Drought Severity Analysis Using RS & GIS: A Case Study of Arid Zone of Tharparkar

By

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Dedicated to my beloved family and parents.

ACKNOWLEDGEMENTS

All praise be to ALLAH the Almighty the Exalted, the Lord of all the worlds and gratitude to the last Prophet MUHAMMAD (ﷺ).

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Sami Ullah Shah

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
MODIS	Moderate-Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
SPI	Standardized Precipitation Index
SPEI	Standardized Precipitation and Evapotranspiration Index
TRMM	Tropical Rainfall Measuring Mission
PMD	Pakistan Meteorological Department

ABSTRACT

Tharparkar is an arid region in south eastern province of Sind, Pakistan and experienced drought as a regular phenomenon in the past. Fragile agro-ecosystem of Tharparkar is highly depended upon monsoon rain. Seasonal variability in monsoon can inflict heavy human and livestock loss. There was a need to characterize drought severity across Tharparkar to provide early warning of drought for provincial government to undertake appropriate measures with onset of drought. Complex nature of drought and sparsely located network of met stations handicapped reliable spatial and temporal analysis of drought severity across Tharparkar. Freely available Tropical Rainfall Measuring Mission (TRMM) rainfall satellite data and moderate-resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI) satellite data fulfilled this gap and were used to generate drought indices. This study developed a new drought index called *"standardized normalized vegetation index (NDVI) anomaly"* and compared with traditional indices i.e. standardized precipitation index (SPI), standardized precipitation and evapotranspiration index (SPEI) for modeling drought severity condition in the arid and fragile agro-ecosystem of Tharparkar. The standardized NDVI anomaly data significantly correlated with meteorological drought indices (SPI, SPEI) and revealed vegetation dynamics under rainfall and temperature variations. The weighted overlay analysis in geographical information systems (GIS) depicted accurate onset of 2014 drought across Tharparkar. This study provided useful information for drought characterization with newly developed drought index that can be used for drought monitoring and early warning system in the data scarce arid and semiarid regions.

Chapter 1

INTRODUCTION

There is no single definition of drought (Wilhite and Glantz, 1985). Drought is a natural calamity that develops after abnormally low or no rainfall for some time period (Mckee et al., 1993). It's a slowly occurring natural hazard, affected by the relative prevailing conditions that leaves negative impacts and affect many sectors including agriculture. Drought gives warning before its occurrence, initial indication usually quite a few months prior to the disaster, is the point where the population will be affected, environmental effects of it remain there for a longer time period due to which shortage of water in soil particularly soil moisture and resultantly water table decreases that has impacts on economic, social and environmental aspects (Patel and Chopra, 2007).

Droughts occur at slow rate but are one of the natural disasters which inflict heavy economic, agricultural losses and environmental degradation. Droughts are difficult to quantify as they occur at a slow pace, slowly creeping in and hence pose problems with the quantification of their onset, end and spatial extent (Vicente-Serrano, 2010). Drought has been translated into various perspectives by different users because of the complex relationship between human factors and a particular drought event. The useable water sources related with drought get affected by the droughts at different time scales. Reservoir storage, ground water, soil moisture and stream flow are some of the useable resources of water where deficit occur due to drought at certain time period length. Therefore, the time scale at which water deficit occur in a particular water source forms an important characteristic of drought and functionally separates different types of droughts (Mckee et al., 1993). For example meteorological and agricultural droughts effect soil moisture and hence are quantified at shorter time scales. Common Types of Droughts are: Meteorological, Hydrological, Socioeconomic, and Agricultural Drought. These drought types differ from one another in duration, intensity and spatial coverage depending upon the length of time period for which the drought prevails (WMO, 2012).

1.1 Role of Remote Sensing Data in Drought Analysis

Numerous objective indices have been developed world wide for quantitation and monitoring of droughts using various data primarily meteorological and vegetation data. However, this data is not generally available for far flung arid regions in developing countries. Non availability of reliable data constrains the institutional ability of governments to quantify spatial and temporal extents of drought severity and hence leaves them clueless with regards to the management of drought events. Remote sensing of meteorological and vegetation data can fill this gap with remotely sensed meteorological and vegetation data at variety of spatial and temporal scales (Perez et al, 2012). Yadvanshi et al, 2015 used satellite remote sensing data for drought monitoring over tropical region in India. Li et al, 2014 used remote sensing derived vegetation index to assess agricultural drought in semi- arid region of China. Dutta et al, 2015 used remote sensing derived index to assess agricultural drought across Rajhastan.

1.2 Rainfall in Drought Indices

Though numerous objective indices have been developed world wide for quantitation and monitoring of droughts using various parameters. However, versatility in definition of drought made it difficult to develop a unique and universal drought index which could integrate all the critical data required to assess drought and give realistic information about drought severity (Heim, 2002). To characterize drought with a single index is not sufficient. Identifying rainfall as the single most important factor responsible for initiating drought conditions, World Meteorological Organization (WMO) recommended Standardized

Precipitation Index (SPI) to be used by all national meteorological and hydrological services for monitoring droughts at various time scales (WMO, 2012).

1.3 Limitations of SPI

Though, various studies have shown variation of SPI in response to soil moisture, river discharge, reservoir storage, vegetation activity, crop production and piezometric fluctuations at different time scales (Vicente-Serrano, 2006, Patel et al, 2007, Khan et al, 2008, Shaheen et al, 2011, Karabulut, 2015). However, one of the drawbacks in SPI is that it does not take into account variation of other climatological parameters such as temperature, wind speed and evapotranspiration. Abramopoulos et al. 1988 and Vicente-Serrano, 2006 reported that temperature rise can significantly affect drought severity and evapotranspiration can consume up to 80% of rainfall.

1.4 Role of Temperature in Drought Severity and SPEI

During the past 150 years, there has been a general temperature increase (0.5−2°C), and climate change models predict a significant increase during the 21st century (Lemke et al, 2007). It is estimated that this temperature rise will have drastic consequences for drought severity conditions, with increase in water demand due to evapotranspiration. Vicente-Serrano et al, 2010 suggested the use of SPEI based on monthly rainfall and air temperature data to analyze variability of temperature along with rainfall for detecting, monitoring and exploring consequences of temperature variability on vegetation and drought conditions (Vicente-Serrano et al, 2010). SPEI is also a multi-scalar drought index and incorporates changes in potential evapotranspiration (PET) caused by temperature fluctuations.

1.5 Development of Standardized NDVI Anomaly

Remotely sensed NDVI forms a robust index, extracted from directly observed vegetation satellite data, for monitoring wet as well as drought conditions. Though NDVI and NDVI anomalies have been extensively used for drought assessment and vegetation change dynamics along with meteorological drought indices (Sheffield et al, 2008; Wang et al, 2009; Murthy et al, 2009; Quiring et al, 2010; Zhao et al, 2011; LadĂĄnyi et al, 2011and Fang et al, 2014). However, NDVI anomalies do not allow easier and meaningful profile comparison with SPI and SPEI. This is due to the fact that both SPI and SPEI are standardized and generate a value around zero after incorporating the effect of long term data as against NDVI or NDVI anomalies. This study developed a new and simple index by standardizing NDVI anomalies like SPI and SPEI. The newly developed Standardized NDVI Anomaly allowed meaningful profile comparison with meteorological drought indices (SPI, SPEI) and furnished critical insight into variability of vegetation data in response to variations in rainfall and temperature across arid region of Tharparkar.

1.6 Importance of Drought Severity Mapping Through Weighted Overlay Analysis in GIS

Drought indices give separate picture of drought severity across study area based on input data of drought indices. Information from all variables is needed on one layer to generate a composite picture of drought hazard across study area. Weighted overlay analysis in GIS provides a method to generate composite response of drought hazard and gives clear picture of drought severity by emphasizing common information from all drought indices brought on equal scale. Shaheen et al., 2011 used weighted overlay analysis to generate composite drought hazard maps at meteorological and agricultural scale in arid region of Thal Doab, Pakistan. Shahid et al., 2008 generated composite drought hazard maps for Bangladesh using different drought monitoring indices. This study used drought severity layers of SPI, SPEI and newly developed standardized NDVI anomaly to generate composite drought hazard maps at meteorological and agricultural scale through weighted overlay analysis in GIS.

1.7 Rationale

Drought has become a frequent phenomenon in the Pakistan especially, in Sindh due to an increase in pollution and climatic changes. There was no study available on Tharparker which could characterize relationship between the amount of rainfall and vegetation and may prove helpful for decision makers to take appropriate measures for disaster mitigation prior to onset of drought conditions. Fragile agro-ecosystem of Tharparkar is highly depended upon monsoon rain. Seasonal variability in monsoon can inflict heavy human and livestock loss. There was a need to characterize drought severity across Tharparkar to provide early warning of drought for provincial government to undertake appropriate measures with onset of drought.

1.8 Objectives

The objective of this study is to perform spatial-temporal analysis of vegetation dynamics and drought severity across arid region of Tharparkar using remote sensing derived indices. The study included analysis of vegetation dynamics, analysis of meteorological and agricultural droughts, development of new drought index i.e., Standardized NDVI Anomaly and modeling of drought severity across Tharparkar using SPI, SPEI and standardized NDVI anomalies through weighted overlay analysis in GIS. The results of this study presented an effective model for drought severity analysis across data scarce arid regions to aid in drought preparedness and response.

Chapter 2

MATERIAL AND METHODS

2.1. Study Area

Tharparkar is a desert region and classified as arid climate in the south eastern part of Sindh province, Pakistan (Figure. 1.1). The Study area lies between 69°*E* and 29°*N* to 71°*E* and 24°*N*. Tharparkar has tropical climate with min temperatures during winters in Dec and Jan (4 – 6°C) while max temperature ranges from 38°C to 41°C during summers. Rain fed agriculture and livestock remains the only source of livelihood for Thari people. Both of these sources of income depend directly or indirectly on monsoon rainfall in monsoon season from June to October (Herani et al, 2007). The main crops of Tharparkar are cluster beans, millet, pulses, and fodder. Soil of Tharparkar is infertile and sandy in nature with severe wind erosion. The vegetation consist mostly scrub and bush. The ground cover is provided by patches of grasses used as a fodder for the livestock. With underground water mostly brackish, dug wells and scattered rainwater ponds remain only source of drinking water at limited spots.

It is bounded in the east by Indian province of Rajasthan, in the south west by District Badin, in the North West by District Mirpur Khas, in the north by District Sanghar, and by Runn of Kutchh in the south. Study area consists of five sub regions i.e., Chachro, Diplo, Mithi, Nagarparkar and Umar kot as shown in figure 1, with total area of 27,135 km^2 with a population of about 1.5 million. Tharparkar being remote area of Sindh province remains disadvantaged with low Indicators of education, health with recurring droughts making life more difficult.

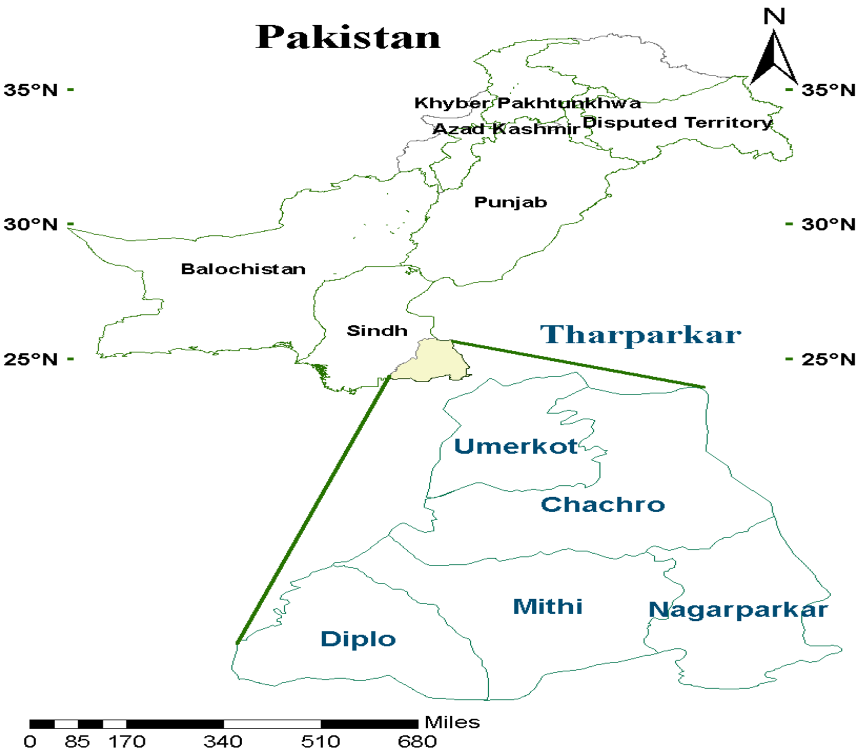

Figure 1.1 Study area.

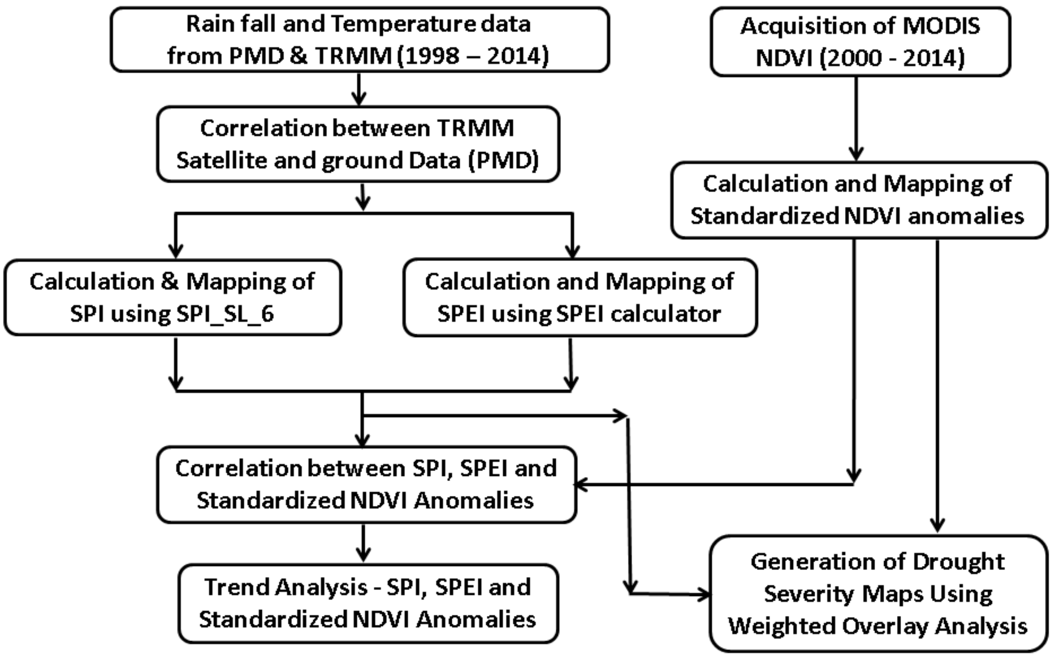

Figure 1.2 Research methodology.

Tharparkar consists of homogeneous topography with barren tracts of sand dunes. The sand dunes are irregular and generally form closed valleys where natural vegetation grow if left uncultivated after rainfall in monsoon season. The ground relief in Tharparkar varies from 170 m in the north east area of Chachro to about 5 m in the south west south east area of Diplo. The only hills are in Nagarparkar, on the Northern edge of the Runn of Kutchh. This is a small area quite different from the desert. The main hill range is Karoonjhar which is 19 km in length and attains a height of 305 m.

2.2. Research Approach

Research approach adopted for study has been highlighted in Fig. 3. Grid points were generated across study area to extract TRMM 3B43 monthly rainfall data at these points.

Grid points were generated with a view to have equal spacing among the grid points; however, grid points were added and adjusted to account for the spatial variation of precipitation across the study area as shown in Fig. 1.3. Monthly rainfall amounts at these grid points were extracted from the TRMM 3B43 data sets while the monthly mean air temperatures were extracted from interpolated observed monthly mean air temperature data from two met observatories i.e., Chor and Badin from 1998 to 2014.

To achieve spatial and temporal variability of rainfall across study area, TRMM 3B43 multi satellite precipitation analysis products were used to extract monthly precipitation data from 1998 to 2014. TRMM precipitation is a combination of datasets from Visible and Infrared Scanner, Special Sensor Microwave Imager, Microwave Imager, PR (Precipitation Radar) and Global Precipitation Climatology Center (GPCC) rain gauge data available at 0.25° x 0.25° spatial resolution. TRMM 3B43 algorithm, combines 3-hourly integrated high-quality data, infrared (IR) estimates (3B42) with the monthly accumulated Climate Assessment Monitoring System. The data was downloaded from http://disc.sci.gsfc.nasa.gov.

Estimated TRMM 3B43 monthly rainfall data was initially correlated with observed monthly precipitation data at Chor and Badin to check feasibility for using TRMM 3B43 data sets across study area. Estimated TRMM 3B43 rainfall data obtained a very strong correlation of r = 0 .975** (p≤ 0.01) with observed precipitation data (Figure 2). TRMM slightly overestimated monthly rainfall in monsoon season, especially during the months which received higher rainfall amount.

Global MODIS vegetation indices provide continuous temporal and spatial information about vegetation conditions. The MODIS 1 km MOD13A3 VI NDVI images were used to calculate one – monthly, three – monthly and six – monthly standardized NDVI anomalies. The monthly 1-km MOD13A3 VI product is generated using the 16-day 1-km MODIS VI output using a temporal compositing algorithm based on a weighted average scheme to create a calendar-month composite. MODIS images were downloaded from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table.

2.3 Data

2.3.1 Observed Rainfall and Air Temperature Data

Processed monthly rainfall and temperature data (Max, Min) was acquired from Pakistan Meteorological Department (PMD) at two met observatories i.e., Chor and Badin as shown in figure 2. However, the monthly rainfall data acquired from PMD could not provide spatial variability of precipitation over study area which was necessary to map and analyze the spatial and temporal variability of drought over the study area. The air temperature having strong relation with topography of the area varies with lapse rate of -0.98 °C for dry air to about -0.4 °C for saturated dry air with each 100 m rise in altitude (Dodson and Marks, 1997).

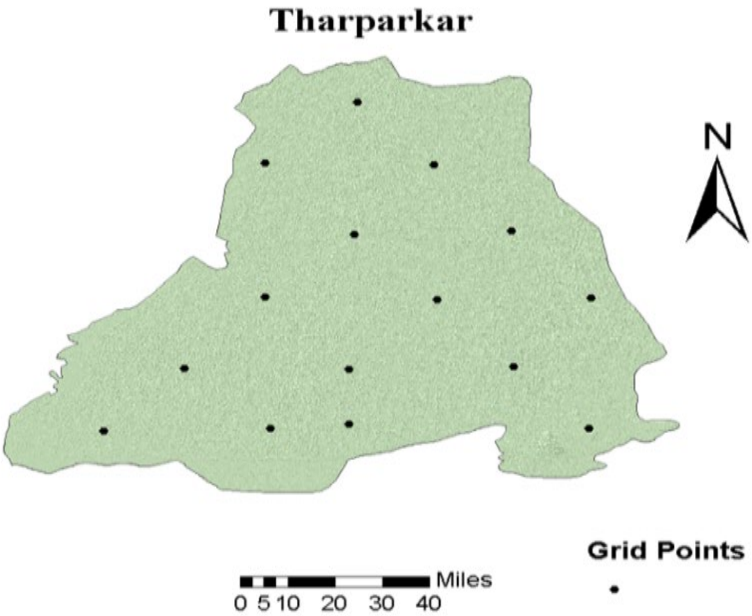

Figure 1.3 Grid points generated for data extraction from Tropical Rainfall Measuring Mission (TRMM) satellite data and interpolated air temperature data (Pakistan Meteorological Department)

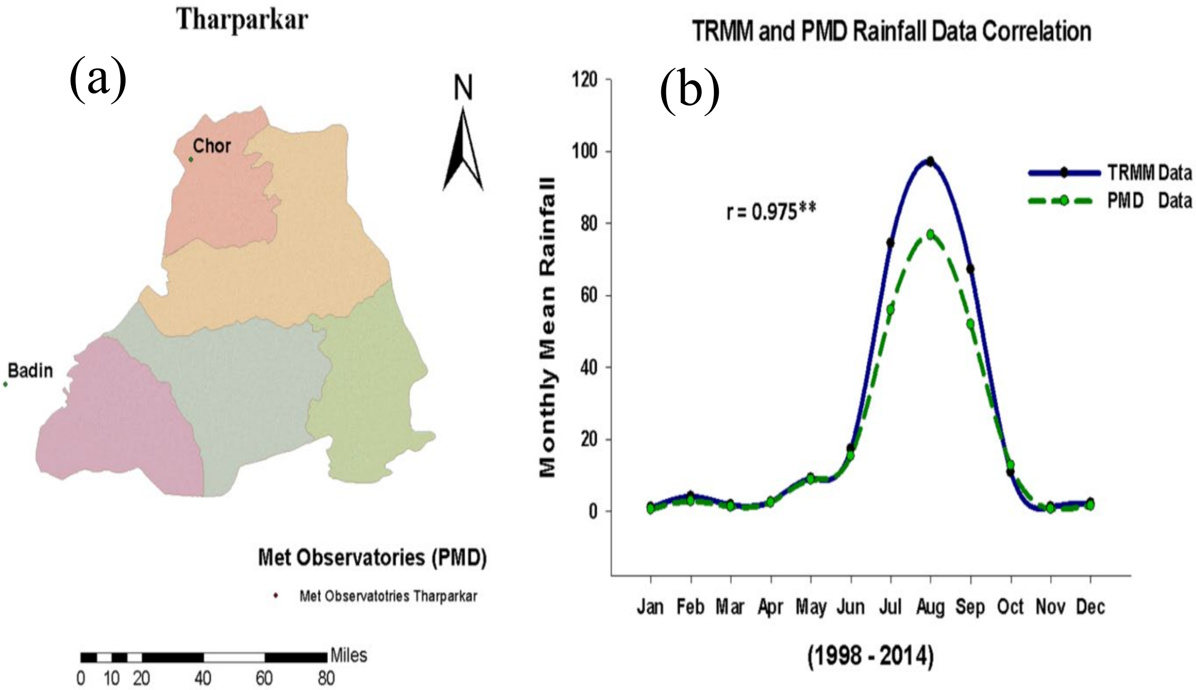

Figure 1.4 (a) showing location of met observatories at and near Tharparkar (b) showing significant correlation between TRMM and Pakistan Meteorological Department (PMD) monthly rainfall data at Chor and Badin.

Tharparkar has homogeneous topography with altitude variation of only 170 m across the entire area except in southern part of Nagarparkar where in the small hills range (19 km), altitude varies to 305m. The Inverse Distance Weighted (IDW) method works well with air temperature interpolation in homogeneous and relatively flat terrain (Dodson and Marks, 1997). Thus the observed air temperature at Chor and Badin was interpolated using IDW to achieve spatial variation of temperature across the study area.

2.3.2 TRMM 3B43 Monthly Rainfall Dataset

In this study, to achieve spatial and temporal variability of rainfall across study area, TRMM 3B43 multi satellite precipitation analysis products were used to extract the monthly precipitation data for the period from 1998 to 2014. TRMM precipitation is a combination of datasets from Visible and Infrared Scanner, Special Sensor Microwave Imager, Microwave Imager, PR (Precipitation Radar) and Global Precipitation Climatology Center (GPCC) rain gauge data available at 0.25° x 0.25° spatial resolution. TRMM 3B43 algorithm, combines 3-hourly integrated high-quality data, infrared (IR) estimates (3B42) with the monthly accumulated Climate Assessment Monitoring System (Huffman et al., 2007). The data was downloaded from http://disc.sci.gsfc.nasa.gov. Estimated TRMM 3B43 monthly rainfall data was first correlated with the observed monthly precipitation data at Chor and Badin to check feasibility for using TRMM 3B43 data sets across the study area. Estimated TRMM 3B43 rainfall data obtained a very strong correlation of r = 0 .975** with the observed precipitation data as shown in figure 2. The TRMM overestimates the monthly rainfall in monsoon season especially during the months which receive high rainfall amount. However, the consistency of utilizing the same data sets for the study gives relative temporal estimates and hence is not critical.

2.3.3 MOD13A3 1km Monthly NDVI Dataset

Global MODIS vegetation indices provide continuous temporal and spatial information about vegetation conditions (Lunetta et al., 2006). The MODIS 1 km MOD13A3 VI NDVI images were used to calculate 1 – monthly, 3 – monthly and 6 – monthly standardized NDVI anomalies. The monthly 1-km MOD13A3 VI product is generated using the 16-day 1-km MODIS VI output using a temporal compositing algorithm based on a weighted average scheme to create a calendar-month composite (MODIS vegetation index user guide, 2015) MODIS images can be downloaded from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table.

2.4 Calculation of SPI

SPI at these grid points were calculated using SPI program SPI_SL_6.exe available at http://drought.unl.edu/MonitoringTools/DownloadableSPIProgram.aspx with the input files generated at each grid point using monthly mean rainfall amounts at each grid point. The SPI at a location is found by series of equations as below. Precipitation time series at a location was found to fit gamma distribution well by (Thom et al. 1958). The probability density function defined gamma distribution for x>0

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \qquad (1)$$

Where α is shape and β is scale parameter, x is precipitation and Γ (α) is gamma function and

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad (2)$$

$$\beta = \frac{\bar{x}}{\alpha} \qquad (3)$$

$$A = ln\,(\bar{x}) - \frac{\sum ln\,(x)}{n} \qquad (4)$$

and n is the number of observations. The cumulative probability of the observed precipitation is found by equation 5 as below:

$$H(x) = q + (1 - q)G(x) \qquad (5)$$

Where q is probability of zero G(x) (Khan et al., 2013). This probability is converted to the standard normal random variable Z, which is the SPI index value.

2.5 Calculation of SPEI

SPEI at the grid points was calculated using the SPEI calculator available at https://digital.csic.es/handle/10261/10002?locale=en. Mathematically, the SPEI is similar to the Standardized Precipitation Index (SPI), but includes the role of temperature and latitude of the location to calculate PET at a particular location. Calculation of PET is difficult requiring numerous parameters such as humidity, vapor pressure, sensible heat fluxes and ground – atmosphere latent heat etc., which are generally not available. Alternatively, empirical equations have been proposed for PET calculation where data are scarce (Allen et al., 1998). Therefore, Thornthwaite model was used which only requires the monthly mean temperature data to calculate PET. The aim of including PET in the drought index calculation is to obtain a relative temporal estimation, and therefore the method used to calculate the PET is not critical (Vicente – Serrano, 2010).

2.6 Calculation of standardized NDVI anomalies

For ease of comparison and correlation analyses the NDVI anomalies were standardized by the variability of data. The resulting standardized NDVI anomaly value was a deviation from the zero same as SPI and SPEI. The NDVI anomalies were calculated using the following equation:

$$Std\ NDVI\ Anomaly = \frac{NDVIi\ - NDVImean}{\sigma} \quad (6)$$

Where $Std\ NDVI\ Anomaly$ is the deviation from the long term mean. $NDVIi$ is the current NDVI value $NDVImean$ is the long term mean and σ is the standard deviation of the long term NDVI values.

2.7 Correlation between drought indices and weighted overlay analysis

Three monthly SPI, SPEI and standardized NDVI anomalies were generated for three critical months of July to August which received maximum rainfall to characterize meteorological drought conditions during each year. Six monthly SPI, SPEI and standardized NDVI anomalies were generated from May to October each year to characterize agricultural drought conditions during each year. Monthly drought indices were also generated from Jun to October during each year to perform correlation analysis among three indices to characterize relationship of rainfall and temperature data with vegetation across study area.

United States drought monitor values for SPI were used for classification of both SPI and SPEI maps. Classification values, available at http://droughtmonitor.unl.edu/Home.aspx, while Standardized NDVI anomalies values, available at http://www.bom.gov.au/climate/austmaps/about-ndvi-maps.shtml, were used with slight modification for classification of standardized NDVI anomalies maps as shown in Table 1.

Standardized NDVI anomaly was given first priority while assigning weights, for weighted overlay analysis, being direct estimation of vegetation data across study area followed by SPEI and SPI which was based on correlation analysis between SPI, SPEI and standardized NDVI anomalies. Weights between prioritized drought indices layers were calculated and balanced through analytic hierarchy process (AHP) program with consistency ratio of less than 10 percent (TSOI, 2001). Drought severity classes in all the layers as given in Table 1 were scaled on a common scale of 1 to 9 with 1 for severely wet and 9 for exceptional drought. Weighted overlay analysis was completed in ArcGIS with SPI, SPEI and Standardized NDVI anomalies layers to generate meteorological and agricultural drought severity maps for Tharparkar.

Table 1.1 Drought classification values of SPI, SPEI and standardized NDVI anomalies.

Drought Classification	Standardized NDVI Anomaly	SPI	SPEI
Exceptional Drought	-2 and Less	-2 and Less	-2 and Less
Extreme Drought	-1.5 to -2	-1.6 to -1.9	-1.6 to -1.9
Severe Drought	-1 to -1.5	-1.3 to -1.5	-1.3 to -1.5
Moderate Drought	-0.5 to -1	-0.8 to -1.2	-0.8 to -1.2
Abnormally Dry	-0.1 to -0.5	-0.5 to -0.7	-0.5 to -0.7
Normal	0.1 to -0.1	-	-
Wet	0.1 to 1	-	-
Moderately Wet	1 to 1.5	-	-
Severely Wet	1.5 and above	-	-

Chapter 3

RESULTS AND DISCUSSION

3.1 Vegetation response to average rainfall variations across Tharparkar

Monsoon season in Tharparkar spans from June to October each year with corresponding response from vegetation cover. Monsoon season starts in June, ascending to peak in July or August and finally ends by October. Vegetation in Tharparkar reciprocates to the time and amount of monthly rainfall during monsoon season by conforming to corresponding monthly NDVI response as exhibited by monthly rainfall. Other months do not receive any or an occasional rainfall event without any pattern. Figures 5a and 5b represent monthly mean rainfall and monthly mean NDVI from 1998 to 2014, respectively. Monthly mean rainfall marks optimum monthly rainfall pattern across Tharparkar for time period from 1998 to 2014 and creates threshold of monthly rainfall for optimum growth of vegetation types across Tharparkar (Lázaro et al, 2001; Turner et al, 1989; and Bertilleret al, 1991). Monthly mean NDVI pattern also exhibited that after each monsoon season NDVI response diminishes gradually from November through May next year with lowest NDVI in May. NDVI gradually sustains itself during a cycle of no rainfall between two monsoon seasons coming to lowest level before start of next monsoon season. Thus vegetation condition which extends to next monsoon season plays its role in carry over effect of drought conditions to next season.

3.2 Correlation analysis –vegetation response to rainfall variations

Table 2 shows correlation coefficient pattern between SPI, SPEI and standardized NDVI anomalies from 1998 – 2014. Correlations of SPI and SPEI with standardized NDVI anomalies varied from significant correlation in June ($P \leq 0.05$) to highly significant correlation in July ($P \leq .0005$). Correlation decreased after its peak in July to strong significant correlation in August and September ($P \leq .005$) before reducing to no correlation in October. Correlation between SPI and SPEI remained highly significant ($P \leq .0005$) from June to September before decreasing to significant correlation ($P \leq 0.05$). Correlation configuration of SPI and SPEI with standardized NDVI anomalies implied that vegetation gave strongest response to monthly rainfall during July followed by August. Thus time and amount of monthly rainfall from June to October played vital role for vegetation growth cycle during monsoon season across Tharparkar. Correlation analysis of SPI and SPEI with standardized NDVI anomalies implied that vegetation was adapted to timing and amount of monthly rainfall across arid zone of Tharparkar (Li et al, 2014 and Lázaro et al, 2001). Correlation configuration between SPI and SPEI suggested that the moisture loss due to evapotranspiration did not become significant for months which received higher rainfall, however, correlation difference between SPI and SPEI increased for months which received lesser rainfalls.

3.3 Vegetation dynamics – Normal, near normal and wet years

Tharparkar experienced normal, near normal or wet conditions during 1998, 2001, 2003, 2006, 2007, 2008, 2009, 2010, 2011, 2012 and 2013. 1998, 2003, 2006, 2010, 2011 and 2013 were wet years with rainfall above normal (371mm) during monsoon season while 2001, 2007, 2008, 2009 and 2012 received comparatively less than normal rainfall and faced normal or near normal conditions (Figure 1.6).

3.3.1 Vegetation response dynamics – Normal and near normal years

Tharparkar face high spatial and temporal variability of rainfall alongside very high temperatures during monsoon season with maximum temperature ranging from 35°C to over 40°C (Shahid et al, 2008). For optimum or maximum growth of vegetation it was essential

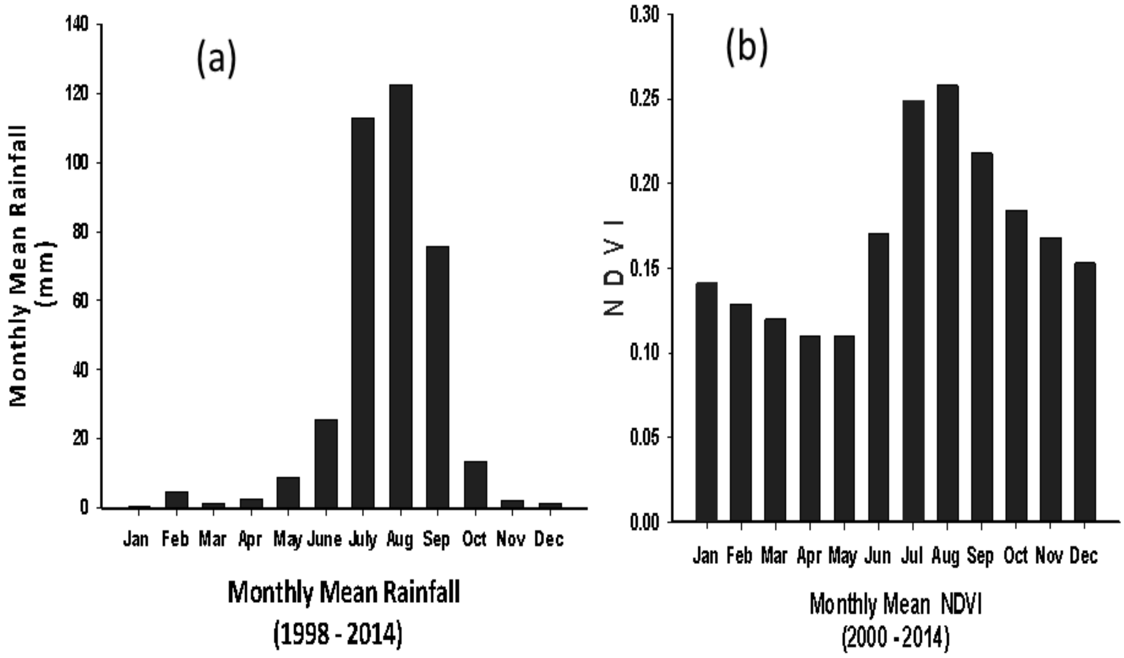

Figure 1.5 Average monthly rainfall vs average monthly NDVI (a) monthly mean rainfall (b) monthly mean NDVI

Table 1.2 Correlation between SPI, SPEI and standardized NDVI anomalies from 1998 - 2014.

Duration	Standardized NDVI Anomalies VS SPI	Standardized NDVI Anomalies VS SPEI	SPI VS SPEI
Jun	0.46	0.58	0.80
Jul	0.81	0.81	0.96
Aug	0.71	0.73	0.95
Sep	0.64	0.68	0.83
Oct	-0.0056	0.02	0.46
3 Monthly Correlation (Jul - Sep)	0.87	0.88	0.95
6 Monthly Correlation (May - Oct)	0.85	0.80	0.93

for rainfall to follow optimum or more than optimum pattern of rainfall during complete monsoon season across Tharparkar. Absence or lower than normal rainfall during any of the months while accompanied by high temperature anomalies badly affected vegetation growth cycle and reduced overall NDVI response at end of monsoon season (Li et al, 2014). During 2001 monthly rainfall pattern initiated on time in June, with higher than normal monthly rainfall during June, but lasted up to August only with lower than normal rainfall both in July and August. Lower than normal rainfall during July and August (Appendix 1) while positive monthly temperature anomalies in September and October resulted in negative NDVI anomalies during August, September and October reducing overall response of vegetation across Tharparkar. Thus three and six monthly drought indices indicated normal values for 2001 (Figure 1.6).

Tharparkar experienced normal conditions continuously from 2007 till 2009 after wet conditions in 2006 (Figure 1.6). During 2007 monthly rainfall varied with alternatively higher than normal rainfall in June and August while lower than normal rainfall during July, September and October. Lower rainfall in July, September and October together with higher monthly temperature anomalies in September and October resulted in normal conditions at meteorological and agricultural drought scale. Monthly NDVI anomaly attained maximum value in July 2007 but decreased sharply in August 2007 (Appendix 1).

Though monsoon season in 2008 almost received analogous monthly rainfall and air temperature anomalies pattern as in 2007 yet three and six monthly standardized NDVI anomalies indicated lower than normal values for 2008 (Figure 1.6). This contradiction was explained by carry over effect of vegetation condition from one monsoon season to another. After wet year of 2006 monthly NDVI anomalies from November 2006 till May 2007 remained positive while monthly NDVI anomalies were negative in May 2008 (Appendix 1) thus imparting additive affect to slightly dry conditions during monsoon season in 2008. This phenomenon repeated as monsoon season of 2009 approached which received more than normal rainfall during monsoon season but yet produced three and six monthly NDVI anomalies almost same as in 2007 (Figure 1.6).

3.3.2 Vegetation response dynamics - wet years

Wet years received over 450mm to 731mm of rainfall during monsoon seasons. Though rainfall quantity was well above normal rainfall (371mm) during wet years monsoon seasons yet standardized NDVI anomalies response varied between wet years due to variations in monthly rainfall distributions. The 2011 (731mm) and 2006 (617mm) were most wet years in terms of total amount of rainfall yet standardized NDVI anomalies exhibited peak values in 2003 and 2010 signifying that 2003 (534mm) and 2010 (544mm) were the most green years (Fig. 6). This variation in response of Standardized NDVI anomalies was explained by monthly rainfall variations during monsoon season when compared with optimum monthly rainfall pattern for Tharparkar from 1998 – 2014 (Figure 1.7).

2003 and 2010 were the only two wet years during which July and August received highest rainfalls in sequence (Appendix 2). In addition, 2010 was only year when monthly rainfall pattern during monsoon perfectly followed optimum configuration of rainfall from June until September and resulted in highest standardized NDVI anomalies during complete time series (Figure 1.6).

Though 2006 and 2011 received highest monsoon rainfalls but monthly rainfall pattern did not conform well to optimum monthly configuration of rainfall during July and August as in 2003 and 2010 (Figure 1.7). Rainfall pattern during 2013 received well over normal monthly rainfall during entire monsoon season except critical month of August (Appendix 2). Thus impeding vegetation growth cycle during significant month of August and resulted in lower standardized NDVI anomalies (Figure 1.6).

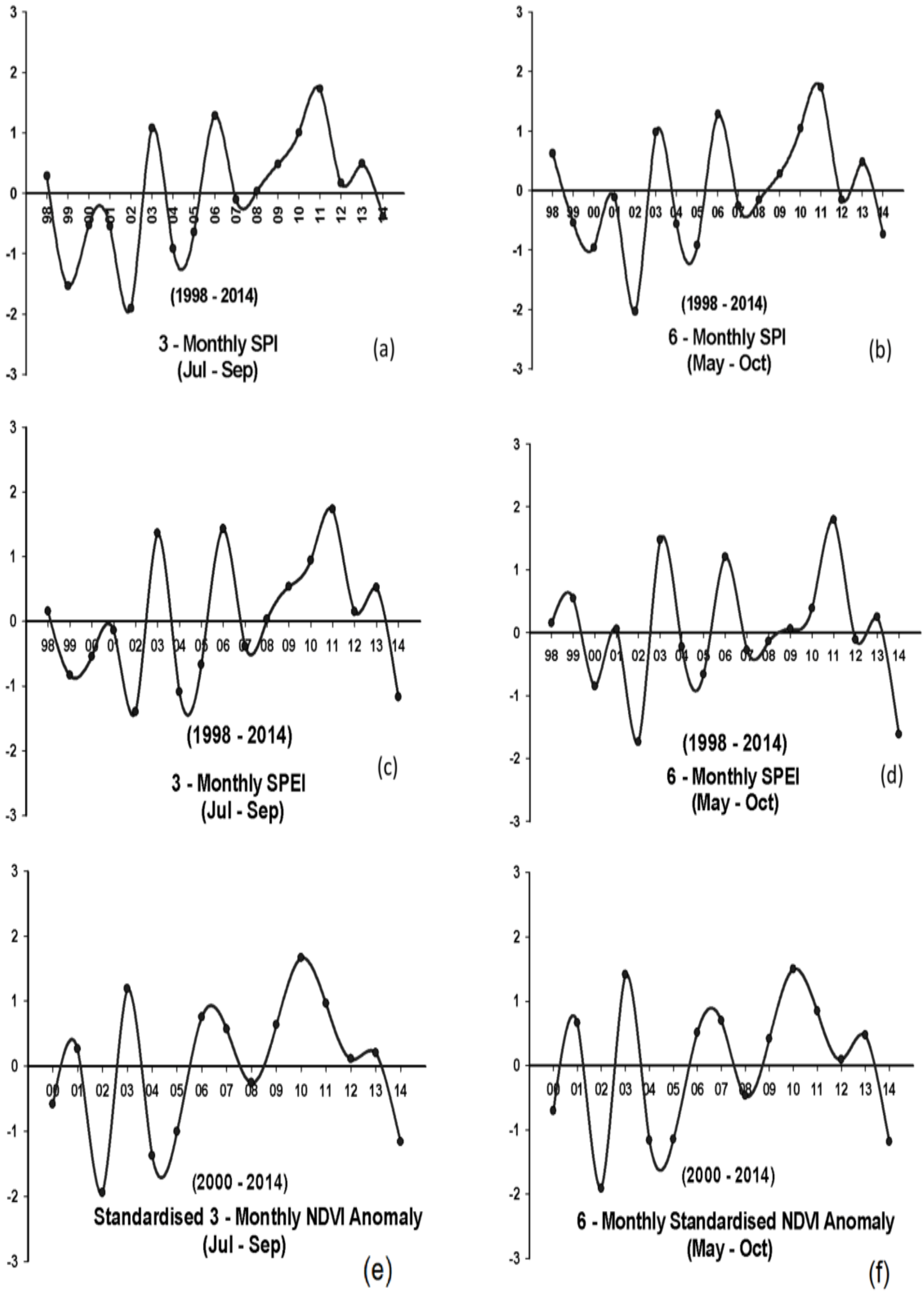

Figure 1.6 Temporal variation of drought indices (a) three monthly SPI (b) six monthly SPI (c) monthly SPEI (d) six monthly SPEI (e) thee monthly standardized NDVI anomalies (f) six monthly standardized NDVI anomalies.

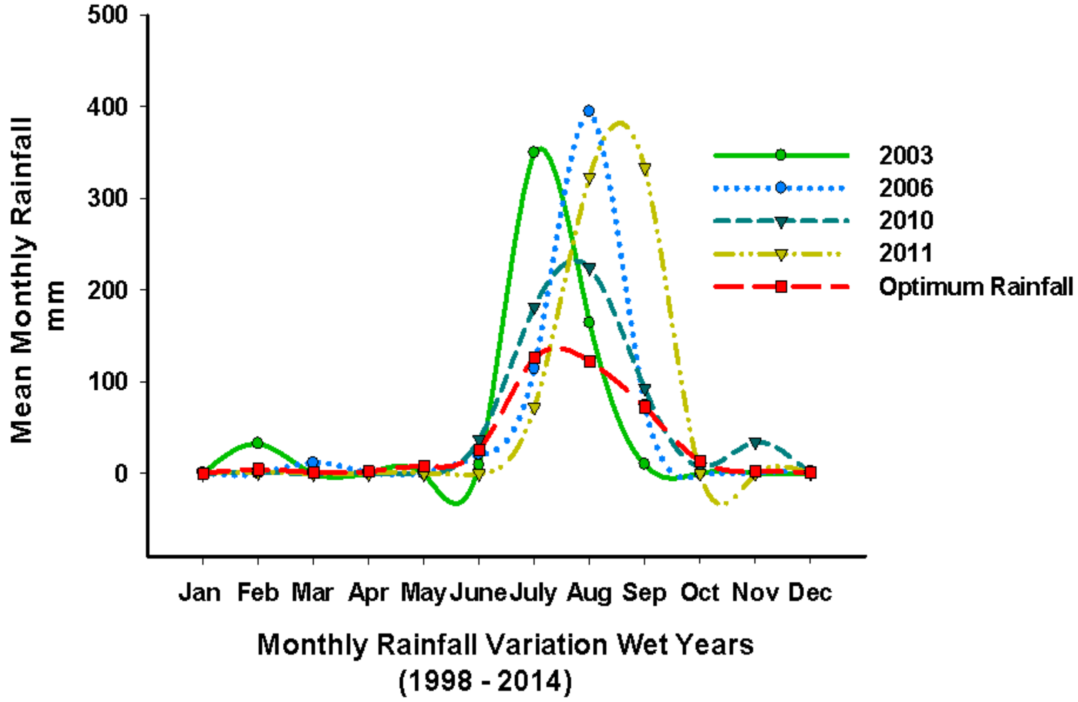

Figure 1.7 Monthly rainfall variation of wet years in comparison with optimum pattern of rainfall from 1998 – 2014.

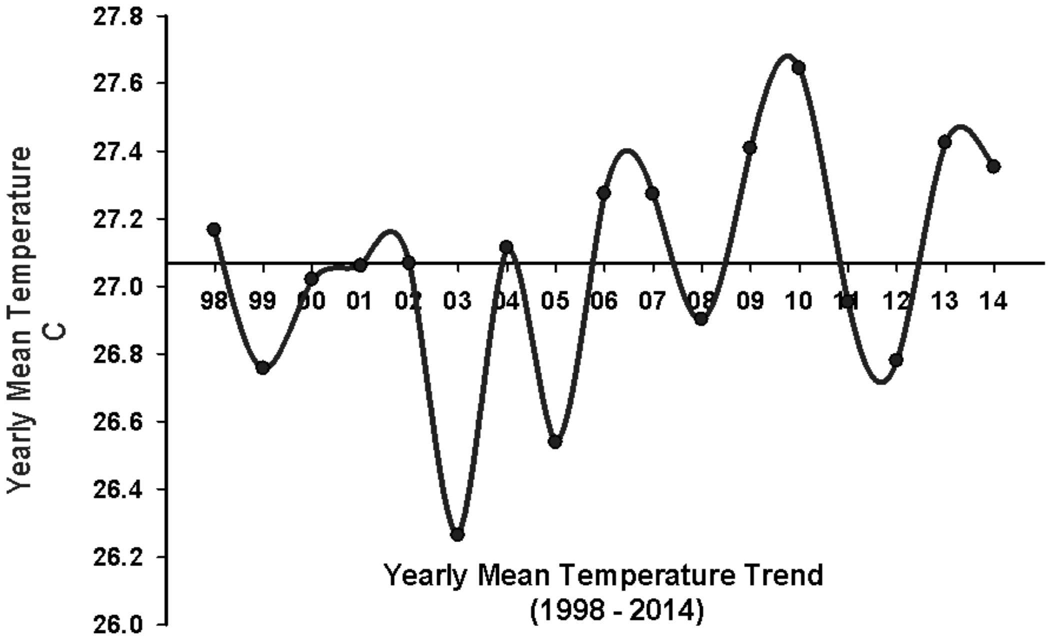

Figure 1.8 Yearly mean temperature trend from 1998 to 2014.

3.3.3 Temperature anomalies Variations – Wet and normal years

The greenest years across Tharparkar i.e., 2003 and 2010 had opposite pattern of temperature anomalies during monsoon seasons. The 2003 experienced low negative temperature anomalies during entire monsoon season while 2010 experienced high positive anomalies during entire monsoon season except August (Appendix 2). Monthly rainfall remained dominating factor for vegetation growth cycle as long as amount of monthly rainfall remained above optimum quantity during a particular month of monsoon season without any influence of temperature rise. However, significant lower monthly rainfall during any of the months of monsoon season coupled with high positive temperature anomalies badly affected vegetation growth cycle and reduced overall vegetation response at agricultural scale for example in August 2000, August 2004, June 2009, June 2011, July 2012 and during complete drought year of 2014 which have been discussed in detail under 3.4.2.

3.4 Temporal and spatial variation of drought intensity across Tharparkar

Tharparkar faced droughts during 1999, 2000, 2002, 2004, 2005 and 2014 over the period under study and saw either near normal or wet conditions during remaining period. Impact of variation in rainfall and temperature on drought intensity was evaluated through analysis on temporal and spatial variations of drought indices across Tharparkar.

3.4.1 Impact of rainfall and temperature on temporal variations of drought intensity across Tharparkar

Tharparkar faced severe meteorological drought during 1999 triggered by very low rainfall during critical months from July to September. Three monthly SPI exhibited (-1.53) extreme meteorological drought while three monthly SPEI indicated (-0.83) moderate meteorological drought however six monthly SPI (-0.54) and SPEI (0.54) depicted abnormally dry and normal conditions respectively. Meteorological drought in 1999 was mainly initiated due to very low rainfall during three critical months from July to September however intensity of drought was reduced due to late season rainfall in October (46mm) and low monthly temperatures during monsoon season as illustrated by significant negative temperature anomalies (Appendix 3). Negative temperature anomalies also resulted in depicting low intensity of drought by SPEI as against SPI. Contrary to 1999 drought in 2000 started with low meteorological drought severity as SPI (-0.53), SPEI (-0.55) and standardized NDVI anomalies (-0.59) exhibited abnormally dry conditions. However, agricultural drought severity was increased to moderate drought as displayed by all drought indices (Figure. 6). This was explained through monthly rainfall variations during monsoon season in 2000 as monsoon season only received normal rainfall during July and low rainfall during August but other months did not receive any or appreciable rainfall causing increase in agricultural drought severity. Monthly temperature anomalies during monsoon season in 2000 remained near normal values (Appendix 3) thus SPI, SPEI and standardized NDVI anomalies exhibited approximately similar values without showing any dissimilarity in drought intensity.

SPEI exhibited low drought intensity when monthly temperature anomalies were negative in 1999 and depicted almost same drought intensity as SPI during 2000 when monthly temperature anomalies were around normal values. Tharparkar faced extreme to exceptional drought in 2002 with very small amount of rainfall in June (34mm) and August (22mm) while other months received no or little rainfall. Monthly temperature anomalies remained at normal during June and August while remaining negative during July and September (Appendix 3). Owing to normal or negative temperature anomalies during monsoon season, SPEI indicated severe meteorological and extreme agricultural drought while both SPI and standardized NDVI anomalies demonstrated severe to exceptional meteorological and agricultural drought conditions. Hence SPI matched drought intensity of standardized NDVI anomalies generated from vegetation data during 2002 while SPEI depicted lower drought severity due to lower monthly temperature anomalies. Tharparkar faced droughts consecutively during 2004 and 2005. Though rainfall season of 2004 received more rain as compared to 2005 still drought intensity as indicated by standardized NDVI anomalies was more as compared to 2005 (Figure 1.6). There were two prominent reasons for this difference, one was lower monthly rainfall during critical months from July to September and second was higher positive monthly air temperature anomalies during rainfall season of 2004 as compared to 2005 (Appendix 3).

From 2006 till 2013 Tharparkar either experienced normal or wet conditions till 2013. After 2005, Tharparkar faced drought conditions in 2014. From 2006 till 2013, Tharparkar came across either normal or near normal conditions as in 2007 and 2008, or very wet meteorological conditions as in 2010 and 2011 during critical months of monsoon season. It was also observed that yearly mean temperature across Tharparkar also started rising from 2006 (Figure 8).

3.4.2 Effect of rise in temperature on drought intensity across Tharparkar during 2014

Monthly rainfall variations in monsoon seasons of 2005 and 2014 presented an ideal case to illustrate the effect of rise in temperature on drought severity during 2014 due to two significant reasons. Despite the fact that monsoon season in 2014 not only received more rainfall than monsoon season of 2005 and monthly rainfall pattern during 2014 also followed more closely to optimum rainfall pattern from July to September as against 2005, yet standardized NDVI anomalies displayed more drought severity in 2014 than 2005 (Figure 1.6). This contradiction was explained well by SPEI and temperature anomalies during rainfall seasons of 2005 and 2014. The effect of rise in temperature was indicated by comparison of statistical variations in areas of drought severity classes.

Table 3 shows areas covered, in terms of percentage, with drought severity classes by three drought indices during droughts in 2005 and 2014. SPI displayed more area under higher drought classes in 2005 as against drought year of 2014 at both meteorological and agricultural drought level. SPI showed more drought severity in 2005 compared to 2014 while SPEI and standardized NDVI anomalies exhibited more areas under higher drought severity classes specifically under severe and extreme drought classes respectively, at both meteorological and agricultural drought level. This inconsistency was explained by temperature anomalies during rainfall season which were highest for monsoon season months during 2014 for entire study period (Table 3). The effect of rise in temperature coupled with lower rainfall during monsoon season was adequately taken into account by SPEI and standardized NDVI anomalies while SPI could not incorporate the effect of rise in temperature (Vicente-Serrano et al, 2010).

3.5 Spatial variation of meteorological and agricultural drought severity across Tharparkar during drought years

Drought indices gave reasonable display of spatial variation of areas affected by type of drought severity classes across Tharparkar (Figures 1.9 & 2.0) but any single variable could not incorporate important information from other variables. In case of drought year of 2014, while SPI depicted less drought severity than standardized NDVI anomalies, SPEI showed more drought severity than standardized NDVI anomalies. In order to get composite maps at both meteorological and agricultural drought scales with optimum scalable information fused from all drought indices, weighted overlay analysis in ArcGIS was done. Composite drought severity maps for drought years of 2002, 2005 and 2014 as depicted by

Figure 2.1 gave very clear representation of areas affected by drought severity classes across Tharparkar. Weighted overlay analysis emphasized information of drought severity classes contained in three drought indices layers and furnished clear information about areas affected by respective drought severity classes across Tharparkar at both meteorological and agricultural drought scale (Figure 2.1).

Meteorological drought severity map for 2014 exhibited northern area of Mithi, central and north eastern area of Chachro, southern part of Umer kot and central area of Nagarparkar affected by severe drought. Diplo on the whole was affected by abnormally dry conditions. Agricultural drought severity extended further in spatial extent to as exhibited by meteorological drought. During 2005 meteorological and agricultural drought severity maps depicted central, southern, northern and north western parts of Tharparkar affected by moderate to severe drought while remaining area was mostly affected by abnormally dry conditions. The 2002 drought was worst drought year during period under study. Complete Tharparkar was effected by severe to exceptional drought with north western and south western part affected by exceptional drought conditions.

Table 1.3 Showing areas covered by drought severity classes of SPI, SPEI and standardized NDVI anomalies across Tharparkar during drought years of 2005 and 2014.

Drought Year	Drought Index (3 Monthly, 6 Monthly)	Area Covered by Drought Severity Classes in Percentage					
		Normal & Wet	Abnormally Dry	Moderate Drought	Severe Drought	Extreme Drought	Exceptional Drought
2005	SPI	(21,15)	(29,17)	(50,59)	(0,9)	(0,0)	(0,0)
	SPEI	(13,25)	(31,28)	(56,47)	(0,0)	(0,0)	(0,0)
	Standardized NDVI Anomalies	(9,5)	(11,8)	(27,26)	(31,32)	(16,21)	(6,8)
2014	SPI	(74,9)	(26,39)	(0,52)	(0,0)	(0,0)	(0,0)
	SPEI	(5,0)	(3,0)	(42,25)	(50,75)	(0,0)	(0,0)
	Standardized NDVI Anomalies	(6,6)	(10,7)	(21,21)	(30,33)	(26,25)	(7,8)

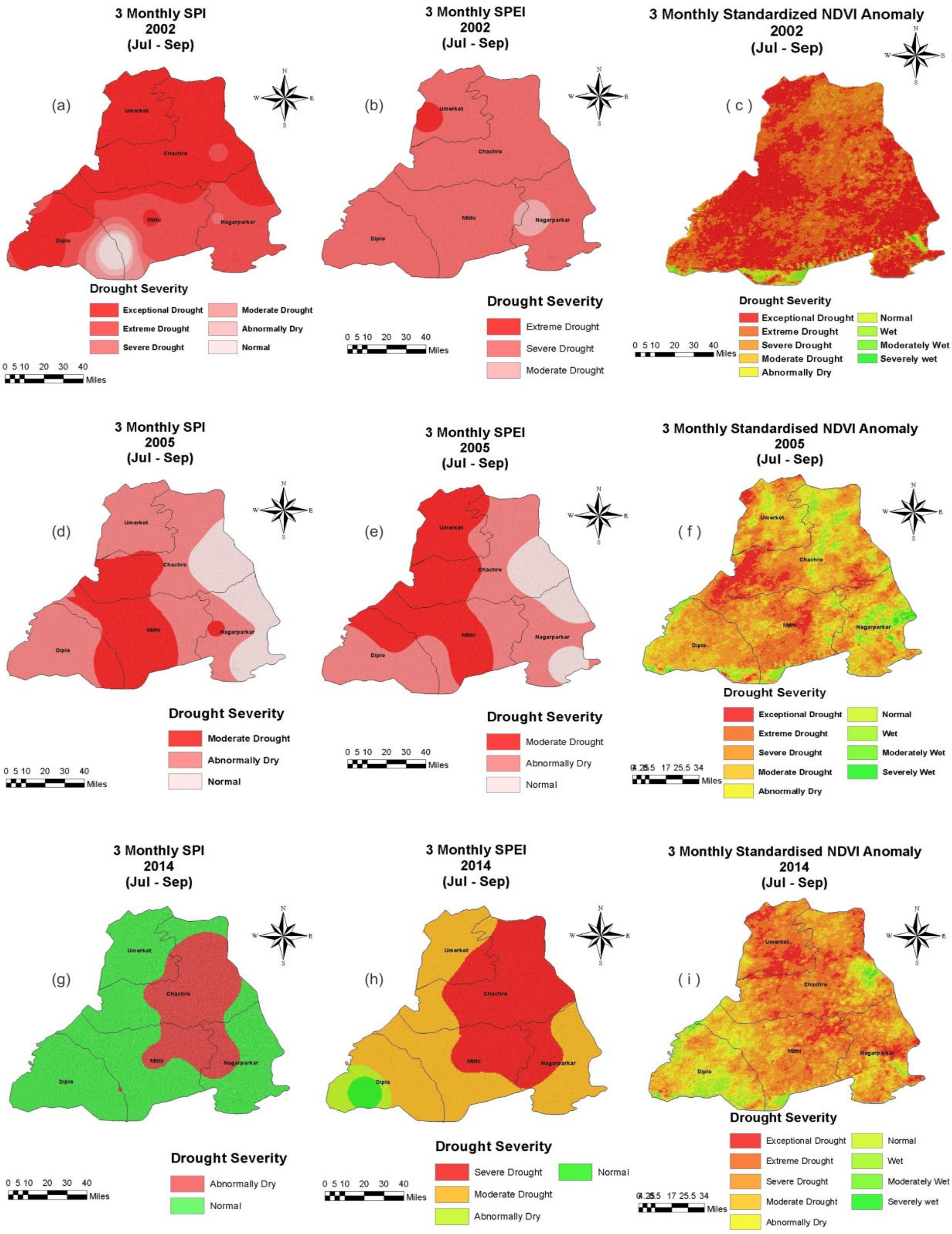

Figure 1.9 Spatial variation of drought severity across Tharparkar as shown by drought indices (a) three monthly SPI - 2002 (b) three Monthly SPEI - 2002 (c) three monthly standardized NDVI anomalies - 2002 (d) three monthly SPI - 2005 (e) three Monthly SPEI - 2005 (f) three monthly standardized NDVI anomalies - 2005 (g) three monthly SPI - 2014 (h) three Monthly SPEI - 2014 (i) three monthly standardized NDVI anomalies - 2014.

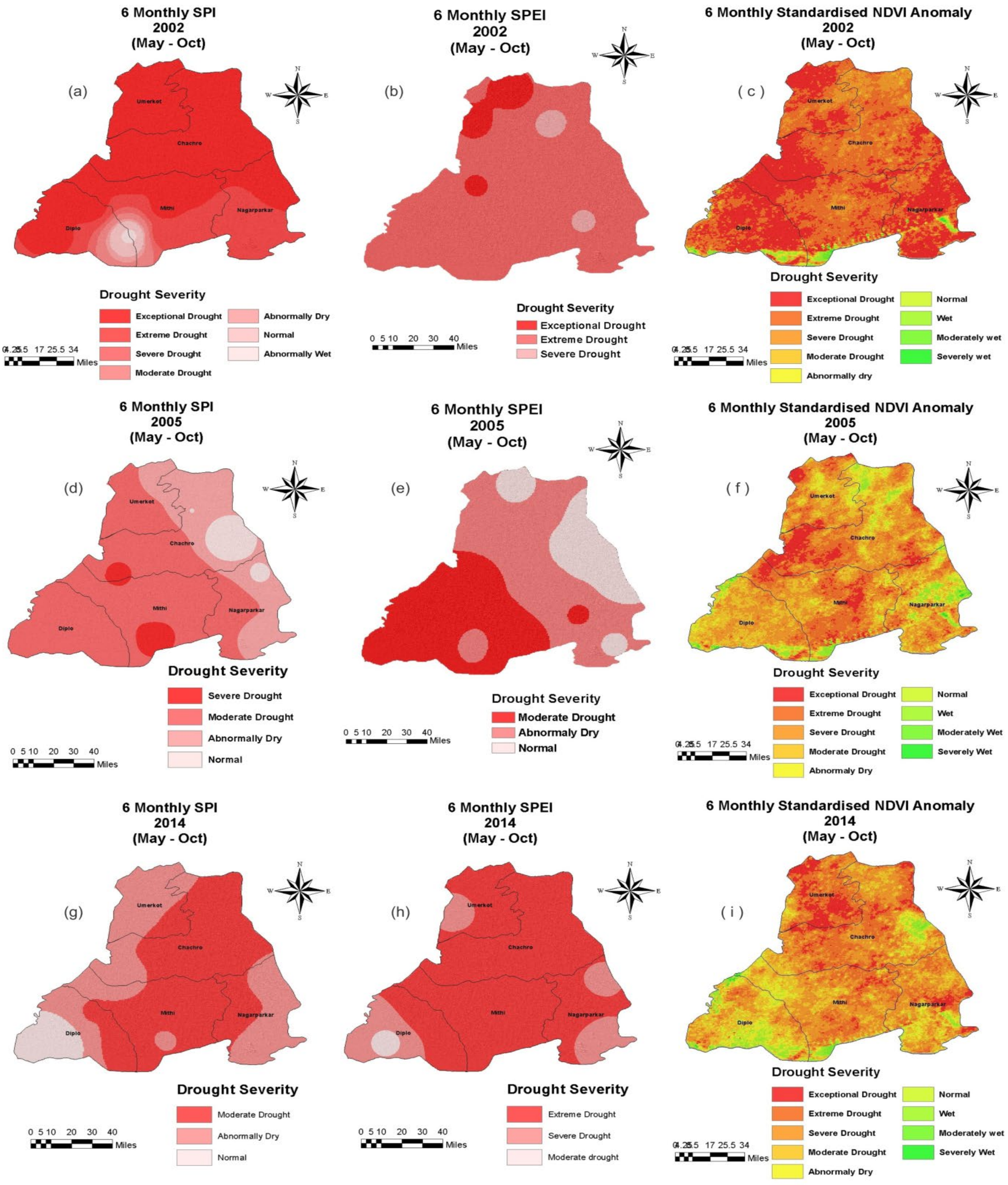

Figure 2.0 Spatial variation of drought severity across Tharparkar as shown by drought indices (a) six monthly SPI - 2002 (b) six Monthly SPEI - 2002 (c) six monthly standardized NDVI anomalies - 2002 (d) six monthly SPI - 2005 (e) six Monthly SPEI - 2005 (f) six monthly standardized NDVI anomalies - 2005 (g) six monthly SPI - 2014 (h) six Monthly SPEI - 2014 (i) six monthly standardized NDVI anomalies - 2014.

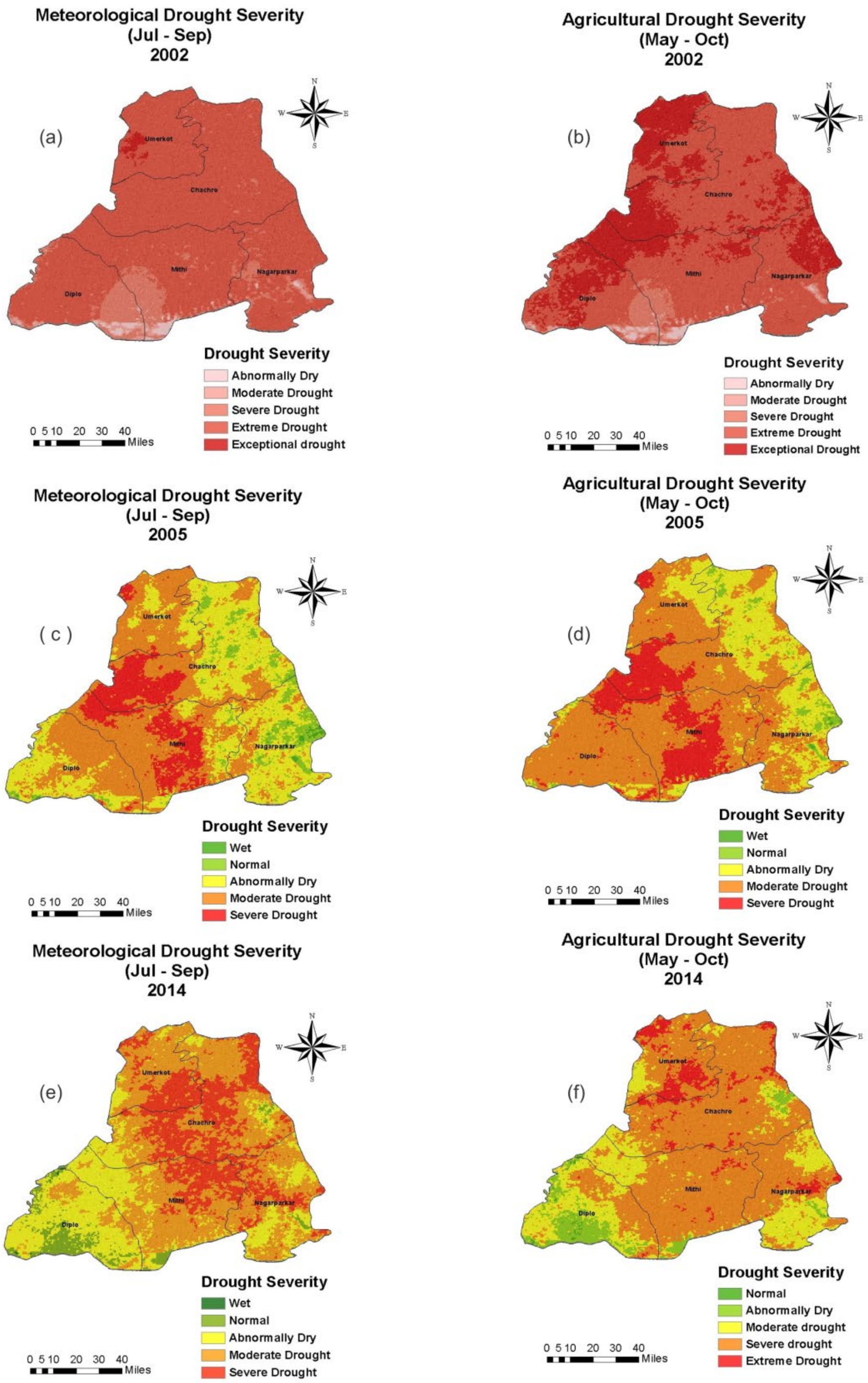

Figure 2.1 Spatial variation of composite meteorological and agricultural drought severity across Tharparkar (a) meteorological drought severity map - 2002 (b) agricultural drought severity map - 2002 (c) meteorological drought severity map - 2005 (d) agricultural drought severity map - 2005 (e) meteorological drought severity map - 2014 (f) agricultural drought severity map - 2014.

3.6 Discussion

This study depicted average yearly temperature increase across Tharparkar from 2006 in a fluctuating manner (Fig. 8). Rise in temperature was accompanied by rise in rainfall during monsoon seasons with average rainfall ranging over 300mm, during normal and near normal years, to above 700mm during monsoon seasons from 2006 to 2013 as predicted by IPCC 2007. The study characterized precipitation–vegetation interaction at monthly, three monthly and six monthly temporal scales. The results depicted that vegetation was adapted to timing and amount of monthly rainfall across Tharparkar with highly significant and strongly significant response from vegetation during July and August (Lázaro et al, 2001; Turner et al, 1989; and Bertilleret al, 1991), respectively which was in line with findings of Lázaro et al., 2001 and Li et al., 2014. Average monthly rainfall in monsoon season formed optimum threshold of rainfall with corresponding response from vegetation and was found consistent with previous studies (Li et al, 2014; Lázaro et al, 2001). Correlation configuration between SPI and SPEI confirmed higher loss of moisture during lower rainfall periods as presented by Vicente-Serrano, 2006.

In this study, the incorporation of newly developed standardized NDVI anomalies offered easier and meaningful insight into response of SPI and SPEI to vegetation across Tharparkar during wet and drought conditions across Tharparkar. Trend analysis of Standardized NDVI anomalies with SPI and SPEI furnished vegetation response dynamics to monthly rainfall and temperature variations. It was observed that monsoon season which received highest rainfall was not the greenest year (2011) rather monsoon season during which monthly rainfall followed optimum pattern of rainfall was greenest year (2010) and confirmed vegetation response pattern as given by Li et al., 2014 for arid regions. The study presented that effect of higher positive temperature anomalies did not hamper vegetation growth response as long as monthly rainfall pattern remained at or above optimum threshold for example during wet year of 2010. The results exhibited that SPI values corresponded well with standardized NDVI anomalies under normal and wet conditions irrespective of temperature anomalies while SPEI values corresponded well with standardized NDVI anomalies under normal and below normal rainfall conditions coupled with higher positive temperature anomalies.

Variation of temperature remained insignificant until rainfall remained at or higher than normal during monsoon season across Tharparkar. The study presented that the effect of higher temperature anomalies adversely affected vegetation growth and aggravated drought severity under normal or lower than normal monthly rainfall. Lower average monthly rainfall accompanied by higher positive temperature anomalies affected cycle of vegetation growth and suppressed overall response of vegetation at agricultural scale which was found consistent with results of study conducted by Shaheen et al., 2011 during their research in arid region of Thal Doab, Pakistan. The study demonstrated that negative or lower NDVI anomalies variations between consecutive monsoon seasons carried over influence of poor vegetation conditions from previous season into next growing season. Negative monthly NDVI anomalies before start of monsoon seasons during 2005 and 2008 depicted carry over effect of poor vegetation conditions after drought and below normal year, respectively into next growing season thereby producing additive effect to dry or low vegetation conditions in succeeding year (Lázaro et al, 2001; Webb et al, 1978 and Haase et al, 1995).

Rainfall was found to be primary factor in initiating drought conditions across Tharparkar during drought years. Though SPI played important role in depicting drought conditions across Tharparkar (McKee et al, 1993 and WMO, 2012), however, results of this study indicated that under drought conditions generated by lower than normal rainfall and higher temperature anomalies, during growing cycle of vegetation, role of temperature was predominant and further aggravated drought severity as predicted by Goyal, 2004 during his research on future trends of drought in neighboring arid region of Rajasthan, India (Goyal, 2004). Drought years of 2005 and 2014 presented an instance when monsoon season of 2014 received better rainfall than 2005 but faced highest positive temperature anomalies in entire time series. SPI could not establish the effect of rise in temperature during 2014 and depicted less drought severity as compared to 2005 while SPEI and standardized NDVI anomalies took into account effect of temperature rise during 2014 and depicted realistic drought conditions as against SPI. It underscored importance of a drought index to be incorporated in analysis of drought severity which could capture effect of increased evapotranspiration associated with rise in temperature across arid regions as suggested by previous studies under global warming scenario (Goyal, 2004; Vicente-Serrano, 2006 and Lemke et al, 2007).

Drought severity maps of SPI, SPEI and standardized NDVI anomalies furnished isolated information about drought hazard across Tharparkar at meteorological and agricultural scale based on separate input data (Figures 1.9 & 2.0). However, any single drought index could not establish clear picture of spatial extent of drought severity at meteorological and agricultural drought level. Weighted overlay analysis in GIS generated very clear spatial extents of drought severity classes across Tharparkar at both meteorological and agricultural scale (Figure 2.1) as consequence of two important steps. One was through emphasizing information of common drought severity classes captured by drought indices and secondly by allocation of relative weights to drought indices layers, calculated through analytical hierarchy process.

The results of this study presented an effective model for drought analysis across arid zone of Tharparkar which could be aptly implemented by utilizing freely available remote sensing data for drought hazard analysis in data scarce arid regions. Though this study confirmed effectiveness of using remote sensing data for analyzing vegetation dynamics in response to rainfall and temperature variations at coarse temporal scale of 1 month across arid region of Tharparkar, however, to carry out analyses for specific vegetation types detailed data such as soil moisture, vegetative growth and crop yield etc., would be required. The study confirmed effectiveness and importance of a drought index which incorporated effect of rise in temperature on drought severity across arid regions exposed to higher temperatures.

CHAPTER 4

CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

This study provided an important insight into vegetation change dynamics and drought severity across Tharparkar which can be quite useful for relevant departments and relief agencies to respond affectively and timely in drought struck areas. The study could also be of help to the decision makers to help compensate farmers and affected people according to the drought severity in affected areas. . The methodology adopted for this study could be replicated on data scarce arid regions experiencing frequent droughts under higher temperatures.

4.2 Limitations

This study confirmed effectiveness of using remote sensing data for analyzing vegetation dynamics in response to rainfall and temperature variations at coarse temporal scale of 1 month across arid region of Tharparkar, however, to carry out analyses for specific vegetation types detailed data such as soil moisture, vegetative growth and crop yield etc., would be required.

4.3 Recommendations

It is recommended that:-

- Local and provincial governments should take initiatives to introduce new crop varieties more resistant to evapotranspiration stress due to increased temperatures.
- Local and provincial governments must ensure training of local communities on rain water harvesting and soil water conservation techniques to help reduce effects of lower rainfall and higher temperatures which further aggravate drought severity.

- To carry out analyses for specific vegetation types detailed data such as soil moisture, vegetative growth and crop yield etc., be used to establish mechanics of specific crop species to rainfall and temperature variations under drought conditions

APPENDICES

Appendix 1 Showing monthly rainfall, monthly NDVI anomalies and monthly temperature anomalies for normal years.

Year	Monthly Data	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
2001	Monthly Rainfall (mm)	0	0	0	5	13	111	103	73	10	7	0	0
	Monthly NDVI Anomalies	-0.022	-0.019	-0.019	-0.020	-0.020	0.144	0.070	-0.002	-0.017	-0.005	0.004	0.008
	Monthly Temperature anomalies	-0.491	-0.148	-0.172	-0.358	0.509	-0.603	-1.540	-0.079	0.130	1.247	0.282	1.246
2007	Monthly Rainfall (mm)	0	16	7	0	2	35	81	132	41	0	0	6
	Monthly NDVI Anomalies	0.032	0.021	0.022	0.020	0.026	0.037	0.075	0.019	0.016	0.006	0.006	0.003
	Monthly Temperature anomalies	0.697	2.234	-0.768	0.628	-0.167	-0.202	0.113	0.552	0.897	-0.928	0.475	-0.972
2008	Monthly Rainfall (mm)	0	1	1	10	1	25	97	140	45	0	1	12
	Monthly NDVI Anomalies	0.002	0.004	0.001	0.000	-0.002	-0.053	-0.006	-0.026	-0.018	-0.016	-0.01	-0.012
	Monthly Temperature anomalies	-1.485	-2.254	1.228	-0.511	-0.367	-0.168	0.147	-0.494	0.696	0.510	-0.151	0.971
2009	Monthly Rainfall (mm)	2	0	0	0	0	11	296	69	11	0	0	0
	Monthly NDVI Anomalies	-0.014	-0.012	-0.011	-0.010	-0.011	0.004	0.070	0.057	-0.004	-0.009	-0.007	0.000
	Monthly Temperature anomalies	1.384	1.717	1.083	0.019	0.616	0.379	0.326	0.219	-0.388	-0.475	-0.815	0.127
2012	Monthly Rainfall (mm)	0	0	0	3	0	1	34	88	184	0	0	1
	Monthly NDVI Anomalies	0.020	0.015	0.018	0.019	0.018	-0.041	-0.073	0.040	0.054	0.025	0.021	0.012
	Monthly Temperature anomalies	-0.266	-2.154	-0.924	-0.093	-0.101	-0.104	0.260	0.591	-0.407	-0.513	-0.097	0.459

Appendix -2 Showing monthly rainfall, monthly NDVI anomalies and monthly temperature anomalies for wet years.

Year	Monthly Data	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
1998	Monthly Rainfall (mm)	0	6	3	0	0	34	61	73	201	89	0	0
	Monthly NDVI Anomalies	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data
	Monthly Temperature anomalies	-0.023	-0.566	-0.940	0.742	0.695	0.652	-0.150	0.729	0.713	-0.205	-1.148	0.791
2003	Monthly Rainfall (mm)	0	32	0	0	0	9	350	164	10	0	0	0
	Monthly NDVI Anomalies	-0.043	-0.020	-0.010	-0.015	-0.016	0.124	0.098	0.109	0.022	0.025	0.029	0.038
	Monthly Temperature anomalies	0.191	0.114	-0.506	-0.577	-0.693	-0.398	-0.566	-0.58	-1.243	-0.982	-2.803	-1.495
2006	Monthly Rainfall (mm)	0	0	12	1	0	21	114	395	74	0	0	2
	Monthly NDVI Anomalies	-0.020	-0.021	-0.024	-0.024	-0.021	-0.025	0.037	0.055	0.053	0.032	0.031	0.026
	Monthly Temperature anomalies	-0.146	3.614	-0.755	-0.088	0.353	0.299	0.379	-1.43	-0.155	0.743	0.157	-0.384
2010	Monthly Rainfall (mm)	0	1	0	0	0	37	182	224	93	8	34	0
	Monthly NDVI Anomalies	-0.003	-0.006	-0.009	-0.008	-0.004	0.021	0.097	0.139	0.087	0.047	0.027	0.020
	Monthly Temperature anomalies	0.707	0.278	2.715	1.616	1.571	0.147	0.615	0.336	0.078	0.707	-0.365	-1.374
2011	Monthly Rainfall (mm)	1	2	0	0	0	0	72	323	333	0	0	0
	Monthly NDVI Anomalies	0.018	0.015	0.012	0.011	0.008	-0.027	0.037	0.080	0.069	0.050	0.037	0.029
	Monthly Temperature anomalies	-0.494	0.027	0.228	-1.212	-0.521	0.148	0.496	-0.30	-1.709	-0.477	2.063	0.478

Appendix-3 Showing monthly rainfall, monthly NDVI anomalies and monthly temperature anomalies for drought years.

Year	Monthly Data	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
1999	Monthly Rainfall (mm)	0	9	0	0	113	9	47	18	16	46	0	0
	Monthly NDVI Anomalies	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data	No Data
	Monthly Temperature anomalies	0.444	0.442	-0.55	0.176	-1.46	-1.820	-0.652	-0.81	-0.33	0.396	0.639	-0.08
2000	Monthly Rainfall (mm)	0	0	0	0	3	3	122	51	13	0	0	0
	Monthly NDVI Anomalies	-0.017	-0.02	-0.01	-0.01	-0.02	-0.011	-0.009	-0.05	-0.05	-0.04	-0.03	-0.02
	Monthly Temperature anomalies	0.676	-0.79	-1.03	0.592	-0.41	0.081	-0.104	0.376	-0.13	0.606	-0.60	0.27
2004	Monthly Rainfall (mm)	0	0	1	0	1	41	20	98	21	63	0	1
	Monthly NDVI Anomalies	0.039	0.033	0.025	0.024	0.023	-0.042	-0.095	-0.11	-0.06	-0.015	-0.014	-0.01
	Monthly Temperature anomalies	0.056	0.280	0.934	1.075	-0.33	-0.236	0.164	0.587	-0.05	-1.774	-0.605	0.562
2005	Monthly Rainfall (mm)	0	0	0	1	6	21	54	40	78	0	0	0
	Monthly NDVI Anomalies	-0.015	-0.01	-0.01	-0.01	-0.01	-0.057	-0.095	-0.075	-0.03	-0.034	-0.031	-0.028
	Monthly Temperature anomalies	-0.941	-1.01	-0.09	-1.48	-0.56	0.462	0.032	-0.563	0.76	-0.895	-0.359	-1.59
2014	Monthly Rainfall (mm)	0	0	0	5	10	3	74	72	62	0	0	0
	Monthly NDVI Anomalies	0.010	0.008	0.009	0.013	0.012	-0.054	-0.096	-0.074	-0.05	-0.038	-0.029	-0.024
	Monthly Temperature anomalies	-0.992	-0.56	-0.89	-0.06	-0.09	0.900	0.750	1.070	1.25	0.511	1.577	0.056

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