THAMMASAT REVIEW
PRINT ISSN: 0859-5747 ONLINE ISSN: 2630-0303

Volume 25 No 1 (Janaury-June) 2022 [Page 178-201]

Control of Tobacco Planting Areas in Thailand Using Remote Sensing Technology

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Received 18 March 2022; Received in revised form 7 June 2022
Accepted 8 June 2022; Available online 23 June 2022

Abstract

This paper reports the results of a remote sensing project conducted in Thailand. The purpose of this study was to identify and assess tobacco planting areas to support the Thai government's efforts related to tobacco cultivation control and management. The study areas included 13 provinces and represented 94% of tobacco planting areas in Thailand. The remote sensing application was based on the combined pixel-based and object-based classifications approach and was conducted using Thaichote satellite imagery. A field survey was also conducted in 3 test areas to validate the overall accuracy of the combined classification method. The findings indicated that tobacco cultivation and distribution were identified accurately using remote sensing based on a combined pixel-based and object-based classifications method at the highest accuracy level of 95% with significant agreement based on the kappa coefficient of .832 at 99% confidence level. The tobacco planting areas identified in this study were 35% larger than the registered areas recorded by the Excise Department. Farmers revealed that generally they cultivated 20%-30% more tobacco than they reported in order to secure the next year's quota in case the tobacco yield was less than expected. The difference reduced the tax revenue that the Excise Department should receive. The tobacco products produced from illegal cultivation were not inspected for quality control. This is likely harmful to consumers. The remote sensing application can provide the necessary precise information of the tobacco planting areas. This would support the Thai government to improve tobacco production control and management and increase their revenue.

Keywords

Remote Sensing, Tobacco planting area, Tobacco production control, Combined pixel-based object-based classifications

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Introduction

Tobacco is one of the most important economic crops in Thailand (Kitiwatcharajaroen, 2005). Tobacco production is a major contributor to the tax base of Thailand. Since 2017, the tobacco tax has contributed 2% to the Thailand gross revenue with an average of 65,734 million baht per year (Ministry of Finance, n.d.). However, tobacco consumption also has a negative impact on people's health and the Thai economy. Health costs related to tobacco use represent 0.78% of GDP compared to the 0.57% that tobacco contributes to the economy (Aungkulanon et al., 2019). Tobacco consumption remains a significant global health issue and the tobacco industry continues to find devious ways of keeping demand and consumption high. This relates to the challenging, and often neglected, issue of tobacco cultivation and supply (Lencucha et al., 2022). The Thai government attaches great importance on Tobacco Control Policies (TPCs). Thailand has been praised for its comprehensive measures such as increased tobacco taxes and smoking cessation programs. These policies are largely focused on the demand side, tobacco products sales and consumption. Meanwhile, the extent to which these controls have implications for tobacco farmers, or the supply side have not yet fully been recognized and need to be improved (Promphakping et al., 2021). The Thai government has continuously encountered problems related to control and managing tobacco cultivation. These problems are caused by the difficulty assessing the actual area used for tobacco cultivation (The Secretariat of the Prime Minister, 2014). The lack of precise information on tobacco planting areas leads to many issues such as excessive planting areas, irregularity in quality, imprecise crop yield estimates, disaster monitoring and related compensation to the farmers (The Secretariat of the Prime Minister, 2014; Li et al, 2013).

To solve these problems, remote sensing technology was applied along with the most recent field classification approaches not applied before with tobacco crop. This study used remote sensing data to distinguish tobacco from other plants and to calculate the actual planting areas in the key tobacco cultivation provinces in Thailand. Remote sensing was used because it provides a low cost but highly efficient method for observation over large areas at regular intervals (Svotwa et al., 2014; Peng et al., 2009). A field survey was also conducted to validate the accuracy of the remote sensing method. Overall accuracy was tested with the kappa coefficient (Collani & Dräger, 2001).

Literature Review

Background of Tobacco Cultivation

Tobacco cultivation in Thailand includes 3 high value tobacco varieties: Virginia, Burley, Turkish, and some low value local varieties. According to the Thailand Tobacco Products Control Act B.E. 2560 (2017), tobacco cultivation, and sale must have legal registration from the Excise Department. In 2019, 29,191 farmers registered to cultivate tobacco on 49,817 acres of land (Kongsakon & Pattanateepapon, 2020). The registered planting area was less than the 53,072 acres reported by the Department of Agriculture Extension (DOAE, n.d.). The Thai government found that farmers made inadequate or duplicate registration to grow tobacco exceeding their quota and illegally sold the excess or sold the high value as local variety (The Secretariat of the Prime Minister, 2014). Local products are sold as tobacco sachet with a 0.1% per kilogram tax rate. This is much lower than the cigarettes tax rate at 20% per cigarette pack (Ministry Regulation on Tobacco Stamp Rates No. 2 B.E. 2556). This causes the government to lose income from taxation. Moreover, the extra quota of tobacco leaves and illegal sales are not inspected for quality which is harmful to consumer health (The Secretariat of the Prime Minister, 2014). Aitken et al. (2009) found that illicit tobacco smokers had significantly worse health than legal smokers. Tobacco consumption remains a significant global health issue. The tobacco industry continues to find despicable ways of keeping high demand and consumption. In the background lies the challenging, and often neglected, issue of tobacco cultivation and supply (Lencucha & Drope, 2022).

For the Thai government, it is important to identify actual tobacco planting areas. This will be an important reference to improve tobacco production management, land optimization and planting regulation. It will increase the control of tobacco production and safeguard the market as well as limit the illegal tobacco production. Illegal tobacco production increases the negative impacts of smoking inferior varieties (The Secretariat of the Prime Minister, 2014; Peng et al., 2009).

Remote Sensing Technique

Remote sensing collects information about objects, areas, or phenomena without touching objects or areas. The information is captured at a distance from above Earth’s surface usually in the form of satellite images. Satellite images record the reflectance value of the object's light spectrum as a digital number (DN) of each wavelength. This is because each object on the Earth's surface has a different reflection, absorption, and transmission of its energy. Objects can be distinguished from each other. Remote sensing is useful in providing spatial information that is otherwise difficult or impossible to obtain (Read & Torrado, 2009). Remote sensing is a widely useful tool for agricultural land use planning and management. Satellite images provide accurate agricultural information such as crop identification and classification, crop condition monitoring, crop growth, crop area and yield estimation (Vibhute & Gawali, 2013). For example, The Southern Sudan 2012 Crop and Food Security Assessment Mission used remote sensing to acquire information for crop monitoring & production forecasting. Pakistan is using remote sensing for crop monitoring system for its ongoing project on the improvement of national and provincial agricultural crop yield forecast and estimates (Cumani & Latham, 2012).

Remote Sensing Image Classification Approaches

A remotely sensed image consists of rows and columns of pixels, which contain the value of spectral reflectance. There are many classification methods related to satellite imagery and land use information. A typical approach uses the maximum likelihood methods of pixel-based image classification and the condition based and nearest neighbor methods of object-based classification (Vibhute & Gawali, 2013; Avci et al., 2011).

The pixel-based classification approach directly classifies individual pixels according to their spectral properties. The pixel-based used spectral reflectance and normalized difference vegetation index (NDVI) to differentiate the vegetation on the Earth's surface (Svotwa, 2014; Peng et al., 2009). The NDVI, derived from remote-sensing data, is a measure of surface reflectance and gives a quantitative estimation of vegetation growth and biomass (Arabameri & Pourghasemi, 2019). Vegetation measured as the difference between the distinct wavelengths of visible red light and near-infrared (NIR) sunlight reflected. The NDVI ranged from −1 to +1, a densely vegetated area is given positive values, whereas water and built-up areas are represented by near zero to negative values (Viana et al., 2019). This approach has been used extensively and is viewed as a traditional approach. It is the most useful technique for supervised classification (Vibhute & Gawali, 2013; Avci et al., 2011; Liu & Xia, 2010; Casals-Carrasco et al., 2000). However, pixel-based classification may provide non-continuous and non-homogeneous results.

Object-based classification overcomes this problem by an approach similar to human sight and understanding action (Liu & Xia, 2010). The object-based classification approach is currently the preferred method. It first aggregates image pixels into spectrally homogenous image objects using an image segmentation algorithm and then classifies the individual objects. It primarily involves concentrating on recognizing the objects and then evaluating properties and relationships for identification (Avci et al., 2011; Liu & Xia, 2010). Although the object-based approach has advantages over the pixel-based approach, it has its own limitations. Two types of errors often exist in image segmentation including over-segmentation and under-segmentation subsequent to classification errors. The image objects do not represent the properties of real objects on the Earth's surface (e.g., shape and area). These two types of errors could reduce the classification accuracy (Kampouraki et al., 2008; Möller et al., 2007; Song et al., 2005).

The combined pixel-based and object-based classification approaches have been used in various studies. The combined method makes full use of each applications advantage, and overcomes their disadvantages (Li & Wan, 2015; Brik et al., 2014). The combined approach is better at identifying and classifying land use and land cover (Bernardini, 2010).

A critical theoretical issue for remote sensing is the interpretation of the data generated by the applications. Each of the current conventional applications has limitations (Liu, et al, 2018)

Extraction of Tobacco Planting Areas Using Remote Sensing

The difficulty of acquiring the actual tobacco fields in Thailand is supported by case studies from other countries. The United States, China, Malaysia and other developed countries have established remote sensing assessments of crop planting areas and crop yield estimation (Launay & Guerif ,2005; Tso & Mather, 1999; Moran et al., 1997). China has also carried out research on the crop cultivation area measurement and yield estimation using remote sensing technology (Ma et al., 2017; Han et al., 2007; Peng et al., 2006; Wu & Liu, 1997). The extraction of crop areas including tobacco cultivation areas using remote sensing carried-out in Pakistan, Iran, USA and Zimbabwe has an accuracy from 68%-98% depending on the classification methods (Ahmed et al., 2015; Svotwa et al, 2014; Myint, et. al, 2011, Matinfar, et. al, 2007, Yuan and Bauer, 2006).

The pixel-based classification method resulted in a 67%-82% accuracy in Pakistan, Iran and USA (Ahmed et al., 2015; Myint, et. al, 2011; Matinfar, et. al, 2007; Yuan and Bauer, 2006). Object-based classification achieved higher overall accuracy at around 90% - 93% in Iran and USA (Myint, et. al, 2011; Matinfar, et. al, 2007; Yuan and Bauer, 2006). Remote sensing research related to identification of tobacco planting areas has been mostly based on pixel-based or object-based classification. The current combined approach with the highest accuracy was applied to other agricultural crops effectively (Li & Wan, 2015; Brik et al., 2014).

This study applied the combined pixel-based and object-based classification approach to identify the actual tobacco planting areas of tobacco crops in Thailand. It will help the Thai government improve tobacco control and management because of the lack of precise information on tobacco cultivation e.g., excessive planting areas, irregularity in quality, imprecise crop yield estimation.

Research Methodology

Remote sensing technology was applied using the combination of pixel-based and object-based classification approaches to isolate tobacco from other plants and identify tobacco fields in Thailand. The areas selected for this study were provinces that cultivated more than 790 acres of tobacco and with permission from the government to cultivate high value varieties (i.e., Virginia, Burley and Turkish). With this criteria, 13 provinces covering approximately 46,558 acres of tobacco planting were selected (Figure 1). The study area represented 94% of the tobacco planting areas in Thailand. Remote sensing data were acquired by Thaichote satellite (THOES). A field survey was also conducted at the same time as the remote sensing data acquisition to verify the accuracy of the remote sensing data and validate accuracy of tobacco cultivation areas.

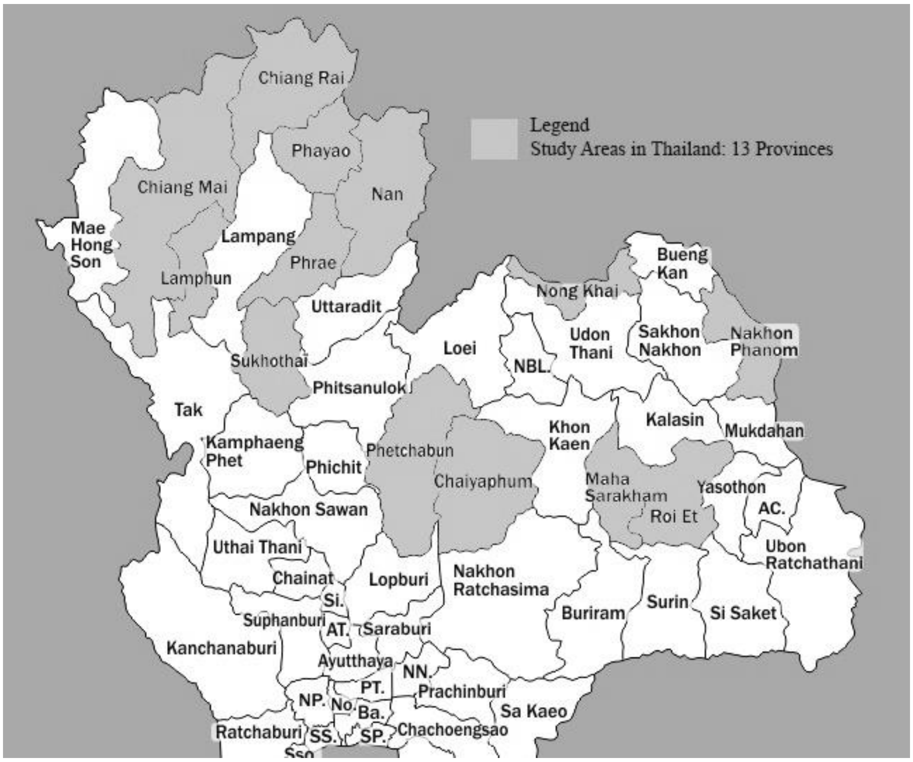


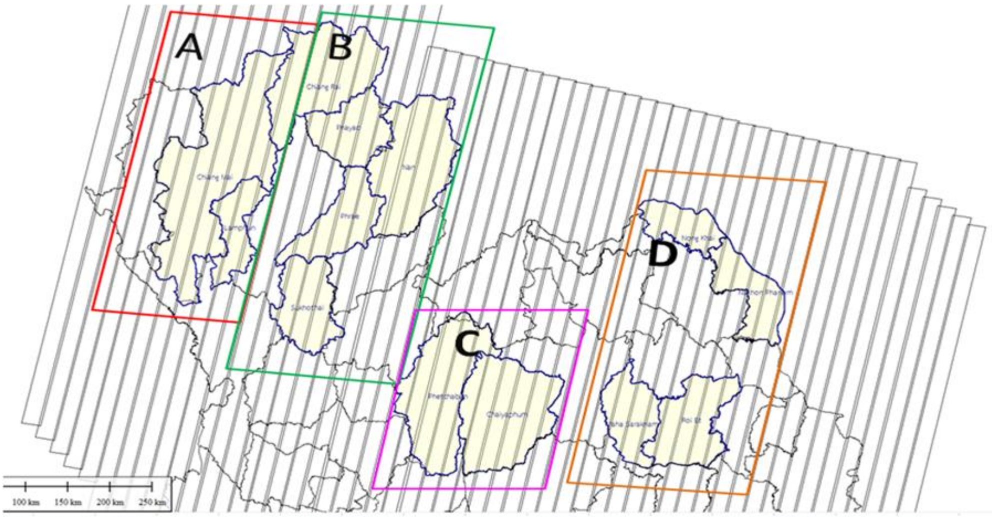
Figure 1 Study areas in 13 provinces

Source: Adapted from d-maps.com

Data collection and preparation

Remote Sensing Data Collection

This study used satellite imagery from the Thaichote satellite (THEOS). THEOS imagery provides 2 meters resolution at best, spectral ranged from 0.45-0.90 nanometer and 8 bits information depth. The output covers 22 km. x 22 km. The available time for satellite imagery data acquisition for tobacco identification and extraction was during December - March. This is the typical time for tobacco planting in Thailand (Excise Department, 2017). Satellite images covered the study area. The period of satellite availability is an important factor for accurate interpretation. Time series imagery composed of multi-temporal images has demonstrated the capability to measure tobacco automatically by utilizing the phenological characteristics of the plant (Peng et al., 2009). The time of acquisition was based on the annual tobacco planting period from the Department of Agricultural Extension and confirmed by the practice of farmers in the target province. The largest tobacco planting areas covered all high value varieties. The acquisition date was set at the most suitable period of tobacco growth (45 - 75 days) in the season (Excise Department, 2017). The satellite images would have the most accuracy according to the visibility of the tobacco canopy and leaf. The priority orbit and coverage area were identified from the tobacco planting district at the province level from the Department of Agricultural Extension to specify the most suitable images in each area. Acquisition in the period of December - March included all 13 provinces involved in tobacco production. The coverage of THEOS in each area along the orbit from northwest to southwest are shown in Figure 2.



Group A	Group B	Group C	Group D
7 Sitrps	10 Sitrps	10 Sitrps	11 Sitrps
16_5 - 18_3	18_4 - 20_4	20_5 - 22_4	22_6 - 24_6

Figure 2 Satellite Acquisition of Study Area

Source: Author

Field Survey Data Collection

Field surveys were conducted in accordance with the satellite imagery acquisition period of the THEOS in the selected test areas. There were three test areas selected by purposive sampling to synchronise with the remote sensing data collection based on the time limit of THEOS availability. The selected 3 provinces were Phrae, Phetchabun and Roi-et. These test areas are under the supervision of the Tobacco Authority of Thailand, to assure that these are actual crop areas with high value tobacco varieties. These provinces had the largest tobacco cultivation areas for all 3 high value varieties (Virginia, Burley and Turkish) and covered 90% of registered tobacco planting in Thailand.

A random survey within a test area of 1 tobacco plot (1 plot covered the area of 1 km2) in each province was conducted 3 times at different growing stages of the tobacco plant

(15 - 75 days after planted). For the purpose of accuracy, a number of sample or N points within the test area 1 tobacco plot were calculated based on the Binomial Distribution Model.

$$P(x) = \binom{n}{x} p^x q^{n-x} = \frac{n!}{(n-x)!\,x!} p^x q^{n-x}$$

Where:

P(x) = probability of success

n = sample of trials (the number being sample)

x = the number of success desired

p = probability of success in one sample

q = probability of failure in one sample (1-p)

Based on the above formula, at least 246 sample points were collected in each test area. This sample size determined by the Binomial Distribution Model had a probability of 80% accuracy with a 95% success level (Collani & Dräger, 2001).

The survey team collected the location coordinates and spectral reflectance value of tobacco, other plants and soil (land blank) in the training areas as a benchmark for the interpretation and accuracy assessment of the tobacco crops. Spectral reflectance data were collected using a portable spectroradiometer. In Thailand, the Geo-Informatics and Space Technology Development Agency (a public organization) is the only agency that provides spectroradiometer expertise. The field survey period needed to be consistent with the available time of the spectroradiometer experts and the schedule of the THEOS image acquisition.

Data Analysis

To assess the tobacco cultivation areas, digital analysis from pixel-based and object-based classification were used.

The spectral reflectance values acquired from the field survey by the spectroradiometer were extracted and transformed into CSV format carried out by FSF processing toolbox ver.1.3.8. For pixel-based classification, the tobacco spectral values in CSV form and satellite imagery were processed by ERDAS IMAGINE ver.9.2 to classify the tobacco planting areas. For the combined pixel-based and object-based classification, data acquired by satellite multispectral (MS) imagery and spectral value from the spectroradiometer were processed by eCognition (Figure 3).

This study also examined the results by visual interpretation from a GIS expert to confirm the tobacco planting area results. Visual interpretation is widely used for a better accuracy, especially with meter-scale high-resolution remote sensing. This included information related to land use, geological, hydrological, and urban planning that are essential for better classification and estimation of the extent of tobacco cultivation (Peng et al., 2009). The actual tobacco planting areas obtained from the study were compared with the legal tobacco crop data from the Excise Department to determine the differences between the actual areas and the regulated areas.

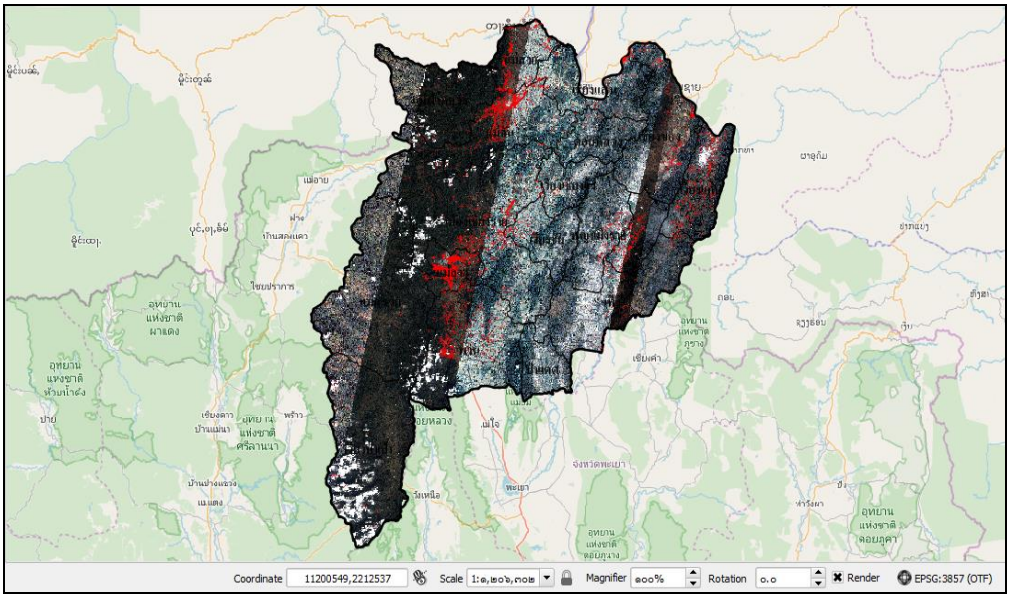


Figure 3 The visual results from remote sensing after processing

Source: Author

Accuracy Validation

The validation of the accuracy of the actual tobacco planting areas from the remote sensing was conducted through a field survey. An error matrix was prepared to specify the classification accuracy of the remote sensing technique. It statistically indicates the overall accuracy, omission error and commission error. The indications describe how well a certain area can be classified and indicated the probability that a sample classified on the map/image represents that category on the ground. In addition to these descriptive techniques, discrete multivariate analysis (Cohen's KAPPA) was used to test whether the classification accuracy differs significantly from chance agreement (Krauser, 2016; Congalton, 2001). Kappa coefficient is a statistical measurement derived from the values in an error matrix. The Khat statistic is computed as:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i} + Xx_{+1}\right)}{N^{2} - \sum_{i=1}^{r}\left(x_{ii} Xx_{+1}\right)}$$

Where:

r = number of rows in the error matrix

Xii = number of observations in row *i* and column i success desired

Xi+ = total of observation in row i (shown as marginal total to right of the matrix)

X+I = total of observation in column i (shown as marginal total to right of the matrix)

N = total number of observations included in matrix

The Kappa coefficient (KHAT) is a widely used measurement for classification accuracy and recommended by Rosenfield & Fitzpatrick-Lins (1986). KHAT values range from +1 to –1, between the remote sensing classification and the reference data, positive KHAT values are expected (Krauser, 2016; Banko, 1998). Landis & Koch (1977) characterized the possible ranges for KHAT into three groups: a value greater than 0.80 (i.e., 80%) represents strong agreement; a value between 0.40 and 0.80 (i.e., 40%-80%) represents moderate agreement; and a value below 0.40 (i.e., 40%) represents poor agreement.

Research Findings and Validation

Findings

An analysis of the THEOS Multi-Spectral images with the reference spectral reflectance values that collected by spectroradiometer in the test areas showed that tobacco spectral reflectance of the wavelengths RED band (630-690 nanometer) and NIR band (760-900 nanometer) were distinct from corn, chili and cassava grown in the in the same study areas. However, the spectrum characteristics of all tobacco varieties, Virginia, Burley, Turkish and local were difficult to distinguish (Figure 4).

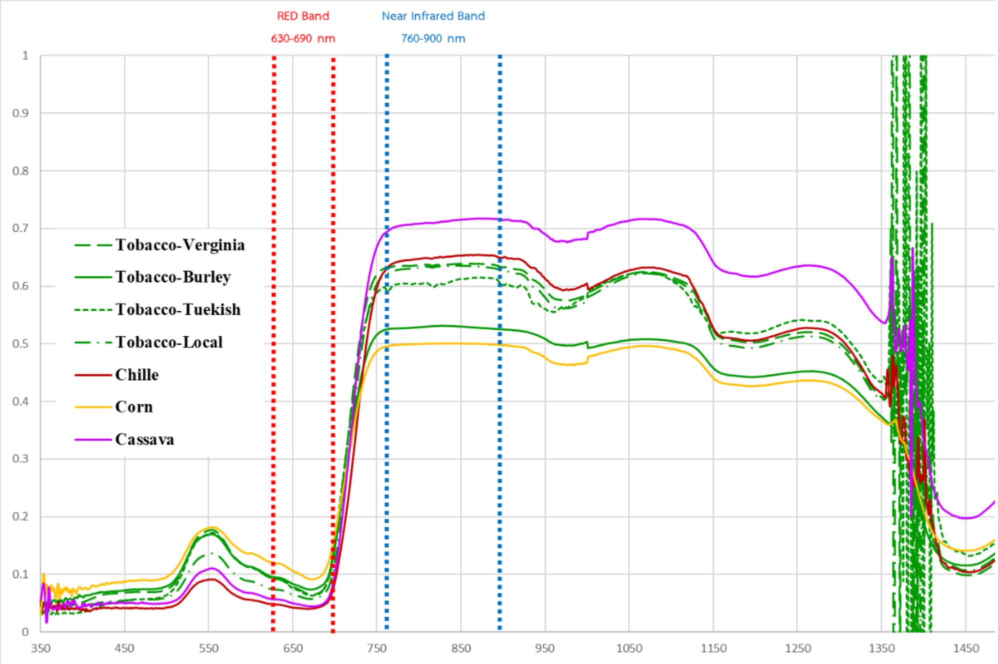


Figure 4 Spectral Reflectance of Tobacco and other plants in the Study Areas

Source: Author

To extract the tobacco planting area, data required for processing based on the combined pixel-based and object-based approach were identified. The reference spectral reflectance values of tobacco for the pixel-based approach were specified in the digital number of the NIR band and NDVI. This was done using spectroradiometer in the test area. Table 1 shows the values used as reference. For the object-based approach, the 3 parameters used as reference were scale, shape/color and smoothness/compactness. All parameters were adjusted based on the THEOS MS images processing together with the field survey assessment in order to identify the appropriate value to process for tobacco planting area identification. The appropriate value of the 3 parameters from this study are presented in table 2. All required data which were acquired by satellite multispectral imagery and spectral value from spectroradiometer were processed by eCognition to extract and calculate tobacco planting area. Visual interpretation was also used to determine the results of the tobacco planting areas. Figure 3 shows an example of the visual result from remote sensing data processing.

Results of tobacco planting area calculation based on the combined pixel-based and object-based classifications approaches are demonstrated in table 3. When compared with the Excise Department's official registered planting area, 35% more land was used for tobacco cultivation (Table 3).

Table 1 Reference Values of Tobacco Using for Pixel-based Classification

Training Area	Tobacco Varieties	NIR	NDVI
Roi-et Province	Turkish	116 – 193	0.75 – 0.90
Phare Province	Virginia	99 – 135	0.75 – 0.95
Phetchabun Province	Burley	98 – 170	0.75 – 0.90
	Local	85 – 140	0.75 – 0.90

Table 2 Object Parameter Values of Tobacco Using for Object-based Classification

Training Area	Tobacco Varieties	Scale parameter	Shape/Color Parameter	Smoothness/ Compactness Parameter
Roi-et Province	Turkish	50	0.1/0.9	0.5/0.5
Phare Province	Virginia	50	0.1/0.9	0.5/0.5
Phetchabun Province	Burley	50	0.1/0.9	0.5/0.5
	Local	50	0.1/0.9	0.5/0.5

Table 3 Tobacco Planting areas from Remote Sensing Findings VS Officially Registered with the Excise Department

Province (Tobacco Variety)	Tobacco Planting areas (acres)			
	Remote Sensing	Excise Department	Difference	
Phetchabun (Burley and Local Varieties)	13,713	14,629	-916	-6%
Roi Et (Turkish)	6,706	9,223	-2,517	-27%
Sukhothai (Burley)	12,651	7,112	5,539	78%
Nongkhai (Virginia, Burley)	4,687	4,115	572	14%
Nakorn Panom (Virginia, Burley, and Turkish)	3,096	2,802	294	11%
Chiang Rai (Virginia)	7,136	2,148	4,989	232%
Chiang Mai (Virginia and Local)	4,320	1,808	2,512	139%
Phayao (Virginia and Local)	1,152	1,254	-102	-8%
Phrae (Virginia)	4,469	1,252	3,218	257%

Table 3 Tobacco Planting areas from Remote Sensing Findings VS Officially Registered with the Excise Department (Continued)

Province (Tobacco Variety)	Tobacco Planting areas (acres)			
	Remote Sensing	Excise Department	Difference	
Maha Sarakham (Turkish)	930	952	-21	-2%
Nan (Virginia and Local)	695	563	132	23%
Lamphun (Virginia)	899	506	393	78%
Chaiyaphum (Local)	2,379	195	2,183	1118%
Total	**62,834**	**46,558**	**16,276**	**35%**

Validation

The Accuracy validation of the actual tobacco planting areas from the remote sensing was conducted through field survey of 3 selected test areas in Phrae, Phetchabun and Roi-et provinces. Each test area was conducted with random samples at least 246 points according to Binomial Distribution Model. This method provided a sample distribution accuracy of over 80% and a 95% success level. The accuracy validation in each training area were reported as follows.

Test Area in Phrae Province

The tobacco planting areas identified by the combined classification method indicated an overall accuracy of 95% with a .832 kappa coefficient and a 99% confidence level (Table 4). The strongly significant agreement indicated that the tobacco planting areas identified by the remote sensing classification method represents the actual tobacco planting area on the ground. Figure 5 shows the combined results of the remote sensing images and the field survey for Phrae province. The overlapping areas indicate the level of accuracy of the tobacco cultivation which was 95%.

Table 4 Error Metrix and Accuracy Validation of Phrae Province

Error Metrix		**Reference Data from Field Survey**			**User Accuracy**	**Commission Error**
		Tobacco Crop	Other Crops or Land Blank	Total		
Classification Data from Remote Sensing	Tobacco Crop	139	4	143	97.20%	2.80%
	Other Crops or Land Blank	10	127	137	92.70%	7.30%
	Total	149	131	280		
Producer Accuracy		93.29%	96.95%	**Overall Accuracy:**		**95.00%**
Omission Error		6.71%	3.05%			
Cohen's Kappa Analysis		**KHAT**	**Asymp. Std. Error**		**Z Statistic**	**Sig.**
Measure of Agreement		.832	.034		13.924	.000
N of Valid Cases		280				

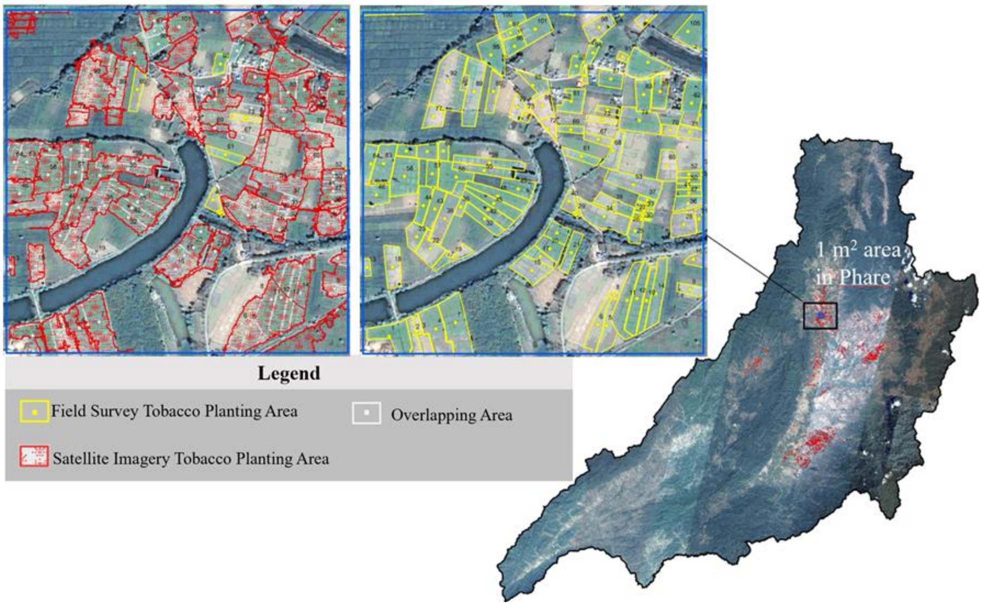


Figure 5 Analysis of the Accuracy Validation of Phrae Province

Source: Author

Test Area in Phetchabun Province

The tobacco planting areas identified by the combined classification method indicated an overall accuracy of 91.2% with a .762 Kappa coefficient and a 99% confidence level (Table 5). The overall accuracy indicates that the tobacco planting areas identified by remote sensing represent the actual tobacco planting areas on the ground. Figure 6 shows the combined results of the remote sensing images and the field survey for Phetchabun province. The overlapping areas confirmed the level of accuracy of the tobacco cultivation.

Table 5 Error Metrix and Accuracy Validation of Phetchabun Province.

Error Metrix		**Reference Data from Field Survey**			**User Accuracy**	**Commission Error**
		Tobacco Crop	Other Crops or Land Blank	Total		
Classification Data from Remote Sensing	Tobacco Crop	178	7	185	96.22%	3.78%
	Other Crops or Land Blank	15	50	65	23.08%	76.92%
	Total	193	57	250		
Producer Accuracy		92.23%	87.72%	**Overall Accuracy:**		**91.20%**
Omission Error		7.77%	12.28%			
Cohen's Kappa Analysis		**KHAT**	**Asymp. Std. Error**		**Z Statistic**	**Sig.**
Measure of Agreement		.762	.048		12.091	.000
N of Valid Cases		250				

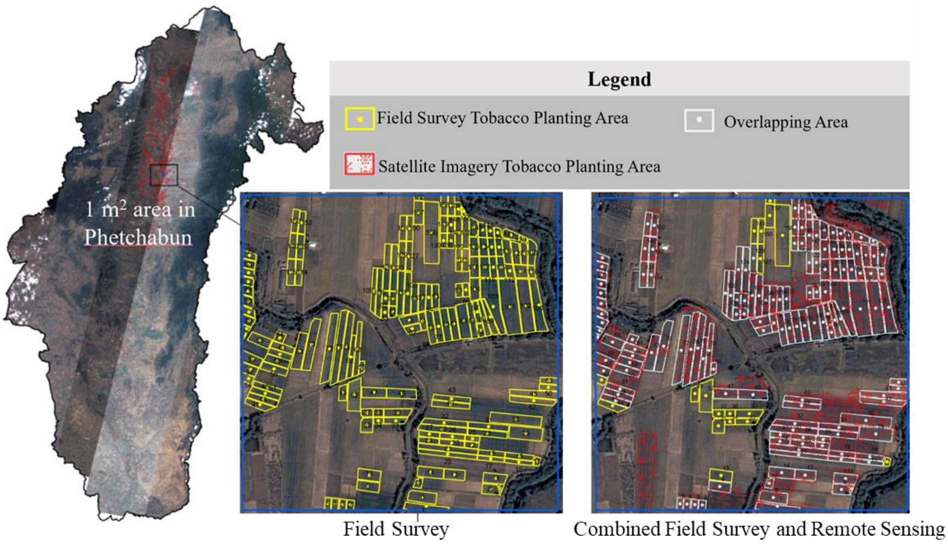


Figure 6 Analysis of the Accuracy Validation of Phetchabun Province

Source: Author

Test Area in Roi-et Province

The tobacco planting areas identified by the combined classification method indicated an overall accuracy of 50.7% with a .159 Kappa coefficient at a 99% confidence level (Table 6). This poor overall accuracy indicates that the tobacco planting areas identified by remote sensing is limited in identifying the actual tobacco cultivation area. The low overall accuracy of the overlapping tobacco cultivation was confirmed. Figure 7 shows the combined results of the remote sensing images and the field survey for Roi-et province.

Table 6 Error Metrix and Accuracy Validation of Roi-et Province

Error Metrix		**Reference Data from Field Survey**			**User Accuracy**	**Commission Error**
		Tobacco Crop	Other Crops or Land Blank	Total		
Classification Data from Remote Sensing	Tobacco Crop	98	196	294	33.33%	66.67%
	Other Crops or Land Blank	16	120	136	11.76%	88.24%
	Total	114	316	430		
Producer Accuracy		85.96%	62.03%	**Overall Accuracy:**		**50.70%**
Omission Error		14.04%	37.97%			
Cohen's Kappa Analysis		**KHAT**	**Asymp. Std. Error**		**Z Statistic**	**Sig.**
Measure of Agreement		.159	.031		4.712	.000
N of Valid Cases		430				

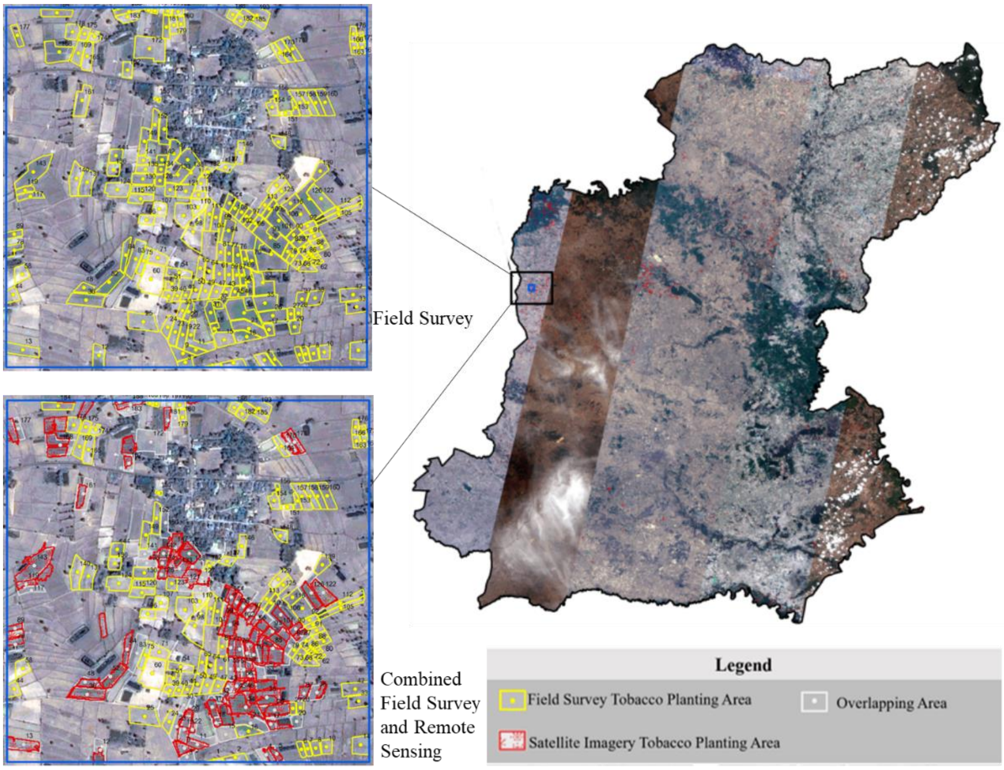


Figure 7 Analysis of the Accuracy Validation of Roi-et Province
Source: Author

Discussion

In this study, the accuracy of tobacco planting area identification and extraction in the test areas had acceptable accuracy 91% - 95% except for the result from Roe-et test area. The low accuracy in Roi-et where Turkish tobacco was cultivated (50.7%) was caused from the THEOS image resolution limitation and the inappropriate time of the THEOS image acquired. THEOS image provides a ground sample resolution at 2 meters at best with image area nadir at 22 km. x 22 km, whereas the Turkish the tobacco variety planted in Roi-et province has a canopy dimension 0.40 - 1.2 meter. The low accuracy of tobacco identification came from the object-based classification method. In addition, the THEOS image acquisition time was taken when the farmers were starting to harvest the tobacco leaves. Some tobacco plots marked by the field survey team did not match the tobacco planting areas identified by the remote sensing technique.

Through combined remote sensing and field study, tobacco cultivation expanded by 16,276 acres, 35% larger than the registered area with the Excise Department. The larger area was complemented with interviews with tobacco farmers during the field survey. The farmers revealed that if they produced less tobacco than the quota allowed by the Excise

Department, their quota would be reduced the following year. Effects of climate change and plant pests and diseases may cause these lower tobacco yields. Farmers usually cultivate 20%-30% more than their quota to ensure their tobacco leaves production. The unregistered 35% difference is tax revenue that the Excise Department could not collect. The products produced from inferior tobacco from illegal channels are excluded from quality control and inspection by the Excise department. Inferior tobacco may be more harmful to the consumer's health. The remote sensing technique employed in this study can solve the lack of precise information regarding tobacco planting areas throughout Thailand. This will help the Thai government to improve tobacco production control and management.

Theoretical and Practical Implications

The theoretical issue related to remote sensing is the efficacy of using one type of application to achieve valid results. The combination of pixel-based and object-based remote sensing application was very effective in the identification of cultivation areas. The overall accuracy of the data depends not only on the view from space but also from the ground. Field testing provided the data which indicated the overall adequacy of the analysis. This was confirmed by a GIS expert review.

From a practical viewpoint the combined remote sensing application and the field testing of 3 tobacco cultivation areas increased the overall accuracy of the number of areas of tobacco crops. This was complemented by a GIS expert review and by interviews with farmers to understand their situation. The result indicated that there were 16,216 more acres than registered by the Excise Department. This represents a loss of tax revenue approximately $2.8 million. This means that government funding to support farmers in quality management of tobacco or alternative crops is not available.

From the control perspective, the data allows the government to identify and reduce the amount of low-quality tobacco used in illegal products. This would also lead to lower health costs from consumers using inferior and illegal products.

Conclusion

The findings from this study indicate that tobacco cultivation and distribution were identified accurately using remote sensing based on a combined pixel-based and object-based classification method together with visual interpretation and land use information at a high accuracy level of 95%. The tobacco planting area assessment showed 35% more area than the registered land the Excise Department has collected. Without adequate control, tobacco leaves from the 16,276 acres will be used illegally in low quality tobacco products which are tax exempt or at a lower tax rate. This will increase their negative health impacts.

Limitations and Recommendations

The importance of using a combined remote sensing application, complemented with a field survey, a GIS expert review, and interviews with farmers was demonstrated. Timing was a key factor in the limited overall accuracy of the data in Roi-et province. This was unavoidable because of time pressures of data collection. To overcome this problem, it is recommended that future research synchronizes the time acquisition of satellite images with the growing period of tobacco cultivation. Using other Satellites such as SPOT satellite from France or Landsat satellite from NASA that provide higher ground sample resolution would improve the image accuracy, but may not be cost effective.

The Excise Department should require registered farmers to provide the location coordinates of their planting area. The Excise Department can match this information with the area identified by remote sensing for tobacco planting control and tax collection management.

Future study should also focus on providing tobacco cultivation and distribution maps using remote sensing and a GIS as the basis for efficient land use planning and to improve the accurate estimation of the crop yield.

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