Assessment Of Land Use Cover Changes Using Ndvi And Dem In Puer And Simao Counties, Yunnan Province, China

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ABSTRACT: Change detection is the technique, which is used for the assessment of resources, where multi-date images are compared to find out the type and amount of change have occurred. The various applications of change detection are in agricultural, hydrological, forestry, environmental and ecological field. The rapid growth of Puer-Simao area and its agricultural area have probably resulted very rapidly and have had an unfavorable effect on the environment and therefore multi-temporal Landsat TM imagery for assessment land cover change has proven to be the best tool in this study. The performance of image classifiers that utilize only the remote sensing data may deteriorate, especially in mountainous regions, payable to the presence of shadows. In our study, a multisource classification approach to map land cover in Puer_Simao counties with high mountain peaks having elevations up to 2800 m above mean sea level has been adopted. Remote sensing data from Landsat TM image along with NDVI and DEM data layers have been used to perform multi-source classification using Maximum Likelihood Classifier. The change detection method used was NDVI differencing. From the results the forest or shrub land and Barren land cover types have decreased by about 6% and 23% from 1990 to 1999 respectively, while agricultural land, built-up and water areas have increased by about 19%, 4 % and 7% respectively. [Report and Opinion 2010;2(9):7-16]. (ISSN: 1553-9873).

Keywords: agricultural; hydrological; forestry; environmental; ecological; Puer-Simao

I. INTRODUCTION

The obtainment and updating of information about the current condition and the continuous dynamic changes of our earth's surface in remote high-mountain regions is a task where remote sensing technologies can best display their advantages.

Due to the historical development of remote sensing platforms and technology, reconstructing land cover changes in a sub watershed over periods greater than fifteen years requires multiple sources of information [Hyman, 2002].

LULC assessment is one the most important parameters to meaningfully plan for land resources management. LULC inventories are assuming increasing importance in various resources sectors like agricultural planning, settlements surveys, environmental studies and operational planning based on agro-climatic zones.

The knowledge of spatial land cover information is essential for proper management, planning and monitoring of natural resources (Zhu, 1997). For example, it is a desired input for many agricultural, geological, hydrological and ecological models. Satellite remote sensing imagery is a viable source of gathering quality land cover information at local, regional and global scales (Csaplovics, 1998; Foody, 2002). Moreover, remote sensing data are on the whole, useful for land cover change detection and mapping in mountainous regions such as Puer and Simao counties in the mountainous Yunnan Province.

Nowadays, amount of studies to map land use land cover change using remote sensing data in high mountain areas have been reported with varying degrees of accuracy. This may be due to a large number of factors that influence the remote sensing process. These include the presence of shadows caused by high altitude of the terrain, the cloud cover, deep narrow valleys and ravines, low sun angles, steep slopes and differential vegetation cover. For that reason, classification only on the basis of spectral data from a remote sensing sensor alone may not be sufficient to gather effective land cover information (Arora and Mathur, 2001). Keeping in view the existing conditions, in our study an attempt has been made to detect land use cover changes of Puer-Simao counties.

The lack of information at scales higher than 1:500000 and high spatial resolution imagery, such as aerial photos, or images without clouds in the study areas, has forced us to study the changes detection based only on data available, comparable and accurate at a mid range resolution, for the years 1990 and 1999 using Landsat TM data.

The performance of image classifiers that utilize only the remote sensing data may deteriorate, especially in mountainous regions, with high mountain peaks having elevations up to 2800 m above mean sea level, due to the presence of shadows.

Digital Elevation Models (DEMs) and NDVI were used as ancillary data. Recently, Eiumnoh and Shrestha (2000) exploited the advantages of incorporating both NDVI and DEM in the classification process and showed an improvement in the classification accuracy of the order of 10 to 20%.

Radiance differences observed on multidate imagery can be caused by land cover and land use changes but also by differences in: atmospheric conditions, solar angle, sensor calibration, vegetation phenology, image registration. Minimizing these differences with appropriate: choice of imagery, pre-processing of data, and choice of change detection method represents the challenge in change detection procedures (Théau J., 2006)

To trace LULC change in a local area, we used the NDVI image differencing method. Vegetation Index Differencing has been used successfully for detecting change (Sohl, 1999). Yuan and Elvidge (1998) were able to detect urban change using Normalized Difference Vegetation Index (NDVI) differencing in the Washington, D.C. area. There are many options for creating differencing image, among which (Schowengerdt, 1997) image radiance/reflectance differencing, NDVI differencing, tasseled cap transformation plus change vector differencing are widely used. However, the last step i.e. threshold used to determine whether a detected change is indeed a real change, is far more difficult and only few studies have investigated this problem. One frequently used approach is using standard deviation of the differencing image as a possible threshold. Simple differencing is the most widely used change detection technique and has been used in a great variety of environments and with a wide assortment of satellite data (Singh 1989, Jensen 1996).). Simple differencing has been found to be one of the more accurate change detection techniques (Woodwell *et al*. 1983, Singh 1989).Classification method of two Landsat images 1990 and 1999 is carried out by using maximum likelihood method. Maximum Likelihood algorithm is the most widely used supervised classification algorithms (Wu and Shao, 2002; McIver and Friedl, 2002).

The aim of this study is to detect land use land cover change in Puer-Simao mountainous counties using landsat TM imagery according to the two objectives as follows;

(i) To assess LUC change using NDVI differencing technique, which reduces impacts of topographic effects and illumination

(ii) To assess the LULC change according to the Digital Elevation Model (DEM) data.

II. MATERIALS AND METHODS

2.1 STUDY AREA AND DATA

The study area of about 6900 km2, is situated between Longitudes 100°20′ 07”-101°36′17” E and Latitudes 22°49’32”- 22°52′11” N in the southern part of Yunnan province in south China (Fig. 1). Puer, called Simao before January 21, 2007 is a major town with a population of 75 000. Simao Metropolitan County contains four urban townships, two rural townships and two ethnic rural townships. Its boundaries are: Jinghong(Sichuangbanna) in south, ….The climate is subtropical monsoon without hot summers or harsh winters. The mean annual rainfall of the area is around 1300 to 1400 mm, while the mean annual temperature is around 15°C to 18°C. It is neither extremely hot in summer nor terribly cold in winter. The terrain is highly rugged with elevations varying from 304 m to 2442 m above mean sea level. The major landforms are mountains, highlands, small basins and valleys**.** The vegetative cover is of the type of savanna or tropical arid shrubby steppe. Puer Tea is grown in the mountainous forests of subtropical and tropical areas with an altitude of 1200 to 1400 meters. The shrubs include governorsplum (Flacourtia indica), boxleaf atalantia (Atalantia buxifolia) and the grasses are dominated by tangle head (Heteropogon pers). The soils are part of a series, which belongs to the group of Red Soils with erosion and water loss. According to the classification works (Vogel, Mingzhu and Huang, 1995), the soil is called Ferralic Cambisol or Haplic Phaeozem. It is called Aridic Haplustoll, according to the USDA soil taxonomy, 1992 or Haplic Dry Red Soil after Chinese Soil Classification system-Soil Taxonomic Classification Research Group, 1993. It has been called savanna red soil, red brown soil, red cinnamon soil or purple soil. Without irrigation the soils can be used for planting xerophilous plants like sisal, puer tea or produce low yields of traditional crops like maize. With irrigation the soils can be used for rice, sugar-cane, flowering quince, water melon and peanut.

Two cloud-free Landsat TM scenes, acquired on July 11, 1990 and December 25, 1999 were obtained for the study. Obtaining images at near anniversary dates is considered important for change detection studies (Jensen, 2007). However, the summer image in 1999 was unavailable. Both time series were found from Landsat TM, path 130, row 044 with. The images were corrected to remove atmospheric effects and then geo-rectified using ground control points collected by GPS. The images were re-sampled to 30m pixel size for all bands using the nearest neighbor method. The resultant root mean squared error was found to be 0.53 pixel (about 16 m on the ground) for the 1990 image, 0.51 pixel (about 15 m on the ground) for the 1999 image. All the data were projected to an Universal Transverse Mercator (UTM) coordinate system, Datum WGS 1984, zone 49 North using 1:50 000 topographic map of the study area.

The Digital Elevation Models (DEM) data together with landsat images data were purchased from LCGF for 22 counties in the south of the province. The slope and aspect maps were generated by the Slope command of Arc-GIS 9.2.

In mountainous areas, a major variation in the brightness values of pixels can be found due the presence of shadows. This may lead to erroneous classification.

Therefore, the Digital Elevation Model (DEM) was used as ancillary data in the classification process to reduce some confusion between shadowed areas and water bodies. Moreover, the elevation and the slope information from DEM may also act as a commonsense rule to eliminate the presence or absence of certain classes in some elevation zones. For example, agricultural land is not expected to exist at higher elevations in many tropical countries, like so the soils are protected against water erosion. These areas thus should be categorized as barren land.

The NDVI data layer was generated from NIR and Red bands of Landsat TM image and is defined as:

$$NDVI= (NIR-R)/(NIR+R) \quad (1),$$

whereas NIR represents the spectral reflectance in near infrared band while R represents red band.

The positive values represent different types of vegetation classes, whereas near zero and negative values indicate non-vegetation classes, such as water, snow, built-up areas and barren land. Vegetation indices have long been used in remote sensing for monitoring temporal changes associated with vegetation.

2.2 CHANGE DETECTION

2.2.1 Image Classification and Accuracy assessment

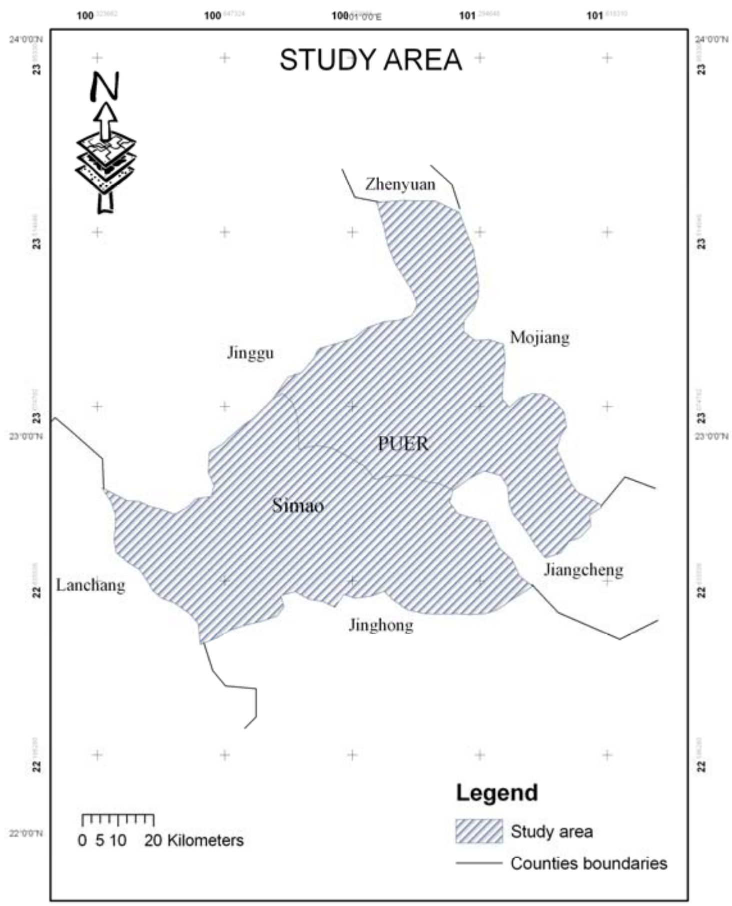
Over the years, a number of image classifiers have been developed. Maximum Likelihood Classification has been found to be the most accurate and commonly used classifier, when data distributional assumptions are met. Wu and Shao, 2002; McIver and Friedl, 2002 reported that the Maximum Likelihood decision rule is still one of the most widely used supervised classification algorithms. In our study, two dated Landsat images jointed to NDVI and DEM layers were compared supervised classification technique. Once the training sites (table 2) were determined, a supervised classification was performed on both images using Maximum Likelihood algorithm in ENVI 4.3. The supervised classification technique is preferred, because the data of the study area is available and the author has a prior knowledge of the study area. It is considered to give very accurate results (Mengistu, 2007; Reis, 2008) and was applied to classify and to map land cover in Himalayan region with high mountain peaks having elevations up to 4785 m above mean sea level (Saha et al. 2005). This classifier is based on the decision rule that the pixels of unknown class membership are allocated to those classes with which they have the highest likelihood of membership (Foody *et al*., 1992, 2002).

From there the LULC maps were derived with the following five classes: 1. Built-up Land, 2. forest or Rangeland 3.water, 4. Agricultural land, 5. Barren or unused land (Table 1).

The land use cover types were stratified according to the U.S. Geological Survey's land-Use/Land-cover classification system for Use with Remote Sensor Data (Anderson *et al*., 1976).

(i)

(ii)



(iii)

Figure 1: Location of the study area:(i) in CHINA, (ii) in Yunnan Province (iii) Boundaries with others counties

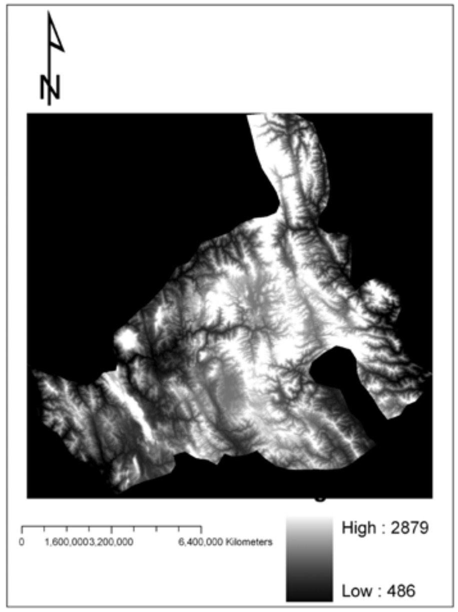


Figure 2: The Raster Digital Elevation Model over Puer-Simao Hills

Table1. Land use/land cover classification Scheme.

LULC types	Description
Built-up Land	Areas that have been populated with residential, commercial, industrial, transportation and facilities.
Forest or Rangeland	Areas covered with mature trees, shrubby plants and other plants growing close together.
Water	Areas covered with water such as rivers and lakes.
Agricultural land	Rain fed cropping, planted and irrigated cropping areas Areas covered mainly with herbaceous vegetation with shrubs
Barren land	Mountainous or hilly areas, areas with no vegetation cover, degraded land and all unused area

Table 2 Number of training pixels for each land use/cover class used in classification

LULC	Number of Training Pixels
Built-up Land	1565
Forest or shrub land	1531
Water	1565
Agricultural land	1544
Barren land	1566

An image classification can not be complete unless its accuracy has been assessed.

To determine the accuracy of classification, a sample of testing pixels is selected on the classified images and their class identity is compared with the reference data (ground truth). The choice of a suitable sampling scheme and the determination of an appropriate sample size for testing data play a key role in the assessment of classification accuracy (Arora and Agarwal, 2002).

Standard criteria were used to assess the accuracy of the classifications: Overall accuracy and Kappa coefficient.

(1) The Overall accuracy was defined as the total number of correctly classified pixels divided by the total number of reference pixels (total number of sample points) (Rogan *et al.* 2002)
(2) Kappa coefficient was defined as a statistical measure of accuracy that ranges between 0 and 1, it measures how much better the classification is compared to randomly assigning class values to each pixel. For example, a Kappa of 0.76 means the classification accuracy is 76% greater than chance (Miller and Yool, 2002).

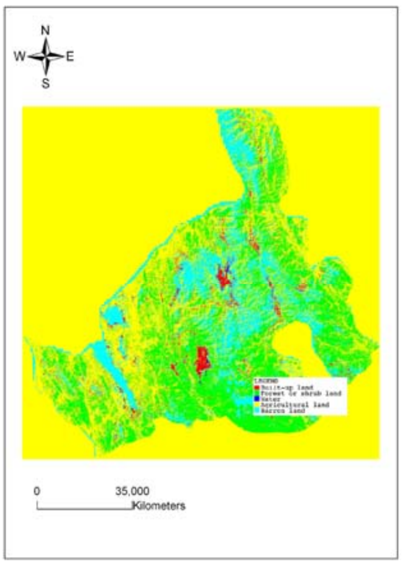


Figure3: Land use/cover Map, 1990

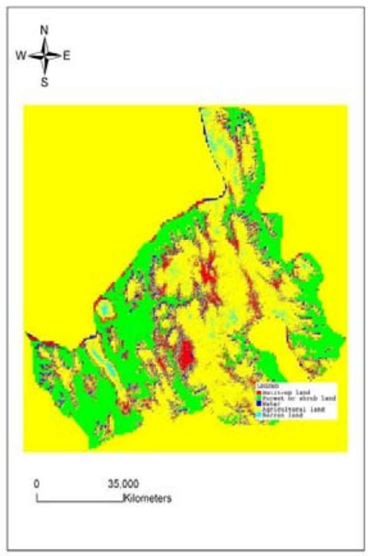


Figure4: Land use/cover Map,1999

2.2.2 NDVI - differencing

Image differencing is based on subtracting two different time periods of the same location or scene. Image Differencing is a relatively simple and effective tool amongst common change detection techniques. It is a simple process of subtracting the two different times pixel by pixel to create the difference image. In this case, a difference image was created between the Normalized Difference Vegetation Index (NDVI) images.

The resultant image was threshold based on the standard deviation of the percentage change image. The table 3 and figure 3 contributed to compute the threshold. The categories are: negative change (-1 std to 0) in red, positive change (0 to +1std) in green, no change (0 std) in yellow.

The NDVI real values, by definition, would be between -1 and +1, where increasing positive values indicate increasing green vegetation and negative values indicate non-vegetated surface features such as water, barren land, ice, snow, or clouds.

Image differencing technique is used in many applications, it can be applied not only to images of two different dates, and it can apply to comparison of vegetation index information derived from multiple dates of imagery. In this paper, NDVI difference was used for land-cover change detection in Puer and Simao counties, i.e.

VID= NDVI(t1) –NVDI(t2).

If there is an increase in reflectance, the image appears light tone while the image appears dark tone if there is a decrease in reflectance. If the image appears gray, it may imply that the area has no or minimal change between two dates.

VID is often regarded as an effective method to enhance the difference among spectral features and suppress or reduces impacts of topographic effects and shade effects. Thus, the difference of vegetation indices between two dates has the potential to detect land cover change more effectively. Lyon et al., 1998 compared seven vegetation indices from three different dates of Landsat MSS image data for land cover change detection and concluded that the NDVI differencing technique demonstrated the best vegetation change detection. In spite of its simple algebra, it is a fast and effective tool to detect changes over two remotely sensed images of different dates despite it has limitation of not showing information about the nature of change.

Table 3: Descriptive statistics NDVI values for LULC classes

LULC types	1990 values Min	Max	Mean	Stdev	1999 NDVI Values Min	Max	Mean	Stdev	NDVI Change
Settlement	-0.096	0.071	-0.012	0.033	-0.066-	0.082	-0.008	0.010	
Forest or Shrub land	0.406	0.741	0.573	1.614	0.380-	0.678	0.529	0.686	
Water	-0.600	-0.096	-0.348	0.980	-0.512	-0.066	-0.289	0.375	
Agricultural land	0.238	0.406	0.322	0.907	0.231-	0.380	0.305	0.395	
Barren land	0.071	0.238	0.154	0.434	0.082-	0.231	0.156	0.202	

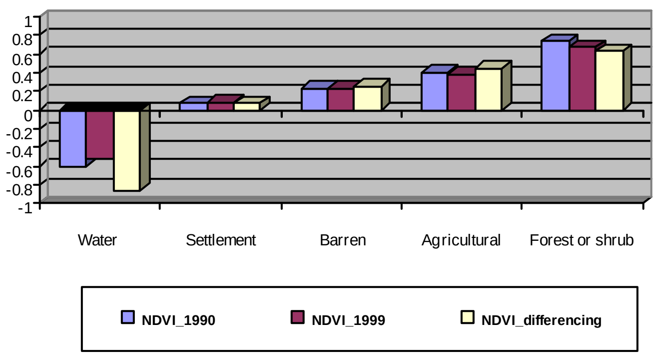


Figure 5: NDVI and NDVI differencing values for LULC classes

III. RESULTS

3.1 Accuracy assessment

Accuracy assessment was performed by using a random sampling scheme. Various maps, field data, Puer Quickbird image of 2009, were used as references data. Our knowledge of the area also played an important role in this process. Confusion matrices were created to check accuracy of the LULC maps. The overall accuracy 90.50% and kappa value 0.87 for the classification method against corresponding values of 96.55% and 0.94 for the NDVI differencing method are enough good. Separation was found to be especially good between settlement and forest or shrub land cover classes. According to the recommendation of US Geological Survey the NDVI image differencing meets 85% level for acceptability of overall accuracy classification results (Hayes and Sader, 2001).

3.2 LULC Changes detection

The table 3 shows the statistics of LULC types NDVI values, the figure 5 was built to facilitate its visualization. Both are contributed to facilitate the comprehension of the change trend. The NDVI value decreased from 1990 to 1999 for forest and agricultural land but increased for the water.

Figure 4 shows Change/no-change resultant maps generated from the NDVI differencing classification. The non-changed pixels are comprised between the NDVI decrease part (low pixel value) and NDVI increase part (high pixel value).

The value-sliced percentage change image shows the magnitude of change in the study area from 1990 to 1999. The following categories were found: negative change (-1 std to 0) in red, positive change (0 to +1std) in green, no change (0 std) in yellow or 39, 27and 34 % respectively.

On the change/no-change maps, the red areas denote decrease, the green areas represent the increase areas, and all no-change areas in yellow are between negative and positive changes.

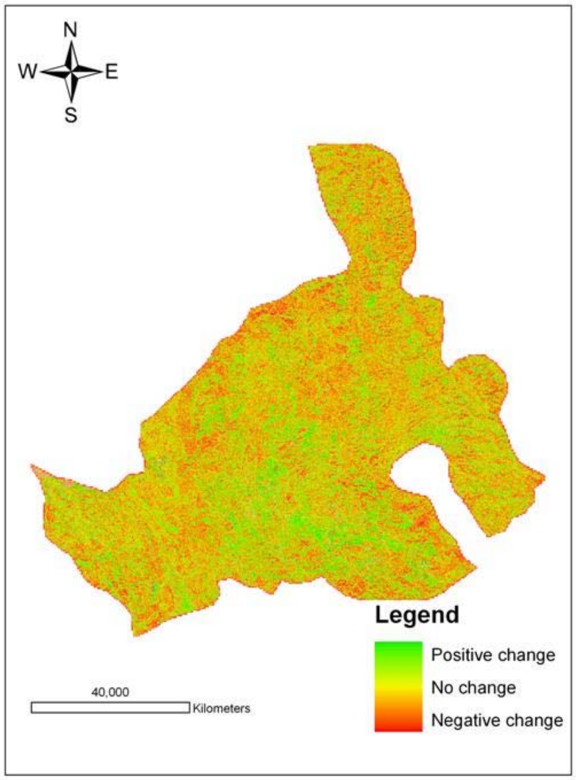


Figure 6: Change/no-change resultant maps generated from the NDVI differencing classification results

3.3 LULC changes according to topography

The LULC classes' distribution all through the study area in the time period of 1990-1999, was detected using Digital Elevation Model (DEM). The results of LULC distribution analysis in 1990, performed according to altitude, are given in Figure 8a. In accordance with this figure, the settlements are in majority located in regions with 1058-1311 m of altitude. The biggest cities (Puer-Simao) were detected there and in the region up to 1311 m i.e. the following elevation, which was the second populous region. The forest or shrub land and water cover types are mostly located in the region of 1058-1311 m of altitude. The agricultural and barren lands are frequently located in the region of 458-1058 m of altitude.

The results of LULC distribution analysis in 1999, performed according to altitude, are seen in Figure 8b, According to which, settlements, forest or shrub land and water land cover types are mostly located in regions with 1058-1311 m of altitudes.

The agricultural and barren lands are densely located in the region of 458-1058 m of altitude as it was in 1990. From the results the general tendency is land use activities decrease with the increasing altitude.

Figures 9a and 9b show the LULC classes location according to the slope. The settlement and water land cover types are densely located in the region with 0-9% slope value in both years 1990 and 1999. The values show that the settlements are decreased with increasing on the slope degree. Forest or shrub land, agricultural and barren land cover types are heavily located in regions with 15-22% slope level in 1990 and 1999. Their second densely location is the region with 9-15 % slope degree for the study period.

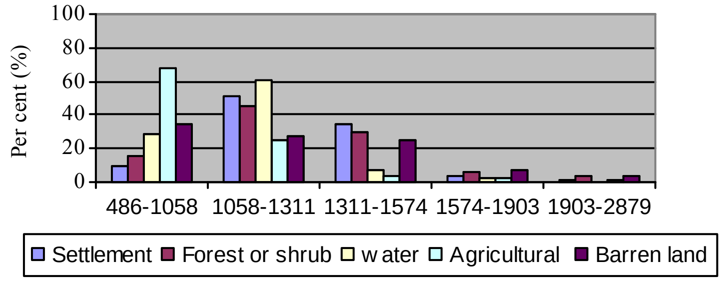


Figure 8a: LULC classes distribution per elevation range 1990

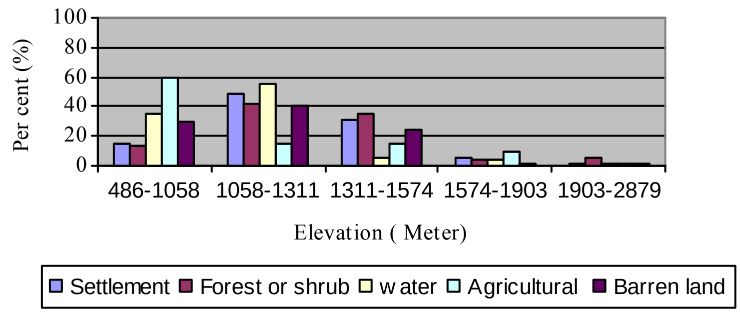


Figure 8b: LULC classes distribution per elevation range in 1999

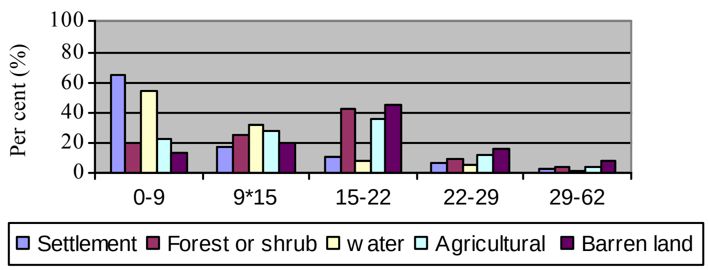


Figure 9a : LULC classes distribution per slope range in 1990

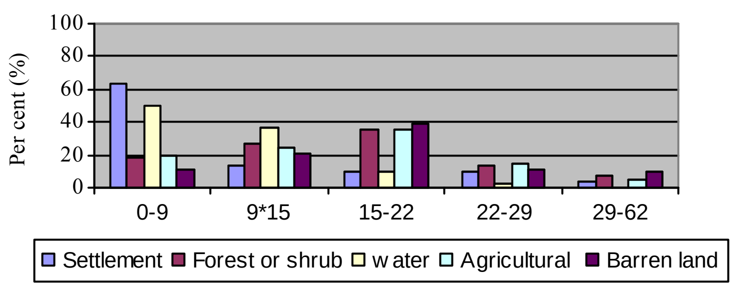


Figure9b: LULC classes distribution per slope range in 1999

IV. DISCUSSIONS

The accuracies of classification were turned out to be better than expected. The high overall accuracies of all classification process can be explained by the fact that the total number of correctly classified pixels was high. That can be attributed to many factors among which, the use of ancillary data (DEM and NDVI), the use of Quickbird image as reference data and the fieldwork investigations. In one of our preceding study (Diallo et al., 2009), the accuracy was another because some confusion were made between pixels or spectral signatures of different LUC classes, e.g. unused area and fallow, fallow and croplands.

The NDVI differencing method is relatively easy to implement and simple to interpret, but it cannot provide complete matrices of change directions (Lu et al. 2004) and the index differencing is also subject to registration error (Gong et al. 1992). When using the NDVI differencing method, some changes caused by no-LULC change such as plant

phenological change, illumination difference, and atmospheric condition change

between two dates may contaminate final change detection results.

In other words the difference between the NDVI values of the same land cover type may suggest differential vegetation responses to climate conditions such as responsiveness to precipitation or limitations from high temperatures. Such differential responses have been observed at intra- and interspecific levels in the south-western United States (Lin et al., 1996; Weltzin and McPherson, 1997; Williams and Ehleringer, 2000).

Although the overall accuracy and kappa value of the investigated method are both good, the method do not allow the user to distinguish slight changes from stronger changes.

With reference to the LULC classes location according to the altitude, 84% of landforms in Yunnan are mountains, 10% are highlands, 6% are small basins and valleys, the Vegetative cover is up to 40% of land cover classes , and the area with soil erosion and water loss is about 14,000 sq. km, accounting for 37% of total land in the province. With a population of 4.5 million and a territory of 394,000 sq, the populations have no choice and are oblige to live on altitude. The two biggest cities are in the regions with relatively high altitude. Along with the increasing of industrialization process an important migration movement took place from rural regions to the metropolitan cities and this migration process has not ended yet. Areas, that can be used for agricultural activities are also very limited. But as the hometown of the world-renowned “Pu’er tea” and it is also the origin and distribution center of “Pu’er tea”, many altitude regions are under tea fields e.g tea field pic in Simao on July 24, 2009. That can explain the presence of agricultural land many high regions of the study area. The decrease of the agricultural land with increasing the altitude can be explained by the fact that transport is one the important problems because of the rugged topography, and may be according to the country law agricultural activities are prohibit in the regions with very high altitude. It may possibly for the same reason the settlements, forest and water were decreased with the increasing of the altitude. This observation was consistent with the general observation.

On the subject of slope level, Puer-Simao is a sloping area. For that reason, land cover changes are investigated according to slope in Figures 9a and 9b. The densely populated settlements areas in the region with 0-9% slope value in 1990 and 1999 can be explained by the fact that populations know the risk living in the high sloping regions, in like sloping regions the residential policies regulate the construction. For all those reasons the settlements are decreased with the increasing of the slope degree. That is found to be similar to those observations reported elsewhere. The greatly existence of the water in the same region is a quite phenomenon, as always people are living there, where is a water. But despite the fact that, it is the lowest region it may be the suitable place to receive all

the erosion water from more sloping regions. That is why the water cover type is decreased with the increasing of the slope level. Agricultural, forest or shrub land and barren are mostly populated in the relatively sloping region because of the lack of enough places in less sloping regions. It is because of the fact that, since the areas with lower slope values is extremely limited in the region; these areas were mostly used for agricultural activities or puer tea growth activities. That is valuable for barren and forest or shrub land.

V. CONCLUSIONS

The results of this study confirm the utility of NDVI and DEM for characterizing and detecting the LULC change in mountainous Puer, Simao counties of Yunnan province.

The main change observed for the time period of 1990-1999 was that the agricultural land was increased in some regions with high altitude.

In 1990 its values in the regions having altitude of 486-1058m, 1058-1311m, 1311-1574m, 1574-1903m, 1903-2879m were 68, 25, 4, 2, 1 % respectively, while in 1999 it was increased in the last three highest regions with values of 15, 9, 2 respectively. In regions having altitude of 486-1058m, contrary to decreasing agricultural areas, the settlement was increased. At the same time in 1999 it was increased in the region with altitude of 1574-1903 compare to its value in 1990. Compare to its location in the sloping region with range of 22-29 in 1990 the settlement was more detected in 1999. This observation is exactly the same for agricultural land. The agricultural land in the regions having altitude more than 1574m and slope range more than 22% are essentially Puer tea growth areas. That was investigated during the fieldwork of July, 24 2009, During the study period the change detected in reference with the location of LUC types in the different regions with up mentioned altitude and slope ranges was not significantly different. Because of the mountainous and sloping topographic structure of the region and complex vegetation of the area, it was not possible to discriminate Puer tea from other agricultural growth on the Landsat TM images. Change detection procedures using remotely sensed imagery offer a good potential for characterizing and understanding severe changes occuring for the study period in mountainous Puer-Simao counties.

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