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Agricultural drought assessment using MODIS satellite data in Kurunegala District, Sri Lanka.

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ABSTRACT

Drought is a climatic anomaly characterized by long spell scarcity of water. Agricultural drought is defined more usually by less availability of soil water to maintain crop and forage growth by the deficiency of normal precipitation over an identified period of time. Since drought is a creeping phenomenon which appears slowly and resulting web of impacts, not only to agriculture but also for all other aspects, monitoring, forecasting, evaluating impact and proposing solutions to drought hit areas are challenging than other disasters. Distinct to point observations of ground data, remote sensing provides direct spatial information on vegetation stress occur due to drought conditions. This facilitates to utilize time series Vegetation Indices derived using time series satellite data to continuous monitoring of vegetation conditions and tracking drought occurrences. MOD13Q1 (250m, 16-day) satellite images, which contain NDVI (Normalized Difference Vegetation Index), were used in this study and Vegetation Condition Index (VCI) was calculated using ENVI 4.5 GIS and remote sensing software for agricultural drought monitoring in Kurunegala District during the year 2000-2015. Spatial variability of drought frequencies was evaluated and mapped using ILWIS 3.4 free software. Map accuracy was assessed using actual drought data available for Kurunegala district in the database of Disaster Management Center. According to the results, North and North-West parts of Kurunegala District were identified as severe agricultural drought prone areas. In order to enhance the accuracy, water mask was recommended.

Keywords: Agricultural drought, MODIS, NDVI, VCI, Kurunegala District

1.0 INTRODUCTION

Drought is considered as a chronic, potential natural disaster, which is extremely challenging human survival by affecting the agricultural production, social stability and sustainable development of resources and eco-environments. According to operational definition, there are four types of drought; meteorological drought, agricultural drought, hydrological drought and socio-economic drought (Dogondaji and Muhammed, 2014). The main concerns in agricultural drought studies are the plant's water demand and available soil moisture.

Unlike point observations of ground data, satellite sensors provide direct spatial information on vegetation stress caused by drought conditions (Shaw and Krishnamurthy, 2009). Agricultural drought is usually monitored using Vegetation Indices and surface temperature detections by satellite sensors. Among the various Vegetation Indices, NDVI (Normalized Difference Vegetation Index) is widely used as the base for operational drought assessment.

Green and healthy vegetation reflects much less solar radiation in the visible (Ch_1) compared to those in near-infrared (Ch_2). More importantly, when vegetation is under stress, Ch_1 values may increase and Ch_2 values may decrease. The NDVI is defined as the following equation (1) (Rouse, 1974);

$$NDVI = \frac{(Ch_2 - Ch_1)}{(Ch_2 + Ch_1)} \quad \text{---------(1)}$$

NDVI ranges from -1 to +1. Water has negative NDVI while clouds and barren lands have zero NDVI. Vegetation always has positive NDVI which represent the density and also the vigor and the higher index values being associated with greater green leaf area and biomass (Department of Agriculture and Cooperation- India, 2012).

The primary aim of developing VCI (Vegetation Condition Index) is to assess changes in NDVI signal through long time dataset, by reducing the influence of geographic and ecosystem variables such as weather, soils, vegetation type and topography. VCI can be defined as the following equation (2).

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$$VCI = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100 \quad \text{---------(2)}$$

$NDVI_i$ is the NDVI value for data i, $NDVI_{max}$ is the maximum and $NDVI_{min}$ is the minimum NDVI values from all images within the dataset. Here, VCI below 50% is considered as drought. VCI below 35% is considered as extreme drought (Kogan, 1995).

Moderate Resolution Imaging Spectroradiometer (MODIS) is the primary sensor for monitoring the terrestrial ecosystem in the NASA (National Aeronautics and Space Administration) Earth Observing System (EOS) program (Thenkabail *et al*., 2004). Time series of MODIS images provide close real-time, continuous and comparatively high resolution data (Modis.gsfc.nasa.gov, 2015). MODIS/Terra Vegetation Indices (NDVI/EVI) 16-Day L3 Global 250m SIN Grid [Collection 5] data, also known as MOD13Q1 is a higher level MODIS product. It includes both Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) (Lpdaac.usgs.gov, 2015).

Though drought is the least common among many types of disaster events happened in Sri Lanka (1974-2008), it cannot be underestimated as it has caused severe agricultural losses than the other natural disasters (DMC, 2014). When considering the Districts in Sri Lanka crop loss is higher in Kurunegala District, than other districts due to agricultural drought, affecting livelihood of farm community. Therefore, in this study, Kurunegala District was selected to assess agricultural drought in aid of future drought management procedures. The objectives of this study are; to identify major agricultural drought years in Kurunegala District by vegetation condition assessment using time series vegetation indices derived based on satellite data, to map spatial variability of agricultural drought in Kurunegala district and to assess drought map accuracy using actual drought and rainfall data.

2.0 METHODOLOGY

2.1 Study Area: Kurunegala District

Kurunegala District is located between Latitude 7⁰16’N 8⁰12’N and Longitude 79⁰55’E 80⁰55’E (Department of Census and Statistics of Sri Lanka, 2015). It consists with 4816 km^2 area including inland water bodies of 192 km^2 (kurunegala.dist.gov.lk, 2011). Kurunegala District belongs to the North-western Province of Sri Lanka and consists with 30 DSDs (Divisional Secretariat Divisions) (Figure 1).

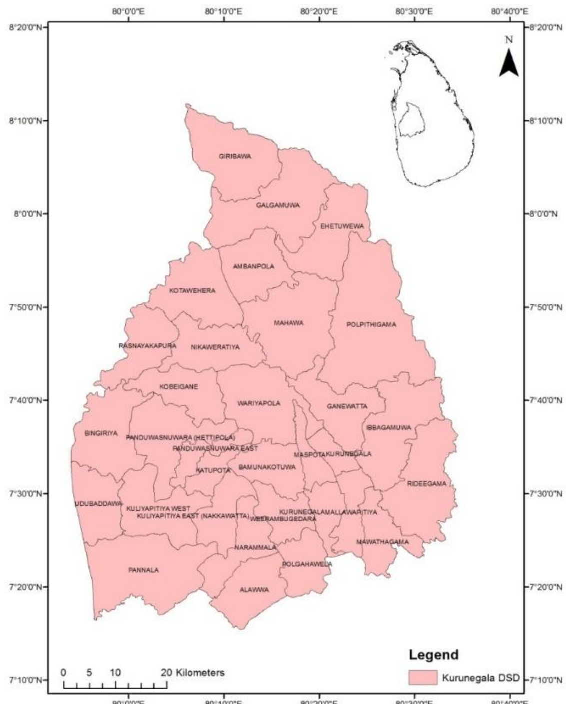

Figure 1: The map of Kurunegala District

2.2 Data Collection

MOD13Q1 data for Kurunegala District (tile identifier h25v08) from February 2000 to February 2015 were acquired from NASA Reverb ECHO (EOS Clearing House) free web portal (URL: http://reverb.echo.nasa.gov/reverb/). NDVI image extraction was done using MODIS Conversion Toolkit in ENVI 4.5 software and images were layer stacked according to the Julian date. Stack layers were masked out

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using Kurunegala District boundary shape file, which was created by using ArcGIS 10.2.2 software. These masked stack NDVI layers were used as the basic secondary data for agricultural drought assessment for the study period of February 2000 to February 2015.

Information on recorded actual drought events for each Divisional Secretariat Division of Kurunegala District were obtained from DMC DesInventar Disaster Information System (URL: http://www.desinventar.lk:8081/DesInventar/main.jsp?countrycode=srandcontinue=y) for map validation process and available rainfall data of several agro-meteorological stations in Kurunegala District were obtained from NRMC (Natural Resources Management Centre of Sri Lanka), for the same study period, for further clarifications.

2.3 Data Analysis

VCI was calculated for each NDVI image in each stacked layer using the Band math tool of ENVI 4.5 software and the calculated images were layer stacked according to their Julian date. In order to identify the major agricultural drought years, these stack layers were imported in to Ilwis 3.4 software. Using the density slicing option in image processing tool of Ilwis 3.4 software, the images were density sliced according to the categorization introduced by Kogan, 1995 (Table 1).

Table 1: Density slicing of VCI images

VCI data range	Drought category	Upper boundary of the domain	Color of the representation
0 – 0.35	Severe drought	0.35	Maroon
0.35 – 0.5	Drought	0.5	Orange
0.5 – 1	No drought	1.0	Forest green

(Source: Kogan, 1995)

Images with major agricultural droughts were identified using the histogram of each density sliced image of VCI. This is done using statistics tool of Ilwis 3.4 software. If the number of pixels of Drought category or/and Severe drought category surpasses the number of pixels of No drought category, that was considered as an image representing a major agricultural drought. The years with highest number of such images were identified as major agricultural drought years of Kurunegala District for the study period.

In order to map spatial variability of drought, the imported VCI images were weighted according to their drought category by using Ilwis 3.4 software (Table 2).

Table 2: Drought category weighting

Drought category	Weight	Formula used for weighting
Severe drought	100	Output map 1= IFF (Input map x< upper boundary value, 100, Input map x)
Drought	10	Output map 2= IFF (Output map 1< upper boundary value, 10, Output map 1)
No drought	1	Output map 3= IFF (Output map 2 <upper boundary value, 1, Output map 2)

The total weight for each Julian date was calculated separately for VCI weighted images in order to identify the drought frequency. Then, the total weights of all Julian dates (23 in numbers) were added together to obtain the images of "VCI total weight". The density distribution of the image was obtained. As the distribution was bell-shaped, the mean and standard deviation of the distribution were used to categorize and to illustrate drought areas (Table 3) by using Density slicing tool of Ilwis 3.4. This image was opened in ArcGIS 10.2.2 software and the final VCI drought spatial variation map was created.

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Table 3: Drought categorization according to histogram area

Area of the histogram	Drought category	Representation color in the map
<Mean	No drought	Forest green
Mean to SD_1	Drought	Yellow
SD_1 to SD_2	Moderate drought	Orange red
SD_1<	Severe drought	Reddish brown

SD= Standard deviation

Results obtained for identifying agricultural drought years were validated by using the actual drought data. From the data obtained from DMC DesInventar database, the number of drought events happened in each DSD was calculated and it was visualized through a map created by using ArcGIS 10.2.2 software. This map was compared with the created AVI and VCI drought maps. In addition, graphed annual rainfall variations of selected agro-meteorological stations were used for further clarifications.

3.0 RESULTS

According to table histogram data of density sliced VCI images, year 2001, 2004, 2005, 2009, 2012 and 2014 can be identified as agricultural drought years for Kurunegala District. From these years, year 2009 can be recognized as the most severe drought year as its spatial distribution, magnitude and duration can be identified higher than the other years.

When considering VCI variation (Figure 2), it's evident that the beginning of the drought falls in early January and it has shown its maximum severity at the month of May. Though the drought has lowered its effects on the months of September, October and November, Ehetuwewa, Mahawa and Polpithigama DSDs has gone through severe drought condition in the month of December.

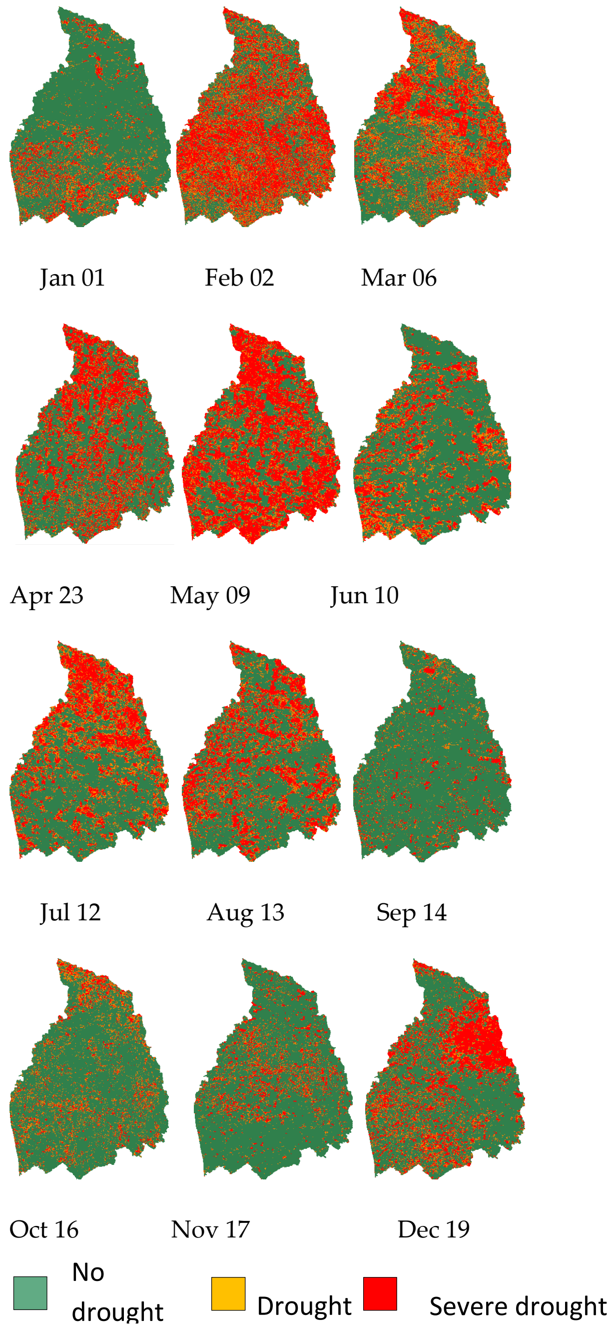

Figure 21: VCI variation of year 2009

The image obtained after adding all the weighted VCI images, "VCI total weight" has bell-shaped density distribution. The density distribution statistics are; mean is 6853.43, median is 6712.000 and standard deviation is ±1204.98. "VCI total weight" image was density sliced according to Table 3. The final output is "VCI drought spatial variation map" (Figure 3).

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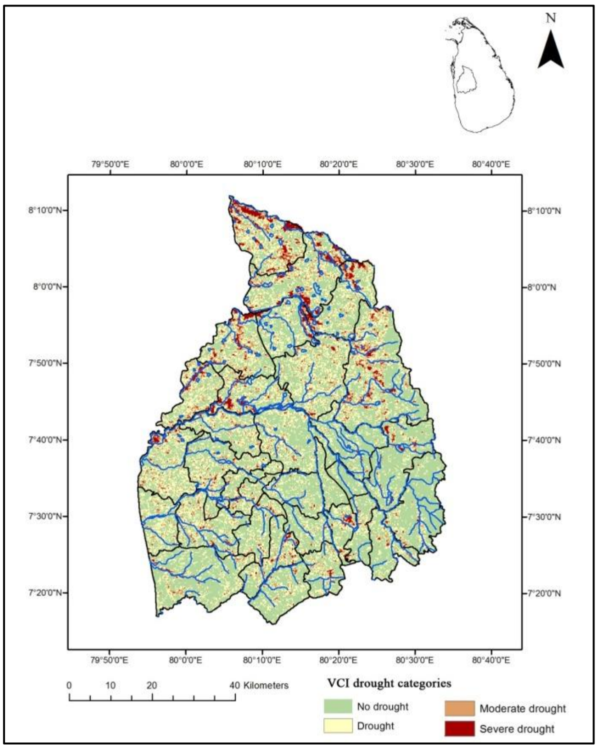

Figure 3: VCI drought spatial variability map

In order to assess the map accuracy, the map of the number of actual drought events that affected each DSD (Figure 4) was compared with Figure 3.

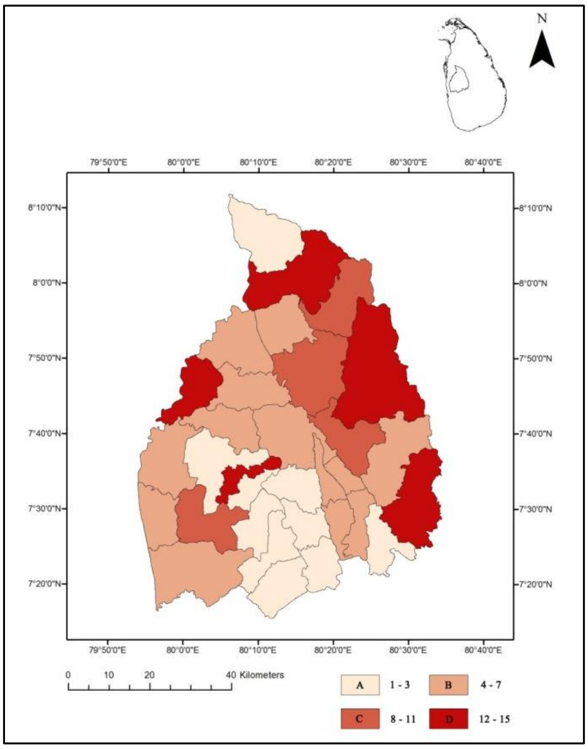

Figure 2: DSD category according to the number of actual drought events (Source: http://www.desinventar.lk, 2015)

According to the VCI drought spatial variability map (Figure 3), the areas in Northern part of the district have received the highest number of high negative vegetation conditions during the study period. According to Figure 4, Galgamuwa and Ehetuwewa DSDs have received high number of drought events. But Giribawa DSD has not received high number of drought events though it is represented as a severe drought prone area in the VCI drought vulnerability map. Polpithigama DSD area has received the highest number of drought events and it is clearly visible in the VCI drought map.

4.0 DISCUSSION

In this study, the use of NDVI and NDVI based vegetation indices for drought monitoring has shown both advantages and disadvantages. They use simple algorithms and according to the resolution of the data set, cover a large geographical area. The current NDVI products such as MOD13Q1, use special techniques to reduce atmospheric noise such as clouds hence broadly differentiate vegetation from other land uses. But satellite based NDVI also embedded with some disadvantages. According to Nagler *et al*. 2005, the 250m resolution NDVI datasets obtained from MODIS sensor lacking accuracy for some applications such as monitoring change in urban areas and riparian buffer zones. NDVI also undergoes scaling and nonlinearity saturation which are similar to other ratio-based standardized vegetation indices such as Standardized Vegetation Index (SVI). In thick foliage or multi-layered canopy, where large biomass is present NDVI tends to saturate (Zargar *et al*, 2011). Though there are methods to remove contaminated pixels from atmospheric noise such as clouds, smoke, haze and aerosols, the contaminations can still happen and sometimes only partial removal take place. For example, MOD13Q1 data are derived by taking the maximum NDVI value for 16 days. But with rainy weather conditions such as monsoonal periods, the maximum NDVI can be affected by clouds though the vegetation shows good health conditions. This will provide false alarms of stressed vegetation conditions. Clouds even cannot be masked because clouds represent the NDVI value of zero, so as the barren lands. Anisotropy is another problem for NDVI as

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surfaces with vegetation reflect light/radiation in different directions as vegetation act as a coarse surface (Burgess *et al*., 1995).

Other than those technical disadvantages, NDVI also contain some disadvantages in its performance. Huete *et al*. (1985) have described that NDVI is sensitive to dark (brown and black) and wet soil backgrounds and NDVI might differ with soil moisture deviations. Peters *et al*, 2002 has identified that vegetation stress is influenced by more factors than moisture conditions alone. These include regional rainfall patterns and soil type as well as the events such as floods, insect infestation, wildfire, etc.

Though with these limitations still satellite based drought monitoring using NDVI based vegetation indices are popular among researchers due to its advantages compared to the other methods available for drought monitoring.

In this study, MOD13Q1 data were used as raw data for agricultural drought assessment. The derived NDVI image was not masked for water as the final outputs contain an over-laid water body layer, and when masking out the other districts, the value was given as -2 because NDVI values range from +1 to -1.

4.1 Agricultural Drought Years of Kurunegala District: Year 2000-2014

When temporal variation of agricultural drought was considered, the highest number of agricultural droughts has occurred in Kurunegala District during the months of February, March and April. But the highest number of actual drought events has occurred during the months of January and August. It is a month before the agricultural drought takes place. As actual drought data are derived based on socio-economic effects of drought on human, it is confirmed that humans are affected just before the vegetation is affected from drought. Wang (2001) described that it is a limitation of the NDVI in drought monitoring because the temporal lag between the rainfall shortage and its appearance in the vegetation health and the consequent change in the NDVI values. Gu (2007) has conducted a five-year history investigation of MODIS NDVI and NDWI (Normalized Difference Water Index, which calculates using near infrared and short wave infrared) to identify the water content and found out that the NDWI was more sensitive than the NDVI to the onset of drought and drought magnitude. Therefore, according to this study, agricultural drought monitoring can be recommended for drought studies which can be used to identify drought prone areas in Kurunegala District rather than an early warning technique.

Major agricultural drought years may vary according to DSD. But with the method that has followed in this study, DSD level major drought years were not identified. But that is not impossible with few more modifications to the study.

4.2 Agricultural Drought Map

The main process of agricultural drought map preparation is image weighting according to the drought category and adding them together to take the total weight. This was done basically for obtaining an idea about the drought frequency according to the drought category; severe drought, moderate drought and no drought.

For countries like Sri Lanka, as two monsoons take in action, some months may show healthy vegetation while some may show stressed vegetation. Taking the total is better than taking the average because; averaging does not indicate the frequency of severity of the drought. It neutralizes the effects and will give a weight in between healthy and stressed vegetation.

Total weights provide a bell-shaped density distribution which will makes things easy. This is because it provides the information about weight values in the majority. Therefore, using mean and standard deviation, the pixels that have deviated from the mean in an increasing manner can be categorized into drought zones. In this study, the obtained density distributions were not normally distributed as they were not symmetrical.

In this study, water is not masked before the analysis as final output contains the overlaid water body layer. Water could be masked by masking the negative NDVI values or by making a layer which includes water pixels using screen digitizing. But there are some limitations in both ways. Though it is said that the water contains negative NDVI values, it may range from very low positive values to very low negative values due to its water quality conditions (Jensen, 2007). Screen digitized layer of water can be hard to obtain for this study due to the resolution of the image. As most of the rivers and streams do not have a width of 250m,

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the entire pixel is not counted as water but the vegetation. Other than that due to the riparian vegetation the water is shaded in most of the rivers.

Though the number of pixels that contains water is low, it is evident that the unmasked water body areas have obtained the drought category “severe drought” and have influenced on the final output of the data. As these data contribute to the density distributions, they have shifted the values of actual severe drought prone land areas into less drought categories. Therefore, in order to obtain a reliable result, it is better to mask the water before the image analysis begins.

4.3 Map accuracy

When considering the accuracy of the obtained drought probability maps, some areas were questionable. This is because in some areas the vegetation has not shown significant drought conditions, but those areas have historical records of drought according to actual drought data. Some areas do not have records of actual drought events but vegetation has indicated significant drought conditions. Following reasons might be behind this.

When considering water bodies, the effect of drainage system in the district may have influenced on the drought map. This is because Sri Lanka has a radial drainage system which is fed from upcountry and flow along lower dry lands nourishing them. Kurunegala District consists of four major river basins. Though the considered area has not received enough rainfall, the rivers may carry enough water to make vegetation to be in their healthy status. Not only natural water bodies, but also man-made water bodies such as reservoirs which are used for irrigation, distribute water for dry areas to minimize the water shortage and vegetation stress.

If the drought map is closely observed, it is evident that the drought prone areas are scattered almost all the areas in the district. Using ground observations and observations using Google Earth software, most of them could be identified as paddy lands. This is because in paddy cultivation, before sowing the ground is ploughed. In this period, the land acts as a bare land which has the NDVI value of zero. As paddy cultivation is one of the major land use types in Kurunegala District, in order to obtain a reliable output either the paddy containing pixels should be masked or the images which are taken during the ploughing season should be avoided. Masking paddy containing pixels does not seems to be reliable as there are considerable number of pixels contain paddy. Therefore, it can be recommended that the images that are taken during the ploughing season should be avoided for map modifications.

Urban or city areas have also affected the NDVI values. As those areas contain less vegetation, paved lands, and concrete structures, a false alarm of drought can be alerted.

Other than these, plant adaptations and their physiology can also be considered. This is because most of the plants in dry areas show adaptations to low water conditions. These adaptations may lead to minimize the stress of the plants due to water shortages hence plants show healthy vegetation conditions even during drought conditions. Some vegetation is deciduous and shed the leaves during dry seasons. Deep-rooted forests can tap into groundwater and thereby mitigate the effect of drought conditions. But as agricultural drought is considered in this study, if the vegetation is in healthy condition, it is not considered as drought.

It is recommended on identification of agricultural drought years on DSD level instead of district level. This is because, according to the study, some DSDs have shown frequent area specific severe drought conditions. In order to enhance the map accuracy, water mask application can be recommended before the image analysis. This is because pixels containing water effect on density slicing of the pixel density distributions. It can be recommended that the images that are taken during the ploughing season of Kurunegala District should be avoided to remove drastic variations that ploughed lands cause on NDVI and NDVI-based indices. Meteorological drought indices, hydrological drought indices or hybrid drought indices can be recommended to use on map validation process, rather than using actual drought data and rainfall data.

5.0 CONCLUSIONS

Agricultural drought can be monitored using remotely sensed MODIS images. According to that, year 2001, 2004, 2005, 2009, 2012 and 2014 can be identified as agricultural drought years for Kurunegala District. Severe agricultural drought prone areas are located in South-East, North and

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North-west parts of Kurunegala District according to AVI and VCI drought spatial variability maps. Further studies should be needed for map accuracy assessment because actual drought data and rainfall data only seems incompatible to validate the maps accurately.

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