

Land Degradation Indicators: Spectral Indices

Sabine Chabrillat

*GeoForschungsZentrum (GFZ) Potsdam, Dept 1: Geodesy and Remote Sensing, Section 1.4:
Remote Sensing, Telegrafenberg, D-14473 Potsdam, Germany*

Abstract: Desertification is a land degradation problem of major importance in the arid regions of the world. Deterioration in soil and plant cover has adversely affected nearly 70% of the drylands. Combating desertification involves having an accurate knowledge on current land degradation status and the magnitude of the potential hazard. The status of dryland systems is controlled to a large extent by a fragile equilibrium between soil, vegetation and water resources. Understanding of processes involves also the quantitative description of the interplay between soil and vegetation components. Dryland degradation may be triggered by (global) climatic change and/or human mismanagement. While the former may result in longer and more frequent drought events, the latter mainly consists of inappropriate land use practices. Both may induce changes in surface properties that can be detected remotely by measuring the spectral characteristics of the land surfaces from remote sensing data. Global soil and vegetation maps derived from satellite data are one of the primary sources of information for operational monitoring of the Earth. Advanced optical remote sensing techniques such as imaging spectrometry allows the determination of enhanced land degradation variables. It includes vegetation parameters and soil-related information such as green vegetation cover, senescent vegetation, leaf water content, photosynthetic pigments (chlorophyll, carotenoid, anthocyanins), foliage chemistry (nitrogen, cellulose), soil chemical properties (iron, organic matter, clay, carbonate content), soil moisture, salinity, detection of biological/structural crust, and runoff. These land surface variables can be directly linked to land degradation status. Spectral indices have been developed based on diagnostic features in the visible near-infrared (VNIR) and short wave infrared (SWIR) reflectance spectrum, allowing qualitative and quantitative description of the Earth's surface changes in terms of bio- and geophysical/chemical properties, as a major step toward the quantitative monitoring of land degradation and desertification.

Key words: Desertification, land degradation indicators, remote sensing, hyperspectral, spectral indices.

Current Concepts

Desertification and land degradation: Introduction

The word "desertification" was introduced by the French scientist Aubréville (1949) in his report "Climats, forêts et désertification de l'Afrique

tropicale". The concept was discussed earlier by European and American scientists in terms of increased sand movement, desiccation, desert and Sahara encroachment and man made deserts (e.g., Hubert, 1920; Boville, 1921; Renner, 1926; Stebbing, 1938; Lowdermilk, 1935; Jones, 1938). The concept of desertification has been the

subject of continuous debate ever since the term was introduced, with major disagreements on the causes, impacts, reversibility, environmental setting, rate of progress and cures (Verstraete and Schwartz, 1991; Thomas and Middleton, 1994). The last definition of desertification was revised in 1992 by the United Nations at the UNCED, and recognizes that desertification is the same thing as land degradation. "Desertification is land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activities" (UNCED, 1992). The general processes playing a major role in desertification are influencing mostly arid and sub-arid zones (drylands), i.e. where the aridity index, the ratio of the mean annual precipitation P , to mean annual potential evapotranspiration PE , is less than 0.65 for the period 1951-1980 (UN Environment Program, 1992). Arid and semi-arid lands cover approximately one

third of the continental surface of the Earth. The semi-arid ecosystems provide important land resources for adapted agricultural production and grazing systems. Considered areas are at risk among the drylands in the context of global climatic change and worldwide desertification dynamics. About 70% (3,600 Mha) of the drylands are already in some stage of degradation (UN, 1991), associated with enormous direct loss in income and indirect economic and social costs for the people affected. The vulnerable areas (Fig. 1) are spread worldwide, in Africa, Asia, America, Australia, and Mediterranean countries.

The UN Convention to Combat Desertification (UNCCD, 1994), ratified by almost 180 nations worldwide, in particular emphasizes the need to assess land degradation and desertification processes, and call for specific tools of assessment, surveillance, early warning, and monitoring of desertification. Indeed, the knowledge

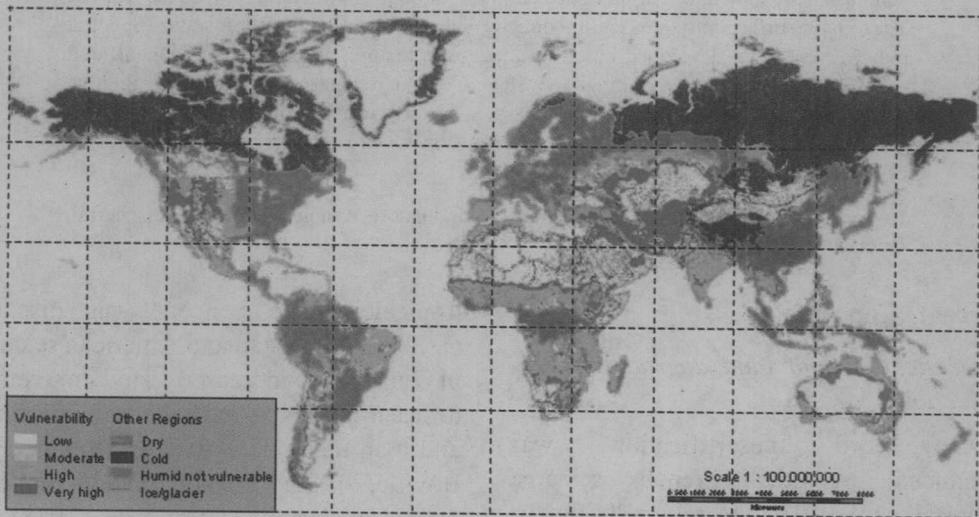


Fig. 1. Global desertification vulnerability (From Schlesinger, 1997).

on a current land degradation status or the magnitude of the potential hazard is for the most part incomplete and fragmented (Boer, 1999).

Land degradation results in the reduction of biological productivity of ecosystems caused by soil and vegetation degradation. A global database of soil degradation, the GLASOD (Global Assessment of Human-Induced Soil Degradation), which besides contains information about the severity of anthropogenic soil degradation, was collected in the 1980s. It defines soil degradation as a human-induced phenomenon, which lowers the current and/or future capacity of the soil to support human life (Oldeman *et al.*, 1990). Two categories of soil degradation process were identified: degradation by displacement of soil material caused by water and wind erosion, and internal soil deterioration by physical and chemical processes. Water erosion involves the displacement of soil material in three main stages: detachment of individual grains from the soil mass, transport over the land, and deposition as sediment on a new site. Wind erosion involves the loss of topsoil, terrain deformation, and over blowing of sediments. Chemical deterioration occurs when land use methods are rather intensive and combined with the cultivation practices, i.e. use of fertilizers and irrigation practices. Salinization, organic matter loss, soil nutrient depletion, acidification, and pollution, are all chemical deterioration processes. The processes involving physical deterioration of the soils can be sealing and crusting of topsoil, the compaction of topsoil, deterioration of soil structure due to the dispersion of soil material by salts

in the subsoil (sodification), waterlogging, aridification (leading to a more water-deficient soil system), and subsidence of organic soil.

Links between desertification, soil degradation and vegetation are complex. Indeed, vegetation has a recovery rate much faster when compared to soil degradation, and an effectively permanent undesirable change to vegetation can occur only when the soil resource itself has been severely degraded. On the other hand, drylands vegetation generally displays a sensitivity to natural climatic variability, e.g., reducing production and an ability to lie-dormant are two strategies displayed by arid land plants for survival at times of moisture deficiency. For example, desertification has been used to describe land degradation along the southern border of the Sahara desert, where the desert was found to be expanding southward at 5.5 km per year in the Sudan and Sahel (UN survey, 1975). In fact, this expansion, reaching its peak in 1984, was effectively reversed with a return to a period of greater rainfall in more recent years, and there was no long-term loss in the productive capacity of the land in most areas (Tucker *et al.*, 1991; Prince *et al.*, 1998). It may thus be very difficult to distinguish if a particular vegetation state at a particular time is a consequence of natural short-term climatic variability or a longer-term trend induced by soil degradation (Menenti *et al.*, 1999). These factors contribute to the absence of an adequate global database of vegetation degradation. But vegetation cover may help to indicate vulnerability to soil degradation (limited plant cover and low biomass), and the type of communities of the vegetation cover may indicate that soil degradation has occurred or is taking place.

assessment scheme based on the combination of spectroscopic indicators of soil and vegetation degradation with climate and ancillary data using an index called land degradation index (LDI):

$$\text{LDI} = \text{SD} + \text{VD} + \text{C} + \text{A} \quad \dots(2)$$

where,

SD = Spectroscopic indicator of soil degradation severity

VD = Vegetation degradation severity

C = Climate data (precipitation + potential evapotranspiration)

A = Ancillary data (population)

Following another spectral approach to express land degradation, a Land Degradation Index (LDI) was also proposed by Chikhaoui *et al.* (2005) and successfully implemented using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images to analyze and evaluate the risks of the expansion of soil degradation in Northern Morocco. This index was based on the concept of soil line derived from spectroradiometric ground measurements.

Science and Technology

Reflectance spectroscopy and imaging spectroscopy

When light interacts with a mineral, rock, or a leaf, light of certain wavelengths is preferentially absorbed while at other wavelengths it is transmitted in the substance. The quantity of interest, reflectance, is defined as the ratio of the intensity of light reflected from a sample to the intensity of light incident on it. Reflectance is measured with spectrometers,

which separate light reflected from a source into various wavelengths. The light from the source interacts with the sample and the intensity of reflected light at various wavelengths is measured by a detector, relative to a reference standard of known reflectance. Thus a continuous reflectance spectrum of the sample is obtained in the wavelength region measured. Many of the Earth's materials exhibit significant spectral absorption features in the 400-2500 nm spectral range, within atmospheric windows, that can serve as diagnostic indicators. These absorption mechanisms constitute the basis for the characterization of surface properties in drylands, for both soils and vegetation processes, based on reflectance spectroscopy. Figure 3 shows a synthetic reflectance spectrum from a target composed of green photosynthetic vegetation (observation of chlorophyll absorption features ~450 and 680 nm, and strong "red-edge") mixed with soils (observation of clay absorption band ~2200 nm), and locates wavelength regions recommended per parameter.

Remote sensing of the surface of the Earth from an aircraft and from a spacecraft provides information not easily acquired by surface observations. Until recently, the main limitation of remote sensing was that surface information lacked detail due to the broad bandwidth of available sensors. Work in the laboratory and at the telescope over the past few decades has amply demonstrated the utility of reflectance spectroscopy for determining the composition of the surface materials of the Earth and other planetary bodies (e.g., Hunt and Salisbury, 1970; Clark *et al.*, 1990). Recent advances in several key sensor

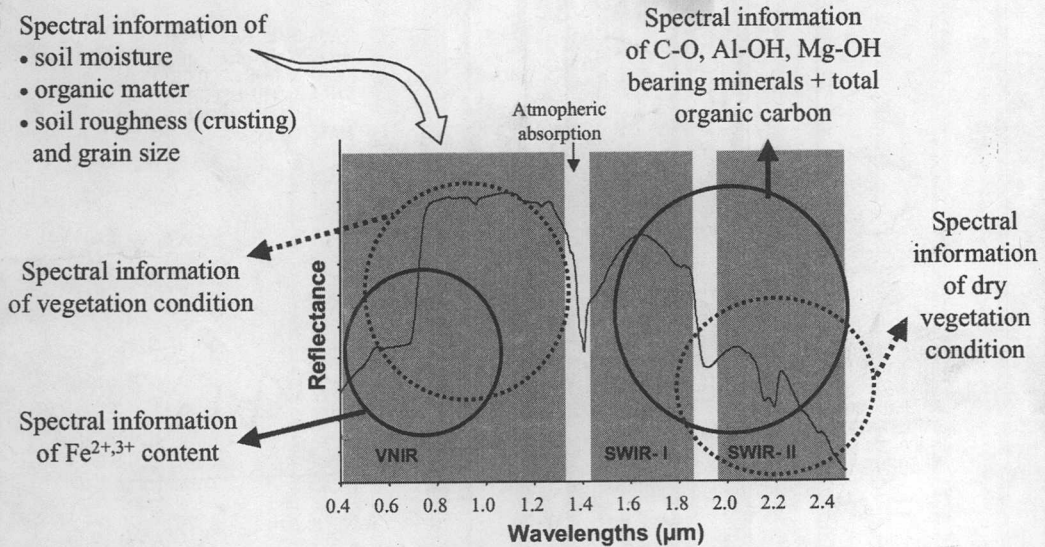


Fig. 3. Extraction of drylands biogeochemical parameters from reflectance spectroscopy.

technologies now make it possible to combine the power of spectroscopy with the advantages of imaging to acquire spectroscopic information over large areas. This new approach to narrow-band optical (and/or thermal) remote sensing is called *imaging spectroscopy* or *hyperspectral imagery*.

The concept underlying imaging spectroscopy is illustrated in Figure 4. It consists of acquiring images in many (>100) narrow contiguous spectral bands (Goetz *et al.*, 1985), thus providing a continuous spectrum for each pixel, unlike multispectral systems that acquire images in a few (<10) wide spectral bands. Conventional sensors (e.g. Landsat MSS and TM, and SPOT) acquire information in a few separate spectral bands of various widths, typically in the order of 100-200 nm, thus under sampling to a large extent the reflectance characteristics of the surface (Goetz and Rowan, 1981). Hyperspectral images

acquire information in spectral bandwidths typically on the order of 10-20 nm, which is sufficient for analysis of the composition of each picture element (*pixel*) in the image (Green *et al.*, 1998).

Retrieval of biogeochemical and biophysical spectral information

Spectral features of rocks and soils originate from electronic and vibrational transitions that characterize the specific minerals that are contained. The location of features at definite wavelengths derives from the characteristics of the crystal lattice, such as co-ordination number, nature of ligands and nature of the central ion. Co-ordination number and ligands define the electric field exerted on the central ion and, thereby, the order of magnitude of electronic or vibrational processes (Hunt and Salisbury, 1970). Mineral identification according to spectral absorption features is feasible for minerals containing molecules

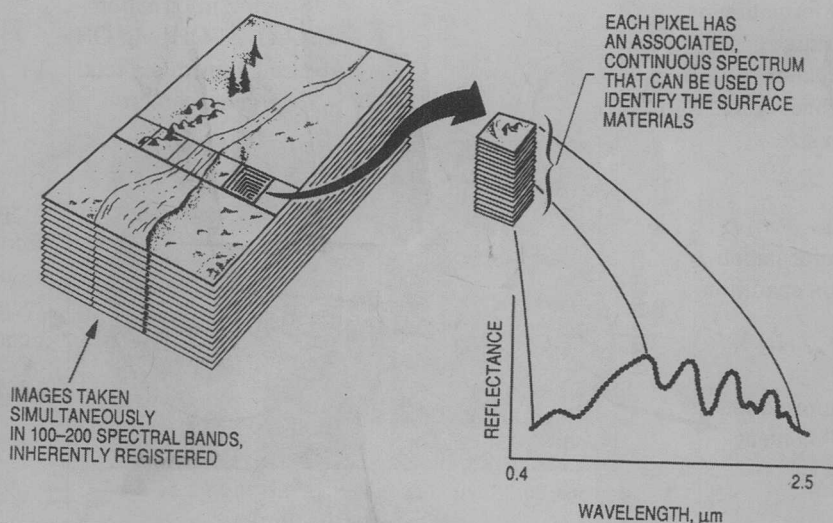


Fig. 4. The concept of imaging spectroscopy or hyperspectral imagery (from Vane *et al.*, 1993).

or anions like H_2O , OH^- , SO_4^{2-} , CO_3^{2-} or CH . This encompasses the phyllosilicates, most sorosilicates, the hydroxides, some sulphates, the amphiboles and the carbonates. Electronic features at ~ 500 , 650 , and $900\text{-}1000$ nm are caused mainly by charge transfer bands and crystal field transitions of iron in the bi- and trivalent state and can be related to iron content. The dominance of the ferrous and ferric ion in the visible-near infrared (VNIR) spectral range ($400\text{-}1300$ nm) is due to their large distribution on the Earth's surface and their ability to replace many other ions (e.g., Mg^{2+} , Al^{3+} , Si^{4+} , and Mn^{2+}) in various minerals. Absorption features due to vibrational transitions are located in the short-wave infrared (SWIR) spectral range ($1300\text{-}2500$ nm), and are caused by overtones and combination tones originating from the fundamental modes in various multiplicities. These features arise from molecule vibrations or vibrations of atomic

groups, which form independent oscillatory units within the molecules. Widely spread oscillatory units in naturally occurring minerals are Al-OH , Mg-OH and C-O . Minerals containing one of these groups show characteristic frequencies within narrow wavelength ranges around 2200 nm (Al-OH) and 2300 nm (Mg-OH/C-O) that have been used to identify respectively clay minerals (e.g. Chabrilat *et al.*, 2002a) and carbonates (e.g. Kruse, 1988; Clark *et al.*, 1992) in rocks or soil surfaces based on imaging spectroscopy. The exact position of the frequency is determined by the neighboring molecules or parts of them.

The reflected solar radiation covering the wavelength region from about 400 to 2500 nm is also excellent for detecting vegetation species, vegetation health, and green leaf water content. The visual portion of the spectrum is characterized by strong pigment absorptions such as chlorophyll in the $630\text{-}690$ nm region and by

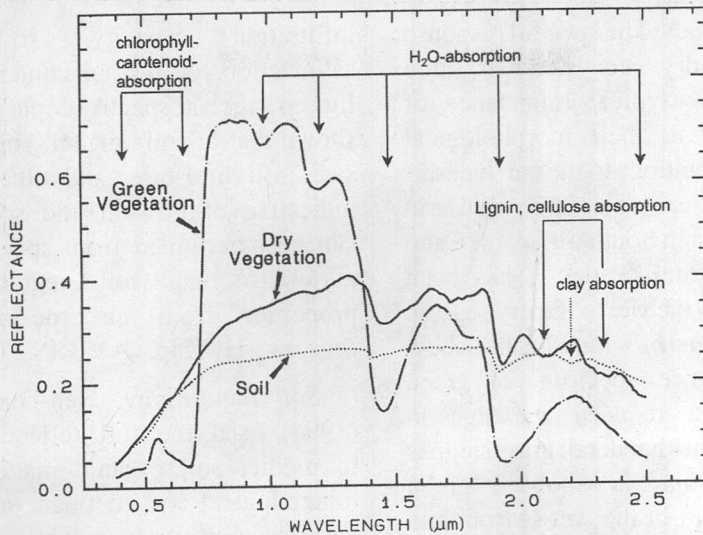


Fig. 5. Typical spectra of a fresh green leaf, an advanced stage of dry leaf weathering, and a bare clay soil, assigning spectral absorption bands used to differentiate. The dry grass residue here lacks a red-edge feature.

chlorophyll/carotenoid in the blue range. The near infrared (NIR) is marked by a steep increase of reflectance, called red-edge, that can be related to biomass, state and type of cellular arrangement, density, geometry and water content (e.g., Tucker, 1979). Absorptions due to leaf liquid water are caused by O-H bonds of water. A shift of the red-edge to shorter wavelengths is related to chlorophyll decrease, which can in turn be an indication of heavy metal or water stress. A strong relationship exists between spectral reflectance and the amount of green vegetation. Biochemical contents of leaves and canopies, including nitrogen-containing compounds and lignin, absorb radiation at fundamental stretching frequencies, generally in the NIR but also in the SWIR regions. The absorption bands in this wavelength region mainly originate as harmonics and overtones of the fundamental

stretching frequencies of C-H, O-H, and N-H bonds together with various combination bands. The dry vegetation has got three characteristic absorption features with maximum values around 1730 nm, 2100 nm and 2300 nm. These absorption features are caused by the overlapping of the absorption from the cell components lignin, starch and sugar (1730 nm), cellulose and starch (2100 nm), cellulose, starch and sugar (2300 nm) (Gao and Goetz, 1994; Curran, 1989; Kokaly and Clark, 1999).

Figure 5 shows typical drylands spectral signatures, mainly associated with green photosynthetic vegetation activity, non-photosynthetic biological activity (dry grasses, desert shrubs, plant residues), and soil components. In arid regions, plant cover usually consists of perennial plants (which are neither abundant nor very dense) and some short-lived (i.e., annual) herbaceous vegetation that only appears for some weeks

after the rainy periods. The spectral response of perennials in dry ecosystems is quite different from the typical reflectance of green plants due to their morphological and structural adaptations to the harsh desert environment. For example in a semi-arid Mediterranean area in Southern Spain (Cabo de Gata-Níjar Natural Park), it has been observed that from the wet to the dry season, palm trees (*chamaerops humilis* L.) show a typical reflectance spectrum of green vegetation with a reduced red-edge in summer. On the other hand, tall grass steppes of *Stipa tenacissima* L. show a green vegetation spectrum in the wet season, and a typical dry plant residue spectral signature in the dry season, with a small red-edge that can be totally lacking, and dry matter (lignin, cellulose) signatures in the SWIR part of the spectrum (Chabrillat *et al.*, 2005; Escribano *et al.*, 2007). Also, depending on desert species and interannual variability within wet and dry season, both photosynthetic (PV) and non-photosynthetic (NPV) biological activities can be monitored and differentiated through remote sensing and in particular using narrow-band hyperspectral sensors covering the VNIR-SWIR range of the spectrum.

Mapping Soil and Plant Properties Using Spectral Indices

Indicators of soil degradation

Spectroscopic indicators of soil degradation have been developed based on direct or indirect measurements of the following variables: soil mineralogy (chemical composition, mineralogy: iron content, carbonate content, organic matter content), lithological background, biogenic/mineralogic crust, organic/inorganic carbon,

infiltration capacity, soil moisture, salinization, rock vs. soil content, and runoff. Indeed, recent spectroscopic studies have shown that organic matter, soil types, grain size, soil moisture, and other parameters indicative of erosion and soil conditions can be determined from spectral data and allow to map soil degradation-related properties from airborne hyperspectral sensors (HyMap, AVIRIS, DAIS 7915).

Soil mineralogy: Ben-Dor and Banin (1994) used the full reflective spectrum to predict soil organic matter and other mineralogical and chemical soil properties based on multivariate statistics. Multivariate analyses of spectral data have been used as well to assess soil degradation (Leone and Sommer, 2000) and soil swell potential (Goetz *et al.*, 2001). Palacios-Orueta *et al.* (1999) developed spectral models to determine organic matter and iron content and successfully applied them to predict soil mineralogy from imaging spectroscopy.

Soil moisture: Several studies focused on the study of relationships between soil reflectance and surface moisture, and developed methodologies to predict soil moisture content from reflectance spectroscopy data based on the full spectrum (Weidong *et al.*, 2003; Whiting *et al.*, 2004) or on narrow-band indices such as the Normalized Soil Moisture Index NSMI (Haubrock *et al.*, 2007; Table 1).

Organic/inorganic carbon: Hill and Schütt (2000) proposed a successful method to retrieve organic carbon in xeromorphic soils, which highlights areas of accumulation and relative stability (sediment sinks). Jarmer *et al.* (2005) successfully mapped content of inorganic carbon in the Judean Desert, Israel.

Soil erosion: Common indicators of erosion are a decrease of organic matter, associated with the appearance of lower soil horizons at the surface. In the presence of iron-rich soils, the estimation of organic matter content is difficult (Richter *et al.*, 2005; Palacios-Orueta and Ustin, 1998), since the presence of organic matter would flatten spectral shape in the VNIR range, where iron diagnostic absorption bands would occur. Then, when organic matter content is low and iron content is high, iron content can be used as an indicator of erosion. Richter *et al.* (2007) successfully predicted soil iron content using HyMap images in a semi-arid environment in southern Spain, and could relate the appearance of iron-rich soil layers at the surface with the erosion of upper soil layers.

Rock/soil content: Since soil erosion leads to an increase in rock cover in source areas and the accumulation of soil material as colluvium elsewhere, rock content can be used as an indicator of degradation. Methodologies such as the spectral mixture analysis, or spectral unmixing (Adams *et al.*, 1993) have been used to estimate the relative amounts of rock fragments and soil particles on the surface.

Salinization: One of the major causes of soil degradation is salinity. The presence of salt-affected soils can be monitored based on its effect on the optical properties of the upper soil layers. Taylor *et al.* (2001) showed that dryland salinity in the Dicks Creek catchment in Australia could be characterized by the occurrence of spectrally distinctive smectitic clays around surface salt scalds. Dehaan and Taylor (2002, 2003) demonstrated HyMap imagery capability to map various categories of salt-affected

soils, and the accompanying halophytic vegetation.

Biological soil crust: In many dryland ecosystems biological crusts are dominating the soil surface. The ecological importance of these crusts is related to their resistance against erosion caused by wind or surface runoff, and to the protection of infiltrated rainwater against excessive evaporation. Optically active components in the biological crust that can be identified with remote sensing systems are protein, carbohydrate and chlorophyll contents. Hill *et al.* (1998) used spectral unmixing of reflectance signatures for the successful identification and spatial differentiation of soil substrates and biological crusts in sandy arid ecosystems using DAIS 7915 images. The spectral information used not only depended on characteristic well-known spectral features at definite wavelengths, but on the detailed analysis of the albedo and shape of the full reflective spectrum in the VNIR and SWIR.

Mineralogical soil crust/runoff: A common cause of runoff of rain and overhead irrigation water is the structural crust (term defined by Hillel, 1959) that develops over bare soils during rainfall or irrigation. The structural crust is associated with the formation of a seal in the soil's upper layer due to raindrop impact energy that disintegrates soil aggregates and rearranges soil particles. This significantly affects the physical properties of the soils such as reducing infiltration rate and hydraulic conductivity and leads to increased water runoff affecting land degradation processes. It has been shown that the formation of a structural crust affects the optical properties of the upper soil layer

Table 1. Spectral indices recommended for the assessment of soil parameters (Modified from Ustin *et al.*, 2005)

Index	Formula	Estimated soil parameter
NDI	$(R_{840} - R_{1650}) / (R_{840} + R_{1650})$	Discriminates soil and dry matter
SACRI	$\frac{\alpha (R_{840} - \alpha R_{1650} - \beta)}{R_{1650} - \alpha R_{840} - \alpha \beta}$	Improved NDI discrimination
NSMI	$(R_{1800} - R_{2119}) / (R_{1800} + R_{2119})$	Soil moisture content
TM Indices:		
BI	$BI = \sqrt{(TM1^2 + TM2^2 + TM3^2)} / 3$	Average soil reflectance
SI	$SI = (TM3 - TM1) / (TM3 + TM1)$	Spectral slope
HI	$HI = (2 \times TM3 - TM2 - TM1) / (TM2 - TM1)$	Dominant wavelength
CI	$CI = (TM3 - TM2) / (TM3 + TM2)$	Hematite/Hematite+goethite ratio
RI	$RI = TM3^2 / (TM1 \times TM2)$	Hematite content

NDI: Normalized Difference Index (McNairn and Protz, 1993); SACRI: Soil Adjusted Crop Residue Index (Biard and Baret, 1997); NSMI: Normalized Soil Moisture Index (Haubrock *et al.*, 2007); BI: Brightness Index (Escadafal *et al.*, 1994); SI: Saturation Index, HI: Hue Index (Escadafal and Huete, 1991); CI: Coloration Index (Mathieu *et al.*, 1998; Madeira *et al.*, 1997); RI: Redness Index (Maderia *et al.*, 1997).

that change colors in the presence of crusted soils (Goldshleger *et al.*, 2001; Ben-Dor *et al.*, 2003). Relationships between spectral reflectance and infiltration rate were developed, allowing the monitoring of infiltration rate based on hyperspectral imagery (Ben-Dor *et al.*, 2004).

Soil indices: In order to monitor and assess desert conditions and desertification, it is essential to develop accurate maps of soil properties. Based on specific absorption features, soil indices were defined that allow the production of global maps of soils with low amount of vegetation. For this purpose, different soil indices automatically applicable from wide-band (Landsat TM, ASTER, AVHRR, SPOT HRV) or narrow-band (MeRIS, CHRIS-PROBA, Hyperion) spaceborne remote sensing sensors (as long as the required spectral bands are present) have been developed, and are shown in Table 1.

The soil indices developed are related to the discrimination of soils from dry matter, and the estimation of crop residue, or soil water content, or soil color (mineralogy). Soil color is defined by parent material, weathering, and topography that are related to soil biophysical properties; therefore color might be used as an indicator of erosion or deposition or as an indicator of surface organic matter/iron. Redness indices are important for characterizing soil weathering and oxidation. Madeira *et al.* (1997) and Mathieu *et al.* (1998) found high correlation between the Helmholtz definition of color and Thematic Mapper indices in an arid environment. Soil moisture is an important variable for erosion and land degradation models. The NSMI soil moisture index has been developed for field conditions in an arid environment and is applicable for remote sensing applications (Haubrock *et al.*, 2005) provided that the soils are well exposed.

Indicators of vegetation change

Spectroscopic indicators of vegetation changes linked to land degradation processes can be developed from the determination of the following variables: fractional vegetation cover, fraction dry vs. green vegetation cover, fractional perennials vs. annuals, leaf water content, foliage chemistry. These variables have the potential to be derived, directly or indirectly, from VNIR-SWIR optical data, as it has been shown in many studies.

Fraction ground cover: Ground cover fraction estimates are frequently used parameters in land degradation models (e.g. Boer and Puigdefabregas, 2003), since the type (bare soil or plants), the degree (sparse vs. dense canopies) and the spatial distribution pattern alter the surface runoff and thus the erosion potential. Fraction ground coverage is estimated for photosynthetically active vegetation (PV), non-photosynthetically active and dead vegetation (NPV), bare soil and rocks. In order to extract quantitative ground cover fractions, approaches based on the linear mixture model were successfully applied in a large number of studies (e.g. Asner and Lobell, 2000; Drake *et al.*, 1999; Hill *et al.*, 1995). Current examples of improved approaches such as multiple endmember spectral mixture analysis (MESMA, VMESMA), that were applied in semi-arid ecosystems are published by e.g. Asner and Lobell (2000) Garcia-Haro *et al.* (2005), Okin *et al.* (2001), Roberts *et al.* (1998), Martinez *et al.* (2005), Bachmann *et al.* (2005). These approaches use the full spectral shape in the VNIR-SWIR, rather than specific bands.

Green vs. dry vegetation cover: In arid regions, because water and chlorophyll pigment contents of green leaves are rather low and the dominant parts of perennial desert plants are woody components, strong spectral features of photosynthetic plants are much less developed than in plants from more humid regions. This applies for the chlorophyll absorption around 450 and 670 nm, the steep spectral transition of the red edge between 650 and 750 nm, and the liquid water absorption around 975 and 1180 nm. The spectral response of vegetation in arid areas depends mainly on the proportions of green to dry and woody parts, respectively. An additional complication is introduced through the fact that dry and woody plant material does not exhibit a unique but highly variable spectral response, depending mainly on the level of plant decomposition (e.g. Elvidge, 1990). Nevertheless, dry matter components such as lignin and cellulose show diagnostic spectral properties in the SWIR region (Escribano *et al.*, 2007). Based on the optical properties differentiating green photosynthetic plants from dry residues, many authors were able to discriminate and map green and dry vegetation components using hyperspectral imagery, based on spectral mixture analysis or automatic classification algorithms (e.g. Okin *et al.*, 2001; Spengler *et al.*, 2007).

Biomass, leaf water content, foliage chemistry: In order to give first estimates of vegetation status and leaf area, remote sensing techniques based on broad-band indices are commonly used, but accuracy can be low due to large influences of soil background and dry plant components. As an improvement, the narrow bandwidths

of hyperspectral sensors allow the identification and parameterization of absorption features. The quantitative estimation of biochemical concentrations is possible by linking and validating these indices to laboratory measurements using regression models, or by the use of empirical relationships. Another approach for the accurate estimation of vegetation parameters is using canopy reflectance models. Techniques based on the inversion of radiative transfer models (e.g. Jacquemoud *et al.*, 1996) are widely applied for the determination of crop canopy properties, but only few models were developed for natural plant communities in drylands (e.g. Chopping *et al.*, 2003).

Vegetation indices: Spectroscopic indicators of vegetation changes focus on the accurate estimation of fraction vegetation cover and plant parameters mainly based on high signal-to-noise ratio imaging spectrometer sensors covering the VNIR-SWIR range and deployed during local airborne campaigns. Vegetation indices derived from satellite data on the other hand are one of the primary sources of information for operational monitoring of the Earth's vegetative cover. The estimation of green vegetation cover and the production of global vegetation maps based on satellite remote sensing data is needed as a major source of input for desertification modeling. For this purpose, an extensive range of vegetation indices has been developed that are based on specific absorption features of plants. Table 2 lists widely used vegetation indices associated with green vegetation cover and pigments, leaf water content, and foliar chemistry. In particular, a compilation of promising

spectral indices for the assessment of dryland vegetation properties is included.

Green vegetation cover indices (SR, NDVI, EVI, SGR) are sensitive to plant cover and provide an estimate of the "greenness" of the area. They are based on the strong contrast between red and near-infrared (NIR) reflectance produced by green foliage. These indices are related to vegetation vigor and amount. The NDVI has been the most widely used broadband vegetation indices. It minimizes the topographic effects (Holben and Justice, 1981), is independent from the surface character and offers a high sensibility to photosynthetic active vegetation. The scale of the NDVI varies from -1.0 to +1.0 (Myneni *et al.*, 1992; Tucker, 1979). The algebraic combinations of red and NIR reflectance were designed in particular to minimize the effect of external influences such as solar irradiance changes due to atmospheric effect and due to variations in soil background optical properties in the vegetation canopy spectral response. Soil background is one source of variation that has received much attention in recent years, and soil adjusted vegetation indices (SAVI, MSAVI, OSAVI) have been introduced to address this issue. Pigment indices (mNDVI, PRI, RGR, NPCI) focus on photosynthetic pigments, primarily chlorophyll the dominant photosynthetic pigment of green vegetation. However, some like the PRI identify xanthophylls cycle pigments, which are important in regulating light absorption in high light intensity environments. Leaves possess a range of accessory photosynthetic pigments, including carotenoids and xanthophylls, which serve functions to regulate and increase photosynthetic

Table 2. Spectral indices recommended for the assessment of plant parameters

Index	Formula	Estimated plant parameter
SR	R_{NIR}/R_{red}	Index of green vegetation cover
NDVI	$(R_{NIR} - R_{red})/(R_{NIR} + R_{red})$	Index of green vegetation cover
EVI	$2.5 \times \frac{R_{NIR} - R_{red}}{R_{NIR} + 6 R_{red} - 7.5 R_{blue} + 1}$	Index of green vegetation cover
SGR	$\frac{599}{\sum_{n=500} R_n}$	Index of green vegetation cover
SAVI	$(1 + L) \times \frac{R_{NIR} - R_{red}}{R_{NIR} + R_{red} + L}$	Leaf area (mostly insensitive to soil brightness)
MSAVI	$2R_{NIR} + 1 - \frac{\sqrt{(2R_{NIR} + 1)^2 - 8(R_{NIR} - R_{red})}}{2}$	Improved SAVI
OSAVI	$\frac{R_{NIR} - R_{red}}{R_{NIR} + R_{red} + Y}$	Improved SAVI
mNDVI	$(R_{750} - R_{705})/(R_{750} + R_{705})$	Leaf chlorophyll content
PRI	$(R_{531} - R_{570})/(R_{531} + R_{570})$	Ratio of carotenoid to chlorophyll in leaves
RGR	$(R_{600-699})/(R_{500-599})$	Anthocyanins/chlorophyll
PCI	$(R_{680} - R_{430})/(R_{680} + R_{430})$	Total pigments/chlorophyll
NWI	$(R_{860} - R_{1240})/(R_{860} + R_{1240})$	Leaf water content
WI	R_{900}/R_{970}	Leaf water content
SIWSI	$(R_{860} - R_{1640})/(R_{860} + R_{1640})$	Vegetation water content
NDNI	$\left[\log \left(\frac{R_{1680}}{R_{1510}} \right) \right] / \left[\log \left(\frac{1}{R_{1680}} R_{1510} \right) \right]$	Foliar nitrogen concentration
NDLI	$\left[\log \left(\frac{R_{1680}}{R_{1754}} \right) \right] / \left[\log \left(\frac{1}{R_{1680}} R_{1754} \right) \right]$	Foliar lignin concentration
CAI	$0.5(R_{2020} + R_{2220}) - R_{2100}$	Cellulose and lignin content, discriminates plant litter from soils

SR: Simple Ratio (Tucker, 1979); NDVI: Normalized Difference Vegetation Index (Tucker, 1979); EVI: Enhanced Vegetation Index (Huete *et al.*, 2002); SGR: Summed green reflectance (Fuentes *et al.*, 2001); SAVI: Soil Adjusted Vegetation Index (Huete, 1988); MSAVI: Modified Soil Adjusted Vegetation Index (Qi *et al.*, 1994); OSAVI: Optimized Soil Adjusted Vegetation Index (Rondeaux *et al.*, 1996); mNDVI: Modified NDVI (Fuentes *et al.*, 2001); PRI: Photochemical Reflectance Index (Gamon *et al.*, 1992); RGR: Red:green ratio (Fuentes *et al.*, 2001); NPCI: Normalized Pigments (Penuelas *et al.*, 1995); NDWI: Normalized Difference Water Index (Gao, 1996); WBI: Water Band Index (Elvidge, 1990); SIWSI: Short wave Infrared Water Stress Index (Zarco-Tejada *et al.*, 2003); NDNI: Normalized Difference Nitrogen Index (Serra *et al.*, 2002); NDLI: Normalized Difference Lignin Index (Serrano *et al.*, 2002); CAI: Cellulose Absorption Index (Nagler *et al.*, 2003).

performance. Water indices (NDWI, WBI, SIWSI) estimate the amount of water content in leaves, based on the strong absorption of water in the NIR-SWIR spectral range. Most of the narrow-band water indices use the 970 or 1240 nm water absorption features, or the slope of the saturated 1450 nm water band (on the right hand of the absorption band), although broadband indices have been sometimes used for vegetation water assessment (e.g. Landsat bands 4,5,7). Foliar chemistry indices (NDNI, NDLI, CAI) were used specifically in semi-arid shrublands and environments to estimate nitrogen, lignin and cellulose content of senescent plants (Serrano *et al.*, 2002; Nagler *et al.*, 2003). The CAI in particular may be useful in arid and semi-arid regions where green vegetation is seasonally sparse and much of the biomass is in undecomposed plant litter and stems.

Future Challenges

Desert and dryland ecosystems spanning moisture conditions from dry grasslands to barren hyper-arid landscapes are the largest terrestrial biome, about 41% of the terrestrial landmass (Millennium Ecosystem Assessment, 2005). Deserts tend to be fragile ecosystems, requiring little in the way of perturbations in order to cause tremendous changes in the landscape (Schlesinger *et al.*, 1990). Remote sensing sensors have the ability to assess biophysical indicators of land degradation and desertification, based on specific optical properties associated with desert surface components. Furthermore, the multi-temporal analysis of remote sensing images builds the basis for understanding of specific surface changes e.g. vegetation, soil components, and their interplay.

Soil spectral indices are related to the discrimination of soils from dry matter, and the estimation of crop residue, soil water content, or soil color (mineralogy). For example, Escadafal *et al.* (1994) and Hill *et al.* (1995) have been able to use parameters indicative of soil conditions and hence, to apply concepts taken from pedology and geomorphology to obtain qualitative indications for soil degradation or erosion processes. Vegetation spectral indices are radiometric measures of the spatial and temporal patterns of vegetation photosynthetic activity that are related to canopy biophysical variables such as leaf area index, fractional vegetation cover, biomass etc. Vegetation indices have little sensitivity at low leaf area, particularly when the soil background is highly variable. Because of their low organic matter content, soils in desert areas tend to be bright and mineralogically heterogeneous. All of these factors tend to swamp out the spectral contribution of vegetation in individual pixels (e.g., Escadafal and Huete, 1991; Huete and Tucker, 1991). In desert environments, vegetation indices must be able to discriminate vegetation at low cover, from zero up to about 50%, and to extract information about vegetation properties, while minimizing soil, atmosphere and sun and view angle effects. Since in arid environments soil is the most significant contribution to scene variance, a correction for soil background effects is necessary. In this sense, the NDVI is less accurate in regions with low vegetation cover, because of the soil signal that influences the remote sensing signal directly. To solve this difficulty, improved variations of the NDVI like the Soil-Adjusted Vegetation Index (SAVI) or the Optimized Soil

Adjusted Vegetation Index (OSAVI) that include a soil factor (Gilbert *et al.*, 2002) were used. Nevertheless the need for a soil factor reduces the global applicability of the method. Spengler *et al.* (2007) showed that the combination of the NDVI and Cellulose Absorption Index (CAI) vegetation indices is particularly adapted to determine vegetation cover in arid areas independently from phenological status and to quantify vegetation vitality, although some algorithms limitations are observed for areas of very sparse vegetation cover.

In parallel with the use of spectral indices, sophisticated spectroscopic indicators of soil degradation and/or vegetation changes have been widely used to estimate enhanced land degradation variables, such as soil chemical properties, organic matter, soil water content, fraction vegetation cover, senescent vs. photosynthetically active (green) vegetation. Narrow-band sensors, including both VNIR and SWIR wavelength range, are particularly adapted for land degradation monitoring in arid areas. Indeed, narrow bands in the 400-1300 nm spectral range are essential to map green vegetation biophysical properties, and soil iron content. Narrow bands in the 2000-2450 nm spectral range are critical to discriminate soils from dry matter components, and to estimate clay or carbonate content in soils. The overall spectral shape over the 400-2450 nm is essential to determine organic matter content, soil moisture, and soil texture. Based on optical properties and the use of hyperspectral remote sensing systems, a range of spectral methods has been developed (e.g. multivariate statistics, linear spectral unmixing analyses, reflectance

modeling) that were used to assess plant and soil parameters related to land degradation processes in drylands. In particular, the spectral unmixing methodology, because of its direct response to pre-selected component spectra (i.e., typical desert shrubs and appropriate substrate elements) and increased robustness against soil color differences in the absence of dense vegetation, is particularly suited to overcome the limitations of two-band vegetation indices. Improved estimates in particular of vegetation abundance were obtained using hyperspectral data in e.g. semi-arid parts of California (Smith *et al.*, 1990; Okin *et al.*, 2001), although this is still challenging (Ustin *et al.*, 2005; Okin *et al.*, 2001).

The review of plant and soil spectral characteristics that are detectable using optical sensors and have potential for monitoring arid ecosystem processes show that significant progress has been achieved. On the other hand, although the absorption characteristics of the major biochemical constituents of plants and soils are generally understood, overlapping absorption features of plants and soils, and mixing at the remote sensing scale (pixel) preclude direct assessment of many biogeochemicals of interest. Despite significant progress in developing fundamental understanding of ecosystem processes and optical properties, further studies are needed toward the development of fully predictable quantitative methods. For example, the retrieval of vegetation parameters from remote sensing presents some significant challenges in arid environments, that have been listed by Okin and Roberts (2004), and are as follow: low vegetation cover

over bright soils means that the vegetation signal can be swamped out of the pixel-averaged signal. Exposed, variable soil surfaces can contribute significantly to within-scene variability. Many remote sensing techniques (e.g., that do not include the SWIR spectral range) are insensitive to non-photosynthetic vegetation signal, which can be a major and important component of total cover in deserts. Open canopies and bright soils in desert areas can contribute to significant multiple scattering and non-linear mixing in deserts. Desert vegetation is spectrally dissimilar to its humid counterparts lacking, most notably, a strong red edge. Rapid phenological changes are accompanied by spectral changes in desert vegetation that can lead to significant temporal and spatial intraspecies spectral variability.

Despite these challenges, it is possible to retrieve quantitative information about vegetation and soil parameters remotely as shown above in this paper. Nonetheless, in the application of remote sensing to problems in desert regions, the limitations and considerations must be anticipated and worked around. For example, it is very highly recommended for remote sensing of arid areas and detection of desert vegetation (discrimination from soils) to use narrow-band remote sensing images capable of detecting the lignin/cellulose absorption feature centered at 2100 nm (CAI index). It would dramatically increase the accuracy of the retrieval of vegetation cover including desert plants, and allow discrimination of dry matter from soils. Indeed, only the 2100 nm dry vegetation absorption band cannot be confused with e.g. soil absorption features that could result

from the presence of carbonate soils in the area (~2300 nm). Unfortunately, these spectral bands are not available from any satellite sensor currently in space, except in the Hyperion spaceborne imaging spectrometer. Hyperion is a technology demonstrator that was not designed for arid land monitoring, and low signal-to-noise ratio in the SWIR spectral range would prevent the Hyperion sensor to detect the cellulose absorption feature. In this sense, the upcoming future availability of high signal-to-noise ratio satellite imaging spectrometers such as EnMap starting from 2011 on (Kaufmann *et al.*, 2006), is a major step toward the operational quantitative monitoring of land degradation processes in drylands.

Conclusions

Desertification is a key environmental process that affects all continents (except Antarctica). Because nearly one-third of the human population lives in arid regions, the threat of desertification ranks among the most important environmental problems and has significant impacts on meeting human well-being. The size, remoteness and harsh nature of many of the world's deserts make it difficult and expensive to map or monitor these landscapes or to determine the effect of land use on them. Remote sensing has long been suggested as a time- and cost-efficient method for monitoring change to desert environments, since it can serve both to enhance monitoring efforts as well as provide valuable information on drylands degradation in specific areas. We have reviewed the spectral characteristics of plants and soils that are detectable using optical sensors

and methods to identify and quantify properties that have potential for monitoring arid ecosystem processes. A range of spectral indices recommended for the assessment of soil and plant parameters is compiled. Current multispectral wide-band satellite sensors offer soil indices and vegetation indices based on 2 to 3 band ratios that allow to operationally monitor changes at the Earth's surface. Narrow-band spectral indices adapted for hyperspectral sensors provide enhanced estimation of plant and soil parameters related to arid environments. It includes desertification indicators such as chemical properties, organic matter content, mineralogical content, soil crusting and runoff, as well as vegetation cover, foliar chemistry, discrimination of senescent and photosynthetically active vegetation. The wealth of existing information on the reflectance of desert plants, soils and other materials, combined with new modeling and index approaches will lead to improved capability for global monitoring of arid environments. In particular, including narrow spectral band imagery capable of detecting the cellulose absorption band at 2100 nm is a must, since it is diagnostic of senescent (dry) vegetation. Advanced hyperspectral remote sensing has proven to be a valuable tool for the derivation of enhanced land surface variables in drylands, and should dramatically increase the accuracy in drylands monitoring. Accumulated dry plant material on the soil surface, as is characteristic of many arid systems, and overlapping absorption features of plants and soils challenge the measurements. Further studies are needed, toward a better understanding of the desertification processes, and the

development of fully predictive quantitative methods for the determination of land degradation indicators based on optical properties.

Acknowledgments

This research is conducted within the GFZ Dryland degradation program. The author wishes to thank Prof. Charly Kaufmann for the support of hyperspectral and land degradation activities. The author wishes to thank Christiane Scheidt for her help in assembling the references and preparing some figures.

References

- Abrahart, R.J., Kirkby, M.J., McMahon, M.L., Bathurst, J.C., Kilsby, C.G., White, S.M., Diamond, S., Woodward, I., Hawkes, C., Shao, J. and Thornes, J.B. 1996. MEDRUSH—spatial and temporal river basin modelling at scales commensurable with global environmental change. *Application of GIS in Hydrology and Water Resources Management*, Wallinford, IAHS, 47-54.
- Adams, J.B., Smith, M.O. and Gillespie, A.R. 1993. Imaging spectroscopy: Interpretation based on spectral mixture analysis. In *Remote Geochemical Analyses: Elemental and Mineralogical Composition* (Eds. C.M. Pieters and P.A.J. Englert), pp. 145-166. Cambridge Univ. Press, Cambridge, UK.
- Asner, G.P. and Lobell, D.B. 2000. A Biogeophysical Approach for Automated SWIR Unmixing of Soils and Vegetation. *Remote Sensing Environment* 74: 99-112.
- Aubréville, A. 1949. Climats, forêts et désertification de l'Afrique tropicale. Paris, Ed géographiques, maritimes et coloniales.
- Bachmann, M., Müller, A., Habermeyer, M., Schmid, M. and Dech, S.W. 2005. Iterative mesma unmixing for fractional cover estimates - evaluating the portability. In *Proceeding of the 4th Workshop on Imaging Spectroscopy: New Quality in Environmental Studies* (Eds. B. Zagajewski and M. Sobczak), pp. 529-536.

- EARSel & Warsaw University, Warsaw, Poland.
- Ben-Dor, E. and Banin, A. 1994. Visible and near infrared (0.4-1.1 μm) analysis of arid and semiarid soils. *Remote Sensing Environment* 4: 110-124.
- Ben-Dor, E., Goldshleger, N., Benyamini, Y., Agassi, M. and Blumberg, D.G. 2003. The Spectral Reflectance properties of Soil's structural crust in the SWIR spectral region (1.2-2.5 μm), *Soil Science Society of American Journal* 67: 289-299.
- Ben-Dor, E., Goldshleger, N., Bonfil, D., Agassi, M., Margalit, N., Binayminy, Y. and Karnieli A. 2004. Monitoring of Infiltration Rate in Semiarid Soils using Airborne Hyperspectral Technology. *International Journal of Remote Sensing* 25: 1-18.
- Biard, F. and Baret, F. 1997. Crop residue estimation using multiband reflectance. *Remote Sensing Environment* 59: 530-536.
- Boer, M.M. 1999. Assessment of dryland degradation, linking theory and practice through site water balance modeling. *Ph.D. Dissertation*, Utrecht (Netherlands Geogr. Studies, Utrecht).
- Boer, M.M. and Puigdefabregas, J. 2003. Predicting potential vegetation index values as a reference for the assessment and monitoring of dryland condition. *International Journal of Remote Sensing* 24: 1135-1141.
- Boville, E.W. 1921. The encroachment of the Sahara on the Sudan. *Journal of Royal African Society* 20: 175-185, 259-269.
- Chabrillat, S., Goetz, A.F.H., Olsen, H.W. and Krosley L. 2002a. Use of hyperspectral images in the identification and mapping of expansive clay soils and the role of spatial resolution. *Remote Sensing Environment* 82: 431-445.
- Chabrillat, S., Kaufmann, H., Escribano, P. and Palacios-Orueta, A. 2005. Land degradation monitoring: Spectral variability in a semi-arid Mediterranean ecosystem (Natural Park Cabo de Gata-Níjar, Spain). Proceeding of the 4th Workshop on Imaging Spectroscopy: New Quality in Environmental Studies (Eds. B. Zagajewski and M. Sobczak), pp. 139-146. EARSel & Warsaw University, Warsaw, Poland.
- Chabrillat, S., Kaufmann, H., Hill, J., Mueller, A., Merz, B. and Echtler, H. 2002b. Research opportunities for studying land degradation with spectroscopic techniques. In *Proceedings of the SPIE Remote Sensing for Environmental Monitoring, GIS Applications and Geology II* (Ed. M. Ehlers), pp. 11-19 SPIE, Bellingham, WA.
- Chikhaoui, M., Bonn, F., Bokoye, A.I. and Merzouk, A. 2005. A spectral index for land degradation mapping using ASTER data: Application to a semi-arid Mediterranean catchment. *International Journal of Applied Earth Observation and Geoinformation* 7: 140-153.
- Chopping, M.J., Rango, A., Havstad, K.M., Schiebe, F.R., Ritchie, J.C., Schmutge, T.J., French, A.N., Su, L., McKee, L. and Davis, M.R. 2003. Canopy attributes of desert grassland and transition communities derived from multiangular airborne imagery. *Remote Sensing Environment* 85: 339-354.
- Clark, R.N., King, T.V.V., Klejwa, M. and Swayze, G.A. 1990. High spectral resolution reflectance spectroscopy of minerals. *Journal of Geophysical Research* 95(B8) 12: 653-680.
- Clark, R.N., Swayze, G. and Gallagher, A. 1992. Mapping the mineralogy and lithology of Canyonlands, Utah with imaging spectrometer data and multiple spectral feature mapping algorithm. *Summaries of the Third Annual JPL Airborne Geoscience Workshop*, pp. 1: 11-13. Jet Propulsion Laboratory, Pasadena, CA (Pasadena, CA. JPL Publ 92-14).
- Curran, P.J. 1989. Remote sensing of foliar chemistry. *Remote Sensing Environment* 26: 271-278.
- De Jong, S.M. 1994. Applications of reflective remote sensing for land degradation studies in a Mediterranean environment. Utrecht: KNAG/ Faculty of Geography Studies, Utrecht University.
- Dehaan, R.L. and Taylor, G.R. 2002. Field-derived spectra of salinized soils and vegetation as indicators of irrigation-induced salinization. *Remote Sensing of Environment* 80: 406-417.
- Dehaan, R. and Taylor, G.R. 2003. Image-derived spectral endmembers as indicators of salinity. *International Journal of Remote Sensing* 24: 775-794.
- Drake, N.A., Mackin, S. and Settle, J. 1999. Mapping vegetation, soils, and geology in semi-arid shrublands using spectral matching and mixture

- modeling of SWIR AVIRIS Imagery. *Remote Sensing Environment* 68: 12-15.
- Elvidge, C.D. 1990. Visible and NIR reflectance characteristics of dry plant materials. *International Journal of Remote Sensing* 11: 1775-1795.
- Escadafal, R. and Huete, A. 1991. Etude des propriétés spectrales des sols arides appliqué à l'amélioration des indices de végétation obtenus par télédétection. *C.R. Académie des Sciences Paris* 312: 1385-1391.
- Escadafal, R., Belghith, A. and Ben Moussa, H. 1994. Indices spectraux pour la dégradation des milieux naturels en Tunisie aride. 6ème Symp. Int. Mesures Physiques et Signatures en Télédétection. Val d'Isère, France, ISPRS-CNESA.
- Escribano, P., Palacios-Orueta, A., Chabrillat, S. and Oyonarte, C. 2007. Quantifying spectral differences in an arid environment (Cabo de Gata-Níjar N.P, Spain) with spectroscopy data. Basis for monitoring degradation processes. *Remote Sensing Environment*. Submitted.
- Fuentes, D.A., Gamon, J.A., Qiu, H.L., Sims, D.A. and Roberts, D.A. 2001. Mapping Canadian boreal forest vegetation using pigment and water absorption features derived from the AVIRIS sensor. *Journal of Geophysical Research* 106(D24): 33,565-33,577.
- Gamon, J.A., Penuelas, J. and Field, C.B. 1992. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. *Remote Sensing Environment* 41: 35-44.
- Gao, B.-C. 1996. NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing Environment* 58: 257-266.
- Gao, B.-C. and Goetz, A.F.H. 1994. Extraction of dry leaf spectral features from reflectance spectra of green vegetation. *Remote Sensing Environment* 47: 369-374.
- Garcia-Haro, F.J., Sommer, S. and Kemper, T. 2005. A new tool for variable multiple endmember spectral mixture analysis (VMESMA). *International Journal of Remote Sensing* 26: 2135-2162.
- Gilabert, M.A., González-Piqueras, J., Garcia-Haro, F.J. and Meliá, J. 2002. A generalized soil-adjusted vegetation index. *Remote Sensing Environment* 82: 303-310.
- Goetz, A.F.H., Chabrillat, S. and Lu, Z. 2001. Field reflectance spectrometry for detection of swelling clays at construction sites. *Field Analytical Chemistry and Technology* 5: 143-155.
- Goetz, A.F.H. and Rowan, L.C. 1981. Geologic remote sensing. *Science* 211: 781-791.
- Goetz, A.F.H., Vane, G., Solomon, J.E. and Rock, B.N. 1985. Imaging spectrometry for Earth remote sensing. *Science* 228: 1147-1153.
- Goldshleger, N., Ben-Dor, E., Benyamini, Y., Agassi, M. and Blumberg, D. 2001. Characterization of soil's structural crust by spectral reflectance in the SWIR region (1.2-2.5 μm). *Terra Nova* 13: 12-17.
- Green, R.O., Eastwood, M.L., Sarture, C.M., Chrien, T.G., Aronsson, M., Chippendale, B.J., Faust, J.A., Pavri, B.E., Chovit, C.J., Solis, M., Olah, M. and Williams, O. 1998. Imaging spectroscopy and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). *Remote Sensing Environment* 65: 227-248.
- Haubrock, S., Chabrillat, S. and Kaufmann, H. 2005. Application of hyperspectral imaging for the quantification of surface soil moisture in erosion monitoring and modeling. In *Proceeding of the 4th Workshop on Imaging Spectroscopy: New Quality in Environmental Studies* (Eds. B. Zagajewski and M. Sobczak), pp. 197-206. EARSeL & Warsaw University, Warsaw, Poland.
- Haubrock, S.-N., Chabrillat, S., Lemnitz, C. and Kaufmann, H. 2007. Surface soil moisture quantification models from reflectance data under field conditions. *International Journal of Remote Sensing* (in press).
- Hill, J. 2000. Assessment of semi-arid lands: Monitoring drylands ecosystems through remote sensing. *Encyclopedia of Analytical Chemistry - Instrumentation and Applications*, John Wiley & Sons.
- Hill, J., Mégier, J. and Mehl, W. 1995. Land degradation, soil erosion and desertification monitoring in Mediterranean ecosystems. *Remote Sensing Reviews* 12: 107-130.
- Hill, J. and Schütt, B. 2000. Mapping complex patterns of erosion and stability in dry Mediterranean ecosystems. *Remote Sensing Environment* 74: 557-569.

- Hill, J., Udelhoven, Th., Schütt B. and Yair, A. 1998. Differentiating biological soil crusts in a sandy arid ecosystem based on hyperspectral data acquired with DAIS-7915. In *Proceeding of the 1st European Association of Remote Sensing Laboratories (EARSeL) Workshop on Imaging Spectrometry*, pp. 427-436. University of Zurich, Switzerland, 6-8 October 1998. EARSeL, Paris.
- Hillel, D. 1959. Studies of Loessial Crusts. *State of Israel Agricultural Research Bulletin* 63.
- Holben, B.N. and Justice, C.O. 1981. An examination of spectral band rationing to reduce the topographic effect on remotely sensed data. *International Journal of Remote Sensing* 2: 115-121.
- Hubert, H. 1920. Le dessèchement progressif en Afrique occidentale française. *Bulletin Comité d'études Historiques et Scientifiques de l'Afrique Occidentale française* 1920: 401-437.
- Huete, A.R. 1988. A soil-adjusted vegetation index (SAVI). *Remote Sensing Environment* 25: 295-309.
- Huete, A.R., Didan, K., Muiira, T., Rodriguez, E.P., Gao, X. and Ferreira, L.G. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing Environment* 83: 195-213.
- Huete, A.R. and 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.
- Hunt, G.R. and Salisbury, J.W. 1970. Visible and near-infrared reflectance spectra of minerals and rocks, I: Silicate minerals. *Modern Geology* 1: 219-228.
- Jacquemoud, S., Ustin, S.L., Verdebout, J., Schmuck, G., Andreoli, G. and Hosgood, B. 1996. Estimating leaf biochemistry using the PROSPECT leaf optical properties model. *Remote Sensing Environment* 56: 194-202.
- Jarmer, T., Lavée, H., Sarah, P. and Hill, J. 2005. The use of remote sensing for the assessment of soil inorganic carbon in the Judean Desert (Israel). In *Proceedings of the 1st International Conference on Remote Sensing and Geoinformation Processing in the Assessment of Land Degradation and Desertification (RGLDD)* (Eds. A. Röder and J. Hill), pp. 68-75. University of Trier, Trier, Germany.
- Jones, B. 1938. Desiccation and the West African colonies. *Geographical Journal* 91: 401-423.
- Kaufmann, H., Segl, K., Chabrillat, S., Hofer, S., Stuffer, T., Mueller, A., Richter, R., Schreier, G., Haydn, R. and Bach, H. 2006. EnMAP - A Hyperspectral Sensor for Environmental Mapping and Analysis. In *Proceedings of the 2006 IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2006) & 27th Canadian Symposium on Remote Sensing*. Denver, USA, on CD-ROM, 0-7803-9510-7/06, 2006 IEEE.
- Kokaly, R.F. and Clark, R.N. 1999. Spectroscopic determination of leaf biochemistry using band-depth analysis of absorption features and stepwise multiple linear regression. *Remote Sensing Environment* 67: 267-287.
- Kruse, F.A. 1988. Use of Airborne Imaging Spectrometer data to map minerals associated with hydrothermally altered rocks in the northern Grapevine Mountains, Nevada and California. *Remote Sensing Environment* 24: 31-51.
- Leone, A.P. and Sommer, S. 2000. Multivariate analysis of laboratory spectra for the assessment of soil development and soil degradation in the Southern Apennines (Italy). *Remote Sensing Environment* 72: 346-359.
- Lowdermilk, W.C. 1935. Man-made deserts. *Pacific Affairs* 8: 409-419.
- Madeira, J., Bedidi, A., Cerville, B., Pouget, M. and Flay, N. 1997. Visible spectrometric indices of hematite (Hm) and goethite (Gt) content in lateritic soils: The application of a Thematic Mapper (TM) image for soil-mapping in Brasilia, Brazil. *International Journal of Remote Sensing* 18(13): 2835-2852.
- Martinez, B., Verger, A., Camacho de Coca, F., Garcia-Haro, F.J., Gilabert, M. and Melia, J. 2005. An operational methodology (VMESMA) to derive biophysical parameters for land degradation processes assessment. In *Proceedings of the 1st International Conference on Remote Sensing and Geoinformation Processing in the Assessment of Land Degradation and Desertification (RGLDD)* (Eds. A. Röder and J. Hill), pp. 76-83. University of Trier, Trier, Germany.
- Mathieu, R., Pouget, M., Cerville, B. and Escadafal, R. 1998. Relationships between satellitebased radiometric indices simulated using laboratory reflectance data and typical soil color of an arid

- environment. *Remote Sensing Environment* 66: 17-28.
- McNairn, H. and Protz, R. 1993. Mapping corn residue cover on agricultural fields in Oxford County, Ontario, using Thematic Mapper. *Canadian Journal of Remote Sensing* 19: 152-159.
- Menenti, M., Azzali, S. and Boss, M. 1999. Early warning on desertification and land degradation. *Report for the 3rd Meeting of the EC/MS Expert Group on Desertification*, Brussels, The Netherlands.
- Millennium Ecosystem Assessment 2005. *Ecosystems and Human Well-being: Desertification Synthesis*. UN Convention to Combat Desertification (UNCCD).
- Myneni, R.B., Ganapol, B.D. and Asrar, G. 1992. Remote sensing of vegetation canopy photosynthetic and stomatal conductance efficiencies. *Remote Sensing Environment* 42: 217-238.
- Nagler, P.L., Inoue, Y., Glenn, E.P., Russ, A.L. and Daughtry, C.S.T. 2003. Cellulose absorption index (CAI) to quantify mixes soil-plant litter scenes. *Remote Sensing Environment* 87: 310-325.
- Okin, G.S. and Roberts, D.A. 2004. Remote sensing of arid regions: Challenges and opportunities. In *Manual of Remote Sensing* (Ed. S.L. Ustin), 3rd Ed., Vol. 4, John Wiley & Sons, Inc., USA.
- Okin, G.S., Roberts, D.A., Murray, B. and Okin, W.J. 2001. Practical limits on hyperspectral vegetation discrimination in arid and semi-arid environments. *Remote Sensing Environment* 77: 212-225.
- Oldeman, L.R., Hakkeling, R.T.A. and Sombroek, W.G. 1990. World map of the status of human-induced soil degradation (GLASOD), *An Explanatory Note*. UNEP/ISRIC, The Netherlands.
- Palacios-Orueta, A., Pinzón, J.E., Ustin, S.L. and Roberts, D.A. 1999. Remote sensing of soils in the Santa Monica Mountains. II. Hierarchical foreground and background analysis. *Remote Sensing Environment* 68: 138-151.
- Palacios-Orueta, A. and Ustin, S.L. 1998. Remote sensing of soil properties in the Santa Monica Mountains. I. Spectral analysis. *Remote Sensing Environment* 65: 170-183.
- Penuelas, J., Baret, F. and Filella, L. 1995. Semi-empirical indexes to assess carotenoids/chlorophyll a ratio from leaf spectral reflectance. *Photosynthetica* 31: 221-230.
- Prince, S.D., Brown de Colstoun, E. and Kravitz, L.L. 1998. Evidence from rain-use-efficiencies does not indicate extensive Sahelian desertification. *Global Change Biology* 4: 359-374.
- Qi, J., Chehbouni, Al., Huete, A.R., Kerr, Y.H. and Sorooshian, S. 1994. A modified soil adjusted vegetation index (MSAVI). *Remote Sensing Environment* 48: 119-126.
- Renner, G.T. 1926. A famine zone on Africa: The Sudan. *Geographical Review* 16: 583-596.
- Richter, N., Chabrillat, S. and Kaufmann, H. 2005. Preliminary analysis for soil organic carbon determination from spectral reflectance in the frame of the EU project DeSurvey. In *Proceedings of the 1st International Conference on Remote Sensing and Geoinformation Processing in the Assessment of Land Degradation and Desertification (RGLDD)* (Eds. A. Röder and J. Hill), pp. 96-101. University of Trier, Trier, Germany.
- Richter, N., Chabrillat, S. and Kaufmann, H. 2007. Enhanced quantification of soil variables linked with soil degradation using imaging spectroscopy. In *Proceeding of the 5th EARSeL Workshop on Imaging Spectroscopy: Innovation in Environmental Research*, Bruges, Belgium (in press).
- Roberts, D., Gardner, M., Church, R., Ustin, S.L., Scheer, G. and Green, R. 1998. Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models. *Remote Sensing Environment* 65: 267-279.
- Rondeaux, G., Steven, M. and Baret, F. 1996. Optimization of soil-adjusted vegetation indices. *Remote Sensing Environ* 55: 95-107.
- SAND 2002. Spectral analysis of dryland degradation for a global desertification assessment. Submitted to ESA for the 2nd call for Earth Explorer Opportunity Missions.
- Schlesinger, W.H. 1997. The global water cycle. In *Biogeochemistry: An Analysis of Global Change*, 2nd Ed., Academic Press, San Diego (<http://www.gps.caltech.edu/~ge148/10.html>).
- Schlesinger, W.H., Reynolds, J.F., Cunningham, G.L., Huenneke, L.F., Jarrell, W.M., Virginia, R.A.

- and Whitford, W.G. 1990. Biological feedbacks in global desertification. *Science* 247: 1043-1048.
- Serrano, L., Penuelas, J. and Ustin, S.L. 2002. Remote sensing of nitrogen and lignin in Mediterranean vegetation from AVIRIS data: Decomposing biochemical from structural signals. *Remote Sensing Environment* 81: 355-364.
- Smith, M.O., Ustin, S.L., Adams, J.B. and Gillespie, A.R. 1990. Vegetation in deserts: I. A regional measure of abundance from multispectral images. *Remote Sensing Environment* 31: 1-26.
- Spengler, D., Chabrillat, S., Escribano, P., Bachmann, M. and Kaufmann, H. 2007. Development of an automatic classification algorithm for differentiation of vegetation status in semi-arid environments using multi-temporal HyMap data. In *Proceeding of the 5th EARSeL Workshop on Imaging Spectroscopy: Innovation in Environmental Research*, Bruges, Belgium (in press).
- Stebbing, E.P. 1938. The advance of the Sahara. *Geographical Journal* 91: 356-359.
- Taylor, G.R., Hemphill, P., Currie, D., Broadfoot, T. and Dehaan, R.L. 2001. Mapping dryland salinity with hyperspectral imagery. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Scanning the Present and Resolving the Future*. 1: 302-304. Institute of Electrical and Electronic Engineers, Piscataway, NJ, USA.
- Thomas, D.S.G. and Middleton, N.J. 1994. *Desertification: Exploding the Myth*. Chichester, John Wiley & Sons.
- Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing Environment* 8: 127-150.
- Tucker, C.J., Dregne, H.E. and Newcomb, W.W. 1991. Expansion and contraction of the Sahara desert from 1980 to 1990. *Science* 253: 299-301.
- UNCED 1992. United Nations Conference on Environment and Development (Earth Summit'92). *Managing fragile ecosystems: Combating desertification and drought*.
- Ustin, S.L., Jacquemoud, S. Palacios-Orueta, A. Li L. and Whiting, M.L. 2005. Remote sensing based assessment of biophysical indicators for land degradation and desertification. In *Proceedings of the 1st International Conference on Remote Sensing and Geoinformation Processing in the Assessment of Land Degradation and Desertification (RGLDD)* (Eds. A. Röder and J. Hill), University of Trier, Trier, Germany, 2-21.
- Vane, G., Duval, J.E. and Wellman, J.B. 1993. Imaging spectroscopy of the earth and other solar system bodies. In *Remote Geochemical Analyses: Elemental and Mineralogical Composition* (Eds. C.M. Pieters and P.A.J. Englert), pp. 121-144. Cambridge University Press, Cambridge, UK.
- Verstraete, M.M. and Schwartz, S.A. 1991. Desertification and global change. *Vegetatio* 91: 3-13.
- Weidong, L., Baret, F., Xingfa, G., Bing, Z., Qingxi, T. and Lanfen, Z. 2003. Evaluation of methods for surface soil moisture estimation from reflectance data. *International Journal of Remote Sensing* 24: 2069-2083.
- Whiting, M.L., Li, L. and Ustin, S.L., 2004. Predicting water content using Gaussian model on soil spectra. *Remote Sensing Environment* 89: 535-552.
- Zarco-Tejada, P.J., Rueda, C.A. and Ustin, S.L. 2003. Water content estimation in vegetation with MODIS reflectance data and model inversion methods. *Remote Sensing Environment* 85: 109-124.