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Spatial and temporal assessment of drought in the Northern highlands of Ethiopia

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ABSTRACT

With the development of global changes, researchers from all over the world increasingly pay attention to drought detection, and severe droughts that may have resulted from climate change. In this paper, spatial and temporal variability of drought is evaluated based on precipitation data and remotely sensed images. The standard precipitation index (SPI) and vegetation condition index (VCI) are used to evaluate the spatial and temporal characteristics of meteorological and vegetative drought in Tigray, Northern Ethiopia. Based on the drought critical values of SPI and VCI defining drought, the spatial and temporal extent of droughts in the study area is established. We processed 396 decadal images in order to produce the multi-temporal VCI drought maps. The results of the SPI and VCI analysis reveal that the eastern and southern zones of the study region suffered a recurrent cycle of drought over the last decade. Results further show that there is a time lag between the period of the peak VCI and precipitation values obtained from the meteorological stations across the study area. A significant agreement was observed between VCI values with the current plus last two-months of precipitation. The study demonstrates the utility of the vegetation condition index in semi-arid and arid regions.

1. Introduction

Although the name “Water Tower of Africa” has been given to Ethiopia, the country is one of the Horn of Africa countries that is highly vulnerable to drought. The country’s main economic activity, agriculture, is overwhelmingly dependent on the timely onset, amount, duration and distribution of rainfall. An incident of drought generally implies substantial and extended deviation from the normal rainfall pattern, which affects crop production and vegetation growth.

In Ethiopia drought is a frequently recurring phenomenon. It is the single most important climate related natural hazard impacting on the country from time to time. Historical drought events reveal that Ethiopia frequently faces drought and famine. In the past nine centuries there were about 30 major drought episodes. Of these drought episodes 13 of them are known to have covered the entire nation and they were reported as severe. From 1970 onwards, drought hit the country at least once in every 10 years during the last years the event is becoming even more frequent. It is now recurring every two or three years at different levels of intensity (Margaret, 2003). In recent years the spatial extent and frequency of droughts have both increased causing significant water shortages, economic losses and adverse social consequences.

Climatic conditions during drought years are characterized by either almost total failure of rainfall or a late or too early onset of inadequate rainfall during both the short and the main rainy seasons locally known as “Belg” and “Kiremit”. A continuous dry spell or poor rainfall in successive years hinders ground-water recharge and imparts stress on ground-water resources leading to severe water deficit in many parts of the region during both the wet and the dry seasons.

The droughts of the last decades have produced a complex impact, which spans many sectors of the economy, especially the agriculture sector. Droughts of the year 1984–1985 took the lives of an estimated one million people, destroyed crops, contributed to the death of animals, and threatened the lives of millions of people with starvation. The drought caused the then biggest famine affecting an estimated 5.8 million people forcing them to be dependent on food hand-outs or food aid (Benson, 1998). As a result, a considerable part of the society proved vulnerable to famine that in turn caused a deep-seated destitution. The recent drought of 2002–2003 with affected 13.5 million people showed once more the magnitude and the proportion of the problem (Wagaw et al., 2005).

The chronology of Ethiopian drought history further indicates that most of the drought and food crisis events have been geographically concentrated in two broad zones of the country. The first consist of the central and northern highlands, stretching from northern Shewa through Wello and Tigray, and the second consists of low-lying agro-pastoral lands ranging from Wello in the north, through Hararghe and Bale to Sidamo and Gamo Gofa in the south

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(Ramakrishna and Assefa, 2002). They indicated the eastern and northern parts of the country as the most vulnerable.

Major parts of Northern Ethiopia experience year-round water deficit. Drought is frequent due to abnormally low and untimely rainfall. Even commencement of rainfall at the right time cannot guarantee a drought-free season since frequency, intensity; amount and duration of rainfall all play crucial roles in the occurrence of drought. Tigray region is dry for most of the year except during the rainy season, and exhibits a semi-arid climate. Recurrent droughts form the major threat to rural livelihoods and food security in the region. Almost every year, the study region experiences localized drought disasters causing crop failure and jeopardizing development activities. The region's agro-ecosystem is highly sensitive to rainfall fluctuations and even a slight change has a large impact on the socio-economic activities of the region. As a result, rural livelihoods and agricultural systems in the region are subject to continuous and widespread disequilibrium dynamics.

Despite the fact that drought forms the major uncertainty that farming households have to deal with, it has attracted little scientific attention and no attempts have been made to quantify the spatial and temporal characteristics of drought within the study region. Furthermore, recent studies reveal that climate change in Ethiopia could lead to extreme temperatures, extraordinary rainfall events, and more intense and prolonged droughts and floods (UNDP, 2008). Thus, expected changes in spatial and temporal patterns of precipitation can trigger new characteristics of drought in affected regions. Consequently, the need for a drought assessment and monitoring mechanism is crucial to minimize socio-economic losses. This can be achieved by developing drought indices that are capable of characterizing and timely assessing drought at different spatial and temporal scales.

This paper attempts to provide a detailed analysis of seasonal drought dynamics in order to identify the spatial and temporal characteristics of drought over the last decade by employing standard drought index methods with meteorological and remote sensing data. Despite the fact that in literature several indices are used for monitoring and assessment of drought, in this study the standardized precipitation index (SPI) and the normalized difference vegetation index (NDVI) are used to analyze meteorological and vegetative drought respectively. Since agricultural activities and ecological changes are controlled by rainfall, our analysis focuses on drought during the wet seasons. In this study, drought is considered to be a meteorological phenomenon characterized by prolonged periods of abnormal precipitation deficit. To our knowledge this paper is the first research attempt to develop reliable drought information linking meteorological and remote sensing indices enabling us to identify and to map spatial and temporal aspects of droughts for Tigray region. It is our view that development of a drought monitoring system, based largely on meteorological and remote sensing data, can be a great aid for early assessment of drought impacts.

1.1. Calculation of the standard precipitation index (SPI)

A variety of indices using meteorological data have been used to quantify droughts (Heim, 2002). However, the most widely used today is the SPI (McKee et al., 1993, 1995), which is now considered as the most reliable index for measuring the intensity, duration and spatial extent of drought (Guttman, 1998; Lloyd-Hughes and Saunders, 2002). This index enjoys several advantages over the others. Calculation of the SPI is easier than on more complex indices such as the Palmer drought severity index (PDSI) (Palmer, 1965), because the SPI requires only precipitation data, whereas the PDSI uses several parameters (Souleĭ, 1992). Moreover, the PDSI has some shortcomings in spatial and temporal comparability (Alley, 1984; Karl, 1986; Guttman, 1998). However, the SPI provides a comparison of the precipitation over a specified period with the precipitation totals of the same period for all the years available in the historical record. The SPI is comparable in both time and space, and it is not affected by geographical or topographical factors (Lana et al., 2002).

The SPI is a probability index that considers only precipitation. The probabilities are standardized so that an index of zero indicates the mean precipitation amount. The index is negative for drought, and positive for wet conditions. As the dry or wet conditions become more severe, the index becomes more negative or positive. The duration of every drought appearance is determined by negative index values. Accumulated totals of negative values of SPI could also be used as a measure of drought severity. The relative simplicity of the SPI is one strong advantage of the index (Logan et al., 2010). Moreover, it is spatially consistent in its interpretation and the magnitude of the departure from zero is a probabilistic measure of the severity of a wet or dry event that can be used for risk assessment (Guttman, 1999). The SPI can track drought on multiple time-scales, i.e. 1-, 3-, 6-, 9-, 12-, and 48-months, but the index is flexible with respect to the period chosen. The SPI requires different interpretations according to its time scale. Among users there is a general consensus about the fact that the SPI on shorter time scales (say 3 and 6 months) describes drought events affecting agricultural practices, while on the longer ones (12 and 24 months) it is more suitable for water resources management purposes (Raziei et al., 2009). SPI for 3 and 6 months time steps are used in this paper to study the characteristics of drought in short and medium range time scales.

Computation of the SPI involves fitting a gamma probability density function to a given frequency distribution of precipitation totals of a station. The alpha and beta parameters of the gamma probability density function are estimated for each station and for each time scale of interest (3-, 6-, 12-, 24-, 48-months, etc.). The resulting parameters are then used to find the cumulative probability of an observed precipitation event for the given month and time scale for the station in question. The cumulative probability is transformed to the standard normal random variable Z with a mean of zero and variance of one, which is the value of the SPI. Gamma distribution functions are most often found to fit the precipitation data well because the distribution of rainfall totals is not normally distributed (US National Drought Mitigation Centre, 2010).

The gamma distribution is defined by its frequency or probability density function:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for}\, x > 0 \tag{1}$$

where $\alpha \succ 0$ is the shape parameter, $\beta \succ 0$ is a scale parameter and $x \succ 0$ is the amount of precipitation. $\Gamma(\alpha)$ defines the gamma function. α and β are parameters to be estimated for each station for each time step of interest. The maximum likelihood solutions are used to optimally estimate the gamma distribution parameters α and β:

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

and

$$\hat{\beta} = \frac{\bar{\chi}}{\hat{\alpha}} \tag{3}$$

where

$$A = \ln(\bar{\chi}) - \frac{\sum \ln(\bar{\bar{\chi}})}{n} \tag{4}$$

and n = number of precipitation observations. This allows the rainfall distribution at the station to be effectively represented by a mathematical cumulative probability function given by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} dx \quad (5)$$

Since the gamma function is undefined for $x = 0$ and a precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(x) = q + (1-q)G(x) \quad (6)$$

where q is the probability of a zero. The cumulative probability $H(x)$ is then transformed to the standard normal distribution to yield SPI (McKee et al., 1993). The complete procedure used for the calculation of the SPI is reported in (Vicente-Serrano et al., 2006).

Although it is a quite a recent index, the SPI was already used in Turkey (Komuscu, 1999; Touchan et al., 2005), Argentina (Seiler et al., 2002), Spain (Lana et al., 2002), Korea (Min et al., 2003), China (Wu et al., 2001) Europe (Lloyd-Hughes and Saunders, 2002), Italy (Bordi et al., 2001), and South Africa (Mathieu and Richard, 2003) for real time monitoring or retrospective analysis of droughts. It is also becoming an increasingly important tool for initiating drought response actions at state, regional and local level (Wilhite et al., 2000). Therefore, SPI is used here to study the spatial and temporal characteristics of meteorological drought in the region of Tigray, which has a history of recurrent droughts.

1.2. Vegetation based drought analysis

Drought indicators like the SPI assimilate information on rainfall, but do not express much spatial detail. Furthermore, drought indices calculated at one location are only valid for a single location. Thus, a major drawback of climate based drought indicators is their lack of spatial detail as they are dependent on data collected at weather stations which sometimes are sparsely distributed affecting the reliability of the drought assessment indices (Brown et al., 2002). In contrast remote sensing or satellite imageries have proven to be effective tools that provide spatially continuous information regularly in timely manner with improved detail. The vegetation indices developed using band combination of satellite imagery has been used for monitoring drought over large areas since mid-1990s. A range of vegetation indices based on remote sensing have been thus used to monitor greenness of vegetation (Bannari et al., 1995).

Satellite-derived drought indices typically use observations in multispectral bands, each of which provides different information about surface conditions. Because droughts are naturally associated with vegetation state and cover, vegetation indices are commonly used for this purpose (Tucker and Choudhury, 1987), utilizing data in the visible red (R), near infrared (NIR), and the shortwave infrared bands. The most commonly used vegetation index is the normalized difference vegetation index (NDVI) (Tucker, 1979) and is given by the equation:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \quad (7)$$

where NIR is reflectance in the near-infrared wavelengths and RED is reflectance in the red wavelengths. The temporal variations in the NDVI reflect the vegetation's response to weather variability (Potters and Brooks, 1998). Consequently, this index has been widely used to monitor ecosystem dynamics, crop yield assessment/forecasting and to detect the spatial extent of drought episodes and their impact (Tucker and Choudhury, 1987; Marsh et al., 1992; Di et al., 1994; Kogan, 1995, 1997; Groten and Octare, 2002).

However, many studies report that the spatial and temporal variability of NDVI values is closely related to the contribution of geographical resources to the amount of vegetation. This contribution fluctuates considerably depending mainly on climate, soils, vegetation type and topography of an area (Di et al., 1994; Ichii et al., 2002; Li et al., 2002; Domenikiotis et al., 2004). Thus, in tropical rainforest areas, high NDVI values could result from the lush tropical forest vegetation, whereas, in deserts, low NDVI values are to be expected. Obviously, these differences are not due to the impact of the weather. For this reason the NDVI is not comparable in space, especially in non-homogeneous areas (Vicente-Serrano, 2007).

Furthermore, surface moisture and aerosol signals may limit the accuracy of the observed NDVI in arid or semi-arid regions (Funk and Brown, 2006). Soil formations in the most arid areas may also play an important role in intensifying the effects of drought on vegetation. Land degradation and specific soil erosion may in part also prevent the development of a high amount of vegetation cover (Guerrero et al., 1999). These vegetation indices, NDVI, are also mainly linked to vegetation biophysical factors and problems exist because of external factor effects, such as soil background variations (Huete et al., 1985; Huete, 1989).

Accordingly, Huete (1988) proposed a soil-adjustment factor to account for first-order soil background variations and obtained a soil-adjusted vegetation index (SAVI), which reduced the influence of the soil type below the vegetation. According to Huete (1988), SAVI is much better than NDVI for areas with low vegetation cover and can be used to characterize the arid zone vegetation. However, the SAVI is a method by which spectral indices requires local calibration so that soil substrate variations are effectively normalized and are not influencing the vegetation measure. Furthermore, since it is difficult to predict how soil effects are manifested within large pixel areas, which aggregate soils and vegetation of many different types, each of which requires in principle, separate calibration which makes the method not easy to apply for large areas. We believe, however, that the most appealing approach to apply in our case is to rely on NDVI as is difficult to have access to such calibration values for our study region, which covers 53,000 km^2.

Moreover, though natural vegetation has developed a great capacity for physiological adaptation and resistance to long droughts and soil moisture below the theoretical wilting points, precipitation is considered as the primary limiting factor for plant growth in semi-humid and semi-arid areas (Wang et al., 2003; Reynolds et al., 2004). But when NDVI is used for analysis of weather impact on vegetation, the non-weather effect must be separated. Accordingly we applied the VCI for study.

The maximum amount of vegetation is developed in years with optimal weather conditions, because such conditions stimulate efficient use of ecosystem resources. Conversely, minimum vegetation amount develops in years with extremely unfavourable weather, which suppresses vegetation growth directly and through a reduction in the rate of ecosystem resources use (Domenikiotis et al., 2004). Therefore, the absolute maximum and minimum of NDVI, calculated over several years, contains the extreme weather events. The resulting maximum and minimum values can be used as criteria for quantifying the potential of geographical areas (Kogan, 1995, 1997). This is expressed by the VCI, which is given by the equation:

$$\mathrm{VCI} = \left(\frac{\mathrm{NDVI} - \mathrm{NDVI}_{\min}}{\mathrm{NDVI}_{\max} - \mathrm{NDVI}_{\min}} \right) \times 100 \quad (8)$$

where NDVI, $\mathrm{NDVI}_{\min}$, and $\mathrm{NDVI}_{\max}$ are the smoothed 10-day NDVI, its absolute multi-year minimum and its multi-year maximum NDVI respectively for each pixel. The VCI, given by Kogan (1995), has been used to estimate the weather impact on vegetation. The method is useful to separate the short-term weather signal in the NDVI data from the long-term ecological signal and in this sense it is a better indicator of water stress condition than NDVI (Kogan and Sullivan, 1993; Maselli et al., 1993; Kogan, 1997). The VCI provides accurate drought information not only for well defined, prolonged, widespread, and intensive droughts, but also for very

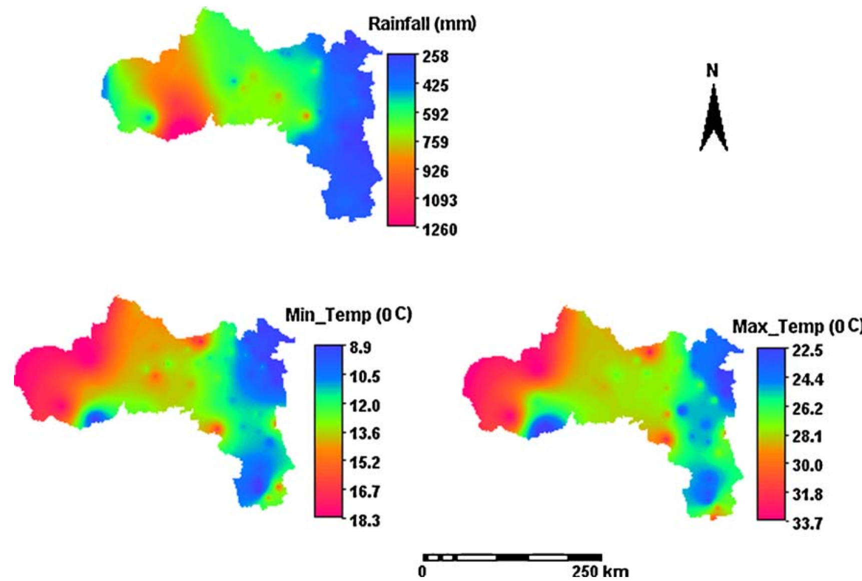

Fig. 1. Climate distribution of monsoon rainfall, annual minimum and maximum temperature in the study region for the year 2008.

localized, short-term, and well-defined droughts (Kogan, 1995). The VCI varies from 0 to 100 corresponding to changes in the vegetation condition from extremely unfavourable to optimal condition (Kogan, 1995; Kogan et al., 2003). Based on Kogan's (1995) VCI classification threshold, VCI values of 35% or less is considered to be as an indicator of drought condition. VCI values around 50% are considered as a fair vegetation condition, while VCI values between 50 and 100% are judged optimal or above normal conditions. The VCI algorithm was developed and tested in several areas of the world with different environmental and economic resources (Kogan, 1990, 1995).

2. Study area and data used

2.1. Study area

Tigray is one of the national regional states of Ethiopia located in the North Eastern part of the country, covering a total area of 53,000 km^2. Geographically, it lies between latitudes 12°15′N and 14°57′N and longitudes 36°27′E and 39°59′E. The state is structured into 6 administrative zones and 34 districts. Intervening mountain ranges rise locally to 3000 m above sea level. These high elevations result in a more temperate climate than would normally be associated with the latitude (Virgo and Munro, 1978).

Climatically, the region belongs to the sub-tropical region where monsoon weather prevails throughout the year. Three distinct seasons can be recognized from a climatic point of view: the dry winter season from October to February; the pre-monsoon hot season from March to May; and the rainy monsoon season which lasts from June to September (locally called kiremt), during which 80% of the crops are cultivated. Rainfall is distributed very unevenly in the study region. The data from the Ethiopian National Meteorological Services Agency (ENMSA) reveals that the climate of the study region is characterized by large spatial variations which range from about 1000–1300 mm over some pockets areas in the Southwest to about less than 260 mm over the Northeast lowlands (Fig. 1). The mean annual rainfall of the region is estimated to be 560 mm while the mean annual monsoon rainfall is 473 mm, 84% of the annual rainfall. The coefficient of variation (CV) of annual rainfall is found to be 38%, which is high compared to the national figure of 8%.

The southern and eastern zones of the region receive much lower rainfall than other parts of the region (Fig. 1). The distribution of monsoon rainfall over the region is characterized by large spatial variation. The inter-annual variability of the monthly average minimum and maximum temperature based on the data from Ethiopian National Meteorological Services (ENMSA) for the period of 1979–2009 shows that the minimum temperature is highest in May–June and reaches its lowest value in December–January, while the maximum temperature over the region is highest in May and reaches its lowest in August (Fig. 2). Mean temperature distribution over the region varies from about 13.4 °C over the highlands of the Southwest and East to about 28 °C over Western lowlands in 2008.

2.2. Data used

Historical records of monthly precipitation data for the time period 1954–2009 were acquired from the Ethiopian National Meteorological Services Agency for a total of 46 meteorological stations within Tigray (Fig. 3). However, the period of records for these stations varies and some have missing records. Thus, the period of study has been chosen as long as possible depending on the availability of recorded data for 25 stations in the region, being 1979–2009.

Besides the above mentioned data, geo-referenced SPOT vegetation ten day composite Normalized Difference Vegetation (NDVI) images (S10 product) were acquired from vgt4africa of the DevCoCast project website, http://www.vgt4africa.org, for the period of April 1998–December 2009. In this paper drought is studied using

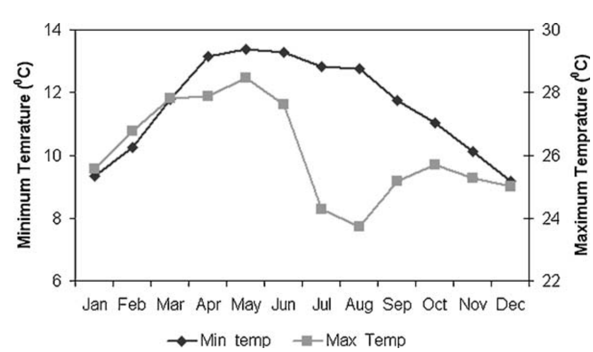

Fig. 2. Inter-annual variability of the average monthly minimum and maximum temperature in Tigray for the period 1979–2009.

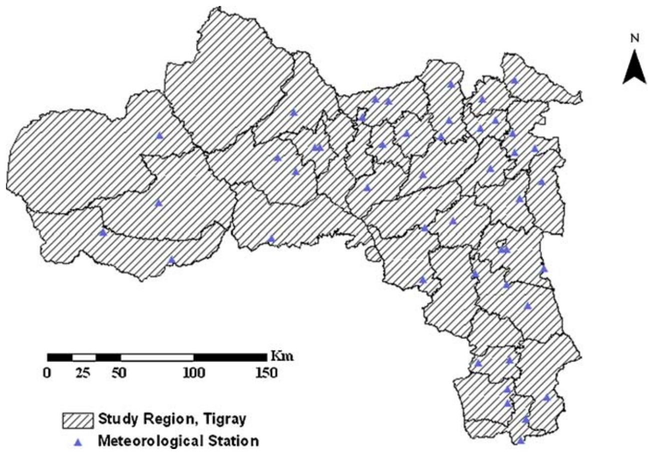

Fig. 3. Location of rain-gauge stations in Tigray.

11 years SPOT NDVI data at 1 km × 1 km resolution data, which covers the African continent. The NDVI product acquired is a 10-day synthesis. The satellite data on SPOT vegetation are applied for several procedures in order to ensure the quality of the NDVI product. The product can be used for crop and agricultural monitoring; early warning of failing growing seasons; and as an indicator and alert function for drought events. The multi-temporal NDVI data was selected due to its provision of opportunities to recognize vegetation changes at a longer time span.

3. Methods

3.1. Drought evaluation using the SPI

In this study, the SPI series were computed for 25 weather stations of Tigray region from January 1979 to December 2009 at a temporal scale of 3- and 6-month to study the characteristics of drought at short and medium ranges. These scales are useful for monitoring various drought types (Edwards and McKee, 1997). The 3- and 6 months SPI is used to describe the drought events affecting agricultural practices and characterize seasonal droughts due to rainfall deficit during the main rainy season. The SPI program developed by the National Drought Mitigation Centre, University of Nebraska–Lincoln, was used to generate time series of drought indices (SPI) for each station in our study region and for each month of the year at 3- and 6-month time scales. The 3-month SPI calculated for September uses the precipitation total for July, August and September while the 6-month SPI calculated for September uses the precipitation total for April to September. Since drought is a regional phenomenon, the SPI values of the meteorological stations have been spatially interpolated using inverse-distance moving average interpolation technique in the software package ILWIS to create drought severity maps for the region at multiple time scales of the year. An inverse distance moving average technique was employed as it is better suited for interpolation of rainfall distribution over heterogeneous topographical terrain. SPI classification threshold values proposed by McKee et al. (1995) and explained by Edwards and McKee (1997) were used in order to map the spatial extent of meteorological drought intensities corresponding to the SPI value (Table 1).

3.2. Drought evaluation using the VCI

A 10-day composite NDVI for each month of the indicated period was produced for the study region. The decadal composite NDVI data set was then divided into groups for analysis i.e. the main rain season or monsoon months (June, July, August and September) and the dry season (March, April and May). The monsoon months was only used for the analysis as this study was focused on drought due to water stress during the rainy season. All negative values have been reclassified to 0 in all data set so that scaled NDVI data contain only positive values, which are required for further analysis.

Table 1
Drought classification by standardized precipitation index (SPI) value.

SPI values	Drought category
<−2.00 and less	Extreme drought
−1.50 to −1.99	Severe drought
−1.00 to −1.49	Moderate drought
0 to −0.99	Near normal or mild drought
Above 0	No drought

After the production of average monsoon NDVI (June–September), absolute NDVI minimum and maximum maps for each monsoon season were generated for the period 1998–2009. After the production of these images VCI composite images were produced for each year monsoon season using Eq. (8). Accordingly 396 decadal images were processed in order to produce the multi-temporal drought maps and determine the relationships between average monthly precipitation and vegetation indices at a station level. Kogan's (1995) VCI classification threshold values were then applied in order to prepare the annual vegetative drought maps. Pearson correlation analysis was performed to correlate VCI values with precipitation data. In order to investigate the time lag between the occurrence of the precipitation and VCI response, correlation between VCI data and various precipitation schemes including the current month and the current month plus last two preceding months were examined.

4. Results and discussion

4.1. SPI based drought identification

4.1.1. Temporal drought pattern

Meteorological drought indicates the deficiency of rainfall compared to normal rainfall in a given region. The temporal and spatial characteristics of drought in Tigray region was identified from SPI time series of multiple-time steps. In our study, SPI for 3- and 6-months time steps are computed to examine the characteristics of drought in short and medium time periods. The 3-month SPI provides a seasonal estimation of precipitation and the 6-month SPI indicates medium term trends in precipitation patterns (Lia et al., 2004). The 3-month SPI is thus used to describe the monsoon drought for the crop growing season, while the 6-month SPI is used to characterize seasonal droughts that occur due to rainfall deficit in monsoon months.

Appearance of drought is happening every time when SPI is negative and its intensity comes to −1.0 or lower. Drought stops when SPI is positive. The duration of every drought appearance is determined by negative index values. Accumulated totals of negative values of SPI could also be used as a measure of drought severity. The regional SPI time series for all the stations selected were calculated at 3 and 6-months time steps. A representative example of the evolution of the SPI for Mekelle station between 1979 and 2009 with a time scale of 3- and 6-months is shown in Fig. 4. According to the criteria of McKee et al. (1995), severe and extreme droughts correspond to the categories of $-1.99 < SPI \leq -1.5$ and $SPI \leq -2.0$ respectively. Consequently, several drought episodes were detected from the temporal evolution of the SPI, the most severe or extreme droughts occurred in 1984, 1985, 1986, 1987 and 1991 (Fig. 4).

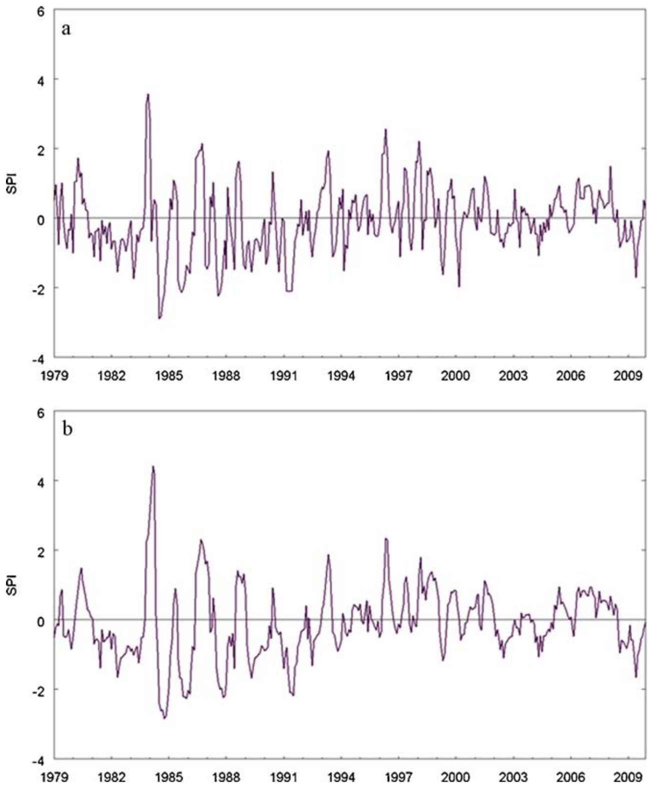

Fig. 4. Values of Spatial Precipitation Index for Mekelle station (a) 3-month and (b) 6-month time steps.

The analysis shows that four extreme drought event occurred around the Mekelle station in the case of SPI-3 whereas in the case of SPI-6, five extreme drought events were evident during the recorded period. All these episodes were prolonged in time with critical and extreme situations. Two extreme drought events (1984 and 1985) lasted for 3–6 months with critical and extreme situation. Especially, the annual precipitation of the year 1984 is the smallest for the 30 years of analysis. The drought occurring in 1984 is the most severe drought ever experienced in Tigray region in general. The annual minimum 3-month SPI for this drought event occurred in July 1984 (SPI = −2.89), whereas the annual minimum 6-month SPI observed in October 1984 (SPI = −2.84). Successive moderate drought episodes were also recorded during the period 1992–2009 at the two short and medium term time scales.

Severe drought events occurred in 1982, 1983, 1985, 1987, 1988, 1989, 1991, 1999, 2000 and 2009. Severe droughts are much more prolonged drought events than the drought event of 1984. The period 1985–1989 except for the year 1986 was characterized by rainfall shortages during the rainy season. The minimum 3-month SPI was observed in October 1987 (SPI = −1.88) and a minimum 6-month SPI was observed in September 1987 (SPI = −1.99). This prolonged drought event caused exploding water demands and subsequent impacts in Mekelle area and Tigray region in general. The annual minimum SPI values for the 3-month and 6-month time scale most frequently occur during July and October. The temporal analyses of 3-month and 6-month SPI values show that Tigray region was predominantly characterized by frequent moderate droughts.

4.1.2. Spatial characteristics of drought

Although the estimation of drought severity at a certain point gives useful information for water management, it is important to assess the drought over a specified region. The regional drought analysis is useful for determining the spatial distribution and characteristics of drought, and evaluating the most affected areas for a specific drought event. In this study, the spatial analysis was performed using the SPI values estimated for 3- and 6-month time scales. Using the developed SPI database and the abilities of ILWIS software package, one can visualize the distribution of SPI values across the area of interest for the various time scales. As an example, Figs. 5 and 6 show the variation of SPI across Tigray for the period 2000–2009 for time scales of 3- and 6-month respectively.

The spatial analysis of moderate drought occurrences indicates that they tend to occur in the eastern and south zones of Tigray at a 3-month time step, while the northwest and western parts are characterized with the lowest frequencies at the same time step (Fig. 5). In other words, the majority of the historical droughts that occurred in the eastern and southern zones of the study region were of moderate severity in short-time steps. At a 3-month time step, moderate droughts occurred more frequently and covered nearly two-thirds of the study region during the worst drought of 2002. As the time step increases to 6-month, severity of drought increased in some pocket areas.

Severe to extreme drought occurred during 2000–2009 in discrete pockets in two seasons. During 2002, 2004, and 2009 monsoon, most parts of the region suffered drought conditions. In the years 2000, 2001, 2003, 2006 and 2007 years, the monsoon period was mostly drought-free. Severe drought was observed in the year 2002, when the eastern and southern zones of the regions were affected by severe to extreme drought. During 2002, the monsoon was poor and as a result the whole region suffered drought conditions. During 1999–2009, just within a span of 10 years, monsoon-drought appeared throughout the Tigray region five times.

In 2002, 62% of the study area was affected by drought, among which, 3% was affected by severe droughts and 24% was by moderate monsoon drought. In 2004, 2005, 2008 and 2009, the whole study area was affected by drought. About 67% of the area in 2004 and 63% of the area in 2009 was affected by mild drought.

The spatial extent of the 6-month SPI shows that in 2002, almost 64% of the study area was affected by drought, with almost 29% of the area affected by moderate drought for the 6-month time scale (Fig. 6). In 2004, about 65% of the area was affected by drought, with almost half of the region affected by mild drought. The spatial extent of both 3- and 6-month SPI's show that in most of the drought years the eastern and southern zones had an SPI less than −1.0. Drought is persistent for more than four seasons particularly in the southern and eastern zones of the region over the last five years (Figs. 5 and 6). The spatial distributions of drought for a 3-month and 6-month time step are shown in Figs. 5 and 6 respectively.

The SPI maps indicate that meteorological drought in the study region appears continuously in the monsoon seasons. The analysis of drought at the 3-month and 6-month time-steps further indicates that southern and eastern zones of Tigray are most vulnerable to droughts. Besides, certain pockets particularly in the northwest zone of the region have also suffered from water stress. From the two time scales it can also be concluded that droughts in Tigray are of a more seasonal than a long-lasting character. Based on the standard precipitation index the southern and eastern zones of the region can be delineated as a drought prone zone.

However, Tigray is one of the Ethiopian regions where meteorological stations are generally inadequate and the networks are not well-developed. Weather stations are sparsely located from each other and hence the spatial resolution of rainfall data derived from these weather station data has been approximately 100–150 km^2. Besides, continuous rainfall records are scarce or difficult to obtain in a timely fashion for all weather stations as infrastructural networks are very low. Consequently, SPI assimilated information on rainfall does not express much spatial detail and could have draw-

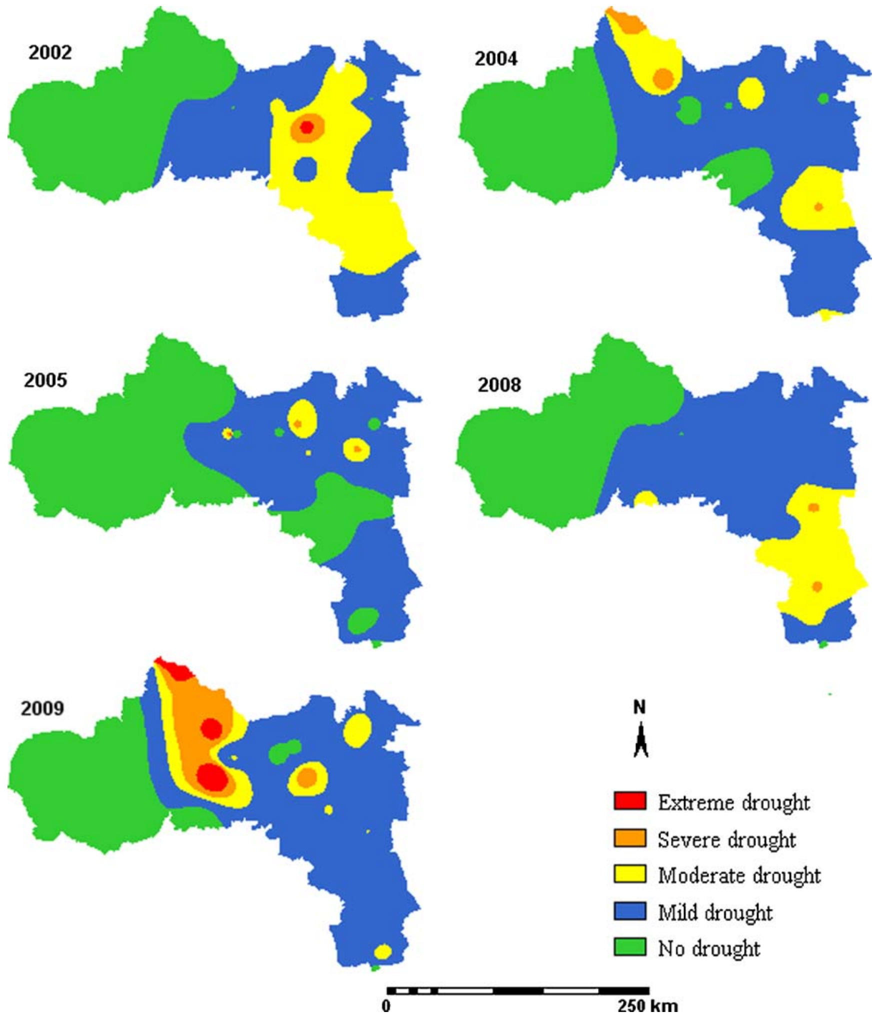

Fig. 5. Spatial distribution of 3-month standard precipitation index computed for the month of September for five drought years.

backs in identifying localized drought at a regional level, which in turn hinders the possible prediction, monitoring and mitigation effects of drought disaster.

4.2. Vegetation based drought identification

4.2.1. Mean vegetation and rainfall patterns

The average rainfall for the monsoon season gives an overview of the general distribution of rainfall as the main crops are cultivated during June–September in the whole part of the region. Fig. 7 provides a visual comparison of average monsoon rainfall and NDVI for the period 1998–2009. During the monsoon season, the southern and eastern zones of the study region receive low rainfall as compared to the other zones of the region. The figure shows an increasing rainfall pattern from southern zone to western region. The spatial pattern of NDVI for the growing season of the period 1998–2009 correspond well with the monsoon rainfall pattern with the most pronounced vegetation signal for the northwest and western zones of the Tigray region. The above normal greening of this region obviously is associated with high rainfall during the months of June–September in the area. We performed a correlation analysis on average monsoon rainfall and NDVI for the period (as discussed in Section 4.1.4). The average monsoon precipitation and NDVI/VCI pattern for the whole study region for the period 1998–2009, reveal that there is a positive correlation between monsoon NDVI/VCI and rainfall (see Fig. 11). The high similarity in spatial pattern of both NDVI and rainfall illustrates the impact of rainfall on vegetation condition.

4.2.2. Spatial extent of vegetative drought

The annual cycle of vegetation in Tigray region is basically unimodal similar to the rainfall regime. As discussed before, a monsoon drought was analysed using time series VCI. Based on Kogan's VCI threshold of 35% or less as extreme drought condition, VCI time series data was used to determine the drought. At a VCI of around 50%, fair or normal vegetation conditions exist. When VCI values are close to 100%, the brightness vegetation for the monsoon/September is equal to the long-term Maximum for the pixel. Low VCI values indicate drought period in that year. A consistently low VCI value over several consecutive time intervals indicates drought development. Accordingly, VCI indicates that the study area was affected by drought condition in the monsoon year 2002, 2004, 2005, 2008 and 2009 (Fig. 8). During the monsoon of 2002, the vegetation experienced stress and loss of vegetation health. The region experienced an exceptionally continuous drought spell from the monsoon of 2002 until 2009 particularly in the southern and eastern zones of the region due to poor rainfall in the last consecutive monsoon seasons (Fig. 8). The worst situation was encountered during the year 2004, 2008 and 2009 monsoon when 20.1%, 18.1% and 17.4% of the region suffered drought condition respectively; having VCI values less than 35%. In the year 1999–2001, most of the study area except for some pocket areas had VCI values higher than

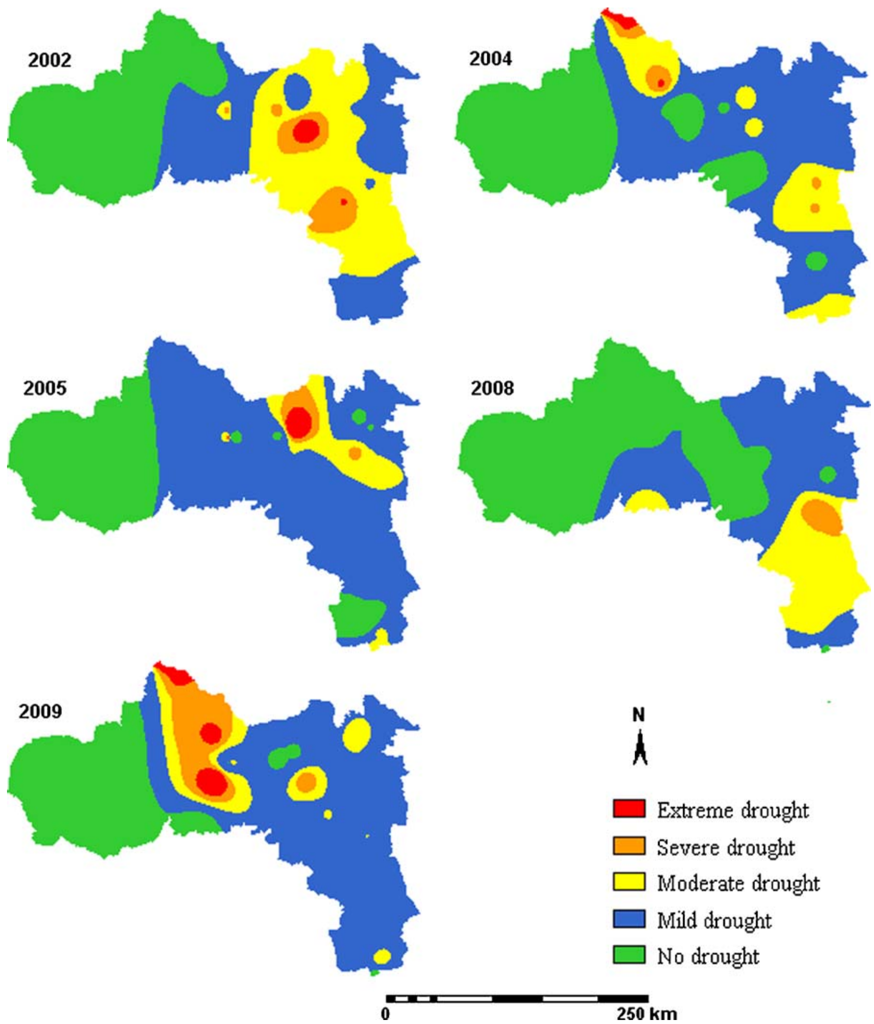

Fig. 6. Spatial distribution of 6-month standard precipitation index computed for the month of September for five drought years.

35 and thus there were normal conditions. Agricultural practices, in particular in times of sowing and harvesting have significant bearing in shaping the NDVI patterns. Agriculture was severely affected during the year 2004, since crops could not be sown due to failure of rainfall commencement particularly in the southern part of the region.

Furthermore, a high intensity of drought condition occurred in 2004, 2005 and 2008 due to failure of rainfall during the last crop growing period, mostly around September as is illustrated in Fig. 9. Fig. 9 indicates the VCI of September 1999–2009, the severity of drought in 2004, 2005 and 2008 appeared relatively higher.

Our result of vegetative drought analysis illustrates that the spatial and temporal analysis of drought using vegetation condition index were found useful in characterizing spatial patterns and temporal aspects, and in evaluating drought proneness across the spatial units. Multi-temporal VCI maps are useful in assessing the severity of droughts at spatial details, implying the utility of the Vegetation condition index in semi-arid and arid regions.

4.2.3. Precipitation, NDVI and VCI variations

Inter-annual variability of the monthly average NDVI and precipitation is shown in Fig. 10 for six sample stations reflecting monthly average values. The figure shows that the average monthly NDVI reaches its maximum value in September for the sample stations. The temporal pattern of the NDVI has high similarity with the temporal pattern of rainfall, which is relatively high in the rainy period from June to September. Fig. 10 also shows that there is no agreement between the peak NDVI and current month precipita-

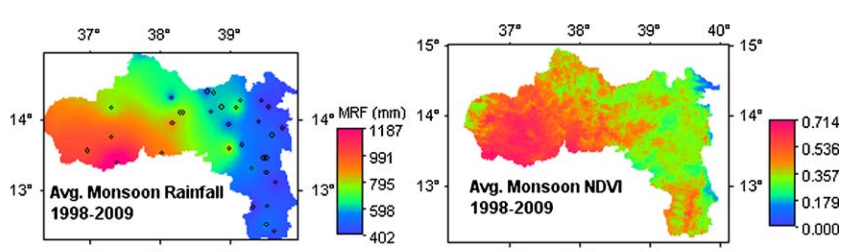

Fig. 7. Multi-year average monsoon rainfall (MRF) and the multi-year average monsoon NDVI for the period 1998–2009.

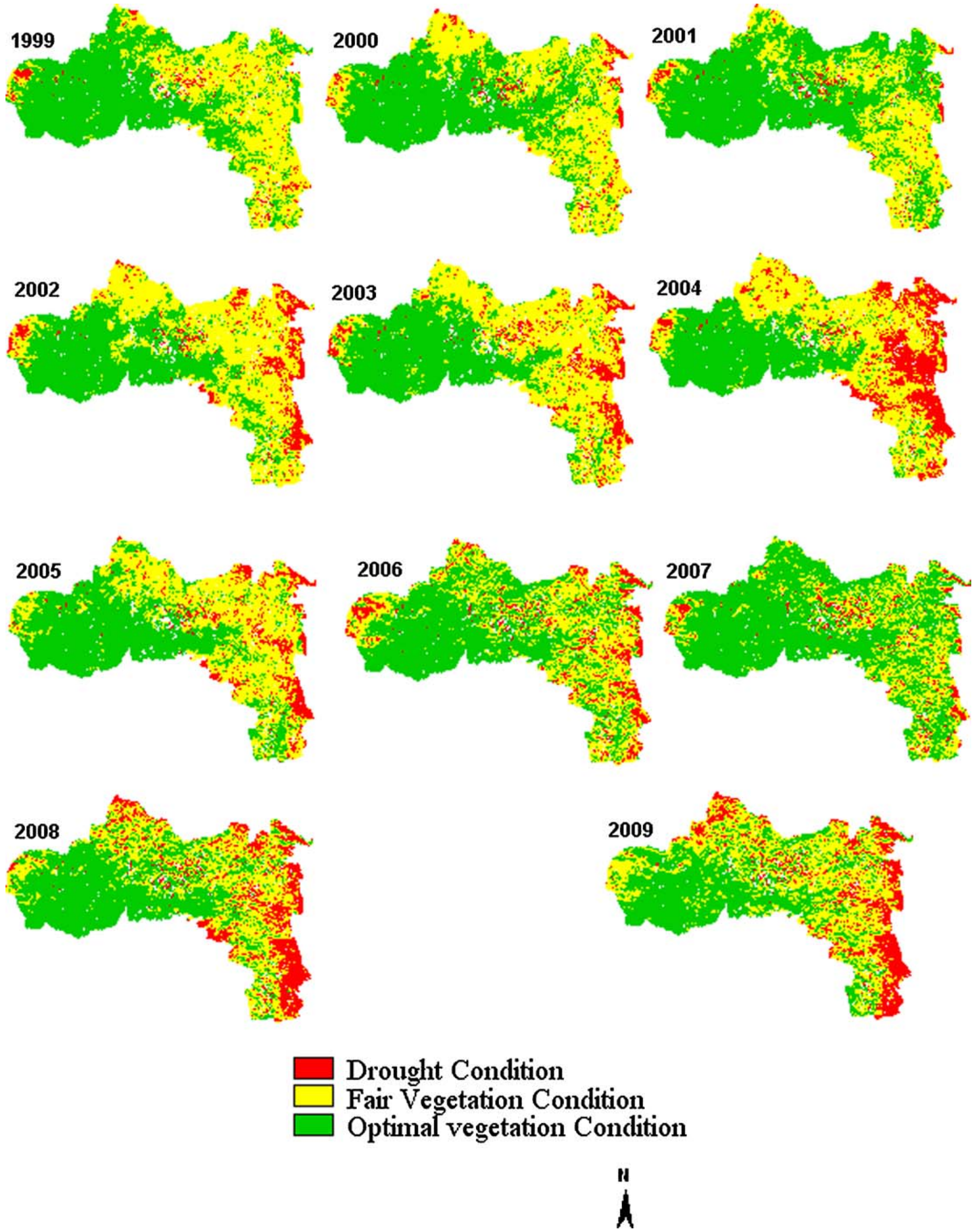

Fig. 8. Drought frequent region using VCI for monsoon season, 1999–2009.

tion values rather it shows that there is a time lag between the period of the peak NDVI and precipitation values.

4.2.4. Correlation analysis

Although, the variations in vegetation indices can aid to recognize the effect of climatic factors on local vegetation, the variations will be of little practical value when planning for large-scale mitigation. Hence, determining the associations between precipitation and vegetation indices on a regional scale would provide better insight into drought onset and severity.

Thus, the statistical relationships between various time lag periods and NDVI/VCI were investigated by performing a Pearson correlation analysis between the values of vegetation indices and precipitation data for 28 meteorological stations (Table 2). For the Alamta and Maichew stations the VCI values are correlated with the current month precipitation. However, the VCI exhibited significant correlations with current plus last two-month precipitation in nearly all the stations (Table 2). This shows that vegetation is responsive to rainfall over a three-month period indicating a brief time–lag in the vegetation response to rainfall.

In the case of NDVI, NDVI values are correlated with the current month precipitation at Adigudom, Alamata, Hagereselam and Waja stations. Significant correlations are observed with the current plus two-month precipitation data for 21 stations. In general, nearly in more than half of the meteorological stations, highest correlation coefficients are obtained when NDVI or VCI values are correlated with the current plus last two-month precipitation data. Our result further reveals that VCI has a higher correlation than NDVI for the

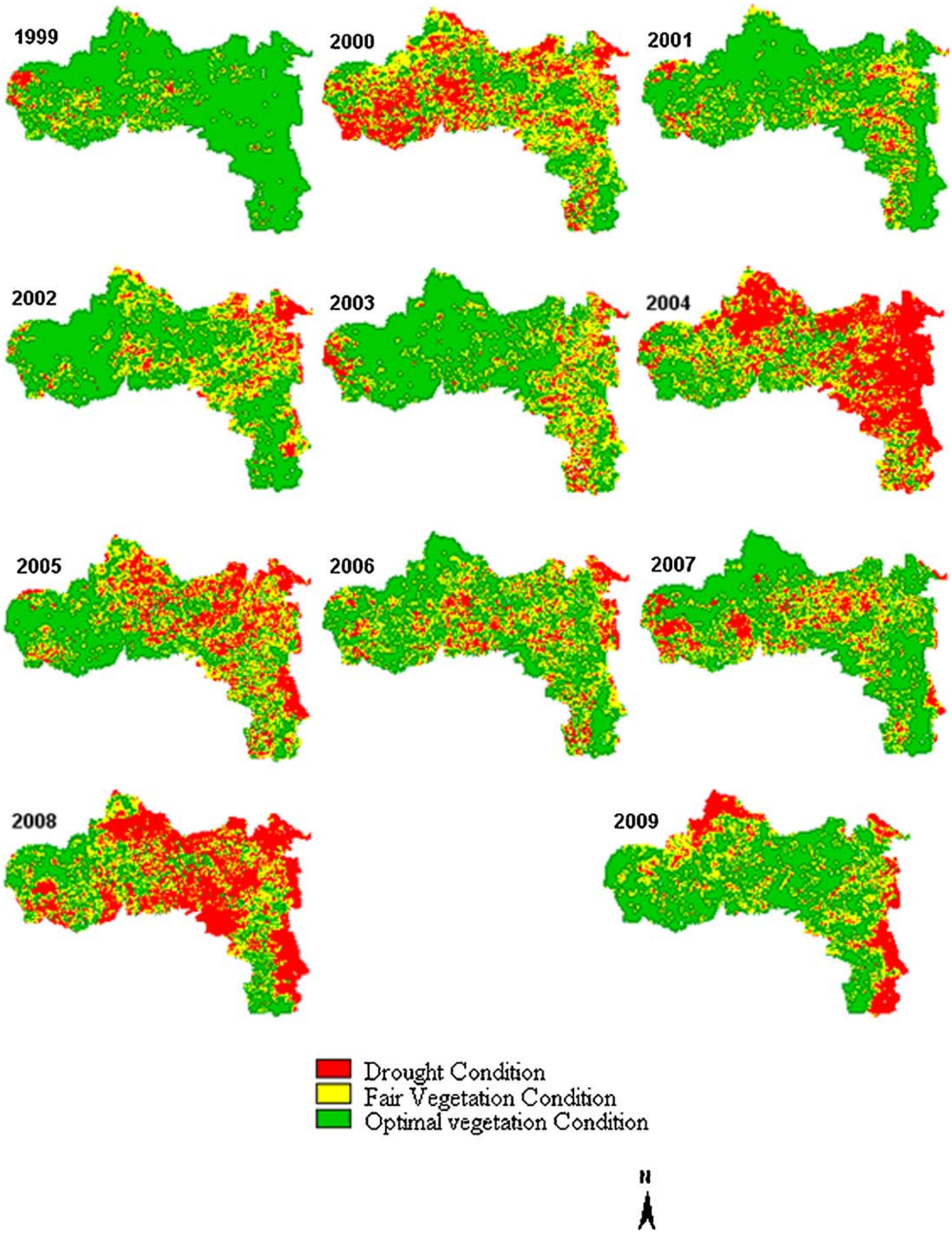

Fig. 9. Drought frequent region using VCI for the month of September, 1999–2009.

individual stations indicating that VCI can provide more accurate information on the impact of weather on vegetation, and can be used as good indicator of vegetation changes and in turn, as indicators of drought conditions for individual stations in the study area.

Moreover, the relationships between precipitation and vegetation indices on a regional scale would also provide better insight into drought onset and severity. Therefore, average NDVI and VCI values of all 28 meteorological stations in the study area were determined as “average NDVI” and “average VCI” and their correlation with average precipitation data were observed. Because the results of individual stations showed better correlations between NDVI/VCI values and multi-month precipitation, only the average of three-month precipitation of all stations in the entire study area for the period 1999–2009 was used (Fig. 11). It can be clearly seen from the scatter plots that VCI values responded well to precipitation. The correlation coefficient (r) for this relationship was found to be 0.85 at 0.01 level of significant, which indicates a strong positive linear relationship between three-month precipitation and VCI.

A similar trend is observed when the average NDVI of the study area is plotted versus three-month precipitation. An agreement is easily observed which is confirmed by a good r-value of 0.78. The correlation was found to be significant at 0.01 level.

Generally, a very good agreement is observed between NDVI/VCI values and average three-month precipitation. Thus, the general agreement between VCI values and precipitation data clearly shows

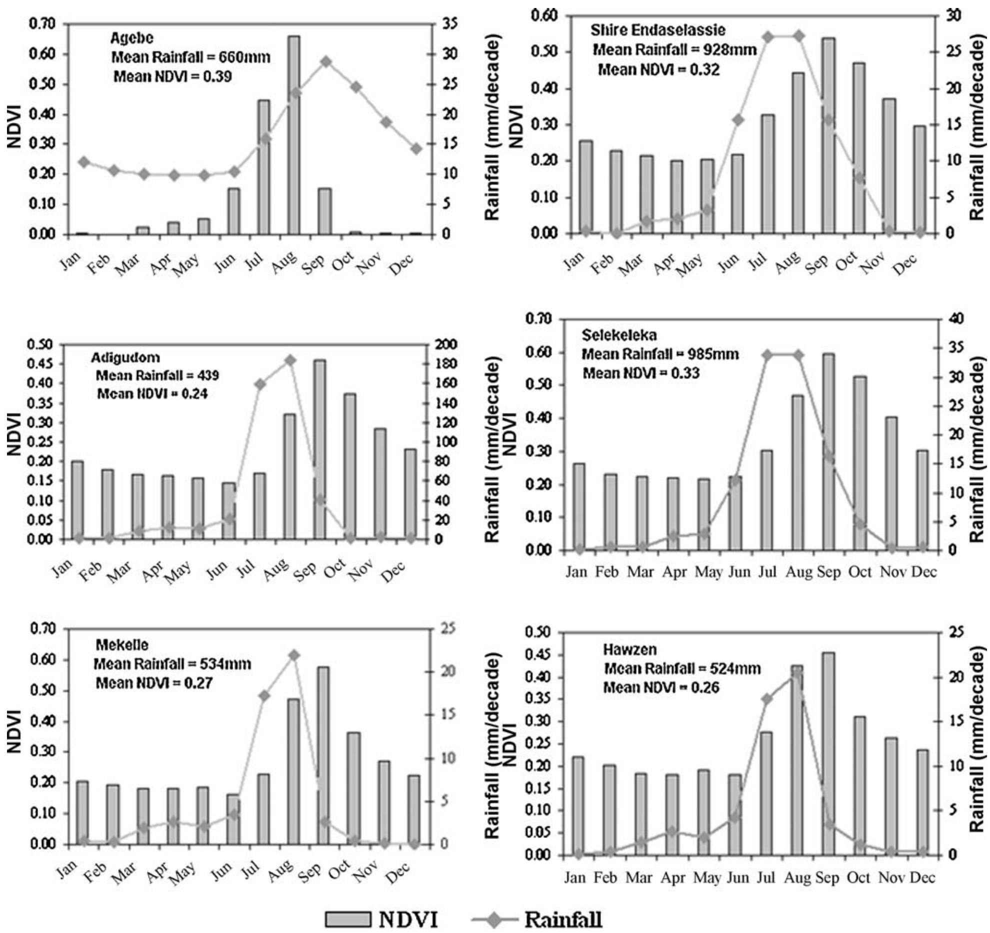

Fig. 10. Inter-annual variability of monthly NDVI for sample stations, 1999–2009.

Table 2
Pearson correlation coefficient between NDVI/VCI and precipitation.

No.	Station name	NDVI		VCI	
		Current month	Current + preceding two months	Current month	Current + preceding two months
1	Abi-adi	0.516	0.364	0.220	0.529*
2	Adigudom	0.495**	0.586*	0.356	0.670*
3	Adiremese	0.270	0.406	0.133	0.375
4	Adidaero	0.056	0.105	0.366	0.531**
5	Adigrat	0.242	0.689*	0.007	0.580*
6	Adwa	0.362	0.026	0.209	0.264
7	Agebe	0.119	0.408**	0.142	0.517*
8	Alamata	0.650*	0.827*	0.579*	0.759*
9	Axum	0.216	0.092	0.034	0.346
10	Aynalem	0.083	0.563*	0.157	0.622*
11	Dengolat	0.026	0.490**	0.113	0.717*
12	Edagahamus	0.070	0.439**	0.212	0.443**
13	Endabaguna	0.232	0.167	0.146	0.428*
14	Enticho	0.141	0.832*	0.147	0.867*
15	Feresemay	0.159	0.592*	0.208	0.768*
16	Hagereselam	0.484**	0.650*	0.364	0.630*
17	Hawezen	0.254	0.533*	0.202	0.603*
18	Korem	0.194	0.687*	0.093	0.663*
19	Maichew	0.187	0.384	0.433**	0.677*
20	Maykenetal	0.070	0.656*	0.052	0.710*
21	Mekelle	0.155	0.525*	0.208	0.620*
22	Ramma	0.225	0.308	0.282	0.587**
23	Selekeleka	0.292	0.523*	0.217	0.615*
24	Sheraro	0.275	0.575**	0.307	0.650*
25	Shire Endaselassie	0.135	0.157	0.100	0.515*
26	Waja	0.407**	0.614*	0.326	0.556*
27	Wedisemero	0.217	0.277	0.263	0.247
28	Wukero	0.189	0.562*	0.337	0.726*

** Correlation is significant at 0.05 level (2-tailed).
* Correlation is significant at 0.01 level (2-tailed).

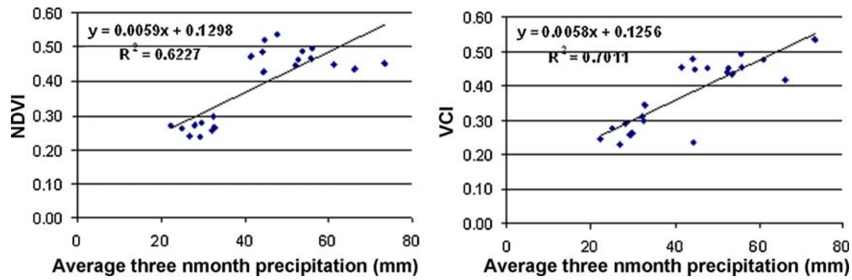

Fig. 11. Average NDVI and VCI versus average three month precipitation for the whole study area.

that the maximum and minimum NDVI values used to determine the VCI at a station level have been influenced by the weather condition. Drought area dynamics studied by VCI images represent the negative impact of adverse meteorological conditions on vegetation and show a more useful way to monitor regional drought evolution in time and space.

5. Conclusion

The spatial and temporal characteristics of droughts in Tigray region were examined using standard precipitation index and vegetation condition index. Drought potential mapping is one of the major steps in drought mitigation and planning. The study reveals that the eastern and southern zones of Tigray are most likely to suffer from drought. The SPI maps indicate that meteorological drought appears in the southern and eastern zone in most of the monsoon seasons over the past decade. It is observed that there is strong relation between the rainfall distribution and drought potential zones in the region. The meteorological drought conditions change continuously with seasons depending upon rainfall amount and its spatial distribution.

The result of vegetative drought analysis further illustrates significant correlations between VCI values and precipitation data for individual stations. Therefore, VCI indices can be used to detect unfavourable environmental conditions, particularly the current drought status as well as to analyze the characteristics of the drought at a regional scale. The study further indicated that VCI values have strong correlation with precipitation as compared to the NDVI. This indicates that rainfall characteristics may not be the only factor to influence NDVI values. Other local factors, such as soil characteristics, stress in previous years, and land cover characteristics of the area could also have an influence on vegetation.

From the SPI and VCI drought dynamics pattern analysis we conclude that the identification, classification, and analysis of drought dynamics are highly influenced by the monitoring parameters. SPI monitors precipitation deficit, the primary cause for drought development but takes no account of the impact. A region could be free from water-stress and might maintain normal vegetation despite of negative SPI. Negative SPI anomalies therefore not always correspond to drought (Bhuiyan et al., 2006). SPI classification scheme rely on the assumption of drought to follow the scale of probability and normal statistics which is debatable. Drought area dynamics studied by VCI, however, characterize the negative impact of unfavourable meteorological conditions on vegetation and show a more useful way to monitor regional drought evolution in time and space, and therefore represent a better picture of drought than the SPI.

Furthermore, in developing countries like Ethiopia meteorological stations are generally inadequate and the networks are not well-developed. Weather stations are sparsely located far from each other and hence the spatial resolution of rainfall data derived from these weather stations has been approximately more than 100 km^2. Besides, continuous rainfall records are scarce or difficult to obtain in a timely fashion as infrastructural networks are very low in developing countries. Consequently, SPI assimilated information on rainfall does not express much spatial detail and could have drawbacks in identifying drought proneness across the spatial units, and thereby affects the reliability of the drought indices. Similar findings were reported by Brown et al. (2002).

However, the result from the satellite derived vegetation condition indices indicates that VCI are useful to identify the spatial diversity of drought conditions over large areas, offering the possibility for early prediction of droughts as is necessary for drought risk management. Similar studies in Africa, South America, and Asia by Kogan and others (Kogan, 1995, 1997; Liu and Kogan, 1996; Unganai and Kogan, 1998) also reveal that drought area dynamics studied by VCI images demonstrated more clearly the intensity of droughts at a regional scale and showed to be an effective tool to detect regional drought evolution in time and space than those by other types of drought delineation. However, Bajgirana et al. (2008) found VCI values to be unreliable in Northwest Iran. This is mainly explained due to the short time span, 5 years, of the satellite data used for their study, which is difficult to make a firm comment on the applicability of the VCI index.

Developing countries like Ethiopia can therefore benefit from the remote sensing tools that provide better real time and spatially continuous data that can be used for rigorous analysis of drought proneness over large areas. The use of satellite based monitoring of vegetation also plays an important role in drought monitoring, early warning and mitigating the effects of drought disaster. Cognizant with this we are able to detect the spatial diversity of drought in Tigray by employing a rich database. Our result further indicates that detailed studies at a regional level will support for appropriate spatial identification and regionalization of the drought phenomena. This in turn provides evidence for policy makers to tailor appropriate policies to local conditions in order to mange the risks of drought. Thus, it is hoped that our study has demonstrated the importance of vegetation condition index in assessing the severity of droughts in semi-arid and arid region, indicating the utility of the tool in assisting policy makers in guiding the operational responses in drought risk reduction.

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