# Analysis of Fallow System Development in Laos using Historical Satellite Images

**Master's Thesis**

for the Master of Science degree in Mountain Forestry

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# Abstract

For more than 400 years the Khmu, one of the oldest ethnic groups of Oudomxay province, Northern Laos, South-east Asia, coexisted in relative harmony with their environment. Rapid population growth in the last 50 years has been the main cause for the abandonment of a sustainable fallow management practice. Other factors included: state policies to intensify agriculture and to discourage the use of slash-and-burn cultivation, wilderness areas given over to protected sites and the selling of large tracts of land for rubber tree plantations.

The aim of this research is to develop a methodology that can identify the pattern and magnitude of spatial and temporal changes of land-cover using remote sensing techniques. Particular attention is given to fallow age class distribution, frequency of slash-and-burn events, and areas of intensive agricultural production.

The definition of land-cover classes in this research is based on the reflectance characteristics of the land-cover types in the spectral bands registered by the Landsat7 ETM+ sensor. Unsupervised classification of a multi-temporal Normalised Difference Vegetation Index (NDVI) data set was used to analyse the land-cover changes between three dates of imagery This method adopts a technique to visualize change in land-cover using multi-temporal NDVI imagery and interpretation concepts of colour additive theory. Comparing on a category-by-category basis the relationship between known ground reference data from field work and the corresponding results of the unsupervised classification, it was possible to carry out an accuracy assessment of the classification.

One outcome from the development of a methodological approach to identify change in land-cover in the province of Oudomxay was the production of a thematic map indicating levels of land pressure. Low pressure areas were found in the less populated and inaccessible mountainous regions of Oudomxay. High pressure areas were found in the wider and low lying valleys where large populations have settled and where there is good infrastructure with major rivers and roads providing links to the provincial and international markets.

*Keywords*:
South-east Asia; shifting cultivation; remote sensing; multi-temporal; NDVI; unsupervised classification

## Kurzfassung

Mehr als 400 Jahre lebten die Khmu, eine der ältesten ethnischen Gruppen der Provinz Oudomxay im Norden von Laos (Südostasien) in Einklang mit ihrer Umwelt. Das rasche Bevölkerungswachstum in den letzten 50 Jahren hat jedoch dazu geführt, dass die Landwechselwirtschaft, eine nachhaltige Bewirtschaftungsform, nur mehr wenig Anwendung findet. Andere Faktoren für diese Entwicklung sind staatliche Bestrebungen, die Landwirtschaft zu intensivieren und Brandrodung zu unterbinden, die Eingliederung von Wildnisgebieten in Schutzgebiete und der Verkauf von großen Flächen für das Anlegen von Kautschukbaum-Plantagen.

Ziel dieser Arbeit ist die Entwicklung einer Methode, die es ermöglicht, das Muster und Ausmaß räumlicher und zeitlicher Veränderungen der Landbedeckung mit Hilfe von Fernerkundungsmethoden zu erkennen. Besonderes Augenmerk wurde auf die Verteilung von Brachflächen-Altersklassen, die Häufigkeit von Brandrodungsereignissen und auf Flächen intensiver landwirtschaftlicher Produktion gerichtet.

Die Definition von Landbedeckungsklassen in dieser Arbeit basiert auf den Reflexionscharakteristiken der Landbedeckungsarten in den spektralen Bändern des Sensors Landsat 7 ETM+. Durch nichtüberwachte Klassifikation eines multi-temporalen NDVI (Normalised Difference Vegetation Index) Datensatzes wurden die Veränderungen der Landbedeckung zwischen drei Aufnahmezeitpunkten analysiert. Für die Visualisierung und Interpretation der Landbedeckungsveränderungen wurde das Konzept der additiven Farbmischung angewendet. Anschließend wurde für jede Kategorie das Ergebnis der nichtüberwachten Klassifikation mit Referenzdaten verglichen und die Klassifikationsgenauigkeit abgeschätzt.

Im Zuge der Entwicklung eines methodischen Ansatzes zur Erkennung von Veränderungen der Landbedeckung in der Provinz Oudomxay wurde eine thematische Karte bezüglich Landnutzungsdruck erstellt. Gebiete, die einem geringen Druck unterliegen, wurden in dünn besiedelten und schwer zugänglichen Regionen von Oudomxay festgestellt. Gebiete unter starkem Landnutzungsdruck konnten in den breiten und niedrig gelegenen Tälern ausfindig gemacht werden, wo die Bevölkerungsdichte hoch ist und es eine gute Infrastruktur und Anbindung zu den Märkten der Provinz und zu internationalen Märkten durch das Vorhandensein von größeren Flüssen und Straßen gibt.

*Schlagwörter*: Südostasien; Landwechselwirtschaft; Fernerkundung; multi-temporal; NDVI; nichtüberwachte Klassifikation

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# 1. Introduction

Aims

The aim of this thesis is to develop a methodology that can identify the pattern and magnitude of spatial and temporal changes of land-cover in the province of Oudomxay in Northern Laos, using remote sensing techniques. Particular attention is given to fallow age-class distribution, frequency of slash-and-burn events, and areas of intensive agricultural production.

Motives

Land-cover classification is one of the most widely used applications of remote sensing. Since the launch of the first satellite over thirty years ago, great effort has been devoted to developing and improving methodologies to define land-cover classes. It is the purpose of this thesis to demonstrate a method that continues in this effort. The work of this thesis is carried out within the framework of a project in Laos co-ordinated by CIAT (*Centro Internacional de Agricultura Tropical*) Columbia. The Laos project was initiated in December 2004 and will come to completion at the end of 2007. The project comprises of three inter-related components:

1. Spatial analysis of fallow systems by remote sensing and GIS
2. Livelihood analysis
3. Market chain analysis & Learning Alliance

Expected Use of Results

Land-cover change analysis has enabled researchers to understand landscape change on both a temporal and spatial scale. This thesis contributes towards the first component of the Laos project. The land pressure map derived from the classification of the multi-temporal NDVI images provides information on the pressure on natural resources in the province of Oudomxay. It is expected that this information will be used with the community socio-economic survey data concerning the driving forces of agricultural change and help to identify opportunities and risks from further agricultural intensification proposals.

Rationale for research site selection

Northern Laos has a varied mountainous landscape with a rich tapestry of land-cover types. Shifting cultivation is the dominant agricultural activity where young secondary forests become temporary fallow phases within the agricultural cycle creating a mosaic of land cover classes. Demands by an increasing human population and changes in agriculture policy (such as eliminating shifting cultivation practice and the adoption of more permanent and intensive forms of agriculture) are two reasons for reduced fallow periods. Others include wilderness areas given over to protected sites and the selling of large tracts of land for rubber tree plantations. It is the right time to document and evaluate land-cover change in Northern Laos through processes of research and development.

Methodological approaches

The identification of land-cover classes in this research is based on the reflectance characteristics of the land-cover types in the spectral bands registered by the Landsat7 ETM+ sensor. A problem with differentiating land-cover types can be due to similar spectral responses of different land-cover types owing to their similar leaf area index or phenological stage. The way to tackle this problem has been to use a multi-temporal dataset. Unsupervised classification of a multi-temporal Normalised Difference Vegetation Index (NDVI) data set was used to analyse the land-cover changes between three dates of imagery (February 2001, February 2002, and February 2003). This method adopts a technique to visualize change in land-cover using multi-temporal NDVI imagery and interpretation concepts of colour additive theory. An accuracy assessment of the classified image using an error matrix was carried out by comparing on a category-by-category basis the relationship between known ground reference data (from field work) and the corresponding results of the unsupervised classification.

# 2 Literature Review

## 2.1 Introduction

This chapter gives a review of the most relevant research which has incorporated time series of spectral vegetation index data and other reference data for identifying the pattern and magnitude of spatial and temporal changes in land-cover.

The chapter begins by giving background information on the satellite sensor chosen for the acquisition of image data. Image pre-processing methods to correct distorted or degraded image data (such as geometric correction, radiometric calibration and noise elimination) are presented. The value of field data collection for remote sensing investigations is emphasised especially with reference to its relevance in image classification. Normalised Difference Vegetation Index (NDVI) and its use in land-cover classification are explained. The object, intention and methods of image classification and interpretation are presented. This is followed by a review of the literature on research developments on the classification of multi-temporal datasets using change detection techniques. One of these techniques was influential in shaping this thesis' methodological approach. This was the technique developed to visualise land-cover change using multi-temporal NDVI imagery and interpretation concepts of colour additive theory. The chapter ends by reviewing the literature on two procedures that are performed on classified data: post-classification smoothing and accuracy assessment.

## 2.2 Sensor

In 1972 NASA launched the first in a series of Landsat satellites designed to provide repetitive global coverage of the Earth's landmasses. Landsat was originally named "ERTS" i.e. Earth Resources Technology Satellite. Landsat satellites scan the Earth's surface across the satellites' track as the satellites move in their descending orbit (moving from north to south) over the sunlit side of the Earth, so that they cross every point on the Earth about the same time once every 16-18 days (USGS 2005). Landsat 7 was launched in 1999 and carries the Enhanced Thematic Mapper Plus (ETM+), which operates as a whiskbroom scanner and acquires data for the visible, near-, mid-, and thermal infrared spectral bands. The ETM+ ground sampling distance is 30 m for the reflective bands, but 60 m for the thermal band. The ETM+ also acquires data for the panchromatic band (band 8) with a 15 m ground sampling distance. The ETM+ scans a 185 km cross-track swath as it travels along the orbital paths. Horning (2004) describes some of the features of Landsat 7 ETM+ bands and how they are tailored for detecting different features. These are listed below.

**Band 1** (0.45-0.52 µm, blue-green): This short wavelength of light is used to monitor sediment in water, mapping coral reefs, and water depth. Unfortunately it is the 'noisiest' of the Landsat bands since short wavelength blue light is scattered more than the other bands.
**Band 2** (0.52-0.60 µm, green): This has similar qualities to band 1 but not as extreme.
**Band 3** (0.63-0.69 µm, red): Since vegetation absorbs nearly all red light this band is useful for distinguishing between vegetation and soil and in monitoring vegetation health.
**Band 4** (0.76-0.90 µm, near infrared): Since water absorbs nearly all light at this wavelength water bodies appear very dark. This contrasts with bright reflectance of soil and especially of vegetation so it is a good band for defining the water/ land interface.
**Band 5** (1.55-1.75 µm, mid-infrared): This band is very sensitive to moisture and is used to monitor vegetation and soil moisture. It is also good at differentiating between clouds and snow.
**Band 6** (10.40-12.50 µm, thermal infrared): This is a thermal band and can be used to measure surface temperature. It is primarily used for geological applications but it is sometimes used to measure plant heat stress. It is also used to differentiate clouds from bright soils since clouds tend to be very cold. One other difference between this band and the other multi-spectral ETM bands is that the resolution is half of the other bands (60 m pixel size instead of 30 m).
**Band 7** (2.08-2.35 µm mid-infrared): This band is also used for vegetation moisture although generally band 5 is preferred for that application, as well as for soil and geology mapping.

On 31 May 2003 Landsat 7 experienced a Scan Line Corrector (SLC) failure during imaging. The SLC is an electromechanical device that compensates for the forward motion of the satellite. When operating properly the SLC allows successive forward and reverse scans of the ETM+ scan mirror to image in a series parallel scans. With a non-functioning SLC the ETM+ scans the Earth's surface with individual scans alternately overlapping with large gaps left at the edge of the imagery (USGS 2003). Only in the centre of the image (band width of approx. 20 km wide) do the scans give near-contiguous coverage of the surface scanned below the satellite.

## 2.3 Image pre-processing

Image pre-processing denotes the procedures used to prepare image data for further manipulation. It aims to correct distorted or degraded image data and create a more faithful representation of the original scene. It is termed pre-processing because the procedure normally precedes further manipulation and analysis of image data (Lillesand et al. 2004). Lillesand et al. (2004) highlight three procedures to image rectification and restoration. These are (i) to correct for geometric distortion, (ii) to calibrate the data radiometrically, and (iii) to eliminate noise. The nature of the restoration process is highly dependent on the characteristics of the sensor used.

### 2.3.1 Geometric correction

Raw digital images can contain geometric distortions arising from many sources: variations of altitude and velocity of the sensor platform, panoramic distortions, earth curvature, atmospheric refraction and relief displacement. The intent of geometric correction is to compensate for the distortions and produce a georeferenced image. The images used in this thesis were already georeferenced and projected to UTM Zone 48N coordinate system using the WGS 84 datum.

### 2.3.2 Radiometric calibration

Radiometric pre-processing manipulates the brightness values of an image to correct for sensor malfunctions and to adjust the brightness values to compensate for atmospheric degradation and / or topographical effects. Koukal (2004) describes that the distortion of pixels is caused by the interplay of the direction of radiation from the sun, atmospheric absorption and scattering, topography, and directional reflectance characteristics of forest canopy surfaces. Radiometric calibration techniques used in this thesis fall into two categories: Atmospheric correction and topographic correction methods.

#### 2.3.2.1 Atmospheric correction

Sensors observing the earth's surface using the visible or near visible radiation record a mixture of two kinds of brightness. One is due to the reflectance from the earth's surface and the other observes the brightness of the atmosphere itself (Campbell 2002). The object of atmospheric correction is to identify and separate these two kinds of brightness.

The electromagnetic radiation (EMR) signals collected by satellites in the solar spectrum are modified by scattering and absorption by gases and aerosols while travelling through the atmosphere from the Earth's surface to the sensor. This is illustrated in Figure 1. As radiation passes through the earth's atmosphere, the atmosphere affects it. It acts as a filter attenuating large portions of the electromagnetic spectrum through the process of absorption and scattering by gases, water vapour, and particulate matter (Koukal 2004). The three main constituents that absorb radiation in the visible and in the infrared part of the spectrum are ozone, carbon dioxide, and water vapour. When and how to correct the atmospheric effects depends on the remote sensing and atmospheric data available, the information desired, and the analytical methods used to extract the information (Song et al. 2001).

Scattering occurs when particles or large gas molecules present in the atmosphere interact with and cause the electromagnetic radiation to be redirected from its original path. There are three types of scattering which take place: Raleigh, Mie and Non-selective scatter. Due to scattering, areas that would otherwise not receive direct solar radiation are now no longer 'in the dark' (shadow) as they are irradiated by diffuse radiation (Koukal 2004). The effects of the atmosphere vary depending on path length, atmospheric conditions, and wavelength.

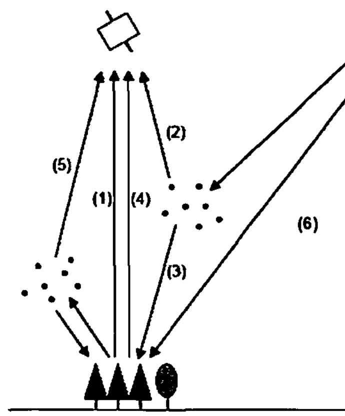



Figure 1: Radiation paths (Koukal 2004)

(1) Reflected solar radiation
(2) Path radiance
(3) Radiation scattered to the ground (diffuse sky radiation)
(4) Reflected diffuse radiation
(5) Surface-reflected radiation partly scattered both directly to the sensor and to the ground
(6) Direct solar radiation

The atmosphere scatters solar radiation to the sensor. The result is a decrease in image contrast. Haze compensation procedures minimise the effect of path radiance which is estimated by observing reflectance of deep water (digital number = zero value) in the near IR region of the spectrum. Any signal observed over such areas is equal to 'path radiance value', which is then subtracted from all pixels in this band. Path radiance is scattered radiation received directly by the sensor without reaching the earth's surface. This procedure is known as the "Dark Object Subtraction" (DOS) method (Chavez, 1989). DOS is the simplest yet most widely used image-based absolute atmospheric correction approach for classification and change detection applications (Song et al. 2001; Woodcock et al. 2001). However Pax-Lenney et al. (2001) believe that few surfaces reflect absolutely nothing.

#### 2.3.2.2 Topographic correction methods

Topographic correction or topographic normalisation is the process of removing the effect of different solar illumination caused by the irregularities of the earth's terrain. The effect of topography on reflected solar radiation in satellite imagery has been recognized for as long as satellite sensors have orbited the earth (Stohr and West 1975; Shepherd and Dymond 2003). As Figure 2 shows, the slopes facing towards the sun receive more light and appear brighter than slopes facing away from the sun (Riaño et al. 2003). Not only is illumination modified by topography, but the proportion of radiation reflected towards the satellite also varies with the geometry of the sun, target and viewer; and this geometry varies with topography (Teillet et al. 1982, Hugli and Frei 1983). In order to maximize the information content in satellite imagery of hilly or mountainous areas, it is necessary to remove, or account for, the effect of topography (Teillet 1986).

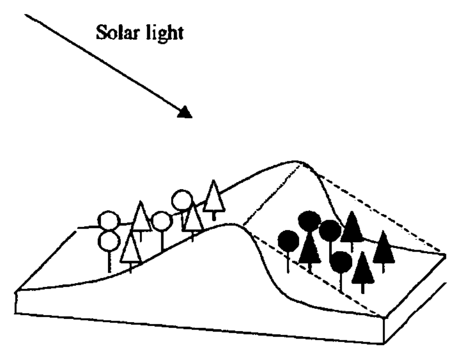



Figure 2: Effect of topography on reflectance (Riaño et al. 2003)

Riaño et al. (2003) describe various methods for correcting the topographic effects. These may be grouped into two categories: one is based on band ratios and the second requires digital elevation models (DEMs). The first group assumes reflectance increases or decreases proportionally in the two ratio bands. The amount between them will compensate for topographic effects. This method is suitable for incident angles which are wavelength independent but not for diffuse irradiance which changes in each spectral band. The second group of methods model illumination conditions. They require a DEM of the same resolution as the image to be corrected. The DEM is used to compute the incident angle which is defined as the angle between the normal to the terrain and the direction of the sun.

**Digital Elevation Models (DEM)**

DEMs are digital representations of the shape of the earth's surface. A DEM is represented as an array of values that record topographic elevations observed at equal intervals in the earth's surface. Each pixel represents an elevation measurement rather than a brightness value (Campbell 2002). Data for DEMs are compiled from different sources. An original method of generating a DEM involves digitising contours from maps and converting them to vector files with elevation values. Another method involves photogrammetric methods directly from stereoscopic images. In February 2000 onboard the Space Shuttle Endeavour, the Shuttle Radar Topography Mission (SRTM) obtained elevation data on a near-global scale to generate the most complete high-resolution digital topographic database of Earth to date. It represents elevation at a three arc-second resolution i.e. around 90m.

The second group of methods for correcting the topographic effects are further grouped by Riaño et al. (2003) into "Lambertian" or "non-Lambertian" depending on whether they assume that reflectance is independent of observation and incidence angles or not. According to Lambert's cosine law when an object is radiating as a result of being illuminated by an external source, the irradiance (energy or photons / time / area) landing on that object is proportional to the cosine of the angle between the illuminating source and the normal. This “Lambertian reflector” will then reflect light according to the same cosine law as a “Lambertian emitter”. This means that although the radiance of the surface depends on the angle from the normal to the illuminating source, it will not depend on the angle from the normal to the observer.

**Lambertian Methods**

The Lambertian methods assume reflectance is independent of the observation and incident angles. Two methods were considered for this thesis. These were the Cosine correction method and the C-correction method proposed by Teilet et al. (1982).

**Cosine correction**

The cosine correction or sun elevation correction is a strongly trigonometric approach based on a fundamental physical law assuming a Lambertian reflection characteristic of objects and neglecting the presence of an atmosphere. The amount of irradiance reaching an inclined pixel is proportional to the cosine of the incidence angle *i*, where *i* is defined as the angle between the normal on the terrain at the site of the pixel in question and the zenith direction (Teillet et. al 1982). Through this process image data acquired under different solar illumination angles are normalised by calculating pixel brightness values, assuming the sun was at the zenith on each date of sensing.

$$L_H = L_T \frac{\cos(sz)}{\cos(i)}$$

$L_H$ = radiance observed over horizontal surface

$L_T$ = radiance observed over sloped terrain

$sz$ = sun's zenith angle

$i$ = sun's incidence angle on the terrain (i.e. angle between direction to the sun and the normal on the terrain)

Thus, data on the sun's zenith angle and the sun's meridian angle on the terrain are needed for the correction of slope-aspect effects. The cosine correction models the direct part of the irradiance. However, weakly illuminated regions receive a considerable amount of diffuse irradiance. On such areas, the cosine correction has a disproportional brightening effect. The smaller cos(i), the stronger this overcorrection is. For pixels in complete self-shadow (cos (i) = 0), where a division by 0 occurs, the Digital Numbers saturate and lead to artefacts in the corrected image (Meyer et al. 1993).

**C-Correction**

Meyer et al. (1993) demonstrated that the C-correction method improved classification accuracy in faintly illuminated areas by 5% and in forest stand areas between 10-30%. This semi-empirical slope-aspect correction method first described by Teillet et al. (1982) is used on images that are already corrected for atmospheric effects. It brings in a parameter *c*, which was the quotient of *b* (= intercept of the regression line) and *m* (= slope of the regression line) into the cosine law.

$$c = \frac{b}{m}$$

$$L_H = L_T \left[ \frac{\cos(sz) + c}{\cos(i) + c} \right]$$

However, this equation requires areas of interest with exactly the same land-cover / land-use on both the illuminated slope and shaded slope. There is no certainty that homogenous land-cover or land-use exists on the slopes of Oudomxay province.

**Non-Lambertian Methods**

The non-Lambertian method assumes that reflectance is dependent on the observation and incident angles. Many land-cover types are rugged and therefore the Lambertian assumption may be too simple and unrealistic (Riaño et al. 2003; Campbell 2002). The bidirectional reflectance distribution function (BRDF) describes how reflectance varies in each cover. BRDF is a mathematical description of the optical behaviour of a surface with respect to angles of incidence and observation, given that it has been illuminated with a parallel beam of light at a specified azimuth and elevation (Campbell 2002).

**Minnaert**

Minnaert proposed that all surfaces do not reflect incident radiation uniformly. Most of the non-Lambertian methods are based on the ideas of Minnaert who first proposed a semi empirical equation to assess the roughness of the moon's surface (Riaño et al. 2003). The equation is a modification of the cosine correction equation to counteract overcorrection of the cosine algorithm.

**SCS Correction**

The Sun–Canopy–Sensor (SCS) Correction is a terrain correction model devised by Gu and Gillespie (1998). It normalizes the changes of subpixel-scale sunlit canopy area rather than the pixel-scale irradiance on various terrain slopes. The SCS model is as simple as the cosine correction model, but it has improved accuracy in removing topographic effects in forest images (Gu and Gillespie 1998). It is comparable to or better than the C-correction and the Minnaert correction models. The SCS correction method was deemed unsuitable for this research methodology for two reasons. Firstly it only considers forest and not all land-cover. Secondly, it is applicable for alpine forest where the architecture of the trees is distinctly conical whereas the architecture of the trees in Laos is more rounded, similar to the architecture of deciduous trees.

### 2.3.3 Noise elimination

Images can contain random noise superimposed on the pixel brightness values due to (i) noise generated in the sensors that acquire the image data, (ii) systematic quantisation noise in the signal digitising electronics, and (iii) noise added to the video signal during transmission (Lillesand et al 2004). It shows as a speckled 'salt and pepper' pattern on the image in regions of homogeneity. This can be removed by the process of low pass filtering or smoothing but at the expense of high frequency information in the image. It was not necessary to apply noise elimination to the images used in this research.

## 2.4 Field Research

Field data collection is important in remote sensing (Congalton and Green, 1999; Campbell 2002). Campbell (2002) states that field data serves one of three purposes. First field data can be used to verify, to evaluate or to assess the results of remote sensing investigations. Second, they can provide reliable data to guide analytical process, such as creating training fields to support supervised classification. Thirdly, field data provide information to model the spectral behaviour of specific landscape features (Campbell 2002).

Procedures or practical field guides of field data collection for remote sensing purposes could not be sourced in the literature. Campbell (2002) suggested that three kinds of information be sought from field data: (i) measurements that describe ground conditions at a specific place (biophysical data: land-cover / land-use, species); (ii) observations linked to a location and size (location data: GPS, slope, elevation) enabling attributes / measurements to be correctly matched to points in image data; (iii) observations described with respect to time / date (illumination variability, seasons, and agricultural calendar). These suggestions provided the guidelines to the planning and conducting of this thesis' field research.

## 2.5 Image Classification and Interpretation

The objective of image classification is to replace visual interpretation of images with quantitative techniques for automating the identification of features in a scene. It usually involves the analysis of multi-spectral data and the application of decision trees or statistically based decision rules for determining the land cover identity of each pixel in an image. Decision rules are based on spectral, spatial and / or temporal pattern recognition. Spectral pattern recognition refers to a set of radiance measurements obtained in various bands of each pixel. It utilises the pixel-by-pixel spectral information as the basis of automated land-cover classification. Spatial pattern recognition involves the categorisation of image pixels on the basis of their spatial relationship with pixels surrounding them. For instance, the feature size, shape or texture. Temporal pattern recognition uses time as an aid in feature identification (Lillesand et al. 2004).

The intent of the classification process is to categorise all pixels in a digital image into one of several land-cover classes based on the pixels data file values (Lillesand et al. 2004). If a pixel satisfies a certain set of criteria, the pixel is assigned to the class that corresponds to that criterion. The pixels assigned to a class on a map or an image, so that after classification the digital image is presented as a mosaic of uniform parcels each identified by a colour. These classes are, in theory, homogenous (Campbell 2002). There are two ways to classify pixels into different categories: 'supervised' or 'unsupervised'. In supervised classification the image analyst 'supervises' the pixel categorisation process by specifying to the computer algorithm numerical descriptors of the various land-cover types present in a scene. Supervised classification is the method chosen for the classification of individual scenes and is described in Section 2.5.2. Unsupervised classification involves the categorisation of digital image data by computer processing based solely on the image statistics without availability of training samples. Unsupervised classification was the method chosen for the classification of multi-temporal NDVI datasets and is described in Section 2.5.3.

The classification system for remotely sensed data varies depending on the kind of the satellite data used and the objective of the classification. Due to these variations, the nomenclature and definition of land-cover types tend to vary considerably in the literature. Giri and Shrestha (1995) proposed the following criteria for classification:

- The classification system should have land-cover classes detectable in the satellite data used and be supported by the ground information and ancillary information available
- The classes discernible should have practical meaning in terms of their application

- The accuracy of the analysis of satellite data should be 85% or more, however a general rule of thumb is "Accuracy of the classification results is inversely proportional to the number of classes used"
- The same results within the threshold accuracy should be attainable by different analysts using imagery from different seasons.

### 2.5.1 Information classes

Information classes are the categories of interest to the user of the data (Campbell 2002). These classes are not directly recorded in remotely sensed images but can be derived indirectly through interpretation and classification of digital image data. Information classes are composed of spectrally distinct groups of pixels which originate from features on the earth surface with different spectral reflectance properties. Each feature on the earth's surface records its unique signature in a satellite sensor. This provides opportunities for discriminating between different objects on the earth's surface. Objects on the earth's surface that are in-distinguishable with the satellite data are not taken as separate classes nor are those classes which are discernible by the sensor but have no practical use to the end-user: cloud, cloud shadow, or dark objects.

Once the classes are selected it is necessary to define them properly. There is a great tendency to mix two commonly used terms *viz.* land-cover and land-use, principally because they are closely interlinked. Land-cover can simply be defined as the physical attributes of the land that can be seen readily as opposed to the land-use, which describes a pattern of human activities undertaken within a social and economic context (Giri and Shrestha 1995). Land-cover has visual effects, visible by the remote sensor, as it is what covers the land at the time of satellite observation. Examples of land-cover are forest, snow, grassland etc. with an exception of barren land without any cover. A more difficult problem can be encountered in defining individual land-cover classes. Forest, for example, is the most controversial one.

### 2.5.2 Supervised Classification

The image analyst 'supervises' the pixel categorisation process by specifying to the computer algorithm numerical descriptors of the various land-cover types present in a scene. To do this, representative sample sites of known cover type i.e. 'training areas' are used to compile a numerical 'interpretation key' that describes the spectral attributes for each land-cover class. Two steps are involved: i) Parameters of statistical distribution of pixel values for each category are determined; ii) Each pixel is assigned to a category on the basis of these statistical distributions.

The set of land-cover classes that segment an image must be decided first. These classes are known as 'information classes'. Representative or prototype pixels from each information class form the 'training data'. The area defined is called the 'training field'. The training data are used to estimate the parameters of a particular classifier algorithm. These parameters will either be the properties of the probability model used or will be the equations that define partitions in the multi-spectral space. Once the signatures of all training areas are obtained they can be evaluated.

ERDAS Imagine (2003) can display graphs of signature statistics as sets of ellipses in a Feature Space image. Each ellipse is based on the means, standard deviations and covariances of the signatures of a set of pixels. A graph can be generated for one or more sets of training pixels (from one or more information classes). By comparing the ellipses for different pixel sets for a one band pair, it is possible to see if the signatures represent similar groups of pixels by seeing how much the ellipses overlap in Feature Space. When ellipses do not overlap, the signature values represent sets of pixels that are different in the two bands plotted. This is desirable for classification. Some overlap is expected because it is rare that all classes are totally distinct. Overlapping ellipses suggest that signatures represent similar pixels. This is not so desirable for classification.

Computing the statistical distance between the signatures of different pixel sets it is possible to determine how distinct the pixel sets are from one another and to find the best subset of bands to use in the classification. Various measures of distance can be used: Euclidean spectral distances between the means, Jeffries-Matusita distance, divergence or transformed divergence (ERDAS 2003). Summary reports list the separability for band combinations with best average and best minimum separability.

### 2.5.3 Unsupervised Classification

Unsupervised classification involves the categorisation of digital image data by computer processing based solely on the image statistics without availability of training samples. The pixels in an image are examined by the computer and classified into spectral classes. The grouping is based solely on the numerical information in the data and the spectral classes are later matched by the analyst to information classes. In order to create an unsupervised classification the analyst typically specifies the number of spectral classes to identify and a computer algorithm will find pixels with similar spectral properties and group them accordingly (CGIS 2007).

Clustering algorithms such as the Iterative Self-Organizing Data Analysis Technique (ISODATA) in ERDAS Imagine are used to determine the statistical groupings in the data (Tou and Gonzalez 1974, cited in ERDAS Field guide 2003). The analyst specifies the parameters to determine how close pixels' digital numbers must be to be considered in the same information class. Once the clustering process has run, the analyst may combine or further break down some clusters. Thus, unlike its name suggests, an unsupervised classification in fact requires interaction with an analyst (CGIS 2007).

### 2.5.4 Visual Image Interpretation

Visual image interpretation of digital imagery is a simple and inexpensive operation. It involves looking at various objects in an image and identifying different tones, shapes, sizes, patterns, textures, shadows, and associations. Some of these objects are easily identifiable while others are not depending on individual perceptions and experience, the nature of the objects, and the quality of the images being utilized. Visual image interpretations occur at various levels of complexity from simple recognition of objects on the earth's surface to the derivation of detailed information regarding complex interactions on the surface and below the surface (Lillesand et al. 2004).

Disadvantages of visual interpretation of digital imagery provided by remote sensing platforms are as follows. It does not allow for full exploitation of the data provided. A human can only visually interpret 3 layers of remotely sensed information at a time. Also humans are not able to identify all spectral differences in imagery visual. Interpretations are subjective and qualitative. Automated processing of imagery on the other hand allows for objective and quantitative analysis of all spectral bands in imagery simultaneously, and is able to detect subtle differences that humans cannot.

Four types of information contained in a digital image are often utilised for image interpretation (CRISP 2007):

- Radiometric information (i.e. brightness, intensity, tone)
- Spectral information (i.e. colour, hue)
- Textural Information
- Geometric and contextual information

For this study, radiometric, spectral, and contextual information were used in the image interpretation process. The image interpretation process is influenced by the specific goals of the task and the interpretation equipment available. Many applications of image interpretation involve the delineation of discrete area units throughout images. For example the mapping of land-cover requires the interpreter to outline the boundaries between areas of one cover type and another. This is not always easy as the boundary may not have a discrete edge. Before area units are delineated, two issues must be addressed. Firstly, the classification system or criteria must be defined to separate the various categories of features occurring in the images. Secondly, the minimum mapping unit (MMU) that determines the extent of detail conveyed by the interpretation must be selected. The MMU is defined as the smallest size entity to be mapped as a discrete area (Lillesand et al. 2004). Small MMUs result in detailed interpretations. The MMU selected for this study is 4-5 pixels of the Landsat7 ETM+ image or 0.5 hectares.

## 2.6 Normalised Difference Vegetation Index (NDVI)

NDVI can be used to identify health and vigour in vegetation from estimates of green biomass, leaf area index (LAI), or changes in canopy cover (Hayes and Sader 2001). To determine NDVI researchers must observe the distinct wavelengths of visible and near-infrared solar radiation reflected by plants. The plant pigment chlorophyll absorbs visible light (from 0.4 to 0.7 μm) for use in photosynthesis. The mesophyll tissues in the leaves reflect near-infrared light (from 0.7 to 1.1 μm). In general, if there is more reflected radiation in the near-infrared wavelengths than in visible wavelengths, then the green vegetation in that pixel is dense and may be some type of forest. If there is very little difference in the intensity of visible and near-infrared wavelengths reflected, then the green vegetation is sparse.

NDVI is calculated from the visible and near-infrared radiation reflected by vegetation. Nearly all satellite vegetation indices employ this difference formula to quantify the density of plant growth on the Earth: near-infrared radiation minus visible radiation divided by near-infrared radiation plus visible radiation (USGS 2005). The result is called the Normalised Difference Vegetation Index:

$$\mathbf{NDVI = (NIR - R) / (NIR + R)}$$

where **NIR** is the near-infrared (Band 4) and **R** is the red band (Band 3) for Landsat 7 ETM+. The NDVI may be influenced by atmospheric effects (Song et al., 2001; Van Leeuwen et al., 2005). Song et al. (2001) state that contributions from the atmosphere to NDVI can be significant and amount to 50% or more over thin or broken vegetation cover.

Guerschman et al. (2003) found that using NDVI instead of Landsat TM bands 3, 4 and 5 increases biological interpretability. They demonstrated the use of NDVI in land-cover classification and state that NDVI is:

i. Good indicator of absorbed photosynthetic active radiation

ii. Provides an easy interpretable index due to the strong association with the status of the vegetation
iii. Allows a reduction in the dimensionality of the data.

Lyon et al. (1998) compared vegetation indices to detect land-cover change by analyzing NDVI values from different dates (NDVI image differencing) and reported that NDVI is not affected by topographic factors. This fact is backed by Lillesand et al. (2004) who say that a ratio image such as an NDVI image conveys the spectral or colour characteristics of image features regardless of variations in scene illumination conditions since the colour content of the data is emphasised not the brightness variation.

Yemefack, Bijker and De Jong (2006) and Guerschman et al. (2003) highlight the problems with using NDVI in classification. Guerschman et al. (2003) report that although the classification analyst was able to derive signatures that are easy to interpret in biological terms they did so at the expense of reducing the accuracy of the overall classification result. They also recognised that information can be lost when discarding the mid-infrared band (Band 5). This band in combination with NDVI can provide additional information about vegetation type and condition (Vieira et al. 2003). Yemefack, Bijker and De Jong (2006) claim that NDVI can yield inaccurate biomass estimates in areas where there is 100% vegetation cover and would therefore have limited value in characterising shifting cultivation in tropical forest areas. They suggest two reasons for this. Firstly, the NDVI from the initial stages of forest regeneration tends to saturate after a certain biomass density. Secondly, the canopies of older fallow or forest areas are dominated by tall old trees whose leaves no longer absorb much of the visible red light. As a result the NDVI value may not be indicative of what really exists in terms of vegetation biomass.

## 2.7 Multi-temporal Analysis

Change detection uses multi-temporal data sets to discriminate areas of land-cover change between dates of imaging. Lillesand et al. (2004) state that data should be acquired by the same sensor, recorded using the same spatial resolution, geometry, spectral bands, radiometric resolution and time of day and year. Registration of less than one pixel is required to prevent errors occurring when comparing images. Lillesand et al. (2004) describe various approaches to differentiate change over a time series of images. These include: post-classification comparison, classification of multi-temporal datasets, principal component analysis, temporal image differencing, and temporal image ratioing.

The post-classification comparison and classification of multi-temporal datasets are the two change detection procedures used in this study. Lillesand et al. (2004) describe post-classification comparison where multiple dates of imagery are independently classified and registered. An algorithm is then employed to determine pixels with a change in classification between dates. Additionally, statistics can be compiled to express the specific nature of the changes between dates of imagery. The accuracy of this procedure depends on the accuracy of each of the independent classifications.

The second approach used in this study is the classification of multi-temporal datasets. This procedure uses spectral pattern recognition. A single classification is performed on a combined data set for variable dates. Both supervised and unsupervised classification can be used to categorise the land-cover classes in the multi-stack image. The success of this change detection procedure depends upon the extent to which the changed classes are spectrally different from the classes with no change. Lillesand et al. (2004) raise a note of caution when using this procedure. They say the dimensionality and complexity of the classification especially if all bands from each image are used can be too great and lead to redundancy in their information content.

Van Leeuwen et al. (2005) state that there are many users employing geo-spatial tools that incorporate time series of spectral vegetation index data (with NDVI being the most widely used index) along with other reference data for spatially and temporally explicit natural resource monitoring. The use of multi-temporal image analysis is demonstrated by Sader and Winne (1992), Pax-Lenney and Woodcock (1997), and Seidenberg et al. (2003). Sader and Winne (1992) developed a technique to visualize land-cover change using multi-temporal NDVI imagery and interpretation concepts of colour additive theory. When simultaneously projecting each date of NDVI through the red, green, and blue (RGB) computer display write functions, major changes in NDVI (such as green biomass) between dates appear in combinations of the primary (RGB) colours. Figure 3 gives an illustration of the primary and complimentary colours used in colour composite images. Identifying which date of NDVI is coupled with each display colour, the analyst can visually interpret the magnitude and direction of biomass changes in the study area over the research period (Hayes and Sader 2001). Sader and Winne (1992) performed an automated classification on three dates of NDVI by unsupervised cluster analysis. Change and no-change categories were labelled and dated by interpreter analysis of the cluster statistical data and guided by visual interpretation of RGB-NDVI colour composites.

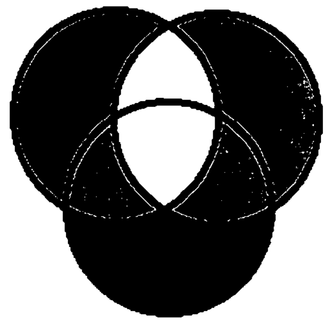


Figure 3: The three primary colours (red, green and blue) and three complimentary colours (yellow, magenta and cyan) illustrated in colour composite images.

Later Hayes and Sader (2001) investigated and evaluated three change-detection techniques: one of which was RGB-NDVI classification. The three techniques were compared on the basis of their ability to classify temporal forest states (clearing, regeneration, no change) in forest cover over a time period. The method's efficiency in computation, processing and ease in interpretation were also tested. Bands 3 (visible red), 4 (near infrared), and 5 (mid-infrared) were extracted from the original Landsat TM data sets to reduce between-band correlation, data volume, and processing time. Previous studies have shown that selecting one band from the visible, near- and mid-infrared spectral regions results in the optimal waveband combination for vegetation discrimination (DeGloria 1984; Horler and Ahern 1986; and Sader 1989 cited in Hayes and Sader 2001). Hayes and Sader (2001) performed an automated classification of NDVI by unsupervised cluster analysis (instead of using a thresholding technique) to classify forest clearing, regeneration and no-change areas between image dates. 50 spectral clusters were produced. Classes of no interest: water, cloud or cloud shadow, were masked for all dates to avoid confusion in the change-detection classification. Change and no-change categories were labelled and dated by interpreter analysis of the cluster statistical data and guided by visual interpretation of RGB-NDVI colour composites. The RGB-NDVI method produced an overall accuracy of 85% (Hayes and Sader 2001).

Pax-Lenney & Woodcock (1997) monitored the state of agriculture land in the Nile Delta and adjacent Western Desert in Egypt. They used ten Landsat TM images from different years and were able to separate land-cover types into agriculture, urban, water, desert and wetland classes. They applied a similar technique to Sader and Winne's (1992) using multi-temporal NDVI imagery and interpretation concepts of colour additive theory. They created NDVI images for each image. In their colour composites of three NDVI images they were able to identify areas of consistent values (such as water and desert sands) across dates as the appeared grey. Areas with variable NDVI values such as seasonal agricultural fields appeared in combinations of red, green and blue. Their results indicated the success in using multi-temporal

NDVI datasets derived from Landsat TM data in distinguishing healthy cultivated lands from uncultivated and non-productive lands. They achieved an overall accuracy of 95%.

Seidenberg et al. (2003) assessed the rate at which individual pixels change from one land-cover class to another through a time series of images. Land-cover maps were generated for each year (1989, 1992, 1995, 1997, and 1999) from five Landsat TM satellite images and subjected to a change detection routine to compare the classified images on a pixel-by-pixel basis. The change matrix used to estimate fallow periods and duration of cultivation included three study years. The fallow periods were calculated by assessing the rate at which individual pixels change from cultivation to forest and back to cultivation. The cultivation period was investigated by assessing how many forest class pixels changed to cultivation class from one image to the next. The change detection analysis revealed that there was a steadily decreasing fallow period throughout the study period (1989-1999) from 10-15 years to 4-5 years. The forest cover analysis showed that even though the overall annual deforestation rate is stable (except near villages) young forests increasingly replace old forests.

## 2.8 Post-classification smoothing

Classified data often have a 'salt-and-pepper' appearance because of the inbuilt spectral variability encountered when an image is classified on pixel-by-pixel basis. Pixels from one class appear as the minority in a class where other pixels are in the majority. It is often desirable to 'smooth' the classified output to show the dominant class. Post-classification smoothing algorithms operate on the basis of logical operations as opposed to simple arithmetic computations (Lillesand et al. 2004). One way to 'smooth' or filter the classification is by using the majority filter. A majority filter simply assigns each pixel in a moving window the most commonly occurring class using the original class codes not the labels as modified from the previous window positions. If the centre pixel of the window is not the majority class its identity is changed to the majority class. If there is not a majority class the identity of the centre pixel is not changed. The windows can be 3 x 3, 5 x 5 or 7 x 7 pixel filter. Another way to reduce the speckled effect of minority pixels is to use ERDAS Imagine (v 8.7) GIS analysis and neighbourhood filtering method.

## 2.9 Accuracy Assessment

Accuracy assessment determines the quality of information derived from remotely sensed data (Congalton and Green 1999). The same authors state there are many reasons for performing an accuracy assessment. They list four: (i) curiosity about how good something is; (ii) to identify and correct sources of error; (iii) to compare techniques, algorithms, analysts or interpreters; and (iv) to measure quality.

### 2.9.1 The Error Matrix

Accuracy is determined empirically by selecting a sample of pixels from the thematic map and checking their labels against classes determined from reference data. The percentage of pixels from each class labelled in the image correctly by the classifier can be estimated as well as the proportion of pixels from each class erroneously labelled into every other class. These results are expressed in tabular form and are referred to as the 'error matrix' (Lillesand et al. 2004) Congalton and Green (1999) describe the error matrix as:

> "...a square array of numbers set out in rows and columns expressing the number of sample units (pixels, clusters or polygons) assigned to a particular category in one classification relative to the number of sample units assigned to a particular category in another classification."

Generally one classification is considered to be correct i.e. the reference data. The columns usually represent the reference data and the rows represent the classification generated from the remotely sensed data. Table 1 below illustrates an example of an error matrix. The error matrix provides information on the map accuracy as individual accuracies of each category are described along with both the errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification. An error is therefore an omission from the correct category and a commission to a wrong category.

Field measurement

Visual call

| Class # | 1 | 2 | 3 | 4 | Sum | User's Acc. |
|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 0 | 1 | **100** |
| 2 | 1 | 3 | 1 | 0 | 5 | **60** |
| 3 | 0 | 0 | 17 | 5 | 22 | **77** |
| 4 | 0 | 0 | 1 | 11 | 12 | **92** |
| Sum | 2 | 3 | 19 | 16 | **40** | |
| **Prod.'s Acc** | **50** | **100** | **89** | **69** | | |

Table 1: Example of an Error Matrix (Congalton and Green 1999)

The Producer's, User's and Overall accuracies and Kappa statistic are calculated from the error matrix as follows:

**Producer's accuracy** = number of correctly classified pixels in each category ÷ total number of training set pixels used for the category (i.e. column total)

**User's accuracy** = number of correctly classified pixels in each category ÷ total number of pixels classified in that category (i.e. row total)

**Overall accuracy** = Σ total number of correctly classified pixels (i.e. Σ elements along major diagonal ÷ total number of reference pixels). In the example above, the overall accuracy = 80 %

**Kappa statistic** is the overall accuracy adjusted for the chance agreement between the reference data and a random classifier.

### 2.9.2 Objectivity and Accuracy Assessment

Accuracy assessments should be objective. Congalton and Green (1999) suggest three ways to ensure objectivity and consistency:

- Reference data for accuracy assessments must be kept independent of training data
- Data is collected consistently from sample site to sample site
- Quality control procedures are developed and implemented in all steps of data collection

One means to collect data consistently is to design a data collection form. All 'fields' in the data form are filled in the same way no matter if there is a change of data collection personnel. A data collection form was designed for collecting ground reference data for this study.
If the accuracy assessment is to be a fair one, Congalton and Green (1999) state that the reference data must be 100% correct. One way to achieve this is to collect reference data as close to the date of the remotely sensed data.

According to Guerschman et al. (2003) land-cover classification accuracy is affected by:

- Temporal resolution – number if images and the combination of them
- Categorical resolution – number of land-cover classes
- Spectral resolution – using a few spectral bands rather than all bands: NDVI ratio
- Spatial resolution – pixel size

In their study to distinguish between age-classes of secondary forest and other land-cover types in eastern Amazonia, Vieira et al. (2003) derived an error matrix by overlaying the GPS points taken in the field onto the classified image using Arc GIS. They then compared the field description with the classification for the corresponding pixel. They evaluated the quality of the classification using the Kappa statistic.

## 2.10 Conclusion

Time series has proved to be a powerful tool to ascertain the extent and configuration of changes in land-cover over time and space. Since the aim of this thesis is to develop a methodology that can identify the pattern and magnitude of spatial and temporal changes of land-cover, literature was sought on change detection methods to classify multi-temporal datasets. The technique identified as key to shaping this thesis' methodological approach was a method developed by Sader and Winne (1992) to visualise land-cover change using the classification of multi-temporal NDVI imagery and interpretation concepts of colour additive theory.

# 3 Research Site and Methods

## 3.1 Introduction

This chapter is divided into two parts. The first part gives a background of the research site: its geography, climate, socio-economic situation, ecology (including forestry, agriculture and shifting cultivation practices), land tenure, and government policies. The second part gives an account of two techniques performed to incorporate a time series of spectral vegetation index data and other reference data for identifying the pattern and magnitude of spatial and temporal changes in land-cover in the province of Oudomxay in Northern Laos.

## 3.2 Research Site

The study was conducted in the province of Oudomxay in Northern Laos (or Lao PDR). Laos is a landlocked country surrounded by China, Thailand, Myanmar, Cambodia, and Vietnam in South-east Asia. Figure 4 (below) shows the location of Laos and of Oudomxay province:


Figure 4: Location of Lao PDR in South-east Asia

## Forgotten citation

The following should be referenced to Leek, K. (2006) MSc Draft Research Proposal: Natural Resources and Rural Livelihood Strategies in Oudomxay, Lao PDR. Unpublished manuscript, Vienna.

**Page 23:**
Rainfall varies regionally, with the northern mountainous region and the floodplain region of the Mekong River receiving an annual rainfall of approximately 1,500 - 2,000 mm and the central and southern mountainous region receiving an annual rainfall of approximately 2,500 – 3,500 mm.

This northern mountainous province has a moist to dry sub-tropical climate. The area experiences a cooler dry season and higher variation in temperature during the year than other parts of the country.

47 ethnic categories were recognized in the National Census of 1995; however, between 130 - 230 ethno linguistic groups have been identified within four linguistic families: the Tai-Kadai, the Mon-Khmer, the Hmong-Mien and the Sino-Tibetan.

**Page 24:**
The Lao Loum live in the plains around the Mekong river valley and constitute 68% of the population. The Lao Theung live in the middle slope region and account for 22% of the population. The Lao Soung live in the remote highlands and account for 9% of the total population. The final 1% of the population is mainly ethnic Vietnamese or Chinese.

While the Khmu are a minority in Laos, they are the majority in Oudomxay. The Khmu are one of the oldest ethnic groups in northern Laos.

In 1986 the government adopted its New Economic Mechanism and open door policy allowing the country to change to a market-driven economy thus allowing liberalization of foreign investment.

An estimate in 1996 on Oudomxay residents indicates that the majority (50-60%) of their income comes from non timber forest products (NTFP's) with additional income being derived from livestock, rice, other crops and only 1% coming from off-farm activities.

Although the poverty rate for the country is decreasing the inequality between rich and poor is increasing. The second-poorest province in the country is Oudomxay with a poverty index of 73.2%.

**Page 25:**
There are currently 20 National Protected Areas (NPAs) and two corridor zones in Laos covering approximately 13% of the country.

The World Conservation Union (IUCN) - NTFP Project has identified more than 700 species of NTFPs. Examples of some common NTFPs, for subsistence or commercial use, are mulberry bark, cardamom, bamboo shoots, rattan, fish and wildlife.

**Page 28:**
Agriculture in Laos varies depending on the area. Most farmers employ one of two cultivation systems: either the wet-field paddy system (rain-fed or irrigated lowland system), practiced primarily in the plains and valleys, or the traditional shifting cultivation system (slash-and-burn) with rain-fed upland systems, practiced primarily in the hills.

Recently, non-timber forest products (NTFPs) are being cultivated and domesticated, such as paper mulberry.

**Page 32:**
Priorities and policies of the set out in the programme are for the stabilisation and elimination of shifting agricultural cultivation and opium production, increasing service provisions, decentralization, and implementing land allocation programs and relocation programs.

### 3.2.1 Geography and Climate

Laos has an area of 236,800 $km^2$. Its maximum length is about 1,080 km while its narrowest width is about 120 km. 89% of the land area is mountainous (UNEP 1998). Elevation ranges from 70 m along the Mekong River where it is mostly flat land to 2,819 m at Phou Bia in Xieng Khouang province (Bouahom et al. 2003; FAO 2006). The capital of Laos is Vientiane at latitude and longitude: 17°57'N 102°34'E.

The climate is tropical monsoon: the rainy season starts in April or May and ends in October. The cool dry season is from November through February; and the hot dry season is from March to April (CIA 2006). Rainfall varies regionally, with the northern mountainous region and the floodplain region of the Mekong River receiving an annual rainfall of approximately 1,500-2,000 mm and the central and southern mountainous region receiving an annual rainfall of approximately 2,500 – 3,500 mm (Bouahom et al. 2003).

Oudomxay has an area of 15,370 $km^2$. It shares a short border (15 km) with China in the north and borders five other provinces of northern Laos: Bokeo, Luang Namtha, Phongsaly, Luang Prabang and Sayaboury. The Mekong River flows through the south of Oudomxay along part of the border of Luang Prabang and Sayaboury. In northern Laos slopes are steep and elevation is generally >1000 m (Bouahom et al. 2003; FAO 2006). Only 5 - 6 % of northern Laos has a slope <20 %, while 46 – 50 % has a slope > 30 % (Bouahom et al. 2003; Fobbes 2004). This northern mountainous province has a moist to dry sub-tropical climate. The area experiences a cooler dry season and higher variation in temperature during the year than other parts of the country (Bouahom et al. 2003). Oudomxay has seven districts: Beng, Houn, La, Namo, Nga, Pakbeng and Xay. Field research was conducted in the area of four villages located in three of the seven districts; Ban Houy sang (La district), Ban Mang (Beng district), Ban Chang vang and Ban Phoulath (Houn district). The ages of the villages in 2003 were: 6 years, 187 years, and 41 years old. No data exists for Ban Phou lath. The provincial capital is Muang Xay in Xay district.

### 3.2.2 Socio-Economics

The population of Laos is approximately 6.4 million with an annual growth rate of 2.39% (CIA 2006). Laos is one of the least densely populated of the Asian countries with 23.3 people per $km^2$. Around 85% of the population is classified as rural. Laos has a diverse range of ethnic groups, indigenous communities and languages. 47 ethnic categories were recognized in the National Census of 1995; however, between 130 - 230 ethno linguistic groups have been identified within four linguistic families: the Tai-Kadai, the Mon-Khmer, the Hmong-Mien and the Sino-Tibetan (Bouahom et al. 2003; Chazée 2002). These linguistic families can be incorporated into three main geographical categories: the Lao Loum, Lao Theung and the Lao

Soung. The Lao Loum live in the plains around the Mekong river valley and constitute 68% of the population. The Lao Theung live in the middle slope region and account for 22% of the population. The Lao Soung live in the remote highlands and account for 9% of the total population. The final 1% of the population is mainly ethnic Vietnamese or Chinese (Bouahom et al. 2003; CIA 2006). The two common religions in Laos are Buddhism and Animism. Other (for example, Christian and Islamic) religious fractions are also found (CIA 2006).

In a 2004 estimate the population in Oudomxay was 275,300. This gives a population density of 18 inhabitants per $km^2$. The largest ethnic group in Oudomxay is the Khmu who are a part of the Lao Theung geographical category (Foppes et al. 2004). While the Khmu are a minority in Laos, they are the majority in Oudomxay. The Khmu are one of the oldest ethnic groups in northern Laos (Foppes et al. 2004). Other ethnic groups found in Oudomxay are the Be-Tai, Hmong, and Kho. The Khmu villages comprise of between 30 and 150 families and are often found in valleys of altitude 400-800 m. The average size of a family farm is 1.2 ha which they rotate annually. They rely on slash-and-burn agriculture for their livelihood with many young secondary forests as temporary fallow phases within the agricultural cycle. When the forest was extensive and the population small the Khmu coexisted in relative harmony with their environment for more than 400 years (Chazée 2002).

Laos became a Communist state when the Pathet Lao came into government after the war in 1975. In 1986 the government adopted its New Economic Mechanism and open door policy allowing the country to change to a market-driven economy thus allowing liberalization of foreign investment (UNDP 2001). A 2005 estimate of the GDP is $2.523 billion with a growth rate of 7.2%. Agriculture accounts for 45.5% of the GDP. Services (wholesale and retail) account for 25.8% of the GDP and industry (garment manufacturing, food processing and low technology assembly) account for 28.7% of the GDP (FCO 2006). It is expected that the mining and hydropower sectors will contribute significantly to Lao's GDP over the coming years. An estimate in 1996 on Oudomxay residents indicates that the majority (50-60%) of their income comes from non timber forest products (NTFP's) with additional income being derived from livestock, rice, other crops and only 1% coming from off-farm activities (Foppes and Ketphanh 1997). A 2002 estimate of poverty indicates a national poverty rate of 34% (CIA 2006), and a rural poverty rate of 40% (Foppes and Dechaineux 2000; Rigg 2003). Although the poverty rate for the country is decreasing the inequality between rich and poor is increasing. The second-poorest province in the country is Oudomxay with a poverty index of 73.2% (IFAD 2006).

### 3.2.3 Ecology

#### Forest

The forests in Laos are rich in biodiversity with over 10,000 species of vascular plants and wildlife (Bouahom et al. 2003). Forest cover is widespread especially in the mountainous regions of northern Laos. Today around 40% of Laos is covered with forests but in the 1940s 70% of the country was forest. This drastic reduction in forest cover is mainly due to the rapid population growth resulting in over utilization of the forest, logging (both legal and illegal) and a large conversion of forest to agriculture land (Foppes and Ketphanh 2000; Seidenberg et al. 2003). What is happening in Laos is similar to what Rerkasem (2001) reports from Northern Thailand:

> "As a result of the implementation of forest protection and watershed conservation measures, establishment of national parks, wildlife sanctuaries, industrial plantations, reforestation projects, selling of land to the private sector for intensive production of annual cash crops there is considerable increase in the demand for land in the mountainous areas from these various stakeholders. This trend is continuing with more and more land being taken away from the local people. The severe land shortage in the lowlands has also forced lowland farmers to move into the uplands and open up new land for intensive agriculture. "(Rerkasem 2001)

Major tree species include *Irvingia malayana* and *Castanopsis echinocarpa*. Teak plantation started in early 1990's and rubber tree plantations in 2006. There are currently 20 National Protected Areas (NPAs) and two corridor zones in Laos covering approximately 13% of the country (Hansen & Jeppesen 2004). 315,000 ha have protected status in Oudomxay. Large amounts of Non-Timber Forest Products (NTFP) are known to grow in the forests. The World Conservation Union (IUCN) - NTFP Project has identified more than 700 species of NTFPs (Foppes and Ketphanh 2000). Examples of some common NTFPs, for subsistence or commercial use, are mulberry bark, cardamom, bamboo shoots, rattan, fish and wildlife. NTFPs are becoming a major contribution to household food security and cash income in certain regions.

#### Forest Classification

It is believed that the most authoritative descriptions of Lao forest habitats were made by Xu who carried out a detailed study in Odomxay Province in 1994 as part of a feasibility study for a botanical garden (Rundel 1999). Malyvanh and Feldkötter (1999) report that there are two sets of forest cover data for Laos generated by two different institutions. One is the Lao National Forest Inventory (NFI) and the other is the Mekong River Commission (MRC) Forest Cover Monitoring Project (FCMP). The forest and land-cover classes generated by FCMP were defined on the basis of experience and from internationally accepted criteria. International definitions for "forest" vary with respect to the threshold values used for the tree height and percentage crown cover to categorize forest and non-forest areas. For example, the global definition of forest in land-cover classification stated in the FRA 2000 on Definition of Forest and Forest Change (FAO1998) is:

> "Land with tree crown cover of ≥10 % and an area of ≥ 0.5 ha. The trees should be able to reach a minimum height of 5 m at maturity. May consist either of closed forest formations where trees of various storeys and undergrowth cover a high proportion of the ground; or open forest formations with a continuous vegetation cover in which tree crown cover exceeds 10 percent. Young natural stands and all plantations established for forestry purposes which have yet to reach a crown density of 10 percent or tree height of 5 m are included under forest, as are areas normally forming part of the forest area which are temporarily unstocked as a result of human intervention or natural causes but which are expected to revert to forest."

Forests were defined in the FCMP as land with tree cover where the crown cover was ≥ 20% and tree height was ≥ 10 m. Crown cover (Cc) refers to the density (percentage) of the crowns of woody plants above 5-10 m. Examples of different percentage crown covers are illustrated in Figure 5 below.

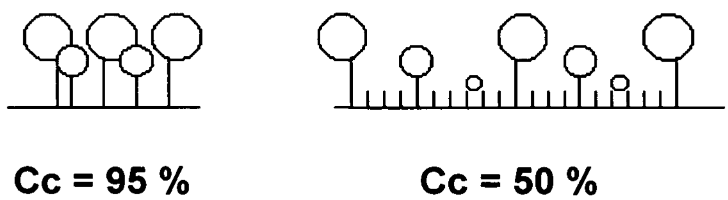



Figure 5: Crown cover % defined by FCMP (Malyvanh and Feldkötter 1999)

Forest cover (Fc) was defined in the FCMP as the percentage of the area within a minimum mapping unit (MMU) where the crown cover was ≥ 20%. Examples of different percentage forest covers (forest is shown in black) are illustrated in Figure 6 below.

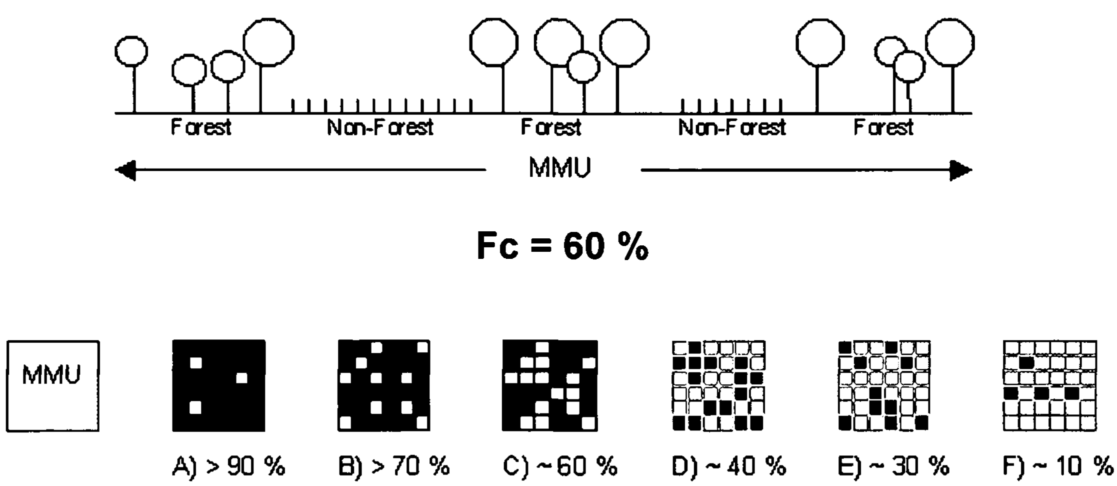



Figure 6: Forest cover % defined by FCMP (Malyvanh and Feldkötter 1999)

The minimum mapping unit (MMU) was defined as the smallest unit to be mapped by an interpreter. An international recognized standard for the MMU in forest and land-cover mapping is 4 x 4 mm at source scale. This is equivalent to 1 $km^2$, assuming a scale of 1:250,000. The FCMP used a 2 x 4 mm MMU, which is equivalent to 0.5 $km^2$ (assuming a scale of 1:250,000). The smaller MMU enabled a more detailed classification of the heterogeneous land-cover classes associated with Laos. The FCMP then further classified each MMU into one of three canopy density classes (high, low-medium and mosaic). To be classified as 'Forest, High Canopy Density', a MMU had to have Fc density $\geq$ 90 % and this Fc must have Cc $\geq$ 70 %. If Fc is assumed to have a Cc $\geq$ 70 %, the areas A – F in Figure 6 would be classified as follows:
**A** = Forest, high canopy density
**B** = Forest, low canopy density
**C** and **D** = Forest mosaic
**E** and **F** = non-Forest
These examples show that this classification system is conservative in assigning areas to the class 'Forest; high canopy density' and generous in assigning areas to the class 'Forest mosaic'. Therefore it is necessary to note these characteristics when interpreting the FCMP forest and land-cover statistics (Malyvanh and Feldkötter 1999).

In 2002, the Nam Ha Protected Area Management Unit (HNMU), the Forest Inventory and Planning Division (FIPD) and the Wildlife Conservation Society (WCS) conducted a wildlife survey and forest inventory of Nam Ha National Protected Area (NPA). The Nam Ha National Protected Area is the fourth largest protected area in Lao PDR. Following the field work, classification was made with SPOT and Landsat satellite imagery to determine forest type and land use intensity. It was hoped that the field data could be used to guide the forest classifications of the satellite images. However the resolution of the images were said to be too coarse to allow interpretation (Malyvanh and Feldkötter 1999).

On the local level, forests are classified according to the forest use. Four types are described:

1. Holy - almost every Lao village has a holy / spirit forest. These forests are traditionally honored as burial grounds or a refuge for spirits. The forests are 1-2 ha though larger forests are found where there is no encroachment from outside settlers
2. Protection - forests provide protection along watercourses. There is no harvesting allowed in these forests.
3. Construction - trees in forest areas close to village settlements are selectively cut for the construction of homes or for fencing materials.
4. Conservation - forests known to be rich in flora and fauna are protected and there is no harvesting of forest products.

**Agriculture**

Agriculture in Laos varies depending on the area. Most farmers employ one of two cultivation systems: either the wet-field paddy system (rain-fed or irrigated lowland system), practiced primarily in the plains and valleys, or the traditional shifting cultivation system (slash-and-burn) with rain-fed upland systems, practiced primarily in the hills. 45% of the rural villages in Laos are dependent upon slash-and-burn agriculture for their subsistence. Approximately 40,000 ha are cultivated in Oudomxay with upland rice as the major crop. Other important crops are maize, job's tear, soybean, sesame, cassava, coffee, sugarcane, tobacco, cotton, tea and peanuts. Recently, non-timber forest products (NTFPs) are being cultivated and domesticated, such as paper mulberry. Livestock grazing is also an important component of rural livelihoods, with water buffalo, pigs, cattle and poultry being the principle livestock. The Khmu keep livestock for subsistence and for cash income, but also as a form of barter trade. Although the government is attempting to eliminate opium production, it is still cultivated in some regions (Bouahom et al. 2003).

**Shifting Cultivation**

Shifting cultivation is based largely on the cyclical use of young secondary vegetation, though limited use of older forest also takes place in certain areas (Seidenberg et al. 2003). Generally, neither tillage nor inputs of fertiliser or pesticides are used. Rice is by far the most important crop and is farmed in monoculture or mixed with other crops on the cultivated area.

**Types of shifting cultivation**

Rerkasem (2001) suggests that traditional shifting cultivation is divided into two different types:

- Rotational
- Pioneering

'Rotational' shifting cultivation is managed on a permanent basis around an established village in which local households rotate their fields and fallow forests. A large tract of land is slashed and burned before the onset of the wet season. The fields may be cropped for only 1-2 years to avoid intensive use of land leading to severe soil fertility depletion and increasing weed infestation. The community then decides collectively to choose the next field in rotation, leaving the first field to lie fallow and naturally regenerate. After fallow regeneration reaches mature stage providing sufficient biomass to enable productive re-cultivation, the full cycle of shifting cultivation is complete. This may take 10-15 years. The belief that rotational shifting cultivation is a sustainable system has been well documented by Kunstadter et al. 1978; Rambo 1990; and Lovelace 1991 (cited in Rerkasem 2001).

In contrast to rotational shifting cultivation, the 'Pioneer' system usually involves non-permanent villages that move into the primary forests for longer periods of intensive cultivation, perhaps 10-15 years. When the soil fertility is severely depleted, the fields are abandoned and left to regenerate. Farmers then move to a new location in another area with primary forest. The practice of pioneer shifting cultivation is said to be unsustainable and destroy natural vegetation, and results in a grass climax such as *Imperata cylindrica* or *Chromolaena odonata.*
Lowlanders who recently encroached and/or transmigrated to the uplands are sometimes counted as another type of shifting cultivators, but they are not traditional shifting cultivators and their practices are destructive to natural vegetation and the environment (Rerkasem 2001).

**Phases of shifting cultivation**

Giller and Palm (2004) identify 4 main phases in a cycle of slash-and-burn agriculture:

(i) cutting / clearing
(ii) burning
(iii) crop cultivation
(iv) abandonment

The first phase involves the felling of trees and slashing of the shrub layer. This phase occurs during the dry season so that the slashed vegetation can dry out to allow burning (second phase) at the end of the dry season or beginning of the rainy season. An important factor is the length of time the cut vegetation is left to dry, and whether heaps or piles are made before burning. The intensity and effects of burning depend substantially on how the vegetation and fire are managed. Piling of biomass tends to achieve a more complete burn, but leaves behind little organic matter. Giller and Palm (2004) explain how elements such as C, N, and S are readily oxidized to gases during burning. Other nutrients (Ca, Mg, K and to some extent P) are returned to the soil in the ash and serve as fertilizer for the subsequent crops.

Crops cultivated in the third phase are typically fast-growing and nutrient-demanding cereal crops such as maize or upland rice. A rapid decline in soil organic matter and soil fertility is characteristic of the cropping phase and is often accompanied by an increase in weed pressure. The investment of labour in weeding exceeds the return in crop productivity, so that moving and clearing new plots are more favourable option than continued cropping. At this point, the ground returns to fallow (fourth phase) and the forest begins to regenerate (Giller and Palm 2004).

The length of fallow required to restore the original productivity of the land depends on many factors, especially on the length of the preceding cropping phase and the age of the fallow before clearing. Recovery of soil fertility is often stated as one of the main reasons for the fallow phase; however, the level of nutrients in the soil can decline during the fallow phase as nutrients are transferred from the soil to the vegetation. Therefore, it is the total nutrient stocks in the soil plus vegetation system that is important to the recovery of fertility (Giller and Palm 2004).

**Calendar year**

Shifting cultivation starts in February or March with the preparation of tools and the slashing of the fallow or forest. This work is carried out by the men. The day of burning is carefully chosen before the expected first heavy rain and on a day that is windy. The land is cleared after burning. Logs are stacked and smaller poles and sticks are carried to villages as fuel wood. Sowing takes place in April / May. The seeds are dropped by women and children into holes drilled with a long, pointed rattan or wooden planting stick. Weeding is carried out 2-3 times by the women and children between May and July. Weeding can account for up to half of the labour needed during cultivation of rice. Harvesting starts in September with the short cycle rice varieties and ends in November (Chazée 2002). Figure 7 illustrates the annual cultivation cycle.

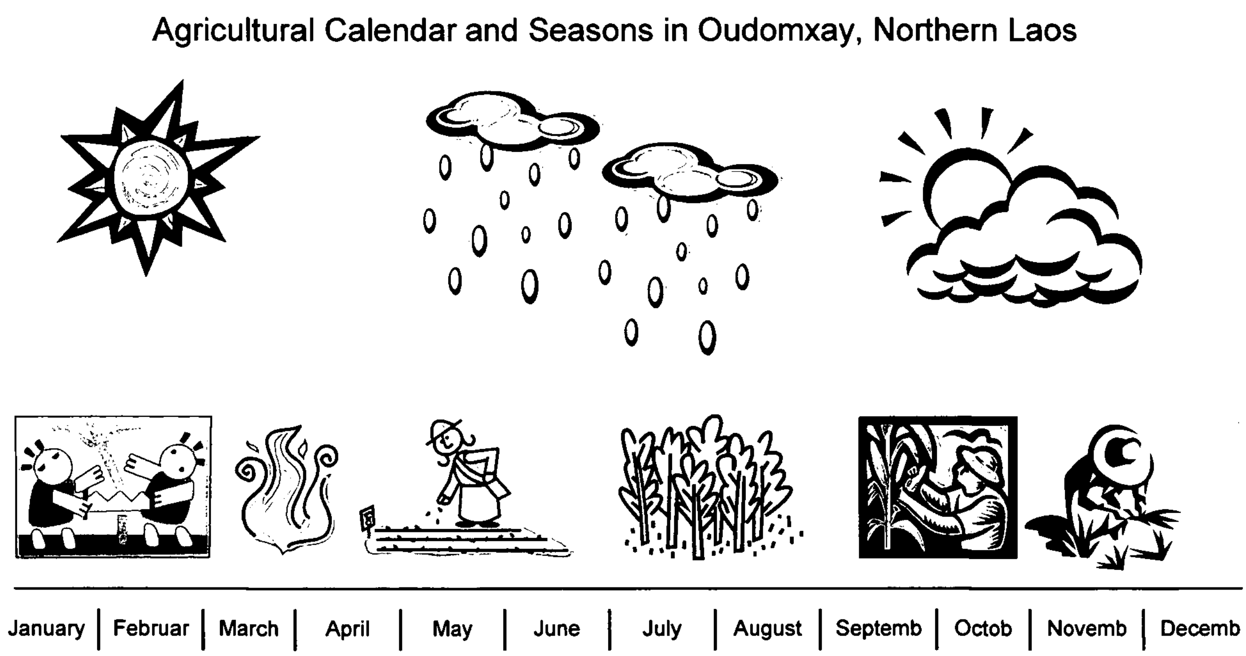



Figure 7: Shifting cultivation and Calendar Year

**Shifting cultivation and sustainability**

Shifting cultivation causes temporary deforestation during the cropping period, but allows for regrowth of secondary forest. Secondary vegetation exists in many different stages in shifting cultivation areas, and while lacking the conservation and carbon storage value of mature forest, it usually provides better ecosystem services than permanent farming (Seidenburg et al. 2003).

Under the "swidden" agricultural system, which is the term used by Evrard and Goudineau (2004) for shifting cultivation, long fallow periods are required for the productivity of the land to recover. Trenbath et al. (1985) attempted to model shifting cultivation with respect to soil fertility and vegetation change. They demonstrated that long fallow periods of 10-20 years would allow shifting cultivation to function on a sustainable basis whereas intensification and shorter fallow periods would lead to the deterioration of soil fertility and weed, disease or pest increase. Seidenburg et al. (2003) claims that fallow left for 7-10 years produces optimum yields and avoids increase in labour for weeding. However, farmers can no longer afford the luxury of long fallow periods that allow recovery of secondary forest and rejuvenation of exhausted soils. This is because of increasing population density from both endogenous growth and in-migration needing more land, while at the same time land is being sold to commercial rubber tree plantation companies or given protected status and also restrictive government's agricultural policies on shifting cultivation are reducing older fallow cycles to 3-5 year fallow rotations (Cairns and Garity 1999; Chazée 2002).

**Previous studies of shifting cultivation in Oudomxay**

An area in Oudomxay province was investigated by Giri et al. (2001) using multi-temporal analysis of remotely sensed data. SPOT Vegetation and NOAA AVHRR data were used to assess land-cover change from 1985 to 2000. They identified various stages of shifting cultivation practices from land preparation (burnt and exposed soil) to short and long fallow covered by thick bushes in satellite images and on the ground. Shifting cultivation areas ranged from 2 - 650 ha. This was said to be associated with the family size of the shifting cultivators. The shifting cultivation areas were distributed in the upper watershed of two major river systems: Nam Tha and Nam Beng. Forest areas were located on steep slopes and paddy cultivation was found in river valleys. It was suggested that the intensity, distribution and large plot size of shifting cultivation areas was caused by increasing population of shifting cultivators and in-migration from other provinces. Informal interviews with local villagers revealed gradual decline of forestry and agricultural productivity in the area (Giri et al. 2001).

### 3.2.4 Land tenure

Traditionally, land tenure in rural areas was regulated by informal agreements between households and the village headman, and use rights to a given area were acquired by bringing unclaimed land under cultivation (cited Seidenberg et al. 2003). Land was viewed as a free and abundant asset for the community, and land allocation ensured all households sufficient land to sustain their livelihood at subsistence level (Souvanthong 1995; Pravongviengkham 1998).Today few formal land tenure rules exist in the upland land use systems, which during the last 25 years have been altered by governmental resettlement programmes and relocation, in part due to the Indochinese War. More recently, formalised land allocation and titling have been initiated and are now a precondition for rural development projects.

### 3.2.5 Policies

**Poverty Eradication**

The National Growth and Poverty Eradication Strategy (NGPES) is the main framework for the development and implementation of all government poverty eradication programmes.This strategy was developed from the National Poverty Eradication Programme (NPEP). The ultimate objective is for Laos to no longer be categorized as a least developed country by 2020. The strategy's goal is to reduce rural poverty and conserve natural resources through the holistic transformation of upland livelihoods (Thomas 2003). Priorities and policies of the set out in the programme are for the stabilisation and elimination of shifting agricultural cultivation and opium production, increasing service provisions, decentralization, and implementing land allocation programs and relocation programs (Baird and Shoemaker 2005; IMF and IDA; Lao PDR). The strategy focuses on the poorest districts in the country of which five of the seven districts in Oudomxay were listed as priority poor districts and one is a poor district.

**Forest Policy**

In 1979 the National Decree on Forest Protection included provisions for the prohibition of shifting cultivation in watershed areas, logging permits and restoration of forest areas through tree planning activities. Directions for forest sector development were set in the first National Forestry Conference in 1989. A number of strategic directives were agreed upon during this conference to address sustainable forest management:

- To preserve forests and improve forest management to increase production
- To rationalize the use of forests and to increase their economic value
- To make permanent settlements by the year 2000 for 60% of the 1.5 million people engaged in shifting cultivation.

To translate the general government forest policy into action, a National Forestry Action Plan was prepared in the early 1990's. This plan was guiding forestry development in Lao PDR throughout the 1990s. A number of decrees and laws were promulgated after the first forest conference (Tsechalicha and Gilmour 2000). These included:

i) Decree 117/CM (1989) Management, Use of Forest and Forest Land.

ii) Decree 169/PM (1993) Management of Forest and Forest Land

iii) Decree 186/PM (1994) Allocation of Land and Forest Land for Tree Plantation and Forest Protection

iv) Forestry Law (1996)
v) Land Law (1997)
vi) Prime Minister's Order No. 11 (1999)
Decrees 169 and 186 have been replaced by the Forestry Law.

The first comprehensive Forestry Law promulgated in 1996 provided directions and a regulatory framework for forestry development. The law promoted the participation of people in forest management, protection and conservation. It made a provision for allocating degraded forests and forested land to individuals and organizations for management according to prescribed purposes. According to the 1996 Forest Law, individuals and organizations have a duty to protect the environment. Biodiversity has also to be protected outside the conservation forests. In August 1996, the Government of Lao PDR signed the international Convention on the Conservation of Biodiversity. This had implications for the policy and regulatory framework for biodiversity conservation in Lao PDR (Tsechalicha and Gilmour 2000).

Also in 1996, the Prime Minister's Office issued instructions on implementing forestland allocation. The first Nationwide Review Conference on Land Management and Forestland Allocation was held in the same year. The conference resulted in a number of resolutions to guide forestland allocation in the future (FAO 1998).

In 1997 a "Vision 2020" was developed by the Department of Forestry to translate policy into strategies. As part of this policy vision, the Government aimed to increase forest cover to 70% by the year 2020. The achievements to date are rather modest compared to the target set.

The Prime Minister's Order 11(1999) indicates that many provinces in Laos have violated logging regulations decreed in the Forestry Law in 1996. The intention of the Order was to strengthen the role of the central government in regulating and controlling all forestry-related activities in order to halt and reverse the destruction of Lao PDR's forests. One clause stipulates that for every cubic meter of timber cut 20 trees must be replanted under the supervision of the government. It was not clear what conditions apply to the harvesting of NTFPs. Another clause promotes reforestation by offering land tax exemptions for individuals and organizations whose land is used for tree planting. This is intended to apply where the stocking rate of the planted forest is ≥ 1,100 trees / ha (Tsechalicha and Gilmour 2000).

## 3.3 Methodology

### 3.3.1 Introduction

The aim of this thesis is to develop a methodology that can identify the pattern and magnitude of spatial and temporal changes of land-cover in the province of Oudomxay Northern Laos, using remote sensing techniques. Particular focus is to identify fallow age-class distribution, frequency of slash-and-burn events, and areas of intensive agricultural production.

This section begins by describing the acquisition of satellite data and explains the pre-processing techniques used before the digital image data are further manipulated and analysed. Principally three procedures are considered: geometric correction, radiometric calibration and noise elimination. This part is followed by a description of how the field research was conducted in the province of Oudomxay to collect ground reference data for the verification, evaluation and assessment of the classification results. The section goes on to describe in detail the two approaches undertaken to discriminate land-cover changes from three dates of imagery. One approach employs the 'post-classification comparison' (Lillesand et al. 2004) using the supervised classification technique. The second approach involves the 'classification of multi-temporal Normalised Difference Vegetation Index (NDVI) data sets' (Lillesand et al. 2004) using the unsupervised classification technique. Since only the second approach is continued after classification, this section ends by describing three procedures that are performed on the classified data of the multi-temporal NDVI classified image. These include: post-classification smoothing, accuracy assessment and production of thematic maps.

### 3.3.2 Data

Images from three dates captured by Landsat 7 ETM+ (worldwide reference system path 129, row 046) are chosen for this research. Figure 8 shows the location of this scene. The images come from the Spatial Analysis team of the Centre for International Tropical Agriculture (CIAT Columbia). Field data is used to either create 'training fields' in the supervised classification of individual scenes or used to evaluate and assess the results from the unsupervised classification of the multi-temporal NDVI imagery.

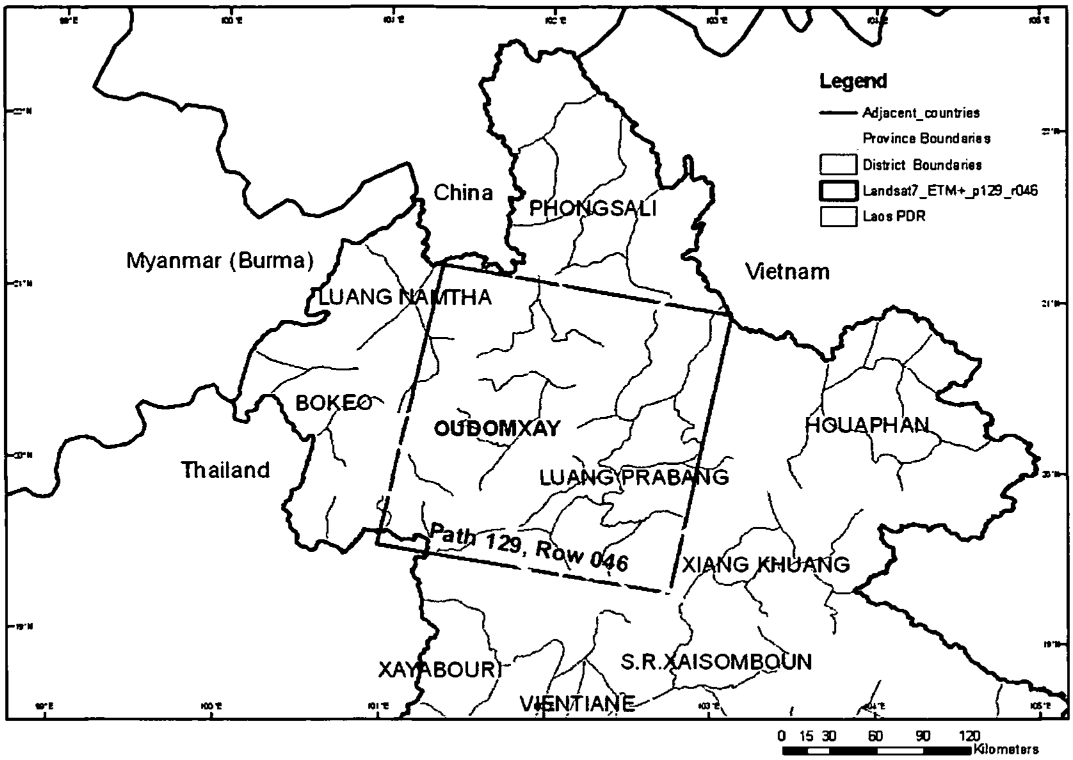



Figure 8: Location of scene path 149, row 046 captured by Landsat 7 ETM+

### 3.3.2.1 Satellite data

Multi-band datasets (output type = 8 bit) from each of the Landsat 7 ETM+ images using bands one to five and band seven are created. The images chosen have limited cloud cover over Oudomxay province in Northern Laos because they were taken during the peak of the dry season. February is also the time of year when the shifting cultivators are actively cutting fallow or forest so areas of bare soil are easily recognisable. More recent scenes are not selected owing to the SLC failure aboard Landsat 7 in May 2003. The time series of images includes February from three consecutive study years (2001, 2002 and 2003). For pre-processing and analyses of the satellite imagery, ERDAS Imagine software (v. 8.7) is used.

#### Image pre-processing

This operation corrects distorted or degraded image data and creates a more faithful representation of the original Landsat 7 ETM+ scene. Three pre-processing procedures are used for the image rectification and restoration. These are (i) to correct for geometric distortion, (ii) to calibrate the data radiometrically, and (iii) to eliminate noise. Prior to correcting any distortion or degradation of the image data, the area of the satellite scene is reduced by creating a mask for the specific study area.

**Provincial mask**

A mask is created for the province of Oudomxay to reduce the volume of the data and processing time required to correct and standardise the image data of the original three Landsat 7 images. The mask is generated using Arc GIS (9) by creating a shape file for the province and converting the vector file to a raster dataset.

**(i) Geometric correction**

All images are supplied in geo-rectified form and projected to the UTM Zone 48N coordinate system using WGS 84 datum.

**(ii) Radiometric calibration**

Two radiometric pre-processing techniques are applied to the images for the post-classification comparison method. These are atmospheric correction and topographic correction. The classification of multi-temporal Normalised Difference Vegetation Index (NDVI) data sets are corrected for atmospheric affects only since it is assumed that topographic factors do not greatly influence NDVI.

**Atmospheric correction**

The dark object subtraction method (DOS) is applied to account for atmospheric scattering. It is assumed that signals to the satellite sensor from 'dark' ground features are entirely due to scattered path radiance. The 'path radiance value' for ETM+ bands 1 - 5 and band 7 for each Landsat 7 ETM+ image is determined from pixel histogram minima. This number (histogram minimum) is subtracted from all pixels in each band respectively.

**Topographic correction methods**

Topography modifies illumination and therefore affects the amount of radiation reflected towards the satellite sensor. To maximize the information content in the Landsat 7 ETM+ imagery of the mountainous areas of Oudomxay province, it is necessary to remove, or account for, the effect of topography. A Digital Elevation Model (DEM) with the same resolution as the Landsat 7 images (30 m pixel size) is used to compute the incident angle. The DEM is generated from the SRTM at 90 m resolution to 30 m by CIAT (Columbia) by resampling and interpolating the SRTM-DEM data. It is important that the DEM fitted to the Landsat 7 ETM+ images so that they have the same:

- Spatial resolution
- Spatial extent
- Rows and columns

A Lambertian method is chosen to remove topographic effects. In doing so it is assumed that reflectance is independent of the observation and incident angles. The C-correction method is used on images that are already corrected for atmospheric effects.

The concept of the C-correction is to determine the direct solar radiation ($C_s$) values of incoming radiance for each spectral band in a scene. The C-correction method requires areas of interest with exactly the same land-cover / land-use on both the illuminated (SE) slope and shaded (NW) slope. There is no certainty that homogenous land-cover or land-use exists on the slopes of Oudomxay province. This method brings in a correction parameter *c*, which is the quotient of *b* (= intercept of the regression line) and *m* (= slope of the regression line) into the cosine law. This equation is illustrated in Chapter 2.3.2.2 (page 9).

The solar zenith and azimuth angles are taken from the metadata for each scene of the Landsat 7 ETM+. Using the model maker in ERDAS Imagine, the topographic correction as described above is applied to bands of the Landsat ETM+ images after Dark Object Subtraction (DOS) application. The model is run repeatedly for different $C_s$ values ranging from 0.1 to 0.9 for each band of the same image. A visual analysis of the images is carried out by comparing the 'normalised' image with the DOS image using different $C_s$ values for each band. The optimal $C_s$ value is one that shows the most satisfactory removal of the topographic effects. An example of the decision making process for calculating the optimum $C_s$ values is seen in Appendix 1. The procedure is mirrored for the same scene but from different years. A summary of the $C_s$ values selected for individual bands for each scene is shown in Table 2 below.

| | $C_s$ value | | | | | |
|---|---|---|---|---|---|---|
| **Band No.** | **1** | **2** | **3** | **4** | **5** | **7** |
| 2001.02.06 | 0.35 | 0.5 | 0.55 | 0.55 | 0.65 | 0.7 |
| 2002.02.09 | 0.3 | 0.5 | 0.6 | 0.6 | 0.65 | 0.7 |
| 2003.02.28 | 0.35 | 0.4 | 0.55 | 0.6 | 0.7 | 0.7 |

Table 2: Optimised $C_s$ values for three Landsat 7 ETM+ images

Having the optimised $C_s$ values for each individual band the model is run once more to obtain the optimal normalised C-corrected image.

**(iii) Noise elimination**

It is not necessary to apply noise elimination to the satellite images used for this research.

### 3.3.2.2 Field Data

Field data is needed for both supervised classification and unsupervised classification procedures. Supervised classification requires field data to create training fields for the different land-cover types. Field data in unsupervised classification is used to identify the information class of every spectral class.

Land-cover surrounding the four villages: Ban Houy sang, Ban Mang, Ban Chang vang and Ban Phoulath in three districts: La, Beng and Houn respectively (in the province of Oudomxay, Northern Laos) are determined in the field in May 2006. May lies at the beginning of the rainy season and therefore at the start of the planting season. Areas of recent slash-and burn are obvious in the landscape. Ground reference data are taken at points and not polygon areas as it is too difficult to access the fallow, forest, or slash-and-burn areas owing to the steepness of the terrain and / or the thickness of the forest vegetation. GPS readings are recorded at the locations of these points

Before travelling to Laos to conduct the field research it is important to draw up a plan that identifies the requirements of collecting 'ground truth' or reference data. It is important to think ahead to the 'image interpretation stage'. Firstly, the minimum mapping unit (MMU) is selected. It has to be distinguished from the resolution of the satellite sensor (30 m), which determines the extent of detail of the land-cover. The MMU selected for this study is 4-5 pixel size or 0.5 ha. Secondly, the classification system or the criteria used to separate the various categories of land-cover classes is defined. The placement and location of the ground reference points is considered to facilitate their identification later in the image display.

A topographical map (scale 1:250,000) for Oudomxay Province is acquired from the National Geographic Department in Vientiane, Laos. There are no aerial photographs available. Multi-spectral images from Landsat 7 ETM+ path 129, row 046 are printed for the four village areas on A4 paper at scales 1:25,000; 1:50,000 and 1:100,000 with band combinations of 3,2,1; 4,3,2; 5,4,3; and 7,4,2. Various band combinations are selected to give information on land-cover class features, since land-cover appears differently with different band combinations in colour images as described by Horning (2004).

Interviews with local government staff in the District Agricultural and Forest Office (DAFO) in Oudomxay provides information on local conditions and the accessibility to research sites. Village farmers guide the field research in their respective areas and avail of existing trails or paths to reach different land-cover classes.

Data forms are designed to gather accurate and consistent quantitative information. An example of one may be viewed in Appendix 2. Information required for each point include: 'Date', 'GPS number', 'WGS coordinates', 'Land-cover / Land-use class', 'Area', 'Photo no.'. 'Additional information' such as previous land-use or cultivation history, fallow age, forest use is obtained from interviews with the farmers or local government staff. Land-cover classes are broadly divided into fallow, forest and permanent agriculture. Fallow is sub-divided into five age classes: < 1 year, 1-2 years, 3-4 years, 5-6 years and > 6 years. Returning to the same village for more than one field day is necessary to get an adequate sample of ground reference points for the different land-cover classes in that village area. It is important that the same farmer and local government staff (who act as interpreter and field assistant) accompany all field visits in their respective villages to prevent inconsistencies in data collection.

Local government officials are briefed on the overall aim and objectives of the field research and given a daily breakdown of the plan of operation. Issues around field data collection are addressed. These include: measurement and note taking accuracy, continuity between data collectors, area and extent of different land-cover areas sampled, and land-cover homogeneity for the collection of ground control points. Field assistants are trained in the use of the field instruments. The field instruments consist of a handheld GPS unit ("Garmin etrex") and a digital camera. A test-run is conducted on the accuracy of the field instruments before commencing the data collection. GPS coordinates are tested against 'known' coordinates from geo-referenced satellite images. Field data are monitored to ensure consistency and accuracy. Changes are made to the preliminary field work plan to improve the effectiveness and efficiency of the field data collection.

### 3.3.3 Image classification

The aim of this image classification is to identify change in land-cover with particular attention to fallow age class distribution, frequency of slash-and-burn events and areas of agricultural production using multi-temporal data sets. Two approaches are tried to discriminate land-cover changes between three dates of imagery. These are the post-classification comparison and the classification of multi-temporal data sets.

The first step in either classification procedure is to decide on a set of land-cover types or 'information classes'. The information classes are selected owing to the capability of the satellite sensor to distinguish between these features on the earth's surface. Ten information classes are selected. These are listed below.

1. Slash-and-burn areas from the year 2000
2. Slash-and-burn areas form the year 2001
3. Slash-and-burn areas from the year 2002
4. Slash-and-burn areas from the year 2003
5. Fallow
6. Forest
7. Maize
8. Lowland rice,
9. Urban
10. Water bodies

Cloud and cloud shadow are masked as described in Chapter 3.3.3.2 (page 41).

### 3.3.3.1 Post-classification comparison

According to Lillesand et al. (2004), post-classification comparison uses multiple dates of imagery that are independently classified and registered. In this research individual images captured in February from the three study years 2001 to 2003 are classified using the supervised classification procedure. Supervised classification is performed using maximum likelihood decision rule and ERDAS Imagine (v. 8.7) software. Thus the statistical probability of each pixel value being a member of a particular land-cover class is computed using the mean vectors and the covariance matrix. The pixel is then assigned the most likely information class. Having decided on the ten information classes, the next step involves selecting representative or prototype pixels for each class. These pixels form the 'training data' and the area defined is called the 'training field'. The training data are used to estimate the parameters of the class probability distributions. The probability distributions of the classes are given by the means, variances and covariances from the pixels included in the polygons for each class and date.

Using the polygon and region growing (seed) tools, areas representative of the 10 information classes are delineated. The seed tool determines which pixels in a geographic neighbourhood are considered contiguous (of similar value) in feature space to the seed pixel or any 'accepted' pixel. A Euclidean spectral distance of 10 is used for region growing of training fields. A value of '300' is selected as the geographic constraint area and island polygons are accepted. An evaluation is carried out on the classification of the image of February 2003 using tools available in ERDAS Imagine (v 8.7). The information classes are not properly classified using Maximum Likelihood Classification because of spectral overlap. Therefore, application of this method was discontinued. The classification of multi-temporal NDVI datasets is pursued instead.

### 3.3.3.2 Classification using multi-temporal NDVI data sets

A single unsupervised classification is performed on a combined data set for three dates of imagery. For this approach a technique first developed by Sader and Winne (1992) to visualize change in land-use using multi-temporal NDVI imagery and interpretation concepts of colour additive theory is adopted. The Normalised Difference Vegetation Index (NDVI) is calculated for each of the Landsat 7 ETM+ images from February 2001, 2002 and 2003 using the formula entered in Chapter 2.6 (page 15).

An image is generated by superimposing three NDVI images in red, green, and blue (RGB) image layers. Various colour assignments are tried until a combination is found for easy interpretation of NDVI changes. The NDVI from February 2001 is selected for the red band, NDVI from February 2003 for the green band, and the NDVI from February 2002 for the blue band. Changes in NDVI appear in combinations of the primary (RGB) colours. By identifying which date of NDVI is coupled with each display colour, it is possible to visually interpret the magnitude and direction of biomass changes in the study area over the three years.

**Masks**

Before performing an unsupervised classification of the multi-temporal NDVI dataset, a second mask is created to exclude areas of cloud and cloud shadow, which can create spurious results in the classification. Both February 2001 and 2002 images are free of clouds in the region of Oudomxay province but there is 15% cloud cover over the entire image in February 2003. A mask is created to eliminate cloud and cloud shadow. This mask is combined with the provincial mask and a new NDVI image is created for the classification.

**Visual image interpretation**

To be able to use the 10 information classes used in the supervised classification, it is necessary to evaluate whether these classes can be interpreted from the display colours of the multi-temporal NDVI image. A visual image interpretation is carried out. The spectral profiles for each of the colour renditions are analysed from a multi-band NDVI image. Although it is only possible to view three bands at any one time, it is possible to view more bands from the spectral profile. An additional five NDVI images from March 2000 to November 2002 are stacked with the original three NDVI images. These additional bands provide information on NDVI values for vegetation at different phenological stages in the calendar year.

**Unsupervised classification**

Unsupervised classification is performed on the multi-temporal data set of the original three NDVI images by means of ERDAS Imagine (v. 8.7) software. ERDAS uses the ISODATA algorithm to perform an unsupervised classification. 200 classes are selected with maximum number of iteration of '24' and the convergence threshold set to '0.95'. This threshold prevents the ISODATA utility from running indefinitely. After the classification is performed, information classes are assigned to each of the 200 spectral classes. This is done by means of using spectral colour and the pattern recognition ability of the human visual system.

The opacity for all of the spectral classes is set to zero before analysing the spectral classes individually. One spectral class is selected at a time and given the opacity of 1. The coloured cluster of pixels representing a spectral class is identified in the classified image and at the same time identified in the multi-temporal NDVI image by geo-linking the images. Size, shape, colour, pattern, and context of the pixels are analysed in the multi-temporal NDVI image. By observing the spectral class in a number of different areas of the image and analysing its features in the multi-temporal NDVI image, it is possible to assign an information class to the spectral class. Once the 200 spectral classes are analysed, the thematic raster layer is recoded.

### 3.3.4 Post-classification filtering

It is desirable to smooth / filter the classified image to remove the speckled effect caused by individual / small clusters of pixels of one information class appearing in a dominant class. Lillesand et al. (2004) suggest different ways to 'smooth' or filter the classification. The method selected in this thesis is the majority filter with a window of 3 x 3 pixels. This filter assigns each pixel in a moving window to the most frequently occurring class using the original class codes. This option is compared with the 5 x 5 and 7 x 7 pixel filters.

### 3.3.5 Accuracy Assessment

An accuracy assessment is carried out to determine the success of the classification and to identify the sources of error. An error matrix was used to determine the thematic accuracy of the map derived from the unsupervised classification of the multi-temporal NDVI image. As Table 1 (page 20) illustrates, the columns represent the ground reference data collected in the field and the rows represent the classification generated from the remotely sensed data.

**Ground reference points**

Ground reference points are taken during the field visit to Laos in May 2006. All but one information class has ground reference points. In order to run the error matrix correctly, ground reference points are needed for Class 3 (i.e. slash-and-burn in 2001, fallow in 2002 and again cultivated in 2003). This is achieved by locating Class 3 on the multi-temporal NDVI image and geo-linking the points to the original DOS images from each image year. If the colour rendition in the NDVI colour-composite image is consistent with the colours of the 4-3-2 colour composite of the original images, the coordinates of this point are used as the reference point for this class. Figure 9 below illustrates this procedure.

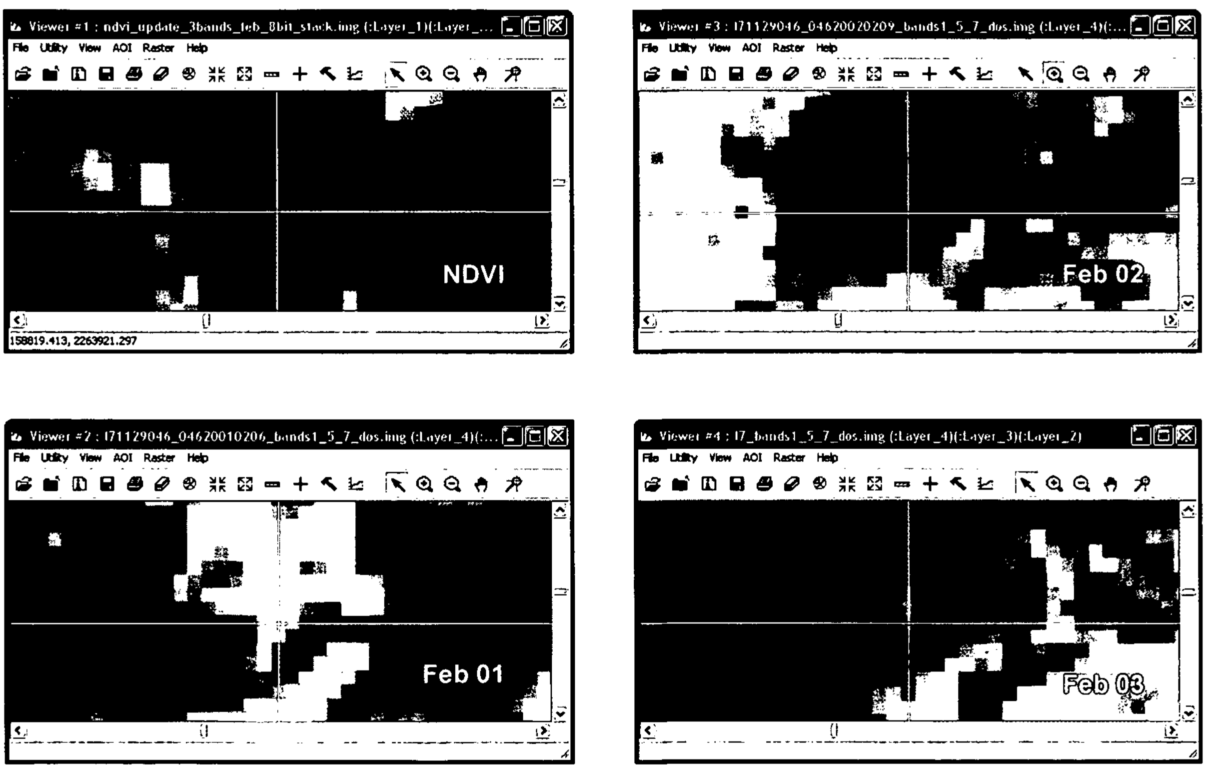



Figure 9: Acquiring additional ground reference points for Information Class 3

### 3.3.6 Land Pressure Map

Central to this thesis is the concern of the International Centre for Tropical Agriculture (CIAT) about the abandonment of sustainable fallow management practice and shortening of fallow rotations in northern Laos. Therefore the subject of the thematic map needs to address this issue. If a thematic map is produced from the ten information classes selected the map would show the distribution of areas undergoing slash-and-burn cultivation, permanent agriculture, forest or fallow. It would not in itself provide information on areas that are at risk from overexploitation. Such areas are undergoing frequent fallow rotations or converted to permanent agricultural land. The information classes are analysed and categorised according to whether the descriptions of their class would yield low, medium or high pressure on the natural resources in the surrounding environment. A summary of the classes and pressure categories is found in Table 3 below.

Very low pressure is indicated using the colour green. Low pressure is indicated using the colour yellow. Medium pressure was indicated using the colour orange. High pressure is indicated using the colour red. The display colours in the attribute table of the unsupervised classification image are changed using the four land pressure indicator colours and a thematic map is produced for the province of Oudomxay. Shape files for major roads, rivers and villages surrounding the four study village areas are added to the land pressure image in Arc GIS for analysis.

| Class | Pressure Level | Description of class |
|---|---|---|
| 1 | Low | Slash-&-burn 2000, Fallow 2001-2003 |
| 2 | Medium | Slash-&-burn 2001, cultivated 01 and 02, Fallow 03 |
| 3 | Medium | Slash-&-burn 2001, Fallow 02, cultivated 03 |
| 4 | Low | Slash-&-burn 2001, Fallow 02 and 03 |
| 5 | Medium | Fallow 01, Slash-&-burn 2002, cultivated 02 and 03 |
| 6 | Low | Fallow 01, Slash-&-burn 2002, Fallow 03 |
| 7 | Low | Fallow 01 and 02, Slash-&-burn 03 |
| 8 | [illegible] | Fallow |
| 9 | [illegible] | Forest |
| 10 | [illegible] | Permanent agriculture, urban |

Table 3: Land Pressure Level and Information Class

### 3.3.7 Conclusion

This chapter was divided into two parts. This first part gave a background to the province of Oudomxay in Northern Laos: its geography, climate, socio-economic situation, ecology (including forestry, agriculture and in particular the country's shifting cultivation practices), land tenure, and government policies. The second part gave an account of two techniques performed to incorporate a time series of spectral vegetation index data and other reference data for identifying the pattern and magnitude of spatial and temporal changes in land-cover. One approach employed the post-classification comparison using the supervised classification technique. The second technique involved the classification of multi-temporal Normalised Difference Vegetation Index (NDVI) data sets using the unsupervised classification technique. The first approach was abandoned after carrying out the classification and so the latter technique was pursued. This was a method developed in this research from an earlier approach originating from Sader and Winne (1992) who used the classification of multi-temporal NDVI imagery and interpretation concepts of colour additive theory to visualise land-cover change. The section ended by describing three procedures that were performed on the classified data of the multi-temporal NDVI classified image. These were: post-classification smoothing, accuracy assessment and production of thematic maps.

# 4 Results

## 4.1 Introduction

This chapter presents the results from the application of a methodology that identifies the pattern and magnitude of spatial and temporal changes of land-cover in the province of Oudomxay in Northern Laos. Two change detection methods were tried but only one gave successful results. This chapter focuses on the outcomes of the classification of multi-temporal NDVI data sets.

Results from the calculation of NDVI from the individual Landsat 7 ETM+ images and the construction of the NDVI multi-band image are presented. This is followed by the visual image interpretation results of the multi-temporal NDVI image using the image display colours and spectral profiles. The information classes selected for the unsupervised classification are described. The spectral classes from the classified image are interpreted. A post-classification method was applied to the classified image and the outcome is illustrated in a map. An accuracy assessment was performed on the classified data and the results are revealed. This chapter concludes by explaining the results from categorising the information classes into land pressure groups and presenting these results in a land pressure map for the province of Oudomxay.

## 4.2 Image Classification

The aim of the image classification was to identify change in land-cover with particular attention to fallow age class distribution, frequency of slash-and-burn events and areas of agricultural production using multi-temporal datasets. Two change detection methods were applied to discriminate land-cover changes between three dates of imagery. These were the post-classification comparison method and the classification of multi-temporal data sets

### 4.2.1 Post-classification comparison using supervised classification

This procedure involved the independent classification and registration for multiple dates of imagery. A supervised classification of the radiometrically calibrated image from February 2003 was run. An evaluation of this classification revealed that the information classes were not properly classified using Maximum Likelihood Classification because of spectral overlap. The results were more or less the same whether the spectral classes were selected using a region growing tool with a specified Euclidean distance and variable geographic constraint areas or whether the spectral classes were selected using the polygon tool and visual analysis. Application of this change detection method was discontinued.

### 4.2.2 Classification of multi-temporal NDVI data sets

The second change detection method used was the classification of multi-temporal NDVI data sets. For this method a technique to visualize change in land-cover using multi-temporal NDVI imagery and interpretation concepts of colour additive theory was adopted. The first step of this methodology involved calculating the NDVI for each Landsat 7 ETM+ image (Feb 2001, Feb 2002 and Feb 2003). The NDVI for each year were superimposed in the red, green and blue bands. The analyst then interpreted the image display colours. Each display colour reflected forest or fallow canopy change and / or changes in the green biomass over the three year study period. Regions with consistent NDVI values appeared grey, and were interpreted as forest or older fallow areas. Areas with variable NDVI values appear in different combinations of primary colours and were interpreted as slash-and-burn areas or soils cultivated for crop production. Altogether twelve display colours were interpreted. A summary of the display colours and a description of how the colours were interpreted are given in Table 4 below.

| Display colour | Display colour | Red<br>NDVI Feb 01 | Green<br>NDVI Feb 03 | Blue<br>NDVI Feb 02 | Interpretation relative to fallow or forest canopy change |
|---|---|---|---|---|---|
| | dark blue | low | low | high | Cut pre Feb 01, possible permanent agriculture |
| | cyan | low | high | high | Cut pre Feb 01, regrowth Feb 02 and Feb 03 |
| | dark green | low | high | low | Cut pre Feb 01, possible permanent agriculture |
| | light green | low | high | low | Cut pre Feb 01, cultivated 01 & 02, fallow Feb 03 |
| | red | high | low | low | Fallow Feb 01, cut pre Feb 02, cultivated 01 & 02 |
| | orange | high | low | low | Fallow Feb 01, cut pre Feb 02, cultivated 01 & 02 |
| | magenta | high | low | high | Fallow Feb 01 & 02, cut pre Feb 03 |
| | pink-grey | high | high | high | Cut pre Feb 00, fallow 01, 02 and 03 |
| | pink | high | high | high | Fallow or forest Feb 01 - Feb 03 |
| | yellow | high | high | low | Fallow Feb 01, cut pre Feb 02, fallow Feb 03 |
| | white | high | high | high | No change, high NDVI as forest |
| | black | low | low | low | No change: urban, water, lowland rice etc. |

Table 4: Interpretation of NDVI levels according to colour additive theory

To assist visual image interpretation, spectral profiles were taken from five reference points in the eight-band multi-temporal NDVI image as shown in Figure 10 (page 48). The spectral profiles provided detailed information on the cultivation history of the area. It was possible to estimate the year when slash-and burn occurred because of the marked decrease in NDVI value. It was also possible to decipher crop cultivation areas from areas of young fallow because the NDVI value would decrease at the time when the crops were harvested (September to November), or the NDVI values continued to rise, in the case of fallow.

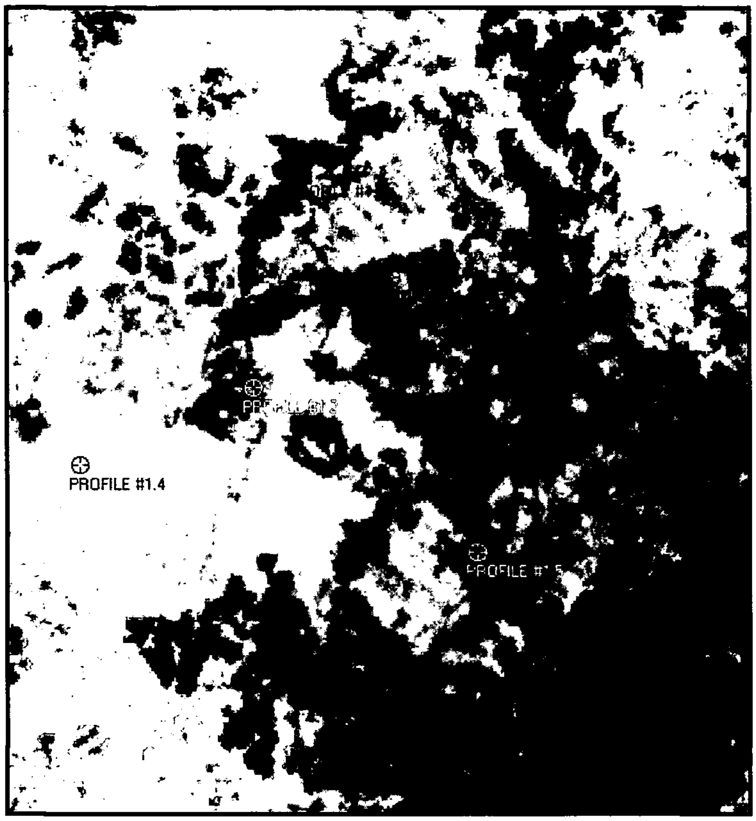



Figure 10: Spectral Profile points for interpretation on the NDVI multi-band image

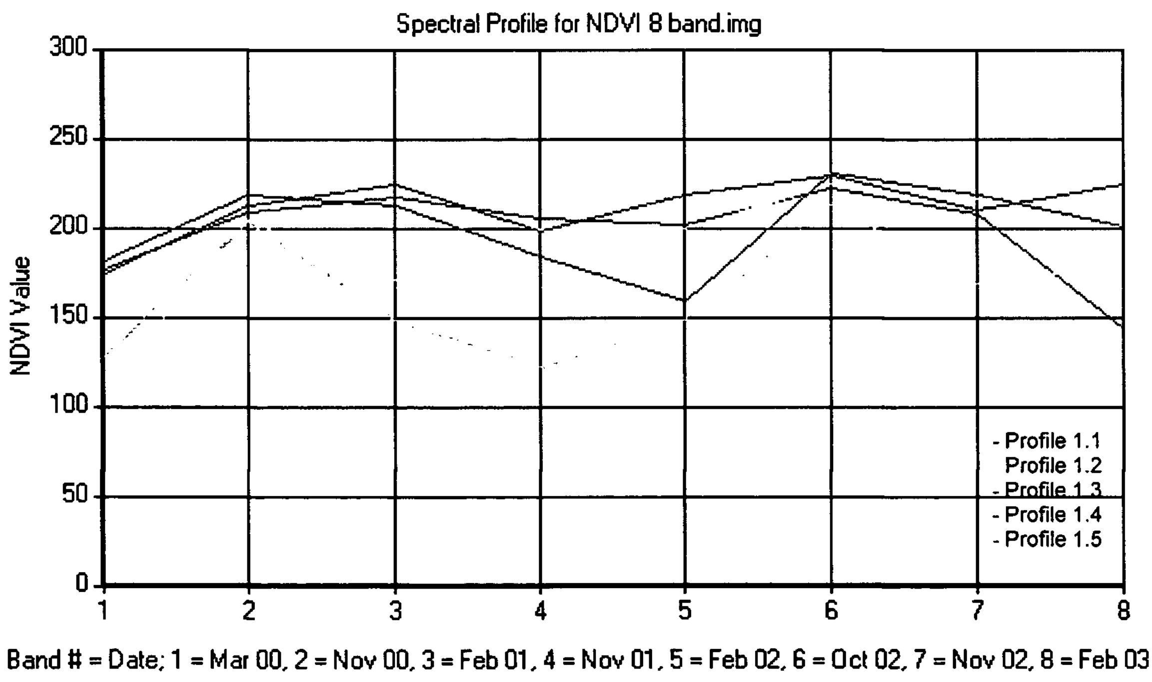



Figure 11: Spectral Profiles for the multi-temporal NDVI image using 8 bands

**Results from Spectral Profile Interpretation**

The five spectral profiles (in Figure 11) were interpreted as follows:

Profile 1.1: In March 2000 the NDVI value of the pixel at this point was 175. This NDVI value indicates either old fallow or forest. The NDVI value continued to rise to 220 in February 2001. It fell slightly during the growing season of 2001 but increased again until October 2002. The sharp decrease in NDVI in February 2003 indicates slash-and-burn was carried out after November 2002 but before February 2003.

Profile 1.2: In March 2000 the NDVI pixel value was 110. This NDVI value indicates the area was recently slash-and-burned as bare soil was the dominant land-cover. The sharp increase in NDVI between March 2000 and November 2000 indicates that a slow growing variety of rice was cultivated during the growing season of 2000. The rice was harvested soon after the scene was captured in November 2000 as a fall in NDVI occurred between November 2000 and February 2001. Following the harvest the ground was left to fallow as the continual increase in NDVI indicates an increase in green vegetation biomass.

Profile 1.3: The NDVI pixel value in March 2000 was 180. This NDVI value indicates either old fallow or forest. The NDVI value continued to rise to 220 in November 2000. A small decrease in NDVI value appears after November 2000 because of the occurrence of the dry season. The fall in NDVI value between February 2001 and February 2002 indicates that the area was slash-and-burned in preparation for rice cultivation. The sharp increase in NDVI between February 2002 and October 2002 indicates that rice was cultivated and then harvested in October 2002 as the NDVI value began to decrease after October 2002.

Profile 1.4: In March 2000 the NDVI pixel value was 175 indicating old fallow or forest. The NDVI value continued to rise to 225 in February 2001. A small decrease in NDVI value appeared between February 2001 and November 2001 as indicative of the other fallow / forest spectral profiles. This small decrease may be due to a poor rainy season. The NDVI value reached a maximum of 235 in October 2002. Since there were no significant decreases in the NDVI value throughout the spectral profile period, and the NDVI value was relatively high, it was assumed that this spectral profile reflected a forest area.

Profile 1.5: In March 2000, the NDVI pixel value was 140. This NDVI value indicates that bare soil was the dominant land-cover. The sharp increase in NDVI between March 2000 and November 2000 indicates that rice was cultivated during the growing season of 2000. The continual decline in NDVI value between November 2000 and November 2001 indicates that green vegetation biomass failed to grow. This spectral profile was taken at a point located near a small river. The lowland paddy fields in this area would have been irrigated by the river. During the growing season of 2001 it seemed the rains failed and the river diminished. Therefore rice was not able to grow. The increase in NDVI value after November 2001 indicates that rice was cultivated during the growing season of 2002. The rice was then harvested as a sharp decrease in the NDVI value appeared after October 2002.

**Information classes**

The information classes were revised for the classification of the multi-temporal NDVI dataset since complex shifting cultivation practices were revealed when interpreting the colour rendition of the multi-temporal NDVI image throughout the study area. It was observed that some areas were cultivated more than once in the three year study period. These areas were either cultivated on subsequent years or after just one year of fallow. It is important to differentiate these areas from slash-and-burn areas exposed to only one year of cultivation so three new classes were created to illustrate the increase in demand for land for crop cultivation. These were slash-and-burn in 2001 and 2002; slash-and-burn in 2001 and 2003 and one year fallow in 2002; and slash-and-burn in 2002 and 2003. Such areas would be at risk of over exploitation if this practice of continuous crop cultivation were to continue. The two types of permanent agricultural areas (maize and rice) were grouped into one class since it was not possible to differentiate between these areas in the multi-temporal NDVI image. Urban areas were grouped along with this class as their spectral reflectance values were similar. In both cases, bare soil was the dominant land-cover. Water bodies (rivers) were also grouped into this class because of their close association with permanent agricultural areas. The remaining six classes were the same as the original classes. A summary of the information classes and their descriptions are seen in Table 3 (page 44).

**Unsupervised Classification**

A single classification was performed on the combined NDVI data set of the 3 NDVI images by means of ERDAS Imagine 8.7 software. ERDAS used the ISODATA algorithm to perform the unsupervised classification. 200 classes were selected with maximum number of iteration of 24 and the convergence threshold of 0.95. The decision rule applied to this classification for determining the land-cover class of each pixel in the multi-temporal NDVI image was based on spectral and temporal recognition. Information classes were assigned to the 200 spectral classes by visual analysis. This was achieved by observing the size, shape, colour, pattern, and context of the pixels for each spectral class in the original three-band multi-temporal NDVI image. For example, when using colour it was possible to differentiate between slash-and-burn years. Bare soil areas caused by recent slash-and-burn were displayed in the following colours in the multi-temporal NDVI image: Magenta for areas where slash-and-burn occurred in 2003, yellow for areas where slash-and-burn occurred in 2002, cyan for areas where slash-and-burn occurred in 2001 and cyan/pink for areas where slash-and-burn occurred in 2000.

Figure's 12 and 13 (page 52) illustrate the process of visual image interpretation of the classified spectral classes. The three images along the top of Figure 12 and in the middle of Figure 13 (black background with one spectral class highlighted) are the classified images where the opacity is set to zero for all but one spectral class. The three images in the second row of Figure 12 and top row of Figure 13 are the colour composite images from the original three-band multi-temporal NDVI image. The first of the three classified images in the first row was geo-linked to the first of the multi-temporal NDVI images in the second row of Figure 12. The same operation was applied to the second and third images of each row in Figure 12 and those in Figure 13. Various scales were used to analyse the pattern, shape and context of the spectral classes as shown in Figure's 12 and 13. It was not possible to visually differentiate the colour renditions of fallow and forest so an enquiry was made to identify the NDVI value at the pixel site. This is illustrated in Figure 13. The NDVI value at the pixel site in the example shown in Figure 13 was 185 for forest, whereas the NDVI value for fallow at the pixel site was 145. A threshold level for fallow was approximated to be 160. Any pixel with NDVI value > 160 was assumed to be forest.

After the 200 spectral classes were assigned an information class, the thematic raster layer was recoded to merge the spectral classes with the same information class into one class. A new thematic raster layer was created.

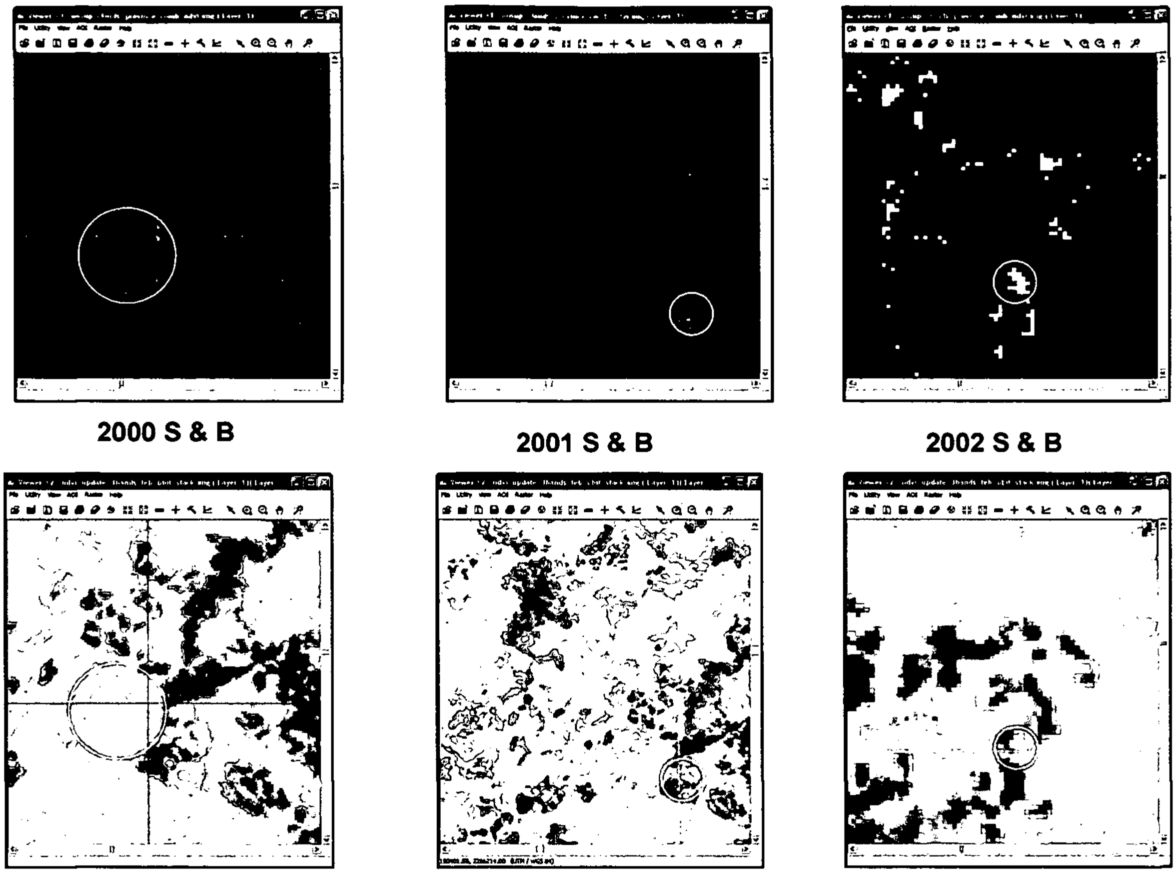



Figure 12: Assigning an Information Class to a Spectral Classes (slash-and-burn areas)

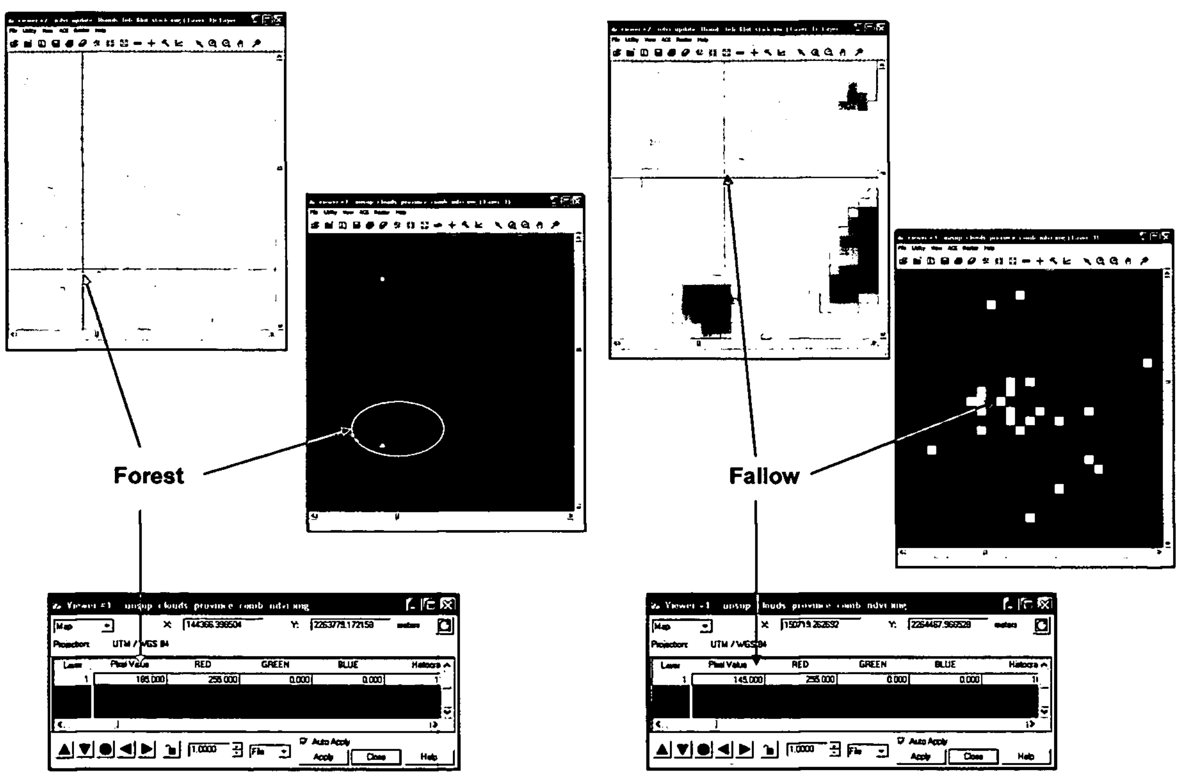



Figure 13: Assigning an Information Class to Spectral Class (forest and fallow areas)

### 4.2.3 Post classification filtering

Since the image was classified on pixel-by-pixel basis, the classified data showed a salt-and-pepper appearance. To remove this effect a post-classification smoothing or filtering method was applied. The majority filter with window 3 x 3 pixels was compared with other sized windows: the 5 x 5 and 7 x 7 pixel filters with the original classified image. The 3 x 3 pixels window retained more of the original number of pixels for each information class than the other windows. The result of running the unsupervised classification model for the province of Oudomxay using the ten information classes is shown in Figure 14 (page 54).

### 4.2.4 Accuracy Assessment

An error matrix was used to determine the thematic accuracy of the map derived from the unsupervised classification of the multi-temporal NDVI image. The results are expressed in tabular form as shown in Table 5 below. The columns represent the ground reference data (collected in the field) and the rows represent the classification generated from the remotely sensed data. The error matrix revealed both successful and erroneous results from the classification. These results are discussed in Chapter 5.3 (page 58).

**The Error Matrix**

| Class Description | Class # | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Sum | User's Acc. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2000_s_b | 1 | 13 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 17 | **76.5** |
| 2001_02_s_b | 2 | 0 | 8 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 11 | **72.7** |
| 2001_03_s_b_02_fal | 3 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 7 | **85.7** |
| 2001_s_b | 4 | 1 | 3 | 0 | 13 | 0 | 0 | 0 | 0 | 0 | 4 | 21 | **61.9** |
| 2002_03_s_b | 5 | 0 | 0 | 0 | 0 | 12 | 1 | 0 | 0 | 0 | 0 | 13 | **92.3** |
| 2002_s_b | 6 | 0 | 4 | 0 | 0 | 1 | 11 | 0 | 0 | 0 | 1 | 17 | **64.7** |
| 2003_s_b | 7 | 0 | 0 | 1 | 1 | 1 | 0 | 10 | 0 | 0 | 0 | 13 | **76.9** |
| fallow | 8 | 8 | 0 | 0 | 4 | 0 | 1 | 0 | 38 | 17 | 0 | 68 | **55.9** |
| forest | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 20 | 0 | 25 | **80.0** |
| agric_urban_water | 10 | 0 | 1 | 7 | 1 | 1 | 0 | 0 | 0 | 0 | 27 | 37 | **73.0** |
| | Sum | 22 | 17 | 14 | 21 | 15 | 14 | 11 | 44 | 37 | 34 | **229** | |
| | **Prod.'s Acc** | **59.1** | **47.1** | **42.9** | **61.9** | **80.0** | **78.6** | **90.9** | **86.4** | **54.1** | **79.4** | | |

| | | |
|---|---|---|
| **Overall** | **69.0** | **%** |
| **Kappa** | **64.3** | **%** |

Table 5: Error matrix performed on the classification

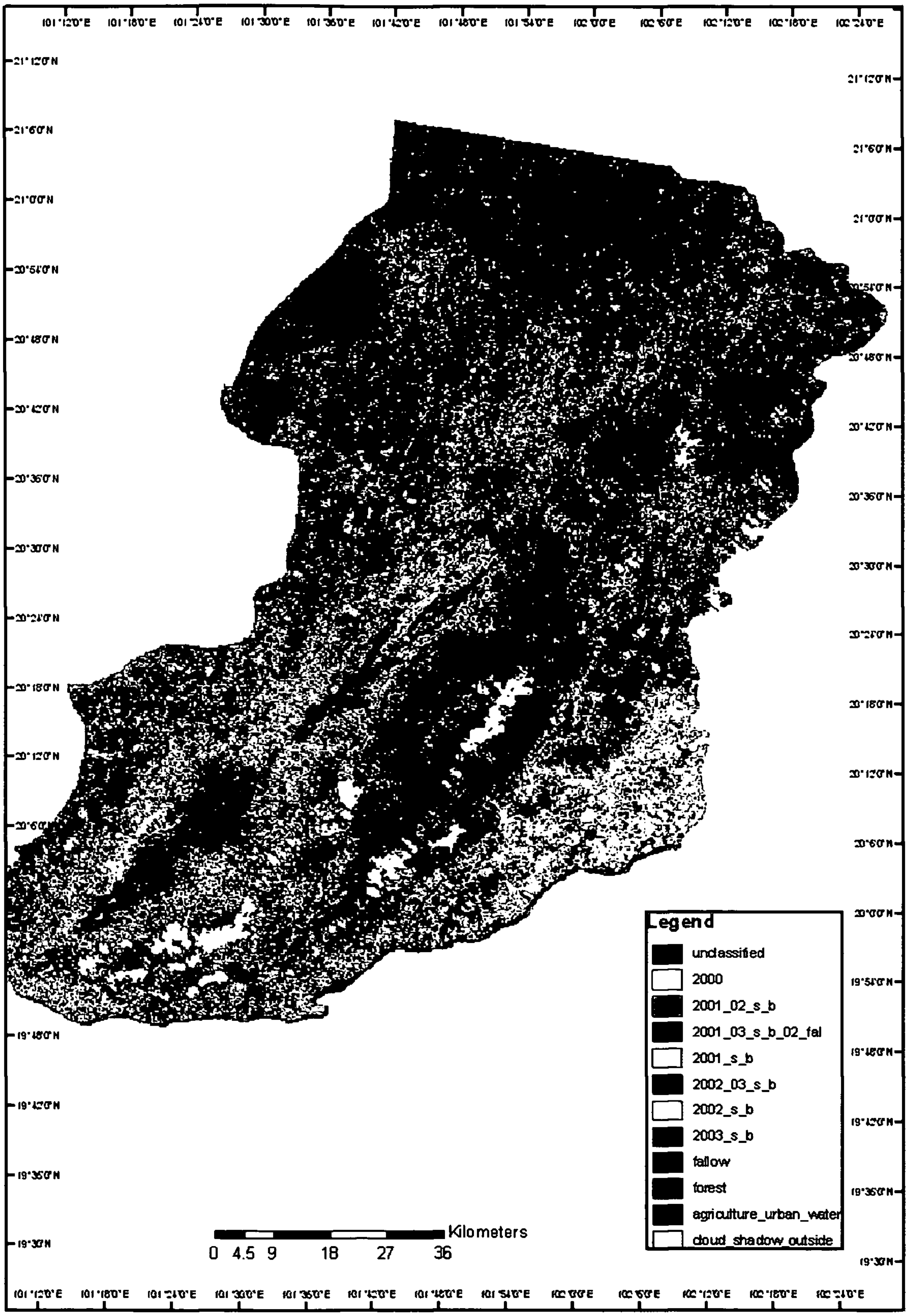



Figure 14: Result from the Unsupervised Classification

## 4.3 Land pressure map

The ten information classes were categorised into four land pressure groups (refer to Table 3, Chapter 3.3.6, page 44) and presented in thematic maps for Oudomxay province and for each of the study areas surrounding the villages: Ban Houy sang, Ban Mang, Ban Chang vang and Ban Phou lath. To determine which land pressure group each class was assigned, a decision was based on two factors:

(i) frequency of slash-and-burn events

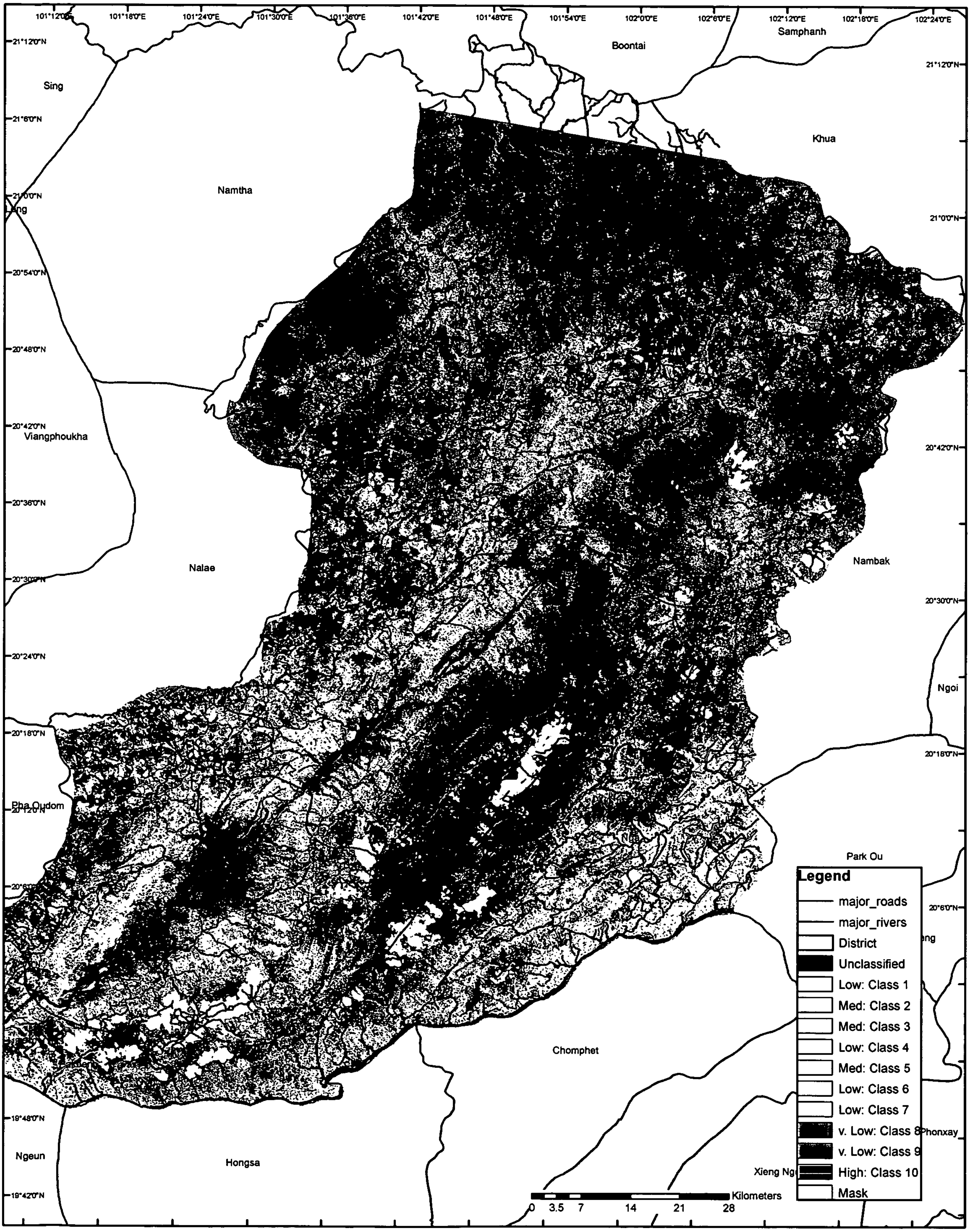
(ii) intensity of agriculture production

In general, low and very low pressure areas were found in the less populated and inaccessible mountainous regions of Oudomxay. Medium pressure areas were identified where fallow rotation periods were reduced and the frequency of crop cultivation increased. High pressure areas were found in the wider and low-lying valleys where there is good infrastructure. In these areas, large populations have settled along the major rivers and roads providing links to both the provincial and international markets. The results from the thematic maps at scale 1.50,000 produced for each of the four study villages illustrate land pressure is greatest in the area around Ban Mang. Most of the area surrounding Ban Chang vang, Ban Phou lath and Ban Houy sang are categorized as either very low or low pressure areas. The areas of medium or high pressure areas are relatively small in a 1:50,000 map, but these 'hot spots' are more significant on a local scale. The medium to high pressure areas near the villages reflect an increase in land pressure. Land pressure maps for the four villages are found in Appendix 3.

## 4.4 Conclusion

This chapter presented the results from the application of a methodology that identifies the pattern and magnitude of land-cover changes in the province of Oudomxay in Northern Laos. Two change detection methods were tried but only one gave successful results. The post-classification comparison method using the supervised classification procedure did not produce satisfactory results. It was not possible to properly classify the information classes using Maximum Likelihood Classification because of spectral overlap. The second method, the classification of multi-temporal NDVI data sets using unsupervised classification techniques, produced better results. Classification procedures that apply visual analysis of land-cover change using multi-temporal NDVI imagery and interpretation concepts of colour additive theory were relatively easy to use. It proved successful in classifying the fine-structured heterogeneous land-cover patterns of the province of Oudomxay.

# Land Pressure Map (2001-2003)
# Oudomxay Province, Northern Laos



# 5 Discussion

## 5.1 Introduction

This chapter begins with a review of the classification systems selected to determine fallow system development in Northern Laos. It is followed by a discussion of the results from the classification of multi-temporal NDVI data sets. Explanations are given on the results of the accuracy assessment on the classified data. The production of the land pressure map and how it illustrates reduced fallow rotation periods is discussed. It is followed by describing how the aim of the research was achieved and why this thesis investigated the development of fallow systems in Northern Laos. The chapter ends with conclusions of the research and recommendations to CIAT.

## 5.2 Classification system

Two change detection methods were selected for image classification: (i) Post-classification comparison method using supervised classification on individual images and; ii) Classification of multi-temporal NDVI data sets using unsupervised classification on a combined data set of three dates of imagery. The post-classification method proved too difficult to apply as it was not possible to properly classify the information classes using Maximum Likelihood Classification because of spectral overlap. This may be explained by the resolution of satellite sensor used. The resolution of Landsat 7 ETM+ may not have been high enough to separate the fine-structure heterogeneity of land-cover in Northern Laos.

The classification of multi-temporal NDVI data sets produced better results. This method was selected on the basis of research carried out by the following authors: Sader and Winne (1992); Pax Lenny et al. (1996); Lyon et al. (1998); and Guerschman et al. (2003). These authors noted the benefits in using NDVI in land-cover classification. In any single NDVI image however, it was not possible to distinguish between areas of 1, 2 or 3-year fallow (with similar density cover), or non-vegetation areas such as urban areas and recently cleared land. To solve this, the scene over Oudomxay province was observed over a series of dates revealing characteristic trends in fallow management. Multi-temporal image analysis has been demonstrated by a number of authors (refer to Chapter 2.6, page 16). This research selected multi-temporal NDVI data sets on three dates of imagery. To use more than three dates of imagery in the classification of the multi-temporal NDVI data sets, information on NDVI values for vegetation at different phenological stages from the additional bands may have given a more detailed account on the land-cover patterns of the province of Oudomxay.

## 5.3 Research results

An error matrix was used to determine the thematic accuracy of the map derived from the unsupervised classification of the multi-temporal NDVI image. The error matrix produced information on the map's overall accuracy, producer's and user's accuracy, and the kappa statistic. The overall accuracy was calculated to be 69%. This percentage is lower than what is claimed to be 'acceptable' in the literature. Congalton and Green (1999) state an acceptable overall accuracy is ≥ 85%. Others suggest an overall accuracy ≥ 80%. The kappa statistic was estimated at 64%. Landis and Koch (1977) (cited in Congalton and Green 1999) proposed a kappa statistic ≥ 80% showed strong agreement, 40-60% represented moderate agreement and < 40% was said to represent poor agreement. The kappa statistic for this thesis classification has a moderate to strong agreement. The sources of error responsible for the low overall accuracy are identified as follows:

**i) Misregistration**

Misregistration between images is known to cause false identification of land-cover class. It is particularly a problem in fine structured land-cover patterns, as found in this study area. A misregistration of 2-3 pixels was discovered in the multi-temporal NDVI image. Evidently this was one of the causes of error. Lillesand et al. (2004) suggest a registration of < 1 pixel is required to prevent errors occurring when comparing images.

**ii) Topography influence**

Lyon et al. (1998) and Lillesand et al. (2004) state that NDVI is not affected by topographic factors. They claim it is because a ratio image such as an NDVI image conveys the spectral or colour characteristics of image features regardless of variations in scene illumination conditions since the colour content of the data is emphasised not the brightness variation. However, the results of this research illustrate how topography influenced the NDVI as artefacts were found in the multi-temporal NDVI image. By assuming the NDVI was not influenced by topography, a topographic correction was not applied to the DOS images. Teillet et al. (1982) and Hugli and Frei (1983) oppose the view of Lyon et al. (1998) and Lillesand et al. (2004), and state that the effect of topography must be always accounted for to maximise the information content in satellite imagery.

**iii) Spectral similarity of information classes**

When the visual image interpretation was carried out on the spectral classes of the NDVI multi-temporal image, it was difficult to distinguish between fallow areas > 4 years old and forest areas. This was possibly due to the similarity of their surfaces sending similar reflectance to the satellite sensor. Two reasons suggested by Yemefack, Bijker and De Jong (2006) are (i) NDVI becomes saturated after a certain biomass density; and (ii) the canopies of older fallow or forest areas are dominated by tall old trees whose leaves no longer absorb much of the visible red light and therefore give higher NDVI values. As a result, the NDVI values in these two examples are not representative of what vegetation class really existed on the ground. Calculating accurate threshold levels for each information class may improve the process of assigning information classes to spectral classes created in the unsupervised classification and therefore improve the overall classification accuracy.

**iv) Inaccurate field data**

Congalton and Green (1999) state that ground reference data must be 100% correct if the accuracy assessment is a fair one. A field data form was designed for the collection of accurate, consistent and quantitative field information. However, a limitation to this field research was obtaining quality information from the 'informants'. The field work was conducted in May, which marks the beginning of the planting season. Key farmers who knew about the cultivation history in their village areas were often too busy to accompany the field visits. More than one day was needed in the village area for the collection adequate ground reference points for the different land-cover classes. This often resulted in different farmers being interviewed about the cultivation history of the village area. It was found that discrepancies arose between the different farmers on the estimates of cultivation dates and those seen in the Landsat 7 ETM+ images.

To achieve maximum accuracy, these factors must be considered and solutions found. Alternatively, another change detection method such as Principal Component Analysis (PCA) could be explored.

## 5.4 Land pressure maps

The result of the classification of multi-temporal NDVI data sets was to produce a thematic map which addressed the abandonment of sustainable fallow management practice and reduced fallow periods in the province of Oudomxay in Northern Laos. The ten information classes were categorised into four land pressure groups. These were 'very low', 'low', 'medium' and 'high'. To determine which land pressure group each class was assigned, a decision was based on two factors: (i) frequency of slash-and-burn events; and (ii) intensity of agriculture production. Frequent slash-and-burn events indicated high pressure on the land's resources as the land was not left to fallow for > 1-2 years. Soil fertility and structure are affected by the intensity of agriculture production. Therefore, areas of permanent agriculture production were categorised as high pressure areas.

In general, low and very low pressure areas were found in the less populated and inaccessible mountainous regions of Oudomxay. These areas had very low frequency of slash-and-burn events. Fallow and forest cover were constant for the duration of the study period. Medium pressure areas were identified where fallow rotation periods were short and crops were cultivated more than once in the three year study period. High pressure areas were found in the wide and low lying valleys. Large populations have settled in these areas and cultivate lowland rice and maize annually. Major rivers and roads in these valleys are used to connect farm produce to both the provincial and international markets.

The results of this thesis' classification show similar land-cover change patterns and magnitude to Giri's et al. (2001) study. They identified shifting cultivation areas were mainly distributed in the upper watershed of two major river systems: Nam Tha and Nam Beng, while forest areas were located on steep slopes. Lowland rice cultivation was found in river valleys and the intensity of agriculture activities decreased with distance from roads or rivers.

The results from the land pressure maps at scale 1:50,000 produced for each of the four study villages (refer to Appendix 3) illustrated the area around Ban Mang had the most adverse land pressure of the 4 villages. One obvious reason relates to the age of the village. In 2003, Ban Houy sang (La district) was 6 years old, Ban Mang (Beng district) was 187 years old and Ban Chang vang (Houn district) was 41 years. There was no age found for Ban Phoulath. Population density, infrastructure and accessibility to the provincial and international markets for the sale of agricultural crops were other reasons identified. A short road (14 km) connects Ban Mang to the main provincial road. This enabled good access to the market chains. The other three villages were more remote. The areas surrounding Ban Chang vang, Ban Phou lath and Ban Houy sang were categorized as either very low or low pressure areas. Areas of medium or high pressure areas were relatively small when illustrated in the 1:50,000 map. These areas were located close to the village centre's. On a finer scale, these medium and high pressure areas would have been more significant.

A similar observation was recorded in Seidenburg's et al. (2003) research in shifting cultivation practices in province of Huamuang in Northern Laos. They suggested a reason for the high pressure areas close to villages were due to villager's preferences for shorter travel distances to the fields. To confirm the reasons suggested above, it is recommended that livelihood analyses are conducted for the four study villages.

## 5.5 Was the aim of the research achieved?

The results of this research demonstrated that during the course of this study period (February 2001 to February 2003), a distinct pattern of land-cover change had occurred with varying degrees of magnitude in the province of Oudomxay. A shift in traditional shifting cultivation practice with long fallow periods to the adoption of more intensive forms of agriculture and shortened fallow periods were revealed through temporal and spatial analyses of land-cover using remote sensing techniques. This shift was brought about mainly because of increasing population as Chapter 5.6 below discusses. This was illustrated in the land pressure map which showed areas of high land pressure were directly correlated to areas of high population.

## 5.6 Why this thesis investigates the development of fallow systems in Northern Laos?

Shifting cultivation had been a sustainable farming practice for centuries. Chazée (2002) explained that the Khmu, one of the oldest ethnic groups of Oudomxay province and dominant group of the four study villages, coexisted in relative harmony with their environment for > 400 years when the forest was extensive and the population was small. As forest cover decreased dramatically in the last 50 years (from 70% to around 40%), it was impossible for the traditional slash-and burn farmers to carry out sustainable shifting cultivation practices. This tradition was replaced by more intensive forms of agricultural production.

Seidenberg et al. (2003); Chazée (2002); Evrard and Goudineau (2004) and Trenbath et al. (1985) studied the change in shifting cultivation practice in South-east Asia in the last 10 years. They suggest that at one time fallow periods were known to be as long as 15-20 years but in recent years the fallow period has shortened to 3-5 years. Seidenberg et al. (2003) showed a decreasing fallow period during their study period (1989-1999) from 10-15 years to 4-5 years. The results of this thesis have shown fallow periods to be as short as 1 year during the study period 2001-2003.

Reducing the fallow period goes against sustainable fallow management practices. Evrard and Goudineau (2004) demonstrated that long fallow periods are required for the productivity of the land to recover. Trenbath et al. (1985) claimed that long fallow periods of 10-20 years allowed shifting cultivation to function on a sustainable basis but intensification and shorter fallow periods led to the deterioration of soil fertility and an increase in weeds, disease and / or pests This research has shown areas where fallow rotations were greatly reduced because of high land pressure. It is therefore necessary that these areas are further investigated and solutions implemented before the land deteriorates too much to become a worthless entity to the local farmers.

Cairns and Garity (1999); Chazée (2002); Giri (2001); Pravongviengkham (1998); Seidenbeurg et al. (2003) have researched the causes for the decline in fallow periods in South-east Asia. They claim an increased population density from both endogenous growth and in-migration was the main cause of shortened fallow periods. They also suggest that land availability for cultivation has been reduced because large tracts of land were either designated for national and international protected status or converted to intensive agricultural areas and commercial rubber tree plantations. Also government resettlement programmes have created land tenure problems to communities who would have otherwise been accustomed to free and abundant access to the local environment. It was not possible in this thesis to investigate the causes of the shortened fallow periods in the province of Oudomxay. It is therefore recommended that livelihood analysis is conducted in these four villages to explain the causes and also the effects of the decline in fallow periods in the area.

## 5.7 Conclusions

This thesis demonstrated a method that identifies the pattern and magnitude of spatial and temporal changes in the province of Oudomxay in Northern Laos, using remote sensing techniques. Two techniques were employed: the post-classification comparison method using supervised classification procedure and the classification of multi-temporal NDVI data sets using unsupervised classification techniques. The post-classification comparison method produced unsatisfactory results. The classification of multi-temporal NDVI data sets produced better results. This method built on a classification approach which used the classification of multi-temporal NDVI imagery and interpretation concepts of colour additive theory to visualise land-cover change. The definition of land-cover classes was based on the reflectance characteristics of the land-cover types in the spectral bands registered by the Landsat7 ETM+ sensor.

The change detection method selected allowed the classification analyst to recognise visually the spectral and temporal changes, while at the same time apply statistically based decision rules that determined the land-cover change of each pixel. Unsupervised classification was carried out on a multi-temporal NDVI data set from three dates of imagery. An accuracy assessment was performed on the classified data by comparing on a category-by-category basis the relationship between known ground reference data (collected from field work) and the corresponding results of the unsupervised classification.

This thesis identified a number of factors which influenced the accuracy of the classification of NDVI multi-temporal images. These were misregistration between images, topography influence on NDVI, cloud and cloud shadow, categorising spectral classes with similar display colours in a digital image, and inconsistencies in the collection of ground reference data.

This thesis contributes towards the first component of the Centre of International Tropical Agriculture (CIAT) Laos project, which is to carry out spatial analysis of fallow systems using remote sensing techniques. CIAT are interested in establishing programmes where there is need to diversify agriculture activities in order to bring economic growth and improved social wellbeing to communities and at the same time conserve the natural environment. By targeting communities where there is evidence of increased land pressure CIAT can focus their resources to those areas of most need.

The land pressure map produced from the classification of multi-temporal NDVI images gives information on the pressure on natural resources on a spatial and temporal scale in the province of Oudomxay. It is expected that this information will be used with the community socio-economic survey data concerning the driving forces of agricultural change and help to identify opportunities and risks from further agricultural intensification proposals.

## Recommendations to CIAT

Livelihood analysis is conducted in the four study villages to explain the causes and also the effects of the decline in fallow periods in the area.

Development projects in Laos should not rule out shifting cultivation since 45% of the rural villages in Laos are still dependent upon slash-and-burn agriculture for their subsistence.

Projects should create a favourable socio-economic environment in which land tenure is secure, and provide appropriate extension services that address sustainability.

Areas for intensive land-use should be identified where fertile ground exists and access to the market is tangible. Continuous research is needed to examine the response of farmers in Oudomxay province to future policy and environmental change.

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# Appendices

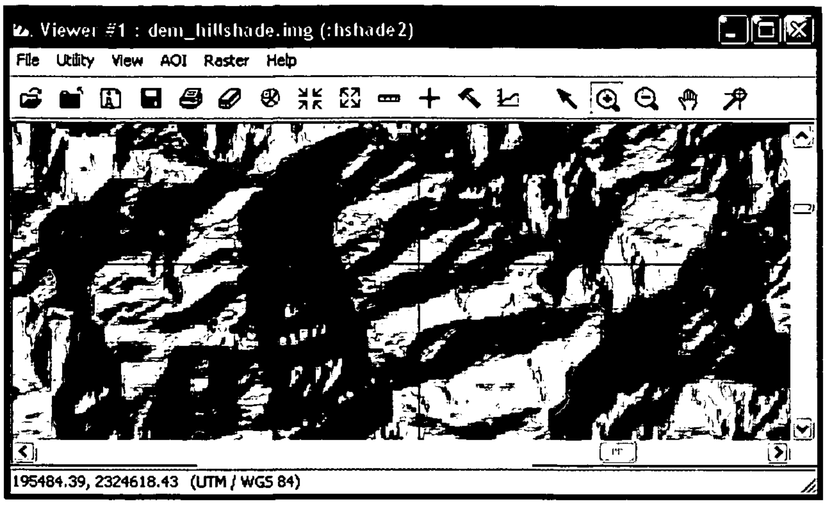
**Appendix 1 – Calculating Cs value**

**Appendix 2 – Field Data forms**

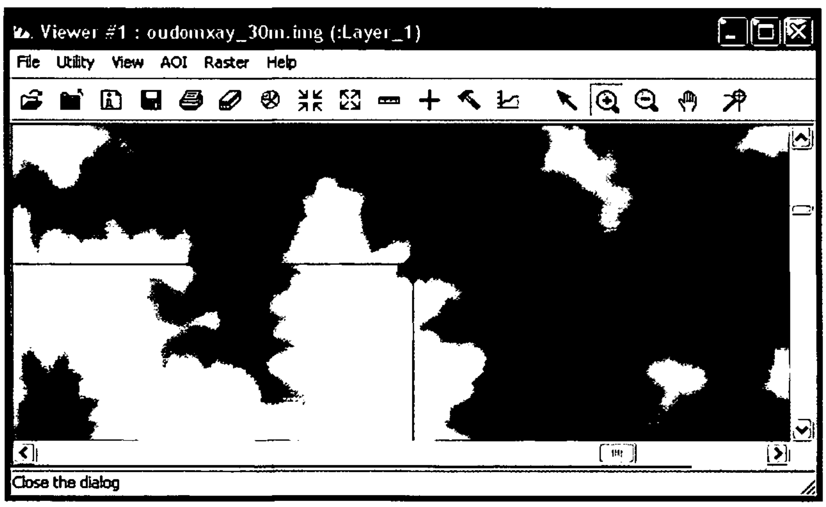
**Appendix 3 – Land Pressure maps for the four study villages: Ban Houy sang, Ban Mang, Man Chang vang and Ban Phou lath**

# Applying a Cs Value to Landsat ETM+ 2003 02 28

Hill shade

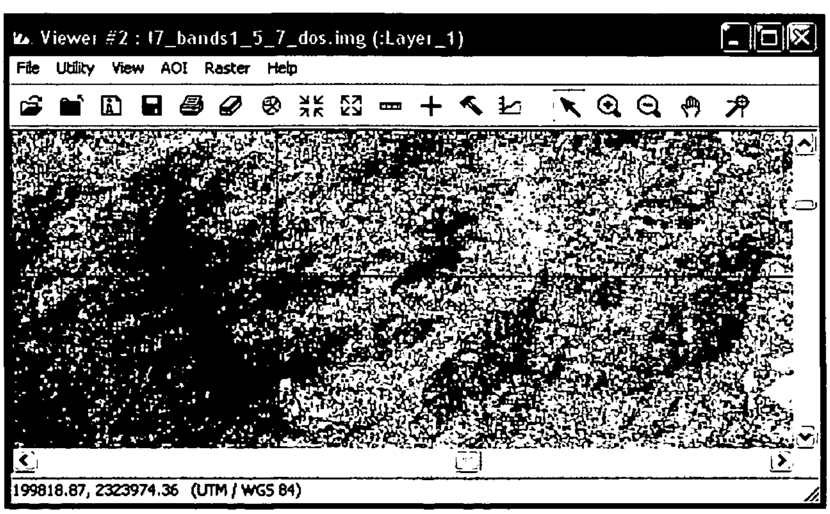



DEM



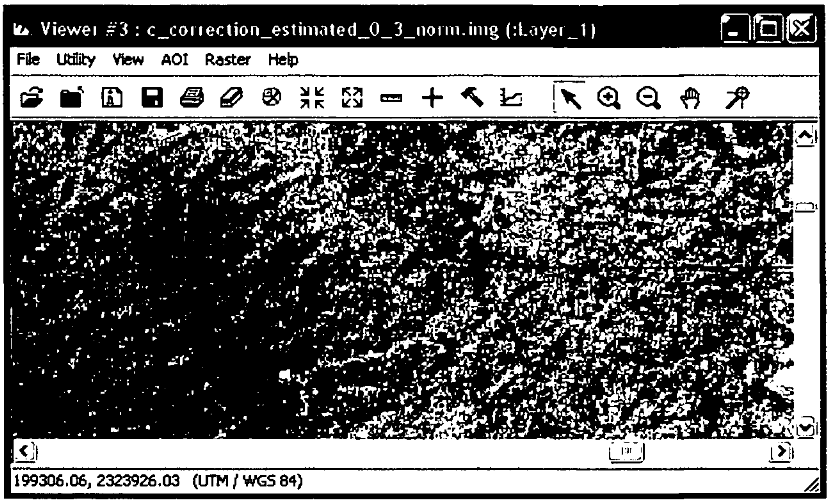

**Band 1**

Original image with dark object subtraction



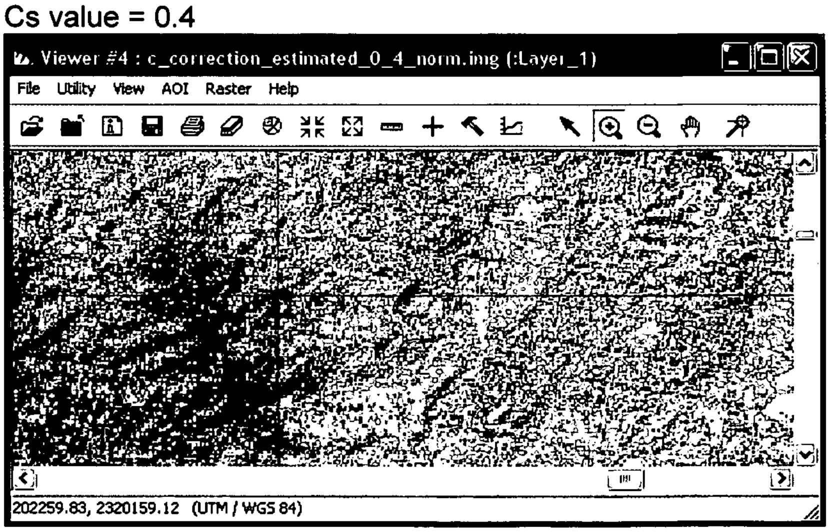
**Band 1**

Cs value = 0.3

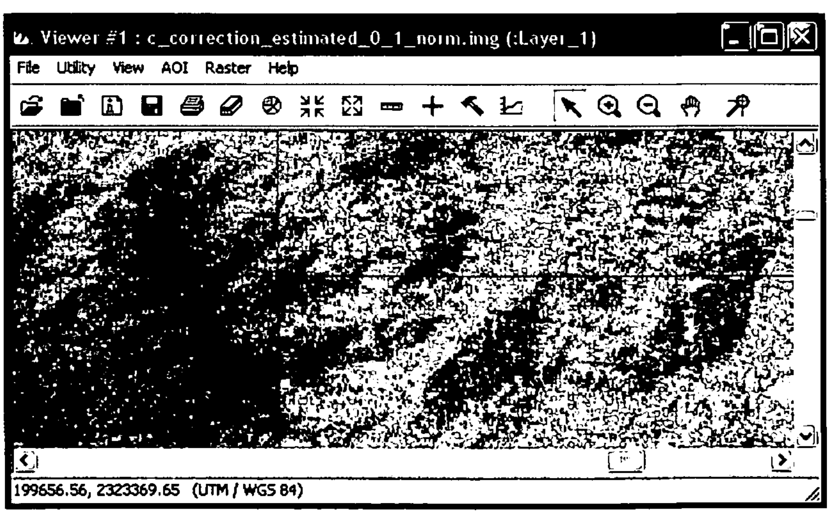



Cs value = 0.35 is chosen since optimised value lies between Cs = 0.3 and 0.4

Cs value = 0.4

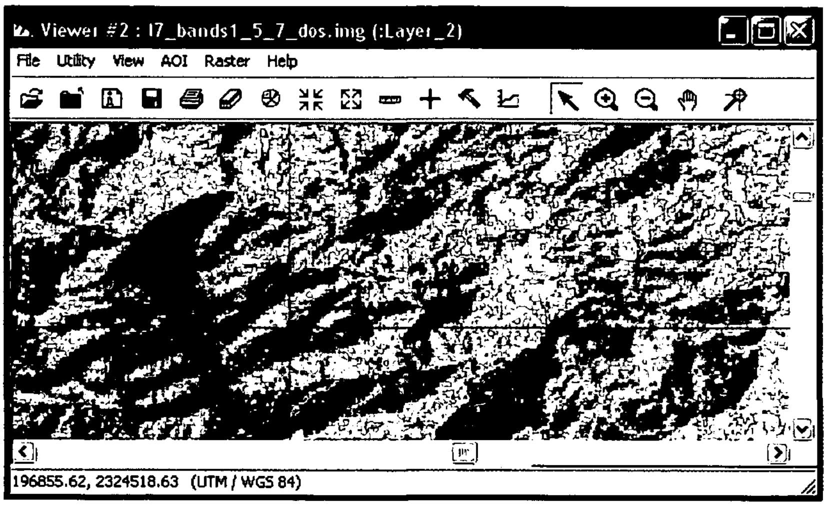



Cs value = 0.1 is not chosen for band 1 since topography is still evident

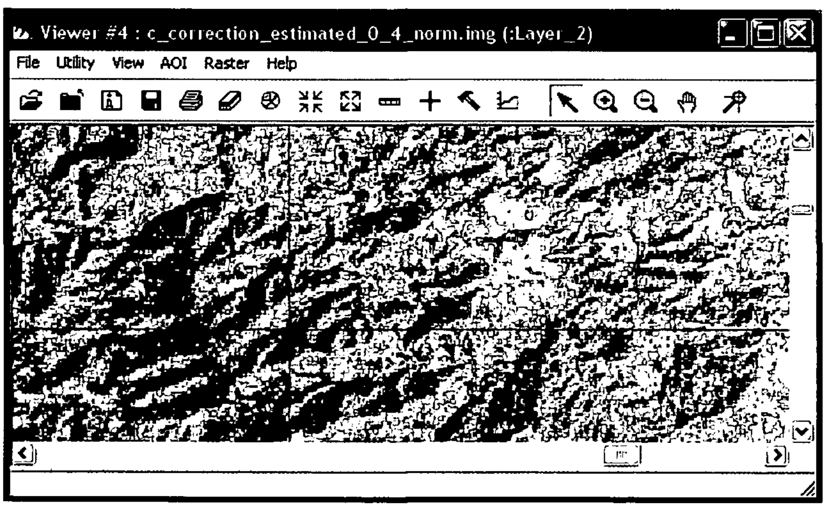


## Band 2

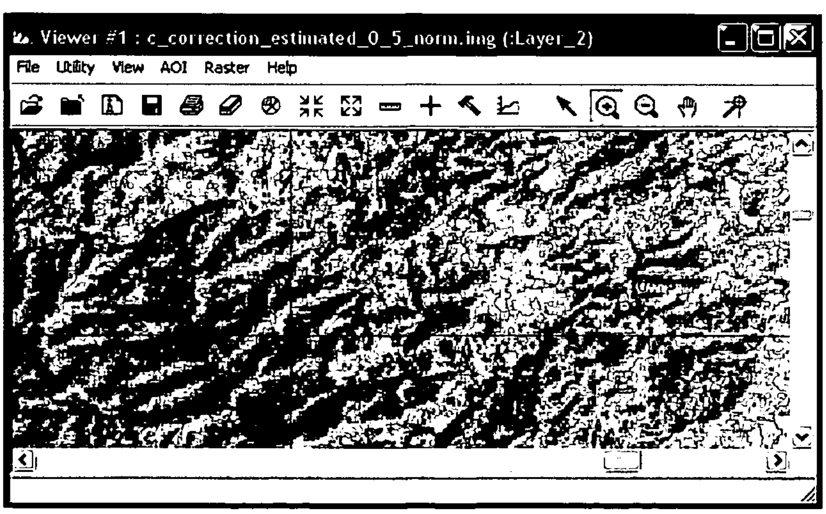
Original image with dark object subtraction




Cs value = 0.4 is chosen

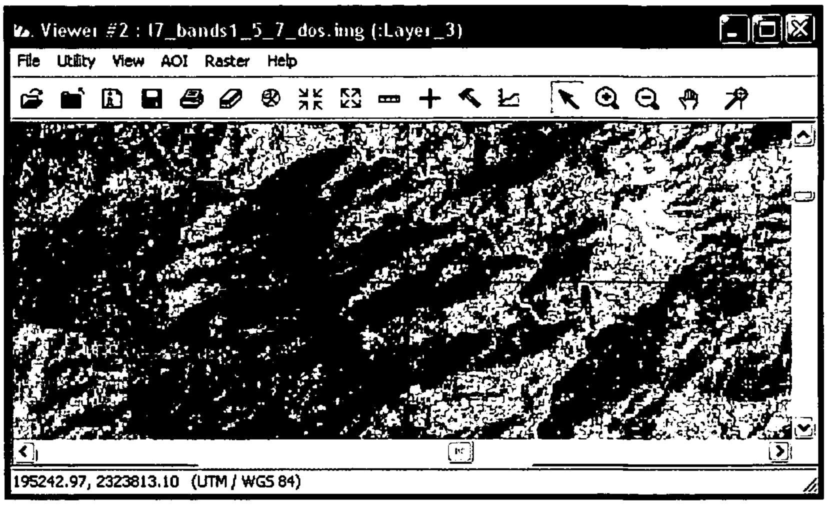


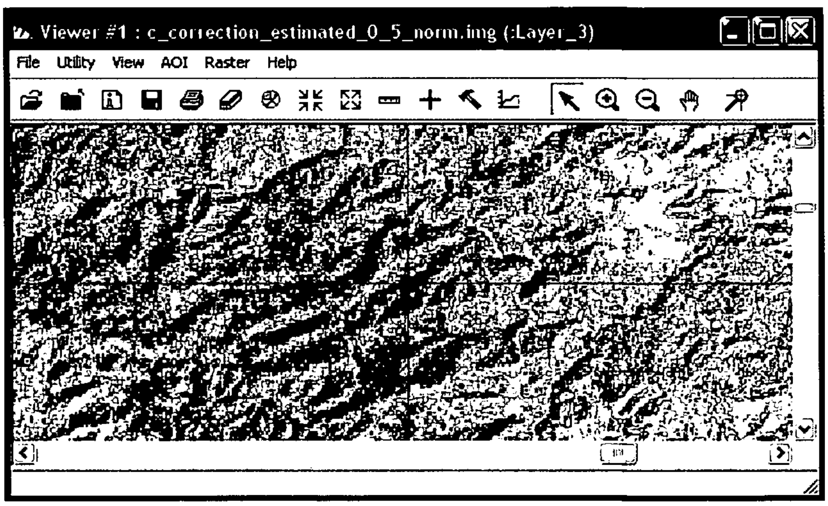

Cs value = 0.5 is not chosen as too much illumination



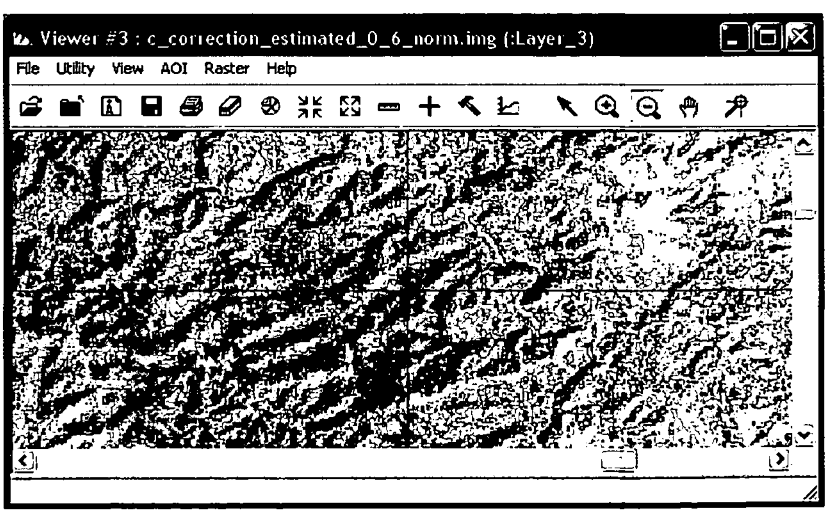
**Band 3**

Original image with dark object subtraction

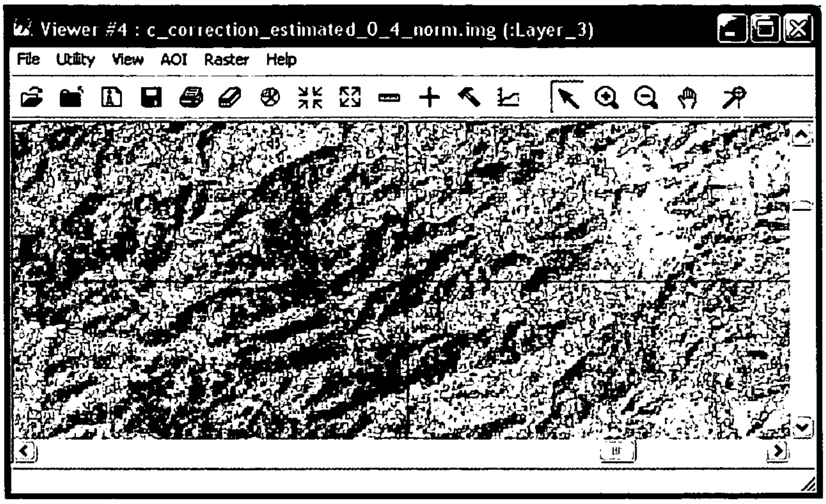



Cs value = 0.55 is chosen as optimised Cs value lies between 0.5 and 0.6

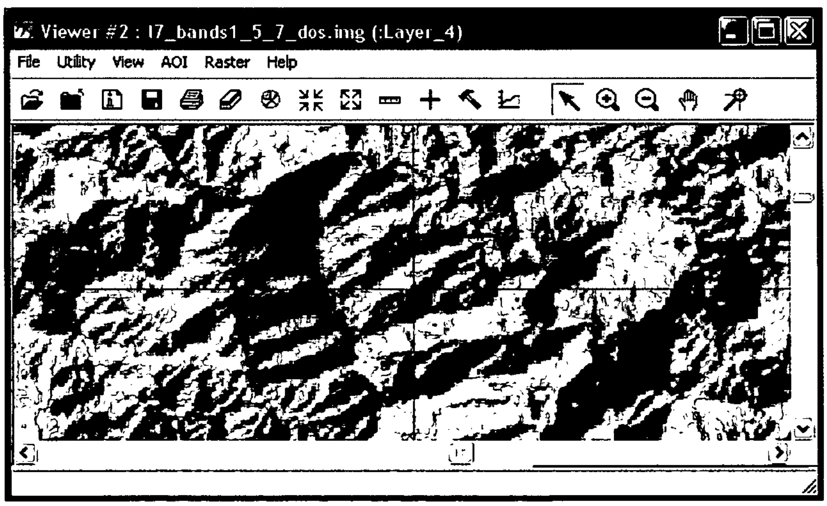


Cs value = 0.4 is not chosen since it shows topographical features

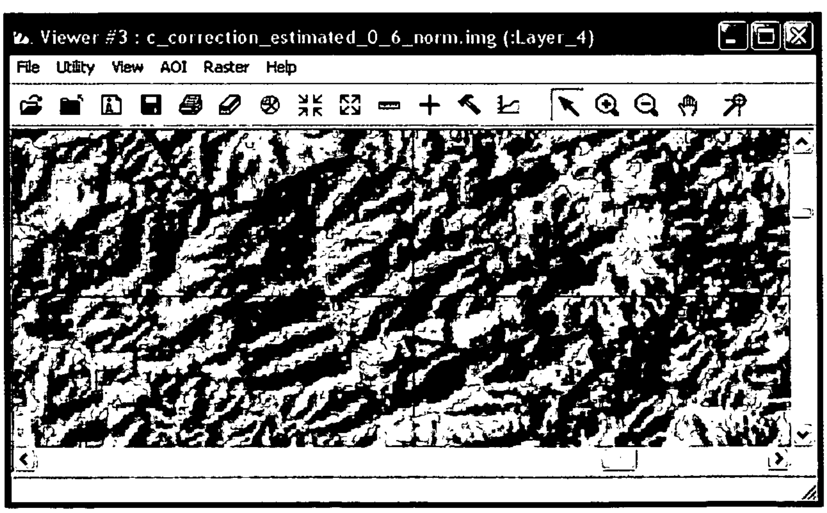



**Band 4**

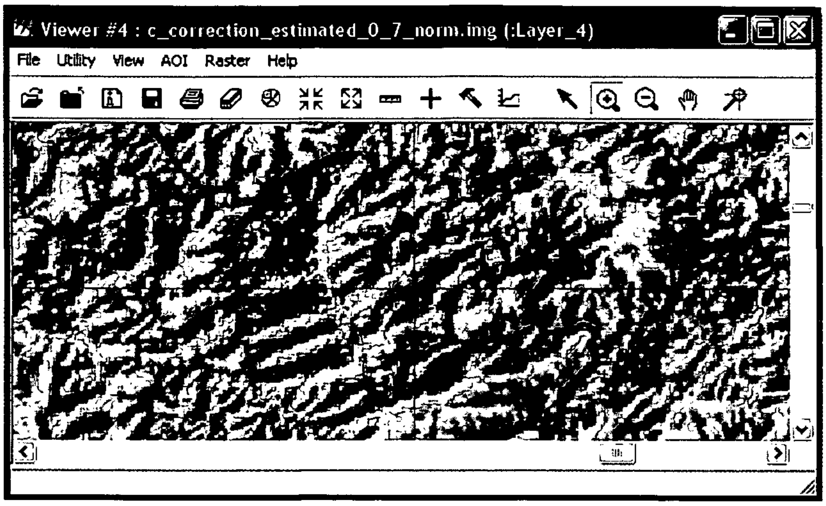
Original image with dark object subtraction




Cs value = 0.6 is chosen as optimised value

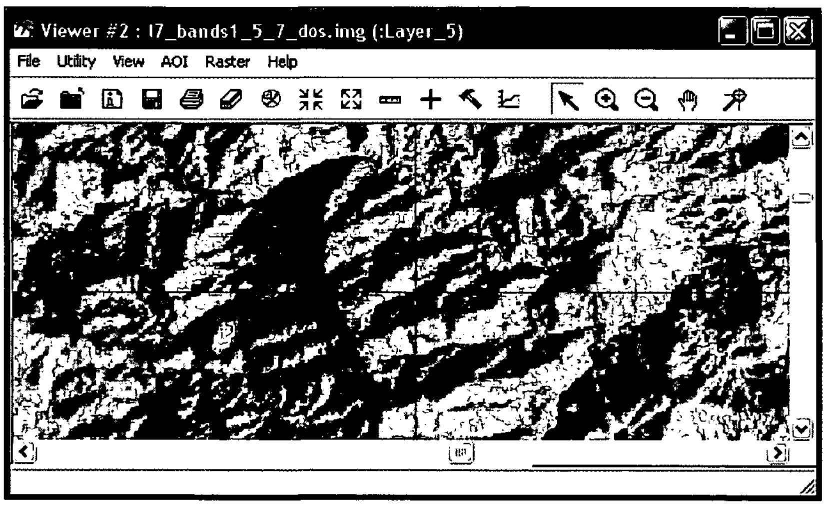


Cs value = 0.7 is not chosen as over illuminated

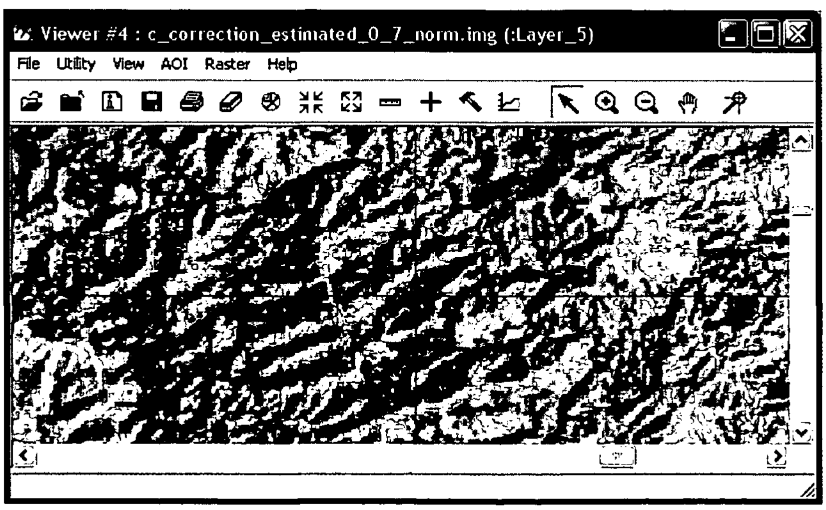



**Band 5**

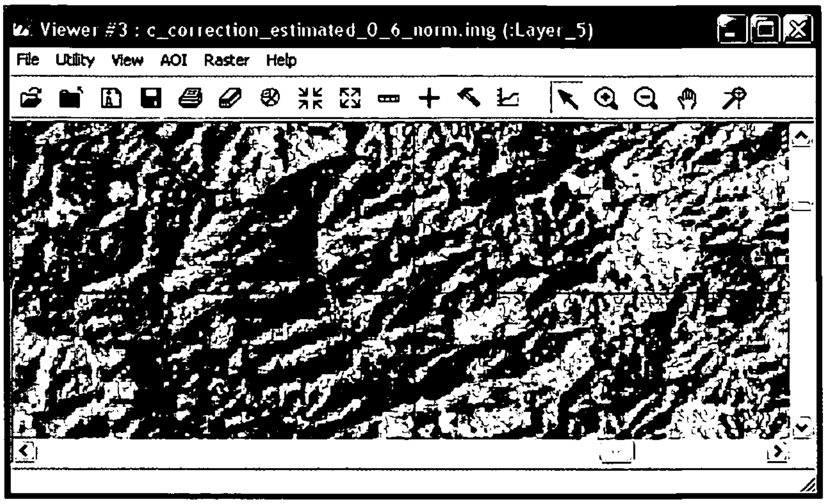
Original image with dark object subtraction




Cs value = 0.7 is chosen

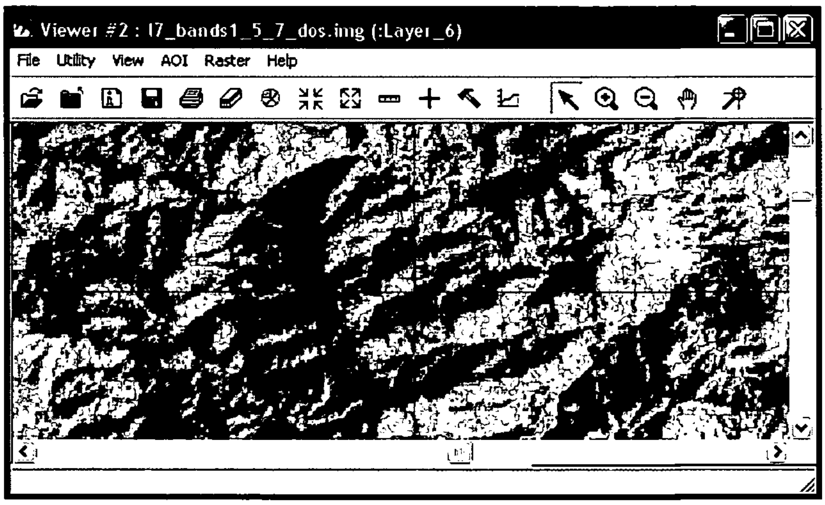


Cs value = 0.6 is not chosen as features topography

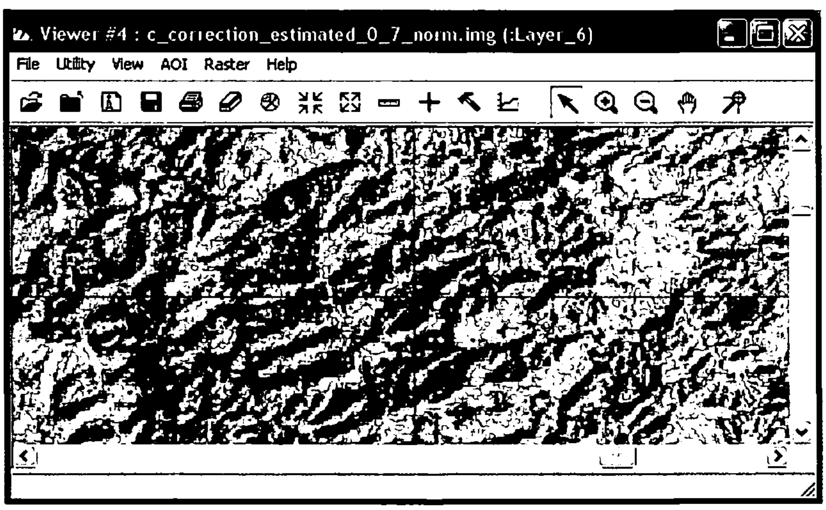



**Band 7**

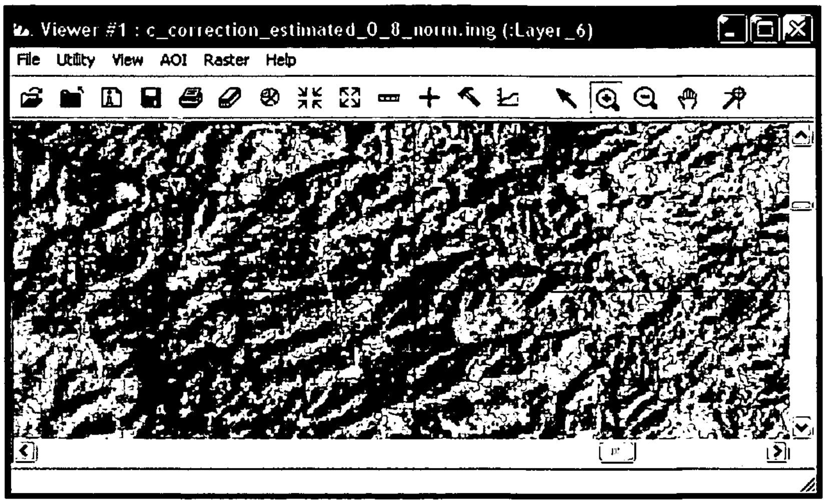
Original image with dark object subtraction




Cs value = 0.7 is chosen



Cs value = 0.8 is not chosen as over illuminated



## Ground Control Points for Geo-referencing and Fallow Age Classification - Oudomxay May 2006

| Date May | GPS ID No. | UTM 48 Zone 48 | | WGS 84 | | Name of location | Fallow | | | | | Area (ha) | Photo # | Additional Information |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Latitude | Longi-tude | North | East | | 2006 | 2004-5 | 2002-3 | 2000-01 | pre 2000 | | | |
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## Ground Control Points for Geo-referencing and Forest Classification - Oudomxay May 2006

| Date May | GPS ID No. | UTM 48 Zone 48 | | WGS 84 | | Name of location | Forest Type | | | | Area (ha) | Photo # | Additional Information |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Latitude | Longi-tude | North | East | | DE | De E | MMXD | DMXD | | | |
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## Ground Control Points for Geo-referencing and Agriculture Classification - Oudomxay May 2006

| Date May | GPS ID No. | UTM 48 | | WGS 84 | | Name of location | Agriculture Crop | | | | | Area (ha) | Photo # | Additional Information |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Latitude | Long-itude | North | East | | upland rice | lowland rice | maize | soya | other | | | |
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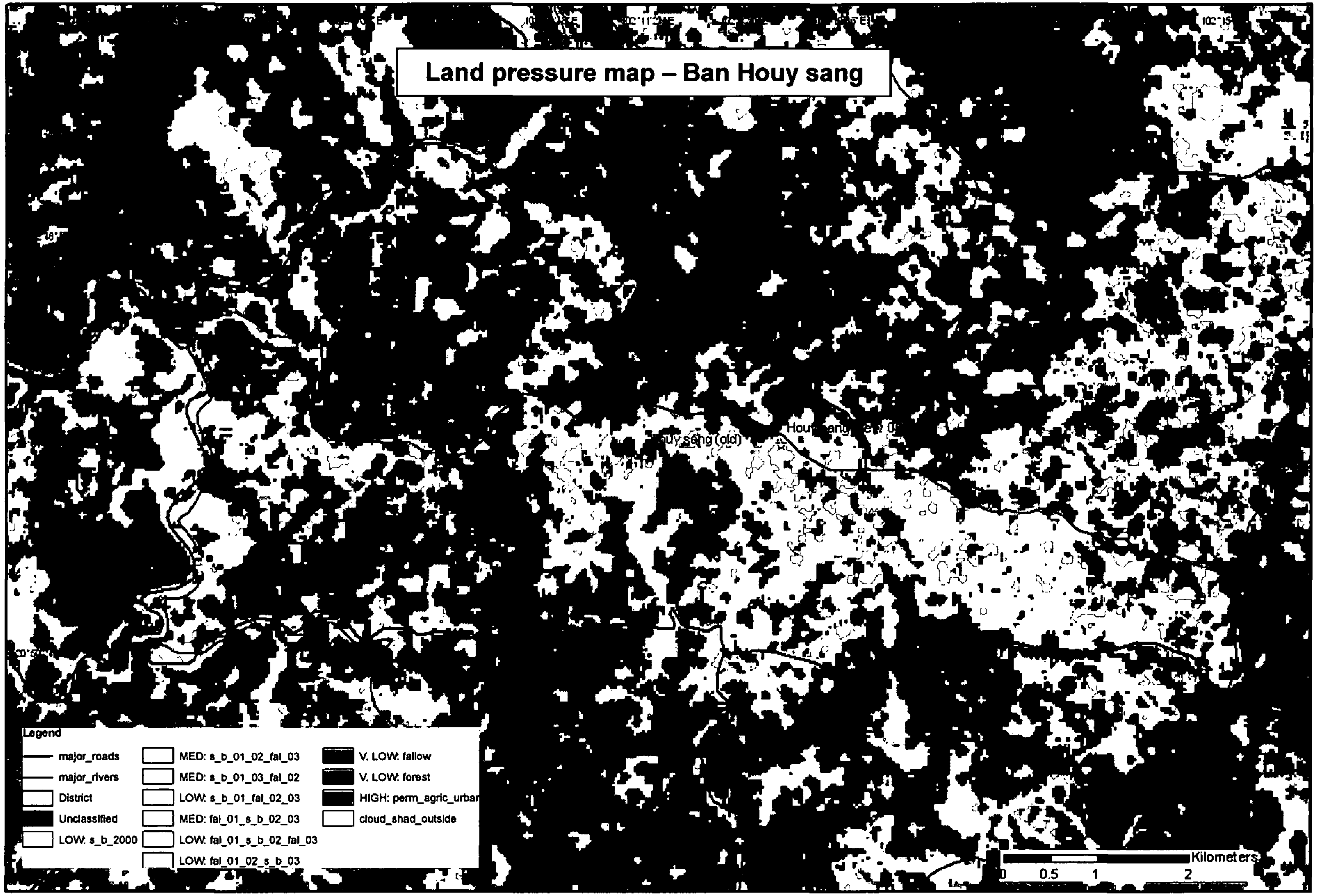
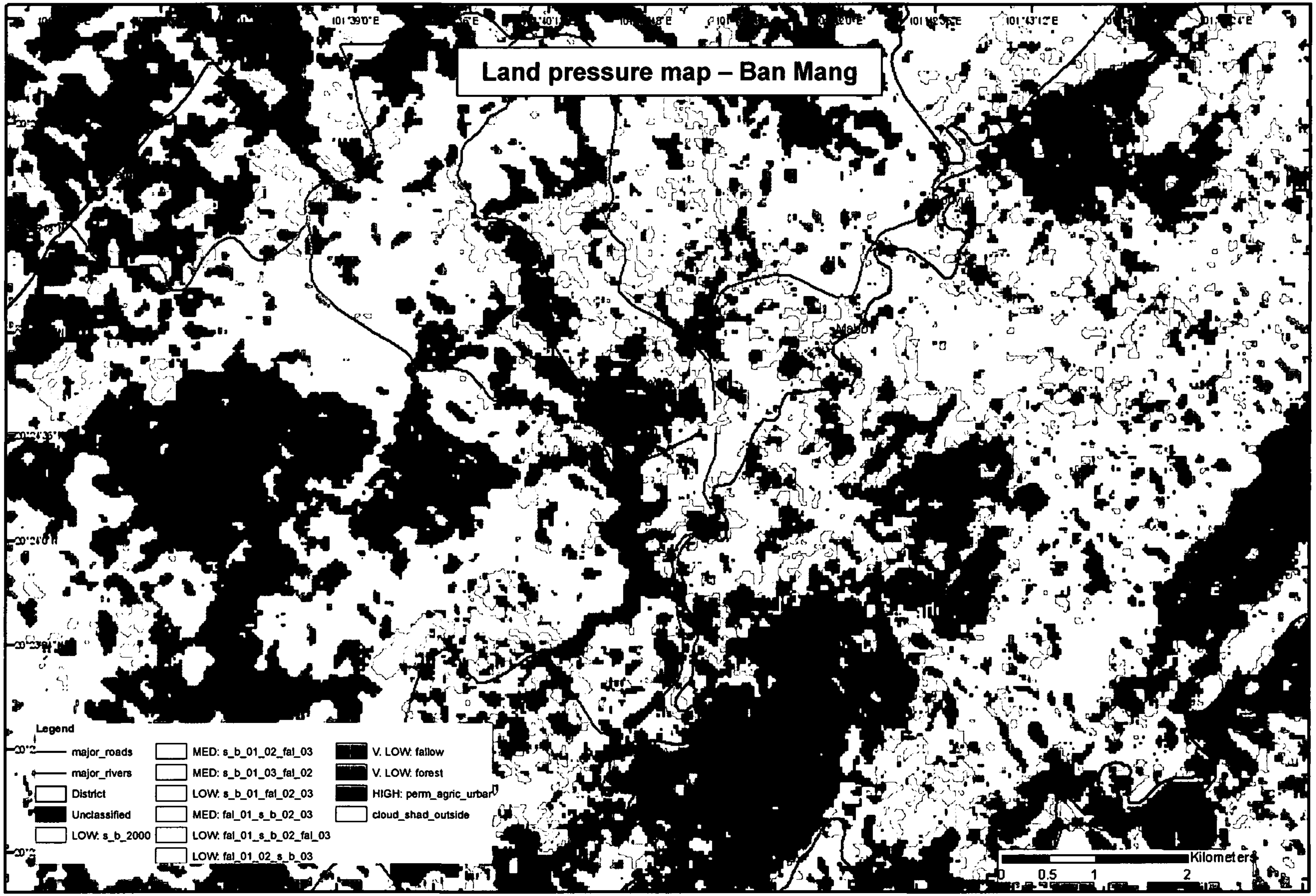
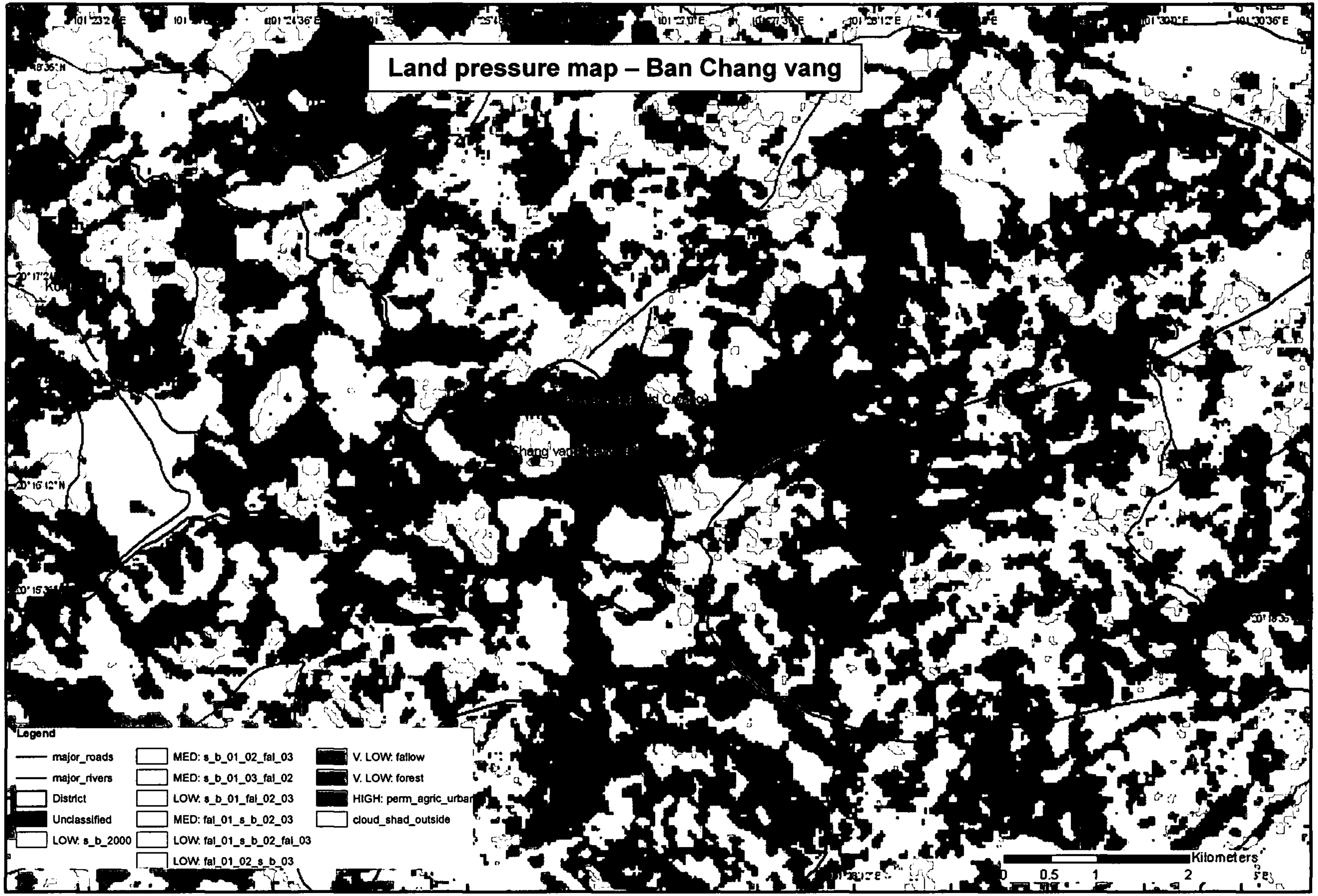
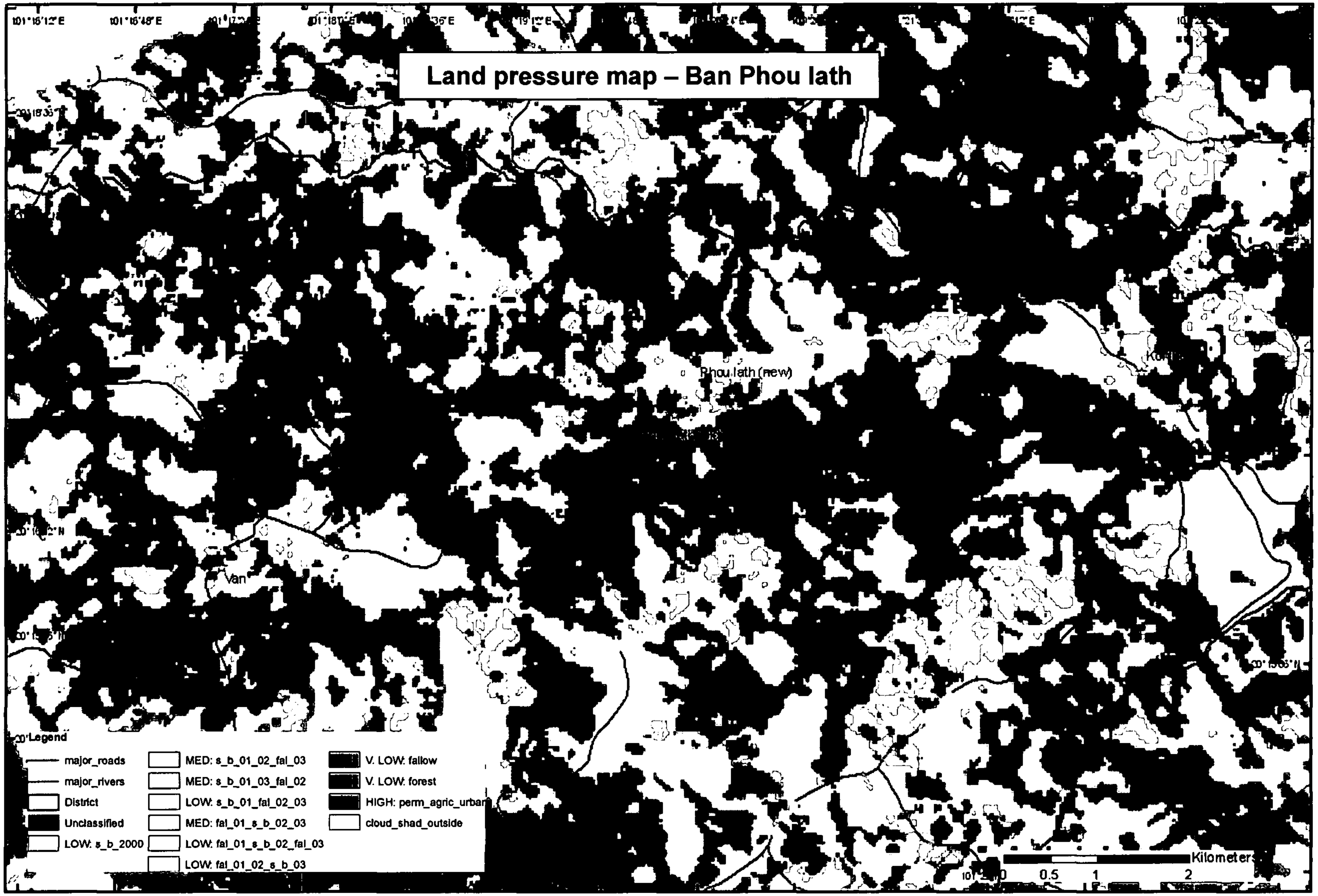

Land pressure map – Ban Houy sang
Legend
major_roads
major_rivers
District
Unclassified
LOW: s_b_2000
MED: s_b_01_02_fal_03
MED: s_b_01_03_fal_02
LOW: s_b_01_fal_02_03
MED: fal_01_s_b_02_03
LOW: fal_01_s_b_02_fal_03
LOW: fal_01_02_s_b_03
V. LOW: fallow
V. LOW: forest
HIGH: perm_agric_urban
cloud_shad_outside
Kilometers
0 0.5 1 2


Land pressure map – Ban Mang
Legend
major_roads
major_rivers
District
Unclassified
LOW: s_b_2000
MED: s_b_01_02_fal_03
MED: s_b_01_03_fal_02
LOW: s_b_01_fal_02_03
MED: fal_01_s_b_02_03
LOW: fal_01_s_b_02_fal_03
LOW: fal_01_02_s_b_03
V. LOW: fallow
V. LOW: forest
HIGH: perm_agric_urban
cloud_shad_outside
Kilometers
0 0.5 1 2


Land pressure map – Ban Chang vang
Legend
major_roads
major_rivers
District
Unclassified
LOW: s_b_2000
MED: s_b_01_02_fal_03
MED: s_b_01_03_fal_02
LOW: s_b_01_fal_02_03
MED: fal_01_s_b_02_03
LOW: fal_01_s_b_02_fal_03
LOW: fal_01_02_s_b_03
V. LOW: fallow
V. LOW: forest
HIGH: perm_agric_urban
cloud_shad_outside
Kilometers
0 0.5 1 2


Land pressure map – Ban Phou lath
Phou lath (new)
Van
Legend
major_roads
major_rivers
District
Unclassified
LOW: s_b_2000
MED: s_b_01_02_fal_03
MED: s_b_01_03_fal_02
LOW: s_b_01_fal_02_03
MED: fal_01_s_b_02_03
LOW: fal_01_s_b_02_fal_03
LOW: fal_01_02_s_b_03
V. LOW: fallow
V. LOW: forest
HIGH: perm_agric_urban
cloud_shad_outside
Kilometers
0.5
1
2
101°16'12"E
101°16'48"E