

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE
ENGINEERING AND TECHNOLOGY

**MONITORING SOIL SALINITY VIA REMOTE SENSING TECHNOLOGY
UNDER DATA SCARCE CONDITIONS: A CASE STUDY FROM TURKEY**



M.Sc. THESIS

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**Department of Environmental Engineering
Environmental Science and Engineering Program**

MAY 2016

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

**KISITLI VERİ ŞARTLARINDA UZAKTAN ALGILAMA TEKNOLOJİSİ İLE
TOPRAK TUZLULUĞUNUN İZLENMESİ: TÜRKİYE'DEN BİR VAKA
ÇALIŞMASI**

YÜKSEK LİSANS TEZİ

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To my family,



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ABBREVIATIONS

RS	: Remote Sensing
GIS	: Geographical Information System
NDVI	: Normalized Difference Vegetation Index
CSCRS	: Center for Satellite Communications and Remote Sensing
EC	: Electrical Conductivity
FAO	: Food and Agriculture Organization
ESP	: Exchangeable Sodium Percentage
EMI	: Electromagnetic induction
EM	: Electromagnetic
NIR	: Near-infrared
TM	: Thematic Mapper
ETM	: Enhanced Thematic Mapper
ASTER	: Advanced Space borne Thermal Emission and Reflection Radiometer
SVI	: Spectral Vegetation Index
EVI	: Enhanced Vegetation Index
SAVI	: Soil-Adjusted Vegetation Index
NDSI	: Normalized Differential Salinity Index
BI	: Brightness Index
RVI	: Ratio Vegetation Index
CRSI	: Canopy Response Salinity Index
NSSRI	: Normal Soil Salt Content Response Index
SI	: Salinity Index
HJ-HSI	: HuanJing-Hyper Spectral Imager
PCA	: Principal Component Analysis
LSU	: Linear Spectral Unmixing
PLSR	: Partial Least Square Regression
DTA	: Decision-tree Analysis
IG	: Inverted Gaussian
SWIR	: Shortwave Infrared
SMP	: Soil Matric Potential
CA	: Conservation Agriculture
PB	: Permanently Raised Bed
RR	: Residue Retention
RH	: Residues Harvested
PGPB	: Plant Growth-Promoting Bacteria
AVP1	: Arabidopsis Vacuolar H ⁺ - Pyro phosphatase Gene
EUNIS	: European Nature Information System
CORINE	: Coordination of Information on the Environment
NASA	: National Aeronautics and Space Administration
OLI	: Operational Land Imager
TIRS	: Thermal Infrared Sensor
CLC	: CORINE Land Cover

EU	: European Union
DNs	: Digital Numbers
AC	: Atmospheric Corrections
UTM	: Universal Transverse Mercator
WGS	: World Geodetic System
MARS	: Multivariate Adaptive Regression Splines
MODIS	: Moderate Resolution Imaging Spectroradiometer





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MONITORING SOIL SALINITY VIA REMOTE SENSING TECHNOLOGY UNDER DATA SCARCE CONDITIONS: A CASE STUDY FROM TURKEY

SUMMARY

In arid and semi-arid regions of the world, soil salinization is one of the most crucial environmental problems due to its adverse effects on agriculture productivity and sustainable development. Soil salinity prevents majority of plants to grow due to its detrimental effects on seed germination and decreases the osmotic potential of soil water which results in inability of plants to take in water from root zone.

Another adverse effect of soil salinity is decreasing water quality for both drinking and irrigation purposes that in turn lead to social, environmental and economic problems. It also disturbs ecological health of streams and it threatens biodiversity by loss of various habitats. One more negative impact of salt accumulation in soil is the accelerating rate of surface run-off since water cannot penetrate to saline soils; consequently, it may pose flood risks. As known, flood transfers soil nutrients and makes soil more degraded.

Unconscious irrigation and practising old irrigation techniques extremely damage the fertile land and accelerate water logging and salt accumulation in soil. Moreover, irrigating agricultural land with water rich in salt, land clearing and using fertilizer containing nitrogen and potassium salts are among the other human-induced activities that cause soil salinity. In addition, natural factors such as parent material in soil structure, closeness of salty groundwater table to the surface, weathering of the parent rock and sea water intrusion exacerbate soil salinity occurrence.

Therefore, Salinity mapping and monitoring plan should be considered as part of any project dealing with the use of saline water in irrigation. In agricultural lands, an effective salinity monitoring plan must be proposed to track salinity changes especially in the root zone to inspect the impact of management options to overcome or alleviate salinity effects, and to assure that root zone salinity does not rise above crop threshold level to prevent yield losses. Such monitoring programs help to identify the problem and areas at risk for salinization at the regional and national levels. Accordingly managers, scientists and decision-makers take essential and prompt action to tackle the problem in order to avoid extending the problem to other areas that may have significant social and economic impact on national economies.

Extensive exploration utilizing satellite imagery for detecting, mapping and monitoring soil salinity has been conducted all over the recent years, principally with multispectral sensors. These incorporate Landsat Thematic Mapper (TM), Landsat Multispectral Scanner System (MSS), Landsat7, Landsat8, Landsat Enhanced Thematic Mapper (ETM), SPOT, Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER), IKONOS, MODIS and Indian Remote Sensing (IRS).

Mitigating soil salinity problem is related to saline agricultural land reclamation by using various methods and techniques. Considering characteristics of each salt-affected land and reasons which exacerbate salinity problem, proper solutions need

to be generated. common solutions for alleviating soil salinity problem are replacing traditional irrigation methods with recent irrigation techniques, modifying soil management practices, managing crop cultivation sequence and mapping both salt-affected areas and lands which are at risk of salinization.

It is an important concern to predict and monitor soil salinity in order to take protective measures against further deterioration of the soil; particularly, if it is used for agricultural activities similar to lands in the vicinity of Tuz Lake Region in Turkey.

Tuz Lake is the second largest lake in Turkey which is located between three provinces; Konya, Aksaray and Ankara that occupies an area of about 1.500 km² with an altitude of 905m.

Agriculture, livestock breeding, salt production and tourism are the main human activities that have impact on economic condition in this region. Loss of trees and bushes due to intense agricultural activities in some parts of the basin lead to soil erosion. Besides, soil salinization due to both human-induced activities and natural factors has exacerbated its condition regarding agricultural land development. Therefore, monitoring long-term changes in soil salinization and tracking land cover changes will be helpful for mitigating the adverse effects in this region.

This research focuses mainly on generating soil salinity maps of Tuz Lake Region in order to track changes in the areas of salty spots in years 1990, 2002, 2006, 2011 and 2015. Besides, this study detects land cover changes in the area from year 2000 to 2006, and from 2006 to 2012.

In addition, the most commonplace practices alongside with new methods for mitigating soil salinization as a worldwide problem are reviewed. These methods can be utilized for each salt-affected area after studying sources of salinization in detail. For Tuz Lake Region, further studies and also in-situ experiments are required in order to select best practical methods for lessening adverse effects of soil salinization and reclaiming of salt-affected lands.

A total number of 25 Landsat-5 TM, Landsat-8 images obtained between 1990 and 2015 were analysed in this study. Field electrical conductivity measurements (EC) for 322 soil samples in year 2002 were checked and among them 19 proper samples in the vicinity of the lake were selected for generating salinity maps. Also, CORINE vector change data for years 2000 to 2012 were overlaid on satellite images for detecting land cover changes.

All satellite images were radiometrically and atmospherically corrected using ENVI and ERDAS softwares prior to classification. Following the pre-processing step, five soil salinity indices alongside with Normalized Different Vegetation Index (NDVI) were applied on all satellite images by using Arc map 10.2. Then, 19 soil samples were overlaid on images in order to extract the exact index values related to soil samples. Both linear and exponential regression analysis were conducted as the next step for all indices separately in year 2002 which is the only year that corresponds to spatial EC values. Salinity maps for years 1990, 2006, 2011 and 2015 were then produced utilizing the exponential regression equation for year 2002.

In this research, exponential regression analysis yielded better results than linear regression analysis since for various Indices which were used in this study, EC values raised exponentially in Y- axis as a result of increasing SI values on X- axis.

Among all salinity indices which are applied for generating salinity maps, salinity index $(SI) 1 = \sqrt{B1 * B3}$ depicts best results for both regression analysis and exponential analysis by showing R^2 values 0,778 and 0,961 respectively. Therefore, the most accurate salinity maps for years 1990, 2006, 2011 and 2015 are generated based on exponential regression results between $(SI) 1 = \sqrt{B1 * B3}$ reflectance values and EC values in 2002.

Utilizing Remote Sensing (RS) and Geographical Information Systems (GIS) as modern technologies contributed producing various salinity maps despite limited knowledge and information about ground truth data.

In this research, 30 salinity maps with five classes including none-saline, slightly saline, moderately saline, highly saline and extremely saline classes were generated for different years as a result of various indices. Besides, 5 NDVI maps were generated with 11 classes. Changes in the area of each salinity class and each NDVI class for years 1990-2015 were calculated.

In this study, also utility of recent remote sensing analysing techniques and methods including linear spectral unmixing, Decision-Tree Analysis (DTA), principal components analysis, inverted Gaussian function, partial least square regression technique approaches are discussed. Examples of the spatio-temporal changes in salt-affected soils are referred too.



KISITLI VERİ ŞARTLARINDA UZAKTAN ALGILAMA TEKNOLOJİSİ İLE TOPRAK TUZLULUĞUNUN İZLENMESİ: TÜRKİYE'DEN BİR VAKA ÇALIŞMASI

ÖZET

Toprak tuzlanması, tarımsal üretim ve sürdürülebilir kalkınma üzerinde yarattığı olumsuz etkiler nedeniyle özellikle dünyadaki kurak ve yarı kurak bölgelerde rastlanan önemli çevresel problemlerin başında gelmektedir. Bilinçsiz sulama ve eski sulama tekniklerinin halen kullanılması verimli tarım topraklarına ciddi oranda zarar vermekte; bunun yanı sıra toprakta tıkanma ve tuz birikmesine de sebep olmaktadır. Bu etkilerin yanı sıra, sulama suyunun içerisinde bulunan yüksek miktardaki tuzlar, toprağı tarım yapmak adına tarlaya çevirirken üst tabakasını sıyırmak ve toprağı uygulanan ticari gübrenin içerisinde yüksek oranda azot ve potasyum tuzlarının bulunması gibi durumlar da esasında insan eliyle yaratılan ve tuzlanmaya neden olan diğer etkenler olarak sıralanabilir. Tuzlanma nedeniyle tohumların çimlenme devresinde birçok bitkinin büyümesi engellenmekte ve topraktaki su içeriğinin osmotik potansiyeli de azalarak, bitkinin kok bölgesinden bünyesine su alma kabiliyeti de durmaktadır.

Toprak tuzlanması sadece toprak ve toprakta yetişen bitki ve ürünler üzerinde olumsuz etki yapmamaktadır. Yağışlarla birlikte akışa gecen yüzeysel sular, tuzlanmış toprakların üst yüzeylerini yıkayarak, en yakın alıcı ortama ulaşmaktadır. Böylelikle, gerek içme-kullanma suyu, gerekse de sulama suyu olarak kullanılan akarsuların kalitesi de bozunmaktadır. Bu durum da sosyal, çevresel ve ekonomik problemleri beraberinde getirmektedir. Suyu karışan tuzlar akarsuların ekolojik sağlığını bozmakta ve ortamdaki biyoçeşitliliği tehdit ederek bazı habitatların kaybolmasına neden olmaktadır. Tüm bu olumsuzlukların yanı sıra, tuzlanmış toprakta suyun dikey hareketle sızması azalarak, yüzeysel akış hızı artmaktadır. Bu durum da, zaman zaman sellere neden olabilmektedir. Bilindiğı üzere, sel baskınları ile topraktaki besin maddeleri yüzeyden sıyrılarak alıcı ortama ulaşmakta ve böylece toprak kalitesi daha da düşmektedir.

Toprakta ayrıca bazı doğal nedenlerle de tuzlanma görülebilir. Bunların başında, toprak yapısı içerisindeki ana madde, tuzlu yeraltı suyu seviyesinin yüzeye yakın olması, ana kayanın zamanla bozunması ve ayrışması, kıyısız alanlarda deniz suyunun karaya girişim yapması sayılabilir. Dolayısıyla, toprak tuzluluğunun izlenmesi ve öngörülerin yapılabilmesi, toprağın tuzluluk nedeni ile daha da bozunmasını önlemek adına alınması gerekli olan tedbirlerin belirlenmesi açısından son derece önemlidir. Özellikle bu durum, tez kapsamında vaka çalışmasına konu olan Türkiye'deki Tuz Gölü Bölgesinde tarım yapılan arazilerde öne çıkmaktadır.

Toprak tuzluluğunun topraktan numuneler alınarak, laboratuvarlarda elektriksel iletkenlik deneyleri ile saptanmasının yanı sıra özellikle son yıllarda topraktaki tuzluluğu belirlemek, izlemek ve haritalandırmak amacıyla, uydu görüntülerinden de yararlanılmaktadır. Özellikle *cokluspektral sensörler* bu amaca hizmet etmektedir. Bu modern teknolojik araçlar arasında, Landsat Tematik Haritalama (TM), Landsat Cokluspektral Tarama Sistemi (MSS), Landsat7, Landsat8, Geliştirilmiş Landsat Tematik Haritalama (ETM), SPOT, Gelişmiş Uydu Bağlantılı Termal Emisyon ve Yansıyan Görüntü Radiome (ASTER), IKONOS, MODIS ve Hindistan Uzaktan Algılama sistemi (IRS) sayılabilir.

Tuz Gölü Türkiye'nin ikinci büyük gölü olup, Konya, Aksaray ve Ankara illeri arasında yer almaktadır. Yüzey alanı 1500 km² ve rakımı 905 m'dir. Bölgede tarım, hayvancılık, tuz üretimi ve turizm öne çıkan ekonomik faaliyetlerdir. Yoğun tarımsal faaliyetlerin yapılabilmesi için bölgede bazı kısımlarda ağaçlar ve çalılıklarda kayıplar yaşanmaktadır. Bu durum toprak erozyonuna neden olmaktadır. Bu şartların yanı sıra, diğer doğal ve insan faaliyetleriyle de artan toprak tuzluluğu, tarımsal alanların gelişmesini de olumsuz yönde etkilemektedir. Dolayısıyla, toprak tuzluluğunun uzun dönemler boyunca izlenmesi, arazi kullanımı değişikliklerinin takip edilmesi bölgede olumsuz koşullarla mücadele edebilmenin önemli bir yardımcısı olacaktır.

Bu araştırmada ağırlıklı olarak Tuz Gölü Bölgesi'nde tuzluluk haritalarının 1990, 2002, 2006, 2011 ve 2015 yılları için hazırlanmasına odaklanılmıştır. Böylece yıllar boyunca toprak tuzluluğunun ve arazi kullanımının değişimi takip edilebilmektedir. Ayrıca, çalışmada 2000-2006 ve 2006-2012 yılları arasındaki arazi kullanım dağılımlarındaki değişim de ortaya konulmaktadır. Bu amaçlar doğrultusunda çalışmalar yürütülürken, bir taraftan da dünyada toprak tuzluluğunu azaltabilecek yeni yöntem ve gelişmeler ile güncel uygulamalarda incelenmektedir.

Tuzluluğu aşırı olan belirli yerlerde bu durumun nedenleri detaylı olarak araştırıldıktan sonra, bu yeni ve güncel tuzluluğu azaltma yöntemleri kullanılabilir. Tuz Gölü Bölgesinde toprak tuzluluğunun olumsuz etkileri ve tuzdan etkilenen toprakların ıslahına yönelik araştırmalar yapılarak en uygun ve pratik tuzluluk azaltma yöntemi seçilirken mutlaka araziden alınacak toprak numuneleri üzerinde deneysel çalışmalar ve ilave araştırmalar da sürdürülmelidir.

Araştırmada, 1990 ile 2015 yılları arasındaki dönemi incelemek üzere toplamda 25 Landsat-5 TM ve Landsat-8 görüntüleri analiz edilmiştir. Mayıs-Temmuz 2002 döneminde Tuz Gölü Bölgesi'nde T.C. Gıda Tarım ve Hayvancılık Bakanlığı'na yürütülmüş kapsamlı arazi çalışmaları esnasında alınan 322 toprak numunesinin deneysel analizi ile elde edilen elektriksel iletkenlik (EC) sonuçları da değerlendirilmiştir.

Bölgenin tuzluluk haritalarının hazırlanması esnasında da 322 toprak numune istasyonundan göle en yakın ve inceleme alanı içerisinde yer alan 19 istasyonda elde edilen tuzluluk değerleri yersel veri olarak kullanılmıştır. Benzer şekilde, 2000-2012 yılları arasında seçili alandaki arazi dağılımındaki değişikliği de sayısal olarak

değerlendirebilmek adına CORINE vektörel değişim verileri uydu görüntüleri üzerine çakıştırılmıştır.

Tüm kullanılan uydu görüntüleri radiometrik ve atmosferik olarak ENVI ve ERDAS yazılımları kullanılarak sınıflandırma öncesi düzeltilmiştir.

Bu ön işlemler tamamlandıktan sonra, 5 toprak tuzluluk indeksi ile birlikte Normalize Edilmiş Farklı Bitki Örtüsü İndeksleri (NDVI) Arcmap10.2 kullanılarak tüm uydu görüntülerine uygulanmıştır. Daha sonra, seçilmiş olan 19 toprak numune istasyonu görüntülerde koordinatlı olarak işlenmiştir.

Bu çalışmadaki amaç, numune alma noktalarındaki gerçek indeks değerlerinin bulunabilmesidir. Takip eden aşamada, tüm söz konusu indisler için ayrı ayrı 2002 yılındaki tek yersel tuzluluk verileri kullanılarak hem lineer hem de üstel regresyon analizi yapılmıştır. 2002 yılına ait geliştirilen üstel regresyon denklemi kullanılarak 1990, 2006, 2011 ve 2015 yıllarına ilişkin tuzluluk haritaları üretilmiştir.

Bu araştırma kapsamında, üstel regresyon analizi sonuçları lineer regresyon analizine nazaran daha iyi sonuçlar ortaya koymuştur. Çalışmada kullanılan çeşitli indisler bazında, X-ekseninde tuzluluk indis değerlerinin artmasına paralel olarak Y-ekseninde EC değerleri üstel olarak yükselmektedir.

Tuzluluk haritalarının oluşturulmasında uygulanan tuzluluk indeksleri arasından en iyi sonucu (SI) $1 = \sqrt{B1 * B3}$ vermiştir. Bu indeks, gerek lineer analiz gerekse de üstel analize göre, R^2 değerleri sırasıyla 0,778 ve 0,961 olarak hesaplanmıştır. Dolayısıyla, en doğru tuzluluk haritaları (SI) $1 = \sqrt{B1 * B3}$ indeksinin üstel reflektans değerleri ile 2002 yılına ait topraktaki iletkenlik değerleri kullanılarak 1990, 2006, 2011 ve 2015 yılları için üretilmiştir.

Uzaktan Algılama (UA) ve Coğrafi Bilgi Sistemleri (CBS) gibi modern teknoloji araçları yersel kısıtlı bilgi ve veri olmasına karşın çeşitli tuzluluk haritalarının üretilmesinde önemli katkılar sağlamıştır. Bu çalışmada, 5 farklı tuzluluk sınıflandırması (tuzsuz, az tuzlu, orta tuzlu, tuzlu ve çok tuzlu) kullanılarak değişik yıllara ait çeşitli indislere dayanarak 30 tuzluluk haritası hazırlanmıştır.

Ayrıca, 11 sınıf içeren 5 NDVI haritası da üretilmiştir. Her bir tuzluluk sınıfı için zamansal alan değişimleri ve yine her bir sınıf bazında NDVI değişimleri 1990-2015 yılları arasındaki dönemler için hesaplanmıştır.

Bu vaka çalışmasında kısıtlı yersel veriye rağmen üretilen tuzluluk haritaları esnasında kullanılan yöntemler ve izlenen adımlar sadece Türkiye için değil, benzer toprak tuzluluğu problemi ile karşılaşan diğer gelişmekte olan ülkeler içinde önemli bir rehber ve yol haritası niteliğindedir.

Çalışmada, son yıllarda gündemde olan ve kullanılan uzaktan algılama analiz teknikleri ve yöntemleri de tartışılmaktadır. Bunlar arasında en önemliler lineer spektral karışımama, Karar-Ağaç Analizi (DTA), ana bileşenler analizi, ters Gaussian fonksiyonu, kısmi en küçük kareler regresyon tekniğidir. Son olarak tuzdan etkilenmiş topraklardaki yersel-zamansal değişimlere de değinilmiştir.



1. INTRODUCTION

Soil salinization is one of the significant phenomena accelerating land degradation processes, which in turn, cause loss of soil productivity and reduction in biomass production. Due to high spatial and temporal variability of soil salinity, predicting, mapping and monitoring its changes is an essential issue for anticipating natural disasters like desertification and for mitigating severe economic and social consequences in especially arid and semi-arid regions of the world. These areas are usually under high pressure to supply the required food and fibre for their rapidly increasing population with harsh climatic conditions.

Climatic conditions and soil properties are among the fundamental factors that affect salinization which becomes even more pronounced as secondary salinization results from inappropriate irrigation and weak soil drainage conditions leading to land degradation. Over the past few decades, Remote Sensing (RS) technologies have highly contributed to rapid and accurate salinity assessment (Vasques et al.,2010).

These approaches are fast, non-destructive, and can potentially be used to map and monitor topsoil salinity across large areas after conducting adequate corrections. Multispectral data and particularly, hyperspectral data are important bases for monitoring salt content of soil in different scales ranging from local to global. Use of multispectral data obtained at short and periodic intervals has enabled the detection of changes in soil salinity and assessing the rate of salinization.

Traditionally, soil salinity prediction and monitoring are often carried out with intensive field work and sampling. Most previous studies have focused on differentiating salinized and non-salinized soil qualitatively by analysing the salinity distribution and monitoring its dynamics. In recent years, Remote Sensing (RS), Geographical Information Systems (GIS) and modelling have outperformed the traditional methods. Soil salinity mapping has progressed from qualitative to quantitative mapping due to large area coverage, multiple spectral information and nearly constant observation via RS systems.

Knowledge and data gained from RS of saline soils is intensely utilized as part of worldwide agricultural activities. Rapid population growth and advances in technology have allowed continual cultivation resulting in over-exploitation and impoverishment of the soil. Besides, intensive cropping and excessive use of fertilizers made the situation even worse. Furthermore, in arid and semi-arid climate zone, water for agriculture is an increasingly limited resource due to priority for urban and industrial use. Therefore, policies and economic conditions dictate that saline water bearing poor quality for soil fertility is now frequently used for irrigation of crops (Postiglione, 2002).

The salinity at the landscape surface can be distinguished from remotely sensed data either straightforwardly on exposed soils or indirectly through the biophysical attributes of vegetation as these are influenced by saltiness. In zones of thickly vegetated soils, using vegetation indices in the evaluation and mapping of soil salinity will yield promising results whereas soil salinity indices will be the appropriate method in the case of exposed soils or soils with low scattered vegetation.

In this research, five soil salinity indices and Normalized Difference Vegetation Index (NDVI) are applied on Landsat-5 TM and Landsat-8 images of Tuz (Salt) Lake Region in Turkey ranging from 1990 to 2015. . Covering an area of about 1.500 km², Tuz Lake is the second largest lake in Turkey. Agriculture is one of the main human activities in the region despite presence of the extremely saline lake, and of saline parent materials causing soil salinization in arable lands. For mitigating with the negative effects of saline soils on agricultural production, it is necessary to track changes in saline areas by generating salinity maps. Therefore, in this study, 30 different salinity maps related to years 1990, 2002, 2006, 2011 and 2015 are generated with five classes namely none-saline, slightly saline, moderately saline, highly saline and extremely saline. Besides, prevalent practices and recent methods from the world for mitigating soil salinity effects are reviewed.

1.1. Objective of the thesis

There are three main objectives for conducting this research:

- Combining Remote Sensing (RS) and Geographical Information Systems (GIS) techniques for generating soil salinity maps in Tuz Lake Region in order to track and monitor changes in the areas of salty places within years 1990, 2002, 2006, 2011 and 2015.

- Identifying probable human-induced causes of soil salinization in the area by detecting land cover changes from year 2000 to 2006 and 2006 to 2012.
- Reviewing the most commonplace practices alongside with new methods for lessening adverse environmental impacts of soil salinization as a worldwide problem in different regions of world.

The most practical methods can be selected for each salt-affected region after comprehensive study about its environmental condition, natural and human-induced causes of soil salinization and its climatic status. Likewise, accurate in-situ studies are required in future for Tuz Lake in order to select the most appropriate methods for alleviating soil salinity problems in agricultural land.





2. BACKGROUND INFORMATION ON SOIL SALINITY

2.1 Soil Salinity

Soil salinity can be defined as the presence of high amount of soluble salts in the soil profile either naturally or anthropogenically. Cations such as (Na^+), potassium (K^+), magnesium (Mg^{2+}), and calcium (Ca^{2+}), beside anions like chloride (Cl^-), sulfate (SO_4^{2-}), and carbonate in the form of bicarbonate (HCO_3^-) are the most common elements found in water and soil. Saline soil is characterized by electrical conductivity (EC). A lot of crops lose their normal yield at high EC values ranges 8 to 16 ds/m whereas lower ECs between 4 to 8 ds/m also bring yield decline for many crops (Munns, 2005).

2.1.1 Natural causes of soil salinity

Parent materials and rocks containing salt minerals are the main sources of salt. In fact, formation of salt in the soil is mostly due to weathering and transportation of these primary minerals by natural forces like wind and water.

Rainfall and further evaporation due to high temperature leads to accumulation of salts in both surface and subsurface soil since there is not enough water to leach down the salts. Moreover, the water in soil profile brings up salts to the surface; in this condition, the net movement of water is upwards. This process continues specifically in dry seasons on lands which are located in arid and semi-arid regions of the world (Sciences, 2006). Nearness of salty groundwater table to the land surface either naturally or as a result of over irrigation is another reason which makes soil more saline. Closeness to sea, brackish water and salty lakes is an alternative natural factor that brings soluble salts to soil by saline water floods, intrusion and salty water sprays (Sciences, 2006).

Topography is an additional instinctive factor that can affect approximately everything related to the water movement, and as a consequence lead to leachate of salts.

2.1.2 Human-induced causes of soil salinity

Human-induced salinization or secondary salinity occurs as a consequence of man-made activities in agricultural practices including traditional cultivation methods, old irrigation techniques, and wrong selection of crop sequences in the field. Irrigating agricultural land with saline and low quality water is the main cause of soil salinization. Besides, improper drainage systems result in failure in leaching salts from soil and plant root zone. Releasing saline and polluted industrial and domestic wastewater into soil is among the other causes of soil salinization together with forest clearance, overgrazing and cutting bushes that accelerate saltiness in groundwater which in turn lead to soil salinization(Shrestha and Farshad, 2009).

Utilizing excess amount of fertilizers, manure and compost can be addressed as extra factors increasing soil salinity. Additionally, salts which are used for de-icing roads can affect the salinity of soil due to surface run- off. The common reasons for soil salinization are depicted in Figure

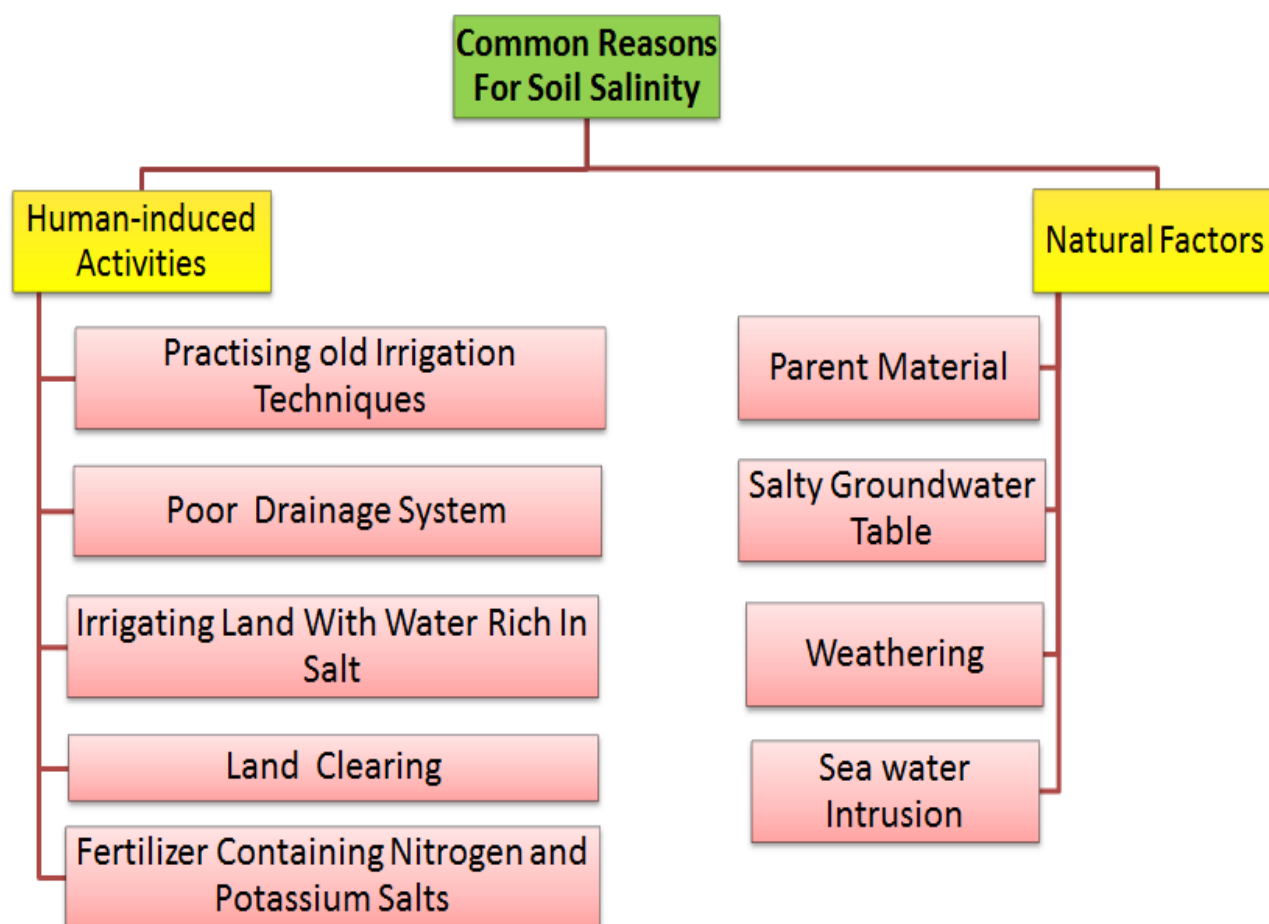


Figure 2.1 : Common primary and secondary sources of soil salinization.

2.1.3 Soil salinity as a worldwide environmental problem

Soil salinity is a widespread environmental problem in many regions of the world that have higher evaporation rate and lower rainfall in comparison with other places. It can easily be understood how soil salinity is a real threat to arid and semi-arid soils by inspecting Figure 2.2 and Figure 2.3 that present the distribution of drylands in the world and the distribution of type and severity levels of salt-affected soil in the world, respectively.. Based on the Food and Agriculture Organization (FAO) Soil Map of the World, 397 million hectares (ha) of land are saline. Besides, the total area of sodic soils are 434 million ha that are not certainly arable; but cover all salt-affected lands at the global scale. Among 230 million ha of irrigated land, approximately 45 million ha are salt affected soils due to secondary salinization (Koohafkan, 2008).

Soil salinization reduces the area of farmland land 1 to 2% per year and it continues to increase. Saline soils have lower productivity and are not preferred for agricultural practices due to their adverse effects like declining crop yields; but through making use of today's technological advances and by means of careful management and mitigation practices saline soil fertility can be improved. As numerous nations are utilizing salt-influenced soils, it is necessary to expand scientific and engineering solutions to optimize their use, figure out their potential, productivity, sustainability and suitability for growing different crops, and identify proper integrated management practices.

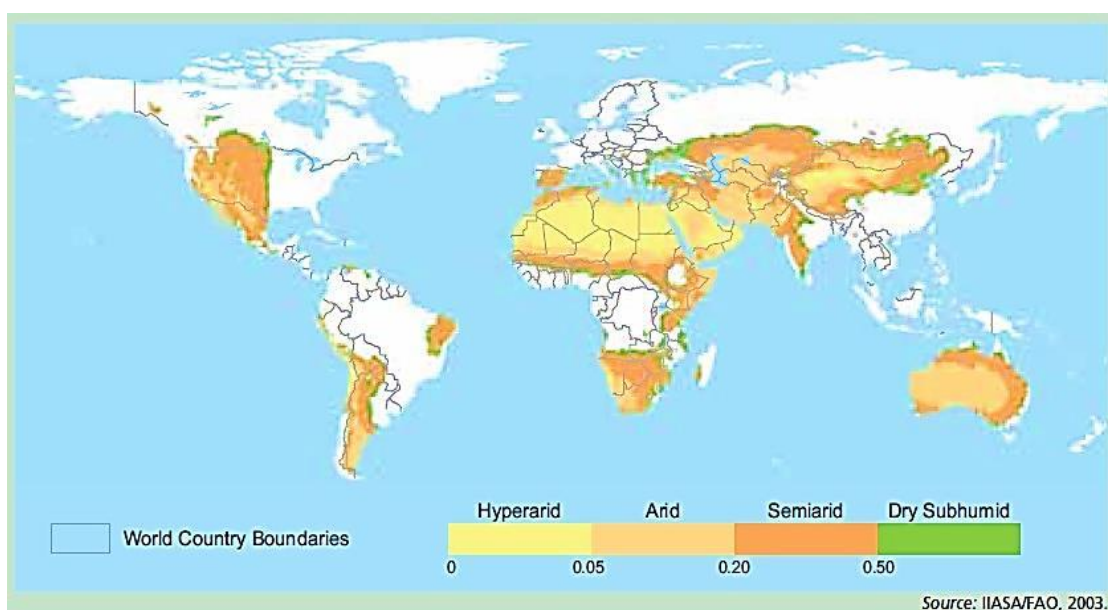


Figure 2.2: Distribution of drylands in the world (Url-2).

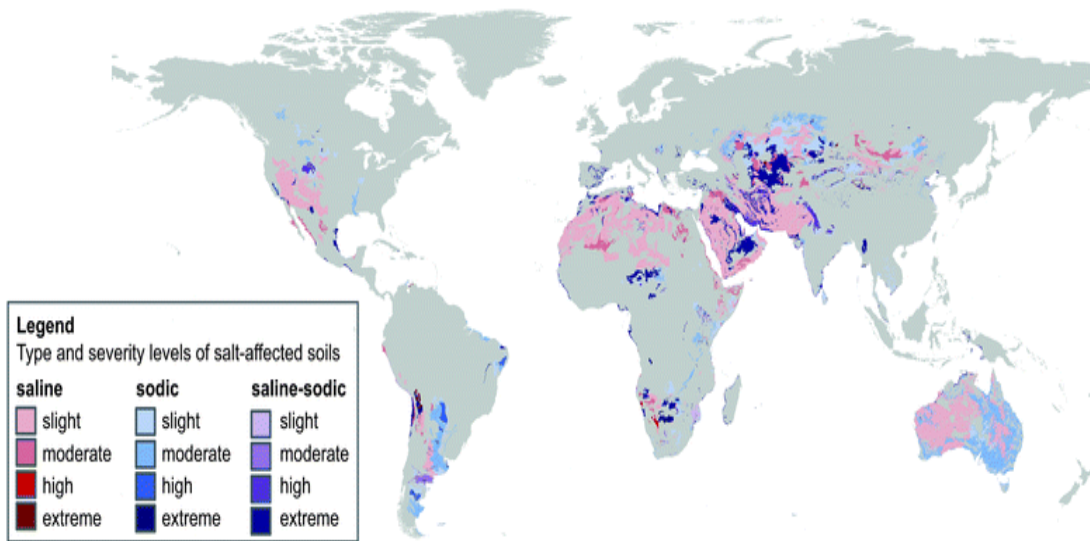


Figure 2.3: Distribution of type and severity levels of salt-affected soil in the world (Url-3).

2.1.4 Adverse effects of soil salinity

Soil salinity prevent majority of plants to grow due to its detrimental effects on seed germination and decrease osmotic potential of soil water which results in inability of plants to take in water from root zone. Albeit, various plants and crops exert different sensitivity and tolerance to salinity since there are some scientific evidences which prove plant organs, tissues and cells at each growing step displaying different degree of tolerance to environmental conditions(Baht et al., 2008).

Table 2.1 illustrates effects of various values of EC on different crops and their corresponding yield loss. As an example, crop yield can be diminished by 25% for broccoli when EC is 5.5. It is known as a salt-tolerant crop indicating minimum yield reduction for diverse EC values(Horneck, Ellsworth, Hopkins, Sullivan, & Stevens, 2007). Among all terrestrial plants, halophyte trees are more salt-tolerant due to their capability to osmotic adjustment and ion transport system which is completely different from glycophytes. Halophyte trees have functions in recycling saline agricultural wastewater and rehabilitating saline soils. Besides, they can be used as forage, oil, seed meal and grains for animal feeding systems(Glenn et al., 2016). Soil salinity increases exchangeable sodium percentage (ESP) which is the relative amount of sodium ion within the soil profile. As ESP rises, soil structure deforms; and as a result, the seepage rate of water into soil and its movement may be declined. When this condition happens, salts including high amount of sodium cannot be

leached and accumulation of sodium leads to ion toxicity(Horneck et al., 2007). Figure 2.4 illustrates various effects of salt stress on plants.

Table 2.1: Effects of various EC values on different crops and their corresponding. yield loss(Horneck et al., 2007).

Crop	None	Expected yield reduction (%)		
		10%	25%	50%
		Electrical conductivity (EC), ds/m		
Barley	8.0	10.0	13.0	18.0
Wheat	6.0	7.4	9.5	13.0
Sugarbeet	4.0	4.1	6.8	9.6
Alfalfa	2.0	3.4	5.4	8.8
Potato	1.7	2.5	3.8	5.9
Corn(grain)	1.7	2.5	3.8	5.9
Onion	1.2	1.8	2.8	4.3
Beans	1.0	1.5	2.3	3.6
Apples, Pears	1.7	2.3	3.3	4.8
Strawberries	1.0	1.3	1.8	2.5
Sudan grass	2.8	5.1	8.6	14.0
Grapes	1.5	2.5	4.1	6.7
Broccoli	2.8	3.9	5.5	8.2
Cucumbers	2.5	3.3	4.4	6.3

Another adverse effect of soil salinity is decreasing water quality for both drinking and irrigation purposes that in turn lead to social, environmental and economic problems. It also disturbs ecological health of streams and it threatens biodiversity by loss of various habitats. One more negative impact of salt accumulation in soil is the accelerating rate of surface run-off since water cannot penetrate to saline soils; consequently, it may pose flood risks. As known, flood transfers soil nutrients and makes soil more degraded.

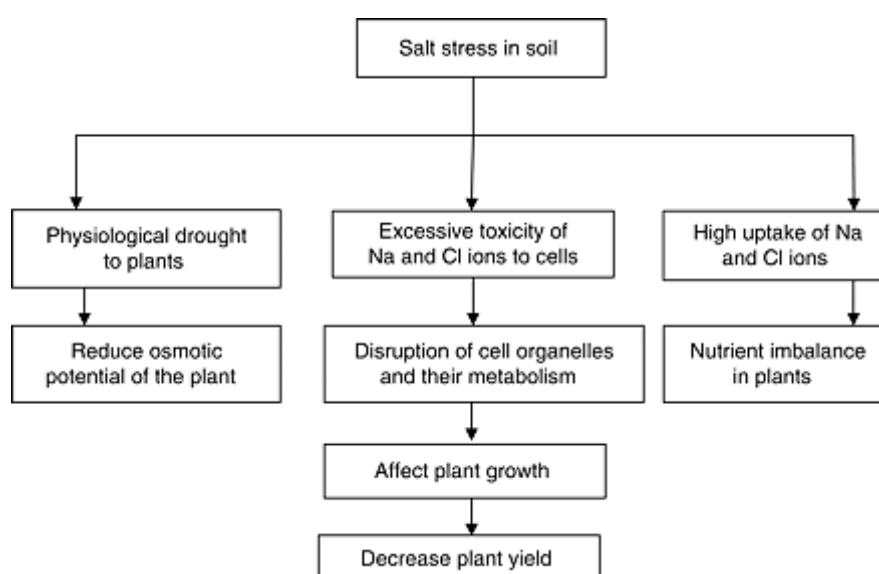


Figure 2.4: Effects of salt stress on plants (Url-4).

2.2 Importance of Soil Salinity Detection And Monitoring

Boring Soil salinity might not be as destructive and devastating as catastrophic events like earthquakes, large-scale landslides and flooding; but, it is definitely a severe environmental hazard(Metternicht and Zinck, 2003).

As one of the most significant land degradation issues, it constrains sustainable production, especially in arid and semi-arid regions. Moreover, soil dispersion, soil erosion, engineering problems and economic damages are all probable consequences of soil salinity. It is anticipated that soil salinization is likely to be raised with forthcoming climate change scenarios like sea level rise, impact on coastal areas, and temperature increase that will correspondingly accelerate evaporation and salinization.

Therefore, to keep track of changes in salinity and project more degradation monitoring and mapping is required for taking reasonable and prompt decisions to alter the management practices and to find a way to apply mitigating procedures, methods and techniques to overcome or diminish soil salinity problems. Monitoring salinity means the attempt of detecting the places where salts concentrate and, secondly, tracking the temporal and spatial alteration. Periodical changes in soil salinity can be determined only by proper monitoring techniques. Due to importance of preventing the negative effects soil salinity, monitoring and mapping saline soils at the regional, national, and farm levels is becoming more and more substantial for environmental scientists, decision- makers and managers to find solutions for avoiding land degradation and applying reclamation practices.

It is estimated that over 1 billion ha of the land surface in the world is covered with distinct kinds of saline soils. The process of soil salinization is dynamic; it is likely to change seasonally due to effects of climatic conditions. Besides, soil salinity is extensive and dispersed over 100 countries, and no continent even Antarctica is not entirely free from salinity on this planet. Despite the general understanding of the problem and enhancements in the assessment methods, salinization keeps on rising specially in Argentina, Egypt, India, Iraq, Pakistan, Syria and Iran(Polous et al.,2011).

The degree of salinity differs among trans-country and even within the country at various locations, land forms, and irrigated agricultural lands to farmers' fields. In fact, as it is depicted in Figure 2.5 local climatic, environmental, and agricultural

management practices constitute the salinity problem. In order to understand the effects of these factors, various case studies have been reviewed and their corresponding results are summarized in Table 2.2.

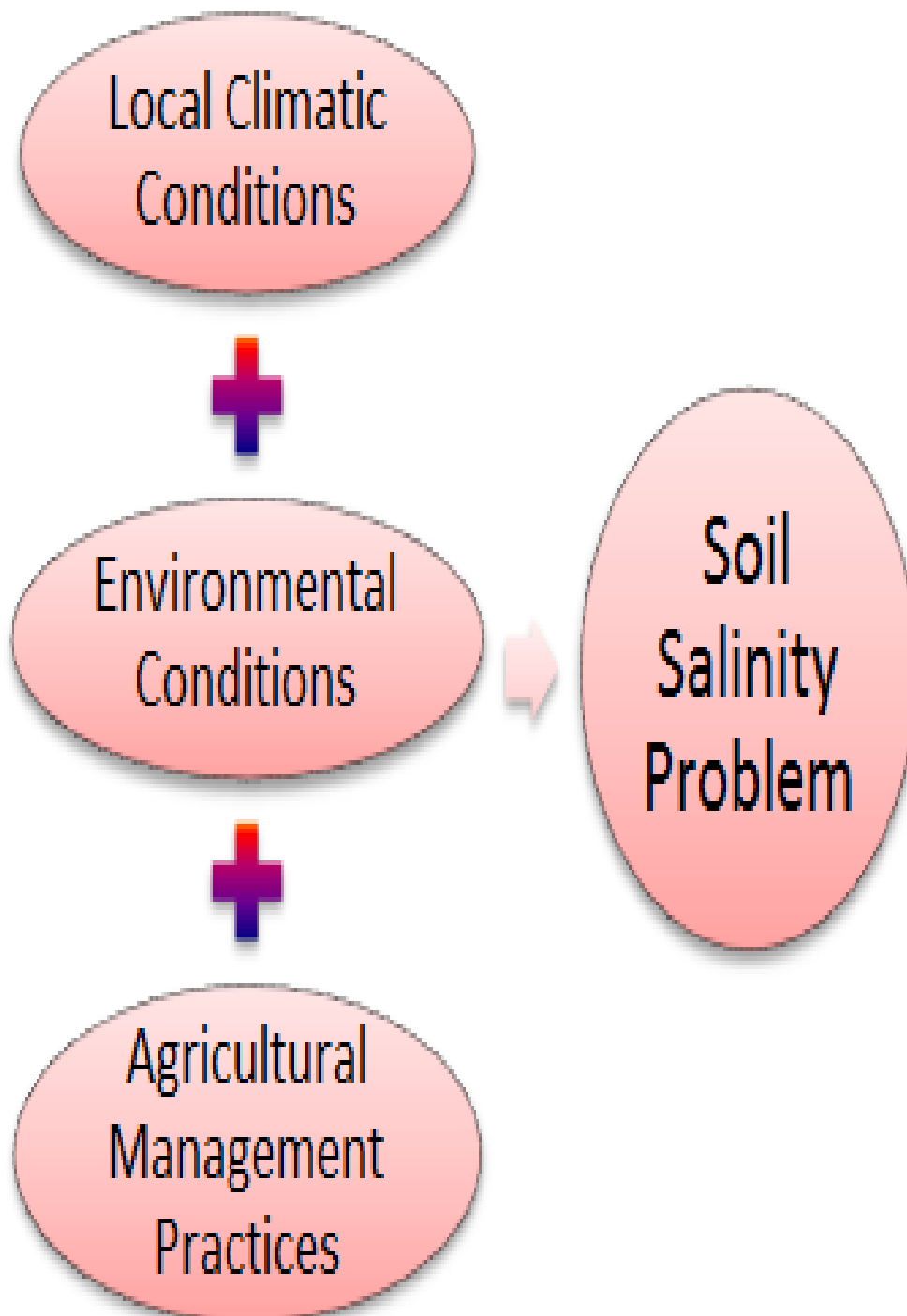


Figure 2.5: Factors that determine soil salinity problem.

Table 2.2: Case studies indicating various salinity problem.

Location	Conditions determine the salinity problem			Concern	PREVENTIVE ACTIONS/ PRECAUTIONS
	Climatic	Environmental	Management		
Pakistan- Punjab			•	Poor management of canal irrigation	More research is needed to set up the reclamation impacts and, in particular, the reasons why progress have not been obtained in line with the targets and how stakeholder engagement can make a real difference to salinity management programs(Abbas, Khan, Hussain, Hanjra, & Akbar, 2013)
China- Inner Mongolia			•	Providing traditional drainage in the form of surface and subsurface drainage has proven to be costly(J. Wu, Vincent, Yang, Bouarfa, & Vidal, 2008)	To protect land from salinity hazard, an alternative method named “dry drainage” was suggested for salinity control.
North of Australia		•		The tropical savannas in Northern Australia, in particular, the Alligator River Region (ARR) in the Northern Territory, are continuing to experience saltwater intrusion(Bell, Menges, Ahmad, & van Zyl, 2001)	Attempts have been made to restrict the saltwater intrusion by creating physical earth barrages.
Morocco			•	Combination of poor land management and crude irrigation practices.	Monitoring and mapping the area by Characterization of Slightly and Moderately Saline and Sodic Soils in Irrigated Agricultural Land using Simulated Data of Advanced Land Imaging (EO-1) Sensor(Polous et al., 2011).
China, Xinjiang	•		•	Because of both the extreme continental climatic condition and ill-managed/irrational irrigation activities, soil salinization in the study area is common	combining both near sensing (EM38) and remote sensing (images and spectral indices) technologies to produce quick, low-cost, and reasonably accurate ways to monitor, evaluate and predict soil salinity(Ding & Yu, 2014).

Evaporation from soil profile leads to accumulation of salts on the surface and makes soils more saline, poor drainage exacerbate this condition specially when the groundwater is near to surface. In this condition, water level increases to the surface due to capillary motion. As a consequence, instead of downward percolation of water through soil profile, it rises to the surface and then evaporates; thus, salts will accumulate on the surface (Stockle, 1996).

In extreme cases, due to high crop yield lost or seed germination limits, land is actually being abandoned.

As irrigation makes the effects of primary salinity worse, it is understood that salinity has been associated with irrigated agriculture since its early beginning. Projections indicate that approximately 1/3th of the irrigated land in the major irrigation countries

are already inadequately affected by salinity or are anticipated to become so in the coming years. Table 2.2 demonstrates the distribution of irrigation-induced salt-affected lands in various countries. Such salinity takes place in both large and small irrigation systems. In recent years, many farmers have been relinquishing their fields in coastal irrigation schemes due to occurrence of salinity.

Table 2.3: Irrigation-induced soil salinization(Abbas et al., 2013).

Countries	Distribution of irrigation-induced salt-affected lands (%)
India	27
Pakistan	28
Israel	13
Australia	20
China	15
Iraq	50
Egypt	30

Recognizing the importance of soil salinity management results in applying improved irrigation techniques to mitigate soil salinity problem. Besides, proper drainage systems can provide reuse of drainage outflow for irrigation purposes(Stockle, 1996).

Arable and nutrient rich soils are poor resources in both arid and semi-arid regions. Frequently, these areas suffer from inadequate freshwater resources that unfortunately utilize marginal quality water for agriculture. Excessive utilization of agricultural lands by poor management of soil and water resources for short-term benefits without any attention to long-term adverse effects to soils is the major reason for increasing soil salinity in fertile lands. In order to promptly identify soil salinization for sustainable production, the issue of tracking temporal and spatial changes of soil salinity, as a significant element, should be considered. In fact, assessment of salt affected soils begins with detection and continues by mapping and monitoring(Polous et al., 2011;Metternicht and Zinck, 2003;Abbas et al.,2013)

Laboratory analyses and field surveys as traditional methods for soil salinity monitoring are insufficient and are unsuited to the rate of expansion of this worldwide problem. Thus, modern technological tools such as Remote Sensing (RS) and Geographical Information Systems (GIS) can be used for mapping and continuous monitoring of the progression of this phenomenon by their rapid and synoptic coverage and the sensitivity of the electromagnetic signal to soil parameters at the first few centimeters of surface layer(Lhissou et al., 2014).

Salinity mapping and monitoring plan should be considered as part of any project dealing with the use of saline water in irrigation. In agricultural lands, an effective salinity monitoring plan must be proposed to track salinity changes especially in the root zone to inspect the impact of management options to overcome or alleviate salinity effects, and to assure that root zone salinity does not rise above crop threshold level to prevent yield losses. Such monitoring programs help to identify the problem and areas at risk for salinization at the regional and national levels. Accordingly managers, scientists and decision-makers take essential and prompt action to tackle the problem in order to avoid extending the problem to other areas that may have significant social and economic impact on national economies.

2.2.1 Assessment of saline soils using advanced technologies

Soil salinity monitoring and mapping can be accomplished for both small and large scale regions by utilizing advanced technologies such as

- Remote Sensing (RS),
- Geographical Information Systems (GIS),
- Geo statistics, and
- High-tech electromagnetic induction.

Various case studies achieved reasonable results for predicting and modeling soil salinization using either combination of RS and GIS or applying each separately. RS of soil salinity is understood as rapid, non-destructive, synoptic and low cost application of satellite images(S.Kumar et al., 2015).

On the other hand, GIS is a proper way of collecting map information electronically considering the capability for retrieval of that information quickly whenever it is required. Generating maps by GIS has a number of advantages over old-style maps; one is that since the data are saved electronically, they can be analyzed properly and fastly by computer. On the other hand, as rainfall, topography and soil type are parameters which can determine the extent of soil salinization, utilizing the electronical data by GIS can first help to detect regions which are vulnerable and susceptible to salinity, and then predict similar areas which might be at risk of soil salinization. Besides, RS can provide valuable information for large-area water and salt balances and identification of parameters such as evapotranspiration, rainfall distribution, and crop types and intensities can be used as indirect measures of salinity and waterlogging.

Furthermore, there exist models to address salinity problems in agriculture fields and landscapes vulnerable to soil salinization and try to predict areas which are prone to salinity hazard. For decision making, numerical models can be used as evaluation tools in predicting soil and water salinity-related-dependent parameters.

In addition, model outputs and results support evaluating possible scenario analysis. However, extensive data requisites for developing acute models might be a limitation factor, models that incorporate all governing elements of nature such as soils, water, crops, and agro- meteorology produce better results as they symbolize the nature to a large extent. calibration and validation of numerical models have to be done in order to attain proper result.

Geo statistics is a new method used for mapping of surface components such as soil, vegetation and water by utilizing limited sample data in order to estimate values at unsampled locations. Thus, soil salinity mapping and prediction is also one of the applications of Geo statistics.

Ground data electrical conductivity (EC) measurement is a complement parameter for satellite images data to perform various analysis such as linear or exponential regression analysis. Matching satellite data with accurate ground data can be quite practical for mapping saline soils. New instruments such as advanced electromagnetic induction (EMI) outperform traditional methods for measuring EC values. In fact, this equipment can measure EC values rapidly on a second- by-second basis. Therefore, measured data population can be large and farming or agricultural land may be covered entirely in short time in comparison with traditional measurement methods.

In general, there are two main advantages of electromagnetic (EM) method compared to conventional surveys. Initially, EC measurements can be done approximately as fast as one can walk from one sample location to the other, and secondly, large volume of sample data provide more reliable mean value for a specific area or a region, and also reduces the variability and make it easy to ignore outranged values.

2.2.1.1 Spectral behavior of salt-affected soils

Cations (Na^+ , Mg^+ , K^+ and Ca^{++}) and anions (Cl^- , SO_4^- , CO_3^- and HCO_3^-) as different proportions of saline soils emerge in soil in the form of either salt crust deposit or

solution. Apparently, salt crust can directly be detected by utilizing optical remote sensing due to the fact that salt minerals have detectable spectral characteristic which can be sensed in both visible near-infrared and shortwave near-infrared region. Nevertheless, this type of detection is applicable only while salt accumulation in soil is considerably adequate to crystalize and evaporate mineral formed at the surface. As salt concentration in surface soil declines, the number and brightness of diagnostic band decreases simultaneously(J Farifteh et al., 2008).

Earth's surface data with various levels of detail is achieved by the electromagnetic energy reflected from various objects. Due to this fact, the spectral reflectance of the salt characteristics at the soil surface has been broadly investigated through RS. In fact, spectral reflectance of salt crust at the surface is used for soil salinity monitoring and mapping. Nevertheless, applying this kind of direct approach is not proper for slightly saline areas, since the crust salt is imperceptible on the surface or salts are combined with other soil components. In such cases, using direct approach will lead to inaccurate results(Allbed and Kumar, 2013).

There is also another approach for detecting soil salinity and mapping saline areas indirectly by using spectral reflectance from vegetation. Since unhealthy vegetation has less photosynthetic activity, visible reflectance from vegetation will rise and near-infrared reflectance (NIR) will decrease (Weiss et al.,2016).

Thus, comparing spectral behavior of visible and near-infrared regions of spectrum for healthy and unhealthy plants will help detecting salinity indirectly. Figure 2.6 illustrates spectral reflectance values for vegetation, water, normal soil, salt crust and salt-affected soil. Higher reflectance values of salt crust and salt-affected soils in comparison with good soil can be detected easily in all bands of ASTER(Al-Khaier, 2003)

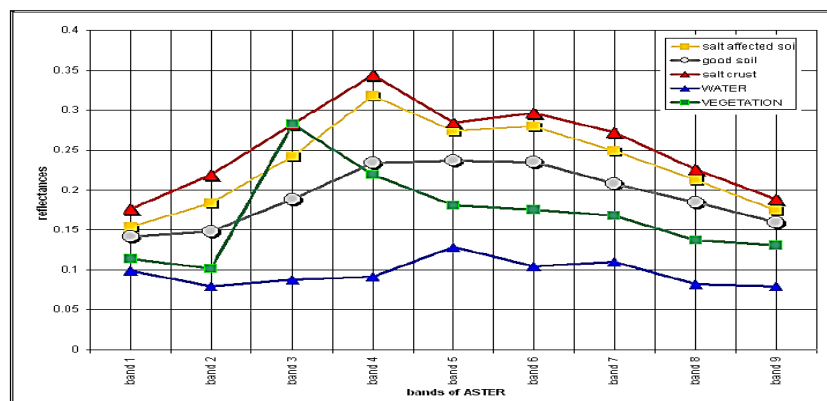


Figure 2.6: spectral reflectance values for vegetation, water, normal soil, salt crust and salt-affected soil(Al-Khaier, 2003).

2.2.1.2 Factors that affect saline soil reflectance

In most cases, quantity and mineralogy of salts, color, surface roughness and moisture content are predominant factors affecting saline soils reflectance based on results of ground observation and radiometric measurement (Metternicht and Zinck, 2003).

Generally, salty crusts which are smoother in comparison to nonsaline areas and cultivated surfaces have higher reflectance in the visible and near-infrared bands. Silt and saline soils that have more cracks compared to smooth salt crust show lower reflectance. Likewise, cultivated nonsaline surfaces exhibit lower spectral reflectance due to approximately higher roughness made by massive clod in ploughed areas (Metternicht and Zinck, 2003).

Additionally, salt mineralogy or in other words amount of carbonate, sulphates and chlorides establish existence of absorption bands in the electromagnetic spectrum. Normally dry, smooth and light salt in the surface soil has higher tendency to reflect visible and near-infrared radiation in comparison with wet, coarse and dark salt (Allbed et al., 2014).

Figure 2.7 shows reflectance variations of surface features due to differences in crusting and land management practices.

Various studies show that the more salt accumulate on surface soil, the higher the spectral reflectance will be observed in the visible and NIR regions of the spectrum.

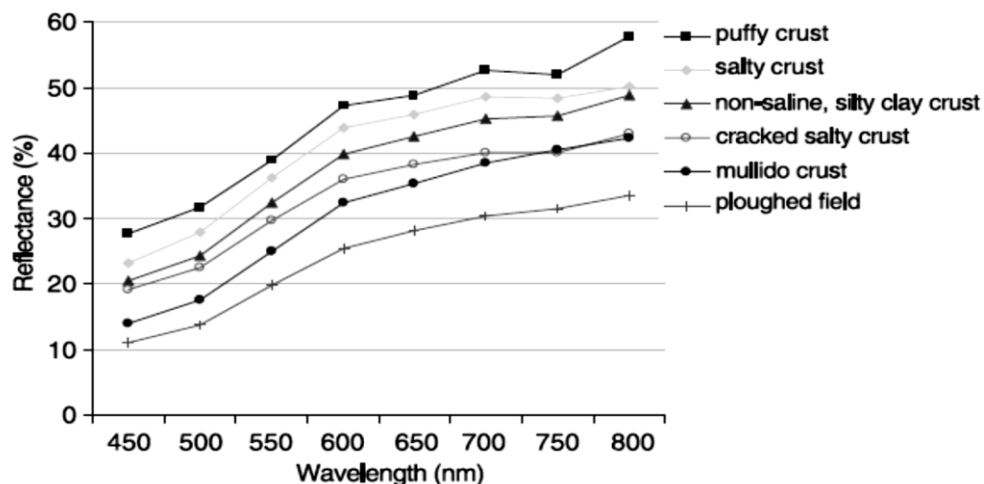


Figure 2.7: Reflectance variations of surface features due to differences in crusting and land management practices (Metternicht and Zinck, 2003)

2.2.1.3 Soil salinity classes in terms of electrical conductivity (ECe)

For simplifying and expediting soil salinity monitoring, electrical conductivity measurement has significant advantages over laboratory measurements. Fast, accurate and cost effectiveness results can be achieved utilizing EC measurement. Besides, this method is applicable in the field, and it can also cover relatively large areas. The standard unit of electrical conductivity is expressed in deci siemens per meter (ds/m) at 25 °C (Brown, 1954).

There are 5 salinity classes based on EC values which are proposed by the United States Salinity Laboratory. The effects of each salinity class on crops are shown in Table 2.3.

Table 2.3: Soil salinity classes - electrical conductivity (ECe) (Brown, 1954).

Salinity class	ECe (ds/m)	Salinity effects on crops
Non-saline	0-2	Salinity effects are negligible
Slightly saline	2-4	Yield loss for very sensitive crops
Moderately saline	4-8	Many crops are affected and their yield is restricted
Highly saline	8-16	Only tolerant crops bear this condition
Extremely saline	>16	Only a few very tolerant crops resist

Soil porosity, amount and type of soluble salts in solution, texture, moisture and soil temperature are factors that affect electrical conductivity of soils. Besides, precipitation, as an external factor, highly impact EC values. Extreme levels of precipitation can leach soluble salts from soil profile, and significantly reduce EC. On the contrary, in arid soils with low levels of precipitation, soluble salts have higher tendency to aggregate in soil profiles causing high EC.

2.2.1.4 Application of multispectral and hyperspectral satellite sensors for soil salinity assessment

Extensive exploration utilizing satellite imagery for detecting, mapping and monitoring soil salinity has been conducted all over the recent years, principally with multispectral sensors. These incorporate Landsat Thematic Mapper (TM), Landsat Multispectral Scanner System (MSS), Landsat7, Landsat8, Landsat Enhanced Thematic Mapper (ETM), SPOT, Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER), IKONOS, MODIS and Indian Remote Sensing (IRS) (Gorji et al., 2015) (Allbed and Kumar, 2013).

Table 2.4 shows different case studies for soil salinity assessment using various multispectral satellite sensors. Correspondingly, Figure 2.8 is related to a map showing exact places which are mentioned in Table 2.4.

Multispectral satellite sensors have still been the preferred strategy for mapping and checking soil salinity. This is basically due to the low cost of the imagery (e.g., Landsat, SPOT) and the capability to map extreme surface expressions of salinity. Nevertheless, multispectral data has constrained diagnostic capability because of its coarse spatial and spectral resolutions (Allbed and Kumar, 2013).

The use of multispectral images for detecting salts is hampered by a set of factors. Among them, the quantity of salts concentrated on the soil surface plays a primary role. It seems to be that below 10–15% salt content, salts are difficult to discriminate by multispectral sensors from other soil surface components (Metternicht, 2003).

Important restrictions may arise through direct mapping of soil salinity with multispectral imagery especially when there are no salt attributes on the soil surface, and where saline soils are dominated by halophyte plants. Additionally, multispectral satellite sensors may lead to implicated reflectance, as non-saline soils may be confused by barren and extremely saline land. On the other hand, spectral resolution of Landsat becomes inadequate as the distinction between the spectra of saline and waterlogged land is highly weak to permit spectral separation.

Direct mapping of soil salinity with multispectral imagery had significant restrictions that emerge, particularly where there are no salt attributes on the soil surface and where saline soils are dominated by halophyte plants.

Multispectral sensors generally measure reflectance at a few wide wavelength bands and are usually limited to identifying broad categories of land cover or surface condition. This type of data is most successful at high to extreme levels of soil salinity which are frequently dominated by extensive bare, salt scalded areas and tolerant halophytic vegetation.

The advancement of airborne and satellite-based hyperspectral sensors has overwhelmed a percentage of spatial and spectral restrictions of multispectral satellite imagery for monitoring and mapping soil salinity, both regionally and locally. Hyperspectral sensors offer an extensive number of spectral bands with high spatial resolution that permit the separation of halophyte plants from non-halophyte plants, and additionally, the distinguishing proof of surface salt features in more

detail than the multispectral sensors. Hyperspectral imagery has also been applied to investigate details of surface properties that are undetectable using other types of imagery. For instance, hyperspectral images have been used to identify soil characteristics containing moisture, organic content and salinity (Shippert, 2004).



Figure 2.8: Geographical location of the case study areas, (1) Morocco, (2) Algeria, (3) Egypt, (4) Syria, (5) Turkey, (6) Spain, (7) Tunisia.

Table 2.4: Different case studies for soil salinity assessment using various multispectral satellite sensors.

Item	Location	Reasons for soil salinity problem	Main problems and their effects	Satellite data	Objectives
1	Tadla region, Morocco	•Increased use of ground and surface water •Salty groundwater •Closeness of water table to the surface	Soil degradation and loss of land productivity	Thematic Mapper(TM) Landsat sensor(Lhissou et al., 2014)	Soil salinity mapping
2	Cheliff plain, Algeria	•.Parent Materials •Increased use of groundwater for irrigation	Threatens the environment in the region Endangers agricultural production	Landsat 7 SPOT2 satellite Data	Estimation of the spatial distribution of soil salinity (Yahiaoui, Douaoui, Zhang, & Ziane, 2015) Salinity mapping (Douaoui, Nicolas, & Walter, 2006)
3	Egypt	•Parent Materials •Landform, water table, depth to water •Topography	Waterlogging and threat of salt on agricultural production	Landsat 5, 7 and 8 ASTER	Evaluating changes in the waterlogging and salt-affected areas (Arnous & Green, 2015)
4	Syria	•Parent Materials •Salty groundwater •Closeness of water table to the surface	Limiting plant growth	Landsat 7 ASTER	Detection, monitoring and mapping of the salt-affected soils in order to manage and plan for sustainable land use (Al-Khaier, 2003) .

5	Turkey	•Parent Materials •Brackish marshes which are formed where streams join the lake	Not given	Landsat 5	Investigating the effects of soil moisture and salinity on the penetration depth of light into the soil (Faculty & Division, 2003).
6	Province of Alicante ,Spain	Low quality water that is used in the poorly drained soils located in the coastal plains	Endangers agriculture sustainability	Landsat 5	Evaluating the use of different remote sensing techniques to analyse salinization processes in an agricultural coastal area (Melendez-Pastor, Hernández, Navarro-Pedreño, & Gómez, 2012). Determining different soil salinity classes, detection of soil features and patterns of saline soil and prediction of soil salinity(Triki Fourati, Bouaziz, Benzina, & Bouaziz, 2015).
7	Tunisia	•Parent Materials	Negative impact on crop productivity and soil fertility	Landsat 8	

2.2.1.5 Vegetation and salinity indices

Various analysts have conducted studies on mapping soil salinity utilizing different soil salinity indices and distinctive Spectral Vegetation Indices (SVI). It can be noticed that no specific vegetation or salinity index could be utilized over every natural condition with proper results despite the fact that vegetation and salinity indices are useful for assessing soil salinity.. These indices change with various natural conditions, soil types, vegetation cover and density.

Summary of some vegetation and soil salinity indices that have been proposed and used for soil salinity mapping and monitoring in different studies are illustrated in Table 2.5.

2.2.2 Application of common RS techniques for soil salinity mapping

Researchers have so far used different satellite images and applied various digital image processing techniques to monitor and map soil salinity in the world. Applications of various RS techniques are depicted in Table 2.6. Besides, commonplace RS techniques which are used for soil salinity assessment in different case studies are discussed in the following sections.

Table 2.5: Vegetation and soil salinity indices for various case studies.

Satellite Data	Sensitive spectral bands	Location	Applied Indices	Equations	Note
MODIS	1, 2, 3, 4, 5, 6 and 7	Yellow River Delta, China	Enhanced Vegetation Index (EVI)	$EVI = G \left(\frac{(P_{NIR} - P_{red})}{(P_{NIR} + C1 \times P_{red} - C1 \times P_{blue} + L)} \right)$	• G is a gain factor (G=2.5) • P_{NIR}, P_{red}, and P_{blue} are partially atmospherically corrected surface reflectance for the respective MODIS near-infrared, red, and blue bands • L is the canopy background adjustment (L=1) • C1 and C2 are coefficients of the aerosol resistance term (a Huete, Justice, & Liu, 1994).

IKONOS	1, 2, 3, 4	Al-Hassa Oasis, Saudi Arabia	- Soil-Adjusted Vegetation Index (SAVI) - Normalized Differential Salinity Index (NDSI)	$SAVI = \frac{(NIR-R)}{(NIR+R+L)(1+L)} [27]$ $NDSI = \frac{(R - NIR)}{(R + NIR)}$	- B is Blue band - G is green band - R is red band - NIR is Near infrared band - L is a soil adjustment factor
Quick Bird	1, 2, 3, 4	Pingluo County, China	- spectral indices - Brightness Index - Normalized Difference Vegetation Index (NDVI) - Soil Salinity Indices - Ratio Vegetation index(RVI)	$RVI = \frac{NIR}{R}$ $NDVI = \frac{(NIR - R)}{(R + NIR)}$ $BI = \sqrt{R^2 + NIR^2} [28]$	- R is red band - NIR is Near infrared band
Landsat 7 ETM+	4, 5 and 7	Western San Joaquin Valley, California, USA	Canopy Response Salinity Index (CRSI).	$CRSI = \sqrt{\frac{(NIR \times R) - (G \times B)}{(NIR \times R) + (G \times B)}} [30]$	- R is red band - NIR is Near infrared band - B is Blue band - G is green band
HuanJing-Hyper Spectral Imager (HJ-HSI)	continuum-removed reflectance bands 1 and 2	Rudong County, China	1.Normal Soil Salt Content Response Index (NSSRI)	$NSSRI = \frac{(B1-B2)}{(B1+B2)} (Li et al., 2015)$	- R is red band - NIR is Near infrared band - L is a soil adjustment factor
Indian Remote Sensing (IRS)	1, 2, 3	Punjab, Pakistan	2. Soil Adjusted Salinity Index (SAVI)	$SAVI = \frac{(NIR-R)}{(NIR+R+L)(1+L)} [27]$ $S1 = \frac{B1}{B3}$ $S2 = \frac{(B1 - B3)}{(B1 + B3)}$ $S3 = \frac{(B2 \times B3)}{B1}$	B1 and B2 are the CR-reflectance of the bands 1 and 2, produced by hyperspectral analysis, respectively.
			Salinity indices		- S1-S3 are salinity indices - B1-B4 are four bands of IRS data

Table 2.6: Applications of various Remote Sensing techniques for different case studies.

Item	Location	Satellite data	Methods of analysing data	Field data	Success rate (correlation with the ground reference)
1	Tadla region, Morocco	Earth Observing (EO)-1 ALI 9 and 10 spectral bands	Empirical relationships between the electrical conductivity (EC) and different spectral salinity indices(Bannari, Guedon, El-Harti, Cherkaoui, & El-Ghmari, 2008).	Spectroradiometric measurements on 28 bare soil samples	52,91%
		Thematic Mapper(TM) Landsat sensor	Principal component analysis (PCA) and spectral indices of soil salinity (Lhissou et al., 2014)	Electrical conductivity field measurements collected simultaneously with the acquired satellite images	90%
2	Cheliff plain, Algeria	Landsat 7	Multiple linear regression model(Yahiaoui et al., 2015)	109 soil samples were collected	45%
		SPOT2 satellite Data	Ordinary kriging Regression-kriging(Douaoui et al., 2006)	3980 samples were used	95%

3	Egypt	Landsat 5, 7 and 8 ASTER	Principal Components Analysis (PCA)(Arnous & Green, 2015)	Fieldwork	Not given
4	Syria	Landsat 7 ASTER	Empirical reflectance method using ASTER data Biophysical method using landsat 7 data(Al-Khaier, 2003)	200 samples were collected from 98 different points	86%
5	Tuz Lake, Turkey	Landsat 5	Regression analysis	Spectroradiometric measurements in the field(Faculty & Division, 2003)	99%
6	Province of Alicante ,Spain	Landsat 5	Spectral mixture analysis Principal Components Analysis (PCA) Linear spectral unmixing (LSU)(Melendez-Pastor et al., 2012)	116 soil samples taken from the top 5 cm soil	Best results of linear regression models: $R^2=0,16$
7	Tunisia	Landsat 8	Partial Least Square Regression (PLSR)(Triki Fourati et al., 2015)	Randomly collected 75 samples from the top 10 cm	52%

2.2.2.1 Principal components analysis (PCA)

Principal Components Analysis (PCA) transforms dimensional image data into a new set of images (components) orthogonally. New components are uncorrelated with each other and ordered with respect to information they represent from the original image; thus, the first

components bear highest amount of information (Eastman, 2001). Mean, standard deviation, correlation coefficient, and variance/covariance matrices calculated from images are used in this method. As an example, in the north-eastern part of Egypt near the Mediterranean Sea, Principal Components Analysis (PCA) was carried out on the multi-temporal Landsat8 images whose result indicate promising potential of PCA technique in identifying and discriminating between all different classes; particularly the hydro- salinized wastelands such as the permanent, temporary waterlogged, salt-affected areas, bare land and vegetation. In the study, Normalized Difference Salinity Index (NDSI) is applied for illustrating the change of salt-affected and waterlogged areas distribution (Arnous, 2015).

2.2.2.2 Linear spectral unmixing (LSU)

This is a well-known method to estimate the fractions of different land cover/use categories for a given pixel. Pure reflectance of related categories called ‘end members’ is needed to apply this method. It is assumed that each pixel is composed

of linear combination of all end members in the image frame (Ramak et al.,2015).

As a case study, this method was applied to 2003 and 2010 dated Landsat Enhanced Thematic Mapper plus (ETM+) images in the north-western coast of Egypt. The unmixing results of LSU turned out to be accurate for quantifying the proportional physical abundance of salts. Corresponding result shows that the prediction of salinity levels was linear and significantly high at $R^2 = 0.84$ for LSU (Masoud, 2014).

2.2.2.3 Decision-tree analysis (DTA)

Soil salinity maps can be developed over large areas using decision-tree analysis (DTA) which is a predictive mapping technique. In DTA, not only the spectral properties of the soil surface; but, also some environmental parameters that considerably affect soil salinity could be incorporated into the classification procedure. Use of additional data such as geologic maps, terrain and landform maps could significantly enhance delineations of map classes including salty classes. Most of the pixel-based traditional classification techniques such as Maximum Likelihood Classification, Minimum Distance etc. only counts for spectral information which might not be enough to identify salty classes when only limited spectral bands are available from the sensors. Compared to traditional mapping methods, utilizing DTA could significantly improve the accuracy of soil salinity mapping. As an example, in Malheur County at the south-eastern Oregon in USA, DTA yielded a predictive soil salinity map with an overall accuracy of 98.4%(Elnaggar and Noller,2009).

2.2.2.4 Inverted gaussian function

Inverted Gaussian (IG) method is used to quantify salt content in soil considering the variations in spectral reflectance in various case studies. As an example, this model was carried out on soil samples which were collected from the island of Texel in the north- west of The Netherlands in north-east Hungary. Spectral reflectance curves obtained in the near-infrared (NIR) and shortwave infrared (SWIR) region were used for the analysis. Parameters of spectral reflectance of salt-affected soil in IG model are generally sensitive to both overall reflectance and maximum reflectance positions. With the increase of soil salinity level, maximum reflectance value shifts towards shorter wavelengths (Farifteh et al., 2010).

In this research the authors presented the lab-based spectral reflectance curves of salt

affected-soil. As an example, soil having 27.70 EC value had the maximum reflectance value around 1200 nm; whereas, soil having EC values of 1.60 and 2.50 had their maximum spectral values around 2000 nm.

2.2.2.5 Partial least square regression

Considering inferential capability of Partial Least Square Regression (PLSR) approach, it can be used to model the relationship between salt concentrations in soils and measured spectral reflectance values (Farifteh et al., 2007).

As a case study, in the Pingluo County of China, partial least squares regression (PLSR) predictive model was used to estimate soil salinity by using QuickBird data and soil spectral reflectance measurements. They found high correlation between Quickbird image-derived spectral reflectance and measured spectral reflectance values with $R^2 = 0.940$. Based on their analysis, highest contribution to the soil salinity estimation is from NIR band, followed by blue and green bands. On the other hand, green band has the lowest impact on salinity calculation. PLSR method can be used for the accurate prediction of soil salt content based on visible and NIR spectral reflectance values (Sidike et al., 2014).

2.3 Commonplace methods for reclamation of salt-affected soils

Mitigating soil salinity problem is related to saline agricultural land reclamation by using various methods and technique. Considering characteristics of each salt-effected land and reasons which exacerbate salinity problem, proper solutions need to be generated. As shown in Figure 2.9, common solutions for alleviating soil salinity problem are replacing traditional irrigation methods with recent irrigation techniques, modifying soil management practices, managing crop cultivation sequence and mapping both salt-affected areas and lands which are at risk of salinization.

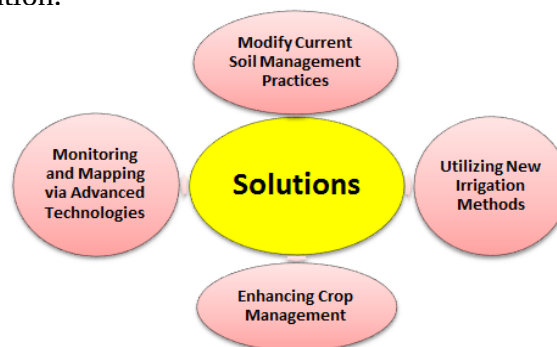


Figure 2.9: Common solutions for alleviating soil salinity problem.

2.3.1 Soil salinity sensors

RS and GIS are rather useful in monitoring large scale areas whereas, soil salinity sensors are proper for small scale in situ field monitoring of salt-affected soils since they have minimal disturbance to the soil profile. Salinity at selected depths can be monitored over a long period with sufficient accuracy for intermediate-term monitoring. In order to detect dynamic changes in soil salinity via sensors, two electrodes embedded in a fine-textured ceramic element are used and implanted in the soil profile. Generally, soil salinity sensors are incorporated in agricultural lands to assist farmers to monitor salinity easier and take on time preventive actions in order to mitigate adverse effects on plant growth. User-friendly application and rapid monitoring are two significant advantages of soil salinity sensors (P. Kumar, 2015). Figure 2.10 shows a soil salinity sensor.



Figure 2.10: Soil salinity sensor (Url-5).

2.3.2 Best irrigation method and agricultural practices for mitigating soil salinization.

Among various types of irrigation techniques, drip irrigation is considered as the most efficient irrigation method, since it applies water precisely and constantly at high frequencies. In addition, it compensates decreased osmotic potential plants as a result of saline water by maintaining high soil matric potential (SMP) which is

equivalent to high capillary or adsorption forces that in a plant are forces such as those at the cell walls(Sun et al., 2012).

More frequent irrigation not only decreases plant stress, but also dilutes the soil solution and sometimes accelerates the leaching of salts. The salts from irrigation water that accumulate in soil can be leached from the soil profile by applying a greater depth of irrigation than is needed to satisfy the crop's water requirement.

The irrigation method should be matched to the soil type and irrigation water quality since it will affect the amount and location of salt accumulation. The crop type should be selected considering soil type, irrigation method and irrigation water quality in order to decreased obtain optimum crop yield and highest soil reclamation (Rengasamy,2010)

Conservation Agriculture (CA) practices have considerable effects on soil salinity dynamics in irrigated production systems. As a case study, conservation agricultural practice with two tillage method; namely permanently raised beds with residue retention and premanently raised bed with residue harvested has been conducted in a cotton-wheat-maize rotation system. Soil salinity on top of the beds has risen over time in the absence of crop residues on the soil surface in raised bed systems.

On the contrary, while crop residues are retained on the surface, accumulation of saline soils will decrease considerably since there will be less evaporation, and consequently higher soil moisture content that keeps soils less saline. Such a reduction in soil salinization rate will have considerable importance in a region where land degradation due to secondary salinization is extensive. Therefore, raised bed planting with residue retention is a promising alternative to slow down the continuous soil salinization in salt-affected irrigated arid lands (Devkota et al., 2015).

Crop yield, irrigation water demand and water productivity change according to climatic conditions, particularly the variation of precipitation. In order to model an optimized irrigation regime, it is necessary to consider the effects of climatic variation on these parameters (Wang et al., 2015).

In many regions, farmers apply excessive irrigation water, and also irrigation departments are not capable of investing adequate drainage systems; besides, planners of irrigation schemes do not account sufficiently for the downstream adverse effects of excessive irrigation. They assume that the surface run-off or deep percolation from one farm is beneficial to other farms. Thus, soil salinization is

continuous in those regions, and it is necessary to provide successful management of salinity and waterlogging by implementing sustainable irrigation methods (Wichelns and Qadir, 2015).

In this regard, there is a three-part strategy for achieving sustainable irrigation.

- Correlative drainage systems with irrigation are the first strategy. It is necessary to develop drainage solutions simultaneous with irrigation schemes. Otherwise there will be a risk of potential harm that can arise when drainage systems are not installed in a timely manner. Proper and deep tillage can be applied in order to improve drainage by breaking up the compacted soil surface and hard pans which restrict downward flow of water. The better downward movement of water, the more leaching of saline soil; therefore, leaching works better on saline soils that have good structure and proper drainage system.

- Region based solutions must defined in local areas that excessive irrigation causes a shallow water table to rise beyond the borders of individual farms. In this case, a regional drainage system is required.

Water has to be used gently and sparingly in order to restrict the rise of shallow groundwater tables (Wichelns and Qadir, 2015).

2.3.3 Managing soil salinity with permanent bed planting

Permanently raised beds planting in irrigated production system is another way to confine rising of shallow groundwater tables since the depth of soil profile is increased, and as a consequence irrigation water will not percolate and reach to shallow groundwater table rapidly and easily. In this regard, there are two types of permanently raised beds planting. One is permanently raised bed with residue retention (PB + RR), and the other one is permanently raised beds with residues harvested (PB + RH).

Generally, in raised bed systems, soil salinity on top of the beds are accumulated over time in the absence of crop residues on the soil surface compared to the conventional practices. On the contrary, by maintaining crop residues, the increase in soil salinity on raised beds is significantly declined; however, decreasing in soil salinity is also dependent on the soil depth. Such a reduction in soil salinization rate will have noticeable significance in a region like Central Asia where land degradation due to secondary salinization is extensive. Therefore, raised bed planting

with residue retention is a proper approach to decelerate the continuous soil salinization in salt-affected irrigated arid lands since residues minimize the evaporation and prevent loss of soil moisture (Devkota et al., 2015). In addition to residues, mulching can also help to lower evaporation.

2.3.4 Chemical treatments

Adding calcium in a soluble form such as gypsum will help reducing and exchanging sodium content in soil profile. After calcium treatment, sodium can be washed away through the soil along with other soluble salts. Various types of approaches are suggested in order to alleviate soil salinization while farmers face with different soil profile characteristics which are shown in Figure 2.11.

		Situation						
		A	B	C	D	E	F	G
Top Soil		Neutral	Neutral	Alkaline	Sodic	Saline	Saline & Sodic	Acid
Sub Soil		Sodic	Saline	Sodic (Alkaline)	Saline	Sodic (Alkaline)	Saline & Sodic (Alkaline)	Sodic

Figure 2.11: Scheme of different soil profile characteristics that farmers are likely to encounter when analyzing soil samples (Rengasamy, 2010).

When top soil is neutral and sub soil is sodic, gypsum as a source of calcium should be applied in order to displace sodium from soil profile; however, surface application of gypsum will reclaim the sodic subsoil just during rainfall or irrigation with sufficient water to leach gypsum to the subsoil.

In case the top soil is neutral and sub- soil saline, the single solution is to wash away salt below the root zone. In regions where the water table is deep, high volume of water can seep into the below root zone and remove salt, but planting crops that use a lot of water slow down leaching process of salts. Therefore, cultivating salt-tolerant crops which uses less volume of water might be more supportive.

While top soil is alkaline or sodic and/or sub- soil is sodic or saline, again application of proper amount of gypsum will help reclamation of soil profile. Besides, enough water should seep into the sub-soil in order to leach salt and sodium ions.

High levels of salinity in top soil result in serious damage to crop germination. This condition is exacerbated when sub-soil is sodic because sub-soil sodicity prevent leaching of top soil clear away salts. Therefore, utilizing organic matter in the top soil will be supportive since it makes water percolation easier.

Soil profiles which contain acidity at top and sodicity at bottom can be reclaimed by applying mixture of lime and gypsum since lime can decrease adverse effects of acidity and gypsum will decline sodicity (Rengasamy,2010).

Using selenium (Se) in soil profile is another way to make plants more tolerant in saline condition. Selenium (Se) is considered as an essential trace element for some microbes, animals and humans; but its essentiality for plants is yet to be proved (N. Kaur et al., 2014).

As a case study, the effects of addition of various doses of Selenium (Se) in salt-stressed mung bean plants on their reproductive function, oxidative damage, sucrose metabolism and seed yield is evaluated. Corresponding results show that selenium at some concentration(s) can cause partial protection to mungbean plants against soil salinity (S.Kaur and Nayyar, 2015).

2.3.5 Cultivating salt-tolerant crops

One of the most significant strategies to mitigate the problem of soil salinity is planting salt-tolerant crops. Expansion of salt-tolerant crops has been an important objective of plant breeding programs for years in consideration of preserving crop productivity in semi arid and saline lands. Salt-tolerant crops, will not only help effective use of poor quality irrigation water, but also enhance physical properties of soil in terms of organic content and porosity since root structure of salt-tolerant plants and crops will establish granular soil particles. Moreover, decayed roots and deadwood improve the portion of organic matter in the soil (L.Zhang, 2004).

Growing salt-tolerant crops and trees in saline soils makes bare soil cover by plants; as a consequence, soil evaporation will be replaced by plant transpiration, thereby declining or preventing the salt accumulation on both surface area and through the tillage layer. In this condition, salt-tolerant and halophilic plants assimilate salt from the soil and concentrate it in various parts of the plants like leaves. Then, harvesting will remove the salt from the plant.

Selection of proper plant species capable of satisfactory biomass production, and also defining suitable sequence for crop cultivation is essential for soil salinity

amelioration. Table 2.7 shows crop threshold for root-zone salinity. Among those, tomato is the high tolerant crop since it does not lose its yield even in condition that soil electrical conductivity reaches up to 5 ds/m (Biswas, 2009).

Table 2.7: Various crop threshold for root-zone salinity (Biswas, 2009).

Crop	EC (ds/m) Threshold for maximum production-	EC (ds/m) Threshold for reduced yield levels-
Orange	3,4	6,6
Grapefruit	3,4	6,6
Lemon	3,4	6,6
Apricot	3,2	5,2
Peach	3,4	5,8
Carrot	2,0	5,8
Onion	2,4	5,6
Potato	3,4	7,6
Tomato	5,0	10,0

The widespread and continuous occurrence of waterlogging and salinity recommend that the causes and complications belonging to irrigation and drainage are fundamental, and they apply through the world across a extensive range of geographic and cultural conditions. In most places, the two significant elemental reasons for water logging and salinity are improper irrigation water management and postponed establishment of an adequate drainage system. The origin and effects are similar alongside the world. Potential solutions are limited to similar physical, economic, and social factors. Therefore, proper actions and investments are required to minimize salinity and waterlogging as inevitable hazards to agricultural lands. These actions should include supportive institutions, training, economic analysis, policies, and private sector participation.

2.3.6 Desalination plants

Advances in desalination technologies may give an opportunity for providing cost-effective and also climate-independent water resources for agricultural purposes. Since huge amount of available water resources are utilizing for irrigation and demand for irrigating agricultural lands increasing year by year, number of desalination plants for supplying high quality water for agricultural purposes is also rising. Consequently, generating and building up more cost effective desalination plants and technologies is necessary to provide high quantity and quality of water for agricultural applications. So, if the expenses for supplying desalinated water continue to decline, its application is estimated to become more practical due to several advantages (Burn et al., 2015).

- Irrigation water with low EC value will be provided.
- It allows reclamation of saline soil by irrigation with high quality water.
- Increase quality of agricultural products, and
- Water production by this method may be increased in comparison with others

2.3.7 Global potential of generating bioenergy from salt-affected soils

Bio-saline forestry is an approach whereby salt-tolerant trees, shrubs and crops are cultivated on saline soils. Utilizing this approach not only contributes considerably to energy supply in specific regions; but, it also helps to reclamation of salt-affected soils. As a consequence, low-productive lands convert to sources of energy and income for land owners. As it is depicted in Figure 2.12, biomass yield on salt-affected soils range between 0 to 27 oven dry ton/ha.year in different regions of the world (Wicke et al., 2011).

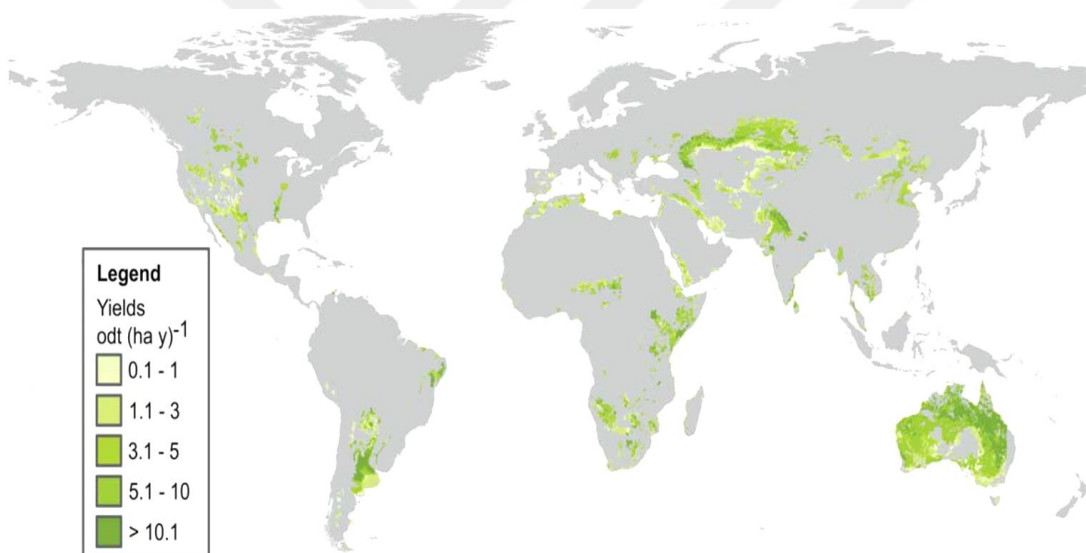


Figure 2.12: Various levels of yield production in salt-affected soils in the world
Further research is required in the field of bio-saline forestry to minimize production cost and enhance management techniques in order to boost biomass energy production and accelerate salt-affected soil reclamation.

2.4 Recent Findings And Solutions For Mitigating Soil Salinization

Salinization of fertile and arable lands displays an increasing trend even though considerable efforts are paid to land rehabilitation and reclamation practices. However there is a need to develop simple and low- cost biological methods for salinity stress management, which can be used on short term basis. Ionic toxicity, osmosis pressure and nutritional disorders are factors which limit crop growth and

constrain its productivity on saline soils. Therefore, enhancement of productivity under stressed conditions and increased resistance of plants against salinity stress by application of new methods is becoming more and more essential (Shirvastava and Kumar, 2015).

2.4.1 Microorganisms and genetic engineering role for soil salinity mitigation

Microorganisms could play a significant role in this respect. I Introduction of plant growth-promoting and salt-tolerant microbes to soil can protect plants from salt effects, if their unique properties such as tolerance to saline conditions, genetic diversity, synthesis of compatible solutes, and production of plant growth promoting hormones, bio-control potential, and their interaction with crop plants are exploited. As a case study, the plant growth-promoting fungus penicillium is applied to the sesame plant soil profile. Despite, salinity stunted sesame plant growth, introducing penicillium to its root zone soil profile, significantly promoted shoot length in comparison with untreated plants as illustrated in Figure 2.13. In fact, salinity will reduce the amount of chlorophyll-a, which is the main factor for plant photosynthesis, but presence of some plant growth-promoting and salt-tolerant microbes like fungus penicillium will prevent damages to chlorophyll-a and mitigate adverse effects of salinity problem (Radhakrishnan and Lee, 2015).



Figure 2.13: Light microscopic root structure of sesame without (Pen-) or with Penicillium (Pen+) association (Radhakrishnan and Lee, 2015).

Various approaches have been established in order to decline the toxic effects originated by high salinity on plant growth, including plant genetic engineering.

Activation and regulation of specific stress-related genes are bases of molecular control mechanisms in plant genetic engineering. These genes are included in the whole steps of stress responses, such as signaling, transcriptional control, protection of membranes and proteins, and toxic-compound cleaning up. Currently, investigation into the molecular mechanisms of stress responses has started to bear fruit. Besides, genetic modification of stress tolerance has also illustrated hopeful outcomes that may eventually apply to agriculturally and ecologically valuable plants (Ie, 2003).

Utilizing plant growth-promoting bacteria (PGPB) is another recent application which have been done for plant growth promotion, nutrient management and lessening toxicity in saline soils. These favorable microorganisms colonize the rhizosphere of plants and enhance growth of the plants over different direct and indirect functions. In addition, osmotic stress as a result of soil salinization can be mitigate by utilizing microorganisms and plant growth-promoting bacteria (Dimkpa, et al., 2009;Haji and Zarea, 2012).

Other recent survey indicates applying the Arabidopsis vacuolar H⁺-pyrophosphatase gene (AVP1) to transgenic barely will improve the shoot biomass and enhance its grain yield in greenhouse conditions. The potential for this gene to increase the grain yield of cereal crops in saline field has yet to be examined (Schilling et al., 2014).

2.4.2 Application of humic substances in mitigating the harmful effects of soil salinity and improve plant productivity

There are both indirect and direct impacts of humic substances on plant soil system to lessen soil salinization. Enhancing physical, chemical and microbiological characteristics of soils are among the indirect effects of humic substances. On the other hand, accelerating seed germination, promoting plant root and shoot growth and hormone like activity are direct effects of humic substances on plants and crops. They can experience harmful effects of salt stress by strengthening root, changing mineral uptake process and minimizing membrane damage (Ouni et al., 2014).

3. STUDY AREA

Tuz Lake is the second largest lake in Turkey which is located between three provinces; Konya, Aksaray and Ankara. It is the biggest salt lake with specific kinds of flora and fauna in Anatolia Region. Agriculture, livestock breeding, salt production and tourism are the main human activities that have impact on economic condition in this region (Mergen and Karacaoglu, 2015).

Tuz Lake Basin occupies an area of about 1.500 km² with an altitude of 905m(Ucan and Dursun, 2009).

For most of the year, Tuz Lake is a shallow saline lake approximately 80 km long and 50 km wide; but, during July and August the lake dries out exposing a salt flat as there is no precipitation and the temperature is high (Kilic, 2010). Figure 3.1 shows the geographical location of the lake in Turkey coupled with a satellite view. Figure 3.2 illustrates a near view photo of the lake where salt layer is clearly observed near the shoreline.

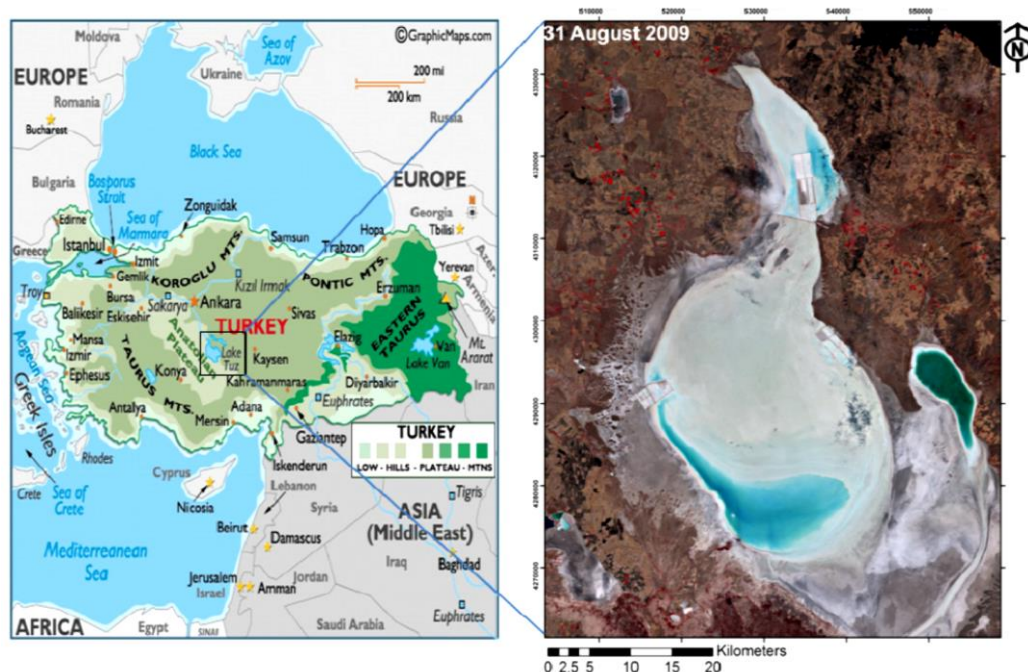


Figure 3.1: Geographical location of Tuz Lake (Odongo, Hamm, & Milton, 2014).



Figure 3.2: Tuz Lake (Url-6).

Since the lake is losing water and correspondingly, salinity is getting more and more results in bird kills. Plankton that normally eats red algae rapidly grows and makes the lake red in some period of the year as shown in Figure 3.3 Url-7.



Figure 3.3: Tuz Lake appears red due to presence of red algae (Url-8).

3.1 Habitat Classification of Tuz Lake

According to European Nature Information System (EUNIS), a system for the identification and classification of European habitat types, twelve different habitat classes are determined in Tuz Lake area as given in Table 3.1 (Mergen and Karacaoglu, 2015).

Table 3.1: Twelve different types of habitat in Tuz Lake determined in 2007 by the European Nature Information System (EUNIS) (Mergen , 2015).

Item	Habitat type	Area (ha)
1	Permanent oligotrophic lakes, ponds and pools	191
2	Permanent inland saline and brackish lakes, ponds and pool	179270
3	Inland salt marsh	45652
4	Perennial calcareous grassland and basic steppe	42498
5	Agricultural land and heavily fertilized grassland	285236
6	Continental inland salt steppes	138269
7	Arable land with unmixed crop pattern	1490
8	Small-scale ornamental and domestic garden areas	828
9	Low density residential areas	11600
10	Highly artificial man-made waters and associated structures	5876
11	Artificially vegetated areas	-
12	Salt lake Island	-

3.2 Environmental Problems of Tuz Lake

In Tuz Lake Region, industrial activities accelerated in recent years and some new artificial areas are under construction; therefore, industrial wastes have a tendency to increase. In addition microbiological, biological and physical pollution is increasing due to insufficient wastewater treatment systems. Excess pesticides, nitrogen, phosphorus together with heavy metals originating from agricultural activities are among the other environmental problem in the region. Loss of trees and bushes due to intense agricultural activities in some parts of the basin lead to soil erosion.

Environmental problems in this region do not only harm the habitats of the lake vegetation, but also threatens the lives of a variety of animals such as birds and fishes (Ucan and Dursun, 2009).

In addition, Within the context of water resources management and development in Turkey, former Special Environmental Protection Agency has initiated some projects in the registered special protection areas within years. One of these projects were realized at Tuz Lake Region which has been declared as a Special Protection Area in 2000 with the basic aim of determining the protection-utilization principles of this sensitive area regarding its protection from further pollution.

Tuz Lake area hosts a variety of migrating seabirds and is registered as A Class wetland according to RAMSAR Agreement. The area is well known with its rich biodiversity and those A Class wetlands are the ones that have international importance. It is the second largest lake of the country and has risen its interest due

to its high saline water hosting step habitats, biological diversity and finally due to its increasing significance as an industrial production centre. Moreover, intensive agriculture prevails at the area due to its fertile soil characteristics which is actually an outstanding property of the area.

Apart from these important ecological and environmental characteristics, the area is under the pressure of pollution basically arising from discharge of urban wastewater to the lake together with other environmental problems. Other leading problems are overuse of groundwater, misuse of agricultural production and irrigation techniques. These problems accelerated the realization of this detailed Project within years 2002-2004 where soil and land characteristics of the area are analysed with the aid of modern technological tools of RS and GIS. In this Project, initially the total area of 7000 km² was classified based on soil taxonomy. Furthermore, real land quality was determined via CORINE. Surface and groundwater surveys and analyses were also conducted to better understand the fate of pollutants in the water environment. Fertility of land, soil classes, soil problems. Soil pollution was searched as well. Finally, socio-economic structure is put forth in order to find out conflicts between environment and agriculture. All 322 soil samples EC values related to this project are referred in the Appendix A.

3.3 Tuz Lake Climate

The basin is categorized as continental climate. It is one of the most arid regions of Turkey with low precipitation level during the year. Long-term daily average rainfall and temperature of Tuz Lake from year 1984 to 2009 are shown in Figure 3.4. It can easily be understood that temperature is increasing and precipitation is decreasing year by year due to climate change in this region, and as a consequence, the basin becomes more dry (Odongo et al., 2014).

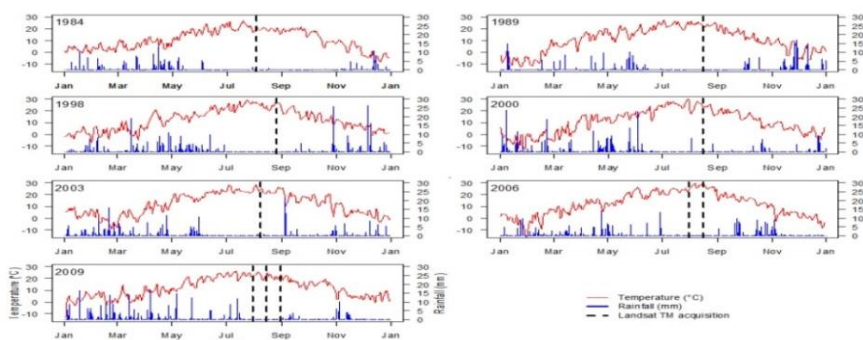


Figure 3.4: Long-term daily average rainfall and temperature at Tuz Lake (Odongo et al., 2014).

Regarding to Meteorological data, Figure 3.5 illustrates Aksaray region yearly precipitation from 1981 to 2015 with average amount of 351.3 mm. Since Aksaray is very close to Tuz lake region, the precipitation pattern is also similar to this area.

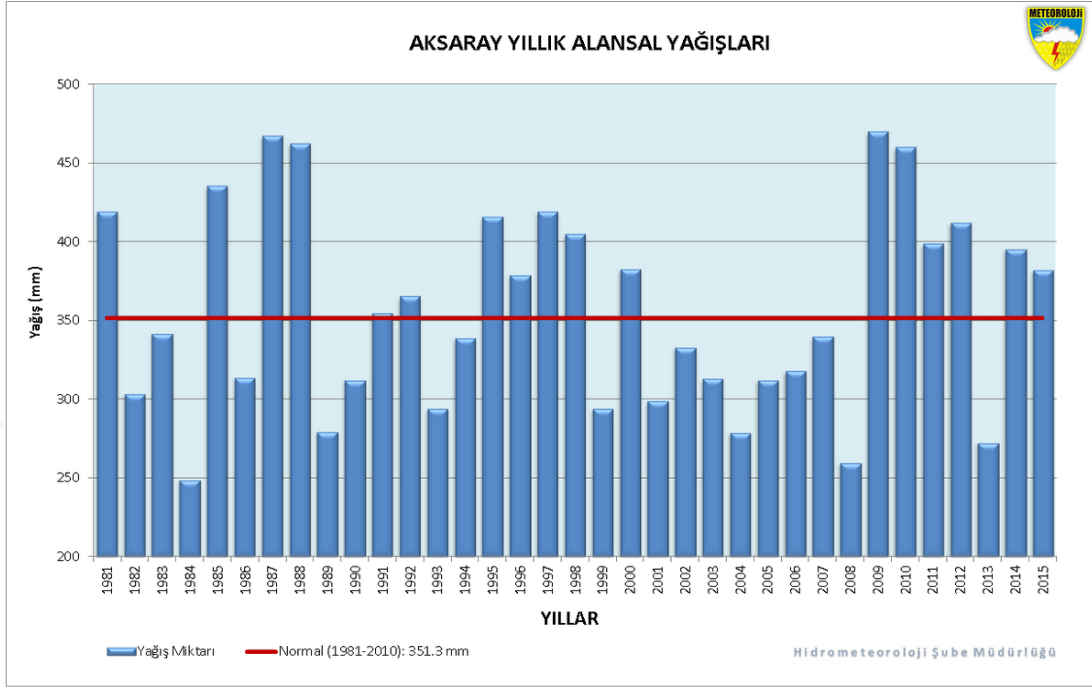


Figure 3.5: Aksaray yearly precipitation pattern from 1981 to 2015 with average amount of 351.3 mm (Url-9).



4. MATERIALS AND DATA USED

For generating soil salinity maps, monitoring multi-temporal changes in saline soils and detecting land-use change in the study area, three groups of data; namely, Landsat satellite images, coordination of information on the environment (CORINE) land cover data, and field Electrical Conductivity (EC) measurements for 19 soil samples are used.

Land sat Thematic Mapper 4 and 5 images for years 1990, 2002, 2006 and 2011 are used for generating saline maps. Besides, one image from Landsat 8 is utilized for year 2015.

Totally, 19 field Electrical Conductivity (EC) measurements samples are selected from all 322 samples which were obtained in year 2002. Those 19 samples are representative of various places around the lake with different Electrical Conductivity (EC) ranges. It is attempted to consider homogenous distribution and variety of EC ranges in selecting those 19 samples. Since the whole area related to Tuz lake satellite images is too large, this research is done for just the lake and a limited region around the lake. Therefore, most of the samples are not used because they were not within the boundaries of selected area. In addition all satellite images are cropped to a specific and similar size.

Regarding to Corine data it should be considered that two sets of vector data one is related to changes from 2000 to 2006 and the other related to 2006 to 2012 are utilized for detecting land cover changes in the study area.

4.1 Landsat Thematic Mapper 4 and 5 (TM4 and TM5)

The Landsat program that began in 1972 is one of the important National Aeronautics and Space Administration (NASA) earth-observation program. Landsat Thematic Mapper is a sensor flying on Landsat 4 and 5 satellites. Landsat 4 was launched in 1982 and ended operation in 1993. Landsat 5 was launched in 1984 and carried on to obtain imagery in 7 spectral bands until November 2011. The Landsat

program is arranged for utilizing different satellite images in various studies such as forestry, agriculture, geology and land-use planning. The advantages of Landsat satellite images are generally seen as its regular acquisition schedule; it actually revisits each spot on the earth every 16 days. In addition, its free archive history that include images from year 1982, provide multi-temporal monitoring applications for numerous analysis.

On the other hand, restraint of Landsat data is that it is a moderate-resolution image source with 30 meters resolution (Table 4.1).

Characteristics of Landsat 4-5 spectral bands with their corresponding wavelength are shown in Table 4.1.

At the beginning of this study, all available Landsat-4 and -5 TM data for years 1990, 2002, 2006 and 2011 were checked in order to select the most appropriate data set for this research. Proper images for month June and July were used for generating soil salinity maps. Besides, some other images for years 2003, 2007, 2009, 2010 were utilized for applying Normalized Difference Vegetation Index in order to provide information about the spatial distribution and condition of vegetated areas in the selected area.

Table 4.1: Spectral and spatial information about Landsat TM (Table 4.1).

Landsat 4-5 Spectral Bands	Wavelength (micrometres)	Resolution (m)
Band1-Blue	0.45-0.52	30
Band2-Green	0.52-0.60	30
Band 3- Red	0.63-0.69	30
Band 4- Near-Infrared	0.76-0.90	30
Band 5- Near-Infrared	1.55-1.75	30
Band 6- Thermal	10.40-12.50	120
Band 7- Mid-Infrared	2.08-2.35	30

4.2 Landsat 8

Landsat 8 satellite including two main sensors; namely, the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) as part of the Landsat Data Continuity Mission was successfully launched on February 11, 2013.

Operational Land Imager is collecting images using 9 spectral bands in different wavelengths of visible, near-infrared, and shortwave light to observe an approximate scene size which is 170 km north-south by 183 km east-west in 15-30 m resolution covering wide areas of the earth's landscape while providing sufficient resolution to distinguish features like urban centers, farms, forests and other land uses. Landsat 8 spectral bands with their corresponding spatial resolutions are depicted in Table 4.2. In this study, Landsat 8 images for the year 2015 are analysed and the proper image is selected to generate saline map for the study area.

Table 4.2: Spectral and spatial information about Landsat 8 (Url-12).

Landsat 8 Spectral Bands	Wavelength (micrometres)	Resolution (meters)
Band 1 - Coastal aerosol	0.43 - 0.45	30
Band 2 - Blue	0.45 - 0.51	30
Band 3 - Green	0.53 - 0.59	30
Band 4 - Red	0.64 - 0.67	30
Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
Band 6 - SWIR 1	1.57 - 1.65	30
Band 7 - SWIR 2	2.11 - 2.29	30
Band 8 - Panchromatic	0.50 - 0.68	15
Band 9 - Cirrus	1.36 - 1.38	30
Band 10 - Thermal Infrared	10.60 - 11.19	100 (30)
Band 11 - Thermal Infrared	11.50 - 12.51	100 (30)

4.3 Coordination of Information On The Environment (CORINE) Land Cover Data.

CORINE land cover (CLC) program provides integrated and comparable land cover and land- use data for all European Union (EU) Member States. There are 5 main land cover classes namely artificial surfaces, agricultural areas, forest and semi-natural areas, wetlands, waterbodies and overall 44 sub-classes that illustrate different type of land cover in each class in detail. Table 4.3 demonstrates 3 different levels related to CORINE land cover (CLC) classes Url-13.

Table 4.3: Corine land cover classes (Url-14).

1 Artificial surfaces		3 Forest and semi-natural areas	
1.1	Urban fabric	3.1	Forests
1.1.1	Continuous urban fabric	3.1.1	Broad-leaved forest
1.1.2	Discontinuous urban fabric	3.1.2	Coniferous forest
1.2	Industrial, commercial and transport units	3.1.3	Mixed forest
1.2.1	Industrial or commercial units	3.2	Scrub and/or herbaceous vegetation associations
1.2.2	Road and rail networks and associated land	3.2.1	Natural grasslands
1.2.3	Port areas	3.2.2	Moors and heathland
1.2.4	Airports	3.2.3	Sclerophyllous vegetation
1.3	Mine, dump and construction sites	3.2.4	Transitional woodland-shrub
1.3.1	Mineral extraction sites	3.3	Open spaces with little or no vegetation
1.3.2	Dump sites	3.3.1	Beaches, dunes, sands
1.3.3	Construction sites	3.3.2	Bare rocks
1.4	Artificial, non-agricultural vegetated areas	3.3.3	Sparsely vegetated areas
1.4.1	Green urban areas	3.3.4	Burnt areas
1.4.2	Sport and leisure facilities	3.3.5	Glaciers and perpetual snow
2	Agricultural areas	4	Wetlands
2.1	Arable land	4.1	Inland wetlands
2.1.1	Non-irrigated arable land	4.1.1	Inland marshes
2.1.2	Permanently irrigated land	4.1.2	Peat bogs
2.1.3	Rice fields	4.2	Maritime wetlands
2.2	Permanent crops	4.2.1	Salt marshes
2.2.1	Vineyards	4.2.2	Salines
2.2.2	Fruit trees and berry plantations	4.2.3	Intertidal flats
2.2.3	Olive groves	5	Water bodies
2.3	Pastures	5.1	Inland waters
2.3.1	Pastures	5.1.1	Water courses
2.4	Heterogeneous agricultural areas	5.1.2	Water bodies
2.4.1	Annual crops associated with permanent crops	5.2	Marine waters
2.4.2	Complex cultivation patterns	5.2.1	Coastal lagoons
2.4.3	Land principally occupied by agriculture, with significant areas of natural vegetation	5.2.2	Estuaries
2.4.4	Agro-forestry areas	5.2.3	Sea and ocean

In this study, CORINE land cover (CLC) data in years 2000, 2006 and 2012 are analyzed for the Tuz Lake Region in consideration of land cover and land- use change detection. The main changes are related to conversion of natural grassland and vegetated areas to agricultural arable land from 2000 to 2006, and conversion of agricultural arable land to pastures and artificial surfaces from 2006 to 2012.

4.4 Field Electrical Conductivity (EC) Measurements.

Generating soil salinity maps requires both proper satellite images and field survey outcomes. Gathering exact information about soil electrical conductivity (EC) depend on accurate and reliable field measurements. In this study, 19 soil samples from proper areas in the vicinity of Tuz Lake are selected based on the results of a thorough field survey conducted by the Ministry of Food, Agriculture and Livestock of Turkish Republic (MoFAL) . Table 4.4 illustrates coordinates of those soil samples with their corresponding electrical conductivity (EC) values. In addition, Figure 4.1 illustrates the location of All 322 soil samples that are provided by Ministry of Food, Agriculture and Livestock of Turkish Republic (MoFAL).

Table 4.4: Soil samples with their corresponding Electrical Conductivity values.

Coordinate				Coordinate			
Item	Y	X	EC(ds/m)	Item	Y	X	EC(ds/m)
1	4228651	547298	1.216	11	4312723	521295	0.763
2	4228109	537395	1.898	12	4318085	506000	0.668
3	4229575	536553	1.757	13	4310476	507517	1.004
4	4232965	545336	0.906	14	4306242	510614	0.71
5	4239038	480960	1.108	15	4299320	497177	0.454
6	4248085	487555	4.433	16	4274562	513018	5.431
7	4234462	521930	1.538	17	4335033	523365	0.46
8	4239408	511370	2.316	18	4329478	514021	0.524
9	4301906	550710	0.852	19	4306641	549340	0.745
10	4318715	525148	1.111				

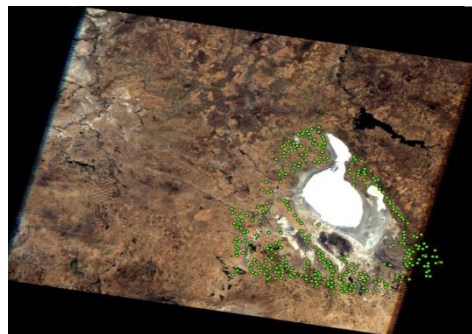


Figure 4.1: Location of all 322 soil samples are shown in the study area with green dots.



5. METHODOLOGY

This research contains two main analyses. Image processing techniques that are used for generating soil salinity maps followed by CORINE data examination in consideration of land- use/ land cover change detection will be discussed.

5.1 Image Processing Techniques

Most of the common image processing functions available in image interpretation systems includes 4 categories; namely pre-processing, image enhancement, image transformation, image classification and interpretation.

Satellite images commonly include some distortions due to various reasons such as sensor instabilities, topography or scattering, and absorption of reflectance radiance by atmosphere molecules. Therefore, it is crucial to conduct corrections and pre-processing on remotely sensed data.

For this research, as shown in Figure 5.1, appropriate satellite images and field data are initially provided. Then, radiometric and atmospheric correction is done as image pre-processing, after that salinity indices are utilized for image classification, and finally regression analysis has been conducted for accuracy assessment. Resultantly, soil salinity maps are generated.

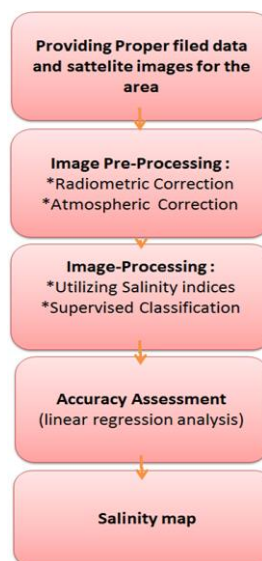


Figure 5.1: Steps of soil salinity map generation.

5.1.1 Pre-processing

Pre-processing techniques contain removing or minimizing distortion, improper and distracting elements of the satellite image. Pre-processing step contains radiometric calibration, atmospheric corrections, topographic corrections and geometric corrections. For this study, radiometric and atmospheric corrections are applied for all images.

5.1.1.1 Radiometric calibration

There are various techniques that enhance distorted raw remote sensing data radiometrically, and make them fit better for information extraction. Modifying and altering Digital numbers (DNs) support various objectives.

Correcting data for failing of the sensor while detector cells of a camera have all a marginally contrasting response. In this case, radiometric calibration contributes to determining the differences.

Instead of using only one detector per channel, scanners utilize several detectors per channel most of the time for scanning wider strip on the ground. Detectors might have slightly contrasting radiometric response, which results in appearance of stripes.

In addition, a worse condition is that when one detector fails, one line in the image appears black. Random noise is another detector problem which deforms satellite images by adding black and white dots to the image, and as a consequence distort radiometric information.

Moreover, failure in sensor platform system will also lead to distortion of satellite images. Therefore, radiometric calibration is helpful for correcting all distorted satellite images and recovering proper radiometric information (Tempfli,2009).

For this research, all satellite images are corrected by utilizing ENVI software radiometrically. After importing satellite image Meta data file to ENVI, it is necessary to change the calibration type from radiance to reflectance for performing radiometric calibration. Figure 5.2 and Figure 5.3 show a raw satellite image and its radiometrically corrected version for the study area, respectively.

It can be easily understood radiometrically corrected image is more proper and clear for applying various analysis.

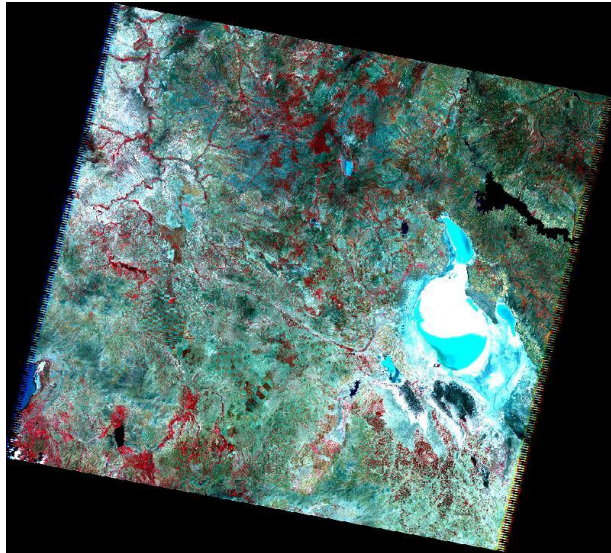


Figure 5.2: Salt Lake LANDSAT_5 satellite image in 2002.

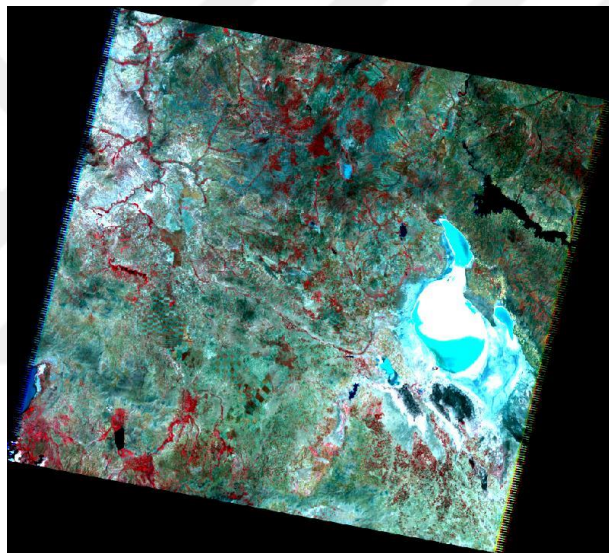


Figure 5.3: Salt Lake LANDSAT_5 radiometrically corrected satellite image in 2002.

5.1.1.2 Atmospheric correction

Accurate retrieval of surface reflectance becomes more and more significant in all surveys that are related to ground surface; such as agricultural evaluation, forest management, water resource estimation, and soil salinity assessment. Unluckily, a large portion of satellite images extremely distorted by atmospheric effects includes molecular and aerosol scattering by water vapor, clouds, ozone, oxygen and aerosols. Satellite images can be conceivably more useful if atmospheric effects can be removed. This procedure for retrieving surface reflectance is commonly named atmospheric correction.

Ozone and oxygen concentration are almost stable over both time and space; therefore, molecular scattering and absorption because of ozone and oxygen are comparatively easy to correct. On the other hand, eliminating the effects of aerosols is the most difficult part of atmospheric correction since most of them are distributed disparately. Regarding to Landsat satellite images, the effect of water vapor absorption is significant for the TM/ETM+'s near- infrared (IR) channels (Liang et al., 2001).

Atmospheric corrections contribute a significant step in the pre-processing of remote sensing data. Methods of atmospheric corrections (AC) are required to “clean” the images from distortions caused by atmospheric effects, in order to allow the retrieval of perfect ground radiances from the surface. The same AC procedures can be used in both visible and thermal range since the physics behind the AC techniques in the visible and in the thermal range are basically the same (Tempfli,2009).

For this analysis, all satellite images are atmospherically corrected by utilizing ERDAS software.

The most basic option is converting pixel values to physical reflectance using the top of atmospheric reflectance workflow. Image acquisition time and radiance values are only two required information for this procedure. Haze removal and cloud masking is another procedure whereby haze is removed before atmospheric correction. Another alternative is ground reflectance atmospheric correction, which is mainly used for this research. Reflectance values at surface are calculated to eliminate atmospheric effects in satellite imagery and preparing all related images for classification and utilizing various indices. Figure 5.4 illustrates Salt Lake Landsat_5 atmospherically corrected satellite image in 2002.

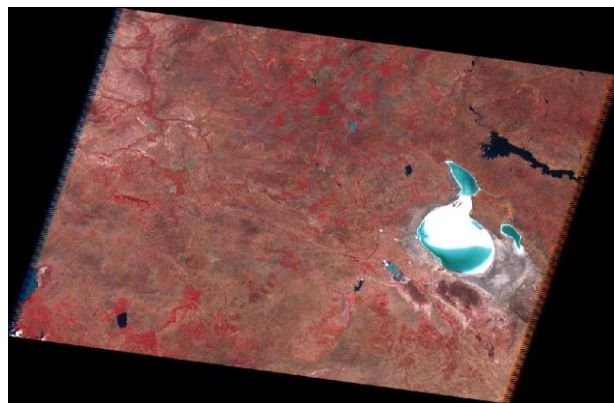


Figure 5.4: Salt Lake LANDSAT_5 atmospherically corrected satellite image
in 2002

Radiometrically corrected images are imported as TIFF format to ERDAS and ATCOR module is used for atmospheric correction several alternatives are supported by ATCOR module for performing various atmospheric corrections.

5.2 Utilizing Indices

In order to generate soil salinity maps including 5 classes; namely, non-saline, slightly saline, moderately saline, highly saline and extremely saline for Salt Lake Region, 5 soil salinity indices are applied to images for years 1990, 2002, 2006, 2011 and 2015. Besides, Normalized Difference Vegetation Index (NDVI) is utilized in consideration of detecting variation in vegetation density in the study area.

5.2.1 Soil salinity indices

Generally, extremely and highly saline areas can be detected by all sorts of soil salinity indices. In some cases, even there is no need to perform any index since salt crust are easily visible due to their bright reflectance. However, recognizing slightly saline and moderately saline areas required accurate examination of various soil salinity indices in order to find optimized results. Therefore, in this research, 5 salinity indices are examined which had already been used in different case studies. Table 5.1 demonstrates these mentioned salinity indices.

Table 5.1: Soil salinity indices used for generating salinity maps.

Index	Description
Salinity index (SI) 1 = $\sqrt{B1 * B3}$	B1=Band 1 - Blue , B3= Band 3 - Red
SI 2= $\sqrt{B2 * B3}$	B2=Band 2- Green , B3= Band 3 - Red
SI 3= $\sqrt{(B2)^2 + (B3)^2 + (B4)^2}$	B2=Band 2- Green , B3= Band 3 - Red , B4= Band 4 - Near Infrared
SI 4= $\sqrt{(B2)^2 + (B3)^2}$	B2=Band 2- Green , B3= Band 3 - Red
SI 5= $\sqrt{(B3)^2 + (B4)^2}$	B3= Band 3 – Red , B4= Band 4 - Near Infrared

After applying each index for every satellite image in different years, pixel values with various ranges in all images are extracted. Then, corresponding Electrical Conductivity (EC) values are compared with their exact pixel value with similar coordination.

All indices in this research are formulated in ENVI software using band math tool. The output images, as a result of band math procedure, are imported to Geographical Information System (GIS) software for determining soil salinity classes. Utilizing Universal Transverse Mercator (UTM) projection system both satellite images and sample points is set to world Geodetic System (WGS-1984) zone 36 N. After that, corresponding pixel values for each sample is extracted by using Arc toolbox. Then, in layer properties symbology item, classes are defined based on appointing proper pixel values to electrical conductivity values 2 ds/m, 4 ds/m, 8 ds/m and 16 ds/m.

5.2.2 Normalized difference vegetation index (NDVI)

NDVI is the ratio of the difference between the near-infrared band (NIR) and the red band (R), and the sum of these two bands as shown in the below formula.

$$NDVI = \frac{(NIR - R)}{(R + NIR)}$$

Where, NIR is reflectance in Near-Infrared, and R is reflectance of visible red band.

According to the NDVI concept, it can be understood that less visible light and more near-infrared are reflected by green vegetation, while less near-Infrared and more visible light are reflected by sparse and low dense vegetation. In addition, NDVI is an index related to photosynthetic capacity. The range of values obtained are always between (-1 to +1) Thus, the positive values correspond to vegetated zones and the higher the value, the greater the chlorophyll content of the plant (Tengberg , 2014).

In this research, NDVI is applied to different images for years 1990, 2002, 2006, 2011 and 2015 and as a result, corresponding maps for each year are generated showing how vegetation cover in study area is changing within years. ERDAS software is used for generating NDVI images, since it has the function in the raster tool and there is no need to define the formula for NDVI manually.

5.2.3 Accuracy assessment

Generating accurate soil salinity maps and assessing how well salinity classes are categorized, precise relationship between ground data EC values measured in field and salinity index values from satellite image is required. Therefore, in this study, two sorts of analysis; namely linear regression analysis and exponential regression analysis have been conducted using excel software plots. Regarding the generated

plots, it should be mentioned that electrical conductivity (EC) values are placed in Y-axis, since they should be estimated for unmeasured locations by using known salinity index values of same location. X-axis includes known values (independent variable) which is satellite image derived index values.

Relationship between EC values of 19 locations and values of indices from satellite image is provided via a formula which can be used to find out EC values for whole study area. Each pixel index value is put into the regression equation, and possible EC value for that pixel location is calculated.

5.2.3.1 Linear regression analysis

Generally, regression analysis is a type of predictive modelling technique which examines the relationship between a dependent (target) and independent variable (predictor). Predicting, time series modeling and determining the link between dependent and independent variables are among applications of this technique.

Particularly, linear regression is one of the most extensively used predicting technique for different case studies. It sets up a relationship among dependent variable on Y-axis and one or more independent variables on X-axis by providing a regression line and a mathematical function $Y = AX + B$.

Normally, the function is represented by a mathematical equation like $Y = AX + B$ whereby target variable can be predicted by giving predictor variable. After plotting all data on Y- and X-axis, model performance can be evaluated by utilizing R-square parameter. It is a value between 0 - 1. The higher the R-square value, the better fitting and accuracy in model is achieved.

In this study, linear regression analysis has been conducted to all satellite images which generated separately by different salinity indices in 2002. In fact, the model is established in 2002, since both EC ground data and satellite images existed simultaneously.

5.2.3.2 Exponential regression analysis

Exponential function models use non-linear trend to establish the required model. The exponential regression model determines the equation of an exponential function of the form $y = ab^x$ that properly fits a set of data. The value b is considered the base of the exponential function. Similar to linear regression analysis, the respective predictive power of an exponential model is designated by R-square value. The more

close the value is to 1, the more accurate the model is Url-16. For this research, linear regression analysis has been conducted to all satellite images which generated separately by different salinity indices in 2002 using excel software. In fact, the model is established in 2002 since both EC ground data and satellite images are existed simultaneously.

5.3 CORINE Data Examination

CORINE Land Cover (CLC) data is a data of the European environmental landscape based on interpretation of satellite images.

Detecting land- use /land cover changes based on CORINE data is a necessary tool for providing proper and extensive information for both decision makers and administrative managers for better natural resource management and sustainable development.

Human-induced activities such as expanding agricultural lands for food supply, population growth and urbanization, technological and economic development are affecting land cover changes. Besides, natural causes such as climate change and drought impacts on land cover changes.

Therefore, information about land- use /land cover changes is required to monitor these changes year by year in order to make proper decisions to mitigate negative effects of these alterations on environment (Das, 2009).

For this study, CORINE land cover (CLC) data for years 2000, 2006 and 2012 are analyzed for the Salt lake Region in consideration of CLC change detection. For this study, working units No: 52 and No: 60 from Corine 2006 data for Turkey are used in order to determine land cover classes in Salt Lake Region.

All classes with their coresponding areas are calculated after importing CORINE data to ArcMap software. Besides, land cover changes are analyzed using CORINE change shape file for years 2000, 2006 and 2012.

The main changes are related to conversion of natural grassland and vegetated areas to agricultural arable land from 2000 to 2006, and then conversion of agricultural arable land to pastures and artificial surfaces from 2006 to 2012.

6. RESULTS AND DISCUSSION

In this study, two main types of salinity maps are generated based on linear regression and exponential regression results of year 2002.

Then, based on acceptable exponential regression results, estimated maps for years 1990, 2006, 2011 and 2015 are generated considering salinity map of year 2002 since both EC ground data and satellite images existed for this specific year.

NDVI maps for years 1990, 2002, 2006, 2011 and 2015 are further produced and vegetation cover areas for different classes are calculated in order to track the changes in vegetated land cover.

CORINE Land Cover (CLC) change map is also generated in consideration of monitoring land cover changes from year 2000 to 2006 and likewise from year 2006 to 2012.

6.1 . Salinity Maps And Exponential Regression Analysis

Exponential regression results for 5 different salinity indices in year 2002 are illustrated in Table 6.1. Utilizing Salinity index (SI) $1 = \sqrt{B1 * B3}$ leads to highest result with $R^2 = 0.961$.

Salinity classes are defined as none-saline (0-2 ds/m), slightly saline (2-4 ds/m), moderately saline (4-8 ds/m), highly saline (8-16 ds/m) and extremely saline (above 16 ds/m) .

Exponential regression equation $y = 0.0289e^{9.8434x}$ is used for calculating the corresponding salinity index values for EC measurements of 2, 4, 8 and 16 by inserting these values as 'y' in the equation for calculating the related 'x' values. Calculated x values, expressed as salinity index values, are then used for predicting EC salinity maps for different years.

Table 6.1: Exponential regression analysis results for five different salinity indices.

Index	Index Range	Date of Satellite Image	Number of Samples	R ²
Salinity index (SI) 1 = $\sqrt{B1 * B3}$	0-1	25.06.2002	19	0,961
SI 2= $\sqrt{B2 * B3}$	0-1	25.06.2002	19	0,936
SI 3= $\sqrt{(B2)^2 + (B3)^2 + (B4)^2}$	0-1.73	25.06.2002	19	0,90
SI 4= $\sqrt{(B2)^2 + (B3)^2}$	0-1.42	25.06.2002	19	0,927
SI 5= $\sqrt{(B3)^2 + (B4)^2}$	0-1.42	25.06.2002	19	0,8704

Exponential regression analysis has been conducted in some other case studies appearing in literature. As an example, in the District Faisalabad, the Central Punjab of Pakistan, researchers utilized Indian Remote Sensing (IRS) satellite images for establishing empirical relationships or models using indices such as (SI) 1 = $\sqrt{B1 * B3}$ and ground truth data. An exponential function of 3rd order was found as highly promising with significant results (Abbas et al., 2013).

In another study conducted in the lowermost portion of the Basin of Mexico Landsat-ETM satellite images were used to calculate Combined Spectral Response Index (COSRI) for bare soils and vegetation. In addition, correlation coefficients between COSRI and soil salinity were obtained and a model was adjusted to predict the soil salinity. As a result, the exponential correlation between COSRI and EC was found as 0.88 (Fernández-Buces, Siebe, Cram, & Palacio, 2006).

6.1.1 Salinity index (SI) 1

The most accurate map is generated as a result of applying Salinity Index (SI) 1 = $\sqrt{B1 * B3}$ using exponential regression analysis. Regression graph and salinity map with five classes are shown in Figure 6.1 and Figure 6.2, respectively. Related salinity maps for years 1990, 2006, 2011 and 2015 are given in Appendix B.

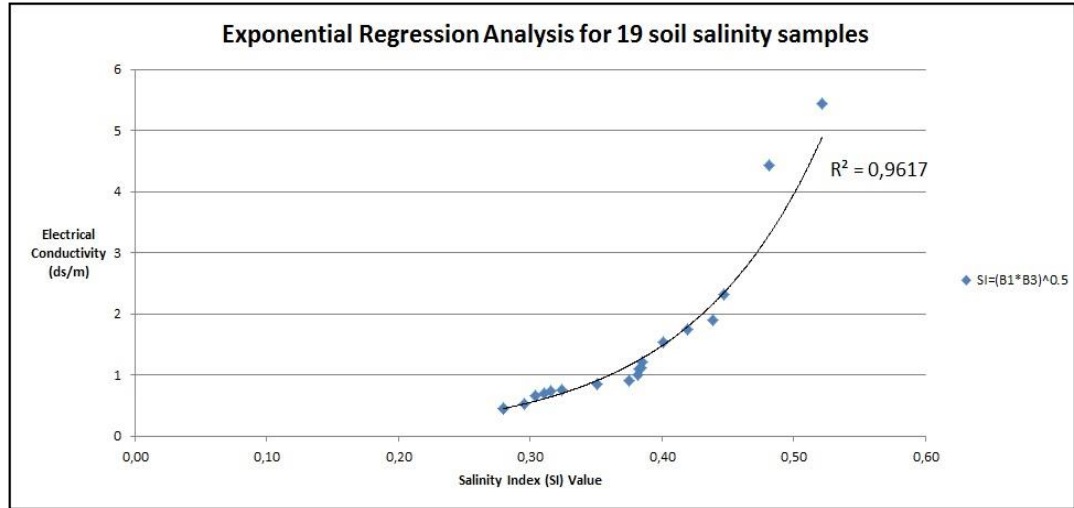


Figure 6.1: Exponential regression analysis between EC and SI 1 values.

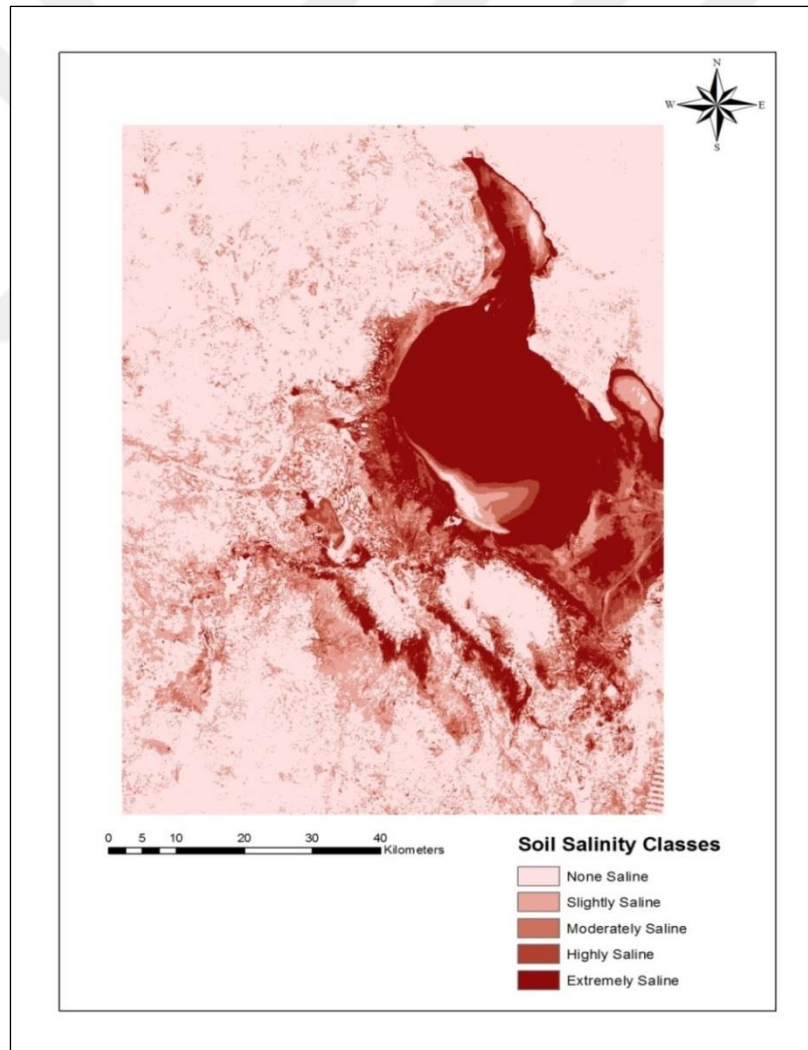


Figure 6.2: Tuz Lake salinity map for 2002 as a result of Salinity Index

(SI) $1 = \sqrt{B1 * B3}$ and exponential regression analysis.

6.1.2 Salinity index (SI) 2

Exponential regression equation of $y = 0.0392e^{12.077x}$ is used for generating salinity map. Regression graph and salinity map with five classes are shown in Figure 6.3 and Figure 6.4, respectively. Related salinity maps generated for years 1990, 2006, 2011 and 2015 are given in Appendix B.

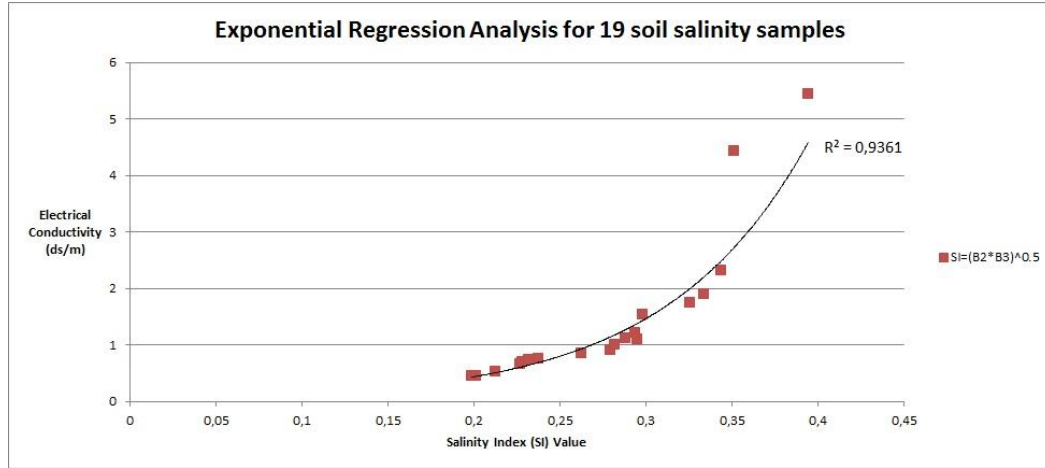


Figure 6.3: Exponential regression analysis between EC and SI 2 values.

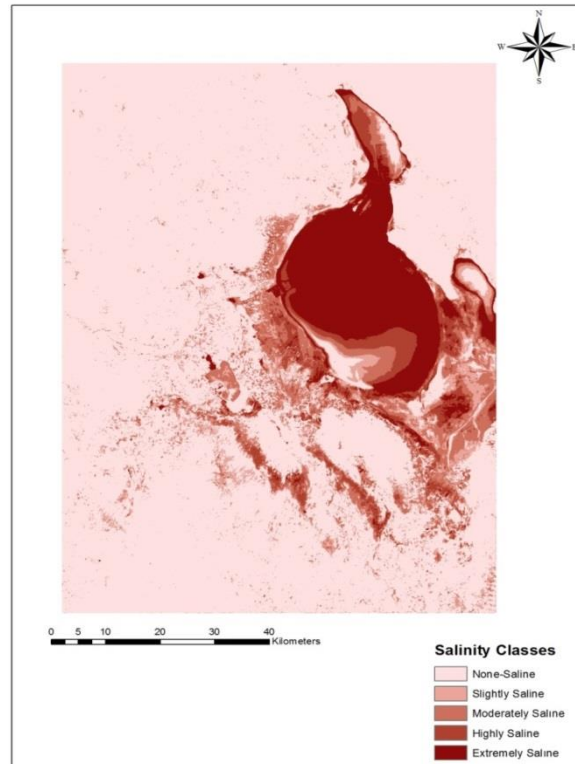


Figure 6.4: Tuz Lake salinity map for 2002 as a result of Salinity Index

(SI) 2 = $\sqrt{B2 * B3}$ and exponential regression analysis.

6.1.3 Salinity index (SI) 3

Exponential regression equation of $y = 0.0137e^{7.6218x}$ is used for generating salinity map. Regression graph and salinity map with five classes are shown in Figure 6.5 and Figure 6.6, respectively. Related salinity maps for years 1990, 2006, 2011 and 2015 are given in Appendix B.

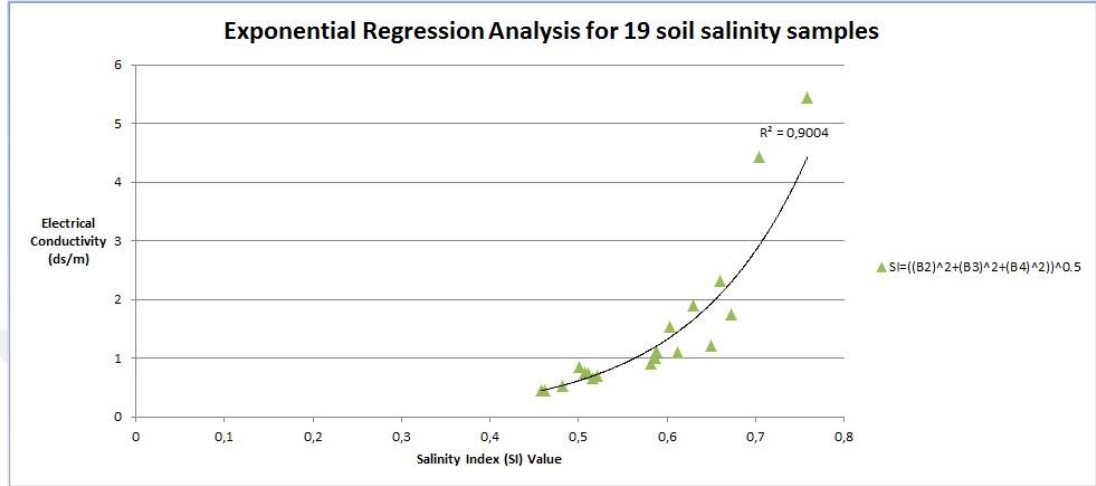


Figure 6.5: Exponential regression analysis between EC and SI 3 values.

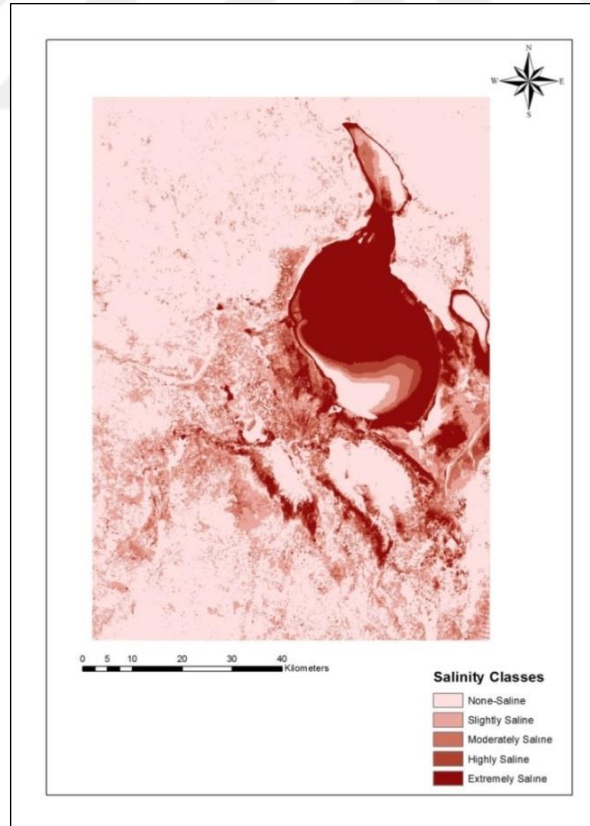


Figure 6.6: Tuz Lake salinity map for 2002 as a result of Salinity Index (SI) 3

$$= \sqrt{(B2)^2 + (B3)^2 + (B4)^2} \text{ and exponential regression analysis.}$$

6.1.4 Salinity index (SI) 4

Exponential regression equation of $y = 0.0402e^{8.2183x}$ is used for generating salinity map. Regression graph and salinity map with five classes are shown in Figure 6.7 and Figure 6.8, respectively. Related salinity maps for years 1990, 2006, 2011 and 2015 are given in Appendix B.

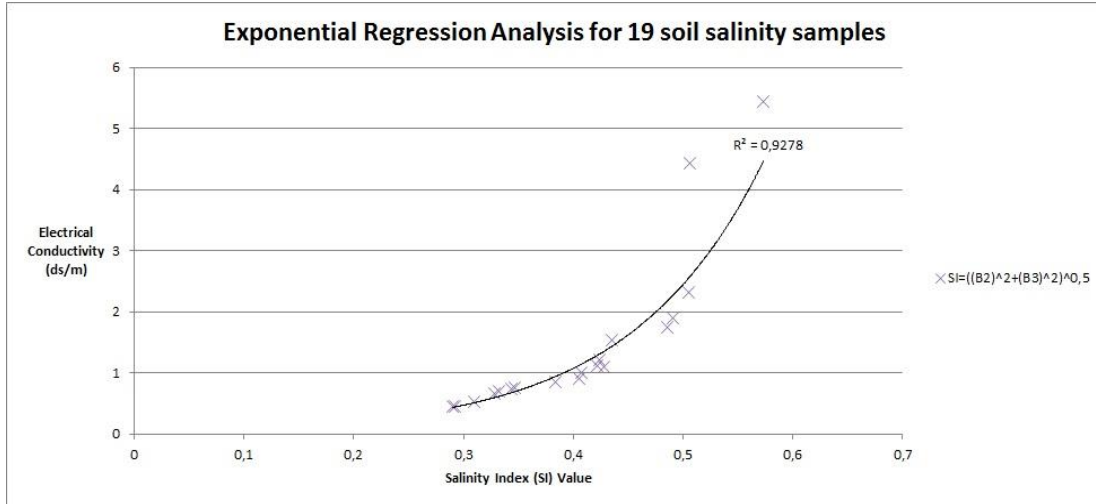


Figure 6.7: Exponential regression analysis between EC and SI 4 values.

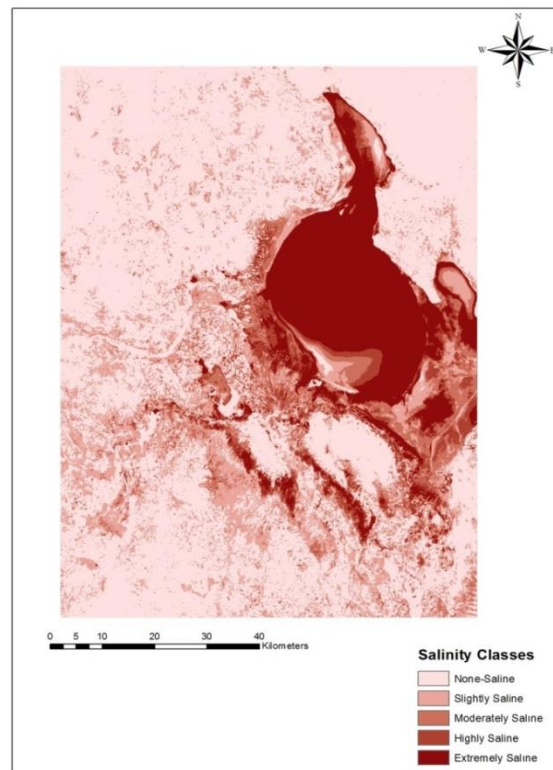


Figure 6.8: Tuz Lake salinity map for 2002 as a result of Salinity Index

(SI) 4 = $\sqrt{(B2)^2 + (B3)^2}$ and exponential regression analysis.

6.1.5 Salinity index (SI) 5

Exponential regression equation of $y = 0.0113e^{8.6917x}$ is used for generating salinity map. Regression graph and salinity map with five classes are shown in Figure 6.9 and Figure 6.10, respectively. Related salinity maps for years 1990, 2006, 2011 and 2015 are given in Appendix B.

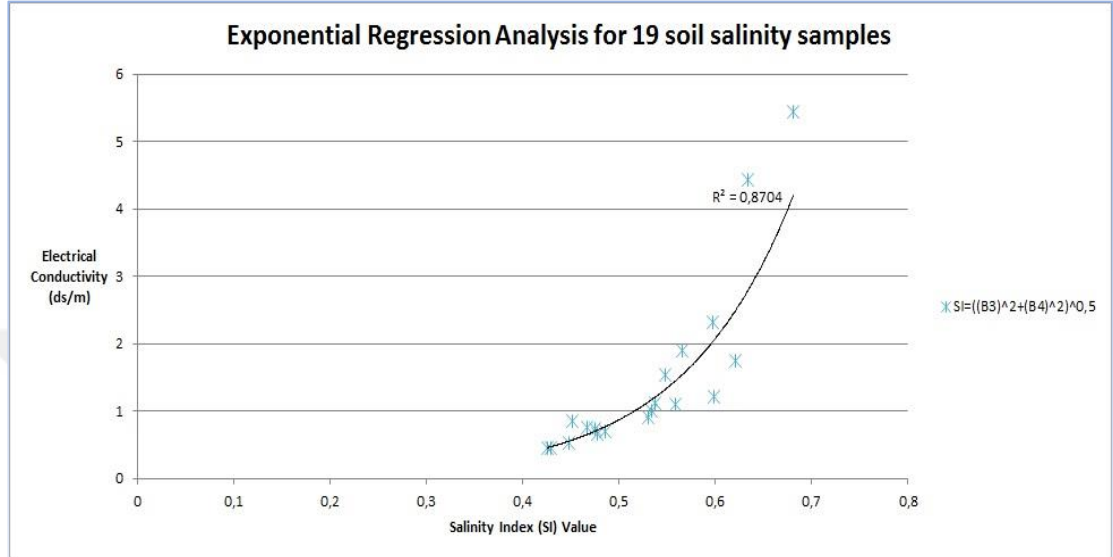


Figure 6.9: Exponential regression analysis between EC and SI 4 values.

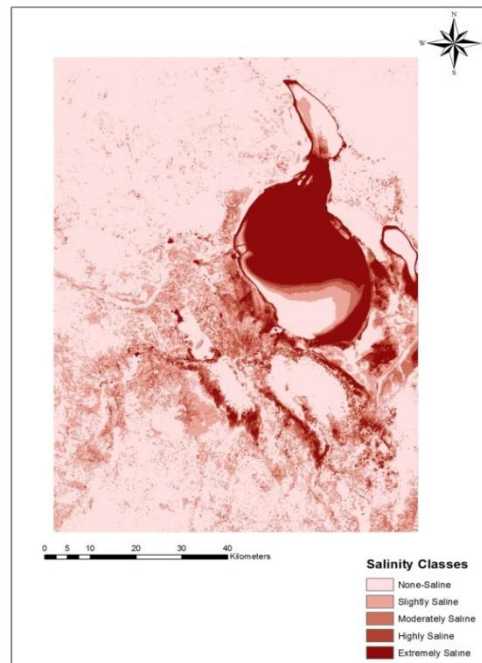


Figure 6.10: Tuz Lake salinity map for 2002 as a result of Salinity Index

(SI) 5 = $\sqrt{(B3)^2 + (B4)^2}$ and exponential regression analysis.

6.1.6 Areal changes of salinity classes based on exponential regression analysis

Changes in the area of each salinity class based on Salinity Index (SI) $1 = \sqrt{B1 * B3}$ for years 1990-2015 are shown in Figure 6.11. According to this chart, it can be seen that salinity increased in the area from 1990 to 2006 and to 2011 due to natural and human- induced factors which will be discussed in section 6.4 based on CORINE land cover change map, and also a slight decline in the salinity level in year 2015 is observed.

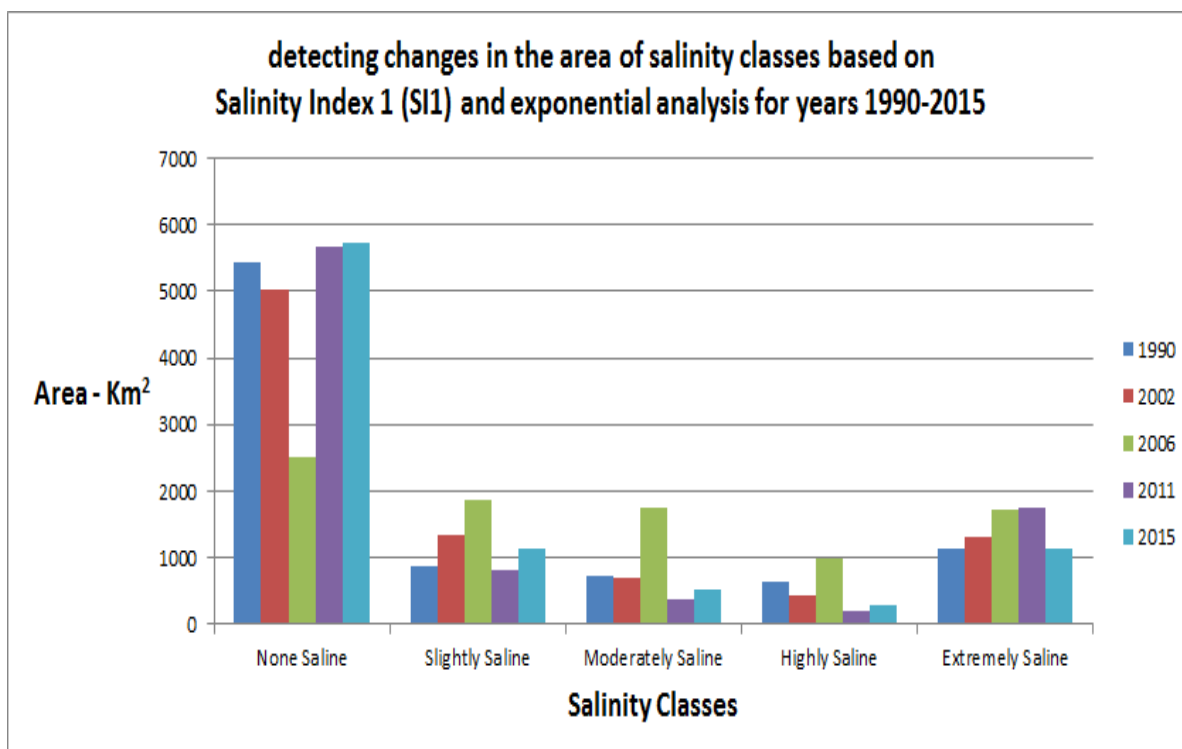


Figure 6.11: Changes in the area of each salinity class based on Salinity Index (SI) $1 = \sqrt{B1 * B3}$ for years 1990-2015.

6.1.7 Comparison of salinity indices performance by means of their classification pattern

Each salinity index classifies the study area specifically and differently from other salinity indices. As depicted in Figure 6.12, each salinity index leads to a certain type of classification and results in different areal values for any class despite the fact that all indices classify the study area with almost identical area for each soil salinity class. None- saline class includes the highest area as a result of applying salinity indices followed by slightly saline and extremely saline class. The minimum area is related to highly saline class as a result of all salinity indices which are used for generating salinity maps.

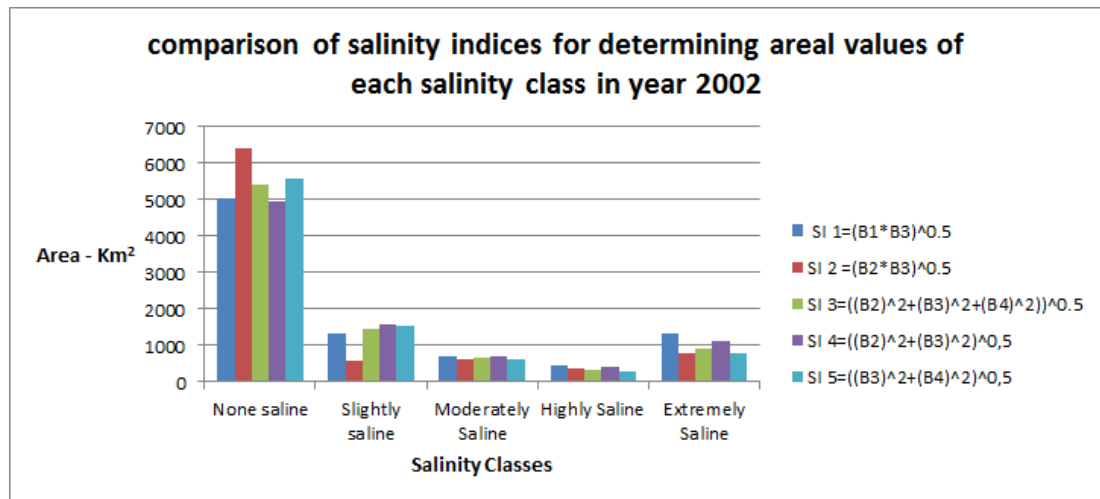


Figure 6.12: Performance of different salinity indices in classifying areas of each salinity class in year 2002.

6.2 Salinity indices and linear regression analysis

Linear regression results for five different salinity indices in year 2002 are illustrated in Table 6.2. Utilizing Salinity index (SI) 1 = $\sqrt{B1 * B3}$ leads to the highest result with $R^2 = 0.778$.

Linear regression equation of $y = 17,75x - 1,04$ is used for calculating corresponding salinity index values for EC measurements of 2, 4, 8 and 16 by inserting these values as 'y' in the equation for calculating the related 'x' values. Calculated 'x' values that are the salinity index values are used for predicting EC salinity maps for different years. Regarding to linear regression analysis, only Salinity Index (SI) 1 = $\sqrt{B1 * B3}$ is used for generating salinity maps; since other indices have comparatively low R^2 value as a result of regression analysis which are given in Appendix B.

Table 6.2: Linear regression analysis results for five different salinity indices.

Index	Index Range	Date of Satellite Image	Number of Samples	R^2
Salinity index (SI) 1 = $\sqrt{B1 * B3}$	0-1	25.06.2002	19	0,778
SI 2 = $\sqrt{B2 * B3}$	0-1	25.06.2002	19	0,720
SI 3 = $\sqrt{(B2)^2 + (B3)^2 + (B4)^2}$	0-1.73	25.06.2002	19	0,708
SI 4 = $\sqrt{(B2)^2 + (B3)^2}$	0-1.42	25.06.2002	19	0,70
SI 5 = $\sqrt{(B3)^2 + (B4)^2}$	0-1.42	25.06.2002	19	0,680

Linear regression analysis has been conducted in various case studies as a step towards generating soil salinity maps. In El-Tina Plain located on Northwestern Sinai Peninsula in Egypt, researchers utilized two predictive models namely Partial Least Squares Regression (PLSR) and Multivariate Adaptive Regression Splines (MARS) based on the measured electrical conductivity (ECe) and laboratory soil reflectance spectra resampled to Landsat sensor's resolution. The result for PLSR and MARS linear regression analysis resulted in R^2 value of 0.73 and 0.70 which were quite satisfactory for predicting new EC value for different spots in various years (Nawar, Buddenbaum, Hill, & Kozak, 2014). Another study conducted in Central Iraq for mapping soil salinity multi-temporal changes by applying Generalized Difference Vegetation Index (GDVI) to Landsat 4, Landsat 5 and Landsat 7 ETM+ images resulted in R^2 value of 0.94 (W. Wu et al., 2014). In the Lower Cheliff Plain of Algeria, researchers utilized five soil salinity indices namely $SI_1 = \sqrt{B2 * B3}$, $SI_2 = 2*B2 - (B3+B4)$, $SI_3 = \sqrt{(B2)^2 + (B3)^2}$, $SI_4 = (B3-B4) / (B3+B4)$ and Soil Adjusted Salinity Index ($SASI = B3 / (100 * (B1)^2)$) on Landsat 7 images in order to detect and predict soil salinity in the region. They also generated multiple linear regression model for soil salinity prediction based on elevation and the Soil Adjusted Salinity Index ($SASI = B3 / (100 * (B1)^2)$) with R^2 value of 0.45 between measured EC and predicted EC (Yahiaoui et al., 2015). Furthermore, in Tadla-Azilal Region of Central Morocco, several soil salinity indices depicted in Table 6.3 are applied on Landsat TM satellite images in order to detect and map soil salinization. The best result similar to this thesis research is obtained from $SI_1 = \sqrt{B1 * B3}$ with R^2 value equal to 0.68 (Lhissou et al., 2014).

Table 6.3: Linear regression analysis results for several salinity indices used in Central Morocco (Lhissou et al., 2014).

Spectral indices	Equation	R^2
Brightness Index (BI)	$\sqrt{(B3)^2 + (B4)^2}$	0.47
Salinity index (SI) 1	$\sqrt{B1 * B3}$	0.68
SI 2	$\sqrt{B2 * B3}$	0.55
SI 4	$\sqrt{(B2)^2 + (B3)^2}$	0.53
SI 5	$B5/B7$	0.06
SI 6	$(B5-B7)$	0.5

In another study conducted in Yellow River Delta situated on the Northeast coast of China for detecting soil salinity with Moderate Resolution Imaging Spectroradiometer (MODIS) and utilizing Enhanced Vegetation Index (EVI). The relationship between plant biomass and salt stress were investigated using linear regression method. Biomass decreased linearly with the increased soil salinity in crop land, and the linear regression model resulted in R^2 value of 0.85 (T.-T. Zhang et al., 2015). Regional scale soil salinity evaluation using Landsat 7 was conducted in California, United States. In this study, researchers found EC ground-truth relationship with Landsat 7 reflectance after applying Salinity Index= $(B2*B3)^{0.5}$. and the result showed R^2 value of 0.85(Scudiero et al., 2014).

6.2.1 Salinity index (SI) 1

Regression graph and salinity map with five classes are shown in Figure 6.13 and Figure 6.14, respectively. Related salinity maps for years 1990, 2006, 2011 and 2015 are shown in Appendix B. The result of linear regression analysis categorizes salinity maps extensively in two highly and moderately saline levels rather than extremely saline level since EC value of 16 ds/m is corresponding to salinity index values of 0.96 in linear analysis and of 0.64 in exponential analysis. Therefore, exponential regression analysis place all index values within the range of 0,64 to 1 in extremely saline class; however, linear regression analysis set all index values within the range of 0,96 to 1 in extremely saline class.

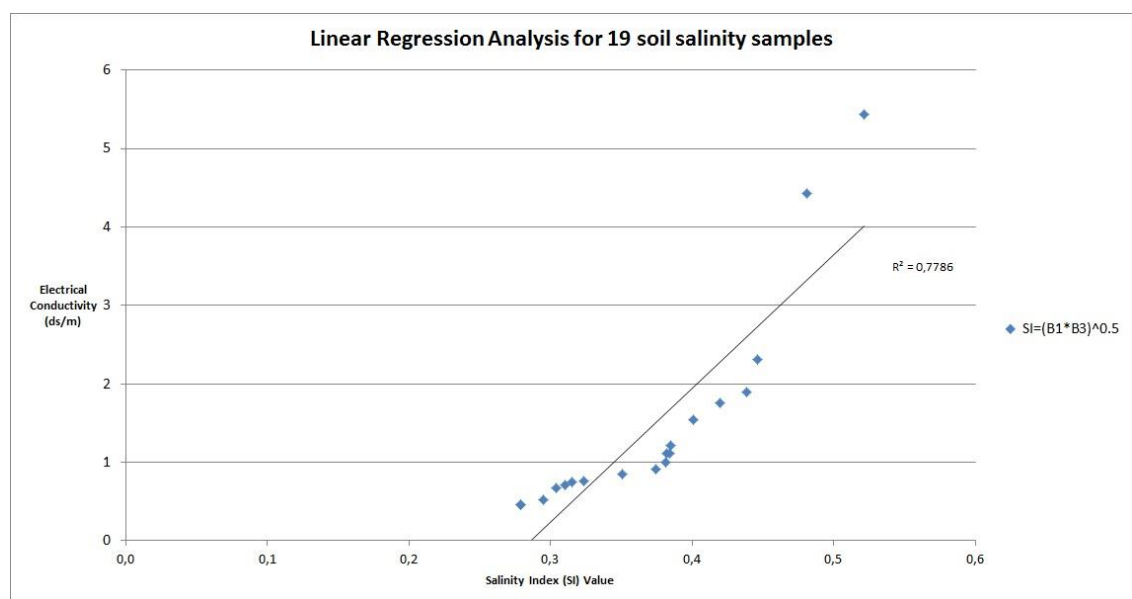


Figure 6.13: Linear regression analysis between EC and SI 1 values.

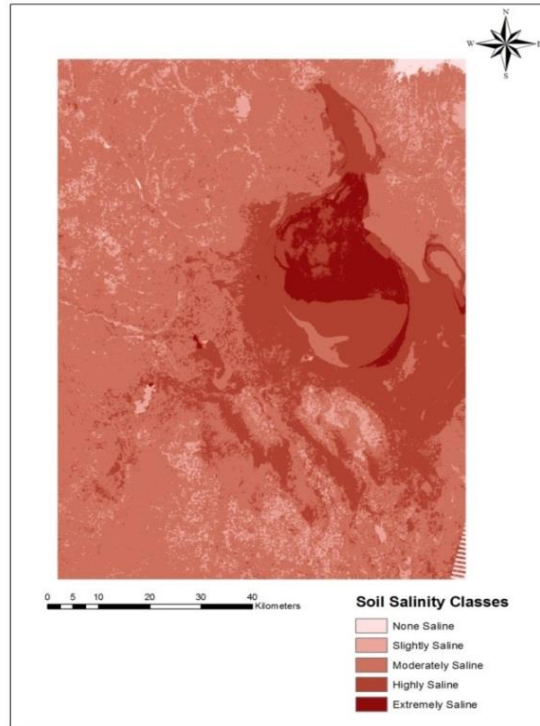


Figure 6.14: Tuz Lake salinity map for 2002 as a result of Salinity Index

(SI) $1 = \sqrt{B1 * B3}$ and linear regression analysis.

6.2.2 Areal changes of salinity classes based on linear regression analysis

Changes in the area of each salinity class based on Salinity Index (SI) $1 = \sqrt{B1 * B3}$ for years 1990-2015 are shown in Figure 6.15. It is seen that salinity increased in the area from year 1990 to 2006 and to 2011 due to natural and human- induced factors which will be discussed in Section 6.4 based on CORINE land cover change map, and also a slight decline in salinity level in year 2015 is observed from the corresponding graph.

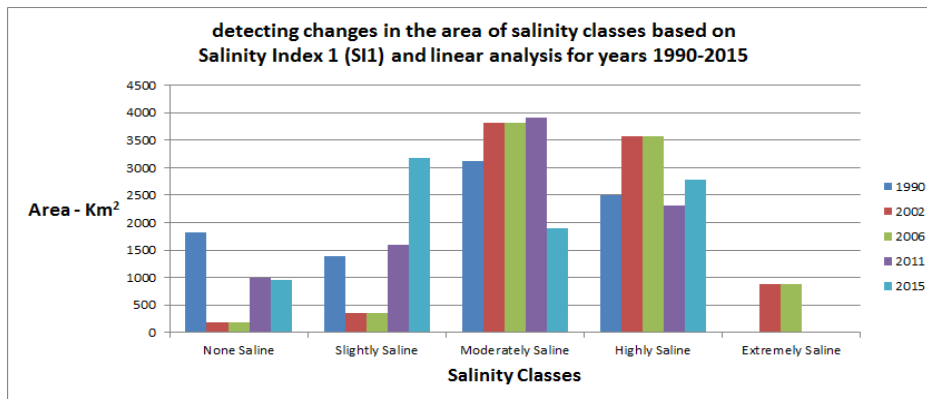


Figure 6.15: Changes in the area of each salinity class based on Salinity Index (SI) 1

$= \sqrt{B1 * B3}$ for years 1990-2015.

6.3 NDVI Maps

NDVI images are generated with 11 classes in the range of (-1 to 1) using ERDAS software. Figure 6.16 shows NDVI map for year 2002. Maps related to years 1990, 2006, 2011 and 2015 are illustrated in Appendix B. Areal changes in vegetated and none vegetated land based on NDVI index for years 1990-2015 are shown in Figure 6.17. It can be easily be understood that in year 1990 the region was covered with dense vegetation since in all classes with NDVI value were higher than 0,3. The graph shows higher area for year 1990 in comparison to other years. Generally, by comparing NDVI maps for all years, it can be determined that vegetation cover intensity is decreasing from year 1990 to 2011, and then there is a slight increase in 2015.

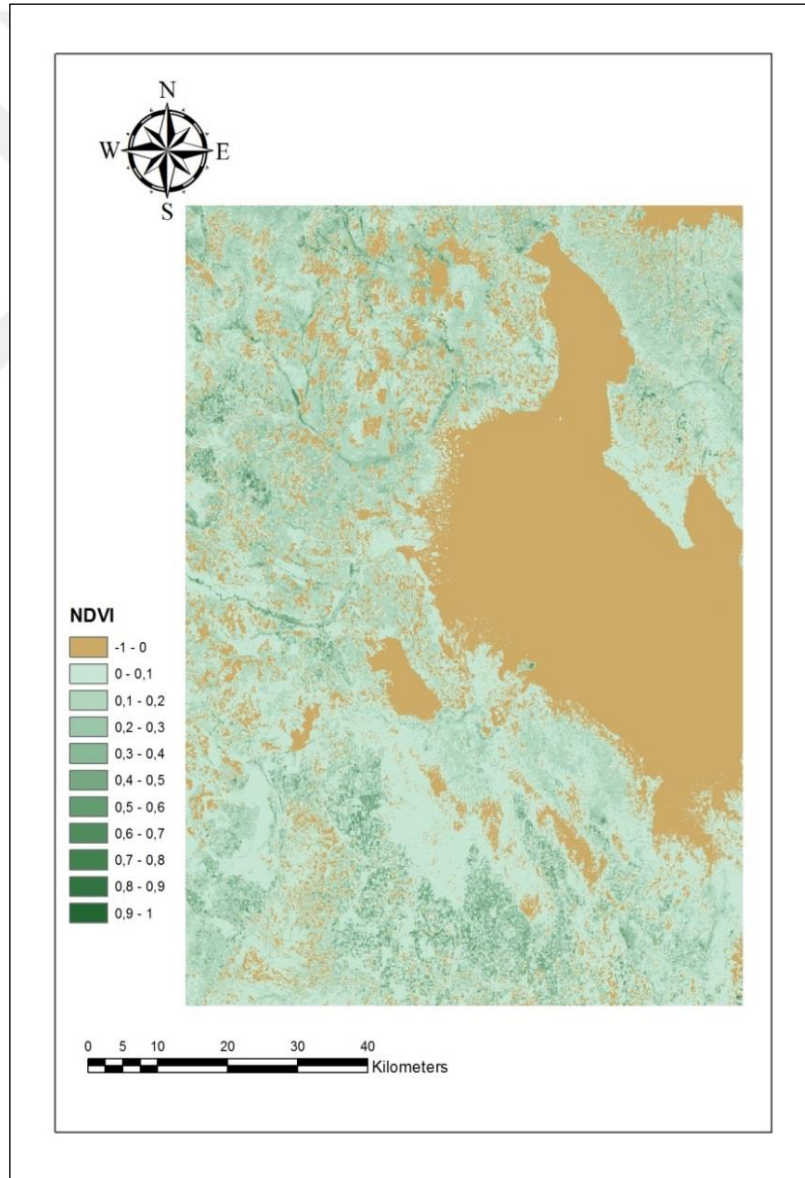


Figure 6.16: Tuz Lake NDVI map for 2002

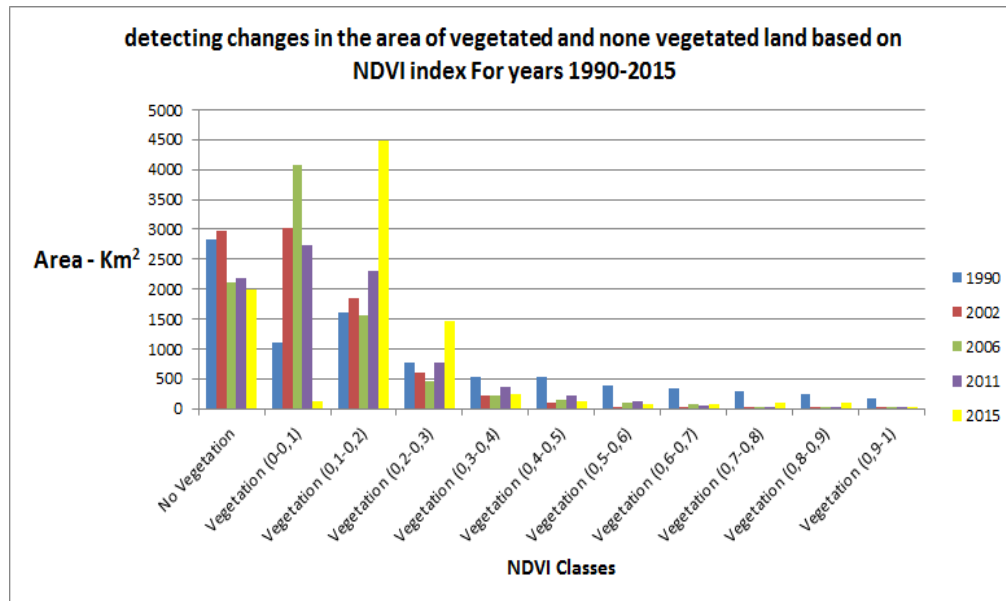


Figure 6.17: Changes in the area of vegetated and none vegetated land based on NDVI index for years 1990-2015.

6.3.1 Comparing NDVI map with salinity map for year 1990

As shown in Figure 6.18 that illustrates NDVI map and salinity map for year 1990 it can easily be seen that in all areas which are classified as none saline with light pink color, there are dense vegetation cover in the corresponding NDVI map that is depicted with dark green color. It can be concluded that as more salt accumulates in soil, the less vegetation density occurs.

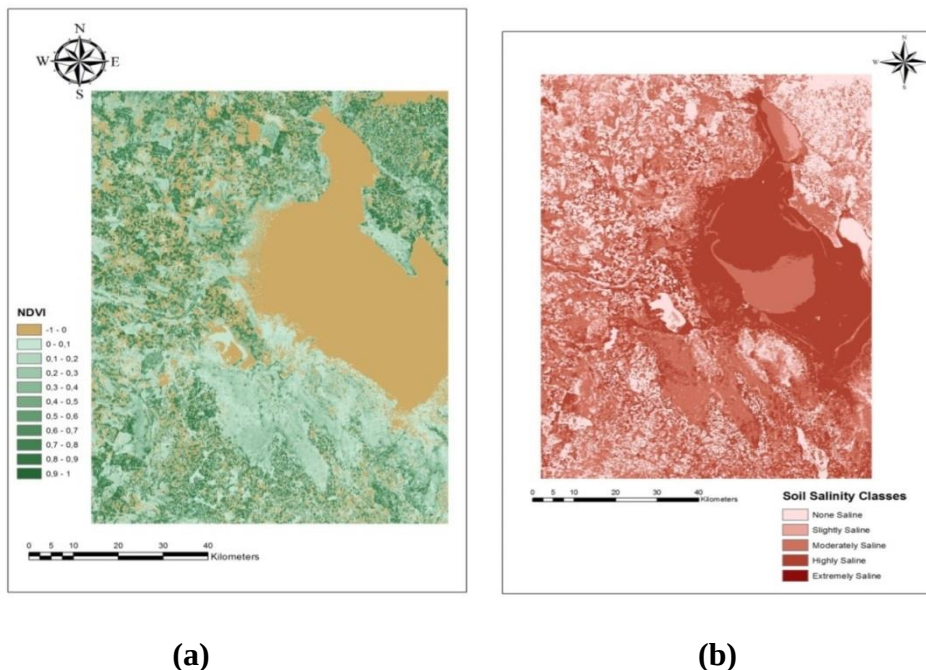


Figure 6.18: (a)NDVI map, and (b)soil salinity map for 1990.

6.4 CORINE Land Cover (CLC) Change Map

Regarding to CORINE land cover changes from 2000 to 2006, the most significant areal changes are due to conversion of natural grassland and vegetated areas to both permanently irrigated and non-irrigated arable lands as shown in Table 6.4, and it might be one of the reasons of salt accumulation in the spot of these changed lands since irrigation causes secondary salinization most of the time. Figure 6.19 illustrates CORINE land cover changes on 2002 salinity map with corresponding ground EC sampling stations.

Comparing CORINE land cover changes from 2006 to 2012 shown in Table 6.5 with similar changes from 2000 to 2006, one can recognize that minor changes that occurred from 2006 to 2012 are not considered as significant regarding secondary soil salinization; but changes from 2000 to 2006 might have been caused soil salinization. In addition, by comparing the overall area of the region with CORINE land cover changes areas, it can be concluded that human-induced soil salinization had slight impact on soil salinization in comparison to natural factors like presence of salt lake, and as a result, occurrence of salty ground water tables in the region.

Table 6.4: CORINE land cover changes from 2000 to 2006.

from 2000		to 2006		Changed area (ha)
3.3.3	Sparsely vegetated areas	2.1.2	Permanently irrigated land	44
3.2.1	Natural grasslands	2.1.2	Permanently irrigated land	1595
3.2.1	Natural grasslands	2.1.1	Non-irrigated arable land	3746
2.1.1	Non-irrigated arable land	1.2.1	Industrial units	8
3.2.1	Natural grasslands	1.2.1	Industrial units	7
Total				5400

Table 6.5: CORINE land cover changes from 2006 to 2012.

from 2006		to 2012		Changed area (ha)
2.1.1	Non-irrigated arable land	2.3.1	Pastures	236
2.1.1	Non-irrigated arable land	1.2.1	Industrial units	18
2.3.1	Pastures	1.3.3	Construction sites	24
2.1.2	Permanently irrigated land	2.3.1	Pastures	22
2.3.1	Pastures	2.1.1	Non-irrigated arable land	104
Total				404

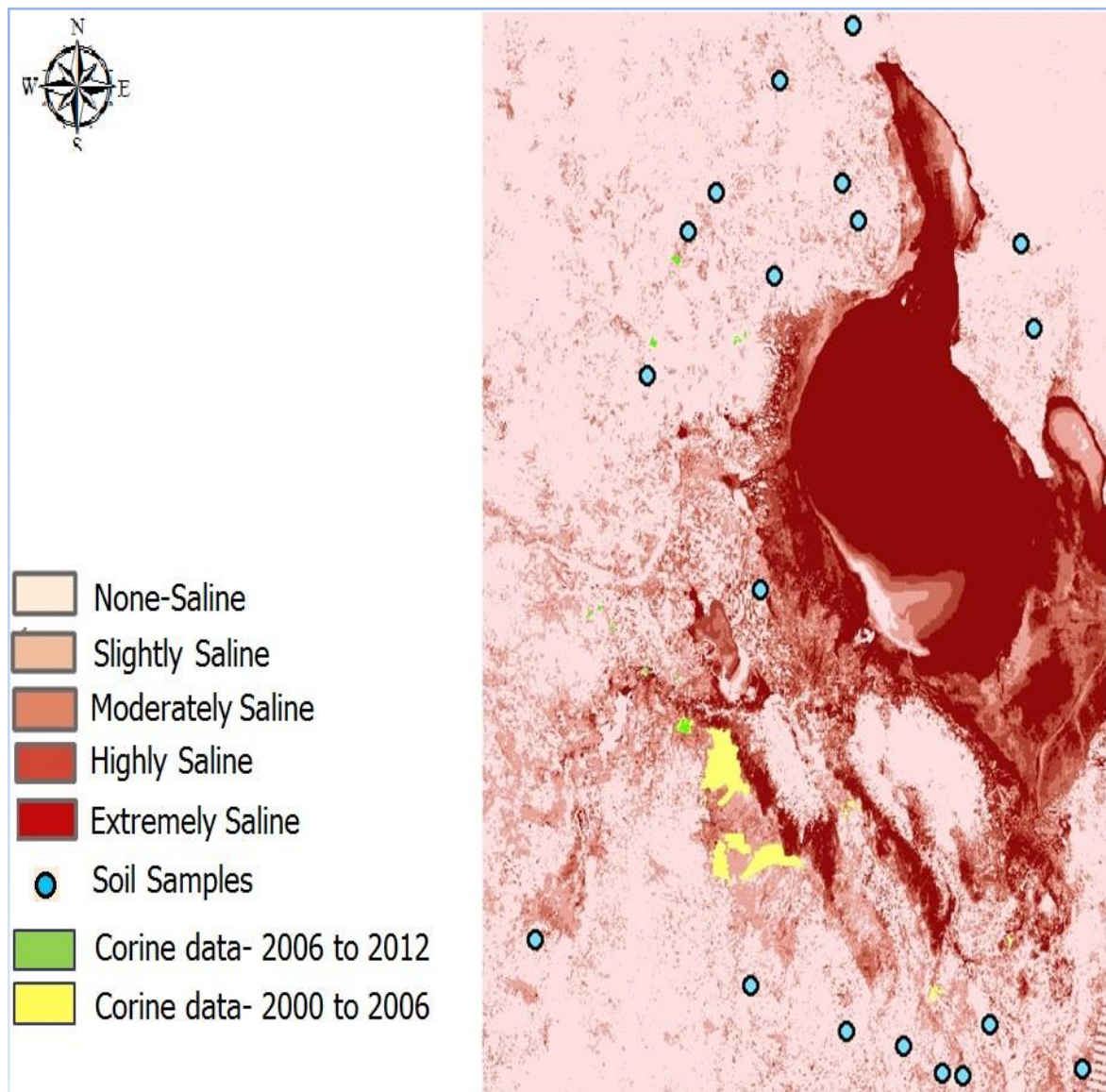


Figure 6.19: CORINE land cover changes in 2002 salinity map with corresponding ground EC sampling stations.

6.5 Final Evaluation For Selecting Best Index And Proper Regression Analysis

All salinity indices which are applied for generating salinity maps, Salinity Index (SI) $1 = \sqrt{B1 * B3}$ depicts best results for both regression analysis and exponential analysis by showing R^2 values 0,778 and 0,961 respectively. Also, this index presented best result among all indices which were used in another study in Central Morocco (Lhissou et al., 2014) by giving R^2 values 0,68. Therefore, the most accurate salinity maps for years 1990, 2006, 2011 and 2015 are generated based on exponential regression results between (SI) $1 = \sqrt{B1 * B3}$ reflectance values and EC values in 2002.

7. CONCLUSIONS AND RECOMMENDATIONS

In this study, a comprehensive review in consideration of soil salinity phenomenon is given that shows soil salinization is one of the significant worldwide problem accelerating the land degradation processes, which in turn cause loss of soil productivity and reduction in biomass production. Population is increasing rapidly and arable lands for supplying food and fabric to human is becoming less and less due to soil salinization. Therefore, it is essential to face with this issue like other environmental catastrophes. However, soil salinization is not as debatable as environmental issues like global warming, climate change, water pollution and scarcity, air pollution and deforestation among scientist and environmental engineers but it should not be underestimated since it is understood if soil salinization will increase in future with this rate, a lot of countries will suffer from producing enough amount of food for their population. For this reason, this study is reviewed natural and human-induced causes of soil salinization and then it is explained that what are best methods for detecting, mapping and predicting soil salinization. In addition commonplace and new methods are introduced for mitigating soil salinization adverse effects .

Due to high spatial and temporal variability of soil salinity, mapping and tracking its changes it is an essential issue for anticipating natural disasters like desertification and for mitigating severe economic and social consequences in especially arid and semi-arid regions of the world. Traditionally, soil salinity monitoring and prediction are often carried out with intensive field work and sampling. Most previous studies have nowadays focused on differentiating salinized soil and non-salinized soil, qualitatively analyzing the distribution of soil salinity and monitoring the dynamics of soil salinity. In recent years, Remote Sensing, GIS and modelling have become the preferred technological tools to map soil salinity due to large area coverage which is of utmost importance both from the agricultural and environmental perspectives. Remote sensing data makes it possible to obtain multi-temporal data for varying

spatial domains and conditions which is a key element to monitor and detect soil salinity. After reviewing various case studies related to soil salinization, a case study for generating salinity maps in Tuz Lake region is conducted by utilizing five different salinity index and two types of regression analysis in order to detect multi-temporal soil salinity changes from year 1990 to 2015. In addition, NDVI maps are generated for tracking changes in vegetation patterns. Also, results of land cover changes using CORINE data shows very little areas are effected by human-induced activities from year 2000 to 2012. therefore, natural parameters are dominant factors for soil salinization in this region.

It is recommended, proper plans and projects in future will be defined for studying and detecting all natural causes of soil salinization in the study area as further research in order to mitigate negative effects of soil salinization. These projects can contain tasks for cultivating halophilic plants in lands which are highly saline and as a result salt-tolerant plant can be effective for reclamation of saline soils.

Introducing new irrigation techniques and designing proper drainage systems, might be another plan for minimizing adverse effects of traditional methods such as flooding irrigation which makes soils more saline.

Further study in utilizing new techniques in genetic engineering for enhancing crop performance in saline condition is also another option for improving agricultural productivity, making crops more salt-tolerant and as a result reclaiming salty soils in the study area.

REFERENCES

- Abbas, A., Khan, S., Hussain, N., Hanjra, M. a., and Akbar, S., 2013.** Characterizing soil salinity in irrigated agriculture using a remote sensing approach. *Physics and Chemistry of the Earth, Parts A/B/C*, 55-57, 43–52.
- Acosta, J. a., Faz, a., Jansen, B., Kalbitz, K., and Martínez-Martínez, S., 2011.** Assessment of salinity status in intensively cultivated soils under semiarid climate, Murcia, SE Spain. *Journal of Arid Environments*, 75(11), 1056–1066.
- Al-Khaier, F., 2003.,** Soil salinity detection using satellite remote sensing. *Geo-Information Science and Earth Observation*.
- Allbed, A., and Kumar, L., 2013.,** Soil Salinity Mapping and Monitoring in Arid and Semi-Arid Regions Using Remote Sensing Technology: A Review. *Advance in Remote Sensing*, 2(December), 373–385.
- Allbed, A., Kumar, L., and Aldakheel, Y. Y. 2014.,** Assessing soil salinity using soil salinity and vegetation indices derived from IKONOS high-spatial resolution imageries: Applications in a date palm dominated region. *Geoderma*, 230-231, 1–8.
- Arnous, M. O., and Green, D. R. 2015.,** Monitoring and assessing waterlogged and salt-affected areas in the Eastern Nile Delta region, Egypt, using remotely sensed multi-temporal data and GIS. *Journal of Coastal Conservation*, 19(3), 369–391.
- Atasoy, A. D. 2008.,** Environmental problems in vertisol soils: The example of the Harran Plain. *Fresenius Environmental Bulletin*, 17(7a), 837–843.
- Bannari, a., Guedon, a. M., El-Harti, a., Cherkaoui, F. Z., and El-Ghmari, a. 2008.,** Characterization of Slightly and Moderately Saline and Sodic Soils in Irrigated Agricultural Land using Simulated Data of Advanced Land Imaging (EO-1) Sensor. *Communications in Soil Science and Plant Analysis*, 39(19-20), 2795–2811.
- Bell, D., Menges, C., Ahmad, W., and van Zyl, J. 2001.,** The Application of Dielectric Retrieval Algorithms for Mapping Soil Salinity in a Tropical Coastal Environment Using Airborne Polarimetric SAR. *Remote Sensing of Environment*, 75, 375–384.
- Bhatt, M. J., Patel, A. D., Bhatti, P. M., and Pandey, A. N. 2008.,** EFFECT OF SOIL SALINITY ON GROWTH , WATER STATUS AND NUTRIENT ACCUMULATION IN SEEDLINGS OF *Ziziphus mauritiana* (RHAMNACEAE), 16, 383–401.
- Biswas, T., Bourne, J., Schrale, G., and Mccarthy, M. 2009.,** IRRIGATION MANAGEMENT Update Salinity Management Practice Guidelines.

- Brown, J. W., Hayward, H. E., Richards, A., Bernstein, L., Hatcher, J. T., Reeve, R. C., and Richards, L. A.** 1954., Diagnosis and Improvement of Saline and Alkali soils, United States Department of Agriculture, Agriculture handbook, NO 60.
- Burn, S., Hoang, M., Zarzo, D., Olewniak, F., Campos, E., Bolto, B., and Barron, O.** 2015., Desalination techniques — A review of the opportunities for desalination in agriculture. *Desalination*, 364, 2–16.
- Das, T.** 2009., Land Use / Land Cover Change Detection: an Object Oriented Approach. thesis master of science in geospatial technologies. Institute of Geoinformatics, University of Münster.
- Devkota, M., Martius, C., Gupta, R. K., Devkota, K. P., McDonald, a. J., and Lamers, J. P. a.** 2015., Managing soil salinity with permanent bed planting in irrigated production systems in Central Asia. *Agriculture, Ecosystems & Environment*, 202, 90–97.
- Dimkpa, C., Weinand, T., and Asch, F.** 2009., Plant – rhizobacteria interactions alleviate abiotic, 1682–1694.
- Ding, J. and Yu, D.** 2014., Monitoring and evaluating spatial variability of soil salinity in dry and wet seasons in the Werigan–Kuqa Oasis, China, using remote sensing and electromagnetic induction instruments. *Geoderma*, 235–236, 316–322.
- Douaoui, A. E. K., Nicolas, H., and Walter, C.** 2006., Detecting salinity hazards within a semiarid context by means of combining soil and remote-sensing data. *Geoderma*, 134(1-2), 217–230.
- Eastman, J. R.** 2001., Release 2 Guide to GIS and Image Processing Volume 1, 1.
- Elnaggar, A. a., and Noller, J. S.** 2009., Application of Remote-sensing Data and Decision-Tree Analysis to Mapping Salt-Affected Soils over Large Areas. *Remote Sensing*, 2(1), 151–165.
- Faculty, C. E., and Division, R. S.** 2003., Use of Real-Time Remote Sensing Data for Evaluating Soil Moisture and Salinity Effects on Light Penetration Depth.
- Farifteh, J., Meer, F. Van Der, Meijde, M. Van Der, and Atzberger, C.** 2008., Geoderma Spectral characteristics of salt-affected soils: A laboratory experiment, 145, 196–206.
- Farifteh, J., Tolpekin, V., Van Der Meer, F., and Sukchan, S.** 2010., Salinity modelling by inverted Gaussian parameters of soil reflectance spectra. *International Journal of Remote Sensing*, 31(12), 3195–3210.
- Farifteh, J., Van der Meer, F., Atzberger, C., and Carranza, E. J. M.** 2007., Quantitative analysis of salt-affected soil reflectance spectra: A comparison of two adaptive methods (PLSR and ANN). *Remote Sensing of Environment*, 110(1), 59–78.
- Fernández-Buces, N., Siebe, C., Cram, S., and Palacio, J. L.** 2006., Mapping soil salinity using a combined spectral response index for bare soil and vegetation: A case study in the former lake Texcoco, Mexico. *Journal of Arid Environments*, 65(4), 644–667.

- Glenn, E. P., Brown, J. J., Blumwald, E., Glenn, E. P., Brown, J. J., and Blumwald, E.,** 2016., *Critical Reviews in Plant Sciences Salt Tolerance and Crop Potential of Halophytes Salt Tolerance and Crop Potential of Halophytes*, Vol. 2689.
- Gorji, T., Tanik, A., and Sertel, E.,** 2015., Soil Salinity Prediction, Monitoring and Mapping Using Modern Technologies. *Procedia Earth and Planetary Science*, 15, 507–512.
- Haji, S., and Zarea, M. J.,** 2012., Yield and yield components of wheat as affected by salinity and inoculation with *Azospirillum* strains from saline or non-saline soil. *Journal of the Saudi Society of Agricultural Sciences*, 11(2), 113–121.
- Horneck, D. A., Ellsworth, J. W., Hopkins, B. G., Sullivan, D. M., and Stevens, R. G.,** 2007., Managing Salt - affected S oils for Crop Production.
- Huete, a., Justice, C., and Liu, H.,** 1994., Development of vegetation and soil indices for MODIS-EOS. *Remote Sensing of Environment*, 49(3), 224–234.
- Huete, a.,** 1988., A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309.
- Ie, E. V, Wang, W., Vinocur, B., and Altman, A.,** 2003., Plant responses to drought , salinity and extreme temperatures : towards genetic engineering for stress tolerance, 1–14.
- Kaur, N., Sharma, S., Kaur, S., and Nayyar, H.** 2014., Selenium in agriculture : a nutrient or contaminant for crops , 0340.
- Kaur, S., and Nayyar, H.** 2015., Scientia Horticulturae Selenium fertilization to salt-stressed mungbean plants reduces sodium uptake , improves reproductive function , pod set and seed yield, 197, 304–317.
- Khan, N. M., Rastoskuev, V. V., Sato, Y., and Shiozawa, S.** 2005., Assessment of hydrosaline land degradation by using a simple approach of remote sensing indicators. *Agricultural Water Management*, 77(1-3), 96–109.
- Kilic, O., and Kilic, A. M.** 2010., Salt crust mineralogy and geochemical evolution of the Salt Lake (Tuz Gölü), Turkey, 5(11), 1317–1324.
- Koohafkan, P.** 2008., Water and Cereals in Drylands. The Food and Agriculture Organization of the United Nations and Earthscan.
- Kumar, P.** 2015., Design & Development of Automatic Soil Salinity Control System, 5(3), 191–196.
- Kumar, S., Gautam, G., and Saha, S. K.** 2015., Hyperspectral remote sensing data derived spectral indices in characterizing salt-affected soils: a case study of Indo-Gangetic plains of India. *Environmental Earth Sciences*, 73(7), 3299–3308.
- Lhissou, R., El, A., and Chokmani, K.** 2014., Mapping soil salinity in irrigated land using optical remote sensing data, 3, 82–88.
- Li, J., Pu, L., Zhu, M., Dai, X., Xu, Y., Chen, X., and Zhang, R.** 2015., Monitoring soil salt content using HJ-1A hyperspectral data: A case study of coastal areas in Rudong County, Eastern China. *Chinese Geographical Science*, 25(2), 213–223.

- Liang, S., Member, S., Fang, H., and Chen, M.** 2001., Atmospheric Correction of Landsat ETM + Land Surface Imagery — Part I : Methods, 39(11), 2490–2498.
- Masoud, A. a.** 2014., Predicting salt abundance in slightly saline soils from Landsat ETM+ imagery using Spectral Mixture Analysis and soil spectrometry. *Geoderma*, 217-218, 45–56.
- Melendez-Pastor, I., Hernández, E. I., Navarro-Pedreño, J., and Gómez, I.** 2012., Mapping Soil Salinization of Agricultural Coastal Areas in Southeast Spain. *Remote Sensing Applications*, 117–140.
- Mergen, O., and Karacaoglu, C.** 2015., Tuz Lake Special Environment Protection Area , Central Anatolia , Turkey : The EUNIS Habitat Classification and Habitat Change Detection between 1987 and 2007, 9, 1–9.
- Metternicht, G., and Zinck, J.** 2003., Remote sensing of soil salinity: potentials and constraints. *Remote Sensing of Environment*, 85(1), 1–20.
- Munns, R., and Munns, R.** 2005., Genes and salt tolerance : bringing them together. *New Phytologist*, 167: 645–663.
- Nawar, S., Buddenbaum, H., Hill, J., and Kozak, J.** 2014., Modeling and Mapping of Soil Salinity with Reflectance Spectroscopy and Landsat Data Using Two Quantitative Methods (PLSR and MARS). *Remote Sensing*, 6(11), 10813–10834.
- Odongo, V. O., Hamm, N. A. S., and Milton, E. J.** 2014., Spatio-Temporal Assessment of Tuz Gölü, Turkey as a Potential Radiometric Vicarious Calibration Site, 2494–2513.
- Ouni, Y., Ghnaya, T., Montemurro, F., Abdelly, C., and Lakhdar, A.** 2014., The role of humic substances in mitigating the harmful effects of soil salinity and improve plant productivity.
- Polous, K., Farshad, A., Zarinkafsh, M., and Roozitalab, M. H.** 2011., Evaluation of the spatio-temporal of soil salinity variation using data mining approach. *Proceedings 2011 IEEE International Conference on Spatial Data Mining and Geographical Knowledge Services*, 81–86.
- Postiglione, L.** 2002., 13 Soil Salinization in the Mediterranean: Soils, Processes and Implications. *Mediterranean Desertification: A Mosaic of Processes and Responses*, 163.
- Radhakrishnan, R., and Lee, I.** 2015., Penicillium – sesame interactions : A remedy for mitigating high salinity stress effects on primary and defense metabolites in plants. *Environmental and Experimental Botany*, 116, 47–60.
- Ramak, R., Valadan Zouj, M. J., and Mojaradi, B.** 2015., Improving Linear Spectral Unmixing Through Local Endmember Detection. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XL-3/W2, 177–181.
- Rengasamy, P., North, S., and Smith, A.** 2010., Diagnoses and Management of Sodicity & Salinity in soil and water in the Murray Irrigation region. Report from University of Adelaide, Australia. ISBN: 0975013440.

- Schilling, R. K., Marschner, P., Shavrukov, Y., Berger, B., Tester, M., Roy, S. J., and Plett, D. C.** 2014., Expression of the Arabidopsis vacuolar H⁺-pyrophosphatase gene (AVP1) improves the shoot biomass of transgenic barley and increases grain yield in a saline field, 378–386.
- Sciences, M.** 2006., Causes, origin, genesis and extent of soil salinity in the sultanate of oman, 43, 1–6.
- Scudiero, E., Skaggs, T. H., and Corwin, D. L.** 2014., Regional scale soil salinity evaluation using Landsat 7, western San Joaquin Valley, California, USA. *Geoderma Regional*, 2-3, 82–90.
- Shippert, P.** 2004., Why Use Hyperspectral Imagery?, *Photogrammetric Engineering & Remote Sensing*, 377–379.
- Shrestha, D. P., and Farshad, A.** 2009., Mapping Salinity Hazard: An Integrated Application of Remote Sensing and Modeling-Based Techniques. *Remote Sensing of Soil Salinization: Impact on Land Management*, 257–272.
- Shrivastava, P., and Kumar, R.** 2015., Soil salinity: A serious environmental issue and plant growth promoting bacteria as one of the tools for its alleviation. *Saudi Journal of Biological Sciences*, 22(2), 123–131.
- Sidike, A., Zhao, S., and Wen, Y.** 2014., Estimating soil salinity in Pingluo County of China using QuickBird data and soil reflectance spectra. *International Journal of Applied Earth Observation and Geoinformation*, 26, 156–175.
- Stockle, C. O.** 1996., Environmental impact of irrigation: a review, 1–15.
- Sun, J., Kang, Y., Wan, S., Hu, W., Jiang, S., and Zhang, T.** 2012., Soil salinity management with drip irrigation and its effects on soil hydraulic properties in north China coastal saline soils. *Agricultural Water Management*, 115, 10–19.
- Tempfli, K., Kerle, N., Huurneman, G. C., Janssen, L. L. F., Bakker, W. H., Feringa, W., and Woldai, T.** 2009., Principles of Remote Sensing, An introductory textbook , the international institute for Geo-information science and earth observation.
- Tengberg, A. E., Tucker, C. J., Yengoh, G. T., Dent, D., Olsson, L., Tengberg, A. E., and Compton, J.** 2014., The use of the Normalized Difference Vegetation Index (NDVI) to assess land degradation at multiple scales : a review of the current status , future trends , and practical considerations. A report by commissioned by the Scientific and Technical Advisory Panel of the Global Environment Facility (STAP/GEF).
- Triki Fourati, H., Bouaziz, M., Benzina, M., and Bouaziz, S.** 2015., Modeling of soil salinity within a semi-arid region using spectral analysis. *Arabian Journal of Geosciences*, 11175–11182.
- Tuz Lake Report, 2004.** Final Report of the Project on the Determination of Alternative Agricultural Practices and Quality Classification of Soil and Land at Tuz Lake Special Protection Area, TR Ministry of Environment and Forestry General Directorate of Special Environmental Protection Agency & Ankara Research Institute under the General Directorate of Village Affairs, October 2004, Ankara, 391 pages.

- Ucan, H. N., and Dursun, S.** 2009., Environmental Problems of Tuz Lake (Konya-Turkey), 231–233.
- Vasques, G. M., Grunwald, S., and Harris, W. G.** 2010., Spectroscopic Models of Soil Organic Carbon in Florida, USA. *Journal of Environment Quality*, 39(3), 923.
- Wang, X., Yang, J., Liu, G., Yao, R., and Yu, S.** 2015., Impact of irrigation volume and water salinity on winter wheat productivity and soil salinity distribution. *Agricultural Water Management*, 149, 44–54.
- Weiss, E., Marsh, S. E., and Pfirman, E. S.** 2016., Application of NOAA-AVHRR NDVI time-series data to assess changes in Saudi Arabia ’ s rangelands, 1161.
- Wichelns, D., and Qadir, M.** 2015., Achieving sustainable irrigation requires effective management of salts, soil salinity, and shallow groundwater. *Agricultural Water Management*, 157, 31–38.
- Wicke, B., Smeets, E., Dornburg, V., Vashev, B., Gaiser, T., Turkenburg, W., and Faaij, A.** 2011., The global technical and economic potential of bioenergy from salt-affected soils. *Energy & Environmental Science*, 4(8), 2669.
- Wu, J., Vincent, B., Yang, J., Bouarfa, S., and Vidal, A.** 2008., Remote Sensing Monitoring of Changes in Soil Salinity: A Case Study in Inner Mongolia, China. *Sensors*, 8(11), 7035–7049.
- Wu, W., Mhaimed, A. S., Al-Shafie, W. M., Ziadat, F., Dhehibi, B., Nangia, V., and De Pauw, E.** 2014., Mapping soil salinity changes using remote sensing in Central Iraq. *Geoderma Regional*, 2-3, 21–31.
- Yahiaoui, I., Douaoui, A., Zhang, Q., and Ziane, A.** 2015., Soil salinity prediction in the Lower Cheliff plain (Algeria) based on remote sensing and topographic feature analysis. *Journal of Arid Land*, 7(6), 794–805.
- Zhang, L.,** 2004., A biological approach to salinized soil amelioration in arid Northwest China – Saline water irrigated trees and shrubs on saline sodic soil, 165–182.
- Zhang, T.-T., Qi, J.-G., Gao, Y., Ouyang, Z.-T., Zeng, S.-L., & Zhao, B.** 2015., Detecting soil salinity with MODIS time series VI data. *Ecological Indicators*, 52, 480–489.
- Url-1**<<http://www.fao.org/docrep/012/i0372e/i0372e01>>, accessed at 12.02.2016.
- Url-2**<<http://www.fao.org/docrep/012/i0372e/i0372e01.pdf>> accessed at 11.12.2015.
- Url-3**<<http://pubs.rsc.org/en/content/articlehtml/2011/ee/c1ee01029h>> accessed at 08.10.2015.
- Url-4**<<http://www.intechopen.com/books/responses-of-organisms-to-water-stress/comparison-between-the-water-and-salt-stress-effects-on-plant-growth-and-development>> accessed at 20.09.2015.
- Url-5**< <http://www.delta-t.co.uk/product-display.asp?id=WET-2%20Product&div=Irrigation%20and%20Horticulture> > accessed at 20.09.2015.
- Url-6**<<http://www.csb.gov.tr/projeler/ockb/index.php?Sayfa=sayfa&Tur=7793>> accessed at 22.10.2015.

- Url-7** <<http://abcnews.go.com/International/salt-lake-turkey-turns-red-algae-bloom/story?id=32590572>> accessed at 21.08.2015.
- Url-8** <<http://abcnews.go.com/International/salt-lake-turkey-turns-red-algae-bloom/story?id=32590572>> accessed at 09.02.2016.
- Url-9** <<http://www.mgm.gov.tr/veridegerlendirme/yillik-toplam-yagis-verileri.aspx?m=aksaray#sfB>> accessed at 17.01.2016.
- Url-10** <http://wiki.landscapetoolbox.org/doku.php/remote_sensor_types:landsat_tm_5> accessed at 17.04.2016.
- Url-11** <http://landsat.usgs.gov/about_landsat5.php> accessed at 16.08.2015.
- Url-12** <http://landsat.usgs.gov/band_designations_landsat_satellites.php> accessed at 11.11.2015.
- Url-13** <<http://www.eea.europa.eu/publications/COR0-landcover>> accessed at 16.08.2015.
- Url-14** <http://wiki.openstreetmap.org/wiki/Corine_Land_Cover> accessed at 16.05.2015.
- Url-15** <<http://www.analyticsvidhya.com/blog/2015/08/comprehensive-guide-regression/>> accessed at 14.01.2016.
- Url-16** <http://dufu.math.ncu.edu.tw/calculus/calculus_pre/node8.html> accessed at 11.02.2016.



APPENDICES

APPENDIX A: EC values with related SI values and EC values for 322 soil samples

Table A.1: Groundtruth EC values (ds/m) with their corresponding SI 1
 $= (B1 * B3)^{0.5}$ Values in year 2002.

Sample No	EC values (ds/m)	SI 1 Values $SI = (B1 * B3)^{0.5}$
1	1,216	0,3850
2	1,898	0,4383
3	1,757	0,4196
4	0,906	0,3748
5	1,108	0,3823
6	4,433	0,4815
7	1,538	0,4010
8	2,316	0,4465
9	0,852	0,3505
10	1,111	0,3841
11	0,763	0,3239
12	0,668	0,3039
13	1,004	0,3817
14	0,71	0,3102
15	0,454	0,2793
16	5,431	0,5215
17	0,46	0,2793
18	0,524	0,2953
19	0,745	0,3155

Table A.2: Ground truth EC values (ds/m) with their corresponding SI 2 Values
 $SI=(B2*B3)^{0.5}$ in year 2002.

Sample No	EC values (ds/m)	SI 2 Values $SI=(B2*B3)^{0.5}$
1	1,216	0,2939
2	1,898	0,3340
3	1,757	0,3257
4	0,906	0,2796
5	1,108	0,2950
6	4,433	0,3511
7	1,538	0,2983
8	2,316	0,3437
9	0,852	0,2628
10	1,111	0,2879
11	0,763	0,2377
12	0,668	0,2270
13	1,004	0,2819
14	0,71	0,2280
15	0,454	0,1988
16	5,431	0,3944
17	0,46	0,2012
18	0,524	0,2126
19	0,745	0,2320

Table A.3: Ground truth EC values (ds/m) with their corresponding SI 3 Values
 $SI=((B2)^2+(B3)^2+(B4)^2)^{0.5}$ in year 2002.

Sample No	EC values (ds/m)	SI 3 Values
		$SI=((B2)^2+(B3)^2+(B4)^2)^{0.5}$
1	1,216	0,6502
2	1,898	0,6289
3	1,757	0,6720
4	0,906	0,5817
5	1,108	0,6120
6	4,433	0,7034
7	1,538	0,6026
8	2,316	0,6601
9	0,852	0,5014
10	1,111	0,5876
11	0,763	0,5070
12	0,668	0,5156
13	1,004	0,5862
14	0,71	0,5213
15	0,454	0,4574
16	5,431	0,7585
17	0,46	0,4619
18	0,524	0,4822
19	0,745	0,5105

Table A.4: Ground truth EC values (ds/m) with their corresponding SI 4 Values
 $SI = ((B2)^2 + (B3)^2)^{0,5}$ in year 2002.

Sample No	EC values (ds/m)	SI 4 Values $SI = ((B2)^2 + (B3)^2)^{0,5}$
1	1,216	0,4243
2	1,898	0,4906
3	1,757	0,4853
4	0,906	0,4053
5	1,108	0,4283
6	4,433	0,5059
7	1,538	0,4348
8	2,316	0,5049
9	0,852	0,3841
10	1,111	0,4215
11	0,763	0,3468
12	0,668	0,3285
13	1,004	0,4077
14	0,71	0,3326
15	0,454	0,2897
16	5,431	0,5733
17	0,46	0,2920
18	0,524	0,3095
19	0,745	0,3435

Table A.5: Ground truth EC values (ds/m) with their corresponding SI 5 Values
 $SI = ((B3)^2 + (B4)^2)^{0,5}$ in year 2002.

Sample No	EC values (ds/m)	SI 5 Values $SI = ((B3)^2 + (B4)^2)^{0,5}$
1	1,216	0,5983
2	1,898	0,5660
3	1,757	0,6204
4	0,906	0,5306
5	1,108	0,5584
6	4,433	0,6333
7	1,538	0,5482
8	2,316	0,5968
9	0,852	0,4512
10	1,111	0,5370
11	0,763	0,4664
12	0,668	0,4774
13	1,004	0,5337
14	0,71	0,4851
15	0,454	0,4258
16	5,431	0,6811
17	0,46	0,4291
18	0,524	0,4478
19	0,745	0,4751

Table 4.4: All soil samples with their corresponding Electrical Conductivity values.

Coordinate				Coordinate			
Item	Y	X	EC(ds/m)	Item	Y	X	EC(ds/m)
1	4259167	575850	0,682	49	4246659	581623	1,428
2	4257529	573415	0,803	50	4247023	584533	0,775
3	4258207	571741	1,1	51	4250820	580021	1,413
4	4258580	566102	2,936	52	4250771	576603	1,025
5	4259727	564439	3,204	53	4248924	573300	2,183
6	4258164	560630	9,174	54	4246601	572602	2,864
7	4253963	570332	1,777	55	4246602	568670	4,375
8	4251426	575375	1,71	56	4249177	569472	1,759
9	4251517	576666	2,125	57	4249661	566327	1,333
10	4247238	583708	1,113	58	4253421	567390	1,667
11	4250592	582093	1,123	59	4252598	568813	3,973
12	4246376	577840	15,494	60	4255373	568319	1,775
13	4244609	576037	4,506	61	4259358	565952	2,596
14	4245135	570157	3,433	62	4262948	566044	2,803
15	4244638	567393	1,512	63	4264949	566086	2,235
16	4245114	558952	2,225	64	4266864	565705	3,251
17	4245997	556089	14,903	65	4264224	570748	1,518
18	4247607	536831	1,385	66	4263340	572341	0,832
19	4245748	539875	1,052	67	4255831	572867	1,362
20	4243300	542013	1,781	68	4255835	575248	1,512
21	4239477	544362	0,724	69	4257243	577153	0,813
22	4236039	543965	2,782	70	4228141	531015	0,746
23	4234187	551766	10,748	71	4228374	534780	1,042
24	4235428	553520	3,61	73	4228109	537395	1,898
25	4237109	562299	1,972	74	4229575	536553	1,757
26	4244633	577742	1,903	75	4229545	538961	0,812
27	4241550	578188	1,439	76	4229020	541213	0,763
28	4240708	577127	1,001	77	4233237	540873	2,856
29	4237946	578761	0,534	78	4232965	545336	0,906
32	4236013	568478	1,264	79	4235114	546135	0,772
38	4232440	557434	5,152	80	4236507	547895	0,577
40	4230949	556685	0,752	81	4237907	546904	1,131
41	4228805	552640	2,227	82	4239597	544243	0,765
43	4228651	547298	1,216	83	4240349	540915	1,513
44	4229896	545649	0,909	84	4241362	538472	2,043

Table 4.4: Continued.

Coordinate				Coordinate			
Item	Y	X	EC(ds/m)	Item	Y	X	EC(ds/m)
85	4236466	533926	1,098	120	4248085	487555	4,433
86	4235622	536088	2,085	121	4255343	488532	0,835
87	4231949	539654	0,927	122	4259834	489487	1,008
88	4232305	537640	1,848	123	4264750	492618	0,936
89	4233077	537241	0,61	124	4266321	504518	0,948
90	4232395	536004	0,694	125	4267163	514166	1,432
91	4231759	534910	0,731	126	4267389	515336	0,523
92	4232300	531971	0,989	127	4271705	523461	24,638
93	4233967	529902	1,322	128	4264622	518515	0,685
94	4236500	529864	1,038	129	4262884	516482	1,113
95	4238865	530035	0,873	130	4260440	518205	0,896
96	4241055	530625	0,95	131	4257034	521826	0,763
97	4243805	532110	0,921	132	4253007	523250	1,089
98	4249914	534514	1,044	133	4246805	526260	1,037
99	4247217	528876	0,888	134	4241634	522206	1,002
100	4247869	528211	1,085	135	4232621	522575	1,057
101	4249489	525460	0,993	136	4234462	521930	1,538
102	4248796	524040	1,891	137	4236817	521670	0,87
103	4251448	525220	0,634	138	4234922	520016	0,829
104	4254342	523991	1,063	139	4236066	517074	0,804
105	4246586	529019	0,838	140	4238491	517260	1,022
106	4244340	529482	1,139	141	4238645	514792	0,891
107	4243721	527704	1,096	142	4242809	516412	2,299
108	4242480	527879	0,723	143	4246082	518028	1,38
109	4240001	523240	1,354	144	4247606	518046	0,889
110	4239433	521617	1,461	145	4253031	502022	0,911
111	4238971	524041	0,975	146	4255321	499974	0,81
112	4236108	525714	1,701	147	4255936	498130	0,723
113	4235664	526460	1,23	148	4257973	499313	0,943
114	4234013	528089	1,307	149	4259566	501935	2,829
115	4232556	528257	2,028	150	4260630	504211	0,938
116	4231128	529769	1,234	151	4256690	504462	0,787
117	4239038	480960	1,108	152	4250411	505654	5,681
118	4241228	482170	1,982	153	4247101	507320	1,028
119	4241983	483007	0,887	154	4243510	510311	0,948

Table 4.4: Continued.

Coordinate				Coordinate			
Item	Y	X	EC(ds/m)	Item	Y	X	EC(ds/m)
155	4241983	509651	0,908	190	4304980	539089	0,461
156	4238601	509160	0,759	191	4297187	540730	0,84
157	4237300	510410	1,088	192	4302156	540785	0,492
158	4239408	511370	2,316	193	4303226	542895	1,617
159	4244818	507087	1,1	194	4304977	542998	0,532
160	4244828	504350	3,183	195	4306816	543358	2,625
161	4243423	502399	1,106	196	4306004	545925	1,617
162	4240830	501768	0,87	197	4304193	546408	7,616
163	4240667	503568	1,169	198	4301906	550710	0,852
164	4242371	505218	0,524	199	4300121	551532	1,011
165	4238465	505410	0,91	200	4297270	552091	1,394
166	4236778	504578	1,61	201	4294685	553944	0,75
167	4236646	501856	1,02	202	4289680	557673	1,57
168	4237326	499060	0,966	203	4286761	558613	2,578
169	4236321	497973	0,996	204	4322371	505042	0,527
170	4240500	490558	0,441	205	4323069	506426	0,391
171	4239620	492127	0,463	206	4325754	508555	1,617
172	4241772	494831	0,756	207	4324395	511044	0,513
173	4239750	496484	0,536	208	4322675	512681	1,324
174	4241742	497570	0,969	209	4322490	514503	1,336
175	4242944	499200	0,974	210	4321131	517731	1,147
176	4246850	500440	0,574	211	4318972	522039	0,538
177	4249878	499930	0,927	212	4318715	525148	1,111
178	4248107	497124	0,912	213	4314759	527835	0,607
179	4245006	496171	0,624	214	4312338	526391	0,52
180	4243780	493532	0,816	215	4312169	523490	1,125
181	4243013	489373	1,225	216	4315094	524137	0,487
182	4245543	489777	0,879	217	4312723	521295	0,763
183	4247400	493125	0,484	218	4313454	516908	1,137
184	4248755	491344	0,492	219	4317069	514895	1,074
185	4253157	485873	0,874	220	4317171	517210	0,492
186	4315472	541034	0,464	221	4319699	511643	1,207
187	4313753	541598	1,182	222	4321928	509528	0,506
188	4311336	539973	0,899	223	4318902	508520	1,113
189	4307579	538924	0,574	224	4318085	506000	0,668

Table 4.4: Continued.

Coordinate				Coordinate			
Item	Y	X	EC(ds/m)	Item	Y	X	EC(ds/m)
225	4315955	506257	0,463	265	4287110	506397	0,764
226	4314021	502374	0,411	266	4286470	507408	0,964
227	4310476	507517	1,004	267	4284313	507763	0,779
228	4310708	511311	0,429	268	4281715	508866	0,801
229	4311735	513737	0,492	269	4277534	511576	0,81
230	4309545	513367	1,207	270	4274562	513018	5,431
231	4306242	510614	0,71	271	4272329	514601	0,689
232	4304419	506969	0,623	272	4332411	517581	0,537
233	4306952	504812	0,466	273	4330401	518495	0,585
234	4304060	503796	0,766	274	4328181	519186	0,448
235	4299335	504438	0,917	275	4326673	521423	0,505
236	4299320	497177	0,454	276	4324405	520678	0,616
237	4294392	495222	0,438	277	4323852	521769	0,731
238	4292474	498090	0,488	278	4323067	523984	0,633
239	4293257	499425	0,454	279	4322062	525791	0,631
240	4251638	482672	0,537	280	4324564	526495	0,743
241	4253627	482465	0,561	281	4326864	525975	0,692
242	4255860	483159	0,541	282	4328503	525342	0,572
243	4257167	482320	0,694	283	4331809	523337	0,593
244	4260116	481753	0,388	284	4335033	523365	0,46
245	4262218	482458	1,32	285	4333736	520004	0,516
246	4260856	484061	0,472	286	4332100	515855	0,514
247	4266566	486063	0,509	287	4330689	515354	0,773
248	4268881	484754	0,642	288	4329478	514021	0,524
249	4270066	482717	0,478	289	4330222	513047	0,522
250	4272346	481329	0,471	290	4294762	553639	0,693
251	4275151	483422	0,539	291	4292641	555499	0,867
252	4271826	484231	0,469	292	4289180	557358	0,847
253	4274067	485313	1,463	293	4285220	558780	0,699
254	4277418	487675	0,625	294	4283108	560596	0,8
255	4278960	485435	0,471	295	4281377	560793	0,663
256	4278450	482908	0,615	296	4280158	561961	0,679
257	4279468	480508	0,472	297	4277662	563428	0,879
258	4281873	480080	0,397	298	4276411	564721	0,704
259	4274740	490481	0,856	299	4272464	567728	1,082
260	4273595	494005	1,819	300	4275040	565485	0,734
261	4280115	495950	0,83	301	4312755	544752	1,018
262	4283071	496788	0,52	302	4306641	549340	0,745
263	4285662	497627	0,71	303	4307798	546334	0,669
264	4287529	503736	0,593	304	4265190	574514	0,832

Table 4.4: Continued.

Coordinate				Coordinate			
Item	Y	X	EC(ds/m)	Item	Y	X	EC(ds/m)
305	4300414	546047	0,78	315	4282950	493186	0,879
306	4296501	547711	0,757	316	4279157	498189	0,588
307	4254940	581384	1,444	317	4266375	498591	5,408
308	4237864	565170	0,432	318	4267109	488000	0,53
309	4233182	556428	2,211	319	4300844	553006	0,473
310	4238570	562569	1,389	320	4230251	545793	0,736
311	4251062	537676	6,393	321	4238113	577009	0,995
312	4261066	486648	8,191	322	4246019	566657	2,249
313	4264651	486567	0,485				

APPENDIX B: NDVI, salinity maps and regression analysis results.

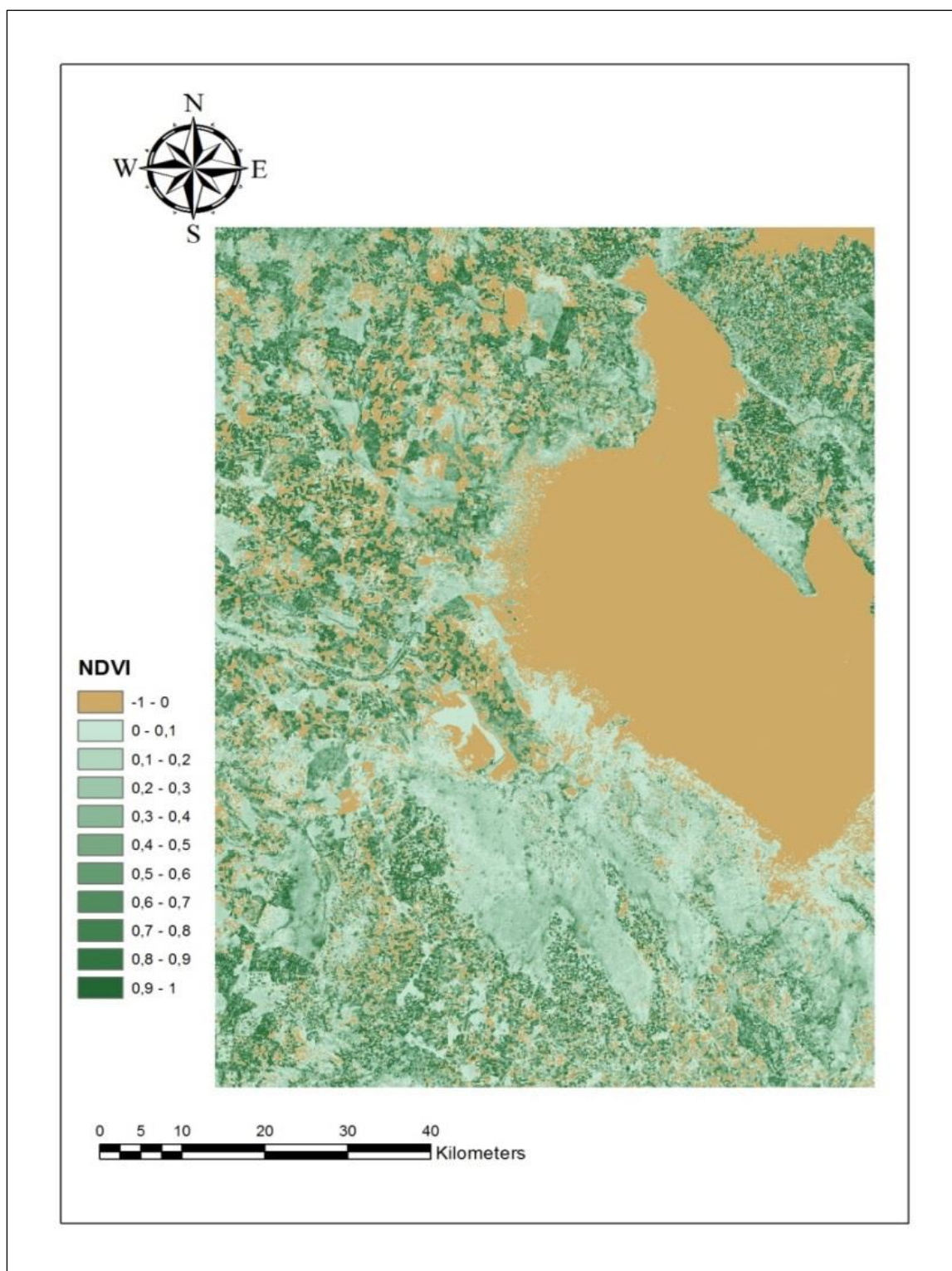


Figure B.1: NDVI map for year 1990

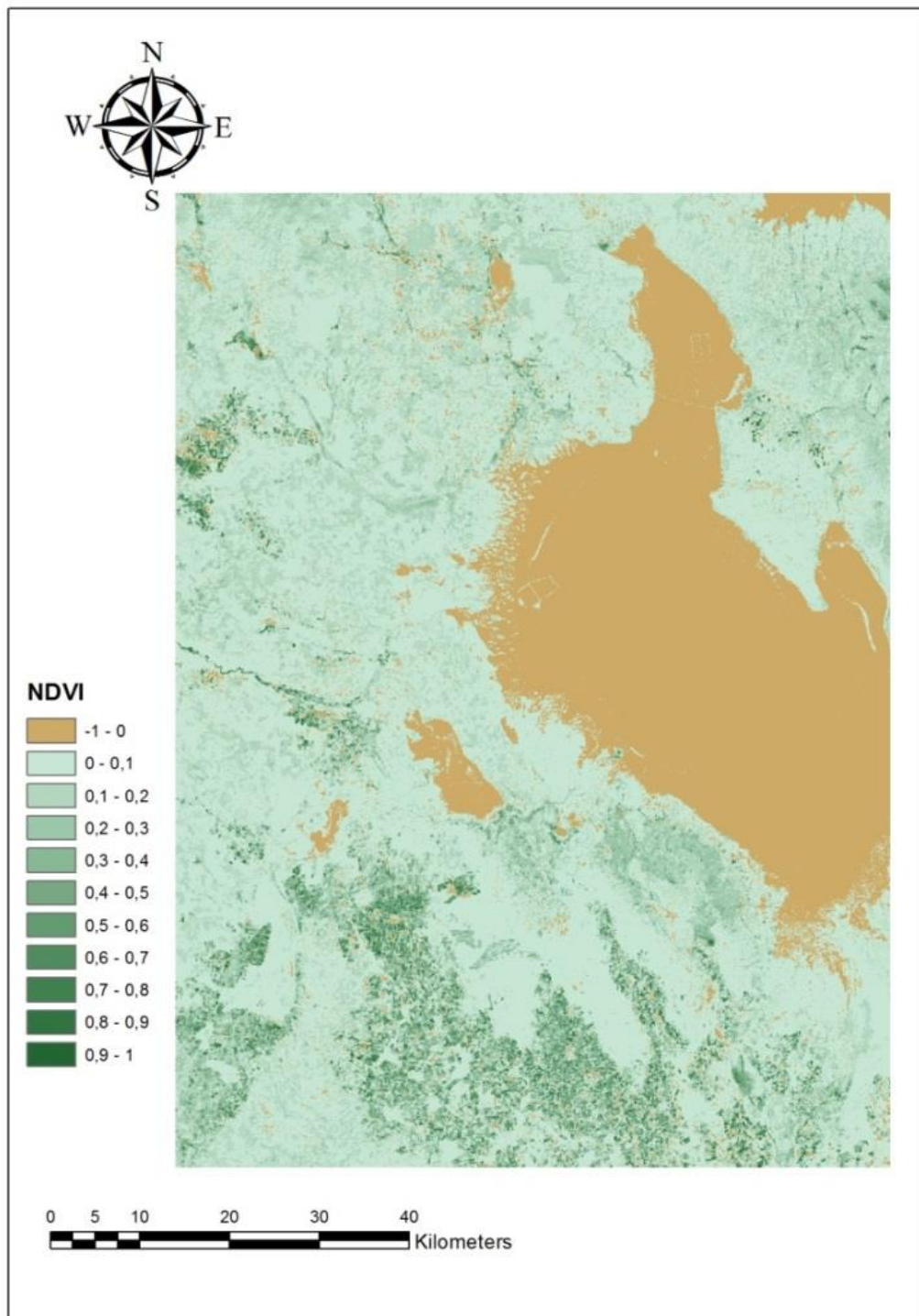


Figure B.2: NDVI map for year 2006

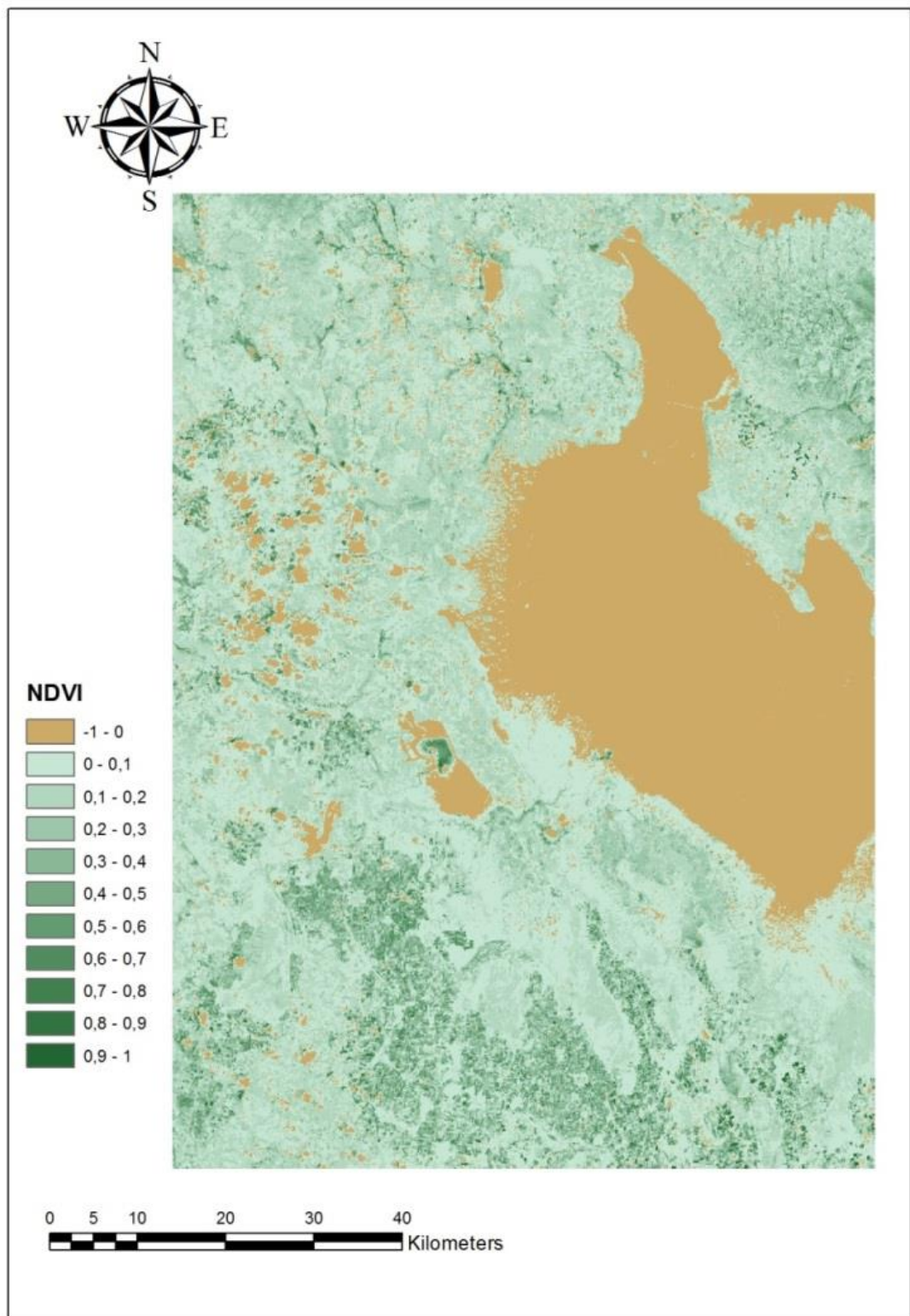


Figure B.3: NDVI map for year 2011

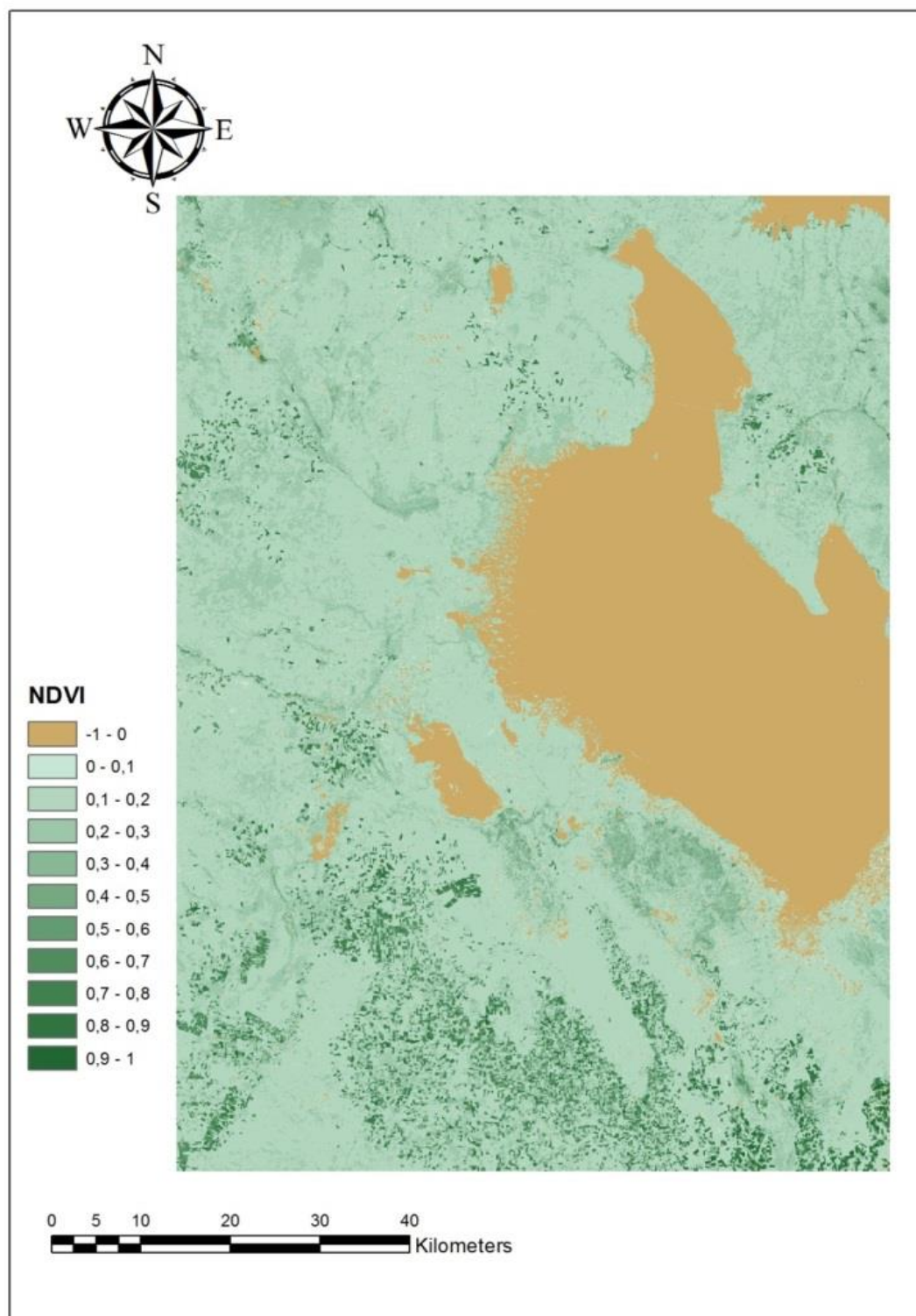


Figure B.4: NDVI map for year 2015

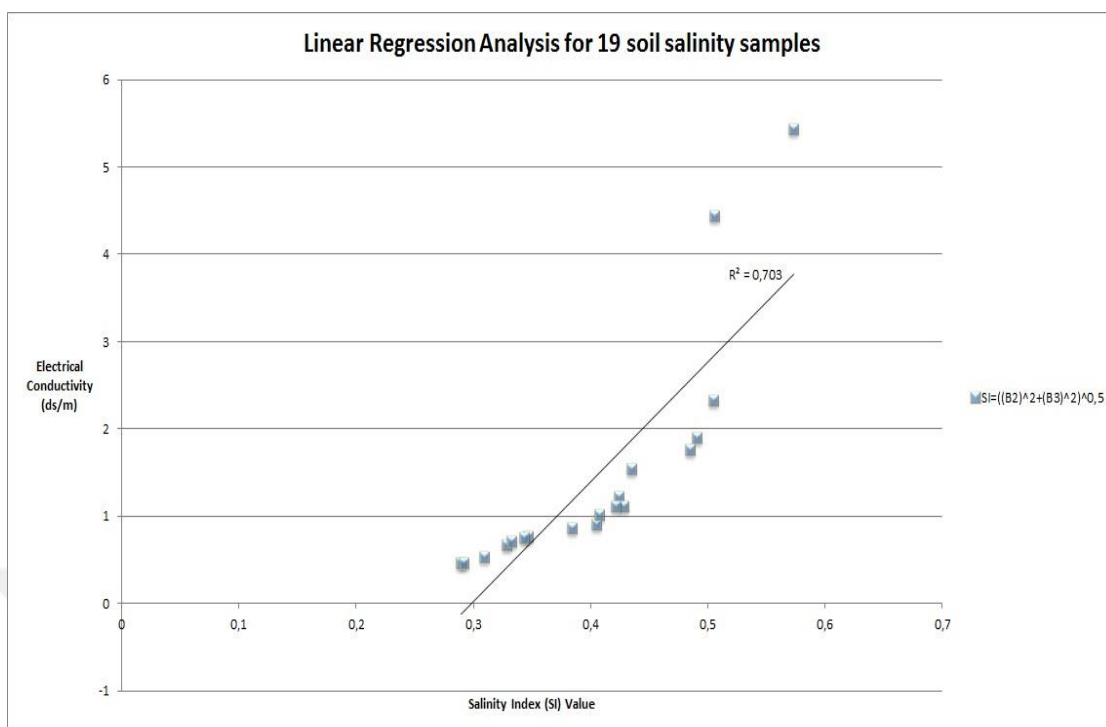


Figure B.5: Linear regression analysis using SI 4

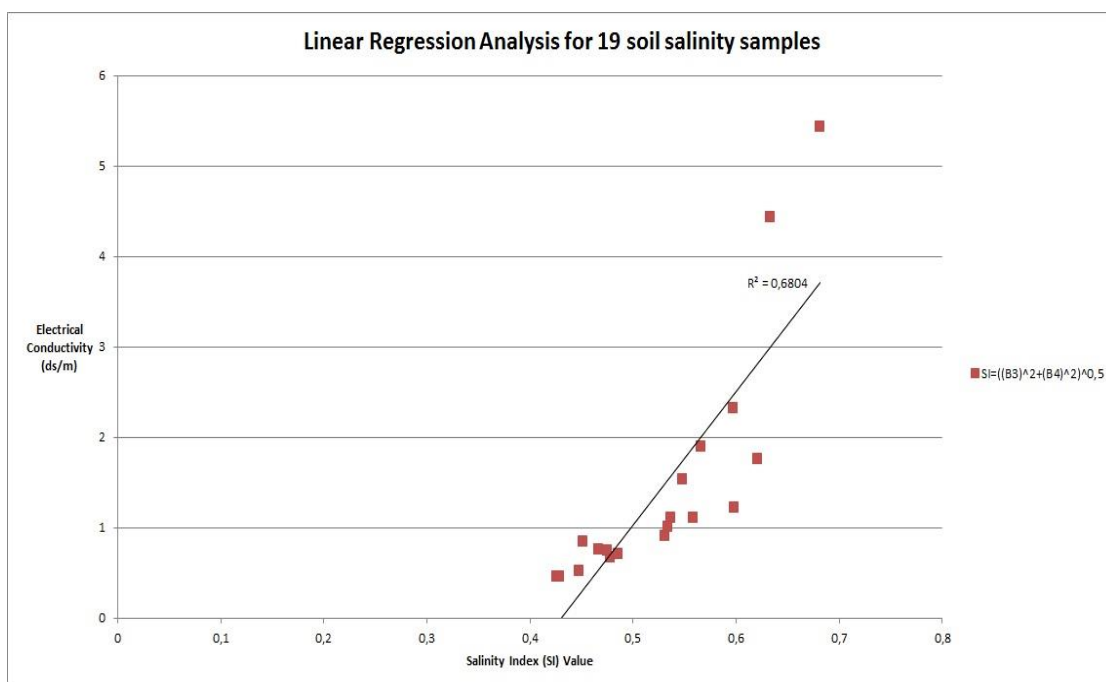


Figure B.6: Linear regression analysis using SI 5

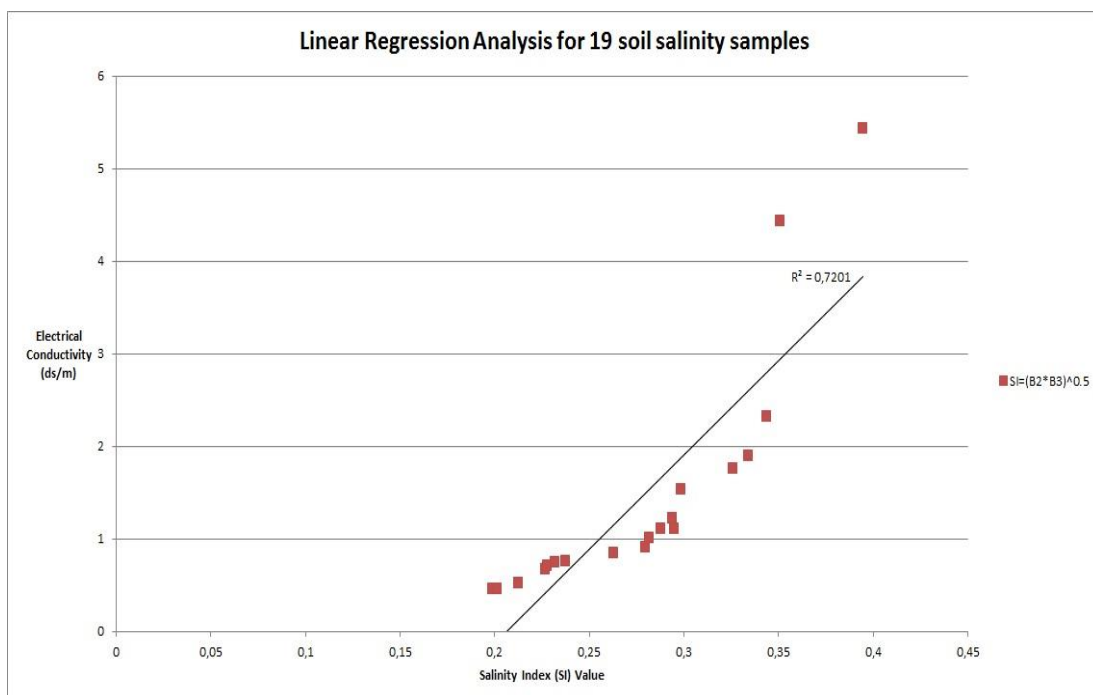


Figure B.7: Linear regression analysis using SI 2

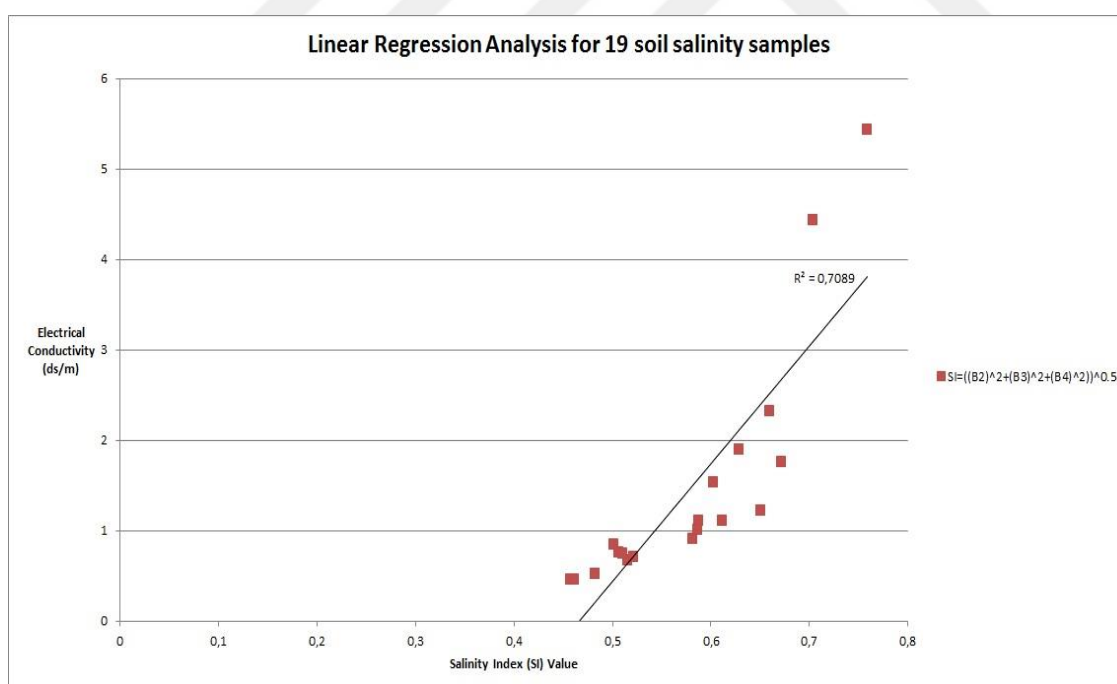


Figure B.8: Linear regression analysis using SI 3

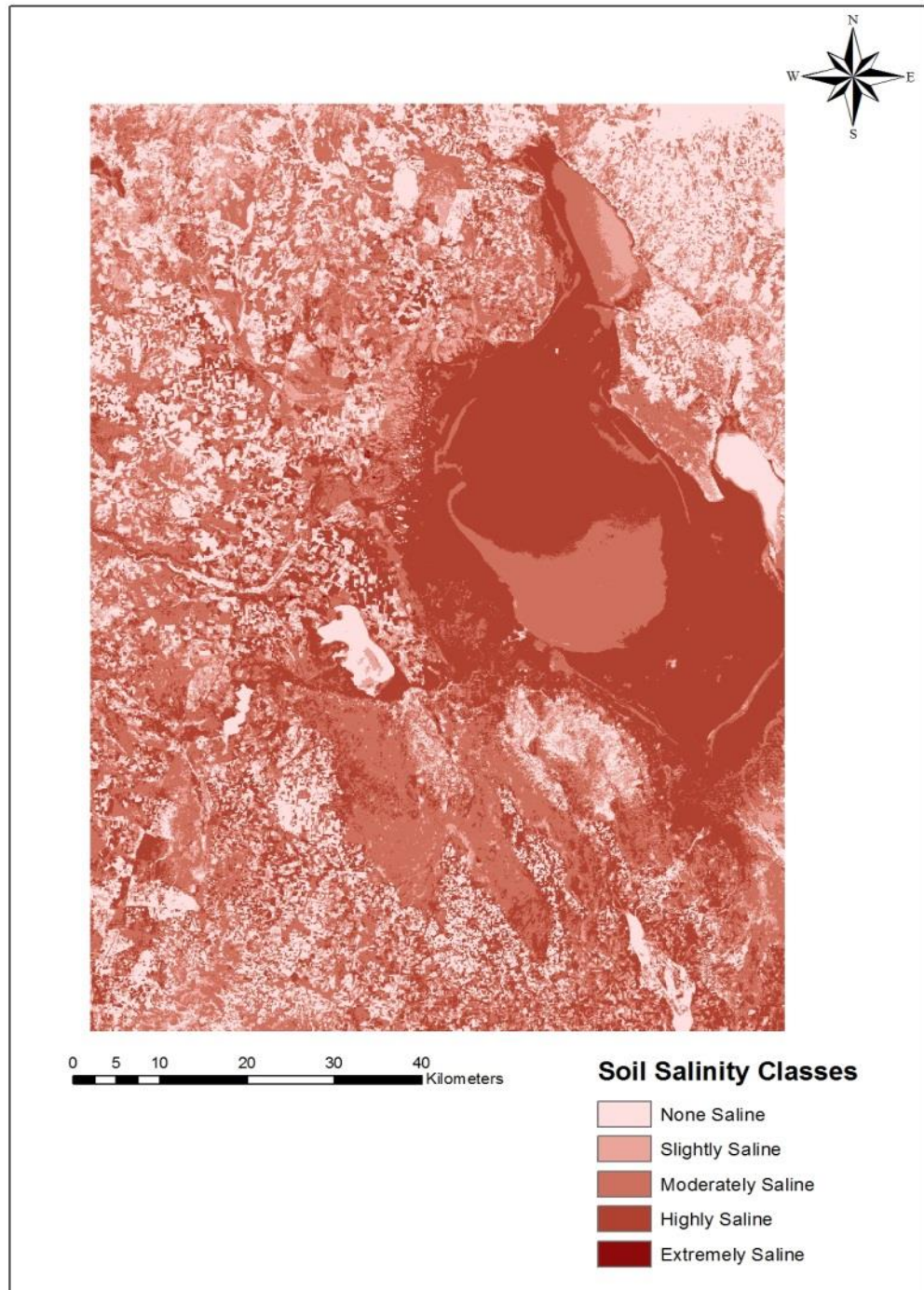


Figure B.9: Tuz Lake salinity map in 1990 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and linear regression analysis.

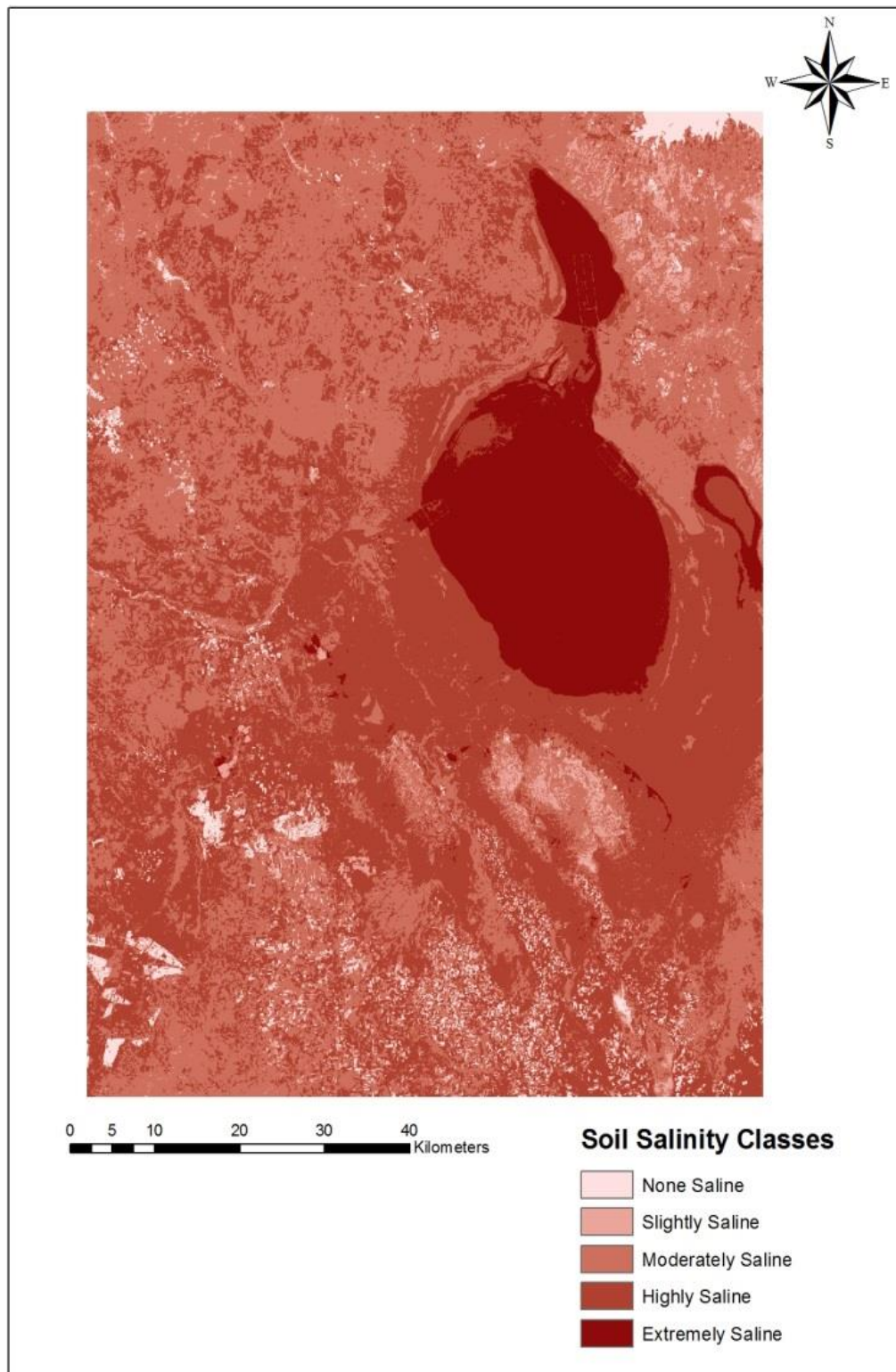


Figure B.10: Tuz Lake salinity map in 2006 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and linear regression analysis.

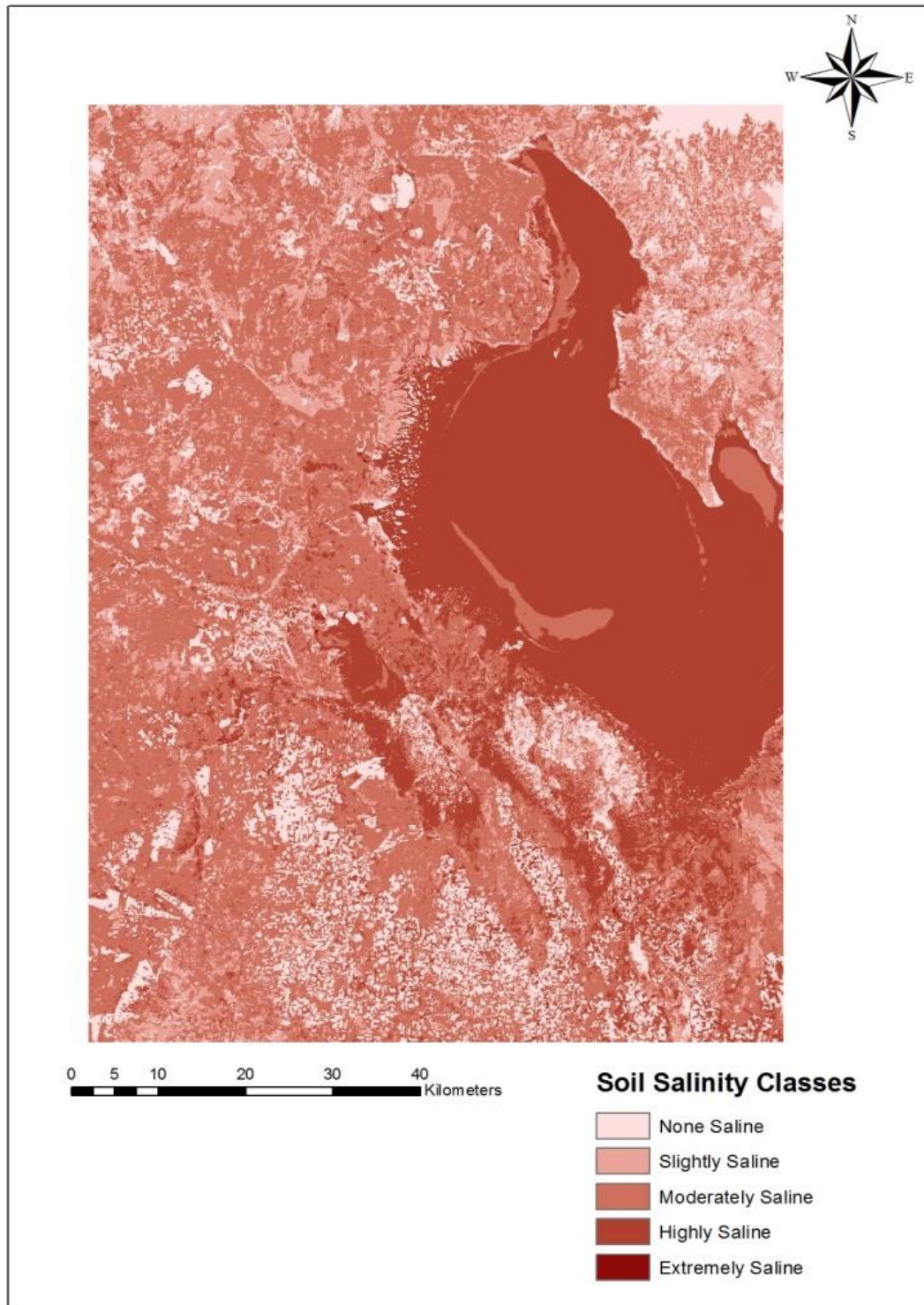


Figure B.11:Tuz Lake salinity map in 2011 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and linear regression analysis.

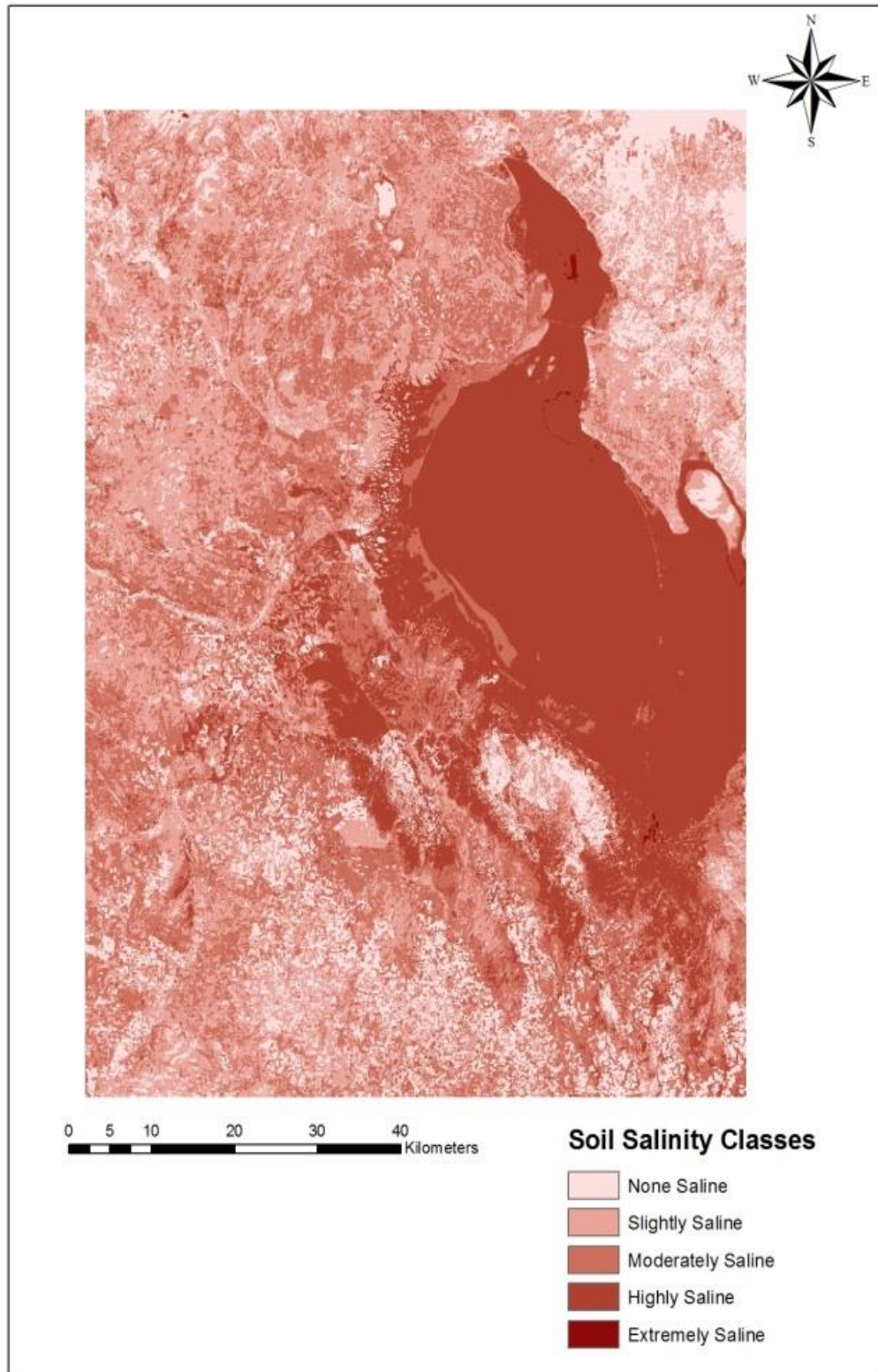


Figure B.12: Tuz Lake salinity map in 2015 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and linear regression analysis.

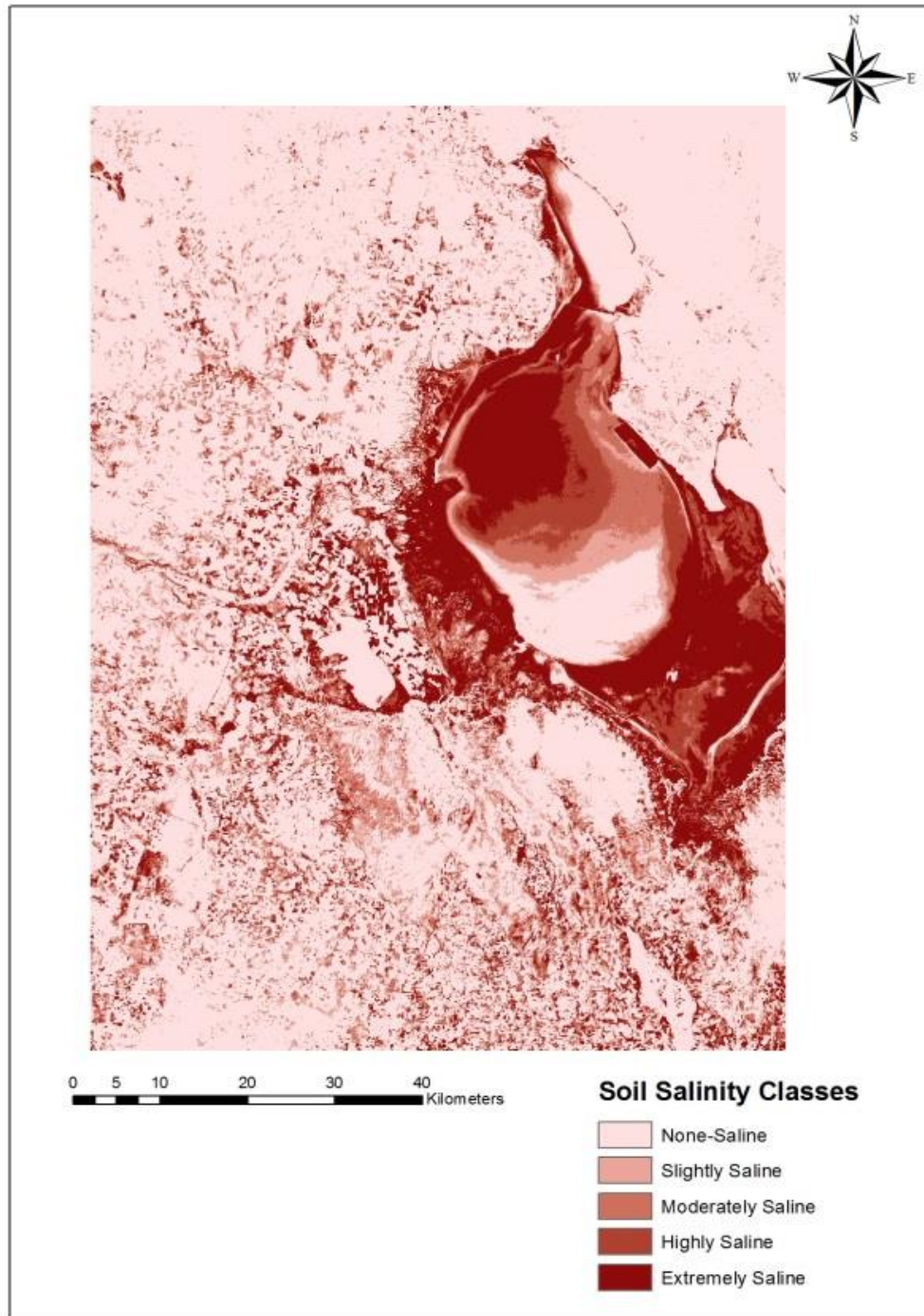


Figure B.13: Tuz Lake salinity map in 1990 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and Exponential regression analysis.

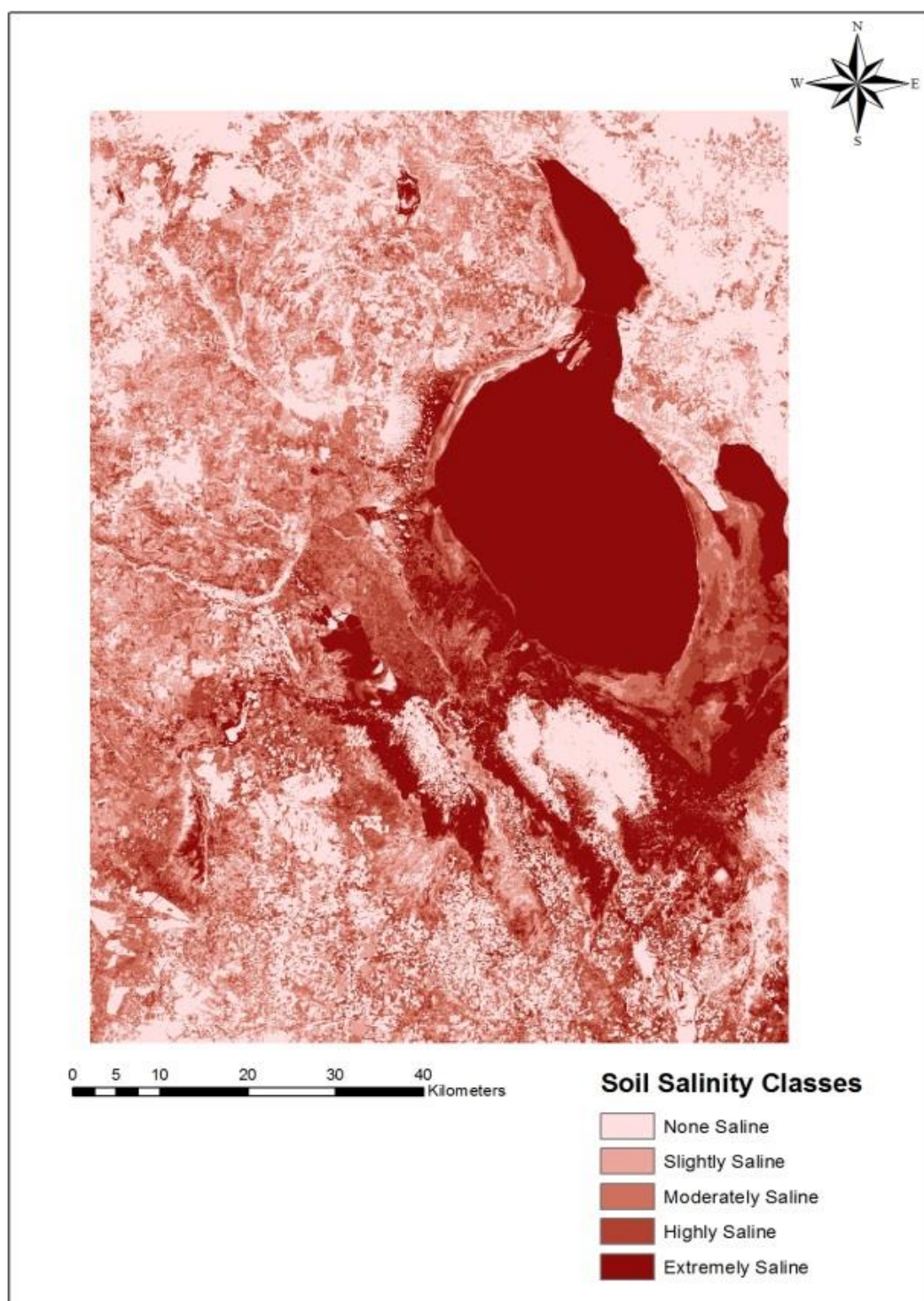


Figure B.14: Tuz Lake salinity map in 2006 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and Exponential regression analysis.

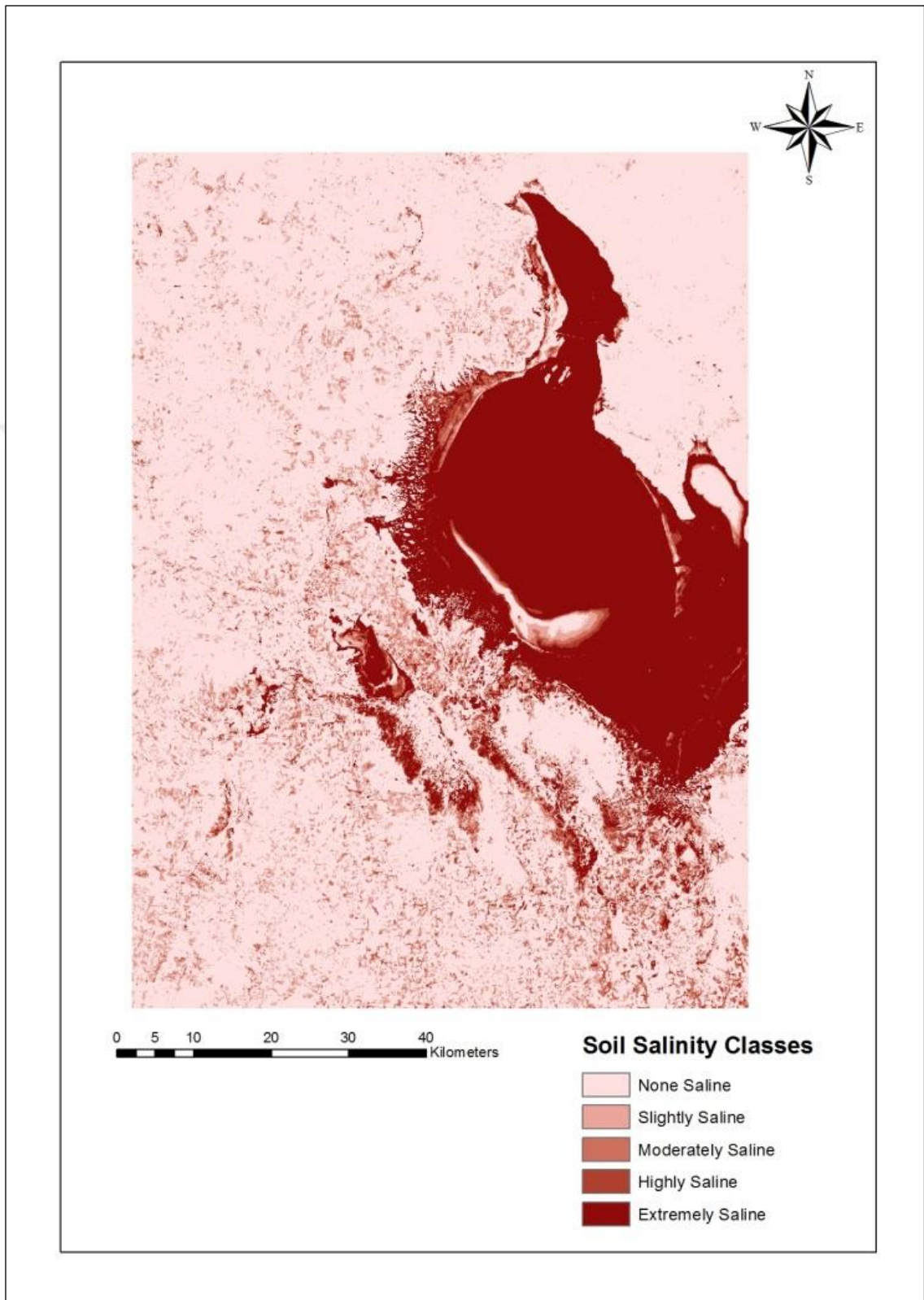


Figure B.15: Tuz Lake salinity map in 2011 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and exponential regression analysis.

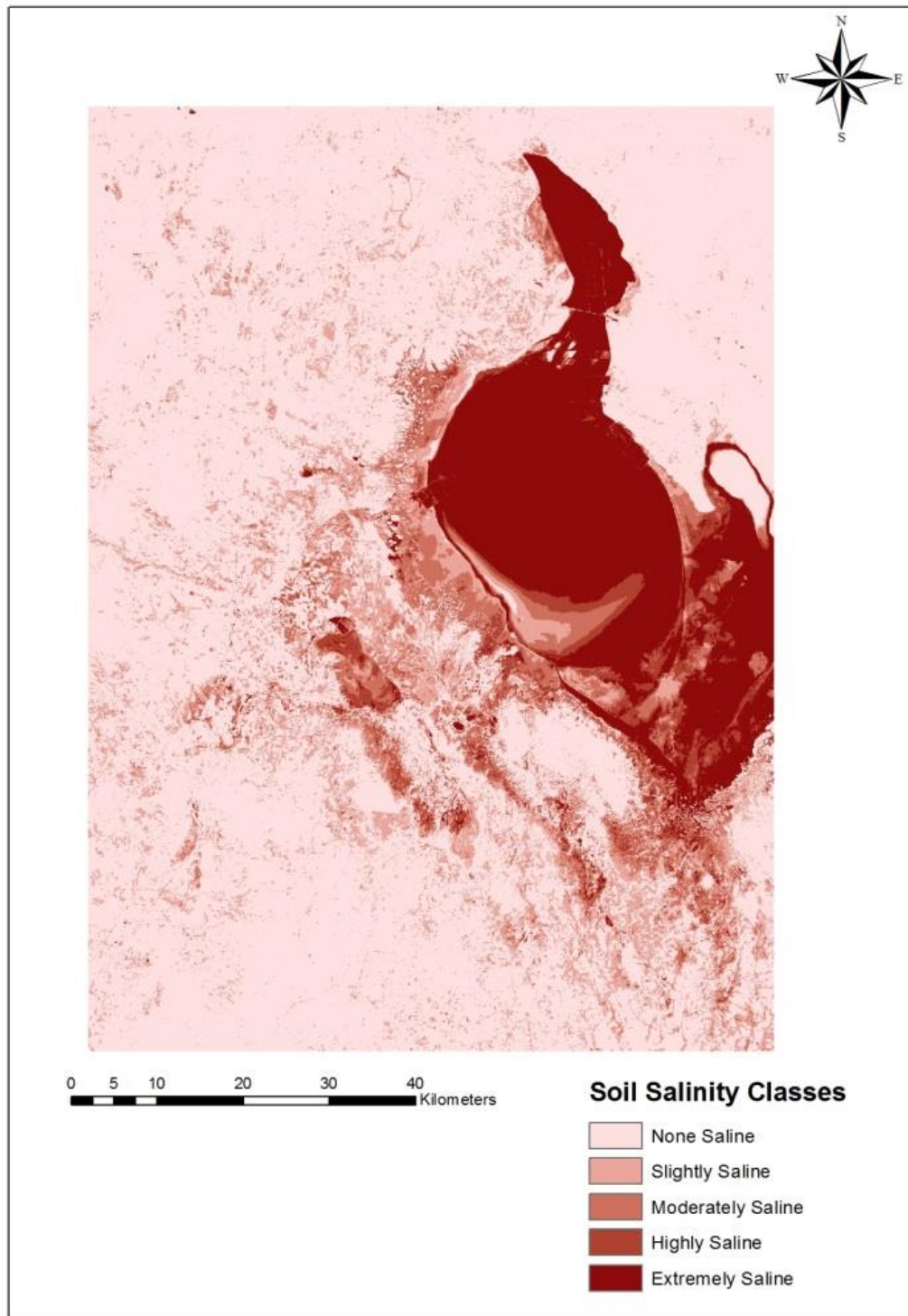


Figure B.16: Tuz Lake salinity map in 2015 as a result of Salinity Index (SI) $1 = \sqrt{B1 * B3}$ and exponential regression analysis.

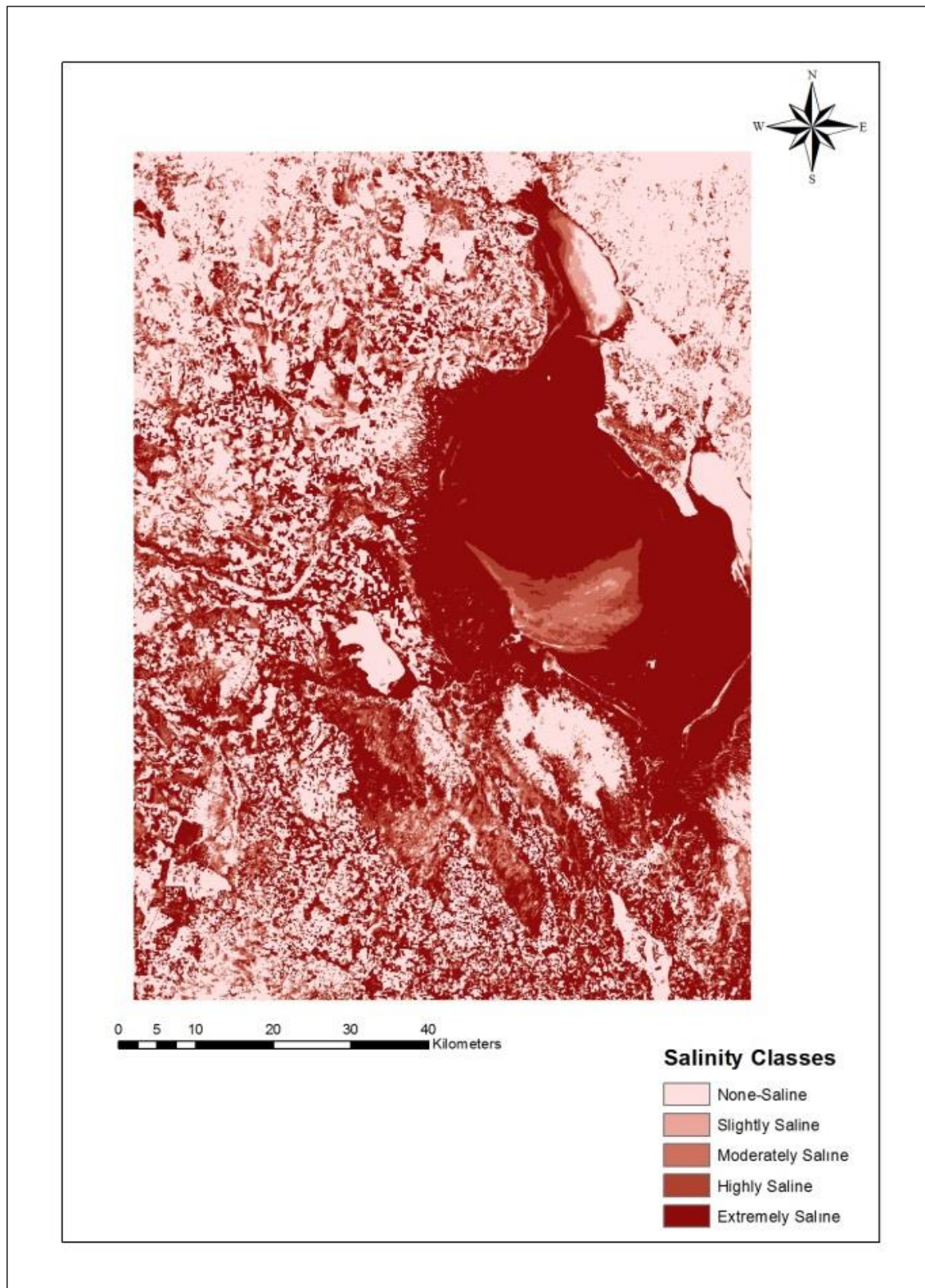


Figure B.17: Tuz Lake salinity map in 1990 as a result of Salinity Index (SI) $2 = \sqrt{B2 * B3}$ and exponential regression analysis.

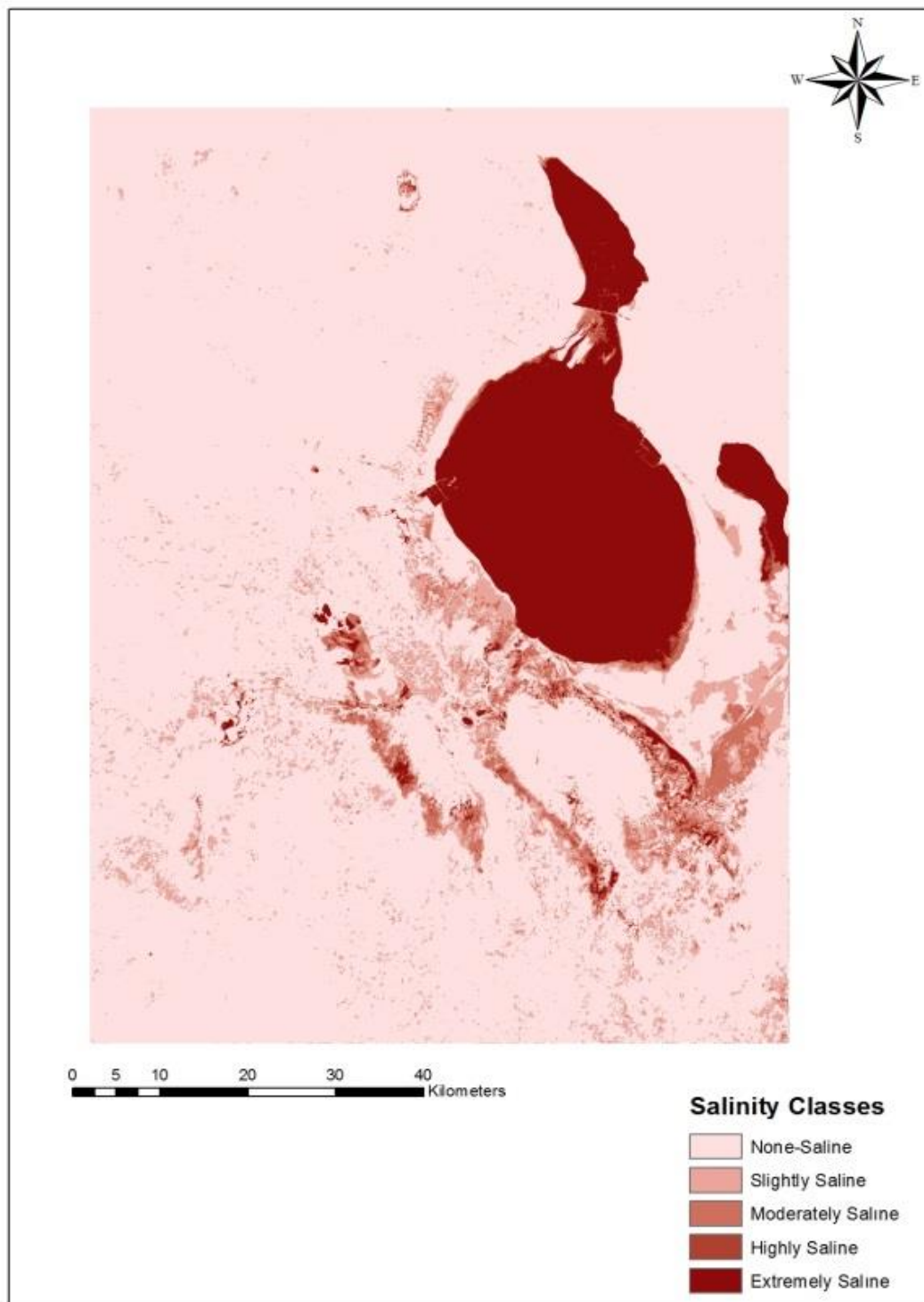


Figure B.18: Tuz Lake salinity map in 2006 as a result of Salinity Index (SI) 2 $=\sqrt{B2 * B3}$ and exponential regression analysis.

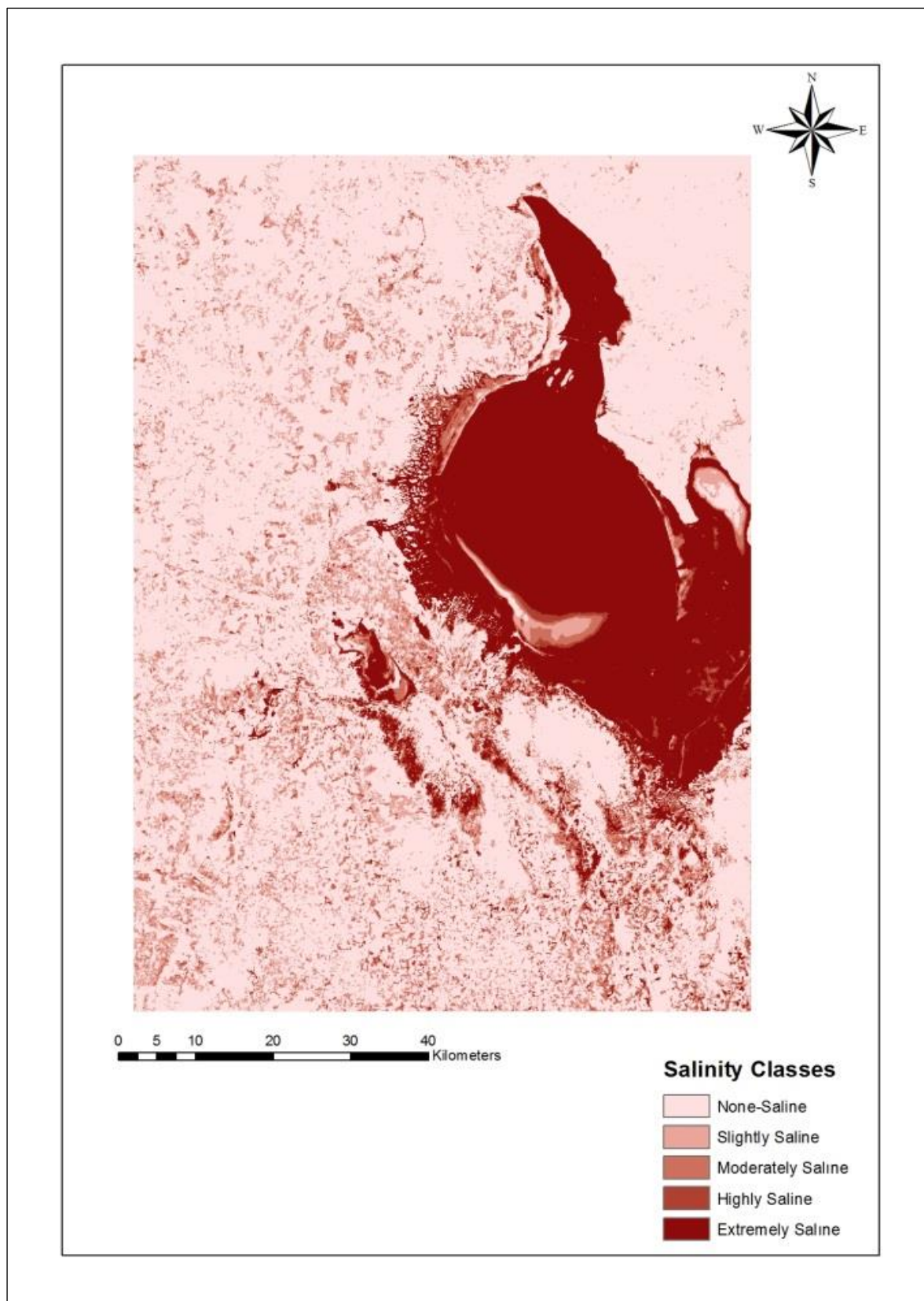


Figure B.19: Tuz Lake salinity map in 2011 as a result of Salinity Index (SI) $2 = \sqrt{B2 * B3}$ and exponential regression analysis.

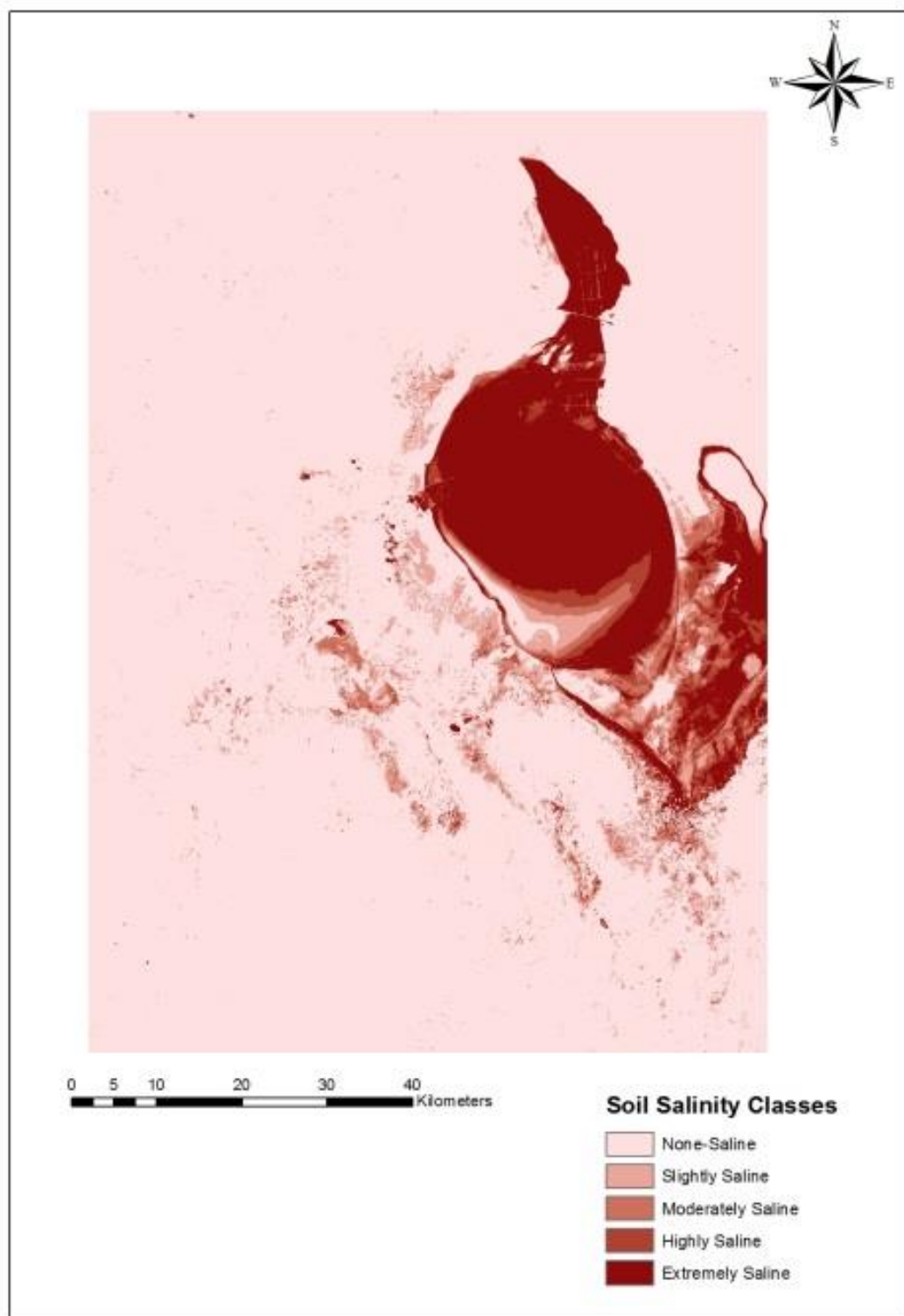


Figure B.20: Tuz Lake salinity map in 2015 as a result of Salinity Index (SI) $2 = \sqrt{B2 * B3}$ and exponential regression analysis.

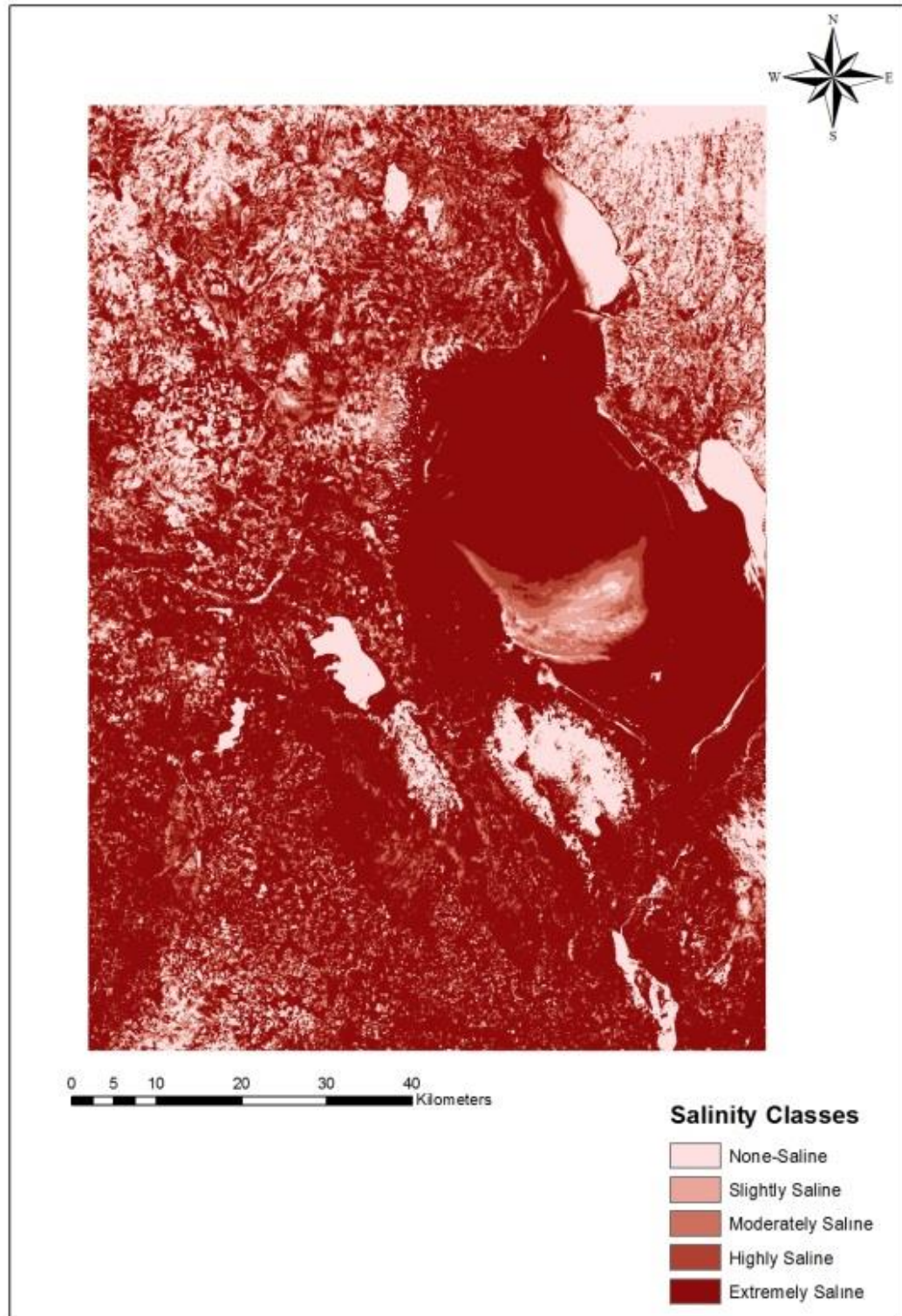


Figure B.21: Tuz Lake salinity map in 1990 as a result of Salinity Index (SI) $3 = \sqrt{(B2)^2 + (B3)^2 + (B4)^2}$ and exponential regression analysis.

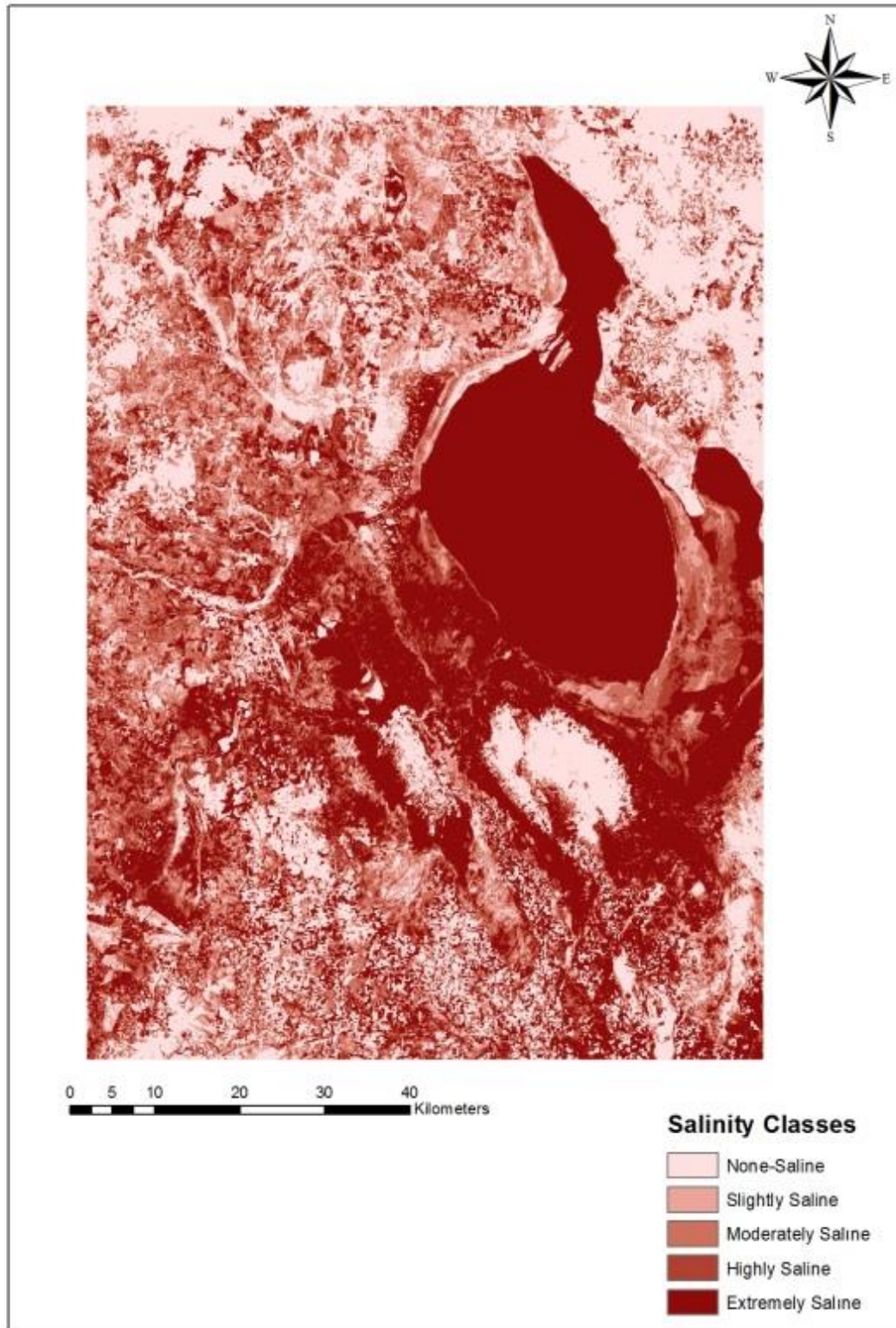


Figure B.22: Tuz Lake salinity map in 2006 as a result of Salinity Index (SI) $3 = \sqrt{(B2)^2 + (B3)^2 + (B4)^2}$ and exponential regression analysis.

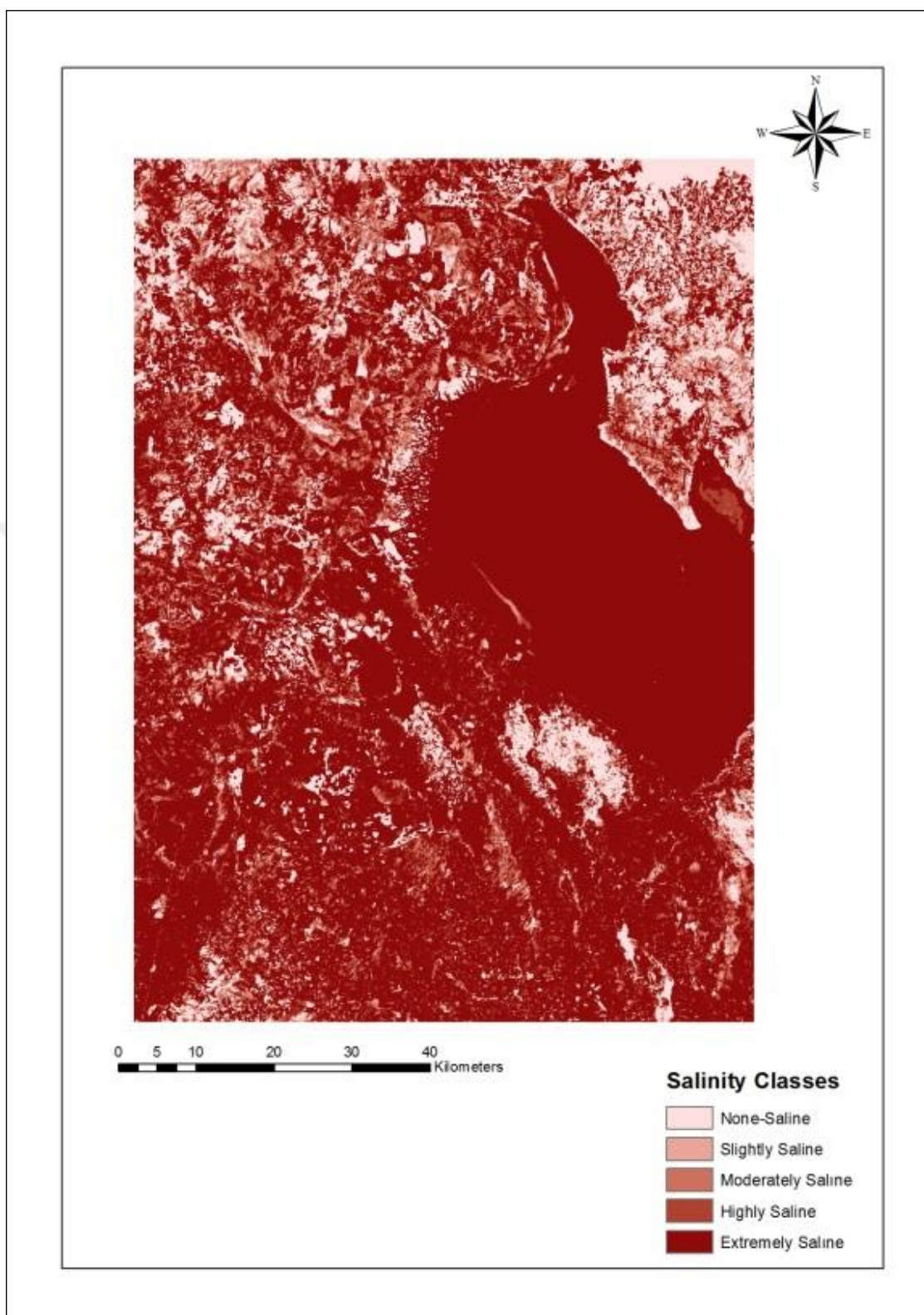


Figure B.23: Tuz Lake salinity map in 2011 as a result of Salinity Index (SI) $3 = \sqrt{(B2)^2 + (B3)^2 + (B4)^2}$ and exponential regression analysis.

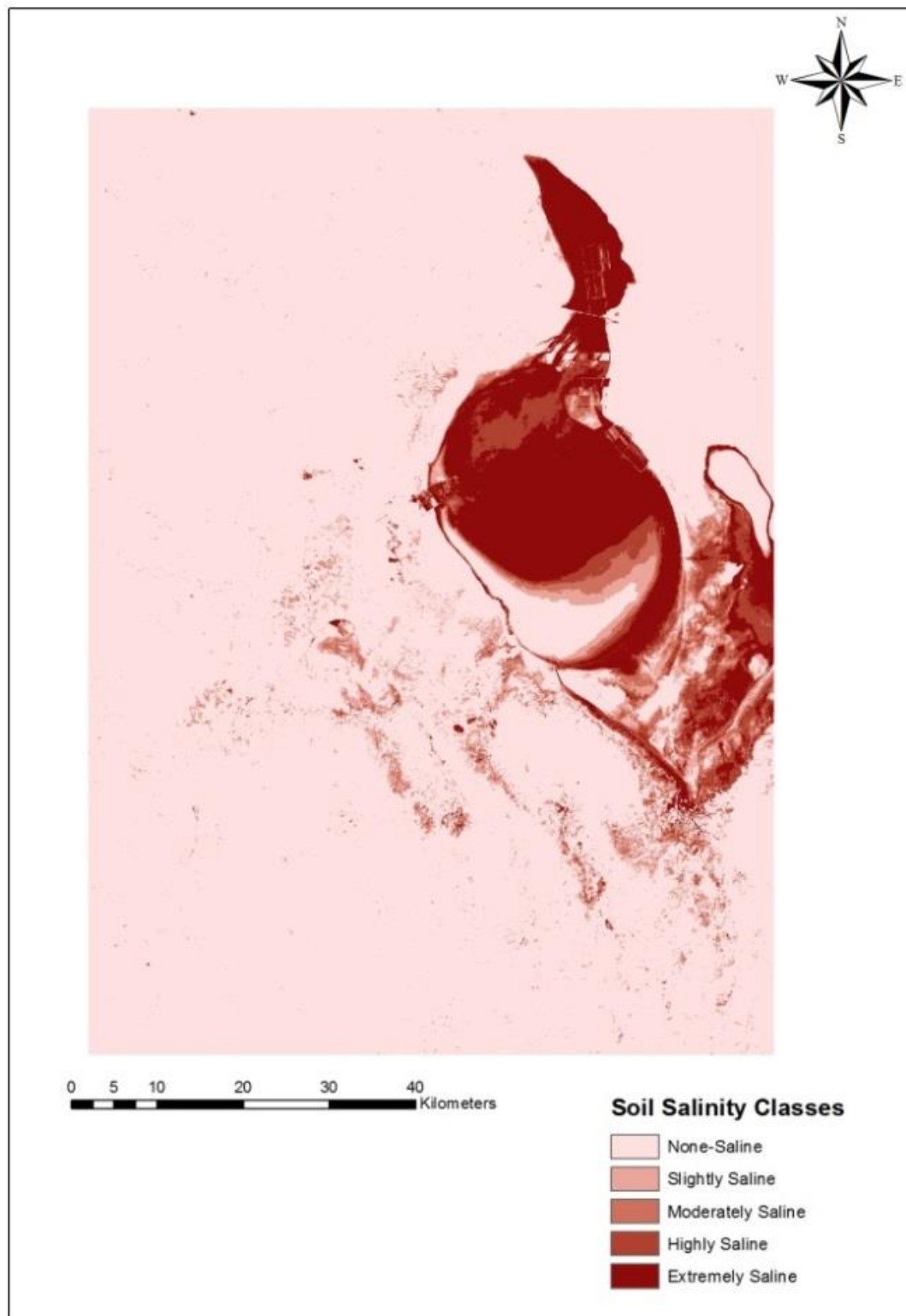


Figure B.24: Tuz Lake salinity map in 2015 as a result of Salinity Index (SI) $3 = \sqrt{(B2)^2 + (B3)^2 + (B4)^2}$ and exponential regression analysis.

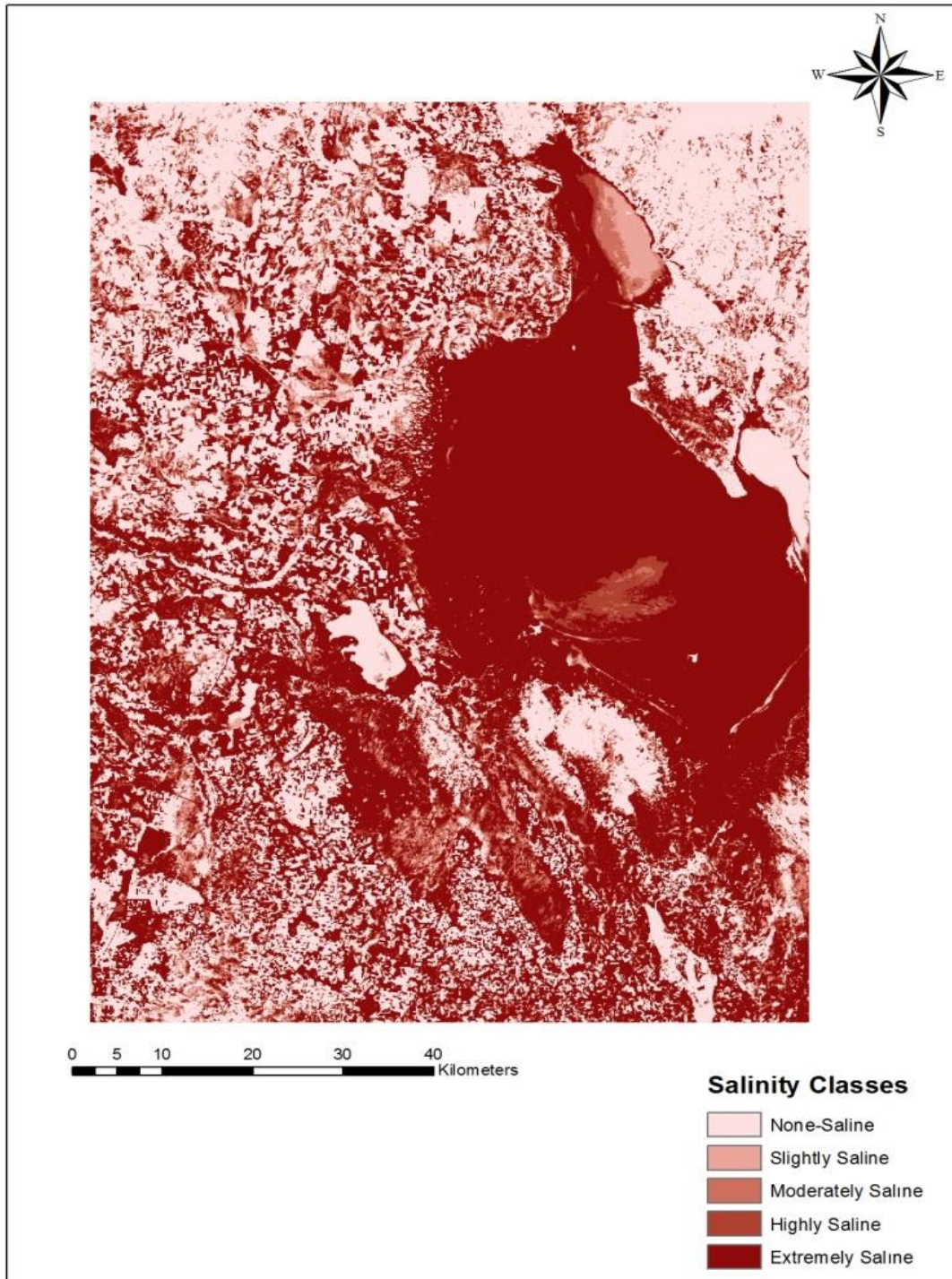


Figure B.25: Tuz Lake salinity map in 1990 as a result of Salinity Index (SI) $4 = \sqrt{(B2)^2 + (B3)^2}$ and exponential regression analysis.

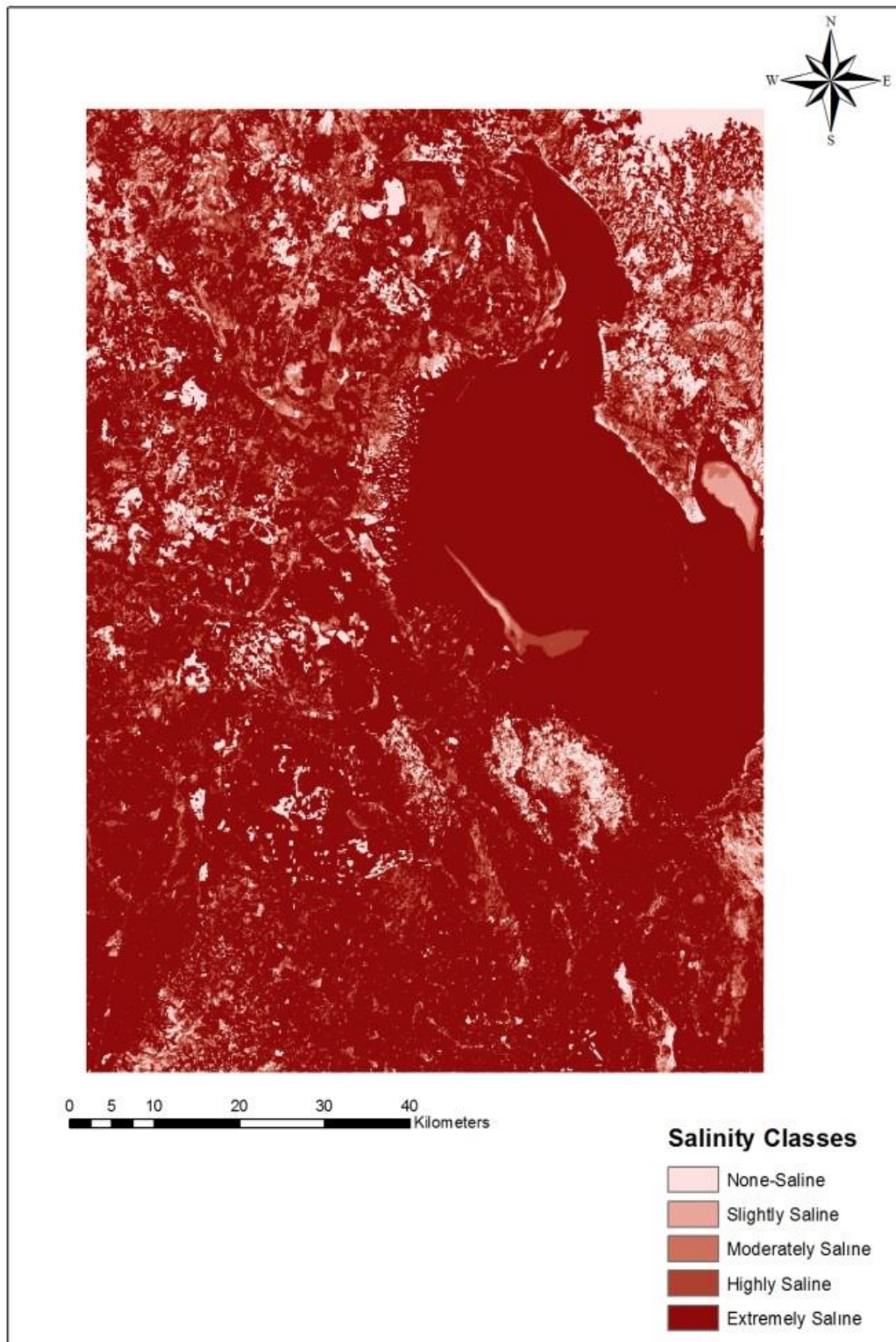


Figure B.26: Tuz Lake salinity map in 2006 as a result of Salinity Index (SI) $4 = \sqrt{(B2)^2 + (B3)^2}$ and exponential regression analysis.

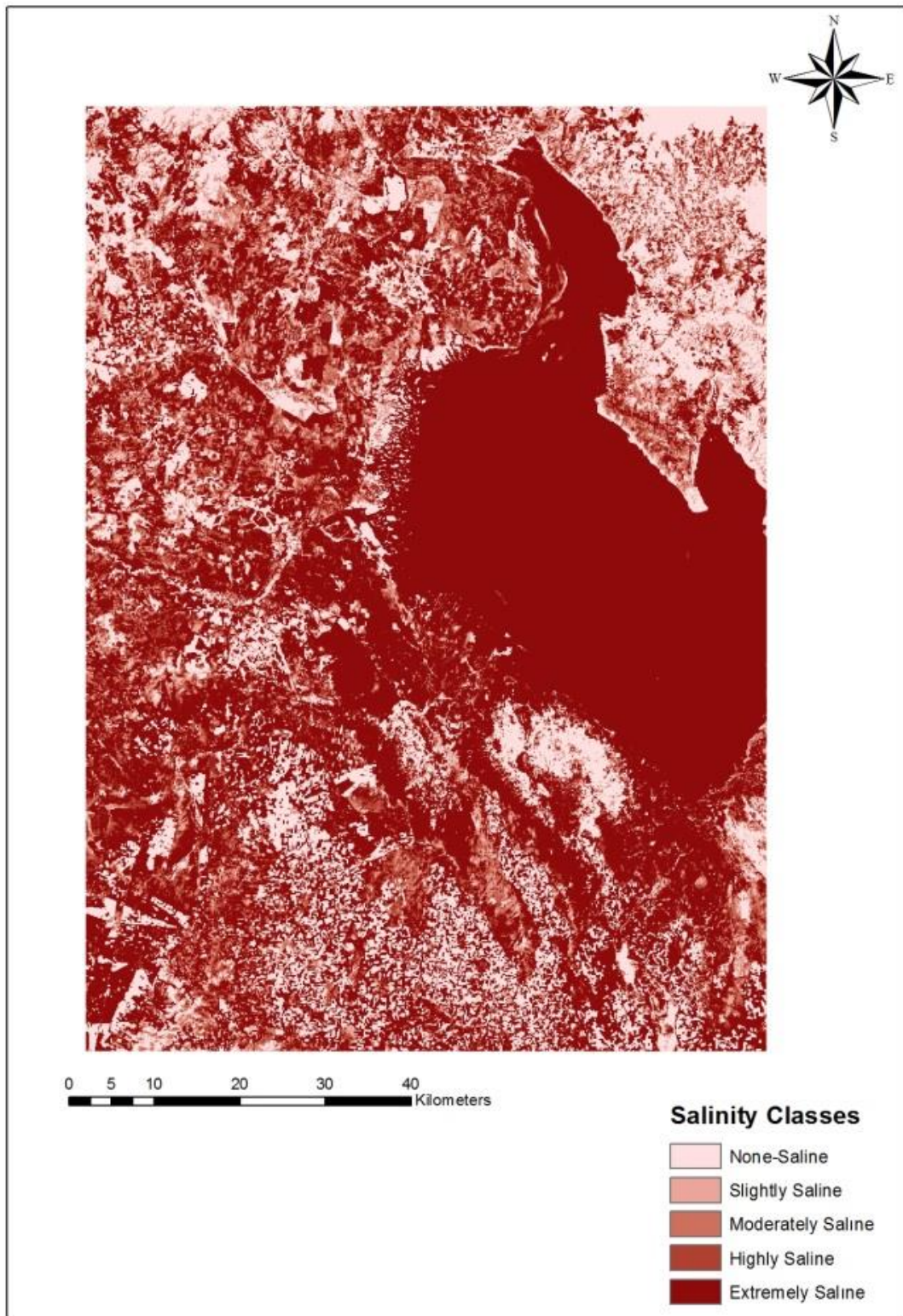


Figure B.27: Tuz Lake salinity map in 2011 as a result of Salinity Index (SI) $4 = \sqrt{(B2)^2 + (B3)^2}$ and exponential regression analysis.

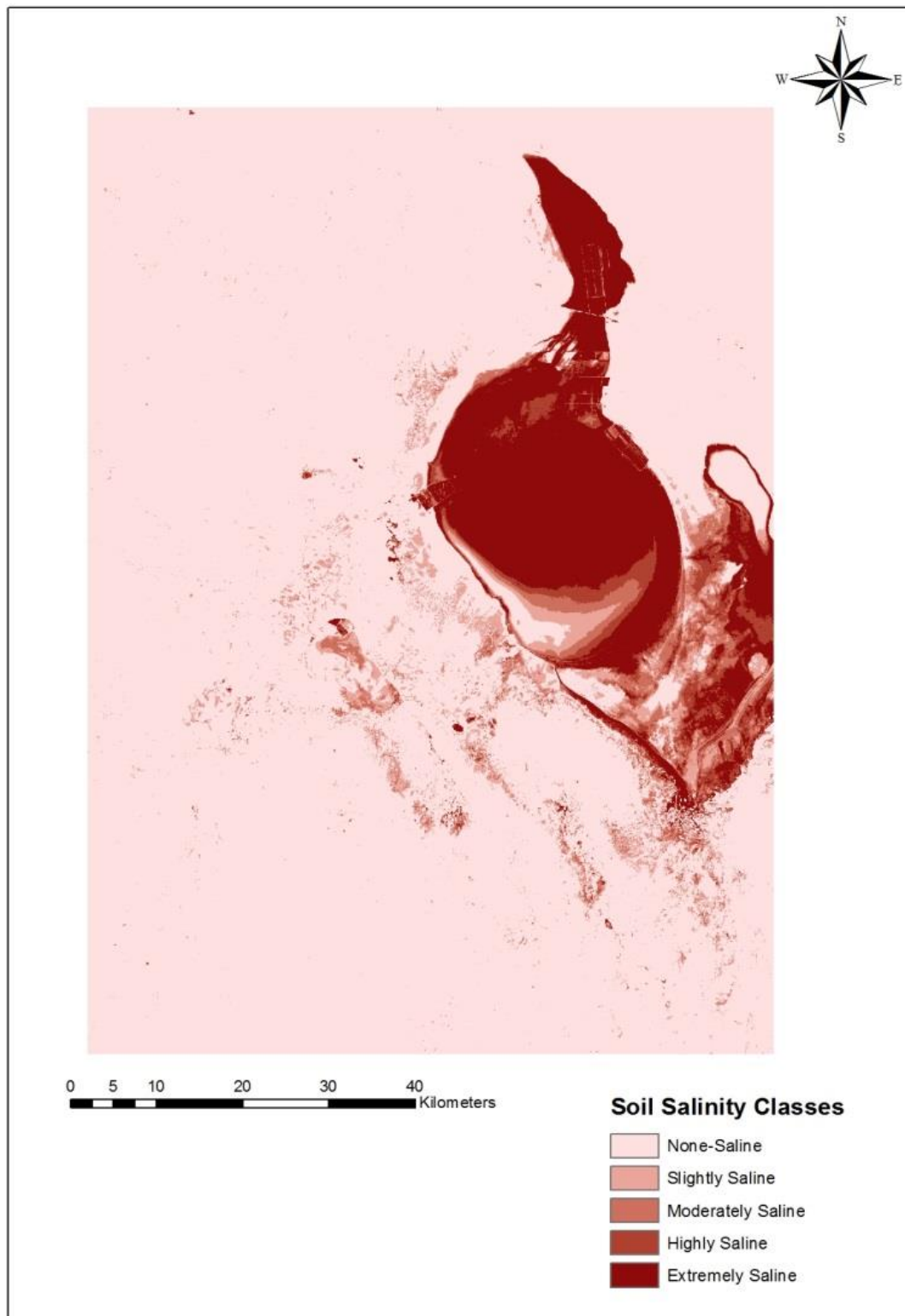


Figure B.28: Tuz Lake salinity map in 2015 as a result of Salinity Index (SI) $4 = \sqrt{(B2)^2 + (B3)^2}$ and exponential regression analysis.

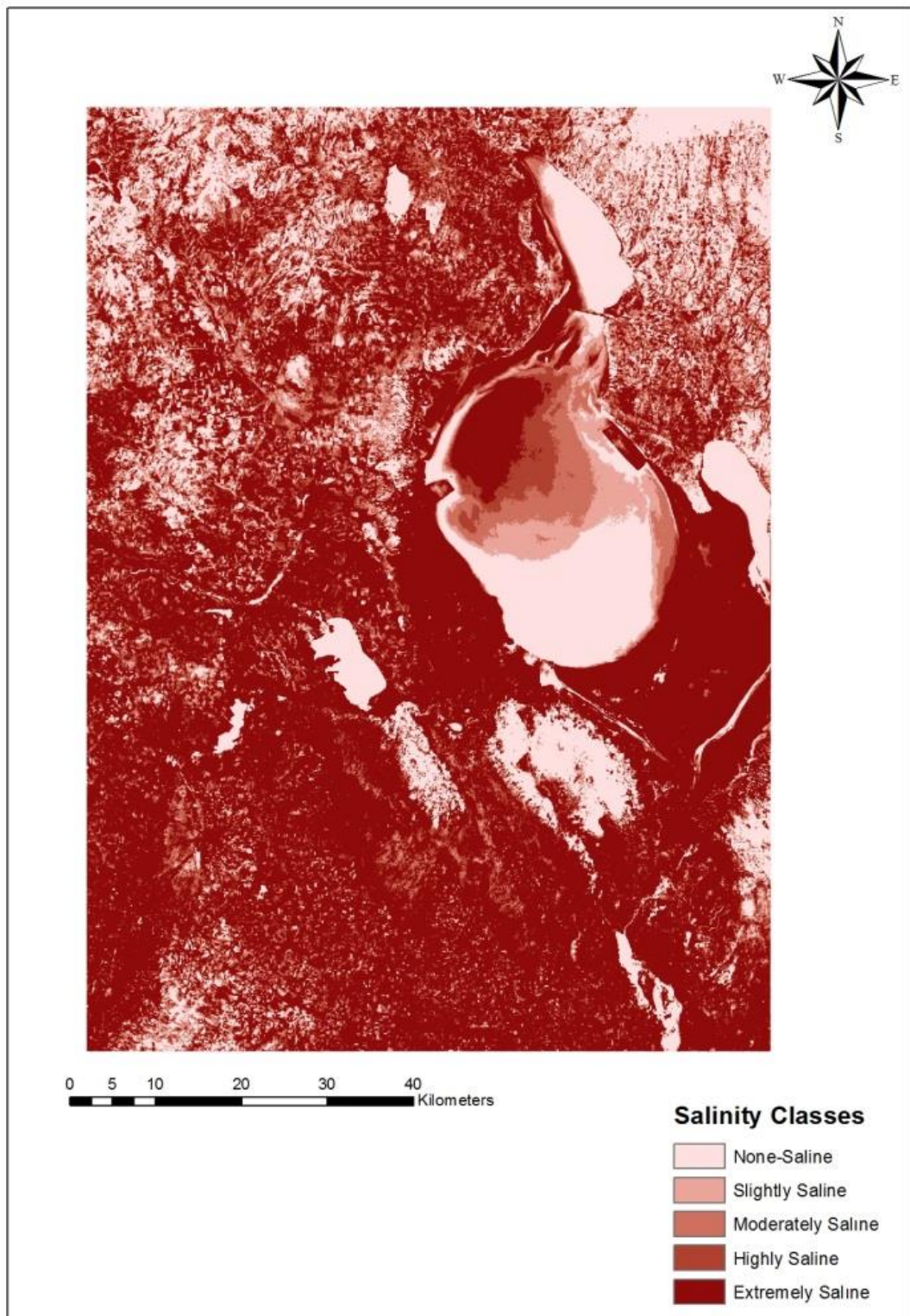


Figure B.29: Tuz Lake salinity map in 1990 as a result of Salinity Index (SI) $5 = \sqrt{(B3)^2 + (B4)^2}$ and exponential regression analysis.

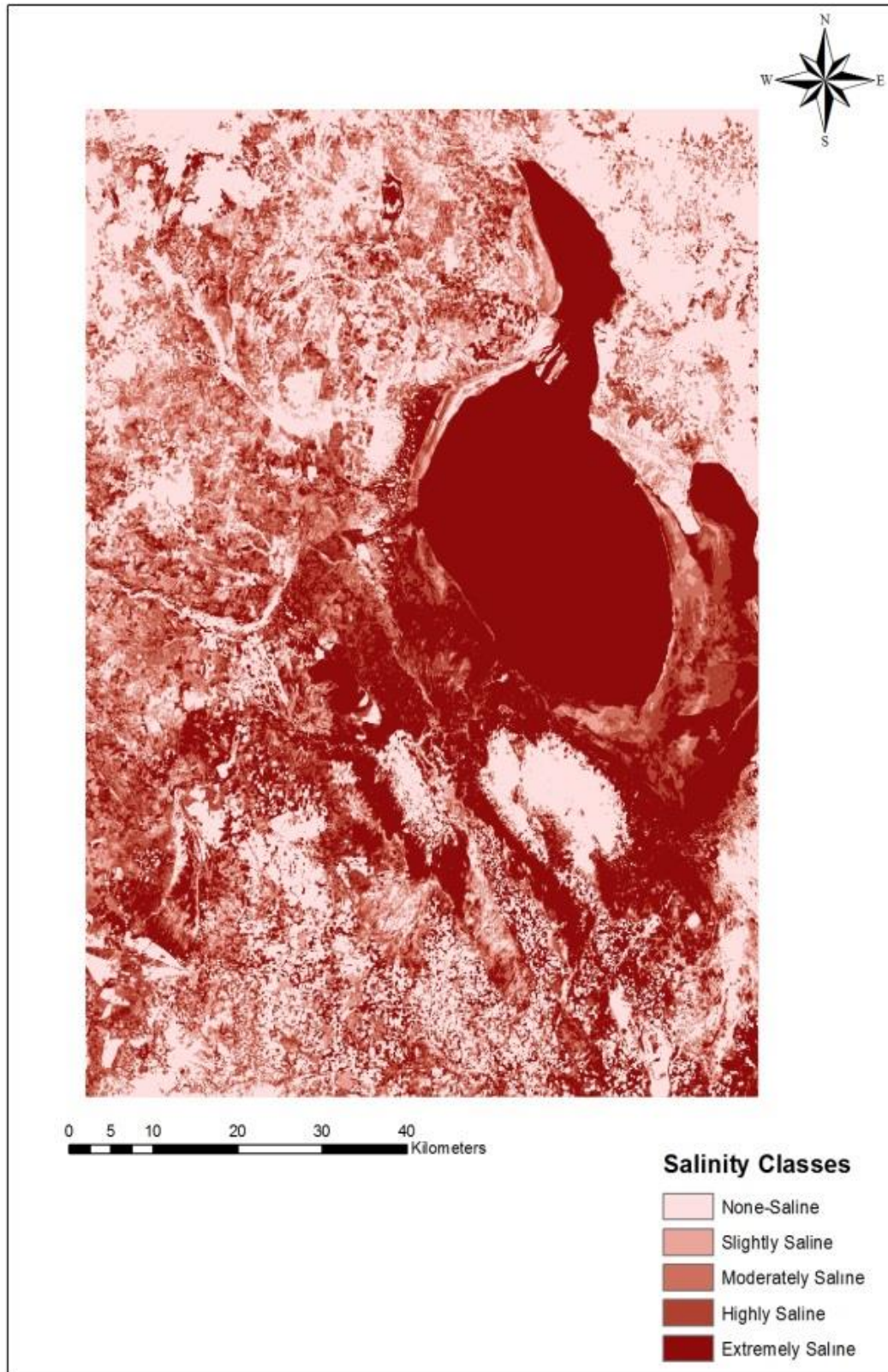


Figure B.30: Tuz Lake salinity map in 2006 as a result of Salinity Index (SI) $4 = \sqrt{(B3)^2 + (B4)^2}$ and exponential regression analysis.

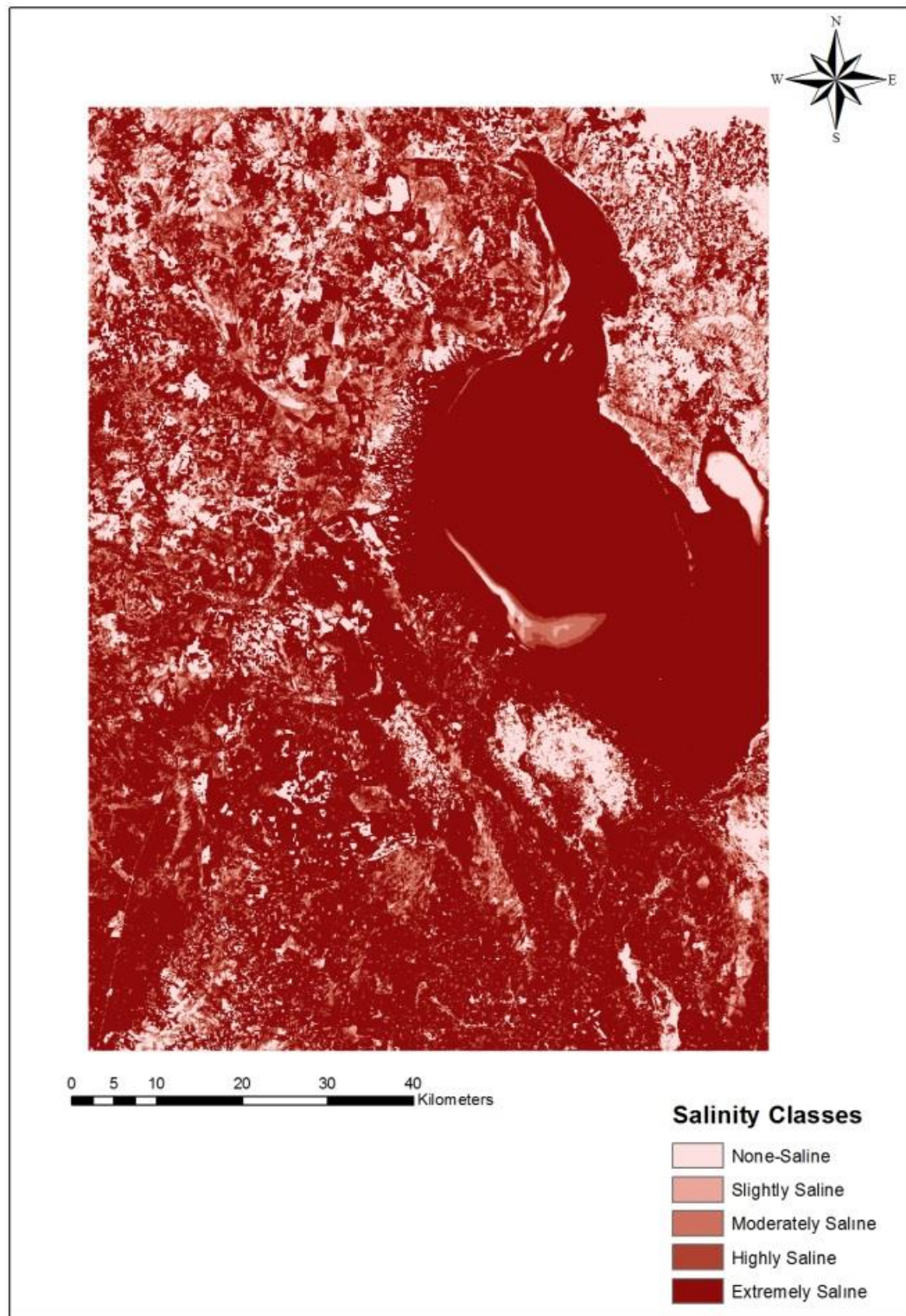


Figure B.31: Tuz Lake salinity map in 2011 as a result of Salinity Index (SI) $5 = \sqrt{(B3)^2 + (B4)^2}$ and exponential regression analysis.

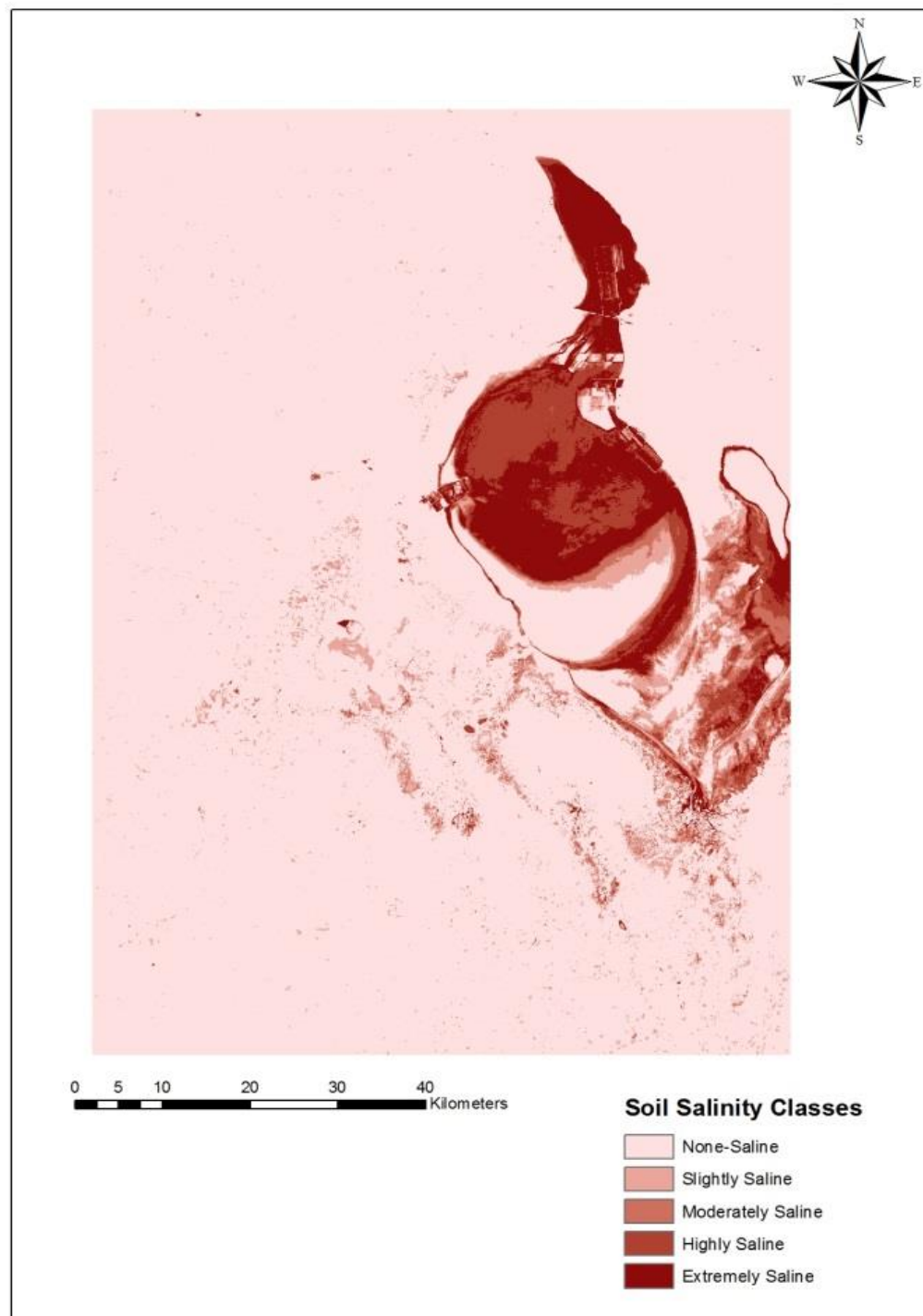


Figure B.32: Tuz Lake salinity map in 2015 as a result of Salinity Index (SI) $4 = \sqrt{(B3)^2 + (B4)^2}$ and exponential regression analysis.



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PUBLICATIONS/PRESENTATIONS ON THE THESIS

- **Gorji, T., Tanik, A., Sertel, E., Tanik, A., 2015.** Soil Salinity Prediction, Monitoring and Mapping using Modern Technologies, procedia earth and planetary science, world multidisciplinary earth science symposium. (Published)
- **Gorji, T., Sertel, E., Tanik, A., 2016.** Recent Satellite Technologies for Soil Salinity Assessment with Special Focus on Mediterranean Countries, 18th International Symposium On Environmental Pollution and its Impact on Life in the Mediterranean Region September 26-30, 2015 Crete – Greece. (Accepted- Under publishing procedure)