MONITORING OF WATER CLARITY, AND SUBMERGED AND EMERGENT PLANT COVERAGES IN SHALLOW LAKE WETLANDS USING REMOTE SENSING TECHNIQUES

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ABSTRACT

MONITORING OF WATER CLARITY, AND SUBMERGED AND EMERGENT PLANT COVERAGES IN SHALLOW LAKE WETLANDS USING REMOTE SENSING TECHNIQUES

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Shallow lake wetlands, for which aquatic plants (macrophytes) and water clarity are the key indicators of ecological status, provide valuable services to wildlife and humanity. Conservation of these ecosystems requires development of rapid and large scale monitoring strategies, where remote sensing and Geographic Information Systems (GIS) can be advantageous.

In this study, high spatial resolution Quickbird and IKONOS and medium spatial resolution Landsat and Aster images were used for monitoring the aquatic plants and water clarity in Lakes Mogan and Eymir.

Classification of emergent plants with high spatial resolution data yielded overall accuracies greater than 90% for both lakes, while overall accuracies obtained from the medium spatial resolution data ranged between 80% and 93% for Lake Mogan and between 70% and 78% for Lake Eymir. It was found that there was 23ha reed bed loss in Lake Mogan between 2002 and 2005 and an additional 14ha was lost between 2005 and 2006. In Lake Eymir, no significant change in reed bed area was detected from high spatial resolution images; however medium spatial resolution images revealed 8ha of change which was attributed to the presence of mixed pixels due to low resolution.

The overall accuracies for submerged plant coverage classification from Quickbird images in Lake Mogan were 83% (2005) and 79% (2006) and for classification of submerged plants species were 72% (2005) and 69% (2006).

Moreover, it was found that blue band together with the ratio of red band to blue band, were the best predictors of Secchi disc depth.

Keywords: Classification, Geographical Information Systems, macrophytes, Secchi disc depth.

ÖZ

SIĞ GÖL SULAKALANLARINDA SU BERRAKLIĞININ VE SUİÇİ VE SUÜSTÜ BİTKİLERİNİN UZAKTAN ALGILAMA TEKNİKLERİYLE İZLENMESİ

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Şubat 2007, 99 sayfa

Yaban hayatı ve insanlık için değerli hizmetler sağlayan sığ göl sulakalanlarındaki ekolojik durumunu gösteren en önemli belirteçler su bitkileri (makrofitler) ve su berraklığıdır. Bu ekosistemlerin korunmalarına yardımcı olmak için gerekli olan hızlı ve büyük ölçekli izleme stratejileri geliştirilmesinde Uzaktan algılama ve Coğrafi Bilgi Sistemleri (CBS) avantaj sağlayan araçlar olabilirler.

Bu çalışmada Mogan ve Eymir Gölleri'ndeki su bitkilerinin ve su berraklığının izlenmesi için yüksek mekansal çözünürlüklü Quickbird ve IKONOS görüntüleri ile orta mekansal çözünürlüklü Landsat ve Aster görüntüleri kullanılmıştır.

Suüstü bitkilerinin yüksek mekansal çözünürlüklü görüntülerle sınıflandırılmasından elde edilen genel doğruluklar her iki göl içinde %90'dan yüksekken, orta mekansal çözünürlüklü görüntülerden elde edilen doğruluklar Mogan Gölü için %80 ve %93 arasında, Eymir Gölü için ise %70 ve %78 arasında değişmiştir. Mogan Gölü'ndeki saz yatağı alanında 2002 ile 2005 yılları arasında 23 hektarlık 2005 ve 2006 yılları arasında ise 14 hektarlık kayıpların olduğu bulunmuştur. Eymir Gölü'ndeki saz yatağı alanında yüksek mekensal çözünürlüklü görüntülerde önemli bir değişim bulunmazken, orta mekansal çözünürlüklü görüntülerdekarışmış piksellerin varlığından ötürü 8 hektarlık bir değişim gözlenmiştir.

Mogan Gölü'ndeki suiçi bitkilerinin Quickbird görüntülerinden sınıflandırılması sonucunda elde edilen genel doğruluk değerleri %83 (2005) ve %79'dur (2006). Suiçi bitki türlerinin sınıflandırılmasından ise %72 (2005) ve %69 (2006) genel doğrulukları elde edilmiştir.

Ayrıca, mavi bant ve kırmızı bant ile mavi bantın oranlarının birlikte Secchi disk derinliğini en iyi tahmin ettikleri bulunmuştur.

Anahtar sözcükler: Sınıflandırma, Coğrafi Bilgi Sistemleri, Makrofitler, Secchi disk derinliği.

To Burak

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CHAPTER 1

INTRODUCTION

1.1. Shallow Lakes, Water Clarity and Importance of Aquatic Plants

Most of the world's freshwater area is shallow and made up of small individual lakes dominated by littoral (shallow plant-dominated) communities that are more productive per unit area of water than deep ones (Moss, 1998). However, more than half of the Worlds' former wetlands have been already destroyed, and are still being destructed. Shallow lake wetlands are among the most important and vulnerable freshwater ecosystems on the Earth. They have conservation, aesthetic and economic values and provide several goods and services for humanity and wildlife (Moss, 1998; Mitsch and Gosselink, 2000). The monetary value of lakes and wetlands on a world scale is immense as shown by budgets made by Costanza et al. (1997) for the value of natural goods and services provided by them. The total value of the World's natural systems amounted to over thirty trillion US dollars per year and the contribution of wetlands was over 10% and of wetlands together with lakes and rivers as a whole, over a quarter (Constanza et al., 1997). Main services provided by lakes and wetlands were mentioned as water supply, water regulation and waste treatment and also wetlands was mentioned to have the greatest share in gas and disturbance regulations among all biomes (Constanza et al., 1997). Apart from these services, shallow lake wetlands provide habitat for many species such as fish, plants, waterfowls, mammals, invertebrates, zooplankton, and phytoplankton (Jeppesen et al., 1997), which makes them very important for the conservation of biodiversity. For all of these reasons, conservation of lakes and wetlands is very crucial and it requires monitoring of their ecological status.

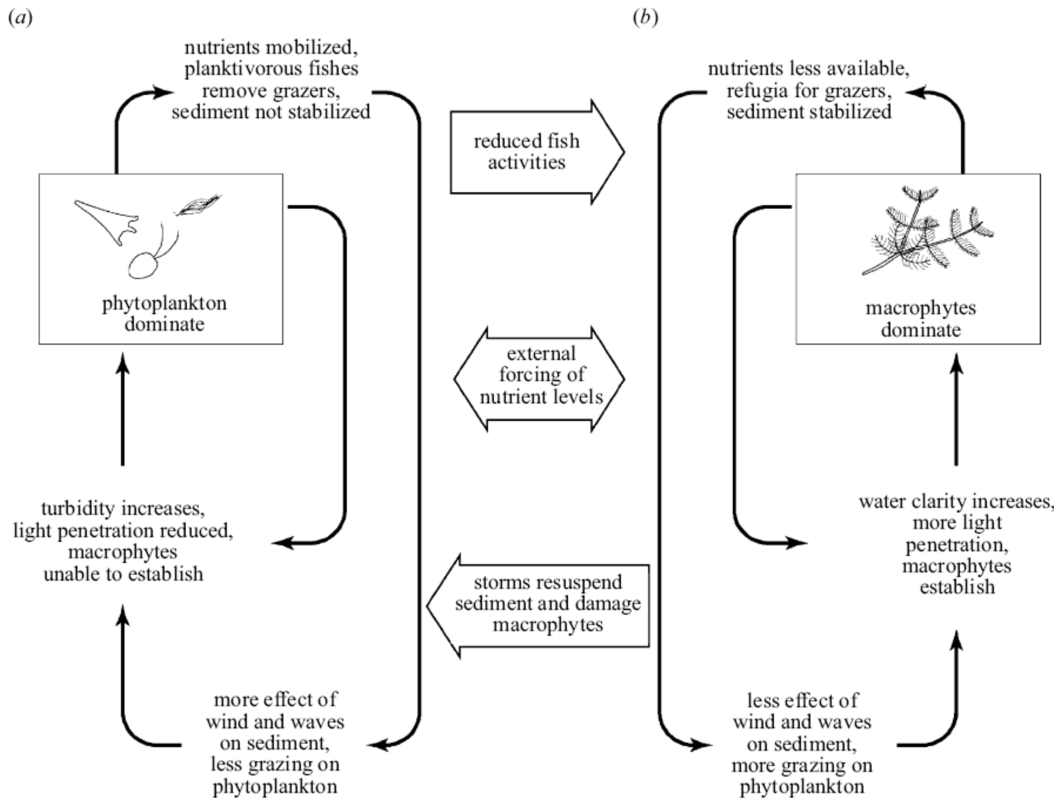


Figure 1.1. Conceptual model for multiple states of water clarity in shallow lakes. (a) Feedbacks associated with the turbid state, and (b) feedbacks associated with the clear-water state. Processes that can move the system from one state to the other are shown between (a) and (b). (Taken from Dent et al., 2002).

Shallow lake wetlands switch between the two alternative stable states: a macrophytes (aquatic plant) dominated clear water state or a phytoplankton dominated turbid water state (Scheffer, 1998). The two alternative states can exist together over a range of intermediate value of the control factors such as nutrient levels (Jeppesen, 1998). Changes in nutrients or water levels, or benthi-planktivorous fish might cause a shift from one stable state to the other (Scheffer et al., 1993). After that, both alternative states tend to stabilize themselves through several stabilizing mechanisms. The processes causing shifts and the stabilizing mechanisms are illustrated in Figure 1.1.

The presence or absence of aquatic plants and water clarity are the main indicators of the ecological status of the shallow lake ecosystems (Meerhof et al., 2003; Moss et al., 1996; William et al., 2004). The reasons for that are the structurizing and stabilizing buffer mechanisms provided by aquatic plants. This structure given by the aquatic plants creates a greater potentiality for niches in which other organisms can live. Aquatic plants maintain clear water through providing refuges for invertebrates and zooplankton such as *Daphnia* against fish predation and through absorbing wind and wave energy which minimise sediment resuspension preventing turbidity (Moss et al., 1996; Gulati et al., 2002; William et al., 2004). They provide habitat for attached algae, food for invertebrates, and cover, habitat and spawning ground for fish. Aquatic vegetation also provides habitat, food and nesting sites for birds (Moss et al., 1996). In several studies it was shown that number of bird populations increased with the increasing aquatic plant density (Perrow et al., 1997; Noordhuis et al., 2002) since aquatic plants form a great portion of the diet of the waterfowls (Perrow et al., 1997). The other services of aquatic plants involve bank edge protection against erosion, products such as reed, sedge, biomass, fish and fowl and conservation (Moss et al., 1996). Emergent aquatic plants, such as reeds, also filter nitrogen through denitrification (Burnak and Beklioglu, 2000) and phosphorus through direct uptake (Headley et al., 2003).

At pristine state, phosphorous and nitrogen are limiting nutrients and their stock in the freshwater ecosystems set an upper limit for the algal growth (Moss, 1998). Thus, primary production is dominated by aquatic plants and water is clear since a healthy aquatic plant community competes out phytoplankton. Through eutrophication the amounts of nitrogen and phosphorus increase in the lake system and phytoplankton dominates primary production (Moss, 1998). Phytoplankton domination, inturn, causes loss of water clarity and the resulting toxic blooms lead to fish kills (Moss, 1998). In general when shallow lake wetlands lose their aquatic vegetation and consequantly their water clarity, they lose their ecological and conservation values (Moss, 1998). Aquatic plants dissappear from the lake ecosystems in response to the changes in water level (Beklioglu et al., 2006), increases in the amounts of benthivorous fish (Beklioglu et al., 2000), eutrophication (Moss, 1998; Beklioglu and Moss, 1996), and direct removal of plants from the lakes and wetlands by people. Loss of aquatic plants cause invertebrates, fish and waterfowls lose their feeding, nesting and breeding sites. Therefore, monitoring of aquatic plants and water clarity can provide valuable information about the ecological status of shallow lakes and wetlands.

1.2. Monitoring Aquatic Plants and Water Quality Parameters

1.2.1. Field Surveys

Aquatic vegetation and water clarity of wetlands can be determined and monitored by field surveys. The most common method of aquatic vegetation monitoring is transect-based sampling method where the whole lake surface is divided into transects with fixed intervals and along these transects, on selected points again with fixed intervals sampling is carried out. The methodology for the aquatic vegetation monitoring is given by Eurolimpacs at URL 1. Sampling, on each point is carried out in a 1mX1m quadrate. The distances between each transect and each sampling point on these transects should be representative for whole lake that is under study. For lakes with dense vegetation, these distances must be closer. Although estimation of aquatic plants for ecological status of shallow lake wetlands provide reliable results, the transect-based sampling method has several disadvantages such as being very time consuming, labour intensive, and thus cost inefficient (Baban, 1997) especially when lakes with large surface areas are considered. For instance, aquatic vegetation monitoring study of Lake Mogan takes four to five days with an experienced staff when the lake is moderately vegetated. Lake Mogan has 6 km^2 of surface area, but most lakes of Turkey have larger surface areas such as Lake Beysehir (730 km^2) and Lake Uluabat (230 km^2). These shallow lake wetlands that have rich aquatic plant community are also rich in biodiversity. In Turkey, there are 200 natural lakes, 75 dams, and 700 ponds (Kazanci et al., 1995), which all have the total surface area of 10,000 km^2. Therefore, the necessity of new approaches to aquatic vegetation monitoring is very obvious (Baban, 1997; Malthus and George, 1997; Vis et al., 2003; Coops et al., 1999; Sawaya et al., 2003).

In addition, water clarity is monitored by measuring Secchi disc depth at representative stations with adequate sampling frequency. Despite producing reliable results, such point measurements of light transparency of the water column fail to be representative for lakes with large surface areas (Giardino et al., 2001). At this point, the remote sensing and the Geographic Information Systems (GIS) are shown to be very promising as new techniques to impove the lake management strategies (Baban, 1999), and monitoring studies.

1.2.2. Remote Sensing and Geographical Information Systems (GIS)

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analyses of data acquired by a sensor that is not in direct contact with target that is being investigated (Pietroniro and Leconte, 2005). There are four concepts that are important in choosing the appropriate satellite images for a particular study (Barrett and Curtis, 1992):

a) Spatial resolution: This is the measure of smallest ground objects that can be identified as a separate entity that is as a single pixel on the imagery (Baban, 1999, Reinke and Jones, 2006).

b) Spectral resolution: This is the capability of a sensor to record spectral information at a particular range of wavelengths (Baban, 1999, Reinke and Jones, 2006).

c) Radiometric resolution: This defines the capability of a sensor to record the actual range of electromagnetic energies falling on a satellite sensor (Baban, 1999).

d) Temporal resolution: This is the time between the regular revisits of a sensor to a given location on the Earth (Baban, 1999).

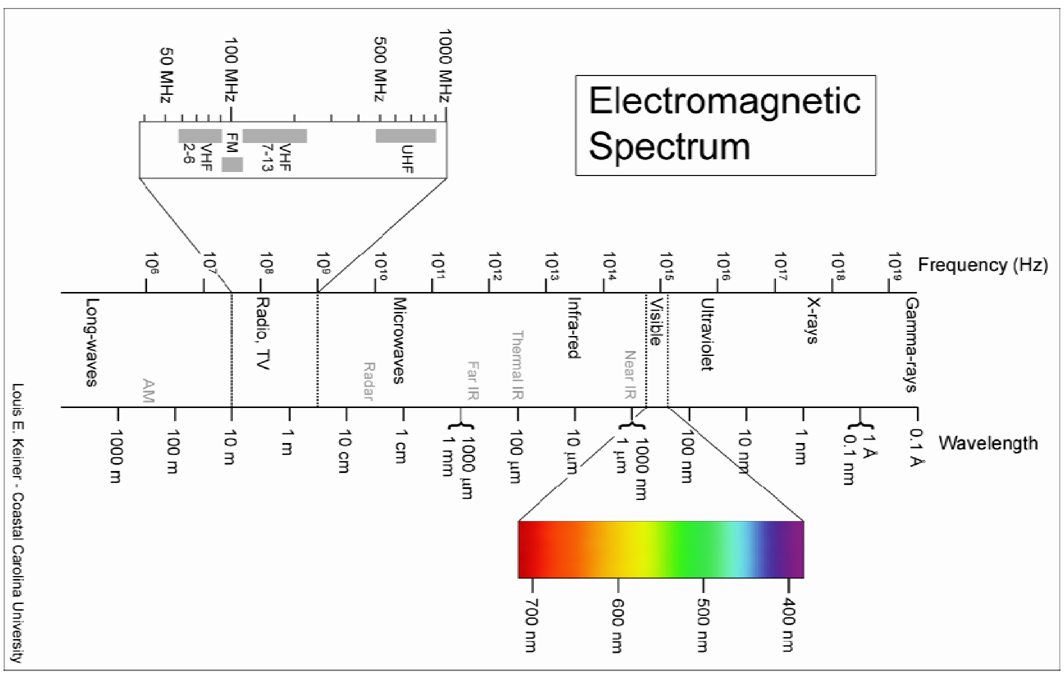


Figure 1.2. The Electromagnetic Spectrum (Taken from URL 2).

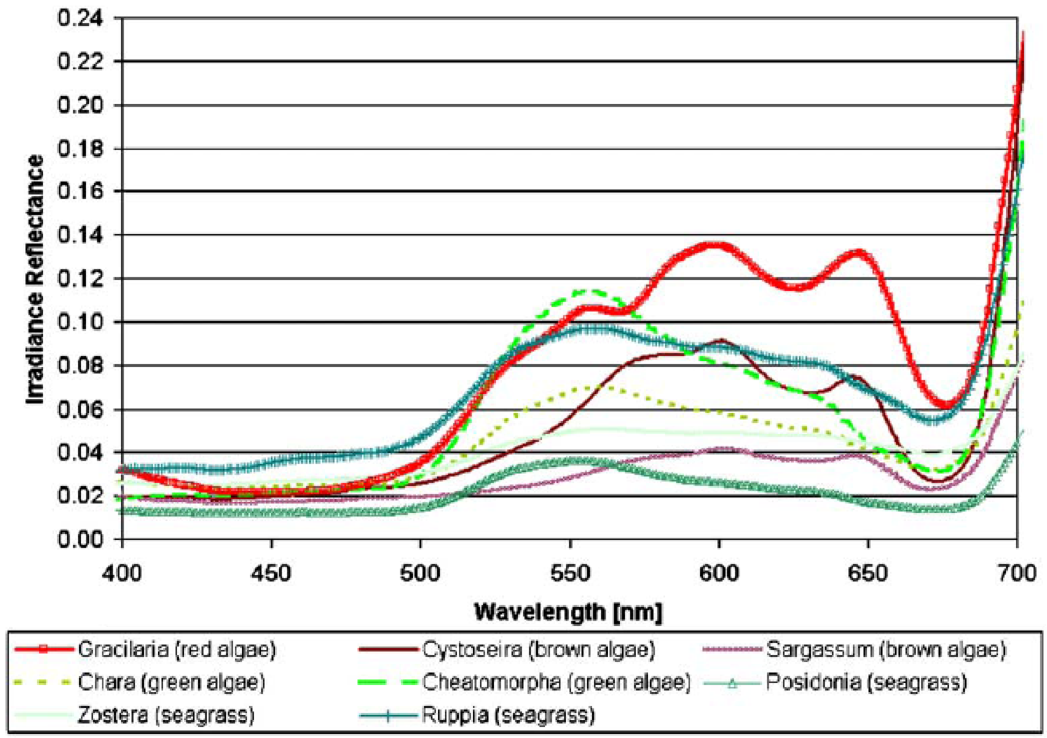


Figure 1.3. Averaged benthic substrate reflectances of several algae and seagrass species measured in August using the RAMSES field spectroradiometer (taken from Dekker et al., 2005).

The remote sensing technology makes use of the properties of the electromagnetic waves emitted, reflected or diffracted by the sensed objects. Given the electromagnetic spectrum in Figure 1.2 and the reflectance curve of some algae and seagrass species in Figure 1.3, the suitable wavelengths for lake studies can be derived. Curran et al. (1985) stated the most suitable wavelengths for the lake studies are visible (0.4-0.7µm), near infrared (0.7-2.0µm) and thermal infrared (3.0-50µm) wavelengths. Clear water surface strongly absorbs the near infrared wavelengths that are also strongly reflected by the plants. Since clear water also absorbs red wavelengths but shows less absorption and increased scattering in the blue wavelength, the upwelling radiation of clear water is mainly blue (Pehuelas, 1993).

On the other hand chlorophyll strongly absorbs blue and red wavelengths and shows absorption minimum in the green wavelength and therefore, chlorophyll in the water decrease the ratio of blue to green upwelling radiance (Pehuelas, 1993). During growing season the submerged vegetation absorbs visible red electromagnetic radiation and thus can be detected by remote sensors (Kirkman, 1996). Differences in reflectances of different species can be attributed to the differences in growth habits as well as the depth and turbidity of the surrounding water (Malthus and George, 1997). Aquatic macrophytes display red-edge shoulders like terrestrial plants (Malthus and George, 1997).

GIS can be defined as a powerful set of tools for capturing, storing, checking, combining, manipulating, analysing, and displaying data which are spatially referenced to the area under study (Burrough, 1986; DeMers, 1997).

a) Data collection and input are defined as the conversion of the spatial information from an existing format into a digital format that is compatible with GIS (Jensen, 1996). It includes manual digitizing, scanning maps, keyboard entry of attribute information, online retrieval from other databases, and transformation of ground data into digital maps (Baban, 1999).

b) Data storage and retrieval (data management): Spatial data are kept in a form that can be quickly retrieved by the user and therefore, updating data becomes more accurate and rapid (Baban, 1999).

c) Data manipulation and analysis: The user can perform analyses and produce estimates on data using GIS (Baban, 1999).

d) Data reporting includes display of the database, output from spatial models in tabular or map form (Jensen, 1996; Baban, 1999).

Together with GIS, remote sensing can provide rapid and large scale monitoring and understanding of changes in lakes and furthermore, use of remote sensing as a data source and of GIS as an analytical tool enable development of conservation and management strategies for lakes (Baban, 1999). Remote sensing can also provide reliable information about the spatial distributions of species under investigation (Baban, 1997), good spatial and temporal coverages, and possibility of measuring many lakes simultaneously (Koponen et al., 2002). Satellite remote sensing offers a great potential to contribute to lake researches especially aquatic plant monitoring, identification, and classification due to high spatial resolution, good spatial and temporal coverage, and multi-spectral measurements. High spatial resolution sensors like Quickbird and IKONOS are very promising for the identification of aquatic plants, when they are integrated with the ground data (Sawaya et al., 2003) and their importance increases when lakes of small surface area are under consideration. The efficiency of remote sensing in identifying aquatic plants is affected by the image quality, water depth, turbidity, and wind, therefore calibrating image data with the ground data is important (Vis et al., 2003). However, for most of the time the limited amount of the ground data becomes a limitation for investigation of relationships between ground data and satellite images. In order to have reliable results from long term monitoring studies, different sensors should be compared and calibrated with each other (Brivio et al., 2001). Models and algorithms developed for one particular sensor can also be verified for the other sensors (Sawaya et al., 2003).

1.3. Remote Sensing Applications in Wetlands, Lakes and Other Aquatic Ecosystems

Applications of satellite remote sensing in wetland and lake studies, especially in aquatic vegetation monitoring studies, are new. Mapping submerged plants over large areas has been performed using either aerial photography (Kirkman, 1996) or medium resolution satellite data (Roelfsema et al., 2003). Airborne remote sensing is most suitable for small and shallow waters where cloud-free data with high spatial resolution are needed (Yang, 2005). Today’s high spatial resolution sensor images, such as Quickbird and IKONOS, provide an improved spatial resolution that is as good as airborne photographic products (Sawaya et al., 2003).

Malthus and George (1997) used Daedalus Airborne Themetic Mapper (ATM) data and true-colour aerial photographic imagery in order to monitor the distribution of submerged, floating leaved and emergent aquatic plants in Cefni Reservoir on the Isle of Anglesey. Comparing the ATM images to the ground based spectroradiometric measurements of the reflectance caharteristics of the water and stands of aquatic plants, Malthus and George (1997) found that good identification of plants could be achieved by a combination of green, red, and near infrared wavebands.

Airborne Imaging Spectrometer for Applications (AISA) and Envisat Medium Resolution Imaging Spectrometer (MERIS) data were used to classify the three water quality measurements in eleven southern Finish lakes (Koponen et al., 2002). The accuracies found to be 90% for three Secchi disc depth classes, 79% for the five turbidity classes, and 78% for the five chlorophyll-a classes (Koponen et al., 2002).

Medium spatial resolution Landsat TM images were used to classify aquatic plants and water quality in Danube Delta lakes and the resulted three categories of lakes icluding: clear/aquatic plant-dominated, intermediate, and turbid/poorly vegetated (Coops et al., 1999). They used the 1-4 spectral bands of Landsat TM to classify the water types and classified each pixel into on of the categories such as clear water, algal blooming, suspended solids (low, intermediate, and high levels), submerged vegetation, and floating vegetation (Coops et al., 1999). In the end, Coops et al. (1999) concluded that Landsat images were not applicable for a classification of surface water because of the restriction in spectral information and spatial resolution as Lehmann and Lachavanne (1997) suggested.

Remote sensing can also be used to monitor algal blooms which are of great importance due to the environmental hazards they cause. Chang et al. (2004) used Landsat TM data to establish an empirical model to detect algal blooms in the Techi reservoir, Taiwan. The bloom prediction model established from the ratios of logarithm transformed radiance values from Landsat TM data to dinoflagellete densities revealed 74.07% overall accuracy (Chang et al., 2004). However, Chang et al. (2004) concluded that increased spectral sensitivity and spatial resolution in remote sensing data would increase the accuracy.

In order to detect the concentration and spatial distribution of cyanobacteria in Lake Erie, Vincent et al. (2004) used Landsat 7 ETM+ and Landsat 5 TM data. The relative content of phycocyanin, a light harvesting pigment of cyanobacteria, and turbidity were measured in Lake Erie using remote sensing technology (Vincent et al., 2004). The concentration and distribution of cyanobacteria can be estimated from the measurements of phycocyanin. Vincent et al. (2004) compared the images obtained with ground data and observed that Landsat TM-derived datasets and ground derived data sets showed high similarity.

In another study, chlorophyll-a concentration, Secchi disc depth and water surface temperature in a sub-alpine Lake Iseo, Italy were mapped using Landsat TM data (Giardino et al., 2001). The spectral reflectance values from thebands 1 and 2 of the atmospherically corrected Landsat TM and in situ measurements were used to develop models which provided high determination coefficients like R^2 values of 0.99 and 0.85 for chlorophyll and Secchi disc depth, respectively (Giardino et al., 2001). In order to detect surface water temperature changes, Giardino et al. (2001) used the band 6 of Landsat TM and found high similarities between the Landsat TM-derived datasets and ground-derived data sets.

Kloiber et al. (2002) analyzed ten Landsat Thematic Mapper (TM) images and four Multispectral Scanner (MSS) images of the Twin Cities Metropolitan Area spanning 25 years (1973–1998). They found that a three-coefficient regression model using the TM1/TM3 ratio and TM1 was a consistent and reliable predictor of Secchi disc transparency (SDT) (R^2 values of 0.70–0.80). For the MSS2 and MSS3 bands, and MSS2/MSS1 band ratio the mean absolute correlation coefficients were 0.69, 0.66, and 0.63, respectively. Kloiber et al. (2002) concluded that R^2 values of regression models between satellite brightness data and measured SDT decreased with increasing size of the time interval between image collection and ground observation of SDT.

Some studies investigated potential of the satellite remote sensing in estimating the amount of the coloured dissolved organic matter (CDOM) which is important for the structure and function of lake ecosystems (Kutser et al., 2005; Brezonik et al., 2005). Kutser et al. (2005) carried out model simulations to evaluate the suitability of several different satellite sensors like Landsat, IKONOS, and the Advanced Land Imager (ALI) for mapping the amount of CDOM in concentration ranges that occur in boreal lakes of the Nordic countries. The results of this study showed that the 8-bit radiometric resolution of Landsat 7 is not adequate for mapping the amount of CDOM while the 11-bit radiometric resolution of IKONOS is more suitable. Kutser et al. (2005) also found that there is a high correlation ($R^2 = 0.84$) between the 565 nm/660 nm ALI band ratio and the CDOM absorption coefficient in lakes according to the 18 sampling stations in 15 lakes.

In the other study, Brezonik et al. (2005) used ground-based measurements with wide ranges of optical properties and Landsat TM data of 15 Minnesota lakes to evaluate the effect of humic colour on satellite-inferred water quality conditions. They reported that there was good statistical relationships between optical properties of lake water and measured brightness of various Landsat TM bands and the best relationships for chlorophyll-a were revealed with the band ratio 1 to 3 ($R^2 = 0.88$).

Pantanal of South America, one of the largest tropical wetlands of the world (Mitsch and Gosseslink, 2000) contains thousands of geochemically diverse lakes, ranging from dilute to brackish to saline in composition and these lakes form the backbone of the habitat that supports the highly diverse flora and fauna (Costa and Telmer, 2006). The area is very remote and the lakes are very numerous, therefore remote sensing can be an essential tool to understand the type of lakes and their spatial distribution, as well as the dynamics of the Pantanal ecosystem (Costa and Telmer, 2006). In that respect, Costa and Telmer used RADARSAT S1 and S7, and JERS-1 imagery and field measurements for water geochemistry and characteristics of emergent aquatic vegetation for fresh and brackish lakes of the Nhecolândia region. They used the relationships between backscattering values, plant assemblages, and geochemistry to map the type and distribution of the lakes in the study area. Brackish lakes were separated from fresh water lakes with a total accuracy of 91% (Costa and Telmer, 2006).

Sawaya et al. (2003) assessed the potential of high-resolution IKONOS and Quickbird satellite imagery for mapping and analysis of water resources at local scales in Minnesota for water clarity and aquatic plants. They calibrated the Landsat image with Secchi disc transparency measurements. To perform a multiple regression Sawaya et al. (2003) used log-transformed SDT data as the dependent variable and Landsat TM band 1 (TM1) and the TM1/TM3 ratio as independent variables and obtained a regression model with $R^2 = 0.76$. After that, in order to compare the compatibility of IKONOS imagery with Landsat TM imagery, Sawaya et al. (2003) calibrated the IKONOS image using two different datasets derived from SDT field measurements and water clarity measurements extracted from the Landsat image. They found strong relationships between both water clarity datasets (TM-derived and SDT-derived) and the spectral-radiometric response of the IKONOS data (R^2 = 0.89 and R^2 = 0.94 for TM-derived and SDT-derived datasets, respectively). The aquatic vegetation classification was carried out in the Swan Lake and the obtained overall accuracy was 79.5% for submerged vegetation (Sawaya et al., 2003).

Wolter et al. (2005) used Quickbird sensor data for mapping submerged vegetation using isodata unsupervised classification at three different sites (Little tail point, Erie marsh, and Portage bay) across the Great Lakes in USA with multi-temporal classification approach. In Little tail point, Wolter et al. (2005) obtained 80% overall accuracy for mapped four classes. The user's and producer's accuracies for the submerged vegetation class were 85% and 76%, repsctively. In Erie Marsh, the classification to two classes, submerged vegetation and water, yielded an overall accuracy of 93%. For Portage Bay, Wolter et al. (2005) performed both multi-date and single-date classifications for 5 classes including muck, sand, dense submerged vegetation, sparse submerged vegetation and deep water. For multi-date classification the obtained overall accuracy was 83%, while it was 71% for the single date classification. For both types of classifications the obtained user's and producer's accuracies of dense submerged vegetation were equal or greater than those of sparse submerged vegetation.

1.4. Aim of the Study

The aim in this study is to use remote sensing and Geographic Information Systems (GIS) as tools for determining and monitoring of aquatic vegetation and water clarity of a system of two Central Anatolian shallow lakes. Additionally, it is also aimed to compare the capability of different sensors in monitoring of aquatic vegetation and water clarity. In order to fulfil these goals, classification, identification, and change detection of aquatic vegetation in both lakes were carried out and performances of different sensors were compared with respect to the spatial resolution and lake size. Furthermore, the relationship between the field measurements and satellite data for Secchi disc depth were investigated for algorithms that define such relationships.

CHAPTER 2

MATERIALS AND METHODS

2.1. Study Site

Study sites are Lake Mogan (39^{o}47'33''E and 39^{o}46'05''N) and Lake Eymir (39^{o}49'54''E and 39^{o}49'32''N). The lakes are a system of two shallow lakes located in the Central Anatolia, 20 km south of the capital city Ankara, Turkey, where Lake Mogan is the upstream and Lake Eymir is the downstream (Figures 2.1 and 2.2).

Lake Mogan is a large, shallow freshwater lake (total wetland area: 714.28 ha, surface area: 584.97 ha, Z_{max}: 3.5m, Z_{mean}: 2.1m) with four major inflow sources (Yavrucak, Çölovası, Gölcük and Sukesen brooks), and one major outflow namely Mogan Outflow which empties into Lake Eymir. Lake Mogan is surrounded by a large emergent plant wetland dominated by reed (*Phragmites australis*) and Yavrucak, Çölovası and Gölcük brooks reach to the lake through this wetland after running through the agricultural lands. However, since 2004 the emergent plant wetland surrounding the lake had been heavily removed for lake shore recreational purposes. The lake has the protection status of Specially Protected Area (SPA) given by the Ministry of Environment in 1990 and Important Bird Area (IBA) since it hosts >20,000 waterfowls in winter (Kirac et al., 1995; Ozesmi, 1999). Downstream Lake Eymir is smaller in area (total wetland area: 129.41 ha, surface area: 104.43 ha) and deeper (Z_{max}: 4.3-6m, Z_{mean}: 2.6-3.2 m) than Lake Mogan. Lake Mogan empties into Lake Eymir through the Mogan Outflow at the southwest corner of the Lake Eymir, and then it is named as Eymir In 1. The other inflow to Lake Eymir is Kışlakçı brook and the outflow is namely Eymir Out1. Lake Eymir is also surrounded by reed beds like a belt with a width of 10-20 m.

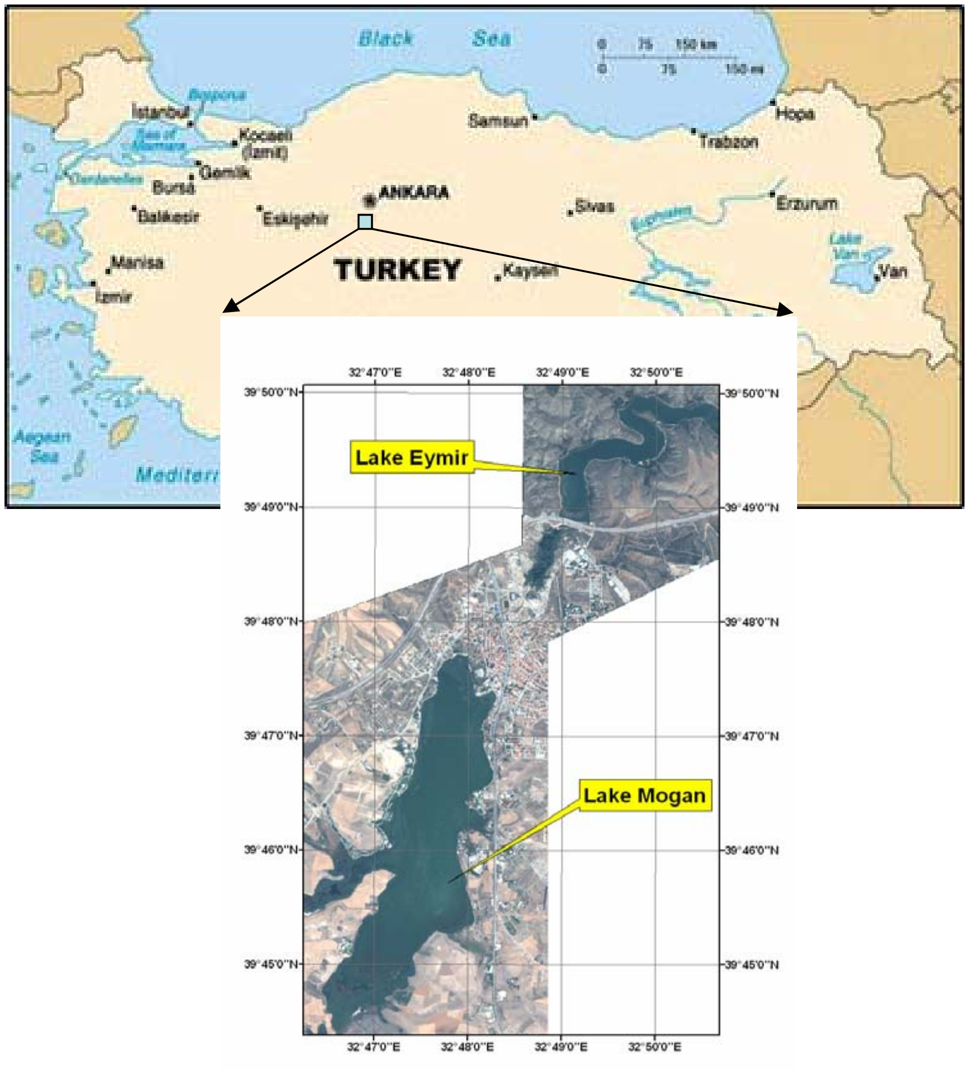


Figure 2.1. Location of Lake Mogan and Lake Eymir on Turkey and the image of the lakes.

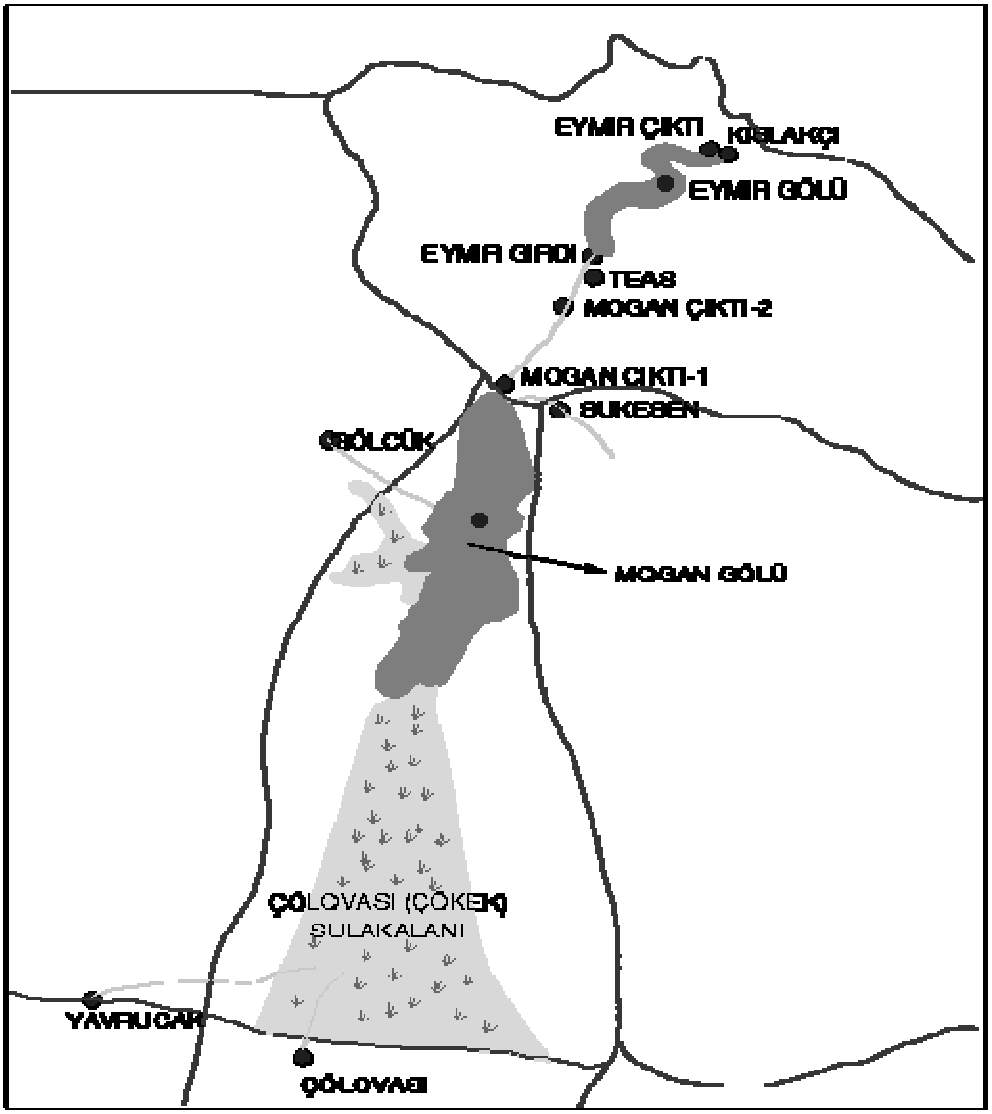


Figure 2.2. Sketch of Lake Mogan and Lake Eymir with their inflows and outflows.

Lake Mogan is a large, shallow freshwater lake (total wetland area: 714.28 ha, surface area: 584.97 ha, Z_{max}: 3.5m, Z_{mean}: 2.1m) with four major inflow sources

(Yavrucak, Çölovası, Gölcük and Sukesen brooks), and one major outflow namely Mogan Outflow which empties into Lake Eymir (Figure 2.2). Lake Mogan is surrounded by a large emergent plant wetland dominated by reed (*Phragmites australis*) and Yavrucak, Çölovası and Gölcük brooks reach to the lake through this wetland after running through the agricultural lands. However, since 2004 the emergent plant wetland surrounding the lake had been heavily removed for lake shore recreational purposes. The lake has the protection status of Specially Protected Area (SPA) given by the Ministry of Environment in 1990 and Important Bird Area (IBA) since it hosts >20,000 waterfowls in winter (Kirac et al., 1995; Ozesmi, 1999). Downstream Lake Eymir is smaller in area (total wetland area: 129.41 ha, surface area: 104.43 ha) and deeper (Z_{max}: 4.3-6m, Z_{mean}: 2.6-3.2 m) than Lake Mogan. Lake Mogan empties into Lake Eymir through the Mogan Outflow at the southwest corner of the Lake Eymir, and then it is named as Eymir In 1. The other inflow to Lake Eymir is Kışlakçı brook and the outflow is namely Eymir Out1 (Figure 2.2). Lake Eymir is also surrounded by reed beds like a belt with a width of 10-20 m.

Table 2.1. Selected geographical, hydrological and physical features of Lakes Mogan and Eymir

	Lake Mogan	Lake Eymir
Maximum Depth (m)	3.5	4.3-6m
Mean Depth (m)	2.1	2.6-3.2 m
Surface area (ha)	584.97	104.43 ha
Wetland area (total) (ha)	714.28	129.41 ha
Elevation (m.a.s.l.)	972.25	967.33
Length (m)	5120	Meandering shape
Width (m)	1050	392
Perimeter (m)	26323.9	10902.2

Lake Mogan and Lake Eymir were selected as study sites because both lakes have been extensively sampled since 1997 for hydrological, physical, chemical, and biological parameters and their dynamics were well known (Zhang et al., 2003; Beklioglu et al., 2003; Tan and Beklioglu, 2005; Muluk and Beklioglu, 2005; Sandsten et al., 2005; Tan and Beklioglu, 2006; Jeppesen, et al., 2007). The close location of the study site became advantageous during the field studies and directly increased the quality of field data produced. Also Lake Mogan with large surface area and Lake Eymir with small surface area and a unique meandering shape provided comparisons for size and shape dependent efficiency of remotely sensed images.

2.2. Field Data

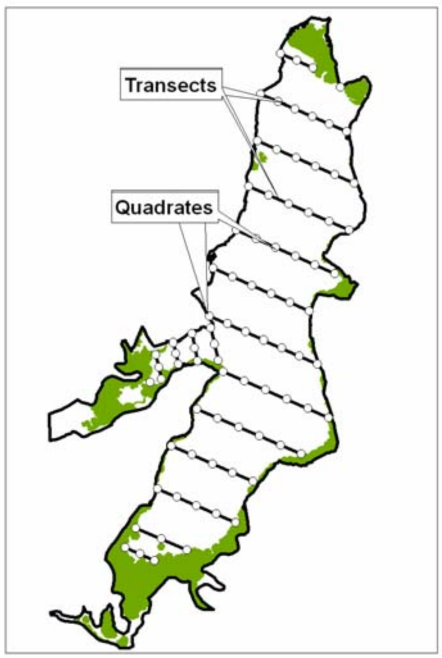
In this study, the field data was collected according to the transect-based sampling method in late summer of years 2004, 2005, and 2006 from Lake Mogan and Lake Eymir. Also the field data for years 2001-2003 were obtained and involved into the study (Tan, 2002). All field data were transferred into the GIS environment using ArcGIS versions 8.3, 9.0 and 9.1 software, except the field data for Lake Mogan in 2002, because of the problems in the coordinates of this year's data. The date of the field surveys, number of transects and sampling points used in the surveys and measured mean Secchi disc depth (SDD) and relative plant percent coverage values for the field data transformed into the GIS environment are given in Table 2.2.

Table 2.2. The date, number of transects and sampling points used measured mean Secchi disc depth (SDD) and relative plant percent coverage values in field surveys.

Date of the field survey	Name of the lake	Number of transects	Number of sampling points	Mean SDD (cm)	Relative coverage (%)
21-25 August 2006	Mogan	23	87	107.3	18.9
14-18 August 2006	Eymir	22	60	253.3	0
23 August-2 September 2005	Mogan	15	66	49	34.9
16-19 August 2005	Eymir	22	62	19	0
21-24 September 2004	Mogan	20	77	41.9	24.5
14-16 September 2004	Eymir	18	53	140.3	5
Second half of August 2003	Mogan	15	64	77.9	30
Second half of August 2003	Eymir	28	112	82.6	45
Second half of August 2002	Eymir	19	94	100.7	60
Second half of August 2001	Mogan	30	165	118.1	90
Second half of August 2001	Eymir	17	51	138.8	90

The main procedure included 200-300m intervals between each transect and 200m to 300m intervals between sampling points along each transect. The transect-based sampling method is illustrated in Figure 2.3. All datasets contained the measurements of Secchi disc depth, water depth, identification of plant species, plant percent coverage at the surface, and plant height at each sampling point on the transects. During the field studies coordinate information of each sampling point has also been recorded by the help of a GPS device. The projection system and the datum used were UTM zone 36 and ED50 respectively in recording the coordinates. The plant species were identified using the guides including Altinayar

(1988) and Haslam et al. (1986). Furthermore, plant height and percent coverage and water depth were determined for estimating Plant Volume Inhabited (PVI) which is the percentage of the total lake volume that is inhabited with aquatic plants, and calculated as the ratio of plant height to water depth multiplied by plant percent coverage (Canfield et al., 1984).

a) 

b) 

Figure 2.3. a) Illustration of transect-based sampling method including the transects and quatrates along the transects on a Lake Mogan figure, b) 1m X 1m quadrate used in assessment of plant percent coverage at surface at the points on each transect.

2.3. Satellite data

2.3.1. Sensors and their Characteristics

The satellite data used in this study belongs to the Quickbird, IKONOS, Aster (Advanced Spaceborne Thermal Emission and Reflection Radiometer) and Landsat sensors. In Table 2.3, some characteristics of these sensors are listed. Table 2.4 presents the wavebands recorded by the Quickbird, IKONOS, Aster and Landsat ETM+ sensors and the overlapped portion of the electromagnetic spectrum. Further information is available at URL 3, URL 4, URL 5, and URL 6. All sensors listed are passive sensors that they detect the radiation reflected or emitted by the Earth's surface (Curran, 1985).

Table 2.3. Characteristics of the sensors used in this study.

	Quickbird	IKONOS	Landsat ETM+	Aster
Launch date	October 2001	September 1999	April 1999	December 1999
Altitude (km)	450	680	705	705
Spatial resolution (nadir, m)	Panchromatic: 0.60 Multispectral: 2.4	Panchromatic: 1 Multispectral: 4	Panchromatic: 15 Bands 1-5 &7: 30 Band 6: 60	VNIR subsystem: 15 SWIR subsystem: 30 TIR subsystem: 90
Radiometric resolution	11 bit	8 bit -11 bit	8 bit	VNIR & SWIR subsystems: 8 bit TIR subsystem: 12 bit
Temporal resolution	3-7 days	3 days	16 days	16 days

Table 2.4. Wavebands recorded by the Quickbird, IKONOS, Aster and Landsat ETM+ sensors.

<table>
<tr><th colspan="2">Electromagnetic Spectrum</th><th colspan="2">Quickbird wavebands (µm)</th><th colspan="2">IKONOS wavebands (µm)</th><th colspan="2">Landsat wavebands (µm)</th><th>Aster wavebands (µm)</th></tr>
<tr><td rowspan="2">Visible portion</td><td>Blue
Green</td><td rowspan="3">Black & White -Panchromatic :0.445-0.9</td><td>Blue: 0.45-0.52
Green: 0.52-0.60</td><td rowspan="3">Black & White -Panchromatic :0.45-0.9</td><td>Blue: 0.45-0.52
Green: 0.51-0.60</td><td rowspan="3">Band 8 -Panchromatic :0.45-0.9</td><td>Band 1: 0.45-0.52
Band 2: 0.52-0.6</td><td>Band 1: 0.52-0.6</td></tr>
<tr><td>Red</td><td>Red: 0.63-0.69</td><td>Red: 0.63-0.70</td><td>Band 3: 0.63-0.69</td><td>Band 2: 0.63-0.69</td></tr>
<tr><td rowspan="3">Infrared portion</td><td>Near IR</td><td>NIR: 0.76-0.90</td><td>NIR: 0.76-0.85</td><td>Band 4 NIR: 0.76-0.9</td><td>Band 3: 0.76-0.86</td></tr>
<tr><td>Mid IR</td><td colspan="4" rowspan="2"></td><td colspan="2">Band 5 NIR: 1.55-1.75
Band 7 MidIR: 2.08-2.35</td><td>Band 4: 1.6-1.7
Band 5: 2.145-2.185
Band 6: 2.185-2.225
Band 7: 2.235-2.285
Band 8: 2.295-2.365
Band 9: 2.360-2.430
Band 10: 8.125-8.475
Band 11: 8.475-8.825
Band 12: 8.925-9.275</td></tr>
<tr><td>Thermal IR</td><td colspan="2">Band 6 Thermal: 10.4-12.5</td><td>Band 13: 10.25-10.95
Band 14: 10.95-11.65</td></tr>
</table>

2.3.2. Satellite images used in the study

In this study, both high spatial resolution images including Quickbird and IKONOS and medium spatial resolution images including Aster and Landsat were used. In addition two Landsat multispectral data were merged with Landsat panchromatic data to increase the spatial resolution. The spatial resolutions for images listed in Tables 2.3 and 2.4 are the nadir view spatial resolutions meaning that point on the ground vertically beneath the perspective centre of a sensor (Curran, 1985). The images used in this study did not always have the nadir looking spatial reolution. Table 2.5 lists the satellite images used in this study and their actual spatial rsolutions. All images are presented as true colour composites in Figures 2.4 to 2.7.

Table 2.5. Satellite images used in the study.

Satelite image	Acquisition date	Spatial resolution (m)		Lakes in the area
		X	Y	
Landsat	18.09.2001	34.987	34.974	Mogan & Eymir
Landsat	21.09.2002	28.951	28.915	Mogan & Eymir
Landsat	20.08.2005	28.718	28.696	Mogan
Aster	26.07.2002	16.968	16.958	Mogan & Eymir
Aster	15.08.2005	17.285	17.285	Mogan & Eymir
IKONOS	04.08.2001	3.978	3.976	Eymir
IKONOS	04.08.2002	4.018	4.018	Mogan
Quickbird	06.08.2005	2.411	2.411	Mogan & Eymir
Quickbird	27.08.2006	2.416	2.415	Mogan & Eymir

Figure 2.4. IKONOS image of Lake Eymir acquired on 04.08.2001.

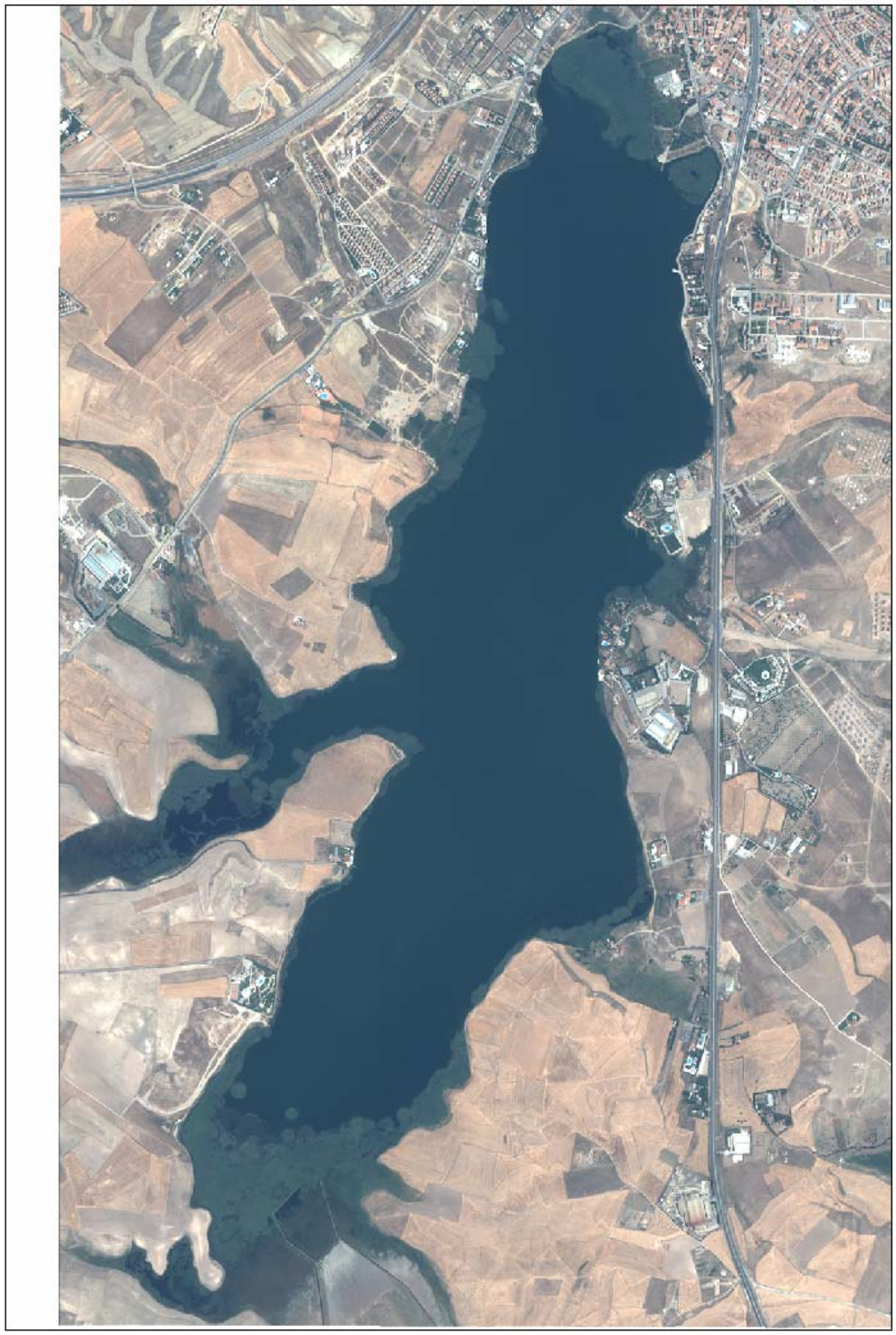


Figure 2.5. IKONOS images of Lake Mogan acquired on 04.08.2002.

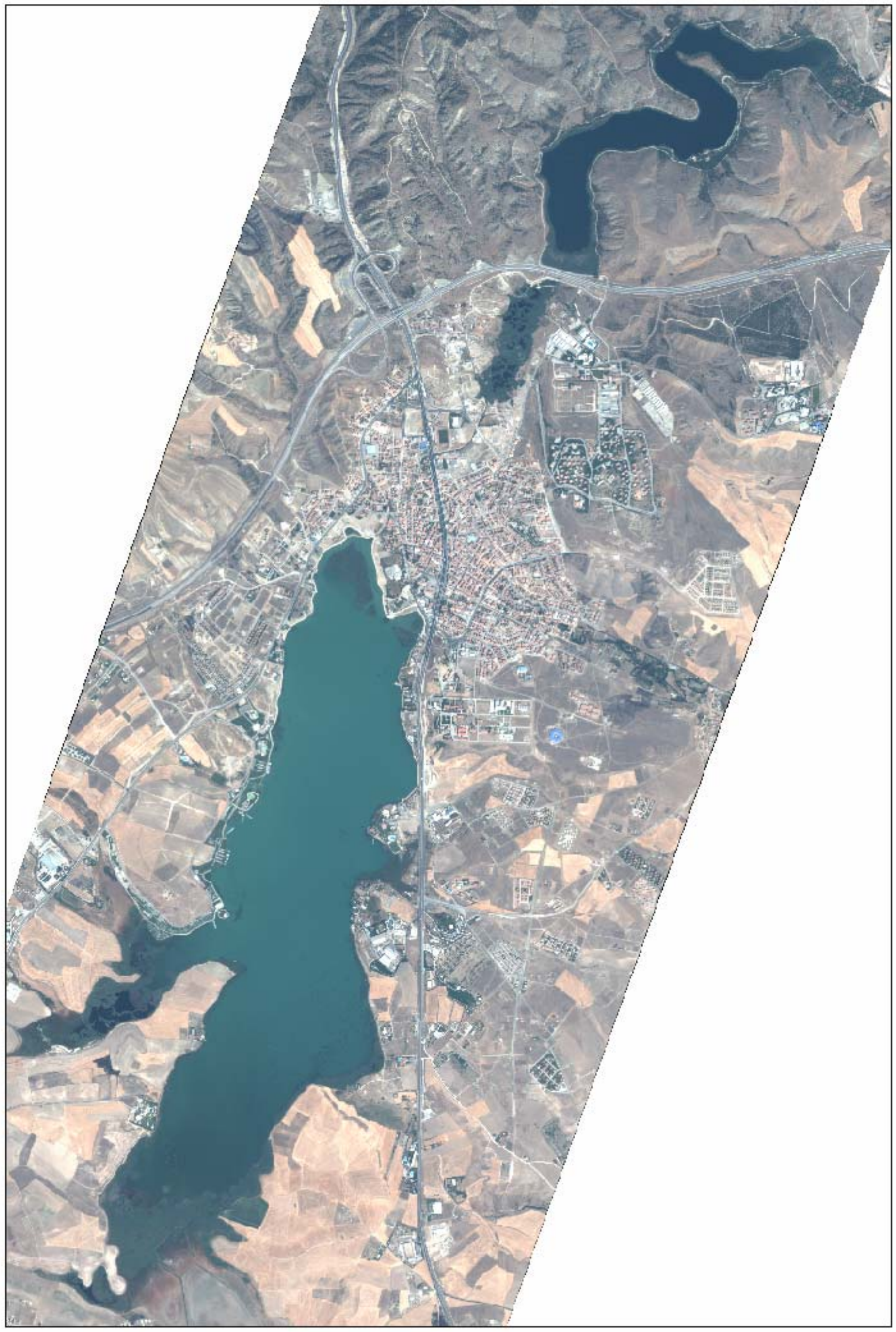


Figure 2.6. Quickbird image of Lakes Mogan and Eymir acquired on 27.08.2006.

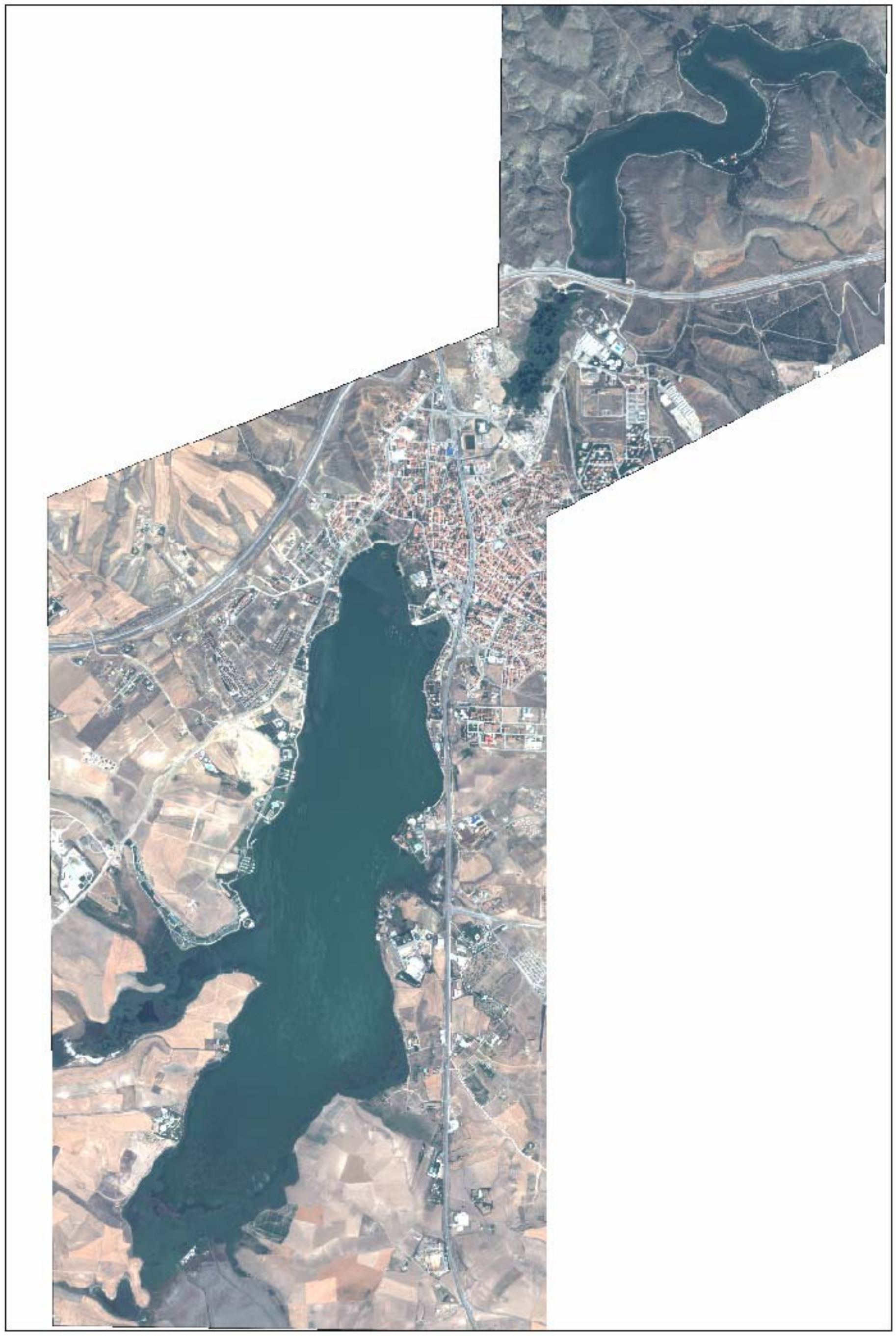


Figure 2.7. Quickbird image of Lakes Mogan and Eymir acquired on 06.08.2005.

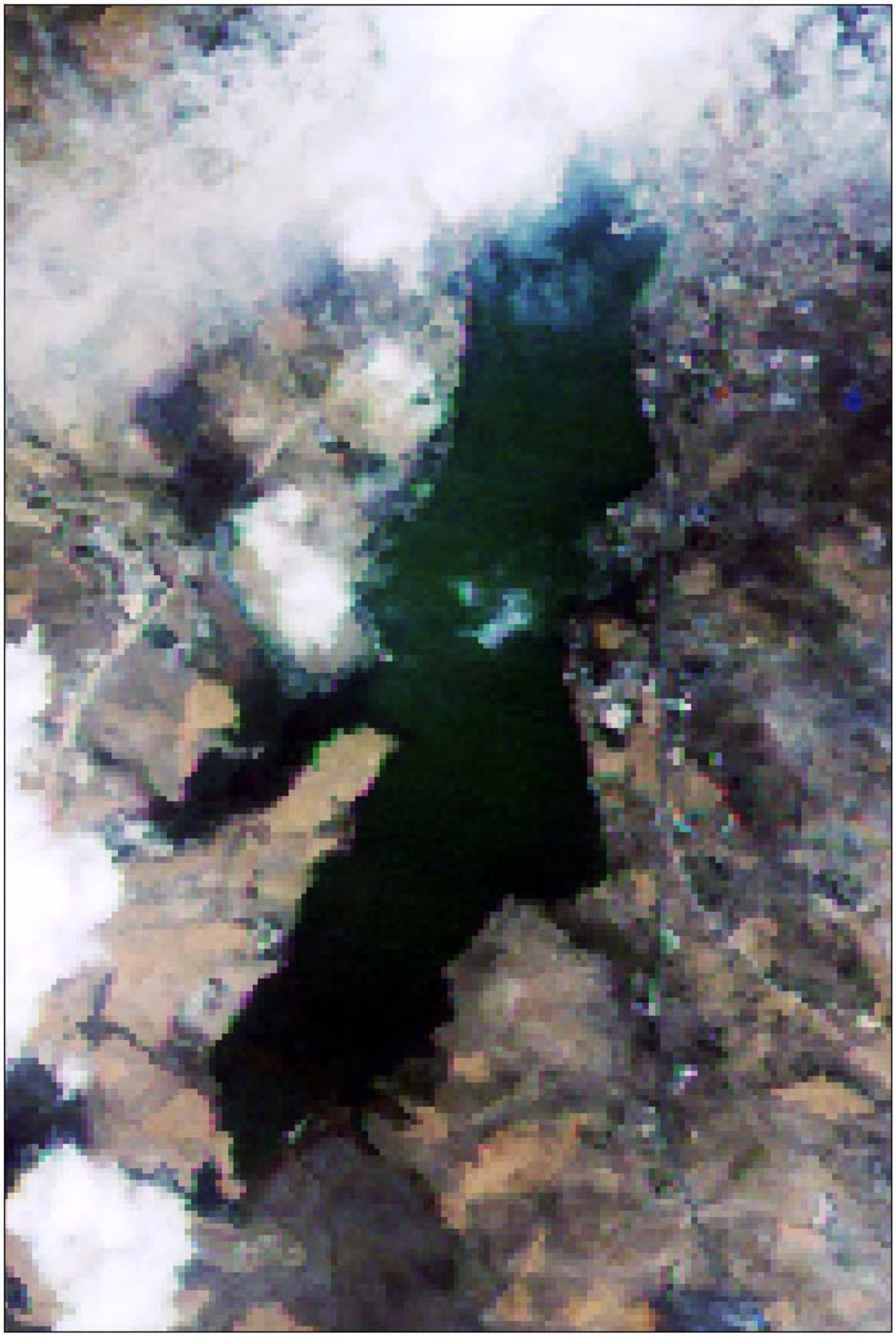


Figure 2.8. Landsat image of Lake Mogan acquired on 20.08.2005.

Figure 2.9. Original Landsat image of Lakes Mogan and Eymir acquired on 18.09.2001.

Figure 2.10. Merged Landsat image of Lakes Mogan and Eymir aquired on 18.09.2001.

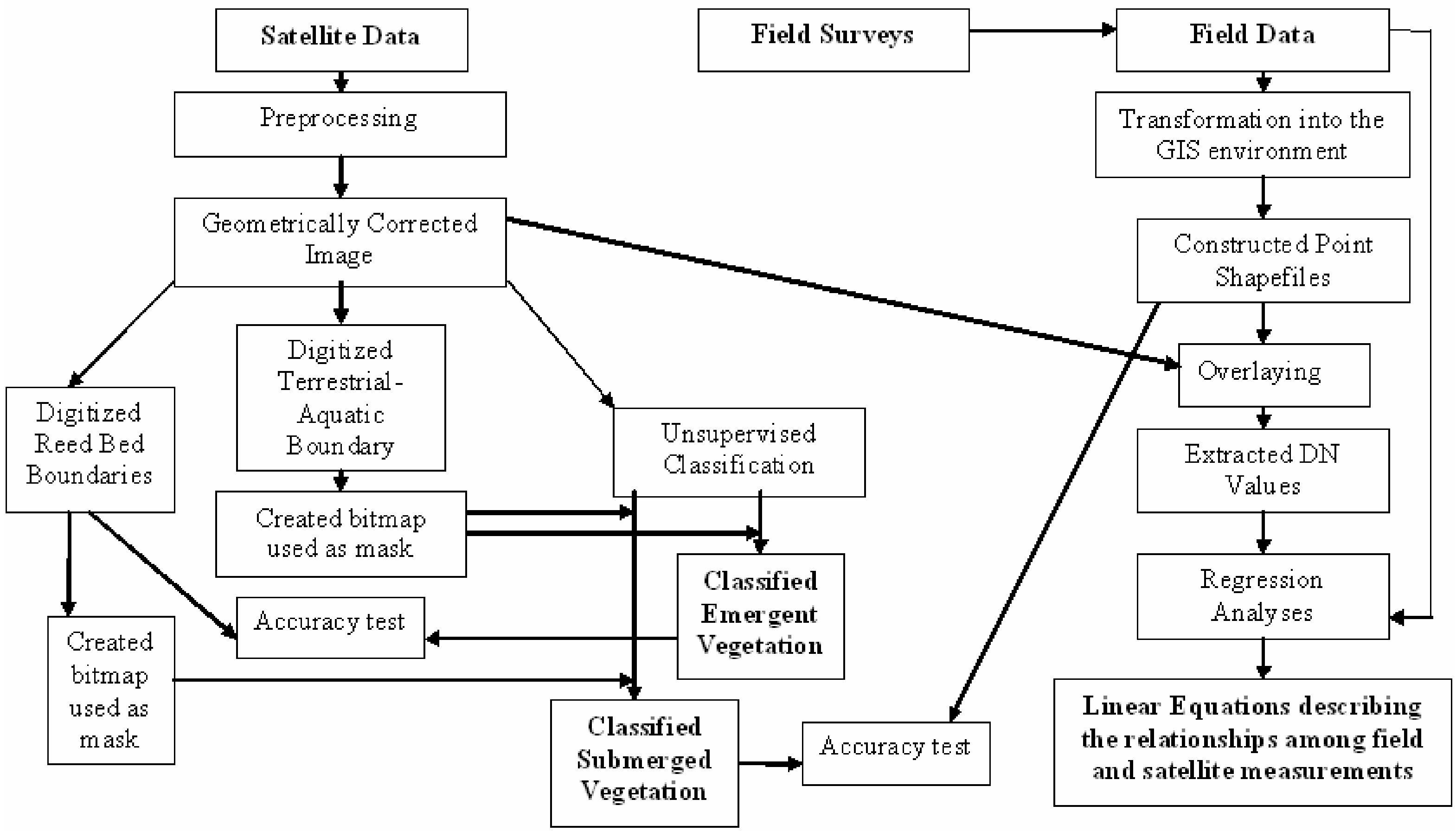
Figure 2.11. Original Landsat image of Lakes Mogan and Eymir acquired on 21.09.2002.

Figure 2.12. Merged Landsat image of Lakes Mogan and Eymir acquired on 21.09.2002.

2.4. Methodology

Field surveys were done to collect field samples of water clarity and aquatic vegetation. The field measurements were then transformed into the GIS environment in the point shape file formats for further analyses. The purchased satellite images were geometrically corrected and using them as templates aquatic-terrestrial boundaries and reed bed boundaries were digitized. The digitized boundaries were converted into bitmaps, which were used as masks in classification steps. Unsupervised classifications of the images were carried out to identify emergent and submerged vegetation. For the classified emergent vegetation the accuracy test was done with respect to the digitized reed bed boundaries. For the classified submerged vegetation the accuracy was tested with respect to the field data. On the other hand the field and satellite data were overlaid to extract the digital number values of the pixels at the same location with sampling points. Then the two datasets were plotted against each other and regression analyses of the field data with respect to the band and band ratios were carried out to obtain linear equations. The methodology used in this study was summarized in the flowchart in Figure 2.13.

Figure 2.13. Summary of the methodology used in this study.



2.5. Analyses

2.5.1. Preprocessing of satellite images

Geometric correction is an essential preprocessing technique, where geometric distortions in the image are removed by the help of ground control points (GCPs). A GCP is a point on the Earth's surface where both image and map coordinates can be identified (Jensen, 1996). In this study, thirteen GCPs were collected in the field on 10^{th} October 2005 with two Global positioning system (GPS) devices (Magellan GPS 315 and Garmin GPS III Plus) to increase the accuracy of GCP collection. The coordinates recorded by the two GPS devices were consistent with each other. In order to rectify the Quickbird image of 6^{th} August 2005, GCPs recorded by Magellan GPS 315 device was used because the same device was used in the aquatic vegetation surveys. In Table 2.6 some of the GCPs recorded by the two different GPS devices were listed. The location of the thirteen GCPs was illustrated in Figure 2.14. All other images were geometrically corrected according to the image-to-image geomertric correction technique. The projection system and datum were set as UTM zone 36 and ED50 (European 1950) respectively and PCI Geomatica version 9.1.0 was used for geometric correction steps. The resulting root-mean square errors were presented in Table 2.7.

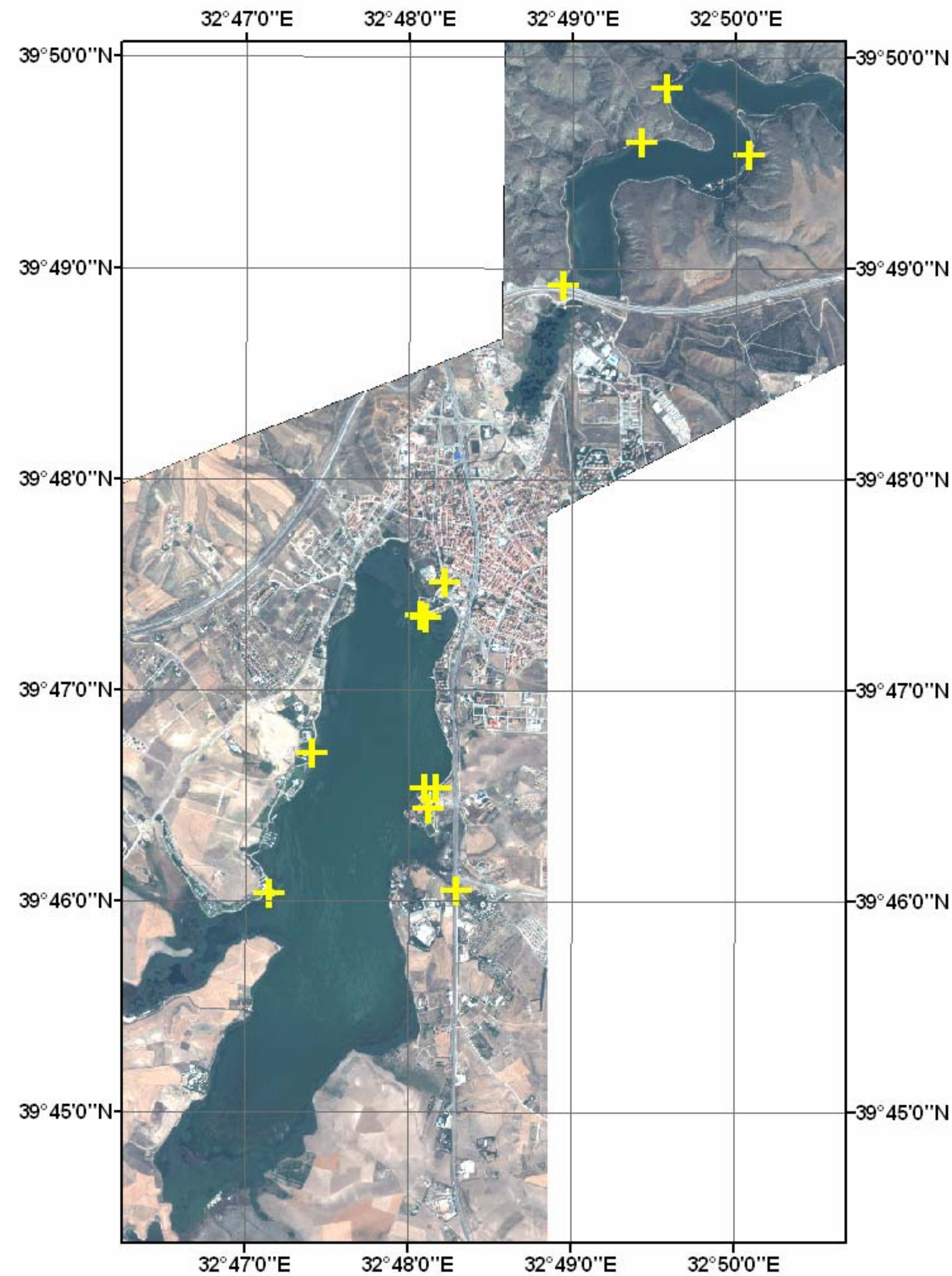


Figure 2.14. Location of the Ground Control Points.

Table 2.6. Some of the ground control points (GCPs) recorded by the two global poisoning system (GPS) devices (Projection system: UTM Zone 36, datum: European 1950).

GPS device	Magellan 315		Garmin III Plus	
Ground Control Points	Easting	Northing	Easting	Northing
1	483304	4402050	483306	4402050
2	484246	4407349	484249	4407357
3	483027	4402759	483028	4402760
4	483068	4402763	483070	4402763
5	484936	4408601	484943	4408616
6	485155	4409081	485162	4409095

Table 2.7. The resulting Root Mean Square (RMS) Errors from the geometric correction of images.

Image	Acquisition date	RMS Error for X	RMS Error for Y
Landsat	18.09.2001	0.29	0.22
Landsat merged	18.09.2001	0.20	0.33
Landsat	21.09.2002	0.20	0.24
Landsat merged	21.09.2002	0.15	0.22
Landsat	20.08.2005	0.28	0.13
Aster	26.07.2002	0.21	0.26
Aster (frame 1)	15.08.2005	0.09	0.16
Aster (frame 2)	15.08.2005	0.12	0.09
IKONOS	04.08.2001	0.44	0.25
IKONOS	04.08.2002	0.30	0.26
Quickbird	06.08.2005	0.31	0.46
Quickbird	27.08.2006	0.09	0.09

2.5.2. Digitizing of aquatic-terrestrial and reed bed boundaries

The terrestrial-aquatic and the reed bed boundaries of Lake Mogan and Lake Eymir were digitized using the high spatial resolution Quickbird images acquired on 6^{th} August 2005 and 27^{th} August 2006, and IKONOS images acquired 4^{th} August 2001 and 4^{th} August 2002, as templates. Digitizing processes were performed by visual interpretation using ArcGIS 8.3, 9.0, and 9.1 softwares. The digitized boundaries were in the shape file format with polygon geometry and were later used in the establishment of bit-maps and masks which inturn were used in classification and change detection procedures. In Figure 2.15, the digitized terrestrial-aquatic and reed bed boundaries of Quickbird image acquired on 6^{th} August 2005 are shown.

2.5.3. Classification of Emergent Plants

In order to classify emergent macrophytes, reeds (*Phragmites australis*), in Lakes Mogan and Eymir, all images were classified according to the fuzzy k-means unsupervised classification method. An unsupervised classification aims to group cases together into classes by their relative spectral similarity (Foody, 2002). The fuzzy k-means unsupervised classification technique is similar to a cluster analysis and it provides a significant amount of information about the variability and character of the data (Gorsevski et al., 2003).

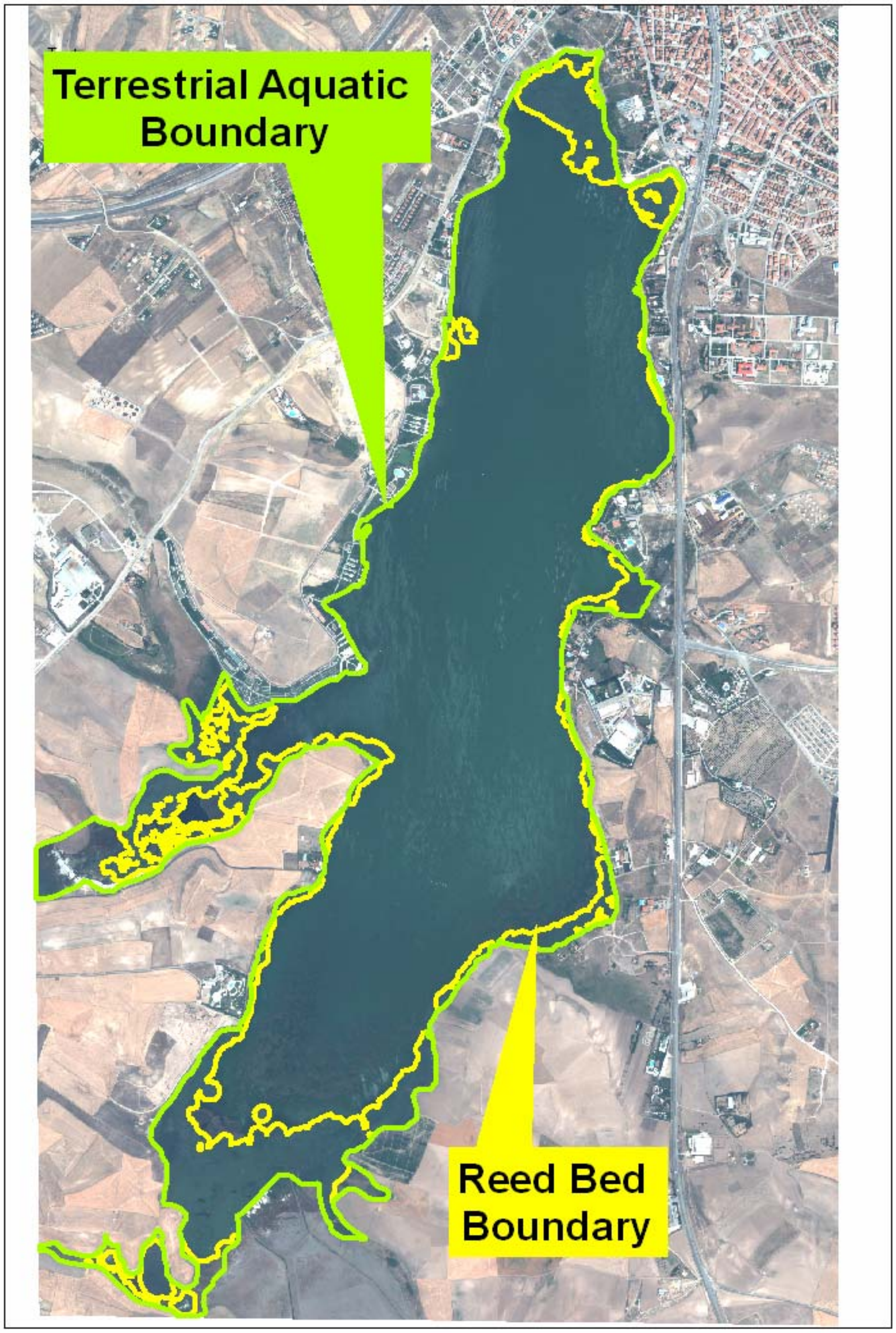
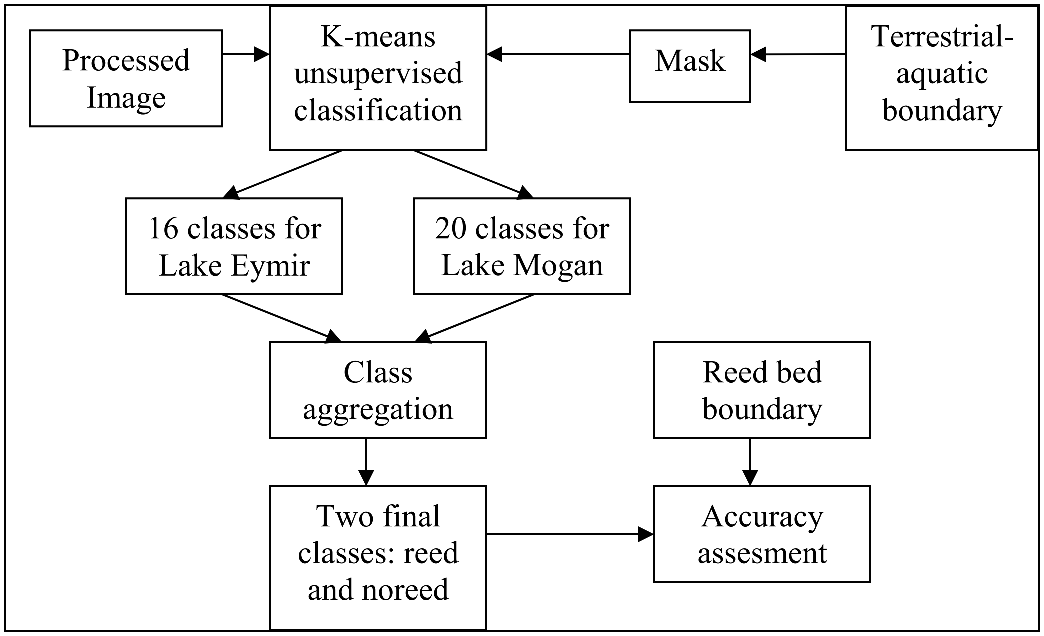


Figure 2.15. Digitized terrestrial-aquatic and reed bed boundaries of Quickbird image acquired on 6th August 2005

In classification steps, all four bands of Quickbird and IKONOS images were used. For Aster images only the first three bands and for Landsat only the first four bands were used. All images belonging to Lake Mogan were classified into 20 classes where as all images belonging to the Lake Eymir were classified into 16 classes because Lake Mogan had more diverse vegetation and also a greater surface area than Lake Eymir. So, it was expected to see greater variation in Lake Mogan, which could be better represented with a higher number of classes. The bit-maps created from the digitized aquatic-terrestrial boundaries were used to mask the terrestrial areas. The post classification steps involved the aggregation and the accuracy assessment. In the aggregation step, the 20 and 16 classes of Lake Mogan and Lake Eymir images, respectively, were aggregated into two final classes as 'reed' and 'no-reed' using the class spectral similarity values among classes. Then, the accuracy tests for all images were done according to the 512 random samples generated, using the digitized reed bed boundaries as reference data. The methodology followed to classify emergent macrophytes, was presented in Figure 2.16. The resulting overall accuracies according to the 95% confidence interval were computed and the classified images were used in the change detection of emergent macrophyte coverages. All steps were performed using PCI Geomatica Software.



Fligure 2.16. The methodology followed to classify emergent macrophytes.

2.5.4. Detection of Changes in the Emergent Plant Coverages

Monitoring and assessment of amount and location of change in the natural ecosystems have great importances and digital change detection is a good technique for such purposes. However, all digital change detection is affected by spatial, spectral, temporal, and thematic problems (Coppin and Bauer, 1996). In this study post-classification comparison change detection technique was used in order to investigate the changes in the emergent vegetation coverages of the lakes. ‘Delta classification’ or ‘post-classification comparison’ is a quantitative change detection technique that involves independently produced spectral classification results from each end of the time interval of interest, followed by a pixel-by-pixel comparison to detect changes in cover type (Coppin and Bauer, 1996; Lu et al., 2004; Jensen, 1996). In this technique, the problem of radiometric calibration is minimized since separately classified images are used (Coppin and Bauer, 1996;

Lu et al., 2004) and at the same time, sensor and environmental differences are minimized (Lu et al., 2004). The overall accuracy of post-classification comparison change detection depends on the accuracies of the images involved into the procedure.

Post classification comparison change detection was applied to the images that were classified as 'reed' and 'noreed'. In this part of the study, both high and medium spatial resolution images were used in order to investigate out the effect of spatial resolution for detecting changes in emergent plant coverage. The high spatial resolution images included Quickbird and IKONOS images and the medium spatial resolution images were Aster images. The resulting change detection matrices from the pixel-by-pixel comparison of classified images involved:

- Quickbird 2006 Lake Mogan Image versus Quickbird 2005 Lake Mogan Image
- Quickbird 2006 Lake Eymir Image versus Quickbird 2005 Lake Eymir Image
- Quickbird 2005 Lake Mogan Image versus IKONOS 2002 Lake Mogan Image
- Quickbird 2005 Lake Eymir Image versus IKONOS 2001 Lake Eymir Image
- Aster 2005 Lake Mogan Image versus Aster 2002 Lake Mogan Image
- Aster 2005 Lake Eymir Image versus Aster 2002 Lake Eymir Image

2.5.5. Classification of Submerged Plants

Classification of submerged plants was carried out only in Lake Mogan because submerged macrophytes were lost in Lake Eymir as the lake shifted to turbid water state. The Quickbird multispectral images acquired on 6th August 2005 and 27th August 2006 were used in classification of submerged macrophytes. No other image was used in classification of submerged macrophytes because Quickbird images provided highest spatial resolution and also the time windows between the dates of image acquisition and field survey were the least for Quickbird images among the other images in the study. All four bands of Quickbird images were involved in the classification. The summary of the procedure followed is presented in Figure 2.17. The terrestrial area was masked by the bit-maps created from the digitized terrestrial-aquatic boundaries and the bit-maps created from the reed bed boundaries were used to mask emergent macrophytes. Additionally, a water mask was established using GREEN>RED>NIR and $NIR<NIR_{threshold}$ band reflectance values of a specific location to mask water pixels. Water shows strong absorption to NIR wavelength and the NIR absorption of calm, clear, and deep water is so strong that NIR reflectance over such water becomes nearly zero (Wolter et al., 2005). In this study, $NIR_{threshold}$ was determined as 80 in 2005 and as 95 in 2006.

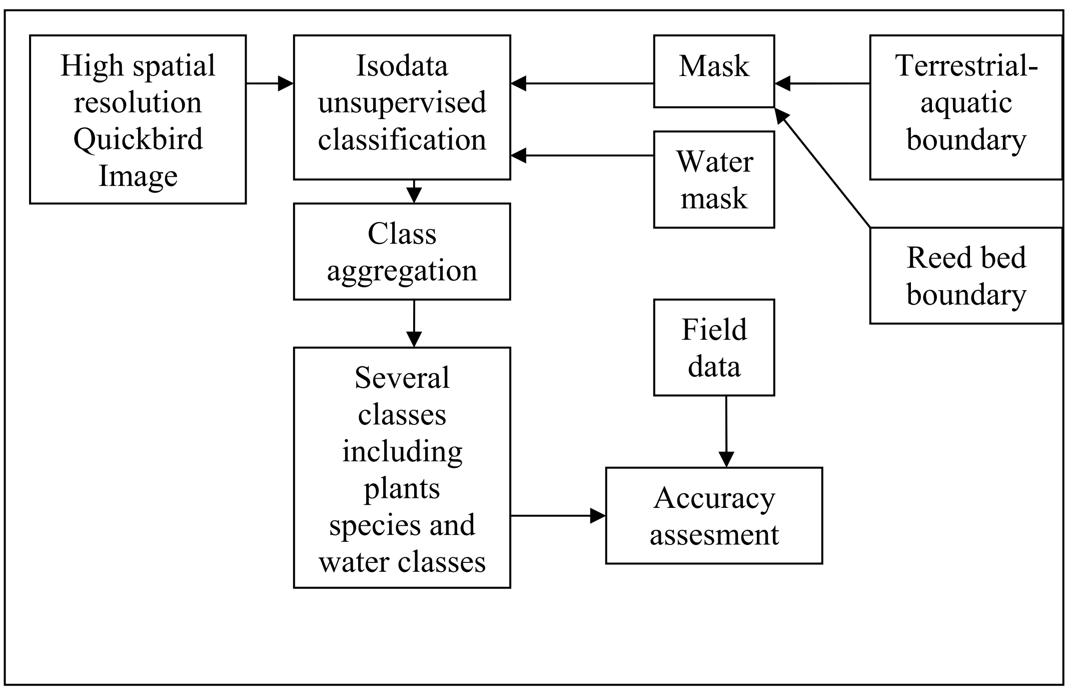


Figure 2.17. The summary of the procedure followed in classification of submerged macrophytes.

The remaining parts of the images were classified according to the isodata unsupervised classification method. In 2005, isodata classification was carried out with respect to 50 isodata classes while in 2006, 100 isodata classes were used. The reason of using more classes in 2006 compared to the 2005 was the decrease in the diversity of the plant species in Lake Mogan in 2006. Aggregation of the isodata classes was done in two different ways. In the first case, the isodata classes were aggregated into two classes as water and submerged vegetation. Secondly, the isodata classes were aggregated in a different way which involved a more detailed classification. In 2005, five classes including water where 2 (Secchi Disc Depth) > Water Depth, water where 2 (Secchi Disc Depth) < Water Depth, *Potamogeton pectinatus*, *Najas* sp. at surface, and *Najas* sp. below surface, were used. When Secchi disc depth is greater than the half of the water depth then, light penetrates to the bottom of the lake and this may cause reflectance differences, thus two different water classes were used to discriminate this fact. In 2006, classification was performed at three class level; Water, *Potamogeton pectinatus*, and *Najas* sp. The accuracy assessments of all aggregated classes were done with respect to the field data.

In 2005, it was found that vegetation coverages less than 30 %, which were also regarded as low vegetation, were confused with water pixels and this assumption was validated in the classification carried out in the 2006. Such pixels were accepted as water pixels in the classification of both years' data. In order to eliminate the distortions that might be caused from the field conditions 9 pixels around the sampling points were used in accuracy assessment test instead of using one pixel. All image classification, aggregation and accuracy assessments were carried out using PCI Geomatica 9.1.

2.5.6. Inferring water clarity from satellite data

In order to investigate the relationship between the satellite data and the field data, satellite images were overlaid with the field data of the same date. Using ArcGIS, the digital number (DN) values were sampled for the nine pixels within a 3X3 kernel centred at the sampling point in the field data. DN values of all four bands of Quickbird and IKONOS images were sampled while for Aster images, DN values of the first three bands and for Landsat images, DN values of the first four bands were sampled. Then, two sets of DN values were established: a set of DN value that was formed from the centre pixel for a waveband and represented as B1, B2, B3, or B4, indicating Band 1, Band 2, Band 3, or Band 4 respectively; and another set of DN values that was formed from the nine pixels around the centre pixel for a waveband and represented as MB1, MB2, MB3, or MB4, indicating mean values for Band 1, Band 2, Band 3, or Band 4 respectively. The procedure for extraction of DN values was summarized in Figure 2.18. Then each of these two sets of DN values for each waveband was plotted against the natural logarithm of field measurements for Secchi disc depth. While plotting not only the values for bands themselves but also the band ratios against the field measurements were plotted, and also bands and band ratios were plotted together against the field measurements like Kloiber et al. (2002) and Sawaya et al. (2003) performed. In years 2001, 2002, and 2005, plots were established for the Secchi disc depth values smaller than the half of water depth in order to eliminate the differences that may be caused by the illumination to the bottom parts. In 2006, no such separation was done because all Secchi disc depth values for the both lakes were greater than the half of water depth. Furthermore, linear trendlines were constructed for each plot. During constructing linear trendline, represented by the $y = mx + b$ equations, Pearson correlation coefficients were computed for each band or band ratio. The equations represented as $y = mx + n (z/x) + b$ and the R-squared values for the equations computed by the regression analyses where natural logarithm of Secchi disc depth values measured in the field was acted as y variable and a band with a band ratio acted as x variables. These equations and their R squared values were recorded and equations with a high R-squared values were used to predict the values of Seccdi disc depth for the whole lake surface.. The R-squared value is an indicator from 0 to 1 that reveals how closely the estimated values for the trendline correspond to the actual data. A trendline is most reliable when its R-squared value is at or near 1. It is also known as the coefficient of determination. These were perfomed by the help of Microsoft Excel Sotfware and SPSS version 13. Later, the predicted values were validated according to some other field measurements. Moreover, the maps produced were filtered with a 3X3 mode filter and filtered values were again validated with field measurements. Other maps were produced by interpolation from the field measurements for the Secchi disc depth values and these maps were again validated.

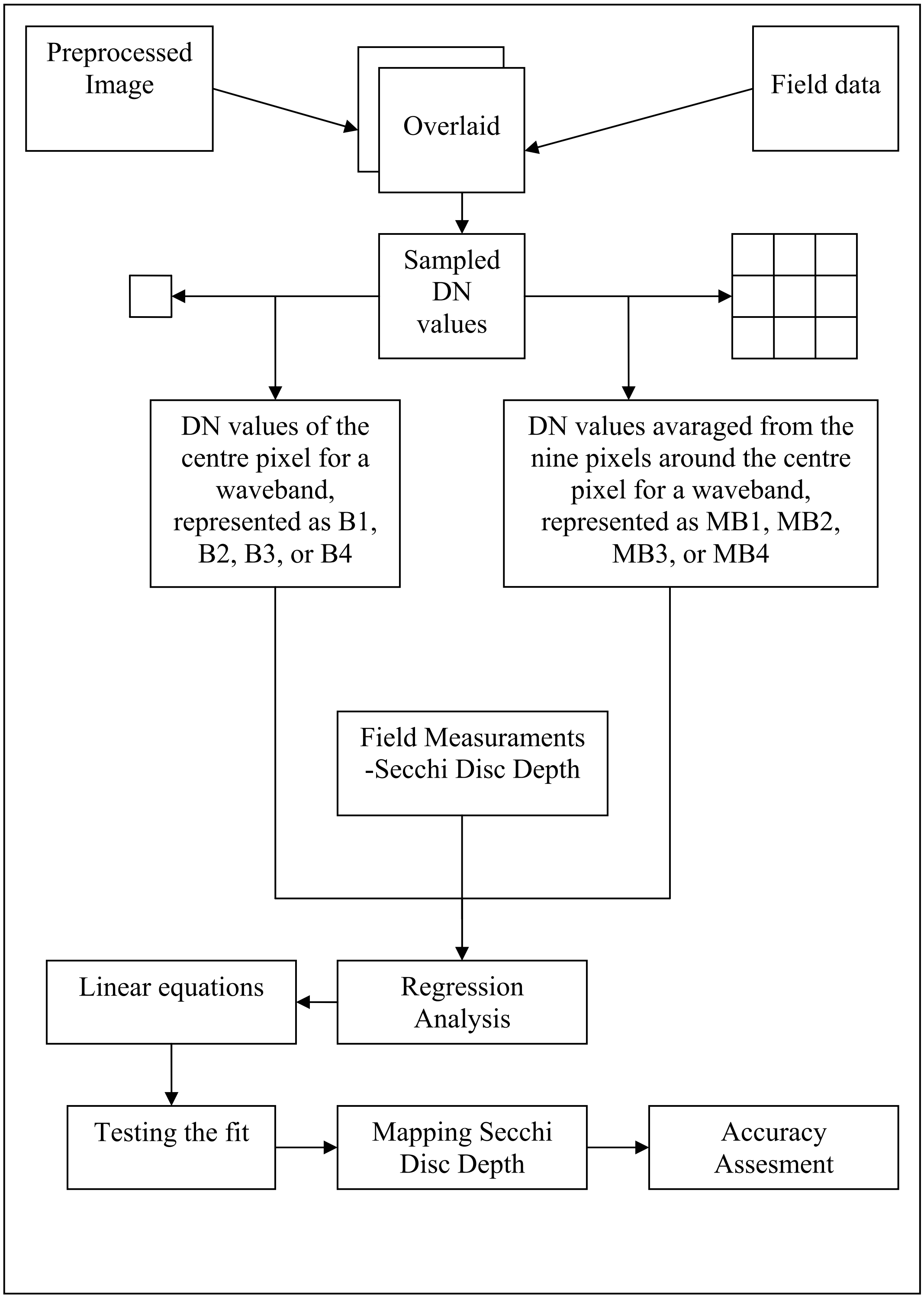


Figure 2.18. The procedure for extraction of digital number (DN) values.

CHAPTER 3

RESULTS

3.1.1. Classification of Emergent Plants

Table 3.1 presents overall accuracies, within the 95% confidence interval, computed for all classified images. The resulting overall accuracies were greater than 90% for all high spatial resolution Quickbird and IKONOS images. For the medium spatial resolution Aster and Landsat images, the overall accuracies ranged between 70% and 93%. For Lake Eymir, the accuracies for classification decreased as the spatial resolution decreased. For Lake Mogan the accuracies for classification decreased as the spatial resolution decreased as well but not as dramatically as for Lake Eymir.

3.2. Detection of Changes in the Emergent Plant Coverage

The resulting change detection matrices from the pixel-by-pixel comparison of classified images were presented in Tables 3.2-3.7. The resulting change images are presented in Figures 3.1 and 3.2. For Lake Eymir there was not a remarkable change observed in high spatial resolution images between years 2001-2005 and 2005-2006, however approximately 8 ha of decrease in the reed bed area was observed in medium spatial resolution images between 2002 and 2005. For Lake Mogan, both high spatial resolution and medium spatial resolution images revealed nearly same results. In Lake Mogan there was a 23 ha decreasing in the reed bed area between 2002 and 2005. The major reed beds decrease occurred at the western part of the lake and a small reed beds decrease occurred at the southern part of the lake. In the other parts of the lake reed areas increased in amount. The decrease in reed bed area between 2005 and 2006 was 18.4 ha which occurred mainly at the northern part and a 14.3 ha increase in the reed bed area were observed.

Table 3.1. The Resulting Overall Accuracies of Classified Images

Classified Image	Overall Accuracy	95% Confidence Interval
Quickbird 2005 Lake Mogan	94.685%	92.636%-96.734%
Quickbird 2005 Lake Eymir	94.336%	92.236%-96.436%
Quickbird 2006 Lake Mogan	95.490%	93.591%-97.389%
Quickbird 2006 Lake Eymir	97.200%	95.654%-98.746%
IKONOS 2001 Lake Eymir	90.820%	88.222%-93.419%
IKONOS 2002 Lake Mogan	93.359%	91.105%-95.614%
Aster 2002 Lake Mogan	86.914%	83.895%-89.933%
Aster 2002 Lake Eymir	74.414%	70.537%-78.291%
Aster 2005 Lake Mogan	92.194%	89.674%-94.715%
Aster 2005 Lake Eymir	77.117%	73.064%-81.170%
Landsat 2001 Lake Mogan	83.008%	79.657%-86.359%
Landsat Merged 2001 Lake Mogan	81.055%	77.563%-84.547%
Landsat 2001 Lake Eymir	77.539%	73.827%-81.252%
Landsat Merged 2001 Lake Eymir	72.461%	68.494%-76.428%
Landsat 2002 Lake Mogan	80.078%	76.521%-83.636%
Landsat Merged 2002 Lake Mogan	87.109%	84.109%-90.110%
Landsat 2002 Lake Eymir	76.172%	72.384%-79.960%
Landsat Merged 2002 Lake Eymir	70.508%	66.460%-74.555%
Landsat 2005 Lake Mogan	85.845%	82.446%-89.224%

Table 3.2 Change matrix of Quickbird 2006 and Quickbird 2005 Lake Mogan Images.

Lake Mogan (in hectar)		Quickbird 2006 image Reed	Noreed	Unclass	Total
Quickbird 20065 image	Reed	102.9	18.4	0.8	122.1
	Noreed	14.3	576.3	1.5	592.1
	Unclass	3.9	2.5		
	Total	120.1	616.2		

Table 3.3. Change matrix of Quickbird 2005 and IKONOS 2002 Lake Mogan Images.

Lake Mogan (in hectar)		Quickbird 2005 image Reed	Noreed	Unclass	Total
IKONOS 2002 image	Reed	85.7	23.3	5.8	114.8
	Noreed	34.0	566.5	6.3	606.8
	Unclass	2.4	2.4		
	Total	122.1	592.1		

Table 3.4. Change matrix of Aster 2005 and Aster 2002 Lake Mogan Images.

Lake Mogan (in hectar)		Aster 2005 image Reed	Noreed	Unclass	Total
Aster 2002 image	Reed	84.2	18.5	12.3	115.0
	Noreed	20.3	566.5	4.7	591.5
	Unclass	5.1	3.0		
	Total	109.6	588.1		

Table 3.5. Change matrix of Quickbird 2006 and Quickbird 2005 Lake Eymir Images.

Lake Eymir (in hectar)		Quickbird 2006 image			
		Reed	Noreed	Unclass	Total
Quickbird 2005 image	Reed	23.1	1.0	5.5	29.6
	Noreed	1.3	103.3	0.3	104.9
	Unclass	3.3	0		
	Total	27.7	104.3	5.8	

Table 3.6. Change matrix of Quickbird 2005 and IKONOS 2001 Lake Eymir Images.

Lake Eymir (in hectar)		Quickbird 2005 image			
		Reed	Noreed	Unclass	Total
IKONOS 2002 image	Reed	20.7	1.5	2.2	24.4
	Noreed	2.9	103.2	0.4	106.5
	Unclass	1.0	0.1		
	Total	24.6	104.8		

Table 3.7. Change matrix of Aster 2005 and Aster 2002 Lake Eymir Images.

Lake Eymir (in hectar)		Aster 2005 image			
		Reed	Noreed	Unclass	Total
Aster 2002 image	Reed	15.8	10.6	3.4	29.7
	Noreed	5.0	95.8	0.9	101.7
	Unclass	1.1	0.7		
	Total	21.9	107.1		

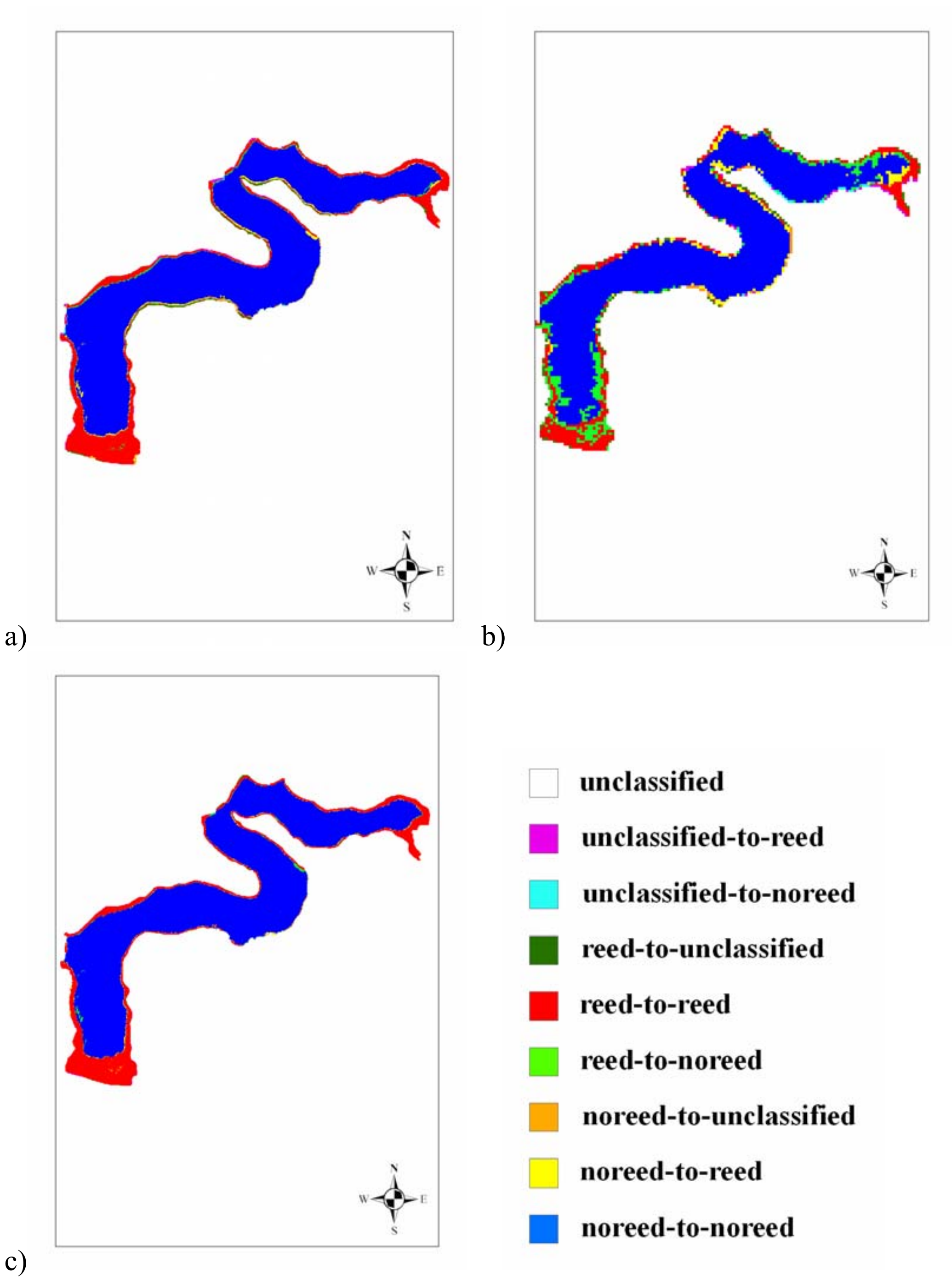


Figure 3.1. Changes in images of a) Quickbird 2005 for Lake Eymir versus IKONOS 2001 for Lake Eymir, b) Aster 2005 for Lake Eymir versus Aster 2002 for Lake Eymir, c) Quickbird 2006 for Lake Eymir versus Quickbird 2005 Lake Eymir.

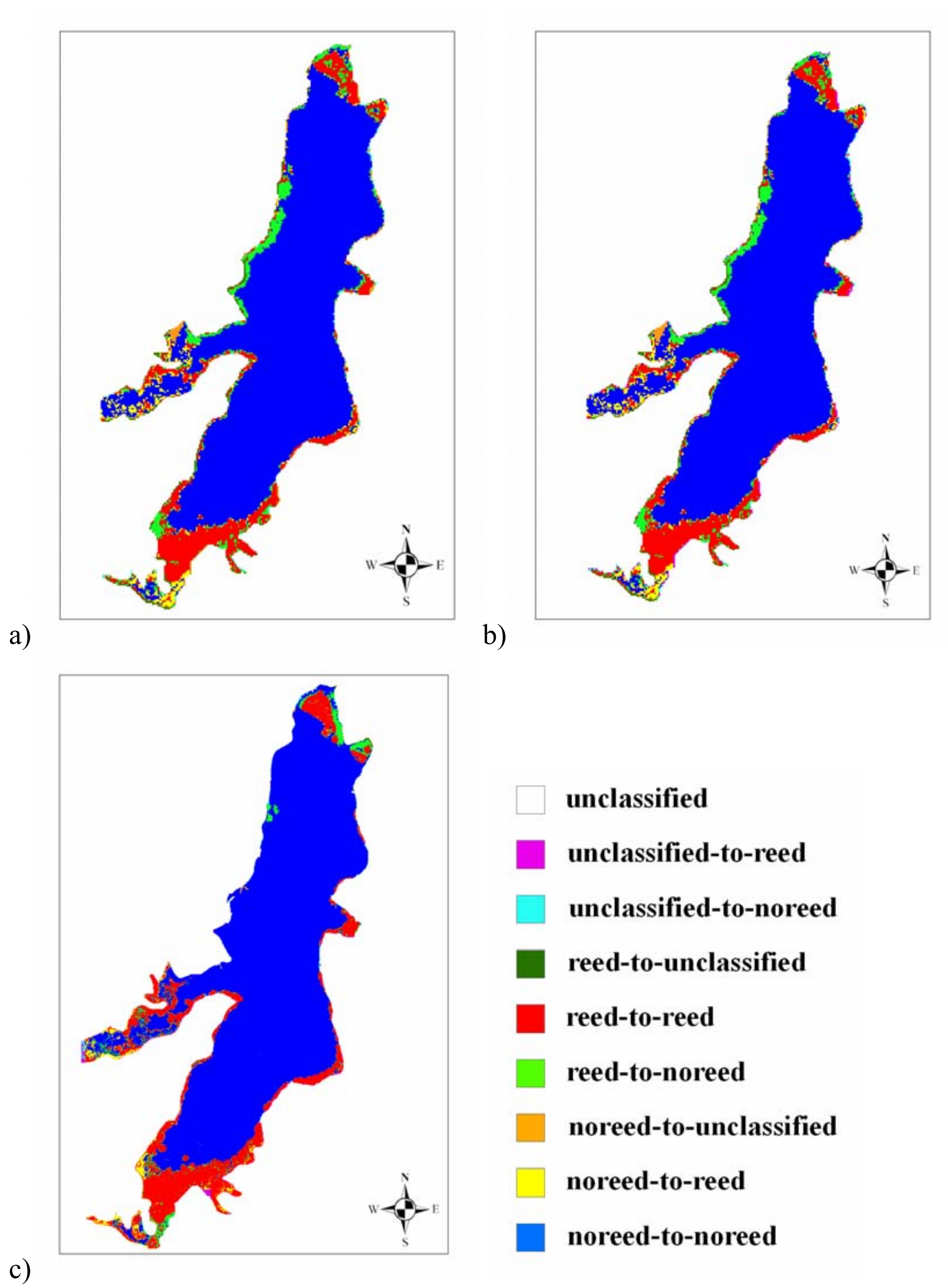


Figure 3.2. Change in images of a) Quickbird 2005 for Lake Mogan versus IKONOS 2002 for Lake Mogan, b) Aster 2005 for Lake Mogan versus Aster 2002 for Lake Mogan, c) Quickbird 2006 for Lake Mogan versus Quickbird 2005 for Lake Mogan.

3.1.3. Classification of Submerged Plants

In 2005, submerged vegetation coverage was classified with 83.02 % overall accuracy. Furthermore, different submerged plant species was classified with 71.69 % overall accuracy. In 2006 the overall accuracy obtained from the classification for different submerged plant species and water classes was 69.01%. In Table 3.8, the accuracy test results of the two different aggregation approaches of submerged vegetation classification are presented.

Table 3.8. Overall accuracies of the isodata unsupervised classification of Quickbird sensor data for submerged vegetation.

	Overall Accuracy
Classification of submerged vegetation coverage, 2005	83.02%
Classification of different plant species, 2005	71.69%
Classification of submerged vegetation coverage, 2005	78.89%
Classification of different plant species, 2006	69.01%

In the Tables 3.9 and 3.10, the error matrices for the classification of different plant species were presented for 2005 and 2006, respectively. The vegetation class that had the highest confusion was *Najas* sp. below surface in 2005 while *Potamogeton pectinatus* had the highest error in 2006, because it has both characteristic of the water and vegetation together. The least confused classes are the water classes in both years. However, since only two reference points fell in water class (2 Secchi disc depth < Water depth) in year 2005, the accuracy test can not be considered as dependable. The resulting thematic maps of the classifications are presented in Figures 3.3 and 3.4 for years 2005 and 2006, respectively.

Table 3.9. Error (Confusion) matrix of the classification of different plant species and water classes for Lake Mogan in 2005 (SDD: Secchi disc depth, WD: Water depth).

Classified data	Reference Data					
	Water (WD < 2X SDD)	Water (WD > 2X SDD)	*Potamogeton pectinatus*	*Najas* sp. at surface	*Najas* sp. below surface	Total
Water (WD < 2X SDD)	1	0	0	0	1	2
Water (WD > 2X SDD)	0	21	0	0	1	22
Potamageton pectinatus	0	0	4	1	2	7
Najas sp. at surface	1	0	1	4	0	6
Najas sp. below surface	1	2	3	2	8	16
Total	3	23	8	7	12	53

Table 3.10. Error **(**Confusion) matrix of the classification of different plant species and water classes for Lake Mogan in 2006.

Classified data	Reference Data			
	Najas sp.	*Potamogeton pectinatus*	Water	Total
Najas sp.	**4**	1	2	7
Potamogeton pectinatus	6	**6**	4	16
Water	3	6	**39**	48
Total	13	13	45	**71**

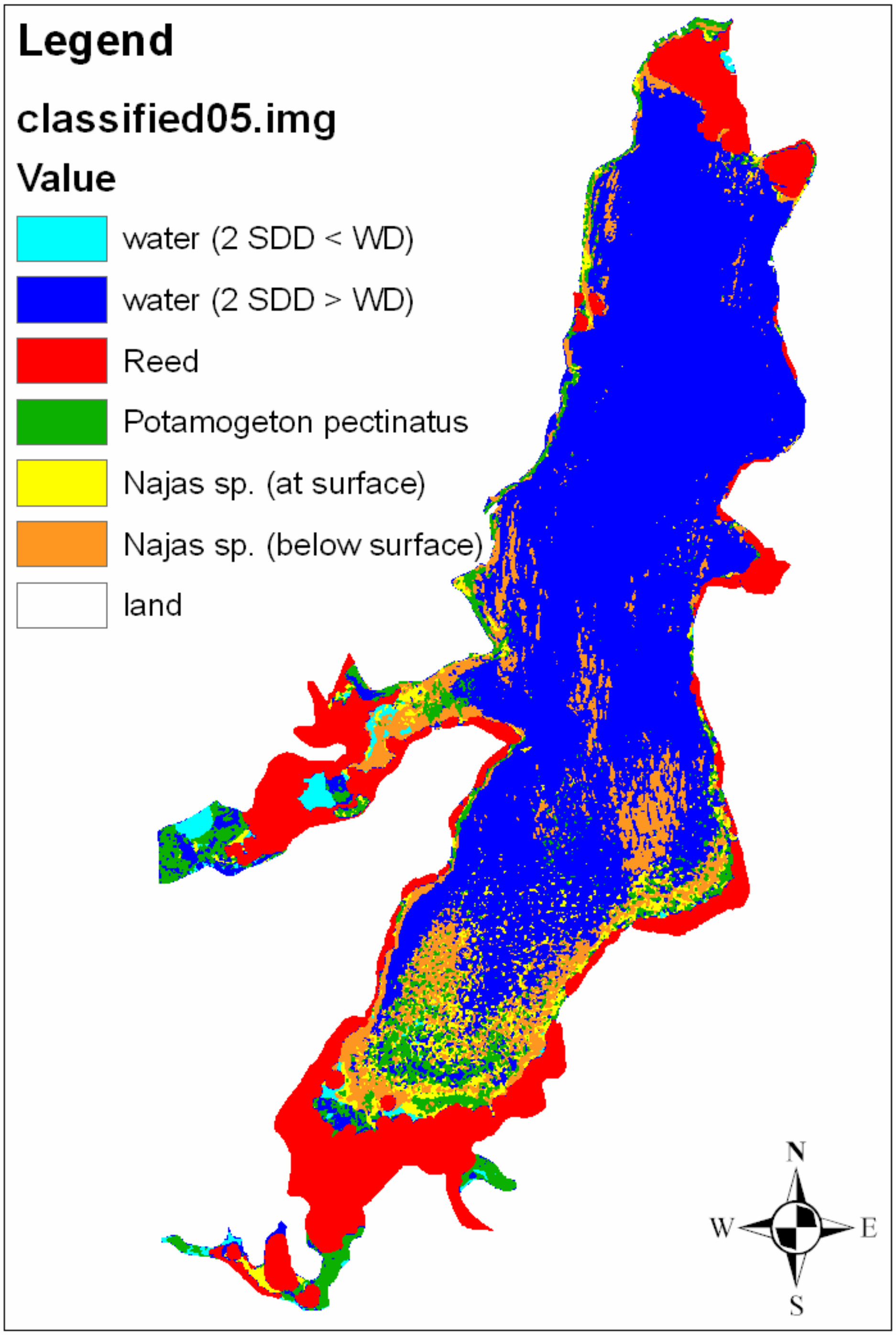


Figure 3.3. Resulting thematic map of classification for different plant species and water classes in Lake Mogan, in 2005 (SDD: Secchi Disc Depth, WD: Water Depth).

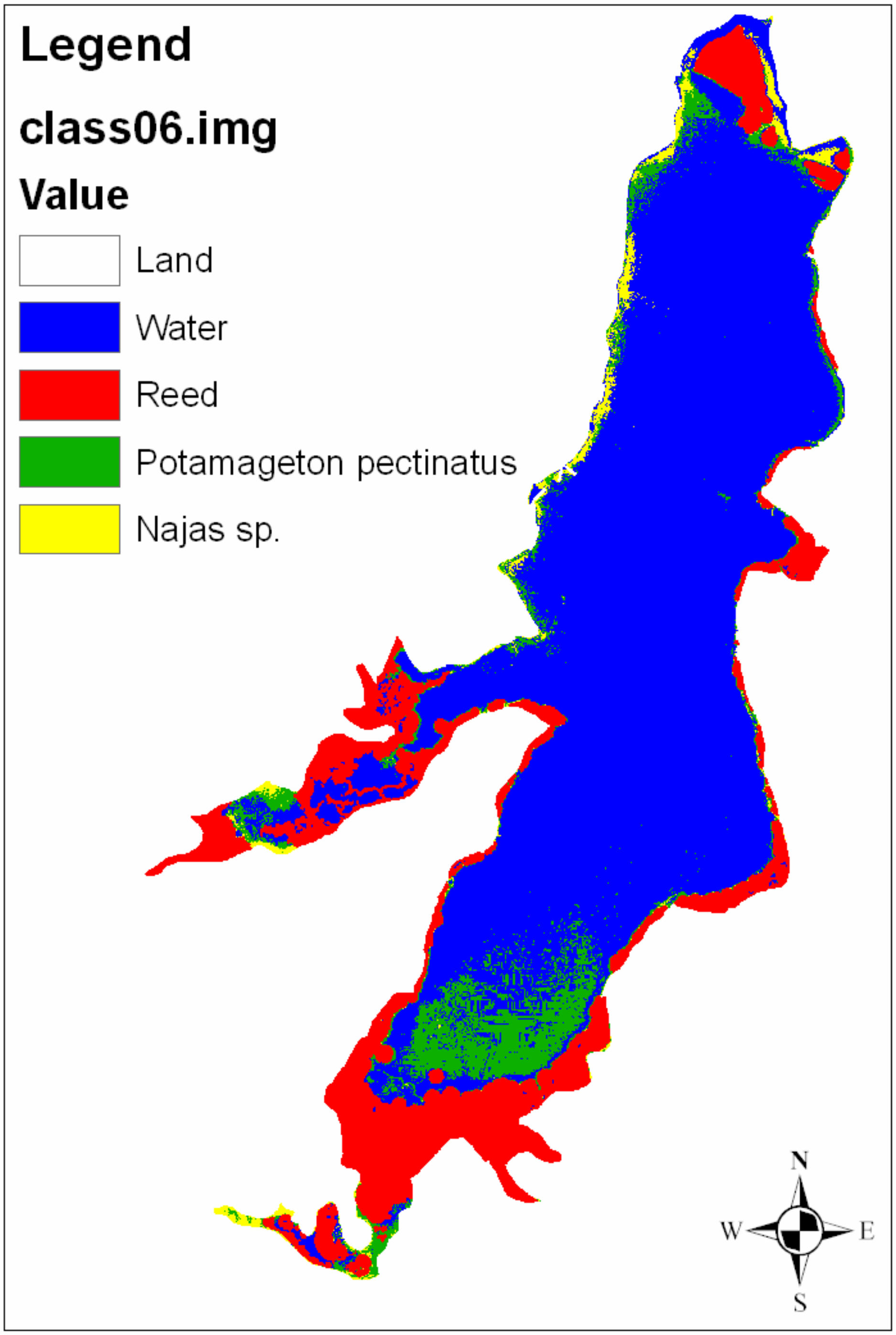


Figure 3.4. Resulting thematic map of classification for different plant species and water classes in Lake Mogan, in 2006.

3.2. Inferring Water Clarity from the Satellite Data

Pearson correlation coefficients of field measurements and satellite image derived values for Secchi disc depth were presented in Tables 3.11 for bands and band ratios. These coefficients represented the Multiple R values.

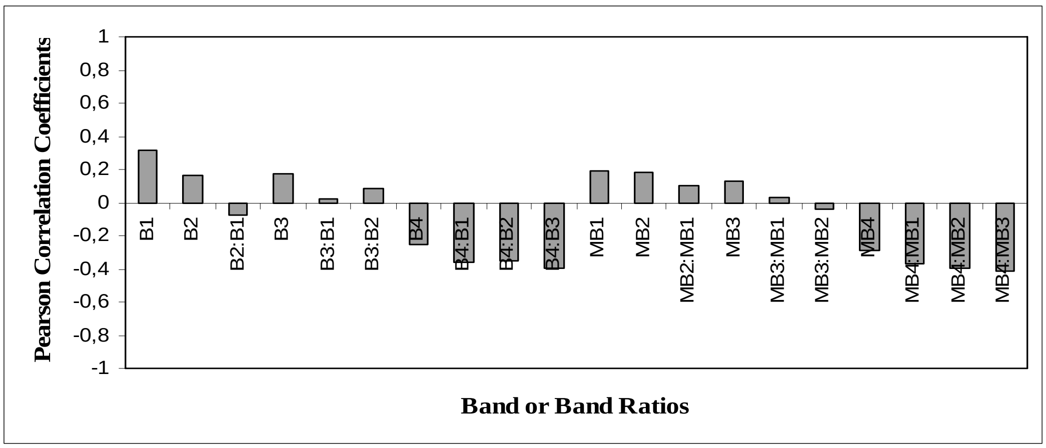


Figure 3.5. Pearson correlation coefficients for bands or band ratios of Quickbird 2005 Lake Eymir Image.

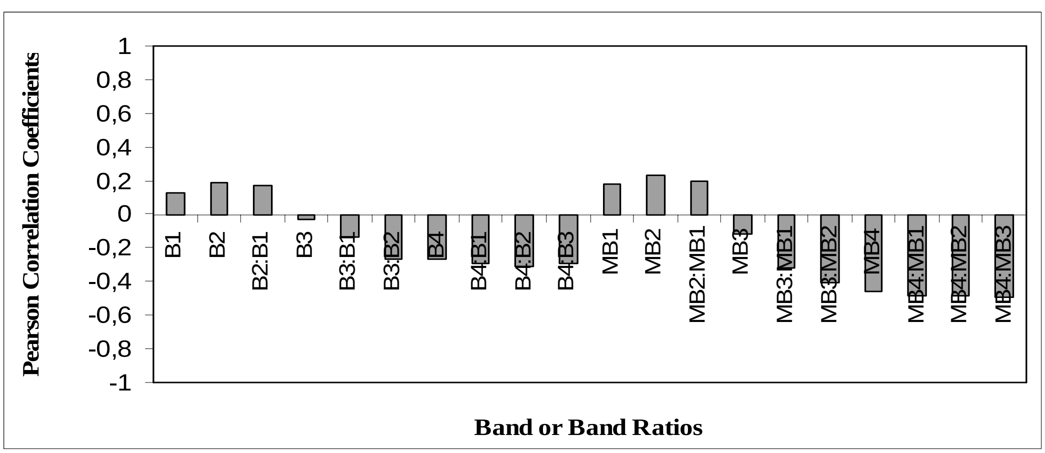


Figure 3.6. Pearson correlation coefficients for bands or band ratios of Quickbird 2005 Lake Mogan Image.

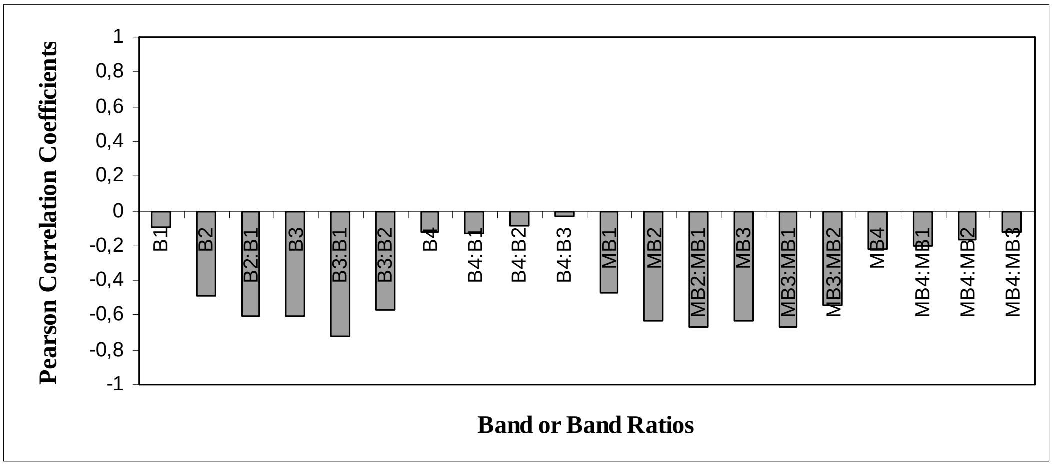


Figure 3.7. Pearson correlation coefficients for bands or band ratios of Quickbird 2006 Lake Eymir Image.

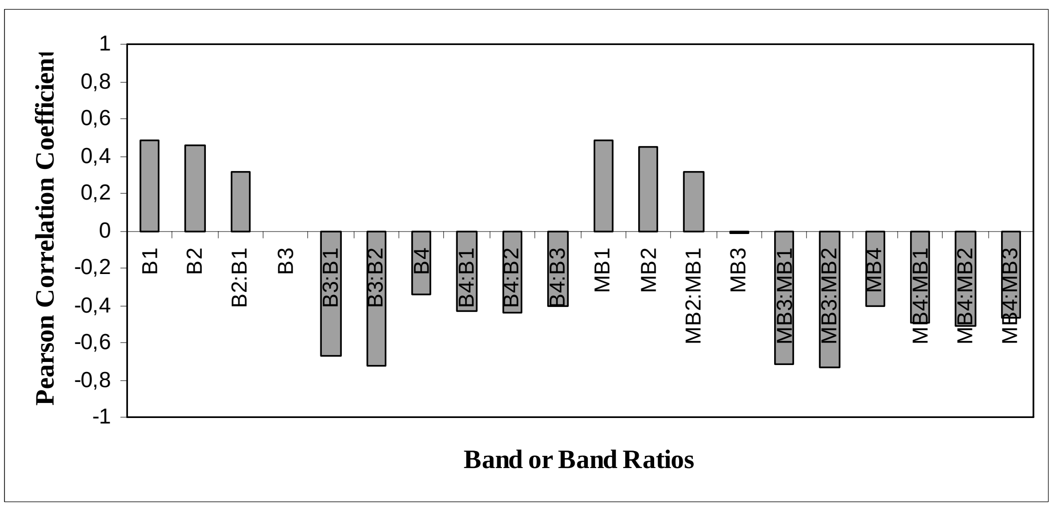


Figure 3.8. Pearson correlation coefficients for bands or band ratios of Quickbird 2006 Lake Mogan Image.

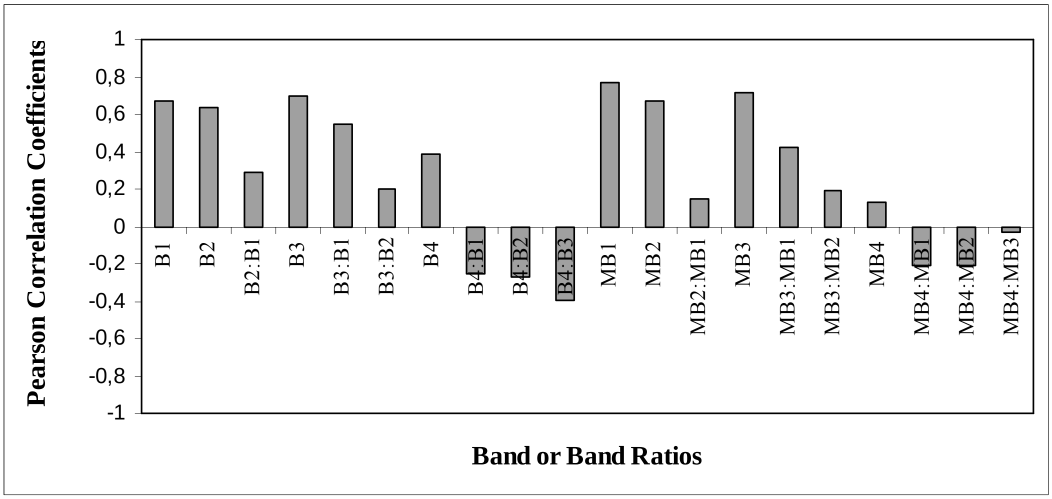


Figure 3.9. Pearson correlation coefficients for bands or band ratios of Landsat 2005 Lake Mogan Image

The equations developed from the regression analysis and their R-squared values computed for the images of Lake Mogan and Lake Eymir, are listed in Tables 3.11 and 3.12, respectively. The marked equations in Tables 3.11 and 3.12 were then mapped to predict the values of Secchi disc depth for the whole lake surfaces. Also, thematip maps were constructed by interpolation. At the same time, for the thematic maps of 2006, a mode filter was applied. All thematic maps were presented in Figures 3.11 and 3.13 for Lake Eymir amd in Figures 3.10 and 3.12 for Lake Mogan. After that, the accuracy assessment was carried out for the thematic maps of 2006. The resulting graphs can be found in Figures 3.14 to 3.16 for Lake Mogan and in Figures 3.17 to 3.19 for Lake Eymir.

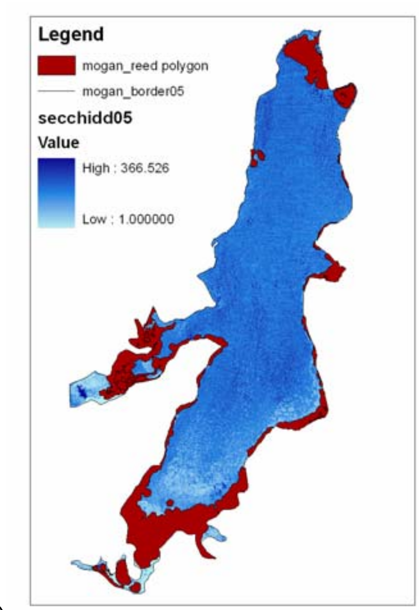
Table 3.11. Equations resulted from regression analyses and the R-squared values, for Lake Mogan.

Lake Mogan			
Processed Image	R Square Value	Equation	Mapped
Aster 2005	0,151	$\ln SDD = -0.022B1 - 7.218\frac{B2}{B1} + 10.433$	
	0,305	$\ln SDD = -0.034MB1 - 11.116\frac{MB2}{MB1} + 13.964$	
Quickbird 2005	0,039	$\ln SDD = 0.004B1 + 0.762\frac{B2}{B1} + 1.890$	
	0,054	$\ln SDD = 0.008B1 - 1.699\frac{B3}{B1} + 3.318$	X
	0,056	$\ln SDD = 0.005MB1 + 0.935\frac{MB2}{MB1} + 1.220$	
	0,241	$\ln SDD = 0.018MB1 - 5.070\frac{MB3}{MB1} + 3.533$	
Quickbird 2006	0,236	$\ln SDD = 0.011B1 - 0.142\frac{B2}{B1} + 2.034$	
	0,548	$\ln SDD = 0.007B1 - 6.260\frac{B3}{B1} + 7.174$	X
	0,248	$\ln SDD = 0.014MB1 - 1.704\frac{MB2}{MB1} + 3.490$	
	0,598	$\ln SDD = 0.007MB1 - 7.190\frac{MB3}{MB1} + 7.922$	
Landsat 2005	0,461	$\ln SDD = 0.039B1 + 1.709\frac{B2}{B1} - 0.667$	
	0,487	$\ln SDD = 0.033B1 + 4.544\frac{B3}{B1} - 1.308$	
	0,600	$\ln SDD = 0.045MB1 + 3.336\frac{MB2}{MB1} + 0.379$	
	0,620	$\ln SDD = 0.052MB1 - 6.504\frac{MB3}{MB1} + 1.872$	

Table 3.12. Equations resulted from regression analyses and the R-squared values, for Lake Eymir.

Lake Eymir			
Processed Image	R Square Value	Equation	Mapped
Aster 2002	0,159	$\ln SDD = 0.006B1 + 0.409\frac{B2}{B1} + 3.897$	
	0,154	$\ln SDD = 0.005MB1 + 0.927\frac{MB2}{MB1} + 3.637$	
Aster 2005	0,104	$\ln SDD = -0.003B1 - 4.820\frac{B2}{B1} + 6.251$	
	0,092	$\ln SDD = -0.005MB1 - 4.552\frac{MB2}{MB1} + 6.271$	
IKONOS 2001	0,132	$\ln SDD = 0.001B1 - 0.451\frac{B2}{B1} + 5.117$	
	0,174	$\ln SDD = 0.001B1 - 1.133\frac{B3}{B1} + 5.169$	
	0,315	$\ln SDD = 0.001MB1 - 2.722\frac{MB2}{MB1} + 7.561$	
	0,177	$\ln SDD = 0.001MB1 - 1.026\frac{MB3}{MB1} + 5.231$	
Quickbird 2005	0,138	$\ln SDD = 0.018B1 - 1.508\frac{B2}{B1} + 1.310$	
	0,130	$\ln SDD = 0.019B1 - 1.972\frac{B3}{B1} + 0.255$	X
	0,039	$\ln SDD = 0.009MB1 - 0.467\frac{MB2}{MB1} + 1.666$	
	0,052	$\ln SDD = 0.012MB1 - 1.726\frac{MB3}{MB1} + 1.556$	
Quickbird 2006	0,364	$\ln SDD = 0.003B1 - 7.553\frac{B2}{B1} + 14.012$	
	0,551	$\ln SDD = 0.020B1 - 12.251\frac{B3}{B1} + 8.679$	X
	0,449	$\ln SDD = -0.09MB1 - 10.096\frac{MB2}{MB1} + 19.636$	
	0,463	$\ln SDD = 0.024MB1 - 14.088\frac{MB3}{MB1} + 9.246$	

a)



b)

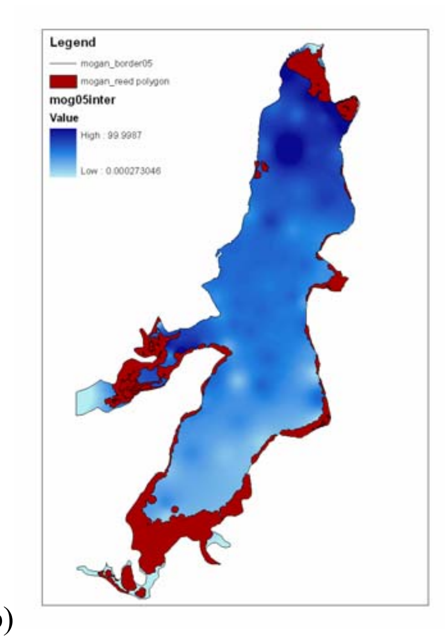
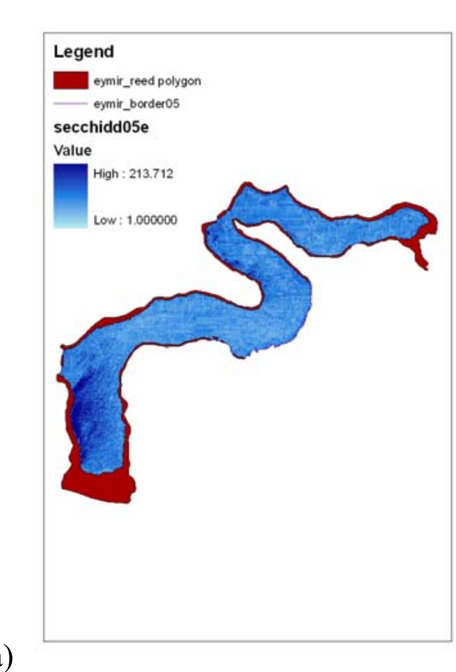


Figure 3.10. Thematic maps of Secchi disc depth distribution a) derived from the Quickbird 2005 Lake Mogan Image, and b) interpolated from field measurements.

a)



b)

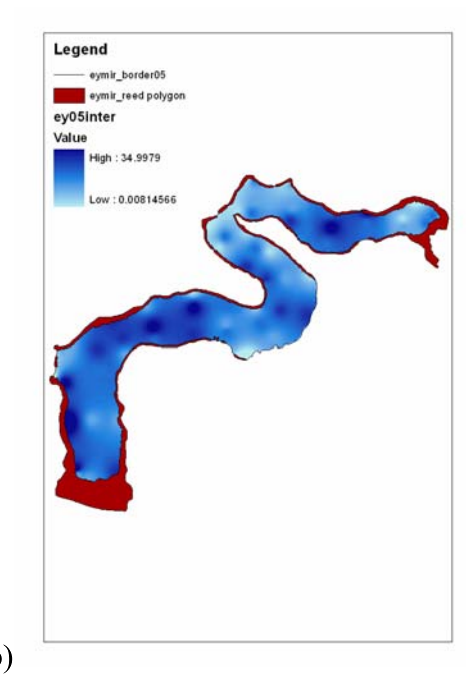
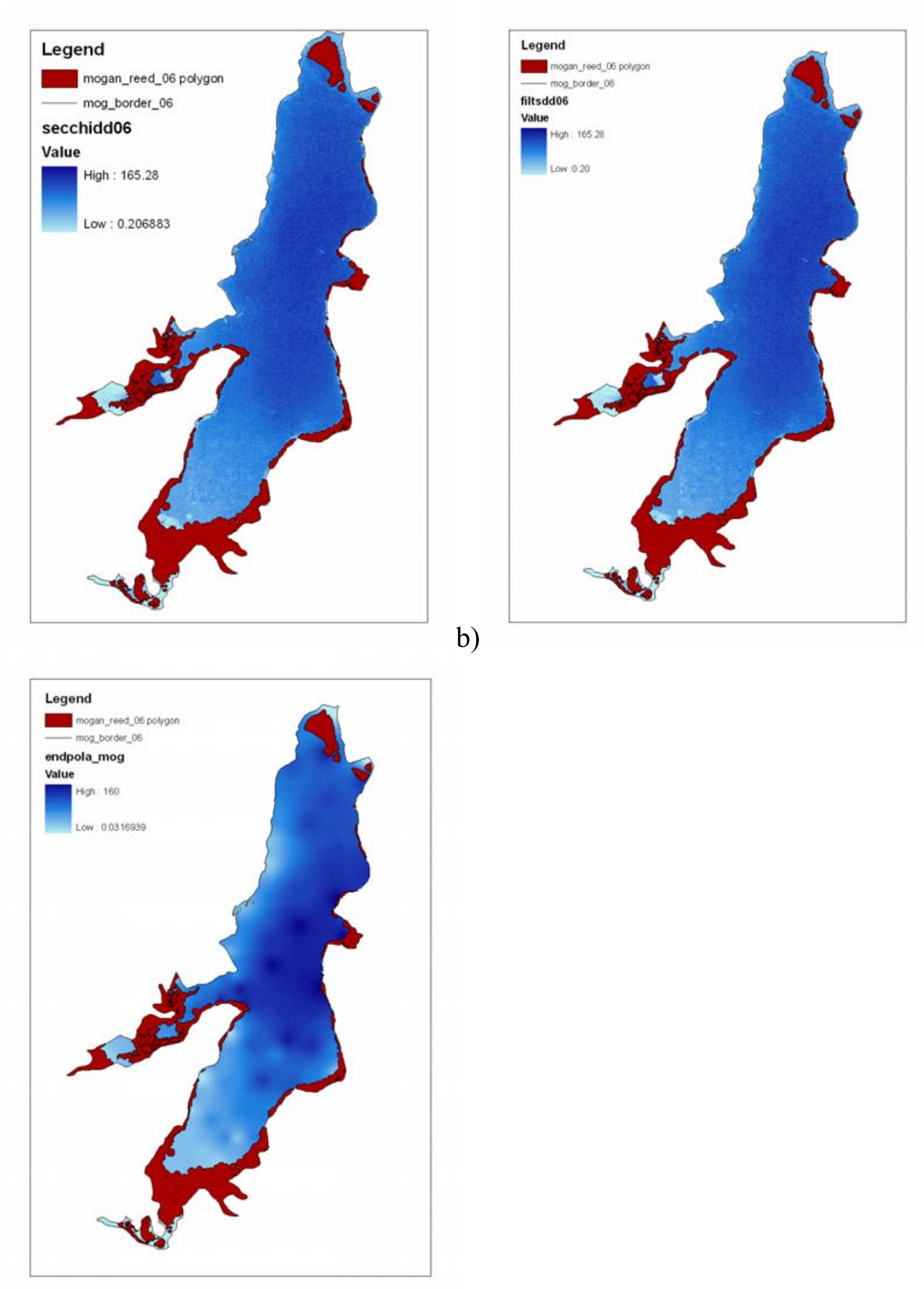


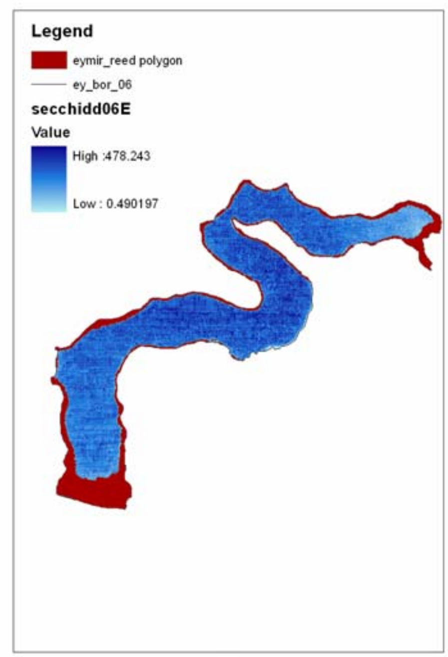
Figure 3.11. Thematic maps of Secchi disc depth distribution a) derived from the Quickbird 2005 Lake Eymir Image, and b) interpolated from field measurements.



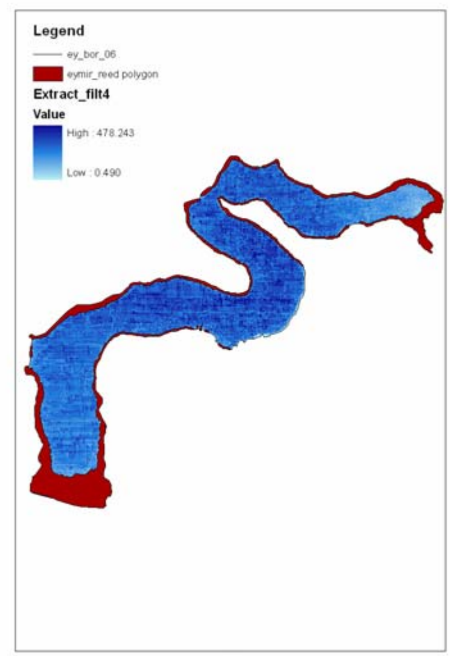
a) b)

c)

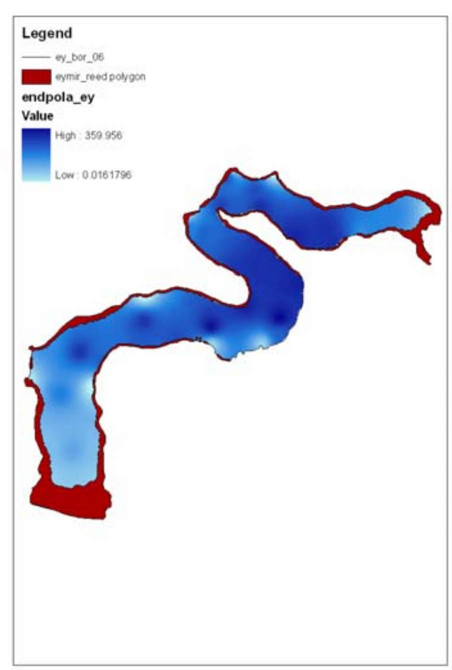
Figure 3.12. Thematic maps of Secchi disc depth distribution a) derived from the Quickbird 2006 Lake Mogan Image, b) after a mode filtre applied to the satellite image derived values, and c) interpolated from field measurements.



a)



b)



c)

Figure 3.13. Thematic maps of Secchi disc depth distribution a) derived from the Quickbird 2006 Lake Eymir Image, b) after a mode filtre applied to the satellite image derived values, and c) interpolated from the field measurements.

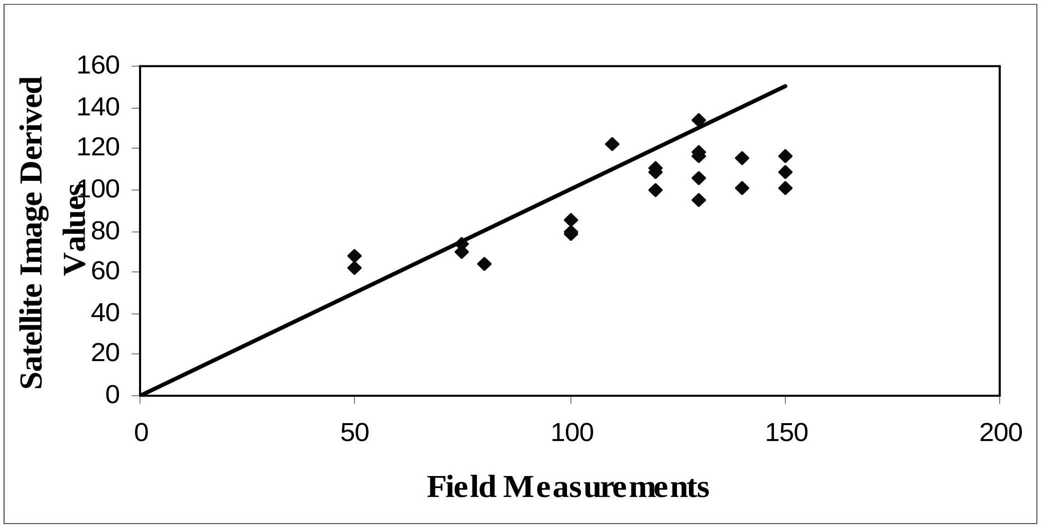


Figure 3.14. Quickbird 2006 Lake Mogan image derived Secchi disc depth values versus field measurements.

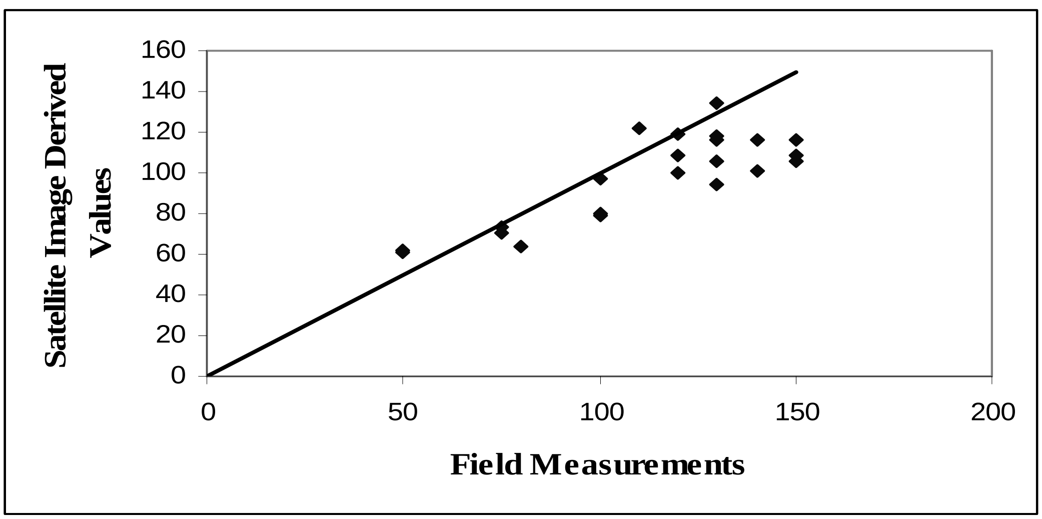


Figure 3.15. Filtered Quickbird 2006 Lake Mogan image derived Secchi disc depth values versus field measurements.

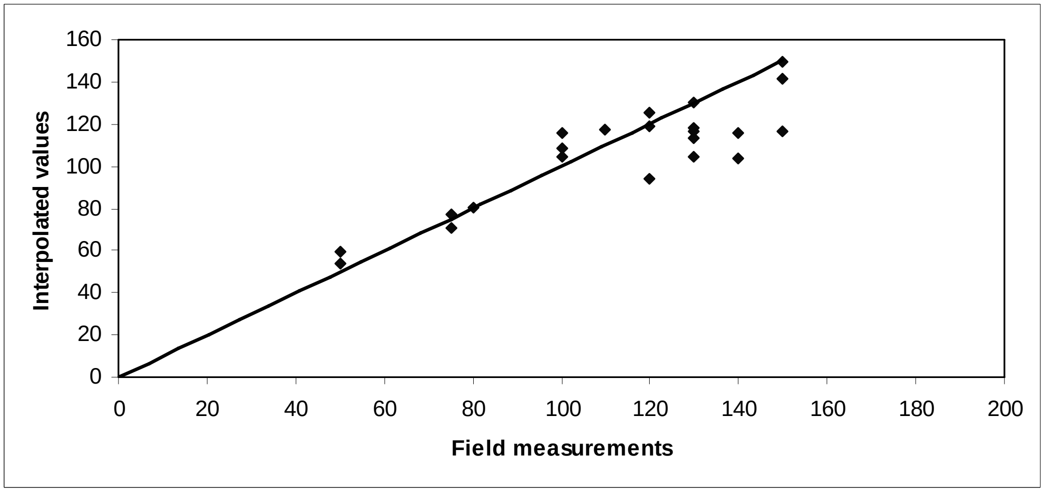


Figure 3.16. Interpolated Secchi disc depth values versus field measurements for Lake Mogan, 2006.

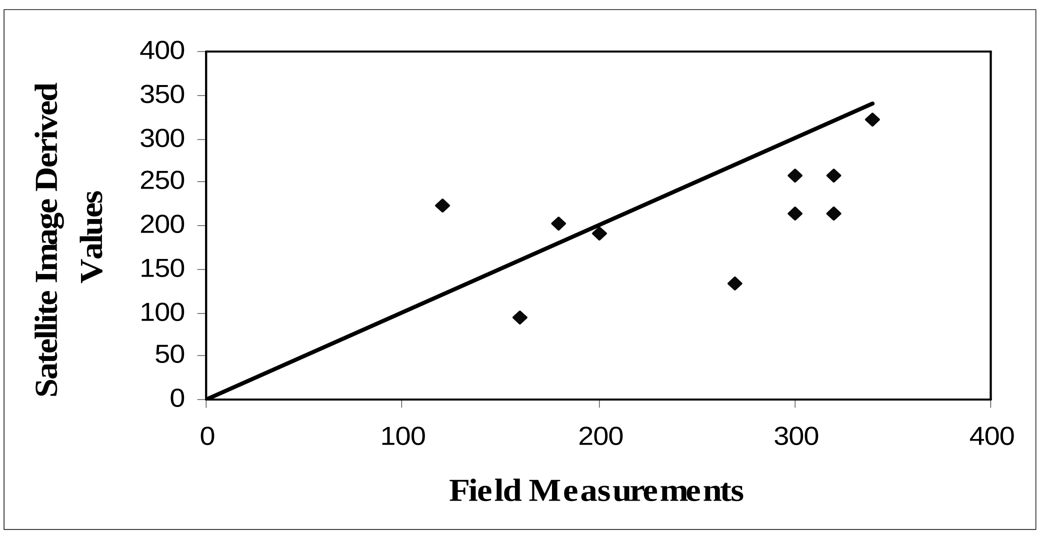


Figure 3.17. Quickbird 2006 Lake Eymir image derived Secchi disc depth values versus field measurements.

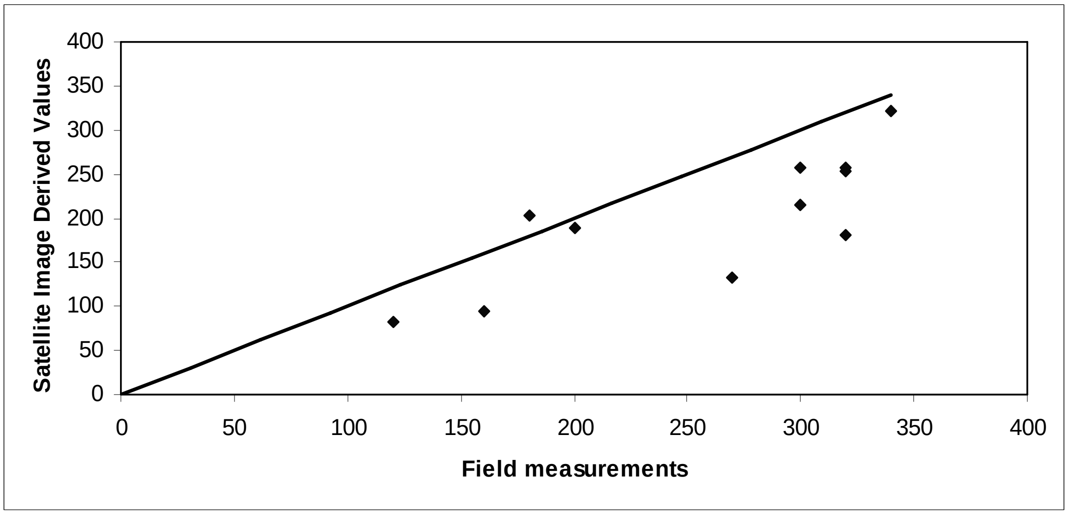


Figure 3.18. Filtered Quickbird 2006 Lake Mogan image derived Secchi disc depth values versus field measurements.

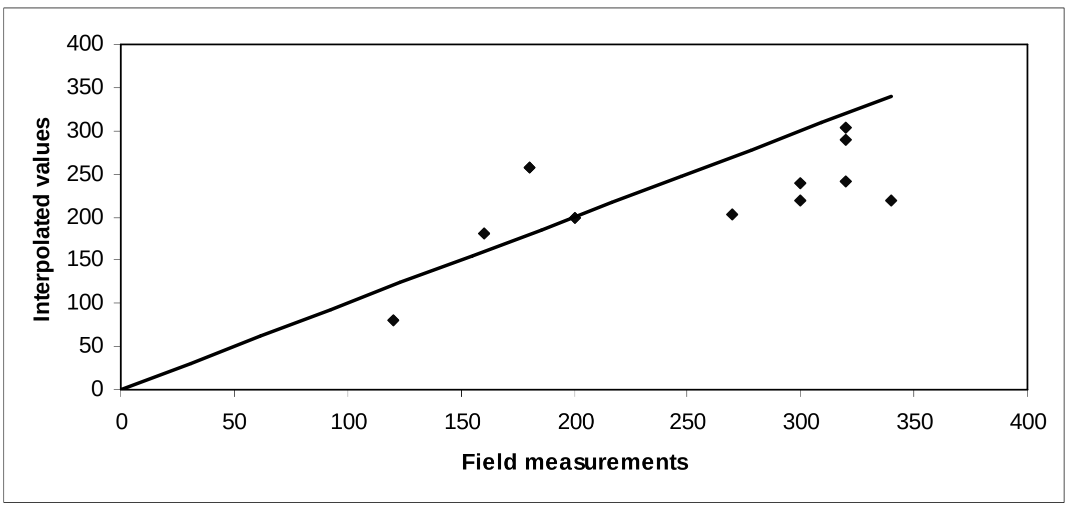


Figure 3.19. Interpolated Secchi disc depth values versus field measurements for Lake Eymir, 2006.

CHAPTER 4

DISCUSSION

Lakes and wetlands provide habitat for wide range of aquatic plants. In shallow lake wetlands, submerged and emergent aquatic plants have many important functions including suppressing phytoplankton, provision of habitat for invertebrates, fish and waterfowls and refuges for zooplankton and stabilizing sediment by their roots (Moss et al., 1996; Jeppesen et al., 1997; Gulati et al., 2002; Meerhoff et al., 2003; William et al., 2004), thus they are of great importance for conservation of biodiversity. Loss of aquatic plants coincides with loss of water clarity (William et al., 2004) and loss of ecological and conservation values (Moss, 1998). Therefore, identification and monitoring of aquatic plants possess a great value for conservation of lakes and wetlands.

Turkey is a very rich country in lakes with 200 natural lakes, 75 dams, and 700 lagoons and most of these are shallow and very large yielding to about 10,000 km^2 of total surface area covered by lakes (Kazanci et al., 1995). Because of this richness in number and sizes of lakes, it is too hard to monitor them all with field studies based on transect sampling method which becomes time-consuming, labour intensive, and expensive. Thus, new, rapid, dependable, and large scale technologies are needed for monitoring of lakes (Coops et al., 1999; Vis et al., 2003; Sawaya et al., 2003). Since during growing season the submerged vegetation absorbs visible red electromagnetic radiation and thus can be detected by remote sensors (Kirkman, 1996), remote sensing together with GIS offers a great potential to contribute to the lake studies including aquatic plant monitoring due to good spatial and temporal coverage, and multi-spectral measurements.

4.1. Classification of Emergent Plants

Emergent plants provide habitat for many waterfowls, birds, fish and other species. In this study emergent plants were classified in Lake Mogan and Lake Eymir using k-means unsupervised classification method. The images used in the classification ranged from high spatial resolution Quickbird and IKONOS images to medium spatial resolution Aster and Landsat images. The resulted overall accuracies were presented in Table 3.1. In Lake Mogan, slightly higher overall accuracies obtained for high spatial resolution images than medium spatial resolution images. However, for Lake Eymir, there was a greater accuracy difference between the high and medium spatial resolution images. This difference can be attributed to the area and shape difference of the two lakes as Lake Mogan is approximately six times larger than Lake Eymir with a more or less ovulate shape whereas Lake Eymir has a shape of a meandering river. Also differences in topography, catchment size and terrestrial vegetation around lakes could be the other factors. The overall accuracies revealed from Quickbird and IKONOS images for Lake Mogan and Lake Eymir were all greater than 90%. On the other hand, the overall accuracies obtained from medium spatial resolution images ranged between 80% and 93% for Lake Mogan and between 70% and 78% for Lake Eymir. The results imply that high spatial resolution images reveal higher accuracies than medium spatial resolution images especially for lakes with smaller surface areas. For classifying and detecting the changes in the emergent vegetation coverages, Valta-Hulkonnen et al. (2004) and Maheu-Girous and Blois, (2005) used aerial photography so that they got the advantage of high spatial resolution. Valta-Hulkonnen et al. (2004) found 78%, 80%, and 83% overall accuracies for three different years where as Maheu-Girous and Blois computed 71-87% overall accuracies from panchromatic images and 77-88% overall accuracies from colour images.

4.2. Detection of Changes in the Emergent Plant Coverage

In this study, the post-classification comparison change detection technique was used since this technique enables detection of change from independently produced classification results. Furthermore, none of the images in this study were atmospherically corrected and therefore, this made post-classification comparison change detection technique most suitable, as it minimizes the problem of radiometric calibration (Coppin and Bauer, 1996; Lu et al., 2004). Thus, using classification results from different images with different spatial resolution, such as Quickbird and IKONOS images, to detect changes became possible. However, in post-classification comparison change detection technique, the final accuracy depends on the quality of the classified image of each date (Lu et al., 2004). Therefore in this study, change detection results computed from high spatial resolution images were expected to be more accurate, especially for Lake Eymir.

Aster and Landsat images could provide good identification and change detection results too, but only for lakes with large surface areas. Schmid et al., (2005), used Aster and Landsat ETM+ images to detect the changes in a saline wetland of area 500ha in Central Spain. They grouped the images into five endmembers such as soil, salt crust, and vegetation and computed the change from these derived endmember maps. Schmid et al., (2005) concluded that grouping images into endmembers and then computing the change increased the accuracy of change detection compared to the medium spatial resolution of the images.

The resulting changes in the images were presented in Figures 3.1 and 3.2. Lake Mogan had been prone to reed bed removal since 2003 for opening part of lake shore for recreational pıurposes by the Municipality of Ankara, whereas Lake Eymir, acted as a control system for the removal detection since there was no major change in the coverage of the reeds. There was not a remarkable change in the reed bed area in Lake Eymir (Figures 3.1(a) and 3.1(c), Tables 3.3 and 3.7) observed in high spatial resolution images between 2001 and 2006, however medium spatial resolution images showed an approximately 8 ha of decrease in the reed bed area between 2002 and 2005 (Figure 3.1(b) and Table 3.6). On the other hand, in Lake Mogan, both high spatial resolution and medium spatial resolution images revealed nearly same results (Figure 3.2(a) & 3.2(b) and Tables 3.3 & 3.4) between 2002 and 2005. Lake Eymir has a smaller surface area and a very different shape than Lake Mogan. Especially its unique meandering shape with narrow width might have been the reason for the accuracy differences between the high and medium spatial resolution images. The difference in obtained in high spatial resolution images of Lake Eymir might be due to the spectral confusions caused by the variations in small scale at aquatic-terrestrial and emergent vegetation-water boundaries which may not be detected by Aster images of 15 m spatial resolution. Furthermore, the overall accuracies of classified Aster images of Lake Eymir were not as high as those of high spatial resolution images. This implies that change detection result of medium spatial resolution images did not have a high accuracy. Consequently, while selecting satellite images for wetlands studies spatial resolution emerge as a significant factor especially for relatively small sized wetlands with strong indentedness.

In Lake Mogan, the major reed beds removal occurred at the western part of the lake between 2002 and 2005. A small reed beds removal occurred at the southern part probably for opening area for agricultural purposes. In the other parts of the lake reed areas increased in amount probably as a result of drop in the water level. In April 2003, the water level was 973.42 metres above sea level (m.a.s.l.), the highest of the last five years and in September 2005 the water levels dropped to 972.25 m.a.s.l. Lake Mogan has a mean depth of 2.1 (Table 2.1.), therefore one metre drop in water level might have allowed the encroachment of emergent plants, as rise in water levels is inversely correlated with the encroachment of plants (Rogers et al., 2005). Therefore, considering the large surface area of Lake Mogan, one metre drop accounted for a large area. The total loss in reed bed areas equaled to 23 ha, while the total increase was 34 ha. As it can be seen from the satellite data, the western and northern parts around the Lake Mogan were urbanized parts. Therefore, the northern and western parts of Lake Mogan were prone to human impact and were once determined as the potentially risky areas for diffuse sources of nitrogen using GIS based risk analysis (Gokmen, 2004). Thus, the increase in the reed bed area of the lake in the southern or south-eastern parts of Lake Mogan can not sustain the loss of nutrient retention capacity of the reed bed areas at the western part.

Moreover, the further change in reed bed area in Lake Mogan between 2005 and 2006 was computed from high spatial resolution Quickbird images. An area equal to 18.4 ha of reed beds were also removed from Lake Mogan at the northern part between 2005 and 2006. The total reed bed area increase was calculated as 14.3 ha, which might be due to the decrease in the water level.

4.3. Classification of Submerged Plants

Submerged vegetation classification is harder compared to emergent vegetation because spectrally it is easier to identify emergent plants than submerged plants (Williams et al., 2003). While the reflectance properties of emergent vegetation resembles to those of terrestrial vegetation, the nature of being submerged in the water brings about the problems of mixed pixels to submerged vegetation classification. Similarly, the accuracies of the emergent vegetation classifications were higher in this study. Previous part of the study showed that the Aster images could provide a good identification for large surface areas but for studies that may require higher levels of identification (e.g. submerged plants), medium spatial resolution may have a limitation. It was suggested that high spatial resolution images such as Quickbird and IKONOS can be very promising for submerged plant identification (Sawaya et al., (2003); Wolter et al., 2005). In this study, for classification of submerged plants, Quickbird images of 2005 and 2006 were selected due to their high spatial resolutions which were matched with the availability of the detailed field data. The overall accuracies obtained for submerged plant coverages were 83.02% and 78.88% for 2005 and 2006 respectively (Table 3.8). These results were consistent with the literature (Sawaya et al, 2003; Wolter et al., 2005). Sawaya et al., (2003) merged all submerged vegetation classes into one class for accuracy assessment which yielded user and producer accuracies of 54.2 % and 92.9 % respectively using IKONOS sensor data. On the other hand, Wolter et al., (2005) used Quickbird sensor data for mapping submerged vegetation at three sites across the Great Lakes in USA with multi-temporal classification approach. They obtained 80 % overall accuracy for mapped four classes as a result of single-date classifications of submerged vegetation.

Classification of submerged plant species in lakes with satellite remote sensing is a very new task in literature. Most of the studies for classification of submerged plants using remote sensing are limited that submerged vegetation was classified according to the density classes. For instance, Sawaya et al. (2003) classified submerged vegetation according to the density and depth profiles and Wolter et al. (2005) classified submerged vegetation as dense and sparse together along with other classes of water as sand bottom, muck bottom, and deep water. For submerged vegetation coverage classifications, this study successfully achieved higher accuracy than recorded in the literature. Furthermore, this study managed for the first time to classify submerged plant species using satellite data.

Classification of submerged plant species with water classes revealed 71.69% and 69.01% overall accuracies in 2005 and 2006 respectively (Table 3.8) and the resulting thematic maps were presented in Figures 3.3 and 3.4. These results may not seem high but they are satisfying when compared to the 85% accuracy target of land cover classification. Foody (2006), sugested that for such detailed classifications reaching that 85% accuracy target is unrealistic (Foody, 2006).

Also, a part of a reduction in accuracy can be attributed to the field conditions that might have caused some shifts in the coordinates of sampling locations which in turn might lead to distortions affecting the overall accuracies. To eliminate such distortions caused by field conditions, a 3X3 nine pixel kernel was used in the accuracy test. However, mixed pixel problem might still be present. The submerged plant species in Lake Mogan were not to be easily spectrally separable since both Potamogeton pectinatus and Najas sp. (Najas marina and Najas minor) have alternate dissected leaf structure (see Appendix B). In addition, both species had sparse growth and therefore it was difficult to classify them compared to the dense growing plants with homogenous large patch of areas can be classified more accurately compared to heterogeneous areas (Sawaya et al., 2003). Where as in this study, in some areas, the species were observed mixed with each other. Moreover, Myriophyllum spicatum was observed in the field in both years but at very low amounts that this species was not included in the classification. It was also found that locations where submerged plant coverage was less than 30%, these locations acted as water pixels for both species. Percent coverage less than 30% was also regarded as low vegetation. To eliminate this confusion these locations were accepted as water pixels in the accuracy test in both years. Although applying water masks in both years, additional water classes were used in classifications because the threshold determined might not be sufficient to describe all vegetation types. In the error matrix of 2005 (Tables 3.9), it was seen from that water classes and vegetation classes (Najas sp. at surface and Potamogeton pectinatus) at surface were not confused. The vegetation class that had the highest confusion was Najas sp. below surface because it has both characteristic of the water and vegetation together. The least confused classes are the water class (2 Secchi disc depth > Water depth) the water class (2 Secchi disc depth < Water depth). Since only two reference points fell in water class (2 Secchi disc depth < Water depth), the accuracy test can not be considered as dependable. In the error matrix of 2006, more confusion observed between classes, which may have caused from the decreased relative coverages of submerged plant species in Lake Mogan.

In order to classify the submerged vegetation coverages and submerged plant species, several classification techniques were applied. However, it was observed that. Fuzzy k-means classification technique revealed high accuracies for emergent vegetation coverages in this study, however for submerged vegetation classification, fuzzy k-means approach failed to provide high accuracies. The overall accuracies obtained for submerged vegetation coverage classifications were ranged between 45%-55%. Moreover supervised classification technique revealed even lower accuracies which were ranged between 45%-50%. The reason behind was the assigning training areas according to the point measurements which might be insufficient for dfining areas. Thus, the results of this study recommend the use of isodata unsupervised classification technique for classifying the submerged vegetation coverages and submerged plant species.

4.4. Inferring Water Clarity from the Satellite Data

In the last part of the study, it was aimed to predict water clarity from the satellite data. Several studies in the literature concluded that ratio of red bands to blue bands of remote sensors were highly correlated with Secchi disk depth field measurements (Kloiber et al., 2002; Sawaya et al., 2003). The relationships among satellite and field data were investigated with respect to the natural logarithm of field measurements and satellite derived values of Secchi disk depth. For this purpose several satellite data from different sensors were used. The results from the present study are in accordance with the earlier studies with the years 2005 and 2006 in Quickbird and Landsat images. For years 2001 and 2002 the same conclusion could not be derived because there were problems in the projection systems of the coordinates of field data belonging to these dates, which might cause shifts in the sampling locations. For instance, field data of 2002 for Lake

Mogan was eliminated from the study because the correction of the distortions in the coordinates was not manageable. On the other hand, the time window between field and satellite data was greater 2001 and 2002, compared to the years 2005 and 2006, since for the past years such research was limited to the available archive satellite data. The figures summarizing the Pearson correlation coefficients for band and band ratio values of years 2001 and 2002, and Aster images were presented in Appendix A.

The Quickbird data provided high multiple R values for both lakes in 2005 and 2006, with comparatively higher values in 2006 (Figures 3.3-3.8). The patterns obtained for the Pearson correlation coefficients of bands and band ratios were very resembling to each other in 2005 and 2006 datasets of Lake Mogan and in 2005 datasets of Lake Eymir. However this pattern was different in the 2006 datasets of Lake Eymir, where the lake was in a clear water state. The average of measured Secchi disc depths were 107.3 for Lake Mogan in 2006, 49.0 for Lake Mogan in 2005, 235.3 for Lake Eymir in 2006, and 19.0 for Lake Eymir in 2005. At the same time the 2006 datasets with highest Secchi disc depth values of Lake Eymir revelaed the highest multiple R value for the band ratio 3:1. The R square values of the equations for both lakes were low in 2005 but high in 2006. Yet the coefficients of the equations were consistent among the years.

Pearson correlation coefficients derived from Landsat data were high for datasets of 2005 (Figure 3.9), but too low for datasets of 2001 and 2002 (See Appendix A). The time window between the dates of field surveys and the image acquisition dates was about a month in years 2001 and 2002. Apart from the considered distortions in the coordinates of field data, that time difference might be the cause of such low correlation among the field and satellite datasets of both lakes' original and merged images. In 2005, both the Pearson correlation coefficients for bands and band ratios and the R square values of the developed equations were high. High correlation values of R= 0.673, R= 0.637, and R= 0.698 for the single

Band 1, Band 2, and Band 3 of Landsat sensor, respectively and the highest correlation for a band ratio was observed for 3:1. Equations developed for 2005 Landsat dataset for Lake Mogan had the highest (R2= 0.600 and R2= 0.620) R square values among all the datasets evaluated in this study.

For IKONOS data, observed highest multiple R value was for band ratio 4:3 (R= 0.669), where as the band ratios of 3:1 was not that high (R= 0.247). The mean Secchi disc depth value was 138.8 in 2001 in Lake Eymir. Because of the possible distortions listed above, this result from a single date data was not enough to conclude about the reliability of IKONOS data for predicting Secchi disc depth. The equations developed from a band and a band ratio for IKONOS data (Table 3.26), implied that blue band (Band 1) was not an important component in the equations, but the ratio of green band to blue band was more determining component.

The obtained multiple R values from the Aster data were not reliable enough to predict Secchi disc depth in Lake Eymir. The R square values of the equations developed for Lake Eymir was also low. The main reason for that might be the lack of blue band in Aster sensors, which disables to talk about the band ratios of red to blue (Band 3: Band 1). However, the pattern observed in relations in 2002 and 2005 weas nearly the opposite. The reason for that might be the different ecological conditions of Lake Eymir on those dates. In 2002 the lake was at clear water state where as in 2005 the lake was algal blooming. In Lake Mogan, high correlations of field and satellite datasets of 2005 were observed for some bands and band ratios, but the R square values obtained for the develop equation of a band and a band ratio were not satisfying.

The equations developed for Lakes Mogan and Eymir from Quickbird 2005and Quickbird 2006 datasets, were used to predict and map the Secchi disc depth values for the whole lake surfaces. The thematic maps were derived from satellite images and interpolated from field measurements were presented in Figures 3.10 to 3.13. The graphs for validating the thematic maps were presented in Figures 3.14 to 3.19. Comparison of predicted and actual Secchi disc depth values for both lakes, revealed that the developed equations could predict values but with a little under estimation. On the other hand, the filtered values provided better fit with the field measurements.

CHAPTER 5

CONCLUSION

Shallow lakes provide several valuable services to wildlife and humanity and the aquatic plants and water clarity can be defined as the key indicators of the ecological status of these valuable ecosystems. In order to cope up with the ongoing global scale destruction of shallow lakes and wetlands and to help their conservation, development of rapid and large scale monitoring strategies is needed. This study showed that satellite remote sensing has a great potential to contribute to the lake studies.

It was found that as the spatial resolution decreases the accuracy of the classification decreases especially for the lakes with small surface area, like Lake Eymir due to the increase in the number of mixed pixels. It was derived as conclusion that together with other factors lake size and lake shape are important in classification. For lakes with larger surface areas both high and medium spatial reolution images could provide reliable results.

The overall accuracy results obtained for submerged plant coverages and identification of plant species together with water classes were very satisfying suggesting the use of high spatial resolution Quickbird satellite data in such studies.

This study showed that the water clarity can be described or predicted by a linear equation where natural logarithm of field measured Secchi disc depth was best predicted by blue band and the ratio of red bad to blue band. However it should be noted that calibration of such equation with field measurements was important.

Together with Advances in Earth Observation technologies, especially sensors that can detect subsurface features such as LIDAR, rapid and dependable large-scale monitoring will be enabled. Increasing spatial resolution of satellite sensors will also provide highly detailed information.

5.1. Recommendations

Applying filters to eliminate the distortions caused by rough lake surface are recomended.

The models developed for Secchi disc depth could be made stronger by adding time component by long term monitoring and calibration.

It is recommended to make use of all sensors for long term monitoring studies, use of high spatial resolution data for detailed classifications and use of Landsat and Aster for studying many lakes simultaneously.

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Appendix A

Figures showing the Pearson correlation coefficients of field measurements and satellite image derived values for Secchi disc depth.

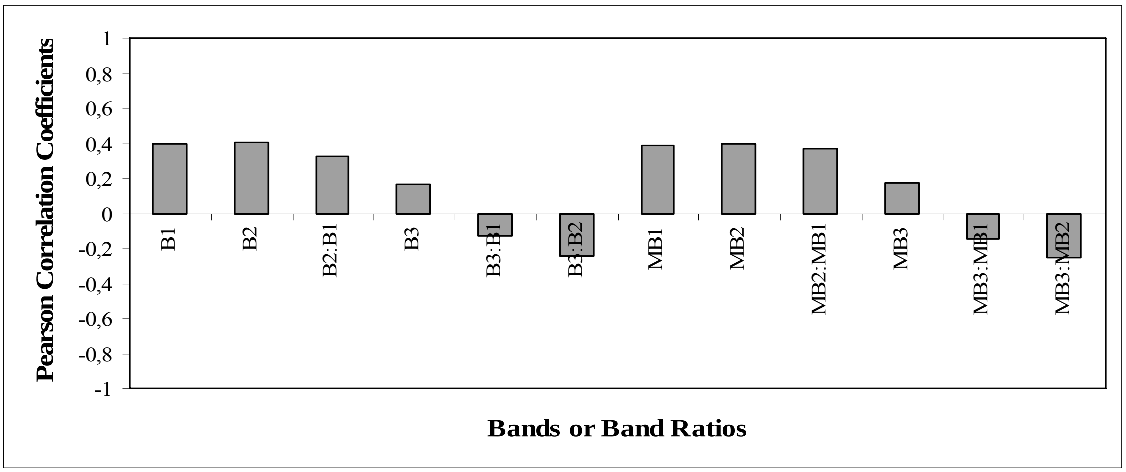

Figure A.1. Pearson correlation coefficients for bands or band ratios of Aster 2002 Lake Eymir Image.

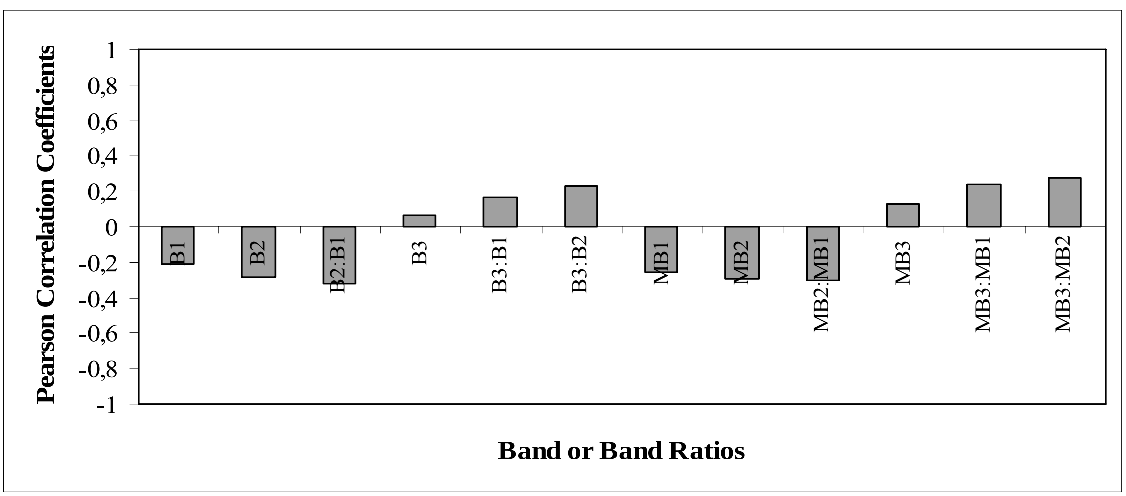

Figure A.2. Pearson correlation coefficients for bands or band ratios of Aster 2005 Lake Eymir Image.

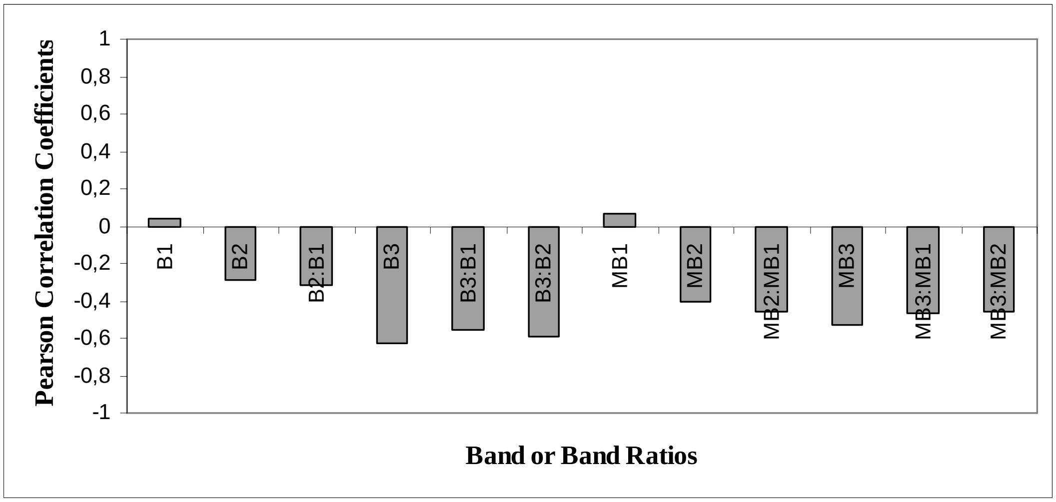

Figure A.3. Pearson correlation coefficients for bands or band ratios of Aster 2005 Mogan Image.

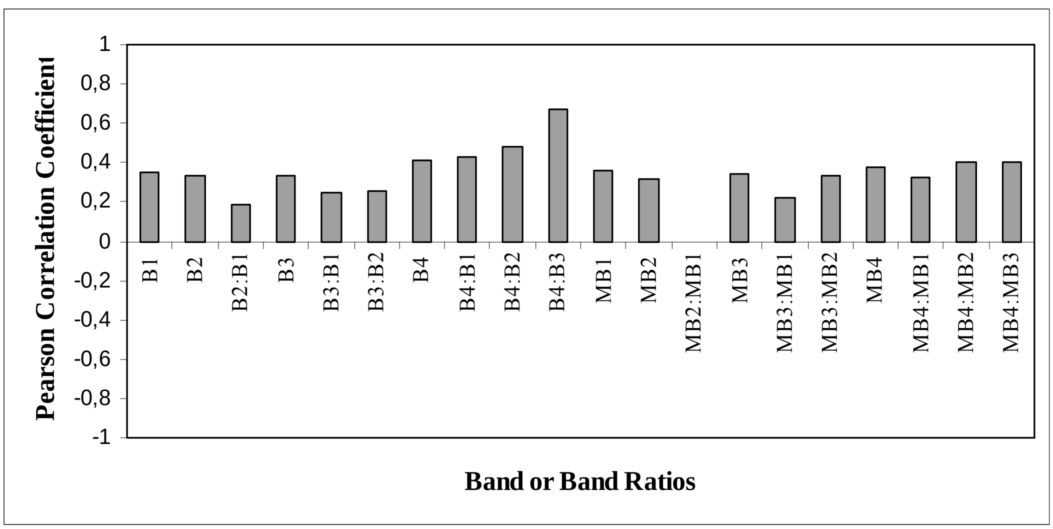

Figure A.4. Pearson correlation coefficients for bands or band ratios of IKONOS 2001 Lake Mogan Image

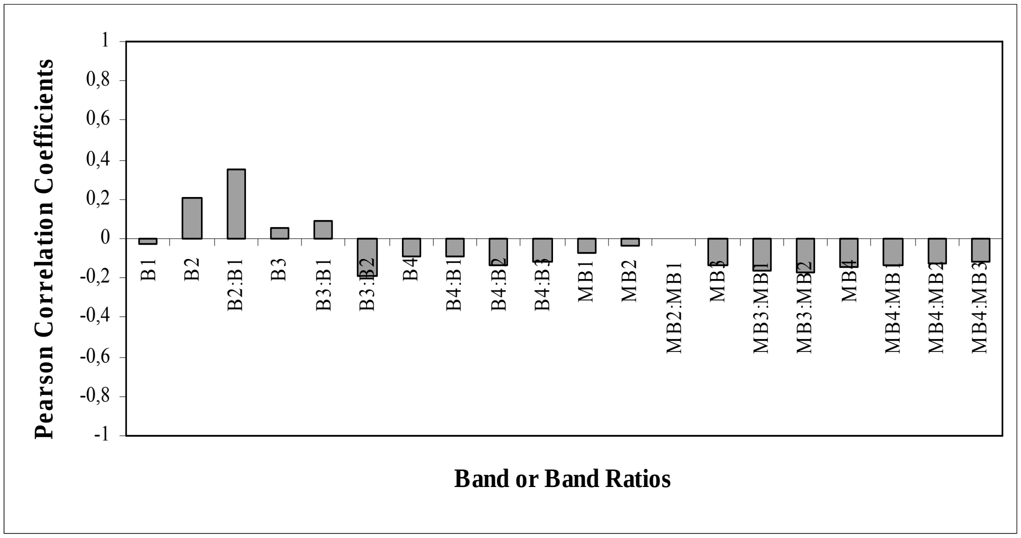

Figure A.5. Pearson correlation coefficients for bands or band ratios of Landsat 2001 Lake Eymir Image

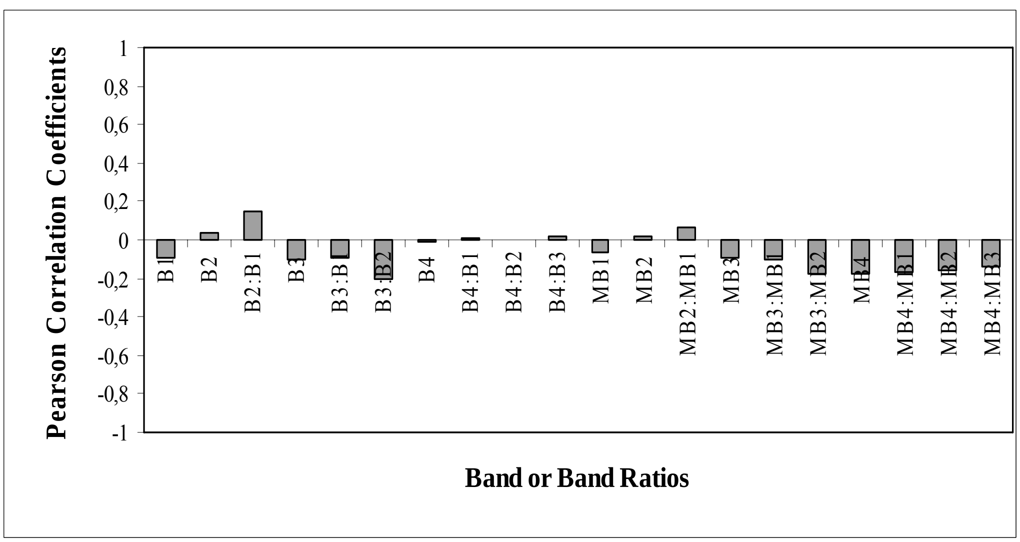

Figure A.6. Pearson correlation coefficients for bands or band ratios of Landsat 2001 Lake Eymir Merged Image

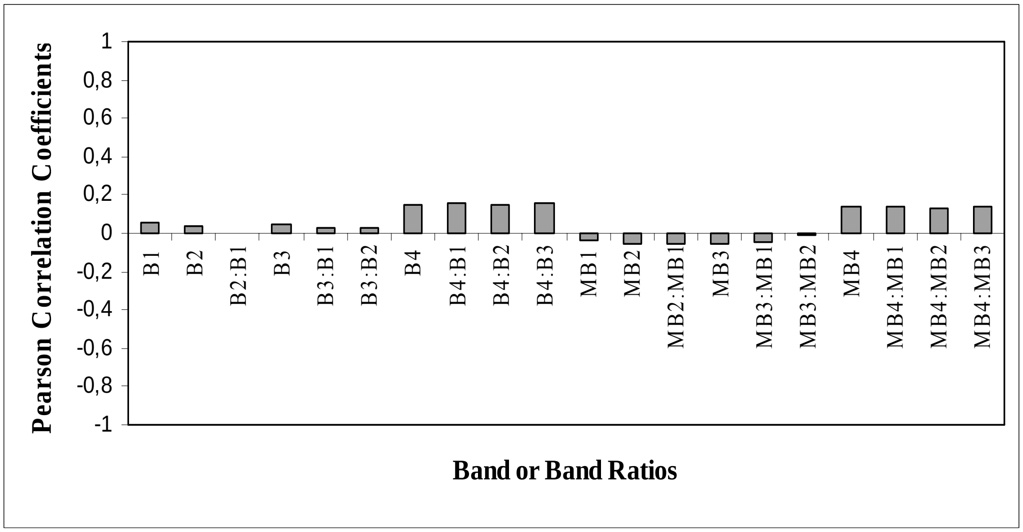

Figure A.7. Pearson correlation coefficients for bands or band ratios of Landsat 2001 Lake Mogan Image

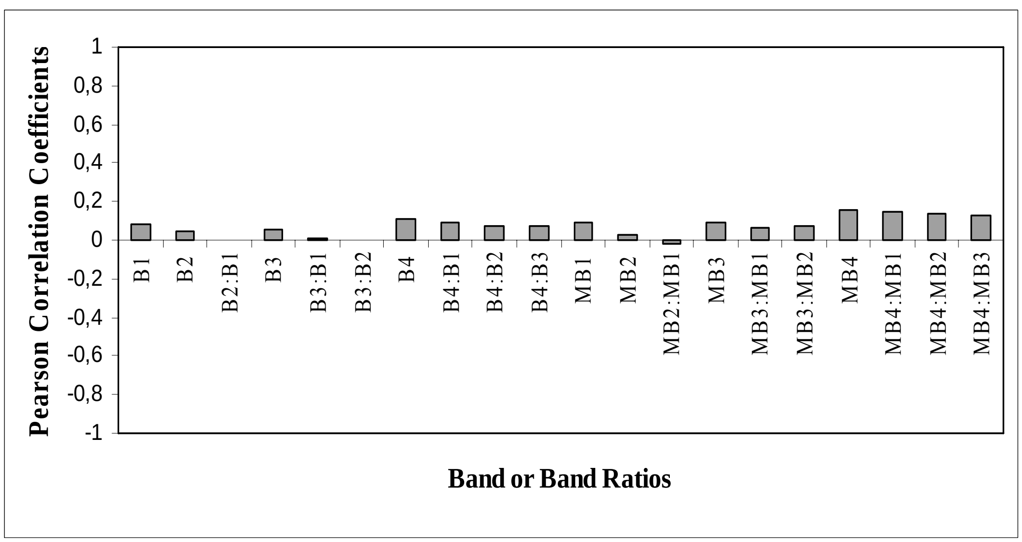

Figure A.8. Pearson correlation coefficients for bands or band ratios of Landsat 2001 Lake Mogan Merged Image

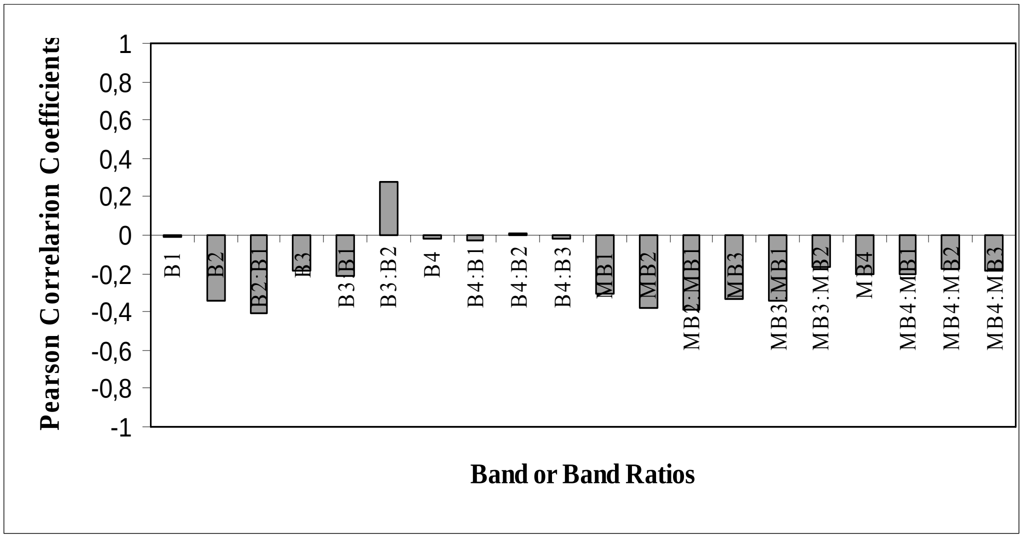

Figure A.9. Pearson correlation coefficients for bands or band ratios of Landsat 2002 Lake Eymir Image.

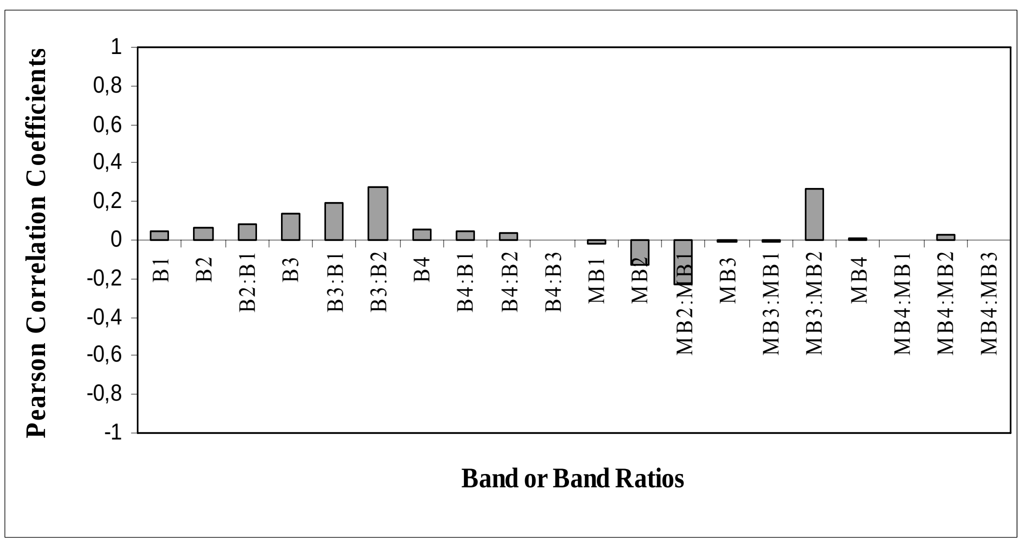

Figure A.10. Pearson correlation coefficients for bands or band ratios of Landsat 2002 Lake Eymir Merged Image

Appendix B

The drawings of the classified plant species in Lake Mogan.

Figure B.1. *Potamogeton pectinatus* (Sago pondweed), (taken from Altinayar, 1988).

Figure B.2. *Najas minor* (Brittle waternymph), (taken from Altinayar, 1988).

Figure B.3. *Najas marina* (Spiny naiad), (taken from Altinayar, 1988).