Predicting the Meteorological Drought based on the NDVI and Rainfall by using Long Short-Term Memory Algorithm

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***Abstract*—Myanmar is exposed to almost all types of natural hazards. Drought is a slow onset hazard type. The central dry zone in Myanmar is the most vulnerable area of the country from drought. The frequency and severity of drought are getting increased year after year because of global warming and climate change. This paper examines the relationship between rainfall and NDVI from 2015 to 2019 by using Google Earth Engine (GEE) to observe the meteorological drought in the past which is useful for identifying the drought response action plans and tries to predict the meteorological drought in the future by using long short-term memory algorithm.**

***Keywords*— drought, NDVI, GEE, GIS, disaster management, LSTM**

I. Introduction

In the last several decades, the global well-being has been threatening from the climate change. Drought is one of the most important weather-related natural disasters which are often intensified by human action, because it can affect very wide areas for an extended time from several months to years and thus leads to a serious impact on regional food production, life expectancy for entire populations and economic performance of large regions or several countries.

Drought can be both of slow on set character and long term character. In Myanmar, the drought event is mainly happened due to the synoptic weather patterns that favor to the weakening of monsoon wind, late monsoon onset and earlier monsoon withdrawal according to the report of the Department of Meteorology and Hydrology. It was observed that June and September were the highest frequency of drought events especially in the Upper region in Myanmar during 1951-1980 periods while September was the highest frequency of drought in the Lower part of the country. Due to the effect of global warming and impacts of Climate Change, Myanmar also exposed to an increase in the prevalence of drought events in varying rainfall patterns with increasing extreme high temperature. Water resources management for hydropower electrification, agriculture, livestock and environmental conservation sectors are being affected by the impacts of drought.

The changes in rainfall pattern and the longer period for the dryness seriously affected to the agricultural sector. Myanmar suffered from drought in the past and the recent drought was occurred in 2019. According to the statistic described in the State owned Newspaper issued on 20th, Nov; 2019, the drought affected more than 270,000 acres of groundnuts and over 1.3 million acres of sesame grown in the early monsoon season in Magway Region located in the dry zone of Myanmar.

Drought is a major challenge in agricultural sector affecting food production of the country, livelihoods of the rural communities and it costs the government billions of budgets in relief efforts. It highlighted that the impacts of drought has been already faced in the country and it is necessary to have the risk informed and evident-based decision making system for the concerned personnel from both sectors of agriculture and disaster management. In present days, there are many different ways for monitoring drought, and the common methods can be considered as site-based and remote sensing-based indices.

Drought and its impact can be monitored and assessed by using remote sensing and GIS [1]. The role of remote sensing and GIS for drought detection is crucial because the different range of spatial-temporal scales data can be done. There were many different approaches and models to perform the analysis on drought in different countries.

Several researches have been already applied the data by means of remote sensing or satellite-derived to monitor and detect drought, and meaningful results have been achieved. Setting up the ground observation stations for drought monitoring can be costly and sometime it is time-consuming while remote sensing techniques can offer an capable means for drought monitoring for the wide area like a country or regional scales with low cost in a timely manner [6].

The Normalized Differential Vegetation Index (NDVI) is widely applied to define the area of drought and desertification. Meteorological drought is primary drought type and it is directly related to the rainfall over an area. The use of satellite rainfall data is crucial to get the rainfall information where the conventional rain gauges are sparsely installed.

A web-based service called, Google Earth Engine (GEE) can store a petabyte archive of Earth observation and related data and provides efficient processing software, which enables users to develop complex geospatial analyses and visualizations utilizing high-performance computing resources like cloud computing technology [2]. The GEE platform is very valuable, especially for developing countries where are normally lack of historical data and high-performance data processing platforms for monitoring slow onset disaster like drought or forecasting the crop yield and its capabilities have been utilized for a range of applications, including soil mapping, malaria risk assessment, and automated cropland mapping.

The tool for Flood Risk Index Mapping has been achieved by using 30 years Landsat imagery in Google Earth Engine and cloud computing technologies [3]. The GEE platform is also very efficient for classifying multi-temporal satellite imagery with potential to apply the platform for a larger scale like country level and multiple sensors such as Landsat-8 and Sentinel-2. Because of these capabilities in

GEE, it can enable the users not only to acquire, process, analyze and visualize Earth observation data rapidly but also to monitor or assess any natural hazard situation like drought and flood in a specific location on the earth for any time interval such as historical or real-time.

Monitoring and assessing drought risk is more difficult comparing to the other types of natural hazard because of its slow onset behavior. Droughts can be lengthy for a long time (a year or more), or just can be lasted for a very short time (several weeks). In order to provide the early warning of meteorological drought, it is required to know which amount of rainfall and NDVI will lead to the drought situation. Time-series meteorological data like rainfall has irregularities and the meteorologists usually perform their forecast prediction results based on the models of numerical prediction (NWP) which is using the data from current weather conditions [4]. Long short term memory (LSTM) neural network is suitable for predicting the time-series data modeling like temperature because it is recurrent neural network (RNN) type [5]. LSTM is well appropriate to use the predicting time series data because LSTM has four gates and all of the four gates can carry the previous state as input to the current state [6].

Predicting the drought is critical not only for forecasting weather and climate but also for prevention of the harmful impacts to the living things. Therefore, this study tries to identify the drought hazard condition in the study area by means of derivation the correlation between Landsat 8 NDVI and CHIRPS rainfall data. After detecting the correlation between NDVI and rainfall for the study area, the predicting the drought by giving two inputs: NDVI and rainfall are being provided to the LSTM neutral network. The time-series data acquisition and analysis of Landsat 8 NDVI and CHIRPS rainfall data were processed by using GEE. The specific objective of this study is to have the automatic detection for drought hazard situation for the future. The remainder of the paper is organized as follows.

Materials and preliminaries for data processing for this research work will be explained in section 2. In section 3, the proposed methodology will be discussed. Section will explain about the Long Short Term Memory algorithm for predicting the upcoming drought. Experimental results will be described in section 4 followed by section 5 for conclusions for the research work.

II. MATERIALS AND PRELINIARIES FOR DATA PROCESSING

A. Study Area for Predicting the Meteorological Drought

The central dry zone in Myanmar has the area over 54,000 km and encompasses 54 townships in 13 districts spread across 3 Regions namely Sagaing (Lower), Mandalay and Magway as per the Dry zone Greening Department (Hazard Profile of Myanmar, 2009) by having approximately one-quarter of the nation’s population (Figure 1). The study area got limited amount of rainfall comparing to the other parts of the country because the Rakhine mountain ranges can happen the weakness in southwest monsoon onset and lessen the rainfall. The temperature is very high and it used to reach over 40 Degree Celsius especially in March, April and May. The changes in land use and land cover also leads to the dryness incorporating with insufficient amount of rainfall and high temperature and the communities in those area are a greater risk of drought which can threaten to the food security.

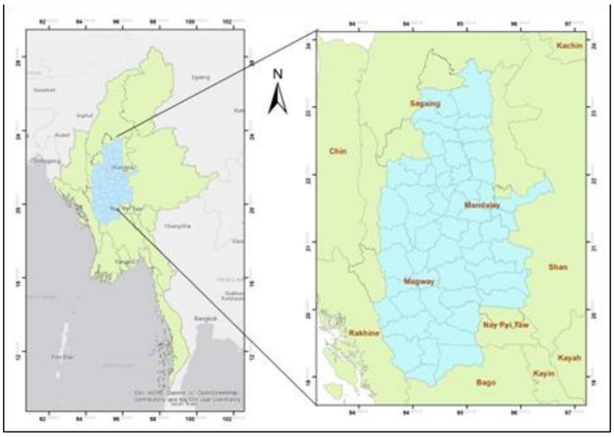


Fig. 1. Study Area

B. Data Used for Observing Historical Drought Events

In order to learn the behavior of meteorological drought in the past by detecting the correlations between Landsat 8 NDVI and precipitation for each township of the study area from 2015 to 2019, Landsat 8 8-Day NDVI Composite data and Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) data are used in this study as data preprocessing for training dataset for deep learning.

Landsat 8 8-Day NDVI Composite data were prepared from Level L1T orthorectified scenes by means of computed top-of-atmosphere (TOA) reflectance. These can be available for every 8-day period with total 46 satellite images for a year. The NDVI values of the intended period in the study area were extracted in the Google Earth Engine (GEE) platform.

Analyzing rainfall pattern and phenomenon is crucial for monitoring on meteorological drought and the rainfall data acquisition can be done by Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) by incorporating with 0.05° resolution satellite imagery with on-ground observation station data which has 30+ year quasi-global rainfall dataset.

C. Methdology of the Research Work

The drought is a cross-cutting issue in nature, and it is slow on-set type disaster having repeated or persistent condition. The policymakers and the media have less attention the severity of drought compared to the rapid-onset ones because of its slow on-set nature. Therefore, knowledge of what to do and how to react in drought situations is fundamental by knowing the actual existence of drought in the region for planning on preparedness and response measures.

In this study, in order to identify the meteorological drought hazard, the necessary data of the Landsat 8 NDVI and CHIRPS rainfall data for five consecutive years from 2015 to 2019 for the study area are extracted from Landsat 8 8-Day NDVI Composite data and CHIRPS by using the computing power of Google Earth Engine which is useful and helpful to access the time-series satellite images without high end desktop workstations. The correlation between NDVI and rainfall for each township in the study area has been derived to understand the nexus of NDVI and amount of rainfall in each township. Long short-term memory algorithm has been applied to forecast drought condition for

2020 after understanding the behavior of meteorological drought based on the NDVI and rainfall in the past.

For detecting the drought, the most, simplest, efficient and commonly used vegetation index is the Normalized Difference Vegetation Index (NDVI). The NDVI is usually applied for the identification of vegetation conditions by means of remotely sensed data traditionally which is calculated by dividing the difference between reflectance values in the visible red (VR) and near infrared (NIR) wavelengths by the overall reflectance in those wavelengths. The mathematical formula is as below:

$$NDVI = (NIR - VR) / (NIR + VR)$$

In this study, the monthly NDVI acquisition for each township of the study area of Dry Zone in Myanmar was done in Google Earth Engine Platform for the period of 2015-2019. The period of 2015-2016 was observed as the very strong El Nino year for the Southeast Asia.

The rainfall data from CHIRPS was also extracted by the Google Earth Engine by identifying the same period with Landsat 8 NDVI from 2015-2019 for the study area to learn what amount of less rainfall can happen the meteorological drought.

Long short-term algorithm (LSTM) which is a kind of recurrent neural network known to be suitable for time-series data modeling was proposed in this research work for predicting the meteorological drought in the coming days by using the past NDVI and rainfall for training dataset.

The forecasting system is applied the extracted NDVI values and the CHIRPS rainfall to detect relationship between NDVI and rainfall for drought. Then these two types of values were used to train for forecasting drought for the future. NDVI and rainfall data for five years from 2015-2019 were used as the trained data set and the data of year 2020 were applied as testing data.

The system flow diagram for the research work is shown as Figure 2.

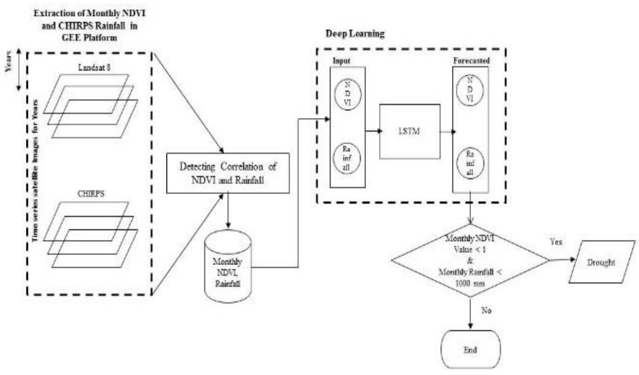
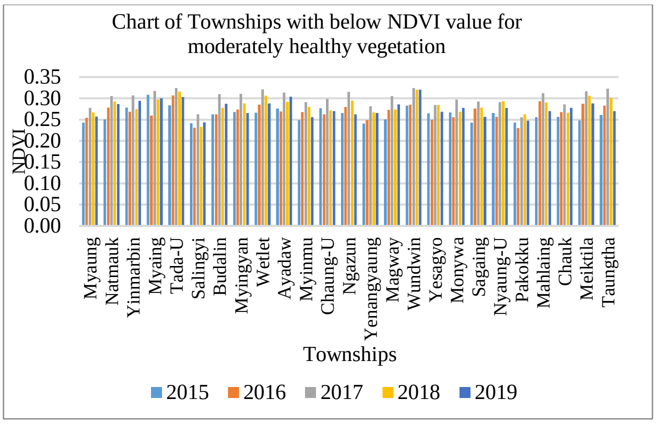


Fig. 2. Flow Chart

III. Algorithm For Forecasting NdviAND Rainfall To Detect Drought

After understanding the behavior of meteorological drought based on the correlation of NDVI and rainfall for the study area, the predicting the drought for a defined area can



be applied by using the Long Short Term Memory (LSTM) of Deep Learning which is suitable for forecasting the future in remembering information from time series data. LSTM has four elements, namely; input gate, forget gate, output gate and cell input. The function of each elements is as below: Input gate allows the flow of new values in the memory, Forget gate manage the extent the values remains in the memory, the output gate performs to control the extent to which the value in the cell is used to compute the output activation of the LSTM unit and cell input is for monitor the dependencies between the elements of the input sequence. Having a chain like structure in LSTM, it can carry the previous state as input along with the current input. LSTM can perform computing a mapping from an input sequence x to an output sequence y by calculating the network unit activations using the following equations iteratively from t = 1 to t = τ with initial values C0= 0 and h0 = 0 :

$$i = \sigma(Vixt + bi) \quad (1)$$

$$f[t] = \sigma(Vfxt+ Rfh[t-1] + bf) \quad (2)$$

$$g[t] = \tanh(Vgx\,[t] + Rgh[t-1] + bg) \quad (3)$$

$$o[t] = \sigma(Vox\,[t] + Roh[t-1] + bo) \quad (4)$$

$$c[t] = f[t]\,(\times)\,c[t-1] + i\,(\times)\,g[t] \quad (5)$$

$$h[t] = o[t]\,(\times)\,\tanh(c[t]); \quad (6)$$

where t is the time step ($1 \leqslant t \leqslant T$), the input gate, forget gate, and output gate are denoted i[t], f[t] and o[t] respectively, g[t] is the cell input, h[t − 1] is the recurrent input, c[t − 1] the cell state from the previous time step and V , R and b the trainable parameters like NDVI values and rainfall from the previous event in the network.

IV. Experiment Results

A. *Examining NDVI values*

The yearly NDVI values for each township in the study area were examined for 5 years and it was found that the vegetation in the study area was below the range of moderately healthy plant of 0.33 – 0.66. During the study period from 2015-2019, especially in 2015 which was resulted as El Nino year, unhealthy vegetation condition was found in 41 townships out of 54 township in the study area which was about 75 % of the study area. Among 41 townships, the NDVI condition in 25 townships was in unhealthy plant situation during the study period as show in the bar chart of figure 3.

Fig. 3. Chart of Townships with below NDVI value for moderately healthy vegetation

B. *Analyzing Rainfall Condition*

Although most area of Myanmar is rich in rain, the annual rainfall amount in the central dry zone is the lowest which got average annual rainfall about 600-1,000 mm. The rainfall amount of the study area during from 2015-2019 was examined by using the data acquired from CHIRPS and it was found that the annual rainfall amount in 16 out of 54 townships were less than 1000 mm in the study period. The maximum total rainfall amount was 2088.95 mm in 2016 in Ngape Township of Magway Region. The rainfall pattern for the study period has getting decreased in the following years and highlighted that the study area has been facing dry condition. The townships where receiving rainfall amount less than 1000 mm for five consecutive years are as shown in the graph below:

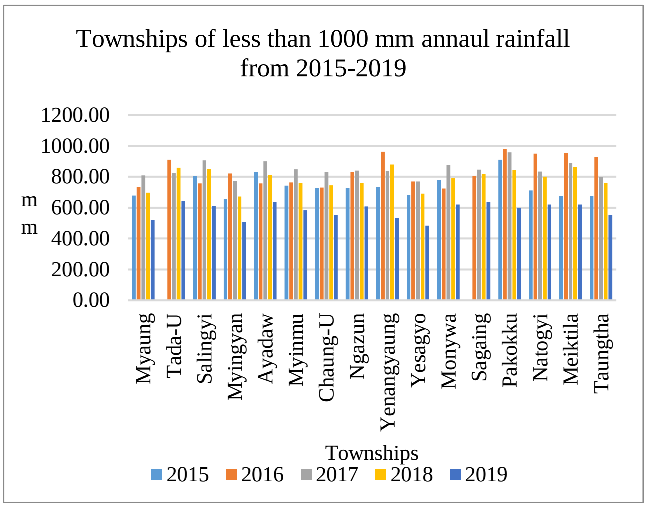


Fig. 4. Chart of Townships with less than 1000 mm annual rainfall from 2015-2019

C. *Detecting correlation between Normalized Differential Vegetation Index (NDVI) and Rainfall for meteorological drought*

In order to detect the linear relationship between NDVI and rainfall, linear regression was applied and it was observed that there was strong linear relationship with R2 value is 0.61. The result of linear regression is as shown in Figure 5. The NDVI got better when the rainfall amount was getting higher. It was exposed that NDVI was directly proportionated to the rainfall. When the total rainfall amount was less than 1500 mm, NDVI value was low and has become less than 0.30 and it often reached 0.23 in minimum. The higher NDVI value in the study area was observed in 2018 it was 0.48 with the total rainfall amount of 2088.95 mm in 2016.

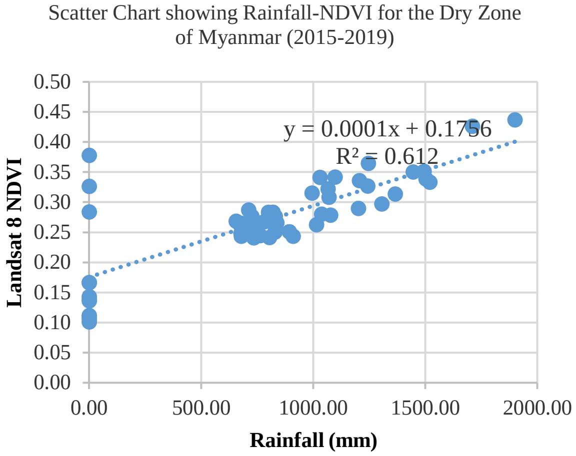


Fig. 5. Chart of Township of less than 1000 mm annual rainfall from 2015-2019

D. *Extracting Meteorological Drought based on NDVI*

According to the findings based on the NDVI values extracted from Landsat 8 in Google Earth Engine platform, there was meteorological drought in the study area during the study period. The lower NDVI values were mainly found in the central area of the study area while the NDVI values of the moderately healthy vegetation were found in the border area especially near the area of east highland in Shan State, and closed to the Naga Land and Chin Hill and Rakhine Mountain Ranges. The resulted NDVI based meteorological drought map from Google Earth Engine is as shown in Figure 6.

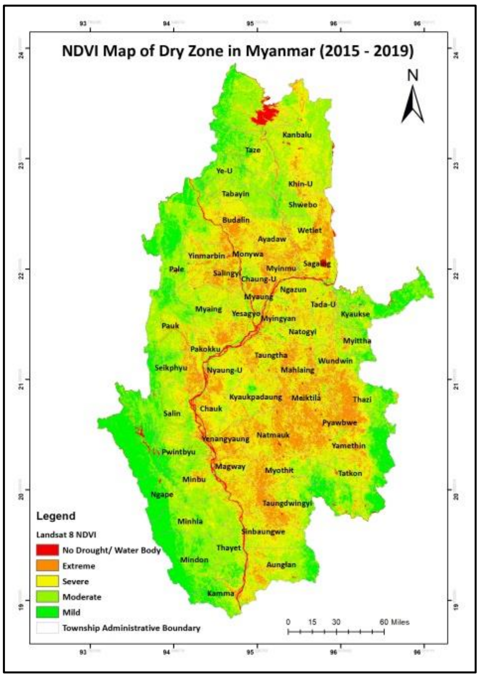


Fig. 6. Chart of Township of less than 1000 mm annual rainfall from 2015-2019

E. *Predicting the NDVI and Rainfall for forecasting drought*

The research work is intended to predict the NDVI and Rainfall for the coming months based on the past data acquired from the Landsat8 NDVI and CHIRPS rainfall for forecasting drought by using long short-term memory neural network which is able to learn longer period of data. This algorithm is necessary to get a huge amount of training data to have a better accuracy. The weather-related factors can be varied and dynamic in nature according to the land interaction and human behaviors. The predicted values for NDVI and rainfall from the LSTM are generally acceptable based on the seasonal behavioral of Myanmar. The algorithm predicted that significant monthly rainfall amount in July, August, September and October and these months are fallen in the monsoon period of Myanmar. Similarly, the forecasted NDVI values are also reasonable because the NDVI values in October, November and December are good and the condition for vegetation can be moderately healthy while the other months are in poor NDVI due to the effect of dry season. The forecasted NDVI and rainfall for 2020 are as shown in the table 1:

TABLE I. FORECASTED NDVI AND RAINFALL FOR 2020

Month	NDVI	Rainfall
Jan	0.3	2.049
Feb	0.3	3.796
Mar	0.3	1.244
Apr	0.2	29.224
May	0.2	83.756
Jun	0.3	109.565
Jul	0.3	145.193
Aug	0.3	238.567
Sep	0.3	126.536
Oct	0.4	180.055
Nov	0.5	33.688
Dec	0.5	6.355

V. CONCLUSIONS

The main purpose of the research work is to understand the meteorological drought and attempts to forecast drought for the future. The findings from this research work have shown that the central dry zone of Myanmar has been occurring meteorological drought during the study period. The annual rainfall amount can affect to the NDVI values. The data acquired from the satellite observations like Landsat 8 NDVI and CHIRPS rainfall are hugely provided for spatial and temporal coverage for detecting meteorological drought.

Moreover, the trend of meteorological drought for each township in this study can be explored which can subsidize for the preparedness and response of drought especially for agricultural sector to have the agricultural action plan for the food security by ensuring the drought resilient cropping pattern for each township in the dry zone.

Furthermore, the necessary data for detecting meteorological drought can be done in the GEE platform as the technological benefit which can reduce the time consumption for data acquisition, processing and analyzing of time-series satellite images by using the GEE Code Editor of an integrated development environment by applying the JavaScript (JS) API.

Due to the importance of forecasting drought for the agricultural country like Myanmar, long short-term memory (LSTM) algorithm is applicable for developing drought forecasting model. The trained dataset of NDVI and rainfall were derived only one time for the study period. The LSTM requires a huge amount of training dataset to get better accuracy results. The forecast model structure used LSTM allows for the other input features like vegetation indexes and land-use/ land-cover for better result on prediction. Predicting the meteorological data has many irregularities because land interaction factor like changes in land use, reforestation and human behavior can also make effect to the meteorological data.

Through this research work, drought can be forecasted for the coming month when rainfall amount in previous month was less than 1000 mm and NDVI value of previous month was below 0.33 (condition for unhealthy plant) based on the detected patterns of rainfall and NDVI for the studied area. The better accuracy for the predicting model can be achieved after examining the outputs from the model with the station observation and this research work can be applicable for forecasting other weather factors like temperature or relative humidity or wind speed in the future.

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