FLOOD EXTENT DETECTION WITH DIFFERENCING WATER INDICES USING LANDSAT 8 DATA

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ABSTRACT

In the past, flood occurred in Thailand caused damage to people's lives and properties, environment and the ecosystem of a certain area. Flood occurs in Lainan sub-district, Wiang Sa district, Nan province every year. Major factors are from heavy rain influenced by monsoon wind and reinforcing factor like physical characteristics of the geography such as slope, stream density, land use including roads, etc. From the problem, the researcher focused on using data from Landsat 8 for conducting an analysis to detect flood affected areas in conjunction with 2 physical models; 1) Normalized Difference Water Index (NDWI) and 2) Modified Normalized Difference Water Index (MNDWI). The findings from the study showed that the water index from both methods; NDWI and MNDWI, could significantly detect flood affected areas. The NDWI method produced overall classification accuracy of 90.00% and Kappa statistics of 0.93 while the MNDWI produced overall classification accuracy of 95.00% and Kappa statistics of 0.95. In this regard, MNDWI was the method producing the most overall classification accuracy.

1. INTRODUCTION

Natural disasters or natural hazards have an impact on humans, making humans unable to live a normal life, causing huge damage to lives and properties and deteriorating societies (Blanc et al., 2012; Rotjanakusol et al., 2019). One of the most frequently occurring natural disasters is flood, accounted for 41.4%, followed by earthquakes and storms. Asia continental has the most impact (Milly et al., 2002). As for Thailand, it is found that damage from floods increased from 6,000 million baht in 1990 to 40,000 million bath in 2000 and 1.44 trillion baht in 2011 (Asian Disaster Reduction Center, 2012). The 2011 flood in Thailand was ranked as the world's fourth costliest disaster after the 2011 earthquake and tsunami in Japan, the 1995 earthquake in Japan and the 2005 Hurricane Katrina in the United States of America, respectively (Department of Disaster Prevention and Mitigation, 2013). Thailand occupies a total area of 513,115 km^2. It is a country at the center of Indochinese peninsula in Southeast Asia. In the past, Thailand experienced floods every year in every region of the country due to geographical factors. Thailand is located in a tropical climate zone, influenced by southwest monsoon and northeast monsoon as well as storms that pass throughout the year (Kim, 2014). An urgent necessity that cannot be missed for assessing levels of damage and severity of floods is information or maps showing areas affected by disasters (Rotjanakusol & Laosuwan, 2018). Conventional methods used in the past; for example, a flood map using ground surveying method, required a high cost and was time consuming. Furthermore, some areas are large and difficult to be accessible. In this regard, the application of remote sensing technology using data from a satellite that collects phenomena on the earth by means of the reflection of electromagnetic waves to sensors on the satellite (Uttaruk & Laosuwan, 2016; Laosuwan & Uttaruk, 2016; Uttaruk & Laosuwan, 2018) in conjunction with a physical model has been carried out as a tool to assess the potential damage of a flood event. Satellite data can cover large areas or areas with difficult access with less costs compared to the ground surveying method (Singh & Singh, 2017; Rotjanakusol & Laosuwan, 2020).

Lainan sub-district, Wiang Sa district, Nan province is influenced by southwest monsoon that sweeps humidity to cover the whole region, brining heavy rain during the rainy season from May to September. Consequently, Nan province is an area being at risk for flooding since it has a lot of mountains that lead to rapid flash flood, giving a direct effect on floods in lowlands. A study on areas of Nan province in 2016-2020 found that floods occur every year in lowlands, causing damage to properties, houses, agricultural areas including natural resources. As a consequence, this study focused on presenting a method to detect flood affected areas using Landsat 8 satellite data in conjunction with 2 physical models; 1) NDWI and 2) MNDWI in the area of Lainan sub-district, Wiang Sa district, Nan province in the years 2020.

2. AREA OF THE STUDY AND DATA

2.1 Area of the study

Lainan sub-district – is a sub-district in Wiang Sa district, Nan province (Figure.1). It is located in the east of the district on the left bank of Nan River. It occupies an area of 125.01 km^2.

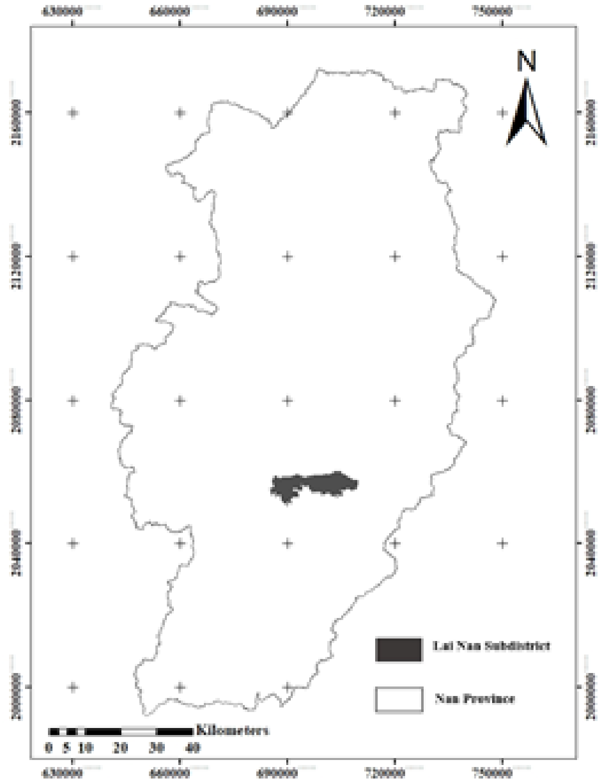

Figure 1. Lainan sub-district, Wiang Sa district, Nan province.

2.2 Satellite data

Landsat 8 is a satellite for surveying natural resources of United States of America. It was developed from the collaboration between NASA and USGS. On 11 February, 2013, it was launched into Earth orbit. It can collect repeated data of the same location every 16 days.

It has two main sensors; OIL and TIRS, with 11 wavelength ranges. For this study, Landsat 8 satellite data covering Lainan sub-district – is a sub-district in Wiang Sa district, Nan province in the years 2020 were employed.

3. METHODOLOGY

The details of the study can be described as follow:

1) NDWI analysis was proposed by McFeeters (1996), NDWI is calculated from the ratio between reflectance difference and sum of green band and NIR band of objects on the earth for separating Earth's water bodies. NDWI values range from -1 to +1 which help analyze and separate water bodies easier. NDWI ranging -1 to 0 represents vegetation fraction cover and NDWI close to +1 represents water bodies. NDWI calculation is shown in equation 1.

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \tag{1}$$

Where;
GREEN = Green wavelength (Band 3)
NIR = Near Infrared wavelength (Band 5)

2) MNDWI was proposed by Xu (2006), MNDWI was developed to separate land areas and water areas with more precision. Emphasis is placed on spectral data of land cover being water on the surface of the earth and the reduction of wave disturbance from construction, vegetation and soil. MNDWI is calculated from the ratio between reflectance difference and sum of green band and MIR band. MNDWI values range from -1 to +1. Water has greater positive value than in NDWI as it absorbs more in MIR than in NIR and vegetation reflects more in MIR band than in green band. The calculation of MNDWI is shown in equation 2.

$$MNDWI = \frac{GREEN - MIR}{GREEN + MIR} \tag{2}$$

Where;
GREEN = Green wavelength (Band 3)
MIR = Middle Infrared wavelength or SWIR1 wavelength (Band 6)

The analysis results from both 2 models were used for field data survey. There were 30 surveying points around the area of the study. Kappa statistic was used to measure accuracy. Kappa statistic over 80% shows the data analysis result was high accurate, Kappa statistic ranging from 40-80% means the data analysis result is moderately accurate. Kappa statistic lower than 40% means the data analysis result is poorly accurate.

4. RESULT

4.1 Satellite data analysis result

Landsat 8 satellite data analysis results in conjunction with the 2 physical models: 1) NDWI and 2) MNDWI are shown below:

4.1.1 NDWI analysis result

NDWI is calculated from the ratio between reflectance difference and sum of green band and NIR band of objects on the earth for dividing Earth's water bodies. NDWI values range from -1 to +1 which help analyze and divide water bodies easier. NDWI ranging -1 to 0 represents vegetation fraction cover and NDWI close to +1 represents water bodies. In this study, the lowest value of NDWI was -0.549948, the highest value was 0.636856, the mean was -0.167055 and SD was 0.192698. As for spatial analysis, this study divided NDWI analysis result into 5 ranges (see in Figure 2), namely, the values of data range 1 were 1.000- to -0.700, representing high vegetation cover, the values of data range 2 were 0.700-to0.400- , representing moderate vegetation cover, the values of data range 3 were 0.400 -to 0.100-, representing low vegetation cover, the values of data range 4 were 0.100 -to 0.200, representing areas with low to moderate water, and the values of data range 5 were 0.200 to 0.500, representing areas with a lot of water. According to NDWI spatial analysis, it was found that during flood occurrence, the data range 1 occupied the area of 0 km^2, the data range 2 occupied the area of 44.93 km^2, the data range 3 occupied the area of 66.94 km^2 , the data range 4 occupied the area of 7.73 km^2 and the data range 5 occupied the area of 0.47 km^2 .

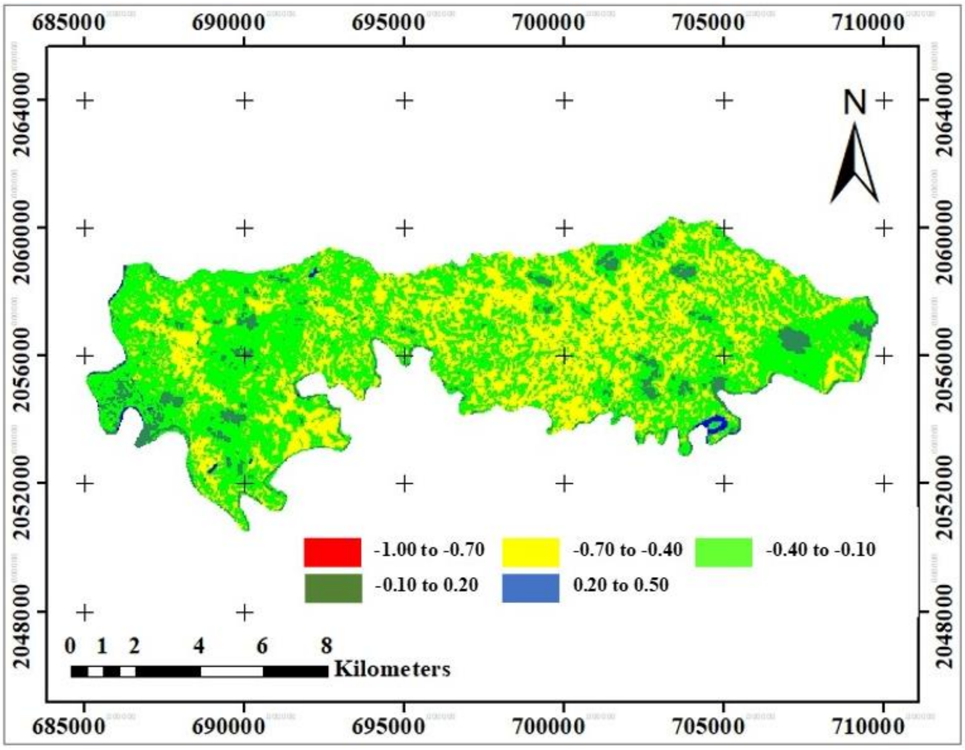

Figure 2. NDWI analysis result.

4.1.2 MNDWI analysis result

As mentioned above, MNDWI is a method used to separate water in soil or vegetation from the amount of solar radiation reflecting from soil or vegetation in green band and in MIR. The calculation of MNDWI produces 3 results: (1) water has greater positive value than in NDWI as it absorbs more in MIR than NIR and vegetation reflects more in MIR than green band. The values of MNDWI range from -1 to +1 similar to those of NDWI. According to the data analysis result in this study, the lowest MNDWI value was 0.405830, the highest value was0.857356 , the mean was 0.582446 and SD was 0.040856. As for spatial analysis, this study divided MNDWI analysis result into 5 ranges (Figure 3), namely, the values of data range

1 were -1.000 to -0.600, representing high vegetation cover, the values of data range 2 were -0.600 to -0.200, representing moderate vegetation cover, the values of data range 3 were -0.200 to 0.200, representing low vegetation cover, the values of data range 4 were 0.200 to 0.600, representing areas with low to moderate water, and the values of data range 5 were 0.600 to 1.000, representing areas with a lot of water. According to MNDWI spatial analysis, it was found that during flood occurrence, the data range 1 occupied the area of 0 km^2, the data range 2 occupied the area of 0 km^2, the data range 3 occupied the area of 0 km^2, the data range 4 occupied the area of 67.11 km^2 and the data range 5 occupied the area of 52.96 km^2.

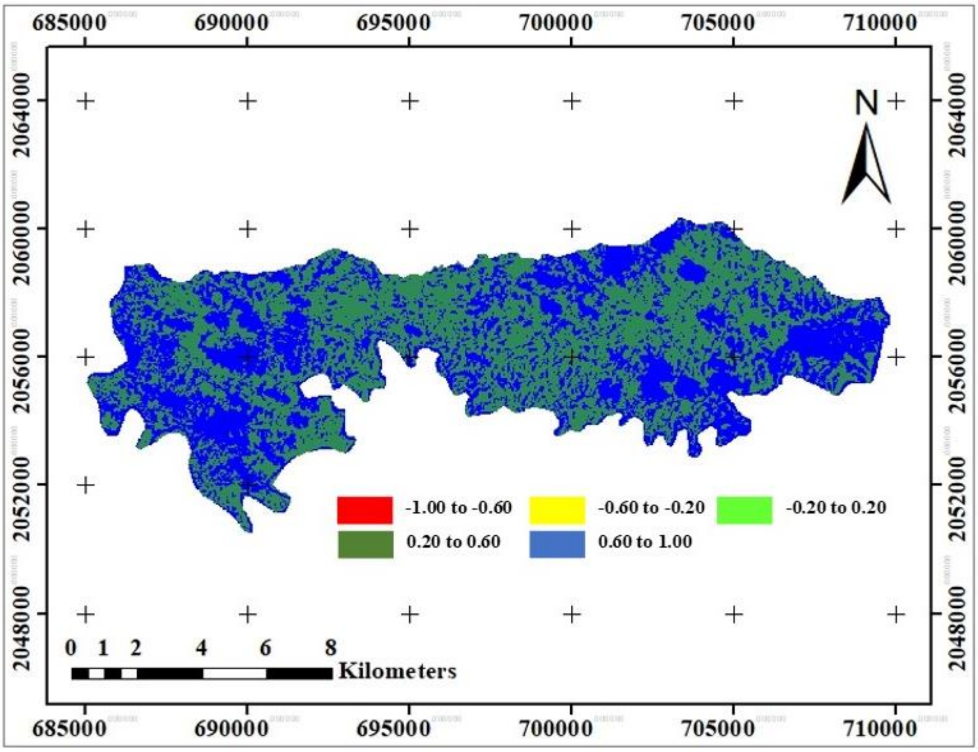

Figure 3. MNDWI analysis result.

4.2 Results from the field survey and accuracy assessment

In this study, accuracy assessment results from the separation of water bodies from lands were considered: 1) According to the NDWI model, overall classification accuracy was 90.00% and Kappa Statistics was 0.93 and 2) according to the MNDWI model, overall classification accuracy was 95.00% and Kappa Statistics was 0.95. The consideration of Overall Accuracy and Kappa Statistics of both physical models found the MNDWI model had the highest percentage of accuracy, based on the analysis.

5. CONCLUSION

Thailand is under the influence of 2 monsoons, namely southwest monsoon and northeast monsoon, making Thailand have 2 outstanding seasons, wet and dry seasons, alternately. As for drought season, consideration in detail stage finds it can be separated into 2 seasons as summer and winter. Therefore, there are 3 seasons in Thailand, namely, summer, rainy season, and winter. In this study, emphasis was placed on methods to detect flood affected areas using index by employing Landsat 8 satellite data in conjunction with the 2 physical models, NDWI and MNDWI, in Lainan sub-district, Wiang Sa district, Nan province in the years 2020. The study result found the MNDWI model had the highest percentage of accuracy according to the analysis. This study result should be used as decision criteria for areas affected by flood rationally. It can be used to examine and warn areas that can be rapidly flooded. Relevant agencies can be used this method to analyze flood affected areas and prepare plans for flood prevention and mitigation in a sustainable manner.

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