Spatial Decision Support System for Climate Change Impact Assessment in Selected Blocks of Purulia and Bankura

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ABSTRACT

A Spatial Decision Support System has been developed to analyze the specific problems related to water availability, agriculture and livelihood at 40 selected villages of Purulia and Bankura District. This micro-level analysis is crucial to farmers and various stakeholders to properly formulate strategies and reduce the vulnerability of the area to drought. Drought analysis at village level was carried out with drought indices like the Standardized Precipitation Index (SPI), Temperature Condition Index (TCI) and Vegetation Condition Index (VCI). An in-depth analysis of rainfall data of 115 years (1901-2015) in Kashipur & Chhatna blocks has been done using the Mann-Kendall test and Sen Slope estimator.

Keywords: *Spatial Decision Support System, Standardized Precipitation Index, Temperature Condition Index, Vegetation Condition Index, Drought, Mann-Kendall test and Sen Slope estimator.*

1. Introduction

The two districts, Purulia and Bankura of West Bengal, are prone to repeated droughts. These two districts also rank low in comparison to other districts of West Bengal in terms of composite human development index. The community perceive drought as a major recurrent disaster in their life and livelihood. With rising winter temperature and increasing variability of rainfall due to climate change, the vulnerability of the agriculture sector will worsen in future. This ailing state of agriculture is further going to make poverty reduction and food security more challenging (WWAP, 2019). The objective of developing this Spatial Decision Support System (SDSS) is to identify the specific problems related to water availability and agriculture at the village level and for formulating strategies to reduce the vulnerability to climate change and water availability for irrigation, through proactive management and drought preparedness. Places, where new water reservoirs and wells at village levels are to be built and the old ones which need repairing, are being identified using this SDSS.

2. Data and Method

A micro-level drought analysis has been carried in 40 selected villages of Bankura (Chhatna Block) and Purulia (Kashipur Block) utilizing Geospatial techniques as shown in Figure 1. The geographical coordinates of the areas under study fall between 23.28°N to 23.42 °N and 86.65°E to 87.00°E.

IMD's daily gridded rainfall data for 115 years (1901 – 2015) have been considered in this study (NCC, 2016). These data have been cropped according to the boundaries of each of the two districts and the cumulative monthly spatial mean of each of the units computed. The rainfall trend analysis was performed using non-parametric, Mann-Kendall test on daily historical data of 115 years (1901-2015) provided by the National Climate Centre, IMD (NCC, 2016). This method is widely used for studying spatial and temporal trends in hydroclimatic series (Hipel & McLeod, 1994). The Mann-Kendall test is a special case of Kendall Rank Correlation (Kendall, 1975), developed by Kendall to ascertain if two series are independent of each other.

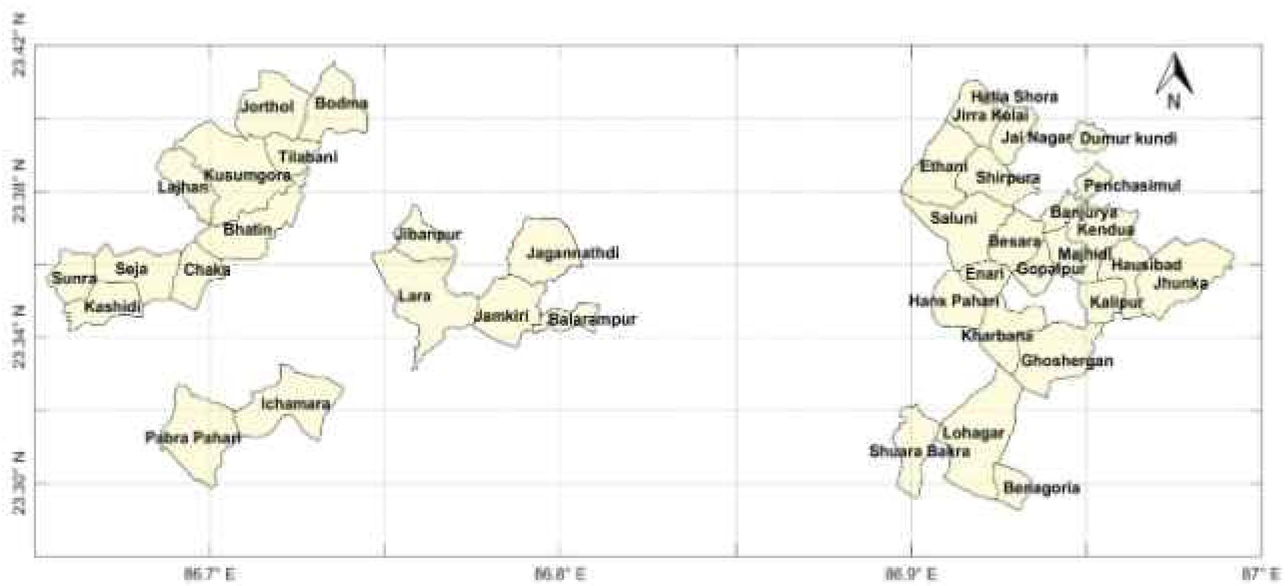

Figure 1: Locations of 40 villages under study.

In addition to the Mann-Kendall test, Sen Slope Estimator, has also been used to find the magnitudes of increasing significant trends and decreasing significant trends (Sen, 1968). The non-significant trends have been separated from significant trends using the Mann- Kendall test at 95% confidence level. These data are separately shown in the form of an interactive map of the 40 villages under study in Figure 2(a).

Standard Precipitation Index (SPI) has been used to compute the meteorological drought primarily. Drought periods during the time period 1901- 2015 have been identified by relatively high negative deviations. The drought intensity of SPI has been further categorized into a mild drought (0 to -0.99), moderate drought (-1.0 to -1.49), severe drought (-1.5 to -1.99) and extreme drought conditions (less than -2.0) (McKee et al., 1993). A drought period starts when SPI value reaches the value of -1.0 and ends when its positive again (McKee et al., 1993). SPI calculated for January has been shown in Figure 3(d).

Monthly data from Global Land Data Assimilation System (GLDAS) at a spatial resolution of 0.25 degree have been used to find the soil moisture at four different depths, rate of evapotranspiration and trans rate of transpiration. GLDAS2.1 Noah are generated through temporal averaging of GLDAS-2.1 Noah 3-hourly data are obtained with the Noah Model 3.3 in Land Information System (LIS) Version 7. The data set contains 36 land surface fields from January 2000 to the present (Beaudoing et al., 2019). Evapotranspiration, transpiration and soil moisture data have also been used.

Moderate Resolution Imaging Spectroradiometer (MODIS/Terra) 16 – Day L3 Global 1 km SIN Grid Normalized Difference Vegetation Index (NDVI) has been used here to compute Vegetation Condition Index (VCI). This 16-day product is generated using the 8-day pre-composited surface reflectance data (Didan, 2015). VCI was computed using the given mathematical expression:

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100$$

where NDVI, $NDVI_{min}$ and $NDVI_{max}$ are monthly smoothed NDVI, its multiyear minimum and multiyear maximum calculated NDVI for each pixel in each of the villages (Kogan, 1995).

MODIS (Terra) Land Surface Temperature (LST) 8-Day Level 3 Global Gridded was used to compute the Temperature Condition Index (TCI) to find out the level of drought when combined with VCI. This product provides an average 8-day LST with a spatial resolution of 1 km.

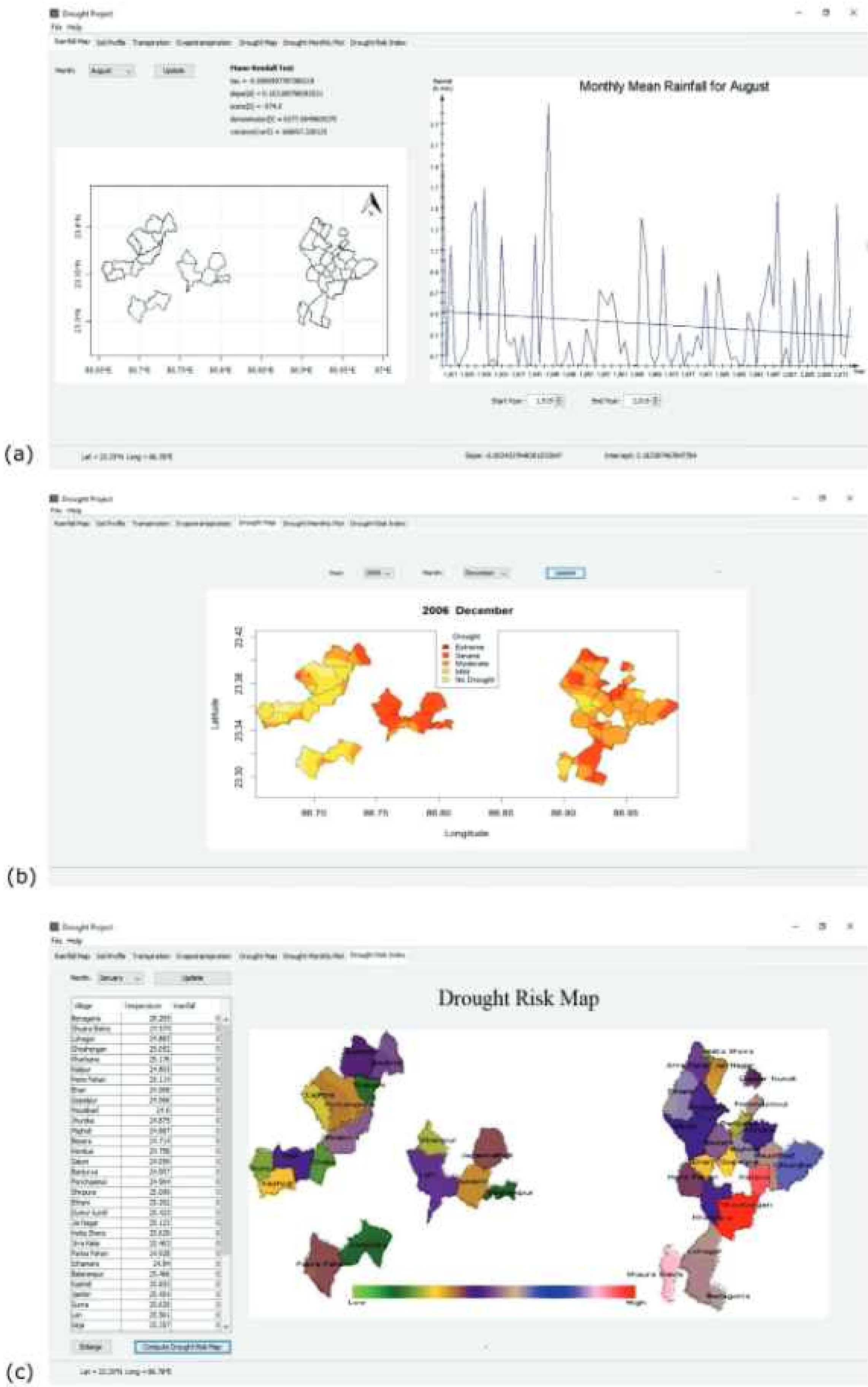

Figure 2: Interactive Drought Risk Assessment.

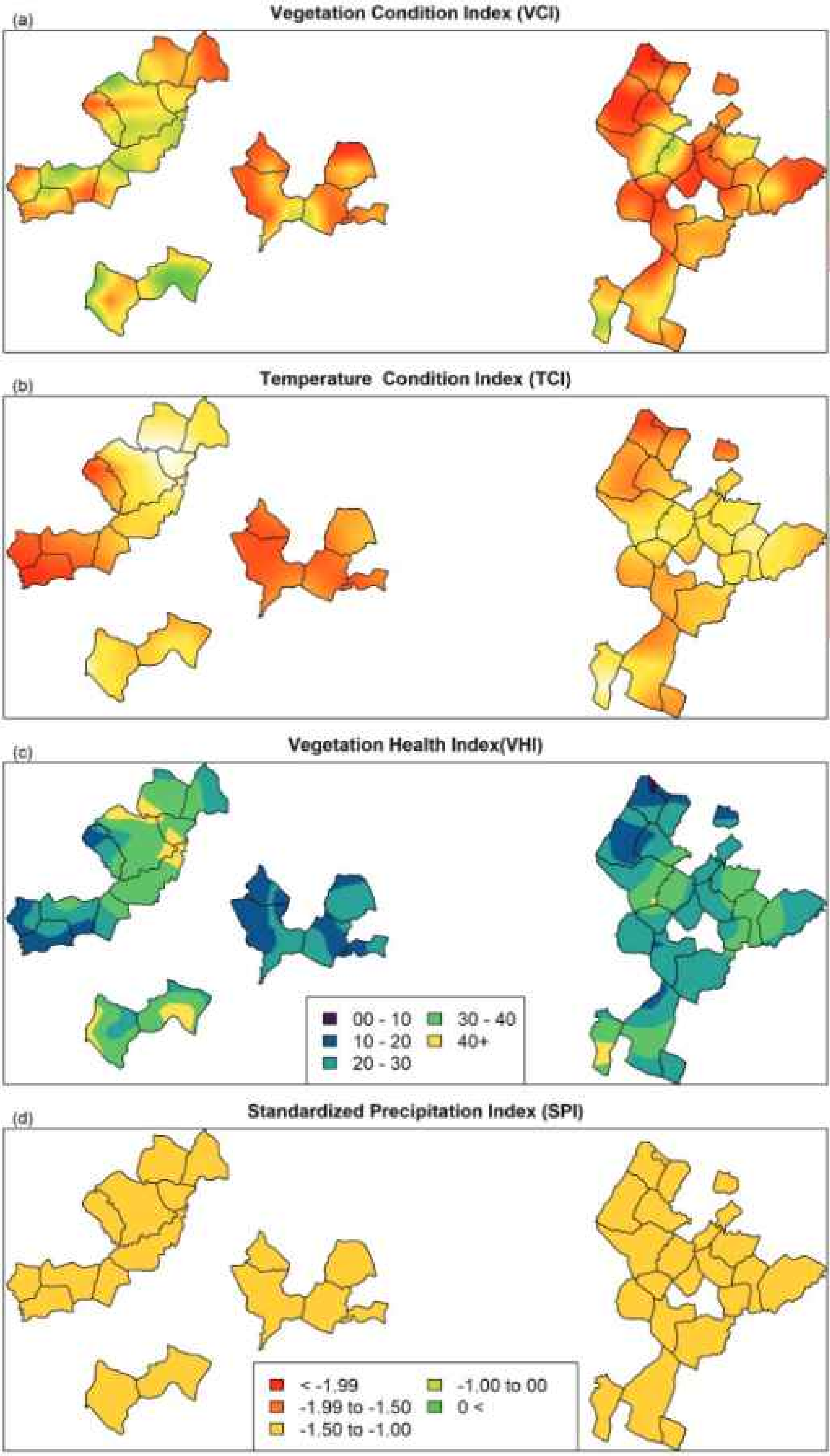

Figure 3: Computed VCI, TCI, VHI & SPI for the month of January 2018 across the 40 villages under study.

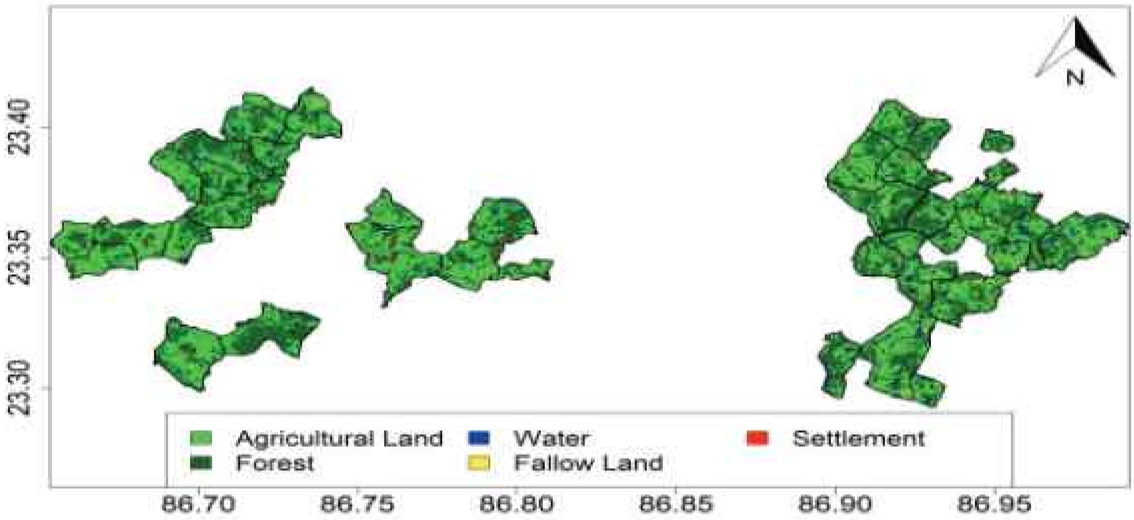

Figure 4: Land Use Land Cover (LULC) map derived from Landsat-8 Operation Land Imager (OLI).

Each pixel value in the MOD11A2 is a simple average of all the corresponding MOD11A1 LST pixels collected within that 8-day period (Wan & Hulley, 2015). TCI was calculated using the following formula:

$$TCI = \frac{BT_{max} - BT}{BT_{max} - BT_{min}} \times 100$$

where BT, BT_{min} and BT_{max} are monthly smoothed Brightness Temperature (BT), its multiyear minimum and multiyear maximum calculated BT for each pixel in each of the villages (Kogan, 2001).

From the above computed monthly VCI and TCI, VHI has been calculated using the well-established mathematical expression (Kogan, 2001):

$$VHI = a(VCI) + b(TCI)$$

Here we have considered values of both the variables a and b to be 0.5 (Ghosh & Mukhopadhyay, 2012). VHI being calculated from TCI and VCI for January 2018 has been illustrated in Figure 3 (a), (b) & (c), which are in turn computed from brightness temperature and NDVI. While the intensity of drought according to VHI has been further categorized into an extreme drought (0 to 10), severe drought (10 to 20), moderate drought (20 to 30), mild drought (30 to 40) and no drought conditions (greater than 40) (Bhuiyan, et al., 2006). These findings computed for the past 18 years (2001 – 2019) have been shown in a separate tab in Figure 2(c).

Total agricultural area and forest area were derived from. Land Use Land Cover (LULC) computed from Landsat-8 Operation Land Imager (OLI) (USGS, 2013) (Figure 4).

Various population data such as the number of agricultural labourers, woman, children and the total population in a village have been used from census 2011 data (Census, 2011). Onsite surveys were done to collect the number of ponds, dug wells, dams and number of animals in each of the 40 villages under study for computing drought risk ranking (Hazra et al., 2017).

Finally, a relative ranking of drought risk among the 40 villages was computed using SPI, VHI, evapotranspiration, transpiration, soil profile at four different levels, total forested area, total agricultural land, number of women, children, agricultural labourers, livestock, dug wells, dams, ponds and current temperature and rainfall. According to the ranking, a real-time drought risk map is generated. This whole methodology of downloading the individual datasets, computing each of the indices and finally generating the drought risk maps for each set of parameters has been shown with the help of a flowchart (Figure 5).

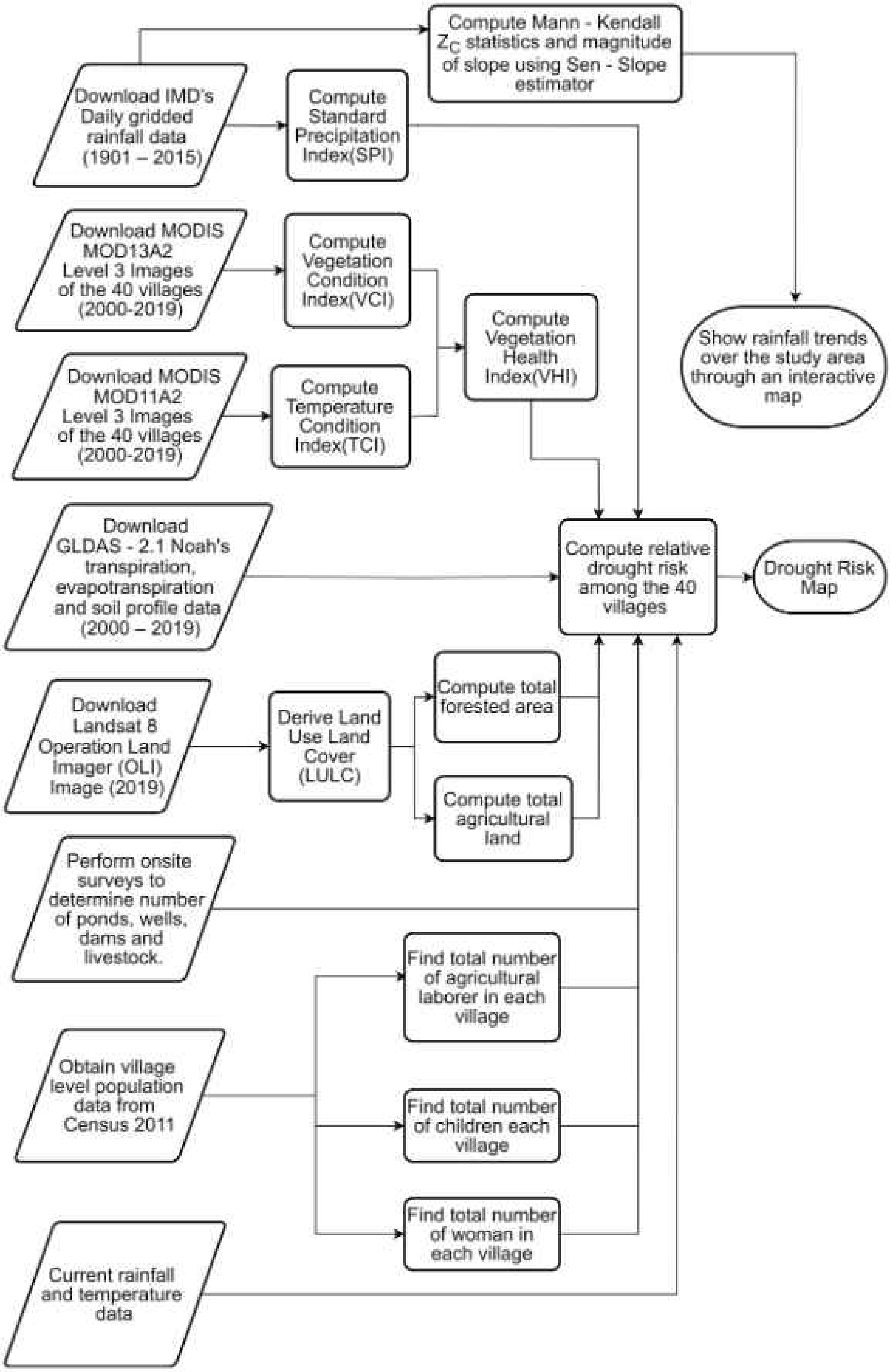

Figure 5: Flowchart showing the methodology of the Spatial Decision Support System.

The spatial visualization capabilities of this application were done using the J2SE framework, while the pre-analysis of data was done using the R programming language.

3. Conclusions

The primary function of this application is to provide a real-time dynamic computation of relative drought vulnerability index of the 40 villages in our study. It is envisaged that such a system would be beneficial for district and village level policymakers to plan and prepare against monthly or long-term drought incidences.

There are certain areas that need to be focused in the SDSS. For example, there should be a provision for the user to input satellite images and weather data, and a means by which the software can update itself automatically with the latest weather data, from both ground stations and satellite datasets available online. In other words, enabling it to produce output to the users in real time. Also, an option to export the data visualizations for further analysis needs to be incorporated into the application.

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Within the framework of the Development Research Communication and Services Centre (DRCSC) Project Climate Change Adaptation (CCA) (DRCSC , 2015) with funding support from National Bank for Agriculture and Rural Development (NABARD) this SDSS has been created.

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