Chapter 2
Review on Tools and Techniques

This chapter reviews approaches, models, methods and techniques on modeling basin and station level rainfall variability and drought assessment. Initially, it describes factors influencing crop yield and drought and its dependence on other parameters. A literature review of earlier methods and models developed by researchers to analyze the rainfall variability, to define the onset of monsoon and its forecasting and to compute the drought indices for identifying the distribution, extent and severity of drought has been carried out.

2.1 Factors affecting Agriculture yield and drought:

Drought is water shortage condition for plants to extract water from root zone. Its onset and end are often difficult to determine as it is dependant on rainfall conditions as well as moisture availability in soil profile. Rainfall and soil moisture deficiencies results into limited water availability for plant growth which in turn responsible for low crop yield.

Pielke et al (1988) has been of the opinion that crop yield affects the human well being. The major factors affecting crop yield variability are weather and agricultural parameters. Sushila Kaul (2007) in her study on Bio- Economic Modeling of Climate Change on Crop Production in India showed that excessive rains and extreme variation in temperature would affect the productivity of the crops adversely. Cannon et al (1999) in his study on forecasting ISMR used sea level pressure and geo-potential height fields to compare the neural network and
multiple regression models. Parthsarthy et al (1993) used 12 numbers of regional/global circulation parameter to develop a regression model for forecasting ISMR. Sivakumar (1988) stated in his research study that the variable nature of rainfall often led to crop failures and food shortages. Monteith (1991) in his work found that the intra-seasonal rainfall distribution has been prominent over total seasonal rainfall. The amount of water available to plants strongly depends on the monsoon onset and length of the rainy season (Ati et al., 2002) and the crop yield. Stewart (1991) in his research study found that the monsoon onset is the most agriculturally relevant variable. The monsoon onset has been considered the only parameter for determining the planting dates in arid and semi-arid regions, Saria-Dodd and Jolliffe (2001) has found that planting too early leads to crop failure, and planting too late leads to a reduced crop period. Crop failure and reduced crop period, both results into low crop yield. Walter (1967) in his research established relationship between rainfall events and soil moisture availability to avoid crop failure. Therefore, understanding on monsoon onset is important for soil moisture variability and crop yield estimation.

2.2 Literature review and earlier developments

There are several studies related to spatio-temporal variability of rainfall for different parts of India. Mohapatra and Mohanty (2006) have studied the spatio-temporal variability of summer monsoon rainfall over Orissa in relation to low pressure systems and found significant variations. Kawamura, Uemura and Ramaswamy (2005) focused on the recent change of Indian summer monsoon with ENSO relationship and found that the recent weakening of the relationship between ISM and ENSO based on the IMR actually represents a change in dominance of the spatial correlation pattern, from northwest to northeast after the late 1970s. De (2000) worked on ENSO and monsoon over India and effect of temperature and June rainfall on monsoon activity and strength over Gujarat by Dubey (2000). Munot and Kothawale (1999) worked on intra-seasonal, inter-
annual and decadal scale variability in summer monsoon rainfall over India and discovered that summer monsoon rainfall of WC-India and NW-India is dominated by the quasi-biennial oscillation (QBO), whereas summer monsoon rainfall of NE-India and PEN-India is dominated by ENSO-type periodicities. Khandekar (1997) put emphasis on space-time structure of monsoon inter-annual variability and at a same time Sperber, Slingo and Annamalai (1998) studied the relationship between intra-seasonal and inter-annual variability during the Asian summer monsoon. Krishnakumar et al (2000) studied characteristic features and anomalous vertical and horizontal wind shears of the easterly jet stream during the contrasting years of monsoon. Bhadram et al (2000) analyzed variation of monsoon months using rainfall data. Although significant progress has been made on rainfall variability with dependent climatic parameters, but the spatial extent and use of analysis for decision making has been limited. It is necessary to investigate the potential of data collected for Sabarmati basin to support water resources applications. Meteorological drought indicates the deficiency of rainfall compared to average rainfall in a given region. The area in which long-term average rainfall is less, year-to-year variability is greater and so the likelihood of drought is greater. The major impact of drought is felt in semiarid regions where the incidence of drought years is fairly high. Krishnamurthy and Shukla (1999) analyzed inter annual and intra-seasonal variability of the summer monsoon rainfall over India and found that major drought years are characterized by large-scale negative rainfall anomalies covering nearly all of India and persisting for the entire monsoon season. A large number of papers have analyzed inter annual variability of the summer (June-September) mean monsoon rainfall average over India (Parthasarthy and Mooley 1978; Shukla 1987; Parthasarthy et al 1994), stating inter annual standard deviation of the mean seasonal rainfall to be 10% of the long-term mean value. Makridakis, et al, (1978) stated that effective and efficient operations of water resource systems frequently demand the prediction of hydrological sequences like rainfall.
A drought index is typically a single number value used for indicating severity of a drought. Drought Indices are combinations of indicators which are based on meteorological and hydrological data. Hyes (2004) and Wilhite (2005) has given a complete analysis of Drought Indices while Tsakiris et al (2006) give a comprehensive overview. Due to multidisciplinary importance of droughts, several drought indices can be found in the literature (Bates 1935, Palmer 1965 and 1968, Gibbs and Maher 1967, Frere and Popov 1979, Petrasovits 1990, Rao et al 1981, Sastri 1993, Heddinghaus 1991, Tate et al. 2000). Though rainfall is the primary factor that controls the generation and maintenance of drought conditions, evapo-transpiration is also an important variable. However, due to the inherent difficulty in quantifying evapo-transpiration rates, it is always advisable to use a drought index that use rainfall only for its computation. Drought indices like percent of normal (PN), deciles, standardized precipitation index (SPI), effective drought index (EDI), etc. use only rainfall data for their computation. The indices based on only rainfall data are not only simple to compute, it has also been shown that these indices perform better compared to more complex hydrological indices (Oladipio, 1985). Table 2.1 gives the description of various drought Indices used by researchers in which different weather parameters has been used for calculation of drought index.

During the past few decades, several drought indices based on remote sensing data such as Normalized difference vegetation index (Jordan 1969, Tucker 1979), Enhanced vegetation index (Huete et al 2002) Vegetation condition index and Temperature condition index (Kogan 1995 and 1997) etc. have also been developed. In India also there has been studies related to drought using drought indices based on the rainfall data only. These studies were mainly for the monsoon season (June to September) which contributes about 75-90% of the total annual rainfall over most parts of the country. Most of these studies were also based on the PN as the drought index. Using PN as the drought index and using
subdivision wise areas and rainfall data, Banerji and Chabra (1964) considered severe drought conditions in the State of Andhra Pradesh, India to be coincident with seasonal rainfall of less than 50% of normal. Ramdas (1950) considered a drought to arrive when actual rainfall for a week is half of normal or less. Appa Rao (1991) classified the drought-prone areas drought on the basis of summer monsoon rainfall data for the period 1875-1999. Using district rainfall data of 424 districts over India, Guhathakurta (2003) studied the spatial variability of drought in the district scale and probability of drought conditions during 14 all India normal monsoon years 1988-2001. Gore et al (2010) using PN examined the probability of drought incidence in the subdivision scale using rainfall data of 319 districts for the period of 1901-2000. Gore et al (2010) also examined spatial variation of drought probability over India. However, so far there has not been any comprehensive drought study over India in the district level particularly using drought indices other than PN as long time series of district-wise data were not available. Pai et al (2010) studied the district wise drought climatology of the south west summer monsoon season over India based on Standardized Precipitation Index (SPI) and Percent of Normal (PN). A comparison of the drought climatology based on SPI has been made with that of PN which shows that SPI is a better index for monitoring drought conditions over smaller spatial scale like districts, sub divisions.
Modeling of rainfall variability and drought assessment in Sabarmati basin, Gujarat, India

Table 2.1 Description of various drought Indices

<table>
<thead>
<tr>
<th>Name Of Drought Index</th>
<th>Data Required</th>
<th>Time scale</th>
<th>Formula</th>
<th>Main concept</th>
<th>Source, year created</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDI (Effective Drought Index)</td>
<td>$R_f$</td>
<td>d</td>
<td>$Edi = DEP / std.dev of DEP$</td>
<td>A standardized index using effective precipitation (EP) the summed value of daily precipitation with a time-dependent reduction</td>
<td>Byun and Wilhite (1999)</td>
</tr>
<tr>
<td>PDSI (Palmer Drought Severity Index)</td>
<td>$R_f, t, et, sm, rf$</td>
<td>M(2w)</td>
<td></td>
<td>Based on moisture input, output, and storage. Simplified soil moisture budget.</td>
<td>Palmer (1965)</td>
</tr>
<tr>
<td>Deciles</td>
<td>$R_f$</td>
<td>m</td>
<td></td>
<td>Dividing the distribution of occurrences over a long-term record into sections, each represents 10%.</td>
<td>Gibbs and Maher (1967)</td>
</tr>
<tr>
<td>CMI (Crop Moisture Index)</td>
<td>$R_f, t$</td>
<td>w</td>
<td></td>
<td>Like the PDSI, except considering available moisture in top 5 ft of soil profile.</td>
<td>Palmer (1968)</td>
</tr>
<tr>
<td>SPI (Standardized Precipitation Index)</td>
<td>$R_f$</td>
<td>3m, 6m, 12m, 24m, 48m</td>
<td>$\frac{R_{ij} - R_{fm}}{\sigma}$, $R_{ij}$= Seasonal rainfall, $R_{fm}$= Mean rainfall, $\sigma$= Std. Deviation</td>
<td>Standardized anomaly for multiple time-scale after mapping probability of exceedance from a skewed distribution</td>
<td>McKee et al (1993)</td>
</tr>
<tr>
<td>NDVI (Normalized difference vegetation index)</td>
<td>$R_f$</td>
<td>d</td>
<td>$\frac{Ch_2-Ch_1}{Ch_2+Ch_1}$</td>
<td>Reflects the vegetation condition through ratio of responses in near infrared and visible bands of Advanced Very High resolution Radiometer of NOAA</td>
<td>Tucker et al 1987, Justice et al 1989</td>
</tr>
<tr>
<td>VCI (Vegetation condition index)</td>
<td>$R_S$</td>
<td>d, 2w</td>
<td>$VCI = 100 \times (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})$</td>
<td>Separates the short term weather related NDVI fluctuations from the long term eco-system changes.</td>
<td>Kogan 1990, Lozana-Garcia et al 1995, Liu and Kogan, 1996</td>
</tr>
</tbody>
</table>

$R_f$- rainfall, $et$- evapo-transpiration, $t$- temperature, $sm$- soil moisture, $rf$- runoff, $w$- week, $m$- month, $s$- season, $yr$- year, 3m-3 months, $RS$- remote-sensed data
Various methods and models were used by the earlier researcher to predict the rainfall and onset of monsoon in India. All the methods and models used for prediction of rainfall in a particular region require long term weather data for that region. Researchers used weather parameters like rainfall, temperature, wind velocity, sea surface temperature, evapo-transpiration, etc. Soft computing techniques were also used for prediction of rainfall. The Indian Meteorological Department (IMD) makes an official prediction of ISM onset every year using a subjective method. Ananthakrishnan and Soman (1988) derived dates of Monsoon over Kerala (MOK) by using transition from the light to heavy rainfall category with the provision that the average daily rainfall during the first 5 days after the transition should not be less than 10 mm. Li and Yanai (1996) suggested that the reversal of land–sea thermal contrast associated with large temperature increase over the Tibetan Plateau in May–June acts as a climate driver of the ISM onset. Fasullo and Webster (2003) have given another objective method of defining monsoon onset over India using vertically integrated moisture transport instead of rainfall. Goswami et al (2006) proposed an ISM onset index based on reversal of the large-scale meridional temperature gradient in the upper troposphere south of the Tibetan Plateau. In recent studies, strengthening of low-level wind over the low-latitude Indian region has been noticed to be a good indicator of the ISM onset (Taniguchi and Koike 2006). They first emphasized the relationship between the Indian monsoon onset and abrupt strengthening of the low-level wind over the Arabian Sea. Wang et al (2008) proposed an objective circulation Index (OCI) for the Indian summer monsoon over Kerala based on the analysis of NCEP reanalysis data. Laux et al (2009) developed a fuzzy logic-based algorithm for estimating the on set of rainy season (ORS) and the optimal planting date based on daily rainfall data. According to Sivakumar (1988), the variable nature of rainfall is often given as the main reason for frequent crop failures and food shortages, and the intra-seasonal distribution of rainfall is more important than the total seasonal rainfall amounts (e.g. Monteith, 1991). Wheeler et al (2005) showed the simulated effect of evenly and unevenly distributed intra-seasonal rainfall on crop productivity for a station in India, independent of the seasonal rainfall amount.
Several rainfall forecasting methods have been reported in the literature, varying from heat-mass transfer, to singular spectral analysis, fuzzy optimum neural network, machine learning support vector mechanism, first order Markov chain, and integrated time series models. The forecast accuracy of each method found to be variable, depending upon length of data availability and boundary conditions. The selection of an appropriate model for analyzing a particular problem depends on many factors such as number of series to be forecasted, required accuracy of forecasts, ease of use of models, ease of interpretation of forecasts and modeling costs. Therefore, an accurate rainfall forecast may help to alleviate such problems by planning for appropriate cropping patterns corresponding to available water.

Sosa et al (2000) established an ARIMA based model for prediction of rain attenuation in a Mexican tropical area. The authors utilized interactive phenomenological analysis on rain rate, rain drop size and rain distribution for prediction of rainfall amount. Delleur et al (1978) applied ARIMA model for forecasting and generation of cyclically standardized monthly rainfall square roots series. The authors have shown that the forecasting capabilities of seasonal differenced models may be impaired by the fact that they may not take into account the seasonal variation in the seasonal standard deviation. The early attempt by Box and Jenkins (1973) developed a coherent, versatile three-stage iterative cycle for time series identification, estimation, and verification. With the advent of the computer, it popularized the use of autoregressive integrated moving average (ARIMA) models and their extensions in many areas of earth system science. Indeed, forecasting discrete time series processes through univariate ARIMA models, model transfer function, and multivariate ARIMA models has given birth to application forecasting. Zellner (1971) used a Bayesian analysis and derived the predictive distribution of future observations by treating the parameters in the ARMA model as random variables. Kim (2003) considered parameter estimation and forecasting of AR models in small samples and suggested that bootstrap bias-corrected parameter estimators produce more accurate forecasts than the least squares estimator. Landsman and
Damodaran (1989) presented evidence that the James-Stein ARIMA parameter estimator improves forecast accuracy relative to other methods, under an MSE loss criterion. If a time series is known to follow a univariate ARIMA model, forecasts using disaggregated observations are, in terms of MSE, at least as good as forecasts using aggregated observations.

In a comparative study by Newbold et al (1994) on software packages use showed that forecast difference can be quite substantial between models. Authors recommended the use of maximum likelihood and the effect of parameter estimation errors on the probability limits of the forecasts. The problem of incorporating external (prior) information in the univariate ARIMA forecasts has been considered by Cholette (1982), Guerrero (1991), and de Alba (1993). Several software vendors have implemented automated time series forecasting methods such as Geriner and Ord (1991), Tashman and Leach (1991), Tashman (2000) resulting into black box models. Some guidelines on the choice of an automatic forecasting method are provided by Chatfield (1988). Rather than adopting a single AR model for all forecast horizons, Kang (2003) empirically investigated the case of using a multi-step-ahead forecasting AR model selected separately for each horizon. The forecasting performance of the multi-step-ahead procedure depend on optimal order selection criteria, forecast periods, forecast horizons, and the time series to be forecasted.

2.3 Rational for correlating rainfall with drought and crop yield

Drought has major impact in water resources management as it is considered as meteorological conditions depending on rainfall amounts. Drought is related to very scarce rainfall during a longer time span over a relatively large region. Recent interest in global warming has also increased concerns about the possible changes of flood and drought patterns rather than the rainfall amount itself (Frederick and Rosenberg 1994). The inter-annual pattern of the drought and its intra-annual behavior is of great concern. However, it is known to be very difficult or even
impossible to predict their possible changes. Any proper and reliable criterion (or
threshold) of rainfall has not yet been defined.

As the agricultural production is closely dependent on monsoon rainfall and
its variability, it is necessary to understand the past monsoon trends and future
predicted changes in the patterns associated with global change. The studies on
changes in rainfall and air temperature over Northwest India by Pant and Hingane
(1988) showed that there is a marginal increase in the rainfall by 141mm in the past
100 years. The drought of 1979 caused a decline in food grain productions by 17%
(109million tons) as compared to production of 131.4million tons during 1978-79. In
the year 1987, agricultural activities were adversely affected in 43% (58.6 million ha)
of cropped area in 263 districts in 15 states and 6 union Territories. In the state of
Gujarat, the rainfall was less then 50% from normal rainfall in the year 1987. Table 2.1
gives details of area and production of food grains and oil seeds in year 1986-87 and
1987-88.

In the year 1999, deficiency of rainfall in Gujarat was 38% and 9421 villages of
17 districts were affected due to drought. 25million human population and 7million
livestock were affected in the drought. As per the survey carried out by Narain et al
(2000) for the severely drought affected districts of Gujarat shows that 135 (100%)
villages were affected in the district of Banaskantha.

<p>| Table 2.2 Details of area and production of food grains and oil seeds in year 1986-87 and 1987-88 |
|---------------------------------|----------------|----------------|----------------|----------------|----------------|</p>
<table>
<thead>
<tr>
<th>Category</th>
<th>Area sown (m. ha.)</th>
<th>Production (m. tons)</th>
<th>% change</th>
<th>Area sown (m. ha.)</th>
<th>Production (m. tons)</th>
<th>% change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total kharif* food</td>
<td>81.46</td>
<td>74.45</td>
<td>-8.6</td>
<td>80.20</td>
<td>3.89</td>
<td>-7</td>
</tr>
<tr>
<td>Total rabi food grains</td>
<td>45.74</td>
<td>44.26</td>
<td>-3.2</td>
<td>63.22</td>
<td>64.52</td>
<td>+2</td>
</tr>
<tr>
<td>Total food grains</td>
<td>127.20</td>
<td>118.71</td>
<td>-6.7</td>
<td>143.42</td>
<td>138.41</td>
<td>-3</td>
</tr>
<tr>
<td>Kharif oilseeds</td>
<td>11.51</td>
<td>11.47</td>
<td>-0.3</td>
<td>6.38</td>
<td>6.28</td>
<td>-1</td>
</tr>
<tr>
<td>Rabi oilseeds</td>
<td>7.12</td>
<td>8.53</td>
<td>+19.9</td>
<td>.89</td>
<td>6.10</td>
<td>+24</td>
</tr>
<tr>
<td>Total oilseeds</td>
<td>18.63</td>
<td>20.00</td>
<td>+7.4</td>
<td>11.27</td>
<td>12.38</td>
<td>+10</td>
</tr>
</tbody>
</table>
Source: The Drought of 1987-Response and Management, Vol-I, DAC, Ministry of Agriculture, Govt. of India *Kharif - rainy season

2.4 Closure:

This chapter describes the work carried out by the researchers in the field of rainfall variability analysis and assessment of drought conditions using different methodology and models. The literature review of these methods, models and approaches has been used to develop new approach for monsoon onset in the study area, to analyze the rainfall variability at spatial and temporal scale and to define a drought index for the study area.