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National Policy's Influence on Baoxing County's Landscape Patterns and Giant Panda Population

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Abstract

As one of the most important hometowns of Giant Panda, Baoxing county's landscape, which is mainly influenced by National Policy Change the ,national policy change, plays an important role in Giant Panda's protection. Thus, it is crucial to understand how and what the national policy change on landscape patterns change in Baoxing county. In this paper, Landsat MSS data in 1975, Landsat TM data in 1994 and Landsat ETM data in 2002, with the dates corresponding to the same time as the time of national policy changes, are classified to make the landscape patterns, change. The results indicate that, from 1975 to 1994, due to the crawling in this area, the forests have decreased about 5.92% with fragments created, grassland has decreased about 2.64%, farmland has increased about 1.5% and settlement place has increased about 7.15%. Accordingly, the Giant Panda's population shows all fall from 328 to 75. But from 1994 to 2002, owing to the policies to protect the Giant Panda and its habitat, the forests has increased about 0.12%, grassland has increased about 0.55%, farmland has decreased about 0.58% and the fragment of forests in 2002 is lower than in 1994. Accordingly, the Giant Panda's population show as increase from 75 to 143. This indicates that the national performed actioned during 1990s has much positive influence on the landscape patterns and the Giant Panda population in Baoxing county.

Keywords: *Baoxing, landscape, Giant Panda, policy, supervised classification*

INTRODUCTION

The pattern of land-use is based on and influenced by a variety of factors and processes in different sectors: natural site conditions, policy, cultivation traditions preferring regional techniques, social development, as well as economic forces and even religious rules are working intertwined in a complex system in the past and the present. They are all changing over time constrained by technical possibilities and thus the pressure on land availability for wild creatures use will increase [Bartel 2000; Jacquin, Misakova et al. 2008; Thielen, José et al. 2008]. The policy change is almost the most important one. Since the 1950s, with the national policy changes and socio-economic development, the habitat of the Giant Pandas altered accordingly, which can be inferred from the population changes of the Giant Pandas in the 3 national surveys [National-Forest-Ministry 1989; National-Forest-Ministry 2006]. Thus, monitoring the policy change's impact on the change of Giant Panda's habitats and then taking some action positive would make a valuable contribution to the Giant Panda protection.

Land use change can be characterized by the complex interaction of behavioral and structural factors associated with demand, technological capacity, and social relations, which affect both demand and environmental capacity, as well as the nature of the environment in question. The impacts of land use changes have received considerable attention from ecologists, particularly with respect to effects on aquatic ecosystems and biodiversity.[Lin, Hong et al. 2007]. Remote sensing can provide considerable cost and time savings when mapping the distribution of land cover over large areas. It can play an important role in biological monitoring by providing spatially explicit, continuous, and extensive data on the composition and condition of wildlife habitats[Laurent, Shi et al. 2005; Lucas, Rowlands et al. 2007; Pasher, King et al. 2007; Stow, Hamada et al. 2008]. Often, the assessment of land use change results in changes in landscape pattern. Landscape composition, configuration, and connectivity are primary descriptors of the landscape patterns. Landscape patterns can be quantified using spatial landscape indices or metrics to characterize and quantify landscape composition and configuration. The composition of a landscape denotes the features associated with the variety and abundance of patch types within a landscape. The spatial configuration of a landscape denotes the spatial character and arrangement, position, or orientation of patches within class or landscape. These metrics may include the number of patches, area, patch shape, total edge of patches, nearest neighbor distance, landscape diversity, interspersion and contagion metrics to represent landscape patterns, including compositions and configurations[Lin, Hong et al. 2007]. Moreover, landscape metrics may also be useful as a first approximation of broad-level landscape patterns and processes, and for characterizing differences among planned and design alternatives, have been suggested as an appropriate tool for land use planning and design[Lin, Hong et al. 2007; Scott and Shannon 2007]. With the recognition of the importance of ecosystem services, many communities are trying to reduce the negative effects of the conversion of natural land-covers to anthropogenic land-covers by requiring or encouraging the use of retention and/or detention basins, porous pavement, vegetative buffers, and the preservation of existing trees. Nevertheless, land-cover alterations that result from development can have profound effects on the environment. These effects include the loss of native bio-diversity, the introduction of exotic species, elevated soil erosion, and degraded water quality.[Collinge 1996] Habitat loss and isolation associated with land conversion for human activities constitute the most serious threat to the Earth's biological diversity[Collinge 1996; Sánchez-Flores, Rodríguez-Gallegos et al. 2008]. Remote Sensing Techniques have also proven to be successful in providing timely information about the spatial characteristics of the invasions[Sánchez-Flores, Rodríguez-Gallegos et al. 2008]. Habitat loss and increasing landscape fragmentation are known to be key forces driving the ongoing loss of plant species diversity. While the combined effects of increasing isolation and decreasing population size have been studied intensively; it is less understood how plant population performance in heterogeneous landscapes is affected by changes in fragmentation alone [Körner and Jeltsch 2008]. The loss of species following a delay after landscape degradation is of major importance because it may determine how much extinction or other ecosystem change is pending [Pacha and Petit 2008].

Taking Baoxing county, one of the key area of Panda habitat, is the study area, This paper maps the change of landscape patterns in the study area with remote sensing data in 1974, 1989 and 2002, complementing the old-policy and new policy, Hoping to get the idea of the policy change's impact on the land use. Also, this paper presents the population changes synchronously in the study area to see how the policy changes on the Giant Panda population change. The significance of this paper lies in the following:

1. Although many scholars have studied the policy change's impact on land use change, but little have studied the policy change's impact on wild creature's habitat.
2. The study area is the most style Panda habitat and it has the biggest wild Giant Panda, thus, to study the policy change's impact on Giant Panda's population change can give some ideas to protect Giant Panda.

MATERIAL & METHODS

Study area

Baoxing County lies in the western edge of the Sichuan Basin, one hundred and twenty kilometer from Chengdu City. This area is over three thousand square kilometer, includes eight townships, and a total population of fifty thousand. Baoxing is where many species including the Giant Panda and Golden Monkey were discovered. The Fengtongzhai National Nature Reserve is located in Baoxing County. The Fengtongzhai National Nature Reserve is an important conservation area for Giant Panda habitat within the Sichuan Giant Panda Sanctuaries World Heritage site, which was inscribed on the World Heritage list in 2006. Fengtongzhai Nature Reserve was established in July 1979 with its major objective to protect a number of threatened and endemic species of wildlife and their habitats, including the Giant Panda. As the world- famous hometown of Giant Pandas, Baoxing is place where the first Panda was discovered. The number and density of the Giant Pandas in Baoxing rank the first over the world. Figure 1 is the location of Baoxing County.

Data Collection

Landsat ETM data from 2002, Landsat TM data from 1989 and Landsat MSS data from 1975 of the study area are collected. Also, the Panda number and the policy change of these years are also collected.

Going through the literature, we can deliberate that national policies have changed ; much from the year 1970 to the year 2000. In 1970s, for the poverty of the whole nation, foodstuffs become the main policy to feed people, so the forests were forced to make way for food plantation; In the 1980s, fixing of farm output quotas for each household was the main policy of the nation, and the nation become richer and richer, so food was turmed to the second order following nature, some nature reserves being built at this time; In the 1990s and 2000s, returning land for farming to forestry was the main policy in this area.

Classification Methods

Many experts have studied wildlife habitats with classification methods, Hill and Kelly[1987] used the unsupervised classification method to map kangaroos' habitat. Hugh-Jones, et al.[1992] used the unsupervised classification method to identify Amblyomma variegatum [Acari: Ixodidae] habitats in Guadeloupe; Hansen, et al.[2001] used a Hybrid Decision Tree [HDT] Classifier combined with maximum likelihood decision rule to map Caribou habitat; Théau, et al.[2005] used an enhancement classification method to map lichen in a caribou habitat; Pasher, et al.[2007] used supervised maximum likelihood classification [MLC] and logistic regression [LR] to map potential nesting habitat for hooded warbler; Linderman, et al.[2004] and Linderman, et al.[2005] used a back-propagating neural network to map the spatial distribution of understory bamboo from remote sensing data. As we know, supervised maximum likelihood classification [MLC] has a higher accuracy than other methods in habitat classification; it also plays an important role in habitat classification. Hence, supervised maximum likelihood classification was used to map potential nesting and non-nesting habitats in order to address the objectives of this research.

Process Flowchart

Figure 2 shows the process flowchart used in this paper. First, we use MLC to classify LANDSAT MSS, TM, and ETM into land use classification map then; with landscape knowledge, we get landscape map from landuse map, and do landscape analysis on the landscape map Last, with the policy change analysis, we analyze the policy change's influence on the landscape pattern change. In this paper, we classify landscape patterns of Baoxing County into 10 types: Broad leaves, Coniferous, Shrubby, Mash, Grassland, Farmland, River, Ice, Settlement place and Rock.

RESULTS & DISCUSSION

Baoxing's landuse map in 1975, 1989 and 2002

Figures 3, 4, 5 shows the landsuse map of Baoxing County in 1975, 1989 and 2003, and table 1 indicates the statics result, figure 6 represent the statistics chart. From table 1 and figure 6, we can figures out that in 1975, coniferous is the main landuse in Baoxing county, but in 1989, its area is cut down from 54.06% to 36.18%, so let the shrubby run from 21.61% up to 41.32%, .In the meantime, settlement place changes from 0.0% to 1.46%, this means human begin have some major influence on the landuse change. Table 1 and figure 6 also indicate that coniferous coverings have increased some and shrubby coverings decreased some, but the total of the two have increased some, also the settlement place changes from 1.46% in 1989 to 0.07% in 2002, this also means human being have some major influence on landuse. Taking the national policy change into account, we can see that, national policy change has a lot of pull with the land use change.

Baoxing's landscspe analysis

Tables 2, 3, 4 are indicative of the class metrics of Baoxing's landscape patterns in 1975,1989 and 2002, table 5 indicates the landscape pattern of Baoxing's landscape metrics in 1975;1989 and 2002. In the tables; CA means Total Class Area; PLAND means Percentage of landscape; NP means Number of Patches; PD means Patch Density; LPI means Largest Patch Index; LSI means Landscape Shape Index; AREA_MN means Patch Area Distribution; NLSI means Normalized Landscape Shape Index; TA means Total Area; TE means Total Edge and ED means Edge Density. From these tables; we can see that degree of fragmentation in 1989 is the largest; then come the years 2002; and the best is in 1974. That is because there are many trees which are hewed in 1970s and 1980s, leading to the largest fragmentation in 1989, then with the national policy of returning land for farming to forestry, the forests recover some, but the degree of fragmentation is still big, so work should continue.

Panda population change

Figure 6 is representative of the Panda population change in boxing in 1975, 1994 and 2002. In the figure we can see that from 1974 to 1989, the Panda population goes down sharply, and from 1989 to 2002, the Panda population increases some, but the Panda population in 2002 is still smaller than that in 1974. Compared to the landscape pattern change, we can see that the Panda population change is according to the landscape change, for smaller landscape fragmentation can supply more habitats for Panda. And national nature reserve has some active influence on the Panda population's incense.

The results indicate that, from 1975 to 1994, due to the crawling in this area, the forest covering has decreased about 5.92% with fragments created- grassland has decreased about 2.64%, farmland has increased about 1.5% and settlement place has increased about 7.15%. Accordingly, the Giant Panda's population changes from 328 to 75.

But from 1994 to 2002, owing to the policies to protect Giant Panda and its habitat, the forests has increased about 0.12%, grassland has increased about 0.55%, farmland has decreased about 0.58% and the fragment of forests in 2002 is lower than in 1994. Accordingly, the Giant Panda's population changes from 75 to 143.

This states that the national policy implemented during 1990s has much positive influence on the landscape patterns and Giant Panda population in Baoxing County.

In the past years, the Chinese government and Chinese local government at different levels have drawn up several policies to protect ecological environment, which has brought notable results. But how to measure the results is a challenge. The authors did this by using remote sensing and landscape pattern analysis technology in this paper, and got a result corresponding to the literatures about Baoxing County.

But some problems need to be addressed more:

1. Other factors: Policy is the main driving power to protect ecological environment, but other factors such as soil erosion, hew, graze, etc. should be taken into account when analyzing landscape pattern.
2. Image resolution: The resolution of image will affect the classification precision, In the following work, the authors plan to employ higher resolution image.
3. Climate change: With the global warming, ecological environment have changed much, so this factor should also be considered when analyzing landscape pattern.

CONCLUSION

The paper focuses on CVM applied to urban parks management where stakeholders are supported by economics and statistical analysis: it is a planning process of green urban areas based on bottom up analysis.

It is possible to underline a low efficiency of environmental planning documents in Tuscany that they do not consider green urban areas safeguard. There are three different levels of planning documents: regional PSR, provincial PTCP and local PRG which include some theoretic rules but they do not consider practical rules.

The analysis of the characteristic and behaviour of parks user's gives complex results because of this stakeholders need specific rules and instrument for making the right choice.

Through 495 questionnaires the typical characteristic of Florentine parks users have been defined: the average age of them is 50 years old, most of them are female [55%], 33% of users have a high school degree, 29% have a secondary school degree while primary degree users and university degree users are respectively 20% and 14% of all. Many users go to parks for bringing children outside [41%] and for walking [26%], they use urban parks for relaxing [67%] and for protecting themselves from urban noise [13%].

4.564 euro per year is their average willingness to pay for a better urban areas planning and no limit access to parks. A contingent valuation limit is to analyze heterogeneous data of complex users' characteristics and thus cluster analysis has been operated to solve it. Through this statistical method three uniform groups of users have been obtained. Each group has a different average age of users [71, 45, 27 years old].

The groups analysis underlines how the first group has a lower number of female than the others, in general school degree is linked to the age of interviewees, in fact group 3 [average age 27 years old] has an average higher school degree than group 1 [average age 71 years old]. The principal reason of park use is bring children to play inside it [34% of users of group 1 and 62% of group 2], while for group 3 [24% of users] is spending free time for walking.

A common element of these groups is the opinion about functional aspect of the parks: it is more important than aesthetic aspect. All the groups appreciate parks for relax and because they are a natural barrier against urban noise. A the same time all the groups seem to prefer typical plants rather than animals like life's quality indicators.

Highest willingness to pay is 4.935 euro per year [group 2] while lowest wtp is 4.220 euro per year [group 3]. This result shows how income represents the constraining factor in the wtp for a general good.

This elaboration is the first step of VET urban parks definition. Present target is to join economics methods [CVM] and statistical methods [Cluster analysis] in a bottom up analysis where citizen are involved. This method can also represent a valid instrument for stakeholders decision planning and it can be a valid support to integrate legislative documents with practical topics.

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Table 1. Statistics of landuse of Baoxing county in 1975, 1994 and 2002.

Vegetation Type	MSS Classification(%)	TM Classification(%)	ETM Classification(%)
Broad leaves	15.64	15.40	3.90
Coniferous	54.06	36.18	43.35
Shrubby	21.61	41.32	35.86
Grassland	3.01	0.02	13.82
Farmland	2.80	2.98	0.11
Rock	1.92	1.40	0
Settlement place	0	1.46	0.07
Ice	0.79	0.96	2.68
River	0.14	0.28	0.18
Marsh	0.03	0	0.03

Table 2. Landscape patterns class metrics of Baoxing county in 1975.

Type	CA	PLAND	NP	PD	LPI	LSI	AREA_MN	NLSI
Broad leaves	51471.09	9.34	4980	0.90	0.33	89.57	10.34	0.12
Coniferous	177929.90	32.29	3154	0.57	17.07	73.57	56.41	0.052
Shrubby	71122.32	12.91	8790	1.60	6.20	118.70	8.09	0.13
Grassland	9914.67	1.80	6299	1.14	0.10	82.97	1.57	0.25
Farmland	9209.97	1.67	2551	0.46	0.13	65.35	3.61	0.20
Rock	6313.14	1.15	1919	0.35	0.10	50.12	3.29	0.19
Ice	2615.76	0.47	586	0.11	0.026	32.47	4.46	0.19
River	473.04	0.09	461	0.08	0.0057	25.12	1.03	0.34
Marsh	93.78	0.02	200	0.04	0.0005	14.75	0.47	0.44

Table 3. landscape patterns class metrics of Baoxing county in 1994.

Type	CA	PLAND	NP	PD	LPI	LSI	AREA_MN	NLSI
Broad leaves	50691.6	9.20	40612	7.37	0.22	261.17	1.25	0.35
Coniferous	119053.71	21.61	23847	4.33	3.95	167.30	4.99	0.14
Shrubby	135994.68	24.68	38144	6.92	3.27	259.089	3.57	0.21
Grassland	67.05	0.012	224	0.041	0.0011	16.33	0.30	0.59
Farmland	9785.79	1.78	15307	2.78	0.054	160.71	0.64	0.49
Rock	4600.62	0.834	3167	0.57	0.14	69.29	1.45	0.30
Settlement place	4804.74	0.87	10778	1.96	0.034	127.46	0.45	0.55
Ice	3170.61	0.58	2067	0.38	0.15	49.01	1.53	0.26
River	933.66	0.17	1722	0.31	0.022	53.91	0.54	0.53

Table 4. landscape patterns class metrics of Baoxing county in 2002.

Type	CA	PLAND	NP	PD	LPI	LSI	AREA_MN	NLSI
Broad leaves	12833.01	2.33	29715	5.40	0.080	208.40	0.43	0.5513
Coniferous	142674	25.91	26913	4.89	7.93	187.63	5.30	0.1484
Shrubby	118005.2	21.43	35401	6.43	4.12	315.51	3.33	0.275
Grassland	45488.07	8.26	15089	2.74	0.79	132.45	3.01	0.1852
Farmland	361.8	0.066	2634	0.48	0.002	54.55	0.14	0.8595
Settlement place	245.34	0.045	2108	0.38	0.0003	47.51	0.12	0.9134
Ice	8816.85	1.60	5409	0.98	0.12	87.45	1.63	0.2771
River	596.7	0.11	3566	0.65	0.0058	65.74	0.17	0.8058

Table 5. landscape patterns landscape metrics of Baoxing county in 2002.

	TA	NP	PD	LPI	TE	ED	LSI	AREA_MN
1975(MSS) Classification	550971	28940	5.25	17.07	20616390	37.42	70.53	11.37
1994(TM) Classification	550971	135868	24.66	3.95	49061730	89.05	166.33	2.42
2002(ETM) Classification	550710	121609	22.08	7.93	48454350	87.99	164.32	2.71

Fig1. Location of study area.

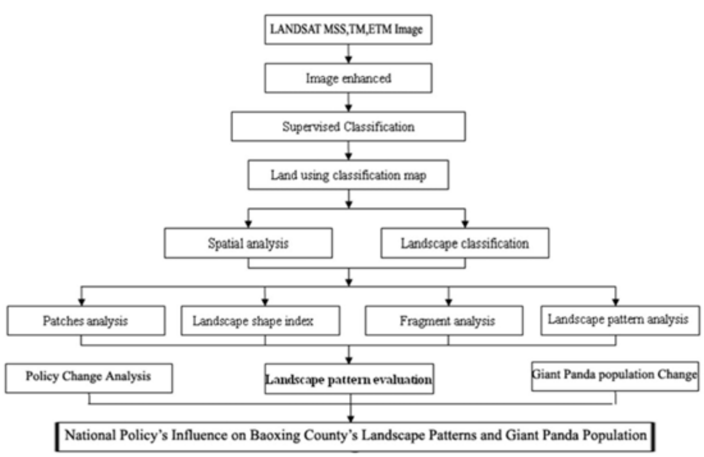

Fig 2. Process Flowchart.

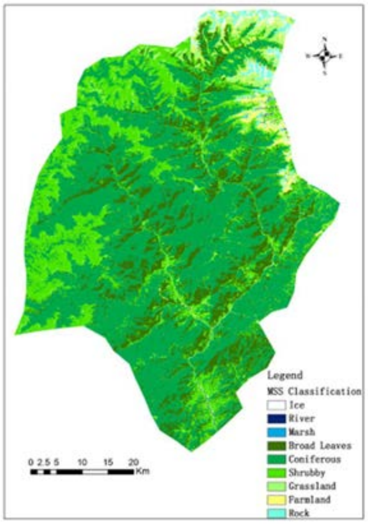

Fig 3 Landuse map in 1975.

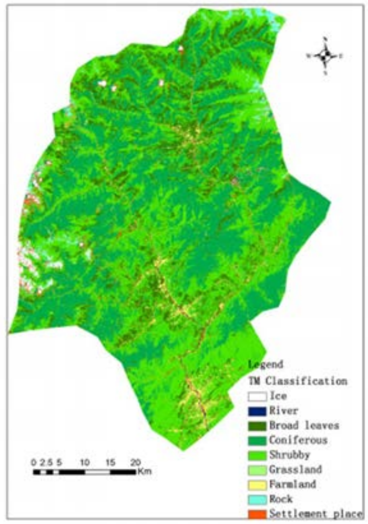

Fig 4. Landuse map in 1989.

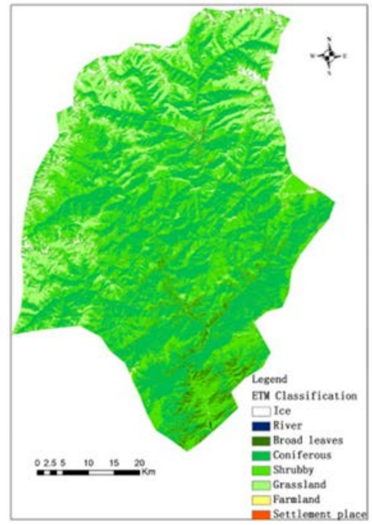

Fig 5. Landuse map in 2002.

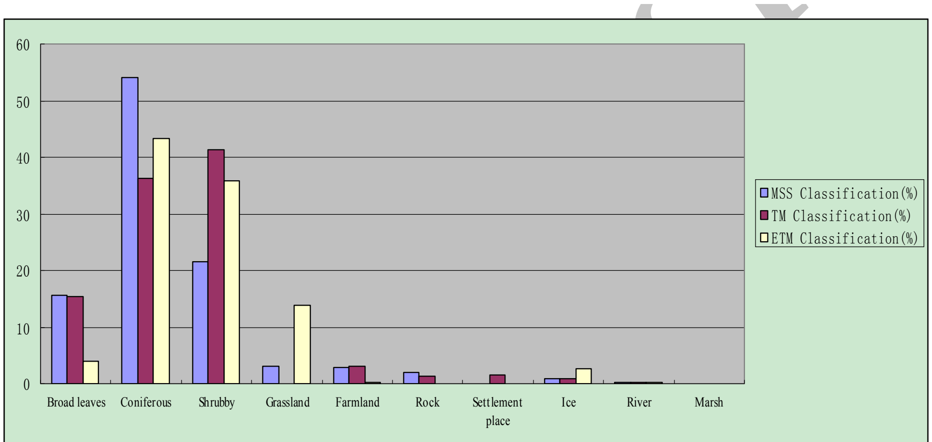

Fig 6. Statistics chart of landuse of Baoxing County in 1975,1994 and 2002.

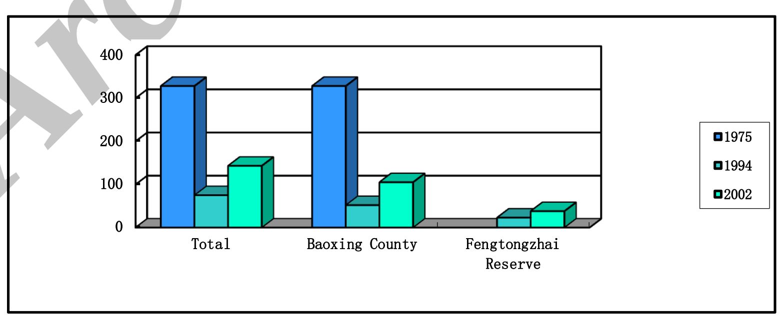

Fig 7. Statistics chart of landuse of Baoxing County in 1975, 1994 and 2002.