



**HAL**  
open science

# Remotely-sensed optical and thermal indicators of land degradation

Bernard Lacaze

► **To cite this version:**

Bernard Lacaze. Remotely-sensed optical and thermal indicators of land degradation. 24th EARSeL Symposium, May 2004, Dubrovnik, Croatia. pp.211-218. halshs-00260491

**HAL Id: halshs-00260491**

**<https://shs.hal.science/halshs-00260491>**

Submitted on 4 Mar 2008

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

## Remotely-sensed optical and thermal indicators of land degradation

B. Lacaze

*PRODIG, CNRS UMR 8586, Paris, France*

Keywords: remote sensing, land degradation, desertification, vegetation, drought

**ABSTRACT:** Land degradation monitoring systems must take into account several indicators like vegetation cover, rain-use efficiency, surface run-off, soil erosion. Some of these indicators may be derived from remote-sensing data. Estimation of vegetation cover from satellite-data relies mainly on conventional or improved vegetation indices, although evidences of better results in arid zones have been obtained from the use of spectral unmixing techniques. Estimation of vegetation condition is generally achieved through drought-related indices, obtained from a combination of NIR and SWIR data (canopy water content) or from a combination of NDVI and thermal data (health condition, dryness). NOAA-AVHRR archive data remain the reference data source for identifying temporal trends, but recently available satellite data (EOS-MODIS, MSG-SEVIRI) should give significantly improved monitoring results due to better spectral, spatial or temporal resolutions.

## 1 INTRODUCTION

Land degradation generally signifies the temporary or permanent decline in the “productive capacity” (UN/FAO definition) or “biological potential” of the land. Although there may be natural causes to land degradation (severe droughts, landslides, ...), the most frequently recognized main causes of accelerated land degradation are human-induced and include:

- (i) overgrazing of rangeland;
- (ii) over-cultivation of cropland;
- (iii) waterlogging and salinization of irrigated land;
- (iv) deforestation; and
- (v) pollution and industrial causes.

Land degradation can not be simply defined, and it is doubtful if there will ever be proof or even consensus about the biophysical processes behind degradation (Warren, 2002). The “productive capacity of land” cannot be assessed simply by any single measure. Therefore, land degradation is difficult to grasp in its totality, and we have to use a set of indicators and to identify “monitorables” through remote-sensing.

Indicators are variables which may show that land degradation has taken place : decline in yields of a crop may be an indicator that soil quality has changed, which in turn may indicate that soil and land degradation are also occurring. Soil degradation is, in itself, an indicator of land degradation. In arid, semi-arid and sub-humid areas, desertification is the most widely recognized and most common form of land degradation, resulting from various factors, including climatic variations and human activities. Rubio & Bochet (1998) suggest the following desertification indicators groups for European areas :

- (i) SOIL e. g. run-off rate, soil loss rate, compaction, organic matter content, salinization, acidification;
- (ii) CLIMATE e. g. rainfall amount, rainfall intensity, rainfall frequency, rainfall variability, wind speed, temperature, evapo-transpiration;
- (iii) VEGETATION e. g. percentage cover, density, Leaf Area Index, growth rate, morphology, root depth, richness, endemism;
- (iv) TOPOGRAPHY e. g. slope angle, slope length, slope shape, aspect;
- (v) SOCIO-ECONOMICS e. g. human density, unsuitable practices, risk of forest fire, conservation practices, abandonment of land.

Remote-sensing has long been suggested as a time- and cost-efficient method for monitoring desertification (Hill *et al.*, 1995; Hill & Peter, 1996). Symeonakis and Drake (2004) developed a desertification monitoring system that uses four indicators : vegetation cover, rain use efficiency, surface run-off and soil erosion. These indicators have been derived from continental-scale remotely sensed data (NDVI) and ancillary data, and they were tested over sub-Saharan Africa for one year (1996) on a ten-daily temporal and 0.1 ° spatial resolutions.

Vegetation cover appears as a key parameter, as degradation processes involve a reduction in perennial vegetation cover and/or annual vegetation cover. However, in arid areas, vegetation cover fluctuates between and within years according to rainfall variations. A more effective desertification indicator is then the rain use efficiency (RUE), defined as

the ratio of Net Primary Productivity (NPP) to precipitation (Le Houérou, 1984). It is calculated on a yearly basis and expressed as  $\text{kg dry matter ha}^{-1} \text{ year}^{-1} \text{ mm}^{-1}$ . In arid and semi-arid zones, between 500mm and 150mm annual precipitation, RUE tends to decrease when aridity and potential evapo-transpiration increase; this trend has been observed from ground measurements (Le Houérou *et al.*, 1988), and also from remote-sensing derived estimates of RUE (Lacaze *et al.*, 2003). All other conditions being equal, it has been shown that RUE is lower in degraded areas than in equivalent un-degraded areas (Le Houérou, 1984 and 1989) and can be considered as a reliable desertification indicator. Using NOAA-AVHRR data archive to estimate NPP from cumulated NDVI, several studies have shown a stability or even a slight increase of RUE in sub-Saharan areas during recent periods of 10 to 15 years (Nicholson *et al.*, 1998; Prince *et al.*, 1998; Lacaze *et al.*, 2003).

This paper is focused on two basic components of land degradation monitoring systems: estimation of vegetation cover, and assessment of drought processes.

## 2 ESTIMATION OF VEGETATION COVER

### 2.1 Using Normalized Difference Vegetation Index

Vegetation cover fraction can be estimated from vegetation indices derived from spectral responses in the visible (VIS) and near-infrared (NIR) bands. Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index:

$$\text{NDVI} = (\text{R}_{\text{NIR}} - \text{R}_{\text{VIS}}) / (\text{R}_{\text{NIR}} + \text{R}_{\text{VIS}})$$

where  $\text{R}_{\text{NIR}}$  and  $\text{R}_{\text{VIS}}$  are reflectance of the two bands.

NDVI has been available since 1981 on a routinely basis (10-days maximum value composites) at a global scale with coarse resolution, and many studies have used these archived data to identify trends in vegetation phenology and productivity during the last two decades. New sensors are now available, which provide a continuity of NDVI measurements, but also improved features (Table 1).

Table 1. Characteristics of low resolution satellite sensors for vegetation cover monitoring.

Sensor	VI	Spatial resolution (nadir)	Temporal frequency	Availability since	Temporal synthesis
NOAA-AVHRR	NDVI	1.1 km	daily	1981	10 days
SPOT-VEGETATION	NDVI	1.1 km	daily	1998	10 days
EOS-MODIS	NDVI, EVI	0.25 km, 0.5 km, 1 km	1 – 2 days	2000 (TERRA) 2002 (AQUA)	16 days
MSG-SEVIRI	NDVI	3km 1km (panchro)	15 mn	2003 (METEOSAT-8)	4 - 5 days (*)

(\*) suggested synthesis, to be tested at 3km and 1 km spatial resolutions (MSG-ATR, 2004)

The estimation of vegetation cover can be obtained through a scaled NDVI, defined as :

$$\text{NDVI}^* = (\text{NDVI} - \text{NDVI}_0) / (\text{NDVI}_{100} - \text{NDVI}_0)$$

where  $NDVI_0$  and  $NDVI_{100}$  are respectively the values observed for bare soil (vegetation cover = 0) and for full canopy cover (vegetation cover = 100%).

Several studies (Choudhury *et al.*, 1994; Gillies & Carlson, 1995, Carlson and Ripley, 1997) have established a simple relationship between scaled NDVI and vegetation fractional cover:

$$FC = (NDVI^*)^2$$

Other authors (Leprieur *et al.*, 2000) are using a linear relationship between FC and  $NDVI^*$ :

$$FC = NDVI^*$$

In the studied Sahelian semi-arid region of Niger, Leprieur *et al.* (2000) made use of atmospherically corrected values of NDVI :  $NDVI_0 = 0,20$  (estimated from observed bare soil values, SPOT HRV data) and  $NDVI_{100} = 0.72$  (estimated from radiometric ground measurements over fully developed canopy of millet).

Some empirical studies have attempted to link directly field measurements of vegetation cover with satellite NDVI measurements. Zhang (1999) calculated the following linear relationship between FC and NOAA-AVHRR NDVI:

$$FC = 1.333 + 131.877 NDVI$$

which implies that  $NDVI_0 = -0.010$  and  $NDVI_{100} = 0.748$ ; Symeonakis & Drake (2004) used this relationship to map vegetation cover for the whole continent of Africa, from NDVI archive data extracted from a continental database generated by the NASA Global Inventory Monitoring and Modelling Studies (GIMMS) group.

Purevdorj *et al.* (1998) studied the relationship between vegetation cover of grasslands (Mongolia, Japan) and vegetation indices (ground measurements simulating AVHRR NDVI); they found a second-order polynomial regression :

$$FC (\%) = -4.377 - 3.733 NDVI + 161.968 NDVI^2$$

## 2.2 Using improved vegetation indices

The assumption of constant value of  $NDVI_0$  for bare soils and rocks is often unrealistic; an alternative method is based upon "soil-adjusted" vegetation indices, like SAVI (Huete, 1988) or related indices (TSAVI, MSAVI, ...).

Ferreira & Huete (2004) compared the use of NDVI and SAVI to follow the phenology of major vegetation types encountered in the Brazilian Cerrado: they conclude that SAVI responds primarily to near infrared variations, while the NDVI shows a strong dependence on the red reflectance. Both NDVI and SAVI show limitations in the detectability of very low vegetation cover (less than 15%) in hyper-arid areas (Saltz *et al.*, 1999).

Another improvement of vegetation indices comes from the use of a third channel in the blue region : this allows the definition of "atmospherically-resistant" vegetation indices. Both approaches (soil-adjustment and atmospheric-resistance) have been implemented in the newly available EVI (Enhanced Vegetation Index) derived from MODIS sensor aboard TERRA and AQUA satellites. EVI is defined as :

$$EVI = G[(R_{NIR} - R_{RED})/(L + R_{NIR} + C_1 R_{RED} - C_2 R_{BLUE})]$$

where  $R_{BLUE}$ ,  $R_{RED}$ ,  $R_{NIR}$  are respectively the reflectances in the blue, red and near-infrared channels and assigned values are  $G = 2.5$ ,  $L = 1$ ,  $C_1 = 6$ ,  $C_2 = 7.5$  (Huete *et al.*, 2002).

Fensholt *et al.* (2002) compared NOAA-AVHRR NDVI and MODIS NDVI (also called CVI “Continuity Vegetation Index”) in a semi-arid environment : they found that CVI, because it is obtained from narrower bands than AVHRR NDVI, gives better correlations with in situ spectral measurements and ground measurements of vegetation cover. Further comparisons of NDVI, CVI and EVI are still needed to optimize a vegetation cover monitoring system and to ensure continuity with historical data from NOAA-AVHRR or SPOT-VEGETATION.

### 2.3 Using Spectral Mixture Analysis

Spectral Mixture Analysis (SMA) is useful for evaluating the proportion of different basic components of a mixed pixel. SMA is very appropriate to monitor desertification processes, since the mixture of vegetation and bare soil is very common in arid areas. Even with a limited number of spectral channels, unmixing of basic components like green vegetation, bare soil and water is possible: this has been done, for example, using only 2 channels derived from AVHRR data (NDVI and brightness temperature) to map green vegetation fraction seasonal and multi-annual dynamics in the Mediterranean basin (Lacaze *et al.*, 2003).

At a regional scale, SMA has been successfully applied to monitor desertification from the use of multitemporal Landsat data (Hill *et al.*, 1995; Lacaze *et al.*, 1996; Hill *et al.*, 1998; Collado *et al.*, 2002; Hostert *et al.*, 2003). Linear spectral unmixing generally gives better results than the use of vegetation indices, especially in areas with complex patterns of rock and bare soils with different surface conditions. Unlinear spectral unmixing techniques may appear more appropriate in desert-like conditions (Ray & Murray, 1996).

## 3 DROUGHT ASSESSMENT

### 3.1 Using Normalized Difference Water Index

The water content of a vegetation canopy can be estimated through the use of a combination of near infrared (NIR) and short-wave infrared (SWIR) bands (Gao, 1996; Ceccato *et al.*, 2001). The Normalized Difference Water Index (NDWI) is defined as:

$$NDWI = (R_{SWIR} - R_{NIR}) / (R_{SWIR} + R_{NIR})$$

where  $R_{SWIR}$  and  $R_{NIR}$  are respectively the reflectance of the two bands.

It is possible to derive NDWI from SPOT-VEGETATION data. Using MODIS data, two indices may be obtained, using either SWIR channel 5 (1230 – 1250nm) or SWIR channel 6 (1628 – 1652nm) in combination with NIR channel 2 (841-876nm). Both combinations appeared useful as an indicator of canopy water stress in a semi-arid environment (Fensholt & Sandholt, 2003).

Jang (2004) proposed a new vegetation index combining NDVI and NDWI. The Normalized Moisture Index (NMI) is defined as:

$$NMI = NDVI + NDWI$$

and has been used for the evaluation of thermal-water stress of forests in southern Québec.

### 3.2 Using Vegetation Condition Index and Temperature Condition Index

Vegetation monitoring from AVHRR time series is usually based upon a comparison of present NDVI with some reference values derived from the available archive data. For example, for a given

week or 10-days period, NDVI can be scaled using maximum and minimum values to obtain a Vegetation Condition Index (VCI) :

$$VCI = 100 (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})$$

where  $NDVI_{min}$  and  $NDVI_{max}$  are respectively the absolute minimum and maximum value observed during the same period from 1985 to 2000, after removal of high temporal frequency noise (clouds, sun and sensor angular effects, ...).

Kogan *et al.* (2004) proposed to use in a similar way a scaled brightness temperature condition index (TCI) :

$$TCI = 100 (BT_{max} - BT) / (BT_{max} - BT_{min})$$

where BT is the brightness temperature derived from thermal infrared radiance in the 10.3 to 11.3  $\mu m$  AVHRR channel. Then a Vegetation Health index (VH) can be computed by combination of VCI and TCI :

$$VH = a (VCI) + (1-a) TCI$$

VCI, TCI and VH characterize moisture, temperature and vegetation health respectively. These indices can be used for real-time assessment of pasture condition and biomass condition, especially in areas where weather data are not available or non-representative (Kogan *et al.*, 2004).

### 3.3 Using LST-NDVI scattergrams

Many studies have demonstrated the possible use of a combination of optical (NDVI) and thermal (Land Surface Temperature : LST) data for vegetation condition assessment and dryness monitoring.

Karnieli & Dall'Olmo (2003) derived yearly drought indicators using several geometrical expressions based on the two extreme points of the Surface Temperature - NDVI scatterplot of AVHRR multitemporal data .

Scatterplot analysis of LST vs NDVI derived from coarse resolution satellite data shows that a triangular shape can be identified, from which a Temperature Vegetation Dryness Index (TVDI) can be defined (Sandholt *et al.*, 2002). This approach has been successfully applied to Senegal, using AVHRR data. Improved results should be obtained from EOS-MODIS and MSG-SEVIRI data.

## 4 CONCLUSIONS AND PERSPECTIVES

Estimation of vegetation cover from satellite-data relies mainly on conventional or improved vegetation indices, although evidences of better results in arid zones have been obtained from the use of spectral unmixing techniques.

Estimation of vegetation condition is generally achieved through a combination of NIR and SWIR data (canopy water content) or a combination of NDVI and thermal data (health condition, dryness).

Most monitoring studies rely on present vegetation condition assessment with reference to some statistical values derived from historical data. It is generally assumed that either the used spectral index is normally distributed or its range represents all the possible variations with the same frequency and probability. A more realistic alternative, proposed by Sannier *et al.* (1998) and applied to Jordan by Al-Bakri & Taylor (2003), is to define a Vegetation Productivity Indicator (VPI) by assessing the severity of departures from normal, taking

into consideration the actual statistical distribution of the spectral index, following the method generally used for the assessment of extreme hydrological events.

NOAA-AVHRR archive data remain the reference data source for identifying temporal trends, but recently available satellite data should give significantly improved monitoring results :

- improved temporal resolution and higher quality of temporal synthesis of vegetation indices from Meteosat Second Generation (MSG);
- improved spatial and spectral resolutions and high number of preprocessed data (EOS-MODIS).

MODIS data include not only NDVI and EVI indices, but also routinely estimations of LAI and FAPAR (Fensholt *et al.*, 2004), allowing an estimation of net primary productivity of ecosystems; combining these estimates with rainfall estimates (possibly derived from MSG data) will give improved estimates of rain-use efficiency, which in turn can be used as a desertification indicator on a yearly basis.

## 5 REFERENCES

- Al-Bakri, J. T. & Taylor, J. C. 2003. Application of NOAA AVHRR for monitoring vegetation condition and biomass in Jordan. *J. of Arid Environments* 54: 579-593.
- Carlson, T. N. & Ripley, D. A. 1997. On the relation between NDVI, Fractional Vegetation Cover, and Leaf Area Index. *Remote Sensing of Environment* 62: 241-252.
- Ceccato, P., Flasse, S., Tarantola, S., Jacquemoud, S. & Grégoire, J. –M. 2001. Detecting vegetation leaf water content using reflectance in the optical domain. *Remote Sensing of Environment* 77: 22-33.
- Choudhury, B. J., Ahmed, N. U., Idso, S. B., Reginato, R. J. & Daughtry, C. S. T. 1994. Relations between evaporation coefficients and vegetation indices studied by model simulations. *Remote Sensing of Environment* 50: 1-17.
- Collado, A. D., Chuvieco, E. & Camarasa, A. 2002. Satellite remote sensing analysis to monitor desertification processes in the crop-rangeland boundary of Argentina. *J. of Arid Environments* 52: 121-133.
- Fensholt, R. & Sandholt, I. 2003. Derivation of a shortwave infrared water stress index from MODIS near- and shortwave infrared data in a semiarid environment. *Remote Sensing of Environment* 87: 111-121.
- Fensholt, R., Sandholt, I. & Rasmussen, M. S. 2002. Earth observation of vegetation status in a semi-arid environment: comparison of Terra MODIS and NOAA AVHRR satellite data. In: *Proceedings of IEEE International Geoscience and Remote Sensing Symposium*. Toronto, Canada, 4: 2205-2207.
- Fensholt, R., Sandholt, I. & Rasmussen, M. S. 2004. Evaluation of MODIS LAI, fAPAR and the relation between fAPAR and NDVI in a semi-arid environment using in situ measurements. *Remote Sensing of Environment* 91: 490-507.
- Ferreira, L. G. & Huete, A. R. 2004. Assessing the seasonal dynamics of the Brazilian Cerrado vegetation through the use of spectral vegetation indices. *International J. of Remote Sensing* 25 (10): 1837-1860.
- Gao, B. –C. 1996. NDWI- A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 58: 257-266.



- Gillies, R. R. & Carlson, T. N. 1995. Thermal remote sensing of surface soil water content with partial vegetation cover for incorporation into climate models. *J. of Applied Meteorology* 34: 745-756.
- Hill, J. & Peter, D. 1996. The use of remote sensing for land degradation and desertification monitoring in the Mediterranean basin. Proceedings of a workshop jointly organized by JRC/IRSA and DGXII/D-2/D-4, Valencia, Spain, 13-15 June 1994. Luxembourg: Office for the Official Publications of the European Communities.
- Hill, J., Hostert, P., Tsiourlis, G., Kasapidis, P., Udelhoven, T. & Diemer, C. 1998. Monitoring 20 years of increased grazing impact on the Greek Island of Crete with earth observation satellites. *J. of Arid Environments* 39: 165-178.
- Hill, J., Mégier, J. & Mehl, W. 1995. Land degradation, soil erosion and desertification monitoring in Mediterranean ecosystems. *Remote Sensing Reviews* 12: 107-130.
- Hostert, P., Röder, A., Hill, J., Udelhoven, T. & Tsiourlis, G. 2003. Retrospective studies of grazing-induced land degradation in central Crete, Greece. *International J. of Remote Sensing* 24 (20): 4019-4034.
- Huete, A. 1988. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* 25: 295-309.
- Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X. & Ferreira, L. G. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* 83: 195-213.
- Jang, J. -D. 2004. Evaluation of thermal-water stress of forest in southern Québec from satellite images. Ph. D. thesis, Université Laval, Québec, Canada. English version available at Internet address : <http://www.theses.ulaval.ca/2004/21726/21726.html>
- Karnieli, A. & Dall'Olmo, G. 2003. Remote-sensing monitoring of desertification, phenology, and droughts. *Management of Environmental Quality* 14 (1): 22-38.
- Kogan, F., Stark, R., Gitelson, A., Jargalsaikhan, C., Dugrajav, C. & Tsooj, S. 2004. Derivation of pasture biomass in Mongolia from AVHRR-based vegetation health indices. *International J. of Remote Sensing* 25 (14): 2889-2896.
- Lacaze, B., Aït-Bachir, S. & Sommer, S. 2003. Analyse diachronique de l'efficacité des pluies pour la production végétale dans le bassin méditerranéen de 1982 à 1996. *Téledétection* 3 (2-3-4) : 165-174.
- Lacaze, B., Caselles, V., Coll, C., Hill, J., Hoff, C., de Jong, S., Mehl, W., Negendank, J. F. W., Riezebos, H., Rubio, E., Sommer, S., Teixeira Filho, S. & Valor, E. 1996. Integrated approaches to desertification mapping and monitoring in the Mediterranean basin. Final report of DeMon 1 Project (Hill, J., ed.), EUR 16448EN. Luxembourg: Office for the Official Publications of the European Communities.
- Le Houérou, H. -N. 1984. Rain-Use Efficiency : a unifying concept in arid land ecology. *J. of Arid Environments* 7: 1-35.
- Le Houérou, H. -N. 1989. *The Grazing Land Ecosystems of the African Sahel*. Berlin: Springer-Verlag.
- Le Houérou, H. -N., Bingham, R. E. & Skerbek, W. 1988. Relationship between the variability of primary production and the variability of annual precipitations in world arid lands. *J. of Arid Environments* 15: 1-18.

- Leprieur, C., Kerr, Y. K., Mastorchio, S. & Meunier, J. C. 2000. Monitoring vegetation cover across semi-arid regions: comparison of remote observations from various scales. *International J. of Remote Sensing* 21 (2): 281-300.
- MSG-ATR.2004. *Goupe de Recherches Météosat Seconde Génération-Analyse en Temps Réel*. cf. Internet address <http://prodig.univ-paris1.fr/msg/>
- Nicholson, S. E., Tucker, C. J. & Ba, M. B. 1998. Desertification, drought, and surface vegetation: an example from the West African Sahel. *Bulletin of the American Meteorological Society* 79: 815-829.
- Prince, S. D., Brown de Coulston, E. & Kravitz, L. L. 1998. Evidence from rain-use efficiencies does not indicate extensive Sahelian desertification. *Global Change Biology* 4: 359-374.
- Purevdorj, Ts., Tateishi, R., Ishiyama, T. & Honda, Y. 1998. Relationships between percent vegetation cover and vegetation indices. *International J. of Remote Sensing* 19 (18): 3519-3535.
- Ray, T. W. & Murray, B. C. 1996. Nonlinear spectral mixing in desert vegetation. *Remote Sensing of Environment* 55: 59-64.
- Rubio, J. L. & Bochet, E. 1998. Desertification indicators as diagnosis criteria for desertification risk assessment in Europe. *J. of Arid Environments* 39: 113-120.
- Saltz, D., Schmidt, H., Rowen, M., Karnieli, A., Ward, D. & Schmidt, I. 1999. Assessing grazing impacts by remote sensing in hyper-arid environments. *J. of Range Management* 52: 500-507.
- Sandholt, I., Rasmussen, K. & Andersen, J. 2002. A simple interpretation of the surface temperature / vegetation index space for assessment of surface moisture status. *Remote Sensing of Environment* 79: 213-224.
- Sannier, C. A. D., Taylor, J. C., Du Plessis, W. & Campbell, K. 1998. Real-time vegetation monitoring with NOAA-AVHRR in Southern Africa for wildlife management and food security assessment. *International J. of Remote Sensing* 19: 621-639.
- Symeonakis, E. & Drake, N. 2004. Monitoring desertification and land degradation over sub-Saharan Africa. *International J. of Remote Sensing* 25 (3): 573-592.
- Warren, A. 2002. Can desertification be simply defined? In: *CCD: Implementing the United Nations Convention to Combat desertification. Past experience and future challenges* (Markussen, H. S., Nygaard, I. & Reenberg, A. eds.). SEREIN Occasional Paper 14: 19-46. Copenhagen: University of Copenhagen, Sahel-Sudan Environmental Research Initiative.
- Zhang, X. 1999. Soil-erosion modeling at the global scale using remote sensing and GIS. Ph. D. Thesis, King's College, London. (available at : <http://crsa.bu.edu/~zhang/thesiscover.htm>).