Georg-August-University Göttingen

Faculty of Forest Sciences and Forest Ecology
Institute of Forest Management
- Forest Assessment & Remote Sensing, Forest Growth, Forest Planning -

Göttingen, August 2005

Tracing shifting cultivation in the Nam Ton watershed (Lao PDR) by multispectral image-to-image change detection techniques with statistical verification

MSc thesis submitted by:

Stijn Cleemput

to obtain the degree of
Master of Science in Tropical and International Forestry

Supervisor:
Prof. Dr. Christoph Kleinn

F 2006 B 42

Georg-August-University Göttingen

Faculty of Forest Sciences and Forest Ecology
Institute of Forest Management
- Forest Assessment & Remote Sensing, Forest Growth, Forest Planning -

Göttingen, August 2005

Tracing shifting cultivation in the Nam Ton watershed (Lao PDR) by multispectral image-to-image change detection techniques with statistical verification

MSc thesis submitted by:

Stijn Cleemput

to obtain the degree of
Master of Science in Tropical and International Forestry

Supervisor:
Prof. Dr. Christoph Kleinn

Acknowledgements

The successful completion of this study would not have been possible without the direct assistance, contribution and support of the following individuals and institutions/organizations to which I like to record my sincere gratitude and appreciation.

The GTZ-Watershed Management Component that supports the Irrigation Forestry and Agriculture Programme within the Mekong River Commission Secretariat and more particularly Dr. Cornelis Van Tuyll the programme coordinator is sincerely acknowledged for offering his full capacity. Christoph Feldkoetter for offering his full guidance that could steer the study on course till to the end. Without his expertise and wisdom the study would not be where it is today. I would also like to thank Prof. Dr. Christoph Kleinn from the Institute of Forest management and Yield science in a special way, for all the hard work he putted in the preparation, organization and statistical parts of this master thesis. András Balázs is acknowledged while giving highly relevant statistical input and encouragements during the whole period of study.

The study is also grateful to the Irrigation Forestry and Agricultural Programme, especially to Dr. Vitoon Viriyasakultorn and Mr. Sengkham Inthiravongsy for their warm and excellent cooperation.

Deep appreciation and gratitude is extended to all the staff members of the Watershed Management Component especially the following:

The project secretary Ms. Pamouane and data managers: Mrs. Iris Richter, Mr. Inthava Sanouvong and Ms. Amphaygneun Sounthala who were offering their assistance during the literature study.

Last but not least we would not like to forget the staff of the University of Göttingen for their technical support: more specifically Hans Fuchs and Axel Buschmann, who provided the technical backstopping for the exercise and Utah Fricke who helped us with the final corrections. It is not possible to mention every one by name, however all those who contributed in one way or the other during the execution of this study are sincerely acknowledged in their respective capacities.

Abstract

When looking for critical areas in the context of erosion and degradation in Laos, the regions that are affected by shifting cultivation are prior and most distinct visual. Up to now the distribution and extent of these areas is still unknown. This makes it unclear whether the extent and distribution of this practice has a cause in the further depletion of Laos natural forest resources. In order to find more accurate figures, the following study compares different satellite remote sensing techniques that monitor shifting cultivation. An unsupervised classification method of a tasseled cap transformation had a best overall accuracy of 84.5% in comparison with unsupervised classification according to principal components analysis (81.9%) and vegetation indexing (71.4%). It is concluded that the applied techniques are very useful applications in the monitoring of shifting cultivation in the catchments in Laos. This is due to their fast delivery of timely and accurate relevant information.

Table of Contents

1 Background of the study

At present 300,000 ha of the total of 11.2 million ha of forest land in Lao PDR is affected by shifting cultivation. The total number of shifting cultivators is estimated at about 253,000 families. These are mainly distributed in the north, where about 70% of the population (177,100 families) practice shifting cultivation. The number of shifting cultivating families in the central region is approximately 40,000 over an area of about 60,000 ha (Phanvilay 1990). In the south only 36,000 families are practicing shifting cultivation. The total area under shifting cultivation in the south of Laos is 25,000 ha. These figures prove that shifting cultivation nowadays is a considerably important factor in the land management system of Lao PDR.

In 2001 the UNEP/EAP-AP (United Nations Environmental Program, Environment Assessment Program for Asia and the Pacific) selected one specific region in Lao PDR for the monitoring of major landcover changes: the Oudomxay province situated in the North. Besides this study there are no real reliable figures available, both with respect to the areas subject to the practice of shifting cultivation and the impact on forests.

Reliable figures about shifting cultivation are important while in literature these practices and the related slash and burn activities are mostly associated with environmental change and degradation processes:

- Slash and burn activities are a well known cause for landcover change in Lao PDR (Roder et al. 1994),
- Most land degradation in Lao PDR is caused by shifting agriculture (Phanvilay 1990)
- Officially, most land degradation occurs from shifting agriculture, correspondingly, Lao upland farmers face significant problems of lowering soil fertility, weed infestation and rapid loss of soil moisture that typically come with reduction of fallow periods (AusAid 1996).

Farm surveys in various parts of the country have shown that fallow period of less than 10 years cause general degradation of soil fertility, weed infestation and rapid loss of soil moisture (Stea 2000a). This is a figure to be worried about while during the past century the fallow period of shifting cultivation has increasingly reduced. Roder et al. (1994) reported that the average fallow periods for the 1950s, 1970s and 1992 were 38, 20, and 5 years, respectively.

It is also clear that shifting cultivation is a type of land use that is highly dynamic and is influenced by numerous factors such as land tenure, population pressure, soil condition, past political events, market facilities etc. This gives policy makers many reasons to conclude that shifting cultivation is related with environmental problems such as deforestation, flooding, droughts, economic problems, and social problems (Bass and Morrison 1994). In the absence of clear information on the extent of shifting cultivation, policy-makers tend to assume that shifting cultivators are the central cause of many of these problems (Bass and Morrison 1994). At the moment the Lao government places than also a high priority on the reduction of shifting cultivation (Yamane and Chanthirath 2005). This priority setting had major consequences. For example a couple of years ago the government has started a national program that includes the "reduction of shifting cultivation" (Yamane and Chanthirath 2005).

They have introduced several measures (Yamane and Chanthirath 2005) such as (i) allocation of land to local peoples, (ii) classification of agricultural and forest land, (iii) local peoples' participatory forest management and (iv) capitalization of the productivity of upland agricultural land. As a result of such new policies 19,300 households have given up shifting cultivation between 1996 to 1997 (Yamane and Chanthirath 2005).

This result of this policy for the reducement of shifting cultivation has on the other hand more opposite effects (Grandstaff 1980, Roder et al. 1994). For example in the northern part of Lao PDR it is reported that the government its priority setting for reducing the area under shifting cultivation and thereby limiting farmers access to land combined with rapid population growth, have enforced it driving forces resulting in shorter fallow cycles and consequently increased weed problems and soil deterioration (Roder et al. 1994).

These examples convince that before environmental decision making, sound scientific results that give a figure about the extent and distribution of shifting cultivation in Lao PDR should be provided. This while starting of any discussion can have major consequences on the dynamics of shifting cultivation and its driving forces.

To prevent that policy makers and/or scientists are blindly estimating how much of the total area in Lao PDR is under the influence of this practice and in which areas it is concentrated, the aim of the study is to find a scientific tool in the evaluation of shifting cultivation and its extent by testing different satellite remote sensing detection techniques. With the hoped result that these techniques can be helpful for detecting landcover change in relation with shifting cultivation on a more broad spatial scale, i.e. the whole Mekong region.

2 Objectives

As manually handling of remote sensing data for change detection is a formidable task, there is a need for a change detection system, which will automatically correlate and compare two sets of imagery taken of the same area at different times and display the changes and their locations to the interpreter.

The objectives of this study are to:

(1) identify vegetation cover conversion hot spots due to increasing human activity, and
(2) characterize landcover dynamics related to shifting cultivations during the last decade,
(3) develop a work flow for dynamical landcover mapping for the evaluation of ongoing Landcover dynamics

3 Literature study: Assessment of Landcover change with help of remote sensing data

At the moment the mapping of land cover dynamics is still a major challenge, this only due to the heterogeneity visible in the satellite data set and diversity in conversion possibilities. Remote sensing as an application for monitoring landcover changes however has proven its usefulness in a diverse extent of historical research. Jusoff and Souza (1997) for example investigated the potential of satellite remote sensing in the Malaysian forestry sector and concluded that there is a high potential for remote sensing as a tool in monitoring logging and forest change especially with Landsat and Spot data supported with aerial photographs. Guild et al. 2004 examined Landsat imagery for identifying hot spots of deforestation and cattle pasture formation in Brazil, they compared a tasseled cap (TC) transformation with a principal components analysis of a stack of TC images to identify deforestation. Lambin and Ehrlich (1997) designed a methodology that detected tropical deforestation 'hot spots' at broad spatial scales in West Africa. Su (2000) discovered its usefulness in the context of hydrological studies, combining two classification methodologies for calculating leaf area indices for meso-scale river basins in the Sauer River Basin in Germany.

Apart from Landsat and Spot images, other imagery is widely used in the detection of Landcover change. The UNEP-Environmental assessment Programme for the Asian and pacific region (1998) recently used National Advanced Very High Resolution Radiometer (AVHRR) National Oceanic and Atmospheric Administration (NOAA)-14 imagery, in combination with spot multispectral and Landsat to find out the determinant factors behind the major land cover transformation in the Mekong region. This data type was found to be useful in identifying and locating gross changes occurring in land cover types and even it was also possible to find out the driving forces responsible for these changes. In a study of Gimeno et al. (2004) Synthetic Aperture Radar (SAR) image series were used in Mediterranean forest environments for detection of burnt areas using neural network classification. This research has proven that SAR data is more sensitive to determine the severity of the burnt areas (Gimeno et al. 2004). Finally aerial photography has been widely used in marking the extent of shifting cultivation, Eden (1986) examined the impact of shifting cultivation on the forest conditions by comparing sequential black-and-white panchromatic aerial photographs (scale 1530 000 to 1560 000) with a Landsat image from the Landsat I Return Beam Vidicon (RBV) camera. He was able to quantify and map the immature forest regrowth and some regenerating forest sites.

The technical service division of the Mekong river commission based in Laos disposes of an exhaustive satellite data set, varying from regular Landsat images till high detailed multi-spectral aerial photographs. Until now this data was used for monitoring cycles focusing on the forest cover of the Mekong region. This resulted in outputs that presented the reduction of the forest cover in the riparian countries for the seventies and nineties. However the application to focus on shifting cultivation is not tested until now, this requires the interpretation of the single individual Landsat satellite images. It is hoped that in this study a methodology is found that can become helpful for monitoring the forest cover reduction related with shifting cultivation in the Mekong Region.

4 Materials and methods

4.1 Study area

4.1.1 Climate

The Nam Ton watershed is situated at 18°15' N latitude and 102°10' longitude, in the outer tropical zone. Its climate is mainly influenced by the Inner tropical Convergence Zone, characterised by annual temperature variations between 5 and 12°C (Lauer 1993). Its typical monsoon climate has a strongly developed rainy and dry season, caused by the cyclical occurrence of two main monsoon winds. The N-E Monsoon consists of dry continental air coming from China and causes the dry season from October to March. The S-W monsoon causes the rainy season from April to September based on humid-hot air from the Indian Ocean with a distinguishable period from April to May characterized by short and heavy rainfalls entailing stormy winds and thunderstorms (DDFD 1997).

4.1.2 Administrative situation

The watershed of the Nam Ton river is located some 70 km northwest of Vientiane. The watershed its lower and central part is located in the Sangthong district, whereas its upper part is situated in the Hinheup district. In general the study area is suitable for the cultivation of lowland rice. Its topology is characterised by an alluvial flood plain figure 1, bordered to the west and the east by mountain ranges up to 700 meters high.

The Nam Ton river transects the watershed starting in the North-western part of the watershed, most of its distance parallel with an all weather gravel road network that passes through the main villages in the eastern and western side of the watershed. The most important farming activities of the area are lowland paddies, livestock raising and shifting cultivation. Nowadays the villages have large areas of paddy (lowland rice). Therefore they are not longer entirely dependent on shifting cultivation.

4.1.3 Historical overview major changes in the Nam Ton watershed

Some historical reports characterize the study area as being degraded especially in the last decades. Foppes describes in 1995 that up to 20-30 years ago, the land in the Sangtong district (also that of the watershed) was mainly covered with forests, whereas nowadays these forests are depleted due to the increase of the population inside the watershed. For example an interview with a 90 year old man in the village of ban Koua, which is situated in the north (figure 2) reveals that at 70 years ago only 5 houses were existing at that time, whereas at this time it is about 54 houses.

According to historical reports (Manivong 2004, Foppes 1995), the major change in the area is caused by the arrival of logging companies in the late seventies. This has caused the loss of valuable timber tree species like *Pterocarpus macrcarpus* and *Dalberghia spp.* Logged by a Japanese company "Osaka" for about three years. Recent reporting convinces that this logging is still going on today, with the combination of high cost investments, it can be expected that the logging companies are still involved (figure 1). Due to this exploitation nowadays almost no or very less primary forest is left (Manivong 2004, Foppes 1995). However one of the main improvements of the watershed was done in 2001 when a management intervention plan was implemented. This led to the establishments of plantations, enrichment plantings, and a better forest and land use planning (Kollert 2000).

Figure 1 a logging site and truck spotted inside the north of the Nam Ton watershed (December 2004).

4.2 Justification of the study area

- Monitoring of the landcover can be performed at relatively broad spatial scales, using remote sensing techniques; however the specific change processes behind landcover transformations can only be understood from fine spatial scales. The Nam Ton watershed covers a relative low area compared with other catchments in Laos and is for this reason quite good for relating the small scale changes with further events downstream.

- At the moment the Nam Ton watershed is affected by human induced Landcover change, however there is no intensive reporting about shifting cultivation going on. For example a mission report of the Vientiane forestry college in 1995 states that the villages along the Nam Ton reside on paddy rice and are not depending on shifting cultivation.

- Since the Nam Ton watershed is a part of the Nam Ton pilot project area in the Lao PDR. The subsistence use of its area and progress of the management systems are most eager for environmental change descriptions. This makes that the area is well described by the means of aerial photographs series (1995 and 1998) and inventories.

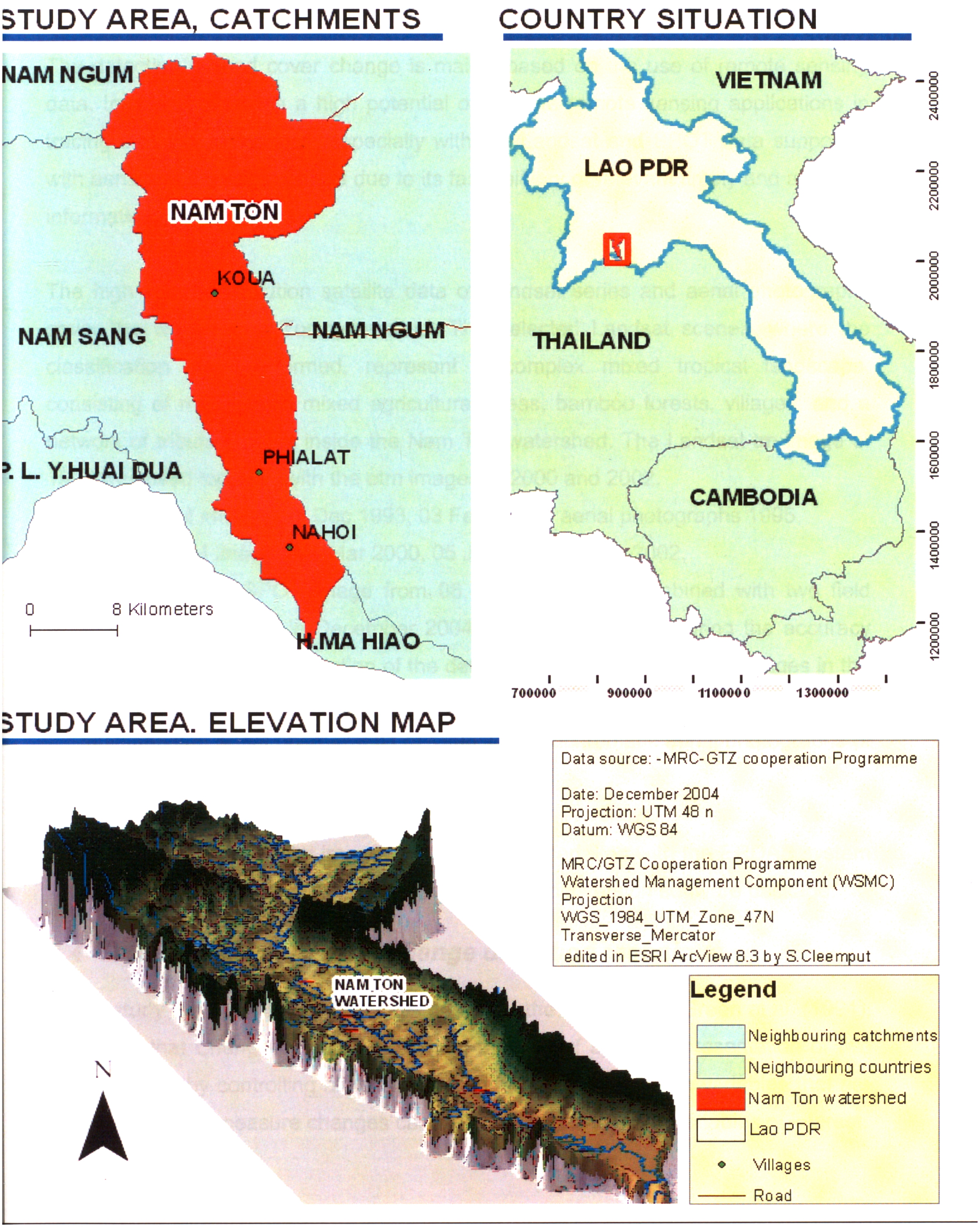


Figure 1 a situation map of the Nam Ton watershed

4.3 Dataset

The detection of land cover change is mainly based on the use of remote sensing data. In general there is a high potential of satellite remote sensing applications in tracing Landcover changes, especially with the Landsat and SPOT data supported with aerial photographs. This is due to its fast delivery of relevant timely and accurate information.

The high spatial resolution satellite data of Landsat series and aerial photographs cover the whole Nam Ton watershed. The selected Landsat scenes, where the classification was performed, represent a complex mixed tropical landscape, consisting of many small mixed agricultural areas, bamboo forests, villages, and a network of tributary rivers inside the Nam Ton watershed. The Landsat tm image of 1997 was used together with the etm images of 2000 and 2002.

- Landsat TM images: 25 Dec 1993, 03 Feb 1997 - aerial photographs 1995,
- Landsat ETM images: 07 Mar 2000, 05 Jan 2001 09 Feb 2002,
- a multi-spectral SPOT image from 08 Feb 2003 was combined with two field surveys respectively in December 2004 and January 2005 during the accuracy assessment for the verification of the detection of major landcover changes in the 2002 image,
- multi-spectral aerial photographs of 1995 and panchromatic aerial photographs of 1998,

the whole process of digital image analysis was undertaken with the ERDAS system version 7.4, this together with an ESRI ArcMap 8.2 trial version software package.

4.4 Developing the optimal change detection technique

In this study the detection of change is based on the definition of Green et al. (1994), who says that Change detection is the comparison of spatial representation of two points in time by controlling all variances caused by differences in variables that are of interest and to measure changes caused by differences in the variables of interest.

Based on the available remotely sensed data and the objectives of the study, it is scoped to detect only annual landcover change that is related to shifting cultivation.

To detect landcover change, different techniques exist. Each technique will have unique characteristics and goals in which it will be the most optimum. In this study simple image to image comparison approaches were chosen. Following paragraphs describe the process that decided on the selection of the most optimal change detection techniques.

4.5 A review of change detection methods

Change detection methods through application of remote sensing data have been widely described in the literature over the past ten years. The approach of mapping Landcover after detecting change is diverse. In a review of change detection techniques Lu et al. (2004) grouped all methods into seven categories: (1) algebra, (2) transformation, (3) classification, (4) advanced models, (5) Geographical Information System (GIS) approaches, (6) visual analysis, and (7) other approaches. A review of the main characteristics, advantages and disadvantages, key factors affecting change detection results, and some application examples for the methods applied in this study are provided in table 1. Not all categories are discussed in this study, the reasons for selecting certain categories of interest are given in following paragraphs.

4.5.1 Algebra

Based on a simple algorithm, these methods are relatively simple and easy to implement, on the other hand they do not provide complete matrices of change information (Lu et al. 2004).

For the distinction of different vegetation types Normalized Vegetation Indexing (NDVI) is the best known method in this category. For example in a tropical moist forest in Guatemala, Normalized Differenced Vegetation Indexing (NDVI-method) was the best suited method for classification to detect forest clearing and regrowth (Hayes and Sader 2001). The method produced the highest overall accuracy (85%),

and was compared with a principal components analysis and an image differencing technique.
The crucial step in the data processing for this category is to select the most suitable image bands or vegetation indices and select suitable thresholds to identify the changed areas (Lu et al. 2004). It is preferable to test different algebraic options (vegetation indexing, IR/R, TNDVI) before classification, this while areas that support more complex vegetation like woody and herbaceous vegetation are sometimes requiring different enhancements than those of agricultural land.

4.5.2 Transformation

The two methods discussed in this study are the principal components analysis and the tasseled cap transformation. Inside the transformation category these methods are most often used approaches for detecting change/non-change information (Lu et al. 2004). These methods basically transform the data to obtain a reducement of the data redundancy between the bands and to emphasize the different information in the derived components. This can even result that more detailed data related to the vegetation cover can be extracted. In a related study of Almeida and De Souza (2004) it was possible with the help of principal components analysis to identify different vegetation types, including identifying riparian forests, burn grasslands and resurgence zones, crops and several types of savannah and pastures.

4.5.3 Post-Classification

As the images are already classified it is crucial to perform the classification step as accurate as possible. This method was and is still the most popular for the application of dynamical landcover mapping. However it should be remarked that the whole process of post-classification is difficult and often leads to unsatisfactory change detection results (Lu et al. 2004). As a recent example out of the literature, Li et al. (2004) examined with the help of post-classification major transition rates among land-use types over a period of 14 years. The study demonstrates that the integration of satellite remote sensing and GIS was an effective approach for analysing the direction, rate and spatial pattern of land-use change. However the results can be doubted while only a simple qualitative field accuracy assessment was performed resulting in an overall accuracy of the land use classification of 95%.

Table 1. Summary of change detection techniques, the levels of complexity of the change detection techniques from 1-5; Lu et al. 2004

TECNNIQUES	1 CHARACTERISTICS	1 ADVANTAGES	DISADVANTAGES	KEY FACTORS
Category I algebra				
1.Vegetation index differencing	Produces vegetation index separately, then subtracts the second-date vegetation index from the first-date vegetation index	Emphasizes differences in the spectral response of different features and reduces impacts of topographic effects and illumination	Enhances random noise or coherence noise	Identifies suitable vegetation index and tresholds
Category II. Transformation				
2.Principal component analysis (PCA)	Assumes that multi-temporal data are highly correlated and change information can be highlighted in the new components. Two ways to apply PCA for change detection are:(1) put two or more dates of images into a single file, then perform PCA and analyse the minor component images for change information; and (2) perform PCA separately, then subtract the second-date PC image from the corresponding PC image of the first date	Reduces data redundancy between bands and emphasizes different information in the derived components	PCA is scene dependent, thus the change detection results between different dates are often difficult to interpret and label. It cannot provide a complete matrix of change class information and requires determining tresholds to identify the changed areas	Analyst's skill in identifying which component best represents the change and selecting tresholds
3.Tasseled Cap (KT)	The principle of this method is similar to PCA. The only difference from PCA is that PCA depends on the image scene, and KT transformation is independent of the scene. The change detection is implemented based on the three components: brightness, greenness and wetness	Reduces data redundancy between bands and emphasizes different information in the derived components KT is scene independent	Difficult to interpret and label change information, cannot provide a complete change matrix; requires determining tresholds to identify the changed areas. Accurate atmospheric callibration for each date of image is required.	Analyst's skill is needed in identifying which component best represents the change and selecting tresholds
Category III. Classification				
4.Post classification comparison	Separately classifies multi-temporal images into thematic mas, then implements comparison of the classified images pixel by pixel	Mimimizes impacts of atmospheric sensor and environmental differences between multi-temporal images provides a complete matrix of change information	Requires a great amount of time and expertise to create classification products. The final accuracy depends on the quality of the classified image of each date	Selects sufficient training sample data for classification

4.6 Guidelines for the detection of annual land cover change

The first step for detecting land cover change which is associated with patterns of shifting cultivation is to distinguish land use changes which are real changes, for example deforested areas or newly built villages. To detect this kind of change it should be optimal to compare different images over time, the multi-data images that were selected were almost in the same season, to eliminate the effects of seasonal change. The study area has a large area of agricultural lands like lowland and paddy rice fields. These types of land change seasonally.

Due to the type of change detection (image to image) an a priori distinction between forest types and agricultural land is not possible. This makes it difficult to specify the causes of the individual Landcover changes on the image. This means that not only land use practices focusing on shifting cultivation and burning are included in the results, but also shifting cultivation related activities are detected, such as village resettlements; land slides and forest fires are included. These kinds of changes are reflected in the spectral signatures of the images. This spectral signature variable can help when making a clear distinction between shifting cultivation and landcover changes which have basically a different vegetation background. This resulted in the development of a simple classification of the land (landcover) (table 1), simplified by separating the land in cleared and non- cleared areas. The 8 main strata as shown in table 1 below are used for the mapping of the cleared areas. It should be remarked that these classes are not yet revealing any detailed information concerning the related causes of clearance and for this are not always related to the shifting cultivation and its representation in the Nam Ton watershed.

Table 1 LANDCOVER CLASSES AND THEIR RESPECTIVE MAPPING CODES

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

4.6.1 Cleared areas vs. vegetated areas

Vegetated areas inside the Nam Ton watershed are having a vegetation cover varying from mixed low vegetation to dense forests. This includes bamboo, dense grass patches as well as forested lands. This diversity in ground covers, including deciduous forests, makes it impossible to restrict the term cleared area to the conversion from forested to non-forested land.

Cleared areas are areas that are cleared between two recorded Landsat images and this should be spectral visual on the Landsat image. The distinction between cleared and non-cleared area is visualised by data processing techniques. This means that for example a transformation or algebraic conversion of the pixel values is applied, which makes for example an area visible that is cleared from bamboo or grassland to (non)-permanent agricultural or bare land.

The class permanently cleared refers in most of the cases to rice fields or bare land. This can also be land that is repeatedly disturbed for cultivation purposes or erroneously were a vegetation cover spectral similar to rice or bare land is dominant, for example deciduous forests or grass patches.

The class permanently vegetated is spectral familiar with permanently covered areas like forests and bamboo.

4.6.2 Definition of shifting cultivation

Over the last century a dramatic reduction in fallow length of shifting cultivation took place in Lao PDR, this while the population pressure increased and/or government regulations started limiting access to land. The average fallow periods reported for the 1950s, 1970s and 1992 were 38, 20, and 5 years, respectively (Roder et al. 1994). This means that areas that were once primary forest are nowadays more frequently encroached for the purpose of shifting cultivation. The question is then also justified whether these areas are nowadays sustainable managed through shifting cultivation or just depleting under the negative effects of intensified slash and burning.

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:

(i) 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

(ii) assessment of land that is cleared in 1997 and supports again vegetation in 2000 and 2002

(iii) 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

Note that in the calculation for shifting cultivation a burning pattern of less than 5 years is not accepted, this can be an extra distinction for separating shifting cultivation patterns with areas under a regular slash-and burning regime. For example land that is cleared in 1997 and cleared again in 2000 but supports again vegetation in 2002 is not included in the calculation of the shifting cultivation for the years 1997 and 2000. This is also the reason that it is not possible to estimate the area under shifting cultivation for the year 2002.

Despite the decreasing fallowing periods, the five year period of monitoring (1997-2002) is too short to integrate other clearing patterns. With this type of short term monitoring it is however still possible to detect changes that deviate from the normal vegetative succession and seasonal variation. However in forestry, the changes may be also caused by cuttings, human resettlements, man made disturbances as well as damage. Another important necessity of measuring shifting cultivation is to distinguish the shifted cultivated areas from other hazardous effects like forest fires and landslides.

Following additional information was considered:

- If only two observations were made it would be not possible to discern shifting cultivation from patterns that can have other causes. For example it is not possible to discern between artificially irrigated fields and the permanent rice fields. This while irrigated fields are sometimes not irrigated or the irrigation is not functional A whole portion of land is becoming in this case vegetated again. By increasing the numbers of observations till three, bias towards these changes which only require two observations (Istvan Heiler and Miguel-ayanz 1998) is avoided.

- Cleared areas that are caused by forest fires are spectral visible because the area of burning has a kind of vagueness in its boundaries. These boundaries cause a lot of confusion and are not suited for this method. The Nam Ton watershed has such areas on top of its eastern hill boundaries. These burned areas however were coincidently excluded with the delineation of the study area.

- After classification large cleared areas that appear to have different causes like irrigation fields and resettlements are manually subtracted from the total cleared areas

4.6.3 Miminum mapping units

When interpreting a landcover classification with the help of raw satellite images, problems of interpretation are frequently encountered, which have to do with similar spectral signatures of different Landcover cover types. These anomalies can lead to wrong conclusions if no other variables are determined that define a class. Without general guidelines for the definition of a landcover class, variations between one interpreter and another can be so common that the different approaches become very subjective. A standard procedure to reduce this error of interpretation, due to mixed pixels is to set a minimum mapping unit for every class. When setting these minimum mapping units, it should be clear which software is used, while this can influence the final result. In this study there are two software packages used (Erdas Imagine 8.6 and eCognition 3). In Erdas imagine 8.6 the options to set the minimum mapping unit in the mapping process is restricted to the post-classification, this by including an extra vectorizing step or filtering. When applying the software package it was chosen not to include these extra steps. Several reasons and advantages of this choice are given below:

- Large minimum class sizes will lead to many generalisations with possibilities of losing important information.

- The final product of this study does not have to be a clear readable map so it is not irrelevant to set the area of one pixel (28.5 m x 28.5 m) as a minimum size.
- In a normal classification minimum mapping unit is used as a help when defining the landcover classes. In this simple classification however the classes differ only in the sequence of cleared and non-cleared areas over the years. No special vegetation characteristic is observed in the classes. Therefore it is not necessary to include a minimum mapping unit as an extra description for the class
- There is no reason that cleared areas don't have a minimum size smaller or equal than one pixel (28.5m x 28.5m).

In the other case when the classification is based on segmentation, the setting of a minimum mapping is related to the "Scale parameter" control value. This setting can modify the size of the resulting image objects after classification based segmentation. This step seemed not to give an extra problem of computation and loss in accuracy, because it was related with the first segmentation step. Therefore the minimum scale parameter in the eCognition mapping process was used in the setting of the Minimum Mapping Unit.

5 Chronological discussion of the workflow

The entire land cover change tracing procedure that is used within this study includes following flow of work. A detailed description of each different step in the change detection process is given in figure 2.

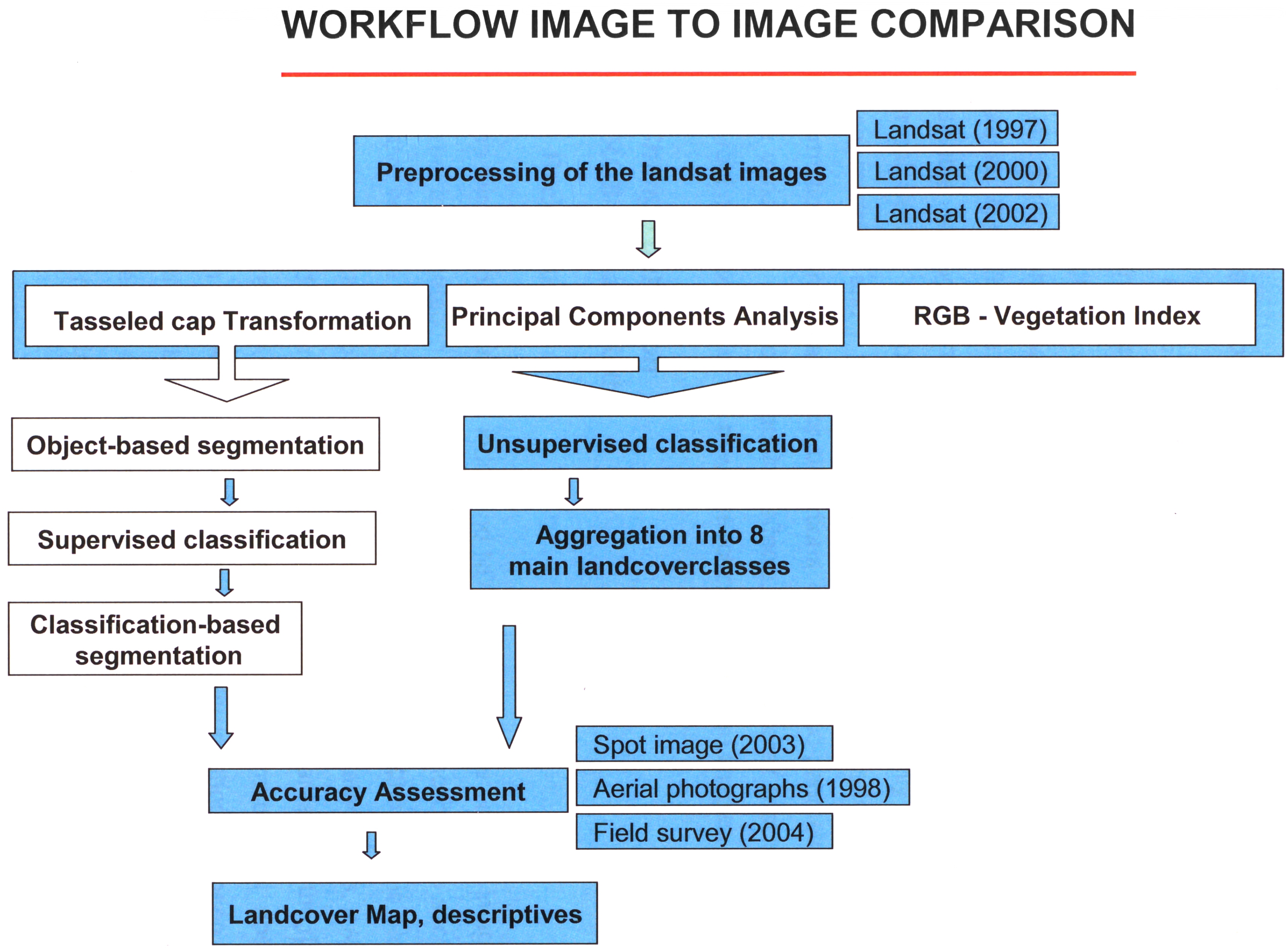


Figure 2 Workflow for the three different change detection techniques

5.1 Preprocessing of the landsat images

The Landsat TM and ETM images were compared after ortho-rectification was performed using an updated digital terrain model for the lower Mekong basin. This model is based on the American topographic maps (1:50000) and partially on Russian topographic maps (1:100000), which was mainly created by former Watershed Classification Projects. More details are included in the Watershed Sustainable Management Project Technical Reports (available at the MRCS Technical Service Division). The images were geometrically adjusted using the Landsat model (5 and 7 respectively for the TM and ETM series). This model and transformation compensates for distortions due to senso-geometry satellite orbit, altitude variations, and topographical effects. For the overall precision an average overall root mean square of 8.4 m was reached for the three images.

5.2 Change detection

5.2.1 RGB-vegetation Index

5.2.1.1 Background

After the third band, vegetation index and NDVI images of the Landsat images were compared; the vegetation index seemed to give a better distinction. The second best alternative was the 3-band multiple-date image composite, although this seemed to give the clearest distinction between vegetated and non-vegetated areas, it showed a large variation inside the more complex low vegetation cover areas like the rice fields and the grassy areas. As these bands clearly show the presence or absence of vegetation cover in the field, red band image differencing method has been found to be more than useful in both vegetated and urban areas (Jensen and Toll 1982). However it has been not clear whether visible red band image differencing can prove accurate results in moist tropical regions (Lu et al. 2004).

Finally the Normalized Difference Vegetation Index (NDVI) which is more related to the vegetation index was considered but soon it was clear that the normalization step compensated also for changing illumination conditions like the cleared lands due to shifted cultivation and forest clearing. In other words this normalization made it impossible to distinguish cleared and non-cleared areas. The only algebraic method that was giving an acceptable result was the RGB-vegetation index method.

5.2.1.2 Change detection procedure

The vegetation index was generated for the 1997, 2000, and 2002 images. Band 3 was subtracted from band 4, in this way cleared areas and water bodies are better distinguished from areas which are well vegetated, this while the latter has respectively higher leaf area values. For comparing the Landcover over the three years these images were stacked into a 3 -band vegetation index image of 1997, 2000, and 2002. A brightness inversion was applied on this image, this makes it possible to have similar spectral signature as the principal components and tasseled cap transformation. Finally one image was produced stacking the red, green and the blue band into one image (sequence of the bands: R, G, B; 3, 2, 1; 2002, 2000, 1997).

5.2.2 Principal components transformation

5.2.2.1 Background

Principal components analysis (PCA) is a method of multivariate statistics and intends to reduce the number of variables in data sets with large numbers of variables (Sabarowski 2003). This technique is especially useful when analyzing a satellite image. The transformation of raw remotely sensed data using PCA can result in new principal components images that may be more interpretable than the original data. To perform PCA, a transformation to a correlated set of multispectral data is applied. This will result in another uncorrelated dataset with correlated data of a lower level (Soumitri 2001)

PCA identifies the optimum linear combination of the original channels that can account for variation of pixel values in an image. Linear combinations are of the form:

$$A = C1X1 + C2\,X2 + C3X3 + C4X4$$

Where X1, X2, X3, and X4 are pixel values in four spectral channels, and C1, C2, C3, and C4 are coefficients applied individually to the respective channels. A represents a transformed value for the pixel.

The previous linear transformation ensures that the produced values account for maximum variation within the entire data set. Thus, this set of coefficients provides maximum information that can be conveyed by any single channel formed by the linear combination of the original channels. If an image is made from all the values, by applying this procedure to an entire image, a single band of data is generated, that provides an optimum depiction of the information present within the four channels of the original scene.

5.2.2.2 Change detection Procedure

In the tasseled cap transformation the stacks of the different components were compared visually. Even so after performing the principal components analysis, that generated the first six components, a decision was needed for selecting the bands which would serve for making a final stack for the image classification. For this the different components of each year were compared with the other years in a component-table. In this correlation matrix the correlation between images was quantified looking to the change in the loading sign. This matrix-change is related to changes that occurred between the acquisitions of the two images (Gimeno et al. 2004). This pre-analysis was done, while the components that represent change typically can show absence of correlation among the bands between the different dates (Hayes and Sader 2001). This information on the type of change represented by each component can be helpful when examining the eigenvectors of each band at each date, and selecting the final stack of bands for classification. For investigating this pre-analysis option, table 2 illustrates the eigenvalues of this transformation.

Table 2 shows the eigenvalues of the five first principal components of the 1997 Landsat ETM image, with their percentages of variations.

EIGENVALUE TABLE

IMAGE CODE*	BANDS	COMPONENT 1	2	3	4	5
12947_970203_m	97-1	0.15	0.20	-0.47	0.00	0.15
	97-2	0.11	0.11	-0.36	-0.01	0.16
	97-3	0.24	-0.30	-0.59	-0.08	0.16
	97-4	0.21	0.89	-0.37	-0.05	0.13
	97-5	0.82	0.04	0.41	-0.10	0.38
12947_000307_m	2000-1	0.08	-0.21	-0.33	0.12	-0.79
	2000-2	0.12	-0.24	-0.44	0.07	-0.21
	2000-3	0.24	-0.48	-0.54	0.01	0.56
	2000-4	0.00	0.71	-0.58	-0.40	0.02
	2000-5	0.74	0.36	0.06	0.56	0.04
12947_020209_m	2002-1	0.16	-0.23	-0.47	0.00	-0.03
	2002-2	0.12	-0.13	-0.36	-0.02	0.14
	2002-3	0.24	-0.35	-0.59	-0.09	0.54
	2002-4	0.27	0.89	-0.36	0.06	0.02
	2002-5	0.90	-0.10	0.40	-0.11	-0.03

*image code → used in database of Technical service Division of the Mekong River Commission

Table 2 shows some patterns of change in eigenvectors, mainly in the component 1, 2 and 5. These differences can help to explain why the clearing areas are spectrally distinct from surrounding forest in a multiple date image stack of the first component.

Although some change is seen between the eigenvectors of the fifth component only the first component is stacked in the multiple year composite used for interpretation. Reasoning that no significant change (over the three years), caused by variance in vegetation cover is seen in the eigenvector values until the 5th component of the transformed image, a second reason is that the first component accounts for the largest percent of variation, thirdly higher numbered principal components in particular require significant contrast stretching in order to make them interpretable. And finally Hayes and Sader (2001) advocate that the variation in the fifth component can have other causes, such as soil moisture changes between dates and not changes of the forest covers.

5.2.3 Tasseled cap transformation

5.2.3.1 Background

The tasselled cap transformation uses the same principle rule of transformation of raw correlated satellite data as the principal components analysis. The only difference is that the coefficients applied individually to the respective channels are fixed (Kauth and Thomas 1976), with this it is possible to derive a linear transformation for the four Landsat MSS bands. This linear transformation established four new axes in the spectral data, which can be interpreted as vegetation components useful for agricultural crop monitoring (Soumitri 2001). This tasseled cap transformation rotates the Multispectral signature data so that the majority of information is contained in two components or features that are directly related to physical sense characteristics (Soumitri 2001).

The tasselled cap transformation highlights the most important (spectrally observable) phenomenon of crop development in a way that allows discrimination of specific crops, and crops from other vegetative cover, in Landsat multitemporal and multispectral imagery (Soumitri 2001), with this transformation it is possible even to discriminate specific crops.

The advantage of the tasselled cap transformation in comparison to the principal component analysis is that it uses fixed axes for the transformation. In this way the result of the transformation doesn't depend too much on the quality of the raw satellite images. Besides, the tasseled cap transformation is ideal to show sharp contrasts between forest, regrowth and cleared land (Guild et al. 2004, figure 4). In this study it is particularly useful for monitoring the dynamics of land conversion related to shifting cultivation.

5.2.3.2 Change detection procedure

Tasseled cap images were used to generate the brightness, greenness and wetness indices for the 1997, the 2000 and the 2002 images. The number of spectral bands that are used for the purpose of the change analysis, was not restricted but chosen to be the same in all three images (Istvan Heiler and Miguel-Ayanz 1998), this was done by subsetting the 1997 Landsat TM image to 6 bands. The bands in all images represent the same wavelengths. This 3 layer composite offers a way to optimize data viewing that is associated with conversion of vegetated land into bare agricultural land. Seasonal changes between the different years were diminished as much as possible selecting the Landsat images taken in the same year period (February and March). After selection and transformation of the images the three images were stacked into different levels of component stack images. In figure 3 the first component image is compared with a stack of greenness values (2nd component) and a nine components image:

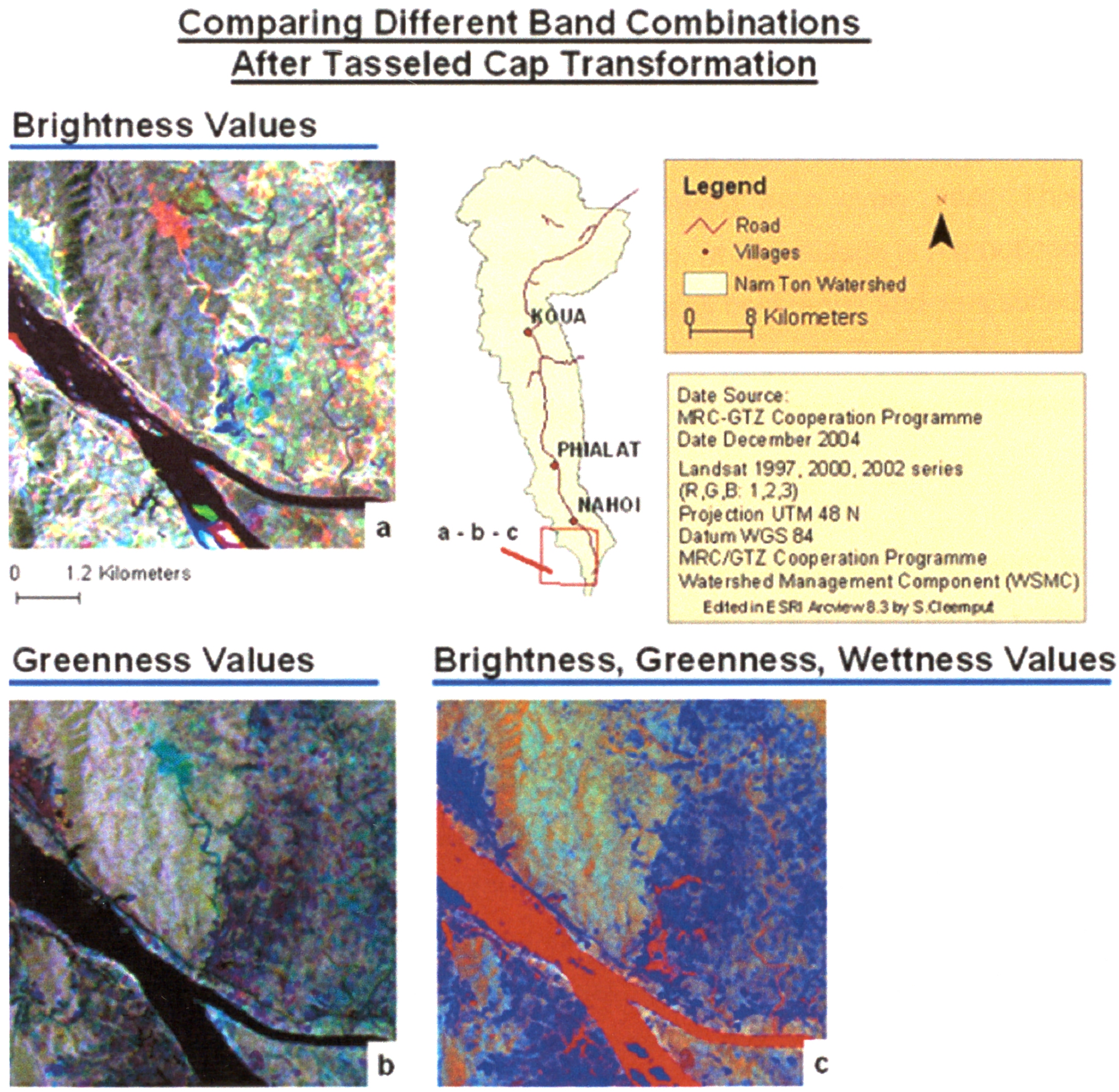


Figure 3 shows the difference between the different tasseled cap transformations. a) is the stack of brightness values over the three years, while b) is the stack of greenness values over the three years, and c) is a 9 band composite of tasselled cap transformations for every year.

For all, 1997, 2000, and 2002 data, the first three components or brightness values are best suited to describe the information content on the scenes, related to cleared areas (figure 3 a). In other words the eigenvectors of the first tasseled cap component are revealing positive contributions from all spectral bands and the stacked image is clear, detailed and of high contrast. This image shows the sharpest delineation of the converted land within the scene.

The second tasseled cap component image shows more detail, but also variance within each of the vegetation patches (figure 3b). This can be explained why the second component is being analogous to the greenness axis (Kauth and Thomas 1976). The cleared land however is insufficient visible (figure 4b. the riverbanks are not visible). The stacked layer, (figure 3c), includes every band related to the vegetation information (Brightness, greenness, wetness) from every year. This solution doesn't make every detail visible on the scene, (a new village is not noticed figure 3c). It was concluded that figure 3a had the overall best result and was suited for further classification. The first components of the different years, used for the final tasseled cap transformation are shown in Figure 4. In this figure following details should be observed:

- The river banks of the Mekong River in the south of the catchment. A variation in river bank size would be related to seasonal change, due to alternating water levels. The images however are showing equal sized river banks over the years.

- Another result of the application of the change detection technique is seen in figure 4c, where a resettlement was spotted, established between 2000 and 2002. After ground truthing this resettlement appeared to be the village of Huay kwam. its inhabitants are mainly shifting cultivating farmers who were relocated from the northern Luang Prabang district. It can be assumed that this village resettlement is the result of the policy of the Lao government which made priority of the resettlement of all shifting cultivators by the year 2000.

- A third remark should be made for the impossibility to distinguish the different vegetation types. This while after the transformation and the rejection of the vegetation component, very little information remains inside the pixel values that can be related to the different vegetation types in the area.

Tasseled Cap Transformation Time Series

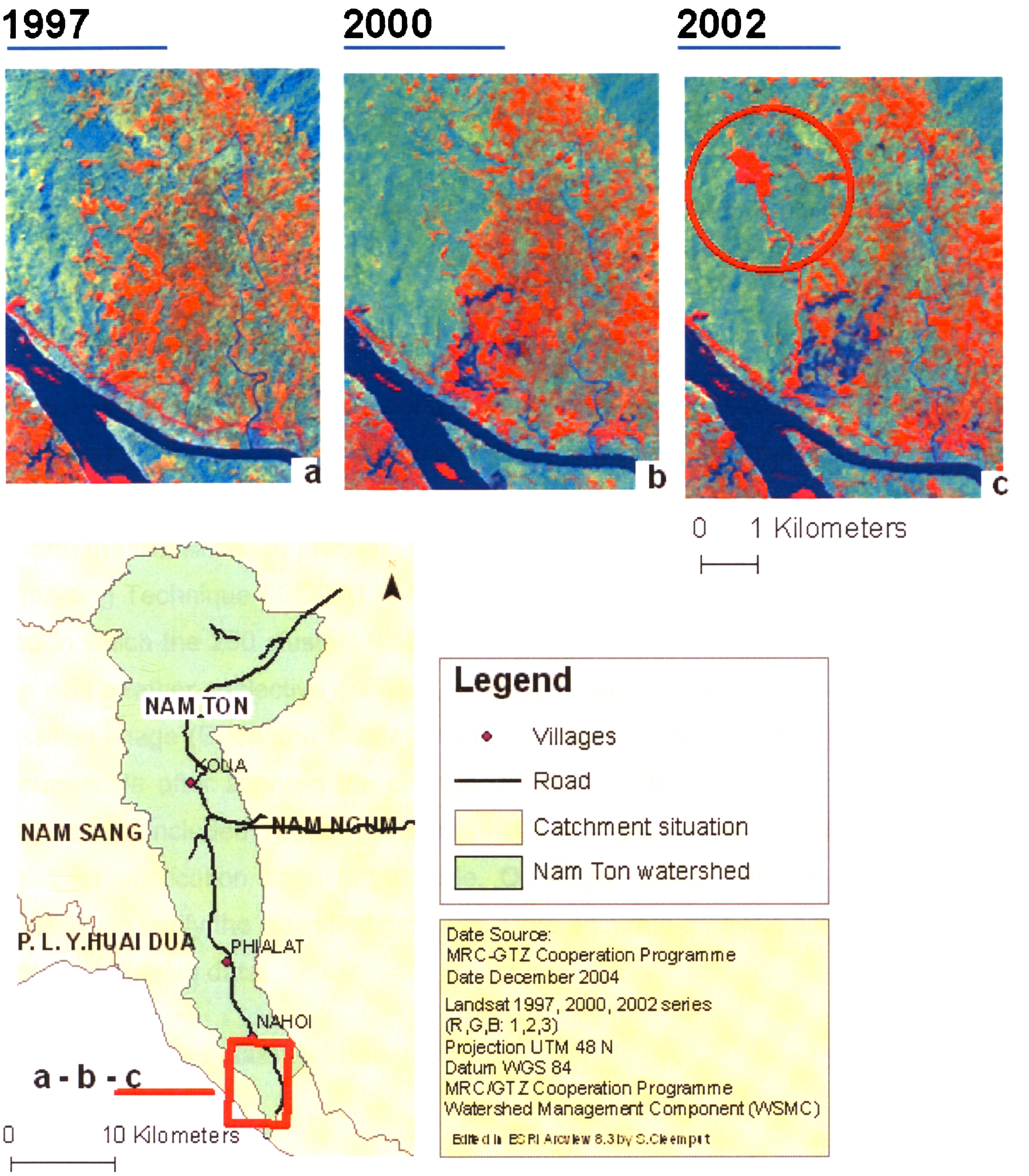


Figure 4 shows the band tasselled cap transformation (brightness band) of a) 1997 b) 2000 and c) 2002 image. The red circled area shows bare land that is caused through a village resettlement between 2000 and 2002

5.3 Classification

In this research a supervised and unsupervised classification approach were compared. The unsupervised clustering algorithm of the Erdas Imagine 8.6 was chosen in combination with a subjective clustering procedure for final classification of all the remote sensing satellite image transformations and differencing methods.

As an alternative supervised strategy the segmentation based classification approach was tested for the tasseled cap transformation in eCognition 3.0.

5.3.1 Unsupervised classification

As there is no minimum, at least not at a useful number of clusters that is appropriate for an optimal performance of an unsupervised clustering algorithm (Duda and Canty 2002), it was decided that an ad hoc choice of 250 clusters was made in order to perform the classification process. The clustering algorithm used is the Iterative Self-Organizing Technique (ISODATA) (Tou and Gonzalez 1974). The number of classes used in which the 250 clusters were grouped was chosen to be 8. This aggregating step was a rather subjective decision, as a high spectral complexity, is present in the classified image (Duda and Canty 2002). This aggregating was mainly based on the colour visible after applying the change detection technique. The use of reference data was not included. A good reason is that this change detection method should be suited for application on a large scale. On large scales there is not always the possibility to verify the classified data with more accurate data like aerial photographs or ground truthing data.

5.3.2 Supervised classification

5.3.2.1 Background

An alternative supervised classification method was applied in eCognition 3.0 on the tasseled cap transformation. With the application of this new classification concept it is possible to validate the results of Erdas imagine 8.6.

In general this technique is similar to the supervised clustering procedure in Erdas Imagine 8.6. The difference is that before classification the image is segmented into objects (segments) consisting of individual pixels. This segmentation process of pixels starts with one pixel objects merging them into bigger ones. This growing of the objects stops when the smallest growth object exceeds the threshold defined by the scale parameter. These objects were used for training 8 land cover classes. After segmentation and training, the image was classified using an algorithm based on a fuzzy classifier with the standard Nearest Neighbours.

After the classification step the image objects are still in a first level of segmentation. As this method is entirely based on relatively general homogeneity criteria, the resulting image objects are better described as image object primitives. After this step it is still not possible to calculate the areas of the individual features. To transform these object primitives into more meaningful image objects a classification based segmentation method is applied. Classification-based segmentation is a method to extract or refine image objects following a more complex knowledge base. It is based on the classification of already existing image objects and the structure groups edited in the class hierarchy. After this final step it is possible to calculate more meaningful feature characteristics like mean feature area, and feature position.

5.3.2.2 Procedure

The choice of the settings of the segmentation algorithm has a direct influence on the classification results. The segmentation mode was set at normal default, with a scale parameter at a level of 5. The choice of the scale parameter was done after trial and error testing of different levels: 10-2. 5 was the biggest possible scale which still distinguishes the different image regions. As the scope was to map spectral homogeneous areas the criteria for the smoothness and colour was set at a high value of 0.9. The shape criteria and compactness were set at low values of 0.1, with this the quality of the segmentation results are still kept optimal. Before the segmentation process was started each Landsat image was enhanced using standard deviation contrast stretching to improve the image quality.

5.3.3 Comparing supervised with unsupervised classification

In the supervised method in Erdas Imagine 8.6 the process of finding and verifying training areas can be rather labour-intensive, since the analyst must select representative pixels for each of the classes (Duda and Canty 2002). This must be done by visual examination of the image data and by information extraction from additional sources such as aerial photographs or existing maps (Schowengerdt 1997). Unlike the supervised classification process, unsupervised methods require no training sets at all. Instead they attempt to identify the underlying structure automatically by organizing the data into classes sharing similar, i.e. spectrally homogeneous, characteristics. The analyst 'simply' needs to specify the number of clusters present. Another advantage of this technique in comparing with supervised classification is that error due to overlapping between classes of the training areas is avoided (Brook and Kennel 2002).

5.4 Accuracy assessment

5.4.1 Definition and factors of influence

The accuracy assessment of a change detection technique is a step that validates the methodology for its use. The accuracy of a change detection technique is influenced by many factors. In this study following factors which influence the accuracy of a change detection technique are considered (Lu et al. 2004):

1. **precise geometric registration between multi-temporal images,**
2. **calibration or normalization between multi-temporal images,**
3. **availability of quality ground truth data,**
4. **change detection methods or algorithms used,**

Other factors like analyst's skills and experience, knowledge, familiarity of the study area, time and cost restrictions or the complexity of landscape and environments of the study area, were restricted by the choice of a small scale study area as discussed before in the justification of the study area chapter.

1. **precise geometric registration between multi-temporal images**

Accurate georeferencing and registering of multidate imagery acquired from aerial platforms over areas of extreme relief is critical to change detection, the first step to obtain quite good accuracy was the geometric registration process or the rectification of the images to the same co-ordinate system. In this rectification the pixels were set to a regular raster in this way the multitemporal images overlapped exactly over time.

2. calibration between multi-temporal images

Noise and image enhancements didn't showed any visual improvements of the imagery, therefore the multi- temporal images were held in their original form of acquisition, no special calibration procedure was followed

3. availability of quality ground truthing data

26 panchromatic aerial photo's of 1998 were scanned at a resolution of 1600 dpi. No ortho-rectification was performed on the aerial photographs. The lightness, brightness and shadow values were set optimal to cover the whole photographs. These series covered the whole study area, when necessary these aerial photographs were used to compare the change that happened in 1997. The spot image was used to detect the changes from 2002. The other change classes were found back on the original image. In addition 119 multispectral aerial photos of 1995 were scanned at 1200 dpi with a photogrammetric scanner.

4. change detection methods or algorithms used

When classifying a multispectral satellite data, several unsupervised clustering algorithms can be used. Examples of clustering algorithms found in literature (Duda and Canty 2002) are K-means, extended K-means, agglomerative hierarchical, fuzzy K-means and fuzzy maximum likelihood. The clustering algorithm, used is the Iterative Self-Organizing Technique (ISODATA) (Tou and Gonzalez, 1974).

5.4.2 Accuracy assessment and error matrix

The accuracy of the classified image was assessed with the help of co-registered aerial photographs of 1998 and a spot image of 2003. Although these additional datasets were used the error matrix was produced after setting a one stage equalizied stratified random sample of clusters (3 x 3 block) on the raw composite imagery. 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), an additional validation of the land cover change classes came from knowledge based upon experiences of groundtruthing in the watershed.

According to Hay (1979) a sample size with less than 50 elements gives an unsatisfying result, in most cases it is necessary to take a sample between 50 and 100 samples. In this research only 30 random clusters were selected, these clusters were located in a nine by nine window. The plots are the primary sampling units (PSUS) of the sample. The secondary sampling units are the plots chosen for comparison with the reference data (SSUS).

The simple clear majority rule of Erdas was used for the identification of the class of interest. This makes that in one cluster the pixel number can vary between 2 and 9 pixels, when an equal class number is present the central pixel class is chosen for referencing (figure 5). Following rule of agreement was used: 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 (USGS 2004) was obtained a positive result is reported for the whole cluster. This principle is called extreme within-cluster homogeneity. This rule is gives only two options, the whole cluster is correctly classified or the whole cluster is incorrectly classified. 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 identifiable.

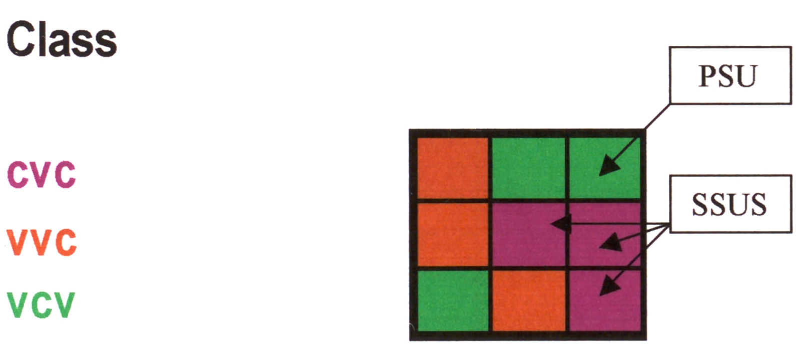


Figure 5 a cluster of nine pixels, in this example the simple clear majority is equal sized, the pink class pixels (while central pixel class) are chosen for comparison with the reference data

Practically this rule of agreement was followed by using an equalized stratified random sampling method (Devries 1986), selecting the simple clear majority assignment option in Erdas Imagine 8.6. This means that in each frame generated after the random stratified sampling procedure, only the dominant pixel colour is evaluated with the reference data. 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. It should be stressed that this verification of the assignment was done neglecting the individual pixel values, surrounding areas of this pixel block were considered as a more important decision factor for the class assignment.

The result of the assessment was noted in Excel tables as shown in table 3.

Table 3 Accuracy assessment for the sample plots for the VVV class

VVV	**CLASS**								
Plot nr.	**VVV**	CCC	CVV	CCV	VCC	VVC	CVC	VCV	Total Pixel nr./plot
1	**9**								9
2	**9**								9
3	**9**								9
...	...	...	...	...	...	...	...	...	...
17	**0**						9		9
18	**9**								9
19	**9**								9
20	**9**								9
21	**9**								9
22	**9**								9
23	**9**								9
24	**9**								9
25	**9**								9
26	**9**								9
27	**0**							3	3
28	**0**							9	9
29	**8**								8
30	**6**								6
TOTAL	**122**	0	0	0	0	0	9	12	143

The main reasons for not choosing a direct comparison for each SSU is given below:

- Individual pixels can present a rather mixed data due to edge effects besides it is rather impossible to retrieve the individual pixels on the spot image or aerial photographs.

- Another reason is that individual pixels are sometimes not exactly overlapping in the different years, due to geometric distortions from the geometric model. Whenever a mixed data plot was seen the larger class area was chosen to be a solution for the class.

- Another advantage of the method is that it is considerably faster than verifying every pixel using all three satellite images. Referencing an accuracy assessment of an image to image comparison requires in this case three times as much evaluation work (three satellite images) compared to a normal classification accuracy assessment procedure with only one satellite image.

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. The producer's accuracy is the number of correctly classified samples of a particular category divided by the total number of reference samples for that category. User's Accuracy measures individual category accuracy as well. It is the number of correctly classified samples of a particular category divided by the total number of samples being classified as that category. 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 factoring in this intensity value helps to relate the individual pixel values with the total area that is assessed in the accuracy assessment. Additionally a kappa coefficient was calculated. Essentially, the kappa coefficient gives a value for the percentage 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). Kappa Coefficient (K) is a multivariate accuracy assessment technique developed by

Cohen (1960) to determine if one error matrix is significantly different than another. It measures how the classification performs as compared to the reference data, using all cells in the error matrix, taking commission and omission errors into account. The Kappa coefficient is the measurement of the actual agreement (indicated by the diagonal elements of the matrix) minus change agreement (indicated by the product of row and column marginal) (Guild et al. 2004).

5.4.3 Accuracy assessment and Confidence intervals

An appropriate scientific application of landcover change analysis requires accuracy assessments that estimate accuracy per class with known confidence limits. Based on a simple formula the confidence intervals were calculated for the producer's and user's accuracies of the individual classes for every class of the different classifications.

Following formula was used for the calculation of the confidence interval margin of error for the population proportion of the samples:

$$E = z_c \sqrt{\frac{p\,(1-p)}{n-1}}$$

n = Total Number of Sampled Pixels

p = Proportion of Number of Correct Classified Pixels

E = Margin of Error

Z_c = 1.96 or the value of the standard normal distributed value at a confidence level of 95%.

5.4.4 Area estimation and confidence intervals

Considering that the remote sensing is the main source of data, previous chapters made it possible to output optimal remote sensing suitable for the calculation of aerial statistics. 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)

Following different formula were used to calculate the confidence intervals for the different strata (Shiver and Borders (1996) and Balázs (2005)) (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 j^{th} stratum

y_i = number of investigated pixels of one class in the i^{th} cluster of the j^{th} stratum

x_i = total number of investigated pixels in the i^{th} cluster of the j^{th} stratum

n = number of clusters (50)

j = number of strata (4)

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: $\frac{N_j - \sum_{i=1}^{n} x_i}{N_j} \approx 1$.

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

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

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

w_j = weight of the i^{th} stratum

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

N_j = total pixel number of the i^{th} stratum

M = total pixel number of the image

The variance is calculated according to Scheaffer et al. (1996):

$$\hat{\text{var}}(\bar{y}) = \sum_{j=1}^{4} w_j^2 \cdot S_{\hat{R}j}^2$$

The confidence interval was calculated with the following formula, at 95% confidence level z=1,96.

$$\bar{y} \cdot 100 \pm z \cdot \sqrt{\hat{\text{var}}(\bar{y})} \cdot 100$$

5.4.5 Example of the area calculation

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:

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

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

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

5.4.6 Qualitative Ground truthing

A qualitative ground truthing was organized in December of 2004. Qualitative reflects on the way of assessing the map. 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 exact location of the points was determined with a GPS (Global Positioning System). These sites were surveyed for any vegetation and landcover characteristics this description was improved with the help of digital photographs. Besides the measurement of the points an interest was given for the environmental situation of the Nam Ton

6 Results

6.1 Tasseled cap transformation

6.1.1 Unsupervised Classification and error matrix

Clearing of land was easily spotted in this land cover change detection approach. Out of the classification process it was possible to detect 8 different classes. An error matrix (table 4) and thematic map (figure 6) was created with all 8 change classes present. It should be remarked that the water class is erroneously represented in the permanent vegetation class. This decision was made while the cluster related to the water class was representing also vegetated area. With the exception of a few pure classes, the majority of classes are containing mixed pixel values. This can be explained, while the grouping analysis was largely dependent upon the resolution of the final unsupervised classification after tasseled cap transformation. The output thematic maps can be seen in figure 6. The error matrix which is an effective way to represent map accuracy is shown below (table 4).

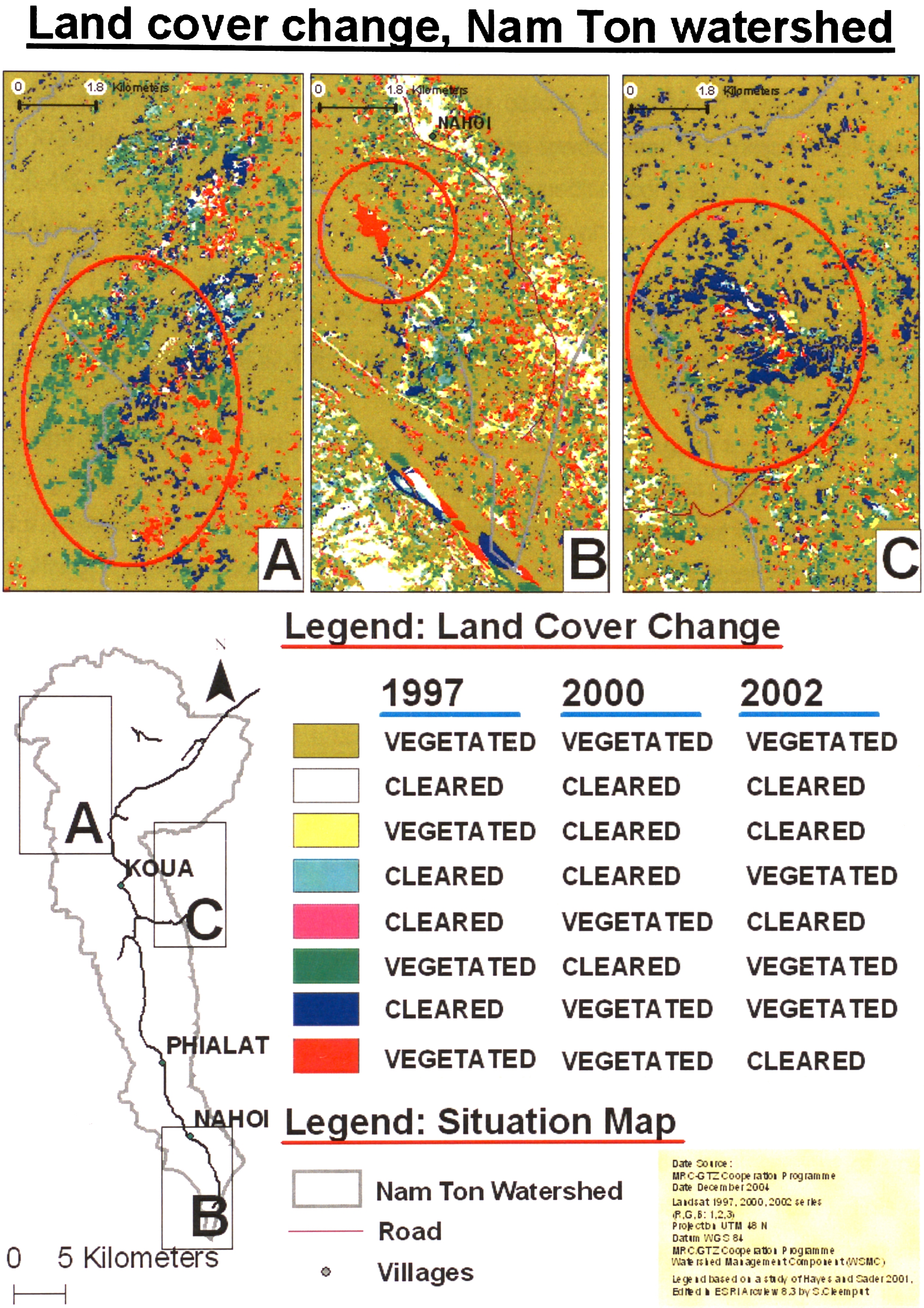
CLASSIFIED DATA	CODE	REFERENCE DATA (ACCURACY ASSESSMENT CLASS) ccc	ccv	cvc	cvv	vcc	vcv	vvc	vvv	Total N	USER'S ACCURACY	95% Confidence Interval -	+
CODE													
ccc		**157**	4	9	7		4			181	86.7	81.8	91.7
ccv			**136**		8	4	9			157	86.6	81.3	92.0
cvc		8		**64**				42	13	127	50.4	41.7	59.1
cvv			5	27	**174**					206	84.5	79.5	89.4
vcc		8	5			**101**	4	3	3	124	81.5	74.6	88.3
vcv		7	4			6	**119**		7	143	83.2	77.1	89.4
vvc				4				**168**		172	97.7	95.4	99.9
vvv				3			9	9	**236**	257	91.8	88.5	95.2
TOTAL N		180	154	107	189	111	145	222	259	1367			
PRODUCER'S ACCURACY (%)		87.2	88.3	59.8	92.1	91.0	82.1	75.7	91.1	Total Correct = 1155			
95% Confidence Interval													
-		82.3	83.2	50.5	88.2	85.6	75.8	70.0	87.6				
+		92.1	93.4	69.1	95.9	96.3	88.3	81.3	94.6				

OVERALL TOTAL ACCURACY (%) = 84.5
OVERALL KAPPA INDEX = 82.1 %
OVERALL TOTAL ACCURACY 95% UPPER AND LOWER CONFIDENCE INTERVAL = -82.4 +86.6

CODE DESCRIPTION

	1997	2000	2002
ccc	CLEARED	CLEARED	CLEARED
ccv	CLEARED	CLEARED	VEGETATED
cvc	CLEARED	VEGETATED	CLEARED
cvv	CLEARED	VEGETATED	VEGETATED
vcc	VEGETATED	CLEARED	CLEARED
vcv	VEGETATED	CLEARED	VEGETATED
vvc	VEGETATED	VEGETATED	CLEARED
vvv	VEGETATED	VEGETATED	VEGETATED

Figure 6 The result after the mapping exercise: A) shifting cultivated areas in the north, B) a village resettlement in the south and C) burned areas in the east of the watershed



The tasseled cap classification gave an overall accuracy of 84.5 %, the pertinent lower limit of the confidence interval has a value of 82.4%, the upper limit at 86.6%. An overall kappa index of 82.1 was generated. The tasseled cap classification gave high producer's accuracies 75.7-92.1% for classes that were only once cleared over time. The class that represents clearance before 97, regrowth between 1997 and 2000 and cleared again in 2002, had also the lowest user's accuracy of all classes 50.4%. This low accuracy is probably by a spectral confusion of regrowth areas (Guild et al. 2004). The no change classes had high producers accuracy (ccc; vvv: 87.2%; 91.1%), and a higher user accuracy (ccc; vvv: 86.7, 91.8%). In other words, 91.1% of all the area that is permanent vegetated within the classification were actually the class and 91.8% of the area was correctly identified as such an area.

Within the map it is not possible to distinguish between a regular forest conversion for the purpose of logging and other causes of land conversion as land that is converted for resettlement. It can be however expected that change which is related with shifting cultivation occur especially in more mountainous for example in the north western area of the catchment (see Figure 6).

6.1.2 Specific conclusions and discussion

- After the clustering it is easier to delineate changed areas in remote areas than those in the built up areas. This is probably caused because by the level of disturbance in built up area. Therefore there are more mixed pixels in these higher accessible areas, what may lead to a mixture of different change patterns within the same type of vegetation.

- The distinction between cleared areas and forest regrowth after two years of clearing was not clearly visual in the accuracy assessment. An explanation could be that at rice harvest, tree and bamboo species develop slow to fill the gap left after the rice harvest. By progressing fallow period the replacement of grass species by trees and bamboo occurs only gradually (Roder et al. 1997). This can explain the difficulty in distinction between the pioneer grasses that come up after the clearing of an area and the rice covered areas. This is specially seen in the class that has a clearing over two-year with a regrowth period in 97-2000. This class has both a low producer's (59.8%) and user's accuracy (50.4%).

- Large change patterns mainly occur locally inside the catchment area. In figure 6 it is seen that a large changes occurred upland to the northwest of the catchment area. Outside the watershed in the central part, on the upper east slopes mainly grass fires occurred this leading to the loss of vegetated lands before 1997.

- In the southern part the major changes are a village resettlement (cleared in 2002), road constructions and irrigations fields (cleared from 2000-2002).

6.1.3 Supervised classification after object based segmentation

After a total of 396 segment-samples were manually selected the classification process was started. The number of misclassifications was reduced by iteratively adding image object samples of the correct class to the sample editor and repeating the classification process. These data were classified using the standard nearest neighbour function of eCognition. After the classification the initial image object levels (object primitives) were rejoined by the classification-based fusion procedure of eCognition. This resulted into 6157 objects with an average object size of 9.6 ha. The accuracy assessment was performed resulting in the error matrix which details are given on following page (table 5).

Table 5 ACCURACY ASSESSMENT ERROR MATRIX

CLASSIFIED DATA	REFERENCE DATA (ACCURACY ASSESSMENT CLASS)								Total	USER'S	95% Confidence Interval	
CODE	CCC	CCV	CVC	CVV	VCC	VCV	VVC	VVV	N	ACCURACY	-	+
CODE												
CCC	**122**	4	22		9		51	6	214	57.0	50.4	63.7
CCV	15	**153**		19					187	81.8	76.3	87.4
CVC	6		**155**	32					193	80.3	74.7	85.9
CVV	6		9	**161**				32	208	77.4	71.7	83.1
VCC	9		5		**154**		8	5	181	85.1	79.9	90.3
VCV	10	8			32	**113**	12	29	204	55.4	48.6	62.2
VVC			14		8		**158**	16	196	80.6	75.1	86.2
VVV	14		9	9		15	9	**191**	247	77.3	72.1	82.6
TOTAL N	**182**	**165**	**214**	**221**	**203**	**128**	**238**	**279**	**1630**			
PRODUCER'S ACCURACY (%)	**67.0**	**92.7**	**72.4**	**72.9**	**75.9**	**88.3**	**66.4**	**68.5**	**Total Correct = 1207**			
95% Confidence Interval												
-	**66.5**	**92.5**	**72.2**	**72.9**	**75.7**	**88.3**	**66.0**	**68.4**				
+	**67.5**	**92.9**	**72.7**	**72.9**	**76.1**	**88.3**	**66.7**	**68.6**				

OVERALL TOTAL ACCURACY (%) = 74.0
OVERALL KAPPA INDEX = 70.3 %
OVERALL TOTAL ACCURACY 95% UPPER AND LOWER CONFIDENCE INTERVAL = 76.1 71.9

CODE DESCRIPTION

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

The result of the mapping for the tasseled cap transformation with the eCognition software had an overall accuracy level of 74.0 %. A kappa index of 70.3% was reached, which is still lower than the value of 82.1% reached with unsupervised classification. As this value is lower, the area statistics were calculated after unsupervised classifications. The eCognition 3.0 software however allows for easily calculating feature related statistics that can be useful in the further interpretation of the data of the different classes. These individual feature characteristics like mean area can be used for refining the result of the unsupervised classification. For example the Mekong river could be correctly delineated in the supervised clustering procedure, without including false vegetated classes (0.84 km^2). It was however not possible to give an estimate for the Nam Ton River and other water bodies. Other individual areas that were calculated were the village resettlement (0.38km^2), which was cleared in 2002. Without correction, this area would have been included in the calculation for the total area of shifting cultivation in 2002.

The mean area for each class is estimated based on the analysis of the supervised classification. When using these estimated means, the reliability of the estimate has to be assessed through analysis of the following related statistics, Number of sample plots, Standard Deviation (StDev) and Coefficient of Variation.

The Standard Deviation and Coefficient of Variation measure the variation of individual areas of the objects after classified based segmentation. The variations among samples depend primarily on the inherent variability within the population mean and the size of the sample (n) (Freese 1984). The lower the dispersion around the mean, the higher is the precision of the estimate. The estimated mean area and related statistics for the main change classes are tabulated below (table 6).

Table 6 shows some of the feature characteristics of the different change classes after supervised classification in eCognition

Class	Nr. Objects	Mean Area (ha)	StDev	Coefficient of Variation
vvv	851	57.8	1607.7	27.8
ccc	1099	3.4	11.9	3.5
cvv	803	1.8	2.9	1.6
vcv	1663	1.5	2.3	1.5
vvc	1007	1.5	2.0	1.3
ccv	116	1.3	2.8	2.1
cvc	244	0.9	1.0	1.1
vcc	374	0.7	0.6	0.8

Table 6 shows the Landcover change per class in total numbers. The Nr. Objects refers to the number of segments after the classification based segmentation procedure (merging the region specified objects into class specified objects). The coefficients of variation range from 1-28%, this is not abnormal, while the area distribution is not homogeneous. The classes with a low coefficient of variation are the classes that are most frequent cleared. Logically these classes have a low surface area, while frequently clearing requires a lot of labour input.

Another interesting statistic is that the classes that were only once cleared in the monitored period show higher membership values with the permanent vegetation class 0.93 – 0.95 than the classes which were cleared several times (0.38 - 0.88). Low values or very similar values mean that the class descriptions are not very well suited to separate the classes. Individual membership values can be useful to introduce existing knowledge into the classification. In other words it means that with these class assignments it is possible to refine the result of the segmentation based on the distinction between areas that are only once cleared from areas that are cleared several times.

6.1.4 Advantages and disadvantages of eCognition 3.0

- There is no salt and pepper effect after segmentation. This while eCognition uses an object based classification instead of a pixels based classification like in Erdas Imagine 8.6.

- The user friendliness of the software makes it possible to combine the results of the unsupervised classification in Erdas 8.6 with the results of the supervised approach in eCognition 3.0.

- The advantages of eCognition compared with the Erdas Imagine 8.6 software is that detailed feature statistics of the mapped data can be queried. For example the position statistic can determine where the highest occurrence of shifting cultivation occurs in the watershed.

- The advantage of eCognition is that it is powerful software. Its low classification results in this study are probably having more to do with the practice of the supervised technique rather than the software on itself.

- A disadvantage is that the eCognition supervised approach of classification requires the trying out of different parameter combinations. This is only controlled after understanding its concepts. The software uses a pure supervised approach for the classification. With this the quality of the entire classification depends on the initial segmentation class model.

6.2 Vegetation index

6.2.1 Unsupervised Classification and accuracy assessment

The change detection was done by using an unsupervised classification (ISODATA) of the 3 vegetation index bands of 1997, 2000, and 2002. Only six classes are delineated. A total number of 1181 pixels were tested against the reference. Of these 1181 pixels, 70 pixels were situated in the classes that are composed of multiple colours, like the cleared in 97, cleared in 2000 and vegetated in 2002 or the cleared in 97, vegetated in 2000 and cleared again in 2002. These last two classes are however absent in this error matrix. The following two reasons for this absence are given: (1) the cleared in 97, cleared in 2000 and vegetated again in 2002 was only available in low pixel numbers (lower than 1 percent of the classified area), therefore sampling frames of these pixels could not be set (2) The class that was cleared in 97, vegetated in 2000 and cleared in 2002 was not spectrally delineated after unsupervised classification.

Table 7 ACCURACY ASSESSMENT ERROR MATRIX

CLASSIFIED DATA CODE	REFERENCE DATA (ACCURACY ASSESSMENT CLASS) ccc	vcv	vcc	vvc	cvv	vvv	cvc	ccv	Total N	USER'S ACCURACY	95% Confidence Interval -	+
CODE												
ccc	**115**	20	39	13	9	6			202	56.9	50.1	63.8
vcv		**146**				43			189	77.2	71.3	83.2
vcc	20	15	**82**	15	8	31			171	48.0	40.4	55.5
vvc			10	**155**		10			175	88.6	83.8	93.3
cvv	11	8	24		**126**	5			174	72.4	65.8	79.1
vvv		22		9		**169**			200	84.5	79.5	89.5
cvc									N.A.	N.A.	N.A.	N.A.
ccv									N.A.	N.A.	N.A.	N.A.
TOTAL N	146	211	155	192	143	264	N.A.	N.A.	1111			
PRODUCER'S ACCURACY (%)	78.8	69.2	52.9	80.7	88.1	64.0	N.A.	N.A.	Total Correct = 793			
95% Confidence Interval												
-	72.1	62.9	45.0	75.1	82.8	58.2	N.A.	N.A.				
+	85.4	75.4	60.8	86.3	93.4	69.8	N.A.	N.A.				

OVERALL TOTAL ACCURACY (%) = 71.4
OVERALL KAPPA INDEX = 65.6 %
OVERALL TOTAL ACCURACY 95% UPPER AND LOWER CONFIDENCE INTERVAL = -68.7 +70.0

CODE DESCRIPTION

	1997	2000	2002
ccc	CLEARED	CLEARED	CLEARED
vcv	VEGETATED	CLEARED	VEGETATED
vcc	VEGETATED	CLEARED	CLEARED
vvc	VEGETATED	VEGETATED	CLEARED
cvv	CLEARED	VEGETATED	VEGETATED
vvv	VEGETATED	VEGETATED	VEGETATED
cvc	CLEARED	VEGETATED	CLEARED
ccv	CLEARED	CLEARED	VEGETATED

The RGB vegetation index classification gave an overall accuracy of 71.4 % the pertinent lower limit of the confidence interval has a lower value of 68.7 %, whereas the upper limit has a value of 70.0%. In the mapping process it was seen that the classes that describe a permanent cleared area are overlapping with the regrowth areas where perennial species are also dominant (figure 7 1-2). These cleared areas were not visible during the ground truthing. The vcc class has the lowest producer's accuracy (52.9%) and user's accuracy (48.0%)

6.2.2 Specific conclusions and discussion

One of the causes for the spectral differences seen when adapting the different image conversions in the Nam Ton watershed is related to the spectral characteristics of the dominant type of fallow vegetation Nam ton watershed. Foppes describes (1995) that mainly broadleaved weed, dominate in 2- 5 years after clearing the area. And that starting from 3-6 years onwards, bamboo species appear. It takes ten years, when these individual trees start to emerge above the bamboo canopy. Only after 20 to 30 years, these trees start to dominate. This succession of vegetation types makes it very difficult to distinguish between cleared and regrowth areas only after a period of 2 years.

6.3 Tasseled cap versus vegetation indexing method

For each change detection technique the whole methodology starting from the grouping till the final accuracy assessment is repeated. It should be remarked that was preferred not to use same spectral signatures for aggregation of the results of the unsupervised classifications. The advantage is that in this way the whole methodology can be appraised. The error matrix shows already that the tasselled cap is doing better than the RGB vegetation index. When comparing the two methods for their user comfort, the tasselled cap is ranked higher than the vegetation indexing method. Spectrally it is visual that the areas where shifting cultivation is occurring are better delineated and are showing less vagueness in the tasseled cap than in the RGB vegetation index method (figure 7). The overall accuracy of the six classes that both classifications are having in common is 88.2 % for tasseled cap compared to 71.4 % for the RGB vegetation index method.

Comparing the Tasseled Cap Transformation with the RGB Vegetation Index Method

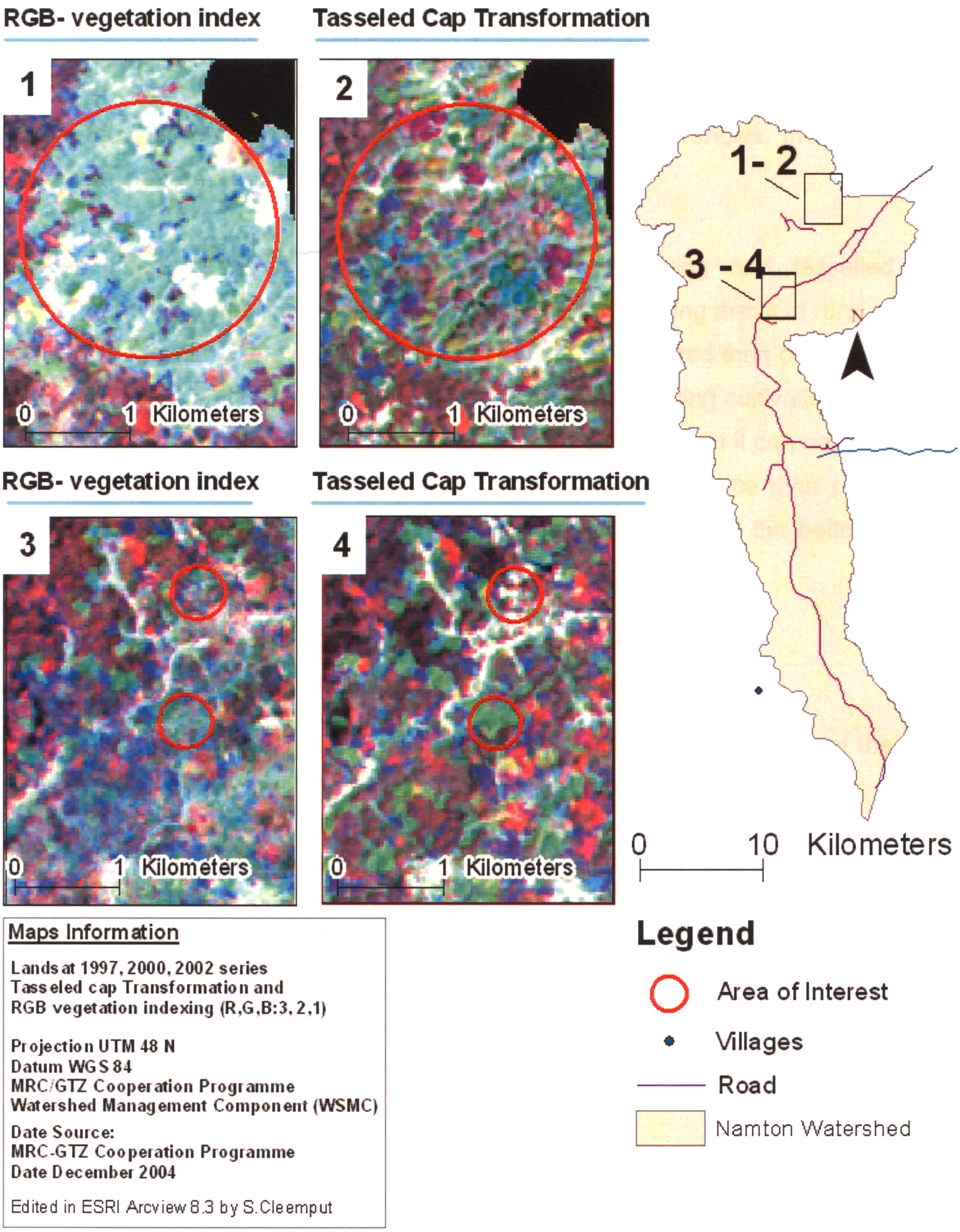


Figure 7 shows two scenes, 1-2 are differences on a large scale, while 3-4 are small scale spectral differences. These differences are important for a better result after unsupervised classification

Figure 8 1- 2 shows spectral differences on the macro-level between the two image processing techniques while figure 8 3-4 show contrast differences on the micro-level. Figure 8 1-2 shows that the RGB-vegetation indexing classified the area in the north as homogenous and cleared in the three monitored years, while tasselled cap transformation classified more variability in change. The ground truthing proved that this area was cleared in the eighties by a logging company. At the moment however he area in plates one and two is dominated by low mixed vegetation is dominated by grasses and in contrary to what the RGB vegetation index shows, the area is not permanent cleared.

Another difference in comparing RGB-vegetation indexing and tasselled cap transformation is the efficiency in delineating shifting cultivating areas in rural built up areas (micro-level). Plate 3 of figure 8 is more various coloured than plate 4 of figure 8 which shows a better distinction between the different shifting cultivating areas. As reality on the ground proves this area is subject to disturbing and it can not be clearly referenced if situation 3 is not better describing human influence than plate 4 for classification purposes on the other hand plate 4 and plate 1 are the better starting materials.

6.4 Principal components analysis

6.4.1 Unsupervised Classification and accuracy assessment

The result of the unsupervised classification was evaluated with the help of the error matrix, presented in table 7.

Figure 7 1- 2 shows spectral differences on the macro-level between the two image processing techniques while figure 7 3-4 show contrast differences on the micro-level. Figure 7 1-2 shows that the RGB-vegetation indexing classified the area in the north as homogenous and cleared in the three monitored years, while tasseled cap transformation classified more variability in change. The ground truthing proved that this area was cleared in the eighties by a logging company. At the moment however he area in plates one and two is dominated by low mixed vegetation is dominated by grasses and in contrary to what the RGB vegetation index shows, the area is not permanent cleared.

Another difference in comparing RGB-vegetation indexing and tasseled cap transformation is the efficiency in delineating shifting cultivating areas in rural built up areas (micro-level). Plate 3 of figure7 is more various coloured than plate 4 of figure 7 which shows a better distinction between the different shifting cultivating areas. As reality on the ground proves this area is subject to disturbing and it can not be clearly referenced if situation 3 is not better describing human influence than plate 4 for classification purposes on the other hand plate 4 and plate 1 are the better starting materials.

6.4 Principal components analysis

6.4.1 Unsupervised Classification and accuracy assessment

The result of the unsupervised classification was evaluated with the help of the error matrix, presented in table 8.

Table 8 ACCURACY ASSESSMENT ERROR MATRIX

	REFERENCE DATA (ACCURACY ASSESSMENT CLASS)								Total	USER'S	95% Confidence Interval	
CLASSIFIED DATA — CODE	ccc	ccv	cvc	cvv	vcc	vcv	vvc	vvv	N	ACCURACY	-	+
CODE												
ccc	**140**	14	7	6	10			6	183	76.5	70.3	82.7
ccv	4	**89**						6	99	89.9	83.9	95.9
cvc	31		**130**						161	80.7	74.6	86.9
cvv	7	50	13	**179**				23	272	65.8	60.2	71.5
vcc					**122**	24	15	6	167	73.1	66.3	79.8
vcv						**159**		7	166	95.8	92.7	98.8
vvc					4	6	**172**	9	191	90.1	85.8	94.3
vvv	3				9	3		**198**	213	93.0	89.5	96.4
TOTAL N	185	153	150	185	145	192	187	255	1452			
PRODUCER'S ACCURACY (%)	75.7	58.2	86.7	96.8	84.1	82.8	92.0	77.6	Total Correct = 1189			
95% Confidence Interval												
-	75.2	57.8	86.4	96.6	83.8	82.8	92.0	77.5				
+	76.1	58.5	86.9	96.9	84.5	82.8	92.0	77.8				

OVERALL TOTAL ACCURACY (%) = 81.9
OVERALL KAPPA INDEX AND CONDITIONAL KS = 79.2 %, 55.2 %
OVERALL TOTAL ACCURACY 95% UPPER AND LOWER CONFIDENCE INTERVAL = -79.5 + 84.3

CODE DESCRIPTION

	1997	2000	2002
ccc	CLEARED	CLEARED	CLEARED
ccv	CLEARED	CLEARED	VEGETATED
cvc	CLEARED	VEGETATED	CLEARED
cvv	CLEARED	VEGETATED	VEGETATED
vcc	VEGETATED	CLEARED	CLEARED
vcv	VEGETATED	CLEARED	VEGETATED
vvc	VEGETATED	VEGETATED	CLEARED
vvv	VEGETATED	VEGETATED	VEGETATED

The accuracy assessment of the principal components has an overall accuracy result similar with the tasseled cap transformation. The principal component classification gave an overall accuracy of 81.9%. The lower limit of the confidence interval has a value of 79.8 %, the upper limit a value of 83.8%. one remarkable result of the principal components transformation is situated in the vcv class. This class has a producer's accuracy value of 97% for the class were clearance occurred in 97 (code: vcv). In other words, 97% of all the area that is cleared only in 97 within the classification is actually the class, although only 66% of the area was correctly identified as such an area. It is not on option to compare the procedures accuracy's of the same classes over the different classification; this while no fixed sampling plot system was used.

6.4.2 Principal Components Analysis vs. Tasseled Cap Transformation

The difference in kappa values between the tasseled cap transformation and the principal components analysis is only 2.3%. One of the causes for this small difference between the classification after tasseled cap transformation or principal components analysis is the subjective aggregation into the 8 classes after unsupervised classification. It can be however assumed that an additional difference of the two classifications is caused by the fact that the coefficients applied on the respective channels are fixed in the tasseled cap while depending on image quality in the principal component analysis.

6.5 Area statistics

6.5.1 Area statistics of the change classes

In this chapter the results of the mapping exercise, which aimed at determining the area of the land cover change at the level of the Nam Ton watershed are presented. Note that the area of the Mekong River is 0.84 km² (classified erroneously within VVV). This area was delineated in the alternative supervised classification of eCognition 3.0. The naïve estimation refers to the pixel numbers is extracted from the landcover map after aggregation into 8 classes (table 8). A corrected estimation of the raw pixel numbers (naïve estimation) with the help of the individual correctly classified pixel-ratios of c in the error matrix is also given in table 9.

Table 8 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 9 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 10 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 10 shows some derived land cover types. The area classification is based on the calibrated estimation out of table 9

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 11 shows some derived land cover types. The area classification is based on the corrected area estimation method

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

6.5.2 Pattern of shifting cultivation

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.

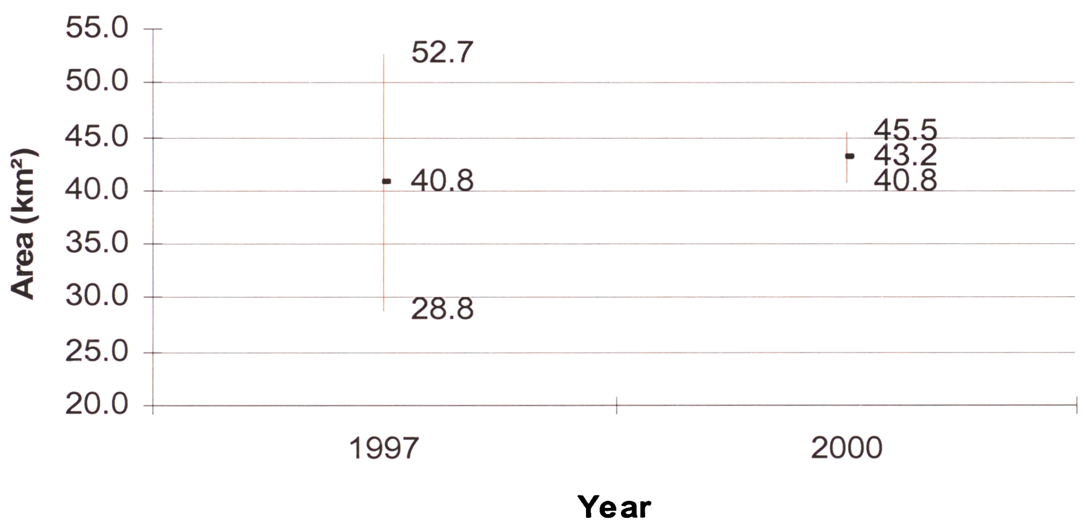


Figure 8 The pattern of shifting cultivation

Balázs (2005) used a post classification change detection technique for estimating the total area under cropland and settlement (≈ total cleared area). This 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.

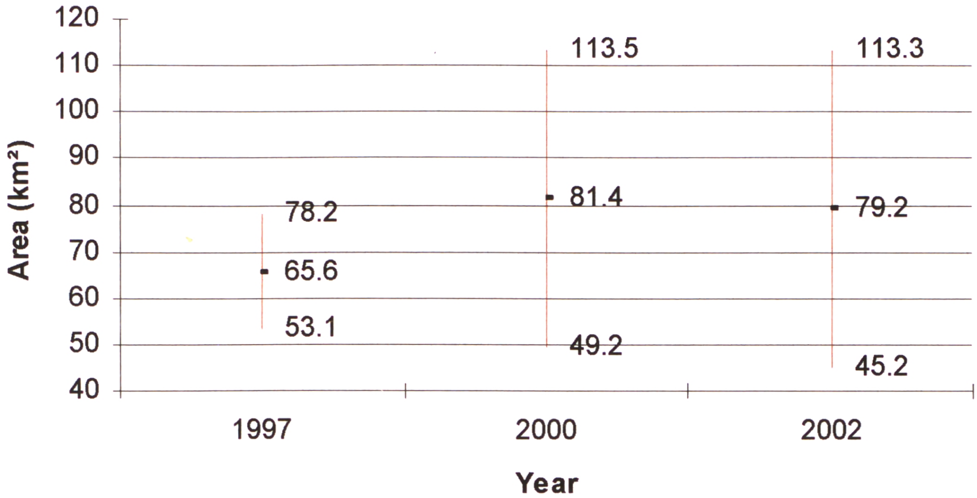


Figure 9 the pattern of the total cleared area

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%.

7 Examples of monitored landcover change in Nam Ton

After studying the maps; a fieldtrip was planned; during this fieldtrip different sites were visited, a review of impressions of the environmental situation based on informal interviews is given.

7.1 Southern part of the Nam Ton watershed

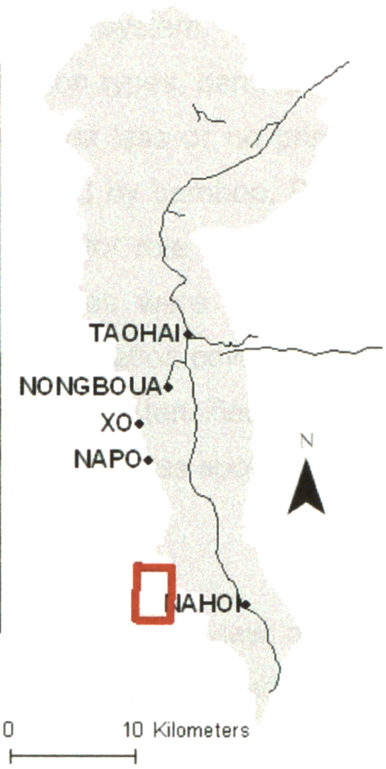
The resettlement of the village of Huay kuam is one of the most remarkable land cover changes that occurred in the past 4 years. Another area that has been more intensively cleared, are the irrigated areas in the south of the catchment. Further no large cleared areas were spotted in the south western part of the catchment, except from some small cleared patches inside the forest and on the eastern hillside nearby the village of Napor.

The landscape in the south of the catchment can be described as a mixed pattern of remnant forests with a dominance of bamboo, rice paddies and periodically slashed and burnt upland fields. Home gardens exist within the villages nearby, on a very small scale to supply vegetables, herbs, fruits and different kind of species. This type of cultivation practices is representative for wide areas in Laos. This was one of the reasons that in this area a management intervention zone has been established, which planning and implementation scopes to lead to better land management practices, this programme started in 2001 for a period of 10 years (Kollert 2000). The map on the following page (Figure 10) shows one of the irrigated areas that was already cleared in 1997, in 2002 there was no clearance. The explanation of the local farmers was that the pumps are sometimes not functioning in certain years. This leads towards critical food security situations while the crop production completely depends of this irrigation system.

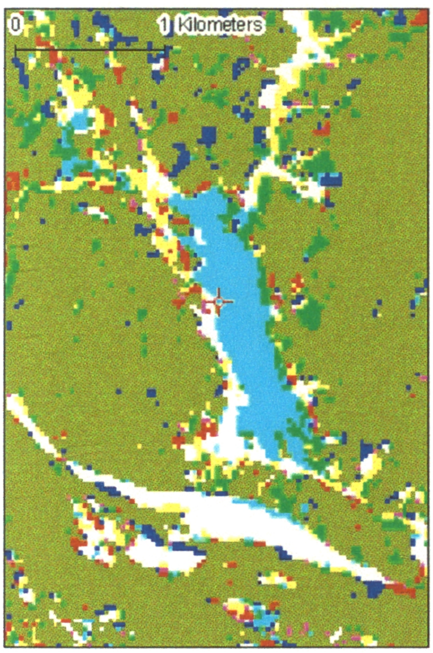
Southern Part of The Watershed

Situation Photo

Situation Map



Land Cover Change



Legend

- Verification Point
- villages
- Road
- Nam Ton

Date Source:
MRC-GTZ Cooperation Programme
Date December 2004

Tasselled Cap Transformation
of Landsat 1997, 2000, 2002 series

Projection UTM 48 N
Datum WGS 84
MRC/GTZ Cooperation Programme
Watershed Management Component (WSMC)

Edited in ESRI ArcView 8.3 by G.Cleemput

	1997	2000	2002
	VEGETATED	VEGETATED	VEGETATED
	CLEARED	CLEARED	CLEARED
	VEGETATED	CLEARED	CLEARED
	CLEARED	CLEARED	VEGETATED
	CLEARED	VEGETATED	CLEARED
	VEGETATED	CLEARED	VEGETATED
	CLEARED	VEGETATED	VEGETATED
	VEGETATED	VEGETATED	CLEARED

Figure 10 shows a verification example of the tasseled cap transformation, an irrigated area was spotted in the southwestern part of the Nam Ton watershed

7.2 *Central part of the watershed*

The central part (Figure 11) is covered by mixed agricultural land where permanent rice fields with fishponds are a dominant part of the farming system. The mixed agricultural lands in the villages show a big variety of vegetation types, bananas and palm trees even so cassava are cultivated. It was noticed that less or no primary forest was left. Most forested land is secondary forest bordered by bamboo. During the field trip it was observed that the communities play a major role in the forest management, many encroachments for tree logging purposes were seen. The difference with the southern part of the watershed is that the vegetation cover is more changing into grassy patches. This indicates the presence of an intensified burning activity. This presence of burning became even clearer when a site was spotted were the trees showed a dark bark caused by fire in the past.

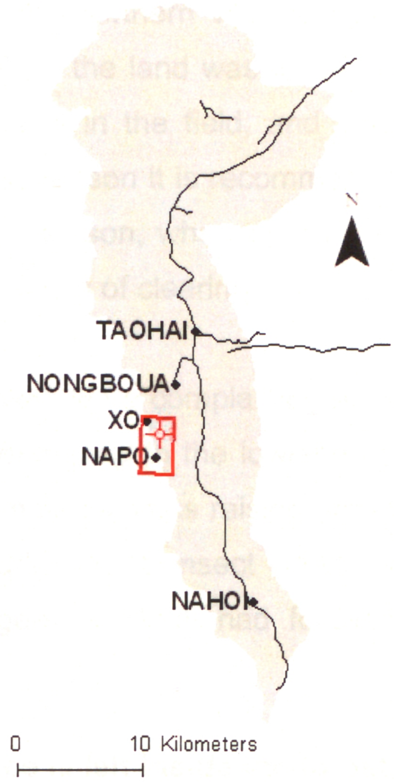
From the higher points in the landscape, it was possible to have a view on the northern part. From these points it was possible to spot completely cleared areas, which were scattered over the steeper parts of the hills.

The map and photo on following page show a field verification point that was cleared in 2000 and the verification in 2004 proved that shifting cultivators were indeed present in this area.

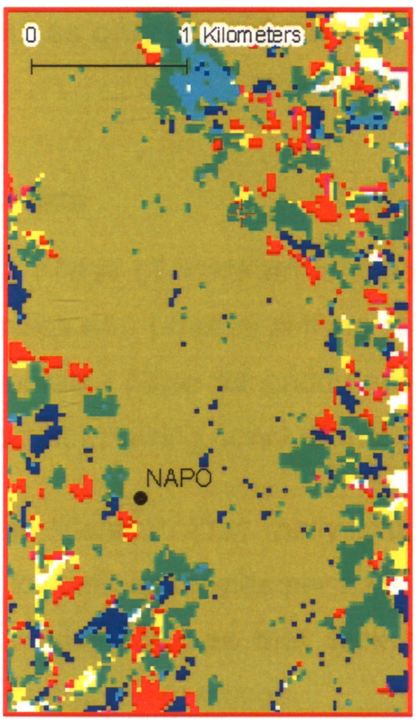
Central Part of The Watershed

Situation Photo

Situation Map



Land Cover Change



Legend

- Verification Point
- villages
- Road
- Nam Ton

Date Source:
MRC-GTZ Cooperation Programme
Date December 2004

Tasselled Cap Transformation
of Landsat 1997, 2000, 2002 series

Projection UTM 48 N
Datum WGS 84
MRC/GTZ Cooperation Programme
Watershed Management Component (WSMC)

1997	2000	2002
VEGETATED	VEGETATED	VEGETATED
CLEARED	CLEARED	CLEARED
VEGETATED	CLEARED	CLEARED
CLEARED	CLEARED	VEGETATED
CLEARED	VEGETATED	CLEARED
VEGETATED	CLEARED	VEGETATED
CLEARED	VEGETATED	VEGETATED
VEGETATED	VEGETATED	CLEARED

Figure 11 View on the northeastern side of the hill of the Nam Ton watershed, (red star). This area of shifting cultivation is made visible on the tasselled cap transformation image (colored in green), what means that the area was already cleared in 2002.

7.3 Northern part of the watershed

After review of the change maps, the northern part is the most critical area for the occurrence of shifting cultivation. The figure 12 shows the northern villages which were visited. One of the objectives was to find out whether the land was cleared in the year visible on the map. While no farmer was active in the field, and could confirm our data, this objective was not reached. For this reason it is recommended to make verifications with shifting cultivation in the rainy season, when the farmers are planting the rice, and are available to verify the exact years of clearing.

In most of the villages which were visited, the village chiefs were complaining about the low yield of the highland rice (shifting cultivation) comparing to the lowland rice varieties. This makes it understandable why one of the main incomes raising activity during the dry season was the selling of the wood. During our transect walks this logging was frequently encountered, one of the villagers of Mouk had following remark:

"Logging should be stopped while less of the balance is left inside the forest, but as only little of our rice goes to the market, we see selling of wood as an only alternative to raise or income"

Vienkam

The village of Vienkam is situated central in the north and is mainly dominated by families who practise shifting cultivation. The hilly area surrounding it is not creating a favourable place for paddy rice fields. A short-interview with the chief of the village brought following conclusions:

- In Vienkam they really want to have more permanent rice fields, this while the lowland rice yields per ha about 3 ton, while highland cultivars only yield 1900 kg of rice, but as they lack materials, they are obliged to continue their shifting cultivation practices.

- The farmers are limited by geographical conditions like low soil fertility and the steep mountainous areas to work with lowland paddy rice fields

- At the moment the annual harvest can only sustain their families for 8 months, even selling rice at the market is not enough for themselves. The other time they are raising income out of alternatives like the logging industry or labour.

- Governmental authorities were visiting the village to elaborate a new regulation that will further restrict the practice of shifting cultivation. For example this year a planning for the land allocation was discussed. Also it is noticed that when they ask permission to the government they will ask for cutting permission for the trees.

Nearby Vienkam, a small temporary settlement of Lao Kahn people was spotted. The farmers explained that they cultivate the soil for about 5 years. The main reason for shifting their highland rice fields is caused by the high weed pressures. When chemicals are used to control the weeds, it is possible to stay even longer. The same people confirmed that a total of 10 families owns about 6 – 7 ha of land. This means that each family cultivates about 0.6 ha.

Mouk village

The village of Mouk was visited, this village situated at the west of the road provides the livelihood for about 80 families. The village chief explained that two ethnic groups are dominating in Mouk, Lao Loum and Lao Kahn. The Lao Loum people are mainly depending on rice paddy fields whereas the Lao Kahn people are involved in shifting cultivation. Logging is the alternative dry season practice, this extensive logging has the advantage of alternative income generation but villagers explained that this practice causes a high pressure on the remaining forest land.

Village of Suanamon,

The area in the eastern part of the village of Suanamon is characterised by a further state of degradation. The area is mainly covered by grass. The village chief explained that this area was cleared after 1982. The village chief told also that at the moment a more or less organized logging is still going on.

Village of Nawai

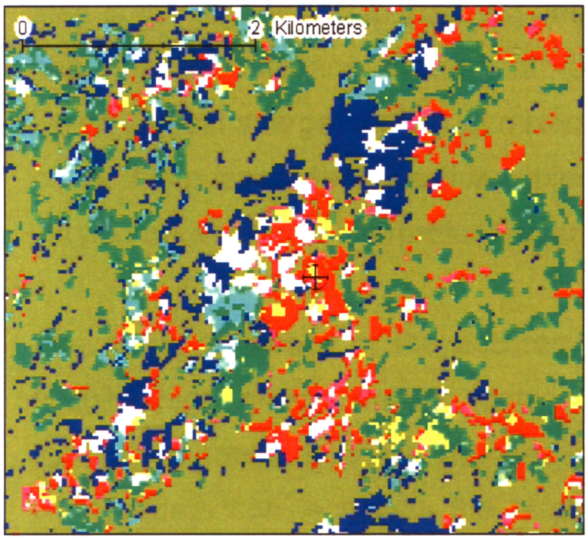
The village of Nawai situated at the east side of the road is having a mixed ethnic population consisting of Lao Loum and Lao Kahn. A diversity of agricultural practices are seen (plantations, pig farm, distillery). A lot of paddy rice fields are seen surrounded by small scale shifting cultivation areas. The guide remarked that this area is overall more fertile and well suited for cultivating rice paddy fields.

The map on the following page describes the situation in the northern part. This area shows a large extent of patterns were serious clearing is going on. The arrival of the logging companies was probably one of the main driving forces in this process. This while remote areas became more accessible by roads (Figure 12, situation photo shows that roadsides can be used for collection of logged trees). The map and photo shows that the patterns of clearing in the area are very intensive and are very scattered over the steep mountainous areas.

Northern Part of the Watershed

Situation Photo

Land Cover Change



Legend

	1997	2000	2002
(olive)	Vegetated	Vegetated	Vegetated
(white)	Cleared	Cleared	Cleared
(yellow)	Vegetated	Cleared	Cleared
(light blue)	Cleared	Cleared	Vegetated
(pink)	Cleared	Vegetated	Cleared
(green)	Vegetated	Cleared	Vegetated
(dark blue)	Cleared	Vegetated	Vegetated
(red)	Vegetated	Vegetated	Cleared

Situation Map

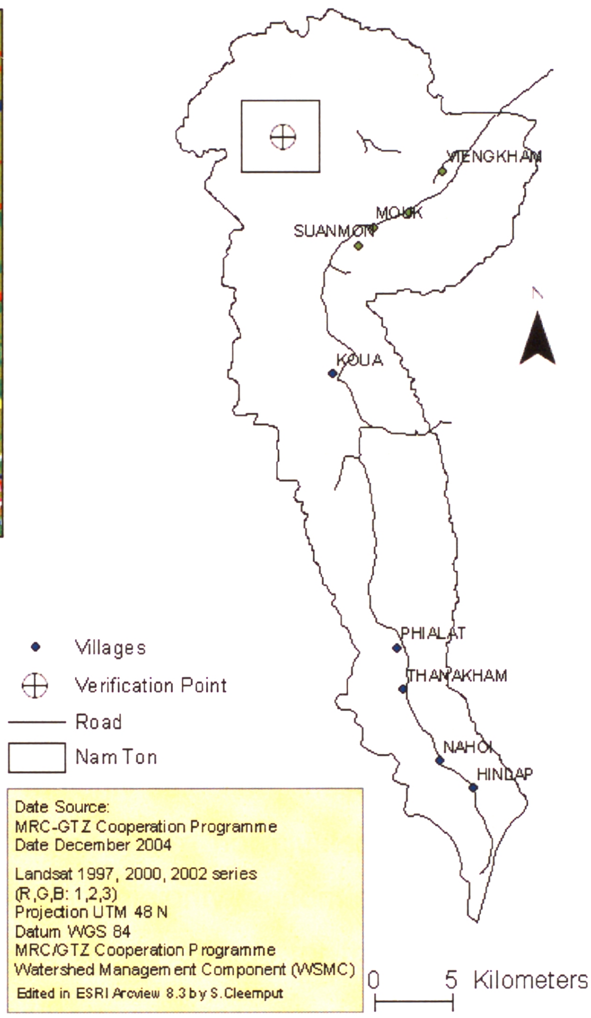


Figure 12 a Situation example of an area with shifting cultivation in the north of the Nam Ton watershed

8 Discussion

8.1.1 Conclusions for the classification and accuracy assessment

- Because it is so difficult to relate what really happened, the whole change detection classification method and its respective accuracy assessment is a balancing exercise between what you see and what the satellite image registered it was. For example a road can be registered in the first year as only row line of pixels while in the second year it can be two rows of pixels just because a calibration error between the multi- temporal satellite images. It is also difficult to use a same pixel colour for an area covered with vegetation. This makes the interpreting, somewhat different over the three Landsat images. This is probably due to a quality difference for the different satellite images. A second subjective step is the grouping step after the unsupervised classification process. This step has the most influence on the final aerial descriptive, while large pixel numbers, which contain a large number of mixed pixels, have to be grouped into the correct class. It is possible that due this subjective grouping of these clusters, results are varying between one interpreter and another.

- The major drawback of the accuracy assessment is that it is most difficult to acquire high quality training data. This is necessary because in traditional supervised methods, only changes that are known can be sampled. In this change detection technique the reference was limited to the extensive ground truthing and the raw Landsat satellite image data.

- It can be expected that the accuracy assessment is positively biased for the unsupervised procedure in Erdas Imagine 8.6. This while the isolated individual pixels are overseen in the simple clear majority selection, these individual pixels are scattered over the entire map. While they are not clustered they are less probable to be chosen during the simple clear majority random stratified sampling procedure. The eCognition procedure has an advantage for this, while it is not classifying individual pixels but object values.

- Finally the optimistic values that are associated with the calculation of the confidence intervals (approx. 2%) for the overall accuracy of each classification are probably caused by the sampling agreement. Due to this sampling agreement it was not necessary to assess the correctness on an individual pixel base. The simple clear majority agreement inside each frame was the decision factor, whereas the final result presented in the error matrix was the aggregation of the number of classified pixels inside the sample frames. This results into a large number of sample pixels, which are however only reflecting the error ratio of individual 9x9 pixels sampling frames.

8.2 Conclusions of the field survey

Out of the maps and the field survey it can be concluded that the catchment shows a large area of uncontrolled clearing and burning in the North western part of the watershed. It is clear that for understanding how much and how fast areas are cleared by shifting cultivators one should look to its main causes. The present interviews learn that the period of 1997-2002 is probably not a crucial period in the whole process of land conversion in the Nam Ton watershed. It can be however speculated that the monitored period is just a small fraction of a larger time frame were a negative trend is setting. On this historical time-line it makes sense that the trigger for the current loss in forest cover was given with the arrival of logging companies, twenty years ago. At the moment the extensive way of logging intensified with the presence of private companies, continues pondering the ecological functions of the watershed. The shifting cultivators however never changed their agricultural system over the past years and with the present practices, all the legendary problems like erosion and low yielding are intensified. This makes the shifting cultivators getting more intense attention from governmental authorities, whereas other synergetic effects like uncontrolled logging activities are neglected (presence of organized logging in the watershed, figure 1). The continuation of this research combined with periods of surveying can lead to revealing the deeper laying causes of a Landcover change. Therefore it is hoped that the offered monitoring system can be used as a leaning point to focus further coordination on the critical regions in the Mekong region. With these efforts to conserve the remaining forest lands, local forest depletion can be curbed with the help of well focused reforestation programmes, in the zones where intensified forest depletion is reported.

8.3 *Recommendations for the accuracy assessment*

- The accuracy assessment is biased towards the inclusion of mixed pixels. This study didn't include a correction for separating the mixed pixels from the pure pixels. Therefore a study that estimates the proportion of mixed pixels can improve the classification otherwise it is recommended to add a class only consisting of mixed pixels. This mixed pixel class can be combined with a proportion estimator, which can help to un-mix the image. This un-mixing can be especially useful in the areas where the landcover patches are generally smaller than a pixel.

- The accuracy assessment that helps to interpret the change detection method is mainly based on the subjective interpretation between the cleared and the non-cleared areas. This arbitrary step can lead to an erroneous classification of certain areas inside the classification. Before moving on to the arbitrary interpretation during the accuracy assessment, a helpful step would be to investigate whether a statistical framework for the selection of thresholds can be designed that distinguishes between areas of change and areas of no change.

- It is recommended to test whether a supervised classification with fixed training sites is performing a better overall result than the subjective clustering process with manual selection of sampling sites of this study.

- It is recommended to perform the accuracy assessment more than one time. When repeating such a procedure subjectivity can be excluded through the training of the eye.

- The accuracy assessment should be using fixed plots, in this way the different producers' and user's accuracies of the different classes can be compared for the different classifications.

- In the qualitative accuracy assessment no result was obtained while it was too difficult to relate which human related event occurred in the sample area. A better option would be to perform the field accuracy assessment in the rainy seasons, while this season is the time the farmers are on their fields and they can give a detailed description about the changes that occurred.

8.4 *Scientific recommendations*

- The problem of the area calculation was somehow avoided by following a simple method, based on the calibration with the confusion matrix. However a broad range of other possible methodologies can result in improved estimations. For example area estimation by photo-interpretation or regression estimators (Gallego 2004). A second failure in the area estimation is that his study assumed that the impact of mixed pixels and missing data is negligible, this however never proven to be right. This makes the criteria for the grouping of the pixel clusters debatable. Therefore an idea of the mixed pixels inside the landcover should be obtained, this by modelling the mixed pixels or alternative sub-pixel analysis (Gallego 2004).

- The figures in the image to image comparison study were not sufficient to describe the rates of deforestation in the Nam Ton watershed. An alternative would be to estimate the available dry matter and yield of woody and herbaceous vegetation in the watersheds. A good reason is that biomass and its dynamics are proven to be good parameters which can be related with the different landcover strata (National Biomass Study 2002). With this valuable information, forest yield and stocking can be balanced out. With this information relations with other environmental functions like water yield and quality can be further investigated.

- This study of a small-scale watershed proved that it is easier to analyse landcoverchange at the micro-level, the effects of landcover change are better analysed. This can be even refined with the help of a botanical study on the fallow vegetation. These details can further reveal the importance of shifting cultivation for its relation with land degradation and can find further relations with the hydrological function of the watershed.

9 References

- Almeida T. I. R. and De Souza F. C. R., 2004. Principal component analysis applied to feature-oriented band ratios of hyperspectral data: a tool for vegetation studies. Int. J. Remote Sensing, Vol. 25, No. 22, 5005 – 5023.
- AusAID, 1996. Natural Resource Management in the Mekong River Basin: Perspective for Australian Development Corporation, Final Overview Report, Australian Agency for International Development, Online Document URL: www.usyd.edu.au/su/geography/hirsch/5/5/htm
- Balázs A., 2005. Landcover-change-detection using different post-classification techniques to assess deforestation on a time scale of 40 years in the Nam Ton Watershed, Lao P.D.R, IWW, University of Göttingen, Germany
- BOURDET, I., 1998. The Dynamics of Regions IN: UNEP 2001. LAO PDR : State of the environment url: www.rrcap.unep.org/reports/soe/laosoe.cfm.
- Bass S. and Morrison E. 1994. Shifting Cultivation in Thailand, Laos and Vietnam: Regional Overview and Policy Recommendations 1994 Forestry and Land Use Programme. IIED Forestry and Land Use Series No. 2.
- Blackburn G. A. and. Milton E. J 1997. An ecological survey of deciduous woodlands using airborne remote sensing and geographical information systems (GIS). Int. J. Remote Sensing, Vol. 18, No. 9, 1919 – 1935.
- Brook, R.K. and Kennel N.C.. 2002. A multivariate approach to vegetation mapping of Manitoba's Hudson Bay Lowlands. Int. J. Remote sensing Vol. 23, No 21, 4761 - 4776.
- Carfagna, E. unpublished. Using Remote Sensing for Agricultural Statistics url:www.stat.fi/isi99/proceedings/arkisto/varasto/carf0470.pdf.
- Cohen, W.B., Fiorella M., Gray G., Helmer E. and Anderson K., 1998. An efficient and accurate method for mapping forest clearcuts in the Pacific Northwest using Landsat imagery, Photogrammetric Engineering and Remote Sensing, 64: 293- 300 IN: Hayes, D. J., and Sader, S. A., 2001, Comparison of change detection techniques for monitoring tropical forest clearing and vegetation regrowth in a time series. Photogrammetric Engineering and Remote Sensing, 67, 1067–1075.
- Devries P.G. 1986. Sampling theory for forest inventory. IN: Schreuder H.T. Ernst, R. Ramirez-Maldonado. H., 2004. Statistical techniques for sampling

and monitoring Natural Resources. General technical report USDA Forest service.

- DDFD 1997. Integrated Forest management plan for the college intervention area, TMF, Sangthong District, Vientiane Municipality. DDFD/Profep. Dong Dok, Laos.
- Duda T. and Canty M. 2002. Unsupervised classification of satellite imagery: choosing a good algorithm Int. J. Remote Sensing, Vol. 23, No. 11, 2193 - 2212
- Eden M. J., 1986, monitoring indigenous shifting cultivation in forest areas of south west Guyana using aerial photography and Landsat. In Remote Sensing and Tropical L and Management, edited by M. T. Eden, and J. P. Parry, (Chichester: John Wiley and Sons Limited), pp. 255± 272. IN: Jusoff K. and Souza G. D. 1997. Use of satellite remote sensing in Malaysian forestry and its potential. Int. J. Remote Sensing, Vol. 18, No. 1, 57 - 70.
- Foppes 1995. Mission report farming and forest use systems survey and recommendations for community forestry in the Sangtong training and model forest. Vientiane forestry college .lao german forestry team GTZ project office P.O. box 5653 Vientiane Lao PDR.
- Freese F. 1984, Statistics for Land Managers. Paenony Press, Jedburgh, Scotland. In: National Biomass Study 2002, Technical Report, Forest Department, Ministry of Water Lands and Environment.
- Gallego F. J. 2004, Remote sensing and land cover area estimation, Int. J. Remote Sensing, Vol. 25, No. 15, 3019–3047.
- Gimeno M., San-Miguel-Ayanz J. and. Schmuck G., 2004 Identification of burnt areas in Mediterranean forest environments from ERS-2 SAR time series Int. J. Remote Sensing, 2004, Vol. 25, No. 22, 4873–4888.
- Guild L.S., Kauffman J.B. and Cohen W.B., 2004. Detection of deforestation and land conversion in Rondônia, Brazil using change detection techniques. Int. J. Remote Sensing, Vol 25 No 4, 731 – 750.
- Grandstaff T. B., 1980. Shifting Cultivation in Northern Thailand, ©The United Nations University,
- Green K., Kempka D., and Lakey L., 1994, Using remote sensing to detect and monitor land-cover and land-use change. Photogrammetric Engineering and Remote Sensing, 60, 331–337.

- Hammond T.O. and Verblya D.L., 1996. Optimistic bias in classification accuracy assessment. International journal of Remote Sensing, 17: 1261-1266. IN: USGS, 2004, Accuracy assessment of 1992 National land cover data: Methods and results, u.s. department of interior, u.s. geological survey. Url: http://landcover.usgs.gov/accuracy/index.asp.
- Hay A., 1979. Sampling designs to test land-use mapping accuracy. Photogrammetric engineering and remote sensing, Vol 45, No. 4, 529 -533. IN: Thea Pröbsting, 1991. Stichprobenkonzepte zur Verification von aus Fernernkundungsdaten hergestellten thematischen Karten. Diplomarbeit, WWI, Georg August Universität Göttingen, Deutschland.
- Hayes D. J., and Sader S. A., 2001, Comparison of change detection techniques for monitoring tropical forest clearing and vegetation regrowth in a time series. Photogrammetric Engineering and Remote Sensing, 67, 1067–1075.
- Li Z., Li X, Wang Y., Ma A. and Wang J., 2004. Land-use change analysis in Yulin prefecture, northwestern China using remote sensing and GIS Int. J. Remote Sensing, Vol. 25, No. 24, 5691–5703
- Istvan Heiler and San Miguel-Ayanz, 1998. An unsupervised change detection and recognition system for forestry. Int. j. remote sensing, Vol. 19, No. 6, 1079± 1099
- Jusoff K. and Souza G. D., 1997. Use of satellite remote sensing in Malaysian forestry and its potential. Int. J. remote sensing, Vol. 18, No. 1, 57± 70
- Mausel E. B. and Moran E. 2004. Change detection techniques Int. J. Remote Sensing Vol. 25, No. 12, 2365–2407
- Jensen J. R., and Toll D. L., 1982. Detecting residential land use development at the urban fringe. Photogrammetric Engineering and Remote Sensing, 48, 629–643. IN: Lu D, Mausel P., Brondízios M. and Moran E., 2004. Change detection techniques Int. J. Remote Sensing, 20 June, 2004, Vol. 25, No. 12, 2365–2407.
- Kauth R. J., and Thomas, G. S., 1976. The Tasselled Cap a graphic description of the spectral -temporal development of agricultural crops as seen by Landsat. IN: Blackburn G. A. and. Milton E. J 1997. An ecological survey of deciduous woodlands using airborne remote sensing and geographical information systems (GIS). Int. J. Remote Sensing, Vol. 18, No. 9, 1919 - 1935

- Manivong K. 2004, Socio-economic study -Namton Pilot Area. Mekong River Commission (MRC), Agriculture, Irrigation and Forestry Programme (AIFP) Watershed Management Component (WSMC). Draft Report Mekong River Commission (MRC) Agriculture, Irrigation and Forestry Programme (AIFP) Watershed Management Component (WSMC) Vientiane, Laos.
- National Biomass Study 2002, Technical Report, Forest Department, Ministry of Water Lands and Environment, Kampala, Uganda
- Kleinn, C., 2002. Lecture notes, Forest Inventory. Institute of Forest Management, Georg-August-University Göttingen.
- Kollert 2000 (management plan for forest resources development, training and research in the management intervention are of Sangthong district, Vientiane municipality 2001- 2010. National university of Laos, Faculty of Forestry, promotion of forestry education project.
- Lambin E.F., and Ehrlich D. 1997. The identification of tropical deforestation fronts at broad spatial scales. Int. J. Remote Sensing, 18:3551-3568.
- Lauer, W. 1993. Climatology. In: Pancel, L.: Tropical Forestry Handbook, Vol. 1. Springer. Berlin/Heidelberg/New York.
- Lu D., Mausel P., Brondízio E., and Moran E., 2004. Change detection techniques. Int. J. Remote Sensing, 2004, Vol. 25, No. 12, 2365–2407
- Phanvilay K. 1990. Forest and Soil Conservation in Laos. Regional Community Forestry Training Center. Bangkok, Thailand, December 1990.IN: Land use/land cover change in south-east Asia. Case Study 1: Oudomxay Province, Lao P.D.R. UNEP, Environment Assessment Program for Asia and the Pacific. url: www.rrcap.unep.org/lc/cd/html/hotspot/laos/result1.html
- Roder W.B., Phouaravanh S., Phengchanch B. K. and Maniphone S. 1994. Upland agriculture – activities by Lao-IRRI Project. Pages 152-169 In: shifting cultivation and rural development in the Lao PDR. Report of the Nabong Technical Meeting, Nabong College, Vientiane.
- Roder W.B, Phengchanh S, Maniphone S., 1997. Dynamics of soil and vegetation during crop and fallow period in slash-and burn fields of northern Laos. Geoderma 76 131-144.
- Sabarowski J., 2000. Lecture notes: statistical data analysis and experiment planning, institute für forstliche biometrie und informatik, Georg-August-Universität goettingen, ss 2000

- Scheaffer, R. L., Mendenhall, W., Ott, L., 1996. Elementary survey sampling. Wadsworth Publishing Company, Belmont.
- Schowengerdt R. A., 1997, Remote Sensing: Models and Methods for Image Processing, 2nd edition Academic Press London. IN: T. Duda and Canty M. 2002, Unsupervised classiffication of satellite imagery: choosing a good algorithm. Int. J. Remote Sensing, 2002, Vol. 23, No. 11, 2193–2212.
- Shiver, B. D., Borders, B. E., 1996. Sampling techniques for forest resource inventory. John Wiley & Sons, Inc., New York.
- Soumitri D., 2001. Lecture notes: Forestry 5254: Remote Sensing of Natural Resources Laboratory 3: PCA, Vegetation Indices, and Texture
- Stea 2000a: National Environmental Action Plan 2000, Science Technology and Environmnetal Agency, Lao PDR IN: State of the environment Lao PDR 2001, United Nations Environment Programme 2001 Regional Resource Centre for Asia and the Pacific UNEP RRC.AP. Klong Luang Thailand.
- Stehman S.V., 1999. Comparing thematic maps based on map value. International Journal of Remote Sensing, 20(12): 2347-2366, 1999, IN: Rossiter DG, 2004. Technical Note: Statistical methods for accuracy assessment of classified thematic maps. ITC, Enschede, the Netherlands. url: www.itc.nl/~rossiter/teach/R/R_ac.pdf
- Stemmler J., and Su Z. 1993, Landnutzungsklassifikation von vier landsatszenen unter anwendung von RUB-LUCS, unpublished report, Institute for Hydrology, Water Resources and Environmental Engineering, Ruhr University Bochum, Bochum IN: Su. Z. 2000. Remote sensing of land use and vegetation for Mesocale hydrological studies. Int. j. Remote Sensing, 2000, Vol. 21, No. 2, 213 - 233
- Tou J. T. and. Gonzalez. R.C 1974. Pattern Recognition Principles. Reading, Massachusetts: Addison-Wesley Publishing Company IN: Erdas Imagine 8.6 Field Guide 2002, sixth edition, Atlanta, Georgia url: www.statler.al.umces.edu/~ckingdon/ErdasGuides.html
- UNEP-EP-AP 1998. UNEP Environment Assessment Programme for Asia and the Pacific Bangkok. Environment Assessment Technical reports, United Nations Environment Programme 1998, Bangkok, Thailand.

- USGS, 2004, Accuracy assessment of 1992 National land cover data: Methods and results, U.S. department of interior, U.S.. Url: www.landcover.usgs.gov/accuracy/index.asp
- Yamane M. and Chanthirath K. 2005 International review for environmental strategies url: www.iges.or.jp/en/fc/phase1/ir99/4-12-yamane.pdf

To whom it may concern,

Göttingen, August 2005

Authors' confidentiality

With this writing I confirm that this thesis is well referenced for its information that was not obtained by own experimentation. Other information sources were used with explicit permission of the respective author/source;

Stijn Cleemput