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Evaluate of THEOS Pan-sharpened Images using the Vegetation Indices for Orchard Classification

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Abstract — ***THEOS pan-sharpened image is the high-resolution image. Nevertheless, the problem with the THEOS pan-sharpened image is the issue of the agriculture classification. The objective of this research are to the evaluate of THEOS pan-sharpened image using vegetation indices and the classification of orchard or perennial tree using fuzzy k-mean. The NDVI and RVI used for evaluating the pan-sharpened image by used the OIF value to indicate the optimum of four bands to classified land use using the fuzzy k-mean. The results of the combination of band NDVI and RVI show the OIF value and the accuracy assessment of land use classification was higher than the original image.***

Keywords: ***Optimum Index Factor, Fuzzy K-mean, Vegetation Indices, Unsupervised Classification, Remote Sensing***

I. INTRODUCTION

The process of land cover classification for satellite imagery is to be extracted and interpretation of information from the images. As knows, there are two main the classification methods can be divided into supervised classification and unsupervised classification methods. Supervised classification used the training data set to determines each class for classified using the various methods such as maximum likelihood, minimum-distance classification and mahalanobis distance. Unsupervised classification is the methods to identify the number of classes by users and generated of classes using the cluster techniques. It's a fast and effective to run for automatics classified images. ISODATA and K-mean techniques are the classics of unsupervised classification have most used in classified of land cover with multi spectral characteristics of remote sensing data [1-3]. Both technique process on numerical operations to performed that search the distance of spectral properties of pixels to determine the information each class.

The techniques for unsupervised classification in pan-sharpened images is a challenging problem solving for the research in the land cover classify [4-6]. However, the problem of both the spatial and spectral resolution of an images are very important in order to be able to correctly classify the pixels. The effects of pan-sharpening on vegetation indices showed the results of NDVI and simple ratio (SR) some loss of spatial enhancement on the pan-sharpened images [7]. The problem of THEOS pan-sharpened images using IHS fusion methods was showed too much blue color in vegetation area [8]. Also, the problem of THEOS pan-sharpened image from the IHS fusion method is the distortion of spectral characteristics of multispectral images of the variation on hue before and after the fusion process has appeared [9].

According, vegetation indices are one of the most widely used for land use and land cover classification of the remotely sensed data. Vegetation indices have been developed that implement various band combinations of different remote sensing data. This study has proposed the technique for classifying of an orchard or perennial tree from the THEOS pan-sharpened images based on vegetation indices and fuzzy k-mean clustering.

II. Materials and Methods

2.1. Data collection and study area

This study used the data from THEOS pan-sharpened images in Path 127 Row 49, the characteristics of THEOS imagery show in table 1. For an area of the orchards belonging to eleven farmers at Sang Kho sub district, Phu Phan district, Sakon Nakhon province in northeast Thailand lies between 16.54º to 16.58º N Latitude and 103.54º to 103.56º E Longitude. These areas were a pilot area of carbon credit project through the agricultural sector for carbon sequestration assessment of the orchards or perennial tree. The study area was variety type of land cover; it is difficult to classify the land cover shown in Figure 1.

Table 1. The Characteristics of THEOS [8].

	PAN	MS
Resolution	2 m	15 m
Imaging swath	22 km	90 km
Spectral ranges (μm)	0.45 – 0.90 mm	B1 : 0.45 -0.52 mm B2: 0.53 – 0.60 mm B3: 0.62 – 0.69 mm B4: 0.77 – 0.90 mm

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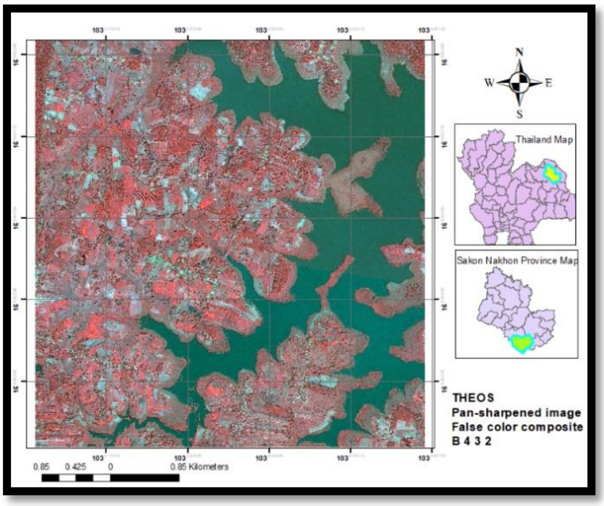

Figure 1. The location of the study area

2.2. Vegetation indices

The normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) was used to improve the ability to separate healthy vegetation from other land cover types. In their original equations, they provide normalized values in the interval from −1 to 1. These vegetation indices have the advantage of being less dependent on illumination and having a good discrimination between different land cover types. They show higher values for vegetation, positive low values for water and bare soils and negative index values for clouds. The NDVI is a normalized ratio of NIR (near infrared) and Red (red band) defined as [10]:

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad (1)$$

The ratio vegetation index (RVI) is calculated by simply dividing the reflectance values of the near infrared band by those of the red band defined as [11]:

$$RVI = \frac{NIR}{Red} \qquad (2)$$

The result clearly captures the contrast between the red and infrared bands for vegetated pixels, with high index values being produced by combinations of low red (because of absorption by chlorophyll) and high infrared (as a result of leaf structure) reflectance [12].

2.3. The evaluation of bands selection using optimum index factor (OIF)

The evaluated of this proposed the vegetation indices with THEOS pan-sharpened image for orchard classification using the optimum index factor (OIF). The OIF was used to evaluate the statistics value the band combination of four bands in a satellite image which the optimum combination for image classification. The OIF was developed by Chavez et.al (1984) [13] to determine the optimal band combination is the large standard deviation between bands and the small the correlation coefficient between the bands. The OIF determine by the following formula:

$$OIF = \frac{\sum_{k=1}^{n} s_k}{\sum_{j=1}^{n} Abs(r_j)} \qquad (3)$$

Where s_k is the standard deviation for band *k*, and r_j is the absolute value of the correlation coefficient between any two of the *n* bands being evaluated. The highest of OIF value is the possibility of the *n* band combination for classifying of land use/land cover from the satellite imagery.

2.4.Unsupervised classification using fuzzy k-mean clustering

Fuzzy k-mean clustering is an unsupervised clustering algorithm, which also known as soft clustering for divide the partition of data into k cluster. Fuzzy k-means is a generalization of k-means algorithm based on the scope of fuzzy logic [14]. The algorithm takes into account that in some cases an element (pixel) may belong to different groups, although with different possibility degrees. The process of fuzzy k-mean clustering to find out the degree of membership in each cluster. The algorithm is performed with an iterative optimization of minimizing a fuzzy objective function [15].

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$$J = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^{m}, d_{ij} \quad (4)$$

Where J = minimized the objective function,

c = number of clusters,

n = total number of pixels,

u_{ij} = degree of membership of pixel x_j in the cluster i,

d_{ij} = the Euclidean distance between pixel x_j and cluster center v_i.

m = an exponential weight (or fuzziness) for each fuzzy membership, degree of fuzziness of each cluster increases along with the m.

The matrix of u_{ij} to transition from "hard" to "fuzzy" clustering should satisfy the following constraint:

$\sum_{j=1}^{n} u_{ij} = 1$, for $i=1$ to c

$\sum_{i=1}^{c} u_{ij} > 0$, for $j=1$ to n (5)

The process of image clustering is performed using fuzzy k-means is now presented as follows.

1) Initial number of clusters c and randomly to select cluster center.
2) Calculate the membership u_{ij} using the following equation:

$$u_{ij} = \left(\left(d_{ij}\right)^{1/m-1} \sum_{j=1}^{n} \left(\frac{1}{d_{ij}}\right)^{1/m-1} \right)^{-1} \quad (6)$$

3) Calculate the cluster center v_i as following equation:

$$v_i = \frac{\sum_{j=1}^{n} \left(u_{ij}\right)^{m} x_j}{\sum_{j=1}^{n} \left(u_{ij}\right)^{m}} \quad (7)$$

4) Compare the minimum the objective function of J value.
5) Repeat step 2) and 3) until the minimum J value is achieved.

2.5. Accuracy Assessment of land cover classification.

The accuracy assessment of this paper to a comparison of the proposed method with fuzzy k-mean clustering by using confusion matrices. According to base on binomial probability theory with the desired level of confidence 85 percent. The matrixes were performed on 526 samples of the reference points to evaluate the classification procedure. The overall accuracy [16,17] and the kappa coefficient [16,17] were used to evaluate classified.

2.6. Proposed methods

This study was proposed methods base on vegetation indices and clustering methods to classify the orchard or perennial tree from the pan-sharpened image of THEOS satellite. Furthermore, the assessment of carbon sequestration using spatial analysis base on the statistical regression model. The first step calculating vegetation indices of NDVI and RVI from pan-sharpened image. The second step combination of NDVI and RVI with band 3 and 4 of pan-sharpened image. The OIF values were used to evaluate band combination. The third step classifies land use using the k-mean and fuzzy k-mean methods. The accuracy assessment using the kappa coefficient and overall accuracy to compare the results of fuzzy k-mean methods.

III. RESULTS

3.1. 3.1The evaluation of bands selection using optimum index factor (OIF)

The optimal band combination and OIF value of the experiment data were applied to the original pan-sharpened image and the vegetation indices. According to performed the proposed method of the combination of vegetation indices into the pan-sharpened image can be show the correlation coefficients values are listed in Table 2. The OIF of four band combination show the sixth of high value are listed in Table 3.

Table 2. Correlation between original bands with NDVI and RVI.

	Band 1	Band 2	Band 3	Band 4	NDVI	RVI
Band 1	1	0.98	0.96	0.52	0.29	0.28
Band 2	0.98	1	0.97	0.54	0.3	0.3
Band 3	0.96	0.97	1	0.43	0.17	0.17
Band 4	0.52	0.54	0.43	1	0.95	0.96
NDVI	0.29	0.3	0.17	0.95	1	0.99

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RVI	0.28	0.3	0.17	0.96	0.99	1

Table 3. **OIF values and rank of possible four band combination between original bands with NDVI and RVI.**

Rank	**OIF Band combination**				**OIF value**
1	Band 1	Band 3	Band 4	NDVI	19.09
2	Band 1	Band 3	Band 4	RVI	19.08
3	Band 1	Band 2	Band 3	Band 4	17.75
4	Band 2	Band 3	Band 4	NDVI	15.85
5	Band 2	Band 3	Band 4	RVI	15.8
6	Band 1	Band 2	Band 3	RVI	13.68

The summarize of Table 3 show that the combination of band 1, 3, 4, and NDVI provide the highest OIF value with the value of 19.09 and the first rank. The second rank is band 1, 3, 4, and RVI with a value of 19.08 the value less than the first rank was 0.01. The combination of the original band provides the OIF value with the value of 17.75.

3.2. Land use classification using fuzzy k-mean and accuracy assessment.

The results of land use classified of the original pan-sharpened image and the vegetation indices using fuzzy k-mean have been applied with the first five rank of the OIF values. Confusion matrices were used compared to the accuracy assessment of land use classified. The land use was classified into 7 classes are the forest (F), water bodies (W), paddy field (PF), field crop (FC), bare land (BL), orchard or perennial (OP), and miscellaneous (M) the results following:

The results comparison of the land use classifications using the fuzzy k-mean technique shown the percentage values of an area shown in Table 4. As Table 4 shows that the percentage of an orchard or perennial tree from combinations of bands 1, 3, 4, and RVI with 23.82 %. Secondly, the combination of bands 1, 3, 4, and NDVI with 12.06 % and lastly, the combination of bands 1,2,3, and 4 is less than another combination with the percent of 5.38 %. Also, the percentage of field crop and water bodies from the combination of bands 1, 3, 4, and RVI was higher than band combination with 20.64 % and 24.05 %, respectively. The combination of bands 1, 2, 3, and 4 show the forest area was the higher than band combination with 24.57 %. The combination of bands 1, 2, 3, and NDVI show the percentage of bare land and paddy field were higher than band combination with 26.20 % and 13.08 %, respectively. The highest percentage of the miscellaneous area was the combination of bands 2, 3, 4, and NDVI with 14.87 %. The results of land use classification maps shown in Figure 2, 3, 4, 5, and 6, respectively.

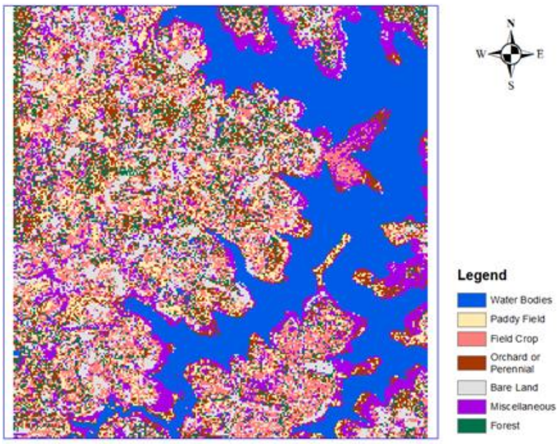

Figure 2. Land use classification using fuzzy k-mean from combination of band 1, 3, 4, and NDVI.

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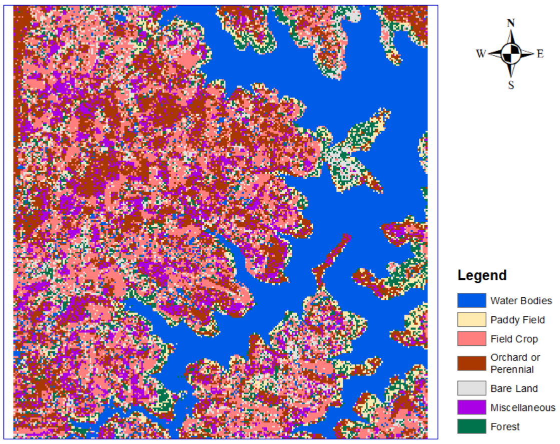

Figure 3. Land use classification using fuzzy k-mean from combination of band 1, 3, 4, and RVI.

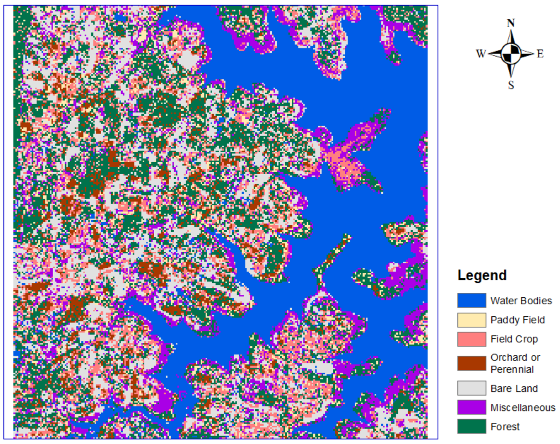

Figure 4. Land use classification using fuzzy k-mean from combination of band 1, 2, 3, and 4.

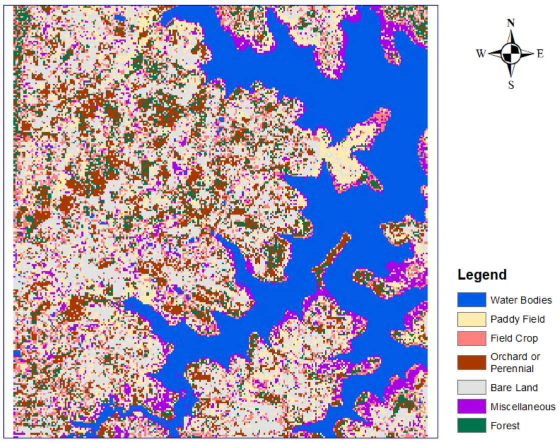

Figure 5. Land use classification using fuzzy k-mean from combination of band 2, 3, 4, and NDVI.

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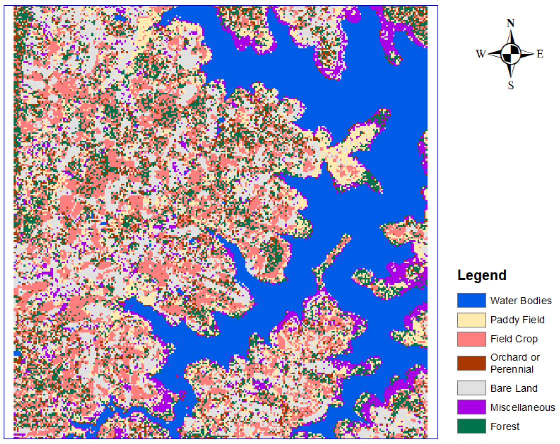

Figure 6. Land use classification using fuzzy k-mean from combination of band 2, 3, 4, and RVI.

Table 4. **The percentage values of LU classification from bands combination with OIF rank using the fuzzy k-mean technique.**

LU class	Band Combination (Percent)				
	1,3,4, NDVI	**1,3,4, RVI**	**1,2,3, 4**	**2,3,4, NDVI**	**2,3,4, RVI**
W	21.18	24.05	23.15	21.37	21.06
PF	11.42	6.19	4.83	13.08	12.35
FC	16.79	20.64	13.46	10.98	19.72
OP	12.06	23.82	5.38	12.24	6.89
BL	13.61	7.05	16.42	26.20	19.79
M	14.84	10.71	12.18	7.78	7.16
F	10.10	7.55	24.57	8.35	13.04
Total	100.00	100.00	100.00	100.00	100.00

An accuracy assessment of a land use classification of the fuzzy k-mean technique by using confusion matrices and kappa coefficient to compared of band combination with OIF methods. For this research, were used the 526 points has been selected randomly using stratified sampling methods. Confusion matrices and kappa coefficient measures of land use classified from four band combination with OIF methods is presented in Table 5, 6, 7, 8, and 9. The overall accuracy and kappa coefficient of land use classified from the combination of band 1, 3, 4, and NDVI were 72.62 and 67.51, respectively. The overall accuracy and kappa coefficient of land use classified from the combination of band 1, 3, 4, and RVI were 40.49 and 28.65, respectively. The overall accuracy and kappa coefficient of land use classified from the combination of band 1, 2, 3, and 4 were 64.87 and 57.28, respectively. The overall accuracy and kappa coefficient of land use classified from the combination of band 2, 3, 4, and NDVI were 40.87 and 30.86, respectively. The overall accuracy and kappa coefficient of land use classified from the combination of band 2, 3, 4, and RVI were 59.68 and 52.11, respectively.

Table 5. **Confusion matrices and kappa coefficient of land use classified from Band 1,3,4 and NDVI.**

LU class	Reference data							Total
	W	**PF**	**FC**	**OP**	**BL**	**M**	**F**	
W	114	0	0	0	0	0	0	114
PF	0	20	23	12	0	3	2	60
FC	0	0	74	6	6	3	8	97
OP	0	7	5	34	2	9	11	68
BL	0	0	9	2	53	1	2	67
M	0	0	4	1	6	62	2	75
F	0	0	2	12	1	5	25	45
Total	114	27	117	67	68	83	50	526
Overall accuracy:72.62								

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Kappa coefficient:67.51

Table 6. Confusion matrices and kappa coefficient of land use classified from Band 1,3,4 and RVI

LU class	Reference data							Total
	W	**PF**	**FC**	**OP**	**BL**	**M**	**F**	
W	113	0	1	2	2	4	3	125
PF	0	1	3	2	1	24	0	31
FC	0	0	37	7	53	7	9	113
OP	1	17	13	47	4	8	32	122
BL	0	0	20	1	8	7	1	37
M	0	9	37	8	0	5	3	62
F	0	0	6	0	0	28	2	36
Total	114	27	117	67	68	83	50	526
Overall accuracy:40.49								
Kappa coefficient:28.65								

Table 7. Confusion matrices and kappa coefficient of land use classified from Band 1,2,3 and 4

LU class	Reference data							Total
	W	**PF**	**FC**	**OP**	**BL**	**M**	**F**	
W	113	0	1	2	2	3	3	124
PF	0	11	8	4	0	3	0	26
FC	0	0	56	4	4	4	6	74
OP	0	7	17	9	0	0	0	33
BL	0	0	17	3	56	6	3	85
M	0	0	3	1	2	54	1	61
F	1	9	15	44	4	13	37	123
Total	114	27	117	67	68	83	50	526
Overall accuracy: 64.87								
Kappa coefficient: 57.28								

Table 8. Confusion matrices and kappa coefficient of land use classified from Band 2,3,4 and NDVI

LU class	Reference data							Total
	W	**PF**	**FC**	**OP**	**BL**	**M**	**F**	
W	112	0	0	0	1	0	0	113
PF	0	4	20	5	13	31	2	75
FC	2	1	1	13	6	11	19	53
OP	0	14	25	16	0	5	4	64
BL	0	3	64	10	40	1	13	131
M	0	0	0	0	8	30	0	38
F	0	5	7	23	0	5	12	52
Total	114	27	117	67	68	83	50	526
Overall accuracy: 40.87								
Kappa coefficient: 30.86								

Table 9. Confusion matrices and kappa coefficient of land use classified from Band 2,3,4 and RVI

LU class	Reference data							Total
	W	**PF**	**FC**	**OP**	**BL**	**M**	**F**	
W	113	0	0	0	0	0	0	113
PF	0	14	16	3	0	27	4	64
FC	0	9	68	23	4	7	12	123
OP	1	1	2	10	1	4	12	31
BL	0	0	29	7	58	5	3	102
M	0	0	0	0	2	32	0	34
F	0	3	2	24	3	8	19	59
Total	114	27	117	67	68	83	50	526
Overall accuracy: 59.69								
Kappa coefficient: 52.11								

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IV. Discussion and Conclusion

The study area was a variety type of land cover; it is difficult to classify the land cover shown in Figure 1. The evaluation of THEOS pan-sharpened image using the vegetation indices to classify of an orchard or perennial tree from the study area. First, the OIF value used to identify an optimal combination of four bands in Table 3 show that OIF indicates bands 2, 3, 4, and NDVI are the best for the land used classification. As well as, the second OIF value of bands 2, 3, 4, and RVI show that the vegetation indices can enhance the spatial information of pan-sharpened image.

The experiment results of land use classification by using the fuzzy k-mean technique show the percentage of the orchard or perennial tree from most of all band combined with the vegetation indices is higher than the original pan-sharpened image shown in Table 4. Similarly, the percentage area of the paddy field and field crop from all band combinations is higher than the original pan-sharpened image. Accordingly, the combination of the original band with vegetation indices band provides for the improve the THEOS pan-sharpened image. Accuracy assessment of the fuzzy k-mean technique from all band combined shows the overall accuracy and kappa coefficient of the combination of band 1, 3, 4, and NDVI is higher than each of band combined. Comparison of the commission errors in the orchard or perennial tree classified from all band combined using the fuzzy k-mean show the combination of bands 1, 3, 4, and NDVI is less than each of band combined was 50%. The combination of bands 1, 3, 4, and RVI the commission error was 61%, bands 1, 2, 3, and 4 the commission error was 73%, bands 2, 3, 4, and NDVI the commission error was 75%, bands 2, 3, 4, and RVI the commission error was 68%. A comparison of the producer's accuracy of the fuzzy k-mean of the orchard or perennial tree show the combination of bands 1, 3, 4, and RVI is higher than each of band combined was 70%. The combination of bands 1, 3, 4, and NDVI the producer's accuracy was 50%, bands 2, 3, 4, and NDVI the producer's accuracy was 24%, bands 2, 3, 4, and RVI the producer's accuracy was 15%, bands 1, 2, 3, and 4 the producer's accuracy was 14%. As a result of a classified show that the vegetation indices can be evaluated of THEOS pan-sharpened image and vegetation indices combined with bands of THEOS pan-sharpened image correlations for classified the separated the crop type land use [18].

The problem of THEOS pan-sharpened image is the distortion of spectral characteristics of multispectral images in the vegetation area. This study evaluates the THEOS pan-sharpened image using vegetation indices name of NDVI and RVI for classified land use classes. The combination of band NDVI and RVI with the original pan-sharpened image to select the optimize of the band for classified land use classes. The OIF value is used to identify an optimum of four band selection of the band combination. The result shows that the combination of band NDVI and RVI is the best for optimum band selection. Furthermore, the results of land us classified using the fuzzy k-mean are confirmation of the combination of band NDVI and RVI is higher than the original of THEOS pa-sharpened image. In particular, the fuzzy k-mean technique performs to classified the agricultural or crop type from the band combination image. The accuracy assessment of land use classified show that the vegetation indices can evaluate the THEOS pan-sharpened image.

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