DETECT HABITAT CHANGES IN MABIAN GIANT PANDA NATURE RESERVE, CHINA*

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ABSTRACT:

Due to that the vegetation has been influenced by human activity for a long period, such as logging, grazing and trampling, giant pandas' habitat has been fragmented gradually, which has threatened the survival of the giant panda. Therefore, it would be an essential issue to inspect the spatial pattern of the giant panda's habitat and analyze the factors which drive these habitat changes. The aim of this study is to detect the giant panda's habitat changes by using decision tree classification approach.
The study area is Mabian-Dafengding Nature Reserve (MDNR) in Liangshan Mountains of Sichuan Province. Our data include field survey samples, GIS data and Landsat TM images. Decision tree classification approach was applied to detect the giant pandas' habitat change. Compared with traditional classification method, decision tree is more capable of using both spectrum and non-spectrum information as to improve classification accuracy. According to the local climate and vegetation type, 9 habitat types were defined. Our results firstly show that the decision tree method is an effective approach on detecting the habitat change. Our results also show that the area of the mixed evergreen and deciduous broadleaf forest increases the most, while that of the mixed deciduous broadleaf and conifer forest decrease the most. In spatial, most changes were detected along the boundary and the river of MDNR, which reflects substantially that human being has strong impacts on the surrounding habitat type. All these changes should be paid attention to by the local managers for a better conservation.

1. INTRODUCTION

The Liangshan Mountains is one of the homes of giant pandas. It also provides suitable living condition for some other rare and endangered species. The integrity and diversity of habitat are essential for preserving the endangered species and maintaining ecosystem balance in the Liangshan Mountains. However, the vegetation has been experienced logging, grazing and trampling for a long time. The habitat quality is degrading, which has an unpredictable impact on the wildlife's survival and distribution. Besides, the managers are lack of the pattern information of habitat types and may not do planning and protect wildlife's habitat effectively.

Nowadays, change detection approach based on geographical information system (GIS) and remote sensing (RS) technology has been well developed. Comparing with traditional field survey methods for collecting habitat information, not only does this approach need less labour and time, but also it can provide more comprehensive results and is a more convenient approach for data accumulating and reusing. It is well known that maximum likelihood classification (MLC) is a quick and widely-used approach for change detection. It has become a common and effective tool for habitat pattern analysis. (Zheng et al., 2004) However, after a long-term research, it is found that MLC cannot avoid the influence from terrain factor in classification. Terrain factor may cause shadow in some mountain slopes, which would influence spectrum information and consequently lead some habitat types misclassified (Skidmore, A.K., 1989; Chen and Wang, 1996). As a new method for classification, decision tree has no limitation to only using spectrum information layers, and allow to include other non-spectrum layers into classification, such as DEM, slope, aspect and so on. Information from these layers can largely improve classification accuracy in those terrain-shadowed areas (Chen and Wang, 1996; Liu, 2002).

In this article, decision tree method was applied in classification for detecting habitat type changes based on two TM images acquired on June 26, 1994 and April 21, 2002. The aims are (1) to detect accurate habitat type changes by classifying and mapping and (2) to provide an effective way for change detection and nature reserves' management.

2. STUDY AREA

The study area is Mabian-Dafengding Nature Reserve (MDNR), located in Mabian County, Sichuan Province, China. Its geo-location is 103°14′ - 103°24′ E, 28°25′ - 28°44′ N and it has a total area of 301.64 km^2 (Figure 1a-c). MDNR settles in the transitional zone from Sichuan basin to Yungui plateau. The elevation ranges from 800m to 4042m with a height span of 3200m approximately (Figure 1d). The annual mean temperature is about 10℃ and the annual precipitation is about 1900mm. The moderate climate provides a suitable condition for many living species. The vegetation is well developed with a more complete vertical distribution under a influencing of the sub-tropical monsoon climate, changing from ever green forest to alpine meadow and screes. Bamboo also has a wide understory distribution (MDNNRA, 2000; Song et al., 2004).

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MDNR is one of the most important giant panda nature reserves and was established in 1978. There is no people dwelling in it, but many people live around it and depend on the resources from it. Due to lacking better management, this area has been heavily disturbed by the surrounding human activities, such as logging, gathering shoots and collecting rare medical plants until 1998 when the natural forest was prohibited from cutting by law (MDNNRA, 2000). During these 20 years, MDNR habitat has changed a lot from its original state. The habitat change detection can help result in a better management and preservation of giant pandas and their habitat.

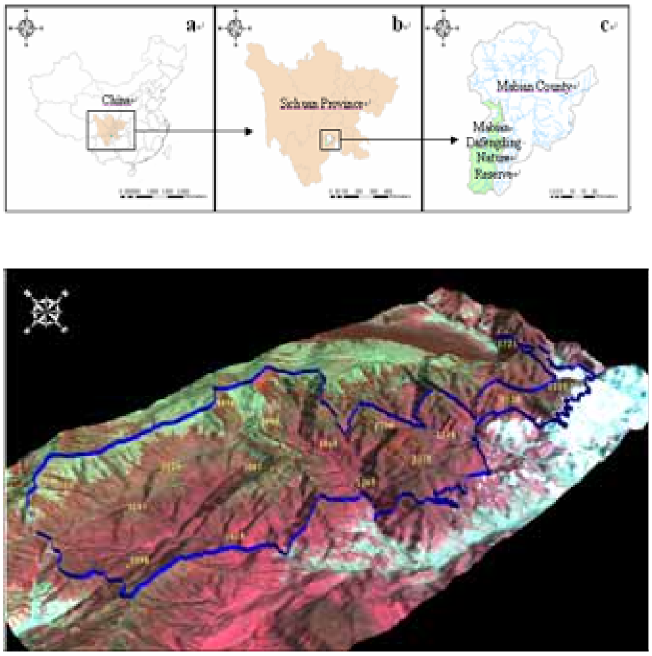

Figure 1. The geo-location and terrain of the study area: Mabian-Dafengding Nature Reserve

a. China b. Sichuan province c. Study area d. 3D display of study area

3. RESEARCH METHODS

3.1 The algorithms of decision tree

The decision tree is one of expert system classifiers based on hypothesis, rules and conditions, which are connected with each other by nodes. The decision tree grows in depth when the hypothesis of one rule is referred to by a condition of another rule. The terminal hypotheses of the decision tree represent the final classes of interest (ERDAS Inc).

Figure 2 defines the terms of across branch and along branch and shows how confidences are calculated from given condition confidences. This figure was illustrated as an example to explain the assumed confidences in each condition. Equations (1) and (2) are used for calculation in the decision tree. In figure 2, the confidence of each rule is derived from calculating the confidence of conditions, and the confidence of hypothesis is the confidence of rule with the highest value (ERDAS Inc).

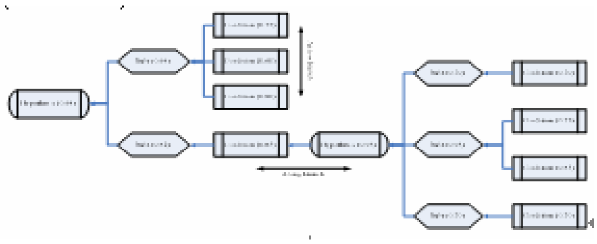

Figure 2. The algorithms of a decision tree

$$\text{Along branch: Confidence} = \prod_{i=1}^{n} c_i \quad (1)$$

$$\text{Across Branch: Confidence} = 1-\left(\prod_{i=1}^{n}(1-c_i)\right) \quad (2)$$

Where:

c_i = the confidence value of node (i)

$\prod c_i$ = the product of the confidence values

$1-c_i$ = the error probability

n = the number of nodes in a branch

3.2 Data and preparing

This research used vector data (including boundaries; rivers; sample points), raster data (including DEM; slope model; aspect model), and Landsat TM images acquired on June 26 1994 and April 21 2002. All map layers have been geo-referenced to have the same coordinator system and spatial resolution of 30*30m^2, and were integrated into one image. We also used the sample data collected from the field survey in 2004. Then classification results were derived from decision tree classification approach.

According to the local climate and vegetation characteristics, the 9 habitat types were defined as: (1) secondary forest (SEF), (2) evergreen broad leaf forest (EBF), (3) mixed evergreen and deciduous broadleaf forest (EDF), (4) mixed deciduous broadleaf and conifer forest (BCF), (5) conifer forest (CF), (6) bamboo (BAM), (7) water area (WAR), (8) rock-bare land (RBL), (9) alpine meadow and screes (AMS) (MDNNRA, 2000).

Due to that one image was acquired 11 years ago in 1994, some adjustments were made during classifying based on our experience on the spectrum from classifying 2002-image and the relationship between elevations and habitat types. By applying the vegetation characteristics of vertical distribution, some more sample points were taken into account in order to increase certainty in classifying 1994-image.

3.3 Constructing the decision tree and classifying

Probability distribution of each habitat type in each layer is the basis for running the decision tree classification. Two steps for getting probability distribution are (1) extracting spectrum information based on all sample points from all data layers, and (2) figuring the probability distribution of each habitat type for all data layers (Zhu and Mao, 1997). Figure 3 shows the structure of our decision tree for this study (Fu, 2004; Liu, 2001).

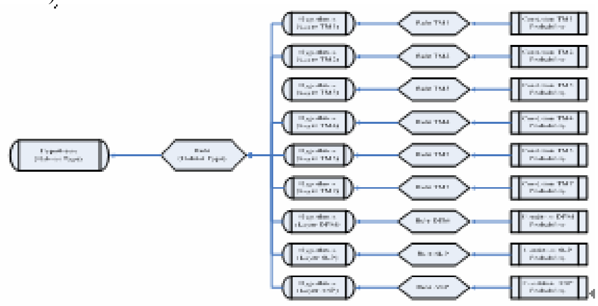

Figure 3. The structure of the decision tree in this study

In figure 3, the obtained probability distribution was used as the condition for running decision tree classification. When classifying, this condition was used to calculate the interim confidence that one pixel belongs to a certain habitat type in each layer by rules. These interim confidences were then assigned to the hypothesis of the corresponding layer. The system (hypothesis of habitat type) calculates the final confidence by using these interim confidences. Finally the highest confidence determines which habitat type this pixel belongs to.

The error matrix and Kappa methods were used to assess the mapping accuracy. The overall mapping accuracy only considers the correction of diagonal elements in the matrix, while the kappa method also takes the other elements in the matrix into account, which can compensate the disadvantage of the error matrix method. In general, the mapping results are evaluated as very good, better, good, normal, bad, worse, very bad to corresponding with the kappa values ranges of 0.8-1.0, 0.6-0.8, 0.4-0.6, 0.2-0.4, 0-0.2, and <0 (Liu et al., 1998).

3.4 Detecting changes of habitat types

The map of habitat type changes was obtained through minus calculation of two produced habitat type maps from 1994 and 2002 images. The changing locations, areas and trends were statistically analyzed. Due to the cloud cover of the 2002-image scene, the same-size area was subtracted from both 1994 and 2002 images.

4. RESULTS

4.1 Maps of habitat types for two years

The distribution patterns of habitat types from two different-period images were shown in figure 4. In general, the EDF covers most areas in both images, especially in low elevation areas from 1500m to 2500m. The BCF is located at upper slope of the mountain. The CF is identified along the mountain ridge with an elevation from 3000m-3500m. The AMS is located at the southwest near the boundary at an elevation of more than 3500m. Most of the detected BAM patches are distributed in the northern part. The RBL and rivers were identified mostly in the valleys. The EBF was found in the 2002-image but with a very small area along the valley. Among 9 habitat types, the EDF covers the largest area, while the SEF the smallest one.

The accuracy assessment of two habitat mapping shows that their overall accuracies are 69.34% for 1994-image and 71.68% for 2002-image respectively, and the kappa values are 0.6529 and 0.6718. Two Kappa values are all greater than 0.6 which indicates the mapping results meet the accuracy requirement. SEF-secondary forest, EBF-evergreen broadleaf forest, EDF-mixed evergreen and deciduous broadleaf forest, BCF-mixed deciduous broadleaf and conifer forest, CF-conifer forest, BAM-bamboo, WAR-water area, RBL-rock-bare land, AMS-alpine meadow and screes.

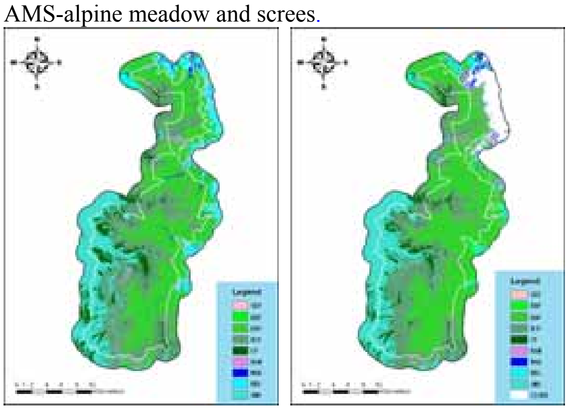

Figure 4. Maps of habitat types in Mabian-Dafengding Nature Reserve. **a.** map from image of June 26, 1994; **b.** map from image of April 21, 2002. The light line is the boundary of the nature reserves.

4.2 Change detection Map and quantification

Figure 5 visually describes the spatial changing of habitat types. It clearly displays that most obvious changes are appearing in a lower elevation areas along and outside the boundary. Only a few changes were detected distributing on the southern part of the nature reserve. Compared with figure 4, these changed habitat types mainly are the EDF and the BCF. Some changes are detected in the northern part of MDNR. Those are not the changes of habitat types actually. They are caused by both the shadow of cloud and the vapor around it.

Table 1 shows the figures of changing area for each habitat type. The EDF has the largest increase on area from 1994 to 2002, while the BCF has the strongest decrease during the same time span. Some other habitat types nearly remain relatively stable, such as the secondary forest, evergreen broadleaf forest, water and rock-bare land. For 1994-image, there is a larger area covered by the BCF, while for 2002-image the MDNR has more distributions of the EDF, bamboo and AMS.

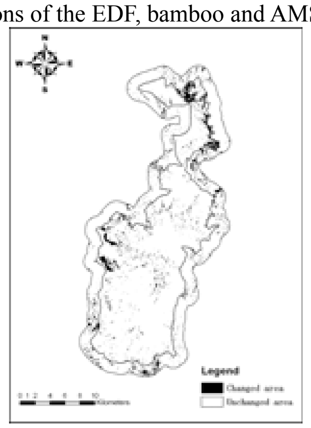

Figure 5. Changing map of habitat types from 1994 to 2002 in Mabian-Dafengding Nature Reserve in the Liangshan Mountains.

Habitat type	1994 Area (km^2)	2002 Area (km^2)	Changes Area (km^2)

SEF	0.39	0.30	-0.09
EBF	0.00	1.28	1.28
EDF	131.20	142.93	11.73
BCF	94.35	80.09	-14.26
CF	21.95	17.96	-4.00
BAM	6.64	9.54	2.91
WAR	2.23	4.16	1.92
RBL	2.93	2.85	-0.08
AMS	41.94	42.52	0.58

Table 1. The changing areas of all habitat types from 1994 to 2002 in Mabian-Dafengding Nature Reserve in the Liangshan Mountains. SEF-secondary forest, EBF-evergreen broadleaf forest, EDF-mixed evergreen and deciduous broadleaf forest, BCF-mixed deciduous broadleaf and conifer forest, CF-conifer forest, BAM-bamboo, WAR-water area, RBL-rock-bare land, AMS-alpine meadow and screes.

5. DISCUSSION

Results of habitat types mapping and change detection show that most changes occur near or along the valleys and also the boundary of MDNR. It indicates that people often go in to these areas for logging, gathering bamboo shoots and mushroom, and also collecting medical plants. All these human activities may have caused the long-term impacts on the surrounding forest environment. The consequence of forest cutting is the simplification of forest structure and reduction of species diversity.

The establishment of MDNR has made a big difference on habitat between inside and outside MDNR (see Figure 1d). Obviously, the remote sensing image acquired in 2002 shows many patches outside the nature reserve. According to our survey in 2004, we found most of those patches are the clear-cutting areas from mining. As known, local people were exploring phosphorite from the mountain areas. With exploring, road constructing was occurring. These two activities devastated mountain vegetation very much and resulted in more bare lands. If it is assumed that these areas were inhabited by giant pandas, the animals must have disappeared from these places. However, these human activities have been prohibited inside the reserve boundary since its establishing.

The decision tree classification approach provides an effective way for mapping and detecting habitat changes. Compare with the MLC approach, it can not only avoid the influence of terrain factor which has an impact on the classification results, but also enhance the ability for discriminating the habitat types with similar spectrum information by using additional GIS information, such as DEM, slope and aspect models, and more spatial layers could be involved into if available. Through these efforts, the accuracy of habitat mapping and change detection can be largely improved. For further study, we could try to integrate other information layers, such as texture, patch shape and so on, for high quality mapping (Ma and Guan, 2000; Wang et al., 2002).

6. CONCLUSION

The decision tree classification approach is an effective method on change detection. It has successfully detected the habitat changes from years 1994 to 2002 in MDNR. The detected habitat changes should call for attention from the local managers. For the decision tree method, there is still some imperfectness in this research, such as the weight of each layer for determining the final results and the correlation between each layers need to be analyzed as to decrease the repetition of using same data information. More work need to be done for higher classification accuracy by using decision tree approach.

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