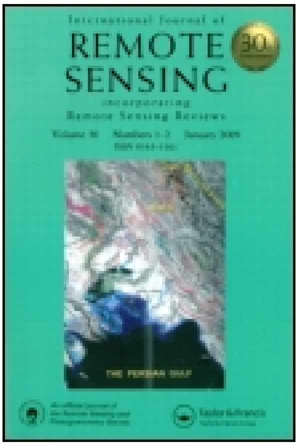

International Journal of Remote Sensing
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tres20

Improving tropical forest mapping using multi-date Landsat TM data and pre-classification image smoothing

C. Tottrup [a]

[a] Institute of Geography, University of Copenhagen, Øster Voldgade 10, DK-1350 Copenhagen K, Denmark E-mail:

Version of record first published: 07 Jun 2010.

To cite this article: C. Tottrup (2004): Improving tropical forest mapping using multi-date Landsat TM data and pre-classification image smoothing , International Journal of Remote Sensing, 25:4, 717-730

To link to this article: http://dx.doi.org/10.1080/01431160310001598926

INT. J. REMOTE SENSING, 20 FEBRUARY, 2004,
VOL. 25, NO. 4, 717–730

Improving tropical forest mapping using multi-date Landsat TM data and pre-classification image smoothing

C. TOTTRUP
Institute of Geography, University of Copenhagen, Øster Voldgade 10, DK-1350 Copenhagen K, Denmark; e-mail: ct@geogr.ku.dk

(*Received 8 November 2001; in final form 15 May 2003*)

Abstract. The present study explores the possibility of using Landsat imagery for mapping tropical forest types with relevance to forest ecosystem services. The central part in the classification process is the use of multi-date image data and pre-classification image smoothing. The study argues that multi-date imagery contains information on phenological and canopy structural properties, and shows how the use of multi-date imagery has a significant impact on classification accuracy. Furthermore, the study shows the value of applying small kernel smoothing filters to reduce in-class spectral variability and enhance between-class spectral separability. Making use of these approaches and a maximum likelihood algorithm, six tropical forest types were classified with an overall accuracy of 90.94%, and with individual forest classes mapped with accuracies above 75.19% (user's accuracy) and above 74.17% (producer's accuracy).

1. Introduction

There are a number of ecosystem services related to the world's tropical forests. These services include the provision of food and raw materials (Lambin 1994), protection against soil erosion, sedimentation and flooding (Douglas 1999), water cycling and impacts on rainfall patterns (Koninck 1999), exceptional biological diversity (Whitmore 1991) and carbon storage in regenerating tropical forests (Foody *et al*. 1996). These forest ecosystem services vary with forest type and consequently knowing the extent of the various forest types becomes important for the effective management of the tropical forests. However, quantitative data on the extent and variation of the tropical forest ecosystem are incomplete and sometimes inaccurate. Often the tropical forests are inadequately mapped due to great survey costs, which are a consequence of the large spatial extent and poor accessibility of these areas. It has therefore been suggested that space-borne sensors have the potential for delivering reliable estimates of the extent, quality and changes of the tropical forests (Foody and Curran 1994). Still, many applications of remote sensing use just one or only a few broad forest classes such as the Landsat Pathfinder project (Chomentowski *et al*. 1994) and the Tropical Ecosystem Environment Observation by Satellite (TREES) project (Achard *et al*. 2001). But the broad categories mapped in these studies fail to deliver valuable and useful information on the variation within the tropical forest environment. A better

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online © 2004 Taylor & Francis Ltd
http://www.tandf.co.uk/journals
DOI: 10.1080/01431160310001598926

impression of the tropical forest environment and related ecosystem services could be achieved with greater classification detail and the full potential of remote sensing for distinguishing tropical forest types has still to be exploited (Hill and Foody 1994). Detecting subtle vegetation changes in diverse tropical forest environments requires relatively high-resolution satellite sensor data and in this sense the Landsat programme offers good value for money in terms of spatial and spectral resolution. The overall objective of the present study is to support tropical forest management by using satellite remote sensing to map tropical forest classes with relevance to forest ecosystem services. In that respect the immediate objectives are to evaluate the ability of the Landsat sensor to map tropical forest classes and to suggest some classification approaches that may be routinely used.

2. Study area

The study area is located in the upper Ca river basin in the province of Nghe An in north-central Vietnam, approximately 300 km south of Hanoi (figure 1). The Ca river flows in a south-eastern direction from Laos into Vietnam and through Nghe An province before it flows into the Bay of Tonkin.

The area is located in a monsoon zone with a cold and dry season from November until March caused by the north-east monsoon and a hot and humid season due to the south-west monsoon (locally called the Lao wind) blowing from April to October. Average temperatures are 22–24°C, with the highest temperatures

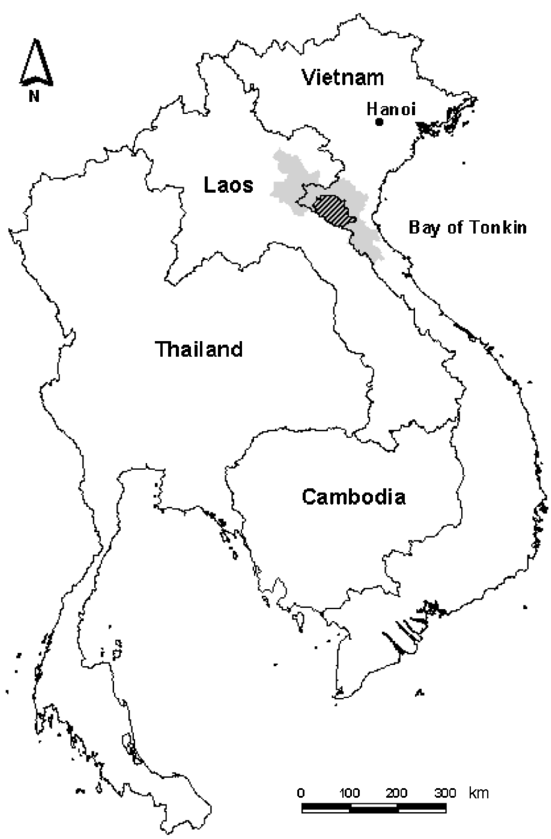

Figure 1. Location map of the Ca River basin (grey region) and the study area (hatching).

reaching 40°C in June, while the lowest temperatures can drop to 5°C around January. Annual precipitation in the upper Ca river basin is close to 1500 mm with a mean humidity of around 80–85% (Cuc *et al.* 1999). Nghe An province has the third largest forest cover in Vietnam although the distribution of forestland is highly variable within the province as a whole. Forests have been destroyed completely at lower altitudes, while deforestation has been less destructive in the midland and mountain regions including the upper Ca river basin where around 40% of the area remains forested (Cuc *et al.* 1999). The dominant forest formation is the broad-leafed evergreen and semi-deciduous tropical moist forest found within the lowland and lower montane zone. Although not as abundant in the upper Ca river basin, true deciduous forest might be found in smaller patches at lower altitudes. Steep limestone formations often referred to as karst are scattered throughout the study region, supporting a special forest environment mainly composed of broad-leafed evergreen trees and shrubs. Bamboo is the natural undergrowth invading abandoned croplands and rapidly growing back in forest openings caused by dead falls or selective logging. Montane forest is found at altitudes above 1200 m above sea level and this forest formation is characterized by the absence of dominating trees and a canopy height typically not exceeding 10 m. The main human activities with respect to the forest environment are traditional shifting cultivation, farming by settled lowland migrants and logging practices. The latter is seen both as high-volume commercial logging and low-volume selective logging carried out by individuals or small groups (Tran *et al.* 2000, Tottrup 2002).

3. Ground data

Ground data were collected during two field trips in the spring of 2000. The ground data were acquired at five main sites. The sites were selected to cover a range of physical and human environments believed to support different forest types. All together 118 samples were collected and the information collected at each sample was geographical location, habitat, land cover, tree height and percentage canopy cover. The information was obtained using a Garmin 12XL Global Positioning System (GPS), compass, clinometer and measuring tape. As real time acquisitions of Landsat Enhanced Thematic Mapper (ETM)+/Thematic Mapper (TM) data could not be guaranteed, an important aspect of the ground observations was to reveal whether the visited sites had undergone changes since the latest known available Landsat TM images from 1998. Moreover, photos and sketches were taken and drawn at most points. All information was recorded on a check-sheet and after the fieldwork was completed a database was created referring all coordinates to their respective attributes. Additionally ground data were available from the European Commission supported programme 'Social forestry and nature conservation in Nghe An province'. These ground data were collected in 1997, 1999 and early 2000. Part of these data was used as support for the classification process while the other part was used as independent reference data in the accuracy assessment.

4. Methodology

Tropical forest mapping from satellite imagery is normally performed using either supervised and/or unsupervised classification techniques. The spectral complexity of tropical forest classes has further led to numerous suggestions for procedures and techniques to improve classifications including for example stratification by ecological zone (Thenkabail 1999, Helmer *et al.* 2000), topographic normalization (Colby and Keating 1998), spatial filtering (Hill and Foody 1994), image segmentation (Hill 1999), object-oriented classifications (Foody *et al.* 1996), vegetation indices (Boyd *et al.* 1996, Helmer *et al.* 2000) and multi-temporal image data (Lucas *et al.* 1993). However, no standardized classification approach has been developed for tropical forest mapping as the approaches vary according to objectives and scale of study, environmental settings and software abilities (Thenkabail 1999). In the following it is suggested that pre-classification image smoothing and the use of multi-date information has the potential for improving tropical forest mapping as well as being routinely used, not the least, due to their sound rationality and ease of implementation. Both methodologies have individually produced promising results (e.g. Conese and Maselli 1991, Hill and Foody 1994) and in the present study their individual and combined ability to improve tropical forest mapping was evaluated using separability analyses, standard measures of accuracy and Kappa analyses. In the following the logic behind image smoothing and multi-date information are presented followed by a brief presentation of the image processing steps.

4.1. *Pre-classification image smoothing*

Low spectral separability of tropical forest types has been observed in Landsat imagery (e.g. Singh 1987, Salas and Brunner 1998). This has mainly been attributed to the rapid regrowth, the constant high level of greenness and the density of the vegetation canopy (Salas and Brunner 1998) and to the complex texture of the reflectance patterns (Hill 1999). The textural complexity becomes especially evident in higher resolution imagery where it has been suggested that for tropical forest classes the in-class spectral difference is significant relative to the between-class spectral variation (Thenkabail 1999, Hill 1999). However, the use of pre-classification image smoothing could suppress the influence of in-class spectral variance while enhancing the between-class spectral separability. A smoothing filter reduces the in-class spectral variability by averaging the pixel values inside a sizeable kernel moved throughout the image. The present study tested the above logic by evaluating the effect of smoothing filters on forest class spectral separability and classification accuracies. It is important to be aware that image smoothing may also blur edges between forest and other land cover classes and thus in heterogeneous landscapes only small sized kernels should be used (Hill 1999).

4.2. *Multi-date information*

Areas with complex topography and heterogeneous surfaces possess an extreme challenge to land cover classifications based on remote sensing. However, multi-date acquisitions are likely to enhance classification possibilities because they supply spectral information related to changing phenological stages (Conese and Maselli 1991) and canopy roughness (Foody and Curran 1994). Variability in reflected energy with the geometry of illumination and observation might be a valuable indicator of canopy roughness (Foody and Curran 1994). Land cover classes are typically non-Lambertian, i.e. they display a class-specific angular reflectance response which is related to surface roughness. Thus forest studies combining spectral information from varying Sun angles could provide a unique spectral response pattern related to canopy roughness. Also vegetation shows well defined variations in spectral responses related to phenological cycles and the acquisition of satellite imagery from different seasons is expected to greatly enhance the discrimination performance of the satellite imagery (Conese and Maselli 1991). The present study investigated the above rationales by comparing single- and multi-date classifications. The multi-date approach assumes that surfaces examined do not vary in extension and distribution between acquisition dates. On the other hand, it should also be evident that the acquisitions should not be too close in time as the success of the multi-date approach depends on phenological changes as well as Sun angle differences.

4.3. *Satellite sensor data and image processing*

Two near cloud-free Landsat TM images, from 15 May 1998 and 7 November 1998, were acquired and co-registered. Thirty-six ground control points were used to rectify the November image to a UTM map projection (zone 48N, datum WGS84) using a nearest neighbour resampling routine that maintained the original 30 m resolution. The second order polynomial transformation had an RMS error of 0.87 pixels. The May image was then co-registered to the November image using an image-to-image registration and resampled with an estimated RMS error of 0.37 pixels. Clouds and cloud shadows were masked out using visual interpretation and on-screen digitizing. All visible and infrared bands were available for the analyses. However, the thermal infrared bands were excluded due to their lower spatial resolution. Also the visible blue bands were excluded, as high minimum histogram entries and low data depths suggested that these bands were affected by atmospheric scattering and with only modest contribution to class separability. Consequently, the feature selection resulted in the following datasets: two single-date 5-band combinations and a multi-date 10-band combination. Each of the feature sets was analysed in three different modes consisting of raw data, 3×3 smoothed data and 5×5 smoothed data. Training and reference data were manually digitized using the ground truth information and various false colour composites. Training classes were grouped according to major physiognomic and structural properties and class separability was investigated using graphical displays and statistical analyses. The statistical analyses were based on the Jeffries–Matusita (JM) distance, which has an upper value of 1.414 ($\sqrt{2}$) indicating maximum separability and a lower value of 0 indicating no separability at all (Jensen 1996). Before the classification it was ensured that all training classes fulfilled the statistical requirement of approximating a Gaussian distribution. Training area statistics were extracted from each of the nine combinations of input bands and filtering modes and used as input for nine individual maximum likelihood classifications. During classifications all classes were set with equal *a priori* values and without any reject fraction. To remove salt-and-pepper noise the resulting images were cleaned using a 3×3 kernel majority filter. In the final part of the study, the nine classification results were compared using standard measures of accuracy and Kappa analyses. The goal was to determine whether there was any statistical verification for using pre-classification image smoothing and the more costly multi-date approach.

5. Results and discussion

5.1. *Separability analysis*

The separability of forest types defined by their major physiognomic properties is seen in figure 2. It appeared that three forest types (evergreen shrub, bamboo and deciduous forest) displayed a high degree of spectral separability. However, the broad-leaf evergreen forest class had a spectral overlap with the karst forest class.

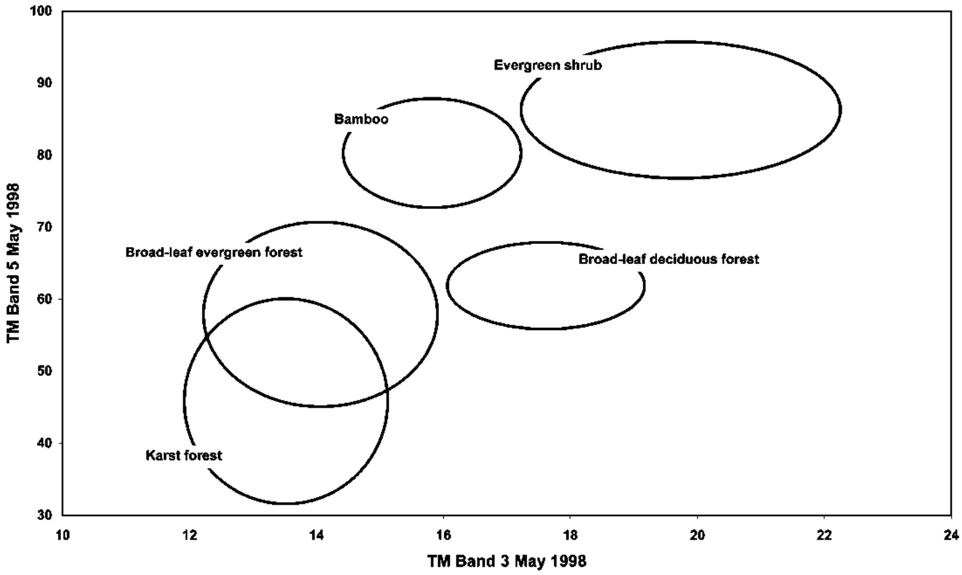

Figure 2. Ellipse scattergraph of training samples for forest physiognomic properties (note: ellipses are one standard deviation from the mean).

Still, the overlap was not considered serious as any classification error between these classes could be considered minor, as the karst forest constitutes a special type of broad-leaf evergreen forest. Instead it was explored whether it was possible to subdivide the broad-leaf evergreen forest class. Human disturbance was expected to have an impact on forest structural properties and therefore it was explored whether the broad-leafed forest class could be divided by means of canopy closure and tree height. It appeared that using only one of these structural properties did not allow for sufficient separability of subclasses (figures 3 and 4). However, by combining the structural properties it was possible to divide the broad-leafed evergreen forest into a primary forest class and a human disturbed forest class denoted by degraded forest. Degraded forest consisted of what in the field was designated as either young secondary forest or open forest. The former represents forest regrowth following clear-cutting activities such as logging and shifting cultivation, while the opening of forest at larger scales is mainly attributed to selective logging practices. For young secondary forest, canopy cover may exceed 50% but tree height is below 15 m. In contrast the open forest class is characterized by an above 15 m tree height but a less than 50% canopy cover. As the two classes were similar in both spectral characteristics and land use (human intervention) it was found appropriate to merge them into a degraded forest class. A full description of the identified forest classes can be found in table 1.

A multidimensional tabular representation of forest class spectral separability using both raw and smoothed data is found in table 2. It appears that image smoothing has the potential for increasing class separability. Although separability could have been slightly improved further using a kernel of 7×7 pixels, it should be stressed that a balance between training class separability and a possible real world blurring must be considered. Especially, it is important to realize that training areas are chosen because of their rather large homogeneous extension and therefore they

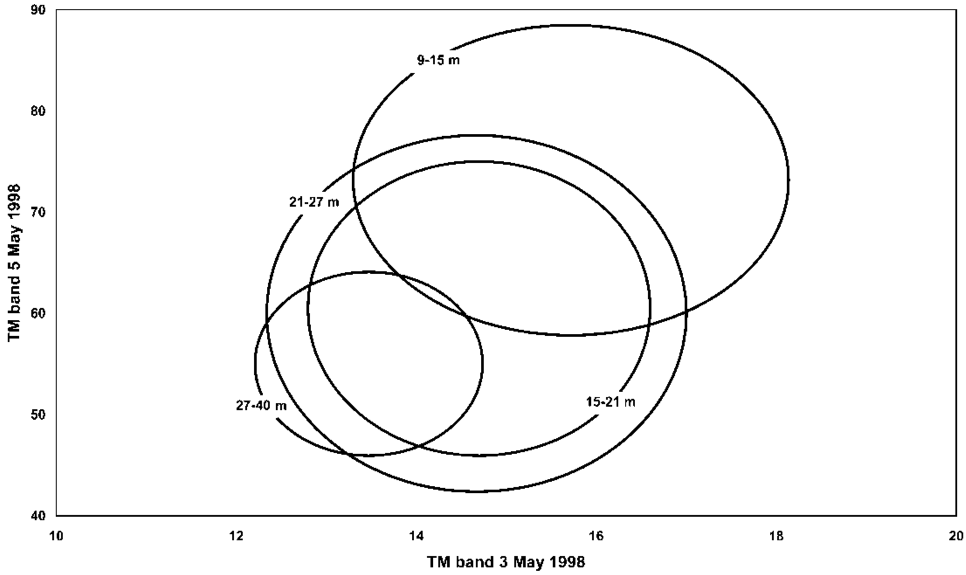

Figure 3. Ellipse scattergraph of training samples for tree height of the broad-leaf evergreen forest class (note: ellipses are one standard deviation from the mean).

do not represent the true heterogeneity of the landscape. For that reason the kernel of 5×5 pixels was chosen as the optimal filter.

The apparent success of image smoothing for enhancing the spectral recognition pattern of tropical forest types is probably related to forest structural patterns. For example, the spectral signature of degraded forest can appear as mature forest in any given pixel, while in some pixels mature forest can appear as degraded forest.

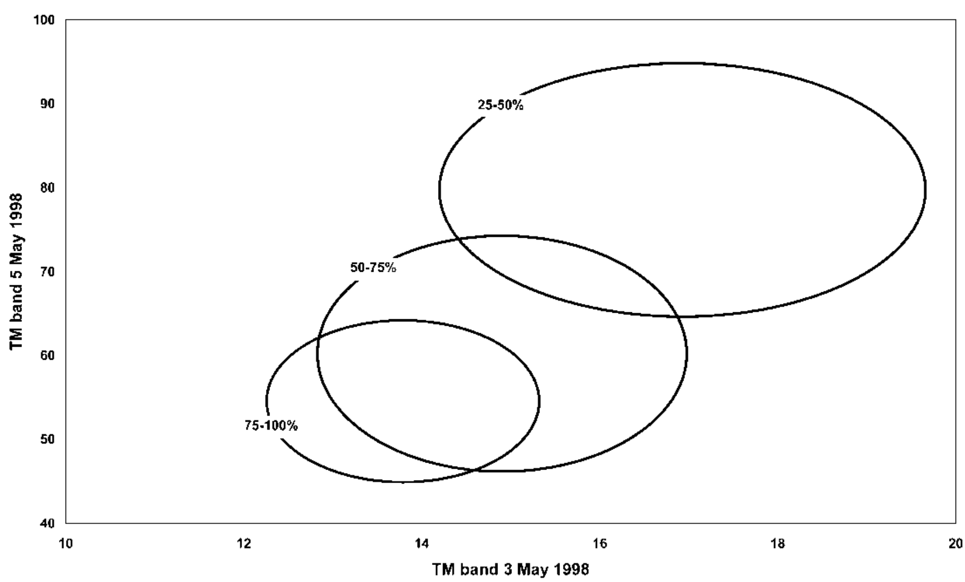

Figure 4. Ellipse scattergraph of training samples for canopy closure of the broad-leaf evergreen forest class (note: ellipses are one standard deviation from the mean).

Table 1. Physiognomic and structural forest types within the upper Ca river basin in north-central Vietnam.

Class name	Description	Subclass	Description
1. Primary forest	Undisturbed broad-leaf evergreen and semi-deciduous forest stands. They are characterized by a canopy closure of more than 50% and tree height various from 18 m to as high as 45+ m. Although designated primary forest this class includes areas that have been exposed to low-volume selective logging as well as old secondary forest (approximately >20 y).	Montane forest	Elfin and pine forests found at altitudes from 1200+ m above mean sea level.
2. Karst forest	Special forest type mainly found on the top and in the cracks of steep limestone formations.		
3. Deciduous forest	True broad-leaf deciduous forest stands. Found below approximately 800 m above mean sea level.		
4. Degraded forest	Forest areas with a considerable human disturbance. These areas might include forest growing back from clear-felling resulting from either shifting cultivation or logging (secondary forest) or areas affected by pronounced selective logging.	Open forest	Broad-leafed evergreen and semi-deciduous forest areas where selective logging has taken place. Canopy closure is below 50% and tree height rarely exceeds 20+ m. Shrub and bamboo are found in the openings followed by selective logging.
		Young secondary forest	Forest growing back in clear-cuts resulting either from agriculture or logging (approximately <20 y). Canopy closure may exceed 50% but tree height is less than 15 m.
5. Bamboo	Areas dominated by bamboo. The term bamboo refers to old, naturally occurring bamboo areas as well as to second growth bamboo following clear felling. Finally some bamboo areas are the result of nursery and planting.		
6. Shrub	Areas dominated by evergreen shrub and bushes reaching a height between 3–9 m. These areas are often associated with fallow vegetation (approximately 2–5 y). Some taller woody species might be interspersed.		

Table 2. Measures of Jeffries–Matistuta derived from raw and smoothed multi-date Landsat TM data.

	[0]	[1]	[2]	[3]	[4]	[5]
(a) Raw data						
[0] Primary forest	–	0.888	1.362	0.876	1.213	1.307
[1] Karst		–	1.341	0.916	1.205	1.279
[2] Deciduous forest			–	1.340	1.359	1.343
[3] Degraded forest				–	0.851	1.129
[4] Bamboo					–	1.026
[5] Shrub						–
(b) 3 × 3 smoothed data						
[0] Primary forest	–	1.051	1.410	0.931	1.308	1.365
[1] Karst		–	1.413	1.106	1.362	1.368
[2] Deciduous forest			–	1.411	1.413	1.409
[3] Degraded forest				–	0.961	1.251
[4] Bamboo					–	1.169
[5] Shrub						–
(c) 5 × 5 smoothed data						
[0] Primary forest	–	1.159	1.414	1.035	1.354	1.390
[1] Karst		–	1.414	1.186	1.393	1.398
[2] Deciduous forest			–	1.414	1.414	1.414
[3] Degraded forest				–	1.060	1.301
[4] Bamboo					–	1.214
[5] Shrub						–

This also applies for other spectral similar classes such as degraded forest versus bamboo and bamboo versus shrub. It follows that this would lead to classification errors when analysing on a per pixel basis using raw data. However, these dissimilar spectral pop-ups are moderated in the smoothing process where deviating spectral values are replaced with an average value within a user-determined kernel.

5.2. *Classification accuracy*

The classification performances were evaluated using independent reference data and standard measures of accuracy and Kappa analyses. A comparison of the overall accuracy, Kappa agreement and Zeta statistics for all nine classifications are found in table 3 while the resulting classification error matrix of the best achieved classification is seen in table 4.

From table 3 it appears that all band combinations are significant at the 95% confidence level, i.e. they fail the null-hypothesis that the classifications are no better than a random assignment of pixels (Congalton 1991). Furthermore, the table clearly displays the strength of the methodology with generally improved accuracies when using image smoothing and a multi-date band combination. The success of the multi-date approach can be understood as a function of: (1) a sufficient time between image acquisitions that assured a different geometry of illumination caused by significant Sun angle changes; (2) the satellite scenes being acquired at different seasons and thus representing varying phenological stages. The argument that image smoothing and multi-date imagery produces better results can be further validated by using Kappa analyses to compare individual matrices two at a time to determine whether they are significantly different (Congalton and Green 1998). A comparison of raw versus filtered data and of the single-date versus the multi-date approach are found in table 5.

Table 3. Overall accuracy measures, Kappa analysis results and test of significance for individual maximum likelihood classifications.

Band combination	Filter	Overall accuracy (%)	Kappa statistic (%)	Variance	Z statistic*
TM 2, 3, 4, 5 and 7 May 1998	None	59.39	46.90	0.0004208	22.9
TM 2, 3, 4, 5 and 7 Nov. 1998	None	70.84	60.70	0.0004385	29.0
TM multi-date 1998	None	79.57	72.56	0.0003292	40.0
TM 2, 3, 4, 5 and 7 May 1998	3×3 smoothed	71.66	62.59	0.0003827	32.0
TM 2, 3, 4, 5 and 7 Nov. 1998	3×3 smoothed	76.74	68.69	0.0003709	35.7
TM multi-date 1998	3×3 smoothed	85.83	81.09	0.0002453	51.8
TM 2, 3, 4, 5 and 7 May 1998	5×5 smoothed	79.34	72.30	0.0003472	38.8
TM 2, 3, 4, 5 and 7 Nov. 1998	5×5 smoothed	76.03	68.43	0.0003485	36.6
TM multi-date 1998	5×5 smoothed	90.94	88.40	0.0001745	66.1

*$Z_c=1.96$ at the 95% confidence level. H_0: $K=0$ is rejected when $Z>Z_c$.

Table 4. Classification error matrix. Based on the maximum likelihood classification of a 5×5 smoothed multi-date Landsat TM dataset.

	Reference data								
Classified	[0]	[1]	[2]	[3]	[4]	[5]	[6]	Row total	User's accuracy (%)
[0] Primary forest	335	2	0	2	0	0	–	339	98.82
[1] Karst	0	142	0	0	0	0	–	142	100.00
[2] Deciduous forest	0	0	59	0	0	0	–	59	100.00
[3] Degraded forest	0	0	0	97	24	8	–	129	75.19
[4] Bamboo	0	0	0	10	89	4	–	103	86.41
[5] Shrub	0	0	0	5	7	101	–	113	89.38
[6] Other	0	0	5	10	0	5	–	20	
Column total	335	144	64	124	120	118	–	*905*	
Producer's accuracy (%)	100.00	98.61	92.19	78.23	74.17	85.59			
Accurately classified pixels (along diagonal)					823				
Total number of pixels used for reference					905				
Overall classification accuracy					90.94%				
Overall Kappa statistics					88.40%				

Table 5. Kappa analysis results for the pairwise comparison of error matrices.

Pairwise comparison I	Z statistic*	Pairwise comparison II	Z statistic*
Raw vs 5×5 smoothed (May 1998)	9.1717	May 1998 vs November 1998	1.4686
Raw vs 5×5 smoothed (November 1998)	2.7593	May 1998 vs Multi-date 1998	6.6048
Raw vs 5×5 smoothed (Multi-date 1998)	6.5753	Nov. 1998 vs Multi-date 1998	8.3076

*$Z_c=1.96$ at the 95% confidence level. H_0: $(K_1-K_2)=0$ is rejected when $Z>Z_c$.

The figures in table 5 are consistent with the above arguments and show that it is statistically significant to apply image smoothing and incorporate multi-date imagery when mapping tropical forest types. Besides, it is noteworthy that there is a statistical agreement between the two single-date approaches, i.e. classifications based on either May or November imagery do not differ significantly. In figure 5 there is a presentation of the final forest and land cover map. Note that a number of non-forest classes have been mapped as well. However, due to lack of independent reference data the classification accuracy of the non-forest classes has not been assessed. Still, with regard to the specific objective concerning the forest classes, it is important to stress that classification errors induced by non-forest classes on forest classes is very limited (cf. table 4).

6. Conclusion

Information on tropical forest quality is essential for the effective management of forest resources since regarding the tropical forest as a homogeneous unit may over- or underestimate the ecosystem services provided by the tropical forest. It is therefore important to develop methodologies that can locate and quantify various types of tropical forest. The use of remote sensing has been suggested as a suitable and cost-efficient way to provide this information. The present study has

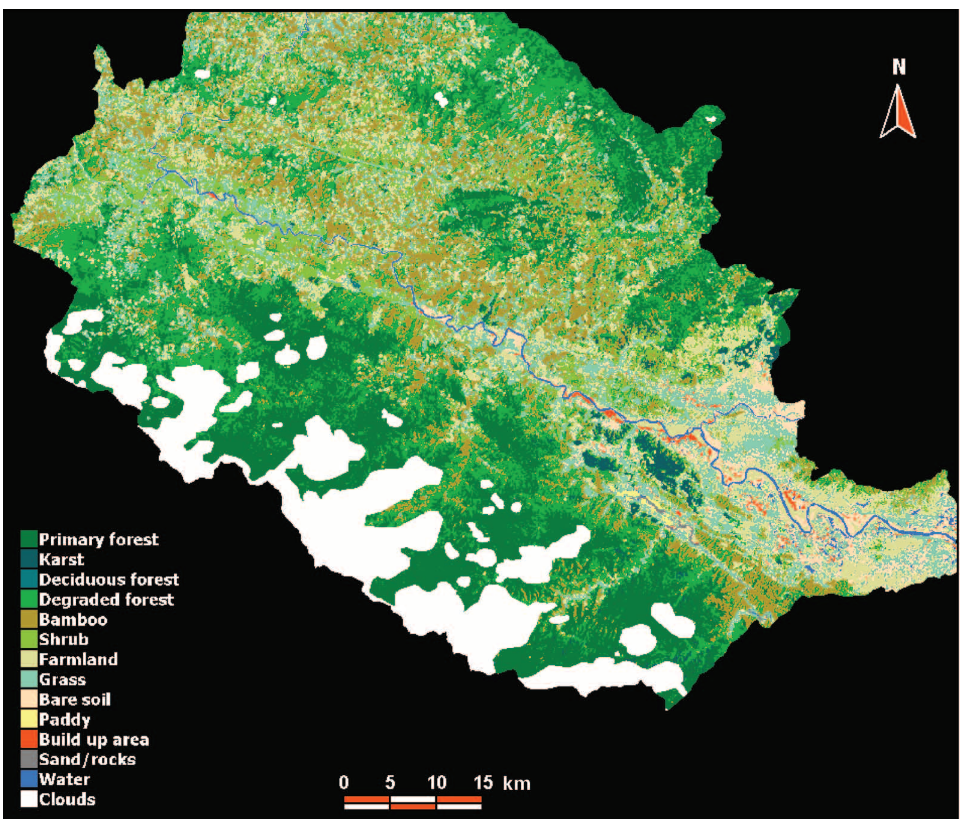

Figure 5. Forest and land cover map of the upper Ca River basin in north-central Vietnam. The map is the result of a maximum likelihood classification of a 5×5 smoothed multi-date Landsat TM dataset.

demonstrated how Landsat TM data with simple classification approaches can be used to map several tropical forest types. Forest types were identified using forest physiognomic and forest structural properties and the potential for mapping such forest types was evaluated using raw versus smoothed input data and single- versus multi-date image information. The use of separability analyses showed how small kernel pre-classification image smoothing effectively helped to reduce in-class spectral variability while enhancing between-class spectral differences. The impact on the classification was improved overall accuracies. This was further supported by Kappa analysis comparisons, showing a significant improvement in classifications based on smoothed input data relative to raw input data. Furthermore, the study argued that multi-date imagery contains information on canopy structural properties and phenological changes and has the potential to improve classification accuracies. The multi-date approach was tested against two single-date classifications and the value of using multi-date information was evident in terms of a higher overall classification accuracy and a statistical significant improvement in classification results. The highest classification accuracy was achieved when using both pre-classification image smoothing and multi-date imagery. Doing that, it was possible to map six forest types with an overall accuracy of 90.94% and with individual forest types mapped with accuracies above 75.19% (user's accuracy) and above 74.17% (producer's accuracy). The simplicity and rationale of both pre-classification image smoothing and multi-date imagery indicates that they have the potential for being routinely applied in tropical forest mapping. However, in an operational context, two aspects concerning the multi-date approach must be considered. The first is the increased cost of using an additional satellite scene, which could make the approach less attractive. However, the argument has lost some significance as the new pricing policy followed by the launch of Landsat 7 now means that Landsat data can be obtained at very reasonable costs. Also, it can be expected that the cost of remote sensing data will decrease in the future as the number of instruments with Earth resource mapping capabilities increases. Secondly, the main limitation to a multi-date approach is the possibility of acquiring satellite scenes of adequate quality. The use of optical sensors in humid regions is hampered by high occurrences of clouds and thus the acquisition of several cloud-free satellite scenes at crucial times within a year can be difficult. Nevertheless, when successfully applied, the prospect of the study has high relevance for improved natural resource management as it gives an up-to-date synoptic view of the state of the tropical forest with information related to forest ecosystem services. The study, however, does indicate a number of recommendations for future research. For example, there is a need to elaborate methodologies that can distinguish between various classes of degraded forest as each class has its own economic, social and environmental impacts as well as its own management implications. In that sense microwave backscatter measured by Synthetic Aperture Radars (SAR) may have the potential to improve tropical forests mapping by providing information on leaf and woody biomass as well as canopy roughness (Foody and Curran 1994). Furthermore, it appears that the only practical solution to cloud cover might be to increase the temporal resolution through a multiple satellite sensor approach. This would enhance the possibility for acquiring cloud-free imagery and thus assure a better continuality in tropical forest inventories using satellite remote sensing. The latter is important as the dynamics of tropical forest ecosystems should be investigated using satellite imagery with annual or near-annual repeatings.

Acknowledgments

I would like to thank Dr Michael Schultz Rasmussen from the Institute of Geography (University of Copenhagen) for his encouragement, good discussions and valuable advice. Moreover, I am grateful for the support from Dr Tran Duc Vien and his staff at the Centre for Agricultural Research and Ecology Studies (CARES) at Hanoi Agricultural University. In this respect a very special thank you to Dr Pham Tien Dung and Mai Van Thanh from CARES for their assistance during the field trips in Nghe An province. A thank you also to Stephen Leisz and 'Social forestry and nature conservation in Nghe An province' for data sharing and helpful advice. The financial support for the research came from the Danish component of the Resource Policy Support Initiative (REPSI) phase II 1999–2001 (administration by NORDECO and funding by DANIDA) and a grant from the World Wildlife Fund, 'WWF Verdensnaturfonden/Novo Nordisk biodiversitetslegat'. I highly appreciate this support.

References

ACHARD, F., EVA, H., and MAYAUX, P., 2001, Tropical forest mapping from coarse spatial resolution data: production and accuracy assessment issues. *International Journal of Remote Sensing*, **22**, 2741–2762.

BOYD, D. S., FOODY, G. M., CURRAN, P. J., LUCAS, R. M., and HONZAK, M., 1996, An assessment of radiance in Landsat TM middle and thermal infrared wavebands for the detection of tropical forest regeneration. *International Journal of Remote Sensing*, **17**, 249–261.

CHOMENTOWSKI, W., SALAS, B., and SKOLE, D. L., 1994, Landsat Pathfinder project advances deforestation mapping. *GIS World*, **7**, 34–38.

COLBY, J. D., and KEATING, P. L., 1998, Land cover classification using Landsat TM imagery in the tropical highlands: the influence of anisotropic reflectance. *International Journal of Remote Sensing*, **19**, 1479–1500.

CONESE, C., and MASELLI, F., 1991, Use of multitemporal information to improve classification performance of TM scenes in complex terrain. *ISPRS Journal of Photogrammetry and Remote Sensing*, **46**, 187–197.

CONGALTON, R. G., 1991, A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, **37**, 35–46.

CONGALTON, R. G., and GREEN, K., 1998, *Assessing the Accuracy of Remotely Sensed Data—Principles and Practices* (Washington, DC: Lewis Publishers).

CUC, L. T., TRAN, D. V., HUNG, D. T., and SON, H. V. (eds), 1999, Ca river basin environmental impact assessment. Center for National Resources and Environmental Studies (CRES), Hanoi, Vietnam.

DOUGLAS, I., 1999, Hydrological investigations of forest disturbance and land cover impacts in South-East Asia: a review. *Philosophical Transactions of the Royal Society of London, Series B*, **354**, 1725–1738.

FOODY, G. M., and CURRAN, P. J., 1994, Estimation of tropical forest extent and regenerative stage using remotely sensed data. *Journal of Biogeography*, **21**, 223–244.

FOODY, G. M., PALUBINSKAS, G., LUCAS, R. M., CURRAN, P. J., and HONZAK, M., 1996, Identifying terrestrial carbon sinks: classification of successional stages in regenerating tropical forest from Landsat TM data. *Remote Sensing of Environment*, **55**, 205–216.

HELMER, E. H., BROWN, S., and COHEN, W. B., 2000, Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery. *International Journal of Remote Sensing*, **21**, 2163–2183.

HILL, R. A., 1999, Image segmentation for humid tropical forest classification in Landsat TM data. *International Journal of Remote Sensing*, **20**, 1039–1044.

HILL, R. A., and FOODY, G. M., 1994, Separability of tropical rain-forest types in the Tambopata-Candamo reserved zone, Peru. *International Journal of Remote Sensing*, **15**, 2687–2693.

JENSEN, J. R., 1996, *Introductory Image Processing—A Remote Sensing Perspective* (New Jersey: Prentice Hall).

KONINCK, R. D., 1999, Deforestation in Vietnam. International Development Research Center, Ottawa, Canada.

LAMBIN, E. F., 1994, *Modelling Deforestation Processes: A Review*. TREES Series B, Research Report No. 1, EUR 15744 EN (Brussels: European Commission).

LUCAS, R. M., HONZAK, M., FOODY, G. M., CURRAN, P. J., and CORVES, C., 1993, Characterizing tropical secondary forests using multi-temporal Landsat sensor imagery. *International Journal of Remote Sensing*, **14**, 3061–3067.

SALAS, B., and BRUNNER, J., 1998, Technical guide for change detection with multi-temporal Landsat data: Ca river basin forest cover analysis. Complex Systems Research Centre, University of New Hampshire, USA. http://www.wri.org/pdf/repsi_brunner2.pdf.

SINGH, A., 1987, Spectral separability of tropical forest cover classes. *International Journal of Remote Sensing*, **8**, 971–979.

THENKABAIL, P. S., 1999, Characterisation of the alternative to slash-and-burn benchmark research area representing the Congolese rainforests of Africa using near real time SPOT HRV data. *International Journal of Remote Sensing*, **20**, 839–877.

TOTTRUP, C., 2002, Deforestation in the upper Ca river basin in north central Vietnam—a remote sensing and GIS perspective. Geographica Hafniensia C12, University of Copenhagen, Denmark.

TRAN, D. V., HUONG, P. T., and RASMUSSEN, M. S., 2000, The social and environmental dimensions of changes in land use in the Ca river basin, Vietnam. In *Institutions, Livelihoods and the Environment: Change and Response in Mainland Southeast Asia*, edited by A. Straub (Copenhagen: Nordic Institute of Asian Studies).

WHITMORE, T. C., 1991, *An Introduction to Tropical Rain Forests* (Oxford: Clarendon Press).