Mapping and Modelling the Habitat of Giant Pandas in Foping Nature Reserve, China

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"Mapping and Modelling the Habitat of Giant Pandas in Foping Nature Reserve, China"

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1 Bamboo flowering is a natural phenomenon and should not be considered as a threat to the giant panda.
Adopted from Hu, J. 1987. Being careful of moving the giant panda eastwards. Wild Animal, No,6, 11-12. (in Chinese)

2 Human encroachment into and fragmentation of the panda habitat is the most serious factor which threatens this animal's survival.

3 Mapping panda habitat with its rough and hardly accessible terrain is improved by using an integrated expert system and neural network algorithm.
This thesis

4 Panda habitat "preference" is statistically proved by analysing radio-tracking data and panda habitat types.
This thesis

5 It is still not clear what make pandas regularly move from their winter activity range to the summer activity range and stay only for two months in Foping Nature Reserve.
This thesis

6 It is hard for a woman higher educated to put her in a right point between career and family.

7 When planning for a year, plant corn. When planning for a decade, plant trees. When planning for life, train and educate people.
Chinese proverb

8 Desired changes can be incorporated in future studies, but time spent can never be regained.
Sanderson, G. C. 1966. The study of mammal movements - a review. Journal of Wildlife Management. Vol. 30, No.1, 215-235.

To my parents

献给我的父母亲

To Xiaoming and Bingjie

献给小明和冰洁

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Liu, Xuehua
May 31 2001

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General Introduction

Giant panda in
Foping Nature Reserve
Photo: Yange Yong

Landscape in
Foping Nature Reserve
Photo: Yange Yong

CHAPTER 1 General Introduction

1.1 Giant panda population, habitat and survey

Literature and public documents show that there are only about 1000 giant pandas (*Ailuropoda melanoleuca*) left and that only some 29,500 km^2 of panda habitat remains in the west part of China (see Figure 1.1), making it an urgent issue in the world to save this endangered animal species and protect its habitat. The actions taken to save the giant panda started in the 1960s, including construction of panda nature reserves and breeding centres, ground surveys at various levels for estimating panda population and distribution as well as collection of basic environmental information. Two national-level ground surveys were conducted in 1974-1977 and 1985-1988 (MOF and WWF 1989). Most of the information on panda population and distribution came from these two surveys. Panda habitat was also inventoried in Wolong Nature Reserve (NR) in 1979-1980 (WNR and SNU 1987) and in Qinling Mountains in 1986-1987 (Pan et al. 1988). MacKinnon et al. (1994) reported that the locations of the occupied panda range were obtained from ground surveys and the existing description of bamboo condition was also based on ground surveys. The results from these two national-level ground surveys showed a big loss of panda habitat by 1987. However, after 10 years, further changes have probably occurred within panda habitat, and the extent and condition of panda habitat from that time until now is unknown. Current information about panda habitat needs to be collected. Therefore, the third national level survey on panda population and habitat started in 2000 and will end in 2002.

Due to the mountainous terrain covered by dense forests, a large amount of money, labour and time has been invested in panda population and habitat surveys. For instance, 3000 people were involved in the first national-level panda census, and in the second panda census, over 30 counties were surveyed (MOF and WWF 1989). Both these censuses took about three years, and now the third on-going one is no exception. So, the question arises here: Can remote sensing (RS) and geographical information system (GIS) play an effective role in supporting wide-range panda census to shorten survey time, save man power, and consequently reduce survey costs through accurate mapping?

1.2 GIS, RS and wildlife habitat mapping

Geographical information systems are computer-based systems that are used to store and manipulate geographic information, and ultimately used to produce information needed by users (Aronoff 1991). Wildlife depends on the presence of an appropriate mix of resources within a geographically defined area. An important component of wildlife management is the prediction of the effects of natural events and human activities on wildlife populations. GIS techniques can be used to analyse such factors as the availability of food and cover, protection from predators, and the suitability of areas for nesting and denning sites, and have been used to analyse the habitat of a wide range of animal species such as the volcano rabbit (Velazquez and Bocco 1994), the kangaroo (Skidmore et al. 1996a) and various bird species (Miller et al. 1989, Li et al. 1999).

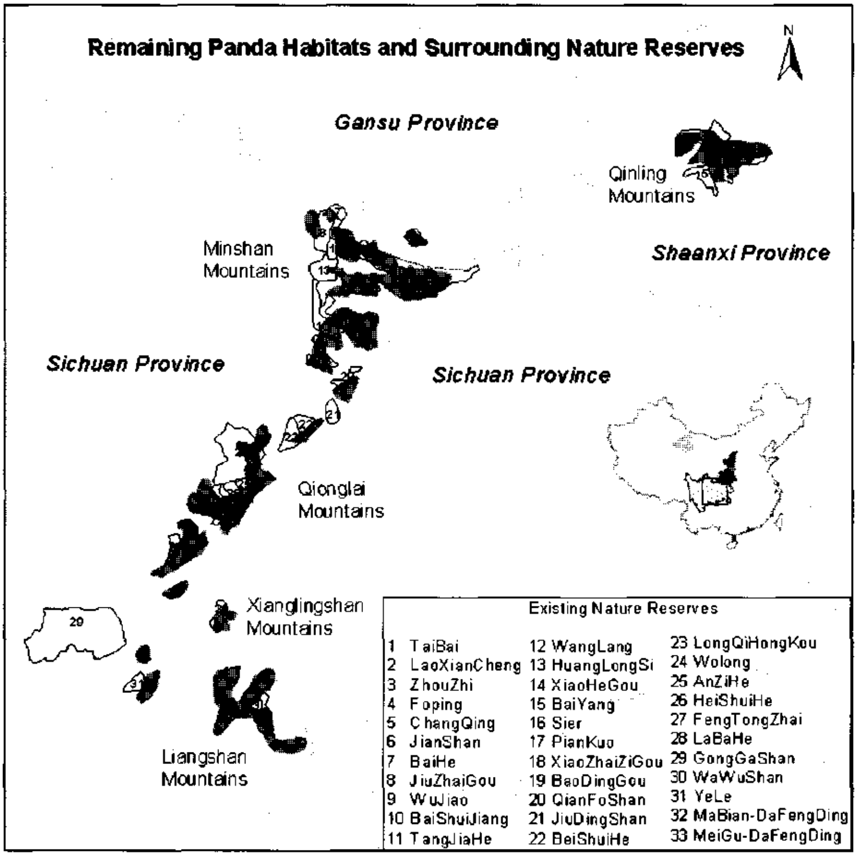


Figure 1.1 The remaining panda habitats (shown by grey patches) and existing associated nature reserves (shown by closed line boundary with number) in the west part of China (modified from Loucks et al. 2001).

Remote sensing is the instrumentation, techniques and methods to observe the Earth's surface at a distance and to interpret the images or numerical values obtained in order to acquire meaningful information of particular objects on Earth (Buiten and Clevers 1993, Janssen 2000). Due to their continuity in both time and space dimensions, RS data have widely been used and the relevant image processing techniques have been applied to wildlife habitat research on, for example, caribou (Thompson et al. 1980), white-tailed deer (Ormsby and Lunetta 1987), snow leopard (Prasad et al. 1991), migratory bird (Sader et al. 1991), and Nemorhaedus goral (Roy et al. 1995).

Richards (1993) addressed the real challenge which arises in RS/GIS when data of mixed types are to be processed together. The issue is complicated further when much of the non-spectral, spatial data available is not in numerical point form but is in nominal area or line format. It is pointed out that knowledge-based methods show good prospects for coping with data complexity in a GIS.

Hollander (1994) mentioned that a new integrated approach joined with an artificial intelligence system was expected to apply on habitat evaluation due to GIS and RS weakness. Expert systems (ES) have been used for mapping forests (Goldberg et al. 1985, Skidmore 1989), as well as identifying homogeneous training areas for analysis of remotely sensed imagery (Goodenough et al. 1987). Neural networks (NN) have been used for image processing and have shown great potential in the classification of remotely sensed data (Zhuang et al. 1994). According to Skidmore et al. (1997), the neural network backpropagation algorithm will not probably become a significant classification and analysis tool for GIS and remotely sensed data when implemented as a pure neural network. However, it may be very useful when combined with the rule-based expert system. Short (1991) has developed a pipeline system of a real-time expert system and a neural network for the classification of remotely sensed data. Nevertheless, examples of integrating the expert system and the neural network system in wildlife habitat evaluation and management are still rare.

1.3 RS/GIS application in panda habitat research and problems

The underlying issue is to what extent RS/GIS has been applied to panda habitat mapping and evaluation. As we know, quite a lot of people are interested in the research fields of panda behaviour, reproduction, nutrition and bamboo regeneration. Not much attention was paid to panda habitat. Therefore, not much detailed data analysis has been done with using many factors, including physical environmental factors, biological factors, and human influence factors. How can we obtain information of panda habitat in an effective way? From the previous ground surveys, it is clear that a ground survey in such a complicated terrain area with dense forests is time consuming and labour intensive. In such circumstances, RS is undoubtedly the most efficient way to acquire habitat data quickly and at low cost (De Wulf et al. 1988). Multi-spectral classification of land cover and land use has been the main approach for mapping and defining the distribution of wildlife, and detecting the change in wildlife habitat.

However, panda habitat research based on remote sensing is limited. De Wulf et al. (1988 and 1990) and MacKinnon et al. (1994) mapped panda habitat using LANDSAT MSS images and LANDSAT TM images. Some work has been done on the evaluation of the extent of forest loss for the giant panda in China, the prediction of the corridors in Min Mountains, and the mapping of panda habitat in Wolong NR. All this work was based on visual interpretation of multi-temporal images from 1975 and 1983. The LANDSAT TM images were also visually interpreted and used to make a land cover map for the Xinglongling panda area in the Qinling Mountains (Pan et al. 1988, Chui and Zhang 1990). So, before 1998, panda habitat analysis based on RS data was still at a level of visual interpretation, not at a level of digital analysis. The main disadvantages of visual interpretation are its inconsistency and time-consumption. It is also realised that, at a level of digital analysis, conventional image analysis methods do not yield satisfactory classification results at the forest type level, and therefore it is difficult to get an accurate map using conventional classification methods to map the forest types (Skidmore 1989, Skidmore et al. 1997).

In terms of GIS application to panda habitat, Ouyang et al. (1996) published their work on reserve management and design of the panda database in Wolong NR, which includes the current physical environment, biodiversity, and social-economic data. Liu (1997) and Liu et al. (1997) published their work on human factors influencing the panda habitat in Wolong NR and their spatial distribution. Bouwman (1998) assessed the impact of human activities on the panda habitat and distribution in Wolong NR based on the interview data and GIS analysis. Liu et al. (1998) evaluated the suitability of panda habitat in Wolong NR through evaluating suitable elevation range, slope range and distribution of bamboo species in GIS. As a useful tool for acquiring, storing, extracting, processing, and presenting data, exploration on integrating GIS with new expected algorithm of RS to obtain more information of panda habitat is worthwhile.

Is it possible to develop a new approach, an integrated expert system and neural network algorithm, based on RS/GIS in order to achieve a satisfactory level of accuracy for mapping panda habitat - a forest environment? And how to further use the mapping results to analyse panda habitat use and selection and help to explain regular panda movements?

In summary, the research problems are:

- information about the current extent and quality of panda habitat is lacking;
- ground surveys are not only time-consuming and expensive but also inadequate for the collection of all kinds of continuous information on panda habitat;
- conventional image classification methods for mapping a forest environment can not achieve a satisfactory accuracy;
- lack of an integrated approach for mapping panda habitat;
- lack of thorough study on panda movement; and
- lack of statistical analysis of panda habitat use and selection as well as panda-habitat relationship.

1.4 Objectives of this study

This study only focuses on Foping NR. The general research objective is to evaluate panda habitat through mapping and modelling. It is achieved by the following sub-objectives:

- To evaluate the existing mapping techniques;
- To develop an integrated expert system and neural network classifier (ESNNC) for mapping with a high accuracy;

- To apply the explored ESNNC approach to map panda habitat patterns and derive panda habitat information (types, extents and spatial distribution);
- To analyse panda movement patterns and their linkage with the environment;
- To model the relationships between the panda presence and the biotic (such as woody plant species richness and spatial structure of tree and bamboo layers) as well as abiotic environmental factors (elevation, slope gradient and aspect).

1.5 Outline of thesis

This thesis basically presents several research papers that, as a whole, fulfil the objectives of the study. Papers have been or are going to be submitted to international peer-reviewed journals. Each of these papers has been presented as a thesis chapter. The general link between each other is shown in Figure 1.2. Chapter 2 and Chapter 3 aim at exploring a new approach for mapping, which uses an additional data set from Lemelerburg, the Netherlands. The explored and optimised algorithm was then applied to map habitats of the giant panda (Chapter 4) and the mapping results were further used in later analysis of panda-habitat relationship (Chapter 6). Accurate habitat maps are required for analysing wildlife and its habitat relationship. Chapter 5 is a relatively independent topic which focuses on panda movement analysis. The following is an outline of this thesis.

- Chapter 1 provides a brief research background, clarifies the research problems, shows the research objectives, and finally describes the main study area: Foping NR. This chapter is to show why, what, where, and how this research was undertaken.

- Chapter 2 looks at several different mapping techniques and focuses on the artificial neural network techniques with comparison to the other two traditional algorithms (maximum likelihood classification algorithm and parallelepiped classification algorithm). This chapter aims to check the discrimination capability of the backpropagation neural network algorithm on the ground cover types, and to indicate that the neural network algorithm needs to be improved and used for mapping panda habitat in this study.

- Chapter 3 explores two new mapping algorithms by combining the advantages of the different classification algorithms in order to optimise the mapping algorithm with high mapping accuracy. One is a consensus builder that links three individual classifiers (maximum likelihood classifier, expert system classifier and neural network classifier) together. The second is an integrated expert system and neural network classifier.

- Chapter 4 applies the optimised mapping approach, the integrated expert system and neural network classifier, to map panda habitat in Foping NR. Two categories of panda habitat types are introduced and mapped, i.e. ground-cover-based potential panda habitat types and suitability-based panda habitat types.

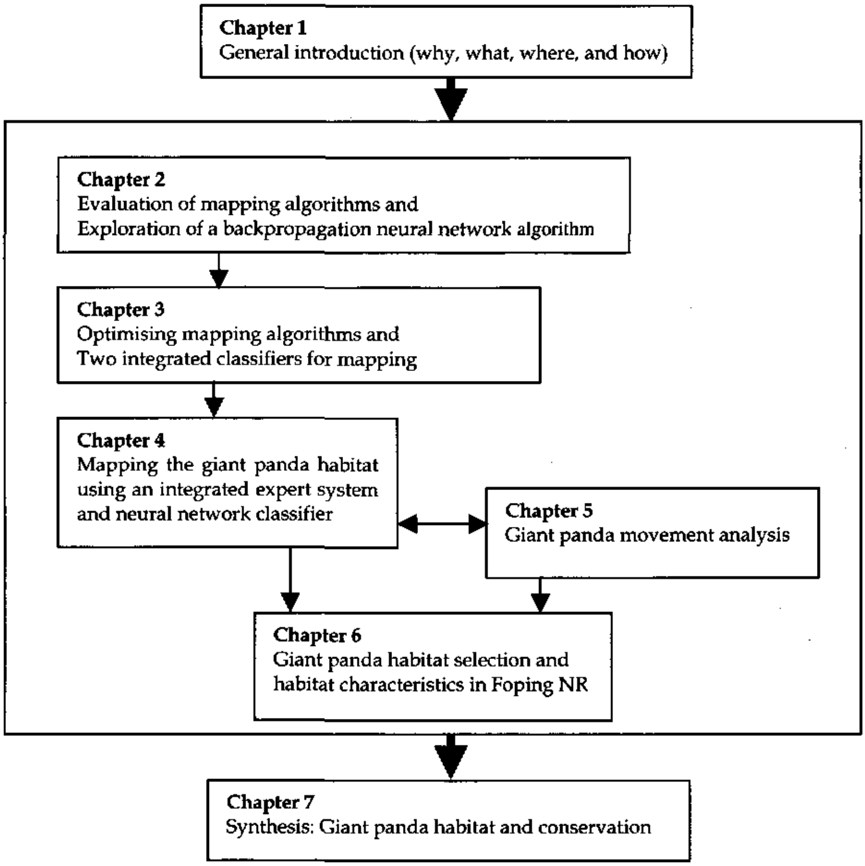


Figure 1.2 The thesis structure and linkage between chapters.

- Chapter 5 analyses the movement pattern of pandas in Foping NR by using radio-tracking data in order to gain an insight into how pandas move in their territory and the linkage between their movement pattern and the environment.

- Chapter 6 details the habitat use and selection by pandas, as well as habitat characteristics which may direct panda habitat use and selection. The mapped ground-cover-based potential panda habitat is used to analyse habitat use and selection. The survey plot data are used to analyse the panda habitat characteristics in various suitability-based panda habitat types, and to analyse the differences of biotic structure between panda-presence and panda-absence habitats.

- Chapter 7 summarises all the research results and conclusions of the previous chapters and highlights the implications of these results as well as the research approach to the future conservation of the giant panda and its habitat not only in Foping NR but also in other panda nature reserves in China.

1.6 Description of Foping Nature Reserve

The east-west Qinling Mountains (see Figure 1.1) play an important role as the natural geographical defences that stop the cold air flow coming from the north and they form the most northern refuge of pandas. Foping NR is located on the middle part of the southern slope of the Qinling Mountains (33°32'-33°45' N, 107°40'-107°55' E), and in the southern part of Shaanxi province (Figure 1.3). The reserve covers about 293 km² and occupies the northern part of Foping County. It extends 24 km from west to east and 22 km from north to south. It was established in 1978 to conserve the endangered giant panda and its habitat.

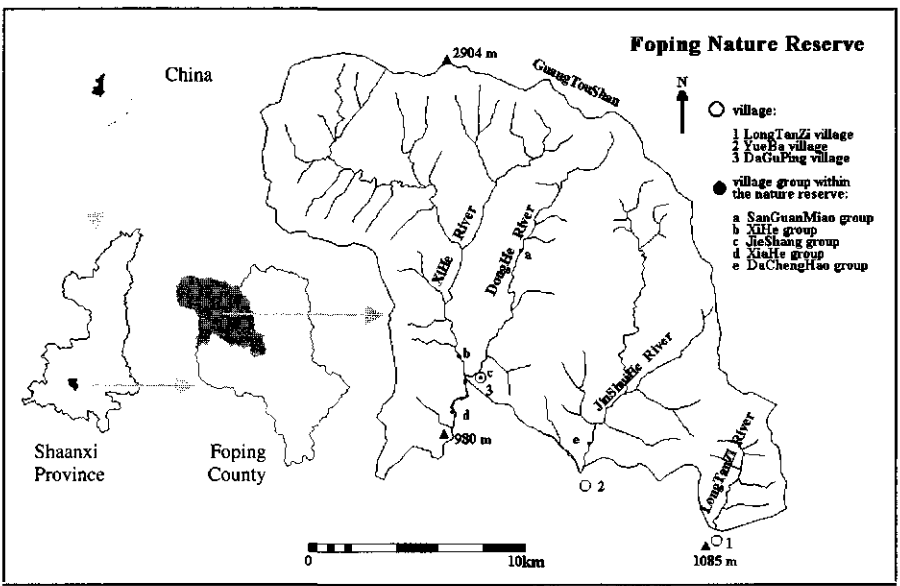


Figure 1.3 Location of Foping Nature Reserve in China. It is located in Foping county, Shaanxi province, and covered by four main drainage systems: XiHe, DongHe, JinShuiHe, and LongTanZi.

Terrain and drainage system

The terrain of Foping NR drops down from the high north-west to the low south-east. The elevation ranges from 980 to 2904 m. The area below 1500 m is the steep-slope and narrow valleys of the middle mountains with human activities, between 1500 and 2000 m the gentle-slope and wide valleys and flat mountain ridges of the middle mountains, and above 2000 m the steep-slope and wide mountaintops of the middle mountains (Ren et al. 1998). Four drainage systems cover the whole nature reserve, e.g. XiHe, DongHe, JinShuiHe and LongTanZi Rivers (Figure 1.3). They all flow from the north to the south.

Climate

The climatic data from 1976 to 1995 were analysed and the average monthly rainfall, humidity, temperature and sunshine hours were plotted in Figure 1.4. The high rainfall (about 200 mm) occurs in July, high temperature (about 23 ^{0}C) in July and August, and high humidity (83%) in July, August and September. The longer sunshine (over 180 hours per month) starts from May and ends in August. The total annual rainfall is about 920 mm. The average annual temperature is about 13 ^{0}C. On average, the extreme lowest temperature, about -3 ^{0}C, occurs in January and the extreme highest temperature, about 28 ^{0}C, occurs mostly in July.

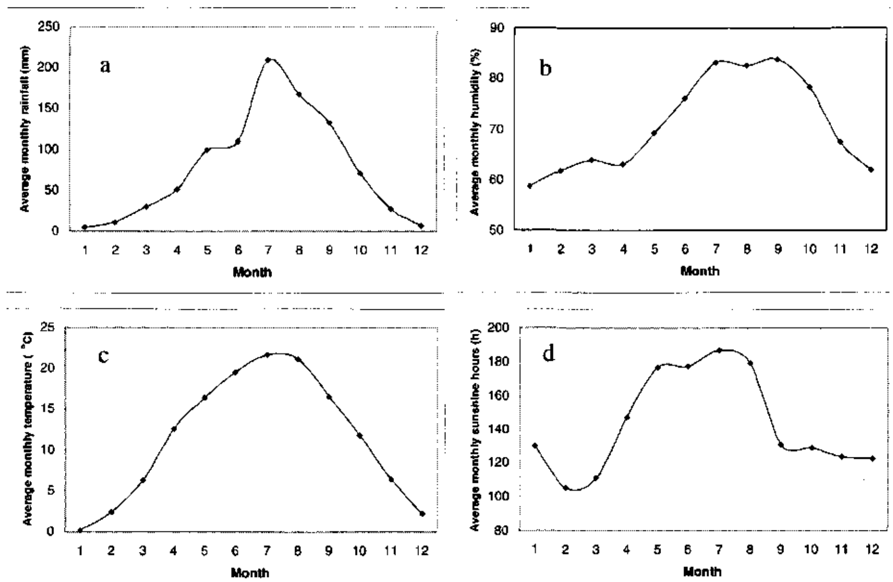


Figure 1.4 The climatic conditions in Foping Nature Reserve, China: average monthly rainfall (a), humidity (b), temperature (c), and sunshine hours (d).

Soil

The soil types show obvious vertical distribution: yellow-brown soil (below 1500 m) developed under deciduous broadleaf forests in the north sub-tropical zone, brown soil (1500-2300 m) developed under deciduous broadleaf forests or mixed conifer and broadleaf forest in the temperate zone, and dark brown soil (above 2300 m) developed under mixed conifer and broadleaf forest in the temperate zone (Ren et al. 1998).

Vegetation

Natural vegetation grows well in Foping NR. There are differences in the description of the natural vegetation and its vertical distribution in Foping NR. According to Ren et al. (1998), the main natural vegetation types are deciduous broadleaf forests (below 2000 m), birch forests (2000-2500 m), conifer forests (above 2500 m), as well as shrub and meadow. CVCC (1980) defined that the deciduous broadleaf forest is distributed below 1300 m, mixed conifer and deciduous broadleaf forest between 1300 and 2650 m, and conifer forest above 2650 m. There are two main bamboo species for pandas to feed on: *Bashania fargesii* and *Fargesia spathacea* (Pan et al. 1988, Tian 1989 and 1990, Yong et al. 1994, Ren et al. 1998). The bamboo of *Bashania* is distributed in the area below 1900 m, in general, and the bamboo of *Fargesia* in the area above 1900 m.

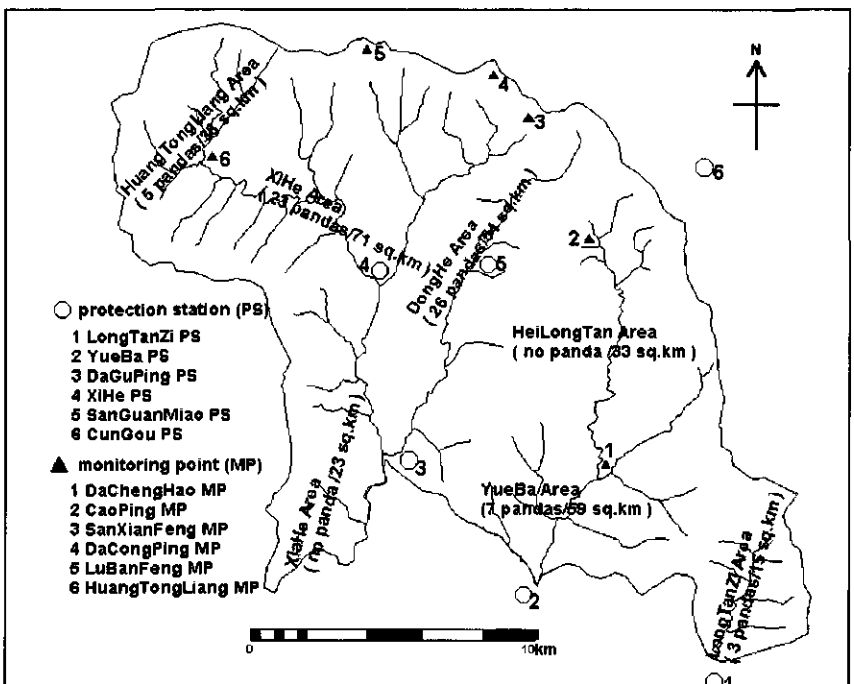


Figure 1.5 The spatial distribution of the giant panda population in Foping Nature Reserve according to the survey in 1990 (Yong et al. 1993), and locations of six protection stations as well as six monitoring points.

Giant panda population

Panda population surveys have been conducted several times in Foping NR since the 1970s. The survey in 1983 estimated that the panda population was between 45 and 65. According to the survey in 1990 (Yong et al. 1993), the estimated panda population was about 65 with an average density of 1 individual per 5 km^2. The result of a survey conducted in 1998 again confirmed about 65 panda individuals in the reserve. Figure 1.5, based on the result from the 1990 survey, illustrates differences of the spatial distribution of panda population.

Local human population and activities

About 300 local people reside inside the nature reserve in 1998 (Table 1.1). They are mainly concentrated in five inner-reserve village groups: SanGuanMiao, XiHe, JieShang, XiaHe and DaChenHao (see Figure 1.3). The human activities are mainly developed in the river valleys and the areas near the southern boundary but SanGuanMiao in the centre of the nature reserve is an exception. The main human activity is farming. However, mushroom-production (Figure 7.4-right), which provides local people with an impressive income (for example in DaGuPing, from 14010 yuan RMB in 1996 to 74520 yuan RMB in 1998), developed very fast after 1995 and might have had an influence on panda habitat in Foping NR.

Table 1.1 The local population of three villages inside or around the boundary of Foping NR in 1998

Village	Village group	Inside or around the boundary of the nature reserve	Population (persons)	Total
DaGuPing	SanGuanMiao group	inside	52	
	XiHe group	inside	59	
	JieShang group	inside	92	282
	XiaHe group	inside	47	
YueBa	DaChengHao group	inside	32	
	MaJiaGou group	outside	62	
	JieShang group	outside	82	
	ShangYueBa group	outside	127	
	BeiMaGou group	outside	113	
	XiaoBeiMaGou group	outside	81	
LongTanZi	ZhuanBa group	outside	51	889
	TangJiaGou group	outside	39	
	LuoJiaBa group	outside	52	
	JieShang group	outside	142	
	BaoZi group	outside	77	
	ShiYuan group	outside	63	

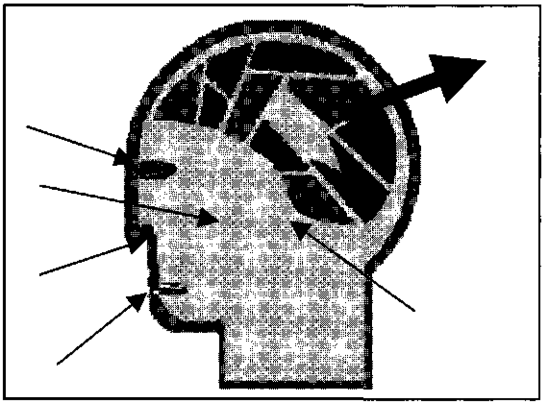
Field management in Foping NR

For conservation purposes, the whole nature reserve is divided into six regions, each of which has a "protection station (PS)" with permanent staff. They are LongTanZi PS, YueBa PS, DaGuPing PS, XiHe PS, SanGuanMiao PS and CunGou PS (shown in Figure

1.5). Some conservation activities are conducted regularly, such as monthly patrols to record signs of panda and other animals as well as habitat information. Within these six regions, smaller blocks are further delineated in order to further locate the area for convenient conservation activities. In the more remote areas, there are six extra "monitoring points (MP)" with simple and crude sheds. They are DaChengHao MP, CaoPing MP, SanXianFeng MP, DaCongPing MP, LuBanFeng MP and HuangTongLiang MP (shown in Figure 1.5). All these management facilities and conditions made my research possible.

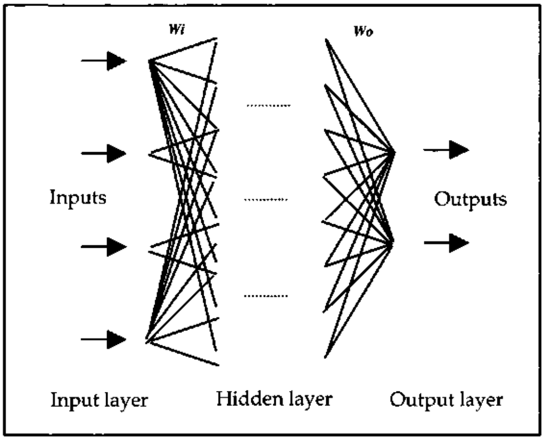
CHAPTER 2

Evaluation of Mapping Algorithms and Exploration of Spectral Discrimination Capability of a Neural Network Algorithm



Natural neural network

Artificial neural network



CHAPTER 2 Evaluation of Mapping Algorithms and Exploration of Spectral Discrimination Capability of a Backpropagation Neural Network Algorithm *

Abstract

Data were generated for two classes in a simulated feature space, with the classes having a varying amount of spectral overlap. It was hypothesised that the backpropagation neural network would be able to distinguish the classes in the situation of no overlap. Our results confirmed that two non-overlapping classes can be discriminated with 100% overall accuracy by the backpropagation neural network. The backpropagation neural network classified the simulated data sets with a significantly higher accuracy than the maximum likelihood or the parallelepiped classifier. When the experiment was repeated using remotely sensed imagery with more complicated spectral overlap among classes (for a land cover classification at Lemeleberg in the eastern Netherlands), the neural network yielded again a significantly higher classification accuracy than the maximum likelihood classifier or the parallelepiped classifier. Differences between the map outputs imply that integrating the different classification algorithms may improve the overall mapping accuracy.

Key Words: backpropagation neural network, degree of overlap in feature space, mapping algorithm, maximum likelihood classifier, parallelepiped classifier, spectral discrimination capability.

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1. This chapter is based on Liu, X., A. K. Skidmore, and H. Van Oosten. (in press). An experimental study on spectral discrimination capability of a backpropagation neural network classifier. International Journal of Remote Sensing.

2. Part of this work was presented at XIXth Congress of the International Society for Photogrammetry and Remote Sensing (ISPRS), 2000, Amsterdam, The Netherlands. The presented title: Discrimination Ability of Neural Network and Maximum Likelihood Classifiers.

2.1 Introduction

Backpropagation neural networks (BPNNs) have successfully classified remotely sensed data (Hepner et al. 1990, Zhuang et al. 1994, Weeks and Gaston 1997). There are significant differences between backpropagation neural networks and many conventional statistical classifiers such as the maximum likelihood classifier (MLC) (Bischof et al. 1992, Chen et al. 1993, Paola and Schowengerdt 1995, Weeks and Gaston 1997):

(1) BPNNs make no assumptions about the form and distribution of input data;
(2) BPNNs form non-linear decision boundaries in the feature space;
(3) BPNNs are robust when presented with partially incomplete or incorrect input patterns;
(4) BPNNs can generalise input.

In a comprehensive review, Paola and Schowengerdt (1995) concluded that backpropagation neural network classifiers yield similar (or slightly higher) accuracy when compared to conventional statistical methods, such as the maximum likelihood classifier (see Hepner et al. 1990, Key et al. 1990, Bischof et al. 1992, Kanellopollos et al. 1992, Paola and Schowengerdt 1994). As a result of the marginal improvement in mapping accuracy by neural network classifiers, Skidmore et al. (1997) recommended maximum likelihood classifiers, as they are easier to use. Indeed, some authors have found that maximum likelihood classifiers give a higher mapping accuracy than neural networks (Benediktsson et al. 1990a, Solaiman and Mouchot 1994).

Fierens et al. (1994) were unable to understand why these classifiers have differences in accuracy. One of the reasons may be that the experimental set-ups are not comparable. For instance, texture measures have been used with BPNNs, but the same texture measures have not been utilised by conventional classifiers (Hepner et al. 1990, Bischof et al. 1992, Paola and Schowengerdt 1994, Skidmore et al. 1997). Another reason for differences in classification accuracy is that the assumptions of a classifier may be better met by a particular image data set. For example, Key et al. (1990) theorised that the neural network avoids assumptions of statistical normality, and has greater flexibility to classify non-normal classes. Further evidence comes from Benediktsson et al. (1990a) who used data from a random number generator with normalised distribution and found the accuracy of the maximum likelihood classifier was higher than that of a backpropagation neural network. Thus it may be assumed that normalised distribution allows the maximum likelihood method to perform well.

The performance of a backpropagation neural network is affected by many factors. A number of researchers have focused on exploring the behaviour of the BPNNs by adjusting factors such as the input data types (raw or normalised data), input data sequence, number of hidden layers, number of nodes in different layers, as well as different training parameters such as momentum, learning rate and number of epochs (Benediktsson et al. 1990a, Heermann and Khazenie 1990, Zhuang et al. 1994, Ardo et al. 1997, Gong et al. 1997, Skidmore et al. 1997). However, no authors have investigated the effect of the degree of overlap between classes in feature space on the performance of a BPNN or conventional classifiers.

A two-dimensional feature space can be simply visualised by plotting the brightness values of one band along the horizontal axis, and the brightness values of a second band along the vertical axis. In this space, each pixel of an image plots as a vector with co-ordinates given by the brightness value of an image pixel. Feature space may be "filled" with simulated data sets. The use of simulated data as a complement to real images is very common in remote sensing research; the main advantage is that it is easy to control the experiment and to gain insight into the results (Skidmore et al. 1988, Benediktsson et al. 1990a, Heermann and Khazenie 1990, Chen et al. 1993). In this study, a feature space comprising three bands was simulated.

In summary, the aims of this paper are, by using different degrees of overlap between classes, to compare: (1) the accuracy of the backpropagation neural network classifier (BPNNC) in response to different degrees of overlap in the simulated data sets as well as remotely sensed imagery; and (2) the performance of the BPNNC, the maximum likelihood classifier (MLC) and the parallelepiped classifier (PPC) under different levels of overlap in feature space.

2.2 Background and assumptions of three classifiers

The parallelepiped classifier (PPC) is a very simple supervised classifier, having a decision boundary defined by the range of brightness in each band. The "box" in feature space (see Figure 2.1a) may be defined using a measure of central tendency (e.g. mean or median) as well as a measure of variation (e.g. standard deviation or inter-quartile distance) of training sample sets (as used in this study), or by using the minimum and maximum values of training sample sets. The main drawback of the PPC is that the pixels can not be assigned to a class when they fall in more than one box or do not belong to any box.

The maximum likelihood classifier (MLC) is the most commonly used supervised classification method. The decision rule is defined by the multidimensional normal distribution around a class mean (see Figure 2.1b). Consequently, multi-modal or non-normally distributed data will lead to an incorrect classification. In addition, overlapping decision boundaries in feature space will be problematic, especially if the training data do not physically overlap, but the decision boundaries do overlap (Skidmore et al. 1988, Fierens et al. 1994).

The backpropagation neural network classifier (BPNNC) recognises spectral patterns by learning from training sets. They contain three or more layers of nodes viz. one input layer, one or more hidden layer(s) and one output layer. The error between the network output and the target (i.e. training data) is reduced by adjusting all weights of the network until the system error falls below a user specified threshold. After training, the neural network system fixes all weights and maintains the original learning parameters. The classification process calculates the output of each pixel using the parameters learnt from the training phase, and then decides the class of the pixel. Richards (1993) hypothesised that a hyperplane decision surface between two different classes may also be created for neural network classifiers that can divide the pattern space into different regions (see Figure 2.1c). Solaiman and Mouchot (1994) emphasised that the multi-layer perceptron is also a decision-surface based classifier.

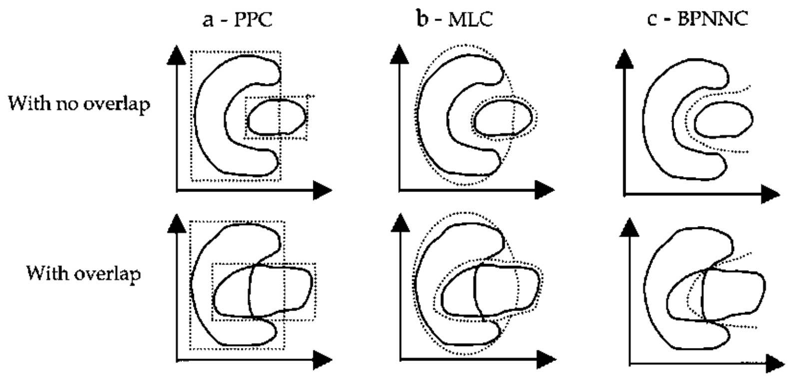

Figure 2.1 Decision rules for the three different classifiers in a two-dimensional feature space (after Skidmore et al. (1988) and Richards (1995)). PPC, MLC and BPNNC represent the parallelepiped classifier, the maximum likelihood classifier and the backpropagation neural network classifier respectively.

2.3 Methods

2.3.1 Data sets

We simulated two data sets with only two classes varying from a condition of no overlap, to a condition of overlap, in order to test the effect of feature separability and overlap degree on three classifiers (BPNNC, MLC and PPC). The two classes were randomly generated in three bands (e.g. band1, band2 and band3) with 5000 pixels per class. Band1 and band3 have a normal distribution, while band2 has a two-modal distribution. Table 2.1 details the experimental data. Figure 2.2 shows the feature space of the simulated data sets, in which the red dots represent class1 and the blue dots represent class2. Areas of visual overlap, but not real overlap in feature space, are identified by the green dots. Areas of real overlap in feature space are identified by the white dots.

In addition to the synthetic data sets, the performance of the three classifiers was also tested using remotely sensed imagery (i.e. Landsat Thematic Mapper and SPOT-panchromatic imagery acquired in 1995 and 1997 respectively) over the Lemeleberg region of the Netherlands (see details in Chapter 3). The images were geometrically rectified and geo-referenced to a common pixel size of 10 m by 10 m. The sub-images (435 by 348) contain five ground cover classes, which contain probably more complicated overlap situations among these five classes in their feature space. The five ground cover types are forest (F), pasture (P), heath (H), arable land (A), and built-up area (B). This data set was chosen to provide a situation with more complicated overlap in feature space compared with the two simulated classes with simple overlap.

Table 2.1 Statistical parameters for the two classes simulated in three bands: band1 to band3. Min., Max. and Std. are minimum, maximum and standard deviation respectively.

		With no overlap			With overlap		
		Band1	Band2	Band3	Band1	Band2	Band3
Class1	Min.	17	10	37	16	10	37
	Max.	34	30	54	34	30	54
	Mean	22.3	20.0	42.4	23.9	20.0	44.7
	Std.	±3.8	±4.5	±3.8	±3.4	±4.5	±3.1
Class2	Min.	25	17	45	22	17	42
	Max.	37	23	57	39	23	59
	Mean	31.0	20.0	51.0	30.3	20.0	53.3
	Std.	±2.5	±1.3	±2.4	±3.4	±1.3	±3.4
Variance-covariance	Band1	29.1	0.1	24.6	21.5	0.1	10.8
	Band2		10.8	0.2		10.8	0.1
	Band3			29.1			18.7
Correlation	Band1	1.00	0.00	0.84	1.00	0.01	0.54
	Band2		1.00	0.01		1.00	0.01
	Band3			1.00			1.00

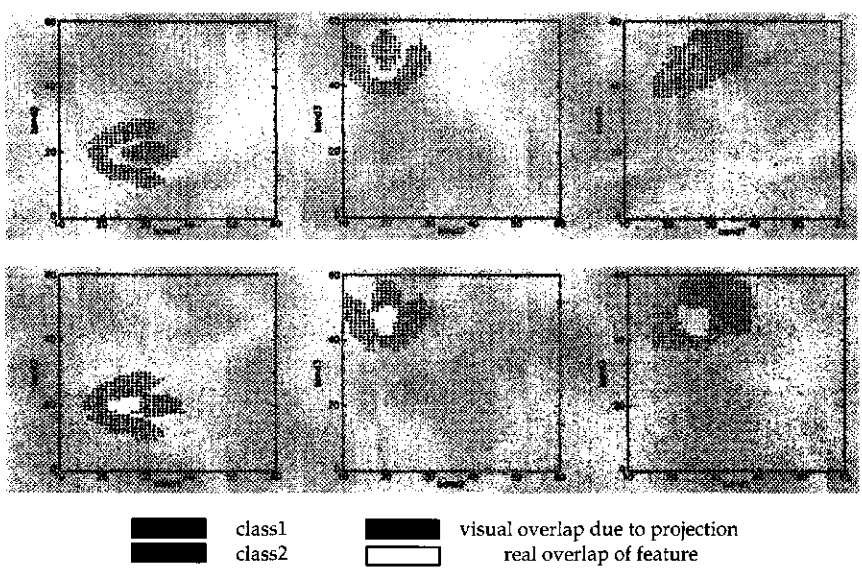

Figure 2.2 The feature space of the simulated data sets with two classes. The top three show the feature spaces under a no overlap situation. The bottom three show the feature spaces under an overlap situation.

2.3.2 Defining separability and degree of overlap of the classes

Accuracy of classification depends on the separability of the classes in feature space. As two classes become further apart, they have less overlap and may be classified with greater accuracy. Two measures are used in this study: the Jeffries-Matusita (*JM*) distance (ERDAS 1991, Richards 1993) and the simplified Skidmore et al. non-parametric test of overlap (Skidmore et al. 1988).

Mathematical separability is normally used to discard classes with little contribution to a classification (Richards 1993). The *JM* Distance is a parametric measure of the average distance between the density function of two classes. For normally distributed classes, *JM* Distance may be defined as:

$$JM_{ij} = 2(1 - e^{-B}) \tag{1}$$

where i and j are two classes being compared, B is the Bhattacharyya Distance:

$$B = 1/8(\mu_i - \mu_j)^t \{\frac{Ci + Cj}{2}\}^{-1}(\mu_i - \mu_j) + 1/2\ln\{\frac{|(Ci + Cj)2|}{\sqrt{|Ci|}\sqrt{|Cj|}}\} \tag{2}$$

where μ_i and μ_j are the mean vectors of the two classes, and C_i and C_j are the variance-covariance matrices of the two classes. The *JM* distance ranges from 0 where the two classes completely overlap to 2 where the two classes are completely separate from each other.

Skidmore et al. (1988) developed a general algorithm to quantify the degree of overlap of classes. It is a non-parametric test of overlap that does not depend on statistical parameters such as mean and standard deviation. The Skidmore et al.'s *Ri(f)* value ranges from 0 to 1, where 0 equates to complete overlap, while 1 means there is no overlap between the two classes, that is the two classes are completely separate from each other (Skidmore et al. 1988). In this study, a simplified Skidmore et al. non-parametric test was used (Equation 3). If $Ri = 1$, this class has no overlap with other classes, while if $Ri < 1$, the class has overlap with other classes. An example of how to calculate *Ri* is shown in Table 2.2.

$$Ri = Fi / Ni \tag{3}$$

where *Fi* is defined as the frequency of pixels in the training set purely belonging to class *i*, *Ni* is the total number of pixels in the training set of class *i*, and *Ri* is the proportion of *Fi* and *Ni*. It is used to indicate the degree of overlap between class *i* and other classes.

In order to find out how the overlap of two classes in the feature space influences classification, different sizes of training samples were studied for the simulated data because the *JM* distance and the simplified *Ri* depend on sample size. The sample sizes used were 200, 400, 800, 1600 and 2500 samples for both classes. For the remotely sensed imagery, only one sample set was used, which includes five ground cover types varying in their degree of overlap.

Table 2.2 Non-parametric test of overlap degree under the overlap situation. In the formula of $Ri = Fi/Ni$, Ri is the proportion of the number of pixels (Fi) in the training set purely belonging to class i to the total number of pixels (Ni) of the training set of class i.

Sample size in training set	Feature pattern in training set with overlap	Number of pixels with same feature pattern but belonging to different classes		$Ri = Fi/Ni$
	[Band1 Band2 Band3]	Class1	Class2	
200	[26 21 49]	1	1	R_1=(200-1)/200=0.9950 R_2=(200-1)/200=0.9950
400	[24 21 49]	1	1	
	[25 19 46]	1	1	R_1=(400-4)/400=0.990
	[26 20 43]	1	1	R_2=(400-5)/400=0.9875
	[26 21 49]	1	2	
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

2.3.3 Configuring the backpropagation neural network in this study

A backpropagation neural network with three layers (1 input layer, 1 hidden layer and 1 output layer) was constructed with a varying number of nodes. The number of input and output nodes was decided by the number of data layers (input) and the classes (output) respectively. In order to find a better neural network structure to optimise training and obtain higher overall mapping accuracy, the parameters, such as total system error level, number of hidden nodes, learning rate and momentum coefficient were studied. First of all, we subjectively used 5 hidden nodes and a small momentum (0.01) as well as a small learning rate (0.001) to test how the total system error influences the classification accuracy and to select a better and practical system error level. The number of hidden nodes and the different combinations of momentum coefficients and learning rates were then explored. The criterion for selecting these parameters is the "highest test accuracy" (Gong et al. 1997). In summary, a number of different input conditions for the neural network classifier were tested for both simulated data sets and remotely sensed imagery, including:

- system error levels (0.1, 0.075, 0.05, 0.03, 0.01 and 0.005),
- number of hidden nodes (1X, 2X, 3X, 6X, 10X) with X=3 which represents the number of input nodes,
- different combinations of momentum coefficients and learning rates (0.7/0.7, 0.5/0.7, 0.1/0.7, 0.01/0.7; 0.7/0.5, 0.5/0.5, 0.1/0.5, 0.01/0.5; 0.7/0.1, 0.5/0.1, 0.1/0.1, 0.01/0.1; 0.7/0.01, 0.5/0.01, 0.1/0.01, 0.01/0.01; 0.7/0.001, 0.5/0.001, 0.1/0.001, 0.01/0.001).

2.3.4 Comparing three classifiers using both simulated and remotely sensed data

Both simulated data and remotely sensed imagery were classified using the optimised BPNNC, MLC and PPC in order to test the effect of feature separability and degree of overlap on classification accuracy. The same training and test data sets were used for the three classifiers. For the simulated data set, we used the whole data set to test final classification accuracy. The remotely sensed imagery has an independent test sample set. The classifiers were tested for statistical differences in their accuracy of classification using the KHAT statistic (Congalton et al. 1983, Foody 1992) calculated for each image, and a Z statistic to test whether any two classification results were significantly different (Cohen 1960).

2.4 Results

2.4.1 Measuring the separability and overlap degree

The *JM* distances and the simplified-*Ri* values from different sizes of training sample sets for the simulated data set are detailed in Table 2.3a. The *JM* distance is approximately 1.52 under the no overlap situation and 1.51 under the overlap situation. The similarity of these results indicates that the two classes cannot be completely separated using this measure of separability. In comparison, the simplified-*Ri* values are all equal to 1 under the no overlap situation; while the *Ri* values vary from 0.969 to 0.995 under the overlap situation. Table 2.3a also confirms that in the overlap situation, *Ri* stabilises to an asymptotic condition as the size of the training sample set increases.

Table 2.3b shows the *JM* distances of pairs of classes as well as the simplified-*Ri* values based on the sample sets for remotely sensed imagery. The highest separability is between pasture and forest, followed by forest and arable land, pasture and heath, pasture and built-up area. The *Ri* values of the forest (R_F =1) and pasture (R_P =1) classes similarly indicate that these two classes do not overlap with the other classes in feature space of the training sample set, while the other three classes (e.g. built-up area, arable land and heath) exhibit more overlap (R_H =0.937, R_A =0.913, and R_B =0.897) than the two simulated classes.

2.4.2 Performance of the BPNNC under various experimental conditions

The system error has a strong influence on the classification accuracy under all three-overlap situations (Figure 2.3). For the simulated data set (with or without overlap), the large sample size and small system error of the neural network increased the classification accuracy (Figure 2.3a and 2.3b). For the image data set (with more overlap), it was confirmed that a small system error increased the classification accuracy (Figure 2.3c). However, the classification of two "no overlap" classes for the simulated data set did not reach an accuracy of 100%. Therefore, the training set with 2500 samples was selected for further experimentation. The minimal system error levels for the different experiments (0.005 for the two simulated classes with "no overlap", 0.03 for the two simulated classes with simple overlap, and 0.12 for the remotely sensed imagery with more complicated overlap) were selected to ascertain the influence of the number of hidden nodes. The reason for selecting 0.03 and 0.12 under situations of overlap is that the BPNNC took a very long time for calculation to reach the smaller system error levels of 0.029 and 0.11 (see iterations in the parentheses in Figure 2.3b and 2.3c).

Table 2.3 Jeffries-Matusita (*JM*) distance between two classes and simplified *Ri* value of each class. *Ri* is the proportion of the number of pixels (*Fi*) in the training set purely belonging to class *i* to the total number of pixels (*Ni*) of the training set of class *i*.

a: The *JM* distances and simplified *Ri* values under different sampling schemes for the simulated data sets with only two classes.

Class	Samples per class	With no overlap		With overlap	
		JM distance	Simplified *Ri*	*JM* distance	Simplified *Ri*
1	200 samples	1.5188	R_1=1.0000	1.5092	R_1=0.9950
2	200 samples		R_2=1.0000		R_2=0.9950
1	400 samples	1.5182	R_1=1.0000	1.5087	R_1=0.9900
2	400 samples		R_2=1.0000		R_2=0.9875
1	800 samples	1.5173	R_1=1.0000	1.5087	R_1=0.9738
2	800 samples		R_2=1.0000		R_2=0.9700
1	1600 samples	1.5176	R_1=1.0000	1.5088	R_1=0.9750
2	1600 samples		R_2=1.0000		R_2=0.9719
1	2500 samples	1.5176	R_1=1.0000	1.5087	R_1=0.9708
2	2500 samples		R_2=1.0000		R_2=0.9692

b: The *JM* distances and simplified *Ri* values for the real image case study. Five ground cover types are defined: forest (F), pasture (P), heath (H), arable land (A) and built-up area (B).

Class	Training Samples	*JM* distance between any two classes					Simplified *Ri*
		F	P	H	A	B	
Forest (F)	285	0	1.609	1.514	1.595	1.536	R_F=1
Pasture (P)	473		0	1.569	1.538	1.551	R_P=1
Heath (H)	300			0	1.545	1.506	R_H=0.937
Arable land (A)	480				0	1.519	R_A=0.913
Built-up area (B)	312					0	R_B=0.897

The influence of the number of BPNNC's hidden nodes, based on the conditions defined above, is shown in Figure 2.4. No pattern in classification accuracy occurred with a changing the number of hidden nodes (Figure 2.4). The optimised BPNNC achieved an accuracy of 100% under the "no overlap" situation when the number of hidden nodes increased to 6 (Figure 2.4a). In other words, that the neural network can discriminate completely two classes with "no overlap" in their feature space. However, under the "overlap" situation, the highest overall accuracy of 97.22% for two simulated classes and of 83.36% for remotely sensed imagery with five classes was achieved when the number of hidden nodes increased to 9 (Figure 2.4b and 2.4c). So, we selected 6, 9 and 9 hidden nodes together with the previously selected parameters to search for a better combination of momentum coefficient and learning rate.

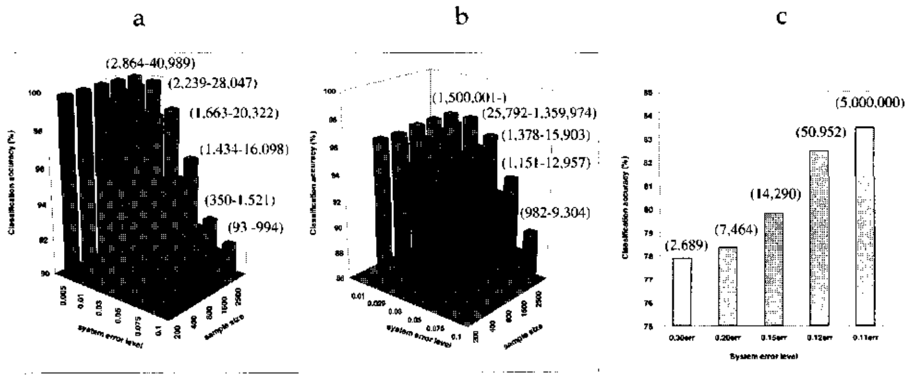

Figure 2.3 Backpropagation neural network experimentation with different sizes of sample sets as well as system error levels under three varying overlap conditions: a – two simulated classes with no overlap; b - two simulated classes with simple overlap; c - five ground cover classes with more complicated overlap. Numbers in parentheses are iteration numbers of neural network training.

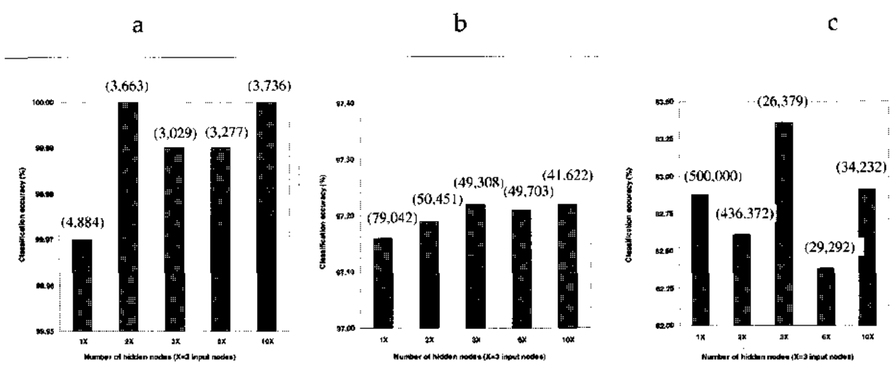

Figure 2.4 Backpropagation neural network experimentation with different numbers of hidden nodes under three varying overlap conditions: a – two simulated classes with no overlap; b – two simulated classes with simple overlap; c – five ground cover classes with more complicated overlap. Numbers in parentheses are iteration numbers of neural network training.

Based on the previous experiments, the influence of the combination of learning rate and momentum coefficient is shown in Figure 2.5. For the two simulated classes with no overlap, the various combinations of momentum and learning rate did not produce any change to the classification accuracy of 100% (Figure 2.5a). For the simulated two overlap classes as well as the remotely sensed imagery with five classes, the combination of different momentum and learning rate does influence the classification accuracy (Figure 2.5b and 2.5c). However, no obvious pattern emerged. The highest classification accuracies, e.g. 97.25% and 82.95%, were produced by the momentum-learning-rate combination of 0.5/0.7 for two simulated classes and of 0.7/0.1 for the remotely sensed imagery.

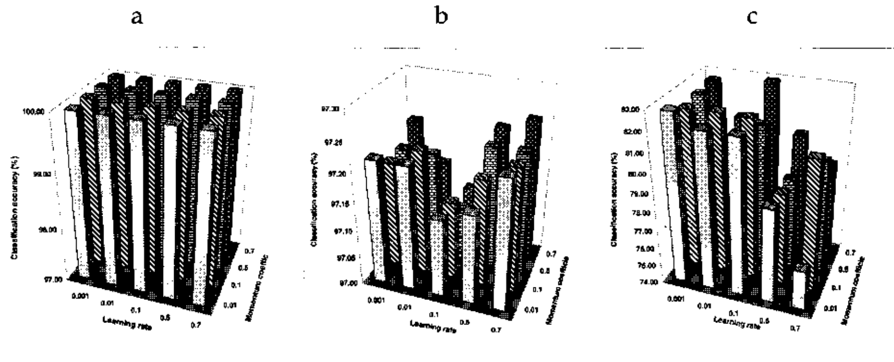

Figure 2.5 Backpropagation neural network experimentation with different combinations of momentum coefficients and learning rates under three varying overlap conditions: a - two simulated classes with no overlap; b - two simulated classes with simple overlap; c - five ground cover classes with more complicated overlap.

2.4.3 Different responses of the BPNNC, MLC and PPC to sample size

As the size of the training sample set increased, the number of correctly classified pixels in both class1 and class2 changed slightly for all three classifiers under two overlap situations (Figure 2.6). There are slightly more pixels correctly classified by BPNNC than MLC, and both much more than PPC. An interesting result is that under an overlap situation, the MLC can classify class1 with a higher classification accuracy (Figure 2.6-2a), while the BPNNC can classify class2 better (Figure 2.6-2b).

2.4.4 Classification and pairwise comparison of the BPNNC, MLC and PPC

The optimised BPNNC has the highest classification accuracies, the MLC produces intermediate classification accuracies, while the PPC has the lowest accuracies (Table 2.4). When viewed as classified images, Figure 2.7 highlights the performance of the three classifiers on classification of the simulated data sets as well as the remotely sensed imagery (Figures 2.7 (1a, 2a, and 3a for the BPNNC; 1b, 2b, and 3b for the MLC; 1c, 2c, and 3c for the PPC)). The BPNNC (at the error level of 0.005, with 2500 sample sizes and 6 hidden nodes) can separate two no-overlap classes with an accuracy of 100%. The BPNNC (at the system error level of 0.027, with 2500 samples and 9 hidden nodes, and with a combination of momentum and learning rate of 0.5/0.7) produced the highest classification accuracy of 97.32% for two simulated classes with overlap.

The highest classification accuracy, 83.47%, for the remotely sensed imagery with 5 ground cover classes was obtained by the BPNNC (at the system error level of 0.1, with 9 hidden nodes, and with momentum of 0.01 and learning rate of 0.001. The PPC produced many unclassified pixels for both simulated data sets and remotely sensed imagery.

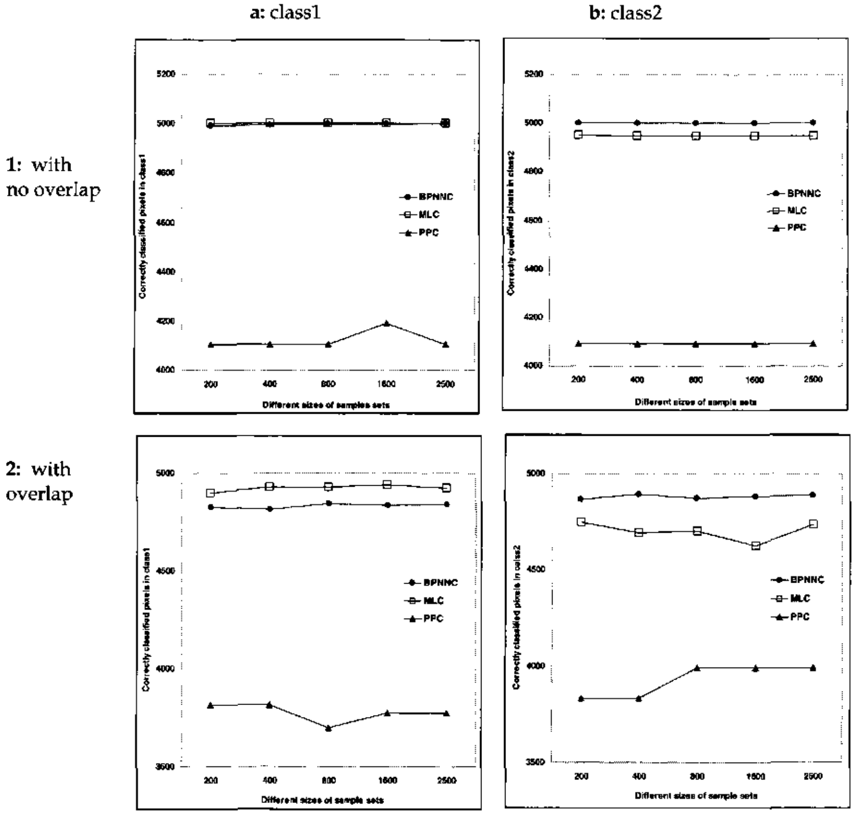

Figure 2.6 Response of the backpropagation neural network classifier (BPNNC), maximum likelihood classifier (MLC) and parallelepiped classifier (PPC) to the different sizes of training sample sets for the simulated data sets. Note that BPNNC has a system error level of 0.005 for the "no overlap" situation and of 0.03 for the "overlap" situation.

In this study, under all three overlap situations (e.g. two simulated classes with no overlap, two simulated classes with simple overlap, and five classes with more complicated overlap), Z statistic tests show that both the optimised BPNNC and MLC produced significantly higher accuracies than the PPC, and the BPNNC was significantly better than the MLC (Table 2.5).

Table 2.4 The classification accuracies of the three classifiers: the optimised backpropagation neural network classifier (BPNNC), the maximum likelihood classifier (MLC) and the parallelepiped classifier (PPC)

Classifier	Simulated data sets*		Remotely sensed imagery
	Two classes with no overlap	Two classes with simple overlap	Five classes with more complicated overlap
Optimised BPNNC	100.00	97.32	83.47
MLC	99.47	96.55	81.35
PPC	81.96	77.64	54.13

* all results from the training set with 2500 samples per class.

Table 2.5 Pairwise comparison using Z-statistic between the confusion matrices for the three classifiers: the optimised backpropagation neural network classifier (BPNNC), the maximum likelihood classifier (MLC) and the parallelepiped classifier (PPC).

Pairwise comparison	Z for simulated data sets		Z for remotely sensed imagery
	Two classes with no overlap	Two classes with simple overlap	Five classes with more complicated overlap
BPNNC-MLC	7.3990 *	3.1609 *	2.7685 *
BPNNC-PPC	46.9158 *	44.0775 *	32.3173 *
MLC-PPC	44.7468 *	41.6100 *	29.0271 *

* with significant difference at 95% C.I. (if Zt >1.96).

2.5 Discussion

One important result of this study is that the BPNNC can separate the two "no overlapping" classes in feature space, while the MLC and PPC cannot. Since a decision hyper plane can be formed by the neural network between two classes (Richards 1993), just like the MLC and PPC (see Figure 2.1), theoretically, the neural network should be able to classify two non-overlapping classes with an overall accuracy of 100% if the neural network is well trained. Our experimental result confirmed this description of Richards' (1993). With an increase of the overlap degree in feature space, the classification accuracy decreases for all three classifiers (BPNNC, MLC and PPC). But the BPNNC can be relatively well-trained and optimised to produce a significantly better classification result than the MLC and PPC.

The simplified Skidmore et al. *Ri* value can indicate the overlap degree between two classes in feature space. According to Richards (1993), a *JM* distance of 2.0 implies that the classes may be discriminated with an accuracy of 100%. Based on this, the *JM* values in table 3a show that the classes may not be discriminated for the "no overlap" situations, which is not the case according to our result discussed previously. However, if we look at the simplified Skidmore et al. *Ri* values, the "no overlap" situation has a *Ri* value equal to 1.0, correctly indicating there is no overlap between two classes. Thus, the *JM* distance informs a user on how well two classes may be classified, but gives no information about the degree of overlap. When remotely sensed imagery (Landsat TM and SPOT-panchromatic), with a more complicated overlap situation among five classes, was investigated, the highest simplified Skidmore et al.'s *Ri* values for the forest and pasture classes indicated that these two classes, based on the sample set, do not overlap with any other classes in feature space. The "built-up area" class has a high level of overlap with other classes in feature space due to its lowest *Ri*-value of 0.897 and *JM*-value of 1.506. Since both the simplified Skidmore et al.'s *Ri* value and the *JM* distance are calculated from the sample set, the sample design (i.e. size of sample set, position of samples, representative of samples) will influence the accuracy of the *Ri* value and the *JM* distance.

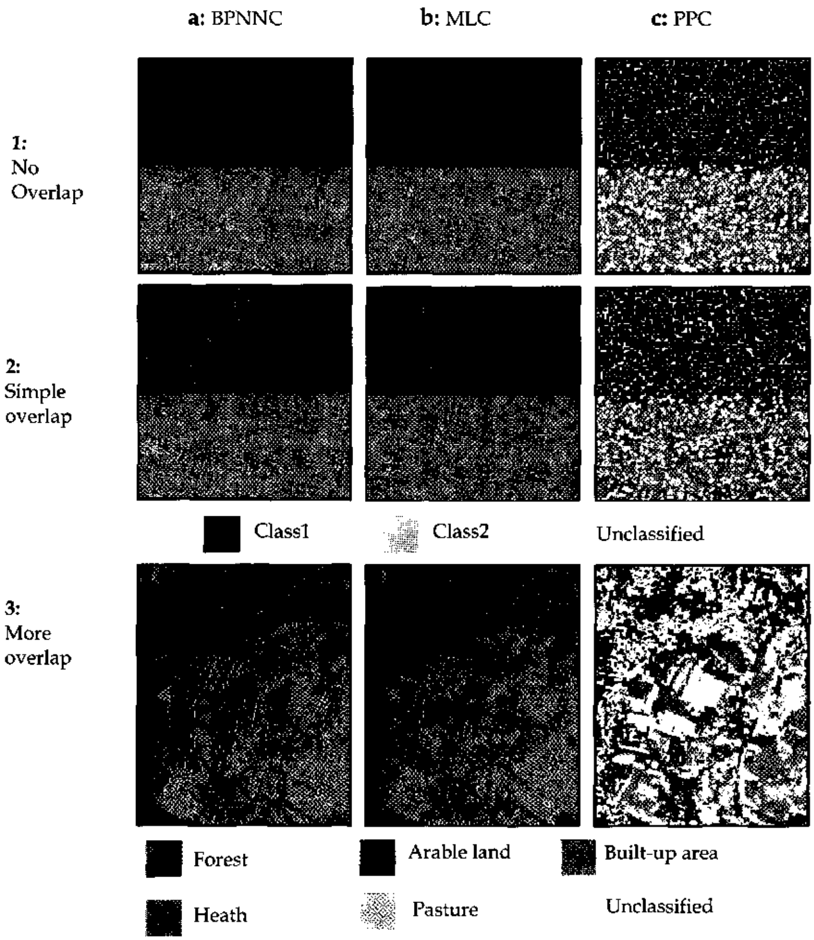

Figure 2.7 The classified images from the backpropagation neural network classifier (BPNNC), maximum likelihood classifier (MLC) and parallelepiped classifier (PPC) for both simulated data sets and remotely sensed imagery. The left column is the outputs from BPNNC, the middle column from MLC, and the right column from PPC.

The parameters of the BPNNC do influence the classification accuracy, especially, the total system error level. The system error level represents a distance between the network output and the defined target, therefore, a large system error gives a wide range of variance for similar feature patterns to be trained and classified. Few studies of neural network applications provide clear criteria for defining the system error level. Skidmore et al. (1997) found that the total system error is inversely correlated with the percentage of correct training data, but is not correlated with the test accuracy. The result of this study shows that low system error produces higher classification accuracy. The proper number of hidden nodes and the combination of momentum coefficient and learning rate requires more experimentation. Gong et al. (1997) recommended terminating the neural network training after reaching the best overall accuracy.

Turning now to the response of individual classifiers to the simulated two classes with overlap in the feature space, it has been shown that the MLC classifies class1 with a high accuracy, while the BPNNC yields better accuracy with class2. The MLC is a parametric method which utilises the mean and standard deviation of each band. Therefore, as class1 covers a large spectral range, the MLC can classify class1 better using the shortest Mahalanobis distance and also decides its lower accuracy in classifying class2 due to its decision rule (see Figure 2.1b). A similar result was also obtained by Downey et al. (1992), who found that the neural network classifier achieved accuracies of 90.59% and 12.49% for woodland and cropland classes respectively compared to 34.99% and 66.46% for the same two classes using the MLC. It implies that integrating two classifiers together in a hybrid system may produce higher classification accuracy because they compensate for each other.

2.6 Conclusion

Overlap of training classes in feature space produces misclassification by the BPNNC, MLC and PPC for both simulated data and remotely sensed imagery. Experiments based on the simulated data sets show that the BPNNC and MLC have different accuracies in mapping two classes. A well-trained neural network classifies the simulated data sets significantly better than the MLC, and the BPNNC successfully discriminates between two spectrally discrete classes when using the simulated data set. Classification of remotely sensed imagery (Landsat TM and SPOT-panchromatic) shows again that there is a significant difference between the BPNNC and MLC, and both are significantly better than the PPC.

Acknowledgement

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CHAPTER 3

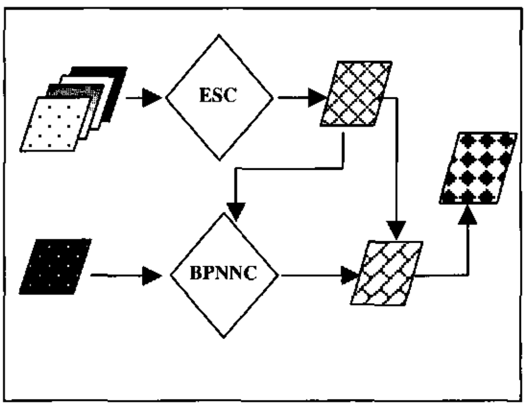
Optimising Mapping Algorithms and Two Integrated Classifiers for Mapping

$$P(Ha / Eb) = \frac{P(Eb / Ha)P(Ha)}{P(Eb)}$$

$$P(Eb) = \sum_{a=1}^{n} P(Eb / Ha)P(Ha)$$

Integrated ESC and BPNNC

Bayesian probability theory



CHAPTER 3 Optimising Mapping Algorithms and Two Integrated Classifiers for Mapping *

Abstract

Classifiers, used to recognise patterns in remotely sensed images, have complementary capabilities. This study tests whether integrating the individual classifiers or the results from individual classifiers improves classification accuracy. Two integrated approaches were undertaken. One approach uses a consensus builder to adjust classification output in the case of a discrepancy in classification between maximum likelihood, expert system and neural network classifiers. When the output classes differed, the producer accuracies for each class were compared and the class with the highest producer accuracy was selected to represent the pixel. The consensus builder approach did not produce a map with statistically significantly higher accuracy when compared with the backpropagation neural network classifier, but it did significantly better than the maximum likelihood and the expert system classifiers. A second approach integrates the output of a rule-based expert system with a neural network classifier (ESNNC); this is a new technique in the field of image processing. The ESNNC approach produced maps with the highest accuracy.

Key Words: integrated, neural network, expert system, consensus builder, mapping accuracy

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1. This chapter is based on Liu, X., A. K. Skidmore, and H. Van Oosten. (in review-a). Two integrated classifiers improve the accuracy of land cover mapping. ISPRS Journal: Photogrammetry and Remote Sensing.

2. Part of this work was presented at The 2nd International Symposium on Operationalisation of Remote Sensing. 1999, Enschede, The Netherlands. The presented title: Integrated Classification Systems.

3.1 Introduction

Different classification algorithms produce different results even with the same training sets (Benediktsson et al. 1990b, Benediktsson et al. 1990a, Hepner et al. 1990, Key et al. 1990, Bischof et al. 1992, Kanellopoulos et al. 1992, Civco 1993, Paola and Schowengerdt 1994, Solaiman and Mouchot 1994, Skidmore et al. 1997, see also Chapter 2). For some application fields, neural network classifiers yield better results, while for other applications a statistical classifier (such as the maximum likelihood classifier) performs better (Kanellopoulos et al. 1993). For example, Brown et al. (1998) applied the backpropagation neural network classifier (BPNNC) and the maximum likelihood classifier (MLC) to classify glaciated landscapes. The BPNNC mapped rare classes with a high accuracy, whereas the overall pattern (of all classes) was better reproduced with the MLC. Brown et al. (1998) analysed the reasons for different results produced by the MLC and BPNNC and surmised that because of the statistical nature of the MLC, the spatial auto-correlation patterns that were fairly strong in the original variables were maintained in the classification. In comparison, the spatial structure of the BPNNC output reflects its non-linearity, so the BPNNC is sensitive to slight variations in the inputs, resulting in less spatially coherent output patterns. Such conclusions require further testing and analysis, as the cause of differences in accuracy between classifiers is not completely understood (Fierens et al. 1994).

It has been shown that no image processing classifier is perfect (Matsuyama 1987). However, classifiers may also be assumed to have complementary capabilities (Matsuyama 1987). Therefore, a useful and practical approach for optimising classification performance is to combine classifiers in order to increase classification accuracy (Kanellopoulos et al. 1993, Brown et al. 1998).

Combined methods can take advantage of two or more lines of evidence based on different algorithms. For instance, a combination of the MLC and BPNNC may use the ability of the MLC to identify the overall pattern and the ability of the BPNNC to discern fine details. Lu (1996) integrated classification results derived from individual classifiers using the Dempster-Shafer theory of evidence. In another integrated classification method, Kanellopoulos et al. (1993) used a second BPNNC to train only those pixels where there was a discrepancy between classes produced by the MLC and the first BPNNC. The combined classifier had an improved performance compared with the single classifiers. Ho et al. (1994) used class set reduction and reranking methods to combine different classifiers. Another approach is to sum the class membership values for each class derived from different methods and to assign the class to the pixel with the highest combined value (Brown et al. 1998).

In the field of pattern recognition, multiple classifier systems have proven to be a powerful solution for difficult pattern recognition problems involving large class sets and noisy input, for example, handwriting recognition (Ho et al. 1994, Brown et al. 1998). Achieving an optimal organisation is a challenging and open problem (Ho et al. 1994). Research on integration of classifiers is still at an early stage and much more exploration needs to be done (Kanellopoulos et al. 1993). This study tests whether two new integrated approaches (*viz.* 1. a consensus builder system; 2. a combined expert system and neural network system) can improve classification accuracy.

3.2 Description of classifiers

3.2.1 Three individual classifiers

The maximum likelihood classifier (MLC) is a well-known parametric method. It is based on the assumption that the data may be modelled by a set of multivariate normal distributions (Gaussian). With statistical parameters, a changed "Mahalanobis Distances" can be calculated. Details of the MLC can be found in Tou and Gonzalez (1974) and Richards (1993). The decision rule of the MLC is that the shortest modified "Mahalanobis Distance" to a class mean for a pixel will define the pixel to that class. This distance can represent the probability of a given pixel value being a member of a particular class. This algorithm looks at the shape, size and orientation of the training sample locations. If the assumption of a normal distribution (in feature space) for each class training area is correct, then the classification has a minimum overall probability of error and the MLC is the optimal choice (Swain 1978, Paola and Schowengerdt 1994). However, the distribution of each training set is sometimes not normal.

The second individual classifier considered in this study is the standard backpropagation neural network classifier (BPNNC). The advantages of the BPNNC include (Paola and Schowengerdt 1995, Skidmore et al. 1997, Openshaw and Openshaw 1997): (1) non-parametric nature, (2) arbitrary decision boundary capabilities to manage nonlinear modelling tasks, (3) easy adaptation to different types of data and input structures, (4) capability of identifying subtle patterns in training data, (5) fuzzy output values, (6) good generalisation of the input data, (7) capability to process noisy data.

There are two stages involved in the BPNNC: the training stage and the classification stage. The network system is trained until the targeted system error is achieved between the desired and actual outputs of the network. Once training is complete, the trained system is used for classification. This algorithm is a popular learning method capable of handling very large data sets. The backpropagation algorithm minimises the error function in weight space using the method of gradient descent or convergence (Rojas 1996). Details of the BPNNC may be found in Richards (1993), Demuth and Beale (1994) and Skidmore et al. (1997). Problems with the BPNNC include difficulties that the user faces in deciding the input parameters, as well as the output from a BPNNC being stochastic, due to the starting network weights being chosen randomly (Skidmore et al. 1997).

The third individual classification system used in this study is the expert system classifier (ESC), also known as a knowledge-based system. Both the ESC and BPNNC have been used to integrate information from geographical information systems (GIS) during the image understanding process (Wilkinson et al. 1992). Expert or knowledge-based methods differ quite considerably from neural networks although they are often grouped together as "artificial intelligence" (AI) techniques (Wilkinson et al. 1992). The expert system structures vary widely. However, they have been characterised by two components (Forsyth 1989, Skidmore 1989, Skidmore et al. 1996b): the "knowledge base" to store expert knowledge and rules, and the "inference engine" which processes the system. Two other components are also important, "a knowledge-acquisition module" and "an explanatory interface". The inference engine may be based on the Dempster-Shafer model of evidence integration to combine the individual pieces of "evidence" (Wilkinson et al. 1992), or a rule-based model through Bayesian probability reasoning (Skidmore 1989, Skidmore et al. 1996b).

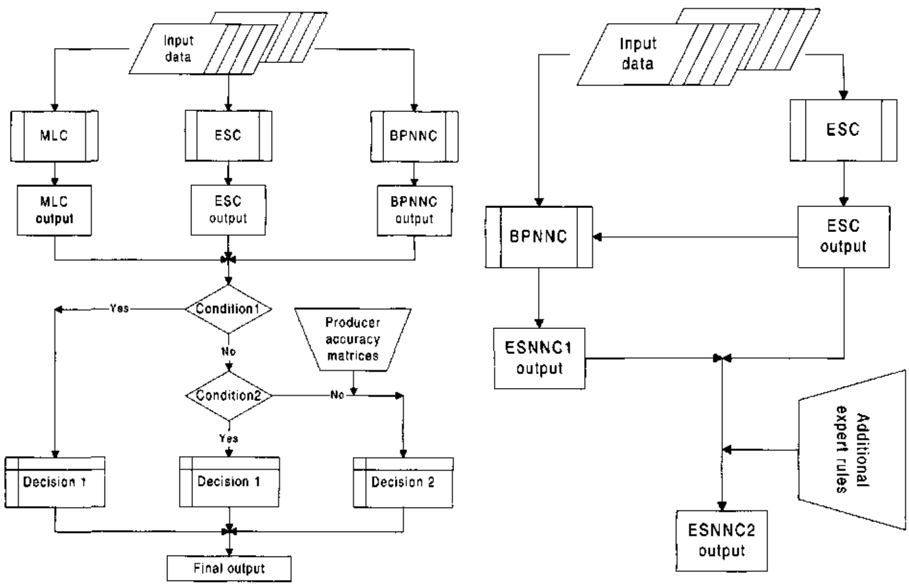
The Bayesian method is based on a well-understood technique from probability theory and is the most widely used approach in dealing with uncertainty (Lu 1996). The basis of the Bayes' algorithm is that the likelihood of a hypothesis occurring given a piece of evidence, may be thought of as a conditional probability (Skidmore et al. 1996b). Attributes of the raster cell of the data layers are input to the system and matched with the information in the knowledge base. An expert system then infers the most likely class at a given cell, using Bayes' Theory. It is commonly applied in remote sensing where topographic information provides *a priori* probabilities of a pixel containing a given vegetation type, and then spectral information is used to revise these probabilities, resulting in improved vegetation cover classification accuracy (Strahler et al. 1978, Richards et al. 1982, Pereira and Itami 1991). Details of how the Bayesian expert system works may be found in Forsyth (1989) and Skidmore (1989).

However, the Bayesian approach has been criticised for requiring a user to assign *a priori* probability to every event subjectively (Lu 1996), thereby taking a long time to develop the rule base. However, this method of data base creation appears to be best for user comprehension and transparency. It is also possible that an expert system could be used in combination with a neural network. Such a concept of an integrated neural network and expert system has already been suggested outside of the remote sensing field (Caudii 1990, Wilkinson et al. 1992).

3.2.2 Two new integrated classifiers

The consensus builder (CSB) uses classification results (specifically the producer accuracies of classifiers) to improve map accuracy (Figure 3.1a). The producer accuracy is the proportion of the correctly classified pixels in a class to the total pixels of that class in the reference data (Congalton 1991). The outputs of the three individual classifiers (MLC, ESC and BPNNC) are input into the CSB. The first phase of the algorithm checks whether the same class is predicted for a given grid cell (*condition1*). If *condition1* is satisfied, the CSB accepts the class for the pixel (*decision1*). If the result does not satisfy *condition1*, then the CSB uses *condition2* to check whether there is an agreement among any two of three classifiers. If the CSB finds such an agreement, *decision1* is used to accept the class for that pixel. If three classifiers have completely different results for a certain pixel (*condition3*), the producer accuracies are used to make a judgement. The class with the highest producer accuracy is taken as the output of the CSB for that pixel (*decision2*).

The integrated expert system and neural network classifier (ESNNC) includes two parts (Figure 3.1b). The first part of the ESNNC is a cascaded classification system (ESNNC1). The output of the rule-based expert system is used as an extra information layer for the neural network. Then, the producer accuracies of ESC and ESNNC1, as well as some additional expert rules, are used to re-judge the output at the second part (ESNNC2).



a. System of a consensus builder (CSB).
Condition1 - when three classifiers all agree.
Condition2 - when any two of three agree.
Decision1 - assign the class with agreement.
Decision2 - assign the class with the highest producer accuracy.

b. System of an integrated expert system and neural network classifier (ESNNC). It includes two parts: ESNNC1 and ESNNC2.

Figure 3.1 Two integrated classifiers: **a** - a consensus builder, and **b** - an integrated expert system and neural network classifier.

3.3 Study area

The study area is situated in the Overijssel Province of the eastern Netherlands (see Figure 3.2). Singh et al. (1996) have described the area in detail. It lies between 52°26'30" and 52°30' north latitude and 6°21'30" and 6°27'30" east longitude. Temperature ranges from 10 °C to 33 °C during summer and from -11 °C to 10 °C during winter. The mean annual rainfall varies from 700 to 725 mm in the area. The area has an undulating hilly terrain with an altitude of 5 to 80 m above mean sea level. The study area consists of two hills mostly covered with forest and heath, which are surrounded by alluvial plains used mainly for intensive agricultural production. Agricultural fields are also found along the gently sloping hillsides. Soils in the area are mainly sandy with the hills having coarser sands than the plains. Agricultural soils are reclaimed from marshland in the lower plains where the water table is high.

Eleven land cover classes were obtained based on visual interpretation of the aerial photographs and field survey: pine forest (PF), mixed forest with other conifer and deciduous broadleaf trees (MF), open woodland (OW), heath (H), grass (G), bare soil (BS), pasture (P), arable land (A), built-up area (B), road (R), and water (W).

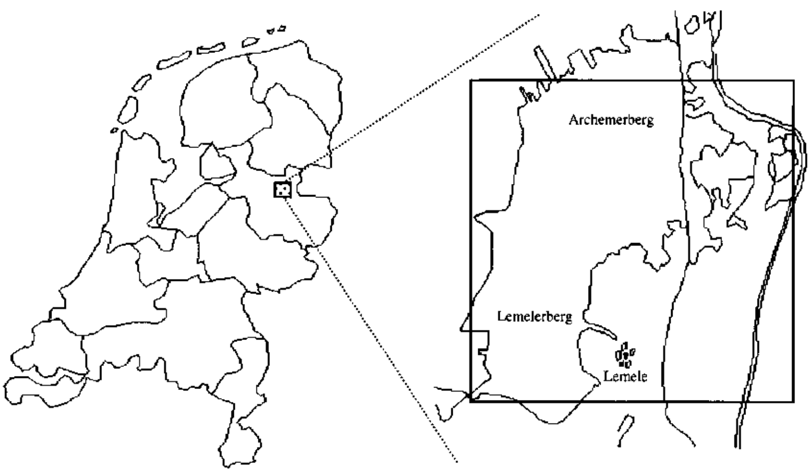


Figure 3.2 The study area consists of two hills called Lemelerberg and Archemerberg in the Netherlands.

3.4 Methods

3.4.1 Data preparation

Remote sensing data including Landsat TM images (1995) and a SPOT panchromatic image (1997) were used as input to the classifiers. Ancillary GIS data include elevation, slope gradient and aspect, soil type and terrain type, which were georeferenced to the same coordinate system (UTM) as the remotely sensed imagery. Both the remotely sensed and ancillary data were resampled to a pixel size of 10 m by 10 m. From aerial photographs, obtained in 1995 and 1997, sample areas, including training and testing sets, were selected and checked in the field with recording the land cover types.

Highly correlated data layers were excluded from the analysis in order to reduce the data, and ease the expert knowledge extraction bottleneck discussed above. Table 3.1 shows the correlation coefficients between pairs of data layers. The threshold value for excluding correlated data layers was subjectively set at r^2=0.75 for RS data layers (Table

3.1a) and r^2=0.65 for GIS data layers (Table 3.1b), resulting in six data layers being selected for the study (i.e. SPOT-panchromatic, Landsat TM2 and TM4, elevation, slope aspect and soil type).

Table 3.1 Correlation analysis of data layers.
a: correlation analysis of remotely sensed data layers

	SPOT-PAN	TM1	TM2	TM3	TM4	TM5	TM7
SPOT-PAN	1.00	0.68	0.71	0.72	0.31	0.69	0.74
TM1		1.00	0.88	0.90	0.37	0.68	0.84
TM2			1.00	0.94	0.56	0.77	0.84
TM3				1.00	0.42	0.77	0.89
TM4					1.00	0.55	0.36
TM5						1.00	0.85
TM7							1.00

b: correlation analysis of other GIS data layers

	Slope aspect	Elevation	Slope gradient	Soil type	Terrain type
Slope aspect	1.00	-0.29	-0.34	-0.04	0.26
Elevation		1.00	0.65	-0.17	-0.78
Slope gradient			1.00	-0.09	-0.67
Soil type				1.00	0.19
Terrain type					1.00

Expert knowledge is central to the operation of the ESC (Skidmore 1989). The estimation of the *a priori* probabilities for the expected classes and the initial conditional probabilities for all the evidence (i.e. the selected data layers) need to be estimated before running the ESC. They were extracted from the expertise and knowledge from ground survey (Table 3.2).

3.4.2 Classification and testing

Following data preparation, classification by the three individual classifiers and two new integrated classifiers were executed using the same input data layers and training sample sets. The ESC did not depend on the training sample sets since it is based on the expert knowledge and Bayesian probability reasoning. All the experiments of the BPNNC are based on the experience obtained from work in Chapter 2.

The three-layer BPNNC was implemented by using a neural network package in PCI software (PCI 1998). It was configured with 6 input nodes, 8 hidden nodes and 11 output nodes. The parameters of learning rate, momentum and total system error were set at 0.001, 0.01 and 0.5 respectively, based on the experimental results suggested by Skidmore et al. (1997). The MLC was executed in IMAGINE (ERDAS 1991). The ESC and CSB were developed for this study in IDL (Interactive Data Language) (RSI 1997).

The accuracies of the output maps produced by the different classifiers were estimated using the overall accuracy and Kappa or $\hat{K}HAT$ statistic (Cohen 1960, Congalton 1991).

Cohen (1960) described a Z test, based on the Kappa value, to check whether there is a statistically significant difference between two error matrices.

Table 3.2 Expert knowledge extraction from data layers for the expert system classifier.
a: *a priori* probabilities estimation for the expected classes

Classes	PF	MF	OW	H	G	BS	P	A	B	R	W
Probability	0.18	0.14	0.08	0.06	0.03	0.01	0.21	0.16	0.08	0.02	0.03

b: Initial conditional probabilities estimation for the selected data layers

Evidences		PF	MF	OW	H	G	BS	P	A	B	R	W
	4-7	0.01	0.01	0.01	0.01	0.01	0.01	0.9	0.2	0.01	0.01	0.9
	7-11	0.2	0.4	0.01	0.01	0.01	0.8	0.6	0.6	0.9	0.9	0.01
Ele.	11-17	0.2	0.5	0.7	0.1	0.05	0.01	0.2	0.8	0.01	0.5	0.01
(m)	17-31	0.8	0.6	0.7	0.3	0.1	0.01	0.01	0.7	0.01	0.01	0.01
	31-41	0.9	0.6	0.7	0.5	0.5	0.01	0.01	0.01	0.01	0.01	0.01
	41-56	0.8	0.8	0.6	0.9	0.7	0.8	0.01	0.01	0.01	0.01	0.01
	56-82	0.3	0.6	0.6	0.5	0.9	0.05	0.01	0.01	0.01	0.01	0.01
	NE	0.8	0.7	0.8	0.8	0.7	0.1	0.1	0.1	0.01	0.01	0.01
	ES	0.8	0.7	0.01	0.9	0.6	0.1	0.3	0.2	0.7	0.9	0.01
Asp.	SW	0.8	0.7	0.01	0.6	0.8	0.8	0.5	0.9	0.4	0.8	0.01
	WN	0.8	0.7	0.8	0.1	0.8	0.8	0.1	0.1	0.01	0.01	0.01
	NO	0.3	0.2	0.01	0.5	0.5	0.1	0.9	0.5	0.9	0.5	0.9
	1	0.01	0.01	0.01	0.01	0.9	0.01	0.01	0.01	0.01	0.01	0.01
	2	0.01	0.01	0.01	0.01	0.01	0.01	0.8	0.7	0.01	0.01	0.9
	3	0.01	0.01	0.01	0.01	0.01	0.01	0.7	0.01	0.01	0.01	0.01
Soil	4	0.4	0.01	0.01	0.01	0.01	0.01	0.7	0.01	0.01	0.01	0.01
type	5	0.5	0.01	0.3	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	6	0.01	0.01	0.01	0.01	0.01	0.01	0.8	0.01	0.01	0.01	0.01
	7	0.9	0.8	0.8	0.9	0.9	0.8	0.01	0.5	0.01	0.01	0.01
	8	0.8	0.8	0.7	0.9	0.01	0.8	0.7	0.5	0.9	0.9	0.01
	9	0.4	0.3	0.01	0.01	0.01	0.01	0.5	0.9	0.9	0.9	0.01
	32-40	0.9	0.8	0.05	0.1	0.1	0.01	0.01	0.01	0.01	0.01	0.01
	41-50	0.3	0.2	0.8	0.9	0.9	0.01	0.9	0.05	0.01	0.01	0.9
SPP	51-60	0.01	0.01	0.1	0.1	0.2	0.01	0.3	0.9	0.9	0.9	0.9
	61-80	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.9	0.4	0.01	0.01
	81-122	0.01	0.01	0.01	0.01	0.01	0.9	0.01	0.01	0.01	0.01	0.01
	13-17	0.9	0.8	0.3	0.4	0.01	0.01	0.05	0.05	0.01	0.8	0.05
	18-23	0.05	0.05	0.9	0.9	0.9	0.01	0.9	0.9	0.9	0.7	0.9
TM2	24-35	0.01	0.01	0.01	0.01	0.6	0.3	0.05	0.3	0.01	0.01	0.01
	36-39	0.01	0.01	0.01	0.01	0.05	0.9	0.01	0.01	0.01	0.01	0.01
	14-25	0.9	0.01	0.03	0.2	0.01	0.01	0.01	0.9	0.2	0.05	0.7
	26-35	0.1	0.9	0.9	0.8	0.01	0.05	0.01	0.8	0.8	0.9	0.5
TM4	36-45	0.01	0.1	0.03	0.01	0.8	0.05	0.3	0.4	0.05	0.01	0.01
	46-55	0.01	0.01	0.01	0.01	0.5	0.3	0.9	0.01	0.01	0.01	0.01
	56-67	0.01	0.01	0.01	0.01	0.05	0.9	0.5	0.01	0.01	0.01	0.01

Ele.-elevation, Asp.-aspect, SPP-SPOT-panchromatic, TM-Landsat Thematic Mapper. PF-pine forest, MF-mixed forest (other coniferous and deciduous broadleaf species), OW-open woodland, H-heath, G-grass on hill, BS-bare soil on hill, PL-pasture in the plain area, A-arable land in the plain area, B-built-up area, R-road, W-water.

3.5 Results

Table 3.3 includes all error matrices from the two integrated algorithms (labelled "a" and "b" respectively for the error matrices of the ESNNC and CSB) and the three individual classifiers (labelled "c", "d" and "e" respectively for the error matrices of the BPNNC, ESC, MLC). The classified images are shown in Figure 3.3 with the same label sequence from "a" to "e".

Table 3.3 Error matrices of the integrated expert system and neural network classifier (ESNNC), the consensus builder (CSB), the backpropagation neural network classifier (BPNNC), the expert system classifier (ESC) and the maximum likelihood classifier (MLC). Note: PF-pine forest, MF-mixed forest with deciduous broadleaf and other conifer tree species, H-heath, G-grass, BS-bare soil, P-pasture, A-arable land, B-built-up area, R-road, W-water, OW-open woodland, PRA-producer accuracy, and OVA-overall accuracy.

a:		From Image Classification											
ESNNC		PF	MF	H	G	BS	P	A	B	R	W	OW	PRA
From Reference	PF	84	3	0	0	0	0	0	0	0	0	3	0.93
	MF	6	57	0	0	0	0	0	3	0	0	3	0.83
	H	0	0	65	0	0	0	0	0	0	0	25	0.72
	G	0	1	0	89	0	0	0	0	0	0	0	0.99
	BS	0	0	2	0	81	0	0	0	0	0	7	0.90
	P	0	0	0	0	0	63	0	0	0	0	0	1.00
	A	0	0	0	0	0	0	78	1	1	0	0	0.97
	B	0	0	0	0	0	7	0	66	17	0	0	0.73
	R	0	0	0	0	0	6	7	19	34	3	5	0.46
	W	0	2	0	0	0	0	18	0	2	53	0	0.71
	OW	4	4	7	7	0	0	0	8	1	0	32	0.51

Average PRA =80%

OVA=80%

B:		From Image Classification											
CSB		PF	MF	H	G	BS	P	A	B	R	W	OW	PRA
From Reference	PF	82	8	0	0	0	0	0	0	0	0	0	0.91
	MF	2	67	0	0	0	0	0	0	0	0	0	0.97
	H	1	0	74	1	7	0	0	0	0	0	7	0.82
	G	0	0	0	80	0	10	0	0	0	0	0	0.89
	BS	0	0	1	0	87	0	2	0	0	0	0	0.97
	P	0	0	0	0	0	63	0	0	0	0	0	1.00
	A	0	0	0	0	0	0	78	0	2	0	0	0.97
	B	0	0	0	0	0	10	18	26	34	2	0	0.29
	R	0	0	0	0	0	16	15	6	24	3	10	0.32
	W	0	0	0	0	0	4	15	0	10	46	0	0.61
	OW	5	5	21	13	1	0	9	5	3	0	1	0.02

Average PRA =71%

OVA=72%

C:		From Image Classification											
BPNNC		PF	MF	H	G	BS	P	A	B	R	W	OW	PRA
From Reference	PF	77	6	0	0	0	0	0	0	0	4	3	0.86
	MF	5	64	0	0	0	0	0	0	0	0	0	0.93
	H	1	0	72	1	0	0	0	0	0	0	16	0.80
	G	0	3	0	80	0	6	0	0	0	0	1	0.89
	BS	0	0	0	0	90	0	0	0	0	0	0	1.00
	P	0	0	0	0	0	63	0	0	0	0	0	1.00
	A	0	0	0	0	0	0	60	2	7	11	0	0.75
	B	0	0	0	0	0	7	2	39	40	2	0	0.43
	R	0	0	0	0	0	6	8	7	31	11	11	0.42
	W	0	0	0	0	0	0	0	0	10	65	0	0.87
	OW	8	2	17	12	1	0	0	17	3	0	3	0.05

Average PRA =73%

OVA=74%

D:		From Image Classification											
ESC		PF	MF	H	G	BS	P	A	B	R	W	OW	PRA
From Reference	PF	66	14	7	0	0	0	0	0	0	0	3	0.73
	MF	0	56	7	0	0	0	0	6	0	0	0	0.81
	H	26	2	40	0	0	0	0	0	0	0	22	0.44
	G	0	0	12	67	0	8	3	0	0	0	0	0.74
	BS	0	19	14	2	15	0	34	2	0	0	4	0.17
	P	0	0	0	0	0	63	0	0	0	0	0	1.00
	A	0	0	0	0	0	0	79	1	0	0	0	0.99
	B	0	0	0	0	0	4	33	53	0	0	0	0.59
	R	3	1	0	0	0	10	41	15	0	3	1	0.00
	W	0	0	0	0	0	4	18	0	0	53	0	0.71
	OW	4	9	4	3	0	0	11	7	0	0	25	0.40

Average PRA =60%

OVA=59%

E:		From Image Classification											
MLC		PF	MF	H	G	BS	P	A	B	R	W	OW	PRA
From Reference	PF	83	7	0	0	0	0	0	0	0	0	0	0.92
	MF	9	54	0	6	0	0	0	0	0	0	0	0.78
	H	1	0	67	1	7	0	0	0	1	0	13	0.74
	G	0	0	0	83	0	6	0	0	0	0	1	0.92
	BS	0	0	1	0	82	0	7	0	0	0	0	0.91
	P	0	0	0	0	0	63	0	0	0	0	0	1.00
	A	0	0	0	0	0	0	69	0	11	0	0	0.86
	B	0	0	0	1	3	13	6	0	67	0	0	0.00
	R	0	0	0	2	1	16	1	0	42	0	12	0.57
	W	0	6	0	0	0	2	0	0	63	0	4	0.00
	OW	1	1	35	16	0	0	0	0	9	0	1	0.02

Average PRA =61%

OVA=62%

The integrated ESNNC produces the highest overall accuracy of 80 percent as well as the highest producer accuracies (Table 3.3a and Figure 3.3a) when compared to the CSB and three individual classifiers. The CSB yielded an overall accuracy of 72 percent (Table 3.3b and Figure 3.3b); slightly lower than the BPNNC (Table 3.3c and Figure 3.3c) but higher than the ESC (Table 3.3d and Figure 3.3d) and the MLC (Table 3.3e and Figure 3.3e). The BPNNC incorrectly mapped the "water" class in the south-western corner of the study area, but was corrected by the CSB approach. The "built-up area" class output from the CSB exhibits an obviously different pattern compared with the three individual classifiers.

Among the individual classifiers, the BPNNC produced the highest overall accuracy of 74 percent, followed by the MLC with an overall accuracy of 62 percent and the ESC of 59 percent. The BPNNC classification appears similar to the output of the ESNNC. Table 3.4 summarises the overall accuracy, Kappa value and Kappa variance for the different classifiers. The ESNNC has the highest Kappa value and the smallest Kappa variance.

Using the values in Table 3.4, pairwise comparisons (using the Z statistic test) of the three individual and the two combined classifiers show that there are significant differences between the integrated ESNNC and the other four classifiers (Table 3.5). There are also significant differences between the CSB, MLC as well as the ESC.

In summary, the backpropagation neural network classifier (BPNNC) has a higher accuracy than both the traditional maximum likelihood classifier (MLC) and the rule-based expert system classifier (ESC), whilst the combined ESNNC produces the highest mapping accuracy.

Table 3.4 Overall mapping accuracies, Kappa values and Kappa variances from different classifications.

	Overall accuracy	Kappa value	Kappa variance
Integrated expert system and neural network classifier (ESNNC)	0.80	0.78	0.00024
Backpropagation neural network classifier (BPNNC)	0.74	0.71	0.00025
Consensus builder (CSB)	0.72	0.69	0.00026
Maximum likelihood classifier (MLC)	0.62	0.58	0.00031
Expert system classifier (ESC)	0.59	0.55	0.00031

Table 3.5 Z statistics for pairwise comparison between any two of five classifiers: integrated expert system and neural network classifier (ESNNC), consensus builder (CSB), backpropagation neural network classifier (BPNNC), expert system classifier (ESC) and maximum likelihood classifier (MLC).

	ESNNC	BPNNC	CSB	MLC	ESC
ESNNC	-				
BPNNC	3.33 *	-			
CSB	4.27 *	0.94	-		
MLC	8.80 *	5.45 *	4.49 *	-	
ESC	10.17 *	6.77 *	5.80 *	1.26	-

* Significant difference at 95% C.I.

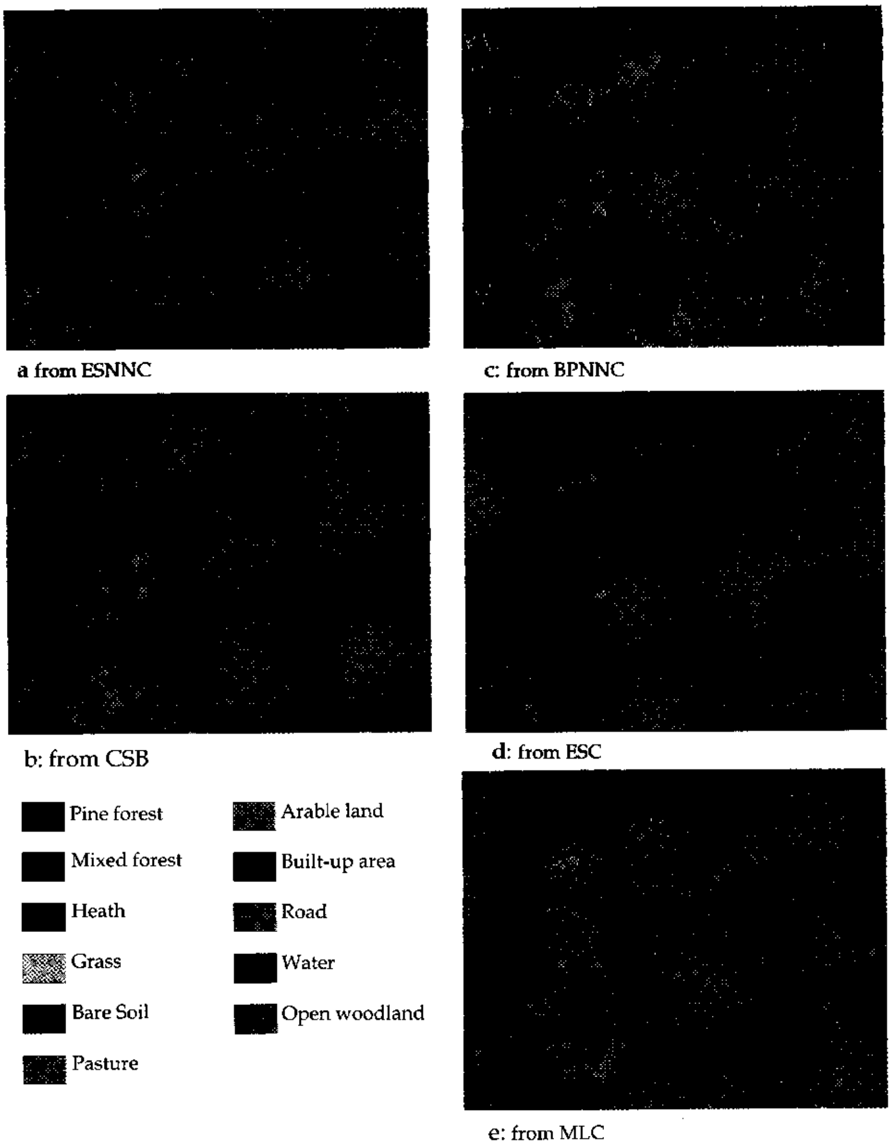


Figure 3.3 Classifier images from the integrated expert system and neural network classifier (ESNNC), consensus builder (CSB), backpropagation neural network classifier (BPNNC), expert system classifier (ESC) and maximum likelihood classifier (MLC).

3.6 Discussion

In this study, two new methods for integrating individual classifiers were developed to improve mapping accuracy. For the CSB, the innovation is to take the producer accuracy of each classified pattern into account. In the ESNNC approach, the novel approach is to use the ESC output as an input layer to the BPNNC (e.g. represented by ESNNC1 in Figure 3.1b). Then, the producer accuracies of the classes produced by the ESC and ESNNC1, as well as the expert rules, were used to classify the ESNNC1 output in order to obtain the final map.

The integrated ESNNC yielded the highest classification accuracy. The improvement in accuracy is attributed to the explicit knowledge of experts. The knowledge assists the neural network classifier in recognising "common-sense" relationships between output class and environmental variables (such as bare soil, open woodland etc) and these relationships form patterns in the final output map. The study also hints that more accurate and reasonable expert knowledge may allow the combined ESC and BPNNC to achieve an even higher mapping accuracy. This might be applied to mapping at Anderson-level-III (e.g. forest types) (Skidmore et al. 1997) and detecting vegetation-based habitat types. Interestingly, the individual ESC classifier has the lowest overall accuracy of 59 percent, perhaps because knowledge remains poor in this study area.

The information from different layers may be "diluted" in the process of classification by multiple classification methods. The classified image with the highest overall accuracy from the initial stage (ESNNC1) was improved by a final-stage correction, based on the output map of the expert system and some additional expert rules, thereby allowing the output patterns and expert rules to be re-emphasised in the final classification. Hutchinson (1982) proposed a similar post-classification technique to that implemented in this case.

The combined CSB obtained an intermediate level mapping accuracy, between the BPNNC and the MLC. The CSB increases the chance for a certain pixel to belong to a certain class when there is an agreement on it between at least two classifiers. Where the three classifiers (BPNNC, MLC, ESC) assign different classes to a pixel, the decision taken based on the producer accuracy is a crisp decision, which may increase the possibility for assigning the correct class to a pixel, but may also cause an error when the overall accuracies of different classifiers have a large difference. This is, probably, a reason for the CSB obtaining an intermediate accuracy compared with the three individual classifiers, indicating that an integrated algorithm may not out-perform an individual classifier (Lu 1996).

The classifiers overestimated the area of the "water" class - for example, it should not appear in the south-western corner of Figure 3.3c as well as in many places in the eastern side of the classified images (Figure 3.3-a, b, d). One possible explanation could be that there is a high water table in the flood plain, reducing the DN values of the remotely sensed images.

Both the ESC and BPNNC are more "expensive" algorithms than for example the classical MLC. The ESC requires time to extract and tune the knowledge in order to create rule bases, while the BPNNC requires hefty computer resources to train the system with the different configurations. Although both techniques have been criticised on this aspect, we explored the advantages of combining these techniques.

3.7 Conclusions

The classifiers tested in this study perform differently, and produce different classifications. The integrated approach, ESNNC, achieved the highest mapping accuracy and is significantly better than the integrated consensus builder classifier and the other three individual classifiers. It may be concluded that incorporating expert knowledge improves the classification accuracy of the neural network.

Acknowledgements

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CHAPTER 4

Mapping the Giant Panda Habitat Using an Integrated Expert System and Backpropagation Neural Network Classifier

Panda winter habitat
Photo: Xuehua Liu

Panda summer habitat
Photo: Xuehua Liu

CHAPTER 4 Mapping the Giant Panda Habitat Using an Integrated Expert System and Backpropagation Neural Network Classifier *

Abstract:

For effective panda conservation, it is important to be aware of the extent and change over time of the spatial pattern of panda habitats. Mapping is an effective approach for wildlife habitat evaluation and monitoring. Little work has been done to map panda habitat with remote sensing and geographic information system (GIS). The application of recently developed artificial intelligence tools, including the expert system approach and the neural network approach, may have an impact on panda habitat mapping. Both allow the integration of qualitative and quantitative information for modelling complex systems and can be built into a GIS. This research builds, for the first time, a mapping approach for panda habitat assessment which integrates expert system and neural network classifiers and uses multi-type data within a GIS environment. Results show that both the ground-cover-based potential panda habitat and the suitability-based panda habitat in Foping Nature Reserve are mapped with higher accuracy (above 80%) compared with non-integrated classifiers: expert system, neural network as well as maximum likelihood algorithms. Z-statistic test shows that the integrated expert system and neural network classifier (ESNNC) is significantly better than those non-integrated classifiers.

Key words: expert system, neural network, remote sensing, GIS, integrated mapping algorithm, spatial analysis, panda habitat, Foping Nature Reserve, China.

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1. This chapter is based on Liu, X., M. C. Bronsveld, A. K. Skidmore, T. Wang, G. Dang, and Y. Yong. (in review-b). Mapping the giant panda habitat using an integrated expert system and neural network algorithm. International Journal of Geographical Information Science.

2. Part of this work was presented at Panda 2000 Conservation Priorities for the New Millennium - An International Conference in San Diego, US, October 15-18, 2000. The presented title: Mapping panda habitat suitability.

4.1 Introduction

Habitat is any spatial unit that can be occupied by an individual animal, no matter how briefly (Baker 1978). The condition of wildlife habitat types influences the species' distribution and performance, therefore, wildlife habitat evaluation has become a part of world biodiversity research as reflected by Miller's book (1994). Wildlife habitat evaluation requires recognising the environmental factors which relate to the organism under consideration, and generally includes four main research fields: habitat availability (Scepan et al. 1987, Sader et al. 1991) and utilisation (Johnson 1980, Augustine et al. 1995), habitat spatial pattern (Gustafson et al. 1994) and fragmentation (Tabarelli et al. 1999), habitat suitability rating (Prasad et al. 1991, Roy et al. 1995, Amuyunzu and Bijl 1996), and habitat change detection (Sader et al. 1991, Prasad et al. 1994).

Wildlife habitat mapping is an important aspect in these research fields. Mapping various wildlife habitat types provides data for inventory and analysis, and so provides the habitat manager with information for monitoring (Kerr 1986). There are several purposes to map wildlife habitat in wildlife habitat management (Cooperrider et al. 1986): to show geographic locations and relationships of wildlife habitat types; to show community (types of habitat) interspersion; to quantify wildlife habitat types; to overlay wildlife habitat types with other resource inventories; and to provide geographic locations to record site-specific animal occurrence and use. Wildlife habitat mapping is similar to any type of land cover mapping (De Wulf et al. 1988). For instance, Thompson et al. (1980) mapped the caribou's habitat through delineating broad vegetation cover types, and Ferguson (1991) mapped the most important summer foraging habitat for muskoxen including the wet sedge meadow, graminoid tundra and graminoid/dwarf shrub tundra cover types.

The giant panda (*Ailuropoda melanoleuca*) is an endangered animal species and surviving now in only six mountain regions in China. Over time, its forest-environment habitat has been reduced and fragmented. Although the shrinking of the panda's range is partially the result of climatic changes during the Pleistocene epoch, it has mostly been caused by people (Schaller 1993, Schaller et al. 1985, WNR and SNU 1987). The economic development and population explosion in China has increased the loss of panda habitat. Mapping of forest cover, by MacKinnon and De Wulf (1994), showed that the area of potential panda habitat in Sichuan has shrunk from 20,000 km^2 in 1974 to only 10,000 km^2 in 1988. The situations in Gansu and Shanxi are similar (MOF and WWF 1989). For effective panda conservation, it is important to know the current panda habitat and its changes. Restoration of lost panda habitat may be impossible, but the remaining panda habitat can be maintained and protected. De Wulf et al. (1988) emphasised that, in the long term, the creation of a digital panda habitat database and a panda habitat monitoring system would provide useful tools for efficient conservation management.

Remote sensing (RS) and geographical information systems (GIS) are two suitable techniques for analysing, monitoring and managing the earth resources (Al-Garni

1996). The need for relatively quick and potentially less expensive ways to compile habitat information has led to the use of satellite data (Ormsby and Lunetta 1987), and, with the aid of a GIS, to reproduce or update surveys and to manipulate the data to illustrate relatively complex spatial habitat relationships (Wheeler and Ridd 1984). GIS has been applied in panda habitat research (Ren et al. 1993, Ouyang et al. 1996, Liu et al. 1997 and 1998, and Chen et al. 1999). The importance of integrating RS and GIS has been realised by many scientists who explored and applied this approach to wildlife habitat evaluation (Scepan et al. 1987, Tappan et al. 1991, Roy et al. 1995, Amuyunzu and Bijl 1996). However, application of remote sensing techniques to wildlife habitat mapping is still a developing field (Li 1990). Panda habitat research based on RS is even more limited.

Obtaining information relating to panda habitat in an effective way is a key area of research at present. In most cases, the panda habitat information has been acquired from ground surveys. During the past two national panda censuses in 1974-1977 and 1985-1988, mapping panda habitat (such as cover types, extent, panda locations) was done mainly based on topographic maps and ground surveys. It is clear that such ground surveys in a mountainous terrain covered by dense forests are time consuming and labour intensive. In such circumstances, RS is undoubtedly the most efficient way to acquire habitat information quickly and at low cost, and the repetitive coverage by satellite systems adds a temporal dimension to habitat mapping (De Wulf et al. 1988). The multispectral and multitemporal imagery can provide much information about land cover and be used for mapping wildlife habitat (Roy et al. 1986, Ferguson 1991, Prasad et al. 1991). Although RS data have been applied to panda habitat assessment in a few panda nature reserves, the assessments were implemented mostly based on visual interpretation (Morain 1986, De Wulf et al. 1988 and 1990, Ren 1989, Chui and Zhang 1990, Li 1990, Ren et al. 1993, MacKinnon and De Wulf 1994). The disadvantage is that visual interpretation of the remotely sensed images brings subjectivity into defining the boundaries between different land cover types, therefore, a different interpreter may produce a different land cover classification.

However, in digital image analysis, conventional methods do not yield satisfactory classification results at the forest type level, and it is difficult to get an accurate map using conventional classification methods for mapping the forest types (Skidmore 1989, Skidmore et al. 1997). Hollander et al. (1994) mentioned that a new integrated approach joined with an artificial intelligence (AI) system was expected to be applied to wildlife habitat evaluation. The application of AI tools and techniques may have an impact on mapping the forest types, since learning procedures could be built into a GIS to help it adapt to the imprecise and voluminous nature of geographically-based data as the system acquires knowledge about the phenomenon (Peuquet et al. 1993). Such an integrated RS/GIS/AI can deal with a large amount of data input, like image data, field survey data, and radio-collar data used in this study. In general, AI includes both expert systems and neural networks. Expert systems allow integration of qualitative and quantitative information for modelling and handling complex systems (Davis 1993), which have been used for mapping forest types (Skidmore 1989) as well as identifying homogeneous training areas for analysis of remotely sensed imagery (Goodenough et al. 1987). Neural networks have been successfully used in image processing and classification (Zhuang et al. 1994). According to Skidmore et al. (1997), the neural network backpropagation algorithm will probably not become a significant classification and analysis tool for GIS and remotely sensed data when implemented as a pure neural network. However, it may be very useful when combined with the rule-based expert system.

This study maps and assesses the complicated panda habitat by using an integrated expert system and neural network classifier (ESNNC). The aim of ESNNC is to integrate effectively the remote sensing data (Landsat TM images), the environmental data (digital elevation, slope gradient and aspect), the ground data (survey plot data and radio-tracking data) and the expert knowledge in order to map panda habitat and extract habitat information with a high accuracy. The approach used for mapping panda habitat in this study is an empirical method. Two categories of panda habitat types will be mapped, namely ground-cover-based panda habitat types and suitability-based panda habitat types which are described in the Method section.

4.2 Study area

Figure 4.1 shows study area: Foping Nature Reserve. It covers about 290 km^2. Its detail is described in Chapter 1, such as its location in China and terrain (Figure 1.3) and its climatic conditions (Figure 1.4). The typical vegetation types are conifer forests, mixed conifer and broadleaf forests, deciduous broadleaf forests, shrub and meadow (Ren et al. 1998, CVCC 1980). There are two main bamboo species that are important for panda forage: *Bashania fargesii* and *Fargesia spathacea* (Pan et al. 1988, Tian 1989 and 1990, Yong et al. 1994, Ren et al. 1998). The *Bashania* bamboo generally grows in the area below 1900 m, and the *Fargesia* bamboo in the area above 1900 m. The panda population is between 60 and 70 with an average density of one panda per 5 km^2 according to the survey in 1990 (Yong et al. 1993), and the spatial distribution of panda populations is shown in Figure 1.5. About 300 local people reside inside the nature reserve (from data of 1998) and are mainly living in five village groups: SanGuanMiao, XiHe, JieShang, XiaHe and DaChenHao (Table 1.1). Some other village groups are located just outside the southern boundary of the nature reserve.

4.3 Methods

In the study, two categories of panda habitat types were produced: ground-cover-based potential panda habitat types and suitability-based panda habitat types. The former is defined by the ground cover types including: (1) conifer forest, (2) mixed conifer and broadleaf forest, (3) deciduous broadleaf forest, (4) bamboo groves (or mixed with the shrub-meadow), (5) shrub-grass-herb land, (6) farm-lands and settlements, (7) rock and bare-land, and (8) water area. The suitability-based panda habitat types include: (1) very suitable summer habitat, (2) suitable summer habitat, (3) very suitable winter habitat, (4) suitable winter habitat, (5) transition habitat, (6) marginal habitat, (7) unsuitable habitat, and (8) water area.

In the next section, the mapping algorithms, including the ESNNC and several other classifiers, are firstly explained. Secondly, it is explained how the ESNNC was applied to map the ground-cover-based potential panda habitat types by using Landsat TM images and field survey plot data. Lastly, how the same algorithm was used to map the suitability-based panda habitat types through combining Landsat TM images, field survey plot data, radio-tracking data and social data is described.

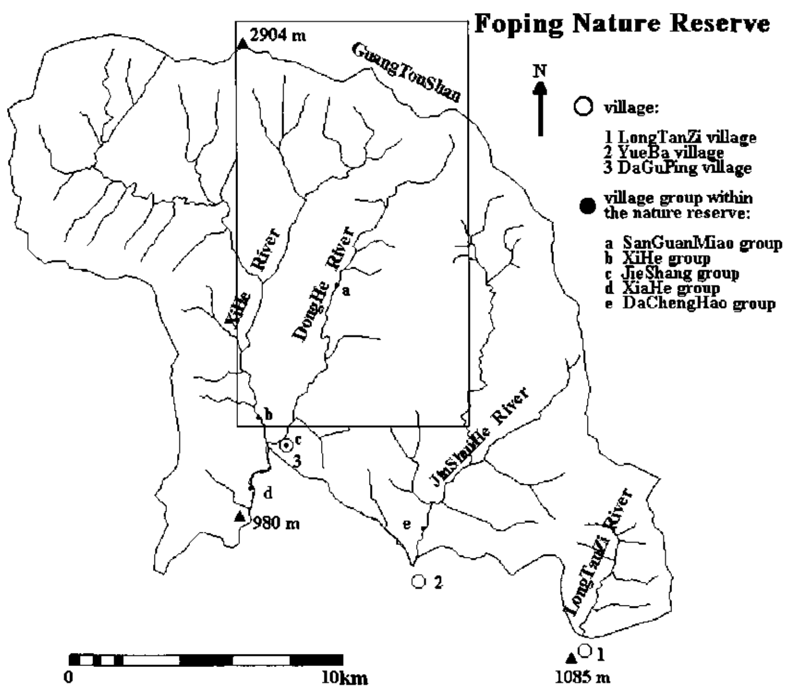

Figure 4.1 Study area: Foping Nature Reserve, China. The box in the map shows the area of radio tracking applied to six pandas.

4.3.1 Algorithm of the integrated expert system and neural network classifier

The two types of panda habitat mentioned above were produced by the ESNNC described in Chapter 3 and Liu et al. (1999). Different input data layers and training sample points were used in two different mapping. For comparison purposes, three individual classifiers were applied, which are the expert system classifier (ESC), the backpropagation neural network classifier (BPNNC), and the traditional maximum likelihood classifier (MLC). The whole mapping approach is shown in Figure 4.2. The BPNNC learns from the training sample data and so depends on the accuracy of the information the sample data set provides. However, expert knowledge in the ESC was extracted from the sample data sets based on the impression of data distributions in different classes and on the field survey experience, but no training sample data were used for image processing. Therefore, the ESC is a sample-free method.

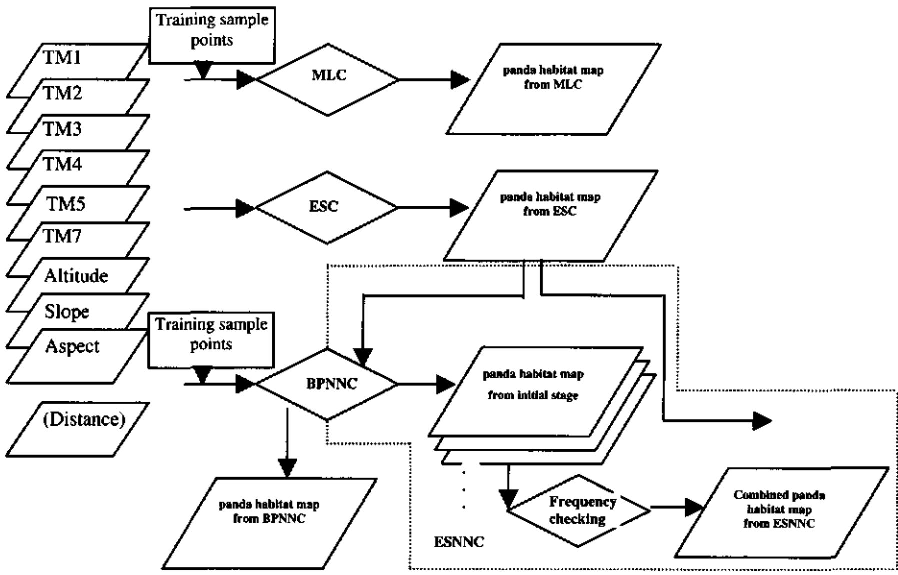

Figure 4.2 An integrated expert system and neural network classifier (ESNNC) for mapping both the ground-cover-based potential panda habitat types and the suitability-based real panda habitat types. "TM1-5 and 7" represents Landsat TM image bands 1-5 and 7. "Distance" represents the distance map to the human activity area which is used only in mapping the suitability-based panda habitat types. MLC, ESC, BPNNC and ESNNC are four classifiers: maximum likelihood classifier, expert system classifier, neural network classifier and integrated expert system and neural network classifier.

The ESNNC approach integrates the ESC and the BPNNC, and trains the whole system to reach the targets through learning from known samples. The ESC result contains very useful information and is used in the BPNNC before and after running the system. The initial stage of the ESNNC (namely inputting the output of the ESC into the BPNNC as an additional information layer) is based on the principle that the neural network system is very sensitive to subtle changes in the input data. The system was then trained by different sample sets (described in the later parts) and resulted in several output maps. A frequency-checking program was used to compare all output maps in order to obtain the majority class for one certain pixel and assign that pixel with the majority class. Thus, the combined habitat map was formed. The second stage is to use the output of the ESC through producer accuracy and some new built-in rules based on the expert knowledge to correct the output of the initial stage of the ESNNC. For example, the winter panda habitat should not occur in the high elevation area and the slope steepness of suitable panda habitat should not be greater than 35 degrees based on the definitions of the classes. For three individual classifiers (e.g. BPNNC, ESC and MLC), only one-time classification using one of the training sample sets was carried out.

4.3.2 Mapping the ground-cover-based potential panda habitat types

The mapping approach is shown in Figure 4.2. The assumptions are that the images can reflect the ground cover conditions, and that field sample plots with measured habitat parameters or observed information, according to Doering III and Armijo (1986), are capable of reflecting habitat conditions.

In this approach the sample point data consists of 160 points (Figure 4.3) with records of the ground cover types from field survey. The field survey was carried out in July and August of 1999 being concurrent with the Landsat TM images acquired in July 1997. The line transect sampling method was adopted in the field survey in order to get as many habitat types within the shortest route as possible. The eight ground cover types were defined based on literature information (Ren et al. 1998, CVCC 1980), and pre-classification of the images. They are conifer forest (cf), mixed conifer and broadleaf forest (dbfcf), deciduous broadleaf forest (dbf), mixed bamboo and meadow (bam), shrub-grass-herb land (shgr), farm-lands and settlements (fas), rock and bare-land (rab), and water area (war).

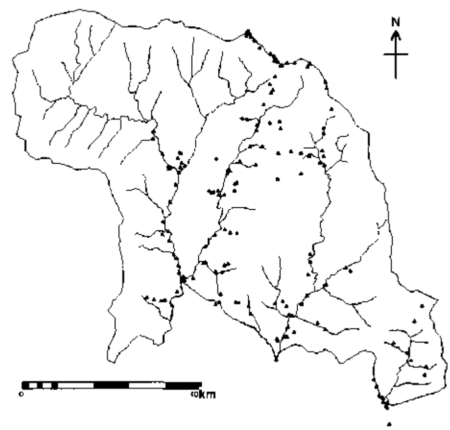

Figure 4.3 Distribution of 160 sample points in Foping Nature Reserve, China.

For image classification, the stratified random sampling strategy was applied to 160 sample points in order to get random training and testing samples for each class. Therefore, 50 samples were randomly selected from 160 points first as a separate testing set and 80 training samples were again randomly selected from the remaining 110 points (shown in Table 4.1a). The classification of ground-cover-based habitat types was carried out 15 times with the 15 different randomly-selected training sets by the ESNNC. All the classified outputs were tested by the same 50 testing points to assess mapping accuracy.

The nine initial data layers, including remote sensing data (Landsat TM band 1 to 5 and 7, acquired in July 1997) and terrain data (elevation, slope steepness, slope aspect), were used in mapping by ESC, BPNNC, ESNNC as well as the traditional MLC. Figure 4.4a gives examples of how the expert knowledge about the eight ground cover types was extracted from survey data.

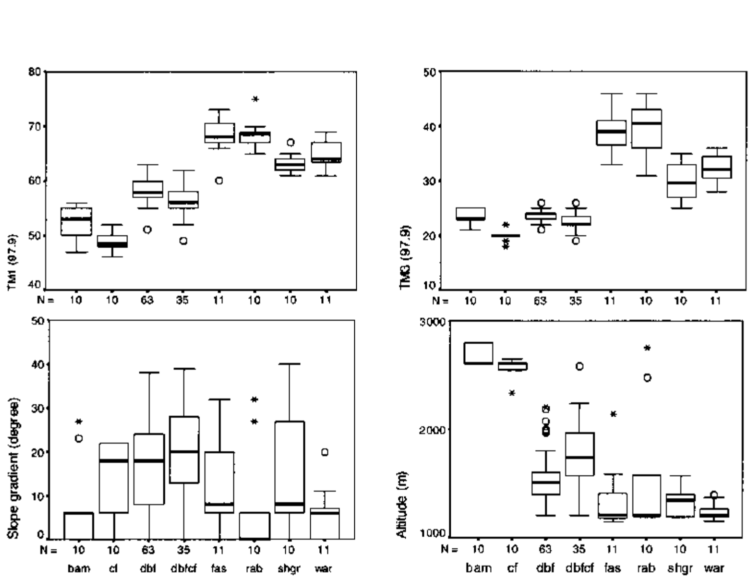

Figure 4.4a Boxplots show data distributions in 8 ground-cover-based potential panda habitat types in Foping Nature Reserve: conifer forests (cf), mixed conifer and broadleaf forests (dbfcf), deciduous broadleaf forests (dbf), bamboo grove (or mixed shrub-meadow) (bam), man-made shrub-grass-herb land (shgr), farm-lands and settlements (fas), rock and bare-land (rab), water area (war). "N" represents the number of samples.

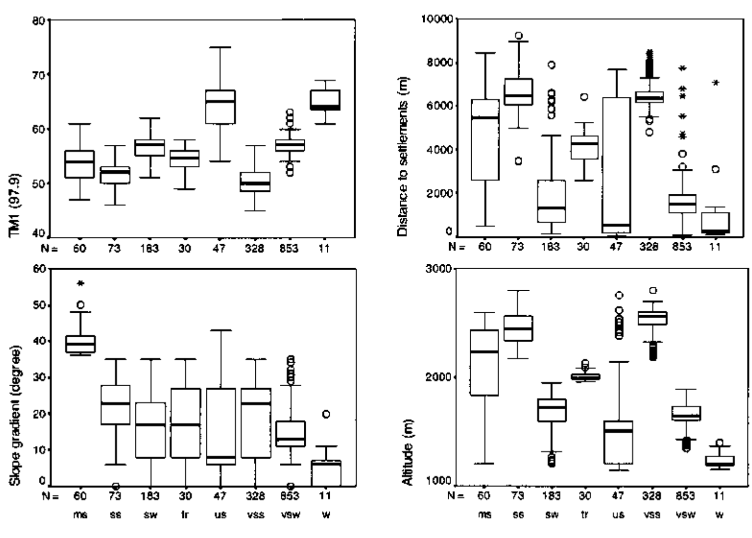

Figure 4.4b Boxplots show data distributions in 8 suitability-based real panda habitat types in Foping Nature Reserve: very suitable summer habitat (vss), suitable summer habitat (ss), very suitable winter habitat (vsw), suitable winter habitat (sw), transitional habitat (tr), marginal habitat (ms), not suitable habitat (us) and water area (war). "N" represents the number of samples.

Table 4.1 Stratified random sampling for mapping ground-cover-based (a) and suitability-based (b) panda habitat types in Foping Nature Reserve, China.

a: for mapping ground-cover-based potential panda habitat types through 160 sample points

Class name	Total collected samples	Testing samples	Selected training samples	Remaining samples
conifer forest	10	4	4	2
mixed conifer and broadleaf forest	35	9	20	6
deciduous broadleaf forest	63	17	34	12
bamboo (or mixed with meadow)	10	4	4	2
shrub-grass-herb land	10	4	4	2
farm-lands and settlements	11	4	5	2
rock and bare-land	10	4	4	2
water area	11	4	5	2
Total	160	50	80	30

b: for mapping suitability-based panda habitat types through 1585 sample points

Class name	Total collected samples	Testing samples	Selected training samples	Remaining samples
very suitable summer habitat	328	150	150	28
suitable summer habitat	73	30	30	13
very suitable winter habitat	853	376	377	100
suitable winter habitat	183	80	80	23
transitional habitat	30	14	14	2
marginal habitat	60	25	25	10
unsuitable habitat	47	20	20	7
water area	11	5	4	2
Total	1585	700	700	185

4.3.3 Mapping suitability-based panda habitat types

The same approach was used (Figure 4.2) for mapping the suitability-based panda habitat types. Suitability of panda habitat was assessed and mapped based on both the field survey data and radio tracking data. The assumptions are that the sites with a lot of feeding signs and droppings are suitable habitats with satisfactory environmental requirements to pandas, and radio tracking data are capable of reflecting habitat selection of the giant pandas.

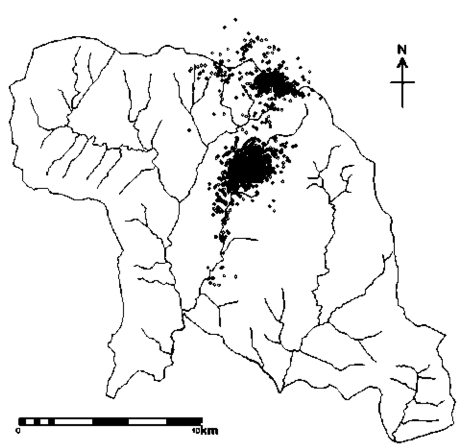

Figure 4.5 Distribution of radio tracking data in Foping Nature Reserve, China.

Therefore, mapping the suitability-based panda habitat types involved a total of 1585 sample points including

160 field survey points and 1425 non-overlapping radio tracking points (Figure 4.5). When panda signs (feeding, dropping, and nesting) were evident, these were recorded for all 160 field-survey points. There were six pandas collared in the SanGguanMiao area (illustrated by the box in Figure 4.1) during a five-year period from 1991 to 1995 (for details see Chapter 5). The triangulation method by using two bearings was used to calculate the collected radio-tracking data to establish the panda locations (White and Garrott 1990).

Table 4.2 The criteria to define suitability-based panda habitat types to the sample points for mapping in Foping Nature Reserve, China.

Criteria for 8 suitability classes		vsw[a]	sw	tr	vss	ss	ms	us	war
Elevation (m)		≥ 2158		1949-2158	≤ 1949				
Panda signs		many	pre-sent		many	pre-sent			
Slope (°)		≤ 35	≤ 35		≤ 35	≤ 35	> 35		
Ground cover-based habitat types								fas[b] rab shgr	war
Distance[3] to the centre of summer activity ranges (m)					≤1000	>1000			
Distance[c] to the centre of winter activity ranges (m)	005 & 043[d]	≤1500	>1500						
	127 & 065	≤1300	>1300						
	045 & 083	≤1000	>1000						
Distance to the centre of mating activity ranges (m)	043	≤500	>500						
	045	≤1000	>1000						

a vss, ss, vsw, sw, tr, ms, us and w represent 8 suitability-based panda habitat types: very suitable summer habitat, suitable summer habitat, very suitable winter habitat, suitable winter habitat, transitional habitat, marginal habitat, unsuitable habitat and water area.

b fas, rab, shgr and war represent four ground-cover-based panda habitat types: farm-lands and settlement, rock and bare-land, shrub-herb-grass land and water area.

c "Distance to the centres of panda activity ranges" is described in Chapter 5.

d 005 to 127 refer to identity codes of individual pandas (see Chapter 5).

There are no standard methods for defining or quantifying habitat quality because this depends very much on species as well as study population and study area. The suitability types were defined by several criteria (Table 4.2): the panda signs found at field survey points, distance to the centres of the winter, summer and mating activity ranges of each panda (see Chapter 5), terrain factors (i.e. elevation and slope), as well as ground cover types. Eight types of suitability-based panda habitat were subjectively defined: very suitable summer habitat (vss), suitable summer habitat (ss), very suitable winter habitat (vsw), suitable winter habitat (sw), transitional habitat (tr), marginal habitat (ms), unsuitable habitat (us), and water area (war). Therefore, all 1585 sample points were subjectively assigned to one of the suitability classes based on the criteria.

Similar to mapping the ground-cover-based panda habitat types, the stratified random sampling strategy was applied for a total of 1585 points in order to obtain random training and testing samples for each class. Therefore, 700 samples were initially taken out as an independent testing set and the remaining 885 points were used to select 700 training samples randomly (Table 4.1b). The classification was carried out 15 times here using 15 different randomly-selected training sets. All outputs were tested by the same 700 independent testing points to assess mapping accuracy.

There are ten digital data layers used as the initial information source of the whole classification system: remote sensing data (Landsat TM band 1 to 5 and 7), terrain data (elevation, slope steepness, slope aspect) and social data (distance to human activity area). Figure 4.4b shows examples of how the expert knowledge about these eight suitability-based habitat types was extracted from the sample point data.

4.4 Results

The map of ground-cover-based potential panda habitat types obtained from the ESNNC is shown in Figure 4.6. Foping NR is mainly covered by deciduous broadleaf forests and mixed conifer and broadleaf forests. Conifer forests and *F. spathacea* bamboo groves or mixed with meadow occur along the mountain ridges around the boundary area in the northern and north-western parts. The rock and bare-lands appear mostly in two areas, at the mountaintops or in the river valleys. The shrub-grass-herb land was mapped mainly in the lower elevation area along the valleys, which is mainly caused by human activity. However, it was also found scattered in the high elevation area, especially along the mountain ridges, which is naturally developed. The farm-lands mostly appear in YueBa and LongTanZi villages, which are generally located outside the southern boundary of the nature reserve. Areas with water are located in the valleys.

Table 4.3a gives the areas of 8 different ground-cover-based potential panda habitat types from GIS calculation. The total area of rock and bare-land, shrub-grass-herb land, farm-lands and settlements, and water area occupy only a very small part of the whole nature reserve (about 3%). The area of *F. spathacea* bamboo groves mixed with meadow located at or near the mountaintops is less than 1% of the size of Foping NR. However, the other areas are covered by deciduous broadleaf forests, mixed conifer and broadleaf forests, and conifer forests.

The map of suitability-based panda habitat types obtained from the ESNNC is shown in Figure 4.7. The suitable and very suitable summer habitats are found in the area surrounding Foping NR, and they occur mainly in the northern, northwestern and northeastern boundaries. The very suitable summer habitat occupies only a small part of the total summer habitat in GuangTouShan. The suitable and very suitable winter habitats are mainly mapped in the centre and southern areas together with the human activity areas. There is a transition zone between the pandas' two seasonal habitats, which is very wide in the northeastern area. The marginal habitats with a slope gradient steeper than 35 degrees are scattered in the regions of XiHe River, DaChengHao and the southern slope of GuangTouShan. Only a small part of the nature reserve is not suitable for pandas, including rock and bare-lands (rab), farm-lands and settlements (fas), shrub-herb-grass land (shgr). Unsuitable areas (namely "rab", "fas" and "shgr") are located at the mountaintops or in the river valleys.

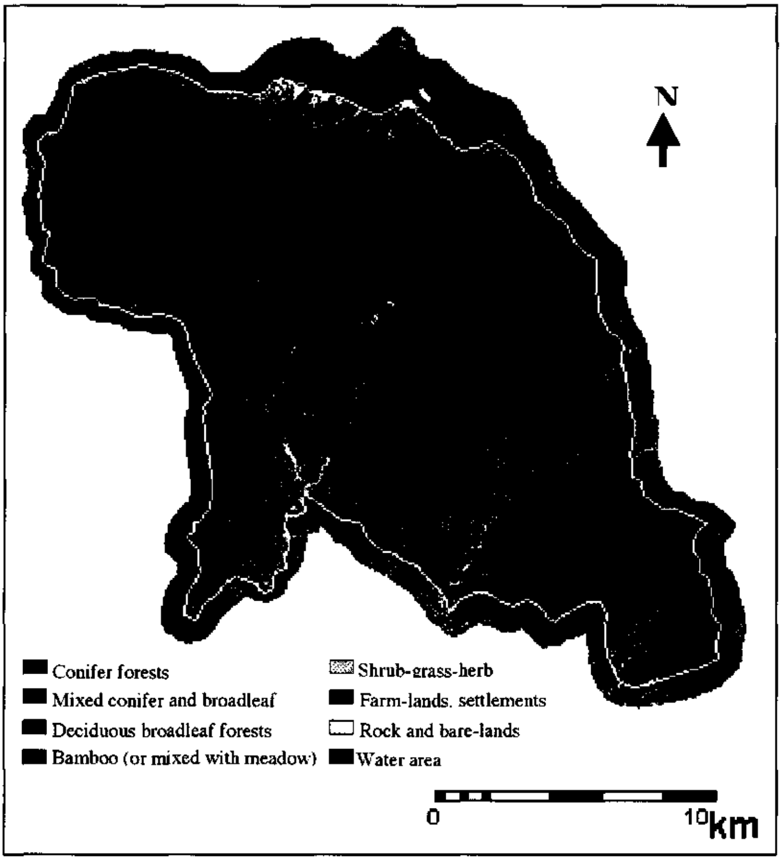

Figure 4.6 Ground-cover-based potential panda habitat map from the integrated expert system and neural network classifier (ESNNC) in Foping Nature Reserve, China. The white line gives the boundary of the Foping Nature Reserve. The area outside the boundary shows the surrounding environment.

Table 4.3 Availability of different panda habitat types mapped from the integrated expert system and neural network classifier (ESNNC) in Foping Nature Reserve, China.

a: Availability of ground-cover-based potential panda habitat types

	Area (km²)	% of the nature reserve
conifer forest	16.5	5.6
mixed conifer and broadleaf forest	174.2	59.4
deciduous broadleaf forest	92.0	31.4
bamboo (or mixed with meadow)	1.7	0.6
shrub-grass-herb land	6.0	2.0
farm-lands and settlements	0.4	0.1
rock and bare-land	1.6	0.5
water area	1.0	0.3
Foping Nature Reserve	293	100

b: Availability of suitability-based panda habitat types

	Area (km²)	% of the nature reserve
very suitable summer habitat	16.6	5.7
suitable summer habitat	29.3	10.0
very suitable winter habitat	64.9	22.1
suitable winter habitat	88.4	30.1
transitional habitat	57.4	19.6
marginal habitat	31.4	10.7
unsuitable habitat	4.6	1.7
water area	0.7	0.2
Foping Nature Reserve	293	100

Table 4.3b details the suitability-based habitat types. More than 50% of the Foping NR consists of panda winter habitat, in which almost half of the area is very suitable for pandas to stay in the winter season. The panda summer habitat is less than 20% of the reserve. The transitional habitat occupies almost one fifth of the nature reserve, and the marginal habitat together with the unsuitable habitat is less than 13% of Foping NR. The identified "water area" is almost the same as the "war" identified in mapping the ground-cover-based panda habitat.

To assess the four classifiers and their classification results in mapping the two different defined panda habitat systems, the number of identified classes, the overall mapping accuracy (OVA), the Kappa value and the Kappa variance are shown in Table 4.4. The traditional maximum likelihood classifier did not yield satisfactory classification results for panda habitat mapping. The MLC recognises only three classes in mapping the ground-cover-based potential panda habitat types and seven classes in mapping the suitability-based panda habitat types. Only the classes with enough samples can be identified by the MLC because insufficient samples cannot form the statistical parameters for the MLC to run the classification.

The integrated expert system and neural network classifier (ESNNC) produced panda habitat maps with the highest mapping accuracy (*viz.* 84% in mapping the ground-cover-based potential panda habitat types and 83% in mapping the suitability-based real panda habitat types), and its classification error matrices are shown in Table 4.5. In mapping the ground-cover-based panda habitat types, the ESC created an overall accuracy of 76%, higher than that of the BPNNC (70%). In mapping the suitability-based panda habitat types, the ESC created an overall accuracy of only 48%, lower than that of the BPNNC (76%).

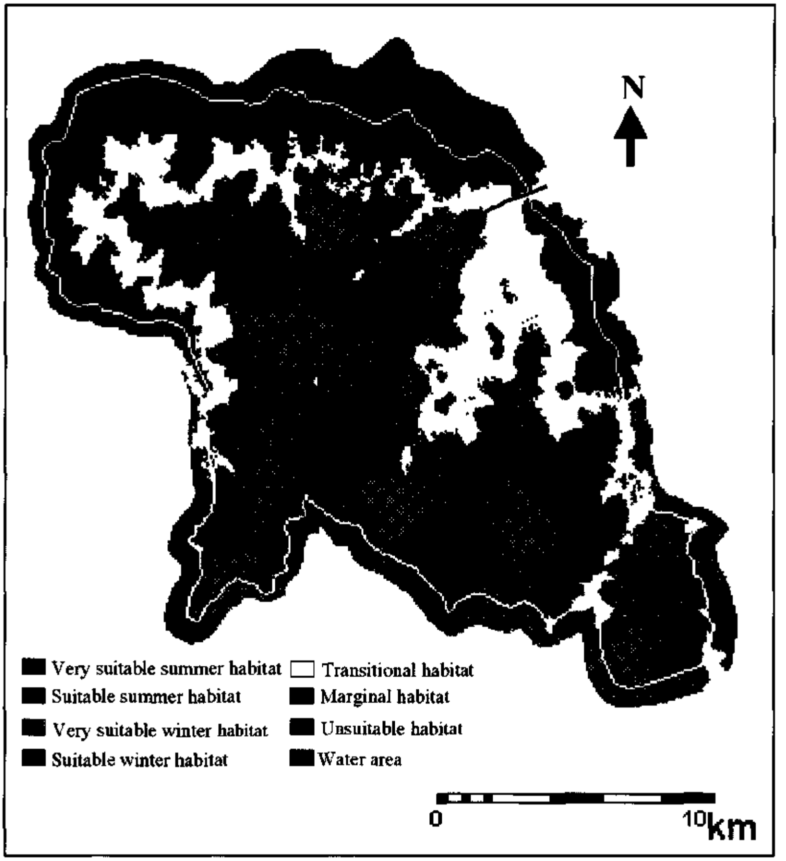

Figure 4.7 Suitability-based panda habitat maps from the integrated expert system and neural network classifier (ESNNC) in Foping Nature Reserve, China. The white line gives the boundary of the Foping Nature Reserve. The area outside the boundary shows the surrounding environment. The black arrow line shows the path used by local people and tourists move between the SanGuanMiao village group and outside of Foping NR.

Pairwise comparison between the ESNNC and the BPNNC as well as the ESC, which have identified all 8 classes, is also shown in Table 4.4. The values from Z-statistic in the table show that the ESNNC does not produce the ground-cover-based habitat map with significantly better accuracy than the ESC but significantly better than the BPNNC at 90%C.I.. However, in mapping the suitability-based habitat types, the ESNNC created a significantly higher accuracy than the ESC and the BPNNC at 95%C.I..

Table 4.4 Accuracy assessment and pairwise comparison through Z statistic between the integrated expert system and neural network classifier (ESNNC) and the other four classifiers respectively (i.e. the neural network classifier (BPNNC), the expert system classifier (ESC) and the maximum likelihood classifier (MLC)) in mapping panda habitat types in Foping Nature Reserve, China.

Mapping Types	Classifiers	Number of identified classes	OVA (%)	Kappa value	Kappa variance	Z statistic
Mapping ground-cover-based panda habitat types	ESNNC	8	84	0.801	0.0041	
	BPNNC[a]	8	70	0.622	0.0066	1.73*
	ESC	8	76	0.703	0.0055	1.00
	MLC	3	NM	NM	NM	NM
Mapping suitability-based panda habitat types	ESNNC	8	83	0.742	0.0004	
	BPNNC[a]	8	76	0.640	0.0005	3.25**
	ESC	8	48	0.358	0.0005	12.72**
	MLC	7	NM	NM	NM	NM

a - a single running of BPNNC; * - significant difference at 90%C.I., ** - significant difference at 95%C.I. "NM" means "not mentioned" because the MLC did not identified all 8 classes in both mapping.

Table 4.5 Classification error matrices for mapping ground-cover-based (a) and suitability-based (b) panda habitat types by the integrated expert system and neural network classifier (ESNNC) in Foping Nature Reserve, China.

a: mapping ground-cover-based potential panda habitat types

		From classification							
		cf	dbfcf	dbf	bam	shgr	fas	rab	war
From testing samples	conifer forest (cf)	**3**	1						
	mixed conifer and broadleaf forest (dbfcf)		**7**	2					
	deciduous broadleaf forest (dbf)		1	**16**					
	bamboo (or mixed with meadow) (bam)				**4**				
	shrub-grass-herb land (shgr)			1		**2**	1		
	farm-lands and settlements (fas)						**2**	2	
	rock and bare-land (rab)							**4**	
	water area (war)								**4**
									Overall accuracy=84.00%

b: mapping suitability-based panda habitat types

		From classification							
		vss	ss	tr	sw	vsw	ms	us	war
From testing samples	very suitable summer habitat (vss)	**132**	18						
	suitable summer habitat (ss)	19	**10**					1	
	transitional habitat (tr)			**14**					
	suitable winter habitat (sw)				**45**	35			
	very suitable winter habitat (vsw)				36	**333**		2	
	marginal habitat (ms)						**25**		
	unsuitable habitat (us)		1	1	1		3	**14**	
	water area (war)								**5**
									Overall accuracy=83.17%

4.5 Discussion

This study mapped and assessed panda habitat in Foping NR using remote sensing data combined with radio-tracking data, ground survey data and human influence data by GIS. Mapping results objectively show the reserve maintains a good quality habitat for pandas. Ground-cover-based mapping shows that 97% of the nature reserve area is covered with forest which forms pandas' potential habitat. Suitability-based mapping shows that 68% of the reserve area is suitable habitat for pandas in winter or summer season and 20% of the reserve area forms the transition habitat for pandas to move between two seasonal habitats. It is also shown that the XiHe and DongHe River regions are ideal panda habitat with easy landscape connection between the winter and summer habitats, in which the transition zone exists but is not as wide as the large transition area in the northeastern part. In reality, the 1990's survey showed that the panda population in the DongHe and XiHe Rivers consisted of 26 and 23 individuals respectively (Yong et al. 1993), which were two larger panda sub-populations in Foping NR. The wider transition zone represents the comparatively flat area which takes pandas more time to pass through under adverse environmental conditions. Since the transition zone lacks well-growing bamboo, the pandas were assumed to select a transition zone with a less steep slope and suitable width in order to move between their winter and summer habitats. Pandas in the LongTanZi and YueBa areas probably need more time to move between two seasonal habitats.

The total suitable summer habitat within the reserve boundary is limited, about 46 km^2 (16% of the reserve area), which is not sufficient for the requirement of a total of about 60 to 70 pandas from the panda survey in 1990 (Yong et al. 1993). The neighbouring area of Foping summer habitat outside the boundary forms another important part of the panda summer habitat. The 6 radio-collared pandas moved along the ridge of the GuangTouShan in the summer season and used the summer habitats both inside and outside of the reserve boundary, which is shown in Figure 5.2. The average summer activity range of each panda was calculated in that paper and is about 2.5 km^2.

Therefore, maintaining the limited summer habitat and keeping its continuity is important for pandas. There is a path in the northeastern corner, where the transition area crosses the boundary (as shown by arrow in Figure 4.7), for local people and also tourists to move between the SanGuanMiao village group and outside of Foping NR. The local government plans to construct a tourist site in LianFengYa (near CunGou PS as shown in Figure 1.5) in the northeastern corner for tourists to visit SanGuanMiao. The path goes through the very suitable winter habitat patch before reaching SanGuanMiao. This is highly detrimental for pandas living in this area. Moreover, the summer habitat in the northeastern corner appears as a narrow strip along the mountain ridge and is used as the limited summer habitat or necessary corridor for pandas in LongTanZi and YueBa to move to the larger summer habitat in GuangTouShan.

The explored mapping approach in this study may be applied to detect and monitor the change of pandas' forest environment. There has been a natural resource conflict between the local people and the giant pandas in terms of forest environment, especially in the low elevation areas. As shown in Figure 4.7, the suitable and very suitable winter habitats are mainly mapped in the centre and southern areas which are also the human activity areas. For example, pandas use the understory bamboo as their staple food and the canopy forest as shelter. However, the local people cut the deciduous broadleaf trees in order to produce mushrooms to increase their income, and clear away the understory bamboo groves. This may rapidly change forest environment to other land cover types and causes panda habitat fragmentation or loss. Due to SanGuanMiao's central location surrounded by the suitable and very suitable winter habitats, it would be ideal to relocate the local people in SanGuanMiao to other parts so as to provide pandas with a large un-fragmented habitat. Mushroom production which cuts the understory bamboo and canopy trees in panda winter habitat should be forbidden.

The use of radio tracking data for mapping and assessing panda habitat is a new aspect in the field of panda habitat research. Radio tracking data have been used only for analysing the pandas' behaviour, such as movement (Hu et al. 1985, Schaller et al. 1985, Hu 1990, Yong et al. 1994, Liu et al. in review-c) and daily activity pattern (Hu et al. 1985). Smith (1986) stated that the classification of habitat must consider both the level of habitat resolution and the spatial scale at which habitat patches are considered to be homogeneous units. In the past, the habitat requirements of species were based on qualitative descriptions relating the presence or absence of species to the general forest type or structure of the vegetation. In recent years, however, there has been a growing interesting in the use of more quantitative techniques to describe the habitat-selection patterns of animals (Capen 1981). Schamberger and O'Neil (1986) emphasised two assumptions: (1) a species will select and use areas that are best able to satisfy its life requirements; and (2) as a result, greater use will occur in higher quality habitat. These views form the basis of using the radio tracking data for mapping the suitability-based panda habitat types in this study. Nortan and Poslinghan (1993) stated that the reliability of predictions generated by popular habitat simulation models is very uncertain and remains to be adequately tested. With a need for greater accuracy in mapping wildlife habitat, an increase in the development and use of forest simulation models (Shugart and West 1980) has accompanied the development of statistical approaches to habitat classification. The mapping approach involving radio tracking data and some advanced technologies could produce more accurate results, which have been confirmed by this study.

4.6 Conclusions and recommendations

This study provides the ESNNC approach for mapping panda habitat based on the multi-data layers. We, through applying the ESNNC, obtained the highest accuracies on mapping both the ground-cover-based potential panda habitat and the suitability-based panda habitat, and produced more and clearer information of panda habitat in a direct and obvious way for panda conservation and natural management. It is a practical mapping approach using limited samples in a very difficult area. Mapping results show that Foping NR maintains a good quality habitat for pandas: 97% of the reserve area covered with forests being pandas' potential habitat and 68% of the reserve area being pandas' suitable winter and summer habitats. However, it is suggested that the SanGuanMiao area should be returned to the giant pandas, and that constructing a tourist site in the northeastern corner along the boundary should not proceed.

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CHAPTER 5

Giant Panda Movement Analysis

Panda migrate in Foping NR
Photo: Yange Yong

Panda migrate in Foping NR
Photo: Yange Yong

CHAPTER 5 Giant Panda Movement Analysis *

Abstract:

Spotting the giant panda in the remote mountains of Foping Nature Reserve (NR) is difficult due to the dense vegetation and steep terrain. Radio tracking is an effective way to study this animal and understand its behaviour and habitat use. In this study, radio-tracking data for 6 pandas (3 males and 3 females) were used to study the movement pattern of pandas between 1991 and 1995 in Foping NR. The use of a geographical information system (GIS) combined with statistical tools in the study to analyse radio-tracking data is a new aspect in the panda ecological research. Our results show that the giant pandas in Foping NR occupied two distinct seasonal ranges (specifically winter and summer activity ranges) and had a regular seasonal movement between winter range below 1950 m and summer range above 2160 m. The pandas climbed from the winter to the summer habitats within a period of 8 days from June 7 to 15, and descended to the winter habitat between September 1 and October 6. Therefore, the pandas spent three quarters of the year (average 243 days) in their winter activity range, and an average of 78 days in the summer activity range. This is the first thorough quantitative study to show panda movement pattern in Foping NR.

Key words: China, Foping Nature Reserve, giant panda, GIS, movement pattern, quantitative study, radio-tracking.

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1. This chapter is based on Liu, X., A. K. Skidmore, T. Wang, Y. Yong, and H. H. T. Prins. (in review-c). Giant panda movement pattern in Foping Nature Reserve, China. Journal of Wildlife Management.

2. Part of this work was presented at Panda 2000 Conservation Priorities for the New Millennium - An International Conference in San Diego, US, October 15-18, 2000. The presented title: Panda Movement Pattern and Habitat Selection in Foping Nature Reserve, China.

5.1 Introduction

It was emphasised by White and Garrott (1990) that a gradual shift has taken place from descriptive movement studies to quantitative investigations aimed at studying animal activity patterns, habitat use, and survival rate. Radio tracking is one of the approaches to achieve this. It has been applied to many animal species, including locating mule deer (Lee et al. 1995), long distance movements of elephants (Thouless 1995), seasonal movement of moose (Baker 1978), the home range and activity of brown lemming (Banks et al. 1975), as well as survival rates of wild turkey hens (Kurzejeski et al. 1987). The track of an individual animal migrating or moving from one place to another place has a certain pattern that results partially from the orientation and navigation mechanism(s) employed by the individual and partially from environmental forces (Baker 1978, Geist 1971).

The giant panda (*Ailuropoda melanoleuca*) is an endangered species. It is a solitary animal, which makes spotting difficult in remote mountain areas covered with dense vegetation. In the forested mountains of China, radio tracking should be an effective way to study the giant panda, and understand this animal's behaviour and its utilisation of the habitat.

Some work on the movement of the giant panda has been undertaken in Wolong NR in Qionglai Mountains and Changqing NR in Qinling Mountains. Analysis of the radio tracking data showed that the pandas in Wolong NR remain at a high elevation for most of the year and feed on the arrow bamboo (*Bashania fangiana*). They move down to the lower elevation during May and June to forage on umbrella bamboo (*Fargesia robusta*) shoots (Hu et al. 1985). The pandas in Changqing NR exhibit a different movement pattern compared to the pandas in Wolong NR according to Pan et al. (1988). The pandas stay for most of the year at the low elevations feeding on *Bashania fargesii* bamboo, and occupy the high elevation areas to utilise *Fargesia spathace* bamboo from June to August.

Movement patterns of panda populations in different mountains may not be the same and remain unclear (Pan et al. 1988). The pandas in Foping NR remain an enigma even though they have been the subject of numerous studies. The first panda population and distribution survey was carried out in Foping NR in 1973 (SBRS 1976). Preliminary ecological observations were conducted in Foping NR in the 1970s and 1980s (Wu 1981 and 1986, Yong 1981 and 1989, Ruan 1983). More advanced ecological research has also been carried out in Foping NR. Yong et al. (1993 and 1994) analysed the panda population and distribution as well as movement habit. Li et al. (1997) reported their work on panda population viability analysis in Foping NR. Research on panda habitat has just started recently (Yang et al. 1997 and 1998, Yang and Yong 1998, and Ren et al. 1998). It has been reported that there are two main seasonal habitats in Foping NR occupied by pandas as their winter and summer habitats respectively, and the pandas move between these two seasonal habitats (Pan et al. 1988 and 1989, Yong et al. 1994). However, it is not so clear when, where and how the animals move. In order to study the giant panda and its habitat, radio telemetry was introduced to track the giant pandas in Foping NR during a 5-year period from 1991 to 1995. The achievements of the radio-tracking program have not been published internationally, with only descriptive results in two Chinese reports by Yong et al. (1994) and Pan et al. (1988).

Geographical information system (GIS) represents a flexible tool for managing resources and understanding and predicting complex and changing systems (Peuquet et al. 1993). This study aims to use GIS combined with statistics to analyse radio-tracking data of six pandas, as well as to visualise their movement patterns. In order to understand the characteristics of panda movement, aspects such as activity patterns, period of moving, areas of activity range, duration of seasonal activities, as well as the distance of movement are analysed.

5.2 Study area

Foping Nature Reserve (33°32'-33°45'N, 107°40'-107°55'E) is located in the middle part of the Qinling Mountains (Figure 1.1) and is the most northern panda refuge (Figure 5.1). The reserve covers an area of approximately 290 km², and the elevation ranges from about 980 to 2900 m. There are four drainage systems in the reserve, *viz.* XiHe, DongHe, JinShuiHe and LongTanZi Rivers. The detailed description of Foping NR is shown in Chapter1, such as its climatic conditions (Figure 1.4), human population and activities, and panda conservation and management (Figure 1.5) etc..

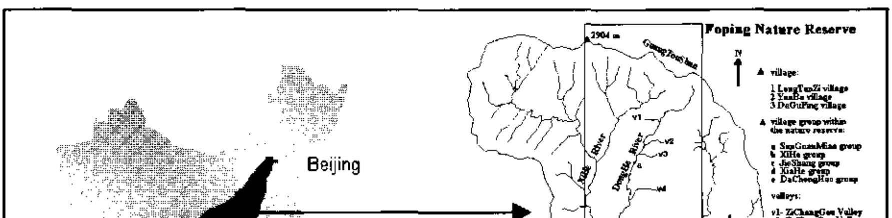


Figure 5.1 Study area: Foping Nature Reserve, and its location in China. The left map shows the change of the panda range, in which the small black patches are the six mountain blocks with the remaining pandas and the middle density shading area plots the historical panda distribution range. The right map shows Foping Nature Reserve, in which the box illustrates the range of radio tracking in the SanGuanMiao-GuangTouShan region.

The broad vegetation types include conifer forests, mixed conifer and broadleaf forests, deciduous broadleaf forests, shrub and meadow (Ren et al. 1998, CVCC 1980). There are two main bamboo species which compose the pandas' staple food, namely *Bashania fargesii* and *Fargesia spathacea* (Pan et al. 1988, Tian 1989 and 1990, Yong et al. 1994, Ren et al. 1998). They are mostly the understorey species, and only *F. spathacea* appears as pure bamboo groves at the top of the mountain. The distribution of the two species varies with the elevation. *B. fargesii* occurs mostly below 1900 m, while *F. spathacea* is located in higher altitudes of more than 1900 m.

There were about 60 to 70 giant pandas within Foping NR, with an average density of one panda per 5 km^2 according to the survey conducted in 1990 (Table 5.1) (Yong et al. 1993). DongHe and XiHe Rivers are two areas with more pandas (about 75% of the whole panda population in Foping NR) (see Figure 1.5). The results of a survey in 1998 again confirmed a similar number (about 65) of panda individuals in the reserve. The radio tracking was carried out in the SanGuanMiao-GuangTouShan region illustrated by the box in Figure 5.1.

Table 5.1 The sub-populations (individual) as well as density (individual/km^2) of the giant panda in different watersheds in Foping Nature Reserve, China in 1990 (Yong et al. 1993)

Watershed	Area (km^2)	Number of pandas (individual)	Density (individual/km^2)
DongHe	54	26	0.5
XiHe	71	23	0.3
LongTanZi	15	3	0.2
YueBa	59	7	0.1
HuangTongLiang	38	5	0.1
HeiLongTan	33	0	0
XiaHe	23	0	0
In total	about 290	between 60 and 70	On average 0.2

5.3 Methods

The study deals with the seasonal movement and activity range of the giant panda. The terms movement and migration are used inter-changeably. Baker (1978) standardised the terminology and described migration as an activity of moving from one spatial unit to another, while movement is just a change in position. Thus movement is defined relative to the Earth's surface and includes a vertical component. In this paper, the term "movement" is used to describe the giant panda's changing position. Regarding the activity range of animals, the concept of "home range" is frequently used. Burt (1943) defined home range as "that area traversed by the individual in its normal activities of food gathering, mating and caring for young". Baker (1978) described home range as the area physically visited by an animal in a given time interval. However, biologists have differed widely in their approaches to the determination of home range (Sanderson 1966). Due to the existence of two obvious seasonal activity ranges of the pandas in Foping NR, the terms of "winter activity range" and "summer activity range" have been adopted for this study.

The radio-tracking equipment (Telonics Company, US) was used only in the SanGuanMiao-GuangTouShang region (illustrated by the box in Figure 5.1) and consisted of a MOD-500 telemetry collar, a TR-2 receiver and a RA-2AK hand-held H-style antenna. A total of 59 receiving towers were used across the radio-tracking region. They were distributed along the ridge of the GuangTouShan Mountain (approximately an east-west direction) for tracking pandas in the summer and autumn seasons, and through the DongHe River valley (approximately a south-north direction) for tracking pandas in winter and spring seasons. Six pandas (3 males and 3 females) were fitted with telemetry collars and tracked for different periods, the longest lasting from 1991 to 1995 (detailed in Table 5.2). Tracking started in May 1991, and stopped in December 1995. The data were collected daily. However, many factors caused missing data.

Table 5.2 Detailed information of six radio collared pandas in Foping Nature Reserve, China, in which "c", "s" and "a" represent panda cub (<1.5 years), sub-adult (1.5 - <5 years), and adult (>=5 years) respectively based on the definition of Hu et al. (1985) and Schaller et al. (1985).

Name with tracking Nr	Sex	Age in different year (year)					Tracking duration	Tracking days/months
		1991	1992	1993	1994	1995		
panda127	M	10a	11a	12a	13a	14a	May 91 - May 95	465/34
panda043	F	12a	13a				July 91 - Aug. 92	106/9
panda065	M		< 1c	2s	3s	4s	Feb. 92 - Dec. 95	463/34
panda045	F		6a	7a	8a	9a	May 92 - Dec. 95	400/29
panda005	M				15a	16a	Apr. 94 - Dec. 95	213/20
panda083	F					< 2s	Jan. 95 - Aug. 95	113/9

There are 1760 raw records in total from the radio-collar latitude-longitude telemetry transformed to UTM co-ordinates. The location of the panda was estimated from the cross point of two bearings received at two towers by triangulation (White and Garrott 1990). After careful checking based on expertise, suspicious data were eliminated, and the final data set comprises 1639 records. All samples were plotted on a background map. The centres of each panda's winter, summer and mating activity ranges were obtained by calculating the average of the UTM-x and UTM-y co-ordinates respectively. The centres of the activity ranges were displayed to discern their spatial separation. The distance between all tracking locations and the centres of each panda's winter, summer and mating activity ranges was calculated and plotted to obtain an impression of the spread of each individual and its activity centre.

According to the literature and local expertise, it is known that there are two seasonal activity ranges in Foping NR. The time for the giant pandas to move from the winter to the summer activity ranges is in May and June, generally, and to descend from the summer to the winter activity ranges is in August and September. In order to determine the exact period for pandas to move up and down between two seasonal activity ranges, the average elevations of six pandas from May to June and August to October were calculated for each year and plotted. The periods for pandas to change their seasonal activity ranges were subjectively defined. The length of the periods that pandas remain in two seasonal activity ranges was then calculated.

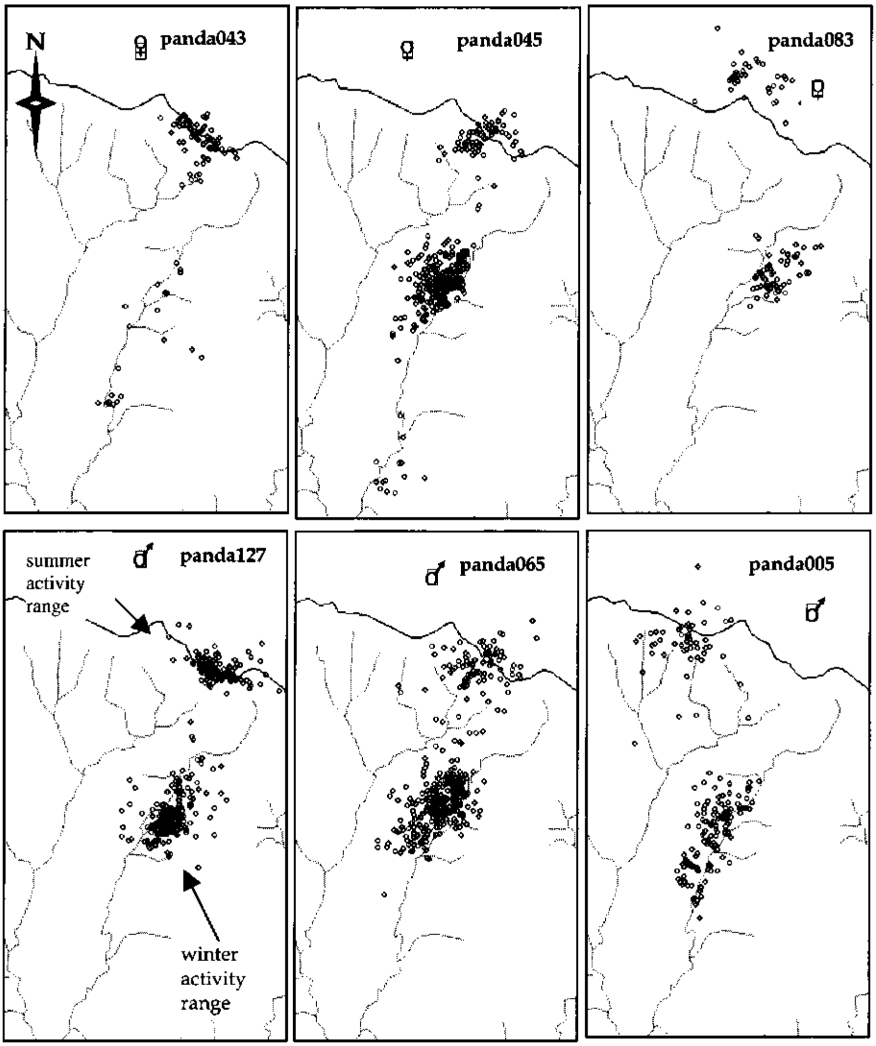


Figure 5.2 Activity patterns of 6 pandas from radio tracking in the SanGuanMiao-GuangTouShan region in Foping Nature Reserve, China from 1991 to 1995. All six maps show two obvious areas with very dense tracking points (as shown in the bottom-left panel). The lower cloud of tracking points represents the pandas' winter activity range, while the upper one is the summer activity range. The area inbetween can be defined as the transition range.

These movement periods defined three elevation ranges, *viz.* winter, summer and transition ranges. Because the elevation data were non-normally distributed, the non-parametric boxplot method (Moore and McCabe 1998, 44-49) was used, and the upper and lower whiskers (SPSS 1997, 40-41) of the boxplots defined the elevation ranges of the pandas' winter and summer activity. A hypothesis here is that there is a significant difference between the elevations of the pandas' winter and summer activity ranges.

The area of both the winter activity range and the summer activity range in different years for each adult panda (panda005, panda127, panda043 and panda045) was calculated by the minimum convex polygon method (White and Garrott 1990). The transition range was excluded from these two seasonal activity ranges because it is used only as a temporary movement corridor. Two hypotheses were formulated: firstly, the male pandas had larger winter and summer activity ranges respectively than female pandas; secondly, the pandas used a larger area for winter activity than for summer activity.

The average monthly distance travelled over two consecutive days was calculated to overview the monthly pattern in a year, and to test the hypothesis that adult male pandas move farther within two consecutive days than adult female pandas. All hypotheses in the study were tested using the Mann-Whitney U test at 95%C.I. significant level.

5.4 Results

5.4.1 Panda activity patterns

Each panda had two well-delineated winter and summer activity ranges (Figure 5.2). The lower cluster represents the panda's winter activity range, while the upper one the summer activity range. Some individuals overlapped in space. Panda127 and panda043 overlapped to some degree in the summer activity range, while panda045 and panda065 overlapped in both the summer and winter activity ranges. The summer range of panda083 was on the northern side of the GuangTouShan ridge, far from other individuals. In the winter range, panda045, panda065 and panda005 stayed on the west side of the

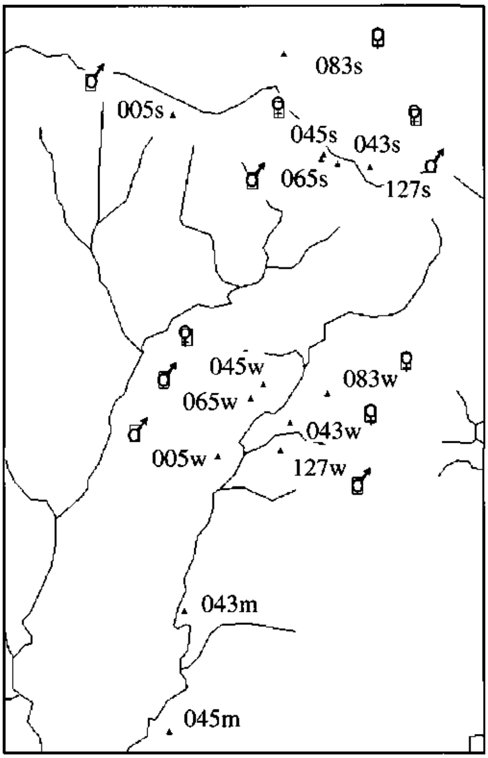


Figure 5.3 Centres of pandas' winter and summer activity ranges, as well as mating sites in Foping Nature Reserve, China. 005 to 127 refer to identity codes of individual pandas, while "s" stands for "centre of summer range", "w" for "centre of winter range" and "m" for "centre of mating site".

DongHe River, while panda043, panda083 and panda127 occupied the east side of the DongHe River.

Figure 5.3 shows the centres of six pandas' winter and summer activity ranges as well as mating sites for female panda043 and panda045. The figure shows that, in the summer range, panda083 and panda005 stayed away from the other four pandas which were living very near each other. These four pandas (i.e. panda043, panda045, panda065 and panda127) overlapped in their summer activity ranges in varying degrees. The distances between the centres in the winter range are slightly larger than the distances of the centres in the summer range. We found that the mating sites of two females (e.g. panda045 and panda043) were situated in the ShuiJingGou Valley, located at the southern part of the tracking area. Female panda083 was only 1.5 years old in 1995 and had no mating activity.

Figure 5.4 shows the distances of all panda tracking locations to the centres of the individual panda's winter (Figure 5.4a) and summer (Figure 5.4b) activity ranges. The different pandas have various distances spreading from their winter and summer activity centres. The male panda005 had the largest spread distance and the male panda127 the smallest spread distance in both winter and summer activity ranges. The outliers in the figure indicate that the pandas sometimes spread very far from their activity centres.

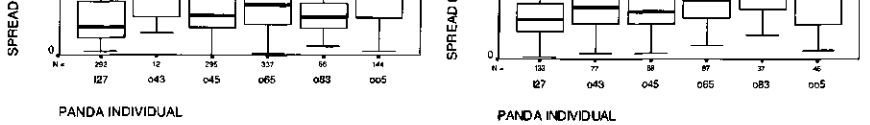
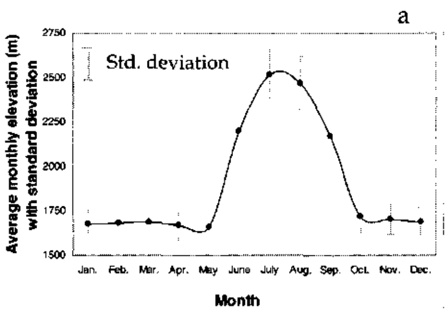


Figure 5.4 Boxplots show distribution of distances between tracking locations and activity centres of panda individuals in their winter (a) and summer (b) activity ranges in Foping Nature Reserve, China. Symbols "o" and "*" represent those extreme values, or outliers. "N" is the number of tracking points.

5.4.2 Periods of movement between and duration in winter and summer ranges

The giant pandas in Foping NR remained in their winter activity ranges at about 1700 m from October to May in the following year and occupied the summer activity ranges at an elevation of approximately 2500m in July and August (Figure 5.5a). They transferred between the winter and the summer activity ranges in June and September (Figure 5.5a). The pandas' transfer between two seasonal activity ranges is associated with a large change in elevation (shown by the standard deviations in Figure 5.5a). However, once the pandas were in the winter or the summer activity ranges, they maintained activities at a relatively constant elevation with a standard deviation of about 150-300 m.



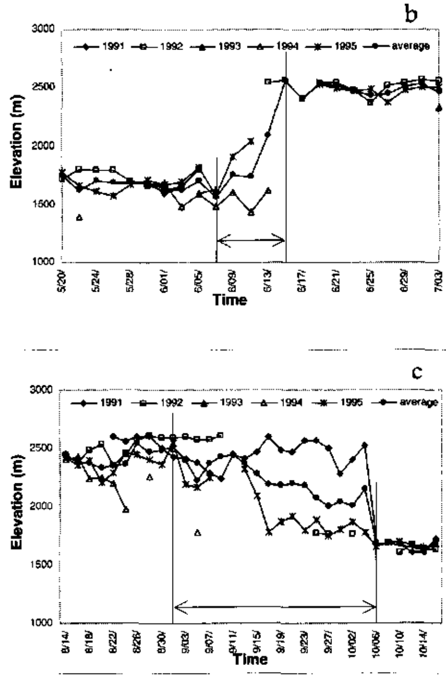


Figure 5.5 Determination of the pandas' moving period between two seasonal activity ranges based on the elevation change.
a: average elevation and standard deviation per month for six pandas;
b: sudden elevation change of pandas when ascending from the winter to the summer ranges from June 7 to 15 (see the average elevation curve with symbol of black dot);
c: gradual elevation change of pandas when descending from the summer to the winter ranges from September 1 to October 6 (see the average elevation curve with symbol of black dot).

The pandas' moving period was subjectively defined according to the curves of average elevation in Figure 5.5b-c. It is revealed that the pandas moved up quickly from the winter to the summer activity ranges within a range of 8 days from June 7 to 15 (Figure 5.5b), but took about 36 days from September 1 to October 6 to descend from the summer to the winter activity ranges (Figure 5.5c). So, in total, the pandas spent 44 days transferring between two seasonal activity ranges. Consequently, the giant pandas stayed in the winter range for approximately 243 days from October 7 to June 6 in the second year (e.g. autumn-winter-spring period) and in the summer range for only 78 days from June 16 to August 31 (e.g. summer period).

5.4.3 Elevation ranges for three activity ranges

The elevation of the pandas' tracking records in three activity periods (e.g. autumn-winter-spring period, transfer period, and summer period) defined by Figure 5.5b-c was plotted in Figure 5.6. It shows that the elevations of the tracking points in both the autumn-winter-spring period and the summer period have smaller ranges than the elevation of the tracking points in the transfer period. The upper and lower whiskers of the boxplots subjectively defined the elevation ranges of the pandas' winter and summer activity ranges. The winter activity range is thus found from about 1410 to 1950 m and the summer activity range from about 2160 to 2800 m. Therefore, the pandas remained below 1950 m in the autumn-winter-spring period and above 2160 m in the summer period. There is a significant difference between the medians of elevation of these two activity ranges (*df = 1, P < 0.01*, Mann-Whitney U). The elevation gap between the upper whisker of the winter elevation range and the lower whisker of the summer elevation range from 1950 to 2160 m is defined as the transition range.

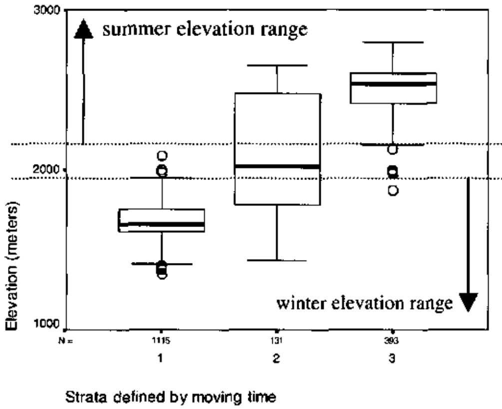


Figure 5.6 Boxplots show the elevation distributions defined by the pandas' activity periods: 1: autumn-winter-spring period (before June 7 and after October 6); 2: transfer period (between June 7 and June 15, as well as between September 1 and October 6); 3: summer period (between June 16 and August 31).

5.4.4 Areas of two seasonal activity ranges

The areas of each adult panda's winter and summer activity ranges based on the results obtained above are detailed in Table 5.3. It can be noted that each panda has a varied area of winter and summer activity ranges in different years. However, in general, the average winter activity range is larger than the average summer activity range. The male pandas, on average, use larger summer activity ranges than the female pandas, while male and female pandas use similar areas in the winter activity range.

The result of the Mann-Whitney U test confirms that there is no significant difference between adult male and female pandas' winter activity ranges (*df = 1, P > 0.05*, Mann-Whitney U) as well as their summer activity ranges (*df = 1, P > 0.05*, Mann-Whitney U). Adult male pandas use a similar area for their winter range as they do for their summer range (*df = 1, P > 0.05*, Mann-Whitney U). However, for adult female pandas, the area of the winter activity range used is significantly larger than the area of the summer activity range (*df* = *1*, $P < 0.05$, Mann-Whitney U).

Table 5.3 Area (km²) of the winter ("w") and the summer ("s") activity ranges from four adult pandas (male panda005 and panda127, female panda043 and panda045) in different years in Foping Nature Reserve, China. The comparison was tested using the Mann-Whitney U test. Note: "ns" indicate a not significant difference ($p > 0.05$), and "s" means a significant difference ($p < 0.05$).

Winter activity range

Sex	Male	Female
	3.1	2.3
Area	5.2	2.7
	1.1	4.2
	2.2	2.6
	6.0	4.5
	4.2	
N	6	5
Average	3.6	3.3

Summer activity range

Sex	Male	Female
	4.3	1.4
Area	2.1	0.7
	1.6	1.2
	2.3	2.4
N	4	4
Average	3.3	1.4

(ns $p > 0.05$) (ns $p > 0.05$)

(ns $p > 0.05$) (s $p < 0.05$)

5.4.5 Distance moved over two consecutive days

Figure 5.7 shows the pattern of the average monthly distance travelled over two consecutive days for both adult male and female pandas (means with 95% C.I.). It can be observed that the giant pandas in Foping NR travelled shorter distances (< 300 m) with small distance variation in January and February, and travelled a slightly larger distance (< 400 m) with also small distance variation in two summer months (July and August) as well as two winter months (October and December). In the other months, pandas travelled further than 400 m within two consecutive days with slightly larger distance variation.

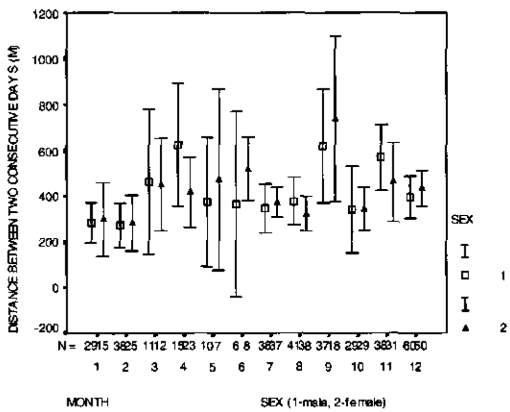


Figure 5.7 The pattern of average monthly distances travelled over two consecutive days for 2 adult male and 2 adult female pandas in Foping Nature Reserve, China. The means with 95% C.I. are shown in the figure.

Apparently, the pandas increased their moving distance in March and April, which may be related to the fact that this is the mating season. In May, the bamboo in the low elevation area started shooting and the pandas moved in a wider range and traversed greater distances per day to search for new bamboo shoots. In June and September, the pandas ascended to and descended from the summer activity ranges and covered larger distances. The average monthly moving distances in these 5 months (March, April, May, June and September) have very large variations. There is no statistically significant difference in two consecutive days' movement distance between adult male and female pandas ($df = 1$, $P > 0.05$, Mann-Whitney U). Even in April, June and September, there is no statistically significant difference in the distance travelled within two consecutive days ($df = 1$, $P > 0.05$, Mann-Whitney U) although Figure 5.7 shows a difference between adult male and female pandas in these three months.

5.5 Discussion

Spatial and quantitative analysis of the pandas' activity pattern from 5-year radio-tracking data from Foping NR has been undertaken for the first time. The 6 pandas' activity patterns all show two spatially distinct (e.g. winter and summer) seasonal activity ranges. Spatial distribution patterns of these 5-year radio-tracking data for 6 pandas show some overlap in varying degrees. However, it only shows the overlap of activity ranges in a relatively long period, not an individual panda's daily activity range.

The elevation change of the pandas' activity in June (from June 7 to 15) and September (from September 1 to October 6) gives the appearance of a regular annual movement between the winter and summer activity ranges. This has confirmed Pan et al.'s work (1988) in the neighbouring Changqing NR, but with a small difference: the seasonal movement in Changqing NR occurs between May and June, and September to October. The six pandas in Foping NR take in reality only two or three days for moving upwards over one year. The average value of 8 days (from June 7 to 15) represents the range for all six pandas for the whole period of five years. Yong et al. (1994) analysed 12-months' radio tracking data (from April 1991 to April 1992) of only two pandas. Due to the limited data used in Yong et al.'s work (1994), their result about the period for pandas to move up shows a difference with the result obtained in this study. The correctly defined transfer periods of the giant panda can be used not only to determine the elevation boundaries of the winter and the summer activity ranges, but also to help to estimate the area of the winter and the summer activity ranges separately.

The existence of separate winter and summer ranges is an important component of the concept of migration (Baker 1978). An example of using subjective judgements in order to formulate some definitions for a mule deer population was presented by Garrott et al. (1987). Our study took a statistical approach to define the vertical seasonal activity ranges of the giant panda. The results show that the area above approximately 2160 m is the pandas' summer range and the area below about 1950 m is the pandas' winter range. These elevation boundaries for the two ranges are different from the ones reported by Pan et al. (1988). They found that the winter range in their study area of

Changqing NR, neighbouring to Foping NR, was below 1900 m and the summer range above 2300 m.

The aim to estimate the area of the pandas' winter and summer activity ranges is to provide us with an image of how pandas use their territory. In panda research, the terms "winter activity range" and "summer activity range" have not often been used. The total of winter and summer activity ranges can be used to compare with the situation in Wolong NR. The average total activity range of males is 6.2 km^2 and of females 4.7 km^2 in Foping NR. In Wolong NR, a male usually has an activity range of about 6-7 km^2 and a female has a smaller activity range of about 4-5 km^2 (Hu 1990), which are markedly similar. However, the measure of home ranges of the pandas in Wolong NR included the areas for seasonal movement, i.e. the transition area.

Limited summer habitat, only about 15% of the nature reserve (see Chapter 4), might be a reason for pandas in Foping NR to move into close proximity at the top of the GuangTouShan Mountain. The food (e.g. *F. spathacea* bamboo) in the panda summer habitat grows in dense groves, and pandas stay in the summer habitat for just two and half months (about 78 days). This may explain why pandas can stay near each other. Hu (1990) also concluded that the giant panda is able to survive in a small activity range if plenty of bamboo is available. According to the local staff in Foping NR, the summer range of female panda083 in 1995 on the northern slope of GuangTouShan was assumed to be the dispersion behaviour because she was only two years old in that summer and utilised an area far away from other individuals.

One of the advantages of calculating the sizes of the pandas' winter and summer activity ranges is to estimate the panda population in Foping NR. According to the mapping work which we are carrying out (see Chapter 4), the available winter habitat in Foping NR can be deduced. Based on the average area of pandas' winter activity range, the panda population may be estimated by two parameters (e.g. available winter habitat and average area of panda winter activity range) with considering degree of overlap, which may provide a useful guide for a panda population survey.

Based on the work in Wolong NR, Hu (1990) concluded that the giant pandas are rather inactive for most days of a year and have a movement distance of 500 m or less. The result of this study shows the giant pandas have varied distances of movement in different time periods. Within two consecutive days, distance of movement can be less than 300 m on average in January and February, and between 300 m and 400 m in July, August, October and December, or further than 400 m in March, April, May, June, September and November. The male and female pandas have different movement distances in different months. On average, male pandas move larger distances than females, which is in agreement with the research finding in Wolong NR that "the male usually walks farther than the female" (Hu 1990).

The period for pandas to transfer between two seasonal activity ranges in Foping NR generally coincides with that of the giant panda group in the neighbouring nature reserve in the Qinling Mountains: moving up the mountain from middle April to early June and moving down from early September to October like in Changqing NR (Pan et al. 1988). The pandas in Wolong NR, however, while living in a different mountain range, namely the Qionglai Mountains, live in the arrow bamboo (*B. fangiana*) area above 2700 m for most of the year. They move down to the umbrella bamboo (*F. robusta*) area below 2700 m only in late April or early May until the middle of June when the umbrella bamboo shoots come out. Some of the pandas even stay in the arrow bamboo area all year (Pan et al. 1988). Panda ecology in these two mountain ranges is thus not the same, which may have important repercussions for the evaluation of terrain characteristics for suitability for panda re-introduction.

5.6 Management implications

The results obtained in this research will provide not only the managers, working staff and local people in the nature reserve but also the scientific researchers with more accurate information about the pandas' movement quantitatively and visually, which can contribute to panda conservation on the following aspects: (1) The pandas' moving periods found in the study will guide local staff and managers in panda tracking and reduce the chance of missing tracking data; (2) The winter and the summer activity ranges defined by elevation ranges can be applied in panda habitat management, for instance, to calculate how large these two panda activity ranges are respectively and to estimate indirectly the panda population; (3) The difference of the panda movement pattern found between Foping NR and its neighbouring Changqing NR, as well as far-away Wolong NR, shows the wildlife managers, wildlife ecologists, etc. that various strategies need to be taken into account in scientific research and panda population surveys in different geographical regions.

Acknowledgement

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CHAPTER 6

Panda Habitat Selection and Habitat Characteristics in Foping Nature Reserve, China

Panda feeding signs
Photo: Xuehua Liu

Panda droppings
Photo: Xuehua Liu

CHAPTER 6 Panda Habitat Selection and Habitat Characteristics in Foping Nature Reserve *

Abstract

Analysis of habitat selection has been a common and important aspect of wildlife science. However, little is known about habitat selection of the giant panda, especially about the relationship between panda presence, and bamboo and tree layers. This study presents data on panda habitat use and selection as well as habitat characteristics which may direct panda habitat selection in Foping Nature Reserve (NR). A total of 1066 from 1639 effective radio-tracking records were used for analysing panda habitat selection, and 110 quadrates for extracting characteristics of different habitat types and their relationships with panda presence. We found that: (i) Pandas in Foping NR select mostly three habitat types: conifer forest, deciduous broadleaf forest, and *Fargesia* bamboo groves. (ii) In the winter range, pandas spend more time in deciduous broadleaf forest with an elevation range of 1600 to 1800 m, a slope range of 10 to 20 degrees, and south-facing slopes. In the summer range, pandas use more conifer forest with an elevation range of 2400 to 2600 m and a slope range of 20 to 30 degrees. (iii) Pandas select the *Bashania fargesii* bamboo area with short and dense culms from different ages in the winter activity range, while they select the *Fargesia spathacea* bamboo area with a high coverage of tall and thick culms from one to two year-old in the summer activity range.

Key Words: giant panda, habitat selection, habitat use, habitat characteristics, radio tracking, Foping Nature Reserve, China

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1. This chapter is based on Liu X., A. G. Toxopeus, A. K. Skidmore, G. Dang, T. Wang, and H. H. T. Prins. (in review-d). Giant panda habitat selection and habitat characteristics in Foping Nature Reserve, China. Journal of Applied Ecology.

2. Part of this work was presented at the 8th Annual Conference of the Wildlife Society on September 25-29, 2001 in Reno/Tahoe, Nevada, US. The presented title: Giant panda habitat selection in Foping Nature Reserve, China.

6.1 Introduction

Habitat is any spatial unit that can be occupied by an individual animal, no matter how briefly (Baker 1978). Habitat requirements of species were generally based on qualitative descriptions relating the presence or absence of species to the general forest type or structure of the vegetation. In recent years, however, there has been a growing interest in the use of more quantitative techniques to gain an insight into the habitat-selection patterns of animals (Capen 1981). Schamberger and O'Neil (1986) emphasised that habitat-use data were capable of documenting the species' use of particular areas within its range based on two assumptions: (1) a species will select and use areas that are best able to satisfy its life requirements; and (2) as a result, greater use will occur in higher quality habitat. Johnson (1980) stated that ecological research often involves comparison of the usage of habitat types or food items to the availability of those resources to the animal. Analysis of habitat selection has been a common and important aspect of wildlife science (Alldredge and Ratti 1986).

Habitat preference, habitat use and habitat selection are described and used differently. White and Garrott (1990) stated that habitat preference means that the animal population selects some habitat types more than others and thus spends more time in these habitats than would be expected based on the availability of each habitat type. Habitat use means that locations taken for each animal are classified as to the habitat types in which they occur, thus the percentage of time each animal spends in a particular habitat type can be estimated. If one habitat type is preferred, than more time will be spent in this habitat type than expected by chance alone (White and Garrott 1990). The definition of "habitat selection" is not found in the publications. However, the term "habitat selection" has been widely used (Babaasa 2000, Alldredge and Ratti 1986, Augustine et al. 1995, Reid and Hu 1991, Wei et al. 1996 and 1999). We consider that habitat selection mainly emphasises the action of choosing the habitats, and can be reflected by analysing habitat use and habitat preference. Svardson (1949) and Hilden (1965) pointed out that habitat selection includes two processes: primary selection of general environmental features under the different habitats, and then further selection of specific habitat based on detailed features. According to Johnson (1980), animals follow an order in habitat selection: firstly, selection of geographical region, secondly, selection of home range in the geographical region, and lastly, selection of different type of habitat components. Wiens (1981) described that habitat selection may occur at a number of spatial scales and need not be based on the same criteria at each.

Schaller et al. (1985) had pointed out that little is known of habitat selection of the giant pandas (*Ailuropoda melanoleuca*), except that they seem to concentrate their activities in mountainous areas, live in a bamboo environment and feed almost exclusively on bamboo species. However, there is a substantial variation in the growth pattern (e.g. culm density, annual shoot production) and morphology (e.g. culm height and basal diameter) of bamboo culms when growing under different conditions, and these may direct panda habitat selection (Reid and Hu 1991). Wei et al. (1996) again commented that some work had been done on panda habitat selection by Reid and Hu (1991) in Wolong NR. Based on that, Wei et al. (1996 and 1999) applied the same method to analyse panda habitat selection in Mabian Dafengdin NR and compared the habitat selection between the giant panda and the red panda in Yele NR.

It has been reported that there are two main habitats occupied by pandas in Foping NR: the winter habitat with bamboo species *B. fargesii* and the summer habitat with bamboo species *F. spathacea* (Pan et al. 1988 and 1989, Yong et al. 1994). Tian (1986, 1989, 1990, and 1991) published his research work on characteristics of bamboo species and flowering within the whole range of the Qingling Mountains. However, no details have been reported on analysing the bamboo layer and its relationship with panda presence and canopy tree layer. Tian (1990) described, based on the field observation, that pandas do not feed in the areas where bamboo stems are very dense or very sparse, bamboo closure very high or very low, the understorey environment very dark, as well as the slopes very steep. The survey conducted in Foping NR in 1984 showed that 20% of the bamboo area has never been used or used very little by pandas. Tian (1990) also mentioned that pandas select only the bamboo stems with an age of one or two years old to feed. Tian described his findings based only on his field observation and no statistical method has been used to test whether there was a significant difference in terms of the aspects mentioned above between panda-presence or panda-absence habitats.

Panda research using more advanced methods to analyse panda habitat has just started recently in Foping NR. Yang et al. (1997 and 1998) as well as Yang and Yong (1998) showed their research results on panda summer and winter habitats. They mainly focused on analysing environmental factors, both biophysical and abiotic, in panda regions, looking at their impact, and clustering the survey plots based on these factors. Ren et al. (1998) focused their research on flora and vegetation, as well as the relationship between plant species richness and elevation. Quantitative analysis of panda habitat selection and linking panda presence with bamboo as well as tree structures has not been done in Foping NR.

This study reports the relationship between the presence of pandas and their habitat factors such as vegetation type, elevation, slope gradient and slope aspect by using radio tracking data, survey plot data and mapping results from Chapter 4. Furthermore, the study aims to gain an insight into habitat selection of pandas, to look at the difference between various panda habitat types, and, therefore, to find the specific characteristics of panda-presence habitat.

6.2 Study area

Foping NR is located in the south of Shaanxi province (Figure 1.3), on the middle part of the southern slope of the Qinling Mountains (Figure 1.1). The reserve covers about 290 km^2, and the elevation ranges from approximately 980 to 2900 m. The description of Foping NR is detailed in Chapter 1. The main vegetation types are conifer forests, mixed conifer and broadleaf forests, deciduous broadleaf forests, shrub and meadow (Ren et al. 1998, CVCC 1980). There are two main bamboo species for pandas to feed on: *B. fargesii* and *F. spathacea* (Pan et al. 1988, Tian 1989 and 1990, Yong et al. 1994, Ren et al. 1998). *B. fargesii* is generally distributed in the area below 1900 m, while *F. spathacea* occurs mainly in the area above 1900 m. The estimated panda population is about 64 with an average density of one individual per 5 km² according to the survey conducted in 1990 (Yong et al. 1993).

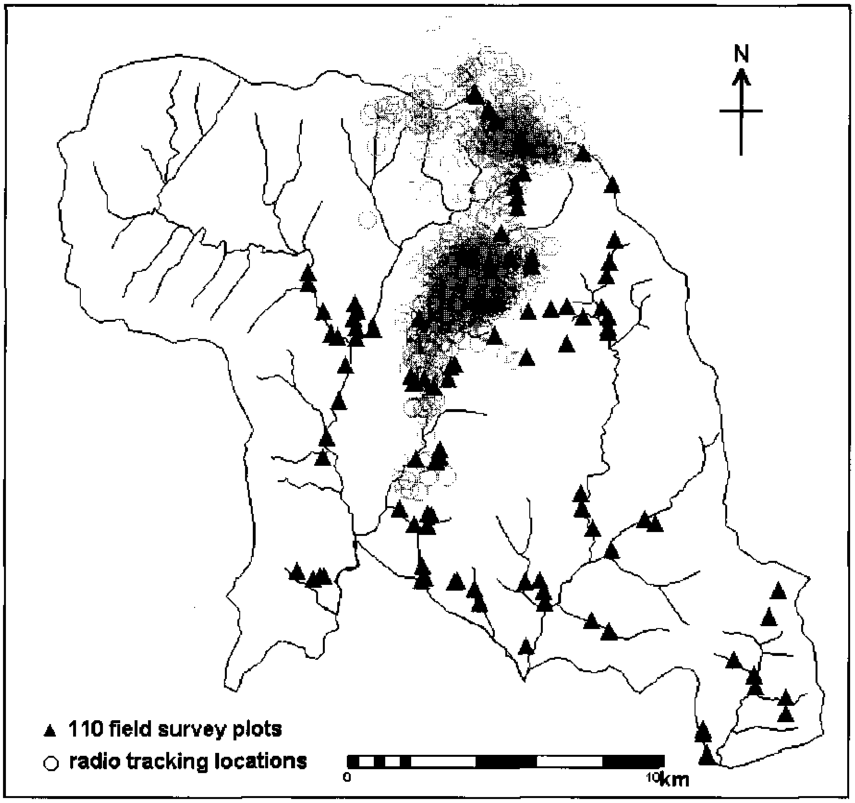

Figure 6.1 Distribution of radio-tracking locations (the grey circles) and 110 field survey plots (the black deltas) in Foping Nature Reserve, China.

6.3 Methods

6.3.1 Data

Radio-tracking data: Radio tracking data were assumed to be able to reflect the principles of panda habitat selection. Six pandas (3 female and 3 male) with telemetry collars were tracked in different periods (see Table 5.2). The longest period lasted about 5 years from 1991 to 1995. The earliest tracking started in May 1991 and the latest one was in December 1995. A total of 59 receiving towers were used in the nature reserve and mainly distributed along the top ridge of GuangTouShan Mountain with west-east direction for tracking in summer and autumn seasons, and the DongHe River Valley with south-north direction for tracking in winter and spring seasons. All 1760 raw tracking records were carefully checked and finally a total of 1639 effective tracking records were kept (see detail in Chapter 5); their distribution is shown in Figure 6.1. One tracking record is used as one day for calculating panda habitat use and selection.

Habitat survey data: A habitat survey was conducted in summer 1999 (July and August). Global Position System (GPS) has been used to record the geo-locations of all survey plots. In total, 110 quadrats (10 m by 10 m) have been surveyed (shown in Figure 6.1) and each of them contains four bamboo plots (1 m by 1 m) for calculating average bamboo parameters for the whole plot. Detailed habitat information has been collected through measuring and recording of:

- tree layer (≥5 m): species, number or stems, diameter at breast height (DBH) per stem, height per stem, and canopy coverage per species, total canopy coverage in 10 m by 10 m plot;
- shrub layer (≥ 1 m and < 5 m) except bamboo species: species, individual height, and coverage per species in 10 m by 10 m plot;
- bamboo layer: species, number of culms, basal diameter (BD) per culm, average bamboo height in 1 m by 1 m bamboo plot, and total bamboo coverage in 1 m by 1 m bamboo plot;
- main terrain factors: elevation, slope gradient and direction;
- signs of panda presence: feedings, droppings and nesting sites;
- ground-cover-based panda habitat types: (1) conifer forest, (2) mixed conifer and broadleaf forest, (3) deciduous broadleaf forest, (4) bamboo (or mixed with meadow), (5) shrub-grass-herb land, (6) rock and bare-lands, (7) farm-land and settlements, (8) water area.

6.3.2 Categories of panda habitat types

Two categories of panda habitat types were used in this study. Both categories were described and their spatial patterns were mapped by an integrated neural network and expert system with a high mapping accuracy in Chapter 4. The first category of habitat types is defined based on ground cover types as listed above, and used to analyse panda habitat use and selection. The second category of habitat types is defined based on habitat suitability for pandas decided by several criteria (thus suitability-based panda habitat types). It consists of (1) very suitable summer habitat, (2) suitable summer habitat, (3) very suitable winter habitat, (4) suitable winter habitat, (5) transition habitat, (6) marginal habitat, (7) unsuitable habitat, and (8) water area. This is used to compare the woody species composition.

6.3.3 Data Analysis

Parts of the radio-tracking data (1066 tracking records) from several pandas that cover more or less one complete year (see Table 5.2 and Table 6.1) were used to estimate the percentage of time an animal spends in a particular habitat type so as to ascertain panda habitat use. The habitat type of a radio-tracking location can be obtained through recording in the field, plotting the location on an existing hardcopy of a habitat map, or extracting directly from a georeferenced digital habitat map. In this study, the ground-cover-based panda habitat types for all tracking records were extracted from a georeferenced digital habitat map produced in Chapter 4 because between 1991 and 1995 tracking was carried out without recording the habitat types. To analyse panda habitat use, the percentage of time over one year that pandas spend in different habitat types was calculated. The study assumes that all pandas have the same choice of different ground-cover-based habitat types.

In order to understand how pandas utilise the habitat types in the winter and summer activity ranges, the same data were also used to illustrate the frequency of panda occurring in the different habitat types in two seasonal activity ranges. Furthermore, other physical environmental factors (namely elevation, slope gradient and aspect) were used to overview panda habitat selection determined by different terrain factors.

A x^2 test is performed to test for the goodness-of-fit of utilised habitats to available ground-cover-based habitat types in order to gain an insight into panda habitat selection (see detail in Neu et al. 1974, Byers et al. 1984, White and Garrot 1990). The two null hypotheses are tested by the x^2 test. The first null hypothesis is that habitat usage occurs in proportion to habitat availability considering all habitats simultaneously using Equation (1); and the second null hypothesis is that habitat usage occurs in proportion to habitat availability considering each habitat separately using Equation (2).

$$\chi^2 = \sum \frac{(observed - \exp ected)^2}{\exp ected} \qquad (1)$$

$$p_{oi} - Z_{\alpha/2k}[\frac{p_{oi}(1-p_{oi})}{n}]^{\frac{1}{2}} \le P_i \le p_{oi} + Z_{\alpha/2k}[\frac{p_{oi}(1-p_{oi})}{n}]^{\frac{1}{2}} \qquad (2)$$

in which P_i is the calculated confidence interval for habitat type i, p_{oi} is the proportion of panda observations in habitat type i, n is the number of total observations, $Z_{a/2k}$ is the upper standard normal table value corresponding to a probability tail area of $a/2k$, and k is the number of habitat types tested.

Equation (1) is used to test whether there is a significant difference between observation and expectation. If there is a significant difference, the first null hypothesis is rejected which means that panda has "habitat selection". After "habitat selection" in general has been confirmed, the expected panda locations are calculated from the availability proportion multiplied by total observed panda locations. Equation (2) is used to calculate a confidence interval and then to test which habitat type pandas select more. To determine whether the animal selects a habitat type "frequently", "in proportion to", "less frequently", or "not at all", the confidence interval is checked for overlap with the availability proportion of the corresponding habitat type. If the confidence interval includes the availability proportion, the hypothesis, i.e. "in proportion to" this habitat type, cannot be rejected. However, if the lower boundary of the interval exceeds the availability proportion, the panda has shown its frequent selection of this habitat type. If the upper boundary of the interval is less than the availability proportion, the panda has shown less frequent selection or avoidance of this habitat type. The availability (i.e. area) of each ground-cover-based habitat type comes from our habitat mapping results (see Chapter 4).

The woody species composition of suitability-based panda habitat types were analysed based on our 110 field survey plots. The importance value (*IV*) for each species was calculated using a formula modified from Mueller-Dombois and Ellenberg (1974) and Acharya (1999), which considers the canopy coverage per species in the plot, the individual density per species in the plot, and the chance of occurrence among 110 plots. All these three parameters range from 0 to 100. Species importance value was then calculated using the following equation:

$$IV_i = (C_i + D_i + O_i)/300 \qquad (3)$$

in which IV_i is the importance value of species i, C_i is the canopy coverage of species i in a 10 m by 10 m plot, D_i is the density of species i in a 10 m by 10 m plot, and O_i is the chance of species i for occurring among 110 plots .

Species in tree layer (≥ 5 m) and shrub layer (≥ 1 m and < 5 m) were treated respectively. Then all species were sorted according to the suitability-based habitat types as well as the importance value. The top 10 species for different suitability-based panda habitat types were selected and used to compare difference of species composition. Only 6 suitability-based habitat types which have tree cover and bamboo cover were used: very suitable summer habitat, suitable summer habitat, very suitable winter habitat, suitable winter habitat, transition habitat, and marginal habitat.

The structure of habitat components (tree layer and bamboo layer) was analysed in detail for two situations: panda presence and panda absence, in order to find whether and how the structure of habitat components influences the presence of pandas. Checking for any significant difference of the structure parameters of tree and bamboo layers has been executed between panda-presence habitat and panda-absence habitat. These parameters are total tree canopy coverage, total bamboo coverage, number of tree stems, number of bamboo culms, height for both tree and bamboo species, DBH of tree stems, and BD of bamboo culms. The Mann-Whitney U test was used to test all the hypotheses in the study. The hypotheses were set up based on Tian's (1990) field observation and our field survey. In general:

- There is a significant difference between panda-presence and panda-absence habitats on tree canopy coverage, number of tree stems, tree DBH and tree height;
- There is a significant difference between panda-presence and panda-absence habitats on bamboo coverage, number of bamboo culms, bamboo basal diameter and bamboo height; number of bamboo culms with different ages (such as < 1, 1 - 2, and ≥ 2 year-old) as well as number of dead culms.

6.4 Results

6.4.1 Habitat use and selection by pandas

Table 6.1 shows panda habitat use based on 6 one-year periods for 4 pandas. Consequently the percentage of time, on average, in a year for pandas staying in each different habitat type is about 13% in conifer forests, 40% in mixed conifer and broadleaf forests, 45% in deciduous broadleaf forests, 2% in bamboo (or mixed with meadow), and appearing by chance in shrub-grass-herb land (< 1%) as well as rock and bare-lands (< 1%). Pandas have not been located in farm-land and water area by radio tracking. It shows that pandas stay in deciduous broadleaf forest and mixed conifer and broadleaf forest most of the year.

Figure 6.2 illustrates panda habitat use of ground-cover-based habitat types as well as three physical environmental factors (e.g. elevation, slope gradient and direction) in two seasonal activity ranges. In the winter range, pandas stay mostly in deciduous broadleaf forests as well as mixed conifer and broadleaf forests with an elevation range of 1600 to 1800 m, a slope range of 11 to 20 degrees, and south-facing slopes. In the summer range, pandas often use conifer forests and also mixed conifer and broadleaf forests with an elevation range of 2400 to 2600 m, a slope range of 21 to 30 degrees, and north and west exposed slopes. 9% of the tracking records in the winter activity range fall in the "no aspect" class and only 1% in the summer range, which means pandas more frequently use flat areas in their winter activity range than in their summer activity range.

Table 6.1 Analysis of panda habitat use by using radio tracking data in Foping Nature Reserve, China - the percentage of time spent in each different habitat type (cf: conifer forest, dbfcf: mixed conifer and broadleaf forest, dbf: deciduous broadleaf forest, bam: bamboo (or mixed with meadow), shgr: shrub-grass-herb land, fas: farm-land and settlements, rab: rock and bare-land, war: water area).

panda	Tracking period	Tracking days in different habitats								
		cf	dbfcf	dbf	bam	shgr	fas	rab	war	Total days
045 (F)	June 92 - May 93	15	57	77	0	1	0	0	0	150
065 (M)	June 92 - May 93	23	62	78	1	0	0	0	0	164
127 (M)	June 92 - May 93	45	61	76	12	0	0	0	0	194
045 (F)	Jan. 95 - Dec. 95	19	91	94	3	0	0	0	0	207
065 (M)	Jan. 95 - Dec. 95	15	102	67	1	0	0	0	0	185
005 (M)	Jan. 95 - Dec. 95	17	57	82	2	5	0	3	0	166
Total days		134	430	474	19	6	0	3	0	1066
% of time in a year		12.6*	40.3	44.5	1.8	0.6	0.0	0.3	0.0	100

* 12.6=134/1066*100

Calculation of habitat selection is shown in Table 6.2. The x^2 goodness-of-fit (Table 6.2a) shows significant difference between overall habitat availability and usage ($p < 0.001$, $df = 7$, $x^2 = 259$). It means that pandas show "habitat selection" when considering all habitat types together. Checking availability proportion of each habitat type with the 95% confidence interval reveals that three habitat types are frequently selected by pandas: conifer forest, deciduous broadleaf forest as well as bamboo groves (Table 6.2b). Pandas use the "rock and bare-land" areas by chance but in proportion to the availability of this habitat type. However, the remaining four habitat types (e.g. mixed conifer and broadleaf forest, shrub-grass-herb land, farm-land and settlements, as well as water area) are less frequently selected or not selected by pandas (see discussion).

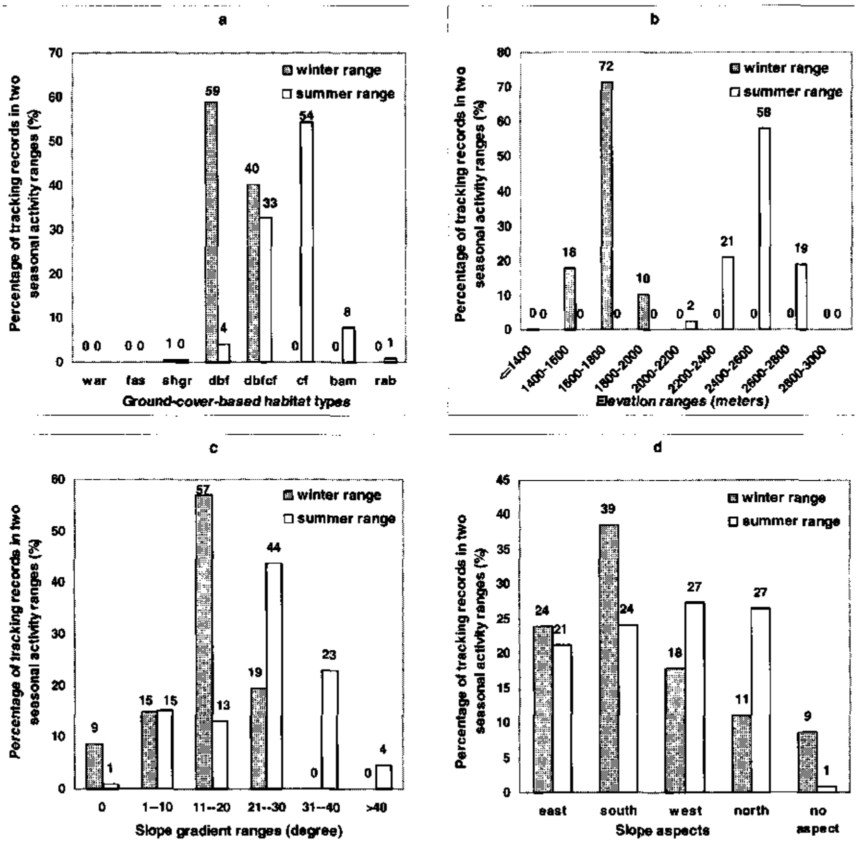

Figure 6.2 Analysis of panda habitat use in two seasonal activity ranges in Foping Nature Reserve, China. **a** - use of eight ground-cover-based habitat types: conifer forest (cf), mixed conifer and broadleaf forest (dbfcf), deciduous broadleaf forest (dbf), bamboo (or mixed with meadow) (bam), shrub-grass-herb land (shgr), rock and bare-land (rab), farm-land and settlements (fas), as well as water area (war). **b** - use of elevation ranges. **c** - use of slope gradient ranges. **d** - use of 5 classes of slope aspect: east (E: 46-135 degrees), south (S: 136-225 degrees), west (W: 226-315 degrees), north (N: 316-360 and 0-45 degrees), and no aspect (No).

Table 6.2 Analysis of panda habitat selection in Foping Nature Reserve, China by comparing the expected with observed panda occurrence numbers, and calculating x^2 and confidence interval.

a: calculating x^2 in order to see panda habitat selection when considering all habitat types together. The area of each habitat type comes from our habitat mapping result in Chapter 4, and the observed radio-tracking locations are from Table 6.1.

Habitat type	Habitat availability		Location of radio-tracking		Expected observations[3]	χ^2 test
	Area (km²)	Proportion $:p_a$[1]	Observed	Proportion $:p_{oi}$[2]		
1 conifer forest	16.5	0.056	134	0.126	60	91.47
2 mixed conifer and broadleaf forest	174.2	0.594	430	0.403	633	65.06
3 deciduous broadleaf forest	92.0	0.314	474	0.445	334	58.42
4 bamboo (or mixed with meadow)	1.7	0.006	19	0.018	6	26.62
5 shrub-grass-herb land	6.0	0.020	6	0.006	22	11.45
6 farm-land and settlements	0.4	0.001	0	0.000	1	1.45
7 rock and bare-land	1.6	0.005	3	0.003	6	1.36
8 water area	1.0	0.003	0	0.000	4	3.63
Total	293.4	1	1066	1	1066	259.47

b: calculating 95% C.I. and checking with availability proportion of each habitat type.

Habitat type	Proportion of availability $:p_a$	Proportion of observations $:p_{oi}$	95% C.I. on proportion of occurrence: P_i	Habitat selection
1 conifer forest	0.056	0.126	$0.098 <= P_{cf} <= 0.155$	Frequent
2 mixed conifer and broadleaf forest	0.594	0.403	$0.362 <= P_{dbfcf} <= 0.446$	Less frequent
3 deciduous broadleaf forest	0.314	0.445	$0.403 <= P_{dbf} <= 0.488$	Frequent
4 bamboo (or mixed with meadow)	0.006	0.018	$0.007 <= P_{bam} <= 0.029$	Frequent
5 shrub-grass-herb land	0.020	0.006	$-0.001 <= P_{shgr} <= 0.012$	Less frequent
6 farm-land and settlements	0.001	0.000	0	Not selected
7 rock and bare-land	0.005	0.003	$-0.002 <= P_{rab} <= 0.007$	In proportion
8 water area	0.003	0.000	0	Not selected

1. p_a is a proportion of the area of each habitat type to the total area, for example, 16.5/293.4=0.056.
2. p_{oi} is a proportion of observed locations in each habitat type to the total observed locations, for example, 134/1066=0.126.
3. Expected locations of animals are calculated by multiplying the availability proportion (p_a) and the total observed locations, for example, 0.056*1066=60.

6.4.2 Comparison of characteristics of panda habitat types

Woody plant species composition

The woody plant species composition shows differences among six suitability-based panda habitat types. The top ten species with the highest importance values (*IV*) for both tree layer and shrub layer were selected and are shown in Table 6.3 and Table 6.4 respectively. There is less repetition of species with high *IV* between "very suitable summer habitat" (vss) and "suitable (ss) summer habitat" than between "very suitable winter habitat" (vsw) and "suitable (sw) winter habitat".

Table 6.3 The woody plant species with their importance value (*IV*) in the tree layer (≥ 5 m) in six different suitability-based panda habitat types in Foping Nature Reserve, China.

Woody species in tree layer	Suitable summer habitat		Suitable winter habitat			
(≥ 5 m)	vss	ss	vsw	sw	tr	ms
1 *Abies fargesii*	0.29					
2 *Crataegus wilsonii*	0.08					
3 *Meliosma cuneifolia*	0.07					
4 *Cornus macrophylla*	0.07					
5 *Sorbus koehneana* *	0.06					
6 *Corylus tibetica*	0.21				0.29	
7 *Cerasus tomentosa* *	0.20				0.12	
8 *Populus purdomii*	0.10				0.17	
9 *Betula albo-sinensis var. septentrionlis*	0.40		0.23	0.27	0.30	0.30
10 *Pinus armandi* *	0.10	0.13				0.09
11 *Sorbus tapashana*		0.07				
12 *Acer mono*		0.06				
13 *Sorbus hemsleyi*		0.04				
14 *Betula platyphylla*			0.19			
15 *Tilia amurensis*			0.21			
16 *Carpinus turczaninowii var. stipulata*			0.21		0.11	
17 *Populus davidiana*			0.30		0.30	0.10
18 *Castanea mollissima*			0.21			0.18
19 *Quercus aliena var. acuteserrata*			0.39	0.32		0.15
20 *Dendrobenthamia japonica* *			0.33	0.30		0.15
21 *Quercus glandulifera var. brevipetiolata*			0.26	0.33		0.10
22 *Juglans cathayensis* *			0.20	0.21		
23 *Pinus tabulaeformis*				0.28		
24 *Euptelea pleiospermum*				0.26		
25 *Tsuga chinensis*				0.24	0.31	
26 *Quercus spinosa* *				0.22		0.09
27 *Carpinus turczaninowii*				0.26		0.15
28 *Picea wilsonii*					0.24	
29 *Litsea pungens* *					0.11	
30 *Acer ginnala* *					0.10	
31 *Platycarya strobilacea*						0.10

Note: "vss", "ss", "vsw", "sw", "tr" and "ms" represent six suitability-based panda habitat types: very suitable summer habitat, suitable summer habitat, very suitable winter habitat, suitable winter habitat, transition habitat and marginal habitat. Symbol "*" indicates the species occurring in both the tree and shrub layers.

The typical tree species (Table 6.3) in "vss" and "ss" are *Abies fargesii, Crataegus wilsonii, Meliosma cuneifolia, Cornus macrophylla, Sorbus koehneana, Sorbus tapashana, Acer mono, Sorbus hemsleyi.* However, the specific tree species in "vsw" and "sw" are different and consist of *Betula platyphylla, Tilia amurensis, Juglans cathayensis, Pinus tabulaeformis,* *Euptelea pleiospermum*. Only *Betula albo-sinensis var. septentrionlis* occurs in the whole elevation range with high *IV* in the tree layer. The tree species in both transition and marginal habitats can appear in both winter and summer habitats. In the transition habitat, three tree species are typical: *Picea wilsonii, Litsea pungens* and *Acer ginnala.*

Table 6.4 The woody plant species except bamboo species with high importance value (*IV*) in the shrub layer (≥ 1 m and < 5 m) in six different suitability-based habitat types in Foping Nature Reserve, China.

Woody species in shrub layer (≥ 1 m and < 5 m)	Suitable summer habitat		Suitable winter habitat		tr	ms
	vss	ss	vsw	sw		
1 *Sorbus koehneana* *	0.08					
2 *Ribes fasciculatum var. chinense*	0.08					
3 *Rosa tsinglingensis*	0.07					
4 *Rosa omeiensis*	0.11				0.30	
5 *Philadelphus incanus*	0.11				0.13	0.08
6 *Acer cappadocicum*	0.20		0.14			
7 *Viburnum betulifolium*	0.38		0.24	0.26	0.25	0.23
8 *Euonymus phellomanus*	0.32	0.23	0.35	0.29		
9 *Litsea pungens* *	0.16	0.20	0.16		0.21	
10 *Cerasus tomentosa* *	0.08	0.07				
11 *Spiraea alpina*		0.16				
12 *Lonicera taipeiensis*		0.10				
13 *Maddenia wilsonii*		0.08				
14 *Rhododendron capitatum*		0.07				
15 *Berberis pseudothunbergii*		0.06				
16 *Daphne giraldii*		0.04				
17 *Syringa oblata*		0.03				
18 *Carpinus cordata*			0.19			
19 *Chamaecereus sylvestri*			0.14			
20 *Dendrobenthamia japonica* *			0.25	0.25		
21 *Lespedeza dahurica*			0.19	0.26		
22 *Smilax scobinicaulis*			0.21			0.12
23 *Smilax stans*			0.20	0.22	0.51	0.27
24 *Viburnum mangolicum*				0.22		
25 *Juglans cathayensis* *				0.27		
26 *Rubus corchrorifolius*				0.24	0.17	
27 *Smilax galbra*				0.24		0.13
28 *Abelia engleriana*				0.20		0.11
29 *Acer ginnala* *					0.23	
30 *Syringa villosa*					0.12	
31 *Abelia biflora*					0.12	
32 *Cotoneaster acutifolius taycz. var. villosulus*					0.11	
33 *Quercus spinosa* *						0.07
34 *Pinus armandi* *						0.07
35 *Lonicera hispida*						0.06
36 *Padus racemosa*						0.04

Note: "vss", "ss", "vsw", "sw", "tr" and "ms" represent six suitability-based panda habitat types: very suitable summer habitat, suitable summer habitat, very suitable winter habitat, suitable winter habitat, transition habitat and marginal habitat. Symbol "*" indicates the species occurring in both the tree and shrub layers.

The woody species in the shrub layer shows an obviously different composition (Table 6.4), but some species in the tree layer occur in the shrub layer as well: *Sorbus koehneana, Litsea pungens, Cerasus tomentosa, Dendrobenthamia japonica, Juglans cathayensis, Acer ginnala, Quercus spinosa,* and *Pinus armandi*. It indicates that these woody species regenerate well in Foping NR. *Euonymus phellomanus, Viburnum betulifolium* and *Litsea* *pungens* occur at all elevation ranges. There are more species with high *IV* in the shrub layer than in the tree layer in the suitable summer habitat (ss). More species with high *IV* only occur in the transition habitat (such as *Acer ginnala, Syringa villosa, Abelia biflora,* and *Cotoneaster acutifolius taycz. var. villosulus*) and the marginal habitat (like *Quercus spinosa, Pinus armandi, Lonicera hispida, and Padus racemosa*).

Structure analysis of tree layer

Several parameters reflecting the structure of the tree layer (i.e. total tree canopy coverage, average height of tree stems, number of tree stems, and average DBH of tree stems) were compared between panda-presence and panda-absence habitats. Figure 6.3 shows that there were no panda signs found in the area where no bamboo grows under the tree canopy. Figure 6.3 also shows that the habitats without understorey bamboo groves have significantly more tree stems than the habitats with bamboo groves (p = 0.007 and 0.009), while there is no significant difference for the other three tree parameters. Figure 6.4 shows that, when bamboo species (either *B. fargesii* or *F. spathacea*) exist under the tree canopy, no significant differences of these tree parameters were found between panda-presence and panda-absence habitats ($p > 0.05$).

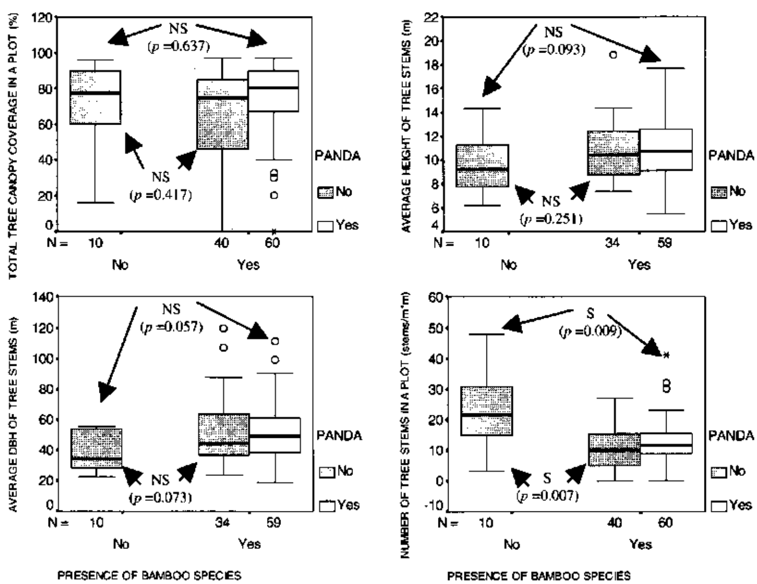

Figure 6.3 Comparison of tree parameters with or without understorey bamboo between panda-presence and panda-absence habitats. "N" represents the number of plots. "NS" means no significant difference and "S" means significant difference at 95%C.I. level. "p" represents the probability at a certain significant level. "o" and "*" represent the statistical outliers and extreme outliers. The grey boxplots show analysis under no panda and the white boxplots show analysis under panda presence. "DBH" represents the tree diameter at breast height.

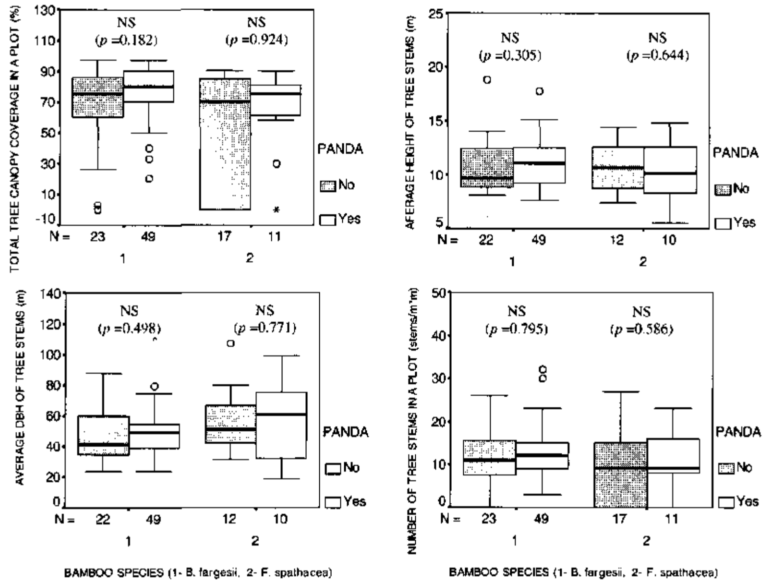

Figure 6.4 Comparison of tree parameters with understorey bamboo between panda-presence and panda-absence habitats. "N" represents the number of plots. "NS" means no significant difference and "S" means significant difference at 95%C.I. level. "p" represents the probability at a certain significant level. "o" and "*" represent the statistical outliers and extreme outliers. The grey boxplots show analysis under no panda and the white boxplots show analysis under panda presence. "DBH" represents the tree diameter at breast height. "1" and "2" mean *Bashania fargesii* and *Fargesia spathacea*.

Structure analysis of bamboo layer

Figure 6.5 shows comparison of four bamboo structure parameters between panda-presence and panda-absence habitats. In *B. fargesii* groves, no significant difference was found for the total bamboo coverage and the average basal diameter of bamboo culms between panda-presence and panda-absence habitats (p = 0.798 and 0.186). However, pandas do select short and dense groves at a significant level of 95% C.I. (p = 0.004 and 0.001). In *F. spathacea* groves, only the density of bamboo culms is similar between panda-presence and panda-absence habitats (p = 0.221), but the panda-presence habitat has significantly higher bamboo coverage, taller and thicker bamboo culms (p = 0.037, 0.004 and 0.000).

Figure 6.6 shows the relationship between bamboo-culm ages and habitats with panda presence or absence. Pandas significantly select the areas with more one to two year-old culms as well as dead culms (p = 0.002, 0.004, 0.031 and 0.015) for both bamboo species. In the *B. fargesii* area, pandas also significantly select the habitat with more two or over two year-old bamboo culms (p = 0.001). However, in the *F. spathacea* area, pandas do not show significant difference in selecting the habitat with more two or over two year-old bamboo culms (p = 0.438). For the density of less than one year-old culms in both bamboo areas, no significant difference was found between the panda-presence and panda-absence habitats (p = 0.913 and 0.408).

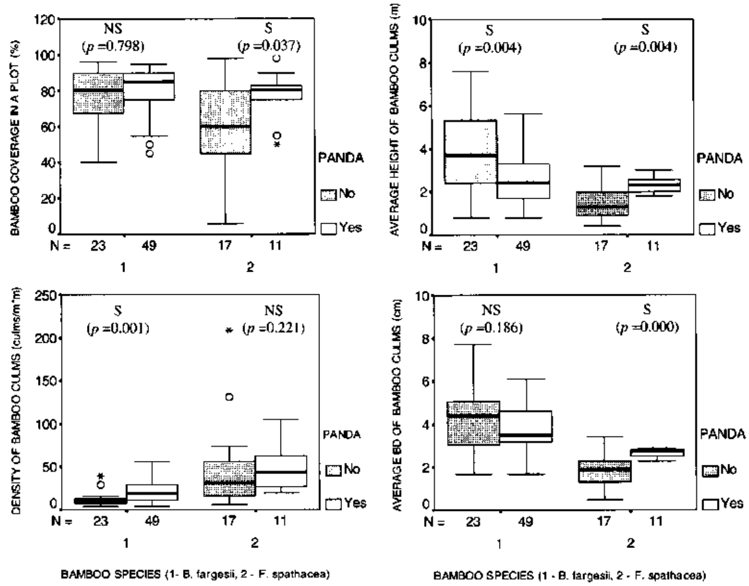

Figure 6.5 Comparison of four bamboo structure parameters between panda-presence and panda-absence habitats. "N" represents the number of plots. "NS" means no significant difference and "S" means significant difference at 95%C.I. level. "p" represents the probability at a certain significant level. "o" and "*" represent the statistical outliers and extreme outliers. The grey boxplots show analysis under no panda and the white boxplots show analysis under panda presence (see legend at the right side). "BD" represents the bamboo basal diameter. "1" and "2" mean *Bashania fargesii* and *Fargesia spathacea*.

6.5 Discussions

Babaasa (2000) stated that animal habitat selection appears to coincide with seasonal changes and correspond to food availability. In Foping NR, the vegetation types have a vertical distribution along the elevation. Radio tracking data analysis showed that the area below about 1950 m in Foping NR is the panda winter habitat and the area above about 2160 m the panda summer habitat (see Chapter 5). In the winter habitat, deciduous broadleaf forest and mixed conifer and deciduous broadleaf forest occupy a large area with well-growing understorey bamboo *B. fargesii*, which provides pandas with a large food supply in the winter season. The summer habitat is covered by conifer forest and mixed conifer and deciduous broadleaf forest as well, which provides *F. spathacea* bamboo as the pandas' summer food. The results in Table 6.1, i.e.

pandas spend 45%, 40% and 13% of the year respectively in deciduous broadleaf forest, mixed conifer and deciduous broadleaf forest, and conifer forest, reveal that panda habitat selection coincides with seasonal changes as the pandas occupy specific vegetation types in specific seasons (see Chapter 4 and Chapter 5).

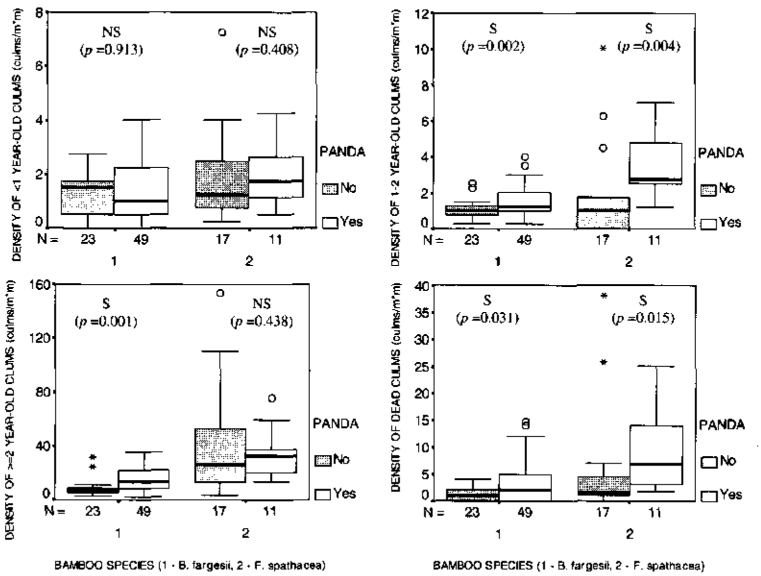

Figure 6.6 Comparison of bamboo age between panda-presence and panda-absence habitats. "N" represents the number of plots. "NS" means no significant difference and "S" means significant difference at 95%C.I. level. "*p*" represents the probability at a certain significant level. "o" and "*" represent the statistical outliers and extreme outliers. The grey boxplots show analysis under no panda and the white boxplots show analysis under panda presence. "1" and "2" mean *Bashania fargesii* and *Fargesia spathacea*.

Pandas do not use the whole elevation range evenly in Foping NR. They mainly stay in the areas between 1600 and 1800 m in winter and use mostly the areas between 2400 and 2600 m in summer. The area from 1950 to 2160 m is only covered by scattered bamboo groves, and hardly any signs of long-time residence of pandas have been recorded (see Figure 6.2b). This has been proven by our field survey conducted in summer 1999 as well as by analysis of five-year radio-tracking data in Chapter 5. It has been termed by the local staff and defined in our mapping work in Chapter 4 as a transition habitat, which is used by pandas to move between two seasonal activity ranges only in June and September.

It has been reported that pandas occupy the areas with a gentle slope gradient. This has been confirmed in this study. In winter, pandas select the areas with a slope range of 10 to 20 degrees. The summer habitat in Foping NR has mostly steeper slopes than the winter habitat, and consequently pandas use the areas with slopes between 20 to 30 degrees. The frequency for pandas to appear in the areas with slopes over 30 degrees is much higher in summer than in winter activity ranges, occupying 27% of the summer tracking-records, while no panda tracking record was found to appear in the areas with slopes over 30 degrees in the winter range. This result agrees with Yang and Yong (1998). When comparing the situation in Wolong NR, pandas select the flat areas or gentle-slope areas between 10 to 20 degrees the whole year (Ouyang et al. 1996). One of the reasons could be that the summer habitat in Foping NR is limited and mostly has a slope of 20 to 30 degrees.

Analysis of habitat selection through calculating x^2 and confidence interval shows that pandas do not frequently select the habitat type "shrub-grass-herb land". This seems reasonable because it has no tree and bamboo cover based on the definition of this habitat type in Chapter 4, and therefore it is concluded that this habitat type is avoided by pandas. However, this is not the case for the habitat type "mixed conifer and broadleaf forest" selected less frequently by pandas, as shown in Table 6.2b. The result of less frequently selecting "mixed conifer and broadleaf forest" does not mean that pandas avoid this habitat type, but might be due to that fact that it covers a large area in Foping NR (60% of the nature reserve). Figure 6.2a also shows that pandas often occupy this habitat type both in summer and winter seasons. Therefore, it might be concluded that mixed conifer and broadleaf forest is less frequently selected but not avoided by pandas. Clearly, pandas seem to avoid areas influenced by humans, like "farm-lands and settlements".

a b

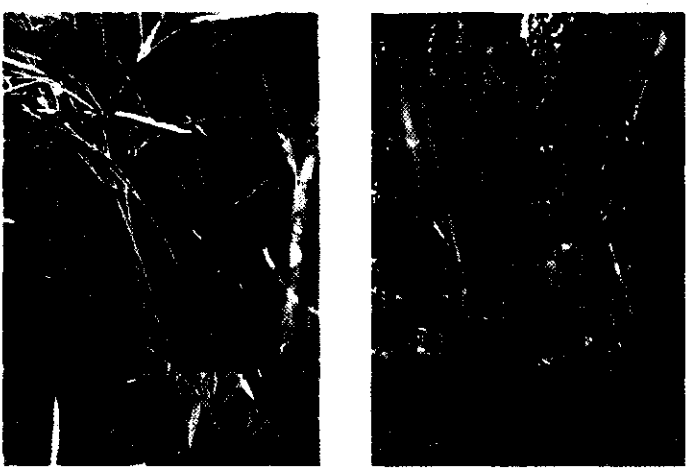

Figure 6.7 Photos show the "ZhuYangZi" *B. fargesii* habitat (a) with short (about 2 m) and dense culms with more branches caused by multiple feeding events by pandas, and the high mature *B. fargesii* habitat (b) with tall (about 4 m) and sparse culms with no branches in Foping Nature Reserve, China. (*Photo : Xuehua Liu*)

During the winter season, pandas stay in the areas with *B. fargesii* and frequently select the so-called "ZhuYangZi" bamboo groves (called by local people), which means that the bamboo culms are short (about 2 m high) and dense with more culms as well as branches caused by multiple feeding events by pandas (Figure 6.7a). The statistical results in Figure 6.5 confirmed that the structure parameters of "ZhuYangZi" bamboo groves are significantly different from those of the normal *B. fargesii* groves with tall (about 4 m) and sparse culms with no branches (Figure 6.7b). It might be necessary to separate these two quite different *B. fargesii* habitats from a conservation point of view. These two different habitats can be termed as the "ZhuYangZi" *B. fargesii* habitat and the high mature *B. fargesii* habitat based on our field observation. Mostly, the high mature *B. fargesii* habitat is thought not to be used by pandas. However, this is not true. During our survey in summer 1999, evidence was found of the remains of a few droppings and piles of the remaining parts of bamboo shoots. Therefore, that pandas still use the high mature *B. fargesii* habitats in the spring season for foraging thick bamboo shoots was confirmed. The shoots consumed by pandas consequently disappear from the groves and panda droppings from eating these shoots cannot exist for a long time due to easy decomposition. This means that no signs are left in the high mature *B. fargesii* groves, which, in turn, gives people the wrong impression that pandas do not use the high mature *B. fargesii* groves.

F. spathacea bamboo in summer habitat has shorter and thinner culms, and grows more densely. It was found that pandas select *F. spathacea* bamboo groves with higher coverage, taller and thicker culms in the summer activity range. Two reasons may explain this phenomenon: (1) the biomass of individual *F. spathacea* culm is small; and (2) the summer habitat is steep. These make pandas select suitable bamboo groves with higher bamboo biomass (taller culms, thicker basal diameter, and higher coverage due to more culms and leaves) without often climbing the steep slope. No significant difference on bamboo density was found between panda-presence and panda-absence habitats in the high elevation area, which is similar with pandas in Wolong NR which select *B. fangiana* in high elevations (Reid and Hu 1991). One of the reasons could be that, in general, most of the bamboo groves in the high elevation areas grow densely. For example, *F. spathacea* grows densely in the high elevation area in Foping NR and *B. fangiana* grows densely in the high elevation area in Wolong NR.

There are more one and two-year-old as well as dead culms in panda-presence habitat than in panda-absence habitat for both bamboo species. This implies that the bamboo groves regenerate well, and so, are frequently used by pandas. However, no significant difference was found for culms with age of less than on-year-old between panda-presence and panda-absence habitats, which agrees with Reid and Hu (1991) that the proportion of current-year-old culms alone does not seem to be an important factor to explain bamboo patch selection of pandas in Wolong NR.

6.6 Conclusion

The radio tracking data and habitat plot data were thoroughly analysed to gain insights into panda habitats and usage of these habitats. The results of analysis show that pandas in Foping NR do select their habitat types. In the winter season, pandas frequently select the areas with deciduous broadleaf forest and mixed conifer and broadleaf forest with an elevation range of 1600 to 1800 m, a slope range of 10 to 20 degrees and south-facing slopes. In the summer season, pandas mostly select conifer forest, mixed conifer and broadleaf forest, and bamboo groves with an elevation range of 2400 to 2600 m and a slope range of 20 to 30 degrees. The results also show that the characteristics of tree and bamboo layers may direct panda habitat selection. Pandas often use the *B. fargesii* areas with shorter and denser culms from different ages and less tree stems in winter, while they select the *F. spathacea* areas with higher coverage, taller and thicker culms from one-two year-old ages in summer.

Acknowledgement

We give our grateful thanks to Mr Zhao Junjun who helped us in field data collection and devoted his entire life to panda conservation and unfortunately passed away late in the year 2000 during the 3rd national-level panda survey. We thank Dr Shao Xiaoming from the Chinese Agricultural University for helping us to identify plant species in the field survey in 1999. We would like to thank also State Forest Administration (SFA), China for its permission to get into Foping Nature Reserve to carry out the field survey. We sincerely thank the directors of the nature reserve (Zhang Jian, Wang Xuejie, Zhao Dehuai) for their support on all aspects. Without them, the fieldwork could not be carried out. We thank Dr Lalit Kumar and Mr Uday B. Nidumolu for reviewing and commenting on the draft version of paper.

CHAPTER 7

Synthesis:
Giant Panda Habitat and Conservation

Recovered panda habitat with bamboo and trees after relocation of human being in Foping Nature Reserve
(Photo : Xuehua Liu)

CHAPTER 7 Synthesis: Giant Panda Habitat and Conservation

7.1 Introduction

The main objective of this thesis is to evaluate the giant panda habitat in Foping NR through effective and accurate mapping and modelling. The whole of the thesis reflects this. The thesis was presented by compiling a number of papers with relevant topics which link to each other and ultimately relate to the main aim of this study. In this final chapter, I firstly want to emphasise the most important results from and the coherence between the previously presented chapters, and to see whether the research questions addressed before starting this research have been answered adequately. I then discuss the applicability of the approach used in this study to other panda nature reserves in the Qinling Mountains. Thirdly, the work which has not been included in this PhD research due to time limitation are discussed in this chapter in order to have a wider field of vision of this study, and highlight the possible topics for future research. Lastly, I address the management relevance of this study to pandas and their habitat conservation.

7.2 Panda habitat mapping and modelling

Nature-reserve-based panda habitat evaluation is important for panda conservation. Mapping is no doubt an effective method for panda habitat evaluation. However, accurate mapping is required to produce panda habitat maps, which can be further used in panda habitat modelling and monitoring and consequently provide the proper information for panda habitat conservation and management.

In digital image processing, different classification algorithms produce different classifications. Fierens et al. (1994) mentioned that they did not understand why the classifiers have differences in mapping accuracy. **Chapter 2** evaluated three different mapping techniques: the parallelepiped classifier (PPC), the maximum likelihood classifier (MLC) and the backpropagation neural network classifier (BPNNC). The spectral discrimination capability of the BPNNC was also explored in Chapter 2. The research question for Chapter 2 is to what extent the neural network algorithm can separate two classes with no spectral overlap in their feature space. The result shows that the BPNNC can separate two non-overlap classes with an overall accuracy of 100%. However, the traditional MLC cannot do this when using the same data set. This provides the BPNNC a potential in land cover and land use mapping as well as wildlife habitat mapping. The result also shows that the BPNNC produced the highest mapping accuracy compared to the MLC and the PPC.

Richards (1993) pointed out that knowledge-based methods show good prospects for coping with data complexity in a GIS. Skidmore (1997) recommended that the neural network backpropagation algorithm might be very useful when combined with the rule-based expert system. Therefore, the research question is: Can the neural network system and expert system be combined together as an integrated classification algorithm to get higher mapping accuracy than the conventional MLC and other techniques? **Chapter 3** developed two integrated mapping algorithms: the consensus builder classifier (CSB), and the integrated expert system and the neural network classifier (ESNNC). Mapping results show that the ESNNC achieved a significantly higher overall accuracy (80%) than the consensus builder classifier (72%), the backpropagation neural network classifier (74%), the expert system classifier (59%), and the maximum likelihood classifier (62%). We found that the classification information from different classifiers may be "diluted" by the consensus builder approach which made this mapping algorithm produce only a middle-level overall accuracy, i.e. higher than the MLC and the ESC but lower than the BPNNC. We also found that the expert system classifier (ESC) requires a high level of expertise to construct the rule base and has difficulty in achieving high mapping accuracy.

Chapter 4 applied the developed ESNNC to map panda habitat. There are three research questions in chapter 4: (i) How to define panda habitat types for mapping? (ii) Can the ESNNC identify the habitat type with a limited number of training samples? (iii) Can the developed ESNNC map the giant panda habitat with a high accuracy?

There are different interpretations of the concept of "habitat" (Moen 1973, Baker 1978, Morrison et al. 1992). So, how to define different habitat types of a species or population is a common problem in wildlife conservation. In this research, we defined habitat types of the giant panda based on the ground cover types and the suitability classes, and termed in the thesis the ground-cover-based potential panda habitat types and the suitability-based panda habitat types. The former was mapped using a total of 160 field survey points with records of the ground cover types, while the latter was mapped using not only 160 survey points (with recordings of panda "presence" or "absence") but also 1425 non-overlapping radio-tracking points. We assume that the areas with many panda signs in survey plots or with dense panda tracking records are suitable for pandas. The criterion to define the elevation ranges of the panda winter and summer habitats was based on the results of Chapter 5.

The classification results show that the ESNNC mapped both the ground-cover-based and suitability-based panda habitat types with the highest accuracy (both over 80%) and is significantly better than the BPNNC, ESC as well as MLC. The mapping results also show that the ESNNC could discriminate the habitat type with few training samples, such as "conifer forest", "bamboo (or mixed with meadow)", "shrub-grass-herb land", "farm-land and settlements", "rock and bare-land", as well as "water area". However, the traditional MLC failed to identify these classes with few training samples due to its parametric mechanism. It was confirmed by the mapping results that panda habitat in Foping NR is good, and over 95% of the nature reserve is covered by forest. The giant pandas can use 16% of the reserve area as their summer habitat, 52% as their winter habitat, and 20% as their transition habitat to move between the winter and summer habitats.

Chapter 5 thoroughly analysed the radio-tracking data, which have been used in Chapter 4 for mapping the suitability-based panda habitat types, in order to gain insight into panda movement patterns in Foping NR. Spotting pandas in the forest-covered mountains is very difficult. Therefore, radio-tracking is an effective way to study the giant panda and understand its behaviour and habitat use. Through analyses, we should answer (i) when, where and how the giant pandas move? and (ii) whether there is a significant difference in panda activity range between male and female, and between winter and summer? Analysis of a total of 1639 effective radio-tracking data recorded in a five-year period (from 1991 to 1995) showed us that pandas climbed from the winter to the summer activity ranges within a period of 8 days from June 7 to 15, and descended over several weeks between September 1 and October 6 from the summer to the winter ranges. So, pandas spent 243 days in the winter range below 1950 m and 78 days in the summer range above 2160 m. The average distance moved over two consecutive days varied in different months. Pandas move longer distances with also larger variation in March, April, May, June and September. However, in December, January, February, July and August, pandas move a short distance in their winter or summer range. It was found that there is no significant difference on distance travelled within two consecutive days between male and female pandas. The result of the Mann-Whitney U test showed there is no significant difference between adult male and female pandas using the winter activity range as well as using the summer activity range. Adult male pandas use a similar area for the winter range as for the summer range, while adult female pandas use a significantly larger area for the winter range than for the summer range.

As mentioned previously, the panda radio-tracking data can also be used to analyse panda habitat use and selection. **Chapter 6** tackled this issue. However, the radio-tracking data were recorded without any habitat information, such as cover types, during the tracking period from 1991 to 1995. So, the mapping result from ESNNC in Chapter 4 was used to extract the ground-cover-based panda habitat types for radio-tracking records. The question that needs to be answered is whether the giant pandas use/select some habitat types significantly more than other types. We found that pandas in Foping NR do exhibit habitat selection behaviour. They select mostly four habitat types: deciduous broadleaf forest, mixed conifer and broadleaf forest, coniferous forest, and *Fargesia* bamboo groves. In the winter range, pandas spend more time in deciduous broadleaf forest with an elevation range of 1600 to 1800 m, a slope range of 10 to 20 degrees, and south-facing slopes. In the summer range, pandas use more conifer forest with an elevation range of 2400 to 2600 m and a slope range of 20 to 30 degrees.

Chapter 6 also looked at panda habitat characteristics (woody plant species composition, structure parameters of tree layer and bamboo layer) by analysing 110 surveyed plots with detailed measurements in order to find differences in habitat characteristics between panda-presence habitat and panda-absence habitat. Analysis results showed us that pandas stay in the area where bamboo grows, and they select the *B. fargesii* bamboo area with short and dense culms from different ages in the winter activity range, while they select the *F. spathacea* bamboo area with a high coverage of tall and thick culms from one to two years old in the summer activity range.

7.3 Applicability in Qinling panda refuges

Figure 7.1 is a Landsat TM image which shows the landscape of the main part of the Qinling Mountains. Four neighbouring nature reserves with the main aim of protecting the giant pandas and their habitat are illustrated by their boundaries. They are Foping, ChangQing, LaoXianCheng and ZhouZhi NRs. The remaining one, TaiBai NR is on the northern side of LaoXianCheng NR (see Figure 1.1). As we see, Foping NR is located almost at the centre of the neighbouring three nature reserves. I consider it to be a very important pilot nature reserve together with LaoXianCheng NR in the Qinling Mountains. It plays a role as a "bridge" which links the neighbouring three nature reserves, and further through LaoXianCheng NR links with TaiBai NR. Pandas in Foping NR share the summer habitat, where the mountaintops are located, with pandas from the neighbouring three nature reserves (see Figure 4.5). I think it is necessary and also important to apply the same work done in this research to other nature reserves in the Qinling Mountains. Detailed panda habitat evaluation by mapping and modelling is worth undertaking in each individual panda nature reserve. Consequently, in the long-term, modelling panda-habitat relationship and monitoring panda habitat condition will be improved by nature-reserve-based panda habitat mapping. Due to the adjacency of these nature reserves in the Qinling Mountains, the characteristics of panda behaviour and habitat should share more similarities than differences, which may make the application of this research approach in the other reserves easier. However, slight adjustment in panda habitat evaluation and panda-habitat relationship modelling in this northern panda refuge needs to be considered.

Landsat TM images show clearly that the habitat conditions of the giant pandas in these four panda nature reserves are different. Some areas were used for commercial logging before, such as LongCaoPing (the area below ZhouZhi NR) and TaiBai Forest Bureau (the area above ChangQing NR). Detailed habitat evaluation should be carried out as well in the surrounding areas outside the existing panda nature reserves. Loucks et al. (2001) evaluated the panda habitat in the Qinling Mountains at a geographically large scale, which may guide future work from a broad view. Panda habitat mapping and evaluation at both levels (i.e. the nature-reserve-based and the Qinling-mountain-based) are required and need to be integrated.

Pan et al. (1988) pointed out that movement patterns of panda populations in different mountains might not be the same and they remain unclear. I assume that there are also differences in panda movement patterns and panda habitat use and selection among the panda nature reserves in the Qinling Mountains. More research on panda movement is expected to be done in the future using the same methods to analyse the available radio-tracking data for comparison purposes.

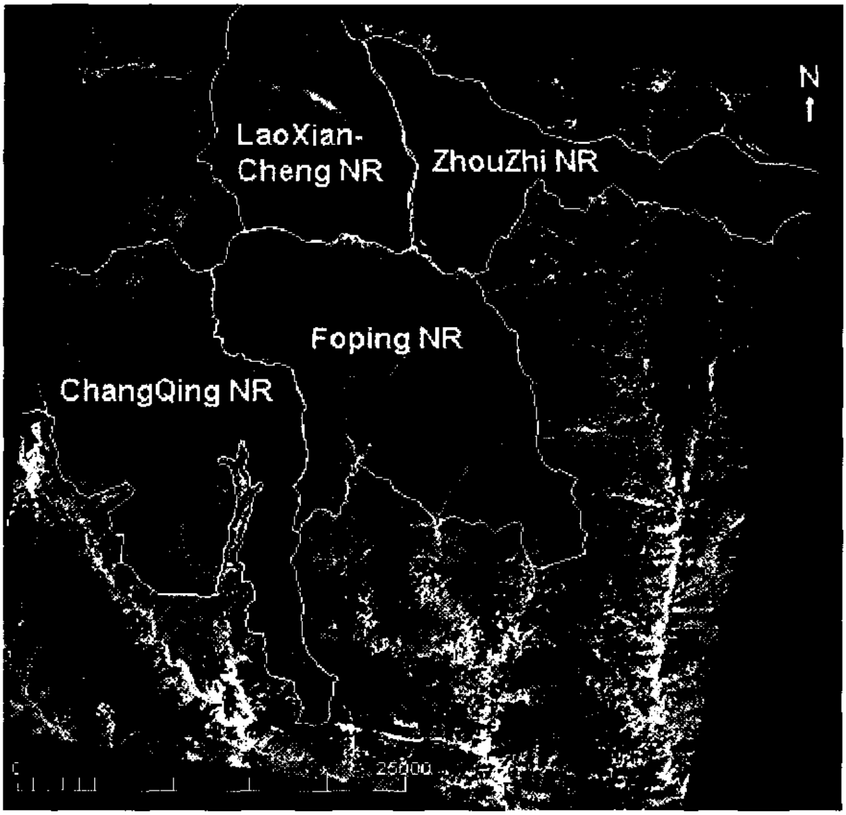

Figure 7.1 Panda nature reserves in the Qinling Mountains as shown on Landsat TM images (acquired on September 8 1997, RGB-TM5, TM3, TM2). Note: The unit of scale is meters. NR represents nature reserve.

7.4 Additional research topics

Two sub-topics in the initial design of this PhD research were omitted because of the time limitation and also data unavailability. They are (i) mapping panda habitat in Wolong NR using the same approach and modelling panda habitat use and selection, and (ii) habitat change detection in both Foping and Wolong NRs.

As addressed in Chapter 5, pandas in Foping NR show different movement behaviour compared to pandas in Wolong NR. We should ask "why?". There are certainly many factors that influence panda movement behaviour, such as climatic conditions, terrain characteristics, and vegetation distribution. And all these consequently influence panda habitat conditions that are related to panda activities. Figure 7.2 shows similarities as well as differences in climatic conditions between Foping and Wolong NRs. The two panda homes have similar total annual rainfall and yearly highest temperature, while they differ obviously on yearly mean humidity, total annual sunshine, yearly mean temperature, and yearly lowest temperature. Compared with Wolong NR, Foping NR has more sun shine hours, higher temperature and therefore lower humidity.

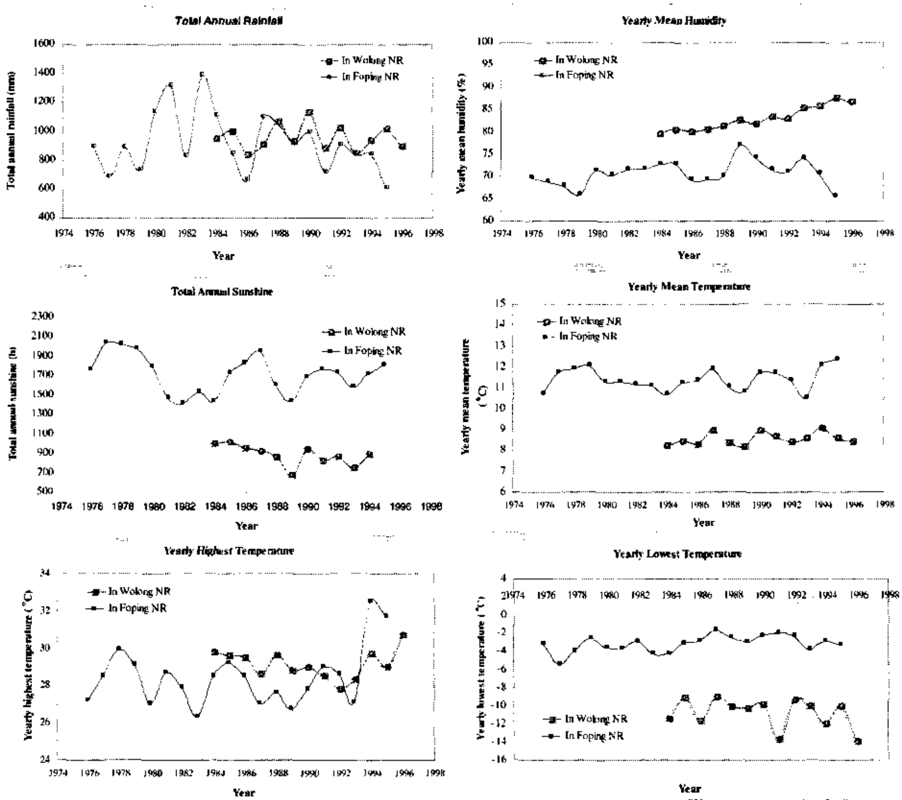

Figure 7.2 Differences in climatic conditions between Foping and Wolong Nature Reserves: total annual rainfall, yearly mean humidity, total annual sunshine, yearly mean temperature, yearly highest temperature, and yearly lowest temperature.

Figure 7.3 illustrates the different terrain factors (i.e. elevation, slope gradient and aspect) in these two nature reserves concerning panda winter and summer activity ranges. The whole elevation range can be used by pandas in Foping NR (293 km²), while only the area below 3600 m can be used by pandas in Wolong NR (1110 km²). The boundaries for winter and summer ranges was defined based on panda movement analysis for Foping NR (see Chapter 5), and based on expertise and literature information for Wolong NR (Hu et al 1985, Liu 1997). They are 1950 and 2160 m in Foping NR, and 2500 and 2600 m in Wolong NR. However, pandas in Wolong NR do not use the area below 2200 m because of serious human encroachment. So, Figure 7.3 shows us that the winter range is larger than the summer range in Foping NR, while the summer range is larger than the winter range in Wolong NR. Both in panda winter and summer ranges, Foping NR has more flat areas or areas with slope less than 20 degrees than Wolong NR. The slope aspect is similar in both nature reserves, however, Foping NR has more flat area with no slope in the summer range. There are more south-facing slopes in Foping NR, while there are more north-facing slopes in Wolong NR. The general vegetation types in the two nature reserves are similar, however the species composition is different.

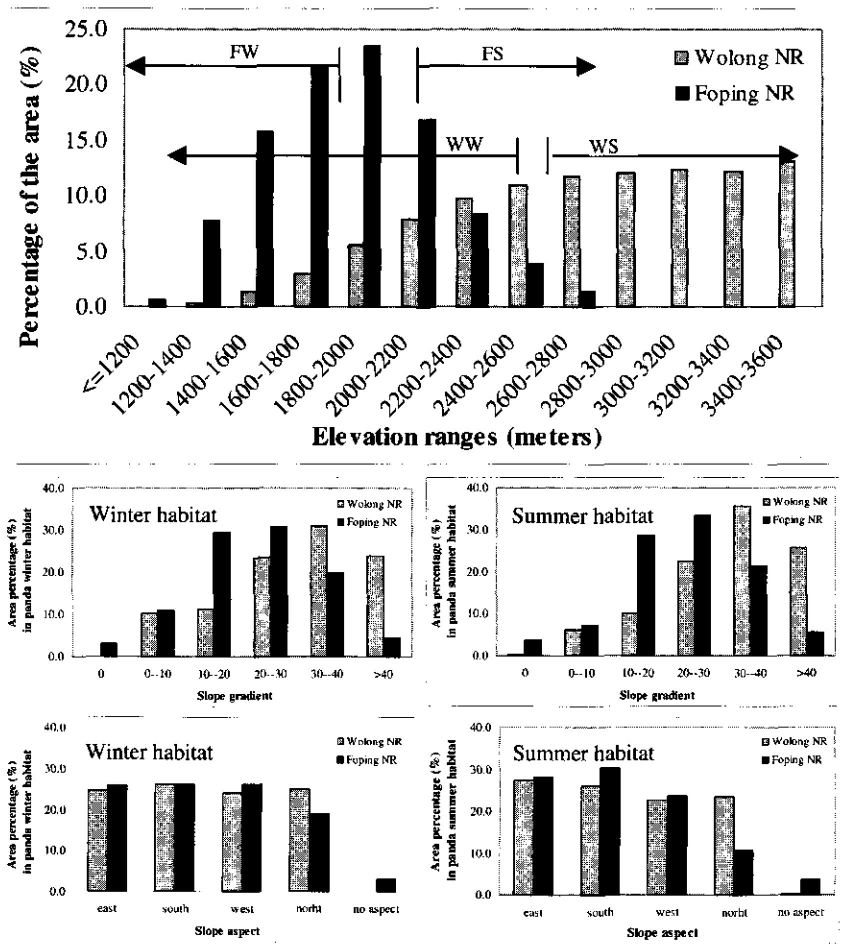

Figure 7.3 Different terrain factors (i.e. elevation, slope gradient, and slope aspect) in Foping and Wolong Nature Reserves (NR). FW – winter habitat in Foping NR, FS – summer habitat in Foping NR, WW – winter habitat in Wolong NR, and WS – summer habitat in Wolong NR.

Therefore, both the similarities and differences between these two panda homes, located in the Qinling and Qionglai Mountains respectively, tell us that it is worth mapping panda habitat and model panda movement and panda habitat use and selection using the same approach for whatever the comparison purpose or conservation purpose.

The aim of detecting panda habitat change is to monitor panda habitat within a certain period. Wolong NR was established in 1963 and Foping NR in 1978 respectively. We may ask: (i) *Does the creation of the nature reserves protect panda habitat? (ii)* How do the increased human population and human activities influence panda habitat? Based on our survey conducted in Foping NR in summer 1999 and several surveys in Wolong NR in 1996, 1997 and 1999, I found that mushroom production in Foping NR and firewood collection in Wolong NR are the threatening human activities to panda habitat (Figure 7.4). Both may have already produced a serious impact on panda habitat in these two nature reserves because of tree cutting. Liu (1997) analysed the spatial distribution of the identified human activities in Wolong NR and their influence on panda habitat. The ecological degradation in Wolong NR was further confirmed by Liu et al. (2001). However, the key issue is that the same methods for detection should be applied, including similar data, image processing methods, etc. Such proposed research tasks have never been carried out in the field of panda habitat research. The change detection of panda habitat in Foping NR has never been done before.

Figure 7.4 Photos show firewood collection in Wolong Nature Reserve (left) and mushroom production in Foping Nature Reserve (right). (*Photo : Xuehua Liu*)

7.5 Management relevance

The findings obtained in this research are closely related to the panda and its habitat conservation and may be used in conservation management. For instance, mapping results showed that the path (as shown in Figure 4.5) used by the local people and tourists passes through the suitable and even the very suitable winter habitats where panda radio-tracking records are dense (Figure 6.1). This should be brought to public attention. The fragmented panda suitable summer habitat in the north-east corner, which this path goes through, should be protected carefully in order to link the panda summer habitat as a whole. Otherwise, pandas in LongTanZhi and YueBa will not have enough suitable summer habitats. Intense human activities, such as mushroom production, should be strongly controlled or even forbidden in SanGuanMiao area, the centre of panda suitable habitat.

The identified movement pattern may guide the panda population survey and radio tracking in Foping NR. The tracking data showed that only a few records were obtained in June over a 5-year period. That was because pandas climbed up from their winter range to the summer range within a range of 8 days from June 7 to 15 (Chapter 5) and resulted in their disappearance from the range of radio tracking. Now, this has been identified and it can be rectified to provide more accurate information in future research. The fact that pandas stayed in the areas below 1700 m with the shortest movement distance (Figure 5.7) and smallest activity ranges in January and February tells us that these two months may be the best time for conducting a panda population survey in Foping NR. The movement distances are also short in July and August. However, plotting tracking data (Figure 5.2) showed pandas also use the summer habitat outside the nature reserve. This can easily give an erroneously low estimation when a survey is conducted in the summer season. In addition, surveying pandas when they are in the high elevation area may also cost more manpower, more money and more time.

To conserve panda habitat effectively, ecologists, managers and local staff etc. need to know how panda habitat types are distributed spatially, their extents, how pandas move in these different habitat types and how they make their habitat selection. I think that our approach may be applied in various degrees to other panda nature reserves with some modification, and eventually provide the managers or policy makers with more useful and accurate information.

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Summary

The fact that only about 1000 giant pandas and 29500 km^2 of panda habitat are left in the west part of China makes it an urgent issue to save this endangered animal species and protect its habitat. For effective conservation of the giant panda and its habitat, a thorough evaluation of panda habitat and panda-habitat relationship based on each individual panda nature reserve is necessary and important. Mapping has been an effective approach for wildlife habitat evaluation and monitoring. Therefore, mapping is also an important step in evaluating panda habitat and further being used to analyse panda-habitat relationship. Only Foping Nature Reserve is focused in this study. The objectives of this research are: (1) to develop a highly accurate mapping method which can map panda habitat using multi-type data (remote sensing data, digital terrain data, radio tracking data, and plot data from field survey) in GIS; (2) to study panda movement patterns; and (3) to analyse panda habitat use and selection.

A general introduction to the thesis is given in **Chapter 1**. It describes the research background and problems, and formulates the objectives and outlines of the research.

In order to find a potentially better mapping algorithm, three algorithms (i.e., parallelepiped algorithm, maximum likelihood algorithm, and backpropagation neural network algorithm) were evaluated using simulated data sets as well as the remotely sensed imagery in **Chapter 2**. The discrimination capability of the backpropagation neural network algorithm was also explored in this chapter. The results show that the backpropagation neural network classifier has completely discriminated two spectrally discrete classes, and obtained a significantly higher mapping accuracy than the other two algorithms using both simulated data sets and remotely sensed imagery.

Since different mapping techniques have complementary capabilities, two integrated mapping approaches were developed in **Chapter 3** so as to combine the advantages from different mapping algorithms. The expert system algorithm based on Bayesian probability theory was firstly discussed in this chapter. One integrated mapping approach is the consensus builder, which is used to adjust classification outputs in the case of a discrepancy in classification between maximum likelihood, expert system and neural network classifiers. The second approach is termed the integrated expert system and neural network classifier (ESNNC), which integrates the output of the rule-based expert system classifier with the backpropagation neural network classifier (BPNNC) before and after running the neural network system. The ESNNC produced maps with the highest accuracy compared to not only the individual backpropagation neural network classifier, expert system classifier and maximum likelihood classifier, but also the combined classifier – consensus builder.

The giant panda habitat in Foping Nature Reserve was mapped using the ESNNC in **Chapter 4**. Two categories of panda habitat types were defined and mapped: ground-cover-based potential panda habitat types and suitability-based panda habitat types. Mapping the ground-cover-based potential panda habitat types used only field survey

plot data with records of ground cover types, while mapping the suitability-based panda habitat types used not only the field survey plot data but also radio tracking data - meaning actual panda occurrence. Results show that both the ground-cover-based and the suitability-based panda habitat types were mapped with significantly higher accuracy compared with non-integrated classifiers: expert system, neural network and maximum likelihood classifiers. The classified maps show us that 97% of the nature reserve is covered by forest and about 68% of the nature reserve is a suitable habitat for pandas.

With radio tracking data, panda movement patterns were studied in **Chapter 5**. The use of GIS combined with statistical tools to thoroughly analyse radio-tracking data to reveal panda movement patterns is a new aspect in panda ecological research. Results show that pandas in Foping NR occupied two distinct seasonal activity ranges (i.e., winter and summer activity ranges) and had a regular seasonal movement between the winter range below 1950 m, and the summer range above 2160 m. Pandas spent about 8 days (from June 7 to 15) to climb up to the summer habitats, while they took about 36 days (from September 1 to October 6) to descend to the winter habitats. Consequently, they spent about 243 days in their winter activity range and about 78 days in the summer activity range. Research also shows that pandas travelled shorter distances with small variation in October, December, January, February, July and August, and longer distances with larger variation in March, April, May, June and September.

Analysis of wildlife habitat use and selection has been a common and important aspect of wildlife science. Little is known about panda habitat use and selection, especially about the relationship between panda presence and structures of the bamboo layer as well as the tree layer. In **Chapter 6**, tracking data were used to analyse panda habitat use and selection, and 110 field survey plots with measured information were analysed to identify differences of characteristics between panda-presence and panda-absence habitats. In the winter range, pandas spend more time in deciduous broadleaf forest with an elevation range of 1600 to 1800 m, a slope range of 10 to 20 degrees, and south-facing slopes. In the summer range, they use more conifer forest with an elevation range of 2400 to 2600 m, a slope range of 20 to 30 degrees. In *Bashania fargesii* bamboo areas with panda presence, bamboo groves have shorter and denser bamboo culms from different ages. In *Fargesia Spathacea* bamboo areas with panda presence, bamboo groves have higher coverage, taller and thicker bamboo culms which are mainly one to two years old.

Conclusions from the whole study are summarised in **Chapter 7**. It is recommended that the whole approach used in this study may or should be applied to the neighbouring panda nature reserves in the Qinling Mountains. The uncompleted research tasks are discussed in this chapter. Therefore, this chapter has shown some possible research topics for future panda conservation studies.

In summary, the following are the main findings of this research:

- Backpropagation neural network classifier can discriminate two classes with no overlap in their feature space.

- The integrated expert system and neural network classifier was developed and applied in mapping panda habitats, and obtained significantly higher overall mapping accuracy than non-integrated classifiers: expert system classifier, backpropagation neural network classifier, and maximum likelihood classifier.
- The integrated expert system and neural network classifier can identify a class which has only few samples, while the traditional maximum likelihood classifier fails because insufficient samples cannot form the statistical parameters to run the classification.
- The integrated expert system and neural network classifier successfully classified panda habitat types using multi-type input data: remote sensing data (TM1-5 and 7), terrain data (elevation, slope gradient and slope direction), social data (settlement distance), radio-tracking data, as well as field survey plot data.
- Radio-tracking data were involved in mapping panda habitat for the first time. They can be a good indicator of suitable habitats for pandas.
- The movement pattern of pandas in Foping Nature Reserve was thoroughly studied and revealed using GIS combined with statistical tools. Pandas spent a very short period of 8 days in June to move from winter to summer habitats, while they used more than one month in September to descend from summer to winter habitats.
- The finding that pandas in Foping Nature Reserve have a shorter movement distance and a small activity range in January and February indicates these two months may be a good time for conducting a panda population survey.
- Panda habitat maps produced by the integrated expert system and neural network classifier with higher accuracy have been used for analysing panda habitat use and selection. Pandas in Foping Nature Reserve mainly select deciduous broadleaf forest in the winter activity range, and select conifer forest and *Fargesia* bamboo groves in the summer activity range.
- The structure parameters of the bamboo layer in panda-presence habitats are significantly different from those in panda-absence habitats.

Samenvatting (Summary in Dutch)

Gezien het feit, dat slechts ongeveer 1000 panda's en 29500 km^2 panda habitat overgebleven zijn in het westelijke deel van China, is van het grootste belang deze bedreigde diersoort te redden en zijn habitat te beschermen. Om de panda en zijn leefgebied effectief te kunnen beschermen, is een gedegen evaluatie van de panda habitat en de relatie tussen de panda en zijn habitat in elk panda reservaat nodig. Kartering is een effectieve benadering voor de evaluatie van wild en zijn habitat. Daarom is kartering dan ook een belangrijke stap in de evaluatie van de panda habitat en voor de analyse van de relatie tussen de panda en zijn habitat. In deze studie is alleen onderzoek gedaan in Foping Nationaal Park. De doelstellingen van deze studie zijn: 1) het ontwikkelen van een karteringsmethode, die de panda habitat zeer nauwkeurig in kaart kan brengen, met gebruik van verschillende typen gegevens (afkomstig van: remote sensing, digitale terrein modellen, radio tracking en veldmetingen en -observaties) in een GIS; 2) het bestuderen van de bewegingspatronen van de panda; en 3) het analyseren van de panda habitat gebruik en habitat keuze.

In **hoofdstuk 1** is een algemene inleiding gegeven van dit proefschrift. Het beschrijft de achtergrond en problemen van het onderzoek en formuleert de doelstellingen en structuur van het onderzoek.

Om een potentieel betere karteringsmethode te vinden, zijn er drie algoritmen geëvalueerd ('parallelepiped' algoritme, 'maximum likelihood' algoritme, en 'backpropagation neural network' algoritme), waarbij zowel gesimuleerde gegevens als 'remote sensing' gegevens zijn gebruikt. Het onderscheidingsvermogen van de 'backpropagation neural network' algoritme is onderzocht in **hoofdstuk 2**. De resultaten geven aan, dat het 'backpropagation neural network' algoritme twee spectraal verschillende klassen goed kan onderscheiden en daarbij een significant hogere classificatie nauwkeurigheid heeft dan de twee andere algoritmes, wanneer zowel gesimuleerde gegevens als gegevens van 'remote sensing' gebruikt worden.

Aangezien verschillende karteringsalgoritmes complementaire capaciteiten hebben, zijn in **hoofdstuk 3** twee geïntegreerde karteringsbenaderingen ontwikkeld, om zodoende de voordelen van de verschillende karteringsalgoritmes te combineren. 'Expert system' algoritmes, gebaseerd op de 'Bayesian probability' theorie, worden in dit hoofdstuk ook bediscussieerd. Een geïntegreerde karteringsbenadering is de 'consensus builder', welke gebruikt wordt om geclassificeerde uitkomsten aan te passen in het geval van tegenstrijdigheden in de classificaties tussen 'maximum likelihood', 'expert system' en 'neural network' classificeerders. De andere benadering is genaamd de geïntegreerde 'expert system' en 'neural network' classificeerder (ESNNC), die de uitkomst van het op regels gebaseerde 'expert system' integreert voor en na het uitvoeren van de 'backpropagation neural network' classificeerder. De door de ESNNC geproduceerde kaarten hebben de hoogste nauwkeurigheid.

De habitat van de panda in het Foping Nationaal Park is in kaart gebracht gebruikmakend van de ESNNC en beschreven in **hoofdstuk 4**. Twee verschillende panda habitattypen zijn in kaart gebracht: de potentiële pandahabitat gebaseerd op grond-bedekking en de pandahabitat gebaseerd op geschiktheid. Voor het in kaart brengen van op grond-bedekking gebaseerde habitat zijn alleen veld waarnemingen gebruikt, waarbij de grond-bedekking werd geregistreerd. Voor het in kaart brengen van de op geschiktheid gebaseerde panda habitat zijn zowel veldwaarnemingen als 'radio tracking' gegevens gebruikt. De resultaten laten zien, dat het in kaart brengen van de beide panda habitat typen significant hogere nauwkeurigheid geeft vergeleken met resultaten van niet-geïntegreerde classificeerders: 'expert systems', 'neural network' en 'maximum likelihood' classificeerders. De geclassificeerde kaarten laten zien, dat 97 % van het Nationaal Park bestaat uit bos en ongeveer 68 % van het Nationaal Park geschikt is als panda habitat.

In **hoofdstuk 5** is, met gebruik van de reeds eerder genoemde 'radio tracking' gegevens, het migratie patroon bestudeerd. Het is een nieuw aspect in ecologisch onderzoek aan de panda dat een gedegen analyse van 'radio tracking' gegevens met behulp van GIS wordt gecombineerd met statistiek. Resultaten geven aan, dat panda's in Foping Nationaal Park twee duidelijk verschillende seizoensgebonden leefgebieden hebben (nl. winter en zomer leefgebied) en dat ze een regelmatige seizoensgebonden migratie vertonen tussen hun winter leefgebied, beneden de 1950 meter, en hun zomer leefgebied, boven de 2160 meter. Panda's doen er ongeveer 8 dagen over (van 7 tot 15 juni) om naar hun zomer leefgebied te klimmen, terwijl ze er ongeveer 36 dagen (van 1 september tot 6 oktober) over doen om af te dalen naar hun winter leefgebied. Daardoor verblijven ze ongeveer 243 dagen in hun winter leefgebied en ongeveer 78 dagen in hun zomer leefgebied. Onderzoek gaf ook aan, dat panda's in oktober, december, januari, februari, juli en augustus (met relatief kleine variaties) over kortere afstanden verplaatsen, en in maart, april, mei, juni en september (met relatief grote variaties) over langere afstanden.

Het onderzoeken van selectie en gebruik van hun habitat door wild is al lang een belangrijk aspect in wild studies. Er is slechts weinig bekend over de selectie en het habitat gebruik van panda's, met name over de relatie tussen de aanwezigheid van panda's en de structuur van bamboe en of bomen. In **hoofdstuk 6** zijn 'radio tracking' gegevens gebruikt om dit te onderzoeken. Daarnaast zijn 110 locaties met veldopnames geanalyseerd om het verschil te zien in de karakteristieken tussen de habitats met en zonder de aanwezigheid van panda's. Gedurende de winter verblijven de panda's vooral in loofverliezend bos op een hoogte tussen de 1600 en 1800 meter, met hellingen van 10 tot 20 graden, die naar het zuiden gericht zijn. Gedurende de zomer verblijven ze meer in naald bos op een hoogte tussen de 2400 en 2600 meter, met hellingen van 20 tot 30 graden. In de *Bashania fargesii* bamboe gebieden, waar panda's voorkomen, heeft het bamboe dicht opeen staande kortere stengels in diverse groei stadia. In *Fargesia spathacea* bamboe gebieden, waar ook panda's voorkomen, het bamboe heeft een hogere bedekking en langere en dikkere stengels, en zijn ze doorgaans een tot twee jaar oud.

De conclusies van de hele studie zijn samengevat in **hoofdstuk 7**. Het is aanbevelenswaardig dat de gehele methodologie zoals gebruikt in deze studie zal worden toegepast in the aangrenzende panda Nationale Parken in de Qinling Gebergte. De nog uit te voeren onderzoekstaken zijn besproken in dit hoofdstuk. Daarom geeft dit hoofdstuk een indicatie voor toekomstig onderzoek ten behoeve van de bescherming van de panda.

De belangrijkste bevindingen van dit onderzoek zijn als volgt samengevat:

- 'Backpropagation neural network' classificeerder kan twee klassen onderscheiden, zonder overlap in hun 'feature space'.
- Het geïntegreerd 'expert system' en 'neural network ' classificeerders zijn ontwikkeld en toegepast in het karteren van panda leefgebieden, en hebben een significant hogere nauwkeurigheid in het karteren van panda leefgebieden, dan de niet-geïntegreerde classificeerders; 'expert system' classificeerders, 'backpropagation neural network' classificeerders en 'maximum likelihood' classificeerders.
- Het geïntegreerde 'expert system' en 'neural network' classificeerders kan een klasse identificeren, die slechts enkele waarnemingspunten heeft, terwijl de traditionele 'maximum likelihood' classificeerder faalt, omdat door te weinig waarnemingen, de statistische parameters niet voldoen zijn om de classificatie uit te kunnen voeren.
- Het geïntegreerde 'expert system' en 'neural network' classificeerder heeft de panda leefgebieden met succes geclassificeerd, met gebruik van meerdere vormen van gegevens: 'remote sensing' gegevens (TM1-5 en 7), terrein gegevens (hoogte, hellingshoek en hellingsrichting), sociale gegevens (afstand tot nederzettingen), 'radio tracking' gegevens, en veld waarnemingen.
- 'Radio tracking' gegevens zijn voor het eerst gebruikt om het panda leefgebied te karteren. Deze gegevens kunnen goede indicatoren zijn voor locaties van geschikte panda leefgebieden.
- Migratie patronen van de panda's in Foping Natuur Reservaat zijn in detail bestudeerd, gebruikmakend van GIS in combinatie met statistische methodes. Panda's migreren in een zeer korte periode van 8 dagen in juni van hun winter verblijf gebied naar hun zomer verblijf gebied. Daarentegen gebruiken ze meer dan een maand in September om van hun zomer verblijf gebied af te dalen naar hun winter verblijf gebied.
- Gezien de uitkomst van dit onderzoek, dat panda's in het Foping Natuur Reservaat in januari en februari zich over kortere afstanden bewegen en een geringe leefgebied hebben, is dit een aanwijzing, dat deze twee maanden met name geschikt zijn voor het uitvoeren van een panda populatieonderzoek.
- De panda habitatkaarten, die gemaakt zijn met behulp van het geïntegreerde 'expert system' en 'neural network' classificeerder, zijn gebruikt voor het onderzoeken van de panda's gebruik en keuze van habitat. Panda's in Foping Natuur Reservaat selecteren hoofdzakelijk loofverliezend bos gedurende de winter en selecteren naaldbos en *Fargesia* bamboe gebieden gedurende de zomer.
- De parameters met betrekking tot het groeistructuur van bamboe zijn significant verschillend in gebieden, waar de panda wel voorkomt, dan wel waar de panda niet voorkomt.

中文摘要 (Summary in Chinese)

据估计，全球野生大熊猫种群数量现仅约1000只左右，分布在中国的秦岭山，岷山，琼崃山，大小相岭山，及凉山一带，其自然栖息地仅存约29500平方公里。这使得保护大熊猫这个濒危动物物种及其自然栖息地成为当务之急。为了有效地保护大熊猫及栖息地，迫切需要寻求有效的手段对各个大熊猫保护区的栖息地以及大熊猫与其栖息地之间的关系进行全面评价。如今利用多光谱遥感影像进行专题分类与制图，已经成为评价及监测野生动物栖息地的有效途径，因此它无疑也是评价大熊猫栖息地并进一步用于分析大熊猫与栖息地之间关系的一个重要手段。

该研究选择佛坪自然保护区(国家级大熊猫自然保护区)为研究示范区，旨在，(1)创建一个途径 从而在地理信息系统环境下能够处理多种类型数据(如遥感数据，数字地形数据，大熊猫电颈圈追踪数据，以及野外样点数据)，进而绘制精度较高的大熊猫栖息地类型图，(2)研究大熊猫的移动格局及与栖息地的关系，(3)分析大熊猫对栖息地的利用及选择状况。论文共分七个章节。

第一章为研究概要，阐述了研究背景和存在的问题，提出了具体研究目标，并描述了论文大纲。

为了寻找具有较好潜力的分类算法，第二章利用模拟数据和实际的遥感影像分别对三种算法(平行六面体分类法，最大似然分类法，及反向传播神经网络分类法)进行了评价，并着重对反向传播神经网络算法的光谱辨别能力进行了探讨。研究结果显示反向传播神经网络分类器能够完全区分所模拟的两个在光谱空间分离的"类型"，而应用较广的传统最大似然分类器却无法将它们百分之百分辨。并且，反向传播神经网络分类器所获得的制图精度显著高于最大似然分类器及平行六面体分类器的精度。

由于不同的分类算法之间具有一定的互补性，为了使不同分类算法优势互补，第三章设计并探讨了两个新的综合制图算法。该章首先讨论了基于贝叶斯概率论的专家系统分类算法，在此基础以及第二章的研究基础上提出了第一个综合制图算法，即通过一个"一致性检验器"对三个不同分类器(最大似然分类器，专家系统分类器，及反向传播神经网络分类器)的分类结果进行基于象元基础上的再判断，如果三种分类结果不统一，则"一致性检验器"的一系列规则便发挥作用，故被称为一致性检验分类法。第二个综合制图算法是将专家系统分类器与反向传播神经网络分类器通过多阶段的结合从而获得较高精

度的分类图，故被称为综合专家系统及神经网络分类法。综合专家系统及神经网络分类器在制图中所获得的精度显著高于其它分类器(一致性检验分类器，反向传播神经网络分类器，专家系统分类器以及最大似然分类器)。

第四章应用创建的综合专家系统及神经网络分类器对佛坪自然保护区的大熊猫栖息地类型进行判别制图并评价，绘制了两套不同的大熊猫栖息地类型图，一是以土地覆盖类型为基础的潜在大熊猫栖息地类型图，利用了1999年夏季野外调查的具有土地覆盖类型记录的160个样点数据，另一是以适宜性为基础的大熊猫栖息地类型图，不仅利用了1999年调查的具有大熊猫痕迹记录的160个样点数据，而且利用了六只大熊猫的无线电颈圈跟踪数据。制图结果进一步证实了综合专家系统及神经网络分类器显著优于其它单一的分类器(专家系统分类器，反向传播神经网络分类器，及传统的最大似然分类器)。制图结果还显示佛坪自然保护区97%的区域有森林覆盖，为大熊猫提供了大面积的潜在自然栖息地，而68%的区域是大熊猫的适宜冬夏季栖息地。

第五章深入分析了宝贵的无线电颈圈跟踪数据，对佛坪大熊猫的移动格局进行了细致研究。结合地理信息系统与统计方法分析无线电跟踪数据，以了解大熊猫的移动格局，这在大熊猫的生态研究领域是一个新的方面。分析结果显示佛坪的大熊猫拥有二个明显的季节活动区(即海拔1950米以下的冬季活动区与2160米以上的夏季活动区)，并常年有规律地移动于冬夏季活动区之间。6只熊猫五个年分的数据分析表明佛坪大熊猫从低于1950米的冬季活动区移至高于2160米的夏季活动区平均只需8天时间(6月7日至15日)，而由夏季活动区返回到冬季活动区却需平均约36天时间(9月1日到10月6日)。因此，大熊猫一年内在冬季区的活动时间达243天，几乎是在夏季场所活动天数(78天)的3.5倍。研究结果还显示大熊猫在刚下山的10月，冬季的12月，1月及2月，还有夏季的7月和8月里，所移动的距离(指相邻两天内的移动距离)短且变化幅度小，但在春季的3月，4月和5月，以及季节迁移期的6月与9月，移动距离大且变化幅度大。

分析研究野生动物对栖息地的利用及选择已成为野生动物学科的一个重要方向并已得到广泛关注。由于人们对大熊猫在栖息地的利用及选择方面了解不多，尤其是关于竹子层及树木层与大熊猫活动之间的关系了解不深，第六章利用无线电颈圈追踪大熊猫的数据以及所绘制的大熊猫栖息地类型图分析了大熊猫对栖息地的利用及选择状况，利用110个具有多类测定数据的野外调查样方对熊猫的出现与竹子层的结构参数(竹层覆盖度，竹竿密度，竹竿平均高度，竹竿平均基径，竹竿年龄级)和树木层的结构参数(冠层覆盖度，树干密度，平均树干高度，平均树干胸径)之间的关系。研究发现大熊猫在冬季活

动区多数时间选择在海拔1600至1800米，坡度为10至20度，坡向朝南的，植被为落叶阔叶林的栖息地内活动，而在夏季活动区则多数选择在海拔2400至2600米，坡度为20至30度，植被为针叶林的栖息地内活动。统计分析结果显示，有大熊猫活动痕迹的巴山木竹林，其竹竿矮(约2米)，竹竿密度大(每平米约25株)，竹竿具各种年龄，而在有大熊猫活动痕迹的松花竹林，竹层盖度大(80%)，竹竿高(约2米)，竹竿的基径粗(约2.5厘米)，主要是1至2年生竹竿。

第七章概括了各章的研究结论，并提出该研究的整体可以推广应用到整个秦岭山区的互相毗邻的大熊猫自然保护区(长青，周至，老县城，以及太白自然保护区)，该章还对未能实施的相关研究进行了简单讨论，由此也提出了未来保护大熊猫可能的相关研究。最后阐述了该研究的结果对大熊猫保护管理的可能影响。

该研究体现了如下几个主要成果或发现，

- 研究发现反向传播神经网络分类器能够完全识别在光谱特征空间没有重叠的二个“类型”，而传统的最大似然分类器却不能。
- 创建了综合专家系统及神经网络分类器，并将其应用在大熊猫栖息地制图上，且制图精度显著高于所应用的其它单一非综合分类器。
- 综合专家系统及神经网络分类器能够识别采样点很少的土地覆盖类型，而传统的最大似然分类器却不能。
- 综合专家系统及神经网络分类器在大熊猫栖息地类型制图中有效地处理了多种类型数据，遥感数据(陆地卫星TM波段1至5及7)，地形数据(海拔高程，坡度及坡向)，人为活动影响数据(人口居集中心扩散距离)，无线电颈圈追踪数据，以及野外样点调查数据。
- 由于无线电颈圈追踪数据能够很好反映大熊猫的适宜栖息地，该研究首次将无线电颈圈追踪数据应用到大熊猫栖息地制图评价上。
- 结合GIS与统计分析方法对佛坪大熊猫的移动格局进行了较全面的研究，结果发现佛坪大熊猫由低海拔的冬季活动区上移至高海拔的夏季活动区只需8天时间，而下移返回到冬季区却需36天时间。
- 研究发现佛坪大熊猫在冬季的1月及2月移动的距离最短，活动面积小，表明这个时间段可能是野外调查大熊猫数量的合理时间。
- 由综合专家系统及神经网络分类器所绘制的大熊猫栖息地类型图被有效地用在发析大熊猫栖息地的利用及选择上。结果揭示佛坪大熊猫在

其冬季区主要活动在1600至1800米内的落叶阔叶林中，而在其夏季区却主要选择2400至2600米内的针叶林以及纯松花竹林内。

- 有大熊猫活动痕迹的竹林的结构参数(如竹层盖度，竹竿的高度，基径及密度)与无大熊猫活动痕迹的竹林的结构参数显著不同

Curriculum Vitae

Liu, Xuehua was born in 1964 in Xinyu, Jiangxi Province, China. She successfully completed her education in secondary and high school in Xinyu.

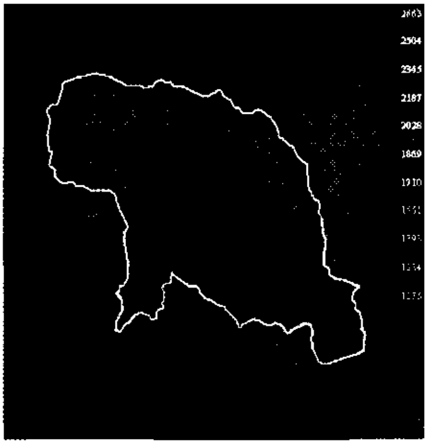
In 1982, she joined Nanjing University to study Biology with specialisation in Botany, and graduated in 1986 with a Bachelor of Science degree and immediately started working as a research assistant in Institute of Geography, Chinese Academy of Sciences (CAS). She left this position in 1988 and joined Research Centre of Eco-environmental Science, CAS for pursuing a Master of Science degree study in Ecology. She graduated with a M.Sc. degree in 1991. She returned back to Institute of Geography, CAS to continue her research career as an assistant professor till 1995.

Later in 1995, she left China to join International Institute for Aerospace Survey and Earth Sciences (ITC) in the Netherlands where she obtained her second Master of Science degree in Environmental System Analysis and Monitoring (ESM) in April 1997. She later won a scholarship from ITC for further Ph.D. study in Wildlife Conservation for Natural Resource Management (NRM). She started her Ph.D. research in the beginning of 1998 and will complete the research at the end of 2001.

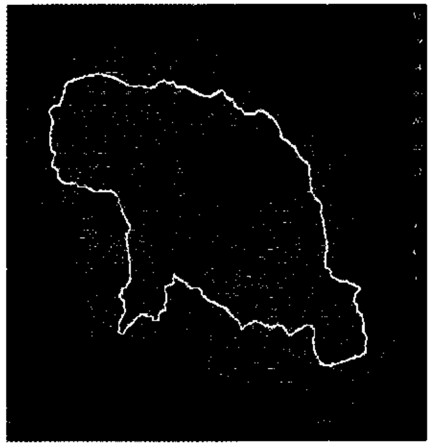
Since 1986, she has published over 15 scientific papers in Chinese or in English, as a senior author or as a co-author.

Appendix I

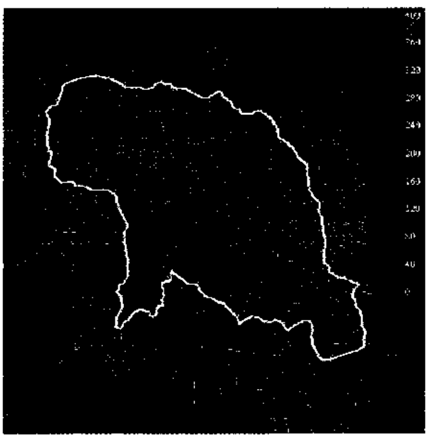
Basic GIS Map Layers



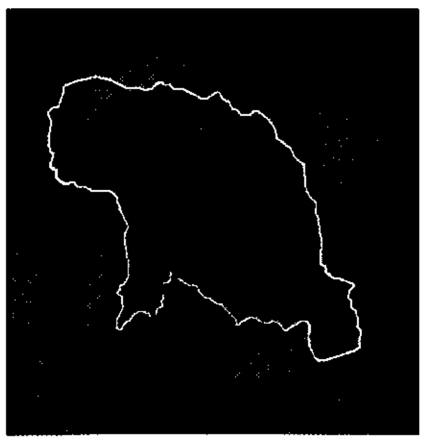
Digital Elevation Model of Foping Nature Reserve



Digital Slope Gradient Model of Foping Nature Reserve



Digital Slope Aspect Model of Foping Nature Reserve (Value 400 inside the boundary represents no aspect.)



Digital Distance Model to Human Settlements in Foping Nature Reserve

False colour composition of Landsat TM image (see Figure 7.1).

Appendix II

ITC PhD Dissertation List

1. **Akinyede**, 1990, Highway cost modelling and route selection using a geotechnical information system
2. **Pan He Ping**, 1990, 90-9003757-8, Spatial structure theory in machine vision and applications to structural and textural analysis of remotely sensed images
3. **Bocco Verdinelli, G.**, 1990, Gully erosion analysis using remote sensing and geographic information systems: a case study in Central Mexico
4. **Sharif, M**, 1991, Composite sampling optimization for DTM in the context of GIS
5. **Drummond, J.**, 1991, Determining and processing quality parameters in geographic information systems
6. **Groten, S.**, 1991, Satellite monitoring of agro-ecosystems in the Sahel
7. **Sharifi, A.**, 1991, 90-6164-074-1, Development of an appropriate resource information system to support agricultural management at farm enterprise level
8. **Zee, D. van der**, 1991, 90-6164-075-X, Recreation studied from above: Air photo interpretation as input into land evaluation for recreation
9. **Mannaerts, C.**, 1991, 90-6164-085-7, Assessment of the transferability of laboratory rainfall-runoff and rainfall - soil loss relationships to field and catchment scales: a study in the Cape Verde Islands
10. **Ze Shen Wang**, 1991: 90-393-0333-9, An expert system for cartographic symbol design
11. **Zhou Yunxian**, 1991, 90-6164-081-4, Application of Radon transforms to the processing of airborne geophysical data
12. **Zuviria, M. de**, 1992, 90-6164-077-6, Mapping agro-topoclimates by integrating topographic, meteorological and land ecological data in a geographic information system: a case study of the Lom Sak area, North Central Thailand
13. **Westen, C. van**, 1993, 90-6164-078-4, Application of Geographic Information Systems to landslide hazard zonation
14. **Shi Wenzhong**, 1994, 90-6164-099-7, Modelling positional and thematic uncertainties in integration of remote sensing and geographic information systems
15. **Javelosa, R.**, 1994, 90-6164-086-5, Active Quaternary environments in the Philippine mobile belt
16. **Lo King-Chang**, 1994, 90-9006526-1, High Quality Automatic DEM, Digital Elevation Model Generation from Multiple Imagery
17. **Wokabi, S.**, 1994, 90-6164-102-0, Quantified land evaluation for maize yield gap analysis at three sites on the eastern slope of Mt. Kenya
18. **Rodriguez, O.**, 1995, Land Use conflicts and planning strategies in urban fringes: a case study of Western Caracas, Venezuela
19. **Meer, F. van der**, 1995, 90-5485-385-9, Imaging spectrometry & the Ronda peridotites

20. **Kufoniyi, O.**, 1995, 90-6164-105-5, Spatial coincidence: automated database updating and data consistency in vector GIS
21. **Zambezi, P.**, 1995, Geochemistry of the Nkombwa Hill carbonatite complex of Isoka District, north-east Zambia, with special emphasis on economic minerals
22. **Woldai, T.**, 1995, The application of remote sensing to the study of the geology and structure of the Carboniferous in the Calañas area, pyrite belt, SW Spain
23. **Verweij, P.**, 1995, 90-6164-109-8, Spatial and temporal modelling of vegetation patterns: burning and grazing in the Paramo of Los Nevados National Park, Colombia
24. **Pohl, C.**, 1996, 90-6164-121-7, Geometric Aspects of Multisensor Image Fusion for Topographic Map Updating in the Humid Tropics
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26. **Metternicht, G.**, 1996, 90-6164-118-7, Detecting and monitoring land degradation features and processes in the Cochabamba Valleys, Bolivia. A synergistic approach
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28. **Roshannejad, A.**, 1996, 90-9009284-6, The management of spatio-temporal data in a national geographic information system
29. **Terlien, M.**, 1996, 90-6164-115-2, Modelling Spatial and Temporal Variations in Rainfall-Triggered Landslides: the integration of hydrologic models, slope stability models and GIS for the hazard zonation of rainfall-triggered landslides with examples from Manizales, Colombia
30. **Mahavir, J.**, 1996, 90-6164-117-9, Modelling settlement patterns for metropolitan regions: inputs from remote sensing
31. **Al-Amir, S.**, 1996, 90-6164-116-0, Modern spatial planning practice as supported by the multi-applicable tools of remote sensing and GIS: the Syrian case
32. **Pilouk, M.**, 1996, 90-6164-122-5, Integrated modelling for 3D GIS
33. **Duan Zengshan**, 1996, 90-6164-123-3, Optimization modelling of a river-aquifer system with technical interventions: a case study for the Huangshui river and the coastal aquifer, Shandong, China
34. **Man, W.H. de**, 1996, 90-9009-775-9, Surveys: informatie als norm: een verkenning van de institutionalisering van dorp - surveys in Thailand en op de Filippijnen
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36. **Pereira, Luisa**, 1996, 90-407-1385-5, A Robust and Adaptive Matching Procedure for Automatic Modelling of Terrain Relief

37. **Fandino Lozano, M.**, 1996, 90-6164-129-2, A Framework of Ecological Evaluation oriented at the Establishment and Management of Protected Areas: a case study of the Santuario de Iguaque, Colombia
38. **Toxopeus, B.**, 1996, 90-6164-126-8, ISM: an Interactive Spatial and temporal Modelling system as a tool in ecosystem management: with two case studies: Cibodas biosphere reserve, West Java Indonesia: Amboseli biosphere reserve, Kajiado district, Central Southern Kenya
39. **Wang Yiman**, 1997, 90-6164-131-4, Satellite SAR imagery for topographic mapping of tidal flat areas in the Dutch Wadden Sea
40. **Asun Saldana-Lopez**, 1997, 90-6164-133-0, Complexity of soils and Soilscape patterns on the southern slopes of the Ayllon Range, central Spain: a GIS assisted modelling approach
41. **Ceccarelli, T.**, 1997, 90-6164-135-7, Towards a planning support system for communal areas in the Zambezi valley, Zimbabwe; a multi-criteria evaluation linking farm household analysis, land evaluation and geographic information systems
42. **Peng Wanning**, 1997, 90-6164-134-9, Automated generalization in GIS
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47. **Bishr, Y.**, 1997, 90-6164-141-1, Semantic Aspects of Interoperable GIS
48. **Zhang Xiangmin**, 1998, 90-6164-144-6, Coal fires in Northwest China: detection, monitoring and prediction using remote sensing data
49. **Gens, R.**, 1998, 90-6164-155-1, Quality assessment of SAR interferometric data
50. **Turkstra, J.**, 1998, 90-6164-147-0, Urban development and geographical information: spatial and temporal patterns of urban development and land values using integrated geo-data, Villaviciencia, Colombia
51. **Cassells, C.**, 1998, Thermal modelling of underground coal fires in northern China
52. **Naseri, M.**, 1998, 90-6164-195-0, Characterization of Salt-affected Soils for Modelling Sustainable Land Management in Semi-arid Environment: a case study in the Gorgan Region, Northeast, Iran
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55. **Wang Donggen**, 1998, 90-6864-551-7, Conjoint approaches to developing activity-based models
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59. **Cheng Tao**, 1999, 90-6164-164-0, A process-oriented data model for fuzzy spatial objects
60. **Wolski, Piotr**, 1999, 90-6164-165-9, Application of reservoir modelling to hydrotopes identified by remote sensing
61. **Acharya, B.**, 1999, 90-6164-168-3, Forest biodiversity assessment: A spatial analysis of tree species diversity in Nepal
62. **Akbar Abkar, Ali**, 1999, 90-6164-169-1, Likelihood-based segmentation and classification of remotely sensed images
63. **Yanuariadi, T.**, 1999, 90-5808-082-X, Sustainable Land Allocation: GIS-based decision support for industrial forest plantation development in Indonesia
64. **Abu Bakr**, Mohamed, 1999, 90-6164-170-5, An Integrated Agro-Economic and Agro-Ecological Framework for Land Use Planning and Policy Analysis
65. **Eleveld, M.**, 1999, 90-6461-166-7, Exploring coastal morphodynamics of Ameland (The Netherlands) with remote sensing monitoring techniques and dynamic modelling in GIS
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80. **Farah, Hussein**, 2001, 90-5808-331-4, Estimation of regional evaporation under different weather conditions from satellite and meteorological data. A case study in the Naivasha Basin, Kenya
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