Unintended consequences: Factors influencing oil palm plantation expansion

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Abstract. We investigated the landscape variables affecting the current dramatic expansion of oil palm plantations in Lam Thap district Krabi Province Thailand. THEOS satellite data was used to map land use classifications using the support vector machine method. Seven land use classes were consolidated into oil palm plantations and other rural uses. A logistic regression model was then applied to search for the relationship between two land use classes and the landscape variables of slope (three classes) and soil drainage (four classes). Overall, slope and drainage were statistically significant in explaining oil palm plantation expansion. Flat areas with poor drainage were the strongest factors. This contradicts the known optimal agronomic requirements for oil palms of well drainage. We suggest that what is observed is an unintended consequence of government oil palm support policies.

Keywords: Biodiesel, renewable energy, GIS, THEOS, land use

1. Introduction
Oil palm has become one of the most rapidly expanding crops in the world [1]. Many countries have promoted its cultivation as part of a development agriculture policy with an aim at producing both foods and biodiesel as a renewable energy. Cultivating oil palm in unsuitable areas increases operational costs and reduces yield [2, 3]. In addition, avoiding unnecessary deforestation is desirable [4, 5].

Thai government policy settings focus on promoting renewable energy from oil palm production with a goal of expanding plantation areas to 1,600 sq. km. (10 million rai) by 2029. Krabi province, southern Thailand, is the target area because its geographical conditions are most suitable for oil palm growth. Our previous study on oil palm expansion [6] showed that the highest rates were occurring in Lam Thap district where between 2000–2009 oil palm has been expanded by a factor of four; increasing from 20 sq. km. (12,500 rai) to 86 sq. km. (53,750 rai).

Today, remote sensing technology combined with GIS makes it possible to monitor oil palm expansion effectively and precisely, and if superimposed on other relevant geospatial data allows interpretation and analyses. Our study seeks to test this approach in Lam Thap district, Krabi Province, Thailand, as a case study for an investigation of oil palm expansion in relation to soil drainage and slope.
2. Methodology

2.1. Study area
Lam Thap district, Krabi Province, Thailand covers an area of 287 sq. km. (figure 1). In the past, economic crops in this area were dominated by paddy fields, coffee plantation and para rubber plantation. After 2000, oil palm plantation has been introduced to the area as alternative economic crops. This is due to the government policies to support the deployment of food crops and renewable energy.

2.2. Data sources
GIS data used in this study were soil drainage characteristics obtained from the Department of Environmental Quality Promotion, Thailand, and a set of contour lines, spot heights, and a topographic map obtained from the Royal Thai Survey Department. A digital image from the THEOS satellite for the 8th of February 2012 was obtained from the Geo-Informatics and Space Technology Development Agency, Thailand.

2.3. Data processing
In the present study, several techniques were applied to land use analysis. These included pre-processing, principal component analyses, ground survey, classification, and accuracy assessment.

Pre-processing: To reduce differences arising from changing instrument errors and differences, a radiometric calibration was performed by converting raw digital numbers into at-sensor spectral radiance for each band, subsequently, to reflectance values \([7, 8]\). Then, data were geometrically corrected and geo-referenced by projecting to the UTM Zone 47N and the WGS 1984 reference datum protocols with a spatial resolution of a 15x15 m pixel and a remaining root mean square error of less than 1 pixel. These data were then registration to overlay the topographic map as the independent data layer.

![Figure 1. Study area](image)
Principal component analysis (PCA): All interrelated four reflective THEOS bands were used as an input to a PCA for producing a smaller set of new, uncorrelated components that contains as much as possible of the variation present in the spectrum information of the original data. Then, the first principal component image was used for a further step because it has the most common information to all the bands [9]. PCA was performed on the reflectance spectrum data. THEOS surface reflectance measures the fraction of solar radiation that is reflected from targets on the ground to the satellite sensor. Different materials reflect and absorb differently at different wavelength bands. Thus, the targets can be separated by their spectral reflectance signatures in the satellite images.

Classification: Land use types were pre-classified using the ISODATA method along with ground survey with a stratified sampling; 278 points from field survey data and 15 inaccessible points were checked using Google Earth. We then used a Support Vector Machines (SVM) as a classifier for our image. The SVM classifier identified discreet hyperplanes that represent components of the image. Initially, we classified land use types into seven categories; oil palm, mixed oil palm, para rubber, water bodies, urban, forest and others. Then the data was further combined to optimally separates two classes, namely oil palm and all other classes [10].

Accuracy assessment: The location of those 293 stratified random points were chosen for a validation of the land use classification. The accuracy was assessed by way of the overall (OA), user’s (UA) and producer’s (PA) accuracies and the Kappa coefficient (K) derived from a confusion matrix [11].

2.4. Geospatial indicators
Our selection of independent variables was guided by reviewed literature on suitable areas for oil palm cultivation [12, 13] with a focus on geospatial factors. Slope and soil drainage were chosen because they reflected the major variables of landscape for oil palm growth. Both were in a GIS format and were georeferenced with the UTM Zone 47N and the WGS 1984 reference datum protocols. Each data layer was gridded analysis at 15x15 m before it was added to the logistic model. A digital elevation model (DEM) was generated from contour lines and spot. We converted the DEM to percent slope and then classified it into three categories; 0–12 %, 12.01–23 % and >23 %. Four of the seven Thai drainage categories occurred in our study area; these were poorly, slow, moderately and well drained. Vector data was converted to raster data by the method of maximum combined area.

2.5. Statistical method
Logistic regression generates the model statistics for determining the probability of an event of occurring in relation to a set of independent variables [14, 15]. The model used presence or absence of the oil palm plantations at a selected grid area (dependent variable) in relation to two geospatial indicators; slope (three classes) and soil drainage (four classes).

The dependent variable is a binary variable, representing the oil palm plantation or other land uses. The probability of an event is calculated by the logistic function:

\[
P(X) = \frac{e^Z}{1+e^Z}
\]

\[
Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2
\]

\[
\log \left( \frac{P(X)}{1 - P(X)} \right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2
\]

where \( P(X) \) is the probability of the oil palm plantation being found at a selected grid area; \( X_1 \) and \( X_2 \) are independent indicators; \( \beta_0 \) is the constant of the equation; \( \beta_1 \) and \( \beta_2 \) are the coefficients of the independent indicators. These coefficients in the log-odds equation are estimated by using the
maximum-likelihood method. The baseline are areas with 0 – 12 % slope and well-drainage soil. If the coefficient is positive, areas with steeper slope (or with poorer drainage) tend to have higher probabilities of oil palm presence than baseline areas.

3. Results and discussion

3.1. Land use
Ground truth survey resulted in an average overall accuracy of 93.8 % and kappa coefficient of 0.91 for all testing points. The user and producer accuracy were higher than 80 %. Producer's accuracy is the accuracy that how often are reality on the ground correctly displayed on the classified map. The user's accuracy is the reliability that how often the class on the map will actually be present on the ground. We focused on the user accuracy for this study because it minimised the confusion that can occur across several of the land use classes which have similar spectral characteristics. Land use classification in Lam Thap district, Krabi province in 2012 is reported in table 1 and land use distribution is shown in figure 2. It was found that agricultural areas of 250.3 sq. km.; represented 87.3 % of total area.

3.2. Slope and soil drainage
The Lam Thap district is flat (table 2) with slopes of 0–12 % making up 78 % of the total area. Soil drainage depends on soil type, thickness, continuity and porosity of the soil. Well and poorly drainage soils have the most coverage area with approximately 98 sq. km. (34 %) and 105 sq. km. (36 %), respectively. Drainage is consistent with the topography of our study area. Well drainage areas occur at higher elevations and poorly drained at low elevations.

### Table 1. Land use classification in square kilometers and its accuracy in Lam Thap district.

| Land use                        | Areas (%) | UA     | PA     |
|---------------------------------|-----------|--------|--------|
| Oil palm                        | 126.5 (44.1) | 95.68  | 94.62  |
| Mixed crops with oil palm       | 32.4 (11.2) | 83.33  | 80.00  |
| Para rubber                     | 91.5 (32)   | 96.90  | 93.06  |
| Water bodies                    | 0.6 (0.2)   | 100.00 | 100.00 |
| Urban                           | 8.0 (2.8)   | 92.30  | 96.00  |
| Forest                          | 23.0 (8.0)  | 93.33  | 100.00 |
| Others                          | 5.0 (1.7)   | 84.00  | 100.00 |
| Total                           | 287 (100)   |        |        |

### Table 2. Slope and drainage in Lam Thap district (Area in square kilometres).

| Slope  | Area (%) | Drainage | Area (%) |
|--------|----------|----------|----------|
| 0-12%  | 223.5 (77.9) | Poor     | 104.6 (36.4) |
| 12.01-23% | 17.3 (6.0)  | Slow     | 2.5 (0.9)   |
| >23%   | 46.2 (16.1) | Moderate | 24.8 (8.6)  |
|        |           | Well     | 97.5 (34.0) |
|        |           | No data  | 57.6 (20.1) |
| Total  | 287.0 (100.0) | Total   | 287.0 (100.0) |
3.3. Logistic regression
The logistic regression analysis used a base line of 0–12 % slope and well-drainage soil. The result shows that both slope and drainage influence oil palm plantation distribution. The model result emphasized on the report of the probability of the oil palm plantation in a selected grid being observed in relations to the soil and slope conditions, and narrow 95 % confidence intervals ensured precise estimation of population parameters. Table 3 shows that while the results for slope are consistent with known requirements for oil palm, namely flat terrain, the values suggest that oil palm is moving from well drainage soils to less suitable poor drainage soils. Similarly, land suitability for growing oil palm plantation has recently been reported as flat areas with well drainage [16].

![Figure 2. Land use classification in Lam Thap district, Krabi province in year 2012.](image)

| Table 3. Logistic regression using a base of 0–12 % slope and well-drainage soil. |
|----------------------------------|----------|---------|----------|---------|
| Factor              | Coef.    | SE.     | Lower    | Upper   |
| Poor drainage       | 0.120    | 0.004   | 0.003    | 0.021   |
| Slow drainage       | 0.933    | 0.025   | 0.883    | 0.984   |
| Moderate drainage   | -0.040   | 0.007   | -0.054   | -0.026  |
| 12.01-23 %          | -0.238   | 0.010   | -0.259   | -0.217  |
| >23 %               | -0.489   | 0.010   | -0.510   | -0.469  |
| Intercept           | 0.743    | 0.003   | 0.737    | 0.750   |
3.4. Understanding the discrepancies

The oil palm plantations have surprising relationship with poor and slow drainage in a positive direction (table 3). Areas that are moderate drainage have a negative direction suggesting that oil palms are less likely to be planted in these areas. The situation with slope is however clear that any planting occurs on slopes less than 12 %. Previous studies suggest that oil palm require flat land with well drainage [12, 13]. It would appear that farmers are expanding oil palm plantings regardless of established knowledge of land suitability. Remote sensing technique can be used to observe a wider area so that it is an alternative tool to detect suitable lands for a better agricultural management in the region.

4. Conclusions

The primary objective of the study was to determine the geospatial factors affecting oil palm plantation in Krabi province, Thailand. Our study has shown that well drained soils and flat terrain remain the preferred characteristics of oil palm plantation sitting. However, our data also reveals that plantings are occurring on less suitable areas with the strongest tendency being towards area of poor soil drainage.

This result is disturbing as it suggests that factors other than agronomic ones are at play. What may be occurring are the unintended consequence of oil palm promotion policies where an economic incentive is creating potentially non-viable oil palm plantation.

Further studies have three potential directions. The first is to establish if there is a correlation between oil palm plantation age and the introduction of current policy settings. The second would be to introduce others environmental factors and social and economic factors into this analysis. The third would be to model areas suitable for plantations to build a GIS bases decision support system that includes optimal terrain characteristics and also other landscape values such as food production potential and biodiversity values.

This study and its expansion are important because inappropriate subsidy driven land use changes frequently have social and political consequences.

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