

## Change Detection Using Data Stacking and Decision Tree Techniques in Puer-Simao Counties of Yunnan Province, China

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**Abstract:** Classification performing expert system Decision Tree and Ctree model were used to assess the land use cover change (LULCC). The Classification was done in Excel CTree program and the land cover change analyzing in ENVI software tools. Tree based Classification Model consisted of four steps (i) input the data, (ii) model processing, (iii) Analyzing of tree built and (iv) rules generation. The logic contained in the decision rules derived by that program was used to build a decision tree classifier with ENVI's interactive decision tree tool. The premise of a rule-based modeling approach is that distinct land cover types are associated with different ranges of environmental and spectral gradients, and that "rules" can be drawn from spectral and ancillary modeling layers to correctly identify the spatial distribution of land cover classes. Rules are normally expressed in the form of one or more "IF condition THEN action" statements. All the three classification dates achieved high overall accuracies of 94, 97 and 92% for 1999, 2002 and 2005 respectively. The integration of Ctree program and Decision Tree was a good opportunity in land use land cover change detection in Puer-Simao counties, it can be implemented in others similar studies.

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**Key words:** change detection, data stacking, expert system decision tree, land use cover change (LULCC), Ctree model

### 1. Study Statement

Decision trees are a topic of Artificial Intelligence, which are constructed by learning and reasoning from feature-based examples and can be applied to a single image or a stack of images. Artificial intelligence or knowledge-based expert systems offer further opportunities. They provide a way to integrate other features of vegetative cover categories besides spectral change information, thereby overcoming some of the limitations of the traditional statistical classifiers. Such change category recognition methods make use of existing or prior knowledge of the scene content (e.g. original ecosystem status, location, size, relationship with other cover types, shape, socioeconomic data, etc.) to guide and assist the classification, which follows spatial reasoning lines. Although artificial intelligence approaches to natural ecosystem change detection have largely remained in a conceptual design stage (McRoberts et al. 1991), researchers developing ecological models have started incorporating inputs from remote sensing and GIS techniques to analyse spatial patterns and processes (Ustin et al. 1993), also the incorporation of econometric techniques has been

documented (Kaufmann and Seto 2001). Thus it allows extracting information from human experts to build a knowledge base in order to develop an expert system for classification and prediction applications. Decision trees have similarities to other machine learning approaches. They use recursive partitioning algorithms to derive classification rules from training samples, which is often referred to as data mining (Read 2000). One of the strengths of decision trees is the flexibility in handling large datasets, making this approach interesting for multispectral, hyperspectral data and others. In other word the advantages of decision tree classifier over traditional statistical classifier include its simplicity, ability to handle missing and noisy data, and non-parametric nature. Decision trees are not constrained by any lack of knowledge of the class distributions. It can be trained quickly, takes less computational time. Decision Trees for remote sensing applications were already evaluated in the 1970s (Swain and Hauska 1997). Yet, only in recent years did this method gradually emerge from business applications into natural science and provided successful land cover classifications (Hansen et al. 2000, Lawrence and Wright 2001, Vogelmann et

al. 2001). Expert systems may also be used to detect change in complex heterogeneous environments (e.g., Stefanov et al., 2001; Yang and Chung, 2002; Stow et al., 2003). ENVI provides a decision tree tool designed to implement decision rules, such as the rules derived by any number of excellent statistical software packages that provide powerful and flexible decision tree generators. Our study objectives are as follows:

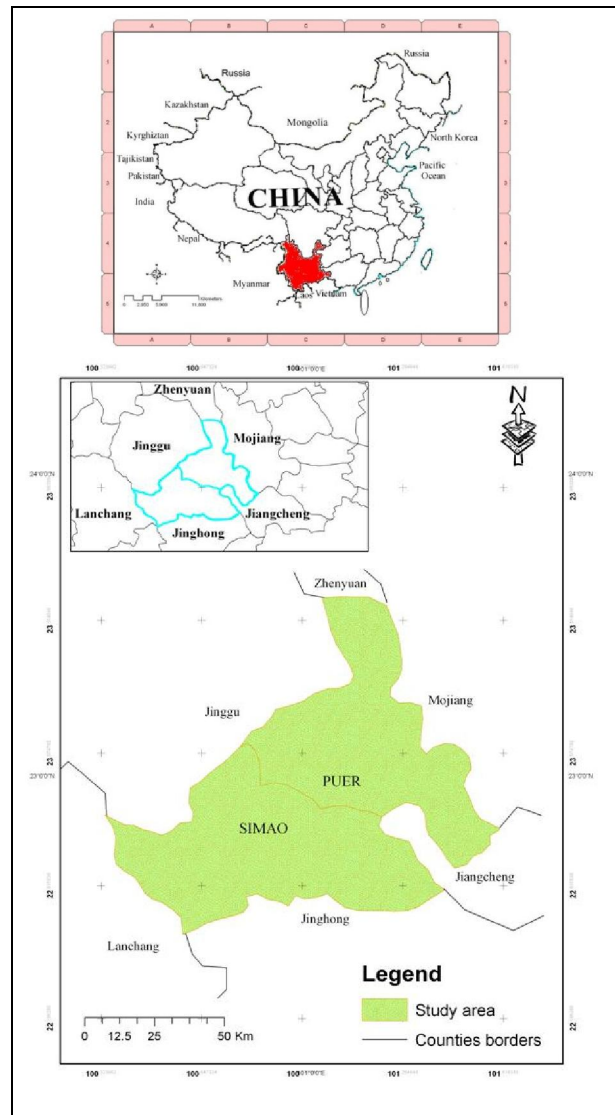
(i) To contribute to accurately establish LULC classes in three Landsat TM/ETM+ images in 1999, 2002 and 2005. (ii) To assess the LULC classification performing expert system Decision Tree and Ctree model land use cover change techniques.

The rest of the paper is organized as follows: section two presents the study area; Section three presents the materials and our proposed methods; Section four presents our change results; Section five presents our discussions and finally section six conclusions.

## 2. Study Area

The study was conducted in Puer and Simao, two counties of the southern part of Yunnan Province. The area is situated between Longitudes 100°20'07"-101°36'17" E and Latitudes 22°49'32"-22°52'11" N (Figure 1). Puer, called Simao before January 21, 2007 is a major town with a population of 75000 persons. Simao Metropolitan County contains four urban townships, two rural townships and two ethnic rural townships. The climate is subtropical monsoon without hot summers or harsh winters. The mean annual temperature range is between 15°C and 18°C, while the mean annual rainfall of the area is around 1200 to 1400 mm. It is neither extremely hot in summer nor terribly cold in winter. The topography is extremely irregular. 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, or produce low yields of traditional crops. With irrigation the soils can be used for rice, sugar-cane, flowering quince, water melon and peanut.



**Figure 1: Location of the study area: (i) in China, (ii) in Yunnan Province and its borders with surroundings counties**

## 3. Material And Methods

### 3.1 Data acquired and data sources

An area of 6900 km<sup>2</sup> was delineated on the Landsat scene covering the study area.

There are several Earth Resources Satellites, which share the same characteristics of capturing radiation in the visible light, and NIR spectrum at a medium spatial resolution and a return period of around 20 days. The LULC mapping and change detection for the area was based on Landsat 5TM/ 7 ETM+ of December 1999, April 2002 and January 2005 data. 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 from Landsat TM, path 130, row 044 with. In order to prepare two or more satellite images for an accurate change detection comparison, it is imperative to geometrically rectify the imagery (Macleod and Congalton, 1998). To minimize the impact of misregistration on the change detection results, geometric registration was performed on a pixel by- pixel basis. Erroneous land cover change results may result if any misregistration greater than one pixel occurs (Lunetta and Elvidge, 1998). The images were corrected to remove atmospheric effects and then geo-rectified using 20 ground control points collected by GPS. The accuracy of image registration is usually conveyed in terms of Root-Mean-Square (RMS) error. For landsat TM imagery acceptable RMS error is approximately 0.5 pixels (Yuan and Elvidge, 1998). The registration error (RMS) obtained was 0.232 pixel for TM 2005 image and 0.225 pixel for ETM+(1999, 2002) images respectively. All the data were projected to a Universal Transverse Mercator (UTM) coordinate system, Datum WGS 1984, zone 49 North. Six bands (1 to 5 and 7) were used. Quickbird image was used as reference data.

### 3.2 Decision tree and ctree modeling

CTree.xls Program used in the current study is an Excel based program, which builds decision trees. CTree decision tree classification method has fruitful been used to explore the Effects of C-Reactive Protein (CRP) and Interleukin-1 $\beta$  Single Nucleotide Polymorphisms on CRP Concentration in Patients With Established Coronary Artery Disease (LIN et al., 2007), it was been exploited in comparison of clusters between phylogenetic trees made easy (Archer and Robertson, 2007). CTree program was developed essentially as a learning aid and the "performance is not too bad" (Finbarr and Saha, 1999). It is easy to use and it only requires the user to have Excel on the computer. The logic contained in the decision rules derived by that program can be used to build a decision tree classifier with ENVI's interactive decision tree tool. Rule-based image classification capitalizes on the availability of multiple spatial modeling datasets, and the recognition that other "ancillary" datasets, independent of the remotely sensed imagery provide valuable information that can be used to more effectively map vegetative land cover. The premise of a rule-based modeling approach is that distinct land cover types are associated with different ranges of environmental and spectral gradients, and that "rules" can be drawn from spectral and ancillary modeling layers to correctly identify the spatial distribution of land cover classes.

A rule is a series of conditional statements that

identify the range of values in each modeling dataset that define the target cover types. Tables 2, 3 and 4 show the classification rules in 1999-2002, 2002-2005 and 1999-2005 respectively.

Rules are normally expressed in the form of one or more "IF condition THEN action" statements. The description of rules parameters are as follow:

b1= bands 1 differencing, b5= bands 5 differencing, b8= bands 2 ratio, b9= bands 3 ratio, b10= bands 4 ratio, b11=bands 5 ratio b13=NDVI differencing, b14=elevation value, b15= slope value and b16= aspect value

CONDITION If {b1 $\geq$  233 AND b10 $<$  0.973 and b14 $<$  1297 AND b9 = 0.642} THEN type= no change took place in the period 1999-2002 (table 2).

Rule-based mapping is conducted at the pixel level. With the above example, pixels in the resulting classification image are assigned a value representing no change when pixels in the input datasets (bands1differencing, bands 5 ratio, Elevation and bands 3 ratio) meet the criteria in the above rule.

CONDITION If {b10 $<$ 0.875 AND b13 $<$  0.1983 AND b14 $<$  1382 AND b14 $\geq$ 1203 AND b15 $<$  5.2447} THEN type= unused land to forest or shrub took place in the period 2002-2005 (table 3). Rule-based mapping is conducted at the pixel level. With the above example, pixels in the resulting classification image are assigned a value representing unused land> forest or shrub, when pixels in the input datasets (bands 4 ratio, NDVI differencing, elevation value, and slope value) meet the criteria in the rule.

The pre-modeling process includes data collection according to the table1, whereas

1. B dif means bands differencing, 2. B rat means band ratio, 3. NDVI dif means NDVI differencing, 4. DEM is a Digital elevation model, followed by 5. slope and 6. aspect. Then start the training site sampling and the modeling. According to the figure 2 the land cover classification was done using CTree program, repeated in ENVI decision tree algorithm and the land use cover change analyzing was executed performing ENVI decision Tree algorithm.

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CONDITION If {b10<0.875 AND b13< 0.1983 AND b14< 1382 AND b14>=1203 AND b15< 5.2447} THEN type= unused land to forest or shrub took place in the period 2002-2005 (table 3). Rule-based mapping is conducted at the pixel level. With the above example, pixels in the resulting classification image are assigned a value representing unused land > forest or shrub, when pixels in the input datasets (bands 4 ratio, NDVI differencing, elevation value, and slope value) meet the criteria in the rule.

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Within ENVI, the input to the decision tree classification can be one image, or a set of images of the same area, that is our case.

The Modeling procedure consists of following points:

I. Conversion of \*.roi to \*.txt format (ENVI IDL)

The training samples were collected and the pixels converted to readable by existing model text file.

II. Building a Tree based Classification Model (CTree program on C4.5 algorithm).

There are four important steps as follow:

Step 1:

Enter your data in The Data worksheet, starting from the cell L24 Number of rows; Data should be between 10 and 10,000; Application won't build model for less than 10 data points and it can't handle more than 10,000 data points.

Step 2: Fill up Model Inputs in the User Input Page and start modeling by Clicking the 'Build Tree' (near cell K48).

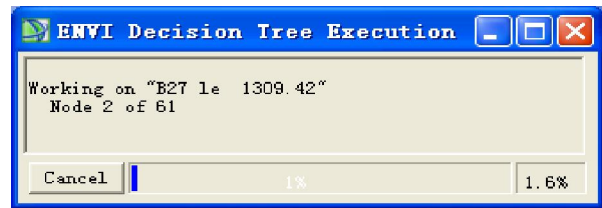
Step 3: Results of Modeling

When the run is over, the classification tree can be seen and analyzing in Tree sheet.

Step 4: Rule Generation: After the tree is grown, tree is further processed to generate

Rules.

III. Execute Existing Decision Tree running ENVI software



By opening of this message box the Decision Tree was executed. The success of the execution depends on how pairing are the file. The result is a classification images designated to further explore, analyze interpret for possible land use cover change detection.

**Table 1: Decision tree bands stacking Data**

File	Description
1. B1dif.99_02 B1dif.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above
2. B2dif.99_02 B2dif.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above
3. B3dif.99_02 B3dif.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above
4. B4dif.99_02 B4dif.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above
5. B5dif.99_02 B5dif.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above
6. B7dif.99_02 B7dif.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above
7. B1rat.99_02 B1rat.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above
8. B2rat.99_02 B2rat.99_02.hdr	Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province ENVI header for above

- 9. B3rat.99\_02 Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province  
B3rat.99\_02 hdr ENVI header for above
- 10. B4rat.99\_02 Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province  
B4rat.99\_02 hdr ENVI header for above
- 11. B5rat.99\_02 Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province  
B5rat.99\_02 hdr ENVI header for above
- 12. B7rat.99\_02 Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province  
B7rat.99\_02 hdr ENVI header for above
- 13. NDVI dif.99\_02 Landsat 7 ETM+ image of Puer- Simao counties, Yunnan Province  
NDVI dif.99\_02 hdr ENVI header for above
- 14. DEM Spatial subset of USGS DEM of Puer and Simao counties, Yunnan Province  
DEM.HDR ENVI header for above
- 15. SLOPE Spatial subset of USGS DEM of Puer and Simao counties, Yunnan Province  
SLOPE.HDR ENVI header for above
- 16. ASPECT Spatial subset of USGS DEM of Puer and Simao counties, Yunnan Province  
ASPECT.HDR ENVI header for above

**Table 2: Rules text of Classification Tree in1999-2002**

	Rule1	IF	b10 >= 0.973		
		AND	b11 >= 0.9315		
		THEN	type = forest-shrub>water		
	Rule2	IF	b14 < 1297		
		AND	b9 < 0.642		
		THEN	type = builtup>forest-shrub		
	Rule3	IF	b14 < 1297		
		AND	b9 >= 0.642		
		THEN	type = water>agricult		
	Rule4	IF	b10 < 0.973		
		AND	b14 < 1350		
		AND	b14 >= 1297		
		THEN	type = no change		
	Rule5	IF	b10 < 0.973		
		AND	b14 >= 1350		
		THEN	type = unused>forest-shrub		
	Rule6	IF	b10 >= 0.973		
		AND	b11 < 0.9315		
		AND	b14 < 1423		
		THEN	type = forest-shrub>builtup		
	Rule7	IF	b10 >= 0.973		
		AND	b14 >= 1423		
		THEN	type = forest-shrub>unused		
	Rule1	IF	b1 >= 233		
		AND	b10 < 0.973		
		AND	b14 < 1297		
		AND	b9 < 0.642		
		THEN	Type=nochange		



**Table 3: CTree Classification Rules in 2002-2005**

Rule1	IF	b10 < 0.875
	AND	b14 < 1405
	AND	b14 >= 1297
	THEN	type = no change
Rule2	IF	b10 >= 0.875
	AND	b11 < 0.9315
	AND	b14 >= 1405
	AND	b5 >= 216
	THEN	type = no change
Rule3	IF	b1 >=243
	AND	b14 < 1203
	AND	b8 < 0.8508
	THEN	type = builtup>forest-shrub
Rule4	IF	b14 < 1203
	AND	b8 >= 0.8508
	THEN	type = water>forest-shrub
Rule5	IF	b10 < 0.875
	AND	b13 < 0.1983
	AND	b14 < 1382
	AND	b14 >= 1350
	AND	b14 >= 1203
	AND	b15 < 5.2447
	THEN	type = unused>forest-shrub
Rule6	IF	b10 >= 0.873
	AND	b14 < 1423
	AND	b16 < 194.5195
	THEN	type = forest-shrub>builtup
Rule7	IF	b14 < 1203
	AND	b9 >= 0.650
	THEN	type = fwater>builtup
Rule8	IF	b10 >= 0.875
	AND	b11 >= 0.9315
	THEN	type = forest-shrub>water
Rule9	IF	b10 >= 0.875
	AND	b14 >= 1405
	THEN	type = forest-shrub>unused

**Table 4: CTree Classification Rules in 1999-2005**

Rule1	IF	b10 < 0.973
	AND	b14 < 1373
	AND	b14 >= 1226
	THEN	type = no change
Rule2	IF	b10 >= 0.693
	AND	b14 < 1413
	AND	b16 < 194.5195
	THEN	type = from veget to built
Rule3	IF	b10 >= 0.693
	AND	b11 < 0.7513
	AND	b16 >= 194.5195
	THEN	type = veget_unused
Rule4	IF	b14 < 1226

	AND	b9 <= 0.564
	THEN	type = from water to veget
Rule5	IF	b14 < 1238
	AND	b9 >= 0.412
	THEN	type = from water to builtup
Rule6	IF	b13 < 0.1983
	AND	b14 <= 1350
	THEN	type = unused>agricultural
Rule7	IF	b5 >= 232
	THEN	type = no change

**4. Results**

**4.1 Decision tree accuracy assessment**

Table 5 shows the accuracy assessment results. All the three classification dates achieved high overall accuracies of 94, 97 and 92% for 1999, 2002 and 2005 respectively, while the kappa coefficient sufficient well for all the classification images. Its lowest value (0.91) was yield with 2005 image, while the 2002 image received the best score with 0.97. That shows the high proportion of all reference pixels, which are classified correctly. In 2005 the agricultural land cover type received the lowest User accuracy score with 89% of pixels being correctly classified; while the best score value (100%) was received by the forest or shrub land cover type for the same date image. That means the probability a classified pixel in each class actually represents that category in reality is quiet high. The lowest Producer accuracy (92%) was found in 2002 for unused land cover type, while the water cover type gave the best producer accuracy (100%) in 1999.

From up mentioned table the unused land cover type presented a relatively low user accuracy score of 92%, as some pixels were incorrectly classified as agricultural land.

LUC types	1999		2002		2005	
	Prod.%	User%	Prod.%	User%	Prod.%	User%
Built up	95	97	99	96	99	93
Forest or shrub	98	99	99	99	97	100
Water	100	97	98	99	97	96
Unused land	94	93	92	98	96	92
Agricultural land	95	92	93	99	97	89
Overall Accuracy %	94		97		92	
<i>Kappa Coefficient%</i>	0.94		0.97		0.91	

**Table 6: Land use cover conversion matrix from 1999 and 2002 in hectares.**

Period	LUC classes					Total
	1	2	3	4	5	
1999-2002						
1. Built-up Land	25830	12788	0	0	0	38618
2. Forest or shrub	10469	138600	0	2618	0	153717
3. Water	0	3631	83160	0	0	86791
4. Unused Land	0	20494	0	127776	0	148270
5. Agricultural land	0	0	2030	0	110000	110000
Total	36299	175513	85190	130394	110000	537396

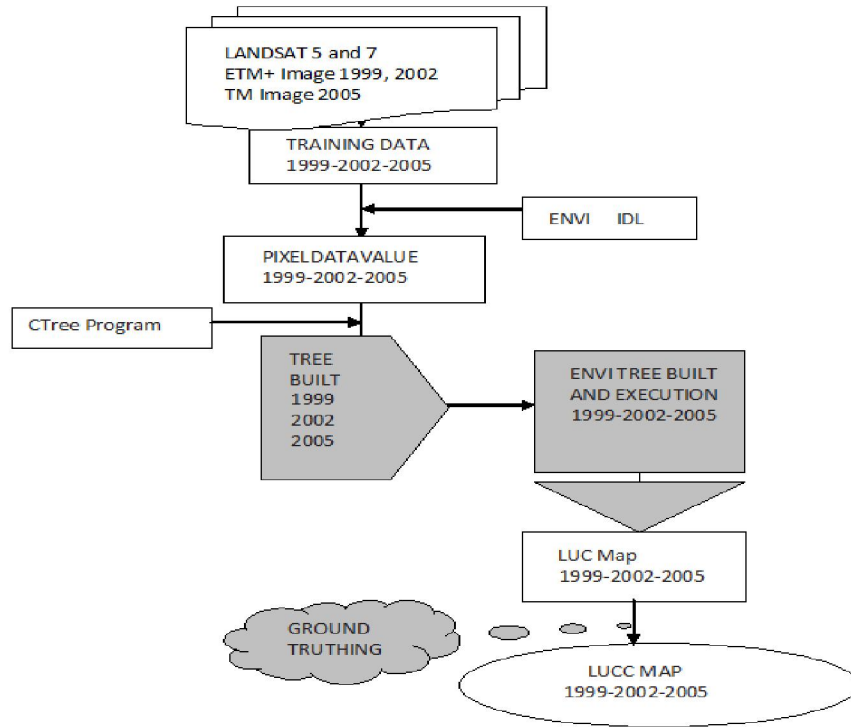


Figure 2: Flowchart depicting the methods used in Decision Tree

**Table 7: Land use cover conversion matrix from 2002 and 2005 in hectares.**

Period	LUC classes					Total
	1	2	3	4	5	
2002 - 2005						
1. Built-up Land	51678	12834	471	0	0	64983
2. Forest or shrub	527	191730	450	3366	0	196073
3. Water	0	964	112860	0	0	113824
4. Unused Land	0	63	0	128000	0	128063
5. Agricultural land	0	0	0	0	115300	115300
Total	52205	205591	113781	131366	115300	618243

**Table 8: Land use cover conversion matrix from 1999 and 2005 in hectares.**

Period	LUC classes					Total
	1	2	3	4	5	
1999-2005						
1. Built-up Land	23166	27475	100	0	0	50741
2. Forest or shrub	0	85470	6642	0	0	99670
3. Water	0	0	97416	0	0	97416
4. Unused Land	0	15136	0	139392	0	154528
5. Agricultural land	0	0	0	7558	122500	130058
Total	30724	128081	104158	146950	122500	524855

built-up; 2= Vegetation; 3= Water; 4= Unused Land 5= Agricultural land

1=



### 4.2 Land use cover changes

Through an integration CTree program and D.T in ENVI software were built the classification trees in 1999, 2002, 2005 and between three (3) study period as follow: 1999-2002, 2002-2005, 1999-2005. Figures 3, 4, and 5 show the LULC maps of the study area for 1999-2002 and 2002-2005, 1999-2005. The tree building prerequisites (decision rules If-THEN) in 1999-2002, 2002-2005 and 1999-2005 are in tables 2, 3 and 4 respectively. Table 9 shows the comparison of areas and change of the four LULC classes in the entire study area.

Tabulations and area calculations provide a comprehensive data set in terms of the overall landscape changes, which have occurred. The class area was measured by the number of pixel multiplied by the Landsat TM5-7 spatial resolution, i.e. 30m. The pixel number was given by the post-classification analysis. The change was calculated as a pixel number difference between two periods date (1999-2002; 2002-2005 and 1999-2005). The three last columns indicate an average change; it was computed by the pixel number difference between two periods. The change matrix in tables 6, 7, and 8 contribute to facilitate the understanding of the change types (conversion, transformation). In the study periods Forest or shrub land constituted the most extensive type of LULC. Accordingly, it accounted for about 49, 35 and 30% of the total area in 1999, 2002 and 2005 respectively, followed by Agricultural and Unused land occupying 17, 19, 25% and 24, 19, 18% of the total area respectively. LULC units under Water and Built-up land covered 18, 23, 22 and 09, 20, 23 % of the total area respectively.

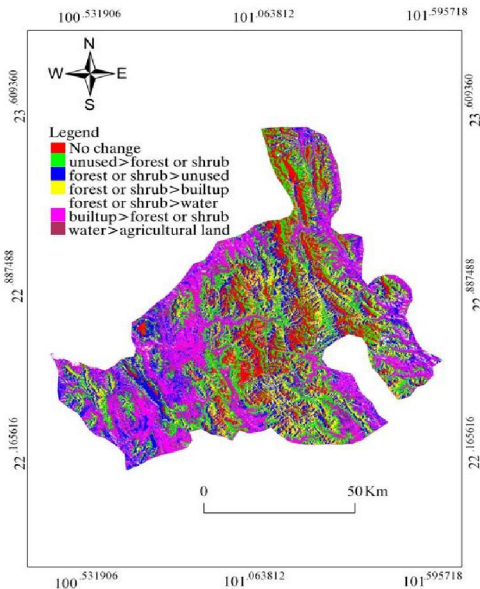


Figure 3: LUC Change MAP 1999-2002

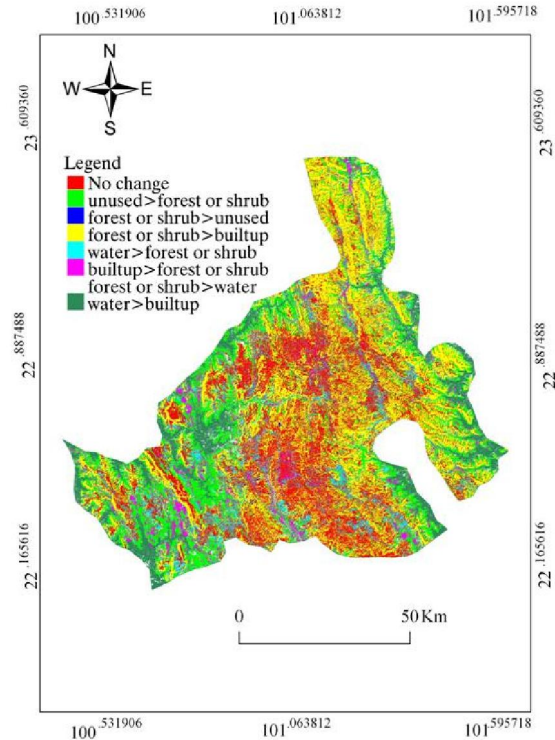


Figure 4: LUC Change MAP 2002-2005

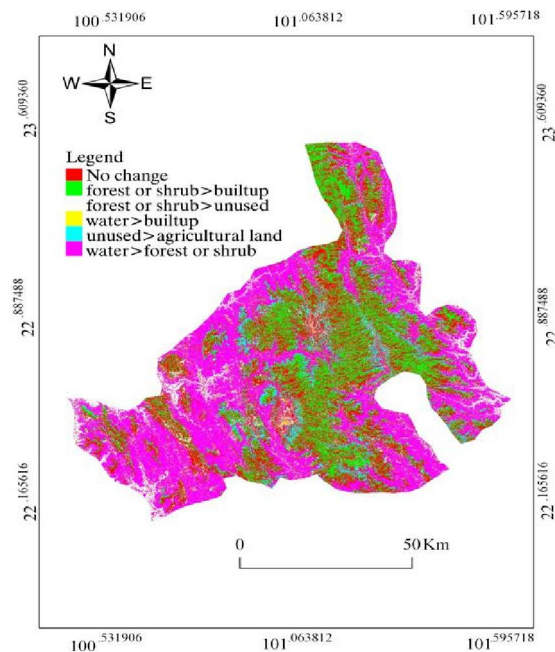


Figure 5: LUC Change MAP 1999-2005

From 1999 the Forest or shrub land (49%) decreased continuously to about, 35 and 30% of the total vegetation area in 2002 and 2005 respectively. The unused land area decreased slightly to about 19, and 18% in 2002 and 2005 respectively, while the

Built-up and Agricultural land increased progressively to about 20, 23% and 19, 25% in 2002 and 2005 respectively.

Further, the from- to change matrix is shown in tables 6, 7 and 8 in 1999-2002, 2002-2005 and 1999-2005 respectively. Figure 3 and its rules text ( table 2) for the period 1999-2002, whereas, the from *forest or shrub land* into *Unused land* (20494 ha) was the most significant change in the area. *The from forest or shrub land into built-up* (12834 ha) was the most noticeable change in the area of the period from 2002 to 2005, while in 1999-2005 the most significant change in the area was the from *forest or shrub land* into *Built-up land* (27475 ha).

## 5. Discussions

The excellent overall accuracies of all classification process can be explained by the fact that the total number of correctly classified pixels was high. The LULC types were correctly chosen and the transition from Ctree program to ENVI software was efficient. The high quality of user and producer accuracy could be explained by the fact that the probability that a classified pixel actually represents that category in reality is very high. That was found to be consistent with the range reported elsewhere (Mas et al 2004, Yuan et al. 2005, Hazeu and De Wit, 2004). But the comparatively lower user and producer accuracies of unused land area and agricultural land cover type in 1999 and 2005 could be explained by the fact that several of agricultural land pixels were misclassified as unused area and vice-versa. Consequently for classifying agricultural land, there was some confusion with unused land and for classifying unused land there was confusion with agricultural land area.

The satellite-based analysis reveals some interesting trends as regards the land cover development in the study period. From our results figures 3, 4 and 5 it is evident that the study area had been subjected to intensive use influence and degraded with +61% and -63% of change under built-up and vegetation respectively. The increase in built-up and agricultural land and the decrease in vegetation cover were found as deforestation at the profits of built-up elsewhere (Mengistu and Salami, 2007, Reis, 2008). In line with this, the LULC data of the up mentioned years indicated a change. The retreating of areas covered with vegetation and expanding of built up and agricultural land is common in the region. This indicates the encroachment of buildings and agricultural land towards vegetative areas; this was established by the field investigation on June 2009. The phenomenon is found to be a forest clearing and caused by anthropogenic disturbance (Roy, Chowdhury and Schneider, 2004). The same

phenomenon was found using the up mentioned post classification technique. LULC changes reflect the dynamics observed in the socio-economic condition (demography, Gross Domestic Product, Gross Output Value of Industry and Agriculture) of the study area. As saying up the changes might due to the government policies that aim to balance the need to encourage rural development, the removal of compulsory grain crop quotas, promoting livestock with ecological stability. That is found to be similar to the situation in a neighboring area Xishuangbanna Prefecture (Xu et al., 1999). The driving force for building area (urban) expansion of current study area as Chinese city might be the phenomenon of development zones that are created to host innovative activities and foreign investment. Hence, the expansion of built -up was responsible for the disappearance of the vegetation cover type in the study period, even if the 1999 and 2005 images were taken in winter period. It is possible that ETM+ image of 2002 might have done better if the data were collected in late spring or early fall. According to some opinion, summer is not the best season for a forest classification. Other studies confirm that times when leaves are either senescent or not fully developed are best for forest classification. The relationships between the vegetation and built-up areas was found to be consistent with the range reported elsewhere (Fearnside, 2001, Lambin et al. 2003, Velazquez and al., 2003).

## 6. Conclusions

Results indicate that the predictors, namely b11 (band 5 ratio), b9 (band3 ratio), b10( band 4 ratio), and b14(elevation value) influenced the target variable (the change) in descending order( see table 5). Likewise b1(bands 1 differencing), b5(bands 5 differencing), b8(bands 2 ratio), b9(bands 3 ratio), b10(bands 4 ratio), b11(bands 5 ratio), b13(NDVI differencing), b14(elevation value), b15(slope value ) and b16 (aspect value) influenced whole the change in this study( see tables 3-5, 3-6 and 3-7). This is helpful in ranking the predictor variables.

Thus, decision trees play an important role in the management of change vector. The above decision rules will be helpful in assessing the land use land cover change. Hence, by observing above decision rules appropriate control measure can be implemented to monitor and plan land use activities like that carried out in Diamou (Diallo et al., 2009).

Decision Tree showed the similar trends, whereas from 1999 the Forest or shrub land (49%) decreased continuously to about, 35 and 30% of the total vegetation area in 2002 and 2005 respectively. The Built-up land increased progressively to about 20, 23% in 2002 and 2005 respectively, while the

agricultural land cover type increased to 19 and 25% in 2002 and 2005 respectively.

The first conclusion that can be drawn from this study is that retreating of areas covered with vegetation and unused land and expanding of built up land and agricultural land areas indicate the encroachment of buildings and agricultural activities towards vegetative areas and unused land which justifies our fears; this was established by the field investigation on June 2009.

It was not possible to discriminate a famous Tea Mountain area from others growth in agricultural land cover type.

The integration of Ctree program and Decision Tree was a good opportunity in land use land cover change detection in Puer-Simao counties, it can be implemented in others similar studies.

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### References

1. Archer J, Robertson DL., 2007, CTree: comparison of clusters between phylogenetic trees made easy. *Bioinformatics*, 23 (21): 2952–2953.
2. Diallo Y., Hu G. and Abdurazak H. A., 2009, Simulation Planning for Sustainable Use of Land Resources: Case study in Diamou, *Journal of Mathematics and Statistics* 5 (1): 15-23.
3. Fearnside, M.P., 2001. Saving tropical forests as a global warming countermeasure: an issue that divides the environmental movement. *Ecological Economics* 39, 167–184.
4. Finbarr O’Sullivan, A. Saha, 1999, Use of Ridge Regression for Improved Estimation of Kinetic Constants from PET Data. [IEEE Transactions on Medical Imaging](#) 18 (2).
5. Hansen, M. C., R. S. DeFries, J. R. Townsend and R. Sohlberg. 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach, *International Journal of Remote Sensing*. Vol. 21, No. 6 & 7, pp 1331-1364.
6. Hazeu G.W. and Dewit A.W., 2004, Corine land cover database of the Netherlands: monitoring land cover changes between 1986 and 2000. In the proceedings of EARSel conference pp. 382-387.
7. Jensen, J.R., 2007. *Introductory Digital Image Processing: a remote sensing perspective*. 3<sup>rd</sup> Edn., science Press and Pearson Education Asia Ltd: Beijing ISBN:978703018819-9 pp. 467-494.
8. Kaufmann, R. K., and Seto, K. C., 2001, Change detection, accuracy, and bias in a sequential analysis of Landsat imagery in the Pear River Delta, China: econometric techniques. *Agriculture Ecosystems and Environment*, 85, 95–105.
9. Lambin EF, Geist H, Lepers E (2003). Dynamics of land use and cover change in tropical regions. *Annual Rev. Environ. Resour.* 28: 205–241.
10. Lawrence, R. and A. Wright. 2001. Rule-based classification systems using Classification and Regression Trees (CART) Analysis. *Photogrammetric Engineering and Remote Sensing*. Vol. 67, No. 10.
11. Lin J. W., MD, Dai d.F., MD, Chou Y.H., Li-Ying BS, Huang, BS, and HWANG J. MD, 2007, Exploring the Effects of C-Reactive Protein (CRP) and Interleukin-1 $\beta$  Single Nucleotide Polymorphisms on CRP Concentration in Patients With Established Coronary Artery Disease- A Classification Tree Approach, *International Heart Journal*, 48(4): 463-475.
12. Lyon J G, Yuan D, Lunetta R S, et al. 1998, A change detection experiment using vegetation indices. *Photogr Eng Remote Sens*, 64(2):143—150.
13. Macleod, R. B., and Congalton, R. G., 1998, A quantitative comparison of change detection algorithms for monitoring eelgrass from remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, 64, 207–216.
14. Mas, J.F.; Velazquez, A.; Gallegos, J.R.D.; Saucedo, R.M., Alcantare, C.; Bocco, G.; Castro, R.; Fernandez, T.; Vega, A.P., 2004, Assessing land use/cover changes: a nationwide multirate spatial database for Mexico. *International Journal of Applied Earth Observation and Geoinformation*, 5: 249-261.
15. Mengistu D., A., and Salami A.T., 2007, Application of remote sensing and GIS inland use/land cover mapping and change detection in a part of south western Nigeria, *African Journal*

- of Environmental Science and Technology 1(5): 099-109.
16. Read, J. M., and Lam, N. S.-N., 2002, Spatial methods for characterizing land cover and detecting land cover changes for the tropics. *International Journal of Remote Sensing*, 23, 2457–2474.
  17. Reis S. 2008, Analyzing land use/land cover changes using remote sensing and GIS in Rize, North-East Turkey, *Sensors*, 8: 6188-6202.
  18. Roy Chowdhury, R., Scheneider, L.C., 2004. land cover and land use classification and change analysis, pages 105-141, in Turner II, B.L., Geoghegan, J., Foster, D.(Eds), *Integrated Land change Science and Tropical Deforestation in the Southern Yucatan: Final Frontiers*. Clarendon Press/Oxford U.P., Oxford.
  19. Stefanov, W.L., Ramsey, M.S. and P.R. Christensen, 2001, “ Monitoring Urban Land cover change: An Expert System Approach to Land Cover Classification of Semiarid to Arid Urban centers,” *Remote Sensing of environment*, 77:173-185.
  20. Stow, D., Coulter, L., Kaiser, J., Hope, A., Service, D., Schutte, K. and A. Walters., 2003, “Irrigated vegetating Assessments for Urban Environment“ *Photogrammetric Engineering and Remote Sensing*, 69(4): 381-390.
  21. Swain, P.H. and H. Hauska, 1997, “The Decision Tree Classifier: Design and Potential,” *IEEE Transaction on Geoscience and Remote Sensing*, 15: 142-147.
  22. Ustin, S. L., Roberts, D. A., and Hart, Q. J., 1998, Seasonal vegetation patterns in a California coastal savanna derived from Advanced Visible/Infrared Imaging Spectrometer (AVIRIS) data. In *Remote Sensing Change Detection: Environmental Monitoring Methods and Applications*, edited by R. S. Lunetta and C. D. Elvidge (Chelsea, MI: Ann Arbor Press), pp. 163–180.
  23. Velazquez, A., Durana E., Ramirez I., Mas J., F., Bocco G., Ramirez G., Palacio J., L., 2003, Land use-cover change processes in highly biodiverse areas: the case of Oaxaca, Mexico, *Global Environmental Change* 13: 175–184.
  24. Vogel, A.W., Wang M. and Huang X., 1995; people’s Republic of China: Red Reference Soils of the subtropical Yunnan Province. *Soil Brief China*1. Institute of Soil Science-Academica Sinica, Nanjing, and International Soil Reference and Information Centre, Wageningen. pp. 10-27.
  25. Vogelmann, J.E., S.M. Howard, L. Yang, C. R. Larson, B. K. Wylie, and J. N. Van Driel, 2001, Completion of the 1990’s National Land.
  26. Xu, J., Fox, J., Xing, L., Podger, N., Leisz, S., Xihui, A., 1999. Effects of swidden cultivation, state policies, and customary institutions on land cover in a Hani village, Yunnan, China. *Mountain Research and Development* 19 (2): 123–132.
  27. Yang, C. and P. Chung, 2002, “Knowledge-based automatic Change Dtection Positioning for Complex Heterogeneous Environments,” *Journal of Intelligence and Robotic Systems*, 33: 85-98.
  28. Yuan, D. and Elvidge, C. D.: 1998, ‘NALC land cover change detection pilot study: Washington D.C. area experiments’, *Remote Sens. Environ.* 66, 166–178.
  29. Yuan, F.; Sawaya, K.E.; Loeffelholz, B.C.; Bauer, M.E. 2005, Land cover classification and change analysis of the Twin Cities (Minnesota) metropolitan areas by multitemporal Landsat remote sensing. *Remote Sensing of Environment* 98, 317-328.