SPATIOTEMPORAL DISTRIBUTION OF AQUATIC INVASIVE PLANTS IN KUTTANAD WETLAND ECOSYSTEM

By

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(2010-20-104)

ACADAMY OF CLIMATE CHANGE EDUCATION AND RESEARCH

VELLANIKKARA, THRISSUR – 680 656

KERALA, INDIA

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THESIS

Submitted in partial fulfillment of the requirement

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Kerala Agricultural University, Thrissur

ACADAMY OF CLIMATE CHANGE EDUCATION AND RESEARCH

VELLANIKKARA, THRISSUR – 680 656

KERALA, INDIA

DECLARATION

I hereby declare that this thesis entitled “**SPATIOTEMPORAL DISTRIBUTION OF AQUATIC INVASIVE PLANTS IN KUTTANAD WETLAND ECOSYSTEM”** is a bonafide record of research done by me during the course of research and that the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar title of any other University or Society.

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CERTIFICATE

Certified that this thesis, entitled **"SPATIOTEMPORAL DISTRIBUTION OF AQUATIC INVASIVE PLANTS IN KUTTANAD WETLAND ECOSYSTEM"** is a record of research work done independently by **Ms. Krishnaveni R.Y (2010-20-104)** 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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SYMBOLS AND ABBREVIATIONS

AC	Alappuzha-Changanassery
ACCER	Academy of Climate Change Education and Research
Afr.	Africa
AIS	Aquatic Invasive Species
AM	Aquatic Macrophytes
Am.	American
Appl.	Applied/ Applications
Aquat.	Aquatic
ArcIMS	Arc Internet Map Server
Assess.	Assessment
ASTER	Advanced Spaceborne Thermal Emission and Refelection Radiometer
Avg	Average
Biol.	Biologia
Bot.	Botany
Bras.	Brasileria
Chem.	Chemistry
CIR	Color Infrared
Conserv.	Conservation

DEM	Digital Elevation Model
Dev.	Development
Distrib.	Distributions
DT	Doubling time
DTM	Digital Terrain Model
Ecol.	Ecology
Eng.	Engineering
Environ.	Environment/ Environmental
EPA	Environmental Protection Agency
et al	and other people
ETM	Enhance Thematic Mapper
FAI	Floating Algal Index
FCC	False Color Composite
FVI	Floating Vegetation Index
Front.	Frontier
Geogr.	Geography
Geoinf.	Geoinformations
Geosci.	Geoscience
GIS	Geographic Information System

GPS	Global Positioning System
GUI	Graphical user Interphase
Ind.	Industrial
IFOV	Instantaneous Field of View
ILWIS	Integrated Land and Water Information System
Int.	International
IRS	Indian Remote Sensing Satellite
ISODATA	Iterative Self Organizing Data Analysis Technique
ITC	International Institute for Aerospace Survey and Earth Sciences
J.	Journal
KCAET	Kelappaji College of Agricultural Engineering and Technology
km	Kilometer
KML	Keyhole markup Language
KVWE	Kuttanad Vembanad Wetland Ecosystem
KWE	Kuttanad Wetland Ecosystem
LDCM	Landsat Data Continuity Mission
LST	Land Surface Temperature
Manag.	Management
mm	Millimeter

MODIS	Moderate Resolution Imaging Spectroradiometer
Monit.	Monitoring
MSL	Mean Sea Level
MSSRF	M.S.Swaminathan Research Foundation
MTMF	Mixture Tuned Matched Filtering
NASA	National Aeronautics and Space Administration
Nat.	Nature
NDVI	Normalized difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near Infrared
nm	nanometer
NWR	National Wildlife Refuge
Observ.	Observations
PCA	Principal Component Analysis
Photo.	Photogrammetric
PHP	Hypertext Preprocessor
Phy.	Physics
RARS	Regional Agricultural Research Station
Res.	Research

Rev.	Revistia
RGR	Relative Growth Rate
RRS	Rice Research Station
SAM	Spectral Angle Mapper
SAV	Submerged Aquatic Vegetation
Sci.	Science/ Scientific
Sens.	Sensing
SMA	Spectral Mixture Analysis
Soc.	Society
Stud.	Studies
Sustain.	Sustainable
SWIR	Short wave Infrared
TIR	Thermal Infrared
TM	Thematic Mapper
Trop.	Tropical
USGS	U.S.Geological Survey

CHAPTER 1

INTRODUCTION

Aquatic macrophytes are aquatic photosynthetic organisms that are large enough to be visible with the naked eyes, grow permanently or periodically submerged below, floating on, or growing up through the water surface. Aquatic macrophytes are significant components of wetlands as they play an important role in contributing food and shelter for animals as well as maintaining the chemistry of the open water (McLaughlin 1974, Frodge *et al.* 1990). These aquatic vascular plants can increase habitat heterogeneity in a wetland. The distribution and its diversity are correlated to the environmental factors of the system (Spence, 1967; Heegaard *et al*., 2001). The term aquatic weed refers to an unscrupulous growth of a plant that influence adverse physical demand or biological effects on a water body with its resultant aesthetic and economic losses (Gupta, 1979).

The invasive alien species are considered as an essential global risk which requires an immediate action, since these are the key pressures on world's biodiversity i.e., altering ecosystem processes and services, decreases native species occurrences, and reduces genetic diversity of ecosystems. Invasive plants are aggressive colonizers that have adjustable habitat requirement and capability to compete with the native species. These immigrants are spreading as a 'biological fire' ranging out of control. They create a serious risk to the sustainable management of the natural ecosystem.

Aquatic weeds primarily affects the aquatic productivity creating issues to fisheries, inland water navigation as well as provides congenial breeding grounds for mosquitoes, pests and vectors of contagious diseases causing health hazards and affects the fragile oxygen balance of water bodies through decay. These weeds interrupt with agricultural operations leading to higher evapotranspiration as they occur in paddy fields and enhances the use of fertilizer considerably. The weed ceases the exchange of gases in-between the atmosphere and water.

Weed threat is an important environmental hazard faced globally. It is seen that even the most developed nations such as USA and UK utilize a huge amount of resources not to eradicate but just to keep the spread of weeds under control. Rest of the countries throughout the world also continue with their efforts to keep the weeds population under control, especially the aquatic and wetland weeds, as they became major environmental nuisance for the water resources (Abbasi *et al.*, 1988).

Ecological impact of aquatic weeds interfere with cultivation of crops, choking of irrigation and navigational canals, loss of biodiversity and ecosystem resilience, decrease in available water in water bodies. Ecological processes may alter as the invading species have distributed in the area. In contrast, where ecological processes are adequately disturbed, the native species can be replaced, rising plant community susceptible to further regeneration and invasion of the invasive plants. When perturbation of ecosystems exceeds the ecological thresholds, ecosystem change can be so profound that controlling the weeds may not re-establish the ecosystem to a desired condition (Hobbs and Humphries, 1995). Ecosystem processes such as stream sedimentation, nutrient cycling, hydrological cycle, and native plant regeneration can be changed by alien plant invasions. The weeds also cause menace to species designated as endangered or threatened by decreasing the quality of natural areas established to protect the habitats demanding to the survival of these desirable species.

The modern scientific tools such as Digital Image Processing (DIP) techniques of Remote Sensing Imageries, GIS (geographic information system) and GNSS (Global Navigation Satellite System) are exceptionally important in the development of databases and to estimate the aquatic weed infestation area in an integrated manner. The availability of synoptic and multispectral data from different satellites like IRS, SPOT, and LANDSAT have helped to gather information on identification and distribution of aquatic invasive plants.

Imageries obtained through Remote sensing satellites and aerial photographs have extensively been used to delineate and monitor wetlands and the aquatic macrophyte distribution across the world especially in western countries (Brown, 1978; Bougucki *et al.*, 1980; Gilmer *et al.*, 1980; Ader and Johnston 1982). It is found that multispectral satellite imageries are useful for mapping aquatic macrophyte communities, even though their limited spatial resolution is not sufficient to delineate at the species level. Remotely sensed data on plant distribution and extent of coverage is important in estimating trends, establishing field reports, determining the efficiency of control measures and for giving early warnings before the problem of weed infestation reaches a critical state. Remote Sensing provides a critical tool for monitoring the status of infestations as well as detecting barriers to waterborne navigation caused by aquatic plants infestations. Frequent large-scale monitoring via remote sensing provides managers with real-time assessment abilities important in a broad range of transportation uses, from routing and scheduling the shipping to vegetation control cost analysis.

In Remote Sensing, each vegetation species has its own specific spectral characteristic called spectral signature that helps in distinguishing them from other types of land cover. Remote sensing imaging devices with high spectral and spatial resolution offer the capability to monitor 'invasive species' spread, thus allowing an assessment of areas of huge infestation and enable timely interventions. While the spectral information of high spectral resolution radiometers is used to delineate between aquatic weed species, the spatial overview given by remote sensing imagery allows monitoring the spread in relation to other environmental aspects. The potential of remote sensing to delineate weed species by the usage of vegetation indices will help in preparing appropriate intended aquatic weed control measures (Shekede *et al.,* 2008).

Climate change is expected to substantially alter biodiversity causing variations in phenology, genetic composition and species ranges and affecting species interactions and ecosystem processes (Walther *et al.,* 2002; Root *et al.*, 2003). The response of invasive species to climate change will have both the economic and ecological implications. Impact of global warming on lakes include an extended growing period at high latitudes, intensified stratification and nutrient loss from surface waters etc. The climate change can affect the weeds both in positive and negative manner. Some of the riparian weeds could be benefited from an increase in intense rainfall events that cause floods leading to spread of weeds such as lippie, willows, and noogoora burr (Xanthium strumarium). Also drought events can be advantageous to them.

Rising temperatures are expected to increase the southward distribution of some northern aquatic weeds as well as reduce some southern weeds in range. Current responses of weeds in northern hemisphere to climate change reveal that more species are expanding than contracting in ranges. Most aquatic weeds have a seasonal cycle (Mitchell and Rogers, 1985), growing immediately as temperature increases ten times, becomes dormant during winter, sometimes suffering frost damage. The high temperature optima suggest that most submerged water plants may benefit from rising temperatures up to a point, but it has to be noted that water buffers temperature (Bowes and Salvucci, 1989), which means that a 2°C rise in air temperature may not translate into a 2°C rise in water temperature. Decline in rainfall can both increase as well as decrease the weed infestation depending on their types.

Climate change leading to increased rainfall or conversely, drought may also shift invasive species ranges and present new opportunities for invasion. Climate change will contribute to selective pressures on species, presumably leading to adaptive genetic changes that may influence species success (Barrett, 2000).

Kuttanad Wetland Ecosystem (KWE) of Kerala faces a major problem of explosive infestation of weeds such as *Eichornnia*, *Salvinia*, *Pistia* and a huge number of other invasive plant species. The problem of weeds proliferation leads to reduction of wetland diversity, increased water borne diseases, reduced fish production, blocking of canals and lakes, and reduced flow rates in rivers. In order to reduce the negative impact of aquatic weeds on the livelihood of people in Kuttanad region, it is necessary to assess its distribution and take out action to reduce its effects. The present work has been undertaken to attain the following objectives

1. To assess the spatio-temporal changes of aquatic macrophytes distributed in the Kuttanad Wetland Ecosystem using Remote Sensing.
2. To study the effect of climatic factors on the variation in the spatio-temporal distribution of aquatic macrophytes in the Kuttanad Wetland Ecosystem.

CHAPTER 2

REVIEW OF LITERATURE

A critical review of the previous research studies related to the spatiotemporal distribution of aquatic invasive plants, especially using the remote sensing and GIS techniques is given here.

2.1 Use of LANDSAT imageries in determination of areal vegetative cover

Weng *et al.* (2004) studied the relevancy of vegetation fraction derived from a spectral mixture model as an alternative indicator of vegetation abundance based on the examination of a Landsat Enhanced Thematic Mapper Plus (ETM+) image of Indianapolis City, in USA. The converted ETM+ image was unmixed into three fraction images (green vegetation, dry soil and shade) with a constrained least-square solution. These fraction images were then used for land cover classification based on a hybrid classification procedure that combined maximum likelihood and decision tree algorithm.

Yuan *et al.* (2007) in studies used Landsat imageries for comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects. Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data were used to estimate the land surface temperature (LST).

Marjanovic *et al.* (2012) studied about urban land cover change of Olomouc city using Landsat images for the period 1986-2009. In this study, a remote sensing approach was used for tracking the variations in land cover units in urbanization and trends in temporal and spatial aspects. Two approaches were used. The first approach dealt with the unsupervised classification whereas the second one was semi-supervised classification, involving the combination of pixel-based and object-based classifiers. Then the resulting land cover maps were quantified for the distribution of urban area unit and its trend through time, acquiring the correlation of spatial and temporal development of the urban area unit and also for urban area unit stability.

2.2 Use of remote sensing and GIS

Remote sensing and geographic information systems (GIS) have raised as important tools in the management and inventory of aquatic macrophyte distributions (Brown, 1978; Bogucki *et al.* 1980; Gilmer *et al*. 1980; Ader and Johnston, 1982; Carter, 1982).

Sawaya *et al.* (2003) in his study has made use the potential of high resolution IKNOS and Quick Bird satellite imagery for mapping and analysis of land and water resources at local scales in Minnesota, which is computed in three different applications. The applications and accuracies assessed in his study include classification of lake water clarity, mapping of urban impervious surface area and aquatic vegetation surveys of emergent and submerging plant groups. Also found that high resolution satellite data has excellent potential to expand satellite remote sensing beyond what has been possible with aerial photography and Landsat data. The principal objective of this study was to examine the capability of high resolution satellite imagery to map and classify aquatic plant groups.

2.3 Importance of wetlands

Howland (1980) studied about the use of multispectral aerial photography for wetland vegetation mapping. In this study vegetation in various wetland types in Vermont was mapped using small scale such as 1:52 000 and 1:104 000 colour and black and white aerial photographs from am NASA mission in September 1972. Nearly all important area was visited and classified into major habitat types from June to September. Then a central representative sample site was taken for selecting 140 signature areas and also visual and large scale photographic estimation made of the dominant species. Tabulation of species composition of the communities and corresponding signature characteristics were done. The study analysed that the colour infrared was best and conventional colour was better than small scale black and white multiband photography which is interpreted by colour enhancement techniques. Actinic infrared is suggested for future use.

Prasad *et al*. (2002) reviewed about conservation of wetlands of India. This review deals with the status and distribution of wetlands and causes and cost of wetland losses. It also provides an overview of the use of Remote Sensing and Geographic Information System (GIS) tools in flood zonation mapping, in monitoring irrigation and cropping patterns, water quality analysis and modelling, examination of changes and in mapping of surface water bodies and wetlands. It also provides a methodology and an action plan for evolving a nationwide network of conservation of wetlands. The major factors of the mentioned methodology involve the use of IRS LISS III sensors for putting up the turbidity, aquatic vegetation and major geo-morphological classes of wetlands. An in-depth fieldwork to generate attribute information on biodiversity and socioeconomic themes is a vital component of the suggested methodology. GIS tools to integrate habitat information with the field information are envisaged to be the final element in evolving a conservation network of wetlands for the entire country.

Ozesmi and Bauer (2002) studied about satellite remote sensing of wetlands. This study identifies classification technique suitable for identifying the wetlands and delineating the from other land cover types. Difficulty in wetland classification is due to its spectral confusion with different types of wetland and other land cover classes. Change detection studies have utilized the advantage of the repeat coverage and archival data availability with remote sensing techniques. Wetland classification could be enhanced by using radar and optical data together.

Everrit *et al.* (2004) studied about usage of aerial colour-infrared photography and Quick Bird satellite imagery for mapping wetland vegetation in two freshwater lakes on the Welder Wildlife Refuge in south Texas. Field spectral assessment done on plant species and vegetation mixtures showed significant variations in visible and near infrared reflectance and could be distinguished in the aerial photos and satellite images. Accuracy evaluation done on computer classified photos of the two lakes had accuracies of 84 per cent and 87 per cent respectively whereas satellite imageries had accuracies of 69 per cent and 76 per cent. The lower accuracies of satellite image classifications were due to their coarser spatial resolution.

Sugumaran *et al.* (2004) studied about using remote sensing data to study wetland dynamics in Iowa. In this study both multispectral and hyperspectral images were tested for wetland classification using different classifiers. Also compared traditional classifiers with an object oriented classification technique to enhance wetland mapping accuracy. In general, the object oriented classifier behaved superior than traditional pixel-based techniques (Maximum likelihood and ISODATA) for the CIR and Landsat imagery and improved than the Spectral Angle Mapper (SAM) technique for the hyperspectral image. Also a Web-based tool was created using ArcIMS (Arc Internet Map Server) to disperse the data developed from this study to stakeholders.

Mathew *et al.* (2009) studied about the floating islands in a tropical wetland of peninsular India. The study has declared that three types of floating islands in Kuttanad Vembanad Wetland Ecosystem (KVWE) have changed considerably in their origin, species composition, development, physical and community structure and sustenance even though having common vegetative factors. Among them, the first one, which formed in deep excavated portions of abandoned rice fields, is created as the biotic climax in the ecological succession. Uninterrupted abandoning of rice fields, stagnation, nutrient enrichment, proliferation of exotic invasive plants and less salinity and tidal flow are the major ecological factors which are found promoting this recent formation of floating islands here indicating the level of the decline of the ecosystem. KVWE is one of the fast changeable wetland spots of the world situated in Kerala, India with well advanced ancient culture, art, economy, and rich biodiversity.

Adam *et al.* (2010) studied about multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation. This study discussed about the application of remote sensing in differentiating and mapping wetland vegetation and determining some of the biochemical and biophysical parameters of wetland vegetation. The study was focused on giving basic information relating to the spectral characteristics of wetland vegetation, determining leaf area index, biomass and water content as well as differentiating wetland vegetation using narrow and broad bands. Remote sensing of wetland vegetation has some challenges such as an in-depth understanding of the factors affecting the interaction between wetland vegetation and electromagnetic radiation in a particular environment, selecting suitable spectral and spatial resolution as well as suitable processing techniques for obtaining spectral information of wetland vegetation.

2.4 Aquatic weed identification through remote sensing

Best *et al.* (1981) studied about spectral reflectance of hydrophytes which will help in the separation and classification of wetlands using remotely sensed images. In this study, an Exotech radiometer was used to estimate the spectral reflectance of 10 plant species during flowering, phonological stages, senescent and early emergent. The reflectance data were assessed to determine significant differences ($P < 0.5$) between species in each of the four spectral regions during each phenological stage. It is observed that eight species had significantly ($P < 0.05$) different reflectance's during the flowering and early seed stage. The results proved that the films sensitive to both visible as well as infrared spectra should enable determination of different species of plants.

Ackleson and Klemas (1987) studied about remote sensing of submerged aquatic vegetation in lower Chesapeake Bay. A comparison and analysis to detect submerged aquatic vegetation (SAV) of Landsat Multispectral Scanner and Thematic Mapper imagery obtained simultaneously over Guinea Marsh and VA. An unsupervised algorithm was used in each image, where the input classification variables are defined as functions of apparent sensor noise. It was found that for a submerged canopy, that is morphologically and optically similar to *Zostera marina* is isolated by masking optically deep water. And for mess dense canopies, the effect of increasing the depth of water is apparent which may result in a classification error.

Mapping of submerged aquatic vegetation using satellite information has concentrated on supervised and unsupervised classifications based on signal changes in the multispectral bands, mainly those in the short visible wavelengths with high water penetration (Ackleson & Klemas, 1987; Lyzenga, 1981; Marshall & Lee, 1994; Maeder *et al.,* 2002; Ferguson & Korfmacher, 1997; Pasqualini *et al.,* 2005).

Anderson (1990) studied about the identification and inventory of aquatic plant communities using remote sensing. In this study, weeds and floating leaved plants of the Swedish lakes Malaren, Hjalmaren, Vattern and Vanern has been mapped during the period 1965- 1975. Since the plant communities have spread in large areas along the lake shores, no other methods rather than aerial photography could be used to map the distribution of plant communities. Infrared films and field survey were used in the study to facilitate interpretation of images. For measuring the biomass of the lakes and noting the future changes, stratified sampling and counting of vegetation along random transects was done. The development of remote sensing techniques made it easy to validate whether data from an airborne multispectral scanner could be used for mapping aquatic vegetation.

Marshall and Lee (1994) studied about mapping aquatic macrophytes through digital image analysis of aerial photographs. The utility of image analysis approach was discussed in this research. Distributional maps of aquatic vegetation are commonly produced from aerial photographs using visual interpretive techniques. Image analysis represents an alternative technique through which this process can be automated. Through this line of study it has been concluded that, spectral signatures are not transportable over space or time. Image analysis technique was assessed to be a productive one to map the emergent vegetation with more aptness and efficiency under the tested conditions.

Venugopal (1998) monitored the effects of biological control of water hyacinths using remotely sensed data in Bangalore. The research has used SPOT multitemporal data to monitor the infestation of water hyacinths in Bangalore, India. The study put forth areas of clearing and new infestation in the fresh water tanks by using Normalized Difference Vegetation Index (NDVI). It is concluded that the host specific weevils can eliminate water hyacinths in large areas but reinfestation relics an invariable problem.

Zhang (1998) did a case study of the Honghu Lake, China on the estimation of biomass of submerged vegetation using Landsat thematic mapper (TM) imagery. This study reports that the wavelength of visible and near infrared bands can be used to measure the biomass of submerged plants in a shallow water body. Also found that the Principal Component Analysis (PCA) of Landsat thematic mapper (TM) bands 1+_4 mapped submerged plants efficiently in shallow lake. The result showed that the first principal component had a close relationship with the submerged plant biomass and the second principal component showed the depth between the canopy of submerged plant and water surface, which manifested the biomass of submerged plants indirectly. Regression analyses were conducted between the biomass and principal components and linear relationship was obtained. This was used to measure the total biomass of submerged vegetation.

Everitt *et al.* (1999) studied about the usage of remote sensing and spatial information technologies to detect and map two aquatic macrophytes. This study described the light reflectance characteristics of water hyacinth (*Eichhornia crassipes*) and hydrilla (*Hydrilla verticillata)* and the application of airborne videography using global positioning system (GPS) and geographic information system (GIS) technologies for distinguishing and mapping the distribution of these two aquatic weeds in waterways of southern Texas. Field reflectance measurements made at several locations showed that water hyacinth generally had higher near-infrared (NIR) reflectance than associated plant species and water. A portion of the Rio Grande River in extreme end of southern Texas was flown with the video system to detect water hyacinth and hydrilla infestations. The GPS coordinates on the CIR video scenes depicted that the water hyacinth and hydrilla infestations were entered into a GIS to map through the distribution of these two noxious weeds in the Rio Grande River at the end of the study.

Steeves *et al.* (1999) studied about aquatic macrophyte mapping using thematic mapper imagery and a geographic information system. A Geographic Information System was used to link field-acquired data on the dispersion of floating, emergent, and submersed aquatic plants in a small number of lakes to the same distributions mapped on simultaneously acquired Thematic Mapper images of the lakes. Those nexus are used to attribute picture elements in the Thematic Mapper images to one of the four vegetation-cover classes: open water (no macrophytes), moderately covered (up to 50 per cent) with floating or emergent aquatic plants, densely covered (51-100 per cent) with floating or emergent aquatic plants, and covered to any extent with submersed aquatic plants. The assignments are then being extended to any lake that appears in the same Thematic Mapper scene.

Everitt *et al.* (2000) studied about light reflectance characteristics and film image relations among three aquatic plant species. This study revealed that the radiometric plant canopy light reflectance measurements at two visible wavelengths and one NIR wavelength varied greatly for American lotus (*Nelumbo lutea),* water hyacinth *(Eichhornia crassipes)* and hydrilla *(Hydrilla verticillata).*The variations in reflectance among the three plant aquatic plants was related to varying foliage colours and plant canopy densities. These three species could be easily differentiated using colour infrared (CIR) aerial photographs. Also the reflectance measured could be related to the CIR film tonal responses of the different species.

Ullah (2000) studied about characterizing spectral signatures for three selected emergent aquatic macrophytes. In this study homogenous and heterogeneous stands of the selected aquatic plants were scanned by using a hyperspectral field radiometer at four times during the growing season. This was performed to characterize the multidate vegetation spectra to test the statistical significance of differences among plants in different spectral regions and at various growth stages and also to estimate the growth stages of maximum distinguishability. It is found that the spectral responses of both individual species and mixed groups were totally different from one other in both the visible and near infrared regions. The results suggested that flowering stage is best to differentiate among species.

Everitt *et al.* (2002) studied about using spatial information technologies to detect and map invasive weeds in Texas riparian zones and waterways. In this study ground reflectance measurements have been used in combination with some of the studies to estimate the spectral characteristics of plants. Infestations were quantified from airborne images by computer analysis and also the accuracy of classified images was assessed. Video imagery integrated with geographic information system and global positioning system was used to map noxious weed infestations.

Jakubauskas *et al.* (2002) studied about the mapping and monitoring of invasive aquatic plant obstructions in navigable waterways using satellite multispectral imagery. Aquatic plant infestations contribute to the commercial and recreational traffic through navigable waterways, block ports and passenger ferry terminals, and exert dangerous damaging pressure upon transportation infrastructure. Timely, accurate information on aquatic plant distribution and density both by public agencies charged with the management of navigable waterways, and by private companies engaged in aquatic plant control efforts are required. Traditional field-based mapping and monitoring of the extent and density of aquatic plant infestation present have certain limitations, including inaccessibility of areas for field sampling, rapid changes in aquatic plant location, extent, and density, and budget constraints on field sampling and monitoring. Remote sensing technology has significant potential to assist managers in detecting infestations that may be an impediment to transportation, prioritizing areas of plant infestation for control efforts, providing detailed information on plant extent and density for estimating control costs, and for assessing the effectiveness of aquatic plant control operations. The project has evaluated the ability of satellite remotely sensed imagery to map water hyacinth and hydrilla in the lower Rio Grande River, Texas.

Vis *et al.* (2003) studied approaches used for determining the distribution and biomass of emergent and submerged aquatic macrophytes over large fluvial lakes. This study has used three empirical models connecting local macrophyte biomass with multiple and single environmental variables to determine the spatial distribution and biomass of aquatic plants. The aquatic plant types distribution such as submerged and emergent were assessed separately by remote sensing. Also commended that the remote sensing techniques were not suited to determine underwater plants distribution, since there are constraints in identifying them in coloured muddled water. They suggest that environmental models in association with GIS can be opted to assess the aquatic vegetation spreading over large areas and also to determine probable variation in macrophyte growth in various environmental conditions.

Everrit *et al.* (2003) studied light reflectance characteristics and remote sensing of water lettuce. The work aimed to assess the conceivability of remote sensing technology to separate water lettuce affected areas in Texas waterways. Also to discover the practicability of usage of colour-infrared (CIR) videography and photography for discriminating infestation by water lettuce in southeast Texas. Field reflectance assessment exhibited that the water lettuce had higher reflectance in visible green than related plant species. In both aerial colour-infrared (CIR) video-graphic and photographic images water lettuce could be identified, such as it had pink to pinkish-white image tonal responses having an overall accuracy of 84 per cent and 86 per cent respectively.

Verma *et al.* (2003) in the study assessed about the changes in water hyacinth coverage of water bodies in northern part of Bangalore city using temporal remote sensing data. Indian Remote Sensing Satellite (IRS) LISS-II and III images of different years/seasons (1988–2001) were used to compare the water-covered areas and the water hyacinth-covered areas of six water bodies (Doddabommasandra, Yelahanka, Jakkur, Rachenahalli, Nagavara and Hebbal) in and around the northern parts of Bangalore city, Karnataka, India, giving the exact areas under hyacinth cover in the study. The finding showed that the area under water-hyacinth cover has increased in then recent times compared with previous years. The study infer that these parameters are important for understanding the issues of management of freshwater resources; and monitoring the temporal changes in water hyacinth would be useful to understand the dynamics of a weed and its ecology as the most successful colonizer.

Albright *et al.* (2004) studied about the abundance and distribution of water hyacinth in Lake Victoria and the Kagera river basin during 1989-2001. Water hyacinth (*Eichhornia crassipes*) is an invasive aquatic macrophyte associated with major negative economic and ecological impacts to the Lake Victoria region since the plant's establishment in the 1980s. To assist the management and mitigation of the above problem, Clean Lakes, Inc. and the U.S. Geological Survey's EROS Data Centre have acquired and analysed remotely sensed imagery, conducted field work, and compiled reports to document the abundance and distribution of this plant, from its establishment to then. Remotely sensed imagery was processed and analysed to identify areas inhabited by water hyacinth. Maps were produced and coverage was quantified for each country, as well as for numerous gulfs and bays. Results confirmed the severity of the water infestation – especially in the northern portions of the lake. A maximum lake-wide coverage of approximately 20,000 ha was attained in late 1998. Following that, a combination of factors, including management practices and probable changes in environmental conditions, contributed to a major decline in water hyacinth in the most affected portions of the lake, found in the study. The study concluded with the suggestion that non-remotely sensed estimates of water hyacinth coverage compiled from pre-existing published reports are highly inconsistent and should be used only with caution.

Werstak (2004) studied on spectral separation of submerged aquatic vegetation using two-meter multispectral digital imagery. This study investigates the ability of two-meter airborne digital multispectral imagery for the spectral delineation of five species of submersed aquatic vegetation (SAV) sampled within the Bear Lake NWR (National Wildlife Refuge) in Idaho. Using a Kruskal-Wallis single factor, sampled brightness values for the SAV types were analysed for variations. It was found that the variations in ranked means were statistically significant. Multiple comparisons tests were done to evaluate which SAV types were contrasts. The Tukey-Kramer tests for the green, red, and near-infrared bands confirmed that the brightness values for Chara vulgaris are different than those of Hippuris vulgaris. The Tukey-Kramer tests were used to four band ratios such as the Simple Ratio (near-infrared/red), NDVI or Normalized Difference Vegetation Index (near-infrared – red/near-infrared + red), near-infrared/green ratio, and red/green ratio. Test outcomes for the Simple Ratio, NDVI exhibited that there were no important variations occurred between any of the SAV types. Outcomes of the red/green ratio showed that statistically significant differences existed.

Joshi *et al.* (2004) studied about the use of remote sensing and GIS applications for mapping and spatial modelling of invasive species. This paper reflects the application of remote sensing and GIS in mapping the actual and predicting the potential dispersion of invasive species. RS techniques are applied in it and layout of the potential of new RS techniques. The mapping of these invaders delivered little attention so far. The paper has reviewed various possibilities to map non-canopy invader species. Also reviewed the techniques used to map the risk of invasion for areas not invaded so far.

Idawo and Laneve (2004) studied about hyperspectral analysis of multispectral ETM+ data: SMA using spectral field measurements in mapping of emergent macrophytes. This study revealed that acquiring quantitative information about macrophytes using remote sensing continues to prove difficult, because most of the healthy plants show the absorption bands that are alike. Quantifying such minute variations in plants in a predictable way is still a challenge with large amount of species. In this study the main challenge was the limited nature of spectrometric measurements on vegetation and their relatively small quantities. Multispectral Landsat Enhanced Thematic Mapper (ETM+) imagery was used in identifying the possibility for mapping and quantification of macrophytes in a water hyacinth infested area. The image was analysed using hyperspectral processing techniques. Natural resource managers can make use of information about macrophyte weed distribution in weed management programs.

Mironga (2004) studied about the use of geographic information systems (GIS) and remote sensing in the management of shallow tropical lakes. This paper reflects applications of remote sensing and geographic information systems (GIS) techniques to the assessment of tropical waters. Whereas those applications are discussed in the context of specific management objectives and sensors used. The requirement to monitor the spreading patterns of weeds in the tropical waters, land-use changes in the areas surrounding them, change detection, loss of wetlands, efficiency and nutrient status, in order to set up trends and subsequently develop predictive models to facilitate effective management, is highlighted. GIS capability can be used to connect ecological information with the management decisions of these waters. Remote sensing provides useful information in the form of satellite images and aerial photographs that can be incorporated and analysed in a GIS to provide helpful spatial information and temporal changes over large geographic areas affecting the structure and function of tropical waters.

Glenn *et al.* (2005) studied about hyperspectral data processing for repeat detection of small infestations of leafy spurge. This study discussed about the potential of high resolution hyperspectral imagery to give high quality data and methods to identify low and small percent canopy cover development of leafy spruge. Hyperspectral data of the study area during the years 2002 and 2003 were collected and the images were classified with the Mixture Tuned Matched Filtering (MTMF) algorithm. The study assumes that georegistration errors, training endmember selection, small variations in leafy spurge reflectance, field validation and image processing biases between years affect multidate identification limits. It is found that even though the hyperspectral imagery is costly; its capabilities to distinguish economically damaging invasive species outweigh the image and processing costs. In the study it is concluded that high spectral resolution is required to distinguish low percent cover infestations of leafy spurge as high spatial resolution images help in identifying spatially less infestations.

Ouma et al. (2005) studied about the dynamism and abundance of water hyacinth in the Winam Gulf of lake Victoria: evidence from remote sensing and seasonal climate data. The result showed a straight relationship between the hyacinth density and geographic distribution as well as seasonal-climatic patterns. Moderate rainfall, Gentle currents and stable temperatures proliferated the fast sprouting and aggregation of the water hyacinth mats specifically in the sheltered bays. It is seen that high temperatures and high rainfall do not support the spread of the invasive plant; hence fragmentation and movability as the power of the currents rise in magnitude.

Lass *et al*. (2005) reviewed about remote sensing of invasive plants and example of the early identification of spotted knapweed (*Centaurea maculosa*) and babysbreath (*Gypsophila paniculata*) with a hyperspectral sensor. This report gives an idea about the technology and algorithms to be used to detect weeds such as knapweed and babysbreath using hyperspectral sensor. It is recommended that the ground surveys done should be combined with the classified images using remotely sensed data to identity the areal extent of weeds since spread of weeds can occur before the discovery or treatment of an infestation. The classification was done using spectral angle mapper (SAM) algorithm at 1, 2,3,4,5 and 10° angles. In this study hyperspectral imageries of 2m spatial resolution and 400 to 935nm spectral resolution with 12nm increments were utilised to identify the weeds. Ground validation of the classified images showed that 97 per cent and 57 per cent of known babysbreath and known spotted knapweed infestations were observed through the usage of the hyperspectral images and the SAM algorithm.

Schweizer *et al.* (2005) studied about the remote sensing characterization of benthic habitats and submerged vegetation biomass in Los Roques Archipelago National Park, Venezuela. In this study, the visible bands of Thematic Mapper (TM) sensor on board Landsat7 satellite were used for supervised classification of submerged aquatic plants. The TM visible bands were subjected to log transformation and were linearly combined to shorten the depth-dependent variance in the bottom reflectance signal. The report shows that eight bottom types such as sand, dispersed communities over sand (shallow and deep), dispersed seagrass meadows over sand, mixed vegetation over muddy bottom, lagoons, reef communities and dense seagrass could be delineated. Combination of TM bands 2 and 3 accounted for 64 per cent of variability of submerged plant biomass.

Hosny (2005) studied on the application of new technologies in aquatic weeds management in Khors el-Alaky and Toshka, Nasser Lake, Egypt. In this study, Landsat 7 TM satellite imageries covering the areas of Khor El-Alaky and Khor Toska were delineated using band ratio technique and the results were compared with those of supervised and clustered classification methods. The satellite imageries with global positioning system (GPS) with the help of Geographic information system (GIS) are important tools in identifying and mapping aquatic vegetation. It is reported that accurate maps of the aquatic invasive plants distribution in large open areas and complex shoreline (Khors) are necessary for an efficient weed control program. The maps produced in the study showed that the maximum amount of aquatic weed infestation occurs mainly during the period of March-April and declines during the September-November period. It is concluded that band ratio technique has proved to be an efficient method to distinguish the ditch bank weeds from the submerged weeds.

Cavalli *et al.* (2007) studied on the remote sensing techniques for macrophytes and water compound concentrations mapping. The study aims to analyse the benefit of remote sensing techniques applications in environmental management of inland waters. During the field survey the reflectance spectra of the aquatic species available in the lake have been collected. These spectra have been used, in the assessment of the water hyacinth spread using classification techniques to ETM images. This method allowed the distinction of the different weed species and the measurement of hyacinth areas. The correlation be-tween vegetation and water compound concentration maps has highlighted that hyacinth growth is related to water inflow with a high concentration of sediments into the rivers and has allowed defining areas at risk of enormous growing of new macrophytes populations.

Kateregga and Sterner (2007) studied indicators for an invasive species: water hyacinths in Lake Victoria. This paper created and discussed a measure of water hyacinth abundance in Lake Victoria. Water hyacinths have dramatic outcomes on other affairs such as fisheries. Though, to considerate their spread and effects is hampered by the lack of reliable information. Available data on mat coverage was compiled from a numerous scattered reports and used to fit hyacinth growth curves for the three sections of Lake Victoria. It was analysed that estimates of the annual rates of infestation are derived and were found to be appreciably correlated with effect estimates based on hyacinth-attributed generation outages in hydroelectric construction. Outages follow an alike pattern but decline faster.

Everitt *et al.* (2007) studied about mapping Wild Taro with colour-infrared aerial photography and image processing. In this study field reflectance measurements demonstrated that wild taro had significantly different (P = 0.05) visible and near-infrared reflectance from related plant species. It is found that wild taro could be delineated on colour-infrared photographs as it has a bright image response. Supervised image classification was done and found that the accuracy estimation performed on classification maps of photographs from three sites had user's and producer's accuracies ranging from 83.3 per cent to 100 per cent.

Everitt *et al.* (2007) studied about using spatial information technologies for detecting and mapping Eurasian watermilfoil *(Myriophyllum spicatum)*. In this study airborne videography was combined with geographic information system (GIS) and global positioning system (GPS) technologies for mapping the spread of Eurasian watermilfoil. Estimation of field reflectance of Eurasian watermilfoil showed that it could be spectrally separated from other associated plant species in either the visible red, visible green or near infrared regions of the electromagnetic spectrum. It is found that the visible reflectance of Eurasian watermilfoil and water are similar at depths greater than 5cm below the water surface. Surfaced Eurasian watermilfoil could be separated on colour infrared aerial videography and photography as it had a faint pink or greyish-pink image response.

Everitt and Yang (2007) studied about the usage of Quick bird satellite imagery to distinguish two aquatic weeds in south Texas. The study was done to distinguish between water hyacinth (*Eichhornia crassipes*) and water lettuce (*Pistia stratiotes*) using satellite images. From the images three subsets were extracted to use as study areas. It is observed that water hyacinth occurred in all the three subsets whereas water lettuce occurred in one subset only. Both supervised and unsupervised classification was done on the imagery. The results pinpointed that Quick bird satellite images combined with image analysis techniques can be used for identifying water hyacinth and water lettuce infestations.

Hestir *et al.* (2008) studied about the identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. This focus on the estuaries considering it as one of the most invaded ecosystems on Earth, where such invasions have led in part, to the formation of a massive restoration effort in California's Sacramento–San Joaquin River Delta. The doctrine of early detection and rapid response to invasions has been adopted by land and water resource managers, and remote sensing is chosen as the logical tool for identification and detection. However meteorological, physical, and biological heterogeneity in the mentioned large system present unique challenges to successfully detecting invasive weeds. Hence, they present three hyper spectral case studies which illustrate the challenges, and potential solutions, to map invasive weeds in wetland ecosystems such as Perennial pepper weed was mapped over one portion of the Delta using a logistic regression model to predict weed occurrence, Water hyacinth and submerged aquatic vegetation (SAV), firstly composed of Brazilian waterweed, were mapped over the entire Delta using a binary decision tree that incorporated spectral mixture analysis (SMA), spectral angle mapping (SAM), band indexes, and continuum removal products. The study was in the context of providing guidelines for future remote sensing studies of aquatic systems.

Hyun *et al.* (2008) studied about the test of multispectral vegetation index for floating and canopy forming submerged vegetation. This has used spectral characteristics to develop vegetation indices, including Normalized Difference Vegetation Index (NDVI). However, the NIR absorption by water and light scattering from suspended particles reduces the practical application of such indices in aquatic vegetation studies, especially meant for the Submerged Aquatic Vegetation (SAV) that grows below water surface. An experimental test has been conducted to know if NDVI can be used to show canopies of aquatic plants in shallow waters. The results suggest the conventional NDVI can be used to depict SAV canopies at water surface; is not a good indicator for SAV that is adapted to live underwater or other aquatic plants that are submerged during flooding even at shallow waters (0.3 m) and (3) the index values can significantly improve if information on spectral reflectance attenuation caused by water volume increases is collected simultaneously through ground-trusting and integrated.

Everitt *et al.* (2008) studied mapping of Giant Salvinia using Satellite imagery and image analysis. In this study, Quick bird satellite imagery was used. Normal colour, colour-infrared and four band composite images were studied. All the three composite images gave excellent result in delineating giant salvinia. Also the accuracy assessment data can be comparable to that obtained from higher resolution colour infrared photography of giant salvinia. Unsupervised image classification was done and its accuracy ranges from 87.8 per cent to 93.5 per cent. The capability of satellite images to delineate giant salvinia is usable to wetland managers for mapping infestations over inaccessible and large areas. Differences in image tone of giant salvinia are because of the chemical emulsions of the aerial photographic film versus the electronic coding of the satellite images, as well as variations in plant phenology.

Derong *et al.* (2008) studied about distribution patterns and changes of aquatic plant communities in Napahai wetland in north-western Yunnan Plateau, China. In this study the distribution patterns of aquatic plants were investigated utilizing the GPS technology and community research methods for plant communities. It was observed that the types and the numbers of aquatic plant communities have changed i.e. the numbers of plant communities have raised from nine to twelve with the inclusion of two new emergent and one new floating leaved plant communities. The changes in the spread of plant communities show the natural responses to the variation of the wetland ecological environment. Also indicated that human disturbances have led to an inbound movement of the wetland shoreline, reduction in the water quality and wetland habitat.

Abhilash *et al.* (2008) studied about the Eco distribution mapping of invasive weed *Limnocharis flava* Buchenau using Geographical information system. This paper describes the dispersal and autecology of an exotic weed '*Limnocharis flava* Buchenau' (an emergent aquatic weed of 'Limnocharitaceae') in Kumarakom Grama Panchayat. The mapping of *L. flava* in the whole study area has been carried out using Geographical Information System (Arc-info 8.3 version). The study showed that nutrients, water depth and land use patterns were the major factors important for the growth and proliferation of this exotic weed. The schemes for controlling *L. flava* invasion are discussed in detail.

Shekede *et al.* (2008) analysed the feasibility of mapping the spatial extent and abundance of aquatic weeds in Lake Chivero, Zimbabwe using Landsat images. Such information are important for understanding the evolution of weed invasion, its propagation rates, to identify affected areas and relating weed abundance to probable variations in environmental conditions and human actions including management practices within the lake and its catchment. These observations also help in estimating the effectiveness of the control measures and management actions opted. Also found out that the growth of aquatic weeds will continue unless nutrient loadings to the lake are reduced. He concluded that remote sensing is an invaluable tool for the identification of invasions, assessment of infestation levels, monitoring rate of spread and determining the efficiency of weed mitigation measures. The vegetation index, Normalized Difference Vegetation Index (NDVI) was used for determining the spatial extent of aquatic weeds and weed biomass.

Silva *et al.* (2008) examined the importance of remote sensing in mapping aquatic macrophytes. Aquatic vegetation is essential element of wetland and coastal ecosystem. He suggested that remote sensing is a very powerful tool helping in comprehensive determining and monitoring of aquatic plants where surveys are interrupted by logistics problems. Several vegetation components can be assessed from spectral reflectance measurements, like biomass, species composition, plant physiological parameters, and vegetation structure. However, usage of these methods needs a proper understanding of the physical processes behind the interaction between electromagnetic radiation and vegetation.

Ghioca-Robrech (2008) studied the use of multiseason Quick bird imagery for mapping invasive species in a lake Erie coastal marsh. The image used in the study contains four layers, corresponding to blue, green, red, and near-infrared (NIR) wavelengths. The area of interest mask was constructed excluding the non-wetland areas and the lake ward side of the mask was determined digitally by calculating the Normalized Vegetation Index (NDVI). The usage of multiseason imagery was expected to help in determination of other non-persistent emergents, but some constraints arose due to confusion with areas where anthropogenic action had artificially eliminated overlying plant material. Multiseason Quick bird imagery is accurate for delineating certain wetland plant species, but should be used with caution in highly managed areas where vegetation variations may reflect human alterations rather than phenological change.

Akashesh *et al.* (2008) studied about the methods used for detailed mapping of riparian vegetation in the middle Rio Grande River using high resolution multi-spectral airborne remote sensing images. In this study, airborne multi-spectral digital images were taken at 0.5m spatial resolution over the riparian corridor of the Middle Rio Grande River in July 2011. Then the imageries collected were corrected for lens radial distortions, lens vignetting effects, mosaicked, rectified to a base map, calibrated in terms of reflectance and were classified. The accuracy of the classification done was analysed using ground truth data assessed though independent ground truth data and comprehensive field campaigns. Also a longitudinal vegetation distribution analysis was done to observe the changes in vegetation and water surface areas along the river. This indicated an increase in the aquatic invasive vegetation mainly in the downstream direction because of decrease in water surface areas and flow. The use of high resolution airborne remote sensing data proved to be an effective tool for mapping riparian vegetation which is very difficult to map using satellite images because of its high diversity, complexity and spatial variability occurring at finer scales.

Yichun *et al.* (2008) reviewed about use of remote sensing imagery to map and classify vegetation cover. A vegetation classification was first done either at a species or community level for classifying and mapping vegetation cover. Then the correlations of the vegetation types in the images within the classification system were determined. Then the spectral classes were converted to vegetation types using image processing techniques. The determination of vegetation cover through the use of hyperspectral images and image fusion was also examined.

Tellez *et al.* (2008) studied about the water hyacinth, *Eichhornia crassipes*: an invasive plant in the Gudiana river basin. The recent invasion of water hyacinth, *Eichhornia crassipes* in the Guadiana River Basin (Spain) is described and the distribution of this Amazonian floating plant is examined from a geo-botanical and chorological insight. Geo-referenced locations of invasion in Spain and Portugal are presented in this and the relative growth rate (RGR) and doubling time (DT) indexes defined by Gopal (1987) were assessed. The sexual reproductive cycles were set in order to evaluate the invasive capacity at these latitudes. Predictive models of the plant's potential distribution in the Guadiana River were constructed based on expert knowledge and using a Geographic Information System, on the basis of the water's physico-chemical variables.

Cavalli *et al.* (2009) studied about the accuracy of remote sensing water observation for supporting Lake Victoria weed management. This study aims to determine the ability of remote sensing tool for empowering the management of water body resources and to provide an inexpensive way to collect weed infestation distribution on a large area and the optical parameter linked to the water body. Remotely sensed satellite images combined with ancillary ground truth data were used to produce land cover maps and water compound maps through classification techniques and radiative transfer models respectively. It is suggested that if the results are provided with definite time interval, it could be used to identify the preconditions for the occurrence of hazardous events like macrophyte proliferations. Also helps to create an up-to-date decision support system devoted to environment and resource management.

Farghaly *et al.* (2011) studied about the differentiation and extend of aquatic weeds over Lake Kyoga, Uganda by multiple remote sensing technologies. The thick weed mats make fishing mere possible and disrupt water transport, irrigation systems and hydroelectric schemes and thereby result in tremendous environmental and social damage. When such conditions are prevailing, these weeds can be controlled and even utilized in many ways according to their types according to this venture. Remotely sensed imagery as Landsat images covering the period from 1974 till 2009, ASTER images for 2008 and 2009 and TerraSAR-X radar images was processed and analysed in order to identify areas occupied by aquatic weeds and for taxa specification within Lake Kwania and Lake Kyoga as a pilot area primarily. Consequently after the study, it was recommended at the end of the study, to use TerraSAR-X images for monitoring the whole area of Lake Kyoga for better management of aquatic weeds problems within the area.

Namakando (2009) studied about the procedure for monitoring the spread of water hyacinth using remote sensing and geographic information systems (GIS) in Lake Kariba. The objective of this study was to develop a procedure for monitoring the extend of water hyacinth on Lake Kariba using Remote Sensing and Geographic information System. A procedure for monitoring the spread of water hyacinth on Lake Kariba was developed considering its episode, the use of

Global Positioning System and satellite imagery. The extent of water hyacinth on Lake Kariba was estimated at 572 ha in 1995 (Spot), 1422 ha in 1999 (Spot), 455ha in 2001 (Landsat) and not detected by Landsat satellite images captured in 2004 and 2005. The weed spread was estimated to be 50 ha in January 2004, 10ha in December 2005 and 20ha in July 2007 through boat surveys. Totally, water hyacinth spread from 682ha in 1992 to 4510ha in 1998 after which it condensed to very low levels not warranting the use of satellite imagery in 2007.

Fusilli *et al.* (2010) has done time series analysis of satellite multi-sensors imagery to study the recursive abnormal growth of floating macrophyte in the Lake Victoria (central Africa). The consolidated usage of satellite resources granted the evaluation of the temporal variations of physical parameters that were used to i) sample the spatio-temporal spread of the whole floating plants including both weeds and native vegetation ii) estimate the seasonal reoccurrence of the abnormal weeds grow, as well as, their possible association with the hydrological regimes of the rivers. This paper depicts how the 2000 - 2009 MODIS images time series, were assessed to derive the map of floating vegetation of the test area, identify the areas more affected by aquatic vegetation infestations and to delineate the different vegetation species such as weeds from the floating vegetation according to the spectral and spatial resolution of the sensor used (i.e. LANDSAT, ASTER, CHRIS). It was done mainly by using the results of a field campaign completed in the past along the Kenyan coastal areas concerned to prescribe a data base of spectral signatures of the main species. The results whenever correlated to ancillary hydrological information such as the amount of rain, they have shown that the synergy of MODIS images time series with lower temporal frequency time series image is an important tool to evaluate the lake Victoria ecosystem and to check the floating plants extension and also to foresee the ability to set up a model for the abnormal vegetation growing.

Fletcher *et al.* (2010) studied about the use of airborne multispectral digital video to differentiate giant salvinia from other features in northeast Texas. In this study five band multispectral digital video imagery was subjected to an unsupervised computer analysis to acquire a thematic map of the affected area. It is found that user's and producer's accuracies of the giant salvinia class were 74.6 per cent and 87.2 per cent respectively. The study indicated that airborne multispectral digital videography has ability for differentiating species. The discovery of this research support further inquiry of multispectral digital video and true multispectral digital imaging systems for mapping this aquatic weed and other weeds infesting aquatic systems.

Schmidt *et al.* (2010) studied aquatic weed distribution in a river system using SPOT 5 satellite imagery. The main aim of the study was to derive an effective method using remote sensing techniques to monitor and map the variations of dense aquatic weeds occurred in a river system and to obtain an apt spatial scale for the same. They have made use of a multispectral image data with 10 m spatial resolution and a pan-sharpened multispectral image data with 2.5 m spatial resolution for the study. The technique adopted includes radiometric and geometric corrections, along with spectral angle mapper techniques and linear spectral unmixing. This process could be widely adopted for all waterways and offers the possibility for early identification of aquatic floating weeds. The study suggested that remote sensing is an invaluable tool in assessing the distribution of aquatic weeds and their earlier detection. The research suggested that the aquatic plant distribution has increased by a factor of 2 to 3 during the 12 month period in the test area. Also found that the infested area in 2007 was between 13.6 per cent and 15.9 per cent and in the year 2006 was only between 6.2 per cent and 6.8 per cent i.e., almost doubled the infestation in the study area.

Mathew (2010) focused to study on the taxonomy and ecology of aquatic macrophytes of Kuttanad wetland ecosystem, which was conducted during 2004-2007 period. Taxonomic publication was used for the collection and identification. It was found that the long-term ecological succession resulted in the formation of permanent floating islands in all the habitat systems. Spatio-temporal distribution mapping divulged that cultivated rice occupied the maximum extent. There was considerable rise in the area inhabited by aquatic macrophytes over the years. Steady increase in the area occupied by *E. crassipes* and *Cabombo caroliniana* unfold the invasion of these exotics. Temporal pattern in agreement with the seasonal cycling was noted during this field survey.

Yang and Everitt (2010) studied about mapping three invasive weeds using airborne hyperspectral imagery. In this study three case studies were done on the usage of hyperspectral remote sensing for mapping invasive weeds in both the terrestrial and environment habitats. In addition to the standard classification methods, the techniques such as mixture tuned matched filtering (MTMF) and spectral unmixing technique was used for classification.

He *et al.* (2011) studied the benefits of hyperspectral remote sensing for tracking plant invasions. The report is about what hyper-spectral remote sensing can offer for invasion Ecologists and is reflected recent progress made in plant invasion research using hyper-spectral remote sensing. The capability of hyper-spectral remote sensing is reported i.e. mapping, detecting and predicting the spatial distribution of invasive species. An array of topics consisting the trade-off between spectral and spatial resolutions, classification accuracy, the advantages of utilizing time series to fuse phenology in mapping species spread, the ability of physiological and biochemical properties in hyperspectral spectral reflectance for capturing ecosystem variations caused by invasions, and the ability of hyperspectral data as a significant input for quantitative models created for estimating the future distribution of invasive species are considered. It is concluded with some recommendations that the hyperspectral remote sensing can efficiently give a baseline of invasive species spread for future monitoring as well as control efforts. In addition, data on the spatial distribution of invasive species can help land managers to create long-term constructive conservation methods for maintaining and protecting natural ecosystems.

Everitt *et al.* (2011) studied about of use of hyperspectral insitu data to distinguish nine aquatic plants. In this study, two method such as multiple comparisons range tests and stepwise discriminant analysis were used to estimate the optimum bands for delineating among different aquatic species. The study was mainly conducted for May, July and August months. The result of multiple comparison range test for May month showed that delineation among species occurs at 795-865 nm wavelength bands in the near infrared region (NIR) where up to six aquatic species could be separated. For July delineation occurs at red near infrared region i.e., at 715 nm. In august, optimum bands for separation in occurs at green (525-595 nm), red (605-635 nm) and red NIR edge (695-705). The stepwise discriminant analysis found out 11 bands, 15 bands and 13 bands in the blue, green, red-NIR and NIR regions which are necessary to delineate among aquatic species in May, July and August months respectively.

Hyun *et al.* (2012) analysed about remote sensing of submerged aquatic plants. This study reported that the remote sensing tool can't be used to map benthic or submerged aquatic vegetation (SAV) due to various reasons such as variability in water depth and bottom albedo, atmospheric interferences, water column attenuation by absorption and scattering. Accordingly, rectification for the atmospheric and overlying water column side effects is important to fetch any quantitative knowledge for SAV from airborne images and satellites, especially while usage of hyperspectral data. Due to the lack of data on insitu water columns optical properties and water depths misclassification of SAV occurs very often. The radiative transfer models mostly work in relatively clear aquatic environments to map benthic features. The varying water depthscoloured dissolved organic matter and high amounts of suspended particles in shallow littoral zones make it even more difficult to map underwater vegetation using remotely sensed data. Also refined a water depth correction algorithm and it was calibrated and validated using experimental and field data developed conceptually. The outcome of the overlying water column on upwelling hyperspectral signals were shaped by empirically distinguishing the energy scattered and absorbed by the water using data gathered through a sequence of controlled practices. The empirically driven algorithm restored the vegetation signals, mainly in the NIR region. Use of the water reformed airborne data enhanced the NDVI values for the SAV pixels and also increased the seagrass classification accuracy.

Blanco *et al.* (2012) studied about the spectral signatures of hydrilla from a tank and field setting. The invasion of hydrilla in many waterways has caused vital problems resulting in high maintenance costs for eradicating this invasive aquatic weed. Present identification methods assigned for detecting hydrilla invasions that of aerial photography and videos are difficult, costly, and time consuming. Remote sensing has been used for assessing wetlands and other aquatic vegetation, but very little information is accessible for detecting hydrilla invasions in coastal estuaries and other water bodies. Thus the study aimed to construct a library of spectral signatures for identifying and classifying hydrilla invasions. The study concludes with the findings that spectral signatures of hydrilla observed in the tank and the field had similar characteristics with low reflectance in visible region of the spectrum from 400 to 700 nm, but high in the NIR region from 700 to 900 nm.

Fusilli *et al.* (2013) assessed about the abnormal growth of floating macrophytes in Winam Gulf (Kenya) by using MODIS imagery time series. The study aimed to assess the capacity of time-series of MODIS imagery to give information relevant for improving the understanding of temporal cycles demonstrated by the abnormal spread of the floating macrophytes in order to improve management and monitoring action of Late Victoria water resources. It was concluded that a consistent temporal relation exist between the water constituent concentrations within the Winam Gulf and FVI (Floating Vegetation Index).

Shekede *et al.* (2013) studied about the spectral differentiation of six aquatic weeds in Lake Chivero, Zimbabwe. Although aquatic plants are fundamental to the functioning of aquatic ecosystem, their proliferation needs to be controlled and managed. Spectral analysis of aquatic weeds offers an opportunity to understand the distribution and extent of specific aquatic weeds including evolution of weed invasion, propagation and colonization of the affected areas. Thus, the objective of this study was to measure and differentiate aquatic weeds *Hydrocotyle ranunculoides* (Spaghetti Weed), *Eichhornia crassipes* (Water hyacinth), *Pistia stratiotes* (Nile cabbage or Water lettuce), *Typha capensis* (Common bullrush) and *Phragmites australis* (Common reed) in Lake Chivero, Zimbabwe based on their spectral features. The study showed that most of the aquatic weeds analysed in the study possess certain unique spectral characteristics which provided a basis for significant ($p<0.05$) spectral separation of these macrophytes. The research further revealed that increased spectral separability of aquatic weeds is better in long wavelength region than in short wavelength region of the electromagnetic spectrum. The study also points out the need for more research on spectral separabilty of aquatic weeds, not only in Lake Chivero, but in all water bodies which are at risk of aquatic weed invasions, especially using airborne hyper spectral techniques in order to cover larger representative areas.

Sakuno and Kunnii (2013) studied about the estimation of growth area of aquatic macrophytes expanding spontaneously in Lake Shinji using ASTER data. The study estimated the growth area of aquatic macrophytes that have expanded spontaneously in Lake Shinji, located in eastern Shimane Prefecture, Japan, by using Terra satellite Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) data. Visible and near infrared ASTER data from the months April, August, and September 2012 were used. The water depth at which ASTER can detect submersed aquatic macrophytes using in situ spectral reflectance of aquatic macrophytes and a bio-optical model was also examined during the research. Inference drawn out was that, when the threshold value of a normalized difference vegetation index (NDVI) was set to 0, only aquatic macrophytes up to a depth of approximately 10 cm could be detected. The growth area of aquatic macrophytes detected by NDVI from ASTER data was in relatively good agreement with that of the growth area as observed by aerial photography.

Mathew and Nath (2014) studied about the integration of multispectral satellite and hyperspectral field data for aquatic macrophyte studies. The paper looked into the spectral signatures of various AM to decide whether species could be discriminated by remote sensing. In this study, the spectral readings of unlike AM communities identified were carried out using the ASD Field spec Hand Held spectro-radiometer in the wavelength range of 325 – 1075nm. In general, results of this study suggested that high spectral and spatial resolution images provide useful information for natural resource managers especially with regard to the location recognition and sharing mapping of macrophyte species and their communities.

Oyama *et al.* (2015) distinguished surface cyanobacterial blooms and aquatic macrophytes using Landsat/TM and ETM+ shortwave infrared bands. Remote sensing technique can be considered as an appropriate method to analyse the extent of cyanobacterial blooms correlated with the conventional ship surveys because of the patchiness and high spatial and temporal variability of the blooms. It is suggested that most of the current algorithms are not adequate for delineating cyanobacterial blooms and aquatic macrophytes because of their same spectral characteristics in the red and near infrared (NIR) wavelengths. In this study, they conducted an insitu spectral measurements and satellite data inquires for cyanobacterial blooms and aquatic macrophytes to note an efficient method to categorize them based on medium-resolution Landsat satellite images. The reflectance spectra were measured for lake waters and cyanobacterial blooms. In the study several selected indices, such as the normalized difference vegetation index (NDVI), five types of normalized difference water index (NDWI), and the floating algal index (FAI) were calculated to find a convenient index for categorizing cyanobacterial blooms and aquatic macrophytes. The outcome showed that the spectral characteristics of cyanobacterial blooms were incomparably different from that of aquatic macrophytes in the short-wave infrared (SWIR) region, showing that the SWIR bands are necessary for determining cyanobacterial blooms and aquatic macrophytes. The results also showed that the combination of FAI and $NDWI_{4, 5}$ were an efficient method for delineating lake areas.

2.5 Climate Change and Aquatic Weeds

Abou El Ella and El Samman (nd) assessed about the climate change impacts on growth of aquatic weeds in Lake Nubia, Sudan. Over the coming decades, global change will have an impact on food and water security in significant and highly uncertain ways, and there are strong indications that developing countries will bear the brunt of the adverse repercussions, particularly due to climate change. Climate change has the potential to affect many sectors in which water resource managers have a vital role to play. The major engines are changing temperature and precipitation patterns and associated impacts as rise of aquatic weeds. Remote sensing and geographic information system (GIS) are utilized to distinguish and map distributions of ditch bank weeds in the north part of Lake Nubia, which is the area of study. Several LANDSAT satellite images covering the studied area were analysed using supervised, unsupervised and band ratios techniques using the PCI Canadian software. The outcome indicated that infested weed areas vary seasonally where they reach 8738 Fadden in February 2007 and 32611 Fadden in January 2010. The study had its scope of mentioning the inspections monitoring, and management of the aquatic weeds in that reach with the status of water quality should be considered annually to assess the decision maker in management of the limited water resources.

Warmer conditions are of particular concern in temperate regions because many invasive species have range limits set by extreme cold temperatures or ice cover (Grodowitz *et al.*, 1991). Milder winters would not only increase survival but also create longer growing seasons, potentially increasing reproductive output. Because of its pervasiveness and potential effect on fundamental biological processes, climate change will interact with other existing stressors to affect the distribution, spread, abundance, and impact of invasive species (Gritti *et al.*, 2006). Some previous publications suggest that climate change is likely to favour some invasive species (Thuiller *et al*., 2007).

Rahel and Olden (2008) assessed the effects of climate change on aquatic invasive species. A conceptual framework and empirical review of the interactive effects of climate change and invasive species in freshwater ecosystems are presented in the paper. Although most researchers focus on how climate change will increase the number and severity of invasions, some invasive cold-water species may be unable to persist under the new climate conditions. The findings highlight the complex interactions between climate change and invasive species that can impact on how aquatic ecosystems and their biota will respond to new environmental conditions.

Hellmann *et al.* (2008) studied about the five potential consequences of climate change for invasive species. Several stages of invasion known as the “invasion pathway” to associated five nonexclusive consequences of climate change for invasive species. They are altered transport and introduction mechanisms, establishment of new invasive species, altered impact of existing invasive species, altered distribution of existing invasive species and altered effectiveness of control strategies. Then it has been used those consequences to identify testable hypotheses about the responses of invasive species to climate change and present suggestions for invasive-species management plans. Those five repercussions also highlight the need for improved environmental monitoring and expanded coordination among entities involved in invasive-species management.

U.S. Environmental Protection Agency (EPA) (2008) studied about the effects of climate change on aquatic invasive species and implications for management and research. The study has covered the major Global change stressors, including climate change and variability and changes in land use, which are major drivers of ecosystem alterations. This report analysed the state and regional AIS (Aquatic Invasive Species) management plans to determine their capacity to impart information on changing conditions generally, and climate change specifically. Although there is not necessary the states to consider climate change in AIS management plans, state managers can consider predicted effects of climate change on prevention, control, and eradication in order to manage natural resources effectively under changing climatic conditions. The study suggests that further scientific research and data collection are needed in order to equip managers with the tools and information necessary to conduct effective AIS management in the face of climate change.

Low (2009) studied about the climate change and weeds and pests in the Murray-Darling Basin. The main focus of the report is weeds and fish. The cane toad and pig are also assessed in it. Two major categories of weed considered are: waterweeds (which grow in water), and riparian weeds, defined as weeds that grow on riverbanks and periodically inundated floodplains. The report assessed both obligatory riparian weeds, such as willows, and weeds that can grow in a variety of situations but which are especially invasive along watercourses (for example blackberry). Riparian weeds, as terrestrial plants, are very different in their physiology and impacts from waterweeds, and most of section 2 is about addressing the differences between the both. Weeds and pests that occur within the Murray-Darling Basin, but which do not have a particular affinity for water or riparian zones, are not assessed, the exceptions while evaluating. Native plants can sometimes behave as weeds but they are not considered as part of the report. In this study, the river red gum (*Eucalyptus camaldulensis*) was mentioned by one expert as a potential weed because it can colonize water channels and block flow of water.

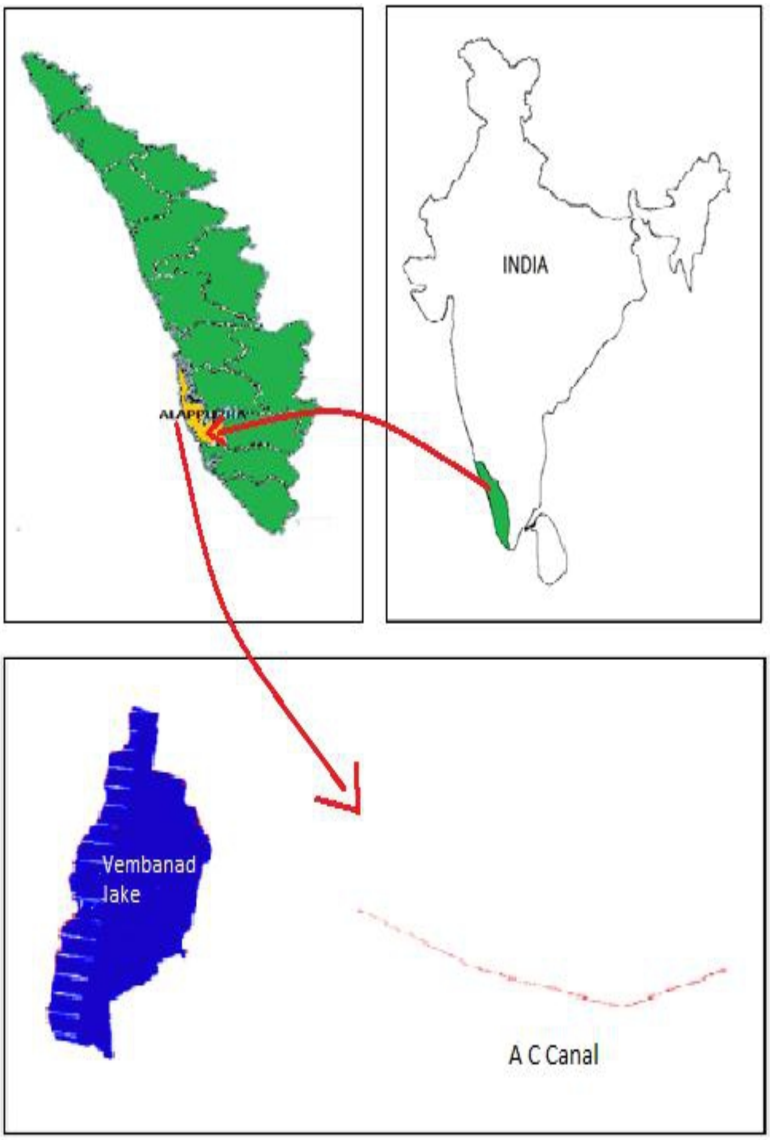
CHAPTER 3
MATERIALS AND METHODS

3.1 Study area

The area of present study is Kuttanad in Kerala, a highly complex ecosystem. Kuttanad wetland is located at the southern part of India's largest Ramsar site, the Vembanad-Kole wetland. It extends between north latitudes 9° 8' and 9° 52' and east longitudes 76° 19' and 76° 44' spread over Alappuzha, Kottayam and Pathanamthitta districts of Kerala. It is separated from Arabian Sea by a stretch of land. Kuttanad is a dynamic, highly complex and unique rice growing agro-climatic tract of Kerala. Most part of this region lies 0.6-2.2m below Mean Sea Level (MSL), so the area is water logged throughout the year. The total geographic area of the region is 1110 km^2.

It is a land of deltaic formation of four major water courses such as Meenachil, Pampa, Achenkovil and Manimala around the Vembanad Lake including 304 km^2 of garden lands, 524 km^2 of low lying rice fields and the rest being water bodies. The region also compasses of dry garden lands including reclaimed and unreclaimed kayal land areas, water spreads as rivers, canals, channels, stretches of backwaters, bounding mangrove vegetation, and rice fields. The garden land is the land where the human population of Kuttanad region is inhabited that is up to 1 m above MSL.

There are different hypotheses on the origin of Kuttanad region. Based on a widely accepted hypothesis, millions of years ago these lands were forest and during a geological event, the Arabian Sea advanced up to the foot of Western Ghats in many places, submerging these areas. Years later there were upliftment and recession of sea, during which the trees of the entire forest that was under submergence got uprooted and buried 'in situ' under varying levels of silt to give rise to the low-lying marshy saline lands of Kuttanad. Soils of these areas have vast organic deposits, fossils of timber and shellfish in varying depth (MSSRF, 2007).


INDIA
Vembanad
lake
A C Canal

Kuttanad wetland ecosystem consists of different ecological subsystems that vary and differ from one another. These subsystems include cultivated rice fields, abandoned rice fields, canals, and river courses. Cultivated rice fields are the major portion of the wetland and undergo rapid variations between the cultivation and fallow period in the post-monsoon and flooded monsoon respectively. Abandoned rice fields include the rice fields that have been abandoned over various periods ranging between 5-10 years. Canals are the arteries criss-crossing the whole Kuttanad wetland. River courses are interlinked by wide canals.

According to the agro-ecological and climatic characteristics such as soil type and fertility, height from the mean sea level, flood risk, influence of rivers, risk of salinity intrusion and the cropping pattern, Kuttanad is classified into six agro-ecological zones such as Upper Kuttanad, Kayal lands, Vaikom Kari, Lower Kuttanad, North Kuttanad and Purrakkad Kari.

The climatic features of Kuttanad are typical of humid tropical climate. Kuttanad has warm climate with fairly uniform temperature throughout the year ranging from 21°C – 36°C. Because of maritime influence Kuttanad region experiences high humidity of 70-80 per cent. Kuttanad is said to be a unique wetland ecosystem because of its location near to equator, high rainfall and solar radiation throughout the year, equitable temperature regime. Kuttanad acts as a receptacle of flood waters from the fast flowing river systems during the monsoon period. These rivers and their tributaries criss-cross Kuttanad wetlands and Vembanad Lake before meeting Arabian Sea. The whole area becomes inundated under extensive sheet of water during the monsoon floods because the above rivers divide into many water courses that are associated to one another. During this time communication and accessibility of the area becomes difficult as the roads get inundated. These flood waters move towards the Vembanad Lake to be drained to the Arabian Sea through the Cochin Estuary. As the north-east monsoon ceases, the area is exposed to tidal incursion of saline water from the Arabian Sea through the Kochi barmouth, leading to a predominantly saline wetland ecosystem. The rivers and canals of the area are widely used for the purposes of transportation, livelihood means and recreation.

Major menace and problems of Kuttanad wetland ecosystem are:

1. Biodiversity loss
2. Depletion of aesthetic value
3. Uncontrollable growth of destructive aquatic weeds
4. Drastic decrease in fish production and rise in rate of fish diseases
5. Decrease in wetland diversity due to invasion of exotic weeds.
6. Obstruction to navigation by accumulation of weeds.
7. Decreased flow rate in rivers because of occurrence of interlocking weeds
8. Pollution due to increased activity in the lake such as boating, water sports
9. Increase in water-borne diseases
10. Scarcity of pure water
11. Over exploitation of resources

Kuttanad is a biodiversity paradise. Kuttanad is the most fertile low lying lands of the world where the cultivation of rice is done below the sea-level. This has significance in view of the projected sea-level rise caused by global warming.

3.2 Data collection

For conducting the study, the Landsat 7 ETM+ SLC-off images of the study area were collected from the web engine Earth Explorer (http://earthexplorer.usgs.gov) launched by USGS (U.S.Geological Survey). The image is composed of eight bands namely, blue, green, red, NIR, SWIR-1, TIR, SWIR-2 and panchromatic bands. An ETM+ image has an Instantaneous Field of View (IFOV) of 30*30 meters in bands 1-5 and 7 while band 6 has an IFOV of 60*60 meters on the ground and the band 8 has an IFOV of 15 meters.

Table 1. Imageries available

Month	No: of images analysed
January	14
February	10
March	9
April	1
September	1
October	1
November	5
December	9

3.2.1 Earth Explorer

Earth explorer provides online search, browse display, metadata export and data download from the archives of the U.S.Geological Survey (USGS). It provides an improved user interface using state-of-the art JavaScript libraries, Hypertext Pre-processor (PHP) and the advanced spatial engine. The USGS Earth Explorer system needs users to register to download the data.

Key features in Earth Explorer include

- Fast, geospatial search engine
- Map viewer for viewing overlay footprints and browse overlays
- Simple, fast Graphical User Interface (GUI)
- Data access tool to search and discover data.
- Textual query capability
- Keyhole mark-up language (KML) export capability to interface with Google Earth
- Save or export queries, results and map overlay for use.
- Request on-demand products
- Access to browse images from standard products
- User authentication service to specialized datasets and tools
- Access to Landsat Data Continuity Mission (LDCM) quality band data

- Standard product downloads
- User notifications of new acquisitions and available products through subscription services
- Updated software code base supporting JavaScript and PHP

The body includes the main Earth Explorer capabilities and is composed of the data search functions and the Google Map components. The Data Search components are divided among four tabs and allow the users to enter search criteria, select databases to query, enter additional criteria and review results in a tabular window. The Google Map application interface embeds Google Maps within the Earth Explorer client. The Google Map is an important tool for defining a search area and for verifying the results fall in the area of interest. Only the registered users can make use of all the features of Earth Explorer such as saving search criteria, downloading data and accessing subscription services.

3.2.2 Ground control points (GCPs)

The ground control points were collected for finalising the aquatic weed area. The following GPCs were selected.

Table 2. Ground control points (GCPs) collected

Area	Latitude N	Longitude E
Poovam	9° 25' 53.51"	76° 31' 35.04"
Manakkachira	9° 26' 1.68"	76° 31' 58.08"
Ponga	9° 27' 15.48"	76° 22' 56.28"
Chembumpuram	9° 27' 43.40"	76° 22' 41.16"
Kalarcode bridge	9° 28' 10.56"	76° 21' 10.80"
Chungam bridge	9° 29' 38.40"	76° 20' 53.16"
Kommady	9° 30' 40.68"	76° 19' 48.36"
Ambalapuzha temple east nada	9° 23' 13.49"	76° 22' 26.40"

3.2.3 Climate data

The climate data of the study area is collected from Rice Research Station (RRS), Moncompu for the period of 1990- 2014 and the Regional Agricultural Research Station (RARS), Kumarakom for the period 1965-2014.

Table 3. Climate parameters collected

Climate Parameters
1. Temperature (°C) 2. Relative humidity (%) 3. Rainfall (mm) 4. Evaporation (mm) 5. Sunshine hours (hrs) 6. Wind speed (Km/hr)

3.3 Image data pre-processing

3.3.1 ILWIS – Remote Sensing and GIS software

The Integrated Land and Water Information System (ILWIS) is a PC-based GIS and Remote Sensing software developed by the International Institute for Aerospace Survey and Earth Sciences (ITC), Enschede, The Netherlands. ILWIS was designed to respond to user demands, to be low-cost and application oriented. It is very user friendly and provides a powerful tool for collection, storage, analysis, transformation and presentation of data. From the input data, information can be generated to model the spatial and temporal patterns and processes on the Earth's surface. ILWIS comprises a complete package of image processing, spatial analysis and digital mapping. It is easy to learn and use; it has full on-line help, extensive tutorials for direct use in courses. It provides a set of documentation, dealing with the basics of GIS and Image Processing as well as its application in many fields, i.e. Land evaluation, urban surveys, natural hazards and environmental management.

Some of the key features include

- Integrated Vector and Raster design
- Import and export of widely used data formats
- On-screen and tablet digitizing
- Comprehensive set of image processing tools
- Orthophoto, image georeferencing, transformation and mosaicking
- Advanced modelling and spatial data analysis
- 3D visualization with interactive editing for optimal view findings
- Rich projection and coordinate system library
- Geo-statistical analyses, with Kriging for improved interpolation
- Production and visualization of stereo image pairs
- Spatial Multiple Criteria Evaluation
- Set of operations on DEMs/DTMs and hydrological processing

3.3.2 Image processing in ILWIS

Classification is a process in remote sensing that is used to allocate complementing levels with respect to groups with homogenous characteristics, with the aim of delineating multiple objects from one another within the image. The aim of classification is to determine and depict the features occurring in an image as a unique colour of features really present on the ground. The level is known as class. Classification will be performed on the basis of spectrally defined features like texture, density etc. in the feature space. Usually multi-spectral data are used to accomplish the classification process and the spectral pattern existing within the data for individual pixel is used the numerical base for grouping. Classification process is the very significant part of digital image analysis.

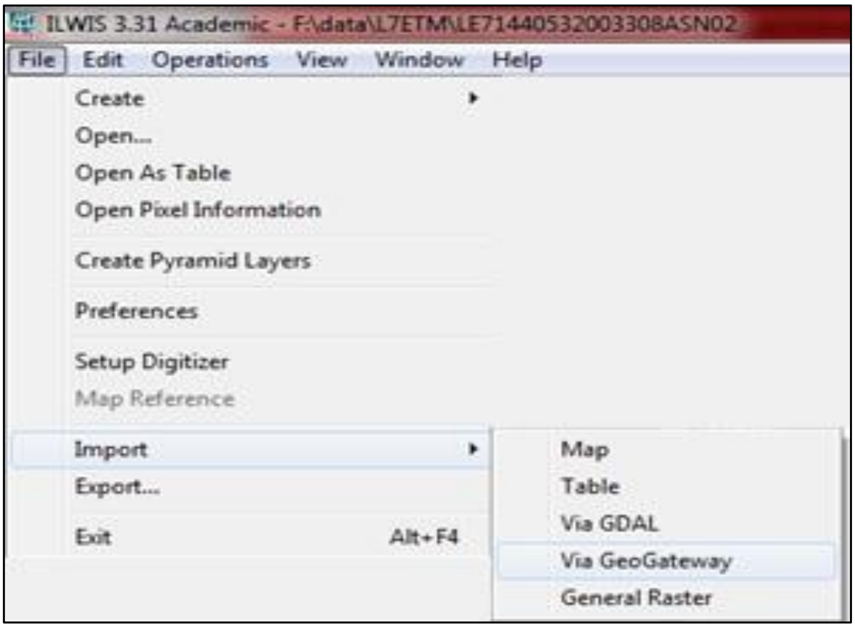


Figure 1. Importing of image to the software

3.3.2.1 Colour composite creation

A colour composite is a colour image created by allowing blue, green and red colours to the separate monochrome bands of a multispectral image and superimposes them. Generally it gives a visual impact of three raster bands. Putting the bands together in a single colour composite map can give a better visual impression on the ground, than by displaying one band at a time.

In Landsat 7 ETM+, Band 2 i.e., green light penetrates clear water, helps to detect oil on the surface of water and vegetation, gives good contrast between turbid and clear water, reflects more green light than any other visible colour. Band 4 i.e. red lights have limited water penetration, useful for distinguishing vegetation types, soils. Band 4, near infrared is very good at detecting as well as analysing vegetation. So a false colour composite (FCC) is created in such a way that the bands 2, 3 and 4 is displayed in blue, green and red respectively. In this image, vegetation is seen as bright red as green vegetation reflects infrared light energy.

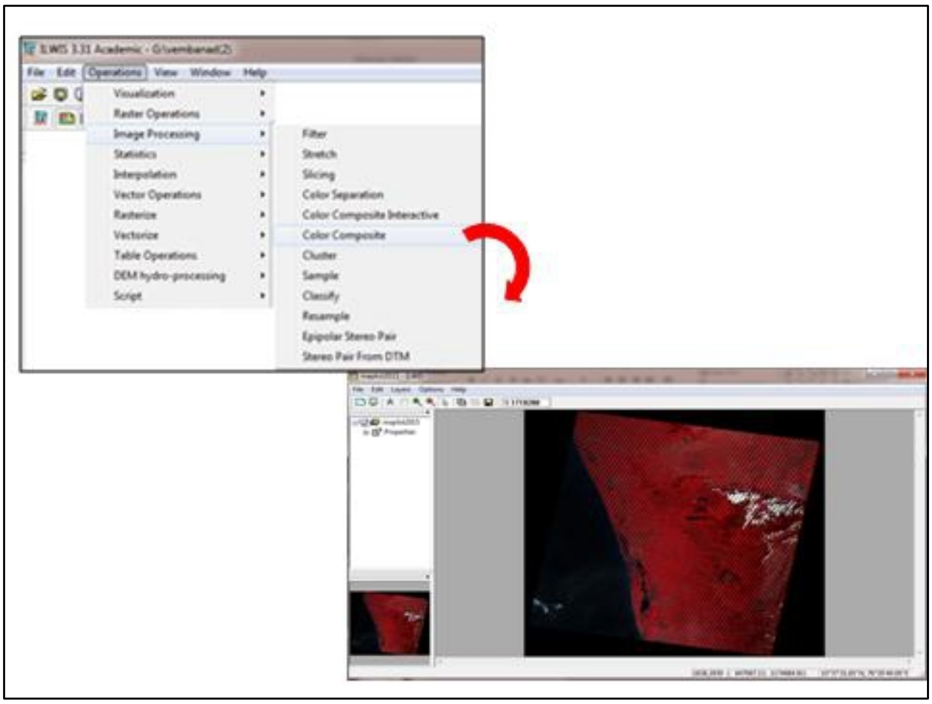


Figure 2. False colour composite of images

3.3.2.2 Sample set creation

A sample set is to be created in which the important data regarding input bands i.e. the map list, cover classes and background image for selecting the training areas is stored.

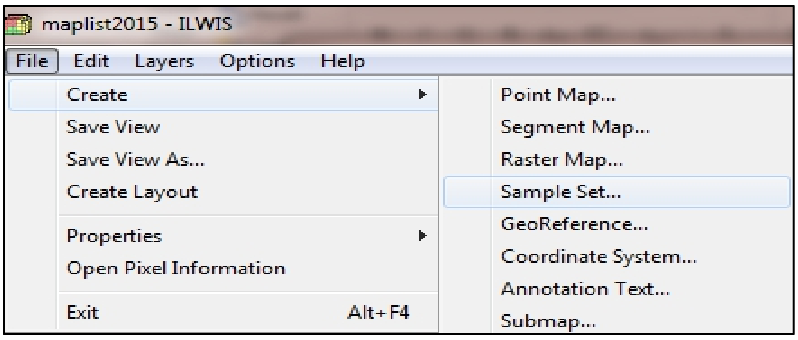


Figure 3. Creation of sample set

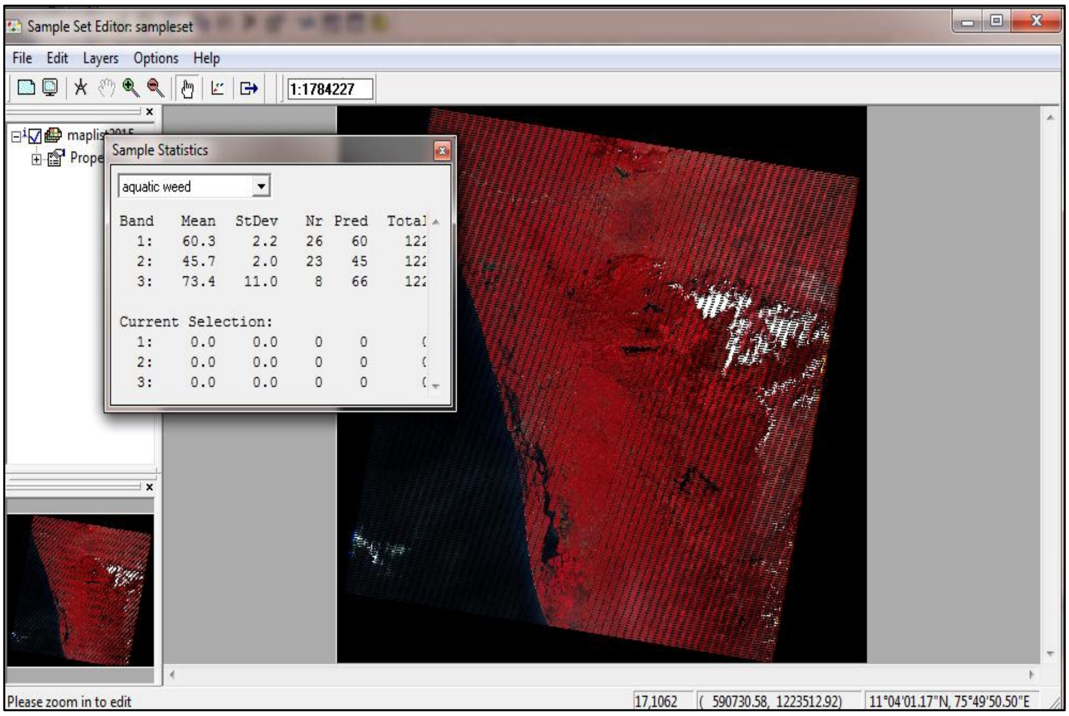


Figure 4. Sample set editor

3.3.2.3 Image classification

After the creation of sample set, the supervised classification is done. The box classifier is used for classification. The statistical analysis of the classified image is done so that the area of aquatic weeds could be estimated. Classify operation performs a multi-spectral image classification according to training pixels in a sample set. Before classification, a sample set has to be prepared.

The following classification methods are available

- Box classifier, using a multiplication factor,
- Minimum distance, optionally using a threshold value,
- Minimum Mahalanobis distance, optionally using a threshold value,
- Maximum Likelihood, optionally using a threshold value, and

- Maximum Likelihood including Prior Probabilities, (option: threshold value).

The training phase: classes of pixels with similar spectral values are defined using Sample algorithm.

The decision phase: each output pixel is assigned a class name if the spectral values of that pixel are similar enough to a training class; if not, an output pixel may be assigned the undefined value using Classify. As Classify uses the training pixels selected by the user, it is a supervised classification.

A supervised classification foremost depends on the spectral values of the pixels selected to serve as training pixels in Sample. Relevant information on the classes for which training pixels have been selected in the sample set, can be viewed in the Sample Statistics. The manner in which the spectral values of input pixels are compared to the known values and statistics of the training pixels, to decide on the class that should be assigned to a pixel, depends on the classification method that we choose, and the parameters we use for that method. In general, to each output pixel, the class will be assigned of which the spectral values are most similar to (or 'nearest') to the spectral values of an input pixel. The bands that you wish to classify should be combined in a map list. This map list is part of the required input sample set. Training pixels should be assigned a class name; this is done in Sample.

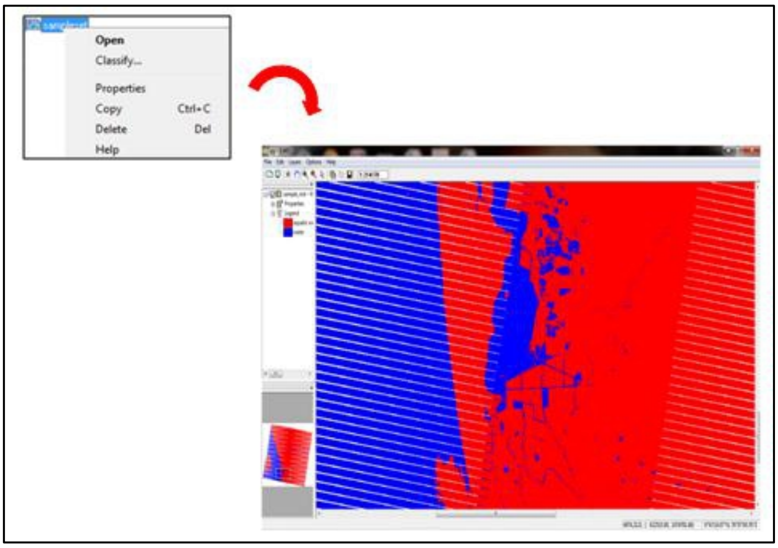


Figure 5. Image classification

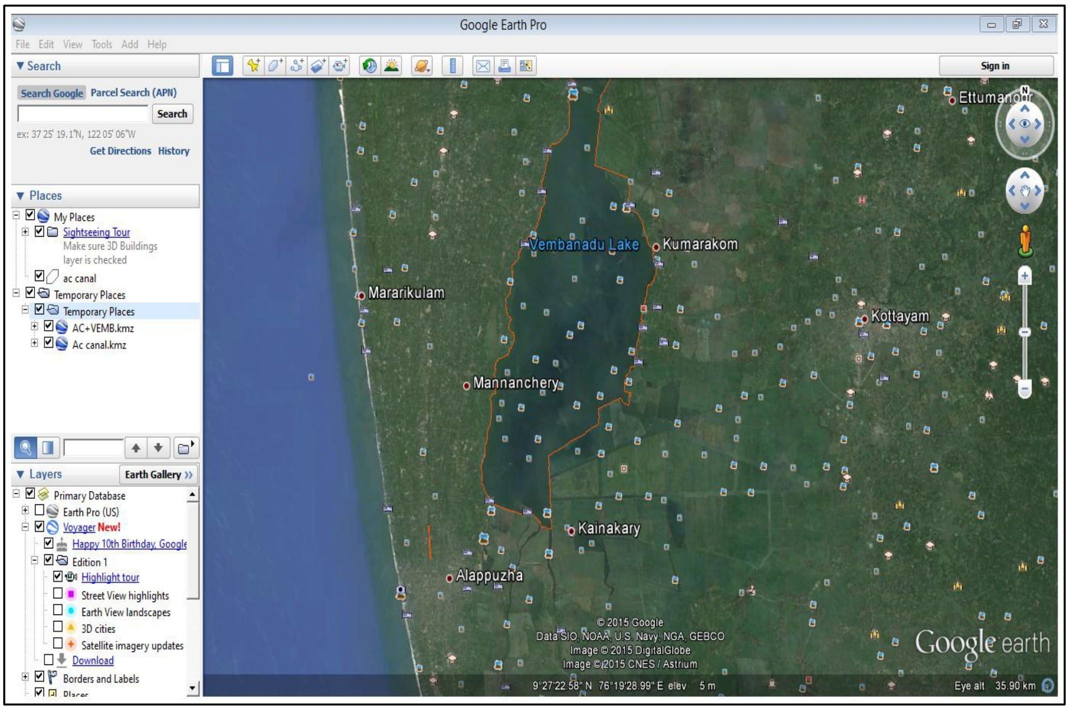


Figure 6. Creation of vector map of the study area

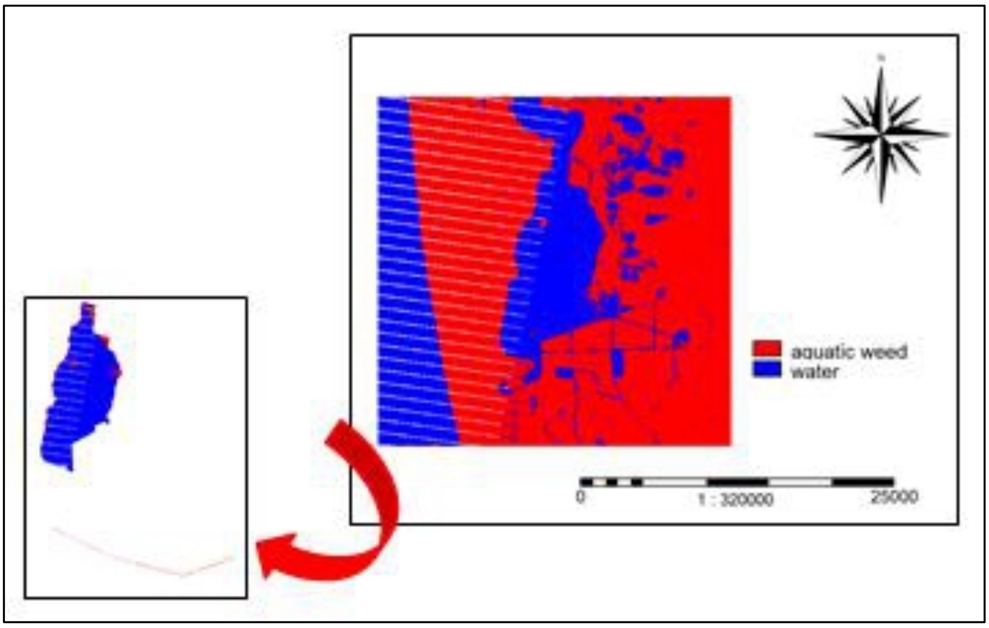


Figure 7. Clipping of the study area

3.3.2.4 Aquatic weed area calculation

For calculating the aquatic weed distribution, histogram of the raster map is calculated. The Histogram operation calculates the histogram of a raster, polygon, segment or point map. Histograms list frequency information on the values, classes, or IDs in your map. Results are presented in a histogram window, both as a table and as a graph. Summary information of a histogram of a raster map which uses a value or the image domain can be viewed in the properties of the histogram: mean, standard deviation, median, predominant, undefined and percentage intervals.

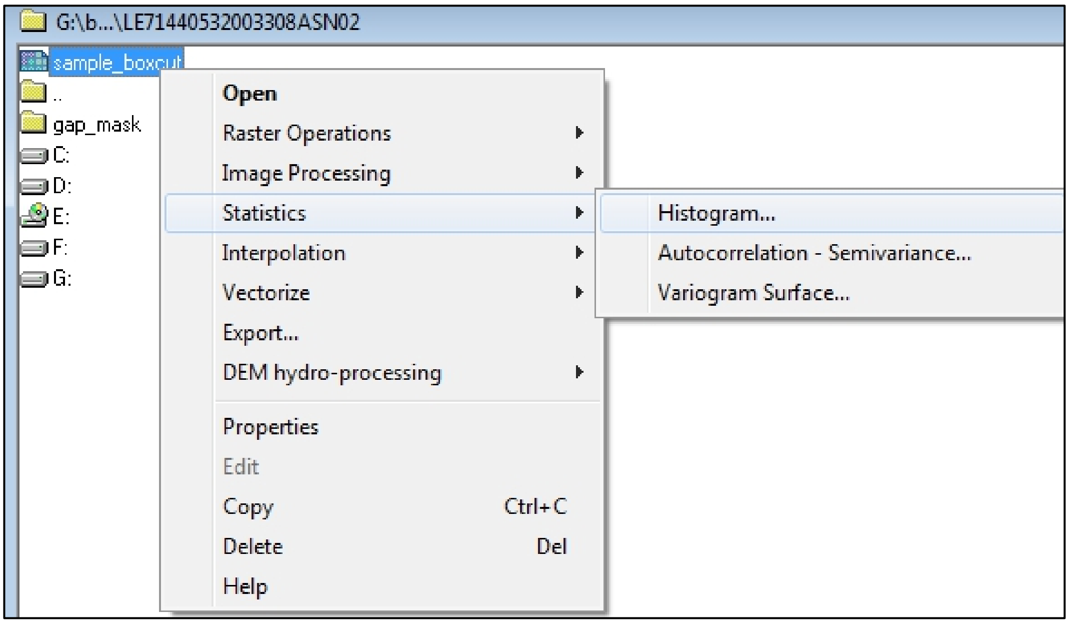


Figure 8. Histogram calculation

A raster histogram lists the number of pixels, the percentages, and the areas per value, class or ID. For value maps (map which use a value, the image, the bit or a bool domain), also the cumulative number of pixels and cumulative percentages are calculated. Further,

- if the input map is an image, the percentages of the total number of pixels excluding pixels with value zero are always calculated;
- if the input map use a value domain and if this map contains undefined values, the percentages of the total number of pixels excluding pixels with the undefined value are calculated;
- If the input map uses a class or ID domain, the percentages of the total number of pixels excluding pixels with the undefined value are always calculated.

3.4 Statistical data analysis

To understand the effect of climate parameters on the distribution of aquatic weed area; correlation analysis, factor analysis and regression analysis can be done. Factor analysis is a class of multivariate statistical methods whose major objective is data reduction that is reducing the number of variables and to detect the structure in relationships between variables. Stepwise regression is a semi-automated process of building a model by successively adding or removing variables based solely on the t-statistics of their estimated coefficients. Both forward and backward stepwise regression can be done.

3.4.1 Correlation analysis

The correlation measures the strength of the linear relationship between numerical variables. The strength of linear association between two numerical variables is determined by the correlation coefficient, ρ, whose range is -1 to +1. The correlation coefficient close to plus 1 means a positive relationship between the two variables, with increases in one of the variables being associated with increases in the other variable. A correlation coefficient close to -1 indicates a negative relationship between two variables, with an increase in one of the variables being associated with a decrease in the other variable. A correlation coefficient close to 0, but either positive or negative implies little or no relationship between the variables. The sign of the correlation, positive or negative is equal to the sign of the slope of straight line.

3.4.2 Factor analysis

Factor analysis is a class of multivariate statistical methods whose major objective is data reduction that is reducing the number of variables and to detect structure in the relationships between the variables.

Principal Component analysis analyse the variance in the variables and recognizes it into a new set of components equal to the number of original variables. Principal components were extracted after removing the redundant information. Principal components analysis is to explain the maximum amount of variance with the fewest number of principal components. The new components are independent. They decrease in the amount of variance in the originals they account for first component most of the variance, second component second most and so on. Only some will be retained for further study. PCA extracts all the factors underlying a set of variables. PCA is used when the variables are highly correlated. First generate a correlation matrix for all the variables. The factor extraction is done. Eigen value is a measure of the amount of variance in all the tests that is accounted for by the factor (it is a sum of squares). Scree Plot is a visual interpretation of a graphical representation of Eigen values. The graph is examined to determine the point at which the last significant drop takes place. Factors with Eigen values greater than one are considered. The Scree (gradual trailing off) plot provides a visual of the total variance associated with each factor. The steep slopes in the Scree plots show the large factors. The gradual trailing off shows the rest of the factors usually lower than an Eigen value of 1. Then factor rotation is done to make more meaningful and interpretable. Variables that have large loadings are considered.

The spatio-temporal distribution of aquatic weeds are correlated with the climatic parameters to understand the effect of climate on its growth and distribution as well as to the changing climate.

CHAPTER 4

RESULTS AND DISCUSSION

The temporal changes in the aquatic invasive plants in the Kuttanad Wetland Ecosystem (KWE) was studied by using the multitemporal and multispectral Landsat remote sensing images using ILWIS digital image processing software. The impact of climate parameters on the distribution and concentration of aquatic invasive species areas were also analysed. The images of the study area for the period 2013-2014 were used.

For the study, clear imageries were not available during all the time periods, because of cloud cover and poor weather conditions at the time of satellite sensor observations. Some of the images available were not suitable for classification because of cloudiness and lack of clarity.

4.1 Spatio-temporal variation in the aquatic macrophytes in Kuttanad wetland ecosystem

The image classification was done by supervised image classification in ILWIS 3.31 and the aquatic weed area of the study region was obtained. Due to the bad weather conditions at the time of satellite sensor observations, imageries were not available for all the period under consideration. The cloud free imageries with less than five per cent cloud cover only was used for the study and the area South of Thannermukkom bund in the upper portion of Vembanad lake and the AC canal was identified for studying the aquatic invasive plant distribution.

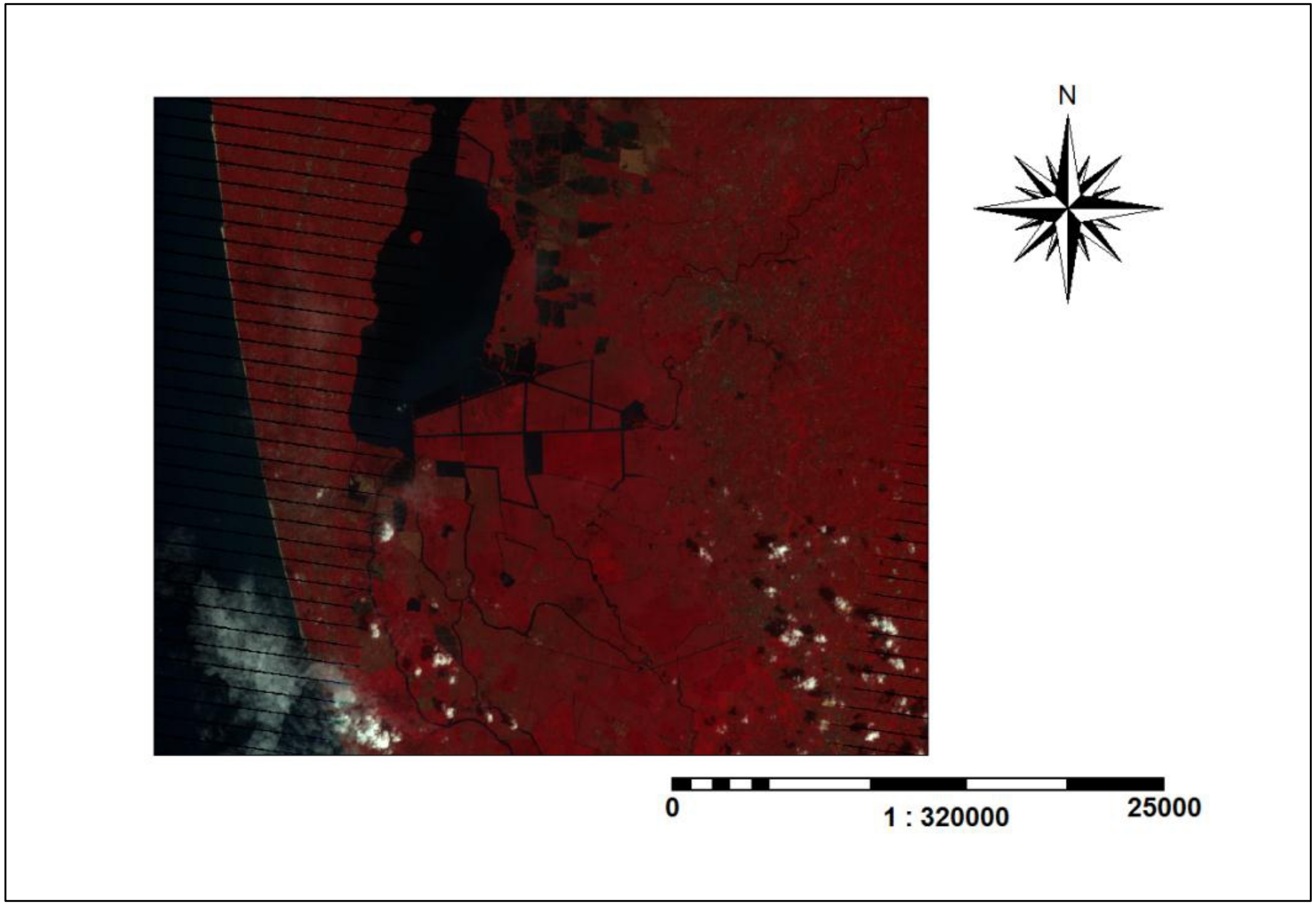


Plate 2. FCC of satellite imagery obtained on 19 February 2014

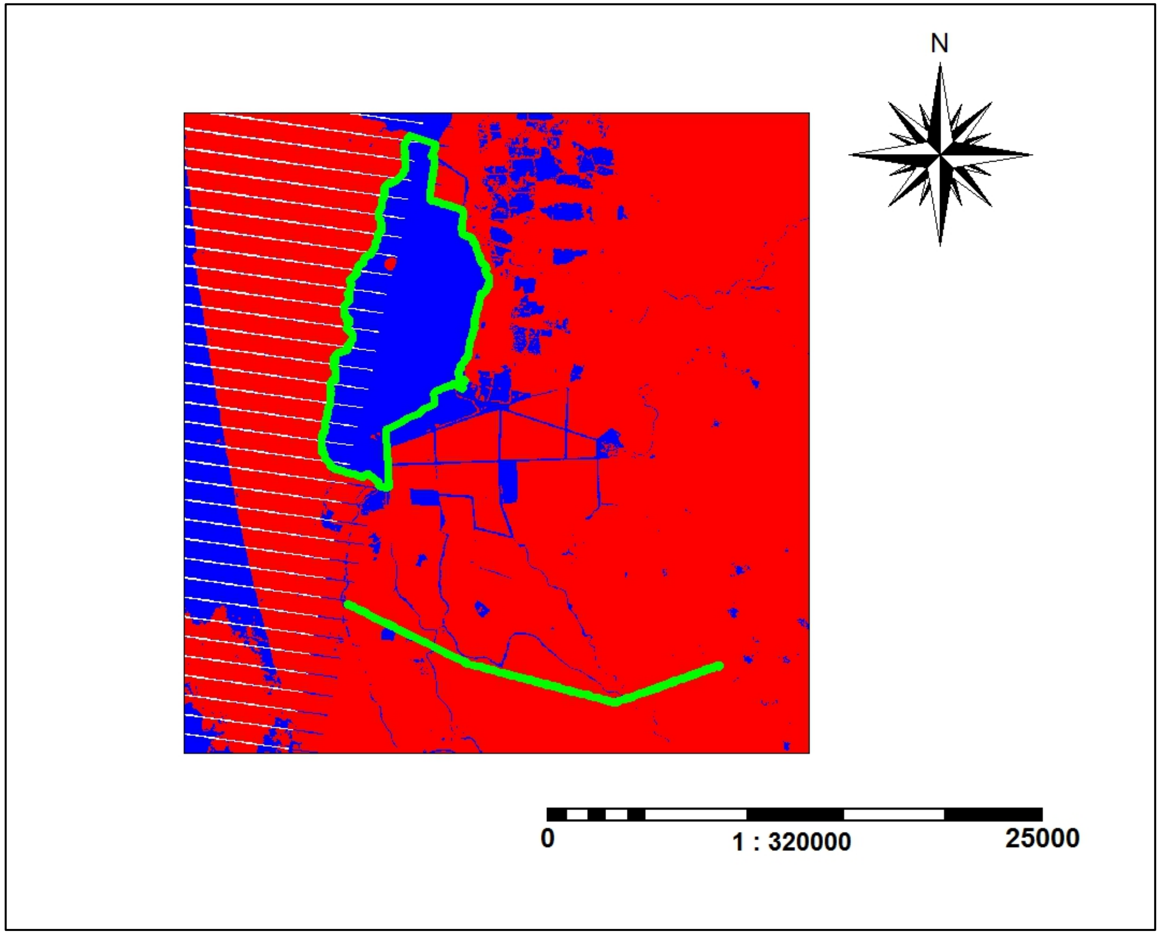


Plate 3. Supervised classification of FCC of satellite imagery obtained on 19 February 2014

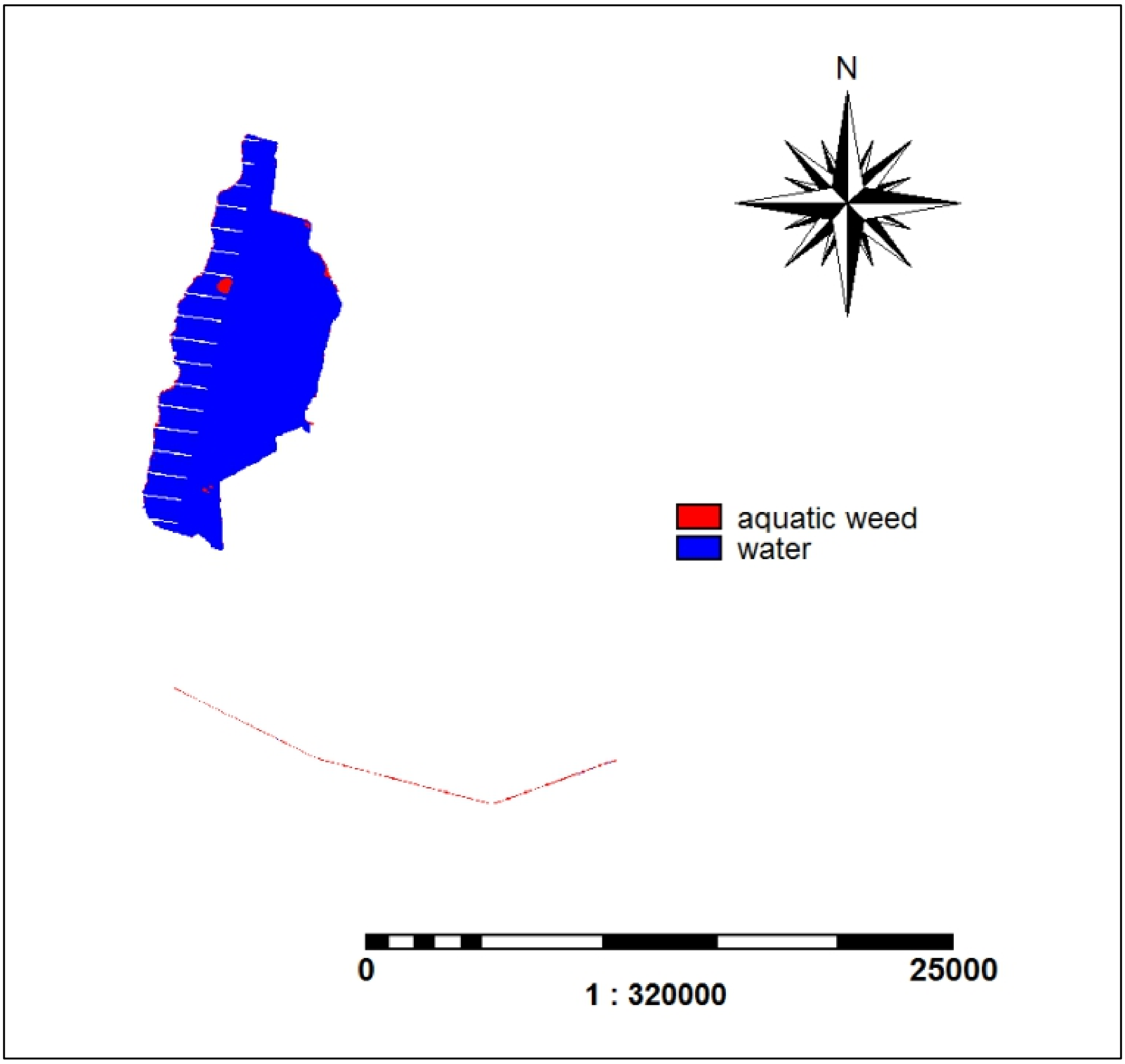


Plate 4. Clipping of the study area

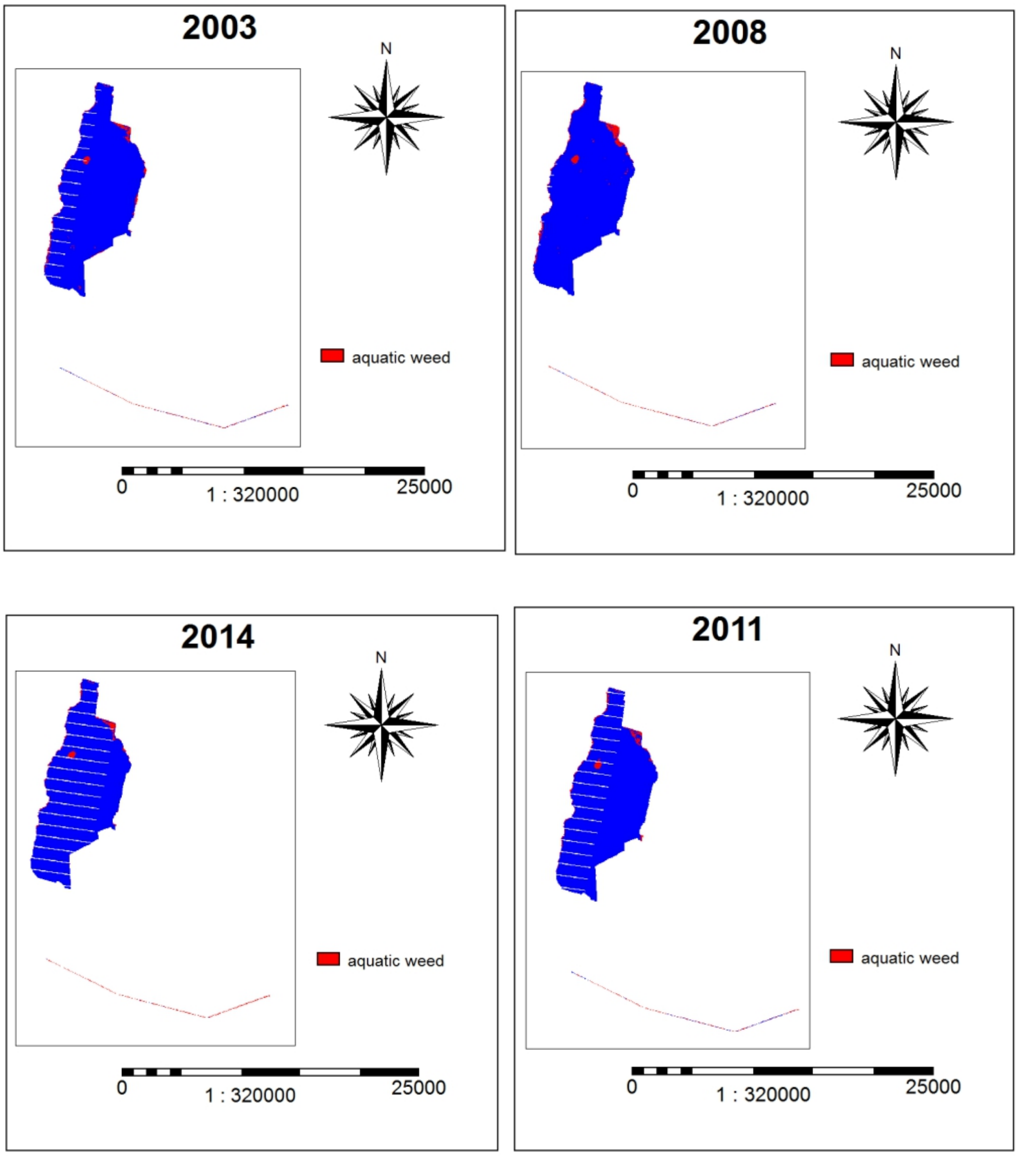


Plate 5. Temporal change in aquatic weed area during 2003-2014 November months

Table 4. Aquatic weed area (km^2)

Time	Aquatic weed area (km^2)	Time	Aquatic weed area (km^2)
4-Nov-03	2.73	3-Dec-08	5.03
6-Dec-03	3.69	20-Jan-09	3.77
11-Mar-04	1.75	5-Feb-09	3.29
24-Dec-04	3.08	25-Mar-09	2.86
25-Jan-05	2.21	7-Jan-10	2.32
10-Feb-05	1.74	23-Jan-10	2.43
26-Feb-05	1.7	8-Feb-10	2.28
14-Mar-05	1.61	24-Feb-10	2.12
27-Dec-05	3.95	10-Nov-11	2.41
28-Jan-06	2.78	13-Jan-12	8.65
1-Mar-06	2.65	14-Feb-12	2.73
30-Dec-06	2.92	1-Mar-12	2.28
15-Jan-07	3.35	17-Mar-12	2.23
31-Jan-07	3.63	28-Nov-12	4.93
16-Feb-07	4.52	15-Jan-13	2.72
4-Mar-07	2.34	31-Jan-13	2.4
5-Apr-07	2.3	17-Dec-13	2.5
12-Sep-07	5.42	2-Jan-14	1.95
1-Dec-07	3.46	18-Jan-14	2.03
17-Dec-07	3.46	3-Feb-14	1.81
2-Jan-08	3.36	19-Feb-14	2.04
18-Jan-08	3.59	7-Mar-14	2.42
8-Feb-08	4.35	1-Oct-14	3.95
6-Mar-08	4.62	18-Nov-14	2.69
17-Nov-08	3.19	4-Dec-14	5.14

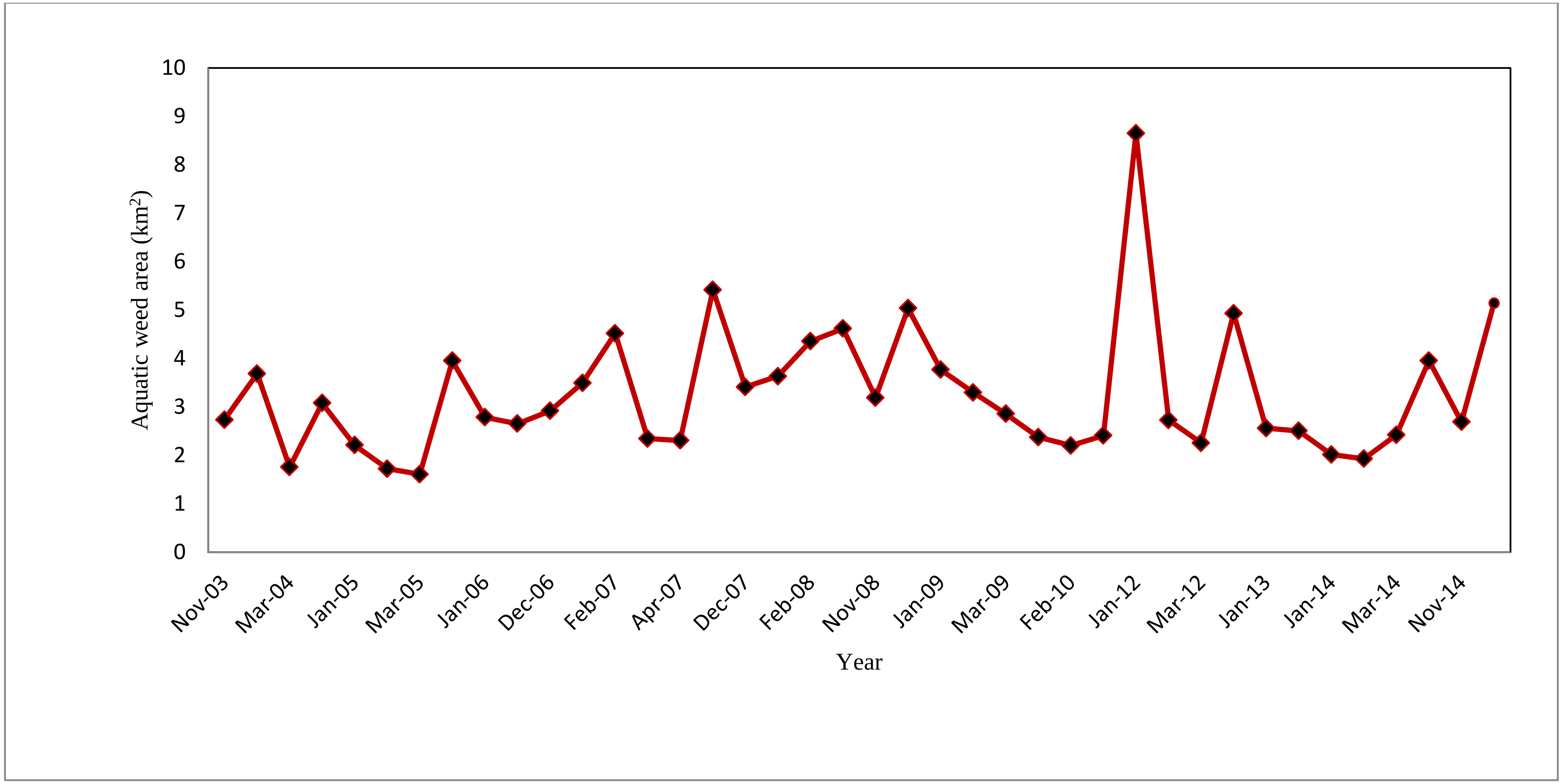


Figure 9. Temporal variation in aquatic weed area during the period from 2003-2014

The extend of aquatic weed distribution inferred from satellite imagery between 2003 and 2014 is presented in the Figure 9. A cyclical trend was seen in the areal distribution of aquatic weeds from the period 2003 – 2004 in KWE i.e., in Vembanad lake [south of Thannermukkom bund] and AC canal. The mean aquatic invasive plant area in the study region was about 3.25 km^2. The standard deviation of aquatic weed area is 1.34 km^2. A periodicity was seen in the distribution as aquatic weeds have rampant growth during some of the months. The peak areal extend of aquatic weeds in the study area was 8.65 km^2, observed on January 2012. A slightly increasing trend was observed in weed areas from November 2003 to November 2014.

The Figure 10, shows an increasing trend in the aquatic weed area distribution during the study period. The maximum aquatic weed area distribution observed was during 2012 about 8.65 km^2, followed by 3.77 km^2 (2009), 3.63 km^2 (2008), 3.49 km^2 (2007), 2.78 km^2 (2006), 2.56 km^2 (2013), 2.21 km^2 (2005) and 2.02 km^2 (2014). From 2005 onwards an increase in the area is observed. The maximum aquatic weed area distribution was obtained during 2012 and the minimum was during the year 2014. But during the year 2008, a steady increase in the aquatic weed distribution was observed, that is, the weed area was about 8km^2. A steady decrease occurred during the year 2013, with a reduction in area up to 2.3 km^2. The R^2 value observed in equation fitting was 0.5864 using a sixth order polynomial equation. The abnormal proliferation of aquatic weed during the year 2012 may be due to the high rainfall (60 mm) which was more compared to the rest of the years. Fusili *et al.* (2013) pointed out that the abnormal proliferation of aquatic weeds may be due to the heavy rainfall. The rains and floods swept agricultural runoff and nutrient rich sediment into the lake. The influx of fertilizer and sediments could have stimulated a new outbreak in growth of the floating vegetation.

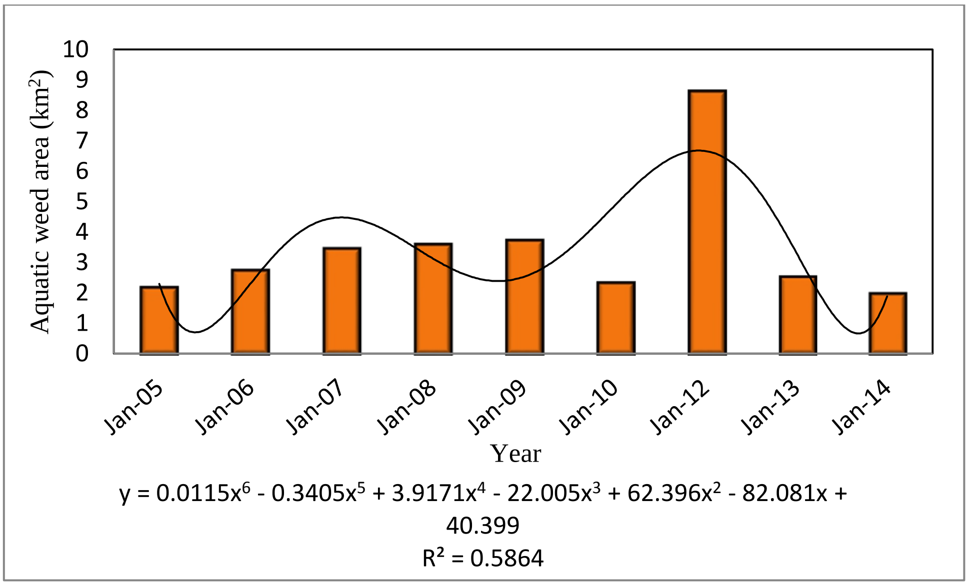


Figure 10. Temporal variation of aquatic weed area of January month during the period from 2003-2014

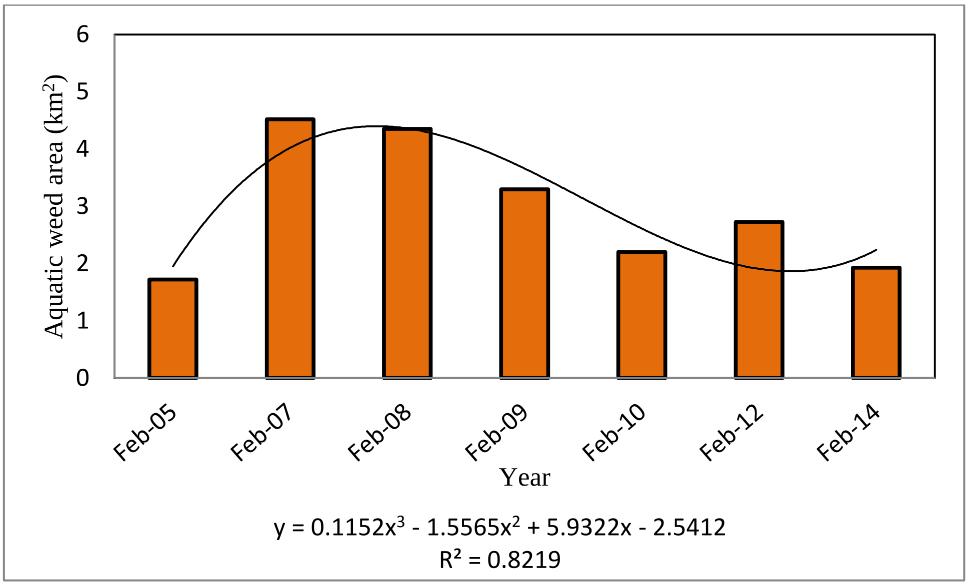


Figure 11. Temporal variation of aquatic weed area of February month during the period from 2003-2014

The Figure 11, shows a descending trend in the aquatic weed areal distribution during the February month in the study area. The maximum aquatic weed growth was observed during the year 2007 about 4.52 km^2, followed by 2008 (4.35 km^2), 2009 (3.29 km^2), 2012 (2.73 km^2), 2010 (2.2 km^2), 2014 (1.93 km^2) and 2005 (1.72 km^2). During the year 2005, the weed area was only 1.72 km^2, a steady rise in the distribution of weed area occurred during 2007 and 2008 that was almost an increase of about 3.7 km^2. But later a decrease in the areal distribution occurred. The trend line shows a decreasing trend in the distribution. The R^2 value observed was 0.8219, when a third order polynomial equation was used.

Figure 12, shows an increasing trend in the aquatic weed area distribution during the March month from the year 2003 to 2014. The maximum aquatic weed growth was seen during the year 2008 i.e. an area of about 4.62 km^2, followed by 2009 (2.86 km^2), 2006 (2.65 km^2), 2014 (2.42 km^2), 2007 (2.34 km^2), 2012 (2.25 km^2), 2004 (1.75 km^2) and 2005 (1.61 km^2). In most of the years the weed distribution in the Kuttanad wetland ecosystem was observed more than 2 km^2. During the year 2008, a steady increase in the aquatic weed distribution was observed, that is almost an increase of 1.6 km^2 than the usual distribution. The rampant proliferation of aquatic weed was due to a hike in the total rainfall during the year 2008 compared to the other years i.e., an amount of 215.8 mm rainfall. Also the evaporation rate was 95 mm which was less compared to the other years. The R^2 value observed was 0.6982 using a sixth order polynomial.

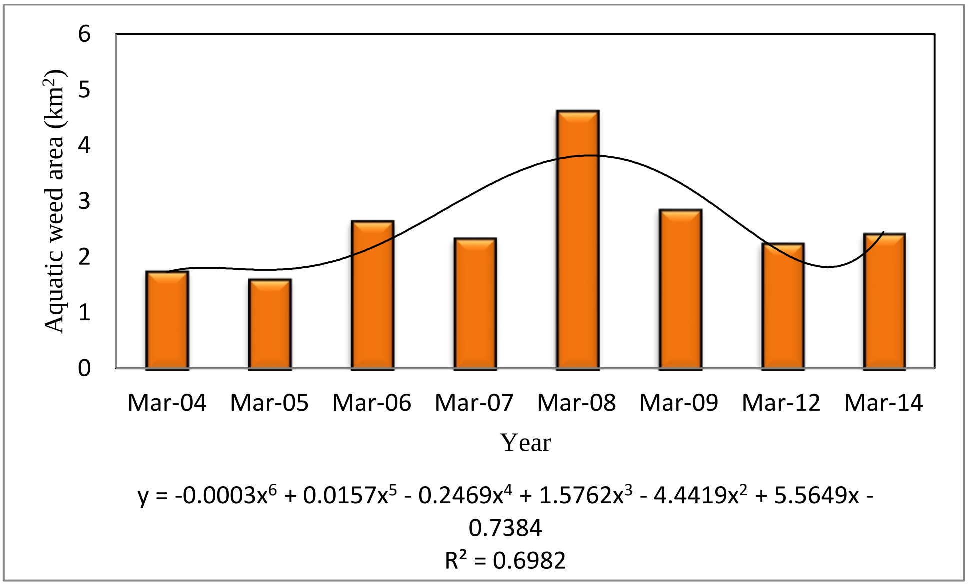


Figure 12. Temporal variation of aquatic weed area of March month during the period from 2003-2014

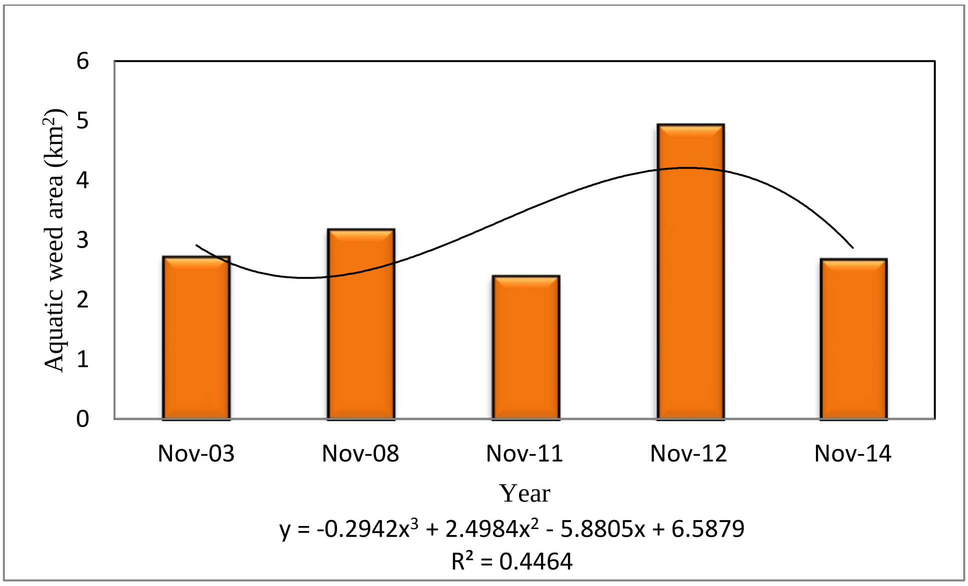


Figure 13. Temporal variation of aquatic weed area of November month during the period from 2003-2014

Figure 13, shows an increasing trend in the aquatic invasive plants distribution during the November month. The mean weed areal distribution was about 3 km^2. The variation seen is about 44.64 per cent i.e., R^2 value is 0.4464. The maximum aquatic weed area was observed during 2012 (4.93 km^2), followed by 2008 (3.19 km^2), 2003 (2.73 km^2), 2014 (2.69 km^2) and 2011 (2.41 km^2).

Figure 14, depicted an increasing pattern in the aquatic invasive plant distribution with a periodicity during December month. The mean weed areal distribution is about 3 km^2. A variation of 0.9946 can be explained. The maximum aquatic weed growth was seen during the year 2014 (5.14 km^2), followed by 2008 (5.03 km^2), 2005 (3.95 km^2), 2003 (3.69 km^2), 2007 (3.41 km^2), 2004 (3.08 km^2), 2006 (2.92 km^2), and 2013 (2.5 km^2).

Figure 15, shows the mean monthly distribution of aquatic invasive plants area. From the graph it can be seen that the weed area was reduced from September month towards April. Aquatic weed area is maximum during the September month, i.e. about 5.34 km^2.The R^2 value obtained for fit is 0.9714. The mean monthly aquatic weed distribution is given in the Table 5.

Table 5. Mean monthly aquatic weed area distribution

Month	Aquatic weed area (km^2)
September	5.34
October	3.75
November	3.08
December	3.62
January	3.42
February	2.90
March	2.51
April	2.30

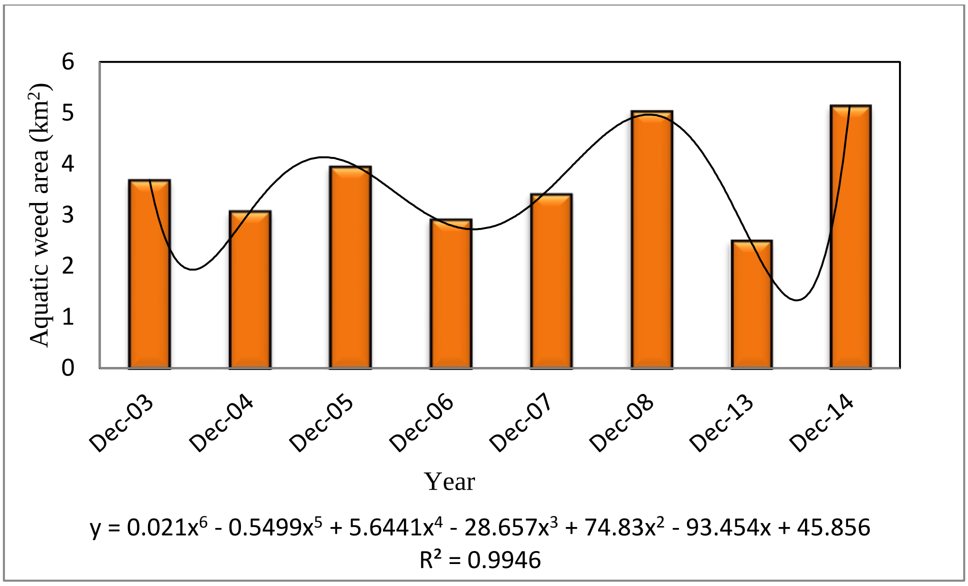


Figure 14. Temporal variation of aquatic weed area of December month during the period from 2003-2014

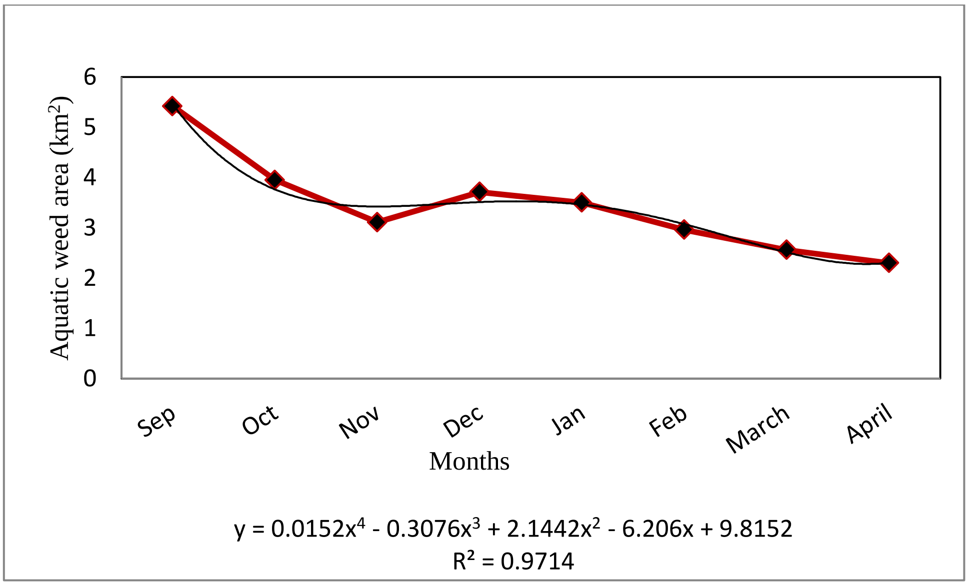


Figure 15. Mean monthly variation in aquatic weed area distribution

Table 6. Seasonal distribution of aquatic weed area during the year 2007

Seasons	Aquatic weed area (km^2)
Winter	3.88
Summer	2.30
Southwest Monsoon	5.34
Northeast monsoon	3.41

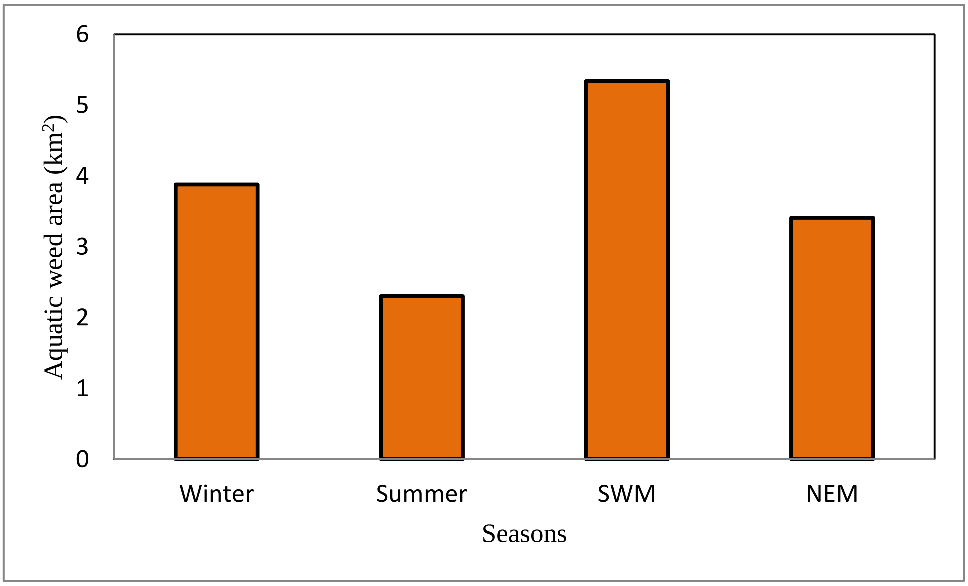


Figure 16. Seasonal changes in the aquatic weed area during the year 2007

In Kerala, the four different seasons are Winter/Cold season (January and February), Premonsoon/ Summer season (March, April, May), Southwest Monsoon season (SWM) (June – September) and Post monsoon or Northeast monsoon (NEM) season (October, November, December).To assess the seasonal change in the aquatic weed area distribution, the representative months were chosen due to unavailability of imageries due to poor weather conditions during some months. Figure 16, represents the seasonal changes in the aquatic weed area during the year 2007. It was noticeable that the aquatic weed area increased during the Southwest monsoon season and was less in the rest of the seasons.

The weed area during the winter season was 3.9 km^2, summer season was 2.3 km^2, Southwest monsoon season was 5.3 km^2 and the Northeast monsoon was 3.4 km^2 i.e. the maximum aquatic weed growth is seen during the SWM season. Fusilli *et al.* (2013) reported that the aquatic weed vegetation is related to the rainy season and rapid growth of floating weeds occurs. Ouma *et al.* (2005) stated that the very high and very low rainfall seasons show a slower proliferation of weeds.

4.2 Effect of climate parameters on the aquatic weed area

The effect of climate parameters on the distribution of aquatic weed area was understood by conducting correlation analysis, factor analysis and regression analysis respectively. In the analyses, the dependent variable considered was the aquatic weed area and the independent variables were maximum temperature, minimum temperature, average temperature, relative humidity, total rain, average rain, evaporation and sunshine hours.

4.2.1 Correlation analysis

From the Table 7, the linear relationship between the dependent variable aquatic weed area and the independent variables climate parameters such as maximum temperature, minimum temperature, average temperature, average relative humidity, total rain, average rain, evaporation and sunshine hours were studied using the correlation analysis. It was seen that the maximum temperature has got the maximum negative correlation with the aquatic weed area i.e., -0.63 compared to other variables. The relationship implied that as the maximum temperature increases the aquatic weed area is reduced. The magnitude of correlation in linear relationship decreases in order from average temperature (-0.50), evaporation (-0.40), total and average rain (0.38), sunshine hours (-0.30), minimum temperature (0.27) and relative humidity (0.15). The relative humidity has the least correlation 0.15, implying little effect on the aquatic weed area variation. The parameters temperature, evaporation and sunshine hours had a negative relationship to the aquatic weed area i.e., when there was an increase in these parameters, the aquatic weed area was shrinked, whereas the parameters, rain and relative humidity has a positive relationship, i.e., when there was an increase in the rainfall, aquatic weed area also increased. Even though relative humidity showed a positive relationship, its value was close to 0, implying little correlation with the aquatic weed area growth.

4.2.2 Factor analysis

4.2.1.1 Principal Component Factor Analysis of the Correlation Matrix

In the Scree plot Figure 17, it was seen that the first three factors aquatic weed area, maximum temperature, and minimum temperature have correlation. The factors such as average temperature, average relative humidity, total rain and average rain have some effect but not considered as the Eigen value is less than 1. From principal component factor analysis it seems that the temperature has got an influence on the aquatic weed area.

4.2.1.2 Maximum likelihood factor component analysis

In the Figure 18, a drastic variance change can be obtained in each factor. Every factor has got impacts. In the Scree plot it was seen that the first three factors have significant correlation. The factors average relative humidity and total rain have some effect but were not considered, as the Eigen value is less than 1. From maximum likelihood analysis, it is seen that the temperature has got a significant influence on the aquatic weed area.

Table 7. Correlation analysis

	Aquatic weed area (km^2)	Max. Temp. (°C)	Min. Temp. (°C)	Avg Temp. (°C)	R.H. Avr. (%)	Total Rain (mm)	Avg. Rain (mm)	Evp. (mm)	Sunshine (hrs)
Aquatic weed area (km^2)	1								
Max. Temp.(°C)	-0.63	1							
Min. Temp.(°C)	-0.27	0.33	1						
Avg Temp.(°C)	-0.50	0.75	0.86	1					
R.H. Avr. (%)	0.15	-0.09	0.34	0.17	1				
Total Rain (mm)	0.38	-0.48	0.36	-0.01	0.35	1			
Avg. Rain (mm)	0.38	-0.48	0.36	-0.01	0.35	0.99	1		
Evp. (mm)	-0.40	0.54	0.04	0.31	-0.33	-0.44	-0.44	1	
Sunshine (hrs)	-0.30	0.65	-0.19	0.22	-0.10	-0.62	-0.62	0.48	1

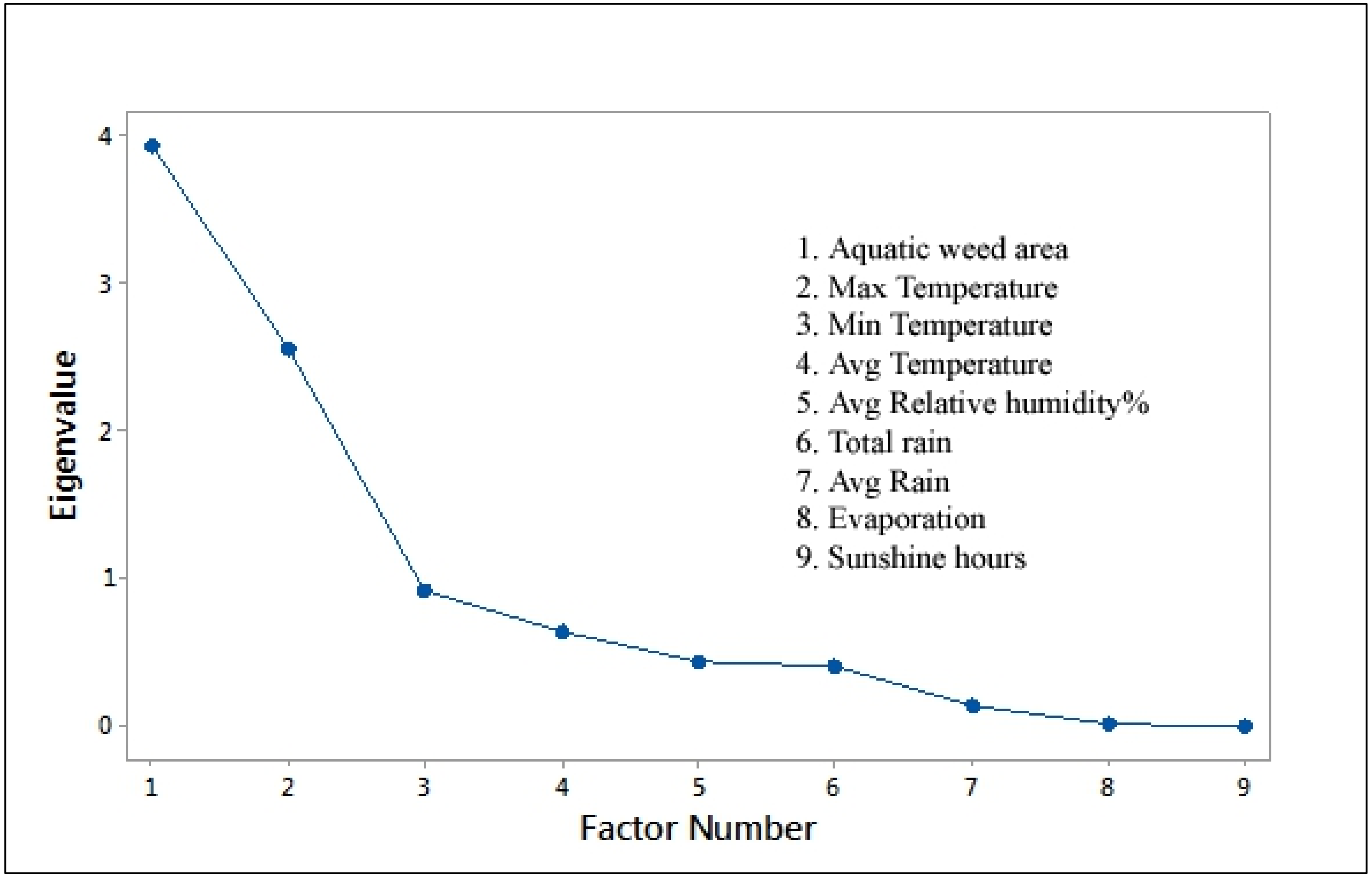


Figure 17. Scree plot (Principal component factor analysis)

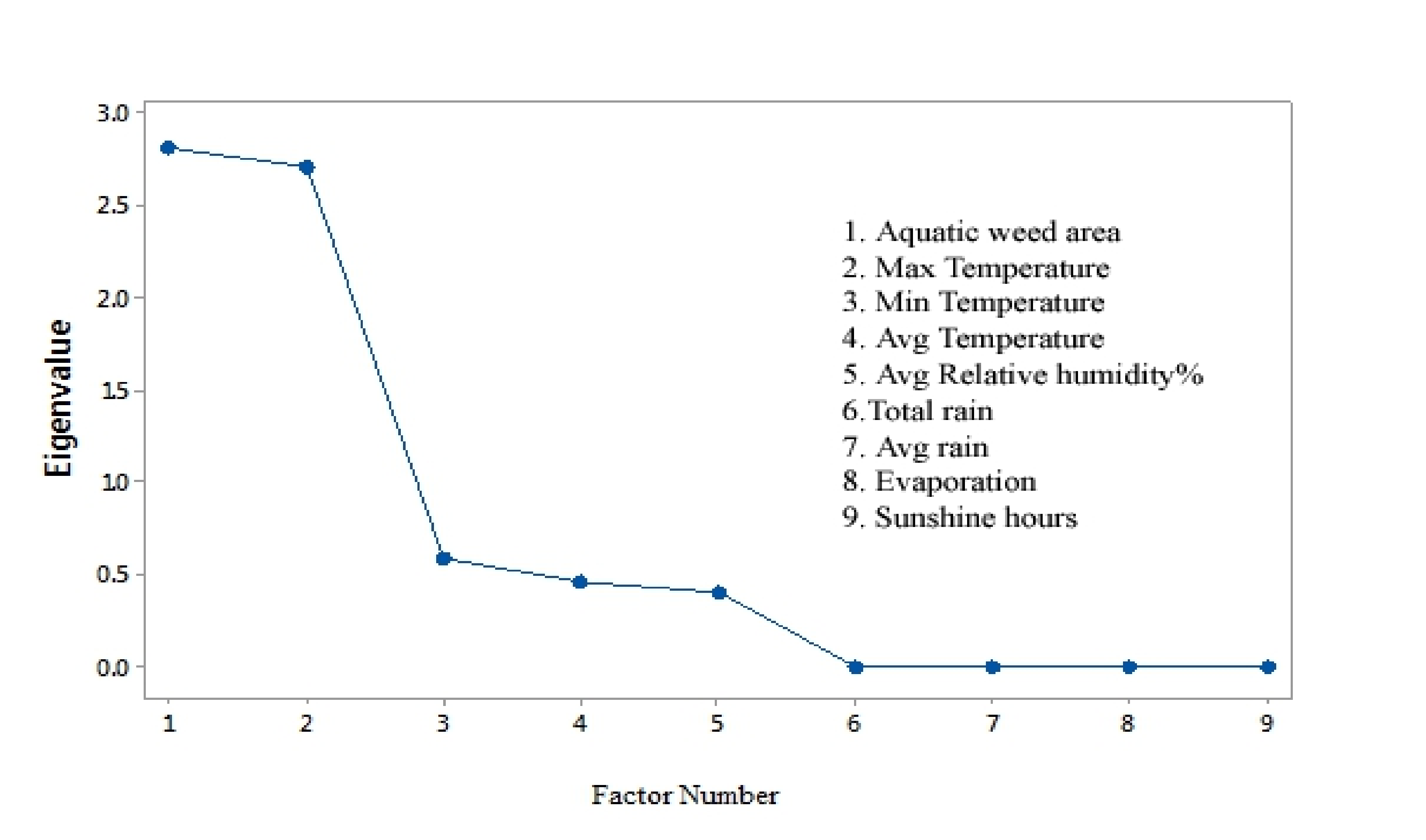


Figure 18. Scree plot (Maximum likelihood factor analysis)

4.2.3 Regression Analysis

4.2.3.1 Multiple Regression analysis

The multiple regression analysis between aquatic weed area, the dependent variable and the climate parameters, the independent variables gave the best results with following regression equation:

AWA = 27.93 - 0.757 T_{max}.

Where AWA = Aquatic weed area (km^2)

$T_{max.}$ = Temperature maximum (°C)

From the scatter plot Figure 19, it was clearly visible that the maximum temperature has a negative correlation with the aquatic weed area. The aquatic weed area was decreased as there was an increase in the maximum temperature. A scatter diagram is a diagram that shows the values of two variables i.e. the dependent and independent variables, along with the way in which the two variables are related to each other.

From the Figure 20, it confirms that there is a statistically significant relationship between the dependent variable aquatic weed area and the independent variable maximum temperature since p-value is 0.001 ($p < 0.10$). A variation of about 39.67 per cent of aquatic weed area can be explained by the regression model.

From the Figure 21, it was seen that the independent variables such as minimum temperature, total rain, average rain and sunshine hours have very little or no correlation with the aquatic weed area whereas the maximum temperature has got a high negative correlation.

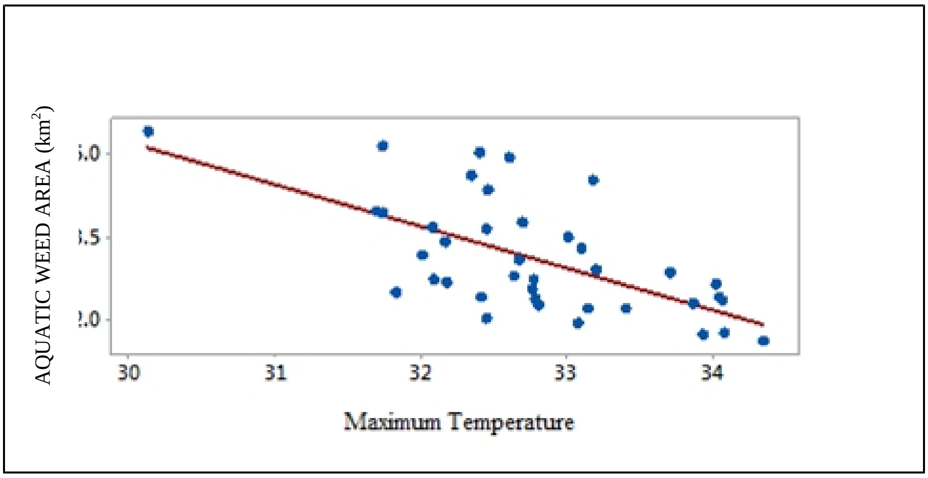


Figure 19. Scatter plot for maximum temperature

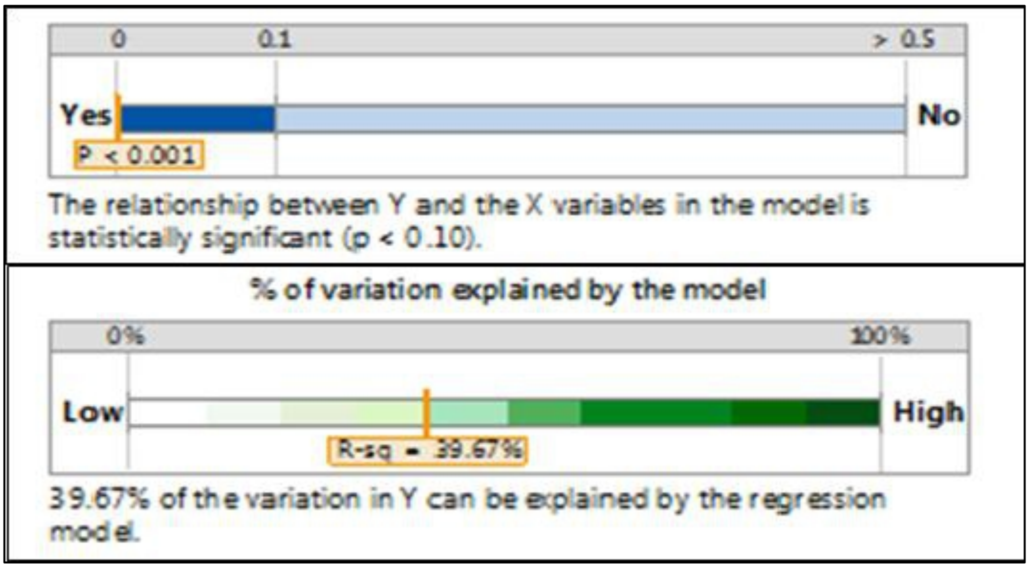


Figure 20. R^2 variation

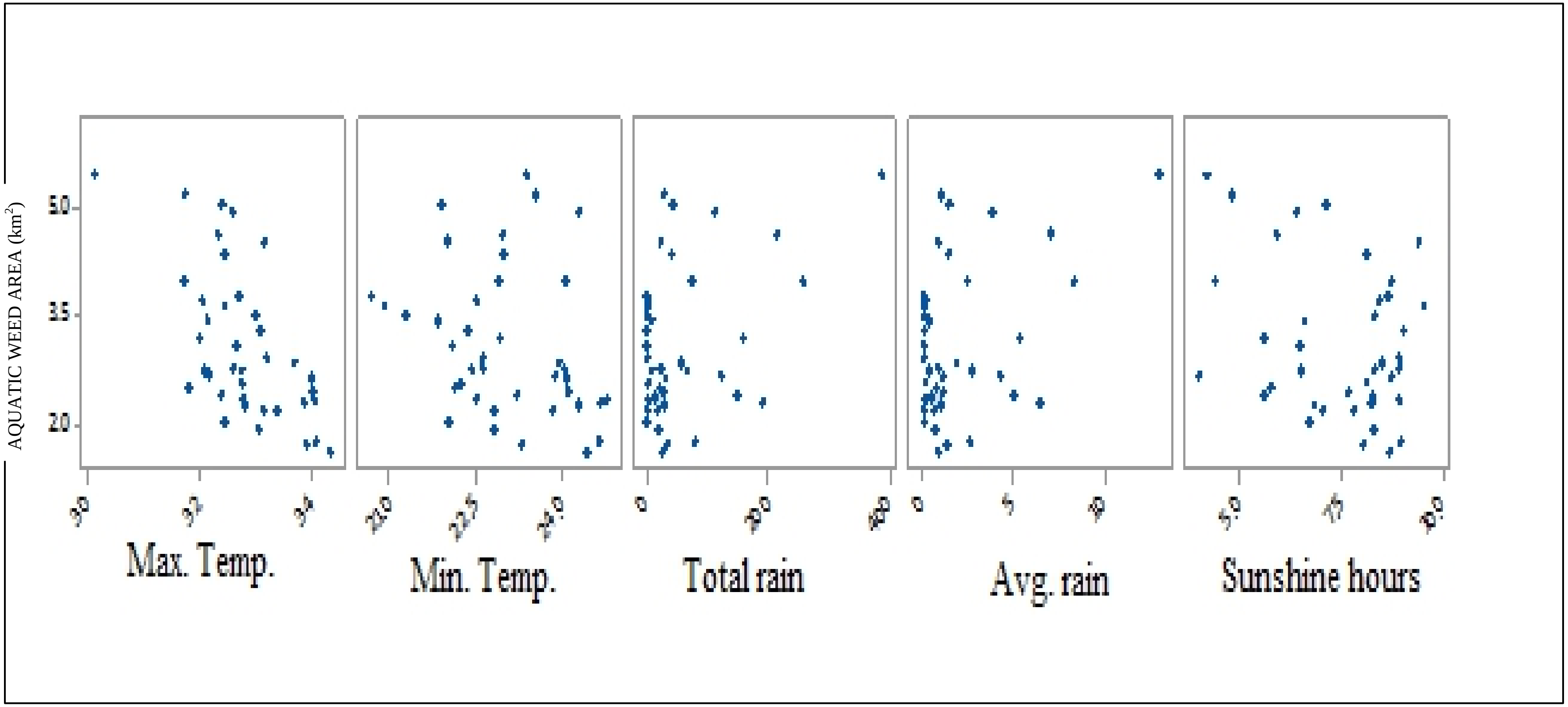


Figure 21. Scatter plot of aquatic weed area v/s different X variable

4.2.3.2 Stepwise regression analysis

Stepwise regression is a semi-automated process of building a model by successively adding or removing variables based solely on the t-statistics of their estimated coefficients. Forward selection is used to provide an initial screening of the candidate variables when a large group of variables exists. The analysis begins with no candidate in the model. Then the variable that has the highest R^2 is selected. At each step, the candidate variable that increases R^2 the most is selected. When none of the remaining variables are significant the addition of variables is stopped. Backward selection begins with all the candidate variables. At each step, the variable that is the least significant is removed. The process continues until no non-significant variables remain. The significance level can be set at which variables can be removed.

4.2.3.2.1 Forward selection stepwise regression

In this method, from the first step itself it was seen that the maximum temperature has got the maximum influence on aquatic weed growth as the p-value was 0.00. The R^2 value obtained is 39.67 per cent. The mallows' cp value obtained is 0.46.

4.2.3.2.2 Backward elimination stepwise regression

In this method, all the candidate variable such as maximum temperature, minimum temperature, average temperature, relative humidity, total rain, average rain, evaporation and sunshine hours were included. The variable with highest p-value gets eliminated. In the first step average relative humidity with p-value 0.752 got eliminated. That is the removal of the less significant predictors tends to increase the significance of the remaining predictors. In the second step average temperature was eliminated which has got a p-value of 0.737. In the third step minimum temperature was eliminated which has a p-value of 0.756. In the fourth step, evaporation variable got eliminated as has got p-value of 0.419. Then the variables such as average rain, total rain, sunshine hours have got eliminated as have p-values 0.195, 0.178 and 0.269 respectively. So from the backward elimination stepwise regression analysis it was found that the maximum temperature has got more influence on the aquatic weed area. There was reduction in mallow's cp as well as R^2 value in each step.

In 2003 Kumar reported that the Thannermukkom barrage had accelerated the growth of weeds, mainly the water hyacinth, as it restricted the flushing action making the upper portion a bowl of agrochemicals. Kotor (2014) reported that aquatic weed promotes increased silting of water, gradually making it shallow and dry and the maximum temperature can have an impact on the aquatic weed area. Albright (2004) pointed that plant health can be influenced by weather and environmental conditions like temperature and humidity and can affect its distribution. Ouma *et al*. (2005) reported that the climate parameters - rainfall and temperature directly influences the ecological functioning within the lakes, which in turn affects the health status of the aquatic weeds.

Maximum temperature was found to have maximum influence in the study. Carry and Werts, 1984; Owens *et al.,* 2004; Room, 1988; Short and Neckles 1999 and Whiteman and room 1991 also found out that the temperature has an influence on the growth of aquatic weeds. However from the other studies related to aquatic weed growth, it was found that other factors are also responsible for aquatic weed growth. Salinity is an environmental factor which changes with distance from the source of salt water as well as over elevation gradients. Divakaran *et al.,* 1980, Haller *et al.,* 1974, Howard and Mendelssohn 1999 and Oliver 1993 pointed that salinity has an effect on aquatic weed growth. The pH has an effect on survival and growth of aquatic invasive plants was reported by Gaudet 1973; McFarland *et al.,* 2004; Mitchel 1979; and Owens *et al.,* 2005. Madsen and Wersal, 2008; Owens and Smart 2010; and Riemer 1984 suggested that aquatic weed was limited due to nutrient availability. Light intensity and light saturation also played an important role in the growth of aquatic invasive plants growth (Rani and Bhambie, 1983; Urban-Beric and Gaberscik, 1989). So from the study statistically it was found that the maximum temperature has the maximum influence on the growth of aquatic weeds, but also other factors has influence on the area dwindling and flourishing of the aquatic invasive plants.

The aquatic weed area is not only influenced by the temperature. The other factors such as dissolved oxygen, nutrient load, light intensity, pH, and salinity also play an important role. The study of these factors is beyond the scope of this study. For studying the total aquatic weed area Landsat ETM+ imagery was enough. The aquatic weed species differentiation was not studied as it requires hyper spectral imageries and the Hyperion images were not available free of cost. So aquatic weeds as a whole destructing the navigable water ways were studied.

CHAPTER 5

SUMMARY AND CONCLUSION

A study on the changes in spatio-temporal distribution of aquatic invasive plants in the Kuttanad wetland ecosystem (KWE) was done using LANDSAT multispectral imageries to assess its magnitude and variation and the effect of climatic parameters on that variation. The study employed medium resolution LANDSAT 7 ETM+ imageries of the study area for the period from 2003 to 2014 for mapping and monitoring the aquatic invasive plant distribution.

The main advantage of satellite remote sensing is that it helps to readily detect and understand the variation in the aquatic vegetation distribution and concentration. The need for readily available multi-temporal data of aquatic weeds is best addressed with the use of remote sensing. The main drawback of using multispectral imageries is the lack of a continuous record of usable imageries due to cloud cover obscuring the spectral reflectance from the land surface during periods of rain. Hence, usable imageries are not available for rainy season and periods around that because of the cloud cover. The satellite imageries from LANDSAT7 ETM+ sensor of the study area in KWE were available for the period from 2003 November onwards, excluding the times of excessive cloud cover. So for the present study, data from 2003 to 2014 were utilized. The remote sensing image processing cum GIS software, ILWIS (Integrated Land and Water Information System) version 3.31Academic, by ITC was used for the image classification and extraction of the aquatic weed area.

In order to understand the influence of different climate parameters, viz. minimum and maximum temperature, rainfall, relative humidity, evaporation and sunshine hours, explanatory data analysis and stepwise regression analysis were done. The explanatory data analysis involved factor analysis using both the Principal Components and Maximum Likelihood Analysis. The forward and backward selection stepwise regression analyses were employed to understand the maximum contributing climate factor towards the variation in the aquatic weed distribution.

Temporal variation in aquatic weed area was studied and it was found that there is an increasing trend in the area for the total period under consideration. The variation in the aquatic weed area was observed to be cyclic with periodic increase and decrease in the area. The monthly temporal variation of the available data showed that the there was a decreasing trend in the aquatic weed area from September to November and again from December to April, while there was an increase from November to December. The rates of decrease in observed area were about 41.14 per cent and 34.29 per cent respectively for the periods from September to November and December to April. The rate of increase in observed area was about16.49 per cent from November to December. The mean monthly aquatic weed area distribution showed that the month of September was having the maximum aquatic weed distribution i.e.; about 5.34 km^2, followed by October (3.7 km^2), December (3.6 km^2), January (3.4 km^2), November (3.1 km^2), February (2.9km^2), March (2.6 km^2), and April (2.3 km^2). On observing the seasonal changes in the variation of aquatic weed area, it was noticed that the period corresponding to the South West Monsoon season was having the maximum aquatic weed area of about 5.4 km^2 followed by the winter season with an area of about 3.88 km^2, North East Monsoon season with an area of about 3.4 km^2, and the summer season with an area of about 2.30 km^2.

The statistical analysis revealed that the maximum temperature is having a high negative correlation with the aquatic weed area. That is clearly seen in the seasonal change in aquatic weed area distribution, that the summer season is having low aquatic weed area distribution. The variables temperature, relative humidity and rainfall have some effect on the aquatic weed distribution, but the variation is less. When considering the effect of only the maximum temperature, it was observed that about 24.84 per cent variation in aquatic weed area can be explained by it. As the regression equation varies, the amount of variation explained also varies.

So the best regression model found as

$$\mathbf{AWA = 27.93 - 0.757\ T_{max}.}$$

where AWA = Aquatic weed area (km^2)

$T_{max.}$ = Temperature maximum (°C)

Analysis established that there is statistically significant relationship between the dependent variable aquatic weed area and the independent variable maximum temperature since p-value is 0.001 ($p < 0.10$). A variation of about 39.67 per cent of aquatic weed area can be explained by the regression model.

The study of aquatic invasive plants spatiotemporal distribution using remote sensing technique gave a realistic knowledge about the aquatic weed area distribution and variation in Kuttanad wetland ecosystem. The statistical analysis helped in establishing the relationship between the climatic factors and the areal distribution of the aquatic weeds.

Future scope of study

- Hyperspectral imageries may be used for differentiating the different species of aquatic weeds in the whole Kuttanad wetland ecosystem..
- The effect of parameters such as dissolved oxygen, salinity, pH, light intensity, and nutrient load on aquatic weed growth need to be studied.

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Appendix I

Temperature in °C (monthly mean) recorded at RRS, Moncompu.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Year	MINIMUM °C											
2003	21.8	23.2	24.2	24.8	23.5	24.1	24.1	23.6	23.5	24.2	24.3	22.4
2004	23.0	23.7	24.5	24.7	25.1	24.5	25.5	24.1	23.6	23.9	23.8	23.2
2005	23.0	23.7	24.5	24.7	25.1	24.5	25.5	24.1	23.6	23.9	23.8	23.2
2006	23.3	22.8	24.2	24.2	24.8	25.4	23.6	24.3	24.3	24.3	24.5	22.3
2007	21.4	22.0	24.8	25.2	25.9	24.8	23.9	24.0	24.5	25.6	24.2	22.7
2008	21.7	23.6	23.6	24.9	25.7	24.3	23.6	24.2	24.2	24.1	24.4	22.7
2009	21.0	22.0	23.9	25.0	25.5	24.4	23.4	24.6	25.4	25.0	24.1	23.7
2010	22.5	24.1	25.3	25.2	25.3	24.3	23.5	24.0	24.5	24.7	24.1	23.6
2011	22.4	22.4	24.0	24.1	26.0	24.6	24.0	24.6	24.8	25.0	23.8	23.1
2012	21.8	22.5	24.5	25.0	26.4	24.9	24.5	24.4	24.6	24.7	24.5	23.4
2013	22.2	23.1	24.6	26.5	26.3	24.0	24.1	24.7	24.5	25.0	24.8	22.6
2014	22.4	22.9	24.4	26.1	26.3	25.7	24.4	24.9	25.4	24.8	24.8	24.4
Avg	22.2	23.0	23.2	25.0	24.2	24.6	25.2	24.3	26.2	24.6	27.2	23.1
MAXIMUM °C												
2003	32.5	32.9	33.3	33.6	31.1	30.4	29.7	30.1	30.2	31.1	31.5	32.9
2004	33.6	34.7	34.1	33.6	33.9	30.7	29.8	31.3	29.9	30.9	31.1	31.8
2005	33.6	34.7	34.1	33.6	33.9	30.7	29.8	31.3	29.9	30.9	31.1	31.8
2006	32.8	33.5	33.9	33.9	32.1	31.4	29.4	29.9	30.4	30.7	31.5	33.3
2007	33.2	32.9	33.6	33.4	32.3	30.6	29.0	29.7	29.7	30.7	31.9	32.2
2008	32.4	32.1	31.9	32.7	32.4	30.9	29.6	30.4	30.9	31.7	31.8	32.7
2009	33.2	33.3	33.4	33.3	32.6	30.6	30.0	30.6	30.9	32.0	32.1	33.0
2010	33.0	33.3	34.4	34.0	32.8	30.3	29.6	29.6	30.2	30.7	30.6	31.4
2011	32.0	32.1	33.2	33.0	32.7	30.2	29.9	29.9	29.8	32.0	32.4	32.1
2012	32.3	32.8	32.5	33.1	32.2	30.9	30.6	30.2	31.2	31.9	32.1	32.9
2013	33.1	33.0	33.5	33.6	32.7	29.2	29.0	30.2	30.3	30.7	31.7	32.0
2014	32.8	33.2	34.0	33.4	32.7	31.2	30.1	30.0	31.1	31.6	32.8	31.7
Avg	32.9	33.2	33.5	33.4	32.6	30.6	29.7	30.3	30.4	31.2	31.7	32.3

Appendix II

Temperature in °C (monthly mean) recorded at RARS, Kumarakom

Month	Jan	Feb	Mar	April	May	June	Jul	Aug	Sep	Oct	Nov	Dec
Year	MINIMUM °C											
2003	21.9	21.7	24.0	24.5	23.8	23.4	23.6	23.9	24.0	23.9	23.7	22.4
2004	22.5	24.7	25.0	24.6	24.0	24.2	23.8	23.6	23.7	23.6	23.3	21.8
2005	23.3	22.9	24.3	24.5	24.9	23.8	23.5	23.3	23.4	23.0	23.2	22.6
2006	22.0	21.7	23.9	24.5	23.8	24.7	23.6	23.9	24.0	24.9	23.3	21.9
2007	21.2	22.0	24.7	24.2	24.0	22.1	21.6	22.6	22.2	22.0	21.9	23.8
2008	20.1	22.4	22.4	22.8	23.0	22.0	21.4	21.8	21.2	21.5	21.4	21.1
2009	20.4	22.7	24.0	25.0	24.0	23.0	23.0	23.0	22.6	22.5	22.1	22.6
2010	22.5	23.5	25.0	25.0	24.8	23.5	22.3	22.4	22.0	21.4	23.4	23.4
2011	22.2	22.5	23.9	24.2	24.7	23.5	23.5	23.5	23.2	23.6	22.6	22.6
2012	21.7	22.3	24.1	23.9	25.5	23.2	22.9	22.6	22.6	24.1	24.1	22.9
2013	22.3	22.9	24.4	25.3	25.3	22.7	22.5	23.7	23.0	22.7	23.1	21.7
2014	21.6	22.7	23.8	24.3	25.0	24.1	22.8	23.0	23.4	23.3	23.0	22.7
Avg	21.8	22.7	24.1	24.4	24.4	23.4	22.9	23.1	23.0	23.0	22.9	22.5
	MAXIMUM °C											
2003	33.0	33.5	34.2	35.5	33.5	31.5	30.3	30.9	32.3	32.2	32.3	32.0
2004	32.9	37.8	34.9	34.4	30.3	30.3	30.0	30.6	31.6	31.4	33.2	32.0
2005	32.7	33.3	34.6	33.9	35.4	29.6	29.9	31.4	30.9	30.7	30.7	31.7
2006	32.5	33.6	34.2	34.2	32.5	31.3	30.7	31.3	31.2	31.4	32.1	33.2
2007	32.9	33.5	34.6	34.4	33.4	31.5	29.5	30.2	30.6	31.5	31.9	32.4
2008	32.5	32.8	32.8	35.6	33.4	31.5	30.5	31.4	31.3	32.1	32.2	32.1
2009	32.2	32.9	34.0	34.4	33.8	31.7	30.7	31.6	31.5	32.3	32.1	32.8
2010	32.6	33.5	34.6	34.6	33.6	31.6	30.6	30.1	31.1	30.8	30.9	31.0
2011	31.9	32.3	33.5	33.2	33.4	31.6	30.4	31.0	31.2	32.7	32.4	32.4
2012	31.8	32.8	33.1	33.6	32.9	31.6	31.1	31.0	31.6	33.1	33.1	32.4
2013	32.4	33.0	33.6	34.2	33.6	29.9	29.3	30.5	30.7	31.6	32.0	31.7
2014	32.1	33.0	34.1	33.9	33.2	31.8	30.0	30.4	31.7	31.8	31.6	31.8
Avg	32.5	33.5	34.0	34.3	33.2	31.2	30.3	30.9	31.3	31.8	32.0	32.1

Appendix III

Temperature in °C (monthly mean) recorded at RRS, Moncompu.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Year	AVERAGE TEMPERATURE °C											
2003	28.3	28.7	29.2	30.4	29.7	27.0	27.2	28.1	28.2	28.1	28.3	27.3
2004	27.1	28.0	28.8	29.2	27.3	27.2	26.9	26.8	26.9	27.6	27.9	27.6
2005	28.3	28.1	29.3	29.2	29.5	27.6	27.7	27.7	26.8	27.4	27.5	27.5
2006	28.1	28.2	29.1	29.1	28.5	28.4	26.5	27.1	27.4	27.5	28.0	27.8
2007	27.3	27.4	29.2	29.3	29.1	27.7	26.5	27.1	27.1	28.2	28.1	27.4
2008	27.1	27.9	27.8	28.8	29.1	27.6	26.7	27.3	27.5	27.9	28.1	27.7
2009	27.1	27.7	28.6	29.1	29.0	27.5	26.7	27.6	28.2	28.5	28.1	28.4
2010	27.8	28.7	29.8	29.6	29.0	27.3	26.5	26.8	27.3	27.7	27.4	27.5
2011	27.2	27.3	28.6	28.6	29.4	27.4	26.9	27.2	27.3	28.5	28.1	27.6
2012	27.1	27.6	28.5	29.0	29.3	27.9	27.5	27.3	27.9	28.3	28.3	28.1
2013	27.6	28.1	29.0	31.0	29.5	26.6	26.5	27.4	27.4	27.9	28.3	27.3
2014	27.6	28.0	29.2	29.7	29.5	28.4	27.2	27.5	28.2	28.2	28.5	28.0

Temperature in °C (monthly mean) recorded at RARS, Kumarakom.

Month	Jan	Feb	Mar	April	May	June	Jul	Aug	Sep	Oct	Nov	Dec
Year	AVERAGE TEMPERATURE °C											
2003	27.5	27.6	29.1	30.0	28.7	27.5	27.0	27.4	28.2	28.1	28.0	27.2
2004	27.7	31.3	30.0	29.5	27.2	27.3	26.9	27.1	27.7	27.5	28.3	26.9
2005	28.0	28.1	29.5	29.2	30.2	26.7	26.7	27.4	27.2	26.9	27.0	27.2
2006	27.3	27.7	29.1	29.4	28.2	28.0	27.2	27.6	27.6	28.2	27.7	27.6
2007	27.1	27.8	29.7	29.3	28.7	26.8	25.6	26.4	26.4	26.8	26.9	28.1
2008	26.3	27.6	27.6	29.2	28.2	26.8	26.0	26.6	26.2	26.8	26.8	26.6
2009	26.3	27.8	29.0	29.7	28.9	27.3	26.8	27.3	27.0	27.4	27.1	27.7
2010	27.6	28.5	29.8	29.8	29.2	27.5	26.5	26.3	26.6	26.1	27.2	27.2
2011	27.1	27.4	28.7	28.7	29.1	27.5	27.0	27.3	27.2	28.1	27.5	27.5
2012	26.7	27.6	28.6	28.8	29.2	27.4	27.0	26.8	26.8	28.6	28.6	27.6
2013	27.4	27.9	29.0	29.8	29.5	26.3	25.9	27.1	26.9	27.2	27.5	26.7
2014	26.9	27.8	29.0	29.1	29.1	28.0	26.4	26.7	27.6	27.6	27.3	27.2

Appendix IV

Relative Humidity in % (monthly mean) recorded in RRS, Moncompu.

Month / Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	83.7	88.7	88.2	88.5	88.9	88.6	88.7	89.9	84.2	79.2	76.3	72.2
2004	70.6	71.8	73.8	74.4	87.1	84.1	91.5	91.2	90.6	91.1	90.6	86.7
2005	89.3	84.6	82.2	82.3	75.4	87.4	91.5	88.9	91.0	89.6	90.9	87.9
2006	90.9	93.6	91.4	90.4	88.8	90.3	88.9	83.4	83.0	80.7	79.1	65.9
2007	66.1	67.1	71.2	73.0	75.0	81.5	90.7	84.6	84.1	80.7	77.4	70.3
2008	69.7	75.8	78.5	75.4	76.7	84.9	85.9	82.5	82.3	79.7	79.8	72.8
2009	68.0	71.0	75.0	77.0	80.0	86.0	87.0	83.0	83.0	80.0	82.0	76.0
2010	67.4	73.9	75.3	75.6	79.1	84.7	86.4	84.9	84.2	83.6	83.1	80.7
2011	77.0	74.5	77.5	77.7	77.3	85.1	85.1	84.2	83.8	77.9	76.6	76.3
2012	74.4	75.2	79.8	78.9	79.1	82.4	82.5	84.1	81.8	79.4	77.2	74.1
2013	74.3	76.8	78.2	76.0	78.7	88.2	87.0	84.5	86.0	83.0	81.0	75.6
2014	71.3	72.5	77.4	75.1	77.9	85.6	86.6	85.8	82.7	82.4	80.6	79.0

Relative Humidity in % (monthly mean) recorded in RARS, Kumarakom.

Month / Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	71.0	80.0	79.0	77.0	88.0	89.0	88.0	87.0	86.0	86.0	80.0	76.0
2004	73.0	67.0	63.0	73.0	85.0	85.0	87.0	88.0	92.0	86.0	62.0	69.0
2005	73.0	70.0	75.0	72.0	77.0	94.0	87.0	82.0	83.0	81.0	75.0	77.0
2006	69.0	64.0	74.0	75.0	82.0	82.0	83.0	80.0	83.0	80.0	78.0	69.0
2007	70.0	72.0	77.0	75.0	80.0	89.8	95.3	90.3	93.6	90.8	85.8	83.6
2008	84.9	87.8	89.6	87.7	82.6	91.8	90.6	92.1	92.5	91.8	91.7	87.2
2009	86.0	86.7	89.4	84.9	87.5	91.3	93.9	90.8	92.9	91.1	90.2	86.8
2010	74.6	72.9	76.9	76.4	80.3	84.0	85.4	88.0	83.9	85.2	83.1	78.0
2011	75.4	73.1	75.4	75.0	77.1	84.0	84.7	84.2	80.3	77.4	72.3	72.3
2012	70.9	72.3	77.7	77.2	82.8	84.5	81.0	83.5	81.1	77.7	77.7	73.2
2013	77.6	73.2	75.5	74.4	78.5	86.7	86.2	83.0	84.1	79.0	80.3	77.0
2014	71.0	76.3	71.5	76.1	76.1	83.2	84.9	86.0	80.5	78.5	75.4	84.3

Appendix V

Total Rainfall in mm recorded at RRS, Moncompu

Month / Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	0	59.0	60.0	159.5	102.4	103.9	95.4	345.2	93.8	496.9	95.4	0
2004	3.8	0	53.4	178.6	825.8	519.8	324.0	306.5	195.8	508.5	244.0	0
2005	16.4	63.6	37.4	200.2	206.8	602	451.3	222.1	528.8	251.0	119.4	73.4
2006	43.4	0	46.0	107.4	511.0	799.2	430.4	349.2	345.9	407.6	188.2	0
2007	0	22.2	3.6	189.2	264.4	632.3	861.3	418.8	363.4	279.7	168.0	13.0
2008	0	60.0	200.9	145.8	62.0	392.8	641.5	236.8	273.1	308.9	171.0	8.8
2009	0	0	78.2	99.1	286.7	629.9	563.8	207.0	214.4	165.7	299.2	97.2
2010	23.4	0	42.2	191.8	346.5	544.8	469.4	253.2	253.6	562.2	241.8	131.0
2011	11.0	40.2	2.8	286.2	289.2	467.0	349.1	252.2	336.6	164.2	160.5	159.0
2012	51.0	0	42.4	227.8	94.1	226.8	249.5	345.8	147.4	122.2	91.0	0
2013	5.8	180.6	47.1	17.8	150.2	943.6	709.0	286.2	258.0	133.8	149.8	20.4
2014	0	23.2	46.6	101.4	227.2	425.0	312.6	633.1	271.8	179.2	125.2	21.4

Total Rainfall in mm recorded at RARS, Kumarakom

Month / Year	Jan	Feb	Mar	April	May	June	Jul	Aug	Sep	Oct	Nov	Dec
2003	0.0	15.0	219.0	59.0	66.0	563.0	457.0	481.0	86.0	514.0	62.0	6.0
2004	3.0	16.0	104.0	89.0	606.0	427.0	351.0	256.0	191.0	425.0	52.0	0.0
2005	18.0	2.2	12.0	269.0	183.0	595.0	529.0	172.0	375.0	467.0	173.0	72.0
2006	4.0	0.0	17.0	94.0	15.0	461.0	500.0	349.0	356.0	398.0	199.0	0.0
2007	0.0	23.0	0.0	194.0	240.0	619.0	832.0	272.0	415.0	344.0	84.0	0.0
2008	0.0	19.0	230.7	201.7	30.8	340.8	452.6	222.9	399.0	353.7	146.7	75.8
2009	0.0	0.0	32.3	65.3	207.3	617.7	516.5	269.8	206.9	138.0	314.8	64.9
2010	1.5	7.5	104.8	116.0	332.8	574.8	447.8	209.0	330.1	503.7	269.4	84.7
2011	49.0	19.2	23.0	158.8	320.9	706.4	432.1	311.4	405.8	97.8	135.6	31.6
2012	33.0	17.0	15.5	198.9	67.3	259.9	233.2	317.6	215.3	170.8	133.5	7.2
2013	0.0	40.1	109.0	75.9	126.8	817.7	817.7	250.0	274.7	216.0	208.2	21.2
2014	0.0	12.3	8.4	115.0	173.6	416.0	440.0	700.5	208.7	335.8	122.5	34.7

Appendix VI

Evaporation in mm (Monthly Mean) recorded at RRS, Moncompu

Month / Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	3.9	3.7	3.9	3.3	2.9	2.7	2.7	3.3	3.7	2.2	2.4	3.5
2004	3.6	3.6	3.6	3.4	2.1	3.7	2.8	3.4	3.5	3.5	3.7	4.0
2005	3.9	4.2	3.8	3.4	3.5	2.9	2.8	2.8	1.9	1.9	2.7	3.5
2006	3.9	4.3	3.4	4.9	3.1	3.5	2.6	2.8	2.7	2.7	2.5	3.4
2007	3.5	4.1	4.3	4.1	3.8	2.1	2.3	3.1	2.7	2.9	4.2	5.1
2008	3.8	3.9	3.1	3.9	4.1	2.6	2.4	3.2	3.3	2.9	2.8	3.2
2009	3.9	4.0	4.2	3.6	3.0	2.1	3.0	3.5	2.9	3.4	3.1	3.5
2010	3.6	4.0	4.6	4.8	3.5	2.7	2.5	2.5	3.0	2.7	2.3	3.6
2011	3.6	4.1	4.8	4.8	4.0	3.1	2.3	2.8	2.5	3.7	3.6	3.3
2012	3.8	4.3	4.7	4.2	3.8	2.9	2.9	2.5	3.3	3.6	3.5	3.7
2013	3.9	3.9	4.2	4.5	3.6	1.5	1.6	3.6	2.0	2.7	3.7	3.8
2014	3.6	4.4	5.2	4.6	3.7	2.9	2.5	2.6	3.2	3.3	2.9	3.1

Appendix VII

Sunshine Hours (Monthly Mean) recorded at RRS, Moncompu

Month / Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	-	-	-	-	-	-	-	-	7.0	5.4	6.5	8.4
2004	9.4	9.4	9.6	8.7	3.5	-	-	-	-	-	-	-
2005	-	-	-	-	-	-	4.4	7.8	4.5	6.6	6.5	8.7
2006	8.9	9.3	8.7	8.9	7.1	3.5	3.8	5.0	4.4	5.2	5.4	8.9
2007	8.3	9.4	8.9	8.2	6.9	3.9	2.3	4.6	4.2	5.1	7.5	6.6
2008	9.5	8.1	5.9	6.6	7.6	3.8	2.8	4.7	6.2	5.6	5.6	7.1
2009	8.9	9.4	8.3	6.5	5.3	4.4	3.5	5.2	4.1	7.5	5.4	7.4
2010	8.4	8.1	8.3	7.7	4.9	3.7	2.4	3.1	4.0	5.1	3.6	5.6
2011	7.2	7.7	7.5	6.6	6.6	4.3	2.7	2.8	4.3	6.2	5.6	6.0
2012	8.6	8.3	6.8	6.0	5.1	3.4	4.3	3.8	4.9	5.5	6.4	6.8
2013	8.1	8.3	6.5	7.0	4.8	1.5	1.8	2.5	1.2	2.7	5.9	7.1
2014	8.0	8.4	7.1	6.8	6.5	4.2	2.9	3.3	5.1	4.4	4.0	4.8

Appendix VIII

Stepwise Regression Analysis:

Forward selection regression analysis

```
Forward Selection of Terms

Candidate terms: Max. Temp., Min. Temp., Avg Temp., R.H.% Avr., Total Rain, Avg.
Rain, Evp.,
     SunShine

             -----Step 1-----
               Coef         P
Constant      27.93
Max. Temp.   -0.757     0.000

S                    0.810635
R-sq                   39.67%
R-sq(adj)              38.04%
R-sq(pred)             34.75%
Mallows' Cp              0.46

α to enter = 0.25
```

```
Analysis of Variance

Source        DF  Adj SS   Adj MS  F-Value  P-Value
Regression     1   15.99  15.9861    24.33    0.000
  Max. Temp.   1   15.99  15.9861    24.33    0.000
Error         37   24.31   0.6571
Total         38   40.30
```

```
Model Summary

       S    R-sq  R-sq(adj)  R-sq(pred)
0.810635  39.67%     38.04%      34.75%
```

```
Coefficients

Term          Coef  SE Coef  T-Value  P-Value   VIF
Constant     27.93     5.03     5.55    0.000
Max. Temp.  -0.757    0.153    -4.93    0.000  1.00
```

```
Regression Equation

AQUATIC WEED AREA = 27.93 - 0.757 Max. Temp.
```

```
Durbin-Watson Statistic

Durbin-Watson Statistic =  1.54878
```

Appendix IX

Backward selection regression analysis

Candidate terms: Max. Temp., Min. Temp., Avg Temp., R.H.% Avr., Total Rain, Avg. Rain, Evp., SunShine

	-----Step 1-----		-----Step 2-----		-----Step 3-----		-----Step 4-----	
	Coef	P	Coef	P	Coef	P	Coef	P
Constant	27.49		28.38		29.12		29.70	
Max. Temp.	-1.013	0.164	-0.989	0.165	-0.775	0.012	-0.837	0.000
Min. Temp.	-0.395	0.644	-0.323	0.690	-0.059	0.756		
Avg Temp.	0.59	0.700	0.50	0.737				
R.H.% Avr.	0.0096	0.752						
Total Rain	0.0611	0.278	0.0637	0.245	0.0691	0.182	0.0723	0.149
Avg. Rain	-1.77	0.302	-1.85	0.270	-2.02	0.202	-2.12	0.163
Evp.	-0.177	0.556	-0.208	0.458	-0.216	0.435	-0.220	0.419
SunShine	0.169	0.285	0.185	0.211	0.195	0.173	0.213	0.102

	Step 1	Step 2	Step 3	Step 4
S	0.828037	0.815951	0.804592	0.793526
R-sq	48.96%	48.79%	48.60%	48.44%
R-sq(adj)	35.35%	37.22%	38.96%	40.63%
R-sq(pred)	24.21%	26.98%	28.18%	32.43%
Mallows' Cp	9.00	7.10	5.21	3.31

	-----Step 5-----		------Step 6-----		-----Step 7-----		-----Step 8-----	
	Coef	P	Coef	P	Coef	P	Coef	P
Constant	30.75		29.89		31.81		27.93	
Max. Temp.	-0.893	0.000	-0.869	0.000	-0.905	0.000	-0.757	0.000
Min. Temp.								
Avg Temp.								
R.H.% Avr.								
Total Rain	0.0662	0.178	0.00269	0.178				
Avg. Rain	-1.93	0.195						
Evp.								
SunShine	0.203	0.114	0.208	0.110	0.128	0.269		

Appendix IX (Contd.)

S	0.789660	0.798022	0.807793	0.810635
R-sq	47.39%	44.69%	41.71%	39.67%
R-sq(adj)	41.20%	39.95%	38.47%	38.04%
R-sq(pred)	34.83%	32.70%	34.07%	34.75%
Mallows' Cp	1.92	1.51	1.26	0.46

α to remove = 0.1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	1	15.99	15.9861	24.33	0.000
Max. Temp.	1	15.99	15.9861	24.33	0.000
Error	37	24.31	0.6571		
Total	38	40.30			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.810635	39.67%	38.04%	34.75%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	27.93	5.03	5.55	0.000	
Max. Temp.	-0.757	0.153	-4.93	0.000	1.00

Regression Equation

AQUATIC WEED AREA = 27.93 - 0.757 Max. Temp.

Durbin-Watson Statistic

Durbin-Watson Statistic = 1.54878

Appendix X

Factor Analysis:

Principal Component Factor Analysis

Principal Component Factor Analysis of the Correlation Matrix

Unrotated Factor Loadings and Communalities

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8
AQUATIC WEED AREA	-0.668	0.331	0.217	-0.449	0.386	-0.207	0.058	-0.002
Max. Temp.	0.846	-0.404	0.077	-0.054	0.120	0.162	0.265	-0.033
Min. Temp.	0.008	-0.950	-0.088	0.039	0.151	-0.187	-0.164	-0.049
Avg Temp.	0.454	-0.865	-0.019	-0.013	0.198	-0.048	0.005	0.067
R.H.%Avr.	-0.336	-0.450	0.756	0.021	-0.295	-0.150	0.047	0.002
Total Rain	-0.819	-0.446	-0.153	-0.213	-0.094	0.229	0.023	0.005
Avg. Rain	-0.820	-0.447	-0.153	-0.205	-0.095	0.230	0.015	-0.004
Evp.	0.710	-0.033	-0.296	-0.492	-0.326	-0.244	0.008	0.001
SunShine	0.769	0.134	0.394	-0.306	0.056	0.321	-0.189	-0.002
Variance	3.9194	2.5442	0.9227	0.6297	0.4396	0.3969	0.1390	0.0081
% Var	0.435	0.283	0.103	0.070	0.049	0.044	0.015	0.001

Variable	Communality
AQUATIC WEED AREA	1.000
Max. Temp.	1.000
Min. Temp.	1.000
Avg Temp.	1.000
R.H.%Avr.	1.000
Total Rain	1.000
Avg. Rain	1.000
Evp.	1.000
SunShine	1.000
Variance	8.9996
% Var	1.000

Factor Score Coefficients

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8
AQUATIC WEED AREA	-0.171	0.130	0.236	-0.713	0.878	-0.521	0.420	-0.243
Max. Temp.	0.216	-0.159	0.084	-0.086	0.272	0.408	1.904	-4.156
Min. Temp.	0.002	-0.374	-0.096	0.062	0.345	-0.472	-1.176	-6.093
Avg Temp.	0.116	-0.340	-0.021	-0.021	0.450	-0.121	0.037	8.301
R.H.%Avr.	-0.086	-0.177	0.819	0.034	-0.672	-0.379	0.335	0.219
Total Rain	-0.209	-0.175	-0.166	-0.338	-0.215	0.577	0.164	0.640
Avg. Rain	-0.209	-0.176	-0.166	-0.326	-0.215	0.580	0.105	-0.486
Evp.	0.181	-0.013	-0.321	-0.781	-0.741	-0.615	0.060	0.098
SunShine	0.196	0.053	0.427	-0.486	0.127	0.809	-1.361	-0.301

Appendix XI

Maximum Likelihood Factor Analysis

Maximum Likelihood Factor Analysis of the Correlation Matrix

* NOTE * Heywood case

Unrotated Factor Loadings and Communalities

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Communality
AQUATIC WEED AREA	0.394	0.502	0.179	-0.012	0.272	0.513
Max. Temp.	-0.427	-0.723	-0.444	0.247	-0.009	0.963
Min. Temp.	0.319	-0.879	0.267	-0.190	-0.000	0.982
Avg Temp.	-0.000	-0.994	-0.038	0.029	0.004	0.990
R.H.%Avr.	0.329	-0.185	0.133	-0.122	0.462	0.389
Total Rain	0.954	0.000	0.000	-0.301	0.000	1.000
Avg. Rain	0.944	0.000	0.000	-0.331	0.000	1.000
Evp.	-0.367	-0.300	-0.217	0.301	-0.241	0.421
SunShine	-0.571	-0.195	-0.475	0.252	0.233	0.708
Variance	2.8083	2.6974	0.5920	0.4673	0.4000	6.9650
% Var	0.312	0.300	0.066	0.052	0.044	0.774

Rotated Factor Loadings and Communalities
Equamax Rotation

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Communality
AQUATIC WEED AREA	-0.422	-0.180	-0.338	0.231	-0.368	0.513
Max. Temp.	0.433	0.186	0.646	-0.549	0.149	0.963
Min. Temp.	0.930	-0.231	-0.060	-0.088	-0.231	0.982
Avg Temp.	0.869	-0.052	0.285	-0.376	-0.096	0.990
R.H.%Avr.	0.182	-0.152	-0.012	0.105	-0.567	0.389
Total Rain	0.099	-0.870	-0.296	0.229	-0.304	1.000
Avg. Rain	0.108	-0.867	-0.285	0.256	-0.298	1.000
Evp.	0.144	0.210	0.247	-0.429	0.332	0.421
SunShine	-0.087	0.374	0.662	-0.348	0.036	0.708
Variance	2.0674	1.8400	1.2838	0.9391	0.8347	6.9650
% Var	0.230	0.204	0.143	0.104	0.093	0.774

Factor Score Coefficients

Variable	Factor1	Factor2	Factor3	Factor4	Factor5
AQUATIC WEED AREA	-0.039	0.084	0.063	0.041	-0.284
Max. Temp.	-0.191	-0.472	0.811	-0.276	0.290
Min. Temp.	0.679	0.523	-0.915	0.160	-0.265
Avg Temp.	0.434	-0.121	0.454	-0.263	-0.149
R.H.%Avr.	-0.048	0.097	0.106	0.043	-0.363
Total Rain	-6.323	-0.652	-16.395	-26.271	-7.279
Avg. Rain	6.068	-0.718	16.915	26.278	7.325
Evp.	0.026	-0.072	-0.043	-0.034	0.231
SunShine	-0.107	0.026	0.263	0.006	-0.360

ABSTRACT

SPATIOTEMPORAL DISTRIBUTION OF AQUATIC INVASIVE PLANTS IN KUTTANAD WETLAND ECOSYSTEM

By

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ABSTRACT OF THE THESIS

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ABSTRACT

A study of aquatic invasive plants of Vembanad Lake south of Thannermukkam bund and AC (Alappuzha-Changanassery) canal in the Kuttanad wetland ecosystem using multispectral imageries was undertaken to assess the spatiotemporal variation in the aquatic weed area, its distribution, extent and trends in variation. The study also aimed to analyse the contribution of climatic factors in explaining the changes in the spatiotemporal distribution of aquatic invasive plants. The study employed medium resolution LANDSAT imageries for mapping and monitoring the aquatic weed distribution. The digital image processing software used for classification of the multispectral satellite imageries to estimate the area of aquatic weeds was ILWIS 3.31 Academic version (Integrated Land and Water Information System) by ITC. The supervised classifications of the multispectral imageries were carried out with the help of the ground truth data collected from several Ground control points (GCPs). The study revealed the usefulness of multispectral satellite imageries obtained from satellites like LANDSAT in studying the spatiotemporal changes in the aquatic invasive plant distribution. However, the effects of cloud cover in obscuring the spectral reflectance data limits the availability of usable imageries.

The study utilised cloud free imageries for the determination of the areal distribution of the aquatic invasive plants and cloud free imageries were not available for the rainy period. The spatiotemporal variations in aquatic invasive plants showed a cyclic trend in its distribution. The mean area of the aquatic invasive plants distribution during the period under consideration was 3.25 km^2. Among the months taken for the study, monthly mean aquatic weed distribution was maximum in the month of September with a value about 5.4 km^2. In the seasonal distribution, the southwest monsoon season (5.4 km^2) had the maximum aquatic weed distribution, followed by the winter season (4.0 km^2), Northeast monsoon season (3.4 km^2) and summer season (2.3 km^2).

Factor analysis and stepwise regression analysis was performed to understand the effect of climatic parameters on the spatio-temporal distribution of aquatic invasive plants. The dependent variable considered in the analysis was the aquatic weed area and the independent variables were maximum temperature, minimum temperature, average temperature, relative humidity, total rain, average rain, evaporation and sunshine hours. Among the climatic factors, temperature has got a negative relationship with the aquatic weed area i.e., as temperature increases the aquatic weed area decreases. From the correlation analysis, it was seen that the maximum temperature has got the maximum negative correlation (-0.63) with the aquatic weed area among the variables considered.

The regression analysis revealed that there is a statistically significant relationship between the maximum temperature and aquatic weed area as the p-value is less than 0.001. It was found that 39.67 per cent of the variation in aquatic weed distribution can be explained by the regression model. The regression equation obtained is

$$\mathbf{AWA = 27.93 - 0.757\ T_{max}}$$

where AWA = Aquatic weed area (km^2)

$T_{max.}$ = Temperature maximum (°C)

The forward and backward step wise regression analysis also showed that the maximum temperature has got more effect on the aquatic weed distribution than the other climatic variables considered. The aquatic weed area was more during the rainy season as nutrient rich sediment from the agricultural lands is swept into the lake by the rains and floods, which lead to the proliferation of the aquatic invasive plants. The areal spread of aquatic invasive plants is not only influenced by the temperature, but also by other factors such as dissolved oxygen, nutrient load, light intensity and pH. The intrusion of saline water from the sea into the fresh water lake also plays an important role as salinity has a detrimental effect on the growth of these aquatic invasive plants.

The regions with the menace of aquatic invasive plants in Kuttanad wetland ecosystem need sustainable management. The study of the spatio-temporal distribution of aquatic invasive plant area using remote sensing techniques provided useful information about the aquatic weed growth in the study area and this method can be utilized for mapping and monitoring the areal spread of aquatic invasive plants.

INTRODUCTION

MATERIALS AND METHODS

REVIEW OF LITERATURE

RESULTS AND DISCUSSION

SUMMARY AND CONCLUSION

ACKNOWLEDGEMENT

APPENDICES

REFERENCES