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Detection of forest clearance and shifting cultivation in the Nam Ton watershed, Lao PDR

Stijn Cleemput[1,2] and Andras Balazs [1,2]

Under the supervision of:
Professor Dr. Christoph Kleinn
The Institute of Forest Management and Yield science

Faculty of Forestry
Georg-August-University of Göttingen

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email: 1,2 stijncleemput@yahoo.com
1,2 sumi76@gmail.com
Ckleinn@gwdg.de

TABLE OF CONTENTS

1. Research problem and justification

Until now the statistical evaluation of land use cover maps is very soberly described in literature. Due to increasing availability of data sources, datasets are becoming more than ever heterogeneous and complex to interpret. By identifying the above identified shortcoming, the following research question has been derived:

What is the best methodology and dataset choice comparing unsupervised and supervised classification techniques vs. multitemporal corrected imagery comparison based classification methods for natural vegetation dynamical monitoring (more specifically shifting cultivation and forest clearance) in Laos?

2. Methods

2.1 Experimental site and materials

The Nam Ton watershed its lower and central part is located in the Sangthong district, whereas its upper part is situated in the Hinheup district. The available dataset consists of detailed Landsat images (1993, 1997, 2000 and 2002) supported by Spot data (2003) and reference multispectral aerial photographs (1995) that cover the Southern part of the watershed and panchromatic photographs (1997).

2.2 Multi-temporal image classification

The image to image comparison is based on a conversion of the digital values of the raw satellite image into a combination of spectral values, which shows a better contrast between cleared and vegetated areas. Before analysis of the raw Landsat images, ortho-rectification and a precise geometric registration of the Landsat images were necessary while individual pixel values were combined over the different years.

The single images where enhanced by applying different spectral enhancements i.e. vegetation indexing, principal components analysis (bands 1,2,3) and tasseled cap transformation. Image segmentation was compared with image classification: the unsupervised classification algorithm classified the stack of enhanced images into an ad hoc number of 250 classes. These 250 clusters were grouped into 8 final classes (Figure 1). This aggregating step was a rather subjective decision, while a high spectral complexity, is present in the classified image (Duda and Canty 2002).

Class	1997	2000	2002
VVV	VEGETATED	VEGETATED	VEGETATED
CCC	CLEARED	CLEARED	CLEARED
VCC	VEGETATED	CLEARED	CLEARED
CCV	CLEARED	CLEARED	VEGETATED
CVC	CLEARED	VEGETATED	CLEARED
VCV	VEGETATED	CLEARED	VEGETATED
CVV	CLEARED	VEGETATED	VEGETATED
VVC	VEGETATED	VEGETATED	CLEARED

Figure 1 landcover classes and their respective mapping codes

The image segmentation (eCognition 3.0), required an additional standard deviation enhancement and the training of the classes (8) the image was classified using an algorithm based on a fuzzy classifier with the standard Nearest Neighbours.

2.3 Post-classification

Prior to any processing of the satellite images, ortho-rectification was done by the Image Geometric Correction Tool of ERDAS. Using the post-classification technique the satellite images were classified individually, i.e. the pixels of the images were sorted into previously defined landcover classes.
After intensified groundtruthing following classes were determined

- Forest
- Bamboo
- Mixed Low Vegetation
- Cropland and Settlement
- Water
- Shadow

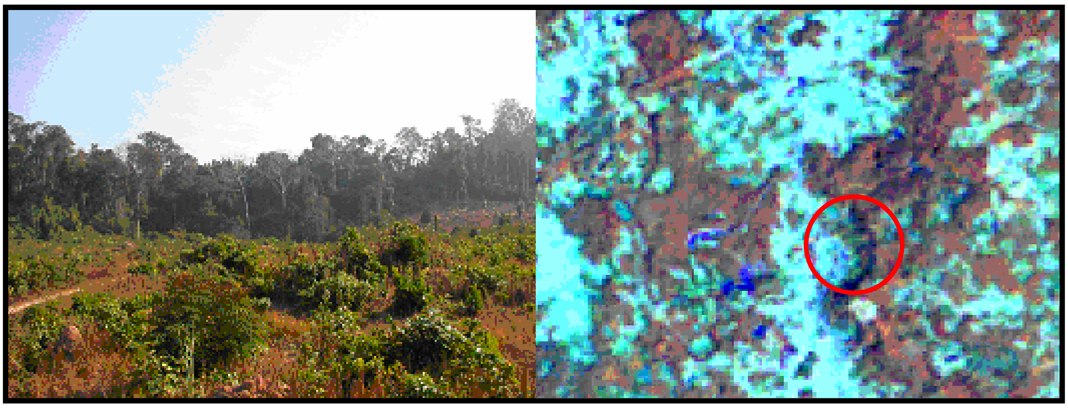


Figure 2. Appearance of the forest on the Landsat ETM 2002 image shown on the picture above

2.4 Supervised vs. unsupervised training, extrapolation

- **Unsupervised training**

The unsupervised classification was carried out with ERDAS IMAGINE 8.6 software. In order to perform unsupervised classification ERDAS is using ISODATA clustering method. According to Vogelmann et al. (1998), one hundred clusters were derived in the classification with the maximum number of iterations set to 25 and convergence threshold set to 0.95.
Afterwards, the generated clusters were investigated and assigned with the Grouping Tool of ERDAS to one of the landcover classes.
However, there were difficulties to classify some clusters possibly belonging to more than one class. This occurred mostly in the “Forest” and “Bamboo” classes. In the case of vagueness, 30 randomly distributed control points were set in the respective cluster and using the principle of simple majority, the decision was made.

- **Supervised training**

1000 circles with 25 m radius were randomized distributed in ArcView 3.2 on the satellite images. This small size of the plots is used to avoid the unwanted edge effect or mixed pixels. The high number of plots made it possible to gain enough suitable training areas for each class. The selection process was done with the help of the aerial photographs from 1995 and 1998 and the SPOT image from 2003. For each of the classes "Forest", "Bamboo" and "Mixed Low Vegetation" the first 30 plots that were representative for the respective class were selected. The classes "Cropland and Settlement" and "Shadow" are significantly more homogenous than the previous three. In these classes, the first 15 plots were accepted as training areas for the supervised classification. Due to the low coverage of the class "Water", there was no plot placed in this category. The missing signature was provided manually by 10 training areas in the Signature Editor application of ERDAS IMAGINE 8.6. This method is acceptable, as this class is of low importance and its occurrence on the image is obvious.
The shape file with the selected plots and the image were opened in the Viewer of ERDAS and the signatures, with the help of the selected plots, were produced in the Signature Editor.

- **Extrapolation**

The supervised classification was conducted after merging the signatures belonging to the same class. The following settings have been used for the classification process: None-parametric rule: None, Parametric Rule: Maximum Likelihood.
For the unsupervised method the extrapolation results into clusters for which the ground truth values or real terrain values are sometimes difficult to define, this requires a high necessity of ground truth knowledge.

2.5 Accuracy assessment for the post-classification

Equalised stratified random sampling combined with cluster sampling was carried out. Because of the irrelevance of the classes „Shadow“ and „Water“, these are excluded from the accuracy assessment. More attention has been paid to the investigation of the other four classes ("Forest", "Bamboo", "Mixed Low Vegetation", and "Cropland and Settlement"). The images were subdivided into these four strata. The subdivision can be easily done with the Accuracy Assessment application of ERDAS by determining the class in which the sample units should be set in each class (stratum) 50 sample plots were placed (Congalton 1991). The properties of the sample plots are defined in the Assignment Options window as following: Window Size: 3 by 3 pixels, Window Majority Rule: Clear Majority. The plots are the primary sampling units (PSUS) of the sample. The secondary sample units (SSUS) are the pixels belonging to the class in which the clusters were set.
The Clear Majority Rule used by ERDAS means that windows will be selected, in which the number of the pixels of the investigated class is at least equal to the number of the pixels of the other single classes in the window. For instance if 3 classes are represented in the window each by 3 pixels it is enough for this window to be selected.

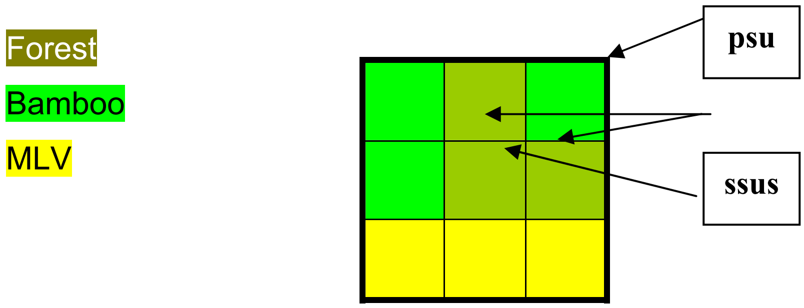


Figure 3 3x3 sample plot set in the class "Forest"

Since in one window the pixels of six different classes can occur, the pixel number of the investigated class in the window can theoretically vary between 2 and 9. The plots were marked by the coordinates of the centre pixel. These coordinates were used to project the plots in ArcView 3.2. The plots were framed afterwards to facilitate the recognition of the pixels belonging to the 3x3 window.

The result of the assessment was noted in Excel tables as shown below.

Table 1. Accuracy assessment table for sample plots in the "Forest" class

Forest	Class				
No. Of Plot	Forest	Bamboo	MLV	C and S	Total pixel no./plot
1	8	1			9
2	2	3			5
3	9				9
4	7				7
5	5	1			6
6	8	1			9
7	5	1			6
8	9				9
9		3			3
10	4	4			8
11	8	1			9
12	9				9
13	4	1			5
…					
45	7	1			8
46	3	5			8
47	4	3			7
48	7	2			9
49	5	3			8
50	6	2			8
Total	295	60	0	0	355

Error matrices and accuracy indicators could be computed for the classified images and for the investigated classes based on the preceding information.

According to Stehman (1997) User's, Producer's and Overall Accuracy, Kappa Indexes were calculated the same way as it has to be done in the case of simple random sampling.

Table 2.: Error matrix of the supervised classified Landsat ETM 2002 image

		Reference Data						
Classified Data	Class	Forest	Bamboo	MLV	C and S	Row Total	User's Accuracy	Conditional KS Coeff.
	Forest	298	32	0	0	330	90	0,88
	Bamboo	37	328	10	0	375	87	0,71
	MLV	0	27	255	46	328	78	0,72
	C and S	0	3	45	240	288	83	0,82
	Column Total	335	390	310	286	1321	Overall Accuracy: 85% KS: 0,76	
	Producer's Accuracy	89	84	82	84			

However Stehman (1996) recommends a different Kappa-estimator (KS) for use with stratified sampling.

$$KS = \frac{N \sum_{h=1}^{q} \hat{N}_{hh} - \sum_{h=1}^{q} N_h \hat{M}_h}{N^2 - \sum_{h=1}^{q} N_h \hat{M}_h}$$

Where:

N = total pixel number of the image,

N_h = total pixel number of the hth class,

N_{hh} = number of correctly classified pixels in the hth class,

M_h = number of pixels belonging truly to the hth class,

n_h = total pixel number of the hth class in the sample,

n_{hh} = number of correctly classified pixels of the hth class in the sample,

n_{hj} = value of the error matrix in the hth row and the jth column,

$\hat{N}_{hh} = \frac{N_h}{n_h} n_{hh}$ unbiased estimator of N_{hh},

$\hat{M}_h = \sum_{h=1}^{q} \frac{N_h}{n_h} n_{hj}$ unbiased estimator of M_h.

It is also possible to calculate a measure of agreement for each class by using the Conditional KS Coefficient. This is calculated for the hth class as:

$$CKS_h = \frac{N\hat{N}_{hh} - N_h \hat{M}_h}{NN_h - N_h \hat{M}_h}$$

Using the method described above (new set of sample plots for every image) the results of the assessments of the single images are independent. This means that the accuracy of the changes between two dates can only be approximated by multiplying the overall accuracies of

the images. Thus the results of the previous method are used to calculate the accuracy of the single images and classes and derive area estimations of the individual classes.
In order to achieve appropriate results on the accuracy of the changes the assessment was performed using the set of sample plots applied for the Landsat TM 1993 image.
At first it was necessary to predefine which pixels should be examined.
In the case of the 1993 image an equalized stratified random sampling is given. To use this advantage the pixels have been investigated which were belonging to the class in which the sample plots were set on the 1993 image. This class was conditionally represented by equal or higher numbers of pixels in the sample plot than the other ones. If it was not fulfilled the pixels of the class which had a clear majority in the sample plot would have been examined.
If an equal number of pixels of three different classes occur in the plot (the pixels of the class in which the sample plot was set are obviously excluded in this case) one class will be chosen optionally. If this situation arises again another class will be chosen following this optional sequence. This is reasonable, since the situation occurred only several times, and the results were solely needed for assessing the overall accuracy of the images.

2.6 Accuracy assessment for the multi-temporal image

The accuracy assessment of the multi temporal image was undertaken by setting an equalized stratified random sample of 30 plots (3 x 3 pixels) for every class (Devries 1986) for the different classifications. These plots were validated with the unclassified calibrated individual satellite images (without enhancements). An additional validation of the land cover change classes came from knowledge based upon experiences of groundtruthing in the watershed. This referencing with the raw satellite image is not significantly different than one prepared with an independent vector data base such as aerial photography interpretation and ground truth methods (Cohen et al. 1998).

When a match between the simple clear majority of an image interpreted pixel frame and the most common class within a 3 by 3 pixel block centered on the sample pixel was obtained a positive result was reported (USGS 2004). This comparison takes into consideration that, for many applications, a certain level of spatial generalization from the original resolution (28.5 meters) land cover data is appropriate (USGS 2004). The estimates based on this comparison likely have an 'optimistic bias' because larger areas are homogeneously and generally easily identified. A reason for this non-single pixel based comparison is that the individual pixels are sometimes not overlapping in the different years, due to geometric distortions from the geometric model. Another advantage is that the accuracy assessment is not so time consuming, while there is no need to validate each and every pixel for every year.

The simple clear majority assignment option in Erdas Imagine 8.6 was chosen. This option selected only frames where the central pixel colour was the dominant one. When for example three pixels of one colour represented the simple clear majority (in this case it means that other classes are present at a maximum number of 2 pixels), only these three pixels were evaluated with the reference. When these three pixels were correctly classified its assignment had a positive result if these pixels were not assigned into the right class the class that was better suited was assigned. When the number of pixels belonging to the same class was equal, the central pixel colour was chosen for comparison against the reference data.

With the information out of the accuracy assessment, an error matrix was generated for the calculation of the producer's accuracy, user's accuracy and the overall accuracy of the classifications. This error matrix is based on the total number of counted pixels of the simple clear majority inside each frame. The summation of all the number of pixels for each sample weighs the intensity of every clear majority assignment. The advantage of including this intensity value helps relating the individual pixel values with the total area that is assessed in the accuracy assessment. Additionally a kappa coefficient was calculated. The Kappa coefficient gives a value for how much percent of the values that are classified by chance. This Kappa coefficient was calculated for comparing the accuracy of all three change detection techniques (Guild et al. 2004).

In addition a qualitative ground truthing was organized. The goal of this qualitative assessment of the change detection map was to compare what we see on the transformed images with what was available on the ground. The ground control points taken during the survey were referenced in the field with a Landsat satellite image of 2002 in a first round in a second round they were verified with a transformed tasseled cap composite map. During this ground truthing attention was given for the different vegetation types and the areas of change (burning sites, shifting cultivation, logged sites).

The pixel counting as area estimator, described by Gallego (2004) is used for the area estimation. This area estimation was done by counting the number of pixels classified as c and multiplying by the area represented by each pixel. This method doesn't exclude the bias caused by (a) the presence of mixed pixels and (b) misclassification of pure pixels.

It was not possible to correct the bias caused by mixed pixels this because no additional ratio estimators were calculated to find out the percentage of mixed pixels. Therefore this area calculation is still biased with an unidentified number of mixed pixels.

However the accuracy assessment can be still very helpful in correcting the estimation for its amount of misclassified pixels. Additionally the calculation of the confidence intervals for the areas can give a better idea for the bias of the estimate

When using the accuracy assessment for correcting the number of misclassified pixels it is required to firstly calculate the ratio estimators and the standard errors of the individual classes (Shiver and Borders 1996)

2.7 Confidence intervals

Following different formulae were used to calculate the confidence intervals for the different strata (Shiver and Borders (1996) (where Zc = 1.96 or the value of the standard normal distributed value at a confidence level of 95%).

Calculation of the ratio estimator: $\hat{R}_j = \frac{\sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} x_i}$

$\hat{R}$j = ratio estimator for one class in the jth stratum
yi = number of investigated pixels of one class in the ith cluster of the jth stratum
xi = total number of investigated pixels in the ith cluster of the jth stratum
n = number of clusters (30 – multi-temporal image) (50 - post-classification)
j = number of strata (8 - multi-temporal image) (4 – post-classification)

Calculation of the standard error: $S_{\hat{R}j}^2 = \frac{1}{\mu_x^2} \frac{S_{uj}^2}{n} \left(\frac{N_j - \sum_{i=1}^{n} x_i}{N_j} \right)$

Due to the big size of the stratum: $\frac{N_j - \sum_{i=1}^{n} x_i}{N_j}$ ≈ 1.

$$S_{uj}^2 = \frac{\sum_{i=1}^{n} y_i^2 + \hat{R}_j^2 \cdot \sum_{i=1}^{n} x_i^2 - 2\hat{R}_j \cdot \sum_{i=1}^{n} x_i y_i}{n-1}$$

$$\mu_x \approx \frac{\sum_{i=1}^{n} x_i}{n}$$

μ_x = population mean
After this the results in each stratum can be summarized, according to Kleinn (2002) and Scheaffer et al. (1996):

$$\bar{y} = \sum_{j=1}^{4} w_j \cdot \hat{R}_j$$

$\bar{y}$ = sum of the weighted ratio estimators of one class
wj = weight of the ith stratum

$$w_j = \frac{N_j}{M}$$

Nj = total pixel number of the ith stratum
M = total pixel number of the image
The variance is calculated according to Scheaffer et al. (1996): $\hat{\mathrm{var}}(\bar{y}) = \sum_{j=1}^{4} w_j^2 \cdot S_{\hat{R}j}^2$

The confidence interval was calculated with the following formula, at 95% confidence level z=1,96: $\bar{y} \cdot 100 \pm z \cdot \sqrt{\hat{\mathrm{var}}(\bar{y})} \cdot 100$

<u>Example</u>: the confidence interval of the VVV class is calculated;

Stratum	VVV					…	VCV			VCC				CVC				
classes	vvv	vvc	…	cvc	cvv	…	vvv	…	cvv	vvv	…	cvc	cvv	vvv	…	vvc	cvc	cvv
Σyi	236		…			…	3	…		3	…			17	…			
Σyi²	2076		…			…	9	…		9	…			73	…			
Σxi*yi	2076		…			…	9	…		9	…			73	…			
Σxi²	2247		…			…	723	…		534	…			573	…			
Σxi	257		…			…	143	…		124	…			127	…			
Nj	583411		…			…	30672	…		8046	…			4402	…			
M	725940																	

Standard error: $\bar{y}_{vvv} = \frac{583411}{725940} \cdot \frac{236}{257} + \frac{30672}{725940} \cdot \frac{3}{143} + \frac{8046}{725940} \cdot \frac{3}{124} + \frac{4402}{725940} \cdot \frac{17}{124} = 0{,}74$

Standard error: $\mu_x \approx \frac{257}{30} = 8.6$

Stratum VVV: $S_{\hat{R}j}^2 = \frac{1}{8{,}6^2} \cdot \frac{2076 + \left(\frac{236}{257}\right)^2 \cdot 2247 - 2 \cdot \frac{236}{257} \cdot 2076}{(30-1) \cdot 30} \cdot 1 = 0{,}0025$

Stratum VCV: $S_{\hat{R}j}^{2} = \frac{1}{8{,}6^{2}} \cdot \frac{9 + \left(\frac{3}{143}\right)^{2} \cdot 723 - 2 \cdot \frac{3}{143} \cdot 9}{(30-1) \cdot 30} \cdot 1 = 0{,}00090$

Stratum VCC, and CVC: $S_{\hat{R}j}^{2} = 0{,}0052$; $S_{\hat{R}j}^{2} = 0{,}0012$

Sum of weighted standard errors:

$$\hat{\text{var}}(\overline{y}) = \left(\frac{583411}{725940}\right)^{2} \cdot 0{,}0025 + \left(\frac{30672}{725940}\right)^{2} \cdot 0{,}00090 + \left(\frac{8046}{725940}\right)^{2} \cdot 0{,}0052 + \left(\frac{4402}{725940}\right)^{2} \cdot 0{,}0012 = 0{,}0016$$

Confidence interval: $1{,}96 \cdot \sqrt{0{,}0016}.100 = 7{,}84$

Permanent vegetated area inside Nam Ton Watershed: 74,00 % ± 7,84 %

2.8 Definition of shifting cultivation

In the Nam Ton Watershed the practice of shifting cultivation is not restricted to the encroachment into old growth forests. The shifting cultivation in Nam Ton watershed is rather a rotational fallow system that uses slash and burn techniques. All together the watershed has only two cropping patterns in the area: permanent lowland rice (and to very small extent fruit (tree) plantations) and non-permanent rotating fallow, where highland rice is cropped. In between there are not much differences. Important for remote sensing is that these practices should (in theory) be relatively easy to discern by the inter- and intra-seasonal pattern of their surface being bare. And that is also what is intended initially: to monitor "critical" land uses in the watershed. This requires a reliable assessment of which areas are temporarily laid bare through human activity (and hence at risk of erosion etc) (Feldkoetter Christoph, personal communication). Based on this definition only following landcover change classes are caused by shifting cultivation, and are used in this study:

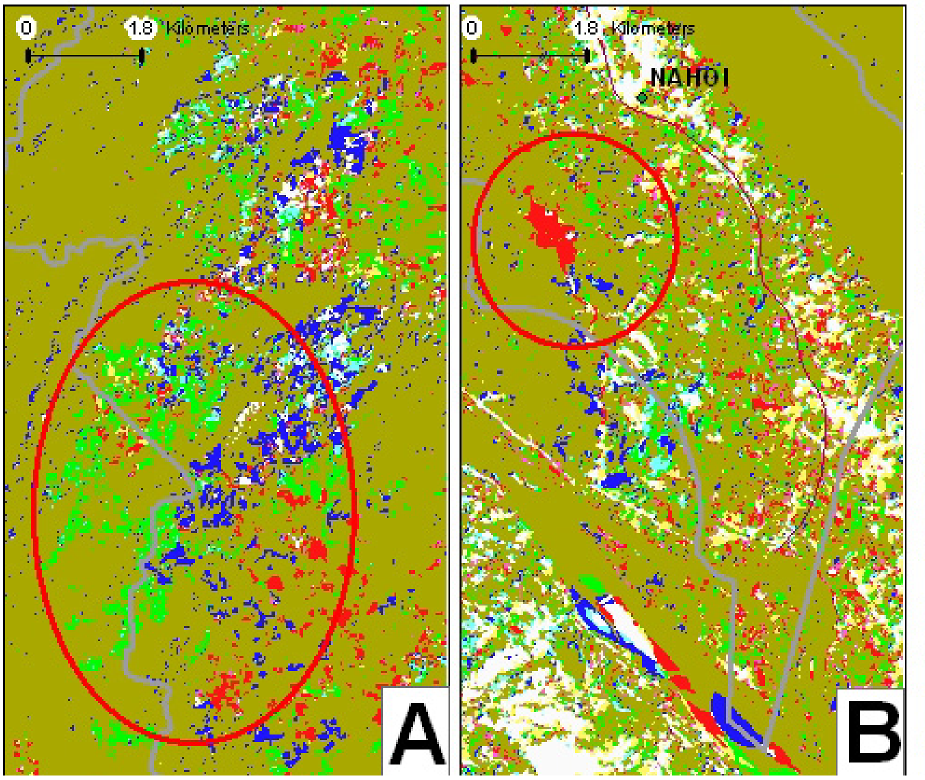
- assessment of land that is cleared in 1997 but supports again vegetation in 2000 and after a fallow of five years is cleared again in 2002
- assessment of land that is cleared in 1997 and supports again vegetation in 2000 and 2002
- assessment of land that was vegetated in 1997, cleared in 2000 and is again vegetated in 2002.

This resulted in the following class based formulas:

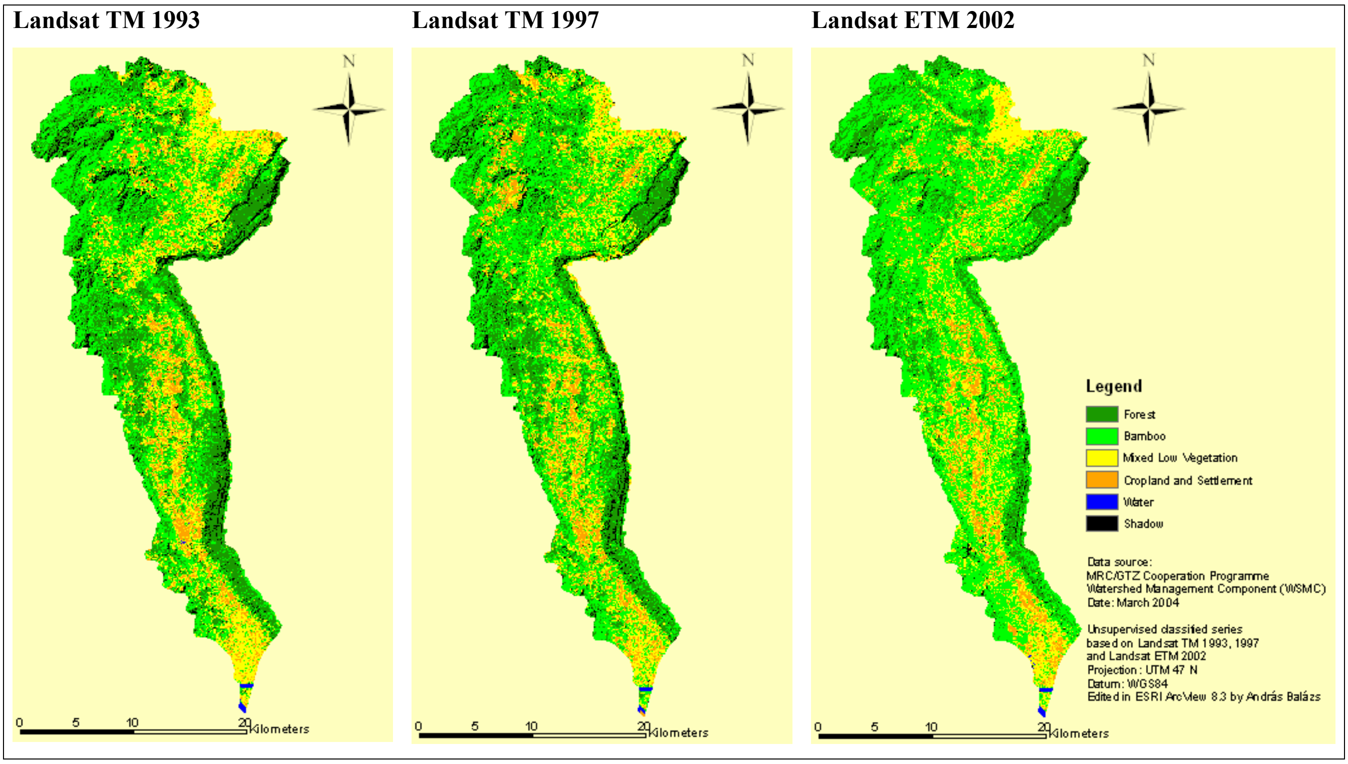
TYPE OF CHANGE	**AREA/YEAR**		
	1997	**2000**	**2002**
Shifting Cultivation	**cvv + cvc**	**vcv**	/
Total Cleared area	**cvv + ccv + cvc + ccc**	**vcv + ccv + vcc + ccc**	**vvc + vcc + cvc + ccc**
Total Vegetated area	**vcc + vvc + vvv + vcv**	**cvc + vvc + cvv +vvv**	**ccv + vcv + cvv + vvv**

3. Results

An example of a classified image after tasseled cap transformation where figure 2 a, is the area situated in the Northwest of the watershed red circle showing shifting cultivation, 2b, area in the south of the watershed, red circle showing a village resettlement



A time series of classified images after LUCC (Land Use/Cover Classification) into 6 classes



The following table compares the accuracies of the classifications comparing the unsupervised and segmented multitemporal images vs. the unsupervised and supervised post-classifications.

- For the enhanced multitemporal stack of images the overall accuracies and kappa indices were calculated

- In the post classification technique the images were paired, calculating the overall accuracy of the change detection by multiplying the accuracies belonging to the individual images (personal consultation with Feldkötter).

Table 3. The comparison of the accuracies of the multitemporal images and the post-classifications, the red frames are showing the best accuracies (the best technique) for the multi-temporal image.

Image to image comparison		
Unsupervised classification		
Transformation or algebraic conversion	**Overall Accuracy**	**Kappa Index**
Tasseled Cap Transformation (1997, 2000, 2002)	**84.5**	**82.1**
Principal Components Analysis (1997, 2000, 2002)	**81.9**	**79.2**
Vegetation Index (1997, 2000, 2002)	**71.4**	**65.6**
Segmentation		
Tasseled Cap transformation (1997,2000,2002)	**74**	**70.3**
Post-Classification Technique		
Unsupervised classification		
1993	**87**	**79**
1997	**85**	**77**
2002	**91**	**81**
Paired Images		
1993-1997	**77**	**/**
1993-2002	**78**	**/**
1997-2002	**79**	**/**
Supervised classification		
1993	**81**	**71**
1997	**80**	**69**
2002	**85**	**76**
Paired Images		
1993-1997	**67**	**/**
1993-2002	**69**	**/**
1997-2002	**71**	**/**

It is clear that a multitemporal stack of images can provide the best accurate and fastest results.

3.1 Limitations of the methods

Landsat image cover a small area this is a problem when investigating larger watersheds for example the Nam Ngum watershed nearby considering the spatial resolution of the Landsat images. Besides this the Landsat ETM has a problem with its sensor, so it is recommendable to buy a new type of imagery (see table). Another disadvantage of the unsupervised classification methods is the subjectivity of grouping the chosen number of clusters (ad hoc) into the final classes, as an alternative it is recommended to explore further image segmentation.

3.2 Muti temporal image classification

One can perfectly distinguish shifting cultivation and the direction of change this because of its temporal frequency, however multi-date images contain only little information about the cause of the change, for this post-classification methods are a better trade-off.

3.3 Post classification

- Supervised classification is not exhaustive for inclusion of every pixel value. This makes the chance of misclassification rather high, which probably causes a lower accuracy.

- Because of mixed pixels, it is a necessity to perform intensive field surveying or acquire the necessary reference data, before classification. This is rather labour intensive and increases the cost factor. The forest class and the Bamboo have a high within variability therefore an intermediate vegetation type between Bamboo and Forest is suggested, this to extend the set of classes with a "Forest-mosaic" class. It can be expected that the variability between the classes will also increase with the size of the land.

3.4 Accuracy assessment

The multispectral aerial photos were not covering the entire watershed; consequently the panchromatic photos were also used for the accuracy assessment of the Landsat TM 1993 image. After more than four years it is fairly difficult to decide whether the pixels of the sample are correctly classified or not.
Here it has to be mentioned, that due to its low scale the multispectral series was very useful. At 1:20,000 scale even single crowns are clearly distinguishable. Hence, for studies on similar levels it is recommended to use airborne photos with this scale if ground-truth data is not available.

Spatial uncertainty is also a significant source of error. It is not a simple task to find the desired site on the reference data, which should fit in with the location on the classified image. Fixing sample points/plots via GPS on the field seems to be the best solution. However, errors made in the georeferencing process cause shifts of the sample plots on the image. On the other hand, these points are useless for the evaluation of images, produced many years before the points were set. Thus the establishment of a set of GPS fixed sample plots on the pilot area would facilitate and improve the accuracy assessment of further image interpretations.

3.5 Area statistics

3.5.1 Multi temporal image

The multidate image was best classified using an unsupervised classification after tasseled cap transformation.

Table 4. The results with the help of the corrected area calculation

Naive area estimation			
Class	**No of pixels**	**Total area (km²)**	**%**
vvv	583411	473.9	80.4
vvc	26579	21.6	3.7
vcv	30672	24.9	4.2
vcc	8046	6.5	1.1
ccc	32438	26.3	4.5
cvc	4402	3.6	0.6
cvv	29965	24.3	4.1
ccv	10427	8.5	1.4

Table 5. The results with the help of the corrected area calculation

Corrected Area Statistics								
Class	**Area (%)**	**C. I. ± (%)**	**LCL (%)**	**UCL (%)**	**Area (km²)**	**C. I. (km²)**	**LCL (km²)**	**UCL (km²)**
vvv	74.0	7.8	66.2	81.8	436.3	46.2	390.1	482.5
vvc	6.6	5.4	1.2	12.0	38.9	31.9	7.0	70.8
vcv	7.3	5.4	1.9	12.8	43.2	32.0	11.1	75.2
vcc	0.9	0.2	0.8	1.1	5.5	1.0	4.5	6.6
ccc	4.1	0.6	3.5	4.6	23.9	3.3	20.6	27.2
cvc	1.9	1.9	0.0	3.8	10.9	11.4	0.0	22.3
cvv	3.7	0.6	3.1	4.4	22.0	3.8	18.2	25.8
ccv	1.5	0.3	1.2	1.8	8.8	2.0	6.8	10.7
Total	**100**				**589.5**			

Table 6 details further about the total cleared shifted cultivated and vegetated areas in the Nam Ton watershed. The areas were calculated using the corrected area estimation approach. Note that the number for cleared area in 2002 includes an area that was affected by a village resettlement (approx. 0.38 km²).

Table 6. The derived land cover types. The area classification is based on the calibrated estimation out of table 5

LAND COVER TYPE	**1997**			**2000**			**2002**		
	Area (km²)	**LCL**	**UCL**	**Area (km²)**	**LCL**	**UCL**	**Area (km²)**	**LCL**	**UCL**
Shifting Cultivation	**40.8**	28.8	52.7	**43.2**	11.1	75.2	**/**	/	/
Total Cleared Area	**65.6**	53.1	78.2	**81.4**	49.2	113.5	**79.2**	45.2	113.3
Total Vegetated Area	**523.9**	459.2	588.6	**508.1**	450.7	565.6	**510.3**	453.9	566.6
Permanent Cleared Area	**23.9**	20.6	27.2	**23.9**	20.6	27.2	**23.9**	20.6	27.2
Permanent Vegetated Area	**436.3**	390.1	482.5	**436.3**	390.1	482.5	**436.3**	390.1	482.5

Table 7 shows some derived land cover types. The area classification is done based on the calculation of the confidence intervals and definition of shifting cultivation

LAND COVER TYPE	1997			2000			2002		
	Area (%)	LCL	UCL	Area (%)	LCL	UCL	Area (%)	LCL	UCL
Shifting cultivation	**6.9**	4.9	8.9	**7.3**	1.9	12.8	**/**	/	/
Total cleared area	**11.1**	9.0	13.3	**13.8**	8.3	19.3	**13.4**	7.7	19.2
Total vegetated area	**88.8**	77.9	99.8	**86.2**	76.4	95.9	**86.5**	77.0	96.1
Permanent cleared area	**4.1**	3.5	4.6	**4.1**	3.5	4.6	**4.1**	3.5	4.6
Permanent vegetated area	**74.0**	66.2	81.8	**74.0**	66.2	81.8	**74.0**	66.2	81.8

In a recent socio-economic study of Manivong (2004) over the larger Nam Ton pilot project area, the area under shifting cultivation was estimated at 33 km². This number was deducted from village interviews and intensive field surveying.

In this study it was only possible to do estimation for the years 1997 (40.8 km²) and 2000 (43.2 km²). After correction of the area estimation no significant change can be observed between 1997 and 2000. Positive means in this case an increase of the area of shifting cultivation. The relative importance of the shifting cultivation in the total cleared areas is presented in the figures below.

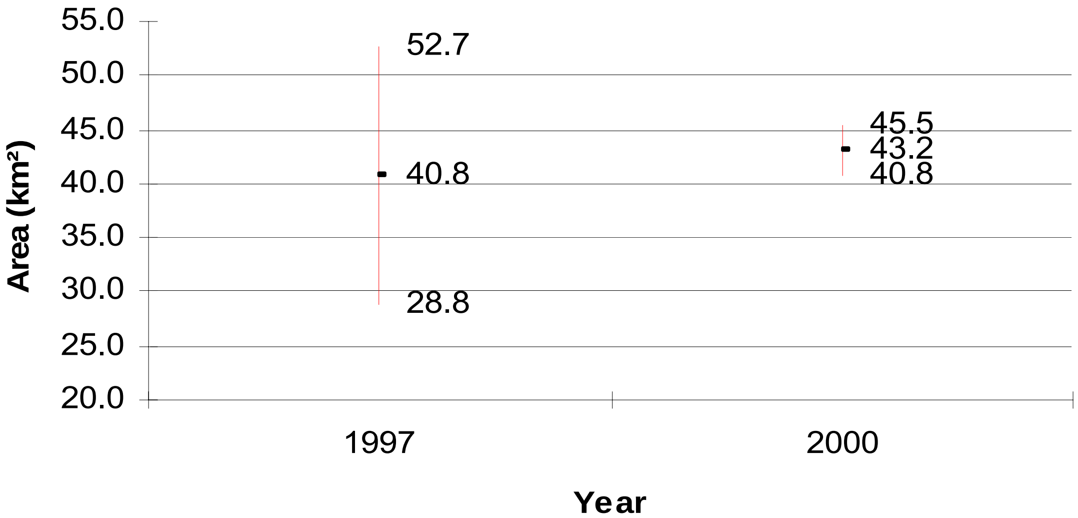


Figure 4 The pattern of shifting cultivation

The use of the post classification change detection technique for estimating the total area under cropland and settlement (≈ total cleared area) resulted in an estimation of 61.35 km² in 1997 (LCL 55.46 km² – UCL 67.24 km²) and for 2002 54 km² (45.96 km² - 49.13 km²) that is under cropland and settlement. The estimation of the total cleared area in Nam Ton is given below.

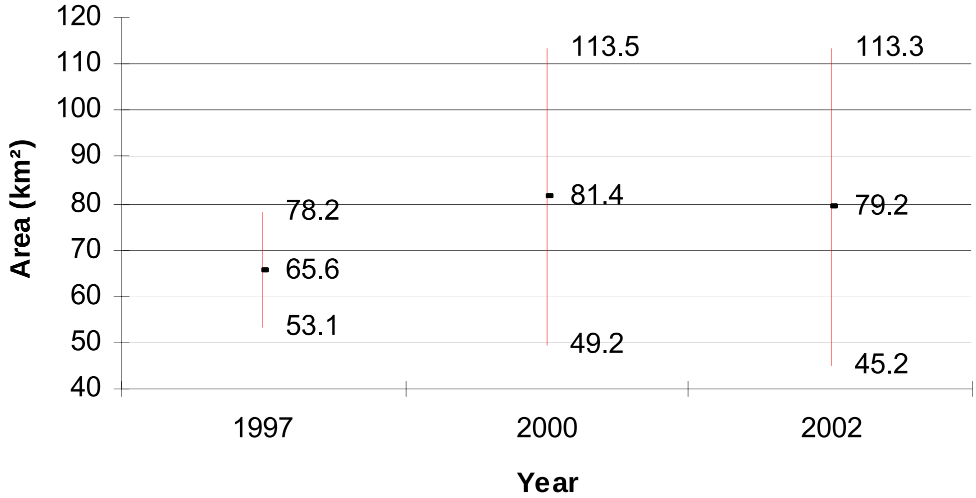


Figure 5 the pattern of the total cleared area

These graphs are proving that it is not possible with the given accuracy assessment to give a significant estimate for the change of the area that is cleared over the monitored period nor for the change of the area under shifting cultivation. However in both estimates more than the half of the cleared area is caused by shifting cultivation. In 1997 it is estimated that 62.2% of the total cleared area is caused by shifting cultivation, whether in 2000 this is 53.1%.

Table 8. Area statistics based on the unsupervised classified images

Class	93 No. Of Pixels	Area (km²)	(%)	97 No. Of Pixels	Area (km²)	(%)	02 No. Of Pixels	Area (km²)	(%)
Forest	208826	169,62	28,77	189991	154,32	26,17	123995	100,71	17,08
Bamboo	276791	224,82	38,13	309101	251,07	42,58	395529	321,27	54,49
MLV	139297	113,14	19,19	121496	98,69	16,74	134154	108,97	18,48
A and S	63265	51,39	8,72	72127	58,59	9,94	60940	49,50	8,39
Water	994	0,81	0,14	679	0,55	0,09	11,10	0,90	0,15
Shadow	36766	29,86	5,06	32545	26,43	4,48	102,11	8,29	1,41
Σ	725939	589,64	100,0	725939	589,64	100,0	725939	589,64	100,0

Please note: pixels classified as shadow have no appropriate spectral information for the landcover assessment, moreover due to its irrelevance the class “Water” was excluded out of the further statistics. In the tables below the results of the area estimations are represented.

Table 9. Corrected area statistics

Class	1993			1997			2002		
Class	Area (%)	LCL (%)	UCL (%)	Area (%)	LCL (%)	UCL (%)	Area (%)	LCL (%)	UCL (%)
Forest	31,75	29,14	34,36	23,97	20,43	27,51	19,52	16,80	22,24
Bamboo	38,66	35,75	41,57	45,53	41,51	49,55	49,56	46,24	52,87
MLV	15,94	14,30	17,57	15,52	13,20	17,84	21,30	18,83	23,78
A and S	8,46	8,09	8,82	10,41	9,41	11,40	8,06	7,79	8,33
Σ	94,80			95,43			98,44		
Class	Area (km²)	LCL (km²)	UCL (km²)	Area (km²)	LCL (km²)	UCL (km²)	Area (km²)	LCL (km²)	UCL (km²)
Forest	187,19	171,81	202,57	141,33	120,48	162,18	115,09	99,06	131,13
Bamboo	227,95	210,81	245,10	268,45	244,73	292,16	292,20	272,65	311,74
MLV	93,96	84,33	103,60	91,52	77,84	105,20	125,61	111,02	140,20
A and S	49,86	47,70	52,02	61,35	55,46	67,24	47,54	45,96	49,13
Σ	558,97			562,65			580,44		

LCL = Lower Confidence Level, UCL = Upper Confidence Level

The confidence intervals of the individual classes are also demonstrated on diagrams. The confidence intervals help to decide, if the changes gained through the area estimations are whether significant or not. If overlap occurs between two different years, no significant change can be established.

Figure 6 Forest landcover change

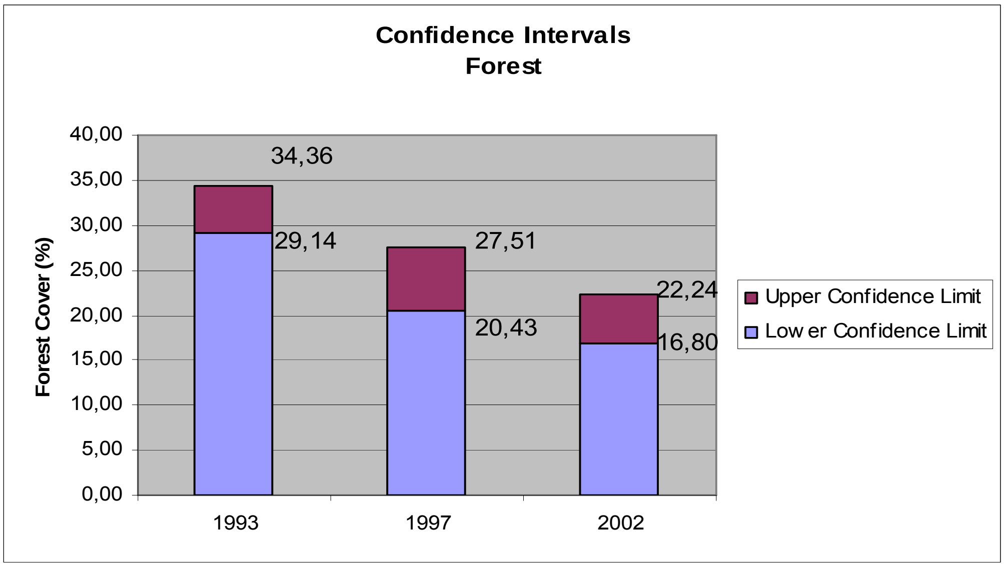


Figure 7 Bamboo landcover change

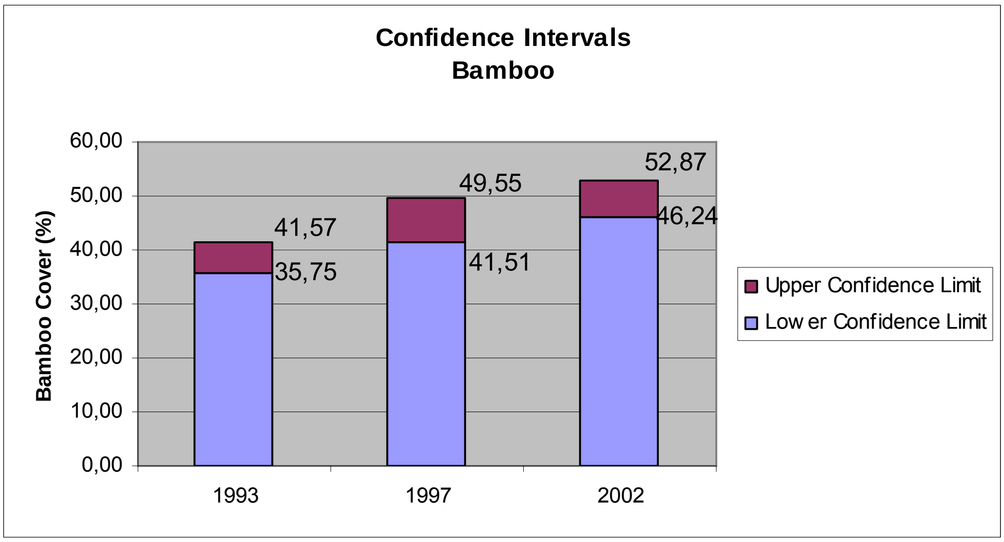


Figure 8 Mixed low vegetation landcover change

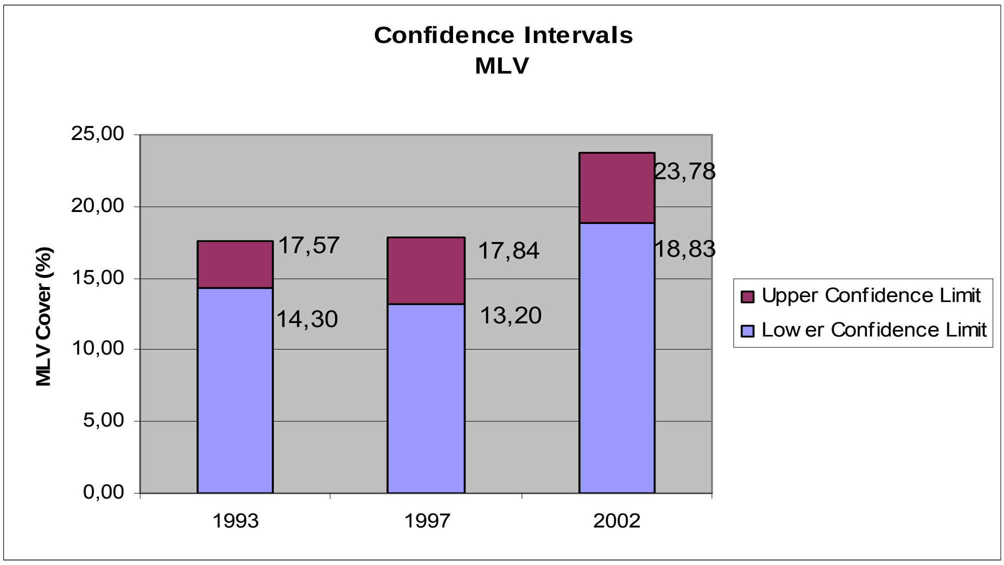
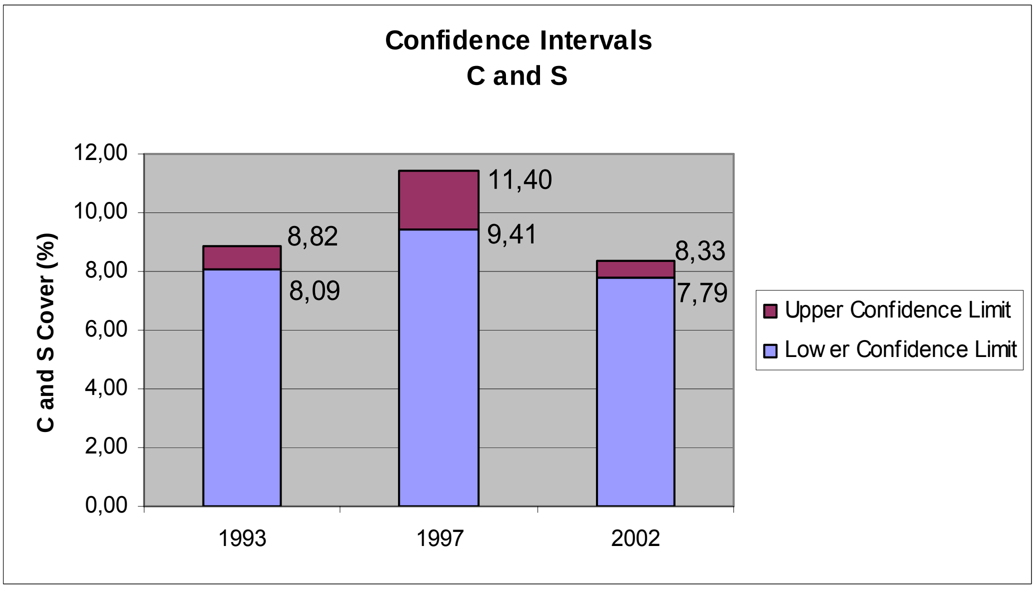


Figure 9 Cropland and Settlement landcover change



Based on the diagrams above the significant changes are marked with orange color in table below. Since the categories of the landcover map based on topographic maps do not correspond with the categories of the satellite images, only the summed area of the "low and high cover density Forest" has been taken into account at the calculation of the changes.

Table 10 Statistics of landcover-change

Class	Changes 1993-1997		Changes 1997-2002		Changes 1993-2002		Changes 1960's-2002	
	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)
Forest	-45,86	-7,78	-26,24	-4,45	-72,10	-12,23	-425,37	-71,56
Bamboo	40,49	6,87	23,75	4,03	64,24	10,90		
MLV	-2,44	-0,41	34,09	5,78	31,65	5,37		
C and S	11,49	1,95	-13,81	-2,34	-2,32	-0,39		

After visual analysis of the classified images, decrease of forest cover and increase of bamboo is fairly conspicuous. All the same, according to the confidence intervals in three cases (Forest and Bamboo) no significant change can be detected. To avoid this, the confidence intervals should become narrower. This is achievable through increase of the sample size. The insufficient sample size can be also explained by the large extent and high heterogeneity of the classes "Forest" and "Bamboo".

On the other hand, in the class "Cropland and Settlement", which is smaller and more homogenous, lower number of sample plots would be sufficient.

Thus the recommended numbers of sample plots are: 40 in the "C and S", and 60 in each of the other three classes.

The diagrams below show the decrease of forest and increase of bamboo covered areas in the watershed.

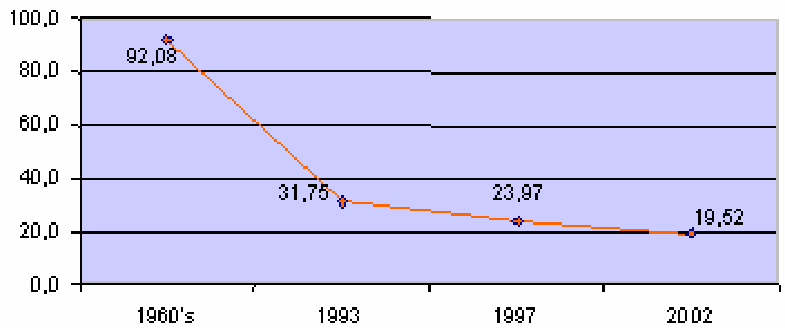


Figure 10 Change of forest area in the watershed

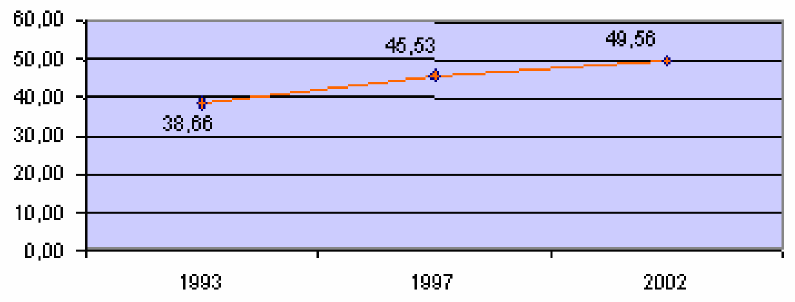


Figure 11 Change of the bamboo landcover in the watershed

3.5.2 Labour intensity of the different approaches

Post-classification: 30-40 hours/image (classification process and accuracy assessment)

Requirement: the completion date of the reference data does not differ more than 2 years to the completion date of the classified image. This facilitates the recognition of the sample plots on the reference data.

Multi-temporal image classification method : 50-60 hours for the multi-temporal image (classification and accuracy assessment)

4. Recommendations for the methodology choice

The choice of the best methodology, multitemporal image classification vs. Post-classification method is a trade-off between the higher amount of information (post-classification is the better choice), and time and costs for processing (multi-temporal image is the better choice). For the overall accuracy the unsupervised classification after tasseled cap transformation of the multi-temporal image provides a better result.

5. Recommendations for the data choice

The spatial resolution of Landsat images is very high; however for up scaling to a larger area a lower spatial resolution is more reasonable. Considering the problems with the Landsat ETM+ mapper (since May 2001) one can definitely look forward to customise imagery of a lower spatial resolution but with higher temporal resolution (MODIS 300x300m), this can better trace the changes over time, whether it is then possible to improve the spatial resolution by customizing DMC 5 imagery. Below one can find a table with most up to date information:

Table 1. Overview of the sensors that can be used, the red framed option is preferred for a high temporal resolution for a large scale mapping application

Cat*	Pixel dimension	Image width	Global coverage	Example
HR	10 -30 m	60-180 km	15-30 days	LANDSAT TM/ ETM+, SPOT-HRV
	32 m	600 km	1 day	DMC (5 satellites)
MR	300m	1500-3000km	1-3 day	Envisat-MERIS, TERRA-MODIS (2bands)
LR	1 km	2850 km	1 day	NOAA-AVHRR, SPOT-VEGETATION
VHR	1- 5m	355-630m	/	CASI, SASI

***With HR: High Resolution, MR: Medium Resolution, LR: Low Resolution, VHR: Very High Resolution**

LANDSAT-TM (Thematic Mapper) is a HR sensor that is operational since 1982 (resp. Landsat 4 and 5). This instrument delivers information in 7 spectral bands (6 short wave, 1 thermal), with a resolution of 30 m and this with a relative wide image size (180km x 180km). The new version ETM+ that is in the LANDSAT7 (since 1999) platform offers also a panchromatic band. Due to a distortion on the sensor; it is however not possible any more to retrieve stripe-less data. At least the LANDSAT5-TM is still operational.

TERRA-MODIS is an American sensor with a daily global vegetation cover monitoring and 36 spectral bands spread over the short- till long wave sense. MODIS is actually a LR-system, because 34 channels are working with a resolution of 1 km. The two most important bands (Red and NIR) were registered with a pixel dimension of 250 m (MR). TERRA-MODIS is operational since the beginning of 2000 and the data is freely available.

ENVISAT-MERIS is a comparable instrument of European satellite (ESA). MERIS' 15 spectral bands however situated in the short wave area, and the base resolution has a width of 1.2 km (LR). Besides a continue 10% earth surface cover registration with a resolution of 300m (MR) the images are free available.

DMC (Disaster Monitoring Consortium) is a very recent initiative. Technically it consists of 5 identically micro-satellites, which have been place the former months in a nearby polar orbit with a distance of 72° (360°/5). Every platform has a sensor which performs registration in 3 channels (Green, Red, NIR) with a sub-nadir resolution of 32 m, that is comparable with TM. Completely innovating is that this is happening over a band of 600km width. Commonly these

5 systems monitor the whole earth surface every day, and this for a high resolution. DMC is cooperation between Great Britain, Algeria, Turkey, Nigeria and China and is guided by the British company SSTL in Surrey. Thematically this consortium has an interest in monitoring disasters, but the images can be also used for other political and data distribution purposes. Very soon the VITO has the image datasets for Africa and China. This means that images with a high spatial and temporal resolution will be available very soon

CASI and SASI hyperspectral data contains between 14 to 120 bands (information from different wavelengths), high resolution (1m to 2.5m), so it is possible to differentiate between different types of vegetation, and in some cases, the health and growth stage of vegetation (Australian department of agriculture forestry and fishery). Earlier investigations were used to calculate the biomass, after calibration based on field plots. The biomass in the plot had an excellent relationship with the calculated biomass (Australian department of agriculture forestry and fishery). Only useful for small scale applications, where a high detail is required.

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