The application of remote sensing, GIS, geostatistics, and ecological modeling in rangelands assessment and improvement

A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Phylosophy (Ph.D.)

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To my parents, my wife, and my daughter

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A. aucheri: Artemisia aucheri

A. sieberi: Artemisia sieberi

AM: soil available moisture

AVHRR: Advanced very high resolution radiometer

CK: Co kriging

DEM: Digital elevation model

EC: Electrical conductivity

ENFA: Ecological niche factor analysis

GARP: Genetic algorithm for rule-set production

GIS: Geographic information system

GLM: Generalized linear model

LDD: Land degradation and desertification

MAP: Mean annual precipitation

Maxent: Maximum entropy model

NDVI: Normalized difference vegetation index

NOAA: National oceanic and atmospheric administration

OK: Ordinary kriging

OM: soil organic matter

RK: Regression kriging

RMSE: Root mean square error

RS: Remote sensing

SAM: soil available moisture

SDM: Species distribution model

TWI: Topographic wetness index

VCP: Vegetation cover percentage

VI: Vegetation index

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Abstract

Human-caused ove rgrazing and drought periods have led to the land degradation which might cause an eventual loss of biodiversity in rangeland ecosystems of Iran. Therefore, assessment of the current condition of rangelands and suggesting efficient strategies for conservation, rehabilitation, improvement, and consequently sustainable management of rangelands are essential. To reach the mentiond purposes, creating the environmental variable (e.g. topography, climate, and soil) maps, monitoring vegetation dynamics, and determining the relations between the vegetation and environmental variables are the firs steps.

This research was conducted in rangelands of Poshtkouh area of the Yazd province in central Iran. The main aims were assessment of the current condition and suggesting efficient strategies for conservation, rehabilitation, improvement, and consequently sustainable management of the rangelands. In addition, evaluating the capability of remote sensing, GIS, geostatistics, and ecological modeling in rangeland assessment and improvement.

In the first step, available data such as topography, geology, and vegetation type maps as well as satellite images were collected and then soil and vegetation samples were taken in the study area. As the first part of the data analyses, three geostatistical methods were applied for soil mapping and the satellite and environmental data were considered as ancillary data. In the next stage, the relationship between precipitation variation and vegetation dynamic was determined using NOAA AVHRR NDVI and climatic maps, as well as the effect of environmental factors on the strength of the relations between the precipitation and NDVI was determined. Then, vegetation cover percentage of the study area was created and the best time interval of the satellite images for vegetation studies was determined. In the last part of the data analyses, using the Maxent model, habitat distribution of *A. sieberi* and *A. aucheri* species were assessed and mapped. In addition, the most effective environmental variables on these habitats were determined.

The results have shown that, taking the ancillary data (satellite images and environmental variables) into account in geostatistical estimations (cokriging and regression kriging methods) has increased the accuracy of the created maps.

Selecting the suitable time interval of satellite images to study the vegetation during its growth period has prominent effect on the results. The best satellite data to study the

vegetation cover in the arid rangelands of the study area can be taken from the images recorded in the month May.

NDVI derived from NOAA AVHRR satellite images is a prominent tool for monitoring the effect of precipitation variation on vegetation dynamic. The strength of the relationship between the precipitation and NDVI depends on species' composition, and some environmental variables like soil available moisture.

Successful modeling of *A. sieberi* and *A. aucheri* has proven that Maxent is a powerful model for species distributions mapping. Futheremore, this model can efficiently find the environmental variables correlation with the geographic distribution of species. Moreover, the results of this research have demonstrated that using the soil data in addition to the climatic and topographic data can improve the predictive capability for habitat distribution mapping of plant species using the Maxent model.

Finally, it can be concluded that remote sensing, GIS, geostatistics, and ecological modeling are the efficient tools for rangelands assessment and sustainable management. Furthoremore, as the overgrazing and climate change are the main threats of Iran's rangelands, monitoring the relations of soil, topography, and climate with vegetation as well as the impact of climate change on rangelands represents basic information for finding the proper strategies of rangeland improvement. Moreover, implementing conservation plans together with planting the suitable endemic species based on the results of the ecological modeling would be of tremendous value in rangeland rehabilitation.

Key words:

Remote sensing, GIS, geostatistics, ecological modeling, rangeland assessment and improvement, environmental variables, soil mapping, precipitation-vegetation relations, habitat distribution.

Chapter 1. General introduction

1.1. Overview

Biodiversity patterns of Iranian rangelands have been significantly changed in recent decades, mainly due to the anthropogenic and climatic effects. Human-caused overgrazing and drought periods have led to the land degradation and desertification which might cause an eventual loss of biodiversity in rangeland ecosystems of Iran.

Regarding the mentioned importance of rangeland conservation and rehabilitation in Iran, monitoring of these areas and suggesting some conservation and rehabilitation strategies were among the objectives of the present study.

In this chapter the aims and research questions of the present study have been explained. Then the ecosystem of drylands and rangelands of Iran have been described briefly. In addition, based on the objectives and the required analyses that have been worked out in this study, some general information about remote sensing, geostatistics, and ecological modeling and their application in rangelands management, assessment and development have been introduced.

1.2. Research Objectives

1.2.1. General Objectives

The general objectives of this research are:

- To develop an assessment and improvement procedure for rangelands using environmental variables (e.g. soil parameters, climatic and topographic data) and their relations with vegetation.
- To evaluate the simultaneous application of remote sensing, GIS, geostatistics and ecological niche modeling for rangeland assessment and improvement.
- To suggest some plans for sustainable management, effective conservation, and rehabilitation of the degraded rangelands.

1.2.2. Specific Objectives

In order to achieve the above mentioned general objectives of the research, the following specific objectives are proposed:

- To map different soil parameters in rangelands using geostatistics, remote sensing, and environmental variables. Moreover, to compare the accuracy of different geostatistical approaches for soil properties mapping in rangelands and determine the benefits of using secondary data in geostatistical predictions.
- To map the vegetation cover percentage in rangelands using remote sensing and find the best annual time intervals of satellite images for vegetation studies and vegetation cover percentage mapping.
- To find the relation between precipitation variation and vegetation dynamics using remote sensing and GIS. Furthermore, evaluating the effect of some environmental variables on precipitation-vegetation relations.
- To model and map the habitat distribution of *Artemisia sieberi* (*A. sieberi*) and *Artemisia aucheri* (*A. aucheri*) as the two endemic and vital species of Iran's rangelands using Maxent model and find the differences between *A. sieberi* and *A. aucheri* habitats (more information about the importance of these species has been represented in sections 1.10 & 6.1).
- To determine the most important environmental variables affecting the distribution of both mentioned species in relation to rangeland quality.

1.3. Research Questions

The research has tried to answer the following questions in the framework of future rangeland assessment, improvement, and suitable management:

- What is the current condition of the rangelands of the study area?

-Which strategies could be useful for sustainable management and improvement of the rangelands?

- What is the efficiency of using satellite images and environmental factors as secondary data in geostatistical predictions of soil properties?

- What is the strength of relations between the vegetation dynamic and the precipitation variation in arid and semi-arid rangelands?

- What is the impact of environmental variables on NDVI-precipitation relations?

- What is the best annual time interval of the satellite images for vegetation studies?

- Which places in the study area are the potential habitats for the mentioned species?

- Which environmental variables are the most effective for the habitat distribution of *A. sieberi* and *A. aucheri*? Are there significant differences between these species?

- Are there significant associations of both *A. sieberi* and *A. aucheri* to common land cover classes (habitats)?

1.4. Organization of dissertation

This dissertation is designed into seven chapters as follows:

In chapter 1, an overview of the research, objectives and aims, research questions, flowchart of the thesis, connection of the different chapters, and finally a general introduction about the different parts of the thesis are presented.

Chapter 2 presents the detailed information about the study area. This chapter includes the description about the general location, topography, climate, geology, vegetation, and soil.

Chapters 3 to 6 have been written in the structure of scientific manuscripts and have been either published or are in press in different international journals. Since the information about the study area has been very briefly addressed in these chapters, the detailed descriptions have been firstly represented in the chapter 2.

In chapter 3, three geostatistical methods for soil mapping have been compared. To create the soil properties maps of the study area, the satellite images and environmental variables such as topographic data, precipitation and soil data have been applied. Efficiency of using the remote sensing and environmental data as a secondary variable in the geostatistical predictions was tested. Finally, different soil parameter maps have been created for ecological modeling. Created soil-property maps have made the basis for further environmental evaluations in the chapters 5 and 6.

Chapter 4 investigated the best annual time intervals of the satellite images for vegetation studies and vegetation cover percentage mapping. The created map is one of the required data for the next analyses in chapters 5 and 6.

Chapter 5 evaluates the relationship between the precipitation variations and vegetation dynamics using the time series of satellite images in which the precipitation maps were evaluated. In addition, the impacts of some environmental variables in precipitation-vegetation relations were assessed.

Chapter 6 focuses on the ecological niche modeling. Maximum entropy (Maxent) model is employed to examine the effect of environmental variables on the habitat distribution of *A. sieberi* and *A. aucheri* as well as predicting, assessing, and mapping the habitats of these speciase. To reach these purposes, resulted maps of the previous chapters (e.g vegetation cover percentage and soil properties maps) with some extra information especially coordinate of the points that the mentioned species are exist will be the inputs of the maxent model.

Finally, in chapter 7 the important points of the achieved results have been summarized and concluded. The strengths and weaknesses of different techniques such as remote sensing, GIS, geostatistics, and ecological modeling also have been discussed. In addition, some suggestions for the future studies are presented.

1.5. Flowchart of the dissertation and the connection of the different chapters

As the main aims of this research were assessment of the Poshtkouh rangelands and suggesting some planning strategies for improvement, sustainable management, conservation and restoration of this area, preparing the environmental variable maps is a critical step before any ecological modeling analysis. The results of Maxent model would be a base for the mentioned decisions. Created habitat distribution map of this model represents the ecological suitability of the study area for planting the target species that could be useful for the future plans for improvement and development of the rangelands with similar ecological conditions.

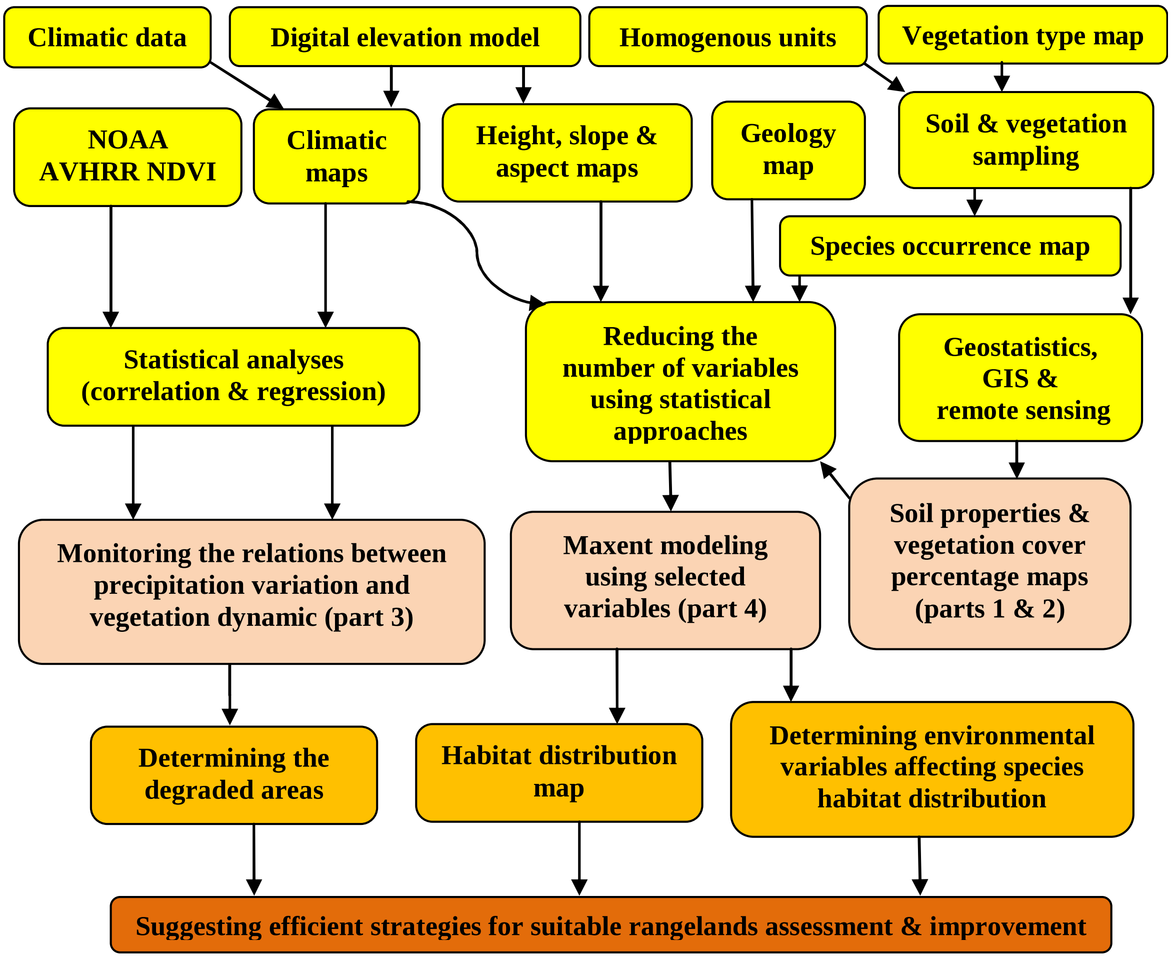

Figure 1.1. Flowchart of the thesis (Framework for an assessment and improvement approach of rangelands using ground truth data, GIS, remote sensing, geostatistics, and ecological modeling.

The connection among different thesis chapters has been illustrated in figure 1.1 which also has been mentioned in section 1.4 (organization of dissertation). Soil properties maps resulted from chapter 3 have been used in chapter 5 to detect the effect of soil available moisture on the strength of relations between precipitation and NDVI. Moreover, these soil maps have been used as the inputs for the Maxent model (chapter 6). The vegetation cover percentage map created in chapter 4 has been used in chapters 5 and 6. Finally, some strategies for sustainable management and rehabilitation of the rangelands of the study area have been suggested based on the results of the chapters 5 and 6.

1.6. Dryland ecosystems

Drylands contain areas that receive less amount of rainfall than the potential evapotranspiration. FAO has defined drylands as those areas with a length of growing period of 1-179 days (FAO, 2000).

About 45 percent of the land surface is occupied by dry lands. Also around 30 percent of the world's total carbon in above and below ground biomass occurs in drylands (Mainguet, 1999). In addition, they consist of grasslands, shrublands, savannas, xerophytic woodlands, and hot and cold deserts (Figure 1.2). Rangelands located in drylands provide forage for wildlife and domestic animals and support nearly 50 percent of the world's livestock.

Drylands classification is based on the value of an aridity index. This index is calculated as the ratio of annual precipitation to annual potential evapotranspiration. According to this method dry lands are classified into hyper-arid (<0.05), arid (0.05-0.20), semi-arid (0.20-0.50), and dry sub-humid (0.50-0.65). Yearly rainfall patterns of drylands are characterized by a dry period which is different from 2 to 10 months in different regions (Propastin, 2006).

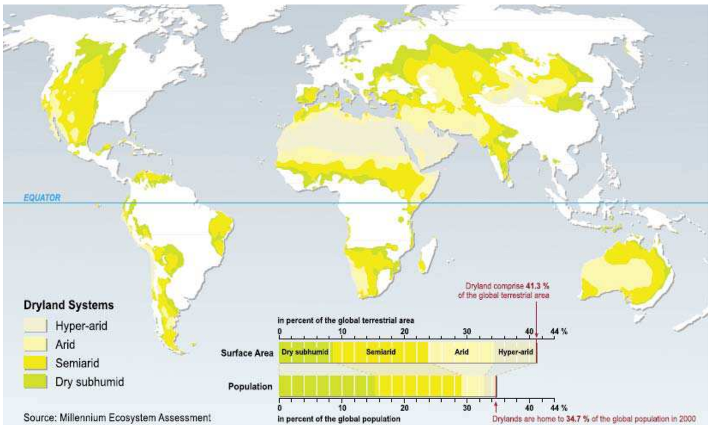

Figure 1.2. Distribution of drylands throughout the world (UNEP, 2000).

One of the typical climatic features in dry lands is seasonal precipitation. In fact, the vegetation in drylands suffers from the water shortage while it can develop adaptations to cope with this phenomenon. Soil dryness and plant transpiration increase, result from the high evaporation of soils and the surrounding atmosphere due to the high temperatures and high air dryness (Propastin, 2006).

Moreover, the climate and soil characteristics greatly affect the composition and distribution of plants in drylands. Due to the moisture deficit throughout the growing period of vegetation, drylands plant species show a high degree of adaptation to aridity. A large variety of grasses, shrubs, and forbs present in dry lands. Generally, in dry regions ecosystem, dynamics are affected by natural hazards such as drought and desiccation. Ecologists emphasize on high dependency of arid and semi-arid rangelands ecosystem dynamics on climatic perturbations (Vetter, 2005; Robinson et al., 2002).

The high variability of climatic conditions in drylands resulted mostly from the high precipitation variations; the coefficient of variation of rainfall is between 25-40 %. Numerous studies in dry regions have demonstrated that long-term ecosystem behavior could be explained better by rainfall variation than by the mean values (Shepherd & Caughley, 1987; Ellis et al., 1993).

In the last two decades, environmental monitoring with the use of remote sensing has provided good facility for monitoring ecosystem variations and ecosystem changes, land degradation as well as their causal relationships. In fact, satellite data detect patterns of inter-annual and seasonal variations in land surface features that are resulted by climatic changes and human activities (Propastin, 2006). Basically, ecosystem variations affect by drought and desiccation (Lambin & Ehrlich, 1996), fluctuations in rainfall (Anymba et al., 2001; Olsson et al, 2006), and temperature growth (Xiao & Moody, 2004). Many of the former researches about ecosystem dynamics in dry regions proved that monitoring of land degradation and desertification need to analyze climatic data and satellite images of a long period of time (Robinson et al., 2002; Propastin and Kappas 2008a,b).

1.7. Importance of rangelands in Iran

Over the past few decades rangelands have been defined in several ways. According to Heady (1975) rangelands are defined as “shrub lands, grasslands and open forests, where dry, saline or wet soils, steep topography and rocks preclude the growing of commercial farm and forest crops”. American society for range management has defined the rangelands as the “lands on which the native vegetation is predominantly grasses, grass like plants, forbs or shrubs suitable for grazing or browsing use which includes lands revegetated naturally or artificially to provide a forage cover that is managed like native vegetation” (McGuire, 1978).

Several estimations have been done to estimate the total rangeland area in Iran. Based on recent studies, approximately 54.6% of the total land area and 65% of natural resources in Iran are occupied by rangelands (Badripour, et al. 2006). Rangelands are major terrestrial ecosystem in the country and have essential role in the economy of the country (Moghaddam, 2006). Rangelands provide medical plants, as well as herbs for animal feeding and meat production. For many pastoralists, rangelands are the major or only source of income (Farahpour 2002).

In Iran, in the semi-arid zones adjoining the desert, animal husbandry has been considered as the most productive use for rangelands (Farahpour, 2002; Moghaddam, 2006). Although rangelands have been degraded in the recent decades, important parts of fodder are still provided by rangelands. Rangelands with 10 million tons of annual dry matter production produce 31 percent of the country‘s meat and 11 percent of milk production in Iran (Farahpour, 2002).

Population of livestock in Iran is about 124 million animal units. 83 million of the total livestock population depends entirely on the rangelands for seven months (Badripour et al., 2006).

In arid and semi-arid areas, the rangelands plant-cover conserves the soil against erosion caused by flooding, and wind (Moghaddam, 2006). Furthermore, Iranian rangelands are important in terms of bio-diversity and rare species including *Stipa barbata, Artemisia sieberi, Poa bulbosa, Carex stenophylla and Noea macronat* (Moghaddam, 2006). In addition, rangelands' vegetation serves as a carbon sink.

Due to untimely grazing (late grazing and early grazing), overgrazing, overstocking, and climate change, the rangelands of Iran have been degraded in recent decades (Eskandari & Chavoshi 2002; Hedjazi 2007; Badripour et al. 2006).

1.8. Investigation of vegetation changes based on remote sensing

Spatial distribution of environmental variables especially precipitation strongly affects distribution of vegetation cover. In arid regions, the climatic factors variations depend meaningfully on the topographic characteristics. Hence, topography can be the most important predicting factor for the vegetation distribution and condition in drylands where lack of moisture exists during the most time of the year. It should be considered that the impact of the topography on vegetation is indirect; it acts through the climatic factors. Topography is also one of the factors affecting the soil variability.

Remotely sensed data frequently are used to map land surface cover for use in a variety of resource assessment, vegetation mapping, land management, and modeling applications (Jones & Vaughan, 2010; Booth, & Tueller, 2003; Hosseini et al., 2004). Relationship of satellite images and ground-based data depends on the satellite imagery precision, time of recording, biological factors (growth forms, the amount of litter and phonological stages), and non-biological factors such as land form, slope, direction and height (Wang et al., 2005; Wylie et al., 2002).

Normalized Difference Vegetation Index (NDVI) derived from satellite images is an appropriate tool for vegetation cover monitoring from global to local scales. It can show seasonal and inter-annual changes in vegetation. This index has effectively been applied in several studies related to the vegetation assessment and desertification (Tucker et al., 1999; Wessels et al., 2004; Symeonakis and Drake, 2004), drought monitoring (Kogan, 1997; Song et al., 2004), and vegetation cover mapping (Booth & Tueller, 2003; Jafari et al., 2007; Wang et al., 2005).

Several studies have reported temporal and spatial correlations between NDVI and climatic factors in different climatic conditions particularly in arid regions (Propastin & Kappas, 2008 a,b; Weiss et al, 2004; Tateishi & Ebata, 2004; Hively et al., 2009). Strong effect of precipitation on the inter-annual variability of vegetation activity especially in dry regions has been demonstrated in other research works (Wang et al, 2005; Li et al., 2002).

Many studies proved that the relationship of NDVI with precipitation and temperature depends on geographical and environmental condition specially vegetation type. In forest and woodland areas, correlation of NDVI and precipitation is lower, while in shrubs and desert vegetation patterns is stronger. In steppe grassland and savanna the highest correlation has been reported (Li et al, 2002; Wang et al, 2005, Li et al, 2004). According to Nicholson & Farrar (1994), the effect of soil types on the NDVI-precipitation relationships is significant.

1.9. Soil properties mapping in rangeland areas using geostatistics and remote sensing

One of the most important issues in natural ecosystems sustainable management especially for rangelands is soil quality. Therefore, soil mapping is a very essential step in landscape ecology, and rangelands rehabilitation (Burke, 2001; Etema, & Wardle, 2002; Kavianpoor et al., 2012; Zhang & McGrath, 2004).

In rangeland areas, spatial and temporal variability of soil properties affect by physical and biological factors such as topography, vegetation cover, soil microclimate, grazing systems and management method (Chaneton & Avado, 1996; Rogerio et al., 2006; Zhao et al., 2007). Hence, detecting the temporal and spatial changes in the soil characteristics is necessary in rangeland management and rehabilitation (Chaneton and Avado, 1996). Vegetation distribution patterns and diversity depend on different environmental variables especially soil properties such as soil moisture, texture, depth, salinity, organic matter, etc. (Noy-Mire, 1973; Burke, 2001).

Numerous studies have proved the relation between soil and vegetation (Etema & Wardle, 2002; Covelo et al., 2008; Zhao et al., 2007). Therefore, awareness about spatial and temporal variability of soil is in tremendous value for natural resources management and ecological modeling (Hangsheng et al., 2005; Wang et al., 2009).

Many studies have been done to determine the effect of soil properties and characteristics such as salinity (Sharma and Shankar, 1991; Abbadi and El Sheikh, 2002), pH, calcium and organic carbon (Abd El-Ghani et al., 2002) on plant species composition. Abd El-Ghani et al., (2002) reported low species richness in an area with high level of salinity and CaCO3. Increasing soil depth, organic matter and water-holding capacity, as well as decreasing pH and CaCO3 amount of the soil have a positive effect on plant growth and species richness (Shaukat et al., 1981).

Among different approaches that have been used for mapping soil parameters, geostatistics and remote sensing seem more efficient and cost-effective. Geostatistics analyzes the soil samples data that have spatial structure (Goovaerts, 1997). Basically, geostatistics is a confident, strong and powerful method that considers spatial variance, location and distribution of samples to determine spatial variability using mathematical and statistical functions (Sauer et al., 2006). Early principal of geostatistics is that the similarity between near samples decreases when the distance increases (Isaak & Srivastava 1989; Goovaerts 1997).

Creating an accurate soil map in a rangeland ecosystem due to the necessity for taking and analyzing a big number of samples is very challenging. Therefore, the application of cost-effective and easily-measurable variables such as elevation and satellite images is suggested as secondary data for soil mapping in large areas (Eldeiry & Garcia, 2008), Several authors have pointed out that remote sensing data is a suitable tool for mapping soil properties with a reduced number of samples. To reach this goal, the existence of meaningful correlation between soil data collected from field and satellite images is necessary (Metternicht and Zink., 2003; Metternicht and Zink., 2009).

1.10. Ecological niche modeling

In recent decades, economic development, climate change and overgrazing have caused considerable pressure on rangeland ecosystems that has led to habitat fragmentation and eventual loss of biodiversity. Determining the status of species has specific importance for ecologists (Hecnar & M’closkey, 1996). Management of rangeland ecosystems is essentially based on a correct understanding of ecological concepts. Measuring ecological and environmental requirements of plant species to determine vegetation patterns, distribution, and richness is very essential towards this understanding. Rangeland ecologists aware that the environmental variables such as; the climate, soil, and topography, can affect the vegetation dynamics, composition, and geographical distribution, considerably. Modeling the distribution of the endemic species in its natural habitat could be useful for the conservation and rehabilitation of degraded rangeland areas. Prediction of the potential spatial distribution of a species or vegetation type would be possible by using ecological niche modeling. This kind of model analyses species occurrence data and environmental variables to predict suitable or unsuitable areas for survival of target species. This could be an adequate methodology to extrapolate the ecological habitats of species based on the collected data to a larger space in desert and mountainous area where the sampling in the whole area is not possible.

Ecological niche models can be used as suitable tools for conservation planning, modeling habitat distribution of single plant species or vegetation types and determining environmental variables affecting habitat distribution of species (Bachman, 2011).

To suggest the best method for ecosystem management and species conservation, ecologist should increasingly rely on predictive models to find information about species distributions (Ferrier, 2002; Loiselle et al., 2003). Inaccessible georeferenced data is a critical problem for ecological modelling. Therefore, in the first step, it is necessary to identify where the species prefer to live and what they require to exist, i.e. their ecological niche (Hutchinson, 1957).

Typically, for this mission, a list of present points that represent where the species have been observed and the locations where the species are surely absent is required. Additionally, information about the environmental variables such as elevation, slope, aspect, precipitation, temperature, soil parameters, vegetation type, geology, etc, which have been measured in the field or in laboratory is necessary. The purpose is to assess which areas have the requirements of the target species' niche and therefore could be part of the species' potential distribution (Anderson & Martínez-Meyer, 2004).

The distribution map demonstrates where the environmental conditions are appropriate for existence of the target species, and has great importance for conservation. By excluding the areas where it has been recognized that the species is absent because of deforestation, desertification or other habitat destruction, the map could also be used to assess the species' real distribution (Guisan, and Zimmermann, 2000).

Generally, statistical models employ empirical data to assess the relationships between current species distributions and environmental variables. Incorporating these models into a geographic information system (GIS) could facilitate the mapping of potential distributions. All of the prediction models are either strictly mathematical or based on certain ecological theories (Elith et al., 2006; Graham & Hijmans, 2006).

Some examples of the mapping methods are; generalized linear models (Guisan et al.1998), regression trees (Moore et al., 1991; Iverson & Prasad, 1998), generalized additive models (Yee and Mitchell 1991), multivariate adaptive regression splines (Leathwick et al., 2005), GARP (Stockwell, 1999), Maxent (Phillips et al., 2006; Phillips & Dudik, 2008), BIOCLIM (Busby, 1986).

In the present study, the distributions of two sagebrush species (*A. sieberi and A. aucheri*) have been modeled. These species have been selected because both of them are endemic of Iran's rangelands. *A. aucheri* occurs only in mountainous areas, while *A. sieberi* occurs in most parts of arid and semiarid rangelands of Iran and recognized as the main plant species of Iran's rangelands. Furthoremore, both of the mentioned species are considered not only for the animal feeding due to the high grazing tolerance but also in nature conservation and degraded land restoration planning. Furthermore, multiple uses of these species especially as medicinal plant may also be taken into account (Moghaddam, 2006; Moghimi, 2006; Mozaffarian, 2010).

The diversity in topography, climate, and soil in the study area can add more potential capability for more satisfactorily and validly mapping the distribution patterns. To reach this purpose, the maximum entropy (Maxent) model (Phillips et al., 2006) was used. Using this model, the environmental factors and geographical point locality data were integrated to assess the current distribution of two sagebrush species.

1.11. Maximum entropy (Maxent) model

Maxent is an approach for modeling habitat distribution of species using only the existing records of target species. Coordinates of occurrence points of species (where the species have been observed) should be used as georeferenced pair of latitude and longitude (Figure 1.3).

Environmental variables of the study area (e.g. topography, climatic, and soil parameters) should be mapped as raster maps with latitude and longitude coordinate (other kinds of coordinate systems cannot be used in Maxent).

Through finding the probability distribution of maximum entropy, the model analyzes the data and assesses the probability distribution of the target species.

There is a restriction for target probability distribution. Expected value of each environmental variable in the estimated probability must be same as its empirical average. Therefore, the target probability distribution could be reliable (Phillips et al., 2006).

The resulted continuous map with the probability values ranging between 0 and 1 shows the suitability of each pixel for occurrence of the target species based on the environmental variables data (Phillips et al., 2006). The higher the probability value, the higher the suitability of adequate environmental conditions for the species at the pixel. (Phillips et al., 2006; Phillips & Dudik, 2008). It also has been proved that Maxent can analyze the low numbers of the recorded occurrence data powerfully (Elith et al. 2006; Phillips et al. 2006; Hernández et al. 2006).

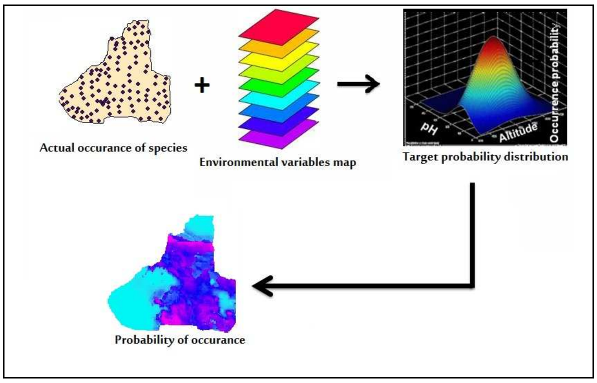

Figure 1.3. An illustration of a workflow for the Maxent model.

Different applications of the Maxent approach are; modeling the distribution of the single species (Buermann et al., 2008), species richness (Guisan & Rahbek 2011), endemism Escalante et al. 2009), and the sensitivity of species to environmental change (Thuiller et al. 2005).

In this study, Maxent was selected due to the following advantages (Phillips et al., 2006):

- It needs presence-only data rather than presence/absence data.

- The model can analyze both of the continuous and categorize environmental variable maps and combine interactions between different predictors.

- Outputs of the Maxent can show contribution of each predictor in the model.

- Maxent is robust to size of samples as low as 10.

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Chapter 2. Study area

The diversity in environmental variables (e.g. topography, climate, vegetation, soil, geology, etc.) was the main reason for choosing Poshtkouh rangelands as the study area.

Although, in each of the next chapters, the characteristics of the study area have been explained very briefly, detailed information in this regard has been presented in this chapter.

2.1. General location:

Poshtkouh rangelands are located in the south-west of Yazd province, in the central Iran with an area of 170000 ha. In the northern parts of the area, Shirkouh highlands are located and Kavir-e-Chahbeygi is in the southern parts. The coordinate of this area is:

Latitude: 31° 04′27″to 31°33′11″N.

Longitude: 53°40′06″to 54°15′ 19″E.

A number of roads connect several villages (e.g. Kahdouieh, Nir, Banadkouk, Ernan, Mortazieh, Sakhvid, Dehshir, Garizat) and farmlands to each other. Figure 2.1 shows the general location of Poshtkouh ranglands.

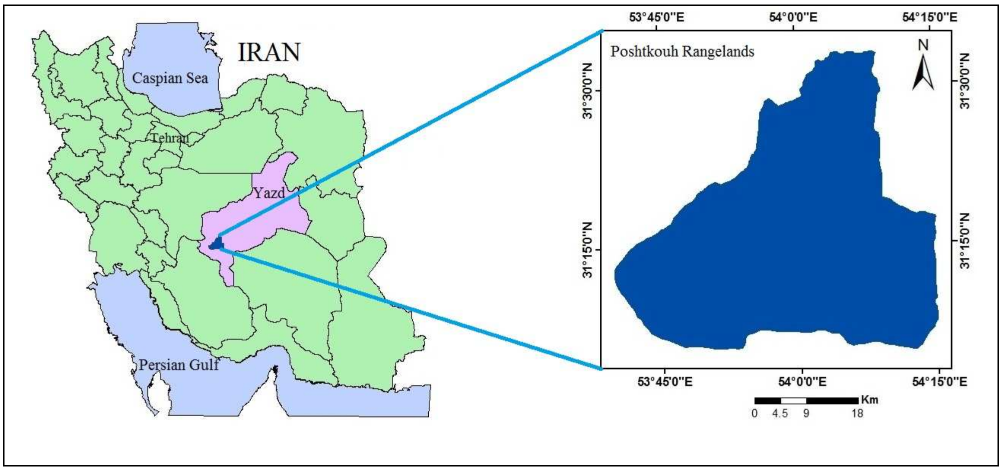


Figure 2.1. General location of the study area

2.2. Topography

Topography (elevation, slope, and aspect) is an important factor which has a significant effect on the climatic factors. It has an influence on spatial patterns of vegetation. Among the topographic factors, elevation is the most influential on the ecosystem (Agren and Anderson, 2011, Odum, 1983).

According to the Digital Elevation Model (DEM) and topographic maps, the maximum elevation of the study area is 3990m in Shirkouh Mountain and the minimum is 1400m in Kavir-e-Chahbeygi. Therefore, the elevation variation is 2590m. Figure 2.2 illustrates the hillshade map of the study area.

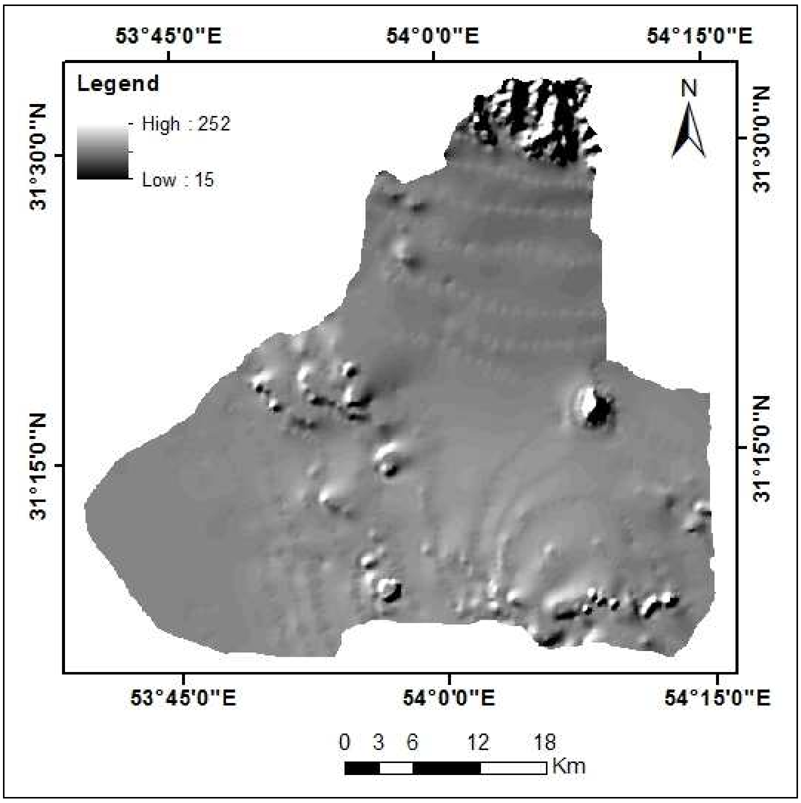


Figure 2.2. Hillshade map of the study area

2.3. Climate

One of the important factors influencing the rangeland soil and vegetation communities is the climatic condition (Odum, 1983; Barbour et al., 1987; Abd El-Wahab et al., 2008). In recent decades, climatic and other environmental factors are used to describe the vegetation distribution patterns in different studies (Brezeziecki et al., 1993; Brovkin et al., 1997; Thuiller et al, 2004; Varges et al, 2004).

Based on the above introduction, to determine the climatic condition in the study area, climatic data of 9 stations were used. Some characteristics of the climatic stations have been summarized in Table 2.1. The relationship between precipitation and temperature with elevation were determined and the maps of climatic parameters were created.

Table 2.1. Climatic stations in the study area

Station Name	X	Y	Height (m)	Mean annual precipitation (mm)	Mean annual temperature (ºC)
Abarkouh	53°28′	31°13′	1506	39	19.1
Dehshir	53°44′	31°28′	1900	100.2	16.3
NasrAbad	53°52′	31°47′	2264	194.4	12.8
Taft	54°14′	31°49′	1680	131	18.2
Manshad	54°13′	31°32′	2250	323	13.3
Mehriz	54°48′	31°57′	1520	66.7	19
Nir	54°18′	31°22′	2470	268.9	11.1
Tezerjan	54°11′	31°26′	2120	288.8	13.1
Gariz	54°06′	31°18′	2420	121.1	15

2.3.1. Precipitation:

Usually the amount of precipitation increases with the increase of altitude to a specific height named optimum elevation. The optimum elevation for Iran is estimated 3500 m

(Mahdavi, 2011). In this study, based on the climatic station data (Table 2.1) and regression analysis, the relationship between the mean annual precipitation and elevation was calculated as following:

$$Y = -0.0005X^2 + 2.0155X - 1930.9 \quad (2\text{-}1)$$

According to the mean annual precipitation map of the study area (Figure 2.3), average annual precipitation varies from 298 mm in Shirkouh Mountains to 43 mm in margin of Kavir-e-Chahbeygi.

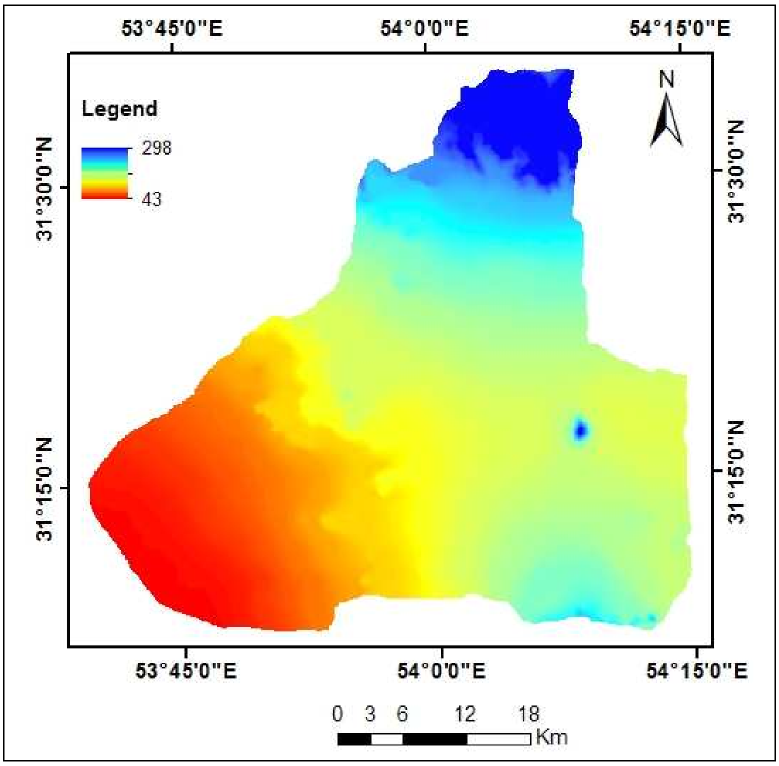


Figure 2.3. Mean annual precipitation map

2.3.2. Temperature:

In present study, the relationship between temperature and elevation was approximated by the following equation:

$$Y = -0.0069X + 29.408 \quad (2\text{-}2)$$

Temperature varies in different parts of the region (Figure 2.4). The southern parts have the maximum temperature (average annual: 18.2ºC), while the northern parts have the minimum temperature (average annual: 9.7 ºC).

Climate type was determined based on the Domartin method. This method gives an empirical relationship between the mean annual temperature (T) and mean annual precipitation (P) to calculate drought index (I) as below (Mahdavi, 2011):

$$I = P/(T+10) \qquad (2\text{-}3)$$

Table 2.2 summarizes climatic classification based on the Domartin method.

Table 2.2. Climate classification in Domarten method

Climate type	Arid	Semi-arid	Mediterranean	Semi-humid	Humid	Very wet
Drought index	0-10	10-20	20-24	24-28	28-35	35-55

Climate type for Nir station in the northern parts and Abarkouh station in the Southwest of the study area were determined based on table 2.2. The climate of the North and Southwest of the area are indicated as semi-arid (I=12.16) and arid (I=1.34), respectively.

Figure 2.5 shows Amberotermic curve for Nir station that is located in the northern part and Abarkouh station in the Southwest of the study area. According to the figure, for the Abarkouh station, the drought season happens between the months April to November, whereas for the Nir station, the drought season is between May to October. Hence, for the whole study area a long drought season happens. Basically, the central part of Iran has a Mediterranean precipitation regime, which means that most of the annual rainfall occurs at the end of autumn and during winter, there is a low amount of precipitation in spring, and summers are mostly dry. This means that there is not enough precipitation during the growing season of vegetation.

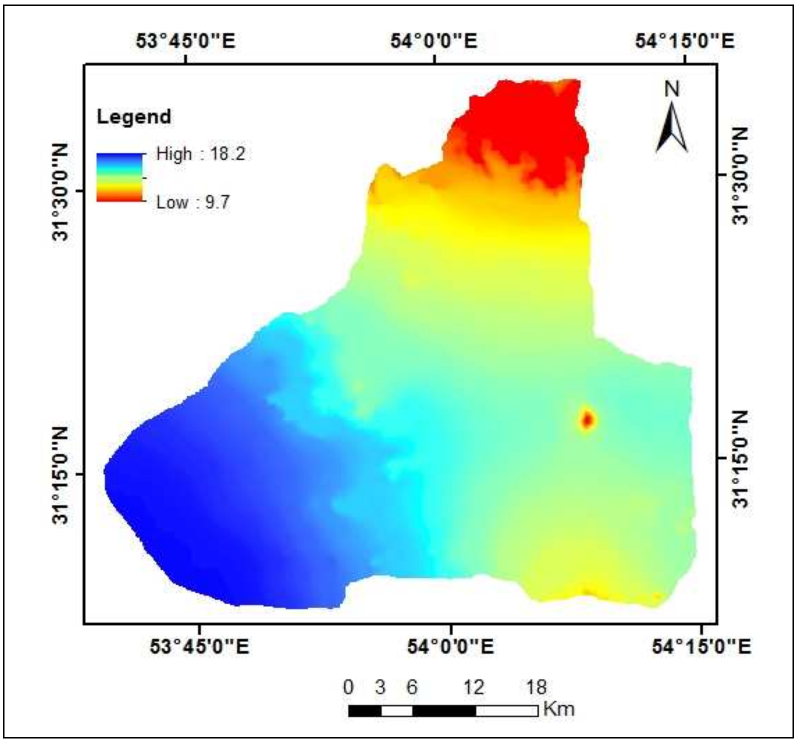


Figure 2.4. Mean annual temperature map

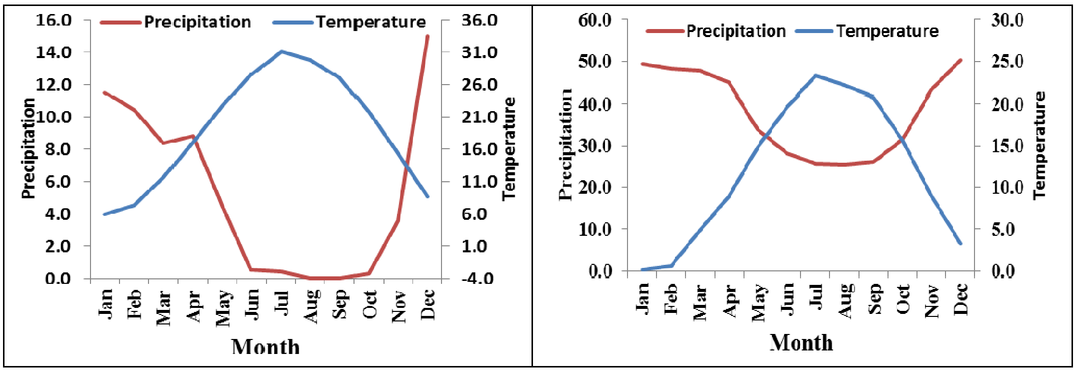


Figure 2.5. Ambrotermic curves of Nir station (right) and Abarkouh station (left)

2.4. Vegetation:

Generally, there are three plant communities in this area; the first community consists of *Artemisia aucheri*, *Astragalus*, and other cushion species is in the northern part of the area on Shirkouh elevations and mountain-foots. Due to the good humid conditions, some natural limitations for animal grazing, and consequently less utilization, some palatable grasses such as *Bromus*, *Festuca*, and some annual forbs exist in this part.

The second community named *Artemisia sieberi* is located on the alluviums at the central part of the study region. There are some Pterophyte and Gypsophyte species such as *Salsola kerneri*, *Salsola tomentosa*, *Ephedra strobilacea* and *Zygophyllum eurypterm* in this part. *Artemisia sieberi* has a high adaptability to this community.

The last community which presents on the saline alluvial sediments of the margin of kavir has been affected by high level of ground water. Some Halophyte species such as *Seidlitzia rosmarinus* and *Tamarix ramosissima* occur in this community.

Figure 2.6 illustrates the vegetation type map and Table 2.3 lists the most important vegetation species in each vegetation type. According to the figure and table, 13 vegetation types exist in the study area. Furthermore, Table 2.4 summarizes some vegetation types characteristics.

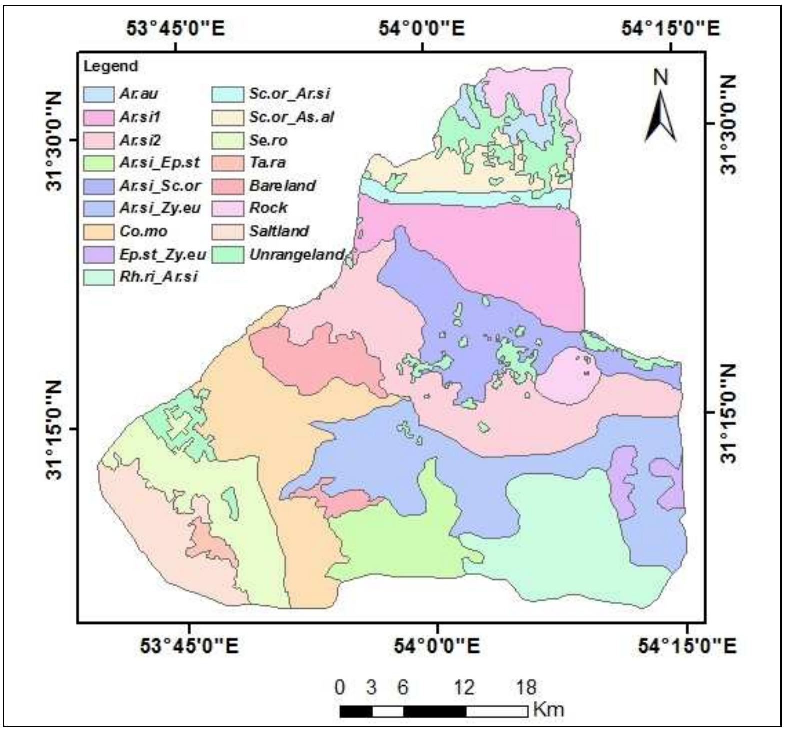


Figure 2.6. Vegetation types map in the study area

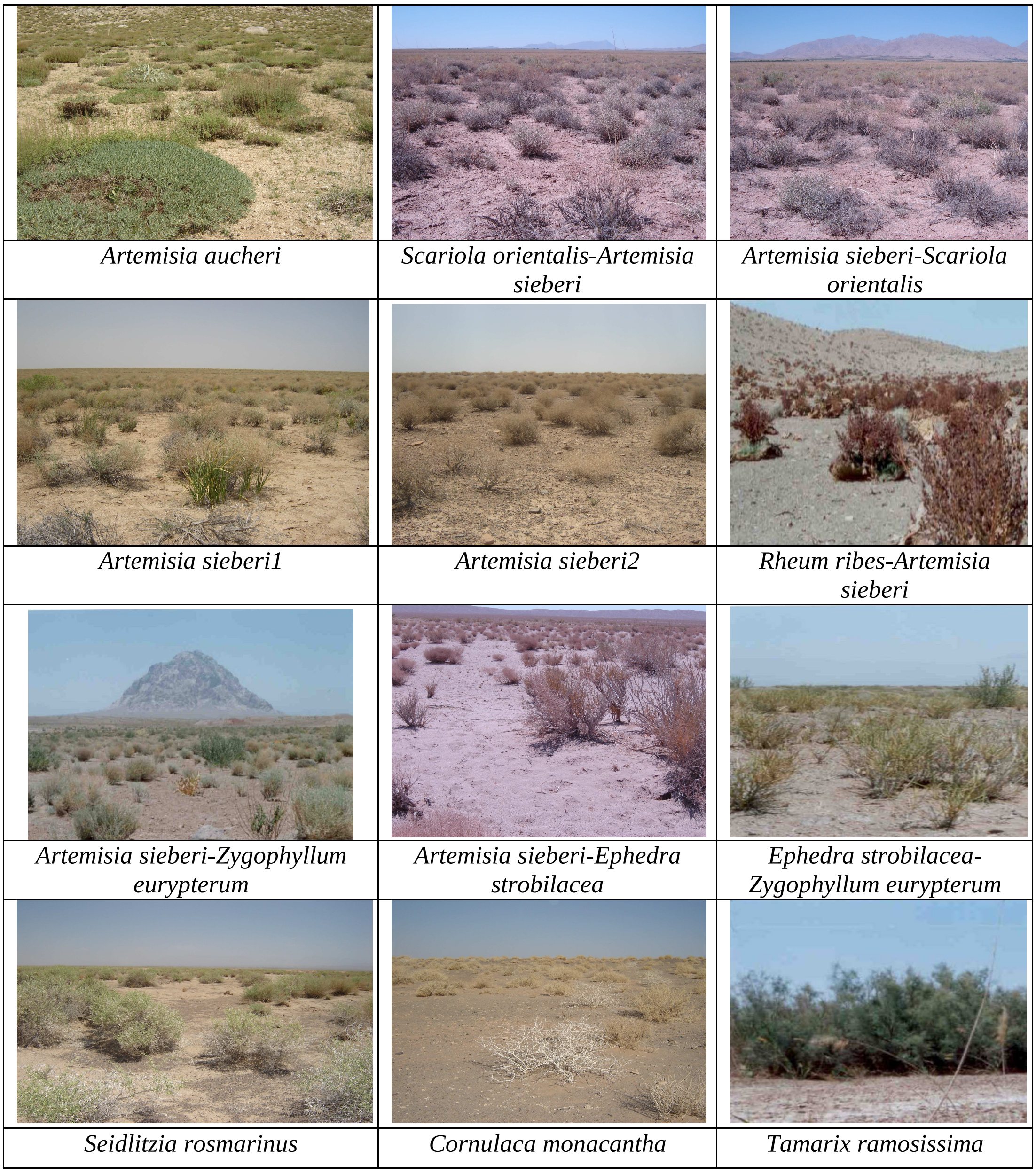
Table 2.3. List of the vegetation types and most important species in Poshtkouh rangelands

Vegetation type	Symbol	Plant species
Artemisia aucheri	*Ar.au*	*Artemisia aucheri,Astragalus ochrochlorus, Astragalus calliphysa, Astragalus myriacanthus, Acanthophyllum spp., Bromus spp.,Stipa hohenackeriana, Acantholimon spp.*
Scariola orientalis-Astragalus albispinus	*Sc.or-As.al*	*Scariola orientalis, Astragalus albispinus, Launaea acanthodes, Acanthophyllum spp., Stipa barbata, Noaea mucronata, Euphorbia heterandena, Echinops orientalis.*
Scariola orientalis-Artemisia sieberi	*Sc.or-Ar.si*	*Scariola orientalis, Artemisia sieberi, Stipa barbata, Euphorbia heterandena, Astragalus albispinus, Launaea acanthodes, Noaea mucronata, Hertia angostifolia.*
Artemisia sieberi-Scariola orientalis	*Ar.si-Sc.or*	*Artemisia sieberi, Scariola orientalis, Euphorbia heterandena, Launaea acanthodes, Astragalus albispinus, Stipa barbata, Acanthophyllum spp., Noaea mucronata*
Artemisia sieberi1	*Ar.si1*	*Artemisia sieberi, Launaea acanthodes, Scariola orientalis, Iris songarica, Salsola spp., Euphorbia heterandena, Astragalus albispinus, Noaea mucronata, Stipa barbata*
Artemisia sieberi2	*Ar.si2*	*Artemisia sieberi, Salsola kerneri, Salsola tomentosa, Astragalus albispinus.*
Artemisia sieberi-Zygophyllum eurypterum	*Ar.si-Zy.eu*	*Artemisia sieberi, Zygophyllum eurypterum, Ephedra strobilacea, Astragalus albispinus, Salsola spp., Dorema ammoniacum*
Artemisia sieberi-Ephedra strobilacea	*Ar.si-Ep.st*	*Artemisia sieberi, Ephedra strobilacea, Zygophyllum eurypterum, Salsola spp.*
Ephedra strobilacea-Zygophyllum eurypterum	*Ep.st-Zy.eu*	*Ephedra strobilacea, Zygophyllum eurypterum, Salsola spp., Dorema ammoniacum, Artemisia sieberi*
Rheum ribes-Artemisia sieberi	*Rh.ri-Ar.si*	*Rheum ribes, Artemisia sieberi,Zygophyllum eurypterum, Scariola orientalis, Stipa barbata, Astragalus albispinus.*
Cornulaca monacantha	*Co.mo*	*Cornulaca monacantha, Calligonum comosum, Stipagrostis plumose,Salsola spp., Ephedra strobilacea.*
Seidlitzia rosmarinus	*Se.ro*	*Seidlitzia rosmarinus, Salsola spp., Haloxylon aphyllum.*
Tamarix ramosissima	*Ta.ra*	*Tamarix ramosissima Phragmites communis.*

Table 2.4. Some characteristics of the vegetation types

Vegetation type	Cover Percentage %	Slope%	Altitude (m)	Annual Precipitation (mm)
Ar.au	25.5	20-30	>2500	>290
Sc.or-As.al	26.5	8-12	2300-2400	200-240
Sc.or-Ar.si	20	5-8	2200-2300	180-200
Ar.si-Sc.or	12.1	5-8	2000-2100	130-160
Ar.si1	16	5-8	2100-2200	160-180
Ar.si2	10.5	5-8	1900-2100	120-150
Ar.si-Zy.eu	8.2	5-8	1600-2100	100-150
Ar.si-Ep.st	6.5	5-10	1700-2000	75-120
Ep.st-Zy.eu	10.2	5-8	2050-2100	150-160
Rh.ri-Ar.si	12.5	8-12	2100-2300	160-220
Co.mo	9	5-8	1500-1700	50-75
Se.ro	10.2	2-5	1400-1500	45-50
Ta.ra	5	0-2	1400	45

In this study, due to the coarse spatial resolution of NOAA AVHRR satellite images which were used for the vegetation cover percentage mapping and determining the NDVI-precipitation relations (see next chapters), the vegetation types with the similar plant species were merged and the number of types was reduced to four types including; alpine plants, sagebrush, gypsophyte, and halophyte. Moreover, for modeling habitat distribution of *Artemisia aucheri* and *Artemisia sieberi* (chapter six) this map was used.



Artemisia aucheri | *Scariola orientalis-Artemisia sieberi* | *Artemisia sieberi-Scariola orientalis*

Artemisia sieberi1 | *Artemisia sieberi2* | *Rheum ribes-Artemisia sieberi*

Artemisia sieberi-Zygophyllum eurypterum | *Artemisia sieberi-Ephedra strobilacea* | *Ephedra strobilacea-Zygophyllum eurypterum*

Seidlitzia rosmarinus | *Cornulaca monacantha* | *Tamarix ramosissima*

Figure 2.7. Some pictures from different vegetation types

2-5- Geology and geomorphology

Poshtkouh area is located in the borders of the Central Iran and Uromia-Dokhtar geological structural zones. In terms of morphology the area can be divided to north highlands, southern hills, more or less single dacitic domes, and plains.

The northern highlands are the highest part of the area and often consist of intrusive Shirkouh granites, cretaceous limestones, and first and second geological period rocks. In these areas cretaceous limestone are deposited over the huge Shirkouh granitic mass and created high cliffs whereas granitic Shirkouh rocks caused more flat elevations.

The majority of the southern mountains comprise of geological third-period volcanic rocks whereas south eastern elevations mainly consist of geological third-period clastic rocks which are the result of the erosion of older mainly volcanic rocks.

Distributed dacitic domes are the most beautiful scene of the area among which Ernan mountain with elevation of 2892 m is the highest. Chahtorsh, Bonakouh, and Hajizamani are among the other crests. In terms of the ages, these domes are related to Pliocene from the late third-geological period. These domes are with two different geomorphology; one with an uneven surface and the other with hill and high grounds-like surface.

The plains are mostly sandy-clayey and include alluvial deposits. These plains were formed from alluvial runoffs, strong-winds eluvials, and clastic or disintegrated materials solution and deposition of them at the lower elevations causing desertification and saliniation.

The vast northern plain expanded around Shirkouh Mountain includes Shirkouh granite disintegrated alluvials. The alluvial particles are fined from elevations and hillsides toward the lower plain and finally end to silt and clay in deserts (Ernan and Chahbeygi).

The geological map of the study area was prepared using Nir and Dehshir sheets with the scale of 1:50000 (Figure 2.8). In the study area thirteen geological units were distinguished those area and characteristics have been summarized in table 2.5. According to the table the biggest area consist of the old alluvial sediments (58.6%), and 14.7% of area Sandstone and Conglomerate.

Table 2.5. Geological units in Poshtkouh rangelands

Number	Unit	Area (%)	Geological description
1	gsh	4.7	Shirkouh granite
2	Qt1	1.8	Young alluvial terraces
3	Qt2	58.6	Old alluvial terraces
4	QSf	1.2	Salt crust
5	Qtr	0.2	Travertine
6	td	0.50	Dacite-andesite
7	Pec	0.4	Kerman conglomerate
8	Mur	14.7	Red to Brown Sandstone
9	PLC	5.7	Non Consolidated Conglomerate
10	Cm	5.4	Color mélange
11	OMr	3.8	Horizon of Red marl, Non Consolidated Conglomerate and Red Sandstone that are Consolidated in some parts by bicarbonate solutions
12	E1m	2.6	Gypsum Ferrous Marl
13	KTL	0.2	Marl and limestone

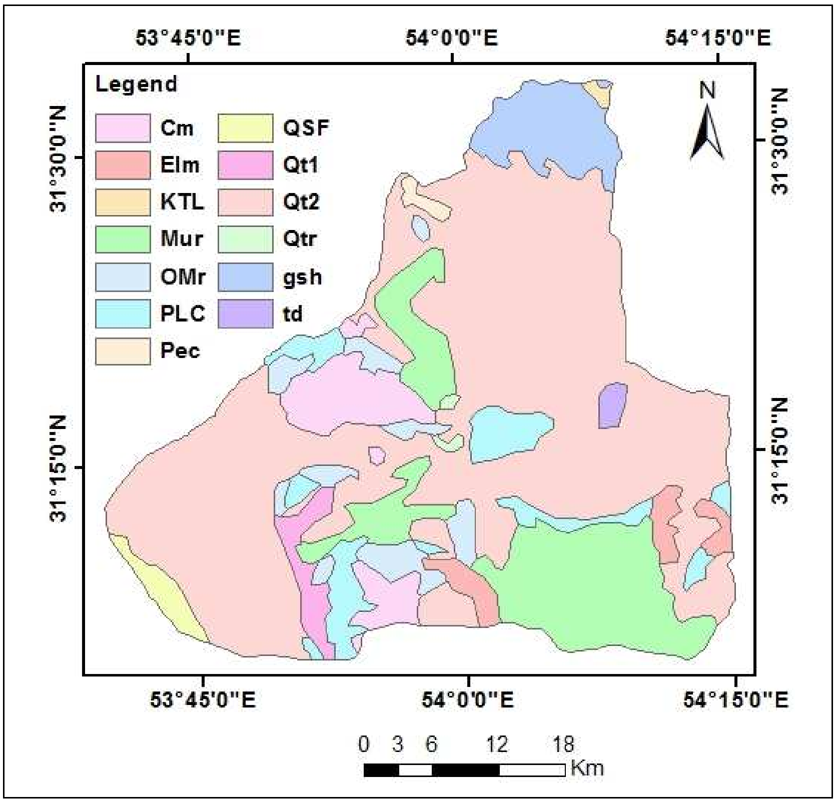


Figure 2.8. Geology map of the study area

Other geological units such as chalky marns, clayey limestones, salt crust, young alluvial, and Shirkouh granite. There is special vegetation cover over each of the aforementioned geological units.

2-6- Soil and landscape

The area of study has five dominant physiographic units: mountain, alluvial fans, plateau, piedmont plain, and low land. As mentioned before, the geology of the mountain is granite, reddish limestone, conglomerate and marl. Alluvial fans, plateau and piedmont plain are developed on alluvial deposits of Quaternary. Low land has a salty clay flat foundation.

As stated before, the environmental variables such as elevation, precipitation and temperature have a high variability in the study area, causing a high spatial variability of soil classes and properties in the region. According to the Soil Taxonomy (Soil Survey Staff, 2010), the soil moisture regimes of the area are aridic and aquic, and temperature regime of the area is thermic. The taxonomic classification (Soil Survey Staff, 2010) of the major soils found in the study area respectively identified Entisols and Aridisols as the smallest and largest in relative abundance. Entisols are located in the mountain physiographic unit of the study area. Typic Torriorthents are the dominant soil in this unit. Aridisols contain several soils which are Typic Calcigypsids, Typic Haplocalcids and Typic Aquisalids. Typic Calcigypsids and Typic Haplocalcids are the dominant soils which have developed in plateaux and piedmont plain units whereas Typic Aquisalids are located in the lower part of the region, called low land or playa. Alluvial fans have a complex soil that include Typic Torriorthents and Typic Calcigypsids. As expects the soils which have formed in the upper part of the region have a high content of gravel and sand whereas the soils which have developed in the lower part of the study area have a high content of clay and salt.

Table 2.6. summarizes some soil characteristics in each of the vegetation types.

Table 2.6. Soil characteristics in different vegetation types

Vegetation type	Soil Texture	Gravel (%)	EC (ds/m)	Soil available moisture (%)	Limestone (%)	Organic matter	pH	Gypse (%)
Ar.au	Sandy-Lom	27	0.2	3.5	<0.5	0.1	7.3	-
Sc.or-As.al	Sandy-Lom	12.3	0.17	3.82	14.2	0.85	7.6	-
Sc.or-Ar.si	Lomy-Sand	10	0.31	2.5	13.8	0.42	7.7	-
Ar.si-Sc.or	Lomy-Sand	10.5	0.41	2.7	15	0.8	7.8	-
Ar.si1	Lomy-Sand	15.3	0.42	3.7	2.3	0.5	7.8	-
Ar.si2	Lomy-Sand	11	0.55	3.8	15.2	0.3	7.7	-
Ar.si-Zy.eu	Lomy-Sand	17	0.6	5.7	10.2	0.3	7.9	0.05
Ar.si-Ep.st	Lomy-Sand	12.2	0.9	5.7	9.6	0.2	7.6	0.9
Ep.st-Zy.eu	Lomy-Sand	12	Surface 1.2 Depth 2.4	6.2	8.1	0.1	7.5	Surface 1.4 Depth 39.4
Rh.ri-Ar.si	Sandy-Lom	19	0.5	3.7	12.7	0.4	7.45	0.2
Co.mo	Sandy-Lom	21	1.1	1.8	19.1	0.06	7.96	0.4
Se.ro	Sandy-Lom	18.2	4.8	4.2	39.1	0.2	8.2	4.9
Ta.ra	Clay	-	51.8	12	15.7	0.35	7.9	6.6

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Chapter 3. Comparison of different geostatistical methods for soil mapping using remote sensing and environmental variables in rangelands of Poshtkouh area, central Iran

Abstract

The aims of this study were; 1) to map the different soil parameters using three geostatistical approaches including; ordinary kriging (OK), cokriging (CK), and regression kriging (RK), 2) to compare the accuracy of maps created by mentioned methods, and 3) to evaluate the efficiency of using ancillary data such as satellite images, elevation, precipitation, and slope to improve the accuracy of estimations. In the rangelands of Poushtkouh area, central Iran, totally 112 soil samples were collected. The maps of different soil parameters were created using the mentioned methods. To assess the accuracy of these maps, cross-validation analyses were conducted. The cross-validation results were assessed by the root mean square error (RMSE) and normal QQ-plot together with sum and average error to suggest the best estimation approach for mapping each soil parameter. The results have shown that, in most of the cases, taking the ancillary data into account in estimations has increased the accuracy of the created maps. Except for Clay that the OK method was suggested as the best estimation method, the RK and CK were the best recommended estimation methods for the rest of the parameters. The results suggest the application of the framework of this study for similar areas.

Keywords

Ordinary kriging, cokriging, regression kriging, soil parameters, ancillary data.

3.1. Introduction

The quality, quantity and type of vegetation in arid rangelands are usually affected by soil properties. Since soil mapping is a critical step in landscape ecology, and rangelands rehabilitation, there is an increasing need to measure and map soil properties in natural ecosystems (Kavianpour et al., 2012; Burke, 2001; Chaneton and Avado, 1996; Zhang and Mc Grath, 2004; Etema and Wardle, 2002).

Geostatistics and remote sensing are among the tools which have been successfully used for soil mapping at large scales (Webster, 1997; Eldeiry et al., 2010; McBratney et al., 2003). Geostatistical approaches in which environmental variables and remote sensing data correlations are taken into account have become increasingly popular. This is because of employing secondary information that is often available at finer spatial resolution than that of the sampled target variable. Such techniques generally generate more accurate results than those of the univariate methods (for example ordinary kriging) when the correlation between primary and secondary variables is significant (Goovaerts, 1997; McBratney et al., 2000; Odeh et al., 1994; Triantafilis et al., 2001). The application of hybrid methods for soil mapping has represented considerable success in several documented studies (Odeh et al., 1995; Bishop and McBratney, 2001; Hengl et al., 2004; Sullivan et al., 2005).

Several ancillary data can be used for digital soil mapping. Digital elevation model (DEM), slope, precipitation, remotely sensed images, and measured soil properties are potential ancillary data for such applications (Adamchuk et al., 2004; Bishop and McBratney, 2002; Hengl et al., 2004; McBratney et al., 2003). It should be evaluated that which ancillary data increase the estimation accuracy of a primary variable at unsampled locations in each study area (Hengl et al., 2004).

Examples of geostatistical hybrid methods that account for environmental correlation are cokriging and regression kriging (Goovaerts, 1997; Odeh et al., 1994; Tajgardan et al., 2010). The difference among these methods is in the assumptions of the way that the primary and ancillary data are related and how the estimation of primary data is inferred from the secondary data (Goovaerts, 1997; McBratney et al., 2003). Various studies have proven the existence of spatial correlation in different soil parameters (Kavianpour et al., 2012; Odeh et al., 1994; Eldeiry et al., 2010; Iqbal et al., 2005; Simbahan et al., 2006).

The main purposes of this research were; 1) mapping different soil parameters using three geostatistical approaches (OK, CK, and RK), 2) evaluating the benefit of using ancillary data such as satellite images, elevation, precipitation, and slope in improving the accuracy of estimation maps, and 3) comparing the accuracy of the maps created by the mentioned approaches.

3.2. Materials and Methods

3.2.1. Study area

This research was conducted in Poshtkouh rangelands, located at southern slopes of the Shirkouh mountains of the Yazd province in central Iran (31°33′ 1″ N, 53°40′06″ E - 31°04′27″ N, 54°15′19″ E). Figure 3.1 displays the general location of the study area. The area is characterized by very diverse terrain conditions. The maximum elevation of the region is 3990 m and the minimum elevation is 1400 m. Thus, average annual precipitation is about 300 mm in Shirkouh Mountain in the northern part of the study region whereas in margin of Kavir_e_Abarkouh (in the southern part of the region) it decreases to 45 mm. Similarly, average annual temperature shows large differences in the study region ranging from 17.1 in the southern part to 10.8°C in the northern part, with absolute minimum and maximum temperatures of 0.2 and 29.4°C.

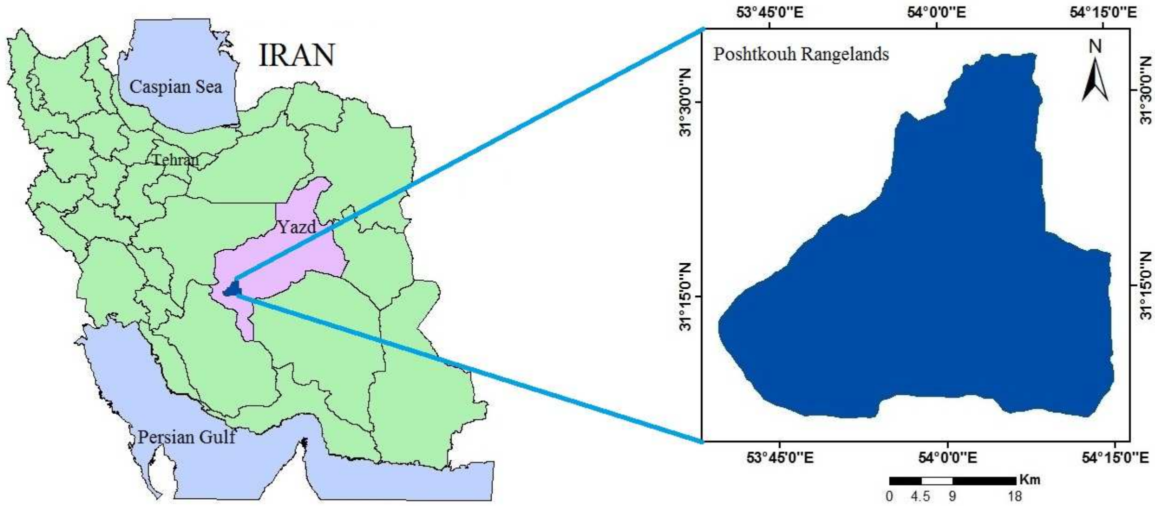

Figure 3.1. General location of the study area

3.2.2. Soil classification and landscape

This area has five dominant physiographic units: mountain, alluvial fans, plateaux, piedmont plain and low land. The geology of the mountain is granite, reddish limestone, conglomerate and marl. Alluvial fans, plateaux and piedmont plain are developed on alluvial deposits of Quaternary. Low land has a salty clay flat foundation.

As mentioned before (2-1- study area) the environmental variables such as elevation, precipitation and temperature have a high variability in the study area, causing a high spatial variability of soil classes and properties in the region. According to the Soil Taxonomy (27), the soil moisture regimes of the area are aridic and aquic, and temperature regime of the area is thermic. The taxonomic classification (27) of the major soils found in the study area respectively identified Entisols and Aridisols as the smallest and largest in relative abundance. Entisols are located in the mountain physiographic unit of the study area. Typic Torriorthents are the dominant soil in this unit. Aridisols contain several soils which are Typic Calcigypsids, Typic Haplocalcids and Typic Aquisalids. Typic Calcigypsids and Typic Haplocalcids are the dominant soils which have developed in plateaux and piedmont plain units whereas Typic Aquisalids are located in the lower part of the region, called low land or playa. Alluvial fans have a complex soil that include Typic Torriorthents and Typic Calcigypsids. As expects the soils which have formed in the upper part of the region have a high content of gravel and sand whereas the soils which have developed in the lower part of the study area have a high content of clay and salt.

3.2.3. Soil data collection and examination

In order to take samples from homogeneous units, hypsometric, aspect, slope and geologic maps were overlaid. Then 3-5 parallel transects with 300-500 m length were located in each unit. Totally 112 soil samples were collected in depth 0-30 cm (Figure 3.2). In the next step, all of the required soil parameters such as available moisture (AM), Clay, electrical conductivity (EC), Gravel, gypsum (Gyps), Sand, and Lime were measured in soil laboratory.

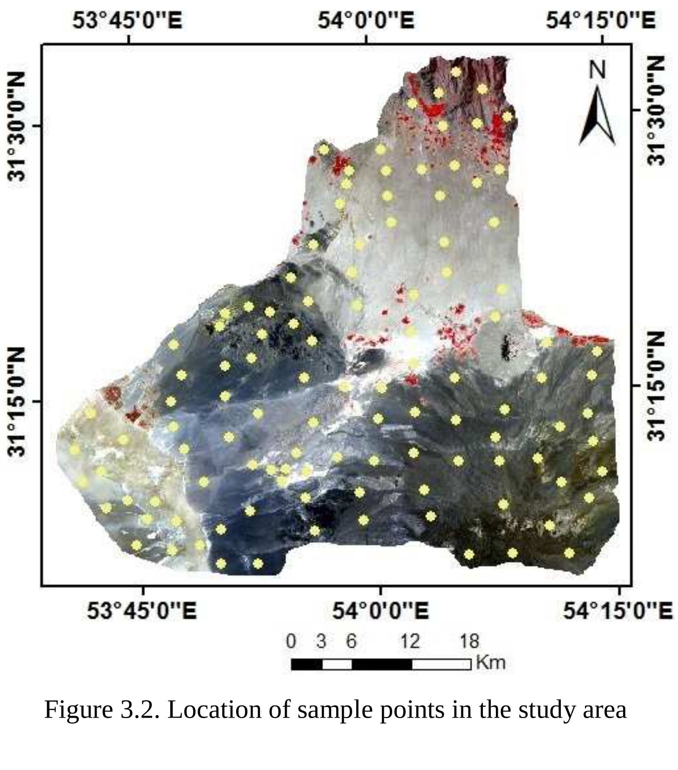

Figure 3.2. Location of sample points in the study area

3.2.4. Ancillary data

In this study, satellite images (Landsat ETM+) and some environmental variables (e.g. elevation, slope, and precipitation together with soil parameters) were used as ancillary data. ETM+ images contained three visible bands (blue, green, and red), one near infrared band, two shortwave infrared bands (MIR-1 and MIR-2), a thermal infrared band, and a panchromatic band. Using the digital topographic maps, the images were geo-referenced. Then, digital number (DN) values converted to reflectance. In the next step, the normalized difference vegetation index (NDVI) was calculated based on red and near infrared bands. The NDVI added as an additional band to the bands set. All of the remote sensing analyses were done in ENVI 4.8. The Digital Elevation Model (DEM) and slope map of the study area were created by the means of digital topographic maps with scale of 1:10000 in Arc GIS 10. Based on climatic data of the study area, precipitation map was created using the cokriging method in combination with the DEM as the secondary variable.

3.2.5. Descriptive statistics

The descriptive statistical evaluation is an important step prior to any geostatistical analysis. One of the essential univariate statistics is variance which is usually applied in estimating the semivariogram sills. It is especially important in recognizing the existence of any considerable trend in each variable when the semivariogram is consistently exceeding the predicted sill.

Bivariate statistical analysis, as the next step, is usual to distinguish the integration capability of secondary data in estimation problems. Among bivariate analyses, regression and correlation analyses have become popular to quantify the relationship between soil parameters and other environmental variables. Regression technique is a useful means to select the variables correlated with soil parameters. The SPSS statistical software can be used for this purpose. In the stepwise regression the best combination of ancillary variables which give the highest R2 and acceptable significance level would be selected.

In order to use ancillary variables for soil parameters mapping, the following process was done:

- Using the geographic information system, data set of each soil parameter was combined with the ancillary variables of the field samples. Then, the pixel values of the related points were extracted.
- To prepare data for statistical analysis, a matrix was constructed. In this matrix, the X- and Y-coordinates were recorded in the first two columns. The measured soil parameter values were placed in the next columns, and the different ancillary data of pixel values were put in the rest of columns. The rows of the matrix represent the number of sample points. This is in accordance with the method was used by Eldeiry and Garcia (2010).
- Pearson correlation coefficient was used to identify the correlation coefficient between the measured soil parameters and ancillary data (Table 3.4) that should be used in cokriging.
- To select suitable parameters and model for predicting and mapping of the soil parameters, the simple and the stepwise regression were applied. Finally, regression models that had the highest correlation with the measured soil parameters data were selected to be used in the regression kriging.

SPSS and Excel software were used for the mentioned statistical analysis.

3.2.6. Geostatistical Analyses

Geostatistical analyses have been conducted in three stages of variography, model evaluation, and estimations. A more comprehensive explanation about each step comes below.

3.2.6.1. Variography

Semivariogram is one of the most essential tools in geostatistical analyses to quantify and model the spatial variability degree of data. These models can later be used to make estimations using kriging, cokriging, and etc.

The experimental semivariogram ($\gamma^*(h)$) for a regionalized variable of Z can be defined as following:

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} \left[Z(x_\alpha) - Z(x_\alpha + h) \right]^2 \qquad (3.1)$$

where N (h) is the number pairs of data locations separated by the vector h (Isaaks 1989).

To deduce the semivariogram values in all points and all directions and to smooth out the effects of fluctuations and ensure the positive definiteness property of semivariograms, analytical models should be fitted to the experimental (or sample) semivariograms.

This analysis of semivariogram behavior and fitting analytical model is termed variography (Goovaerts 1997; Deutsch 2002).

Stationarity is one of the most essential presumptions in geostatistical analyses. It implies that the statistics (such as mean, variance, and so on) is independent of the location of its calculation. Accordingly, the first- and second-order-moment rules should remain invariant.

In the cease of non-stationarity, in which the relevant statistical moments show a dependence on the location, a characteristic so-called trend exists in data-set.

One of the most practical tools to indicate the existence of a trend in a data-set is its semivariogram. The sample semivariogram and its theoretical sill should be plotted and the general behavior of the semivariogram plot relative to the theoretical sill should be evaluated. If the sample variogram increasingly exceeds the expected sill (σ^2), the existence of a trend can be inferred.

In this study, using semivariogram analyses, spatial variability structure of each attribute was determined and proper semivariogram models (e.g., spherical, Gaussian, exponential) were fitted (Table 3.2).

The mentioned analyses were conducted using ArcGIS 10, and GS+ 5.1.1 software.

3.2.6.2. Model evaluation or accuracy assessment:

To ensure that the variogram models being applied in the estimation stages are reliable and appropriate, the variogram models have to be validated first. The validation of the variogram models was done using the cross-validation technique.

Cross-validation is a “leave-one-out” technique in which each sample (with the known variable) is omitted once and its value is estimated using the rest of the samples with different semivariogram models and parameters (Goovaerts 1997).

In order to evaluate the cross validation results, in the first step, scatter plots of measured vs. estimated were evaluated. Then, root mean square error (RMSE), sum errors, average errors, and QQ-plots of cross-validations were simultaneously applied to decide about the best estimation method.

Each of the above mentioned criteria reflects a side of estimation accuracy. For example, RMSE can describe the distance between measured and estimated values. Furthermore, sum errors, average errors, and QQ-plots represent the normality of estimation errors distribution.

3.2.6.3. Estimation methods

The kriging method is applied to estimate the values at unsampled locations by a weighted linear combination of nearby samples. The kriging equations, guarantee the two main characteristics of unbiasedness and minimum errors in estimations. To achieve the mentioned weights for this estimation, semivariogram models are required (Miller et al.

2007). Based on the variation of mean value, the kriging methods can be classified into several techniques such as ordinary kriging, simple kriging, and universal kriging.

Cokriging is an extension of kriging method in which the correlation between a primary and secondary data is taken into account. The application of this method can enhance the quality of estimations.

In this study, three estimation approaches including OK, CK, and RK were applied.

3.2.6.3.1. Ordinary Kriging (OK)

In OK the mean value of regionalized variable is considered constant and unknown thought the study area. The application of OK is proper when the stationarity condition is nearly fulfilled.

3.2.6.3.2. Cokriging (CK)

CK makes the estimations based on probable correlation between the variable of interest and other measured variables such as remote sensing and elevation data (Odeh et al., 1995). CK is among the useful techniques which can be used in estimation when both primary and secondary variable exist and has been used widely in soil science (Vauclin et al., 1983; Trangmar et al. 1987; Yates and Warrick 1987).

In present research, the variables which represented the highest significant correlation coefficient with the variable of interest which generated the most accurate CK maps were selected as ancillary variable for the application in CK method. The RMSE was employed as the criteria to evaluate which CK map was the most accurate.

3.2.6.3.2. Regression Kriging

Regression kriging (RK) is an estimation method that makes use of the combination of a regression predictor (of a primary variable, using ancillary variables) with kriging of the regression residuals. The advantage of RK method is using ancillary variables such as elevation and remote sensing data to improve the accuracy of estimation for primary variable. This method is equivalent to universal kriging and kriging with external drift, where ancillary predictors are used to estimate the mean of the primary variable in kriging equations (Hengel et al., 2004; Pebesma, 2006). It uses the ancillary data to characterize the spatial trend of the primary variable in a regression step before carrying out the simple kriging on the residuals and adding back the trend value to the estimation of residuals (Goovaerts, 1997).

In this research, in order to perform RK, the regression analysis was performed to estimate the trend of primary variables and residuals. Then, simple kriging on the residuals was carried out. The final estimate of every soil variable was achieved by adding the approximated trend to the estimate of the residuals calculated by simple kriging (Goovaerts, 1997; Vanderlinden, 2001).

The estimation parameters such as cell size and number of neighboring data were the same for all of the methods (OK, CK, and RK) applied in this study.

3.2.6.4. Soil texture map

In rangeland management and landscape ecology, in addition to the aforementioned soil maps, soil texture map is also beneficial for different applications such as to investigate the relation between soil and vegetation as well as rehabilitation of the area. In this step, the created maps of Clay and Sand were integrated in GIS environment to create the soil texture map. To do so, a script in ILWIS software was created and employed. The resulted map represents homogeneous soil texture units.

3.3. Results and discussion

Prior to any geostatistical analysis, it is of vital importance to evaluate some general statistical characteristics of data, such as data distribution and variance. In addition, some characteristics of important measures such as semivariogram sills can be approximated by the variance of related data (σ^2). Table 3.1 represents some descriptive statistics of soil parameters. Based on the table, EC and Gyps demonstrate the highest and lowest variances, respectively. It is expected that across the study area these parameters would also represent the highest and lowest variation, respectively.

Table 3.1. Descriptive statistics of soil parameters

Descriptive statistics \ Soil parameter	AM	Clay	EC	Gravel	Gyps	Sand	Lime
Min	0.20	6.2	0.1	0	0	26.40	0.42
Max	15.12	30.5	136.32	28.65	4.19	88.80	46.35
Mean	3.38	13.57	11.64	11.67	.570	71.67	14.36
Std. Deviation	2.84	6.02	26.87	5.9	1.16	14.34	10.72
Variance	8.07	36.27	722.28	34.88	1.35	205.91	115.06

According to the discussion in the material and methods, the stationarity condition of data has been evaluated by examining the general behavior of the semivariograms relative to their theoretical sills. This evaluation does not reflect the existence of any considerable trend in the soil parameters (Figure 3.3).

The spatial dependence of each soil attribute was modeled using analysis of semivariance. Parameters of semivariogram analysis for various soil attributes have been represented in Table 3.2.

In this stage, the quality of each semivariogram model was assessed and the model semivariogram parameters improved by cross-validation method and RMSE criterion for different estimation methods (OK, CK, and RK). The semivariogram interpretations have also been considered during this variography stage. Table 3.5 and Figure 3.5 illustrate the cross-validation results.

Table 3.2. Parameters of semivariogram analysis for soil parameters

Soil parameter	Semivariogram model	Nugget effect (C_0)	Sill (C_0+C)	Structured part to sill ratio (C/[C_0+C])	Effective Range
AM	Spherical	0.01	7.22	0.99	19770
Clay	Spherical	0.1	35.1	0.99	21420
EC	Exponential	1	587.50	0.99	20400
Gravel	Spherical	0.01	31.26	1	18090
Gyps	Spherical	0.001	1.18	0.99	25950
Sand	Spherical	105	620	0.83	94600
Lime	Spherical	21.30	243.50	0.91	97920

C_0: Nugget effect C: Structured part of the semivariogram (=sill- C_0)

Figure 3.3 shows experimental semivariograms of each soil parameter and their corresponding models. Each variogram shows and evaluates the spatial structure of data.

One of the most essential considerations in semivariogram modeling is bearing in mind the semivariogram interpretation and the expert's knowledge and experience about the study area. Usually, there could be a big uncertainty in semivariogram modeling since the data from soil samples can rarely reflect the existing soil condition sufficiently. Hence, the linkage between the soil characteristics and the semivariogram behavior should be understood very well before and during the semivariogram modeling by considering the parameters such as nugget effect, range, and anisotropy. Conversely, the semivariograms and their models can be employed to understand the behavior of the data structure.

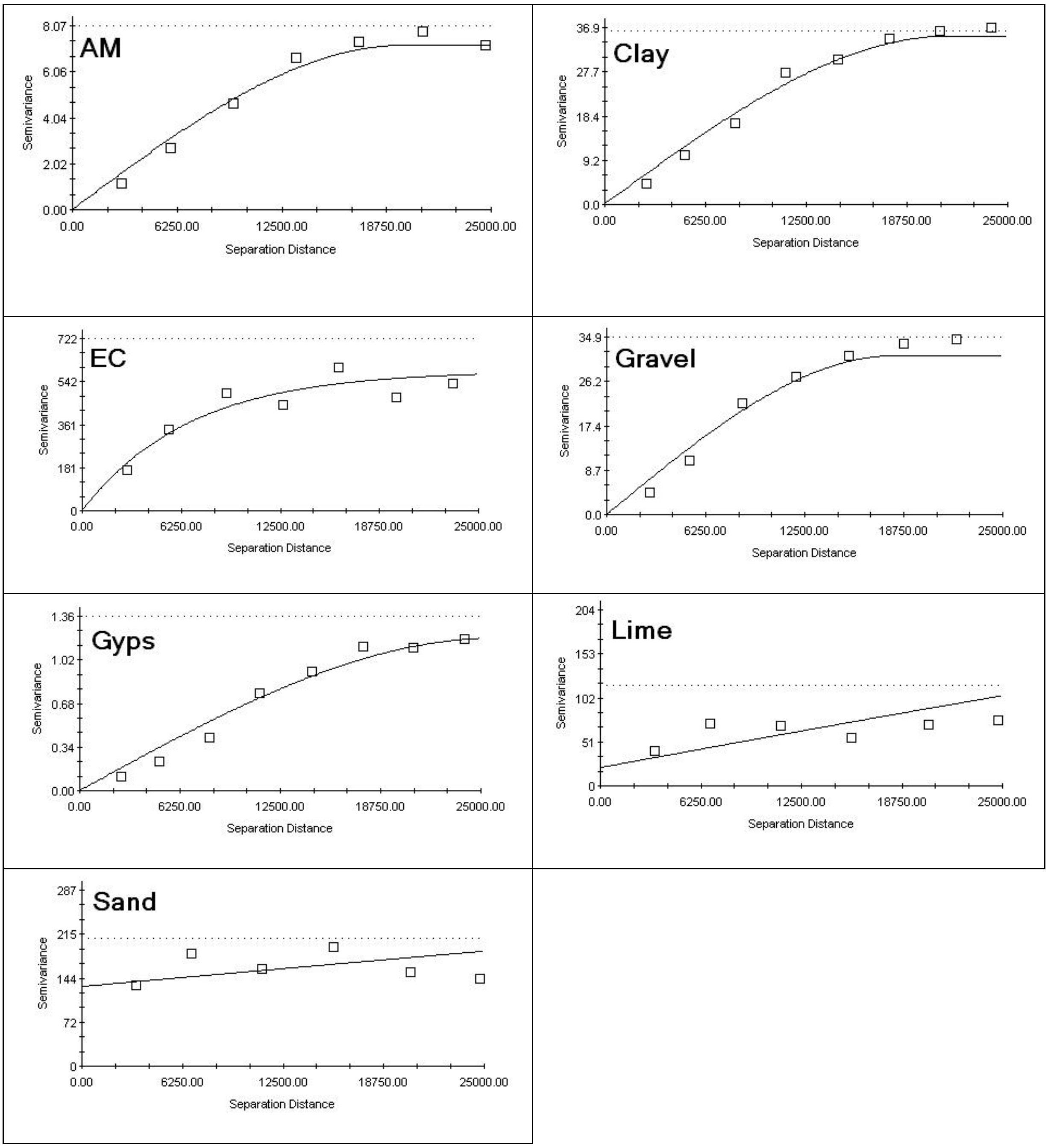

Figure 3.3. Semivariogram of different soil parameters

It is clear in the semivariograms (Figure 3.3) that all of the parameters have spherical model except EC that has exponential model. The exponential model usually represents the quick variation in data. The field observations in this study and previous reports (e.g. Zare Chahouki, 2006) from this area confirm this variability behavior of the EC.

The ratio of structured part of the semivariogram to sill (C/ [C0+C]) was considered as a criterion to evaluate the strength of the spatial variability structure of each semivariogram. Hence, the bigger this ratio, the stronger the spatial autocorrelation of the variable would be. According to the Table 3.2, most of the parameters have a similar structured to sill ratio. Based on this ratio Gravel has represented slightly a stronger spatial variability structure compared to the others.

Semivariograms of Sand and Lime have demonstrated the highest effective range among the all soil parameters, showing the higher degree of continuity for these variables. Gravel semivariogram has the shortest effective range representing that the change of this parameter in very short-distance is higher than others.

Among the investigated variables, the semivariogram models of Sand and Lime have represented the highest nugget effect. This might be interpreted to the existence of rather high spatial variations of Sand and Lime in very short-distances (lower than average sample spacing) compared to those of the others.

Table 3.3 summarizes the best regression equations between soil target parameters and ancillary data. As it can be seen from this table, most of the models have high R2 values, demonstrating good prediction power of the regression model for related soil properties.

Table 3.3. Best regression equations between soil parameters and ancillary data

Regression equation	R^2
$AM = -7.58*Band_7-0.12*Band_{62}+0.22*Clay+1.14*Gyps+8.32$	0.86
$Clay = 15.8*Band_5-0.43*Gravel+1.17*AW+9.91$	0.67
$EC = 229.73*Band_4-283.82*Band_7-0.015*Elevation+3.26*AW+37.35$	0.83
Gravel = -0.79*Clay+22.46	0.78
$Gyps = -6.98*Band_1-0.23*Band_{61}-0.002*Elevation+0.27*AW+12.77$	0.84
Sand = -0.006*Elevation-0.23*EC-1.49*Clay+106.74	0.81
Lime = -0.22*EC1-0.02*Elevation+64.88	0.59

Referring to the table, EC, Gyps, and Lime have negative relationship with elevation. This could be due to the fact that leaching causes the salts move from highlands and mountainous areas to the lowlands. Consequently, the lower the elevation, the higher the concentration of salts. This feature has also been reflected in the corresponding estimation maps (Figure 3.4).

The results of Pearson correlation coefficient were used to select proper secondary variables in CK analysis so that the selected variables (as secondary) had the highest significant correlation coefficient with the target variable. Among the mentioned secondary variables, the ones which produced the CK maps with the lowest RMSE were suggested to be used in estimation of the target variables using CK. Table 3.4 summarizes the selected variables for CK based on the mentioned method and the corresponding correlation coefficient with each target variable.

Table 3.4. Pearson correlations between target and secondary variables used in CK

Target variable	AM	Clay	EC	Gravel	Gyps	Sand	Lime
Secondary variable	Band1	AM	AM	Band2	Band1	Clay	Precipitation
Correlation coefficient	0.55*	0.82**	0.69**	0.62*	0.47**	0.87**	0.69**

* Statistically significant at $p > 0.05$ ** Statistically significant at $p > 0.01$

As the table shows, ancillary data are significantly correlated to the target variables. These significant correlations can suggest the ancillary data which could be cooperated in CK estimation to improve the prediction accuracy.

Table 3.5. Error measure for the compared prediction methods

Error measure	Soil parameter / Estimation method	AM	Clay	EC	Gravel	Gyps	Sand	Lime
RMSE	OK	0.89	2.38	11.40	1.96	0.34	12.73	7.59
	CK	0.74	1.85	11.47	1.8	0.33	9.32	7.22
	RK	0.92	1.72	14.29	1.12	0.38	5.90	6.32
Sum error	OK	1.20	3.18	20.59	-4.22	0.11	-10.66	1.15
	CK	0.70	4.55	21.92	-2.74	0.25	6.53	-2.47
	RK	-1.25	-6.54	5.33	3.20	1.77	-4.64	1.17
Average error	OK	0.01	0.02	0.18	-0.03	0.009	0.16	0.01
	CK	0.006	0.04	0.19	-0.02	0.002	0.10	-0.03
	RK	-0.01	-0.05	0.04	0.02	0.01	-0.007	0.01
	RK	6.32	5.90	0.38	1.12	14.29	1.72	0.92

Table 3.5 demonstrates the root mean square error (RMSE), along with the sum and average error for the compared prediction methods when estimating the soil parameters. As the table shows, the mentioned criteria for different soil parameters are different in different prediction approaches.

Table 3.6. The suggested method for mapping each soil parameter based on different criteria.

Suggested method based on / Soil parameter	AM	Clay	EC	Gravel	Gyps	Sand	Lime
only sum/average error	CK	OK	RK	CK	OK	RK	RK
only RMSE	CK	RK	OK	RK	CK	RK	RK
sum/average error, RMSE, & QQ-plot	CK	OK	RK	RK	CK	RK	RK

As mentioned in the material and methods, RMSE and QQ-plots (Figure 3.6), together with the sum and average errors were considered to suggest the best estimation methods (Table 3.5 and Table 3.6). About AM, Sand, and Lime, all the aforementioned criteria suggest the same method as the best estimation approach. For Clay and EC, because the QQ-plots as well as the sum and average errors represented more acceptable values, in spite of their lower RMSE, OK and RK were suggested as the best estimation methods, respectively. Even though, RMSE values for estimating these two soil parameters were not notably different. For suggesting the best estimation method for Gyps, QQ-plot was the determining factor (Figure 3.6). This is because the sum error for estimating the Gyps by the RK was rather larger than those of the OK and CK methods, while the sum error and RMSE values were not dramatically different. About Gravel, the difference in RMSE for the RK with those of the OK and CK approaches was rather considerable, whereas the QQ-plots (Figure 3.6) along with the sum and average errors of them do not represent remarkable differences.

Figure 3.4 illustrates the best estimation soil attribute maps selected from different estimation methods (OK, CK, and RK). This selection was based on the aforementioned criteria (Table 3.6).

Table 3.7 summarizes the abbreviations of soil texture map legend. According to the maps the highest values of AM, Clay, EC, and Gypsum are related to the south-west of study area. This part of the area is located in lowlands with lowest elevation, highest level of ground water, and high concentration of salts (Zare Chahouki, 2006). Other studies also suggested similar results (e.g. Esfandiarpoor et al., 2010; Bagheri Bodaghabadi et al., 2011). Hydrologic processes can be suggested as one of the main factors that can affect the soil properties in the study area. These processes can directly influence the weathering, decalcification, and clay illuviation. Consequently, soil properties would represent notable variations from the mountainous areas to the lowlands.

Table 3.7. Legend of the soil texture map

Abbreviation	Description
SL	Sandy Loam
SL-L-SCL	Sandy Loam-Loam-Sandy Clay Loam
SCL	Sandy Clay Loam
LS-SL	Loamy sand-Sandy Loam
LS	Loamy Sand
L-SCL-CL	Loam-Sandy Clay Loam-Clay Loam
L-SCL	Loam-Sandy Clay Loam
L	Loam
L-CL	Loam-Clay Loam
SCL-CL	Sandy Clay Loam-Clay Loam
CL	Clay Loam

Figure 3.5 shows the scatter plot of estimated versus measured soil parameters data using OK, CK, and RK Models. Generally, scatter plot is a tool for quality control and accuracy assessment of predictions. It is also useful when there are large numbers of sample points and can provide information about the strength relationship between two variables. Based on the Figure 3.5 all the scatter plots confirm the results of RMSE (Table 3.5). The strongest relationship between measured and estimated for AW, Clay, EC, Gravel, Gyps, Sand, and Lime are observed in CK, RK, OK, RK, CK, RK, and RK models, respectively.

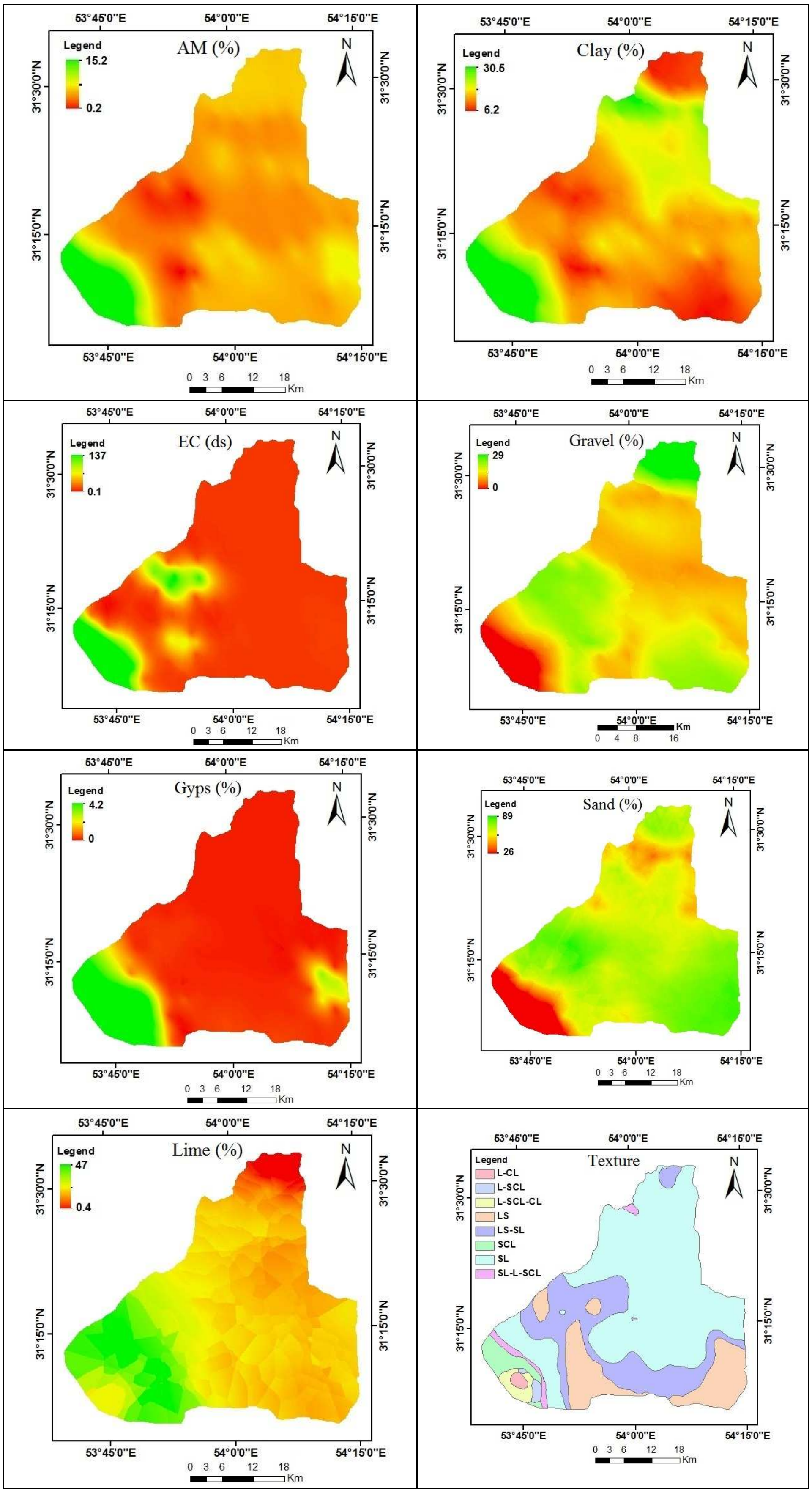

Figure 3.4. Created maps of different soil parameters with highest accuracy

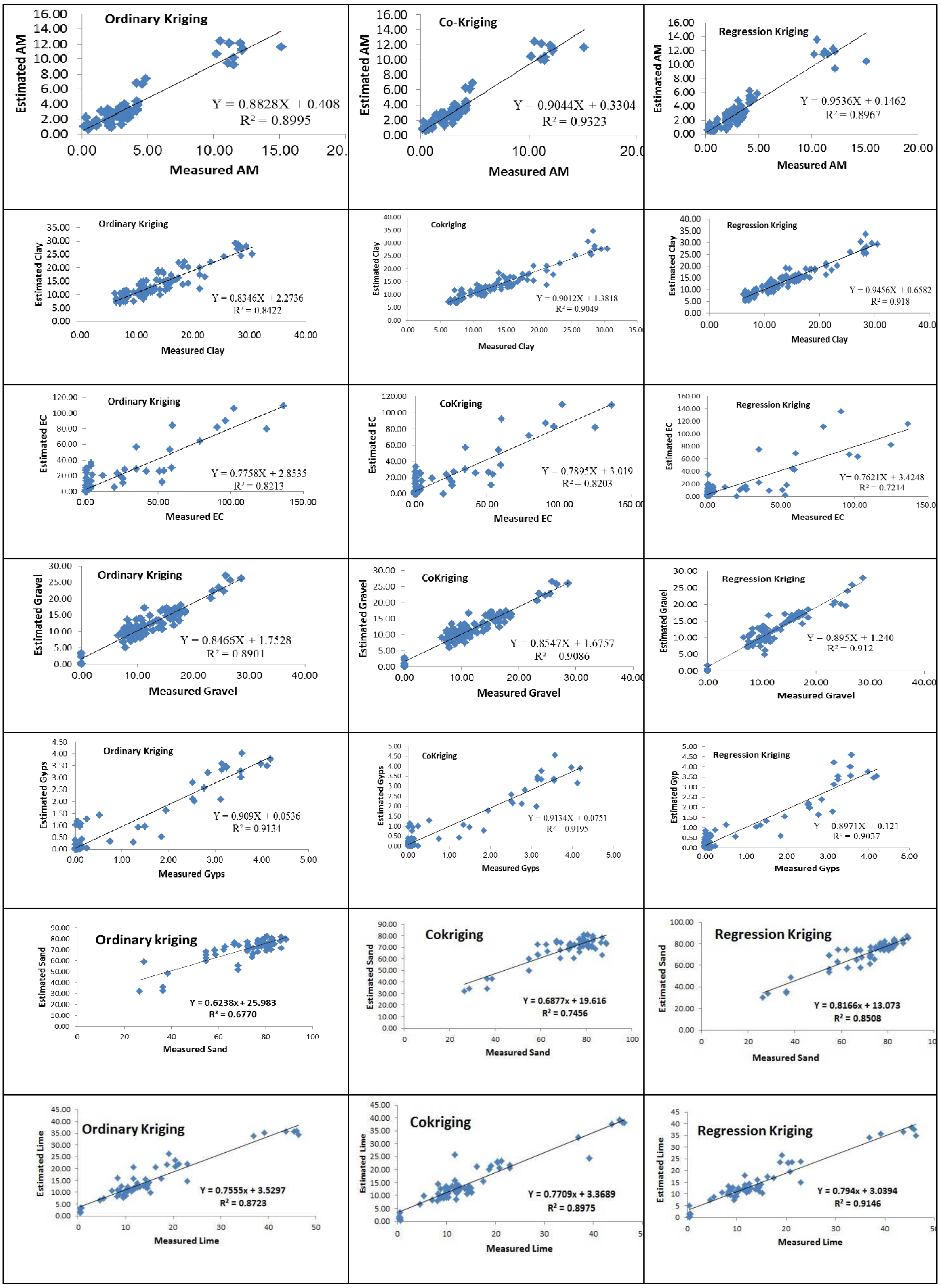

Figure 3.5. scatter plot of estimated versus measured different soil parameters in different estimation methods. Points (diamond symbols) represent the observed values and solid line shows the fitted least square regression line.

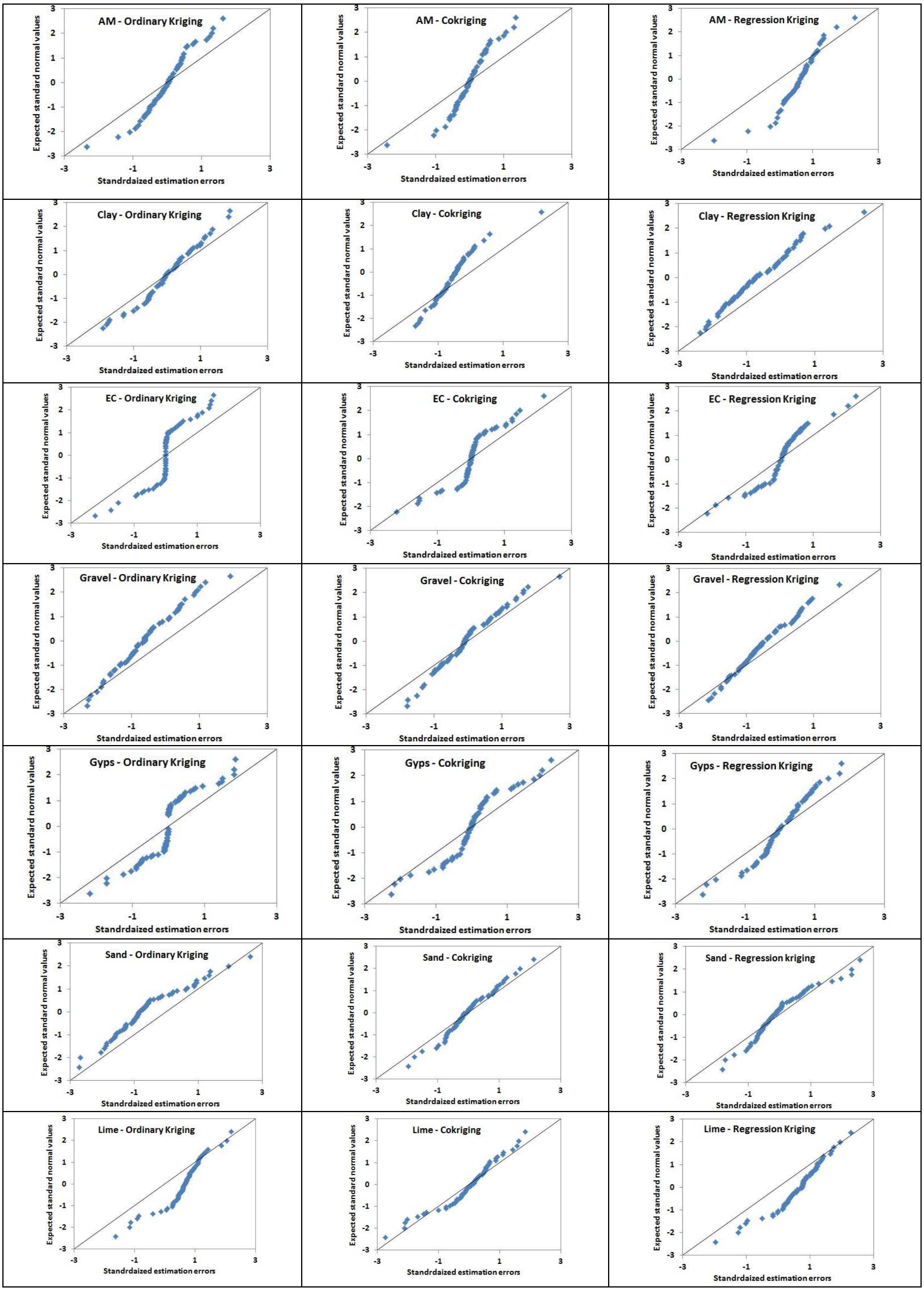

Figure 3.6. Normal QQ-plot of standardized estimation errors of different soil parameters in different estimation methods. Points (diamond symbols) represent the observed standardized error values and solid line shows the ideal standard normal distribution line.

3.4. Summary and conclusions

Creating soil maps with the high accuracies is of vital importance in landscape ecology and rangeland management. In this study, soil data and some ancillary variables including ETM+ images, elevation, slope, and precipitation of Poshtkouh rangelands were collected. The estimation maps of relevant soil parameters were created and compared to each other using different geostatistical methods as the next step. Based on the cross-validation analyses, the results suggest that the application of the ancillary data (ETM+ images and environmental variables) have increased the estimation accuracy in most cases.

The better efficiency of RK over OK and CK for estimating most of the soil attributes might be due to the better capturing of the variations of the residuals of these parameters in the RK framework.

Although with very low differences, for estimating the EC, OK has represented the lowest estimation RMSE compared to those of the CK and RK. However, according to the Table 3.6, considering the QQ-plots along with the sum and average errors besides the RMSE criterion, RK could be suggested as the best estimation approach for EC. This implies the positive role of remote sensing and environmental variables as ancillary variables in improving the estimations.

In the majority of parameters, taking the secondary variables into account has increased the estimation accuracy. Therefore, it is revealed that to improve predictions of soil attributes, it would be very beneficial to use the cheap and easily available ancillary data such as satellite images and elevation data. To achieve the best mapping performance, the secondary variables such as environmental variables and satellite images should be present for the whole study area. Several studies have suggested the use of satellite images and environmental variables in the framework of CK and RK to improve the accuracy of estimations (e.g. Goovaerts, 1999; Bishop and McBratney, 2001; Eldeiry and Garcia, 2008; McKenzie & Ryan, 1999; Triantafilis et al., 2001). The success of this idea depends on the strength of relationships between soil and the ancillary data.

Characterization of soil parameters such as texture, available moisture, and salinity, etc., is a vital step in rangeland rehabilitation, management, and ecological modelling, these methods are considerably useful. In the mentioned applications, a detailed map of soil properties can be more efficient than traditional soil maps. These continuous soil maps will also benefit rangeland scientists to describe the distribution of soil patterns. The created soil attribute maps could be used as input for the ecological models such as species distribution models.

Finally, it can be concluded that the geostatistical approaches can successfully model the spatial variability of different soil properties in rangelands. This is specifically because the geostatistical methods not only take the spatial variability of target parameters into account but they also offer estimation reliability measures such as estimation error and cross validation analyses parameters. The applied framework in this study which is fast and automated in Arc GIS software can be recommended for the similar cases. Using satellite images with higher spatial and spectral resolution as ancillary variable can be suggested to increase the estimation accuracies.

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Chapter 4. Best annual time intervals of satellite images to create vegetation cover percentage map in arid rangelands of Poshtkouh area

Abstract

The aim of this study is to determine the best annual time intervals of the recorded satellite images in order to investigate and map the vegetation cover percentage in arid rangelands. For this purpose, the relations between vegetation cover percentage and Normalized Difference Vegetation Index (NDVI) as well as the variation in their correlation coefficient for four different vegetation types in Poshtkouh rangeland of Yazd province, Iran, were investigated. To calculate the relationships between vegetation and NDVI, the ground data and six series of NOAA AVHRR images in the time interval of growing season were used. To create the related map, the relationship between the best images and cover percentage of the data were modelled. Finally, the created map was reclassified and based on overall accuracy criterion, its accuracy was assessed. Results showed that the correlation coefficient between NDVI and vegetation in different phenological stages within each vegetation type as well as among different vegetation types are different. Depending on the vegetation type, at the end of the growing period, correlation coefficient between vegetation and NDVI decreases. The highest and lowest variation in NDVI and its correlation with vegetation were observed in *Alpine plants* and *Halophyte*, respectively. This investigation demonstrates that the best data to study the vegetation cover in arid rangelands can be taken from the images recorded in May. This indicates that, selecting the suitable time interval to study the vegetation during its growing period has prominent effect on results.

Keywords:

Vegetation cover percentage, arid rangelands, NOAA AVHRR, NDVI, study time.

4.1. Introduction

In recent decades the use of remote sensing, as a tool to measure, evaluate, and map vegetation is significantly increased (Booth and Tueller 2003; Jafari et al., 2007; Sabins 1978; Jones and Vaughan 2010). Depending on the type of the plant, plant age, growth stage, percentage of coverage, amount of biomass, amount of water in the Cell etc, the plant has different spectral reflections (Tueller 1989; Moleele and Ringose 2001; Jones and Vaughan 2010). Investigation on the plant spectral characteristic shows that the normal plant has the maximum absorption in the red and blue spectral area and maximum reflection in the green and infrared region. Changes in the leaves characterizations and the amount of Chlorophyll play the main role in their spectral reflections. Any factor, like diseases or stress, that changes the leaves characteristic, have direct influence in the plant spectral reflection which is more pronounced in the infrared channel of the spectrum. Scientist express that moisture stresses or leaves maturity cause the changes in the leaf cavity and therefore reflection decreases in the near infrared region (Sabins 1978; Lillesand and Kiefer 1994; Jones and Vaughan 2010). Likewise, the seasonal changes and reduction in the photosynthetic activity are one of the main factor affecting the plant spectral reflections and correlation between the vegetation coverage (Behrens et al., 2002; Xie et al., 2008; Jones and Vaughan 2010).

Several studies have demonstrated that the relation between satellite images and ground-based data depends on the satellite imagery precision, time of recording, biological factors (growth forms, the amount of litter and phonological stages) and non-biological factors such as land form, slope, direction and height (Wang et al., 2005; Douglas Ramsey et al., 2004; Fontana et al., 2008; Wylie et al., 2002).

Vegetation cover percentage map is one of the base maps in natural resources management, soil conservation, and rangeland management (Hosseini, et al., 2004;

Rafieyan et al., 2008; Tueller 1989). Mapping the vegetation cover percentage based on traditional methods and field surveying in major part of the study area needs a lot of costs and also is time consuming. Remotely sensed data frequently are used to map vegetation cover needed for a variety of resource assessment, land management, and modeling applications (Loveland, 2000; Booth and Tueller 2003; Bastin and Ludwig 2006; Sabins 1978).

The Normalized Difference Vegetation Index (NDVI) is a commonly used remote sensing vegetation index in vegetation studies (Propastin 2007; Myneni et al., 1997, Zhou et al., 2001, White et al., 1997, Reed et al., 1994, and Stöckli and Vidale., 2004). The NDVI is calculated from the reflectance in the red and near infrared (NIR) bands of the electromagnetic spectrum and is a measure of the photosynthetic activity within the area covered by a pixel (Moleele and Ringose 2001; Hosseini et al., 2012; Tucker and Sellers., 1986).

NDVI is highly correlated with green biomass (Tucker et al. 1985; Propastin 2007; Xie et al., 2008). During the past years this index has been broadly used for vegetation mapping and monitoring (Sannier et al. 1998; Hosseini et al., 2004; Freitas et al., 2005; Jafari et al., 2007), land-cover change detection (Lambin 1996; Lambin and Ehrlich 1997; Wang et al., 2005; Rafieyan et al., 2008; Wylie et al., 2002), crop area estimation, and primary productivity analysis (Gilabert et al. 1995; Moleele et al., 2001).

The main purposes of this research were to determine the best annual time intervals of the recorded satellite images in order to investigate the vegetation cover percentage and to create the related map in arid rangelands.

4.2. Material and methods

4.2.1. Study area

This research was conducted in Poshtkouh rangelands, located at southern slopes of the Shirkouh mountains of the Yazd province in the central part of Iran (31° 33′ 1″ N, 53°40′ 06″ E - 31° 04′ 27″ N, 54°15′ 19″ E).

The maximum and minimum elevations of the region are 3990 m and 1400 m, respectively. Average annual precipitation of the study area ranges from 300mm in Shirkouh Mountain to 45mm at the margin of Kavir_e_Abarkouh. Average annual temperature ranges from 17.1 to 10.8°C, with absolute minimum and maximum temperatures of 0.2 and 29.4°C. Figure 4.1 shows general location of the study area.

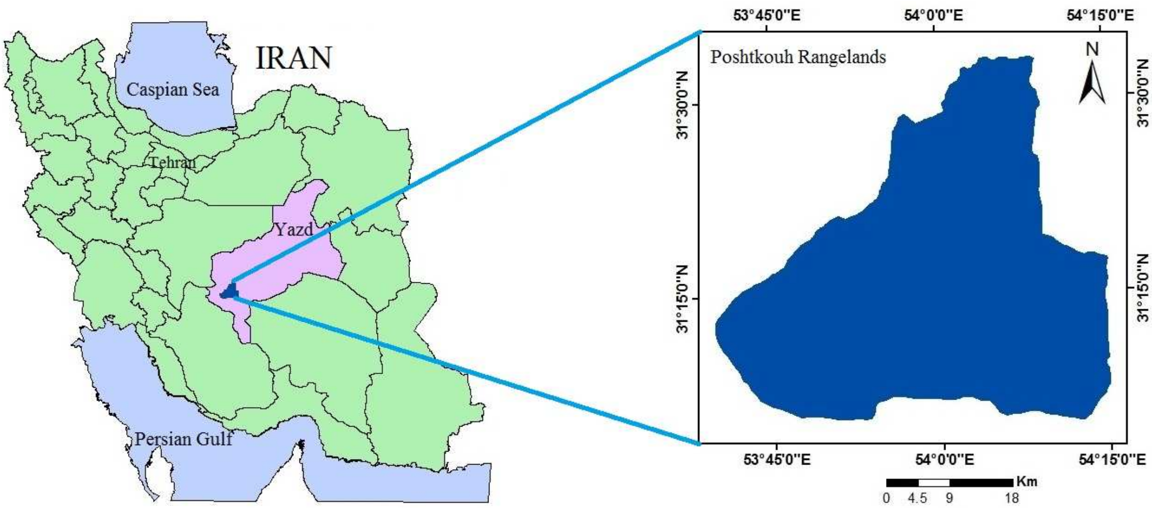

Figure 4.1. General location of the study area

4.2.2. Vegetation types

The variation in climate and topography causes considerable diversity in vegetation that explains the assorted vegetation patterns in the study region (Figure 4.2).

In this study vegetation map produced by Zare Chahouki (2006) was used, that presents the existing of thirteen vegetation types. This map was created based on the homogeneous map of the study area taking from hypsometric, aspect, slope and geologic maps overlaying. Considering the spatial resolution of NOAA AVHRR satellite images, the vegetation types with similar plant species were merged and number of types was reduced to four (Table 4.1. and Fig 4.2).

As Table 4.1 and Figure 4.2 demonstrate the northern mountainous part of the study region is covered by alpine plants consist of bushes and grasses such as *Astragalus* and *Stipa*. Coming from northern mountain (toward the center) vegetation type is dominated by sagebrush containing dwarf shrubs and short grasses like *Artemisia sieberi, Launaea acanthodes, Stipa barbata*, and different species of *Salsola*. Some Gypsophyte plants such as *Salsola*, *Calligonum and Artemisia* present in the lowlands of the central part of the study region having Gypsi soils. *Seidlitzia rosmarinus, Salsola spp., and Haloxylon aphyllum* are the main halophyte species covering saline lands of the southern part. Table 4.1 summarizes the main plant species present in each of the vegetation types.

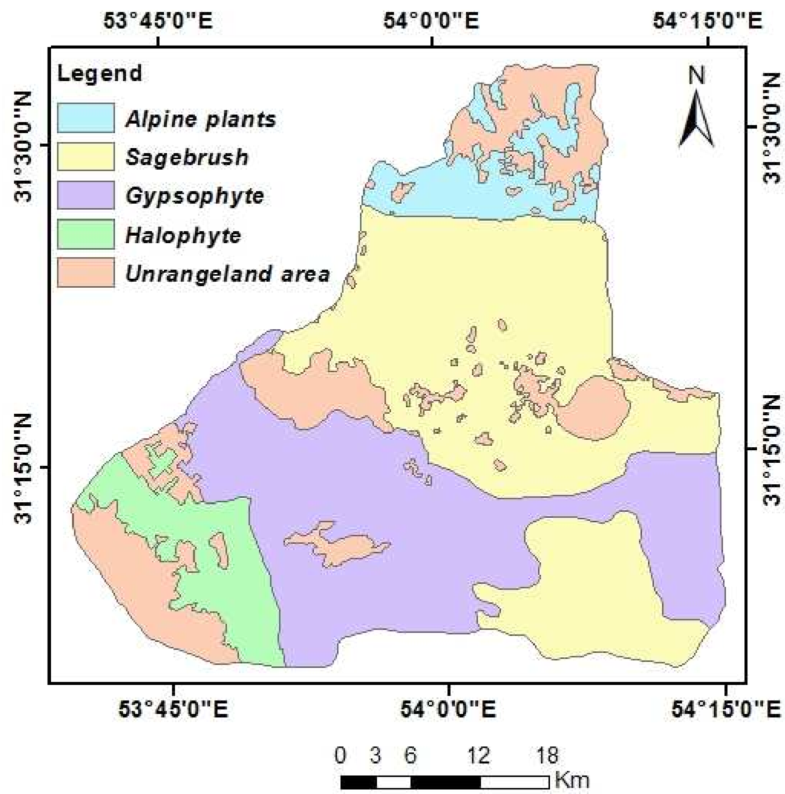

Figure 4.2. Vegetation map of the study area

Table 4.1. Vegetation types in the study area

Vegetation Types	Plant species
Alpine Plants	*Artemisia aucheri, Scariola orientalis, Astragalus ochrochlorus, Astragalus calliphysa, Astragalus myriacanthus, Acanthophyllum spp., Bromus spp., Stipa hohenackeriana, Stipa barbata, Acantholimon spp., Launaea acanthodes, Noaea mucronata, Euphorbia heterandena, Echinops orientalis*
Sagebrush	*Artemisia sieberi, Launaea acanthodes, Scariola orientalis, Iris songarica, Salsola spp., Euphorbia heterandena, Astragalus albispinus., Noaea mucronata, Stipa barbata, Salsola kerneri, Salsola tomentosa, Astragalus albispinus, Rheum ribes*
Gypsophyte	*Salsola spp., Zygophyllum eurypterum, Dorema ammoniacum, Artemisia sieberi, Cornulaca monacantha, Calligonum comosum, Stipagrostis plumose*
Halophyte	*Seidlitzia rosmarinus, Tamarix ramosissima, Salsola spp., Haloxylon aphyllum.*

4.2. 3. AVHRR NDVI data

In this study we used monthly NDVI data of NOAA AVHRR. The GIMMS NDVI data have been preprocessed and corrected for post-launch sensor degradation and atmospheric noises using methods described by Pinzon *et al* (2002 & 2004) and Tucker *et al* (2005).

The NOAA AVHRR NDVI is defined as:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \qquad (4.1)$$

where ρ_{NIR} represents near infrared reflectance (channel 2 of AVHRR) and ρ_{red} red reflectance (channel 1 of AVHRR). Among vegetation indices, NDVI is the most widely used index to monitor and model vegetation (Propastin 2007; Jones and Vaughan 2010; Xie et al., 2008).

4.2.4. Field data collection

As mentioned before, there are four major vegetation types in the study area (Table 4.1 and Figure 4.2). In order to estimate the vegetation cover percentage in the rangelands of the study area 64 random sample sites were selected and in each site at least 20 quadrates were put. The percentage vegetation cover of each quadrate was estimated and the dominant species were also recorded together with the position of the sampling points (using Global Positioning System (GPS)). To get the final value of the cover percentage, the average of each sample site was taken. Figure 4.3 illustrates location of sample points in the study area.

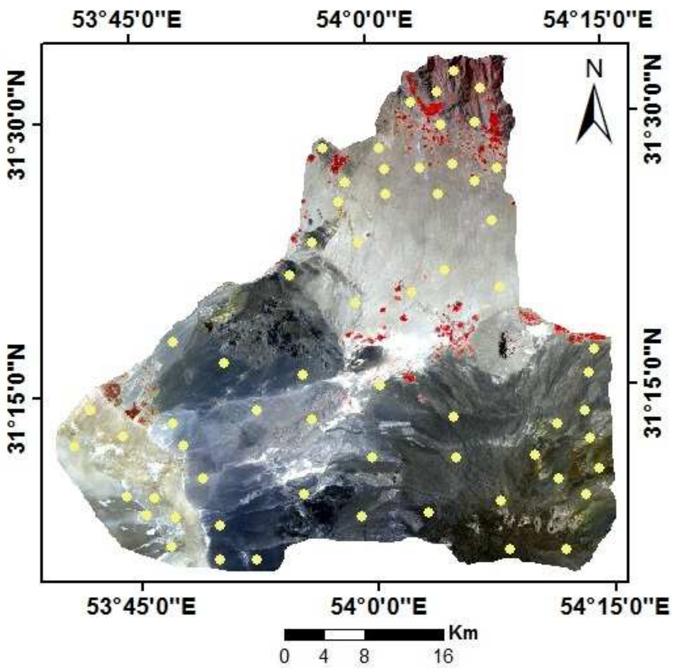

Figure 4.3. Location of sample points in the study area

4.2.5. Statistical analyses

Using the coordinate of the sampling sites recorded by GPS, a vector point map was created in geographic information system (GIS) and the digital number (DN) values of sampling points were extracted. In the next step, a matrix was constructed to prepare data for statistical analysis. In this matrix, the measured vegetation cover percentage values were placed in the first columns, and NDVI of different months were put in the rest of columns. The rows of the matrix show number of the sampling sites. Then, Pearson correlation coefficient between field data and relevant pixels values of the NOAA AVHRR NDVI data of different months were computed to identify the monthly NDVI that demonstrate the highest correlation with vegetation in each of the vegetation types

(Table 4.2). Finally, in order to model the relationship between vegetation data and NDVI, regression models between field data and the NOAA AVHRR NDVI of each month were calculated for the whole study area (Table 4.3).

The mentioned statistical analyses were done in SPSS, and Excel software.

4.2.6. Mapping vegetation cover percentage using NOAA AVHRR NDVI

Based on the results of correlation and regression analyses, the best time interval of NOAA images (monthly NDVI) to study and map the vegetation was determined. Then the related regression model (with the highest R^2) was used to map the vegetation cover. In the last step, the created map was reclassified and its accuracy was assessed based on overall accuracy criterion.

In this study, Arc GIS 10 and ENVI 4.8 software were used for remote sensing and GIS analyses.

4.2.7. Results and discussion

The correlation coefficients of the percentage vegetation cover and NDVI for different months are shown in Table 4.2. The result shows that, based on growing season and different phenological stages, in different vegetation types as well as inside each of them, the rate of correlation changes. Based on the vegetation species and formations, in each type the variation of NDVI and the correlation between NDVI and the cover percentage do differ.

Table 4.2. Correlation coefficient between NDVI and cover percentage for different months.

Month	Alpine plants	Sagebrush	Gypsophyte	Halophyte
April	0.44*	0.78*	0.74*	0.62*
May	0.46*	0.83*	0.76*	0.68*
June	0.32*	0.81*	0.74*	0.62*
July	0.11**	0.73*	0.71*	0.68*
August	0.09	0.75*	0.69*	0.59*
September	0.09	0.68	0.69*	0.60**

* Statistically significant at P = 5% and ** statistically significant at P = 1%

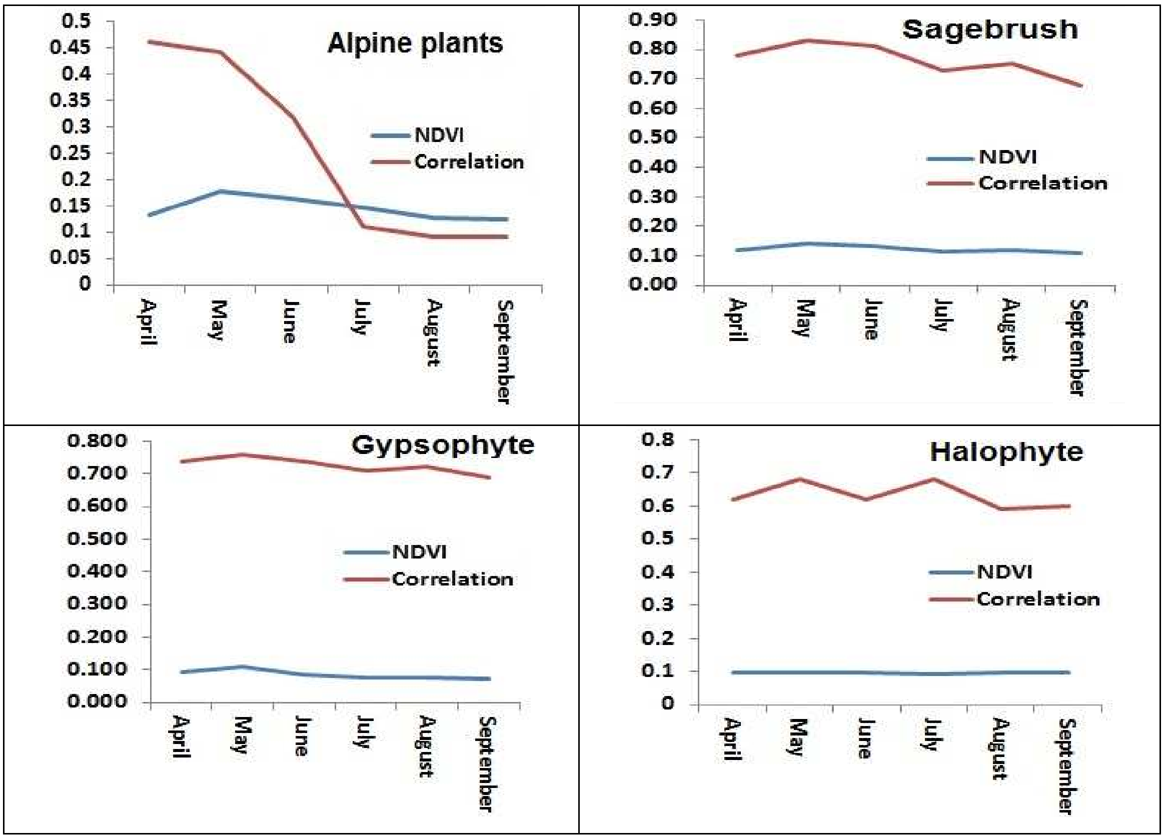

Figure 4.4. Fluctuations in NDVI and its correlation coefficient with cover percentage during growing season.

As illustrated in Figure 4.4, the variation between NDVI and the vegetation cover percentage depends mostly on the variation in NDVI itself. Among the investigated vegetation types, Alpine plants showed the most decrease in NDVI. This is due to the high dependency of this type on soil moisture. However, in the other types, especially Halophytes, a minor decrease in above mentioned quantities is seen. Since Alpine plants are grown in highlands area with the highest rainfall, the highest correlation between NDVI and vegetation cover is observed in the month of May (Table 4.1).

According to Table 4.1, there are several forb and grass species, such as *Scariola orientalis* and *Bromus tomentolus*, in which are categorized in the Alpine type. These species are sensitive to the fluctuations in rainfall and temperature during the growing season as well as different years. Therefore, after May, due to decrease in rainfall, the climate humidity and soil moisture as well as increasing in temperature, there will be a significant reduction in plant greenness and hence a lower correlation between plants and NDVI.

Fluctuations between vegetation and NDVI in Sagebrush are seen to be higher than that of Gypsophyte. Because, the plant species in Sagebrush are mostly forbs, while in Gypsophyte are shrub (Table 4.1).

Figure 4.5 illustrates scatter plots of NDVI vs. vegetation cover percentage for different months and Table 4.3 represents regression models between NDVI of different months and vegetation cover percentage. As shown, the regression model with the highest R^2 is related to May. This is in agreement with results of Pearson correlation coefficient. Therefore, the NDVI of May was used to map the vegetation cover percentage. Figure 4.6 shows the created map. The accuracy of this map is 78.4%.

Table 4.3. regression models between NDVI of different months and vegetation cover percentage

Month	Regression model	R^2
April	Y = 259.13X - 13.77	0.56
May	Y = 123.51X - 2.1123	0.63
June	Y = 114.02X - 0.6924	0.61
July	Y = 133.82X - 1.4934	0.59
August	Y = 145.72X - 3.1909	0.58
September	Y = 154.87X - 3.9007	0.57

Y = vegetation cover percentage X = NDVI

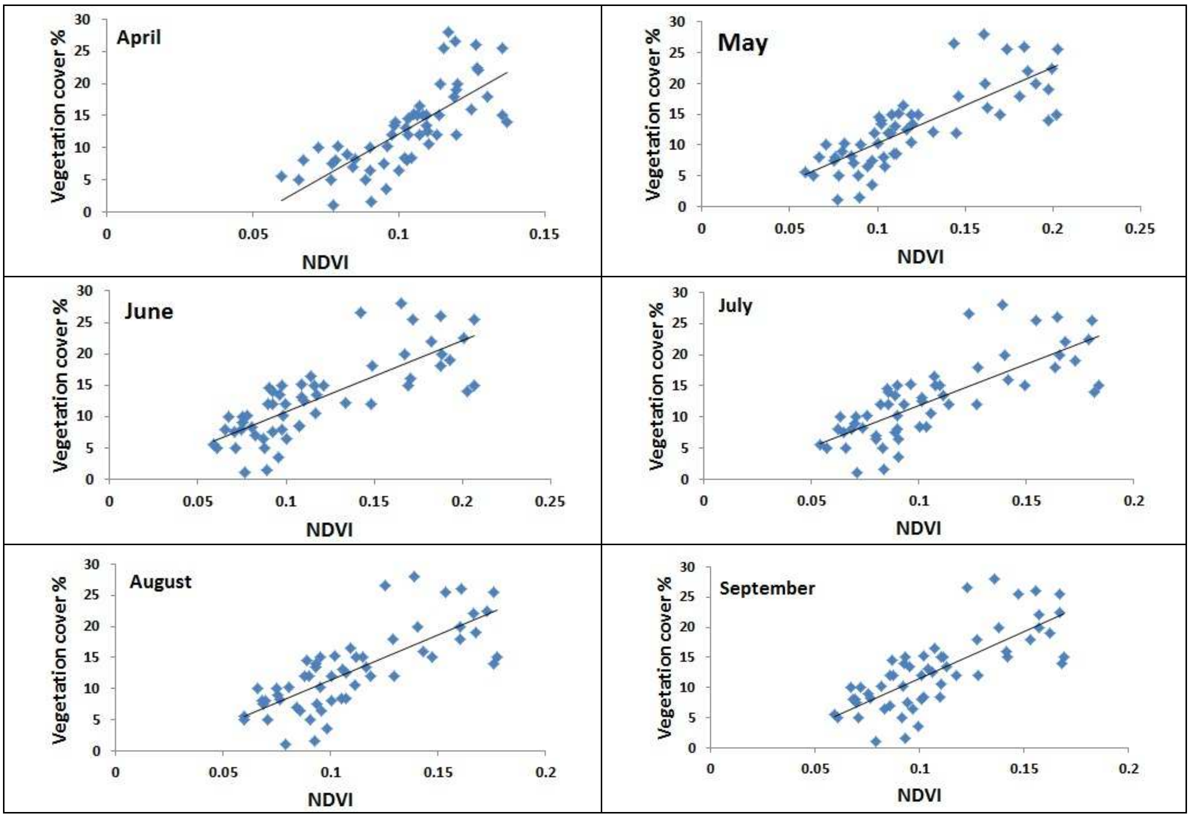

Figure 4.5. Scatter plots of NDVI vs. vegetation cover percentage for different months

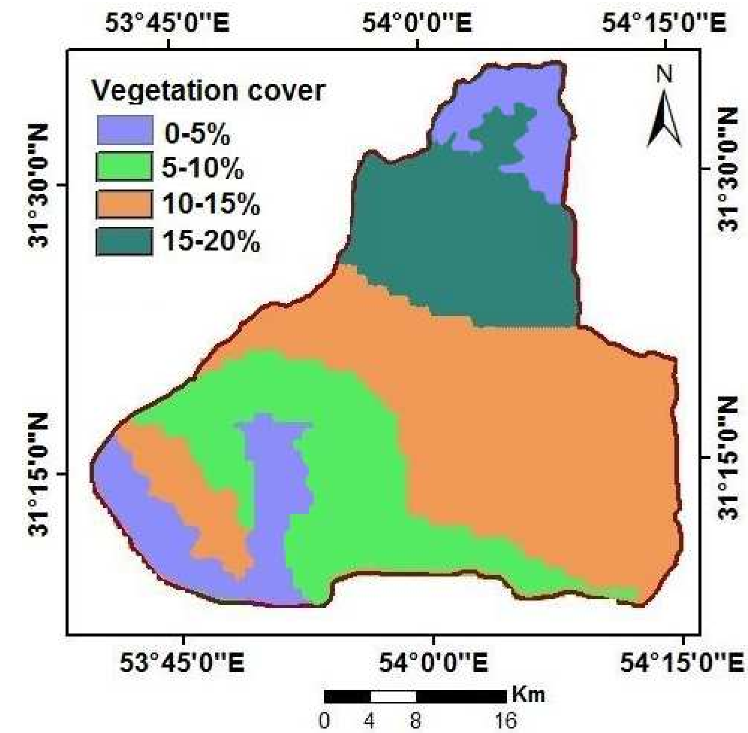

Figure 4.6. Vegetation cover percentage map of the study area

4.2.8. Summary and conclusion

The results show that the relation between greenness and NDVI as well as the correlation between vegetation cover and NDVI are changed based on the growing season (Table 4.2, Table 4.3 and Figure 4.4). These changes will also differ depending on the vegetation type. The fact is that the vegetation coverage plays an important role in the reflection from the plant (more than 50%). The rate of this reflection depends on the amount of water in plant, cell structure, amount of chlorophyll, and the structure of the plant itself (Sabins 1978; Jones and Vaughan 2010; Xie et al., 2008). Therefore, the amount of water has a significant influence in spectral reflection from the plant in Red and Near Infrared bands. However, the amount of water varies depending on the ecosystem and therefore the seasonal changes will change it in photosynthesis of plants (Jones and Vaughan 2010; Lillesand and Kiefer 1994; Zhau et al., 2001; Propastin 2007). There would be difference between plants in different types, based on the growing period and sensitivity of the plant with soil moisture (Hosseini et al., 2012; Tueller 1989; Jafari 2007). That is because the trees compare to grass and forbs are less sensitive to the moisture. Because grasses and forbs have the most dependency on the precipitation, the highest fluctuation in greenness as well as correlation between vegetation coverage and NDVI is seen in Alpine Plants (Figure 4.3, Table 4.2 and Table 4.3). . In the other hand, they have shorter lifetime and less stability than shrubs and trees.

In Halophyte, we have less fluctuation in correlation between vegetation coverage and NDVI as well as NDVI itself. Since trees and shrubs have longer roots, they are able to use moisture available in the deeper layers of the soil. That enables them to be more stable during the growing season.

An increase in NDVI from beginning until maturity of the plant life is observed, but it will be decreased at the end of the growing season (Chang *et al*, 2007 and Senseman *et al*, 1996). In different seasons the plant spectral reflection shows changes in different frequency channels (Prigent, 2001 and Hively *et al*, 2009). The current study confirms these achievements.

The relationships between vegetation and NDVI and also created vegetation cover percentage map in this research would be beneficial to improve rangeland management and natural resources conservation. Predicting and monitoring vegetation cover percentage can be achieved by relating the field data with a satellite derived vegetation index. The results would be useful for natural resources and rangeland managers to detect land degradation in order to rehabilitate the degraded areas. In addition, the results of this research represent the successful application of AVHRR NDVI images on vegetation studies in dry rangelands of Iran. The methodology of this research can be applied to other areas to assess vegetation cover and resources management.

As a general conclusion the date of recorded images to study the forbs and grasses is in a particular importance. While in vegetation types covered with bush, shrub and tree the timing does not play a significant role. Therefore, in order to reach the most accurate results, it is necessary to have knowledge about the vegetation type and satellite data in advance. Furthermore, considering the interaction between different vegetation species and types, climatic factors, especially precipitation and temperature, are suggested. It could lead to the better understanding of the vegetation reflectance in different phonological stages. This would be useful to select the best time interval of satellite images for the vegetation studies.

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Chapter 5. Using remote sensing and a geographic information system to monitor the relationship between vegetation dynamics and precipitation in the Poshtkouh rangelands, central Iran

Abstract:

This study investigates the relationship between the inter-annual and intra-annual dynamics of vegetation and precipitation variations in the Poshtkouh area rangelands in Yazd province, central Iran. The analysis was built on a monthly time series of the Normalized Difference Vegetation Index (NDVI) derived from the Advanced Very High Resolution Radiometer (AVHRR) onboard the meteorological satellite of the National Oceanic and Atmospheric Administration (NOAA) and precipitation data from meteorological stations across the area for the period 1996-2008. Seasonal and annual precipitation maps were created using a combination of co-kriging interpolation and the digital elevation model (DEM). The inter-annual and intra-annual relationships between precipitation variation and vegetation dynamic were examined using non-linear and linear regressions. We assessed the impact of certain environmental variables on the relationship between precipitation and the NDVI. These variables are the mean annual precipitation (MAP), vegetation cover percentage (VCP), soil available moisture (SAM), and topographic wetness index (TWI). To achieve this, we created maps of the mentioned variables using geostatistics and remote sensing. Our results show that the strength of the relationship between precipitation and NDVI depends on species' composition, MAP, VCP, SAM, and the TWI. Vegetation was found to have a strong response to precipitation in the northern and eastern parts of the study area where forbs and grasses are considerably dominant. The non-significant correlation between precipitation and the NDVI in the southwestern parts of the study area are due to the dominance of hardy shrubs and bushes.

Keywords: vegetation dynamic, precipitation variations, AVHRR, NDVI, DEM, environmental variables.

5.1. Introduction

Vegetation responds to different ecological factors, especially climate (Hosseini, et. al 2003). Precipitation has a direct effect on the vegetation composition. Precipitation's effect on vegetation is particularly pronounced in drylands, which occupy more than 40% of the whole land area and represent one of the world's biggest carbon pools (Lal, 2004). Drylands' ecosystems are generally characterized by high inter-annual variation in precipitation, making them susceptible to land degradation and desertification (Veron et al., 2006). Recent studies on land degradation and desertification (LDD) in different arid regions have emphasized the importance of assessing the relationship between vegetation and precipitation (Li et al., 2004; Symeonakis & Drake, 2004). Studies of different regions have shown the magnitude of vegetation's response to precipitation (Wessels et al., 2004; Propastin & Kappas, 2008b). Therefore, it is important to assess the inter-relations between vegetation and climate dynamics (especially precipitation) in drylands.

Researches have recently demonstrated that coarse-resolution satellite sensors, such as the National Oceanic and Atmospheric Administration (NOAA) and Advanced Very High Resolution Radiometer (AVHRR), provide image data that are perfectly designed for broad-scale monitoring vegetation conditions (Loveland et al. 1995, Ehrlich et al. 1994, Running et al. 1994, Goward 1989, Propastin and Kappas, 2008a,b). Such studies often use satellite-derived vegetation indices (VI). The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used vegetation indices for vegetation monitoring. NDVI is highly correlated with green biomass and vegetation structure characteristics, such as vegetation cover and the fraction of absorbed photosynthetically active radiation

(Tucker et al. 1985; Myneni & Williams, 1994; Zeng et al., 2000). Recent studies have demonstrated this index's suitability for investigating vegetation conditions with respect to primary production and crop area assessment (Gilabert et al. 1995). Other application fields of NDVI include the detection of land cover change and mapping vegetation cover (Lambin 1996; Lambin and Ehrlich 1997; Sannier et al., 1998).

Over the last two decades, NOAA AVHRR NDVI has proven to be one of the most effective tools for investigating climate-vegetation inter-relationships. Numerous studies have used NOAA AVHRR NDVI and climate data to quantify differences between regions' vegetation-climate responses (Farrar et al., 1994; Yang et al., 1998; Wang et al., 2003; Propastin and Kappas, 2008b). For example, a 20-year NDVI time series was used to examine the spatio-temporal dynamics of the Northeast Region of Brazil (Barbosa et al., 2006). Foody (2005) examined photosynthetic activity's response to inter-annual rainfall variations using 20 years' (1981-2000) NDVI AVHRR data from the south of the Sahara. Olsson et al. (2005) used NDVI AVHRR to indicate greening trends in the Sahel zone over the last two decades.

Prior researches have mostly used statistical analyses, including regression and correlation techniques, to quantify the vegetation-climate relationships. However, determining how a vegetation type responds to climate remains a challenge. Recent studies have found that the correlation between vegetation and climatic parameters is mostly weaker in woodland and forest vegetation. It has been reported that shrubs and desert vegetation have a weaker correlation with the spatio-temporal dynamics of climatic parameters. Steppe grassland vegetation areas are associated with the most rainfall and highest temperatures (Li et al., 2004; Wang et al., 2003; Richard & Poccard, 1998). However, the response of the NDVI to rainfall and temperature varies geographically (Richard Y. & Poccard, 1998; Schultz & Halpert, 1995). Considering LDD studies, it was also shown that the correlation between vegetation and precipitation in similar cover classes strongly depends on the degree of degradation (Li et al., 2004; Evans & Geerken, 2004).

Several studies have focused on soil moisture's role in determining the properties of vegetation (e.g., Farrar et al. 1994; Mendez-Barroso et al, 2009; Walker and Noy-Meir, 1982.; Zare Chahouki, 2006). Tinley (1982) found that soil moisture determines the spatial distribution of forests, savannas, and grasslands. Other studies have demonstrated that the soil moisture and soil porosity affect vegetation parameters (Eagleson's, 1982 & 1985; Mendez-Barroso et al, 2009; Okitsu, 2005).

Although soil moisture is one of the most important factors affecting vegetation composition and greenness, it is very difficult to measure. Scientists have used various proxies for soil moisture, such as the topographic wetness index (TWI) derived from the DEM within geographic information system (GIS) environments. This index is a relative measure of the long-term soil moisture availability of a given site (Bagheri, 2011; Gruber & Peckham 2008; Iverson et al. 1997).

Iran is the eighteenth largest country in the world (area of 1648195 km^2) and is entirely occupied by drylands. Iranian arid, semi-arid, and sub-humid ecosystems represent very large reservoirs for carbon accumulation and play an important role in the continental and global carbon circle (Mesdaghi, 2004). Despite the potential importance of Iranian biomes in global change, only few studies have been conducted on the vegetation-climate relationships in this country.

This study's objective is to make a small (but important) contribution to closing the existing research gap. We analyzed the within-season and inter-seasonal influences of precipitation on vegetation conditions in various arid and semiarid rangeland biomes in central Iran. In addition to rainfall data, we used NOAA/AVHRR-NDVI, which is an as indicator of vegetation conditions, to analyze the spatial and temporal relationship between these variables for different vegetation types. We focused on finding differences between how vegetation types in various cover classes respond to precipitation. The response differences were then discussed with respect to MAP, VCP, SAM, and TWI. Finally, we concluded this study by making suggestions for improving the application of precipitation-NDVI relationships in rangelands' management.

5.2. Material and methods

5.2.1. Study area

This research was conducted in the Poshtkouh rangelands on the southern slopes of the Shirkouh mountains in the Yazd province, central Iran (31°33′ 1″ N, 53°40′06″ E - 31°04′27″ N, 54°15′19″ E) (Figure 5.1). The area is characterized by jagged terrain conditions. The maximum elevation is 3990 m and the minimum elevation is 1400 m. The high spatial variability of the Poshtkouh rangelands' climate is due to this large elevation variability. The average annual precipitation is about 300 mm in the Shirkouh mountains in the northern part of the study region whereas it decreases to 45 mm at the edge of Kavir-e-Abarkouh in the southwestern part of the region. Similarly, the average annual temperature shows large fluctuations ranging from 17.1°C in the southern part to 10.8°C in the northern part of the study region, with absolute minimum and maximum temperatures of 0.2 and 29.4°C respectively.

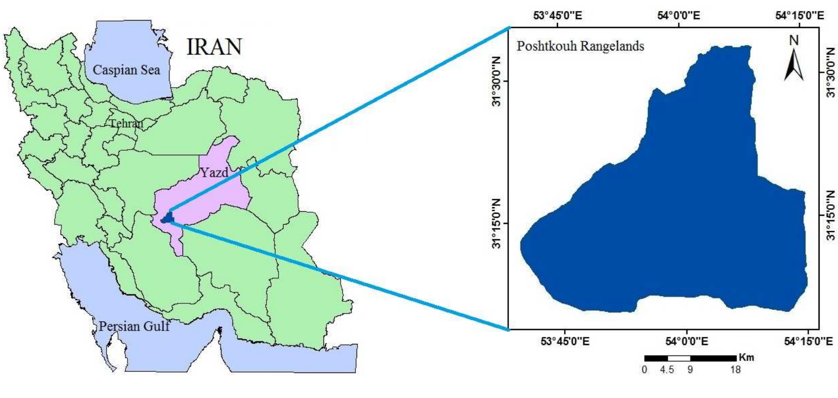

Figure 5.1. General location of the study area

5.2.2. Vegetation types

The diverse climate and terrain conditions determined the vegetation patterns in the study area (Figure 5.2). The northern part is covered by alpine bushes and mixed grasslands; the dominant species are *Astragalus* and *Stipa* (Table 5.1). The vegetation cover in the pre-montane zone is presented by sagebrush dwarf shrubs and short grasses of which *Artemisia sieberi, Launaea acanthodes, Stipa barbata,* and *Salsola* are the dominant species. The ypsic soils of the lowland in the central part of the study region are covered by gypsophytic plants of which *Salsola, Calligonum* and *Artemisia* are the dominant species. The saline areas in the southern part of the region are covered by dense halophytic vegetation, namely *Seidlitzia rosmarinus, Salsola spp.*, and *Haloxylon aphyllum*.

Using Zare Chahouki's (2006) vegetation map, we included thirteen vegetation types in this study (Zare Chahouki, 2006). Owing to the coarse spatial resolution of NOAA AVHRR satellite images, which were used in this research, vegetation types with similar plant species were merged and the number of types was reduced to four (Table 5.1 and Figure 5.2).

Table 5.1. Vegetation types in the study area

Vegetation types	Plant species
Alpine Plants	*Artemisia aucheri, Scariola orientalis, Astragalus ochrochlorus, Astragalus calliphysa, Astragalus myriacanthus, Acanthophyllum spp., Bromus spp., Stipa hohenackeriana, Stipa barbata, Acantholimon spp., Launaea acanthodes, Noaea mucronata, Euphorbia heterandena, Echinops orientalis*
Sagebrush	*Artemisia sieberi, Launaea acanthodes, Scariola orientalis, Iris songarica, Salsola spp., Euphorbia heterandena, Astragalus albispinus., Noaea mucronata, Stipa barbata, Salsola kerneri, Salsola tomentosa, Astragalus albispinus, Rheum ribes*
Gypsophyte	*Salsola spp., Zygophyllum eurypterum, Dorema ammoniacum, Artemisia sieberi, Cornulaca monacantha, Calligonum comosum, Stipagrostis plumose*
Halophyte	*Seidlitzia rosmarinus, Tamarix ramosissima, Salsola spp., Haloxylon aphyllum.*

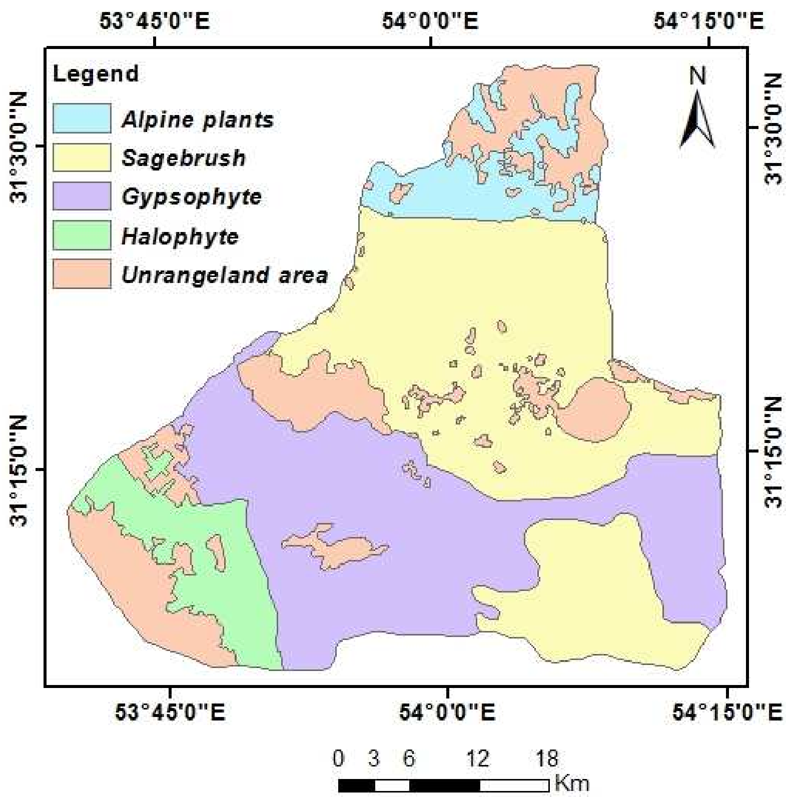

Figure 5.2. Vegetation map of the study area

5.2.3. AVHRR NDVI data

The NOAA AVHRR NDVI is defined as:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \qquad (5\text{-}1)$$

Where ρNIR represents near-infrared reflectance (Channel 2 of AVHRR) and ρred represents red reflectance (Channel 1 of AVHRR). Among the vegetation indices, NDVI is the most widely used for monitoring and modeling vegetation dynamics (Tucker et al. 1985; Sannier et al., 1998; Propastin, 2006).

In this study, we used the 8 km spatial resolution NDVI data set, which the Global Inventory Modeling and Monitoring Studies (GIMMS) group produced from the raw NOAA AVHRR NDVI (Pinzon et al., 2004). Using Pinzon et al.'s (2002&2004) and Tucker et al.'s (2005) methods, we corrected for post-launch sensor degradation and atmospheric noises during the pre-processing of the GIMMS NDVI data. The NDVI images used to produce the GIMMS NDVI data set represent 15-day maximum value composites (Holben, 1986). The GIMMS NDVI data for the period 1996-2008 covering the whole area of Eurasia were downloaded from the GIMMS archive at ftp://pengimms.gsfc.NASA.gov. The originally 15-day composites were compounded to monthly composites. The territory of Iran was extracted from the Eurasian GIMMS NDVI data and used for further analysis.

5.2.4. Precipitation data

We used the Iran Meteorological Organization's monthly rainfall data (January-December) that was collected from nine climatic stations in the study area and adjacent areas between 1996 and 2008. From these data we prepared gridded maps for seasonal and annual precipitation distribution over the study area. The preparation of maps based on interpolation of data between the climate stations. We tested different interpolation techniques (Inverse Distance Weighting, Nearest Neighbor, Thin Plate Spline, Multiple Regression, Polynomial Surfaces, etc.) in order to find the best one. Accuracy of the produced gridded maps was assessed by the lay-one-out cross-validation method. All the tested interpolation approaches produced comparable results distinguishing only a little in their accuracy. However, we selected one of the most robust and accurate – the polynomial multiple regression – and used it for retrieval of all gridded precipitation maps in our study. Since the relief of the study area is well structured and demonstrates close relationships to spatial distribution of climate parameters, additionally to geographic coordinates of the climate stations, the interpolation approach used relief elevation as an external predicative variable.

For this a digital elevation model (DEM) was used. The DEM was extracted from the

Global 30 arc Second Elevation Data Set (GTOPO30) (www1.gsi.go.jp/geowww/globalmap-gsi/gtopo30/gtopo30.html). To match the GIMMS NDVI data set, the produced precipitation maps were resampled to 8 km resolution and co-registered with the composites of the GIMMS NDVI data.

5.2.5. Data analysis

5.2.5.1. Analyzing the relationship between precipitation data and NDVI

We present the data flow and general analysis steps in Figure 5.3. After acquiring the data sets and extracting the study region as described above, both the GIMMS NDVI and gridded precipitation maps of the individual months were composed to the 1996-2008 time series and co-registered in a GIS environment. We moreover inputted the vegetation cover map into GIS and co-registered it with the NDVI and precipitation data sets. Further analyses were also carried out in GIS. In this study, we used SAGA GIS software Version 2.0, which was developed in the Department of Geography at the University of Göttingen, Germany (www.saga-gis.org/en/index.html), to create precipitation maps and analyze vegetation-precipitation relations. ENVI 4.8 was used to process NOAA AVHRR NDVI, and Arc GIS Version 10 was used to conduct some extra analyses.

Linear and non-linear regressions were used to examine the inter-annual and intra-annual relationships between the precipitation amount and NDVI dynamics. We computed the correlation coefficients between NDVI and precipitation to determine the strength of the relationships between these variables, which is indicative of the vegetation's response to the climate. We conducted both spatial and temporal data analyses. Regarding the temporal relationship between variables, the NDVI's response to precipitation was analyzed using both annual and seasonal scales. We used inter-annual analyses to compare the mean annual NDVI concurrent time series and annual precipitation values for the whole study period 1996-2008.

We compared the mean NDVI of individual seasons with the precipitation sums of corresponding seasons (at the concurrent basis) or with the precipitation sums of previous seasons (with time lag). Time lags were implemented into the seasonal analyses to account for the antecedent influence of precipitation on vegetation growth.

Temporal analyses were carried out for each pixel showing spatial patterns in NDVI’s response to precipitation. We subsequently used this information to detect differences in the NDVI-precipitation response among various vegetation classes.

Moreover, we examined the spatial relationship between NDVI and precipitation by deriving correlation coefficients for all pixels of NDVI maps and all pixels of corresponding precipitation maps. In order to investigate the differences in the NDVI-precipitation correlation between the vegetation types, we also calculated correlation coefficients for each vegetation type.

5.2.5.2. Using NOAA AVHRR NDVI to map the vegetation cover percentage (VCP)

We selected 90 sample sites with different vegetation types to estimate the vegetation cover in the field. At least 20 quadrates of each site were randomly located. We estimated each quadrate’s vegetation cover percentage and recorded the dominant plant species therein. The average cover percentage of each site was considered the final value. We used Arc GIS 10.0 software to create a map from the sampling points we recorded using a global positioning system (GPS). Next, the digital numbers (DNs) of sampling points were extracted from NOAA AVHRR NDVI images. We then computed a regression model between the field data and relevant DNs using SPSS 17.0 software. Finally, we calculated the vegetation cover percentage map (Figure 5.7) based on the following regression model:

Cover % = 207.24*NDVI – 8.69 (R^2 = 0.69) (5-2)

5.2.5.3. Using geostatistics to map soil available moisture (SAM)

We collected 112 soil samples from different homogeneous units (vegetation types) to create a soil available moisture (SAM) map. The sampling method we used was similar to the one we used to calculate the vegetation cover percentage. We used a weighting method to measure the SAM in a laboratory and a semivariogram analysis to assess its spatial dynamics (Trangmar et al. 1985, Bailey and Gatrell 1998, Mc Bratney and Pringle 1999). Before running the geostatistical tests, we tested the assumptions of normality and trend. A semivariogram (Goovaerts 1997) was used to estimate the degree of spatial variability between neighboring areas' SAM, and then a model function was used to fit the semivariogram. We tested several model functions, including spherical, exponential, and Gaussian functions to determine the best function of the semivariogram and its parameters (Table 5.2). Finally, a SAM map was created using ordinary kriging. We used ArcGIS 10, and GS+ 5.1.1 to perform a geostatistical analysis.

Table 5.2. Parameters of variogram analysis for SAM

Semivariogram model	Lag distance	Nugget effect	Range	Sill	R^2
Spherical	3800	0.36	36262.9	7.44	0.94

5.2.5.4. Using DEM to map a topographic wetness index (TWI)

This index is defined as TWI=ln(As/tan b), where As represents the specific catchment area (the cumulative upslope area draining through a cell divided by the contour width) and b denotes the local slope (Beven & Kirkby 1979). The specific catchment area is a parameter describing the site's tendency to receive water from an upslope area and the local slope is a parameter describing the tendency to evacuate water (Gruber & Peckham 2008). This index is therefore a relative measure of a given site's long-term soil moisture availability.

We used Ilwis 3.7 software to create the TWI map of the study area based on the DEM. Subsequently, we calculated the mean value of this index for each of the vegetation types.

5.2.5.5. Analyzing environmental variables' effect on the relationship between NDVI and precipitation

This section focuses on measuring the strength of the correlation between NDVI and precipitation versus some environmental factors, such as the vegetation cover percentage (VCP), mean annual precipitation (MAP), soil available moisture (SAM), and topographic wetness index (TWI). To conduct this analysis, we created maps of the VCP, MAP, SAM, and TWI using SAGA GIS Version 2.0.

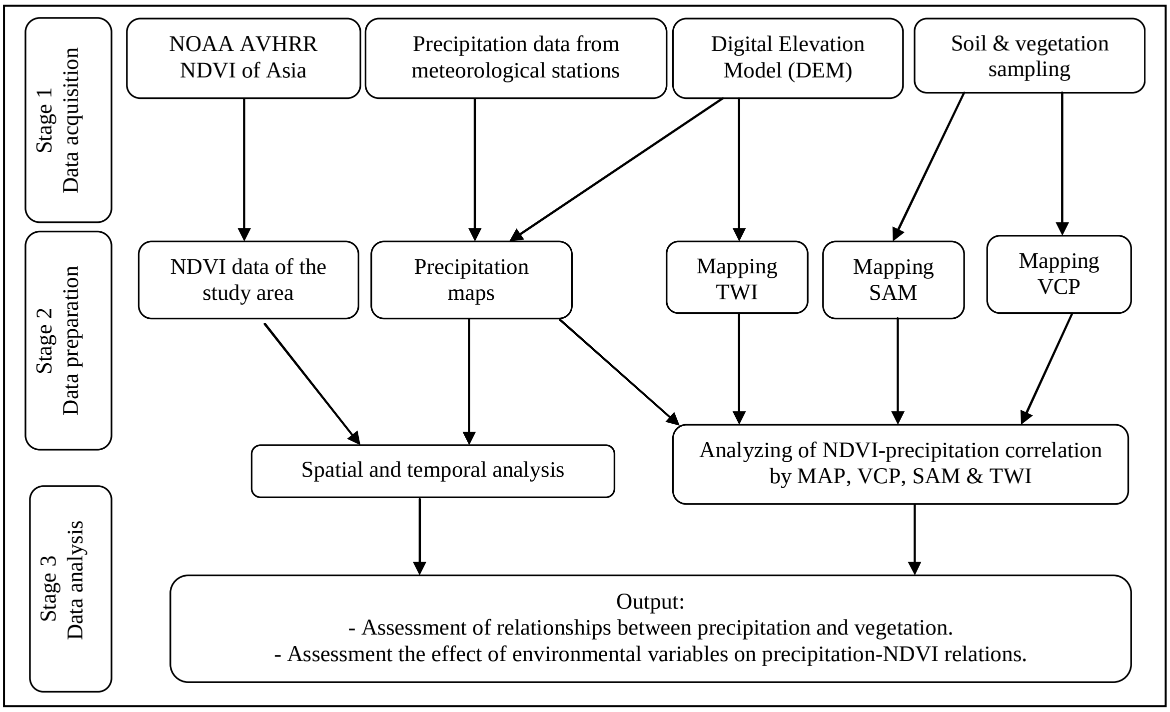

Figure 5.3. Flowchart of the methodology.

5.3. Results

5.3.1. Spatial distribution of NDVI and precipitation in the study area

Figure 5.4 illustrates the spatial distribution of precipitation and NDVI. The spatial trend in precipitation across the study area closely resembles the area's topography, especially elevation. The amount of precipitation is the highest in the mountains in the northern area and decreases towards the saline lands in the southwestern part of the study area. The mean annual NDVI patterns approximately coincide with those of precipitation. But, there are some important differences. For instance, due to the rocky mountains, there is not an strict correspondence between precipitation and NDVI maps in the northern part of the area (figure 5.2 and 5.4).

The NDVI value is characterized by a strong decreasing gradient from the northern to southwestern areas. Figure 5.4 reveals that, in a small part of the southwestern area, the amount of precipitation is very low but the amount of NDVI is high. The vegetation map (Figure 5.2 and Table 5.1) shows that halophyte species dominate this part of the study area. As will be shown in the analyses below (see Tables 5.4, 5.5, 5.6 and Figures 5.6 and 5.8), the growth of halophytes, such as *Haloxylon aphyllum* and *Tamarix ramosissima,* does not depend on precipitation. This shows that the NDVI's spatial distribution does not correspond to precipitation in the whole area. Spatial variation in the NDVI may be due to spatial variability in some environmental variables, such as precipitation, topography, edaphic factors, and type of vegetation.

Some characteristics of different vegetation types have been summarized in Table 5.3. The table reveals that alpine receives the most precipitation and has the highest vegetation cover percentage and NDVI, followed by sagebrush, gypsophytes, and halophytes. Soil available moisture, on the other hand, is the highest for halophytes, followed by gypsophytes and sagebrush, and is the lowest for alpine. In addition, based on some collected information of the study area, the level of groundwater in halophyte communities (southwest of the study area) is very high (Zare Chahouki, 2006).

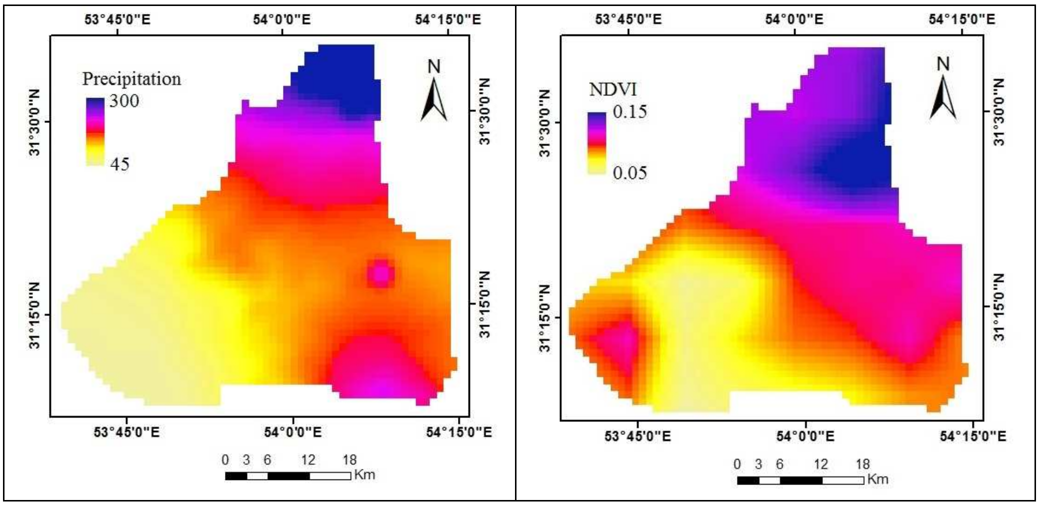

Figure 5.4. Spatial distribution of mean annual precipitation (left) and spatial distribution of mean annual NDVI (right).

5.3.2. The spatial relationship between precipitation and NDVI

Tables 5.4 and 5.5 show a summary of the average correlation coefficients between precipitation and the NDVI in different vegetation categories that represent the relationship between annual and seasonal precipitation (Table 5.4) and the NDVI and annual maximum NDVI (Table 5.5). According to the tables, correlations between annual precipitation and annual mean/maximum NDVI are significant in the alpine, sagebrush, and gypsophyte classes. The relationship was not significant for the halophyte class ($p < 0.05$). This indicates that the annual moisture regime of forbs, grasses, and shrubs mostly depends on the atmospheric precipitation, whereas halophytic vegetation uses soil water. Plants' dependence on atmospheric precipitation is higher in the vegetation classes with a larger cover percentage that require a higher average rainfall, such as grasses and forbs species. There is a significant correlation between alpine plant habitats' annual precipitation and annual maximum NDVI (Table 5.5). Averaged over the hydrologic year, groundwater has a slight influence on alpine plants. As shown in Table 5.6, winter precipitation is the greatest contributor to plant growth, while precipitation in other seasons plays a less important role. This is indicated by correlation coefficients between winter precipitation and the spring/summer NDVI for alpine and sagebrush vegetation. However, precipitation did not have a pronounced influence on gypsophytes during any season, even though there was a slight correlation between the average annual precipitation and the annual NDVI (Table 5.5). In halophyte communities, there is mostly a negative correlation between seasonal precipitation and the annual NDVI, which indicates that the growth of shrubs and bushes is less dependent on precipitation.

Table 5.3. Some characteristics of different vegetation types

Vegetation type	Alpine	Sagebrush	Gypsophyte	Halophyte
Mean annual precipitation	231.33	159.50	121.75	53.50
Mean annual NDVI	0.12	0.09	0.07	0.08
Mean vegetation cover percentage %	24	12.78	8.48	7.60
Mean soil available moisture	4.30	4.28	3.28	8.10
Mean topographic wetness index	14.81	16.09	15.50	17.60

Table 5.4. Spatial correlation coefficient between annual NDVI and annual precipitation

Vegetation type	Alpine	Sagebrush	Gypsophyte	Halophyte
Precipitation-NDVI correlation	0.64*	0.61*	0.55*	-0.34

* statistically significant at the p-level < 0.05

5.3.3. The temporal relationship between precipitation and the NDVI

A comparison of the mean annual precipitation and mean annual NDVI trends illustrate precipitation's inter-annual effects on vegetation. Figure 5.5 shows the precipitation and NDVI trends between 1996 and 2008 in the study area. According to this figure, annual

NDVI and annual precipitation trends roughly correspond with each other. Moreover, the amount of precipitation and NDVI reduced from 1996 to 2008. The calculated coefficient of determination (R^2) between both variables is 0.67 ($p < 0.01$), which indicates that precipitation has a strong effect on the inter-annual dynamics of NDVI.

The annual NDVI and annual precipitation trends in each of the vegetation types are shown in Figure 5.6 and the precipitation-NDVI correlations for each of the vegetation types are represented in Table 5.5. As the figure and table show, the NDVI strongly correlates to the precipitation trends for alpine plants, sagebrush, and gypsophytes, but not for in halophytes.

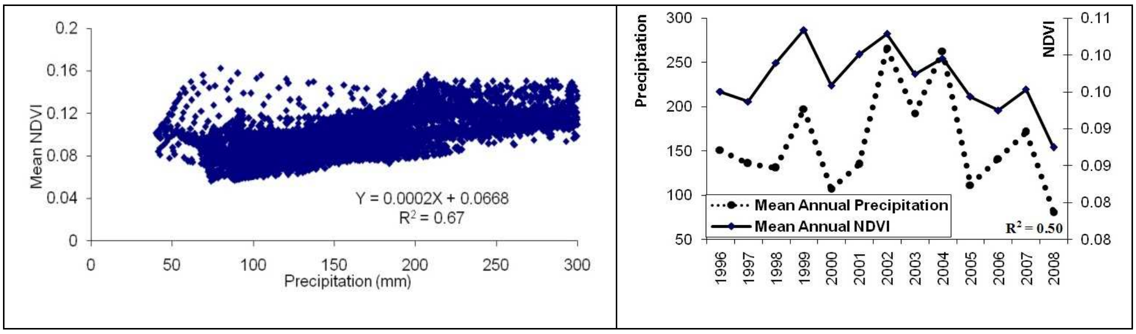

Figure 5.5 Graph of the regression between NDVI and precipitation trend (left) and between mean annual precipitation and NDVI (right)

Table 5.5. Correlation coefficients of annual maximum NDVI with annual and seasonal precipitations

Vegetation type	Alpine	Sagebrush	Gypsophyte	Halophyte
Annual precipitation	0.72*	0.57*	0.36*	-0.15
Winter precipitation	0.51*	0.42*	0.29	0.18
Spring precipitation	0.60*	0.54*	0.32	-0.13
Winter-Spring precipitation	0.67*	0.57*	0.36	0.04
Autumn precipitation	-0.10	0.11	0.20	0.32

*statistically significant at the p-level < 0.05

5.3.4. The effect of precipitation time lag on NDVI

Table 5.6 shows that spring and winter precipitation correlates with spring and summer NDVI, which illustrates the influence of precipitation time lag on NDVI. The correlation coefficients between winter precipitation and the spring NDVI are mostly positive and higher than those of spring precipitation and the spring NDVI. This indicates that there is a time lag between NDVI and precipitation.

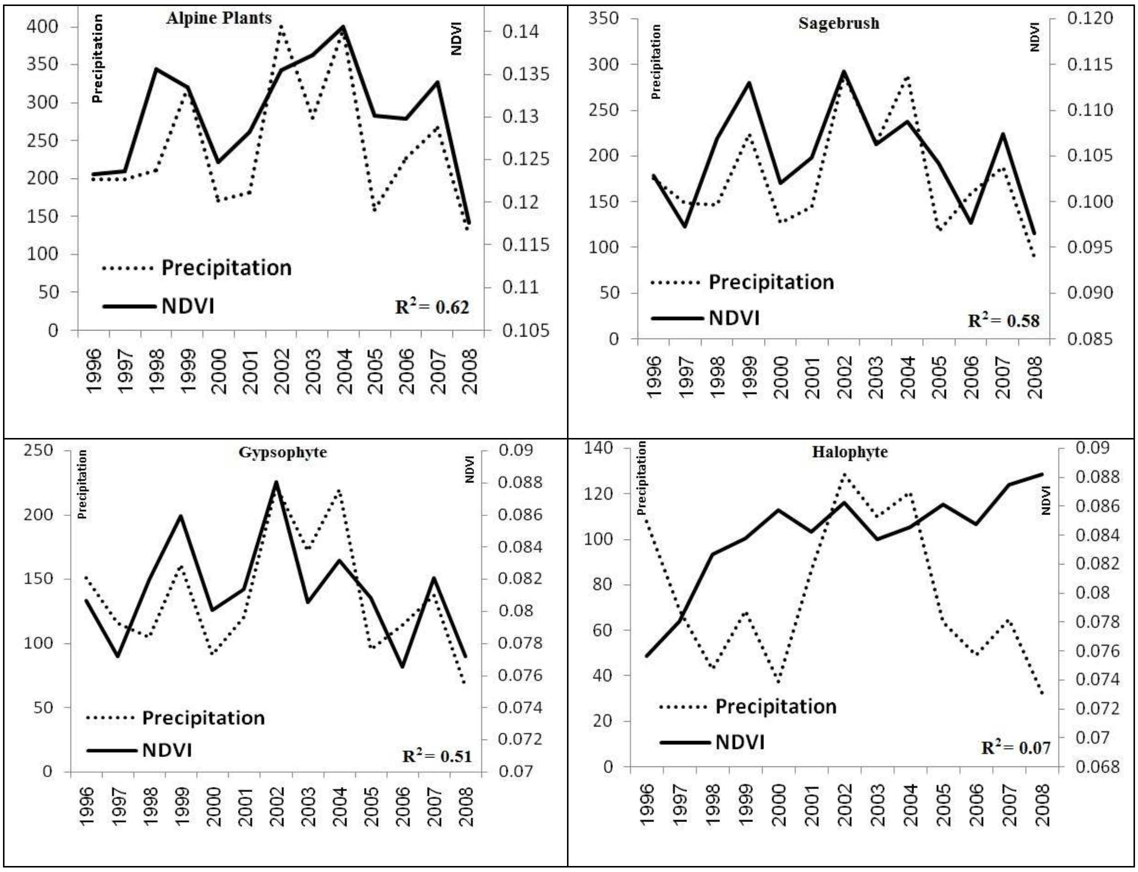

Figure 5.6. Trend of precipitation & NDVI in different vegetation types

Table 5.6. Correlation coefficient of precipitation time lag on NDVI

Vegetation type	Alpine	Sagebrush	Gypsophyte	Halophyte
Spring precipitation and spring NDVI	-0.20	0.01	-0.17	-0.18
Winter precipitation and spring NDVI	0.25	0.42*	0.28	-0.06
Winter-Spring precipitation and spring NDVI	0.40*	0.27	0.07	-0.14
Winter precipitation and summer NDVI	0.41*	0.40*	0.30	0.31

* statistically significant at the p-level < 0.05

5.3.5. The effect of some environmental variables on the NDVI-precipitation relationship

Figure 5.7 shows the maps we created of the SAM and VCP. Figure 5.8 presents the effect of the MAP, VCP, TWI, and SAM on the precipitation-NDVI relationship. The SAM has a negative effect on the NDVI-precipitation relationship. We observed a non-significant correlation between the NDVI and precipitation in halophytes as they grew in areas with higher SAM than other plant types. The MAP and VCP have a positive effect on the NDVI-precipitation relationship.

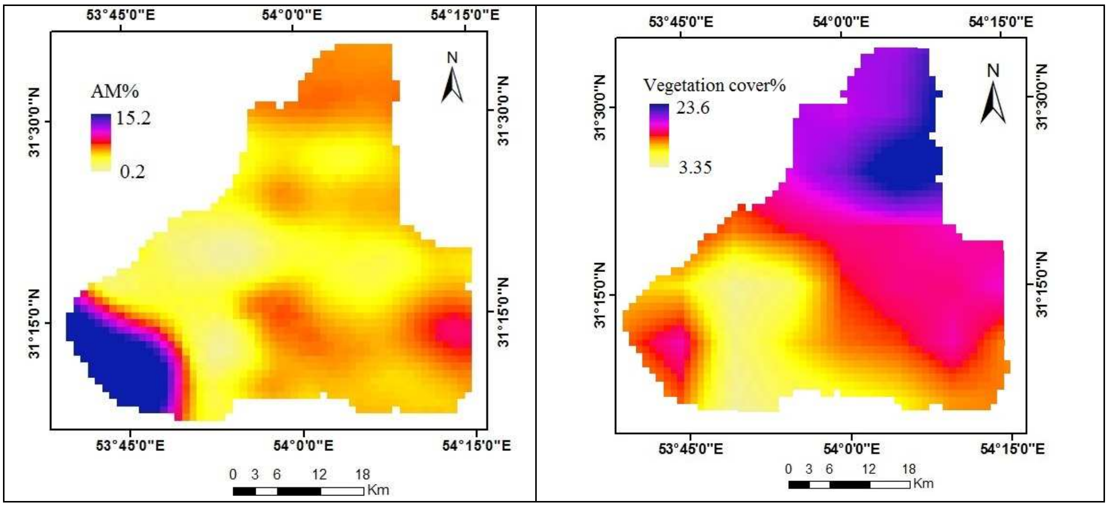

Figure 5.7. Soil available moisture map (left) and vegetation cover percentage map (right)

5.4. Discussion

According to the results, there is a significant correlation between the annual precipitation and annual NDVI in most of the vegetation habitats, while the correlation between seasonal precipitation and the NDVI is usually lower and in some cases negative (Table 5.5). The central part of Iran has a Mediterranean precipitation regime, which means that most of the annual rainfall occurs at the end of autumn and during winter, there is a low amount of precipitation in spring, and summers are mostly dry. This means that there is not enough precipitation during the growing season. Hence, in most parts of the study area, the relationship between seasonal precipitation and NDVI is lower than the yearly precipitation.

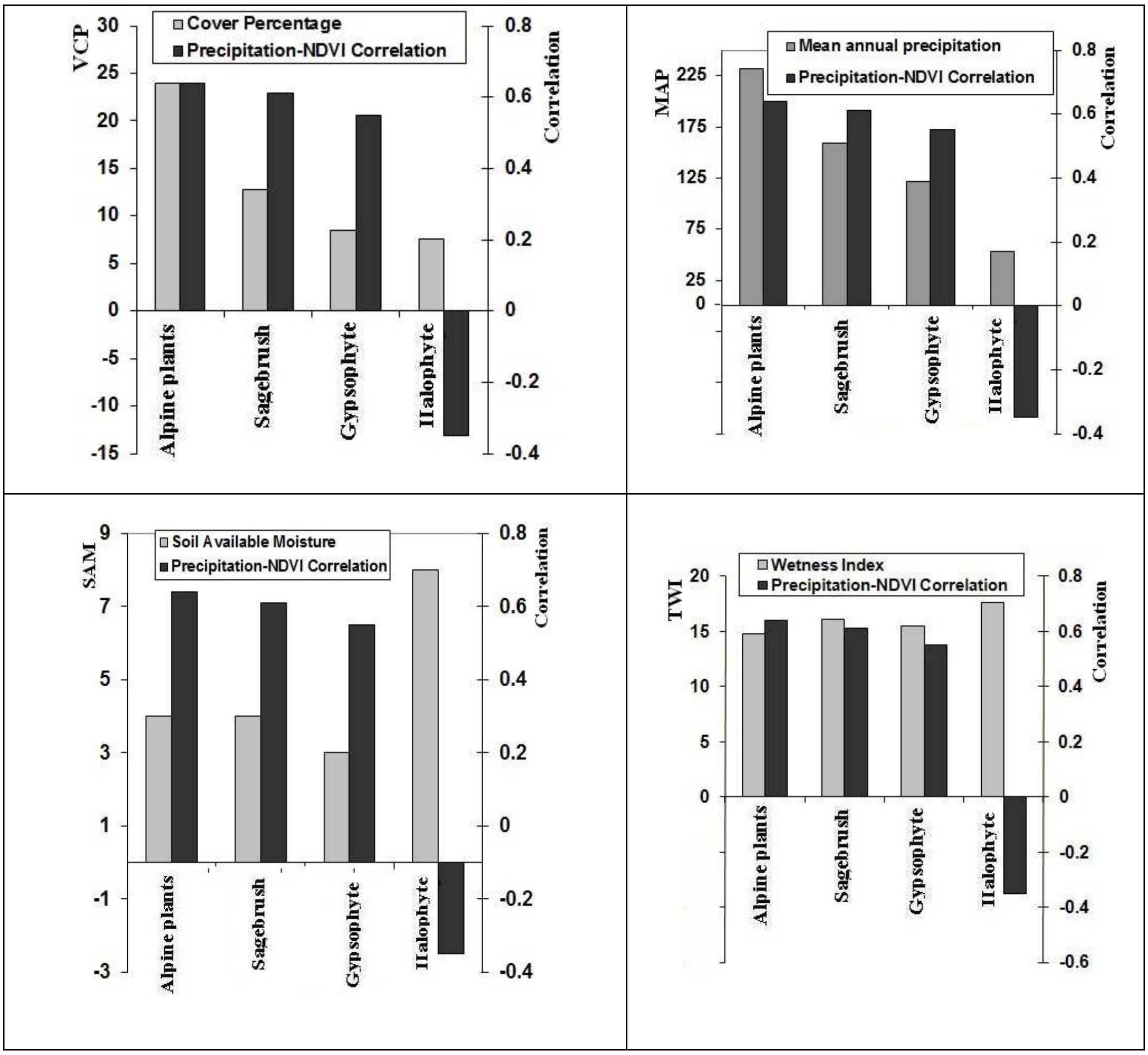

Figure 5.8. Effect of MAP, VCP, SAM, and TWI on the precipitation-NDVI relationship

The significant correlation between seasonal precipitation and the NDVI of some vegetation types is due to their location on the lowlands. Precipitation from surrounding areas is drained to the lowlands (redistribution of water). These vegetation types use the precipitation of adjacent areas; therefore, the growth of vegetation in these parts indirectly depends on seasonal precipitation (Mesdaghi, 2004).

The time lag between precipitation and the NDVI is due to the lower amount of precipitation in spring than in winter. Furthermore, due to heat and evaporation, vegetation cannot use the total spring precipitation. This study's results thus verify similar studies' findings (Mingjun et al. 2007).

The correlation coefficients in this study could not fully explain vegetation variations. Therefore, it can be inferred that the vegetation distribution is driven by precipitation distribution as well as some other environmental variables.

The annual and seasonal correlation coefficients for halophytes is usually lower than for other types. Moreover, according to Figure 5.6, this NDVI habitat trend does not correspond to the precipitation trend. Detailed ground information will likely help explain this weak relationship (Eklundh, 1998). In this habitat, the groundwater level is higher than in other parts of the study area (Zare Chahouki, 2006) and the soil available moisture is also more prevalent than other environmental variables (Table 5.3). This means that the vegetation growth in this area does not depend on precipitation but on groundwater (Figure 5.8).

As Figure 5.8 illustrates, the MAP, VCP, and SAM affect the correlation between vegetation dynamics and rainfall variations. This is similar to results of Nightingale and Phinn (2003). Nevertheless, we did not quantitatively measure these factors' degree of influence on the NDVI-precipitation relationship.

The results demonstrate that the strength of the relationship between precipitation and the NDVI is dependent on environmental variables, especially the species composition, MAP, SAM, VCP, and TWI. Vegetation in the northern and eastern parts of the study area was found to respond strongly to precipitation. In these areas forbs and grasses, such as

Scariola orientalis, *Launaea acanthodes*, *Stipa barbata*, *Euphorbia heterandena*, and *Echinops orientalis,* are considerably dominant. The correlation between the NDVI and precipitation is higher in the alpine habitat due to the area's higher mean annual precipitation and vegetation cover percentage. On the other hand, the non-significant correlation in the southwestern parts of the study area can be explained by the dominance of some hardy shrubs and bushes, such as *Tamarix ramosissima*, *Cornulaca monacantha, Seidlitzia rosmarinus*, *Ephedra strobilacea*, *Haloxylon aphyllum,* and *Calligonum comosum*.

5.5. Conclusions

The results of our comparisons of NDVI and precipitation during the study period revealed that the NDVI data is a powerful tool for quantifying the strength of relationships between vegetation patterns and climatic conditions.

We suggest that future studies consider the effects of environmental factors. These include the amount and distribution of precipitation, precipitation regime, amount of precipitation during the growing season, vegetation cover percentage, type of vegetation, physiology, and phenology of plant species, groundwater level, topographic wetness index, soil available moisture, soil properties, and anthropogenic effects.

Our findings on the relationship between precipitation and the NDVI will be useful to improve the grazing management and to improve and develop rangelands. We need timely data on rangeland conditions in order to monitor herbivore distributions. Forage availability can be predicted by investigating established relationships between climatic variables and vegetation indices. Our findings on climate-NDVI relationships may also be helpful in assessing land degradation.

The predictive models for the relationship between vegetation and precipitation are very useful for understanding vegetation growth constraints (both climatic and anthropogenic). These models provide valuable information on vegetation cover's sensitivity to climate variations and can serve as guidelines for refining the climatological limits of vegetation growth.

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Chapter 6. Modelling potential habitats for *Artemisia sieberi* and *Artemisia aucheri* in Poshtkouh area, central Iran using the maximum entropy model and geostatistics

Abstract

Predicting potential habitats of endemic species is a suitable method for biodiversity conservation and rehabilitation of rangeland ecosystems. The present study was conducted to estimate the geographic distribution of *Artemisia sieberi* (*A. sieberi*) and *Artemisia aucheri* (*A. aucheri*), find the most important environmental predictor variables and seek for similarities and differences in habitat preferences between the two species for Poshtkouh rangelands in Central Iran. Maps of environmental variables were created by means of Geographic Information System (GIS) and geostatistics. Then predictive distribution maps of both species were produced using the Maximum Entropy modeling technique (Maxent) and presence-only data. Model accuracy is evaluated by using the Area Under the Curve (AUC). Lime1, gravel1, lime2 and elevation most significantly affect habitat distribution of *A. aucheri,* while, habitat distribution of *A. sieberi* is affected by elevation, lime1, am1, lime2, and om2. For both species, elevation has an influence on their potential distributions. However, *A. aucheri* depends more on elevation, and consequently climate in comparison to *A. sieberi*. Finally, it is revealed that the potential distribution of *A. aucheri* is limited mostly to mountainous landscapes while *A. sieberi* is present in wide ranges of environmental conditions.

Keywords:

Maxent, geostatistics, environmental variables, habitat distribution, *A. sieberi, A. aucheri*.

6.1. Introduction

Terrestrial ecosystems and global biodiversity patterns have been significantly changed in recent decades, mainly due to anthropogenic and climatic effects. Human caused overgrazing and dry periods have led to land degradation and will cause an eventual loss of biodiversity in rangeland ecosystems of Iran. For conservation and rehabilitation of natural ecosystems especially rangelands monitoring of vegetation dynamic and determination of suitable plant species for planting in different parts with different environmental conditions is necessary.

In recent years, species distribution models have been increasingly used in ecology (Elith et al., 2006; Peterson et al., 2006). These models evaluate relations between existences of species and environmental conditions. Several species distribution models are offered for predicting potential suitable habitats of plant species (Guisan and Zimmermann, 2000; Guisan and Thuiller, 2005; Elith et al., 2006; Guisan et al., 2007a,b; Wisz et al., 2008; Anderson et al., 2003). Generalized Linear Model (GLM) is one of the famous and frequently used methods (e.g. Pearce & Ferrier, 2000; Guisan & Zimmermann, 2000; Beck et al., 2005; Guisan et al., 2002). Some others are neural networks (Manel et al., 1999), and models using presence only data such as Ecological Niche Factor Analysis (ENFA) (Chefaoui et al., 2005; Santos et al., 2006; Martinez et al., 2006), Genetic Algorithm for Rule-set Production (GARP) (Stockwell & Peterson, 1999; Sweeney et al., 2007) and Maximum Entropy (Maxent) (Phillips et al., 2006). Several research papers showed that Maxent is superior in performance (e.g. Sergio et al., 2007; Phillips et al., 2006) compared to ENFA and GARP methods. Phillips et al., (2006), stated Maxent model presents good results even for small sample size. Therefore, Maxent is used in this research.

Artemisia sieberi and *Artemisia aucheri* are endemic in Iran's rangelands. These species distributed only in Iran and surrounding areas. *A. aucheri* occurs only in mountainous areas with high slope, sandy soils and mean annual precipitation of 300-450 mm. Hence, this species has limited ecological distribution. *A. sieberi* occurs in most parts of arid and semiarid rangelands of Iran and recognized as the main plant species of Iran's rangelands. Mean annual precipitation in *A. sieberi* habitats is 50-250 mm (mostly 100-200 mm) and the species grows on different soil types. Therefore, this species has vast ecological distribution. In this research both of the mentioned species are considered not only for animal feeding due to high grazing tolerance but also in nature conservation and degraded land restoration planning. Furthermore, multiple uses of these species especially as medicinal plant may also be taken into account (Moghaddam, 2006; Moghimi, 2006; Mozaffarian, 2010).

The main objectives of the present study are: (1) to estimate the geographic distribution of *A. sieberi* and *A. aucheri* for Poshtkouh rangelands in Central Iran, (2) to find the most important environmental predictor variables and (3) to seek for similarities and differences in habitat preferences between the two species.

6.2. Material and Methods

6.2.1. Study Area

In order to select an appropriate area for the study, three criteria were considered: Variation in landscapes, high biodiversity, and presence of endemic species. The area of interest is Poshtkouh rangelands, located at southern slopes of the Shirkouh mountains of the Yazd province in central Iran (31°33′ 1″ N, 53°40′06″ E - 31°04′27″ N, 54°15′19″ E). Figure 6.1 shows the general location of the study area.

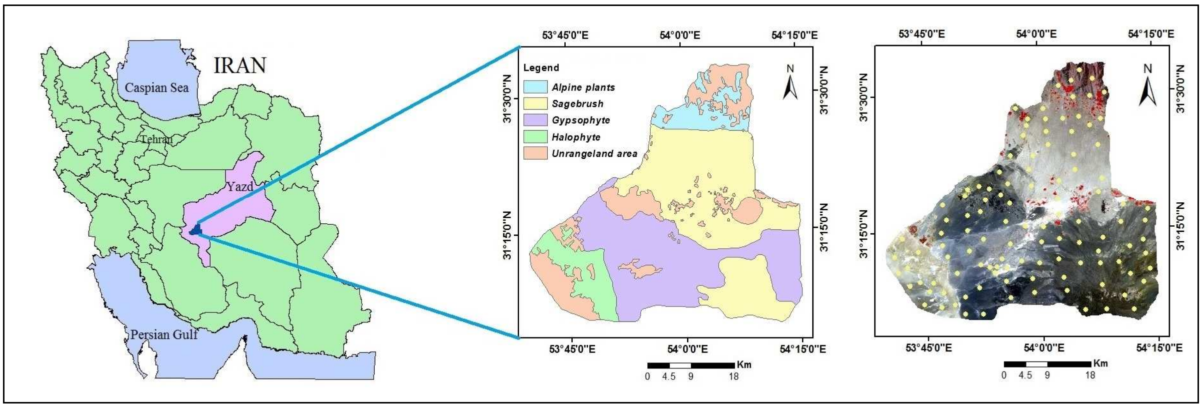

Figure 6.1. General location and vegetation types map of the study area (right)
and location of sampling sites in the study (left)

The area is characterized by very diverse terrain conditions. The maximum elevation of the region is 3990 m and the minimum elevation is 1400 m. The large elevation variability is reflected in the high spatial variability of climate elements in the region. Thus, average annual precipitation is about 300 mm in Shirkouh Mountain in the northern part of the study region whereas at the margin of Kavir_e_Abarkouh (in the southern part of the region) it decreases to 45 mm. Similarly, average annual temperature shows large differences in the study region ranging from 17.1 °C in the southern part to 10.8°C in the northern part, with absolute minimum and maximum temperatures of 0.2 °C and 29.4°C.

The diverse climate and terrain conditions explain the assorted vegetation patterns in the study region (Figure 6.1). The northern part is occupied by alpine vegetation composed by bushes and mixed grassland with domination of several species of *Artemisia aucheri*, *Astragalus* and *Stipa*. In the pre-montane zone, the vegetation cover is presented by *Artemisia* composed by dwarf shrubs and short grasses with dominating species such as *Artemisia sieberi, Launaea acanthodes, Stipa barbata*, and different species of *Salsola*. Gypsi soils of the lowland in the central part of the study region are occupied by gypsophyte plant associations with domination of species of *Salsola*, *Calligonum* and *Artemisia*. The salinized areas in the southern part of the region are covered by dense vegetation composed by halophyte species presented by *Seidlitzia rosmarinus*, *Salsola spp*., and *Haloxylon aphyllum*.

6.2.2. Species Occurrence Data

Due to the lack of accurate and reliable data on absence of species, presence only data were used (Brotons et al., 2004; Anderson et al., 2003). To collect species occurrence data field work was carried out at more than 100 sampling sites. The position of sampling points was recorded using Global Positioning System (GPS).

6.2.3. Geo-database for environmental predictor variables

Previous studies have shown a relationship between environmental variables especially climate, topography, and soil with species distribution, (e.g.O'Brien, 1998; Lennon et al., 2000; Badgley & Fox, 2000; Abdel El-Ghani and Amer, 2003 and Moghimi, 2006). The selected environmental predictors can be classified in three groups: 1) topographical variables, 2) climatic variables, and 3) soil variables. All environmental maps were produced using geostatistical methods with same spatial resolution and stored in a GIS environment. Due to the high precision of the recorded data, all environmental attribute maps were assembled at a resolution of 30 by 30 m. For geostatistical analysis and creating the maps ArcGIS 10 and GS+ 5.1.1 were used.

6.2.4. Topographic maps

Digital topographic maps of the study area at a scale of 1:25000 were used for creating a digital elevation model (DEM). Slope and aspect layers were calculated from the DEM data layer using ArcGIS 10 spatial analyst.

6.2.5. Climatic maps

The climatic data used in this research consist of monthly data (January-December) collected by the Iran Meteorological Organization for 9 climatic stations placed in the study area and around it for the period of 1996-2008. Monthly, seasonal and annual precipitation maps were produced using the co-kriging interpolation approach in combination with a digital elevation model (DEM). Considering the fact that climatic maps and elevation usually demonstrate a high correlation, the elevation could be suggested as a representative for climatic factors Table 6.1 summarizes the mentioned correlations in the study area. The table proves the existence of high correlation between all climatic factors and elevation. Therefore, the climatic maps were not used in Maxent model.

Table 6.1. Correlation between climatic data and elevation

Climatic factor	Correlation with elevation
Precipitation	99.7**
Temperature	99.2**
Humidity	93.2**
Evapor transportation	99.7**
Wind speed	95.6**
Frost days	99.7**

****** Statistically significant at the p-level < 0.01

6.2.6. Soil mapping using geostatistics

In order to take samples from homogeneous units, hypsometric, aspect, slope and geologic maps were overlain and map of the homogeneous units was created. Then 3-5 parallel transects with 300-500 m length were located in each unit and sampling was done along the transects (random-stratified sampling). At each of the sampling points, soil samples were taken in two depths (0-30 and 30-80 cm) in order to cover the root depth of *A. sieberi* and *A. aucheri* which can be more than 60 cm. In total, 112 soil samples were collected in depths 0-

30 and 30-80 cm (figure 6.1). Samples of the first and second depths have been labeled with 1 and 2, respectively (e.g. EC1, EC2, Gravel1, and Gravel2). In the next step, all of the required soil parameters as mentioned in part 6.2.7 were measured in the soil laboratory.

Using semivariogram analyses the degree of spatial variability for each soil attribute was determined. In addition, normality and trend of data were tested. In the next step for ascertaining the degree of spatial variability between neighboring observations for each variable a semivariogram was determined and then appropriate model function was fitted to the semivariogram (Goovaerts 1997). Through analysis of the semivariogram, the best model (e.g., spherical, exponential, or Gaussian) and its parameters were determined.

Finally the maps of soil parameters were created using the kriging method

To ensure that the determined variogram models are appropriate, the models were validated using the cross-validation technique. The average error was considered for evaluating the cross validation results, (Table 6.2). The lower the average error the higher the accuracy of estimation model.

Table 6.2. Average error for different soil parameters

Soil parameter	AM	Clay	EC	Gravel	Gyps	Sand	Lime
Average error	0.01	0.02	0.18	-0.03	0.009	0.16	0.01

6.2.7. Using Principal Component Analysis (PCA) to reduce number of variable in Maxent model

Principal component analysis (PCA) was conducted on vegetation and environmental variables matrix using the program PC-ORD. This analysis is used to reduce the number of input for Maxent model. Below is a list of variables that were implemented as input for the PCA:

Precipitation, temperature, elevation, slope, aspect, vegetation cover percentage, grazing intensity, and a number of soil parameters such as gravel, silt, clay, sand, lime, organic matter (OM), available moisture (AM), gypsum (gyps), Electrical Conductivity (EC), acidity (pH), potassium (K), magnesium (Mg), calcium(Ca), sodium (Na), carbon trioxide (Co3), Chlorine (Cl), bicarbonate (Hco3), and sulfur dioxide (So2).

Finally, based on the result of PCA the following environmental variables were selected as input for Maxent model:

Elevation, aspect, slope, gypsum (gyps), lime, available moisture (AM), electrical conductivity (EC), clay, gravel, organic matter (OM), and acidity (pH).

6.2.8. Modeling habitat distribution of *A. sieberi* and *A. aucheri* using Maximum Entropy (Maxent) model

There are several modeling techniques for predicting the potential habitat of plant species using the environmental variables. In this research prediction of the potential distribution of two sagebrush species was based on the Maximum Entropy (Maxent) modeling technique using the program Maxent 3.3.3 (Phillips et al. 2004, 2006; Phillips & Dudik 2008, AT&T Labs-Research, Princeton University).

Maxent is a general-purpose model with a precise mathematical formulation (Phillips et al., 2006). The basic idea of Maxent is "to estimate (approximate) unknown probability distribution of a species" (Phillips et al., 2006). Maxent (Phillips et al., 2006) is an approach for estimating species distribution by presence only data, that has been proved to work well in practice (e.g. Elith et al., 2006). In the first step, the model assesses environmental layers based on the training data location and then selects the probability of occurrence of each species in the whole study area (Buehler & Ungar, 2001). Fundamentally, when a pixel in the studied region has equal environmental conditions of the training data, higher values are assigned to this pixel. On the other hand, pixels with different environmental conditions are assigned lower values (Negga, 2007).

6.2.9. Presence-absence maps

As output of Maxent model is a continuous map, to determine the presence or absence of the target species a threshold must be set (Negga, 2007). Phillips et al., 2006), used the minimum cumulative value of training sample points as a threshold. However, in this research, predictive continuous maps were classified to binary (1 or 0) or presence-absence maps using equal test sensitivity and specificity.

6.2.10. Model evaluation

Assessing the prediction results is an essential step for validation of any approach in ecological modelling (Verbyla & Litvaitis, 1989). Generally, to develop and test a model, two independent datasets are required as ‘training’ and ‘testing’ data (Fielding & Bell, 1997). Verbyla & Litvaitis, 1989 suggested jackknife as an efficient accuracy assessment method. Nevertheless, in the case of insufficient number of samples, data partitioning can be challenging (Negga, 2007).

6.2.11. Receiver operating characteristics (ROC) curves

The Maxent simulation results can be assessed by analyzing the area under the curve (AUC) of receiver operating characteristics (ROC) graph. The ROC curve is a graph consisting of two axes; the X axis representing the false positive fraction so called 1-specificity, and the Y axis showing the true positive fraction named sensitivity (Fielding & Bell, 1997). The model would be regarded appropriate when the ROC curve represents the maximum values of sensitivity for low values of the false positive fraction. This quality can be measured using the AUC value (Hernández et al., 2006). According to Bachman, 2011 and Segurado & Aráujo 2004, the AUC which reflects the quantity of overall accuracy of the model is independent of thresholds (Deleo, 1993). The AUC ranges usually from 0.5 in the case of no difference in the scores of two groups (true positives and false positives) to 1.0 in the case of no overlap in the distribution of the group scores (= perfect differentiation).

6.2.12. Predictor variable importance

In order to evaluate the importance of each environmental predictor variable, the jackknife operation was used. Jackknife sequentially excludes one environmental variable from the analysis and runs the model using the rest of the variables. Once again, the model would be run separately using the excluded variable only. Therefore, the share of each environmental variable on the total gain of the model (containing all of variables) can be calculated. In the next step, two variables can be selected as the most important ones; the one which reduces the total gain of the model more than all the other variables when omitted, and the one which shared the maximum gain when employed alone (Negga, 2007). More explanation in this regard can be found in the Maxent tutorial (http://www.cs.princeton.edu).

6.3. Results

In this paper the main results consist of species distribution maps, importance of predictor variables, and model evaluation within the Maxent model.

6.3.1. Species distribution maps

The species distribution maps of the two species which were derived using training sensitivity and specificity threshold (*A. aucheri* = 0.278 & *A. sieberi* = 0.384) show broadly different predictions (Figure 6.2). For *A. aucheri* northern parts of the study area (mountainous area) are predicted as presence whereas *A. sieberi* is predicted presence mostly in the central and south parts. For both species the south-western part of the study area is predicted absence.

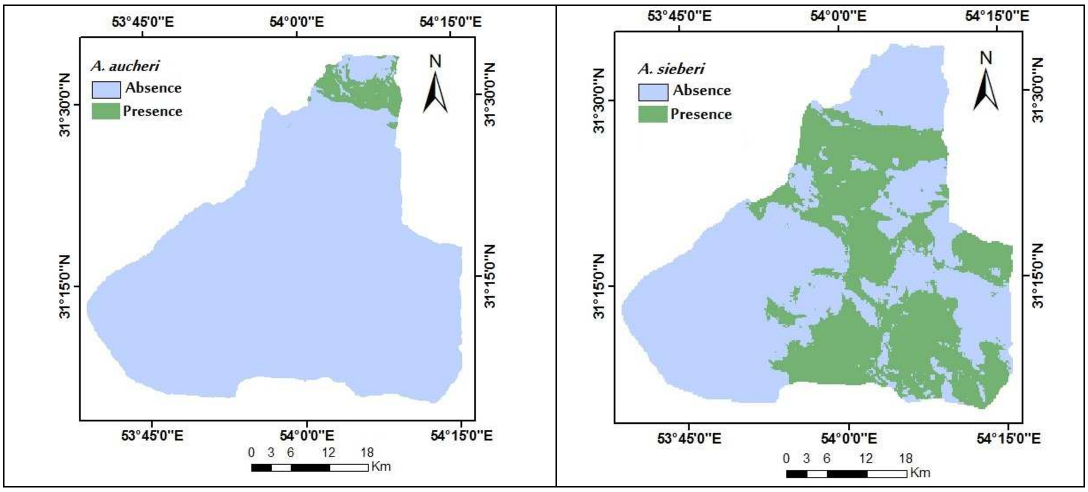

Figure 6.2. Species distribution maps for *A. aucheri* and *A. sieberi*

6.3.2. Predictor variable importance

Based on the jackknife operation results (Figure 6.3) lime1 and gravel1 significantly affects habitat distribution of *A. aucheri* when used individually followed by lime2 and elevation. Figure 6.3 also indicates that habitat distribution of *A. Sieberi* meaningfully is influenced by elevation, lime1followed by am1, lime2, ph1 and om2. Therefore the mentioned variables have the most useful information. Other parameters have low gain when used in isolation. For both of the species if Maxent uses only aspect it achieves almost no gain, so that this variable is not (by itself) useful for estimating the distribution of Sagebrush species. Moreover, gyps2 and om1 are not useful for predicting the habitat distribution of *A. aucheri* and ph2 is not valuable for predicting *A. sieberi* habitat.

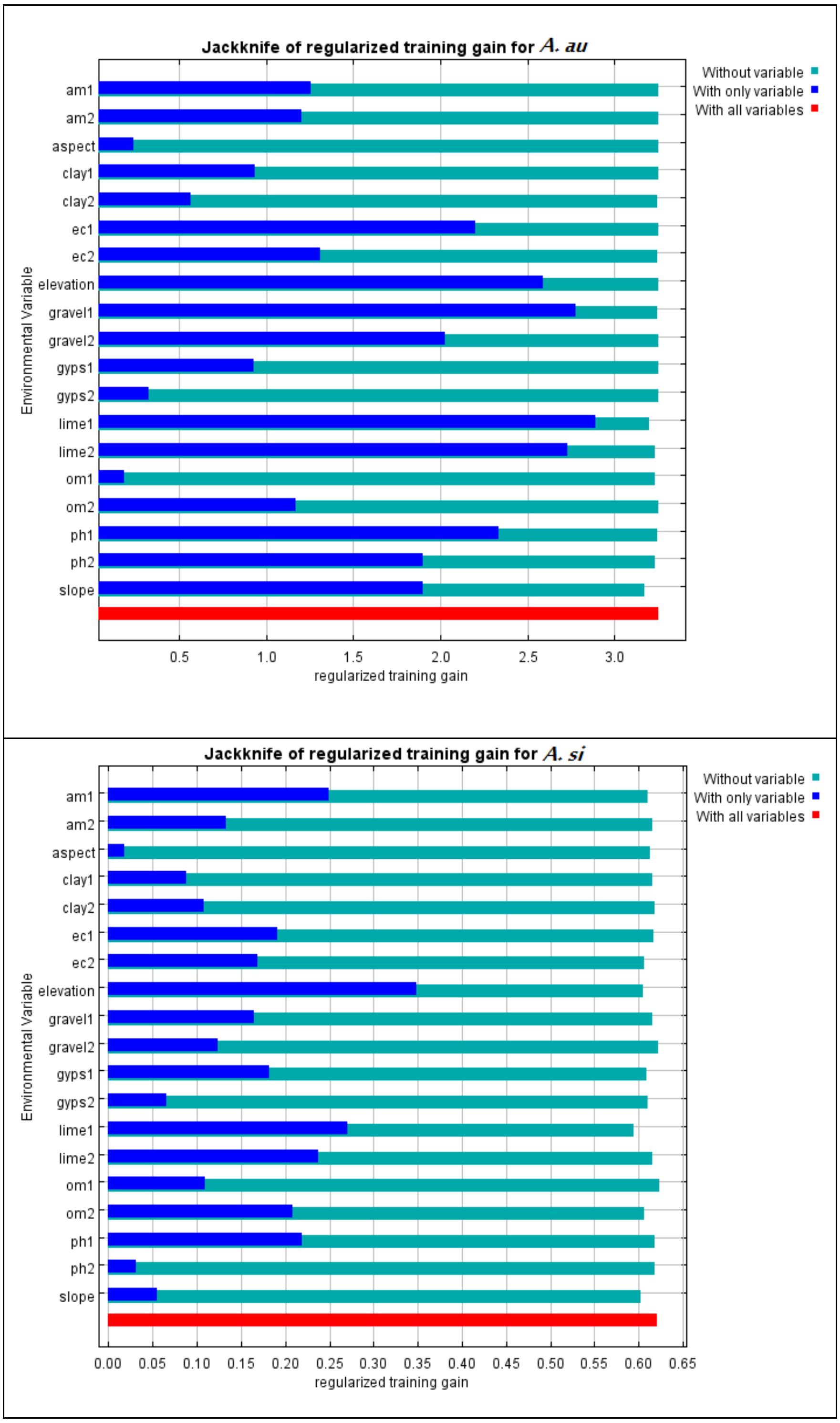

Figure 6.3. Jackknife results of variable importance

6.3.3. Response curves

There is a response curve for each of the environmental variables used in the Maxent model. These response curves represent relationships of environmental variables and the distribution of the species' suitable habitat (Figures 6.4 and 6.5). Lime1, gravel1, lime2 and elevation were the main variables influencing potential *A. aucheri* habitat, while *A. sieberi* habitat distribution was affected by gravel2, OM2, gravel1, gyps1, AM1 and elevation.

The response curves associated with these factors show that there may be environmental thresholds for the ideal growth of both species (Figures 6.4 and 6.5). Based on figure 4 considering lime1, habitat suitability of *A. aucheri* was highest around 1-2 while dramatically decreasing at higher values showing *A. aucheri* has a strong relationship with low-lime soils. This species has also high habitat suitability in the areas with elevation more than 2500 m and consequently higher elevation and lower temperature. The figure also represents that *A. aucheri* grows in areas with high gravel (22-25% and more).

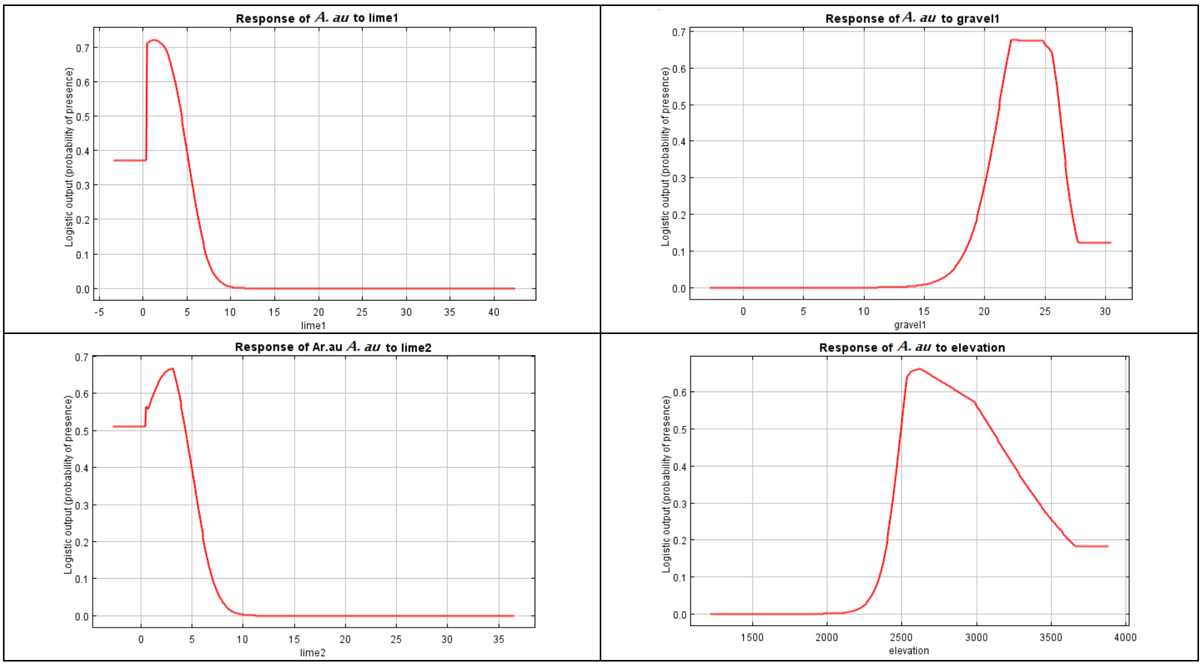

Figure 6.4. Response curves of the most influential predictors for *A. aucheri*.

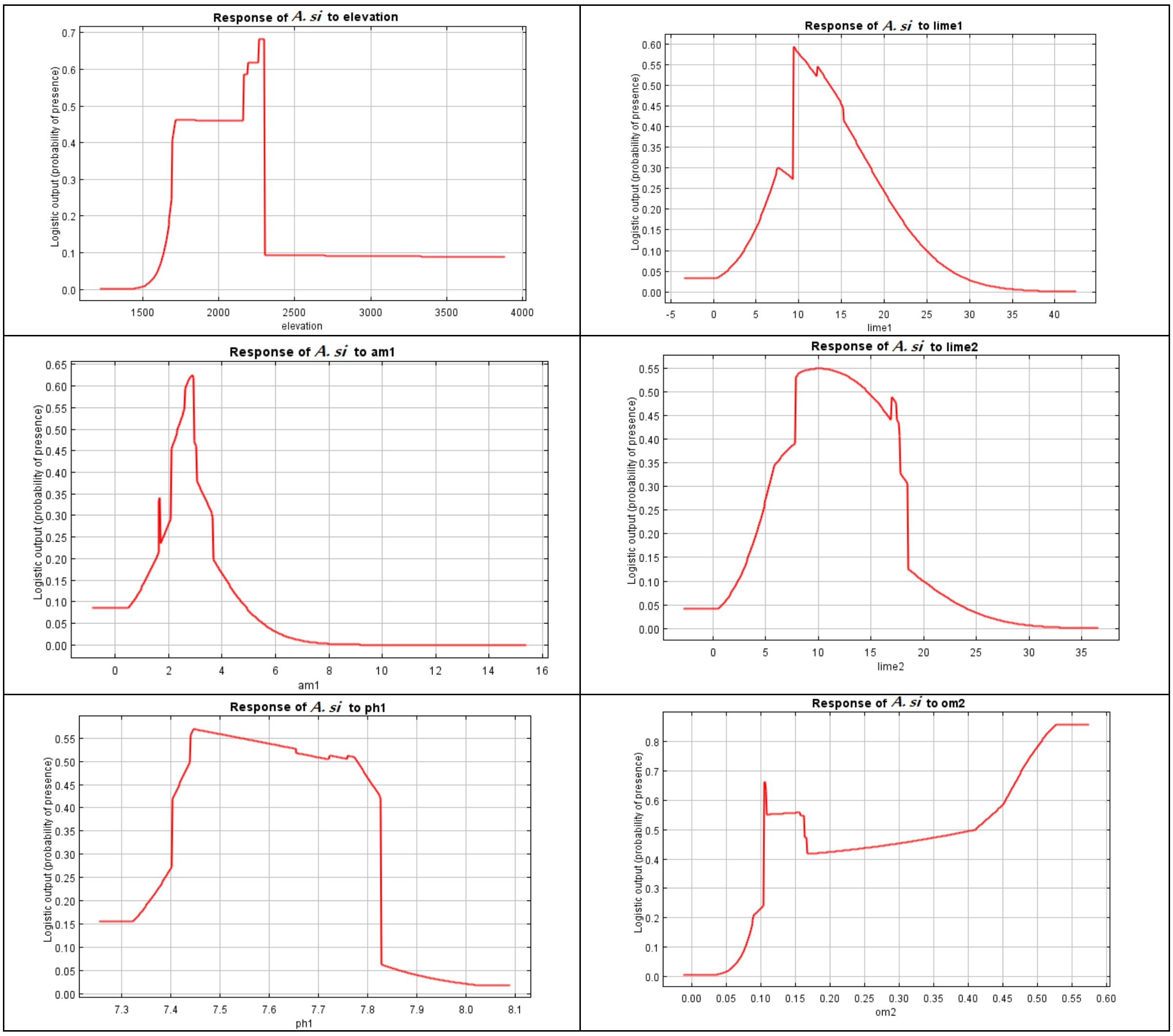

Figure 6.5. Response curves of the most influential predictors for A. sieberi.

Figure 6.5 represents that for suitable habitat of *A. Sieberi* maximum elevation is about 2300 m, optimum percentage of lime1 and lime2 are about 10, optimum am1 is about 10. This species also reveals positive relations with organic matter and tolerates wide ranges of ph1.

6.3.4. Receiver operating characteristics (ROC) curves

Figure 6.6 shows ROC curves for both of the study species. According to the figure, area under the curve (AUC) for *A. aucheri* is bigger than *A. sieberi*. Therefore, the model accuracy for prediction of *A. aucheri* habitat (0.95) is higher than for *A. sieberi* (0.71). This is due to the adaptability of *A. sieberi* to diverse habitat conditions (as has been described in the introduction). Hence, *A. sieberi* habitat could not be separated with high accuracy by the Maxent model.

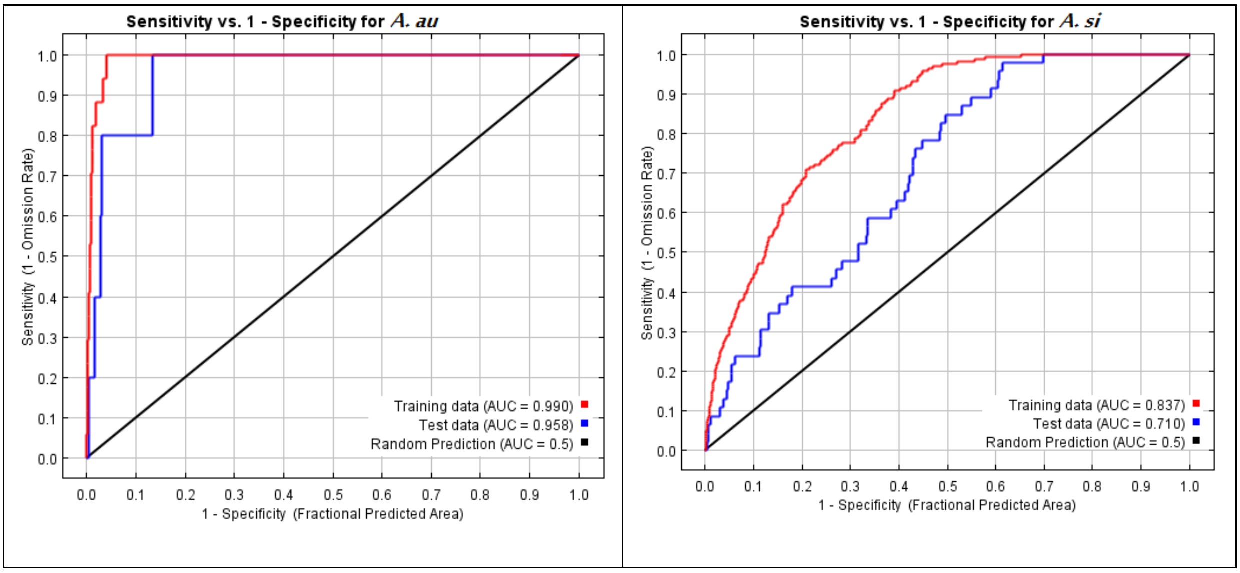

Figure 6.6. ROC curves of sensitivity vs. specificity

6.4. Discussion and conclusion

According to the results elevation is one of the common predictors for both models. Comparing suitable habitat distribution maps of *A. aucheri* and *A. sieberi* (Figure 2) and response curves of these species (Figures 6.4 and 6.5) represent that with respect to elevation there is a significant difference between the species. Furthermore, based on jackknife graphs (Figure 6.3) for both species, the effect of elevation is stronger on *A. aucheri*. As the elevation has direct effect on climate it is revealed that climatic conditions in habitats of these species are significantly different. Therefore, the potential distribution of *A. aucheri* depends more on elevation, and consequently climate in comparison to *A. sieberi*. In other words, the predicted distribution map of *A. sieberi* demonstrates high tolerance of this species to topography and climate, whereas, the habitat of *A. aucheri* is restricted to mountainous areas of the northern part with low temperatures, and high precipitation. Azarnivand et al (2002) reported that elevation is one of the most important factors for separating habitats of *A. aucheri* and *A. sieberi* in rangelands of Vardavard, Garmsar and Semnan.

Since the study area mostly is located at the southern slopes of Shirkouh, using only aspect variable, the Maxent model cannot achieves any gain (Figure 6.3).

Some soil parameters such as lime, gravel, organic matter (OM), and soil available moisture (AM) have an influence on distribution of A. aucheri and A. sieberi (Figure 6.4 & 6.5). Abdel El-Ghani and Amer (2003), Moghimi (2006), and Wilson et al (2004) reported that soil is one of the most important environmental variables affecting vegetation communities in arid lands. Zare Chahouki et. al., (2012) stated that A. sieberi has direct relation with soil available moisture. This is due to the impact of soil available moisture on the occurrence of vegetation types (Barnes and Harrison , 1982).

Lime1 is another common predictor for both models. Based on the response curves (Figure 6.4 & 6.5) *A. sieberi* occurs in wide ranges of soil parameters, whereas habitat of *A. aucheri* is restricted to mountainous area of the northern part with low soil lime and high soil gravel. Therefore, considering soil conditions it is concluded that *A. aucheri* has limited tolerance to soil parameters and there is a significant difference between *A. aucheri* and *A. sieberi* in mean suitable soil parameters ranges. This is in accordance with results of Akbarpour (1994), Zare Chahouki (2010) and Moghimi (2006).

The results revealed that in addition to using climatic and topographic data which have been used in most of the previous researches in the field of ecological modelling, soil data improve the predictive ability for habitat distribution mapping of plant species in central Iran.

Comparison of the vegetation types (Figure 6.1) and the *Artemisia* species distribution maps (Figure 6.2.) represent that the produced potential distribution maps are highly correspondent with an actual land cover map of the study area. Hence, it is revealed that Maxent modeling is very effective at determining habitat distribution for different species. Because it relies only on presence data, it lacks many of the complications associated with presence-absence analytical methods (Phillips et. al., 2006). Moreover, the results of Maxent modeling provided key information about the environmental tolerances of the *Artemisia* species in the study area that can be used for protecting susceptible habitats from future invasion and impacts of climate change. Also conservation planners and rangelands managers of Iran could use the outputs of this research as base information for grazing management and rangelands rehabilitation.

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Chapter 7. General summary and conclusion

This chapter highlights and summarizes the major parts of the thesis and represents an overview about the knowledge obtained from the present and a number of other studies. Furthermore, some ideas that could be useful in future studies will be suggested.

- The main current threats to the Iranian rangelands are desertification due to the over-grazing, climate change, and human activities. Therefore, a continuous and consistent monitoring program of these ecosystems is suggested as a prerequisite for an effective conservation and development strategy.

- Vegetation cover is a good measurable factor that can be considered as an indicator of rangeland ecosystems. Monitoring of this factor by remote sensing is easily possible. Selecting the best annual time intervals of satellite images for this purpose seems an essential factor in accuracy of vegetation mapping and monitoring. More details have been explained in chapter 4.

- As reported in the present and a number of other studies, NDVI has a high sensitivity to inter-annual rainfall anomalies. Hence, it can be used as a suitable tool for monitoring climate variability, vegetation dynamic and land degradation on regional and global scales (Propastin and Kappas 2008a,b; Evans & Geerken, 2004). Taking the effect of environmental variables like soil available moisture into account can help for a better interpretation of NDVI-precipitation relations. In other words, depending on the type and composition of vegetation as well as environmental conditions, the precipitation-NDVI relations vary in different parts of the study area.

- As mentioned in chapter 5, different factors such as climate, topography, soil, and human activities significantly affect vegetation changes and dynamic in rangelands. Typically, discrimination between different causes of change in vegetation is very difficult. But, to evaluate rangelands condition, it is necessary to consider all of the factors and determine and distinguish contribution of each factor in vegetation changes. Recently, a few studies have used some methods to separate anthropogenic effects on vegetation changes using time series of satellite images and climatic data (Evans & Geerken, 2004; Li et al., 2004; Propastin, 2006).

- The accuracy of the environmental variable maps has a direct effect on the accuracy of the Maxent model outputs. Therefore, these maps should be created as much precisely as possible. According to results of this research, geostatistics, GIS and remote sensing techniques have represented good capability for mapping environmental variables.

- In this study three geostatistical approaches (ordinary kriging, cokriging, and regression kriging) have been used for mapping the soil properties. The reason for choosing the geostatistical methods was not only improving the estimation accuracy by taking the spatial variability of soil properties into account but also reflecting the estimation uncertainty for these soil parameters. The success of these methods has been reported in several studies (Eldeiry et al., 2010; Odeh et al., 1994; McBratney, 2000; Hengl et al., 2004). In most of the cases, a significant difference in the accuracy of soil attribute maps created by different geostatistical methods has been observed. Usually, taking the secondary variables into account has increased the accuracy of estimations. Therefore, the application of cheap and easily accessible ancillary data such as satellite images and elevation has been suggested to improve the predictions quality of soil properties (more details in this regard has been elaborated in chapter 3).

- Selecting the suitable environmental variable predictors for Maxent model input would be of tremendous value in ecological modeling. Basically, due to the correlation between different variables, reducing the number of model inputs is essential. Principal component analysis (PCA) is a sound method that can reduce the number of model inputs based on the correlation between different environmental variables. As mentioned in chapter 6 the climatic variables (i.e. precipitation and temperature) have not been selected as the inputs of the Maxent model by PCA. Nevertheless, due to the high correlation between the elevation and climatic factors (table 6.1), it can be concluded that the climatic variables affect the habitat of the *A. sieberi* and *A. aucheri* species as well.

- In most of the previous researches which have been done in the field of ecological modelling, climatic and topographic data were employed as inputs of the ecological models. But, results of this research have been revealed that soil data can improve the predictive ability for habitat distribution mapping of plant species. Therefore, using the soil data together with topographic and climatic data for species distribution modeling is suggested.

- Determining the effective environmental factors and assessing the habitat distribution of the *A. sieberi* and *A. aucheri* were the main aims of chapter 6. The results have proven that Maxent is an efficient model for species distributions mapping despite the small sample sizes or scattered species distributions. In addition, this model can efficiently find the environmental variables correlation with geographic distribution of species. Furthermore, the wide variety of successful applications of this model reported in numerous studies suggests the high potential of this model in ecological studies. Nevertheless, using the other ecological niche models that may represent better accuracies as well as the comparison of different models efficiency is suggested for future studies.

- It should be taken in account that the Maxent model creates the fundamental target species habitat map (the places that the target species free of interference from other species could use the full range of conditions and resources to survive and reproduce) using environmental variables. Hence, the realize habitat (as a result of pressure from, and interactions with, other species (competition), that forced to occupy a niche that is narrower than this, and to which they are mostly highly adapted) may be overpredicted in some areas (Pearson 2007; Murienne et al., 2009).

- Produced distribution map of the Maxent model led to the search for the target species at inaccessible areas which are far from villages and access roads. In the other word, based on predictions, some new presence localities might be found with different ecological conditions. These results can be useful for conservation and restoration of the area (Al-Duais, 2009).

- Global warming is hazardous for biodiversity, since it may worsen the vulnerability of endemic species with restricted ecological range (Malcolm et al., 2006; Thomas et al., 2004). Many studies demonstrated that the ecological models can analyze climatic data and investigate the impact of climate change on vegetation niches to predict future potential distribution of the habitats (Hijmans and Graham, 2006; Ruegg et al., 2006; Thuiller, 2003; Williams et al., 2003). Hence, the prediction of the future of rangelands vegetation types using this model could be useful for conservation planning.

- Several authors have pointed out that the invasion process slowly changes the position and shape of fundamental ecological niche (Broennimann & Guisan, 2009; Medley, 2010). Therefore, considering the invasive plants threats, study of invasive species in their native and invaded ranges by the Maxent model would be beneficial for rangelands conservation and management.

- *A. aucheri* occurs in highlands of the northern part (Shirkouh Mountain). Among the environmental variables, soil texture and elevation have higher correlation with this species. Generally, the habitat of *A. aucheri* starts from 2500m to higher elevations with the annual precipitation of more than 290 mm, slope between 20-30%, and soil depth of more than 50 cm. In such area, the amount of soil salts is not considerable. Due to the suitable humidity condition and inaccessibility to animal grazing, plant biodiversity is higher than other parts of the area (figure 2.6 and table 2.3). According to the literatures, in other parts of Iran, *A. aucheri* presents in the areas with the elevation of 1700-2800m and mean annual precipitation of 300-450 mm (Moghimi, 2006; Zare Chahouki, 2006).

- *A. sieberi* occurs in the areas with 1900-2100 elevation. Depending on elevation and amount of precipitation, various plant compositions exist in different parts of *A. sieberi* habitat. Several studies have reported the occurrence of this species at the areas with the elevation range of 600-2000m (Akbarpour Yasaghi, 1996; Zare Chahouki, 2006, Moghimi, 2006). Elevation and soil salinity are the most important limiting factors for distribution of *A. sieberi* and *Ar. sieberi* (Azarnivand et al., 2006).

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