Chapter-3
Material & Methodology
Chapter 3

Materials and Methods

3.1 Rainfall

Daily rainfall data for 8 year (2000-2006) were obtained from Meteorological department; the data consist of daily rainfall from 30 stations located as shown in Figure. In these stations, rainfall data were collected using manual rain gauge. From daily rainfall, the data were tabulated into monthly data and then analyzed. The rainfall analysis included rainfall difference among 30 stations, variability and frequency of dry months, changing of dry period start and duration, as well as start of rainy season. The data were prepared in Excel program whereas the statistical analysis was done by using excel program. Dry month are classified refer to Oldeman classification who classified agroclimate for agricultural crop based on average number of wet month (P>200 mm/month), and average number of dry months (P<100 m/month).

Figure 3.1 : Location map of Rainguaging stations in Chitrdurga district
3.2 Standardized Precipitation Index (SPI)

Mathematically, SPI is calculated based on equation:

$$SPI = \frac{(X_i - X_m)}{\sigma}$$

Where, $X_i$ is monthly rainfall record of the station; $X_m$ is rainfall mean; and $\sigma$ is the standard deviation. Monthly rainfall data from 2000 to 2006 in 30 rain gauge stations are used as an input. The Standardized Precipitation Index (SPI) is a tool developed by McKee et al., (1993) with the main purpose to defining and monitoring drought. Compared with PDSI (Palmer drought severity index), SPI is a more simple tool because it just based on rainfall data and less calculation effort. Basically the SPI is the number of standard deviations that the monthly rainfall data would deviate from the long-term mean. Firstly, a transformation is applied to make rainfall data follow a normal distribution (McKee et al., 1993). Hayes et al. (1999) used the SPI to monitor the 1996 drought in the United States of America. SPI usefully can detect the start of the drought, its spatial extension and temporal progression and also show that the onset of the drought. The SPI can be computed for different time scales, can provide early warning of drought and help assess drought severity, and is less complex than the Palmer index.

<table>
<thead>
<tr>
<th>SPI Values</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.0 and more</td>
<td>extremely wet</td>
</tr>
<tr>
<td>1.5 to 1.99</td>
<td>very wet</td>
</tr>
<tr>
<td>1.0 to 1.49</td>
<td>moderately wet</td>
</tr>
<tr>
<td>-.99 to .99</td>
<td>near normal</td>
</tr>
<tr>
<td>-1.0 to -1.49</td>
<td>moderately dry</td>
</tr>
<tr>
<td>-1.5 to -1.99</td>
<td>severely dry</td>
</tr>
<tr>
<td>-2 and less</td>
<td>extremely dry</td>
</tr>
</tbody>
</table>

SPI was formulated to calculate rainfall deficit in multiple time scales. The time scale shows drought impact caused by different water sources. Drought caused by soil moisture deficit was a respond of rainfall shortage in
relatively short time scale, while groundwater, streamflow, and reservoir storage reflect longer rainfall anomalies. For several purposes, McKee design SPI for 3, 6, 12, 24, and 48-month time scales and then classified the drought class as shown in Table. 3.1. The droughts occur if SPI reaches -1.0 values or less. Every drought event can be calculated for the duration, intensity, and magnitude (NDMC, 2007).

There was a study focused on three analyses: relationship between NDVI and SPI at different time scales, response of NDVI to SPI during different time periods within a growing season, and regional characteristics of the NDVI SPI relationship. The result shows that the 3-month SPI time scale has the highest correlation to the NDVI, because the 3-month SPI is the best way for determining drought severity and duration (Ji and Peters, 2003).

3.3 Satellite Data

Remote sensing techniques plays a crucial tool for timely decision making processes especially in natural hazard monitoring.

Landsat ETM+ data was used to prepare the landuse landcover maps for Chitradurga district.

The moderate resolution imaging spectroradiometer (MODIS), NASA’s Earth observing system (EOS) Terra satellite provides a comprehensive series of observations of the Earth’s land, ocean, and atmosphere. NASA’s EOS Aqua system, a sister satellite to Terra, has already been launched, and it has an early afternoon observation time, crossing the equator at approximately 1:30 PM MODIS is a key instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites. Terra’s orbit around earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon (Conboy, 2004). At higher temperatures, radiation fluxes are much greater and more representative of surface conditions, therefore it is expected that the afternoon observations allows a significant improvement in drought monitoring. A wide spectral range (36 discrete
spectral bands ranging from 0.4μm to 14.4μm) and spatial coverage and it take measurements in spectral regions that have been used in past and current satellite sensors.

Time series MODIS products are obtained from EOS data gateway for the period of June to January from 2000 to December 2007. This time series represents all season data. All this data is 8 days composite basis and the naming of processed intermediate image has been done.

3.3.1 MODIS product characterization

MODIS/Terra Surface Reflectance 8-Day L3 Global 250m SIN Grid V004 (MOD09Q1)

The surface reflectance product is the input for product generation for several of the land products: Vegetation Indices (VIs), BRDF, Thermal Anomalies, Land cover, Snow/Ice Cover, and LAI/Fpar. It is an estimate of the surface spectral reflectance for each band as it would have been measured at ground level if there were no atmospheric scattering or absorption. This product is a composite using eight consecutive daily 250 m images. The “best” observation during each eight day period, for every cell in the image, is retained. This helps reduce or eliminate clouds from a scene. The file contains the same spectral information as the daily file listed above, centered at 645 nm and 858 nm. There is one additional band of data for quality control. It has three layers and the layer 1 and 2 has been used for NDVI computation. The surface reflectance (MOD09Q1) and NDVI derived from surface reflectance image shown was retrieved from MODIS data from January 2000 over the entire Chitradurga district. It is an example of the MODIS Level 3 surface reflectance product at 250m resolution.
3.4 Normalized Difference Vegetation Index (NDVI)

NDVI was first suggested by Tucker in 1979 as an index of vegetation health and density.

\[
\text{NDVI} = \frac{\lambda_{\text{NIR}} - \lambda_{\text{RED}}}{\lambda_{\text{NIR}} + \lambda_{\text{RED}}}
\]

where, \( \lambda_{\text{NIR}} \) and \( \lambda_{\text{RED}} \) are the reflectance in the NIR and red bands, respectively. NDVI reflects vegetation vigor, percent green cover, Leaf Area Index (LAI) and biomass. The NDVI is the most commonly used vegetation index (Jensen, 2005). It varies in a range of -1 to +1. However, NDVI

- uses only two bands and is not very sensitive to influences of soil background reflectance at low vegetation cover, and
- has a lagged response to drought 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. The lag time is dependent on whether the region is purely rainfed, fully irrigated, or partially irrigated. 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 (DEVNDVI). This deviation is calculated as the difference between the NDVI for the current time step (e.g., January 2007) and a long-term mean NDVI for that month (e.g., an 8-year long mean NDVI of all Januaries from 2000 to 2007) for each pixel:

\[
\text{DEVNDVI} = \text{NDVI}_{i} - \text{NDVI}_{\text{mean, m}}
\]

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 2000 to 2007, there are 21 monthly NDVI values for the same month, e.g., 8 Julys’), and 8 long-term NDVI means (one for each calendar month).
When DEVNDVI is negative, it indicates the below-normal vegetation condition/health and, therefore, suggests a prevailing drought situation. Greater the negative departure the greater the magnitude of a drought is. 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. 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 (Thenkabail et al., 2004).

3.5 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 (Thenkabail et al. 2004; Vogt et al. 1998).

\[ VCI_j = \frac{(NDVI_j - NDVI_{\text{min}})}{(NDVI_{\text{max}} - NDVI_{\text{min}})} \times 100 \]

where, \( NDVI_{\text{max}} \) and \( NDVI_{\text{min}} \) are calculated from the long-term record (e.g., 8 years) for that month (or week) and \( j \) is the index of the current month (week). NDVI values are calculated using equation 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 abovenormal conditions. At the VCI value of 100%, the NDVI value for this month (or week) is equal to \( NDVI_{\text{max}} \). 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.
(Thenkabail et al., 2004). VCI has been used by (Kogan and Unganani) for estimation of corn yield in South Africa; drought detection in Argentina (Sullivan et al. 1998); drought monitoring over India (Singh et al. 2002); monitoring droughts in the southern Great Plains, USA (Wan et al. 2004); drought detection and monitoring in the Mediterranean region (Vogt et al. 2000) and drought assessment and monitoring in Southwest Asia (Thenkabail et al. 2004). These studies suggest that VCI captures rainfall dynamics better than the NDVI particularly in geographically non-homogeneous areas. Also, VCI values

### 3.6 Drought Indices derived from Remote Sensing data

Utility of remote sensing data especially satellite data in drought assessment has long been proven and needs no reiteration. It is far superior to conventional methods at an optimal spatial extent. Remote Sensing technology in its current state of art can help in predicting, mitigating and monitoring of drought. Data from various satellites can be utilized for the purpose of drought assessment, whether it is agricultural, meteorological or hydrological. It enables to understand the manifestations of drought in a larger area more directly than through conventional methods, and of all, in less time consuming manner. Drought monitoring is successfully carried out world over using indices derived from optical remote sensing data. The physics of remote sensing techniques that enables us to observe drought is related to the factors that affect the electromagnetic spectrum at its various wavelengths. The sensors installed in the earth-observation satellites are able to quantify the capacity which the vegetation cover present in the earth’s surface possesses for initiating the process of photosynthesis. When drought strikes, due to notable reduction of the rainfall, the capacity to carry out the chlorophyllian function on the part of the vegetation is notably reduced. This occurrence is demonstrated by the spectral response which the affected vegetation covers provide. The chlorophyllous pigments produce two maximum absorption radiation zones in the green plants, one is the blue region of the spectrum (0.43 micrometers) and
another in the red region (0.66 micrometers). On the other hand, the mesophyll of the leaves – provided with irregularly shaped cells which constitute a surface with large inter-cellular spaces – is very reflective of the radiation incident in the neighbouring infrared (0.75 – 1.1 micrometers). Thus, the response of the green vegetation (in a good physiological and healthy state) is characterized by a substantial absorption in the red region and a large reflection in the infrared region near the electromagnetic spectrum. It has also been observed that the vegetation which is unhealthy, ageing or subject to conditions of stress (such as could be case with vegetation affected by drought), increases its reflectance in the red region of the spectrum while it decreases in the nearby infrared (Alonso et al., 1995) Remote sensing data based indices used for this research work are as follows.

3.7 NDVI - Rainfall relationship as indicator of drought

Several studies have been devoted towards drought with the aid of satellite-derived information. Reflectance in the visible, near-infrared and thermal bands were combined into Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Normalised Difference Vegetation Index (NDVI), which considerably improved early drought detection, watch and monitoring of drought’s impacts on agriculture. Using NOAA Advanced Very High Resolution Radiometer (AVHRR) data, researchers have successfully extended satellite data analysis to large-area vegetation monitoring (Kogan, 1990) and biomass productivity estimates (Townshend and Justice, 1986). Since vegetation indices derived from the AVHRR sensor are directly related to plant vigour, density, and growth conditions, they may also be used to detect unfavourable environmental variables. The relationship between NDVI and rainfall is known to vary spatially, notably due to the effects of variation in properties such as vegetation type and soil background (Li et al., 2002; Nicholson & Farrar, 1994), with the sensitivity of NDVI values to fluctuations in rainfall, therefore, varying regionally. Vegetation amount and
condition are a function of environmental variables such as rainfall. Consequently, a strong relationship, involving a brief time-lag in the vegetation response to rainfall, would be expected between vegetation indices, such as the NDVI [(infrared reflectance (IR)-red reflectance (R))/(IR + R)] and rainfall (Li et al., 2002). Many studies have focused on the relationship between the NDVI and rainfall. A study regarding the modelling of drought risk areas by using remotely sensed was carried out by C. Mongkolsa Wat (et al.) in Northeast Thailand, where drought has the most profound effect on the lives and regional economy. In this paper the severity of drought was considered to be a function of rainfall, hydrology and physical aspect of landscape. Three different types of droughts i.e. meteorological, hydrological and physical drought were analysed after which an overlay matrix operation was performed that yielded the areas which faced drought risk wherein drought risk was classified into four classes. The result obtained was satisfactory confirming that the model developed in this study could help in the mapping of drought risk area in the Northeast Thailand. Another study related to early detection of drought in East Asia was done by Song et al. (2004) NDVI from NOAA/AVHRR had been used wherein standard NDVI and up-to-date NDVI were calculated to derive difference NDVI image, to detect the intensity and agricultural area damaged by drought. The difference images were used to create drought risk maps. The study was successful in detecting and monitoring drought effects on agriculture. Results indicated that the most vulnerable areas to agricultural drought were non-irrigated cropland and rangeland located in areas with a very high probability of seasonal crop moisture deficiency.

Drought risk areas were calculated as a weighted linear combination of a set of input factors such as topography, soil drainage, ground water resource, irrigation area, annual evaporation, average annual rainfall and frequency of rainfall days. The relationship between NDVI change and drought risk level was calculated from the average NDVI change collected by masking each drought risk area. The study concluded that NDVI can be used as a main
indicator to evaluate drought. However the limitation of the study was that it was unable to consider change in species, type, age and characteristic of the vegetation.

3.8 Software Used

The following Image Processing and GIS packages have been used to perform the data processing and analysis.

ERDAS 9.2,
Arc GIS 9.0,
Arc View and
Microsoft Excel for Processing of the data

3.9 Methods
3.9.1 Methodology

The methodology developed for this study is shown below in figure. Each block represents the Sub-processing step to reach up to the final output.
Satellite

NOAA-AVHRR

NDVI temporal

Anomaly = (NDVI - NDVI_mean, m) / (NDVI_mean, m * 100)

Meteorological

Monthly rainfall

SPI: Rainfall Anomaly

Agriculture Statistics

Deviation from Trend

Ancillary

Meteorological Drought

Agro-climatic Statistics

DROUGHT RISK

Figure 3.2.: Flow chart showing the methodology of the study.