# Potential of Sugar cane monitoring using Synthetic Aperture Radar in Central Thailand

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**ABSTRACT:** Sugarcane is an important cash crop in Thailand, especially in central region and its information is very important for productive management. Obtaining sugarcane information from optical images is very difficult due to the tropical climate. Therefore, Synthetic Aperture Radar (SAR) is brought to classify the land use type. This paper presents the classification of sugarcane area using RADARSAT-2 images to make it possible on handling the climate limitation. The process begins with the image pre-processing of three polarizations (HH, HV, and HH-HV) and constructs a time series image of twelve months. Field data collection is performed to obtain Leaf Area Index (LAI) and physical information of sugarcane in every month in 2014. Then, this information is examined the relationship between backscatter coefficient and LAI. Jeffries-Matusita Distance (JM-Distance) is analyzed to examine the discrimination power between sugarcane and other land use types each polarization and select the highest discrimination power polarization to classification process. Maximum likelihood is used to detect different classes and validate by field survey.

The result reveals that HH polarization has good ability on discriminating sugarcane from urban area. HV polarization is good at differentiating sugarcane from moist area such as, rice and water area. HH-HV polarization has good ability on discriminating sugarcane from forest and eucalyptus. After selecting a practical image, classification will be performed to separate sugarcane area from other land use types. The result has shown overall accuracy of sugarcane and non-sugarcane classification at 81.0% and 94.4%, respectively. The overall accuracy of classification is 88.4%.

## 1. Introduction

Sugarcane is one of important cash crop in Thailand. It is mainly used in sugar production industry and export as a commodity. Sugar production in 2014/2015 was reaching 10.4 million metric tons compared to 11.4 million metric tons in 2013/2014 (Bangkok Post, 2014) and sugar export is estimated to 8.5 million metric tons due to large inventories. Sugarcane is expected to expand acreage in 2015/2016 and 2016/2017 as if the Thai government could persuade farmer to drop sugarcane instead of rice (USDA, 2014). According to Office of The Cane and Sugar Board (OSCB, 2015) latest report, 105.9 million metric tons of sugarcane production was crushed by 50 sugar mills in the country located in the northern, central, northeastern, eastern of Thailand.

Central region of Thailand is an important area of sugarcane planting. Especially in Dan Chang District, Suphan Buri Province, there is a sugar industrial company of Thailand (Mitrphol Group) located to supply sugarcane for producing and exporting sugar. Furthermore, this company set up the promoted and sustainability programs to support local farmer who leaves nearby the plant. Therefore, information of sugarcane planting is very important to support the programs which will be launched in the projected areas.

The study area is located in Dan Chang, Doem Bang Nang Buach, and Nong Ya Sai Districts, Suphan Buri Province where it is the main location of rice and sugarcane planting. This area is represented the sugarcane planting area of central Thailand. Many studies reveal advantages of using multi-temporal variation of optical sensors on sugarcane classification (Almeida , et al., 2006; Fortes and Dematte, 2006; Lebourgeois, et al., 2007). However, there is some atmosheric limitation, because this area is located in the tropical zone which there is cloud cover all over the year and this also leads to the limitation on acquiring information from optical sensors. Then, Synthetic Aperture Radar or SAR is selected to the sugarcane mapping around the plant's responsible area. SAR sensors provide the ground measurement through day and night and it is very useful on collecting information. There are some studies demonstrate the use of radar on sugarcane classification and it is increasing nowadays (Baghdadi, et al., 2009; Lin, et al, 2009.). However, in Thailand, there are few studies on sugarcane classification using SAR. Due to its capability, the objective of this study is to use Radarsat-2 SAR images to initiate the sugarcane classification algorithm and examine the potential on classification of sugarcane area in three Districts of Suphan Buri Province, central area of Thailand.

## 2. Experimental examination and result

### 2.1 Relation between backscattering coefficient and ground measurement

Ground measurement from twenty two fields are first examined and found that two of them are shifted to soybeans and regrowth. Therefore, twenty field measurements are brought into statistical analysis to obtain relationship between parameters. In these measurements, height, stem diameter, LAI, and NDVI are collected. After eliminating any errors occurred in this data, all samples are averaged and derived forty five datasets based on assumption that sugarcane has continuously growth which height, stem, and leaves will biophysically be increased. According to that assumption, backscattering coefficient obtained from Radarsat-2 SAR will be increased as well. This could be indicated that backscatter coefficient is related to sugarcane's growth - parameters. Table 1 displays a correlation matrix between average backscatter coefficient (HH and HV polarization) of sugarcane fields and growth – related parameters using Pearson product moment.

Table 1 Correlation coefficient of ground measurement and the backscattering coefficient using Pearson product moment.

| | Diameter | Height | Backscatter HH | Backscatter HV | LAI |
|---|---|---|---|---|---|
| Diameter | 1.00 | 0.96 | 0.93 | 0.93 | 0.85 |
| Height | 0.96 | 1.00 | 0.88 | 0.87 | 0.80 |
| Backscatter HH | 0.93 | 0.88 | 1.00 | 0.96 | 0.81 |
| Backscatter HV | 0.93 | 0.88 | 0.96 | 1.00 | 0.82 |
| LAI | 0.85 | 0.80 | 0.81 | 0.82 | 1.00 |

According to Table 1, these parameters reveal high correlation to each other. In this case, all of datasets are statistically analyzed to obtain types of relationship. In the beginning, biophysical field survey parameters (Stem diameter and Height) are measured a relationship as shown in Figure 1(A) and it reveals an increasing linear relationship of diameter and height measured in sample sites. After that, variation of backscattering coefficient, both HH and HV, are measured as a function of height to extract a corresponding of relationship as shown in Figure 1(B).

Due to Figure 1(B), the variation of backscattering coefficient, both HH and HV, and height show an increasing relationship measured from the study site. In conclusion, if size or height of biophysical data is increasing, the backscatter coefficient would be increasing as well.

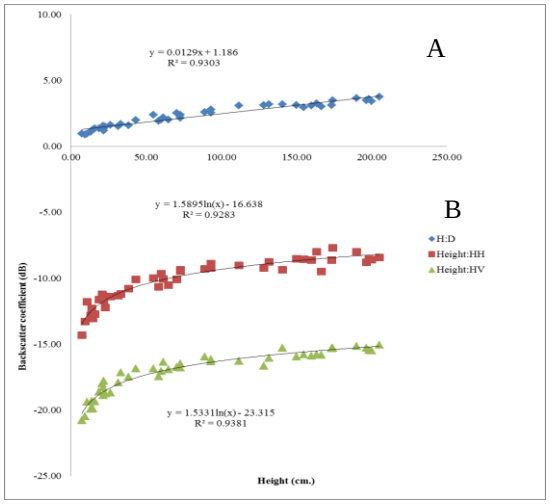


Figure 1 (A) Relationship between diameter and height measured in the study area.
(B) Variation of backscattering coefficient of Radarsat – 2 SAR HH and HV polarization as a function of height.

Leaf Area Index (LAI) which it is collected from study sites simultaneously with biophysical data is used to characterize plant canopy and is defined as one - sided green leaf area per unit ground surface area (LAI = leaf area / ground area, sq.m./ sq.m.). Same as biophysical data, LAI is brought to measure the relationship between height and variation of backscattering coefficient as shown in Figure 2 and 3.

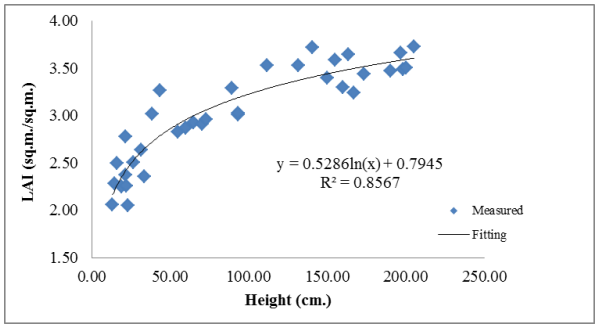


Figure 2 Relationship of the LAI and height measured in the study area.

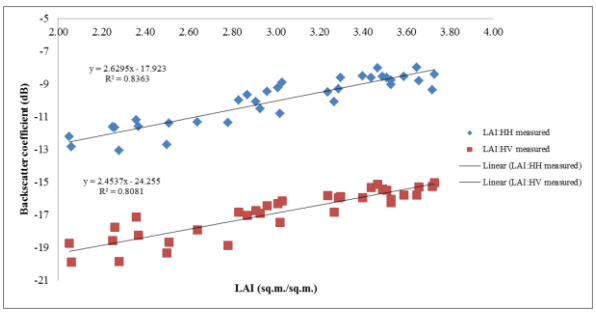


Figure 3 Variation of backscattering coefficient of Radarsat-2 SAR HH and HV polarization as a function of LAI.

Figure 2 shows an increasing relationship of the LAI and height measured in the study area. Figure 3 shows the multi-temporal variation of HH and HV data as a function of LAI. The relationship of HH and HV polarization and LAI is an increasing linear relationship as well. These figures confirm a general trend of increasing backscattering coefficient with LAI.

In conclusion, as the sugarcane grows, its height, stem, and number of leaves are resulting in a corresponding increase of LAI. This relates to an increase of backscattering intensity according to the increase of canopy of sugarcane. That means the growth of sugarcane has an effect on volume scattering and information from Radarsat-2 SAR images and it could be used to extract the multi-temporal profile of sugarcane.

### 2.2 Variation of landuse types extracted from each polarization

According to the relationship between backscattering coefficient of Radarsat–2 SAR and sugarcane's growth, a variation of sugarcane's backscattering coefficient is extracted from the multi-temporal variation imagery to define its phenology. Moreover, we have to extract information not only for the sugarcane, but also the other land cover which they are located in the study area for instances, rice, forest, eucalyptas, water, and urban area to compare the variation in each land cover type as shown in Figure 4.

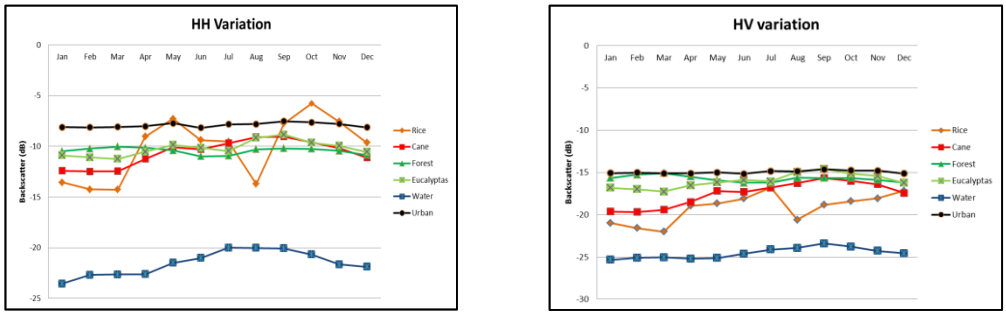


Figure 4 Backscattering coefficient (HH and HV polarization) of land cover types extracted in the study area.

According to Figure 4, average variations of sugarcane (red line in Figure 4) in HH and HV polarization have a similar characteristic. The signal is between -12.3 dB and -9.0 dB in HH and -19.6 dB and -15.6 dB. The signal starts to increase in March and has a peak value in September (180 days average growing period). After September, the signal of sugarcane slightly decreases approximately 2 dB in HH and 1.5 dB in HV. Variation of rice (Orange line in the image) is clearly seen two peak values in HH polarization due to rice planting in Suphan Buri Province has two crops, rainfed, and irrigated. While in the HV polarization, variation differs from HH polarization. It may result from polarization difference and soil distribution because the signal is slightly increasing in vegetative period. It needs more information to indicate the phenology of rice field. However, sugarcane and rice variations in HV polarization have dominate value from January to August which they could be clearly classified from other types of land cover. While in the HH polarization, it has a difference on variation only in January to March.

It is clearly seen that the variation of water (blue line in the Figure 4) is separated from any other types of land cover. The signal value is between -23.5 dB and -20.0 dB in HH and -25.3 dB and -24.1 dB in HV. The other dominant variation is urban area displayed as a black line in the image. This type of land cover has high value of backscatter coefficient between -8.1 dB and -7.5 dB in HH and -15.1 dB and -14.6 dB in HV. These two variations could be clearly disassociated from other land cover types in HH polarization. However, urban area variation in HV polarization has value close to forest and eucalyptas variations. Therefore, HH-HV polarization is constructed to support the differentiation of landuse type as shown in Figure 5

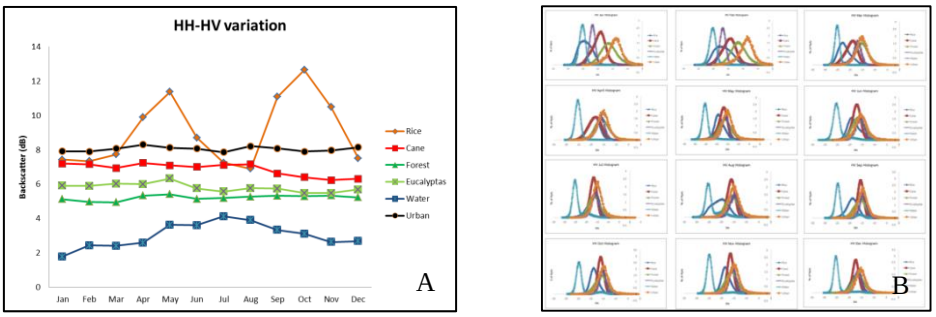


Figure 5 Backscattering coefficient of HH-HV polarization (A) and example of histogram distribution (B)

According to Figure 5, rice field is dominated in HH-HV polarization. Then, volume of DNs from each image (HH, HV, and HH-HV polarization) are brought into a histogram plot to indicate DN distribution and to construct the distributed database as an input in a dissimilarity analysis.

2.3. Dissimilarity of variation analysis

Histogram distribution reveals difference of backscatter coefficient variation for each landuse types. However, some ranges of distribution between landuse types are still associated or have closed values. In this process, histogram of sugarcane distribution will be combined with other landuse types to measure the dissimilarity using Jeffries Matusita Distance (Equation 1) on 3 polarizations.

$$Dist_M(p,q) = \sqrt{\sum_x \left(\sqrt{p(x)} - \sqrt{q(x)}\right)^2} \quad (1)$$

In Equation (1), p and q are values from dissimilarity matrices. The JM Distance has measured range between $2 - \sqrt{2}$ or approximately 0 – 1.41. The higher value represents the more dissimilarity of the combination which the data is practical to use in classification process. The result is shown in Table 2 and called the Combination of Dissimilarity Measurement.

Table 2 Dissimilarity result from JM Distance analysis

| Pol | Combination | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HH | Cane-Rice | 0.77 | 0.53 | 0.65 | 0.42 | 0.68 | 0.28 | **0.86** | 0.55 | 0.57 | 0.10 | 0.15 | 0.36 |
| | Cane-Forest | 0.55 | 0.29 | 0.49 | 0.36 | 0.38 | 0.85 | **0.99** | 0.29 | 0.49 | 0.35 | 0.36 | 0.48 |
| | Cane-Eucalyptas | 0.53 | 0.28 | 0.48 | 0.38 | 0.33 | 0.25 | **0.79** | 0.15 | 0.21 | 0.12 | 0.17 | 0.37 |
| | Cane-Water | 1.10 | 1.02 | 1.07 | 1.01 | 0.97 | 0.93 | **1.23** | 0.89 | 1.11 | 0.93 | 0.96 | 0.96 |
| | Cane-Urban | **1.07** | 1.00 | 1.00 | 0.79 | 0.77 | 0.91 | 0.44 | 0.27 | 0.73 | 0.93 | 0.93 | 1.00 |
| HV | Cane-Rice | **1.14** | 0.85 | 0.97 | 0.82 | 0.84 | 0.81 | 0.71 | 0.89 | 0.84 | 0.85 | 0.93 | 0.85 |
| | Cane-Forest | 0.95 | 0.87 | 0.83 | **1.09** | 0.70 | 0.24 | 0.80 | 0.76 | 0.26 | 0.84 | 0.90 | 0.75 |
| | Cane-Eucalyptas | **1.04** | 0.97 | 0.80 | 0.74 | 0.65 | 0.63 | 0.72 | 0.58 | 0.47 | 0.42 | 0.69 | 0.77 |
| | Cane-Water | **1.27** | 1.19 | 1.21 | 1.17 | 1.10 | 1.04 | 1.04 | 1.10 | 1.10 | 1.00 | 1.07 | 1.08 |
| | Cane-Urban | 0.93 | 0.89 | **0.99** | 0.86 | 0.78 | 0.80 | 0.78 | 0.80 | 0.86 | 0.80 | 0.92 | 0.95 |
| HH - HV | Cane-Rice | 0.57 | 0.56 | 0.82 | 0.83 | 0.83 | 0.86 | **0.92** | 0.86 | 0.85 | 0.87 | 0.79 | 0.52 |
| | Cane-Forest | 0.70 | 0.65 | 0.59 | 0.98 | **0.98** | 0.84 | 0.88 | 0.96 | 0.89 | 0.90 | 0.86 | 0.56 |
| | Cane-Eucalyptas | 0.77 | 0.55 | 0.39 | 0.91 | 0.92 | 0.83 | 0.85 | **0.93** | 0.88 | 0.88 | 0.83 | 0.44 |
| | Cane-Water | 1.02 | 0.93 | 0.91 | 1.11 | **1.15** | 0.99 | 1.00 | 1.02 | 1.08 | 1.08 | 1.10 | 0.90 |
| | Cane-Urban | 0.83 | 0.50 | 0.53 | 0.82 | 0.57 | 0.02 | 0.21 | 0.87 | 0.83 | 0.89 | **0.89** | 0.86 |

According to Table 2, analysis of JM distance provides various results and it can be concluded as follows;

1) Sugarcane and rice: Dissimilarity is very high in Polarization HV with the average at 0.8741. The highest dissimilarity value is detected in January at 1.1365

2) Sugarcane and forest: Polarization HV reveals prominent dissimilarity in January to April and November to October. Highest value is detected in April at 1.0853 and average value is 0.7489. In May to October,

Polarization HH-HV can measure prominent dissimilarity from other polarizations with average value at 0.8152. The highest value is detected in May at 0.9807

3) Sugarcane and Eucalyptas: Polarization HV reveals good dissimilarity value in January to March and in December. The highest value is detected in January at 1.0351 and average value is 0.7073. As for April to November, Polarization HH-HV can reveal good dissimilarity with average value at 0.7658 and the highest value is in August at 0.9335.

4) Sugarcane and water area: All polarizations have distinguished dissimilarity. Polarization HV has high average value at 1.1126 with the highest value in January at 1.2704.

5) Sugarcane and Urban area: HH polarization reveal good dissimilarity with the average value at 0.8203 and the highest value is detected in January at 1.0659

## 3. Classification and mapping sugarcane growth area

### 3.1 Classification and grouping

Radarsat-2 image is brought to the classification process using backscattering coefficient value form pre analysis. The criteria for classifying land use types is shown in Table 3 and examples of classification on sugarcane and rice are shown in Figure 6(A) and 6(B), respectively.

Table 3 Criteria on classifying landuse types

| Landuse type | Polarization | Month | $\sigma$ | Majority analysis | Convolution filtering |
|---|---|---|---|---|---|
| Sugarcane | HV | March | $-18 > \sigma > -21$ | 7×7 | 7×7 |
| Rice | HH-HV | May | $\sigma > 11$ | 7×7 | 7×7 |
| Urban area | HH | Jan | $\sigma > -9$ | 3×3 | 5×5 |
| Eucalyptas, Water, and Forest | HH-HV | Jul | $\sigma < 6$ | 7×7 | 7×7 |

According to table 3, these criteria is brought to classify landuse types and preliminary be divided into four classes for instance, sugarcane, rice, urban area, and others (eucalyptas, water, and forest). Then, these results are grouped as “sugarcane” and “non-sugarcane” area.

### 2.2 Majority analysis and convolution filtering

In these processes, pixels in the result will be adjusted and filtered by different window sizes (3×3, 5×5, and 7×7). Then, the optimal window size would be selected to the process. Majority analysis will adjust the value in the given pixel to the same direction of surrounded pixels due to the window size as shown in Figure 7(A). However, result from the process still has signal or noise in the image and should be corrected by filtering. This leads to the Convolution filtering using Gausian Low Pass filter. This kind of filter has a benefit on preserving edges of pixels and reducing the ringing effect. Examples of result are shown in Figure 7(B).

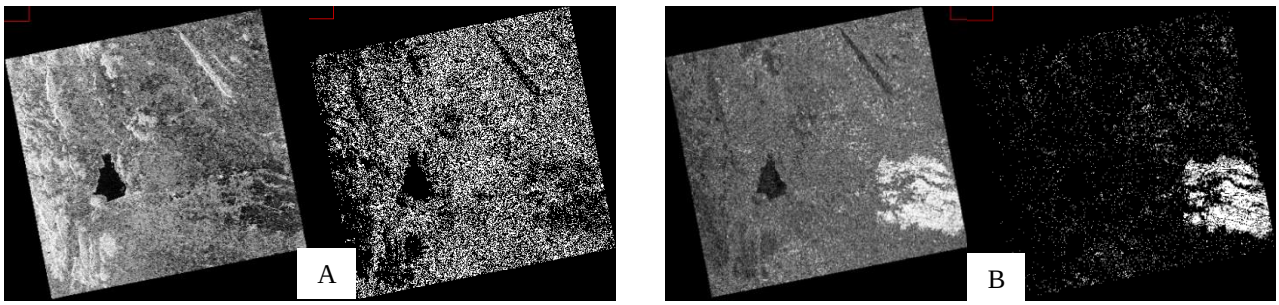


Figure 6 Example results of sugarcane (A) and rice (B) classification

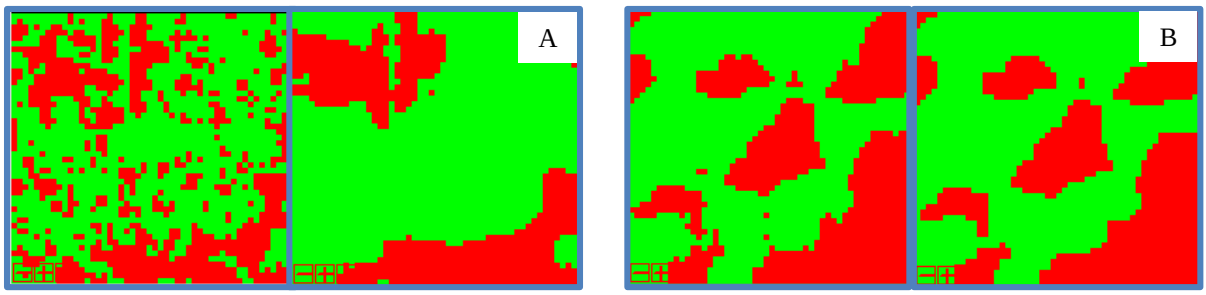


Figure 7 Example results of Majority analysis (A) and Convolution filtering (B)

### 3.3 Extraction sugarcane area

Result from previous processes is divided into two groups as “sugarcane” and “non-sugarcane” and shown in Figure 8(A). In this process, extraction technique is used to erase the “non-sugarcane” area from the sugarcane area. Result displays “sugarcane area” in green colour and “non-sugarcane area” in red color. Dan Chang, Doem Bang Nang Buach, and Nong Ya Sai Districts are overlaid to locate only the area in Suphan Buri Province as shown in figure 8(B).

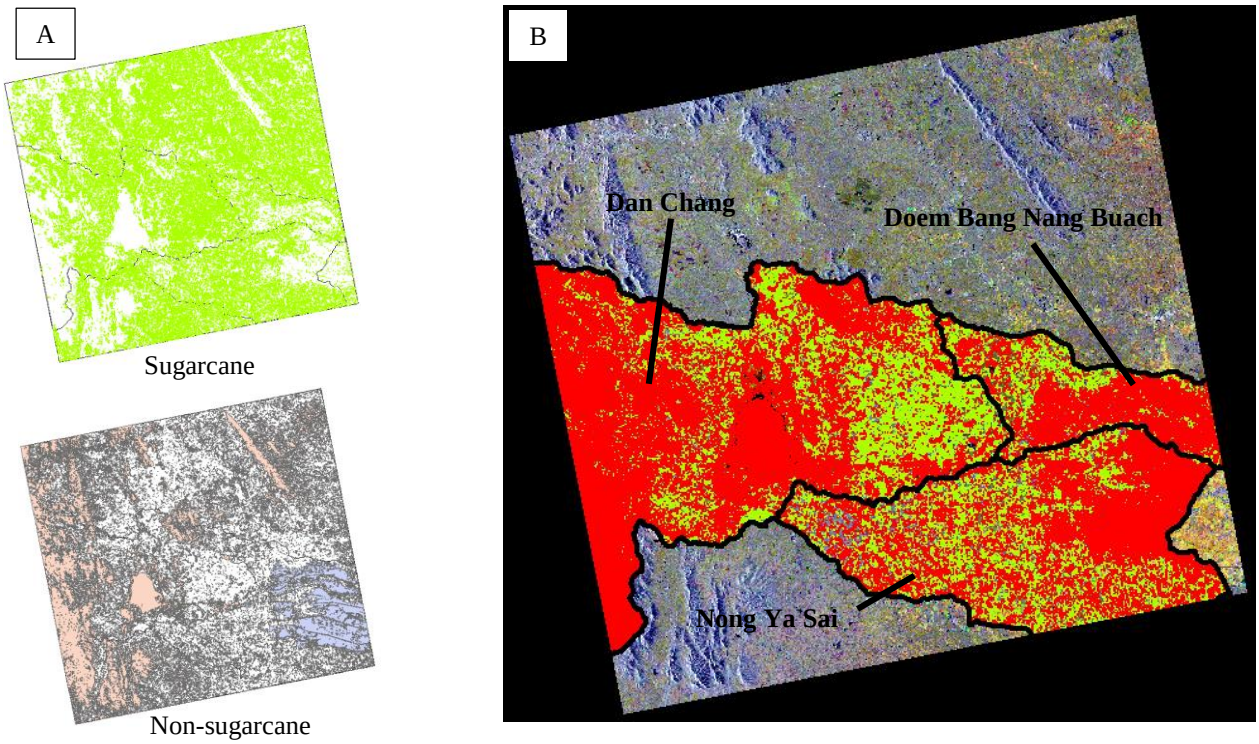


Figure 8 Sugarcane and non-sugarcane area (A); Sugarcane classification result displaying green as sugarcane and red as non-sugarcane area (B)

## 4. Classification accuracy estimation

Result from classification will be brought into the Classification accuracy estimation by randomly selecting sugarcane planting area for 100 points as shown as green point and Non-sugarcane area for 125 points as red point shown in Figure 9.

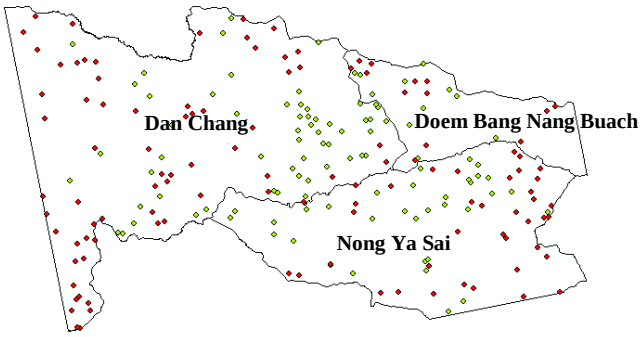


Figure 9 Random points for sugarcane and non-sugarcane

According to Figure 9, all random points are analyzed by comparison to the field survey data and calculate with the matrix table to obtain the percentage of sugarcane, non-sugarcane, and overall accuracy. The result is shown in Table 4.

Table 4 Accuracy of sugarcane and non-sugarcane classification

| | Sugarcane | Non-sugarcane | Total | Accuracy (%) |
|---|---|---|---|---|
| Sugarcane | 81 | 19 | 100 | 81.0 |
| Not sugarcane | 7 | 118 | 125 | 94.4 |
| Overall | 89 | 137 | 225 | 88.4 |

According to table 4, the sugarcane and non-sugarcane classification has User's accuracy at 0.81 and 0.94 respectively. It could be said that pixels which are classified as sugarcane and non-sugarcane are indeed what they are classed with accuracy above 80%. Producer's accuracy is at 0.91 and 0.86 respectively which it reveals the classification of ground area has high accuracy above 86%. The overall accuracy is 88.4%. The different between the observed agreement and expected agreement can be measured by the Kappa index which it is standardized to lie on a -1 to 1 scale. This scale's range could be interpreted as 1 is perfect agreement, 0 is exactly what would be expected by chance, and negative values indicate agreement less than chance. According to table 4, the Kappa index is 0.761 indicated a substantial agreement. This could be interpreted as the result has a high significance on sugarcane's classification.

## 5. Summary and conclusion

The objective of this study is to use Radarsat-2 SAR images to initiate the algorithm of sugarcane classification and to examine the potential of using SAR images on classification in three main sugarcane's planted Districts of Suphan Buri Province located in central of Thailand. SAR images are combined to create the twelve date time-series image. Then, multi-temporal variation of sugarcane's backscattering (HH, HV, and HH-HV polarization) from twenty two sample fields are extracted to analyze the relationship with ground data for instance, LAI, diameter, and height. The increasing of backscatter coefficient as a function of sugarcane's height is observed and found a good relation with a significance higher than 0.8. The combination of dissimilarity measurement is performed to reveal the polarization which it could practical differentiate the sugarcane from other landuse types. The dissimilarity could be support the decision to use HH, HV, or HH-HV polarization on sugarcane's classification and the result could suggest which band is appropriated. Then, the classification is performed according to criteria noted in Table 3. After performing the classification accuracy estimation, the result on sugarcane classification has high accuracy at 81.0% and overall accuracy is 88.4%. The Kappa index is also calculated and reveals high significance on classification. Result indicates the high potential on using Radarsat-2 SAR to classify the sugarcane area. However, there is still some signal or noise left in the result which it is important to eliminate and this will be the future study.

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