A Comparative Study of Vegetation Indices to Analyze Land Use Patterns and Relationship between Vegetation Indices and Land Surface Temperature in San Kamphaeng District, Chiang Mai Province

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Abstract

The objectives of this study including 1) to do a comparative study of vegetation indices to analyze land use patterns 2) to analyze relationship between vegetation indices and land surface temperature (LST). There were 5 different types of vegetation indices in the analysis including Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Building Index (NDBI), Soil Adjustment Vegetation Index (SAVI), and Transform Vegetation Index (TVI) from Landsat 8 OLI. The classification method used maximum likelihood classifier and the accuracy assessment was done by the confusion matrix. Split - window technique was used to analyze LST from Landsat 8 TIRS. Finally, Pearson product moment correlation coefficient and linear regression were used. The results found that NDVI provided the highest overall accuracy and kappa statistic followed by TVI, NDBI, RVI and SAVI, respectively. Analysis of LST presented urban and built-up areas had the highest LST. The relationship analysis between the LST and the vegetation indices found that LST and NDBI had positive correlation. However, LST and RVI, NDVI, SAVI and TVI had negative correlation, respectively. From the result, high accuracy of vegetation indices could be applied to image classification. The analysis of LST, which was received from each of land use, would be useful for urban planning.

Keywords: Vegetation indices, Land surface temperature, Split - window technique, Land use classification, Spectral index

Introduction

Currently, Thailand is developing rapidly from various factors, including an population increasing, economic expansion, tourism, industry, and agriculture. These factors led to physical, economic, and social changes over the past period, and impacted human lives in multiple ways such as changing habitation, increasing or decreasing of land, changing forest area, and urban expansion. Consequently, the environment, land uses, and livelihood have been affected as well.

Chiang Mai is the second-largest province after Nakhonratchasima province. The urban areas of Chiang Mai and its surrounding areas has changed significantly from the past. Pattanasak (2018) studied the change of land use and land cover from satellite image classification. The study found that most of areas in Chiang Mai city had changed to the urban and built-up areas. At the same time, another study showed that urbanization was caused by the increasing population and intensive economic growth (Sangawongse, 2009). San Kamphaeng district, Chiang Mai province was picked for study area. This area was considered as one of Chiang Mai's metropolitan areas. The city had grown rapidly both for its economy and transportation, including the increase in attractions.

Thongtip (2014) studied the vegetation indices, which efficiently identified vegetation and land use. Vegetation indices are used to identify vegetation or non- vegetation land cover and monitor the increase or decrease of vegetation in the study area. Moreover, they are used to study the growth, fertility, canopy, density of land cover, crop yield prediction, and land use classification with high accuracy.

In the study of land use, analysis of land surface temperature (LST) and vegetation indices were the important part to predict the LST from public activities so that the proper planning of land use for the future can be done. LST was the study of earth surface heat, which could be detected with the satellite that could measure the temperature of the earth through layers of atmospheres. Mostly, the study of LST is used to study the earth's changing climate as the heat has been on the rise (Dechapongthana, Karnchanasutham, Nualchawee & Intarawichian, 2017). While, Srivanit and Hokao (2012) used Landsat ETM+ images from 2000 and 2006 to utilize the surface urban heat island (SUHI). This would be analyzed by investigating the relationships with several urban environment and development indices. Thus, this research used LANDSAT 8 OLI/ TIRS satellite images in 2018. They chose the vegetation indices with the highest accuracy to analyze the land use patterns and study LST from land uses by combining the numbers from both band 10 and band 11 to calculate LST.

This study is useful with remote sensing techniques and land use classification. High accuracy of vegetation indices could be applied to image classification. The analysis of LST, which was from each of land use, would be useful for planning of the use of communities' land. Apart from this, the proper vegetation indices could be generalized for further land uses. Therefore, the research objectives are described as follows: 1) to do a comparative study of vegetation indices to analyze land use patterns 2) to analyze the relationship between vegetation indices and LST.

Methods and Materials

Study area

The study area is San Kamphaeng district, Chiang Mai province, Thailand (Latitude 18°39'01" N to 18°48'36" N, Longitude 99°02'31" N to 99°16'12" E). San Kamphaeng district is the surrounding area of Chiang Mai city. This district covers an area of 244 sq.km. with the total population 88,216 people.

San Kamphaeng is locate in the center of Chiang Mai city. It had 10 of sub - district and it on the low land which is on the altitude of 200 - 770 MSL. The study area cover many of land cover which are agriculture land, urban and built - up area, forest land, water body and miscellaneous. The high of mountain area on the east are covered by forest. The boundary of study area is shown in figure 1.

Methods

There are 3 steps of procedures. Firstly, it was the analysis of 5 vegetation indices including Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Building Index (NDBI), Soil Adjustment Vegetation Index (SAVI) and Soil Adjustment Vegetation Index (SAVI) from Landsat 8 OLI to classify the use of each vegetation indices and assess the accuracy of classification of all 5 vegetation indices. Second, it was referred to the analysis of LST from Landsat 8 TIRS and LST in each of land use in the study area. For the last step, the analysis of relation between 5 vegetation indices and LST were conducted by the explanation of correlation and linear regression for prediction of LST in the future. Figure 2 has indicated framework of the analysis of vegetation indices. This is for classifying land use and analyzing LST from each of vegetation indices.

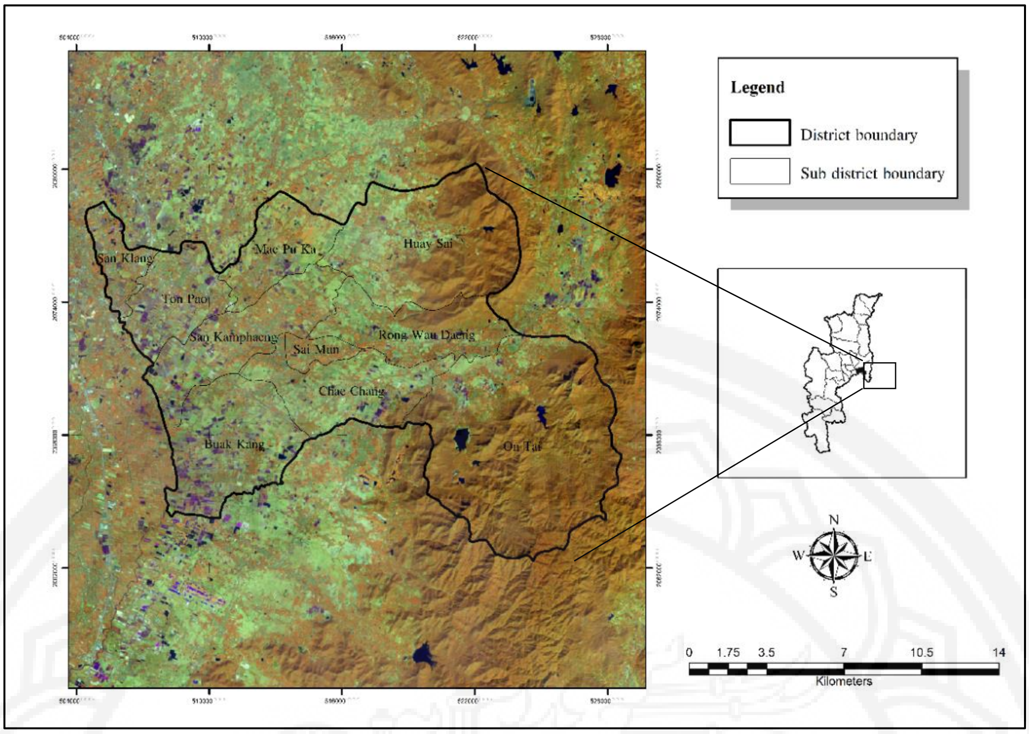

Figure1 Study area

The Landsat 8 OLI/TIRS Satellite images (captured in December 28, 2018) was selected due to cloud which less than 10% of the sky thus, the training areas were obviously selected. Moreover, Landsat 8 satellite image had various bands. Additionally, it presented various thermal infrared bands and it could be analyzed that there are many of vegetation indices and LST. The image modified by geometric correction and atmospheric correction (DN to reflectance) (Kiyoshi, 2005) after that vegetation indices, land surface temperature, correlation and linear regression between LST and vegetation indices were applied respectively.

Geometric correction

This study applied images to map correction (Gao, 2009) by using the topographic map L7018 as the reference. The geometric equation is used with the second polynomial. The error was less than 1 pixel. The brightness calculation was done by the nearest neighbour interpolation method.

Atmospheric correction

Calculating the reflectance value from satellite data using the following equation

$$P\lambda' = M\ pQ\ cal + A\ p \qquad (1)$$

which

$P\lambda'$ = TOA (Top of Atmosphere) planetary reflectance, without correction for solar angle.

M p = Band − specific multiplicative rescaling factor from the metadata

A p = Band − specific additive rescaling factor from the metadata

Q cal = Quantized and calibrated standard product pixel value (DN)

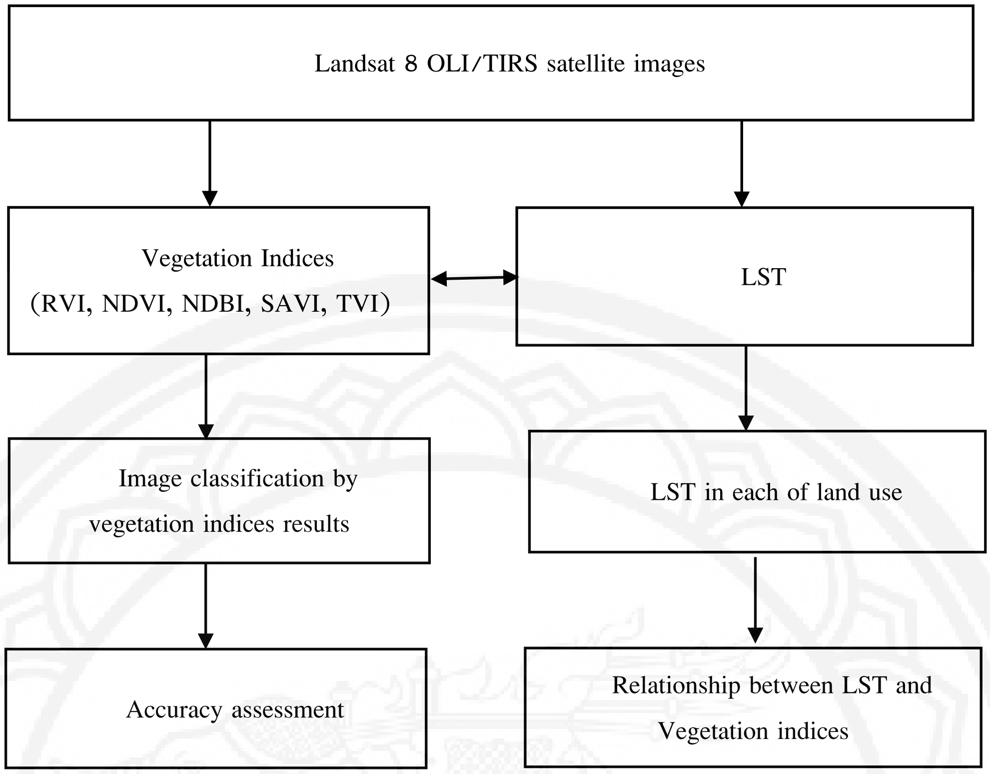

Figure 2 Research framework

Then correct the reflectance value with the sun angle using the following equation

$$P\lambda = P\lambda' \,/\, \cos\theta SZ \qquad (2)$$
$$= P\lambda' \,/\, \sin\theta SE$$

which

$P\lambda$ = TOA (Top of atmosphere) planetary reflectance

$P\lambda'$ = TOA (Top of atmosphere) planetary reflectance without correction for solar angle.

θSZ = Local solar zenith angle; $\theta SZ = 90° - \theta SE$

θSE = Local sun elevation angle.

(U.S. Geological Survey, 2017)

The analysis of vegetation indices

Vegetation indices were used to extract the information for a quantitative amount of vegetation, or greenness in each pixel of the image data. Vegetation indices involved two or more wavelengths. The study used the vegetation indices in various forms including

$$RVI = \frac{NIR}{Red} \qquad (3)$$

$$NDVI = \frac{NIR-Red}{NIR+Red} \qquad (4)$$

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{5}$$

$$SAVI = \frac{NIR - Red}{NIR + Red + L}(1+L) \tag{6}$$

L = The canopy background adjustment. For L = 0.5

$$TVI = \sqrt{NIR - Red / (NIR + Red + L) + 0.5} \tag{7}$$

L = The canopy background adjustment. For L = 0.5

From equation

NIR means near infrared band.

RED means red band in visible ray.

SWIR means short wave infrared band.

Analysis of the patterns of land use and land cover was done by a supervised classification method with maximum likelihood classifier from vegetation indices in each equation (Thongtip, 2014). The land use mapping was done in December 2018. The accuracy assessment was done through the confusion matrix comparing the classification data with the reference map (land use map done by the land development department in 2015). The calculations included the total accuracy, user accuracy, producer accuracy, and kappa statistics. Finally, a field survey in the study area was done for the verification of image classification.

The analysis of LST

LST calculation of each type of land use was done by Split window technique. This technique provided more accuracy than single channel for estimated LST (Juan et al., 2014 cited in Pengpit, Karnchanasutham, Nualchawee & Soytong, 2017). LST could be analyzed by following methods.

1. The analysis of brightness temperature was done by this equation;

$$T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \tag{8}$$

where

T = Brightness temperature (Kelvin)

K_1 = Calibration constant (Band 10 = 774.89, Band 11 = 480.89)

K_2 = Calibration constant (Band 10 = 1321.08, Band 11 = 1201.14)

$L\chi$ = Spectral radiance

2. Land surface emissivity analysis was done by estimating the proportion data of vegetation that covered the land using the fractional vegetation cover, which is shown in this equation.

$$LSE = €_s (1 - FVC) + €_V * FVC \tag{9}$$

where

LSE = Land surface emissivity

ϵ_s = Constant of LANDSAT8 (Band 10 = 0.971, Band 11 = 0.977)

ϵ_V = Constant of LANDSAT8 (Band 10 = 0.987, Band 11 = 0.989)

Fractional vegetation cover (FVC) was the proportion of vegetation covering the land, which is shown in this equation.

$$FVC = \frac{NDVI - NDVI\ (Soil)}{NDVI\ (Vegetation) - NDVI\ (Soil)} \quad (10)$$

where

NDVI (soil) = The lowest value of NDVI

NDVI (Vegetation) = The highest value of NDVI

3. The study on atmospheric water vapor from its ability to transmit through atmosphere layers in TIRS bands was done using the brightness temperature of band 10 and band 11 with a linear regression equation, which is shown in this equation.

$$MV = a + b * T_j / T_i \quad (11)$$

$$\frac{\tau_j}{\tau_i} \approx R_{ji} = \sum_{k=1}^{N}(T_{i,k} - \bar{T}_i)(T_{j,k} - \bar{T}_j) / \sum_{k=1}^{N}(T_{i,k} - \bar{T}_i)^2$$

where

a and b = The coefficients obtained from simulation data

T = The band effective atmospheric transmittance

i and j = Band 10 and band 11 of TIRS instruments

$T_{i,k}$ and $T_{j,k}$ = Brightness temperature of band 10 and band 11

(Ren et al., 2015)

4. The analysis of LSE included the brightness temperature, the land surface emissivity, and the atmospheric water vapor as shown in this equation.

$$LST = TB_{10} + C_1(TB_{10} - TB_{11}) + C_2(TB_{10} - TB_{11})^2 + C_0 + (C_3 + C_4W)(1 - m) + (C_5 + C_6W)\Delta m \quad (12)$$

where

TB_{10} TB_{11} = Brightness temperature of TIRS band 10 and band 11

$C_0 - C_6$ = Constant value of Spilt − window method

W = Constant value of atmospheric water vapor

m = Mean of LSE

Δm = Difference of LSE

LSE = Land surface emissivity

5. The measurement of land surface temperature was done by setting 25 points for each land use type. The sampling of a total of 100 points was selected. The point selection could reduce redundancy in each or land use. Finally, the analysis of the correlation between vegetation indices and LST using the Pearson product-moment correlation coefficient. The linear regression equation is shown in each relation.

Results

The analysis of vegetation indices from Landsat 8 OLI

To do a comparative study of vegetation indices to analyze land use patterns in San Kamphaeng District, Chiang Mai Province. Land use patterns could be categorized into 5 types which were forest areas, horticulture areas, paddy fields, urban and built up areas and Miscellaneous. The selection of land use patterns uses from criteria of Land development department. The analysis of RVI, NDVI, NDBI, SAVI, TVI with image classification using the supervised classification with maximum likelihood classifier, the result of land use is as shown in table 1 and figure 3.

Table 1 Classification of land use patterns by vegetation indices (unit: square kilometers)

Land use \ Vegetation indices	RVI	NDVI	NDBI	SAVI	TVI
Forest areas	76.10	29.47	85.14	79.10	76.89
Horticulture areas	53.84	63.56	56.65	56.28	59.32
Paddy fields	85.24	76.71	92.35	86.68	81.40
Urban and built-up areas	28.82	29.47	11.86	21.95	26.39
Miscellaneous	0.005	0.0018	0.007	0.005	0.04
Total (area)	244	244	244	244	244

The accuracy assessment was done by a confusion matrix. Samples were randomly selected to compare the accuracy between the land use map by the land development department in 2015 and the one from the field survey. Since the study area was small, this study used purposive random sampling by using 25 points for each land use type, counting for a total of 100 points. The analysis of overall accuracy and kappa statistics is shown in table 2.

Table 2 Overall accuracy and kappa statistics

Vegetation indices	Overall accuracy (Percentage)	Kappa statistics
RVI	55	0.40
NDVI	61	0.48
NDBI	57	0.43
SAVI	54	0.39
TVI	59	0.45

The result from table 2 found that NDVI had the highest overall accuracy and kappa statistics when classified by maximum likelihood classifier (61 %, 0.48) followed by TVI, NDBI, RVI, and SAVI, respectively.

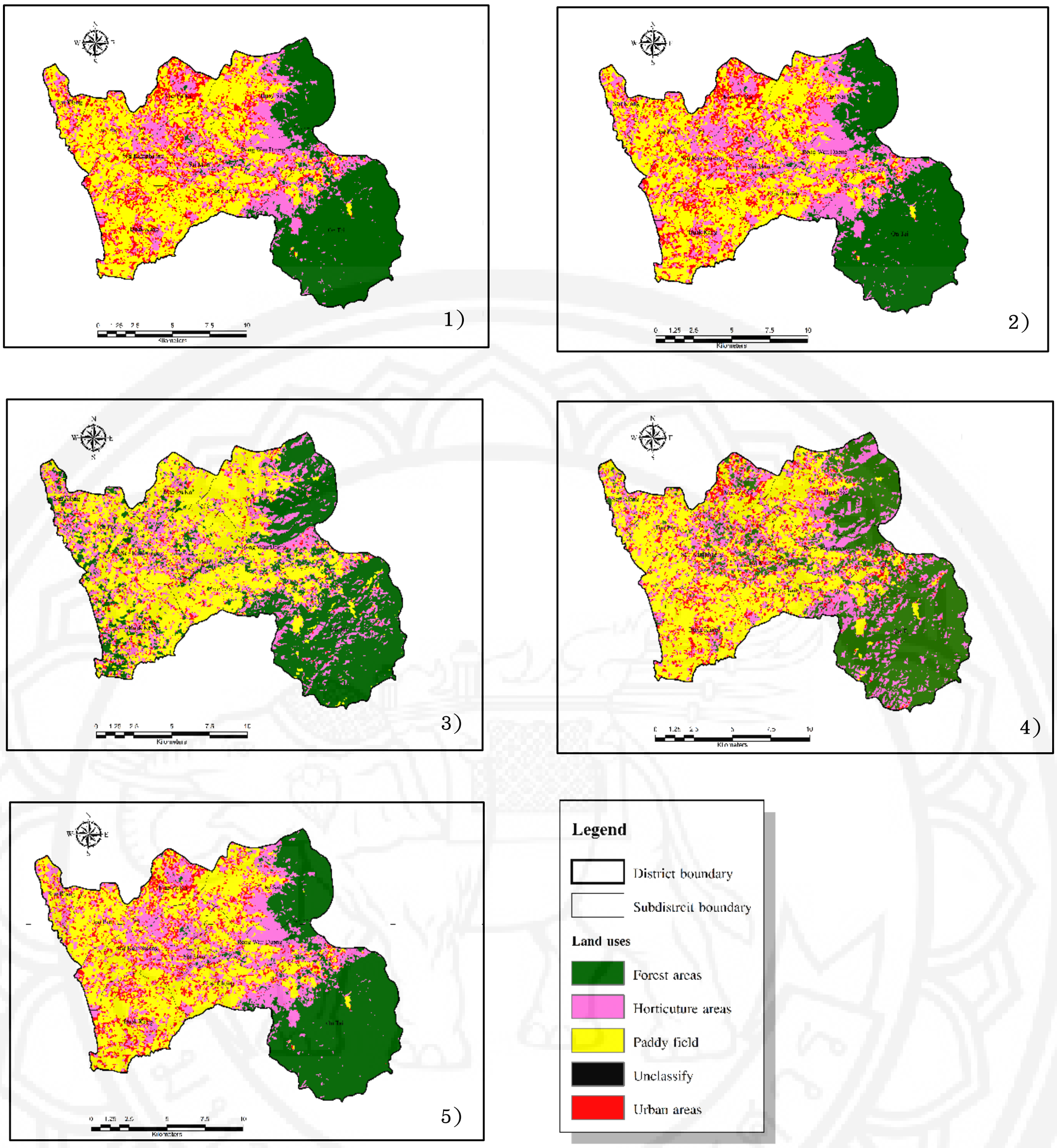

Figure 3 Image classification results from vegetation indices 1) RVI 2) NDVI 3) NDBI 4) SAVI 5) TVI

The analysis of LST

The analysis of LST for each land use type in the study area is done by using the Landsat 8 TIRS (Band 10, 11) images with the split-window technique follow the analysis of LST procedures and follow equation 8 -12.

The study found that the LST of San Kamphaeng district, Chiang Mai Province was between 14.10 - 35.68 degrees Celsius with an average temperature of 23.29 degree Celsius. The LST of the urban and built-up areas is the highest one at 26.40 degree Celsius followed by the paddy field, the horticulture areas, and the forest areas at 26.20, 22.09, and 21.48 degree Celsius respectively as shown in figure 4.

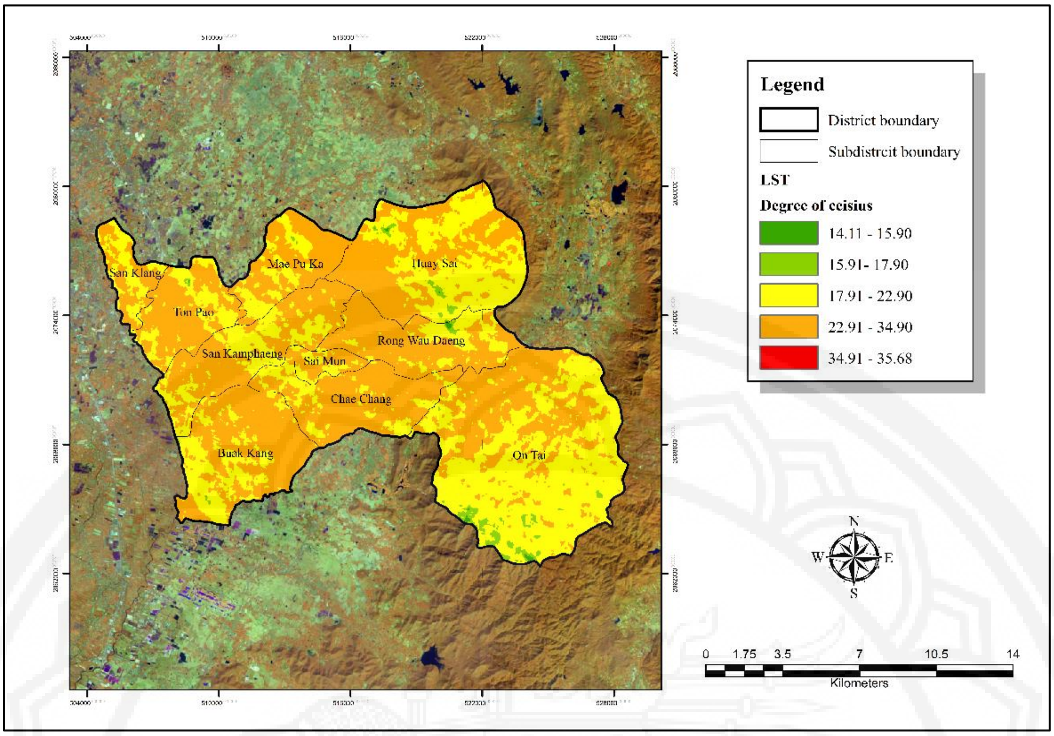

Figure 4 LST of San Kamphaeng district, Chiang Mai province

The study of correlation between LST and vegetation indices

The study of correlation between LST and vegetation indices in San Kamphaeng district, Chiang Mai Province found that LST had the positive correlation with NDBI ($r = 0.649$, $p \leq .01$). Meanwhile the LST had negative correlation with RVI ($r = -0.60$, $p \leq .01$), NDVI ($r = -0.59$, $p \leq .01$), SAVI ($r = -0.47$, $p \leq .01$) and TVI ($r = -0.59$, $p \leq .01$) respectively.

The analysis of the relationship between LST and vegetation indices was done by taking the data from Landsat 8 OLI satellite images of the study area in December 2018 (with mean temperature equals 23.29 degree Celsius), that classified the sample points by its land use. Each land use type had 25 sample points counting for a total of 100 points, and the LST was recorded to analyze the relationship between LST and each type of vegetation indices using the simple linear regression equation and coefficient of determination (R^2) in table 3 and show the relations in figure 5.

Table 3 The equations and coefficient of determination between LST with vegetation indices

LST with vegetation indices	Equations	Coefficient of determination
LST with RVI	$y = -0.7401x + 28.228$	$R^2 = 0.3605$
LST with NDVI	$y = -20.048x + 37.684$	$R^2 = 0.3522$
LST with NDBI	$y = 14.61x + 30.754$	$R^2 = 0.4216$
LST with SAVI	$y = -22.813x + 36.886$	$R^2 = 0.2275$
LST with TVI	$y = -42.946x + 36.886$	$R^2 = 0.3512$

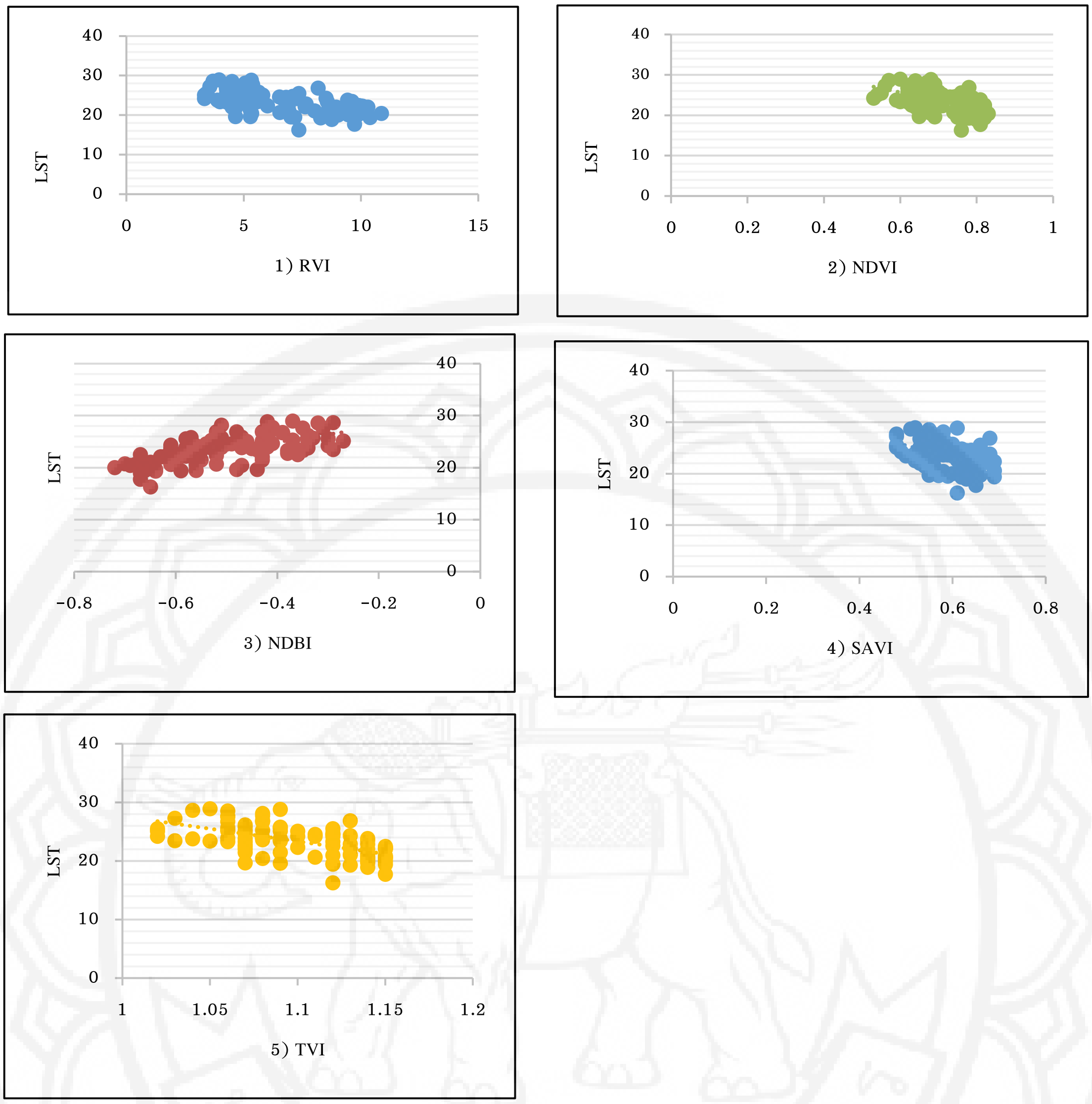

Figure 5 Relation between LST with vegetation indices 1) RVI 2) NDVI 3) NDBI 4) SAVI 5) TVI

The result showed the relation between LST and each vegetation index. From table 3 and figure 5, LST had the highest coefficient of determination with NDBI (R^2 = 0.4216), which means that NDBI can predict the LST with 42.16% accuracy, the rest would depend on other factors. Moreover, the coefficients of determination from the linear equation of RVI, NDVI, TVI, and SAVI were 36.05%, 35.22%, 35.12%, and 22.75% respectively.

Discussion and Conclusion

NDVI had the highest overall accuracy and Kappa statistics for land use classification from Landsat 8 OLI satellite images in San Kamphaeng District, Chiang Mai province (61%, 0.40). This method and result correlate with Thongtip (2014) study, in which NDVI also had the highest accuracy from minimum distance to means for land use classification in Khuan Sai village, Lam Thap subdistrict, Lam Thap district, Krabi province.

The analysis of LST by a split-window method using Landsat 8 TIRS (band 10 and band 11) images and its LST showed that the urban and built-up areas had the highest LST in San Kamphaeng District, Chiang Mai Province (26.40 degree Celsius) followed by the paddy fields (26.20 degree Celsius). The study agrees with Dachapongthana et al. (2017) study, which found that the average temperature in the urban area was 35.55 degree Celsius, followed by the area with perennial plants, the water source area, and the paddy fields with an average LST of 32.65, 32.46 and 32.01 degree Celsius respectively. Moreover, this finding also goes in the same direction as Pengpit et al. (2017) whose study found that LST had a relationship with an urban and built-up area with the correlation coefficient of 0.96.

The result of the relationship study between LST and vegetation indices showed that LST had a positive correlation with NDBI ($p \leq .01$, $r = 0.649$). However, LST had negative correlation with RVI ($p \leq .01$, $r = -0.60$), NDVI ($p \leq .01$, $r = -0.593$), SAVI ($p \leq .01$, $r = -0.474$) and TVI ($p \leq .01$, $r = -0.593$). This result agreed with Sopa and Chayakul (2019), who studied the relationship between LST and vegetation indices in Chonburi province and found that LST had the highest positive correlation with NDBI, EVI and LST provided negative correlation with NDVI. Furthermore, it also corresponds with Pratiwi (2016), who found that LST had a positive correlation with NDBI and NDWI, but a negative correlation with NDVI.

Additionally, the study by Guha, Govil, Dey, & Gill (2018) showed that LST provided a high positive correlation with NDBI and a negative correlation with NDVI including Srivanit and Hokao (2012), showed that mean LST had a positive relation with FAR (Floor area ratio), Density of building (DenBldg) and Building coverage ratio (BCR). While, mean LST had a negative relation with mean NDVI and mean NDWI in Chiang Mai Metripolitan area (CMMA). This is because the surface temperature had a high reflectivity from the uncovered surface area. Therefore, the community areas and buildings which were mostly concrete roads or houses with little heat retention could reflect a lot of heat. That was the reason why LST had a positive correlation with NDBI. On the other hand, other forms of land use such as forest areas, an agricultural area, paddy fields, and water source area had lower heat reflection, so the LST was low. The land use patterns and LST patterns in San Kamphaeng district were interrelated. The urbanized and built-up areas would have higher surface temperatures than the area with vegetation, soil, and water bodies. While, Srivanit and Iamtrakul (2019) who offer urban greenspaces which can effectively mitigate the urban heat island in CMMA by urban greenspaces management and urban landscape planning. In the future, from this study will use NDBI with efficiency of linear equation for analyze LST in San Kamphaeng district, Chiang Mai province. The future studies, from the author's suggestion, should consider object-based image analysis from high of resolution satellite images with land use classification or change detection. Moreover, the selection of sample points could be used with binomial distribution in large area.

Acknowledgments

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