A COMPREHENSIVE MULTI-SENSOR REMOTE SENSING APPROACH IN DROUGHT MANAGEMENT

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Abstract

There have been several attempts in remote sensing-based drought assessment but all segregated and failed to cover pre-post stages of disaster management cycle. We developed a comprehensive remote sensing-based drought assessment approach encompassing both pre-post stages of drought management cycle. Degree of deviation from long-term mean precipitation, using Tropical Rainfall Measuring Mission (TRMM) data was used to classify drought prone areas providing decision support information on drought preparedness and prevention (pre-disaster). The results showed significant correlation when tested against world drought prone area map using long-term in-situ precipitation data (1950-200) at global level, as well as field survey drought reports and maps in Cambodia at country level. Besides, a simplified land surface dryness index (Vegetation Temperature Condition Index, VTCI) was applied for near real-time drought monitoring and response (post-disaster). This index combines Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. It performed very well in demonstrating shorter time-span drought events when tested against (1, 2, 3, 6, 12-months) values of Standardized Precipitation Index (SPI). The results indicate that integration of TRMM data together with MODIS data have significant potential for a comprehensive remote sensing-based drought management.

1. Introduction

Disaster management cycle encompasses all aspects of planning for and responding to disasters, including both pre- and post disaster management (Abesht, 2010). Pre-disaster management includes prevention, mitigation, preparedness and early warning while post-disaster management encompasses emergency response and reconstruction (ADPC, 2008). Among all natural disasters, drought is considered as a slow-moving hazard which affects vast regions for months or years. It is a normal, recurrent feature of climate and differs from aridity which is a permanent characteristic of regions (arid or semi-arid) with low annual precipitation. It occurs when precipitation is less than normal over an extended period of time (IFAS, 1998). Conventional drought indices using long-term meteorological data can provide an understanding of drought characteristics in different regions. However, their application is limited in developing countries with inadequate network of meteorological stations. Therefore, application of remote sensing data and developing remote sensing-based drought indices could be a suitable alternative for meteorological drought indices in these countries. Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) have been used in remote sensing-based drought indices such as vegetation Condition Index (VCI) and Temperature Condition Index (TCI) proposed by (Kogan, 1990, 1995). Application of NDVI and LST was further developed in triangle method proposed by (Price, 1990). Triangle space of temperature vegetation (Ts/VI) has been used in different applications such as surface soil water content (Carlson et al., 1995; Gillies et al., 1997), drought monitoring (Wang et al., 2001), soil moisture status (Wang et al., 2004) and surface evapotranspiration (ET) (Carlson, 2007). Triangle method Ts/VI in Vegetation Temperature Condition Index (VTCI) was suggested as a near-real time drought monitoring approach (Wan et al., 2004). It was also used in Temperature Vegetation Dryness Index (TVDI) for drought assessment (Gao et al.,2011). Proposed remote sensing-based drought indices provide near real-time high resolution spatial information for decision makers to identify severely drought affected areas which can be used for drought response (post-disaster). On the other hand, drought preparedness, mitigation and prevention (pre-disaster) requires reliable information to identify drought hot spots or drought prone areas at regional or country level by in order to mobilize and prioritize limited resources efficiently. Eriyagama et al., (2009) used meteorological data to classify global pattern of drought based on drought relation to long-term average precipitation condition. They tested coefficient of variation as well as probability of annual rainfall in any year being less than 75% of its long-term average, to identify regional differences in drought frequency. We have tested VTCI as a remote sensing-based drought index against a well established meteorological drought index proposed by (McKee et al., 1993), Standardized Precipitation Index (SPI) to evaluate its performance in characterizing drought condition. Subsequently, Tropical Rainfall Measuring Mission (TRMM) data are used to identify drought prone areas at regional or country level.

2. Study area and data

2.1 Study area

Agricultural drought is quite common either due to precipitation shortfall or late monsoon in Cambodia. More than 95% of the total arable land in the country is rain-fed and likely to be affected by drought. Monsoon (rainy season) usually starts in May and ends by October and dry season normally starts by November and continues until April. The study area covering major agricultural land in central part of the country surrounding Tonle Sap Lake and lower part of Mekong River was selected as it can be seen in (Figure 1).

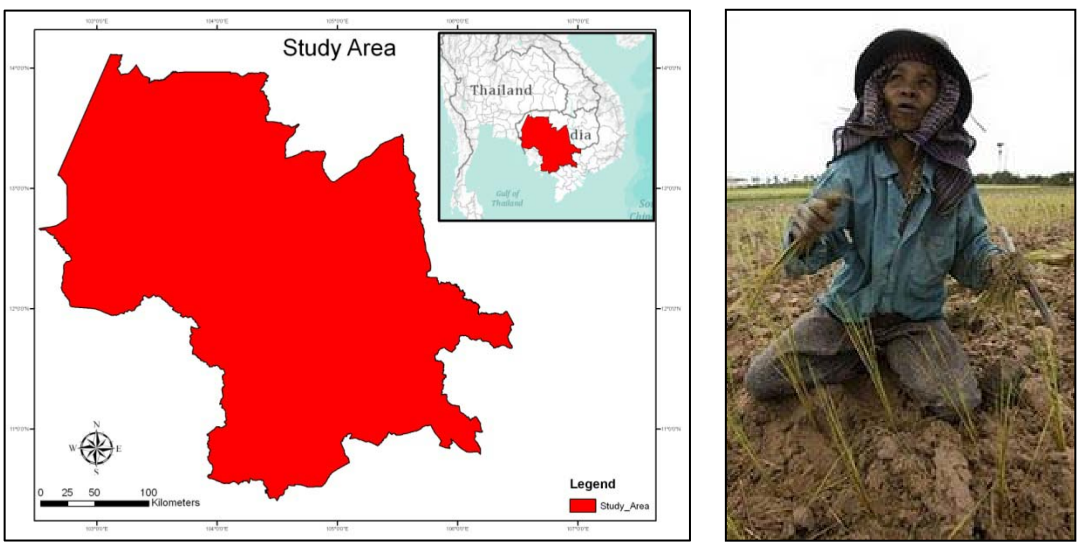

Figure 1) Study area covers agricultural land around Tonle Sap and lower part of Mekong River.

2.2 Data

Monthly remote sensing-based estimation of precipitation from Tropical Rainfall Measuring Mission (TRMM) covering years (1998 to 2010) were collected through NASA ftp site (ftp://disc2.nascom.nasa.gov/data/TRMM/Gridded/ 3B43_V6/). TRMM data has (0.25° spatial resolution) and (3-hours temporal resolution). Remote sensing data from Moderate Resolution Imaging Spectroradiometer (MODIS) including Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) are used to compute VTCI. Eight-day composites of LST (MOD11A2) and sixteen-day composites of NDVI (MOD13A2) with 1-km spatial resolution for one tile (h28v07) covering the study area were collected from anonymous ftp site (ftp://e4ftl01u.ecs.nasa.gov/MOLT/). Monthly precipitation data was collected from two meteorological stations (Siemreab and Pochentong) to compute SPI as a reference meteorological drought index.

Methodology

Annual rainfall using monthly TRMM data were produced and coefficient of variation for each data point was computed in order to identify degree of deviation from long-term average rainfall. SPI values were computed using monthly rainfall data collected from meteorological stations. SPI computation involves fitting a gamma probability density function to a given frequency distribution of precipitation total. The gamma distribution is defined by its frequency or probability density function as given below:

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

VCI and TCI are linearly scaled NDVI and LST from (0 to 100). They can be identified by the following expressions:

$$VCI = 100 \times (NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min}) \qquad (2)$$

$$TCI = 100 \times (LST_{max} - LST)/(LST_{max} - LST_{min}) \qquad (3)$$

VTCI is defined as the ratio of LST differences between all pixels within areas with equal NDVI values. It can be defined:

$$VTCI = \frac{\mathrm{LST_{max}} - \mathrm{LST}}{\mathrm{LST_{max}} - \mathrm{LST_{min}}} \qquad (4)$$

Where:

$$LST_{max} = a + bNDVI \text{ and } LST_{min} = a' + b'NDVI \qquad (5)$$

Dry edge line (LST_{max}) and wet edge line (LST_{min}) are maximum and minimum temperature values defined in a triangle space between NDVI and LST shown in (Figure 2). Coefficients (a, b) are calculated in an area large enough to cover different types of land cover (from bare soil with no vegetation coverage to areas fully covered with vegetation). The coefficients are generally calculated using the scatter plot between NDVI and LST. The value of LST_{min} is considered to be constant for all land-use types and generally equals to LST of water bodies in the study area.

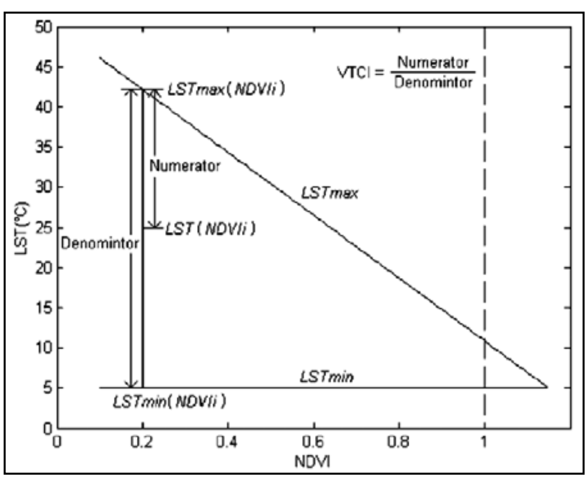

Figure 2) Schematic plot of the physical interpretation of VTCI (Wan, et al., 2004). The vertical dashed line denotes the maximum NDVI value (NDVI~1).

Results and Discussion

Drought prone area mapping using coefficient of variation of annual rainfall, estimated by TRMM data showed significant correlation at global level when tested against maps using meteorological data, computing the probability (%) of annual precipitation in any year being less than 75% of its long-term mean annual value (Figure 3). Western coast of America, North Africa, Middle East and central Australia are identified as highly drought prone areas in both maps. The probability is the highest (red) in the arid areas of the world, due to the high variability in annual precipitation. This makes arid and semi-arid regions of the world to be more prone to droughts. The results at country level showed a very good correlation with drought affected area map reported by (WFP 2003). The results indicated that southern regions of Cambodia are relatively more prone to drought hazard when compared to northern parts of the country (Figure 4). Therefore, southern regions were identified as top priority areas for pre-disaster management measures such as drought preparedness, mitigation and prevention to be implemented.

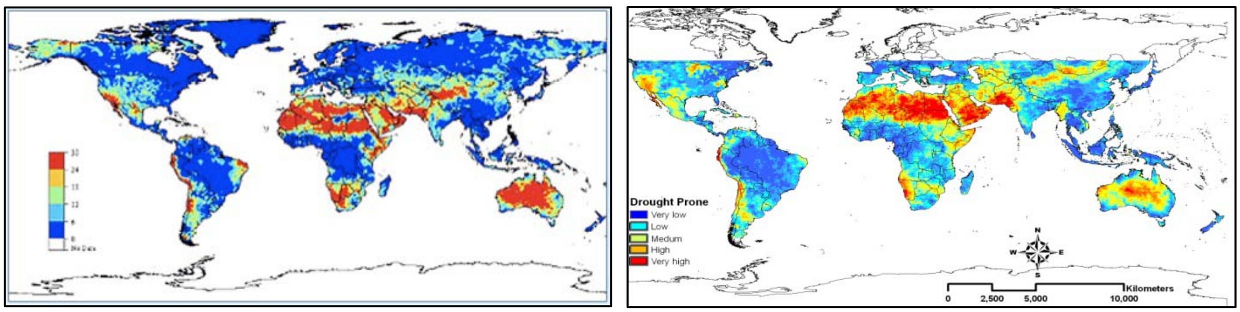

Figure 3) Left: probability (%) of annual precipitation in any year being less than 75% of its long-term mean annual value (Eriyagama, et al., 2009), Right: drought prone area classified using coefficient of variation for TRMM data.

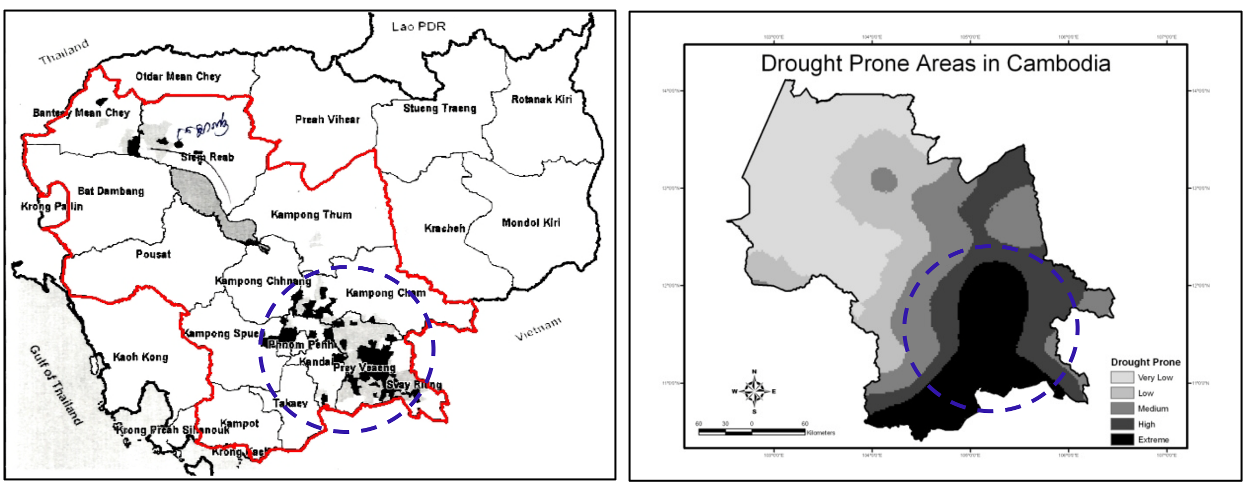

Figure 4) Left: Drought affected areas reported by (WFP 2003), Right: drought prone area using TRMM data.

VCI, TCI and VTCI were tested against in-situ SPI data of different drought time-spans. VTCI performed better than other remote sensing-based drought indices providing valuable spatial information on drought condition. The advantage of VTCI in triangle method (Ts/VI) compared to TCI is that, it evaluates temperature differences in homogenous areas using NDVI. Considering surface temperature of water bodies as (LST_{min}) will significantly reduces the uncertainties in identifying wet edge line. However, there still remains uncertainties in dry edge line (LST_{max}) determination which is an important factor to compute parameters (a, b) in VTCI triangle space. The results indicate that both TCI and VTCI perform much better in characterizing short-term droughts, while VCI performs better with droughts of longer time-span. Correlation between VTCI and 1-month SPI is very significant (r = 0.78) which makes VTCI a reliable remote sensing-based drought index providing near real-time drought information. Correlation values between VCI, TCI and VTCI with (1, 2, 3, 6 and 12-month SPI) are given in (table 1). Spatial variation of drought condition in December 2003 (dry year) and 2005 (wet year) are shown in (Figure 5).

Table 1) Correlation coefficient values between remote sensing based drought indices and in-situ SPI values.

Correlation	SPI 1month	SPI 2month	SPI 3month	SPI 6month	SPI 12month
VCI	-0.21	0.12	0.23	**0.34**	0.26
TCI	**0.51**	0.32	0.16	0.18	0.02
VTCI	**0.78**	**0.61**	0.36	0.14	-0.07

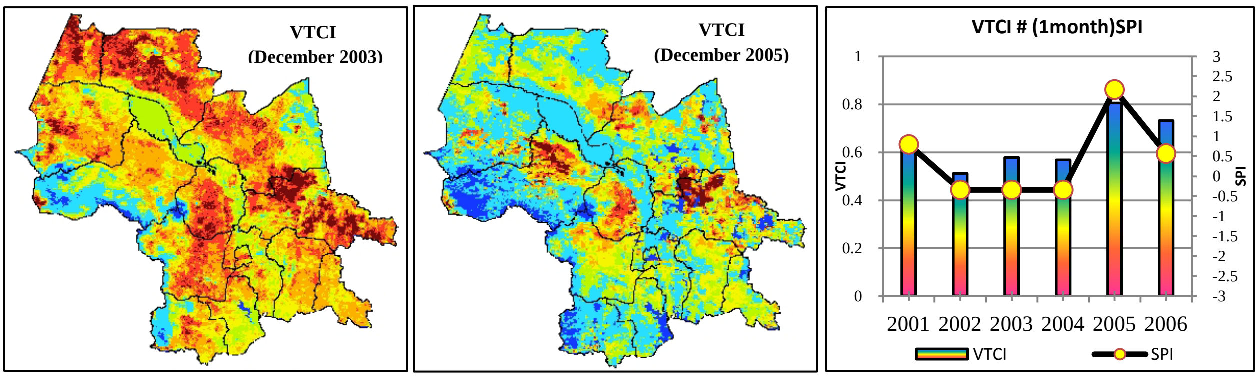

Figure 5) Left: VTCI showing spatial variation of drought condition in 2003 (dry year), Middle: 2005 (wet year) and Right: Correlation between 1-month VTCI and SPI (r = 0.78).

Conclusion

It can be concluded that TRMM data provides invaluable information on rainfall variations at global level as well as regional level to identify drought prone areas. It can be used for drought preparedness, mitigation and prevention strategies in developing countries where access to meteorological data is often limited. Besides, application of LST together with NDVI in VTCI triangle space provides reliable information on near real-time drought monitoring and can be a suitable remote sensing-based drought index. Therefore, application of TRMM together with MODIS data can significantly improve drought management in developing countries where access to meteorological data is limited. Further study to improve dry edge line determination in triangle method is recommended to enhance the performance of VTCI in characterizing drought condition.

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