MAPPING, INVENTORY AND CHANGE DETECTION OF WETLANDS OF THAVANUR GRAMA PANCHAYATH

by

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KERALA, INDIA

2022

DECLARATION

I hereby declare that this project entitled **"MAPPING, INVENTORY AND CHANGE DETECTION OF WETLANDS OF THAVANUR GRAMA PANCHAYATH"** is a bonafide record of project work done by us during the course of study and that the report has not previously formed the basis for the award to us of any degree, diploma, associateship, fellowship or other similar title of another university or society.

Place: Tavanur

Date: 08/07/2022

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CERTIFICATE

Certified that the project entitled **"MAPPING, INVENTORY AND CHANGE DETECTION OF WETLANDS OF THAVANUR GRAMA PANCHAYATH"** is a record of research work done independently by **Ms. M R Chithra** under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associateship to her.

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(2019-18-003)

THESIS

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M R Chithra

Dedicated to All Agricultural Engineers

INDEX

LIST OF TABLES

LIST OF FIGURES

LIST OF PLATES

LIST OF APPENDICES

SYMBOLS AND ABBREVIATIONS

%	Percentage
&	And
Asst.	Assistant
/	Per
min	Minute
sec	Seconds
ºC	Degree Celsius
Dept.	Department
E.g.	Example
Etc.	Etcetera
et. al.	And others
Fig.	Figure
h	Hour
i.e,	That is
L	Litre
m	Meter
cm	Centimetre
Mm	Millimetre
ha	Hectre
ARB	Amur River Basin
API	Application Programming Interface
CRB	Congo River Basin

DLG	Digital Line Graph
DNN	Deep Neutral Network
DT	Dicission Tree
DTC	Decision Tree Classification
FCC	False Colour Composition
GE	Google Earth
GIS	Geographic Informative System
GIW	Geographically Isolated Wetland
GLCF	Global Land Cover Facility Site
GPS	Geographic Positioning System
GW	Ground Water
IDW	Inverse Distance Weighted
ISRO	Indian Space Research Organisation
IRS	Indian Remote Sensing Satellite
LULC	Land Use Land Cover
LTM	Landsat Thematic Map
MNDWI	Modification of Normalised Difference Water Index
NRSC	National Remote Sensing Centre
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
OLI	Operation Land Images
PCC	Post Classification Comparison
PS	Planet Scope
PoI	Point Of Interest

RS	Remote Sensing
SAR	Synthetic Aperture Radar
SOC	Scientific Organisation Control
SWF	Surface Water Fraction
TIN	Triangulated Irregular Network
TM	Thematic Map
USGS	United States Geological Survey
WB	Water Body

CHAPTER I

INTRODUCTION

A wetland is a distinct ecosystem that is flooded by water, either permanently or seasonally (Keddy, 2010). Wetlands are vital for human survival that modifies the human history as well as culture. The primary factor that distinguishes wetlands from terrestrial land forms or water bodies is the characteristic aquatic vegetation (Ramsar convention, 2010). Wetlands are considered among the most biologically diverse of all ecosystems, it serving as home to a wide range of animal and plant species (Dorney et al., 2018). They are one of the most productive environments in the world, cradles of bio-diversity that provide the water and productivity upon which numerous species of animal and plant depend for its survival (Mitsch and Gosselink, 1993). Wetlands play a critical role in climate change, hydrology, biodiversity, and human well-being (Ramsar, 2001). Wetlands regulate both global and local climate through exchange of water, energy, and heat with the atmosphere, and greenhouse gases emission and sequestration (Munger, 2004). For human well-being, wetlands not only provide fundamental materials for human healthcare but also have the potential to generate considerable economic value (Millennium Ecosystem Assessment, 2005). It is an accepted fact that a wetland is an indispensable resource for humans and wildlife, and substantial wetland loss could be irreversible (Millennium Ecosystem Assessment, 2005).

Wetlands are ecotones or transitional zones that are formed intermediate between dry ground and open water. Water predominates in wetland environments, and they have characteristics that are similar to both terrestrial and aquatic environments, as well as properties that are unique to them. Wetlands support a diverse range of flora and fauna, as well as providing a variety of climatic, ecological, and socioeconomic benefits. Wetlands are frequently called the "kidneys" of the earth by scientists. The Ramsar Convention on Wetlands (1971) produced an international, intergovernmental treaty which defined wetlands as “areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six meters" (Ramsar, 2011).

Wetlands are one of the most significant ecosystems on the earth and provide many other important services to human society. Annual and monthly water balances, flood frequency distributions, hydroperiod distributions, soil exceedance values for hydrologic plant compatibility, and retention time distributions are all provided by the simulated daily hydrology of wetlands. With the function of movement of water regulations and groundwater replenishment, Wetlands play an important role in balancing the hydrological cycle which, in turn, supports all ecosystem services and sustainable development (Russi *et al*., 2013). It also performs a variety of useful functions, such as recycle nutrients, prevent floods, purify water, recharge groundwater, maintain stream flow, and also serve in providing drinking water, fodder, fish, wildlife habitat, fuel, buffer shorelines against erosion and recreation to the society. In addition to supplying the subsistence products, wetlands frequently supply products that supplement during difficult times when other sources of income are not available. Furthermore, many wetland areas have great cultural and religious significance.

Kerala is famous for its wetlands and is one of India's greenest states. Kerala's economy is heavily reliant on wetlands. Kokkal *et al.* (2008) reported that the wetland areas in Kerala accounts for as much as one fifth of the land area of the State. The unique wetland ecosystems of Kerala include water-logged terrains, marshy and vast polders (paddy cultivation areas) associated with backwaters, and lakes and the Myristica Swamps in the Western Ghat forests. Kerala also has a few wetlands of national and international significance. These include Vembanad, Kole, Ashtamudi and Sasthamcotta lakes which are also designated as Ramasar sites of Kerala. Nair *et al*. (2001) reported a total of 217 wetland areas in Kerala, of which157 greater than 56.25 ha with an aerial extend of 127930 ha, in which 64 designated as “inland wetlands” (area 34199.5 ha), whereas 93 are “coastal wetlands (area 93730.5 ha).

Sustainable management of wetlands requires comprehensive knowledge of the factors influencing the wetlands hydrodynamics (the flow of water into and out of a wetland). Precipitation, surface water, and groundwater are the main sources of hydrological flows into wetlands. Water flows out of wetlands by evapotranspiration, surface runoff, and subsurface water outflow. Hydrodynamics affects hydro-periods (temporal fluctuations in water levels) by managing the water storage and balance within a wetland (Richardson *et al*., 2001). Cultivation of wetlands has received global attention now. Kerala is well known for its wetland cultivation and play an important role in the economy of Kerala. The variation in available moisture across the field is influenced by field elevation and groundwater fluxes from saturated to unsaturated zone (Oke *et al*., 2010). Satellite-based estimate of surface water dynamics helps to find that surface water extent (SWE) in the area (Becker *et al*., 2018).

Wetlands are in danger all across the world right now. To make space for development, they are contaminated, drained, or filled up. In recent years, the rate of wetland degradation has accelerated. Infrastructure development, such as roads, trains, and other lines of communication, disrupted the wetlands' connectivity and obliterated large swaths of coastal vegetation. Rich and lush mangrove forests were being encroached upon by rapid urbanisation, while rapid industrialization not only polluted the environment but also obliterated any chance of restoration. Since the 1700s, wetlands around the world have degraded to nearly 90% of their original condition, and we are losing wetlands three times faster than forests (World wetland day 2022, Ramsar). Thus, wetlands are under severe threat from reclamation, water diversion, pollution, resource overuse, biological invasion and climate change worldwide especially in fast growing economies. The evidences showed that our wetlands are being destroyed and LULC pattern have been altered.

The relevance and utility of wetlands were first brought to the world's attention in 1971, when a convention on "Wetlands" was held in the Iranian city of Ramsar. The Convention was an intergovernmental agreement that set a framework for national and international action to conserve and wisely utilise wetlands and their resources. There are 154 Contracting Parties to the Convention as of March 9th, 2007, with 1650 wetland sites totaling 149.6 million hectares designated for inclusion in the Ramsar list of Wetlands of International Importance (Ramsar convention, 2008).

However, due to intensive anthropogenic activities, climate change and decreasing biodiversity, the ecological functions of wetlands are retrogressing and triggering numerous environmental and social problems (Gong *et al*., 2010). As a result, effective wetlands management and protection are critical, and accurate and comprehensive wetland classification maps as well as spatiotemporal change information are essential for ecological protection and local government decisions. Wetland inventories are essential for any wetland's management and protection, mostly due to its spatial size. The advancement of geospatial technology has opened up a variety of methodological options for preparing inventories and understanding wetlands dynamics.

The first step in wetland ecological conservation is to determine the location, distribution, size, and type of the wetland. Traditional wetlands measurements, such as field investigations or manual visual interpretation of aerial pictures, have limited spatial or temporal coverage, demand a lot of human resources, and are challenging to carry out. Because satellite images are multi-temporal and multispectral and provide repeated and extensive coverage for monitoring changing conditions (Ozesmi and Bauer 2002), They can be utilised to make mapping and change detection studies easier. Now a days Remote Sensing has been used in combination with Geographical Information Systems (GIS) and Global Positioning Systems (GPS) for effective mapping and change detection.

Digital image processing and visual interpretation techniques are the two methods used for mapping and change detection analysis in GIS. Visual interpretation technique generally involves in viewing images, making measurements on images, performing image interpretation tasks, and transferring interpreted information to base maps (Lillesand *et al.*, 2014). Visual interpretation technique can be used efficiently to classify the complex and heterogeneous landscapes with image pattern characteristics (Zanella *et al*., 2012) which deliver better spatial details (Puig *et al*., 2002) in enhanced quality from medium-resolution satellite data (Ghorbani and Pakravan, 2013), and also help to obtain more precise dynamic changes (Zhang *et a*l., 2014), even if the satellite images containing cloud cover, shadows and illumination problems (Lillesand *et al*., 2014).

Thavanur Grama Panchayath is a land rich in water resources and wetlands. The most important wetlands in Thavanur Panchayath includes Bharathapuzha, Maravanchery kaayal, Varo kaayal, Thavanur kaayal (marshy land), Ayankalam aquaculture, Mannar aquaculture and several other farm ponds. The cultivation and livelihoods of the Panchayath mainly depend on these water sources. Therefore, their variations and changes affect the agriculture and other related activities of the Panchayat. So far, no proper documentation is available on wetland mapping, its inventory and its change detection over the last decade for Thavanur Grama Panchayath.

In view of all the above facts the present study entitled **"Mapping, inventory and change detection of wetlands of Thavanur Grama Panchayath."** was undertaken with the following specific objectives:

- Mapping and inventory of wetlands of Thavanur Panchayath using multispectral satellite imagery
- Monitoring the spatio-temporal change pattern in landuse / land cover over the past decade.
- Evaluation of water table and surface water dynamics of wetlands for sustainable cultivation in the area.

CHAPTER II

REVIEW OF LITERATURE

Wetlands are very sensitive eco systems; and they are fully influenced by the hydrologic conditions of soils. Understanding the functionality of these wetland habitats and the changing degree of hydrologic connection between them requires an understanding of surface water dynamics. Currently, wetlands are being contaminated, drained, or filled to make space for development. In recent years, the rate of wetland destruction has accelerated. Continues monitoring and management is needed to protect wetlands. Hence mapping different wetland types and monitoring their long-term change can serve as a scientific foundation for researchers and planners to understand the trends and dynamics of wetlands. This will aid in the development of wetlands preservation and restoration measures, as well as sustainable agriculture in the area. Satellite remote sensing coupled with GIS and GPS is an effective method to monitor wetland resources and its changes. Here some of the important research studies conducted in this line are reviewed under the following subheads.

2.1. ROLE OF GIS AND REMOTE SENSING IN WETLAND MAPPING

Robbins *et al.* (1997) conducted a study to quantify the temporal changes in seagrass areal coverage by geographic information system (GIS) and low-resolution aerial photography. This study examined at whether aerial images with a resolution of 1:24000 might be used to examine temporal changes in sea grasses in Tampa Bay, Florida, a subtropical estuary. During the decade 1982-1992, the amount of sea grass in Tampa Bay increased by 87 percent. However, this recovery of sea grass area1 extent was only 35% of the area1 extent that had already been recorded.

Caloz and Collet (1997) carried out a study on application of geographic information systems (GIS) and remote sensing (RS) in aquatic botany. The purpose of this study was to offer an overview of the concepts and methodologies used in the field of geographic information systems (GIS). It outlined the major procedures required in spatial data processing and illustrated the wide range of GIS applications. GIS is more than just a group of computerized tools; it's a completely integrated environment for managing and analyzing spatial data, as well as transferring classical inquiry and analytical approaches.

Williams and Lyon (1997) examined the use of historical aerial photographs and geographic information system (GIS) to determine effects of long-term water level fluctuations on wetlands along the St. Marys River, Michigan in USA. The wetlands along the St. Marys River expand and contract in the same way that wetlands on lakes do. The effects of water level changes on the wetland areas of the St. Marys River were studied using data collected from historical aerial pictures and placed into a Geographic Information System (GIS). Between the years for which photographic data was available, the GIS was utilized to measure changes in wetland area. The use of GIS enabled quantification of wetland area changes, determination of reaction rates, and description of inter-class transfer dynamics for five coastal wetland classes affected by long-term water level oscillations. There was a 426 ha difference for the emergent wetland in the study region between 1964 and 1978. This reflected a 32% shift in the area, and a roughly one-third change in the emergent wetland area.

Ferguson and Korfmacher (1997) conducted a study on remote sensing and GIS analysis of sea grass meadows in North Carolina, USA. The reference data for analysing the results using three Landsat TM imagery of coastal North Carolina (1985, 1988, and 1992) came from the interpretation of photographs (March 1985 and April 1988). For a June 1992 image, Landsat classification agreement with reference data was determined to be as high as 72.6%. Despite the limited urbanization of coastal North Carolina, sea grasses directly related with the mainland are rather rare and confined to areas with shallower water than sea grasses and areas near deserted barrier islands. According to the findings, the maximum sea grass depths were 2.0 m close to the banks and 1.2 m on the mainland. The correlations between the infrared bands 4, 5, and 7 are somewhat strong in the June image, low in December, and lowest in the high tide image in October.

Narumalani *et al.* (1997) conducted a study on application of remote sensing and geographic information systems for the delineation and analysis of riparian buffer zones of Iowa River. The land cover of the area was characterized using Landsat Thematic Mapper (LTM) data. The United States Geological Survey (USGS) Digital Line Graph (DLG) data base was combined with the TM-derived taxonomy of surface water bodies to create an updated hydrology data layer. The buffer zones around all surface hydrologic phenomena were created using spatial distance search methods. To locate "critical" areas for the growth of riparian vegetation strips, the buffer zones were combined with remotely sensed categorization data. The results showed that natural vegetation protected the majority of the Iowa River's main channel, whereas more than 44% (or 1008 ha) of the region around its tributaries lacked any protection from non-point source pollution. It is crucial that water resource management strategies concentrate on the creation of riparian zones in order to limit the impact of non-point source pollution because these "important" locations are close to agricultural fields.

Shen *et al.* (2011) carried out a study on application of remote sensing in the extraction of urban land use changes in Beijing. They found the reasons for Land use changes in Beijing were land development and infrastructure development.

Garg *et al.* (2013) conducted a study on wetland assessment, monitoring and management in India using geospatial techniques. First scientific inventory of wetlands in India was carried out in 1998 by Space Applications Centre (ISRO), Ahmedabad using indigenous IRS (Indian Remote Sensing Satellite) data of 1992-93 timeframe, which prompted a surge in the application of geospatial approaches for wetland conservation and management. As a preliminary to the development of a 'National Wetland Information System,' studies were conducted to develop a 'Wetland Information System' for the state of West Bengal and the Loktak Lake Wetland (a Ramsar site) using improvements in GIS. Research was also carried out in order to prepare action plans, particularly for the Ramsar sites across the country. In a ground-breaking study, the utility of GIS technology for biodiversity protection was proven using landscape ecological indicators.

2.2. INVENTORYING, MAPPING AND CHANGE DETECTION OF WETLANDS

Rebelo *et al.* (2008) developed and promoted a multi-purpose wetland inventory through participation and specific analysis on various scales response to past uncertainties and gaps in inventory coverage. They included a study of the Ramsar sites database to map the distribution of Ramsar sites across global eco-regions and to identify the under-represented regions and wetland types in the database. They focused on the use of land surveying information for management of wetlands more effectively. A study was started at the local level to map and analyse remote wetland and individual wetlands utilised for agriculture in eight South African countries. As a baseline for future assessments of land use change, a multi-temporal data set of images was used to evaluate land cover and the extent of inundation at each location. The building of local capacity to plan and conduct such analyses, as well as to relate the findings to wetland management and gather information on the global distribution, extent, and condition of wetlands, was fully incorporated into each of these assessments.

Mamun *et al.* (2013) monitored the changes of land use pattern using remote sensing and GIS in Dhaka city. The study explored the land use change pattern during the period from 1990 to 2010, through an interactive supervised land cover classification using Landsat images and ArcGIS 10. The result showed that the corporation's vegetative cover and open areas were turned into building areas, and low ground and water bodies were transformed into reclaimed built-up lands. Unplanned urban expansion was largely responsible for these changes.

Kantakumar *et al. (*2015) conducted a study on multi-temporal land use classification using hybrid approach. A hybrid classification scheme was developed to prepare a multi-temporal land use classification data set of Sawantwadi taluk of Maharashtra state in India. ISODATA clustering and Maximum likelihood methods were combined in the analysis. The accuracy assessment was very promising with 93% overall accuracy and kappa coefficient 0.92.

Rawat *et al.* (2015) carried out a study on monitoring land use/cover changes using remote sensing and GIS techniques. The study illustrated the spatio-temporal dynamics of land use / cover of Hawalbagh block in Almora district of Uttarakhand. Landsat satellite imageries of two different time periods, namely the Landsat Thematic Mapper (TM) of 1990 and 2010 downloaded from Global Land Cover Facility Site (GLCF) and Earth Explorer Site were used. Supervised classification methodology was done by ERDAS 9.3 Software. The land use in the study area were divided into five different classes viz. plants, cultivation, fallow, built-up and water body. The results indicated the plants and built-up land increased by 3.51 (9.39 km^2) and 3.55 (9.48 km^2) per cent respectively during a period of two decades. Agriculture, fallow land and water resources were declined by 1.52 (4.06 km2). 5.46 (14.59 km^2) and 0.08 (0.22 km^2) per cent respectively.

Fang *et al.* (2016) investigated a study on wetland mapping and wetland temporal dynamic analysis in the Nanjishan wetland using Gaofen-1 data in China. To acquire a qualitative description of the reasons of seasonal wetland changes, the study explored the methods of wetland classification mapping and the analysis of wetland seasonal variations during floods and dry seasons in Nanjishan. The flood and dry seasons were represented by two remote sensing photographs (Gaofen-One [GF-1]). A deterministic approach was proposed to extract wetlands from the GF-1 pictures of the Nanjishan wetland. For the flood and dry seasons, respectively, the decision tree classification (DTC) method generated the highest overall accuracy of 96.12 and 92.76 percent. According to the change detection data, there have been considerable changes in low-density grasslands, swamps, and water bodies, as well as transitions between the other two wetland cover types.

Kavyashree and Ramesh (2016) conducted a study on wetland mapping and change detection using Remote Sensing and GIS in west coast of Karnataka. The thresholding technique and NDWI, NDVI were used to extract wetlands and water bodies. Supervised classification was done using ERDAS IMAGINE software. Integrated land use and wetland map was generated. Change detection analysis was carried out by PCC method. Analysis of satellite data showed that wetlands including water bodies varied from 28.28% to 27.45 % of the total area and the water bodies were decreased at a rate of 982 hectares per year from 1998 to 2008-09 year.

Niu and Gong (2017) conducted a study on large scale wetland mapping and evaluation of 100 globally large RAMSAR Sites. In 2001 and 2013, the top 100 globally major RAMSAR Sites were mapped using MODIS time-series data, and their changing characteristics and landscape integrity were assessed. The global wetland area has stayed unchanged, with less than 1% of wetland area loss, according to the findings. Inland wetland area changes at a quicker rate than coastal and artificial wetland areas. Those RAMSAR sites are still threatened to varying degrees in terms of wetland disturbance/degradation. The findings showed that, in terms of protection area, almost 79 percent of the 91 national wetland reserves were in bad condition. Only 15% of national wetland reserve were adequately safeguarded, and those that were were largely found in the upper reaches of the Songhua River.

Prasad and Ramesh (2018) conducted a spatio-temporal analysis of land use/land cover changes in an ecologically fragile area-Alappuzha District, Southern Kerala. The LULC aspects were categorized into seven classes: water- logged area, water body, built-up land, uncultivated area, mixed vegetation, paddy field and sandy area. It was found that expansion of the built-up land area was proportionate to the rate of population growth.

Maggie *et al.* (2019) conducted a multi-temporal analysis of land use and land cover change detection for Dedza District of Malawi, South Africa using geospatial techniques. The study analysed LULC change dynamics for the years 1991, 2001 and 2015 using remote sensing and GIS. Both unsupervised and supervised classification & PCC techniques were used in the study. The results revealed between 1991 and 2015, water bodies, forest land, marshes, and agricultural land all decreased dramatically, barren ground and while built-up areas increased significantly.

Sebastian *et al.* (2019) developed a high-resolution wetland database and web interface for the Ernakulam and Thrissur Districts in Kerala, India. Visual interpretation method was adopted in this study. They found that the spatial extent of total wetlands in Ernakulam and Thrissur districts were about 74,060 ha. The paddy fields were found to be the dominant wetland type in the districts covering an area of 40,965 ha.

Slagter *et al.* (2020) conducted a study on mapping the wetland characteristics of St. Lucia wetlands, South Africa using temporally dense Sentinel-1 and Sentinel-2 data. The aim of this research was to study the feasibility of high-resolution and temporarily dense sentinel-1 and -2 data for wetland mapping at multiple levels of characterization. Random forests were applied to different taxonomic levels, including generic wetland definition, wetland vegetation, and surface water dynamics, to assess the utilisation of data. The results of the St. Lucia wetlands in South Africa showed that the integration of Sentinel-1 and Sentinel -2 led to higher classification accuracy than the systems used separately. The accuracy of the classification of wetlands with high vegetation was relatively poor, as sub canopy flooding could not be detected using Sentinel-1's C-band sensors operating in VV / VH mode.

Mao *et al.* (2020) developed a hybrid object-based and hierarchical classification approach to map wetlands in China using remote sensing. Wetlands were classified using Landsat 8 imageries. The overall classification accuracy of the wetland map of China was found 95.1%. China's wetlands were estimated as 451,084 ± 2014 km^2, of which 70.5% were inland wetlands. The inland marshes spreading in 14 subdivisions was the largest (area 152,429 ± 373 km^2) and the coastal swamp was the smallest (area-259 ± 15 km^2).

Kumar *et al.* (2020) conducted a study to compile land use / land cover data of three wetlands in Punjab (Harike, Roper, Nangal) through direct on-screen digitization and digital processing using automatic digital indices. The normalised deference water index (NDWI) and the updated normalised deference water index were both used in the study to assess the performance of two band indices (MNDWI). For the study, the two band indices were calculated using Landsat data from 1990–1991 and 2018. The outcome showed that NDWI and MNDWI were very accurate and efficiently used for mapping and monitoring wetlands.

Muro *et al.* (2020) carried out a field study on wetland mapping in Albania. They used all available Sentinel-1 and Sentinel-2 images to build a national wetland map for

Albania. They obtained a variety of indices and temporal metrics and looked at how they interacted in terms of mapping accuracy. For best results, they combined Sentinel-1 with Sentinel-2 and its origin indices. They used morphometric characteristics and knowledge-based principles to eliminate systematic mistakes, boost theme resolution, and obtain an overall accuracy of 82%. The results were contrasted with field inventories as well.

Mishraa *et al.* (2020) evaluated the performance of high-resolution satellite imagery in detecting ephemeral water bodies over West Africa. The aim of this study was to investigate performance applicability of high-resolution Planet Scope (PS) data for locating and monitoring water bodies (WBs) in the Ferlo region of West Africa and was compared with Landsat-8 imagery. The results indicated that, PS data was equivalent to Landsat for cloud-free days ($r > 0.88$; ubRMSE 0.01), while the findings were poor for cloudy days (r 0.49 and ubRMSE > 0.058) because to insufficient cloud masking. At the water fraction threshold of > 40%, PS pictures were able to detect roughly 95% of the WBs, whereas Landsat was only able to identify 32%.

Martins *et al.* (2020) performed a study on wetland mapping by a technique called Deep Neural Network (DNN) using high resolution WorldView-3 and airborne LiDAR data in millrace flats wildlife management area, IOWA, USA. In DNN, strong remote sensing image classification technologies were used. The study was a newly developed framework for wetland mapping using DNN algorithm and world view-3 image. The results showed that DNN has achieved satisfactory results as they observed a higher spatial overlap with the study area (overall accuracy = 93.33%). Results confirmed that the PCA-based feature was effective in optimizing DNN performance, vegetation and the text indexes were the most informative variables.

Yang *et al.* (2021) conducted a study on mapping and assessment of wetland conditions by using remote sensing images and Point of Interest (PoI) data. They established a Knowledge-Based Raster Mapping (KBRM)-based framework and used it to assess wetland biological conditions in Suzhou, China, using remote sensing pictures and Point of Interest (PoI) data. Five ecological indicators were developed and utilised to depict the biological characteristics of wetlands: density maps of water bodies, plant covers, imperviousness, roadways, and POI values. To properly map the wetland biological conditions, the KBRM technique was applied to incorporate these indicators into an overall grade. The validation findings showed a strong agreement between the total wetland condition ratings provided by their method and the values obtained from water quality data for the Water Quality Index (WQI).

2.3. TRACKING LONG-TERM FLOODPLAIN WETLAND CHANGES

Calzada *et al*. (2017) conducted a study entitled on long-term dynamics of a floodplain shallow lake in the Pantanal wetland and its influence on climate changes. Using an ad hoc-designed remote-sensing approach (including a newly built normalised water index, NWI) on 221 Landsat-Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM +) images recorded between 1984 and 2011, mapped regions include riparian floodplain-wetland vegetation, open water, and both. Within the researched time span, they analysed and identified significant inter-annual fluctuations and divided into three major eras. The results demonstrated that riparian floodplain-wetland vegetation was expanding while the open water area of this floodplain-lake ecosystem was decreasing. The system's long-term dynamics were not brought on by climate change, but rather by a number of other reasons. The start of the Manso dam's operation upstream of the system under study, the subsequent river regulation brought on by the dam operation, and climatic oscillations all appeared to be contributing factors to the observed fluctuations.

Jia *et al.* (2020) have done a detailed study to track the long-term floodplain wetland changes in Amur River basin (ARB), China. They developed COHRF, an original and reliable classification method that combines an image compositing algorithm with object-based image analysis and hierarchical random forest classification to distinguish between floodplain wetlands and the surrounding land uses. Using the COHRF classification method and 4622 Landsat images, a dataset with a 30-m resolution was produced, illustrating the dynamics and conversions of floodplain wetlands in ARB from 1990 to 2018. The results showed that: (1) COHRF is a robust classification approach; (2) from 1990 to 2018, CARB experienced a net loss of about 25% of floodplain wetlands, with an area decline from 8867 km2 to 6630 km2; (3) the lost floodplain wetlands were mostly converted into croplands, with 111 of the wetlands lost; and (4) the wetlands lost were mostly converted into wetlands, with a net loss of about 25%.

2.4 WATER TABLE AND SURFACE WATER DYNAMICS IN WETLANDS

Rosenberry and Winter (1997) conducted a study on dynamics of water-table fluctuations in upland between two prairie-pothole wetlands in North Dakota. During the first four years of the study, a water table trough near to the lower semi-permanent wetland was the most common water-table structure, although the severe drought of those years was likely to have contributed to the tub's longevity and size. They calculated the evapotranspiration needed to create the water-table dip between the two wetlands. Evapotranspiration was calculated using diurnal fluctuations. Water levels in wells closer to the semi-permanent wetland frequently showed a different flow direction than those in wells farther away from the wetland.

Oke *et al.* (2010) conducted a study on evaluation of water table dynamics for sustainable cultivation in wetlands for a thorough knowledge of factors that influence wetlands hydrodynamics. It was discovered that field elevation and groundwater fluxes from the saturated to unsaturated zone influenced the variation in available moisture across the field. Despite the lack of water table recharging during the agricultural drought, soil accessible moisture in the non-tidal wetland was determined to be high and sufficient for crop water supply without additional irrigation.

Smith *et al.* (2017) analysed surface water dynamics in an agricultural wetland habitat at a globally important shorebird stopover site Sacramento Valley, California for the period 1983–2015 using Landsat time series, and evaluated the effect of climate on water extent. Several techniques, including supervised classification algorithms and thresholds for spectral bands and indices, were used to identify open water in images. They used receiver operating characteristic curves to establish the appropriate water probability range for the research area and the Random Forest technique to predict the presence or absence of water from the N6200 reference pixels. Compared to previous methods that need more intensive user input, the optimised mid-infrared (1.5-1.7 m) range discovered open water in the Sacramento Valley, California, at 30 m resolution with an average accuracy of 90%. By the end of March, the water area had shrunk by 1300 ha over the previous three decades, mostly as a result of changes in agricultural size and the timing of floods. Water in coastal habitats was highly linked with the water availability index during the height of migration.

Pickens *et al.* (2018) characterized the global inland water dynamics from 1999 to 2018 with Landsat time-series data. They used Landsat 5, 7, and 8 satellite photos to categorise land and water, and after that they carried out a time-series analysis to create maps showing inter-annual and intra-annual open surface water dynamics. In order to produce objective estimators of the area of static and dynamic surface water extent and to evaluate the accuracy of surface water maps, they also used a random sample and a reference time series classification of land and water. According to a high-resolution photography probability sample, At Landsat resolution, an estimated 10.9 percentage of worldwide inland surface water is among mixed pixels, implying that better spatial detail is required for monitoring surface water changes. They are the first unbiased area estimators of open surface water extent and changes, as well as the issues of tracking changes in surface water area using data with medium spatial and temporal resolution.

Gujrati and Jha. (2018) conducted a study on surface water dynamics of inland water bodies of India using Google earth engine (GEE). GEE is an open source application programming interface (API) that provides satellite data and composite resources on a cloud computing platform, thereby reducing the demand for processing power and data accessibility for users. Studying the surface water volume of India's biggest inland lakes involved using five-year Landsat-8 images from the GEE database (2013–18). (over 6000 ha). To distinguish between pixels with and without water, they employed a sorting algorithm based on pixels. The distribution of the Modified Normalized Difference Water Index (MNDWI) and the Normalized Difference Vegetation Index (NDVI) was utilised to cluster classes using a knowledge-based Decision Tree (DT) model. The biggest decline in water volume was discovered to have occurred in 2015–2016, and they misreported a deviation from the 5-year trend line. In order to calculate the maximum water extent, peak extent day, and storage cycle of the water body, a modified Gaussian model was fitted to a time series of surface extent.

Becker *et al.* (2018) conducted a satellite-based estimate of surface water dynamics in the Congo River Basin (CRB) and found that surface water extent (SWE) exhibited marked seasonal patterns, well distributed along the major rivers and their tributaries. The mean annual variation in SWS in the CRB was found 81 ± 24 km^3. It represented about 6 ± 2% of the annual water volume that flowed from the Congo River into the Atlantic Ocean.

Wang *et al. (2018)* analysed the long-term surface water dynamics for Middle Yangtze River Basin using Landsat Imagery and the Google Earth Engine. They suggested a new way to quickly determine what is the annual maximum and minimum extent of surface water and maximum and minimum water levels in 1990, 2000 and 2010. This approach fully utilized the data and computing features of Google Earth Engine, which processed 2343 scenes of cloud platforms and Landsat images. The extensions were acquired by Random Forest Classification. The results showed that (1) annual minimum surface water area was 14,751.23 km^2, 14,403.48 km^2, 13,601.48 km^2 and 15,697.42 km^2 during 1990, 2000, 2010 and 2017 respectively. (2) The maximum annual surface water area was 18,174.76 km^2, 20,671.83 km^2, 19,097.73 km^2 and 18,235.95 km^2 during 1990, 2000, 2010 and 2017 respectively. (3) The accuracy of surface water classification ranges from 86% to 93%.

Amatya *et al.* (2019) analyzed long-term water table dynamics of forested wetlands: drivers and their effects on wetland hydrology in the South-Eastern Atlantic Coastal Plain. In this study, the analysis of long-term data from four drained and six un-drained sites on coastal forested wetlands showed that their growing season water table dynamics depends upon evapotranspiration. The water table was deeper in the un-drained sites than in the drained young sites and was shallower in the older ones. The water table was within 30 cm of the surface for 8% of the time, compared to 31% or higher on un-drained sites. When compared to the baseline level, the water table reaction was similar in both drained and un-drained watersheds shortly after vegetation clearance. During extreme storms, the water table dynamics on all soil types and vegetation responded identically. In the limited yearly mean water table data, there was no discernible pattern.

Qi *et al.* (2019) has conducted a study on surface water storage and subsurface water dynamics using SWAT model for characterizing the hydroperiod of geographically isolated wetlands in Delmarva Peninsula, USA. Using observed daily water level data from four wetlands at two sites, they tested the geographically isolated wetland (GIW) module (including restored and natural wetlands with and with- out a low-permeability soil layer). The results show that both with and without a low-permeability soil layer, the wetland module faithfully reproduced observed water levels in both restored and natural wetlands. The programme could also accurately mimic portions of saturated and unsaturated soil during wet and dry conditions.

Zhu *et al.* (2020) conducted a study for assessing wetland sustainability by modelling water table dynamics under climate change in Florida, United States. This study simulated the addition of essential physical water processes under climate change process-based model distributed with a combination of 20 general circulation models under the representative concentration Pathway Scenes 8.5, 4.5 in 1950-2099. A probable rate was suggested to assess the sustainability of wetlands under climate change. The Results showed that the water table was reduced by 68 cm. Water availability decreased based on the sustainability assessment and wetlands dried up. In 2100, the risk increased from the base rate of 63% -99%.

Lia *et al.* (2020) conducted a study on evaluation of a new 18-year MODIS-derived surface water fraction dataset for constructing Mediterranean wetland open surface water dynamics. They assessed the temporal dynamics of the surface water. The volume of water was effectively collected using MODIS Surface Water Fraction (SWF). 340 distinct reservoirs in the Mediterranean region had their surface water levels recorded between 2000 and 2017 using the previously created 8-day MODIS Surface Water Fraction dataset. They assessed how well the water volume matched the MODIS SWF time period. The Landsat-based dataset and satellite-altimetry data were used to obtain water level information. The association between MODIS and the Landsat-derived SWF, however, was weak in relatively static waters ($r = 0.17$), according to the data. For dynamic reservoirs, the value increased significantly ($r = 0.81$). The amount of water derived from Modis SWF is inversely correlated with the level of the land ($r \geq 0.76$).

Beegum *et al.* (2021) conducted a study entitled "Construction of water table contour map and geohydrological studies in Pathanamthitta using QGIS techniques. 32 Open wells were selected for groundwater depth measurement. They constructed contour map and water table fluctuation map for identification of the ground water potential zone in the area. The contour map showed that the highest ground water level in Pathanamthitta municipality was in ward no. 24 which is Valamchuzhy whereas the lowest ground water level was in ward no. 13, which is Anappara. The fluctuation map showed that the water level is highly decreased in the Thycavu region by 3.82m which was found as the most vulnerable area. The least vulnerable region was found as Azhoor area with a fluctuation of 0.7m, which indicated safe zone.

CHAPTER III

MATERIALS AND METHODS

This chapter describes the details of study area, data and software used and the various methodologies and analyses carried out for mapping, inventory and spatio-temporal change analysis of wetlands of Thavanur Gramapanchayath. The study created time series of wetland maps of the area and also evaluated the water table and surface water dynamics of the wetlands. The various methodologies and analysis carried out to fulfil the proposed research objectives are explained under the following subtitles.

3.1 DETAILS OF STUDY AREA AND ITS LOCATION

The study area selected was Thavanur Gramapanchayath as the area consists of different types wetlands which have not been documented yet properly. The mapping of wetlands and its change analysis is very much important for conservation and management of wetlands. Wetlands affect the lifestyle, agriculture and biodiversity of the area. The proper mapping and identification of the changes that have taken place in these areas over the last ten years provide useful information about how wetland affects the agriculture and other related activities in the area.

Thavanur Grama Panchayat is located in the Ponnani block of Ponnani taluk in Malappuram district of Kerala state, India. The area is located at 10°51’5” N latitude and 75°51’5” E longitude. This Grama Panchayath covers an area of 2530 ha. The Panchayat is bounded by Thriprangode and Kuttipuram Panchayats on the north, Kuttipuram and Aanakkara (Palakkad district) Panchayats on the east, Vattamkulam and Kalady Panchayats on the south and Thriprangode and Kalady Panchayat on the west. The proper Thavanur is a village located on the banks of the river Bharathapuzha, the largest river of Kerala. Bharathapuzha River flows from the north-eastern boundary to the western boundary of the Panchayath. This is one of the largest Panchayath in Kerala. The proximity of the Arabian Sea and the Bharathapuzha and the scattered hills are the major factors influencing the climate of the Panchayath. The location of study area is shown in the Fig. 3.1.

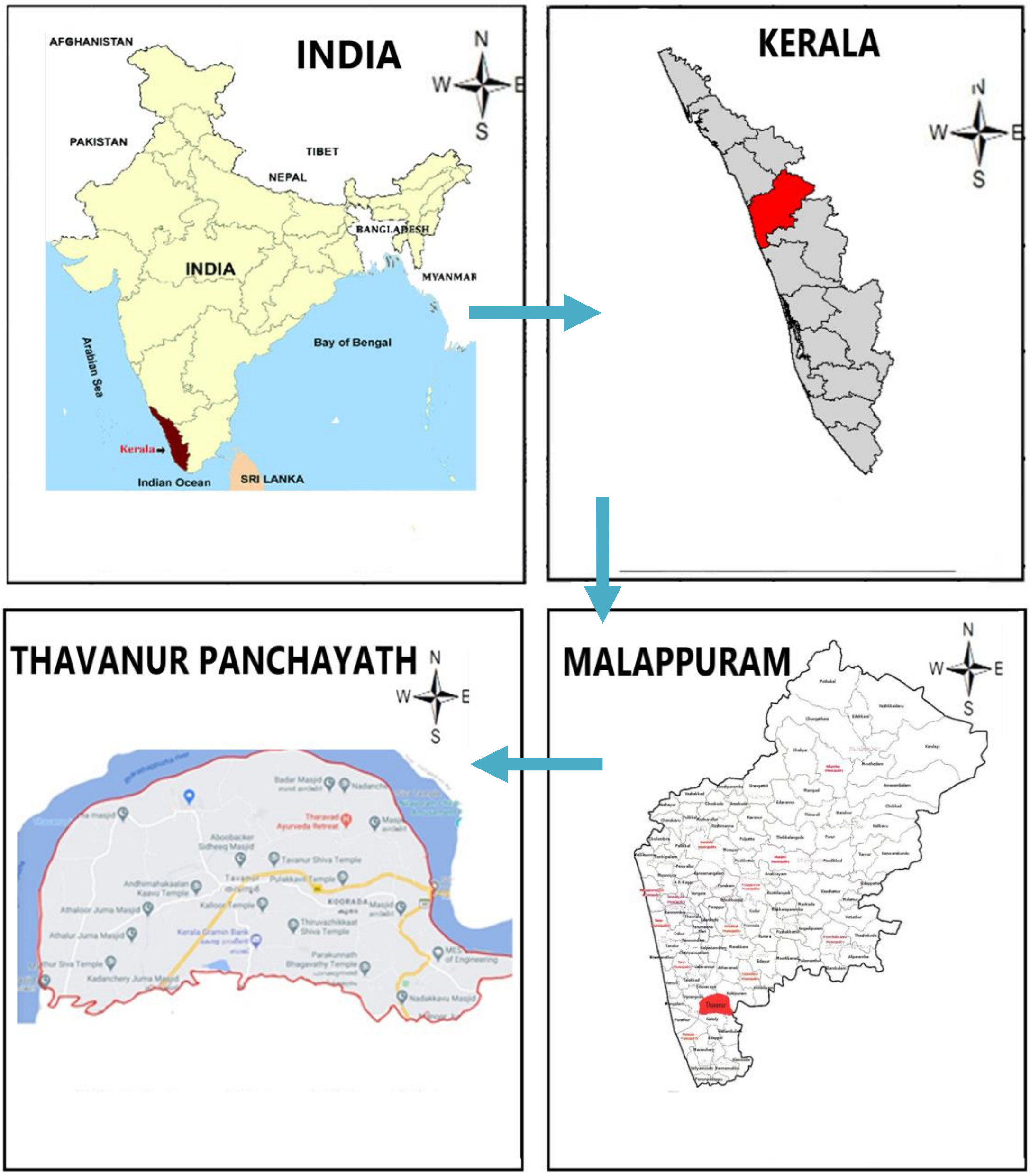


Fig. 3.1 Location map of the study area

3.2 CLIMATE

Thavanur has a tropical humid climate with an oppressive summer and plenty of seasonal rainfall. The average annual normal rainfall is 2952mm. The minimum and maximum temperature prevails between 20°C and 39°C while average annual relative humidity is about 85 %. Maximum temperature ranges from 28.9^0C to 36^0C and minimum temperature ranges from 17^0C to 23^0C. The area receives rainfall during South-West and North-East monsoon. The Major part of rainfall is from South-West monsoon followed by North-East monsoon.

3.3 SOIL TYPE AND VEGETATION

The main soil type of Thavanur Panchayath is lateritic. The main rock type of the Panchayath is mud flat (coastal plain) consisting of 764.25 ha. The coastal plain and lower plateaus (lateritic) are 719.6 ha and 560.6 ha respectively. The mid-land and low-land region of Thavanur is around 1623.7 ha and 878.04 ha respectively. The major crops in Thavanur Panchayath are paddy, coconut and areca-nut. Vegetables, ginger, turmeric, banana and nutmeg are also cultivated. The commonly seen wetland plants in the area are water lilies, lots, sedges, reed etc.

3.4 DATA, SOFTWARE AND TOOLS USED

3.4.1 Remote sensing data

The remote sensing data required was downloaded using the facility of Google Earth Image Downloader version 6.381 of the Kerala State Remote Sensing and Environment Centre (KSREC), Thiruvananthapuram from Google Earth Pro. The cloud-free combined images of Cartosat-1 and Quick bird-1 satellite data set for the years 2008, 2013 and 2018 were acquired. The images were chosen for their quality and availability. Images during the same annual month were downloaded to minimize the effects of seasonal variations and different sun positions. The land use land cover (LULC) map and wetland maps for the years 2008 and 2018 and surface water body maps for the years 2008, 2013 and 2018 were prepared for the study. Table 3.1 presents the details features of the data sets used in this study.

Table 3.1 Details of the satellite data used

Satellites	Spatial resolution (m)	Number of bands	Date of acquisition	Source
Cartosat-1 and Quick bird-1	2.4	3	11-01-2008	Google earth Pro
Cartosat-1 and Quick bird-1	2.4	3	28-12-2013	Google earth Pro
Cartosat-1 and Quick bird-1	2.4	3	30-01-2018	Google earth Pro

3.4.2 Software and Tools used

The following software namely ArcGIS 10.8, Google Earth Image Downloader version 6.381available from KSREC and ordinary MS-Office suit were used for the data creation, data analysis and output generation of the study. The utility of the software used are as follows:

1. ArcGIS 10.8 was used for image processing, mapping, geographical analysis, spatial analysis, overlay analysis, and data editing of the spatial data and creation of various spatio temporal LULC map and wetland maps.
2. Google Earth Pro allows visualization, assessment, overlay, and creation of geospatial data. It provides users with an updated satellite view of the earth. This enables users to collect images of the terrain below and gather and analyse geographic data for planning and decision making.
3. Google earth image downloader version 6.381 is the software for satellite data downloading which was available at KSREC, Thiruvananthapuram.
4. MS Excel was used for preparation of various type of data.
5. Etrex 30 GPS devise was used to locate the GPS points.
6. 10 m tape was used to measure the water table depth from the wells in the study area.

3.4.3 Working window of software

The main window of ArcGIS 10.8 version is shown in Fig. 3.2.

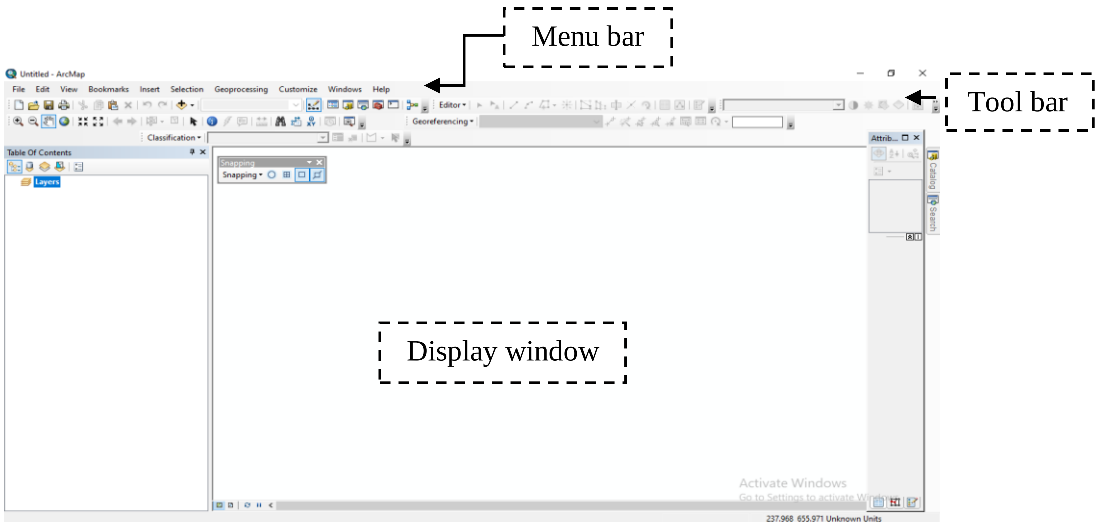


Fig. 3.2 Main window of ArcGIS 10.8

3.5 SPATIAL DATA PROCESSING FOR LAND USE LAND COVER (LULC) MAPPING AND IT'S CLASSIFICATION

ArcGIS 10.8 software was used for LULC mapping, its classification and change detection. The following two methods were adopted for spatial data processing.

1. Digital Image Processing
2. Visual interpretation method

Supervised classification was used for Digital Image Processing. The NRSC LULC classification system was adopted for both the supervised classification and visual interpretation technique. The same NRSC wetland classification system was adopted for wetland inventorying. The details of NRSC – ISRO LULC classification system and NRSC wetland classification system are shown in Table 2 and Table 3 respectively.

Table 3.2 Land use Land Cover classification system of NRSC-ISRO

S. No	LEVEL-I	LEVEL-II
1	Built up Land	1.1Towns/ Cities 1.2 Villages
2	Agricultural Land	2.1 Fallow 2.2 Plantation
3	Forest	3.1 Semi-evergreen / Evergreen 3.2 Deciduous (Moist & Dry) 3.3 Scrub Forest 3.4 Forest Blank 3.6 Mangrove
4	Wasteland	4.1 Salt Affected Land 4.2 Waterlogged Land 4.3 Swampy Land / Marshy 4.4 Ravenous Land / Gullied 4.5 Land with scrub 4.6 Land without scrub

		4.7 Sandy area (Coastal and Desertic) 4.8 Industrial wasteland / Mining 4.9 Barren Rocky / sheet rock area / Stony waste
5	Water Bodies	5.1 Stream / River 5.2 Canals 5.3 Reservoirs / lake / Tank
6	Others	6.1 Shifting Cultivation 6.1 Grazing land / Grass land 6.3 salt pans 6.4 Snow covered / Glacial Area

According to the NRSC-ISRO land use classification, wetlands like waterlogged land and Marshy / Swampy lands are grouped under wasteland class, whereas rivers / streams, canals and lakes / reservoirs / tanks are grouped under water bodies.

Table 3.3 Wetland classification system of National Remote Sensing Centre (NRSC)

Sl.No	Level 1	Level 2
1	Inland wetlands	Oxbow lakes, playas, cut-off meanders, marsh
2	Coastal wetlands	Estuaries, creek, lagoons, bay, backwater, sand / beach, rocky coast, tidal / mud flat, salt/marsh, mangrove, saltpans and hydrophytic vegetation
3	River / Stream / Canal	
4	Water bodies	Pond, lake, tank and reservoirs

Based on Level I and Level II of the NRSC- LULC Classification system, the color code system most commonly used to distinguish different LULC classes adopted in this study is shown in Fig. 3.3.

Classes	Classes
Built Up	**Grass / Grazing**
Urban	Grass/Grazing
Rural	**Barren / Waste Lands**
Mining	Salt Affected Land
Agricultural Land	Gullied/Ravinous Land
Crop Land	Scrub Land
Agricultural Plantation	Sandy Area
Fallow Land	Barren Rocky
Current Shifting Cultivation	Rann
Forest	**Wetlands / Water bodies**
Evergreen/ Semi Evergreen	Water bodies
Deciduous	Rivers/Streams/Canals
Forest Plantation	Inland Wetland
Scrub Forest	Coastal Wetland
Swamp/ Mangroves	**Snow and Glaciers**
	Snow/Glaciers

Fig. 3.3 LULC and color assigned to each class

3.5.1 Digital Image Processing

Digital image processing generally includes data formatting, editing, digital enhancement and automated classification of targets and features. Computer algorithms are used to perform image processing on digital images. The measured reflection values are determined by the earth surface's local features. As a result, the measured reflection values and land cover have a relationship. This relationship must be discovered in order to extract information from the image. Image categorization or digital image processing is the term for the process of determining the relationship.

3.5.1.1 Supervised Classification

The principle behind supervised classification is that the user can choose sample pixels from an image that correspond to particular classes, and then direct the image processing programme to utilise these training sites as references for classifying all other pixels in the image. Based on the user's knowledge, training locations are selected. The user also chooses the limits for how similar pixels must be in order to be grouped together. These boundaries are frequently established with a plus or minus increment dependent on the spectral properties of the training area. The user also chooses the number of classifications that the image is divided into. A cluster is formed in the feature space by a sample of a particular class made up of a number of training pixels. In supervised classification, the user-prepared training sample is used to classify the image. Before starting the selection of training samples, it was necessary to be familiar with the data, the desired classes, and the underlying algorithms.

Main steps of supervised classification are as follows,

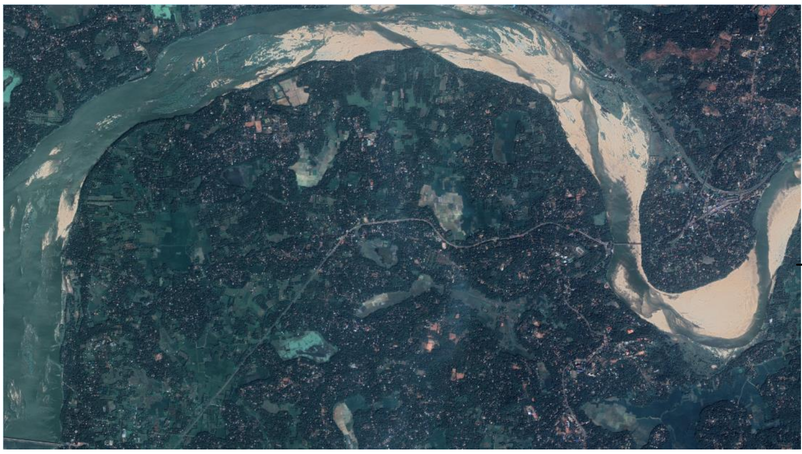
- **Extraction of Satellite Image**
- **Creation Training Sample Manager**
- **Interactive Supervised Classification**
- **Conversion of Raster to Polygon**
- **Dissolution of Each Class**
- **Calculation of Area**

3.5.1.2 Extraction of Satellite Image

For extraction of satellite image, satellite imagery and village boundary shape file in tiff format were added from the system folder using "add data" tool from the ArcGIS tool bar. Then satellite image was cut according to the Thavanur Panchayath boundary shape file. The method of extraction adopted is as follows.

Arc Tool Box→ Spatial Analyst Tool → Extraction → Extract by mask

Once this is done, a new dialogue window is opened. Then the satellite imagery address was entered in the input raster column and the Thavanur Panchayat boundary shape file address was entered in the input raster or feature mask data column. Then ok button was clicked. Thus, all the areas outside the village boundary were removed and only the satellite image pertaining to Thavanur Panchayat remained. Satellite image before and after extraction is shown in the Fig. 3.4.



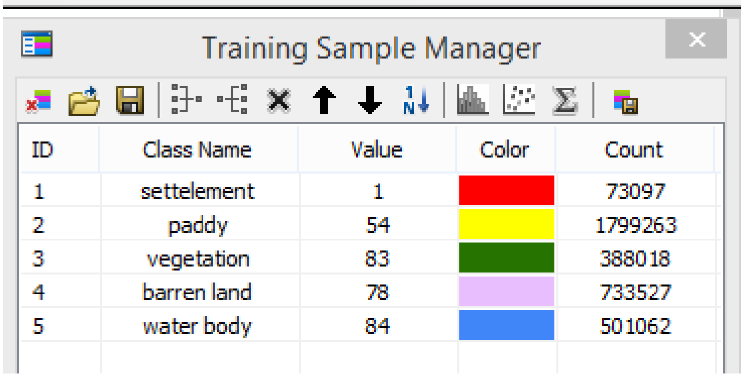
a. Before extraction

b. After extraction

Fig. 3.4 Satellite images before and after extraction

3.5.1.3 Creation of Training Sample Manager

For supervised classification, the first step was activation of the 'Image Classification Tool'. Then the satellite imagery was selected in the layer drop down menu and the training sample manager was opened. The draw polygon icon was clicked to begin the selection of training area. Then started to draw polygon on areas with known land-use, for example first water-body was selected as the first class and polygons were drawn on the image where the water body was able to identify in the satellite image. Thereby polygons were created over the water body and polygons were drawn on the water bodies. Then clicked on the merge tool in the Training Sample Manager window which merged all of the water polygons into one class. Then renaming was done by clicking under the class name and typing the class name as water body and also selected the blue colour for water body. The training areas for the other classes were also created in the same way. The training sample manager window is shown in Fig. 3.5.



ID	Class Name	Value	Color	Count
1	settelement	1		73097
2	paddy	54		1799263
3	vegetation	83		388018
4	barren land	78		733527
5	water body	84		501062

Fig. 3.5 Training sample manager window

3.5.1.4 Interactive Supervised Classification

This is the most important step in supervised classification. This step is followed by the creation of training classes. The "interactive supervised classification" tool was selected from classification option which is shown in Fig. 3.6. The Interactive Supervised Classification tool accelerates the maximum likelihood classification process. This is the most widely used algorithm for supervised classification. All bands from the selected image layer were used by this tool for the classification. Thus, a supervised classified image was obtained.

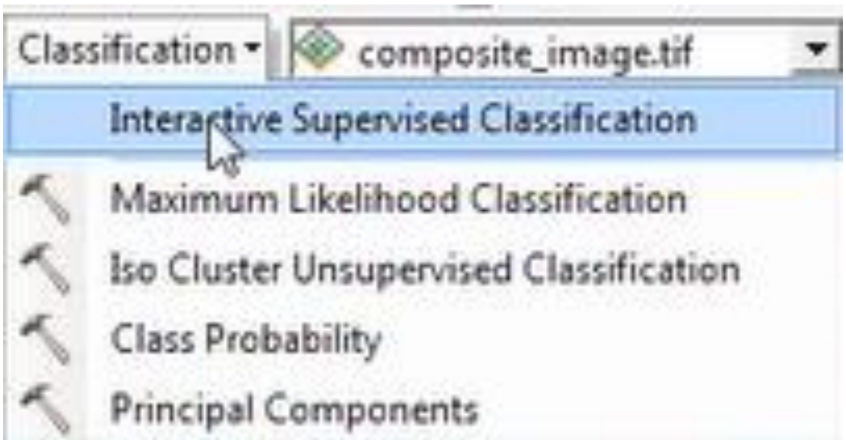


Fig. 3.6 Interactive supervised classification tool

3.5.1.5 Conversion of Raster to Polygon

Supervised images are always in raster form. In order to dissolve each class in the image, the supervised image should be in polygon form. “Raster to Polygon” tool from the tool box was then selected. After that the supervised image as input raster selected and “class name” also selected to simplify the polygons and then clicked ‘ok’ button. Thus, the polygon of supervised image was generated. Now all the polygons were fitted into corresponding land use classes that could be seen in the attribute table as shown in Fig. 3.7.

Table

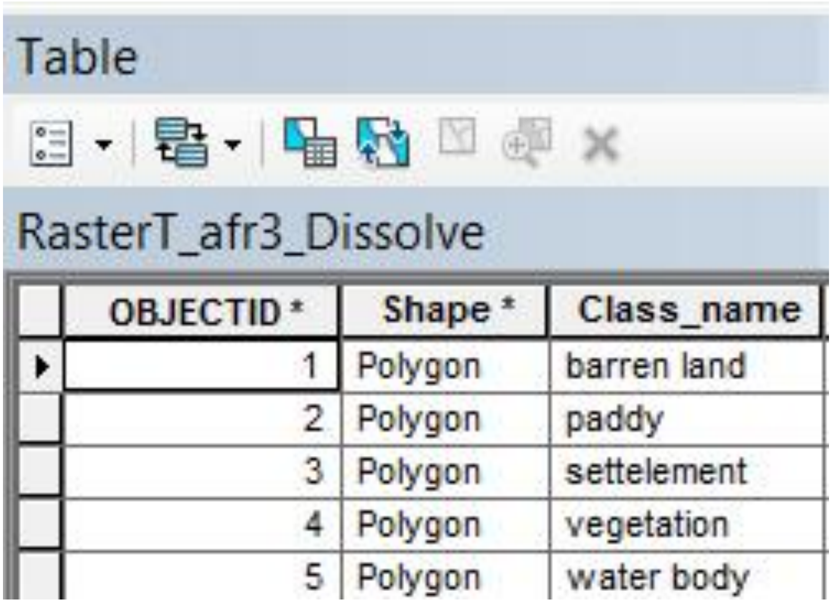
RasterT_afr4

OBJECTID *	Shape *	Id	gridcode	Shape_Length	Shape_Area	Class_name
1	Polygon	1	1	0.00002	0	settlement
2	Polygon	2	1	0.00002	0	settlement
3	Polygon	3	1	0.00002	0	settlement
4	Polygon	4	2	0.000032	0	paddy
5	Polygon	5	4	0.000021	0	wasteland
6	Polygon	6	1	0.000021	0	settlement
7	Polygon	7	1	0.000047	0	settlement
8	Polygon	8	4	0.00002	0	wasteland
9	Polygon	9	4	0.000021	0	wasteland
10	Polygon	10	2	0.000043	0	paddy
11	Polygon	11	4	0.00002	0	wasteland
12	Polygon	12	4	0.000021	0	wasteland
13	Polygon	13	2	0.000071	0	paddy
14	Polygon	14	2	0.00002	0	paddy
15	Polygon	15	1	0.00002	0	settlement
16	Polygon	16	4	0.000054	0	wasteland
17	Polygon	17	1	0.000039	0	settlement
18	Polygon	18	4	0.000021	0	wasteland
19	Polygon	19	1	0.000044	0	settlement
20	Polygon	20	4	0.00002	0	wasteland
21	Polygon	21	4	0.00002	0	wasteland
22	Polygon	22	4	0.00002	0	wasteland
23	Polygon	23	4	0.000059	0	wasteland
24	Polygon	24	1	0.000021	0	settlement
25	Polygon	25	1	0.000076	0	settlement
26	Polygon	26	1	0.00002	0	settlement
27	Polygon	27	2	0.000021	0	paddy
28	Polygon	28	4	0.000108	0	wasteland
29	Polygon	29	2	0.00002	0	paddy
30	Polygon	30	4	0.000021	0	wasteland
31	Polygon	31	4	0.00002	0	wasteland
32	Polygon	32	2	0.00002	0	paddy
33	Polygon	33	4	0.00002	0	wasteland
34	Polygon	34	4	0.000021	0	wasteland
35	Polygon	35	1	0.000054	0	settlement
36	Polygon	36	1	0.000435	0	settlement
37	Polygon	37	2	0.00002	0	paddy
38	Polygon	38	2	0.00003	0	paddy
39	Polygon	39	1	0.00002	0	settlement
40	Polygon	40	2	0.000043	0	paddy
41	Polygon	41	2	0.000046	0	paddy
42	Polygon	42	1	0.000043	0	settlement
43	Polygon	43	2	0.00002	0	paddy
44	Polygon	44	2	0.00002	0	paddy
45	Polygon	45	2	0.00002	0	paddy

Fig. 3.7 Polygon attribute table

3.5.1.6 Dissolution of Each Class

This step is followed by the raster to polygon conversion step. This step groups each polygon into a specific class. “Dissolve polygon” tool was selected from “Geoprocessing” option on the menu bar. After that newly created polygon image address was selected as input feature and class name was selected as dissolve field in the dialogue box and then clicked ok button. Thus, the dissolved file was generated. Now the polygons were grouped according to the classes, as seen in the attribute table, which is shown in Fig. 3.8.



Table

RasterT_afr3_Dissolve

OBJECTID *	Shape *	Class_name
1	Polygon	barren land
2	Polygon	paddy
3	Polygon	settelement
4	Polygon	vegetation
5	Polygon	water body

Fig. 3.8 Dissolved attribute table

3.5.1.7 Calculation of Area of Each Dissolved Class

This is the final step in the supervised classification. Changes in land use between 2008 and 2018 were traced through this phase. Here the difference in the area over a decade was measured in hectares. By selecting the option ‘calculate geometry’ the area was calculated for the corresponding classes in hectare. The path for calculating the area is as follows.

Open attribute table → file → Add field →Calculate geometry → Area calculation in hectare.

3.5.2 Visual interpretation

“The satellite image contains only row image data. These data, when processed by a human interpreter’s brain, it become usable information”. Visual image interpretation is the process of interpreting what we see on images and communicating that information to others so they can assess its significance. Here, the size, shape, and position of objects as well as the contrast and colour saturation are analysed. It is the act of examining photographic images for the purpose of identifying objects and judging their significance. In visual interpretation, analysts draw polygons around visible differences in satellite images on the computer screen (Puig *et al.*, 2002). This process, on the other hand, is not limited to deciding what objects appear in photographs; it also typically includes determining their relative placements and extents. This necessitates the use of at least some basic photogrammetric measurement and mapping techniques.

The interpreter or image analyst studies these graphical data products to extract such aspects from aerial photographs and satellite images, which include a detailed record of the earth surface features. The visual interpretation of remote sensing data is primarily dependent on False Colour Composites (FCCs). During the exposure of a colour negative, FCCs are created by merging data from three different spectral bands into one image by assigning blue, green, and red colours to the data in the three spectral bands, respectively. Depending on the application, you can choose from a variety of band combinations.

3.5.2.1 Preparation of LULC map of 2008 and 2018 by visual interpretation

a. ***Draw polygons as the shape of objects***

Polygon of each land use / land cover was digitised from the shape of each object from the satellite imagery using the cut polygon tool in ArcGIS and then added the class of the object as an attribute. This process was carried out in the satellite imagery data of year 2008 and 2018. The mapping scale adopted was 1:10,000.

b. ***Dissolve Each Class***

This step is to group each polygon into specific classes. “Dissolve polygon” tool was selected from “Geoprocessing” option on the menu bar and selected newly created polygon attribute as input feature, then class name as dissolve field in the dialogue box. Then clicked ‘OK’ and the dissolved file were generated. The polygons were grouped according to the classes in attribute table as shown in Fig. 3.9.

Through this step, changes in land use between 2008 and 2018 were traced. The difference in the area over a decade was measured in hectares. By selecting the option ‘calculate geometry’ the area was calculated for the corresponding classes in hectare. The path for calculating the area is as follows.

Open attribute table → file → Add field → Calculate geometry → Area calculated in hector.

Table

c2008_FINAL_Dissolve2

FID *	Shape *	LULC
1	Polygon	
2	Polygon	Aquaculture
3	Polygon	Barren Land
4	Polygon	Coconut
5	Polygon	Fallow land
6	Polygon	Marshy Land
7	Polygon	Mixed Settlement
8	Polygon	Mixed Vegetation
9	Polygon	Paddy
10	Polygon	Paddy converted to coconut
11	Polygon	Pond
12	Polygon	River
13	Polygon	Road
14	Polygon	Well

Fig. 3.9 Dissolved attribute table

c. *Ground truth verification*

The preliminary photo interpreted maps, with village boundaries and roads were used for the ground truth realities in order to

1. To identify the water bodies and confirm the various wetland classes
2. To check the interpretation accuracy (Sahai, 1979) and
3. To prepare a final wetland map

Ground truth data collection was done by frequent visit to the study area and interaction with people who are living the area helped to know about the history, local name of wetland and its characteristics. Etrex 30 GPS device was used to locate the GPS point which is shown in Fig. 3.10 and the view of taking the GPS points is shown in Plate 3.1.

Fig. 3.10 GPS Device

Plate 3.1 A view of taking location data using GPS

3.6. MAPPING OF WETLAND

3.6.1 Preparation of wetland map of 2008 and 2018

The land use land cover maps prepared were used for identification and delineation of wetlands. Besides the satellite data, ground truth data and collateral data were also used for delineation of wetland types / category. Thus, wetland maps of 2008 and 2018 were prepared by visual interpretation technique. The following ground truth data were collected viz name of the wetland, wetland type, wetland characteristics, size (ha), shape, use, ownership etc.

3.7 ACCURACY ASSESSMENT

A classified image or change detection map needs to be compared against reference data which is assumed to be true, to assess its performance and quantify its accuracy (Foody, 2002). Accuracy assessment is an important step in wetland mapping. It is used for comparing the land cover classification results to actual geospatial data that are assumed to be true. Accuracy assessment was performed for both visual interpretation technique and supervised classification to identify which one is better. To ensure that all of the LULC classes were sufficiently represented based on their proportional area; a stratified random sampling technique was employed to collect a total of 100 reference data. To extract reference data, Google Earth Pro photos were used.

Confusion matrix (error matrix) was prepared for accuracy assessment. The accuracy was assessed in terms of Kappa coefficient, overall accuracy, producer's and user's accuracy derived from the confusion matrix (Congalton and Green 2009; Liu *et al*., 2007). The Kappa coefficient reports the relationship between the classified map and reference data (Lillesand and Keifer, 2000). The accuracy of a map user, not the map developer, is measured by the User's Accuracy. The accuracy of the user fundamentally determines how often the class on the map will be presented on the ground. This is also known as dependability. Producer's Accuracy refers to the map's accuracy from the mapmaker's perspective (or the producer). This is the probability that a given land cover of a region on the ground is classified as such, or how often genuine characteristics on the ground are accurately depicted on the classified map. Overall Accuracy essentially tells us what percentage of the reference sites were correctly mapped out of all of them. The overall accuracy is commonly given in percentages, with 100 per cent accuracy indicating that all reference sites were properly categorised.

The classification results are compared to values generated by chance using the kappa coefficient. It takes values between 0 and 1. The classified image and the ground truth image are 100 percent identical if the kappa coefficient is 1. Classification is not complete until its accuracy is assessed using the known Kappa statistics agreement between the predictive model and a set of field surveyed sample points (Forkuor and Cofie, 2011). In this study the error matrix computed the overall accuracy of all land use classes individually and collectively. The Kappa coefficient was computed using equation proposed by Jensen and Cowen (1999) and is shown as

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \text{ x } x_{+1})}{N^2 - \sum_{i=1}^{r} (x_{i+} \text{ x } x_{+1})}$$

Where: K = Kappa coefficient of agreement

N = Total number of observations (sample points)

Xi = Observation in the line *i* and column *I*

Xi+ = Total marginal of the line *I*

X+1 = Total marginal of the column *i*

The Kappa coefficient agreement values are shown in Table 3.4.

Table 3.4 Kappa coefficient agreement

Sl. No.	Kappa Coefficient	Rating
1.	Less than 0.4	Poor
2.	0.4 < KC < 0.5	Fair
3.	0.55 < KC < 0.7	Good
4.	0.7 < KC < 0.85	Very Good
5.	KC > 0.85	Excellent

The various equations for the accuracy assessment were as follows

$$\text{User's accuracy} = \frac{\text{Number of currently classified pixels in each category}}{\text{Total number of classified pixels in that category (Row total)}} \times 100$$

$$\text{Producer's accuracy} = \frac{\text{Number of currently classified pixels in each category}}{\text{Total number of Reference Pixels in that Category (Column total)}} \times 100$$

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified pixels (TCS) (Diagonal)}}{\text{Total number of reference pixel (TS)}} \times 100$$

$$\text{Kappa coefficient (KC)} = \frac{(\text{TS x TCS})-\sum(\text{column Total x Row Total})}{\text{T }S^2-\sum(\text{column Total x Row Total})} \times 100$$

3.8 CHANGE DETECTION ANALYSIS

The changes brought about in the land use of wetlands during the years 2008 and 2018 were assessed. Change detection quantifies the changes that are associated with LULC changes in the landscape using geo-referenced multi-temporal remote sensing images acquired on the same geographical area between the considered acquisition dates (Ramachandra and Kumar, 2004). The importance of change detection is to determine which land-use class is changing to the other. The various change detection methods include image overlay, post classification comparisons (PCC) of land cover statistics, change vector analysis, principal component analysis, image rationing and the differencing of normalized difference vegetation index, NDVI (Han *et al*., 2009).

Among the different methods, this study employed post-classification comparison (PCC) change detection method to detect the LULC changes of two independently classified maps that occurred between two different dates of the study period (Jensen, 2005). Post-classification comparison is the most commonly used technique to compare maps of different sources despite having a few limitations. The approach provides comprehensive and detailed "from-to" LULC change information as it does not require data normalization between the two dates (Coppin *et al.*, 2004; Jensen, 2005, Teferi *et al.*, 2013; Aldwaik and Pontius, 2013). Change detection study was performed in the ArcGIS software.

3.8.1 Land use and land cover change transition matrix

The use of the PCC technique resulted in a cross-tabulation matrix (LULC change transition matrix). The LULC change transition matrix highlight the land use classes where the change has occurred. It shows how a specific class has transformed into another class over some undefined time frame. The change detection was performed in ArcGIS using MS Exel worksheet. The Classified maps of 2008 and 2018 were imported to the ArcGIS environment and were merged using Geoprocessing tool in ArcGIS and the area was calculated using raster calculator. The attribute table of merged landuse polygon was exported to MS Excel sheet and using the pivot table option available in MS Excel, the change detection transition matrix table was prepared. The general LULC change transition matrix table is shown in Table 3.5.

Table 3.5 General LULC change transition matrix

Time T1								
		LULC 1	LULC 2	LULC 3	LULC 4	LULC 5	Total T1	Loss
Time T2	LULC 1	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{1+}	A_{1+}-A_{11}
	LULC 2	A_{21}	A_{22}	A_{23}	A_{24}	A_{25}	A_{2+}	A_{2+}-A_{22}
	LULC 3	A_{31}	A_{32}	A_{33}	A_{34}	A_{35}	A_{3+}	A_{3+}-A_{33}
	LULC 4	A_{41}	A_{42}	A_{43}	A_{44}	A_{45}	A_{4+}	A_{4+}-A_{44}
	LULC 5	A_{51}	A_{52}	A_{53}	A_{54}	A_{55}	A_{5+}	A_{5+}-A_{55}
	Total T2	A_{+1}	A_{+2}	A_{+3}	A_{+4}	A_{+5}	1	
	Gain	A_{+1-A11}	A_{+2-A22}	A_{+3}-A_{33}	A_{+4}-A_{44}	A_{+5}-A_{55}		

(Maggie *et al.*, 2019)

Where:

Aij = The land area that experiences transition from LULC, from category i to LULC category j

Aii = The diagonal elements indicating the land area that shows persistence of LULC category i while the entries off the diagonal indicate a transition from LULC, from category i to a different category j

Ai+ (total column) = The land area of LULC category i in T1 which is the sum of all j of Aij

A+j (total rows) = Land area of LULC category j in time 2 which is the sum of over all of i of Aij

Losses (Ai+ – Aii) = Proportion of landscape that experiences gross loss of LULC category I, between T1 and T2

Gains (A+i – Aii) = Proportion of landscape that experiences gross gain of LULC category j, between T1 and T2

3.8.2 Annual rate of change

According to Teferi *et al.* (2013), the net change is the difference between gain and loss and it is always regarded as an absolute value. The annual rate of change of LULC at two different years (2008 and 2018) was also calculated according to procedures introduced by Puyravad (2003), Teferi *et al.* (2013) and Batar *et al.* (2017). The following equation suggested by them provides a benchmark for comparing LULC rate of change.

$$r = \left(\frac{1}{t_2 - t_1}\right) \times ln\left(\frac{A_2}{A_1}\right)$$

where: r is the annual rate of change for each class per year

$A2$ and $A1$ are the class areas (ha) at time 2 and time 1 respectively and t is time (in years) interval between the two periods.

3.8.3 Gains and losses of LULC (Net change)

The difference between the gain and loss is the net change (Teferi *et al*., 2013). The gains and losses in land use and land cover between 2008 and 2018 were calculated using the cross tabulation matrix. The overall work flow of spatial data image processing, mapping and accuracy assessment is shown in Fig. 3.11.

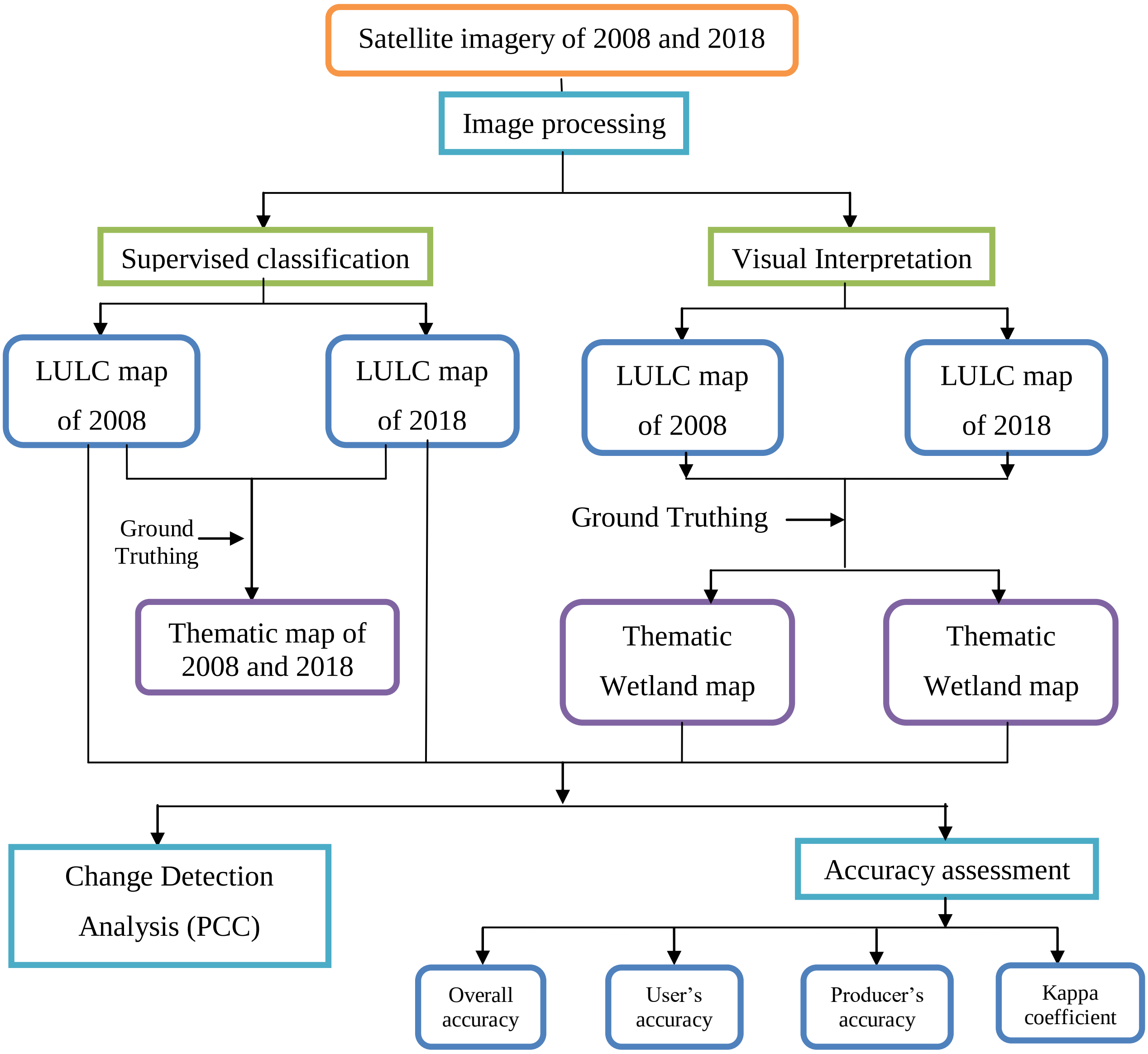


Fig. 3.11 Overall workflow of LULC mapping and accuracy assessment

3.9 EVALUATION OF WATER TABLE AND SURFACE WATER DYNAMICS OF WETLANDS FOR SUSTAINABLE CULTIVATION IN THE AREA.

Sustainable management of wetlands requires a comprehensive knowledge of the factors influencing the wetland hydrodynamics. The use of geographic information systems and continuous surveys are required for accurately assessing and predicting water dynamics in wetlands. Rainfall, evaporation and field elevation are the major factors affecting water table changes and soil moisture. Hence water table and surface water dynamics in the wetland were assessed during the study period from November 2020- October 2021.

3.9.1 Water table evaluation

Totally eleven open wells which are randomly distributed in the study area were identified and selected for recording the changes in water table level. Fig. 3.12 shows the location of the 11 open wells on the satellite image and the details of location are shown in Table 3.6.

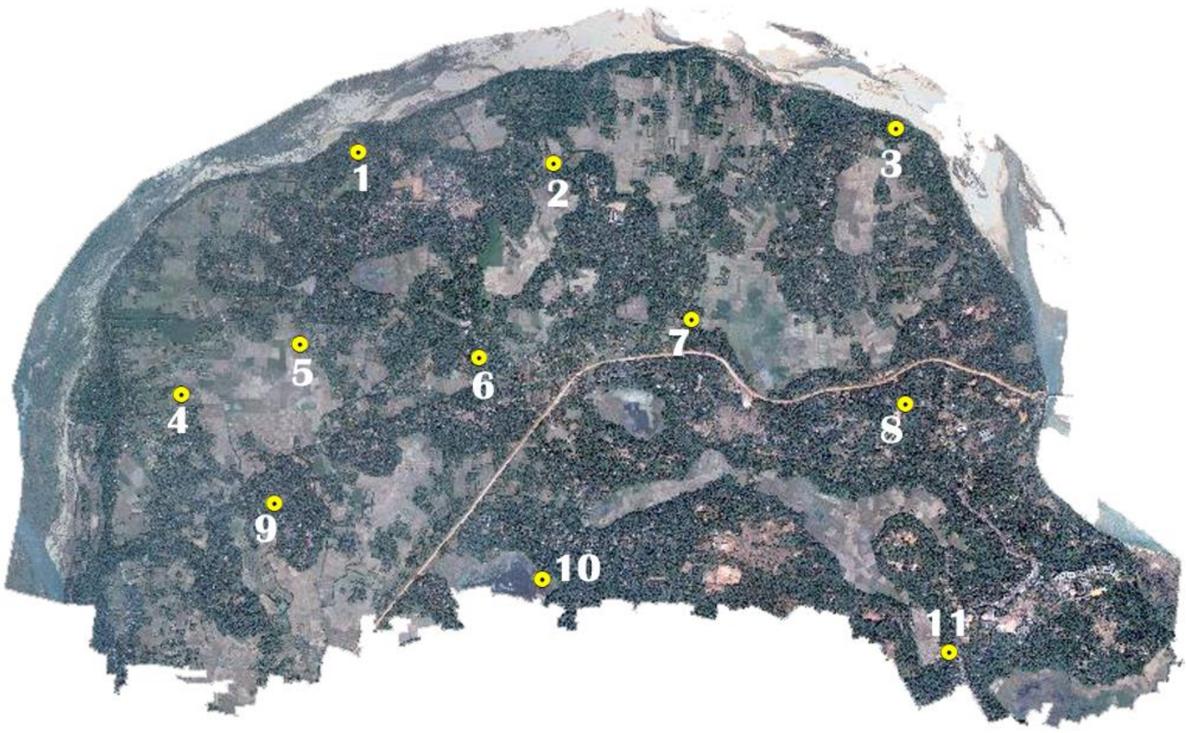


Fig. 3.12 Location of different open wells on satellite image

Table 3.6 Location details of wells selected in the study area

Well No.	Place	GPS Location	Ground Elevation (m)
1	Cheruthirunnavaya	10°51'19.5"N 75°58'56.3"E	0.13
2	Kadakassery north	10°51'17.3"N 75°59'34.5"E	4.00
3	Vellancheri kadavu, Vellancheri	10°51'24.0"N 76°00'41.9"E	0.12
4	Mattam	10°50'31.9"N 75°58'21.4"E	3.00
5	Kannankulam, Thavanur South	10°50'41.9"N 75°58'44.7"E	3.00
6	Kadakasseri	10°50'57.8"N 75°59'38.4"E	6.00
7	Chandanakulam	10°50'03.0"N 76°00'39.1"E	4.00
8	Athalur	10°50'10.7"N 75°58'39.8"E	4.00
9	Anthyalamkudam	10°50'46.6"N 76°00'01.8"E	5.00
10	Maravancheri kayal, Maravancheri	10°49'41.5"N 76°00'52.3"E	3.00
11	Thrikkannapuram-kaanjirakkutty, Kacheriparambu	10°49'55.8"N 75°59'32.3"E	9.00

The water table levels were recorded using a 10-meter tape and the data is shown in Appendix I. The data were taken in fortnightly interval. The data were analysed based on pre monsoon, post monsoon and other seasons as shown in Table 3.7 the view of taking the water table level is shown in Plate 3.2.

Table 3.7 Seasons considered for taking water table data

Seasons	Months
Post monsoon	October, November, December
Winter season	January, February
Pre monsoon	March, April, May
Rainy season	July, August, September


Plate 3.2 View of taking the water table level

Since the wells are selected very near to the wetland area, it is assumed that the changes in the water table of each well are equal to the changes in the water table levels in the wetland area. This gives an indication of changes in water availability in the wetland and its effect on agricultural cultivation in the area.

3.9.1.1 Preparation of water table Contour map

ArcGIS software was used to prepare water table contour map. The various steps involved were

1. Creation of shape files of Water table in Excel file.
2. Creation of triangulated irregular network (TIN)
3. Preparation of water table Contour lines

a. ***Creation of shape file of Water table Excel file.***

Water table data were prepared in Microsoft Excel. It was taken added as point data to ArcGIS to create a water table contour map of the area. This point data exported into shape file.

b. ***Creation of triangulated irregular network (TIN)***

TIN lines form triangles that make up the surface triangle. TIN surfaces are most useful for mapping highly variable surfaces using randomly distributed sample data representing the impact of streams, roads, and lakes. Hence the randomly distributed water table data networks were formed by TIN.

The “TIN (3D Analysis)” tool was selected from the ArcGIS tool box and the shape file was added as input. By clicking ok button, the water table TIN surface was generated.

c. ***Preparation of Contour lines***

This step created the contour lines of water table. The Surface contour (3D analysis) tool was selected from ArcGIS tool box and then TIN file was selected as input. The contour interval was given as 0.5m and the precision was given as one. By clicking ok button, the contour map was generated. The contour lines were then smoothed out using the interpolation algorithm.

3.9.1.2 Preparation of Water table fluctuation map - steps

ArcGIS software was used to prepare water table fluctuation map. The various steps involved were

1. Preparation of shape file for fluctuation value
2. Interpolation

a. ***Preparation of shape file for fluctuation value***

Fluctuation of water table recorded from March to August, 2021 was used. The water table elevation of March month was subtracted from August. Fluctuation data were prepared in Microsoft Excel and converted into points by ArcGIS then the points were made as shape file in ArcGIS.

b. ***Interpolation***

Interpolation method in ArcGIS was adopted for preparation of fluctuation map. Inverse Distance Weighted (IDW) tool of interpolation was used for preparation of fluctuation map.

3.9.2 Evaluation of surface water dynamics

Surface water dynamics are crucial for understanding the effects of global changes and human activities on water supplies. The lifestyle of an area depends on the availability of fresh water in the area. For evaluation of surface water dynamics, satellite imageries of 2008, 2013 and 2018 at five-year interval were selected. The water spread area changes were done by identifying the water spread area on Google earth pro image during the years 2008, 2013, and 2018 by drawing polygons on the water spread area of the Google earth image using ArcGIS 10.8. Thus, the surface water spread area was mapped. The path used for calculating the area is as follows.

Open attribute table → file → Add field → Calculate geometry → Area calculated in hectare.

The overall work flow for evaluation of water table and surface water dynamics of wetlands is shown in Fig. 3.13.

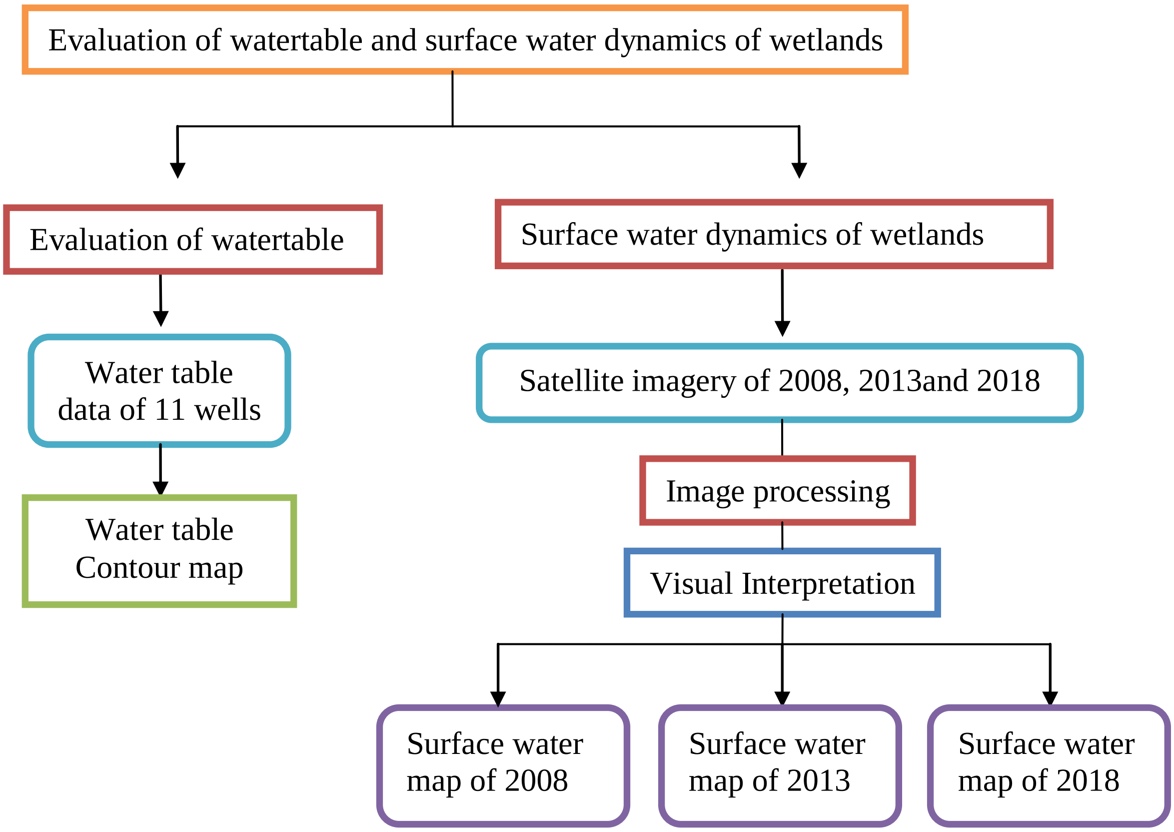


Fig. 3.13 Overall work flow for evaluation of water table and surface water dynamics

CHAPTER IV

RESULTS AND DISCUSSION

The present study was conducted for mapping, inventorying and change detection of wetlands of Thavanur Grama Panchayath and it was carried out using RS and GIS. The evaluation of water table changes and surface water dynamics of the area were also analysed during the study period. The various results obtained from the study are explained and discussed in this chapter under the following subtitles.

4.1 IMAGE PROCESSING AND LAND USE LAND COVER (LULC) CLASSIFICATION

Image processing and Land use land cover (LULC) classification were performed by two different methods. They were,

1. Digital Image Processing (by supervised classification)

2. Visual Interpretation technique.

4.1.1 Supervised classification (SC)

The LULC maps for the years 2008 and 2018 were created using supervised classification method of image processing using ArcGIS 10.8. The land use classes viz. paddy, wasteland / barren land, vegetation, settlement and water body were identified. In the area the LULC map of 2008 and 2018 are shown in Fig. 4.1 and Fig. 4.2 respectively.

It is clear from the supervised maps of 2008 and 2018 that there is a drastic change in the water body during the ten-year period. The area of the river was found very less in 2008 as most of the river portion was seen as wasteland / barren land due to the absence of water and presence of sand dunes. However, in 2018, most of the river area was covered with water. Some portion of the river appeared yellow which indicated as paddy field and some portion as green indicated mixed vegetation in the supervised classification. This showed the presence of mixed vegetation in Thavanur Grama Panchayath. But all other prominent waterbody appeared blue as they are the main water bodies in Thavanur Grama Panchayath. Fig. 4.1 and Fig. 4.2 represent the LULC map of 2008 and 2018 respectevely prepared by supervised classification.

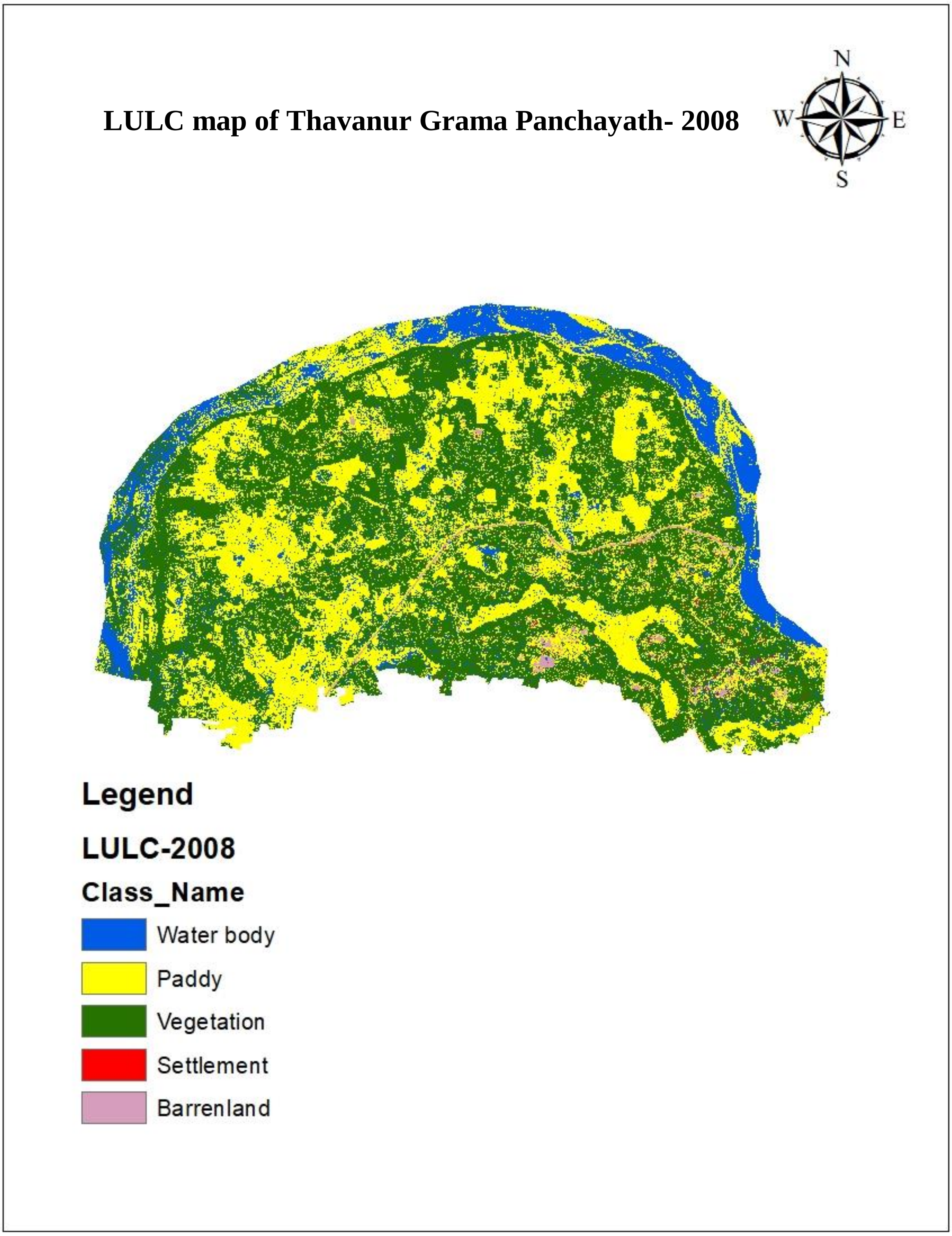


Fig. 4.1 LULC map of Thavanur Grama Panchayath- 2008 Prepared by SC

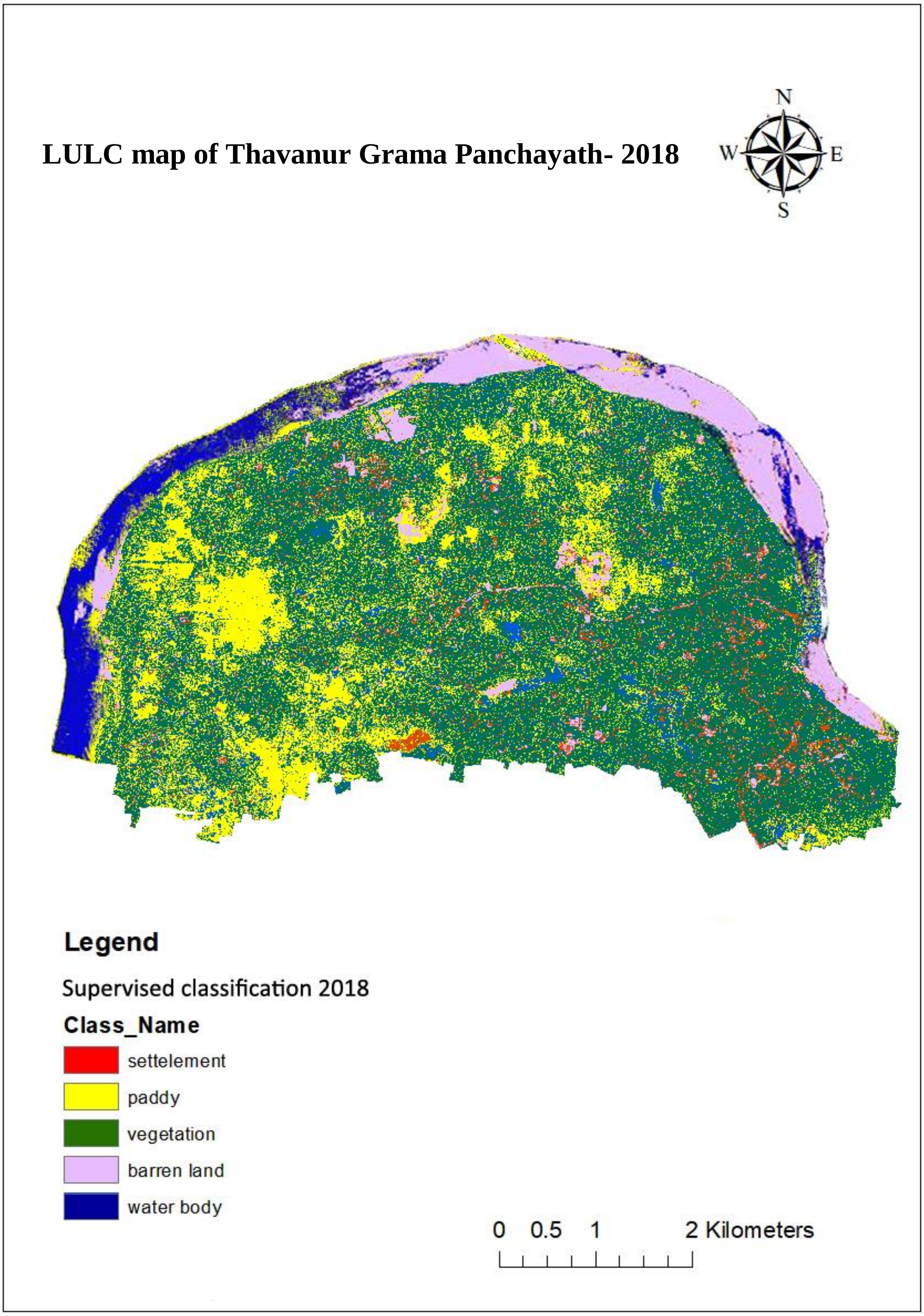


Fig. 4.2 LULC map of Thavanur Grama Panchayath- 2018 prepared by SC

By comparing the area of waterbodies in 2008 and 2018, it was found that the area of waterbody was higher (345.79 ha) in 2008 than that of 2018 (310.56 ha). There was a decrease in paddy field area from 2008 (963.47 ha) to 2018 (796.54 ha) whereas the settlement area increased from 2008 (13.41 ha) to 2018 (22.11 6ha). The mixed vegetation area of Thavanur Grama Panchayath increased from 1175.09 ha to 1352.3 ha during the period from 2008 to 2018. The wasteland/barren land area increased from 32.68 ha 49.23 ha during the same period.

The percentage of area covered by paddy, vegetation, barrenland/wasteland, waterbody and settlement were 38.08 %, 46.44 %, 1.29 %, 13.66 % and 0.53 % respectively in 2008 whereas it was 31.48 %, 53.45 %, 1.94 %, 12.27 % and 0.87 % respectively in 2018. The paddy land decreased by 166.93 ha during the period from 2008 to 2018. The area of waterbody also decreased by 35.23 ha. The area increased in the case of vegetation, settlement and wasteland by 177.2 ha, 8.7 ha and 16.55 ha respectively. The area of LULC in Thavanur Grama Panchayath and its changes during the period from 2008 to 2018 is shown in the Table 4.1 and its distribution is shown in Fig. 4.3.

Table 4.1 LULC of Thavanur Panchayath during 2008 and 2018 and its changes

LULC	Area in 2008 (ha)	%[a]-2008	Area in 2018 (ha)	%[a]-2018	Change (ha)
Waterbody	**345.79**	**13.66**	**310.56**	**12.27**	**-35.23**
Paddy	**963.47**	**38.08**	**796.54**	**31.48**	**-166.93**
Vegetation	**1175.09**	**46.44**	**1352.3**	**53.45**	**177.21**
Settlement	**13.41**	**0.53**	**22.11**	**0.87**	**8.7**
Barren land	**32.68**	**1.29**	**49.23**	**1.94**	**16.55**
Total	**2530.44**		**2530.44**		
Nb: [a]: percentage of each class out of the total area **Negative value denote decline of the area**					

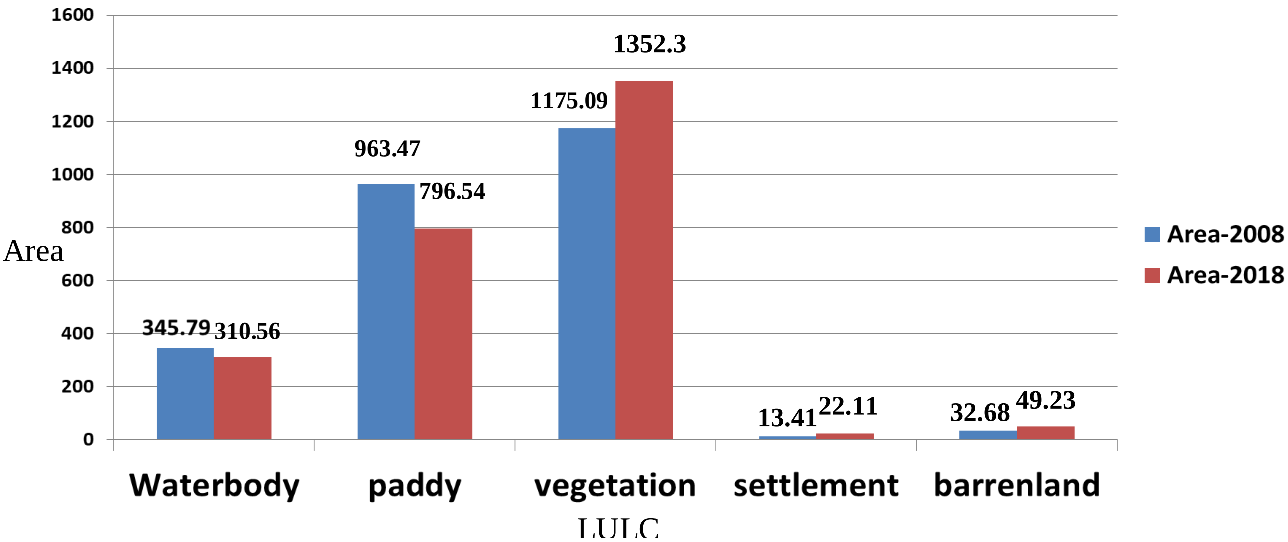


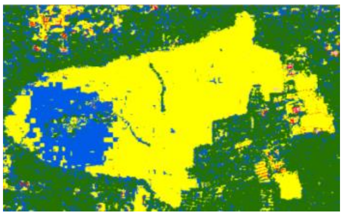
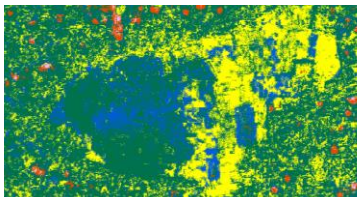
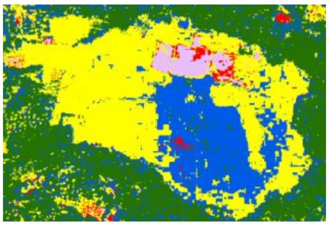
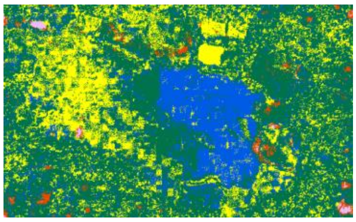
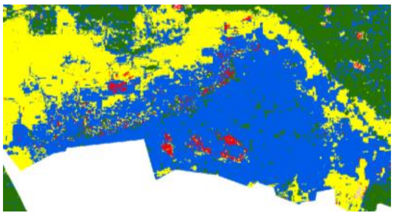
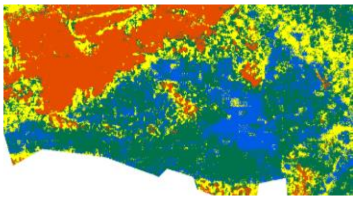
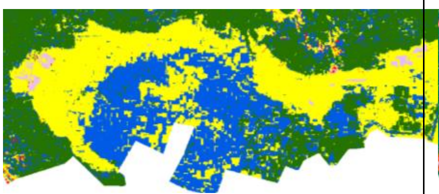
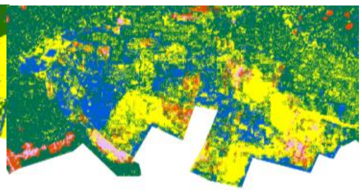
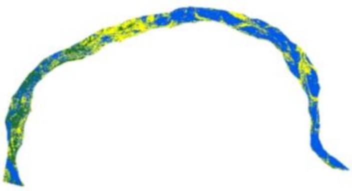
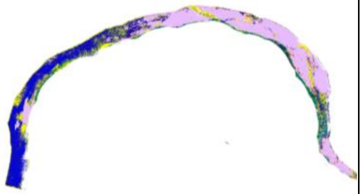
Fig 4.3 Distribution of LULC in Thavanur Grama Panchayath during 2008 and 2018

The map obtained by supervised classification confirmed that all water bodies shown in it were the actual water bodies in real ground too. Among the waterbodies, very small ponds, small streams and some other minute water bodies were not able to identify. Hence only the major wetland waterbodies of Thavanur Grama Panchayath were identified in the LULC map of 2008 and 2018 by supervised classification with the help of field survey and ground truthing. The findings of the field survey for wetland inventory showed that there was disappearance of wetlands in Thavanur Grama Panchayath over the last ten years. The major wetlands identified by Supervised Classification are shown in the Table 4.2.

The majority of land use in Thavanur Grama Panchayath consist of mixed vegetation. Hence it was difficult to distinguish the various LULC classes by supervised classification. The supervised classification showed both waterbody and paddy cultivated area in same colour and in some other places, both paddy and vegetation were in same colour. Also, in some other places, the roof of house and wasteland/barren land showed same colour and identified as same class. This was the shortcoming of the supervised classification in this study. Hence it was found that supervised classification method was not able to identify each and every small wetland of Thavanur Grama Panchayath. Only the major wetlands were identified by supervised classification. Hence visual interpretation method was adopted for better classification of wetlands.

A similar study was conducted by Rawat *et al.* (2015) for monitoring land use/land cover changes using remote sensing and GIS techniques. This study illustrated spatio-temporal dynamics of Land use / cover of Hawalbagh block in Almora district of Uttarakhand by supervised classification.

Table 4.2 Major wetlands of Thavanur Grama Panchayath identified by supervised classification

Sl.No	Name type and location	Wetlands -2008	Wetlands – 2018
1	Marshy Land Thavanur Kayal 10°50'50.7"N 75°58'55.8"E		
2	Marshy Land Ayankalam Kayal, 10°50'20.7"N 75°59'53.7"E		
3	Marshy Land Maravancheri Kayal 10°49'48.1"N 75°59'27.6"E		
4	Marshy land Varo kayal 10°49'20.5"N 76°01'15.0"E		
5	Bharatha Puzha 10°51’41.9”N 75°59’08.5”E		

4.1.2 Visual interpretation Technique (VIT)

The Land uses Land Cover (LULC) map of Thavanur Grama Panchayath obtained by Visual Interpretation Technique are shown in Fig. 4.4 and Fig. 4.5.

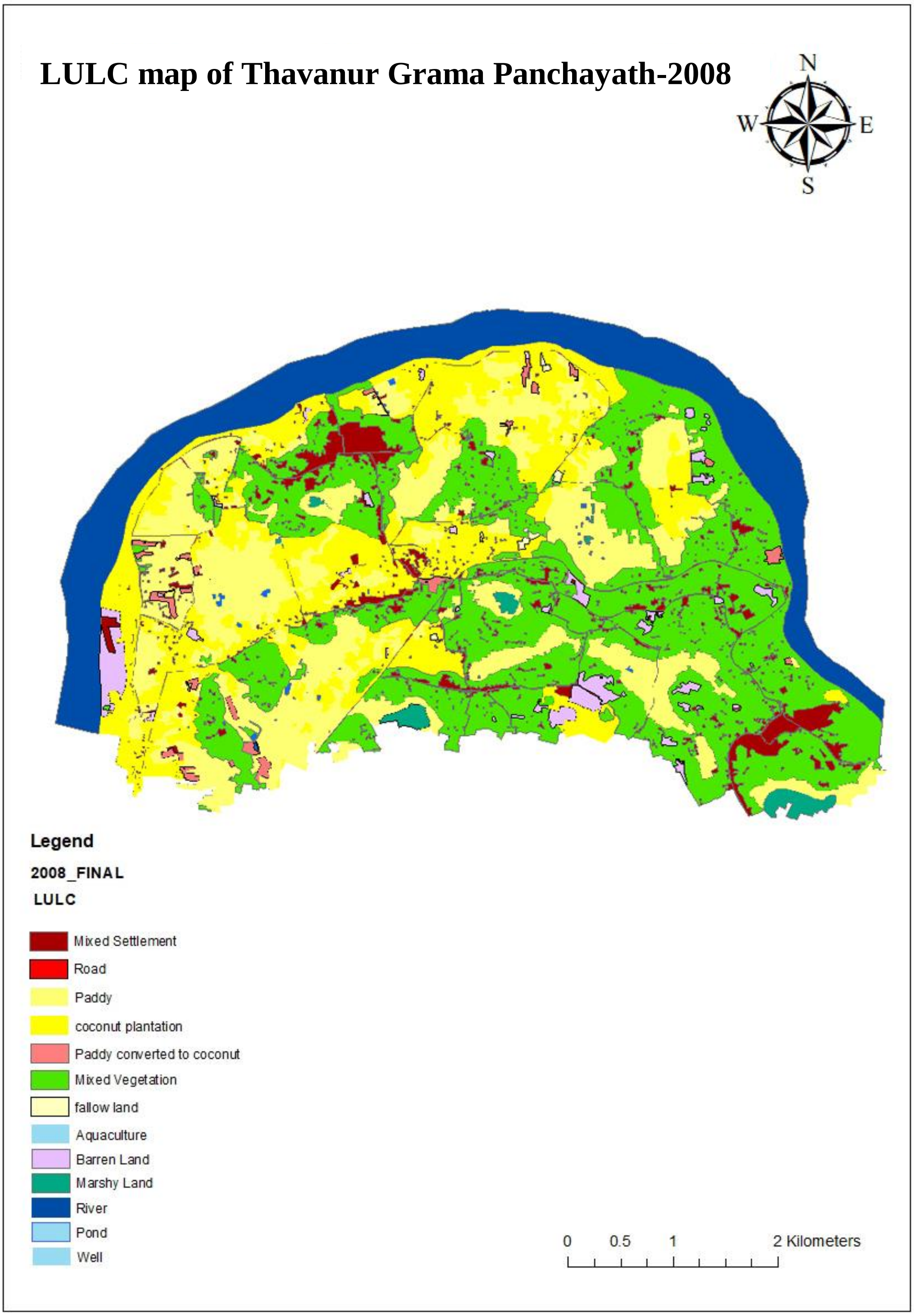


Fig. 4.4 LULC map of Thavanur Grama Panchayath-2008 obtained by VIT

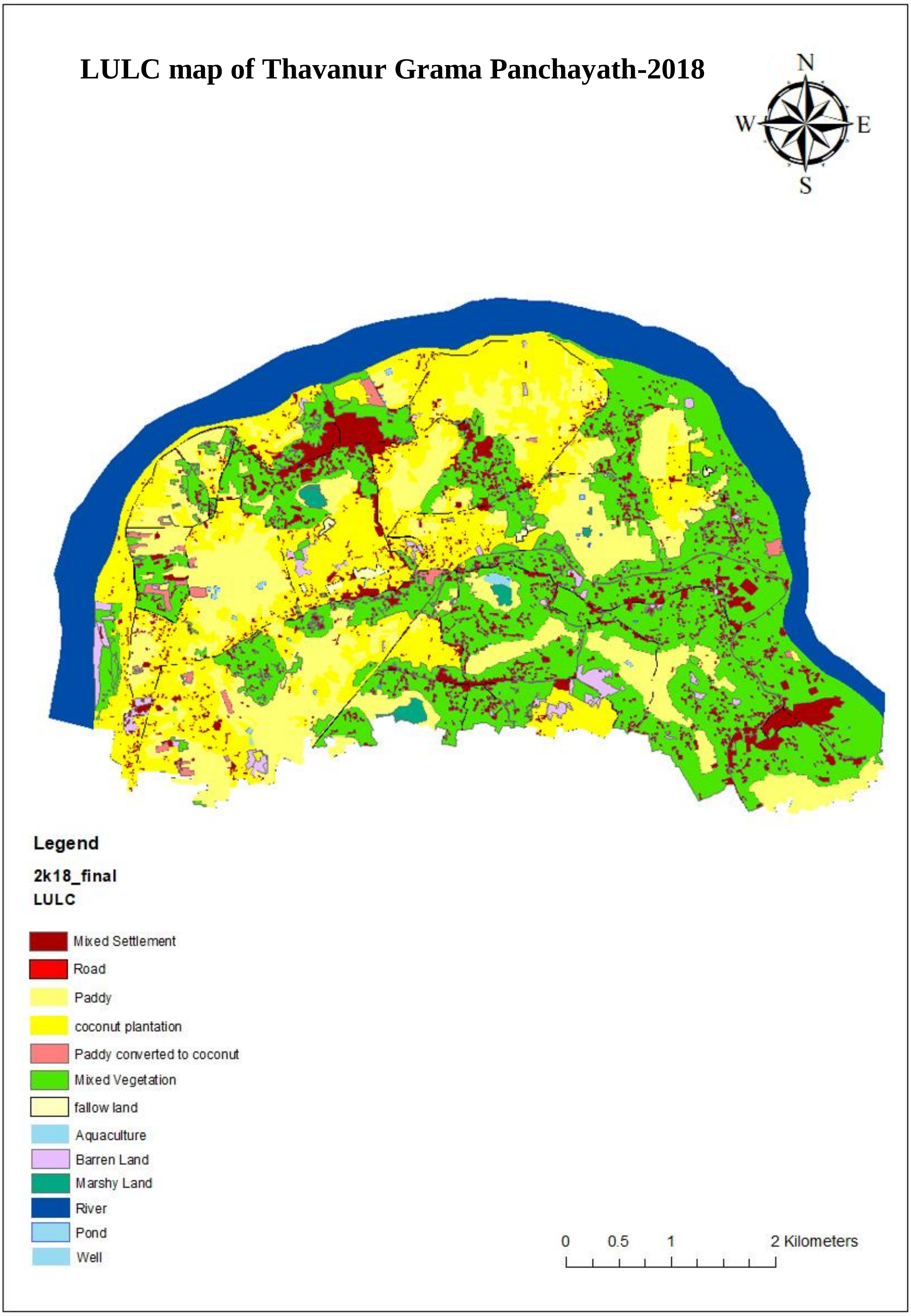


Fig. 4.5 LULC Map of Thavanur Grama Panchayath-2018 obtained by VIT

The areas of LULC classes in 2008 and 2018 and its changes mapped by visual interpretation technique are shown in Table 4.3.

Table 4.3 LULC of Thavanur in 2008 and 2018 and its changes obtained by VIT

LULC-Ist level	LULC-II nd level	Area in 2008 (ha)	% Area in 2008	Area in 2018 (ha)	% Area in 2018
Built up Land	**Settlements (mixed)**	**128.82**	**5.09**	**177.59**	**7.02**
	Road	**28.97**	**1.14**	**28.97**	**1.14**
Agricultural Land	**Paddy**	**568.25**	**22.45**	**506.63**	**20.02**
	coconut	**472.20**	**18.66**	**542.99**	**21.46**
	Paddy converted to coconut	**22.18**	**0.88**	**16.29**	**0.64**
	Mixed Vegetation	**854.65**	**33.77**	**829.14**	**32.76**
	Fallow Land	**3.25**	**0.13**	**6.78**	**0.27**
	Aquaculture	**0**	**0**	**2.18**	**0.09**
Wasteland	**Barren Land / wasteland**	**46.96**	**1.86**	**36.32**	**1.44**
	Marshy Land	**36.58**	**1.45**	**29.54**	**1.17**
Water Bodies	**River**	**372.98**	**14.74**	**374.34**	**14.79**
	Pond	**4.57**	**0.18**	**3.46**	**0.14**
	Well	**0.013**	**0.00**	**0.015**	**0.00**
	Total	**2530.893**		**2530.893**	

Nb: Negative value denotes the decline of area

The total area of the Panchayath was estimated as 2530.89 ha in which the area of built-up land, agricultural land, wasteland and water body in 2008 were 157.79 ha, 1921.33 ha, 83.54 ha and 377.563 ha respectively, and the same in 2018 were 206.51 ha, 1904.01 ha, 65.86 ha and 377.815 ha respectively. Under built-up land, mixed settlements occupied an area of 128.82 ha (5%) in 2008 and the same in 2018 was 177.59 ha. The main settlements were found in the northern and southern region with well-developed road networks which occupied an area of 28.97 ha (1%) both in 2008 and 2018.

Under agriculture land use, the mixed vegetation occupied the largest area coverage compared to other classes with an area of 854.64 ha which represented 34% of the total area in 2008 and the same in 2018 occupied 829.14 ha. Paddy fields spread over 568.25 ha (22%) in 2008 and 506.63 ha in 2018, whereas coconut plantation occupied 472.20 ha (18%) in 2008 and 542.99 ha in 2018. They are concentrated mainly in the northern, western parts and small patches in southern parts of the Panchayath. Fallow lands were found below 1% as small patches here and there (3.25 ha in 2008 and 6.78 in 2018). It was also observed that there was no Aquaculture in the Panchayath during the year 2008 and the same in 2018 was 2.18 ha.

Barren land / waste land occupied an area of 46.96 ha (1.86%) in 2008 and 36.32 ha in 2018, whereas Marshy land occupied an area of 36.58 ha (1.45%) in 2008 and 29.54 ha in 2018. Water body (river) occupied an area of 372.98 ha (14.74%) and 374.34 ha in 2018 and was seen on the western and northern boundary of the Panchayath. Ponds and wells demarcated with an area of 4.57 ha and 0.013 ha in 2008 and 3.46 ha and 0.015 ha in 2018 respectively.

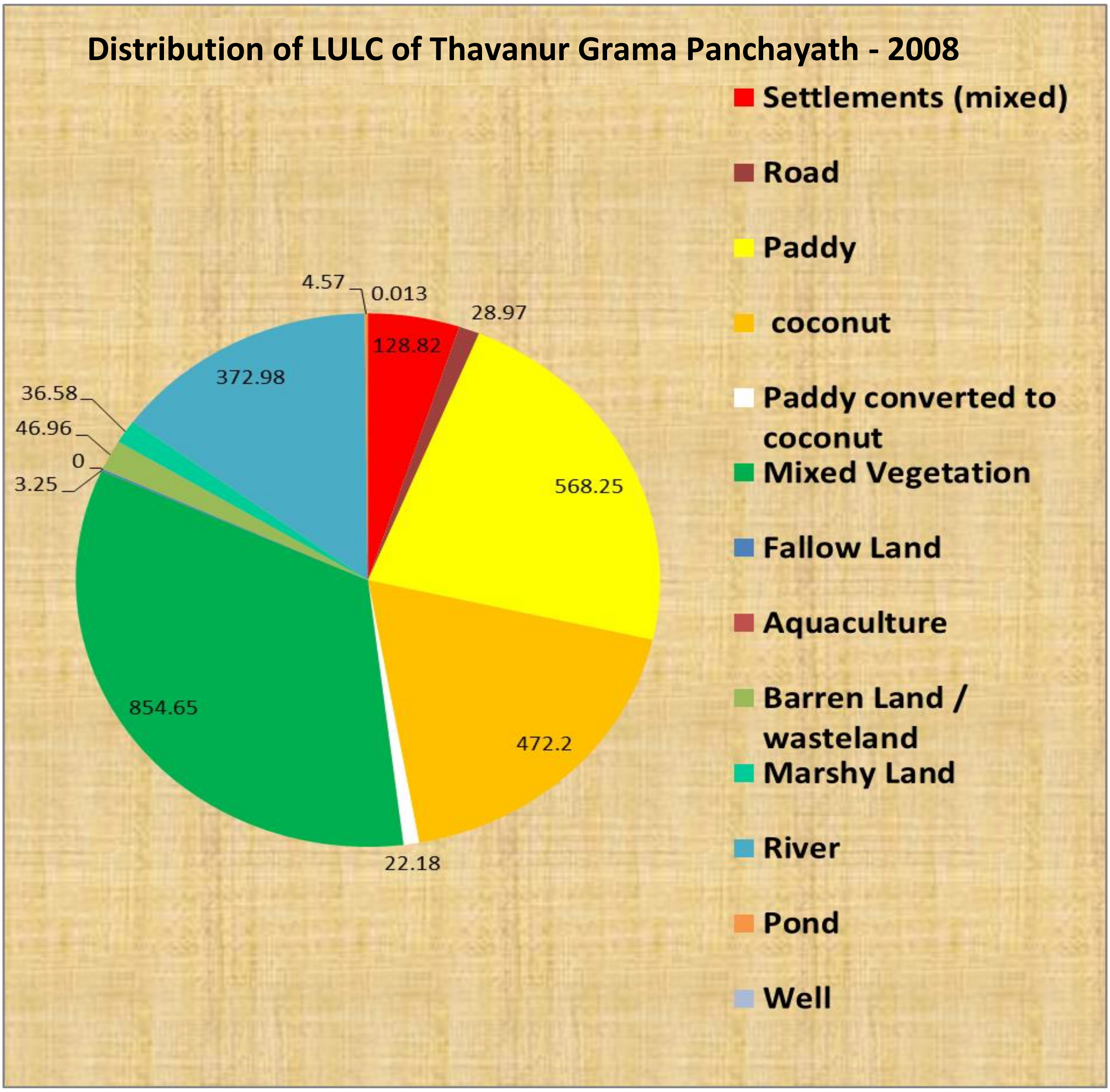


Fig. 4.6 Distribution of LULC of Thavanur Grama Panchayath in 2008 obtained by VIT

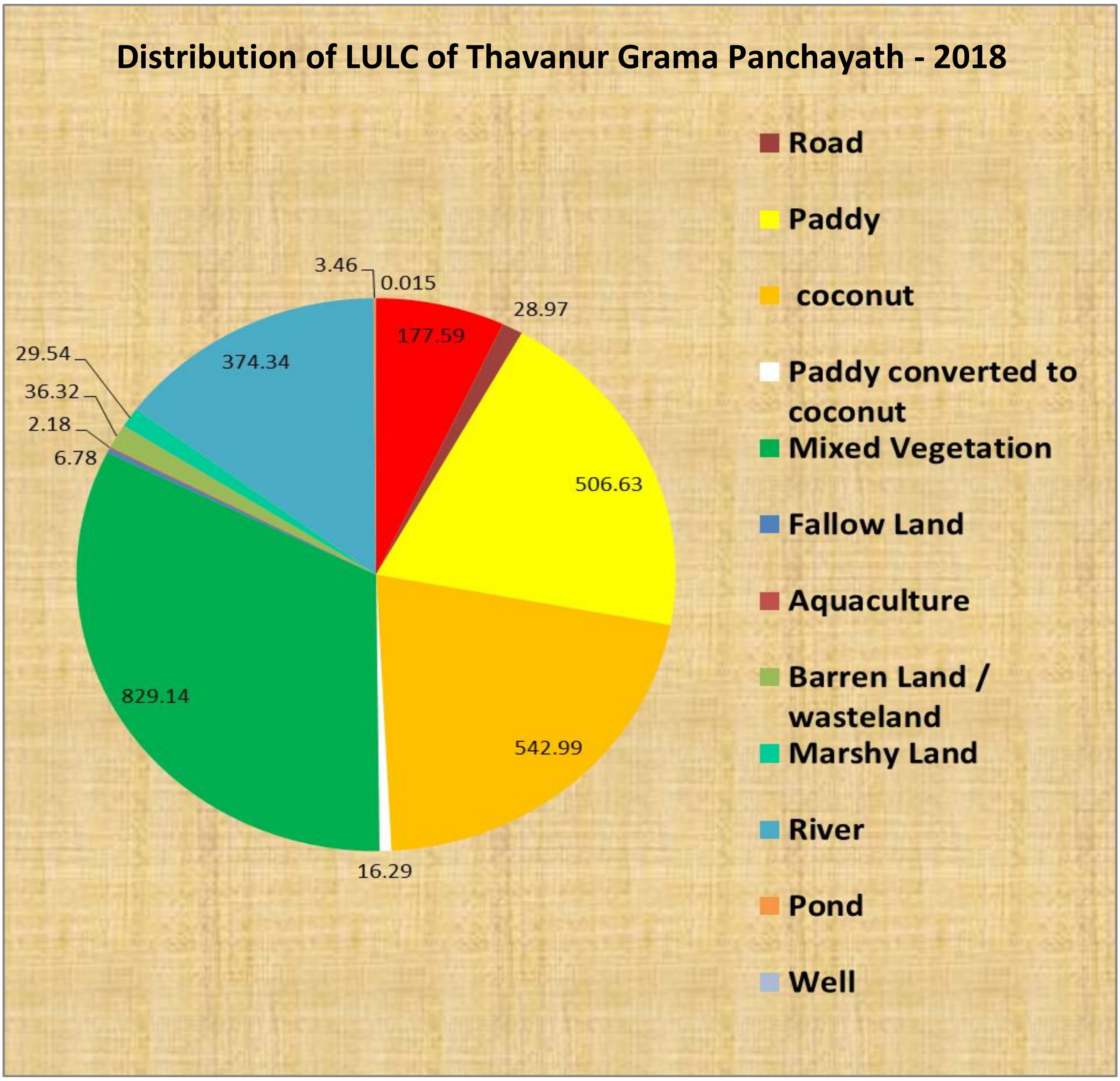


Fig. 4.7 Distribution of LULC of Thavanur in 2018 obtained by VIT

4.2.1 Wetland mapping and inventorying

Field survey and satellite imagery interpretation was carried out to document and make inventories of the wetlands of Thavanur Grama Panchayath. The different wetland classes identified in 2008 were marshy lands (swamps), river and other small waterbodies including ponds and wells. The total area of wetlands in 2008 was 414.16 ha whereas the total area of wetland in 2018 was 409.52 ha which included aquaculture, marshy land (swamps), river and other small waterbodies. Fig. 4.8 and Fig. 4.9 are shows the wetland map of Thavanur Grama Panchayath in 2008 and 2018 respectively.

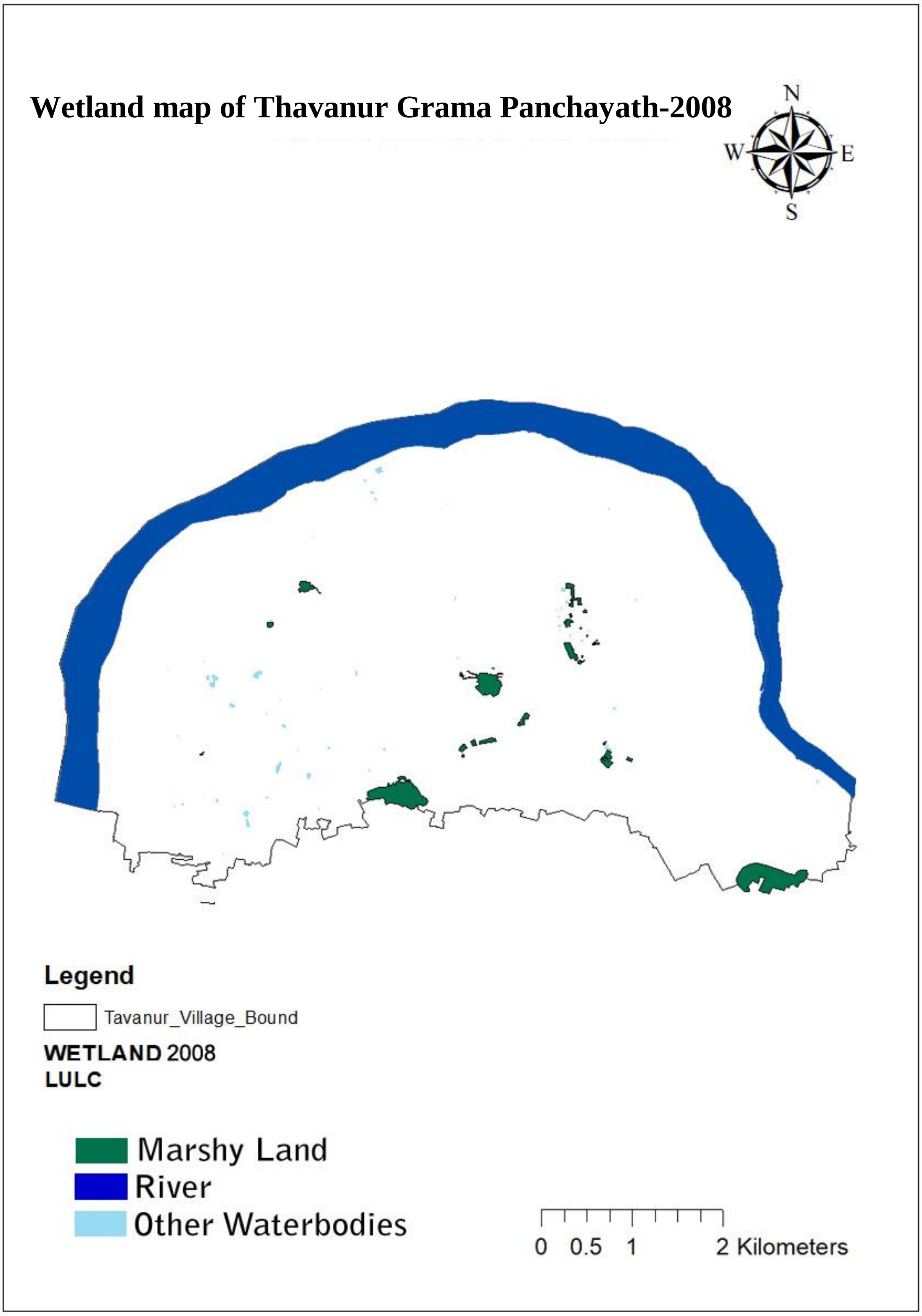


Fig. 4.8 Wetland map of Thavanur Grama Panchayath-2008

Fig. 4.9 Wetland map of Thavanur Grama Panchayath-2018

It is clear from the wetland map that Thavanur Grama Panchayath is dominated by marshy type wetland. An area of 1.82 ha of wetland in 2008 was converted into aquaculture in 2018 and 0.28 ha of new aquaculture set up was started in 2018 Mathur. This was a source of income for the wetland farmer in the area. However, the marshy land decreased from 36.58 ha to 29.54 ha from 2008 to 2018. The marshy land area decreased by 7.04 ha during the ten years. However, the area of Bharathapuzha has increased by 1.36 ha from 2008 to 2018. The areas of other waterbodies decreased from 4.60 ha to 3.46 ha. Hence it is evident that the increase was only for riverine and aquaculture areas may be due to flood during 2018. The areas of all other wetlands decreased significantly during the ten-year period. The Area of each wetland in Thavanur Grama Panchayath were calculated and the same is tabulated in Table 4.4 and its distribution is shown in Fig. 4.10

Table 4.4 Distribution of different types of wetlands in Thavanur during 2008 and 2018

Sl. No	Wetland Type	Area - 2008 (ha)	Area - 2018 (ha)
1	Aquaculture	0.000	2.180
2	Marshy Land	36.580	29.540
3	River	372.980	374.340
4	Others	4.608	3.460
Total		414.168	409.520

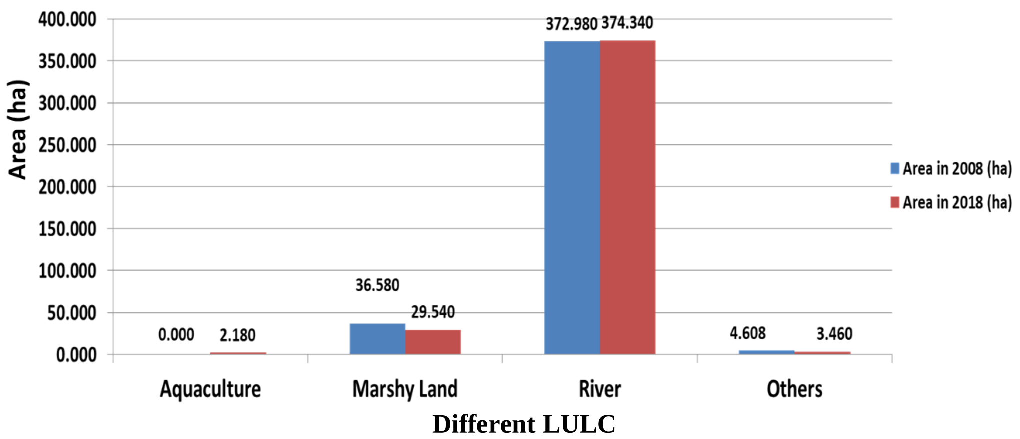
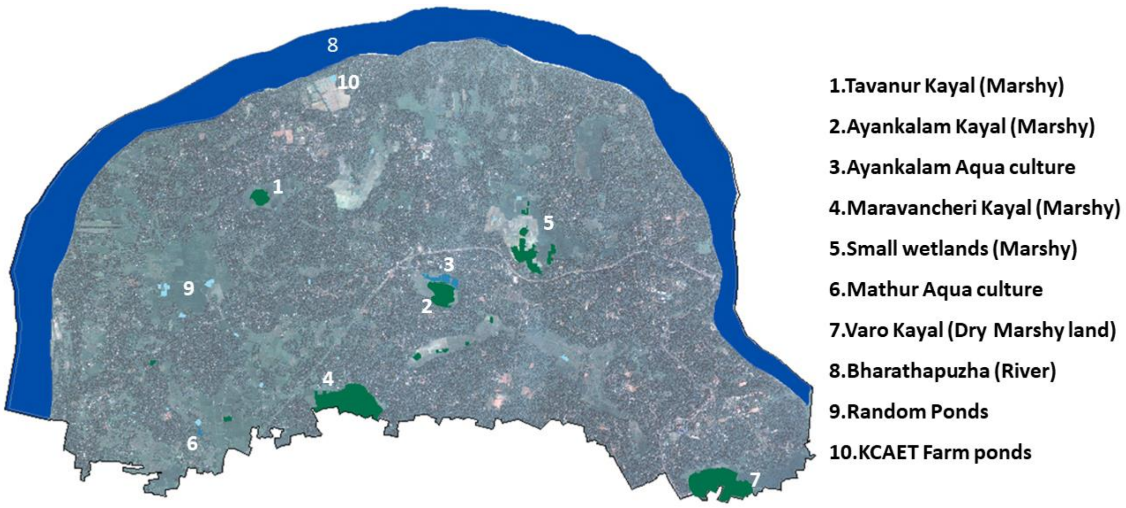


Fig. 4.10 Distribution of area of wetlands in Thavanur 2008 and 2018

4.3 IDENTIFICATION OF MAJOR WETLANDS OF THAVANUR GRAMA PANCHAYATH

The major wetlands of Thavanur Grama Panchayath identified were Thavanur Kayal, Ayankalam Kayal, Ayankalam Fish farm, Mathur Fish farm, Varo Kayal and Bharathapuzha River and their details are shown in the Table 4.3. Visual interpretation technique identified a greater number of wetlands because, aquaculture was not able to identify by the supervised classification for the 2018 satellite data. The name and location of major wetlands of Thavanur Grama Panchayath in 2008 and 2018 are shown in Fig. 4.11 and its details are shown in Table 4.5.

a. Name and location of major wetlands in 2008



b. Name and location of major wetlands in 2018

Fig. 4.11 Name and location of major wetlands in 2008 and 2018

Table 4.5 Details of Main wetlands of Thavanur Grama Panchayath and its particulars

Sl.No	Name, type and location of wetlands	Wetlands -2008	Area in 2008	Wetlands -2018	Area in 2018	Particulars and purpose
1	Tavanur Kayal Marshy Land 10°50'50.7"N 75°58'55.8"E		4.11 ha		2.93 ha	• Irrigation purpose • Domestic purpose other than drinking
2	Ayankalam Kayal Marshy Land 10°50'20.7"N 75°59'53.7"E		4.3 ha		2.6 ha	• Irrigation purpose
3	Ayankalam Fish farm Aquaculture 10°50'25.6"N 75°59'54.4"E	Nil			1.82 ha	• Silopia, bedfish, rohu, anabis, katla, banded snake's head and pangusis are major fish varieties
4	**Maravanchery Kayal Marshy Land** **10°49'48.1"N** **75°59'27.6"E**		**3.11 ha**		**2.56 ha**	• **Water Lilly and lotus are regularly cultivated**
5	**Small wetlands Marshy land** **10°50'41.3"N** **76°00'19.3"E**		**13.16ha**		**12.07 ha**	• **Agriculture uses**
6	**Mathur Fish farm Aqua culture** **10°49'38.2"N** **75°58'37.6"E**	Nil	0		**0.28 ha**	• **Silopia, bedfish, rohu, anabis, katla, banded snake's head and pangusis are the major fish varieties**

7	Varo Kayal Marshy land 10°49'22.0"N 76°01'18.3"E		11.9 ha		9.38 ha	• Agriculture purpose • Almost dried
8	Bharatha Puzha 10°51'41.9"N 75°59'08.5"E		372.98ha		374.34 ha	• Agriculture and livelihood of Tavanur and cheruthirunnavaya Panchayats are mainly depended on Bharathapuzha. • Irrigation purpose • Domestic purpose other than drinking
9	Random Ponds and wells		5.15ha		3.88 ha	Agriculture Purpose
10	KCAET Farm ponds		0.5 ha		0.6 ha	Agriculture Purpose

Area distribution of each wetlands of Thavanur Grma Panchayath is shown in the Table 4.6 and the real ground images of major wetlands in Tavanur in 2021 is shown is shown in Fig. 4.12.

Table 4.6 Area distribution of each wetlands .

Wetland	Area in 2008 (ha)	Area in 2018
Aquaculture	0.000	Ayankalam Aquaculture =1.82 Mathur Aquaculture= 0.28 Total = 2.1
Marshy land	Tavanur kayal- 4.11 Ayankalam kayal- 4.3 Maravancheri kayal- 3.11 Other marshy land- 13.16 Varo kayal- 11.9 Total=36.580	Tavanur kayal- 2.93 Ayankalam kayal- 2.6 Maravancheri kayal- 2.56 Other marshy land- 12.07 Varo kayal- 9.38 Total=29.540
River	372.980	374.340
Others (Ponds and well)	Random ponds and wells- 5.15 KCAET Pond- 0.5 Total- 5.65	Random ponds and well- 3.88 KCAET Pond- 0.6 Total- 4.48
Total	**414.168**	**409.520**

Tavanur Kayal

Ayankalam Kayal

Ayankalam Fish farm

Maravanchery Kayal

Marshy land

Mathur Fish farm

Varo Kayal

Bharatha Puzha

KCAET Farm ponds

Fig. 4.12 A view of real ground images of major wetlands in Tavanur-2021

4.3.1 Particulars and characteristics of main wetlands as on 2021

a. Thavanur Kayal

Location: 10°50'50.7"N,
75°58'55.8"E

Wetland Type: Marshy Land

Area: 2.9 ha

Thavanur Kayal is a marshy type wetland. This located near to actual Thavanur. It is locally named as Thavanur Kayal. It is used for irrigation as well as domestic purpose other than drinking. The satellite image of Thavanur Kayal is shown in the Fig. 4.13.

Fig. 4.13 Thavanur Kayal

b. Ayankalam Kaayal

Location: 10°50'20.7"N,
75°59'53.7"E

Wetland Type: Marshy Land

Area: 2.5 ha

Ayankalam Kaayal is located in Ayankalm junction. It is a perennial type marshy wetland. It is mainly used for irrigation purpose. The satellite image of Ayankalam Kaayal is shown in Fig. 4.14.

Fig. 4.14 Ayankalam Kayal

c. Ayankalam Fish farm

Location: 10°50'25.6"N
75°59'54.4"E

Wetland Type: Aquaculture

Area: 1.84 ha

This fish farm started in 2011. Silopia, bedfish, rohu, anabis, katla, banded snake's head and pangusis are the major fish varieties cultivated in this farm. The yield of fish farm is 14-15 tonnes per year. It is a very encouraging fish farm which receives subsidies from the department of fisheries. Ayankalam Fish farm satellite image is shown in Fig. 4.15.

Fig. 4.15 Ayankalam Fish farm

d. Maravanchery Kayal

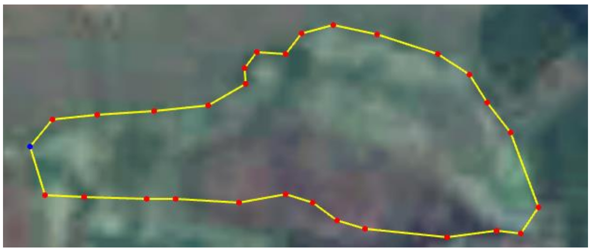


Fig. 4.16 Maravanchery Kayal

Location: 10°49'48.1"N

75°59'27.6"E

Wetland Type: Marshy Land

Area: 2.4 ha

Maravanchery Kayal is located on the border of Thavanur Panchayat and Kalady Panchayat. Hence the service of this wetland is equally available for the inhabitancies of both the Panchayats. Water Lilly and lotus are regularly cultivated crops in Maravanchery kayal. It is a source of income for the people lives in the area. It also helps to maintain the biodiversity and strengthening of food chain in the area. Maravanchery Kayal satellite image is shown in the Fig. 4.16.

e. Mathur Aquaculture

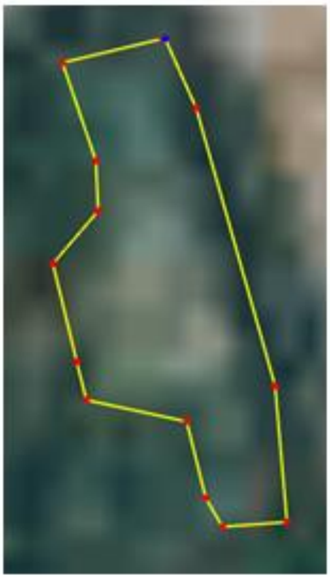


Fig. 4.17 Mathur Aquaculture

Location: 10°49'38.2"N

75°58'37.6"E

Wetland Type: Aquaculture

Area: 0.28 ha

This aquaculture is a newly started one as a part of Subhikshakerala – Rebuild Kerala initiative. Rohu, anabis, katla and Silopia are the major fish varieties cultivating in the farm. This farm is of great impact to the fish farmers of Thavanur Grama Panchayath. The satellite image of Mathur Aquaculture is shown in the Fig. 4.17.

f. Varo Kayal

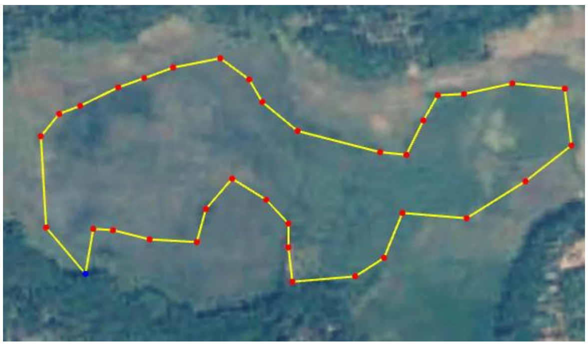


Fig. 4.18 Varo Kayal

Location: 10°49'22.0"N

76°01'18.3"E

Wetland Type: Marshy Land

Area: 9.15 ha

Varo Lake is located on the border of Thavanur Panchayath. The water of this wetland is mainly used for agriculture. Varo Kayal satellite image is shown in the Fig. 4.18.

g. Bharathapuzha River

Location: 10°51’41.9” N

75°59’08.5” E

Wetland Type: River

Total area: 374 ha

Fig. 4.19 Bharathapuzha River

Bharathapuzha is the largest and most important source of water in Thavanur Grama Panchayath. Three sides of Thavanur panchayath are surrounded by this river. This river and Thirunavaya Panchayat. The agriculture and livelihood of both the Panchayats depends on Bharathapuzha. This important Kerala’s culture. Bharathapuzha River satellite image is shown in the Fig. 4.19.

4.3 Accuracy assessment

Accuracy of supervised classification and visual interpretation methods were assessed by finding kappa coefficient, overall accuracy, producer’s accuracy and user’s accuracy. Confusion (error) matrix obtained from LULC map 2018 was used for accuracy assessment. The error matrix computed the overall accuracy of five land use classes (Paddy, wasteland, vegetation, water body, and settlement classes) individually and collectively. Confusion (error) matrix for LULC supervised classification map is shown in Table 4.7.

From Table 4.7 it is clear that the overall accuracy of supervised classification is 83%. Waterbody class showed the lowest producer’s accuracy (66.66 %) which may be due to the reflectance of vegetation associated with the waterbody. Settlement class showed highest producer’s accuracy (93.33 %). This is because, the settlement locations were very easy to identify in the satellite imagery. Paddy class showed the lowest user’s accuracy and wasteland showed the highest user’s accuracy and they are estimated as 66.66 % and 94.44 % respectively. The producer’s accuracy of paddy, wasteland, vegetation, waterbody and settlement were found 90.9 %, 89.47 %, 78.26 %, 66.66 % and 93.33 % respectively. The user’s accuracy for the same classes was found 66.66%, 94.44%, 90 %, 87.5 %, and 87.5% respectively. The Kappa value for supervised classification was found 0.78. The range of values showed that the classification accuracy was reasonably good for supervised classification.

Similar study conducted by Munthali *et al.*, (2019). They selected Waterbody, Wetland, Forest, Agriculture, Barren land and Build up LULC classes for calculating confusion matrix. The overall accuracy of their study obtained 91.86% and Kappa value 0.86.

The accuracy assessment result for visual interpretation technique for the different classes and the corresponding confusion matrix is shown in Table 4.8. From Table 4.8 it is clear that, the overall accuracy of visual interpretation was 94%. The classes mixed settlement, Road, Paddy, Coconut Plantation, Aquaculture, Marshy land, River, Pond and Well showed highest producer's accuracy (100 %). Mixed vegetation showed the lowest producer's accuracy (75%). Road, Mixed vegetation, Aquaculture, Marshy land, River, Pond and well showed the highest user's accuracy (100 %) whereas fallow land showed the lowest user's accuracy (83.33%). The Kappa value for visual interpretation was found 0.93. The range of value showed that the classification accuracy is excellent. It was found that among the two different classification methods used in this study, visual interpretation method was found more accurate than supervised classification in the case of Thavanur Grama Panchayath mapping.

Table 4.7 Confusion matrix of supervised classification

	Paddy	Wasteland	Vegetation	Water body	Settlement	Row total	User's accuracy (%)
Paddy	**20**	-	5	5	-	30	66.66
Wasteland	-	**17**	-	-	1	18	94.44
Vegetation	-	-	**18**	2	-	20	90
Water body	2	-	-	**14**	-	16	87.5
Settlement	-	2	-	-	**14**	16	87.5
Column total	22	19	23	21	15	100	
Producer's accuracy (%)	90.9	89.47	78.26	66.66	93.33		
Overall Accuracy	83 %.						
Kappa Coefficient	0.78						

Table 4.8 Confusion matrix of visual interpretation technique

	Settlements (mixed)	**Road**	**Paddy**	**Coconut plantation**	**Paddy converted to coconut**	**Mixed Vegetation**	**Fallow Land**	**Aquaculture**	**Barren Land / wasteland**	**Marshy Land**	**River**	**Pond**	**Well**	**Row total**	**User's accuracy (%)**
Settlements (mixed)	**8**								1					9	88.88
Road		**8**												8	100
Paddy			**8**			1								9	88.88
coconut				**6**		1								7	85.71
Paddy converted to coconut					**8**	1								9	88.88
Mixed Vegetation						**9**								9	100
Fallow Land					1		**5**							6	83.33
Aquaculture								**6**						6	100
Barren Land / wasteland							1		**8**					9	88.88
Marshy Land										**9**				9	100
River											**8**			8	100
Pond												**7**		7	100
Well													**4**	4	100
Column Total	8	8	8	6	9	12	6	6	9	9	8	7	4	100	
Producers Accuracy	100	100	100	100	88.88	75	83.33	100	88.88	100	100	100	100		
Overall Accuracy = 94%															
Kappa Coefficient = 0.93															

4.4 Change detection analysis

Change detection analysis quantify the changes that are associated with LULC changes using geo-referenced remote sensing images acquired on the same geographical area between the considered acquisition date (Ramachandra and Kumar 2004). This study employed a post-classification comparison (PCC) method for change detection.

4.4.1 Land use and land cover change dynamics

Both in 2008 and 2018, Paddy land and mixed vegetation were the predominant LULC classes. As per the Table 4.9 the percentage changes for various classes viz. Mixed settlements, Road, Paddy, Coconut, Paddy converted to coconut, Mixed Vegetation, Fallow Land, Aquaculture, Barren Land / wasteland, Marshy Land, River, Pond and Well were 27.46%, 0, -12%, 13.03%, -36.15%, -3.08%, 52.06%, 100%, -29.30%, -23.83%, 0.38%, -32.08% and 13.33% respectively. This negative sign indicated the losses in LULC and positive sign indicated the gain in LULC between 2008 and 2018.

The annual rate of change revealed a varied changing progression for each LULC category throughout the study period from 2008 to 2018. There was an annual increase in settlement (0.0321 %), coconut (0.014 %), fallow land (0.0735 %), river (0.0877 %) and well (0.014%). The coconut plantation and aquaculture farming increased to a larger extend from 2008 to 2018. The fish farmers in the area told that aquaculture has supported a greater extend to increase their income. The annual rate of decrease was comparatively low in the case of paddy land (-0.0115 %) and marshy land (-0.0214%). Fig. 4.20 shows the LULC change trend and the annual rate of change.

Table 4.9 LULC change trend and annual rate of change in Thavanur

LULC	Area in 2008 ha	Area in 2018 ha	Change (%) [b] 2018-2008	Annual rate r (%) [c]
Settlements (mixed)	128.82	177.59	27.46	0.0321
Road	28.97	28.97	0	0.0000
Paddy	568.25	506.63	-12.16	-0.0115
coconut	472.20	542.99	13.03	0.0140
Paddy converted to coconut	22.18	16.29	-36.15	-0.0309
Mixed Vegetation	854.65	829.14	-3.08	-0.0030
Fallow Land	3.25	6.78	52.06	0.0735
Aquaculture	0	2.18	100.00	-
Barren Land / wasteland	46.96	36.32	-29.30	-0.0257
Marshy Land	36.58	29.54	-23.83	-0.0214
River	372.98	374.34	0.38	0.0004
Pond	4.57	3.46	-32.08	-0.0278
Well	0.013	0.015	13.33	0.0143
Total	2530.893	2530.893	2530.58	

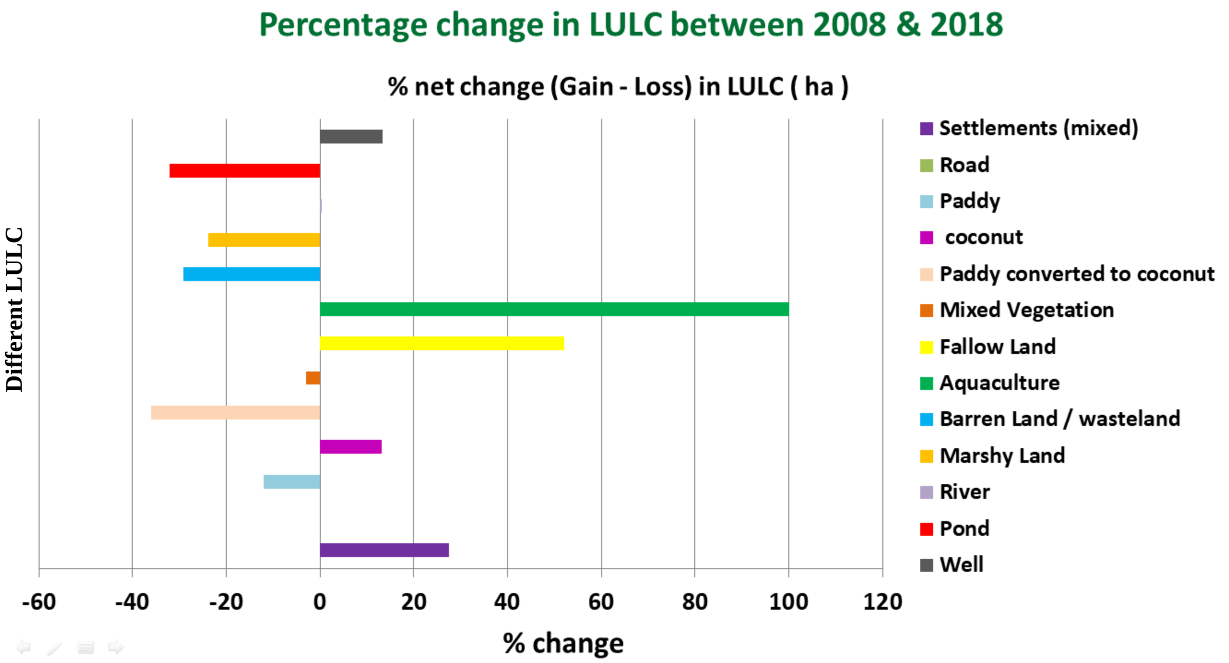


Fig. 4.20 LULC change trend and annual rate of change in Thavanur

4.4.2 Land use and land cover change (transition) matrix

The LULC change (transition) matrix for the period from 2008 to 2018 were shown in Table 4.10. The distribution of main transitions in the thirteen LULC categories showed that there were major changes and transition in all the thirteen LULC classes. Between 2008 and 2018 the land use paddy experienced the major transition that 32.02 ha converted into coconut plantation. In the case of coconut plantation, the majority of it being converted into mixed vegetation (20.42 ha). The barren land experienced transition to paddy land (0.12 ha) and mixed settlement (2.08 ha). Majority of fallow land converted into coconut plantation (1.49 ha). In the case of marshy land, 21.58 ha converted into mixed vegetation. But in the case of paddy land 14.74 ha converted to marshy land. About 47.62 ha of mixed vegetation converted to mixed settlement. There was not much transition found in the case of river, pond, road and well.

Table 4.10 The transition matrix of LULC from 2008 to 2018

		LULC 2018													
		Aquaculture	Barren Land	coconut plantation	fallow land	Marshy Land	Mixed Settlement	Mixed Vegetation	Paddy	Paddy converted to coconut	Pond	River	Road	Well	2008 Total
	Aquaculture														0
	Barren Land		18.309	4.093	0.509		2.088	22.831	0.127						46.96
	Coconut Plantation		0.714	436.845			12.851	20.429	1.363						472.202
	Fallow land			1.495	1.331		0.032		0.391						3.249
	Marshy Land	0.0004				15.667		21.585							36.58
	Mixed Settlement		2.853	2.895			108.895	14.011	0.156				0.011		128.823
LULC 2008	Mixed Vegetation		1.029	60.149	0.016		47.623	744.230	0.214		0.044	1.351	5.3E-06		854.659
	Paddy	1.966	7.726	32.021	4.918	14.740	5.848	27.508	481.106	2.381			0.015	0.015	568.25
	Paddy converted to coconut		1.690	5.387			0.242	0.034	0.921	13.904					22.179
	Pond	0.213		0.110		0.022		0.089	0.744		3.421				4.599
	River							2.5E-07				372.982			372.983
	Road						0.011		0.015			2.6E-07	28.951		28.977
	Well						0.002	0.004	0.005	0.002				0.002	0.014
	2018 Total	2.180	36.32	542.999	6.775	29.5	177.593	829.138	506.68	16.286	3.464	374.333	28.977	0.015	2530.949

Prasad and Ramesh (2018) conducted a similar study on spatio-temporal analysis of land use/land cover changes in an ecologically fragile area-Alappuzha District, Southern Kerala. They found that the expansion of the built-up land area was directly proportional to the growth of the population. Similarly, in Thavanur Panchayat also there was a substantial increase in settlement area and it may be due to the increase in population.

4.3 Evaluation of water table and surface water dynamics

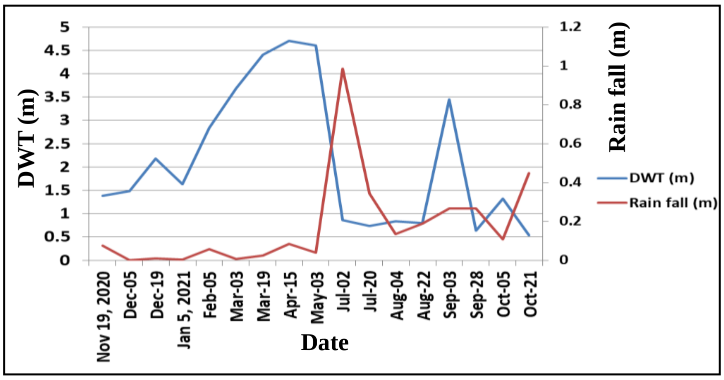
The hydroperiod of wetlands varies with climate and water table condition. Therefore the changes in depth of water table affect the ground water flow. Higher field elevation contributed to the depletion of water table. Hence lower elevated area may be preferred for cultivation. Wetlands are usually characterised by its shallow ground water region and high-water table conditions. So, evaluation of water table condition and surface water dynamics in wetland is very important for planning effective cultivation in the area.

4.3.1 Depth to water table (DWT).

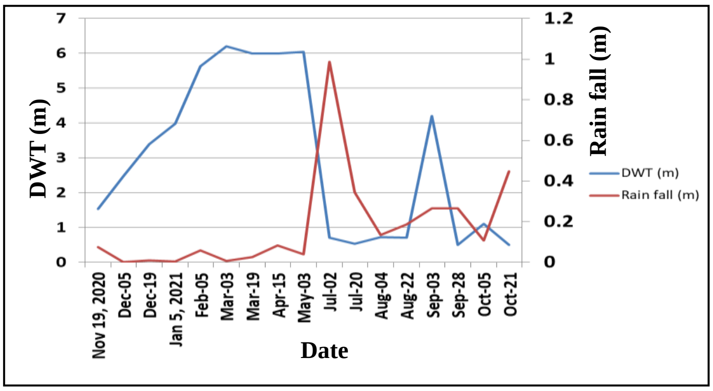
In order to understand the overall water table variation in Thavanur Grama Panchayath, water table depth data was recorded from 11 numbers of wells geographically distributed in the study area. The water table depth data were taken a period of November 2020 to October 2021. The recorded water table depth data and its variations were shown in Fig. 4.21 and Fig. 4.22. The highest depth to water table was recorded during March and April months and the lowest depth to water table was recorded during July August and September months in all the wells. The seasonal level, depth to water table was highest in summer season and lowest during rainy season. The wells located in highest elevation area showed high depth to water table and wells in lower elevation showed low depth to water table.

There was sharp increase in DWT from January 2021 to April 2021. But no variation was found between April 2021 and May 2021. However, from May 2021 to July 2021, there was again a sharp decline in DWT may be because of sudden rain during the months. In July and August, the DWT was almost same. Again, there was a sharp increase, from the first week of August to first week of September and a sudden decrease was found in first week of September to last week of September due to unexpected rain during the period. The period when the Depth to water table is less than 20 cm may not be suitable for cultivation of shallow rooted crops since waterlogging becomes a critical issue (A.O. Oke *et al*., 2010). The major parts of the wetlands showed the depth to water table greater than 20 cm during the period July to November and are suitable for cropping activities. In Thavanur Grama Panchayath the places viz. Kadakasseri north, Vallancheri kadavu, Mattam, Kadakasseri, Chandanakulam, Athalur and Kacheriparamb have depth to water table between 20 cm and 50 cm. So, these places were identified as the best places for cropping activities from July to November. Between July and September, the places Athalur, Maravancheri kayal and Kacheriparamba have showed the depth to water table below 20 cm and hence these places were suitable for cultivation of shallow rooted crops due to waterlogging.

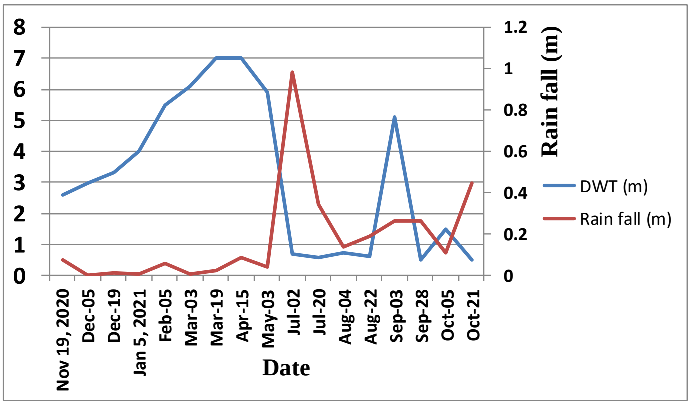
Similar study was conducted by Chen and Qi (2004). They reported that, in wetlands and low lands a high water table and significant hydraulic region exist between the saturated zone and root zone which leads to continues supply of ground water to the root zone. Hence they concluded that areas with low depth to water table are preferred for cultivation. The same situation was found in this area also.



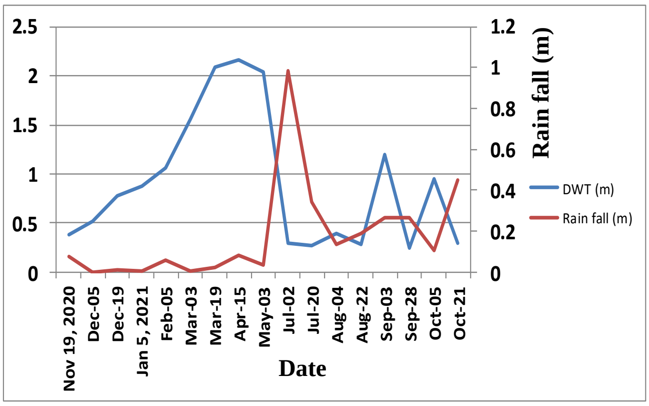
a.Cheruthirunnavaya (CH)



b. Kadakassery North (KN)

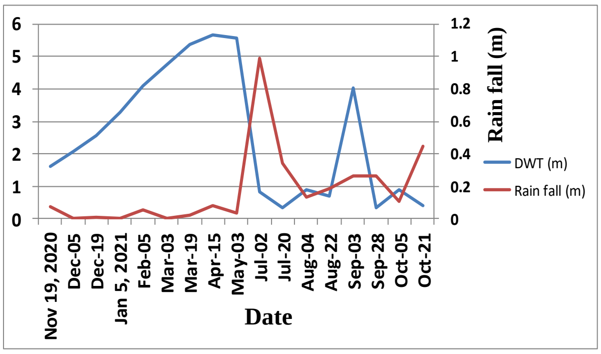


c. Vallancheri Kadavu (VK)

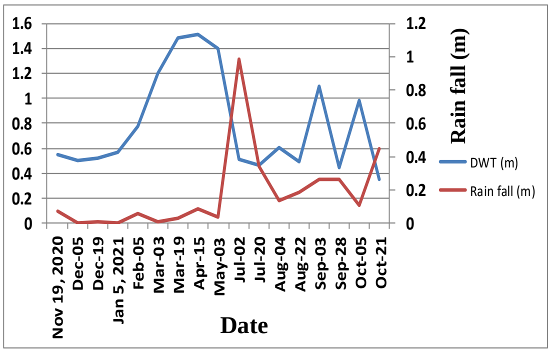


d. Mattam (MT)

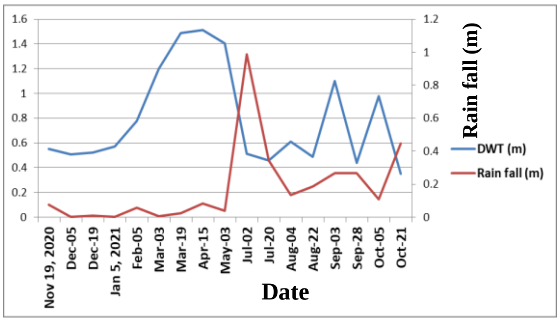
Fig. 4.21 Depth to water table at CH, KN, VK and MT



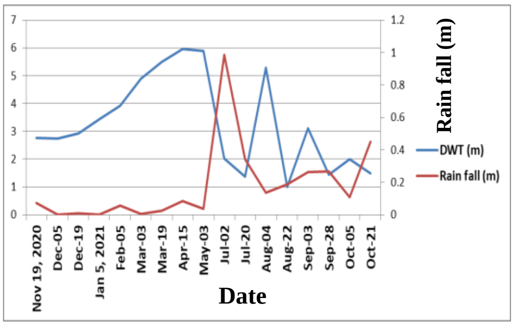
e. Kannankulam (KN)



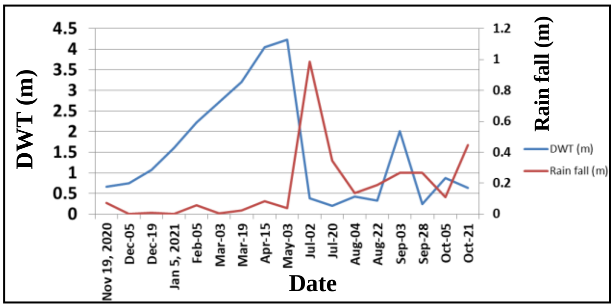
f. Kadakassery (KD)



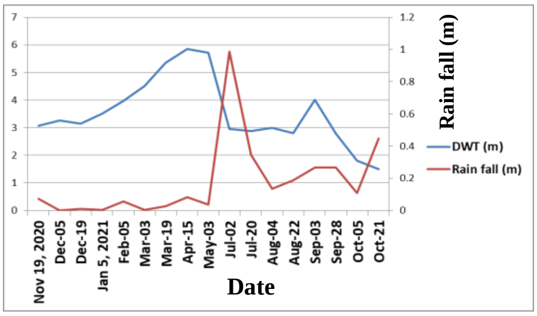
g. Chandanakulam (CK)



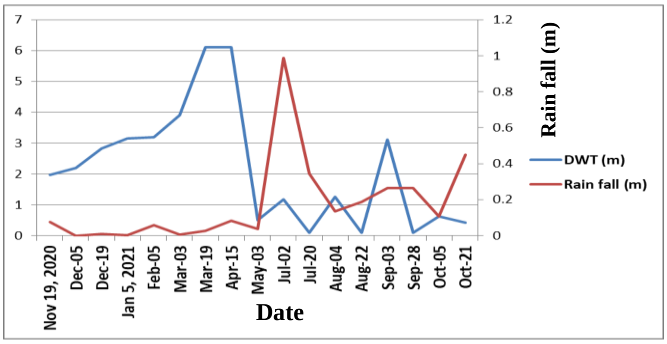
h. Athaloor (AL)



i. Anthyalamkudam (AK)



J. Maravanchery (MC)



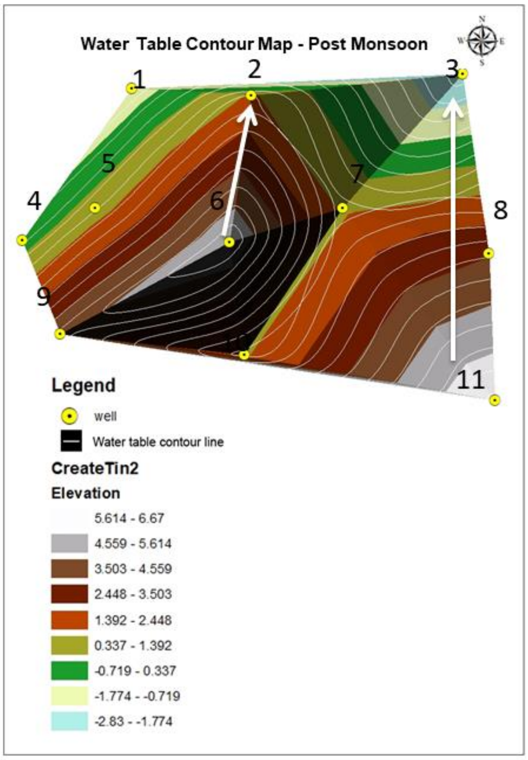
k. Kacheriparambu (KP)

Fig. 4.22 Depth to water table at KN, KD, CK, AL, AK, MC and KP

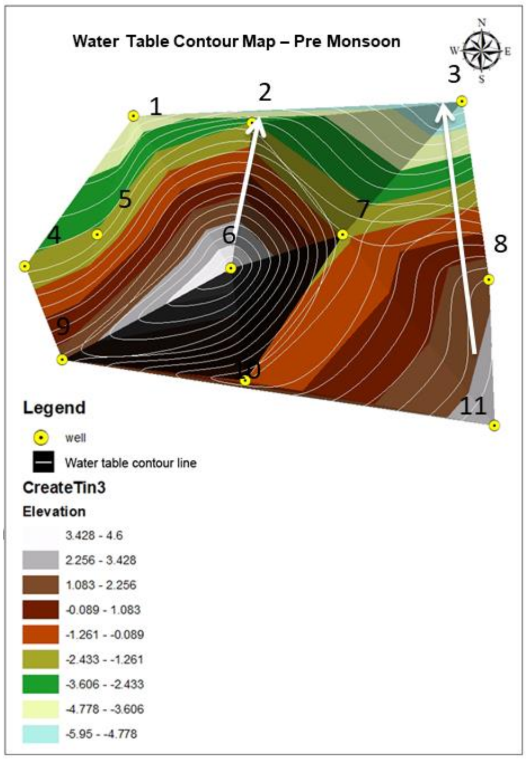
4.3.2 Water Table contour map

Water table contour map for four seasons (Post monsoon, Pre monsoon, Rainy season and Winter season) were created using ArcGIS. The different colour shades indicate the variation in the elevation of area. Water table contour represents lines of equal water table elevations. Water table contour map represents the surface configuration of water table at a specified time. They are useful to determine the direction of groundwater flow. The ground water flow directions are always perpendicular to the contour. It also indicates the location and the extend of high and low water table areas. Ground water always flows from higher elevation to lower elevation. Here the white colour indicates higher elevation and blue colour indicates lower elevation. The arrow mark indicates GW flow direction. In Thavanur Grama Panchayath the ground water flows from Thrikkanapuram – kanjirakutty to Vallancheri Kadavu & Kadakasseri to Cheruthirunnavaya Kadavu in all the seasons except winter season. In winter season there is no ground water flow from Kadakasseri to Cheruthirunnavaya Kadavu. The water table contour maps for different seasons are shown in Fig. 4.23.

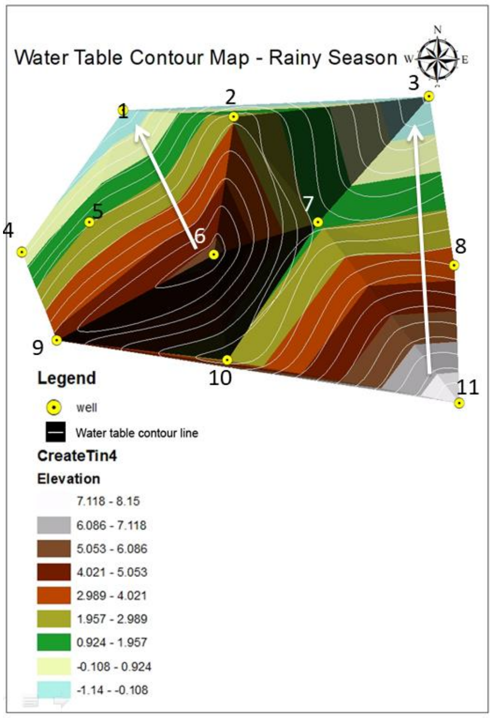
A similar study was conducted by Oke *et al.,* (2010). They evaluated water table dynamics for sustainable cultivation in wetlands of South-Western Nigeria. They concluded that the depth to water table of 20-60 cm was the most prominent in the area and the field presented adequate available water to meet crop water requirements. This study also was found in conformity with this.



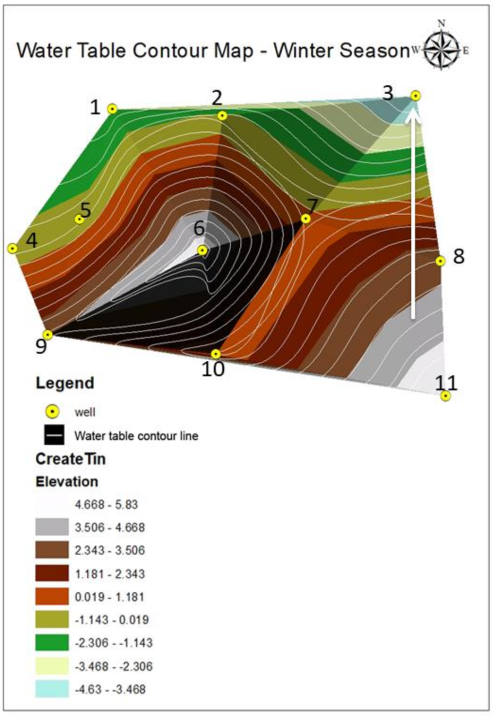
a. **Post monsoon**



b. Pre monsoon



c. **Rainy season**



d. Winter season

Fig. 4.23 Water table contour maps for different seasons

4.3.4 Water Table Fluctuation map

Water table fluctuation was calculated between March to August, 2021. IDW (Inverse Distance Weighted) interpolation method in ArcGIS was used to calculate the fluctuation value. During August 2021 water level in Kadakasseri north region was 3.29 m which decreased to -2.1 m during March. ie. Within five months water level decreased by 5.39 m. In the fluctuation map, red colour indicates high fluctuation area which were the most vulnerable area (not safe) in the Panchayath. In Thavanur Grama Panchayath Kadakassery north, Vallancheri kadavu and Kanjirakutty areas were the most vulnerable areas with fluctuation 4.92 - 5.44m. The green colour indicates low fluctuation area which were the least vulnerable area (safe area). Athallur and Kadakassery (centre) regions were found less vulnerable with fluctuation 0.08-1.31m. This data indicated the likely occurrence of ground water in the region. Fig. 4.24 shows the water table fluctuation map of the study area.

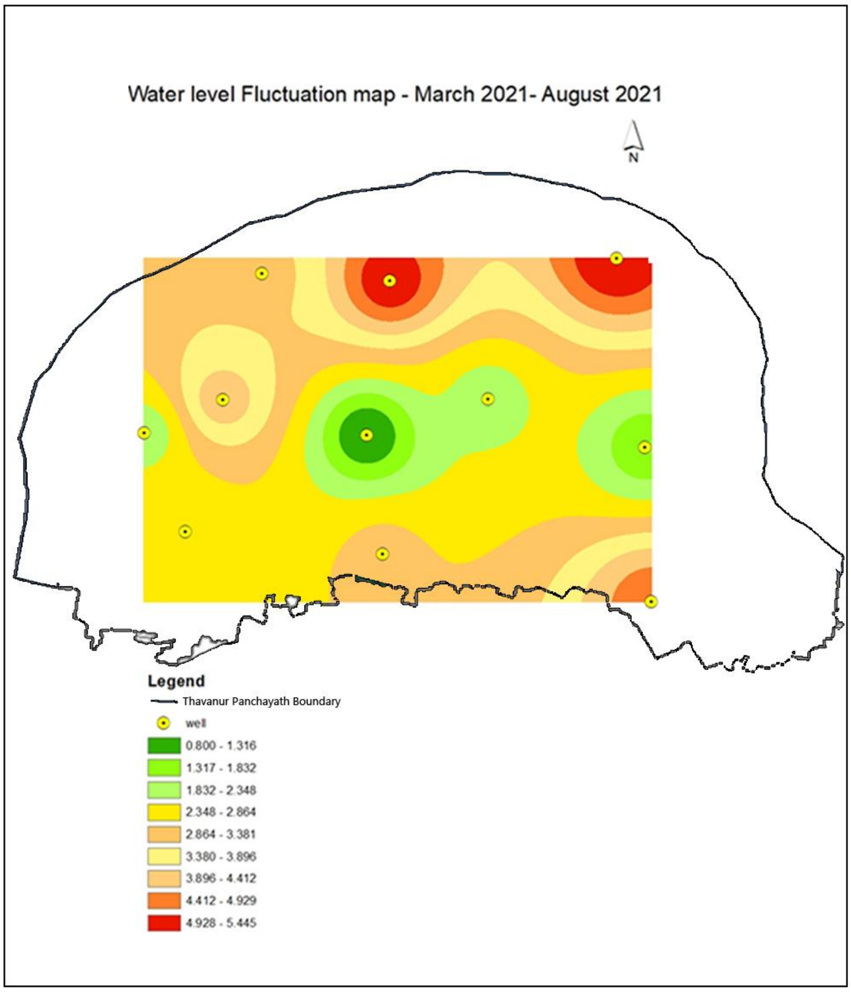
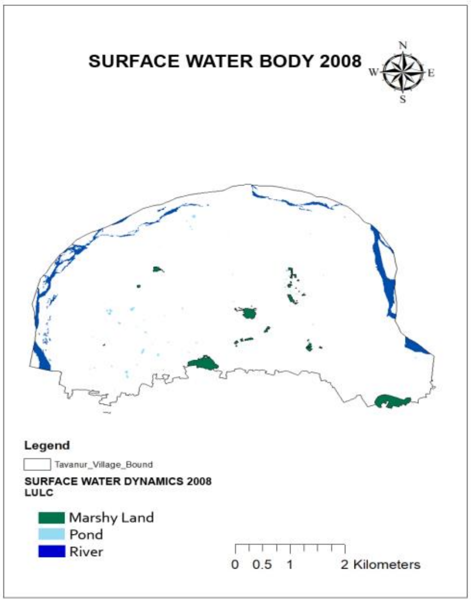
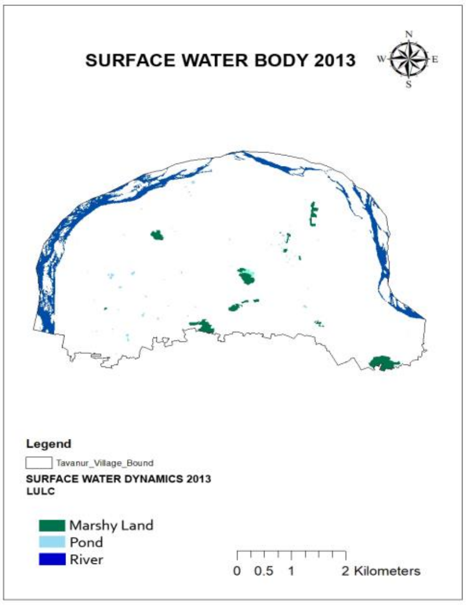


Fig. 4.24 Water table fluctuation map- March 2021 to August 2021

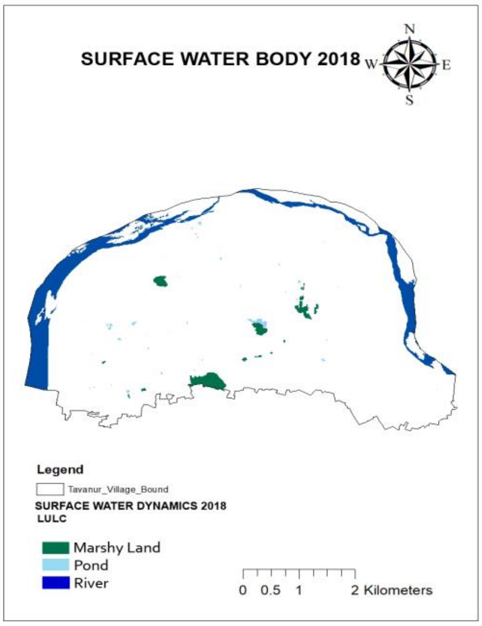
74.3.4 Surface water dynamics

Surface water is one of the prime sources for agricultural production. Surface water dynamics could be studied easily and accurately using remote sensing GIS. Knowing the availability of surface water is very important for planning irrigation and water resources management.





a. 2008 **b. 2013**



c. 2018

Fig. 4.25 Area of surface water body during 2008, 2013 and 2018 (ha)

In this study surface water changes were mapped using satellite imagery of 2008, 2013 and 2018 to know the dynamics of surface water in Thavanur region. The variability of surface water in the area affects the agricultural production in the area.

Marshy lands, ponds and rivers are the major sources of water in Thavanur Grama Panchayath. Surface water map of 2018 showed that there was an increase of total water body in Thavanur Grama Panchayath between 2008 and 2018. The area of river increased from 112.97 ha (2008) to 212.92 ha (2018) whereas marshy land decreased by 9.19 ha during the same period. However, the area of marshyland increased from 31.62 ha to 36.68 ha between 2008 and 2013. But between 2013 and 2018, marshy land decreased by 14.25 ha. The area of ponds increased from 4.61 ha to 6.05 ha between 2008 and 2013 and decreased to 5.89 ha from 2013 to 2018. However, the area of the pond increased from 4.61 to 5.89 between 2008 and 2018. But the area of the river increased from 76.74 ha to 150.14 ha between 2008 and 2013 and 150.14 ha to 184.64 from 2013 to 2018.

In 2008, the marshy land occupied 27.98 % of total surface water area. Between 2013 and 2018, it is decreased from 19.01 % to 12.98 %. The water spread area of pond was 4.08 %, 3.13 %, and 2.68 % respectively during 2008, 2013 and 2018. It also showed a decreasing trend. But in the cas of river, it showed an increasing trend. The river water spread area were 67.92 %, 77.84% and 84.32 % respectively during 2008, 2013 and 2018 and may be due to high rainfall.

The annual rate of change of marshy land between 2008 - 2013, 2013-2018 and 2008-2018 were 0.030, -0.098 and -0.034 respectively. For pond , the annual rate of change was 0.054, -0.005 and 0.025 respectively for the same period. The annual rate of change for river was 0.134, 0.041 and 0.088 respectively for the same period. The detais of surface water change trend and annual rate of change is shown in Table 4.11 and its distribution is shown in Fig. 4.26.

Table 4.11 Surface water change trend and annual rate of change in various types of wetlands

Sl. No	Surface water body	Area - 2008 (ha)	%[a] 2008	Area - 2013 (ha)	%[a] 2013	Area - 2018 (ha)	%[a] 2018	Change (%)[b]			Annual rate (r)[c]		
								2008-2013	2013-2018	2008-2013	2008-2013	2013-2018-	2008-2018
1	Marshy Land	31.62	27.98	36.68	19.01	22.43	12.98	13.79	-63.53	-40.97	0.030	-0.098	-0.034
2	Pond	4.61	4.08	6.05	3.13	5.89	2.68	23.80	-2.71	21.73	0.054	-0.005	0.025
3	River	76.74	67.92	150.10	77.84	184.60	84.32	48.87	18.68	58.42	0.134	0.041	0.088
4	Total	112.97		192.83		212.92							

Nb; [a]: Percentage of each class out of the total area, [b]: Percentage change in the class, [c]: Percentage of annual rate of change in each class
Negative value denotes the decline of area

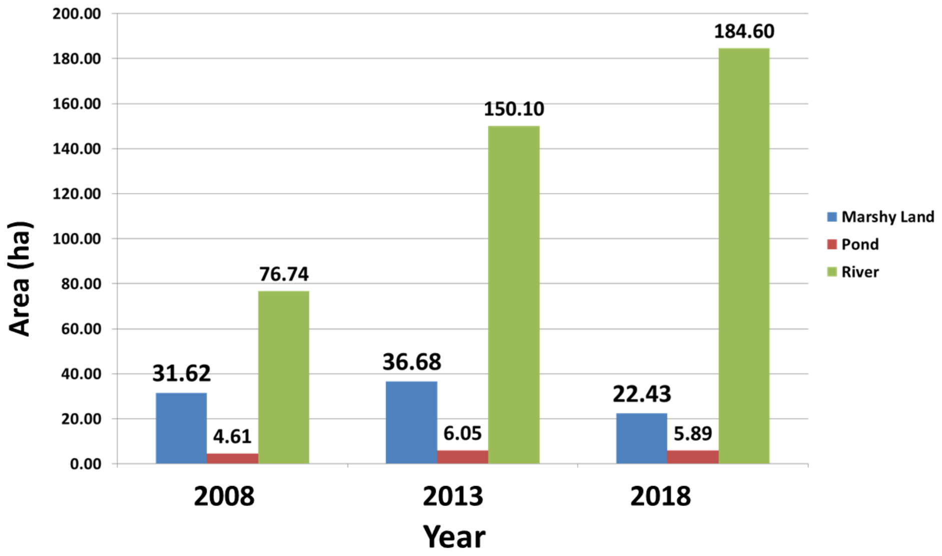


Fig. 4.26 Areas of Surface water body (ha) in different wetlands during 2008, 2013 and 2018

However, the total area of surface water body in Thavanur Grama Panchayath gradually increased from 112.97 ha to 212.96 ha between 2008 and 2018. The area of surface water body increased from 112.97 ha to 192.83 ha between 2008 and 2013. The area of surface water body increased from 192.83 ha (2013) to 212.92 ha (2018). Fig. 4.27 shows the change in area of surface water body during 2008, 2013 and 2018.

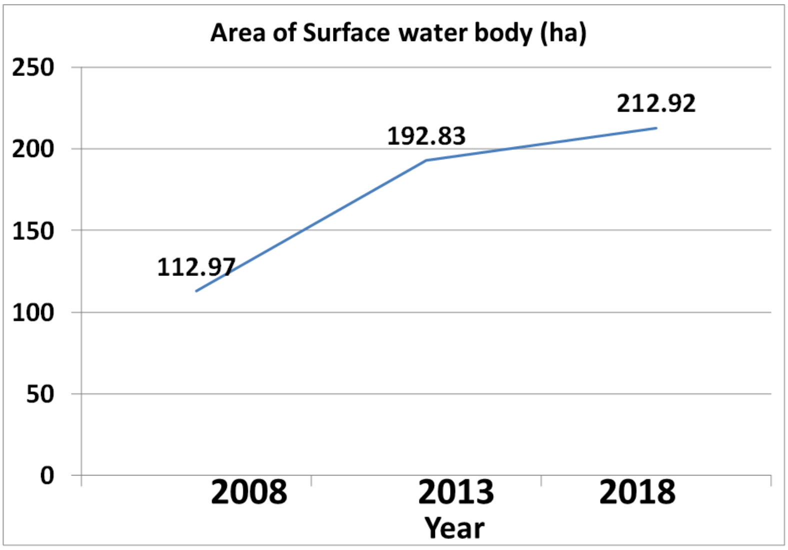


Fig. 4.27 Change in area of surface water body from 2008 to 2018

The physical characteristics of wetland (land use, soil type, geography, vegetation, slope, side) control the climate and the amount & quality of water flowing through it. Any change in the above characteristics affect the quantity and quality of the surface water. Wetlands store carbon in their vegetation and soil instead of releasing it into the atmosphere as carbon dioxide. Thus, wetlands help to moderate global climate conditions. Hence "Sustainable Management of Wetlands ecosystems" is essential to enhance protection of biodiversity in wetlands. This can be achieved through knowledge creation and development of conservation measures for sustainable wetlands management. Hence the study suggested the following different recommendations and suggestions for the preservation and management of wetlands in Thavanur;

- Continuous monitoring of wetlands by Panchayath authority
- Encourage wetland cultivation
- Prevent plant growth other than wetland plants
- Reduce the application of pesticides and fertilizers
- Use compost to improve soil structure and mulch with plant residues to reduce water loss in hottest time of the dry season
- Reduce pollution
- Avoid cultivation in the middle region of wetlands to encourage gulley formation during the flood season to store more water
- Set up a reliable monitoring system that can produce early warning systems on potential alterations of wetlands ecosystems
- Strengthen institutional framework to support wetlands management through cross sectoral consultations on wetlands management issues and priorities
- Construct suitable soil conservation structures in the wetland area to avoid soil erosion

CHAPTER V

SUMMARY AND CONCLUSIONS

The present study entitled “Mapping, inventory and change detection of Wetlands of Thavanur Grama Panchayath” was conducted using RS & GIS. LULC mapping and change dynamics between 2008 and 2018 were done by supervised classification and visual interpretation technique. Accuracy of mapping was checked by confusion matrix (error matrix) and change detection analysis was carried out by PCC method. The wetlands of Thavanur Panchayath during 2008 and 2018 were classified and mapped by visual interpretation technique. Water dynamics of Thavanur Panchayath were studied by analysing depth to water table map, water table contour map, water table fluctuation map and areal extend of surface water body.

The major land use changes during the period 2008 and 2018 were that coconut plantation increased by 70.79 ha, paddy land decreased by 61.62 ha and marshy land decreased by 7.04 ha. The percentage change in land use was found highest for aquaculture (100%) followed by fallow land (56.06%). The annual rate of change of land use was found highest for fallow land (0.074) followed by settlement (0.0321) and paddy converted into coconut (- 0.031). Paddy land experienced the highest transition among the different LULC classes. No appreciable transition was found in the case of river, pond, road and well.

Total area of wetland was estimated 414.17 ha (16.37 %) in 2008 and 409.52 ha (16.87 %) in 2018. Wetland decreased by 4.65 ha between 2008 and 2018. 10 major wetlands were identified and mostly marshy type. Total area of marshy wetland was estimated as 36.58 ha in 2008 (8.83 % of wetland area), 29.54 ha in 2018 (7.21 % of wetland area). There was no aquaculture in 2008 but aqua culture set up was found in 2018 (2.18 ha). The percentage change in wetland during the decade was found maximum for pond and well (-33.18%) followed by marshy land (-23.83%).

Water level in the wetlands were found to affect the water level in well and was very low during March to May and very high during July to August. Kadakassery north , Vallancheri kadavu and Kanjirakutty areas were the most vulnerable areas with a water table fluctuation of 4.92 - 5.44m. Athallur and Kadakassery (centre) regions were the least vulnerable areas with fluctuation in the range of 0.08-1.31m. The water spread areas of surface water body increased from 112.97 ha to 192.83 ha from 2008 to 2013 and 192.83 ha to 212.92 ha from 2013 to 2018. Water dynamics indicated that cultivation is possible in all areas throughout the year except Vallancherikadavu and Thrikanapuram-Kanjirakutty region during March to April.

Hence it is concluded that,

- For mapping wetlands of Thavanur Panchayat, visual interpretation technique was found more accurate than supervised classification in this study.
- The study found that there were conspicuous changes in the land use pattern of Thavanur Panchayat during the last decade and the wetlands were also found slowly disappearing in Thavanur.
- Hence an urgent needs to make aware of the importance and preservation of these wetlands to prevent further degradation.
- The analysis of water dynamics showed that enough water is available for cultivation in the area except during the month of March and April.

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Appendix 1

Depth to water table data of eleven wells between Nov 19, 2020 and Oct 21, 2021

			Depth to water table (m)														
Well No.	Place	Nov-19,2020	Dec-05	Dec-19	Jan-05,2021	Feb-05	Mar-03	Mar-19	Apr-15	Jul-02	Jul-20	Aug-04	Aug-22	Sep-03	Sep-28	Oct-05	Oct-21
1	Cheruthirunnavaya	1.38	1.48	1.63	2.18	2.84	3.69	4.41	4.71	0.86	0.73	0.84	0.8	3.45	0.63	1.32	0.54
2	Kadakassery north	1.53	2.46	3.39	3.98	5.63	6.2	6	7	0.7	0.53	0.72	0.7	4.2	0.5	1.1	0.49
3	Vellancheri kadavu, Vellancheri	2.59	2.96	3.3	4	5.5	6.1	6.12	6	0.69	0.57	0.71	0.62	5.1	0.51	1.5	0.4
4	Ayinikkal	3.07	3.27	3.145	3.505	3.98	4.5	5.35	5.85	2.95	2.88	3	2.8	4.01	2.783	1.8	1.5
5	Kannankulam, Thavanur South	1.61	2.06	2.57	3.27	4.1	4.73	5.35	5.65	0.84	0.35	0.88	0.7	4.03	0.34	0.88	0.4
6	Kadakasseri	0.55	0.505	0.523	0.572	0.778	1.2	1.49	1.51	0.51	0.46	0.61	0.49	1.1	0.44	0.98	0.35
7	Chandanakulam	2.76	2.74	2.92	3.43	3.93	4.9	5.5	5.96	2.03	1.37	5.3	1	3.1	1.44	2.01	1.5
8	Athalur	0.385	0.52	0.783	0.878	1.06	1.56	2.09	2.16	0.3	0.27	0.4	0.28	1.2	0.25	0.95	0.3
9	Anthyalamkudam	0.67	0.75	1.072	1.605	2.22	2.71	3.2	4.05	0.39	0.2	0.42	0.33	2.01	0.25	0.87	0.64
10	Maravancheri kayal, Maravancheri	1.53	1.69	1.91	2.308	2.79	3.5	4.1	4.4	1.06	0.78	1	0.07	2.1	0.71	1.2	0.55
11	Thrikkannapuram-kaanjirakkutty, Kacheriparambu	1.97	2.2	2.82	3.15	3.2	3.9	7	7	1.18	0.09	1.25	0.085	3.1	0.1	0.62	0.42

Appendix 1

Fortnightly Rainfall data collected during Nov - 2020 to Oct - 2021

Months	Rainfall (mm)
Nov1-19, 2020	74
Nov 20-Dec 5	0
Dec 6 – 19	10
Dec 20, 2020 -Jan 5, 2021	3
Jan 6 - Feb 5	57
Feb 6-Mar 3	5
Mar4-19	25
Mar 20- Apr 15	83
Apr 16- May 3	38
May 4- 20	442
May 21 - June 2	163
June 3-20	283
June 21- July 2	71
Jul 3 - 20	344
Jul 21- Aug 4	135

Aug 5 – 22	187
Aug 23 - Sep 3	265.2
Sep 4 – 28	265.7
Sep 29- Oct5	108
Oct 6- 25	448

MAPPING, INVENTORYING AND CHANGE DETECTION OF WETLANDS OF TAVANUR GRAMA PANCHAYATH

By

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PROJECT REPORT

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In

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Faculty of Agricultural Engineering and Technology

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ABSTRACT

A wetland is a distinct ecosystem that is flooded by water (Keddy, 2010). It is distinguished by the characteristic aquatic vegetation (Ramsar convention, 2010). Wetlands Play a critical role in climate change, biodiversity, hydrology and human well-being (Ramsar, 2001). Worldwide, wetlands are in peril now. Wetlands are either being polluted, drained or filled for development also wetlands are being destroyed and LULC pattern altered. Wetland classification maps, inventory and spatio-temporal change information is very important for ecological protection and local government decisions. Use of high resolution remote sensing data along with GIS and GPS is very effective for mapping and change detection of wetlands. No proper documentation on wetland mapping, its inventory, change detection and water dynamics of Tavanur Panchayat. Hence the study was undertaken.

LULC mapping and change dynamics between 2008 and 2018 were done by supervised classification and visual interpretation technique. The accuracy of mapping checked by Confusion matrix (error matrix) and Change detection analysis was carried out by PCC method Wetlands of Tavanur Panchayath in 2008 and 2018 were classified and mapped by visual interpretation technique also the water dynamics of Tavanur Panchayath were studied by analysing Depth to water table, Water table contour map, Water table fluctuation map and areal extend of surface water body.

The percentage change in land use was found highest for aquaculture (100%) followed by fallow land (56.06%) and paddy converted to coconut (-36.15%). Paddy land experienced the highest transition among the different LULC classes. No appreciable transition was found in the case of river, pond, road and well. Thavanur kayal, Ayankalam kayal, Maravancheri kayal, Varo kayal, Ayankalam aqua culture, Mathur aquaculture and some farm ponds are the main wetlands of Tavanur Panchayath. Marshy type is the common type of wetland in Thavanur other than Aquaculture pond and river. Total area of wetland was estimated 414.17 ha (16.37 %) in 2008 and 409.52 ha (16.87 %) in 2018, it decreased by 4.65 ha only.

By studying the water table fluctuation of this Panchayath Kadakassery north , Vallancheri kadavu and Kanjirakutty areas were the most vulnerable areas with a water table fluctuation of 4.92 - 5.44m and Athallur and Kadakassery (centre)regions were less

vulnerable with fluctuation of 0.08-1.31m only. The area of surface water body increased from 112.97 ha to 192.83 ha during 2008-2013 and from 192.83 ha to 212.92 ha during 2013-2018.

For mapping wetlands of Tavanur Panchayat, visual interpretation technique was found more accurate than supervised classification. The study found that there were not much conspicuous changes in the land use pattern of Tavanur Panchayat during the last decade. Wetlands were found slowly disappearing in Tavanur. Hence an urgent need to make aware of the importance and preservation of these wetlands to prevent further degradation. The analysis of water dynamics showed that water is available for cultivation in the area except in the month of March and April