Chapter: IV

4. Data Used and Methodology

The study is broadly emphasising the use of the space borne sensor network along with the available in-situ (ground based) data to have a holistic approach. The data used in the study to design the SDSS has been classified in two broad categories: 1. space based data 2. Ground based in situ data. The SDSS requires the spatial information of the cultivation/vegetation to understand the significant water available for the crop growth. The NDVI is used as the surrogate of the agriculture progression in the region. The Land Surface Temperature (LST) is used as to understand the temperature interaction with the surface; the soil moisture plays an important role in the growth cycle and it varies with the type of soil to slope in the area, with its dynamic in nature. The rainfall is widely distributed but the unavailability of the rain sensor at the desired location is the limitation over and above this the satellite image is having the advantage to give complete distribution information of the region.

Figure 4.1 illustrates the categorised dataset which has been used in the study to identify the drought classes and supporting dataset over the study area. The present study uses the ten years (2002-2016) Sixteen-day composite NDVI product (MOD13A1), daily rainfall (CHIRPS V2.0), MODIS 8-day LST, and Sixteen day NDWI product; these data were acquired for entire year from various websites. In-situ dataset from IMD has been used for validation and generation of climatology. A brief account of the various satellite products are given below.

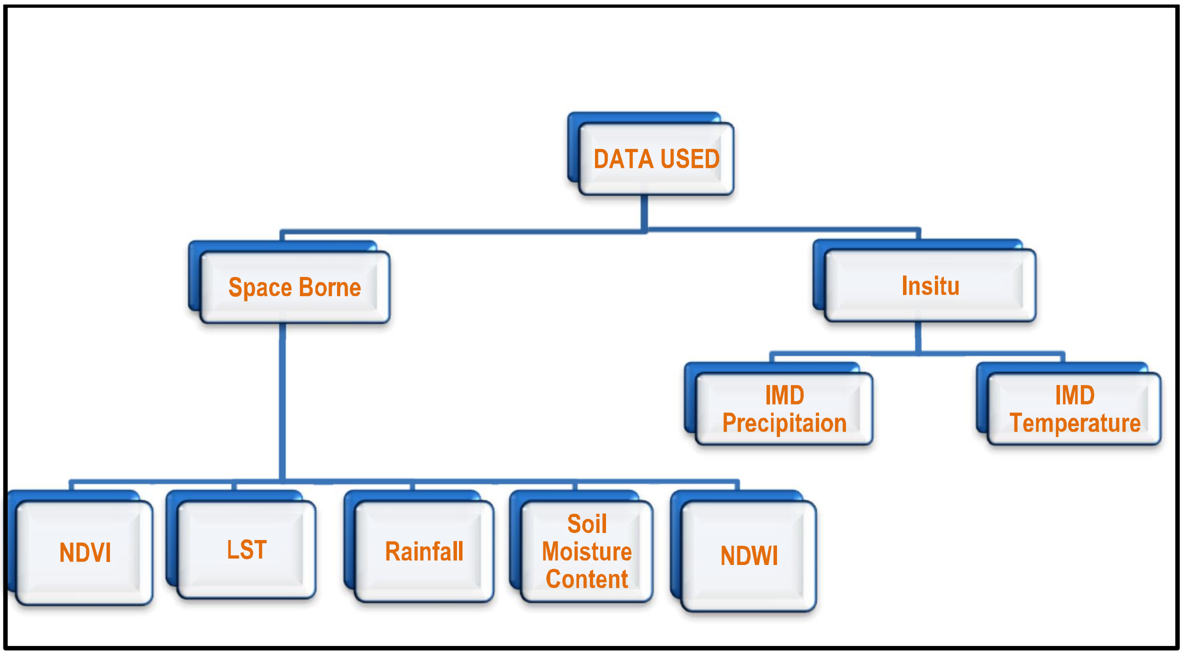

Figure 4.1: Data Used in the Study

4.1 Satellite Data

Table 4.1 represents detailed information about the satellite data used in the study, the spatial resolution of data, platform or sensor name, product or parameter name and sources from where data has been acquired. Satellite dataset has been used to generate various indices where some of the indices were directly used for ISDI computation and some of the indices are used as associated drought indicators.

Table 4.1: Satellite dataset and sources

SN.	Platform / Sensor	Product Name / Parameter	Spatial Resolution	Description (Source)
1.	MODIS	NDVI	0.5 km	Global MOD13A1 product at 16 days temporal resolution. (http://ladsweb.nascom.nasa.gov)
2.	MODIS	LST	1 km	MOD11A2 Product at every 8-days temporal resolution. (http://ladsweb.nascom.nasa.gov)
3.	CHIRPS	Precipitation / Rainfall	5 km	CHIRPS version 2 at daily temporal scale. (ftp://ftp.chg.ucsb.edu/pub/org/chg/products/

				CHIRPS-2.0/global_daily/tifs/p05/)
4.	GCOM AMSR-2	Soil Moisture Content	10 km	Daily Ascending and descending pass. (http://gcom-w1.jaxa.jp/)

4.1.1 MODIS NDVI

Worldwide MODIS vegetation indices are intended to give predictable spatial and temporal examinations of vegetation conditions. Red and NIR reflectance, cantered at 0.645 µm and 0.858 µm respectively, are used to determine the MODIS 16-day NDVI. The MODIS NDVI provides continuity for time series historical applications. Global MOD13A1 data are provided every 16 days at 500-meter spatial resolution as a gridded level-3 product.MOD13A1 product is downloaded from NASA web portal *(http://ladsweb.nascom.nasa.gov)*. The average values of NDVI of all pixels falling within administrative boundaries were calculated further processing and analysis.

4.1.2 MODIS NDWI

The NDWI is a remote sensing based indicator sensitive to the change in the water content of leaves (Gao, 1996). NDWI is computed using the near infrared (Ranges,) and the MIR band from MODIS (Bandwidth: 2105-2155 nm) Band center: 2130 nm. The NDWI product is dimensionless and varies between -1 to +1, depending on the leaf water content but also on the vegetation type and cover. High values of NDWI correspond to high vegetation water content and to high vegetation fraction cover. Low NDWI values correspond to low vegetation water content and low vegetation fraction cover.

4.1.3 CHIRPS Precipitation

Climate Hazards Group InfraRed Precipitation with Station information (CHIRPS) is a 30+ year semi worldwide precipitation dataset. Crossing 50°S-50°N (and all longitudes), beginning from 1981 to approach present, CHIRPS incorporates 0.05° resolution satellite data with in-situ station information to make gridded precipitation time series for pattern investigation and seasonal drought analysis. As of February 12th, 2015, version 2.0 of CHIRPS is complete and available to the public.

The National Aeronautics and Space Administration (NASA), and the National Oceanic and Atmospheric Administration (NOAA), have been developing techniques for producing rainfall maps, especially where surface data is sparse. Estimating rainfall variations in space and time is an important aspect of drought early warning and environmental monitoring. An evolving dryer-than-normal season must be placed in historical context so that the severity of rainfall deficits may be quickly evaluated. However, estimates derived from satellite data provide averages that suffer from biases due to complex terrain which often underestimate the intensity of extreme precipitations events. Conversely, precipitation grids produced from station data suffer in more rural regions where there are less rain gauge stations. CHIRPS was created in collaboration with scientists at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre in order to deliver reliable, up to date, and more complete datasets for a number of early warning objectives (such as trend analysis and seasonal drought monitoring).

Early research focused on combining models of terrain-induced precipitation enhancement with interpolated station data. More recently, new resources of satellite observations such as gridded satellite-based precipitation estimates from NASA and NOAA have been leveraged to build high resolution (0.05°) gridded precipitation climatology. When applied to satellite-based precipitation fields, these improved climatology can remove systematic bias, a key technique in the production of the 1981 to near-present CHIRPS dataset. The creation of CHIRPS has supported drought monitoring efforts by the USAID Famine Early Warning Systems Network (FEWS NET).

4.1.4 GCOM AMSR-2 Soil Moisture Content (SMC)

Surface soil moisture is an important state variable in land surface hydrology and a key link between the land and the atmosphere. It is an important parameter for many weather forecasting and prediction models. Changes in soil moisture have a severe impact on agricultural productivity, forestry and ecosystem health. So, regular measurements of soil moisture are essential for effective water resources management, drought forecast and management and understanding ecological processes etc. AMSR-2, SMC product at 0.1X0.1 degree has been used for moisture content analysis. SMC is also used to calculate weekly deviation from previous year and from previous 3-years average, so that we can identify favourable/non-favourable conditions for crop showing. AMSR-2 SMC product can be accessed from NASA web portal *(http://gcom-w1.jaxa.jp/)*. In the present study Soil Moisture Content dataset has been used as ancillary information which helps in decision forming and analysis.

4.1.5 MODIS Land Surface Temperature (LST):

Land surface temperature (LST) is temperature of the skin surface of land, which can be derived from satellite information or direct measurements. Satellite data provide consistent, continuous, and spatially distributed information on the Earth's surface conditions. The moderate resolution imaging spectro-radiometer instruments installed on the Aqua and Terra Earth observation satellites from NASA, have provided MOD11A2 Product *(http://ladsweb.nascom.nasa.gov)*, which contains daytime and night time LST in 1 km spatial resolution (Wan, K., & Liang, S. 2009; Patel et. al. 2017). LST Data pre-processed and analyzed from the year 2002 to 2016. In the present study LST data is used for temperature variation analysis over the study area.

4.2 In-Situ Data

4.2.1 Rainfall Data from IMD

IMD New High Spatial Resolution (0.25X0.25 degree) Long Period (1901-2013) Daily Gridded Rainfall Data Set over India This data product is a very high spatial resolution daily gridded rainfall data (0.25 x 0.25 degree). The unit of rainfall is in millimeter (mm). Data is for 115 years, 1901 to 2015.Data is arranged in 135x129 grid points. The first data in the record is at 6.5N & 66.5E, the second is at 6.5N & 66.75E, and so on. The last data record corresponds to 66.5N & 100.0E (Pai et al. 2014). Though the data is very useful for the country level analysis of climatology and the spatial resolution is not suited for the small study area. So that this dataset will be used for the validation and supporting dataset as well.

4.2.2 Temperature Data from IMD

IMD High resolution 1-degree By 1-degree gridded daily temperature data (1969-2009) was archived from National Climatic Centre (NCC-IMD, Pune). This data is arranged in 32x35 grid points. Lat 6.5N, 7.5N ... 36.5, 37.5 (32 Values) Long 66.5E, 67.5E ... 99.5, 100.5 (35 Values) Maximum Temperature, Minimum Temperature and Mean Temperature gridded data are in the directories viz. Maximum Temperature ,Minimum Temperature and Mean Temperature. Each directory contains 41 binary data files, and 41 American Standard Code for Information Interchange (ASCII - text) data files one each for 41 years (1969-2009).

The data file is named as MAXT1969.grd; MAXT1969.txt etc. 366 days file for non-leap year and for leap years, 366 days are included. The unit of temperature is in Celsius (Srivastava et al. 2008)

4.3 Methodology

The study has adopted two approaches, first is to identify the drought and its calibration owing to the Agricultural and meteorological variability and second is to develop the SDSS based drought characterization with respect to the different agriculture and meteorological parameters for cropping season. Finally, the effect of drought on the reduced crop yield in the study area was evaluated through the development and calculation of an Integrated Spatial Drought Index (ISDI). Figure 4.2 represents the conceptual flow diagram of parameters and derived indices from given parameters.

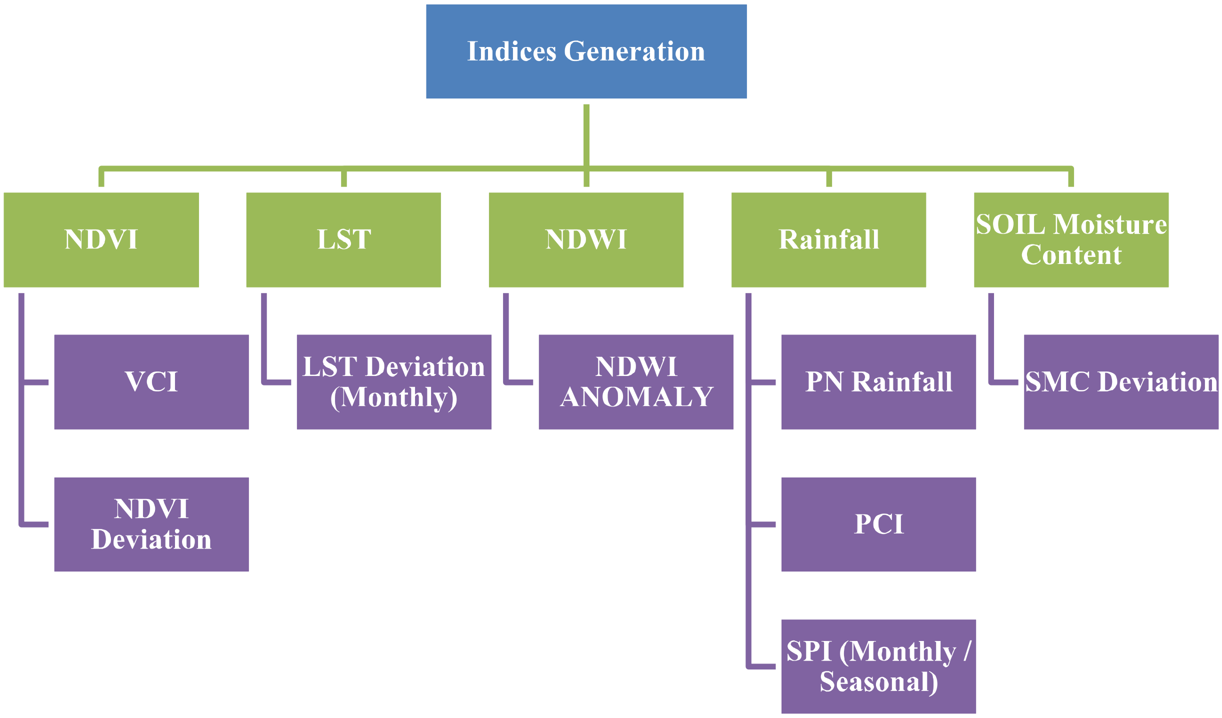

Figure 4.2: Flow Diagram of Indices Generation

4.3.1 Development NDVI based Drought Indicators

Global MODIS vegetation indices are designed to provide consistent spatial and temporal comparisons of vegetation conditions. Red and NIR reflectance, centered at 0.645μm and 0.858μm respectively, are used to determine the MODIS daily NDVI. The MODIS NDVI provides continuity for time series historical applications.

Global MOD13A1 data are provided every 16 days at 500-meter spatial resolution as a gridded level-3 product.MOD13A1 product is downloaded from NASA web portal *(http://ladsweb.nascom.nasa.gov)*. this is enough to gather the synoptic vegetation growth NDVI based drought characterization is categorised in two different methods one is deviation from historical data set (Present year's deviation from previous five years) and another method is based on the linearly scaling NDVI from Zero, minimum NDVI, to maximum NDVI for each pixel and for each acquisition date, the VCI is defined by given equation 4.1 illustrated below.

4.1.1.1. Vegetation condition Index (VCI) computation

Vegetation Condition Index is developed by Kogan (1990), which determines the departure of current NDVI from the minimum NDVI with respect to long-term NDVI. It measures the health of vegetation with respect to the given time frame.

$$VCI = \left(\frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right) \times 100 \ldots eq(4.1)$$

Whereas; $NDVI_i$, is the NDVI for the specific date under the study time.

$NDVI_{max}$ and $NDVI_{min}$ = the maximum and minimum NDVIs, respectively, in the record for the specific month/date;

$NDVI_{max}$ and $NDVI_{min}$ represent maximum and minimum NDVI of each pixel calculated for each sixteen days. VCI value is being measured in percentage ranging from 1 to 100. The range between 50% and 100% indicates above normal condition of vegetation whereas the values ranging from 50% to 35% indicate the drought condition and below 35% indicates severe drought condition (Kogan, 1995) described in table 4.2. This index is normalizes NDVI index and separates the long-term ecological signal from the short-term climate signal and in this sense it proves to be a better indicator for monitoring water stress condition as compared to NDVI (Kogan and Sullivan, 1993). The resulted images of Vegetation Condition Index (VCI) were classified on the basis of VCI values. VCI Analysis has been carried out for every 16-days interval images and seasonal VCI to get overall seasonal vegetation condition. The scope of VCI is from 0 to 100, comparing to changes from very negative to ideal vegetation or healthy vegetation condition. VCI has been applied for monitoring drought and vegetation phenology changes in several studies. (Singh et.al., 2003; Tran et.al, 2017, Kogan et.al., 1997)

Table 4.2: VCI Ranges and Class Values

SN.	VCI Ranges	Class
1	-999	No Data Values
2	0-35	Severe Drought
3	>35 & <50	Drought
4	>50 & <75	Normal
5	>= 75	Healthy Vegetation (No Drought)

4.1.1.2. NDVI Deviation from Short term average (Last Five Years)

Module has been developed for visualization and analysis of NDVI deviation from short term average (from previous five-year average). The NDVI deviation reflect the comparative vegetative condition from previous year and it ranges from -1.0 to 1.0, where -1.0 or less than -1.0 represents extreme negative stress on vegetation, that represents extreme vegetative drought condition illustrated in . Whereas -0.05 to 0.05 represents normal vegetative condition and positive values from 0.5 to 1.0 or greater than 1.0 indicates healthy vegetative condition towards increasing index as compare to short term average. Equation 4.2 is used for NDVI deviation from short term average (STA) calculation. Figure 4.3 illustrates how NDVI deviation equation implemented in python program for automation purpose. Table 4.3 represents NDVI deviation ranges and class distribution.

$$NDVI_{dev} = NDVI_i - \left(\frac{\sum_{j=1}^{5} NDVI_{\frac{month}{day}}}{n} \right) \ldots eq(4.2)$$

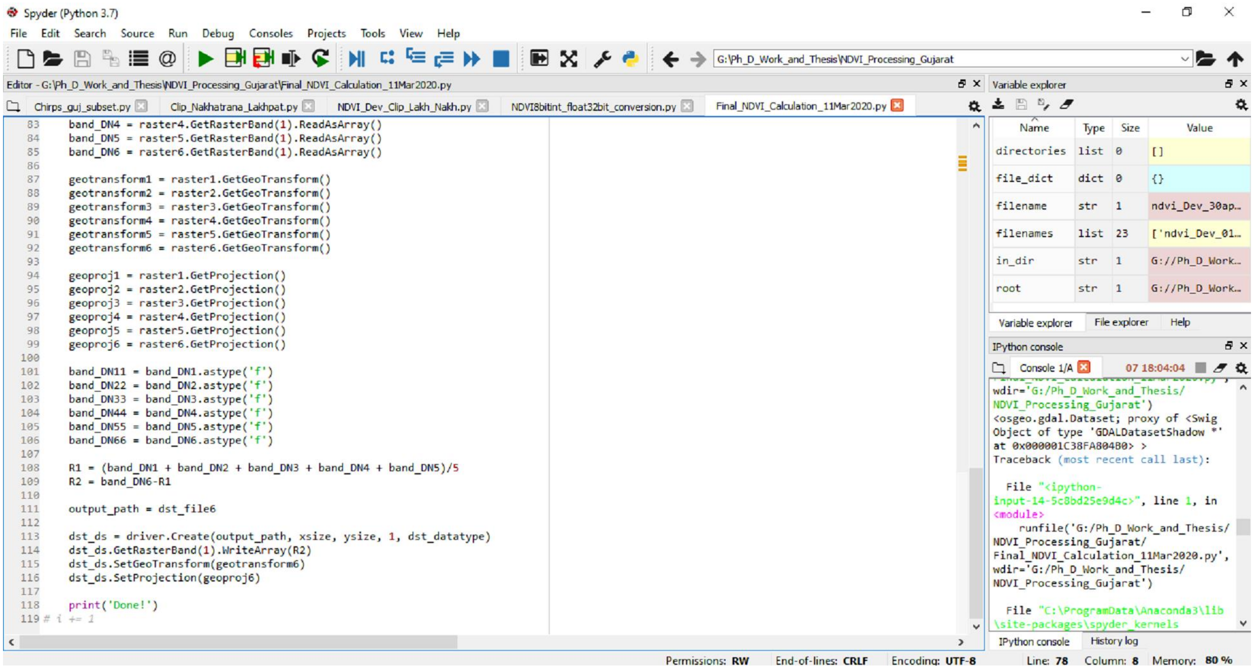

Figure 4.3: Python program to calculate NDVI deviation from previous five years

Table 4.3: NDVI Deviation Ranges and Classes

SN.	NDVI Deviation Ranges	Class
1.	-999	No Data Values
2.	-1	Extreme Negative
3.	-0.75	Severe Negative
4.	-0.5	Moderate Negative
5.	-0.25	Negative with Normal
6.	0	No Change
7.	0.25	Positive With Normal
8.	0.50	Healthy
9.	>75	Extreme Healthy

4.3.2 NDWI Anomaly computation

The NDWI is a remote sensing based indicator sensitive to the change in the water content of leaves (Gao, 1996). NDWI is computed using the near infrared (Ranges,) and the MIR band from MODIS (Bandwidth: 2105-2155 nm) Band center: 2130 nm as mentioned in equation 4.3.

$$Normalised\ Difference\ Water\ Index\ (NDWI) = \frac{(NIR - MIR)}{(NIR + MIR)} \dots eq\ (4.3)$$

NDVI and NDWI anomalies are presented in the form of maps and graphs, providing information both on the spatial distribution of the vegetation water stress and its temporal evolution over longer time periods. This allows for the qualitative and quantitative comparison of the intensity and duration of the NDWI anomalies with recorded impacts.

Anomaly estimation:

NDWI anomalies are produced for every 16-day period as computed using equation 4.4:

$$NDWI\ Anomaly = \frac{(X_i - \bar{X})}{\delta} \dots eq(4.4)$$

Where, X_i is the NDWI of the 16-day period t of the current year and, $\bar{X}$ is the long-term average (2002-2011) NDWI and δ is the standard deviation for the 10 years, both calculated for the same 16-day period i using the available time series. NDWI anomalies are calculated for the given 16-day period from the base period 2002-2011. Table 4.4 represents NDWI Anomalies ranges and Classes.

Table 4.4: NDWI Anomaly ranges and classes

SN.	NDWI Anomalies Ranges	Class
1	<-2	Severe Drought
2	-2 to -1	Moderate Drought
3	-1 to 0	Near Normal
4	0 to 1	Normal Condition
5	1 to 2	Good
6	>2	Extremely Good

4.3.3 Rainfall based Drought Indices computation:

Meteorological drought is the earliest and the most precise event in the process of occurrence and progression of drought condition. Low rainfall is the primary driver of the meteorological drought. In the process of meteorological drought analysis three traditional approaches namely standerdised Precipitation Index (SPI), Percent of Normal (PN) and Precipitation Condition Index (PCI) have been calculated in the study. Precipitation based computation of these three indices methodology has been presented in the section below and the same results has been incorporated in the Spatial Decision Support System for Drought Management (SDSS-DM).

4.1.1.3. Computation of Standardized Precipitation Index (SPI):

Estimating rainfall variations in space and time is a key aspect of drought early warning and environmental monitoring. An evolving dryer-than-normal season must be placed in a historical context so that the severity of rainfall deficits can be quickly evaluated. In the present study, rainfall dataset from Climate Hazards Group Infra Red Precipitation (CHIRPS V2) have been used for the SPI calculation, because of its finest resolution at 0.05 degree global dataset at daily temporal resolution. CHIRPS was created in collaboration with scientists at the USGS Earth Resources Observation and Science (EROS) Center in order to deliver complete, reliable, up-to-date data sets for a number of early warning objectives, like trend analysis and seasonal drought monitoring.

Long term mean has been calculated using dataset from 1981 to 2010 rainfall, and standard deviation of rainfall has been calculated using the equation 4.5 given below.

$$SD = \sqrt{\frac{\sum[X_i - \bar{X}]^2}{N-1}} \dots eq\ (4.5)$$

Where,
X_i= Actual Rainfall (month/ Season)
$\bar{X}$= 30 Years mean rainfall for given month or season.
N=Sample / Population size

Standardized Precipitation Index (SPI) has been computed using the methodology developed by (McKee et al., 1993). It is the most widely used meteorological drought index. Data were computed using the long-term daily precipitation data from 1981 to 2010. Widely used drought index SPI, was calculated for 6 analysis years (2011-2016) of months Jun, July, August, September for each analysis years using equation 4.6 given below. Model for SPI calculation is illustrated in figure 4.4.

$$SPI = \left(\frac{Pi-P}{SD}\right) \dots eq\ (4.6)$$

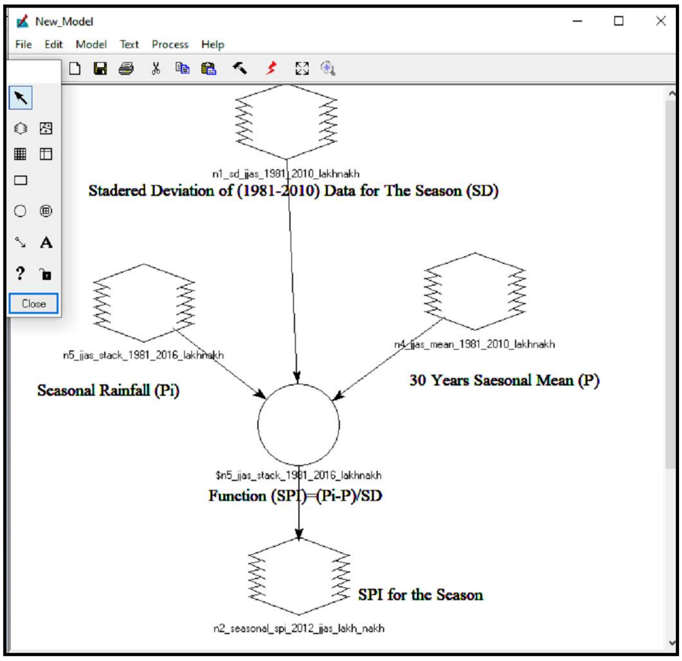

Figure 4.4: Model for SPI calculation

Where Pi is the actual precipitation in the current month or season, P is the mean precipitation for the given month or season (1981-2010), SD is standard deviation of monthly/seasonal precipitation.

4.1.1.4. Percent of Normal (PN) Rainfall Computation:

Precipitation Analyses utilizing Percent of Normal (PN) are viable when utilized for a specific area or a single season. It is determined by partitioning real precipitation by mean precipitation (30-year's Mean) (Patel et al., 2015; Bushair et. al., 2015). PN is computed using equation 4.7.

$$PN = \left(\frac{P_i}{P}\right) * 100 \ldots eq\ (4.7)$$

Where P_i is the actual precipitation in the current month or season for the ith location and P is the mean precipitation.

4.1.1.5. Computation of Precipitation Condition Index (PCI):

Rainfall and other precipitation phenomena are the most crucial factors involved in the drought's outbreak (Palmer 1965; Agnew 2000). Lack of moisture in air and soil are the main factors that lead to long-term drought in the end. PCI is calculated in the same manner as

VCI, but instead of NDVI, values of monthly/seasonal precipitation are used. In this study, CHIRPS V2 precipitation data from 1981–2016 is used for PCI computation. For the PCI computation minimum and maximum precipitation values are computed from 1981 to 2010 dataset and analysis were carried out for the year 2011, 2012, 2013, 2014, 2015 and 2016. Equation 4.8 illustrates the computation formula and process for PCI. Figure 4.5 describes the logical implementation of PCI equation in model.

$$Precipition\ Condition\ Index\ (PCI) = \left(\frac{Pr_i - Pr_{min}}{Pr_{max} - Pr_{min}}\right) * 100 \dots (4.8)$$

Where Pr is the actual precipitation in the current month or season for the i^{th} location and Pr_{min} is the minimum precipitation and Pr_{max} is the maximum precipitation of the given period from climatology.

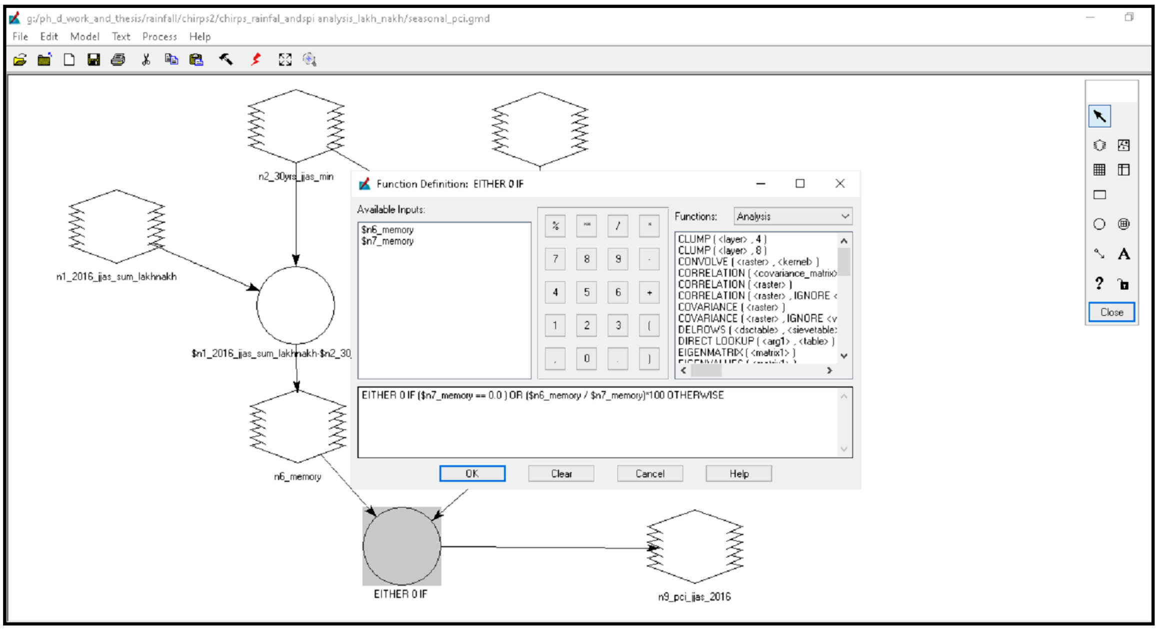

Figure 4.5: Model for PCI calculation

4.3.4 Computation of Soil Moisture Content (SMC) Deviation from Previous Year:

Soil Moisture Content provides a volumetric moistures content as measure of the wetness of the soil near the surface of the earth. Unit of the SMC product is percent "%". AMSR-2 SMC product downloaded from NASA web portal *(http://gcom-w1.jaxa.jp/)* and pre-processed for weekly data preparation. Scale factor of 0.1 multiplied to the DN vales to get the actual soil moisture in percent. Equation 4.9 has been applied for the calculation of deviation from previous year.

$$SMC_{Dev} = SMC_{ij} - SMC_{pj} \ldots eq(4.9)$$

Where SMC_{Dev} is deviation of SMC from previous year, SMC_{ij} represent present year SMC for the given week j, and SMC_{pj} represent previous year SMC for the same week J. This Weekly SMC and its deviation for study area have been integrated into the SDSS-DM for visualization and support parameter.

4.3.5 Land Surface Temperature (LST) Data Processing:

Land Surface Temperature (LST) is temperature of the skin surface of the land, which can be derived from satellite information or direct measurements. Satellite data provide consistent, continuous and spatially distributed information on the earth's surface conditions (Patel et.al. 2015). One of the key parameters in the physics of land surface processes at the local and global scales, the land surface temperature (LST) derived from satellite observations has been used singly or in combination with NDVI to monitor drought (Kogan, 1995; Karnieli et al., 2010). In the study LST has been used as physical parameter to support the vegetation condition analysis.

To retain the temperature values in the real range, all of the annual stacked images were converted using equation 4.10 which converts digital numbers to LST in Kelvin. Methodology to extract LST values from MOD11A2 product, Equation 1 has been used, to convert digital numbers into LST in degree Kelvin, where digital numbers or pixel values multiplied by the scale factor 0.02.

$$Land\ Surface\ Temperature\ (LST) = DN * 0.02 \ldots eq(4.10)$$

4.3.6 Development of Integrated Spatial Drought Index:

Drought intensity values that were computed by various VIs and meteorological condition indices were used to compare with the historical drought events and impacts on agriculture at study area. The number of drought months is the number of months that VIs identifies them as drought (mild, moderate, severe, and extreme drought). Maximum duration is the maximum number of consecutive months showing all kinds of droughts. Based on these attributes, each VI is compared and verified as to whether they reflected the impacts of drought years in the study area. The overall seasonal characterization has been made based on the combinations of PCI and VCI.

The Integrated Spatial Drought Index (ISDI) is computed based on Vegetation condition Index and hydro-meteorological variable. The deficit of drought is represented by NDVI and rainfall deficits, which are considered here as basic inputs to ISDI. The core inputs are satellite based NDVI and rainfall. ISDI is computed using equation 4.11 to identify the drought areas and years over study area. Figure 4.6 illustrates complete methodological flow chart for computation of ISDI. Methodological flow chart describes from data archival to preprocessing, intermediated result generation and finally ISDI derived Drought map generation.

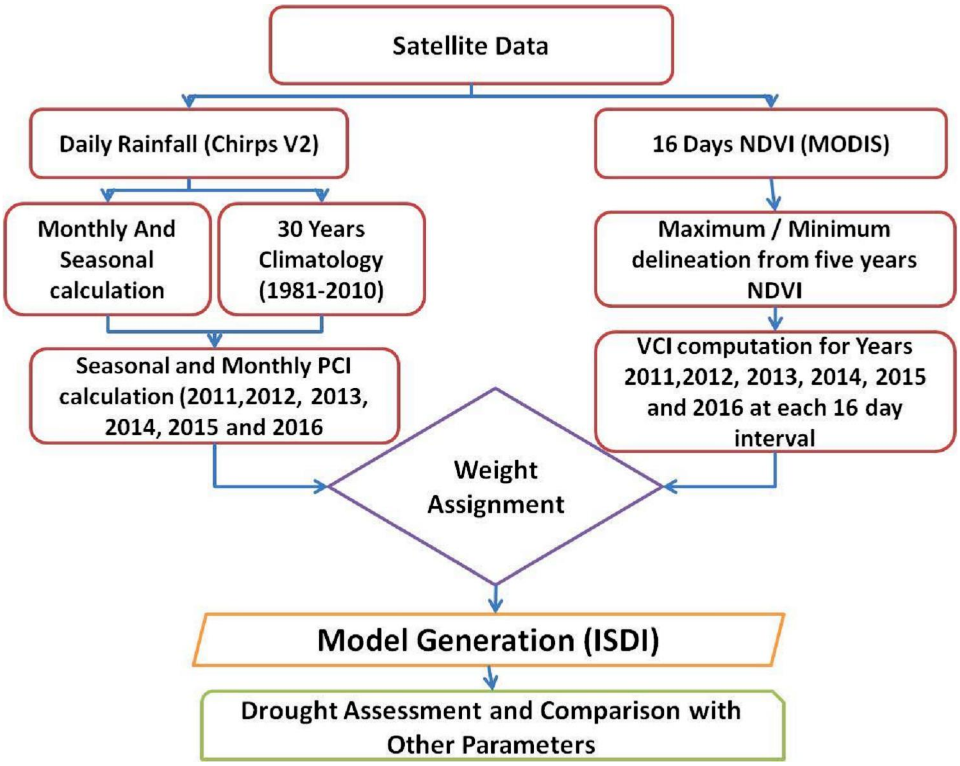

Figure 4.6: Methodological flowchart of ISDI computation

$$Integrated\ Spatial\ Drought\ Index\ (ISDI) = \left[(VCI * a) + \left(PCI * (1 - a)\right)\right] \ldots eq\ (4.11)$$

In equation 4.11, ‘a’ is the weight assigned to VCI at the end of the monsoon season before crop harvesting and (1 - a) is the weight assigned to PCI which is generated from CHIRPS V2 dataset for the monsoon season. In the present study, a simple ranking method (Drobne and Lisec, 2009) was used for assigning weights to the respective parameters. Sensitivity of weights on the stability and performance of ISDI was tested. Here in ISDI, weight for the VCI is 0.6 assigned and weight for the PCI is 0.4 has been assigned. The previous studies indicated that NDVI stress depends on rainfall thus making it effective to differentiate between drought and normal conditions (Bajgiran et al., 2009).

Rainfall deficiency primarily leads to soil moisture stress, which is resulted, into NDVI deviation from long term as well as from previous years. Here, June to September, rainfall derived PCI and end of the October month NDVI derived VCI were used for computing ISDI. Therefore, ISDI is used to quantify and categorise drought over study area. Figure 4.7 illustrates about model for ISDI calculation and Table 4.5 describes about the drought classes based on the ISDI and respective values ranges.

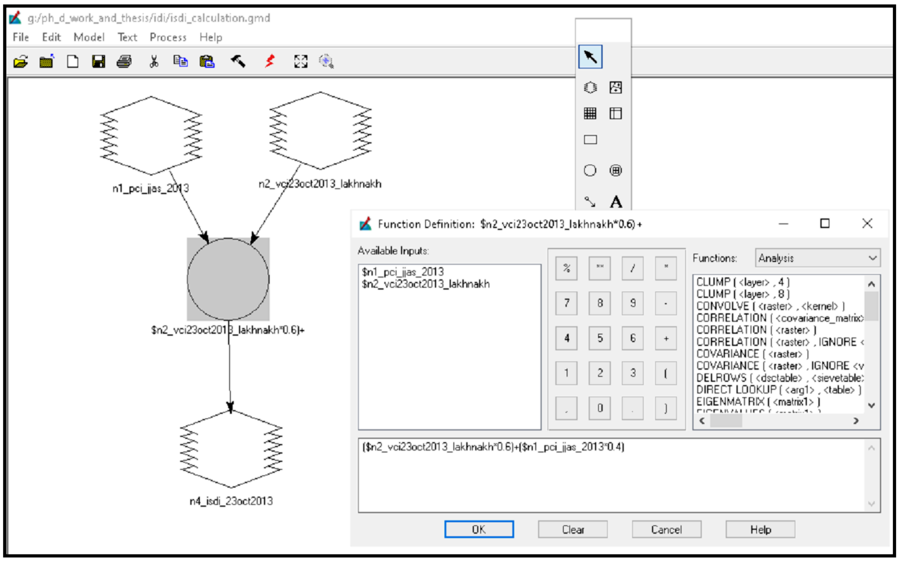

Figure 4.7: Model for ISDI computation

The Integrated Spatial Drought model is based on the agro-meteorological conditions in terms of water demand and supply situation over the study area. The favourable situation leads to spectral emergence of crops with certain lag-response period. The seasonal agricultural drought assessment was performed using the various parameters as described above and ISDI. Based on the ISDI score drought classes has been categorised as illustrated in table 4.5, where ISDI score greater than 75 considered as Normal condition over the study area. ISDI values range from 51 to 75 indicates a mild drought and range from 26 to 50 indicates moderate drought condition. Whereas, ISDI range below 26 indicates very severe drought condition over the study area.

Table 4.5: ISDI ranges and classes

SN.	ISDI Classes	Drought Condition
1	0-25	Severe
2	26-50	Moderate
3	51-75	Mild
4	>75	Normal