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Remote sensing application in evaluation of soil characteristics in desert areas

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Abstract

Soil is one of the most important natural resources covering a large area of the land surface. Soil plays a vital role in biosphere processes, such as energy balance, hydrology, biochemistry, and biological productivity. It supports plants that supply foods, fibers, drugs, and some other human needs. Conversely, desert regions include about one third of earth lands and these regions have increased caused by desertification, which is one of the main three world challenges in 21st century in global scale. Thus, it is important to monitor and map soils (especially in desert regions) and understand how these resources should be utilized, managed, and conserved properly to aim at implementing ecological role. Remote sensing has improved from traditional methods for assessing soils to informative and professional rapid assessment techniques to monitor and map soils. Previous studies have shown the utility of digital aircraft and satellite remote sensor data in the pedologic and geologic mapping process. Remote sensing offers a potential to provide information about soil characteristics over large regions. However, the intent of this paper is to focus on discussion about remote sensing applications to study desert regions. In this review, at first, we would discuss about the remote sensing applications to research on soil properties including soil salinization, crusting, moisture, texture, mineralogy, approaches, and techniques used to classify soils. In second section, we would argue about constraints tied on remote sensing applications data gathering usually conducted about investigation on soil characteristics in arid and semi-arid regions.

Keywords

desert areas, remote sensing, soil evaluation.

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1. Introduction

Information about soils is needed for politicians to make decisions about land resources management, and monitoring the environmental impacts of development. Soil is a natural body consisting of layers (soil horizons) that are primarily composed of minerals, mixed with at least some organic matter, which differ from their parent materials in their texture, structure, consistency, color, chemistry, biology, and other characteristics. It is unconsolidated or loose covering of fine rock particles that covers surface of the earth (Birkeland, 1999).

Soil formation or genesis is strongly dependent on the environmental conditions of both atmosphere and lithosphere components. Soil mass is a product of wide, various factors first observed by Dokuchaev (1883) and afterwards presented by Jenny (1941) in format of Jenny's equation. These factors can be described by soil-forming factors equation that considers climate, time, organisms, topography, and parent materials factors (Ben-Dor et al., 2009). Many soil constituents, including mineral composition, soil moisture, soil texture, surface roughness, organic matter content and many other properties affect soil reflectance in a complex way (Goetz, 1992; Lillesand et al., 2004). In the case of saline soils, the presence of evaporates affects the overall soil spectral reflectance (Melendez-Pastor et al., 2010). Therefore, surface and subsurface characteristics complicate soil spectral measurements and make some constraints to study about soil by remote sensing technique. Global, regional, and local models that address climate change, land degradation, and hydrological processes need soil input parameters with complete area coverage, but currently there are only few spatially exhaustive datasets available about soil properties in a lot of studied regions (Bastiaanssen et al., 2005; Anderson, 2008; Mulder et al., 2011).

In arid and semi-arid environments that include more than 40% area of land surface in global scale (Deichmann and Eklundh, 1991), low vegetation cover, special soil features, and scant water resources are major characteristics. Because of special ecological conditions, arid and semi-arid soils have unique attributes that exclude them from other ecosystems. Soils in arid regions are much more closely implicated in geomorphic factor than they are in humid climates. This is partly a consequence of greater exposure of soils in humid climates, but it is also a result of subsurface soil horizons toughness (Cooke et a1., 1993). Based on these conditions, research about arid and semi-arid soils is different from other regions.

Remote sensing techniques and technologies, known as time and cost-efficient methods, are likely to propose best opportunity for researchers to study changes detection and monitoring in these regions (Okin et al., 2001; Lam et al., 2011). It can be used to collect data to many different parameters that have multi-disciplinary use at various spatial and temporal scales that can be combined with digitized paper maps in geographic information systems (GIS) to allow efficient characterization and analysis of a wide amount of data (Scull et al., 2003). Imaging spectrometry provides large amounts of high spectral resolution data, which can be useful to detect soil properties (Farifteh and Farshad, 2003). In desert regions, remotely-sensed images are utilized to collect data covering both the natural and artificial characteristics of different desert surfaces (Tansey et al., 1998). Remote sensing of the earth is known as a discipline tool to explore large regions in a short time using either solar or artificial radiation. However, there are many challenges involved in terrestrial remote sensing.

This paper aims to review some of the key issues related to applications of remote sensing data to mapping and monitoring of important properties of soil in arid and semi-arid regions by a set of recent papers selected. In other words, the motivation for this review is increasing demand for desert-related information to address a wide range of societal issues (for example water scarcity, food security, dust storm, soil degradation, and economic sustainability), the availability of unique earth observations from many new satellite-based remote sensing instruments, and the advancement of analysis and modeling techniques.

Collectively, the convergence of these factors has resulted in unprecedented new satellite-based estimates of evapotranspiration, subsurface moisture, and vegetation condition over large geographic regions that can support research on arid and semi-arid regions. The first part of this paper discusses the implementation of remote sensing to research the most important properties of arid regions soils. These properties obviously discriminate the differences between soil of arid and semi-arid ecosystem and other ecosystems. The second part highlights constraints of remote sensing applications to investigate soil properties in arid and semi-arid regions. Because of unique ecosystem of arid and semi-arid regions, there are a lot of constraints that each of them is an important issue when we are going to use remote sensing data to study them.

2. Application of Remote Sensing to Study Arid and Semi-Arid Soils

Using remote sensing technology in arid and semi-arid regions, particularly when researcher aims to study soils, is very common and has been started since the beginning of remote sensing technology (Tansey et al., 1998). However, it is in early stages and it might be hoped that, with technological advancements, this technology plays a more important role. Therefore, to study soil properties in these regions, we should pay attention to findings of previous studies. With regard to studies accomplished until now, it can be concluded that many properties of arid and semi-arid regions soil such as coarse texture, shallow soils, and soluble substances can be studied and determined using remote sensing. We divided these properties in two groups including surface and sub-surface properties that will be discussed in the following.

2.1. Surface properties

2.1.1. Soil salinity

Soil salinization is a world-wide land degradation process that occurs in arid and semi-arid regions (Mashimbye et al., 2012; Weng et al., 2010). Salt-affected soils cover about 6% of earth's land surface (Zorrig et al., 2012) and are located mostly in arid and semiarid regions (Munns and Tester, 2008). Soil salinity can be detected by remotely sensed data either directly on bare soils, with salt efflorescence and crust, or indirectly via vegetation type and growth that are controlled by salinity (Mougenot et al., 1993; Metternicht and Zink, 2003). A major constraint to using proximal and remote sensing data to mapping salinity is related to the fact that there is a strong vertical, spatial, and temporal variability of salinity in soil profile (Mulder et al., 2011). A variety of remote sensing algorithms and techniques have been applied successfully to determine and monitor soil salinization (Farifteh et al., 2006; Metternicht and Zinck, 2003). Both radar and optical remote sensing data have been used to map soil salinity (Mulder et al., 2011).

Despite soil reflectance complexity, several spectral ranges can be used to detect soil salinity. Visible (550–770 nm), near-infrared (NIR) (900–1030 nm, 1270–1520 nm), and middle infrared (1940–2150 nm, 2150–2310 nm, 2330–2400 nm) portions of the electromagnetic ranges are very important to soil salinity assessment (Csillag et al., 1993). Farifteh et al. (2008) suggested that study of salt-affected soils in the spectral reflectance regions of NIR and shortwave infrared should be focused on spectral variations rather than diagnostic absorption features. Furthermore, use of derivative approaches to identify spectral diagnostic bands has achieved acceptable results in quantifying soil salinity (Melendez-Pastor et al., 2010), For example, effects of salts on air-dried soil reflectance spectra has been shown in Figure 1.

Most of the studies have only focused on mapping severely saline regions or distinction between saline and non-saline soils using multispectral images (Weng et al., 2010). Using thermal and optical bands of Thematic Mapper (TM) as complementary information can be useful in salinity studies and also detecting gypsiferous soils in desert regions (Alavipanah et al., 2001). Soil characteristic features, specially salinity, mostly occurs in narrow wavelength regions. But multispectral satellite imagery has limitations including low spectral and spatial resolution, which can lead to false classification, obscuring of salt-affected surfaces with salt tolerant vegetation, and misclassification of bare, bright, sandy soils as salt affected (Metternicht and Zinck, 2003; Farifteh et al., 2008). Also, spectral signatures are masked out when bandwidths are wide and/or the spectral bands are limited (Wang et al., 2012) that make it difficult to diagnose between the low and the non-saline soils.

Quantification of salt abundances and salts identification in soils with remote sensing is still not sufficiently researched (Farifteh et al., 2008). Multispectral images have been used to classify soil salinity; however, there are some weaknesses tied with them. In order to overcome these weaknesses, we need extensive field work, and hyper-spectral remotely sensed data as complementary tools (Matinfar et al., 2013). Hyperspectral data make it possible to establish models to quantitative estimation of soil salinity (Ben-Dor et al., 2002; Farifteha et al., 2006; Wang et al., 2012; Weng et al., 2010).

Physical characteristics of different features in desert regions have been affected by severe thermal and climatic conditions. Diurnal surface temperature changes patterns of important surface features in Lut desert were studied and relationship among different surfaces analyzed (Alavipanah et al., 2007a). Diurnal trend in surface temperature of surface types, marl, dark sand, light sand, salt-affected soil, soil at 10 cm depth, as well as dry and wet air temperature within 15 days were recorded in 2 hour intervals in the margin of Lut yardangs while correlations among these surface features and its significance level were investigated (Alavipanah et al., 2007b). The knowledge of diurnal temperature pattern among features can conduct us to have better understanding about behavioral patterns and the trend of surfaces temperature (Fig. 2).

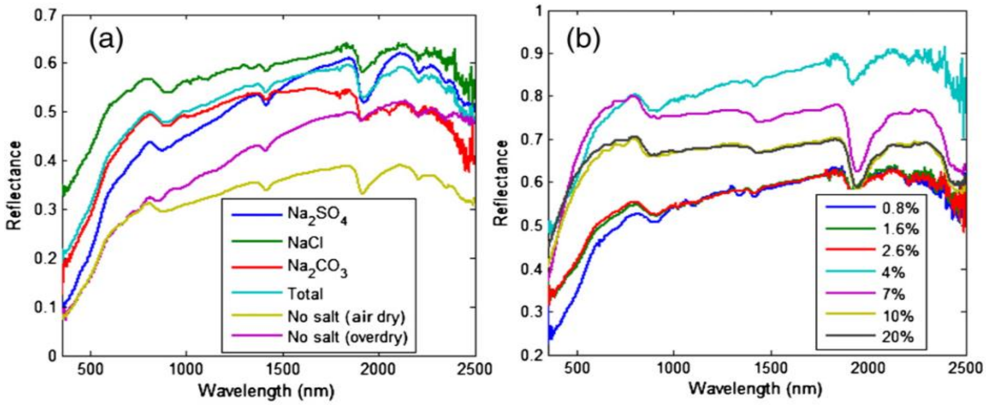

Fig. 1. Effects of salts on air-dried soil reflectance spectra: (a) different salt types (averaged spectra from all seven levels of salt contents); (b) change of reflectance spectra with different levels of Na2SO4 content (Farifteh et al., 2008).

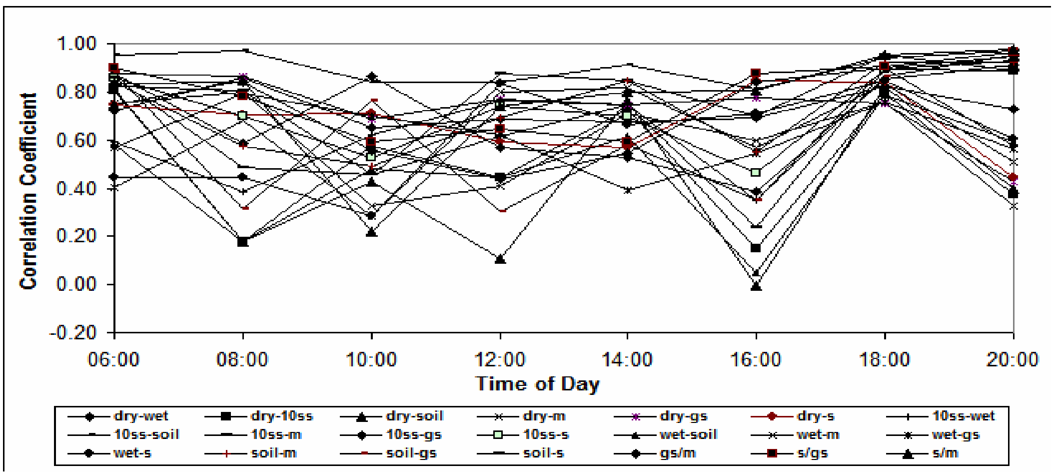

Fig. 2. Daily trend pattern of correlation coefficient of temperature between all under-study surfaces (Alavipanah et al., 2007b).

Microwave C-, P-, and especially L-bands are considered adequate to detect salinity in different levels (Mulder et al., 2011). Because of various behaviors of the real and imaginary parts of the dielectric constant, microwaves are efficient in detecting soil salinity. While the real part is independent of soil salinity and alkalinity, the imaginary part is highly sensitive to variations in soil electrical conductivity, but with no bearing on variations in alkalinity (Metternicht and Zinck, 2003).

Several techniques like unsupervised and supervised classification, fuzzy clustering, expert systems (Metternicht, 2001; Kirkby, 1996), and layer classification have been used to delineate salt-affected soils at regional level (Metternicht and Zinck, 1997; Abbas et al., 2013). In addition, various approaches such as visual interpretation of false-color composites (Rao et al., 1991; Joshi and Sahai, 1993), principal component analysis (Dwivedi, 1996), matched filtering (MF), mixture tuned matched filtering (MTMF), and decision tree analysis (Elnaggar and Noller, 2010) have been used to map soil salinity (Setia et al., 2011). Multivariate statistical techniques such as multiple linear regression (MLR), polynomial regression (PR), principle component regression (PCR), partial least square regression (PLSR), artificial neural networks (ANN), multiple adaptive regression splines (MARS) (Chang et al., 2001), and other data mining techniques (Brown et al., 2006) have been applied to interpret the relationships between soil reflectance spectra and various soil properties including salinity (Wang et al., 2012).

2.1.2. Soil texture

Texture of soil surface controls many important ecological soil and geomorphological processes in arid and semi-arid regions, including infiltration physical crusting, pavement formation, and erosion by wind and water. The effect of soil texture in desert regions can be described following as the water maintains capacity of soil (Cooke et al., 1993). Detailed knowledge of soil surface texture would dramatically improve our ability to model wind erosion and dust emission in desert soil where wind erosion is strongly controlled by surface grain size (Okin et al., 2001; Mahowald et al., 2003).

Remote sensing tools that can produce quantitative information on soil surface texture would be useful supplements to traditional soil maps for planning purposes. Such tools would also prove their valuable effects in the emerging field of predictive soil mapping (Scull et al., 2003). As an example, images gathered over bare soil by airborne MIVIS and space-borne CHRIS-PROBA were used to explore methods for the quantitative estimation of soil texture. For calibrating prediction models for estimation of clay, silt and sand through PLSR Laboratory spectra were used. Tests with remote sensing data show a suitable accuracy of prediction to clay and sand content using both MIVIS and CHRIS-PROBA data, but results vary in response to modality of setting up calibration and validation sets (Casa et al., 2013).

Apan et al. (2002) used bands 2 (visible red), 8 (SWIR) of ASTER image, and first PC1 selected to determine discriminating soil texture. They concluded that VNIR bands have high potential for mapping within field soil variability at relatively broad attribute classes. AVHRR data has been used for mapping the spatial extent of clay content by means of multivariate prediction models (Odeh and McBratney, 2000). Liu et al. (2012) present an approach to mapping soil texture using environmental covariates derived from temporal responses of the land surface to single rainfall event collected through remote sensing techniques. The approach was applied to produce soil texture maps in a low relief region. Differences between the results of multiple linear regression analysis without and with the MODIS derived variables further demonstrated effectiveness of the variables at separation patterns of soil texture. Chang (2003) studied application of ANN models and brightness temperature to classify soil into different textures.

Hyper spectral data can be useful in mapping texture property. For example, a HYMAP image and field spectral measurement was used in a semi-arid region to identify surface features like soil texture. Spectral angle mapper was used to compare field data with remote sensing data and to classify soil properties (Margate and Shrestha, 2001; Shrestha et al., 2005). Furthermore, there are some studies that show the use of passive remote sensing to retrieve soil texture in arid regions. Zribi et al. (2012) used TERRASAR-X data to analyze and estimate soil surface texture over a semi-arid region. A strong correlation is observed between soil texture and a processed signal from two radar images, the first acquired just after single rain event and the second, corresponding to dry soil conditions, acquired three weeks later. Baghdadi et al. (2008) and Anguela et al. (2010) observed TerraSAR-X SAR data variations due to soil texture within agricultural plots.

2.1.3. Surface moisture

Surface soil moisture is a critical factor that interacts with the atmosphere. Surface soil moisture is defined as content of water that is stored in the upper 10 cm of soil (Wang and QU, 2009). Having some difficulties with large-scaled measurements of soil moisture using ground-based networks prompted researchers to look for new and easier methods, like remote sensing. Studies about soil moisture by remote sensing began in mid-1970s. Passive microwave (Bindlish et al., 2006; Jackson, 1993), active microwave (Wagner et al., 1999), thermal (Anderson et al., 2007a; Anderson et al., 2007b; Jackson et al., 1981; Jackson, 1982) or optical (Wang and QU, 2009: 43) remote sensing retrieval techniques (Li et al., 2010) have been used in surface moisture studies. The primary difference among these techniques is the wavelength region of the electromagnetic spectrum used, source of the electromagnetic energy, response measured by the sensor, and physical relation between response and soil moisture content (Wang and QU, 2009).

Microwave data is the most important technique used to study surface soil moisture. Accuracy of active microwave surface soil moisture estimation depends on bare soil types, its vegetation type, fractional vegetation cover, and land surface roughness which also negatively impact the accuracy of soil moisture estimation (Cashion et al., 2005). Coarse scale soil moisture dynamics are often observed using passive microwave systems. Soil moisture estimation at a finer spatial resolution can be obtained through downscaling time series of coarse resolution observations (Wagner et al., 2008). Alternatively, Synthetic Aperture Radar (SAR) systems are renowned based on their abilities to estimate soil moisture content at scales less than 1 km. Major problem tied with SAR is the large sensitivity of backscattered signal to soil surface roughness (Lievens and Verhoest, 2012).

A surface energy balance model is an approach that is used to estimate soil moisture. Most widely used models are the soil energy balance (SEBAL) (Bastiaanssen et al., 2005), the two-source energy balance (TSEB) modelling approach (Aly et al., 2007), and the surface energy balance system (SEBS) (Su, 2005; Van der Kwast, 2009). The main difficulties using surface energy balance models are obtaining all necessary data in a suitable spatial resolution and then calibration of the model. Currently, most advanced index about soil moisture is the soil water index (SWI) (Wagner et al., 2007; Mulder et al., 2011). ASTER and MODIS images have been used to retrieve the surface variables required as inputs for energy balance modelling (French et al., 2005; Su, 2005).

2.1.4. Surface crust

Presence of surface crust is an obvious phenomenon in many deserts all around the world. In a study in West Africa, Stoops (1984) notes crust formation on loamy sand and sandy loam topsoil. Effect of soil on the soil water household is described as reducing infiltration, increasing run off, and increasing water erosion. Desert crusts in Ardakaan region (Iran) have mainly a bright surface that is usually up to 3 to 5 mm thickness. The Desert crusts have a very smooth surface which underly a darker soil (Fig. 3).

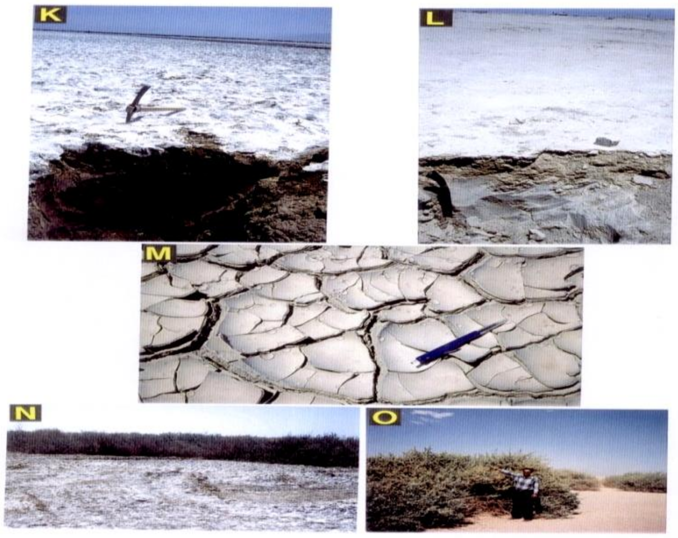

Fig. 3. Some land cover/land use types in Ardakan region: K) Salt crust in the east of the Chah Afzal region, L) Desert crust with a bright surface underlying a gray to brown color soil, M) Sealing and cracks, N) Tamarix plantation project in the Chah Afzal region, O) Atriplex plantation in the very severe saline soil conditions.

Due to global extend of deserts and their effects on increasing surface reflection, further research can be useful to identify various types of crusts. Gossens and Van Ranst (1996) reported that places with intact desert crust are characterized by a very high reflection and these correspond with a lower reflection.

Jong et al. (2009) tried to determine spectral and physical properties of surface crusts in field and investigated potentials of hyperspectral airborne imagery in mapping soil crusts and identifying various crusts types. They showed that differences in some physical properties between crusted and non-crusted surfaces are significant while others showed only marginal variation. Infiltration capacity is largely reduced by crusting. No consistent changes are found in absorption features in the spectra of crusts and non-crusted surfaces. Some of the crusts show stronger absorption features in clay mineral absorption bands at 2200 nm. Spectral feature fitting and linear spectral unmixing algorithms were applied to HyMap images to evaluate mapping of surface crusts.

One of the important soil surface characteristics of severe saline soil in arid lands is coverage of salts due to high evaporation demand and capillary movement. Salts accumulate on the soil surface. Characteristics of salt crust layer and sub-surface soil have a significant impact on the amount of energy absorbed, scattered, and reflected from this surficial portion of the soil. It is likely that the main reflected energy from the soil will be representative of the salt crust. As the salt crust is leached and inorganic salt with the related whitish color is diminished, the surface reflectance will be more representative of the horizon characteristics.

Mougenot et al. (1993) mentioned reflectance variations according to variable terrain surface conditions including crusts with or without low salt evidence, salt crust less than 1mm to 1m thick, puffy structures containing soil aggregates and salt crystals (0.5-5mm) derived from salty clays and sometimes from salt crusts, and wind erosion of puffy structure layers. Karnieli et al. (1999) analyzed (systematically throughout the VIS, NIR, and the SWIR regions of the spectrum) the unique spectral features of cyanobacteria crust relative to bare sands and under different moisture conditions. Based on their findings, using remote sensing data along with laboratory data can be very useful in studying soil crust.

Biological Soil Crusts (BSC) are very common phenomenon in arid and semiarid regions. The BSC covers have a tightly structured surface with a 2 mm variant thickness, relatively homogeneous cyanobacterial crusts, to complicate crusts with different composition of mosses, lichens, algae, fungi, and cyanobacteria of about 15 mm thickness that have different spectral characteristics. Therefore, remote sensing of biological crusts may be useful in digital soil mapping as environmental covariates and in soil and environmental assessments.

In the past two decades, as a result of increasing recognition related to ecological importance of biological soil crusts in desert regions, some studies have been conducted to investigate spectral characteristics of biological soil crusts or its species components and use of remotely-sensed data to classify or map biological soil crusts (Ager & Milton, 1987; Graetz & Gentle, 1982; Jacobberger, 1989; Karnieli & Sarafis, 1996; Karnieli & Tsoar, 1995; Karnieli et al., 1999; Karnieli et al., 1997; Karnieli et al., 1996; O'Neill, 1994; Pinker & Karnieli, 1995; Rollin et al., 1994; Karnieli et al., 1996; Green, 1986; Karnieli, 1997; Lewis et al., 2001; Wessels & Van Vuuren, 1986; Chena et al., 2005).

Yamano et al. (2006) measured the reflectance spectra and photosynthesis of the crusts that have been conducted separately and estimated primary productivity of the crusts in large-scale using remotely sensed data. Moreover, spectrally detected differences in water content between BSC and bare soil can be used to determine extension of BSC cover (Whiting and Ustin, 2004). They used AVIRIS images and K-means classification method to classify BSC cover in an ecological research site called Mojave Global Change Facility. Karnieli et al. (1999) analyzed (systematically throughout the VIS, NIR, and the SWIR regions of the spectrum) the unique spectral features of cyanobacteria crust relative to bare sands and under different moisture conditions.

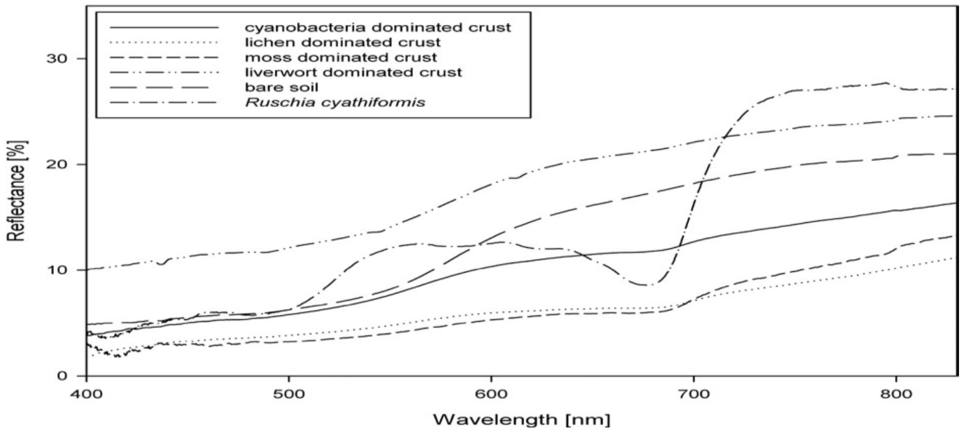

Fig. 4. Spectral characteristics of the different crust types as compared to bare soil and flowering plants (Ruschia cyathiformis). Curves represent mean values of 5 replicates each (Weber et al., 2008).

Karnieli et al. (1999) calculated Normalized Difference Vegetation Index (NDVI) based on BSC's spectra under various wetting conditions and found that when crusts were dried, the NDVI values were low (0.08– 0.13), a level also typical to dry soil/sand and rock. However, under wetting conditions, crusts showed relatively high NDVI values (0.18–0.3). Biggest changes in the NDVI values occurred a few minutes after the crusts were wetted, while, as the crust dried out, NDVI values decreased. Karnieli et al. (1999) found that chlorophyll content of crusts was much higher during 7 days of growth after wetting. Moreover, a correlation was found between NDVI values and chlorophyll content. Furthermore, direct relationships were also found between NDVI values and organic matter content, polysaccharides content, protein content, and crust thickness. Hence, NDVI can serve as an indicator to evaluate many physiological and ecological parameters of the BSC and can help draw conclusions on crust photosynthesis activity (Karnieli et al., 1999).

Karnieli et al. (1996) and Karnieli and Tsoar (1995) point out that high NDVI values in arid regions can lead to false interpretation of higher vegetation biomass or productivity. Previous studies have shown that when vegetation cover is less than 30%, the soil background contributes significantly to spectral signal (Huete et al., 1985; Huete and Tucker, 1991). Hence, satellite images that are taken from regions that are dominated by a wet and active BSC will exhibit high NDVI values with dominant contributions by crusts and not by higher plants.

Other works in this field mainly focus on application of remotely sensed data to classify or map biological soil crusts (Green, 1986; Karnieli, 1997; Lewis et al., 2001; Wessels and Van Vuuren, 1986). Although these studies revealed unique spectral features of biological soil crusts, few studies have made use of their spectral features to develop a robust method to map biological soil crusts based on remotely sensed data. One exception is crust index proposed by Karnieli (1997), who employed remotely sensed data in mapping cyanobacteria, dominated biological soil crusts. However, the index is not suitable about lichen-dominated biological soil crusts, which cover large regions in cool and cold deserts (Belnap, 2003) since cyanobacteria are not dominant species in such crusts (Jin et al., 2005).

2.1.5. Mineralogy

The analysis of mineralogy with spectral remote sensing has made great progress over the past years. In recent years, several institutes have provided spectral libraries with comprehensive collections of a wide variety of materials. For example, the ASTER spectral library version 2.0, which is a collection of contributions from the Jet Propulsion Laboratory, Johns Hopkins University, and the United States Geological Survey, is a widely used spectral library which contains over 2400 spectra of a wide variety of minerals, rocks, vegetation, and manmade materials covering the wavelength range 0.4–15.4 μm (Baldridge et al., 2008). Methods such as partial least square regression (PLSR) can be used to match collected spectral samples with those in the spectral libraries (Viscarra Rossel, 2008; Viscarra Rossel et al., 2009). With remote sensing, mineralogy can be determined from the spectral signature of rock outcrops or from the mineral composition of bare in-situ soils. In order to discriminate between different minerals, subtle differences in the spectral signature throughout the VNIR (Visible and Near Infra-Red)–TIR (Thermal Infrared) are used.

Therefore, satellite data with a fine spectral resolution are needed, as only with a fine spectral resolution can subtle spectral differences be detected in the signal. Additionally, fine spatial resolution is beneficial, as it reduces the number of elements represented within a pixel, which enhances the unmixing results and thereby the detection of minerals. The spatial and spectral resolutions of Landsat TM and MODIS have been found to be too coarse for determining mineral composition (Dobos et al., 2000; Kettles et al., 2000; Teruiya et al., 2008). However, the combination of Landsat TM data and ASTER data has been useful because the general lithological variability is mapped with Landsat TM whereas ASTER maps the different mineral groups. Several methods relying on remotely sensed spectral data have been developed for geological mapping. For example, the Tetracorder tool is consisted of a set of algorithms within an expert system decision-making framework for soil and terrain mapping. The expert system rules are implemented in a decision tree in which multiple algorithms are applied to the spectral data. The system contains a large spectral library with soil mineral properties and land cover types from all over the world. The results obtained with the Tetracorder show that many different minerals can be identified as has been shown in Figure 5 (Clark et al., 2003).

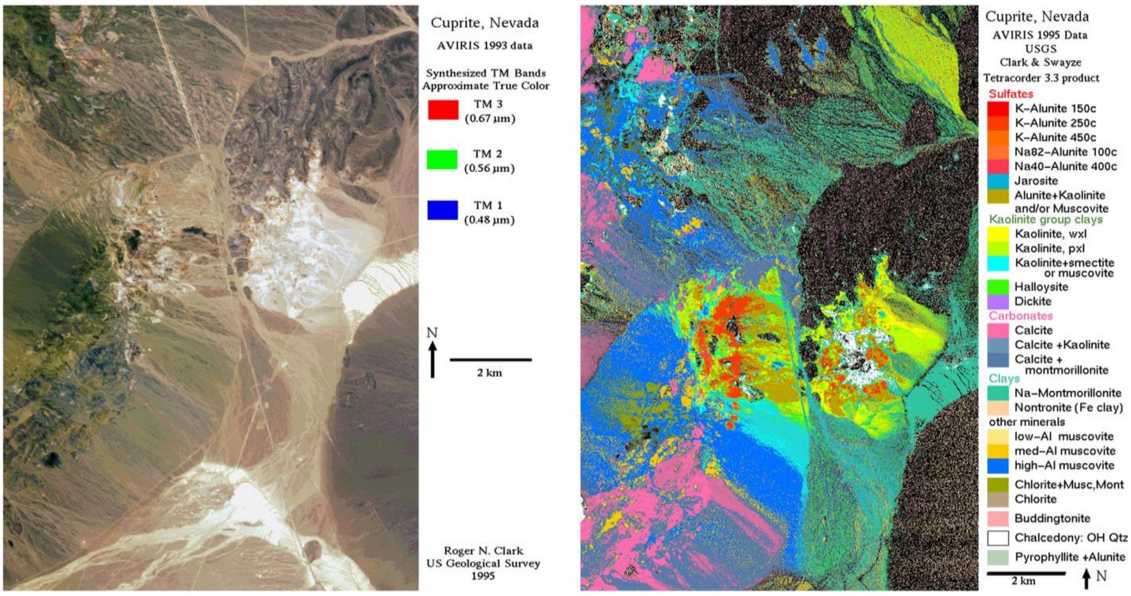

Fig. 5. (Left) True colour composite of Cuprite, Nevada and (right) the corresponding, mineral map derived from AVIRIS data (Clark et al., 2003)

2.2. Subsurface properties

2.2.1. Root-zone soil moisture

Root-zone soil moisture is water content that is available to plants, and is generally considered to be in the upper 200 cm of soil (Wang and QU, 2009). It also controls surface vegetation health conditions and coverage, especially in arid and semi-arid regions, where water content is one of the main controlling factors to vegetation growth (Wang et al., 2007; Schnur et al., 2010).

The most advanced approaches used to estimate root zone soil moisture are based on assimilation of remote sensing observations into soil–vegetation–atmosphere transfer (SVAT) model. These models can be divided into thermal remote sensing and water and energy balance (WEB) approaches. The WEB-SVAT (Water and Energy Balance- Soil Vegetation Atmosphere Transfer Modelling) model uses measured precipitation and predicted evapotranspiration. The model is based on forcing a prognostic root-zone water balance model with observed rainfall and predicted evapotranspiration. In remote sensing SVAT approaches, the radiometric temperature is derived from thermal remote sensing and combined with vegetation information obtained at the VNIR wavelengths in order to simulate the surface energy balance; this method does not explicitly quantify soil moisture but uses a thermal based proxy variable to model availability of soil water in the root-zone and the onset of vegetation water stress (Crow et al., 2008).

Varying climatic conditions at various temporal scales result in temporal deviation of soil moisture from its long-term mean conditions. This soil moisture deviation from the mean condition affects vegetation and causes a change in vegetation characteristics (either by leaf condition, or by surface coverage) from the mean condition. This temporal vegetation change could be captured by NDVI derived from optical remote sensing measurements, which is based on the spectral signature of vegetation in near infrared band and red band, associating with vegetation status and fractional vegetation cover. In a short timeframe (for example hourly period), the NDVI may decrease due to sudden soil moisture increase (rainfall), since increasing top-layer soil moisture would result in a larger decrease of near-infrared reflectance compared to the red reflectance of vegetation. However, in a longer timeframe (such as 8 days in this study), it is expected that NDVI increases as soil moisture increases over the growing season (Wang et al., 2007).

Combining the measurements of Synthetic Aperture Radar (SAR-ESR2) and TM images, Wang et al. (2004) developed a regression model to estimate soil moisture content. Compared with microwave and thermal infrared domains that have been most commonly used in soil moisture estimation (Price, 1980; Wuthrich, 1994; Engman and Chauhan, 1995; Jackson et al., 1995), little attention has been paid to the use of the optical region (Liu et al., 2003). However, many investigations have shown that the solar domain also provides the capability for soil moisture estimation (Schlesinger et al., 1996; Sommer et al., 1998; Leone and Sommer, 2000).

Table 1. Summary of retrieval methods for arid soil attributes

Soil properties in arid areas	Data type	Spectral range	Spatial resolution	Methods and techniques	Objective	Reference
Biological soil crusts	Hyper spectral CASI data	from 426.1 up to 952 nm	1 meter	Continuum Removal Crust Identification Algorithm (CRCIA), MODTRAN	establish a methodology for mapping	Weber et al. (2008)
	ETM+	Band 2 (green): 0.52– 0.60 (Am) Band 3 (red): 0.63– 0.69 (Am) Band 4 (near IR): 0.76– 0.90 (Am)	30 meter	BSCI index, 6S radiative transfer code	detect and map	Chen et al. (2005)
	AVIRIS	2.000–2.100 μm	4 m ground IFOV	minimum noise fraction (MNF) continuum removal (CR) technique maximum likelihood spectral angle mapper, ACORN	spectral detection,	L. Ustin et al. 2009
	Olympus Camedia 5000z digital camera equipped with a Hoya R72 infrared filter	red (600–700 nm) and NIR (800–900 nm)	0.8 mm in the field and 0.2 mm in the laboratory	NDVI GNU Image Manipulation Program I Regression analysis, Geostatistical analysis	field monitoring, gap filling,	Fischer et al. (2012)
Soil texture	TERRASAR-X		1m	Integral Equation Model	Mapping,	Zribi et al. (2012)
	HYMAP hyperspectral image	400 to 2500 nm	5 to 10 m	Spectral Angle Mapper (SAM)	mapping	Margate and Shrestha (2001)
	ASTER ETM+ DEM	visible and near infrared (VNIR) and shortwave infrared (SWIR) bands		minimum distance to means algorithm	discrimination and mapping	Apan et al. (2002)
Soil salinization	MODIS	1B land bands 1, 2, 3, 4, 5, 6, and 7 (centered at 470 nm, 555 nm, 648 nm, 858 nm, 1240 nm, 1640 nm, and 2130 nm, respectively		Linear Spectral Unmixing technique (LSU) Multiple linear regression MLR	assessment and monitoring of salt-affected soil over a large area	Bouaziz et al. (2011)

Table 1. Summary of retrieval methods for arid soil attributes

Soil properties in arid areas	Data type	Spectral range	Spatial resolution	Methods and techniques	Objective	Reference
	Multispectral ASTER			MF & MTMF & LSU	Mapping	Melendez-Pastor et al. (2010)
	Hyperspectral (A laboratory experiment)	350-2500			Modelling salinity effects on soil reflectance under various moisture conditions	Wang et al. (2012)
	Hyperspectral	350-2500		PLSR & ANN	Quantitative analysis	Farifteh et al. (2007)
	Hyperspectral	350-2500		CR	detect	Zhou et al. 2006
	Hyperspectral	350-2500		Continuum-removed (CR)	Spectral characteristics of salt-affected soils	Farifteh et al. (2008)
	Multispectral QuickBird	450-900		PLSR	Clay content, carbonate concentration, organic carbon content and iron oxide content	Summers et al. (2011)
	ETM+	1-7		Decision tree classification		Ding et al. (2011)
	Hyperspectral	400 to 2500		normalized difference salinity index (NDSI), PLSR	Quantitative Estimation of Soil Salinity	Mashimbye et al. (2012)
	Multispectral TM/ETM+	6 band	30 and 120	Soil Adjusted Vegetation Index (SAVI) Land Surface Temperature (LST) Tasseled Cap Transformations(TCT)	Change Detection	Masoud and Koike (2006)
	TM, MSS	1-7 TM & 1-4 MSS (0.5-1.1)	30-68	correlation	correlation obtained between the soil salinity and TM and MSS DN values	Alavipanah et al. (2001)
Soil moisture	MODIS			NDVI, Enhanced Vegetation Index (EVI)	estimate root zone soil moisture	Schnur et al. (2010)
	Thermal and Microwave			soil– vegetation–atmosphere transfer model (WEB-SVAT), Two-Source Model (TSM), LST	estimation root-zone soil moisture	Li et al. (2010)

3. Constraints and Problems

3.1. Dust and Its physical behavior in deserts

Many arid regions all around the world are characterized by the presence of fine, natural dust in the atmosphere that has a large impact on desert ecosystem (Jones and Shachak, 1990). The erosion, transport, and deposition of atmospheric dust are largely determined by the nature and state of desert's surface and the physical characteristics of the atmosphere (Gossens and Offer, 1995). Arid desert regions tend to be fragile ecosystems where little climate perturbations may cause tremendous changes in their landscapes. Additionally, due to their low precipitation rates, arid regions are the world's major source of atmospheric dust that have a significant impact on local, regional, and global climate (Ghedira, 2009). Also, it cannot be sensed using dark targets, since the desert is brighter and dust angular properties may be dominated by the uncertain optical effects of the particle non sphericity (Kahn et al., 1997). Therefore, remote sensing of dust was conducted using thermal properties (Ackerman, 1989; Legrand et al., 1989; Tanré and Legrand, 1991; Wald et al., 1998), reduction of contrasts by dust between dusty and clear days (Tanré et al., 1988).

The physical behavior of dust during day differs from that of the night. This applies to both the transport of the dust in the air, transportation, and the deposition of the dust on the ground

(Alavipanah et al., 2010). In most arid regions, atmosphere is rather unstable during day and stable during night and the accumulation rate is higher during day hours than during night (Alavipanah et al., 2010). However, important seasonal variations are observed: atmospheric instability by day is higher in summer than in winter, where the nights are much more stable in winter than in summer (Ghedira, 2009). Dust also increases atmospheric scattering of electromagnetic waves (Alavipanah et al., 2010). Offer and Goossens (2001) showed that in Negev desert region, the wind speed during summer is more than winter. This change in wind speed can affect the particle size distribution of the air and the amount of electromagnetic radiation reflected from the surface. Israelevich et al. (2003) began to study the annual variation of the desert dust aerosol. They found that the characteristics of desert dust particles have clear changes in different mounts and showed that desert dust particles are generally larger during summer and autumn seasons, than in spring. The real part of the refractive index of the particles is the same between summer and autumn seasons and exceeds the real part of the refractive index measured during the spring. Also, the heights of the dust layer are higher during summer and autumn than in spring (Figs. 6 and 7) (Israelevich et al., 2003). Hereon, any changes in the concentration and accumulation of dust waves can affect scattering of electromagnetic reflectance. Due to the high potential changes of desert dusts in daily, monthly and yearly scale, a significant impact should be expected on the received spectrum of the sensor.

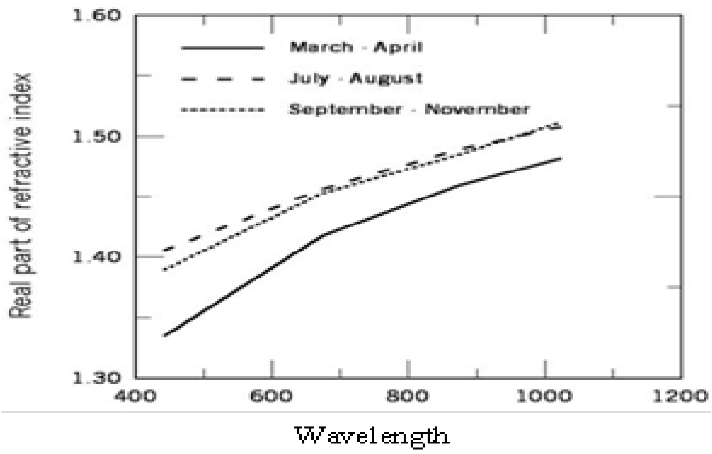

Fig. 6. Dependence of real parts of the refractive index. For the desert dust aerosol loading above the eastern Mediterranean (Solid, dashed, and dotted lines correspond to spring, summer and autumn, respectively) (Israelevich et al., 2003)

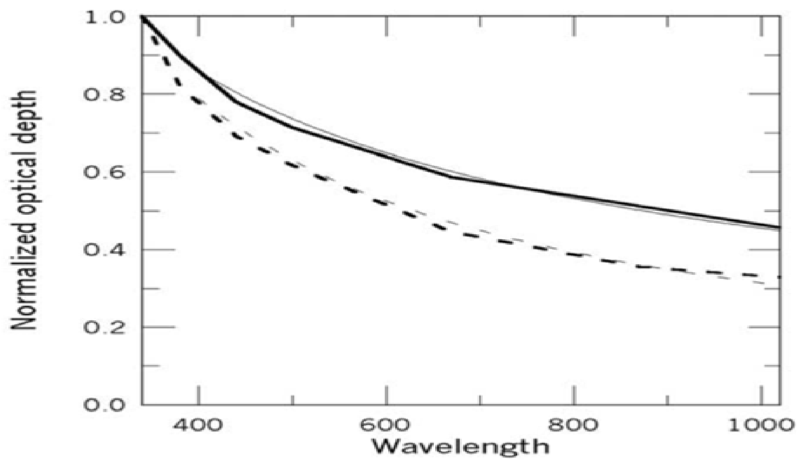

Fig. 7. Dependencies of normalized optical thickness on the wavelength for April (solid line) and October (dashed lines) for the desert dust aerosol loading above the eastern Mediterranean (Israelevich et al., 2003).

3.2. Spectral confusions of soil properties in arid regions

Although all soil properties have their specific spectral reflectance and emissivity, there is some interference under some conditions, especially in arid and semi-arid regions that cause spectral confusion during processing remote sensing data. Soil construction materials, atmospheric conditions, and vegetation cover are the most important factors of spectral interference.

3.2.1. Salinity

The application of remotely sensed data in salinity studies is difficult. Firstly, diagnostic features of salt-affected soils are generally weak because of poor salt crystallization (Hunt et al., 1972). As second limitation, mapping of soil salinity is difficult because many other soil chemical and physical properties (for example moisture, surface roughness, organic matter) also influence soil reflectance (Irons et al., 1989). Finally, from a remote platform, the recorded reflectance is often the (mixed) result of several surface components and features (i.e., mixed pixel problem) (Dehaan and Taylor, 2003), and at the same time atmospheric scattering and absorption processes mask salts diagnostic features (Cloutis, 1996). Detecting and mapping salinity by use of remote sensing is therefore challenging, since most of salt minerals are spectrally featureless and because the strength of signals representing salt-affected soils are relatively weak compared to the "*noise*" resulting from other interfering factors (Ben-Dor, 2002). A problem encountered in saline soil detection is the presence of vegetation or other surface features which may cause spectral confusion with respect to salt reflectance properties (Chang, 2003).

Farifteh et al. (2008) suggested three major problems that interfere with the detectability of salt-affected soils by remote sensing: the process often goes undetected especially when salt minerals have not (yet) severely affected the soils, the physical boundaries separating regions with different salinity levels are fuzzy, and the process of salinization occurs not only at the soil surface but also in the soil profile which cannot be detected by optical sensors. Table 1 shows the vegetation and soil salinity indices used in soil salinity monitoring and mapping (Amal and Lalit, 2013). However, researchers such as Metternicht (2001) and Zhang et al. (2007) argue that detecting soil salinity using the NDVI is challenging because the presence of vegetation could cause spectral confusion

Table 2. Vegetation and soil salinity indices that have been proposed and used for soil salinity monitoring and mapping

	Indices	Equation
1	Normalized Differential Vegetation Index	NDVI=(NIR-R)/(NIR+R)
2	Enhanced Vegetation Index	EVI=2.5(NIR-R)/(NIR+6R-7.5BLUE+1)
3	Soil Adjusted Vegetation Index	SAVI=(NIR-R)/(NIR+R+L)×(1+L)
4	Ratio Vegetation Index	RVI=NIR/R
5	Normalized Differential Salinity Index	NDSI=(R-NIR)/(R+NIR)
6	Brightness Index	$BI = \sqrt{\left(R^2 + NIR^2\right)}$
7	Salinity Index	$SI = \sqrt{BLUE \times R}$
8	Salinity Index	$SI1 = \sqrt{G \times R}$
9	Salinity Index	$SI2 = \sqrt{\left(R^2 + NIR^2 + NIR^2\right)}$
10	Salinity Index	$SI3 = \sqrt{G^2 \times R^2}$
11	Salinity Index	SI-1=ALI9/ALI10
12	Salinity Index	SI-2=(ALI6-ALI9)/(ALI6-ALI9)
13	Salinity Index	SI-3=(ALI9-ALI10)/(ALI9+ALI10)
14	Soil Salinity and Sodicity Indices	SSSI-1=(ALI9-ALI10)
15	Soil Salinity and Sodicity Indices	SSSI-2=(ALI9×ALI10-ALI10×ALI10)/ALI9
16	Salinity Index	$S_1 = Blue/R$
17	Salinity Index	$S_2 = \left(Blue - R\right)/\left(Blue + R\right)$
19	Salinity Index	$S_3 = \left(G \times R\right)/Blue$
20	Salinity Index	$S_4 = \sqrt{Blue \times R}$
21	Salinity Index	$S_5 = \left(Blue \times R\right)/G$
22	Salinity Index	$S_6 = \left(R \times NIR\right)/G$

with the reflectance properties of salt and also because the NDVI is considered as an unreliable indicator, as it is also correlated to other yield variables such as chlorophyll content, biomass, and leaf area. Table 2 shows the several vegetation and soil salinity indices that have been proposed and used in soil salinity monitoring and mapping in the world (Amal, 2013).

3.2.2. Moisture contents of soil

Moisture contents of soils and salts (depending on the types) have similar effects on soil reflectance spectra and cause large anomalies in predicting salinity levels from remotely sensed data (Csillag et al., 1993). Moreover, soil moisture has been recognized as a main factor leading to temporal change of soil reflectance (Liu et al., 2012) and hence further increasing difficulties to monitor soil salt during time. As a result, a moisture resistant estimation method is necessary for early detection and quick monitoring of soil salinity in large spatial scale, viewing from the large spatial and temporal variations of soil moisture, especially in dryland (Wang et al., 2012).

3.2.3. Vegetation interference

Because of harsh environmental conditions, spectral signatures of plants in arid and semi-arid regions are different from humid types (Fig. 8) and a large soil background in arid and semi-arid regions where soils can be bright and mineralogically heterogeneous in many cases swamps out the spectral contribution of plants (Ehleringer and Mooney, 1987; Lam et al., 2011). The dominance of soil reflectance in desert regions makes vegetation detection difficult in thermal and reflective bands. Because of the strong reflection of the soil dominates the radiance, which is measured by sensors; therefore, almost all pixels in satellite images are mixed, thereby identification of pure spectral vegetation is difficult (Komaki and Alavipanah, 2006).

Based on the findings of Huets and Jackson (1987), the senescent vegetation and weathered litter can dramatically impact reflectance of mixtures. The problem of the mixture reflectance is not only due to non-photosynthetic vegetation in different spaces, but also live vegetation in desert regions can be comprised of both photosynthetic and senescent components. The effect of non-photosynthetic vegetation on desert remote sensing exists to, at least, the canopy scale. High spatial resolution remote sensing enables direct imaging of plant individuals that are at least the size of the ground resolution of the remote sensing image (Ackerman, 1989).

Many techniques of remote sensing and spectral band width are insensitive to non-photosyntheticaly vegetation and different degrees of senescence or dryness of plants. Open canopies and variable soil background (usually bright) in desert regions have a significant contribution to multiple scattering and nonlinear mixings in deserts. Desert vegetation lacks a sharp red edge.

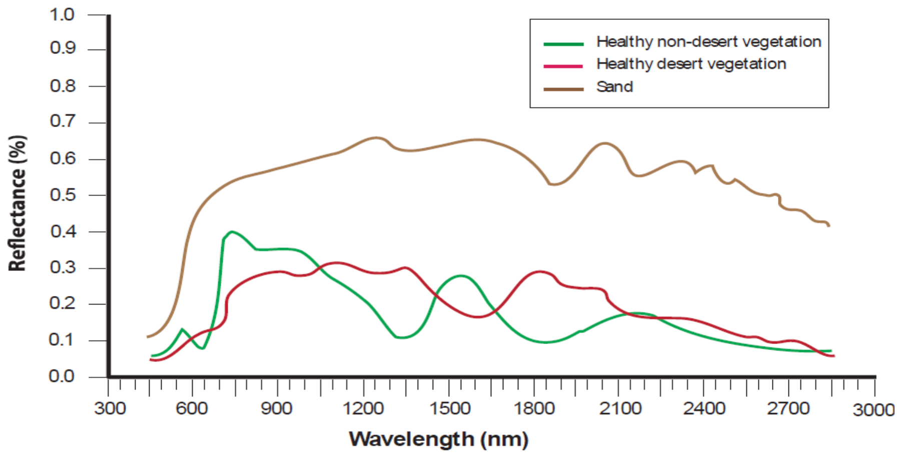

Fig. 8. Spectral response curves for healthy non-desert and desert vegetation, and sand. Notice how the spectral reflectance for desert vegetation are spectrally dissimilar and do not exhibit a strong red edge due to reduced leaf absorption in the visible region of the electromagnetic spectrum and strong wax absorption around the 1,720 nm wavelength region. (Lam et al., 2011)

When vegetation cover is sparse and vascular plants are widely scattered, cover generally has been underestimated because of the mixed composition of materials within large pixels, such as TM. Vegetation, soil, and litter combine to affect the composite spectral response within these pixels which makes it difficult to extract the vegetative component from the spectral reflectance (Sohn and McCoy, 1997; Tanser and Palmer, 1999). Spectral variability within shrubs of the same species can be high in arid and semi-arid regions, as reported by Duncan et al. (1993) and Franklin et al. (1993). There is evidence, however, that NDVI is affected by soil color and is therefore not always comparable across a heterogeneous scene (Major et al., 1990; Elvidge and Lyon, 1985; Todd and Hoffer, 1998).

3.2.4. Root-zone soil salinity

Application of vegetation index as an indirect indicator can avoid limitations tied with the direct use of soil reflectance. These limitations include the influences of complicated soil context (moisture, surface roughness, and organic matter) (Ben-Dor et al., 1999), weak diagnostic features under poor salt crystallization (salt content <10–15%) (Mougenot et al., 1993), and spectral confusions with the presence of vegetation itself and other surface features (Metternicht and Zinck, 2003). Vegetation reflectance has been studied to realize the responses to numerous stress agents, including ozone, pathogens, senescence, dehydration (Carter, 1993), natural gas (Noomen et al., 2006), and metal contamination (Dunagan et al., 2007). The increased visible reflectance (VIS) and the reduced near-infrared reflectance (NIR) have been found to be consistent as responses of chlorophyll reduction and cell structure damage among various species to stress agents (Carter, 1993; Dunagan et al., 2007; Rosso et al., 2005). These changes in VIS and NIR were also found in vegetation responses to salt stress (Tilley et al., 2007; Wang et al., 2002). Based on these findings, soil salinity has been estimated in numerous studies by using vegetation reflectance, and many of these studies preferred the use of vegetation indices (VIs). The normalized difference vegetation index (NDVI) was found to be sensitive to salinity, especially in croplands (Wiegand et al., 1994). The photochemical reflectance index (PRI) reflecting the photosynthetic radiation-use efficiency was found to be a good indicator with R^2 of 0.3 in a brackish subtropical marsh (Tilley et al., 2007). Other VIs responding to chlorophyll, such as the red edge position (REP) and the chlorophyll normalized difference index (Chl NDI), have also been used to delineate the effects of salinity changes (Thorhaug et al., 2006; Tilley et al., 2007). Generally, hyperspectral sensors are a powerful and versatile tool for monitoring environmental stress because of the continuous sampling and the high spectral resolution (50 nm) may lose important spectral information, while narrow bands can discriminate critical spectral differentials in detail. Hyperspectral are sensitive to many plant variables, such as leaf pigment contents (chlorophyll) and water content (Darvishzadeh et al., 2008; Dehaan and Taylor, 2002; Tilley et al., 2007)

3.3. Temporal changes

Suitable timing relates to passive remote sensing data acquisition and must be taken into account in studying soil properties in arid and semi-arid regions (Metternicht and Zinck, 2003). Therefore, temporal changes of temperature, precipitation, salinity, and vegetation cover affect the spectral characteristics of soil in these regions. The phonological change of vegetation has an influence on their seasonal reflectance dynamics. (Schmidt et al., 2000). Due to a high variability horizontally and vertically in soil salinity in time and space, the most suitable data of remotely sensed data acquisition must be take into account. Many investigations have revealed that salt identification is easier at the end of the dry season, and salt dissolves during the raining season. In contrast to white saline surface, pure alkaline soils are usually dark at surfaces because excess sodium causes organic matter to disperse when the soil has been wet (Metternicht and Zink, 2003). On the other hand, the characterization of saline soils using active (radar) imagery and complex dielectric constant determined by the radar back scattering inversion techniques requires some soil moisture conditions, chemical, and biological compositions (Mougenot et al., 1993).

In arid and semi-arid ecosystems, precipitation (P) typically has wide spatial and temporal variability. Interactions between plants cover type and topoedaphic features of the landscape produce complex ecological and hydrological patterns of response to precipitation (Huxman et al., 2004). Rapid changes in the phonology of surface temperature are almost the same as that to aerodynamic surface temperature. Considering these constraints using multitemporal data can be useful and improve the result when remote sensing data are used for soil studies.

Some vegetation responds to individual precipitation events, arid, and semi-arid landscapes as a whole are largely controlled by seasonal changes in temperature and precipitation (Okin and Roberts, 2004). The NDVI time series of the 10-day composites showed a distinct seasonal pattern for different vegetation types, while the NDVI of non-vegetated regions (sand desert) showed low-stable values throughout the year. Huang and Siegert (2006) found that the NDVI of the sparse vegetation in North China varied with the seasonal change of photosynthetic.

The temporal variation in the spectral reflectance of the four main surface components in the sandy environment during the rainy (a) and dry (b) seasons is shown in Figure 9. It can be concluded that there are some important differences between rainy and dry seasons and also between sand, annuals, biogenic crust, and perennials features (Schmidt and Karnieli, 2000).

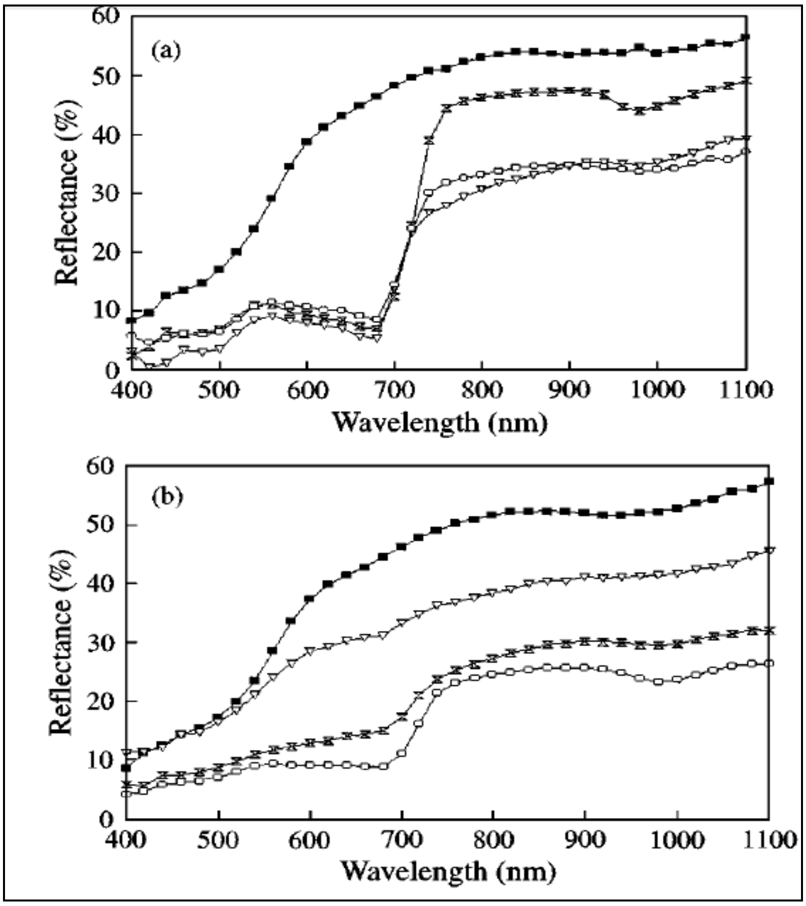

Fig. 9. Spectral ground measurements of different surface components in the sandy environment during: (a) the rainy season, and (b) the dry season. Sand; annuals; biogenic crust; perennials (Schmidt & Karnieli, 2000).

The contribution of the different vegetation components to the overall NDVI signal changes from the beginning to the end of the rainy season (Fig. 10). Perennials do not show any significant change in their NDVI contribution at any time of the year in the sandy and rocky regions. Annual vegetation changes their contribution to the mixed NDVI signal with a peak in the first month of the rainy season. The high percentage cover of biogenic crusts in the sandy environment and the lichens in the rocky environment are responsible for the high contribution of these surface types to the overall NDVI signal (Schmidt and Karnieli, 2000).

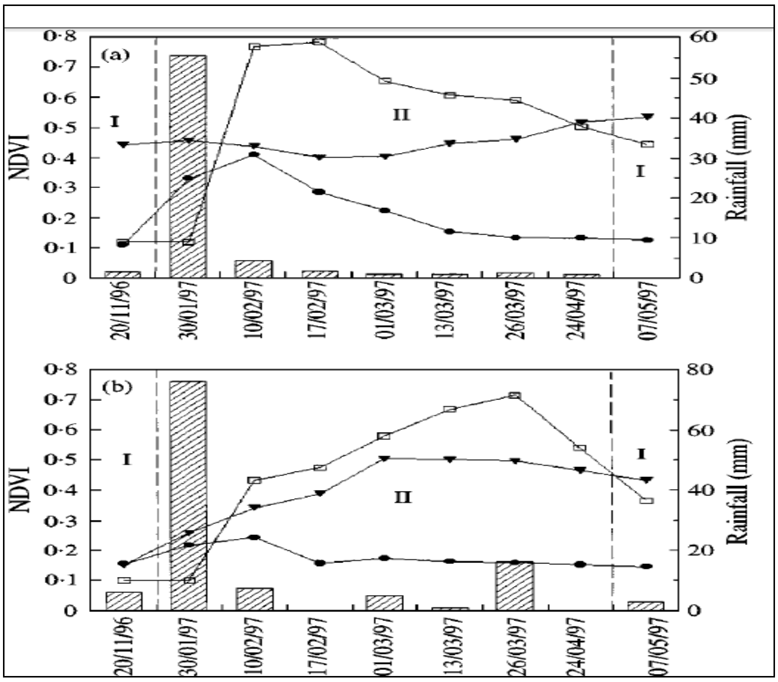

Fig. 10. NDVI of different vegetation components and their response to monthly rainfall (mm) in (a) the sandy environment, and (b) the rocky environment for the rainy season. I, dry season; II, rainy season. Rainfall (mm); annuals; biogenic crusts; perennials (Schmidt & Karnieli, 2000).

4. Conclusion

This article reviewed the application of remote sensing technology on evaluation of soil properties in arid and semi-arid regions. Because of special ecosystem, there are a lot of important factors that are key elements to recognition of soil in these regions. However, the influences of these factors on each other make a complicated condition, for example, changes in vegetation could be the result of change in soil moisture.

Remote sensing is a time and cost efficient method to collect data, monitor, map, and detect arid and semi-arid soil properties. Although traditional field methods are replaced by remote sensing methods, but in order to increase accuracy and precision of results, they should be considered.

Using appropriate data based on the aim of studies is a very important issue. For example, given that soil elements have characteristic features mostly occurring in narrow wavelength region (Weng et al., 2010), using hyper spectral and laboratory data can be useful. Moreover, because of bad atmospheric condition in these regions, using microwave remote sensing is important. Totally, remote sensing data: (1) supports the segmentation of the landscape into rather homogeneous soil–landscape units that soil composition can be determined by sampling or that can be used as a source of secondary information, (2) allows measurement or prediction of soil properties by means of physically-based and empirical methods, and (3) supports spatial interpolation of sparsely sampled soil property data as a primary or secondary data source.

Awareness of constraints and limitations of using remote sensing data and techniques (such as spectral confusion, interference of vegetation, temporal changes, and dust) in these regions and how they affect the performance of image processing and analysis should be considered.

References

1. Abbas, A.; Khan, S.; Hussain, N.; Hanjra, M.A.; Akbar, S. (2013). Characterizing soil salinity in irrigated agriculture using a remote sensing approach. Physics and Chemistry of the Earth. 55-57, 43-52.
2. Ackerman, S.A. (1989). Using the radiative temperature difference at 3.7 and 11 mm to track dust outbreaks. Remote Sensing of Environment. 27, 129–133.
3. Ager, C.M.; Milton, N.M. (1987). Spectral reflectance of lichens and their effects on the reflectance of rock substrates. Geophysics, 52, 898–906.

4. Alavipanah, S.K.; Matinfar, H.R.; Rafiei Emam, A.; Khodaei, K.; Hadji Bagheri, R.; Yazdan Panah (2010). A Criteria of selecting data for studding land resources, Desert. 83-102.
5. Alavipanah, S.K.; Komaki, C.B.; Goorabi, A.; Matinfar, H.R. (2007a). Characterizing Land Cover Types and Surface Condition of Yardang Region in Lut Desert (Iran) Based upon Landsat Satellite Images. World Applied Sciences Journal. 2, 212–228.
6. Alavipanah, S.K.; Saradjian, M.; Savaghebi, G.R.; Komaki, C.B.; Moghimi, E.; Reyhan, M.K. (2007b). Land Surface Temperature in the Yardang Region of Lut Desert (Iran) Based on Field Measurements and Landsat Thermal Data. J. Agric. Sci. 9, 287–303.
7. Alavipanah, S.K.; De Dapper, M.; Goossens R.; Massoudi, M. (2001). The use of TM thermal band for land cover/land use mapping in two different environmental conditions of Iran. J. Agric. Sci. Technol. 3, 27-36.
8. Aly, Z.; Bonn, F.J.; Magagi, R. (2007). Analysis of the backscattering coefficient of saltaffected soils using modelling and RADARSAT-1 SAR data. Geosci. Remote Sens. IEEE Trans. 45 (2), 332–341.
9. Amal, A.; Lalit (2013). Soil Salinity Mapping and Monitoring in Arid and Semi-Arid Regions Using Remote Sensing Technology: A Review. Advances in Remote Sensing. 2, 373-385.
10. Anderson, M.C. (2008). A thermal-based remote sensing technique for routine mapping of land-surface carbon, water and energy fluxes from field to regional scales. Remote Sensing of Environment. 112 (12), 4227–4241.
11. Anderson, M.C.; Norman, J.M.; Mecikalski, J.R.; Otkin, J.A.; Kustas, W.P. (2007a). A climatological study of evapotranspiration and moisture stress across the continental U.S. based on thermal remote sensing. I. Model formulation. J. Geophys Res, 112, 1-17.
12. Anderson, M.C.; Norman, J.M.; Mecikalski, J.R.; Otkin, J.A.; Kustas, W.P. (2007b). A climatological study of evapotranspiration and moisture stress across the continental U.S. based on thermal remote sensing. II. Surface moisture climatology. J Geophys Res., 112:D11112. doi:10.1029/2006JD007507.
13. Anguela, T.; Zribi, M.; Baghdadi, N.; Loumagne, C. (2010). Analysis of local variation of soil surface parameters with TerraSAR-X radar data over bare agricultural fields, IEEE Trans. Geosci. Remote Sens. 48 (2), 874–881.
14. Apan, A.; Kelly, R.; Jensen, T.; Butler, D.; Strong, W.; Basnet, B. (2002). Spectral discrimination and separability analysis of agricultural crops and soil attributes using ASTER imagery. 11th ARSPC. Brisbane, Australia.
15. Baghdadi, N.; Zribi, M.; Loumagne, C.; Ansart, P.; Paris Anguela, T. (2008). Analysis of TerraSARX data and their sensitivity to soil surface parameters, Remote Sensing of Environment. 112, 4370−4379.
16. Baldridge, A.M.; Hook, S.J.; Grove, C.I.; Rivera, G. (2008). The ASTER Spectral Library Version 2.0. Jet Propulsion Laboratory.
17. Bastiaanssen, W.G.M.; Noordman, E.J.M.; Pelgrum, H.; Davids, G.; Thoreson, B.P.; Allen, R.G. (2005). SEBAL model with remotely sensed data to improve water-resources management under actual field conditions. J. Irrig. Drain. Eng. 131(1), 85–93.
18. Belnap, J. (2003). The world at your feet: desert biological soil crusts. Frontiers in Ecology and the Environment. 1(4), 181-189.
19. Ben-Dor, E.; Chabrillat S.; Demattê, J.A.M.; Taylor, G.R.; Hill, J.; Whiting, M.L.; Sommer, S. (2009). Using Imaging Spectroscopy to study soil properties. Remote Sensing of Environment. 113, 38–55.
20. Ben-Dor, E. (2002). Quantitative remote sensing of soil properties. Advances in Agronomy. 75, 173–243.
21. Ben-Dor, E.; Patkin, K.; Banin, A.; Karnieli, A. (2002). Mapping of several soil properties using DAIS-7915 hyperspectral scanner data. A case study over clayey soils in Israel. International Journal of Remote Sensing, 23, 1043−1062.
22. Ben-Dor, E.; Irons, J.R.; Epema, G.F. (1999). Soil reflectance. In: Rencz, A.N. (Ed.), Remote Sensing for the Earth Sciences: Manual of Remote Sensing. Wiley, New York, 111–118.
23. Bindlish, R.; Jackson, T.J.; Gasiewski, A.J.; Klein, M.; Njoku, E.G. (2006). Soil moisture mapping and AMSR-E validation using the PSR in SMEX02. Remote Sensing of Environment. 103, 127–39.
24. Birkeland, P.W. (1999). Soils and Geomorphology. 3rd edition. New York: Oxford University Press.
25. Bouaziz, B.; Matschullat, J.; Gloaguen, J. (2011). Improved remote sensing detection of soil salinity from a semi-arid climate in Northeast Brazil. Geoscience. 343, 795–803.
26. Brown, D.J.; Shepherd, K.D.; Walsh, M.G.; Dewayne Mays, M.; Reinsch, T.G. (2006). Global soil characterization with VNIR diffuse reflectance spectroscopy. Geoderma. 132, 273–290.
27. Carter, G.A. (1993). Responses of leaf spectral reflectance to plant stress. Am. J. Bot. 80, 239–243.
28. Casa, R.; Castaldi, F.; Pascucci, S.; Palombo, A.; Pignatti, S. (2013). A comparison of sensor resolution and calibration strategies for soil texture estimation from hyperspectral remote sensing. Geoderma, 197–198, 17–26.

29. Chang, C.W.; Laird, D.A.; Mausbach, M.J.; Maurice, J.; Hurburgh, J.R. (2001). Near-infrared reflectance spectroscopy—principal components regression analyses of soil properties. Soil Science Society of America Journal, 65, 480–490.
30. Cashion, J.; Lakshmi, V.; Bosch, D.; Jackson, T.J. (2005). Microwave remote sensing of soil moisture: evaluation of the TRMM microwave imager (TMI) satellite for the Little River Watershed Tifton, Georgia. Journal of Hydrology, 307, 242-253.
31. Chang, D.H. (2003). Classification of soil texture using remotely sensed brightness temperature over the Southern Great Plains, Geoscience and Remote Sensing, IEEE Transactions, 41, 664 - 674
32. Chena, J.; Zhangb, M.Y.; Wangc, L.; Shimazakia, H.; Tamuraa, M. (2005). A new index for mapping lichen- ominated biological soil crusts in desert areas. Remote Sensing of Environment. 96, 165–175.
33. Clark, R.N.; Swayze, G.A.; Livo, K.E.; Kokaly, R.F.; Sutley, S.J.; Dalton, J.B.; McDougal, R.R.; Gent, C.A. (2003). Imaging spectroscopy: earth and planetary remote sensing with the USGS Tetracorder and expert systems. Journal of Geophysical Research E: Planets. 108(5), 1-44.
34. Cloutis, E.A. (1996). Hyperspectral geological remote sensing: evaluation of analytical techniques. Int. J. Remote Sensing. 17, 2215-2242.
35. Cooke, R.; Warren, A.; Goudie, A. (1993). Desert Geomorphology. First Edition, UCL Press.
36. Crow, W.T.; Kustas, W.; Prueger, J.H. (2008). Monitoring root-zone soil moisture through the assimilation of a thermal remote sensing-based soil moisture proxy into a water balance model. Remote Sensing of Environment. 112, 1268-1281.
37. Csillag, F.; Pasztore, L.; Biehl, L.L. (1993). Spectral selection for characterization of salinity status of soils. Remote Sensing of Environment. 43, 231–242.
38. Darvishzadeh, R.; Skidmore, A.; Schlerf, M.; Atzberger, C.; Corsi, F.; Cho, M. (2008). LAI and chlorophyll estimation for a heterogeneous grassland using hyperspectral measurements. ISPRS J. Photogramm. Remote Sens. 63, 409–426.
39. Dehaan, R.; Taylor, G.R. (2003). Image-derived spectral endmembers as indicators of salinity. International Journal of Remote Sensing, 24, 775–794.
40. Dehaan, R.L.; Taylor, G.R. (2002). Field-derived spectra of salinized soils and vegetation as indicators of irrigation-induced soil salinization. Remote Sens. Environ. 80, 406–417.
41. Deichmann, U.; Eklundh, L. (1991). Global digital datasets for land degradation studies: A GIS approach. GRID case study series 4.
42. Ding, J.L.; W., M.C.; Tashpolat, T. (2011). Study on soil salinization information in arid region using remote sensing technique. Agricultural Sciences in China, 10(3), 404-411.
43. Dobos, E.; Micheli, E.; Baumgardner, M.F.; Biehl, L.; Helt, T. (2000). Use of combined digital elevation model and satellite radiometric data for regional soil mapping. Geoderma, 97 (3–4), 367–391.
44. Dokuchaev, V.V. (1883). Russian Chernozems. (Russkii Chernozem). *Israel Prog. Sci. Trans*., Jerusalem, Israel, 1967, translated by N. Kaner.
45. Dunagan, S.C.; Gilmore,M.S.; Varekamp, J.C. (2007). Effects of mercury on visible/nearinfrared reflectance spectra of mustard spinach plants (Brassica rapa P.). Environ. Pollut. 148, 301–311.
46. Duncan, J.; Stow, D.; Franklin, J.; Hope, A. (1993). Assessing the relationship between spectral vegetation indices and shrub cover in the Jornada Basin, New Mexico. International Journal of Remote Sensing. 14, 3395–3416.
47. Dwivedi, R. (1996). Monitoring of salt-affected soils of the Indo-Gangetic alluvial plains using principal component analysis. International Journal of Remote Sensing, 17, 1907–1914.
48. Ehleringer, J.R. and Mooney, H.A. (1978). Leaf hairs: effect on physiological activity and adaptive value to the desert shrub. Oecologia, 37, 183-200.
49. Elvidge, C.; Chen, Z. (1995). Comparison of broad-band and narrow-band red and near-infrared vegetation indices. Remote Sensing of Environment. 54, 38-48.
50. Elnaggar, A.; Noller, J. (2010). Application of remote-sensing data and decision-tree analysis to mapping salt-affected soils over large areas. Remote Sensing, 2, 151–165.
51. Engman, E.T.; Chauhan, N. (1995). Status of microwave soil moisture measurements with remote sensing. Remote Sensing of Environment, 51, 189-198.
52. Farifteh, J.; Van der Meer, F.; van der Meijde, M.; Atzberger, C. (2008). Spectral characteristics of salt-affected soils: a laboratory experiment. Geoderma, 145, 196–206.
53. Farifteh, J.; Van der Meer, F.; Atzberger, C.; Carranza E.J.M. (2007). Quantitative analysis of salt-affected soil reflectance spectra: A comparison of two adaptive methods (PLSR and ANN). Remote Sensing of Environment, 110, 59–78.
54. Farifteha, J.; Farshada, T.A.; George, R.J. (2006). Assessing salt-affected soils using remote sensing, solute modelling, and geophysics. Geoderma, 130, 191–206.
55. Farifteh, J.; Farshad A. (2003). Remote sensing and modelling of topsoil properties, a clue for assessing land degradation. Proceedings of 17th WSCC, Thailand, Paper 865, 1-11.

56. Fischera, T.; Vesteb, M.; Eisele, A.; Bensc, O.; Reinhard, W.S.; Hüttlc, F. (2012). Small scale spatial heterogeneity of Normalized Difference Vegetation Indices (NDVIs) and hot spots of photosynthesis in biological soil crusts. Flora, 207, 159– 167.
57. Franklin, J.; Duncan, J.; Turner, D.L. (1993). Reflectance of vegetation and soil in Chihuahuan Desert plant communities from ground radiometry using SPOT wavebands. Remote Sensing of Environment. 46, 291–304.
58. French, A.N.; Jacobb, F.; Andersonc, M.CKustasd, W.P.; Timmermanse, W.; Gieskee, A.; Sue, Z.; Suf, H.; McCabef, M.F.; Lid, F.; Pruegerg, J.; Brunsellh N. (2005). Surface energy fluxes with the Advanced Spaceborne Thermal Emission and Reflection radiometer (ASTER) at the Iowa 2002 SMACEX site (USA). Remote Sensing of Environment. 99, 55–65.
59. Ghedira, H.; Al Rais, A.; Al Suwaidi, A. (2009). Developing a new automated tool for detecting and monitoring dust and sand storms using MODIS and METOSAT SEVERI-MSG data. IEEE, 4, 905-908.
60. Goetz, A.F. (1992). Imaging spectrometry for Earth remote sensing. In: Toselli, F., Bodechtel, J. (Eds.), Imaging Spectrometry. Basic Principles and Prospective Applications. ECSC, EEC, EAEC, Brussels and Luxemburg, 1–19.
61. Gossens, R.; Van Ranst, E. (1996). The use of RS and GIS to detect gypsiferous soils in the Ismailia province (Egypt), proceedings of the International Symposium on Soil with Gypsum. Lieida, 15-21 September, 1996. Catalonia, Spain.
62. Gossens, D.; Offer, Z.Y. (1995). Comparisons of day-time and night-time dust accumulation in a desert region. Journal of Arid Environments, 31, 253-281.
63. Graetz, R.D.; Gentle, M.R. (1982). The relationship between reflectance in the Landsat wavebands and the composition of an Australian semiarid shrub rangeland. Photogrammetric Engineering and Remote Sensing. 48, 1721–1730.
64. Green, G.M. (1986). Use of SIR-A and Landsat MSS data in mapping shrub and intershrub vegetation at Koonamore, South Australia. Photogrammetric Engineering and Remote Sensing. 52, 659–670.
65. Huete, A.R.; Tucker, C.J. (1991). Investigation of soil influences in AVHRR red and near-infrared vegetation index imagery. International Journal of Remote Sensing, 12, 1223–1242.
66. Huete, A.R. (1985). Spectral response of a plant canopy with different soil backgrounds. Remote Sensing of Environment, 17, 37–53.
67. Huete, A.R.; Jackson, R.D. (1987). Suitability of spectral indices for evaluating vegetation characteristics on arid rangelands. Remote Sensing of Environment. 23, 213– 232.
68. Huang, S.; Siegert.; F. (2006). Land cover classification optimized to detect areas at risk of desertification in north China based on SPOT vegetation imagery. Journal of Arid Environments. 67, 308–327.
69. Hunt, G.R.; Salisbury, J.W.; Lenhoff, C.J. (1972). Visible and near-infrared spectra of minerals and rocks. V. halides, phosphates, arsenates, vanadates and borates. Modern Geology, 3, 121–132.
70. Huxman, T.; Smith, M.; Fay, P.; Knapp, A.; Shaw, M.; Loik, M.; Smith, S.; Tissue, D.; Zak, J.; Weltzin, J.; Pockman, W.; Sala, O.; Haddad, B.; Harte, J.; Koch, G.; Schwinning, S.; Small, E.; Williams, D. (2004). Convergence across biomes to a common rain-use efficiency. Nature, 429, 651–654.
71. Israelevich, P.L.; Ganor, E.; Levin, Z.; Joseph J.H. (2003). Annual variations of physical properties of desert dust over Israel. Journal of Geophysical Research, 108, no. d13, 4381, doi:10.1029/2002jd003163, 2003.
72. Irons, J.R.; Weismiller, R.A.; Petersen, G.W. (1989). Soil reflectance. In: Asrar, G., (Ed), Theory and Applications of Optical Remote Sensing. Wiley Series of Remote Sens., J. Wiley & Sons, New York, NY. 66-106.
73. Jackson, T.J. (1993). Measuring surface soil moisture using passive microwave remote sensing. Hydrol Process, **7**, 139–52.
74. Jackson, R.D. (1982). Canopy temperature and crop water stress. Adv Irrig, 1, 43–85.
75. Jackson, R.D. (1981). Idso SB, Reginato RJ, Pinter Jr PJ. Canopy temperature as a crop water stress indicator. Water Resour Res, 17, 1133–1138.
76. Jacobberger, P.A. (1989). Reflectance characteristics and surface processes in stabilized dune environments. Remote Sensing of Environment. 28, 287–295.
77. Jackson, T.J.; Le Vine D.M.; Swift C.T.; Schmugge, T.J.; Schiebe, F.R. (1995). Large area mapping of soil moisture using the ESTAR passive microwave radiometer in Washita ’92. Remote Sensing of Environment, 53, 27-37
78. Jenny, H. (1941). Factors of soil formation: A system of quantitative pedology. New York, NY.: McGraw Hill Book Company, Inc.
79. Jin, X.C,; Xu, Q.J,; Huang, C.Z. (2005). Current status and future tendency of lake eutrophication in China. Science in China Series C–Life Sciences. 48, 948–954.

80. Jones, C.G.; Shachak, M. (1990). Fertilization of the desert soil by rock-eating snails. Nature, 346, 839-841.
81. Jong, S.M.; Addink, E.A.; van Beek, R.; Duijsings, D. (2009). Mapping of soil surface crusts using airborne hyperspectral HyMap imagery in a Mediterranean environment. Anais XIV Simpósio Brasileiro de Sensoriamento Remoto, Natal, Brasil, 25-30 abril 2009, INPE, 7725-7732.
82. Joshi, M.; Sahai, B. (1993). Mapping of salt-affected land in Saurashtra coast using Landsat satellite data. International Journal of Remote Sensing, 14, 1919–1929.
83. Kahn, R.; West, R.; McDonald. D.; Rheingans, B.; Mishchenko, M.I. (1997). Sensitivity of multiangle remote sensing observations to aerosol sphericity. J. Geophys. Res. 102, 16861–16870.
84. Karnieli, A.; Kidron, G.J.; Glaesser, C.; Ben-Dor, E. (1999). Spectral Characteristics of Cyanobacteria Soil Crust in Semiarid Environments. Remote Sensing of Environment. 69, 67–75.
85. Karnieli, A.; Shachak, M.; Tsoar, H.; Zaady, E.; Kaufman, Y.; Danin, A.; Porter, W. (1996). The effect of microphytes on the spectral reflectance of vegetation in semiarid regions. Remote Sensing of Environment. 57, 88–96.
86. Karnieli, A.; Tsoar, H. (1995). Satellite spectral reflectance of biogenic crust developed on desert dune sand along the Israel–Egypt border. International Journal of Remote Sensing, 16, 369–374.
87. Karnieli, K.; Sarafis, V. (1996). Reflectance spectrometry of cyanobacteria within soil crusts—a diagnostic tool. International Journal of Remote Sensing, 8, 1609– 1615.
88. Karnieli, A. (1997). Development and implementation of spectral crust index over dune sands. International Journal of Remote Sensing. 18, 1207–1220.
89. Karnieli, A.; Kidron, G.J.; Glaesser, C.; Ben-Dor, E. (1997). Spectral characteristics of cyanobacterial soil crust in the visible, near infrared and short wave infrared (400– 2500 nm) in semiarid environments. Twelfth International Conference and Workshops on Applied Geologic Remote Sensing, vol. II (pp. 417– 424). Denver, Colorado.
90. Kettles, I.M.; Rencz, A.N.; Bauke, S.D. (2000). Integrating Landsat, geologic, and airborne gamma ray data as an aid to surficial geologymapping andmineral exploration in the Manitouwadge area, Ontario. Photogramm. Eng. Remote Sens, 66 (4), 437–445.
91. Kirkby, S.D. (1996). Integrating a GIS with an expert system to identify and manage dryland salinization. Applied Geography, 16(4), 289-303.
92. Komaki, C.B.; Alavipanah, S.K. (2006). Study of Spectral Separability of the Lut Desert Classes Based on Remotely Sensed Data. Geographical Researches, 37, 13-27.
93. Lam, D.K.; Remmel, T.K.; Drezner, T.D. (2011). Tracking Desertification in California Using Remote Sensing: A Sand Dune Encroachment Approach. Remote Sens, 3, 1-13.
94. Legrand, M.; Bertrand, J.J.; Desbois, M.; Meneger, L.; Fouquart, Y. (1989). The potential of infrared satellite data for the retrieval of Saharan dust optical depth over Africa. J. Appl. Meteorol, 28, 309–318.
95. Leone, A.P.; Sommer, S.; (2000). Multivariate analysis of laboratory spectra for the assessment of soil development and soil degradation in the southern apennines. Remote Sensing of Environment. 72, 346-359.
96. Lewis, M.; Jooste, V.; de Gasparis, A.A. (2001). Discrimination of arid vegetation with airborne multispectral scanner hyperspectral imagery. IEEE Transactions on Geoscience and Remote Sensing. 39, 1471– 1479.
97. Li, F.; Crow, W.T.; Kustas, W.P. (2010). Towards the estimation root-zone soil moisture via the simultaneous assimilation of thermal and microwave soil moisture retrievals. Advances in Water Resources, 33, 201–214.
98. Lievens, H.; Verhoest, N.E.C. (2012). Spatial and temporal soil moisture estimation from RADARSAT-2 imagery over Flevoland, The Netherlands. Journal of Hydrology, 456–457, 44–56.
99. Lillesand, T.M.; Kiefer, R.W.; Chipman, J.W. (2004). Remote Sensing and Image Interpretation. John Wiley and Sons Inc., New York, USA.
100. Liu, F.; Geng, X.; Zhu, A.X.; Fraser e, W.; Waddelle, A. (2012). Soil texture mapping over low relief areas using land surface feedback dynamic patterns extracted from MODIS. Geoderma, 171–172, 44–52.
101. Liu, W.; Baret, F.; Gu, X.; Zhang, B.; Tong, Q.; Zheng, L. (2003). Evaluation of methods for soil surface moisture estimation from reflectance data, international journal of remote sensing. 24(10), 2069-2083
102. Major, D.J.; Baret, F.; Guyot, G. (1990). A ratio vegetation index adjusted for soil brightness. Int. J. Remote Sensing. 11, 727-740.
103. Mahowald, N.M.; Bryant, R.G.; del Corral, J.; Steinberger, L. (2003). Ephemeral lakes and desert dust sources, Geophys. Res. Lett., 30, 1074, doi:10.1029/2002GL016041.

104. Margate, D.E.; Shrestha, D.P. (2001). The use of hyperspectral data in identifying desert-like soil surface features in tabernas area, southeast Spain. The 22nd Asian Conference on Remote Sensing 5-9, Singapore.
105. Mashimbye, Z.E.; Cho, A.; Nell, J.P.; De, W.P. (2012). Van niekerk a. and Turner. d. P. 2012. Model-Based Integrated Methods for Quantitative Estimation of Soil Salinity from Hyperspectral Remote Sensing Data: A Case Study of Selected South African Soils. Pedosphere, 22(5), 640–649.
106. Masoud, A.A.; Koike, K. (2006). Arid land salinization detected by remotely-sensed landcover changes: A case study in the Siwa region, NW Egypt. Journal of Arid Environments, 66, 151–167.
107. Matinfar, H.R.; Alavipanah, S.K.; Zand, F.; Khodaei, K. (2013). Detection of soil salinity changes and mapping land cover types based upon remotely sensed data. Arab J Geosci, 6, 913–919.
108. Melendez-Pastor, I.; Navarro-Pedreño, J.; Koch, M.; Gómez., I. (2010). Applying imaging spectroscopy techniques to map saline soils with ASTER images. Geoderma, 158, 55–65.
109. Metternicht, G.I.; Zink, J.A. (2003). Remote sensing of soil salinity: potentials and constraints. Remote Sensing of Environment, 85, 1 –20.
110. Metternicht, G.I. (2001). Assessing temporal and spatial changes of salinity using fuzzy logic, remote sensing and GIS. Foundations of an expert system. Ecological Modelling, 144, 163-179.
111. Metternicht, G.I.; Zinck, J. A. (1997). Spatial discrimination of salt- and sodium-affected soil surfaces. International Journal of Remote Sensing, 18, 2571–2586.
112. Mougenot, B.; Pouget, M.; Epema, G. (1993). Remote sensing of salt affected soils. Remote Sens. Rev. 7, 241–259.
113. Mulder, V.L.; de Bruin, S.; Schaepman, M.E.; Mayr, T.R. (2011). The use of remote sensing in soil and terrain mapping- A review. Geoderma, 162, 1–19.
114. Munns, R.; Tester, M. (2008). Mechanisms of salt tolerance. Annu. Rev. Plant Biol, 59, 651-681.
115. Noomen, M.F.; Skidmore, A.K.; van der Meer, F.D.; Prins, H.H.T. (2006). Continuum removed band depth analysis for detecting the effects of natural gas, methane and ethane on maize reflectance. Remote Sens. Environ. 105, 262–270
116. Odeh, I.O.A.; McBratney, A.B. (2000). Using AVHRR images for spatial prediction of clay content in the lower Namoi Valley of eastern Australia. Geoderma, 97 (3–4), 237–254.
117. Offer, Z.Y.; Goossens, D. (2001). Ten years of aeolian dust dynamics in a desert region (Negev desert, Israel): analysis of airborne dust concentration, dust accumulation and the high-magnitude dust events. Journal of Arid Environments, 47, 211–249.
118. Okin, G.S.; Roberts, D.A. (2004). Remote Sensing in Arid Regions: Challenges and Opportunities. Remote Sensing for Natural Resource Management and Environmental Monitoring (S.L. Ustin, Ed.), John Wiley and Sons, New York.
119. Okin, G.S.; Roberts, D.A.; Murray, B.; Okin, W.J. (2001). Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments. Remote Sensing of Environment, **77**, 212–225.
120. O’Neill, A.L. (1994). Reflectance spectra of microphytic soil crusts in semiarid Australia. International Journal of Remote Sensing, 15, 675– 681.
121. Pinker, R.T.; Karnieli, A. (1995). Characteristic spectral reflectance of a semi-arid environment. International Journal of Remote Sensing. 16, 1341– 1363.
122. Price, J.C. (1980). The potential of remotely sensed thermal infrared data to infer surface soil moisture and evaporation. Water Resources Research. 16, 787-795.
123. Rao, B.; Dwivedi, R.; Venkataratnam, L.; Ravishankar, T.; Thammappa, S.; Bhargawa, G.; Singh, A. (1991). Mapping the magnitude of sodicity in part of the Indo-Gangetic plains of Uttar Pradesh, Northern India using Landsat-TM data. International Journal of Remote Sensing, 12, 419–425.
124. Rollin, E.M.; Milton, E.J.; Roche, P. (1994). The influence of weathering and lichen cover on the reflectance spectra of granitic rocks. Remote Sensing of Environment. 50, 194– 199.
125. Rosso, P.H.; Pushnik, J.C.; Lay, M.; Ustin, S.L. (2005). Reflectance properties and physiological responses of Salicornia virginica to heavy metal and petroleum contamination. Environ. Pollut. 137, 241–252.
126. Schlesinger, W.H.; Raikes, J.A.; Cross, A.F. (1996). On the spatial pattern of soil nutrients in desert ecosystems. Ecology. 77, 364-376.
127. Schnur, M.T.; Xie, H.; Wang, X. (2010). Estimating root zone soil moisture at distant sites using MODIS NDVI and EVI in a semi-arid region of southwestern USA. Ecological Informatics, 5, 400–409.
128. Schmidt, H.; Karnieli, A. (2000). Remote sensing of the seasonal variability of vegetation in a semi-arid environment. Journal of Arid Environments. 45, 43–59
129. Scull, P.; Franklina, J.; Chadwickb, O.A.; McArthura, D. (2003). Progress in Physical Geography, 27, 171–197.

130. Setia, R.; Lewis, M.; Marschner, P.; Raja segaran, R.; Summers, D.; Chittleborough, D. (2011). Severity of salinity accurately detected and classified on a paddock scale with high resolution multispectral satellite imagery. Land degradation & development, Published online in Wiley Online Library DOI: 10.1002/ldr.1134.
131. Shrestha, D.P.; Margate D.E.; van der Meer, H.V. (2005). Analysis and classification of hyperspectral data for mapping land degradation: An application in southern Spain. International Journal of Applied Earth Observation and Geoinformation, **7**, 85–96.
132. Sohn, Y.; McCoy, R. (1997). Y Mapping desert shrub rangeland using spectral unmixing and modeling spectral mixtures with TM data Photogrammetric Engineering and Remote Sensing. 63, 707–716.
133. Sommer, S.; Hill, J.; Megier, J. (1998). The potential of remote sensing for monitoring rural land use changes and their effects on soil conditions. Agriculture Ecosystems and Environment. 67, 197-209.
134. Stoops, W.A. (1984). Soil formation processes in the west Africa Savanna landscape; implications for soil fertility and agronomic research aimed at different top sequence land types. ISNAR drattreport, July, 1984.
135. Su, H.; McCabe, M.F.; Wood, E.F.; Su, Z.; Prueger, J.H. (2005). Modelling evapotranspiration during SMACEX: comparing two approaches for local- and regional-scale prediction. J. Hydrometeorology, 6, 910–922.
136. Summers, D.; Lewis, M.; Ostendorf, B.; Chittleborough, D. (2011). Visible near-infrared reflectance spectroscopy as a predictive indicator of soil properties. Ecological Indicators, 11, 123–131.
137. Tanré, D.; Legrand, M. (1991). On the satellite retrieval of Saharan dust optical thickness over land: Two different approaches. J. Geophys. Res, 96, 5221–5227.
138. Tanre, D.; Deschamps, P.Y.; Devaux, C.; Herman, M. (1988). Estimation of Saharan aerosol optical depth from blurring effects in Thematic Mapper data. Journal of Geophysical Research. 93 (D12), 15955– 15964.
139. Tanser, F.; Palmer, A. (1999). The application of a remotely-sensed diversity index to monitor degradation patterns in a semi-arid, heterogeneous. South African Landscape Journal of Arid Environment. 43, 477–484
140. Tansey, K.J.; Edwards, M.C.; Milliington, A.C. (1998). Remote sensing of desert regions: a tool to aid research and development. Proceedings IGARSS'98, Seattle, USA.
141. Teruiya, R.K.; Paradella, W.R.; Dos Santos, A.R.; Dall'Agnol, R.; Veneziani, P. (2008). Integrating airborne SAR, Landsat TM and airborne geophysics data for improving geological mapping in the Amazon region: the Cigano Granite, Caraja's Province, Brazil. Int. J. Remote Sens. 29(13), 3957–3974.
142. Thorhaug, A.; Richardson, A.D.; Berlyn, G.P. (2006). Spectral reflectance of Thalassia testudinum (Hydrocharitaceae) seagrass: low salinity effects. Am. J. Bot. 93, 110–117.
143. Tilley, D.R.; Ahmed, M.; Son, J.H.; Badrinarayanan, H. (2007). Hyperspectral reflectance response of freshwater macrophytes to salinity in a brackish subtropical marsh. J. Environ. Qual. 36, 780–789.
144. Todd, S.W.; Hoffer, R.M. (1998). Responses to spectral indices to variations in vegetation cover and soil back- ground. Photogramm. Eng. Remote Sens. 64, 915-921.
145. Van der Kwast, J. (2009). Quantification of top soil moisture patterns: Evaluation of field methods, process-based modelling, remote sensing and an integrated approach. PhD Thesis. KNAG/Fac. Geowetenschappen, 313 p.
146. Viscarra Rossel, R.A. (2008). ParLeS: software for chemometric analysis of spectroscopic data. Chemom. Intell. Lab. Syst. 90(1), 72–83.
147. Viscarra Rossel, R.A.; Cattle, S.R.; Ortega, A.; Fouad, Y. (2009). In situ measurements of soil colour, mineral composition and clay content by vis-NIR spectroscopy. Geoderma. 150(3–4), 253–266.
148. Ustin, S.L.; Valko, P.G.; Kefauver, S.C.; Santos, M.J.; Zimpfer, J.F.; Smith, S.D. (2009). Remote sensing of biological soil crust under simulated climate change manipulations in the Mojave Desert. Remote Sensing of Environment. 113, 317-328.
149. Wagner, W.; Pathe, C.; Doubkova, M.; Sabel, D.; Bartsch, A.; Hasenauer, S.; Blöschl, G.; Scipal, K.; Martínez-Fernández, J.; Löw, A. (2008). Temporal stability of soil moisture and radar backscatter observed by the Advanced Synthetic Aperture Radar (ASAR). Sensors. 8, 1174–1197.
150. Wagner, W.; Naeimi, V.; Scipal, K.; De Jeu, R.A.M.; Martinez-Fernandez, J. (2007). Soil moisture from operational meteorological satellites. Hydrogeology Journal, 15, 121–131.
151. Wagner, W.; Lemoine, G.; Rott, H. (1999). A method for estimating soil moisture from ERS scatterometer and soil data. Remote Sensing of Environment. 70, 191–207
152. Wald, A.; Kaufman, Y.J.; Tanré, D.; Gao, B.C. (1998). Daytime and nighttime detection of mineral dust over desert suing the thermal IR. J. Geophys. Res. 103, 307–32 313.
153. Wang, Q.; Li, P.; Chen, X. (2012). Modelling salinity effects on soil reflectance under various moisture conditions and its inverse application: A laboratory experiment. Geoderma. 170, 103–111.

154. Wang, L.; QU, J.J. (2009). Satellite remote sensing applications for surface soil moisture monitoring: A review. Front. Earth Sci, 3(2), 237–247.
155. Wang, D.; Poss, J.A.; Donovan, T.J.; Shannon, M.C.; Lesch, S.M. (2002). Biophysical properties and biomass production of elephant grass under saline conditions. J. Arid Environ. 52, 447–456.
156. Wessels, D.C.J.; Van Vuuren, D.R.J. (1986). Landsat imagery—its possible use in mapping the distribution of major lichen communities in the Namib Desert, South West Africa. Madoqua. 14, 369– 373.
157. Wiegand, C.L., Rhoades, J.D., Escobar, D.E., Everitt, J.H., 1994. Photographic and videographic observations for determining and mapping the response of cotton to soil-salinity. Remote Sens. Environ. 49, 212–223.
158. Whiting, Michael L.; Ustin, Susan L. (2004). Mapping of desert biological soil crust using hyper spectral water bands. Center for Spatial Technologies and Remote Sensing, Department of Land, Air, and Water Resources, University of California, Davis, CA, USA.
159. Yamano, H.; Chen, J.; Zhang, Y.; Tamura, M. (2006). Relating photosynthesis of biological soil crusts with reflectance: preliminary assessment based on a hydration experiment. International Journal of Remote Sensing. 27, 5393-5399.
160. Zorrig, W.; Rabhi, M.; Ferchichi, S.; Smaoui, A.; Abdelly, C. (2012). Phytodesalination: a solution for salt-affected soils in arid and semi-arid regions. Journal of Arid Land Studies. 22-1, 299 -302.
161. Wang, C.; Qi, J.; Moran, S.; Marsett, R. (2004). Soil moisture estimation in a semiarid rangeland using ERS-2 and TM imagery. Remote Sensing of Environment. 90, 178 – 189
162. Wang, X.; Xie, H.; Guan, H.; Zhou, X. (2007). Different responses of MODIS-derived NDVI to root-zone soil moisture in semi-arid and humid regions. Journal of Hydrology. 340, 12– 24.
163. Weber, B.; Olehowski, C.; Knerr, T.; Hill, J.; Deutschewitz, K.; Wessels, D.C.J.; Eitel, B.; Büdel, B. (2008). A new approach for mapping of Biological Soil Crusts in semidesert areas with hyperspectral imagery. Remote Sensing of Environment. 112, 2187–2201.
164. Weng, Y.L.; Gong, P.; Zhu, Z.L. (2010). A spectral index for estimating soil salinity in the Yellow River Delta Region of China using EO-1 Hyperion data. Pedosphere. 20(3), 378–388.
165. Wuthrich, M. (1994). ERS-1 SAR compared to thermal infrared to estimate surface soil moisture. Proceedings of the 21st Conference on Agricultural and Forest Meteorology. American Meteorological Society, 197-200.
166. Zhou, D.K.; Larar, A.M.; Smith, W.L.; Liu X. (2006). Surface emissivity effects on thermodynamic retrieval of IR spectral radiance. Proc. of SPIE. 64051H, 1-8.
167. Zribi, M.; Kotti, F.; Lili-Chabaane, Z.; Baghdadi, N.; Ben Issa, N.; Amri, R. (2012). Analysis of soil texture using TERRASAR X-band SAR. IEEE International Geoscience and Remote Sensing. 7027–7030.