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Indicators for Assessing Drought Hazard in Arid Regions of India

K.P.R. Vittal, Amal Kar* and A.S. Rao

1. INTRODUCTION

Drought is a normal phenomenon of earth's climate, and is a common feature in the drylands of India. Indian agriculture, which is highly dependent on the monsoon rainfall, is a major victim of drought. Since nearly 70% of the net sown area in the country is rainfed, aberrant behavior of the monsoon such as low and poor rainfall distribution, its delayed onset, or prolonged dry spells during cropping season, often result in low crop yields. Arid western part of Rajasthan state is a frequent victim of moderate to severe droughts, resulting in huge economic loss and natural resources. Severe droughts have reduced food grain production in western Rajasthan by 70% in 1987-1988, and by 50% in 2002-2003 (Anon., 2004a; Narain and Kar, 2005).

Severity and recurrence of drought in the hot arid zones of India (32 million ha; 62% in Rajasthan, 20% in Gujarat) compels the government to spend a huge sum on drought relief and rehabilitation measures, but there is often some confusion or delay in reaching the affected sections of the population, or parts of the region, especially due to poor infrastructural facilities, but also due to delay in proper assessment and warning, which reflect the inadequacies in drought assessment and monitoring tools. Thus a proper assessment of the severity of drought not only depends on the duration, frequency, intensity and geographical distribution of rainfall, but also on the effects on human, animal, crops and vegetation cover of a region. Seasonal temperature, wind velocity, sunshine, density of vegetation and moisture retaining capacity of soil and soil moisture balance in surface and sub-soil, and groundwater influence water demand during drought years.

In this chapter, an overview of various internationally accepted drought indicators and their application to the drought-prone arid Rajasthan, India, has been provided.

2. TYPES OF DROUGHT

Droughts are classified into four main categories as described below.

2.1 Meteorological Drought

Meteorological drought is a situation when the seasonal rainfall over an area is less than 75% of its long-term average. It is further classified as "*moderate drought*", when the rainfall deficit is between 26% and 50% and "*severe drought*" when it exceeds 50%. Meteorological drought can be at local, regional or extensive scale, varying in extent from a few clusters of *tehsils*/districts to several meteorological sub-divisions. In temporal scale, a drought can last for a few weeks or longer.

*Corresponding Author

2.2 Hydrological Drought

Prolonged meteorological drought can result in hydrological drought with marked depletion in surface water input, and consequent drying up of reservoirs, lakes, decline in stream flow and also fall in groundwater table.

2.3 Agricultural Drought

An agricultural drought occurs when soil moisture and rainfall are inadequate during the growing season to support a healthy crop growth till maturity, causing extreme crop stress and drastic reduction in yield.

2.4 Socio-economic Drought

It is a situation, where water shortage ultimately adversely affects the economy of the region. It combines the impact of meteorological, hydrological and agricultural droughts on society, especially in terms of supply and demand of commodities and purchasing power of the people. Severe societal drought may even lead to mass migration in search of food, fodder, water and work, leading to famine, death and social unrest. The worst hit sections of the society during drought are the people below the poverty line and the landless people. In an agriculture-dependent country like India, once the agricultural production declines due to drought, it sets in a chain reaction, leading to lower availability of commodities, lower purchasing power and lower economic growth down the spiral of poverty, hunger and survival of poor people.

3. KINDS OF DROUGHT INDICATORS

Monitoring of drought is usually carried out on the basis of interpretation of a set of indicators on a regular basis during critical periods. For quantitative measurement of the severity of drought, specific limits or threshold values below which the economy is not affected are put to the measured parameters. Various indicators used for drought monitoring can be classified as: *physical*, *biological* or *socio-economic indicators* depending on the aspect covered by the indicator. The *physical indicators* include rainfall or effective soil moisture, surface water availability, depth to groundwater, etc. The *biological or agricultural indicators* are usually comprised of vegetation cover and composition, crop and fodder yield, condition of domestic animals, pest incidence, etc. The *social indicators* are essentially the impact indicators and include food and feed availability, land use conditions, livelihood shifts, migration of human and livestock population, etc. However, the commonly used indicators measure only the levels of precipitation to meet: (a) agricultural need, (b) drinking water supply for both human and livestock, and (c) storage of water reservoirs.

4. METEOROLOGICAL DROUGHT INDICATORS

4.1 Deciles of Precipitation

In this approach, monthly precipitation totals from a long-term record are first ranked from the highest to the lowest to construct a cumulative frequency distribution. The distribution is then split into ten parts (tenths of distribution or deciles). The first decile is the precipitation value not exceeded by the lowest 10% of all precipitation values in a record, the second is between the lowest 10 and 20 per cent, etc. Any precipitation value can be compared with and interpreted in terms of these deciles. A reasonably long precipitation record (30-50 years) is required for this approach.

Decile Indices (DI) are grouped into five classes, two deciles per class. If the precipitation falls into: (i) Deciles 1 and 2 (the lowest 20%) is classified as "much below normal" precipitation; (ii) Deciles 3 and 4 (20 to 40%) as "below normal" precipitation; (iii) Deciles 5 and 6 (40 to 60%) as "near normal" precipitation; (iv) Deciles 7 and 8 (60 to 80%) as "above normal" precipitation; and (v) Deciles 9 and 10 (80 to 100%) as "much above normal".

Merits and demerits: DI is relatively simple to calculate, requires only precipitation data and fewer assumptions than more comprehensive indices like PDSI or SWSI. Deciles are widely used in Australia to trigger drought relief programs (Gibbs and Mather, 1967).

4.2 Precipitation Departures from Normal

India Meteorological Department (IMD) describes meteorological drought from rainfall departure from its long-term averages and declares meteorological drought on a weekly/monthly basis. The percent rainfall anomalies from normal to be qualified as drought of a severity class are shown in Table 1 (Kulshreshtha and Sikka, 1989).

Table 1. Meteorological drought classification

Departure of annual rainfall from normal (%)	*Meteorological drought condition*
> 0	No drought
–1 to –25	Mild drought
–26 to –50	Moderate drought
< –50	Severe drought

Merits and demerits: This is the most accepted measure of drought in India because of its simplicity. When more than 50% area of the country is under moderate or severe drought, the country is described as severely affected; when the affected area is 26-50% of the country, it is categorized as moderate drought. One of its disadvantages is that the average precipitation is often not the same as the median precipitation, which is the value exceeded by 50% of the precipitation occurrences in a long-term climate record. Another drawback is that the distribution or time-scale of rainfall is not taken into account.

4.3 Palmer Drought Severity Index (PDSI)

Palmer (1965) developed a soil moisture algorithm (a model), which uses data on precipitation, temperature and local available water content (AWC) of the soil. It uses the computed values of CAFEC (Climatically Appropriate for Existing Conditions) rainfall, which is the normal value for the established human activities at a place. This parameter can be obtained by water balance technique. The anomaly (PDSI), which is a difference between the actual and the CAFEC precipitation, is used as a drought indicator. PDSI generally varies between –4.0 (extreme drought) and +4.0 (adequate moisture condition). The index values for categories of drought are given in Table 2.

Merits and demerits: The PDSI is a popular index and is widely used for a variety of applications in the United States, including agriculture. It has also been used for drought monitoring to initiate actions associated with drought contingency plans. The index provides decision makers with a measurement of the abnormality of recent weather for a region. It also provides an opportunity to place current conditions

Table 2. PDSI values for drought categories

Index value	*Drought class*
–1.00 to –1.99	Mild drought
–2.00 to –2.99	Moderate drought
–3.00 to –3.99	Severe drought
< –4.00	Extreme drought

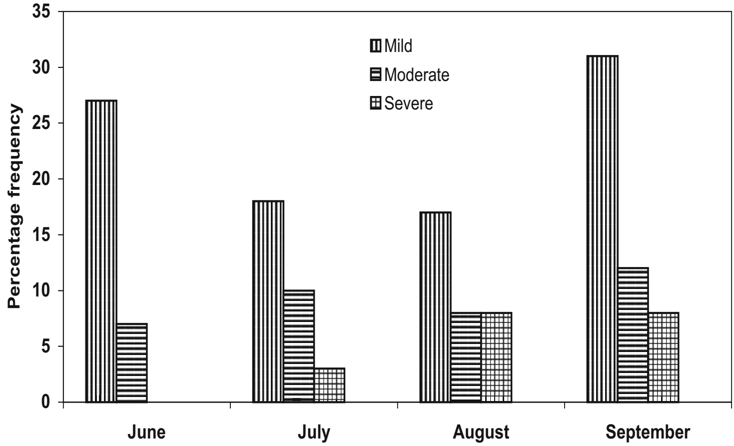

Fig. 1 Palmer's Drought Severity Index for western Rajasthan (long-term, monthly).

in historical perspective, and also spatial and temporal representations of historical droughts. The PDSI is a meteorological drought index, and responds to weather conditions that have been abnormally dry or abnormally wet. However, the Palmer values may lag emerging droughts by several months or weeks and is not suited for mountainous areas or areas that experience frequent climatic extremes. Figure 1 illustrates the pattern of long-term PDSI for the summer monsoon months in western Rajasthan.

4.4 Standardized Precipitation Index (SPI)

The SPI is an index based on the probability of precipitation for any time scale (McKee et al., 1993). Table 3 shows the drought classes based on SPI values. The SPI is calculated as follows:

Table 3. Drought classes based on SPI values

SPI	*Drought class*
Less than –2.0	Extreme drought
–1.50 to –1.99	Severe drought
–1.0 to –1.49	Moderate drought
–0.99 to –0.0	Mild drought

$$SPI = \frac{X - X_{mean}}{\sigma} \quad (1)$$

where X = precipitation for the station, X_{mean} = mean precipitation, and σ = standard deviation.

Merits and demerits: The SPI can be computed for different time scales, can provide early warning of drought, help assess the drought severity, and is less complex than the PDSI. Soil moisture conditions respond to precipitation anomalies on a relatively short time scale. Groundwater, stream flow, and reservoir storage reflect the longer-term precipitation anomalies. For these reasons, the SPI is calculated for 3-, 6-, 12-, 24-, and 48-month time scales. The measured drought condition in western Rajasthan during 2002 (one of the most severe droughts in the region during recorded period) through SPI values, and that during 2003 (overall a normal year), is depicted in Fig. 2. The calculated relationship between SPI and pearl millet (a summer monsoon crop) yield in Jodhpur district between 1971 and 2006 is shown in Fig. 3.

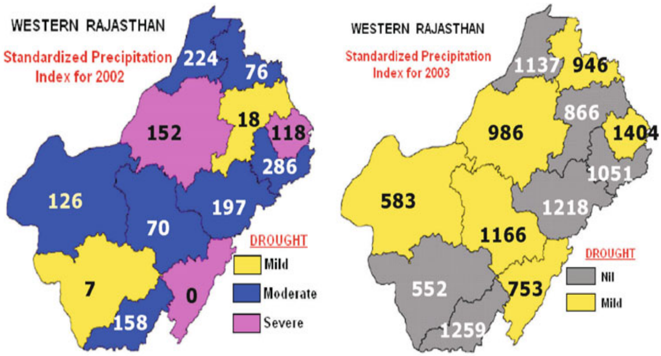

Fig. 2 Pearl millet yield (kg/ha) during severe drought of 2002 and that during a normal year 2003 in western Rajasthan.

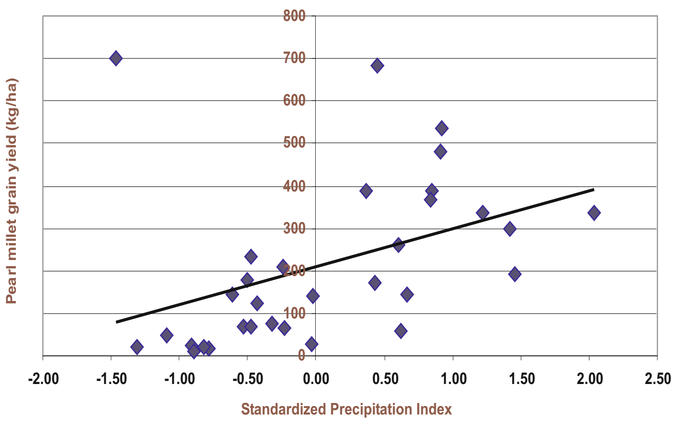

Fig. 3 Relationship between Standardized Precipitation Index and pearl millet yield in Jodhpur district (1971-2006).

5. HYDROLOGICAL DROUGHT INDICATORS

Measurement of both groundwater and surface water levels provide important clues to drought occurrence. Monitoring reservoir water levels and groundwater table through a closed well observation network is important for drought assessment.

5.1 Standardized Water Level Index (SWI)

The SWI is an index based on the probability of water level in a reservoir for any time scale. It is calculated as:

$$SWI = \frac{W_{ij} - W_{im}}{\sigma} \tag{2}$$

where W_{ij} = seasonal water level for the ith and jth observations, W_{im} = seasonal mean water level, and σ = standard deviation of water levels.

Merits: The SWI can be computed for different time scales, and it can provide early warning of water shortage and hydrological drought severity.

5.2 Surface Water Supply Index (SWSI)

This index integrates reservoir storage, stream flow and two precipitation types (snow and rain) into a single index number (Shafer and Dezman, 1982). SWSI is expressed as:

$$SWSI = \frac{aP_{snow} + bP_{prec} + cP_{strm} + dP_{resv} - 50}{12} \tag{3}$$

where a, b, c and d = weights for snow, rain, stream flow and reservoir storage, respectively ($a + b + c + d = 1$), and P_i = probability (%) of non-exceedance for the ith component of water balance. Calculations are performed with a monthly time step. The SWSI is designed for river basins where mountain snow pack is a key element of water supply.

Merits and Demerits: SWSI calculation is unique to a basin or a region, and thus has better focus on the characteristics of the area for a time-series analysis. However, it is difficult to compare SWSI values between different basins or regions. Extreme events also cause a problem if the events are beyond the historical time series, and the index will need to be re-evaluated to include these events within the frequency distribution of a basin component.

5.3 Reclamation Drought Index (RDI)

The RDI has been developed for defining drought severity and duration, and for predicting the onset and end of drought (Table 4). Like the SWSI, the RDI is calculated at the river basin level, incorporating temperature and precipitation, snow pack, streamflow and reservoir levels as inputs.

***Merits and demerits*:** The RDI differs from the SWSI in that it builds a temperature-based demand component and duration into the index. The RDI is adaptable to each particular region and its main strength is its ability to account for both climate and water supply factors. Because the index is unique to each river basin, inter-basin comparisons are limited. The RDI values and severity designations are similar to the SPI, PDSI and SWSI.

Table 4. RDI classification of drought

Values of RDI	Drought classification
4.0 or more	Extremely wet
1.5 to 4.0	Moderately wet
1 to 1.5	Normal to mild wetness
0 to –1.5	Normal to mild drought
–1.5 to –4.0	Moderate drought
–4.0 or less	Extreme drought

6. AGRICULTURAL DROUGHT INDICATORS

In a country like India, where agriculture provides livelihood to maximum population, the impact of drought on agriculture, including livestock, assumes the highest priority. Several indices are available to measure agricultural droughts (Hounam, 1975) of which some commonly used indicators are described in subsequent sections.

6.1 Aridity Index

Aridity index (Thornthwaite and Mather, 1955) is the percentage ratio of annual water deficit to annual water need or annual potential evapotranspiration (PE). Aridity anomaly (I_a) index is the departure of aridity index value from normal, expressed as a percentage (Table 5). India Meteorological Department (IMD) monitors agricultural drought during *kharif* season for the country as a whole and during *rabi* season for those areas which receive rainfall during northeast monsoon. The values of aridity anomaly (I_a) index are then plotted on a map and analyzed for identification of drought intensity.

Table 5. Drought categories based on aridity index

Drought category	*Aridity anomaly value*
Mild drought	Up to 25%
Moderate drought	26-50%
Severe drought	More than 50%

***Merits and demerits*:** The aridity index indicates the water deficit conditions in a region. Crop-water requirements, which vary not only for each crop, but also with geographical location, are not considered in this index. The water balance calculations have also limitations for not properly accounting rainfall-runoff before stored moisture is estimated.

6.2 Moisture Adequacy Index (MAI)

Central Arid Zone Research Institute (CAZRI) developed a technique for the quantification of agricultural drought by taking MAI (AE/PE in percentage) during different phenological stages of a crop (Ramana Rao et al., 1981; Sastri et al., 1981). The MAI is obtained from weekly water balance studies. The drought impact is more important at certain stages than others, and is sought to be identified for a crop through this method. Subsequently, the drought conditions at different phenophases are integrated into a single drought code like mild, moderate and severe. Depending on the values of AE/PE during different phenophases, the drought code varies as S_0, V_1, R_2, S_1, V_2, R_3, etc. When the crop factor is introduced, the drought code in three syllables is unified into a single drought code applicable to one particular crop for a specific region. The scheme for determining drought intensity code at different phenophases is elaborated in Table 6.

Table 6. Phenophase-wise drought intensity codes from MAI

AE/PE (%)	*Drought intensity*	*Phenophase-wise code for stages*		
		Seedling (S)	*Vegetative (V)*	*Reproductive (R)*
76 to 100	No drought	S_0	V_0	R_0
51 to 75	Mild drought	S_1	V_1	R_1
26 to 50	Moderate drought	S_2	V_2	R_2
25 or less	Severe drought	S_3	V_3	R_3

The scheme may be illustrated with an example of pearl millet crop in western Rajasthan. The average growing season of pearl millet crop is about 14 weeks. The duration of different phenophases of the crop in this region are: seedling (S) three weeks, vegetative (V) four weeks, reproductive (R) four weeks, and maturity (M) three weeks. As the water stress during maturity stage does not have much influence compared to the water stress during other three stages, the maturity stage is eliminated and the three syllable agricultural drought code can be unified into a single code. The possible combinations that could normally be derived for the arid region of Rajasthan are shown in Table 7.

Interpreting Table 7, the agricultural drought for pearl millet in western Rajasthan can be defined in the following terms (Ramana Rao et al., 1981; Sastri et al., 1981):

- Agricultural drought for pearl millet crop is severe (A_3) when both vegetative (V) and reproductive (R) stages experience severe drought with any combination of S_0, S_1, S_2 or S_3, as the water requirement during seedling stage is usually less. In these circumstances even the natural grasses too suffer from drought conditions.
- Agricultural drought for the crop is moderate (A_2) when vegetative (V) and reproductive (R) stages experience one moderate and one severe drought each, with any combination of S_0, S_1, S_2 or S_3. During this situation short-duration crops also suffer from drought.
- Pearl millet crop escapes drought situation (A_0) even when mild drought prevails in one or two growth stages, with no drought condition in the third stage.

Table 7. Possible combinations of phenophase-wise drought for pearl millet crop in western Rajasthan

Intensity of agricultural drought			
No drought	*Mild drought*	*Moderate drought*	*Severe drought*
$S_0 V_0 R_0$	$S_0 V_0 R_2$	$S_0 V_0 R_3$	$S_0 V_2 R_3$
$S_0 V_0 R_1$	$S_0 V_1 R_2$	$S_0 V_1 R_3$	$S_0 V_3 R_2$
$S_0 V_1 R_0$	$S_0 V_2 R_0$	$S_0 V_2 R_2$	$S_0 V_3 R_3$
$S_1 V_0 R_0$	$S_0 V_2 R_1$	$S_0 V_3 R_0$	$S_1 V_2 R_3$
$S_1 V_0 R_1$	$S_1 V_0 R_2$	$S_0 V_3 R_1$	$S_1 V_3 R_2$
$S_1 V_1 R_0$	$S_1 V_1 R_1$	$S_1 V_0 R_3$	$S_1 V_3 R_3$
$S_0 V_1 R_1$	$S_1 V_1 R_2$	$S_1 V_1 R_3$	$S_2 V_0 R_3$

Table 8. Influence of commencement of sowing rains on the occurrence of agricultural drought in western Rajasthan (1901-1995)

	Station	*Commencement of sowing rains*	*Frequency of occurrence of agricultural drought with intensity*				
			Nil	*Mild*	*Moderate*	*Severe*	*Total*
1.	Sikar	Early	8	11	8	3	30
		Normal	16	12	7	8	43
		Late	7	5	3	7	22
2.	Jodhpur	Early	6	1	8	4	19
		Normal	13	9	8	13	43
		Late	3	10	4	16	33
3.	Barmer	Early	2	3	6	4	15
		Normal	5	11	6	7	29
		Late	0	13	4	34	51
4.	Jaisalmer	Early	1	0	2	6	9
		Normal	1	2	6	10	19
		Late	2	2	0	63	67

The rest of the situations result in mild drought (A_1) for pearl millet. Short-duration crops like pulses escape drought under these circumstances. Using the above index, Rao (1997) assessed the influence of sowing rains on agricultural drought for some stations across western Rajasthan (Table 8).

Merits and demerits: The water balance calculation takes into account soil characteristics, crop growing period and water requirement of major crops. The drought is specified crop-wise and on a real-time basis. In other words, the calculation is highly data-intensive, and may require field-level information from a large network of monitoring sites. With the gradual advancements in satellite remote sensing and remote monitoring of weather, soil moisture status and crop growth conditions, however, this method has a better prospect.

6.3 Crop Moisture Index (CMI)

The Crop Moisture Index (CMI) uses a meteorological approach to monitor weekly crop conditions. It was developed by Palmer (1968) following the procedures within the calculation of the PDSI. While the PDSI monitors the long-term meteorological wet and dry spells, the CMI has been designed to evaluate short-term moisture conditions across the major crop-producing regions. It is based on the mean temperature and total precipitation for each week within a climate division, as well as the CMI value from the previous week. The CMI responds rapidly to changing conditions, and it is weighted by location and time so that maps, which commonly display the weekly CMI, can be used to compare moisture conditions at different locations.

***Merits and demerits*:** Since CMI is designed to monitor short-term moisture conditions affecting a growing crop, it is not a good long-term drought-monitoring tool. Another limiting characteristic of CMI as a long-term drought-monitoring tool is that it typically begins and ends each growing season near zero. This limitation prevents CMI from being used to monitor moisture conditions outside the general growing season, especially in droughts that extend over several years.

6.4 Crop Water Stress Index (CWSI)

The CWSI value is a daily integration of plant-available soil water, evaporative demand and plant phenological stage susceptibility. It is defined for the growing season as follows (Saxton, 1989):

$$CWSI = \sum_{Planting}^{Harvest} \left(1 - \frac{T}{T_p}\right) SUS \tag{4}$$

where T = computed actual transpiration (mm/day), T_p = potential transpiration (mm/day), and SUS = seasonally dependent weighting factor for grain-yield susceptibility.

Merits and demerits: This index needs the running of a dynamic simulation model, Soil-Plant-Atmosphere-Water Model (SPAW), for simulation of soil water and calculation of effective rainfall used for plant transpiration. The SPAW model needs calibration for each crop and region, and hence has a limitation for its use. However, the estimates obtained from this model are reasonably good (Rao and Saxton, 1995).

6.5 Performance of Different Agricultural Drought Indicators

The comparative performance of different agricultural drought indicators in Jodhpur district of Rajasthan is presented in Table 9. Standardized Precipitation Index, which is a meteorological drought indicator, performed the least (with correlation coefficient = 0.216) and Crop Water Stress Index (SPAW model) performed the best (with correlation coefficient 0.890). Unfortunately, its execution at field-level over a large area demands a huge database on weather, soil and crop parameters that are still difficult to gather reliably in near-real time. Lack of good field-scale details on soils, crop and weather precludes the testing of its actual potential at a zonal to regional scale. Moisture Adequacy Index (MAI), which is simple to calculate on the basis of rainfall and temperature data, has shown more promises in drought monitoring.

Table 9. Comparative performance of agricultural drought indicators in Jodhpur district

Indicator	*Correlation with pearl millet yield (1971-2005) R^2 value*	*Merits and demerits*
1. Standardized Precipitation Index	0.216	Can be computed for different time scales, and is less complex than the PDSI.
2. Aridity Index	0.380	Water balance calculations have limitations for not accounting rainfall-runoff.
3. Palmer's Drought Severity Index	0.473	Meteorological index responds better to abnormally dry or wet weathers.
4. Moisture Adequacy Index	0.673	Can specify drought crop-wise and on a real-time basis.
5. Crop Water Stress Index (SPAW model)	0.890	Simulates soil-water and calculates effective rainfall for plant transpiration, with reasonable results. Model needs calibration for each crop and region.

7. DROUGHT-RELATED INDICES FROM REMOTE SENSING

Several indices for drought monitoring have been developed over the past few decades using remote sensing data. These are calculated from the reflectance of vegetation and other land covers in different wavelength bands of satellite sensors, and may be obtained for each pixel (the size of a pixel depends on sensor resolution). These indices have some advantages over conventional indices, as they cover large areas, and may show, through vegetation condition signatures, how a drought progresses over the area. However, the indices may not always reflect the actual meteorological conditions on the ground, and need some field verification. Some of the indices may have lagged vegetation response to drought (see e.g., Kogan 1990, 1995; Moran et al., 1994; Jupp et al., 1998; Mcvicar and Jupp, 1998; Peters et al., 2002; Sandholt et al., 2002; Wan et al., 2004; Tadesse, et al., 2005; Jiang et al., 2006; Ghulam et al., 2007 for development of indices and limitations). A summary of some useful techniques in the context of Indian Subcontinent is provided in Singh et al. (2003) and Thenkabail et al. (2004).

7.1 Normalized Difference Vegetation Index (NDVI)

Since 1989, National Agricultural Drought Assessment and Monitoring System (NADAMS) is providing bi-weekly drought bulletins for *kharif* season covering 246 districts in India. These bulletins describe prevalence, relative severity level, and persistence through the season at the district level. Drought assessment is based on a comparative evaluation of the satellite-observed green vegetation cover (both area and greenness) in a district during any specific time period to cover in similar periods in the previous year, or a long-term mean of the specified period. The drought interpretation takes into account rainfall and aridity anomaly trends. This nationwide early warning service has been found to be useful for providing early assessment of drought conditions. NDVI is calculated as (Kidwell, 1990):

$$NDVI = \frac{\lambda_{NIR} - \lambda_{RED}}{\lambda_{NIR} + \lambda_{RED}} \tag{5}$$

where λ_{NIR} and λ_{RED} are the reflectances in the near infra-red and red band, respectively. NDVI ranges from –1 to 1. Drought severity may be evaluated as the difference between the NDVI for the current month (e.g., September 2007) and a long-term mean NDVI for this month (e.g., a 30-year long mean NDVI for September).

$$\text{Drought Severity} = NDVI_i - NDVI_{mean,m} \tag{6}$$

where $NDVI_i$ is the current NDVI for the i^{th} month and $NDVI_{mean,m}$ is the long-term mean NDVI for the month m ($m = 1, 2, \ldots, 12$). Positive departure from the mean NDVI indicates that the vegetation condition is better than the normal in this month (i.e., wetter than usual). Negative departure from the mean NDVI points to a dryer condition for the current month than usual. The more negative the departure is, the drier the month is. Bayarjargal et al. (2006) provided a recent assessment of drought severity index and other related indices.

7.2 Enhanced Vegetation Index (EVI)

This index has been developed for use with MODIS data (Liu and Huete, 1995). Unlike NDVI, it takes the advantage of multiple bands. The EVI is calculated by using following formula:

$$EVI = G \times \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1 \times \rho_{RED} - C_2 \times \rho_{Blue} + L} \tag{7}$$

where ρ_{NIR} = NIR reflectance, ρ_{RED} = Red reflectance, ρ_{Blue} = Blue reflectance, C_1 = atmosphere resistance red correction coefficient, C_2 = atmosphere resistance blue correction factor, L = canopy background brightness correction factor, and G = gain factor.

The coefficients adopted in the EVI algorithm were $L = 1$, $C1 = 6$, $C2 = 7.5$, and G (gain factor) = 2.5. EVI is more sensitive in high biomass regions and ensures the improved monitoring through a reduction in atmosphere influences. At the same time, it is computationally intensive and is not widely used at present. EVI may be used in Drought Severity formula above.

7.3 Vegetation Condition Index (VCI)

Vegetation Condition Index (VCI) shows how close is the current month's NDVI to the minimum NDVI calculated from the long-term record of satellite images. It is mathematically expressed as (Liu and Kogan, 1996):

$$VCI_j = \frac{\left(NDVI_j - NDVI_{\min}\right)}{\left(NDVI_{\max} - NDVI_{\min}\right)} \times 100 \tag{8}$$

where $NDVI_{\max}$ and $NDVI_{\min}$ are calculated from the long-term record (e.g., 20 years) for that month or week, and j is the index of the current month or week. The condition (health) of vegetation presented by VCI is reported in percent and may serve as an approximate measure of how dry the current month is. In the case of extremely dry month, the vegetation condition is poor and the VCI is close or equal to zero. The VCI of 50% reflects a fair vegetation condition. At optimal condition of vegetation, the VCI is close to 100%. At this condition, NDVI for the current time step (month or week) is equal to $NDVI_{\max}$. Singh et al. (2003) have demonstrated the application of VCI and TCI (Temperature Condition Index) from AVHRR for drought monitoring in India.

In order to exploit the signatures of lesser green biomass in the dryland vegetation cover on satellite images and to find out deterioration in conditions from changes in such signatures, Pickup and Chewing (1988) developed a model called PD54, which is a 'perpendicular vegetation index' (PVI), rather than a non-dimensional vegetation index (NDVI). It was calculated using graphically plotted perpendicular distances of soil and vegetation signatures in bands 5 and 4 (i.e., red and green spectral bands, respectively of Landsat MSS). A recent study by CAZRI and CSIRO (Australia) to find out the performance of NDVI and PD54 in a rangeland near Jodhpur showed better results from the latter (Anon., 2004b). The PD54 was later improved as SAVI (Soil Adjusted Vegetation Index; Huete, 1988) and then further modified as MSAVI (Qi et al., 1994).

7.4 Temperature Condition Index (TCI)

Temperature Condition Index (TCI) is calculated similarly to VCI. However, in contrast to the VCI, TCI includes the deviation of the current month's (week's) value from the recorded maximum:

$$TCI_j = \frac{\left(BT_{\max} - BT_j\right)}{\left(BT_{\max} - BT_{\min}\right)} \times 100 \tag{9}$$

where BT is the brightness temperature (e.g., AVHRR Band 4. Under the atmospheric conditions, objects emit heat in this thermal band). The maximum and minimum values of BT are calculated from the long-term (e.g., 20 years) record of satellite images for each calendar week or month j (Kogan, 1995, 2002).

The low TCI value (close to 0%) indicates the very high temperature in that month or week. Consistently low TCI values over several consecutive time intervals indicate drought occurrence.

7.5 Merits and Demerits of Available Remote Sensing-Based Indicators

Vegetation conditions, including crops, being an indicator of rainfall, the maps on NDVI and other such indices (EVI, VCI, etc.) can be integrated with meteorological indices as these have larger coverage of area and provide data for areas where ground data is not accessible (Huete et al., 2002). However, during monsoon season the remote sensing data collection for vegetation cover becomes a constraint under cloudy conditions. As a result, analysis of satellite data for NDVI becomes limited by the availability of cloud-free data.

Moreover, in the sparsely vegetated arid regions, NDVI becomes a poor representative of vegetation cover as the background soils provide signatures almost similarly to the vegetation signatures. Also, the signatures of open rangelands are not very dissimilar to that of sparse distribution of *kharif* crops in the arid areas, which add to the problem of estimating actual crop growth and natural vegetation growth.

As we have described above, a number of wavelength bands and processing techniques have been tested and sensors have been experimented to negate the soil effects. Based on the encouraging results, regular monitoring of vegetation conditions are now made using satellite sensors like SPOT Vegetation (France) and MODIS (USA), and analytical products on drought, etc. are produced (e.g., Hayes et al., 2005; Wilhite, 2005). The assessment, mapping and monitoring in the USA involves a coordinated program of activities between the National Drought Mitigation Center (NDMC) at the University of Nebraska, Lincoln, US Department of Agriculture (USDA), and NOAA's Climate Prediction Center at the US National Weather Service (Wilhite, 1990).

A recent development in linking observations from different platforms is the assimilation of indices from ground-based atmospheric monitoring products, and the land information products (especially on land use and land cover, irrigation status, soil-available water capacity and eco-regions) with the satellite-derived indices on greenness conditions and start of season anomaly, to produce a Vegetation Drought Response Index (VegDRI) at 1 km resolution for application in USA (Tadesse et al., 2005; Brown et al., 2008). The products are now regularly displayed in the websites of NDMC and the US Geological Survey for monitoring the conditions of croplands and rangelands at county level, with a statistical database of the phenomenon. Concurrently, based on the meteorological indices (SPI, PDSI and percent long-term average precipitation) a US Drought Monitor (USDM) is prepared by NOAA, with data from many organizations, including USDA, and is regularly published in NDMC and NOAA websites. A variant of this product, the North American Drought Monitor (NADM), is a joint venture of the North American nations. The USDA uses the USDM and VegDRI data along with the predictions of medium range weather forecasting to analyze stresses on crops, rangelands and livestock, as well as the likely impacts on yield.

A different decile-based drought index, the Floating Month Drought Index (FMDI), which is based on calculation of precipitation percentile for current month, length and begin month of the current dry spell, and precipitation percentile for the current dry spell, has been developed for the Australian continent and is also being tested in the USA for inter-comparison of results from USDM. FMDI has the capability to show both wet and dry spell conditions.

One of the major inputs for monitoring crop performance is soil moisture condition, which is generally calculated from the rainfall, temperature and soil texture data, and is an approximation. Microwave satellite sensors are being tested to provide reliable global soil moisture data, and a new satellite, carrying L-band sensors to measure microwave radiation emitted from earth surface at L-band (1.4 GHz) to eliminate the effects of cloud, haze, other weather and atmospheric conditions, as well as vegetation effects, is expected to be launched in the near future by the European Space Agency.

In India, regular satellite-based assessment of crop growth conditions and agricultural drought condition during summer monsoon period are made by the National Remote Sensing Agency (NRSA) for the Ministry of Agriculture, Government of India, which also gathers data from other sources, including the States and Indian Council of Agricultural Research to review the situation on a weekly to fortnightly basis for addressing the emerging issues. NDVI from AWiFS is the major output that is currently analyzed by NRSA, and the results are assessed with soil moisture assessment data and agro-meteorological yield models (Murthy et al., 2006). Samra (2004) provides a summary of the systems of monitoring followed in India.

8. SOCIETAL DROUGHT

Societal drought relates to the impact of meteorological, hydrological and agricultural droughts on the society. Although the indices for measuring meteorological, hydrological and agricultural droughts are now reasonably well developed, those for measuring the societal aspects of drought are not. This is despite the fact that drought hits the agriculture-based economy the most, which in turn impacts the nation’s economy through lower production that creates an imbalance between the supply and demand of commodities, lowers the purchasing power of the people, and slows down the nation’s economy, as has been shown in a recent study on the impact of the drought of 2002 in western Rajasthan (Narain and Kar, 2005). Severe societal drought can lead to mass migration in search of feed, fodder and water. However, there are not many studies on the development of indices. Vulnerability of the society’s different segments to drought is a key issue that ideally determines the kind of counter-measures required.

Considering the above facts, it is necessary to develop a set of social indicators that identify the drought-vulnerable segments of the society and that could be used to link with the indicators on physical aspects in a Decision Support System (DSS) developed in the GIS environment. This will help in not only identifying the vulnerable areas of drought and the vulnerable segments of a society, but also in working out the quantum of relief and rehabilitation measures, as well as identifying the needs of infrastructure development as a long-term strategy for drought proofing.

9. ROLE OF DECISION SUPPORT SYSTEM IN DROUGHT MANAGEMENT

A knowledge-based spatial decision support system (SDSS) is an effective computer tool for drought management by farmers, experts and general end-users. This type of DSS is crucial for a National Drought Management Institute to effectively communicate the location-specific drought-related problems in advance to the stakeholders, risk assessment and options available to mitigate the problems. The DSS can utilize information database (information layer) and develop domain-specific knowledge-based algorithms. Knowledge layer tools even allow experts to interpret the complex problem of drought-risk management. Therefore, there is an urgent need for better data management and computing facilities to analyze climatic and natural resources on spatial and temporal scales and to prepare vulnerability maps, as well as forecast economic and environmental impacts. Some such systems are already in use globally for early warning of droughts.

As has been shown earlier, an elaborate system of assessment and monitoring is followed by the NDMC of the USA that has the potentials for a global coverage. An automated drought analyses system for water-resources analysis called “SPATSIM” (**Spa**tial and **T**ime **S**eries **I**nformation **M**odeling) software package, has been developed jointly by the Institute for Water Research (IWR), Grahamstown, South

Africa, and the International Water Management Institute (IWMI), Colombo, Sri Lanka (Smakhtin and Hughes, 2004). In India, different assessment tools are being used by different affected states for declaring drought. In Rajasthan, more emphasis is given on yield loss estimates at a village level by the village revenue officials (*Patwaris*), which are collated at *tehsildar* level and upwards for a state-level assessment. In Karnataka, the assessment is based on the village/*taluka*-level collection of rainfall amounts and dry weeks, for which both satellite-based information and information from key field functionaries are used. In a novel departure from the IMD-station-based information system, the state is now getting their ground-based rainfall data on a near-real time basis from the automatic rain gauge stations installed in the villages through cell phones. In Andhra Pradesh, drought condition is analyzed from *Mandal*-level data on rainfall and crop sown area, as well as an estimation of yield and length and time of dry spells in relation to sowing period. Both satellite and ground observations are taken into account.

Although simple and less data-demanding for the government-level technocrats and bureaucrats to initiate remedial action in near-real time and monitor future needs, these lack the scientific depth, and do not consider the socio-economic variables (except in Rajasthan; see e.g., Anon., 2007) for a holistic assessment of the situation for targeting the most affected segments of the society. To overcome the drawbacks, and to systematize the integration of different data layers, efforts have been made in Chhattisgarh state to use a number of 'ecological', 'production system' and 'socio-economic' indicators, provide weight and ranking to them, and to find out statistically from their relationships the vulnerable Development Blocks (Gupta, 2002).

Biophysical and socio-economic parameters used by some of the drought early warning and food security systems working mainly for the African continent have been reviewed by CeSIA, Italy (Anon., 1999), and is summarized in Table 10. Although the indicators provide useful information for the organizations carrying out emergency relief and rehabilitation work in the affected African nations, the above review (Anon., 1999) suggested that the indicators could also be used for early warning of desertification. Kar and Takeuchi (2003) made a critical analysis of the indicators of drought early warning and those needed for a desertification early warning to show that the indicators of drought early warning system are inadequate for desertification early warning. Samra (2004) provides a review of drought monitoring and declaration policy followed in India, while Rathore (2005) discusses the system followed in Rajasthan.

10. CONCLUSIONS

There are many drought-monitoring indices, which have different merits and demerits. Our experience suggests that for the Indian arid region, where rural livelihood depends mostly on agriculture and related activities, a simple and reliable set of indicators, including bio-physical and socio-economic, that is amenable to quantitative measurements and modeling, and for which data could be gathered at least at the *Tehsil* level, needs to be developed for forecasting. The availability of real-time remote sensing data products, especially on soil moisture conditions, percent crop and natural vegetation cover (or, biomass yield from croplands and rangelands) at moderate to high resolution will help much in modeling the system that will also take as input ground-based data on meteorological parameters and socio-economic conditions. The information on rangeland production estimates is crucial due to the greater roles played by the livestock component in the rural economy of the region, especially during the droughts when crops fail. The models should be able to estimate the biological production from the land at different time steps, availability of water in the reservoirs, vulnerable areas and segments of population, infrastructure bottlenecks, if any, possible migration routes and areas for animals, and other related aspects that can help in proper agro-advisory, and in relief and rehabilitation. Models should also be developed to provide

Table 10. Indicators of early warning systems for food security used by major systems

	Indicator	*AP3A*	*FIVIMS*	*GIEWS*	*SADC*	*FEWS*	*VAM*
1.	Food crop performance	✓		✓	✓	✓	✓
2.	Crop conditions	✓		✓	✓	✓	✓
3.	Crop production forecast	✓		✓	✓		
4.	Marketing and price information		✓	✓	✓	✓	✓
5.	Food supply/demand		✓	✓	✓	✓	✓
6.	Health conditions					✓	✓
7.	Food crops and shortages			✓	✓	✓	✓
8.	Food supply			✓	✓		
9.	Food consumption			✓	✓		
10.	Crop areas	✓	✓	✓	✓	✓	✓
11.	Pests			✓	✓		
12.	Food balance		✓	✓	✓	✓	✓
13.	Vegetation front	✓					
14.	CCD	✓		✓	✓	✓	✓
15.	NDVI	✓		✓	✓	✓	✓
16.	Biomass	✓					
17.	Seeding risk areas	✓					
18.	Expected season length	✓				✓	✓
19.	Estimated seeded areas	✓			✓		
20.	Estimated seeding date	✓					
21.	Vegetation cover						
22.	Agro-ecological zones						✓
23.	Crop use intensity						✓
24.	Variation coefficient of agricultural production						✓
25.	Cash crop production area	✓		✓	✓		✓
26.	Coping strategies						✓
27.	Average cost to travel to nearest market						✓
28.	Livestock production	✓					
29.	Population density	✓		✓	✓	✓	✓
30.	Access to water						✓
31.	Children education						✓
32.	Rainfall	✓		✓	✓	✓	✓

Notes: AP3A = Alerte Precoce et Prevision des Production Agricoles (by AGRHYMET); FIVIMS = Food Insecurity and Vulnerability Information and Mapping Systems (by FAO); GIEWS = Global Information and Early Warning System (by FAO); SADC = Southern Africa Development Community (from Zimbabwe); FEWS = Famine Early Warning System (by USAID); and VAM = Vulnerability Analysis and Mapping (by World Food Programme).

information on the performance of the infrastructures developed as a long-term measure for drought mitigation. The ultimate goal of researchers is to produce an International Drought Early Warning System that would help to plan the response system to drought, including planning, mitigation and recovery, and to create a database and map that could be accessed globally at near-real time as an effective warning tool (Wilhite et al., 2000; Wilhite, 2005).

REFERENCES

Anon. (1999). Early Warning Systems and Desertification. CeSIA: Accademia dei Georgofili, Florence, Italy.

Anon. (2004a). Drought 2002: A Report. Department of Agriculture and Cooperation, Ministry of Agriculture, Government of India, New Delhi.

Anon. (2004b). Assessing the extent and causes of degradation in India's arid rangelands. ACIAR Research Note 27. Australian Centre for International Agricultural Research, Canberra, pp. 1-4.

Anon. (2007). Drought Management Manual. Disaster Management and Relief Department, Government of Rajasthan, Jaipur, India.

Bayarjargal, Y., Karnieli, A., Bayasgalan, M., Khudulmur, S., Gndush, C. and Tucker, C.J. (2006). A comparative study of NOAA-AVHRR derived drought indices using change vector analysis. *Remote Sensing of Environment*, **105:** 9-22.

Brown, J.F., Wardlow, B.D., Tadesse, T., Hayes, M.J. and Reed, B.C. (2008). The Vegetation Drought Response Index (VegDRI): A new integrated approach for monitoring drought stress in vegetation. *GIScience and Remote Sensing*, **45:** 16-46.

Ghulam, A., Qin, Q., Teyip, T. and Li, Z. (2007). Modified perpendicular drought index (MPDI): A real-time drought monitoring method. *ISPRS Journal of Photogrammetry and Remote Sensing*, **62:** 150-164.

Gibbs, W.J. and Mather, J.V. (1967). Rainfall Deciles as Drought Indicators. Bureau of Meteorology. Bulletin No. 48, Commonwealth of Australia, Melborne.

Gupta, S. (2002). Water Policy for Drought Proofing Chhattisgarh: Report. Institute for Human Development, New Delhi.

Hayes, M., Svoboda, M., Le Comte, D., Redmond, K. and Pasteris, P. (2005). Drought monitoring: New tools for the 21st century. *In:* D.A. Wilhite (editor), Drought and Water Crises: Science, Technology and Management Issues. CRC Press, Boca Raton, pp. 53-69.

Hounam, C.E. (editor) (1975). Drought and Agriculture. WMO Technical Bulletin, 392 pp.

Huete, A., Didan, K., Miura, T., Rodreguez, E., Gao, X. and Ferreira, L. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, **83:** 195-213.

Huete, A.R. (1988). A soil adjusted vegetation index (SAVI). *Remote Sensing of Environment*, **25:** 295-309.

Jiang, Z., Huete, A., Chen, J., Chen, Y., Li, J., Yan, G. and Zhang, X. (2006). Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. *Remote Sensing of Environment*, **101:** 366-378.

Jupp, D.L.B., Tian, G., McVicar, T.R., Qin, Y. and Fuqin, L. (1998). Soil Moisture and Drought Monitoring Using Remote Sensing. I: Theoretical Background and Methods. CSIRO Earth Observation Centre, Canberra, Australia.

Kar, A. and Takeuchi, K. (2003). Towards an early warning system for desertification. *In:* Early Warning Systems, UNCCD Ad Hoc Panel, Committee on Science and Technology, UN Convention to Combat Desertification, Bonn, pp. 37-72.

Kidwell, K.B. (1990). Global Vegetation Index User's Guide. NOAA/National Climatic Data Center/Satellite Data Services Division.

Kogan, F.N. (1990). Remote sensing of weather impacts on vegetation in non-homogeneous areas. *International Journal of Remote Sensing*, **11:** 1405-1419.

Kogan, F.N. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in Space Research*, **15(11):** 91-100.

Kogan, F.N. (2002). World droughts in the new millennium from AVHRR-based vegetation health indices. *EOS Transactions of the American Geophysical Union*, **83:** 562-563.

Kulshreshtra, S.M. and Sikka, D.R. (1989). Monsoons and droughts in India: Long-term trend and policy choices. Proceedings of the National Workshop on Drought Management, New Delhi.

Liu, H.Q. and Huete, A. (1995). A feedback based modification of NDVI to minimize canopy background and atmospheric noise. *IEEE Transactions on Geoscience and Remote Sensing*, **38:** 457-463.

Liu, W.T. and Kogan, F.N. (1996). Monitoring regional drought using the Vegetation Condition Index. *International Journal of Remote Sensing*, **17:** 2761-2782.

McKee, T.B., Docsken, N.J. and Kleist, J. (1993). The relationship of drought frequency and duration to time scale. Pre-prints, Eighth Conference on Applied Climatology, Anchel, C.A., pp. 179-184.

Mcvicar, T.R. and Jupp, D.L.B. (1998). The current and potential operational uses of remote sensing to aid decisions on drought exceptional circumstances in Australia: A review. *Agriculture System*, **57:** 399-468.

Moran, M.S., Clarke, T.R., Inoue, Y. and Vidal, A. (1994). Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sensing of Environment*, **49:** 246-263.

Murthy, C.S., Sesha Sai, M.V.R., Bhanuja Kumari, V. and Roy, P.S. (2006). Agricultural drought assessment at disaggregated level using AWiFS/WiFS data of Indian Remote Sensing satellites. *Geocarta International*, **22:** 127-140.

Narain, P. and Kar, A. (editors) (2005). Drought in Western Rajasthan: Impact, Coping Mechanism and Management Strategies. Central Arid Zone Research Institute, Jodhpur, Rajasthan, 104 pp.

Palmer, W.C. (1965). Meteorological Drought. Research Paper No. 45, U.S. Department of Commerce, Weather Bureau, Washington D.C.

Palmer, W.C. (1968). Keeping track of crop moisture conditions, nationwide: The new crop moisture index. *Weatherwise*, **21:** 156-161.

Peters, A.J., Walter-Shea, E.A., Lei, J., Vina, A., Hayes, M. and Svoboda, M.R. (2002). Drought monitoring with NDVI-based standardized vegetation index. *Photogrammetric Engineering and Remote Sensing*, **65:** 71-75.

Pickup, G. and Chewings, V.H. (1988). Forecasting patterns of soil erosion in arid lands from Landsat MSS data. *International Journal of Remote Sensing*, **9:** 69-84.

Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H. and Sorooshian. (1994). A modified soil adjusted vegetation index. *Remote Sensing Environment*, **48:** 119-126.

Ramana Rao, B.V., Sastri, A.S.R.A.S. and Ramakrishna, Y.S. (1981). An integrated scheme of drought classification as applicable to Indian arid region. *Idojaras*, **85:** 317-322.

Rao, A.S. (1997). Impact of droughts on Indian arid ecosystem. *In:* S. Singh and A. Kar (editors), Desertification and Its Control in the Arid Ecosystem of India for Sustainable Development. Agro-Botanical Publishers, Jodhpur, Rajasthan, India, pp. 120-130.

Rao, A.S. and Saxton, K.E. (1995). Analysis of soil water and water stress for pearl millet in an Indian arid region using the SPAW Model. *Journal of Arid Environments*, **29:** 155-167.

Rathore, M.S. (2005). State Level Analysis of Drought Policies and Impacts in Rajasthan, India. Working Paper 93, International Water Management Institute (IWMI), Colombo.

Samra, J.S. (2004). Review and Analysis of Drought Monitoring, Declaration and Management in India. Working Paper 84, International Water Management Institute (IWMI), Colombo.

Sandholt, I., Rasmussen, K. and Andersen, J. (2002). A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. *Remote Sensing of Environment*, **79:** 213-224.

Sastri, A.S.R.A.S, Ramana Rao, B.V., Ramakrishna, Y.S. and Rao, G.G.S.N. (1981). Agricultural droughts and crop production in the Indian arid zone. *Arch. Met. Geoph. and Bioklim.*, **31:** 127-132.

Saxton, K.E. (1989). Users Manual for SPAW: A Soil-Plant-Atmosphere-Water Model. Pullman, Washington, USDA-ARS, 89 pp.

Shafer, B.A. and Dezman, L.E. (1982). Development of a Surface Water Supply Index (SWSI) to assess the severity of drought conditions in snowpack runoff areas. Proceedings of the Western Snow Conference, Colorado State University, Fort Collins, Colorado, pp. 164-175.

Singh, R.P., Roy, S. and Kogan, F. (2003). Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. *International Journal of Remote Sensing*, **24:** 4393-4402.

Smakhtin, V.U. and Hughes, D.A. (2004). Review of Automated Estimation and Analyses of Drought Indices in South Asia. Working Paper 83, International Water Management Institute (IWMI), Colombo.

Tadesse, T., Brown, J. and Hayes, M. (2005). A new approach for predicting drought-related vegetation stress: Integrating satellite, climate, and biophysical data over the U.S. central plains. *ISPRS Journal of Photogrammetry and Remote Sensing*, **59:** 244-253.

Thenkabail, P.S., Gamage, M.S.D.N. and Smakhtin, V.U. (2004). The Use of Remote Sensing Data for Drought Assessment and Monitoring in Southwest Asia. Report 85, International Water Management Institute, Colombo.

Thornthwaite, C.W. and Mather, J.R. (1955). The water balance. *Publications in Climatology*, **VIII(1)**, Drexel Institute of Climatology, Centerton, New Jersey, 104 pp.

Wan, Z., Wang, P. and Li, X. (2004). Using MODIS land surface temperature and normalized difference vegetation index products for monitoring drought in the southern Great Plains, USA. *International Journal of Remote Sensing*, **25:** 61-72.

Wilhite, D.A. (1990). Planning for Drought: A Process for State Government. IDIC Technical Report Series 90-1, International Drought Information Center, University of Nebraska, Lincoln.

Wilhite, D.A. (editor) (2005). Drought and Water Crises: Science, Technology, and Management Issues. CRC Press, Boca Raton.

Wilhite, D.A., Sivakumar, M.V.K. and Wood, D.A. (editors) (2000). Early warning systems for drought preparedness and drought management. Proceedings of an Expert Group Meeting. Lisbon, Portugal, September 5-7, World Meteorological Organization, Geneva.