Mapping rubber distribution in montane mainland Southeast Asia (MMSEA) using ASTER data

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A case study in Thai-Laos and Sino-Laos border areas

Introduction

Rubber (*Hevea brasiliensis*) is the major commercial crop replacing traditional agriculture and secondary forests in Montane mainland Southeast Asia (MMSEA). MMSEA is a large, ecologically vital region comprising approximately half the land area of Cambodia, Laos, Myanmar, Thailand, Vietnam, and China's Yunnan Province (Fig. 1). It is a region of great biological and cultural diversity that has come under close scrutiny in the last several decades as a result of both real and perceived deforestation, land degradation, and most recently, the conversion from traditional agriculture, including shifting cultivation, to more permanent cash crops driven by regional and global market (Fox and Vogler, submitted).

MMSEA

Rubber plantation

Rubber tree tapping

Figure 1 Montane mainland Southeast Asia and rubber plantation

Conversion from existing land covers to rubber affects local energy, water, and carbon fluxes. Accurate rubber distribution mapping is critical to the study of its expansion and its implications for water and carbon dynamics in MMSEA and provide better understanding of consequences of land cover and land use change on carbon and water cycles.

A major challenge for mapping rubber over a large extent is to generalize patterns in regions far from sampled area. It is also difficult to classify mixed pixels dominated by bare ground and mixed scrub using moderate spatial resolution data. With similar spectral reflectance to tropical evergreen vegetation, rubber is extremely difficult to be distinguished from other tree species such as eucalyptus using moderate spatial resolution remotely sensed data, such as Landsat TM/ETM+.

Further, like most remote sensing classification, the accuracy of classification was limited by the number of samples available. No existing maps incorporate rubber as a distinct class. This study proposed approaches to mapping rubber using ASTER data with limited number of samples.

Methodology

Data

The ASTER data used in this study were On-Demand L3 products which are orthorectified and terrain-corrected images acquired from Land Processes Distributed Active Archive Center (LPDAAC). NASA's Landsat GeoCover products and Google Earth high resolution IKONOS images were used to identify land use and land cover types and to develop both training and testing sites for calibrating and validating the classifiers respectively. Since the main purpose of this experiment was to distinguish rubber from other species, only seven broad classes were digitized for the two study regions.

Each ASTER granule (scene) covers an area of 60 x 60 km^2. For Sino-Laos border, only a single-date ASTER image (acquired on February 8, 2005) was used because finding suitable cloud-free imagery at the desired date was difficult in this area. For Thai-Laos border area, two-date images were used, which were acquired on April 24, 2005 and October 20, 2006, representing spring and fall phonology respectively.

Classifiers

We compared results from conventional classifiers (Maximum Likelihood Classifier (MLC) and Linear Discrimination Analysis Classifier (LDA)) with machine learning classifiers (Multi-Layer Perceptron Neural Network (MLP) and Classification Tree (CTA)) for mapping land cover types in the two selected regions.

Input metrics (independent variables)

A variety of combinations of input variables were examined for the land cover classifications. The input metrics incorporate original spectral bands (both VNIR and Short Wave Infrared), Normalized Difference Vegetation Index (NDVI) and typicality maps based on the Mahalanobis distance.

Mahalanobis typicality

The concept of typicality probabilities (or simply typicalities) suggests whether it is reasonable to assume that a case actually belongs to a class. They can be derived from the Mahalanobis distance, i.e., the distance between a pixel and the centroid of a multivariate normally distributed class (Foody et al., 1992).

$$Mahalanobis\ Distance^2 = (x-\mu_i)^t V_i^{-1}(x-\mu_i)$$

Where x is the vector of environmental measures at a location, μ is the vector of the mean environmental measures for all known instances of the species in question; V is the variance/covariance matrix of the environmental measures for all known instances of the species in question. Mahalanobis Distance has a χ^2 with degrees of freedom equal to the number of independent variables minus one, which can be used to produce the measure known as Typicality Probability.

Different metrics (combinations of input variables)

a. Sino-Laos border (single date imagery)

1. VNIR (3 variables)
2. VINR+NDVI (4 variables)
3. VNIR+SWIR (9 variables)
4. VNIR+SWIR+NDVI (10 variables)
5. VNIR+ TYPICALITY (10 variables)
6. VNIR+NDVI+TYPICALITY (11 variables)
7. VNIR+SWIR+TYPICALITY (16 variables)
8. VNIR+SWIR+NDVI+TYPICALITY (17 variables)

b. and Thai-Laos border (two-date imagery)

1. VNIR (6 variables)
2. VINR+NDVI (8 variables)
3. VNIR+SWIR (18 variables)
4. VNIR+SWIR+NDVI (20 variables)
5. VNIR+TYPICALITY (14 variables)
6. VNIR+NDVI+TYPICALITY (16 variables)
7. VNIR+SWIR+TYPICALITY (26 variables)
8. VNIR+SWIR+NDVI+TYPICALITY (28 variables)

Validation

In addition to visual inspection, a separated testing site was developed to validate performance of different models. Single Kappa index for rubber class and overall Kappa index were chosen to measure agreement between classification maps and ground truth (from IKONOS).

Results and discussion

Table 1. Accuracy assessment for different classifiers (Sino-Laos Border Area)

Classifier	Metric 1	Metric 2	Metric 3	Metric 4	Metric 5	Metric 6	Metric 7	Metric 8
MLC	0.91/0.50	0.96/0.49	0.58/0.54	0.75/0.56	-	-	-	-
LDA	0.91/0.48	0.91/0.48	0.80/0.48	0.84/0.50	0.88/0.50	0.89/0.50	0.78/0.54	0.85/0.56
MLP	0.96/0.59	0.62/0.59	0.64/0.55	0.90/0.63	0.73/0.44	0.60/0.59	0.38/0.22	0.98/0.67
CTA	0.95/0.37	0.96/0.65	0.88/0.36	0.88/0.46	0.76/0.65	0.86/0.45	-	-

Table 2. Accuracy assessment for different classifiers (Thai-Laos Border Area)

Classifier	Metric 1	Metric 2	Metric 3	Metric 4	Metric 5	Metric 6	Metric 7	Metric 8
MLC	0.95/0.85	0.97/0.64	0.93/0.87	0.96/0.88	-	-	-	-
LDA	0.99/0.61	0.98/0.57	0.99/0.94	0.98/0.86	0.67/0.75	0.98/0.57	0.74/0.66	1.00/0.75
MLP	1.00/0.68	0.00/0.28	1.00/0.96	0.06/0.69	1.00/0.68	0.00/0.48	1.00/0.96	0.11/0.44
CTA	0.92/0.57	0.92/0.57	0.93/0.72	0.93/0.69	0.93/0.69	0.84/0.79	0.93/0.56	0.84/0.92

Value a/b:
a – KIA for Rubber class
b – Over all Kappa

a)

b)

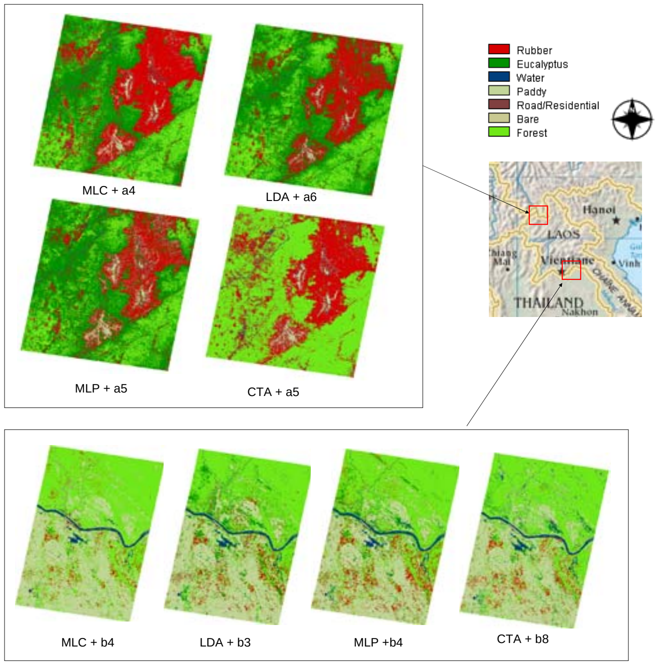

Figure 2 Land use and land cover maps for a) Sino-Laos border; and b) Thai-Laos border

The most reasonable results from different classifiers are listed as above. Incorporating typicalities into input metrics as additional independent variables may improve the capability of prediction, especially for areas that are far from where known samples were collected, and thus increase the capability of generalization. CTA with metrics b8 produced the most reasonable result for Thai-Laos region, while LDA classifier with metric a6 outperformed others for Sino-Laos region. An advantage of using the typicality is that only pixels that are most typical of a particular class as presented in the training sites will be assigned to that class, as such, it greatly reduced the number of pixels that were incorrectly assigned as rubber.

Conclusions

No universally accepted classifiers can be used for large scale mapping. Although decision tree classifiers have been widely applied and been considered as most robust classifiers (Hansen et al, 2006) for global scale mapping, the classification tree used in this study did not outperform conventional classifiers in terms of classifying the Sino-Laos border area. Incorporating SWIR bands, NDVI and Mahalanobis typicalities to ASTER original data may improve classifiers' capability of generalization.

References

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