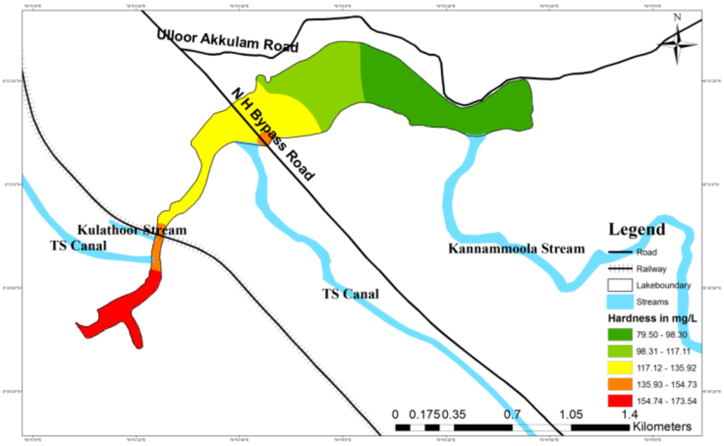


Figure6.35: Spatial Variation of Hardness in Post Monsoon season for the Year 2012

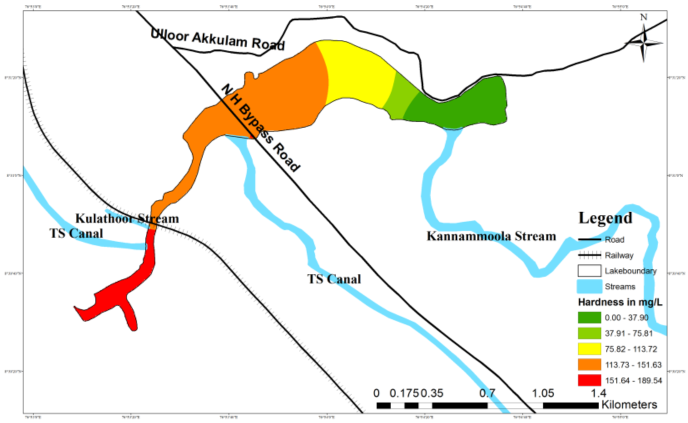


Figure6.36: Spatial Variation of Hardness in Pre Monsoon season for the Year 2013

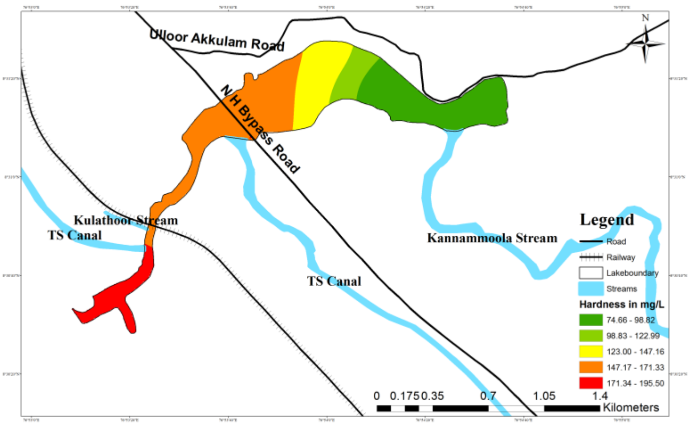


Figure 6.37: Spatial Variation of Hardness in Monsoon season for the Year 2013

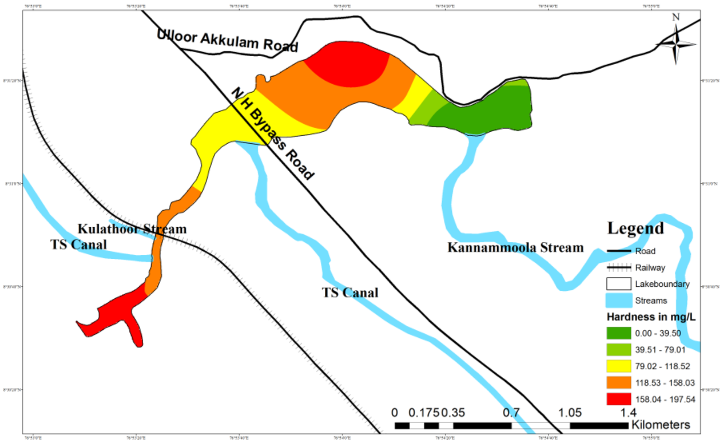


Figure6.38: Spatial Variation of Hardness in Post Monsoon season for the Year 2013

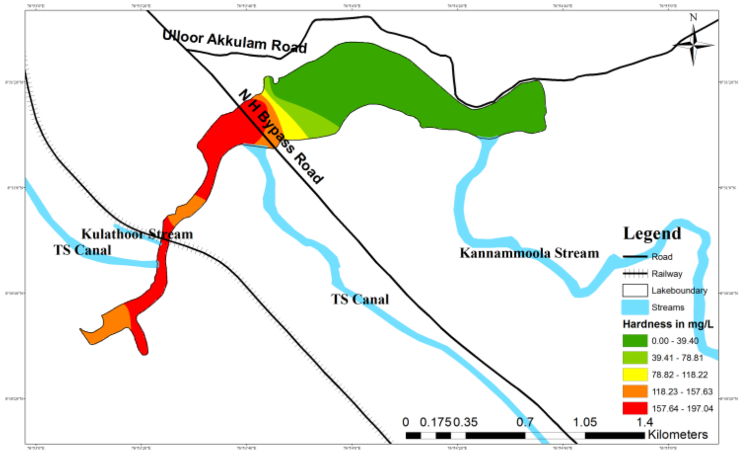


Figure 6.39: Spatial Variation of Hardness in Pre Monsoon season for the Year 2014

6.6.6 Turbidity

Turbidity is the cloudiness or haziness of a fluid caused by individual particles (suspended particles) that are generally invisible to the naked eye, similar to smoke in air. So measurement of turbidity is a key test of water quality..

Figure 6.40 to figure 6.45 show the spatial variation of turbidity of monsoon and post monsoon season for the year 2012, pre monsoon, monsoon and post monsoon season for the year 2013 and pre monsoon season for the year 2014 respectively. From all these maps we can see that the water in Akkulam Veli lake is highly turbid. The effluents of a clay factory existing in the Veli side of the lake have contributed significantly to the increase in turbidity. Further, the wastewater effluent reaching the lake through the urban drains and unauthorized disposal of liquid and solid wastes throughout the lake are also responsible for the increase in turbidity in the lake.

High levels of turbidity increase the total available surface area of solids in suspension upon which bacteria can grow. High turbidity reduces light penetration; therefore, it impairs photosynthesis of submerged vegetation and algae. In turn, the reduced plant growth may suppress fish productivity.

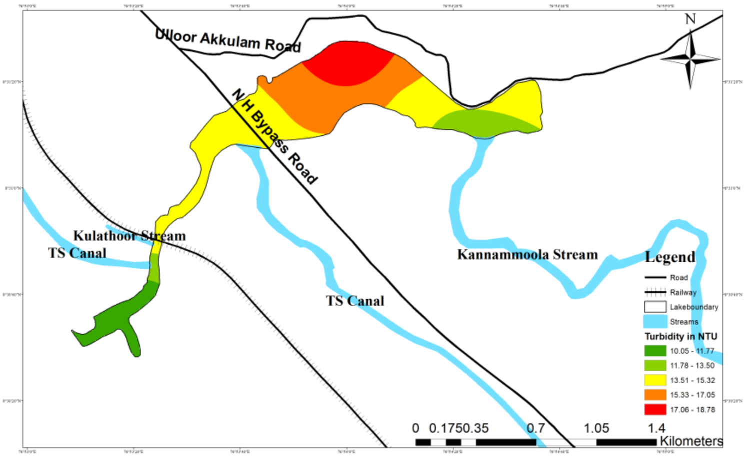


Figure6.40: Spatial Variation of Turbidity in Monsoon season for the Year 2012

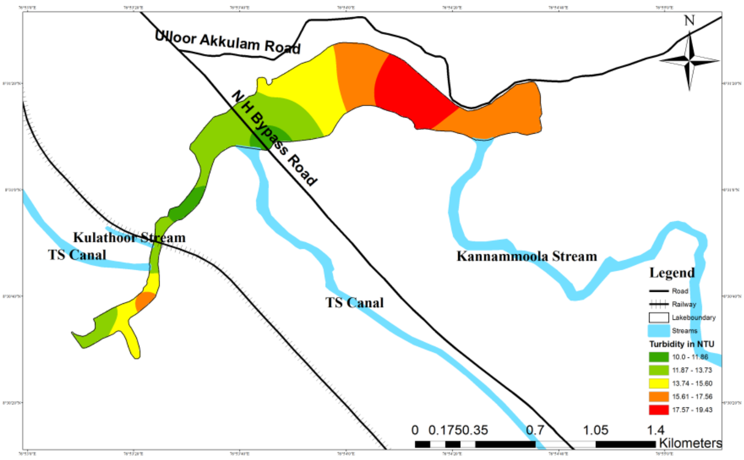


Figure6.41: Spatial Variation of Turbidity in Post Monsoon season for the Year 2012

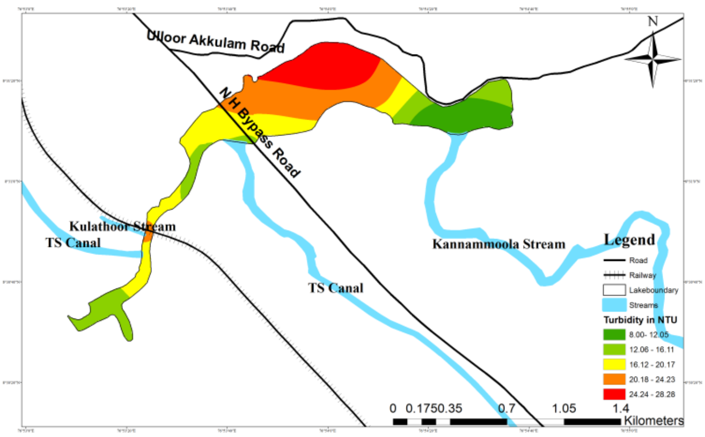


Figure6.42: Spatial Variation of Turbidity in Pre Monsoon season for the Year 2013

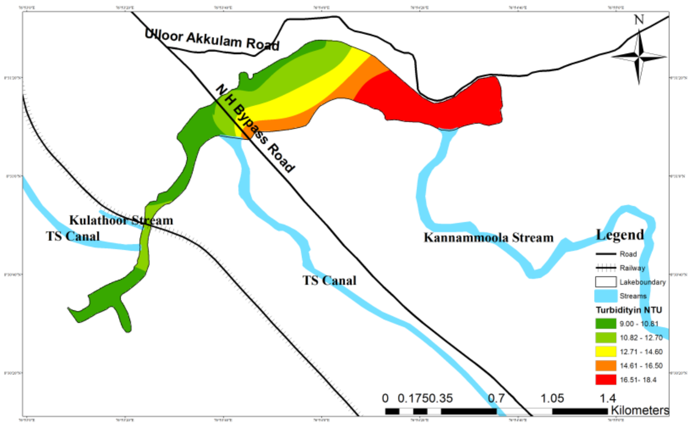


Figure6.43: Spatial Variation of Turbidity in Monsoon season for the Year 2013

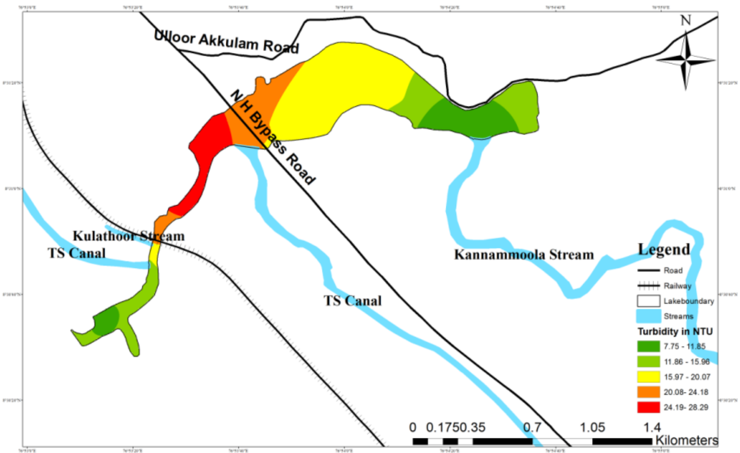


Figure6.44: Spatial Variation of Turbidity in Post Monsoon season for the Year 2013

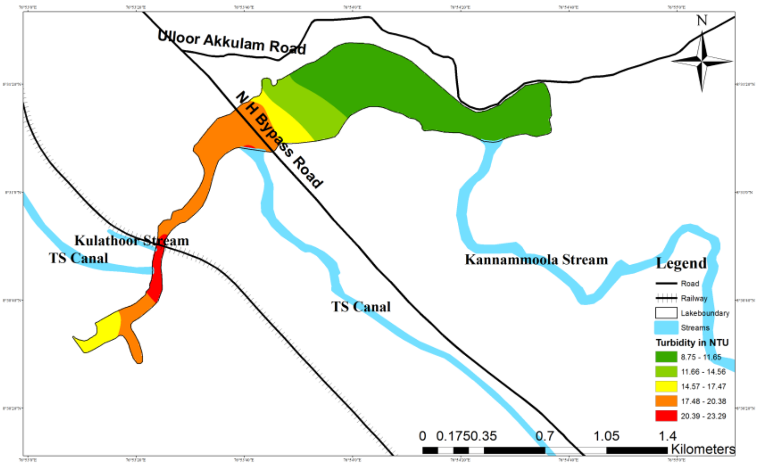


Figure6.45: Spatial Variation of Turbidity in Pre Monsoon season for the Year 2014

6.7 WATER QUALITY INDEX (WQI)

The WQI of the AV lake was calculated using NSFWQI. The raw water quality parameters with different unit of measurement were transformed in to non-dimensional sub-index values. And these sub-indices were multiplied by weight and then combined to give WQI.

6.7.1 Water Quality Index of Akkulam-Veli lake

Average WQI was obtained for the entire lake, yearly wise and season wise. Table 6.9 shows a summary of average values of water quality index calculated for AV lake.

The obtained WQI for the 326 samples collected every month during June 2012 to May 2014 is ranging from 9 to 70 and an average value of 42, this indicates that the Akkulam Veli lake is polluted and quality of water is bad. Yearly wise average WQI is obtained as 44 (range 14-72) for 2012 and 40 (9-66) for 2013, and this shows that the quality of water is degrading year after year

Table 6.9: Average values of Water Quality Index of AV lake

Description	No. of Samples	Range of WQI	Average WQI
Total Average WQI	326	9 -70	42
Yearly average WQI	174	14-72	44

(June 2012- May2013)			
Yearly average WQI (June 2013- May 2014)	152	9-66	40
Seasonal average WQI Pre-monsoon (February –May)	43	9-43	24
Seasonal average WQI Monsoon (June – September)	57	9-66	51
Seasonal average WQI Post-monsoon (October – January)	52	16-60	38

. The water quality index was calculated for the samples for different seasons for the year. For the pre-monsoon season (the obtained WQI is 24 and indicates water quality as very poor. The WQI for summer season is 51 and water quality is medium and for post monsoon season the quality of water is bad as obtained WQI is 38. Among the seasons the water quality of Akkulam-Veli in pre-monsoon is very bad compared to other seasons.

The average rainfall for the different seasons are shown in table 6.10. It is seen that the very bad water quality in pre-monsoon season is due to less rainfall resulting in less dilution of lake water. In the post-monsoon season as the rainfall is higher than the pre-monsoon the water quality was better.

Table 6.10: Rainfall Data

(Source: IMD)

Season	Average rainfall(mm)
Pre-monsoon	3.73
Monsoon	9.7
Post-monsoon	5.1

6.7.2 Water Quality Index of Akkulam - Veli Lake in different stations

The WQI was calculated for each sampling stations in the AV lake. The results obtained are shown in table 6.11.

Table 6.11: Water Quality Index for stations

Station	WQI	Remarks	Station	WQI	Remarks
1	55	Medium	**9**	49	Bad
2	51	Medium	**10**	48	Bad
3	43	Bad	**11**	43	Bad
4	41	Bad	**12**	46	Bad
5	39	Bad	**13**	36	Very bad
6	39	Bad	**14**	32	Vary bad
7	41	Bad	**15**	30	Very bad
8	44	Bad	**16**	25	Very bad

Station 1 which is in Veli lake is least polluted and station 16 in Akkulam lake is highly polluted among the stations. It is seen that the quality of water is degrading as moving from Veli to Akkulam Lake. It may be due to the discharge of waste through Kannamoola thodu in the upstream of the Akkulam lake. The quality of water is medium to bad on Veli lake and bad to very bad in Akkulam lake

6.7.3 GIS Representation of WQI

GIS interpolation was carried out for the season-wise WQI using ArcGIS. Figure 6.46 shows the water quality of pre-monsoon season.

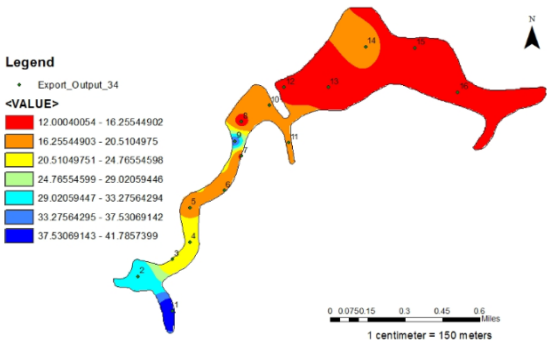


Figure 6.46: GIS interpolation of WQI for pre-monsoon season

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It can be seen that in pre-monsoon season the WQI varies from 12 to 42 indicates that the lake is highly polluted. This might be due to less dilution of water. The figure 6.47 shows water quality of monsoon season.

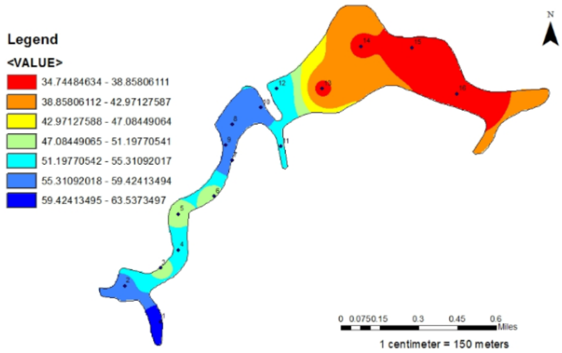

Figure6.47: GIS interpolation of WQI for monsoon season

From the fig 6.47 the WQI varies from 34 to 54. This indicates the lake is less polluted in monsoon season. Fig 6.48 shows the water quality representation of post-monsoon season.

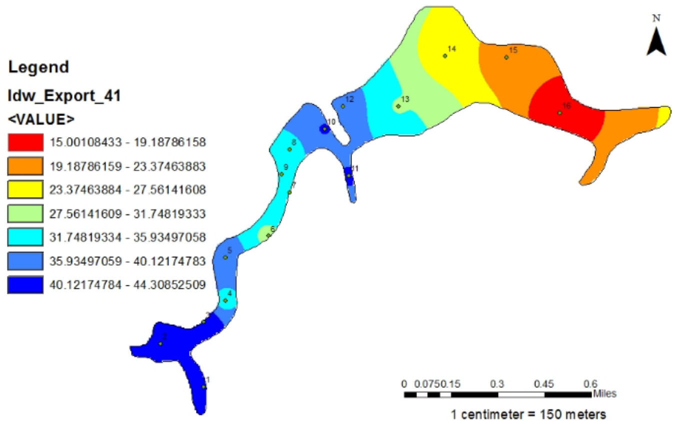

Figure6.48: GIS interpolation of WQI for post-monsoon season

During post-monsoon the WQI varies from 15 to 45. The water quality of the lake during post-monsoon season was comparatively good compared to pre-monsoon.

6.8 DEVELOPMENT OF WQI MODELS

Water quality models are used to monitor water quality of water bodies. In this study models were developed for WQI in regression, ANN and ANFIS. For the validation of models water samples were collected from same sixteen stations on February 2015. The water samples were analysed for various water quality parameters. The calculated WQI is shown in table 6.12.

Table6.12: WQI calculated for the February month 2015

Sampling Stations	WQI	Sampling stations	WQI
1	31	9	27
2	54	10	18
3	47	11	26
4	43	12	36
5	40	13	20
6	26	14	23
7	20	15	21
8	21	16	21

6.8.1 Regression model for WQI

WQI models were developed in multiple linear regressions and multiple loglinear regression. The results were analysed.

6.8.1.1 Linear regression model

A multiple linear equation was developed using SPSS. The input parameters pH, BOD, TS and chlorophyll a were used as independent variables and water quality index was used as dependent variable. The model R^2 obtained was 0.765. The linear regression equation was obtained as,

$$WQI = 72.106 - 1.522pH - 0.920BOD - 0.001TS + 1.171Chlorophyll\ a \qquad (6.1)$$

The water quality data of February month was used for the validation of model. The correlation coefficient(R) obtained between observed and predicted WQI was 0.79. The Chi-squared value obtained with 95% confidence interval with 16 degrees of freedom was 5.6 which is less than Chi-squared distribution table value 7.26. This indicated that the predicted

WQI value fit with the actual data using regression model. The plot between observed and model predicted values is shown in figure 6.49.

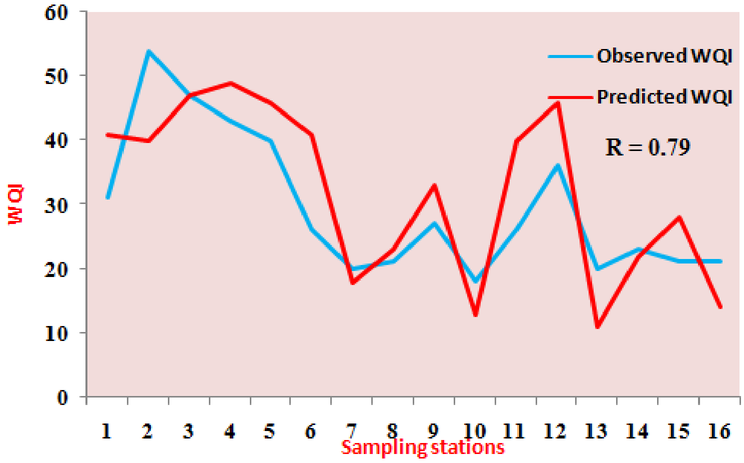

Figure6.49: Validation of WQI Regression Model

6.8.1.2 Log regression model

A multiple linear equation was developed using SPSS. The input parameters logpH, logBOD, logTS and logchlorophylla were used as independent variables and logwater quality index(LogWQI) was used as dependent variable. The model R^2 obtained was 0.850. The log linear regression equation was obtained as

$$LogWQI = 2.390 - 0.289logpH - 0.434logBOD - 0.018logTS + 0.22logchorophylla \quad (6.2)$$

The water quality data of February month was used for the validation of model. The correlation coefficient obtained between predicted WQI and observed WQI was 0.816.

The Chi-squared value obtained with 95% confidence interval with 16 degrees of freedom was 6.1 which is less than Chi-squared distribution table value 7.26. This indicated that the predicted logWQI value is fit with the actual data using regression model. The plot between observed and model predicted values is shown in figure 6.50.

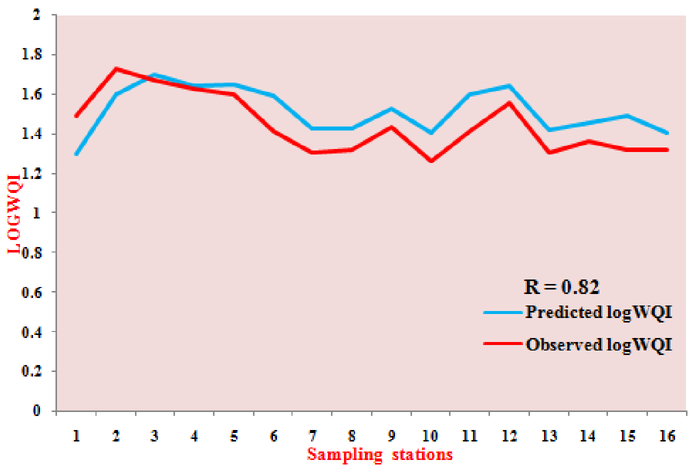

Figure6.50: Validation of WQI log Regression Model

The log regression model has provided good R value compared to linear regression model. By comparing the two regression models it was clear that the relation of water quality parameters with WQI is not linear.

6.8.2 ANN - WQI model

An ANN model was developed using back propagation algorithm to predict the water quality index. The model was developed using five water quality parameters as inputs- pH, dissolved oxygen, biochemical oxygen demand, total solids and chlorophyll a. The membership function used in hidden layers was tansig.

Table6.13: Results of ANN training for WQI

Architecture	Epochs	MSE	RMSE	Remarks
5-1-1	1000	2.61×10^{-3}	0.051088	Max epoch reached
5-2-1	1000	2.09×10^{-3}	0.045717	Max epoch reached
5-3-1	1000	4.59×10^{-4}	0.021424	Max epoch reached
5-4-1	1000	3.99×10^{-4}	0.019975	Max epoch reached
5-5-1	1000	5.28×10^{-4}	0.022978	Max epoch reached
5-6-1	137	2.69×10^{-4}	0.016401	Max gradient reached

5-7-1	1000	2.78×10^{-4}	0.016673	Max epoch reached
5-8-1	1000	1.76×10^{-4}	0.013266	Max epoch reached
5-9-1	1000	1.51×10^{-4}	0.012288	Max epoch reached
5-10-1	101	1.34×10^{-4}	0.011576	Max gradient reached
5-11-1	303	1.43×10^{-4}	0.011958	Max gradient reached
5-12-1	1000	1.21×10^{-4}	0.011	Max epoch reached
5-13-1	1000	1.15×10^{-4}	0.010724	Max epoch reached
5-14-1	484	7.63×10^{-5}	0.008735	Max gradient reached
5-15-1	1000	6.34×10^{-5}	0.007962	Max epoch reached
5-16-1	1000	3.98×10^{-5}	0.006309	Max epoch reached
5-17-1	1000	2.67×10^{-5}	0.005167	Max epoch reached
5-18-1	1000	2.28×10^{-5}	0.004775	Max epoch reached
5-19-1	1000	3.05×10^{-5}	0.005523	Max epoch reached
5-20-1	1000	7.06×10^{-5}	0.008402	Max epoch reached

The trial and error method was adopted to find out best architecture. The trial and error was done by changing the number of hidden neurons from 1 to 20. The best architecture was obtained when hidden neurons were 18 with a least mean square error (MSE) as shown in table 6.13.

The testing of the model was carried out with 18 hidden neurons. The regression plots obtained for training, testing and validation of model is shown in figure 6.51.

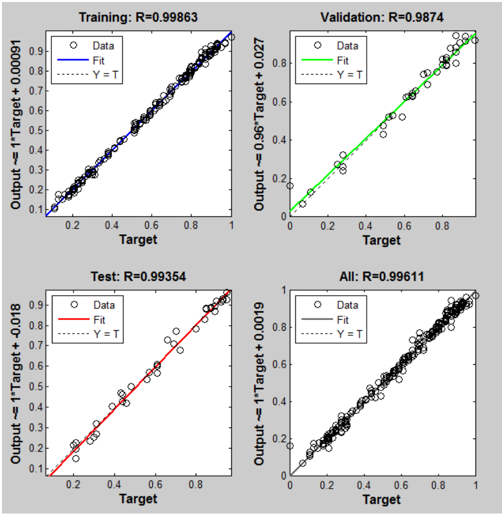

Figure6.51: Regression plots of ANN - WQI model

For the validation of model the water quality data of February 2015 was used. The plot between observed and model predicted values is shown in figure 6.52.

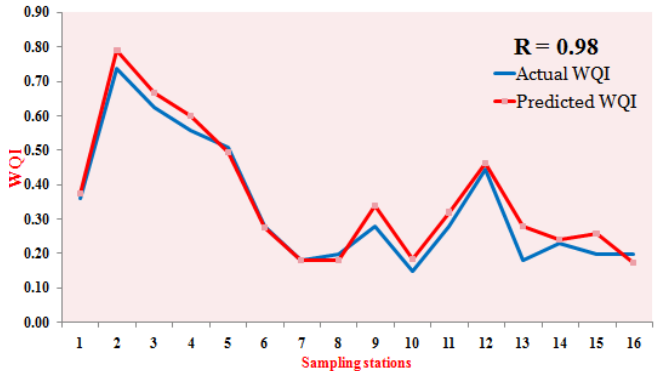

Figure6.52: Validation of WQI ANN model

The Index of Agreement obtained according to 3.10 was 8.7 showing good agreement of predicted values with observed values. The correlation coefficient between actual and predicted values of water quality index was obtained as 0.984 as shown in Fig 6.52. The Index of Agreement obtained according to 3.10 was 8.7 showing good agreement of predicted values with observed values. The result shows that the model can predict WQI with high efficiency. The model predicted the WQI of the February 2015 as 31.

6.8.3 ANFIS - WQI model

An ANFIS model was developed to predict the WQI. The input parameters selected were pH, dissolved oxygen, biochemical oxygen demand, total solids and chlorophyll a. For training of model different membership functions were used. Optimization method used was hybrid. The results obtained while training the model is shown in table 6.14.

Table 6.14: Results of ANFIS – WQI training

Membership function		**Error**	**Epoch**	**Steady epoch**
Input	Output			
Trimf	linear	1.94×10^{-3}	70	30
Trapmf	linear	2.8×10^{-3}	40	20
gbellmf	linear	2.1×10^{-4}	40	40
gaussmf	linear	7.113×10^{-5}	50	40
gauss2mf	linear	1.94×10^{-3}	45	30
Pimf	linear	1.01×10^{-4}	70	60
Dsigmf	linear	7.85×10^{-5}	80	60
Psigmf	linear	7.85×10^{-5}	0	50

During the training of model least error was obtained for gauss membership function. The structure of network developed is shown in figure 6.53.

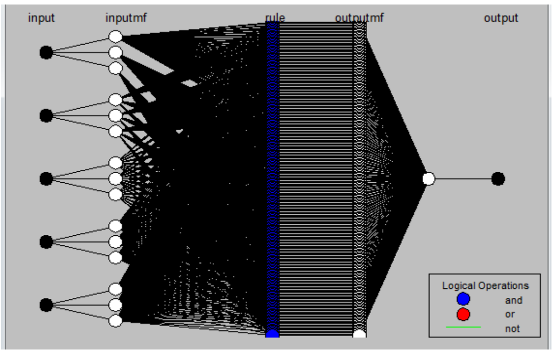

Figure6.53: Structure of Network

The testing of the model was carried out with the gauss membership function. The testing yielded correlation coefficient of 0.779 with an MSE value 0.0227 as shown in figure 6.54.

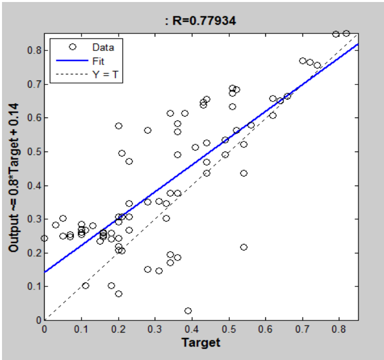

Figure 6.54: Results of ANFIS WQI testing

The validation of the model was done using the water quality data of February 2015. The plot between predicted and actual WQI is shown in figure 6.55.

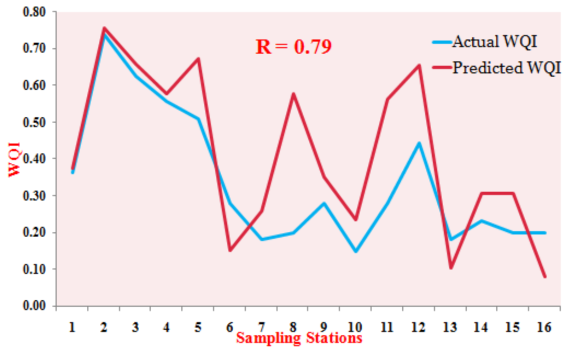

Figure6.55: Validation of ANFIS - WQI model

The Index of Agreement obtained according to 3.10 was 6.9 showing medium agreement of predicted values with observed values. The model provided a correlation coefficient between the observed and model predicted WQI of 0.79. The predicted WQI were renormalized and model predicted WQI for February 2015 is 34.

6.9 COMPARISONS OF WQI MODELS

Table shows the comparison of different WQI models. The actual WQI for February 2015 is 30. The forecasted WQI from different models is shown in table 6.15.

Table6.15: Comparison of WQI models

Name of Model	R	Forecasted WQI
ANFIS	0.792	34
ANN	0.984	31
MLR	0.785	34
Log MLR	0.825	33

The difference in R value of linear and log linear model shows that the variation of input parameters is not linear with the output. The results of ANN show its efficiency in non-linear modelling. ANN model of WQI predicted WQI with high accuracy compared to regression models. The ANN predicted the WQI of February 2015 as 31.

The reasons behind poor WQI predictions with ANFIS may be due to software limitations of ANFIS GUI, use of same input function for all inputs or user errors due to low degree of user friendliness of ANFIS GUI. The results of ANFIS WQI models were not as successful as expected. ANN appeared to be more successful that ANFIS when correlation coefficients and other error showing parameters were considered.

6.10 ANN BASED SENSITIVITY ANALYSIS FOR WQI

An ANN based sensitivity analysis was carried out by leave one out technique. The table 6.16 shows the results obtained when pH was removed.

Table6.16: Results of ANN training WQI model – pH removed

Architecture	Epochs	MSE	Remarks
4-1-1	5	2.72×10^{-3}	Max gradient reached
4-2-1	998	3.27×10^{-3}	Max gradient reached
4-3-1	996	2.26×10^{-4}	Max gradient reached

4-4-1	335	2.42 $x10^{-3}$	Max gradient reached
4-5-1	763	2.11 $x10^{-3}$	Max gradient reached
4-6-1	1000	1.75 $x10^{-3}$	Max epoch reached
4-7-1	938	1.59 $x10^{-3}$	Max gradient reached
4-8-1	988	1.35 $x10^{-3}$	Max gradient reached
4-9-1	1000	1.46 $x10^{-3}$	Max epoch reached
4-10-1	999	1.36 $x10^{-3}$	Max gradient reached
4-11-1	663	8.51 $x10^{-4}$	Max gradient reached
4-12-1	6	2.05 $x10^{-3}$	Max gradient reached
4-13-1	999	7.99 $x10^{-4}$	Max gradient reached
4-14-1	1000	5.16 $x10^{-4}$	Max epoch reached
4-15-1	1000	2.61 $x10^{-4}$	Max epoch reached
4-16-1	1000	5.45 $x10^{-4}$	Max epoch reached
4-17-1	999	5.64 $x10^{-4}$	Max gradient reached
4-18-1	1000	7.12 $x10^{-4}$	Max epoch reached
4-19-1	998	4.06 $x10^{-4}$	Max gradient reached
4-20-1	1000	8.09 $x10^{-4}$	Max epoch reached

The best architecture was obtained when the hidden neurons was fixed as 15.Table 6.17 shows the results obtained when DO was removed.

Table6.17:Results of ANN training WQI model – DO removed

Architecture	**Epochs**	**MSE**	**Remarks**
4-1-1	7	8.02 $x10^{-3}$	Max gradient reached
4-2-1	754	8.44 $x10^{-3}$	Max gradient reached
4-3-1	1000	5.89 $x10^{-3}$	Max epoch reached

4-4-1	735	5.26 x10^{-3}	Max gradient reached
4-5-1	271	4.18 x10^{-3}	Max gradient reached
4-6-1	1000	3.13 x10^{-3}	Max epoch reached
4-7-1	1000	3.96 x10^{-3}	Max epoch reached
4-8-1	1000	2.78 x10^{-3}	Max epoch reached
4-9-1	1000	2.29 x10^{-3}	Max epoch reached
4-10-1	993	1.66 x10^{-3}	Max gradient reached
4-11-1	992	2.67 x10^{-3}	Max gradient reached
4-12-1	998	1.67 x10^{-3}	Max gradient reached
4-13-1	992	1.53 x10^{-3}	Max gradient reached
4-14-1	986	8.68 x10^{-4}	Max gradient reached
4-15-1	6	3.48 x10^{-3}	Max gradient reached
4-16-1	984	3.49 x10^{-4}	Max gradient reached
4-17-1	999	1.34 x10^{-3}	Max gradient reached
4-18-1	1000	6.21 x10^{-4}	Max epoch reached
4-19-1	1000	4.68 x10^{-4}	Max epoch reached
4-20-1	987	6.57 x10^{-4}	Max gradient reached

The best architecture was obtained when the hidden neurons were 16. Table 6.18 shows the training results when the BOD was removed.

Table 6.18: Results of ANN training WQI model – BOD removed

Architecture	Epochs	MSE	Remarks
4-1-1	31	3.52 x10^{-3}	Max gradient reached
4-2-1	991	2.18 x10^{-3}	Max gradient reached

4-3-1	109	1.82×10^{-3}	Max gradient reached
4-4-1	979	2.04×10^{-3}	Max gradient reached
4-5-1	983	1.22×10^{-3}	Max gradient reached
4-6-1	995	1.59×10^{-3}	Max gradient reached
4-7-1	1000	1.26×10^{-3}	Max epoch reached
4-8-1	1000	1.03×10^{-3}	Max epoch reached
4-9-1	988	1.13×10^{-3}	Max gradient reached
4-10-1	997	1.09×10^{-3}	Max gradient reached
4-11-1	993	9.8×10^{-4}	Max gradient reached
4-12-1	1000	8.46×10^{-4}	Max epoch reached
4-13-1	999	6.98×10^{-4}	Max gradient reached
4-14-1	991	2.57×10^{-4}	Max gradient reached
4-15-1	1000	4.45×10^{-4}	Max epoch reached
4-16-1	1000	4.49×10^{-4}	Max epoch reached
4-17-1	985	1.62×10^{-4}	Max gradient reached
4-18-1	992	3.63×10^{-4}	Max gradient reached
4-19-1	1000	3.87×10^{-4}	Max epoch reached
4-20-1	996	1.97×10^{-4}	Max gradient reached

The best architecture was obtained when the hidden neurons were 17. Table 6.19 shows the results obtained when the total solids were removed.

Table6.19: Results of ANN training WQI model – TS removed

Architecture	Epochs	MSE	Remarks
4-1-1	6	2.36×10^{-3}	Max gradient reached

4-2-1	1000	1.07 x10^{-3}	Max epoch reached
4-3-1	1000	5.18 x10^{-4}	Max epoch reached
4-4-1	1000	6.19 x10^{-4}	Max epoch reached
4-5-1	559	5.89 x10^{-4}	Max gradient reached
4-6-1	125	4.46 x10^{-4}	Max gradient reached
4-7-1	995	3.69 x10^{-4}	Max gradient reached
4-8-1	1000	2.54 x10^{-4}	Max epoch reached
4-9-1	1000	2.96 x10^{-4}	Max epoch reached
4-10-1	983	2.75 x10^{-4}	Max gradient reached
4-11-1	227	9.35 x10^{-5}	Max gradient reached
4-12-1	1000	1.62 x10^{-4}	Max epoch reached
4-13-1	1000	2.84 x10^{-5}	Max epoch reached
4-14-1	1000	9.97 x10^{-5}	Max epoch reached
4-15-1	1000	1.11 x10^{-4}	Max epoch reached
4-16-1	1000	7.22 x10^{-5}	Max epoch reached
4-17-1	1000	6 x10^{-5}	Max epoch reached
4-18-1	1000	5.59 x10^{-5}	Max epoch reached
4-19-1	1000	4.02 x10^{-5}	Max epoch reached
4-20-1	1000	1.11 x10^{-5}	Max epoch reached

The best architecture was obtained when the hidden neurons were13. The table 6.20 shows the results when the chlorophyll a was removed.

Table 6.20:Results of ANN training WQI model – Chlorophyll a removed

Architecture	**Epochs**	**MSE**	**Remarks**
4-1-1	6	2.59 x10^{-3}	Max gradient reached

4-2-1	1000	1.38 $x10^{-3}$	Max epoch reached
4-3-1	1000	8.11 $x10^{-4}$	Max epoch reached
4-4-1	124	6.60 $x10^{-4}$	Max gradient reached
4-5-1	1000	5.67 $x10^{-4}$	Max epoch reached
4-6-1	1000	6.49 $x10^{-4}$	Max epoch reached
4-7-1	280	3.43 $x10^{-4}$	Max gradient reached
4-8-1	534	3.25 $x10^{-4}$	Max gradient reached
4-9-1	1000	1.78 $x10^{-4}$	Max epoch reached
4-10-1	514	2.09 $x10^{-4}$	Max gradient reached
4-11-1	1000	1.56 $x10^{-4}$	Max epoch reached
4-12-1	78	1.56 $x10^{-4}$	Max gradient reached
4-13-1	1000	1.60 $x10^{-4}$	Max epoch reached
4-14-1	1000	1.18 $x10^{-4}$	Max epoch reached
4-15-1	1000	1.107 $x10^{-4}$	Max epoch reached
4-16-1	1000	3.03 $x10^{-5}$	Max epoch reached
4-17-1	1000	8.5 $x10^{-5}$	Max epoch reached
4-18-1	917	5.58 $x10^{-5}$	Max gradient reached
4-19-1	1000	3.3 $x10^{-5}$	Max epoch reached
4-20-1	1000	8.53 $x10^{-5}$	Max epoch reached

The best architecture was removed when the hidden neurons were 16.The results of sensitivity analysis are tabulated in Table 6.21.

Table6.21: Results of Sensitivity Analysis

	MSE	**Significance ranking**
pH	2.61×10^{-4}	2
DO	3.9×10^{-4}	1
BOD	1.62 X 10^{-4}	3
Total Solids	2.84×10^{-5}	5
Chlorophyll a	3.03×10^{-5}	4

The significance of the parameters was found out by comparing the MSE values obtained from sensitivity analysis. The model which DO removed gave the highest MSE which indicated that DO is the significant parameter influencing WQI. The model which chlorophyll a removed gave the least MSE and it can be concluded that chlorophyll a is the least significant parameter.

6.11 DEVELOPMENT OF DO MODEL

The DO models were developed in ANN and ANFIS. The DO models serves as a measure to monitor the organic pollution in a lake. The models were validated using the water quality data of February 2015.

6.11.1 ANN- DO model

For the development of DO model using ANN the input parameters selected were temperature, pH, electrical conductivity, turbidity, hardness and chlorophyll a.the training results are shown in table 6.22.

The best architecture was obtained when hidden neurons were 20 with a least mean square error (MSE). The testing of the model was carried out with 18 hidden neurons. The regression plots obtained from ANN model is shown in figure 6.56.

Table6.22: Results of ANN training - DO model

Architecture	Epochs	MSE	Remarks
6-1-1	402	$6.07 x 10^{-2}$	Max gradient reached
6-2-1	1000	$6.43 x 10^{-2}$	Max epoch reached
6-3-1	1000	$4.87 x 10^{-2}$	Max epoch reached

6-4-1	1000	$3.77x10^{-2}$	Max epoch reached
6-5-1	1000	$3.74x10^{-2}$	Max epoch reached
6-6-1	1000	$2.86x10^{-2}$	Max gradient reached
6-7-1	1000	$2.95x10^{-2}$	Max epoch reached
6-8-1	1000	$2.12x10^{-2}$	Max epoch reached
6-9-1	1000	$1.75x10^{-2}$	Max epoch reached
6-10-1	680	$1.66x10^{-2}$	Max gradient reached
6-11-1	1000	$1.1x10^{-2}$	Max gradient reached
6-12-1	1000	$9.96x10^{-3}$	Max epoch reached
6-13-1	516	$6.62x10^{-3}$	Max gradient reached
6-14-1	1000	$6.53x10^{-3}$	Max gradient reached
6-15-1	1000	$5.01x10^{-3}$	Max epoch reached
6-16-1	866	$4.57x10^{-3}$	Max gradient reached
6-17-1	1000	$2.59x10^{-3}$	Max epoch reached
6-18-1	382	$5.66x10^{-4}$	Max gradient reached
6-19-1	1000	$1.63x10^{-3}$	Max epoch reached
6-20-1	1000	$2.54x10^{-4}$	Max epoch reached

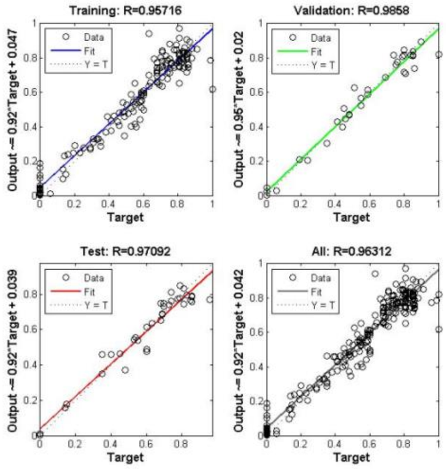

Figure6.56: Regression plots obtained from ANN – DO model

For the validation of model the water quality data of February 2015 was used and the plot is shown in Figure 6.57.

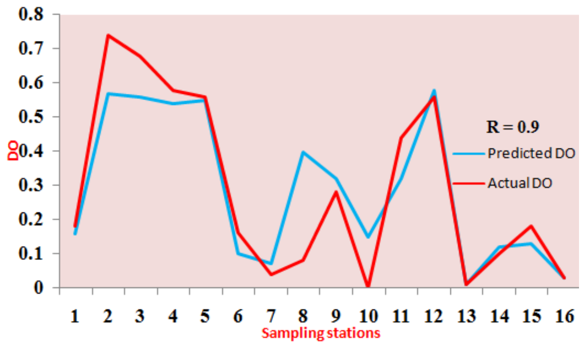

Figure6.57: Validation of ANN-DO model

The Index of Agreement obtained according to 3.10 was 0.84 showing good agreement of predicted values with observed values. The correlation coefficient obtained between predicted values and actual values was 0.9 showing the performance of model is good.

6.11.2 ANFIS model.

An ANFIS model was developed to predict the dissolved oxygen. The input parameters selected were temperature, pH, electrical conductivity, turbidity, hardness and chlorophyll a. For training of model different membership functions were used. Optimization method used was hybrid. The training results are shown in table 6.23.

Table6.23: Results of ANFIS - DO training

Membership function		**Error**	**Epoch**	**Steady epoch**
Input	Output			
Trimf	linear	4.88×10^{-2}	50	15
Trapmf	linear	4.11×10^{-2}	50	30
Gbellmf	linear	2.2×10^{-3}	60	45
Gaussmf	linear	1.69×10^{-4}	60	40
gauss2mf	linear	7.29×10^{-3}	60	45
Pimf	linear	9.1×10^{-3}	70	50
Dsigmf	linear	3.75×10^{-3}	60	40
Psigmf	linear	2.56×10^{-2}	70	50

During the training of model, least error was obtained for gauss membership function. Testing of the model was done with that membership function. In testing obtained R^2 value was 0.622 is shown in figure 6.58.

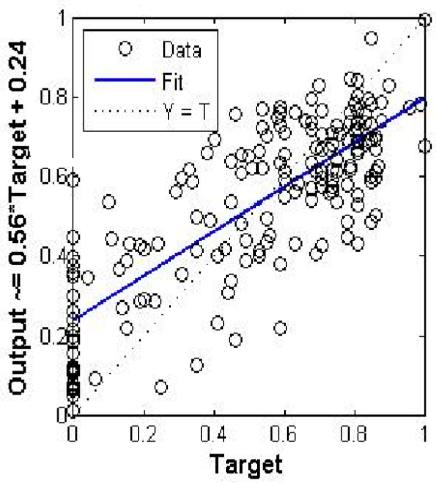

Figure6.58: Results of ANFIS DO testing

For the validation of model the water quality data of February 2015 was used. The Index of Agreement obtained according to 3.10 was 0.61 showing good agreement of predicted values with observed values. The obtained correlation value of 0.75 between actual and predicted DO values are shown in figure 6.59.

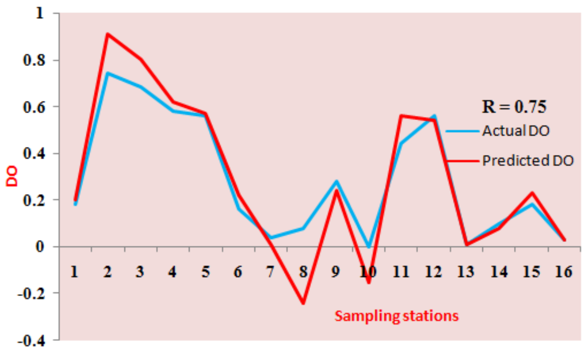

Figure 6.59: Validation of DO – ANFIS model

The results of ANN and ANFIS models of DO show that it is possible to predict DO of AV lake with limited number of input parameters. ANN models were successful in predicting DO of lake compared to ANFIS models. The results of ANFIS model were not as good as expected. This may be due to limitations of ANFIS GUI or use of same membership function for all inputs. Also insufficient past data was one of the limitations of study.

6.12 Application of model for BOD, DO and Turbidity in other water bodies

An attempt has been done to predict the variation of BOD, DO and turbidity in other water bodies. Ashtamudi lake in Kollam district and the downstream of the River Karamana were chosen for study. The model was applied to the land sat imagery taken on 28.07.2020. The variation in Akkulam-Veli lake on that date was also predicted. The prediction of BOD, DO and turbidity is almost in agreement with the field value for that lake and the map showing the variation of those parameters in the Ashtamudi lake, downstream of River Karamana and Akkulam-Veli lake are given below. The study reveals that these equations can be applied for other waterbodies.

CHAPTER 7
CONCLUSION

The present study was focussed on the water quality of Akkulam – Veli lake, a lake in the south-west of Kerala. Four phases of this study helps to identify some major issues in the study area and it also reveals about the capabilities of Remote Sensing in analysing the water quality.

The increase in the deterioration of water quality in the lake system can be observed during the study period. The trophic state of the entire AV lake falls in the 'hyper-eutrophic' condition. The main reason for the hyper eutrophication in the lake system is the discharge of turbid urban waste water from Kannamoola drain, which passes through the Thiruvananthapuram city and this drain joins the Akkulam lake in its upstream portion. The study conducted using NSFWQI value also showed that the quality of water changed from Medium to Bad and thereby indicating increase in pollution in the lake system.

Attempt was made to find out the factors causing the above situation in the lake system and found that increasing trend of land use change is responsible for the degradation of water quality. The trend of land use change in Akkulam-Veli watershed is tremendous in last few years. Within a small period of 2007 to 2013, there is a great change in Land use. Within this six years interval, 13.6 % decrease in vegetation is observed. And built-up was increased by 13.58 %. Barren/Sandy area and the water body didn’t show much variation. So the main change occurring in the study area is the conversion of vegetative cover into built-up area. Assessment was also made find out the relation of water quality with different land uses. The results showed that the reduction in dissolved oxygen and increase in BOD, fecal coliform increases with the increase in built up area in the lake basin.

A model for the prediction of WQI using five water quality parameters as inputs- pH, dissolved oxygen, biochemical oxygen demand, total solids and chlorophyll a was developed using ANN and ANFIS. The prediction with ANN model was highly accurate compared to regression models. Poor prediction was observed in the case of ANFIS model. The reasons behind poor predictions with ANFIS may be due to software limitations of ANFIS GUI, use of same input function for all inputs or user errors due to low degree of user friendliness of ANFIS GUI. The results of ANFIS WQI models were not as successful as expected. ANN appeared to be more successful that ANFIS when correlation coefficients and other error showing parameters were considered.

Attempt was made to predict water quality from the satellite imagery. Landsat and IRS P6 LISS III imagery were used in the study. The models were developed for the water quality parameters (Nitrate, SDD, Chlorophyll a, BOD, DO, pH, Turbidity, NSFWQI, TSI Chla, TSI SDD) using the corresponding measured value of water quality parameter and radiance at the same location in the satellite imagery. The model was then also validated with the corresponding measured values of those parameters in the respective sampling station. Of the imagery used, land sat imagery showed much accurate results than IRS-P6 LISS III imagery. It is due to the presence of Blue band in Landsat 8 imagery. And blue band has high influence in analysing the water quality. These models were also applied for the prediction of BOD, dissolved oxygen and turbidity in other water bodies, namely Ashtamudi lake, down stream of River Karamana and found to be successful for predicting those water quality parameters. Thus we can use those models for the prediction of other water bodies.

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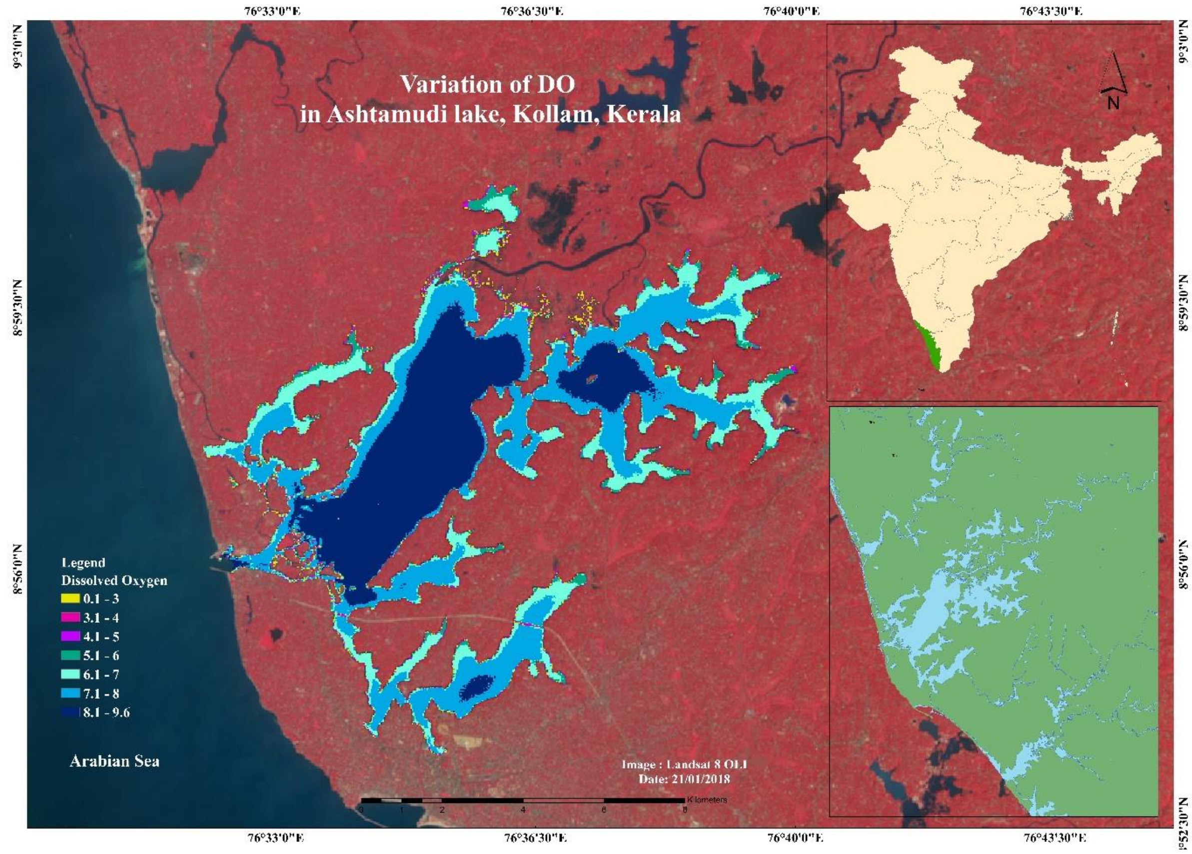
APPENDIX 1

SUMMARY OF STATISTICAL ANALYSIS OF WATER QUALITY DATA

Parameter	Unit	No. of samples	Mean	SE	Median	Mode	SD	Range	Minimum	Maximum	Variance
Temperature	^{o}C	326	9.42	.08	0.00	30.00	.44	6.00	6.00	32.00	2.07
SDD	m	326	.34	.01	.30	0.30	.18	1.25	.05	1.30	0.03
Depth	m	326	.54	.04	.40	1.00	.70	3.40	.30	3.70	0.49
pH	-	326	.68	.04	.60	7.10	.76	3.56	.10	9.66	0.58
Electrical conductivity	µS/cm	326	.81	.14	.94	1.31	.52	16.96	.24	17.20	6.35
ORP	mV	326	1.83	.52	1.50	-3.00	3.61	508	151	357.00	4045.79
Salinity	ppt	326	.95	.06	.55	0.19	.07	5.79	.12	5.91	1.14
DO	mg/l	326	.68	.14	.30	0.00	.50	8.00	.00	8.00	6.25
BOD	mg/l	326	9.40	.89	3.00	4.00	6.06	55.70	.00	58.70	257.87
Total solids	mg/l	326	079.4	6.10	854.5	2079.4	554.53	7700	00.00	7800.00	2416568
TDS	mg/l	326	903.6	22.3	180.0	500.00	208.27	12900	0.00	12950.0	4876466
TSS	mg/l	324	83.09	4.94	50.00	0.00	28.91	3850	.00	3850.00	395531
Turbidity	NTU	326	3.92	.40	3.92	6.00	.18	5.00	.00	38.00	51.50
Alkalinity	mg/l	326	36.55	.76	24.00	00.00	9.78	40.00	0.00	280.00	2477.67
Carbonate	mg/l	326	.26	.99	.00	.00	7.86	20.00	.00	120.00	319.07
Bicaronate	mg/l	326	32.14	.59	20.00	00.00	6.84	40.00	0.00	280.00	2194.22
Hardness	mg/l	326	42.11	.34	40.00	36.00	2.21	58.00	0.00	298.00	1781.32
Calcium	mg/l	326	7.84	.48	6.85	2.06	.62	2.91	.21	60.12	74.27
Magnesium	mg/l	326	8.42	.43	7.92	8.42	.74	2.92	.41	46.33	59.85
Sodium	mg/l	326	3.54	.95	3.54	3.54	5.27	04.40	.00	209.40	1243.81
Pottasium	mg/l	326	5.86	.58	5.50	1.60	0.44	3.00	.20	74.20	109.08
Chloride	mg/l	326	60.93	.12	44.99	60.93	2.37	61.48	5.50	486.98	8532.38
Sulphate	mg/l	326	3.88	.39	2.10	.70	.99	1.80	.10	36.90	48.82
Nitrate	mg/l	326	.67	.04	.60	.20	.77	.50	.00	3.50	0.59

Phosphate	mg/l	326	.46	.02	.40	.40	.33	.30	.10	3.40	0.11
Chlorophyll a	µg/l	326	.69	.05	.62	.65	.83	.62	.15	3.77	0.68
Pheophytin	µg/l	326	.17	.03	.06	.78	.59	.54	.10	2.64	0.34
Faecal Coliform	/100	326	25.32	2.92	084.5	500	316.5	44	85.00	7429	1733273

APPENDIX II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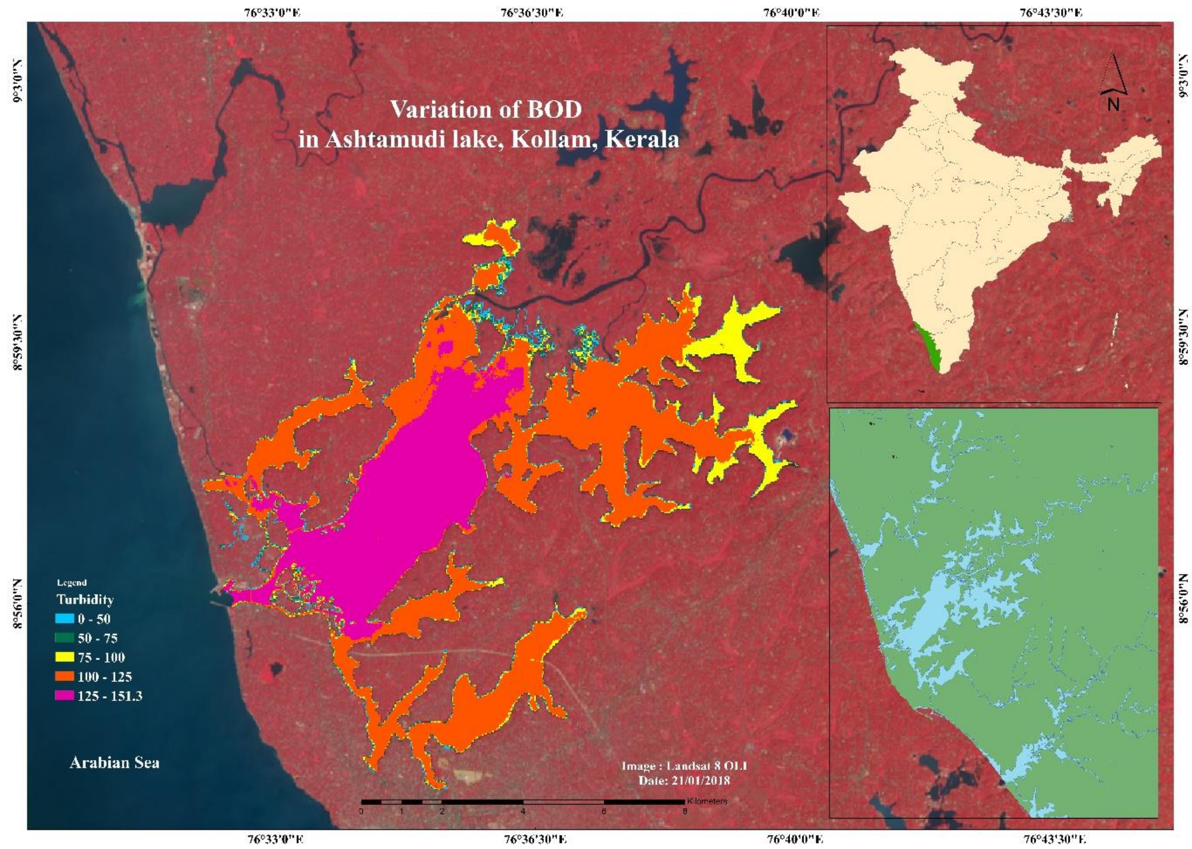
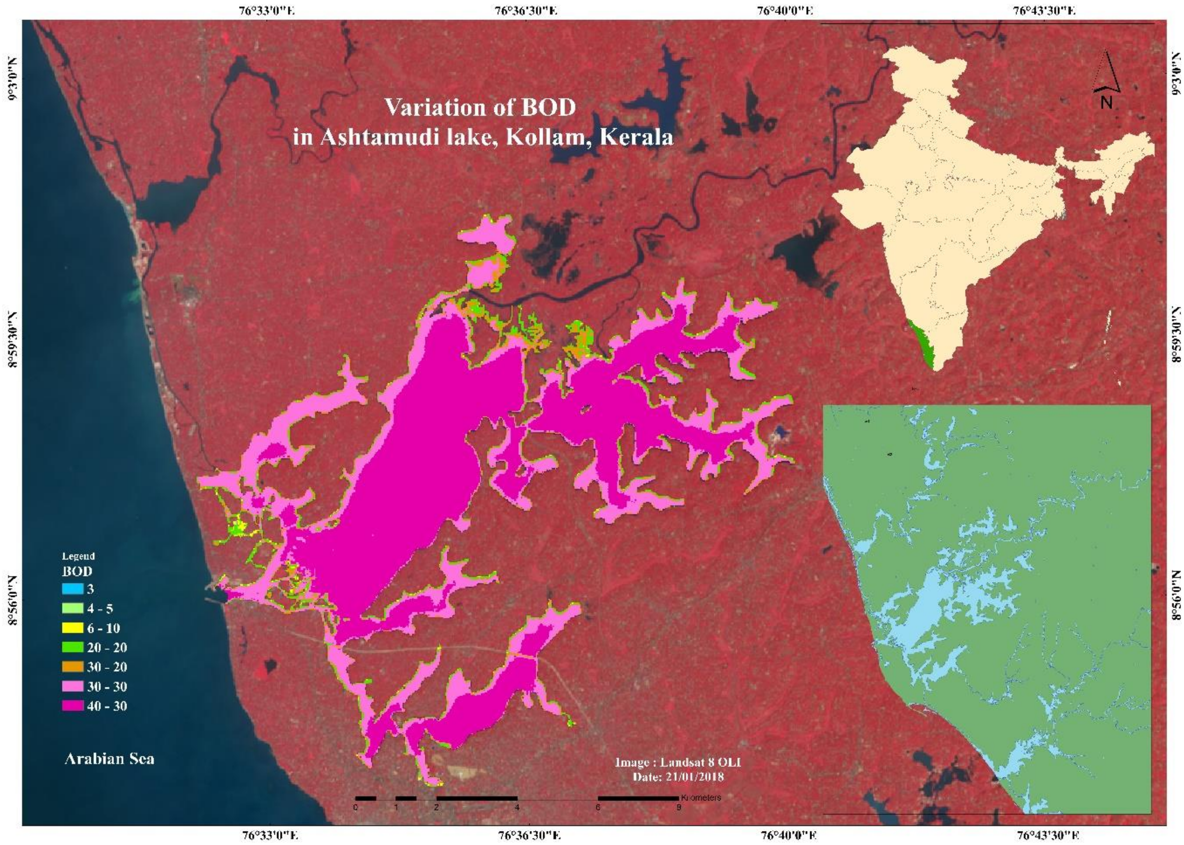
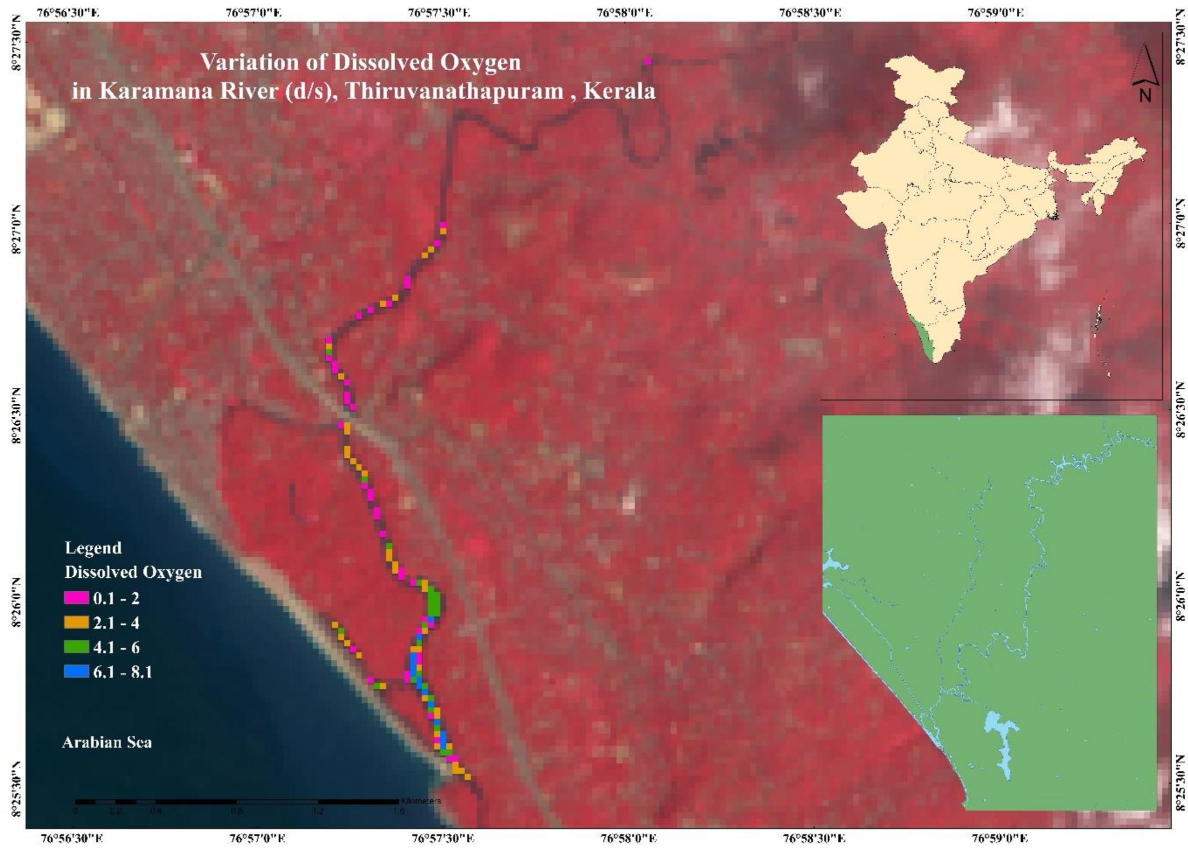
76°36'30"E
76°40'0"E
76°43'30"E
9°3'0"N
8°59'30"N
8°56'0"N
8°52'30"N
Variation of DO
in Ashtamudi lake, Kollam, Kerala
N
Legend
Dissolved Oxygen
0.1 - 3
3.1 - 4
4.1 - 5
5.1 - 6
6.1 - 7
7.1 - 8
8.1 - 9.6
Arabian Sea
Image : Landsat 8 OLI
Date: 21/01/2018
Kilometers


76°33'0"E
76°36'30"E
76°40'0"E
76°43'30"E
9°3'0"N
8°59'30"N
8°56'0"N
Variation of BOD
in Ashtamudi lake, Kollam, Kerala
N
Legend
Turbidity
0 - 50
50 - 75
75 - 100
100 - 125
125 - 151.3
Arabian Sea
Image : Landsat 8 OLI
Date: 21/01/2018
Kilometers


Variation of BOD
in Ashtamudi lake, Kollam, Kerala
76°33'0"E
76°36'30"E
76°40'0"E
76°43'30"E
9°3'0"N
8°59'30"N
8°56'0"N
N
Legend
BOD
3
4 - 5
6 - 10
20 - 20
30 - 20
30 - 30
40 - 30
Arabian Sea
Image : Landsat 8 OLI
Date: 21/01/2018


Variation of Dissolved Oxygen
in Karamana River (d/s), Thiruvanathapuram , Kerala
76°56'30"E
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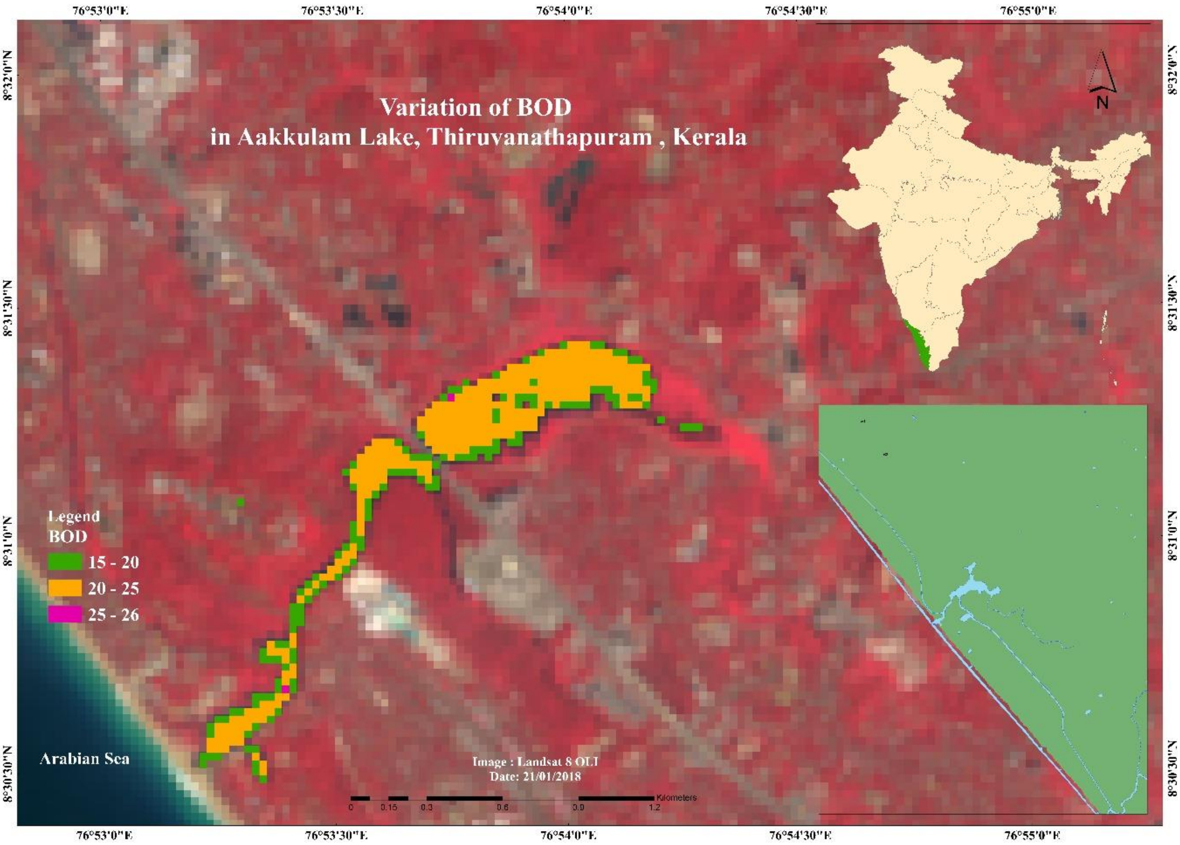
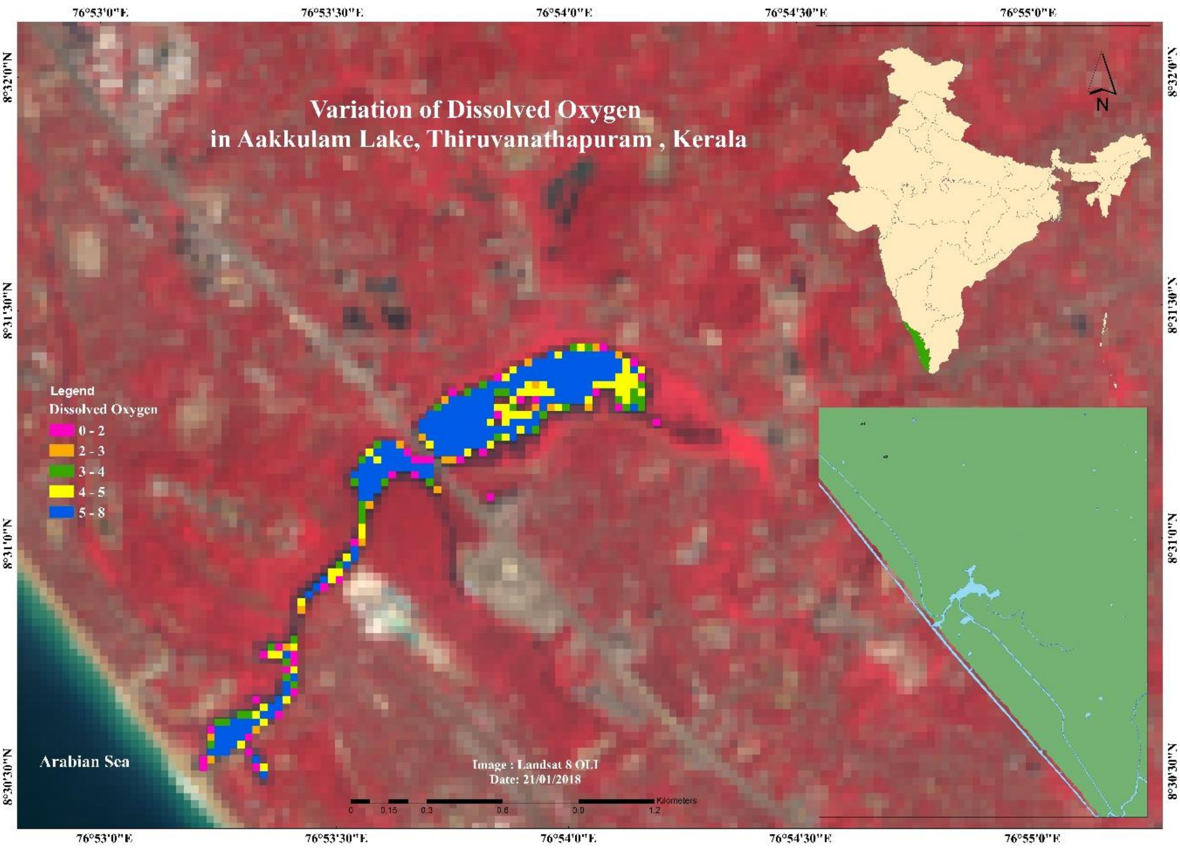
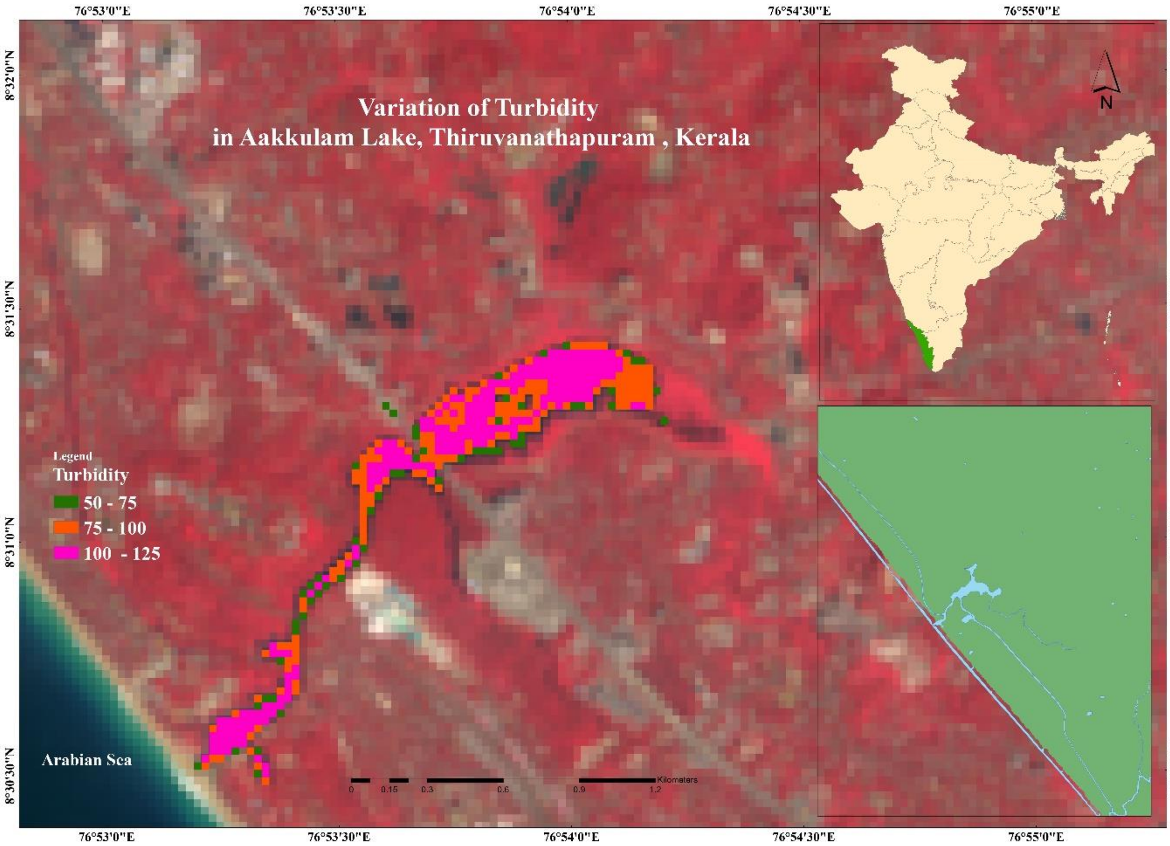
76°57'30"E
76°58'0"E
76°58'30"E
76°59'0"E
8°27'30"N
8°27'0"N
8°26'30"N
8°26'0"N
8°25'30"N
N
Legend
Dissolved Oxygen
0.1 - 2
2.1 - 4
4.1 - 6
6.1 - 8.1
Arabian Sea


Variation of BOD
in Aakkulam Lake, Thiruvanathapuram , Kerala
Legend
BOD
15 - 20
20 - 25
25 - 26
Arabian Sea
Image : Landsat 8 OLI
Date: 21/01/2018
76°53'0"E
76°53'30"E
76°54'0"E
76°54'30"E
76°55'0"E
8°32'0"N
8°31'30"N
8°31'0"N
8°30'30"N
N


Variation of Dissolved Oxygen
in Aakkulam Lake, Thiruvanathapuram , Kerala
Legend
Dissolved Oxygen
0 - 2
2 - 3
3 - 4
4 - 5
5 - 8
Arabian Sea
Image : Landsat 8 OLI
Date: 21/01/2018
76°53'0"E
76°53'30"E
76°54'0"E
76°54'30"E
76°55'0"E
8°32'0"N
8°31'30"N
8°31'0"N
8°30'30"N
N



Variation of Turbidity
in Aakkulam Lake, Thiruvanathapuram , Kerala
Legend
Turbidity
50 - 75
75 - 100
100 - 125
Arabian Sea
76°53'0"E
76°53'30"E
76°54'0"E
76°54'30"E
76°55'0"E
8°32'0"N
8°31'30"N
8°31'0"N
8°30'30"N
N
0
0.15
0.3
0.6
0.9
1.2
Kilometers