REMOTE SENSING DATA ANALYSIS FOR FOREST CHANGE DETECTION USING FEATURE SELECTIONS AND MACHINE LEARNING TECHNIQUES: A CASE STUDY OF THE UPPER YUAM BASIN, MAE HONG SON, THAILAND

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ABSTRACT

Forest change detection is an important technique for supporting forest monitoring and management. This research proposes steps for a forest change detection system. Forest cover changes in the upper Yuam basin between 2007 and 2009 were detected by Landsat-5 TM. The set of rules classified 2.09% land cover change of the study area. In machine learning techniques, the features were extracted from remote sensing data. Sampling from a variety of images was used for training and testing sets. Suitable features were selected by feature selection techniques. Then, the features were compared by decision tree, logistic regression, multilayer perceptron, and support vector machine.

The experimental results showed the performance of fast correlation-based filtering (FCBF) is higher than principle component analysis, correlation-based feature selection, and relief algorithms. The leaf area index (LAI), normalized difference vegetation index (NDVI), and the signature index of SigV are suitable features for forest change detection. When the J48 decision tree classifier with FCBF is used, the accuracy of forest changed detection is 92.17%.

KEY WORDS: REMOTE SENSING / FAST CORRELATION-BASED FILTERING / DECISION TREE

145 pages

การวิเคราะห์ข้อมูลภาพถ่ายระยะไกลสำหรับติดตามการเปลี่ยนแปลงพื้นที่ป่า โดยใช้เทคนิคการเลือกคุณสมบัติ และการเรียนรู้ของเครื่อง: พื้นที่ศึกษาบริเวณลุ่มน้ำยวมตอนบน จังหวัดแม่ฮ่องสอน
REMOTE SENSING DATA ANALYSIS FOR FOREST CHANGE DETECTION USING FEATURE SELECTIONS AND MACHINE LEARNING TECHNIQUES: A CASE STUDY OF THE UPPER YUAM BASIN, MAE HONG SON, THAILAND

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บทคัดย่อ

การติดตามการเปลี่ยนแปลงพื้นที่ป่าเป็นเทคนิคที่สำคัญในการบริหารจัดการทรัพยากรป่าไม้ งานวิจัยฉบับนี้มีวัตถุประสงค์เพื่อออกแบบ และพัฒนาระบบสำหรับติดตามการเปลี่ยนแปลงพื้นที่ป่า โดยใช้ข้อมูลภาพถ่ายจากดาวเทียม Landsat-5 TM สำหรับติดตามการเปลี่ยนแปลงพื้นที่ป่าบริเวณลุ่มน้ำยวมตอนบน ในช่วงปี พ.ศ. 2550 ถึงปี พ.ศ. 2552 ผลการจำแนกประเภทสิ่งปกคลุมด้วยการกำหนดกฎ พบว่ามีการเปลี่ยนแปลงในพื้นที่ศึกษา 2.09% งานวิจัยนี้นำเสนอวิธีวิเคราะห์ เพื่อเพิ่มความแม่นยำในการจำแนกประเภทสิ่งปกคลุม โดยใช้เทคนิคการสกัดข้อมูลลักษณะเฉพาะหรือส่วนสำคัญจากข้อมูลภาพถ่ายระยะไกล จากนั้นสุ่มตัวอย่างจากข้อมูลภาพที่หลากหลายมาใช้ในการเรียนรู้ และทดสอบความสามารถในการจำแนกประเภท รวมถึงหาเทคนิคการเลือกคุณสมบัติที่สามารถช่วยเพิ่มประสิทธิภาพให้กับการเรียนรู้ของเครื่อง แล้วเปรียบเทียบวิธีการจำแนกประเภทด้วย ต้นไม้ตัดสินใจ,การวิเคราะห์การถดถอยโลจิสติก, โครงข่ายประสาทเทียมแบบเพอร์เซฟตรอนหลายชั้น และ ซัพพอร์ตเวคเตอร์แมชชีน

จากผลการทดลอง พบว่า การกรองความสัมพันธ์แบบเร็ว สามารถเลือกคุณสมบัติที่เหมาะสมได้ดีกว่าการวิเคราะห์องค์ประกอบหลัก, การเลือกคุณลักษณะบนพื้นฐานความสัมพันธ์ และอัลกอริทึมรีลีฟ และยังพบว่าค่าดัชนีพื้นที่ใบ, ค่าดัชนีพืชพรรณ และ SigV เป็นคุณสมบัติที่เหมาะสม นอกจากนั้น ผลจากการใช้การกรองความสัมพันธ์แบบเร็ว เมื่อจำแนกประเภทด้วย ต้นไม้ตัดสินใจอัลกอริทึม J48 พบว่าให้ความถูกต้องสูงถึง 92.17%

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CHAPTER I
INTRODUCTION

1.1 Background and problem statement

According to the statistic from department of forestry, Thailand's forest areas in 2008 cover approximate 171,585 square kilometers. To maintain the forests which are enormous and complex, a lot of people are required to do this duty. In addition, only the ground based survey is seems to be so difficult. Remote sensing has been a valuable source of information over the course of the past few decades in mapping and monitoring forest activities. As the need for increased amounts and quality of information about such activities becomes more apparent, and remote sensing technology continues to improve. Thus, the remote sensing is an information source will be increasingly critical in the future [1].

An alternative strategy to study dynamics of the forest is using the data from the combination of satellite imagery and geographic information system to analyze fluctuation. However, the human analyst is unable to discriminate to the limit of the radiometric resolution generally available. Therefore, computer can be used for analysis and could conceivably do so at the pixel level and identify as many pixels as required. Computer analysis of remote sensing image data should be take full account of the multidimensional aspect of the data including full radiometric resolution. Classification is a method which labels may be attached to pixels in view of their spectral character. This labeling is implemented by computer having trained beforehand to recognize pixels with spectral similarities. Hence, the image data for quantitative analysis must be available in digital form. These entire things are called "remote sensing digital image analysis". This is an advantage impetus to monitor forest cover of regions, endorse and support the implementation of natural forest management which conforms to the real situation.

There are two important wildlife sanctuaries, named Doi Viang Lha and Mae Yuam (right-site) located at upper Yuam basin. That covers some part of Mae

Hong Son and Chiang Mai provinces, north of Thailand. Topography is the steep-complex mountain, watershed of several rivers. This study area was an abundant forest which wild animals including conserved and protected wildlife live their life. Therefore, this area is suitable to be the prototyping area to monitor the dynamics of the forest using satellite imagery.

The management of natural resources, especially forest resources, requires several factors for analyzing processes. Capture of land cover information is a key requirement for supporting forest monitoring and management [2]. The purpose of this thesis is to develop the forest change detection system by remote sensing data analysis to monitor the dynamics of the forest at upper Yuam basin assists the official to plan and observe the alteration in the boundary.

1.2 Objectives

The objectives for system development are listed as follow:

1) To design and develop the forest change detection system.

2) To find an algorithm that improves the performance of classification on remote sensing data.

3) To find a feature selection technique that can be applied the remote sensing data, and improve the ability of machine learning algorithms.

1.3 Scope of study

Scope and limitation of study as follows:

1) Remote sensing images restricted from upper Yuam basin, within the Department of National park, Wildlife and Plant Conservation, Thailand. The collected years are 2007 and 2009 from Landsat – 5 TM

2) The topographic map used in this research is based on *Universal transverse Mercator* (UTM); 1:50000; *L7017*.

3) Change detection at two different times contained for nine classes.

4) Probability sampling with systematic random.

5) A total of 6,100 training set and 230 testing set are sampling from study area. This was used in the experiment of machine learning algorithms for forest changed detection.

6) The results of detection will be used in the forest change detection system. This system will be developed for displaying the change area.

7) Decision trees, logistic regression, multilayer perceptron (MLP), and support vector machine (SVM) are used as classifiers.

8) The parameters of SVM will be searched by grid search.

9) There are four feature selection techniques; principle components analysis (PCA), correlation-based feature selection (CFS), relief, and fast correlation-based filter (FCBF); that are compared in this research.

CHAPTER II
LITERATURE REVIEW

2.1 Remote sensing data

2.1.1 Source and characteristics

In remote sensing, energy emanating from the earth's surface is measured using a sensor mounted on an aircraft or spacecraft platform. The measurement is used to construct an image of the landscape beneath the platform [3]. Signal and data flow in a remote sensing system as depicted in Figure 2.1. The remote sensing data were changed into beneficial information.

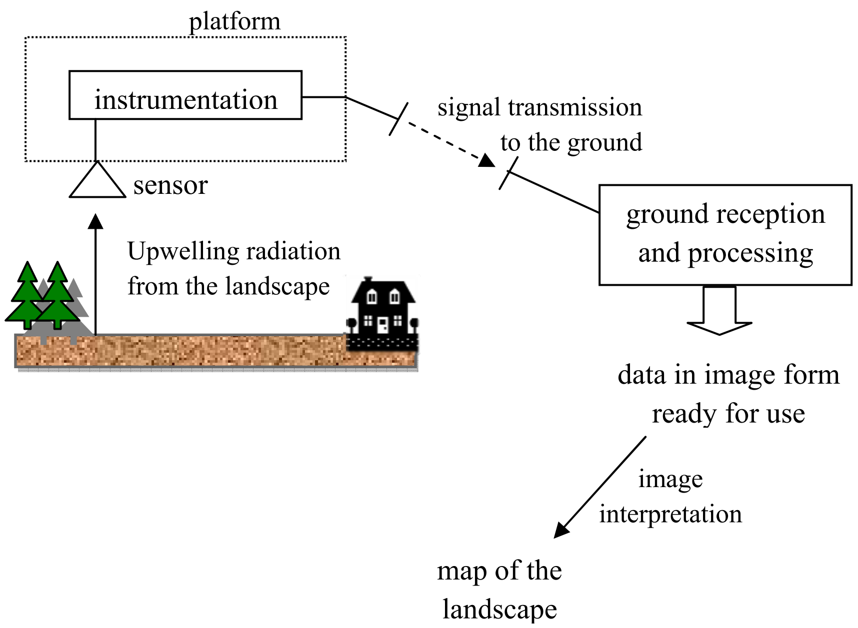


Figure 2.1 Signal and data flow in a remote sensing system

In many ways, sensors on platforms have similar characteristics although differences in their altitude and stability can lead to very different image properties [4]. When the sensor is installed on the aircraft, the data will be brought back down with the sensor on platform. However, if the sensor is installed on the satellite, data will be sent back to earth via radio waves into the ground station. The digital forms are processed to provide accurate. Sensors can retrieve information for the land use and land cover, parameters of the tree canopy, soil moisture, etc. The attribute data are necessary to consider by specialist or digital image processing supporting a decision [5]. A separate of remote sensing device will have resulting image data are different; depend on the characteristics of devices. The data from the remote sensing can be identified the different features. Spectral resolution for satellites data are collected by multispectral remote sensing system, able to identified land cover and the earth over the human eye. Landsat–5 TM is the example of satellite, has equipped Thematic Mapper (TM) [6]. Geographic coverage has image area 185×185 km^2 of the Landsat-5 TM remote sensing systems.

The number of spectral bands, the radiometric resolution, and the spatial resolution are expressed ground in meters. Determine that data volume is generated by a particular sensor, establishes the amount of data to be processed, at least in principle. TM sensor is suitable for mapping land use and land cover classification, responses in seven wavebands with 8 bits radiometric resolution, as shown in Table 2.1.

Table 2.1 Remote sensing of Landsat-5 TM [5]

LANDSAT 5 sensor TM	**Spectral sensitivity (µm)**	**Nominal spectral location**	**Ground resolution (m)**
Band 1	0.45-0.52	Blue	30×30
Band 2	0.52-0.60	Green	30×30
Band 3	0.63-0.69	Red	30×30
Band 4	0.76-0.90	Near-IR	30×30
Band 5	1.55-1.75	Mid-IR	30×30
Band 6	10.4-12.5	Thermal-IR	120×120
Band 7	2.08-2.35	Mid-IR	30×30

Many type of satellite used widely in Thailand. There are a lot device with multi-spectrum such as satellite Landsat TM, SPOT, IKONOS, QuickBird and THEOS [21], as depicted in Figure 2.2.

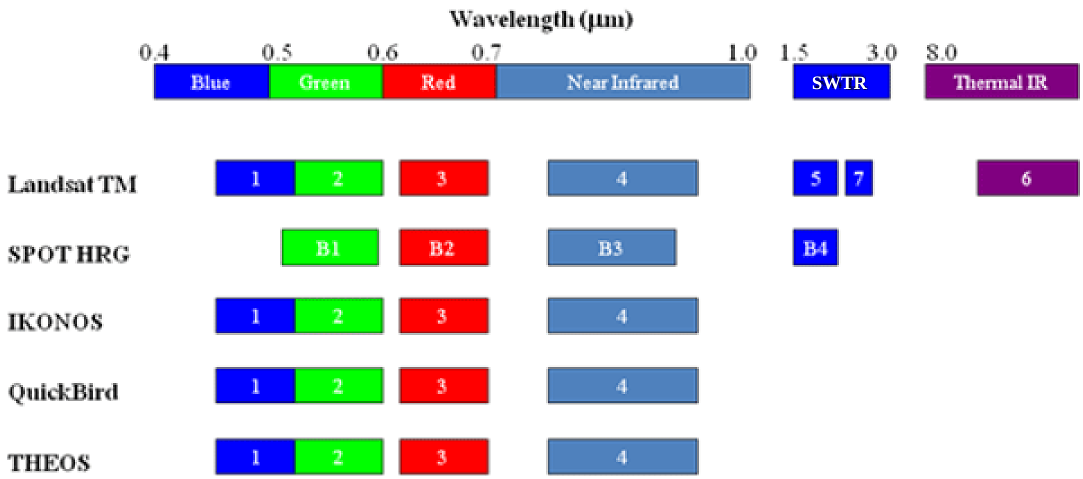


Figure 2.2 Wavelength and spectral resolution by satellite image data that has been used widely in Thailand. [5]

The choice of spectral bands for a particular sensor significantly determines the information for particular application. For example, plants absorb blue and red this required for photosynthesis of plants. In areas of vegetation cover, spectrum of blue and red is very low brightness, but near-infrared spectrum is more than reflected [5].

2.1.2 Geometric distortion

Image data is recorded by sensors on satellites. Image geometry errors can arise [4]. There are many sources of geometric distortion of image data, that has effects are more severe. Source of geometric distortion can be related to factors; nature of distortion such as variation in platform altitude, attitude and velocity are effects related to the image geometry. These lead to image rotation, along track and across track displacement as noted in Figure 2.3.

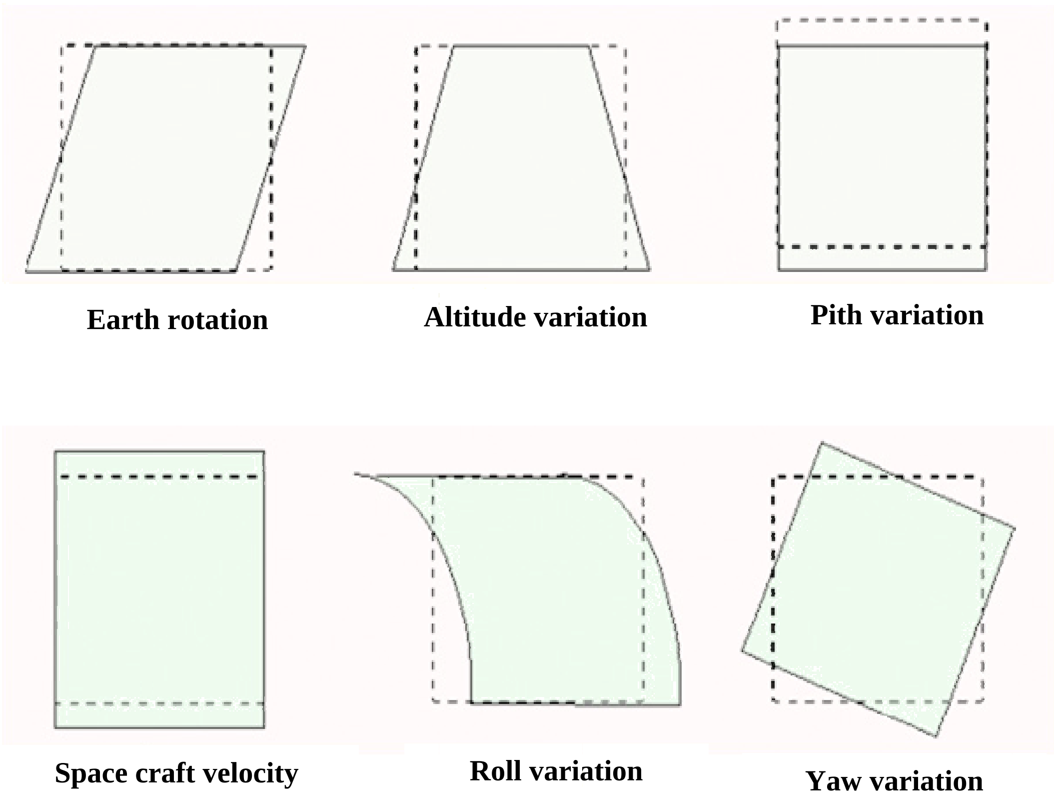


Figure 2.3 Effect of platform position and attitude error on the region of earth being imaged, when this error occur slowly compared with image acquisition.

2.1.3 Image rectification

Geometry errors of image can rectification by reference map or image. The details are following.

2.1.3.1 Georeferencing and geocoding: Using the correction techniques of the preceding section, an image can be registered to map coordinate system. The pixels are addressable in terms of map coordinates; easting and nothings, or latitudes and longitudes etc, rather than pixel and line numbers. Other spatial data types, such as geophysical measurements, image data from other sensors, can be registered similarly to the map thus creating a georeferenced integrated spatial data base of the type used in a geographic information system. Expressing image pixel addresses in terms of a map coordinate base is often referred to as geocoding [3].

2.1.3.2 Image to image registration: Many applications of remote sensing image data require two or more scenes of the same geographical region, acquired at different dates, to be processed together. Such a situation arises for example when changes are interested, in which case registered images allow a pixel by pixel comparison to be made [3].

Two images can be registered to each other by registering each image to map coordinate base separately. Alternatively, if georeferencing is not important, one image can be chosen as a master to which the other, known as the slave, is to be registered. The techniques of mapping polynomials for image correction [3], define two Cartesian coordinate systems. One describes the location of points in the map (x, y) and the other coordinate system defines the location of pixels in the image (u, v). However, the coordinates (x, y) are now the pixel coordinates in the master image rather than the map coordinates. As before (u, v) are the coordinates of the image to be registered i.e., the slave. Furthermore, an artifice known as a sequential similarity detection algorithm can be used to assist in accurate co-location of control point pairs [3]. Control point localization by correlation of value in locating the position of a control point in the master image has identified in the slave.

2.1.4 Spectral signatures

Features on the Earth are reflecting, absorb, transmit, and emit electromagnetic energy from the sun. Special digital sensors have been developed to measure all types of electromagnetic energy as a sensor interacts. Remote sensing used to measure features and changes on the earth, and atmosphere [7].

A measurement of energy of the earth is reflected energy; visible light, near-infrared, etc. The amount of energy reflected from these surfaces is usually expressed as a percentage of the amount of energy striking the objects. Reflectance is 100% if all of the light striking and object bounces off. If none of the light returns from the surface, reflectance is 0%. In the most cases, the reflectance value of each object for each area of the electromagnetic spectrum is somewhere between these two extremes. Across any ranges of wavelengths, the percent reflectance values for landscape features such as water, sand, roads, and forests can be plotted and compared. The plots are called "spectral response curves" or "spectral signatures". Differences among spectral signatures are used to classify remotely sensed images into classes of landscape features since the spectral signatures [7].

Using expert spectral knowledge and library searching have a well-defined. Spectrum means that a scientific approach to interpretation can in principle be carried out. Mach as a sample is identified using spectroscopy in the laboratory through knowledge of spectral features. Usually, a complete spectrum is divided into spectral regions; often under the guidance of an expert, and absorption features are detection in each of the regions. An unknown pixel is then labeled as belonging in a given class if the properties diagnostically significant absorption features match to the spectrum for the class held in a spectral feature library. A complication that can arise with library searching in general and with seeking to match absorption features in particular is that mixtures are often encountered, and save material have similar spectral features. An excellent treatment of the complexities the arise, and handled how can be, is give in Clark [8].

2.1.5 Normalized difference vegetation index (NDVI)

One of the most widely used vegetation indices is the normalized difference vegetation index (NDVI) [9]. A numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyze remote sensing measurements and assess whether the target being observed contains live green vegetation or not. NDVI has found widely in vegetative studies. This index is often directly related to other ground parameters such as percent of ground cover, photosynthetic activity of the plant, surface water, leaf area index and the amount of biomass. NDVI was first used in 1973 by Rouse et al. from the Remote Sensing Centre of Texas A&M University. Generally, healthy vegetation will absorb most of the visible light that falls, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Bare soils on the other hand reflect moderately in both the red and infrared portion of the electromagnetic spectrum [8].

When the behavior of plants across the electromagnetic spectrum, NDVI information can focusing on the satellite bands that are most sensitive to vegetation information, near-infrared and visible red. The bigger the difference therefore between the near-infrared and the red reflectance, the more vegetation there has to be. The NDVI algorithm subtracts the red reflectance values from the near-infrared and divides by the sum of near-infrared and red bands.

$$NDVI = \frac{near\ infrared - visible\ red}{visible\ red + near\ infrared} \tag{2.1}$$

This formulation allows us to cope with the fact that two identical patches of vegetation could have different values if one were, for example in bright sunshine, and another under a cloudy sky. The bright pixels would all have larger values, and therefore a larger absolute difference between the bands. This is avoided by dividing by the sum of the reflectance. Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1 but in practice extreme negative values represent water, values around zero represent bare soil and values over represent dense green vegetation [8].

2.1.6 Geographic information systems (GIS)

The amount of data to be handles in a database that contains spatial sources such as satellite imagery along with maps, is enormous, particularly if the data cover a large geographical region. Quite clearly therefore thought has to be give to efficient means by which the data types can be stored and retrieved, manipulated, and displayed. This is the role of the geographic information system [3]. The other definitions of GIS are following: Other databases may contain location information such as street addresses, or zip codes etc., but all information in a GIS is linked to a spatial reference, database uses geo-references as the primary means of storing and accessing information. GIS are for making decisions. The way in which data is entered, stored, and analyzed within a GIS must mirror the way information will be used for a specific research or decision-making task. To see GIS as merely a software or hardware system is to miss the crucial role, GIS can play in a comprehensive decision-making process [10].

The GIS is designed to carry out operations on the data stored in GIS's database, according to a set of user specifications, without the user needing to be knowledgeable about how the data is store and what data handling and processing procedures are utilized to retrieve and present the information required. Unfortunately because of the nature and volume of data involved in a GIS many concepts developed for data base management systems (DBMS), cannot be transferred directly to GIS design although they do provide guidelines. Instead new design concepts have been needed, incorporating the sorts of operation normally carried out with spatial data, and attention has had to be given to efficient coding techniques to facilitate searching through the large numbers of maps and images often involved.

To understand the sorts of spatial data as listed in Table 2.2, manipulation operations of importance in GIS one must take the view of the resource manager rather than the data analyst. Whereas the latter is concerned with image reconstruction, filtering, transformation and classification, the manager is interested in operations such as those listed in Table 2.3. These provide information from which management strategies and the like can be inferred. Certainly, to be able to implement many, if not amount, of these a substantial amount of image processing may be required.

Table 2.2 Source of spatial data [3]

Point	**Line**	**Area**
Multispectral data	Road maps	Land ownership
Topography	Powerline grids	Town plans
Magnetic measurements	Pipeline networks	Geological map
Gravity measurements		Land use licenses
Radiometric measurements		Land use licenses
Rainfall		Land use maps
Geochemistry (in ppm)		Soil type maps

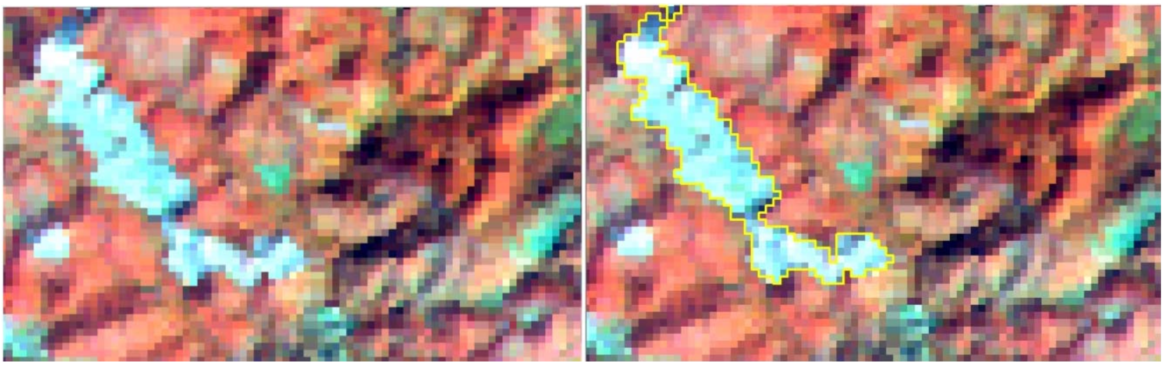
Table 2.3 Some GIS data manipulation operations [3]

Intersection and overlay of data set (masking)
Intersection and overlay of polygons (grid cells, etc.) with spatial data
Identification of shapes
Area determination
Distance determination
Thematic mapping
Proximity calculations (shortest route, etc.)
Search by data
Search by location
Search by user-defined attribute
Similarity search (e.g. of images)

A problem which can arise in image data base of the type encountered in a GIS is the need to identify one image by reason similarity to another. In principle, this could be done by comparing the images pixel-by-pixel; however the computational demand in so doing the images of any practical size. Instead effort has been directed to developing codes or signature for complete images that will allow efficient similarity searching.

2.2 Classification techniques

In classification, some domain knowledge has assumed about the type of problem to solve. This domain knowledge can come from domain experts or sample data from the domain, which constitute the training data set [11]. Imagine a situation where one would like to classify objects as red and light blue pixel from the picture shown in Figure 2.4a



a **b**

Figure 2.4 Sample of objects classification

One way to do that is to separates two classes as a decision surface. Consider Figure 2.4b where the decision surface is shown in yellow line, light blue pixel shown inside polygon. Yellow line in Figure 2.4b can lead this frame, but this line is not separates another frame. The methods that build classification models i.e., “Classification algorithms”, classification rule can use to classified unseen new objects. The classification algorithm requires a geometrical representation of the objects in order to build a decision surface [12]. A hyperplanes can implement a simple rule for classification; all objects lying on one side of the hyperplane will be classified as member of one class and other side will be classified as members of another class. A hyperplane is a linear decision surface that splits the n-dimensional space ($\mathbb{R}^n$) into two parts, where n is number of characteristics of feature or variables. Mathematically are equivalent to $\vec{w}\cdot(\vec{x}-\overrightarrow{x_0})=0$ or $\vec{w}\cdot\vec{x} - \vec{w}\cdot\overrightarrow{x_0}=0$. Define the coefficient $b = -\vec{w}\cdot\overrightarrow{x_0}$ and arrive to the equation of hyperplane: $\vec{w}\cdot\vec{x}+b=0$. Notice that this equation also holds for $\mathbb{R}^n$ where n is greater than three [12].

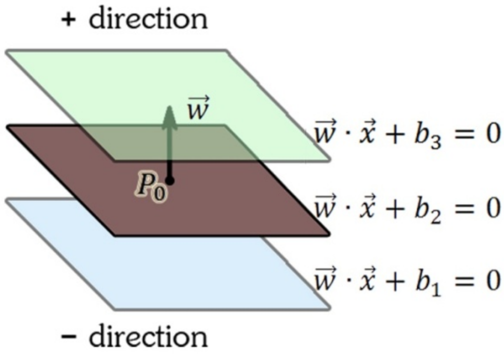


Figure 2.5 Distance between parallel hyperplanes

This worthwhile to observe what happens if the coefficient b changes in a give equation of the hyperplane. In that case, the hyperplane move parallel along the direction of $\vec{w}$ and obtain parallel hyperplanes. Figure 2.5 depicts for an illustration. The distance between two parallel hyperplanes $\vec{w} \cdot \vec{x} + b_1 = 0$ and $\vec{w} \cdot \vec{x} + b_2 = 0$ is given by the following formula: $D = |b_1 - b_2| / \|\vec{w}\|$. A hyperplane together with the above classification rule are essential ingredients of the support vector machine algolithm.

2.2.1 Decision tree classifier

Decision trees are widely used in classification because they are easy to construct and use [11]. The classifier treated in above have all been single stage in that only one decision is made about a pixel, as a result of with labeled as belonging to one of the available class or is left unclassified. Multistage classification techniques are also possible in which a series of decisions is taken in order to determine the correct label for a pixel. The more common multistage classifiers are called decision trees, example of which is show in Figure 2.6. They consist of member of connected classifiers or decision node none of which is expected to perform the complete segmentation of the image data set. Instead, each component classifier only performs part of the task, as nodded in the figure. Perhaps the simplest type is the binary tree in which each component classifier, or node, is expected to perform a segmentation of the data into only one of two possible classes, or groups of classes [3].

The advantages of using a multistage or tree approach to classification include that different data sources, different sets of features, and even different algorithms can be use at each decision stage. Minimizing the member of features to sue in a decision is significant for reducing processing time and for improving the accuracy of small class training. Decision tree designs are three tasks as: finding the optimal structure for the tree, choosing the optimal subset of features at each node, and selecting the decision rule to use at each node. An optimal or suboptimal tree structure may aim for minimum error rate, a minimum member of nodes, or a minimum path length in deciding how to split classes at earth node of the tree; consideration must be give also to means for controlling overlapping classes and for control of how many branches and layer to use [3].

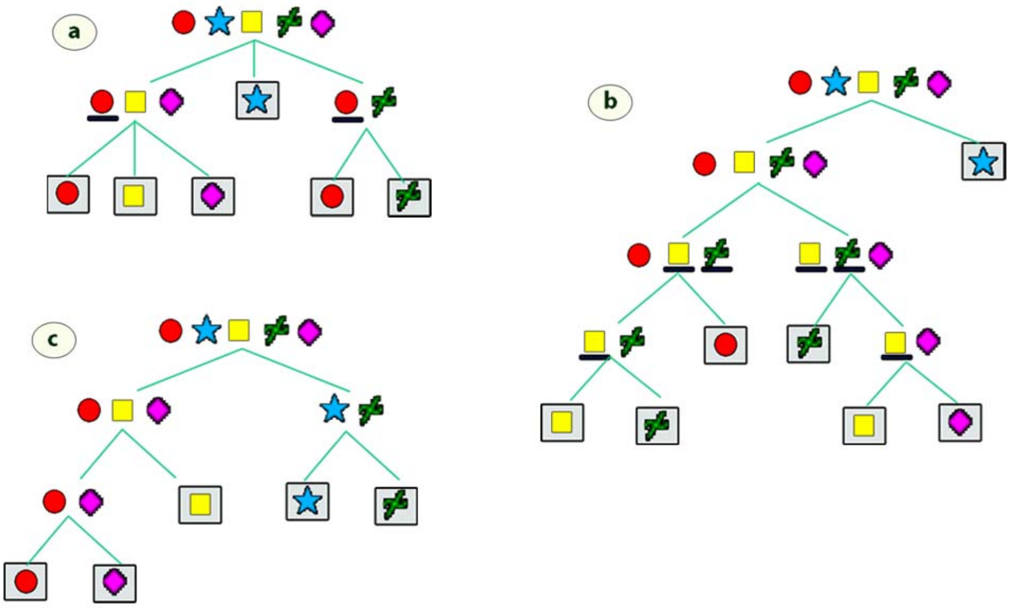


Figure 2.6 Multistage of decision trees classifiers – underlines indicate class overlaps.

a) A general decision tree.

b) A binary decision tree with overlapping classes.

c) A binary tree without overlapping classes

The some set of features and the some classification algorithm are use at each decision node. A more general design philosophy is difficult to devise. However, analyst knowledge often helps in structuring a tree. For example, logical to separate data into water and croplands, and then croplands further into wheat, corn etc. A user might also be able to use algorithm knowledge such as that minimum distance classification is preferred when small classes need to be identified. Moreover, some

GIS data, e.g. elevation, can be segmented by a one dimensional parallelepiped algorithm.

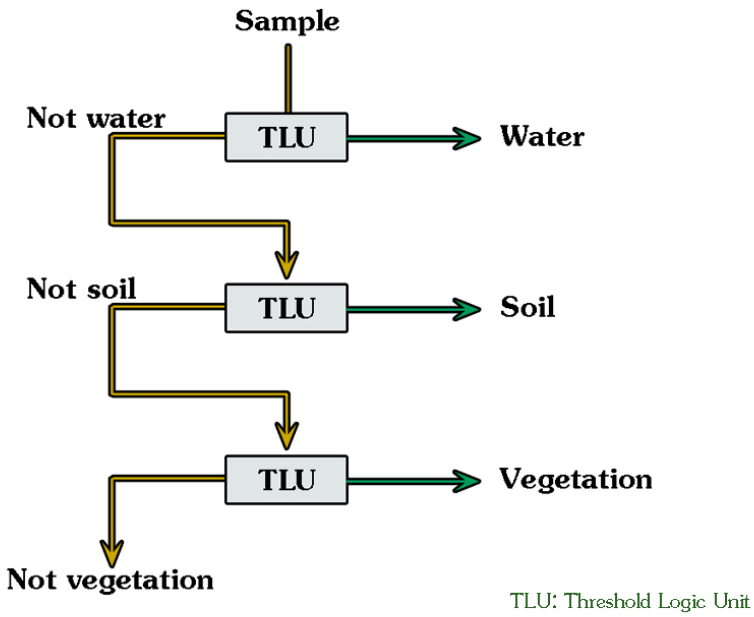


Figure 2.7 Binary decision trees of TLUs used for multi-category classification.

Multi-category classification can be carried out in one of two ways. First a decision tree of linear classification; threshold logic units (TLUs), can be constructed as shown in Figure 2.7 at each decision node of which a decision of the type is made, such as water or not water. At a subsequent not water the category might be differentiated as soil or not soil etc. should be noted that the decision process at each node has to be trained separately [3].

2.2.2 Logistic regression

Linear regression is used to approximate the relationship between a continuous response variable a set of predictor variables. However, the response variable is often categorical rather than continuous. For such case, linear regression is not appropriate, but the analyst can turn to an analogous method, logistic regression, which is similar to linear regression in many ways. Logistic regression refers to methods for describing the relationship between a categorical response variable and a set of predictor variables [13].

Logistic regression assumes that the relationship between the predictor and the response is nonlinear. In linear regression, the response variable is considered to be a random variable $Y = \beta_0 + \beta_1 x + \varepsilon$ with condition mean $\pi(x) = E(Y|x) = \beta_0 + \beta_1 x$. The condition mean for logistic regression takes on a different form from that of linear regression. Specifically,

$$\pi(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}} \tag{2.2}$$

Curves of this form are called "sigmoidal" because they are S-shaped and therefore nonlinear. The minimum for $\pi(x)$ is obtained at $\lim_{a \to -\infty} \frac{e^a}{1+e^a} = 0$, and the maximum for $\pi(x)$ is obtained at $\lim_{a \to \infty} \frac{e^a}{1+e^a} = 1$. Thus, $\pi(x)$ may be interpreted at the probability that the positive outcome is present for records with $X = x$, and $1 - \pi(x)$ may be interpreted as the probability that the positive outcome is absent for such records. The variance of ε is $\pi(x)[1 - \pi(x)]$, which is the variance for a bionomial distribution, and the response variable in logistic regression $Y = \pi(x) + \varepsilon$ is assumed to follow a bionomial distribution with probability of success $\pi(x)$. The logistic transformation is as follows [13]:

$$g(x) = ln \frac{\pi(x)}{1 - \pi(x)} = \beta_0 + \beta_1 x \tag{2.3}$$

No closed-form solution exists for estimation logistic regression coefficients. Thus, maximum likelihood estimation must turn to finds estimates of the parameters for which the likelihood of observing the observed data is maximized. The logistic regression results should always be validated using both the model diagnostics and goodness-of-fit statistics shown in Hosmor and Lemeshow [14], or the traditional data mining cross-validation methods. The logistic model is popular because the logistic function, on which the model is based, provides the following: Estimate that must lie in the range between zero and one and, an appealing S-shaped description of the combined effect of several risk factors on the risk for a disease [16]. Figure 2.8 shows S-shaped or Sigmoid for Logistic Regression.

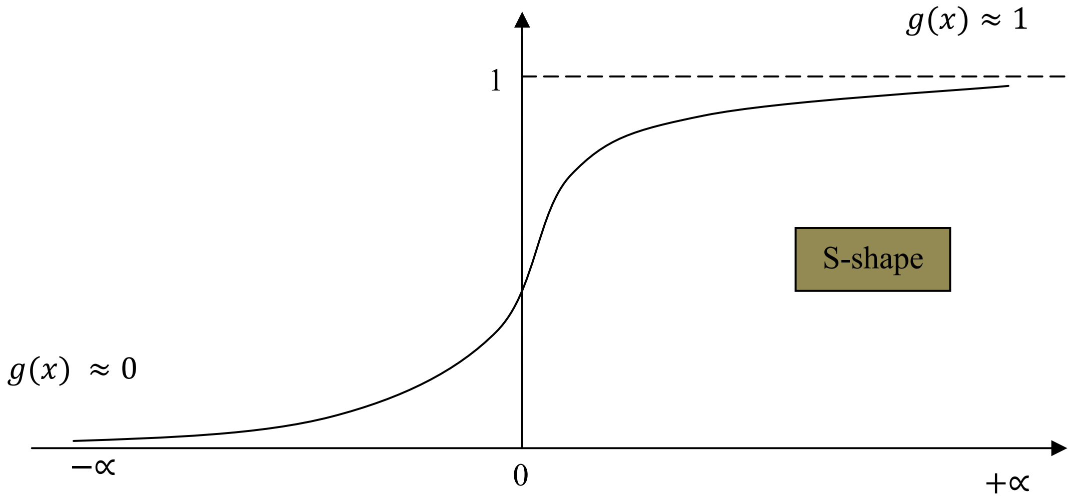


Figure 2.8 S-shaped or sigmoid for logistic regression.

2.2.3 Neural network approach

An artificial neural network (ANN) is a computation model that mimics the human brain in the sense that consists of a set of connected nodes, similar to neurons. The nodes are connected with weighted arcs. The system is adaptive because can change the structure base on information that flows through. In addition to node and arcs, neural networks consist of an input layer, hidden layers, and an output layer [11]. The essential processing node in the neural network is an element as show in Figure 2.9 with many inputs and with a single output. Operation is described by:

$$O = f(\omega^t x + \theta) \tag{2.4}$$

Where θ is a threshold (sometime set to zero), ω is a vector of weighting coefficients and x is the vector of inputs. In general, the number of inputs to a node well be defined by network topology as well as data dimensionality, as well become evident [3].

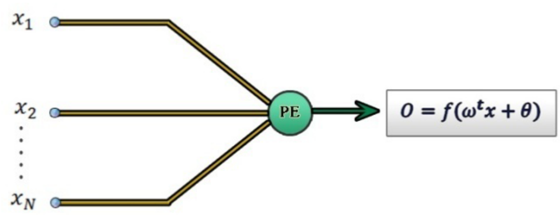


Figure 2.9 Neural network processing element.

The neural network has a more complex structure than that of a perceptron model. The major difference know as the multilayer perceptron (MLP) [3]. The simplest form of ANN is the feed-forward ANN where information flows in one direction and the output of each neuron is calculated by summing the weight signals from incoming neurons and passing the sum through an activation function. A commonly used activation function is the sigmoid function.

$$A(x) = \frac{1}{1 + e^{-x}} \tag{2.5}$$

A common training process for feed foreword neuron networks is the back-propagation process, where go back to modify the weights in the layers. The weight of each neuron is adjusted such that error is reduced, where a neuron's error is the difference between expected and actual outputs. The most well-known feedforeword ANN is the perceptron, which consists of only two layers or no hidden layers and works as a binary classifier, when three or more layers exist in the ANN; at least one hidden layer, then the perceptron is known as the "Multilayer perceptron" [11]. A neural network for use in remote sensing image analysis will appear as shown in Figure 2.10. Conventionally drown with an input layer of nodes with has the function of distributing the inputs to the processing elements of the next layer, and scaling them if necessary and output layer from witch the class labeling information is provided. In between there may be one or more so-called hidden or other processing layer of nodes. Usually one hidden layer will be sufficient, although the number of nodes to use in the hidden layer is often not readily determined [3].

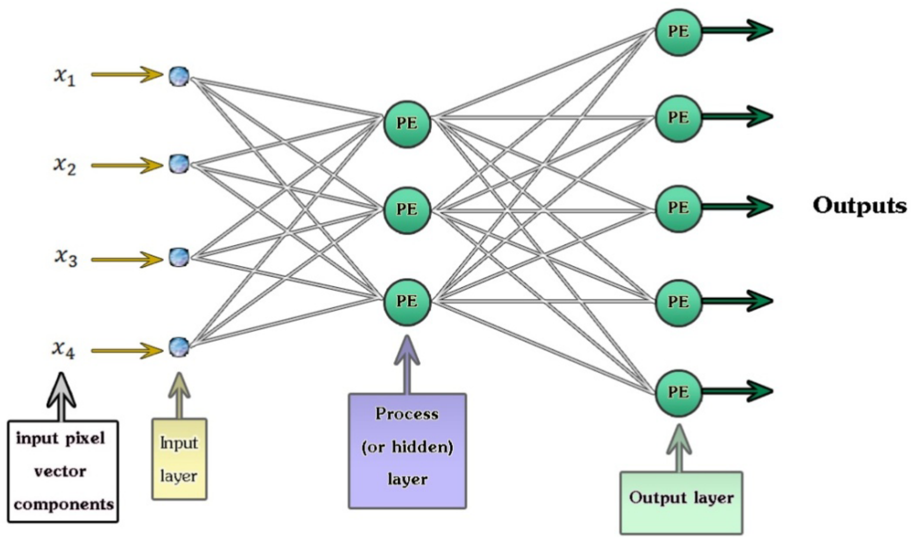


Figure 2.10 A multilayer perceptron neural network, and the nomenclature used in the derivation of the backpropagation training algorithm.

Another type of widely used feedforeword ANN is the “radial-basis function ANN”, which consists of three layers and the activation function is a radial-basis function (RBF). This type of function, as the name implies, has radial symmetry such as a Guassion function and allows a neuron to respond to a local region of the feature space. In other words, the activation of a neuron depends on distance from a center vector. In the training phase, the RBF centers are chosen to match the training samples [11].

2.2.4 Support vector machine (SVM)

The support vector machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships [15]. This technique has shown promising empirical results in many practical applications, from handwritten digit recognition to text categorization. SVM also works very well with high-dimensionality problem. Support vectors are defined as the points closest to the separating hyperplane and the weighted sum of the support vectors is the normal vector to the hyperplane [17].

Support vector machines seek a linear decision surface that can separate class of objects and has the largest distance or “gap” or “margin” between border-line objects that are also called "support vectors". Figure 2.11(a) depicts for an example of several linear decision surfaces that can separate classes of objects shown as lines of different colors. An infinite number of such decision surfaces exist in this data.

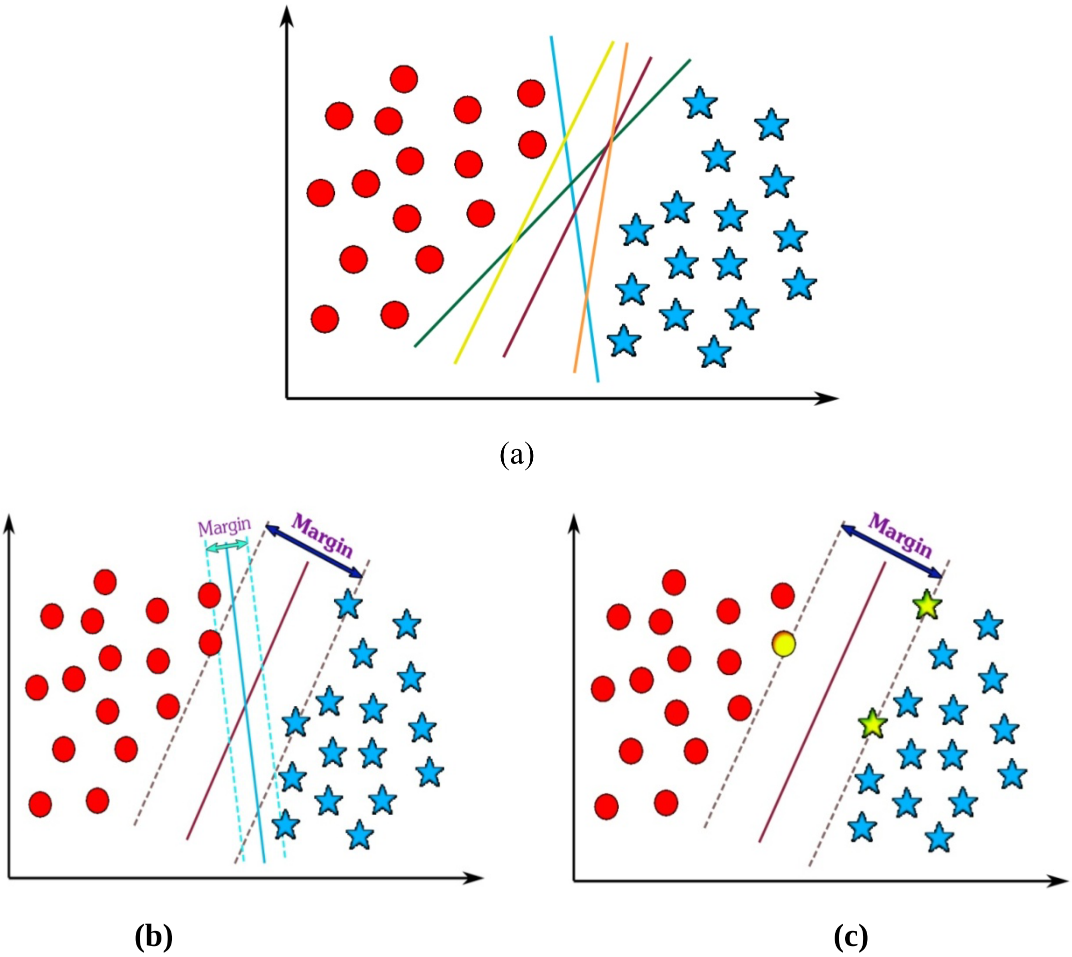


Figure 2.11 Linear decision surface for separate class of objects in SVM
(a) Several linear decision surfaces
(b) Two margin of decision surface
(c) Largest margin between support vectors

Figure 2.11(b) show two margin of decision surface. Maximum-margin or largest distance for SVM algorithm is often referred to a "hard-margin SVM". Figure 2.11(c) depicts for an example of linear decision surface that can separate classes of objects and also has the largest margin between support vectors only one such decision surface exists. Support vectors are three objects that are shown with yellow highlighting in the figure. If for whatever reason the border-line objects informative e.g., due to noise, hard-margin support vector machines may not perform well in the future applications to unseen data objects.

6.3.1.2 Hard-margin linear SVM for linearly separable data: When linear decision surface or hyperplane that can separate two classes of objects in the data without errors. An example of linearly separable data and several hyperplanes that separate classes of objects in the data are show in Figure 2.11(a).

The general statement of the linear SVM classifier: parallel hyperplanes in Figure 2.12 that will differ in the coefficient b. By possible rescaling $\vec{w}$ and b by the same factor, assume these two hyperplanes by equations of the form $\vec{w} \cdot \vec{x} + b = +1$ and $\vec{w} \cdot \vec{x} + b = -1$. Since the SVM algorithm searches for a hyperplane form $\vec{w} \cdot \vec{x} + b = 0$ that maximizes the gap, and need to minimize $\|\vec{w}\|$.

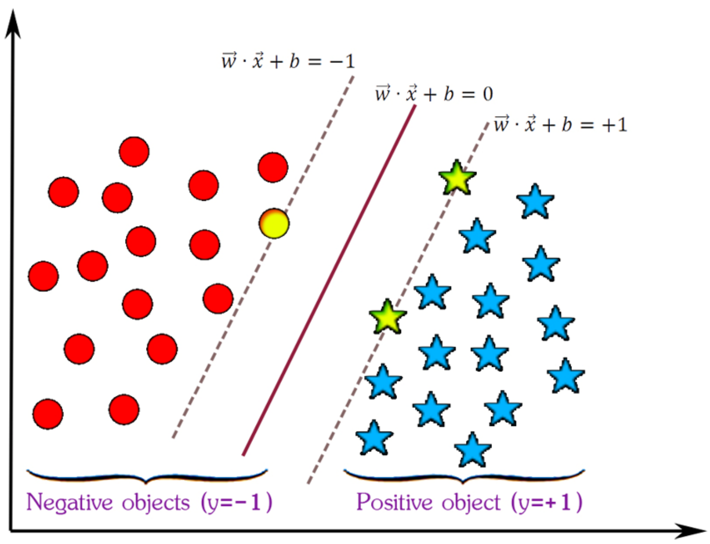


Figure 2.12 Parallel hyperplanes

6.3.1.3 Soft-margin linear SVM for data that is not exactly linearly separable due to noise or outliers: When the data is linearly separable but there are noisy measurements and/or outliers. An example of such data is shown in Figure 2.13.

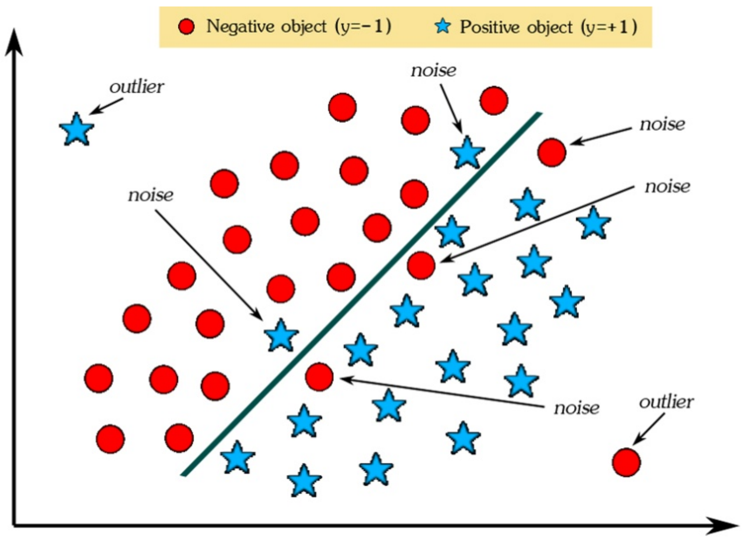


Figure 2.13 Soft-margin linear SVM for data that is not exactly linearly separable due to noise or outliers

6.3.1.4 Non-linear SVM and kernel trick for linearly non-separable data: Linearly non-separable data are no linear decision surface (hyperplane) that can separate two classes of objects in the data without errors. SVMs "map" the data from the "input space" into a higher dimensional space known as the "feature space", where the data is linearly separable and thus the separating linear decision surface exists and determined. The feature space results from a mathematical construction known as the "kernel trick"

Assume that objects are represented by multi-dimension data points $\vec{x}_1, \vec{x}_2, \dots, \vec{x}_N \in \mathbb{R}^n$ and corresponding labels are $y_1, y_2, \dots, y_N \in \{-1, +1\}$. To build a classifier, non-linear SVMs map each object $\vec{x}_i$ from the input space $\mathbb{R}^n$ to the feature space linear decision surface by means of the mapping function with kernel and find a linear decision surface to separate negative objects from the positive ones in the feature space. For example, depicts in Figure 2.14. The RBF is by far the most popular choice of kernel types used in SVM. This is mainly because of their localized and finite responses across the entire range of the real x-axis.

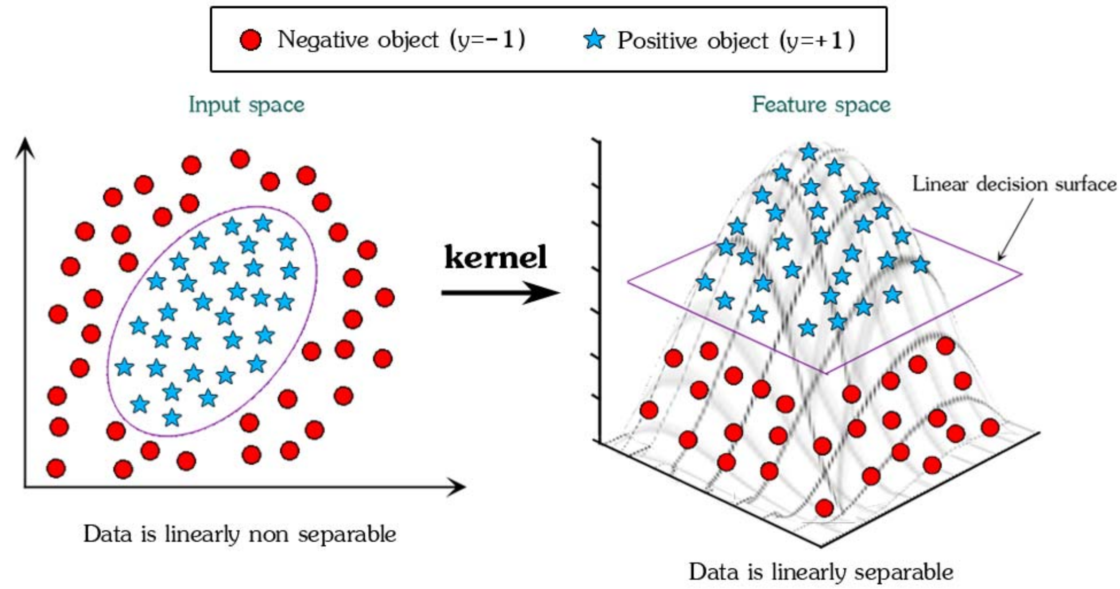


Figure 2.14 Mapping function with kernel

6.3.1.5 SVMs for multi-category classification: The SVM classifier has to be modified to work with multi-category classification, i.e., when there are three or more classes in the data. For example, a researcher may be interested for classifying geospatial images into three different types of vegetation, soil and water. This problem has three classes and multi-category SVMs are suitable for solution.

One-versus-rest SVMs: Assume that there are *k* classes to separate. In this approach, construct *k* binary SVM to separate each class from the rest: class 1 positive versus all other class negative, class 2 positive versus all other class negative, …, class *k* positive versus all other class negative. Then new object are assigned to the class that has a positive vote and the largest distance to hyperplane. Consider the example give in Figure 2.15. This is a simplified problem with three possible outcomes or classes: vegetation, soil and water. Our goal is to build a three category one-versus-rest SVM classifier of land cover for patient band samples that are described by expression value of band 4 and band 5. The application of three binary SVM classifiers to separate each class from the rest results in three hyperplanes that are shown with dashed line in the figure. The shaded regions in the figure correspond to tie situations when two or none classifiers positively vate at the same time for their class. The decision surface for the multi-category one-versus-rest SVM is show with a solid bold line in the figure.

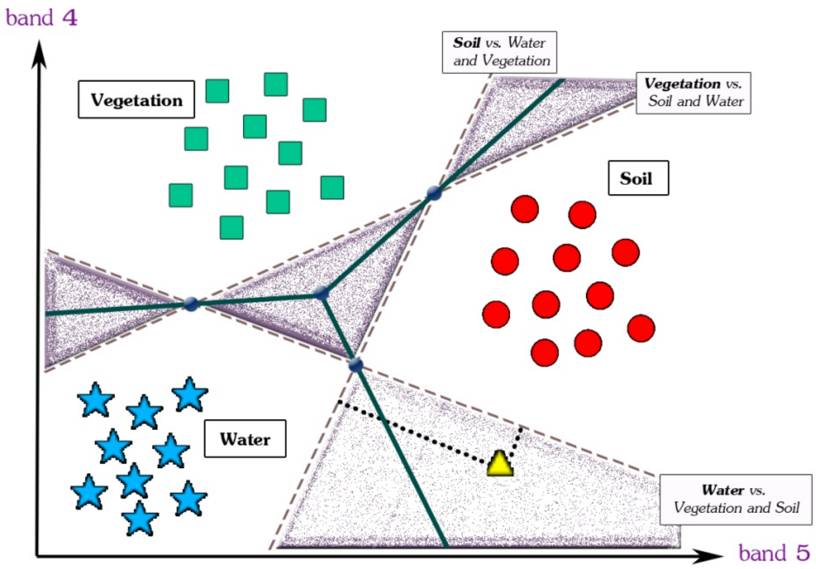


Figure 2.15 One-versus-rest SVMs

Consider that classification of new sample denoted by the triangular shape that lies in the shaded regions in the figure. This sample receives positive votes from both soil and water classifiers; however, its distance from the "soil vs. water and vegetation" hyperplane is larger than that from "water vs. vegetation and soil" hyperplane. Hence, this sample is classified as soil.

One-versus-one SVMs: Again, assume that there are k classes to separate. Here, construct binary SVM classifiers to separate each pair of classes: class 1 versus class 2, class 1 versus class 3, …, class k-1 versus class k. Then new objects are assigned to the class that has the majority of votes. If tie occur e.g., two class get the same maximal number of votes, an object will be assigned a class based on the classification provided by the furthest hyperplane.

Consider the example given in Figure 2.16. Our goal is again to build three category one-versus-one SVM classifier of land cover (Vegetation vs. Soil vs. Water) for sample that are described by expression levels of two band. The application of three binary SVM classifiers to separate each pair of classes, results in three hyperplanes that are shown with dashed line in the figure. The shaded region in the figure corresponds to a tie situation when all three classifiers vote for a different class. The decision surface for the multi-category one-versus-one SVM is shown with a solid bold line in the figure.

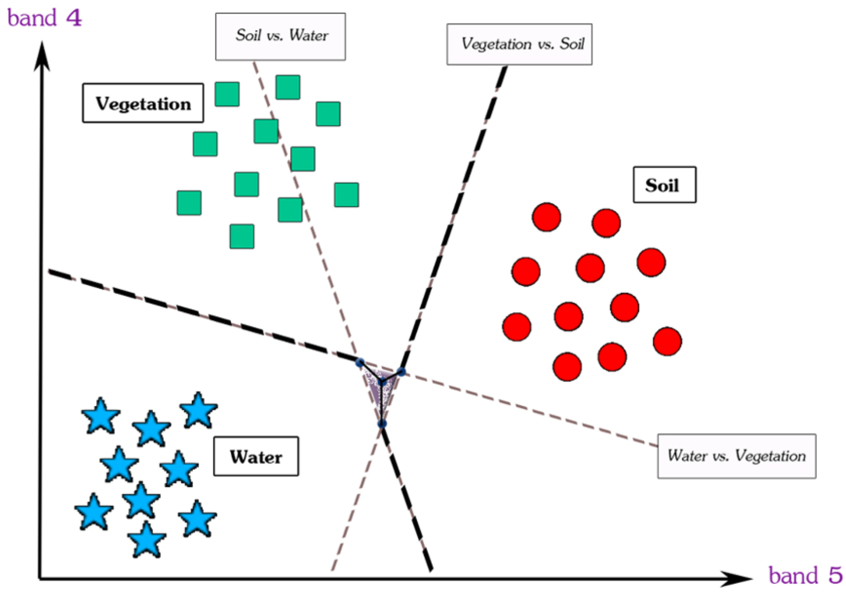


Figure 2.16 One-versus-one SVMs

One of the benefits of one-versus-one multi-category SVM approach is that for every pair of classes to solve an SVM classification problem that utilizes a smaller number of objects than the total number of in the training data. This can yield substantial savings in the total computation time compared to the one-versus-rest multi-category SVM approach. However, in practice the one-versus-rest approach performs with the same or better accuracy than the one-versus-one approach [12].

6.3.1.6 Using an SVM: Many SVM packages already have built-in multi-class classification functionality. *LibSVM* and *LibLINEAR* are both wrapper classifiers that allow third-party implementations of support vector machines and logistic regression to be used in Weka. To use them, the jar file for the library in question must be in the class path for the Java virtual machine. The former gives access to the LIBSVM library of support vector classification and regression algorithms [18], which provides several types of support vector machines for multiclass classification, regression, and one-class problems, and gives a choice of linear, polynomial, radial-basis, and sigmoid kernels. The latter gives access to the

LIBLINEAR library [19], which includes fast implementations of linear support vector machines for classification and logistic regression [20]. Use SVM software package need to specify by choice of parameter C., choice of kernel or similarity function e.g. No kernel “linear kernel”, Gaussian kernel this need to choose σ^2.

2.3 Feature selection methods

Feature selection helps us to focus the attention of an induction algorithm in those features which are to predict a target concept. Feature selection methods try to find a subset of the variable feature to improve the application of learning algorithm. Many methods are based on searching a feature set that optimizes some evaluation function. On the other side, feature set estimators evaluate features individually [21]. The database typically used in data mining may have millions of records and thousand of variables. This is unlikely that all of the variables are independent, with no correlation structure among them. Data analysts need to guard against multicollinearity, a condition where some of the prediction variables are correlated with each other. Dimension reduction methods have the goad of using the correlation structure among the predictor variables to accomplish the following. To reduce the number of predictor components, to help ensure that these components are independent, to provide a framework for interpretability of the results [13].

Search and feature set measures; the good is finding a set of features that allows as to improve a learning activity. The process followed by many feature selection methods based on searching can be divided into two main parts: a search method through the feature set space, and an evaluation function of a given set of selected features. In the search process can identify tree part. The first are choice of a starting point, fellow with process of generating the next set to explore. The finally are stopping criterion. Figure 2.17 show this modular decomposition of the feature selection process [13].

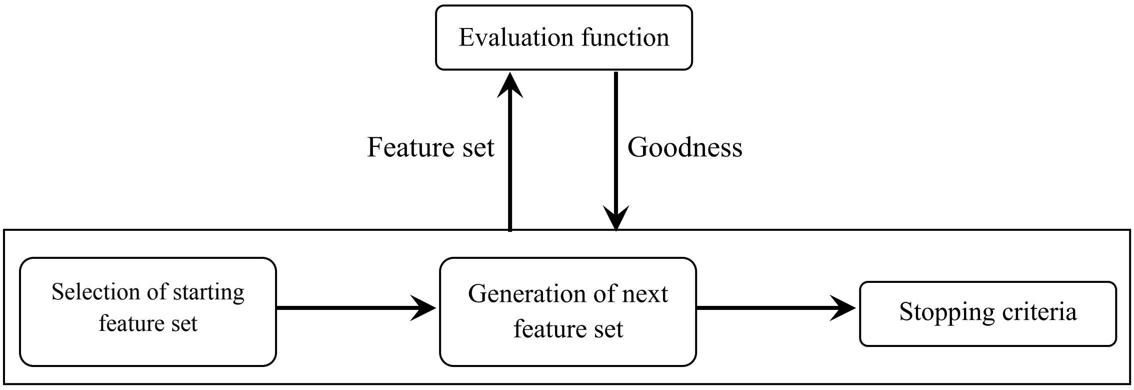


Figure 2.17 Feature selection process.

Classification cost increases with the number of feature used to describe pixel vector in multispectral space –i.e. with the number of the spectral band associated with a pixel. The number of training pixels required increases with the number of bands or channels in the data. For high dimensionality data, such as that from imaging spectrometers, that requirement presents quite a challenge in practice. So keeping the number of features used in a classification to as few as possible is important if reliable results are to be expected from affordable numbers of training pixels. Feature selection cannot be performed indiscriminately. Methods must be devised that allow the relative worth's of features to be assessed in a quantitative and rigorous way. A procedure commonly used is to determine the mathematical reparability of class; in particular, feature reduction is performed by checking how separable various spectral classes remain when reduced set of features are used. Provided reparability is not lowered unduly by the removal of feature then those features can be considered of little value in aiding discrimination [3]. Reduction in the number of band thus helps in maintaining the ratio above the minimum value and is considered as a key preprocessing step before the classification of the multispectral and hyperspectral remote sensing data [22].

In this section, feature selection methods are examining the following: Relief, Principle Components Analysis (PCA), Correlation-based Feature Selection (CFS) and Fast Correlation-Based Filter (FCBF).

2.3.1 Relief and extensions

Relief is a well known and good feature set estimator. While being usually faster feature estimators have some disadvantages [21]. Relief is a feature selection method based on attribute estimation. Relief assigns a grade of relevance to each feature, and those features valued over a user given threshold are selected. The general algorithm that Relief and all its extensions follow is show in Figure 2.18. The extensions differ in the neighbors that are searched and in how the evaluation is performed from the example pairs.

```
RELIEF (Dataset, m)

  1. For 1 to m :
     1.1  E1 = random example from Dataset
     1.2  Neighbors = Find some of the nearest examples to E1.
     1.3  For E2 in Neighbors:
                Perform some evaluation between E1 and E2
  2. Return the evaluation
```

Figure 2.18 General relief algorithm.

The key ideas of relief are: Raising relevance degree to those features that have different values on example pairs that have different concept value, Penalization of features. In parallel to previous idea, Relief reduces relevance degree to those features with different value on pairs that have the same concept value. Pairs are selected from near examples. Given an example, Relief takes other examples, with the same and different class, from neighborhood. This is probably the point where the success of relief resides. Random sampling is use to get each example used in evaluation. In this way, running time is reduced while accuracy is not significantly degraded. This is still recommended to use every example if the dataset is small or can afford. As each example is taken in a step, Relief could take more examples on the fly, if more time is available, to improve estimates, Based on these ideas from Relief. A feature set measure proposes to be used as an evaluation function in the search process [21].

2.3.2 Principle components analysis (PCA)

Feature reduction by data transformation; the emphasis of the existing set of features for the pixel data in multispectral imagery with a view to selecting the most discriminating, and discarding the rest. This also possible to effect feature reduction by transformation the data to a new set of axes in which separability is higher in a subset of the transformed features than in any subset of the original data. This allows transformed feature to be discarded. A number of image transformations could be entertained for this; however the most commonly encountered in remote sensing are the principal components with so-called canonical analysis [3]. PCA seeks to explain the correlation structure of a set of predictor variables using a smaller set of linear combinations of these variables. These linear combinations are called components. The total variables can often be accounted for primarily by a smaller set of k linear combinations of these variables, which would mean that here is almost as much information in the k components as there is in the original m variables. If desired, the analysts can then replace the original m variables with the $k<m$ components, so that the working data set now consists of n records on k components rather than n records on m variable [13].

An interesting application of principal components analysis is in the detection of features that change with time between images of the same region. The principle components transformation maps image data into a new, uncorrelated coordinate system or vector space. Moreover, in doing so, produces a space in which the data has most variance along first axis, the next largest variance along a second mutually orthogonal axis, and so on. The later principal components would be expected, in general, to show little variance. These could be considered therefore to contribute little to separability and could be ignored, thereby reducing the essential dimensionality of the classification space and thus improving classification speed. This is only of value however if the spectral class structure of the data is distributed substantially along the first few axes. Should this not be the case is possible that feature reduction of the transformation data maybe no more likely than with the original data. In such a case the technique of canonical analysis may be better approach [3].

2.3.3 Correlation-based feature selection (CFS)

In CFS features can be classified into three disjoint categories, namely, strongly relevant, weakly relevant and irrelevant features [23][24]. Strong relevance of a feature indicates that the feature is always necessary for an optimal subset; strong relevance cannot be removed without affecting the original conditional class distribution. Weak relevance suggests that the feature is not always necessary but may become necessary for an optimal subset at certain conditions. Irrelevance indicates that the feature is not necessary at all [23]. There are two types of measures for correlation between band: linear and non-linear. Linear correlation may not be able to capture correlations that are not linear. Therefore non-linear correlation measures often adopted for measurement. Correlation is based on the information-theoretical concept of entropy, a measure of the uncertainty of a random variable [24].

2.3.4 Fast correlation-based filtering (FCBF)

Fast correlation-based filtering (FCBF) is an algorithm for subset selection. The algorithm of FCBF is shown in Figure 2.19.

```
input:  S(f1, f2, ....,fN, C)  // a training data set
        δ                      // a predefined threshold
output: Sbest                  // an optimal subset

begin
 for i=1 to N do begin
        calculate SUi,c for fi;
        if (SUi,c ≥ δ)
               append fi to S′list;
 end;
 order S′list in descending SUi,c value;
 fp = getFirstElement(S′list);
 do begin
        fq = getNextElement(S′list, fp);
        if (fq <> NULL)
               do begin
                      f′q = fq;
                      if (SUp,q ≥ SUq,c)
                             remove fq from S′list;
                             fq = getNextElement (S′list , f′q);
                      else fq = getNextElement (S′list , fq);
               end until (fq == NULL);
        fp = getNextElement(S′list, fp);
 end until (fp == NULL);
 Sbest = S′list;
end;
```

Figure2.19. FCBF algorithm [25]

FCBF algorithm analyzes the relevance and redundancy using symmetric uncertainty [26]. FCBF is designed for high-dimensional data and this algorithm has been shown effective in removing both irrelevant feature and redundant features [27]. For each feature, the symmetrical uncertainty value is compared to the threshold. The features, which have the symmetrical uncertainty more than the threshold, will be considered. Then, these features are ordered by the value of symmetrical uncertainty in descending. The algorithms from 9th line to 20th line are used for removing some relevance or redundancy features.

2.4 Case study: upper Yuam basin

Upper Yuam basin has important two wildlife sanctuaries sites, including, Right Mae Yuam wildlife conservation and Doi Wiang La wildlife conservation area. Study area depict in Figure 2.20. This area was under supervision of the Protected Area Regional Office 16, Department of Forest National Park, Wildlife and Plant Conservation, Thailand.

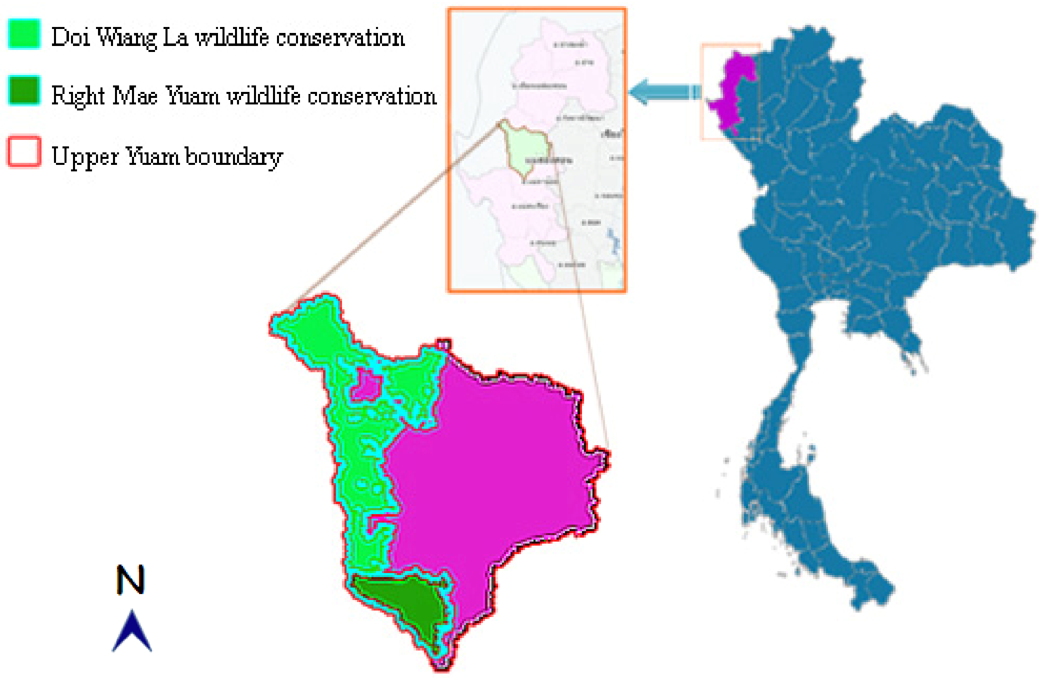


Figure 2.20 Location of the upper Yuam basin

There are 1,228.54 square kilometer of the upper Yuam basin in Mae Hong Son and Change Mai. With three districts including: Mae Chaem, Khum Yuam and Mae La Noi. Administrative district of study area details in Table 2.4.

Table 2.4 Territories in the study areas

No.	Tambon	Amphoe	Province
1	Mae Sug	Mae Chaem	Chiang Mai
2	Khum Yuam	Khum Yuam	Mae Hong Son
3	Mae Row	Khum Yuam	Mae Hong Son
4	Mae Auco	Khum Yuam	Mae Hong Son
5	Mae Yuam Noi	Khum Yuam	Mae Hong Son
6	Mungpon	Khum Yuam	Mae Hong Son
7	Mae Ki	Khum Yuam	Mae Hong Son
8	Mae Tao	Mae La Noi	Mae Hong Son
9	Mae Lalong	Mae La Noi	Mae Hong Son
10	Suntikire	Mae La Noi	Mae Hong Son

2.5 Related research

Spatiotemporal data mining is a significantly more challenging task then simple spatial or temporal data mining. Spatiotemporal data is typically stored in 3-D format that are 2-D space information and time, as discussed in [28].

Many researches proposed the steps of changed detection. A research of Robert et al., [29] proposed to simplify the steps of changed detection, which composed of four steps, i.e., data acquisition, preprocessing and/or enhancement, analysis, and evaluation. This process was applied on remote sensing data. However, the efficiency of detection depends on classification techniques. Robust and accurate classification methods were required to detect complex land cover and land use categories [30]. In [31], time and space are integrated in geo-statistic to map land cover changes. The authors propose a novel spatiotemporal analysis technique to take advantage of the over 30 year's earth monitoring satellite data. In their work, there are three sources of information for the mapping of land cover change: the remotely sensing data, the spatial pattern though which land cover classes are related, and the temporal pattern of classes. Therefore, at any location there are two types of information considered. The first are non-temporal information at a specific instant, which consists of the satellite response and the neighboring land cover indicators, and the seconds are temporal information, which is time series information that consists of transition probabilities that connect the time series indicators through time.

Decision tree classifiers (DTC) were widely used in classification of remote sensing images. In DTC, a classifier can be easily constructed and it does not complicate to apply. In research of Florencio and Zeyuan [32], J48 decision tree classifier was used for the land use changed detection. Furthermore, the efficiencies of DTC were illustrated in the researches of Darren et al., [33], and Steven et al., [34]. Features of data are directly affected to the efficiency of classification or discrimination. Thus, feature extraction is an important step for forest changed detection.

SVMs have the reputation of avoiding over-fitting. Another interesting note is made in the same article. Although in classification, one of the well-known problems is choose of dimension and many algorithms aim at reducing the dimensionality of the feature space, SVMs increase the dimensionality of the feature space. Their way of working efficiently in the height dimensionality space is margin maximization [11]. In [35], an incremental SVM classifier is proposed that utilizes the proximity of each class point to one of the two parallel planes. The advantages of the proposed algorithm are as: ability to add new data very easily, ability to compress large datasets with a height compression rate and, applicability in handling massive data set effectively. In [36], a multiclass classification that is able to support a number of prototypes' per class is built using SVM. This is non convex problem and a greedy optimization algorithm is used that is able to find local optimal solutions. The experimental results showed that using a few linear models per class instead of single kernel per class results in higher computational efficiency. Neural network classification is becoming very popular and one of the advantages is that, neural network is resistant to noise. The input layer consists of the attributes used in the classification, and the output nodes correspond to the classes. Regarding hidden nodes, too many nodes lead to over-fitting and too few can lead to reduced classification accuracy, this depicted in Goharain and Grossman [37]. Interested in using logistic regression for response variables with more than two categories may refer to “Applied logistic regression” by Hosmer [14].

The feature selections are useful feature out of the original ones by eliminating the redundant ones [22]. Preprocessing module consists of geometric correction and various band ratio functions like NDVI, PCA etc. Such as PCA, is used to reduce dimensionality of multi-spatial images from seven channels to two or three channels [38]. Feature selection has a significant value in the multispectral and hyperspectral image, as many of the bands are highly correlated and may provide redundant information for the classification related problems [22]. Fast correlation-based filtering (FCBF) [39] is applied to choose some suitable features. The goodness of the proposed features can be evaluated from the results of FCBF.

CHAPTER III
METHODOLOGY

The role of this chapter is to present steps of work in the “Remote sensing data analysis for forest change detection using feature selections and machine learning techniques”. Each of this will be outlined more detail in the following;

3.1 Steps of work

First step in this work are study around in literature review. The methodologies described in this research are separated into two parts. The first, forest change detection system are development. There are designs for display the result of data analysis. The second part runs of machine learning algorithms. This algorithm is recommended for section of data analysis. The final step is the documentation. Figure 3.1 are shown step of work.

3.1.1 Study

The data used in this research was obtained from the Department of National Park, Wildlife and Plant Conservation. Remote sensing data was collected by Landsat-5 TM, in upper Yuam basin were compared over the same time periods of 2007 and 2009. The results of detection will be used to development in the forest change detection system. This system will be developed for displaying the change area. Machine learning algorithms used sampling from variety of image from Landsat-5 TM. This data are divided into training and testing subsets. Decision trees, logistic regression, multilayer perceptron (MLP), and support vector machine (SVM) are used as classifiers. There are four feature selection techniques; principle components analysis (PCA), correlation-based feature selection (CFS), relief, and fast correlation-based filter (FCBF); that are compared in this research.

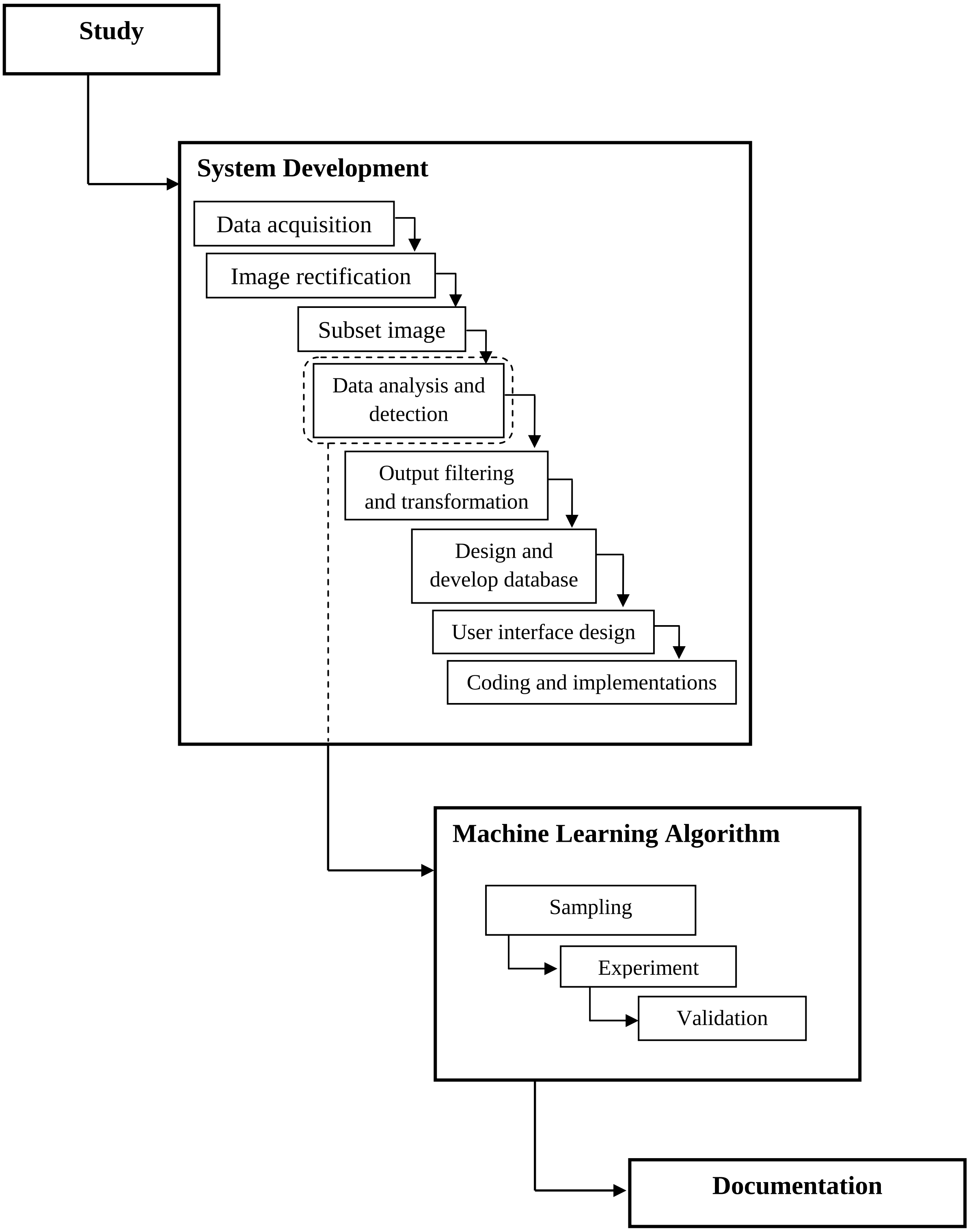


Figure 3.1 Step of work

3.1.2 System development

The aim of this part described is to prototype algorithms with a suitable basis for an operational, case study for the forest change detection system as the upper Yuam basin. The algorithms were developed based on remote sensing digital image analysis.

3.1.2.1 Data acquisitions: two sources of multispectral image data from Landsat-5 TM in year 2007 and 2009 are using for spatial data. Attribute data include; administrative district, forest conservation, mangrove area and wildlife sanctuary.

3.1.2.2 Rectification for registration of image data: this section implements by ERDAS Imagine 9.1 tool. Two steps are peculiarities, First available georeferencing and geocoding; georeferencing based on *Universal transverse Mercator* (UTM); 1:50000, and geocoding by image year 2007. Second, image to image registration. Scenes of the same geographical region, acquired at different dates of year 2007 and 2009.

3.1.2.3 Subset image: scope on study area in upper Yuam basin, office of conservative 16, within the Department of Forest National Park, Wildlife and Plant Conservation.

3.1.2.4 Data analysis: the data analysis will used to detect the forest change area. This important part of system development. The data from analysis will used to data input for the system. Normalized difference vegetation index (NDVI) and spectral signature will be use to analysis. Arc/Info Workstation are matter for coding with AML by programmer. Multispectral image data, band 3 and band 4 are used instead the near-infrared and the red reflectance respectively. The formulation as below in

$$NDVI = \frac{band\ 3 - band\ 4}{band\ 3 + band\ 4} \tag{3.1}$$

The spectral signature is used to calculate for spectral of soil, water and vegetation. The classifying rules for detected the change area may be fixing to the pair of image. Hence, the techniques for training with the variety of image of machine learning may be solving this problem. The step of data analysis with machine learning techniques explains in section 3.1.3.

3.1.2.5 Output filtering and transformation of image data: polygon less than 50 Rais would be deleted, dataset impervious to be null, projection of coordinate system.

3.1.2.6 Design and develop database: the data input for database design are obtains from the result of step of data analysis. Application software is included Microsoft visual studio 2010 for GUI and Crystal report document version 13.0.2000.0 from SAP Business Object.NET component used to generate report. Database management system used Microsoft SQL Server 2008 SP1 express edition and Toad for SQL Server 4.1.

3.1.2.7 User interface design: graphic user interface are design for display the data in database. The system will develop with visual basic language and connect to database with LINQ to SQL. The graphic user interface can joins to ArcGIS for see polygon of change. Coding and implementation is requests. The final step are installed the new components and programs with user manual, and training.

3.1.2.8 System evaluation: used questionnaire to obtain maintenance request, transforming request into change, designing change, implementing change. First version is Yuam and latest modifications to FALCON.

The detail of system development for forest change detection will describe a step by step in Chapter IV.

3.1.3 Machine learning algorithms

Machine learning algorithms are alternative to improve the performances of data analysis step. This part describes about, source of sample, method to compare run of machine learning algorithms on the datasets of satellite remote sensing. Accuracy of algorithms is measured using cross-validation, which performs multiple random splits of a given dataset into disjoint train and test sets. The detail as following:

3.1.3.1 Sampling: The image was collected by Landsat-5 (TM) on a cloud–free day, tile (185×185 kilometer) including a variety of land cover types in upper Yuam basin were compared over the same time periods of 2000, 2007, and 2009. The bands 1-5 and band 7 of sensor cover 0.45 to 2.35 μm range of the electromagnetic spectrum. The ground resolution of the dataset is 30 meter per pixels (accepted band 6 is 120 meter). The image subset for study is 1,600×1,800 pixels. This research presents the change detection for three classes at two different times, the matrix shown in Table 3.1. There are three class of non-change and six class of change. The details of sample described in Table 3.2.

Table 3.1 The change detection contingency matrix at two different times

Class Data*	Reference Data*								
	V	S	W	VS	VW	SV	SW	WV	WS
V	x								
S		x							
W			x						
VS				x					
VW					x				
SV						x			
SW							x		
WV								x	
WS									x

* Nine-class from three different types of Vegetation (V), Soil (S) and Water (W).

The class confusion matrix must consider the possible misclassification of pixels in two dates.

Source : Modified from Congalton and Brennan (1998)

Table 3.2 Sample sets for machine learning

Type	Label	Sample sets
Non Change (Soil)	S	900
Non Change (Vegetation)	V	1,602
Non Change (Water)	W	537
Change from soil to vegetation	SV	524
Change from soil to water	SW	465
Change from vegetation to soil	VS	1,057
Change from vegetation to water	VW	424
Change from water to soil	WS	413
Change from water to vegetation	WV	408
Total		**6,330**

3.1.3.2 Experiment

1) Feature analysis: this section try to analyze the result of feature of NDVI, and NDVI combination with spectral signature index such as SigV. This combination may be increases the accuracy of classification.

2) Feature extraction: in order to improve the accuracy of forest change detection, new features are extracted. These indexes can be calculated from spectral data. However, there are many indexes and each index is good for some kinds of land cover.

3) Preprocess with feature selection: Reduction in the number of band thus helps in maintaining the ratio above the minimum value and is considered as a key preprocessing step before the classification of the multispectral remote sensing data. In this section, feature selection methods are examined in the following: principle components analysis (PCA), correlation-based feature selection (CFS), relief and fast correlation-based filter (FCBF).

4) Classification: Classification techniques in this experiment contain; decision trees, logistic regression, multilayer perceptron (MLP) and support vector machines (SVM).

The steps of machine learning algorithms are recommended. The detail of this technique describes a step by step in Chapter V.

3.1.4 Validation and documentation

This subject is described of validation with classification error type, classifier success measures and generation of the testing and training sets. Detail as followed.

1) Classification error type; there are four different types of outcomes to classification two of which are errors: false positive, false negative, true positive and true negative.

The fore outcome are better depicted in a Table 3.3 know as the confusion matrix.

Table 3.3 Confusion matrix

		Actual Value	
		Positive	*Negative*
Prediction Outcome	*Positive*	True positive	False positive
	Negative	False negative	True negative

2) Classifier success measures; the results will be calculated in term of the accuracy (Acc.), area under receiver operation characteristic curve (ROC), precision (Prec.), and recall (Rec.). The formulas of accuracy, precision, and recall are illustrated in equation (3.2)-(3.4):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3.2}$$

$$Prec. = \frac{TP}{TP+FP} \tag{3.3}$$

$$Rec. = \frac{TP}{TP+FN} \tag{3.4}$$

When TP, TN, FP, and FN are the numbers of true positive, true negative, false positive, and false negative examples, respectively.

3) Generation of the testing and training sets; tenfold cross-validation has become the standard method in practical terms [20]. That is the best scheme for evaluation.

3.2 Research tools

3.2.1 Hardware: Computer

Processor: Intel® Core™2 Duo CPU T6400

Installed memory (RAM): 4.00 GB

System type: 32-bit Operating System

3.2.2 Software

3.2.2.1 Operating System: Microsoft Windows 7 Ultimate.

3.2.2.2 Software: ERDAS Imagine 9.1, ArcGIS, Arc/Info Workstation, Microsoft visual studio 2010 and Crystal report document version 13.0.2000.0 from SAP business object.NET component.

3.2.2.3 Database Management System: Microsoft Office Access 2007, Microsoft SQL Server 2008 SP1 Express Edition and Toad for SQL Server 4.1.

3.2.2.4 Weka version 3.6.6

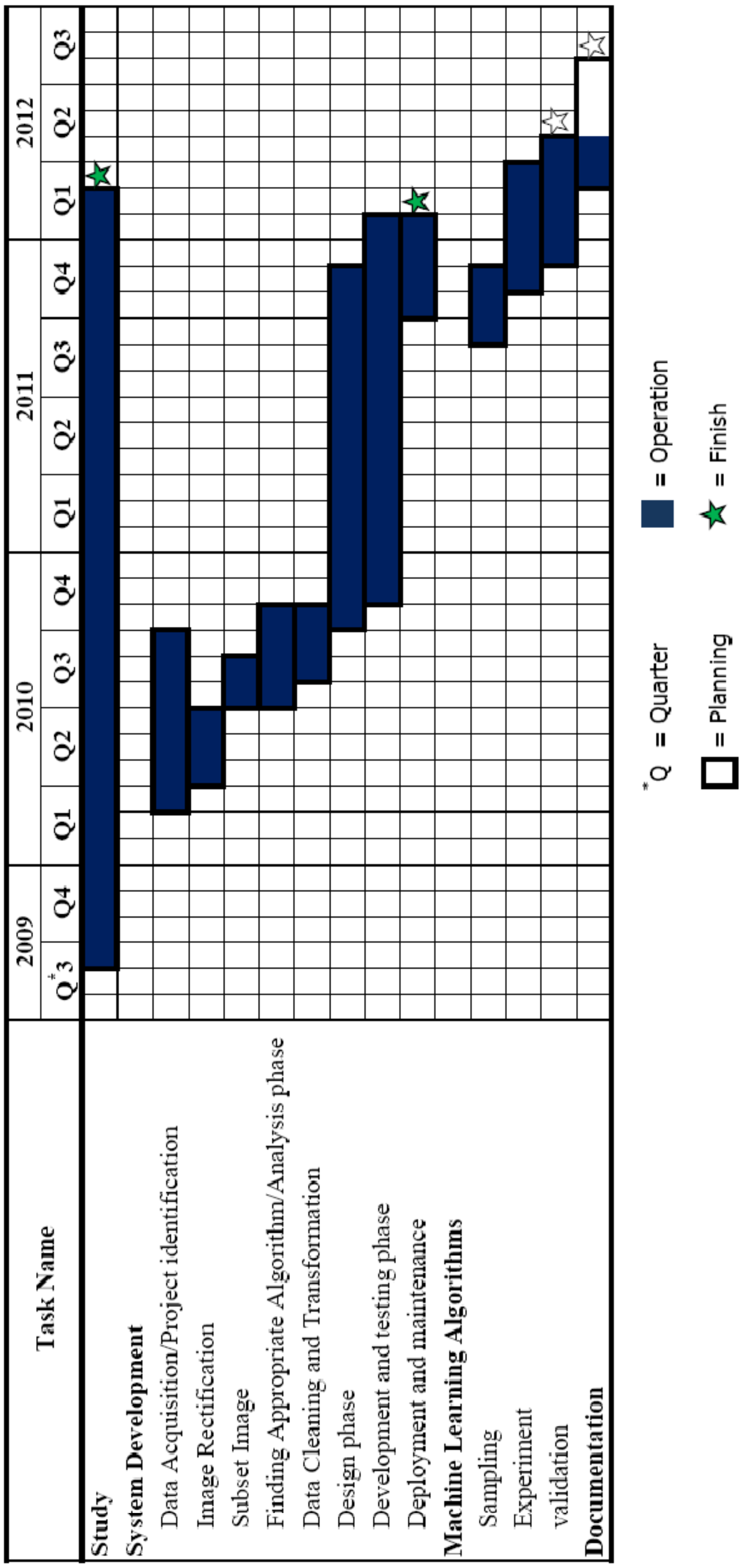
3.2.3 Raw Data

3.2.3.1 Topographic map scale 1:50000, *L7017*

3.2.3.2 Satellite Images: Image from Landsat – 5 TM, year 2007 and 2009; Path/Row is 131/47. Full name of image show as r13147_20070213 and r13147_20090306.

3.2.3.3 Attribute data including forest conservation, wildlife sanctuary, mangrove area, and administrative district.

3.3 Research plan



CHAPTER IV
FOREST CHANGE DETECTION SYSTEM

This chapter aimed to design the systematic of forest change detection. Data acquisition, image rectification and subset image are providing. The remote sensing images are prepared for the next step. Then, the process of data analysis, output filtering and transformation, with is important of the matter of detection. The final part of this chapter describes the detail of designed system database development, user interface coding and implementation. Development process of forest change detection system is shown in Figure 4.1.

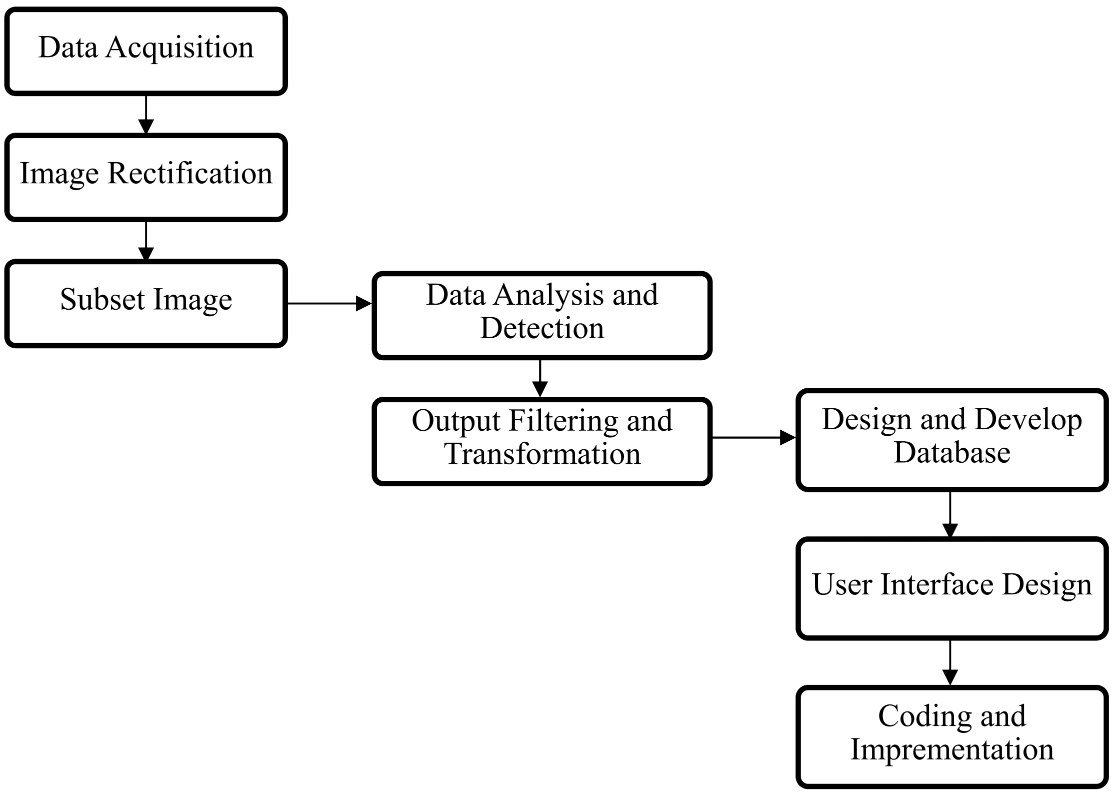


Figure 4.1 Development process of forest change detection system

4.1 Data acquisition

This research obtains the data from the Department of National Park, Wildlife and Plant Conservation, Thailand. The study area covers two important wildlife sanctuaries, Doi Viang Lha and Mae Yuam (right-site). Both areas are located at upper Yuam basin. They cover some parts of Mae Hong Son in the north of Thailand. Topography of these areas composes of the steep-complex mountain, watershed of several rivers.

This section addresses on multispectral digital image, spatially distribute data and non-spatial data in digital format. The data in this research are compound of two multispectral images, topographic map, upper Yuam basin boundary and four of spatial data of forestry, i.e., administrative district, forest conservation, mangrove area and wildlife sanctuary. Eight layer sources are shown in Table 4.1.

Table 4.1 Data for forest change detection system

No.	Spatial data	Description
1	Multispectral data: r13147_20070213	Digital image data from Lansat-5TM in first year (Date: 13-02-2007)
2	Multispectral data: r13147_20090306	Digital image data from Lansat-5TM in second year (Date: 6-03-2009)
3	Topographic data	Digital topographic map, 1:50000
4	Boundaries of upper Yuam basin	Upper Yuam basin boundary
5	Administrative district	Administrative district of Thailand
6	Forest conservation	Forest conservation of Thailand
7	Mangrove area	Mangrove area of Thailand
8	Wildlife sanctuary	Wildlife sanctuary of Thailand

Multispectral data was collected from Landsat-5 TM on a cloud–free day. There are seven wavebands cover 0.45 to 2.35 μm range of the electromagnetic spectrum, without the thermal band. The sixth band is an image that responds to the thermal infrared waves and different ground resolution are not discussed in this chapter. Data with 8 bits radiometric resolution has 256 levels of brightness. The ground resolution of the dataset is 30 meters per pixels. Landsat-5 TM has frame of

185×185 kilometers. Therefore, an image contains 38 million pixels (185×185) kilometers/ (30×30) meters in each of the other six bands. Example of path/row of Landsat–5 TM is depicted on Figure 4.2. The study area lies in path 131/row 47. The variety of land cover types were compared over the same seasons in the periods of 2007 and 2009.

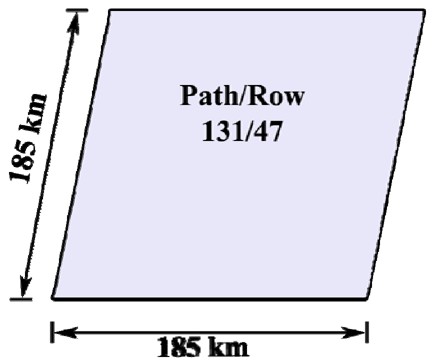


Figure 4.2 Example of path/row of satellite remote sensing

Topographic map is based on Universal Transverse Mercator (UTM); 1:50000; L7017; WGS84 coordinate system. This will use to reference image in section 4.2. The upper Yuam basin covers 1,228.54 square-kilometers. This boundary will use to subset image in section 4.3. Subset image selection is the studied area.

Spatial data consist of vector and raster format. The vector format needs to arrange on raster format before analysis process in section 4.4 – 4.5. The result of this process is used to system design in final part of this chapter.

4.2 Image rectification

The image from sensors on satellites may be containing geometric error. Image rectification is a process to minimize distortions. The example of distorted of satellite image and rectified image shown in Figure 4.3. Methods to registration image in the next sections are detailing.

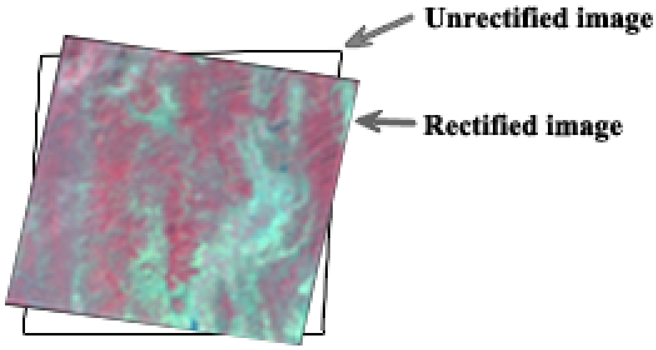


Figure 4.3 Example of distorted image and rectified image

4.2.1 Georeferencing and geocoding

In the first year, the satellite data were adjusted to correct geographic coordinates. Referenced image using the L7017, 1:50000 scale map of the Military Department. Figure 4.4a shows a reference map in the upper Yuam basin and adjacent areas. The reference position used as ground control points that represented by the star symbol. The satellite images of Landsat-5 TM path131/row47 are covering the most of study area. The raw image of r13147_20070213, acquired on February 13, 2007 is used to be an input image. This image is shown in Figure 4.4b. Ground control points on the raw image that represented by the circular symbols. When matching this point to the reference position on the map, this image is called g13147_20070213. Figure 4.4c is shows this geocoding image. The error on each point and automatic synchronization reports detail in the Appendix B. The result of rectifying image coordinates by topographic map reference with 58 ground control points. This root mean square (RMS) error is 0.496.

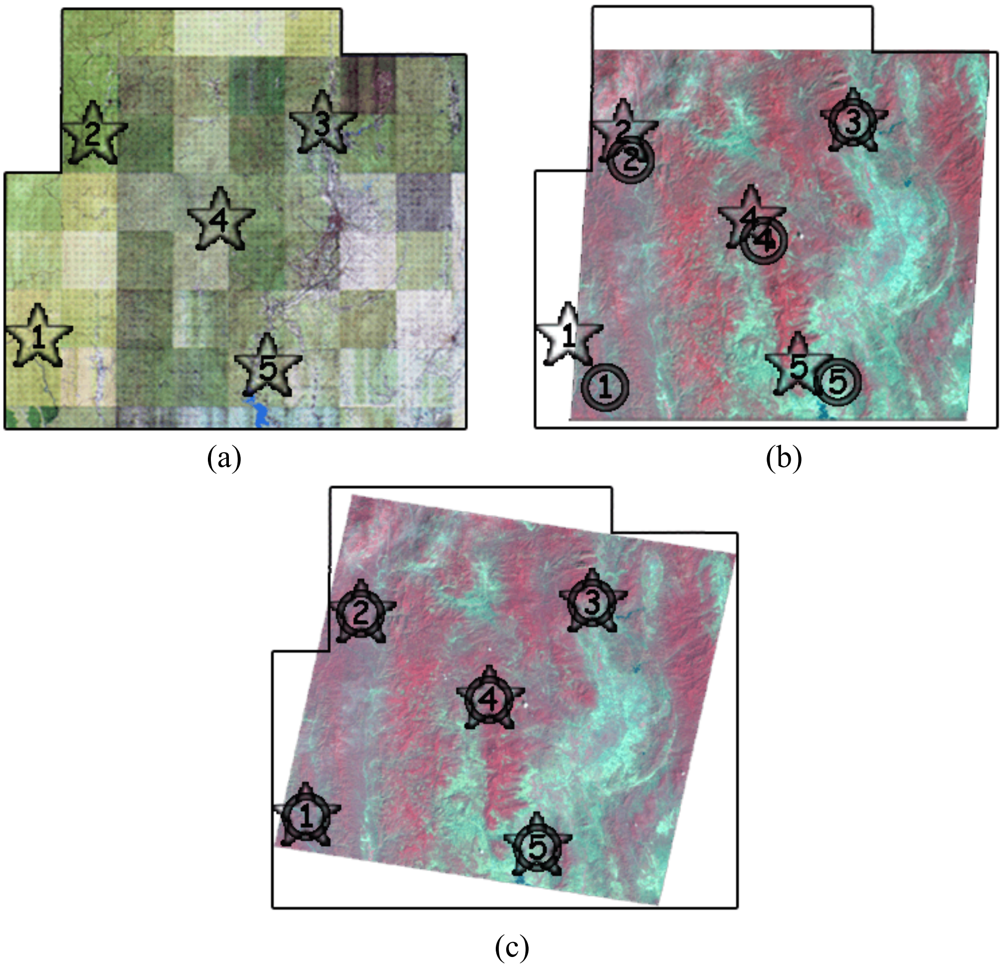


Figure 4.4 Registration of multispectral image path131/row47 from Landsat-5 TM, acquired on February 13, 2007

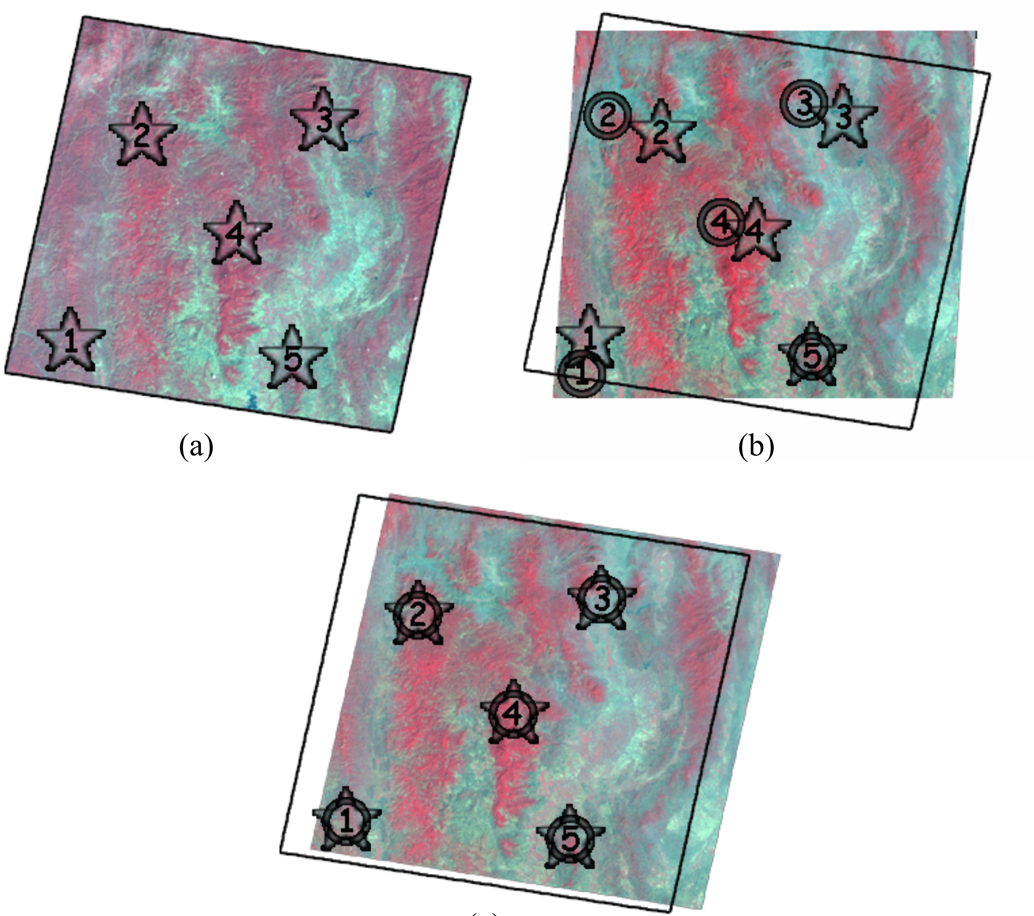
(a) Reference image: topographic map

(b) Input image: r13147_20070213

(c) Output image: g13147_20070213

4.2.2 Image to image registration

Output image from the previous section (g13147_20070213) is used as the reference image that shown in Figure 4.5a. The raw second year of satellite images of Landsat-5 TM path131/row47 is used to input image. The image of r13147_20090306 was acquired on March 6, 2009. This image is shown in Figure 4.5b. The registration image of g13147_20090306 is shown in Figure 4.5c. The result of 347 automatic point measurements (APM) demonstrates in the Appendix C, that shown RMS error 0.412.



(c)

Figure 4.5 Registration of multispectral image path131/row47 from Landsat-5 TM, acquired on March 6, 2009

(a) Reference image: g13147_20070213

(b) Input image: r13147_20090306

(c) Output image: g13147_20090306

The image to image registration method is easier than using a topographic map based. This method can point origin by APM polynomial mapping. However, this method may have some disadvantages. If a source of reference image contains high error, the slave image will have more error.

4.3 Subset image selection

Images obtained from Landsat-5 TM are quite large. Total the tile of path 131/row 47 about 185×185 kilometer. That has an area 34,225 square kilometers or 38 million pixels (34,225 square kilometers / (30×30) mater). This research is scope on upper Yuam basin area. The polygon of this area are 1,228 square kilometers or 0.768 million Rais (1,228 square kilometers × 625 Rais) Thus, a sub image is approximately 2,700 square kilometers or 1.688 million Rais or 3 million pixels of size 1,668 × 1,800 pixels frame of image subset selection, details in Table 4.2.

Table 4.2 The area of image subset selection from Landsat-5 TM

Image	**Tile**	**Area**		
		Square kilometer	Million Rais*	Million pixel
Landsat-5 TM	185x185 km	34,225	21.391	38
Upper Yuam basin	-	1,228	0.768	-
Image subset selection	1,668x1800 pixel	2,700	1.688	3

* 1 square kilometers = 625 Rais

The tile of path131/row47 from Landset-5 TM is selected. The boundary of upper Yuam basin lay on g13147_20070213 and g13147_20090306. These images depicts on Figure 4.6a and Figure 4.6b. The image subset selection of g13147_20070213 shows in Figure 4.6c, and g13147_20070213 shows in Figure 4.6d.

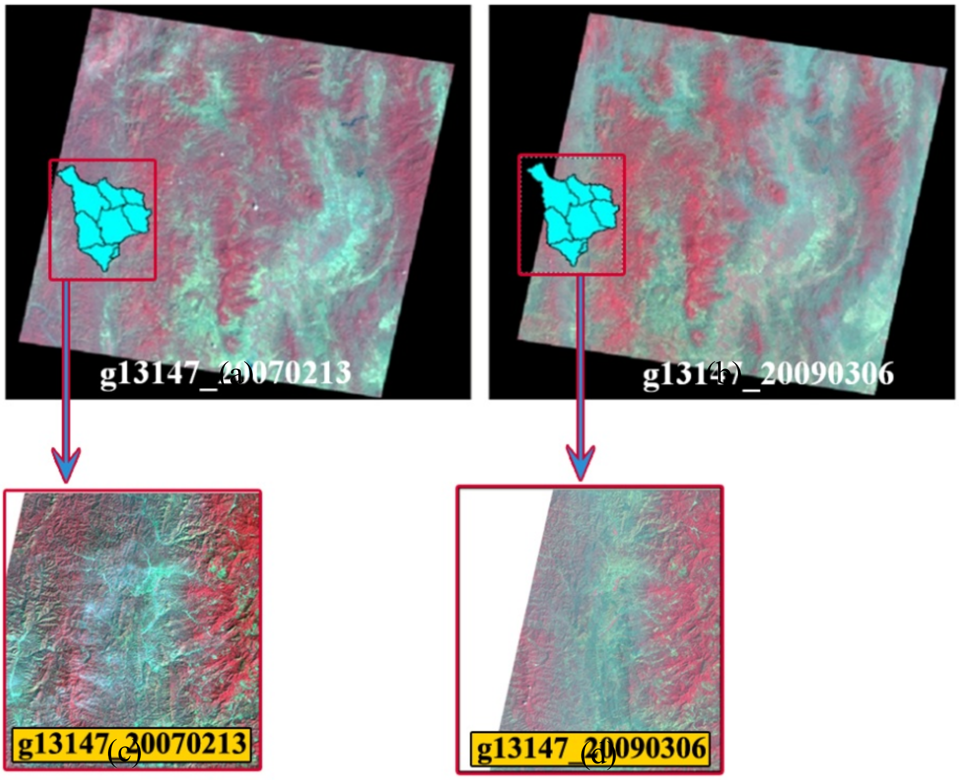


Figure 4.6 The upper Yuam basin boundary and multispectral image path 131/row 47 from Landset-5 TM

(a) g13147_20070213: acquired on 13 February, 2007

(b) g13147_20090306: acquired on 6 March, 2009

(c) Image subset selection of g13147_20070213

(d) Image subset selection of g13147_20090306

4.4 Data analysis and detection

Images that obtained from the previous section are used for forest changed analysis. Each image contains 7 wavebands. The 6th band responds to the thermal infrared waves and different ground resolution. There, the 6th band is not used in this analysis. The example of image and its 6th bands are shown in Figure 4.7.

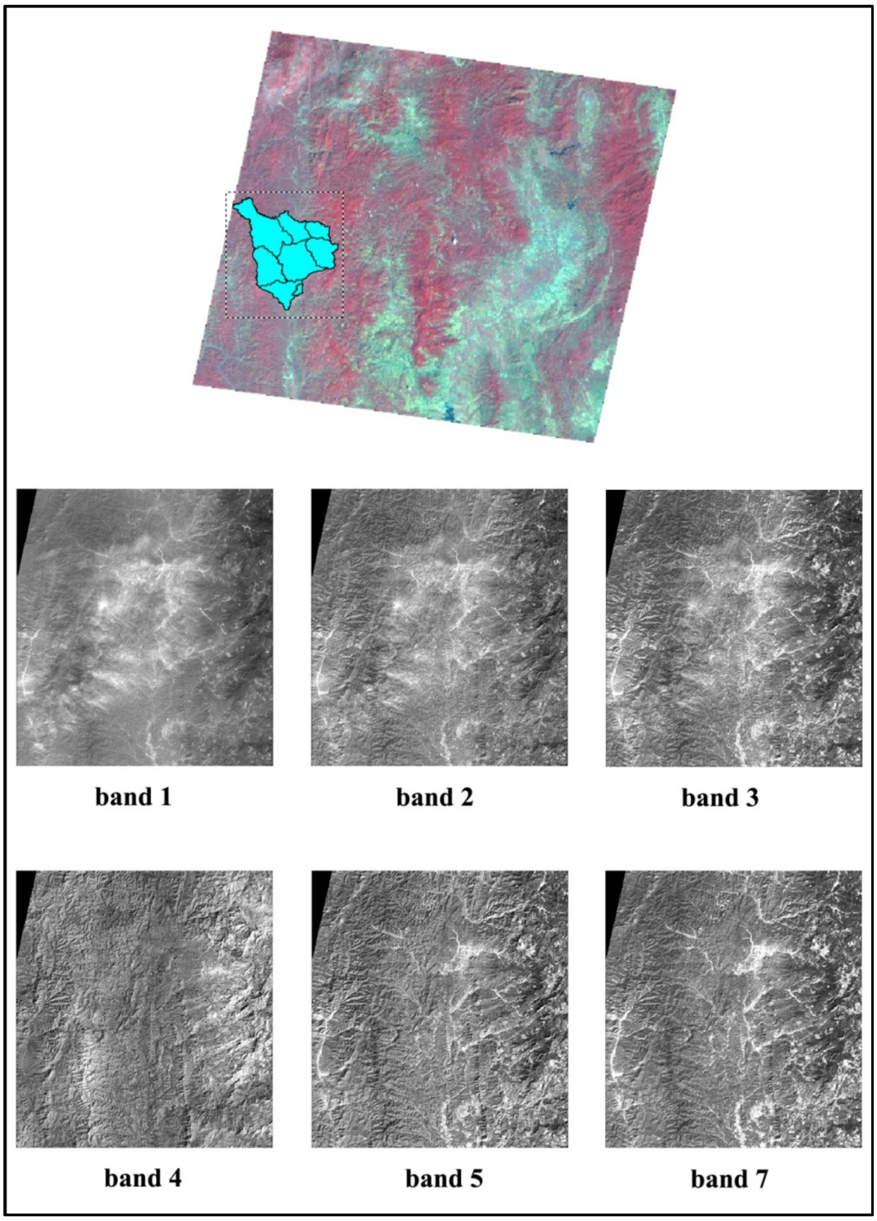


Figure 4.7 Multi-band of Landsat-5 TM in upper Yuam basin and nearby area; image scene of path 131/row 47, receive date: 13 February 2007

The images are converted from vector image to raster image. Three classes of soil, water, and vegetation are shown in the Figure 4.8.

Figure 4.8 Three classes divided according to component environment

Normalized difference vegetation index (NDVI) is one of the most widely used vegetation index. In NDVI, visible red and near infrared bands of electromagnetic spectrum are adopted to analyze remote sensing data. This index is directly related to ground cover, photosynthetic activity of the plant, surface water, leaf area, and the amount of biomass. The operation of NDVI is shown in equation 4.1.

$$NDVI = \frac{near\ infrared - visible\ red}{visible\ red + near\ infrared} \qquad (4.1)$$

Generally, healthy vegetation will absorb most of the visible light and will reflect a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Soils reflect moderately in both the red and infrared spectrum. NDVI focuses on the satellite bands that are most sensitive to vegetation information (near-infrared and red). Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1. In practice, the extreme negative values are represented to water, the values around zero are represented to soil, and the positive values are represented to the dense green vegetation. A line number is represented NDVI values in the same plane. The overlapping value between the 2 classes is ambiguity to classification, as illustrates in Figure 4.9. That can be analyzing with signature as the following.

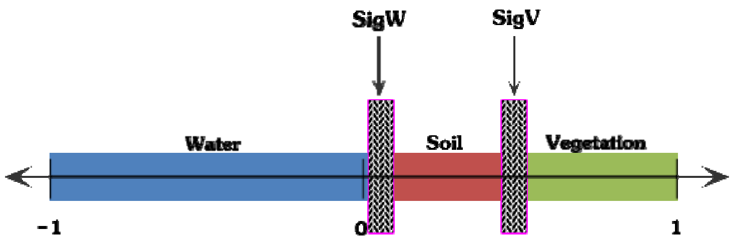


Figure 4.9 NDVI value and overlap of classes

Satellite images are the reflection of brightness value 256 levels in the each pixel. The sample in this analysis represented classes of vegetation, water, and soil, as shown in Figure 4.10. The #1 is the class from the first year and #2 is the class from the second year.

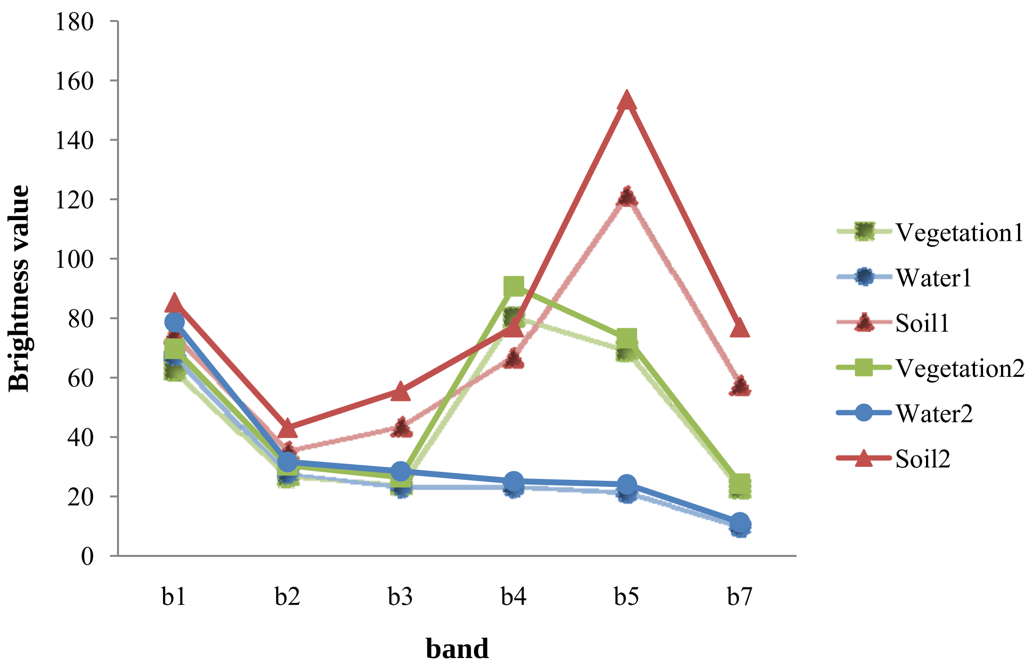


Figure 4.10 Spectral reflectance characteristics of water, vegetation, and soil

Considering the differences between band 2 to band 5 of vegetation and soil in the graph, those have changing in different directions. The ensample of curve sketched in Figure 4.10, visible red has chlorophyll absorption band leaving green reflection of any significance. These explain chlorophyll pigmented plants seeing as green. SigV will be as many weights as band that written as equation 4.2.

$$\begin{aligned} SigV = {} & visible\ green - (2 \times visible\ red) \\ & + (2 \times near\ infrared) \\ & - shot\ wave\ infrared \end{aligned} \tag{4.2}$$

Where the remote sensing data obtain by Landsat-5 TM, visible green represent in band 2, visible red represent in band 3, near infrared represent in band 4, and shot wave infrared represent in band 5. The sample calculated from equation 4.2 shown results of SigV. That detail in Appendix D. The value of SigV will be a very positive part of the vegetation class and opposite direction when the part of soil class. Figure 4.11 are illustrated.

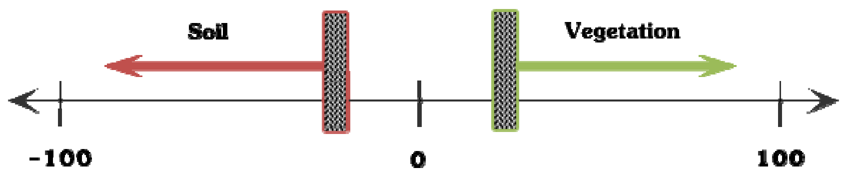


Figure 4.11 The line number of SigV values

The overlapping area between the soil and water from NDVI calculated can be separate with signature. When considering band 2 to band 5 of soil and water in Figure 4.10 that is opposite direction. The value of soil reflectance increases approximately monotonically with wavelength. As the water, slightly value is reflecting from visible light and zero reflecting with infrared – But, a little value may be reflecting from suspended sediments or bottom material. Hence, band4-band5 is a little worth reflection for the water and value higher than for the soil. The formulas of these signatures are shown in equation (4.3)-(4.4). The value from formula is illustration in Figure 4.12.

$$SigS = \ shot\ wave\ infrared - visible\ green \qquad (4.3)$$

$$SigW = \ visible\ green - shot\ wave\ infrared \qquad (4.4)$$

Where visible green represent in band 2 and shot wave infrared represent in band 5 of the remote sensing data obtain by Landsat-5 TM. The sample calculated from there equation detail in Appendix E. The value of SigS will be a very positive part of the water class and opposite direction when the part of soil class. Figure 4.12 are illustrated.

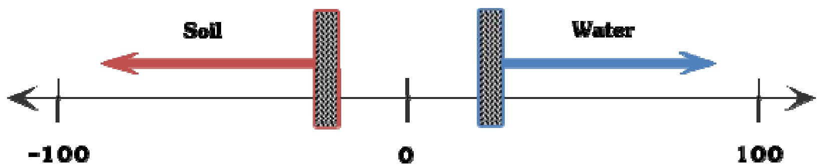
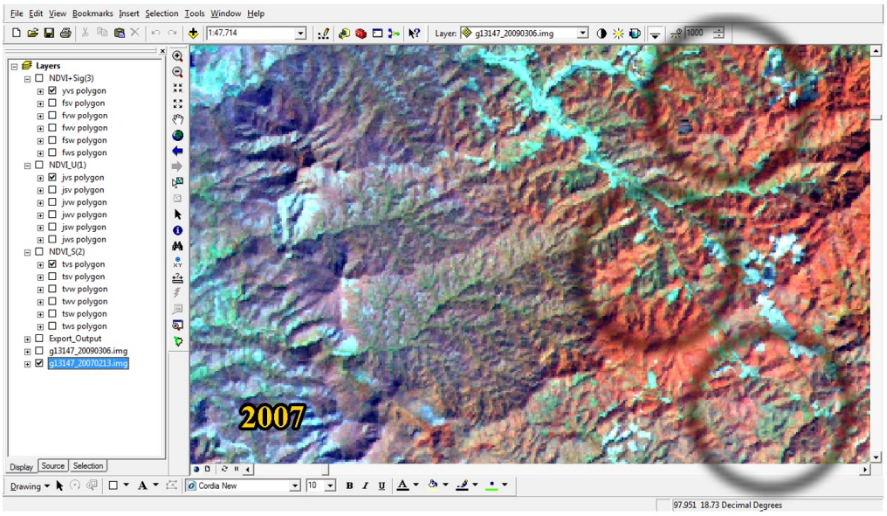
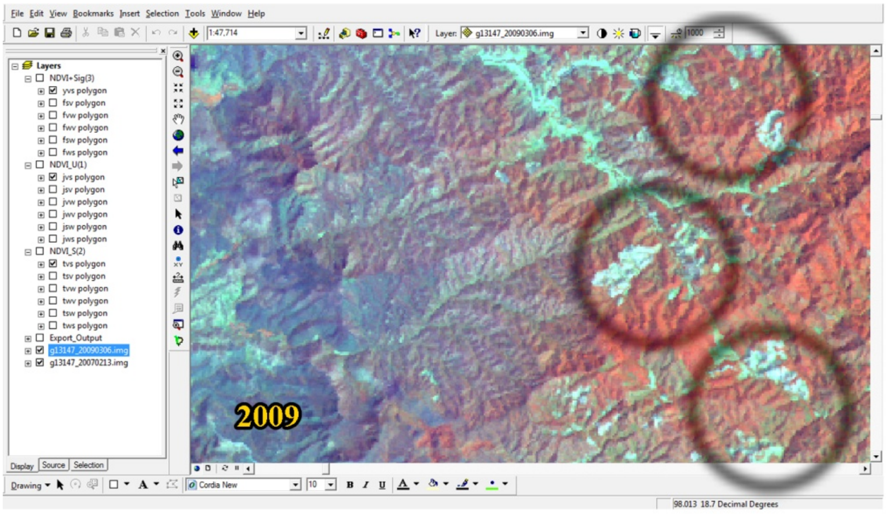


Figure 4.12 The line number of SigS or SigW values

The forest change area on two different time periods will be classified into six classes, i.e., vegetation change to soil, vegetation change to water, soil change to vegetation, soil change to water, water change to vegetation, and water change to soil. Compare the area approximate 1.207 million Rai or 71.54% of subset image selection. The set of rule of NDVI alone and NDVI combination with SigV, SigS, and SigW express in Appendix F. Resample the rule of forest change detection, vegetation area change to soil in each set. Formation of a Landsat-5 multispectral scanner false color composite by display in Figure 4.13; the near infrared band as red, the shot wave infrared band as green and visible red band as blue. Hence, vegetation shows as variations in red-owing to the high infrared response associated with vegetation, and soil show as cyan. The circles are draw to assist visual validation of the change area.



(a)



(b)

Figure 4.13 Landsat-5 multispectral scanner false color composite by band 4, 5, and 3; circle of area of forest change detection

(a) g13147_20070213: show the area of vegetation in 2007

(b) g13147_20090306: show the area of soil in 2009

Example of the rule to class discrimination for vegetation change to soil area is following. The result will shows polygon of change area from each set. This analysis compares the rule of NDVI and the rule combination of NDVI with SigV and SigS.

Classification results only the rule of NDVI shown in Figure 4.14. This rule expressing of the following:

IF ndvi1 > 0.39 **AND** ndvi2 ≥ 0.08 **AND** ndvi2 ≤ 0.33 **THEN** Area change from vegetation to soil

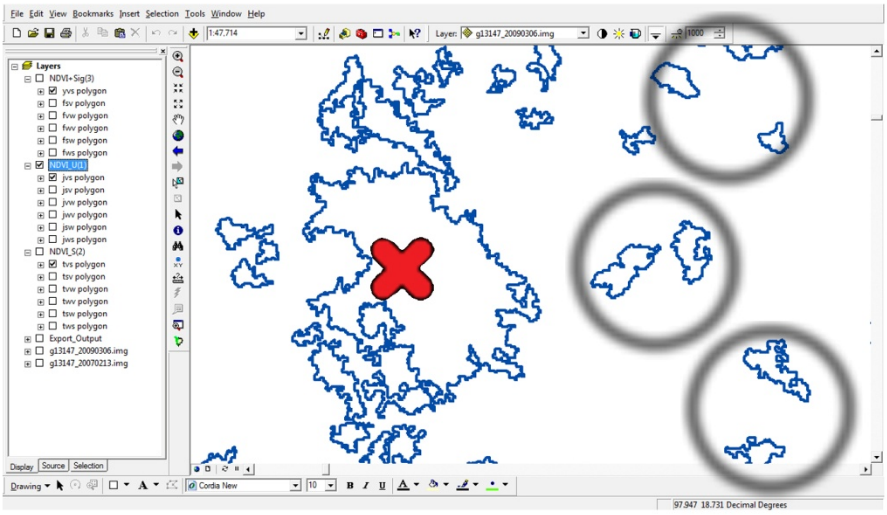


Figure 4.14 The example polygons of forest change detection by the rule of NDVI

In the circled can be detecting the forest cover change area. That a respectable area, but outside this area are non-respect result. Many polygon results by NDVI rule outside the circled. So the signature determines to classify this area.

Class discrimination from the rule combines of NDVI with SigV and SigS shows in Figure 4.15. This is considering example polygons of vegetation change to soil. This rule expressing of the following:

IF ndvi1 > 0.37 **AND** ndvi2 > 0.07 **AND** ndvi2 < 0.38 **AND** SigV1 > 13 **AND** SigS2 > 64 **THEN** Area change from vegetation to soil

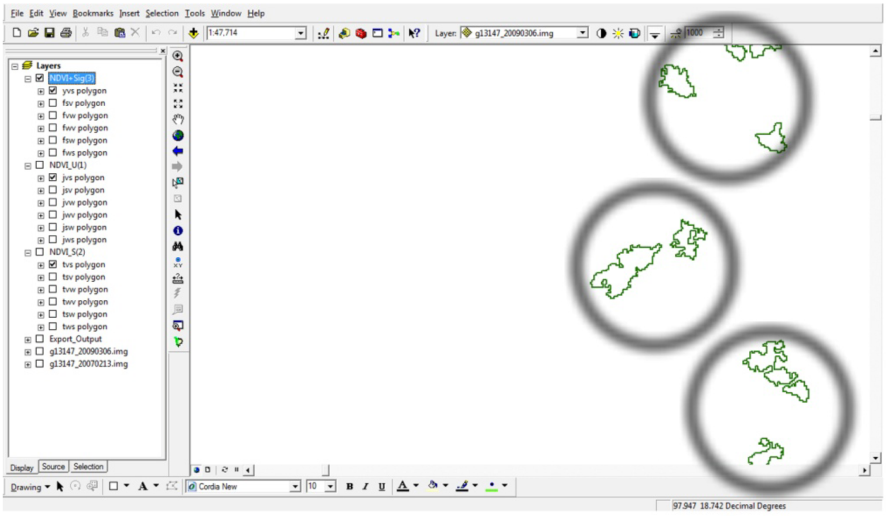


Figure 4.15 The example polygon for forest change detection by the rule combination of NDVI with SigV and SigS

The comparison study between the results of each set classifier. The rule combine of NDVI with SigV and SigS are more realistic and appropriate valuables for forest cover change detection. The result by this way successfully to classification forest change detection in the circled and visible area outside.

The roles of feature to classify the forest change area are comparing in the section 5.2. However, the rule of data analysis can detect the respect of forest change area. But, these rules are fixable to the pair of image. Hence, Machine learning algorithms in Chapter V are alternative way to solve this problem.

4.5 Output filtering and transformation

Filters can be designed to extract noise, polygon area lesser than 50 Rrais or less than 0.08 km^2 are removed. In the second part, development of transformation theory depends upon knowledge of geographic information system. The Universal Transverse Mercator (UTM) geographic coordinate system is differs of latitude and longitude in several respects. UTM zone in Thailand are located between zone 47 and zone 48. The map projection has transformed geographic coordinate from Latitude/Longitude to UTM and UTM transform to Latitude/Longitude.

For example, some of analysis rule are treated in section 4.4. The rule of NDVI, calculated land cover change is 468,230 Rais, about 38.78% of comparison area. This has content high frequency noise. The modification in the manner can be filtering. Frequency components less than 50 Rais will have been deleted. The reconstructed image, 164,194 Rais form those components to be retained. Therefore, the filtering has reduced noise approximate 25.18% of detected area. The output filtered has shown in Table 4.3.

Table 4.3 Show result of forest change detection area

Type	**Set of rules of NDVI**			**Set of rules combination of NDVI with SigV, SigW, and SigS**		
	Polygon	Changed area (Rai)	% Change	Polygon	Changed area (Rai)	% Change
VS	1,395	149,376	12.37%	289	20,717	1.72%
SV	187	14,081	1.17%	57	4,487	0.37%
VW	-	-	-	-	-	-
WV	-	-	-	-	-	-
WS	13	685	0.06%	-	-	-
SW	8	52	0.00%	-	-	-
Total	1,603	164,194	13.60%	346	25,204	2.09%

Table 4.3 summarizes the results after filtering and transformation. The result of forest change detection shows the total area of changed. Image subset selection is 1.688 million Rais. The intersection area of twain image is 1.207 million Rais. That using to detect the area of forest change detection. Set of rules of NDVI,

calculated 13.60% of forest change detection. While combination rules of NDVI with SigV and SigS result only 2.09% of forest changes detection. Illustrations for example of forest cover change area shown in Figure 4.16.

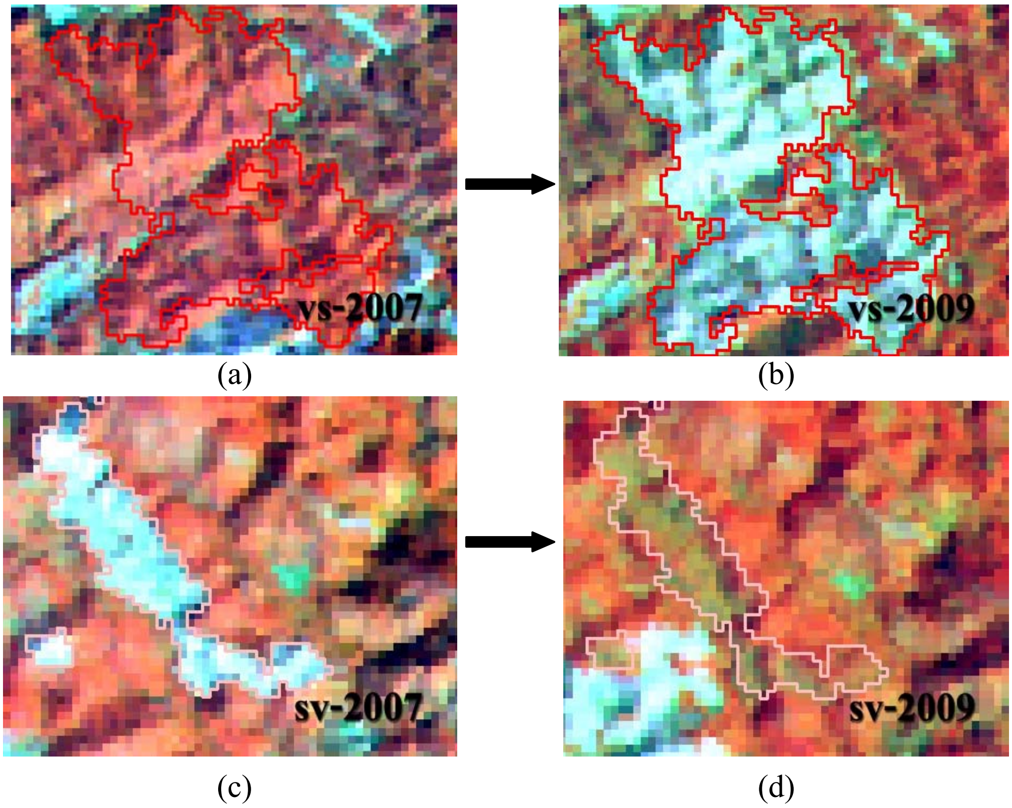


Figure 4.16 Example of polygon of forest cover change detection

(a) Area change from vegetation to soil; show vegetation in 2007

(b) Area change from vegetation to soil; show soil in 2009

(c) Area change from soil to vegetation; show soil in 2007

(d) Area change from soil to vegetation; show vegetation in 2009

Figure 4.16 shows the result of forest change detection. Figure 4.16(a) shown polygon of vegetation in the first year. This area change to soil in the second year depict in Figure 4.16(b). That represents the forest loss, while the forest gains respectively from Figure 4.16(c) change to Figure 4.16(d). The areas outside their polygon are persisting area, or will change with other factor.

4.6 Design and development database

The system is designed for division of geoinformatics, office of protected area rehabilitation and development, the department of national park, wildlife and plant conservation, Thailand. Users can access to the application system via login page. The user interface design for this system wish depicts in the next section. Diagram of forest change detection system illustrate in Figure 4.17.

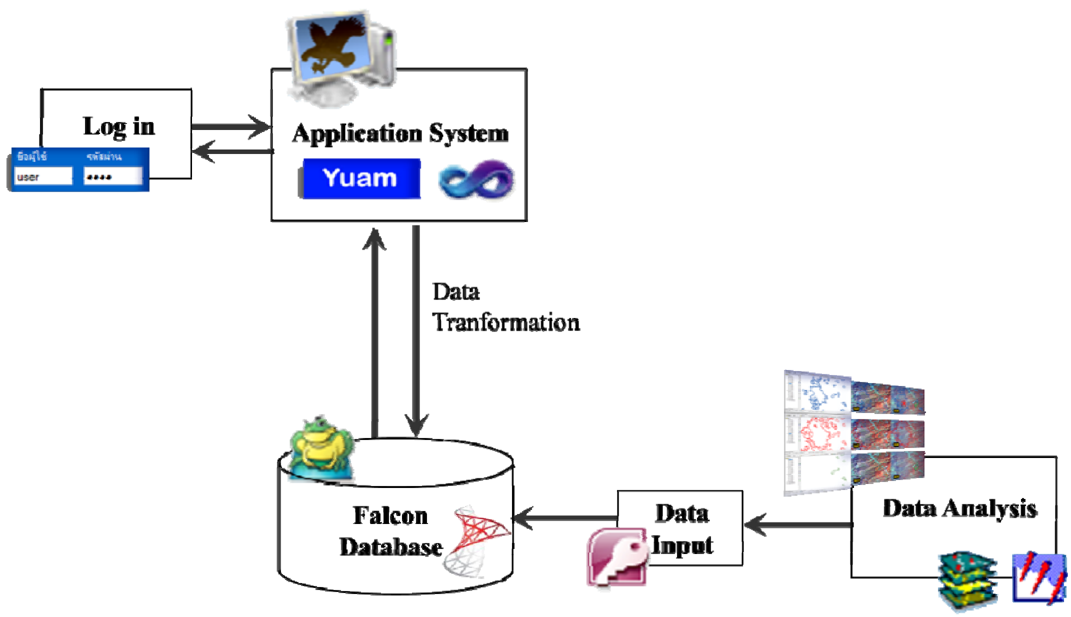


Figure 4.17 Forest change detection system diagram

Experiments design from the previous section has result for forest cover change. Those results of attribute data are used for data input in the system. For develop database to support the big data. The data from Microsoft Access is upsize to SQL server database. The example of upsizing report is details in Appendix G. Entity relationship (ER) diagram design for the Falcon database. The main table relate to administrative district, forest conservation, mangrove area, and wildlife sanctuary. Table experiment are contents the rule from analysis section. Table condition contains the classes for forest change detection. The ER diagram shows in Figure 4.18 and data dictionary expand in Appendix H.

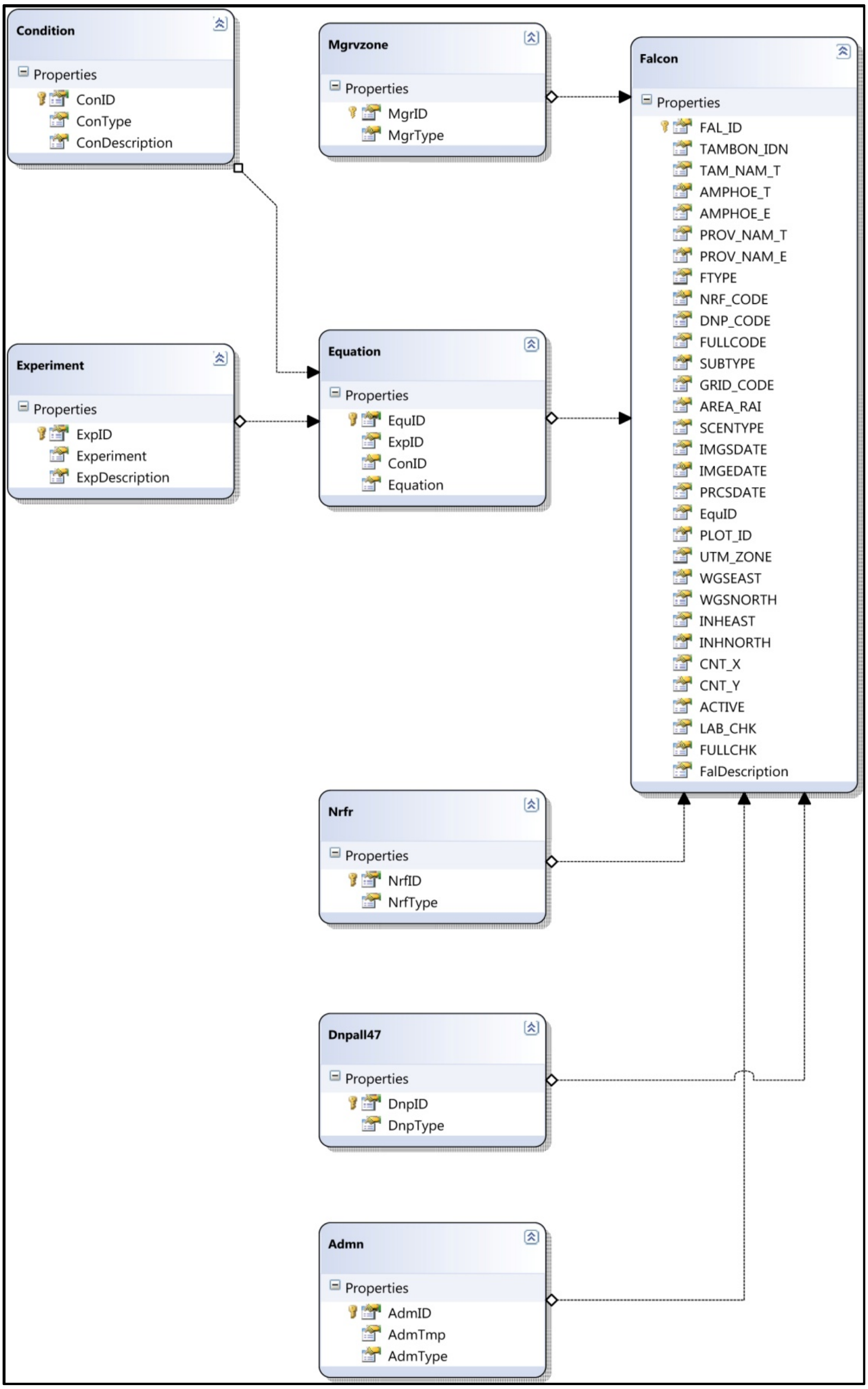


Figure 4.18 Entity relationship diagram

4.7 User interface design

Graphical user interface (GUI) is allows user to interact with application for forest change detection system. This program design easier access to big data in falcon server. The diagram of GUI design shown in Figure 4.19

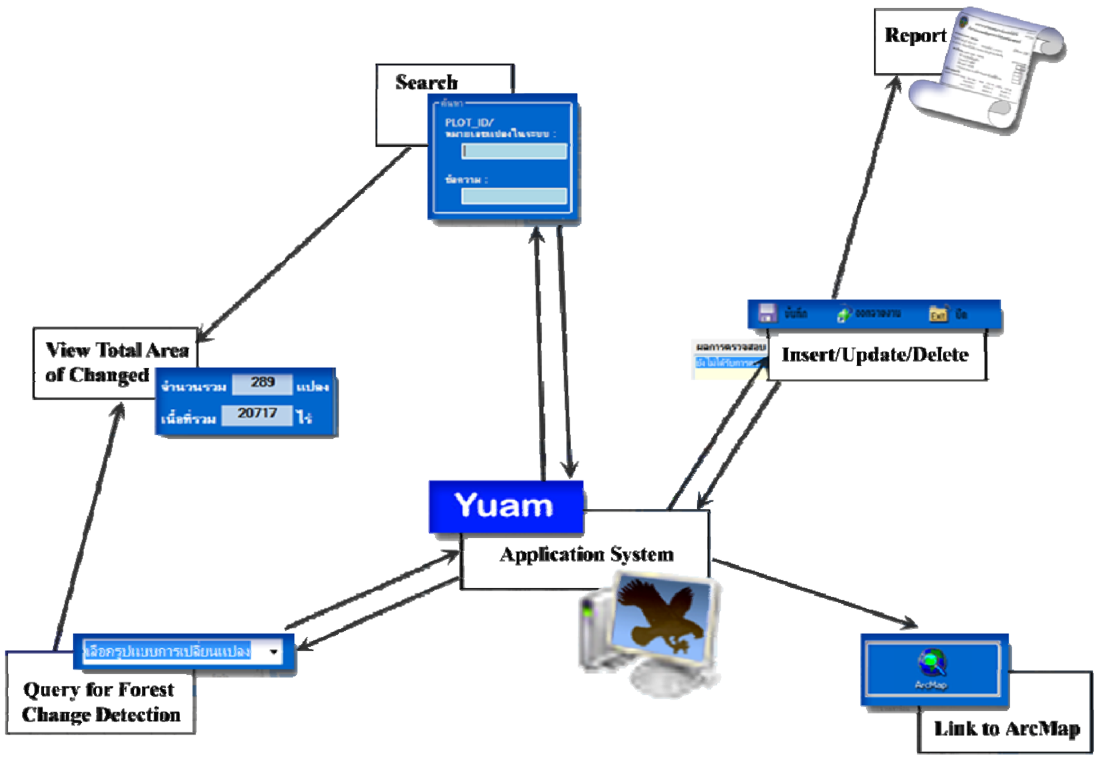


Figure 4.19 User interface diagram

Application in the home page contains the five functions. There are select index change, link to other application, search, grid view, and query. This page interface shown in Figure 4.20.

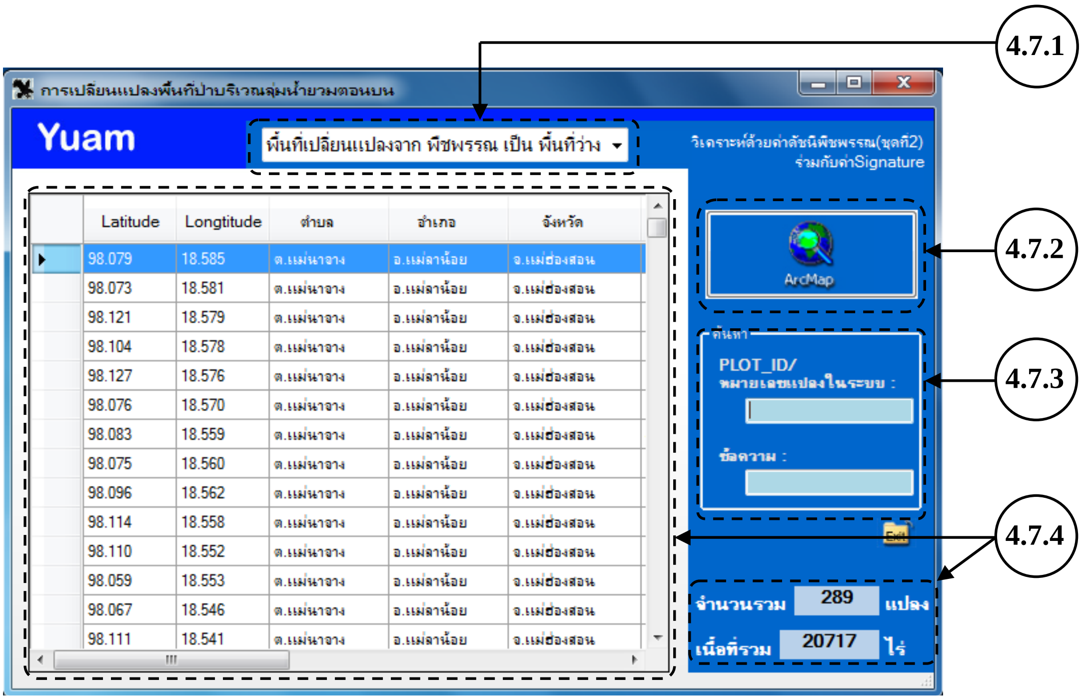


Figure 4.20 The interface of home page

4.7.1 Query for forest change detection

User can select class index of forest change area from the combo box. The number of polygon and total area from data grid view are summation in this function. The data on grid view, text box total count the polygon, and text box summary of total area view update to new list when select index change.

4.7.2 Link to ArcMap

The program of geographic information systems is use to analysis image. User can select code of system conversion (PLOT_ID) from this program, shown in Figure 4.21. This code use to search in the application of forest change detection.

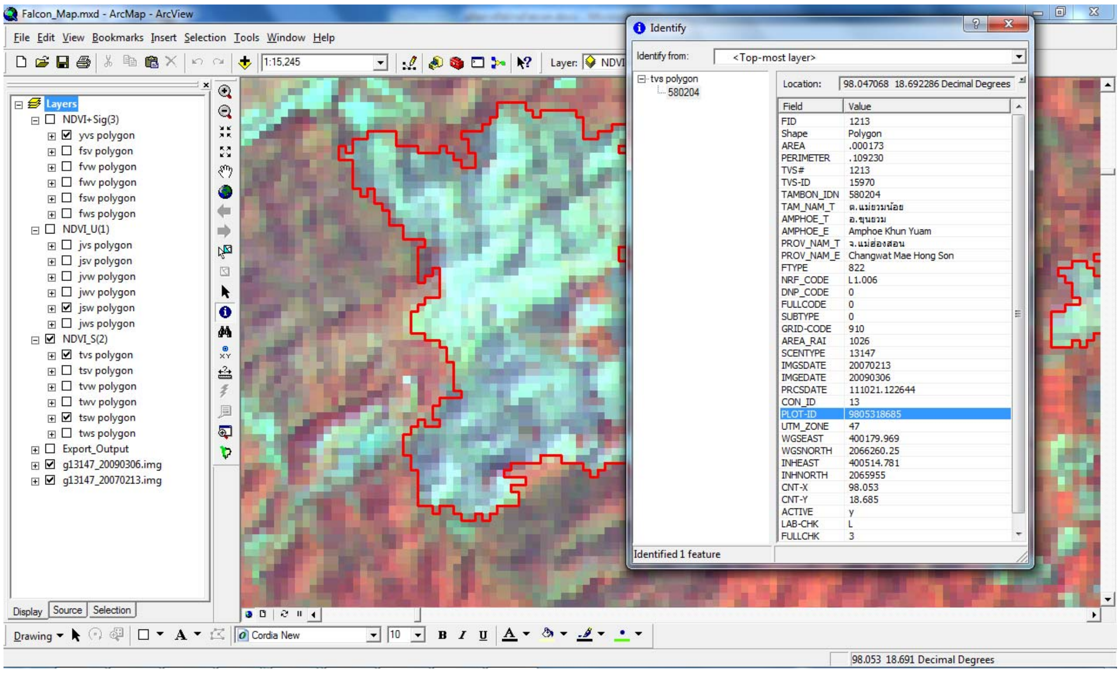


Figure 4.21 ArcGIS tool for example of forest change detection

4.7.3 Searching

In this function, users can search the information by using key down PLOT_ID to text box. Only numeric is using to key down in this search. The data on grid view, text box total count the polygon, and text box summary of total area view update to new list when select index change. On the other hand, users can key the text down to text box search. Search as, name of district, province, or wildlife sanctuary.

4.7.4 Manage information

Data grid view result forest change detection on the home page. Users can double click on the record that shows on the table to get new page for edit information. In new page, users can insert, update, or delete description for this record. When save the record. User can print out report for other division to survey this area. The example of output report was shown in Figure 4.22.

แบบ ศปท.อส. 101
ลำดับที่00000/2554

แบบรายงานการตรวจสอบการเปลี่ยนแปลงพื้นที่ป่าไม้
ด้วยการประมวลผลข้อมูลจากดาวเทียมสำรวจทรัพยากรธรรมชาติ

หมายเลขแปลงในระบบ : 9784218965 เนื้อที่ที่ตรวจพบ 71.00 ไร่

ข้อมูลจากดาวเทียมวันที่ 6 มีนาคม 2009 ประมวลผลเมื่อวันที่ 21 กรกฎาคม 2011

ผลการตรวจสอบ : พื้นที่แปลงนี้ ยังไม่ได้รับการตรวจสอบจากห้องปฏิบัติการด้านการวิเคราะห์ข้อมูล

รหัสสำหรับเจ้าหน้าที่ฐานข้อมูล

สถานที่ที่ตรวจพบ :ต.ขุนยวม อ.ขุนยวม จ.แม่ฮ่องสอน	580201
พื้นที่ สำนักบริหารพื้นที่อนุรักษ์ที่ 16	580201
ป่าสงวนแห่งชาติ ป่าแม่สุรินทร์	L1.002
พื้นที่ป่าอนุรักษ์ ดอยเวียงหล้า	2052
การจำแนกเขตป่าชายเลน นอกเขตพื้นที่การจำแนกเขตการใช้ประโยชน์พื้นที่ป่าชายเลน	822

พิกัดกลางแปลงของพื้นที่ :

Geographic Coordinate on Spheriod:: Datum WGS84	Latitude 97.842 North,	Longtitude	18.965 East
WGS84 UTM Zone 47	378124.563 m.E.,		2097406.500 m.N.
Indian 1975 UTM Zone 47	378459.406 m.E,		2097101.125 m.N.

การดำเนินการเบื้องต้นของคณะทำงานวิเคราะห์ข้อมูล

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☐ มีผลกระทบต่อการเปลี่ยนแปลงพื้นที่ป่าไม้ จัดทำรายงานเสนอผู้บังคับบัญชาตามลำดับชั้น

1.ข้อเสนอจากการวิเคราะห์

เรียน ผู้อำนวยการ ศปท.อส.

ลงนาม...
(ผู้อำนวยการศูนย์)

2.ข้อสั่งการ

เรียน หัวหน้าคณะทำงานปฏิบัติการ

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☐ แจ้ง ศปท.อส.
☐ อื่น ๆ ....

กำหนดเวลาที่ต้องรายงานผล

ลงนาม...
(หัวหน้าคณะทำงานปฏิบัติการ)

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เรียน หัวหน้าคณะทำงานวิเคราะห์ข้อมูล

แจ้งหน่วยงานที่เกี่ยวข้องเพื่อดำเนินการแล้ว

☐ ผ่านระบบ eQSo เมื่อ .... ผู้แจ้ง.......................................
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☐ ส่ง ศปท.อส. เมื่อ .... ผู้ส่ง.......................................

โดยมีผลการตรวจสอบข้อมูลจากหน่วยงานในพื้นที่ ดังนี้

....
....
....

ลงนาม...
(หัวหน้าคณะทำงานวิเคราะห์ข้อมูล)

☐ บันทึกข้อมูลทั้งหมดเข้าระบบแล้ว

หมายเหตุ :: ข้อมูลในส่วนความรับผิดชอบของกรมป่าไม้และกรมทรัพยากรทางทะเลและชายฝั่ง ขอให้ผ่านการตรวจสอบของ ศปท. กรมที่รับฯ หากพบข้อผิดพลาดในเรื่องค่าพิกัดและขอบเขต ขอได้โปรดแจ้งให้กลุ่มปฏิบัติการภูมิสารสนเทศ ส่วนภูมิสารสนเทศ สำนักฟื้นฟูและพัฒนาพื้นที่อนุรักษ์ กรมอุทยานแห่งชาติ สัตว์ป่า และพันธุ์พืช ทราบด้วยเพื่อจักได้ดำเนินการแก้ไขต่อไป

ศปท. อส. โทร 025610777 ต่อ 411 โทรสาร 025799633 จัดพิมพ์รายงานเมื่อ 31 สิงหาคม 2011

Figure 4.22 Output report for forest change detection

The user interface designs are apply by coding and implementations. Process of moving from Microsoft Access to SQL Server is developing for the database. Users can access to this database via application on Windows. The applications are code from Visual Basic.NET. Documentation is written about an application for forest change detection system. That manual is using to training the end-users. The success of implementation qualifies by user satisfied test.

4.8 System evaluation

Questionnaire is used to user acceptance test (UAT). A total of four users from Division of Geoinformatics, Office of Protected Area Rehabilitation and Development, the Department of National Parks, Wildlife and Plant Conservation, Thailand are the target group. The questionnaire is divided into three sections. The first is general information of users. The second is levels of satisfaction. And the final is comments and suggestions. The example of questionnaire is shown in Appendix I. The results of the questionnaire were analyzed. This result shows that all of users have ability to use the tools of geographic information systems (GIS). The comments and suggestions are used to improve the system.

The forest change detection system is evaluated by measuring user satisfaction. The levels of satisfaction in questionnaires is divided into two phase of functional and usability test, and the output satisfaction of the system. Weighted mean score is divided into 6 levels. The ranges of score average point calculate from (n – 1)/n when n is number of levels. Therefore, an average point range 1 – 1.83 is poor, 1.84 – 2.67 is fair, 2.68 – 3.50 is rather fair, 3.51 – 4.33 is rather fine, 4.34 – 5.17 is fine, and 5.18 – 6.00 is excellent. The result described in Table 4.4 and Table 4.5 as following.

Table 4.4 The results functional and usability test

No.	Satisfaction issues	S.D.	Average point	Level of satisfaction
1	Speeds of the system	0.82	5.00	Fine
2	Ability of the information presentation	0.82	5.00	Fine
3	Easy to use	0.82	5.00	Fine
4	Ability of Log in	0.96	5.25	Excellent
5	Ability of interface	0.96	4.75	Fine
6	Ability to edit result	0.00	5.00	Fine
7	Ability of report	0.58	5.50	Excellent
8	Ability of the system in overview	0.50	5.25	Excellent
	Total average point	**0.68**	**5.09**	**Fine**

The results of questionnaire for functional and usability test found that the overall satisfactions from users. Standard deviation of this test is 0.68. Total average point from users in the system for forest change detection is fine.

Table 4.5 The results output satisfaction test

No.	Satisfaction issues	S.D.	Average point	Level of satisfaction
1	Accuracy of the information presentation	0.96	5.25	Excellent
2	Accuracy of usability	0.58	5.50	Excellent
3	Accuracy of Log in	0.96	5.25	Excellent
4	Accuracy of interface	0.82	5.00	Fine
5	Accuracy of edit result	0.82	5.00	Fine
6	Accuracy of report	0.50	5.25	Excellent
	Total average point	**0.77**	**5.21**	**Excellent**

The results of questionnaire found that the output satisfactions from users. Standard deviation of this test is 0.77. Total average point from users in the output satisfaction for forest change detection is excellent.

CHAPTER V
MACHINE LEARNING ALGORITHMS FOR FOREST CHANGE DETECTION

The data analysis in Chapter IV had to be detected and marked manually so the rule will be specified with image that used to analyze before. Hence, machine learning will be used to solve this problem. When analyst want to analyze data from a variety of image, more techniques are required. The purpose of this chapter is to provide an algorithm for feature extraction from remote sensing data and machine learning classification. Figure 5.1 gives the step of machine learning algorithms for forest changed detection from satellite data.

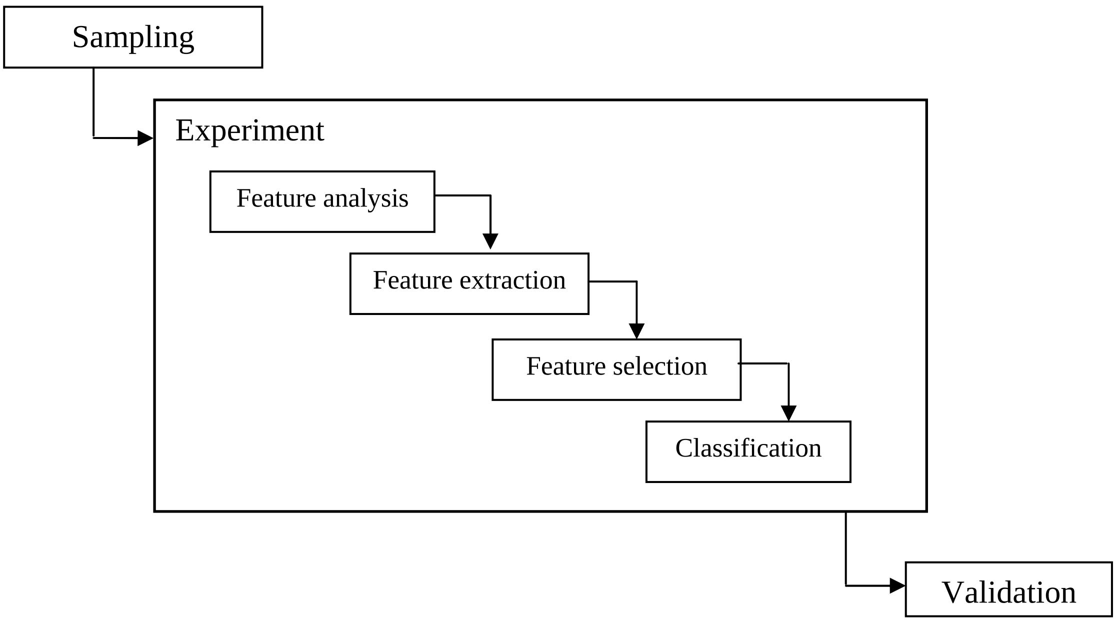

Figure 5.1 Step of machine learning algorithms for forest change detection

The remote sensing data from the satellite are processed. The features are extracted and selected. Then, these features are used for training in order to create a model for forest changed detection system. The techniques of sample set, feature analysis, feature extraction, feature selection, and classification are explained in the following subsection.

.

5.1 Sample set

Machine learning algorithms generally require quality training data to generalize well to unseen sample. This section tries to sampling dataset from variety of image for training and testing. The dataset or image was received from difference time period and difference path/row. The images from Landsat–5 TM were collected from the department of national parks, wildlife, and plant conservation, Thailand. These sources of image depict in Figure 5.2 and detail of image in Table 5.1.

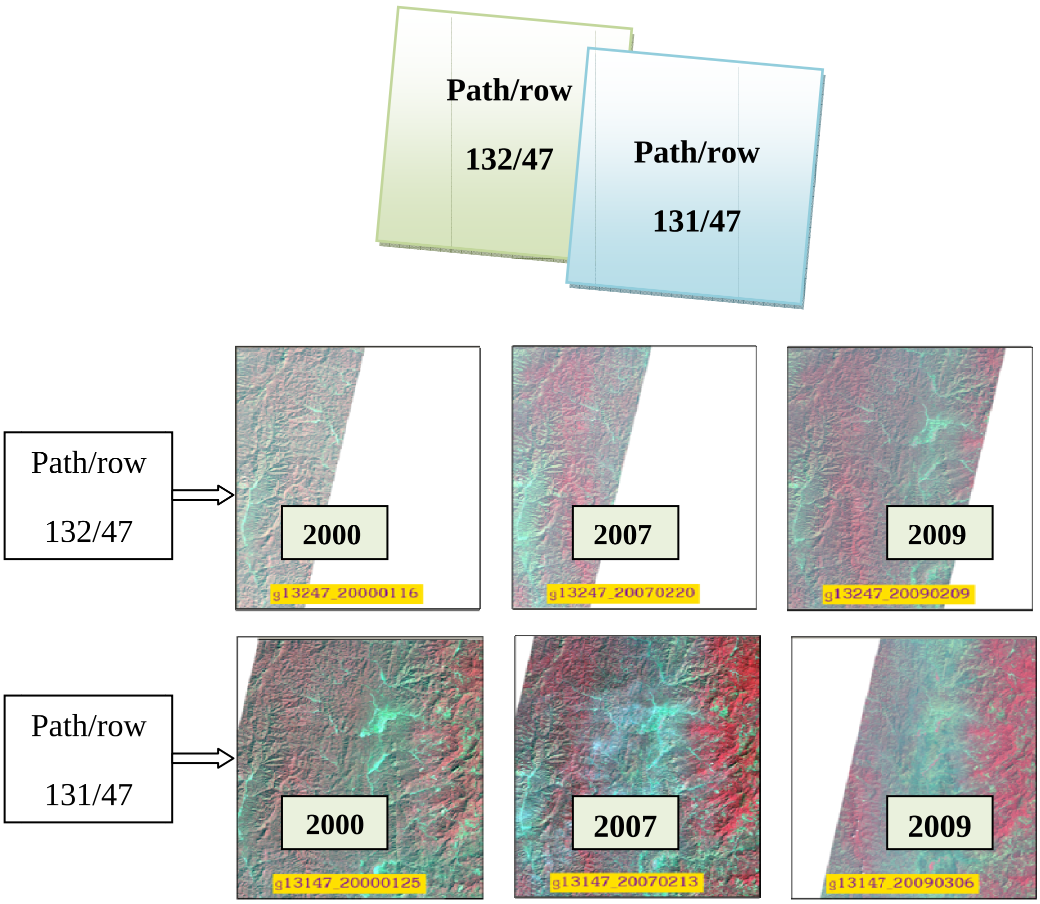

Figure 5.2 The satellite image form Landsat-5 TM acquired around 2000 and 2009, this used for the sample dataset

Table 5.1 Sample image for forest cover change detection

No.	Image name	Path/row	Acquisition date
1	g13147_20000125	path 131/row 47	25 January 2000
2	g13147_20070213	path 131/row 47	13 February 2007
3	g13147_20090306	path 131/row 47	6 March 2009
4	g13247_20000116	path 132/row 47	16 January 2000
5	g13247_20070220	path 132/row 47	20 February 2007
6	g13247_20090209	path 132/row 47	9 February 2009

The sensors without the thermal band cover 0.45 to 2.35 µm range of the electromagnetic spectrum, and ground resolution of the dataset is 30×30 meter per pixels. The images subset selection 1,600×1,800 pixels or approximate 2,700 square kilometers cover study area. This image included the varieties of land cover types on 1,228.54 square kilometers of the upper Yuam basin, Mae Hong Son provinces, Thailand.

After image pre-processing steps, 6,330 couple positions were randomly selected. The labels are assigned to these data points by expertise. Although, the forest changing can be detected by classifying each area on two different time periods and considering the different area after this classification, the changed area from this technique are not accurate. If the results of classification on a time period are wrong, the results of changed detection are also wrong. Hence, two interested time periods are considered together. Spectral information will be classified into nine classes, i.e., S, V, W, SV, SW, VS, VW, WS, and WV, when S is the soil, V is the vegetation, W is the water, and XY is the changing from X to Y. These classes must be considered on two different time period of spectral information. There are three classes for unchanged area and six classes for changed area. Then, these data points are divided into training set and test set; 6,100 data points for training set and 230 data points for test set. The numbers of data for all classes are displayed in Table 5.2.

Table 5.2 Forest classes and number of data for training and testing

Class	Label	Data Set	
		Training	*Testing*
Soil	S	860	40
Vegetation	V	1,566	36
Water	W	508	29
Soil to Vegetation	SV	478	46
Soil to Water	SW	465	0
Vegetation to Soil	VS	978	79
Vegetation to Water	VW	424	0
Water to Soil	WS	413	0
Water to Vegetation	WV	408	0
Total		6,100	230

5.2 Feature analysis

The data analysis in Chapter IV presented effect of classification from features. Only NDVI can detect the forest cover change. SigV and SigW with NDVI usage can reduce non-respect area. The performance of feature analysis will be compared in this part. The features of spectral data, NDVI, SigV and SigW are analyzed. The J48 decision tree algorithm is used to classify changed areas. Then, 6,100 samples are used for training by 10 repetitions of 10-fold cross-validation and 230 samples are tested. The result of experimentation in terms of accuracy (Acc.), ROC, precisions (Prec.) and recall (Rec.) are reported in Table 5.3.

Table 5.3 Result of feature analysis

Feature types	No. of features	Training (10 folds)				Testing (230 sample)			
		Acc.	*ROC*	*Prec.*	*Rec.*	*Acc.*	*ROC*	*Prec.*	*Rec.*
Original set	14	93.60%	0.97	0.93	0.95	85.65%	0.93	0.91	0.86
NDVI	2	84.15%	0.98	0.84	0.92	84.35%	0.95	0.90	0.84
NDVI, SigV, SigW	6	<u>97.60%</u>	<u>0.99</u>	<u>0.98</u>	<u>0.98</u>	91.74%	0.95	0.94	0.92

Table 5.3 shows the result of feature analysis compared the set of NDVI and NDVI combination with SigV and SigS. The set of tree combination are result 97.60% of training (10 fold) accuracy. That more than result from rule of only NDVI. In training set, the combination increase result 7.34% of overall accuracy, more than using only NDVI.

The result clearly demonstrateds that the overall accuracy, ROC, precision, and recall of the group of NDVI, SigV and SigW features are higher than those of original features. The number of NDVI, SigV and SigW features is smaller than the number of original features. This feature type produce the considerable higher accuracy as compare to the conventional original set or used NDVI single feature. This feature group can be successfully applied to classification problems. That corresponds to the hypothesis in section 4.4.

5.3 Feature extraction

The transformed image may make evident features not perceptible in the original data. This alternative might be possible to preserve the essential informed content of the image. In order to improve the accuracy of forest changed detection, new features are extracted. Some feature also find application in preconditioning prior by feature analysis techniques in Chapter IV and section 5.2. The NDVI, SigS, SigV and SigW are considered. These indexes can be calculated from spectral data. However, there are many indexes and each index is good for some kinds of land cover. The following indexes such as LAI, NDWI, WI, PI and MI are added in this section.

a. Leaf area index (LAI) is a key factor for determining plant growth and health [9]. This index gives the important information on the amount of leaf area [9]. NDVI is used for LAI calculation and LAI index can be calculated by equation (5.1).

$$LAI = \frac{log(0.88 - NDVI)}{log2} \times (-1.323) \qquad (5.1)$$

b. Water index (WI) and normalized difference water index (NDWI) [40] are the factors for determining the water areas. These indexes are illustrated in equation (5.2) and (5.3), respectively.

$$WI = \frac{visible\ green - visible\ red}{visible\ green + visible\ red} \tag{5.2}$$

$$NDWI = \frac{near\ infrared - shot\ wave\ infrared}{near\ infrared + shot\ wave\ infrared} \tag{5.3}$$

c. Plus index (PI) and minus index (MI) are the other indexes that can be used for classifying the remote sensing data. These indexes use both NDVI and NDWI in calculation. Plus index and minus index can be calculated by equation (5.4) and (5.5).

$$PI = 1 + NDWI + NDVI \tag{5.4}$$

$$MI = NDWI - NDVI \tag{5.5}$$

The 14 spectral bands from satellite data and nine indexes will be used as the features in the forest changed detection system. If the spectral data and these indexes are used as the features of learning, there are 32 features (14 features + (2×9) features) on the learning vectors. Moreover, we notice that the difference of 2 spectral data was used in many indexes. If the difference of 2 spectral data is used as the features of learning, the accuracy of forest changed detection may be improved. Hence, there are 74 features (32 features + (2×21) features) are extracted. These features are shown in Table 5.4.

Forest changed areas are detected by J48 decision tree classifier. The features are extracted from remote sensing data. NDVI, LAI, WI, NDWI, SigS, SigV, SigW, PI, and MI are calculated for each remote sensing data point. Also, the difference of all possible two spectral data on each data point will be computed. The accuracy of forest changed detection on 14 original features will be compared to the accuracy of all proposed features (74 features). The accuracies of forest changed detection on tenfold cross-validation, 10 repetitions and supplied test data are shown in Table 5.5. The 14 original features are compared to 74 features.

Table 5.4 Features for forest changed detection

Group of feature type	**No. of feature**	**Amount**	**Descriptions**
Original feature	1-7	7	Band 1-7 on a time period
	8-14	7	Band 1-7 on the next time period
Natural indexes	15-23	9	NDVI, LAI, WI, NDWI, SigS, SigV, SigW, PI, and MI indexes on a time period
	24-32	9	NDVI, LAI, WI, NDWI, SigS, SigV, SigW, PI, and MI indexes on the next time period
Spectral Difference	33-53	21	|Band i – Band j|, where i, j = 1,2,3,..,7 and i< j for any bands on a time period
	54-74	21	|Band i – Band j|, where i, j = 1,2,3,..,7 and i< j for any bands on the next time period
Total		74	

Table 5.5 Result of feature extractions for forest changed detection

Feature types	**No. of features**	**Training (10 Folds)**				**Testing (230 Sample)**			
		Acc.	*ROC*	*Prec.*	*Rec.*	*Acc.*	*ROC*	*Prec.*	*Rec.*
Spectral data	14	93.60%	0.97	0.93	0.95	85.65%	0.93	0.91	0.86
All feature	74	**96.63%**	**0.98**	**0.97**	**0.97**	88.26%	0.94	0.93	0.88

The all feature are extraction from remote sensing data. This feature type result overall accuracy more than spectral data – data are none extracted. The results in bold demonstrate that the results of usage of 74 feature are better than the 14 original features. The accuracies, ROC, precision and recall can be improved when 60 features from extraction are added. Some features may be unnecessary for classifying. This problem will be solved in the next section.

5.4 Feature selection

Although, many features can be extracted from remote sensing data, we do not know that which features are suitable for forest changed detection. Furthermore, the features from section 5.3 are calculated by using only 7 bands. Some features may be duplicated or may be unnecessary for classifying the changed area. Thus, feature selection techniques are applied in this section.

The considered features are experimented and these features will be chosen by some feature selection techniques. The suitable features will be used for classifying the changed area. The dimensionality reduction techniques are applied. FCBF will be compared to principle component analysis (PCA), correlation-based feature selection (CFS), and relief algorithms. There feature selection for forest change detection shown in Table 5.6 and detail in Table 5.7.

Table 5.6 Features selections for forest changed detection

Feature selection	Search method	No. of feature	Threshold
PCA	Ranker	7	0.0480
Relief	Ranker	7	0.1423
FCBF	Ranker	7	0.3814
CFS	Best First	24	-
Relief	Ranker	24	0.0982
FCBF	Ranker	24	0.3516

In relief and FCBF algorithms, the features are ranked by the relevance weighting or the symmetrical uncertainty (SU) score. The features that are better than a defined threshold will be selected. For this paper, the number of features of relief and FCBF will be selected as the number of features of PCA and CFS in order to avoid the bias of the different number of features.

Table 5.7 Top outcome from features selections for forest changed detection

No. of features	Relief		FCBF		CFS	PCA	
	ReliefF rank	*Selected attributes*	*SU rank*	*Selected attributes*	*Selected attributes*	*PCA rank*	*Transformed Attribute*
1	0.1824	NDVI#2	0.4522	LAI#2	Band7#1	0.6656	0.195DfB5-7+…
2	0.1694	LAI#2	0.4240	NDVI#1	Band5#2	0.4165	-0.207Band7#2-..
3	0.1652	NDVI#1	0.4200	NDVI#2	NDVI#1	0.2356	-0.261LAI#1+...
4	0.1643	PI#2	0.4133	LAI#1	LAI#1	0.1386	0.342LAI#2+...
5	0.1489	Band4#2	0.3917	SigV#2	NDVI#2	0.0895	0.437DfA2-6+…
6	0.1478	LAI#1	0.3872	Band5#2	LAI#2	0.0666	0.385Band1#2+...
7	0.1423	B3-B4#1	0.3814	SigW#2	SigV#2	0.0480	0.437DfA1-3-...
8	0.1417	PI#1	0.3814	SigS#2	SigW#2	-	-
9	0.1310	B1-B4#1	0.3812	B2-B7#1	MI#2	-	-
10	0.1302	B4-B6#1	0.3799	B3-B4#1	PI#2	-	-
11	0.1290	B2-B4#2	0.3792	Band7#2	B1-B5#1	-	-
12	0.1286	Band4#1	0.3755	B1-B5#1	B2-B3#1	-	-
13	0.1253	B2-B4#1	0.3711	B3-B5#2	B2-B7#1	-	-
14	0.1216	B1-B4#2	0.3666	B4-B5#2	B3-B4#1	-	-
15	0.1194	B4-B7#1	0.3659	B2-B5#1	B4-B5#1	-	-
16	0.1175	B3-B4#2	0.3659	SigW#1	B4-B6#1	-	-
17	0.1054	Band5#2	0.3659	SigS#1	B1-B4#2	-	-
18	0.1049	B5-B7#1	0.3658	Band7#1	B3-B4#2	-	-
19	0.1043	SigV#2	0.3647	B5-B7#2	B3-B7#2	-	-
20	0.1038	WI#2	0.3549	SigV#1	B4-B5#2	-	-
21	0.1033	SigV#1	0.3543	B2-B5#2	B4-B7#2	-	-
22	0.1025	NDWI#2	0.3540	B1-B5#2	B5-B7#2	-	-
23	0.0988	WI#1	0.3534	B5-B6#2	B5-B7#2	-	-
24	0.0982	B2-B5#2	0.3516	Band5#1	B6-B7#2	-	-

The dimensions of data are reduced by PCA and CFS. The features are selected by relief and FCBF. Only 7 features and 24 features are considered because

PCA transforms data and chooses only 7 features and CFS yields on 24 suitable new features. The accuracies are shown in Table 5.8.

Table 5.8 Accuracies of features selections for forest changed detection

Feature types	No. of features	Training (10 Folds)				Testing (230 Sample)			
		Acc.	*ROC*	*Prec.*	*Rec.*	*Acc.*	*ROC*	*Prec.*	*Rec.*
Spectral data	14	93.60%	0.97	0.93	0.95	85.65%	0.93	0.91	0.86
All feature	74	96.72%	0.98	0.97	0.97	88.26%	0.94	0.93	0.88
Dimensionality reduction									
PCA	7	91.84% $^{-}$	0.97 $^{-}$	0.93 $^{-}$	0.94 $^{-}$	86.52%	0.94	0.91	0.87
Relief	7	94.16% $^{-}$	0.99	0.96	0.97	90.00%	0.95	0.93	0.90
FCBF	7	94.16%	0.99	0.96	0.97	85.65%	0.94	0.93	0.86
CFS	24	96.52%	0.99	0.97	0.97	89.57%	0.95	0.94	0.90
Relief	24	95.58%	0.99	0.97	0.97	90.00%	0.94	0.94	0.90
FCBF	24	97.39%	0.98	0.97	0.98	92.17%	0.95	0.94	0.92

When result of values in underline is test base. The value with symbol ($^{-}$) are a lower than the 74 feature (test base). The values indicate in the performance at the 99% confidence level. The results show that the accuracies of forest changed detection with J48 decision tree classifier. The accuracies of forest changed detection can be improved when the suitable feature selection algorithms are applied. PCA is not a suitable algorithm in this research. Only 7 features are created by PCA and these features yield only 91.84% of accuracy on training set. The relief and FCBF yield a higher accuracy then PCA on 7 features. However, the results of relief and FCBF show that both feature selection are only 94.16% of accuracies on training set. The feature selection yields a higher accuracy, while 24 features are applied. This result is equal to the accuracy of all features, but can reduce the dimension of feature. In the comparison on sub experiment details, the FCBF can yield a better accuracy then CFS and relief on 24 features. Although, the accuracy of FCBF at 7 features lower than the accuracy of 74 features, but FCBF achieves to give the highest accuracy on training at 24 features. The result corresponds to the accuracy of testing set. This means that FCBF can improve the performance of forest changed detection on every class by average. Table 5.9 shows 24 features that are on the top selected by FCBF. These features are divided into 3 groups, i.e., original features, natural indexes, and spectral difference.

Table 5.9 Top types of features selected from FCBF

No.	**Selected features (Feature #year)**	**Types of features**		
		Original features	*Natural indexes*	*Spectral difference*
1	LAI #2	-	✓	-
2	NDVI #1	-	✓	-
3	NDVI #2	-	✓	-
4	LAI #1	-	✓	-
5	SigV #2	-	✓	-
6	Band5 #2	✓	-	-
7	SigW #2	-	✓	-
8	SigS #2	-	✓	-
9	B2-B7 #1	-	-	✓
10	B3-B4 #1	-	-	✓
11	Band7 #2	✓	-	-
12	B1-B5 #1	-	-	✓
13	B3-B5 #2	-	-	✓
14	B4-B5 #2	-	-	✓
15	B2-B5 #1	-	-	✓
16	SigW #1	-	✓	-
17	SigS #1	-	✓	-
18	Band7 #1	✓	-	-
19	B5-B7 #2	-	-	✓
20	SigV #1	-	✓	-
21	B2-B5 #2	-	-	✓
22	B1-B5 #2	-	-	✓
23	B5-B6 #2	-	-	✓
24	Band5 #1	✓	-	-
#Features		4	10	10

By FCBF, only 4 features from the 14 original features are selected. Only band 5 and band 7 from both images are used for changed detection. For natural indexes, 10 features are selected from 18 features. LAI and NDVI are selected in the first order to the fourth order. The other selected natural indexes are SigS, SigV, and SigW of both images. This means that these indexes are good choices for forest changed detection. In addition, 10 spectral difference features are selected from 42 features. We notice that band 5 appears on several features. Thus, band 5 is an important feature for the detection. In order to consider trend on the number of features, the accuracies of classification are plotted in Figure 5.3.

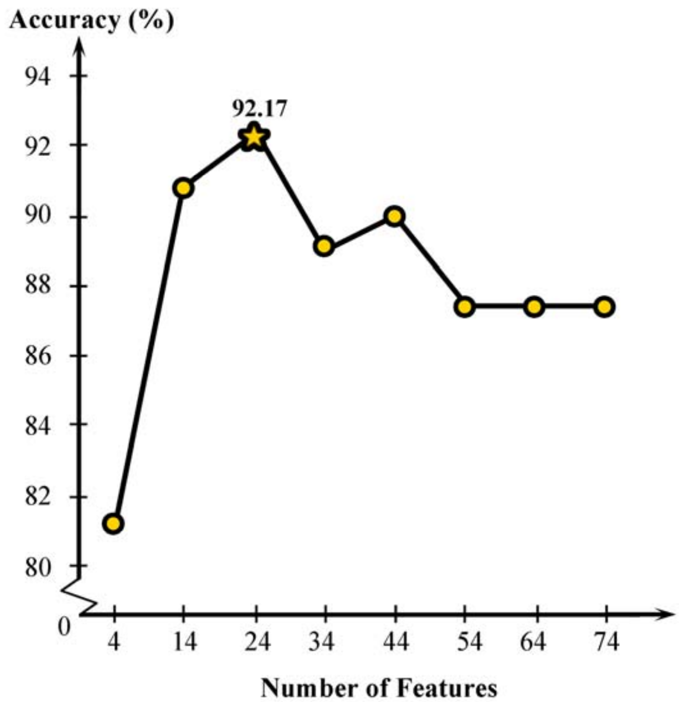

Figure 5.3 A graph of the accuracies of detection with FCBF feature selection

This figure shows that FCBF with 24 features yields the highest accuracy on test set. The top of 20-30 feature selected by FCBF are peak. These features are suitably for DTC on forest changed detection problems. The output tree from 24 features FCBF has 151 nodes and 76 leaf nodes, while a tree of the 14 original features has 333 nodes and 167 leaf nodes. Although the number of features of FCBF is increased, the size of tree is smaller than the usage of 14 original features. In the case of all 74 features, the output tree has 175 nodes and 88 leaf nodes, which is larger than the tree from FCBF feature selection.

5.5 Classification

The aim of this section is to evaluate the effect of the feature selection measures on the level of accuracy, ROC, precision and recall achieved by the four classification algorithms. Decision tree, logistic regression, multilayer perceptron and support vector machine procedures are used in this study. A summary of the properties of each of these classifiers is given in the following.

J48 creates a pruned decision tree. The confidence factor is used for pruning, this factor is 0.25 in the experiment, and smaller values incur more pruning. The minimum number of instances per leaf of tree set as 2. In the multinomial logistic regression model, the maximum number of iterations to perform is equal to minus one and ridge value in the log-likelihood is equal to 1.0E-8. The hidden layers of the neural network are also wildcard values calculated from (features + classes)/2. The radial basis function is used to kernel type for support vector machine classifier. This needed to adjust parameter of cost and gamma. The parameters of SVM are searching by grid search. The appropriate parameters of SVM for each feature groups are shown in Table 5.10.

Table 5.10 Parameter of SVM

Dataset	**No. of features**	**SVM parameter**	
		Cost	*Gamma*
Original set	14	64	4.88E-04
NDVI + SigV + SigW	6	32	4.88E-04
74 Attribute + FCBF	24	32	1.22E-04

Table 5.11 shows the level of classification accuracy achieved by DTC is compared to results from LR, MLP and SVM classifiers.

Table 5.11 Result of classification

Type of feature	**Number of Features**	**Classifier**	**Training (10 Folds)**				**Testing (230 Sample)**			
			Acc.	*ROC*	*Prec.*	*Rec.*	*Acc.*	*ROC*	*Prec.*	*Rec.*
Original set	14	J48	<u>93.77%</u>	<u>0.97</u>	<u>0.93</u>	<u>0.95</u>	85.65%	0.93	0.91	0.86
		LR	94.72%	1.00 +	0.96	0.97	88.70%	0.99	0.93	0.89
		MLP	95.95% +	1.00 +	0.96 +	0.96	89.57%	0.98	0.93	0.90
		SVM (C=64, G=4.88E-4)	96.56% +	0.98	0.97 +	0.97	89.13%	0.94	0.94	0.89
NDVI+ SigV+ SigW	6	J48	<u>97.70%</u>	<u>0.99</u>	<u>0.97</u>	<u>0.98</u>	91.74%	0.95	0.94	0.92
		LR	94.56% -	1.00	0.96	0.97	89.13%	0.99	0.94	0.89
		MLP	96.26% -	1.00	0.96	0.97	91.30%	0.98	0.93	0.91
		SVM (C=32, G=4.88E-4)	96.03% -	0.98	0.96	0.98	89.13%	0.94	0.94	0.89
Feature selection by FCBF	24	J48	<u>97.39%</u>	<u>0.98</u>	<u>0.97</u>	<u>0.98</u>	92.17%	0.95	0.94	0.92
		LR	95.26% -	1.00 +	0.96	0.98	90.43%	0.99	0.94	0.90
		MLP	97.08%	1.00 +	0.97	0.98	90.43%	0.98	0.93	0.90
		SVM (C=32, G=1.22E-4)	96.74%	0.98	0.97	0.97	89.13%	0.94	0.94	0.89

The three group of feature contained; 14 features of original set, 6 features extracted of analysis, and 24 features selection by FCBF. The performance of J48 DTC is compared with LR, MLP, and SVM. The results of experiment that investigates the effect of various classification methods on each feature group. The values indicate in the performance at the 99% confidence level. Underline value means a test base. The plus symbol ($^+$) indicates that value performs improvements, non symbol perform equally well, and minus symbol ($^-$) indicates the value are decline.

The first step, that determine to comparison classifiers in the group of original set. The both MLP and SVM methods give a higher accuracy than the J48 decision tree classifier. The result of J48 is least in this group, this classifier yield only 93.77% of accuracy on training set. In the next step, that determine to comparison classifiers in the group of feature analysis. The feature of NDVI, SigV, and SigW are extracted from satellite image. The results demonstrate that the accuracy of J48 DTC is higher than LR, MLP, and SVM. The J48 DTC give an overall classification accuracy of 97.70% on training set 10 folds cross-validation, 1 repetition. The 91.74%

on testing set 230 samples, 1 repetition are cohering. This is preferred method. The final step, that determine to comparison classifiers in the group of features selection by FCBF. The J48 decision tree classifiers give a higher accuracy than LR method. The accuracy of J48 on the training set perform equally well to MLP and SVM, that yield 97.39%, 97.08%, and 96.74% respectively.

However, the J48 DTC in the final step has a number of leaves and size of the tree smaller than using the group of combination of NDVI, SigV, and SigW – the output tree has 161 nodes and 81 leaf nodes. These results indicate that the performance of the DTC is acceptably good in comparison with LR, MLP, and SVM when used feature extraction and feature selection algorithms.

CHAPTER VI
CONCLUSION AND DISCUSSION

This thesis has objectives to design and developed the forest change detection system for Division of Geoinformatics, Office of Protected Area Rehabilitation and Development, the Department of National Parks, Wildlife and Plant Conservation, Thailand. On the other hand, the values for set of rule are troublesome analysis step in the system. Hence, machine learning algorithms can solve the problem in classification. The feature selection techniques can be improving the ability of this algorithm.

6.1 Conclusion

The satellite images from Landsat-5 Thematic Mapper (TM) were used to remote sensing data analysis for forest cover change detection. The most of upper Yuam basis and nearby area lay on path 131/row 47 and some area lay on path 132/row 47. The frames of image cover area approximate 21 million Rais. The images were rectifying with map base, topographic map series L7017. Image subset selection frame is 1.688 million Rais. This subset images are cover study area in Mae Hong Son, Thailand.

6.1.1 Conclusion on remote sensing data analysis

Normalized difference vegetation index (NDVI) is the good index for classify the class of vegetation. The remote sensing image analysis acquired in the periods of 2007 and 2009 lay on path 131/row 47. The set of rules of NDVI were defined by a threshold value. These set can classify the total of change area about 164,194 Rais that approximate 13.60%. However, this result comes out with non-respect area. Hence, the data analysis and detection in section 4.4 suggest to discrimination ambiguity of NDVI with SigV. The example of set of rules to classify the class of vegetation change to soil is shown in condition of:

IF ndvi1 > 0.37 **AND** ndvi2 > 0.07 **AND** ndvi2 < 0.38 **AND** SigV1 > 13 **AND** SigS2 > 64 **THEN** Area change from vegetation to soil

The result of rule combination of NDVI with SigV, SigW and SigS can reduce non-respect area. The total of forest change detection that classifies from the combination rules is 25,204 Rais that approximate 2.09%. There rules used to image analysis for forest change detection. The results of this analysis are used to display in the forest change detection system. However, there rule are specific with image, that do not apply with other couples detection. Hence, machine learning techniques used to solve this problem.

6.1.2 Conclusion on machine learning algorithms

In machine learning techniques, sampling the sample set from variety of remote sensing image. The couples of image data in the periods of 2000, 2007 and 2009 lay on path 131/row 47 and path 132/row. 6,330 couple positions were randomly selected. The labels were assigned to these data points by expertise. This sample divided into training and testing set. Decision tree were used to classifier. Figure 6.1 is shown the result of feature analysis on training.

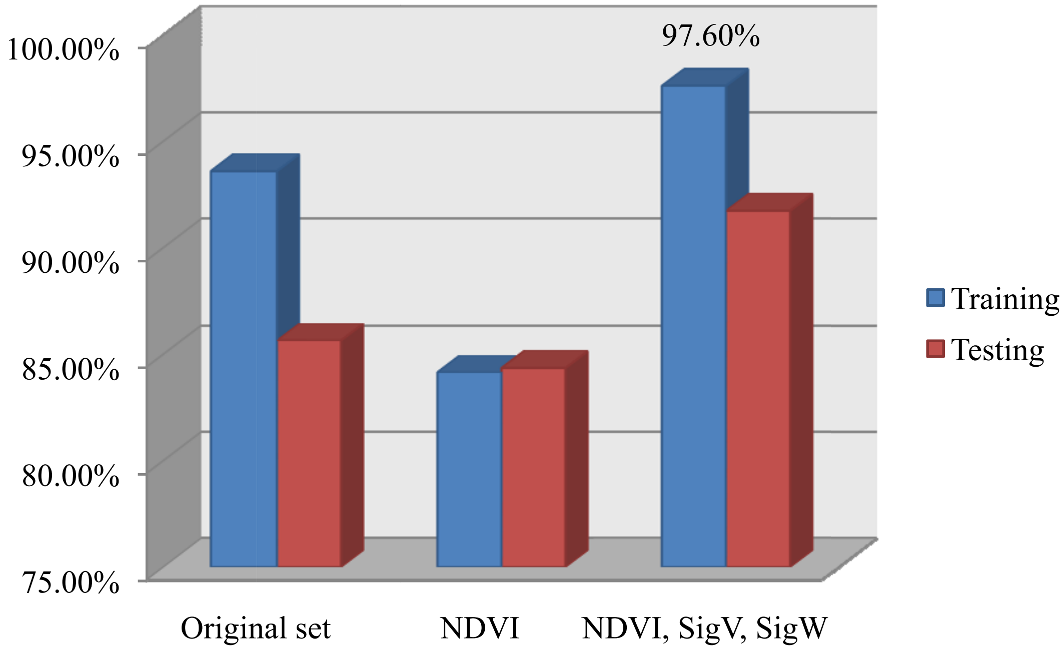

Figure 6.1 The accuracies of feature analysis

The result of feature analysis showed the performance of combination of NDVI with SigV and SigW. This can produce the considerable higher accuracy as compare to the conventional original set or used NDVI single feature. The accuracy of this combination on training is 97.60%.

Feature analysis makes the point that feature extraction can be improve the performance of classification. Hence, 74 features are extracted. The all feature with extraction result accuracy more than original set. However, some features may be unnecessary for classifying. The feature selections are solved this point. The results of feature selection are compared in Figure 6.2.

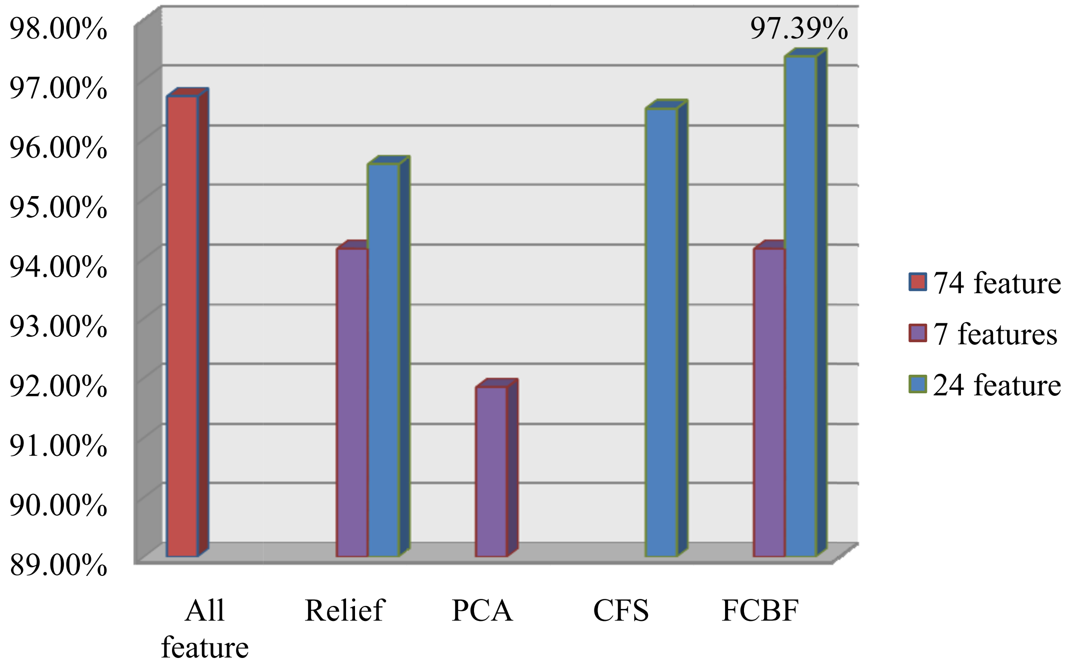

Figure 6.2 The accuracies of feature selection

The experimental results of feature selection techniques show the performance of the fast correlation-based filtering (FCBF) with 24 features that is higher than principle component analysis (PCA), correlation-based feature selection (CFS), and relief algorithms. The accuracy of 24 features selected by FCBF on training set is 97.39%. Moreover, the ability of machine learning algorithms gives the highest overall accuracy of 92.17% on testing when used decision tree classifier with 24 features selected by FCBF.

To compare the performance of classification techniques, the J48 decision tree classifier (DTC) is determine to comparison with logistic regression (LR), multilayer perceptron (MLP), and support vector machine (SVM). The results of classification on training are shown in Figure 6.3.

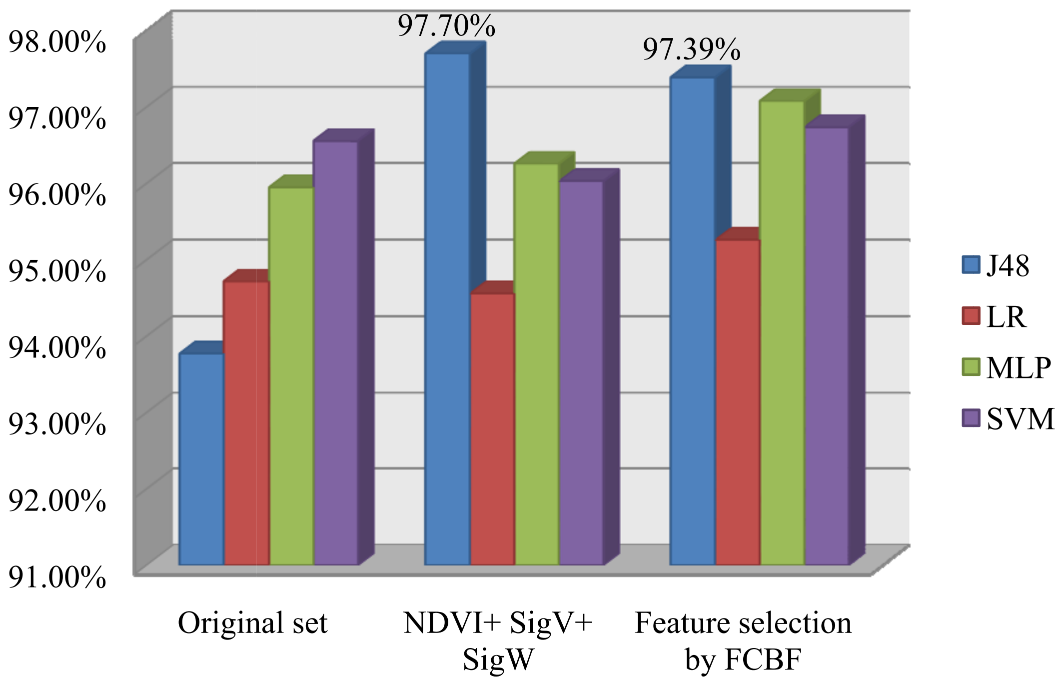

Figure 6.3 The accuracies of classifier

The results demonstrate that the accuracy of J48 DTC on feature extraction and selection are higher than the accuracy of LR, MLP and SVM, that correspond to the result on testing. Hence, this machine learning algorithms may be decided to apply for the forest change detection in the future work.

6.1.3 Conclusion on the forest change detection system

The value for the forest change detection is classified by set of rule. These results are used for data input to display in the system. SQL server designed to accommodate the big data. User can access to the database via application on Windows. The performances of system are evaluated by overall satisfactions from four users. All of users have ability to use the tools of geographic information systems (GIS). The user acceptance test (UAT) for forest change detection system by questionnaire found that the functional and usability test are fine, and the output satisfactions from users test are excellent.

6.2 Discussion

6.2.1 Discussion on forest change detection system

The forest change detection system is design for displaying the result of remote sensing digital image analysis. SQL server used to store database and supports the addition of large amounts of data. This application system can link to the ArcGIS for displaying the shapefile. That is data format of geographic information systems software. User can delineate and report the target area via application. The satisfactions from user are fine in the functional and usability and excellent in output accuracy. However, the efficiency of system depends on the method of analysis. The thresholds in the set of rules are determined by expert’s knowledge. These thresholds are derived for a particular set of images. Hence, the rules cannot be applied for another set of images. These techniques are limitation of the detection system. This research is focused on classifying the image data using machine learning algorithms that treat change detection. Classification by machine learning may be instead of using explicit threshold values of remote sensing data analysis for forest change detection.

6.2.2 Discussion on machine learning algorithms

In machine learning classification, LR and MLP are required a lot of computational time to build the models. The appropriate parameters of SVM are required to generate for each new feature groups. J48 decision tree classifier (DTC) can be trained quickly and is rapid in execution. DTC is easy to understand the output while logistic regression, multilayer perceptron, and support vector machine are more complicate to apply in the detection system. For example, the hidden layers of neural network are concealed. Therefore, DTC are suitable for classification.

The result from machine learning algorithms for forest change detection focuses on the feature extraction from remote sensing data, the feature selection techniques, and the machine learning techniques. The original set from remote sensing data may not perceptible for evident feature. The many features can be extracted; these feature components represent an alternative description of the data, and might be possible to preserve the essential information of the image data.

In the feature analysis, index of NDVI and SigV were extractions from the original feature on remote sensing data. There combination index results the accuracy higher than original index. That determines the significance of feature extraction. Moreover, the natural indexes and spectral differences are proposed to use as the additional features for forest changed detection.

The results show the efficiency of these features via feature selection techniques. FCBF is compared to PCA, CFS, and relief. The performance of the PCA method is worst, while relief method is fair. Both CFS and FCBF yield the better results, but the highest accuracy is occurred when FCBF with 24 features are applied. Some redundancy features can be removed by FCBF. The equation for natural indexes, LAI, NDVI, SigS, SigV, and SigW are selected. Band 5 and band 7 of the original spectral data are still selected as the features for classification. Furthermore, band 5 is used in many features. DTC with these features yields a high accurate result that is verified by accuracy on test data, ROC, precision, and recall. FCBF is a good feature selection technique that gives the qualifying features for forest change detection.

When considering equation for natural index were selected by FCBF. LAI and NDVI are good index for classify vegetation class. That is the most class in this research. The group of SigV contributes to classification their vegetation index. While the index of WI, NDWI, PI, and MI non suitable to classify there class. That has not applied. Hence, the appropriate indexes of feature extraction are consistent with feature selection on the class of classification.

6.2.3 Example of remote sensing data analysis with machine learning algorithm

The example of J48 decision tree classification, classify 6,100 samples with 10-folds Cross-validation. The 24 features are selected by FCBF. In class of vegetation change to soil (VS) are contained 978 samples. The detail of classification is shown in Table 6.1.

Table 6.1 The confusion matrix of FCBF

Class	Classified as									Total
	V	*S*	*WV*	*VS*	*SV*	*SW*	*WS*	*VW*	*W*	
V	1530	4	1	22	6	0	0	3	0	1,566
S	4	833	0	14	6	1	2	0	0	860
WV	2	0	406	0	0	0	0	0	0	408
VS	25	14	0	933	2	0	3	1	0	978
SV	10	7	3	2	455	0	1	0	0	478
SW	0	1	0	0	0	460	1	1	2	465
WS	0	2	0	3	1	0	407	0	0	413
VW	3	0	0	5	0	2	0	414	0	424
W	1	0	0	0	0	0	3	1	503	508

The tree of DTC for 24 features by FCBF is shown in the Figures 6.4. The major part of vegetation change to soil has illustrated. Only 6 features for 7 nodes are selected to this part, from 24 feature of FCBF. The SigV#2 is selected to the root node of binary tree. The most of this class are classifying 672 instances by the condition of:

IF SigV#2 ≤ 14 **AND** LAI#2 > 0.45 **AND** B2-B5#1 ≤ -11 **AND** SigV#1 > 15 **AND** LAI#1 > 1.48 **AND** B7#1 ≤ 35 **AND** SigV#2 ≤ 11 **THEN** Area change from vegetation to soil

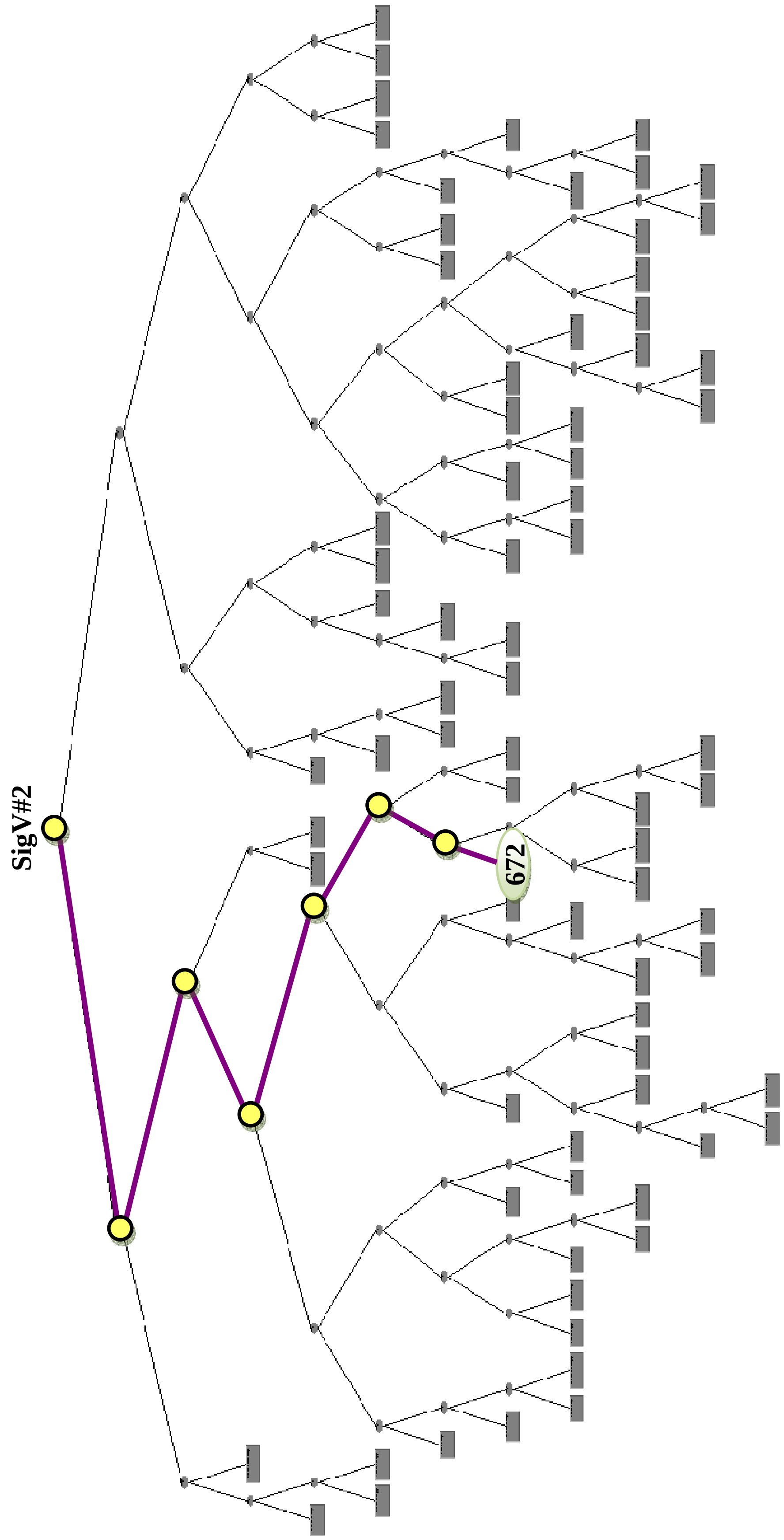

Figure 6.4 J48 decision tree of 24 feature selected by FCBF

For example in the feature analysis, the combination of NDVI with SigV and SigW increase overall accuracy of training and testing. The result produces a higher overall accuracy then does the 14 feature of original set. In class of vegetation change to soil (VS) classify by J48 DTC with this combination details in Table 6.2.

Table 6.2 The confusion matrix of DTC with NDVI, SigV, and SigW

Class	**Classified as**									**Total**
	V	*S*	*WV*	*VS*	*SV*	*SW*	*WS*	*VW*	*W*	
V	1542	3	1	16	4	0	0	0	0	1,566
S	1	836	0	12	6	0	5	0	0	860
WV	2	0	405	0	1	0	0	0	0	408
VS	26	16	0	932	0	0	2	2	0	978
SV	9	7	3	0	459	0	0	0	0	478
SW	0	1	0	0	0	461	0	0	3	465
WS	0	2	0	2	0	0	408	0	1	413
VW	3	0	0	6	0	2	0	413	0	424
W	0	0	0	0	0	1	2	0	505	508

The illustrated of decision tree shown in the Figures 6.5. The SigV#2 is selected to the root node of binary tree. The leaf node to classify 648 instances is the most of VS. All 6 features are used in 7 nodes to classify this part. This direction part is shown in the condition of:

IF SigV#2 $\leq$ 14 **AND** SigW#1 $\leq$ -11 **AND** NDVI#2 > 0.1 **AND** SigV#1 > 15 **AND** NDVI#1 > 0.42 **AND** SigW#1 > -69 **AND** SigV#2 $\leq$ 11 **THEN** Area change from vegetation to soil

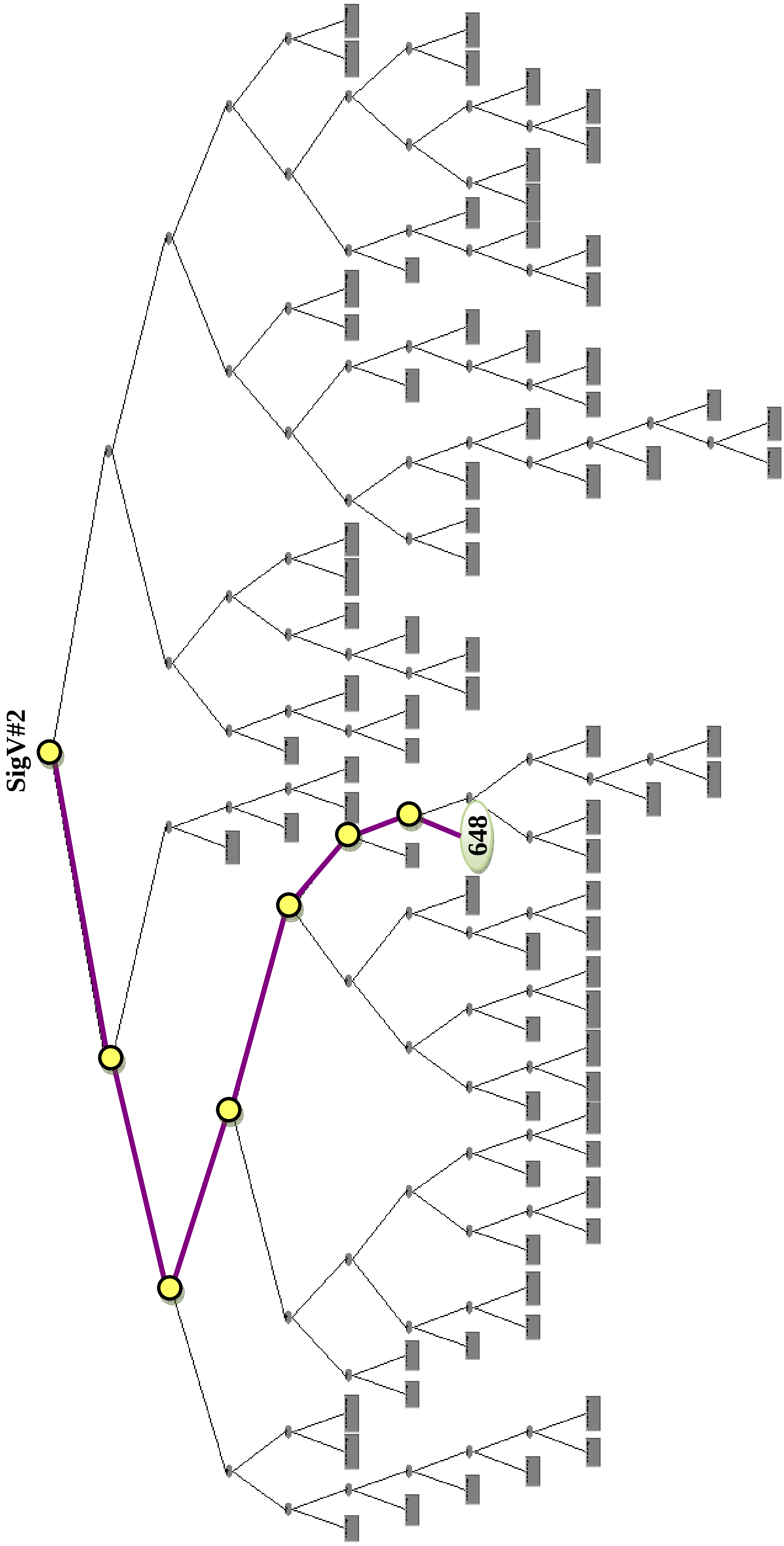

Figure 6.5 J48 decision tree of NDVI, SigV, and SigW

From the example, direction parts to classify the most of VS class of the two samples are resembled. The SigV#2 is repeated twice in there rules. The leaf area index (LAI), normalized difference vegetation index (NDVI), and the signature index of SigV are suitable features for forest changed detection. However, this way has limitation to implements. The major parts of these rules are not entire of the class of VS from the DTC. The size of tree is very large. To obtain the accuracy of classification, maybe adopt with the large set of rules.

6.3 Recommendation

6.3.1 Recommendation on machine learning algorithms

6.3.1.1 Reduced the classes: Differences among spectral signatures are used to classify remotely sensed images into classes for forest change detection. The SigV used weights from many bands. The rules that combined NDVI with SigV are more realistic and appropriate valuables for forest cover change detection. The results of output filtering are divided into two classes of vegetation change to soil (VS) and soil change to vegetation (SV). The results of this method are successfully to classify forest change detection in the target and visible area outside. Hence, the sample class for machine learning may be reduced. The new classes are recommenced, such as 3 classes of forest loss (VS), forest gain (SV), and ignore may be considered. The size of decision tree may be reduced. Moreover, the rules of the J48 decision tree classification may be used to implementation for the forest change detection system.

6.3.1.2 Applying the solutions to different classes: The feature selections and machine learning techniques can be applied to classify another area of forest change detection image. In the classification, the class of land used and land cover may be adapted. Hence, many features may be necessary, such as season or specification of image. More sampling of image and number of studies area are required for training.

6.3.1.3 Predefine the parameter: If the parameters are predefined, the performance of LR, MLP, and SVM may be improved. In the same way, the performance of feature selection techniques such as PCA, CFS, and relief may be improved by predefined parameters. The prediction accuracy of their models may give the higher accuracy to produce the forest change detection.

6.3.2 Recommendation on the forest change detection system

The results of analysis step will be used for displaying in the system. The feature selections and machine learning algorithms may be apply to analysis step of the forest change detection system. After that, Geoinformatics team can generate a report or information for survey in the target area.

6.3.3 Ground check

To measure the accuracy of information from the system, ground check is recommended. For the example, the set of rules can be used for forest covers change detection during 2007 to 2009. The NDVI combination with SigV and SigS classifies 2.09% land cover change. In class of vegetation change to soil, there are 20,717 Rais or approximate 1.72% land cover change of the study area. Some results are illustrated in Figure 6.6.

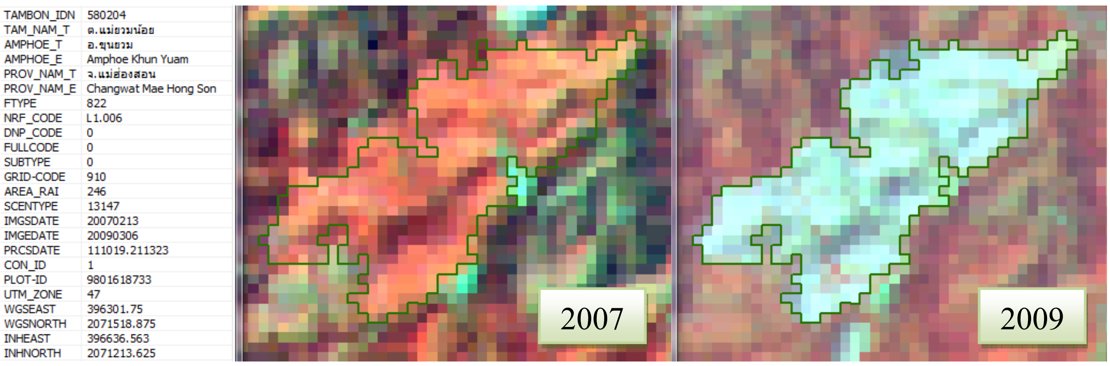

Figure 6.6 Land cover change from vegetation to soil

Land cover change from vegetation to soil in Figure 6.6 showed the identify plot number 9801618733, covered area 246 Rais. This polygon lays on administrative district of Tambon Mae Yuam Noi, Amphoe Khun Yuam, Changwat Mae Hong Son. That area located at Protected Area Regional Office 16. Wildlife sanctuary code (NRF_CODE) L1.006 is the Left Mae Yuam forest. The details of forest change detection report are showed in Figure 6.7.

แบบ ศปท.ยศ. 101
ลำดับที่ 00000/2012

แบบรายงานการตรวจสอบการเปลี่ยนแปลงพื้นที่ป่าไม้
ด้วยการประมวลผลข้อมูลจากดาวเทียมสำรวจทรัพยากรธรรมชาติ

หมายเลขแปลงในระบบ : 9801618733 เนื้อที่ที่ตรวจพบ 246 ไร่
ข้อมูลจากดาวเทียมวันที่ 6 มีนาคม 2009 ประมวลผลเมื่อวันที่ 21 ตุลาคม 2011
ผลการตรวจสอบ : พื้นที่เปลี่ยนแปลงจาก พืชพรรณในปี 2007 เป็นพื้นที่ว่างในปี 2009

สถานที่ที่ตรวจพบ : ต.แม่ยวมน้อย อ.ขุนยวม จ.แม่ฮ่องสอน
พื้นที่ สำนักบริหารพื้นที่อนุรักษ์ที่ 16
ป่าสงวนแห่งชาติ ป่าแม่ยวมฝั่งซ้าย
พื้นที่ป่าอนุรักษ์ นอกเขตพื้นที่การจำแนกเขตการใช้ประโยชน์พื้นที่ป่าอนุรักษ์
การจำแนกเขตป่าชายเลน นอกเขตพื้นที่การจำแนกเขตการใช้ประโยชน์พื้นที่ป่าชายเลน

รหัสสำหรับเจ้าหน้าที่ฐานข้อมูล
580204
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พิกัดกลางแปลงของพื้นที่ :

Geographic Coordinate on Spheriod ::	Datum WGS84	Latitude	98.020 North,	Longtitude	18.730 East
	WGS84 UTM Zone 47		396302 m.E.,		2071519 m.N.
	Indian 1975 UTM Zone 47		396637 m.E,		2071214 m.N.

Figure 6.7 Forest change detection report for ground check

The areas of forest change detection in Figure 6.6 are reported in Figure 6.7. This report contains specific analysis data, geographic coordinate, and geospatial data. The forest change detection report will be used to survey on the ground situation. Furthermore, the accuracy of forest change detection from analysis step on the system may be determined.

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APPENDICES

APPENDIX A
THAILAND FOREST AREA

Table: Forest area in Thailand Between 1961 to 2008.

Forest Area in 1961 - 2008												
Year	North		North - East		East		Central		South		Whole Kingdom	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
1961	116,275	68.54	70,904	41.99	21,163	57.98	35,661	52.91	29,626	41.89	273,629	53.33
1973	113,595	66.96	50,671	30.01	15,036	41.19	23,970	35.56	18,435	26.07	221,707	43.21
1976	102,327	60.32	41,494	24.57	12,631	34.6	21,826	32.38	20,139	28.48	198,417	38.67
1978	94,937	55.96	31,221	18.49	11,037	30.24	20,426	30.31	17,603	24.89	175,224	34.15
1982	87,756	51.73	25,886	15.33	8,000	21.92	18,516	27.47	16,442	23.25	156,600	30.52
1985	84,126	49.59	25,580	15.15	7,990	21.89	17,685	26.24	15,485	21.9	150,866	29.4
1988	80,402	47.39	23,693	14.03	17,244	25.59	17,244	25.59	14,630	20.69	143,803	28.03
1989	80,222	47.29	23,586	13.97	17,223	25.55	17,223	25.55	14,600	20.65	143,417	27.95
1991	77,143	45.47	21,799	12.91	16,616	24.65	16,616	24.65	13,449	19.02	136,698	26.64
1993	75,231	44.35	21,473	12.72	16,408	24.34	16,408	24.34	12,808	18.11	133,554	26.03
1995	73,886	43.55	21,265	12.59	16,288	24.17	16,288	24.17	12,455	17.61	131,485	25.62
1998	73,057	43.06	20,984	12.43	16,049	23.81	16,049	23.81	12,125	17.15	129,722	25.28
2000	96,270	56.75	26,527	15.71	8,438	23.12	21,462	31.84	17,413	24.62	170,111	33.15
2004	92,068	54.27	28,096	16.64	8,240	22.57	21,243	31.52	17,943	25.37	167,591	32.66
2005	89,381	47.31	25,335	15	7,936	21.74	20,679	30.68	17,671	24.99	161,001	31.38
2006	88,368	52.09	24,550	14.54	7,884	21.6	20,555	30.5	17,296	24.46	158,653	30.92
2008	95,154	55.31	27,702	16.51	8,062	21.97	20,009	32.89	21,258	27.43	172,185	33.44
Total (km^2)	**169,644**		**168,854**		**36,503**		**67,399**		**70,715**		**513,115**	

APPENDIX B
AUTOMATIC SYNCHRONIZATION REPORT OF g13147_20070213

TOC: Input/Output Images | Reference Image | Output Parameters | Images | Job Log |

Input/Output Images

Input File	Output File
c:/documents and settings/rin/my documents/u-irc/rectify/raw/r13147_20070213.img	e:/rectify/geo/g13147_20070213.img (details)

Reference Image

c:/documents and settings/rin/my documents/u-irc/rectify/referent/topo13147/mosaic13147_utm.img

Output Parameters

Geocorrection Method	Resample
Delete Input on Success	No
Default Output Directory	e:/rectify/geo/
Default Output File Name Suffix	_output

Resample Settings

Resample Method	Nearest Neighbor
Cell Size	Same as Input Image
Ignore Zero in Statistics	No
Clip to Reference Image Boundary	No

Geometric Model Settings

Output Geometric Model Type	Polynomial
Maximum Polynomial Order	2
Acceptance Threshold	0.500000

Projection Settings

Output Projection	Same as Reference Image

APM Parameters

Input Layer to Use	1
Reference Layer to Use	1
Find Points With	Defined Pattern
Intended Number of Points/Pattern	1
Keep All Points	No
Starting Column	128
Column Increment	256
Ending Column	0
Starting Line	128
Line Increment	256
Ending Line	0
Search Size	17
Correlation Size	11
Least Squares Size	21
Feature Point Density	100
Minimum Point Match Quality	0.800000
Initial Accuracy	10
Avoid Shadow	No

Image 1

Input Image	c:/documents and settings/rin/my documents/u-irc/rectify/raw/r13147_20070213.img
Output Image	e:/rectify/geo/g13147_20070213.img
RMS Error	0.495817

GCPs

Point #	Point Origin	Point ID	X Input	Y Input	X Ref	Y Ref	Z Ref	X Residual	Y Residual	Error	Contribution	Match
1	manual	2	4930.50583336	1296.74552552	502188.83442844	2119423.81214436	0.00000000	0.1977	0.5595	0.5934	0.0247	0.0000
2	manual	3	4685.04782709	1414.07444802	494406.33353928	2117062.99999712	0.00000000	-0.4710	0.3277	0.5738	0.0231	0.0000
3	manual	5	4715.48462270	1209.85338871	496245.71138626	2122977.34977626	0.00000000	-0.4535	0.2124	0.5008	0.0176	0.0000
4	manual	6	4718.92103634	1103.81553081	496830.72684940	2126100.03536643	0.00000000	-0.3343	-0.0414	0.3368	0.0080	0.0000
5	manual	8	4620.50754583	780.96560877	495408.32384937	2136125.72136286	0.00000000	-0.4585	-0.1700	0.4891	0.0168	0.0000
6	manual	10	4538.76123992	342.13365894	495003.27841545	2149514.63931088	0.00000000	-0.2887	-0.4011	0.4942	0.0171	0.0000
7	manual	11	4571.39639669	273.06119387	496284.57246339	2151438.02418857	0.00000000	-0.1005	0.3832	0.3961	0.0110	0.0000
8	manual	13	4669.30186426	251.19880944	499278.23868391	2151633.01385280	0.00000000	-0.0124	0.2535	0.2538	0.0045	0.0000
9	manual	14	4848.00310448	314.56804656	504267.68229372	2148903.15715583	0.00000000	0.0181	-0.6914	0.6916	0.0335	0.0000
10	manual	15	5245.27402872	429.11718501	515484.15736184	2143689.00329223	0.00000000	0.3304	-0.3427	0.4760	0.0159	0.0000
11	manual	16	5258.31889648	389.02690316	516070.29724871	2144831.31195267	0.00000000	-0.1270	0.1610	0.2051	0.0029	0.0000
12	manual	17	5317.61215415	320.80187747	518128.73892625	2146592.78537798	0.00000000	0.2281	0.4416	0.4970	0.0173	0.0000
13	manual	19	6501.57766222	459.40575573	552497.29334143	2137009.69124593	0.00000000	0.3879	-0.3444	0.5187	0.0189	0.0000
14	manual	20	6610.65688428	790.38332682	554215.85374715	2126697.36703595	0.00000000	-0.0754	0.0764	0.1073	0.0008	0.0000
15	manual	21	6623.71345850	943.10879979	553882.97754261	2122099.16531754	0.00000000	0.4297	-0.2295	0.4871	0.0166	0.0000
16	manual	22	6595.82331977	1171.22276570	552023.19496392	2115472.30572254	0.00000000	0.0168	0.2569	0.2575	0.0046	0.0000
17	manual	23	6480.56811954	1260.90909809	548198.74918132	2113330.17178884	0.00000000	0.0749	-0.1593	0.1760	0.0022	0.0000
18	manual	26	4703.26425332	1468.75005251	494671.08695742	2115340.18568315	0.00000000	0.1821	-0.3543	0.3984	0.0111	0.0000
19	manual	27	4723.50823119	1573.37587587	494775.10975919	2112147.16423344	0.00000000	0.6362	-0.3082	0.7069	0.0351	0.0000
20	manual	29	4752.13665355	1894.78148786	494171.21328492	2102509.11638177	0.00000000	-0.1805	0.7127	0.7352	0.0379	0.0000
21	manual	30	4787.40646206	2153.49781133	494017.44410402	2094668.86530350	0.00000000	-0.0093	0.5196	0.5197	0.0189	0.0000
22	manual	31	4978.07888794	2207.48390569	499419.58539904	2092159.77018263	0.00000000	-0.5013	-0.4264	0.6581	0.0304	0.0000
23	manual	32	4825.29339679	2283.75328602	494531.40372042	2090614.52734766	0.00000000	0.1368	-0.0763	0.1567	0.0017	0.0000
24	manual	33	4947.63048272	2507.60305130	497137.34340530	2083406.35449379	0.00000000	-0.4816	-0.2020	0.5222	0.0191	0.0000
25	manual	34	5095.29896859	2557.73261870	501262.67752638	2081252.95412165	0.00000000	-0.0154	0.1672	0.1679	0.0020	0.0000
26	manual	35	5128.29246529	2623.40532638	501926.22402028	2079136.00050634	0.00000000	0.2252	-0.4611	0.5131	0.0185	0.0000
27	manual	36	5802.67196403	2756.29289107	521275.19838218	2072116.70796949	0.00000000	-0.0830	0.5087	0.5155	0.0186	0.0000
28	manual	37	5369.58514095	2734.80263963	508572.97406333	2074733.85284977	0.00000000	-0.4456	0.0627	0.4500	0.0142	0.0000
29	manual	38	4921.24306812	2959.05497694	494274.15987734	2070153.45639782	0.00000000	-0.3036	0.1979	0.3624	0.0092	0.0000
30	manual	39	4719.89664461	3376.40499545	486369.06839451	2058714.82641355	0.00000000	0.6011	0.3481	0.6946	0.0338	0.0000
31	manual	41	6345.18157580	4237.07827204	530501.19961843	2025685.97069824	0.00000000	-0.2589	-0.2837	0.3841	0.0103	0.0000
32	manual	42	6349.47563736	4273.28851094	530464.35934274	2024608.94398164	0.00000000	-0.2743	0.2673	0.3830	0.0103	0.0000
33	manual	43	4387.95290386	4055.01480103	473424.32985540	2040119.16180616	0.00000000	0.4718	0.1453	0.4937	0.0171	0.0000
34	manual	44	4804.35822499	4078.60455914	485636.79309709	2037484.13093639	0.00000000	0.3324	-0.4225	0.5376	0.0203	0.0000
35	manual	45	4661.28563174	4301.07310932	480398.16968122	2031556.83828177	0.00000000	-0.2662	-0.0542	0.2717	0.0052	0.0000
36	manual	46	4505.42443017	4317.85815945	475716.48595916	2031779.33435159	0.00000000	-0.4869	0.0457	0.4891	0.0168	0.0000
37	manual	47	4414.83843182	4384.99836790	472703.52111150	2030221.86346256	0.00000000	0.3625	0.4303	0.5626	0.0222	0.0000
38	manual	48	4245.12289867	4574.69610100	466816.65125029	2025345.49611574	0.00000000	-0.1184	-0.6960	0.7060	0.0350	0.0000
39	manual	49	4046.44242767	4656.25611642	460553.23970249	2023850.78291171	0.00000000	0.2042	-0.4998	0.5399	0.0204	0.0000
40	manual	50	4280.82443581	4775.05101331	466937.16956954	2019263.94258916	0.00000000	0.3944	-0.0610	0.3991	0.0112	0.0000
41	manual	51	6070.19957119	5247.87067788	517701.27682168	1997001.83659598	0.00000000	0.0954	0.0023	0.0954	0.0006	0.0000
42	manual	53	3290.05088585	5325.51564128	435107.65035507	2007518.58243723	0.00000000	-0.5001	0.1781	0.5309	0.0198	0.0000
43	manual	54	2690.09484406	5428.97571800	416851.34950765	2007220.48258774	0.00000000	0.2420	0.1962	0.3115	0.0068	0.0000
44	manual	58	1559.98565173	4475.46473970	387804.06727255	2040685.03582611	0.00000000	-0.0376	0.4920	0.4934	0.0171	0.0000
45	manual	59	1552.37500000	4375.62500000	388054.56738013	2043650.88897644	0.00000000	-0.6886	-0.3471	0.7712	0.0417	0.0000
46	manual	60	3084.75560635	4138.55262662	434485.22628022	2043651.14011279	0.00000000	0.1932	0.4208	0.4631	0.0150	0.0000
47	manual	61	2999.14423077	3583.07540486	434493.13165265	2060491.84397880	0.00000000	0.7140	-0.2867	0.7694	0.0415	0.0000
48	manual	62	2865.05517203	3348.76748337	431615.79449187	2068054.66981312	0.00000000	0.3380	-0.2309	0.4093	0.0118	0.0000
49	manual	63	1498.08451417	3946.73228745	388407.71082002	2056637.54398089	0.00000000	0.0120	0.4264	0.4265	0.0128	0.0000
50	manual	64	1310.40525596	3506.92245269	384877.59560069	2070513.03791615	0.00000000	-0.0668	-0.3439	0.3504	0.0086	0.0000
51	manual	66	1294.52580972	2889.93572875	387264.37262328	2088871.60364477	0.00000000	-0.5114	-0.3874	0.6416	0.0289	0.0000
52	manual	67	1418.22115385	2193.08147774	394123.01905989	2108988.20005754	0.00000000	0.1042	0.3820	0.3960	0.0110	0.0000
53	manual	68	2454.95900810	2048.21305668	425472.92533911	2108497.75169098	0.00000000	0.2279	-0.3132	0.3873	0.0105	0.0000
54	manual	69	2467.72545455	1466.14000000	428519.04780740	2125708.21318710	0.00000000	0.6840	-0.1149	0.6936	0.0337	0.0000
55	manual	71	1084.90718233	923.99248231	390088.71489896	2148139.12713765	0.00000000	0.4339	-0.1143	0.4487	0.0141	0.0000
56	manual	72	1896.83821463	170.27067807	417612.77820487	2166782.36103374	0.00000000	-0.0695	0.5080	0.5127	0.0184	0.0000
57	manual	73	2692.69180162	815.58934282	438196.23221330	2143949.56998168	0.00000000	-0.1912	-0.6341	0.6623	0.0308	0.0000
58	manual	74	2866.29494379	1068.15677622	442183.69668246	2135687.15598712	0.00000000	-0.4633	0.3144	0.5599	0.0220	0.0000

Job Log

APPENDIX C
AUTOMATIC SYNCHRONIZATION WITH APM REPORT OF g13147_20090306

Input/Output Images

Input File	Output File
c:/documents and settings/rin/my documents/u-irc/rectify/raw/r13147_20090306.img	e:/rectify/geo/g13147_20090306.img (details)

Reference Image

e:/rectify/geo/g13147_20070213.img

Output Parameters

Geocorrection Method	Resample
Delete Input on Success	No
Default Output Directory	e:/rectify/geo/
Default Output File Name Suffix	_output

Resample Settings

Resample Method	Nearest Neighbor
Cell Size	Same as Input Image
Ignore Zero in Statistics	No
Clip to Reference Image Boundary	No

Geometric Model Settings

Output Geometric Model Type	Polynomial
Maximum Polynomial Order	2
Acceptance Threshold	0.500000

Projection Settings

Output Projection	Same as Reference Image

APM Parameters

Input Layer to Use	1
Reference Layer to Use	1
Find Points With	Defined Pattern
Intended Number of Points/Pattern	1
Keep All Points	No
Starting Column	128
Column Increment	256
Ending Column	0
Starting Line	128
Line Increment	256
Ending Line	0
Search Size	17
Correlation Size	11
Least Squares Size	21
Feature Point Density	100
Minimum Point Match Quality	0.800000
Initial Accuracy	10
Avoid Shadow	No

Image 1

Input Image	c:/documents and settings/rin/my documents/u-irc/rectify/raw/r13147_20090306.img
Output Image	e:/rectify/geo/g13147_20090306.img
RMS Error	0.411621

Log

APM found 347 tie points

GCPs

Point #	Point Origin	Point ID	X Input	Y Input	X Ref	Y Ref	Z Ref	X Residual	Y Residual	Error	Contribution	Match
1	APM	0001	546.14080811	182.96537781	392133.95471191	2170134.24179077	0.00000000	-0.5360	0.0340	0.5371	0.0049	0.8500
2	APM	0002	645.69757080	130.16778564	395311.70727539	2171232.73654175	0.00000000	-0.0153	-0.3359	0.3362	0.0019	0.8500
3	APM	0003	622.30426025	158.33369446	394504.10961914	2170515.34304810	0.00000000	-0.4756	0.0784	0.4820	0.0040	0.8600
4	APM	0004	919.20013428	171.10784912	403226.50671387	2168759.34585571	0.00000000	0.2159	-0.3164	0.3830	0.0025	0.8600
5	APM	0005	1375.06250000	129.87512207	416942.79638672	2167884.48733521	0.00000000	-0.1435	-0.1229	0.1890	0.0006	0.9400
6	APM	0006	1303.37817383	172.84571838	414607.24877930	2166928.87710571	0.00000000	0.2224	-0.5720	0.6138	0.0064	0.9400
7	APM	0007	1183.85986328	265.14520264	410641.30297852	2164758.43826294	0.00000000	0.2506	-0.0353	0.2530	0.0011	0.8700
8	APM	0008	1515.80700684	153.54704285	421003.27075195	2166551.10928345	0.00000000	0.0467	0.4492	0.4516	0.0035	0.8700
9	APM	0009	1560.56640625	194.32673645	422145.50097656	2165121.17843628	0.00000000	-0.1183	0.0056	0.1185	0.0002	0.9000
10	APM	0010	1554.09875488	262.17114258	421638.67382813	2163140.76452637	0.00000000	-0.0007	0.0576	0.0576	0.0001	0.9000
11	APM	0011	1768.15551758	181.49330139	428348.46972656	2164541.61593628	0.00000000	0.1775	-0.1312	0.2207	0.0008	0.8900
12	APM	0012	1877.93542480	137.74378967	431797.27587891	2165331.27246094	0.00000000	0.3737	-0.2164	0.4318	0.0032	0.8900
13	APM	0013	1796.41394043	223.11293030	428997.89135742	2163179.58947754	0.00000000	0.0891	-0.0219	0.0917	0.0001	0.9000
14	APM	0014	1883.53967285	259.39602661	431419.62890625	2161694.39813232	0.00000000	-0.1475	-0.2226	0.2670	0.0012	0.9000
15	APM	0015	2099.24047852	160.60479736	438265.38867188	2163629.51055908	0.00000000	-0.1013	-0.2317	0.2529	0.0011	0.9300
16	APM	0016	2539.48559570	171.87828064	451264.92333984	2161276.77209473	0.00000000	-0.1860	0.2279	0.2942	0.0015	0.9300
17	APM	0017	2369.49658203	210.83843994	446032.04663086	2160887.86193848	0.00000000	0.2636	-0.4404	0.5132	0.0045	0.9500
18	APM	0018	2720.95019531	166.04441833	456667.51318359	2160613.24530029	0.00000000	-0.1363	0.2537	0.2880	0.0014	0.9500
19	APM	0019	2930.56176758	134.13746643	463017.05639648	2160578.86358643	0.00000000	0.0547	-0.2232	0.2298	0.0009	0.8900
20	APM	0020	2679.77539063	141.14584351	455549.22729492	2161529.60961914	0.00000000	0.2186	-0.2156	0.3070	0.0016	0.8900
21	APM	0021	2863.20532227	206.23167419	460691.02368164	2158762.80615234	0.00000000	0.0799	0.1646	0.1829	0.0006	0.9300
22	APM	0022	3205.77612305	152.27986145	471102.04833984	2158778.63543701	0.00000000	-0.3807	0.1352	0.4040	0.0028	0.9300
23	APM	0023	3418.85766602	142.60021973	477448.77978516	2158081.49432373	0.00000000	-0.0457	0.0720	0.0852	0.0001	0.8900
24	APM	0024	3362.05249023	136.31365967	475797.00732422	2158521.18548584	0.00000000	-0.1621	-0.2177	0.2714	0.0013	0.8900
25	APM	0025	3559.88208008	191.14082336	481415.25732422	2155994.27453613	0.00000000	-0.4219	0.2679	0.4998	0.0042	0.9000
26	APM	0026	3728.40063477	286.18041992	485957.59130859	2152377.38470459	0.00000000	-0.1060	-0.4248	0.4378	0.0033	0.9000
27	APM	0027	4488.64648438	155.30929565	509072.56054688	2152770.94958496	0.00000000	0.0852	0.3455	0.3559	0.0022	0.9300
28	APM	0028	4908.10644531	132.94279480	521588.93847656	2151482.82971191	0.00000000	0.2370	-0.1124	0.2623	0.0012	0.9300
29	APM	0029	5287.26562500	307.72930908	532022.78759766	2144547.79431152	0.00000000	-0.1355	0.0736	0.1542	0.0004	0.8200
30	APM	0030	880.63293457	417.17678833	400958.70336914	2161648.97076416	0.00000000	0.0400	0.0473	0.0619	0.0001	0.8200
31	APM	0031	1184.45336914	571.20416260	409251.54858398	2155692.07397461	0.00000000	0.3316	0.4149	0.5312	0.0048	0.9600
32	APM	0032	1790.20898438	549.46716309	427323.80200195	2153532.57403564	0.00000000	-0.2219	0.1670	0.2777	0.0013	0.9600
33	APM	0033	2151.57128906	351.67599487	438940.90576172	2157730.34161377	0.00000000	-0.1451	0.1075	0.1805	0.0006	0.9100
34	APM	0034	2465.07836914	328.81787109	448333.93359375	2156956.54760742	0.00000000	-0.0742	-0.0712	0.1029	0.0002	0.9100
35	APM	0035	2647.24072266	321.74658203	453767.44482422	2156331.46911621	0.00000000	-0.1442	0.1415	0.2021	0.0007	0.9300
36	APM	0036	2540.92089844	453.40634155	450009.97265625	2152917.92083740	0.00000000	-0.0814	0.1655	0.1844	0.0006	0.9300
37	APM	0037	2743.43237305	318.22320557	456635.52026367	2155992.70349121	0.00000000	-0.1933	0.1748	0.2606	0.0012	0.9700
38	APM	0038	2863.99536133	608.03033447	458878.43261719	2146831.31011963	0.00000000	-0.3312	-0.0885	0.3428	0.0020	0.9700
39	APM	0039	3081.96484375	591.40466309	465396.77050781	2146320.03369141	0.00000000	0.2121	-0.1024	0.2355	0.0009	0.9500
40	APM	0040	3125.28100586	350.44390869	467792.75097656	2153271.20654297	0.00000000	0.0670	0.0422	0.0792	0.0001	0.9500
41	APM	0041	3348.25634766	319.51229858	474521.12548828	2153131.42584229	0.00000000	0.5702	-0.9682	1.1236	0.0215	0.9600
42	APM	0042	3377.44482422	374.44992065	475156.95556641	2151390.07159424	0.00000000	-0.0920	-0.0853	0.1254	0.0003	0.9600
43	APM	0043	3559.31958008	370.01263428	480564.47607422	2150692.15905762	0.00000000	-0.0202	0.2574	0.2582	0.0011	0.8100
44	APM	0044	3758.85327148	572.70269775	485571.91992188	2143769.33349609	0.00000000	-0.9105	0.7858	1.2027	0.0246	0.8100
45	APM	0045	4394.40039063	343.73233032	505401.61669922	2147607.66613770	0.00000000	0.5030	-0.0176	0.5033	0.0043	0.9200
46	APM	0046	4664.24121094	545.50714111	512489.18847656	2140368.70202637	0.00000000	-0.3375	-0.0811	0.3471	0.0020	0.9200
47	APM	0047	5222.79638672	385.84936523	529758.03369141	2142521.34777832	0.00000000	-0.2650	-0.1378	0.2987	0.0015	0.8900
48	APM	0048	5794.82275391	316.23785400	547011.71630859	2141951.20751953	0.00000000	-0.2438	0.2061	0.3192	0.0017	0.8900
49	APM	0049	513.01409912	644.73883057	389021.19104004	2156597.96868896	0.00000000	-0.2583	0.1939	0.3230	0.0018	0.9100
50	APM	0050	626.01525879	772.99133301	391767.90124512	2152272.94647217	0.00000000	0.2156	0.0981	0.2369	0.0010	0.9100
51	APM	0051	1709.95812988	795.54174805	423804.16992188	2146596.27172852	0.00000000	0.0483	-0.1578	0.1650	0.0005	0.8600
52	APM	0052	1457.13891602	883.20452881	415895.61035156	2145151.30920410	0.00000000	0.3555	-0.5971	0.6949	0.0082	0.8600
53	APM	0053	1851.07226563	760.44445801	428173.29418945	2146986.79522705	0.00000000	-0.7709	-0.0047	0.7709	0.0101	0.8600
54	APM	0054	1780.65246582	884.63635254	425490.30395508	2143632.24169922	0.00000000	0.0603	-0.0083	0.0608	0.0001	0.8600
55	APM	0055	1826.07080078	867.82293701	426922.06567383	2143915.40039063	0.00000000	-0.2405	-0.1602	0.2889	0.0014	0.8600
56	APM	0056	2552.09130859	659.04266357	449375.06103516	2146759.26361084	0.00000000	0.5563	-0.1936	0.5890	0.0059	0.8600
57	APM	0057	2636.62182617	762.37365723	451417.70947266	2143308.00622559	0.00000000	0.1508	-0.0020	0.1508	0.0004	0.8100
58	APM	0058	2573.96459961	918.13500977	448840.43041992	2138977.54174805	0.00000000	0.2961	-0.0241	0.2971	0.0015	0.8100
59	APM	0059	2758.29418945	847.65539551	454644.90966797	2140211.26721191	0.00000000	-0.3392	-0.1114	0.3570	0.0022	0.8800
60	APM	0060	3154.35888672	882.13690186	466203.76391602	2137366.29418945	0.00000000	0.2696	0.0257	0.2708	0.0012	0.8800
61	APM	0061	3468.64184570	813.62976074	475835.09912109	2137950.93237305	0.00000000	0.1015	0.2016	0.2257	0.0009	0.9000
62	APM	0062	3343.18237305	835.95642090	472002.55517578	2137854.09960938	0.00000000	0.4677	-0.3332	0.5743	0.0056	0.9000
63	APM	0063	3695.10351563	857.76123047	482350.31103516	2135585.54699707	0.00000000	-0.2764	-0.0795	0.2876	0.0014	0.9100
64	APM	0064	4260.12744141	689.32958984	499847.32031250	2137973.26940918	0.00000000	0.1354	-0.0523	0.1451	0.0004	0.9100
65	APM	0065	4395.47753906	636.38476563	504099.59912109	2138911.85192871	0.00000000	0.0821	-0.2591	0.2718	0.0013	0.8900
66	APM	0066	4512.41552734	786.86407471	506875.57910156	2133903.44934082	0.00000000	-0.1013	-0.3642	0.3780	0.0024	0.8900
67	APM	0067	4582.98046875	771.41748047	509043.71777344	2134063.11987305	0.00000000	-0.2097	0.5862	0.6226	0.0066	0.9600
68	APM	0068	4986.98730469	712.76177979	521246.57958984	2133925.17810059	0.00000000	0.6990	0.1106	0.7077	0.0085	0.9600
69	APM	0069	5212.53515625	886.05914307	527136.46728516	2127731.56311035	0.00000000	0.3502	-0.1575	0.3840	0.0025	0.8800
70	APM	0070	5513.31005859	699.31530762	536908.83398438	2131883.58508301	0.00000000	0.0385	0.0063	0.0390	0.0000	0.8800
71	APM	0071	5691.81054688	834.63494873	541570.76074219	2127039.84814453	0.00000000	0.0099	-0.1052	0.1056	0.0002	0.9300
72	APM	0072	460.82614136	1203.64343262	384885.62475586	2140264.22753906	0.00000000	0.3227	0.0825	0.3330	0.0019	0.9300
73	APM	0073	545.37200928	1082.53076172	387956.95715332	2143449.35192871	0.00000000	0.0044	-0.4187	0.4187	0.0030	0.8400

74	APM	0074	491.08016968	1215.39831543	385744.90979004	2139779.78576660	0.00000000	-0.1913	0.2845	0.3428	0.0020	0.8400
75	APM	0075	833.86138916	1092.17187500	396499.51794434	2141873.97253418	0.00000000	-0.8549	1.0939	1.3884	0.0328	0.9000
76	APM	0076	826.19909668	1098.19287109	396201.46655273	2141734.33081055	0.00000000	0.5847	0.9902	1.1500	0.0225	0.9000
77	APM	0077	1258.25708008	1166.04577637	408717.24023438	2137698.16333008	0.00000000	-0.1602	0.0578	0.1703	0.0005	0.9400
78	APM	0078	1566.27526855	1121.93627930	418026.72070313	2137587.94848633	0.00000000	0.6639	0.0281	0.6645	0.0075	0.9400
79	APM	0079	1752.20690918	1133.37561035	423497.81616211	2136381.10400391	0.00000000	0.2111	-0.2247	0.3083	0.0016	0.8600
80	APM	0080	2003.33532715	1225.83032227	430523.93994141	2132479.49047852	0.00000000	-0.0521	-0.2086	0.2150	0.0008	0.8600
81	APM	0081	2175.78808594	1055.91394043	436409.61401367	2136749.90478516	0.00000000	0.3143	0.6586	0.7297	0.0091	0.8800
82	APM	0082	2353.62426758	1138.80065918	441286.92700195	2133450.93603516	0.00000000	0.6033	-0.0545	0.6058	0.0062	0.8800
83	APM	0083	2588.67480469	1049.84216309	448679.03173828	2135001.04174805	0.00000000	0.0090	-0.0592	0.0599	0.0001	0.9200
84	APM	0084	2895.90747070	1147.56530762	457332.79028320	2130683.01269531	0.00000000	0.0175	-0.0919	0.0935	0.0001	0.9200
85	APM	0085	3311.61108398	1090.53955078	469902.01171875	2130466.55895996	0.00000000	0.3804	0.2732	0.4683	0.0037	0.9400
86	APM	0086	3459.48925781	1232.16064453	473638.26269531	2125579.69079590	0.00000000	0.1400	0.1997	0.2439	0.0010	0.9400
87	APM	0087	3631.69702148	998.52252197	479829.32373047	2131712.33715820	0.00000000	-0.3761	0.2378	0.4449	0.0034	0.9600
88	APM	0088	4820.02392578	1083.21350098	514606.84423828	2123710.61865234	0.00000000	0.4821	0.2268	0.5328	0.0048	0.9600
89	APM	0089	5171.10058594	1124.69287109	524817.00878906	2120840.02551270	0.00000000	0.1814	-0.2778	0.3317	0.0019	0.9000
90	APM	0090	5209.15673828	1241.41601563	525412.08837891	2117213.29248047	0.00000000	0.0703	0.1329	0.1504	0.0004	0.9000
91	APM	0091	482.89596558	1376.32629395	384749.25000000	2135032.40222168	0.00000000	0.1604	-0.2209	0.2730	0.0013	0.8700
92	APM	0092	512.59271240	1466.82238770	385214.66198730	2132221.06970215	0.00000000	0.1715	0.0773	0.1882	0.0006	0.8700
93	APM	0093	827.53051758	1424.82983398	394750.24804688	2132006.19506836	0.00000000	0.0150	-0.1482	0.1490	0.0004	0.8700
94	APM	0094	1090.36547852	1506.59790039	402185.05700684	2128374.43872070	0.00000000	-0.5483	0.1186	0.5610	0.0054	0.8700
95	APM	0095	1386.40478516	1555.44335938	410722.79589844	2125554.96899414	0.00000000	-0.1066	-0.1224	0.1623	0.0004	0.8400
96	APM	0096	1402.94909668	1499.19030762	411470.28295898	2127147.89172363	0.00000000	-0.0429	-0.0901	0.0998	0.0002	0.8400
97	APM	0097	1795.59826660	1518.98376465	422990.69091797	2124768.00036621	0.00000000	0.9732	0.4016	1.0528	0.0189	0.8500
98	APM	0098	2104.11254883	1527.63928223	432118.97753906	2123065.24145508	0.00000000	0.0727	-0.1942	0.2074	0.0007	0.8500
99	APM	0099	2454.12988281	1354.09057617	443282.62133789	2126608.35058594	0.00000000	0.3905	0.1865	0.4328	0.0032	0.9200
100	APM	0100	2739.31958008	1335.72619629	451833.52880859	2125827.47277832	0.00000000	-0.1660	-0.0110	0.1663	0.0005	0.9200
101	APM	0101	2742.50195313	1419.21435547	451550.31372070	2123336.77844238	0.00000000	-0.3800	0.0202	0.3805	0.0025	0.9200
102	APM	0102	3500.33569336	1378.13610840	474178.04150391	2121057.21643066	0.00000000	0.0803	0.0624	0.1017	0.0002	0.9200
103	APM	0103	3703.91040039	1449.32348633	479881.64355469	2118000.27722168	0.00000000	0.0300	-0.0931	0.0978	0.0002	0.9100
104	APM	0104	4208.65087891	1433.19763184	494893.67871094	2116153.01843262	0.00000000	0.4505	0.1031	0.4622	0.0036	0.9100
105	APM	0105	4760.90429688	1291.73559570	511901.00537109	2117782.13964844	0.00000000	0.2799	-0.3053	0.4142	0.0029	0.9200
106	APM	0106	4894.57373047	1322.69287109	515712.08642578	2116242.94262695	0.00000000	0.4091	-0.4169	0.5841	0.0058	0.9200
107	APM	0107	5308.62500000	1468.70947266	527306.43017578	2110010.26098633	0.00000000	0.2321	0.0789	0.2451	0.0010	0.8300
108	APM	0108	5400.70361328	1375.48986816	530469.77343750	2112348.18530273	0.00000000	-0.0635	0.0890	0.1093	0.0002	0.8300
109	APM	0109	5700.74267578	1384.87622070	539308.60107422	2110681.92700195	0.00000000	-0.0766	0.1130	0.1365	0.0003	0.9200
110	APM	0110	5786.48388672	1250.20532227	542480.08154297	2114276.73962402	0.00000000	-0.5645	0.0831	0.5706	0.0055	0.9200
111	APM	0111	499.18380737	1711.19689941	383695.74353027	2125041.93420410	0.00000000	0.0987	0.2451	0.2643	0.0012	0.8900
112	APM	0112	610.11547852	1809.69360352	386523.16918945	2121603.42443848	0.00000000	0.3616	-0.0160	0.3620	0.0022	0.8900
113	APM	0113	885.97302246	1583.64221191	395759.58801270	2127033.06042480	0.00000000	-0.1885	0.0658	0.1996	0.0007	0.8700
114	APM	0114	879.31018066	1727.83984375	394874.98095703	2122786.93286133	0.00000000	0.5839	-0.1015	0.5927	0.0060	0.8700
115	APM	0115	966.70141602	1755.84362793	397360.01953125	2121556.30114746	0.00000000	-0.1490	0.1094	0.1849	0.0006	0.8800
116	APM	0116	899.25469971	1796.43542480	395161.15283203	2120654.18298340	0.00000000	0.2062	-0.2760	0.3445	0.0020	0.8800
117	APM	0117	1402.61022949	1618.55725098	410924.87255859	2123608.39599609	0.00000000	-0.5036	-0.0725	0.5088	0.0044	0.9400
118	APM	0118	1225.69445801	1854.84875488	404583.58740234	2117430.10070801	0.00000000	-0.1378	0.2552	0.2900	0.0014	0.9400
119	APM	0119	1733.16162109	1586.83898926	420850.54907227	2123030.32397461	0.00000000	0.1550	0.0638	0.1676	0.0005	0.8900
120	APM	0120	1824.62158203	1585.08972168	423583.08764648	2122654.80395508	0.00000000	-0.3168	-0.0380	0.3190	0.0017	0.8900
121	APM	0121	1871.90283203	1789.84448242	424037.74804688	2116368.67456055	0.00000000	-0.1397	0.0540	0.1498	0.0004	0.8800
122	APM	0122	2006.50708008	1861.93981934	427697.91210938	2113606.39489746	0.00000000	-0.2296	-0.0352	0.2323	0.0009	0.8800
123	APM	0123	2898.68847656	1587.88952637	455386.06420898	2117613.44970703	0.00000000	0.1555	-0.0538	0.1646	0.0005	0.8400
124	APM	0124	2821.08007813	1637.55505371	452857.21362305	2116501.42785645	0.00000000	0.1961	0.0167	0.1968	0.0007	0.8400
125	APM	0125	2728.13476563	1661.96423340	449998.12939453	2116205.22546387	0.00000000	-0.0508	-0.0029	0.0509	0.0000	0.8900
126	APM	0126	2950.69775391	1837.32958984	455775.59472656	2109980.09692383	0.00000000	0.3062	0.0546	0.3111	0.0016	0.8900
127	APM	0127	3059.13940430	1775.46496582	459288.69287109	2111311.32788086	0.00000000	-0.2181	0.0609	0.2264	0.0009	0.8700
128	APM	0128	3143.31298828	1719.25317383	462050.25952148	2112588.35375977	0.00000000	-0.5246	0.0762	0.5302	0.0048	0.8700
129	APM	0129	3394.04589844	1842.89221191	468884.52246094	2107768.33154297	0.00000000	0.3260	0.1180	0.3467	0.0020	0.8200
130	APM	0130	4545.35839844	1633.36096191	503944.23486328	2108651.84692383	0.00000000	0.4089	-0.1444	0.4337	0.0032	0.8200
131	APM	0131	4548.14648438	1816.62438965	503179.32128906	2103203.05224609	0.00000000	0.5526	-0.1900	0.5844	0.0058	0.8600
132	APM	0132	5036.27929688	1846.93554688	517526.21630859	2100055.70141602	0.00000000	-0.4880	0.3048	0.5754	0.0056	0.8600
133	APM	0133	5426.89160156	1732.69165039	529581.59326172	2101628.65576172	0.00000000	0.5954	-0.1277	0.6090	0.0063	0.8600
134	APM	0134	5331.09716797	1652.98596191	527133.96972656	2104444.64501953	0.00000000	-0.0715	0.2661	0.2756	0.0013	0.8600
135	APM	0135	5408.54589844	1861.74536133	528455.19433594	2097887.07128906	0.00000000	0.2607	-0.0361	0.2632	0.0012	0.9200
136	APM	0136	5729.49023438	1616.34863281	539117.15917969	2103682.60766602	0.00000000	-0.8116	0.2170	0.8401	0.0120	0.9200
137	APM	0137	5715.19091797	1769.89331055	537982.47802734	2099187.26806641	0.00000000	-0.6782	-0.0491	0.6800	0.0079	0.8400
138	APM	0138	5731.34667969	1803.06481934	538315.41064453	2098131.96899414	0.00000000	-0.9024	0.0992	0.9078	0.0140	0.8400
139	APM	0139	431.20578003	2122.44335938	379787.99084473	2113158.28857422	0.00000000	0.0614	0.0886	0.1078	0.0002	0.8500
140	APM	0140	1021.42126465	2058.40771484	397602.58483887	2112333.69140625	0.00000000	-0.5507	0.1893	0.5824	0.0058	0.8500
141	APM	0141	1394.21826172	2073.48657227	408564.44604492	2110162.84570313	0.00000000	0.1304	-0.0239	0.1326	0.0003	0.8300
142	APM	0142	1624.43164063	1915.88220215	416123.23461914	2113770.52075195	0.00000000	-0.1836	-0.0582	0.1926	0.0006	0.8300
143	APM	0143	1911.82336426	2131.62402344	423640.24145508	2106050.38183594	0.00000000	0.1299	0.0094	0.1302	0.0003	0.8800
144	APM	0144	2099.55151367	2135.39672852	429185.17602539	2105080.62011719	0.00000000	0.2338	0.2984	0.3790	0.0024	0.8800
145	APM	0145	2567.53076172	1975.73144531	443794.70141602	2107640.02954102	0.00000000	-0.0361	-0.1048	0.1109	0.0002	0.8800
146	APM	0146	2441.59423828	1913.78784180	440348.98901367	2110057.94018555	0.00000000	-0.0795	-0.1172	0.1416	0.0003	0.8800
147	APM	0147	3158.92285156	1911.99572754	461621.00976563	2106794.35620117	0.00000000	-0.3915	-0.1551	0.4211	0.0030	0.8900
148	APM	0148	3427.13842773	2044.76196289	468949.33007813	2101622.80664063	0.00000000	-0.1426	-0.0226	0.1443	0.0004	0.8900
149	APM	0149	3292.45288086	1958.44299316	465354.09448242	2104807.88671875	0.00000000	-0.0487	0.0603	0.0775	0.0001	0.9000
150	APM	0150	3412.78344727	2130.85009766	468116.95019531	2099126.95605469	0.00000000	0.1726	-0.3900	0.4265	0.0031	0.9000
151	APM	0151	3697.36279297	1987.89025879	477223.25830078	2102084.08959961	0.00000000	-0.2702	0.8071	0.8511	0.0123	0.9000
152	APM	0152	4231.59082031	2048.70678711	492746.82568359	2097793.54174805	0.00000000	0.2842	0.1563	0.3243	0.0018	0.9000

153	APM	0153	5363.67968750	2112.36174609	525980.48437500	2090665.88012695	0.00000000	0.0689	0.1300	0.1471	0.0004	0.8500
154	APM	0154	5442.60107422	2174.09838867	528029.93261719	2088455.42797852	0.00000000	0.0887	-0.3548	0.3657	0.0023	0.8500
155	APM	0155	5861.76123047	1883.96850586	541795.33154297	2095123.84497070	0.00000000	-0.6627	-0.0988	0.6700	0.0076	0.9400
156	APM	0156	5884.40722656	2120.24243164	541377.03076172	2088012.12744141	0.00000000	-0.6057	-0.0804	0.6110	0.0063	0.9400
157	APM	0157	420.03591919	2363.34863281	378341.69091797	2106055.42529297	0.00000000	0.2066	-0.3627	0.4174	0.0030	0.9500
158	APM	0158	392.24884033	2370.42529297	377490.80895996	2105980.23266602	0.00000000	0.0503	-0.1227	0.1326	0.0003	0.9500
159	APM	0159	484.23864746	2461.18310547	379809.78405762	2102850.67895508	0.00000000	-0.3108	-0.5625	0.6426	0.0070	0.8900
160	APM	0160	760.14392090	2384.66259766	388332.36840820	2103873.59033203	0.00000000	0.1987	0.2901	0.3516	0.0021	0.8900
161	APM	0161	1226.97546387	2320.95239258	402477.06188965	2103595.76513672	0.00000000	-0.1952	-0.0520	0.2020	0.0007	0.9100
162	APM	0162	1148.76208496	2320.18334961	400162.39306641	2103967.34545898	0.00000000	-0.2784	-0.4521	0.5309	0.0048	0.9100
163	APM	0163	1361.85107422	2420.49291992	406012.56958008	2100021.82031250	0.00000000	-0.0180	0.0116	0.0214	0.0000	0.8900
164	APM	0164	1439.31494141	2268.36914063	409024.67358398	2104178.84033203	0.00000000	-0.5221	0.1464	0.5423	0.0050	0.8900
165	APM	0165	1608.08459473	2490.16821289	413017.57690430	2096819.51000977	0.00000000	-0.8964	0.0541	0.8980	0.0137	0.9000
166	APM	0166	1914.87805176	2447.15942383	422278.30664063	2096677.05249023	0.00000000	0.1219	-0.1291	0.1776	0.0005	0.9000
167	APM	0167	2241.65869141	2313.81665039	432584.24047852	2099122.00927734	0.00000000	-0.1074	-0.0606	0.1233	0.0003	0.9400
168	APM	0168	2367.69750977	2268.47778320	436526.12109375	2099890.58862305	0.00000000	-0.0077	0.1446	0.1448	0.0004	0.9400
169	APM	0169	2527.55249023	2387.85668945	440725.66113281	2095605.67236328	0.00000000	-0.4299	-0.0223	0.4305	0.0032	0.8100
170	APM	0170	2675.52392578	2313.66455078	445450.10742188	2097120.90087891	0.00000000	-0.3763	-0.0585	0.3808	0.0025	0.8100
171	APM	0171	2715.83007813	2397.79321289	446256.26293945	2094452.65429688	0.00000000	-0.2793	0.3440	0.4432	0.0033	0.9300
172	APM	0172	2910.21606445	2401.63769531	451988.12768555	2093429.83154297	0.00000000	0.0017	-0.0547	0.0547	0.0001	0.9300
173	APM	0173	3321.83081055	2294.60961914	464667.70898438	2094702.61962891	0.00000000	0.2715	-0.0334	0.2736	0.0013	0.8600
174	APM	0174	3688.84594727	2278.80175781	475618.21435547	2093476.72119141	0.00000000	0.0951	0.0671	0.1164	0.0002	0.8600
175	APM	0175	3612.03149414	2377.40917969	472891.49267578	2090906.52392578	0.00000000	0.0086	0.0311	0.0322	0.0000	0.9300
176	APM	0176	3804.21752930	2368.98608398	478626.72509766	2090262.24243164	0.00000000	-0.1428	-0.1260	0.1905	0.0006	0.9300
177	APM	0177	4002.37939453	2365.38061523	484499.93554688	2089452.28417969	0.00000000	0.2733	-0.2055	0.3419	0.0020	0.8800
178	APM	0178	3937.33398438	2376.52148438	482527.15429688	2089432.22314453	0.00000000	0.1567	0.1318	0.2048	0.0007	0.8800
179	APM	0179	4197.02246094	2383.99926758	490182.50976563	2088002.16943359	0.00000000	0.1671	-0.1126	0.2015	0.0007	0.8900
180	APM	0180	414.65451050	2639.83837891	376922.75939941	2097895.45825195	0.00000000	-0.1726	0.0783	0.1895	0.0006	0.8900
181	APM	0181	473.11557007	2719.74438477	378283.69519043	2095253.08154297	0.00000000	-0.0307	-0.0791	0.0849	0.0001	0.9300
182	APM	0182	638.96301270	2657.51000977	383471.75683594	2096326.61279297	0.00000000	0.4828	-0.3585	0.6013	0.0062	0.9300
183	APM	0183	853.28558350	2510.86181641	390513.49438477	2099692.61279297	0.00000000	0.1423	-0.0380	0.1473	0.0004	0.9400
184	APM	0184	915.18328857	2769.08227539	391156.41430664	2091754.77539063	0.00000000	0.2800	0.0234	0.2810	0.0013	0.9400
185	APM	0185	1086.10864258	2577.96459961	397107.77819824	2096635.20629883	0.00000000	0.1767	0.1748	0.2486	0.0011	0.8900
186	APM	0186	1330.05444336	2586.58154297	404315.19653320	2095248.25561523	0.00000000	-0.3354	0.0756	0.3438	0.0020	0.8900
187	APM	0187	1859.17651367	2806.33422852	418978.67724609	2086291.34179688	0.00000000	-0.0031	0.0627	0.0628	0.0001	0.9500
188	APM	0188	2068.66577148	2786.23803711	425282.78906250	2085916.80168750	0.00000000	-0.0975	-0.0089	0.0979	0.0002	0.9500
189	APM	0189	2411.85546875	2629.35131836	436173.74780273	2088985.80468750	0.00000000	-0.0102	0.0950	0.0955	0.0002	0.9300
190	APM	0190	2679.42211914	2680.43188477	443861.71655273	2086228.65307617	0.00000000	0.1477	-0.1429	0.2055	0.0007	0.9300
191	APM	0191	3592.17822266	2661.10009766	471010.08984375	2082612.96166992	0.00000000	-0.2625	0.9583	0.9936	0.0168	0.9500
192	APM	0192	3856.70898438	2589.36376953	479176.26855469	2083491.47387695	0.00000000	-0.4051	0.1337	0.4266	0.0031	0.9500
193	APM	0193	4055.98046875	2651.57739258	484780.98339844	2080725.32299805	0.00000000	-0.0405	0.0851	0.0942	0.0002	0.8600
194	APM	0194	4701.61621094	2742.06420898	503461.11035156	2075055.55883789	0.00000000	0.7247	-0.0143	0.7249	0.0089	0.8600
195	APM	0195	5641.71435547	2695.35400391	531522.21240234	2072084.70483398	0.00000000	0.2392	-0.0649	0.2478	0.0010	0.9100
196	APM	0196	374.62985229	2947.60083008	374315.44519043	2088957.45336914	0.00000000	-0.0565	0.0553	0.0791	0.0001	0.9100
197	APM	0197	760.04650879	2902.92138672	385948.20703125	2088515.62719727	0.00000000	0.0799	0.4607	0.4676	0.0037	0.9000
198	APM	0198	953.46600342	2917.87841797	391609.03234863	2087165.01196289	0.00000000	0.1852	-0.0414	0.1897	0.0006	0.9000
199	APM	0199	1222.24243164	2819.37353516	400037.84948730	2088850.83984375	0.00000000	0.0070	0.2153	0.2154	0.0008	0.8800
200	APM	0200	1724.00061035	2813.63842773	414953.70849609	2086692.28857422	0.00000000	-0.5468	-0.0852	0.5534	0.0052	0.8800
201	APM	0201	1970.71496582	3070.49487305	421061.39941406	2077945.12939453	0.00000000	0.2325	0.0207	0.2334	0.0009	0.8700
202	APM	0202	2246.65161133	2940.19335938	429831.39111328	2080529.26464844	0.00000000	0.4799	-0.1389	0.4996	0.0042	0.8700
203	APM	0203	2176.60742188	3116.93847656	426954.61450195	2075603.45068359	0.00000000	0.0067	-0.4032	0.4032	0.0028	0.9000
204	APM	0204	2496.70678711	2894.19750977	437469.48925781	2080740.55004883	0.00000000	-0.0289	0.0499	0.0577	0.0001	0.9000
205	APM	0205	2943.85913086	2864.91186523	450868.15795898	2079532.04589844	0.00000000	-0.5448	-0.2050	0.5821	0.0058	0.8900
206	APM	0206	2872.30688477	2929.85449219	448441.63476563	2077942.86547852	0.00000000	-0.2694	-0.0665	0.2775	0.0013	0.8900
207	APM	0207	2892.28027344	3063.05932617	448419.37426758	2073907.68896484	0.00000000	-0.2102	0.1310	0.2477	0.0010	0.8300
208	APM	0208	3183.56347656	2900.93676758	457789.85156250	2077364.97875977	0.00000000	-0.0243	0.0228	0.0333	0.0000	0.8300
209	APM	0209	3396.36376953	2933.70092773	463931.71069336	2075414.11962891	0.00000000	0.3811	0.1111	0.3969	0.0027	0.9100
210	APM	0210	4486.33935547	3074.87768555	495564.89355469	2066169.06811523	0.00000000	0.3054	-0.4479	0.5422	0.0050	0.9100
211	APM	0211	4535.42529297	2847.18994141	498061.08251953	2072697.69433594	0.00000000	0.5105	-0.3144	0.5995	0.0061	0.9400
212	APM	0212	5408.78906250	3061.90283203	522950.10791016	2062288.29711914	0.00000000	-0.1221	-0.2096	0.2425	0.0010	0.9400
213	APM	0213	5220.08886719	3020.48461914	517542.44238281	2064388.60693359	0.00000000	0.2673	-0.3242	0.4202	0.0030	0.9300
214	APM	0214	5566.80761719	2895.86059570	528371.58251953	2066484.85620117	0.00000000	0.5794	-0.1539	0.5995	0.0061	0.9300
215	APM	0215	5770.45117188	3073.91772461	533597.40966797	2060268.34423828	0.00000000	0.0339	0.1503	0.1540	0.0004	0.8200
216	APM	0216	496.81536865	3199.43457031	376782.07836914	2080933.40991211	0.00000000	-0.1222	0.2062	0.2397	0.0010	0.8200
217	APM	0217	612.34075928	3431.74218750	379127.27783203	2073510.35156250	0.00000000	0.2136	0.0011	0.2136	0.0008	0.9100
218	APM	0218	1248.09509277	3353.28979492	398340.83093262	2072896.76586914	0.00000000	0.1362	-0.0950	0.1660	0.0005	0.9100
219	APM	0219	1406.46118164	3152.11230469	403976.71289063	2078131.33447266	0.00000000	-0.3293	0.0770	0.3382	0.0019	0.9000
220	APM	0220	1676.83728027	3189.18383789	411829.17407227	2075791.32348633	0.00000000	-0.5578	0.3728	0.6709	0.0077	0.9000
221	APM	0221	1920.71704102	3158.54223633	419176.24218750	2075560.27514648	0.00000000	0.1320	-0.1616	0.2087	0.0007	0.9200
222	APM	0222	2378.60180664	3268.57128906	432245.43457031	2070191.76489258	0.00000000	0.0053	0.1599	0.1600	0.0004	0.9200
223	APM	0223	2396.50170898	3328.88330078	432480.01171875	2068314.11645508	0.00000000	0.5679	-0.1674	0.5921	0.0060	0.8800
224	APM	0224	2675.44677734	3146.20068359	441602.20751953	2072440.19604492	0.00000000	0.0749	-0.0872	0.1150	0.0002	0.8800
225	APM	0225	3182.52587891	3187.07104492	456433.04882813	2068890.43212891	0.00000000	0.2833	0.0913	0.2977	0.0015	0.9100
226	APM	0226	3214.43774414	3429.32373047	456270.96533203	2061553.23339844	0.00000000	-0.0187	-0.1367	0.1380	0.0003	0.9100
227	APM	0227	3577.86596680	3152.32421875	468312.40429688	2068094.28295898	0.00000000	0.0421	0.2009	0.2053	0.0007	0.9100
228	APM	0228	3403.72045898	3283.68017578	462560.18041992	2064992.50048828	0.00000000	-0.3977	-0.1726	0.4335	0.0032	0.9100
229	APM	0229	3697.84619141	3189.19335938	471702.86425781	2066447.96484375	0.00000000	-0.1530	0.2889	0.3269	0.0018	0.9300
230	APM	0230	3702.06030273	3398.55664063	470852.59057617	2060208.49145508	0.00000000	0.1466	-0.2047	0.2518	0.0011	0.9300
231	APM	0231	4789.06396484	3387.78540039	503092.51904297	2055499.52197266	0.00000000	0.2128	-0.1322	0.2506	0.0011	0.8600

232	APM	0232	5518.23535156	3221.75415039	525443.73486328	2057056.58056641	0.00000000	0.2961	0.2270	0.3731	0.0024	0.8600
233	APM	0233	5832.71923828	3327.99047852	534277.10009766	2052439.93212891	0.00000000	-0.2059	-0.0284	0.2078	0.0007	0.9500
234	APM	0234	340.19354248	3468.56762695	370881.37463379	2073663.56469727	0.00000000	0.3416	-0.4124	0.5355	0.0049	0.9500
235	APM	0235	320.82495117	3694.12036133	369283.77502441	2067073.69189453	0.00000000	-0.1456	-0.1592	0.2157	0.0008	0.9400
236	APM	0236	1378.42944336	3493.48315430	401557.51318359	2068136.09692383	0.00000000	0.1739	-0.2161	0.2774	0.0013	0.9400
237	APM	0237	1284.74523926	3595.29272461	398314.41723633	2065549.56884766	0.00000000	0.0610	-0.2580	0.2651	0.0012	0.9400
238	APM	0238	1416.32751465	3691.60620117	401781.52001953	2062097.45947266	0.00000000	-0.2085	0.1309	0.2462	0.0010	0.9400
239	APM	0239	1815.94152832	3560.64770508	414221.50488281	2064128.54663086	0.00000000	0.0669	-0.0490	0.0829	0.0001	0.8800
240	APM	0240	1799.28771973	3466.17553711	414169.74096680	2067002.72900391	0.00000000	-0.1726	-0.1103	0.2049	0.0007	0.8800
241	APM	0241	1902.21569824	3708.33398438	416102.66601563	2059348.96875000	0.00000000	-0.0863	-0.1457	0.1693	0.0005	0.8600
242	APM	0242	2121.55126953	3434.80224609	423851.40600586	2066448.32739258	0.00000000	0.3316	-0.0259	0.3326	0.0019	0.8600
243	APM	0243	2327.07958984	3651.04125977	428950.94531250	2059086.80566406	0.00000000	0.1842	-0.0730	0.1981	0.0007	0.9500
244	APM	0244	2431.65258789	3670.93798828	431957.54663086	2058005.59643555	0.00000000	0.1694	-0.3422	0.3819	0.0025	0.9500
245	APM	0245	2859.58032227	3536.38745117	445288.29785156	2060017.93579102	0.00000000	-0.8265	-0.0993	0.8324	0.0118	0.9400
246	APM	0246	2955.93212891	3703.27612305	447392.19287109	2054632.34545898	0.00000000	-1.3711	0.2171	1.3882	0.0328	0.9400
247	APM	0247	3125.40356445	3528.14135742	453186.13403320	2059039.98046875	0.00000000	-0.2603	0.0447	0.2641	0.0012	0.8700
248	APM	0248	3155.79492188	3708.35180664	453264.91992188	2053558.40332031	0.00000000	-0.5287	0.1153	0.5411	0.0050	0.8700
249	APM	0249	3954.76147461	3710.04418945	476893.99951172	2049813.08056641	0.00000000	0.4888	0.0021	0.4888	0.0041	0.9000
250	APM	0250	4999.07861328	3705.82714844	507835.41503906	2045101.62158203	0.00000000	0.5884	-0.0731	0.5929	0.0060	0.9000
251	APM	0251	5718.15966797	3656.56396484	529395.53320313	2043226.21289063	0.00000000	-0.9501	0.0012	0.9501	0.0154	0.9300
252	APM	0252	314.89840698	3756.17797852	368810.84820557	2065262.47045898	0.00000000	0.2300	-0.2003	0.3050	0.0016	0.9300
253	APM	0253	699.28619385	3893.50878906	379590.44201660	2059429.41430664	0.00000000	-0.1429	0.2469	0.2853	0.0014	0.8300
254	APM	0254	516.87945557	4038.47778320	373513.64831543	2055968.70849609	0.00000000	-0.1819	0.0180	0.1828	0.0006	0.8300
255	APM	0255	1122.00366211	3952.56811523	391826.88391113	2055711.47607422	0.00000000	0.6158	-0.3877	0.7277	0.0090	0.9000
256	APM	0256	1194.38000488	4052.29565430	393521.61437988	2052438.94921875	0.00000000	0.4309	0.2244	0.4859	0.0040	0.9000
257	APM	0257	1774.23291016	3746.83105469	412139.50781250	2058809.56054688	0.00000000	-0.2870	0.2285	0.3669	0.0023	0.9400
258	APM	0258	1883.42932129	3901.80200195	414618.86645508	2053689.09814453	0.00000000	1.0308	-0.7459	1.2723	0.0275	0.9400
259	APM	0259	2649.10302734	3904.60717773	437329.82739258	2050084.44433594	0.00000000	0.0673	0.0170	0.0694	0.0001	0.9100
260	APM	0260	2910.08154297	3906.39331055	445072.60546875	2048823.41088867	0.00000000	-0.5307	0.0706	0.5354	0.0049	0.9100
261	APM	0261	3402.56738281	3781.14965820	460216.85815430	2050253.39208984	0.00000000	0.2196	-0.1912	0.2912	0.0014	0.9400
262	APM	0262	5403.55615234	3958.53491211	518663.74951172	2035736.50195313	0.00000000	0.0132	0.0219	0.0256	0.0000	0.9400
263	APM	0263	5853.94921875	3870.06982422	532384.45019531	2036254.86621094	0.00000000	0.5415	-0.6444	0.8417	0.0121	0.8000
264	APM	0264	303.04620361	4092.66015625	366932.30145264	2055342.36914063	0.00000000	-0.5437	-0.1987	0.5788	0.0057	0.8000
265	APM	0265	367.11773682	4162.39794922	368494.66131592	2052988.37182617	0.00000000	0.0431	-0.0080	0.0439	0.0000	0.9000
266	APM	0266	507.13879395	4220.80761719	372375.79284668	2050617.97924805	0.00000000	0.1519	0.2118	0.2607	0.0012	0.9000
267	APM	0267	727.55065918	4072.06958008	379596.05749512	2054003.16210938	0.00000000	0.1637	0.0586	0.1738	0.0005	0.8900
268	APM	0268	929.79272461	4103.98730469	385449.84338379	2052121.56591797	0.00000000	0.0235	0.0254	0.0346	0.0000	0.8900
269	APM	0269	1056.17919922	4286.93603516	388339.25683594	2046113.12475586	0.00000000	0.5042	-0.1555	0.5276	0.0047	0.9300
270	APM	0270	1725.34570313	4100.56738281	409059.71191406	2048545.77905273	0.00000000	-0.2745	0.0260	0.2757	0.0013	0.9300
271	APM	0271	1916.97583008	4325.06542969	413702.00463867	2041006.12500000	0.00000000	-0.1599	-0.0183	0.1609	0.0004	0.9100
272	APM	0272	2125.45849609	4278.78076172	420111.56176758	2041421.29980469	0.00000000	-0.6851	0.3114	0.7526	0.0096	0.9100
273	APM	0273	2931.77929688	4325.91308594	443780.01416016	2036293.82812500	0.00000000	-0.4083	0.2124	0.4603	0.0036	0.9400
274	APM	0274	2794.68872070	4362.63330078	439533.74560547	2035834.00341797	0.00000000	0.0594	-0.0532	0.0797	0.0001	0.9400
275	APM	0275	3539.11547852	4087.85644531	462841.39746094	2040538.79150391	0.00000000	0.5207	0.0417	0.5223	0.0046	0.9600
276	APM	0276	3544.07202148	4281.89160156	462098.74438477	2034777.50390625	0.00000000	0.4426	0.4847	0.6564	0.0073	0.9600
277	APM	0277	4783.50244141	4353.44091797	498481.62304688	2026896.86865234	0.00000000	0.1654	-0.1954	0.2560	0.0011	0.8700
278	APM	0278	5370.99267578	4200.20800781	516581.14013672	2028720.79541016	0.00000000	0.1824	-0.0828	0.2003	0.0007	0.8700
279	APM	0279	5821.65576172	4176.56298828	530027.30273438	2027346.94482422	0.00000000	0.3482	0.3523	0.4953	0.0042	0.9200
280	APM	0280	306.07019043	4582.57226563	364756.22094727	2040820.64501953	0.00000000	-0.2190	0.0527	0.2253	0.0009	0.9200
281	APM	0281	589.77319336	4456.53173828	373755.20654297	2043252.07470703	0.00000000	-0.3390	0.3109	0.4599	0.0036	0.9400
282	APM	0282	739.94281006	4430.21435547	378315.01135254	2043327.06591797	0.00000000	0.0817	-0.1322	0.1554	0.0004	0.9400
283	APM	0283	1041.95263672	4454.07812500	387152.94873047	2041228.55273438	0.00000000	0.3328	-0.0419	0.3354	0.0019	0.8800
284	APM	0284	1276.31164551	4420.91503906	394259.30456543	2041128.53759766	0.00000000	0.1618	-0.0096	0.1621	0.0004	0.8800
285	APM	0285	1685.66369629	4397.04492188	406519.55786133	2039935.07519531	0.00000000	-0.3815	-0.2272	0.4440	0.0034	0.9300
286	APM	0286	1457.19946289	4633.86328125	398648.30456543	2033985.31054688	0.00000000	-0.0743	0.1256	0.1459	0.0004	0.9300
287	APM	0287	2036.64892578	4473.53662109	416568.79907227	2036055.52880859	0.00000000	-0.2721	0.0856	0.2852	0.0014	0.8900
288	APM	0288	2178.97558594	4469.75732422	420800.62207031	2035499.29833984	0.00000000	-0.1958	-0.2688	0.3325	0.0019	0.8900
289	APM	0289	2284.76635742	4671.51318359	422996.76562500	2029035.14941406	0.00000000	0.1377	-0.1887	0.2336	0.0009	0.9100
290	APM	0290	2469.93383789	4408.00927734	429688.87719727	2035983.66357422	0.00000000	0.4314	-0.3686	0.5674	0.0055	0.9100
291	APM	0291	2756.86596680	4464.81884766	437940.46435547	2032987.22167969	0.00000000	0.1513	0.1574	0.2183	0.0008	0.9100
292	APM	0292	2901.55371094	4460.73144531	442243.39526367	2032435.92187500	0.00000000	0.2367	0.0392	0.2399	0.0010	0.9100
293	APM	0293	3075.59326172	4396.44140625	447714.91772461	2033537.29687500	0.00000000	-0.3743	0.1754	0.4134	0.0029	0.9500
294	APM	0294	3195.83666992	4448.14892578	451047.67602539	2031441.71630859	0.00000000	-0.6892	-0.0037	0.6892	0.0081	0.9500
295	APM	0295	3001.01733398	4664.93408203	444271.92041016	2025923.12695313	0.00000000	-0.5056	0.1243	0.5206	0.0046	0.8600
296	APM	0296	3432.89941406	4541.67480469	457625.63305664	2027577.94482422	0.00000000	-0.1950	0.0910	0.2152	0.0008	0.8600
297	APM	0297	3310.59399414	4667.63671875	453417.55297852	2024406.23876953	0.00000000	-0.0734	-0.0858	0.1129	0.0002	0.9500
298	APM	0298	3746.42358398	4386.12744141	467608.91455078	2030743.49560547	0.00000000	0.5218	0.2012	0.5593	0.0053	0.9500
299	APM	0299	3630.14404297	4668.30468750	462873.43872070	2022909.92724609	0.00000000	0.1805	-0.0402	0.1849	0.0006	0.9100
300	APM	0300	4810.29199219	4475.02636719	498723.22558594	2023180.80761719	0.00000000	-0.0539	0.2416	0.2475	0.0010	0.9100
301	APM	0301	5121.04980469	4442.46240234	508063.45019531	2022704.09619141	0.00000000	0.2866	0.1120	0.3077	0.0016	0.9200
302	APM	0302	5166.63281250	4659.42236328	508418.68359375	2016076.01074219	0.00000000	0.1842	0.6001	0.6277	0.0067	0.9200
303	APM	0303	331.64880371	4951.98876953	363801.82122803	2029767.07910156	0.00000000	0.1761	0.3226	0.3676	0.0023	0.9200
304	APM	0304	510.63641357	4943.52539063	369153.68243408	2029180.41064453	0.00000000	-0.0349	-0.0021	0.0350	0.0000	0.9200
305	APM	0305	800.35412598	4828.37890625	378268.55676270	2031255.78515625	0.00000000	0.2079	0.0366	0.2111	0.0008	0.9000
306	APM	0306	1450.75097656	4721.98486328	398052.08898926	2031394.35937500	0.00000000	-0.1573	-0.1845	0.2424	0.0010	0.9000
307	APM	0307	1905.67565918	4966.55419922	410420.49462891	2022052.57177734	0.00000000	-0.4537	0.1409	0.4751	0.0038	0.8900
308	APM	0308	2492.28515625	4863.96435547	428261.28881836	2022379.84863281	0.00000000	0.1260	0.0653	0.1419	0.0003	0.8900
309	APM	0309	2761.45385742	4731.43505859	436852.43115234	2025061.71093750	0.00000000	-0.0137	0.0790	0.0802	0.0001	0.8700
310	APM	0310	2688.22998047	4964.12890625	433596.24316406	2018495.16210938	0.00000000	0.4002	-0.3168	0.5104	0.0044	0.8700

311	APM	0311	2960.84741211	4930.83007813	441847.00854492	2018218.75488281	0.00000000	-0.2500	-0.2735	0.3705	0.0023	0.8700
312	APM	0312	3930.07153320	4950.89697266	470455.54321289	2013144.82763672	0.00000000	0.1619	-0.0905	0.1855	0.0006	0.8700
313	APM	0313	4819.85449219	4810.43505859	497462.55468750	2013188.44628906	0.00000000	-0.1407	0.0282	0.1435	0.0004	0.9100
314	APM	0314	5052.62744141	4730.15234375	504735.99316406	2014485.74267578	0.00000000	-0.5390	-0.0332	0.5400	0.0050	0.9100
315	APM	0315	5286.13623047	4876.31542969	510957.25048828	2009069.53710938	0.00000000	0.0598	-0.1915	0.2006	0.0007	0.8400
316	APM	0316	5547.50634766	4895.91015625	518609.31884766	2007292.66113281	0.00000000	-0.0252	0.3413	0.3422	0.0020	0.8400
317	APM	0317	5529.00585938	4934.35009766	517886.79931641	2006231.89160156	0.00000000	-0.1368	0.1159	0.1793	0.0005	0.8700
318	APM	0318	620.26550293	5083.22021484	371760.79724121	2024534.38769531	0.00000000	-0.0383	-0.0263	0.0465	0.0000	0.8700
319	APM	0319	670.30651855	5233.60644531	372548.69238281	2019843.39257813	0.00000000	0.0314	-0.1834	0.1860	0.0006	0.8300
320	APM	0320	986.99786377	5296.69970703	381624.92907715	2016514.30810547	0.00000000	0.8215	-0.1813	0.8413	0.0120	0.8300
321	APM	0321	1258.57958984	5087.68310547	390665.46276855	2021457.13769531	0.00000000	0.0270	0.1281	0.1310	0.0003	0.9000
322	APM	0322	1317.10949707	5053.18115234	392566.45935059	2022206.22802734	0.00000000	-0.2080	0.0769	0.2218	0.0008	0.9000
323	APM	0323	1233.88488770	5299.27832031	388950.59069824	2015310.17871094	0.00000000	0.3106	0.3535	0.4706	0.0038	0.8800
324	APM	0324	1713.39941406	5135.90234375	403922.83813477	2017925.12255859	0.00000000	0.1377	0.0902	0.1646	0.0005	0.8800
325	APM	0325	2256.72875977	5116.71386719	420117.62036133	2015976.04394531	0.00000000	0.0382	-0.0573	0.0689	0.0001	0.8800
326	APM	0326	2247.63793945	5230.90771484	419324.33935547	2012643.47900391	0.00000000	0.0018	0.2511	0.2511	0.0011	0.8800
327	APM	0327	2699.65869141	5121.02929688	433220.99707031	2013806.29394531	0.00000000	0.1639	0.1687	0.2352	0.0009	0.9100
328	APM	0328	3219.97900391	5088.95312500	448791.81372070	2012332.63769531	0.00000000	-0.2245	-0.3163	0.3878	0.0026	0.9100
329	APM	0329	3196.56591797	5206.36816406	447565.78125000	2008967.12109375	0.00000000	-0.3877	-0.1080	0.4025	0.0028	0.9400
330	APM	0330	3473.46484375	5190.72705078	455825.89233398	2008152.72363281	0.00000000	0.1333	-0.0558	0.1445	0.0004	0.9400
331	APM	0331	4008.63867188	5147.11035156	471886.21728516	2006968.67138672	0.00000000	-0.0867	0.0309	0.0920	0.0001	0.9300
332	APM	0332	3958.32763672	5070.11816406	470738.85498047	2009469.25927734	0.00000000	0.2394	-0.4937	0.5487	0.0051	0.9300
333	APM	0333	4080.80004883	5240.18945313	473587.19970703	2003880.85107422	0.00000000	0.1771	0.1488	0.2313	0.0009	0.9300
334	APM	0334	4440.96386719	5302.47119141	483967.52050781	2000366.77001953	0.00000000	0.1454	0.1537	0.2116	0.0008	0.9300
335	APM	0335	4855.92333984	5086.70410156	497259.94628906	2004836.94873047	0.00000000	-0.2064	0.1584	0.2602	0.0012	0.9500
336	APM	0336	4912.69238281	5224.14648438	498305.50488281	2000484.44531250	0.00000000	-0.2278	-0.3832	0.4458	0.0034	0.9500
337	APM	0337	5013.15820313	5224.33105469	501281.45068359	2000027.55322266	0.00000000	-0.2276	0.0955	0.2468	0.0010	0.9200
338	APM	0338	5180.67382813	5086.04882813	506878.60839844	2003336.10937500	0.00000000	-0.3047	-0.3406	0.4570	0.0036	0.9200
339	APM	0339	5472.61376953	5206.58251953	514952.08740234	1998426.05419922	0.00000000	0.2255	0.1004	0.2468	0.0010	0.9100
340	APM	0340	370.60540771	5317.59228516	363274.94311523	2018749.39746094	0.00000000	0.0427	0.1312	0.1379	0.0003	0.9100
341	APM	0341	486.59457397	5374.50781250	366456.54876709	2016520.14111328	0.00000000	-0.1326	-0.0854	0.1577	0.0004	0.9300
342	APM	0342	1558.18847656	5315.93896484	398484.21899414	2013295.06787109	0.00000000	0.3237	-0.3955	0.5110	0.0044	0.9300
343	APM	0343	1710.65319824	5400.51464844	402638.97216797	2010101.14160156	0.00000000	-0.4156	0.2897	0.5066	0.0044	0.9500
344	APM	0344	1905.97375488	5328.61230469	408755.22729492	2011323.80126953	0.00000000	-0.2795	0.1219	0.3049	0.0016	0.9500
345	APM	0345	2506.79614258	5306.53710938	426656.67993164	2009204.71142578	0.00000000	-0.0152	0.2905	0.2909	0.0014	0.9100
346	APM	0346	2924.60839844	5371.56103516	438736.62963867	2005336.28320313	0.00000000	-0.0288	0.0131	0.0316	0.0000	0.9100
347	APM	0347	4170.48193359	5344.48193359	475758.94775391	2000369.47705078	0.00000000	0.2693	-0.0478	0.2735	0.0013	0.8800

Job Log

APM found 347 tie points

APPENDIX D

FIRST YEAR SAMPLE FOR CALCULATE VALUE ON THE SET OF RULES (g13147_20070213)

g13147_20070213

No.	Band1	Band2	Band3	Band4	Band5	Band7	NDVI	Vegetation (sigV) b2>b3,b4>b5,b4>b3	Water (sigW) b2>b3>b4>b5	Soil (sigS) b5>b4>b3>b2
:: Vegetation::										
1	53	21	18	93	50	12	0.68	**121**	-29	29
2	56	23	19	76	58	17	0.60	**79**	-35	35
3	56	25	23	88	76	26	0.59	**79**	-51	51
4	70	30	28	68	67	26	0.42	**43**	-37	37
5	64	29	27	66	69	23	0.42	**38**	-40	40
6	63	24	21	68	70	23	0.53	**48**	-46	46
7	69	30	28	80	80	30	0.48	**54**	-50	50
8	57	24	21	93	54	15	0.63	**114**	-30	30
9	63	28	26	80	76	23	0.51	**60**	-48	48
10	55	23	19	84	49	15	0.63	**104**	-26	26
11	63	24	23	58	68	24	0.43	**26**	-44	44
12	62	25	21	81	60	21	0.59	**85**	-35	35
13	63	27	23	83	83	25	0.57	**64**	-56	56
14	62	25	21	73	67	21	0.55	**62**	-42	42
15	61	24	21	77	66	20	0.57	**70**	-42	42
16	57	22	18	59	50	15	0.53	**54**	-28	28
17	62	27	23	78	77	26	0.54	**60**	-50	50
18	63	28	26	70	80	25	0.46	**36**	-52	52
19	62	26	22	58	64	20	0.45	**34**	-38	38
20	62	27	25	72	82	28	0.48	**39**	-55	55
21	71	31	30	78	86	32	0.44	**41**	-55	55
22	73	31	30	81	79	28	0.46	**54**	-48	48
23	63	27	22	70	76	27	0.52	**47**	-49	49
24	56	23	18	105	59	18	0.71	**138**	-36	36
25	53	23	18	98	57	16	0.69	**126**	-34	34
26	54	23	19	85	56	16	0.63	**99**	-33	33
27	53	22	17	68	49	13	0.60	**75**	-27	27
28	57	24	21	91	52	17	0.63	**112**	-28	28
29	61	28	23	107	73	21	0.65	**123**	-45	45
30	55	25	22	102	68	18	0.65	**117**	-43	43
31	68	29	27	80	71	24	0.50	**64**	-42	42
32	65	26	24	64	67	22	0.45	**39**	-41	41
33	68	28	23	69	67	22	0.50	**53**	-39	39
34	69	31	27	103	87	30	0.58	**96**	-56	56
35	65	31	31	72	72	25	0.40	**41**	-41	41
36	65	30	31	84	95	38	0.46	**41**	-65	65
37	65	27	24	69	67	22	0.48	**50**	-40	40
38	73	30	29	81	78	27	0.47	**56**	-48	48
39	68	29	27	80	78	24	0.50	**57**	-49	49
40	62	26	22	61	65	22	0.47	**39**	-39	39
41	67	28	25	69	66	24	0.47	**50**	-38	38
42	59	24	20	82	57	19	0.61	**91**	-33	33
43	60	24	20	86	73	25	0.62	**83**	-49	49
44	63	28	23	100	86	27	0.63	**96**	-58	58
45	66	28	26	92	72	22	0.56	**88**	-44	44
46	61	25	22	84	60	19	0.58	**89**	-35	35
47	67	28	27	91	66	24	0.54	**90**	-38	38
48	56	23	20	80	63	21	0.60	**80**	-40	40
49	59	28	25	89	70	22	0.56	**86**	-42	42
50	69	30	27	88	84	28	0.53	**68**	-54	54
			Avg				0.54	71.18	-42.46	42.46
			min				0.40	**26**	-65	26
			max				0.71	**138**	-26	65
			x = (max-min)/2				0.15	56	20	20
			Avg-x				0.39	15	-62	23
			Avg+x				0.70	127	-23	62
			Minimum - 15%				0.33	**13**	**-75**	**20**
			Maximum + 15%				0.81	159	-20	75

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No.	Band1	Band2	Band3	Band4	Band5	Band7	NDVI	Vegetation (sigV) b2>b3,b4>b5,b4>b3	Water (sigW) b2>b3>b4>b5	Soil (sigS) b5>b4>b3>b2
:: Water ::										
1	68	27	23	22	22	9	-0.02	3	**5**	-5
2	68	25	22	25	17	7	0.06	14	**8**	-8
3	66	25	22	28	26	11	0.12	11	**-1**	1
4	66	26	22	21	11	7	-0.02	13	**15**	-15
5	68	26	23	22	22	11	-0.02	2	**4**	-4
6	72	34	27	18	6	5	-0.20	10	**28**	-28
7	60	23	21	21	19	9	0.00	4	**4**	-4
8	64	24	21	27	20	7	0.13	16	**4**	-4
9	72	32	28	34	27	13	0.10	17	**5**	-5
10	70	28	25	21	19	9	-0.09	1	**9**	-9
11	66	24	21	25	19	10	0.09	13	**5**	-5
12	67	25	23	28	23	11	0.10	12	**2**	-2
13	67	28	24	31	44	20	0.13	-2	**-16**	16
14	65	25	22	28	24	9	0.12	13	**1**	-1
15	65	24	22	17	18	7	-0.13	-4	**6**	-6
16	64	25	20	17	16	8	-0.08	3	**9**	-9
17	66	27	22	24	25	11	0.04	6	**2**	-2
18	64	25	20	17	16	8	-0.08	3	**9**	-9
19	67	26	21	18	19	9	-0.08	1	**7**	-7
20	68	26	22	20	22	9	-0.05	0	**4**	-4
21	66	27	22	21	18	9	-0.02	7	**9**	-9
22	72	29	26	26	24	14	0.00	5	**5**	-5
23	61	25	21	15	15	6	-0.17	-2	**10**	-10
24	68	25	22	25	17	7	0.06	14	**8**	-8
25	67	25	21	22	17	7	0.02	10	**8**	-8
26	67	26	20	19	20	8	-0.03	4	**6**	-6
27	67	25	22	18	15	8	-0.10	2	**10**	-10
28	64	25	21	25	18	8	0.09	15	**7**	-7
29	65	25	21	17	16	9	-0.11	1	**9**	-9
30	63	25	21	16	16	8	-0.14	-1	**9**	-9
31	64	24	21	21	22	10	0.00	2	**2**	-2
32	66	25	22	32	35	15	0.19	10	**-10**	10
33	62	22	21	19	21	11	-0.05	-3	**1**	-1
34	60	23	21	21	19	9	0.00	4	**4**	-4
35	64	24	21	21	22	10	0.00	2	**2**	-2
36	72	36	27	18	11	6	-0.20	7	**25**	-25
37	61	25	21	15	15	6	-0.17	-2	**10**	-10
38	64	24	21	27	20	7	0.13	16	**4**	-4
39	62	23	21	28	20	10	0.14	17	**3**	-3
40	60	24	22	31	30	14	0.17	12	**-6**	6
41	71	33	25	19	19	8	-0.14	2	**14**	-14
42	73	35	27	19	13	10	-0.17	6	**22**	-22
43	75	35	30	31	50	21	0.02	-13	**-15**	15
44	74	35	25	18	14	6	-0.16	7	**21**	-21
45	73	35	27	22	19	11	-0.10	6	**16**	-16
46	76	31	25	29	29	13	0.07	10	**2**	-2
47	71	30	26	34	41	17	0.13	5	**-11**	11
48	67	25	21	23	17	7	0.05	12	**8**	-8
49	71	31	25	21	11	8	-0.09	12	**20**	-20
50	73	30	25	26	28	14	0.02	4	**2**	-2
			Avg				-0.01	6.14	6.10	-6.10
			min				-0.20	-13	**-16**	-28
			max				0.19	17	**28**	16
			x = (max-min)/2				0.19	15	22	22
			Avg-x				-0.20	-8.86	-15.9	-28.1
			Avg+x				0.18	21.14	28.1	15.9
			Minimum - 15%				-0.23	**5**	**2**	**-12**
			Maximum + 15%				0.21	44	52	38

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No.	Band1	Band2	Band3	Band4	Band5	Band7	NDVI	Vegetation (sigV) b2>b3,b4>b5,b4>b3	Water (sigW) b2>b3>b4>b5	Soil (sigS) b5>b4>b3>b2
:: Soil ::										
1	75	39	51	69	161	83	0.15	-86	-122	**122**
2	69	32	44	72	126	55	0.24	-38	-94	**94**
3	65	31	37	49	92	54	0.14	-37	-61	**61**
4	80	39	47	65	144	73	0.16	-69	-105	**105**
5	65	32	42	67	138	73	0.23	-56	-106	**106**
6	76	36	48	62	141	71	0.13	-77	-105	**105**
7	69	33	44	68	120	61	0.21	-39	-87	**87**
8	68	34	46	68	152	76	0.19	-74	-118	**118**
9	76	39	52	72	141	72	0.16	-62	-102	**102**
10	71	31	37	61	96	40	0.24	-17	-65	**65**
11	72	34	44	72	120	54	0.24	-30	-86	**86**
12	68	30	39	65	87	35	0.25	-5	-57	**57**
13	70	33	39	81	112	44	0.35	5	-79	**79**
14	68	34	39	83	126	49	0.36	-4	-92	**92**
15	70	34	42	71	109	49	0.26	-17	-75	**75**
16	76	38	50	69	122	55	0.16	-46	-84	**84**
17	69	30	37	54	102	47	0.19	-38	-72	**72**
18	76	37	45	66	115	50	0.19	-36	-78	**78**
19	76	34	43	61	140	82	0.17	-70	-106	**106**
20	78	39	50	61	119	63	0.10	-58	-80	**80**
21	75	33	39	68	117	51	0.27	-26	-84	**84**
22	71	30	33	50	99	51	0.20	-35	-69	**69**
23	88	46	61	76	170	86	0.11	-94	-124	**124**
24	91	46	61	80	166	83	0.13	-82	-120	**120**
25	69	35	44	61	113	59	0.16	-44	-78	**78**
26	69	34	44	76	133	56	0.27	-35	-99	**99**
27	67	32	39	65	111	50	0.25	-27	-79	**79**
28	68	32	38	57	116	56	0.20	-46	-84	**84**
29	60	26	28	60	89	39	0.36	1	-63	**63**
30	65	32	39	55	118	58	0.17	-54	-86	**86**
31	74	35	41	74	117	55	0.29	-16	-82	**82**
32	69	32	40	70	106	45	0.27	-14	-74	**74**
33	81	36	38	60	78	31	0.22	2	-42	**42**
34	80	37	42	66	100	48	0.22	-15	-63	**63**
35	84	39	47	65	152	77	0.16	-77	-113	**113**
36	73	34	38	56	105	53	0.19	-35	-71	**71**
37	74	34	42	57	142	75	0.15	-78	-108	**108**
38	75	35	41	65	110	49	0.23	-27	-75	**75**
39	81	36	40	56	81	35	0.17	-13	-45	**45**
40	78	35	38	68	108	46	0.28	-13	-73	**73**
41	74	32	38	55	123	60	0.18	-57	-91	**91**
42	74	34	39	56	105	49	0.18	-37	-71	**71**
43	87	43	56	77	158	85	0.16	-73	-115	**115**
44	87	42	53	83	144	66	0.22	-42	-102	**102**
45	79	38	55	84	155	68	0.21	-59	-117	**117**
46	75	36	49	75	120	52	0.21	-32	-84	**84**
47	78	37	46	76	134	58	0.25	-37	-97	**97**
48	73	33	39	60	111	51	0.21	-36	-78	**78**
49	80	39	47	71	149	74	0.20	-62	-110	**110**
50	83	37	37	83	81	31	0.38	48	-44	**44**
			Avg				0.21	-39.38	-86.30	86.30
			min				0.10	**-94**	-124	42
			max				0.38	**48**	-42	124
			x = (max-min)/2				0.14	71	41	41
			Avg-x				0.07	-110.38	-127.3	45.3
			Avg+x				0.36	31.6	-45.3	127.3
			Minimum - 15%				0.06	**-127**	**-146**	**36**
			Maximum + 15%				0.44	55	-36	146

APPENDIX E

SECOND YEAR SAMPLE FOR CALCULATE VALUE ON THE SET OF RULES (g13147_20090306)

g13147_20090306

No.	Band1	Band2	Band3	Band4	Band5	Band7	NDVI	Vegetation (sigV) b2>b3,b4>b5,b4>b3	Water (sigW) b2>b3>b4>b5	Soil (sigS) b5>b4>b3>b2
:: Vegetation::										
1	84	35	35	78	87	29	0.38	**34**	-52	52
2	82	35	33	71	81	28	0.37	**30**	-46	46
3	77	34	30	75	77	26	0.43	**47**	-43	43
4	59	27	21	111	63	15	0.68	**144**	-36	36
5	57	26	22	113	62	14	0.67	**146**	-36	36
6	62	27	21	98	59	19	0.65	**122**	-32	32
7	61	28	22	111	62	19	0.67	**144**	-34	34
8	60	26	20	93	54	15	0.65	**118**	-28	28
9	59	28	21	104	57	17	0.66	**137**	-29	29
10	75	31	27	82	60	18	0.50	**81**	-29	29
11	80	36	33	91	88	30	0.47	**64**	-52	52
12	80	35	30	102	96	33	0.55	**83**	-61	61
13	79	34	29	70	70	27	0.41	**46**	-36	36
14	75	34	30	81	79	26	0.46	**57**	-45	45
15	77	32	29	81	94	33	0.47	**42**	-62	62
16	79	34	32	71	77	26	0.38	**35**	-43	43
17	70	29	27	85	78	26	0.52	**67**	-49	49
18	69	31	27	113	81	26	0.61	**122**	-50	50
19	81	35	30	84	86	30	0.47	**57**	-51	51
20	83	36	33	104	95	35	0.52	**83**	-59	59
21	68	29	25	114	77	23	0.64	**130**	-48	48
22	70	31	25	112	79	24	0.64	**126**	-48	48
23	71	32	26	116	80	24	0.63	**132**	-48	48
24	73	32	28	102	87	28	0.57	**93**	-55	55
25	75	32	30	107	86	29	0.56	**100**	-54	54
26	73	31	28	80	71	26	0.48	**64**	-40	40
27	71	29	25	57	57	20	0.39	**36**	-28	28
28	74	31	27	83	74	26	0.51	**69**	-43	43
29	62	25	19	80	52	16	0.62	**95**	-27	27
30	61	27	23	88	72	24	0.59	**85**	-45	45
31	61	29	23	105	69	22	0.64	**124**	-40	40
32	63	29	26	87	92	37	0.54	**59**	-63	63
33	61	27	21	101	77	22	0.66	**110**	-50	50
34	63	27	24	87	62	23	0.57	**91**	-35	35
35	63	30	25	116	76	23	0.65	**136**	-46	46
36	66	29	26	91	75	22	0.56	**84**	-46	46
37	65	30	26	91	66	22	0.56	**94**	-36	36
38	74	31	27	73	76	27	0.46	**47**	-45	45
39	74	31	28	80	79	26	0.48	**56**	-48	48
40	63	28	23	102	69	21	0.63	**117**	-41	41
41	86	38	39	82	99	45	0.36	**25**	-61	61
42	84	37	36	76	78	29	0.36	**39**	-41	41
43	63	29	24	113	66	18	0.65	**141**	-37	37
44	61	27	23	77	55	19	0.54	**80**	-28	28
45	62	26	23	79	64	21	0.55	**74**	-38	38
46	60	26	20	65	47	16	0.53	**69**	-21	21
47	63	26	23	69	44	14	0.50	**74**	-18	18
48	61	26	21	87	49	16	0.61	**109**	-23	23
49	64	29	25	92	73	24	0.57	**90**	-44	44
50	82	36	33	107	105	35	0.53	**79**	-69	69
			Avg				0.54	85.74	-42.78	42.78
			min				0.36	**25**	-69	18
			max				0.68	**146**	-18	69
			x = (max-min)/2				0.16	61	26	26
			Avg-x				0.38	25	-68	17
			Avg+x				0.70	146	-17	68
			Minimum - 15%				0.30	**21**	**-79**	**15**
			Maximum + 15%				0.81	168	-15	79

g13147_20090306

No.	Band1	Band2	Band3	Band4	Band5	Band7	NDVI	Vegetation (sigV) b2>b3,b4>b5,b4>b3	Water (sigW) b2>b3>b4>b5	Soil (sigS) b5>b4>b3>b2
:: Water ::										
1	83	34	29	26	26	11	-0.05	2	**8**	-8
2	80	33	30	24	13	8	-0.11	8	**20**	-20
3	83	33	27	22	19	10	-0.10	4	**14**	-14
4	81	33	28	24	21	10	-0.08	4	**12**	-12
5	84	34	29	26	12	7	-0.05	16	**22**	-22
6	82	32	28	23	21	8	-0.10	1	**11**	-11
7	76	30	28	20	15	8	-0.17	-1	**15**	-15
8	78	30	29	27	26	12	-0.04	0	**4**	-4
9	92	45	36	21	21	9	-0.26	-6	**24**	-24
10	78	32	30	35	43	20	0.08	-1	**-11**	11
11	83	34	30	29	44	20	-0.02	-12	**-10**	10
12	77	31	27	22	22	12	-0.10	-1	**9**	-9
13	79	31	27	23	19	8	-0.08	4	**12**	-12
14	79	31	29	21	12	6	-0.16	3	**19**	-19
15	78	31	29	24	15	7	-0.09	6	**16**	-16
16	79	32	28	24	13	8	-0.08	11	**19**	-19
17	76	30	29	30	42	19	0.02	-10	**-12**	12
18	78	32	30	36	42	18	0.09	2	**-10**	10
19	82	35	31	23	15	8	-0.15	4	**20**	-20
20	85	34	32	32	38	18	0	-4	**-4**	4
21	78	31	30	25	31	17	-0.09	-10	**0**	0
22	81	32	29	25	37	18	-0.07	-13	**-5**	5
23	80	32	27	22	22	11	-0.10	0	**10**	-10
24	79	31	28	21	18	9	-0.14	-1	**13**	-13
25	78	30	29	21	23	11	-0.16	-9	**7**	-7
26	77	32	31	34	33	14	0.05	5	**-1**	1
27	78	31	30	30	26	11	0.00	5	**5**	-5
28	76	31	31	33	45	20	0.03	-10	**-14**	14
29	79	31	28	30	28	11	0.03	7	**3**	-3
30	75	30	28	22	30	11	-0.12	-12	**0**	0
31	77	29	29	23	27	11	-0.12	-10	**2**	-2
32	79	31	28	25	23	11	-0.06	2	**8**	-8
33	79	32	29	24	16	11	-0.09	6	**16**	-16
34	79	32	30	28	27	13	-0.03	1	**5**	-5
35	80	32	27	24	13	13	-0.06	13	**19**	-19
36	84	32	28	20	18	8	-0.17	-2	**14**	-14
37	82	32	28	21	16	6	-0.14	2	**16**	-16
38	81	32	29	23	15	7	-0.12	5	**17**	-17
39	85	33	28	20	21	10	-0.17	-4	**12**	-12
40	83	33	27	22	19	10	-0.10	4	**14**	-14
41	59	21	16	20	15	5	0.11	14	**6**	-6
42	60	21	19	20	23	6	0.03	0	**-2**	2
43	59	21	18	22	18	8	0.10	11	**3**	-3
44	60	21	17	21	22	10	0.11	7	**-1**	1
45	82	35	31	23	15	8	-0.15	4	**20**	-20
46	81	35	33	40	46	21	0.10	3	**-11**	11
47	82	36	32	23	13	6	-0.16	5	**23**	-23
48	85	34	32	32	38	18	0.00	-4	**-4**	4
49	81	36	32	25	17	9	-0.12	5	**19**	-19
50	85	35	33	25	29	13	-0.14	-10	**6**	-6
			Avg				-0.06	0.88	7.56	-7.56
			min				-0.26	-13	**-14**	-24
			max				0.11	16	**24**	14
			x = (max-min)/2				0.19	14.5	19	19
			Avg-x				-0.25	-13.62	-11.44	-26.56
			Avg+x				0.12	15.38	26.56	11.44
			Minimum - 15%				-0.30	**4**	**4**	**-11**
			Maximum + 15%				0.14	38	51	36

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No.	Band1	Band2	Band3	Band4	Band5	Band7	NDVI	Vegetation (sigV) b2>b3,b4>b5,b4>b3	Water (sigW) b2>b3>b4>b5	Soil (sigS) b5>b4>b3>b2
:: Soil ::										
1	95	47	57	73	173	91	0.12	-94	-126	**126**
2	95	51	67	78	175	103	0.08	-102	-124	**124**
3	88	48	60	86	200	101	0.18	-100	-152	**152**
4	88	44	56	70	170	91	0.11	-98	-126	**126**
5	77	41	55	88	149	64	0.23	-42	-108	**108**
6	79	39	50	80	150	76	0.23	-51	-111	**111**
7	80	42	51	76	165	79	0.20	-73	-123	**123**
8	90	49	64	89	165	88	0.16	-66	-116	**116**
9	90	43	52	77	172	88	0.19	-79	-129	**129**
10	90	46	55	80	163	86	0.19	-67	-117	**117**
11	92	44	56	74	154	71	0.14	-74	-110	**110**
12	89	42	53	69	149	72	0.13	-75	-107	**107**
13	85	40	50	67	142	70	0.15	-68	-102	**102**
14	86	40	48	69	141	61	0.18	-59	-101	**101**
15	88	40	51	64	172	92	0.11	-106	-132	**132**
16	84	40	55	88	145	62	0.23	-39	-105	**105**
17	77	37	52	86	159	68	0.25	-54	-122	**122**
18	83	41	58	88	157	66	0.21	-56	-116	**116**
19	80	40	55	87	151	68	0.23	-47	-111	**111**
20	100	54	70	87	178	101	0.11	-90	-124	**124**
21	82	42	53	72	123	53	0.15	-43	-81	**81**
22	82	41	55	71	127	59	0.13	-54	-86	**86**
23	88	42	57	72	138	64	0.12	-66	-96	**96**
24	84	41	55	74	134	60	0.15	-55	-93	**93**
25	87	44	57	77	139	63	0.15	-55	-95	**95**
26	85	42	56	79	131	55	0.17	-43	-89	**89**
27	83	42	53	74	129	61	0.17	-45	-87	**87**
28	84	48	66	91	140	67	0.16	-42	-92	**92**
29	83	52	75	101	175	103	0.15	-71	-123	**123**
30	77	40	54	76	129	68	0.17	-45	-89	**89**
31	76	40	56	64	166	98	0.07	-110	-126	**126**
32	74	39	50	62	146	78	0.11	-83	-107	**107**
33	85	42	55	73	135	71	0.14	-57	-93	**93**
34	76	36	53	79	161	72	0.20	-73	-125	**125**
35	88	44	55	74	165	86	0.15	-83	-121	**121**
36	91	45	56	77	165	87	0.16	-78	-120	**120**
37	87	43	54	74	145	78	0.16	-62	-102	**102**
38	86	43	49	73	131	67	0.20	-40	-88	**88**
39	84	41	55	86	153	65	0.22	-50	-112	**112**
40	82	41	54	80	151	65	0.19	-58	-110	**110**
41	93	46	55	71	156	89	0.13	-78	-110	**110**
42	92	45	54	71	168	92	0.14	-89	-123	**123**
43	88	44	57	76	190	100	0.14	-108	-146	**146**
44	92	48	62	76	172	95	0.10	-96	-124	**124**
45	77	40	49	75	134	65	0.21	-42	-94	**94**
46	82	43	53	87	154	77	0.24	-43	-111	**111**
47	85	44	60	81	170	89	0.15	-84	-126	**126**
48	88	46	56	78	158	83	0.16	-68	-112	**112**
49	76	39	45	61	145	74	0.15	-74	-106	**106**
50	95	45	53	68	126	66	0.12	-51	-81	**81**
			Avg				0.16	-67.72	-110.60	110.60
			min				0.07	**-110**	-152	81
			max				0.25	**-39**	-81	152
			x = (max-min)/2				0.09	35.5	35.5	35.5
			Avg-x				0.07	-103.22	-146.1	75.1
			Avg+x				0.25	-32.2	-75.1	146.1
			Minimum - 15%				0.06	**-127**	**-175**	**64**
			Maximum + 15%				0.29	-27	-64	175

APPENDIX F
THE SET OF RULES

The set of rule used to class discrimination with only NDVI:

IF ndvi1 > 0.39 **AND** ndvi2 ≥ 0.08 **AND** ndvi2 ≤ 0.33 **THEN** Area change from vegetation to soil

IF ndvi1 ≥ 0.15 **AND** ndvi1 ≤ 0.39 **AND** ndvi2 > 0.33 **THEN** Area change from soil to vegetation

IF ndvi1 > 0.39 **AND** ndvi2 < 0.08 **THEN** Area change from vegetation to water

IF ndvi1 < 0.15 **AND** ndvi2 > 0.33 **THEN** Area change from water to vegetation

IF ndvi1 ≥ 0.15 **AND** ndvi1 ≤ 0.39 **AND** ndvi2 < 0.15 **THEN** Area change from soil to water

IF ndvi1 < 0.15 **AND** ndvi2 ≥ 0.08 **AND** ndvi2 ≤ 0.33 **THEN** Area change from water to soil

The set of rule used to class discrimination with NDVI, SigV, SigS and SigW:

IF ndvi1 > 0.37 **AND** ndvi2 > 0.07 **AND** ndvi2 < 0.38 **AND** SigV1 > 13 **AND** SigS2 > 64 **THEN** Area change from vegetation to soil

IF ndvi1 > 0.07 **AND** ndvi1 < 0.39 **AND** ndvi2 > 0.31 **AND** SigS1 > 36 **AND** SigV2 > 21 **THEN** Area change from soil to vegetation

IF ndvi1 > 0.37 **AND** ndvi2 < 0.12 **AND** SigV1 > 13 **AND** SigW2 > 4 **THEN** Area change from vegetation to water

IF ndvi1 < 0.19 **AND** ndvi2 > 0.31 **AND** SigW1 > 2 **AND** SigV2 > 21 **THEN** Area change from water to vegetation

IF ndvi1 > 0.07 **AND** ndvi1 < 0.39 **AND** ndvi2 < 0.12 **AND** SigS1 > 36 **AND** SigW2 > 4 **THEN** Area change from soil to water

IF ndvi1 < 0.19 **AND** ndvi2 > 0.07 **AND** ndvi2 < 0.38 **AND** SigW1 > 2 **AND** SigS2 > 64 **THEN** Area change from water to soil

APPENDIX G
UPSIZING REPORT

Upsizing Wizard Report

Database

Microsoft Access Database: C:\Users\Public\Documents\Falcon_DB.accdb
SQL Server Database: Falcon

Upsizing Parameters

Table Attributes to Export

- [x] **Indexes**
- [ ] **Validation rules**
- [ ] **Defaults**
- [ ] **Structure only, no data**

Table relationships:
Upsized using triggers

Timestamp fields added:
No tables

Modifications to Existing Database

- [x] **Attach newly created SQL Server tables**
- [ ] **Save password and user ID with attached tables**

Client/Server Modifications

- [ ] **Create a new Access client/server application.**
- [ ] **Save password and user ID with application**

Tables

Table: Admn

	Microsoft Access	SQL Server
Table Name:	Admn_local	Admn
Attached Table Name:	Admn	
Aliasing Query:		
Validation Rule:		

Fields	Microsoft Access	SQL Server
Field Name:	AdmID	AdmID
Data Type:	Text(255)	nvarchar(255)
Field Name:	AdmTmp	AdmTmp
Data Type:	Text(255)	nvarchar(255)
Field Name:	AdmType	AdmType
Data Type:	Text(255)	nvarchar(255)

Table: Condition

	Microsoft Access	SQL Server
Table Name:	Condition_local	Condition
Attached Table Name:	Condition	
Aliasing Query:		
Validation Rule:		

Fields	Microsoft Access	SQL Server
Field Name:	ConID	ConID
Data Type:	Text(255)	nvarchar(255)
Field Name:	ConType	ConType
Data Type:	Text(255)	nvarchar(255)
Field Name:	ConDescription	ConDescription
Data Type:	Text(255)	nvarchar(255)

Table: Dnpall47

	Microsoft Access	SQL Server
Table Name:	Dnpall47_local	Dnpall47
Attached Table Name:	Dnpall47	
Aliasing Query:		
Validation Rule:		

Fields	Microsoft Access	SQL Server
Field Name:	DnpID	DnpID
Data Type:	Text(255)	nvarchar(255)
Field Name:	DnpType	DnpType
Data Type:	Text(255)	nvarchar(255)

Table: Equation

	Microsoft Access	SQL Server
Table Name:	Equation_local	Equation
Attached Table Name:	Equation	
Aliasing Query:		
Validation Rule:		

Fields

	Microsoft Access	SQL Server
Field Name:	EquID	EquID
Data Type:	Text(255)	nvarchar(255)
Field Name:	ExpID	ExpID
Data Type:	Text(255)	nvarchar(255)
Field Name:	ConID	ConID
Data Type:	Text(255)	nvarchar(255)
Field Name:	Equation	Equation
Data Type:	Text(255)	nvarchar(255)

Indexes

	Microsoft Access	SQL Server
Name:	ConID	ConID
Fields:	ConID	ConID
Type:	DuplicatesOK	DuplicatesOK
Name:	ExpID	ExpID
Fields:	ExpID	ExpID
Type:	DuplicatesOK	DuplicatesOK

Table: Experiment

	Microsoft Access	SQL Server
Table Name:	Experiment_local	Experiment
Attached Table Name:	Experiment	
Aliasing Query:		
Validation Rule:		

Fields

	Microsoft Access	SQL Server
Field Name:	ExpID	ExpID
Data Type:	Text(255)	nvarchar(255)
Field Name:	Experiment	Experiment
Data Type:	Text(255)	nvarchar(255)
Field Name:	ExpDescription	ExpDescription
Data Type:	Text(255)	nvarchar(255)

Table: Falcon

	Microsoft Access	SQL Server
Table Name:	Falcon_local	Falcon
Attached Table Name:	Falcon	
Aliasing Query:		
Validation Rule:		

Fields

	Microsoft Access	SQL Server
Field Name:	FAL_ID	FAL_ID
Data Type:	Number (Double)	float
Field Name:	TAMBON_IDN	TAMBON_IDN
Data Type:	Text(255)	nvarchar(255)
Field Name:	TAM_NAM_T	TAM_NAM_T
Data Type:	Text(255)	nvarchar(255)
Field Name:	AMPHOE_T	AMPHOE_T
Data Type:	Text(255)	nvarchar(255)
Field Name:	AMPHOE_E	AMPHOE_E
Data Type:	Text(255)	nvarchar(255)
Field Name:	PROV_NAM_T	PROV_NAM_T
Data Type:	Text(255)	nvarchar(255)
Field Name:	PROV_NAM_E	PROV_NAM_E
Data Type:	Text(255)	nvarchar(255)
Field Name:	FTYPE	FTYPE
Data Type:	Text(255)	nvarchar(255)
Field Name:	NRF_CODE	NRF_CODE
Data Type:	Text(255)	nvarchar(255)
Field Name:	DNP_CODE	DNP_CODE
Data Type:	Text(255)	nvarchar(255)
Field Name:	FULLCODE	FULLCODE
Data Type:	Number (Double)	float
Field Name:	SUBTYPE	SUBTYPE
Data Type:	Number (Double)	float

Field Name:	GRID_CODE	GRID_CODE
Data Type:	Number (Double)	float
Field Name:	AREA_RAI	AREA_RAI
Data Type:	Number (Double)	float
Field Name:	SCENTYPE	SCENTYPE
Data Type:	Number (Double)	float
Field Name:	IMGSDATE	IMGSDATE
Data Type:	Date/Time	datetime
Field Name:	IMGEDATE	IMGEDATE
Data Type:	Date/Time	datetime
Field Name:	PRCSDATE	PRCSDATE
Data Type:	Date/Time	datetime
Field Name:	EquID	EquID
Data Type:	Text(255)	nvarchar(255)
Field Name:	PLOT_ID	PLOT_ID
Data Type:	Number (Double)	float
Field Name:	UTM_ZONE	UTM_ZONE
Data Type:	Number (Double)	float
Field Name:	WGSEAST	WGSEAST
Data Type:	Number (Double)	float
Field Name:	WGSNORTH	WGSNORTH
Data Type:	Number (Double)	float
Field Name:	INHEAST	INHEAST
Data Type:	Number (Double)	float
Field Name:	INHNORTH	INHNORTH
Data Type:	Number (Double)	float
Field Name:	CNT_X	CNT_X
Data Type:	Number (Double)	float
Field Name:	CNT_Y	CNT_Y
Data Type:	Number (Double)	float
Field Name:	ACTIVE	ACTIVE
Data Type:	Text(255)	nvarchar(255)

Field Name:	LAB_CHK	LAB_CHK
Data Type:	Text(255)	nvarchar(255)
Field Name:	FULLCHK	FULLCHK
Data Type:	Number (Double)	float
Field Name:	FalDescription	FalDescription
Data Type:	Text(255)	nvarchar(255)

Indexes

	Microsoft Access	SQL Server
Name:	DNP_CODE	DNP_CODE
Fields:	DNP_CODE	DNP_CODE
Type:	DuplicatesOK	DuplicatesOK
Name:	EquID	EquID
Fields:	EquID	EquID
Type:	DuplicatesOK	DuplicatesOK
Name:	FULLCODE	FULLCODE
Fields:	FULLCODE	FULLCODE
Type:	DuplicatesOK	DuplicatesOK
Name:	GRID_CODE	GRID_CODE
Fields:	GRID_CODE	GRID_CODE
Type:	DuplicatesOK	DuplicatesOK
Name:	NRF_CODE	NRF_CODE
Fields:	NRF_CODE	NRF_CODE
Type:	DuplicatesOK	DuplicatesOK
Name:	PLOT_ID	PLOT_ID
Fields:	PLOT_ID	PLOT_ID
Type:	DuplicatesOK	DuplicatesOK

Table: Mgrvzone

	Microsoft Access	SQL Server
Table Name:	Mgrvzone_local	Mgrvzone
Attached Table Name:	Mgrvzone	
Aliasing Query:		
Validation Rule:		

Fields

	Microsoft Access	SQL Server
Field Name:	MgrID	MgrID
Data Type:	Text(255)	nvarchar(255)
Field Name:	MgrType	MgrType
Data Type:	Text(255)	nvarchar(255)

Table: Nrfr

	Microsoft Access	SQL Server
Table Name:	Nrfr_local	Nrfr
Attached Table Name:	Nrfr	
Aliasing Query:		
Validation Rule:		

Fields

	Microsoft Access	SQL Server
Field Name:	NrfID	NrfID
Data Type:	Text(255)	nvarchar(255)
Field Name:	NrfType	NrfType
Data Type:	Text(255)	nvarchar(255)

Indexes

	Microsoft Access	SQL Server
Name:	NrfrNRF_CODE	NrfrNRF_CODE
Fields:	NrfID	NrfID
Type:	DuplicatesOK	DuplicatesOK

APPENDIX H
DATA DICTIONARY

Table Name : Admn

Description : Administrative district

Primary Key : AdmID

No.	Column Name	Type	Key	Description
1	AdmID	nvarchar(255)	1	Code of district
2	AdmTmp	nvarchar(255)	0	Name of district
3	AdmType	nvarchar(255)	0	Name of Protected Area Regional Office

Table Name : Condition

Description : To store classes for forest change detection

Primary Key : ConID

No.	Column Name	Type	Key	Description
1	ConID	nvarchar(255)	1	Code of condition
2	ConType	nvarchar(255)	0	Name of condition
3	ConDescription	nvarchar(255)	0	Description of condition

Table Name : Dnpll47

Description : Forest conservation

Primary Key : ConID

No.	Column Name	Type	Key	Description
1	DnpID	nvarchar(255)	1	Code of forest conservation
2	DnpType	nvarchar(255)	0	Name of forest conservation

Table Name : Equation

Description : To store equation for forest change detection

Primary Key : EquID

Foreign Key : ExpID (Experiment.ExpID), ConID (Condition.ConID)

No.	Column Name	Type	Key	Description
1	EquID	nvarchar(255)	1	Code of equation
2	ExpID	nvarchar(255)	0	Code of experiment
3	ConID	nvarchar(255)	0	Code of condition
4	Equation	nvarchar(255)	0	Equation for classification

Table Name : Experiment

Description : To store experiment for forest change detection

Primary Key : ExpID

No.	Column Name	Type	Key	Description
1	ExpID	nvarchar(255)	1	Code of experiment
2	Experiment	nvarchar(255)	0	Name of experiment
3	ExpDescription	nvarchar(255)	0	Description of experiment

Table Name : Falcon

Description : To store forest change detection area

Primary Key : FAL_ID

Foreign Key : TAMBON_IDN (Admn.AdmID),
FTYPE (Mgrvzone.MgrID),
NRF_CODE (Nrfr.NrfID),
DNP_CODE (Dnpall47.DnpID),
EquID (Equation.EquID)

No.	Column Name	Type	Key	Description
1	FAL_ID	int	1	Code of forest change detection
2	TAMBON_IDN	nvarchar(255)	0	Code of district
3	TAM_NAM_T	nvarchar(255)	0	Name of district
4	AMPHOE_T	nvarchar(255)	0	Name of amphoe (Thai)
5	AMPHOE_E	nvarchar(255)	0	Name of amphoe (English)
6	PROV_NAM_T	nvarchar(255)	0	Name of province (Thai)
7	PROV_NAM_E	nvarchar(255)	0	Name of province (English)
8	FTYPE	nvarchar(255)	0	Code of mangrove area
9	NRF_CODE	nvarchar(255)	0	Code of wildlife sanctuary
10	DNP_CODE	nvarchar(255)	0	Code of forest conservation
11	FULLCODE	float	0	Full code of forest conservation
12	SUBTYPE	float	0	Sub code of forest conservation
13	GRID_CODE	float	0	Code of change area
14	AREA_RAI	float	0	Area of forest change detection (Rais)
15	SCENTYPE	float	0	Scene number of image data (path/row)
16	IMGSDATE	datetime	0	Date of first image data
17	IMGEDATE	datetime	0	Date of second image data
18	PRCSDATE	datetime	0	Date of processing data

No.	Column Name	Type	Key	Description
19	EquID	nvarchar(255)	0	Code of equation
20	PLOT_ID	float	0	Code of system conversion
21	UTM_ZONE	float	0	Number of UTM Zone
22	WGSEAST	float	0	Geographic coordinate on spheroid: WGS84 East (m.E.)
23	WGSNORTH	float	0	Geographic coordinate on spheroid: WGS84 North (m.N.)
24	INHEAST	float	0	Geographic coordinate on spheroid: Indian 1975 East (m.E.)
25	INHNORTH	float	0	Geographic coordinate on spheroid: Indian 1975 North (m.N.)
26	CNT_X	float	0	Geographic coordinate on spheroid: Latitude
27	CNT_Y	float	0	Geographic coordinate on spheroid: Longitude
28	ACTIVE	nvarchar(255)	0	Number of area monitoring
29	LAB_CHK	nvarchar(255)	0	Number of checking area
30	FULLCHK	float	0	Full number of checking area
31	ChaDescription	nvarchar(255)	0	Description of forest change detection area

Table Name : Mgrvzone

Description : To store mangrove area

Primary Key : MgrID

No.	Column Name	Type	Key	Description
1	MgrID	nvarchar(255)	1	Code of mangrove area
2	MgrType	nvarchar(255)	0	Name of mangrove area

Table Name : Nrfr

Description : To store wildlife sanctuary

Primary Key : DnpID

No.	Column Name	Type	Key	Description
1	NrfID	nvarchar(255)	1	Code wildlife sanctuary
2	NrfType	nvarchar(255)	0	Name of wildlife sanctuary

APPENDIX I
QUESTIONNAIRE FOR USER ACCEPTANCE TEST

แบบสอบถามความคิดเห็นเกี่ยวกับการประยุกต์ใช้งานระบบสารสนเทศภูมิศาสตร์ติดตามการเปลี่ยนแปลงพื้นที่ป่าบริเวณลุ่มน้ำยวมตอนบน ในท้องที่สำนักบริหารพื้นที่อนุรักษ์ที่ 16

วัตถุประสงค์: แบบสอบถามนี้มีวัตถุประสงค์เพื่อสำรวจความพึงพอใจและความคิดเห็นของผู้ใช้ระบบสารสนเทศภูมิศาสตร์ติดตามการเปลี่ยนแปลงพื้นที่ป่าบริเวณลุ่มน้ำยวมตอนบน ในท้องที่สำนักบริหารพื้นที่อนุรักษ์ที่ 16 และนำผลการประเมินไปพัฒนาปรับปรุงแก้ไขงานให้มีคุณภาพต่อไป

แบบสอบถามแบ่งเป็น 3 ตอน ดังนี้

ตอนที่ 1 ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม **ตอนที่ 2** ระดับความพึงพอใจ **ตอนที่ 3** ข้อคิดเห็นและข้อเสนอแนะเพิ่มเติม

ตอนที่ 1 ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม (โปรดทำเครื่องหมาย √ หน้าคำตอบที่ตรงกับความเป็นจริง)

1. เพศ ○ หญิง ○ ชาย
2. อายุ ○ 20-30 ปี ○ 31-40 ปี ○ 41-50 ปี ○ 51 ปีขึ้นไป
3. วุฒิการศึกษาสูงสุด ○ ต่ำกว่าปริญญาตรี ○ ปริญญาตรี ○ ปริญญาโท ○ ปริญญาเอก
4. ผู้ตอบแบบสอบถาม ○ นักศึกษา ○ อาจารย์/ผู้เชี่ยวชาญ ○ ผู้บริหาร ○ ผู้ใช้งานด้าน GIS ○ อื่น ๆ ระบุ.....................
5. เคยใช้งานระบบ GIS มาก่อนหรือไม่ ○ ไม่เคย ○ เคย ระบุ......................

ตอนที่ 2 ระดับความพึงพอใจของผู้ใช้ระบบ (โปรดทำเครื่องหมาย √ ในช่องที่ตรงกับระดับความพึงพอใจของท่าน)

ระดับความพึงพอใจ 6 = มากที่สุด 5 = มาก 4 = ค่อนข้างมาก 3 = ค่อนข้างน้อย 2 = น้อย 1 = น้อยที่สุด

ประเด็นการสำรวจความพึงพอใจ	6	5	4	3	2	1
1. ด้านการใช้งานและความสามารถของระบบ						
1.1 ระบบสามารถใช้งานได้รวดเร็ว						
1.2 ระบบสามารถแสดงผลได้ถูกต้อง						
1.3 ระบบมีความง่ายต่อการใช้						
1.4 การออกแบบในส่วนของการลงชื่อเข้าใช้(Log in) สามารถใช้งานได้สะดวกและเข้าใจง่าย						
1.5 การออกแบบในส่วนของหน้าแสดงผล สามารถใช้งานได้สะดวก และเข้าใจง่าย						
1.6 การออกแบบในส่วนของการแก้ไขผลการตรวจสอบ สามารถใช้งานได้สะดวก และเข้าใจง่าย						
1.7 การออกแบบในส่วนของแบบรายงาน (Report) สามารถใช้งานได้สะดวก และเข้าใจง่าย						
1.8 การออกแบบ และจัดวางองค์ประกอบของระบบ รวมทั้งสีที่ใช้สวยงาม และเหมาะสม						

ประเด็นการสำรวจความพึงพอใจ (ต่อ)	6	5	4	3	2	1
2. ด้านผลลัพธ์ที่ได้จากระบบ						
2.1 ระบบสามารถแสดงผลลัพธ์ได้ถูกต้องตรงตามความต้องการ						
2.2 ผลลัพธ์ที่ได้จากระบบสามารถนำไปใช้ได้จริง						
2.3 ผลลัพธ์ที่ได้จากการลงชื่อเข้าใช้ (Log in) มีความถูกต้องเหมาะสม						
2.4 ผลลัพธ์ที่ได้จากหน้าแสดงผลพื้นที่เปลี่ยนแปลง มีความถูกต้องเหมาะสม						
2.5 ผลลัพธ์ที่ได้จากการแก้ไขผลการตรวจสอบ มีความถูกต้องเหมาะสม						
2.6 ผลลัพธ์ที่ได้จากแบบรายงาน (Report) มีความถูกต้องเหมาะสม						

ตอนที่ 3 ข้อคิดเห็นและข้อเสนอแนะเพิ่มเติม

APPENDIX J

INTERNATIONAL COMPUTER SCIENCE AND ENGINEERING CONFERENCE (ICSEC2012)

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Conference Proceedings

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Signal and Image Processing

Fast Correlation-Based Filtering for Forest Changed Detection on Remote Sensing Data

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Abstract

Forest changed detection is an important technique for supporting forest monitoring and management. This paper proposes the steps of forest changed detection from satellite data. Additional features are extracted from the remote sensing data using some natural indexes. Then, the suitable features are selected by the fast correlation-based filtering (FCBF). The experimental results show the performance of FCBF that is higher than other feature selection methods on this paper. Moreover, leaf area index (LAI) and normalized difference vegetation index (NDVI) are suitable features for forest changed detection.

Key Words: Remote Sensing Data, Fast Correlation-Based Filtering (FCBF), Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI)

1. Introduction

Land use and land cover are always changed. Land changes can be incurred by human or by nature, and they are influence to the natural resource management and city planning. Forest or vegetation is an important resource that is quickly changed. Thus, the forest changed detection is a key for land cover monitoring and natural forest management. Satellite data are a valuable source of information on forest activities. Usage of satellite remote sensing technology allows detecting the changes over large areas [1].

Many researches proposed the steps of changed detection. A research of Robert, et al., [1] proposed to simplify the steps of changed detection, which composed of four steps, i.e., data acquisition, preprocessing and/or enhancement, analysis, and evaluation. This process was applied on remote sensing data. However, the efficiency of detection depends on classification techniques. Robust and accurate classification methods were required to detect complex land cover and land use categories [2].

Decision tree classifiers (DTC) were widely used in classification of remote sensing images. In DTC, a classifier can be easily constructed and it does not complicate to apply. In research of Florencio and Zeyuan [3], J48 decision tree classifier was used for the land use changed detection. Furthermore, the efficiencies of DTC were illustrated in the researches of Darren, et al., [4], and Steven, et al., [5]. Features of data are directly affected to the efficiency of classification or discrimination. Thus, feature extraction is an important step for forest changed detection.

This paper proposes to use some natural indexes and the differences of the original features. These additional features are tested. Moreover, feature selection techniques are considered in this paper. Fast correlation-based filtering (FCBF) [6] is applied to choose some suitable features. The goodness of the proposed features can be evaluated from the results of FCBF. In section 2, remote sensing data are explained. The FCBF is reviewed in section 3. The steps of forest changed detection are explained in section 4. The experimentation and the results are illustrated in section 5 and 6, respectively.

2. Remote Sensing Data

In remote sensing system, the emanated energy from the earth's surface was measured by the sensors that were mounted on an aircraft or spacecraft platform [7]. The signals were transmitted to the ground station. Then, these signals were used to construct an image of the landscape [7]. The signal and data flow in a remote sensing system is displayed in Figure 1.

The sensor on the satellite will send the data back to the earth via radio waves to the ground station [7]. The data in digital form are processed to provide some information of the land use and land cover. The specialists are required to analyze these data. Although the digital image processing system can be applied to analyze these data, the large number of data is still an important problem in the processing process.

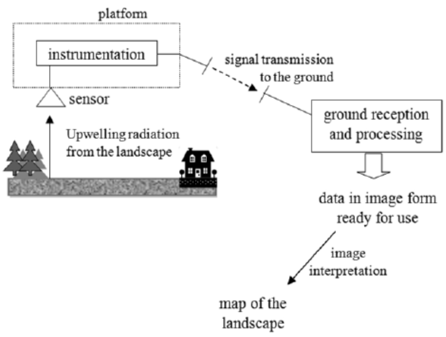

Figure 1. Data Flow in a Remote Sensing System [7]

3. Fast Correlation-Based Filtering

Fast Correlation-Based Filtering (FCBF) is an algorithm for subset selection. This algorithm analyzes the relevance and redundancy using symmetric uncertainty [8]. FCBF is designed for high-dimensional data and this algorithm has been shown effective in removing both irrelevant feature and redundant features [9]. The algorithm of FCBF is shown in Figure 2.

```
input:  S(f1, f2, ..., fN, C)  // a training data set
        δ                      // a predefined threshold
output: S_best                 // an optimal subset

1  begin
2    for i = 1 to N do begin
3      calculate SU_i,c for f_i;
4      if (SU_i,c ≥ δ)
5        append f_i to S'_list;
6    end;
7    order S'_list in descending SU_i,c value;
8    f_p = getFirstElement(S'_list);
9    do begin
10     f_q = getNextElement(S'_list, f_p);
11     if (f_q <> NULL)
12       do begin
13         f'_q = f_q;
14         if (SU_p,q ≥ SU_q,c)
15           remove f_q from S'_list;
16           f_q = getNextElement(S'_list, f'_q);
17         else f_q = getNextElement(S'_list, f_q);
18       end until (f_q == NULL);
19     f_p = getNextElement(S'_list, f_p);
20   end until (f_p == NULL);
21   S_best = S'_list;
22 end;
```

Figure 2. FCBF Algorithm [10]

For each feature, the symmetrical uncertainty value is compared to the threshold. The features, which have the symmetrical uncertainty more than the threshold, will be considered. Then, these features are ordered by the value of symmetrical uncertainty in descending. The algorithms from 9^{th} line to 20^{th} line are used for removing some relevance or redundancy features.

4. FCBF for Forest Changed Detection

This paper proposes a process for forest changed detection from satellite data. Although, the forest changing can be detected by classifying each area on two different time periods and considering the different area after this classification, the changed area from this technique are not accurate. If the results of classification on a time period are wrong, the results of changed detection are also wrong. Hence, two interested time periods are considered together. The remote sensing data from the satellite are processed. The features are extracted and selected. Then, these features are used for training in order to create a model for forest changed detection system. The techniques that are used in each step are explained in the following subsection.

4.1 Remote Sensing Data Preparation

This research uses remote sensing data for forest changed detection. These data are collected from a satellite, Landsat-5 TM. This satellite has equipped thematic mapping (TM) that can be used for collecting the multispectral data [11]. These spectral data are able to use for land cover identification.

Two scenes of data with the different time periods are selected at the same area. The forest changing will be detected on these scenes. These scenes will be adjusted by image processing techniques, i.e., image rectification and image subset selection. These processes are shown in Figure 3.

Then, some coordinates are selected. Spectral data on these coordinates are used as the training data for changed detection on two different time periods. Each scene or TM image composes of seven spectral bands (Band 1-7). Hence, there are 14 attributes on the original data, 7 attributes for each time period and the data on any two periods of time are compared.

However, there are other indexes that can help to classify spectral data into soil, vegetation, or water. If these indexes are applied to machine learning techniques, the detection results may be improved. Therefore, this paper is interesting on the features that will be used for forest changed detection. The feature extraction is considered in the next subsection.

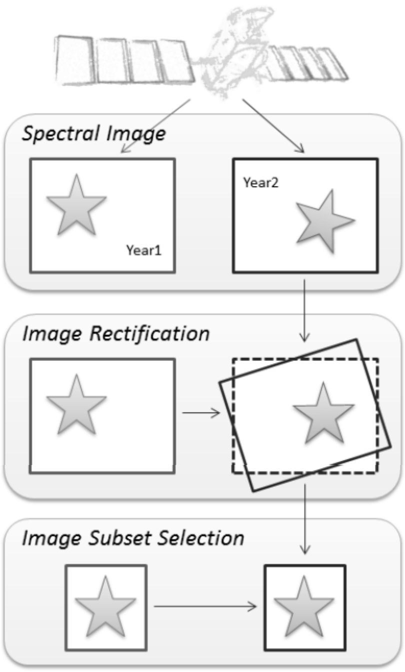

Figure 3. Preprocessing of Spectral Image

4.2 Feature Extraction

In order to improve the accuracy of forest changed detection, new features are extracted. The vegetation and water indexes are considered. These indexes can be calculated from spectral data. However, there are many indexes and each index is good for some kinds of land cover. The following indexes are tested in this paper.

a. Normalized Difference Vegetation Index (NDVI) is one of the most widely used vegetation index [12]. In NDVI, visible red and near infrared bands of electromagnetic spectrum are adopted to analyze remote sensing data. This index is directly related to ground cover, photosynthetic activity of the plant, surface water, leaf area, and the amount of biomass [13]. The value of NDVI can be calculated by equation (1).

$$NDVI = \frac{near\ infrared - visible\ red}{near\ infrared + visible\ red} \quad (1)$$

Generally, healthy vegetation will absorb most of the visible light and will reflect a large portion of the near-infrared light [13]. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Soils reflect moderately in both red and infrared spectrum [13]. NDVI focuses on the satellite bands that are most sensitive to vegetation information (near-infrared and red). Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1. In practice, the extreme negative values are represented to water, the values around zero are represented to soil, and the positive values are represented to the dense green vegetation [13].

b. Leaf Area Index (LAI) is a key factor for determining plant growth and health [12]. This index gives the important information on the amount of leaf area [12]. NDVI is used for LAI calculation and LAI index can be calculated by equation (2).

$$LAI = \frac{log(0.88 - NDVI)}{log2} \times (-1.323) \quad (2)$$

c. Water Index (WI) and Normalized Difference Water Index (NDWI) [14] are the factors for determining the water areas. These indexes are illustrated in equation (3) and (4), respectively.

$$WI = \frac{visible\ green - visible\ red}{visible\ green + visible\ red} \quad (3)$$

$$NDWI = \frac{near\ infrared - shot\ wave\ infrared}{near\ infrared + shot\ wave\ infrared} \quad (4)$$

d. Spectral Signatures are used to classify remote sensing data into classes of landscape features [7]. Soil, vegetation, and water can be classified by SigS, SigV, and SigW, respectively. The formulas of these signatures are shown in equation (5)-(7).

$$SigS = shot\ wave\ infrared - visible\ green \quad (5)$$

$$\begin{aligned} SigV = &\ visible\ green - (2 \times visible\ red) \\ &+ (2 \times near\ inrared) \\ &- shot\ wave\ infrared \end{aligned} \quad (6)$$

$$SigW = visible\ green - shot\ wave\ infrared \quad (7)$$

e. Plus Index and Minus Index [13] are the other indexes that can be used for classifying the remote sensing data. These indexes use both NDVI and NDWI in calculation. Plus index and minus index can be calculated by equation (8) and (9).

$$PLUS = 1 + NDWI + NDVI \quad (8)$$

$$MINUS = NDWI - NDVI \quad (9)$$

The 7 spectral bands from satellite data and these indexes will be used as the features in the forest changed detection system. If the spectral data and these indexes are used as the features of learning, there are 32 features (14 features + (2×9) features) on the learning vectors. Moreover, we notice that the difference of 2 spectral data was used in many indexes. If the difference of 2 spectral data is used as the features of learning, the accuracy of forest changed detection may be improved. Hence, there are 74 features (32 features + (2×21) features) are extracted. These features are shown in Table 1.

Table 1. Features for Forest Changed Detection

No.	Amount	Descriptions
1-7	7	Band 1-7 on a time period
8-14	7	Band 1-7 on the next time period
15-23	9	NDVI, LAI, WI, NDWI, SigS, SigV, SigW, PLUS, and MINUS indexes on a time period
24-32	9	NDVI, LAI, WI, NDWI, SigS, SigV, SigW, PLUS, and MINUS indexes on the next time period
33-53	21	|Band i – Band j|, where i, j = 1, 2, 3, .., 7 and i < j for any bands on a time period
54-74	21	|Band i – Band j|, where i, j = 1, 2, 3, .., 7 and i < j for any bands on the next time period
Total	74	

4.3 Feature Selection by FCBF

Although, many features can be extracted from remote sensing data, we do not know that which features are suitable for forest changed detection. Furthermore, the features from section 4.2 are calculated by using only 7 bands. Some features may be duplicated or may be unnecessary for classifying the changed area. Thus, feature selection techniques are applied in this paper.

The considered features are experimented and these features will be chosen by some feature selection techniques. The suitable features will be used for classifying the changed area. FCBF is considered for choosing the suitable features. The value of symmetrical uncertainty on each feature can be used for ranking. Some relevance or redundancy features can be removed. This is a key preprocessing step that is performed before classifying the multispectral remote sensing data.

4.4 Forest Changed Detection

After a subset of features is selected, these features will be used for forest changed detection. Decision tree classifier (DTC) is considered in this paper. DTC is a simple classification algorithm but yields the good results in many problems. J48 is a variation of decision tree. Pruning step was applied in J48 in order to avoid the over-fitting problem.

This paper uses J48 as the classifier for forest change detection on two different time periods. Spectral information will be classified into 9 classes, i.e., S, V, W, SV, SW, VS, VW, WS, and WV, when S is the soil, V is the vegetation, W is the water, and XY is the changing from X to Y. These classes must be considered on two different time period of spectral information. There are three classes for unchanged area and six classes for changed area.

5. Experimentation

In order to verify the proposed method, two satellite images from Landsat–5 TM were collected from the Department of National Parks, Wildlife, and Plant Conservation, Thailand. These images were collected on 13th February 2007 and 6th March 2009 that is the cloud-free days. The sensors cover 0.45 to 2.35 μm range of the electromagnetic spectrum, and ground resolution of the dataset is 30×30 meter per pixels. Both images included the varieties of land cover types on 2,700 km^2 of the upper Yuam basin, Mae Hong Sorn and Chiang Mai provinces, Thailand. This area is covered by 131st path and 47th row of multispectral image.

After image pre-processing steps, 6,330 couple positions on both images were randomly selected from 1,600×1,800 pixels. The labels are assigned to these data points by expertise. Then, these data points are divided into training set and test set; 6,100 data points for training set and 230 data points for test set. The numbers of data for all classes are displayed in Table 2.

Table 2. Number of Data for Training and Testing

Class	Label	Data Set	
		Training	Testing
Soil	S	860	40
Vegetation	V	1,566	36
Water	W	508	29
Soil to Vegetation	SV	478	46
Soil to Vegetation	SW	465	0
Vegetation to Soil	VS	978	79
Vegetation to Water	VW	424	0
Water to Soil	WS	413	0
Water to Vegetation	WV	408	0
Total		6,100	230

Forest changed areas are detected by J48 decision tree classifier. The features are extracted from remote sensing data. NDVI, LAI, WI, NDWI, SigS, SigV, SigW, PLUS, and MINUS are calculated for each remote sensing data point. Also, the difference of all possible two spectral data on each data point will be computed. The accuracy of forest changed detection on 14 original features will be compared to the accuracy of all proposed features (74 features). Then, the dimensionality reduction techniques are applied. FCBF will be compared to principle component analysis (PCA), correlation-based feature selection (CFS), and Relief algorithms.

In Relief and FCBF algorithms, the features are ranked by the relevance weighting or the symmetrical uncertainty score. The features that are better than a defined threshold will be selected. For this paper, the number of features of Relief and FCBF will be selected as the number of features of PCA and CFS in order to avoid the bias of the different number of features. The results will be calculated in term of the accuracy (Acc.), area under receiver operation characteristic curve (ROC), precision (Prec.), and recall (Rec.). The formulas of accuracy, precision, and recall are illustrated in equation (10)–(12).

$$Acc. = \frac{TP+TN}{TP+TN+FP+FN}, \quad (10)$$

$$Prec. = \frac{TP}{TP+FP}, \quad (11)$$

$$Rec. = \frac{TP}{TP+FN}, \quad (12)$$

when TP, TN, FP, and FN are the numbers of true positive, true negative, false positive, and false negative examples, respectively.

6. Results

The accuracies of forest changed detection on test data are shown in Table 3. The 14 original features are compared to 74 features. Then, the dimensions of data are reduced by PCA and CFS. The features are selected by Relief and FCBF. Only 7 features and 24 features are considered because PCA transforms data and choose only 7 features and CFS yields on 24 suitable new features.

Table 3. Accuracies of Forest Changed Detection

Feature Types	No. of Features	Acc.	ROC	Prec.	Rec.
Spectral Data	14	85.65	0.931	0.907	0.857
All Features	74	88.26	0.936	0.928	0.883
Dimensionality Reduction					
PCA	7	86.52	0.942	0.911	0,865
CFS	24	89.57	0.952	0.939	0.896
Relief	7	90.00	0.951	0.933	0.900
	24	90.00	0.943	0.942	0.900
FCBF	7	85.65	0.943	0.930	0.857
	24	**92.17**	**0.951**	**0.943**	**0.922**

The results demonstrate that the results of usage of 74 attributes are better than the 14 original features. The accuracies of forest changed detection can be improved when the suitable feature selection algorithms are applied. PCA is not a suitable algorithm in this paper. Only 7 features are created by PCA and these features yield only 86.52% on accuracy. CFS yields a higher accuracy, while 24 features are applied.

For Relief algorithm, 7 features and 24 features are selected. The results show that the accuracies of detection with DTC and Relief on both 7 and 24 features are 90.00%. This means that only 7 features from Relief feature selection are adequate for forest changed detection. However, FCBF can yield a better accuracy on 24 features. Although, at 7 features, the accuracy of FCBF is equal to the accuracy of 14 original features, FCBF achieves to give the highest accuracy on testing at 24 features.

FCBF with 24 features also yield the highest ROC, precision, and recall. This means that FCBF can improve the performance of forest changed detection on every class by average. Table 4 shows 24 features that are selected by FCBF. These features are divided into 3 groups, i.e., original features, natural indexes, and spectral difference.

Table 4. Types of Selected Features from FCBF

No.	Selected Features (Feature #Year)	Types of Features: Original Features	Natural Indexes	Spectral Difference
1	LAI #2	-	✓	-
2	NDVI #1	-	✓	-
3	NDVI #2	-	✓	-
4	LAI #1	-	✓	-
5	SigV #2	-	✓	-
6	Band5 #2	✓	-	-
7	SigW #2	-	✓	-
8	SigS #2	-	✓	-
9	B2-B7 #1	-	-	✓
10	B3-B4 #1	-	-	✓
11	Band7 #2	✓	-	-
12	B1-B5 #1	-	-	✓
13	B3-B5 #2	-	-	✓
14	B4-B5 #2	-	-	✓
15	B2-B5 #1	-	-	✓
16	SigW #1	-	✓	-
17	SigS #1	-	✓	-
18	Band7 #1	✓	-	-
19	B5-B7 #2	-	-	✓
20	SigV #1	-	✓	-
21	B2-B5 #2	-	-	✓
22	B1-B5 #2	-	-	✓
23	B5-B6 #2	-	-	✓
24	Band5 #1	✓	-	-
#Features		4	10	10

By FCBF, only 4 features from the 14 original features are selected. Only band 5 and band 7 from both images are used for changed detection. For natural indexes, 10 features are selected from 18 features. LAI and NDVI are selected in the first order to the fourth order. The other selected natural indexes are SigS, SigV, and SigW of both images. This means that these indexes are good choices for forest changed detection. In addition, 10 spectral difference features are selected from 42 features. We notice that band 5 appears on several features. Thus, band 5 is an important feature for the detection.

In order to consider trend on the number of features, the accuracies of classification are plotted in Figure 5. This figure shows that FCBF with 24 features yields the highest accuracy. These features are suitably for DTC on forest changed detection problems. The output tree from 24 features FCBF has 151 nodes and 76 leaf nodes, while a tree of the 14 original features has 333 nodes and 167 leaf nodes. Although the number of features of FCBF is increased, the size of tree is smaller than the usage of 14 original features. In the case of all 74 features, the output tree has 175 nodes and 88 leaf nodes, which is larger than the tree from FCBF feature selection.

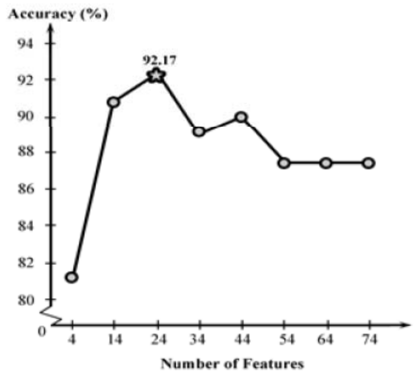

Figure 4. A Graph of the Accuracies of Detection with FCBF Feature Selection

7. Conclusion

This paper focuses on the feature extraction from remote sensing data and the feature selection techniques. The natural indexes and spectral difference are proposed to use as the additional features for forest changed detection. The results show the efficiency of these features via feature selection techniques. FCBF is compared to PCA, CFS, and Relief. Both Relief and FCBF yield the better results, but the highest accuracy is occurred when FCBF with 24 features are applied.

Some redundancy features can be removed by FCBF. For natural indexes, LAI, NDVI, SigS, SigV, and SigW are selected. Band 5 and band 7 of the spectral data are still selected as the features for classification. Furthermore, band 5 is used in many features. DTC with these features yields a high accurate result that is verified by accuracy on test data, ROC, precision, and recall. FCBF is a good feature selection technique that gives the qualifying features for forest change detection.

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