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Recent Progresses on Remote Sensing Monitoring of Desertification

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Abstract: Desertification is one of the serious environment problems faced by many countries in the world. It not only deteriorates the productivity of the fragile ecosystems but also causes serious environmental and social problems. Combating desertification has become the top priority for governments around the world, international organizations, and the United Nations. Remote sensing is the only method of choice for monitoring desertification over large areas because of its capability of collecting data frequently, synoptically, and objectively over such areas. Information derived from remote sensing data has been widely used in modeling and predication of desertification. It has also been used in supporting decision-making for combating desertification. This paper summarizes recent progresses on many aspects of remote sensing monitoring of desertification, including the availability of new remote sensing data and products for desertification research, desert mapping, dust storm monitoring, desertification monitoring, forces of desertification, and desertification modeling. It also presents the future directions in remote sensing of desertification.

Key words: Desertification, remote sensing, desert, modeling, mapping.

Desertification is land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activities (United Nations, 1992). Desertification affects about one-sixth of the world's population, 70% of all dry lands, amounting to 3.6 billion hectares, and one quarter of the total land area of the world (United Nations, 1992). Desertification causes not only the deterioration of the environment and the productivity of the fragile ecosystems, but also the poverty of people living in such regions. It was estimated that the annual direct economic losses due to desertification amounts to more than $42 billion (Layoub, 1998; Dregne and Chou, 1992).

Due to global climate changes and the over-exploitation of ecosystems by the increased human economic activities, desertification is accelerated in many parts of the world. For example, the land desertified annually in China in the 1960-1970's was 1560 km^2, in 1980's 2100 km^2, and in 1990's 2400 km^2 (Di, 2003a; Chen, *et al.*, 2003). Desertification is especially serious in developing countries where people are dependent on the surrounding environment/ ecosystems for living, and resources are not available for restoring the over-exploited ecosystems. More than 80% of 50,000 to 70,000 sq. km of the land desertified annually are located in developing countries. Because desertification changes the land surface characteristics, it also affects regional climate (Xie, 1996). Desertification not only threats the ecosystem health and human living within the region, but also affects areas far away from deserts. For example, dust storms from the Gobi desert have caused significant air quality and traffic problems in Beijing, Seoul, and parts of Japan, and even reached as far as the east coast of North America (Claiborn *et al.*, 2001; Husar, 2001).

Because of the extreme threats of desertification to environment and human living conditions, combating desertification has become the top priority for governments of many countries, international organizations, and non-governmental environment organizations in their environment agenda. United Nations, in Agenda 21, specifically lists the steps to be taken to combat desertification (United Nations, 1992). In order to effectively combat desertification and sustain economic development, monitoring, modeling, and prediction of desertification are important. The Agenda 21 calls for strengthening the knowledge base and developing information and monitoring systems for regions prone to desertification and drought, including the economic and social aspects of these ecosystems. Remote sensing is the only method of choice for monitoring desertification over a large area because of its capability of collecting data frequently, synoptically, and objectively over such an area (West, 2003). Information derived from remote sensing data has been widely used in modeling and predication of desertification. It has also been used in supporting decision-making for combating desertification. This paper summarizes recent progresses on remote sensing monitoring of desertification.

New Remote Sensing Infrastructure for Desertification Research

In recent years, there are two significant advances in the remote sensing infrastructure for facilitating and enhancing the desertification research. The first one is the enhanced remote sensing capabilities for producing a new suite of remote sensing data and products important to the desertification research. The second one is the web-based data discovery and access technology enabling desertification researchers to easily access vast amount of remote sensing data from multiple sources.

With the rapid advance of remote-sensing technology, significant progress on data acquisition capabilities has been achieved in recent years. Many new satellite remote sensing systems have been commissioned to monitor Earth's climate and environment. The most significant one to the desertification research is the Earth Observing System (EOS) program from NASA Earth Science Enterprise (ESE). New remote sensing datasets and derived products from this program have been widely used in the desertification research.

The NASA EOS program was established in 1991 as a US presidential initiative (Asrar and Dozier, 1994). EOS was designed to initiate a new era of integrated global observations intended to advance our understanding of the entire Earth system on a global scale through developing a deeper understanding of the components of that system, their interactions, and how the Earth is changing. EOS plays a critical role in addressing a key challenge – to develop the capability to predict the changes that will occur in the next decade to century, both naturally and in response to human activities (King, 1999). EOS provides the next generation of satellite remote-sensing instruments and platform hardware, a community of funded scientists, and the infrastructure to consolidate data and information from surface campaigns and remote-sensing satellites. It is planned that the EOS program will observe the Earth continuously for the next 15 years (Asrar and Greenstone, 1995). During the first phase of EOS program, which will be completed in the year 2004 with the launch of the Aura satellite, NASA is funding the development and launch of 25 satellites, each carrying multiple remote sensors (Asrar, 1999).

The EOS program provides a new wealth of remote sensing data that were never previously available to Earth scientists and decision makers. Currently EOS program generates more than 2Tb of remote sensing data per day (McDonald and Di, 2003). According to NASA EOS data policy, most of EOS data and products are freely available to scientists worldwide. Because EOS program intended to provide needed data for global change research and desertification is one of major phenomena of global changes, many EOS data sets and products are very useful for desertification research and decision-making. The most significant ones are those collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard both EOS Terra and Aqua satellites (Barnes *et al*., 1998; Guenther *et al*., 2002).

Before MODIS data became available from the Advanced Very High Resolution Radiometer (AVHRR) aboard the NOAA Polar-orbiting Environment Satellites (POES) were widely used in desertification research at regional and global scales (Malo and Nicholson, 1990; Hastings and Di, 1994a,b; Tucker *et al*., 1994; Belward *et al*., 1995; Tucker and Nicholson, 1999). Compared to AVHRR, MODIS has not only higher spatial resolution (250 meters in visible channels compared to AVHRR's 1 km resolution) but also more spectral channels (36 channels in MODIS comparing with 5 channels in AVHRR). MODIS also has much better spectral accuracy than AVHRR. Same as the AVHRR, MODIS data are directly broadcasted to ground stations around the world. This capability enables many real- or near-real time applications, such as monitoring dust storms and forest fires (NASA, 2003; Justice *et al*., 2002). MODIS sensors aboard Terra and Aqua satellites provide twice-daily global coverage. Because of those advantages, MODIS data and products have greater potential than AVHRR in the desertification research.

In addition to the vast amount of free raw remote sensing data newly available for the desertification research, another significant advance in recent years is the availability of large amount of well-validated standard products derived from remote sensing, data assimilations, and modeling. Traditionally, data providers only provide raw data to users. Before those data being used in the desertification research and applications, they have to be processed. Such processing requires significant amount of data processing knowledge and computer resources. Not all desertification researchers have the capability and knowledge to perform such processing. Instead of only providing raw remote sensing data to users, currently data providers also produce and provide the commonly used standard products to users. The NASA EOS program alone produces more than 400 types of standard data products (King *et al.,* 2003). Many of them are extremely important to the desertification research. For example, NASA EOS program provides global vegetation indices (Huete *et al.*, 2002; 1999), leaf area index (LAI) (Tian *et al.*, 2000), fraction of photosynthetically active radiation (FPAR) (Tian *et al.*, 2000), net primary productivity (NPP) (Running, 2000), land use/land cover (LULC) (Borak and Strahler, 1999; Muchoney *et al.*, 1999; Zhan *et al.*, 2000), surface albedo (Liang *et al.*, 1999) and other products derived from remote sensing to users free of charge. All EOS data and products can be discovered and ordered from NASA EOS Data Gateway (EDG, 2003).

In addition to the new data and products available from US sources, new remote sensing data are also available from other nations' remote sensing programs/satellites for global desertification research. Examples of those new data include SPOT VEGETATION from France (Lu *et al.*, 2003; Chen and Cilhlar, 2000), ADEOS I and II from Japan (EORC, 2001), ENVISAT from European Space Agency (ESA, 2003), and CBERS from China and Brazil (Chen *et al.*, 2003; DGI, 2003). Although not all of the data from those satellites are free to worldwide users, most of them are available to researchers at marginal cost.

Desert Mapping

Mapping the extent of deserts is one of the objectives in desertification research. Many existing global environmental data sets contain information about the global desert distribution. However, many such datasets were originally developed by their creators manually, and then put into digital format without being validated thoroughly. Those datasets include many subjective judgments of the dataset authors regarding the state of desertification. Large disagreement exists among those datasets. For example, Hasting and Di (2002), examined the five datasets, which contain desert classes, in NOAA Global Change Data Base (NOAA, 1992) by a coincident analysis. The five datasets involved in the analysis include (1) Primary and Secondary Characteristics of Terrain (FNOCPT and FNOCST in NOAA, 1992); (2) Olson World Ecosystems Version 1.4D (OWE14D in NOAA, 1992); (3) Leemans Holdridge Life Zone Classifications (LHOLD in NOAA, 1992); (4) Matthews Vegetation Types (MVEG in NOAA, 1992); and (5) Wilson and Henderson-Sellers Global Land Cover for General Circulation Climate Models (WHCOV1 and WHCOV2 in NOAA, 1992). It was found that significant difference about the global desert distribution exists among the five datasets.

Satellite remote sensing, because of its large spatial coverage, frequent revisit, and objective observation of the Earth surface, provides a unique capability for mapping the global distribution of deserts. Since early 80's, satellite remote sensing has been widely used to map deserts. Methodologies developed for this purpose are based on the spectral, temporal, and spatial (textural) information domains provided by satellite data. Two common methods have been used, the threshold method with a discriminator, and the land cover classification method.

For the threshold method, the discriminator commonly used for mapping deserts is the Normalized-difference Vegetation Index (NDVI). It is normalized difference between the reflectance of the near-infrared and red bands of remote sensing data. Studies showed that NDVI is related to the vegetation growth status (Ehrlich *et al.*, 1994). Because one of fundamental characteristics of deserts is the lack of vegetation, NDVI is a good discriminator for deserts. The most common method for desert mapping by remote sensing is the threshold method (Tucker *et al.*, 1991; Tucker *et al.*, 1994; Tucker and Nicholson, 1999; Runnstrom, 2000; Rasmussen *et al.*, 2001; Hastings and Di, 2002). The method normally uses a specific NDVI value as the threshold. Pixels with NDVI values lower than the threshold are designated as desert. This method can identify most area of deserts around the globe. However, the method has some limits. First, NDVI values are not only affected by the ground vegetation condition, but also the soil background as well as the atmospheric condition and imaging condition (e.g., solar zenith angle, the scanning angle, etc.) (Di *et al.*, 1994; Di and Hastings, 1994a, b; Di, 2003b). Second, the vegetation conditions at arid and semi-arid zones are particularly sensitive to inter-annual weather variability (Neilson, 1986; Malo and Nicholson, 1990; Laycock, 1991; Ellis and Galvin, 1994; Neilson, 1995; Nicholson *et al.*, 1998). Therefore, a pixel with lower than an established threshold value does not necessarily indicates the existence of desert in the pixel. Meanwhile, a pixel with higher than the threshold value also does not necessarily mean that the place is not desert. For example, drought can significantly reduce NDVI values of a non-desert region, which may mistakenly be identified as desert because of the low NDVI values.

In order to overcome the first problem, in recent years, many studies have been conducted to produce better-calibrated NDVI products. Those efforts included the reprocess of NOAA GVI data products to produce AVHRR Pathfinder Land products (Agbu and James, 1994; Goward *et al.*, 1994; Belward *et al.*, 1995), and produce the new variations of NDVI such as the Enhanced Vegetation Index (EVI) (Huete *et al.*, 1994). In addition, new discriminators derived from remote sensing, such as the leaf area index (LAI) and fractional vegetation cover (FVC), can also be used in desert mapping.

To overcome the second problem, the inter-annual vegetation dynamics caused by weather fluctuations have to be removed. The common way to remove such dynamics is to use the statistical values calculated from a time series that is much longer than the period of inter-annual weather variations. Thanks to long-term archive effort of many international space agencies, we have more than 20-year records of land surface conditions observed by satellite remote sensing. For example, the NASA/NOAA AVHRR pathfinder land product provides global biweekly-calibrated NDVI and other parameters at 8 km resolution from 1981 to present (Agbu, 1994; Young and Anyamba, 1999). The commonly used statistical variables for mapping deserts include multi-year mean, maximum, and medium (Yu *et al.*, 2003; Price *et al.*, 2003). Hasting and Di (2002), has successfully identified deserts by using the maximum composite of multi-year monthly global NDVI time series.

The alternative approach for global mapping of desert is to use the classification methods for producing land use/cover maps. Deserts are identified as classes in such maps. Wide regional desert mapping was achieved using phenological classification of vegetation indices derived mainly from NOAA AVHRR and MODIS images. More detailed mapping at local scales was conducted with multispectral classification using mainly Landsat TM images. Both statistics-based supervised and unsupervised classifications algorithms were widely used in 80's and early 90's to classify remote sensing data for land use/land cover (Loveland and Belward, 1997; Loveland *et al.*, 2000). Comparing with the threshold method, the classification method enables the full use of multi-band information the sensors have collected, but requires much more computational power. It also allows introducing non-remote sensing data, such as temperature, precipitation, and elevation, into the classification scheme for better mapping of deserts. New classification algorithms, including linear unmixed (Collado *et al.*, 2002), and decision tree (Friedl *et al.*, 1999; Friedl and Brodley, 1998), have been developed and applied to produce land use/cover maps.

Traditionally, the land cover classification for desert mapping mainly used the spectral information of remote sensing data taken at one or a few of time steps. The information in the temporal domain was not fully used because of non-availability of the time-series data and the limit of the computational power that made the classification of global multiple-band time series data impossible. With the availability of global time series of remote sensing data and significant increase in computer capabilities, currently most of desert classifications use either time series or multi-temporal datasets as the essential inputs to the classifiers. One of the most commonly used time series for the land use/cover classification are the NDVI time series derived from NOAA/AVHRR data and continued with MODIS (King *et al.*, 2003). The timing and the intensity of annual green-up of the surface are the information used for determining the land cover types. However, the land cover information does not only exist in the NDVI time series. In order to accurately obtain the land cover mapping, additional information related to land cover has been used in the classification. For example, the MODIS land cover algorithm draws information from not only the annual NDVI time series but also directional surface reflectance from several spectral bands, near-infrared image textures, enhanced vegetation index, snow/ice cover, and surface temperature (King *et al.*, 2003).

Dust Storm Monitoring

One of the significant features of desertification is the loss of surface vegetation. As a result, soil erosion caused by winds has become a prominent problem in desert and semi-desert areas. With the worsening of desertification, dust storms, a kind of weather phenomena that makes the horizontal visibility lower than 1 km, caused by dust particles elevated by strong winds, have occurred more frequently and severely in many parts of the world in recent years. For example, in the spring of 2000 alone there were 12 dust storms affecting one-fifth of China (Chen *et al.*, 2003).

Dust storms not only erode the topsoil of arid and semi-arid regions, further deteriorating the environment there, but also cause environment, social, and potential human health problems far away (Qiu *et al.*, 2003). Recent studies showed that dust particles originated in Central Asia could travel to Korea, Japan, and cross the Northern Pacific Ocean to reach as far as the east cost of North America (Husar, 2001; Claiborn *et al.*, 2000). The dust storms are also one of the major sources for the continental aerosols, a significant force in the climate change.

Satellite remote sensing provides the best tool to monitor large dust storms because of its large spatial and frequent temporal coverages. Moulin *et al.* (1997), used Meteosat ISCCP B1 and B2 datasets to provide daily monitoring of Saharan dust load over ocean, although the spatial resolution of Meteosat ISCCP B1 and B2 datasets is quite low. Because of twice daily global coverage, high spatial resolution, and multi-spectral capability of MODIS sensors aboard the NASA EOS Terra and Aqua satellites, MODIS image products have become one of the best data sources for monitoring dust storms around the globe. Figure 1 shows a dust storm over China sensed by MODIS on March 17, 2002. The figure clearly showed the dust storm originated in the Gobi desert reached Korea and the Sea of Japan. Figure 2 shows a true-color composite scene acquired on December 15, 2003 by MODIS flying aboard NASA's Aqua satellite (NASA 2003). There are two distinct sources of dust plumes in the scene. The dust in southeastern New Mexico and northern Mexico is a pale tan color, almost white, whereas the dust in north central Texas is a relatively darker, light brown color. The dust storm was caused by wind gusts in excess of 80 km per hour in the desert and semi-desert regions of New Mexico, and northern Mexico.

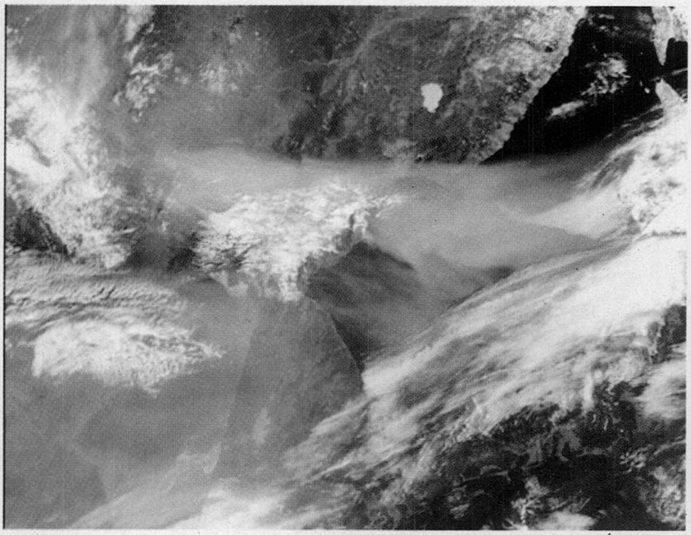

Fig. 1. Dust storm over China and Korea on March 17, 2002 sensed by MODIS.

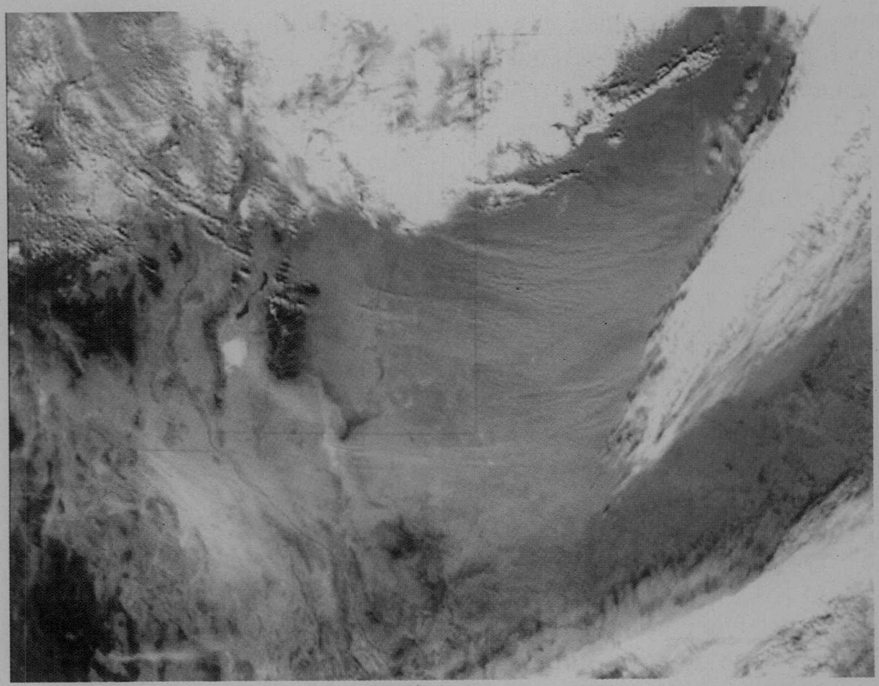

Fig. 2. Dust storm over Taxes on December 15, 2003 sensed by MODIS.

Qiu *et al.* (2003) used MODIS level 1b data to study the frequency of dust storms in Tarim Basin of China, and its relationship with the change in land use and land cover. It was found within the twenty-two months from January 2001 to October 2002, dust or sand storms at various scales occurred on the basin almost year around. However, the basin-wide dust or sand storms were rare and they occurred mostly in March and April. It was also found that all dusts were derived from within and confined to the basin. Only small portion of dusts were able to escape from the basin with strong cold frontal systems. Analysis of land cover map derived from MODIS level 1b data with the dust images revealed that the former Tarim River delta complex and current and past fluvial plains were the major sources of the dusts.

Desertification Monitoring

An activity closely related to remote sensing of desert mapping is the monitoring of desertification. The increased availability of remote sensing time-series data in recent years makes it possible to analyze desertification at regional, continental, and global scales. For continental and global desertification studies, time series data from AVHRR and MODIS are widely used. For the local or regional studies, time series data from Landsat TM and other high-resolution data are used. Same as the desert mapping, there are two common ways to monitor the progress of desertification from remote sensing; the vegetation index/phenological approach and the land use/cover approach.

The vegetation index approach analyzes changes of vegetation index values, such as NDVI and their derivatives, for the same location over a period of time to assess the progress of desertification. Most studies in the early years directly compared NDVI values at the same location acquired at the same phonological state in two different years to analyze the progress of desertification. However, NDVI values are affected significantly by climate factors, especially precipitation at the middle and low latitudes and temperature at high latitudes (Hastings and Di, 1993; 1994a,b). Both meteorological variables exhibit significant inter-annual variations, especially in arid and semi-arid zones where desertification is most prominent. Therefore, using short-term annual NDVI datasets to analyze the progress of desertification is not reliable.

Desertification changes the non-desert ecosystems to desert ones. In order to identify the true ecosystem changes due to desertification, research emphasis in recent years has been placed on monitoring and analyzing the long-term trend of some phenological phenomena observed by remote sensing (Tucker *et al.*, 2001). The most commonly used phenological indictors include the starting and ending dates for a growing season, the coefficient of variation of NDVI time series, and the integration of the annual NDVI curve. The detection of changes of these indicators implies the trend of desertification.

There are two common ways to derive the starting and end of a growing season from NDVI time series. The first one uses an NDVI threshold method (Lloyd, 1990; Myneni *et al.*, 1997, 1998) to identify the starting and the end of a growing season. The second method tries to find a sudden increase in NDVI in the spring as the indicator of the starting of a growing season (Reed *et al.*, 1994; DeFries *et al.*, 1995; Zhan *et al.*, 2000). The threshold method looks into the time series to find a specific date on which the NDVI value is larger than the threshold value. This method is very simple and easy to implement. However, this method requires setting a threshold for each land cover type. Because most land cover types are a mixture of plant types, determining the optimal threshold value for a land cover type for a specific area can be difficult, if not impossible. In addition, NDVI values are also affected by changes in the sensing environment and influenced by soil background, which further complicates the use of this method (Price *et al.*, 2003; Yu *et al.*, 2003). The second method uses the "moving average" approach to smooth the NDVI time-series curve. The smoothed and raw NDVI curves are then superimposed to identify the date the two curves cross, which is defined as the time when the onset of green-up occurs.

In addition to use the NDVI directly, statistical parameters derived from NDVI have also been used in desertification analysis. Weiss *et al.* (2001), assessed the condition of a portion of Saudi Arabia's rangelands and evaluated the effects of grazing by the animal herds of indigenous nomads over the last decade. An analytic methodology for the detection of desertification of arid and hyper-arid rangelands was developed specifically for this project. The conceptual framework for the analysis is the use of the coefficient of variation (COV) of the monthly NDVI maximum-value composite as a measure of vegetative biomass change. A higher NDVI COV for a given pixel (excluding cases of changes in land use) represents a greater change in vegetation biomass in the ground area represented by that pixel. Linear regression was used to determine the trend in COV values for each pixel over the 12-year period for which data were available; pixels with a negative slope are considered to represent ground areas with decreasing amounts of vegetation. Results were validated by tests of statistical significance and by comparison of the theoretical results to vegetation change and land-cover data from the remote sensing systems and from reconnaissance flights over select areas. These desertification trend results were then combined with land-cover information to provide an assessment of desertification status.

NDVI and its derived parameters sometimes are combined with other products derived from remote sensing, such as land surface temperature (LST), leaf area index (LAI), and net primary productivity (NPP), to identify the degree of desertification (Potter *et al.*, 1999; Karnieli and Dall'Olmo, 2003). The combined use of multiple products normally provides more information about desertification than use of NDVI alone. Karnieli and Dall'Olmo (2003), characterized and assessed the temporal dynamics of desertification, phenology, and drought processes in the northern Negev desert by combined use of satellite imageries in the reflectivity and thermal spectral bands. NDVI and LST derived from NOAA-14 AVHRR data covering four years were applied to the sand field in the northwestern Negev (Israel), which is almost totally covered by biological soil crusts, and to an adjacent region in Sinai (Egypt), consisting mainly of bare dune sands. Time series presentation of the NDVI and LST revealed that NDVI values corresponded to the reaction of the vegetation to rainfall and that LST values represent seasonal climatic fluctuation. Scatterplot analysis of LST vs. NDVI showed that the two different biomes (Sinai and the Negev) exhibited different yearly variation of the phenological patterns. Drought indicators were derived by using several geometrical expressions based on the two extreme points of the LST-NDVI scatterplot. The later analysis led to a discrimination function that aims to distinguish between the drought years and the wet years in both biomes. Karnieli and Dall'Olmo's study indicated that a great deal of information on dryland ecosystems could be derived from NDVI and LST and the combined use of these two products provided more information than any product alone.

The land use/cover approach compares the land cover data from two different dates to obtain the expansion or contraction information of deserts, which can be used to determine desertification trends between the time intervals. Therefore, a time series of land cover data can be used to derive information about desertification progress and desert dynamics (Collado *et al.*, 2002; Hölzel *et al.*, 2002; Zhan *et al.* 2002; Gao and Zha, 2001). However, the traditional statistics-based classification algorithms assume a place either is a desert or non-desert, ignoring the fact that desertification is a gradual process. The rate derived from the land cover method also assumes the linear progress of desertification. In reality, land degradation associated with desertification rarely translates into linear, declining trends in vegetation cover due to inter-annual climatic variability. Appropriate indicators of land-cover modifications need to be defined for semi-arid regions subject to desertification. Diouf and Lambin (2001), proposed that land degradation can be measured by: (1) a decrease in the resilience of vegetation to droughts; (2) a decrease in rain-use efficiency; and (3) a modification of floristic composition. Further study on the quantification of degree of desertification through remote sensing is needed.

Because of the coarse spatial resolution of satellite data used in the regional and global studies, each pixel in such data may consist of multiple land cover components. It is better to compare the percentage of each land cover component within a pixel to obtain the information about land degradation. Such kind of approaches requires using subpixel classification algorithms such as spectral unmixing and neural network classifiers. Collado *et al.* (2002), unmixed the vegetation, water and sand components in the crop-rangeland boundary of Argentina for two Landsat TM scenes acquired ten years apart. Simple differences between unmixed images of sand or water revealed dune movement, re-vegetation trends and variations in water bodies, as a result of changing rainfall and land use patterns, enabling more accurate analysis of the desertification process in the study region. Haboudane *et al.* (2002) used the combination of the spectral unmixing and a set of indices describing the spectrum shape for characterizing the land degradation. They also combined spectrally-derived land cover units and geomorphometric units to evaluate ecosystem vulnerability to land degradation and desertification. Results showed that the spatial distribution of regional patterns of land degradation could be reliably mapped by using both indices describing the spectrum shape and spectral unmixing. The latter held great potential for operational mapping of soil conditions and erosion features from optical images. Moreover, landscape-unit analysis showed that Digital Elevation Model (DEM) variables, combined with spectral information, were very useful for land degradation assessment. Seixas (2000), used a 10-year series of Landsat-5 Thematic Mapper images to test the hypothesis that increasing environmental heterogeneity at the landscape scale is evidence for desertification. The proposed methodology, based on spatio-temporal statistical analysis, was implemented for a study area in the inner southern Alentejo region of Portugal. Major findings from the study include the increasing 'greenness' of vegetation patterns and an increasing trend towards spatial heterogeneity of both vegetation and soil variables. The former supports the global model of desertification, which proposes that feedback mechanisms stimulate the adaptation of vegetation to adverse environmental conditions by increasing biomass.

While experimenting the selection of the NDVI thresholds for discriminating deserts from non-desert areas, Hastings and Di (2002), tried using NDVI data sets to map a "fragile fringe" marginal zone between desert and non-desert. Figure 3

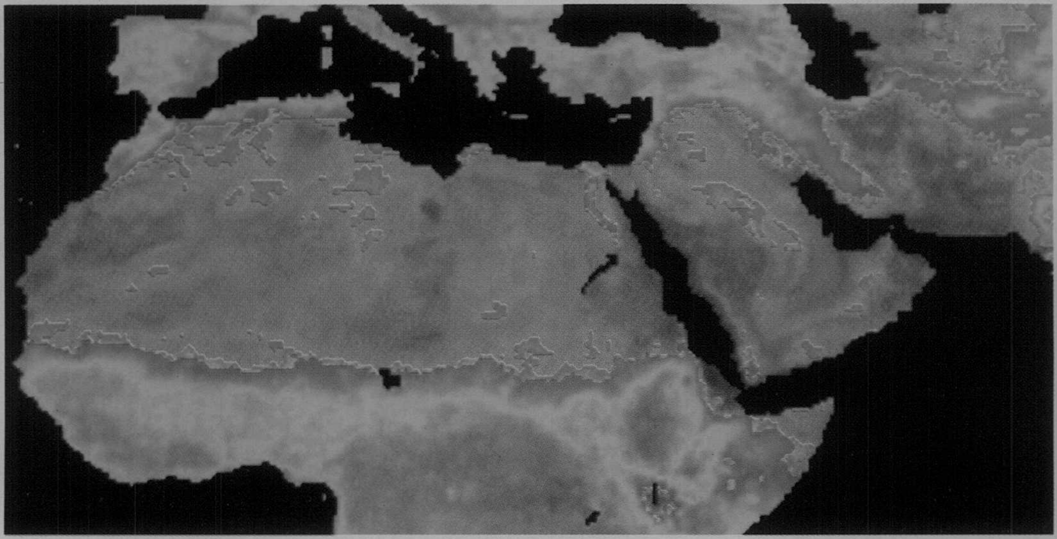

Fig. 3. The fringe areas of deserts in North Africa and much of West Asia.

shows one such map for North Africa and part of West Asia. With the help of specialists working in this field, they divided the fringe areas into two categories. Category one has relatively low global NDVI values, which in many areas may be desert, but which in other areas might contain sparse vegetation (dark red in Fig. 3). Category two has slightly higher global NDVI values, which tend to denote slightly vegetated areas (pink in Fig. 3). For example, the large areas in north-central Saudi Arabia are areas with extensive agricultural development, including center-pivot irrigation systems. The marginal zones could be considered as areas tending to have sparse vegetation, on the edges of deserts, which might be considered "at risk" from desertification if appropriate measures are not taken. Some of these marginal areas are not at the edges of (or within) existing deserts, but are relatively fragile areas surrounded by more robust vegetation. These areas could be damaged by overgrazing or other forms of overuse - to become desert if not cared for properly. Periodic compilations of global NDVI may be used to monitor the distribution and status of fragile areas at risk of desertification.

Although it is simple, Hastings and Di's method cannot quantitatively determine the degree of risk for desertification. The Desert Research Institute and the US Environmental Protection Agency (EPA) developed a quantitative technique for identifying and assessing areas at risk for desertification in the arid, semi-arid, and sub-humid regions of the United States (Mouat *et al.*, 1997). It uses selected environmental indicators integrated into a Geographic Information System (GIS). Five indicators were selected: potential erosion, grazing pressure, climatic stress (expressed as a function of changes in the Palmer Drought Severity Index (PDSI)), change in vegetation greenness (derived from

NDVI), and weedy invasives as a percent of total plant cover. The data were integrated over a regional geographic setting using a GIS, which facilitated data display, development and exploration of data relationships, including manipulation and simulation testing. By combining all five data layers, landscapes having a varying risk for land degradation were identified, providing a quantitative tool that could be used to improve land management efficiency.

Forces of Desertification

One of the questions that desertification studies try to answer is what causes the desertification, by natural forces, anthropologic forces, or combination of the two (Humle and Kelly, 1993; Ellis *et al.*, 2002). Because of its large spatial coverage, frequent temporal coverage, and the objective observation of the surface conditions, satellite remote sensing becomes the choice for such studies. This type of study normally combines remote sensing data with demographic, meteorological, and field observation data. The integrated data are commonly analyzed in geographic information systems (Gao and Zha, 2001; Ries and Marzolff, 2003; Ares *et al.*, 2003).

Yu *et al.* (2003), used the time-series NDVI derived from AVHRR from 1981 to 1999, to analyze the forces of the desertification in the surround areas of Gobi desert. The study took advantage of the huge difference in land use practices between Mongolia and China (Ellis, 1992) to examine if natural or human force is the dominant factor for desertification in the region. It was found that there is no significant difference between Mongolia and China in the study region for desertification despite the huge difference in the land use practices. It was also found that the size of the Gobi desert derived from NDVI is highly correlated with the inter-annual dynamics of precipitation and temperature. Yu's study indicated that nature is the main force for desertification in the region around the Gobi desert.

However, many other studies have indicated that anthropologic forces, mainly the land use practices, are the major force for recent desertification (Hanan *et al.*, 1991; Ojima *et al.*, 1998; Gao and Zha, 2001; Chen *et al.*, 2003; Liu *et al.*, 2003; Ojima *et al.*, 2003). Hill *et al.* (1998), studied the degradation of permanent semi-natural vegetation and the resulting acceleration of soil degradation and erosion processes in Mediterranean basin by remote sensing. The approach is based on describing surface conditions and vegetation cover over time with a long-term series of earth observation satellites. The result indicated that land degradation in the study region was mainly caused by human activities rather than climatic conditions.

Bennouna *et al.* (2000), studied the desertification of rangelands in Morocco by using the combination of high-resolution Satellite Pour l'Observation de la Tene (SPOT) image and field surveys. Close relationships were demonstrated between the abiotic environment and the vegetation. The relevant bio-pedomorphological classes, corresponding to the different types of rangeland, were identified. The cartographic accuracy of these classes was considerably increased by combining the stratification obtained by computer-assisted Visual Interpretation of SPOT image, with a maximum likelihood supervised classification of each stratum. Results indicated that demographic expansion, cereal growing, and overgrazing constitute the principal factors of degradation in the study region.

Liu *et al.* (2003) studied desertification in the farming and grazing interlocked transitional zone along the Great Wall in northern Shaanxi Province, China. Four desertification indicators (vegetative cover, proportion of drifting sand area, desertification rate, and population pressure) were used to assess the severity of desertification in a GIS. The first three factors were derived from multi-temporal remote sensing and land inventory data. The last factor was calculated from census data. It was found that the overall severity of land degradation in the study area has worsened significantly during the last two decades. Risk of land degradation in the study area has increased, on an average, by 155% since 1985. The study revealed that desertification is both a natural and anthropogenic process. Therefore, incorporation of both natural and anthropogenic factors in the analysis provides realistic assessment of risk of desertification.

Desertification Modeling

Satellite remote sensing has become the single most effective approach for observing the desert dynamics, desertification, and land use and land cover changes. However, other useful physical/biological parameters for monitoring the hydrological and ecological states of the arid and semi-arid zones, such as CO_2 flux, evapotranspiration, carbon accumulation etc., cannot be directly measured by remote sensing.

In recent years one of the growing trends of desertification research is to use the geographic, geophysical, and biological parameters derived from remote sensing data as inputs to models for simulating various processes of desertification, estimating the productivity of the desert ecosystems, predicting the future progress of desertification, and supporting decision making on combating desertification (Di *et al.*, 1994; Brasa-Ramos *et al.*, 2000; Stephenne and Lambin, 2001; Zhenghu *et al.*, 2001; Zhan *et al.*, 2003; Okin *et al*; 2003). Bastiaanssen *et al.* (1997), used a surface energy balance model to estimate the evaporation and top soil moisture at European Field Experiment in a Desertification-threatened Area (EFEDA) with parameters derived from remote sensing data as model inputs. Brasa-Ramos *et al.* (1998), showed how to aggregate two different remote-sensing techniques, carried out in the framework of EFEDA, to determine if regional evapotranspiration is a major component of the water balance in Castilla-La Mancha, a semi-arid region in southeast Spain. The first technique is based on satellite measurements, and the other on aircraft flux measurements. Surface temperature derived from NOAA-AVHRR data is used to derive reference and actual evapotranspiration estimates through modeling. The aircraft measurements make use of the principles of turbulent water vapor transport in the lowest layer of the atmosphere to derive the spatial variability of energy and evaporation fluxes, allowing the validation of satellite estimates. The differences between these methods are below 1 mmd, which is within the range of the accuracy of available methods for estimating surface fluxes on a regional scale.

Zhan *et al.* (2003), explored the methodology for sequential continuous estimation of the carbon stocks, CO_2 flux, evapotranspiration, and sensible heat fluxes over desert and semi-desert areas. A CO_2 and energy flux coupled model is used to estimate CO_2, water vapor, and sensible heat fluxes over the Jornada desert in New Mexico, USA. The model is initialized by land surface parameters derived from satellite images and is driven by the observed meteorological data. The model outputs enabled the calculation of the carbon accumulation over the desert area and the exploration of the desert ecosystem to the atmospheric carbon pool.

Remote sensing can detect the vegetation dynamics over semi-arid and arid areas. However, by using remote sensing measurements alone we cannot directly answer the question if such dynamics are in response to the inter-annual climate/ environment variations or the permanent ecosystem change due to desertification. One way to identify the ecosystem change is to find the functional changes of an ecosystem, e.g., the change of the effectiveness of ecosystem's uses of water, heat, and light, through modeling. The modeling process establishes the functional relationship between an indicator or indicators of ecosystems to the climate and environment variables. By examining the change of the functional relationship over time, the ecosystem change can be detected. Di *et al.* (1994), successfully modeled the functional relationship between vegetation activities measured by NDVI and the precipitation at a semi-arid environment. Since then a number of studies have been conducted to model various aspects of desertification process in the arid and semi-arid environments. With the help of a Geographic Information System, Hastings and Di (1994), modeled the relationship between NDVI values for individual ecosystems and various environmental variables, such as precipitation and temperature. Diouf and Lambin (2001), tested the relationships between a remotely sensed indicator of vegetation, rainfall data and field measurements of biomass and floristic composition. The study was based on field measurements of vegetation conditions covering a period of 10 years, in the semi-arid region of the Ferlo in Senegal. Results indicate that land-cover modifications in the Ferlo are best measured by changes in rain-use efficiency. Gao *et al.* (2003), used the modified Common Land Surface Model (CLM) to simulate NPP and assess the response of NPP under different climate controls along an east-west transect in northern China. The run of CLM model requires land/vegetation cover datasets, soil datasets, and meteorological datasets as inputs. The land/vegetation cover datasets were derived from Landsat Thematic Mapper (TM) images. The result showed that the response of NPP to increased temperature was more sensitive to the doubled CO_2 climate because temperature is the limiting factor to vegetation growth in the study area.

Although modeling approach has great potential in the desertification study, such an approach requires, in addition to parameters derivable from remote sensing, meteorological and environment variables, which are sometimes only available through field observations. Examples of such variables include wind speed, relative humidity, surface air temperature, etc. In the past, those variables were not easy to obtain for large desert or semi-desert areas. This obstacle prevents the approach from being widely used in desertification research. However, recent progress in data assimilation makes it possible for providing accurate, high-spatial resolution time-series parameters over the desert and semi-desert areas around the globe. It is expected that in the next few years the modeling approach for desertification study will achieve significant progress.

Conclusion and Future Directions

Remote sensing is the only tool of choice for desertification studies at regional and global scales. In the past several years, significant progresses have been made on all aspects of remote sensing of desertification, including the availability of new global remote sensing data and well-validated time-series products, extensive use of remote sensing time-series data for determining the trends of desertification, matured technology for desert mapping, integration of remote sensing and non-remote sensing data in GIS for desertification analysis and decision supports, expanded and integrated use of spatial, temporal, and spectral information within remote sensing data for improved accuracy of mapping and monitoring, and quantitative measurement of desertification progress and risks through modeling and integration.

It is expected that in the next few years more studies will be conducted to model various aspects of desertification processes. Such models will be able to derive useful information/parameters that cannot be directly obtained through remote sensing but needed for arid and semi-arid ecosystem management and decision support. Coupled models, which treat desertification as one of land surface processes in the land component of the overall Earth system, will be able to predict the progress of desertification. Remote sensing data will provide input to such models. As Shoshany (2000), pointed out, further progress in the remote sensing of vegetation ecology/desertification requires a better synergy of sensors, methods and ancillary data. The modeling approach can serve as a framework for such synergy.

Currently most desertification studies are conducted by the researchers at academic institutes. There is lack of mechanism to transfer the information and knowledge created from those studies to decision makers and the general public. There is also lack of the operational capabilities for the end users to rapidly and easily obtain ready-to-use information and knowledge derived from remote sensing data for combating desertification. Strengthening the knowledge base and developing operation information and monitoring systems for regions prone to desertification and drought are in urgent needs. It is expected such systems will be built in the next couple of years.

New remote sensing methodologies and algorithms will be developed for monitoring different aspects of desertification processes due to the introduction of new remote sensing instruments such as Lidar and off-nadir viewing sensors in the visible and infrared spectral bands. Another area that will experience active methodology development is the retrieval of biophysical information from microwave data, such as Synthetic Aperture Radar (SAR) data. Traditionally desertification research uses optical and thermal infrared data. The use of microwave remote sensing data in desertification research has not been widely explored. It is expected that more and more microwave data will be used in the desertification studies and algorithms for extracting desertification-related information from such data will be developed in the next few years.

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