Correlation of Drought Index Effected by El Nino Phenomenon Using Remote Sensing

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ABSTRACT

This study aims to analyze the correlation of the drought index in two periods: November - December 2015 and January - April 2016, where extremely severe El Nino occurred, and November - December 2017 and January - April 2018 and where it was at the normal condition. The results showed that in March 2016 and November 2017 there was a very severe drought level from VHI assessments of 9.574 and 7.625. The drought assessment from NDWI found that the level was at more or less risk of drought. There are no areas where there was no risk of drought. The highest value for the assessment of NDWI was 0.392. In December 2017, the drought level is at a slight drought risk. The lowest value in February 2018 was -0.680. The analysis of the correlation between VHI and NDWI was statistically significant in a positive same direction between two variables at a confidence level is was 95 percent. The correlation coefficient values which were influenced by the El Nino phenomenon in November - December 2015 and January - April 2016 were 0.8668, 0.7842, 0.8107, 0.8108, 0.8407, and 0.8528 respectively. The correlation coefficients values which normal El Nino phenomenon in November – December were 0.6917, 0.8692, 0.7345, 0.7278, 0.6638, and 0.7200 respectively.

1. INTRODUCTION

El Nino phenomenon has the greatest impact on the global temperature rising than normal. The seasonal rain causing severe drought in many areas that are affecting the global environment and fertility of forests. Forest ecosystems changing may cause by drought. A very severe El Nino which in 2015-2016 cause rising to higher level drought in Thailand.

Nowadays, Remote Sensing Technology has an important role in various situations analysis that occurring in the world. According to the information services are accessible and comprehensive in various fields such as agriculture, environmental, and disasters, etc. Utilizing satellite images analysis can describe incidents that occurred in the study area in the past and can analyze the potential trend in the future. Remote Sensing Technology can be calculated the drought index for measuring the level of drought. It can be also applied for the correlations analysis between Vegetation Health Index (VHI) and Normalized Difference Water Index (NDWI) to explain the occurrence of droughts in El Nino Phenomena as information for monitoring droughts that may occur in the future.

2. MATERIALS AND METHODS

2.1 Study Area

The Nan River Basin is located in the northern of Thailand with a total area of 34,682.04 sq. km., covers 11 provinces. The position is along the North-South direction. The Nan River flows through the valley into the Sirikit Dam, both sides of the lower area are plain which is considered the most important large plain in Thailand. The Nan River flows along the Yom River until it joins at Chum Saeng District in Nakhonsawan province. Then flow through Bueng

Boraphet on the left before the confluence with the Ping River at Muang District, Nakhonsawan Province. When the Nan River joins together with the Ping River it becomes the Chao Phraya River.

2.2 Data Collection

This research used Landsat-8 OLI image, which covering Nan River basin area. The period was from November-December 2015 to January-April 2016 which extreme El Nino occurred, and November - December 2017 to January - April 2018 which normal event.

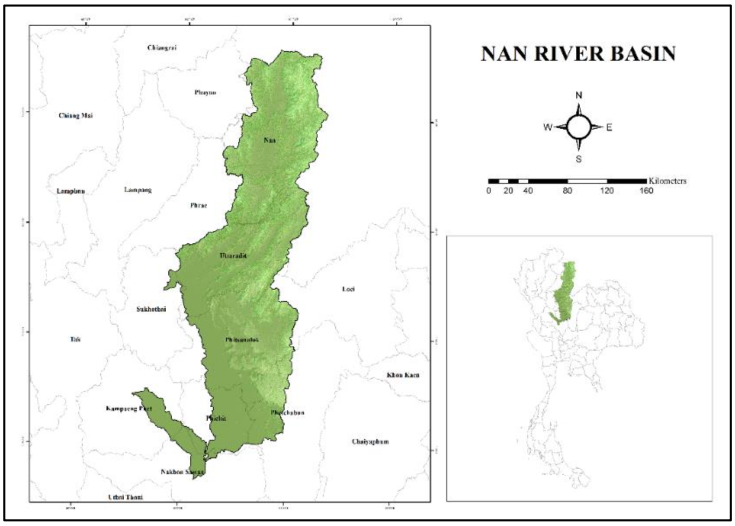

Figure 1. Nan River Basin

2.3 Data Analysis

2.3.1 Vegetation Health Index Analysis

VHI is an index developed to correct errors in the interpretation of drought conditions. It is a combination of the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI). VHI index is the representatives used to characterize the fertility of plants, by evaluating the mutual value between the humidity conditions and the thermal conditions of the area as shown in equation (1)

$$VHI = (0.7 \ x \ VCI) + (0.3 \ x \ TCI) \quad (1)$$

Where: VCI = Vegetation Condition Index
TCI = Temperature Condition Index

VCI is a drought matrix calculated based on the Vegetation Index-Based Drought Metric which developed to monitor the Global Drought-Watch System. Vegetation Condition Index derived from NDVI data.It can be calculated from equation (2).

$$VCI = 100 \ x \ \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (2)$$

Where: NDVI = Normalized Difference Vegetation Index in the study period
$NDVI_{max}$ = The maximum value of Normalized Difference Vegetation Index in the study period
$NDVI_{min}$ = The minimum value of Normalized Difference Vegetation Index in the study period

TCI is an index calculated from satellite data recorded in the Thermal Band of the Landsat-8 TIRS can capably detect surface thermal temperatures. TCI values can be useful for tracking drought conditions better than NDVI and VCI values, especially in the case of excessive soil moisture due to heavy rain or cloudy for a long time .It can be calculated from equation (3).

$$TCI = 100 \; x \; \frac{T_{Max} - T_c}{T_{Max} - T_{Min}} \tag{3}$$

Where: Tc = Surface temperature of the study period (degree Celsius)
T_{Max} = The maximum Surface temperature of the study period (degree Celsius)
T_{Min} = The minimum Surface temperature of the study period (degree Celsius)

The land surface temperature from Landsat-8 TIRS, in the band 10 which is thermal infrared band which can be calculate as follows.

Step 1: Calculating the Top of Atmosphere (TOA) (Conversion to TOA Radiance) is a radiation correction by converting the reflectance value into light energy TOA which be calculated from the absorption data for each wavelength as shown in equation (4).

$$L_\lambda = M_L Q_{cal} + A_L \tag{4}$$

Where: L_λ = Reflected Value (Watts/(m^2 * srad * µm))
M_L = Transformation of specific wavelengths
A_L = Transformation of specific wavelengths
Qcal = Light intensity (Digital Number)

Step 2: Conversion of radiance to brightness temperature as shown in equation (5).

$$Tb = \frac{K_2}{ln(\frac{K_1}{L_\lambda} + 1)} \tag{5}$$

Where: Tb = Brightness Temperature of satellite value (Degrees Kelvin)
L_λ = Reflected Value (Watts/(m2*srad*µm))
K_1 = The conversion constant value of the thermal infrared wavelength.
K_2 = The conversion constant value of the thermal infrared wavelength.

The conversion of temperature units from degrees Kelvin to degrees Celsius can be calculated from equation (6) as follows:

$$Tc = Tb - 273 \tag{6}$$

Where: Tc = The brightness temperature of the satellite Value (degrees Celsius)
Tb = The brightness temperature of the satellite Value (degrees Kelvin)

2.3.2 Analysis of the differential Normalized Difference Water Index

Normalized Difference Water Index (NDWI) is used for drought, soil and vegetation monitoring based on the amount of solar radiation reflected in the Near-infrared spectroscopy (NIR) and Shortwave Infrared (SWIR). NDWI index value ranges from -1 to 1 (with positive values representing water areas, negative values representing non-water features such as vegetation and open spaces) as shown in equation (7).

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \tag{7}$$

Where: NIR = Near-infrared band
SWIR = Shortwave Infrared band

2.3.2 Correlation Analysis

Data from Landsat-8 OLI with spatial resolution of 30 meters was randomly using stratified random sampling techniques and was classified into land use type categories using survey data based on binomial probability theory as follows:

$$N = \frac{Z^2 (p)(q)}{E^2} \tag{8}$$

Where: N = Populations
p = Percentage of expected accuracy
q = Percentage of acceptable Error (1-p)
Z = The area value from the standard normal curve table here defines the confidence level at 95 percent. (Confidence level at 95 percent is equal to1.96)
E = Percentage of acceptable survey errors

In this study, percentage of expected accuracy was set at 80%, and the error resulting from the survey points was allowed to be not more than 10%. These are 62 survey points classified by land use, including Forest land, Urban and built-up land, Agricultural land, Water body and Miscellaneous land. The drought index was calculated from Landsat-8 OLI which were VHI and NDWI to determine the correlation between the two indices during the dry season in the study area.

3. RESULTS

3.1 VHI value from Landsat-8 OLI

Based on the calculation of VHI from Landsat-8 OLI, the highest drought level was 9.57 in March 2016 and the non-drought level was 95.55 in December 2015 of the year influenced by the severe El Nino. The highest drought level was 7.62 in November 2017, and the non-drought level was 85.58, which was in November in a normal event (Figure 2).

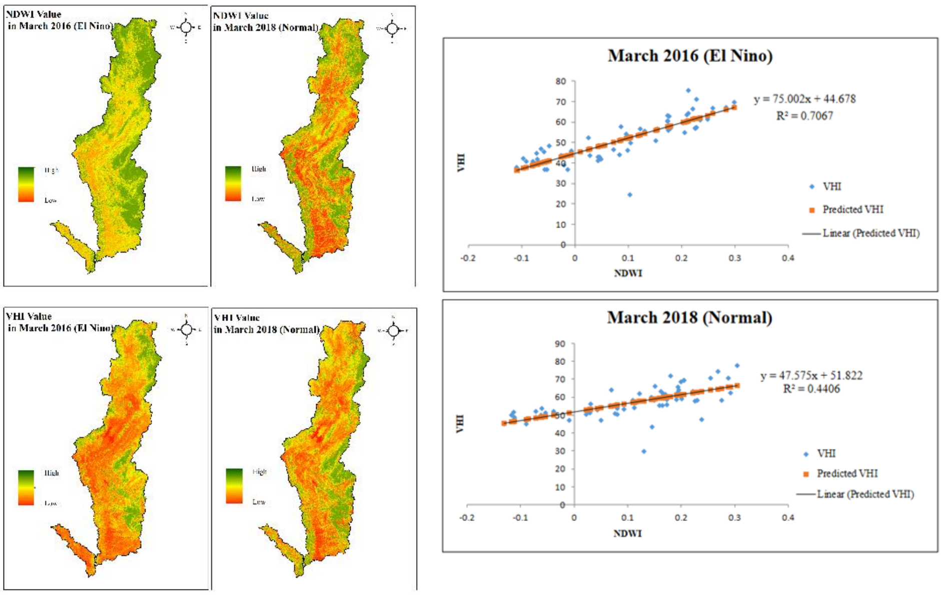

Figure 2. The correlation between VHI value and NDWI value

3.2 NDWI Value from Landsat-8 OLI

NDWI was calculated from Landsat-8 OLI had a drought risk value was -0.653 in February 2016, and a no-risk value of 0.37885 in January 2016 of the year influenced by the severe El Nino. The drought risk value was -0.6795 in February 2018 and the drought no-risk value was 0.39218 in December 2017 of the normal event.

3.3 The correlation between VHI value and NDWI value

The correlation between the VHI value and the NDWI value was found that the VHI value and the NDWI value were statistically significant in a positive direction. The correlation was same direction for both variables, which was 95 percentage of confidence level. The correlation coefficient values which were influenced by the El Nino phenomenon were 0.8668, 0.7842, 0.8107, 0.8108, 0.8407 and 0.8528, respectively. The normal event values were 0.6917, 0.8692, 0.7345, 0.7278, 0.6638 and 0.7200, respectively.

Table 7. The correlation between VHI value and NDWI value.

Month	R	R Square	Month	R	R Square
November 2015	0.8668	0.7513	November 2017	0.6917	0.4784
December 2015	0.7842	0.6150	December 2017	0.8692	0.7556
January 2016	0.8107	0.6572	January 2018	0.7345	0.5394
February 2016	0.8108	0.6574	February 2018	0.7278	0.5296
March 2016	0.8407	0.7067	March 2018	0.6638	0.4406
April 2016	0.8528	0.7272	April 2018	0.7200	0.5184

4. CONCLUSION AND DISCUSSION

This research found out a correlation between the VHI and NDWI that analyzed drought levels from the Landsat-8 OLI. The drought levels from both indices were ranged from very severe drought to no drought occurrence in the whole of the study area. The results were consistent with the drought criteria derived from this study. In March 2016 and November 2017, there were severe drought levels with VHI value 9.574 and 7.625, respectively. In the NDWI drought assessment, the drought levels were slightly drought risk to highest drought risk level. There was no area that was not risk to drought. The highest value from the NDWI was 0.392 in December 2017, with a slightly drought risk level. The lowest value in February 2018 was -0.680.

The correlation between VHI and NDWI was positive or in the same direction. In other words, if the VHI value was higher, the NDWI value would also be higher. In this research discovered that the correlation coefficients had a positive value close to 1. The correlation coefficients in November-December 2015 and January-April 2016 during El Nino period were 0.8668, 0.7842, 0.8107, 0.8108, 0.8407 and 0.8528, respectively. In November-December 2017 and January – April 2018, the correlation coefficient in normal years were 0.6917, 0.8692, 0.7345, 0.7278, 0.6638 and 0.7200, respectively.

5. ACKNOWLEDGEMENTS

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