

Strengthening Regional Capacities for Providing Remote Sensing Decision Support in Drylands in the Context of Climate Variability and Change

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1. Introduction

Dryland ecosystems cover one third of the earth's total land surface, comprise areas with a ratio of average annual rainfall to evapotranspiration of less than 0.65 (MEA, 2005). These regions are fragile environments characterized by unreliable rainfall patterns and support livelihoods of over 2.5 billion people (Reynolds et al., 2007). Widespread episodes of drought, heavy precipitation and heat waves have been reported as a consequence of global sea level increase (Verdin et al., 2005). However, the projections of the impacts of global warming on regional climate are largely uncertain due to the complex and site-specific interdependencies among landscape properties, environmental traits and policy decisions (Boulanger et al., 2005). The predictions of climate changes and their impacts in those dry lands are important because of their characteristics affecting economic activity based on agriculture and the role of natural ecosystems in carbon sequestration and water budget, which could lessen or mitigate the impacts of global changes in the weather system of these regions.

Climate variability and change play a significant role in dryland decision making, at various time scales. Decisions affected by climate considerations include both dryland hardware (infrastructure and technology) and software (management, policies, laws, governance arrangements). Strategic (decadal scale) and tactical (seasonal or interannual scale) decisions regarding such matters as infrastructure for storing water and dryland conservation measures must be made in the face of uncertainty about interdecadal, intraseasonal and interannual flows.

There is a need to understand changes that have occurred in the resources in dryland ecosystems that contain a variety of plant species that have developed special strategies to cope with the low and sporadic rainfall and extreme variability in temperatures. A better understanding of various dynamics at work in drylands will put us in a better position to predict the future of the ecosystems. Sustainable land use under climate change requires

detailed knowledge of the system dynamics. This is particularly pertinent in the management of domestic livestock in semiarid and arid grazing systems, where the risk of degradation is high and likely climate change may have a strong impact. Although these drylands are of environmental and socio-economic importance, they are faced with serious management challenges. Hence, their sustainable management requires an evaluation of the magnitude, pattern, and type of land-use/cover changes and the projection of the consequences of these changes to their conservation. It is also important to precisely describe and classify land cover changes in order to define sustainable land-use systems that are best suited for each place (FAO 1998). Monitoring the locations and distributions of land cover changes is important for establishing links between policy decisions, regulatory actions and subsequent land-use activities. In this regard, there is a need to consider both the socio-economic environment (Giannecchini et al., 2007) and other environmental factors. In this context, there is a need for agriculture administrators and policy makers to better understand the intraseasonal-to-interannual variability of climate and its effects on the landscape properties. The comprehension of interactions of weather variability and those landscape properties could lead to improved understanding of those landscape vulnerability to global changes, enhanced natural-resource management and to a better emergency planning to withstand the effects of extreme episodes on the natural and agricultural systems at regional scale (Rosenzweig et al., 1994). Nonetheless, the climatic data, at adequate spatio-temporal resolution at the regional level is scarce, representing an obstacle to researchers.

Prognostic numerical models are one of the main research tools used to predict past and future states of the Earth system (Cramer et al., 2001), yet persistent problems limit their acceptance in ecological and global change research. Aber (1997) posed the question "Why have models failed to penetrate the heart of ecological sciences?" and found that all too often model predictions are made prior to parameterization, validation, sensitivity analysis, and description of model structure. While today models are more accepted in a wide variety of fields, these issues are still prevalent and still ignored too often. With the advent of global monitoring systems based on satellites, it became possible to understand the nature and response of these ecosystems and drylands to day-to-day fluctuations in weather. In particular, the spatial-temporal analysis of vegetation dynamics (i.e., the response of vegetation to climatic conditions) in the semi-arid tropical region is important in the context of climate change where these dynamics show quicker response in short term climate indices such as the Southern Oscillation Index (SOI) and the Nino Sea Surface Temperatures (Fischer, 1996). The present study aims to cover certain regions across the tropics of arid (R/PE is 0.05 to 0.20) and semi-arid (R/PE is 0.20 to 0.50) nature (where R represents Rainfall and PE , Potential Evapotranspiration). Such regions of this type are Northeastern Brazil, West Sahel in Africa and Andhra Pradesh in India. The rainfall in India is mainly by south-west monsoon (June to September). In Sahel, it is primarily from June to August and to a lesser extent in September. During the positive phase of El Nino Southern Oscillation (ENSO) which is the sudden rise of Pacific Sea Surface Temperatures, an increase is observed the intensity of drought in Northeastern Brazil, and the Sahel (Africa) rainfall changes are also found due to global ocean circulation and patterns of SSTs. This ENSO phases are explicitly seen in inter-annual variability of south-west monsoon in India and play a major role in the agricultural sector of the country. The evaluation of El Nino and La

Nina barely showed that in many cases, La Nina had positive impact and El Nino, a negative one. Due to climate change and variability, the disasters like droughts became frequent in the above said regions. Semi arid Asia is experiencing an increase in the frequency of severity of wild fires. African rainfall changed substantially over last 60 years due to land cover changes and forest destruction. Though, India is not showing any significant trend in its annual rainfall, an increase in extreme weather events are evidenced (Lakshmi Kumar et al., 2011). So it is must to address these issues from the remote sensing perspective, that too in assessing and monitoring droughts. The present chapter aimed to study the land surface and vegetation and their response to climate in the context of climate change and climate variability.

2. Monitoring the ground vegetation – Soil wetness by satellites – Previous studies

2.1 Normalized Difference Vegetation Index (NDVI)

The study of vegetation cover over a region which can be formed either by native or by cultivation attained a great significance. Barbosa et al. (2006), reported that the NDVI is a reliable index to study the ground vegetal cover and to monitor the changes occur in the vegetation due to climatic abnormalities. Study of spatiotemporal variations of NDVI is of great importance now a days in the context of increased greenhouse gases that modulate the global climate systems in terms of short term climate signals such as El Nino and La Nina. The NDVI variations on both space and time scales not only important in view of varying crop stages but also prominent in vegetation-climate feedback mechanism thus giving a challenge to policy makers in proactive and reactive measurements of risk Cihlar et al., 1991; Davenport & Nicholson, 1993; Al-Bakri & Suleiman, 2004; Kazuo & Yasuo, 2005, Ma & Frank, 2006 & Nagai et al., 2007. Global scientific community focused on NDVI as the indicator of agricultural droughts where in crop growth is known by NDVI value and found that the NOAA Advanced Very High Resolution Radiometer (AVHRR) NDVI is one of the best among the other vegetation indices derived from the other satellites. The NDVI can be defined as the ratio of difference between Channel 1 (red) and Channel 2 (near Infrared) which is based on the more absorbance for healthy vegetation and more reflectance for the poor vegetation. In other way, NDVI measures the changes chlorophyl content (via absorption of visible red radiation) and is sponzy mesophyll (via reflected NIR radiation) with in the vegetation canopy, thus NDVI from AVHRR can be written as

$$NDVI = (\rho_{857} - \rho_{645}) / (\rho_{857} + \rho_{645})$$

This NDVI varies from -1 to + 1 and the category in classifying the density of vegetation cover is given below.

NDVI < 0.2 ----- Low vegetation

NDVI < 0.4 ----- Medium vegetation

NDVI > 0.4 ----- High vegetation

Relevant research in changes in vegetation cover in the Sahel demonstrates that the NDVI happens to correlate particularly closely with rainfall, as high as 0.84. The cause of this

significant correlation is two-fold: first, it is commonly known that vegetation growth is limited by water; second, the climate in Sahel, rainfall in particular, is very sensitive to changes in vegetation Charney et al., 1977. Sarma and Lakshmi Kumar, 2006 derived the NDVI from NOAA AVHRR for the state Andhra Pradesh and saw how it varies in accordance with the crop growing periods such as moist, humid, moderate dry and dry as suggested by Higgins and Kassam (1981) and found a good agreement i.e prevalence of good NDVI is subjected to moist/humid periods. Barbosa et al, 2011 studied the vegetation indices such as NDVI and Enhanced Vegetation Index to understand the underlying mechanism of vegetation dynamics in Amazon forests.

2.2 Brightness Temperature (BT)

Studies on the direct measurement of soil moisture are few. Remotely sensed data in terms of brightness temperature is useful in the study of spatiotemporal variability as well as verifying land surface processes (Rao et al., 2001). Soil moisture can be retrieved by making use of remote sensing observations. Pathak et al, 1993 reported the estimation of soil moisture using land surface temperature retrieved from the INSAT - VHRR data. Microwave sensors provide a great opportunity to measure soil moisture because these microwave radiations can penetrate the clouds and vegetation over the land surface. Microwave brightness temperature can be used to measure soil wetness under different surface roughness and vegetation cover conditions (Ahmed, 1995). Thapliyal et al. (2003) reported soil moisture over India using microwave brightness temperature of IRS-P4. Sarma and Lakshmi Kumar (2007), explained the variations in brightness temperature of different soil types in Andhra Pradesh. The data retrieved from the Multichannel Scanning Microwave Radiometer (MSMR) carried by Indian Remote Sensing (IRS) - P4 satellite, is made use in understanding the nature of relation between soil moisture and BT. The BT of 6.6GHz frequency channel of MSMR, taken at 1830hrs Indian Standard Time (IST) for the horizontal polarization is used for the estimation of soil wetness which in turn portrays the drought prevailing conditions over that place.

The brightness temperature depends on the angle of incidence and the plane of polarization, vertical as well as horizontal. It is reported that the horizontal polarization is more sensitive to soil moisture and hence the same is used here. The microwave polarized temperature (MPT) is defined as

$$MPT = TB(1,H)$$

Here 1 refers to wavelength and is related apart from other factors to moisture content of the soil horizon.

Brightness Temperature (BT) at the microwave frequencies can be written as

$$BT = eT_s$$

Where e is the emissivity of the surface and T_s is the surface temperature.

As BT is a function of emissivity and surface temperature, the lands having less emissivity (wet lands) exhibit low signatures and is a good indicator of soil wetness status. Similarly, the lands having high emissivity (dry soils) give high BT signals showing low soil wetness status from which one can assess the moisture condition over the soil to estimate the drought condition (Sarma and Lakshmi Kumar, 2006).

3. Case studies, methodologies and findings

3.1 Analysis of the NDVI temporal dynamics in semi-arid ecosystems: Brazilian Caatinga and African Western Sahel

The Caatinga and Savanna vegetation covers are likely the most sensitive to changes in climate. Satellite observations show that changes in vegetation greenness follow rainfall variability. Because water availability is a key factor in the abundance of vegetation, changes in precipitation are most critical for continued biodiversity and human livelihood opportunities in arid and semi-arid environments. In earlier studies (Barbosa 1998; Nicholson and Farar, 1994) mostly held in the atmospheric dynamics context have incorporated long time series of NDVI data taken by the National Oceanic and Atmospheric Administration (NOAA) AVHRR to monitor the dynamics of the temporal structures of vegetation responses to climatic fluctuations across the Northeastern Brazil and the West African Sahel's landscapes. These investigations have found clear and positive linear relationships between NDVI and rainfall thanks to different analyses across the semi-arid tropical ecosystems where rainfall is below an absolute amount of rainfall of 50-100 mm/month. In this study we have the objective to investigate the NDVI responses to rainfall oscillations at seasonal scale over the last two decades of the 20th century.

Temporal analyses performed in this research were based on the monthly NDVI imagery from the Goddard Distributed Active Archive Center (GDAAC) for the 1982 to 2000 period. The NDVI images were originally in the Goode's Interrupted Homolosine projection, and they were geo-referenced to a geographical coordinate system (latitude and longitude). The 20-year series of monthly NDVI data for Brazilian semi-arid and West African Sahel regions were extracted from NDVI images with a resolution spatial of 7.6 km.

Aiming to characterize the seasonal variability of land cover types in Caatinga and Savanna Biomes to the understanding of their responses to the seasonal rainfall variability, we verified how available GDAAC NDVI are able to capture the climatic variability, and how it could be used in ecological studies, at the local level. Based on the vegetation map published by the Brazilian Institute for Geography and Statistics (IBGE, 1993) and by author's local knowledge, as a basis, four homogeneous vegetation sites covering semi-arid Caatinga in Northeastern Brazil were selected from vegetation classes, and located by ground meteorological stations (sites): site#1-caatinga arbórea aberta (open arboreous shrubbery) (4°31'S; 40°12'W), site#2-caatinga arbustiva densa (dense shrubbery) (4°37'S; 42°07'W), site #3-caatinga arbórea densa (dense arboreous shrubbery) (8°37'S; 42°07'W), and site #4-caatinga arbustiva aberta (open shrubbery) (9°25'S; 41°07'W). For the semi-arid Sahelian region, four vegetation classes were conducted over the UNESCO map produced by White (1983). Representatives from the following land cover types dominated in this classification: site#1-woodland (10°55'N; 14°19'W), site#2-woodland (11°026'S; 7°25'W), site#3-woodland (11°04'N; 7°42'E), and site#4-wooded grassland (11°04'N; 39°47'E) (Figure.1).

The 20-year integrated series of monthly NDVI data were extracted by averaging the NDVI values for a window of 3 by 3 pixel arrays at selected locations within each land cover type in order to characterize the seasonal variability in land cover type for each series. The database consisted of land cover classes from the vegetation maps (1:5,000,000) that were used to guide site locations by using the geo-referenced meteorological stations on the ground in conjunction with NDVI data.

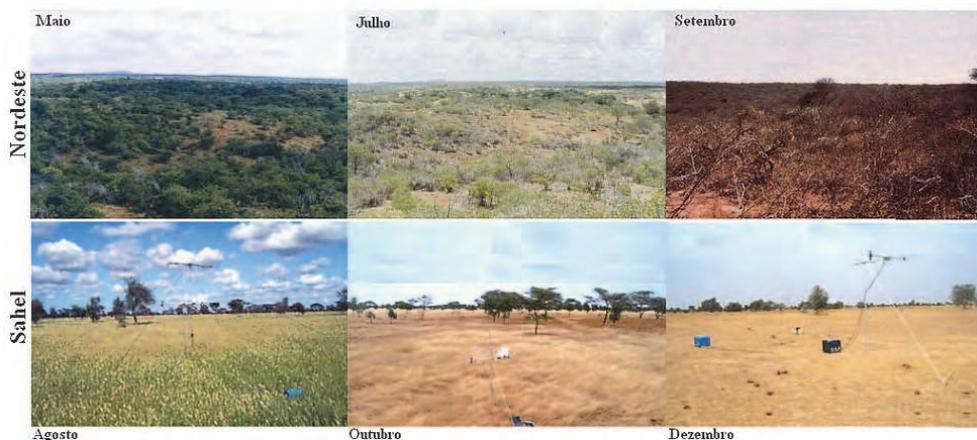


Fig. 1. The vegetation dynamic of the Brazilian Caatinga and the African Savanna is directly connected to the climatic conditions (photos). Site#1: (Nordeste Lat= $-4^{\circ}53'S$; Long= $40^{\circ}20'W$) e (Sahel Lat= $11^{\circ}76'N$, Long= $34^{\circ}35'E$).

Seasonal variations in the NDVI of Caatinga and Savanna vegetation types are illustrated in Figure 2. For each location, the average monthly values of NDVI were extracted from September 1981 to September 2001 (20-years) at a 519.84 km^2 (averaged area of nine pixels) for each site. The average monthly values of rainfall for the specific location within each land cover type are representative over the 30-year climatology period of 1961 to 1990. Both NDVI and rainfall series for the four caatinga types show a clear unimodal seasonal cycle. While the differences in magnitude of the NDVI are different over each site, the NDVI series show that phenological behavior varies slightly from north (site#1) to south (site#4). The annual total rainfall gradually varies from site#4 (549.10 mm) to site#3 (657.2 mm), to site#1 (839.13 mm) to site#2 (1046.12 mm). At these four sites, the beginning of the vegetation season is mostly driven by rainfall, while mean maximum temperature is quite constant during year and around 31°C . Moreover, the NDVI related to dry and rain seasons are very pronounced, with a minimum of 0.21 ± 0.02 over site#4 in August to October and maximum of 0.68 ± 0.02 over site#2 in April to June. On average, NDVI and rainfall have a similar pattern (both increase and both decrease together) with a lagged response due to the differences between the onset of the rainy season occurring in October or November, and the vegetation growth in November or December. Contemporaneously, from May to October there is a downward trend in NDVI values for all four Caatinga types, with the lagged response of the vegetation to rainfall being two months. While the upward trend in NDVI values is certainly due in part to stored soil moisture during the rainy season, the downward trend is likely to be more closely related to the different soil types and their physical properties.

For the West African Sahel, the seasonal pattern of NDVI for all four vegetation types closely responds to the seasonal cycle of rainfall as illustrated in Figure 2, with a peak in rainfall followed by a peak in NDVI. The majority of NDVI and rainfall series in these figures are dominated by an indistinct unimodal pattern, except for site#4 that shows two peaks. These two NDVI peaks capture the effects of two seasonal monsoons that are related

to the north-south movement of the ITCZ. The first peak occurs in early May, when the ITCZ is at its southernmost extent. The second peak occurs when the ITCZ is at its northernmost extent in early October, and is also higher than the first peak. These seasonal variations in rainfall time series represent both meteorological and geographical factors resulting a bimodal greenness pattern in the NDVI time series. The unimodal cycle of the other three selected sites show a similar phenological behavior (peaking in October), but they exhibit differences in amplitude of the NDVI time series among them.

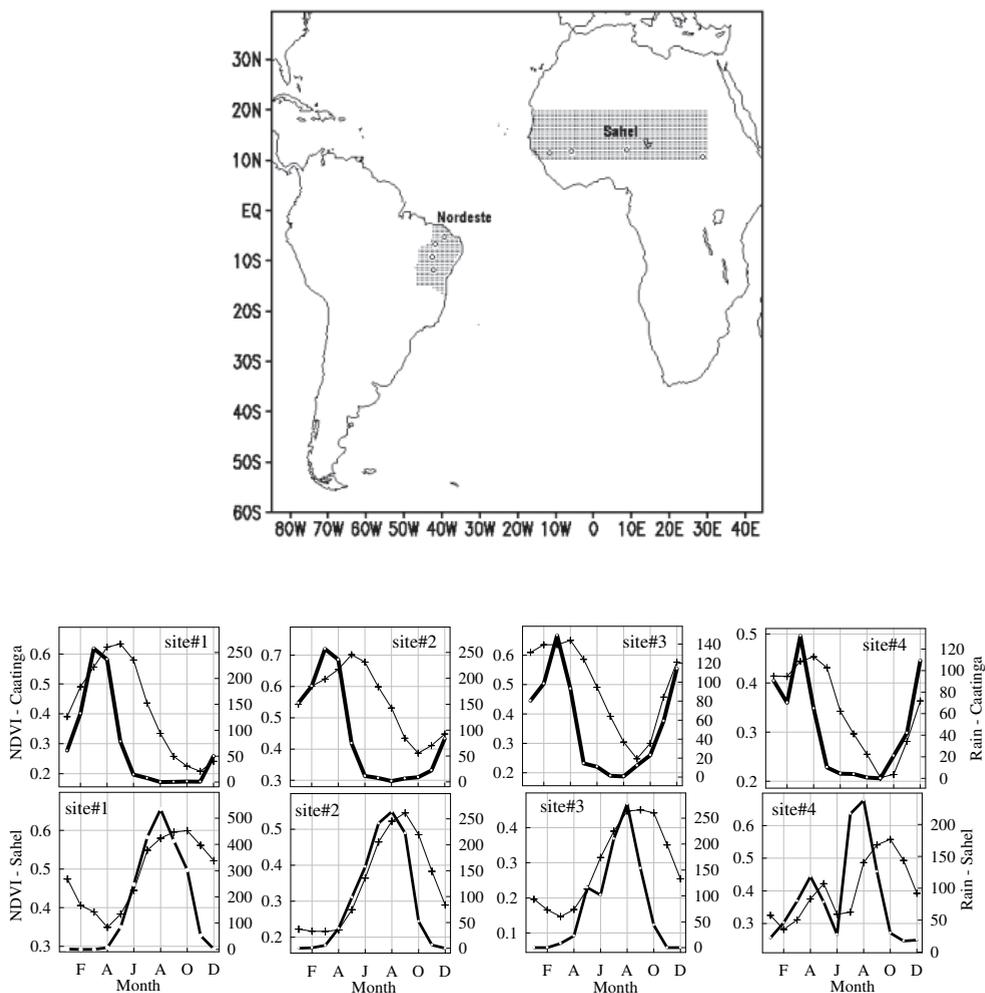


Fig. 2. Time series of monthly composites of NDVI (thin solid line) and rainfall (thick solid line). The monthly composites of NDVI relative to the 20-year Pathfinder data period from 1981 to 2001. The mean monthly rainfall values relative to the 30-year climatological period of 1961-1990.

The figures for the Caatinga and Savanna Biomes discussed above underline the relationships between surface greenness and rainfall (varying from $r^2=+0.1$ to $r^2=+0.6$, $n=360$ (rain), $n=240$ (NDVI), $P<0.05$) and lend support to the time lag between the rainfall and NDVI. The time response of the rate green up due to the rainy season (rainfall) in NDVI profile is longer for semi-arid Sertão caatinga types than Sahelian vegetation types. This is likely because the semi-arid Brazilian is dominated by deeper-rooted arboreal formations. The lagged response of vegetative activity of these deeper-rooted caatinga types to absorb the stored soil moisture is longer than the Sahelian vegetation types, which are dominated by wooded and bushed grassland (herbaceous). In contrast, the time duration of the rate of senescence in the NDVI profile, which is due to the dry season (rainfall deficit), is shorter for Sahelian vegetation type than caatinga types. This might indicate that the caatinga types, which are very drought resistant, have an additional water supply besides rainfall. It is important to note that while the same twenty-year NDVI and thirty-year rainfall periods were used for both the Sertão and Sahel regions, there is a ten-year time shift between the referenced period of the NDVI and rainfall, however, this shift was taken into consideration in our analysis.

A “see-saw” pattern can be also observed from figure 3: while the values of NDVI over the Nordeste present the peak in May, which is associated with peak of humid month, most of values of NDVI over the Sahel present the peak in August, which is associated with peak of humid month. The comparison of the Nordeste curves with the Sahel curves suggest that during the last two decades of twentieth century their Nordeste amplitudes are about half order of magnitude larger than those of Sahel. Considering the whole 1982-2001 period, the Nordeste NDVI increase during the 1980s must be primarily driven by the increase in precipitation during this period. In contrast, the most 1980s and 1990s the NDVI Sahel must be dominated by precipitation decrease. Due to its intrinsically different dynamics, Nordeste and Sahel atmospheric circulations are often regarded separately. For example, in Northeastern Brazil, the inter-annual variability of the atmospheric circulation is predominantly influenced by Sea Surface Temperature (SST) in both the Atlantic and Pacific Oceans, and has exhibited negative anomalies in rainfall during the warm phase of El Niño-Southern Oscillation (ENSO), and positive anomalies during the cold phase (La Niña). The West African Sahel, on the other hand, is mainly influenced by SST in the Indian Ocean with a portion, known as the rain belt being affected by SST in the Atlantic Ocean. Although warm events in the eastern equatorial Pacific and Indian Oceans are known to induce climatic extremes over much of Africa; the tropical Atlantic Ocean often exhibits an opposing response to ENSO which may further enhance these impacts.

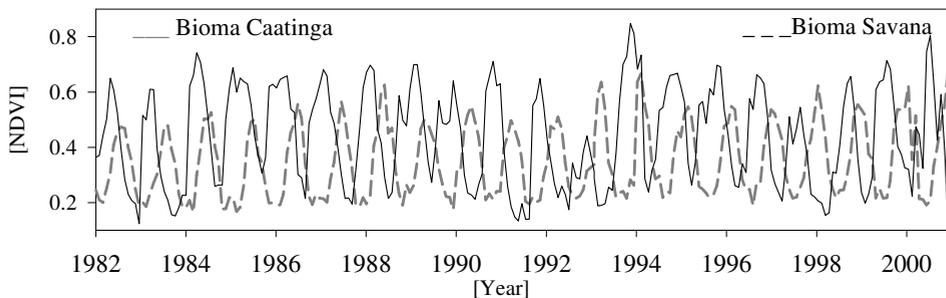


Fig. 3. Time series plot of monthly composites of NDVI over the NEB (solid line) and the Sahel (dashed line) period January 1982 through September 2001.

3.2 Linking sustainable indices and climate variability in the state of Ceará, Northeast Brazil

The rain-fed agricultural production in Northeast Brazil has experienced persistent drought episodes during the last three decades of the 20th century. However, it is necessary to assess the vulnerability of its agricultural production to precipitation variability due to interrelated global-scale fluctuations of sea-surface temperature (SST) in the tropical Pacific and Atlantic Oceans. Most of evidence presented by the recent studies on the influence of a strong ENSO event on agricultural climate of NEB is qualitatively similar to those of the Southern Africa. It is found that, there is a joint effect between the influence of a positive El Niño SST anomaly and positive gradient (SST North Atlantic warmer than South Atlantic), which tends to dramatically decrease rainfall during austral summer and autumn in the region (Alves and Repelli, 1992). While several drought spells were recorded over this region in recent history, the 20th century drought is unprecedented for its severity. Throughout the recorded history of occurrence of drought (meteorological) over this region, there were three in the 17th century, eleven in the 18th century, and twelve in the 19th and 20th centuries. It seems that in the past, the environment was more resilient to climatic variations.

In the Northeast Brazil, (Barbosa 2006, Barbosa 2004) present recent findings from satellite images which reveal a consistent upward trend in vegetation density for the period 1984–1990 and a downward trend for the period 1991–1998, but which demonstrate that such short-term vegetation changes, with a period of 7-8 years, were associated with episodes of unusually wet (years of La Niña activity) and dry (years of El Niño activity) climate oscillations. Trends in global SST patterns explain the recent period of desiccation in the Sahel, but do not present an exact explanation for rainfall in particular years. More strikingly, trends in tropical SST patterns on multi-year to decadal timescales explain the Sahelian desiccation during the last three decades of the 20th century, but do not provide an exact explanation for rainfall in individual years after 1970 (Nobre and Shukla, 1996). Although the challenge remains in confronting of climate variability for a range of locally-specific climate impacts, the understanding of the causes of this variability is still unfolding. Understanding the impact of the occurrence of extreme weather and climate events on the rain-fed agricultural production in Northeast Brazil is crucial to establishing an effective and comprehensive monitoring and early warning system as one component of an effective drought preparedness plan. Indeed, an ideal area of study is the state of Ceará in Northeast Brazil, which is already experiencing significant climate variability. This study, building on findings of previous studies about the impact of rainfall variability crop production and yields in the state of Ceará, carries the analysis of this impact one step further to evaluate connections between SST variability and the attendant impacts on its crop agriculture.

The geographic focus of this study is the state of Ceará located in the Northeast region of Brazil (Nordeste) known as an anomalous area within the equatorial zone because in contrast to other areas such as located in the Amazônia e central equatorial Africa, this state has a semi-arid tropical climate. The Brazilian semi-arid comprises approximately two thirds of the Northeast region (4° and 16° S and 33° and 46° W), which is subject to extreme climate variability and recurrent drought. The main rainy season in the region has an annual average of less than 600 mm, which is typically concentrated between February and April. The interannual precipitation variability is very high, which is usually around +/- 40% from the long term annual average. These fluctuations have motivated numerous studies that collectively documented the high spatial and temporal variability in the region's precipitation to both large-scale oceanic forcing (i.e., region-global SST anomalies and its

distribution) and atmospheric circulation patterns (Hastenrath and Heller, 1977). During strong El Niño conditions, precipitation tends to decrease (i.e., causing drought) on the state. On the other hand, the strong La Niña conditions are the opposite (i.e., causing flood). Because the high frequency and intensity of El Niño years have increased rapidly since the end-1990s, a repeat of such drought episodes may have severe consequences not only for the region's fragile ecosystems but also for the region's seasonal grain production. The great drought of 1958, for instance, forced 10 million people to emigrate from the region (Namias 1972). After 1958, droughts continued to cause severe impacts, but consequences like death casualties have been avoided by policy responses.

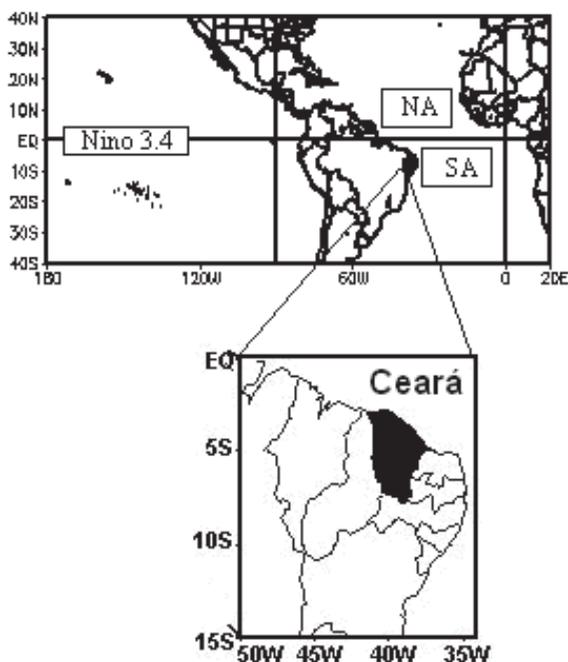


Fig. 4. Location of the state of Ceará in Northeast Brazil, Niño 3.4 and Atlantic Dipole regions (NA - SA).

Nonetheless, as the El Niño drought of 1998 demonstrated, the vulnerability of the rural population remains critically high. On the state of Ceará, around 95% of the state territory (147 thousand square km) is classified as semi-arid (Figure. 4). The state's rural population, most rain-fed farmers, is mostly located beneath the poverty line and suffers extremely vulnerability to drought (Chimelli et al., 2002).

The overall agricultural land use in the Brazilian semi-arid ecosystem is characterized by smallholder crop production and extensive livestock farming. Smallholders in the region produce about 70% of the grain production supplying the market-based agriculture, which include maize, beans and manioc. Approximately 90% of all agricultural areas are smaller than 100 ha, but they cover together only about 30% of the total agricultural production area. Since the 1950s, agricultural community in the state of Ceará has undergone profound

changes, including the growth of small farms but also the development of precarious occupation of land, which cause the impoverishment of small farmers, who have faced increasing difficulty in access to land. These changes have also aggravated the conditions for the social reproduction of this community. In contrast, in the northeast of Ceará, the agricultural community produces cash crops such as cashew, cotton, fruits and vegetables, involving various irrigation projects along the Jaguaribe River.

Total monthly maize and bean production (ton) and yields (kg/ha) from 180 municipalities in the entire state of Ceará were the raw data employed as agricultural observations. Total monthly SSTAs utilized as a climate indicator were delimited by the latitudes 170°W-120°W and longitudes 5°S-5°N (Niño-3.4 region), and also by the gradient between tropical Atlantic North (5°N-25°N) and South Atlantic (5°S-25°S) (known as the Atlantic Dipole index). Agriculture and climate time series were compiled from digital records. The former are available on the databases of the FUNCEME and the latter were obtained from a file of the Comprehensive Atmospheric Ocean Data Set (COADS) for the entire period 1971-2000. The COADS file has data of monthly averages in grade points of 1° x 1° latitude-longitude for a period of 1971 to 2000. Total monthly data are averaged from February to April.

To assess the behavior of the maize and bean production and yields in response to SSTA fluctuations in the study area, the Vulnerability Index (VI) was designated. To measure how much variation at the same rate and scale, the variables in question have deviated from the maximum and minimum values from the long-term record. This index allows a direct comparison among the different variables in question for a given period. It is calculated using the following equation, $VI_j = [(DEV_j - DEV_{min}) / (DEV_{max} - DEV_{min})] * 100$, which DEV represents the deviation that is employed as a measure of variability relative to mean value. It is calculated as the difference between the variable in question for the current time step and the long-term mean for a given period ($DEV_j = \text{variable value}_j - \text{variable value}_{\text{mean}}$). And the DEVmax and DEVmin are measured from the long-term record for a given period and j represents the index of the current time step. DEV represents the deviation that is employed as a measure of variability relative to mean value. The VI is measured in percentage (%) and it varies between 0 to 100%. It reflects, effectively, how close the VI of the current period is in relation to the long-term minimum and maximum. In addition to that, the linear correlation was applied among the variables utilized.

The averaged trimester deviations of maize and bean production from monthly values (February-April) on Ceará for the period 1971-2000 are displayed in Figure 5. The anomaly cycles of maize and bean production vary substantially during the last three decades of the 20th (Figure. 5a). The amplitude of these cycles has increased rapidly by 37% since 1983. This result is particularly striking in relation to the increasing level of maize and bean production in the study area. Nevertheless, the most dramatic decline in maize and bean production occurs before 1981, with concomitant increase in maize and bean yields (Figure. 5b). Over the entire period, the frequency distribution of anomaly for the bean production (bean yields) is in phase with the distribution of maize production (maize yields), but in less magnitude. As is indicated in Figure 5c, there is significant connection between SSTA climate patterns and crop production on the state during the rainy season. Despite the year-to-year changes coherency between extreme SSTAs and crop production, the strength of the correlation is relatively weak (average of $r = -0.42$, $n=30$). Of particular interest is the decline in maize and bean production beginning in 1971 with concomitant increased maize and bean yields that has continued through 1981 with only slight relief in 1975 and 1977. These

results provide the basis for linking seasonally changing SSTAs in Niño 3.4 and Atlantic Dipole regions directly to bean and maize production in the rainy season, when over half of the interannual change in crop production on Ceará is explained by changes in SSTAs. More substantively, changes in maize and bean production for the averaged February-April crop year are closely contemporaneous with well-known drought, specifically 1972, 1979, 1980, 1981, 1982, 1983, 1990, 1992 and 1998. Particularly, the drought of 1982-1983, a $+1.85^{\circ}\text{C}$ and $+0.47^{\circ}\text{C}$ deviations in the Niño 3.4 and Atlantic Dipole regions decreases the maize and bean production by steadily more than 135 ton, while the maize and bean yields increased steadily more than 1.5 kg/ha. The drought story for bean production on Ceará has high similarities to that for maize, but differs in that beans crop is planted and harvested earlier than maize in the rainy season, and it can also substitute partially for bean plantings in drought years. Although increasing in its overall economic importance, maize is still the second most important food staple for most of Cearense's people.

The results in Figure 6 illustrate the vulnerability of the bean production and yield in response to SSTA variability as expressed by the vulnerability index (VI). This index was able to capture the agricultural drought in response to changing in SSTAs. The larger VI for climate (Niño 3.4 plus Atlantic Dipole SSTAs), the stronger is the drought agricultural severity, which indicated by the smaller VI for crop production. In this study, when the VI for SSTAs is generally close to the long-term maximum of 160% during 1971-2000 indicate severe drought agricultural conditions (a VI of 0%). Particularly, the period 1971-1973, the value of VI for bean production decreased sharply from +89 to +49%, while the bean yield increased from +0.1 to 21%. And the value for VI climate varies from moderate humid conditions (+42%) to normal conditions (73%). It is interesting to note that the time series of VI associated with the bean production and yield show distinct differences among the early 1970s, the late 1970s, the late 1980s, and the late 1990s. Separating the fluctuations of VI from varying lengths and intensities, the period 1977-1983 is clearly the worst agricultural drought of the last three decades of 20th. The period 1984-1989 was the optimal agricultural production, broken only by the intense agricultural drought of 1987. Total seasonal maize and bean production are inversely correlated with Niño 3.4 ($r = -0.49$ and $r = -0.36$, $n=30$, $p < 0.05$) and Atlantic Dipole indices ($r = -0.42$ and $r = -0.41$, $n=30$, $p < 0.05$), while maize and bean yields are directly correlated with Niño 3.4 ($r = +0.32$ and $r = +0.34$, $n=30$, $p < 0.05$) and Atlantic Dipole indices ($r = +0.32$ and $r = +0.46$, $n=30$, $p < 0.05$), but inversely related with maize and bean yields ($r = -0.67$ and $r = -0.74$, $n=30$, $p < 0.05$) averaged from February to April.

As suggested by Figure 7, seasonal changes associated with VI for Niño 3.4 and Atlantic Dipole SSTA regions show distinct differences from the early 1970s to the late 1970s and from the late 1980s to mid-1990s, with a transition during 1982-1983. Prior to 1982-1983, year-to-year changes in bean production and yields are primarily associated with North Atlantic SSTA variability (a positive gradient - North Atlantic warmer than South Atlantic- which leads to a decrease in precipitation on the state) that is often, but not always, reduced by La Niña variability (a cold ENSO variability - La Niña conditions - which leads to an increase in precipitation on the state). After 1982-1983, year-to-year changes in bean production and yield reflect the influence of seasonally changing SST associated with ENSO variability (an El Niño and a La Niña variability) that is irregularity amplified (reduced) by North Atlantic variability (South Atlantic variability- a negative gradient-North Atlantic cooler than South Atlantic which leads to an increase in precipitation on the state).

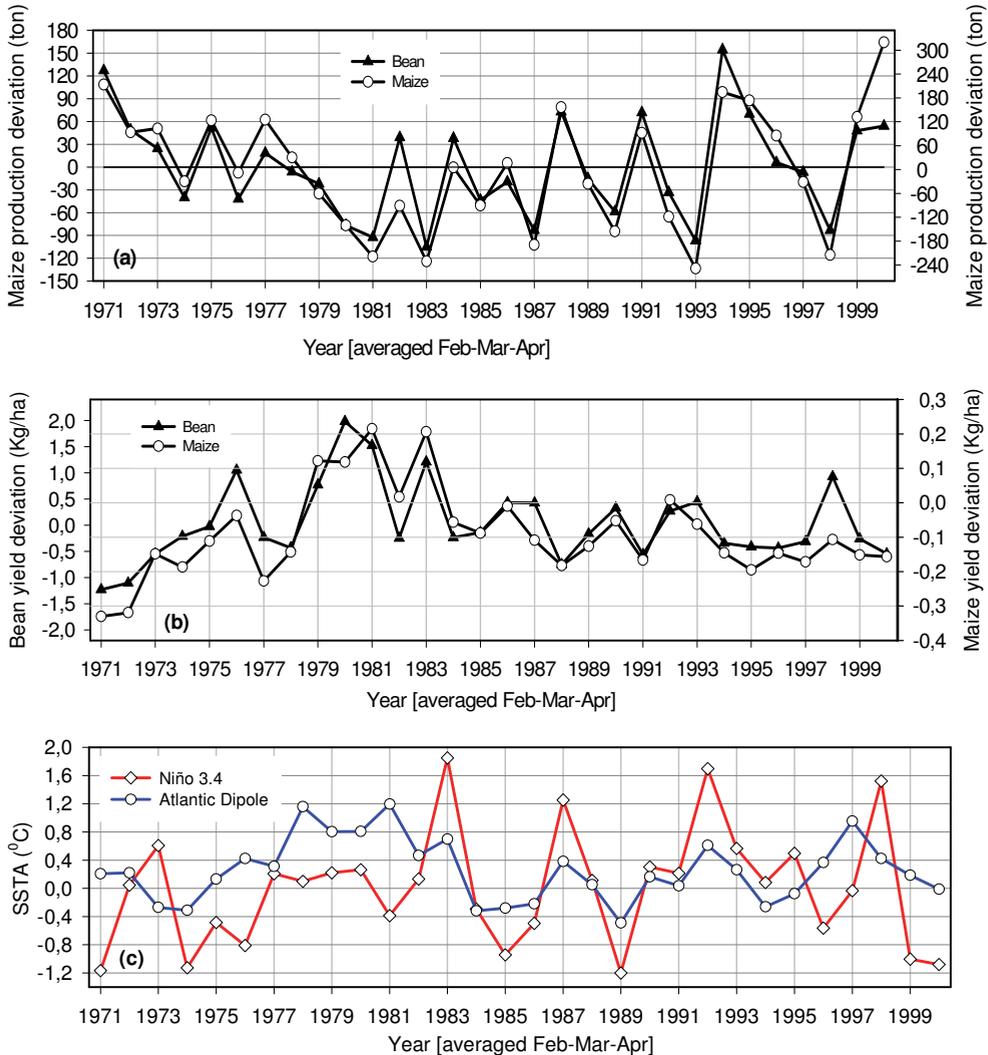


Fig. 5. Normalized deviations (anomaly). (a) Maize and crop production (ton), (b) Maize and crop yields (Kg/ha), and (c) SST ($^{\circ}$ C) in Niño 3.4 and Atlantic Dipole regions for the period 1971-2000, state of Ceará.

These large fluctuations associated with VI for Niño 3.4 [VI values close to 0% (or 100%) lead to a La Niña (or an El Niño)] and Atlantic Dipole [VI values close to 0% (or 100%) lead to a negative gradient (or a positive gradient)] vary almost in-phase for the period from 1985 to 1997, apart from the period 1998 to 2000, when the two VIs are out-phase. The warm phase of the North Atlantic beginning around 1977 is readily associated with the agricultural drought beginning in 1977. The worst drought is the 1983 (a VI of 160%) from 1971 to 2000, which was strongly affected by persistent anomalous warming SST in the

North Atlantic Ocean beginning in 1977. Despite the droughts, the increase in bean production between 1984 and 2000 is striking. Severe droughts (1987, 1992, and 1998) alternated with relatively humid years (1985, 1989, and 1995). This indicates that recovery of rain-fed agricultural production from persistent droughts has been enhanced since about 1983. Moreover, these long-term fluctuations were in phase with global climate variability, specifically, ENSO and the North Atlantic variability. Therefore, the vulnerability of rain-fed agricultural production on Ceará to changing SSTAs and its recoverability after persistent droughts suggest that the long-term rain-fed agricultural production of the Ceará state may be predictable.

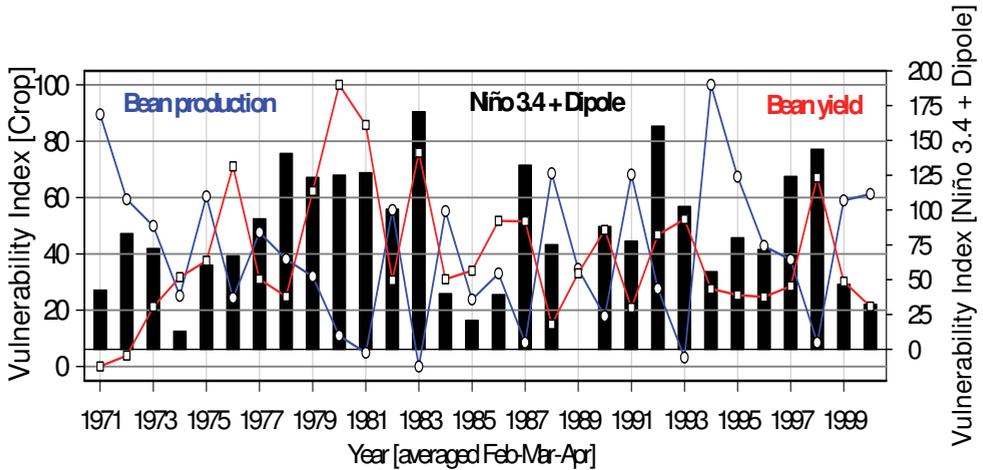


Fig. 6. Vulnerability Index (VI). (a) Bean production (ton), (b) Bean yield (Kg/ha), and (c) Niño 3.4 plus Atlantic Dipole SSTA (°C).

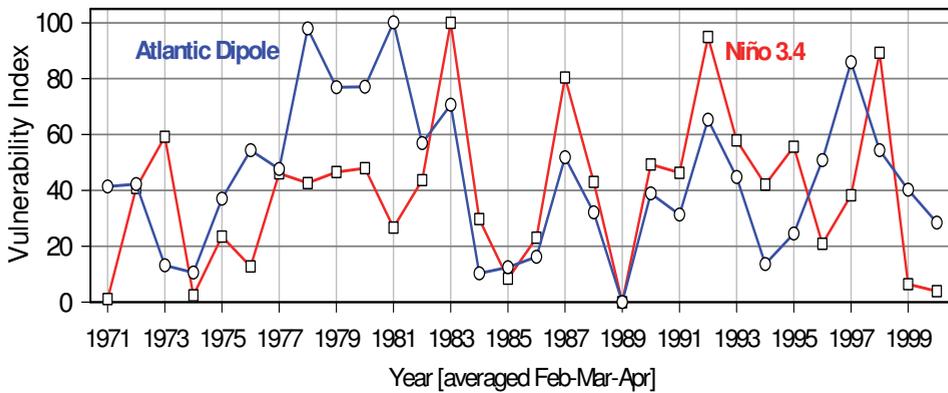


Fig. 7. Vulnerability Index (VI). Niño 3.4 SSTA (°C) and Atlantic Dipole SSTA (°C).

3.3 NDVI as an indicator of crop performance

10- day composite NDVI with 8km resolution retrieved from AVHRR which are supplied by Space Application Centre, Ahmedabad, Indian Space Research Organization (ISRO), Govt of India are used here from 1999 to 2001 during south west monsoon period (June, July, August and September) over Andhra Pradesh, India. Since nearly 80% of annual rainfall is from south west (S-W) monsoon in Andhra Pradesh (Sarma & Lakshmi Kumar, 2010), the present study is focussed during this period.

The study has been carried out at different test sites of Andhra Pradesh state (13S-20S; 77E-84N), covers the parts of Eastern Ghats and Deccan Plateau of India, namely Anantapur (ANT), Ramagundam (RGD), Hyderabad (HYD), Nizamabad (NZB), Kurnool (KRN), Nellore (NLR), Ongole (ONG), Kakinada (KKN), Machilipatnam (MPT) and Visakhapatnam (VSK) that are located in Figure.8.

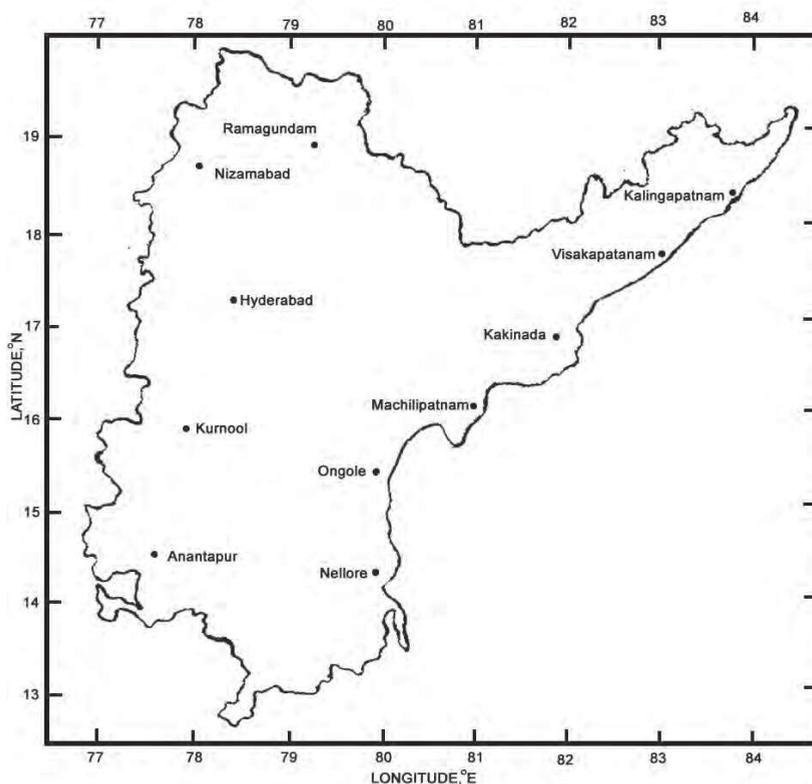


Fig. 8. Study region and locations of test sites – Andhra Pradesh State, India.

The rainfall and potential evapotranspiration data on daily basis were collected for the period 1999 to 2001 and are subjected to determine the crop growing periods. The model identifies the growing period when rainfall exceeds 0.5 times the water need (potential evapotranspiration) and ends with the utilization of assumed quantum of stored soil moisture and the categorization within the growing period is given below.

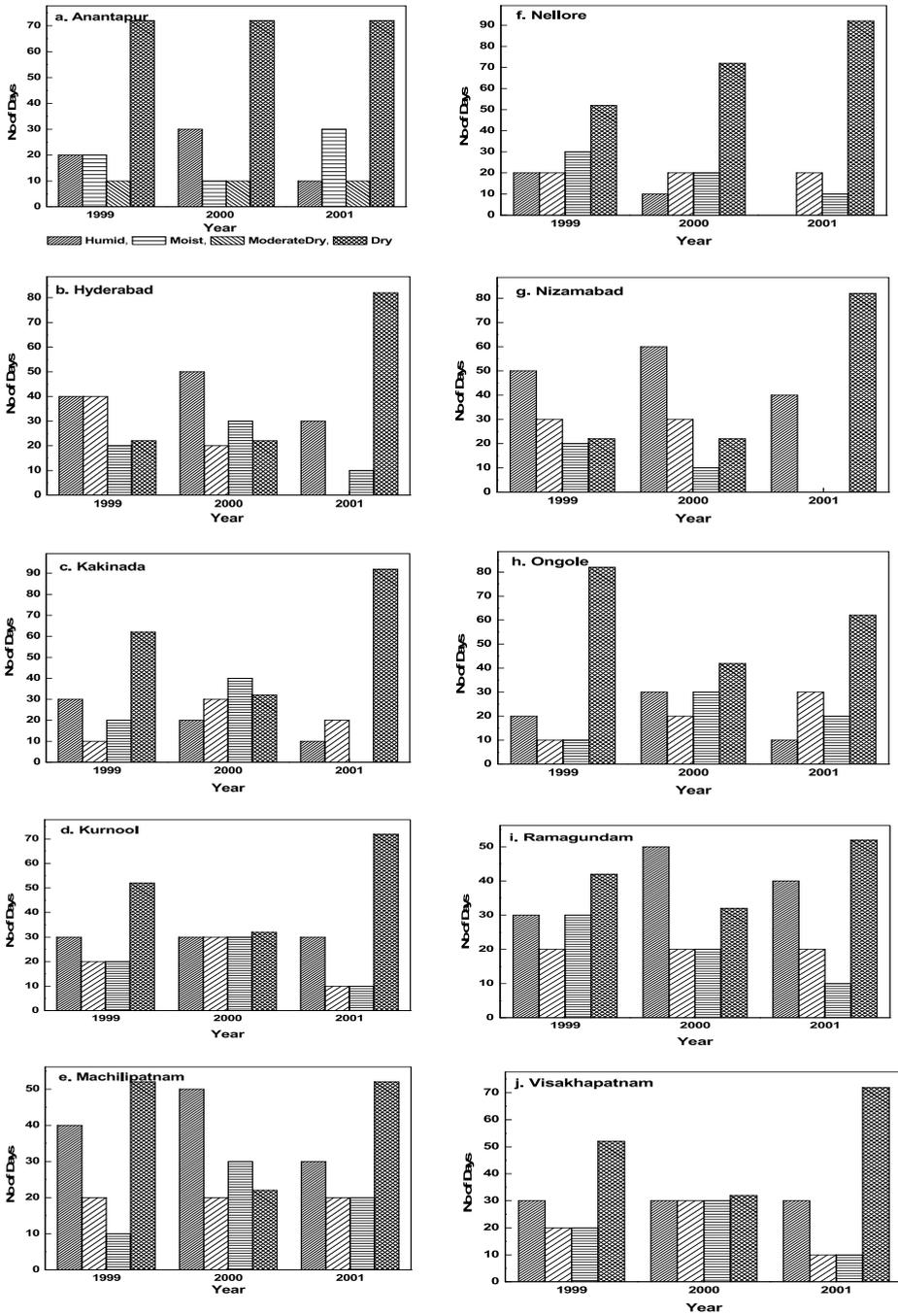


Fig. 9. Crop growing periods of different test sites during southwest monsoon.

If rainfall (P) is

- i. > PE -----Humid period
- ii. ½ PE to PE -----Moist period
- iii. ¼ PE to ½ PE -----Moderate Dry period
- iv. < ¼ PE -----Dry period

The agroclimatic potentiality, soil moisture adequacy is derived using the revised water balance model (Thoronthwaite and Mather, 1955) with the inputs of rainfall and potential evapotranspiration and is calculated by the following formula

$$S_{AD} \text{ in } \% = AE/PE \times 100,$$

Where AE is Actual Evapotranspiration and PE is Potential Evapotranspiration.

The following part dwells first in obtaining the crop growing periods by using rainfall and potential evapotranspiration and secondly the comparison of NDVI with agroclimatic potentialities such as rainfall and soil moisture adequacy to understand how sensitive is NDVI to the crop performance.

3.3.1 Crop growing periods from Higgins & Kassam model

Figures 10 (a-f) show the number of humid, moist, moderate dry and dry days during the south west monsoon season where the crops are subjected in for the years 1999 to 2001. In almost all the years, the dry days dominated the entire season which is expected and the relevance here is about the humid and moist days which play major role in the growth of the crop. The climatology of Andhra Pradesh infers that Anantapur, Kurnool, Nellore, Ongole are in dry subhumid zone where as the other test sites such as Mahaboobnagar, Hyderabad, Kakinada, Nizamabad, Machilipatnam and Visakhapatnam are in moist subhumid zones (Sarma & Lakshmi Kumar, ISRO RESPOND Report, 2005).

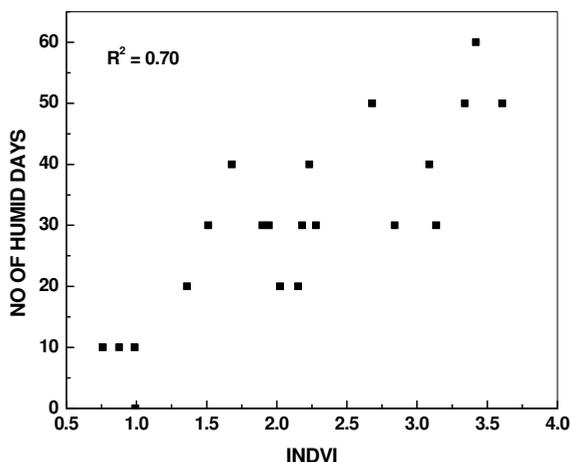


Fig. 10. Scatter plot of INDVI and the number of humid days for all the test sites – Andhra Pradesh.

In accordance with the climatology, the maximum number of humid days where the rainfall dominates the potential evapotranspiration is high in Hyderabad (40days), Nizamabad (50days) and Machilipatnam (40days) while compared with Anantapur (20days), Ongole

(20days) and Nellore (20days). There is no much difference observed in the moist and moderate dry days during the study period.

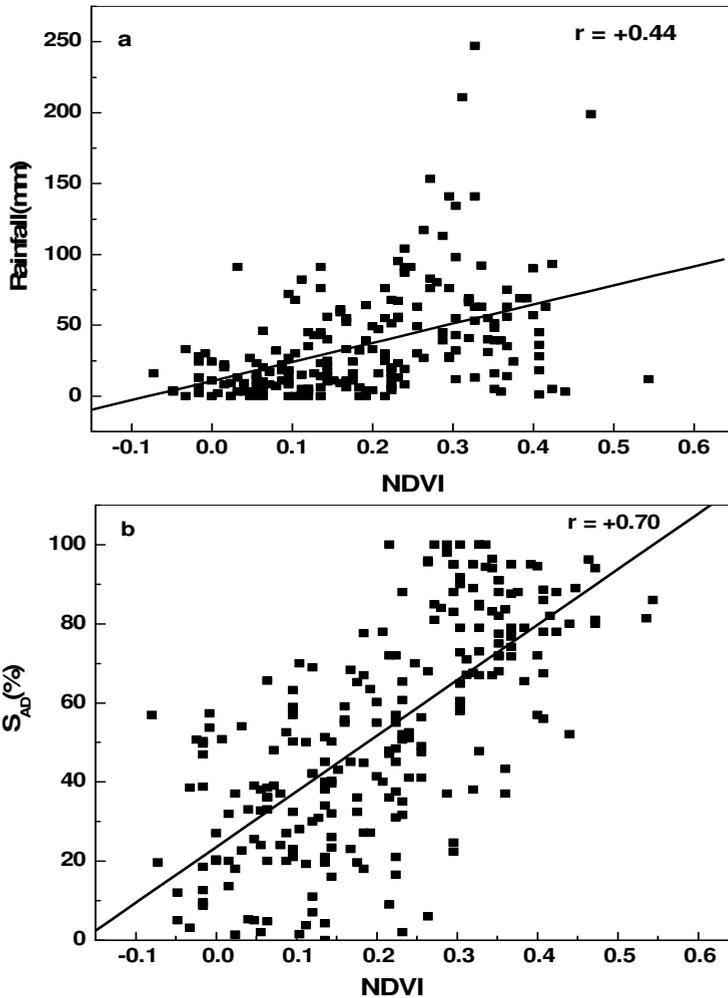


Fig. 11. Correlation of NDVI with a) rainfall and b) Soil moisture adequacy.

Among three years of study, it is unraveled that most of the stations recorded more number of humid days such as Nizamabad (60 days), Ramagundam (50 days) and Machilipatnam (50 days) in the year 2000. This is the reason in the year 2000, Andhra Pradesh is found as the wet year during 1999 to 2001 by means of daily water balance analysis. The number of humid, moist and dry (moderate dry+dry) days are subjected to scatter plot for all the stations with the Integrated NDVI (INDVI) values to understand the mode of response of NDVI during these days. The INDVI is nothing but the sum of the all 10-day composites of NDVI for that particular test site, and the scatter plots inferred the alignment of INDVI with

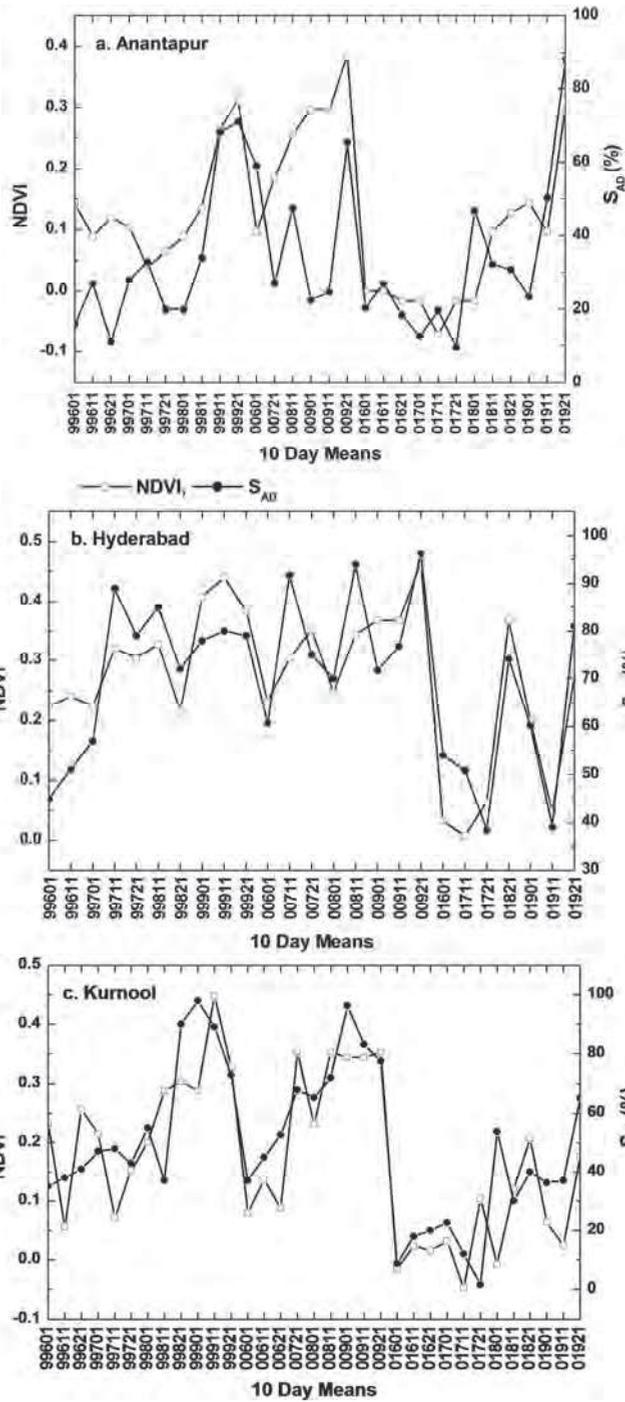
the number of humid days, for the other categories, such as moist and dry days, the plots are much scattered which tells the poor relation with the vegetation indices. The scatter plot for INDVI and number of humid is given in Figure.10 along with the variance which is found to be high ($R^2 = 0.70$).

Test site	Rainfall and soil moisture adequacy during the year						Average during	
	1999		2000		2001		1999 -2001	
	P	S _{AD}	P	S _{AD}	P	S _{AD}	P	S _{AD}
Anantapur	0.67	0.83	-0.35	-0.02	0.78	0.76	0.50	0.59
Hyderabad	-0.09	0.32	-0.67	0.63	-0.27	0.84	-0.28	0.80
Machilipatnam	0.08	0.57	0.50	0.63	0.61	0.70	0.28	0.58
Kurnool	0.67	0.63	-0.30	0.87	0.50	0.43	0.46	0.79
Nellore	0.27	0.34	0.69	0.47	0.21	0.49	0.54	0.63
Nizamabad	-0.3	0.58	-0.34	0.36	-0.15	0.69	-0.15	0.65
Ongole	0.66	0.66	0.13	0.40	0.56	0.83	0.50	0.63
Ramagundam	-0.09	-0.19	0.02	0.43	0.53	0.71	0.34	0.67

Table 1. Correlations of rainfall and soil moisture adequacy (%) with NDVI.

3.3.2 Relation of NDVI with agroclimatic potentialities

An attempt has been made to relate the Normalized Difference Vegetation Index (NDVI) with the rainfall to understand the vegetation growth with the changes in rainfall. The Pearson correlation is obtained between 10-day NDVI and rainfall values and are tabulated in Table. 1. The positive correlation from the table tells us the vegetation is dependant on rainfall. Test sites such as Anantapur, Nellore and Ongole showed considerable correlation compared to other sites. The negative correlation in a few case may be due to heavy rains that manifest the higher rates of run-off, particularly when soil is moist and also because of irrigated areas. The overall correlation for entire Andhra Pradesh is +0.44 (Figure 11(a)), which is also not substantial. So, to reinstate the NDVI and climate relationship, an effort was put up with the soil moisture adequacy, which is the more appropriate parameter since it actually gives the amount of water that crop takes for its growth and is a measure of crop growing season. The correlation is very strong in the cases of both All Andhra Pradesh ($r = +0.70$) (Figure 11(b) and individual test sites. Also, the plots of NDVI with the soil moisture adequacy for each test site is given in Figure (12). From the Figure (12), it can be known that the soil moisture adequacy maintained a very good agreement with NDVI. A maximum of 0.54 of NDVI with the moisture adequacy of 80% in moist subhumid region and a maximum of 0.45 (NDVI) with the corresponding S_{AD} of 88% in dry subhumid region are observed respectively. Among all stations, Nellore and Ongole registered low NDVI values during the three years of study period. It can be seen that the moisture adequacy of Nizamabad, Ramagundam and Nellore has not responded to NDVI very well during the year 1999. The reason for this poor relation might be not only the lack of inter coupling between vegetation and land surface but also the moisture recycling phenomena that paves way in keeping the wet condition over the land. This shows that the soil moisture adequacy is the robust parameter, since it signifies the extent of meeting the water requirement of the place and on which the crop/vegetation performance has bearing.



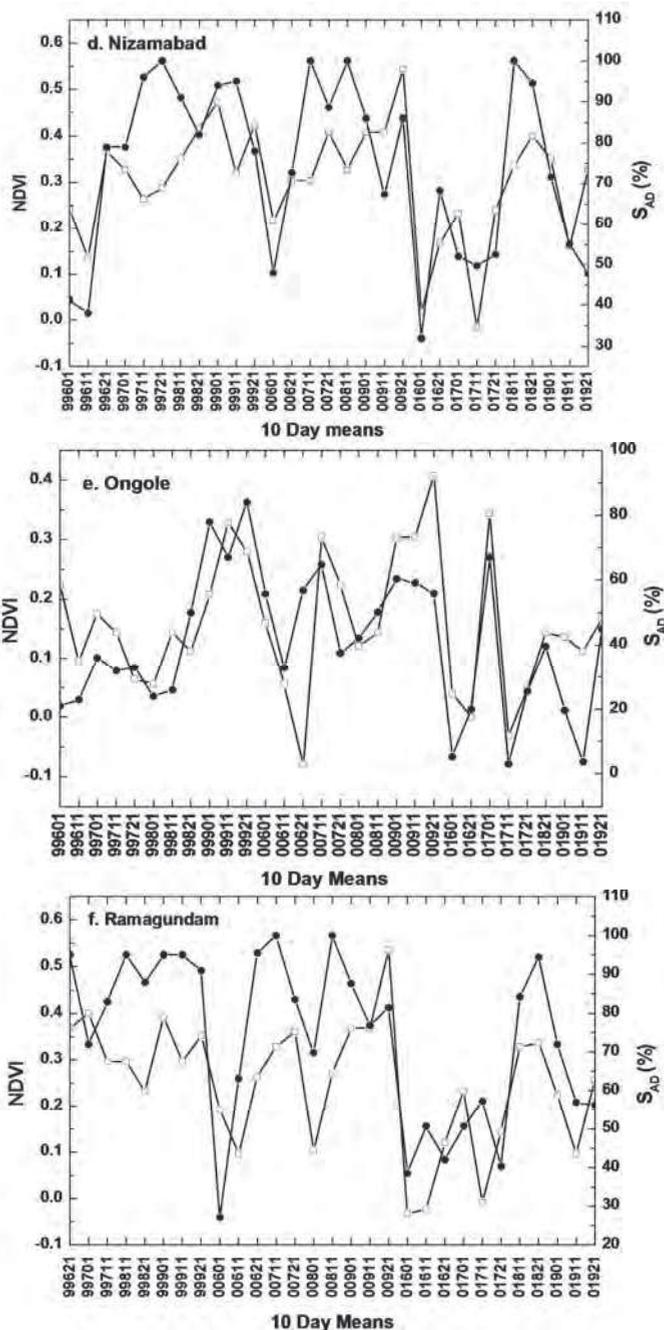


Fig. 12. NDVI and soil moisture adequacy (S_{AD} %) S-W monsoon of 1999 to 2001 (x-axis represents year/month/day).

3.4 Drought monitoring from brightness temperature data

The aim of this study is to estimate soil wetness using remote sensing data. Since the microwave penetrates the earth's surface, this can be used to measure the moisture content available in the soil. The BT data has been collected from the Space Application Centre for the June, July and August months and accordingly the study is made. The established relation which was mentioned in earlier section that the Brightness Temperature is inversely proportional to the soil wetness present in the soil, and understanding the variations in Brightness Temperature leads to assess the soil moisture. Here also the study has been carried out in Andhra Pradesh at different test sites and a linear regression model is developed to estimate the soil moisture from brightness temperature so as to understand the drought conditions.

3.4.1 Deriving soil wetness – Water balance model

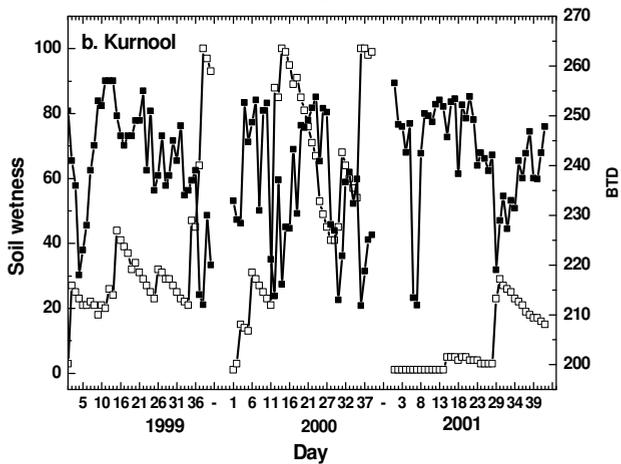
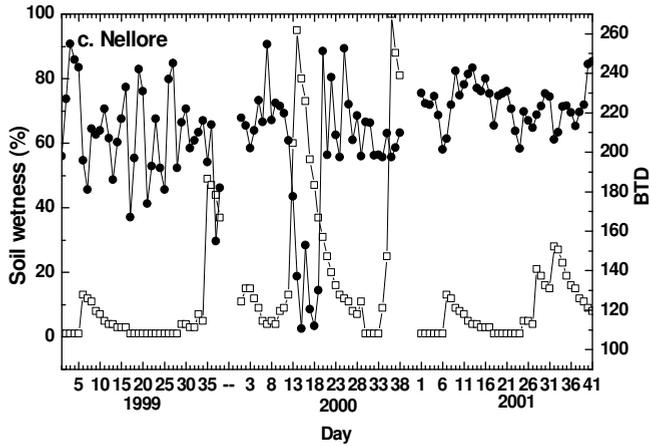
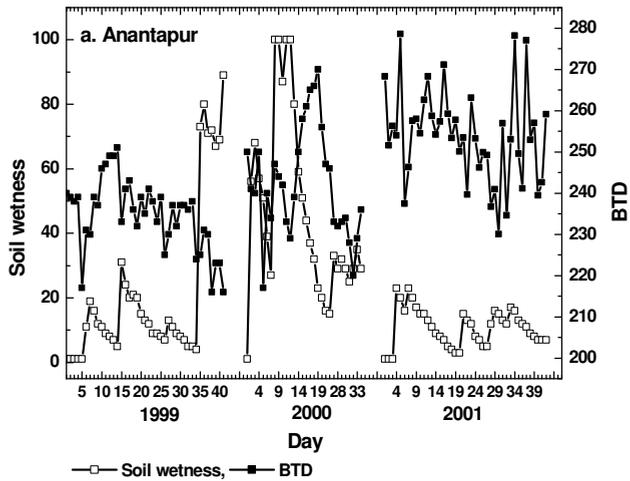
Water balance analysis is accounting of water received in the form of rainfall and expending for evaporation, recharging the soils, surface and subsurface run offs. The modified water balance model as suggested by Sarma et al. (1999) is followed for the land phase of the hydrological cycle and is used in obtaining the surface hydrological fluxes. The budget considers the amount of available water stored in the soil root zone as well as any change in the amount of this storage. It also calculates any surplus of water that is not evaporated, stored or transpired. Water deficit is calculated as part of the budget, because it represents the additional amount of water that plants could have used if it had been available. While these are important parameters associated with the water budget, the primary concept behind the budget is to determine potential evapotranspiration (PE) from the revised concept of Thornthwaite and Mather (1955) and to estimate the soil wetness. Once the storage of water is determined, the percentage of soil wetness can be calculated by following expression,

$$S_{WT} = S_T / F_C \times 100,$$

where S_T is storage and F_C is field capacity of that particular region.

3.4.2 Comparison of soil wetness and brightness temperature data

The temporal variations of Brightness Temperature and soil wetness for the test stations are presented in Figure (13). Ramagundam (Figure 13(e)) and Kurnool (Figure 13(b)) showed the maximum BT of 257K for the 1% soil wetness in the year 2001 and the minimum of 192K and 212K for the soil wetness of 100% in 1999 and 2000 respectively. Ongole (Figure 13(d)) experienced maximum BT of 265K for a soil wetness of 19% in 2001 and a minimum BT of 195K for 100% soil wetness in the year 2000. The BT of Anantapur (Figure 13(a)) showed the highest at 278K for a soil wetness of 5% in the year 2001 and lowest at 216K for soil wetness of 89% in 1999. Nellore (Figure 13(c)) registered a maximum BT of 255K for a soil wetness of 1% in the year 1999 and a minimum at 197K for the corresponding soil wetness of 80% in the year 2000. From the present study, it is known that the BT is mostly varying from 190K to 225K for more than 75% soil wetness and from 250K to 278K for the poor soil wetness (1 to 20%). Both undisputedly, have inverse relation. So, it is evident that the BT of the wet lands with high soil wetness can vary from 192K to 225K and for dry lands, from 250K to 280K.



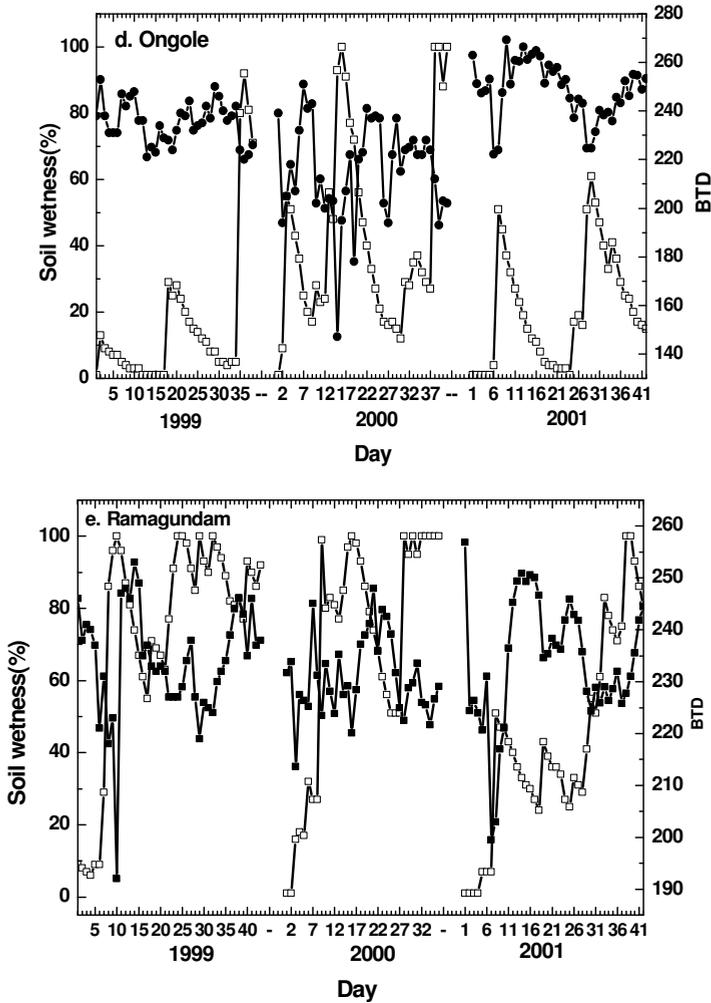


Fig. 13. NDVI and soil wetness – S-W monsoon season of 1999 to 2001

The correlation co-efficients between soil wetness and brightness temperature along with the regression expressions for the selected stations for south-west monsoon period (June to September) of 1999 to 2001 are given in Table.2. The degree of relation between soil wetness and BT is an inverse one i.e as the soil wetness increases, BT decreases and vice versa. Anantapur showed minimum correlation of -0.42 while Ongole recorded the maximum correlation of -0.63 compared to the remaining.

A regression model is developed by taking all the data points of BT and soil wetness from June 1999 to August 2001 to determine the soil wetness using BT over Andhra Pradesh(Figure 14). the correlation in this case is -0.61 which is at 0.01 level of significance and the regression expression is given in the table.

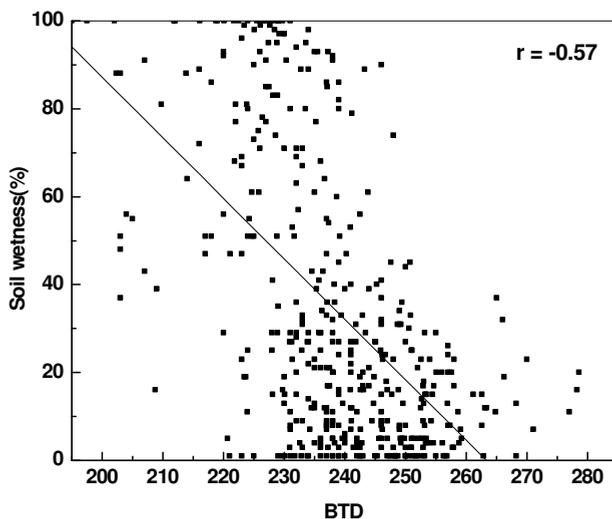


Fig. 14. Linear fit of Soil wetness and BT - Andhra Pradesh

Test site	Correlation (r)	Regression for 1999 to 2001	
		SWT as independent Variable	BT as independent variable
Anantapur	-0.42	$BT = 249.5 - 0.28(S_{WT})$	$S_{WT} = 174.7 - 0.63(BT)$
Kurnool	-0.55	$BT = 247.9 - 0.2(S_{WT})$	$S_{WT} = 398.8 - 1.5(BT)$
Nellore	-0.52	$BT = 220.6 - 0.68(S_{WT})$	$S_{WT} = 96.0 - 0.39(BT)$
Ongole	-0.63	$BT = 245.7 - 0.46(S_{WT})$	$S_{WT} = 231.1 - 0.87(BT)$
Ramagundam	-0.43	$BT = 242.7 - 0.14(S_{WT})$	$S_{WT} = 376.0 - 1.3(BT)$
Andhra Pradesh	-0.56	$BT = 246.4 - 0.24(S_{WT})$	$S_{WT} = 362.4 - 1.4(BT)$

Table 2. Correlation and regression statistics for BT with soil wetness (S_{WT}) for the test sites in Andhra Pradesh.

4. Conclusions

It is reported by the scientific community that there is a significant climate change and variability from which one has to learn lessons on how to tackle it. The importance of the rate of climate change can be understood by comparing the affected systems. Satellite-based observations provide a key source of data at global scales of the earth's environment, climate change, and the provision of climate services. However, observational data collected from satellite should be integrated with in-situ data. In many developing countries, a key constraint is the lack of professional and institutional capacity to make the best use of available information and knowledge for decision making. A particular difficulty is providing incentives to attract qualified staff to remote areas, far away from capital cities, where good decision making often is most critical. Local/national networks are useful for taking cognizance of local hotspots and making operational decisions on issues that relate to

climate variability and change, while global change studies with satellite-based measurements are useful for international comparative assessments. In this context, it ought to strengthen the regional capacities towards decision making about the forthcoming frequent disasters due to climate change. As a result, decision making in the land surface resources could be improved through: i) developing information systems on areas that are prone to drought, and vulnerable to disasters, ii) long term understanding on land degradation because of deforestation and increased urbanization, iii) developing disaster preparedness in view of risk management, iv) development of early warning systems by utilizing the real time satellite data, to mitigate disasters like floods etc, v) assessment of crop failures during early, mid and late seasons, so as to prefix the mitigation measures and vi) educating communities about climate change and variability for better linkage of satellite data with the ground level ones for effective monitoring of drylands.

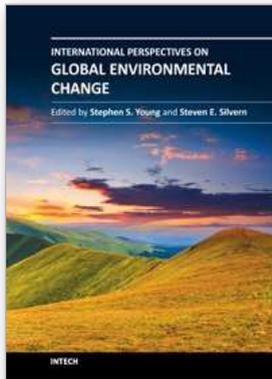
The use of satellite data into land resources decisions must be driven by the needs of the decision makers. Incorporation of satellite data by the land surface resources community requires an understanding of the particular decisions that are faced and the relevant timescales and skill needed to provide decision support. This can only be accomplished through close collaboration between operational land managers and decision makers. Researchers will not have a sense for whether this is true without understanding the needs of the user community which is achieved through close collaboration. Case studies of the incorporation of satellite land surface techniques, in combination with in-situ data, at international level are needed. In view of the above, the present chapter deals with the utilization of satellite data in i) understanding the vegetation dynamics, ii) vegetation response to climate, iii) connection with the agroclimatic indices and iv) underlying land surface processes. The established relations drawn from this chapter are of immense use in studying arid lands from the remote sensing point of view. Since the satellite indices (NDVI & BTI) are proven as the best variables, in accordance with the agrometeorological indices such as rainfall, soil moisture adequacy and soil wetness, they serve as inputs for policy makers. The relation of Brightness Temperature with soil wetness can be applicable in deciding the water supplement of a region. The crop phenological stages that can be studied by NDVI are of great use in assessing the crop health (fair / optical / poor). The response of NDVI to weather can guide in the designing of the agrometeorological advisories. Thus, the provision of remote sensing decisions over drylands will be strengthened by analysing the satellite data carefully can help in the improvising of systems where such satellite derived data can be used for multiple operations. The "lessons learned" from such studies provides critical guidance for enhancing the monitoring of the effects of climate change on land resources, through exploitation of satellite data. Another valuable impact is the enhancement and broadening of international research partnerships in order to encourage scientific exchange.

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