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Discrimination of Soil Types in Southern Kuwait Using Remote Sensing Classification Techniques on Landsat 8 ETM+ Satellite Images

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الملخص: تركز هذه الدراسة على بيانات الأقمار الصناعية لاندسات ٨ تطبيق تقنيات الاستشعار عن بعد لتحديد أنواع مختلفة من التربة باستخدام معالجة الصور الرقمية في الجزء الجنوبي من الكويت. الجزء الجنوبي من الكويت وتضم السهول الصحراوية وحقول النفط، السبخة ومزارع الوفرة. في هذه الدراسة، تم استخدام صور الأقمار الصناعية لتحقيق بسرعة لتصنيف التربة الفعلي . نظرا لعدم إمكانية الوصول للمناطق الصحراوية ، يمكننا الاستشعار عن بعد لاستيعاب التغيرات المكانية و المعلومات . ويشمل النمذجة المكانية استخدام نظم المعلومات الجغرافية لتمثيل النموذج المفاهيمي وأداء العمليات الحسابية البسيطة على نظم المعلومات الجغرافية المخزنة على شكل سمات لعرض نتائج مكانيا .

الكلمات المفتاحية: +ETMلاندسات، نطاقات المرئية ، الاستشعار عن بعد ، أنواع التربة ، الكويت .

Abstract: This study focuses on satellite data Landsat 8 ETM+ and application of remote sensing techniques to delineate various kinds of soils using digital image processing in the southern part of Kuwait. Southern part of Kuwait comprises desert plains, oil fields, sabkha and wafra farms. In this study, satellite imagery is used to achieve rapidly to the actual soil classification. Considering the inaccessibility of the desert areas, RS is essential to accommodate spatial variability and information. Spatial modeling involves the use of GIS for representation of the conceptual model and performance of simple mathematical computations on the stored GIS object attributes for displaying the results spatially.

Keywords: Landsat, ETM +, visible bands, remote sensing, soil types, Kuwait)

1- Introduction:

General Statement

The term "Remote Sensing" refers to methods that employ electromagnetic energy, such as light, heat and radio waves as the means of detecting and measuring target characteristics (Sabins, 1987). Remote sensing can provide information for large areas, and in a relatively short time. In addition, remote sensing is not limited by extremes in terrain or hazardous condition. Generally, remote sensing should be integrated into early stages of investigations and be used in conjunction with traditional mapping techniques. Remote sensing data were used in this study for the purposes of rapid planning and assessment of an area to know the types of soils occurring therein.

There were many attempts to use the remote sensing data and its techniques to detect the types of soils. Some of these studies are summarized below:

Dwivedi (1969) applied principle component analysis of Landsat MSS bands 1, 2, 3 and 4 in delineating salt affected soils. Naseri (1998) suggested that both types of digital classification, unsupervised and supervised, could be used for the proper identification of soils and soil salinity, mostly at a regional level. MSS bands 3, 4 and 5 are recommended for salt detection in addition to TM bands 3, 4, 5 and 7. Sukchan et al. (2001) used Landsat 5 TM integrated with GIS for improvement of classification methods to detect salt-affected areas in Northeast Thailand. They found that the operation of dividing areas according to soil type and landform information derived from map data could lead to a reliable classification with an overall accuracy of 85.26 percent of their salt-affected areas classification.

Menenti, Lorkeers & Vissers (1986) found that TM data of band 1 through band 5 and band 7 are useful for identifying salt minerals, at least when salt is a dominant soil constituent. Moreover, salt minerals affect the thermal behavior of the soil surface. Mulders & Epema (1986) produced thematic maps indicating gypsiferous, calcareous and clayey surface using TM band 3, 4 and 5. They found TM data a valuable aid for mapping soil in arid areas when used in conjunction with aerial photographs. Sharma & Bhargava (1988) followed a collative approach comprising the use of Landsat 2 MSS "FCC" or False Color Composite, survey of topographic maps and limited field checks for mapping saline soils and wetlands. Their result showed that because of their distinct coloration and unique pattern on false color composite imageries the separation of saline and waterlogged soil is possible. Landsat 5 (TM) and Landsat 7 (ETM+) Data Landsat satellites have been collecting multispectral images of the Earth's land surface since the 1970's. This unique data archive has played an important role across disciplines as a tool used toward achieving improved understanding of the Earth's land surface impacts on the environment.

The purpose of the Landsat program is to provide the world's scientists and application engineers with a continuing stream of remote sensing data for monitoring and managing the Earth's resources. Landsat 7 (ETM+) is the latest NASA satellite in a series that has produced an uninterrupted multispectral record of the Earth's land surface since 1972.

Study Area – Southern Kuwait

The State of Kuwait is located at the northwestern part of the Arabian Gulf. Kuwait lies on the northern tip of the Arabian Gulf, bordered by Kingdom of Saudi Arabia to the south and south-west; and the Iraqi Republic to the north and northwest; it lies between longitudes 46^0 33′ 10″ E & 48^0 33′ 29″ E and latitudes 28^0 31′ 29″ N & 30^0 6′ 11″ N. (Figure 1).

Kuwait, like most of the Arabian Peninsula, is characterized by a dry, hot climate, according to land, and the regional topography of the area.

Kuwait desert can be divided into four physiographic provinces: (a) Al-Dibdibah gravelly plain; (b) southern desert flat; (c) coastal flat; and (d) coastal hills. In general, the surface topography is a rather flat to gently rolling desert plain, broken by occasional low hills, scarps and Wadis. The landform and substrate of Kuwait reflect profound change in landscape dynamic over the last 40 million years or so. The rangelands of Kuwait, like most arid rangelands, little rainfall and sparse vegetation dominated by woody shrubs that are less than 2 m in height. As part of the Arabian Desert, Kuwait's climate is characterized by extremely high temperatures during summer, short mild winters, high sunshine hours, low humidity and generally dry conditions. The average daily maximum ambient temperatures are 45°C for July and 18°C for January.

Figure 1: Location of Kuwait in Arabian Peninsula, Middle East Region

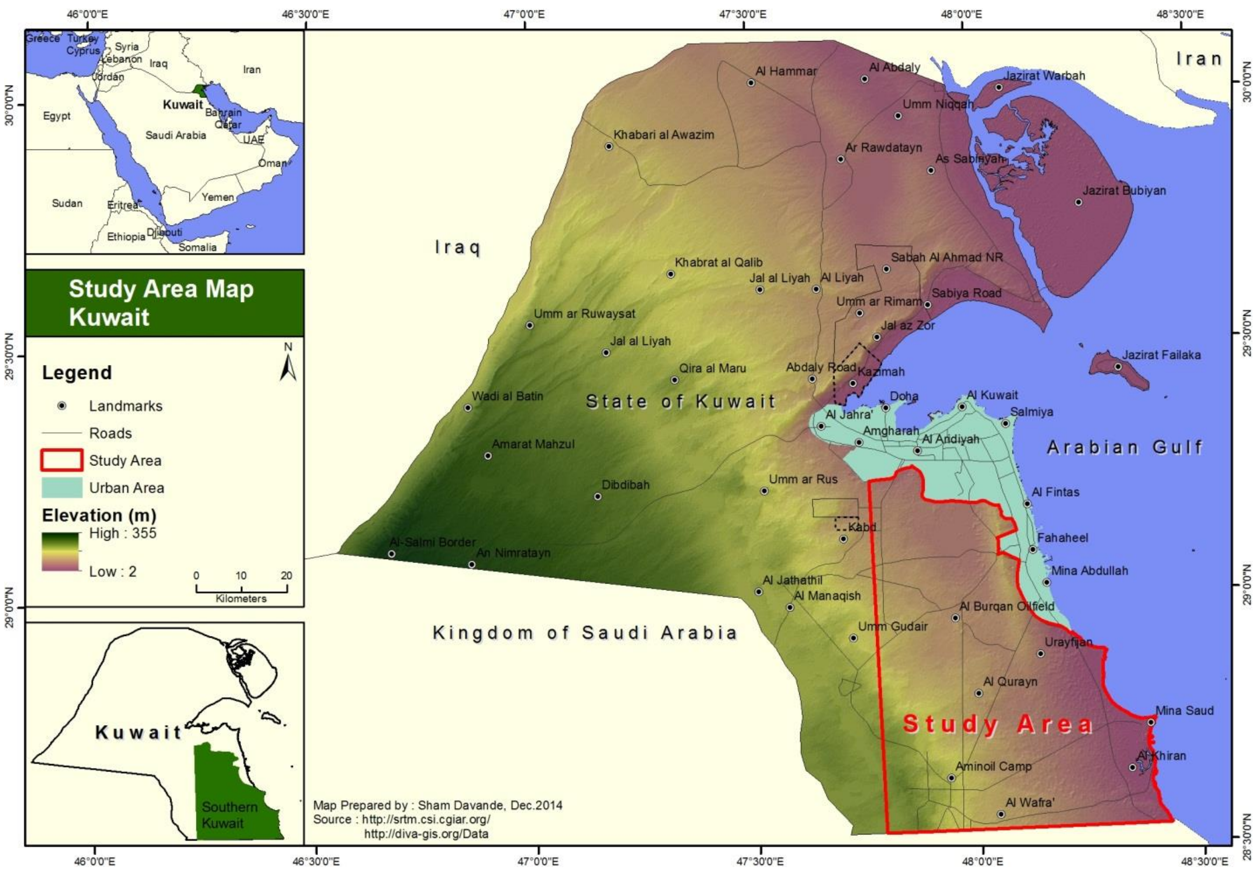

Figure 2: Location of Study Area in Kuwait.

Objectives

Although soil mapping is a long-standing science, broad scale mapping efforts often lack sufficient detail for understanding mechanisms regulating vegetation patterns and dynamics. This is particularly relevant for spatially extensive arid and semiarid regions. Digital, raster-based maps of soil properties are ideally suited for such analyses. Availability of enhanced satellite imagery with increasing spectral, spatial and temporal resolutions provide ample opportunities for predictive soil mapping at different levels of detail across a range of spatial extents. McBratney et al. proposed a framework for predictive digital soil mapping (DSM) that generalized soil forming factors (climate, organisms, relief, parent material, and time) to also consider spatial position and allow for interactions between soil forming factors to predict either spatially-explicit soil classes or discrete soil properties. McBratney et al approach capitalizes on the availability of computing power and the ever-increasing wealth of remotely sensed data sources that serve as environmental covariates. The choice of satellite imagery for soil mapping should be based on cost and logistical (e.g., storage/computing) constraints in conjunction with the requisite detail of mapped result. For the current study, following are the specific objectives considered for GIS Analysis:

- To digitally delineate soil classes using satellite data for Southern Kuwait.
- To compare with existing Soil maps prepared earlier for Southern Kuwait.

2. Material and Methods:

Input Data

Landsat 8 data products are consistent with the all standard Level-1 (ortho-rectified) data products created using Landsat 1 to Landsat 7 data to the following specifications:

Processing : Level 1 T- Terrain Corrected

Pixel Size : OLI multispectral bands 1-7,9: 30-meters

panchromatic band 8 :15-meters

TIRS bands 10-11 : collected at 100 meters but resampled to 30 meters to match

Operational Land Imager (OLI) multispectral bands

Data Characteristics : •GeoTIFF data format

: •Cubic Convolution (CC) resampling

: •Universal Transverse Mercator (UTM) map projection

: • World Geodetic System (WGS) 84 datum

: • 16-bit pixel values

Data Delivery : tar.gz compressed file via HTTP Download

File size : Approximately 1 GB (compressed), approximately 2 GB

Table 1: Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) Band details.

Band	Wavelength	Useful for mapping
Band 1 – coastal aerosol	0.43-0.45	coastal and aerosol studies
Band 2 – blue	0.45-0.51	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 3 – green	0.53-0.59	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 4 - red	0.64-0.67	Discriminates vegetation slopes
Band 5 - Near Infrared	085.-0.88	Emphasizes biomass content and shorelines
Band 6 - Short-wave Infrared (SWIR) 1	1.57-1.65	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.11-2.29	Improved moisture content of soil and vegetation and thin cloud penetration
Band 8 - Panchromatic	0.50-0.68	15 meter resolution, sharper image definition
Band 9 – Cirrus	1.36 -1.38	Improved detection of cirrus cloud contamination
Band 10 – TIRS 1	10.60 – 11.19	100m. res. Thermal mapping and estimated soil moisture
Band 11 – TIRS 2	11.5-12.51	100m.res.Improved thermal mapping and estimated soil moisture

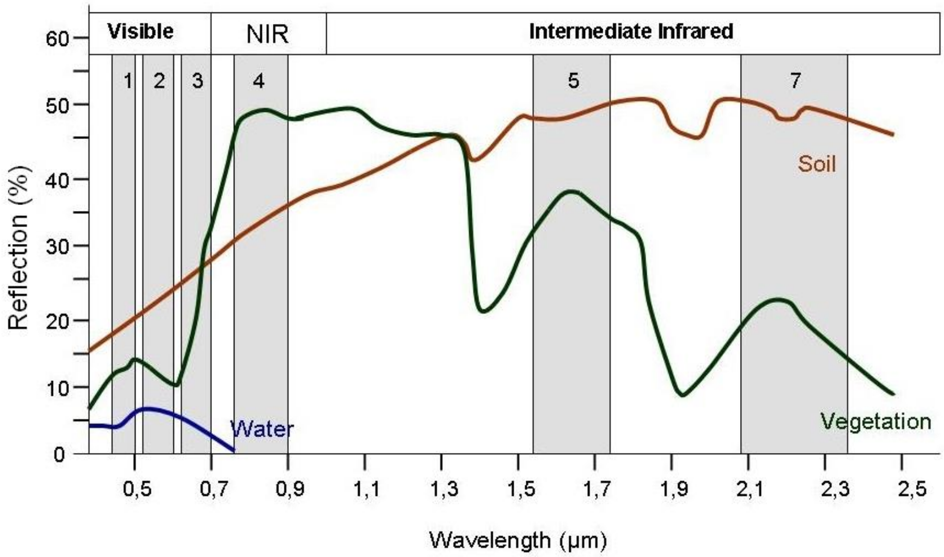

Figure 3: Spectral signatures of soil, vegetation and water, and spectral bands of LANDSAT 7 (Source: Siegmund, Menz 2005 with modifications).

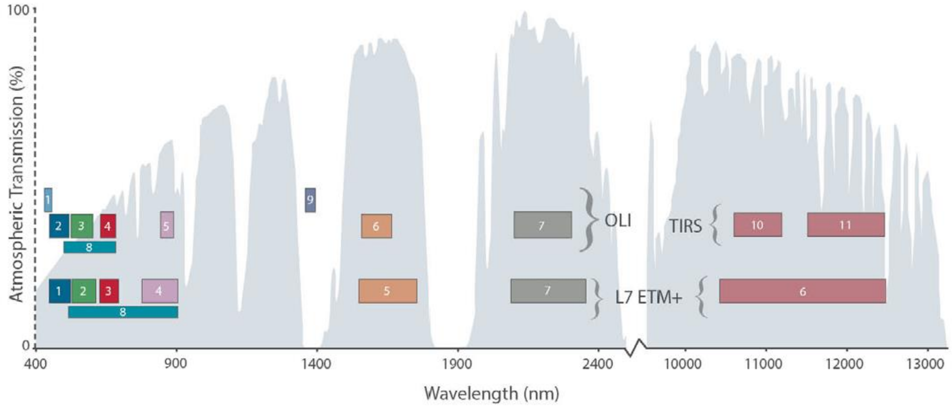

Figure 4: Comparison between LANDSAT7 ETM+ vs LANDSAT8 OLI Spectral signatures

Image Processing

Image processing techniques are applied to correct data errors and geometric distortions, to enhance and extract features related to thematic subjects being under investigation and to suppress redundant information. In this study, standard tools of image processing have been used for digital processing of the satellite data. Digital image processing was used to

- Enhance and to extract features that indicate targets of interest in the data.

In this study, the digital image processing processes were conducted in the following steps:

Image Enhancement

Image enhancement is the modification of an image in order to alter its impact on the viewer (Sabins, 1987). Generally, image enhancement changes the original digital value and it should be carried out after geo-referencing. The purpose of image enhancement is to make the images more interpretable for specific applications. The general aim of image enhancement is to highlight features of thematic interest (lineament, rock and soil properties, etc.) and to suppress redundant information. Major tools applied for the enhancement of the satellite data were histogram analysis and contrast stretching, edge enhancement, Band Ratioing, RGB-Coding such as false color composite. Data processing and image products, a number of processing techniques (Jensen, 1986; Mather, 1987), the contrast of 11 bands data of the Landsat ETM+ imagery was digitally enhanced. The images of all bands were compared in term of contrast and geomorphological appearance of different soil types. As a result of visual evaluation, Landsat 7 band 1 to band 7 data, which record the information at the wavelengths reflected by various types of soils were selected for this study, since it shows good contrast and displays geological lineaments compared to the other bands.

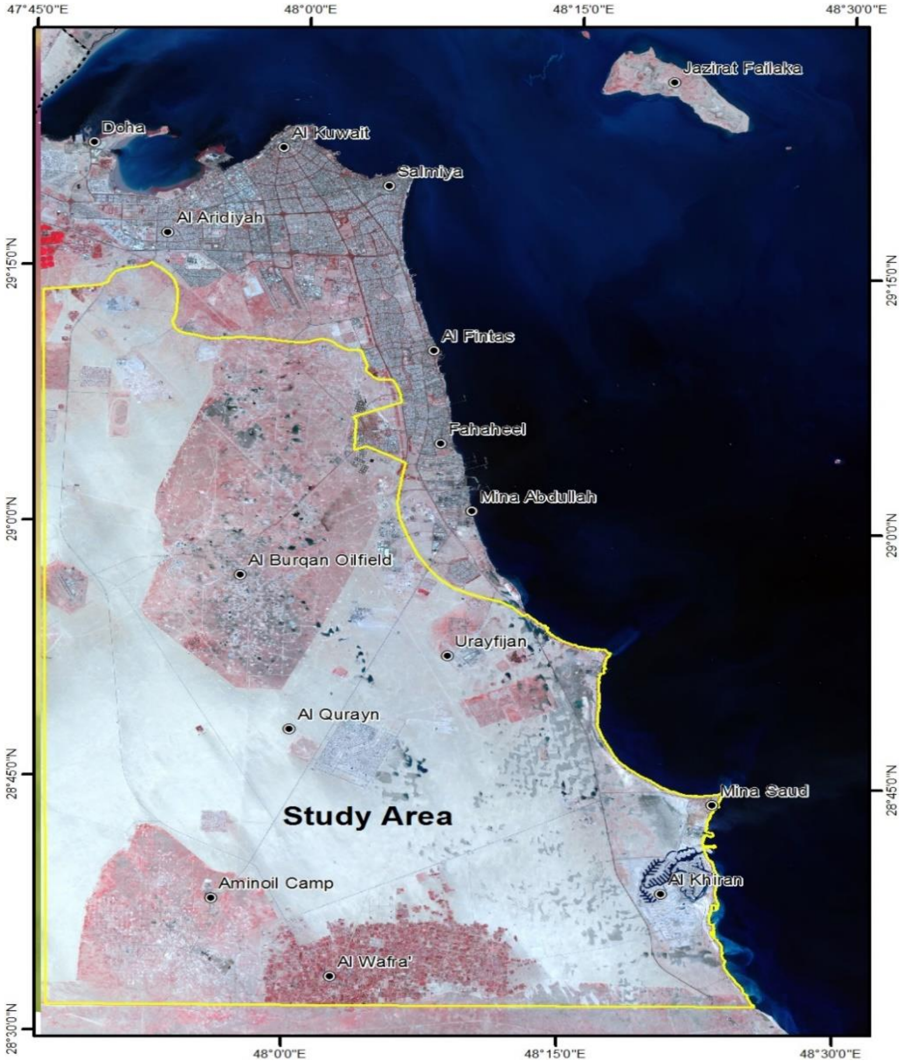

Figure 5: Landsat ETM satellite data bands 543 (14 Feb. 2014) winter season - Study Area.

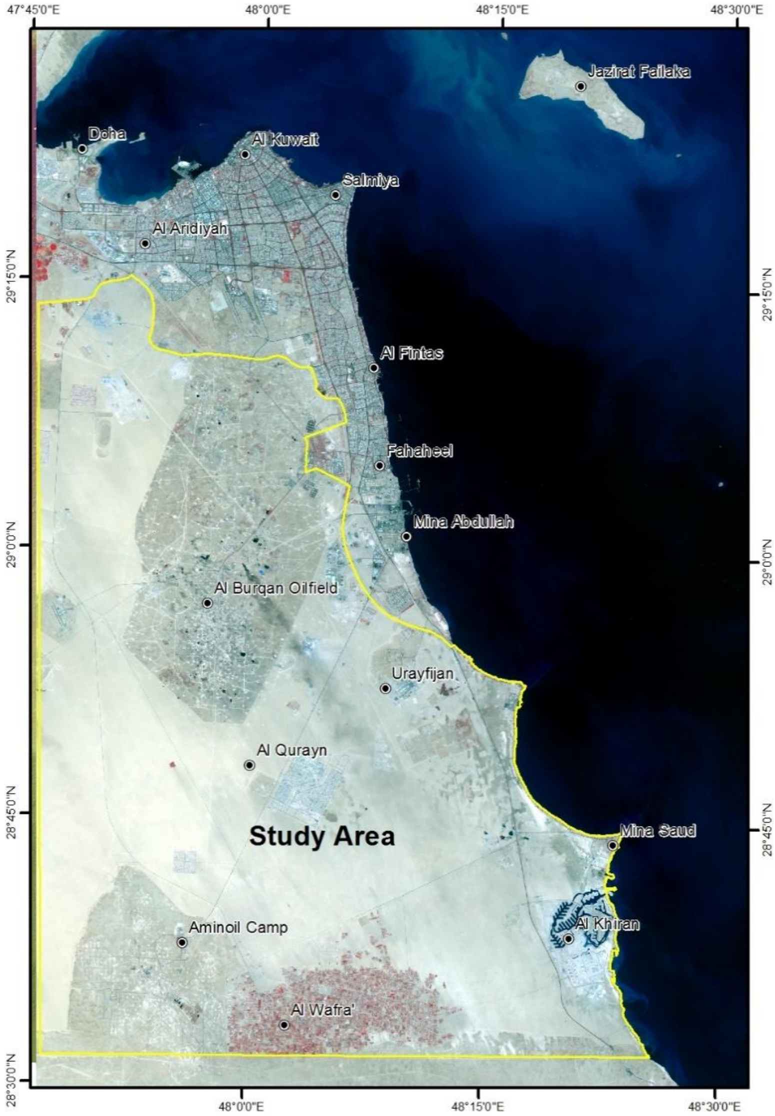

Figure 6: Landsat ETM satellite data bands 543 (24 July. 2014) summer season - Study Area.

Satellite Data Classification

A digital classification using LANDSAT ETM data covering the visible, infrared and microwave regions of the spectrum was carried out to detect the overall soil classes in the areas of Southern part of Kuwait. In this step of the study, the Iterative Self-Organizing Data Analysis (ISODATA) method of unsupervised classification was used. This technique uses a maximum likelihood decision rule to calculate class means that are evenly distributed in the data space and then iteratively clusters the remaining pixels, using minimum distance techniques (Jensen, 1996). The ISODATA algorithm was implemented with the following parameters.

Initially, 15 output thematic classes are selected, with a default convergence threshold of 0.950, initialized clusters using statistics encompassing 95% of the data along the principal axis, and allowed a maximum of 10 iterations. The ISODATA algorithm assigns pixels to clusters based on the minimum spectral distance from the cluster centroid. The centroid is recalculated after each class assignment with the convergence threshold serving as a measure of "classification completion." This threshold represents the proportion of pixels that do not change classes from iteration to iteration. The ISODATA algorithm runs iteratively until either 95% of the pixels do not change clusters or the maximum number of iterations is completed. This process continues until the number of pixels in each class changes by less than a selected pixel change threshold or until a specified maximum number of iteration is reached (Melesse and Jordan, 2002). The 15 spectral signatures representing distinct soil classes of spectrally similar data were output for subsequent analysis and evaluation.

Table 2: Un-supervised classification output classes for Study Area – Summer Season July 2014 Cluster Area and Area proportions.

	Kuwait_Summer_July2014_Class8.img			
Class ID	**Class Name**	**Area sqkm**	**Percent Area**	**No. of Pixels**
1	Urban Area	848	10.3	942573
2	Oil fields	832	10.1	924099
3	Wafra Farms	198	2.4	219627
4	Cluster 4	1167	14.1	1296681
5	Cluster 5	834	10.1	926983
6	Cluster 6	645	7.8	716377
7	Sea Water	2585	31.3	2872682
8	Sea Water Siltation 1	1145	13.9	1272745
	Total Area (sqkm)	8255	100	9171767

Table 3: Un-supervised classification output classes for Study Area – Winter Season Feb. 2014 Cluster Area and Area proportions

	Kuwait_Winter_Feb2014_Class8.img			
Class ID	**Class Name**	**Area sqkm**	**Percent Area**	**No. of Pixels**
1	Urban Area	848	10.3	942573
2	Oil Fields	832	10.1	924099
3	Wafra Farms	198	2.4	219627
4	Cluster 4	1349	16.3	1499218
5	Cluster 5	685	8.3	760655
6	Cluster 6	635	7.7	706064
7	Sea Water	3324	40.3	3693505
8	Sea Water Siltation 1	383	4.6	426026
	Total Area (sqkm)	8255	100	9171767

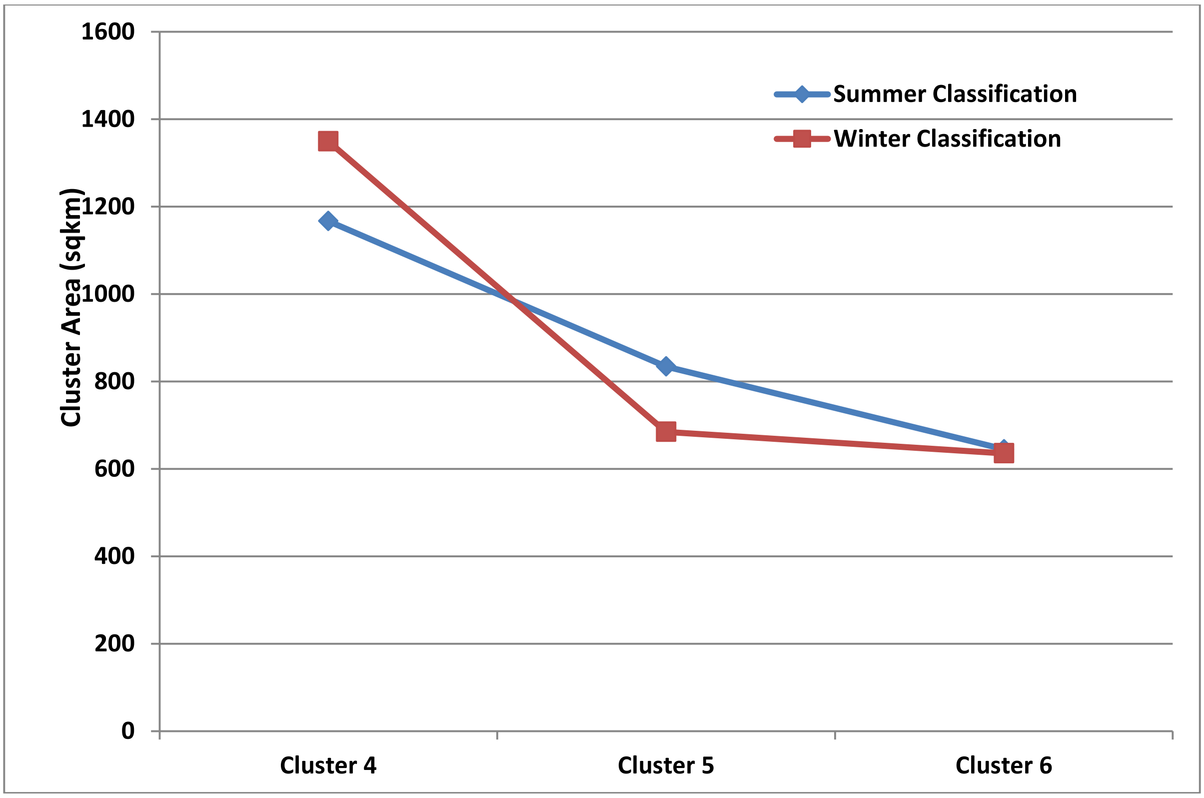

Figure 7: Comparison of Soil Clusters Classified from Satellite data of summer and winter season w.r.t surface areas

3. Results:

Digital Soil Mapping

The three-step process to assess input bands for the unsupervised classification led to the selection of spectral input bands. The first step was to calculate the optimal index factor (OIF) on the seven spectral bands to identify the three-band combination that maximized within-ETM+ scene variance with the least redundancy. The 2, 6, 7 band combination yielded an OIF value of 0.701. The second step was to evaluate the correlation between spectral data bands and indices; and topographic derivatives.

The correlation matrix for the spectral data revealed that the gypsic index exhibited the least correlation with other spectral bands when compared with the other two normalized indices and that band 1 was not strongly correlated with bands 6 and 7. The short-wave infrared bands (6 and 7) were highly correlated (r = 0.959); the TD metric was used to determine which of the two short-wave infrared bands were more informative to characterizing the spectral signatures (i.e., Band 7). In this case, visual inspection of candidate image bands was most effective for identifying topographic derivatives for classifying soils. Selecting candidate image bands for an array of options to drive the image classification, while subjective, is a common procedure best accomplished in conjunction with available ancillary data sources.

Raw unsupervised classification outputs of 15 numbers of classes each for summer and winter season were used as base for identifying the soil types. In the ERDAS imagine software, recode image processing module was used to merge similar classes which covers one kind of soil type areas. The surface soils in areas such as Oil fields, Agriculture Farms and some Industrial areas in southern Kuwait which were fenced and altered for the purpose of its landuse. It is decided not to use or classify the soil types inside such areas but masked as the name of its landuse such as Oil fields, Agriculture Farms.

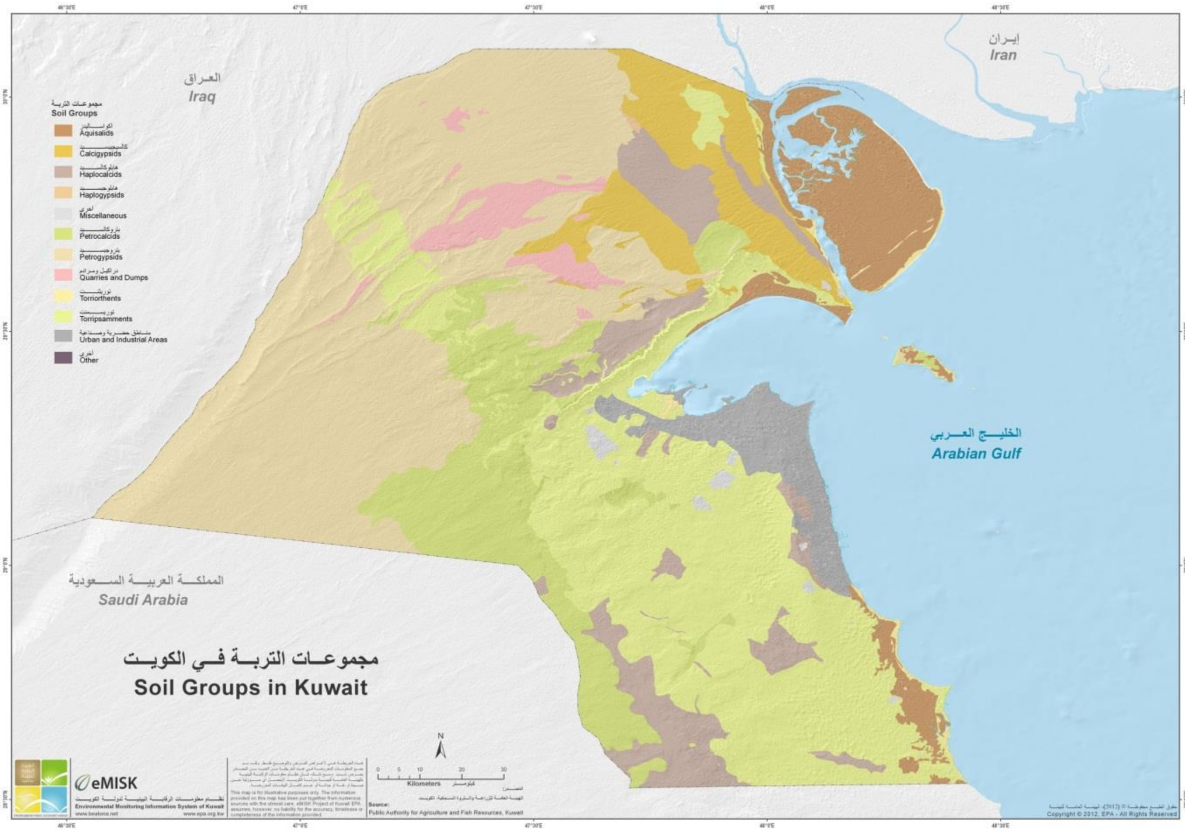

Figure 8: Soil Groups in Kuwait.

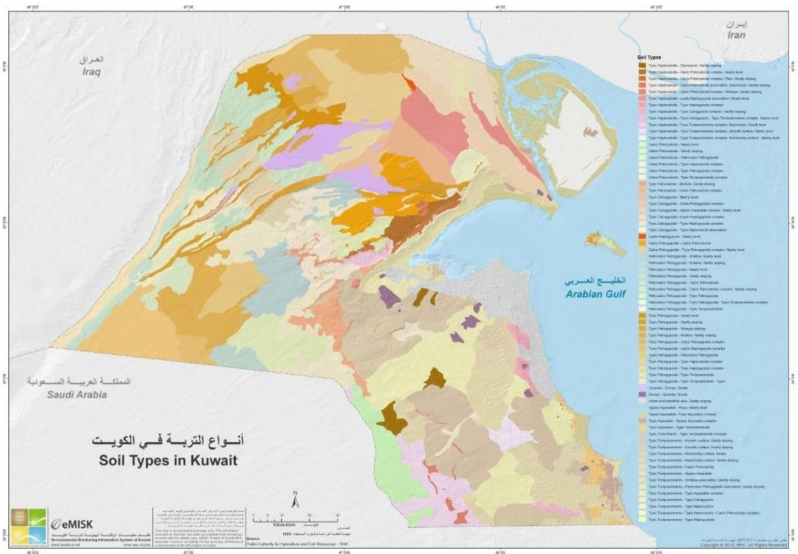

Figure 9: Soil Types in Kuwait.

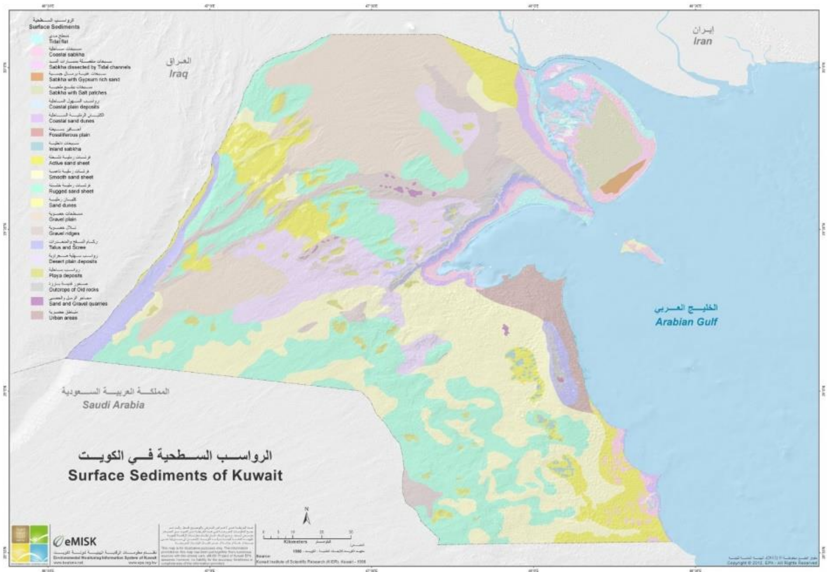

Figure 10: Surface Sediments in Kuwait.

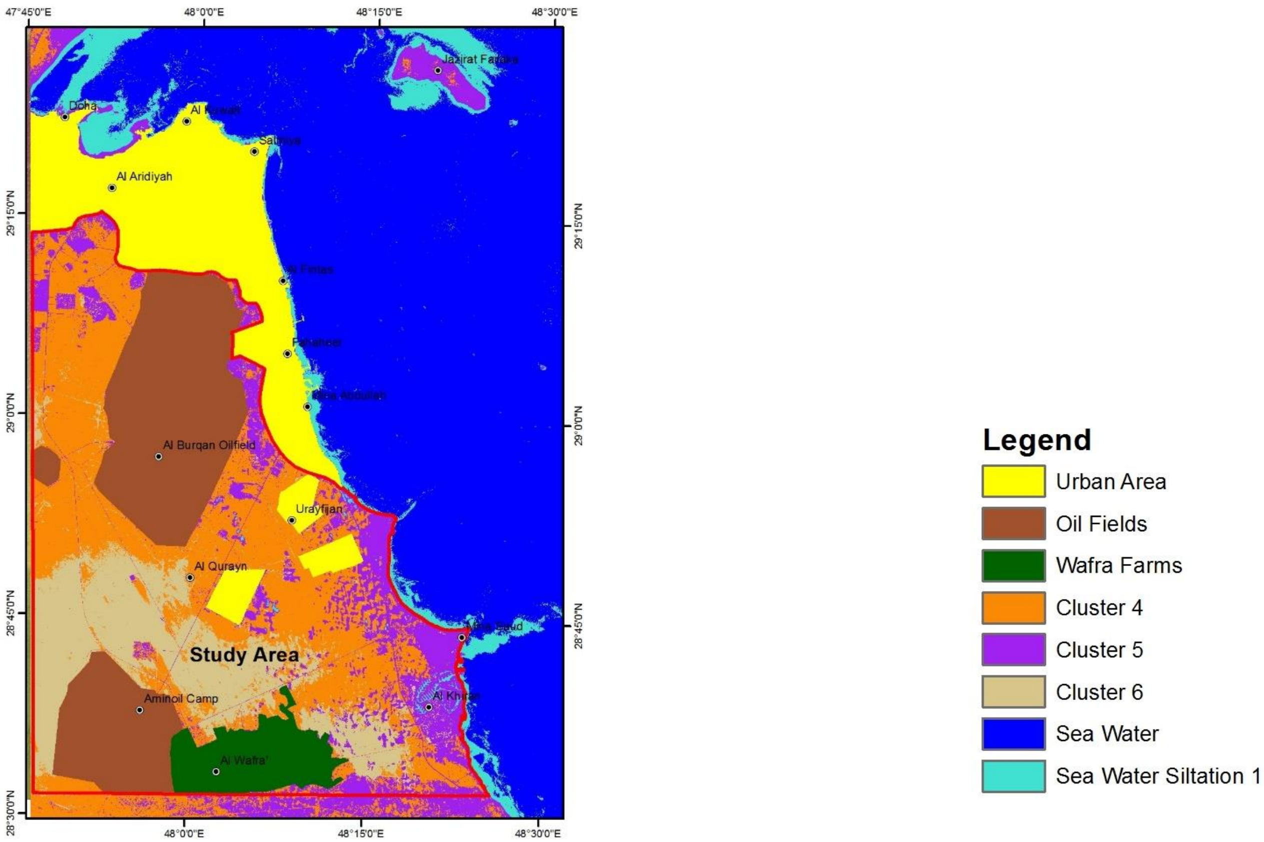

Figure 11: Un-supervised classification 14 Feb. 2014 winter season - Study Area.

4. Discussion:

This study has demonstrated that the use of unsupervised image classification method with an automated approach to derive signatures based on spectral features successfully delineated three soils classes with distinct surface soil properties (soil clusters 4, 5, 6).

Mapping of soil types in the absence of field data and derivation of spectrally distinct signatures during the process of performing unsupervised classification (ISODATA) which requires some guesswork in the soil mapping process. This approach not only yielded an interpretable map of soil classes, but the delineated unique classes that also provide an effective means to utilize for quick planning purpose. Such a classification approach has some advantages over other sampling approaches designed to mimic the natural distribution of soils in that it is effective in capturing soil units (e.g., soil class cluster 6), where a higher number of samples was needed for optimal characterization. The use of unsupervised classifications in digital soil mapping is not necessarily novel. Saunders and Boettinger (2007) combine unsupervised classification techniques with classification trees to compare a semi-automated image classification approach based on expert knowledge and field survey data.

The novelty of this approach was in using a statistical metric to delineate distinct soil classes in the absence of field data or expert knowledge to train the supervised classification and characterizing the mapped soil classes as a means to assess the performance of this approach.

5. Conclusions:

Based upon the results obtained through the approach utilized, the technical approach was selected as the best procedure to classify soils in arid lands. The selection of this procedure was based on the following considerations:

1. The resemblance between output classes and the soil types of existent soil maps were the closest and considerable match with its locations in that region of Southern Kuwait.
2. The technical approach based on the simple basic digital image processing of satellite data in components without losing any major information. In contrast, the simple approach suggests the use of only four bands (2, 3, 6, and 7) compromising therefore, in some degree, the final classification results.
3. The technical approach achieved the better accuracies in the study area. Therefore, to obtain better accuracies in arid regions, the technical approach is recommended.

In Kuwait, principally in the arid regions, soil classification by means of remotely sensing data, may be a good alternative to compliment the information already provided by various organizations. Furthermore, this technique can provide information to those sites where non-digital soils maps at large scale (1:50,000 and larger) have not been produced yet. Map generation by means of remotely sensed data may take advantage of the Soil Taxonomy system.

In general, the simple and the technical approaches showed as better accuracies, but the technical approach is recommended for classifying soils in arid lands because of its data reduction capability that facilitates its digital processing. Despite the fact that soil classification systems are based on subsurface horizons, Enhanced Thematic Mapper scenes can detect a high percentage (~70%) of mappable soil variability.

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