SPATIAL AND TEMPORAL ANALYSIS OF RAINFALL AND DROUGHT AND DEVELOPMENT OF A DROUGHT PREDICTION MODEL BY USING MULTI-MODEL ENSEMBLED APPROACH

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DECLARATION

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Spatial and Temporal Analysis of Rainfall and Drought and Development of a Drought Prediction Model by using Multi-model Ensembled Approach

Abstract

Drought is one of the major catastrophes faced by most of the countries in recent times. Studies have been carried out to find underlying patterns and to implement forecasting systems specified for a particular region. Finding common patterns among diverse regions and implementing forecasting systems have become challenging due to climatological differences. Climatologists have divided drought into several categories for the ease of interpretation and analysis which make analysis and forecasting more complex. Sri Lanka is a climatologically diverse country, where people can experience the climate differences within a hundred kilometres.

This study contains three major components named spatial and temporal analysis, analysis of drought and development of a drought prediction model with drought risk assessment. Spatial and temporal analysis has been carried out for five selected basins in Sri Lanka namely Malwathu Oya, Kirindi Oya, Kanakarayan Aru, Gin Ganga, and Kala Oya by using selected five different drought indices. The results show that the best suited drought index to identify occurrence of drought is Standard Precipitation Index (SPI), while a significant variation is observed within Kirindi Oya basin which spans over several climatological regions.

The development of the drought prediction model has been accomplished for Malwathu Oya basin by using recurrent neural networks with Long Short-Term Memory Networks and Artificial Neural Networks. The model has achieved an accuracy up to 86% in drought prediction in sub basin scale. Different models with different parameters were tested to arrive at the best suited model.

A drought risk assessment has been conducted for Anuradhapura district and comparative risk in each Divisional Secretariat Division (DSD) was identified. The identified risk has been compared with the relief payments and drought affected population data in order to ensure the applicability in Anuradhapura district.

The multi-model ensembled approach developed can be effectively used in drought risk identification and to obtain relative indication of socio-economic implications of drought for similar regions in Sri Lanka and elsewhere and thus can be employed as a decision support system in drought prediction and relief management.

Keywords: Drought Prediction Model, Drought Risk Assessment, Malwathu Oya Basin, Spatial and Temporal Analysis of Drought

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LIST OF ABBREVIATIONS

Abbreviation	Description
ANN	Artificial Neural Networks
DHI	Drought Hazard Index
DI	Deciles Index
DRI	Drought Risk Index
DSD	Divisional Secretariat Divisions
DVI	Drought Vulnerability Index
GLG	Lower Gin Ganga
GMD	Maha Dola
GTE	Terun Ela
GUG	Upper Gin Ganga
GUM	Upper Middle Gin Ganga
KAI	Iranamadu
KAL	Lower Kanakarayan Aru
KAU	Upper Kanakarayan Aru
KIK	Kuda Oya
KIL	Lunugamwehera
KIM	Maha Ara
KIU	Upper Kirindi Oya
KIW	Lower Kirindi Oya
KO	Kuda Oya
KOH	Hewanhella
KOM	Mirisgoni Oya
KOR	Upper Rajanganaya
KOS	Siyambalangamuwa Oya
KOU	Upper Uttumadu Aru
LK	Lower Kirindi Oya
LSTM	Long-Short Term Memory

LU	Lunugamwehera
MA	Maha Ara
MOA	Kal Aru
MOK	Kudahathu Oya
MOL	Lower Malwathu Oya
MOM	Upper Malwathu Oya
MOU	Upper Kanadara Oya
MOY	Maminiya Oya
MRF	Mean Rainfall
PN	Percent of Normal
RAI	Rainfall Anomaly Index
RNN	Recurrent Neural Networks
SPI	Standard Precipitation Index
UK	Upper Kirindi Oya

1 INTRODUCTION

World is experiencing effects of climate change and natural disasters in recent years than ever (Wijkman & Timberlake, 1984; Guha-Sapir, Hargitt, & Hayois, 2004; Guo, 2010). The drought has become one of the major catastrophes faced by mankind in recent times. Different forms of drought can be observed over the world in different severities (Wang, Ertsen, Svoboda, & Hafeez, 2016). Drought is a complex phenomenon; hence a single definition is not available (Wilhite & Glantz, Understanding Drought Phenomenon: The Role of Definitions, 1985; Wilhite, Drought as a Natural Hazard: Concepts and Definitions, 2000). The most used term for drought is "Lack of Rainfall", however, this is only one aspect of drought (Loon, 2015). Climatologists have divided drought into several categories for the ease of analysis and monitoring named meteorological, hydrological, agricultural and socio-economic (Svoboda & Fuchs, 2016; Bayissa, et al., 2018). Above given definition describes the drought in means of meteorological drought.

Meteorological drought occurs when there is a scarcity of rainfall over a longer period of time. All other droughts are followed by meteorological drought because the surface and groundwater hydrology, agriculture and social impacts occur as a result of insufficient rainfall (Zargar, Sadiq, Naser, & Khan, 2011; Shah & Mishra, 2015). Hence, the study of drought in means of all drought types is a challenging task. Further, we should have an accurate estimation and analysis of meteorological drought to analyse other categories. Even though precipitation is the main contributing factor for most of the drought indices, precipitation directly cannot be taken as a measure of drought, as the amount of rainfall differs spatially (Svoboda & Fuchs, 2016).

Different drought indices have been developed to analyse and identify the drought severity and impacts. However, since the climatological changes and variations are different from region to region, no common metric exists (Svoboda & Fuchs, 2016). A drought index which is suitable for one region may not be suitable for a nearby region due to the same reason. Therefore, climate-related studies are carried out to determine the most suitable index or to introduce a new metric (Zargar, Sadiq, Naser, & Khan, 2011).

Meteorological drought occurs when there is no adequate precipitation for a longer period of time. Hence, most of the drought indices that describe meteorological drought measure the deviation from mean calculated precipitation level. Standard Precipitation Index (SPI), Palmers Drought Severity Index (PDSI), Rainfall Anomaly Index (RAI) and Deciles are some widely used metrics (Hayes, 2017). However, for very complex models, precipitation along with evapotranspiration and temperature anomalies are considered. Some indices such as Standardized Precipitation Index (SPI) and Deciles give indications of several drought types, namely meteorological, hydrological and agricultural and this is due to the interdependency of these droughts over the temporal scale (Zargar, Sadiq, Naser, & Khan, 2011).

Unlike in the meteorological drought, satellite products are widely used to monitor agricultural droughts. Normalized Difference Vegetation Index (NDVI) is one such metric that uses a weighted average of thermal bands of satellite IR products (Li, Jiang, & Feng, 2014). However, these techniques are fairly old now as these were introduced in the first era of satellites. Fraction of Absorbed Photosynthetically Active Ration (FAPAR) and Leaf Area Index (LAI) are some new satellite products that can be used in drought analysis and quantification (Xiao, Liang, Wang, & Jiang, 2016).

Hydrological drought considers the anomalies occurred in surface and groundwater hydrology. Gauge station details for hydrometric parameters are the main data source for these types of droughts.

Socio-economic drought measures the impact of drought towards the daily activities of humans, measured by donations and relief aids. The above-mentioned methods are only a sample from the larger set of methodologies that have proven a significant accuracy and relatedness to the study area of the research.

Gauge station data is the main data source for these types of studies. However, in Sri Lanka, obtaining continuous data for a longer period of time for a particular gauge station is challenging (Villarini, Mandapaka, Krajewski, & Moore, 2008). Most of the gauge data have been discontinued from time to time and the accuracy of the measurements are doubtful. Spatial distribution of gauge stations is sparse in Sri Lanka. Hence, remotely sensed parameters are used for this study with the minimum resolution of 0.1 degrees. This research has studied the existing methodologies of analysing and quantifying the effect of the drought and gather remotely sensed data from various data and service providers such as NASA and NOAA and process and extract data to readable document formats (Johnson, Achutuni, Thiruvengadachari, & Kogan, 1993; Thenkabail, Gamage, & Smakhtin, 2004; Beck, et al., 2017).

Evaluating the suitability of the different models for remotely sensed data is necessary to get the most appropriate model that fit the Sri Lankan climate with required bias corrections. At present, neither the selected existing models are validated nor calibrated for Sri Lankan climate parameter values and patterns. These processed data will be used to identify drought and to quantify the effects of drought.

1.1 Scope of the research

Comparative and critical analysis of drought in Sri Lanka has been carried out in the scale of sub basins. This study considers about sub basins of five major river basins of Sri Lanka covering all the major climatological regions, dry zone, wet zone, intermediate zone and arid zone. The river basins considered in this study are Malwathu Oya, Kala Oya, Gin Ganga, Kanakarayan Aru and Kirindi Oya. As the next step of the study, a drought forecasting model was developed for each of the sub basins with deep learning techniques for all the four drought types.

A drought risk analysis has been conducted for Anuradhapura District using an existing model and the model was verified for the area. Finally, an ensemble drought forecasting model for Sri Lanka is implemented which uses climatological parameters and predict the future probability of drought events.

1.2 Problem Statement

Drought Studies have not been conducted for Sri Lanka, considering the spatial variation in the sub basin scale and the basin scale forecasting provides only broader results which may not be accurate. Even though, region wise climate change predictions are there, basin and sub-basin wise prediction models are not available in Sri Lanka. The drought risk and the socio-economic aspects of drought have to be studied in order to facilitate effective planning methodologies

1.3 Overall Objective

The objective of this research is to conduct spatial and temporal analysis of rainfall and drought and develop a drought prediction model in order to facilitate efficient planning and implementing productive methods of drought disaster management and relief distribution, which would lead to an increase in the social wellbeing and living quality of the Sri Lankan community.

1.4 Specific Objectives

- To conduct spatial and temporal analysis of rainfall and drought in selected regions in Sri Lanka using selected drought indices and past data.
- To develop a drought prediction model for meteorological drought by using remotely sensed past data.
- To study about the relationship among several river basins in Sri Lanka in terms of drought distribution and impact.
- To study about the impact of socio-economic drought in three main basins of Sri Lanka.
- Based on the findings of the study, evaluate how the drought and its impacts are associated in Sri Lanka.

2 LITERATURE REVIEW

2.1 Definitions of Drought

According to World Meteorological Organization (WMO), “drought is a prolonged dry period in the natural climate cycle that can occur anywhere in the world” . Due to the complex nature of this disaster, providing one single definition has become impossible (Wilhite & Glantz, Understanding Drought Phenomenon: The Role of Definitions, 1985; Wilhite, Drought as a Natural Hazard: Concepts and Definitions, 2000). Unlike other natural disasters that occur and cease within a small duration of time, drought incidents which may last from months to years are time taking (Wilhite, Drought as a Natural Hazard: Concepts and Definitions, 2000). Furthermore, the adverse impacts of drought may last for a significantly longer duration. Studies conducted by WMO divides drought definitions into two main types, namely, Conceptual Definitions and Operational Definitions (Monacelli, Galluccio, & Abbafati, 2005).

Conceptual Definitions aim to give an understanding of the concept of drought in general terms and can be used in establishing a drought policy. One such definition is “drought is a protracted period of deficient precipitation resulting in extensive damage to crops, further resulting in loss of yield”. Other than that, The American Heritage Dictionary defines drought as “a prolonged period without rainfall mainly during the agricultural seasons”. These conceptual definitions are not providing adequate information for further studies on drought analysis or applications.

Operational definitions of drought provide information on the duration, frequency, and degree of severity of drought and compare the current situation to the historical average. According to WMO recommendations, this historical average requires a 30-year period of record. In order to define drought, data are obtained in daily, hourly or monthly basis and the variations from the expected values were observed. These definitions are helpful in defining drought when studying, of duration, spatial distribution and severity of droughts.

The operational definitions categorize drought into several sub-categories based on the impacts. Meteorological droughts, agricultural droughts, hydrological droughts, and socioeconomic droughts are the four main categories, into which more than 150 of published definitions of drought are summarized.

However, drought is a complex phenomenon and a universal definition cannot be given for drought. This inability causes inconvenience in getting a clear understanding of the existing droughts. As the definitions differ vastly on the situation, it is required to identify the main category of drought in consideration, so that, the definitions are more applicable.

2.2 Categorization of Droughts

Depending on the objective of the drought study, the drought definitions and assessing methodologies may differ. All four drought categories have interconnectivity (Wang, Ertsen, Svoboda, & Hafeez, 2016). More than 150 definitions for drought have been put up into four main categories, namely meteorological, agricultural, hydrological and socioeconomic.

2.2.1 Meteorological droughts

Meteorological droughts occur due to reduced rainfall and can occur frequently and be present for a long period from months to years, but is ceased at the point of occurrence of precipitation. Following are some of the definitions given for meteorological droughts. "A period of more than some particular number of days with precipitation less than some specified small amount" is the definition given in the Meteorological Glossary by Great Britain Meteorological Office (1951) (Wilhite & Glantz, Understanding Drought Phenomenon: The Role of Definitions, 1985). Linsley defines meteorological drought as "sustained period of time without significant rainfall" while Downer brings up it as "a deficit of water below a given reference value, with both deficit duration and deficit magnitude took into account" (Wilhite & Glantz, Understanding Drought Phenomenon: The Role of Definitions, 1985). However, the atmospheric conditions and thus precipitation vary vastly from region to region, leading to limit the definitions of meteorological drought to a specific region (Wilhite & Glantz, Understanding Drought Phenomenon: The Role of Definitions, 1985).

2.2.2 Agricultural droughts

Agricultural droughts occur when the moisture conditions in root zone are reduced due to hot temperature, low humidity and several other reasons. Even though deeper soil strata have adequate moisture, if the root zone is dry, it can be identified as an agricultural drought. The occurrence of agricultural drought in a plant growing season can incur severe adverse impacts on the crop levels and quality of the crop (Potopova, Boreneant, Boincean, & Soukup, 2015). According to Monacelli et al. (2005), agricultural drought is “having set in when the soil moisture availability to plants has dropped to such a level that it adversely affects the crop yield and hence agricultural profitability”. Agricultural drought contains different characteristics of meteorological and hydrological droughts to agricultural impacts. It is mainly linked with precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so forth (Monacelli, Galluccio, & Abbafati, 2005).

2.2.3 Hydrological droughts

The major indications of hydrological droughts are reduced canal flows or reservoir storage. The occurrence of a hydrological drought may happen due to a meteorological drought, and the reduced precipitation levels and higher evaporation levels can lead to soil moisture depletion and low water flows (Wang, et al., 2007). Precipitation deficits occurring for a long time can adversely impact the surface waterways and groundwater conditions leading to a reduction in water availability in canals and reservoirs. It can take a longer period to recover from a hydrological drought once the precipitation is received. According to Linsley, hydrological drought is a “period during which stream flows are inadequate to supply established uses under a given water management system” (Mirza, 2005).

Whipple explained a hydrological drought year as “one in which the aggregate runoff is less than the long-term average runoff” (Wilhite & Glantz, Understanding Drought Phenomenon: The Role of Definitions, 1985). The severity and frequency of hydrological droughts are defined on a river basin or watershed scale. Even though the climate is the main contributor to hydrological drought, factors such as deforestation, changes in land use, land degradation, and construction of dams affect the hydrological characteristics of the river basin which leads to hydrological droughts (Monacelli, Galluccio, & Abbafati, 2005).

2.2.4 Socio-economic droughts

Socio-economic drought can be explained as restricted access to water caused by economic and political factors. This occurs when the physical water shortage starts to affect people, individually and collectively. In other words, this is resulted from the mismatch in supply and demand for water. These operational definitions are also used to analyse drought severity, frequency and duration for a given historical period (Monacelli, Galluccio, & Abbafati, 2005)

Practically, socio-economic droughts are analysed through indirect parameters like drought relief aids, additional water distributions, destructed crop extent, etc.

Even though all the four types of droughts occur due to reduced precipitation, the relationships between each other are complex. Hence the need for a numerical standard in analysing drought emerges. However, due to the difference in definitions of drought and difficulties in quantifying the outcomes, a single drought index is insufficient for all cases. Hence, over the time, many drought indices have been proposed.

2.3 Drought Indices and Drought Indicators

Spatial and temporal studies of drought can be carried out using drought indices. The drought index is a measure of drought and for each drought type, a different set of drought indices have been developed (Svoboda & Fuchs, 2016). There are numerous drought indices developed as a measure of different drought types and its appropriateness may differ depending upon the geography, information accessibility and several other factors (Hayes, 2017).

Drought indicators are parameters and variables that are used to evaluate and describe drought conditions. It includes major parameters such as temperature, precipitation, groundwater, stream flow, soil moisture level, reservoir water level and various other parameters (Svoboda & Fuchs, 2016). Even though the changes of these parameters can be observed during a drought period, they cannot be directly used as the measurement tools for a drought incident since they are spatially and temporally varying and has interconnectivity between each other. If precipitation is taken as an example, during a drought, a significant reduction in precipitation can be observed. However, depending on the area under consideration, the reduction value may differ. The reduced rainfall value in an area in the wet zone can be higher than the average rainfall received in a dry zone area. Hence, a single value cannot be considered for the above parameters, as a drought related decision maker.

Drought indices differ from drought indicators that they provide a common platform to compare drought situations spatially by using numerical expressions (Svoboda & Fuchs, 2016). Thus, drought indices are considered as numerical expressions of drought severity, assessed using climatic and hydro-meteorological inputs. They measure the qualitative state of droughts (Richard & Heim, A Review of Twentieth- Century Drought Indices Used in the United States, 2002; Svoboda & Fuchs, 2016). The World Meteorological Organization (WMO) defines a drought index as "an index which is related to some of the cumulative effects of a prolonged and abnormal moisture deficiency (World Meteorological Organization, 1992)".

Drought indices should be combined with more information like "vulnerability characteristics and exposed assets" and have a higher impact from agricultural cycles. They may also play another major role by providing informative references for planners or decision-makers depending on the index. This provides users with "a probability of occurrence or recurrence, of droughts of varying severities". Climate studies of a region require data for a prolonged period minimum of 30 years (Johnson, Achutuni, Thiruvengadachari, & Kogan, 1993; Thenkabail, Gamage, & Smakhtin, 2004; Beck, et al., 2017). In order to study the drought patterns and the impacts, in the long run, the prolonged period of data are required. Since different drought indices use different parameters and developed and tested for different regions of the world, the applicability of the index for the study area has to be taken into account. Moreover, drought indices can be categorized as follows.

- Meteorological
- Soil moisture-based
- Hydrology based

- Remote sensor based
- Composite or modelled

The complexity of drought phenomenon, the absence of a unique definition and data inaccessibility for a longer duration may lead to variations in results given by different drought indices for the same location and time period. Hence, it is required to identify a suitable drought index for a given area (Bayissa, et al., 2018).

2.3.1 Early time drought indices

The early records of use of drought indices indicate that different nations have used different methods. The accuracy of the results depends on the availability of accurate and continuous records of parameters under consideration. Rainfall records which are available for two centuries and hence for most of the drought indices and definitions, this is considered as the main parameter along with other meteorological parameters. The criterion to be met in order to identify a drought event was given and the severity of the drought event was categorized into classes. Using the drought indices, an implication of the drought duration and the drought intensity was given.

However, when considering the hydrological drought indices, most of them are based on the stream flow, since it can be identified as a result of all the hydro-meteorological activities taking place in the watershed. These studies have considered base and mean flow measurements for a considered period monthly or annually in order to average out and compensate the direct runoff crests (Yevjevich, 1967; Frick, Bode, & Salas, Effect of Drought on Urban Water Supplies. I: Drought Analysis, 1990; Frick, Bode, & Salas, Effect of Drought on Urban Water Supplies. II: Water- Supply Analysis, 1990). During the early nineteen nineties, the U.S. Weather Bureau identified drought as “occurring during any period of 21 or more days with rainfall 30% or more below normal for the period (Richard & Heim, A Review of Twentieth- Century Drought Indices Used in The United States, 2002)”.

Drought measures frequently used at that time were the accumulated departure from normal and accumulated precipitation deficit. Furthermore, some other drought identification criteria used are consecutive fifteen days of period with no rain, obtaining precipitation less than one third of the normal value for period equal or exceeding 21 days, receiving an annual precipitation less than three thirds of the normal value, receiving a monthly precipitation less than 60% of the normal value, or any amount of rainfall less than 85% of normal (Wilhite, Drought as a Natural Hazard: Concepts and Definitions, 2000).

The earliest studies have used rainfall as the drought index, where in 1957, Friedman used annual rainfall to analyse drought in Texas. Other than that, many other countries including Britain, India, and Russia have used a given rainfall value below which they would identify a drought event (Wilhite, Drought as a Natural Hazard: Concepts and Definitions, 2000).

The problem with these definitions is that they are valid only for specific applications in specific regions because the meteorological conditions that result in drought are highly variable and specific to the corresponding regions around the world. Furthermore, indices developed to evaluate and measure the intensity and impact of meteorological drought were inadequate for agricultural, hydrological, or other measuring applications (Zargar, Sadiq, Naser, & Khan, 2011).

2.3.2 The idea of moisture adequacy

This issue in considering a rainfall value as a drought index was addressed by Thornwaite and Mather with the concept of moisture adequacy (Richard & Heim, A Review of Twentieth- Century Drought Indices Used in The United States, 2002). The main argument they raised was that mere rainfall cannot consider the availability of moisture in the environment which ideally causes the drought events. Furthermore, the real need of rainfall is highly dependent on the soil moisture availability at the time of start of no rain period.

Unlike meteorological drought events, the start of an agricultural drought is noted when the soil moisture levels are not adequate, hence moisture adequacy index was introduced by McGuire and Palmer. A national level drought index has to account the total environmental moisture level. However, the introduction of a complex water balance model by W. Palmer can be identified as a huge turning point in drought indices.

When going through literature, it can be found that many researches conducted in drought studies have used several kinds of drought indices. Below discussed are some of the frequently used ones (Richard & Heim, A Review of Twentieth- Century Drought Indices Used in The United States, 2002; Hayes, 2017).

2.4 Traditional Drought Indices

2.4.1 Deciles

Deciles index is mainly involved with all the drought categories except socio-economic drought situations and can be calculated for various time scales and steps. The only parameter used is precipitation and using a simple calculation, the drought index is obtained. The frequency and the precipitation distribution are ranked for the selected location for the entire period of record for the considered location over measured period. The first decile is considered as the rainfall amounts which includes the lowest 10%. Fifth decile includes the median. The extreme drought events are considered to be occurring when the decile value is 5 (Sivakumar, Wilhite, Svoboda, Hayes, & Motha, 2010). The timescales calculated are daily, weekly, monthly, seasonal or annual.

However, non-consideration of other meteorological parameters such as temperature can have a negative impact on the accuracy of the results (Svoboda & Fuchs, 2016). A notable limitation is that the results can be highly dependent on the number of records considered and accuracy will increase with the number since many wet and dry periods are added to the distribution.

2.4.2 Standardized Precipitation Index (SPI)

The SPI is one of the most commonly used drought indices which is applicable for all the climatic regions. This uses historical precipitation records of a particular location and develops a probability of precipitation (Mckee , Doesken, & Kleist, 1993). The SPI is calculated in different time scales, 1 month, 3- month, 6-month any many more. The definition of SPI does not indicate any specific length of time of data (Svoboda & Fuchs, 2016).

However, the availability of additional data for a longer time duration lead to having more extreme events under consideration, hence the result would be robust (Guttman, Comparing teh Palmer Drought Index and the Standardized Precipitation Index, 1998; Guttman, Accepting the Standardized Precipitation Index: A Calculation Algorithm, 1999).The SPI-3 and SPI-1 are generally used for basic drought monitoring while SPI-6 is used for agricultural drought monitoring. Longer spans of SPI are used for hydrological impacts monitoring (Senay, Velpuri, Bohms, Budde, & Young, 2015). The SPI is applicable for any of the precipitation data sources regardless of the method of data retrieval. However, it should represent actual rainfall distribution of study area to get an accurate result.

Even though the most frequent time scale used is monthly basis, by using sophisticated software, it is able to calculate SPI for shorter durations as weekly basis and daily basis. The methodology behind the calculation of SPI remains same regardless of the time scale (Mckee , Doesken, & Kleist, 1993). An intensity scale is used in SPI which has both positive and negative values where positive values are for wet conditions and negative values for dry conditions.

The SPI identifies a drought when the SPI value starts to go below zero and reach -1 and the drought is ceased when the SPI values go above zero and reach +1. However, it is a must to include at least one value below or equal to -1 to identify that period as a drought. The advantage of using SPI is that, the index can be used even with datasets which do not have continuous data. “Ideally, the SPI time series should be complete, but in SPI calculations, it will produce a NULL value if there are a few missing data to calculate a value, and SPI will begin calculating output again as data become available” (Zargar, Sadiq, Naser, & Khan, 2011).

Hence, the SPI can be used for areas with discontinuous datasets. However, there are issues in comparing SPI values in different temperature situations as the precipitation is the only parameter considered in the calculation. Furthermore, this may not be very accurate for shorter drought durations and starting and ending durations of the droughts.

2.4.3 Weighted Anomaly Standardized Precipitation Index (WASP)

The WASP is mainly used in drought monitoring in tropical regions (Lyon, The strength of El Nino and the spatial extent of tropical drought. , 2004) to monitor the developing drought. For that, defined wet and dry periods are taken into account. The only input is precipitation in monthly or annual basis. However, for the areas like Puttalam, Hambanthota and Mullativu where a dry climate prevails more than the wet period, the applicability reduces.

2.4.4 Palmer Drought Severity Index (PDSI)

As explained in pioneering evapotranspiration work carried out by Thornwaite, Palmer Drought Severity Index uses precipitation, moisture supply, and moisture in hydrological systems (Thornthwaite, 1948). The model has two layers and calculates the soil moisture conditions.

The assumptions made in preparing the model are,

- “The plough layer has a field capacity of 1 in. (2.54 cm), moisture is not transferred to the root zone until the plough layer is saturated.
- “Runoff does not occur until both soil layers are saturated” (Thornthwaite, 1948)
- “All of the precipitation occurring in a month is utilized during that month to meet evapotranspiration and soil moisture demand or be lost as runoff”.

In this index, wet values are provided as positive values and dry values are provided as negative values and for normal precipitation and temperature conditions, the index is 0. Some other notations used for Palmer are known as the PDSI and the Z Index.

2.5 Remote Sensing based Drought Indicators

2.5.1 Evaporative Stress Index (ESI)

In this method, “evapotranspiration is compared to potential evapotranspiration” using geostationary satellites. This works similarly to the short term precipitation based drought indices and this can be calculated at a comparatively greater resolution without using precipitation. The main advantage of using this index is its ability to get high resolutions with a spatial coverage of any area. However, its drawbacks are mostly associated with satellite data retrieval such as cloud cover which contaminate and affect results.

2.5.2 Normalized Difference Vegetation Index (NDVI)

This uses global vegetation index data retrieved by mapping four kilometres daily radiance. To calculate NDVI, radiance values measured in both the visible and near-infrared channels are used. The NDVI measures vigour of vegetation and greenness over a 7 day period which reduces the cloud contamination which enable the identification of vegetation stress formed by the drought.

The main advantage of NDVI is the spatial and temporal resolution. Most recent satellites have the capacity to calculate NDVI features in 30m scale compared to old satellites. However, for climatological studies these newer satellites products are less helpful since the temporal span is limited. Similar to the ESI, this suffers from the drawbacks of data retrieval from satellites. However, to compensate this effect, composites/averages over a time period for NDVI is used assuming that the changes in vegetation cover for a 5 days or 16 days is negligible.

2.5.3 Vegetation Condition Index (VCI)

The VCI is implemented to identify drought situations and determine the onset using Advanced Very High Resolution Radiometer (AVHRR) thermal bands. This is used especially in areas where drought periods and episodes are ill-defined. It mainly focuses on the impact of drought on vegetation and also it is able to provide information on the onset. Other than duration, the severity of drought is also produced by analysing vegetation changes and comparing them with previous values. The main advantages of this index are high resolution and good spatial coverage. However, there is a high potential for cloud contamination which leads to inaccurate results and a short period of record (Jiao, et al., 2016).

2.6 Composite or Modelled Drought Indices

2.6.1 Combined Drought Indicator (CDI)

This is a combination of three warning levels (Watch, Warning and Alert) which are obtained by integrating SPI, remotely sensed vegetation data and soil moisture drought indices. When there is a precipitation shortage, it is considered as a “Watch”. When the precipitation shortage leads to a soil moisture shortage, it is called as a “Warning” state. Finally an “Alert” is identified when the rainfall and soil moisture deficits starts to make impact on the vegetation (Sepulcre-Canto, Horion, Singleton, Carrao, & Vogt, 2012).

This method offers a better spatial coverage and achieves this high resolution by using both the remotely sensed data and gauge data. The main drawbacks are the use of a single SPI value which has drawback in several situations and conditions that are discarded but may available in consecutive seasons. However, this system is considered extremely hard to replicate and reproduce making it is unavailable for regions outside Europe.

2.6.2 Global Land Data Assimilation System (GLDAS)

This uses both gauge and remotely sensed data. This is also associated with data assimilation techniques and land surface models to produce information on terrestrial conditions. This output soil moisture characteristics which are used as drought indicators for hydrological droughts. This is useful for determining stream flow, river projections and runoff components accounting on current conditions. Gauge observations, land surface models, classification of vegetation and remotely sensed data are the main inputs to this process of calculating the index.

2.6.3 Multivariate Standardized Drought Index (MSDI)

This uses the information on soil moisture and precipitation to identify drought periods by using deficits in soil moisture and precipitation. It helps to identify drought periods where ordinary precipitation and soil moisture based indicators fail to identify any presence of drought. Cumulated monthly precipitation and soil moisture data obtained from the Modern Era Retrospective Analysis (MERA) are the main inputs to this system.

2.7 Drought in Sri Lanka

Drought is a frequent phenomenon experienced by Sri Lankans. The dry zone is known for experiencing severe droughts in some periods of the year for centuries. However, a well-planned irrigation system which collects excess rainwater in large tanks and releases them during dry seasons has been there since ancient times, so that the disturbances to both agricultural activities and social activities were minimum. Very few studies have been conducted on the spatial and temporal variation of drought in Sri Lanka (Chitranayana & Punyawardena , 2008; Lyon & Zubair, Finescale Evaluation of Drought in a Tropical Setting: Case Study in Sri Lanka, 2009).

2.7.1 Temporal variation of drought in Sri Lanka

According to Chithranayana and Punyawardena (Chitranayana & Punyawardena , 2008), there are three major situations in which Sri Lanka experience drought conditions.

- "During the northeast monsoon season when the air-stream over the island comes from a Northern hemisphere high pressure system and travels over the dry mainland of India immediately before reaching Sri Lanka, a drought season is experienced. Weather conditions in the Bay of Bengal also results in below normal rainfall during October to January. It is said that the resulting dry spells can affect most regions of the Sri Lanka"
- "Precipitation amount during mid-March to early May is mainly occurred due to convection under local thermal conditions. This is influenced by the Inter-Tropical Convergence Zone (ITCZ). Generally, the activity of the ITCZ during this period of time is highly changing and unpredictable. Thus, it causes a below normal rainfall in most regions of Sri Lanka including the dry zone"
- "Monsoon air-stream in south west monsoon season is generally dry because of the deviation of flow direction from its original path. Under these conditions, more dry situations are more likely to happen in agro ecological regions located in wet and intermediate zones"

2.7.2 Spatial distribution of drought in Sri Lanka

The wet zone does not undergo major drought events during Maha season except in the WL3 and WL2b regions which are slightly drought vulnerable. However, all Agro-Ecological Regions (AER) in the mid country and up country intermediate zone do not undergo drought events during Maha season. Out of five agro-ecological regions of the low country intermediate zone except for IL1c and IL2, other three agro-ecological regions are vulnerable to droughts during Maha seasons. Compared to Yala season, majority of the dry zone agro-ecological regions are less likely to experience hazardous drought events in Maha season except the agro-ecological regions located in the extreme north-western and south-eastern regions.

There is a slight probability of drought events occurring throughout the wet zone in Yala seasons. Considering the intermediate zone, it has a relatively high drought proneness when compared to the wet zone of Sri Lanka. All agro-ecological regions in the low country intermediate zone are vulnerable to drought events of varying severity and span during the Yala season except the IL1a region. Almost all agro-ecological regions of the up-country intermediate zone have less probability of experiencing drought conditions in Yala seasons. All the agro-ecological regions in dry zone are highly vulnerable to drought events in most of the Yala seasons when considered the historical drought events (Chitranayana & Punyawardena , 2008).

- **Case study - agricultural drought in Padaviya and Wahalkada areas**

A significant observation made on agricultural drought in Padaviya and Wahalkada areas is that the difference in impacts. Both Padaviya and Wahalkada share similar command areas and storage capacities, but according to remotely sensed analysis, a major difference in cultivation level was observed during severe drought season. While the farmers in Wahalkada area could cultivate 100% of the paddy lands, farmers in Padaviya area could only cultivate 19% of the command area (Burchfield & Gilligan, 2016).

In analysing the issue, the root-cause lies in the population difference in the two areas. Wahalkada having 810 hectares of command area only supports 1185 families while Padaviya has to serve 9000 families with its 970 hectare command area. The low domestic water demand has led the farmers to cultivate the entire command area.

Furthermore, Padaviya area suffered water shortages during both the dry season in 2013 and wet seasons in 2012 and 2013 (Burchfield & Gilligan, 2016).

2.8 Climate Change and Drought

Climate change is a change in the statistical properties of the climate system such as averages, variability and the extremes that persists for several decades or longer (The number of years usually considered is 30 years). Both natural causes and human influence affect climate change. Such natural causes are sun’s radiation, volcanoes or internal variability in the climate system. The human influence can be by causing impacts on creating changes in the composition of the atmosphere or land use.

2.8.1 Evidence for climate change in Sri Lanka - Temperature

Previous analysis indicates a gradual increment of atmospheric temperature in every part of the country. Although varied incrementing rates have been identified in different locations in recent past, the warming trend shows a rapid increase (Costa, 2008).

Annual mean air temperature anomalies have shown significant increasing trends in all stations in past years. Continually retrieved data through gauge stations indicates that nighttime minimum air temperature has a significant contribution towards average increase in annual temperature than day time maximum air temperature (Costa, 2008).

2.8.2 Evidence for climate change in Sri Lanka – Precipitation

In contrast to temperature, no significant trend has been observed in precipitation. However, when it takes the mean annual rainfall, it has shown a small but steady decrease over past years in many stations. However, in some regions, the mean annual precipitation has increased. Hence, no clear statement can be made on this factor. It is noticed that heavy precipitation events are more frequent in central highlands in early twenty first century (Costa, 2008).

Recent researches suggest that the total of consecutive dry periods has increased. They also show that spatial distribution of rainfall is changing which lead to shifted agro-ecological boundaries (Costa, 2008).

2.8.3 Evidence for climate change in Sri Lanka - Extreme events

The frequency and the intensity of the extreme drought events and flood events have increased in recent times. It is noticed that the highland areas of high rainfall intensities and the landslides locations have a strong correlation (Costa, 2008).

2.8.4 Evidence for climate change in Sri Lanka - Sea level rise

Sea level rise of one to three mm/year is noticed in the Asian region which is higher than the global average. An accelerated sea level rising has been observed during 1993-2001 in Asian region (Costa, 2008).

2.9 Data Sources used in Past Research Studies

2.9.1 Data sources and analysis of data: gauge station data

The basic parameters required in producing drought prediction models, precipitation, temperature can be obtained from gauge stations. Using interpolation technique such as Thiessen Polygon method, the area effect has been accompanied with the obtained point data. Most of the drought related researches conducted in Sri Lanka have used precipitation data obtained from gauge stations of Department of Meteorology (Illapperuma & Sonnadara, 2009; Lyon & Zubair, Finescale Evaluation of Drought in a Tropical Setting: Case Study in Sri Lanka, 2009).

2.9.2 Data sources and analysis of data: remote sensing data

Most of the recent drought related studies are based on gridded data obtained from satellites. This improves the spatial resolution of the dataset. However, since the basic parameters like precipitation are measured through indirect mechanisms such as cloud cover and etc., it has to be calibrated with ground truth data. Calibration and bias correction is needed for many of the satellite derived data. Some of the most popular satellite products include GIMMS (Global Inventory Monitoring and Modelling System), NOAA (National Oceanic and Atmospheric Administration), SPOT (Satellite Pour /'Observation de le Terre), Landsat, etc. All of these are capable of measuring indirect parameters to calculate one or more basic parameters. While the main advantage of satellite derived data being high spatial resolutions, main drawback is sensitivity to atmospheric and cloud conditions (Thenkabail, Gamage, & Smakhtin, 2004).

2.9.3 Data Sources and analysis of data - Other data

Other than that, some researchers have used drought relief payments as a parameter to indicate the severity of drought in Sri Lanka under the assumption that the relief payments were distributed among the highly affected community. Sri Lanka has a clear set of data on drought relief distribution in drought prone areas. Similarly, there are various other economic factors related data that are considered as datasets for drought related studies (Lyon & Zubair, Finescale Evaluation of Drought in a Tropical Setting: Case Study in Sri Lanka, 2009).

2.10 Modelling of Drought Variation and Prediction

Many researches are carried out to forecast the drought severity using SPI index (Fernandes, et al., 2011; Mwangi, Wetterhall, Dutra, Di Giuseppe, & Papenberger, 2014), but due to the variations of precipitation pattern in regions, they cannot be directly applied to another region other than the region of study. Several studies are carried out to find mechanisms to obtain a seasonal forecasting of SPI, under the hypothesis of normally distributed and uncorrelated monthly rainfall aggregated at different time scales (Cancelliere, Di Mauro, Bonaccorso, & Rossi, 2007). A recent study was carried out in Avash river basin, Ethiopia to compare the effectiveness and suitability of five data driven models for predicting long term drought conditions. The SPI-12 and SPI-24 were forecasted using a stochastic model (ARIMA) and then compared with machine learning models such as Support Vector Regression (SVR) and Artificial Neural Networks (ANNs) (Belayneh, Adamowski, Khalil, & Ozga-Zielinski, 2014).

The Markov chain models has been used to predict drought intensity by using SPI and standardized self-coefficients as weights in Weibei tablelands and Guanzhong Plain. The prediction temporal scales of the model are set to 1 month, 3 months, 6 months, 9 months and 12 months. The results had shown that the longer the temporal scale, the better the predication (Wang, et al., 2007).

2.11 Summary of Literature Review

In summarizing the literature, drought can be identified as an important phenomenon to be studied. The impacts of drought spans over a vast range from mere rainfall deficit to, reduced stream-flow levels, reduced crop yield and even lack of water for daily activities. Hence, a universal definition for drought cannot be given, and the definitions vary with the situations. Studies have characterized drought into several categories namely, meteorological, hydrological, agricultural and socioeconomic. Even though they have separate definitions, different durations and different impacts, all these are interconnected.

Drought indicators and indices are used to identify and measure droughts. Throughout history, the studies have been conducted and published various definitions for drought indices under subcategories, meteorological, hydrological, agricultural, remote sensor based and coupled/ combined. However not every index can be applied to everywhere, thus selection of indices have to be attempted carefully.

In the context of Sri Lanka, the temporal variation of drought has a significant impact with the rainfall and wind patterns where three main drought-prone periods are identified. The spatial distribution of drought varies drastically over the island and the dry zone is highly vulnerable for drought.

Reviewing past studies, both gauge station data and remote sensing data have been used. Availability of only a few stations and satellite-based data being freely available has led the popularity of using remotely sensed data in drought-related studies. A few studies have tried to incorporate the deep-learning and machine learning techniques in drought studies.

2.12 Identification of Research Gaps

Detailed study of literature in the areas of drought in Sri Lanka and the world as a whole enabled identification of several research gaps.

- A detailed drought study has not been undertaken in the sub basin scale
- Use of deep learning techniques in drought prediction

- Use of remotely sensed gridded data for drought studies
- Drought risk assessment and identification of the prioritization strategy for the communities in Drought-prone areas
- Outdated methods of assessing the agricultural drought by using methods like NDVI

3 STUDY AREA

3.1 Sri Lanka

Sri Lanka is an island nation located in the Indian Ocean between the latitude of 5º 55´ N to 9º 51´ N and longitude of 79º 42´ E to 81º53´ E. The country has 9 provinces and 25 districts covering an overall area extent of 65,610 km^2.

Considering the location of the island which is closer to the equator, it has a tropical climate throughout the year. Towards the Southern Central part of the country, hilly and mountainous terrain is observed and the coastal belt has a flat terrain. The central hill lands consist of many features such as ridges, peaks, basins and valleys. This geography on the island has a significant impact on the climate.

Sri Lanka primarily has a bi-modal rainfall pattern for monsoonal rains. Other than the monsoonal rains, the island experiences several other origins of rainfall namely convectional and depressional. The climate is divided into four different seasons.

1. **First Inter-Monsoon Season**

   This is generally the duration from March to April. During this period, most parts of the country receive a rainfall in the range of 100 mm to 250 mm while southwestern slopes get more than 700 mm and Jaffna Peninsula gets less than 100 mm rainfall.

2. **Southwest Monsoon**

   During this period (from May to September), the southwestern part of the island gets significant rainfall ranging from 100 mm to 3000 mm. Ginigathhena, Watawala and Norton are the areas which get the highest rainfall and that exceeds 3000 mm. These areas have mid-elevation and towards the highest parts of the country, the rainfall reduces rapidly. However, towards the lower parts of the island this reduction is comparatively less and the coastal area gets around 1000-1600 mm rainfall during this season. However, the northern and the south eastern parts of the island do not get much rainfall.

3. **Second Inter-Monsoon**

From October to November, the second inter-monsoonal period comes where the whole island receives rainfall more than 400mm. This can be considered as a duration where the whole island receives significant rainfall.

4. **Northeast Monsoon**

   During this period, the north, Northeastern and eastern areas of the country receive higher rainfall. While the western part receives minimum rainfall.

The island consists of 103 river basins out of which 18 of them have more than 1000 km^2 of the area. The largest river basin is Mahaweli. Most of the basins are small and situated towards the ocean. The discharge of the rivers has a considerable impact from the rainfall even though the impact may vary in different climatic zones. In the wet zone, the river discharges are considered to be 50% ~ 70% affected by the rainfall while in the dry zone it is less than 30%. A major cause is a high infiltration and significantly low surface runoff.

Considering the groundwater availability, most of the aquifers are shallow and small hence nearly 50% of the areas are not facilitated to use groundwater. However, in the dry zone of the country, groundwater is one of the main water sources for rural communities. A special feature in Sri Lanka is the complex but well-planned ancient irrigation schemes. The country consists of 163 major tanks and 2617 minor tanks constructed thousands of years ago and still functioning.

Agriculture is one of the main occupations of Sri Lankans and paddy is the main crop. Paddy cultivation is popular in both the wet and dry zones. However, in the wet zone, rain fed agriculture is a common feature and in the dry zone, irrigated lands are common. Sri Lanka has two main cropping seasons, Yala and Maha. However, several crops are grown in between these seasons.

Drought, as described in the previous chapters, incurs massive adverse impacts on the Sri Lankan society. Dry zone of Sri Lanka is highly vulnerable for drought.

In the present study, spatial and temporal study of drought was conducted using five river basins situated in Sri Lanka. The basins include Malwathu Oya, Kala Oya, Kanakarayan Aru, Gin Ganga, and Kirindi Oya. The selection of the basins was mainly based on the spatial location in Sri Lanka and the situation in agro-ecological regions. Figure 3.1 indicates the locations of the basins in Sri Lanka.

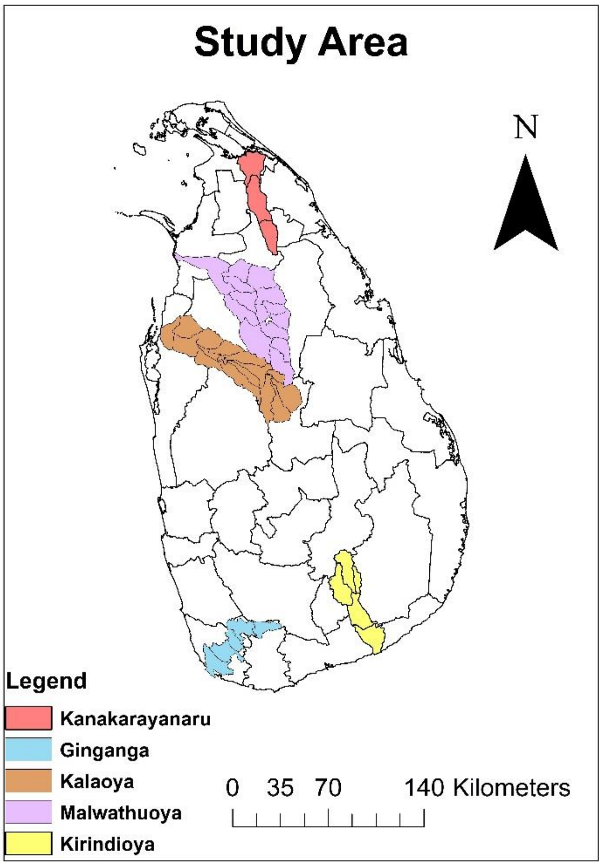

Figure 3.1 : Study area

3.2 Malwathu Oya Basin

The study was mainly focused on Malwathu Oya River Basin. Malwathu Oya basin is the second largest river basin by extent in Sri Lanka lying in an area of 3284 km^2. A large area of the basin lies in the North Central province and the rest is in the Northern Province, in three main administrative districts, namely Anuradhapura, Vavuniya and Mannar. There exist 14 sub-watersheds all situated in the dry zone of Sri Lanka formed by the tributaries of Malwathu Oya contributing to the main watershed.

The average temperature for this area lies around 27.3°C and the mean annual precipitation is 1368 mm. The sub basins and the agro-ecological regions of the basin are given in Figures 3.2 and 3.3. These figures indicate that a major part of the basin is in arid and dry zones with less than 1500 mm annual rainfall. This is a proof for potential droughts in Malwathu Oya basin.

Malwathu Oya basin was selected to develop a sample drought prediction model.

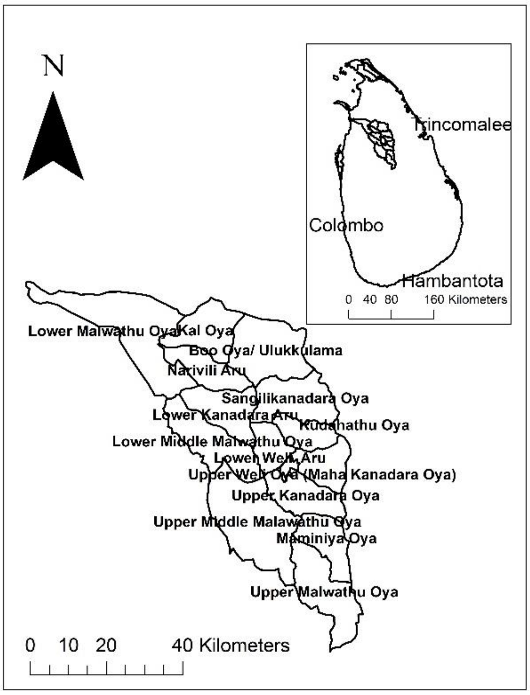

Figure 3.2 : Malwathu Oya sub basins

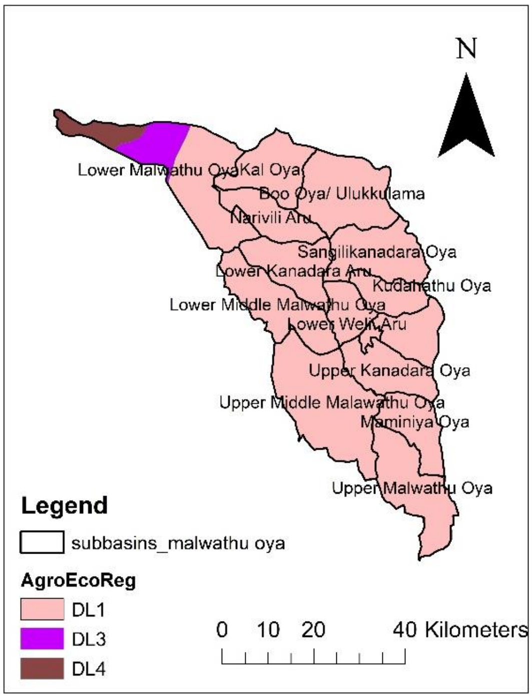

Figure 3.3 : Malwathu Oya agro-ecological regions

3.3 Kirindi Oya Basin

Kirindi Oya starts from Bandarawela and reaches the Indian Ocean at Bundala. The basin is of a land extent of 1176 km^2 and situated in Badulla, Moneragala and Hambantota districts. High temperatures and low relative humidity leading to higher evaporation and comparatively low mean annual rainfall are common features of the area.

A bi-modal rainfall pattern can be observed in the area with a major proportion of rainfall being contributed by North-Eastern Monsoon (September- February) which goes in line with the Maha season. The basin spans over three climate zones, dry, arid and intermediate. However, major part is situated in the dry and arid zones. According to the agro-ecological region map of Sri Lanka, Kirindi Oya spans over the zones; IM2, IU3, I(L1-L2), I(U2-U3), DL1 and DL5. Figures 3.4 and 3.5 show the location of the basin and the agro-ecological region.

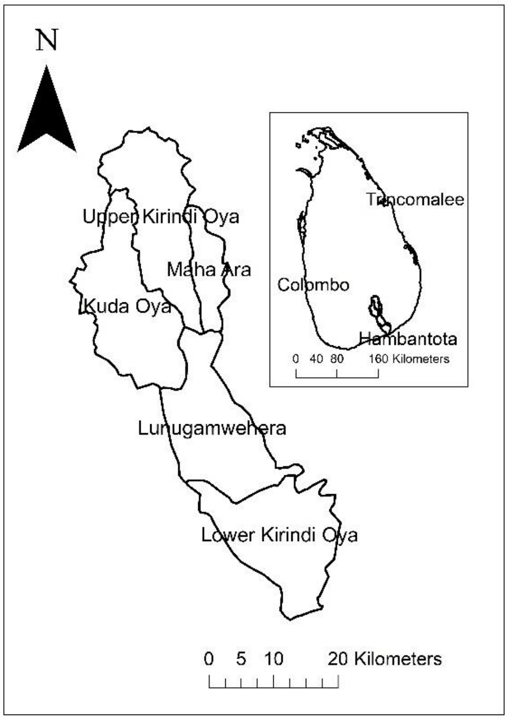

Figure 3.4 : Kirindi Oya sub basins

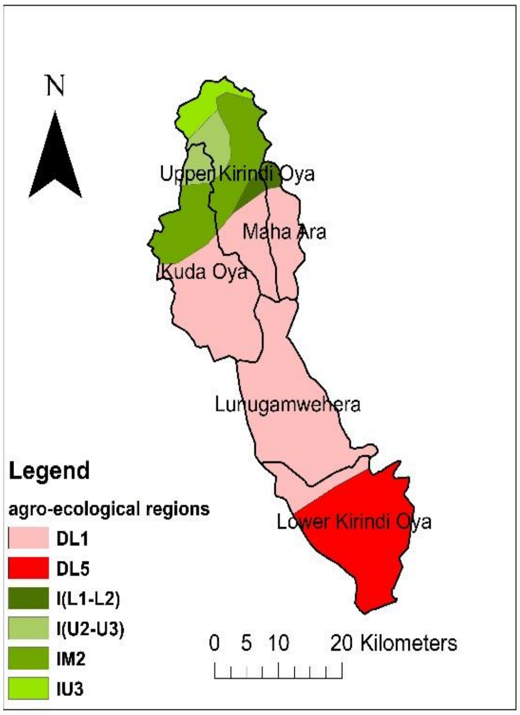

Figure 3.5 : Kirindi Oya agro-ecological regions

3.4 Kala Oya Basin

Kala Oya basin lies in three provinces of the island namely North Central, North Western and Central out of which a major part is situated in the North Central Province. The boundaries of the basin lie in Anuradhapura, Puttalam, Matale and Kurunegala Districts. The basin has a land extent of 2860 km^2.

Kala Oya basin is situated closer to Malwathu Oya basin but, lies in the agro-ecological regions, DL1, DL3, IL3 and IM3. A significant area is situated in the DL1 zone. The river basin consists of 14 river sub-basins and meets the ocean from Puttalam district. Figures 3.6 and 3.7 indicate the sub basins in Kala Oya basin along with the agro-ecological regions.

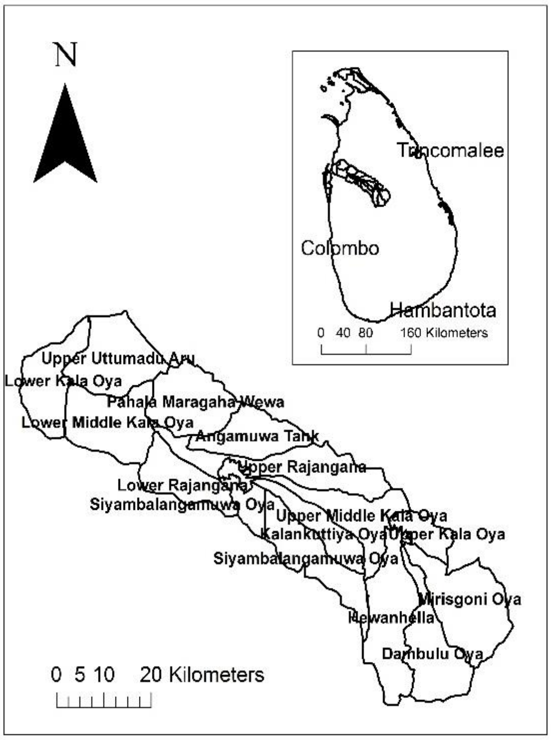

Figure 3.6 : Kala Oya sub basins

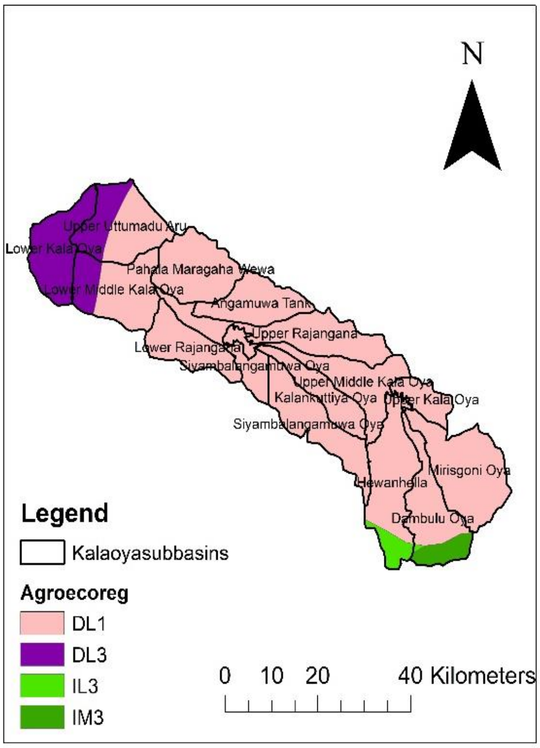

Figure 3.7 : Kala Oya agro-ecological regions

3.5 Gin Ganga Basin

Gin Ganga basin which is of a land extent of 924 km^2 is entirely situated in the wet zone. The agro-ecological regions are WL1, WL2, WL4, WM1, and WU1 and the basin has five sub basins. Southern province has a significant area of the basin while a small area is in the Sabaragamuwa Province.

The upper part of the Gin Ganga is in Matara and Rathnapura Districts while the rest lies in Galle district and flows to the Indian Ocean at Galle. Agriculture in this area is rain fed and adverse impacts of drought are not significant. The area gets frequent rains throughout the year. Figures 3.8 and 3.9 show the Gin Ganga basin and the agro-ecological regions.

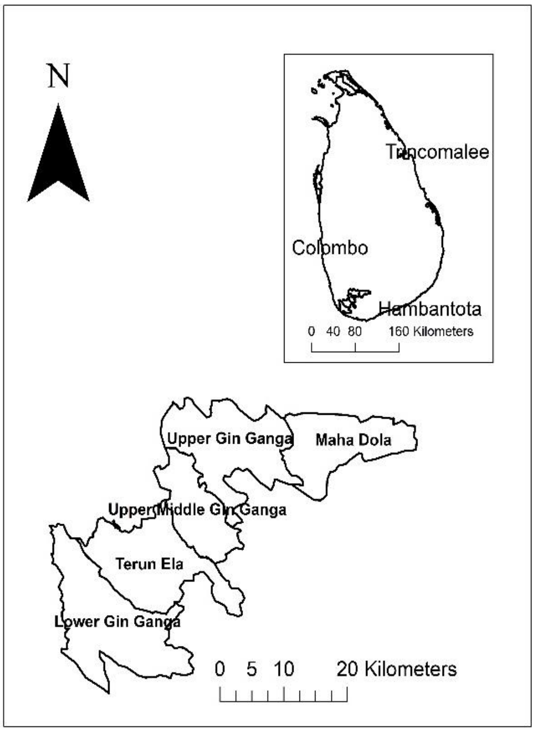

Figure 3.8 : Gin Ganga sub basins

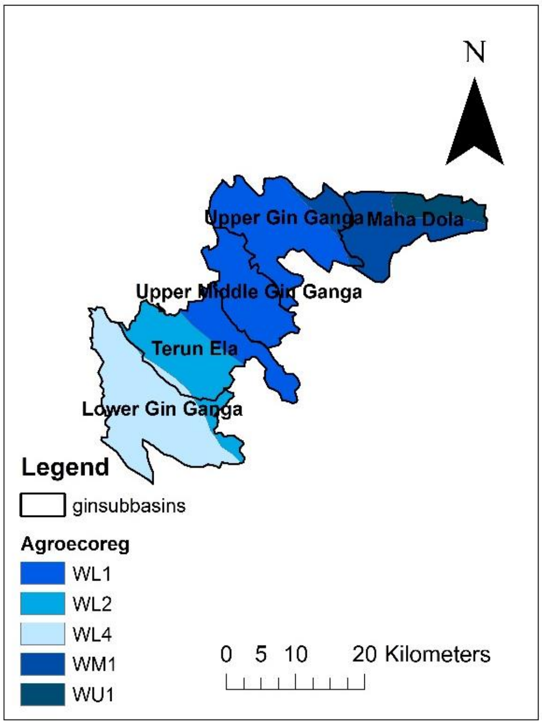

Figure 3.9 : Gin Ganga agro-ecological regions

3.6 Kanakarayan Aru Basin

Kanakarayan Aru is situated in the Northern Province and is of 905 km^2 land extent. The river basin has its area in Kilinochchi, Mulative and Vavuniya districts. In considering the agro-ecological regions, the basin has its spread in DL1, DL3 and DL4 regions.

Out of the three sub basins, two are situated in DL1 region while lower Kanakarayan Aru is going through two agro-ecological regions. However, all three are situated in the dry zone. Figure 3.10 shows the location of Kanakarayan Aru Basin and the agro-ecological regions.

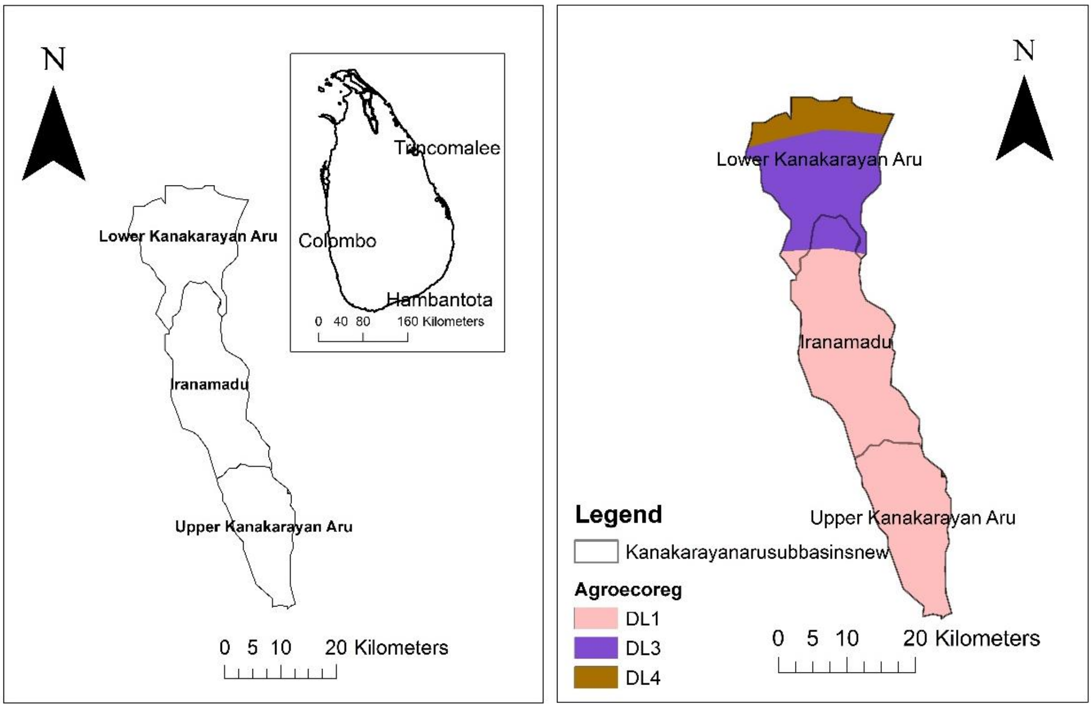

Figure 3.10 : Kanakarayan Aru sub basin and agro ecological regions

4 DATA ACQUISITION AND DATA PRE-PROCESSING

The study has used several data sources and data types. The main data type required for the study is precipitation data. Obtaining daily rainfall data for more than 30 years is a high costly task and there are issues with the continuity of the data set. Due to many issues such as the political situation of the country and war, there are data gaps for months and in some instances for years. Hence it is a time-consuming task to fill the gaps and finalize the data set. As a solution, the applicability of remotely sensed data which is freely available was taken into consideration. Data from different sources are available with different spatial and temporal resolutions.

Out of many data sources, this study has been considered Multi-Source Weighted-Ensemble Precipitation (MSWEP) data set.

4.1 Multi-Source Weighted- Ensembled Precipitation (MSWEP) V2 Dataset

Multi Source Weighted Ensembled Precipitation (MSWEP) data set has a spatial resolution of 0.1 degrees and a temporal resolution of 3 hours (Beck, et al., 2018). However, for this study daily data were considered. The coverage of the data set is global and this includes both the land and water and data are available for a duration of 37 years from 1979 - 2017. The precipitation estimates are obtained based on gauge stations and satellites and many other sources. The source can be identified as a reliable source due to the following features (Beck, et al., 2018).

- Precipitation estimates are given using gauges, WoldClim, GNCHD, GSOD, and many others and satellites, CMORPH, GridSat, GSMap and TMPA
- Reanalysis has been done using ERA-Interim and JRA-55
- Bias corrections have been conducted for the distribution
- Corrections have been done by using 13762 river discharge observations worldwide
- Has used daily gauge data from 76747 gauge-stations
- The data have been corrected for the time variation in different regions

This data source has merged the observations and the reanalysis estimates in order to provide an accurate precipitation data set. The procedure in arriving at the precipitation data is as follows. Obtaining the gauge data and quality control, computing the time of reporting from the gauges, development of IR-based Precipitation Dataset and assessing the satellite and reanalysis data sets. After developing Global weights and wet-day bias maps, the long-term mean was determined. Then corrections have been applied to Precipitation frequency and reference distributions were made. Finally, the satellite and reanalysis data were merged and gauge corrections were imposed. It has been proven that this dataset performs well over a number of dry days, with better trend and peak magnitudes compared to other popular gridded datasets.

Some of the international applications of this data set include analysing diurnal variation of rainfall, investigating the lake dynamics, and evaluating root zone moisture patterns.

However, when the data set is used in this study, the reliability of data for Sri Lankan Basins was checked.

4.2 Reliability Checks

In order to check the reliability of the data sets, gauge station data were used. The area considered was Malwathu Oya Basin. Kekirawa, Maha Iluppallama, Anuradhapura, Kahatagasdigiliya, Pelwehera, Elayapaththuwa, Habarana, Vavuniya and Eppawala are the selected gauge stations.

Gridded data from MSWEP was then compared with gauge station data to check the accuracy and correlation of two datasets. A proper grid is selected for each gauge station while making sure that gauge point lies inside the grid and bilinear interpolation is used to get the point precipitation using neighbouring gridded precipitation data.

The Table 4.1 lists out correlations and measures between two data set types for known stations (Anuradhapura-AP, Pelwehera-PW, Kahatagasdigiliya KG, Kekirawa-KK and Maha Iluppallama-MI). All the gauge stations considered showed a Pearson Correlation greater than 0.87, Root Mean Square Error less than 97.6 and Mean Square Error less than 7.23 which are acceptable.

Table 4.1: Statistical comparison of grid and gauge data

Gauge Station and Grid Centre	MSE	RMSE	Pearson
Kekirawa	6.291	58.764	0.920
Maha Iluppallama	4.791	33.186	0.972
Anuradhapura	4.540	34.923	0.977
Kahatagasdigiliya	7.909	97.618	0.831
Pelwehera	7.233	75.910	0.874
Elayapaththuwa	7.233	75.910	0.874
Habarana	7.233	75.910	0.874
Vavuniya	7.233	75.910	0.874
Eppawala	7.233	75.910	0.874

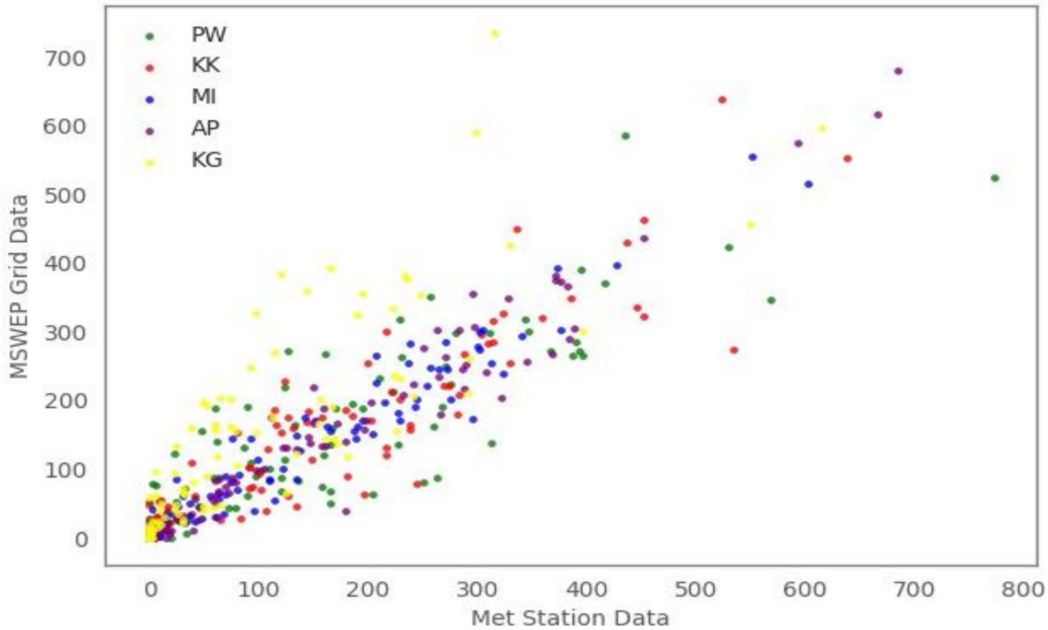

Figure 4.1: Similarity between gauge and gridded satellite data

The correlation between the Gauge station data and MSWEP data is shown in Figure 4.1. It can be observed that there is a significant correlation between the two data sets.

Details of grid point centres are in the below table (Table 4.2).

Table 4.2 : Sub basins and respective grids

ID	Sub Basin	Area (km^2)	Coordinates
1	Upper Malwathu Oya	264	7.95:80.65,8.05:80.55, 8.05:80.65, 8.05:80.75, 8.15:80.55, 8.15:80.65
2	Maminiya Oya	152	8.15:80.55,8.25:80.45, 8.25:80.55
3	UpperMiddle Malawathu Oya	441	8.15:80.45,8.15:80.55, 8.25:80.45, 8.25:80.55, 8.35:80.35, 8.35:80.45
4	Upper Kanadara Oya	176	8.25:80.55,8.25:80.65,8.35:80.55, 8.35:80.65
5	Upper Weli Oya	136	8.35:80.55,8.35:80.65, 8.45:80.55, 8.45:80.65
6	Kudahathu Oya	111	8.45:80.55, 8.45:80.65
7	Sangilikanadara Oya	229	8.55:80.45,8.55:80.55, 8.55:80.65
8	Boo Oya	296	8.65:80.45,8.65:80.55, 8.75:80.45, 8.75:80.55
9	Kal Oya	195	8.65:80.25,8.65:80.35, 8.75:80.35, 8.75:80.45
10	Narivili Aru	147	8.55:80.35,8.55:80.45, 8.65:80.25, 8.65:80.35
11	Lower Kanadara Aru	190	8.55:80.35,8.55:80.45, 8.45:80.45
12	Lower Weli Aru	100	8.45:80.45, 8.45:80.55
13	LowerMiddle Malwathu Oya	249	8.35:80.35,8.35:80.45, 8.45:80.25, 8.45:80.35, 8.45:80.45, 8.55:80.25
14	Lower Malwathu Oya	469	8.55:80.25,8.65:80.15, 8.65:80.25,8.75:80.05, 8.75:80.05, 8.75:80.15, 8.75:80.25, 8.85:79.95

4.3 Calculation of Average Rainfall for Sub-Basins

According to the spatial distribution of precipitation grids in Figure 4.2, it can be observed that there are only few grids that are completely inside a sub basin. It can be erroneous if the precipitation calculation gets the average of the grid cells that are partially in the sub basin. Hence, weighted average method was selected.

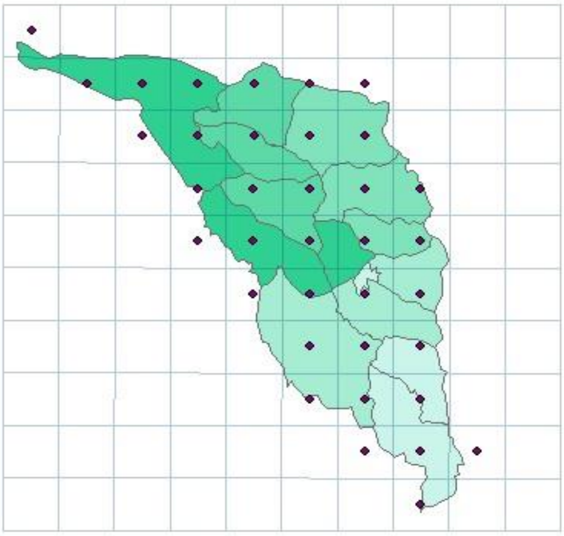

Figure 4.2 : Spatial distribution of grid points in sub basins

$$ARSB(sb, y, m, j) = \frac{\Sigma(P(y, m, j) * a(sb, j)}{A(sb)} \quad (1)$$

Average monthly rainfall for a sub-basin is calculated as follows using intersecting grids.

ARSB= average rainfall for subbasin *sb*, year *y* and month *m*; *P* = precipitation for year *y* and month *m* for grid *j*; *a* = intersecting area of grid *j* with subbasin *sb*; *A* = total area of subbasin

The resulting value for weighted average precipitation is used to calculate drought indices for a given subbasin.

5 METHODOLOGY

5.1 Methodology Flowchart

The overall methodology of the study consists of five basic steps up to data pre-processing as elaborated in Figure 5.1.

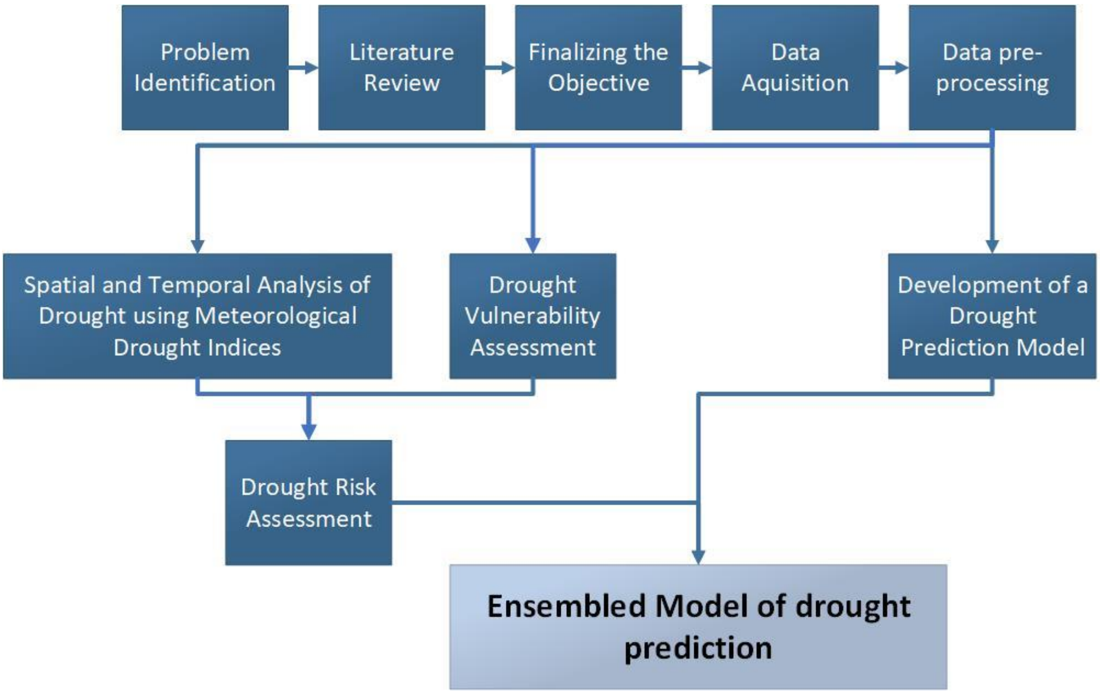

Figure 5.1: Methodology flow chart

Once the data pre-processing is completed, the tasks, Spatial and temporal analysis of drought, Drought vulnerability assessment, Analysis of agricultural drought and Development of a drought prediction model was attempted. The drought hazard, identified in the spatial and temporal analysis was then combined with drought vulnerability assessment by using the model proposed by (Shahid & Behrawan, 2008), and drought risk assessment has been conducted.

All the specific objectives have been ensembled into one platform to provide drought severity indications, comparative risk classifications and future drought predictions.

5.2 Spatial and Temporal Analysis of Drought

The methodology flow chart for the spatial and temporal analysis of drought is shown in Figure 5.2.

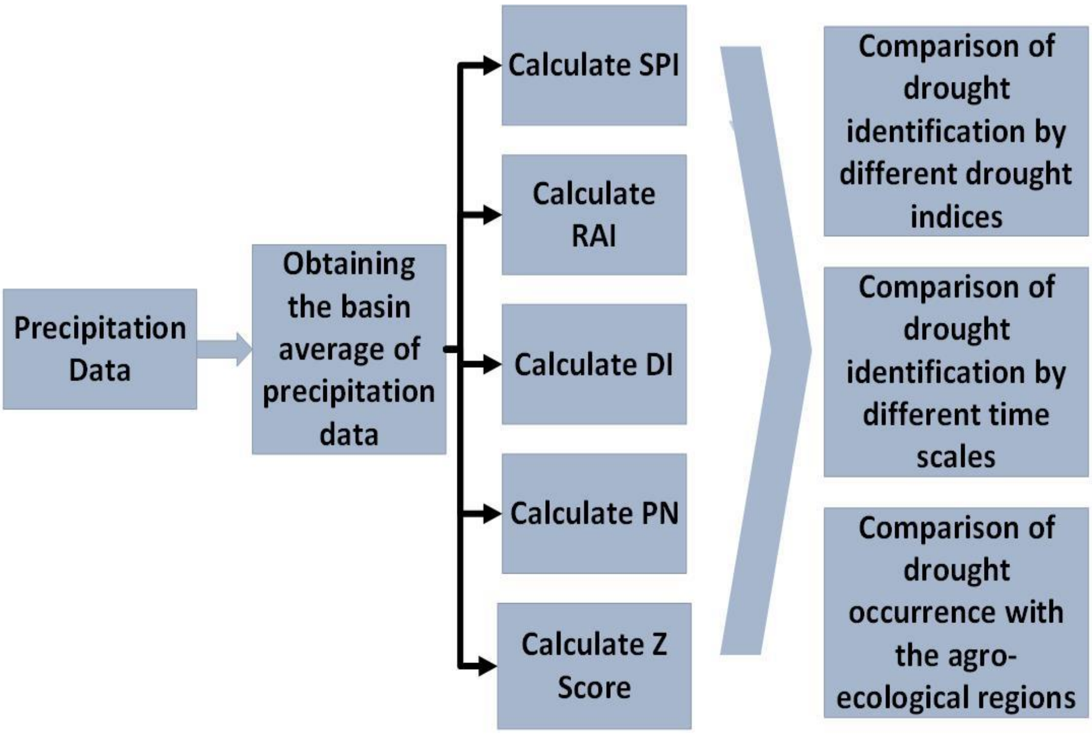

Figure 5.2: Methodology of spatial and temporal analysis of meteorological drought

The methodology has 3 basic steps. They are obtaining sub basin scale precipitation data, calculation of drought indices and comparison of the results spatially and temporally.

Detection and real-time monitoring of drought can be achieved by using drought indices which enables us to identify the drought duration and drought severity. However, the definitions of drought indices differ from one another and the drought measure is a qualitative one. Hence a comparison of different drought indices is complex. However, these qualitative classifications, divide the drought events into five groups, No Drought, Weak Drought, Moderate Drought, Severe Drought, Extreme Drought.

For this study, five identified drought indices, namely Standardized Precipitation Index (SPI), Deciles (DI), Percent of Normal (PN), Rainfall Anomaly Index (RAI) and Z index, were calculated for each sub-basin in Kirindi Oya basin.

5.2.1 Standardized Precipitation Index (SPI)

In calculating the SPI index, the rainfall received in a particular area is fitted to a corresponding gamma distribution and the standard deviation from the long-term mean is considered. This measure indicates the deviation from the historical mean rainfall of a particular area and hence can be considered as a measure of drought. The SPI is calculated for several durations; 1 month, 3 months, 6 months, 9 months, 12 months, 18 months, 24 months and 48 months. However, the SPI values corresponding to a given month can differ from each other, when different durations are considered.

Hence, these different durations can be used when analysing diverse drought scenarios. The 1-month SPI would provide an indication of short-term soil moisture conditions and crop moisture levels and is useful in decision- making during crop growing seasons. The 3-month SPI reflects the seasonal rainfall estimates and meteorological drought. Indications of agricultural drought are given by 9-month SPI while hydrological drought is reflected by 12-month SPI (Senay, Velpuri, Bohms, Budde, & Young, 2015). The SPI is calculated using Equations 1 and 2.

$$\text{g(x)} = \frac{1}{\beta^{\alpha}\tau(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}}, \text{ x>0} \qquad (2)$$

$$A = \ln(x) - \frac{\sum \ln(x)}{n} \qquad (3)$$

Calculated SPI values for each month are categorized into regions as indicated in Table 5.1 (Morid, Smakhtin, & Moghaddash, 2006).

The table is then converted to a common scale with the intention of analysing the results. All the other drought indices are also converted to this common scale for the ease of comparison.

Drought period is indicated by the time period between the first month with below -1.0 index value and first month after that month which has an index value greater than or equal to 0.

Table 5.1: SPI impact levels

SPI Value	Impact Level
2.0 or more	Extremely Wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately Wet
0.99 to -0.99	Near Wet
-1.0 to -1.49	Moderately Dry
- 1.5 to -1.99	Severely Dry
- 2.0 or less	Extremely Dry

5.2.2 Deciles (DI)

This method is one of the simplest methods used to calculate the impact of drought where the precipitation data is arranged in decreasing order and the cumulative frequency distribution is obtained. Then it is split into ten parts using equal probability distribution and each part is called a decile. According to the original work, precipitations that are below 5^{th} decile is considered as drought (Sivakumar, Wilhite, Svoboda, Hayes, & Motha, 2010). The original categorization is converted to above-mentioned scale as in Table 5.2.

5.2.3 Percent of Normal (PN)

In this method, precipitation on a given month (P_i) is expressed as a percentage to the long-term median/normal rainfall (P_n) of a particular area. Precipitations with PN value below 80% is identified as droughts which are calculated as indicated in following equation.

$$PN = \frac{P_i}{P_n} * 100\% \qquad (4)$$

However, since this method does not consider a time window, actual drought can be identified by consecutive months with PN values in drought range. Table 5.2 indicates the impact levels for the PN values.

5.2.4 Rainfall Anomaly Index (RAI)

This index is used to calculate meteorological drought events and considered independent of time and space. This is calculated as in Eq. 4, where Pn and m refer to mean precipitation of 30 years span and mean of 10 greatest rainfalls respectively. The results are interpreted in Table 5.2.

$$RAI = \pm(\frac{P-P_n}{m-P}) \qquad (5)$$

5.2.5 Z Index

Z index is calculated by using the Equation 5 where P_n and $\boldsymbol{\delta}$ refers to the mean precipitation and the standard deviation of the region.

$$Z\ Score = \frac{P-P_n}{\delta} \qquad (6)$$

Table 5.2: Drought impacts in a common scale

	SPI	RAI	PN	Z Index	DI
No Drought	>0.99	>-0.3	>80	-0.25 to +0.25	>=5
Weak Drought	0.99 to -0.99	-0.3 to -1.2	70-80	-0.52 to -0.25	4
Moderate Drought	-1.0 to -1.49	-1.2 to -2.1	55-70	-0.84 to -0.52	3
Severe Drought	-1.5 to -1.99	-2.1 to -3.0	40-55	-1.28 to -0.84	2
Extreme Drought	2 or less	<-3.0	<40	>-1.28	1

Two approaches were taken in calculating the indices where the first approach is to consider the mean precipitation of each sub-basin in index calculation. The other approach was to consider the mean value for the basin as a whole. The results obtained from the two approaches for five drought indices were compared and analysed.

Once the drought indices were calculated, they were categorized into the five classes, no drought, weak drought, moderate drought, severe drought and extreme drought. The table 5.2 indicates the classification criteria.

A comparative analysis of the drought indication using different drought indices was carried out.

Furthermore, different time scales were considered and the variation of drought identification and indication with time scale was analyses. Spatial variation of drought in 5 selected river basins were studies along with their relationship with eth agro-ecological regions.

5.3 Development of a Drought Prediction Model

As indicated in Figure 5.3, the methodology flow chart for the sub- objective, development of a drought prediction model has 6 basic steps. They are namely, Obtaining precipitation data, Calculation of SPI, Parameter estimation and feature selection, Development of LSTM, Fine tuning with ANN and Drought prediction.

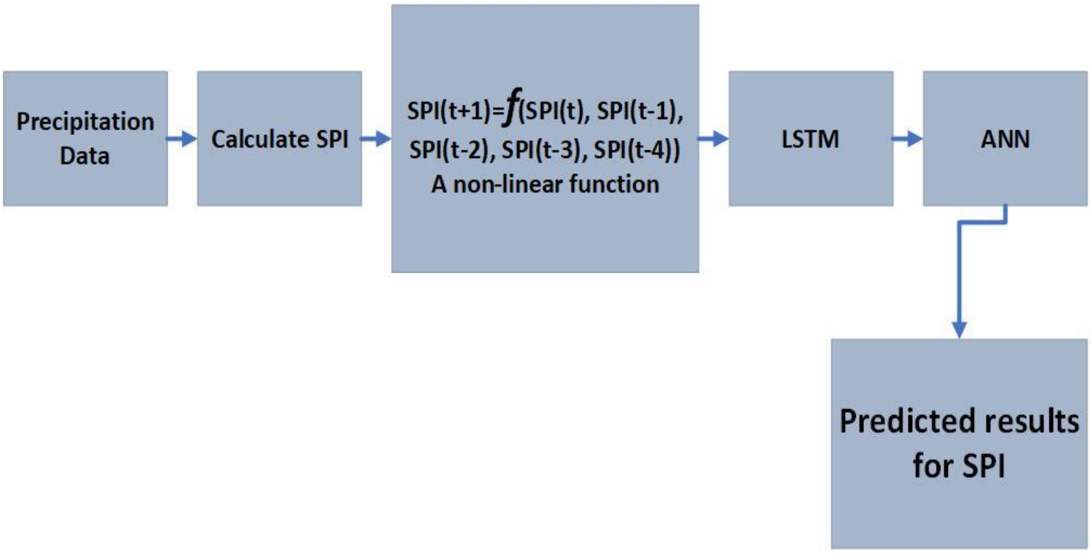

Figure 5.3 : Methodology for drought prediction model

Ability of drought prediction is the most important part in the drought study. The spatial and temporal analysis gave indications of the spatial and temporal differences of drought in different basins analysing the past data. In the next step, the calculated SPI values were used to develop a drought prediction model. LASSO regression was used to select the previous SPI values that mostly affect the future SPI predictions. This was achieved by considering different previous SPI value combinations.

Calculated SPI values for each month are categorized into regions as indicated in Table 5.3 (Morid, Smakhtin, & Moghaddash, 2006).

Table 5.3: SPI Impact Levels

SPI Value	**Impact Level**
2.0 or more	Extremely Wet
1.5 - 1.99	Very Wet
1.0 – 1.49	Moderately Wet
0.99 - (-)0.99	Near Wet
(-) 1.0 - (-} 1.49	Moderately Dry
(-) 1.5 - (-} 1.99	Severely Dry
(-) 2.0 or less	Extremely Dry

Then the Augmented Dickey-Fuller test is carried out to determine to find any underlying time dependent structure in the data. For the sub-basins in which a trend was available, it was eliminated from the observed data. Then it is added back to the predicted data to get the prediction to the original scale and then calculate an error score. “Differencing the data” is used as the method to remove trend in which the observation from the previous time step is subtracted from the current observation. This removes the available trends and leave only the changes to the observations from one-time step to the other.

With the LASSO (Least Absolute Shrinkage and Selection Operator) regression, the parameters (previous SPI that correlates with time t+1 in the training dataset) is selected. It is observed that, the four most correlating parameters change with sub basin to sub basin since the underlined data and patterns are different from each other. Above Figure 5.3 indicates a situation where the four most prominent post data were in time steps *t*-1, *t*-2, *t*-3 and *t*-4.

Objective of the deep learning model applied here is to find the hidden correlation and function which models the future SPI event with previous data points as inputs. Since, SPI is a time dependent parameter as explained in literature review, it was a must to model time dependent behaviour in it. To model that, LSTM – Short-Term Long-Term Memory Networks is used and it is a specific category of RNN – Recurrent Neural Networks. Then the output is sent though several multiple perceptron layers / artificial neural network to get a smooth and more accurate prediction.

Training set was iterative trained using various parameters and optimal value for each parameter was obtained using hyper parameter tuning.

5.3.1 Recurrent Neural Networks (RNN)

The SPI index is calculated based on the climatological mean of the previous rainfall data. Next month's SPI value depends on not only with this month's SPI value but also with historical precipitation values. Typical neural network is not capable of understanding the next value based on the previous SPI values. In real world scenario, it is required to include dryness factor, etc. Traditional neural networks are incapable of achieving this and this is a major shortcoming.

It is hard to explain how a shallow neural network can use its reasoning about past events in the underlying process to be used in later events. Recurrent neural networks are used to overcome this issue. They includes loops within them which allows the information to persist over time. In theory, RNNs are capable of handling such long-term dependencies.

5.3.2 Long Short-Term Memory Networks (LSTM)

Long Short-Term Memory Networks are a special category of RNNs that utilizes a strategy that uses short-term memory that can be kept for a long time. The LSTM networks are composed of LSTM units which essentially contain a cell and three gates, namely, input gate, output gate, and forget gate which regulates the flow of the values in the network. These gates are typically similar to activation functions in neural networks and control the flow of new values, the degree to which the values are used in activation for the output, and degree to which a value is retained in the memory, respectively. The LSTM networks are very effective in predicting the time series data given that the time lags between major events are of unknown size. Thus, this is very effective in predicting the changes in SPI values based on the previous SPI values in comparison to the simple ANNs and most other forms of RNNs.

Figure 5.4 shows the mechanism of the prediction model used in this study. The data set of 37 years was divided into two sets. The first 2/3 of data were used to feed the neural network and rest were used to validate the results. Different combinations of past SPI data were used to identify the relations between past data with the future drought prediction. Though the SPI values are given in numbers, it is generally classified in to classes as given in Table 5.3. Severity and the duration of the drought is determined by the class and time duration to drought index to reach a value greater than 1.0 after it has fallen from -1.0. As the number of classes and the classifications are different in some existing literature, classes in original paper was used.

Given previous drought severities, LSTM network with fully connected layers were used to predict the drought severity in the next month. A number of inputs, a subset of previous drought severities were selected maintaining the prediction error to a minimum. Hyper parametric tuning was used independently for each sub basin to find the best parameters that reduces the error between actual and predicted values of data.

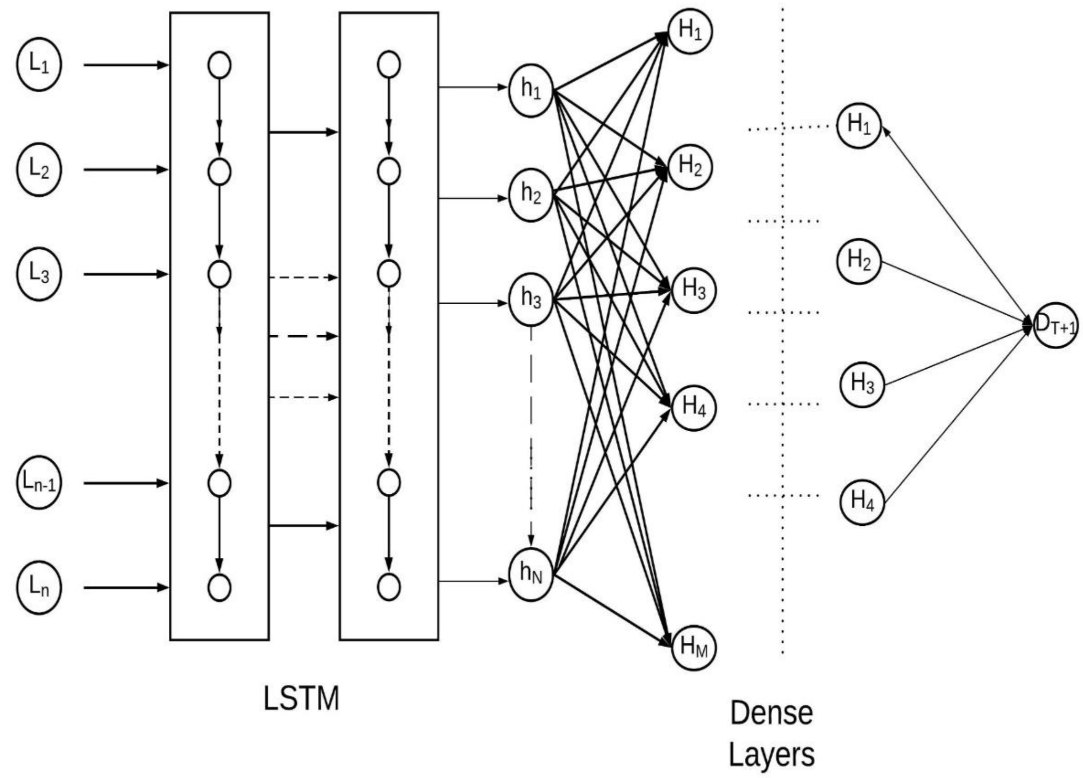

Figure 5.4: Neural network with LSTM layers

5.4 Drought Risk Assessment

The methodology flow chart for the drought risk assessment is shown in Figure 5.5 (Shahid & Behrawan, 2008).

Following the spatial and temporal analysis of drought, the identified hazard was required to be presented in a more meaningful manner to the decision makers and the planners. The step was then extended to application of an existing model to a selected administrative boundary in the dry zone of Sri Lanka, to assess the drought risk in the area.

The study area considered is Anuradhapura District, Sri Lanka. Figure 5.6 shows the boundary of the study area, along with the Divisional Secretariat Divisions (DSDs).

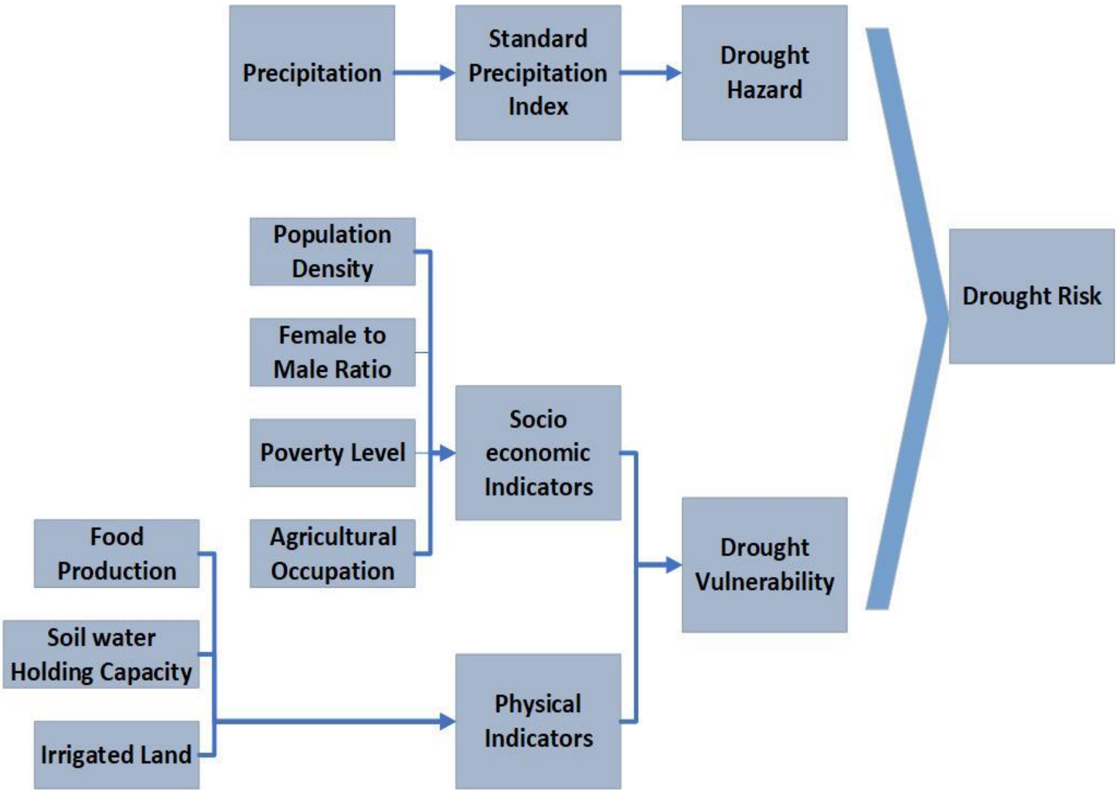

Figure 5.5 : Drought risk assessment methodology

Anuradhapura District is located in the North Central Province, Sri Lanka and the district boundaries are Vavuniya, Mannar, Mulative, Kurunegala, Mathale, Puttalam, Polonnaruwa and Trincomalee. The land extent of the district is 7179 km^2 which include all the 22 DSDs. The whole district is situated in the dry zone of Sri Lanka hence the climate shows the characteristics of the dry zone (Secretariat, 2016). The average annual rainfall is recorded to be 1285 mm and a major proportion of it is obtained during the North East Monsoon from September to February. The average temperature in the district is 32°C.

Considering the population in Anuradhapura district, by the year 2012, the population in the district was recorded as 827,284.

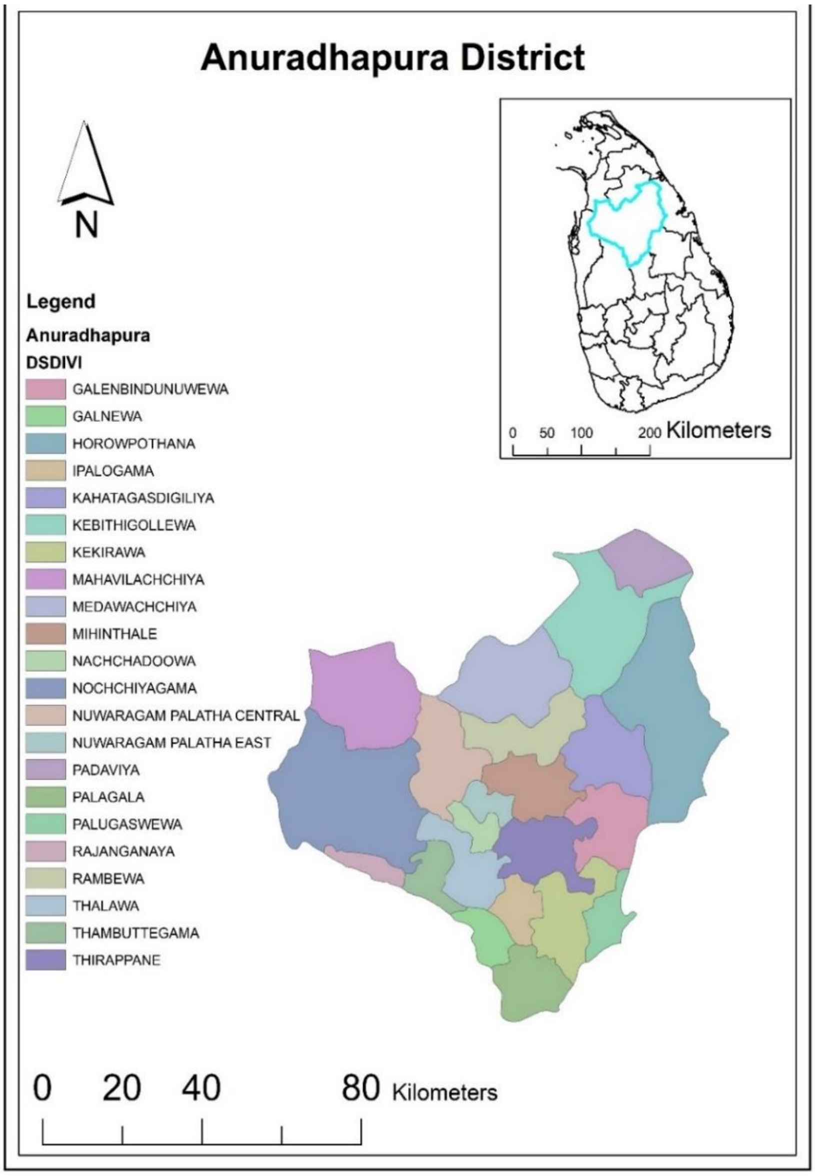

Figure 5.6 :The DSD divisions of Anuradhapura district

A significant proportion of the population depends on agriculture and the main crop is paddy. A major part of the paddy lands is irrigated lands. A complex but well-designed irrigation system can be observed covering the whole district which consists of 12 main tanks, 85 medium tanks and 2974 small tanks.

In order to identify the socio-economic impacts of drought to the communities, not only the drought hazard, but also their vulnerability to drought has to be considered. There are many drought risk models considered around the world and the basic concept behind it is the relationship between the risk, hazard and vulnerability.

The drought risk model proposed by Shahid and Behrawan in 2008 (Shahid & Behrawan, 2008) was applied to Anuradhapura District and the model was calibrated in order to be applied in the selected area. This is carried out as a GIS based modelling work.

First it was assumed that the drought relief payments have a relationship with the drought risk. Drought relief payments were mapped using ESRI Arc GIS in DSD scale and the relief payments are classified into four classes, Very high, High, Medium and Low according to natural breaks.

Drought risk assessment is carried out based on the methodology proposed by Shahid (Shahid & Behrawan, 2008). This drought risk assessment has many similarities with the general approach taken to conduct a climate risk assessment which has two components; hazard and vulnerability. According to National Drought Mitigation Centre (NDMC), drought risk is defined as “the product of drought hazard and drought vulnerability”. Drought studies give a qualitative result of the severity of drought. Hence, the model proposed by Shahid and Behrawan (2008) defines two indices, Drought Hazard Index (DHI) and Drought Vulnerability Index (DVI) where their production gives the Drought Risk Index (DRI). Drought hazard and drought vulnerability has to be assessed separately and later brought together as drought risk.

5.4.1 Drought Hazard Assessment

Drought hazard assessment studies the spatial and temporal variations of drought and its severity. For this, accepted drought indices can be used. As identified in the spatial and temporal analysis of drought for Sri Lanka, SPI index was identified suitable to measure the drought severity and frequency. The identified SPI classification was then used to calculate the probabilities of occurrence of each drought type. Then for each type, a rating was given by dividing into 5 classes according to natural breaks. For the lowest probability, the rating 1 was given and for the highest, rating 5 was given. Mild drought and no drought events were not considered since they have a very less impact.

5.4.2 Drought Hazard Index (DHI)

Then the DHI is calculated as given in the following equation.

$$\boldsymbol{DHI = (MD_r \times MD_w) + (SD_r \times SD_w) + (ED_r \times ED_w)} \qquad \textbf{(7)}$$

MD_r = Moderate drought ranking; MD_w = Moderate Drought Weight; SD_r = Severe drought ranking; SD_w = Severe drought weight; ED_r = Extreme drought ranking, ED_w = Extreme drought weight

The drought hazard maps were prepared based on the Drought Hazard Index. The prepared drought hazard maps were then overlaid on the DSD map in order to obtain a DSD scale drought hazard map. In obtaining drought hazard of each DSD, weighted average of the DHI was taken.

5.4.3 Drought Vulnerability Assessment

Drought vulnerability can be explained as "the extent to which the socio-economic system or the physical assets are either susceptible or resilient to the impacts of natural hazards" (Shahid & Behrawan, 2008; Wilhelmi & Wilhite, 2002). For this study, the vulnerability indicators in the model by Shahid and Behrawan (2008) were used in assessing drought vulnerability. Hence, as socio-economic indicators such as population density, percentage of people living below poverty level, female to male ratio and percentage of agriculture dependent people are considered. Percentage of irrigated land, paddy production and soil moisture holding capacity are considered as the physical indicators.

Using the natural breaks method, four classes were assigned for each vulnerability indicator. The reason for using the natural breaks method is that the data values are close together and using this method ensures a good representation. All the indicators were mapped separately in DSD level. In order to arrive at the composite vulnerability map, Drought Vulnerability Index (DVI) was used.

5.4.4 Drought Vulnerability Index (DVI)

The procedure of calculating the DVI is as follows. Once the natural breaks are observed, each class is given a rating ranging from 0 ~ 1. Higher values were assigned for the higher classes and lower values were assigned for the lower classes except the soil water holding capacity. All the other parameters except the soil water holding capacity have a positive relation with the drought or act as a drought trigger, while higher the soil water holding capacity, the higher the resistant to dry spells. Hence, for the soil water holding capacity, higher the value, lower the assigned value.

Using Equation 6, the DVI is calculated

$$\boldsymbol{DVI = \frac{PD_r + FMR_r + PL_r + AO_r + IL_r + SWHC_r + FP_r}{Number\ of\ Indicators}} \qquad \textbf{(8)}$$

PD_r = Population density rating; FMR_r = Female to male ratio rating; PL_r = Percentage of people living below poverty level rating; AO_r= Agricultural occupation rating; IL_r= Irrigate land rating; $SWHC_r$ = Soil moisture capacity rating; FP_r= Food production rating

5.4.5 Drought Risk Assessment

Drought risk index is obtained by multiplying the drought hazard index and the drought vulnerability index as in Equation 9. Classification is given in Table 5.4.

$$\boldsymbol{DRI = DHI \times DVI} \qquad \textbf{(9)}$$

Table 5.4 : Drought risk index classification

Value Range	**Risk Type**
>20.62	Very High
18.59-20.62	High
16.82-18.59	Moderate
13.64-16.82	Low
<13.64	Very Low

The drought risk maps obtained from the above method were then compared with the historical data of drought relief payments and the drought affected population in order to verify the use of eth model in the selected area.

The drought risk results were compared with drought relief payments and drought affected population data using the following criteria in Table 5.5.

Table 5.5 : Classification criteria

Drought risk / **Drought Relief payments**	**Very high**	**high**	**Moderate**	**Low**	**Very Low**
Very high	VH	H	M	L	VL
High	H	VH	H	M	L
Moderate	M	H	VH	H	M
Low	L	M	H	VH	H
Very Low	VL	L	M	H	VH

6 RESULTS AND DISCUSSION

6.1 Spatial and Temporal Analysis of Rainfall and Drought

The work carried out under the spatial and temporal analysis of drought is described using Kirindi Oya Basin as an example. A sub basin scale analysis has been undertaken.

6.1.1 Rainfall Variation within the Basin

First, the rainfall variation within the basin was analysed to ensure that our main hypothesis – more accurate results can be obtained by sub-basin scaled analysis keeps valid for this basin. Since the precipitation distributions are significantly different among basins, it can be argued that drought patterns and severity may show different distributions.

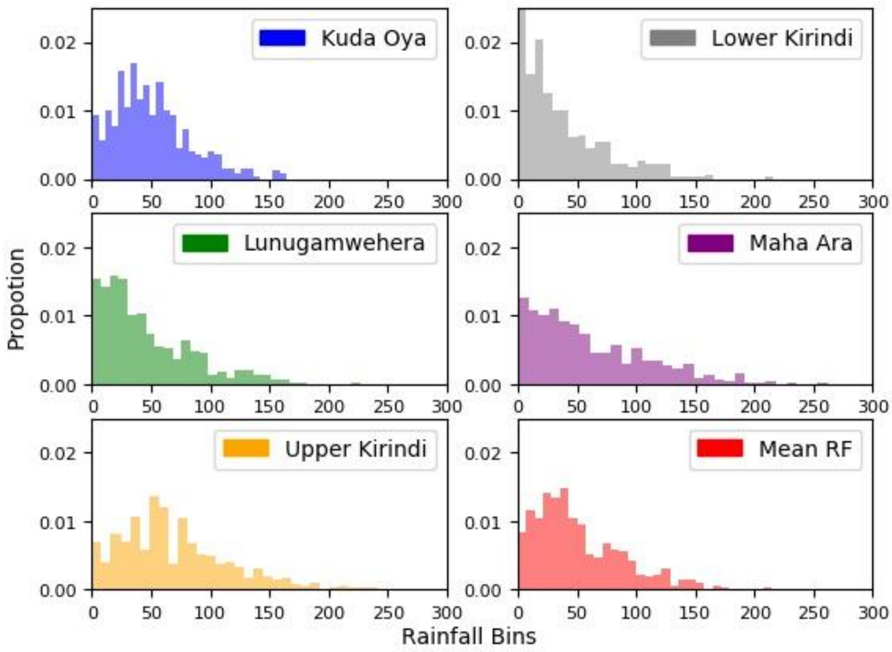

Figure 6.1: Rainfall histogram for sub basins

According to Figure 6.1, for all 5 sub basins, the majority of days have recorded a rainfall less than 150 mm. However, Lower Kirindi Oya and Lunugamwehera sub-basins have undergone more no-rainfall days compared to others. Moreover, they indicate a lower frequency of high-rainfall days compared to the others. Kuda Oya, Lunugamwehera and Lower Kirindi Oya sub basins have hardly received rainfall in excess of 100 mm while Maha Ara and Upper Kirindi Oya shows higher number of high rainfall days.

The highest proportion of rainfall obtained for a given sub-basin differs from each other. The sub-basins closer to each other show a slight similarity while the sub basins away from each other show a significant variation. When the mean rainfall for the basin as a whole is considered, a deviation from the individual basins can be observed. Hence, indicating a one drought condition for the whole basin is not realistic.

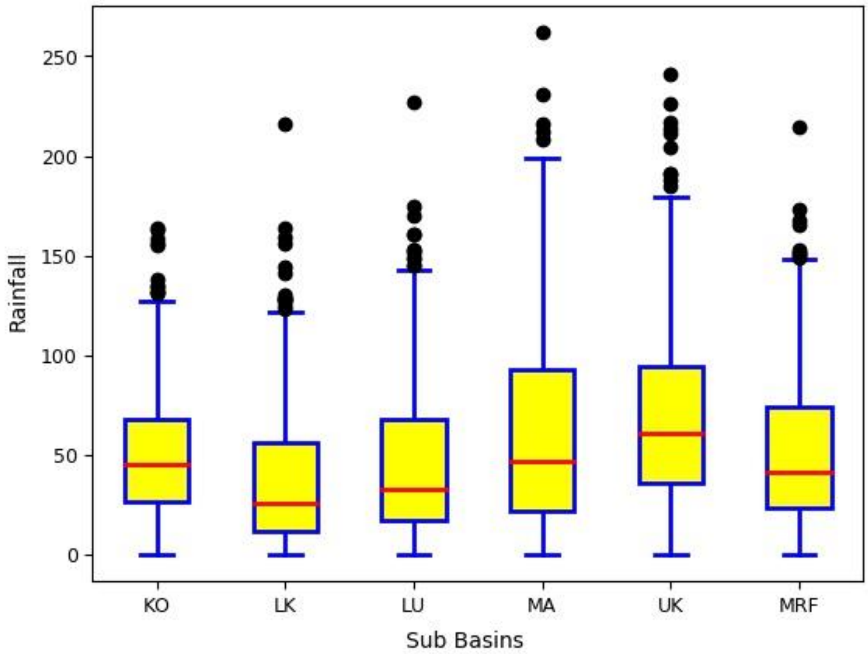

Figure 6.2 : Rainfall distribution in sub basins

According to Figure 6.2, all the sub basins have a median of ~50 mm rainfall. However, outlier points (precipitation greater than 1.5IQR, extreme rainfall conditions) can be observed in each sub-basin. Kuda Oya has the least number of outlier points and they are concentrated around 150 mm whereas Upper Kirindi Oya and Maha Ara which shows extreme rainfall events ~250 mm. This can be explained as extremely high drought events and extremely high rainfall events are common in Maha Ara and Upper Kirindi Oya Sub basins and less in Kuda Oya sub basin. When compared with the mean rainfall, towards the upper part of the basin, the rainfall is recorded to be higher than the mean and towards the lower part the rainfall is less.

6.1.2 Spatial Analysis

- **Comparison of the drought identification of the drought indices**

Spatial distribution of drought categories is indicated in Figure 6.3. The frequency of occurrence of each drought type identified by each drought index is shown. From the total of 456 months considered, ~200 months show a no drought condition according to the majority of the indices. The RAI and Z score shows less number of drought months where Z score records the minimum. The SPI in different time scales have a slight variation in identification of no drought situations. When the weak drought is considered the indices, DI, PN, RAI have identified significantly less number of months while they have higher number for the other drought types. The SPI has identified a significant number of weak drought events and a notable variation can be observed with the time scale considered.

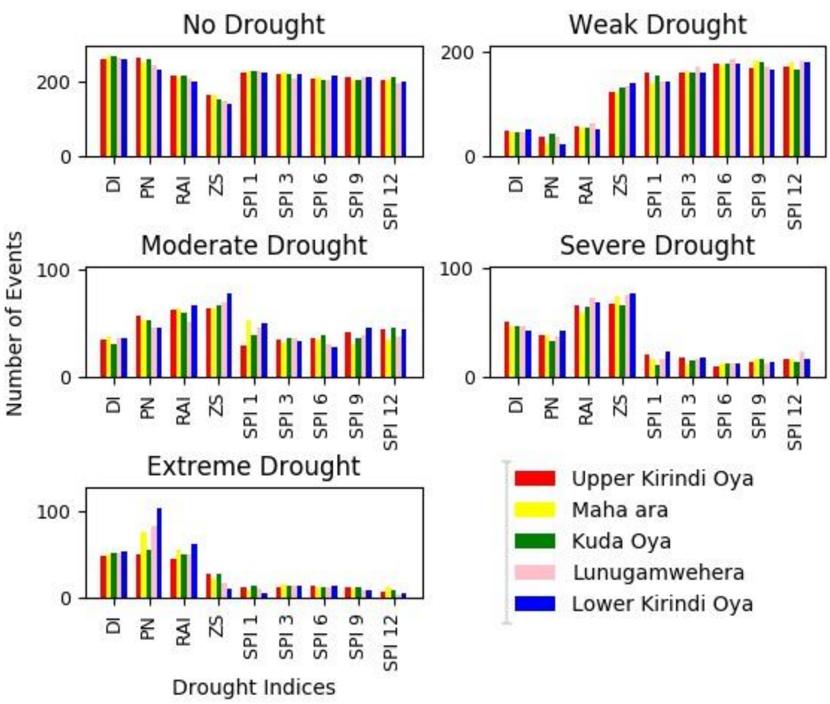

Figure 6.3 : Drought variation in sub basins

For moderate drought type, a moderate number of events have been recorded, while SPI still being recording a lesser number of events. This deviation of drought identification can be significantly observed when it comes to severe and extreme drought types. In general, it can be stated that SPI has a significant difference in identifying the drought type. The SPI has identified the Number of drought months in line with other drought indices while a significant variation is seen in the identification of the drought type in drought month.

- **Drought variation within the basin**

The variation of drought events within the basin is minimum for the weaker drought types. Moderate drought events have varied among sub basins that by using PN index, the Lower Kirindi Oya basin has recorded the minimum number of drought months while Z score has identified it as having the highest number of drought months.

The drought indices, PN, RAI, and Z score have identified a significant variation in occurrence of extreme drought events within the basin and Lower Kirindi Oya sub basin shows the highest frequency. Lower Kirindi Oya basin is situated in the arid zone of the country, hence prone to continuous drought. The rainfall is limited to the area and for a long period of time in a year, the area suffers from lack of rainfall. When it comes to the Upper Kirindi Oya basin, a major part of which is situated in the intermediate zone, has recorded less extreme drought events and more moderate and severe drought events.

The indices, DI, PN, RAI, Z score and SPI 1 have been calculated for 1-month time scale. However, the drought identification shows that SPI 1 has identified remarkably low number of extreme, severe and moderate drought events compared to the other indices. In contrast, SPI for all the time scales considered have identified higher number of weak drought events.

6.1.3 Temporal Analysis

The Temporal Variation of drought in each sub basin is analysed for different drought indices. Use of PN has shown step variations from no drought to extreme drought events. However, drought is a prolonged phenomenon that occurs slowly.

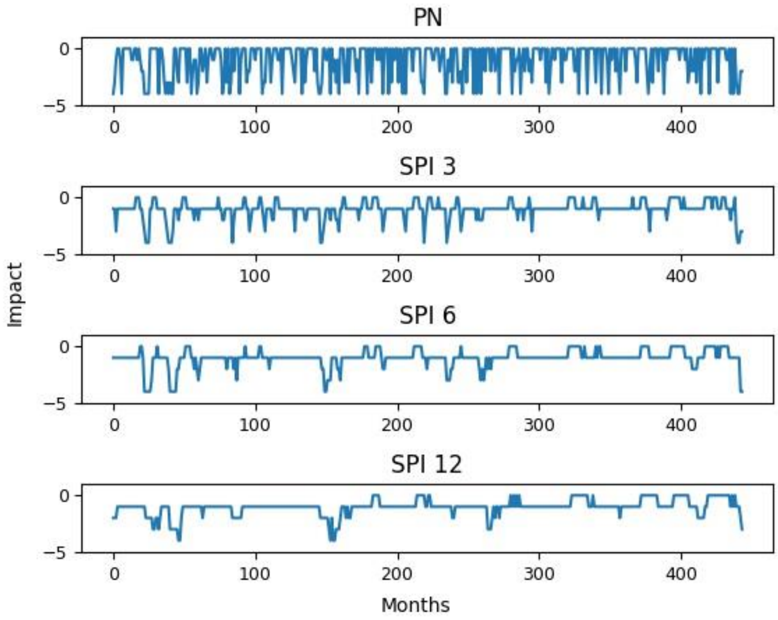

Figure 6.4 : Drought variation in Lunugamwehera

One month of no rainfall where both the adjacent months being rainy would not lead the area to undergo a severe drought. Furthermore, a month with a significant rainfall in a period of a no-rain period would not be enough to seize the existing drought condition.

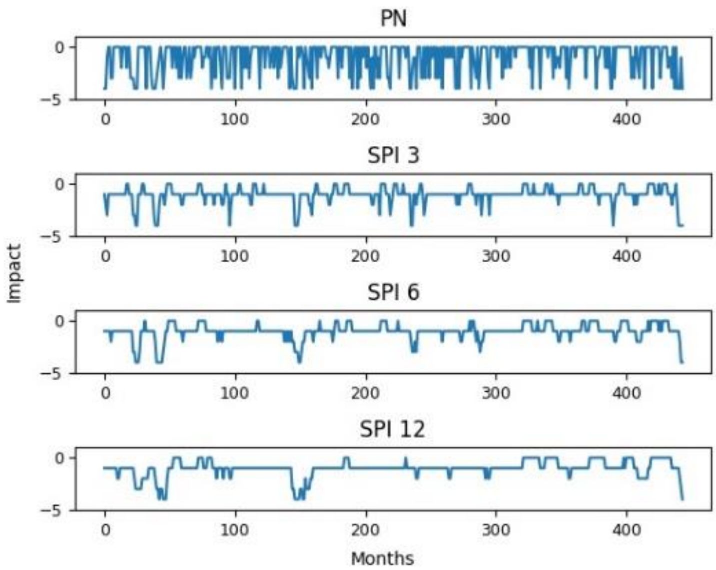

Figure 6.5 : Drought variation in Upper Kirindi Oya

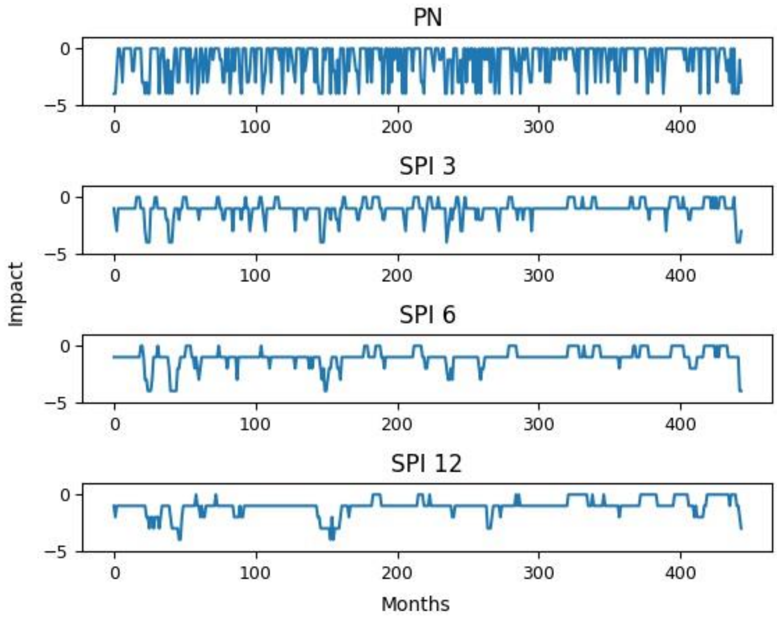

Figure 6.6 : Drought variation in Lower Kirindi Oya

All the indices selected for this study use precipitation as the sole parameter. Hence, if the existing situation or the soil moisture condition was taken into account, the results can be erroneous. However, SPI uses different time scales in calculating the index that with the increase of the time scale considered, the number of identified drought events reduces. This difference can clearly be observed in the Figures 6.4, 6.5 and 6.6. The number of drought events captured by SPI 12 is significantly less. Other than the indications of the drought severity, SPI further provides indications of the drought duration.

6.1.4 Correlation matrices for spatial and temporal analysis

In order to provide a clear representation of the spatial and temporal variation of drought, correlation matrices are used. Both the axis has the names of the sub basins and the correlation of the occurrence of a drought condition in one sub basin with the drought condition in the other sub basins is indicated in each cage. Two correlation matrices are indicated in the Figure 6.7, which have been developed for PN and SPI 3.

For all the sub basins, the correlation with itself is 1.0. The colour of the boxes being different suggest that the similar drought conditions have not been occurred in all the basins at the same time. Furthermore, the nearby basin has shown nearly equal drought conditions over time.

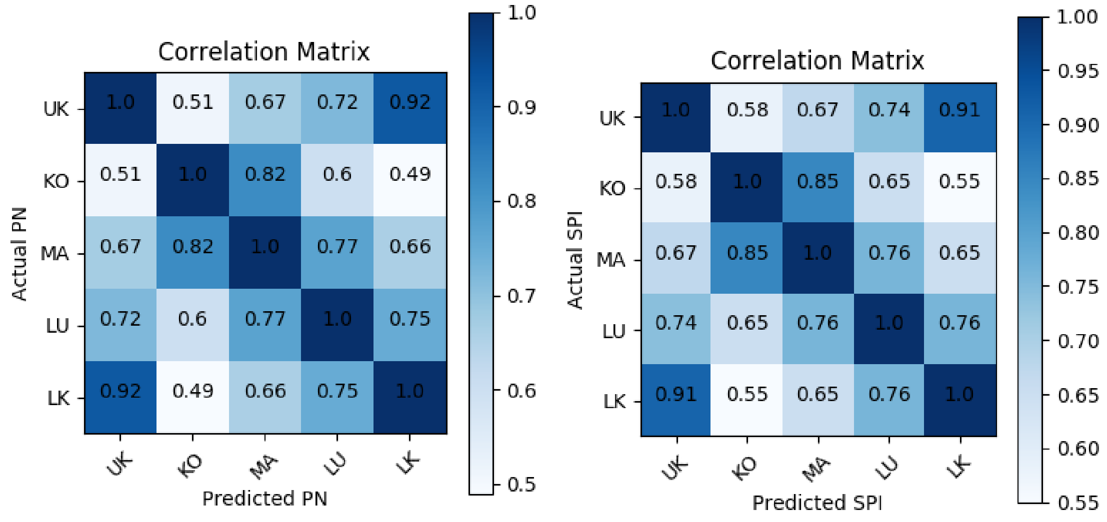

Figure 6.7 : Correlation matrix - PN on left and SPI on right

When one correlation matrix is prepared for all the five river basins considered in the study, Figure 6.8 is obtained. Each river basin can clearly be identified in the matrix. Along the diagonal, the dark red colour squares indicate the relation of the drought conditions over time of 37 years within the basin. It can be observed that Kirindi Oya basin has the highest variation within the basin and the variation in the other basins is not significant when compared to the other basins.

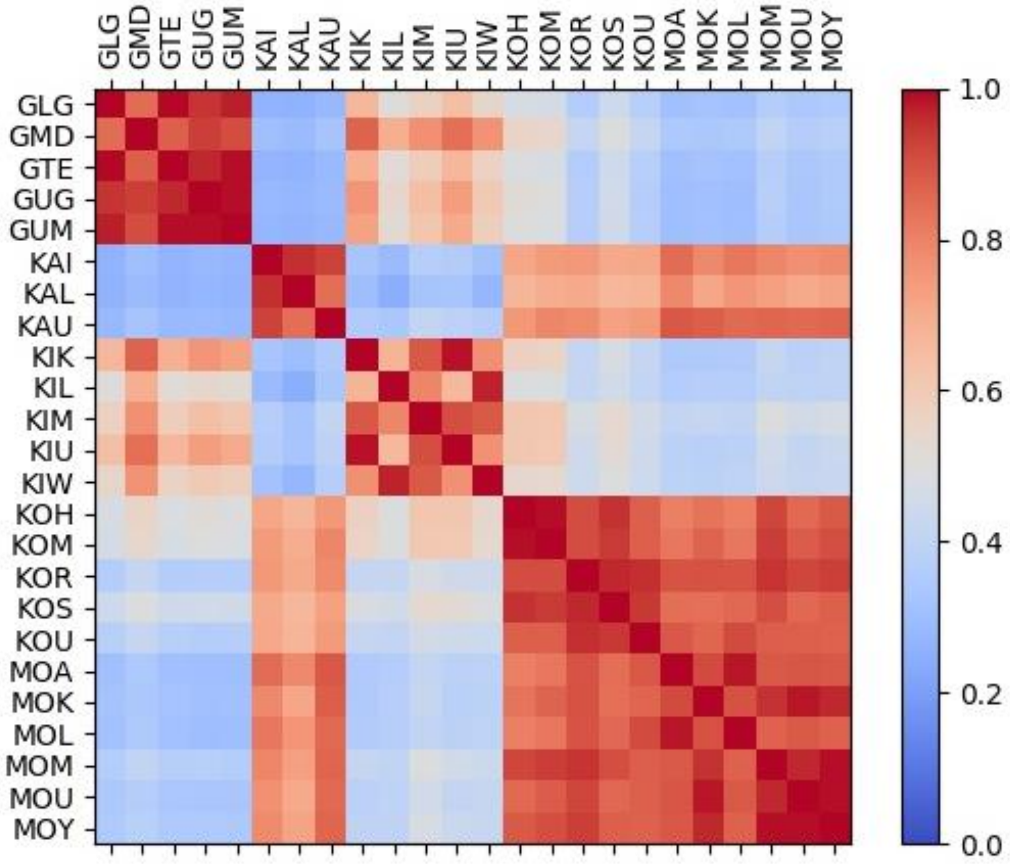

Figure 6.8 : Correlation among sub basins in different basins

The drought conditions identified by SPI in Gin Ganga basin does not impose harmful impacts on the environment and the residents. The correlation of the drought in Gin Ganga basin with the other basins is significantly weak. Kala Oya, Kanakarayan Aru, Malwathu Oya basins show a correlation less than 0.2 hence can be concluded that the drought in Gin Ganga Basin has no relation with the drought in the other three basins. This is clearly elaborated in Figure 6.9.

Two sub basins in Kirindi Oya basin, Upper Kirindi Oya and Kuda Oya show a slight relation to the Gin Ganga basin drought conditions. However, that relation is not strong and only in the range 0.5 ~ 0.7. Gin Ganga Basin is entirely situated in the wet zone of Sri Lanka and major part of Upper Kirindi Oya and Kuda Oya sub basins are situated in the Intermediate Zone of the island. All the other sub basins considered in the study are situated in the Dry zone of the island. Hence a relationship can be observed between the spatial and temporal distribution of drought with the climatological regions of the country.

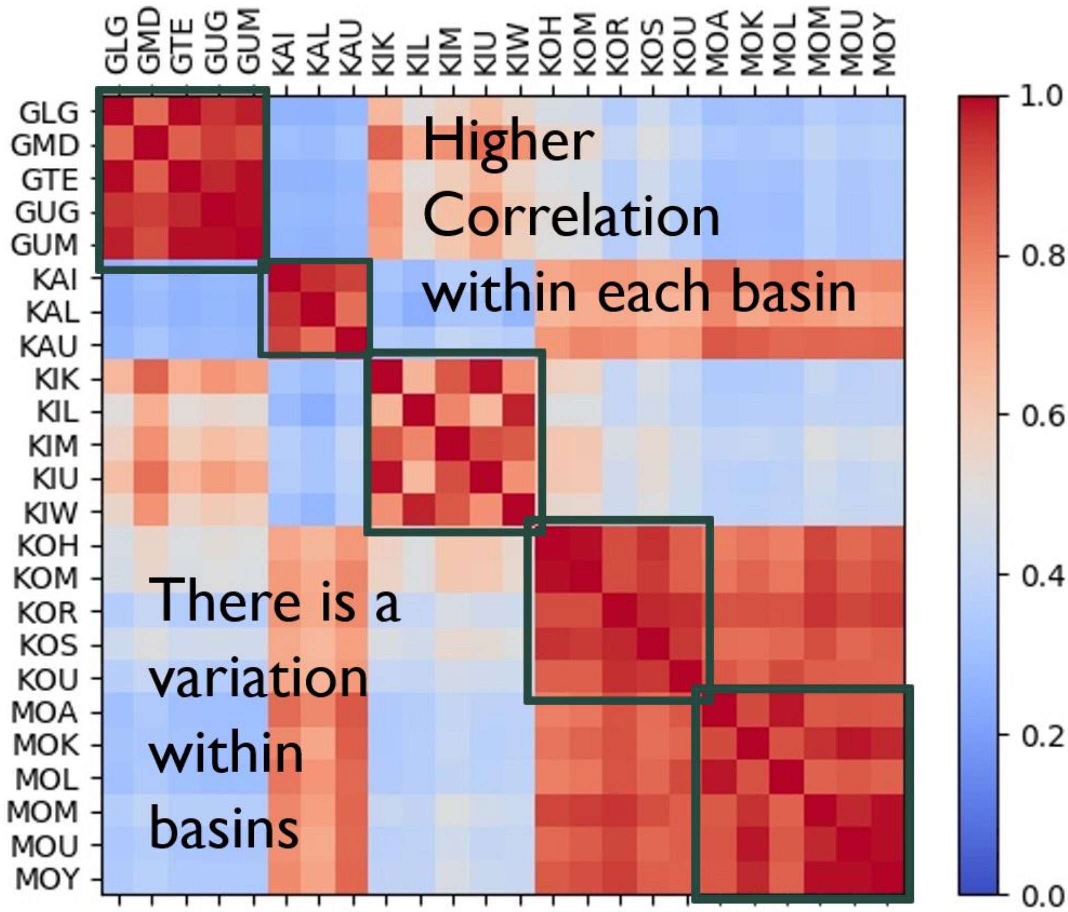

Figure 6.9 : Explained inner basin correlation

When Malwathu Oya Basin is considered, a strong relationship can be observed with Kala Oya Basin over time. Both Malwathu Oya and Kala Oya basins lie in the dry zone of the country, closer to each other than the other basins under consideration. The rainfall is received in a similar manner. Both the rivers reach to ocean from the north western part of the island. Hence the results being similar can be explained. Furthermore, a slight relation is observed with the Kanakarayan Aru basin. Kanakarayan Aru is also situated in the dry zone of the island, but in the North and North Eastern part of the country.

A significant observation is that, the relationship of drought in Kala Wewa and Malwathu Oya basins is very weak with Kirindi Oya and Gin Ganga. The entire Gin Ganga basin is situated in the wet zone of country and considerable part of the Kirindi Oya basin is situated in the intermediate zone. The weak relationship can be justified as the situation of the basins in different climatic regions and rainfall patterns.

In summary, the spatial and temporal analysis of drought in Sri Lanka can be identified as having a significant variability spatially and temporally. The study conducted using Kirindi Oya basin indicated that SPI is the best suited Drought index for the area over five indices considered. Drought can be observed as a seasonal event that occurs in various severity scales. Almost all the sub basins showed nearly similar number of no drought months.

However, the drought severity categorization is different for different sub basins. As an example, the frequency of extreme drought events is high for Lower Kirindi Oya basin in compared to other sub basins, and Kuda Oya and the Upper Kirindi Oya have the lowest. Furthermore, this study has considered five river basins in different geographic locations and in different climatic regions to compare the spatial and temporal variation in drought which indicated several relations among the basins.

6.2 Development of a Drought Prediction Model

By using hyper parametric tuning independently for each sub basin, the best parameters that reduces the error between actual and predicted values of data was identified. The error terms obtained from the implemented LSTM model are given in Table 6.1.

The results show that in the train data set, the maximum RMSE error for any sub basin is 0.3 which are obtained for Boo Oya and Kal Oya and maximum MAE is 0.22 for Kudahathu Oya. However, when it comes to the test data set, the model results show a maximum RMSE of 0.37 for Boo Oya and Kal Oya and Maximum MAE of 0.28 for Boo Oya. Hence it can be observed that in both the case, the error values are minimized and when these values are compared with the results obtained using MLP Neural Networks obtained from past research works, it shows that these results are improved in means of RMSE and MAE (Morid, Smakhtin, & Moghaddash, 2006; Hong & Hong, 2015).

The overall results indicate that the neural network has captured the variation in SPI with RMSE varying in the range 0.33 ~ 0.37 and MAE in the range of 0.24 ~ 0.26 for the predicted SPI values. When comparing the error values with past research, ~5% error reduction was obtained with the proposed method as achieved for the majority of the sub-basins where the actual values spanned from -4.0 to 4.0.

Table 6.1 : Performance of the LSTM model

Malwathu Oya Basin		Train Set		Test Set	
ID	Sub Basin	RMSE	MAE	RMSE	MAE
1	Upper Malwathu Oya	0.29	0.21	0.34	0.24
2	Maminiya Oya	0.28	0.20	0.34	0.24
3	UpperMiddle Malawathu Oya	0.27	0.20	0.34	0.24
4	Upper Kanadara Oya	0.26	0.20	0.33	0.24
5	Upper Weli Oya	0.27	0.20	0.33	0.24
6	Kudahathu Oya	0.27	0.22	0.35	0.25
7	Sangilikanadara Oya	0.28	0.21	0.35	0.25
8	Boo Oya	0.30	0.22	0.37	0.28
9	Kal Oya	0.30	0.22	0.37	0.27
10	Narivili Aru	0.29	0.21	0.35	0.26
11	Lower Kanadara Aru	0.28	0.21	0.34	0.25
12	Lower Weli Aru	0.26	0.20	0.33	0.24
13	LowerMiddle Malwathu Oya	0.27	0.20	0.33	0.24
14	Lower Malwathu Oya	0.29	0.21	0.34	0.25

Even though the prediction model proposed by Illeperuma has obtained lesser error values, the study is basically concentrated on several major stations island wide. Hence the drought variation in finer scale is not expressed (Illapperuma & Sonnadara, 2009).

Figures 6.10, 6.11 and 6.12 show the actual results, prediction using training data and testing data for SPI 12.

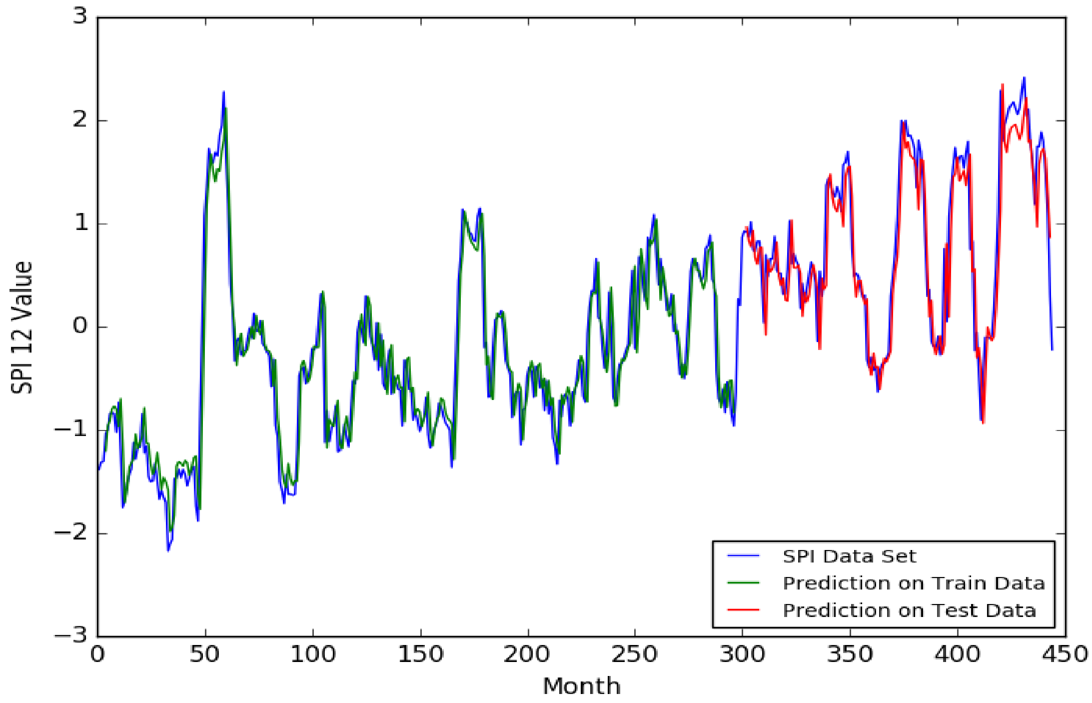

Figure 6.10 : Train set and test set prediction for a sub basin – Kudahathu Oya

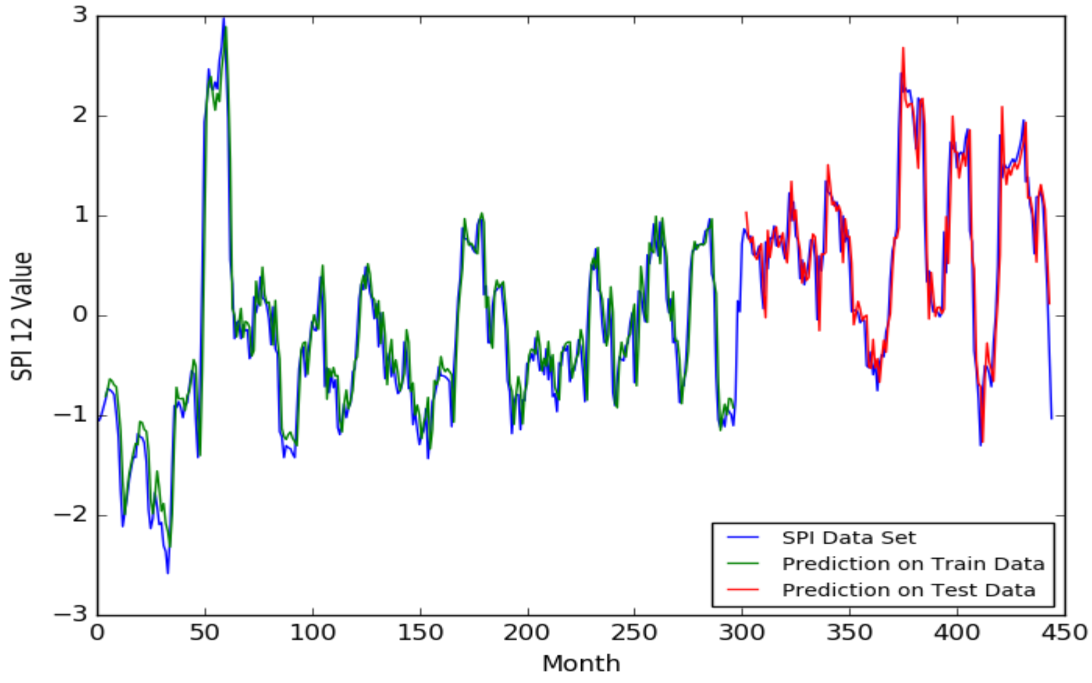

Figure 6.11 : Train set and test set prediction for sub basin - Upper Malwathu Oya

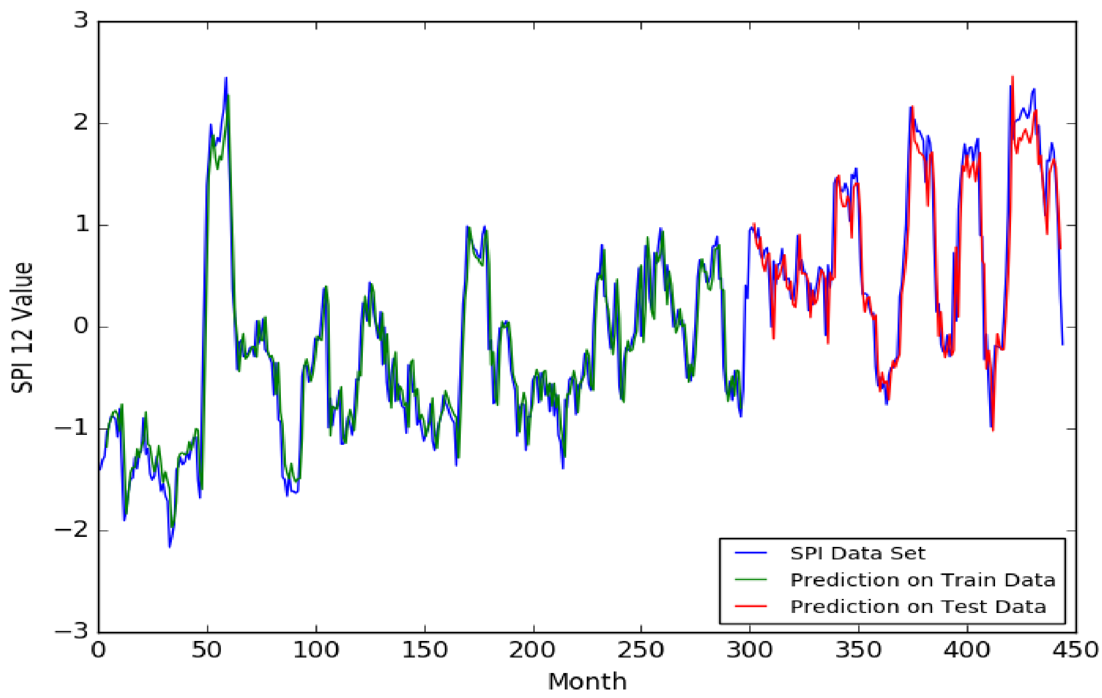

Figure 6.12 : Train and test set prediction for a sub basin - Kanadara Oya

The blue coloured line shows the variation of the actual SPI data variation over time. The green coloured line shows the variation of the prediction using the test data and the red coloured on shows the prediction using the test data. It is significant to note that the model has captured the drought patterns accurately. It was further identified that, in order to arrive at this accuracy, to predict this month's value, it is required to consider past 4 months' drought data. The results are further elaborated in the form of a seven-class confusion matrix.

When there are *N* classes to predict, the confusion matrix would be an *NN* matrix, with the vertical axis showing the true class and the horizontal axis showing the class assigned to an item using the model. Each element *i*, *j* of the matrix would be the number of items with true class *i* that were classified as being in class *j*.

Both the axes have all the possible conditions that can occur. They are namely, Extremely wet (EW), Very Wet (VW), Moderately Wet (MW), Near Wet (NW), Moderate Drought (MD), Severe Drought (SD) and Extreme Drought (ED). If the model has predicted the exact condition in all months, then along the diagonal, the colour should be dark red and all the other grid cells should be dark blue. The number inside each cell is the number events. Hence, when this model is considered, it can be observed that, for each type of drought, the highest value is there along the diagonal. For the moderate drought, the cell colour is dark red indicating a very high similarity between the actual result and the prediction.

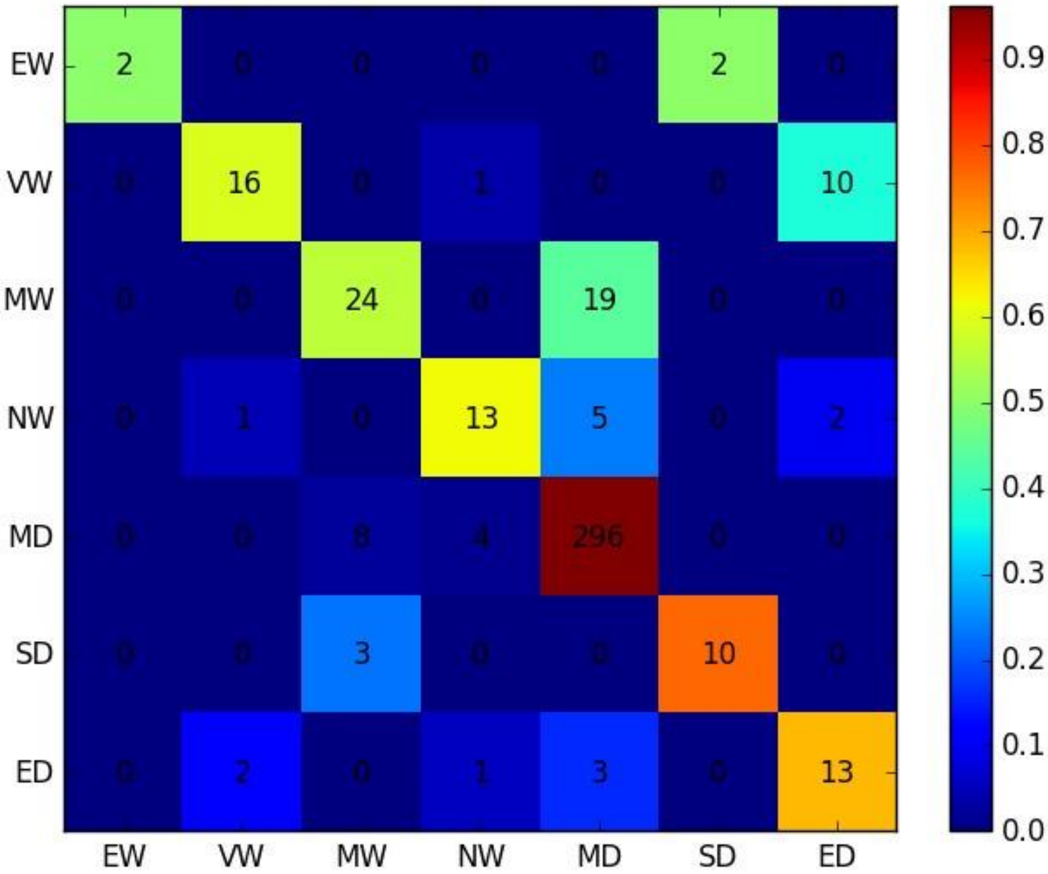

Figure 6.13 : Upper Malwathu Oya confusion matrix

Furthermore, the model seems to be highly accurate for the instances with less severity. When it comes to extreme wet and extreme drought conditions, the model's predictions show a low accuracy, in the range of 50% ~ 60%. However, the occurrence of extreme events is also not common, and for all the 37 years' duration, only 19 months have been recorded with extreme drought, out of which 13 have been correctly predicted. When the extremely wet conditions are considered, only 4 events have been occurred where 2 have been correctly predicted. Considering the low frequency of the event type, it is difficult for the model to tackle the existing trends. However, considering the overall conditions, the model is capable of predicting at an accuracy of more than 84%. In the case of Upper Kanadara Oya sub basin, considered in the example, the accuracy is 86%.

By using a larger data set, the accuracy can be further improved. Furthermore, the current error terms will be reduced by learning on the expected value and the error, similar to an ensemble approach. The proposed prediction methodology is verified by using SPI index, but can be taken in predicting other drought indices as well. Hence, not only meteorological drought, but also, other drought types can be predicted.

The confusion matrices for three other sub basins are shown in Figures 6.13, 6.14 and 6.15.

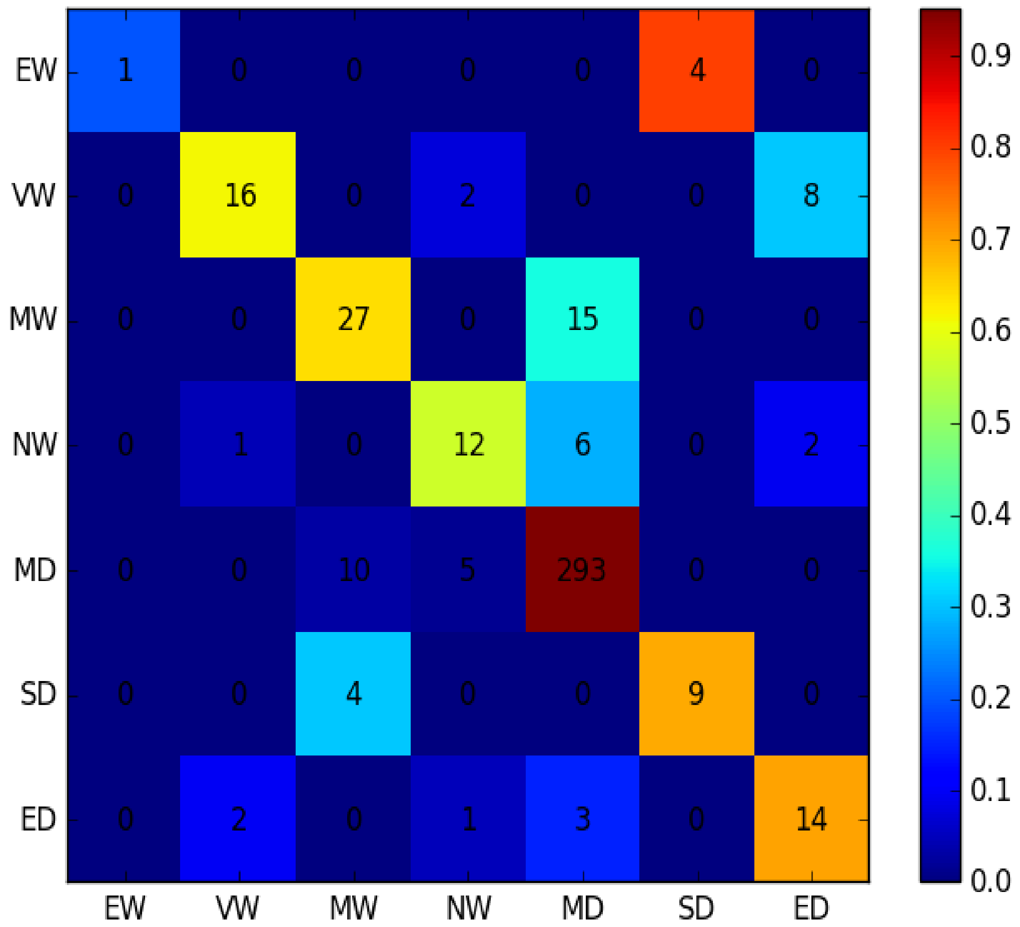

Figure 6.14 : Kudahathu Oya confusion matrix

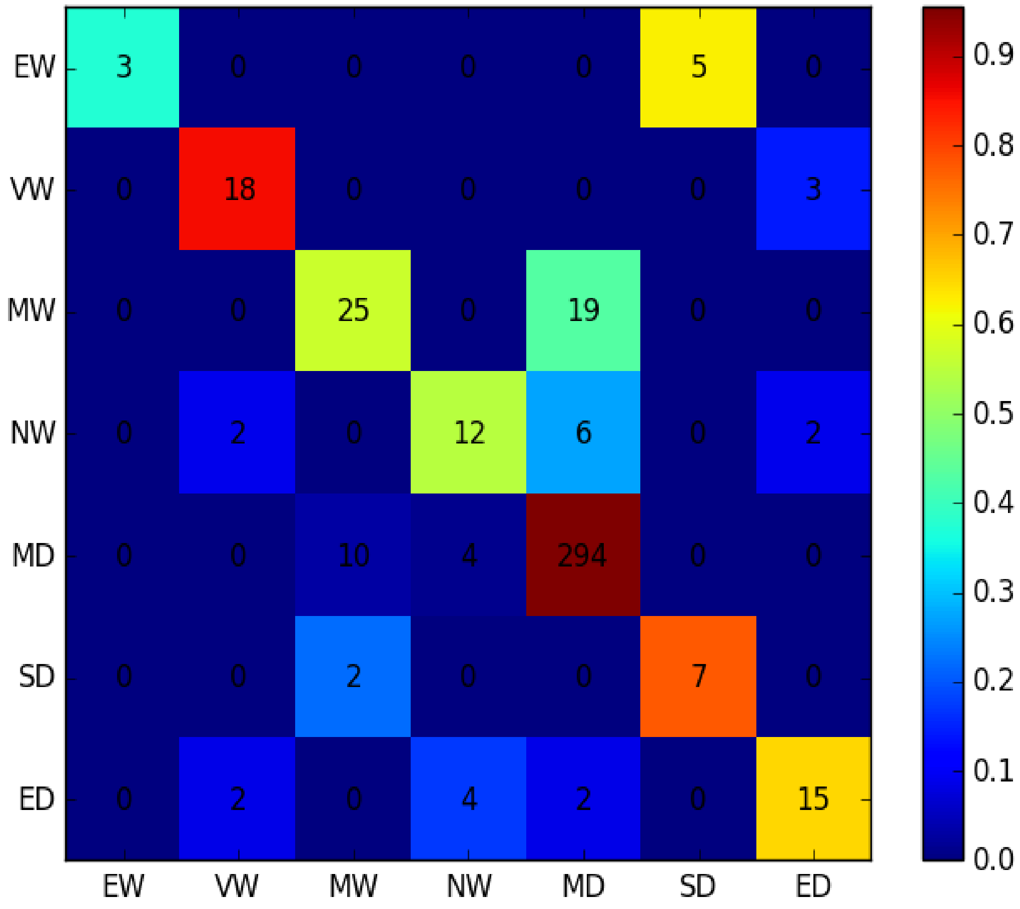

Figure 6.15 : Kanadara Oya confusion matrix

6.3 Drought Risk Assessment

As described in the methodology, in order to ensure the effective use of this drought study, it has to incorporate the socio-economic impacts. Thus, the extent to which the society is vulnerable to drought has to be taken in to consideration. Even through the drought studies have been conducted in different scales, basin scale or sub- basin scale, in order to assist the administrative purposes, it has to be in administrative boundaries. As a result, DSD wise drought hazard map, DSD wise drought vulnerability map and the DSD wise drought risk map have been developed. The results provide a comparative analysis of the drought hazard, vulnerability and risk among the DSDs.

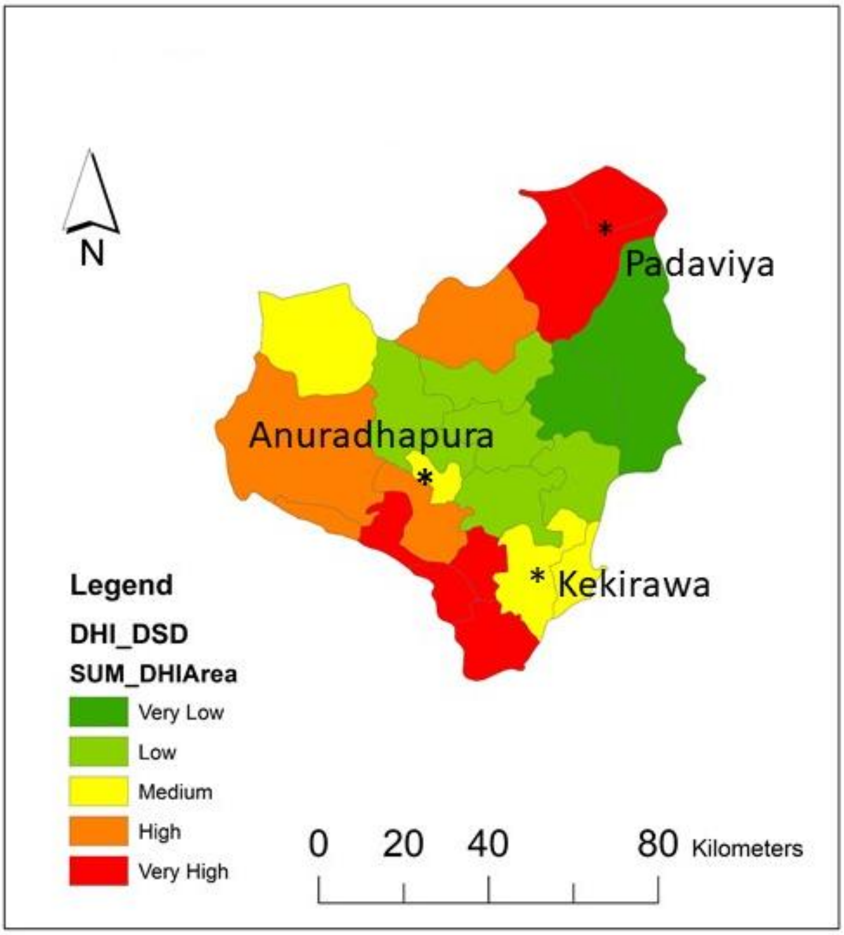

Figure 6.16 : Drought hazard map - DSD scale for Anuradhapura district

The drought hazard map in Figure 6.16 shows the comparative variation of drought hazard within Anuradhapura district. Drought hazard analysis shows that the DSDs that are with very high drought hazard are Galnewa, Ipalogama, Kebithigollawa, Padaviya, Palagala, and Thambuttegama. The DSDs, Medawachchiya, Nochchiyagama, Rajanganaya and Thalawa are categorized under high drought hazard. Hence, out of the 22 DSDs of Anuradhapura district, 10 DSDs have either high or very high drought hazard in compared to other DSDs.

Horowpothana and Kahatagasdigiliya show the lowest drought hazard while, DSDs, Galenbinduwewa, Mihinthale, Nuwaragampalatha Central, Nuwaragam Palatha East, Rambewa and Thirappane show low drought hazard. Out of the 22 DSDs, 8 DSDs show low or very low drought hazard compared to the other DSDs in the district. The method of categorization used is natural breaks.

The vulnerability factors proposed by Shahid and Behrawan (2008), Population density, Female to male ratio, Agricultural occupation, Population below poverty level, Irrigated land, Soil moisture and Paddy production were separately mapped as indicated in the Figures 6.17 and 6.18. A comparative spatial distribution is obtained.

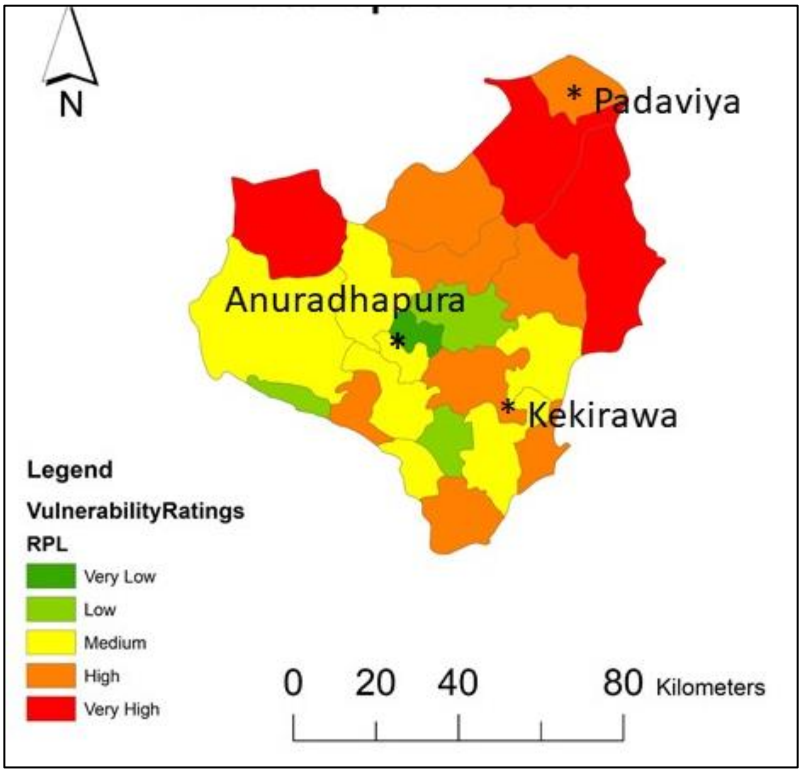

Figure 6.17 : Drought indicators- poverty level

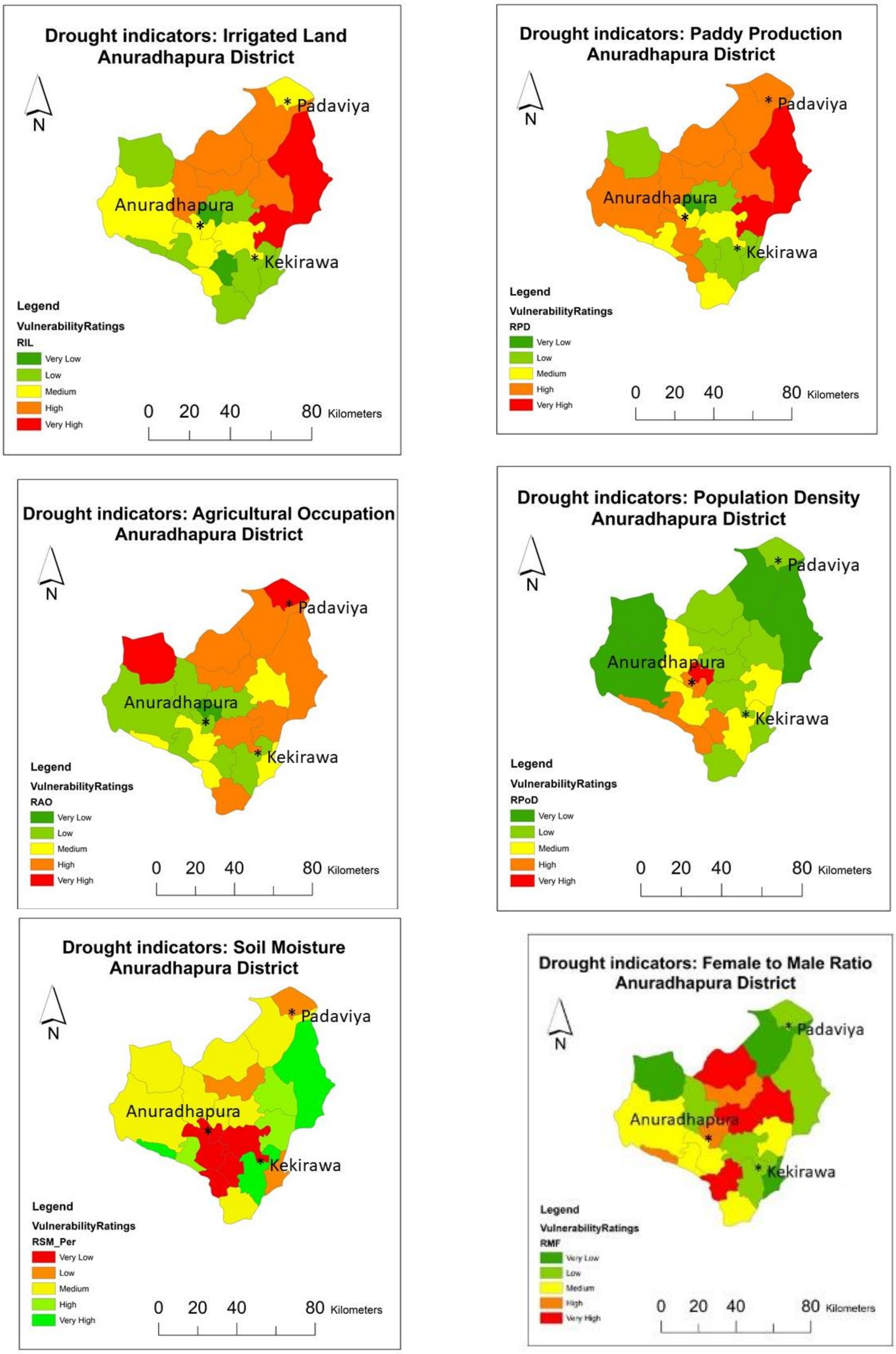

Figure 6.18: Other drought indicators

The drought vulnerability map was obtained by using the drought vulnerability index as shown in Figure 6.19. The results show that, the DSDs, Galenbindunu Wewa and Horowpothana have a very high drought vulnerability from the 22 DSD. Furthermore, the DSDs, Kahatagasdigiliya, Kebithigollawa, Medawachchiya, Padaviya, Rajangana and Rambewa are highly vulnerable. Total of 8 DSDs are highly or very highly vulnerable to drought in Anuradhapura district.

Six DSDs are having a low or very low drought vulnerability and they are, Ipalogama, Mihinthale, Nachchaduwa, Nuwaragampalatha east, Palugaswewa and Thirappane.

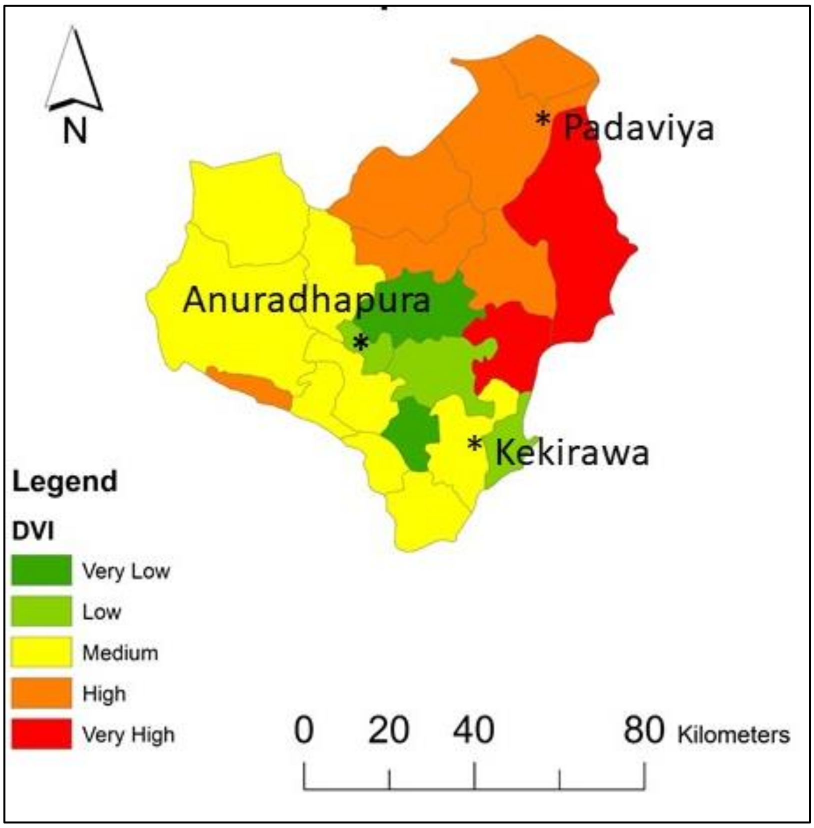

Figure 6.19 : Drought vulnerability map - Anuradhapura district

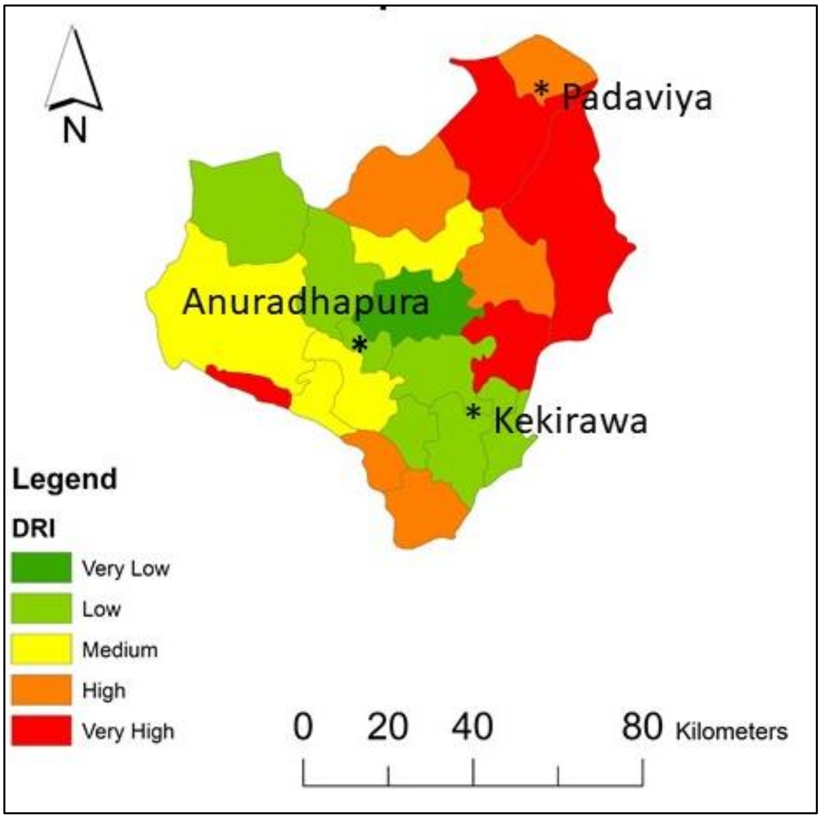

Figure 6.20 : Drought risk - Anuradhapura district

According to the model, the drought risk has been identified for Anuradhapura district based on the drought hazard and drought vulnerability. The drought risk map is indicated in Figure 6.20. The DSDs that are having high/very high hazard and high/ very high vulnerability are Medawachchiya, Kebithigollawa, Rajangana, and Padaviya.

Drought risk analysis shows that the DSDs that are with very high drought risk are Galenbindunu Wewa, Horowpothana, Kebithigollawa and Rajanganaya. The DSDs, Galnewa, Kahatagasdigiliya, Medawachchiya, Padaviya, and Palagala are categorized under high drought risk. Hence, out of the 22 DSDs of Anuradhapura district, 9 DSDs have either high or very high drought risk in compared to other DSDs.

Nuwaragam Palatha East and Mihinthale shows the lowest drought risk while, DSDs, Ipalogama, Kekirawa, Medawachchiya, Nachchaduwa, Nuwaragampalatha Central, Palugaswewa and Thirappane show low drought risk. Out of the 22 DSDs, 9 DSDs shows low or very low drought risk compared to the other DSDs in the district.

Summary of the results are shown in Table 6.2.

Table 6.2 : Drought risk details

DSD	Drought Hazard	Drought Vulnerability	Drought Risk
Galenbindunu Wewa	L	VH	VH
Galnewa	VH	M	H
Horowpothana	VL	VH	VH
Ipalogama	VH	VL	L
Kahatagasdigiliya	VL	H	H
Kebithigollawa	VH	H	VH
Kekirawa	M	M	L
Mahavilachchiya	M	M	L
Medawachchiya	H	H	H
Mihinthale	L	VL	VL
Nachchaduwa	M	L	L
Nochchiyagama	H	M	M
Nuwaragam Palatha central	L	M	L
Nuwaragampalatha east	L	VL	VL
Padaviya	VH	H	VH
Palagala	VH	M	H
Palugaswewa	M	L	L
Rajanganaya	H	H	H
Rambewa	L	H	M
Thalawa	H	M	M
Thambuttegama	VH	M	M
Thirappane	L	L	L

The drought risk assessment model is verified for the western part of Bangladesh by Shahid (2008). The relative risk of the DSDs is identified by the model. The model is applied to Anuradhapura district of Sri Lanka. When the drought risk is compared with the drought relief distributions, for 11 of the DSDs the relation showed high or very high. However, for the rest of the DSDs the relation was either medium or low. Socio-economic aspects of drought are analysed by using drought relief payment data.

The analysis was then carried out to consider the relation between the drought relief payments and the drought risk by varying the parameters and the normalization methods. The method of classification was changed as natural breaks, equal intervals, quantiles, standard deviation and manual method. The highest relationship was indicated by the natural-breaks methods.

In order to fine tune, the number of drought-affected population in each DSD was considered. However, the identified drought risk showed the highest relation with the number of drought- affected population normalized by the drought relief payments.

Drought relief payment data and the number of drought-affected population data were divided into two sets. The first set included values from 2002-2007 and the second set from 2008-2017. According to the statistics, significant drought events have not been occurred every year and the drought occurrence cannot be considered as a yearly event. Each type of drought has different probabilities of occurrence. Hence the two sets were divided in a way that severe drought events also have been captured. The distribution of drought relief payments and the drought affected population are shown in Figure 6.21.

According to Lyon and Zubair, the drought relief payments in Sri Lanka can be identified as a good indication of drought in Sri Lanka. However, this study shows that the accuracy of the drought risk identification is improved when both the relief payments and the affected population taken into account (Lyon & Zubair, Finescale Evaluation of Drought in a Tropical Setting: Case Study in Sri Lanka, 2009).

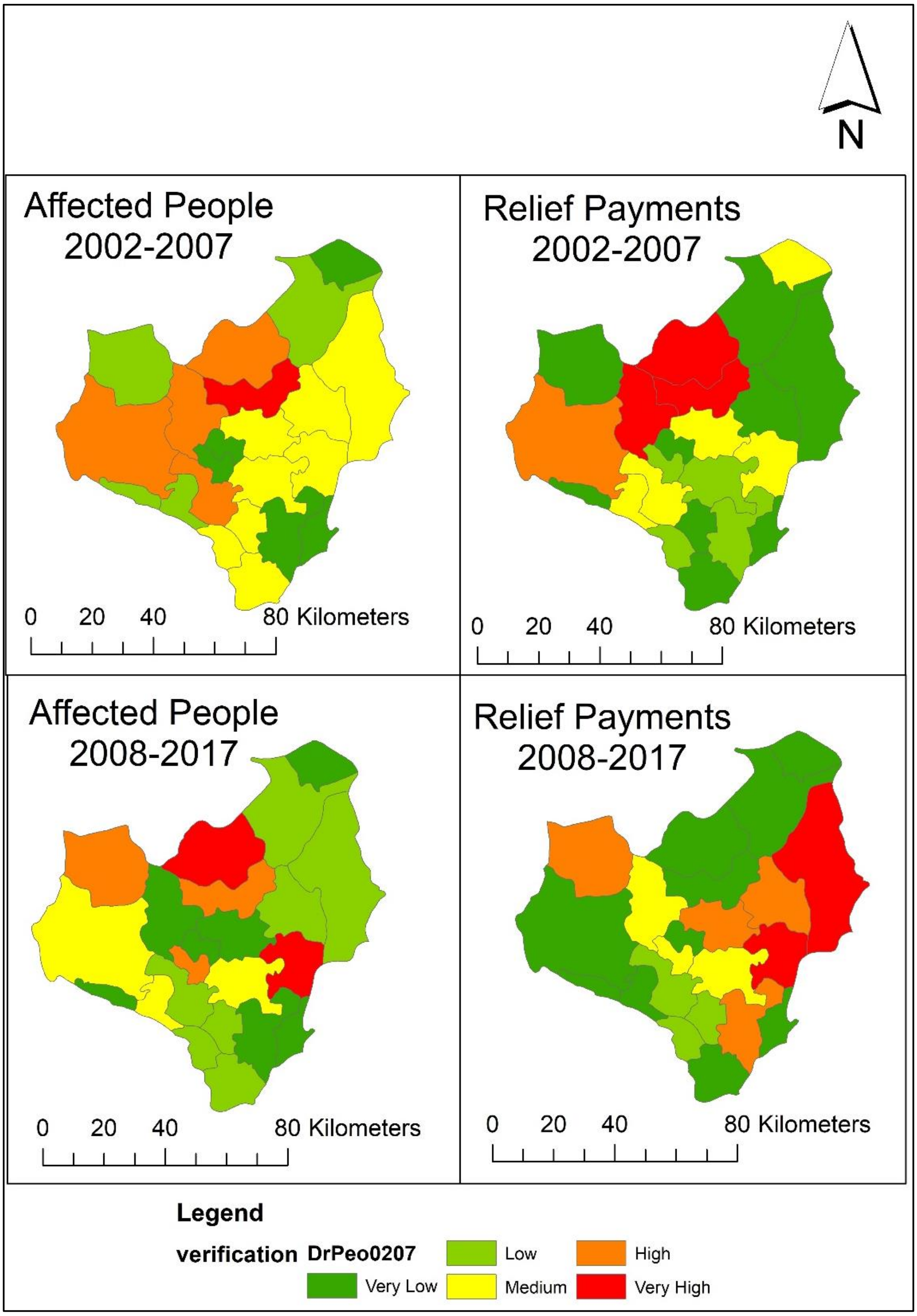

Figure 6.21 : Drought relief payments and affected population

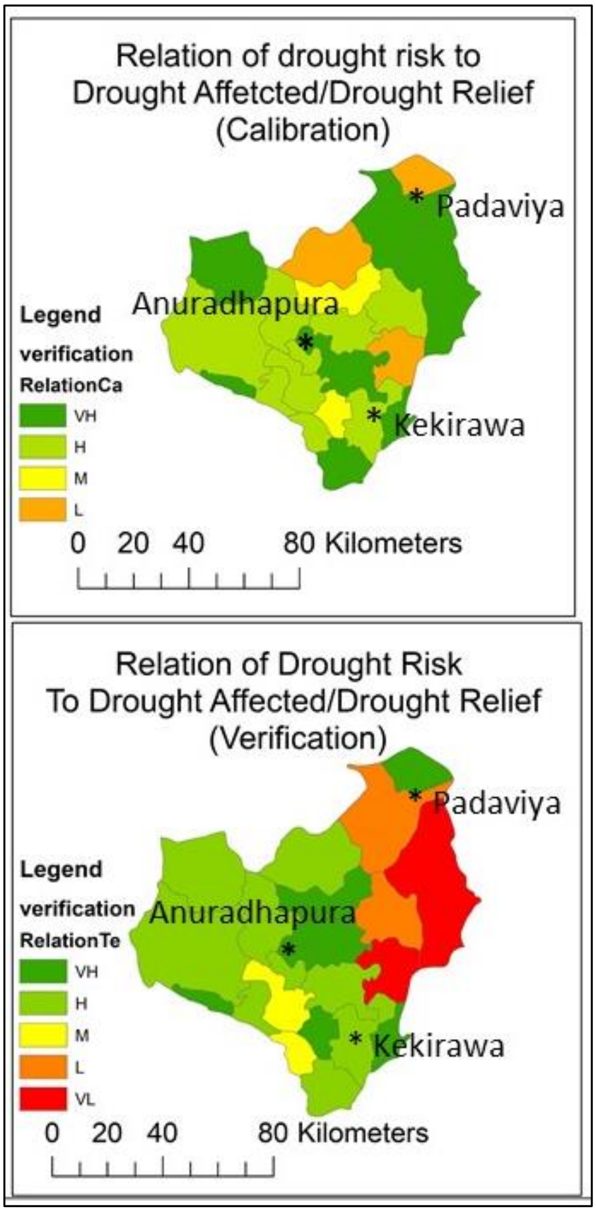

Figure 6.22 : Calibration and verification

Table 6.3 : Calibration and verification comparison

Class	Calibration	Verification	Comparison
Very High	8	7	8
High	9	9	7
Medium	1	2	4
Low	3	2	2
Very Low	0	2	1

The first set was used to calibrate the model. For that, the value of number of affected populations, normalized by the drought relief payments was divided into five classes. This classification was accomplished using manual method. However, the classified ranges for each category showed very close values to natural breaks classification. The identified value ranges were used to validate the applicability of the model to Anuradhapura District. For the identified five class classification, the drought risk showed a significantly good relationship. Figure 6.22 indicates the relation maps for the calibration set and verification sets.

Analysing the summary of results, it shows that 8 DSDs show a very high relation and 9 DSDs show a high relationship. Hence, out of the 22 DSDs, 17 DSDs show high or very high relation. When it comes to the verification, 16 DSDs have shown a high or very high relation while the classes, medium, low and very low have 2 DSDs each. Hence when the percentage of total DSDs is considered, 77.3% DSDs show a high or very high relation. However, when the identified class ranges were applied to the test data set, it can be observed that 72.7% DSDs show a high or very high relation. This can be identified as a significant relation.

However, as shown in Figure 6.21, which shows the drought relief payments and drought affected population for the two data sets, it can be observed that both the drought affected population and relief payments maps shows a close relation between each other in each data set while the two data sets shows noticeable difference.

Comparison of the calibration map and the verification map shows that 15 DSDs have shown high or very high relationship and that is a 68%. That is both the sets have shown same or close class for a given DSD. Another 4 DSDs show a moderate relationship while only 3 DSDs show low or very low relationship. The possible reasons for the deviation of results of calibrating and verifying maps can be identified as the difference of drought affected population and relief payments during the time period considered.

Even though 36 years have been considered in the drought hazard map preparation, the relief payment data is only available for the period from 2002-2017 which is 15 years. When the probability of occurrence of each drought type is considered as an average for Anuradhapura District, as indicated in Table 6.3, it can be observed that extreme and severe drought events have very low probability of occurrence and higher return periods. Hence, for the duration considered, the similar type of drought events may not have been occurred.

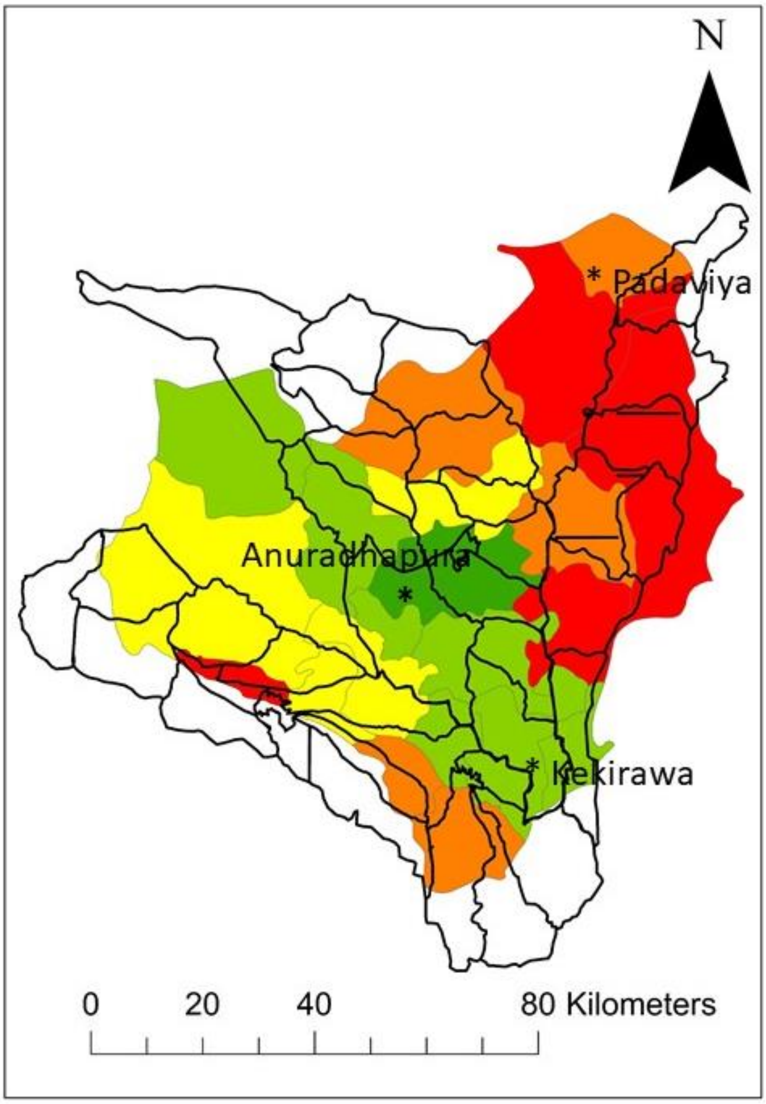

Figure 6.23 : Drought risk in Anuradhapura district - sub basins and DSDs'

Figure 6.23 indicates the drought risk map developed for Anuradhapura district and the location of Malwathu Oya, Kala Oya and Yan Oya basins in it.

6.4 Summary of the Discussion

This study has been conducted in three phases, namely spatial and temporal analysis of drought, development of a drought prediction model and drought risk assessment. In the spatial and temporal analysis, the past data were analysed in order to determine the drought variation, spatially, temporally and together. The spatial drought variation shows that, there is a relation in drought severity and occurrence frequency with the ago-ecological regions of the island.

Drought analysis in sub basin scale has indicated that significant variations of drought conditions can be observed within the basins. Kirindi Oya, which lies in three climatological regions is the example considered. It is observed that nearby sub basins show higher correlation compared to far away sub basins showing lesser correlations. Sub basins in Malwathu Oya are not showing more significant variations compared to Kirindi Oya basin mainly due to climatological and agro-ecological zone differences. Agro-ecological regions in Malwathu Oya are more similar compared to the regions of Kirindi Oya. As an example, Lunugamwehera sub basin of Kirindi Oya is showing nearly 0.45 and 0.49 correlation to Upper Kirindi Oya and Kuda Oya sub basins respectively. Comparing with higher correlation of 0.88 between Lunugamwehera and Lower Kirindi Oya, it can be stated that sub basin scaled study is necessary to identify and understand drought patterns in more complex and diverse basins.

By analysis of drought identification results from five drought indices, SPI was identified as the best suited one for this area due to its windowing techniques and the formula. However, short term indices like PN and RAI has many false positives compared to SPI. That is because of not using windowing techniques in above indices. As an example, considering a 3-month period with monthly precipitation of 150 mm, 10 mm and 200 mm. In this scenario, PN and RAI have higher probabilities of identifying them as drought events which is actually not in real scenario. Hence, SPI is the best candidate among others to continue the drought analysis in this study.

The temporal analysis of drought indicates that the drought frequency reduces with the severity in the past and by using indices which use a month's data to calculate the month's drought condition, the results can highly deviate from the reality. By combining the spatial and temporal aspects of drought, the correlation matrix was developed for the five basins. The matrix indicates that over the time, the variation of drought in the five selected basins shows strong relation with its own sub basins and a considerable relation with the nearby basins. As an example, Malwathu Oya and Kala Oya shows a very high drought correlation and less correlation with the far away basins, Kirindi Oya and Gin Ganga.

For the development of the drought prediction model, Malwathu Oya Basin was selected. Neural Network based model is suggested to model the future SPI values. The model has used LSTM and ANN to predict the future drought conditions up to 1-3 months with an accuracy of 80-86%. The RMSE and MAE are lower when compared to other drought prediction models which has used deep learning techniques (Morid, Smakhtin, & Moghaddash, 2006; Hong & Hong, 2015).

In order to improve the quality of the research, the drought study was linked to a drought risk analysis, where an existing model was applied to Anuradhapura district to analyse the drought risk and the socio-economic impacts of drought. The drought risk was then compared to the drought relief payment distribution and the drought affected population data in order to identify the applicability of the model. The results showed that the calibration data set showed 8 very high, 9 high, 1 moderate, 3 low and no very low correlation between the risk, affected population and the relief payments.

When it comes to the verification data set, the values show a high similarity with 7, 9, 2, 2, and 2 for the aforementioned categories. When compared the two, 8 out of 22 DSDs have shown a very high correlation between the drought identification by two datasets. Furthermore, 7 have shown a high correlation, 4 have shown a moderate correlation and 2 and 1 have shown low and very low relation respectively.

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

- The drought identification using the drought indices considered in this study shows that higher number of drought events including all the drought events identified by SPI have been identified by PN, DI, RAI and Z score.
- However, they have also identified significant difference in rainfall in one month which falls amidst a drought event as cease of drought which is impractical. Hence, drought prediction in Kirindi Oya basin can be effectively achieved by using drought indices which use windowing technique; hence, SPI.
- Drought events in Upper Kirindi Oya basin having significant differences during some drought events while the drought variation in the nearby sub-basins being nearly similar is a main observation of this study. Hence, the findings of this study help understand that the effects of drought can vary even within a river basin and, that sub-basin-scale analysis of drought gives a comparatively accurate interpretation of variation of drought within the basin.
- Furthermore, the present findings confirm that the drought prediction at a sub-basin scale is more effective for river basins which lie in several climatological regions.
- The analysis of the results reveal that the proposed model is capable of predicting drought in Malwathu Oya Basin with error ranging from 0.2 ~ 0.37 which is acceptable.
- The analysis of the results indicates that merely the amount of drought relief payments does not show a very strong relationship with the drought risk and both the drought relief payments and drought affected population has a combined effect on the risk.
- The drought affected population normalized by the drought relief payments shows a very strong relationship with the risk. This observation is realistic that, not only the amount of relief payments, but also the number of affected populations do have a significance. Hence in order to identify the priority criteria for drought relief payment distribution, is very much suitable to consider that the drought risk given

by the model is an indicator of both the drought relief payments and the drought affected population.

- Considering the work carried out, it can be concluded that drought risk assessment can be effectively used in obtaining a relative drought risk identification for Anuradhapura District of Sri Lanka and to obtain indications of socio-economic implications of drought.

7.2 Way Forward

- Spatial and temporal analysis of drought can be carried out for all the river basins in Sri Lanka, and develop a sub basin scale drought analysis.
- Furthermore, the prediction model can be extended to some other major river basins which spread within different geographical regions in Sri Lanka.
- Current error terms can be further reduced by learning on the expected value and the error, similar to an ensemble approach.
- The study can be extended to estimate and prediction of hydrological, agricultural and socio-economic droughts in Sri Lanka, to develop a decision support system for drought forecasting.
- Further studies can be carried out to identify the other local factors affecting the drought vulnerability of the district in order to improve the accuracy of the model.

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