RESEARCH
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85

The Use of Remote Sensing Data for Drought Assessment and Monitoring in Southwest Asia

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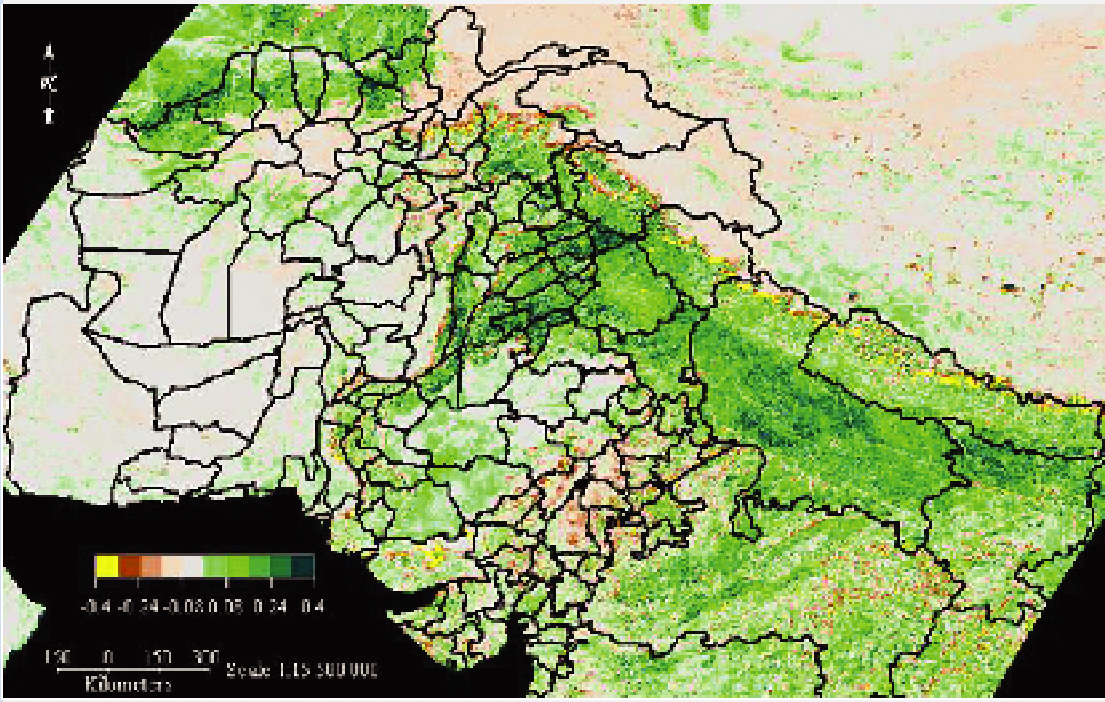

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Research Report 85

The Use of Remote Sensing Data for Drought Assessment and Monitoring in Southwest Asia

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Contents

Abbreviations

AVHRR	Advanced Very High Resolution Radiometer
DAAC	Distributed Active Archive Centers
EDC	EROS Data Center
EROS	Earth Resources Observation Systems
GIS	Geographic Information System
GPS	Global Positioning System
GSFC	Goddard Space Flight Center
DS	Drought Severity (NDVI deviation from long-term mean)
ISRO	Indian Space Research Organization
IWMI	International Water Management Institute
MIR	Mid-Infrared
MODIS	Moderate-Resolution Imaging Spectro-Radiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NESDIS	National Environmental Satellite Data and Information System
NGDC	National Geophysical Data Center
NIR	Near-Infrared
NOAA	National Oceanic and Atmospheric Agency
NPOESS	National Polar Operational Environmental Satellite System
NPP	NPOESS Preparatory Project
TBVI	Two Band Vegetation Indices
TCI	Temperature Condition Index
Terra	Earth Observing System (EOS) satellite-NASA flagship satellite under Earth System Enterprise
VCI	Vegetation Condition Index
VNIR	Visible and Near-Infrared
VIIRS	Visible and Infrared Imaging Radiometer Suite
NRSA	National Remote Sensing Agency

Summary

Droughts are recurring climatic events, which often hit South Asia, bringing significant water shortages, economic losses and adverse social consequences. Preparedness for drought should form an important part of national environmental policies. At present, countries of the region have limited institutional and technical capacity to prepare for a drought and to mitigate its impacts. Information on drought onset and development is not readily available to responsible agencies and to the general public. This report describes the first results of the development of the near-real-time drought-monitoring and reporting system for the region, which includes Afghanistan, Pakistan and western parts of India. The system is being developed using drought-related characteristics (indices), which are derived from remote-sensing data. The indices include a deviation from the normalized difference vegetation index (NDVI) from its long-term mean and a vegetation condition index (VCI).

The study first investigated the historical pattern of droughts in the region using monthly time-step AVHRR satellite data for 1982–1999. Droughts in recent years were studied using 8-day time-interval MODIS satellite images available from year 2000 onwards. The unique feature of the study is the development of regression relationships between drought-related indices obtained from MODIS and AVHRR data, which have different pixel-resolution and optical characteristics. These relationships were established for each month of the year separately, as well as for the pooled data of all months, and explained up to 95 percent of variability. The relationships were validated in randomly chosen districts outside the study area. The results ensure the continuity of the two data sets and will allow the reports on drought development in the region to be made in near-real time with a spatial resolution of 500 meters and at 8-day intervals. A continuous stream of MODIS data is available free of charge, on the Internet, from the USGS EROS data centre. The operational mode for the MODIS-AVHRR-based drought-reporting system is currently being developed. The goal is to make the system available, via Internet, to all stakeholders in the region, including government agencies, research institutions, NGOs and the global research community. It may be used as a drought-monitoring tool and as a tool for decision support in regional drought assessment and management.

The Use of Remote-Sensing Data for Drought Assessment and Monitoring in Southwest Asia

Thenkabail, P. S., Gamage, M. S. D. N. and Smakhtin, V. U.

Introduction

Droughts are recurring climatic events, which often hit South Asia, bringing significant water shortages, economic losses and adverse social consequences. In the last 20 years, increasing population has added to the growing demand for water and other natural resources in the region. The latest drought in South Asia (2000–2003) affected more than 100 million people, with severe impacts felt in Gujarat and Rajasthan States in western India, in Pakistan's Sind and Baluchistan provinces, as well as in parts of Iran and Afghanistan. Political instability, war and economic isolation have further exacerbated the effects of drought.

The need for proper quantification of drought impacts and monitoring and reporting of drought development is of critical importance in politically, economically and environmentally sensitive countries of South Asia. The ability of governments in the region and international relief agencies to deal with droughts is constrained by the absence of reliable data, weak information networks as well as the lack of technical and institutional capacities. Some countries, like Afghanistan, are just beginning to establish relevant drought monitoring and management procedures and institutions. Existing drought monitoring and declaration procedures (e.g., in India) lag behind the development of drought events.

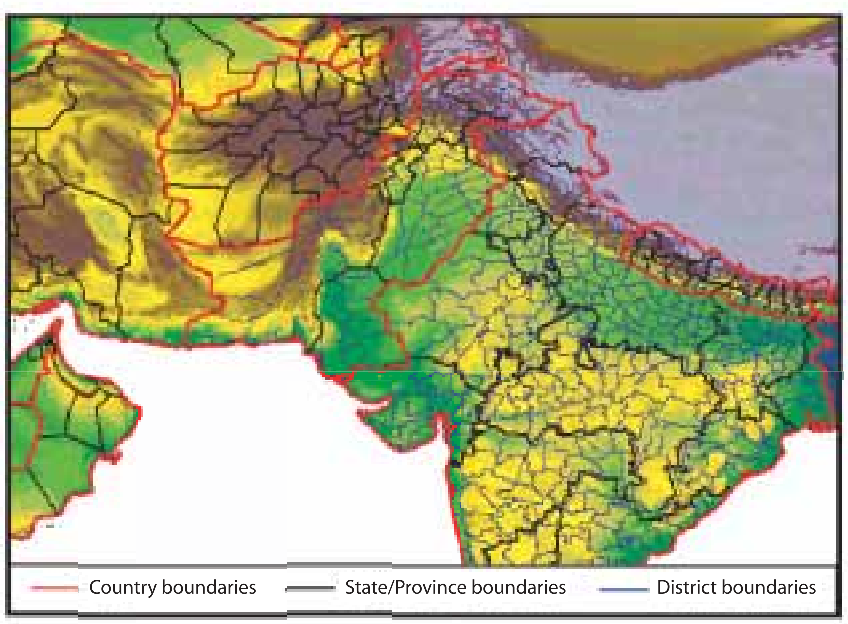
Traditional methods of drought assessment and monitoring rely on rainfall data, which are limited in the region, often inaccurate and, most importantly, difficult to obtain in near-real time. In contrast, the satellite-sensor data are consistently available and can be used to detect the onset of drought, its duration and magnitude (Thiruvengadachari and Gopalkrishna 1993). Even crop yields can be predicted 5 to 13 weeks prior to harvests using remote-sensing techniques (Ungani and Kogan 1998). Vegetative conditions over the world are reported occasionally by NOAA National Environmental Satellite Data and Information System (NESDIS) using the Advanced Very High Resolution Radiometer (AVHRR) data (Kogan 2000).

Drought indicators can be derived for any world region using these data, but the characteristic spatial resolution of 10 km (at which well-calibrated long-term historical data are freely available), is likely to be coarse for effective drought monitoring at small scales (a district or a village). A recent successor to AVHRR is the Moderate-Resolution Imaging Spectrometer (MODIS), an advanced narrow-band-width sensor, from which composited reflectance data are made available at no cost every 8 days by NASA and USGS, through the Earth Resources Observation Systems (EROS) data center (Justice and Townshend 2002a). Raw images are available on a daily basis, but their use involves considerable extra processing. Time series of MODIS imagery provide near-real-time, continuous and relatively high-resolution data, on which the assessment of drought development and severity in regions with scarce and inaccurate on-the-ground meteorological observations (like southwest Asia) could be based.

At present, there is no efficient system in the region to analyze and deliver drought-related information to the stakeholders on the ground. Only the Indian National Remote Sensing Agency (NRSA) has undertaken drought assessment and reporting since 1986, using Indian satellite sensors and AVHRR (Thiruvengadachari et al. 1987; Kumar and Panu 1997; Johnson et al. 1993). The Indian IRS-1C/D wide field sensor (WiFS) could be a strong tool for regional drought assessment with its spatial resolution of 188 m and weekly repeat coverage. However, at present these data and results are available only within the Indian space and remote sensing community (Barbosa et al. 2002). It is, of course, possible that regional cooperation to combat droughts will result in relevant data sharing between countries, at which point, WiFS data may be put to good use. Other new sensors which could contribute towards drought monitoring are the Vegetation wide-field sensor on SPOT satellites, and the MERIS sensor on Envisat, although neither is available as simply in near-real time as MODIS.

The primary goal of this study is to develop methods that allow two generations of sensors (AVHRR and MODIS) to be combined beneficially for a drought assessment and monitoring on a regional and a near-real-time basis. A challenge, therefore, is to develop reliable inter-sensor relationships in order to monitor drought continuously, over as long a time period as possible. This would help compare the characteristics of the future droughts to past events and allow the future drought severity to be interpreted. A reporting system should also allow drought development in the region to be monitored at different scales over the entire study area (southwest Asia, figure 1), through to country level and further to the level of individual states, provinces, and smaller administrative subdivisions within countries.

FIGURE 1.
The topographic map of the study area, showing the country boundaries and the boundaries of smaller administrative subdivisions.



Geographically, this study covers Afghanistan, Pakistan and western parts of India. These regions/countries are known to be drought-prone, and socioeconomic studies were, and are still being, conducted here by different government agencies and NGOs to assess the impacts of the latest drought and to analyze drought-coping strategies of local communities. It was envisaged that the results of such studies may be utilized in the future to assess the performance of the drought-monitoring system under development. However, as will be demonstrated in this report, the principles of the system may be expanded to a larger geographical area covering the entire South Asia from Iran to Bangladesh and from Nepal to Sri Lanka.

The report first describes the historical and modern-day datasets and their characteristics used for drought assessment and reporting. This is followed by a description of satellite sensor-derived vegetation indices, their derivative drought indices and thresholds for drought assessment. The developed inter-sensor relationships between AVHRR and MODIS data are then described and their use for drought monitoring in the region is demonstrated.

Data and Methods

AVHRR Data Acquisition and Preprocessing

The MODIS and its predecessor AVHRR, carried on board Terra-Aqua and NOAA-series satellites, respectively, are cost-effective sensors, which cover the globe at least once a day. The AVHRR sensor (Kidwell 1991) collects radiance data in five spectral bands including red visible (0.58–0.6 µm), near-infrared (0.725–1.1 µm), mid-infrared (3.55–3.93 µm) and two thermal infrared bands (10.3–11.3 µm and 11.5–12.5 µm). Only four bands, together with the normalized difference vegetation index (NDVI, described in the next subsection), are useful for this study (table 1) due to unresolved calibration issues with the mid-infrared band (Smith et al. 1997). The well-calibrated, long-time-series AVHRR radiance data have the spatial resolution of 0.1^{o} (pixels of approximately 10 X 10 km) and are available with a monthly step resolution for the period from 1982 to 2001. These radiance data were preprocessed by NASA Goddard Space Flight Center (GSFC) and are available at their web site *www.daac.gsfc.gov/data/dataset/AVHRR* for free downloading. Preprocessing includes the derivation of maximum value composite (MVC) monthly images from original daily radiance data. The procedure of deriving monthly MVCs includes the examination of daily radiance values for each wave band, together with NDVI values, for each month for each pixel. The highest daily radiance/NDVI value in a month is identified and retained. This minimizes problems of cloud impacts typical of single-date remote-sensing studies (Goward et al. 1994; Eidenshink and Faundeen 1994). Data are further corrected for atmospheric attenuation (e.g., dust or haze, Cihlar et al. 1994), and distortions due to sun angle and satellite sensor-view angle (Kogan and Zhu 2001; Flieg et al. 1983; Cracknell 1997; NGDC 1993).

TABLE 1.
Remote sensing data, indices and thresholds relevant to drought assessment used in the study.

Drought index	Band or index used to compute the index: AVHRR	Band or index used to compute the index: MODIS	Range	Normal condition	Severe drought	Healthy vegetation
1. Normalized difference vegetation index (NDVI)	Band 1 (0.58-0.68µm) Band 2 (0.73-1.10µm)	Band 1 (0.62-0.67µm) Band 2 (0.84-0.87µm)	-1 to +1	Depends on the location	-1	+1
2. Drought severity index (DEV_{NDVI})	NDVI NDVI long-term mean	NDVI NDVI long-term mean	-1 to +1	0	-1	+1
3. Vegetation condition index (VCI)	NDVI NDVI long-term minimum NDVI long-term maximum	NDVI NDVI long-term minimum NDVI long-term maximum	0 to 100 %	50 %	0%	100%
4. Temperature condition index (TCI)	Band 4 (10.3-11.30µm) Band 4 temp long-term minimum Band 4 temp long-term maximum	no thermal band in 7 band data	0 to 100 %	50 %	0%	100%

The preprocessed monthly MVC data were downloaded from the NOAA GSFS web site and then converted to four secondary variables (e.g., NDVI), using the procedures described in Smith et al. (1997) and Rao (1993a, b). These variables are a) at ground reflectance (percentage), b) top of the atmosphere brightness temperature (degrees Kelvin), c) surface temperature (degrees Kelvin), and d) NDVI (nondimensional):

$$Reflectance = (BR_i - 10) * 0.002 \quad (1)$$

$$NDVI = (SNDVI - 128) * 0.008 \quad (2)$$

$$BT = (BR_j + 31990)*0.005 \quad (3)$$

$$T_S = T4 + 3.3\ (T4 - T5) \quad (4)$$

where, BR_i is band radiance for bands 1 or 2 (i = 1 or 2), SNDVI is scaled NDVI (since 1 to +1 range is scaled to 0 to 255), BT is brightness temperature, BR_j is band radiance for bands 4 or 5 (j = 4 or 5), T_S is surface temperature calculated using split window technique, and T4 and T5 are the temperatures in AVHRR band T4 and T5, respectively. These conversions are necessary to enable comparisons of measurements made using different sensors. By converting AVHRR data into percent reflectance, comparisons can be made with percent reflectance measured from MODIS.

The converted AVHRR monthly time series for 1982–1999 were used for historical drought analysis, while 2000–2001 data were used for regression analysis between AVHRR and MODIS, when data from both sensors were available. There were 212 images for each band and for NDVI during 1982–1999 (one MVC for each month, except for 4 months of missing data in 1994, when the satellite failed). For the purpose of further analyses, the 1982–1999 data were composed into two mega files. The first file contained 848 layers (4 bands, each of 212 months) and the second, NDVI data for 212 months.

MODIS, a successor of AVHRR, is the primary sensor for monitoring the terrestrial ecosystem in the NASA Earth Observing System (EOS) program (Justice et al. 2002) and has several advances on AVHRR (table 1). MODIS is more sensitive to changes in vegetation dynamics (Huete et al. 2002) and was found to be a more accurate and versatile instrument to monitor the global vegetation conditions than the AVHRR (Gitelson et al 1998; Justice et al. 2002).

The MODIS sensor acquires data in 36 spectral bands, with variable spatial resolution of 250–1,000 meters (depending on band), in narrow bandwidths and are recorded in 12-bit format. The 36 MODIS bands are a compromise for atmospheric, land and ocean studies, and seven bands are considered optimal for land applications (Justice et al. 2002). Composite MODIS data have a temporal resolution of 8 days and are available from 2000 onwards. The 8-day, 7-band data are made available by USGS EROS DAAC (similar to the preprocessed AVHRR reflectance data by NOAA GSFC), after corrections for molecular scattering, ozone absorption and aerosols. The data are also adjusted to nadir (sensor looking straight down) and standard sun angles, using bidirectional reflectance (BRDF) models (Vermote et al. 2002; Justice et al. 2002). The 7 bands have waveband centers at 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1,640 nm, and 2,130 nm.

All MODIS data are directly downloadable free of charge from the USGS EROS data center (http://edcdaac.usgs.gov). The downloaded data are available as radiance, which needs to be divided by 100 to obtain reflectance in percent. For the entire study area (figure 1), MODIS data were composed into 2 mega files for the 2000–2003 period: a) a file of 1,250 wave bands (45 images per year * 7 bands per image * 4 years), and b) a file of 180 NDVI layers (45 NDVI layers per year * 4 years).

While MODIS data are coarser than Indian IRS-1C/D WiFS data, the latter are not easily available at present, which makes MODIS data the only feasible candidate for regional drought monitoring. There are also a few other issues that make the use of MODIS data more attractive. First, the IRS WiFS data come at a cost, while MODIS data are free. Second, unlike the IRS WiFS, the most recent MODIS data are available within 8 days (in near-real time). Third, MODIS Internet data sources have excellent search and browse facilities that are currently not implemented for IRS WiFS. Fourth, MODIS products undergo numerous calibrations, preprocessing and normalizations (e.g., atmospheric correction) and the data are available as processed products (e.g., reflectance) in contrast to raw digital numbers supplied for WiFS. These capabilities facilitate multi-date comparisons. MODIS data continuity from Terra and Aqua satellites is guaranteed over time with successor satellite and sensor systems already planned and assured, at least, until 2018, with National Polar-Orbiting Operational Environmental Satellite System (NPOESS) series of satellites (Justice and Townshend 2002b). Unlike the MODIS, data continuity plans are not yet announced by the Indian Space Research Organization (ISRO). Finally, WiFS has only 2 spectral bands, while MODIS has 36, of which 7 are considered optimal for land studies (Vermote et al. 2002).

Drought-Monitoring Indices

Drought-monitoring indices are derived from AVHRR and MODIS data (table 1). They are normally radiometric measures of vegetation condition and dynamics, exploiting the unique spectral signatures of canopy elements, particularly in the red and near-infrared (NIR) portions of the spectrum (e.g., Huete et al. 1997, 2002) and are sensitive to vegetation type, growth stage, canopy cover and structure (Clevers and Verhoef 1993; Thenkabail 2003). They utilize reflectance data in two or more spectral bands, thus enhancing the vegetation signal and canceling out the effects of topography, sun angle and atmosphere.

Normalized Difference Vegetation Index (NDVI). NDVI was first suggested by Tucker (1979) as an index of vegetation health and density.

$$NDVI = (\lambda_{NIR} - \lambda_{red}) / (\lambda_{NIR} + \lambda_{red}) \qquad (5)$$

where, λ_{NIR} and λ_{red} are the reflectance in the NIR and red bands, respectively (table 1). NDVI reflects vegetation vigor (Teillet et al. 1997), percent green cover, Leaf Area Index (LAI (Baret and Guyot 1991) and biomass (Thenkabail et al. 2002; Thenkabail et al. 2004).

The NDVI is the most commonly used vegetation index (Jensen 1996). It varies in a range of -1 to + 1. However, NDVI a) uses only two bands and is not very sensitive to influences of soil background reflectance at low vegetation cover, and b) has a lagged response to drought (Reed 1993; Rundquist and Harrington 2000; Wang et al. 2001) because of a lagged vegetation response to developing rainfall deficits due to residual moisture stored in the soil. Previous studies have shown that NDVI lags behind antecedent precipitation by up to 3 months (Justice et al. 1986; Farrar et al. 1994; Wang 2000; Wang et al. 2001). The lag time is dependent on whether the region is purely rain-fed, fully irrigated, or partially irrigated (Farrar et al. 1994; Wang 2000). The greater the dependence on rainfall the shorter the lag time.

NDVI itself does not reflect drought or non-drought conditions. But the severity of a drought (or the extent of wetness, on the other end of the spectrum) may be defined as NDVI deviation from its long-term mean (DEV_{NDVI}). This deviation is calculated as the difference between the NDVI for the current time step (e.g., January 1995) and a long-term mean NDVI for that month (e.g., an 18-year long mean NDVI of all Januaries from 1982 to 1999) for each pixel:

$$DEV_{NDVI} = NDVI_i - NDVI_{mean,m} \qquad (6)$$

where, $NDVI_i$ is the NDVI value for month *i* and $NDVI_{mean,m}$ is the long-term mean NDVI for the same month *m* (e.g., in a data record from 1982 to 1999, there are 18 monthly NDVI values for the same month, e.g., 18 Aprils), and 12 long-term NDVI means (one for each calendar month). When DEV_{NDVI} is negative, it indicates the below-normal vegetation condition/health and, therefore, suggests a prevailing drought situation. The greater the negative departure the greater the magnitude of a drought. In general, the departure from the long-term mean NDVI is effectively more than just a drought indicator, as it would reflect the conditions of healthy vegetation in normal and wet months/years. This indicator is widely used in drought studies (e.g., Johnson et al. 1993). Its limitations are that the deviation from the mean does not take into account the standard deviation, and hence can be misinterpreted when the variability in vegetation conditions in a region is very high in any one given year.

Vegetation condition index (VCI). VCI was first suggested by Kogan (1995, 1997). It shows how close the NDVI of the current month is to the *minimum* NDVI calculated from the long-term record.

$$VCI_J = \frac{(NDVI_J - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} * 100 \qquad (7)$$

where, $NDVI_{max}$ *and* $NDVI_{min}$ are calculated from the long-term record (e.g., 18 years) for that month (or week) and *j* is the index of the current month (week). NDVI values are calculated using equation (5) above. The condition/health of the ground vegetation presented by VCI is measured in percent. The VCI values around 50% reflect fair vegetation conditions. The VCI values between 50 and 100% indicate optimal or above-normal conditions. At the VCI value of 100%, the NDVI value for this month (or week) is equal to $NDVI_{max}$. Different degrees of a drought severity are indicated by VCI values below 50%. Kogan (1995) illustrated that the VCI threshold of 35% may be used to identify extreme drought conditions and suggested that further research is necessary to categorize the VCI by its severity in the range between 0 and 35%. The VCI value close to zero percent reflects an extremely dry month, when the NDVI value is close to its long-term minimum. Low VCI values over several consecutive time intervals point to drought development.

Temperature condition index (TCI). TCI was also suggested by Kogan (1995, 1997) and its algorithm is calculated similar to VCI but its formulation was modified to reflect vegetation's response to temperature (the higher the temperature the more extreme the drought). TCI is based on brightness temperature and represents the deviation of the current month's (week's) value from the recorded maximum.

$$TCI_J = \frac{(BT_{max} - BT_j)}{(BT_{max} - BT_{min})} * 100 \qquad (8)$$

where, BT is the brightness temperature (e.g., AVHRR band 4). The maximum and minimum values of BT are calculated from the long-term (e.g., 18 years) record of remote-sensing images for each calendar month or week *j*. At the TCI of around 50%, the fair or normal temperature conditions exist. When TCI values are close to 100%, the brightness temperature for this month, $BT_{j,}$ is equal to the long-term minimum brightness temperature for the pixel. Low TCI values (close to 0%) indicate very hot weather in that month or week. When TCI is equal to zero percent, brightness temperature for this month, $BT_{j,}$ is equal to maximum long-term brightness temperature for the pixel. Consistently low TCI values over several consecutive time intervals may point to drought development/presence.

In combination with meteorological observations, the relationship between surface temperature and the moisture regime on the ground will detect drought-affected areas before biomass degradation occurs and hence TCI can play an important role in drought monitoring. With high radiometric and temporal resolution, thermal infrared data from MODIS allow changes in surface thermal regime to be more accurately inferred and drought conditions to be more accurately identified.

Linking AVHRR and MODIS Data for Continuous Drought Assessment

Even though MODIS is a successor to AVHRR, both sensors and their related data types have distinctly different features, as was described in relevant sections above (table 1). Apart from this, the two data sets have other differences including, but not limited to, preprocessing methods (e.g., atmospheric correction) and spatial resolution (10 km for AVHRR versus 0.5 km for MODIS). To ensure continuous flow of data for drought assessment, inter-sensor relationships are needed. The two data sets overlap for the 2-year period from 2000 to 2001. This offers the opportunity to explore the relationships between the two data sets (e.g., linking $NDVI_{AVHRR}$ with $NDVI_{MODIS}$). To establish these links, the NDVI values from both sensors were derived for a wide range of land-use and land-cover (LULC) classes that included mountains, irrigated areas, rain-fed agricultural lands, rangelands, water bodies, wetlands, deserts and mixed LULC types.

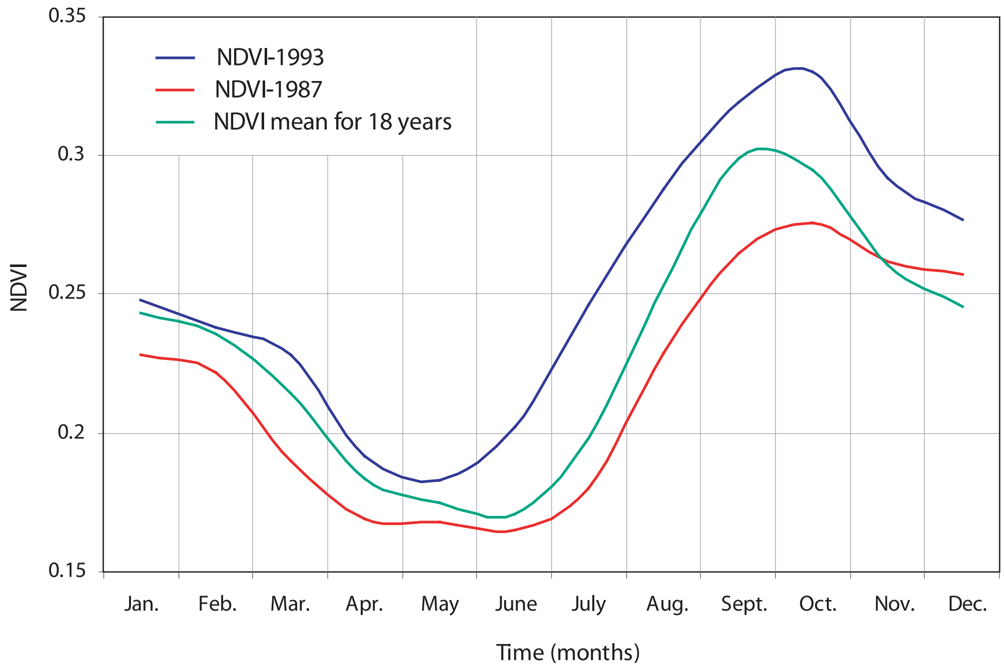
During years 2000 and 2001, there were 19 months (from February 2000 to August 2001) of concurrent data for both AVHRR and MODIS sensors. The AVHRR data are monthly, while MODIS data have the temporal resolution of 8 days. To make both data sets comparable, the four 8-day MODIS NDVI images were composed into 32-day NDVI images through a maximum-value compositing (MVC) procedure. Then the $NDVI_{AVHRR}$ and $NDVI_{MODIS}$ were calculated for the randomly selected large number of administrative units during the 19-month long concurrent period. Even for the concurrent period, the $NDVI_{MODIS}$ will not be exactly the same as $NDVI_{AVHRR}$ due to different sensor characteristics. For example, the narrower MODIS spectral bands eliminate the water absorption region in the NIR and also render the red band more sensitive to chlorophyll absorption (e.g., Huete et al. 2002). Atmospherically corrected $NDVI_{MODIS}$ generally exhibits a higher dynamic range than atmospherically corrected $NDVI_{AVHRR.}$ This is attributed to the narrow band width of MODIS (Huete et al. 2002). The narrow bands result in a greater dynamic range of NDVI for the same given biomass. The $NDVI_{AVHRR}$ is therefore likely to "saturate" faster in the study of vegetation biomass than $NDVI_{MODIS}$, saturation being the loss of sensitivity of a sensor after full canopy cover is achieved. The study established regression models for two NDVI types for each month (as well as for the pooled data of all 19 months) for all terrestrial biomes in the study area. The established relationships between NDVI from two sources allow drought occurrences to be examined across sensors and time periods from 1982 to the present day, and well into the future. The results of regression analyses are discussed in the next section.

Results and Discussion

Historical Drought Interpretation

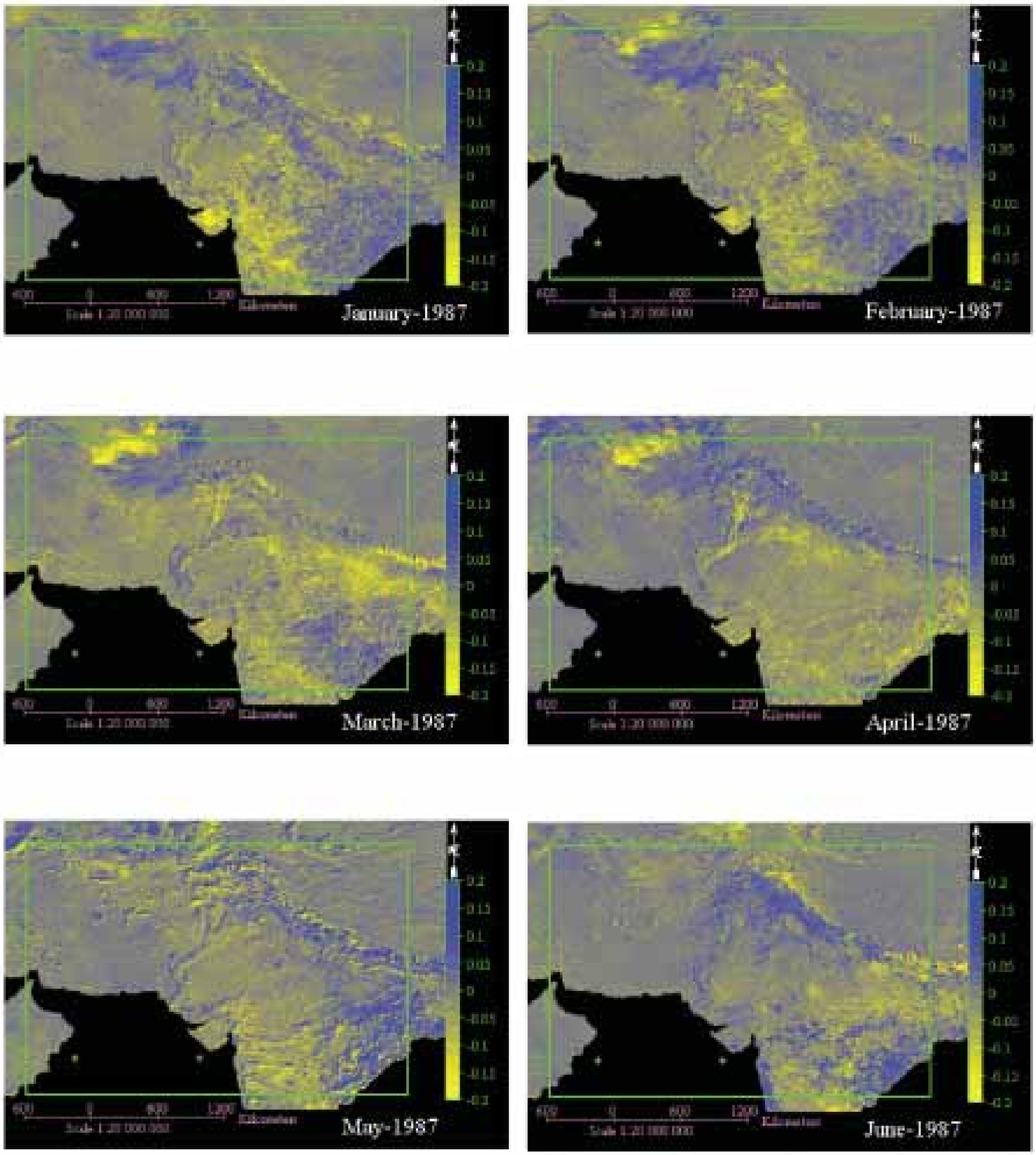
The extent of negative deviation of NDVI from its long-term mean for a pixel, district or region, and the duration of continuous negative deviations are powerful indicators of drought magnitude and persistence. Figure 2 shows the long-term normal NDVI conditions (NDVI means for each month) and relative to it, the driest (1987) and the wettest (1993) years' NDVI values for each month for the entire study area (shown in figure 1). Averaging NDVI values over the entire study area was done primarily to illustrate that, overall, the whole region was dry in 1987 or wet in 1993 (figure 2) despite the spatial variability of wetness or dryness throughout the region in both years.

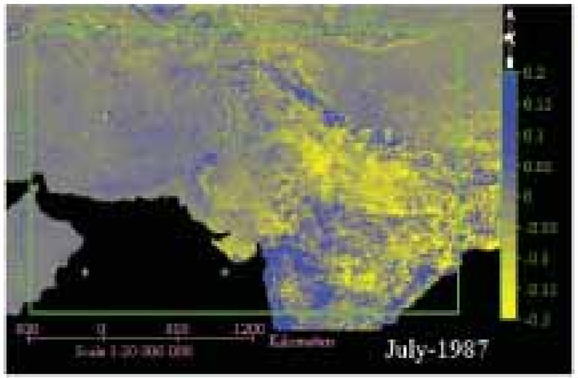
FIGURE 2.
A monthly NDVI time series for a drought year (1987) and a wet year (1993) compared to the NDVI long-term mean (averaged for the study area).

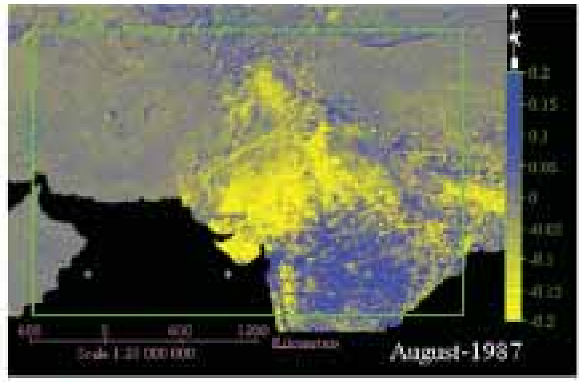


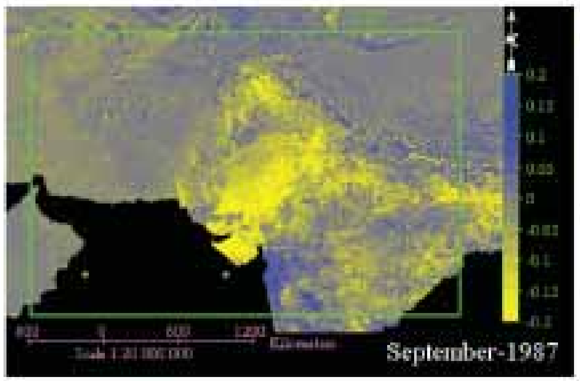
The differences between the long-term NDVI mean values and the NDVI values in specific months are the deviations (DEV_{NDVI}) described in equation (6) above. A month-by-month spatial distribution of DEV_{NDVI} in the study area during the dry year of 1987 is illustrated in figure 3, where areas in different shades of yellow are "drought-affected" and areas in different shades of blue are those with a denser, and healthy vegetation. Most of the pixels in the study area have persistent shades of yellow, indicative of the negative deviation from the NDVI mean. It can be seen how a major drought-affected area is developing in August–November primarily over the States of Gujarat and Rajasthan of India and eastern Pakistan, with a drought in Gujarat persisting until December. These results match well with the regional drought pattern studied using rainfall (Sivasami 2000). The Himalayas, central India and the Indus flood-plain/irrigation network areas remain relatively "drought-free" throughout the year. Similar to the monitoring of the entire region, the drought onset, magnitude and duration/persistence can be monitored at the scale of a country, any administrative unit level (e.g., vector boundaries shown in figure 1), or a single pixel level (10 by 10 km with AVHRR data and 0.5 by 0.5 km with MODIS) using the series of consecutive images.

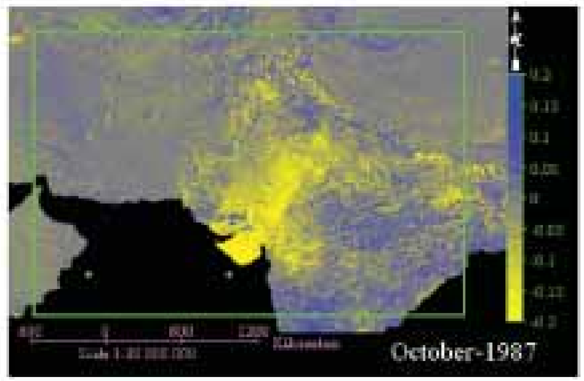
FIGURE 3.
Regional monthly images of DEV_{NDVI} for the drought year of 1987 in the study area.

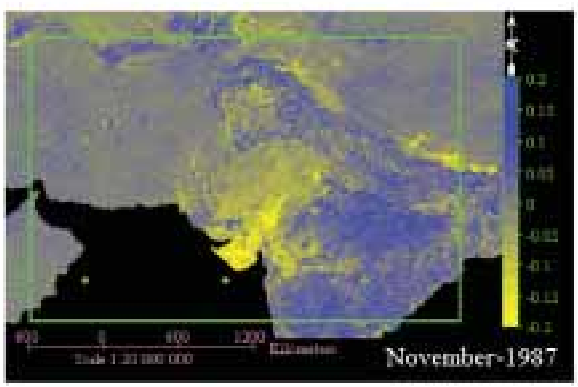


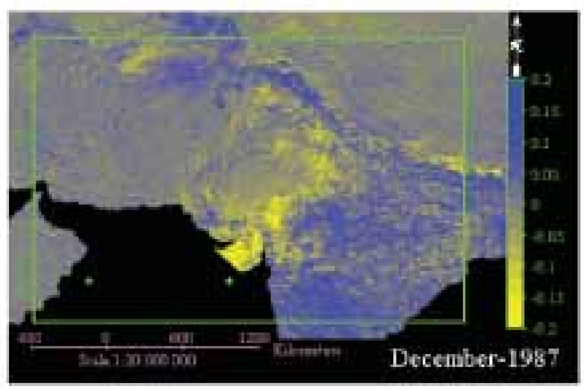






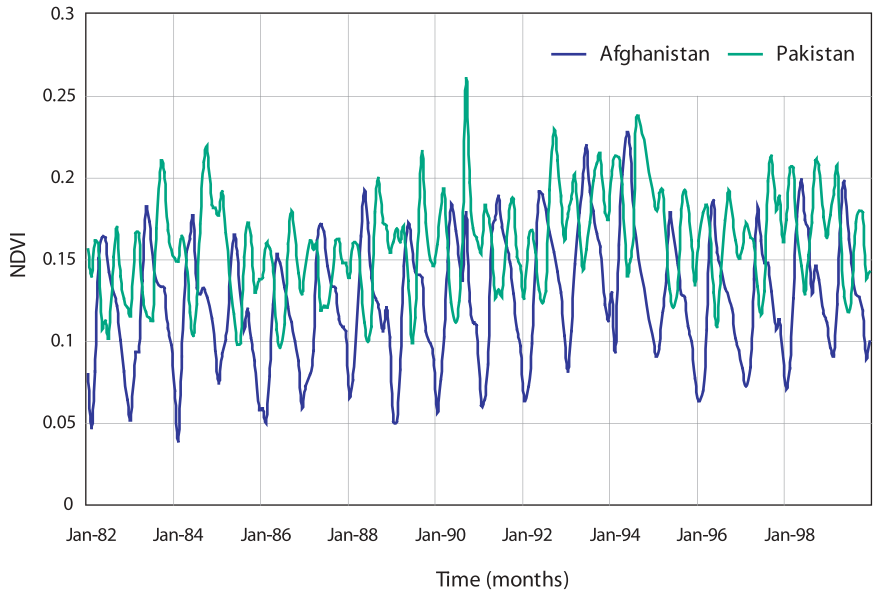






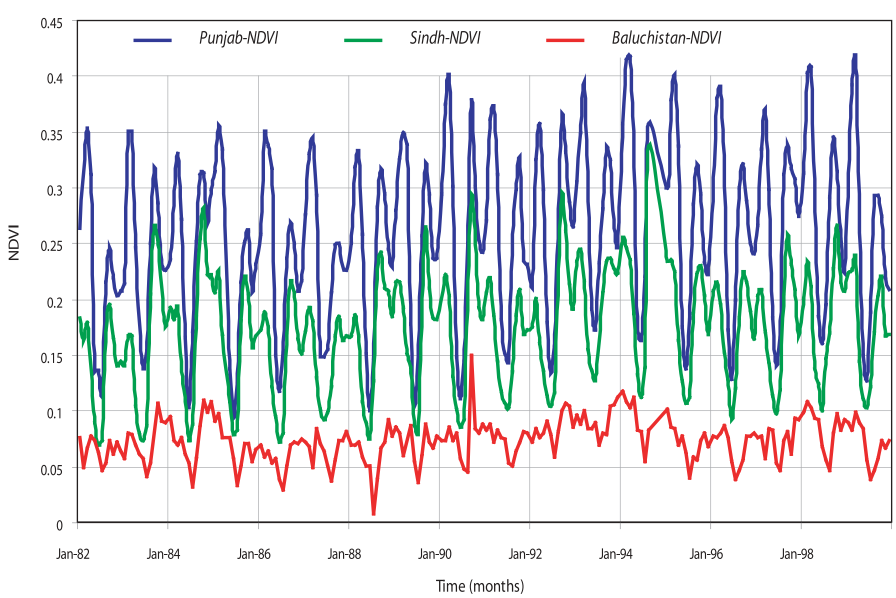
The biomass levels (measured in terms of NDVI) are normally higher in Pakistan as a whole through most of the months when compared with Afghanistan (figure 4). There is also a clear seasonality in biomass fluctuations within and across seasons and years for Afghanistan and Pakistan. The pattern of fluctuation is however very different between the two countries. In Pakistan, with its significant irrigation development, NDVI reflects the impacts of irrigation on crops and, therefore, on the vegetation condition in general. The major part of Afghanistan's vegetation is rain-fed and NDVI follows a predominantly unimodal vegetation condition cycle, determined by precipitation.

FIGURE 4.
The NDVI variability for Afghanistan and Pakistan over 18 years.



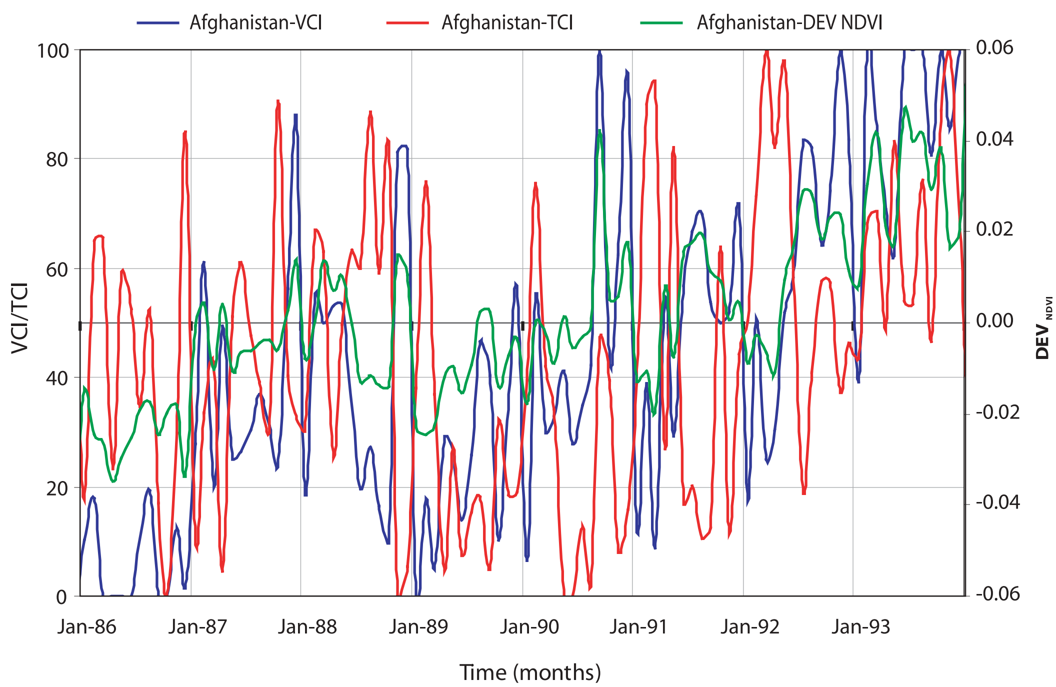
Similar patterns of total biomass and its temporal variability may be traced at smaller scales, such as the provinces within Pakistan (figure 5). In arid Baluchistan, the biomass magnitude is a clear function of rainfall. In the arid, but partially irrigated, Sindh province, it is dependent on a combination of water available for irrigation (from the Indus river) and precipitation. In the Punjab province, a large proportion of the area is irrigated, which is reflected in higher NDVI values relative to Sindh and Baluchistan.

FIGURE 5.
The NDVI variability for three provinces in Pakistan (Punjab, Sindh and Baluchistan).



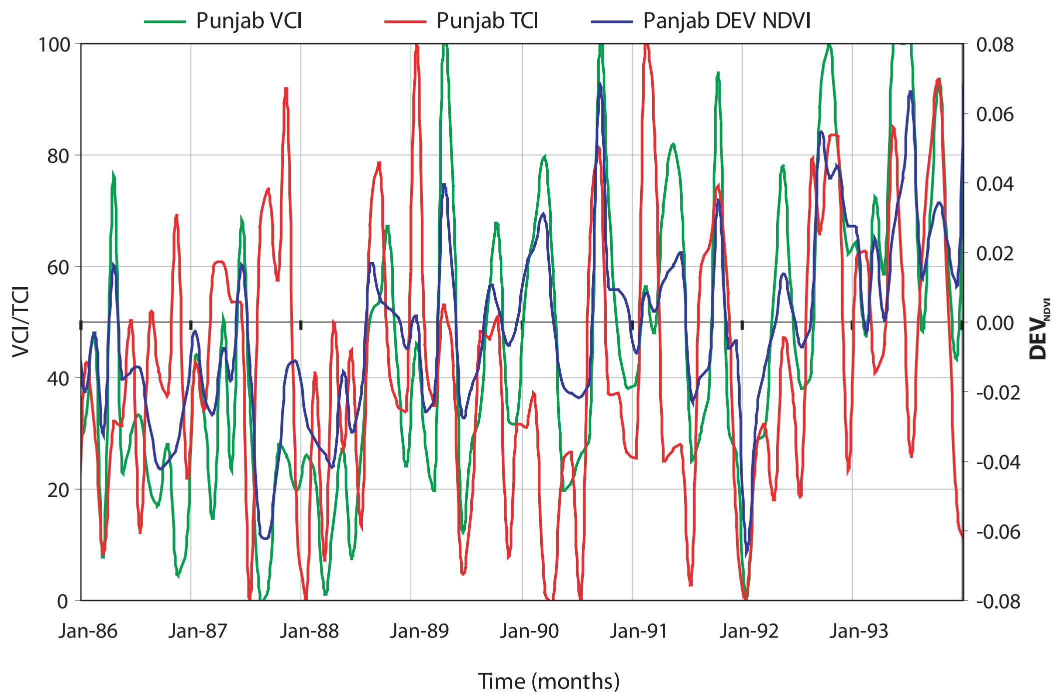
The variability of three drought-related indices (DEV_{NDVI}, VCI, and TCI) for the period 1986–1994 (containing a few successive droughts) is illustrated in figure 6 using Afghanistan as an example. The thick black line indicates the normal condition of the vegetation. When an index deviates below the line for a few successive months, it points to a drought condition. Deviations above the normal for a few successive months in a year point to better-than-normal vegetation conditions. The magnitude of a drought is directly proportional to the magnitude of the deviation below normal. The duration of the successive months below normal conditions and the magnitude of the deviation are two powerful indicators of drought severity. In this context, the period from January 1986 to June 1990 was predominantly a continuous drought in Afghanistan, interrupted only by a few wet months (figure 6). Throughout these years, continuously dry conditions prevailed over the country, adversely affecting biomass, livestock and agriculture.

FIGURE 6.
The illustration of the variability of three AVHRR derived drought-related indices for Afghanistan.



Similar arguments apply to smaller spatial scales, like Punjab province in Pakistan (figure 7). The fluctuation in both VCI and DEV_{NDVI} in irrigation-dominated Punjab is similar to that in the predominantly rain-fed Afghanistan (figure 6). However, in certain periods, as from mid-1989 to mid-1990 when drought was severe in rain-fed Afghanistan, the conditions were above-normal in irrigated Punjab. This suggests that during severe drought periods, even irrigated areas are affected, but during years of moderate drought, the impacts are limited to rain-fed areas.

FIGURE 7.
The illustration of the variability of three AVHRR derived drought-related indices for the Punjab province of Pakistan.



In most cases, the VCI and DEV_{NDVI} complement each other and, therefore, strong correlations should exist between the two (figures 6 and 7). This does not always apply to TCI (figures 6 and 7), which often fluctuates differently from both VCI and DEV_{NDVI} (e.g., during 1991–1992). This can be partially explained by the fact that TCI reflects surface ("skin") temperature. Wherever stress or stunted growth of vegetation and crops due to moisture excess occur, the VCI values are low, the DEV_{NDVI} is below normal, but TCI remains high. For example, this may apply to wetland and/or flooded agriculture. When NDVI is close to its long-term minimum and BT close to its long-term maximum (e.g., for example, many months during 1988–1991), the continuously low consecutive values of VCI, and DEV_{NDVI} indicate severe drought (or vegetation stress) conditions. The TCI variability, however, remains inconsistent with that of the other two indices, which puts a question mark on the utility of a TCI as a drought indicator.

Validation of Inter-Sensor Relationships

The established regression relationship between concurrent NDVI values of MODIS and AVHRR at regional scale is given below

$$NDVI_{MODIS} = 1.0256 * NDVI_{AVHRR} + 0.1151 \qquad (9)$$

This relationship is illustrated in figure 8. The relationships were also developed based on data from specific months (table 2). The monthly models explain up to 95 percent of variability in the data of two sensors. The models presented in equation (9), table 2 and figure 8 are critical in linking the data from two sensors and facilitating continuous monitoring of vegetation conditions, in a drought context, over time and well into the future.

FIGURE 8.
Regression relationship between $NDVI_{MODIS}$ and $NDVI_{AVHRR}$. The regression model is built on the data for 19 months (February 2000 to September 2001) from all administrative units in the study area.

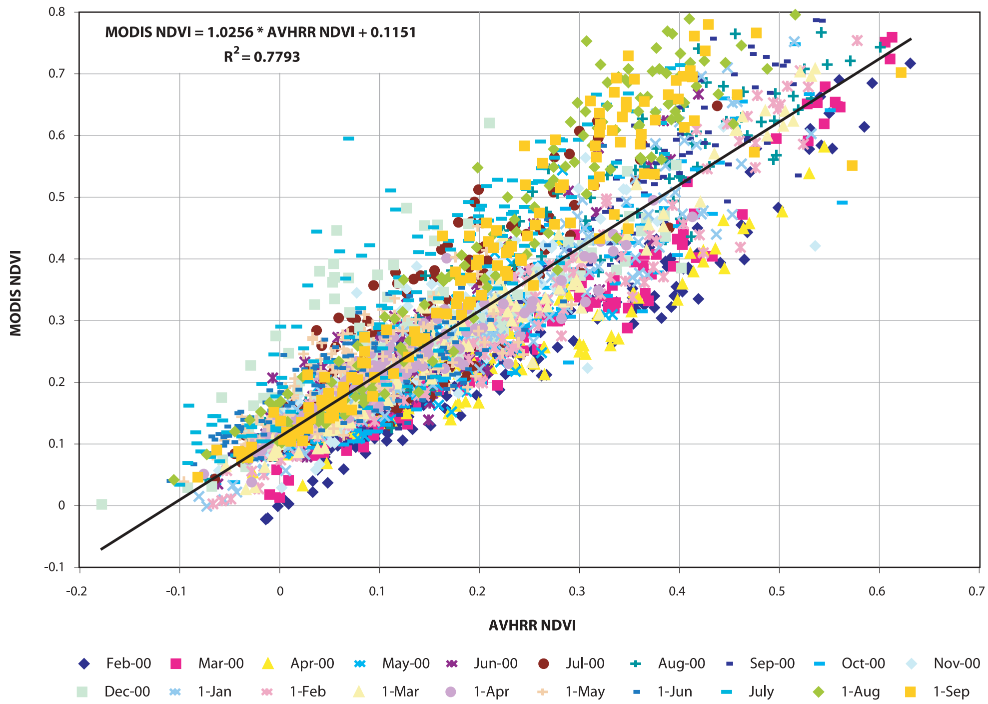


TABLE 2.
Regression models relating 500-m MODIS NDVI data and resampled 500-m AVHRR NDVI values for individual months.

Month	Equation	R^2
January	MODIS NDVI (January) = 0.0799 + 1.0868 AVHRR NDVI (January)	0.9189
February	MODIS NDVI (February) = 0.0109 + 1.013 AVHRR NDVI (February)	0.9479
March	MODIS NDVI (March) = 0.0314 + 1.0357 AVHRR NDVI (March)	0.9528
April	MODIS NDVI (April) = 0.0862 + 0.7714 AVHRR NDVI (April)	0.8705
May	MODIS NDVI (May) = 0.121 + 0.8217 AVHRR NDVI (May)	0.667
June	MODIS NDVI (June) = 0.1152 + 1.0463 AVHRR NDVI (June)	0.7373
July	MODIS NDVI (July) = 0.1282 + 1.2181 AVHRR NDVI (July)	0.7494
August	MODIS NDVI (August) = 0.0998 + 1.1546 AVHRR NDVI (August)	0.9119
September	MODIS NDVI (September) = 0.0672 + 1.2539 AVHRR NDVI (September)	0.9374
October	MODIS NDVI (October) = 0.0586 + 1.0949 AVHRR NDVI (October)	0.8913
November	MODIS NDVI (November) = 0.1183 + 1.0256 AVHRR NDVI (November)	0.7769
December	MODIS NDVI (December) = 0.1664 + 0.823 AVHRR NDVI (December)	0.6354

The limited period of concurrent MODIS and AVHRR observations (19 months) does not offer full possibilities for validating these regression relationships. However, the validity of the equations in table 2 and figure 8 could be illustrated using independent datasets, from outside of the study area. $NDVI_{MODIS}$ values simulated using the established models are referred to as "simulated $NDVI_{MODIS,}$" since they were derived from AVHRR. Two arbitrarily selected districts outside the study area (Mathura in Uttar Pradesh State, and Ambala in Haryana State, India) are used here for illustration. Figures 9a and b illustrate that there is a clear similarity between the observed and simulated NDVI values in the two districts. The marginal differences result from the uncertainties inherent in the models (equation 9, table 2).

A more general accuracy assessment has been done through comparison of "observed" and simulated values over 4 districts outside the study area (76 data points from 19 months of test data in 4 districts). For these districts, $NDVI_{MODIS}$ values were simulated from AVHRR data using equations from table 2 and then compared with actual $NDVI_{MODIS}$ values. The results show (figure 10) that the simulated $NDVI_{MODIS}$ explained 88 percent variability relative to actual $NDVI_{MODIS}$.

Figure 11 compares the spatial distribution of actual versus simulated $DEV_{NDVI\ MODIS}$ for Afghanistan at the resolution of 500 m X 500 m for 3 (arbitrarily selected) months of the year 2000. The left figure in each row shows the actual $DEV_{NDVI\ MODIS}$ coverage, while the right one shows simulated $DEV_{NDVI\ MODIS}$ values. Overall, the comparison of each pair of images per month (figure 11) reveals clear similarities in the NDVI magnitude and spatial distribution. The level of similarity repeats itself for other months.

FIGURE 9a.
Actual and simulated $NDVI_{MODIS}$ for Mathura district in Uttar Pradesh State, India.

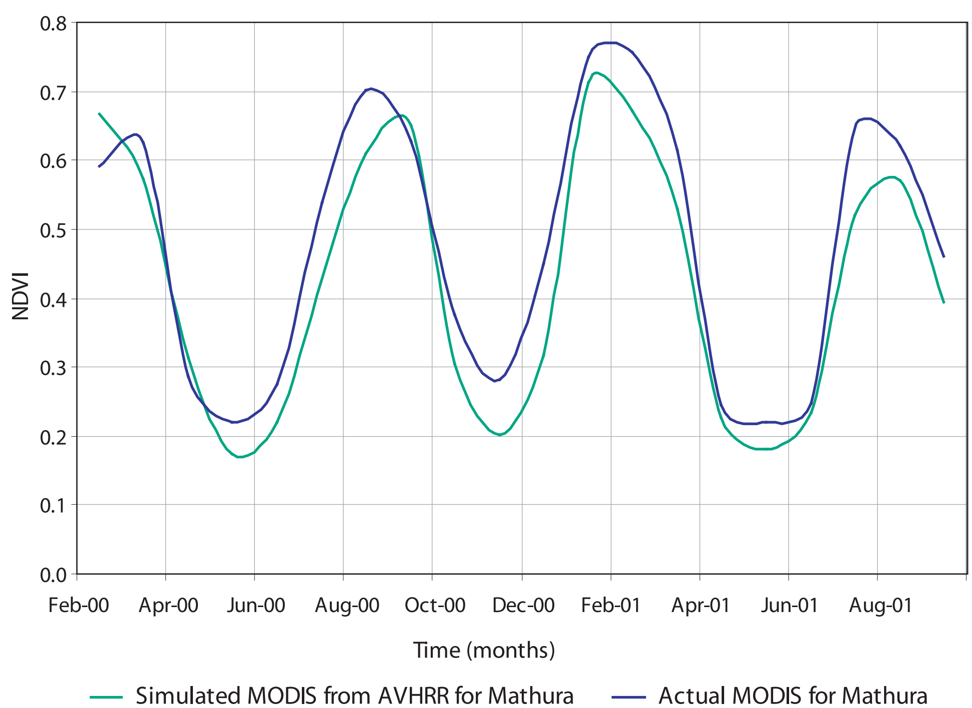


FIGURE 9b.
Actual and simulated $NDVI_{MODIS}$ for Ambala district in Haryana State, India.

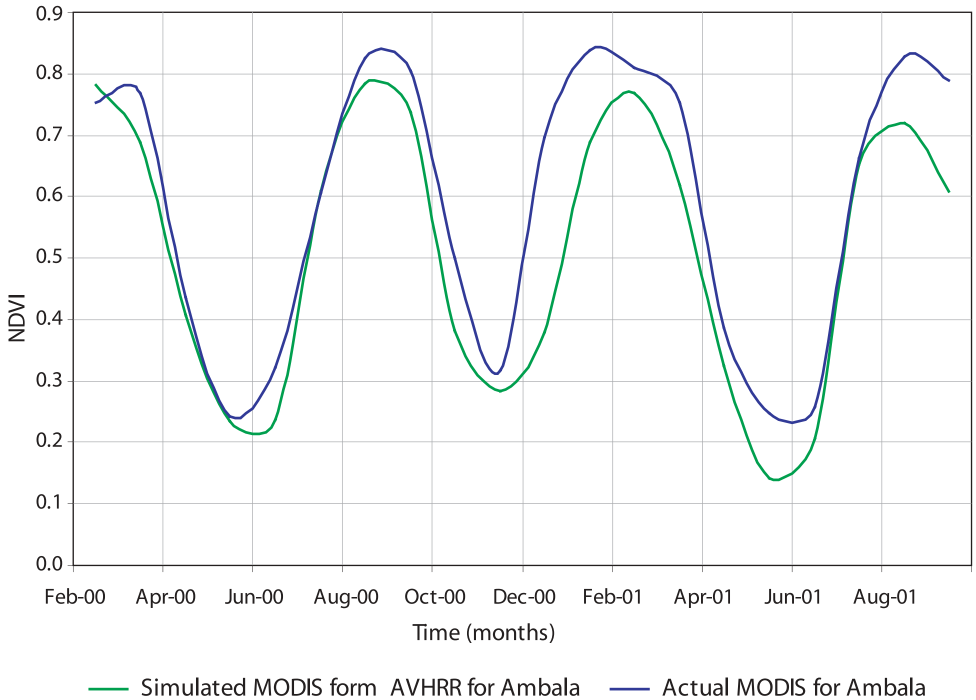


FIGURE 10.
Correlation between actual and simulated $NDVI_{MODIS}$ values for 4 districts outside the study area.

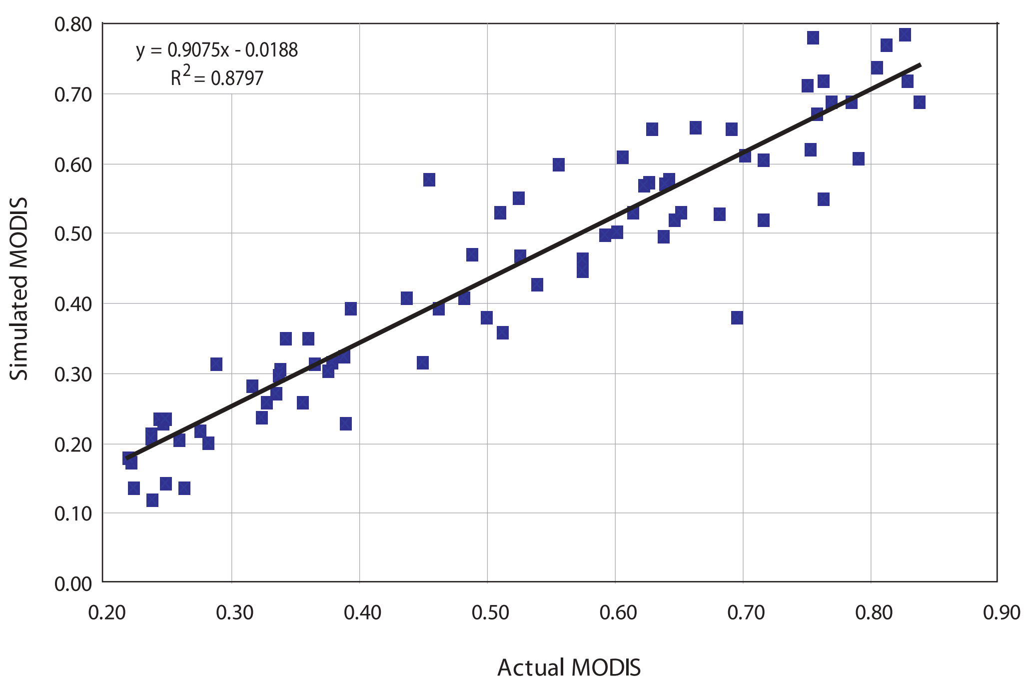
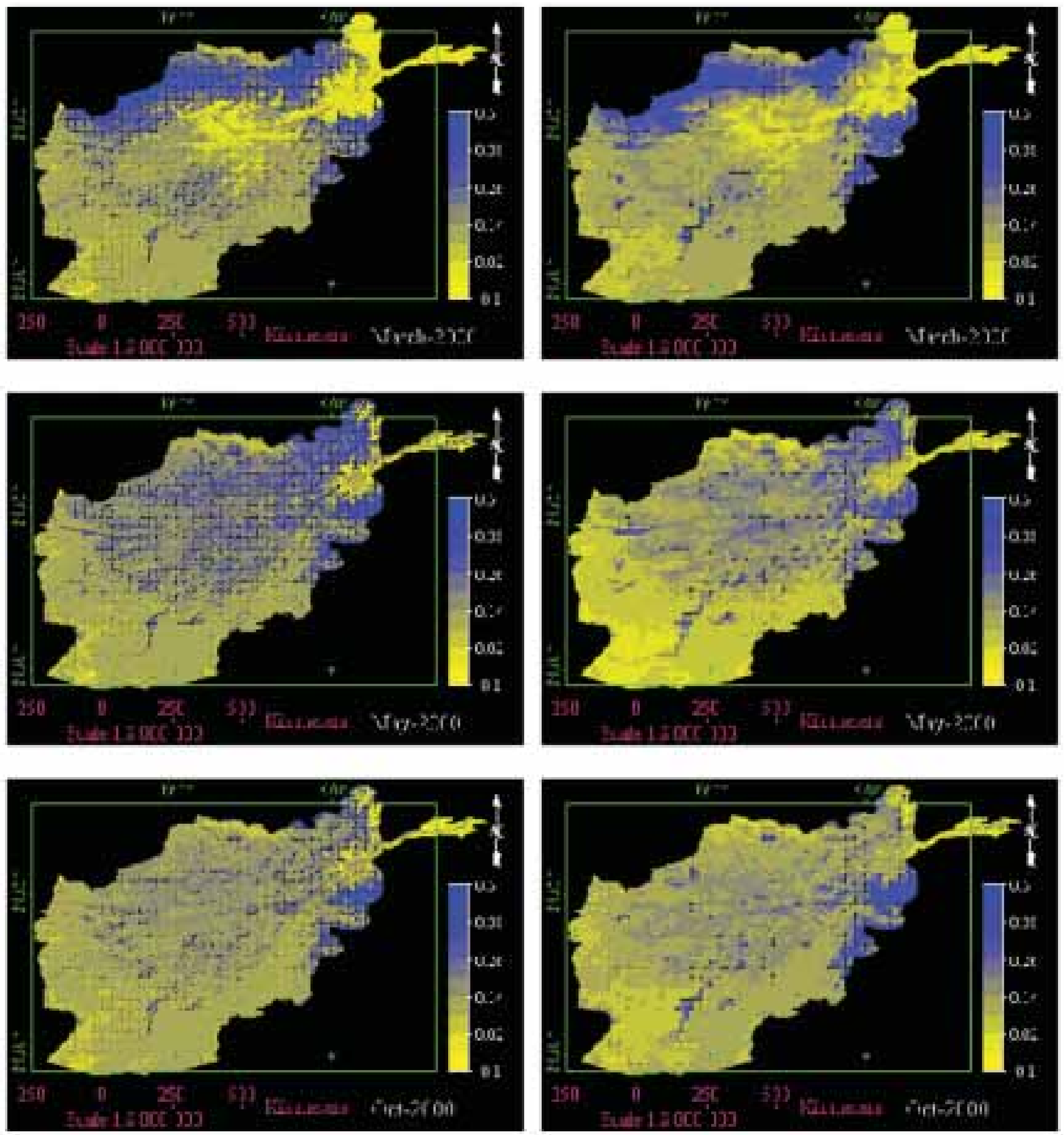


FIGURE 11.
Spatial distribution of actual and simulated values of DEV_{NDVI} for Afghanistan for 3 (arbitrarily selected) months of the year 2000. Images showing actual DEV_{NDVI} values are in the left column and images showing simulated values are on the right.



Implications for Future Drought Monitoring

An important implication for a future drought-monitoring program is the possibility of combining the estimates of maximum, minimum and long-term mean NDVI values derived from the AVHRR data with the actual MODIS data. MODIS data have so far only a "short life" (2000 to the present) and the long-term estimates of three mentioned NDVI drought characteristics (DEV_{NDVI}, VCI, TCI) at the MODIS level of spatial resolution are missing. The equations in table 2 may be used to estimate 500-m MODIS characteristics from the available AVHRR data. Therefore, the required minimum, maximum and long-term NDVI mean values may be estimated at the finer scale and, consequently, DEV_{NDVI} and VCI estimates may be made available at this scale (500-m resolution). As the MODIS NDVI data "build up" with time, long-term NDVI characteristics can be determined directly from the MODIS data.

Therefore, the advantage may be made of complementary features of both types of data, where MODIS data form the basis on which to develop a prototype for a near-real-time drought monitoring system at the scale of a country, state, district or pixel with an 8– or 16–day time interval. The results described feed directly into the development of the regional drought-monitoring system. The prototype monitoring system is currently being set up on the Internet and will include the facilities to explore drought-related characteristics (DEV_{NDVI} and VCI), averaged at the level of districts and other small administrative subdivisions in three countries. The fully functional system will eventually allow these characteristics to be examined at the pixel level (0.5 by 0.5 km) and for different types of land uses, including rain-fed and irrigated areas, mountainous areas, rangelands and deserts. The common steps involved in the maintenance of the system will include the following:

- Routine downloads of MODIS 500-m land-surface reflectance data from USGS data gateway every 8 or 16 days. The data are downloaded in "tiles," six tiles covering the entire study area. Downloading the data from six tiles takes about 5 hours at a speed of 45 kilobytes per second. The downloaded data for one date for the entire study area occupy approximately a gigabyte of disk space. If a similar system is to be reproduced for a specific country in the region, the time and space requirements could be less.
- The downloaded data need to be processed using the commercially available ERDAS software package. Other packages are also available, but ERDAS was found to be the most efficient processing tool. All raw downloaded data are imported into ERDAS and re-projected into geographic latitude and longitude coordinates, using facilities provided by ERDAS.
- The re-projected data of all six tiles are combined into one file covering the entire study area (the procedure known as "mosaicking"). This is followed by the calculation of NDVI values for each pixel in the study area, using equation (5). The "NDVI file" is stored as part of the array of similarly processed images for previous dates. Thus preprocessed data form the time series of images, which are then used for continuous drought monitoring.
- Formulae (6) and (7) are used to calculate current VCI and DEV_{NDVI} for each pixel from NDVI data. Long-term means, maxima and minima, required to calculate these indices for each pixel, are obtained using relationships listed in table 2. Current drought-related vegetation indices can be averaged for all pixels

over a district, state or country. However, the information is obviously most valuable at the fine resolution, pixels or districts, in the current setup. Subdistrict administrative divisions (e.g., *talukas, tensils*) can be incorporated into the system as well.

- The user of the system will be able to interactively select the required district and display the land-use coverage, the VCI and DEV_{NDVI} coverages and the time series graph, showing the long-term mean NDVI for each month of the year, and the current NDVI time series. The start of the plotting period can be interactively selected.
- Categorization of the drought severity based on the available data is being developed. It is also planned to include short reports, which interpret current drought conditions in a lucid format.

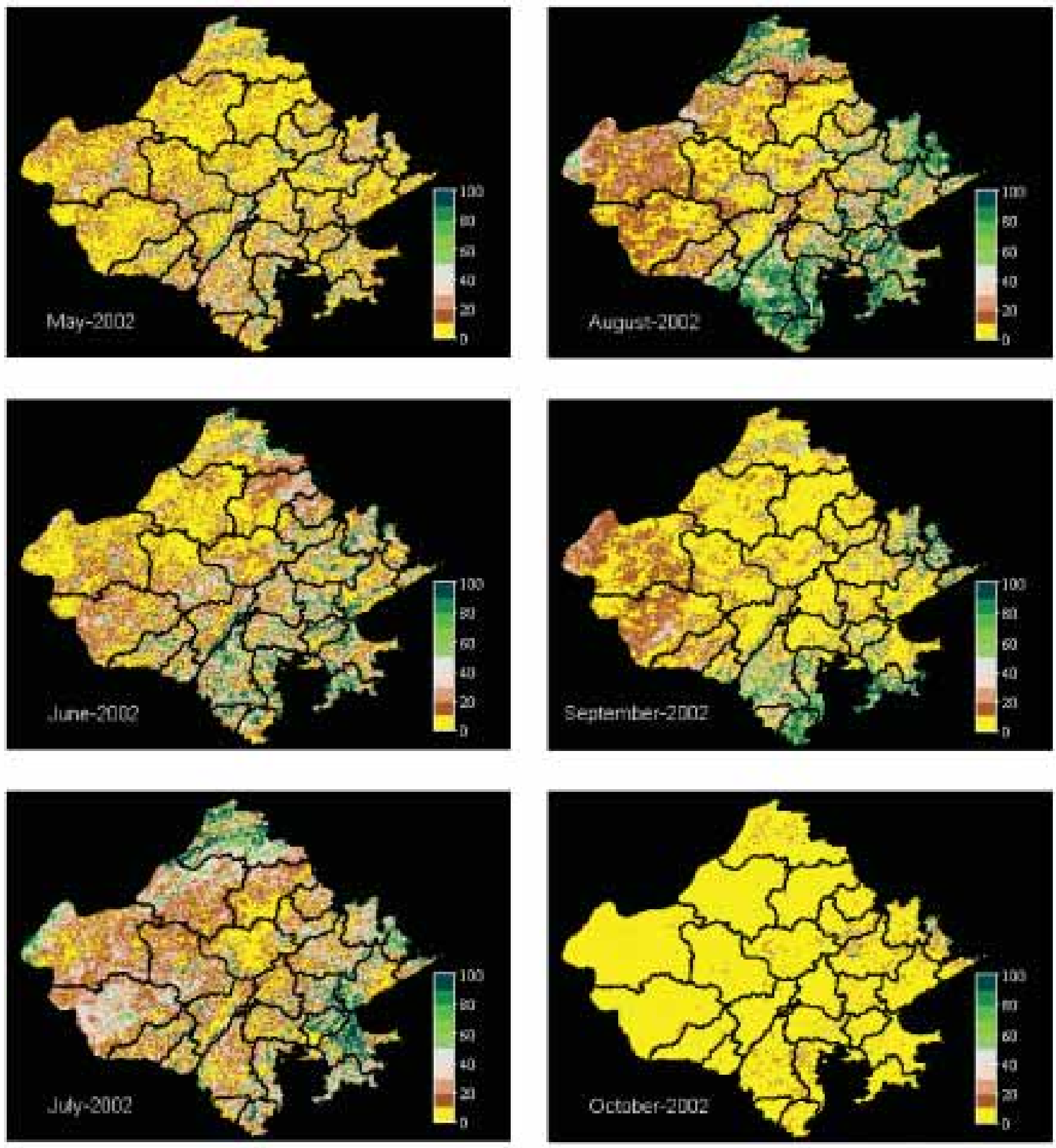
An operational drought-monitoring system could positively impact the efficiency of existing drought policies and declaration procedures. This can be illustrated using the example of the most recent drought of 2002, which severely hit Rajasthan and Gujarat States of India. The recent publication of the Department of Agriculture and Cooperation (2004) reviews, amongst the others, the events that occurred in each state during the drought of 2002. At the end of July 2002, on the basis of ground observations on rainfall and the conditions of crops, the Government of Rajasthan declared that droughts hit all 27 districts of the state. Similarly, in the middle of October 2002, the Government of Gujarat declared that droughts hit 14 out of the 20 districts of the state.

MODIS images for several successive months from the beginning of 2002 were analyzed to establish how many districts could have been identified as drought-hit using remote-sensing information exclusively. For this, the DEV_{NDVI} and VCI values of all 0.5 X 0.5 km pixels in each district of Rajasthan and Gujarat were averaged for the latest MODIS image in each month. Thus one monthly value of DEV_{NDVI} and one monthly value of VCI per district were calculated. The next step was to calculate the number of districts in each state per each month, where monthly indices were below the drought thresholds. For the DEV_{NDVI} the threshold was 0.0 and for VCI, where two thresholds were used, it was 50% and 35%. The first VCI threshold is normally perceived as the one below which the vegetation starts to lose its vigor, which is the first indication of an emerging drought. The second VCI threshold may be perceived as the beginning of a severe drought (Kogan 1995).

In Gujarat, in the month of drought declaration (October 2002), the number of districts, which had their averaged indices values below the selected thresholds (VCI_{50}, VCI_{35} and DEV_{NDVI}) were 14, 10 and 17, respectively. In the previous month of September 2002, the corresponding numbers were 6, 1 and 9, indicating that the state was already moving into a drought (although only one district was found to be under severe drought conditions).

In Rajasthan, in the month of drought declaration (July 2002), the number of districts, which had their averaged indices' values below the selected thresholds (VCI_{50}, VCI_{35} and DEV_{NDVI}), were 21, 18 and 18, respectively. But in the previous months of May and June, the number of districts with index values below any of the three thresholds was always, at least, 16 with May showing all 27 districts as drought-hit in terms of all thresholds. As an example, figure 12 illustrates the distribution of the VCI values over Rajasthan (the district boundaries are shown in black) from May to October. The low VCI values dominated over the state since May 2002 and became extremely low by October.

FIGURE 12.
Spatial distribution of the VCI values over the State of Rajasthan, India, during the drought of 2002.



While such assessment is very crude due to averaging of pixel values by district, no distinction was made between rain-fed and irrigated areas, and this remote-sensing information would effectively allow drought onset to be predicted 2 months in advance of the actual declaration dates in both states. A more detailed evaluation of the remote-sensing data (e.g., against rainfall and/or ground observations on crop density) in different parts of the region is certainly necessary before predictions based on such data can be used reliably in drought mitigation. The categorization of the VCI severity values below 50% should also be carried out (currently, these validations and categorizations are being conducted). Enhancement of the drought-monitoring system with these features will allow droughts to be predicted earlier, their impact areas to be delineated more accurately and their impacts on crops diagnosed before harvest. This should eventually contribute to the food security in the region.

Conclusions

The report suggested methods and techniques for continuous drought monitoring by linking historical AVHRR sensor data with modern day MODIS sensor data. The methodology was tested for a study area in southwest Asia, which includes Afghanistan, Pakistan and two states in western India.

The results indicate that out of the three remote-sensing indices used, DEV_{NDVI}, and VCI are complementary and were found to be sensitive indicators of drought conditions. However, TCI was found to be an unreliable indicator for drought assessment and is not recommended for future drought monitoring.

The development of new indices, which could be used for drought monitoring, was not part of this particular study, and earlier suggested indices (NDVI and VCI) are used. Both are based on the same two thermal channels out of the available seven (in MODIS). The alternative channels however suggest a possibility to explore and possibly develop more effective indices, which could be better indicators of drought conditions. This could be an interesting direction for future research.

The study established and validated methods and techniques of drought assessment across two different sensors. It established reliable relationships between NDVI values derived from both sensors and created the options for the enhancement of existing free remote-sensing data. The best option incorporates the long-term NDVI characteristics calculated from AVHRR into MODIS at 500-m spatial resolution. This option is particularly attractive for the future drought monitoring, as it will have all the advantages of the better MODIS technology. The availability of MODIS data is guaranteed at least till 2018, with continuity missions planned with its successors NPP and NPOESS. Therefore, the AVHRR-MODIS-NPP-NPOESS data sets may effectively form one continuous data stream from 1982 to 2018, and possibly beyond. This would make it the single largest source of spatial data available for the South Asia region (and for the entire globe).

The results of this study are being used for the development of a regional drought-monitoring system. Considering the spread and frequency of droughts in the region on the one hand, and the lack of ground climate observations and technical capacity in the countries of the region to deal with droughts on the other, such a system could play an invaluable role for drought preparedness.

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