COMPARISON OF SPI AND IDSI APPLICABILITY FOR AGRICULTURE DROUGHT MONITORING IN SRI LANKA

Peejush Pani[1], Niranga Alahacoon[1], Giriraj Amarnath [1], Gurminder Bharani[1], Saptarshi Mondal[2], C Jeganathan[2].

[1]International Water Management Institute (IWMI), Battaramulla, Sri Lanka.
[2]Birla Institute of Technology (BIT), Mesra, Ranchi, Jharkhand, India.
Email correspondence: p.pani@cgiar.org and a.giriraj@cgiar.org

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ABSTRACT:

Increasing frequency of drought events coupled uncertainty imparted by climate change pose grave threat to agriculture and thereby overall food security. This is especially true in South Asian region where world's largest concentration of people depends on agriculture for their livelihood. Indices derived from remote sensing datasets signifying different bio-physical aspects are increasingly used for operational drought monitoring. This study focuses on evaluating a newly created index for agricultural drought referred as Integrated Drought Severity Index (IDSI) in comparison with the traditional Standardized Precipitation Index (SPI) primarily representing precipitation condition to delineate drought using custom created ArcGIS toolbox for a period of fourteen years (2001-2014) in Sri Lanka. SPI created using remotely sensed PERSIANN precipitation dataset was compared with the IDSI created using hybrid datasets. IDSI is created based on seamless mosaic of remotely sensed multi-sensor data that takes vegetation (computed from MODIS data product MOD09A1), temperature (MOD11A2) and precipitation (TRMM & GPM) status into consideration. The comparative study was made to assess the efficiency of newly created index and ArcGIS toolbox techniques for near real-time monitoring of spatio-temporal extent of agricultural drought. The result showed significant correlation of 0.85 between the two indices signifying the potential of using IDSI that integrates the response of agriculture drought variables (vegetation, rainfall, temperature and soil moisture) in monitoring short-term drought and application in risk reduction measures.

1. INTRODUCTION

Demand for available finite water resources has increased manifold due to the growth and competing water uses for population and agricultural use, expansion, energy and industrial sectors. Uneven distribution, availability, contamination from over use and climate change have compounded problems of water scarcity, which has been occurring in alarming frequency in recent decades in many parts of the world. Monitoring drought has become an important phenomenon in recent year because of interlinkages between wide variety of sectors in diverse geographical and temporal distribution cascading drought effects. Drought accounts for 5% of all the natural disasters however it impact more than 30% of the total people affected by all natural disasters (EMDAT, 2016). Often indices are used to quantitatively measure, characterize and represent severity of drought conditions by integrating data from one or more variables representing bio-physical features such as rainfall, temperature, vegetation, etc. The body of indices representing different types of droughts, climatic and geographic conditions have exploded in the past two decades due to wide availability of open source remote sensing dataset imaging these features at regular intervals and increased computing resources amplified the applicability of this satellite images for operational or near-real time drought monitoring applications. Number of reviews were undertaken to encompass different drought indices which numbered more than 150 (Mishra and Singh, 2010; Niemeyer, 2008).

Over several decades the Palmer Drought Severity index (PDSI, Palmer, 1965), Standardized Precipitation Index (SPI, McKee et al., 1993), Percentage of Precipitation Anomaly (Zhang et al., 2009) and many others were successfully employed for characterizing drought conditions world over monitoring drought situation across range of spatial scales. In 2010, World Meteorological Organization (WMO) selected the SPI as a key meteorological drought indicator for operational purposes. The Standardized Precipitation Index (SPI-n) is a statistical indicator comparing the total precipitation received at a particular location during a period of n months with the long-term rainfall distribution for the same period of time at that location. SPI is calculated on a monthly basis for a moving window of n months, where n indicates the rainfall accumulation period, which is typically 1, 3, 6, 9, 12, 24 or 48 months (McKee et al., 1993). Estimation of SPI was initially based on the in-situ precipitation gauge information tends to be accurate, but depends on the density and distribution of meteorological stations, which ultimately lacks the spatial information (Brown et al., 2008). This spatial data gap were filled by satellite based information that provides sufficient regular spatio-temporal remote sensing based precipitation data from Tropical Rainfall Measuring Mission (TRMM), Global Precipitation Measurement (GPM), Aphrodite, GPCC, GPCP, etc. (Dutta et al., 2015).

In the recent decade. Several indices have been developed to monitor vegetation stress and drought scenario such as, AVHRR based NDVI (Tucker et al., 1986), Vegetation Condition Index (VCI, Kogan, 1990), Percentage Average

Seasonal Greenness (PASG, Brown et al., 2008), Temperature Condition Index (TCI, Kogan, 1995a) and Temperature Vegetation Dryness Index (TVDI, Sandholt et al., 2002). SPI was commonly used along with these vegetation indices to determine and link how water stress lead to stress in agricultural crops. Researchers have often combined VCI and TCI to derive vegetation health status or used all the three indices to undertake Principal Component technique (PCA) to derive integrated drought information. PCA has its own limitation as it depends on size of data, distribution of data, and PCA results from two MODIS tiles will not have continuity. In order to utilize the seamless data availability particularly from MODIS sensor for near real time drought monitoring a new index called Integrated Drought Severity Index (IDSI) was developed based on the data fusion technique which successfully resolved multi-resolution effect of VCI, TCI and PCI products (Jeganathan et al., 2015). IDSI was used to monitor and evaluate drought conditions across South Asian countries. As a part of the effort to build viable South Asia Drought Monitoring System (SADMS), this study was undertaken to assess the effectiveness of IDSI in capturing drought conditions in Sri Lanka against the conventional SPI. It is envisaged that in predominantly rainfed agricultural systems like Sri Lanka, meteorological drought often transforms into agricultural drought due to the direct linkages between monsoonal rainfall for water dependency and vegetative stress conditions. In this case close correlation will exist between SPI and IDSI representing the cause effect of rainfall on vegetative stress which can be used to evaluate the efficiency of IDSI in Sri Lanka geo-climatic conditions.

2. STUDY AREA AND DATA USED

Sri Lanka lies between 6^o and 10^o N latitude and between 80^o and 82^o E longitude in the Indian Ocean, with a land area of nearly 65,610 km^2 and population of 20 million. With its tropical climate, Sri Lanka receives rainfall primarily from south-west monsoon rain from May to July and north-east monsoon from October to January. The mountains located in the central part of Sri Lanka is major source for majority of rivers. Owing to this monsoonal climate, clear linkages exist between distribution of rainfall and seasonal distribution of droughts. The inter-monsoon period during January-March and August-September show clear relationship with the high number of drought occurrences. Historical record indicate that Southern Sri Lanka, in particular Hambantota province with its semi-arid climate appears to be frequently affected by drought conditions.

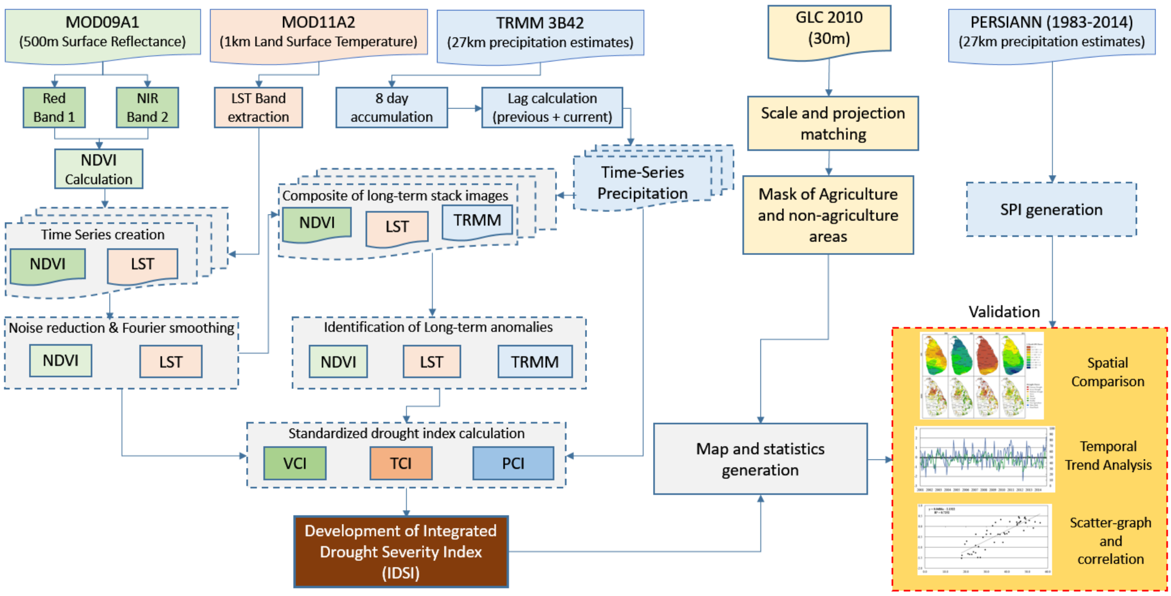
Terra MODIS surface reflectance MOD09A1 (500m) (2001-14) was used to compute time series NDVI and VCI at 8-day interval, MODIS land surface temperature MOD11A2 (1km) (2001-14) was used to compute TCI, TRMM 3B42 (0.25 degree) precipitation estimate (2001-14) was used to compute PCI and PERSIANN CDR (0.25 degree) rainfall estimate of 32 years (1983-2014) was used to prepare the 1-month and 3-month SPI. The summary of datasets, its time period, resolution and data sources are provided in Table 1.

S. No	Data	Detail	Resolution	Duration	Source	Link
1	MODIS Reflectance	MOD09A1 Surface Reflectance 8-day Composite	500m	2001-2014	NASA	http://reverb.echo.nasa.gov/reverb/
2	MODIS Surface Temperature	MOD11A2 Land Surface Temperature 8-day Composite	1km	2001-2014	NASA	http://reverb.echo.nasa.gov/reverb/
3	TRMM Rainfall	3B42 Daily precipitation estimates	0.25 Deg	1998-2014	NASA-JAXA	http://disc.sci.gsfc.nasa.gov/SSW/#keywords=TRMM_3B42_daily%207
4	PERSIANN Rainfall	Daily Global rainfall estimates	0.25 Deg	1983-2015	CHRS, University of California	http://chrs.web.uci.edu/persiann/data.html
5	GLC 2010 Land-use	Global Thematic Map	30m	2010	National Geomatics Centre of China	http://www.globallandcover.com/

Table 1: List of dataset used

3. METHODOLOGY

MODIS surface reflectance MOD09A1 8-day composite (500m) for a period of 2001-14 was availed from the ftp server in the HFD file format using automated python scripting. Similar procedure was followed for MODIS land surface temperature MOD11A2 8-day composite (1km) for the same time period. Both the products were converted to IMG file format using ERDAS Imagine 2014 software package. The red (1) and NIR (2) bands of the surface reflectance data was to compute NDVI using ADAMS tool (Jeganathan et al., 2015). Data gaps and noises were removed using temporal moving window and neighborhood analysis respectively. To enhance the seasonal variation and annual pattern, Discrete Fourier Transformation (DFT) was used considering its ability of smoothening and wide usage (Jeganathan et al. 2010). Considering the large amount of gaps in land surface temperature, linear interpolation technique was adopted and neighborhood analysis was implemented to eliminate the noises. Similar to NDVI, DFT was used smoothen and enhance the seasonal trend of LST. The TRMM precipitation estimates were used in its real form considering the nature of its time-series pattern and zero values coinciding with non-rainy days. The daily TRMM was grossed to 8-day rainfall sum to match with the MODIS 8-day composite data products according to Julian days.



Notes: MOD09A1 – MODIS Surface Reflectance of every 8-Day product at 500m resolution; MOD11A1 – MODIS Land Surface Temperature (LST) daily product at 1,000m resolution; TRMM – Tropical Rainfall Measuring Mission; LULC NRSC – Land Use and Land Cover from National Remote Sensing Centre; Water body mask from Landsat images; NDVI – Normalized Difference Vegetation Index; VCI – Vegetation Condition Index; TCI – Temperature Condition Index (TCI); Precipitation Condition Index (PCI), IDSI – Integrated Drought Severity Index

Figure 1. Methodology for integration of satellite data and other secondary information for drought monitor

3.1. Computation of Indices

The processed NDVI, LST and TRMM data were used to compute Vegetation Condition Index (VCI), Temperature Condition Index (TCI) and Precipitation Condition Index (PCI). All three indices were standardized into values from 0 to100.

3.1.1. Vegetation Condition Index (VCI)

Though NDVI gives a picture of vegetation greenness of a particular time with values ranging from 1- to +1, it fails to enhance the nature of the vegetation type and its growing trend. VCI considers the long-term range of a particular vegetation type and compares the current condition according to this range (Kogan, 1995b). VCI is computed using the following formula:

$$VCI = \frac{NDVI_{curr} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} * 100 \qquad \text{(Eq. 1)}$$

Where, $NDVI_{curr}$ is the current NDVI for a given pixel and the $NDVI_{min}$ and $NDVI_{max}$ are the fourteen years' minimum and maximum NDVI value for that same given pixel. The value closer to zero depicts vegetation stress and values near to hundred reflects healthy condition.

3.1.2. Temperature Condition Index (TCI)

Since the land surface temperature reacts in the inverse manner (lower the temperature, more suitable is the condition for plant growth), it also needs to be standardized. TCI is a thermal stress indicator that identified drought like situation with the temperature condition (Kogan, 1995a). The formula for TCI is as follows:

$$TCI = \frac{LST_{max} - LST_{curr}}{LST_{max} - LST_{min}} * 100 \qquad \text{(Eq. 1)}$$

Where, LST_{curr} is the current LST for a given pixel and LST_{max} and LST_{min} are the fourteen years' maximum and minimum LST value for that given pixel. Values closer to zero shows thermal stress condition for vegetation growth and closer to hundred reflects highly favorable condition.

3.1.3. Precipitation Condition Index (PCI)

Rainfall plays the major and direct role in all kinds of vegetation growth cycle, whether it is evergreen ecosystem or agricultural land. The amount of rainfall in a particular season determines the status of plant growth. Thus looking into the historical scenario of rainfall pattern for a given time in a given place needs to be considered. The equation for PCI is mentioned as follows:

$$PCI = \frac{TRMM_{curr} - TRMM_{min}}{TRMM_{max} - TRMM_{min}} * 100 \qquad \text{(Eq. 3)}$$

Where, $TRMM_{curr}$ is the current net rainfall for 8-days, $TRMM_{max}$ and $TRMM_{min}$ are the fourteen years' maximum and minimum net rainfall for that given time and location.

3.1.4. Integrated Drought Severity Index (IDSI)

S newly developed Integrated Drought Severity Index (IDSI) was computed to assign an area as into different levels of drought stress considering all the three basic components, namely vegetation, temperature and precipitation conditions. The formula for IDSI is as follows:

$$IDSI_{ijk} = \left[L * VCI_{ijk} * \left\{c + \frac{1}{(L*(VCI_{ijk} + TCI_{ijk} + PCI_{ijk} + c)} * \left(TCI_{ijk} + PCI_{ijk}\right)\right\}\right] \qquad \text{(Eq. 4)}$$

This index also ranges from 0-100 with values closer to zero showing extreme drought and that near to zero as healthy condition.

All these indices computation and pre-processing of remote sensing data are complex enough to give an error free output. Thus after intense research, modeling and real-time experiments, a compact package of geoprocessing too was developed to handle all these complexity of multi-source remote sensing datasets. The tool has been named as ADAMS (Agricultural Drought Assessment and Monitoring System) in ArcObject VBA platform of ArcMap.

3.1.5. Agricultural land-cover masking

Since different vegetation type has its own typical growing phenology, and this study concentrates on identifying drought like scenario only on agricultural lands. Crop area were extracted from entire Sri Lanka. This particular process was done using Global Land Cover (GLC-2010) prepared by National Geomatics Centre of China. This particular product is available at 30m spatial resolution with an accuracy level of 83.5%. The cropland from this product was extracted and resampled to 500m resolution to match the IDSI output. The non-agricultural land was then masked out to avoid any misinterpretation. All the analysis of IDSI were then soulfully carried out on agricultural land-cover.

3.1.6. Gridded SPI computation

In the Interregional Workshop on Indices and Early Warning Systems for Drought was organized and held at the University of Nebraska-Lincoln WMO (World Meteorology Organization) accepted SPI to be a standard to identify meteorological drought (Wilhite, 2000). With the development of a SPI toolbox in ArcMap platform as part of ADAMS toolset, availability of long-term gridded rainfall data to establish a climatological trend (30 years) was fulfilled. The in-house SPI (Standardized Precipitation Index) tool is developed in python by using standard python libraries and scipy extension which has inbuilt gamma distribution function required for calculation of SPI the script has been developed by using procedural programming approach, the tool has been engineered to calculate SPI over 1 month to 60 months to study meteorological drought over short to long period of time. The tool has been tested and verified on ArcMap Desktop 10.3 and 10.4. The final output is a raster where every pixel has a SPI calculated based on the passed records over years. The output of the tool has been verified by the WMO (World Meteorology Organization) based windows program which has command prompt user interface.

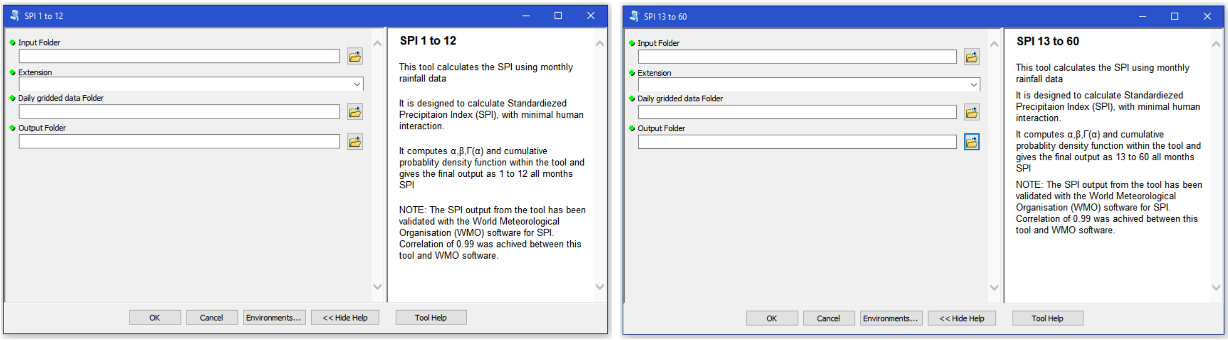


Figure 2: Python tool interface for computing gridded SPI 1-12 month (left) & 13-60 month (right) in ArcMap platform.

4. RESULTS AND DISCUSSION

4.1. IDSI vs SPI Spatial Comparison

The 8-day IDSI was computed and further generalized to monthly mean IDSI for a corresponding comparison with the SPI which uses monthly accumulated rainfall to calculate 1-60 month Index values. In this study, the Yala season (May to September) of Sri Lanka coinciding with the agricultural activity during south west monsoon for four individual years has been considered. A spatial comparison of four years (2006, 2007, 2012 and 2013) for the month of August were made between SPI and IDSI covering whole of Sri Lanka (Fig 6). Two rainfall deficit years (2006 and 2016) are noticeable from the SPI map. During 2006, the central province of Sri Lanka consisting of Anuradhapura and eastern provinces consisting of Polonnaruwa and parts of Batticaloa were mapped to be under drought conditions. The severity of 2012 drought is also evident from the high rainfall deficit across most of the Sri Lanka. Corresponding time period (2006 and 2012) map of IDSI also reveals similar phenomenon revealing drought conditions in North-Central hilly regions and eastern provinces. The Southern province of Hambantota, which were traditionally considered drought prone was under normal condition in both SPI and IDSI map. The hybrid nature of IDSI, enabled it to differentiate between different drought clusters event within individual provinces such as shows extreme and severe drought category within affected Anuradhapura, Polonnaruwa and parts of Batticaloa provinces. The resultant medium resolution gridded index based on IDSI can be used at much local scales compared to the remotely sensed precipitation data derived SPI map which based on pixel density smoothed the areal coverage. Similarly the good years (2007 & 2013), in terms of rainfall, also shows larger spread of normal and healthy classes of IDSI. The year 2007 is better compared to 2013 as represented by both SPI and IDSI.

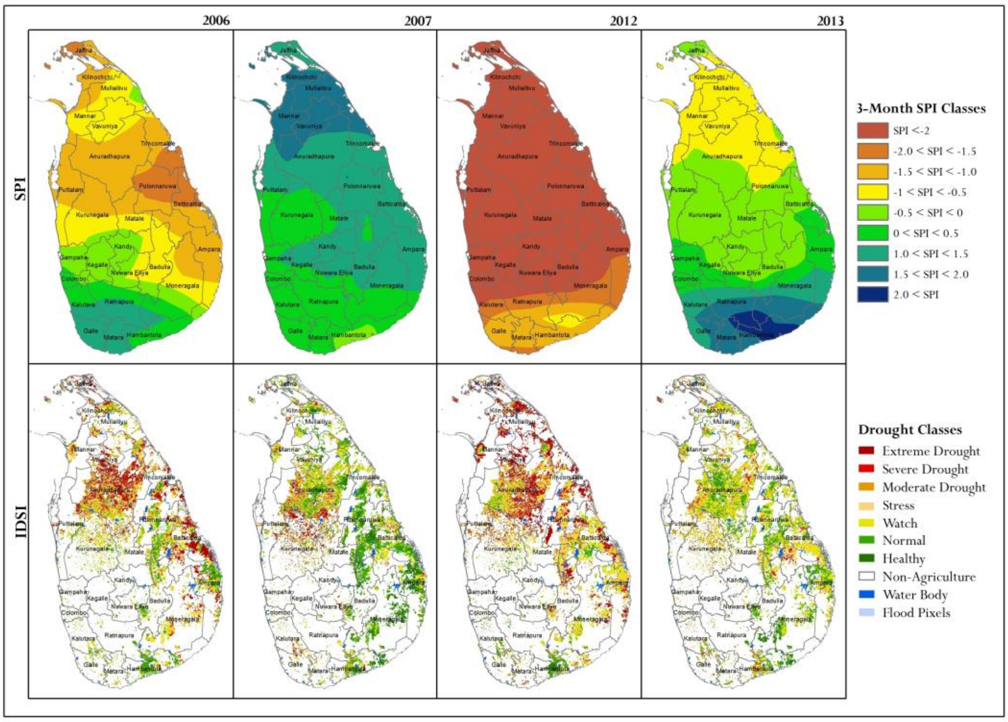


Figure 3: Spatial comparison of 3-month SPI (Jun-Aug) and IDSI August in different years.

4.2. IDSI vs SPI Temporal Comparison

The time series values of spatial average of IDSI in the agricultural area for the study area (Sri Lanka) was plotted against the corresponding spatial average of 3-month SPI of Sri Lanka (Fig. 7). Both the time series profiles from 2001 to 2014 exhibit similar yearly trends. This is particularly evident in the drought years of 2002-03, 2009-10 and 2012-13 where drought conditions are marked with downward spike in both IDSI and SPI profiles. The average IDSI hovers around 45 % and dips significantly whenever SPI tends towards large negative values indicating drought conditions. The trend between the two indices matches close to 72% with each other. The average IDSI in agricultural land for the whole time period lies between 27 and 65 whereas, the average SPI from -2.6 to +2.2. The lower value ranges of IDSI and SPI coincides with the drought years and vice versa. The heterogeneity involved in datasets and approaches cause the remaining deviation in trend between these two indices.

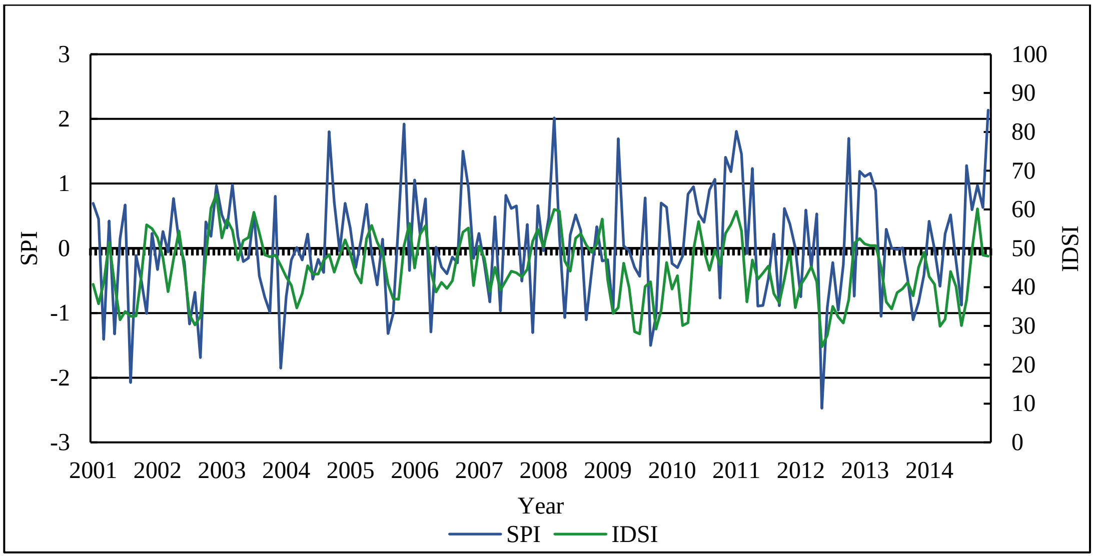


Figure 4: Time series comparison of IDSI and SPI for the time period of 2001-2014 for Sri Lanka.

4.3. IDSI vs SPI correlation

Figure 8 and 9 shows scatter-graphs of monthly IDSI and 3-month SPI where, the mean IDSI of each district's agriculture area is compared with its corresponding SPI values. Each graph containing two years 2006 – 07 and 2012 - 14, comprising of 24 districts' (except Jaffna) spatial mean values of SPI and IDSI were considered. Thus summing up to 48 scatter points in individual scatter-graph for establishing the relationship between the two variables. This comparison shows that there exist significant correlation (r) of 0.85 and 0.86 between the two indices in both the graphs, highlighting severe drought affected years of 2006, 2012 as well as 2014.

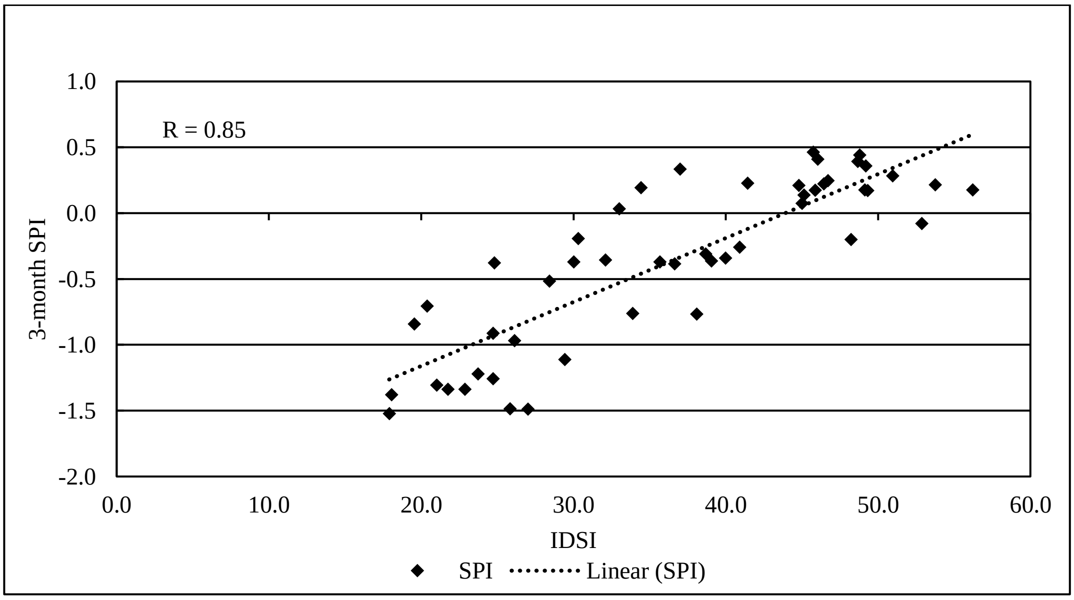


Figure 5: Scatter-graph and linear correlation between IDSI and SPI for the years 2006 (dry) and 2007 (wet).

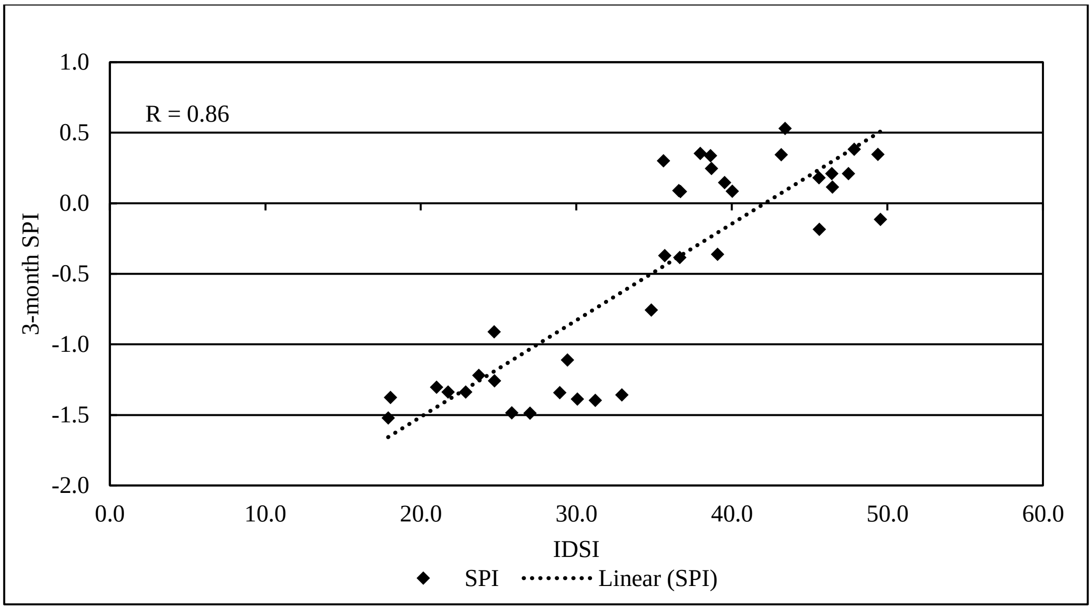


Figure 6: Scatter-graph and linear correlation between IDSI and SPI for the years 2012 and 2014.

5. CONCLUSION

Spatial and statistical analysis to compare the traditionally well-known SPI and the newly developed IDSI shows that there is a good correlation between the indices. The lacking proportion of similarity is also as per expectations. The reason can be attributed to nature, data and difference in the spatial resolution of both the indices. Detailed variation of several important components like vegetation, temperature and rainfall considered in case of IDSI unlike only rainfall in SPI could explain the gap between two indices. The correlation of 0.85 well explains the inter-relationship between agricultural and meteorological drought.

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