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THE EFFECTS OF FOREST HARVESTING
ON GIANT PANDA HABITAT USE
IN WOLONG NATURE RESERVE, CHINA

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THE EFFECTS OF FOREST HARVESTING
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By

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ABSTRACT

THE EFFECTS OF FOREST HARVESTING ON GIANT PANDA HABITAT USE IN WOLONG NATURE RESERVE, CHINA

By

Scott L. Bearer

Forest cover around the world has decreased by over 0.2% annually in the 1990s. Much of this decrease is due to forest harvesting. Decreasing forestland can have significant consequences for species worldwide because forest ecosystems are a major reservoir for global biodiversity, supporting 50-70% of the world's terrestrial species. To minimize impacts on biodiversity and to increase forest cover, many countries around the world have planted vast areas of artificially regenerated forest and initiated bans on logging natural forests. However, many questions remain unanswered concerning the impacts of forest harvesting and plantation reforestation on wildlife.

To address some of the important issues related to logging and reforestation impacts on wildlife, I investigated use of habitats by the giant panda in Wolong Nature Reserve, China. I established 913 plots (443 primary and 470 secondary) that measured 30 m^2 in forested, non-forested, and reforested areas throughout Wolong and monitored panda use via feces presence. Within each plot, I recorded forest and geographic characteristics and also surveyed bamboo stem characteristics in four 1 m^2 subplots. I implemented an adaptive cluster sampling strategy, which sampled 1, 5, or 8 plots depending on whether feces were found. Several statistical and modeling approaches were used to describe results, including the Horvitz-Thompson estimator along with autologistic regression to account for the spatial autocorrelation inherent in the adaptive cluster dataset. I also developed a model that used field data and applied it spatially to quantify the loss of information when field data were scaled up to the landscape level.

Recent harvests (0-10 years) that were <10 ha had some panda use while larger recently harvested areas (10-100 ha) had no use. In older harvested forest (30-100 years), panda use did not differ between small or large harvests and was similar to that in old growth forest. My results agreed with previous research that found bamboo and slope to be primary factors in describing panda habitat, but I found other characteristics were important in identifying panda habitat as forests mature. Populations of bamboo, the primary food of the giant panda, have also been affected by harvesting. Reforested areas that were established in Wolong did not provide suitable habitats for pandas. Reforested areas did, however, offer the potential to supply an alternative fuelwood source, which could limit impacts on natural forest.

This dissertation collectively describes how forest harvesting (i.e., timber harvesting and fuelwood collection) and reforestation activities influence the habitats of one of the world's most endangered species, the giant panda. Results are useful to describe potential impacts of logging activities to other mammalian species worldwide and may also help project potential consequences of logging bans currently being implemented in several countries. Additionally, I implement a novel application of a technique for gathering and analyzing field data of rare species using adaptive cluster sampling while accounting for spatial autocorrelation. Results from this technique can provide a useful comparison of this method to simple random sampling.

To my wife

And our families

Especially my parents

For their endless support and encouragement

"I am ashamed of my emptiness," said the Word to the Work.
"I know how poor I am when I see you," said the Work to the Word.

Rabindranath Tagore- Stray Birds

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BACKGROUND AND RESEARCH SUMMARY

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BACKGROUND AND RESEARCH SUMMARY

Background

Forests are perhaps the most significant renewable resource in the world. Covering nearly one-third of the world's land area (approximately 3800 million ha), forests provide many ecological services (Costanza et al. 1997) in addition to supplying much of the world with many goods and raw materials including timber and fuelwood (Convention on Biological Diversity 2001). As levels of atmospheric carbon dioxide rise and issues of climate change become a part of modern political debate (Stier and Siebert 2002, NOAA 2004), forests are also valuable for the carbon sequestration (forest vegetation and soils currently contain nearly 40% of all carbon stored in terrestrial ecosystems (Matthews et al. 2000)).

Despite all the benefits that forests offer, they are frequently poorly managed and extensively logged, or worse, converted to other land uses altogether. Timber harvesting for wood products is responsible for approximately one-third of global deforestation (Pottinger 2003), and roughly half of this harvesting is done illegally. Illegal harvesting alone may produce nearly 1/10 of the total global timber worth US$150 billion annually (Pottinger 2003). Many countries have adopted policies to improve management, increase conservation or limit illegal harvesting of forests (FAO 2005). However, deforestation and its effects may continue to remain a concern for decades, if not centuries, to come.

Ecological impacts of forest harvesting are significant because forests are thought to be the largest biodiversity banks in the world, housing 60-90% of all terrestrial species

(IUCN: The World Conservation Union 2005). However, many of these species' habitats are not protected (Rodrigues et al. 2004), and even areas that are protected may not necessarily benefit the resident species (Liu et al. 2001).

Logging impacts on biodiversity are particularly significant in Asia. Asia not only has one of the lowest forest to area ratios in the world (432 million ha forest to 3.09 billion ha land (FAO 2000), but also one of the highest deforestation rates (2.5 million ha/yr (FAO 2000)).

Within Asia, the People's Republic of China (Figure 1.1) is by far the largest country (9.6 million km^2) with a wide range of ecosystems (599 terrestrial ecosystems and the second highest diversity of species in the world (6347 vertebrate species, 14% the world total (FAO 2000, Li and Wilcove 2005)). China is also one of the areas in the world at most risk to the environmental problems, including pressures on biodiversity (Li 2004, Liu and Diamond 2005).

China, which is the world's third largest country in size, has one of the highest (approximately 22% of the world's population) and densest (roughly 120 people/km^2) human populations (as opposed to 20 people/km^2 in the United States or 60 people/km^2 in Europe) (Peng and Guo 2000). With a high degree of human pressure, China has one of the largest ecological footprints, second only to the United States (Liu and Diamond 2005).

Because of the pressures on its environment, China has used its forest resources extensively (Li 2004). Deforestation has taken place over thousands of years and has increased to high rates during many periods of Chinese history (Kristof 1993, Liu and Diamond 2005).

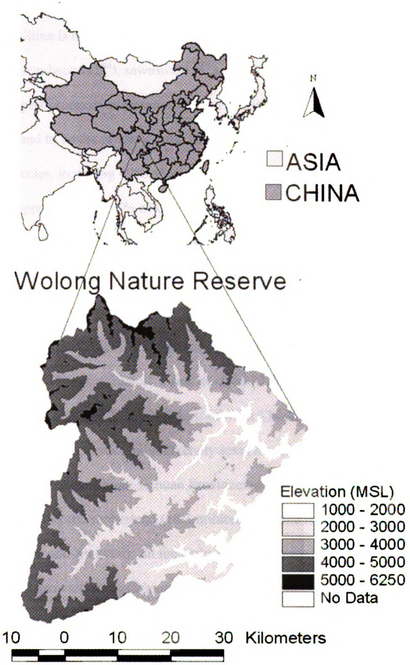


Figure 1.1. Location of the People's Republic of China and Wolong Nature Reserve, in Sichuan Province, southwest China. Shaded relief of Wolong demonstrates the elevation gradient within the Reserve.

Currently, China's rapid economic growth is significantly increasing its demand for forest products. China is now one of the largest consumers of various types of wood, including industrial roundwood (2nd), sawnwood (5th), and pulpwood (2nd), in addition to being the world's largest producer of plywood (Sun et al. 2004, Sun et al. 2005). Logging has been found to be the primary cause of habitat destruction in China, affecting 33% of vertebrate species, including 49% of mammal species (Li and Wilcove 2005). This has resulted in approximately 15% of China's vertebrate species currently being considered threatened with extinction (Li and Wilcove 2005).

Harvesting pressures are particularly high in southwest China, which has the largest amount of forestland (71 million ha) and the highest volume of standing timber (5 billion m^3) in China (Shi and Xu 2000). Harvesting pressures help to explain why the southwestern region lost 39% of its mature forest stock and 25% of its total timber forest stock between 1989-1993 (Shi and Xu 2000). In southwest China, timber harvesting has been one of the leading driving forces in biodiversity loss (Xu and Wilkes 2004).

Located in southwestern China, Sichuan Province has the largest tract of forestland (11.5 million ha) and timberland (10.3 million ha) in the region and the third largest in the nation (Shi and Xu 2000). In the early 1950s, Sichuan had approximately 1.6 billion m^3 of forest growing stock (Wang and Chen 1992, State Environmental Protection Administration of China 1998). However, Wang and Chen (1992) estimated that by 1980 this forest cover had decreased by 550 million m^3, primarily through illegal logging and conversion of forestland to agriculture. Other recent estimates place Sichuan's current timber stock at 1.3 million m^3 (Shi and Xu 2000).

To reduce extensive pressures on its forest resources, China has been implementing and enforcing new forest management regulations. In response to severe flooding in 1998 and in order to avoid additional disasters due to unchecked forest harvesting, the central government established two policies, the Natural Forest Conservation Program and the Sloping Lands Conservation Program (or Grain to Green), which attempt to limit timber harvesting and fuelwood collection and reforest areas on steep slopes in return for grain subsidies, respectively (Xu et al. 2004, Liu and Diamond 2005). These two programs may have long-term effects on China's biodiversity and wildlife habitats, as well as having consequences for other countries in Asia and the world. Due to the recent regulations on harvesting in China, foreign forests now must supply much of China's consumption. Between 1997 and 2003, Chinese forest product imports rose 75% to US$13 billion (Sun et al. 2004). China is currently importing nearly 95 million m^3 of wood, equal to 150% of Indonesia's total annual timber harvest (Sun et al. 2004). Therefore, the threats to biodiversity and wildlife habitats from harvesting due to China's forest product demands, as well as China's new forest regulations, are not only felt in-country, but may impact the entire Asian region.

One of the most charismatic species influenced by timber harvesting that has concerned the Chinese, as well as others throughout the world, is the endangered giant panda (*Ailuropoda melanoleuca*) (Schaller et al. 1985). The influence of timber harvesting and fuelwood collection on the giant panda is of particular concern to researchers and scientists, not only because of its endangered status, with total population numbers estimated around 1750 individuals (Xinhua 2004), but also because the panda is now limited to only a fraction of its original habitat. To protect biodiversity, the Chinese government has established approximately 2,000 nature reserves by the end of 2003 (Liu and Diamond 2005). Forty-five of these reserves were established specifically for the conservation of giant panda habitats. One of the largest of these is Wolong Nature Reserve.

Study Area

The Wolong Nature Reserve (102°52'-103°24'E, 30°45'-31°25'N) is approximately 200,000 ha in size, and is located in Wenchuan County, Sichuan Province, southwestern China (Figures 1.1 and 1.2). Although Wolong is a nature reserve established to conserve panda habitat, majority Han, and minority Tibetan, Chang, and Hui Chinese are still permitted to live within its borders. In 1998, a total of 4320 people were counted living in 942 households (An et al. 2001). This number is a dramatic increase from earlier population estimates (70% increase from 1975 to 1998). Concurrently with this human population increase was a rapid decline in the Wolong panda population. In 1974, 145 animals were estimated to live in Wolong (Schaller et al. 1985) and these numbers fell to 72 animals in 1986 (China's Ministry of Forestry and World Wildlife Fund 1989). The most recent panda census used new techniques and found a larger population (Xinhua 2004), though researchers agree this does not necessarily indicate an increasing population trend (World Wildlife Fund 2004). High quality panda habitat was also found to be declining even after the area was established as a nature reserve (Liu et al. 2001).

In an attempt to understand the relationship between humans and panda habitat, Liu et al. (1999b) found that there are many specific human activities causing a rapid

Figure 1.2. Wolong Nature Reserve, Sichuan Province, People's Republic of China. Wolong is 2000 km^2 in size and represents one of the largest nature reserves established by the Chinese government for the management and protection of the giant panda (*Ailuropoda melanoleuca*). Outlined areas represent distribution of pandas during 1974 census (adapted from (Schaller et al. 1985)). White represent areas found to have bamboo in the understory (Linderman et al. 2004). Regions of Zhuanjinggou and Yingxionggou are areas of previous widespread forest harvesting.

decline in panda habitat. Liu et al. (1999b) note that approximately 41% of the reserve would be suitable habitat for the giant panda on biological factors alone. However, when human influences are considered, approximately 17,000 ha (21%) of panda habitat was lost, leaving a much less suitable, highly fragmented reserve. The majority of these changes took place along the main highway that bisects the reserve and is due mainly to the prevalence of historical timber harvesting and present day fuelwood collection, as well as agricultural practices and livestock grazing.

The Forests and Bamboos of Wolong

Timber harvesting and fuelwood collection have caused a dramatic decrease in suitable panda habitat. In Wolong, the collection of wood for fuel has doubled over the past two decades to more than 9,000 m^3/year (Liu et al. 1999b). Similar to farming and agricultural practices, this activity removes much of the vegetation in the impacted area. Clearings vary in size, but are typically 2 to 6 hectares (Bearer, unpublished data). Location of clearings also varies, but areas harvested for fuelwood collection are typically within 2 to 4 km from the nearest road.

Extensive timber harvesting had been performed throughout Yingxionggou and Zhuanjinggou areas of Wolong (Figure 1.2) throughout much of the 1960s to the mid-1970s by one primary timber extraction company. Personal observation indicated typical forestry practices included removal of >50 % of the overstory canopy cover in areas usually between 0.1 km^2 and 1 km^2. Timber was used in construction and furniture making, as well as for pulpwood. In 1974-75, the primary timber extraction company was relocated to northern Sichuan Province after Wolong was established as a nature reserve. The Sichuan Ministry of Forestry officially banned timber harvesting within Wolong in 1985, however, there is still a high amount of timber harvesting (fluctuating between 1,000-1,400 m^3/year) occurring in the Reserve (Liu et al. 1999b).

The forests in Wolong can generally be divided into different categories along an elevational gradient (Schaller et al. 1985). An evergreen and deciduous broadleaf forest grows between an elevation of 1600 m and 2000 m, covering approximately 13% of the Reserve (Table 1.1). Between 2000 and 2600 m, the forest is composed of mixed conifer and deciduous broadleaf species. Hemlock (*Tsuga* spp.), spruce (*Picea* spp.), and larch (*Larix* spp.) are the main conifers, while birch, maple, basswood, and cherry are the most common deciduous trees. *Fargesia robusta* is the principal bamboo species with small populations of *Bashania fangiana* also being found in this range (Table 1.1). Extending from 2600 to 3600 m is the subalpine coniferous forest, which accounts for the most extensive forest type, covering 317 km^2 (16%) of the total area of the Reserve (Table 1.1). Fir species are the most common in this forest, along with birch and rhododendron. In this elevational zone, *B. fangiana* is the most widespread bamboo (Schaller et al. 1985). Because the giant panda's main range occurs within the latter two forest types (between 2000-2600 m and 2600-3600 m), the majority of the investigations of forest composition related to giant panda habitat have focused on these areas. Schaller et al. (1985) along with Taylor and Qin (1988b, 1988c) provided information on the structure, composition, and regeneration patterns of some of these forests. More importantly, they offered some insight into how the forest may be influenced after harvesting activities such as fuelwood collection (Taylor and Qin 1988a). These studies presented a good

Table 1.1. Elevational gradient and distribution of forest types, bamboo species, and panda habitat within Wolong Nature Reserve, Sichuan, China.

General Elevation (MSL) Categories	Forest Type	Bamboo Species	Panda Habitat
5000	Rock & Snow	No bamboo	
4600	Alpine Coniferous	No bamboo	
4000	Alpine Coniferous	No bamboo	
3600	Alpine Coniferous Subalpine Coniferous	*Bashania fabri*	Occassional
3000	Subalpine Coniferous	*Bashania fabri* *Yushania Chungii*	Main Range
2600	Subalpine Coniferous	*Bashania fabri* *Yushania chungii & Fargesia robusta*	Seasonal
2000	Coniferous and Deciduous Broadleaf	*Fargesia robusta*	Seasonal
1600	Evergreen and Deciduous Broadleaf	*Fargesia robusta*	Rare
1000	Evergreen Broadleaf	Other species	

(from Schaller et al. (1985))

understanding of dynamics of the Wolong forests. However, this is incomplete unless forest disturbance—bamboo dynamics are described.

The significance of understanding bamboo characteristics and elevational placement lies in the fact that it is the main food of the giant panda (Schaller et al. 1985). Because this plant is directly related to the panda habitat, the ecology of the bamboo within Wolong has been investigated on several occasions. Characteristics such as culm dynamics (Taylor and Qin 1987), regeneration patterns (Taylor and Qin 1988b), environmental influences affecting its growth (Reid et al. 1991c), and how it responds to flowering (Taylor and Qin 1993b) have been described. Although the biology of the plant has become well understood through these and other studies, information about bamboo distributions within Wolong has, until recently, been general. DeWulf et al. (1988) generated a general bamboo distribution map using Landsat MSS imagery while Linderman et al. (2004) used artificial neural networks to generate a more accurate bamboo map with Landsat TM data.

As humans continue to impact the local forests, and as the bamboo itself continues to mass-flower and regenerate, bamboo distributions within Wolong Nature Reserve fluctuate over time. This investigation occurred at a time when bamboo densities within the reserve were high, so the locations of panda activity noted in this study may be different than activity during times of low bamboo density. *Bashania fangiana*, which dominates the understory of most subalpine forest stands, mass-flowers every 45-60 years. After these flowering events, the bamboo dies off so that vast expanses of bamboo throughout the reserve are no longer suitable panda forage. The last flowering episode of Bashania in Wolong was in 1983. Many studies were done on bamboo dynamics and panda use during this time (Taylor and Qin 1987, Taylor and Qin 1988a, Taylor and Qin 1988b, Taylor and Qin 1988c, Taylor and Qin 1989, Reid et al. 1991c, Taylor et al. 1991, Taylor and Qin 1993b, 1997). Taylor and Qin (1988a) estimate that it takes 15 years for bamboo populations to recover to fully-stocked densities after a flowering episode. By calculating Electivity Indices and comparing these to previous use, this study provides information concerning panda habitat use during these fully-stocked periods, and will allow for comparisons about how pandas may shift habitat use during times of high and low food availability.

Giant Panda Habitat Use

Although pandas may eat a variety of plants, and occasionally meat, more than 99% of their diet consists of bamboo, including stems, branches, and leaves (Schaller et al. 1985). However, panda digestion of bamboo is inefficient (17% dry matter digestibility) so the animal must invest more than 60% of the day on foraging alone (Schaller et al. 1985). For this reason, pandas are limited regionally and locally by the presence of bamboo. In Wolong, the main panda range is within the subalpine coniferous forest areas where bamboo can occur. Two major species of bamboo are extant within this region. Umbrella bamboo (*Fargesia robusta*) is typically found in the lower elevations, while arrow bamboo (*Bashania fabri*) occurs in the upper elevations (Table 1.1) (Schaller et al. 1985). Schaller et al. (1985) found that pandas spent the majority of the year (>85%) above 2600 m in *B. fabri* bamboo patches. Use below these elevations was limited due to habitat disturbance or steepness of terrain, however pandas did use these areas when new shoots of *F. robusta* were developing in May and June (Schaller et al. 1985). A third, less prevalent bamboo species, *Yushania chungii*, is scattered throughout the higher elevations along with *B. fabri*, but panda use of this species has limited documentation.

Research Summary

This dissertation arises from my interest in determining the role of forest management and timber harvesting in affecting and conserving wildlife habitats. More specifically, as fuelwood continues to be essential for the survival of billions of people worldwide (Gardner-Outlaw and Engelman 1999, Arnold et al. 2003), I investigated both larger area harvesting along with fuelwood collection activities and their effect on panda habitats. It is my hope that the research described in this dissertation can provide another piece to the large puzzle of enhancing human welfare and alleviating poverty, while committing to sustainable forest use and conservation of wildlife habitats. By analyzing field data collected in Wolong Nature Reserve, I can demonstrate how harvesting for timber and fuelwood influences one of the most rare, most peculiar of mammalian species, the giant panda.

The research described in this dissertation is part of a larger socioeconomic ecological research program led by Jianguo Liu at the Center for Systems Integration and Sustainability in the Department of Fisheries and Wildlife at Michigan State University. The purpose of this program is to understand the relationships between human populations and government policies, forests, and giant panda habitat (Figure 1.3) (Liu et al. 1999b). From this framework, I focused on the interaction between the forests of Wolong and panda habitat.

I examined habitat use patterns (determined by feces presence) in areas associated with logging and reforestation activities within the forested and non-forested regions of Wolong. The next five chapters of this dissertation were written as individual manuscripts that will be submitted for peer-review in appropriate journals. Chapters 2 through 5 concentrate on how forest harvesting influence various aspects of panda habitat. Chapter 2 is an investigation into the effects of harvesting on the forest components of giant panda habitat and how this affects panda use. After exploring the forest community, I focus my attention in the next two chapters (Chapters 3 and 4) on the

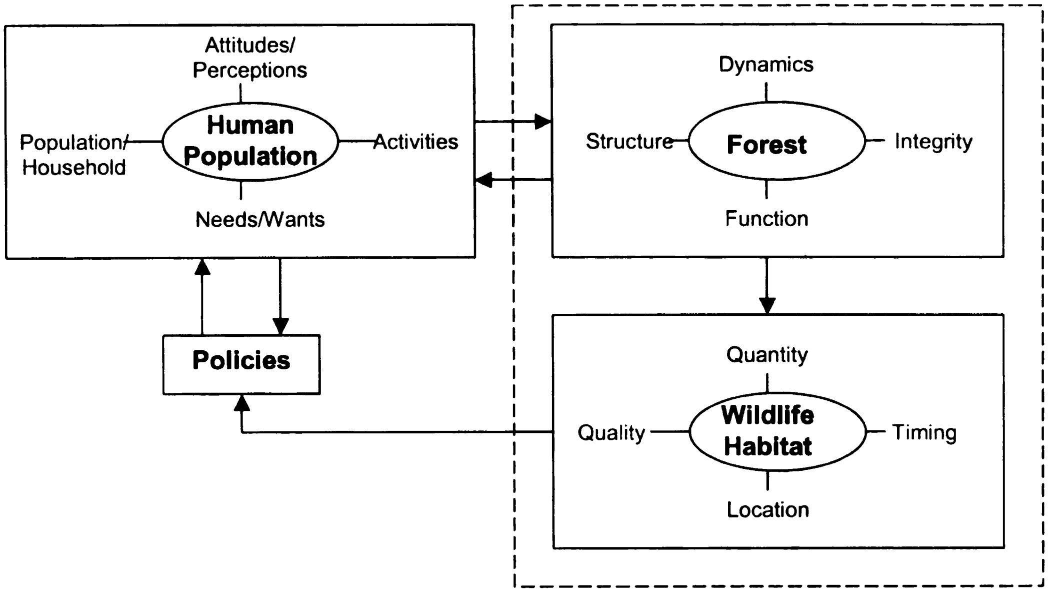


Figure 1.3. Conceptual framework of the relationship between humans, forests, and wildlife habitats (adapted from Liu et al. (1999b)). Dashed box represents the area of focus for this dissertation.

bamboo areas of Wolong. Chapter 3 examines the effects of harvesting on bamboo populations and bamboo stem characteristics. In Chapter 4, I explore how giant pandas are using the bamboo populations throughout Wolong, and how harvesting may be affecting panda use of these bamboo stands. After describing how forest harvesting activities, that is, timber harvesting and fuelwood collection, have affected giant pandas and their habitat, I then illustrate the efforts that are being made by the Wolong Administration and the Chinese central government to protect and regenerate panda habitats. To do this, I research and model the potential benefits of reforestation projects in Wolong in Chapter 5. This chapter uses data collected in reforested areas and surrounding natural forest in Wolong to determine whether reforestation can create or mitigate giant panda habitat. Finally, in Chapter 6, I use the data that I've collected in the field to quantify information loss in landscape models as variables are withdrawn from the dataset to be applied spatially. Conclusions from all chapters and a summary are presented in Chapter 7.

CHAPTER 2

EFFECTS OF TIMBER HARVESTING AND FUELWOOD COLLECTION ON GIANT PANDA HABITAT USE

CHAPTER 2

EFFECTS OF TIMBER HARVESTING AND FUELWOOD COLLECTION ON GIANT PANDA HABITAT USE

Introduction

Global forestland declined by 0.22 percent each year during the 1990's (FAO 2003). Loss of forest has been particularly significant in developing countries, which experienced a total loss of forest area in 1990-1995 equal to 13.7 million ha per year (FAO 2001). In some developing countries that have increasing amounts of forestland, such as China, which increased the size of its forest between 1980 and 1995, the per capita amount of forestland continues to decline due to rapid population growth (PAI 1999). Decreases in forest area can have a significant effect on biodiversity (Caldecott et al. 1996, Jenkins 2003). Wildlife are particularly sensitive to the changes in the ecosystem and increase in habitat heterogeneity that results from logging.

Recent investigations are beginning to uncover the processes involved in how wildlife respond to harvesting, thereby allowing better management policies to be developed and implemented. More specifically, timber harvesting activities have been found to affect various types of wildlife, including invertebrates (Hill 1999, Ghazoul 2002, Hamer et al. 2003, Hill et al. 2003), reptiles (Prior and Weatherhead 1994), amphibians (Petranka 1994, Harper and Guynn 1999, Harpole and Haas 1999, Duguay et al. 2001, Duguay and Wood 2002, Knapp et al. 2003), birds (Ward et al. 1994, Sallabanks et al. 2000, Duguay et al. 2001, King and DeGraaf 2004), small mammals (Cole et al. 1998, Malcolm and Ray 2000, Sullivan et al. 2000, Simard and Fryxell 2003) and large mammals such as bear (McLellan and Shackleton 1989, Wielgus and Vernier 2003).

Effects of harvesting vary between species and even related species within the same guild can have different responses (Lindenmayer and Lacy 1995). For example, mammalian specialists that rely on early successional habitats have traditionally benefited from widespread logging (Heydon and Bulloh 1996, 1997), but are now under pressure as habitat matures (Litvaitis and Villafuerte 1996b, Smith and Litvaitis 2000, Thompson and DeGraaf 2001). On the other hand, mammal species that prefer interior habitats have been negatively impacted from loss or fragmentation of habitat associated with harvesting (Zheng et al. 1995, Green and Catterall 1998, Potvin et al. 1999, Wormington et al. 2002) and from increased exposure to humans after logging roads become developed in core areas (Robinson et al. 1999, Litvaitis 2001).

Harvesting effects on less specialized mammal species can be difficult to ascertain because they demonstrate little response to harvested areas (White 1992, Litvaitis 2001), continue to use remnant patches (Potvin et al. 1999, deBellefeuille et al. 2001), or show a preference for certain stages of regeneration (Smith and Lindenmayer 1992, Johns et al. 1997, Chamberlain et al. 2003). Effects on large mammals, especially bear species, are particularly difficult to quantify because of their rareness, large home range size, and problems in direct sampling (Johns et al. 1997). Recent studies have suggested grizzly bears (*Ursus arctos* Ord) are not deterred by harvesting activities (McLellan and Shackleton 1989) and may actually prefer early succession forests (Mattson 1997, Waller and Mace 1997). The giant panda (*Ailuropoda melanoleuca*

David), on the other hand, appears to spend little time in heavily logged areas (Schaller et al. 1985) and prefers interior forest.

Adding to the complexity is the fact that timber harvests occur in different forms along a disturbance gradient where various levels of overstory, midstory and understory cover are removed. The various types of harvests, such as clearcutting (Kirkland 1990, Sullivan et al. 1999), shelterwood cutting (Anderson and Crompton 2002) and variable retention harvests (Sullivan et al. 2000, Sullivan and Sullivan 2001) have diverse effects on wildlife.

One of the most important forms of harvest in the world today is fuelwood collection. Fuelwood acts as the primary energy source for approximately 3 billion people worldwide (PAI 1999). Over half of the wood harvested in one year is used for fuel (PAI 1999), accounting for over 7 million ha of forest area harvested annually. Developing countries are the primary users of fuelwood, and 75% of forest harvesting in these countries is for fuelwood use (FAO 2000). Yet, despite the widespread use and the potential impacts harvesting can have on forested landscape and wildlife habitats, we are unaware of any study that investigates the effects of fuelwood collection on wildlife habitat use.

We therefore investigate the effects of forest harvesting (i.e., timber harvesting and fuelwood collection) on giant panda habitat use in Wolong Nature Reserve, Sichuan, China. The location was ideal because Asia is one of the largest users of fuelwood, accounting for 46% of global fuelwood production (WEC 2004). Within Asia, the People's Republic of China is the largest country (9.6 million km^2) with the highest population (1.3 billion) but has one of the lowest percentages of forest area (18%, (Liu and Diamond 2005)). In addition, China has one of the largest ecological footprints, second only to the United States (Liu and Diamond 2005) and consumes approximately 440 million tons of fuelwood per year, which accounts for 34% of the total annual consumption of energy in rural China (Kunshan et al. 1997).

The Wolong Nature Reserve (102°52'-103°24'E, 30°45'-31°25'N) is a nature reserve specifically established for the conservation of panda habitat. However, extensive timber harvesting was performed in Wolong throughout much of the 1960's to the mid 1970's. Typical practices included removal of >50% of the overstory canopy cover in areas usually approximating 10 ha but occasionally exceeding 100 ha. The Sichuan Ministry of Forestry officially banned timber harvesting within Wolong in 1985, however, some amount of timber harvesting and fuelwood collection (fluctuating around 7,000-9,400 m^3/year) has continued to occur in the Reserve until recently (Liu et al. 1999a, Liu et al. 1999b).

Several investigations have given some insight into the way native vegetation has been influenced by historical timber harvesting and fuelwood collection and how the habitat matrix of the giant panda would be affected by later forest development (Schaller et al. 1985, Taylor and Qin 1988b, Taylor and Qin 1988c, Reid et al. 1989, Taylor and Qin 1989, Reid et al. 1991c, Taylor and Qin 1993a, 1997). When large openings in the canopy are formed, such as those created by clearcut harvesting operations, the density of arrow bamboo increases to such a degree that tree establishment is severely hindered (Taylor and Qin 1987, Taylor and Qin 1988a, Reid et al. 1991c, Taylor and Qin 1993a, b). Because of this encumbrance, regenerating forest is slow in areas with this type of harvest regime. Harvesting methods of this kind occurred in the Fanzipeng region during the 1930's (Figure 1.2). This area is now primarily a hardwood stand composed mainly of *Betula* spp. with few conifers remaining (Taylor and Qin 1988b, Taylor and Qin 1988c, Taylor and Qin 1989). Large clearcuts also occurred in the Yingxionggou and Zhuanjinggou regions during the 1970's (Figure 1.2). These activities have left many of those areas in a second growth shrub layer consisting mainly of *Rubus* spp., *Sorbus* spp., and *Rosa* spp. (Reid et al. 1991c).

Selective timber logging and fuelwood collection impact the forest differently than all-tree removal methods. Typically, fuelwood collection activities occur over a much smaller area, as usually only several trees are removed at one time. Yet, the cumulative effect of continual fuelwood collection over several years does increase the size of the area impacted. Because of this collective effect, harvest areas vary in size from several square meters (single tree removal) to several hectares or larger, depending on the temporal extent and the number of local people who collected fuelwood.

Despite these insights into how forests regenerate and interact with bamboo, there has been no investigation to date that monitors the age or size of harvest area and how associated forest characteristics directly relate to giant panda use. In addition, the timing of this study is crucial because no studies of panda habitat have been conducted after the bamboo recovery of a mass-flowering episode (Taylor and Qin 1993b). This investigation reports on the effect of timber harvesting and fuelwood collecting on the use of habitats by the giant panda approximately seventeen years after a bamboo mass-flowering event. Our four primary objectives were to: 1) evaluate forest structure composition changes in various sizes and ages after harvesting, 2) assess if a size of harvest effect on panda use was present (i.e., does use in fuelwood collection sites (< 10 ha) differ from use in timber harvested areas 10-100 ha), 3) determine if time since harvest affected panda use, and 4) quantify the environmental factors important to giant panda use over periods of time after harvesting.

It is our hope that by providing a better understanding of how giant pandas use previously harvested areas, we can not only ensure the long-term sustainability of panda habitats, but also provide a baseline for understanding how fuelwood harvest and forest resource utilization may coexist with wildlife conservation.

Methods

Field Sampling Method:

To determine whether harvesting a forest for timber or fuelwood affects the use of habitats by the giant panda, we examined use patterns in previously harvested forests and compared use to uncut forests. Complex site histories made it difficult to characterize any harvesting as a clear-cut or selectively cut operation, so we used size of harvest to quantify type of cut, where smaller sized harvests are typically associated with fuelwood collection, or selective cutting, and clear-cuts were normally larger in size. Data collection took place during May-August 2001, May-November 2002, and June-August 2003.

Use was determined by the presence of fecal droppings, which was considered a useful indicator of panda use because although actual sightings of animals are extremely rare, feces are deposited frequently (97 droppings/day) (Schaller et al. 1985) and remain for several months (personal observation). In an earlier study of panda habitat use, Reid and Hu (1991) used the sample unit of feces groups to determine use mainly associated with feeding behaviors. Our study used general presence/absence of feces to indicate use because it also incorporated habitat use not associated with feeding, such as traveling routes. This was significant because panda use in harvested areas may be more closely associated with daily or seasonal movement, escape or thermal cover, or mate location and may not be as important as foraging habitat (Schaller et al. 1985). Therefore, until a better survey technique is developed and the giant panda radio-collaring ban lifted, feces are the most efficient and effective way to determine use of habitats. Although frequency of defecation is high, the small number of panda individuals, extent of the forest and ability of the animal to travel large distances make detection of feces infrequent.

Due to the infrequency of observing giant panda feces in bamboo forests, we used adaptive cluster sampling to concentrate our sampling effort on areas where feces was more likely to occur. This allowed us to avoid a situation where most sample plots had no feces present. Adaptive cluster sampling is valuable because it is designed to sample rare events (i.e., feces) and allows for focused research in areas where the rare events occur while maintaining proper statistical hypothesis testing protocol (Thompson 1991b, Thompson et al. 1992). Whenever feces were found (i.e., presence=1) in a 30 x 30 m sample plot, all units in its neighborhood (those 30 x 30m plots to the forward, rear, left, and right) were added to the sample. If in turn any of these subsequently added plots had feces that were detected by the observer, the plots of its neighborhood were also added to the sample, so that finally the sampling neighborhood contained 1, 5 (1 primary, 4 secondary), or 8 (1 primary, 7 secondary) sample plots. Adaptive cluster sampling allowed us to increase our sampling efforts around areas that had a higher potential of giant panda activity.

Thirty x thirty-meter sampling plots were located while the team was in the field and were identified by local residents knowledgeable of historical, recent past and present land-use in the area. Age of forest was defined by the last time the forest within the sample plot had been harvested, which was known by the locals. Size of harvest was defined as a relatively homogenous area that differed from its surroundings (Forman 1995). The center position of each 30 x 30 m plot was geo-referenced with a Pathfinder® Pro XRS GPS unit (Trimble Navigation Limited) for subsequent analysis and modeling of the data. Due to logistical and time constraints which prohibit revisitation and reexamination of sample plots for passed droppings, equal probability of feces detection in all habitats was assumed. This assumption was supported by Reid and Hu (1991), who found a low ratio of missed droppings (1.3%) throughout their study sites in Wolong.

The number of sample plots that were surveyed depended upon the size of the harvested area that was sampled, so that approximately 5% of the surface area within the harvest site would be sampled. For example, small harvest areas ($\leq$ 2 ha) had one primary 30 x 30 m plot within the harvested area and one plot in the surrounding uncut forest while large harvested areas ($\geq$ 9 ha) had four primary plots inside and four in the surrounding forest. Using this method, we attempted to sample all age classes of forest in approximate proportion to their extant within the study area. However, several areas, especially those near households, had a complex site history with large, old harvests having smaller, newer harvests within, and were therefore not sampled by this method.

Forest characteristics measured within each plot include: basal area (m^2/hectare, 10-factor prism), total overstory canopy cover (all canopy covers measured with spherical densiometer), conifer overstory cover, deciduous overstory cover, average overstory height, total midstory canopy cover, average midstory height, total shrub cover, average shrub height, total bamboo cover, total understory cover, and average understory height. Topographic factors include: ecological aspect (aspect converted into ecologically significant units (Parker 1982)), elevation (MSL), and slope (degrees).

Statistical Analysis:

Sites were grouped into four harvest age categories to reflect stages of forest succession and were based on our ability to identify forest ages in the field as well as sample size issues: 0-10 years, 11-30 years, 31-100 years and old-growth forest. Sites were also grouped into two patch/harvest size categories: small ≤10.0 ha and large harvest 10-100 ha. Sample sizes varied because only sites that could definitively be categorized were included in this analysis.

We used analysis of variance (ANOVA) along with Tukey's post-hoc comparisons to test for the differences of forest and topographic characteristics across forest age groups. For comparison, we performed all ANOVAs using the primary plots only (simple random samples) and the neighborhood mean and standard error using the Horvitz-Thompson estimator calculated from the adaptive cluster sampling method (Thompson and Seber 1996, Turk and Borkowski 2005). To test for differences in site characteristics between smaller sites and larger sites, we performed nested ANOVAs with age-class as the main factor and size-class nested within.

We used two-way contingency tables along with the binomial proportion test (Ott 1993) to test for differences in the proportion of feces in forests of various ages and sizes. Proportion of feces in harvested areas was compared to that in unharvested sites. We then used the binomial proportion test (Ott 1993) to determine significant differences between proportions of feces present at sites.

To enhance the interpretation of contingency table results, we used logistic and autologistic regression by incorporating patch age and harvest size variables as well as forest and geographic characteristics to determine which were important in predicting panda feces presence. We constructed two independent logistic regression models for each age class, both of which used feces as the response variable. One logistic regression model used data from the primary plots only while the second logistic regression used all primary and secondary plots (from the adaptive cluster sample). Prior to running each logistic regression analysis, we conducted univariate logistic regression analysis (PROC LOGISTIC, SAS Institute) and removed all variables that had P values less than 0.25 associated with the likelihood ratio test scores (G-tests). This somewhat liberal P value was chosen based on the distribution of P values of the variables. We then ran a correlation analysis (PROC CORR, SAS Institute) on remaining variables to detect collinearity. Pairs of variables that had $r > 0.6$ were considered for variable elimination. We eliminated the variable with the less significant univariate G-test score. If scores were similar, we eliminated the variable that led to the most parsimonious multivariate logistic regression model. We tested a variety of logit models by deliberately adding certain topographic and forest variables and determining which made a significant contribution to the prediction of feces presence. Akaike information criteria (AIC) were used to determine which model had the best fit (Quinn and Keough 2002).

Finally, classification trees (Venables and Ripley 1999, De'ath and Fabricius 2000) were used to nonparametrically explore the data and provide further insight into how forest and topographic factors, as well as age and size of harvest, may influence giant panda habitat use. Classification trees were useful because throughout the analysis, all possible binary splits were considered for all of the predictor variables, yet the split that was created was the one that produced two groups with the smallest within group sums-of-squares in the response variable (Quinn and Keough 2002). Four separate trees were performed on: 1) all independent variables, 2) the age of forest and size of forest patch, 3) geographic variables including distance to road, distance to house, elevation, slope, ecological aspect, and basal area, and 4) forest characteristics, including components of the overstory, midstory, shrub, bamboo, and understory layers. All classification trees used a minimum node size of 5 with deviance=0.05 and incorporated a cost complexity pruning using deviance pruning methods to return a minimal node tree as implemented in S-Plus (Venables and Ripley 1999, De'ath and Fabricius 2000). Tree sizes were selected after running a series of 10-fold cross-validations using the 1-SE rule (De'ath and Fabricius 2000).

Results

We sampled a total of 913 30 x 30 m sample plots (443 primary and 470 secondary) during the 2001-2003 sampling period. We found significant changes in all forest and topographic characteristics over time except average understory and shrub height, which did not vary over time (Table 2.1). Results from both the simple random sample of primary plots and the Horvitz-Thompson mean estimations of neighborhoods

Table 2.1. Univariate ANOVA results for forest and geographic characteristics measured in primary plots only and neighborhoods (primary + secondary plots). Neighborhood calculations were based on Horvitz-Thompson means of all plots in that neighborhood.

Variable	Primary Plots Only			Neighborhood Means		
	F	df	p	F	df	p
Elevation	54.65	3,437	<0.001	54.65	3,437	<0.001
Distance to Roadway	97.66	3,437	<0.001	97.9	3,437	<0.001
Distance to Household	106.97	3,437	<0.001	106.96	3,437	<0.001
Slope	8.03	3,436	<0.001	9.01	3,436	<0.001
Ecological Aspect	8.5	3,436	<0.001	8.83	3,436	<0.001
Basal Area	84.11	3,435	<0.001	69.76	3,435	<0.001
Total Overstory Cover	84.86	3,422	<0.001	85.52	3,422	<0.001
Conifer Overstory Cover	34.4	3,395	<0.001	31.72	3,395	<0.001
Deciduous Overstory Cover	20.05	3,394	<0.001	23.47	3,394	<0.001
Avg. Overstory Height	110.79	3,396	<0.001	111.02	3,396	<0.001
Total Midstory Cover	33.98	3,435	<0.001	36.39	3,435	<0.001
Conifer Midstory Cover	4.61	3,396	<0.004	4.41	3,396	<0.005
Deciduous Midstory Cover	30.05	3,396	<0.001	34.02	3,396	<0.001
Avg. Midstory Height	69.47	3,418	<0.001	75.66	3,419	<0.001
Total Shrub Cover	3.36	3,419	0.019	3.62	3,420	<0.001
Avg. Shrub Height	40.87	3,396	0.013	41.96	3,396	0.013
Bamboo Percent Cover	57.75	3,434	<0.001	57.76	3,431	<0.001
Total Understory Cover	26.67	3,417	<0.001	27.84	3,418	<0.001
Avg. Understory Height	2.25	3,412	0.02	1.76	3,413	0.15

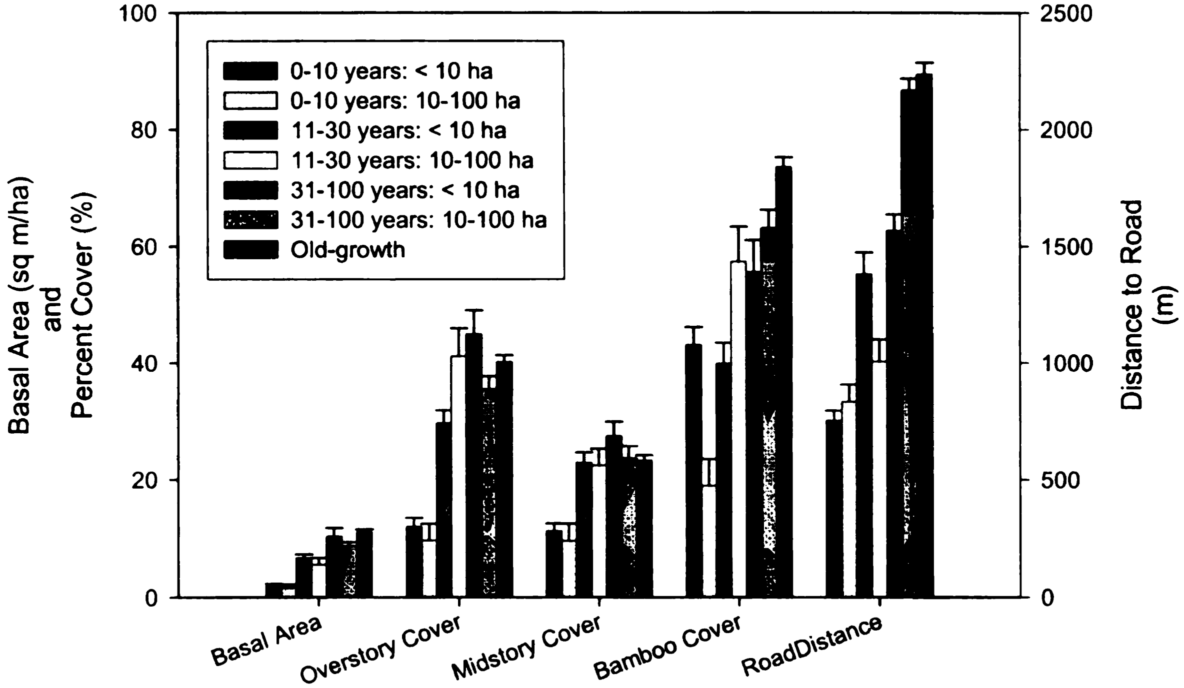


Figure 2.1. Mean values (±*SE*) of topographic and forest characteristics for 30 x 30 meter sample area in categorized age of forest and size of harvest categories (size of patch for unharvested).

were generally the same for all forest and topographic characteristics using ANOVA (Table 2.1). Old harvests (31-100 years) and old-growth sites occurred significantly farther away from the roadway, farther into the interior forest, than newly (0-10 years) and mid-aged (11-30 years) harvests (Figure 2.2). Old harvests and old-growth forest also had significantly higher basal areas than younger forests. Overstory trees were tallest in old harvests and old-growth forest, and significantly shorter in the most recently cut areas, especially in large cuts (Figure 2.2). Conifer, deciduous and total overstory percent cover all increased as the forest aged (Figure 2.2, Appendix I). Total overstory canopy cover increased through the age classes and was significantly higher in old harvests and unharvested areas than middle-aged and new harvests (Table 2.1, Figure 2.2, Appendix I). The conifer component of the overstory was greatest in the large, unharvested areas but was significantly lower in areas that were cut 0-30 years ago (Table 2.1, Appendix 2.I), while the deciduous overstory was lower in new harvests and highest in large, old harvests (Table 2.1, Appendix I). Midstory percent cover generally increased as the forest aged, with one exception. Both conifer and deciduous midstory coverages were lowest in new harvests and highest in old harvests (Table 2.1, Figure 2.2). The lowest mean bamboo percent cover was in large, new harvests while higher bamboo cover was found in old-growth areas. Smaller, unharvested patches had the highest amounts of bamboo (Figure 2.2).

Age of harvests in Wolong ranged from several months to approximately 100 years. Older harvests were typically associated with large-scale timber harvesting operations and newer harvests associated with multiple tree removal for fuelwood and small-scale timber harvesting. The age of the harvested forest had a significant effect on giant panda use (primary χ_3^2 =58.7, p=0.01; neighborhood χ_3^2 =115.1, p=0.01).

Size of patch (primary χ_1^2 =0.2, p=0.83; neighborhood χ_1^2 =0.37, p=0.6) and size of harvest (primary χ_1^2 =0.01, p=0.97; neighborhood χ_1^2 =0.41, p=0.5) indicated no difference between the proportion of feces found in small and large patches and fuelwood collection and timber harvest sites. Patch sizes were significantly related to distance from roadway, with smaller sized patches occurring close to the roadway (0.06 ha, 0-500 m from roadway), and larger patches farther from the roadway (0.29 ha, 3-3.5 km from roadway)($F_{8,862}$=6.159, p<0.001). In harvested areas that were 0-10 years old, use was not detected in the larger harvest sizes (10-100 ha) (Appendix I).

In primary plots, pandas did not use larger harvested areas (10-100 ha) in new harvests (Age = 3.0 ± 0.6 years)(mean ± SE)(Figure 1). Use generally increased as the forest aged ($X^2_{(3, N=99)}$= 24.9, $p < 0.001$). There was some use in large mid-aged forests (22.1 ± 2.1 years), but it was not significantly higher than new harvests. Use was 5.0 and 4.7 times higher, however, in mature harvest (50.0 ± 2.3 years) and old-growth forests (203.6 ± 3.6 years), respectively, than in mid-aged harvests (Figure 2.2).

For primary plots, in smaller harvested areas (< 10 ha), use in old-growth forest (180.7 ± 4.3 years) and mature harvests (44.6 ± 1.7 years) was 8.0 and 5.3 times higher than in new harvested forests (3.7 ± 0.4 years), respectively ($X^2_{(3, N=295)}$= 35.2, $p < 0.001$), suggesting even small-scale tree removal, such as single-tree selection timber harvesting and fuelwood collection, may reduce use by pandas for decades (Figure 2.2).

Overall, in primary plots we found giant panda feces more frequently in older forests than in newly harvested areas ($X^2_{(3, N=393)}$= 56.3, $p < 0.001$). The reason is that as

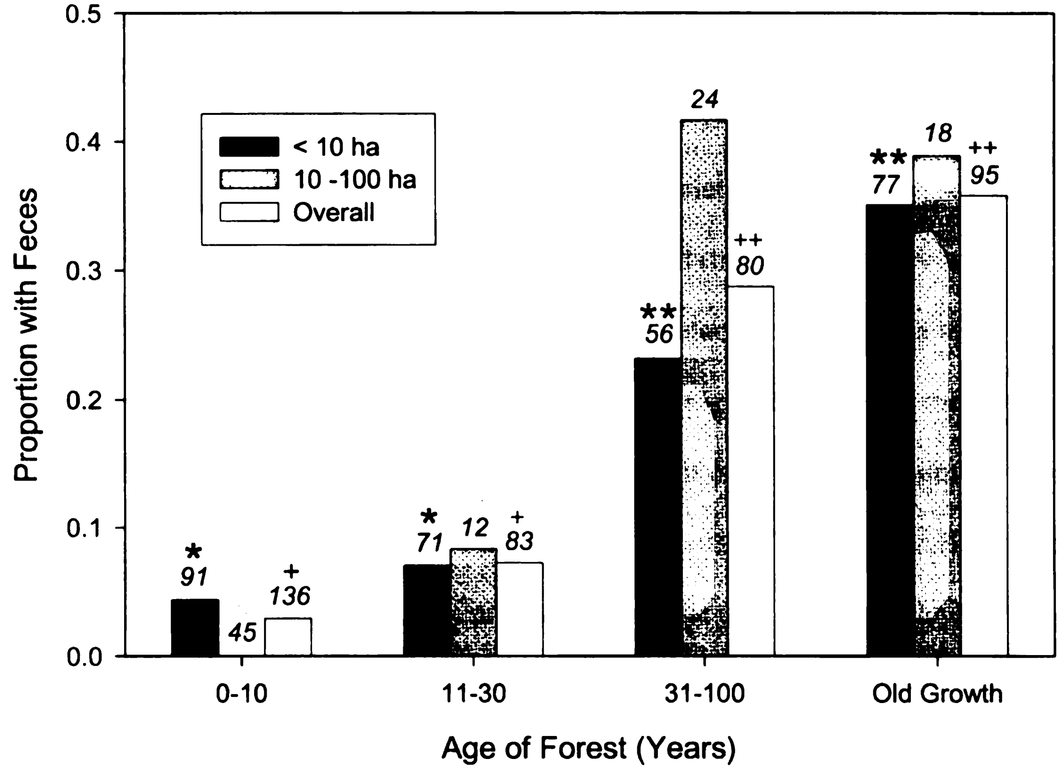


Figure 2.2. Proportion of primary plot sites with giant panda feces in areas with varying forest ages and sizes. Italicized numbers above bars represent plot sample size. Symbols (*, **, +, ++) above bars represent significance groupings in the proportion of survey plots with panda feces by age class for each size using binomial proportion test. The same number (and color) of symbols above bars indicates no significant difference.

the forests recovered, basal area, overstory forest and bamboo covers increased ($F_{3,390}$=72.8, p<0.001; $F_{3,375}$=60.9, p<0.001; and $F_{3,385}$=43.0, p<0.001, respectively). The increasing forest cover and bamboo cover created a more suitable environment for the giant panda (Figure 2.2).

For each forest age class, we performed four varieties of logistic regression using the primary plots only and all plots in the neighborhood (including primary and secondary plots) with both logistic and autologistic (includes autocovariate term) regression techniques (Table 2.2). We believe the autologistic model that includes all neighborhood plots is the most reliable model because it includes a high number of plots while accounting for spatial autocorrelation through the use of the autocovariate term. The logistic model that includes only primary plots is the next most reliable model because it uses a lower number of primary plots but has low effects of autocorrelation. The logistic model that uses all neighborhood plots is the least reliable because it may have a high amount of autocorrelation in the model that is not accounted for.

In recently harvested forests (0-10 years), presence of bamboo was the most significant indicator of giant panda feces presence, as well as shallow slopes and distance from households and roadways (Table 2.2). In mid-aged forests (11-30 years), bamboo cover was also a significant indicator of panda feces in the logistic and autologistic-primary models, but the deciduous component of the overstory and midstory and distance from roads were also important (Table 2.2). In older forests, high bamboo cover continued to predict the presence of giant panda feces in addition to southwest aspects, longer distance from roadways, higher conifer midstory cover, and lower understory height. In old-growth forests, higher bamboo cover, low slope, low ecological aspect

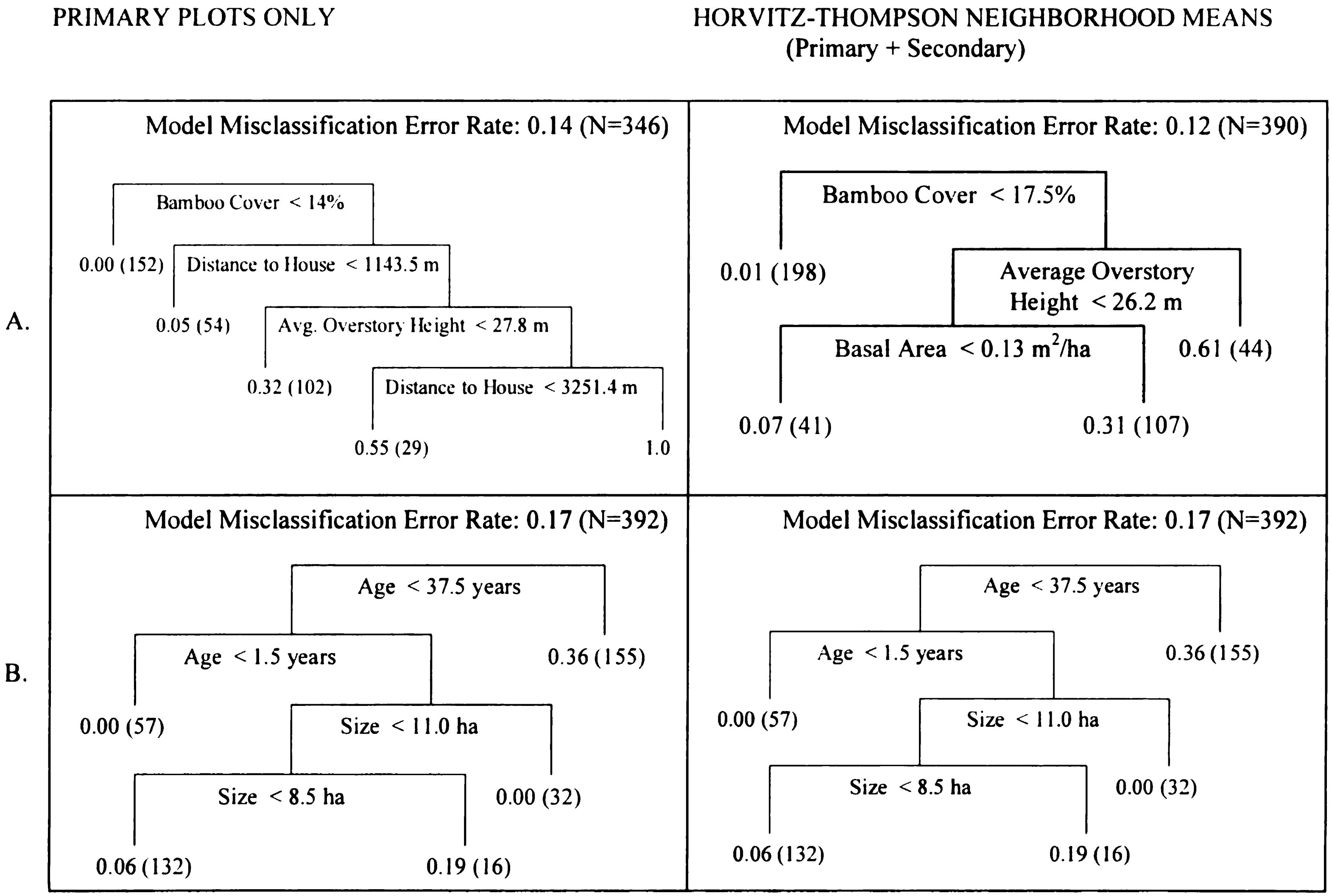
Table 2.2. Significance of forest and geographic characteristics in logistic and autologistic models developed from primary plots only and Horvitz-Thompson models developed from all neighborhood plots (primary and secondary plots).

		LOGISTIC				AUTOLOGISTIC		
	AIC	Variable	Estimate	P-value	AIC	Variable	Estimate	P-value
0-10 years								
Primary Plots	28.36	Intercept	-6.14	<0.01	27.39	Intercept	-8.54	<0.01
		Bamboo cover	0.05	0.02		Bamboo cover	0.05	0.02
						Distance to Road	0.00	0.12
						Euclid Dist. 1000 m	622.70	0.11
Neighborhood	57.25	Intercept	-9.06	<0.01	60.48	Intercept	-6.56	<0.01
		Avg. Midstory Height	0.13	0.01		Slope	-0.08	0.03
		Bamboo cover	0.08	0.01		Bamboo cover	0.05	0.01
						Distance to House	0.00	0.02
						Euclid Dist. 750 m	130.20	0.01
11-30 years								
Primary Plots	38.42	Intercept	-3.59	<.0001	31.43	Intercept	-4.93	0.00
		Bamboo cover	0.03	0.02		Bamboo cover	0.04	0.04
						Euclid Dist. 750 m	95.90	0.01
Neighborhood	83.88	Intercept	-5.04	<.0001	56.47	Intercept	-14.40	<0.01
		Decid. Overstory Cover	0.04	0.02		Decid. Overstory Cover	0.08	0.01
		Decid. Midstory Cover	0.05	<0.01		Decid. Midstory Cover	0.07	<0.01
		Bamboo cover	0.03	<0.01		Distance to Road	0.01	<0.01
						Euclid Dist. 750 m	324.00	<0.01
31-100 years								
Primary Plots	56.51	Intercept	-3.23	<.0001	29.36	Intercept	-2.05	0.03
		Distance to Road	0.00	<0.01		Conif. Midstory Cover	0.12	0.05
						Avg. Understory Height	-0.08	0.03
						Euclid Dist. 50 m	183.40	<0.01
Neighborhood	109.71	Intercept	-3.28	<0.01	159.87	Intercept	-2.86	<.0001
		Ecological Aspect	-0.16	<0.01		Ecological Aspect	-0.06	0.05
		Bamboo cover	0.05	<.0001		Bamboo cover	0.04	<.0001
		Avg. Overstory Height	0.06	0.02		Euclid Dist. 50 m	39.42	0.01
Old-growth								
Primary Plots	93.58	Intercept	-6.52	<0.01	51.93	Intercept	-11.96	<0.01
		Avg. Overstory Height	0.23	<0.01		Avg. Overstory Height	0.27	0.01
		Conif. Overstory Cover	-0.05	<0.01		Slope	0.12	0.03
		Decid. Overstory Cover	-0.05	0.02		Euclid Dist. 500 m	351.70	<.0001
		Distance to House	0.00	0.02				
Neighborhood	378.01	Intercept	-1.91	0.01	337.28	Intercept	-3.57	<0.01
		Slope	-0.07	<.0001		Slope	-0.05	<0.01
		Ecological Aspect	-0.10	<0.01		Ecological Aspect	-0.08	<0.01
		Avg. Overstory Height	0.07	<0.01		Avg. Overstory Height	0.11	<.0001
		Decid. Midstory Cover	0.02	0.01		Decid. Overstory Cover	-0.01	0.08
		Avg. Understory Height	0.01	0.00		Bamboo cover	0.01	0.04
		Patch Size	-1.79	0.00		Avg. Understory Height	0.02	<.0001
		Distance to House	0.00	0.00		Patch Size	-2.15	<.0001
						Euclid Dist. 1250 m	320.40	<.0001

(South-Southwest), tall overstory trees with a low deciduous component, and a far distance to households were the best predictors of giant panda feces (Table 2.2). Euclidean distances for autologistic models in old-growth forest varied from 500-1250 meters.

Classification trees were used to provide further understanding as to which forest and geographic characteristics are used by the giant panda (Figure 2.3). Classification trees using the Horvitz-Thompson means achieved the lowest misclassification rates (12-17%) with models using primary plots only also having low misclassification rates (13-17%). Errors were higher when using all neighborhood plots (primary and secondary plots) (misclassification rates= 24-32%) and no weighting was factored in for the spatial autocorrelation inherent in the dataset. Therefore, results from these classification trees were considered less reliable and are not included in this discussion. The first classification tree used all independent variables to determine the best overall model that characterizes the presence of giant panda feces. Both primary and primary + secondary Horvitz-Thompson model types selected bamboo percent cover as the primary distinguishing factor, with cover percent ranging from 14-17.5% (Figure 2.3). Other useful factors included being a kilometer from households, a tall overstory (>26m) and a high basal area (>0.13 m^2/ha). When considering age of forest and size of forest patch only, primary and Horvitz-Thompson models predicted similar results due to their corresponding datasets. Nevertheless, a forest that has had 38 years to regenerate from a harvesting event is more likely to have giant panda feces (Figure 2.3). When considering only geographic and topographic characteristics of plots, distance from households

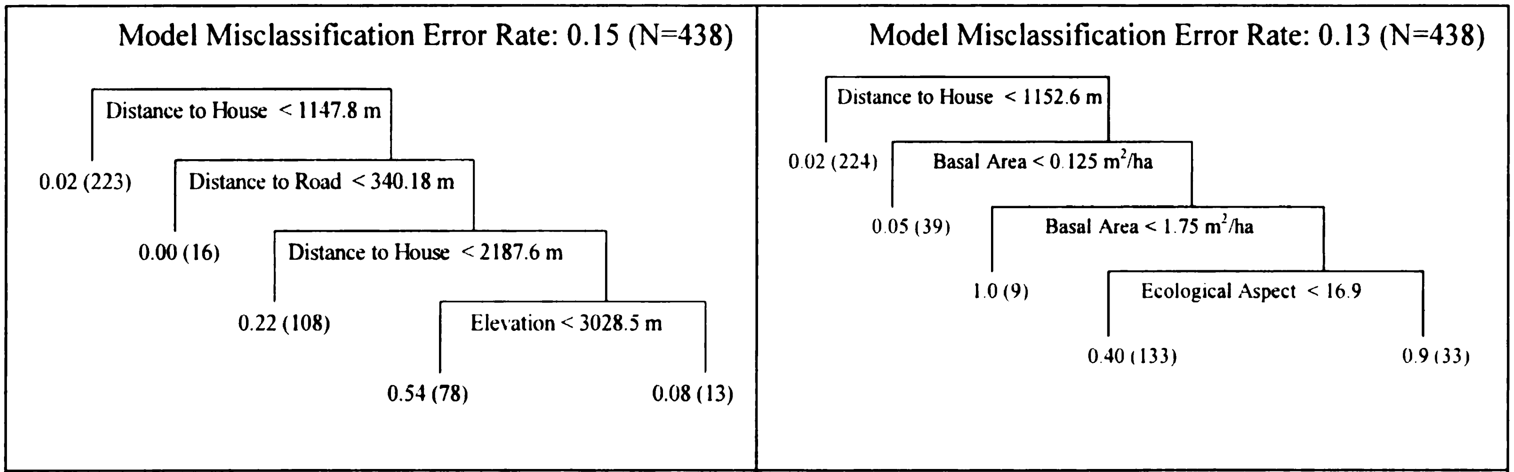
Figure 2.3. Regression trees of A) all forest and geographic characteristics, B) age and size of harvested and unharvested patches, C) geographic characteristics, slope, ecological aspect, and basal area (m^2/ha), and D) forest characteristics. Trees show classification based on the presence of giant panda feces. Residual mean deviance = A) 0.175, B) 0.183, C) 0.186, and D) 0.159. Values at tree leaves represent proportion of plots with feces and sample size (within parentheses).


PRIMARY PLOTS ONLY
HORVITZ-THOMPSON NEIGHBORHOOD MEANS
(Primary + Secondary)
A.
Model Misclassification Error Rate: 0.14 (N=346)
Bamboo Cover < 14%
0.00 (152)
Distance to House < 1143.5 m
0.05 (54)
Avg. Overstory Height < 27.8 m
0.32 (102)
Distance to House < 3251.4 m
0.55 (29)
1.0
Model Misclassification Error Rate: 0.12 (N=390)
Bamboo Cover < 17.5%
0.01 (198)
Average Overstory Height < 26.2 m
Basal Area < 0.13 m²/ha
0.61 (44)
0.07 (41)
0.31 (107)
B.
Model Misclassification Error Rate: 0.17 (N=392)
Age < 37.5 years
Age < 1.5 years
0.36 (155)
0.00 (57)
Size < 11.0 ha
Size < 8.5 ha
0.00 (32)
0.06 (132)
0.19 (16)
Model Misclassification Error Rate: 0.17 (N=392)
Age < 37.5 years
Age < 1.5 years
0.36 (155)
0.00 (57)
Size < 11.0 ha
Size < 8.5 ha
0.00 (32)
0.06 (132)
0.19 (16)

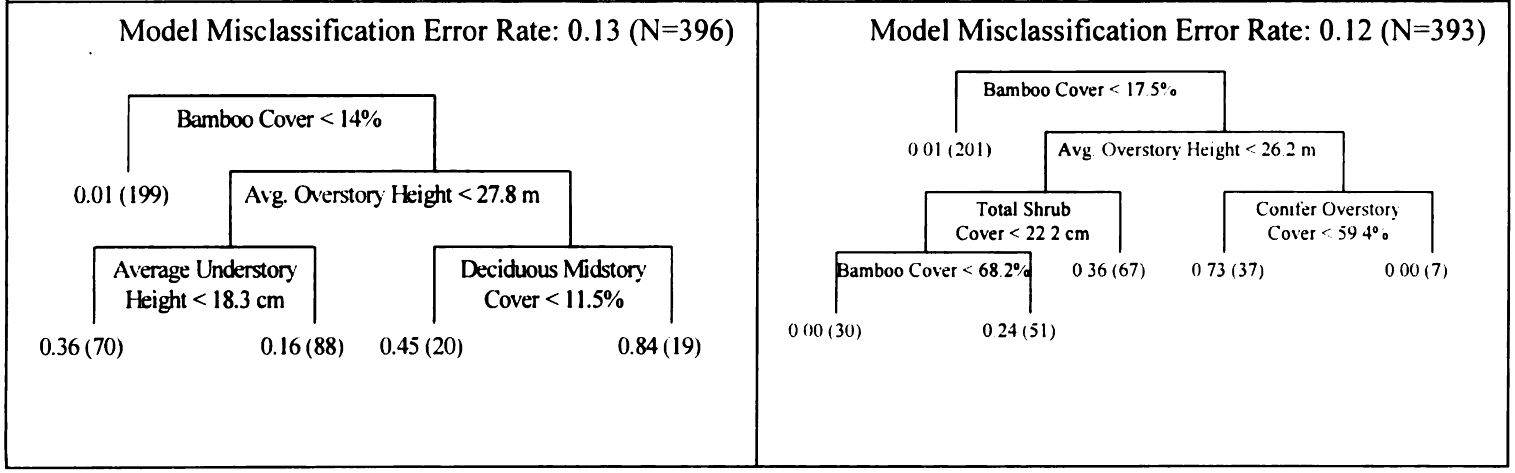
PRIMARY PLOTS ONLY

HORVITZ-THOMPSON NEIGHBORHOOD MEANS
(Primary + Secondary)

C.



D.



(>1100 m) was the most important factor in determining panda feces presence (Figure 2.3). Additionally, a nearness to roadways (<340 m) was negatively related to feces present and a forest with low basal area (<0.125 m^2/ha) was also not used. Classification trees on forest characteristics not only reiterated the importance of bamboo cover (>14%) and overstory height (>26 m), but also indicated a deciduous component to the midstory (>11.5%) may have higher feces presence, or if overstories are tall (>26 m), the conifer overstory component should not be too great (<59%) (Figure 2.3).

Discussion

Timber harvesting and fuelwood collection have created a patchy mosaic of forests in various stages of succession throughout Wolong Nature Reserve. This has several implications for the use of these habitats by the giant panda and also for the conservation of this endangered species. Previous studies on panda use of harvested areas and the surrounding forests show that these activities decrease use because of lower canopy cover, increased bamboo densities, decreased bamboo seedling densities and changed bamboo growth form (Schaller et al. 1985, Reid and Hu 1991, Reid et al. 1991c, Taylor and Qin 1993a, b). However, the majority of those studies were conducted during or shortly after the arrow bamboo flowering and subsequent die-off in 1983. During the die-off period, giant panda activity was altered because of resource limitations, especially those associated with food availability. Our study was performed at a time when bamboo populations would have recovered from the flowering event (i.e., approximately 15 years after flowering) and returned to normal, pre-flowering densities (Taylor et al. 1991).

Information from this study therefore shows patterns of use during a period when the bamboo populations are high and therefore may not be a limiting factor to pandas.

Our study investigated the influences of fuelwood collection and timber harvesting directly by comparing use in harvested areas of various ages to unharvested forests. Use of forested habitats was lowest in newly harvested areas (0-10 years) and highest in unharvested areas and old harvested areas that had been cut between 30-100 years ago. The high amount of feces in old harvests was notable because previous studies have found use to be lower (Schaller et al. 1985) and habitat to be less suitable (Schaller et al. 1985, Reid and Hu 1991, Taylor and Qin 1997) in harvested areas.

There are two primary reasons why the proportion of feces in old harvested areas is as high as unharvested, old growth forests, which has traditionally been considered the primary habitat for the giant panda. First, early harvesting occurred in highly suitable habitat and less suitable habitats (i.e., steep slopes) were not harvested because of difficulty extracting the wood. Second, several decades of forest regeneration has created a forest cover that provides more suitable habitat characteristics for the giant panda.

Highly suitable habitats occur commonly within the interior of Wolong and are therefore significant for movement, foraging, and reproduction. Despite their significance, use decreased after clear-cut harvesting due to the associated change in forest characteristics, including decreased overstory canopy cover, decreased conifer component, increased hardwoods component, and increased bamboo densities (Schaller et al. 1985, Taylor and Qin 1988b, Taylor and Qin 1988c, Taylor and Qin 1989, Taylor and Qin 1997). We found the overstory and midstory conifer component of forests 11-30 years after harvest to be similar to, and in some cases higher than, unharvested forests (except in the large harvested areas), indicating establishment of conifers. The deciduous component of the overstory and midstory, as well as bamboo densities, were also comparable between old harvests and unharvested forests. Because these forest characteristics do not differ from unharvested forests we can assume that the giant panda would begin using these areas sooner and more frequently than if it were within a less suitable habitat area that was harvested at the same time.

The primary objective of historic harvesting was to cut the large conifers (*Abies*, *Picea*, and *Tsuga*) that grew within the subalpine coniferous forests of Wolong. Once in a stand, trees would be selected based on their overall size and the ability to access the tree and transport it out to the nearest road. Since site quality was highest on the shallow slopes, and because these areas were easier to access, harvesting was most frequently done on the interior ridge tops and nearby areas with low slope. However, the giant panda also prefers sites with low slopes (Reid and Hu 1991) because there is a large increase in the metabolic requirements to move up steep inclines (Taylor et al. 1972). For this reason, we would also expect giant panda use to be higher in the old harvest sites since after these sites become marginally utilizable, they would be exploited by the panda who is trying to conserve energy. On the other hand, steep areas were often left uncut by early loggers since it was difficult to access precipitous forests and the ability to move the timber was difficult and often dangerous. To the giant panda, steep, uncut forests are not ideal for the same metabolic reasons and tend to be underutilized, helping to explain why use in unharvested areas was less than that of old harvests.

Another reason why the proportion of feces is high in old harvests is because early timber harvesting was done within the higher elevation (above 2700 m, Table 2.1) subalpine coniferous forest. Elevations here include the primary vertical range of the giant panda as well as its primary food, arrow bamboo (Schaller et al. 1985). In addition, higher elevation forests are not directly juxtaposed along the Pitiao River valley, where the majority of local people reside. Therefore access to these regions by humans is more difficult, allowing areas to remain somewhat undisturbed since the harvesting events occurred. We should note that humans still use these areas intermittently for wildlife research, herb collecting, bamboo gathering, and occasionally for snaring musk deer (currently illegal; personal observation).

In contrast, newer harvested areas typically occur in lower elevations near the Pitiao valley (below 2600 m, Table 2.1), where human disturbance is more common and the less preferred umbrella bamboo grows (Schaller et al. 1985). Lower elevation forests have a complex site history that stems from intense human use over the centuries. This is especially true in areas where illegal fuelwood collection, poaching and medicinal herb collection are still active. These activities have created a landscape in the lower elevations that is heterogeneous and frequently visited and disturbed by humans. This may help to explain why use is low in these areas.

In the thirty to one hundred years since the old harvest areas were cut, most sites have been left to regenerate and many have succeeded to the understory reinitiation stage, where a forest floor stratum of herbs, shrubs, saplings and poles has developed (Oliver and Larson 1996). Bamboo stands are also affected by the change in environmental variables as the forest progresses through succession (Taylor and Qin 1989, Reid et al. 1991c). Therefore, the high amount of use in the old harvest areas may also be explained by the relationship between overstory canopy density and bamboo cover percent that coincides with the findings of Taylor and Qin (1997), with the frequency of feces increasing as forest cover and bamboo cover percent increase. As the forest recovered from the harvesting activity, and as the midstory and later the overstory cover percent increased, feces was found more often in the harvested area, as demonstrated by the increased proportion of use in old harvested areas. Old harvested areas ranged in age by 40 years, making a detailed recovery timetable unavailable. However, it can be seen that as the forest progresses through succession following a harvesting event, suitable habitat can be restored.

Parsimonious logistic regression models demonstrate that bamboo percent cover continues to be the best predictor of giant panda habitat. In newly harvested forests, the traditional characteristics of panda habitat (i.e., high bamboo cover, low slope, and far distance from households (interior forest)) were found to be the best predictors of giant panda feces. As the forest aged (11-30 years), the deciduous component of the midstory and overstory became important indicating the significance of regenerating forests and how the cooler, shaded forests provided by the deciduous trees may be a useful component of the forest as pandas move through the lower elevation forests that have been harvested more recently. Old harvested areas that were used by pandas had bamboo cover, were farther away from the roadway (more in the interior forest), had a low understory, some conifer in the midstory, and a SSW aspect (low ecological aspect). Unharvested and old-growth forest had the most complex characterization of forests used by giant pandas. Logistic and autologistic regressions indicate smaller forest patches with more bamboo, taller understories, less conifer and deciduous trees in the overstory, and low slope with SSW aspect (low ecological aspect) to be the old-growth forest with the greatest likelihood of encountering panda feces (Table 2.2, Figure 2.3).

There were some differences in the variable selection between the logistic regression that used only primary plots and the autologistic regression that used neighborhood (primary + secondary plots) means. However, both methods led to a characterization of a similar type of forest that is selected by pandas. Both methods also showed how this selection changes as the forest ages after harvesting events. A newly harvested forest (0-10 years) requires the presence of bamboo for pandas to use these areas. A forest of 11-30 years also should have bamboo but may also be used if it has a deciduous component in the midstory or overstory, indicating a cooler forest that is farther from the roadway is most preferred. There were discrepancies between the logistic and autologistic models in the characterization of where panda feces occurs in old harvested forests (31-100 years). Logistic regression of primary plots indicated a significance to interior forest (a far distance from roadways), while the autologistic regression showed that bamboo cover, a southern aspect, conifers in the midstory, and low understory are most important for giant pandas. Both logistic and autologistic regressions suggest that forests with tall overstories with a low deciduous component in the overstory is significantly related to the presence of panda feces.

We applied a series of autocovariate terms associated with various Euclidean distances in each of the autologistic regressions and used stepwise procedures to select the best distance associated with panda feces presence. Euclidean distances provided a unique way to determine the spatial level that pandas may be selecting the forest characteristics of their environment and may be useful when determining the connectivity of panda habitats. Euclidean distances selected as significant predictors of feces presence for each autologistic regression model varied by forest age. In younger forests aged 0-30 years, a significant Euclidean distance of 750-1000 meters indicated that pandas use these forests on a larger spatial level, perhaps roaming widely from one usable forest patch to another. As the forest matures (31-100 years), the amount of forest that is usable by pandas increases. Here, the Euclidean distance of the autologistic regressions of both primary and neighborhood plots decreases to 50 meters, demonstrating that pandas begin concentrating their activities on forest patches with the most suitable habitat. These distances increase in old-growth forests, suggesting that old-growth forests are widely usable and pandas do not need to concentrate activities in these areas, but may traverse across these forests.

The findings of this study are significant because they suggest that panda habitats may become usable in a rather short period of time. If forestland is maintained and not converted to agriculture or grazing land, forests that were previously harvested may eventually regenerate and increase the potential for the species long-term survival. This potential for regeneration of habitats of species that prefer old-growth forests may be significant when planning for the long-term conservation of other species worldwide.

CHAPTER 3

BAMBOO CHARACTERISTICS AFTER FOREST HARVESTING IN WOLONG NATURE RESERVE

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Introduction

Logging activities such as timber harvesting and fuelwood collection can have various effects on understory vegetation (Fredericksen et al. 1999, Fredericksen et al. 2000, Scherer et al. 2000, Frey et al. 2003). Removal of overstory and midstory canopy trees alters understory microclimate (Aust and Lea 1991, Laporte et al. 2003) and soil chemistry (Kim et al. 1995, Goodale et al. 2000, Goodale and Aber 2001, Piirainen et al. 2002, Carmosini et al. 2003, Laporte et al. 2003, Howard et al. 2004). These effects may change the structure of understory vegetation already present or alter the species composition on the site (Duffy and Meier 1992, Roberts and Gilliam 1995a, b, De Grandpre and Bergeron 1997, De Grandpre et al. 2000, Roberts 2002, Roberts and Zhu 2002). Changes in understory characteristics by harvesting may then have dramatic effects on the habitats of resident plant and animal species.

Bamboo (Poaceae) is a ubiquitous understory species found throughout much of the world (Linderman et al. 2004). Bamboo species are often a significant component of forests because they compete extremely well with trees (Tanaka 1988, Cao 1995, Takahashi and Kohyama 1999) and have close interactions with other forest components (Takahashi et al. 2003, Ito and Hino 2004, Noguchi and Yoshida 2004, Taylor et al. 2004). In addition, many wildlife species rely on bamboo as understory habitats (Reid et al. 1991a, Johnson et al. 1993, Fidgett et al. 1996, Choudhury 2001, Pradhan et al. 2001, Matsubayashi et al. 2003, Sakuragi et al. 2003).

Understory bamboo is a primary componenet of habitat for the giant panda (*Ailuropoda melanoleuca*), which relies on bamboo as its primary food source (Schaller et al. 1985). Timber harvesting and fuelwood collection may therefore significantly affect giant panda habitat by influencing the local bamboo populations (Linderman et al. 2005b). To properly conserve giant panda habitats, ecosystem management in these areas must consider the interactions between bamboo and forest dynamics (Reid et al. 1989, Reid and Hu 1991, Taylor et al. 1995, Noguchi and Yoshida 2004).

It is critical to understand the relationship between various types of logging and bamboo populations because many people living near highly suitable panda habitat rely on fuelwood collection for heating and cooking while the same forests provide vital habitat for the giant panda (Liu et al. 1999b, An et al. 2001, Liu et al. 2001, Ruiz-Perez et al. 2001, An et al. 2002, An et al. 2003, Linderman et al. 2005a). Timber harvesting affects not only the spatial distribution of bamboo (Linderman et al. 2005b), but also various growth and population characteristics of bamboo species. Previous studies have shown that bamboo stem densities increase (Reid et al. 1991b), seedling densities decrease (Taylor and Qin 1993b) and germination, establishment, and overall regeneration from seed were lower in clearcuts (Taylor and Qin 1988a). When large openings in the canopy are formed, such as those created by clearcut harvesting operations, the density of arrow bamboo increases to such a degree that tree establishment is severely hindered (Schaller et al. 1985, Taylor and Qin 1987, Taylor and Qin 1988a, Reid et al. 1991b, Taylor and Qin 1993a, b). Because of this encumbrance, regenerating forest is slow in clearcut areas. Selective logging, on the other hand, may maintain enough deciduous overstory cover to continue to provide suitable habitat for the giant panda (Reid et al. 1991b, Taylor and Qin 1997).

Recently, several regions around the world (including the Amazon, Africa, Siberia) have taken steps to limit the effects of forest harvesting via the use of logging bans. In Asia, many countries (e.g. the Philippines, Thailand, Vietnam, and China) have implemented bans on timber harvesting and fuelwood collection in an effort to curb past overexploitation of forest resources (Durst et al. 2001). Harvesting bans have the potential of conserving wildlife habitats by allowing the forest to retain standing overstory and midstory densities. However, species that rely on understories in these areas may continue to be affected for some time into the future as previously logged forests regenerate and competition for light, moisture, and space resources evolves through successional stages.

The Chinese government has implemented new policies in an effort to eliminate harvesting of natural forests within its borders, and particularly in nature reserves (Durst et al. 2001, Zhao and Shao 2002, Liu and Diamond 2005). The primary policy, the Natural Forest Conservation Program (NFCP), includes a logging ban that halts all timber harvesting and fuelwood collection in natural forests throughout China (Zhao and Shao 2002, Liu and Diamond 2005). This policy has the potential of influencing the conservation of giant panda habitats because it will decrease the amount of illegal harvesting thereby increasing stand volume and overstory and midstory canopy covers. This, in turn, may allow bamboo to return to preharvesting densities and growth form and forests to progress to an old-growth state, both of which are preferred by the panda.

To determine how fuelwood collection and timber harvesting influence the characteristics of understory bamboo populations, we studied bamboo culm dynamics in Wolong Nature Reserve, Sichuan, China. The objectives of our study were to determine: 1) how different bamboo species are influenced by different sizes of harvesting (fuelwood collection typically in smaller and timber harvesting often in larger areas), 2) how long these effects last, and 3) which forest and geographic characteristics are associated with productive bamboo characteristics. Information gathered on how various harvesting activities influence bamboo populations and culm characteristics will help to determine more appropriate harvesting regulations as well as to conserve giant panda habitats.

Methods

Data collection took place during May-August 2001, May-November 2002, and June-August 2003. A sample plot consisted of a 30 x 30 m area. The center position of each 30 m^2 plot was geo-referenced with a Pathfinder® Pro XRS GPS unit (Trimble Navigation Limited). Geographic and forest characteristics as well as bamboo percent cover were measured over the entire 30-m^2 area. Characteristics measured included: slope, aspect, forest basal area (10-factor prism), overstory height and percent cover, midstory height and percent cover, shrub height and percent cover, bamboo percent cover, and understory height and percent cover. We then established four bamboo subplots measuring 1 m^2 in each 30 m^2 plot. The 1 m^2 bamboo subplots were located 10 m from the center point in the four cardinal directions. We counted density of bamboo stems within each of the four 1m^2 subplots, and measured culm basal diameter and culm height from 5 random stems in each subplot.

We monitored characteristics of three bamboo species in various aged forests throughout the Wolong Nature Reserve. Three native, naturally occurring bamboo species included arrow bamboo (*Bashania fabri*), umbrella bamboo (*Fargesia robusta*), and yushania bamboo (*Yushania chungii*). We studied the first two species because of their documented importance to giant panda foraging (Schaller et al. 1985, Taylor and Qin 1987, Reid and Hu 1991, Reid et al. 1991b, Taylor and Qin 1993b). The third species was identified to also be potentially important for giant panda habitat, especially in higher elevation habitats, and was therefore added to the sampling design. In addition to sampling areas with wild bamboo populations, we sampled areas with no bamboo for comparison.

Documentation of timber harvesting and fuelwood collection history of specific locations in Wolong is limited, therefore local guides knowledgeable of site histories helped us to establish forest age in the field. We examined bamboo characteristics in previously harvested forests of various ages and in uncut forests. Sites were grouped into four harvest age categories based on their general forest stand ecology, our ability to accurately identify forest ages as well as sample size issues: 0-10 years, 11-30 years, 31-100 years, and unharvested forest.

In order to determine if a relationship existed between patch size and bamboo characteristics, we examined both forest patch size (included unharvested forest patches) and harvest patch size (did not include unharvested areas). Size of patch was difficult to accurately measure in the field. We therefore estimated sizes of both forest and harvest patches using a length and width measurement of distinct forest boundaries and calculated size based on the resulting rectangle. Although we realize this type of patch size measurement is a rough approximation, more descriptive forest and harvest patch size measurements were infeasible given time constraints and the topographic relief of the Wolong terrain. Both patch size and harvest size were grouped in small (< 10 ha) and large (10-100 ha) size categories.

Complex site histories made it difficult to characterize any harvesting as a clear-cut or partial cut, so no distinction was made between the two. Instead, we used size of harvest to quantify type of cut. Smaller sized harvests are typically associated with fuelwood collection, or selective cutting, and clear-cuts were often larger in size.

Statistical Analysis:

We compared bamboo cover, density, culm height and width between species using one-way ANOVA. In addition, we tested whether age of forest and forest/harvest patch size had any relationship to bamboo characteristics using two-way ANOVAs for each species. To determine how these characteristics changed over time after harvesting events, we compared bamboo cover, stem density, culm height and width by age for each species using ANOVA. The effects of various size harvests were tested by comparing the same characteristics by size of harvest and size of patch for each species using ANOVA.

We used regression techniques to test the relationship of changes in forest characteristics and geographic characteristics to bamboo (*B. fabri, F. robusta, Y. chungii*) culm characteristics. Initially, forest and geographic variables that were correlated ($r^2 >$

0.60) were removed from analysis. We then used remaining variables in combinations of single and multiple linear regressions to determine the variables that demonstrated the most significant relationship to bamboo variables.

Significant forest and geographic variables from linear regressions were then used in single and multivariate combinations to establish the best localized multivariate loess model. Loess smoothing models were chosen because of their unrestrictive ability to investigate the relationships between bamboo characteristics and forest and geographic information. Variables chosen for the final loess models represent the forest and geographic variables that best explain variation in bamboo characteristics and may be used to determine which variables are most important in conserving giant panda habitats.

Results

We measured a total of 367 plots (30 m^2 each) and 1468 bamboo subplots (1 m^2 each) throughout the sampling period. We found age of forest where each bamboo species occurred to be significantly different (($F_{4,362}=60.75$, $p<0.001$). *B. fabri* occurred in the oldest stands and frequently in unharvested, old-growth forests (Table 3.1). *F. robusta* and *Y. chungii* were also in older forests, while areas with no bamboo were in younger forests (Table 3.1).

Species of bamboo varied between forest patch sizes ($F_{4,354}=5.04$, $p<0.001$). *B. fabri* and areas with no bamboo occurred in larger forest patches while *F. robusta* and *Y. chungii* were found in smaller patches (Table 3.1). The size of harvest was also significantly different among bamboo species. The largest harvest sites had either *B.*

Table 3.1. Mean age, patch and harvest size characteristics of three bamboo species and areas with no bamboo in Wolong Nature Reserve, China.

Species		N	Age (years)	Patch Size (ha)	Harvest Size (ha)
Bashania fabri	Mean	83	147.5	21.0	29.4
	SE		8.7	3.7	6.8
Fargesia robusta	Mean	112	50.7	5.8	6.2
	SE		6.2	1.0	1.2
Yushania chungii	Mean	20	79.1	6.7	8.1
	SE		21.1	3.8	5.0
No bamboo	Mean	116	26.5	25.7	26.9
	SE		3.9	5.4	5.7

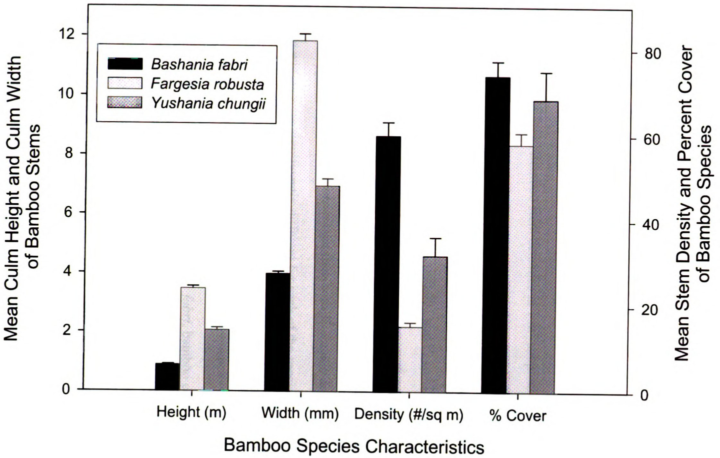

Figure 3.1. Mean characteristics (± SE) of three bamboo species in Wolong Nature Reserve, China.

fabri or no bamboo while *F. robusta* and *Y. chungii* were found in smaller harvested areas (Table 3.1).

Mean bamboo percent cover across the 30 m^2 parcels differed between species ($F_{4,358}$=161.7, p<0.001). All three bamboo species (*B. fabri, F. robusta,* and *Y. chungii*) had significantly higher percent cover than areas with no bamboo indicating greater than sparse densities. *B. fabri* had the highest percent cover, significantly more than *F. robusta* (Table 3.1). Bamboo stem densities in 1 m^2 subplots also differed between species ($F_{4,363}$=193.6, p<0.001). The three bamboo species had significantly higher densities than areas with no bamboo (Table 3.1). Culm diameter and height were different between species ($F_{4,363}$=948.0, p<0.001 and $F_{4,363}$=738.9, p<0.001, respectively), with *F. robusta* being tallest and *B. fabri* being shortest (Table 3.1). Culm heights were significantly different for all species except *B. fabri.* (Table 3.1). For culm width, *F. robusta* was significantly more robust than both *Y. chungii* and *B. fabri* (Table 3.1). All stem widths were significantly different for each of the species.

Few *B. fabri* subplots were available in newly harvested areas and none were available in 11-30 year old forests due to the low frequency of this species in younger forests, resulting in low sample sizes. For *B. fabri*, bamboo cover, stem density and culm height were not statistically different among age classes (Table 3.2). However, bamboo coverage and stem density were highest in old growth forests and lowest in newly harvested areas. Culm width was the only *B. fabri* characteristic that changed since harvesting, with wider culms occurring in newer forest and narrower culms in old growth forests ($F_{2,76}$=3.32, p=0.04). Size of harvested patch did not have any effect on *B. fabri* characteristics over time since harvest.

Table 3.2. Mean bamboo characteristics (±SE) over time since last timber harvest or fuelwood collection activity.

		N	Bamboo Cover (%)	Stem Density (#/m^2)	Culm Width (mm)	Culm Height (m)
Bashania fabri						
0-10 years	Mean	8	52.38	42.91	4.20	0.92
	SE		*14.91*	*12.23*	*0.35*	*0.10*
11-30 years	Mean	0	n/a	n/a	n/a	n/a
	SE		n/a	n/a	n/a	n/a
31-100 years	Mean	21	70.24	51.36	4.12	0.99
	SE		*5.75*	*4.74*	*0.20*	*0.08*
Old Growth	Mean	54	81.28	65.24	3.94	0.87
	SE		*3.56*	*4.03*	*0.08*	*0.04*
Fargesia robusta						
0-10 years	Mean	41	47.17	14.55	12.84	3.49
	SE		*4.97*	*2.15*	*0.39*	*0.13*
11-30 years	Mean	29	56.41	14.03	11.60	3.57
	SE		*5.48*	*1.17*	*0.41*	*0.16*
31-100 years	Mean	22	48.18	19.77	10.38	3.18
	SE		*5.53*	*1.95*	*0.50*	*0.16*
Old Growth	Mean	20	61.83	15.47	11.76	3.66
	SE		*7.29*	*1.88*	*0.45*	*0.15*
Yushania chungii						
0-10 years	Mean	5	71.00	32.95	6.97	2.07
	SE		*12.88*	*7.64*	*0.49*	*0.17*
11-30 years	Mean	4	49.50	26.00	7.85	2.32
	SE		*14.61*	*7.21*	*0.53*	*0.32*
31-100 years	Mean	6	55.33	19.96	6.55	1.88
	SE		*13.26*	*5.34*	*0.34*	*0.09*
Old Growth	Mean	5	88.40	44.20	6.64	2.01
	SE		*6.54*	*11.89*	*0.46*	*0.08*

Fargesia robusta stands occur at lower elevations and are more prone to human disturbance. This resulted in a higher number of *Fargesia* plots in newly harvested forest and a lower number in old growth forest. *Fargesia robusta* showed differences in stem density ($F_{3,108}$=4.03, p<0.01) and culm width ($F_{3,108}$=3.91, p=0.011) with forest age (Table 3.2). Mean *F. robusta* cover percent was highest in old growth forest. Densities were lowest in areas 0-30 years after harvesting, but increased considerably in the period 31-100 years after harvesting, and then generally declined as the forest reached an old growth stage (Table 3.2). Culms were widest in newly harvested forests and generally fluctuated in width afterwards. Size of forest patch was related to the percent cover of *F. robusta* ($F_{1,108}$=2.72, p<0.10), and may be an important characteristic when trying to determine suitable giant panda habitat at low elevations.

Yushania chungii did not occur as frequently as the other two native bamboo species and therefore had lower sample sizes. *Yushania* was found in relatively equal proportions of all age classes, indicating it may be an opportunist species. It showed no differences in its growth characteristics in different aged forests or in various sized patches (Table 3.2), although mean cover percent and stem densities were high both in newly harvested and old growth forests (Table 3.2).

Multivariate loess smoothing models of forest and geographic characteristics ranged from predicting bamboo culm characteristics moderately well (*F. robusta* culm height: r^2=0.48) to very well (*Y. chungii* cover %: r^2=0.97). Slope and elevation occurred most frequently, helping to predict *B. fabri* percent cover, stem density, culm diameter (elevation only), and culm height; *F. robusta* stem density (elevation only), culm diameter

Table 3.3. Multivariate loess model results showing most significant forest and geographic variables that relate bamboo stem characteristics. Variables are listed in alphabetic order: *Age = forest age since last harvest, Basal Area = forest basal area (10 factor prism), BBCover = bamboo cover (%), Elevation = MSL elevation, Slope = slope (degrees), Size = forest patch size (ha), TotOverCover = total overstory cover (%), TotalShrubCover = total shrub cover (%),* and *TotUnderCover = total understory cover (%).*

Bamboo Species	Bamboo Characteristics	r^2	Estimate Standard Error	Significant predictors
Bashania fabri	Percent Cover	0.79	18.37	Elevation * Slope * TotOverCover * TotUnderCover
	Stem Density	0.69	21.79	Basal Area * BBCover * Elevation * Slope
	Culm Diameter	0.62	0.59	Basal Area * BBCover * Elevation * Size
	Culm Height	0.89	0.31	Age * Basal Area * Elevation * Slope
Fargesia robusta	Percent Cover	0.81	16.43	Basal Area * TotalShrubCover * TotalUnderCover * Size
	Stem Density	0.61	8.30	BBCover * Elevation * Size * TotOverCover
	Culm Diameter	0.5	2.35	Elevation * Size * Slope * TotUnderCover
	Culm Height	0.48	0.74	Elevation * Size * Slope * TotUnderCover
Yushania spp.	Percent Cover	0.97	11.41	Elevation * TotUnderCover
	Stem Density	0.85	13.05	BBCover * Slope
	Culm Diameter	0.73	2.00	Basal Area * Elevation * TotalShrubCover
	Culm Height	0.83	0.61	Basal Area * BBCover * TotalShrubCover

and height; and *Y. chungii* cover % (elevation only), stem density (slope only), and culm diameter (elevation only)(Table 3.3). We found bamboo percent cover, forest basal area, understory cover, shrub cover, and overstory cover to be the most important forest characteristics in determining bamboo culm characteristics (in order of decreasing frequency)(Table 3.3). We also found size of forest patch to be significant in determining *B. fabri* culm diameter and *F. robusta* percent cover, stem density, culm diameter and height (Table 3.3).

Discussion

We explored the relationship between bamboo characteristics and timber harvesting and fuelwood collection over time. Culm characteristics were not different for different forest patch and harvest sizes. This indicates that whether harvesting occurs at either the small (< 10 ha) or large (10-100 ha) spatial scale (i.e., fuelwood collection or timber harvesting, respectively), bamboo growth characteristics may not be adversely affected in a particular way. Changes did occur in bamboo culm characteristics over time as various bamboo species responded to the changing understory environment after harvesting.

Our data supported previous findings of widespread, dense stands of *Bashania fabri* and less dense stands of thick-culmed *Fargesia robusta* (Schaller et al. 1985, Taylor and Qin 1987, Reid and Hu 1991, Reid et al. 1991b, Taylor and Qin 1993a, b) throughout the panda range in Wolong Nature Reserve. We found *Bashania* stands in older forest, occurring farther from the Wolong roadway (2342.4 $\pm$ 40.6 m) and at higher elevations (2478-3214 MSL) than younger *Fargesia* stands, which were lower in elevation and closer to the road (1771-2726 MSL; 1324.7 ± 52.4 m, respectively). Therefore, although both species may be impacted by future human activity, including possible harvesting activities, the proximity of *Fargesia* to the roadway and therefore human settlements make it more likely to experience impacts.

Interpretation of the results for *B. fabri* remain conservative because we were unable to sample *B. fabri* stands growing in forests harvested 11-30 years ago due to their limited availability in the field. Because of this, we could neither validate nor refute the findings of others (Taylor and Qin 1988a, Reid et al. 1991b, Taylor and Qin 1993b) who determined that clearcuts favored development of short, dense *B. fabri* stands in turn reducing panda habitat quality. Despite this lack of data, we did observe an increase in overall abundance as well as a decrease in culm width over time since harvest. *B. fabri* was rarely found in forests younger than 30 years old, but in these forests it generally had lower percent cover and stem density, as well as thicker stems. Our data support previous research which identified elevation, slope, forest basal area and bamboo percent cover to be among the factors that contribute to a healthy and productive *B. fabri* stand.

In *F. robusta* stands, percent cover and stem density also generally increased over time, with the highest percent cover occurring in unharvested, old growth forests. Fluctuations in percent cover, stem density, and culm width and height indicated an interaction as the forest reinitiates and grows to a mature stand. Increased percent cover in 11-30 year old forests demonstrates *F. robusta* attempting to colonize forest floor while not substantially increasing its culm width or height. When the forest stand matures to 31-100 years, percent cover decreases while stem density increases. This is most likely because the *F. robusta* stand has established itself spatially and culms at the perimeter died back or were outcompeted and shaded out by surrounding deciduous trees, thereby allowing an increasing density primarily from concentrated root sprouting.

Our study documents the characteristics of another bamboo species, *Yushania chungii*. Few studies are available in English or Chinese that describe the characteristics of this species, even though it occurs throughout the panda's range and offers the potential as an alternative food source. *Y. chungii* was not as common as *B. fabri* or *F. robusta*, and was typically interspersed among stands of *B. fabri*. It occurred in smaller patches and was found in both very young forests (which were uninhabitable by other bamboo species) as well as old-growth stands, demonstrating that it may act as an opportunistic pioneer bamboo species in a diversity of habitats. Little is known about the life history of this bamboo species, though others have found that culm densities decrease as crown canopy cover of fir species increased (Gratzer et al. 1999). Our data suggest that growth forms of *Y. chungii* are similar in different aged forests, whether in a newly harvested forest or one with old-growth characteristics. This has significance for panda habitat because *Y. chungii* therefore has the opportunity to play a key role when other species of bamboo mass-flower and die off.

As part of the effort to protect bamboo populations and giant panda habitats, the local government of Wolong has begun a program of bamboo planting. The primary purpose of the planting is to provide food for the growing number of giant pandas in the Hetaoping Giant Panda Breeding Center, located in the Reserve. Planted bamboos can minimize the impacts of harvesting large sections of naturally occurring bamboo that occur both inside and outside the Reserve. Also, planted bamboo stems offer an alternative to the bamboo collecting by local farmers who use the bamboo for numerous household purposes (brooms, bean poles, roof thatching, etc.). Although the amount of bamboo harvested by locals is undocumented, there is the potential that its impacts on giant panda habitats may be significant, and mitigation of human effects through planting bamboo may be important. We urge further study of these planted bamboo stands to determine how they may be affecting panda habitats.

Understanding the relationship between logging and bamboo dynamics is key to understanding the sustainability of giant panda habitats. Large patches of highly suitable giant panda habitats have been affected by harvesting activities for centuries (Liu et al. 2001). Yet new policies may improve conditions. The expansion of China's reserve system may increase the amount of areas protected and the Natural Forest Conservation Program can increase the quality of protection of habitats. However, the creation of nature reserves and logging bans do not necessarily mean that habitats will be protected (Durst et al. 2001, Liu et al. 2001, Zhao and Shao 2002, China-Daily 2004). The continued risk of harvesting impacts suggests understanding effects of logging remains critical. Our study indicates that logging activities influence understory bamboo characteristics, and while some bamboo species experience perturbations in growth characteristics after a harvesting event, other bamboo species may not. This has significant implications for all understory wildlife habitats in Asia and other parts of the world that are now restricting or expanding harvesting activities.

CHAPTER 4

USE OF BAMBOO PATCHES BY THE GIANT PANDA AFTER FOREST HARVESTING

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Introduction

Timber harvesting and fuelwood collection can have various effects on understory vegetation (Duffy and Meier 1992, Roberts and Gilliam 1995a, b, De Grandpre and Bergeron 1997, Fredericksen et al. 1999, De Grandpre et al. 2000, Fredericksen et al. 2000, Scherer et al. 2000, Roberts 2002, Roberts and Zhu 2002, Frey et al. 2003) and the wildlife species that rely on it (Carey and Johnson 1995, Rawat 1997, Fredericksen et al. 2000). Species that prefer early successional habitats with high understory coverage often benefit from harvesting (Litvaitis and Villafuerte 1996a, Heydon and Reynolds 2000, Smith and Litvaitis 2000, Thompson and DeGraaf 2001), while species that prefer mature or interior forests characteristically do not gain any advantage from harvesting (Zheng et al. 1995, Green and Catterall 1998, Potvin et al. 1999, Wormington et al. 2002).

Bamboo, a prolific understory species found throughout much of the world, is affected by harvesting activities in various ways. Previous research indicated clearcutting affects bamboo by increasing stem density (Reid et al. 1991b), decreasing seedling densities (Taylor and Qin 1993b) and lowering germination, establishment, and overall regeneration from seed (Taylor and Qin 1988a). In large clearcuts, the density of arrow bamboo increases to such a degree that tree establishment is severely hindered (Schaller et al. 1985, Taylor and Qin 1987, Taylor and Qin 1988a, Reid et al. 1991b, Taylor and

Qin 1993b). Regenerating forest is therefore slow to reestablish in clearcut areas. If harvesting occurs in smaller areas, such as in selective logging or fuelwood collection, enough deciduous overstory cover may be retained which can provide suitable conditions for bamboo species that prefer late successional forest (Reid et al. 1991b, Taylor and Qin 1997, Saenz and Guariguata 2001).

Effects of harvesting on bamboo are significant because bamboo is the primary habitat and/or food source for a number of wildlife species, including the endangered giant panda (*Ailuropoda melanoleuca*) (Schaller et al. 1985, Reid et al. 1989). Harvesting may also affect the spatial distribution of bamboo, which can have long term effects on the distribution of panda habitats and connectivity between patches of habitat (Linderman et al. 2005b). A recent census, which began in 1999 and reported results in June 2004, estimated giant panda numbers have increased from 1,100 animals in 1988 to over 1,590 animals currently (China State Forestry Administration 2004, World Wildlife Fund 2004). However, these trends are questionable due to differences in census methods (World Wildlife Fund 2004). Regardless of trends in panda populations, the habitats upon which the giant panda relies continued to decrease in quantity and quality, both in protected and unprotected areas (Liu et al. 2001).

Panda habitats are continuously progressing through competition and successional stages after disturbance events such as harvesting. Logging effects on bamboo have frequently been used as a proxy to describe potential impacts on panda habitat. However, the effects of timber harvesting and fuelwood collection on panda habitats have not been directly studied, and there is a lack of a detailed assessment of the effects of harvesting on giant pandas. In addition, there is currently no description of panda use of bamboo patches after the recovery of arrow bamboo from the last flowering event in 1983. Therefore, the goals of this study were to: 1) determine how giant pandas are using present day bamboo patches in both harvested and unharvested forest, 2) characterize changes in panda habitat selection after timber harvesting and fuelwood collection, and 3) compare selection of habitat features immediately after bamboo flowering as documented by Reid and Hu (1991) to selection of features today.

Methods

Field Methods:

We collected data during May-August 2001, May-November 2002, and June-August 2003. A sample plot consisted of a 30 x 30 m area. Geographic and forest characteristics as well as bamboo cover were measured over the entire 30 x 30 m plot area, including elevation, slope, aspect, forest basal area (10-factor prism), overstory height and percent cover, midstory height and percent cover, shrub height and percent cover, bamboo percent cover, and understory height and percent cover.

Use by the giant panda was determined by the presence of fecal droppings, which was considered a useful indicator of panda use because although actual sightings of animals are rare, feces are deposited frequently (97 droppings/day, 4 droppings/hour) (Schaller et al. 1985) and remain for several months (personal observation). Despite the frequency of defecation, the extremely low density of pandas, the extent of the forest and ability of the animal to travel large distances make detection of feces infrequent. All detected feces, regardless of time since defecation, were surveyed within a plot.

The center position of each 30 x 30 m plot was geo-referenced with a Pathfinder® Pro XRS GPS unit (Trimble Navigation Limited) to allow for subsequent analysis and modeling of the data. Due to logistical and time constraints which prohibit revisitation and reexamination of sample plots for passed droppings, we assumed an equal probability of feces detection in all habitats. Reid and Hu (1991) support this assumption as they found a low ratio of missed droppings (1.3%) in Wolong Nature Reserve.

We surveyed giant panda use in three bamboo species in various aged forests in Wolong. The three naturally occurring bamboo species included arrow bamboo (*Bashania fabri*), umbrella bamboo (*Fargesia robusta*), and yushania bamboo (*Yushania chungii*). In addition to sampling areas with bamboo populations, we studied areas with no bamboo for comparison. We examined bamboo characteristics in previously harvested forests of various ages and in uncut forests. Local guides helped us to estimate harvesting time in specific sites because there is little documentation of harvesting in Wolong. Sites were grouped into four harvest age categories based on general forest ecology, our ability to determine forest age in the field, and sample size issues: newly harvested forest = 0-10 years, middle aged forest = 11-30 years, old harvest = 31-100 years, and old-growth forest.

We examined both patch size (included unharvested forest patches) and harvest size (did not include unharvested areas) to determine if a relationship existed between patch size and bamboo characteristics. Given topographic relief and time/access constraints, forest and harvest patch sizes were estimated using a length and width measurement of distinct forest boundaries and size of the patch was calculated based on the resulting rectangle. Sites were then grouped into two size categories. Both patch and harvest sizes were categorized as follows: Size Class 1 = < 10 ha, Size Class 2 = 10-100 ha.

Adaptive Cluster Analysis:

We used adaptive cluster sampling to assist in detecting differences in panda use (feces presence) between the various harvested and unharvested areas. This method is valuable because it is designed to sample rare events (e.g., panda feces) for species that exhibit a degree of territoriality and allows for focused research in areas where the rare events occur while maintaining proper statistical hypothesis testing protocol (Thompson 1991b, Thompson et al. 1992). Whenever we found feces (i.e., presence=1) in a 30 x 30 m sample plot, we added all units in its neighborhood (those 30 x 30m plots to the North, South, East and West) to the sample. If in turn any of these subsequently added plots had feces, the plots of its neighborhood were also added to the sample, so that finally the sampling neighborhood contained 1, 5 (1 primary + 4 secondary), or 8 (1 primary + 7 secondary) sample plots. The sizes of these neighborhoods were ideal because of time constraints during field sampling. In addition, bias in the final estimate of panda feces presence/absence is introduced into the sample when these stopping rules are implemented in the adaptive cluster (Su and Quinn 2003), but sampling neighborhoods of 5 and 8 plots are ideal when using the Horvitz-Thompson estimator (Su and Quinn 2003), which is not very sensitive to the stopping rule and bias is reduced with low numbers of sample plots (Su and Quinn 2003).

Adaptive cluster sampling allowed us to increase our sampling efforts around areas that had a higher potential of giant panda activity. In addition to adding to the number of sample units, cluster sampling increased the proportion of sites with feces presence and therefore provided a more insightful analysis of forest characteristics influencing panda use. In other words, by focusing our efforts on areas with a higher probability of feces presence, we were able to understand more about the use of forested habitats by the rare giant panda. The spatial autocorrelation bias associated with neighboring plots was factored into all analyses via use of the Horvitz-Thompson estimator, Euclidean weights and autocovariate logistic regression.

The original Horvitz-Thompson estimator for determining a value for a population is

$$\hat{Y}_{HT} = \frac{1}{N}\sum_{i=1}^{n}\frac{y_i}{\pi_i}$$

where π_i is the probability that the *i*th unit is included in the sample and y_i is the measurement for the *i*th unit in a sample of *n* specified units (Thompson and Seber 1996, Cochran 2002, Turk and Borkowski 2005). In this study, we used a modification similar to that described by Lo et al. (1997). The mean proportion of sites with giant panda feces, $\hat{\gamma}_i$, in the *i*th stratum (i.e., bamboo type), was estimated by

$$\hat{\gamma}_i = \frac{1}{A_i}\sum_{j=1}^{k}\frac{\bar{\gamma}_j a_j}{\alpha_j}$$

where A_i is the total area for the *i*th stratum, a_j is the area of the network (number of plots in neighborhood with feces [including the primary plot] x 30 m^2), and *k* is the total number of neighborhoods sampled in the *i*th stratum (Lo et al. 1997). The probability of finding feces in each neighborhood, $\bar{\gamma}_j$, in the *j*th observed plot,

$$\bar{\gamma}_j = \sum_{u=1}^{m_j} \frac{\gamma_{ju}}{m_j}$$

is the sum of plots with feces present in the neighborhood, γ_{ju}, divided by the total number of plots in the neighborhood, m_j. Here, we defined α_j, the intersection probability (the probability that two neighborhoods, *k* and *h*, will intersect by the initial sample), similar to that used by Dryver and Thompson (2005), where

$$\alpha_j(n_k > 0 \,\&\, n_h > 0) = 1 - \frac{\left\{\binom{N-N_k}{n} + \binom{N-N_h}{n} - \binom{N-N_k-N_h}{n}\right\}}{\binom{N}{n}}$$

Because Horvitz-Thompson estimator values were mean proportions of panda use, we calculated differences among groups using prop.test in S-plus.

Statistical Analysis:

Initially, we tested whether giant panda feces were found in greater numbers in different bamboo stands using χ^2 analysis. We then used χ^2 analysis on each bamboo species to test whether harvested forests had fewer feces than unharvested, old growth forests. To test whether the size of the forest (or harvest) patch influenced the proportion of feces found, we again used χ^2 analysis.

Autologistic Regression:

We performed both stepwise logistic and stepwise autologistic regressions to determine which forest and geographic variables most suitably predicted the presence of giant panda feces in each of the three bamboo species stands. Initially, we performed univariate logistic regressions on all independent variables and retained those with *P*-values for likelihood ratios (G-test) less than 0.25 (SAS Institute 1985). We then performed correlation analysis on remaining variables to detect collinearity (SAS Institute 1985). Variable pairs found to be covarying ($r > 0.60$) were examined, and we eliminated the variable with the least significant univariate G-test score. We then considered all two-way interactions among remaining variables and retained those interaction terms with *P*-values for likelihood ratios (G-test) less than 0.25 (Klute et al. 2002).

We used the spdep extension for the R statistical package to determine the degree of spatial autocorrelation using join-count statistics for the binary response variable (feces presence/absence). We generated one thousand Monte Carlo permutations at distances: 0-50, 50-100, 100-250, 250-500, 500-750, 750-1000, ..., 1750-2000 to represent possible levels at which the giant panda may be responding to its environment.

We adapted the autologistic regression procedure described by Klute et al. (2002). The logit of probability of panda feces presence (p_i) was used with the addition of an autocovariate term to measure the spatial relationship:

$$\text{logit}\,(p_i) = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_n X_{ni} + \beta_m auto\,\mathrm{cov}_i$$

where:

p_i is the probability of feces presence at the *i*th stop, β_0 is the model intercept, $\beta_1,\ldots,\beta_n$ are parameter estimates, $X_{1i},\ldots,X_{ni}$ are the values of the predictor variables at the *i*th stop.

$$auto\,\mathrm{cov}_i = \frac{\sum_{j=1}^{k_i} w_{ij} y_j}{\sum_{j=1}^{k_i} w_{ij}}$$

and

$$w_{ij} = \frac{1}{h_{ij}}$$

represents the weight given to stop *j* as the inverse of the Euclidean distance (h_{ij}) between stops *i* and *j* and y_j is 0 when feces is absent, 1 when feces is present (Klute et al. 2002).

We then used PROC LOGISTIC (SAS Institute 1985) to test all autologistic regression models for each of the three bamboo species. For each logistic regression, stepwise regression techniques were used to select the initial variables. Results from both the logistic and autologistic methods were described to show differences from adding in the autocovariation term. We performed each method on both the primary plots only and the neighborhood (primary + secondary plots) to demonstrate differences in results.

Electivity Index:

The last flowering of *B. fabri* occurred in 1983. Shortly after the subsequent bamboo dieoff, Reid and Hu (1991) studied the forest characteristics giant pandas were selecting and presented the data in terms of Vanderploeg and Scavia's Electivity Index (Lechowicz 1982, Reid and Hu 1991). In an effort to better understand what characteristics pandas may be selecting in bamboo areas now after the recovery from the previous flowering event, we also calculated the Electivity Index (see below) (Reid and Hu 1991). Comparisons between giant panda preference shortly after *B. fabri* flowering (Reid and Hu 1991) and during the period of our field study (2001-2003) are discussed through the Electivity Index results.

We calculated the Electivity Index to offer a comparison of association with habitat features now that the bamboo populations have recovered from the previous die off. Selection of habitat characteristics was calculated using Vanderploeg and Scavia's Electivity Index (E_i):

$$E_i = \frac{(W_i - (\frac{1}{n}))}{(W_i + (\frac{1}{n}))}$$

where

$$W_i = \frac{(r_i / P_i)}{\sum r_i / P}$$

P_i is the proportion of sample units in the *i*th class, and r_i is the number of sample units with feces present in the *i*th class. The index is scaled between –1 and +1 (<0 = avoidance, 0 = random, >0 = preference)(Lechowicz 1982, Reid and Hu 1991).

Results

We sampled a total of 913 plots in 443 neighborhoods (443 primary and 470 secondary sites). Of the total sample plots, *B. fabri* and *F. robusta* were encountered more frequently (38.6 % and 29.9%, respectively) than areas with no bamboo (16.2%) and *Y. chungii* (9.1%). Species of bamboo had a significant effect on the presence of giant panda feces ($\chi^2_{0.05,4}$ = 136.05, $p<0.001$). Areas with *Y. chungii* bamboo had the highest proportion with feces (52.63%), significantly higher than *F. robusta* stands (19.01%) and areas with no bamboo (0.71%) (Figure 4.1). *Bashania fabri* (32.17%) also had a significantly higher proportion with feces than areas with no bamboo (Figure 4.1).

For different bamboo species (*B. fabri, F. robusta,* and *Y. chungii*), different forest ages had significantly different proportions of feces. Time since harvest did not influence the presence of feces in *B. fabri* ($\chi^2_{0.05,3}$ = 87.14, $p<0.001$)(Figure 4.1), *F. robusta* ($\chi^2_{0.05,3}$ = 38.89, $p<0.001$)(Figure 4.1), and *Yushania* spp. stands ($\chi^2_{0.05,3}$ = 174.33, $p<0.001$)(Figure 4.1)(Appendix 2A-C). We did not test areas without bamboo because of their extremely low amounts of giant panda activity.

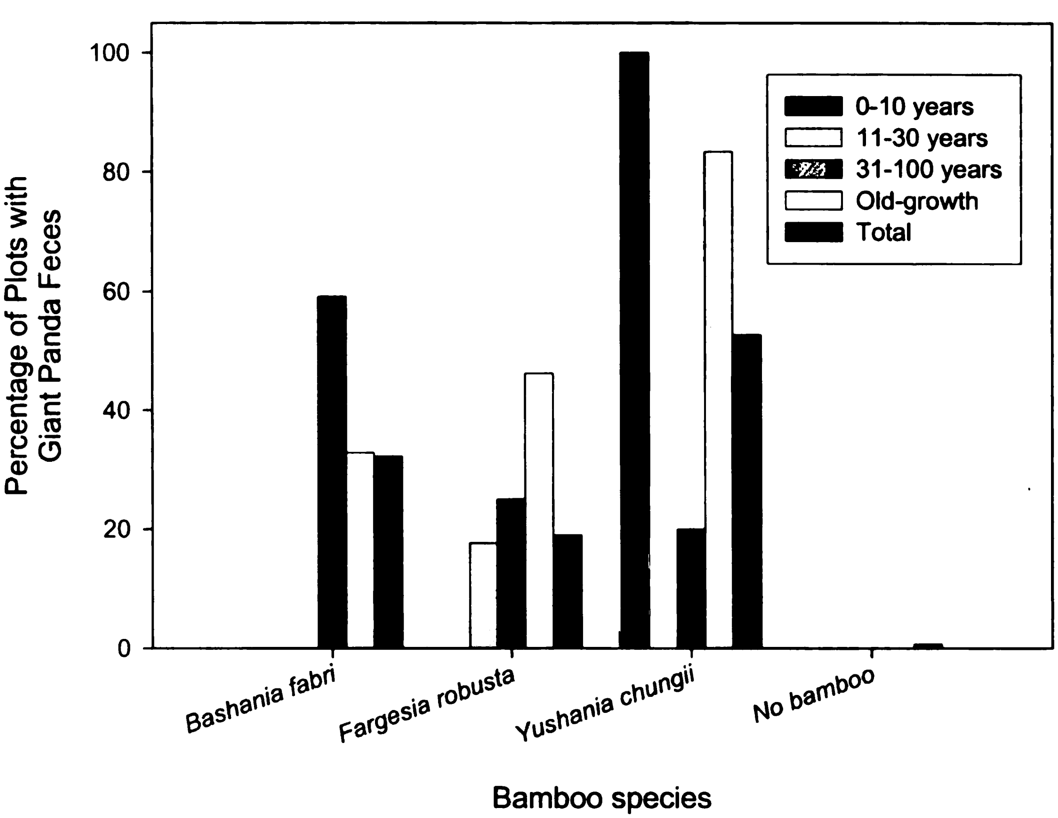

Figure 4.1. Percentage of survey plots in areas with three species of bamboo and areas with no bamboo that have giant panda feces present in various aged forests.

Bashania fabri plots had little giant panda use in new and mid-aged harvests, but use increased significantly as the forest aged ($\chi^2_{0.05,3} = 87.14$, $p<0.001$)(Figure 4.1). Both old harvests and unharvested forests with *B. fabri* had significantly higher proportions of feces than newly harvested and middle aged areas (Figure 4.1)(Appendix 2A). Newly harvested forests with *F. robusta* had significantly less panda feces present than mid-aged, old harvest, and unharvested forests (Figure 4.1)(Appendix 2B).

Newly harvested areas with *Y. chungii* bamboo had relatively higher proportions of giant panda feces but were probably not as important to pandas than stands in unharvested forests (Figure 4.1) (Appendix 2C). Few recently harvested areas and old harvest sites contained *Y. chungii* bamboo, so sample sizes of these areas were low, limiting our ability to interpret results for this age class. Proportion chi-square results indicate significant differences in feces presence among *Y. chungii* forest age classes ($\chi^2_{0.05,3} = 174.33$, $p<0.001$), however, results should be interpreted cautiously as the bamboo does not occur as frequently as other species and sample sizes were therefore low.

There was no difference in the probabilities of encountering feces between small (< 10 ha) and large (10-100 ha) forest patches for *B. fabri* or *F. robusta*. No *Y. chungii* stems were found in large forest patches (10-100 ha) and were therefore not tested. Similarly, within small and large harvests, there was no relationship with the proportion of giant panda feces found between *B. fabri* and *F. robusta*.

All forest and geographic characteristics were initially tested using univariate logistic regression to determine their inclusion in the final logistic regression models.

Univariate models using both the primary plot only dataset and the neighborhood (primary and secondary plots) dataset showed similar results (Table 4.1). Both logistic and autologistic stepwise models suitably characterized ($p < 0.05$) the presence of giant panda feces using univariate and multivariate combinations of forest and geographic characteristics for all bamboo species except for the autologistic primary plot model of *Yushania chungii* (Table 4.2). The autologistic models were considered more reliable because they accounted for spatial autocorrelation of the dataset, which was an issue due to our use of the adaptive sampling methodology. Because the autologistic model accounts for autocorrelation, use of all neighborhood plots, including primary and secondary plots, provides the most useful characterization of variables influencing presence of giant panda feces. Because the logistic model that uses all neighborhood plots does not account for spatial autocorrelation, we believe its results are less reliable.

For *B. fabri*, the logistic model selected the same characteristics (slope, ecological aspect) to describe the presence of panda feces as the autologistic using all neighborhood plots (Table 4.2). Overstory height, which was correlated with total and conifer overstory cover, was also found to be a significant predictor. In stands of *Fargesia robusta*, overstory height and deciduous midstory cover best predicted giant panda feces presence, along with conifer overstory cover (Table 4.2). Elevation and understory height were the most useful characteristics of panda habitat in *Yushania chungii* stands (Table 4.2).

Table 4.1. Univariate logistic regression models of forest and geographic characteristics on primary plots only and Horvitz-Thompson estimators of all neighborhood plots (primary and secondary). *The variable ecological aspect is based on the recharacterization of aspect into 21 ecologically significant units according to Parker (1982).*

		P-value primary plots only	P-value primary and secondary
Elevation	(MSL)	<0.001	<0.001
Distance to Roadway	(m)	<0.001	<0.001
Distance to House	(m)	<0.001	<0.001
Forest Age	(years)	<0.001	<0.001
Patch Size	(ha)	0.84	0.54
Slope	(deg)	0.39	0.04
Ecological Aspect	(N/A)	0.95	0.51
Basal Area	(m^2/ha)	<0.001	<0.001
Bamboo Cover	(%)	<0.001	<0.001
Total Overstory Cover	(%)	<0.001	<0.001
Conifer Overstory Cover	(%)	0.01	0.14
Deciduous Overstory Cover	(%)	0.04	<0.001
Average Overstory Height	(m)	<0.001	<0.001
Total Midstory Cover	(%)	<0.001	<0.001
Conifer Midstory Cover	(%)	0.180	0.54
Deciduous Midstory Cover	(%)	<0.001	<0.001
Average Midstory Height	(m)	<0.001	<0.001
Total Shrub Cover	(%)	0.090	0.00
Average Shrub Height	(m)	<0.001	<0.001
Total Understory Cover	(%)	<0.001	<0.001
Average Understory Height	(cm)	0.00	0.30

Table 4.2. Multivariate logistic and autologistic models for primary plots only (P) and Horvitz-Thompson estimators of neighborhoods (P+S) for three bamboo species, *Bashania fabri*, *Fargesia robusta*, and *Yushania chungii*. *p<0.1, **p<0.05, ***p<0.01.

Bamboo Species	Regression	Samples	AIC	Intercept	Variable	Estimate
Bashania fabri	Logistic	P	99.53	-3.713**	Overstory Height	0.122***
		P+S	321.37	1.16**	Understory Height	0.012***
					Ecological Aspect	-0.059**
					Slope	-0.046***
	Autologistic	P	61.03	-2.377***	Euclidean Distance = 250	155.1***
		P+S	282.65	-0.792	Euclidean Distance = 1000	137.0***
					Overstory Height	0.049***
					Ecological Aspect	-0.103***
					Slope	-0.057***
Fargesia robusta	Logistic	P	98.3	-2.003***	Overstory Height	0.073***
					Understory Height	-0.028**
		P+S	268.43	-3.749***	Overstory Height	0.082***
					Deciduous Midstory Cover	0.026***
					Bamboo Cover	0.015***
	Autologistic	P	64.84	-3.717***	Euclidean Distance = 500	214.4***
					Conifer Overstory Cover	0.052***
		P+S	233.467	-4.942***	Euclidean Distance = 1000	125.6***
					Overstory Height	0.129***
					Deciduous Midstory Cover	0.02**
Yushania chungii	Logistic	P	18.566	-5.689**	Bamboo Cover	0.081**
		P+S	72.899	-18.448***	Elevation	0.007***
					Understory Height	-0.041***
	Autologistic	P	10.071	-171	Euclidean Distance = 500	1673.2
					Elevation	0.072
					Bamboo Cover	0.579
					Distance to Road	-0.047
		P+S	72.89	-18.448***	Euclidean Distance = 500	-58.407***
					Elevation	0.008***
					Understory Height	-0.041***

According to Electivity indices, giant pandas exhibited significant preference for and avoidance of certain habitat features (Table 4.3). Both *B. fabri* and *F. robusta* bamboo stands that occurred on steep slopes were avoided (χ^2 =8.34, $p<0.01$ and χ^2 =1.93, $p<0.18$, respectively). Similarly, in *Y. chungii* patches, preference was shown for flat areas (<15 degrees)(χ^2 =2.12, $p<0.18$). Giant pandas also preferred very tall *F. robusta* stems (> 5 m)(χ^2 =1.77, $p<0.18$) and avoided short (2 – 2.9 m)(χ^2 =2.36, $p<0.18$) and wide (> 13 mm)(χ^2 =1.80, $p<0.18$) stems. Wider *Y. chungii* stems (> 6 mm) also appeared to be avoided (6-7.5 mm; χ^2 =2.73, $p<0.10$), with pandas seeming to prefer narrower *Yushania* stems instead. Electivity values indicate bamboo areas that had low stem density were avoided for the three bamboo species while areas with higher densities were preferred. Pandas were shown to be avoiding very sparse stands of *B. fabri* and *F. robusta* (χ^2 =3.21, $p<0.10$ and χ^2 =3.68, $p<0.10$, respectively) (Table 4.3).

Discussion

Bamboo is not a stagnant resource, but a dynamic organism that exhibits dramatic fluctuations in growth form and densities during sexual reproduction events and after logging activities. In order to best conserve the giant panda, a better understanding of bamboo characteristics, and how pandas perceive bamboo over time, is therefore necessary. We describe use of bamboo stands for three wild bamboo species over time after timber harvesting and fuelwood collection as well as areas without bamboo. This study was performed at a time when *B. fabri*, the most extensive bamboo species

Table 4.3. Electivity Index values for slope, culm height, basal diameter and culm density for *Bashania fabri*, *Fargesia robusta*, and *Yushania chungii*. First column for each species represents categories and sample size in parentheses. Second column indicates Electivity Index values. Electivity Index values are scaled between –1 and +1 (<0 = avoidance, 0 = random, >0 = preference)(Lechowicz 1982, Reid and Hu 1991). $p<0.18$*, $p<0.10$**, $p<0.01$***

	B. fabri		*F. robusta*		*Y. chungii*	
Slope (degrees)	<15 (111)	0.153	<15 (37)	-0.089	<15 (22)	0.123 *
	15-24 (100)	0.140	15-24 (72)	0.096	15-24 (35)	-0.035
	25-34 (64)	0.109	25-34 (103)	0.081	25-34 (19)	-0.032
	>35 (39)	-0.873 ***	>35 (59)	-0.127 *	>35 (7)	-0.082
Culm Height (meters)	0-0.7 (29)	-0.264	0-1.9 (5)	-0.027	0-1.6 (4)	0.200
	0.8-1.0 (22)	0.169	2.0-2.9 (29)	-0.210 *	1.7-2.2 (12)	0.200
	1.1-1.2 (22)	0.169	3.0-3.9 (55)	0.016	2.3-2.6 (3)	0.333
	1.3-1.4 (7)	0.233	4.0-4.9 (18)	-0.118	2.7-3.2 (1)	N/A
	1.4 + (2)	N/A	5.0 + (6)	0.224 *	3.2 + (0)	N/A
Basal Diameter (mm)	0-3.9 (39)	-0.049	0-9.9 (24)	-0.040	0-5.9 (5)	0.282
	4.0-4.4 (23)	0.094	10.0-12.9 (58)	0.144	6.0-7.5 (8)	-0.382 **
	4.4 + (20)	-0.061	13.0+ (30)	-0.150 *	7.5 + (7)	-0.133
Culm Density (stems/m^2)	0-29.9 (12)	-0.268 **	0-6.9 (19)	-0.387 **	0-9.9 (2)	N/A
	30.0-59.9 (31)	-0.146	7.0-14.9 (42)	-0.250	10.0-19.9 (5)	-0.346
	60.0-89.9 (27)	0.053	15.0-22.9 (34)	-0.006	20.0-29.9 (3)	-0.105
	90.0-119.9 (9)	0.013	23.0-29.9 (13)	0.127	30.0-39.9 (3)	0.237
	120.0 + (3)	0.212	30.0 + (5)	0.253	40.0 + (7)	0.351

throughout Wolong, returned to normal pre-flowering densities after the 1983 sexual reproduction event (based on the findings of (Taylor et al. 1991)) who estimated approximately 15 years after 1983 for recovery).

Our research corresponds with other results that suggest giant pandas prefer higher elevation habitats (> ≈2400 MSL). In our study, feces were found more frequently in higher elevation *Y. chungii* and *B. fabri* stands, and less frequently in lower elevation *F. robusta*. These results were expected, as others have noted that pandas spend the majority of their time in areas of higher elevations and come down to lower elevations only sporadically in early spring to eat new shoots and in the late summer to feed on leaves and mature shoots (Schaller et al. 1985). The impacts of timber harvesting and fuelwood collection are relevant to all native bamboo species because logging occurred at all elevations (1771 - 2984 MSL), though forests in lower elevations are more often logged due to the proximity to households and the roadway that bisects the Wolong Nature Reserve.

Giant pandas did not use recently logged (0-30 years) forests that contained *B. fabri* and *F. robusta*. However, forests did not need to be in an old growth stage to be used. Pandas used areas that had been harvested 31-100 years prior as frequently as old growth forest, indicating the ability of these forests to regenerate into suitable habitat. More specifically, our data indicate that forests approximately 60 years in age were frequently used. This amount of time may therefore be necessary for forests to regenerate to a stage where bamboo grows at a level where giant pandas can forage.

Forests that contained *Y. chungii* showed high amounts of use in all age classes except 11-30 years, including 100% use in newly harvested areas (0-10 years). Fewer sample plots were obtained in *Y. chungii* stands and may be a possible explanation for the high percentage of use. *Y. chungii* is less prevalent than *B. fabri* and *F. robusta* and therefore had a lower frequency of occurrence. However, the amount of use in these areas indicates it may be a valuable food source, and its occurrence at higher elevations makes it a prime alternative food source during *B. fabri* die offs.

Within *B. fabri* stands, the ability to predict the presence of feces was best described with slope and aspect. Pandas preferred areas with low slope and forest with a southwestern aspect. Other habitat features, such as conifers in a tall overstory, were also helpful at predicting giant panda feces presence in *B. fabri* stands. Forests with *F. robusta* were used by pandas when the bamboo stands were associated with a forest that had a tall conifer overstory and a dense deciduous midstory. We believe these forest variables may be more indicative of habitats required for the cool, moist conditions preferred by the *F. robusta* bamboo, but the combination of these factors is ideal *F. robusta* panda habitat. Pandas preferred stands of *Y. chungii* that had low ecological aspects (SW facing slopes), higher elevations and low understories.

Electivity values for all three bamboo species indicate pandas do prefer some areas to others. Reid and Hu (1991) also calculated electivity values for *B. fabri* shortly after the 1983 flowering episode. Comparing our electivity values to theirs we find several similarities and differences in panda habitat preferences shortly after *B. fabri* flowering and almost two decades after flowering. Currently, giant pandas are generally less selective (i.e., they act more like generalists) in their choice of habitats than they were shortly after the flowering event. For example, after the flowering event (Summer 1986), pandas avoided areas with sparse bamboo growth (culm density <59 stems/m^2)

and were forced to select areas with higher bamboo density (Reid and Hu 1991). We found that in 2001-2003, pandas avoided areas that had the lowest bamboo stem density, but otherwise used all other areas with no preference. Still, steep areas and areas with low culm density are avoided during both time periods (Reid and Hu 1991).

This study indicates that it may take at least 30 years for *B. fabri* and *F. robusta* to regenerate to levels where panda use was similar to what it was before harvesting. We do not recommend logging as a prescription within Wolong, but our data do suggest that habitat can recover from such events after 30-100 years (mean age *B. fabri* = 53.41 years, mean age *F. robusta* = 50.31 years, Appendix 2A & 2B)

A bamboo species, *Yushania chungii*, is used by pandas even immediately after a harvesting event. This species may therefore be an overlooked resource for giant pandas, especially during *B. fabri* dieoffs, but its smaller areal extant limits its overall importance. Areas with no bamboo were often in grazing areas, old fields or shrublands. Grazing by cow, goats and horses continue to require large amounts of land be kept in grassland. Although we did find one solitary panda feces in the middle of a cattle-grazing pasture, our data suggest pandas do not use these areas even though they are in close proximity to highly suitable habitats. We therefore suggest the Wolong Reserve Administration begin to address the loss of habitat to grazing lands and the potential for these areas to return to forestland and panda habitat.

In addition to the three species of naturally occurring bamboo, a new program has been developed by the local Wolong government to plant bamboo. Planting bamboo began in 2001 as part of the Grain to Green policy in which households are subsidized with grain to plant bamboo. Planted bamboo was located primarily among crops of cabbage, but also among potato and cornrows. In the areas of lower elevation (Gengda Township), planted bamboo stems were growing well, while at higher elevation (Wolong Township) the planted stems were not as successful. We found no evidence of use of planted bamboo by wild giant pandas. However, we did observe a giant panda using corn crops in Crow Valley (LaoYaShan; Gengda Township), indicating pandas may be willing to descend to lower elevations for a human-grown food source. Tempting wild pandas down from their higher elevation habitats should not be encouraged and may only lead to further problems associated with pandas interacting with humans.

Giant pandas eat approximately 150 shoots/day (Schaller et al. 1985). With the current number of captive pandas at the Hetaoping Breeding Center (N=40), approximately 6,000 stems must be harvested daily to sustain the captive population. Forty percent of these stems given to captive pandas are *F. robusta* culms harvested by local people within the Reserve while the remaining 60% is bought from outside the Reserve (Siqiang Zhou, pers. comm.). Our data indicate an average of 15.48 stems of *F. robusta* per square meter. Therefore, if we assume that 40% of captive food comes from Wolong, over 150 m^2 /day of native *F. robusta* bamboo habitat must be harvested to support the panda population in Hetaoping. This means that a large amount of bamboo is cut inside the Wolong Reserve, while an even larger amount is also trucked in several times per week. Transporting bamboo from surrounding counties increases the amount of labor costs and financial pressures, as well as increasing noise and air pollution within Wolong. Bamboo planting within Wolong may help reduce these costs while at the same time offering grain subsidies to local people and local bamboo to the pandas.

The results of this study suggest that harvesting for timber and fuelwood influences understory bamboo growth characteristics and this, in turn, affects the use of habitats by giant panda. Immediately after the harvesting event, different bamboo species respond in different ways, and some species may provide better habitat than others. Over time, bamboo characteristics change as does the pandas selection of different species. Findings from this research can be used toward understanding the relationship between other species which rely on understory vegetation that is influenced by forest harvesting.

CHAPTER 5

IS REFORESTATION EQUIVALENT TO RESTORATION OF PANDA HABITATS: A CASE STUDY IN WOLONG NATURE RESERVE

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Introduction

Plantation reforestation is becoming increasingly common, with over 180 million ha already planted worldwide (FAO 2005). Many countries are using artificially regenerated forests and plantations of certain trees as a means of reestablishing a forest canopy (Kanowski et al. 2003), helping to retain topsoil or prevent desertification (Liu et al. 2002, Stott and Mount 2004, Liu and Diamond 2005), and as a way to provide woody biomass for fuelwood, paper, or crop production (He and Barr 2004, FAO 2005). Asian countries, in particular, have been actively attempting to conserve their forests through plantation reforestation. Asian reforestation projects have accounted for a large portion of global efforts, with over 115 million ha of plantations currently throughout Asia (FAO 2005). Within this region, several countries including Indonesia, Lao PDR, Philippines, Thailand, and Vietnam have all launched programs for reforestation and together have planned to reforest nearly 10 million ha over the next several years (Gilmour 1999, Sayer et al. 2004).

The Chinese government has recently established one of the largest reforestation programs in the world. With one of the highest (approximately 22% of the world's population) and densest (roughly 120 people/km^2) human populations (as opposed to 20 people/km^2 in the United States or 60 people/km^2 in Europe) (Peng and Guo 2000, Liu and Diamond 2005), China has experienced extensive deforestation (Smil 1984, Liu et al.

1999b). To counter deforestation and its effects, the Chinese central government recently adopted two policies, namely the Natural Forest Conservation Program (NFCP) and the Returning Steep Agriculture Slopes to Forest Program (Grain to Green or GTG), which will limit timber harvesting and reforest areas that were previously cleared, respectively (Xu et al. 2004, Liu and Diamond 2005).

China has one of the largest planted forest areas in the world (Zhao and Zhou 2005). Current estimates place the total amount of plantation forest in China to be over 45 million ha (FAO 2005). The Grain to Green program will increase the amount of artificially regenerated forest even further, with estimates of over 7 million ha already planted (Xu et al. 2004) and 14.67 million ha of croplands being converted to forest by 2010 (Xu et al. 2004). Given the current funding for the GTG program (over US$40 billion), it will likely continue to convert a large number of croplands to artificially regenerated forest (Xu et al. 2004).

Yet despite the high level of financial resources being committed to reforestation projects in China and other countries around the world, there are some debates on the potential benefits plantation reforestation will provide biodiversity. More specifically, the possible resources that plantation forests provide to wildlife remain unclear (Stanturf et al. 2001, Hartley 2002).

There is some evidence that reforested areas may be beneficial to wildlife because they provide a certain habitat component that may not be available if an area is left unforested and may do so in a shorter time period than if allowed to naturally regenerate. For example, wildlife may profit from plantations of mast species because they provide readily accessible forage (Twedt and Wilson 2002, Grossman et al. 2003). Wildlife have also been found to use reforested areas (Latham et al. 1996, Matlock et al. 2002, Hemami et al. 2004), with some reforestation species (Twedt et al. 2002), certain forest ages (Nagaike et al. 2003), or particular seasons (Palmer and Truscott 2003) offering more suitable habitat.

Species diversity may also increase after reforestation. Sykes et al. (1989) recorded mammalian diversity and found a marked increase following reforestation of a rangeland. Prior to reforestation activities, nine mammalian species were using the area. Twelve years afterwards, this number increased to 18 species, 12 of which were breeding regularly (Sykes et al. 1989). In addition to species diversity, reforestation areas may influence population abundance. For example, Sykes et al. (1989) found a general increase in the number of roe deer harvested throughout their study area after reforestation. Also, the number of breeding pairs increased from 271 before afforestation to 724 afterwards (Sykes et al. 1989).

Although some species may benefit from reforestation, converting an area to artificially regenerated forest may be detrimental to other species. Some wildlife species may not be able to use areas that are reforested (Twedt and Portwood 1997, Ericsson et al. 2000). Species diversity may also be negatively influenced. For example, Armstrong et al. (1998) determined that reforested lands had a marked negative impact on the biodiversity of some areas in South Africa. They found that several plant and animal species had become locally extinct or threatened within newly reforested lands, and that reforestation projects had been largely responsible for the endangered status of some species (Armstrong et al. 1998). In another study, Allan et al. (1997) compared habitats and found grasslands had higher bird species diversity and had a higher number of endemic and threatened species than reforested areas, even if the plantation area was very small.

Plantations also affect small and large mammal abundance. Taylor and Perrin (1996) caught a high number of small mammals in new, young pine plantations (approximately 0-14/trapnight). However, small mammal numbers declined as the timber trees matured, so that there were very few remaining by the time the stand matured. These numbers, even in the new plantation, were still lower than the small mammal numbers in surrounding natural habitat, where numbers ranged from 18 to 25 mammals/trapnight (Maddock 1988). Hulbert et al. (1996a) also noticed a decline in the presence of two species of lagomorphs using plantations as the forest matured. However, because of the species' adaptability, the authors concluded that in the early years following planting, reforestation is unlikely to influence mountain hare and rabbit populations as long as an abundant ground cover remains available (Hulbert et al. 1996b). Changes in large mammal abundance have also been documented. Extirpation of an African antelope, the oribi, after reforestation was recorded by Viljoen (1982). The oribi were not seen in forest plantations and were found to be avoiding the areas due to preferences for grasslands (Viljoen 1982).

The extent of reforestation occurring throughout Asia, especially in China, has the potential to greatly affect the resident wildlife occurring in these regions. This is especially true for the mammal populations, as China has one of the richest mammal populations in the world (State Environmental Protection Administration of China 1998). However, we are unaware of any study that has identified the relationship between Chinese reforestation and the neighboring wildlife habitats. Therefore, we chose to study habitats of the giant panda (*Ailuropoda melanoleuca*) in Wolong Nature Reserve, Sichuan Province. The giant panda occurs throughout the steep, mountainous regions of Sichuan Province, and its habitats may be influenced directly by GTG reforestation projects (Liu and Diamond 2005).

To understand the relationship between reforestation areas and giant panda habitat, we investigated whether current artificially regenerated forests in Wolong provided habitat to pandas and how artificially regenerated forests may mitigate the impacts of fuelwood harvesting on panda habitats. Our first objective was to determine how pandas currently use reforestation areas in order to establish whether areas that have been reforested can create panda habitat. To accomplish this, we compare panda use of various aged artificially regenerated forest to natural surrounding forests. Our second objective was to evaluate the potential of reforestation areas to mitigate impacts on panda habitat by providing alternative fuelwood sources. For this, we developed a model of reforestation mitigation potential based on field data and information from the literature to address the basic issues related to panda habitat.

Methods

Potential of Reforestation Areas to Create Habitat:

Field Survey Methods:

We surveyed giant panda use in various aged reforestation areas as well as natural forests throughout much of the Wolong Nature Reserve. Use by the giant panda was determined by the presence of fecal droppings, which was considered a useful indicator of panda use because although actual sightings of animals are rare, feces are deposited frequently (97 droppings/day, 4 droppings/hour) (Schaller et al. 1985) and remain for several months (personal observation).

Data collection took place from May-August 2001, May-November 2002, and June-August 2003. We sampled a total of 69 plots in randomly selected reforestation areas and 69 plots in neighboring natural forests. A sample plot was 30 x 30 m in size. The center of each plot was spatially referenced using a Pathfinder® Pro XRS GPS unit (Trimble Navigation Limited). Geographic and forest characteristics as well as bamboo cover were measured over the entire 30 x 30 m plot. We located sample plots while in the field. Sites were grouped into four harvest age categories based on their forest stand ecology, our ability to age the forest in the field, and sample size issues: 0-10 years, 11-30 years, 31-100 years, and unharvested or old-growth forest.

Statistical Analysis:

To determine the potential of artificially regenerated forest to provide suitable panda habitat, we first tested for differences in forest and geographic characteristics between reforestation areas and neighboring natural forests. To test for differences between natural and artificially regenerated forests, we used the paired t-test (when variances tested equal) or the more robust Wilcoxon signed-rank test (when variances tested unequal). Variances were tested using an F-test for variance equality (Insightful Corp. 2003) and were considered equal if $P > 0.2$.

To gain a general understanding of where giant panda feces occurred in artificially regenerated and natural forests, we tested for differences in mean canopy covers (overstory, midstory, shrub, and bamboo strata) in areas with and without feces using ANOVA and Tukey's posthoc comparisons. We then estimated which forest and geographic characteristics best predicted the presence of giant panda feces using logistic regression. We fit two final logistic regression models, one for reforestation areas and one for the surrounding forest. For each model, we initially fit univariate logistic regressions to all variables and retained each variable only if the likelihood ratio test (G-test)(PROC LOGISTIC; (SAS Institute 1985) had $P < 0.2$. Variables that were significant in univariate tests were then tested for collinearity using PROC CORR (SAS Institute 1985). For pairs of variables with $r > 0.60$, we eliminated the variable with the less significant univariate G-test score. A multivariate, stepwise logistic regression was fit using the remaining variables. Significant predictors in the logistic regression helped to describe habitat characteristics preferred by pandas.

Conservation Potential of Reforestation Areas:

To establish the potential of reforestation areas to mitigate impacts on natural giant panda habitats, we first determined the possible extant of fuelwood harvesting impacts on natural giant panda habitats (i.e., natural forest). We simulated impacts by subtracting fuelwood volumes collected by households from natural forest stands. In other words, we estimated forest stand biomass using data collected in the field and then subtracted amounts of biomass used for fuelwood to determine a decrease in forest biomass. Initial stand volumes of natural forest were based on DBH and tree height measurements and tree densities gathered from 342 field plots throughout Wolong Nature Reserve. Each field plot measured 30 x 30 m and numbers of trees in 20 cm categories were counted (10-30, 31-50…71-90, 91+ cm DBH). We calculated volume of tree biomass using (Wenger 1984):

$$V = BA \times \frac{TH}{3}$$

where, BA = mean basal area in each 20 cm category and TH = average overstory tree height. Average household fuelwood use was estimated to be 10.6 m^3/year based on Liu et al. (1999b), who calculated an annual fuelwood consumption of 10,000 m^3/year during a time when the total number of households equaled 942 (Liu et al. 1999b). Since there is a current ban on fuelwood collection (from the NFCP), we also simulated potential effects of reduced fuelwood collection at 50% (5.3 m^3/year), 25% (2.65 m^3/year), and 12.5% (1.33 m^3/year) levels.

We then modeled potential impacts of fuelwood collection on panda use by calculating a change in proportion of feces presence due to a change in forest biomass from fuelwood harvesting. To do this, we created a model to establish the relationship between harvesting and change in panda use. The model was a regression that used measurements of stand volume in 342 forest plots in Wolong and the mean proportion with feces. Using this regression, we then demonstrated the decrease in likelihood of finding feces in a given natural forest stand after it had been harvested.

Finally, we estimated the volumetric growth of reforestation trees to determine their potential for mitigation of fuelwood collection in natural forests. To do this, we began a simulation based on generic 5-year-old saplings that had dimensions equivalent to 0.025 m dbh (1-inch dbh) and 0.6 m height. We then adapted a volumetric growth equation for *Larix potaninii* var. macrocarpa using data from Li (1990). The growth equation was (r^2=0.997):

$$y = 6e^{-4}x - 5e^{-6}x^2 + 9e^{-9}x^3 \qquad (5.1)$$

where x = age of tree in years and y = volume growth in m^3. Because of the difficulty associated with modeling the initial years of seedling growth, and because plantation trees in Wolong were initially grown in nurseries, the growth model was most reliable between year 10 and year 90. Therefore, we only report results between these tree ages. We chose to base our model on *Larix potaninii* var. macrocarpa because it is planted throughout Wolong and was found to have less volume growth than other species making it a more conservative estimate in modeling mitigation potential of fuelwood. We used data from Mingchong Liu in Wolong Nature Reserve (2000-2003) to estimate the amount of forest biomass planted in Wolong for the Grain to Green Program. Tree volumes were determined using an initial stand density of 5000 trees/ha (5 trees/10m^2), an average density calculated in the field, and initial age at year 5. With this estimated initial density, we calculated initial volume to be 0.5 m^3/ha (5000 trees/ha x 0.0001 m^3/tree) of woody biomass 5 years after planting. In addition, we developed a mortality function that was:

$$y = -8e^{-6}x^3 + 0.0018x^2 - 0.1609x + 7.692 \qquad (5.2)$$

which killed off a higher rate of younger trees than older. The function was developed by determining the polynomial regression between the following mortality rates: 7% at year 5, 5% at year 20, and 3% at year 70, and 2% at year 80, year 90, and year 100. The predicted volume grown in plantations was then used for mitigating fuelwood collection on natural forests. In other words, we determined the increase in panda use of natural forests when plantation forests were harvested for fuelwood instead by equating the amount harvested in plantations to an equal amount of forest volume allowed to remain standing in natural forests. The difference in the forest volume that remained in natural forests was then related to a change (an increase) in panda use based on the regression between forest volume in 342 field plots and the mean proportion with panda feces described earlier (p. 97). Using the results of this simulation, we then demonstrated the mitigation potential of reforested areas. We did this by showing the increase in potential of finding panda feces in a natural forest when forest harvesting occurs in plantations instead of natural forest.

Results

Potential of Reforestation Areas to Create Habitat:

The ages of the 69 plots in reforestation areas we surveyed ranged from recently planted (<1 year) to old plantation (50 years). Mean reforestation age was 30.5 ± 3.9 years (±SE). Characteristics of reforestation areas were compared to an equal number (N=69) of neighboring natural forest plots. Distances between the centers of reforest plots and the natural forest plots ranged from 43.5 to 314.7 meters. Natural forest plots

Table 5.1. Mean (± SE) values for reforestation and natural forests with mean comparison tests (Binom. Prop.= Binomial Proportion Test, T-test= 2 sided t-test, Wilcox= Wilcoxan Rank Sum Test).

	Reforested Plantation		Natural Forest				
	Mean	SE	Mean	SE	Score	P Value	Test
Percentage with panda feces	1.45		13.04		-2.40	0.017	*Binom Prop.*
Age (years)	30.47	3.87	54.52	7.01	-1.18	0.237	*Wilcox*
Slope (deg.)	23.18	2.89	25.60	1.30	-2.06	0.040	*Wilcox*
Basal Area (m2/ha)	9.24	0.99	4.16	0.60	4.12	<0.001	*Wilcox*
Total Overstory Cover (%)	42.99	2.90	31.08	2.71	2.99	0.003	*T-test*
Conifer Overstory Cover (%)	41.09	2.90	14.41	2.83	6.56	<0.001	*T-test*
Deciduous Overstory Cover (%)	1.90	0.86	16.84	2.09	-7.38	<0.001	*Wilcox*
Average Overstory Height (m)	15.64	0.71	21.21	0.74	-5.46	<0.001	*T-test*
Total Midstory Cover (%)	9.88	1.65	24.60	2.27	-5.30	<0.001	*Wilcox*
Conifer Midstory Cover (%)	6.00	1.42	2.72	0.77	1.64	0.100	*Wilcox*
Deciduous Midstory Cover (%)	3.88	0.89	19.69	2.06	-6.44	<0.001	*Wilcox*
Average Midstory Height (m)	4.88	0.67	11.65	0.76	-6.65	<0.001	*T-test*
Average Shrub Height (m)	2.66	0.19	4.35	0.25	-5.33	<0.001	*T-test*
Total Shrub Cover (%)	19.39	2.20	26.67	2.29	-2.29	0.023	*T-test*
Bamboo Cover (%)	7.52	2.66	49.82	3.83	-8.57	<0.001	*Wilcox*
Total Understory Cover (%)	64.35	3.50	25.58	3.42	7.91	<0.001	*T-test*
Average Understory Height (cm)	48.56	3.31	25.32	2.86	5.30	<0.001	*T-test*

ranged in age from recently harvested (approx. 1 year) to unharvested (estimated mean age = 150 years), with mean natural forest age 54.5 ± 7.0 years (±SE)(Table 5.1).

Based on the presence of feces, giant pandas showed preference for natural forest habitats to reforestation areas. We found panda feces in only one reforestation plot, so interpretation of results must be conservative. Natural forest had a significantly higher amount of feces than artificially regenerated forest (13.0% and 1.4%, respectively)($Z = -2.3975$, $p = 0.017$)(Table 5.1).

Panda use varied by age of forest ($F_{4,133}=10.49$, $p=0.002$) with higher amounts of use in older harvested and old-growth forest. In natural forest, feces occurred between 11 to 100 years of age as well as in old-growth forest. No feces were found in areas harvested less than 10 years ago. We found high proportions of use between 31-100 years (39.1%) and old-growth forest (27.8%). The proportion of feces in natural forest harvested 31-100 years ago had significantly higher amount of use than areas harvested earlier than 31 years ($F_{1,63}=3.53$, $p=0.01$). The one site in artificially regenerated forest that had feces had been planted approximately 40 years ago and was one of the oldest, most remote plantation sites. Giant pandas were not found to use areas that were planted more recently than 40 years.

Forest structure varied between reforested areas and natural forest sites (Table 5.1, Figure 5.1). Generally, plots in reforested areas with no feces present had higher overstory cover ($F_{3,130}=4.47$, $p=0.005$), lower midstory cover ($F_{3,131}=8.73$, $p<0.001$), and significantly lower bamboo cover ($F_{3,133}=31.37$, $p<0.001$) than surrounding natural forest (Figure 5.1). On average, artificially regenerated forests had higher overstory coniferous canopy cover, and a denser and taller understory (Table 5.1). Natural forests had a taller

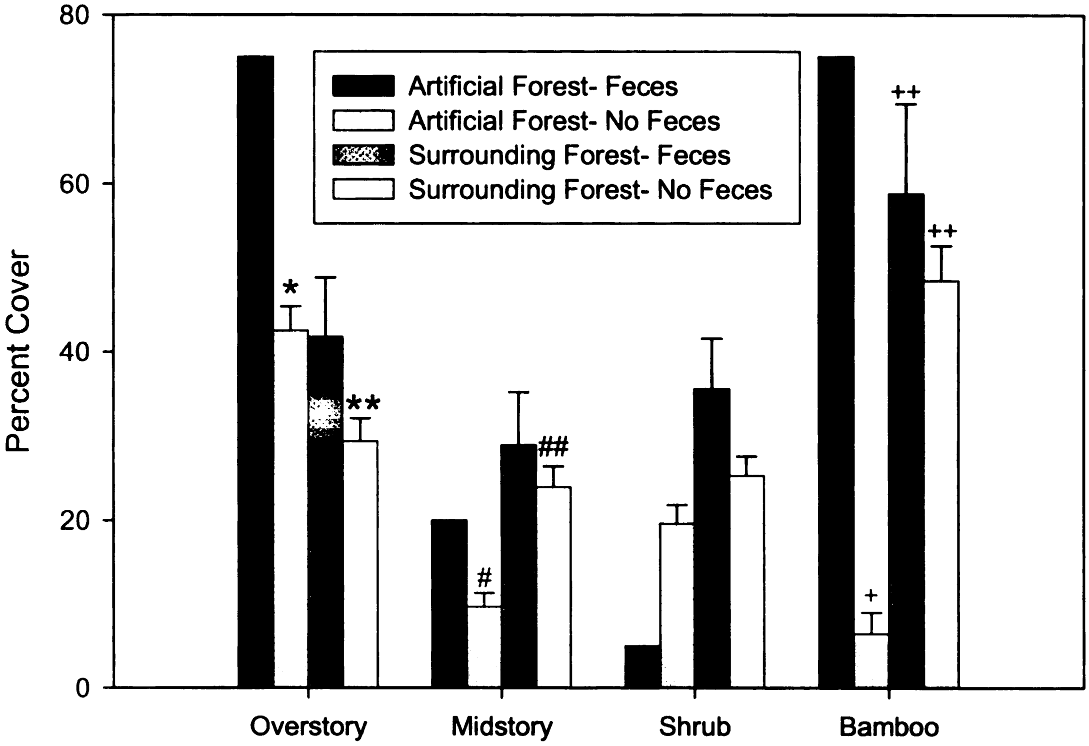

Figure 5.1. Mean (±SE) percent coverages for total overstory, midstory, shrub and bamboo strata in artificially regenerated forest and surrounding natural forest for areas with and without giant panda feces.

overstory with a greater deciduous component and a taller, denser, more deciduous midstory (Table 5.1). Perhaps most significantly, the surrounding natural forest had much higher bamboo coverage than the reforested areas (Table 5.1). The differences in forest structure may help to explain the use of habitats by the giant panda.

Logistic regression models indicated several forest characteristics that best predicted the presence of panda feces. For reforested areas, average midstory height, bamboo cover, and average understory height had the most significant univariate logistic p-values (Table 5.2). When the full logistic model was fit to the reforestation data, bamboo cover was the only variable that predicted panda presence (Table 5.3). Again, we urge cautious interpretation of these results because only one plot had feces present in reforestation areas.

In natural forest, univariate logistic models indicated that conifer midstory cover, conifer overstory cover, forest age, understory height, and forest basal area were associated with panda feces presence (Table 5.2). Unexpectedly, bamboo was not a significant factor in the prediction of panda feces in natural forest surrounding reforestation areas. The full logistic model for natural forest indicated that the coniferous component of the midstory best predicted the presence of panda feces (Table 5.3).

Conservation Potential of Reforestation Areas:

The amount of forest area impacted by forest harvesting differed when various levels of harvesting occurred in different aged forests. Harvesting 10.6 m^3/year/household impacted a greater spatial extant of young natural forests more than older forests. For example, a single household collecting its yearly supply of fuelwood in

Table 5.2. Univariate Logistic Regression P-values.

	Reforestation	Natural Forest
Forest Age (years)	0.7888	0.0351
Patch Size (sq. km)	0.0598	0.1214
Slope (degrees)	0.9940	0.7250
Basal Area (m2/ha)	0.5689	0.0497
Average Overstory Height (m)	0.1302	0.0650
Total Overstory Cover (%)	0.1465	0.1202
Conifer Overstory Cover (%)	0.1343	0.0179
Deciduous Overstory Cover (%)	0.6686	0.1052
Average Midstory Height (m)	0.0013	0.1862
Total Midstory Cover (%)	0.5069	0.4727
Conifer Midstory Cover (%)	0.3520	0.0014
Deciduous Midstory Cover (%)	0.4228	0.7211
Average Shrub Height (m)	0.3659	0.1632
Total Shrub Cover (%)	0.3123	0.1389
Bamboo Cover (%)	0.0424	0.3581
Average Understory Height (cm)	0.0593	0.0479
Total Understory Cover (%)	0.1346	0.5824

Table 5.3. Final multivariate logistic regression models.

	Intercept	Variable	Estimate	P-value	AIC
Reforestation Areas	-6.2458	Bamboo Cover (%)	0.056	0.051	10.32
Natural Forest	-2.8182	Conifer Midstory Cover (%)	0.1614	0.003	36.81

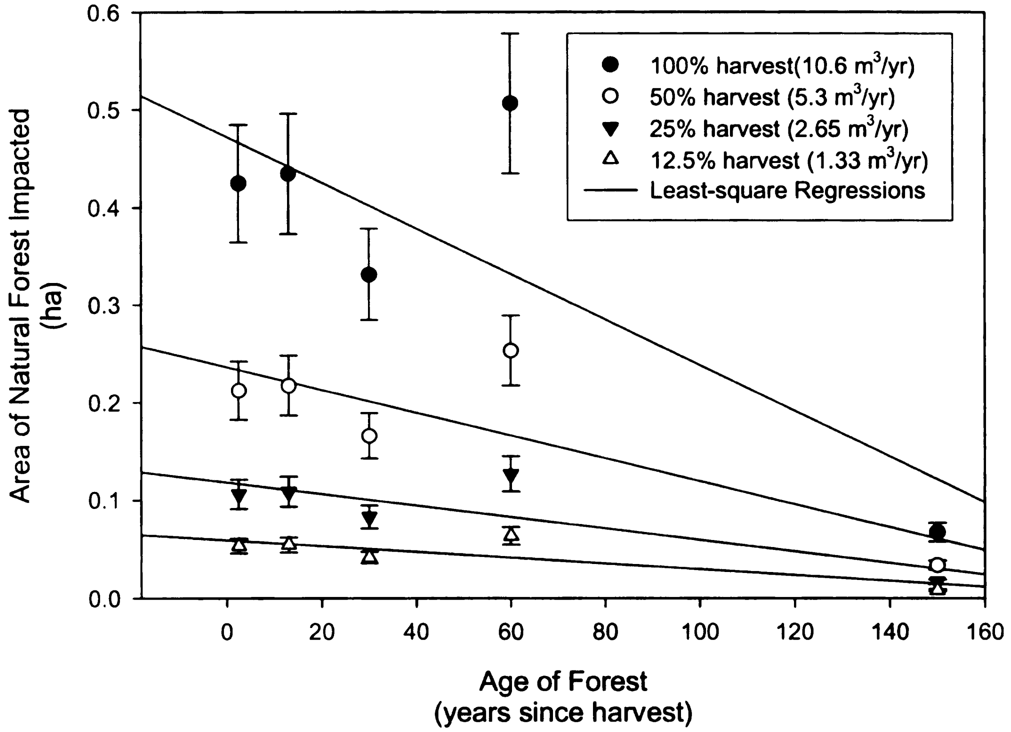

Figure 5.2A. The area of natural forest impacted by various levels of forest harvest (1.33-10.6 cubic meters/year) in different aged natural forests. Values represent mean ages from 5 age classes (0-5, 6-20, 21-40, 41-80 years, and unharvested forest) and forest volume from 342 field plots which established volume per acre.

young forest (0-10 years) impacted nearly 0.5 ha, whereas the same amount of fuelwood collection in old-growth forest (150 years) impacted a smaller area (0.1 ha)(Figure 5.2A).

In terms of forest biomass, a forest with higher volume of woody material had less area impacted by fuelwood collection (Figure 5.2B). If forests had approximately 100 m^3/ha of forest volume, over 0.1 ha was cut (at 100% harvest). Alternatively, in high volume forests (i.e., old-growth forest) where we measured over 500 m^3/ha of forest volume, less than 0.04 ha would be harvested by one household (Figure 5.2B). The large amount of area impacted in newer, low volume forest is due to lower amounts of woody biomass in young forest, thereby causing more areas to be harvested. As expected, decreased levels of harvesting impacted proportionally smaller amounts of natural forest. For example, a decrease in annual fuelwood harvest by 25% (2.65 m^3/year/household) lessened the impact on natural forest by 25% so that only 0.13 ha of young forest were impacted (Figure 5.2). We modeled the relationship between tree volume (m^3) and potential of finding feces using data collected in the field (Figure 5.3). A 2nd order polynomial regression fit the dataset best (r^2=0.64) with the relationship being:

$$y = 0.0049x - 1.0e^{-5} x^2 + 0.1626 \qquad (5.3)$$

where, y = proportion of sites with giant panda feces present and x = volume of woody (i.e., tree) biomass (m^3). Harvesting for fuelwood at the full, half, and quarter levels all reduced the potential of feces presence, but at different amounts. For example, harvesting 10.6 m^3/year in areas with low initial forest volume (10 m^3/ha) caused the greatest decrease (5.2%) in the potential of finding feces (Figure 5.4). Harvesting in

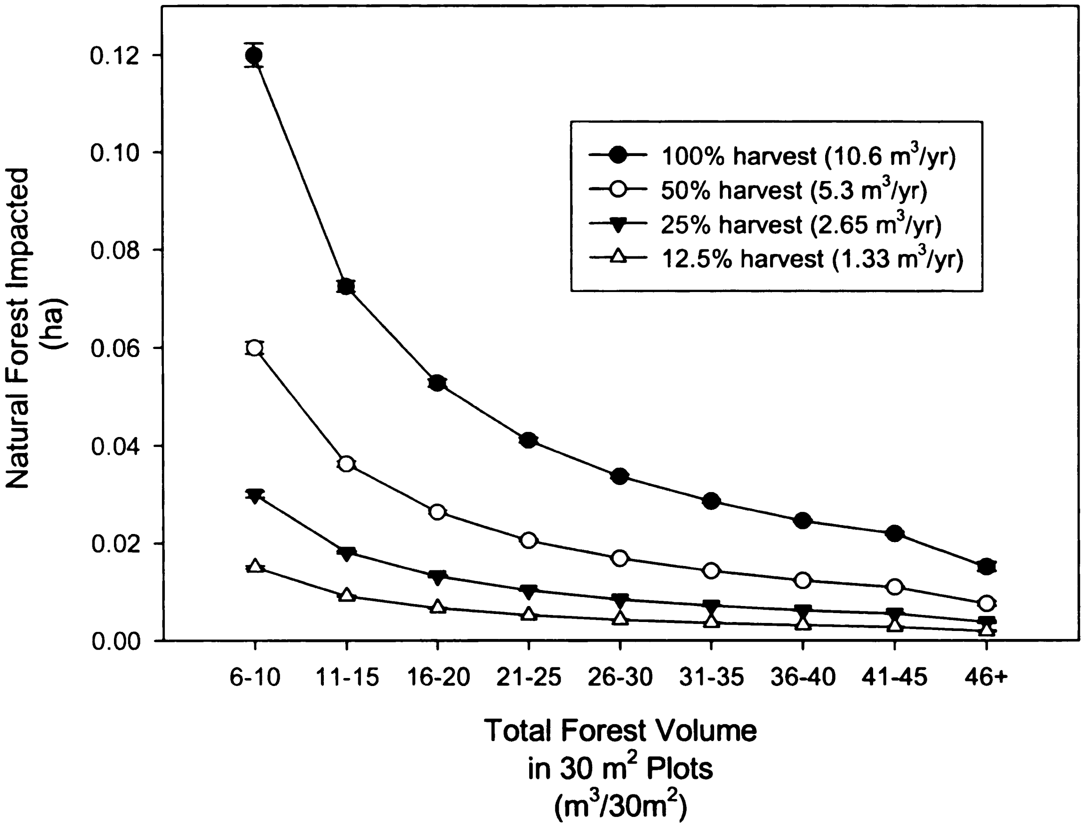

Figure 5.2B. The area of natural forest impacted by various levels of forest harvest (1.33-10.6 cubic meters/year) in natural forests with different volume stands. This direct relationship describes harvesting levels and forest densities found in Wolong Nature Reserve, 2001-2003.

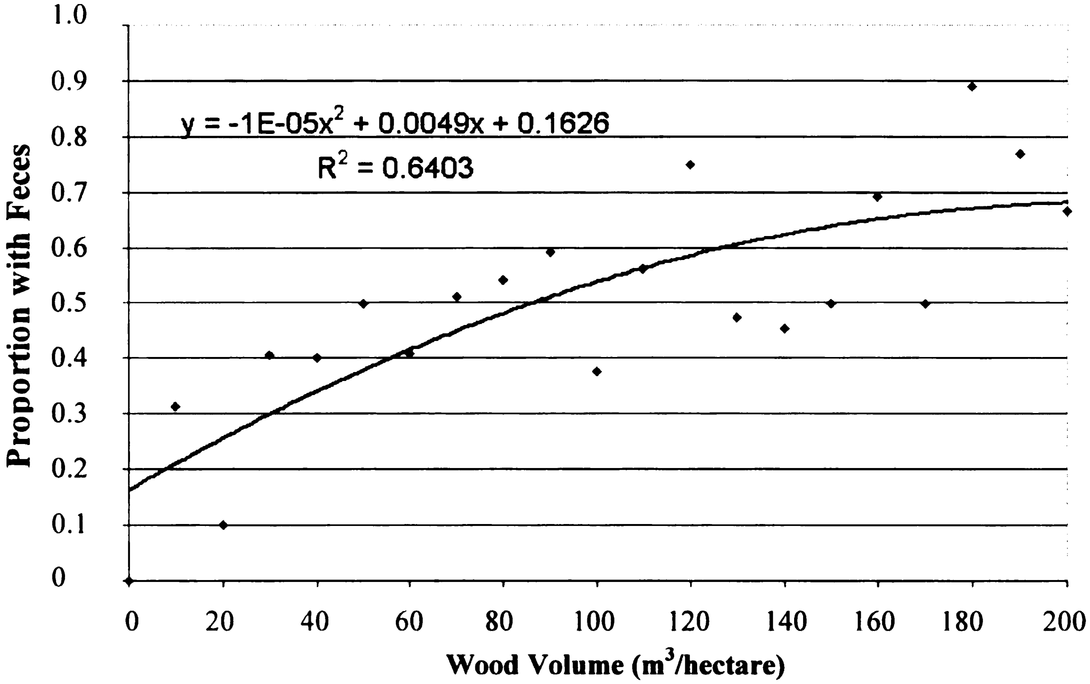

Figure 5.3. A model of the relationship between tree woody volume (m^3) and potential of finding feces using data collected in the field.

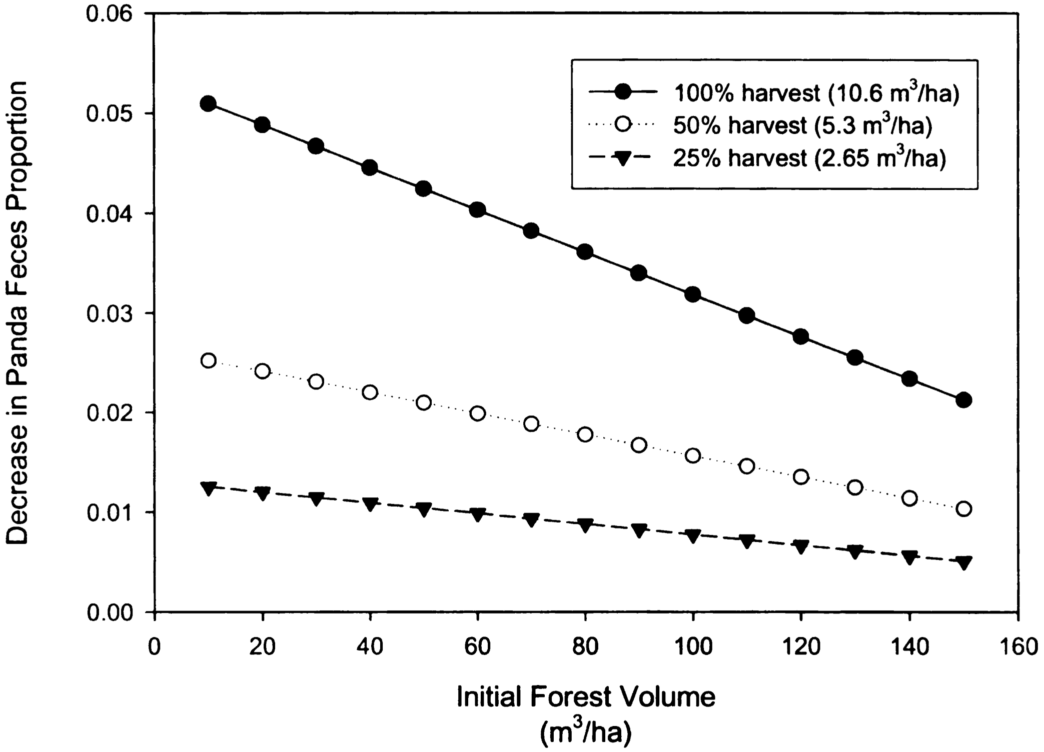

Figure 5.4. Habitat degradation determined by the change in panda feces proportion found in 342 field plots (high decrease = high degradation) from various levels of forest harvest in natural forests that range from having low to high initial forest volume.

areas with higher initial forest volumes also caused a decrease in panda use, but the effect was less. For example, harvesting 10.6 m^3/year in areas that initially had 100 m^3/ha caused a decrease in the potential of finding feces of 3.3% (Figure 5.4). Lowering the fuelwood harvest by half and a quarter reduced the effects by proportionally equivalent amounts (Figure 5.4).

Conservation Potential of Larix potaninii var. macrocarpa:

Plantation volume increased over the first 52 years of stand development to 342.8 m^3/ha. As the plantation aged past 52 years, total volume decreased as individual growth declined and natural mortality continued (Figure 5.5). If 100% of the volume produced were used for fuelwood, it would provide enough annual fuelwood for 10 to 30 households, depending on the age of plantation (Figure 5.5).

To determine the impacts mitigated by harvesting plantation forest, we modeled 100%, 50%, 25% and 12.5% harvesting of plantation forest biomass (Figure 5.6). Harvesting from plantation forests was correlated to an equal amount of natural forest that was not harvested. We modeled this by adding the same amount harvested in plantation to the amount of natural forest volume in natural habitats. The higher the harvest of plantation forest the greater the increase in proportion of sites with panda feces in natural forests because more areas of natural habitat were preserved (Figure 5.6). In other words, a 100% harvest of plantation forests preserved more natural forest than 25% plantation harvest. Generally, older plantations offered more woody biomass for fuelwood and therefore preserved more natural panda habitat. For example, if 100%

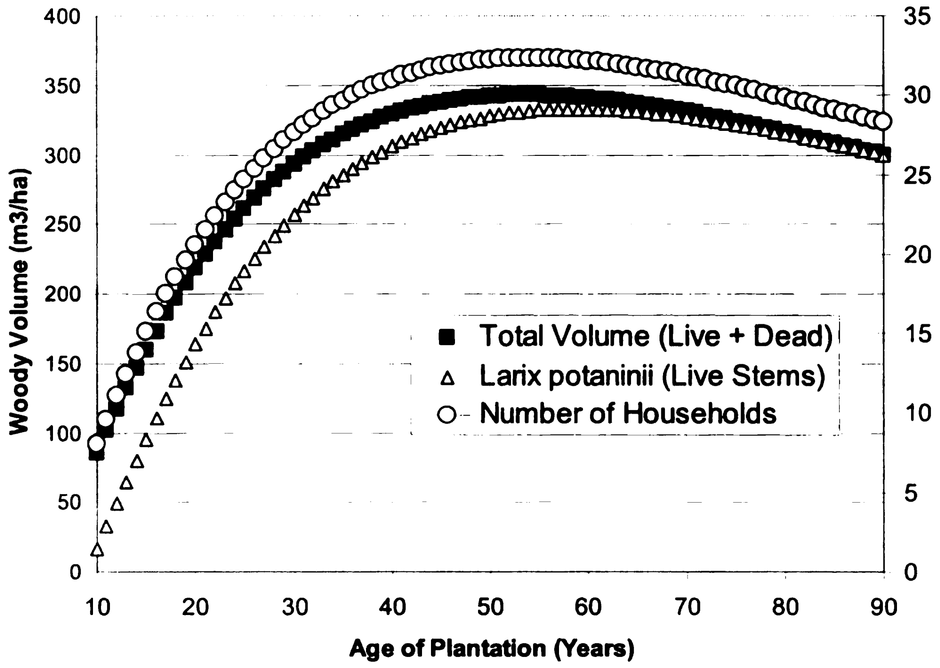

Figure 5.5. Pole volume from plantations of *Larix potaninii* var. macrocarpa and the number of households that can harvest 100% of their fuelwood needs (10.6 cubic meters/year) from the total volume in these plantations. The simulation was conducted between 10-90 years because these were the years available for the species growth equation used in the model.

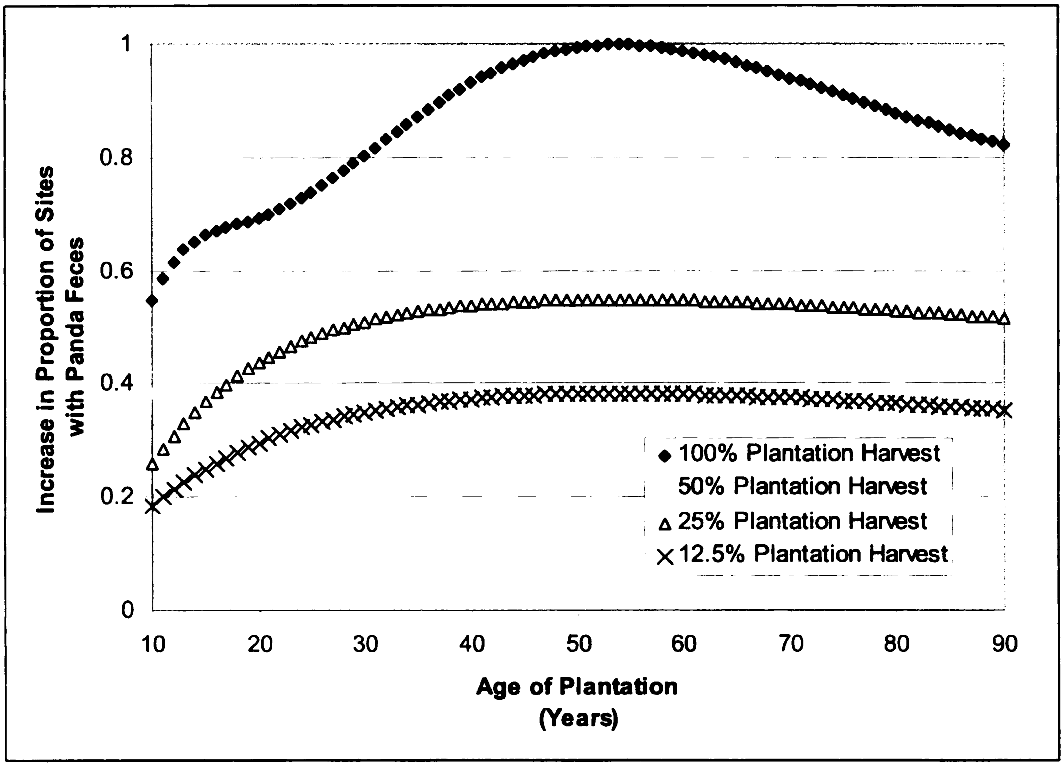

Figure 5.6. Proportional increase in the number of natural forest sites used by giant pandas when plantations are harvested instead of natural forests. This relationship was established based on the woody volume of plantation forests over time (see Figure 5.5) and the proportion of sites with feces in natural forests of varying woody volumes (see Figure 5.3). The simulation was conducted between 10-90 years because these were the years available for the species growth equation used in the model.

of a 50-year-old plantation is harvested, the amount of biomass preserved in natural forest may increase the potential of panda use in those natural habitats by over 80% (Figure 5.6).

Discussion

We found giant panda feces in 1.4% of plots (1 of 69) in reforestation areas, and therefore concluded that pandas rarely use this type of artificially regenerated forest. However, use of this plot is notable because it provides evidence that in some cases, the giant panda is able to use reforested areas if certain conditions can be met. We believe use of this particular reforestation plot by a panda is explained by the plot's location and surrounding forest characteristics. The plot was located far from human disturbance (over 2 km from roadway) and was characterized with a healthy arrow bamboo (*Bashania fabri*) stand, as demonstrated by the high proportion of bamboo in the plot (75%) and evidenced by its significance in the logistic regression of reforestation plots. However, the vast majority of reforestation plots had no bamboo cover or significantly lower bamboo cover and were therefore not used. Given the importance of bamboo in determining the likelihood of use by pandas in reforestation areas, methods to propogate bamboo under the more acidic conditions of *Larix* spp. plantations should be considered.

The majority of the tree species planted in Wolong Nature Reserve are fast growing species (i.e., *Larix* spp.) which are non-native to the forests and climate of Wolong. Other species that are native to Wolong, more suitable for Wolong's climate, or grow easily in Wolong's soil may provide a better fuelwood source and may have the additional advantage of allowing bamboo and other understory, shrub, or midstory vegetation to grow. If different planted species allow more bamboo or other vegetation to grow in its community, the likelihood of these planted forests creating panda habitat may be greater. However, the tree species that are currently used to reforest areas of Wolong do not appear to provide conditions suitable for other native vegetation to grow and therefore do not create suitable panda habitat. Based on the results of this study, care should be taken to not interpret the planting of trees or the reforestation of an area to be equivalent to the creation of panda habitats.

We also evaluate the potential of reforestation areas in Wolong Nature Reserve to mitigate fuelwood collection effects on giant panda habitats by modeling the relationship between natural forest volume, *Larix* spp. growth, and the potential of finding panda feces. Fuelwood collection in Wolong previously occurred in the natural forests surrounding the households (An et al. 2002, Linderman et al. 2005a), however, since the implementation of two new conservation policies in China (the NFCP and the GTG), harvesting has dwindled and amount of reforested areas have increased (Liu et al. 2001, Liu and Diamond 2005). Although present day harvesting does not currently have a large impact on China's natural forests, the two policies may expire in the next several years, at which point increased harvesting may again occur throughout China. Given this time period, trees originally planted as part of the GTG program may grow to a size that may provide a significant source of fuelwood.

We found that an average household in Wolong Nature Reserve harvesting natural forest at the levels described by Liu et al. (1999b) impacts approximately 0.4 ha each year whether harvesting takes place in a young or secondary forest (0-40 years). Harvesting in older natural forest impacts less of an area. Similarly, harvesting in forests with low volume affects larger areas while cutting in high volume forest impacts a smaller area. Currently, while the harvesting ban is in place, harvesting of whole trees continues to be rare and effects of harvesting on panda habitats are therefore minimal.

Our model indicates fuelwood collection in natural forests reduces the likelihood of finding giant panda feces. Forests with greater woody volume are less sensitive to changes in probability of panda feces, and therefore less sensitive to harvesting, than were low volume forests. Harvesting in forests with lower volume has a greater influence on the potential occurrence of giant panda feces because it impacts a larger area and because forests with lower wood volume have lower proportions of feces. This relationship only accounts for proportional change and not total change. Therefore, it does not indicate that harvesting in old growth natural forests has less of an effect on pandas than harvesting in low volume forest because the total probability of panda feces occurring in high volume forest is much greater.

Planted forests can mitigate impacts of fuelwood collection on natural forests, although this varies with species, age, and amount harvested. During the early stages of forest growth, roughly 4 households could collectively gather their fuelwood over 1 hectare due to the low amount of biomass. However, if forests are allowed to grow past this initiation stage, biomass grows steadily until the trees are approximately 70 years old, at which point it could provide enough wood for approximately 10 households for each hectare using 10.6 m^3/ha of fuelwood/year/household (Figure 5.5). If rates of household fuelwood consumption are lower, the number of households that these plantations provide fuelwood for could increase to 20 (at 5.3 m^3/yr/household), 40 (at 2.7 m^3/yr/household), or more.

A cumulative total of 266.7 ha were planted in 2000, 333.3 ha in 2001, 414.6 ha in 2002, and 448.5 ha in 2003 with primarily *Larix* spp. for the Grain to Green program (Wolong Nature Reserve 2003). Assuming a conservative estimate of 1000 trees/ha (1 tree/10 m^2)(20% of the average density measured in the field), woody volume produced by this policy may well exceed 80 m^3/ha after 80 years of growth. Permitting harvesting of the planted trees allows natural forests to regenerate and to experience less human disturbance. Harvesting of planted trees then provides better giant panda habitat in natural forests. If rotations are developed so that harvesting only occurs in reforested areas every 80 years, there is the potential that panda use of natural forests may increase by greater than 80% (Figure 5.6).

The placement of planted trees and reforested areas should be taken into consideration when planting artificially regenerated forests. Our findings show that present reforestation areas do not provide suitable giant panda habitat but do offer a potential alternative fuelwood source. In order to prevent these areas from impacting natural wildlife habitats, they should be placed close to households. This would increase the likelihood of their use, decrease human effort to collect the wood, and decrease levels of pollution and environmental disturbance. In societies where fuelwood is still a necessary source of energy, alternatives should exist that reduce the impacts on natural forests. Artificially regenerated forests may potentially provide that alternative. For this reason, artificial forests may be an significant yet overlooked component of wildlife conservation in these areas.

CHAPTER 6

SCALING UP FROM SURVEY SAMPLES TO THE LANDSCAPE LEVEL: GIANT PANDAS ACROSS HETEROGENEOUS LANDSCAPES

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SCALING UP FROM SURVEY SAMPLES TO THE LANDSCAPE LEVEL: GIANT PANDAS ACROSS HETEROGENEOUS LANDSCAPES

Introduction

To understand the relationships of organisms to their environment, researchers typically collect ecological information from a set of spatially distributed sample plots. They may then attempt to establish key relationships (models) from the plot data based on the premise that the plots are representative of the broader landscape, and extrapolate these relationships to landscape level predictions. Throughout this paper, we refer to this process of using field data to generate landscape level results as "scaling-up." The landscape models that result from scaling-up can then be used in various ways, including: predicting species occurrence (Fleishman et al. 2001, Fertig and Reiners 2002), mapping habitat suitability (Danks and Klein 2002, Gross et al. 2002, Niemuth 2003, Store and Jokimaki 2003), analyzing spatial patterns (Franklin et al. 2002, Ray et al. 2002), and investigating human impacts (Hawks et al. 2000, Cramer and Portier 2001, Rao and Pant 2001).

At the landscape level, we often must use models because it is not practical to study the entirety of a large area in detail. Landscape models have proven to be valuable tools (Turner et al. 1995, Liu and Taylor 2002) because models based on plot data could extrapolate what a survey would have found from the plot level to the entire landscape. However, all models have errors. First, errors may be produced during the statistical analysis used to generate the models. For example, the selection of independent variables may be important in determining the extent of errors that are produced (i.e., the principle of parsimony) (Leger and Altman 1993, Zar 1996). Second, errors may result from necessary assumptions and imperfect knowledge. For example, suppose we know that species 'X' lives only in coniferous forest. At any given point in a landscape, we can reasonably predict its suitability for species X merely by the proportion of conifers present. Now assume we want to map the habitat of X across an entire state. A landscape model is necessary because it is not practical to visit every location. However, a problem arises because our landscape level forest map does not distinguish conifer forest from other forest types. This map only includes a "forest" variable. In this case, the landscape model will perform poorly, not because of a bad model or poor understanding of the species, but because the data limitation leads to an oversimplification of reality. Nearly all landscape models must do this to some degree. However, few models accurately quantify the amount of information lost during this stage. Rather, models are typically selected based on criteria such as Akaike's Information Criteria (AIC). For example, models may be created or resampled at several different spatial scales (e.g. grain size) and the relationship between the scale and a variable are of primary interest. Here, the focus is often on selecting the model with the spatial scale that fits the data best. In many instances, the loss of information from the actual scaling up procedure is not explicitly defined and may be neglected altogether. In addition, even if a variable measured in the field is ecologically significant, it cannot always be mapped at the landscape level or incorporated into the final analyses. This forces the modeler to reduce the number of variables to only those that can be mapped, which may result in the final landscape level model having even less predictive value.

To demonstrate the major issues of scaling-up field data to the landscape level, we did a case study of the giant panda (*Ailuropoda melanoleuca*) in Wolong Nature Reserve, Sichuan, China. Wolong was suitable because spatial data collected in the field were available and could be used towards the development of an effective full model. In addition, this study enabled us to generate a landscape level occurrence probability map for the giant pandas in Wolong.

Using the spatial data collected in the field, we developed logistic regression models to differentiate between areas with and without the presence of giant panda feces. In this paper, we show that at the survey plot level, the model accurately differentiated between areas with a high probability and low probability of giant panda use. However, as we scaled the model up to the landscape level, our ability to differentiate between areas with/without feces progressively declined in performance. Some of the declines were expected since we oversimplifyed the world. Other declines were not expected, and this highlights the future research needs for understanding panda occurrence at the landscape level.

Methods

Study Area

The study was conducted in the Wolong Nature Reserve (102°52'-103°24'E, 30°45'-31°25'N), Sichuan Province, China (Figure 6.1). Wolong Nature Reserve, hereafter Wolong, is one of the largest reserves (approx. 2000 km^2) established specifically for the protection of giant panda habitat (Liu et al. 2001). At the foothills of the Himalayan Mountains, Wolong has a high degree of topographic relief, rising from

1200 m above sea level in the southeast to over 6250 m in the northwest (Schaller et al. 1985, Liu et al. 1999b)(Figure 6.1). This coarse, crumpled topography leads to a wide diversity of forest-types throughout Wolong. Deciduous forests and umbrella bamboo (*Fargesia robusta*) predominate below 2000 m (Schaller et al. 1985). Above 2000 m, coniferous species are often found as well as large patches of arrow bamboo (*Bashania fabri*). Subalpine coniferous forests and vast stretches of arrow bamboo predominate above 2600 m (Schaller et al. 1985). The ages of the forests also vary because local people living within the reserve have historically harvested trees for timber and fuelwood. Thus, the study area is characterized by a highly heterogeneous environment due to factors which include topography, forest and bamboo characteristics, and age of forest due to harvesting.

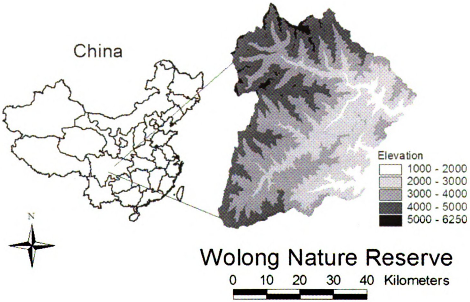


Figure 6.1. The location and elevation of Wolong Nature Reserve, Sichuan, China.

Field Sampling Methods for Data Collection

To determine how giant pandas use heterogeneous landscapes, we examined use patterns in forests of various ages throughout much of Wolong. Data collection took place during May-August 2001, May-November 2002, and June-September 2003. Use was determined by the presence of fecal droppings. Droppings are a useful indicator of panda use because pandas deposit feces frequently, although actual sightings of animals are rare (97 droppings/day, 4 droppings/hour) (Schaller et al. 1985) and feces remain for several months (personal observation, SLB & HJY). Presently, a radio-collaring ban on giant pandas restricts the use of any radio-tracking methods. Until the ban is lifted, feces remain the most efficient way to determine use of habitats. Throughout this paper we refer to the presence/absence and probability of finding panda feces as being equal to the presence/absence and probability of finding the giant panda. Although we realize that this is not the reality, the presence/absence and probability of finding feces is the best available method to relate to actual use by pandas.

In the design of the field survey, we sampled a total of 913 30 m^2 plots. Primary plots were located randomly in the field (in areas where physical access was possible), were placed approximately 200 meters in horizontal distance from the nearest plot, and were identified by local guides knowledgeable of harvesting history in the area. The center position of each 30m^2 plot was geo-referenced with a Pathfinder® Pro XRS GPS unit (Trimble Navigation Limited) and OmniSTAR DGPS real-time correction (OmniSTAR USA, Inc.). Data were then associated with Landsat imagery and other spatial data for analyses. Due to logistical and time constraints which prohibit revisitation and reexamination of sample plots for passed droppings, equal probability of feces detection in all habitats was assumed. Reid and Hu (1991) support this assumption. They found a low ratio of missed droppings (1.3%) throughout their study of panda habitats in Wolong.

Adaptive cluster sampling was used to assist in determining which areas pandas might have visited. This method is designed to sample rare events (i.e., feces) and allows for focused research in areas where rare events occur while maintaining proper statistical hypothesis testing protocol (Thompson 1991a, Thompson and Seber 1996). Whenever feces were found (i.e., presence=1) in a 30 x 30 m sample plot, all units in its neighborhood (those 30 x 30m plots to the North, South, East and West) were added to the sample. If in turn any of these subsequently added plots had feces, the plots of its neighborhood were also added to the sample, so that finally the sampling neighborhood contained 1 (primary only), 5 (1 primary, 4 secondary), or 8 (1 primary, 7 secondary) sample plots. Of the 913 plots sampled, 443 were primary plots and 470 were secondary plots.

Forest characteristics measured include a variety of geographical, forest and bamboo variables (Table 6.1). We changed three variables to pseudo-variables for more appropriate analyses. Aspect was converted to ecological aspect, a value which categorizes 360 degrees into 21 ecologically meaningful units (Parker 1982). Elevation (MSL) was divided into 200 m interval categories and within each category we calculated the proportion of plots with feces. The proportions were then used to give relative weights (values 1-10) to each elevation category. Age of forest was also divided into five class categories (Table 6.1).

Table 6.1. A list of environmental, forest, and bamboo characteristics measured in the field and used in the various models to produce a map of giant panda occurrence.

Variables	Model Type				
	Field Data	Full	Reduced	Simple	Landscape
Elevation	X	X	X	X	X
Age of Forest	X	X	X		
Slope	X	X	X	X	X
Ecological Aspect	X	X	X	X	X
Total Overstory Cover	X			X	X
Conifer Overstory Cover	X	X			
Deciduous Overstory Cover	X	X			
Average Overstory Height	X				
Total Midstory Cover	X				
Conifer Midstory Cover	X				
Deciduous Midstory Cover	X	X			
Average Midstory Height	X				
Total Shrub Cover	X	X			
Average Shrub Height	X				
Bamboo Cover	X	X	X		
Total Understory Cover	X				
Average Understory Height	X	X			

Landscape Data

The landscape data consisted of a forest map and elevation data. The forest map was from a supervised classification of a Landsat 5 image (13 June 2001). Estimated accuracy was 86%. The elevation data were a combination of the Shuttle Radar Topography Dataset (SRTM, available at http://www.jpl.nasa.gov/srtm/) and digitized topographic maps. We used elevation derived from paper topographic maps to fill in data voids in the SRTM data. All landscape level analyses were conducted using ERDAS Imagine 8.6.

Modeling Procedure

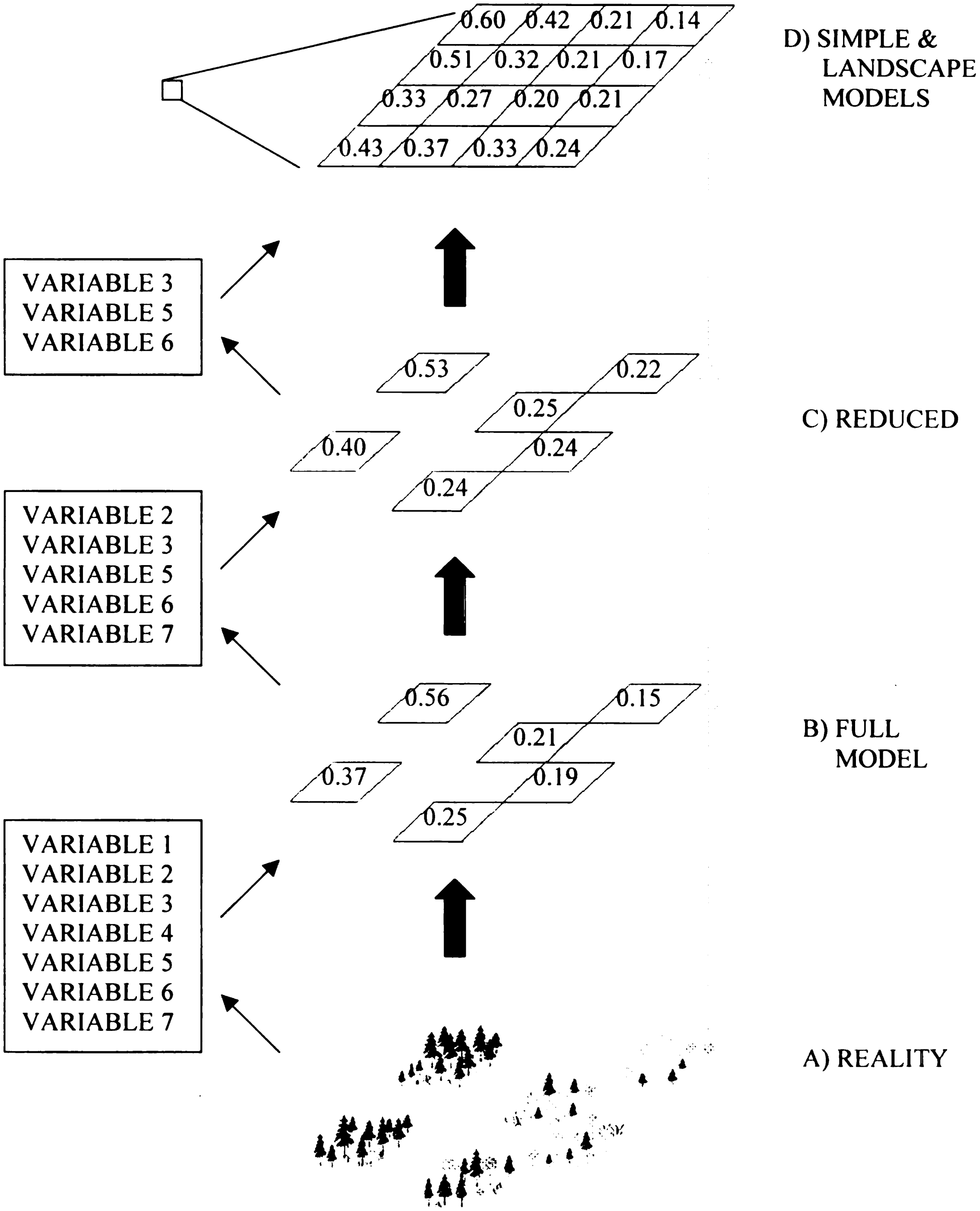
As models are scaled-up, or as field data are integrated into a landscape model, errors might occur in each step of the scaling up process (Figure 6.2). At the initial stage, there are issues related to field data collection (Figure 6.2A). These may include problems with sampling strategy (e.g. were proper sampling methods used?), autocorrelation and sampling errors that may lead to the data being a distortion of reality.

To fully understand the relationship among variables collected in the field, a Full model can be created (Figure 6.2B) that contains all variables from the field data except for those found to be redundant or non-significant. The model simplifies reality but also allows general relationships to be more easily defined. This simplification causes the difference between the model results and reality to become even greater than the difference between field data and reality.

The most complex models (e.g. Full models) are typically undesirable for scaling-up to the landscape level. This is because data for many variables are often not available across an entire landscape. For example, understory height may be an important characteristic for a mammal species, but it is useless at the landscape level unless understory characteristics are known across the landscape. To gain applicability and parsimony, variables that are correlated with other datasets (i.e., independent variables), not found to be significant, or not mapped at a landscape level are removed from the model, creating a model with fewer variables (Figure 6.2C). This Reduced model is theoretically the best model we could make for a landscape analysis. Our expectation is that such a model may still perform well, but not as well as the Full model. If all the remaining variables have spatial datasets available, then the datasets can be implemented into a landscape model and spatial analyses performed. Typically, the number of variables needs further reduction because not all spatial datasets are available for the remaining variables. This creates what we call a Simple model (Figure 6.2D). It is simpler than the Reduced model because it often has only a few variables, making it easier to apply but at the cost of accuracy. Variables used are typically the ones that are available across a landscape, and are not necessarily the ones that are most important for a species of study (Figure 6.2D). The Landscape model is a spatial implementation of the Simple model. Both models are mathematically the same, but the Landscape model uses landscape scale maps, rather than the plot level data used in earlier models.

The resulting loss of modeling power that occurs as variables are removed may have the undesirable effect of model output becoming meaningless. Yet the loss of modeling power that occurs as plot sample data are transitioned to higher spatial levels,

Figure 6.2. A characterization of the scaling-up process. Seven variables are sampled in the field (A) and used to generate a Full Model (B). Numbers within each sampling plot represent probability of species occurrence values for a theoretical scaling-up modeling exercise. A Reduced model (C) includes only five of the original variables because not all variables are mappable. Only three of the variables are presently available to be used as input into a landscape model (D), thereby creating a simplified model that may have higher errors than the Full and Reduced models.


0.60
0.42
0.21
0.14
0.51
0.32
0.21
0.17
0.33
0.27
0.20
0.21
0.43
0.37
0.33
0.24
D) SIMPLE & LANDSCAPE MODELS
VARIABLE 3
VARIABLE 5
VARIABLE 6
0.53
0.22
0.25
0.40
0.24
0.24
C) REDUCED
VARIABLE 2
VARIABLE 3
VARIABLE 5
VARIABLE 6
VARIABLE 7
0.56
0.15
0.21
0.37
0.19
0.25
B) FULL MODEL
VARIABLE 1
VARIABLE 2
VARIABLE 3
VARIABLE 4
VARIABLE 5
VARIABLE 6
VARIABLE 7
A) REALITY

such as the landscape level, is not always fully appreciated. Therefore, we use this method of scaling-up field data on giant panda occurrence. We first create a Full model that includes all independent forest and geographic variables measured in the field. Then, we reduce the number of variables to only those which are significant to develop a reduced model. Eliminating more variables, we reduce the model further until we eventually create simple and landscape models. The results of each of these models allow us to characterize a scaling up procedure. From this, we are able to quantify the loss in interpretive ability as datasets are scaled up from field data to the landscape level.

Statistical Analysis

Using two-thirds of the field data, we developed logistic regression models. One-third of the dataset was reserved for later model validation. To remove non-significant variables, we ran separate univariate logistic regression models for each variable to the presence/absence of panda feces and removed variables with P-values greater than 0.25 in G-test scores. We then used Pearson correlation coefficients to detect redundant variables. Correlated variable pairs with a r-value greater than 0.50 were considered for elimination. For each pair, the variable with the more significant univariate G-test was retained for further analysis (Klute et al. 2002). Following the removal of insignificant and correlated variables, we fit a multivariate logistic regression to the remaining variables. All models were run in SAS v.8.02.

Our logistic regression models used the equation presented in Quinn and Keough (2002):

$$\pi(x) = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots\beta_p X_p}}{1+e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots\beta_p X_p}} \tag{6.1}$$

where π(x) is the probability that panda feces is present for a given covariate value (x), and β_p are coefficients for each variable, x_p, to be estimated. To determine probability values of panda occurrence, we acquired coefficients from logistic regressions, created equations using coefficients (Equation 1), and then calculated probability values for all survey plots. We considered a probability ≥ 0.40 to predict panda feces and therefore panda presence. Although this threshold was arbitrary, we chose it because one-third of the total field plots (primary + secondary) contained feces in the original dataset and the threshold of 0.4 allowed us to reduce omission error without increasing overall errors.

Results

Logistic Regression Models

Of the 913 plots sampled, 320 (35%) had panda feces present. Seven variables were either non-significant or covaried with more influential variables and were not used in the Full model, which contained 10 variables (Table 6.1). The Reduced model included 5 variables, while the Simple and Landscape models both included 4 variables (Table 6.1). One variable, total overstory canopy cover, was initially removed because it covaried with other significant variables. Later we used it in the Simple and Landscape models because landscape level data were available for total overstory canopy cover but not available for other covarying significant variables. Two variables, bamboo cover and forest age, were removed from the Simple and Landscape models despite their significance because spatial data layers across the landscape were unavailable.

All 4 models predicted plots that contained feces as having a higher panda probability than survey plots without feces (Figure 6.3). A larger difference between feces and no-feces points indicates a better ability to discriminate between occurrence and non-occurrence areas or areas with and without giant pandas. This suggests that all models are working appropriately, but they do vary in performance. The Full model shows the largest separation, with the average probability of points with feces having a 30% higher probability than the no-feces plots. However, this separation declines as models become simpler. A comparison of the average probabilities in the Simple and Landscape models indicates a <10% separation (Figure 6.3). The decreasing difference is mainly because of a decrease in the probability associated with feces points rather than an increase in the probability associated with no-feces points (Figure 6.3).

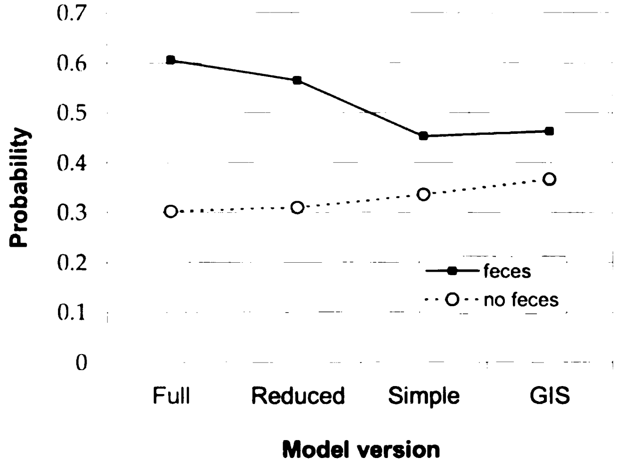


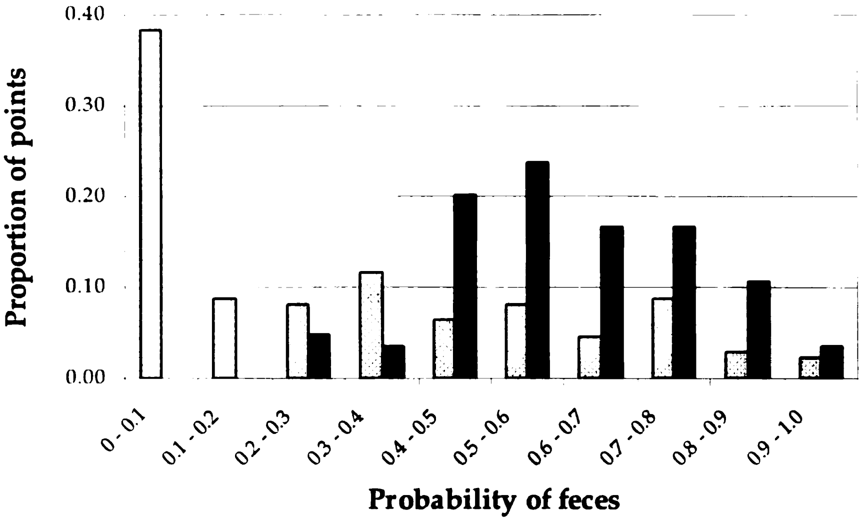
Figure 6.3. Calculated probabilities of giant panda occurrence grouped and averaged by survey plots with/without panda feces.

To further determine what was happening within each model, we examined the probability distribution of feces and no-feces points for each model (Figure 6.4). For all models, the proportion of no-feces points was consistently greater in lower probability areas while feces points were in higher probability areas. This further supports that the models are correctly identifying occurrence/non-occurrence areas (Figure 6.4). In the Full model, the majority of no-feces points occur in areas with very low probability (0.1 probability) and the majority of feces points occur in areas with a probability of 0.4 or greater (Figure 6.4A). Many no-feces points also occur in areas that have higher probability of having feces, suggesting that these points may still be viable habitat even though they do not have feces (Figure 6.4A). The Reduced model shows similar trends to the Full model, with no-feces points occurring in lower probability areas (greatest number at 0.1 probability) and feces points in higher probability areas. However, the number of feces points in higher probability areas declines and there is a more uniform distribution of feces as well as no-feces points across the range of probabilities (Figure 6.4B).

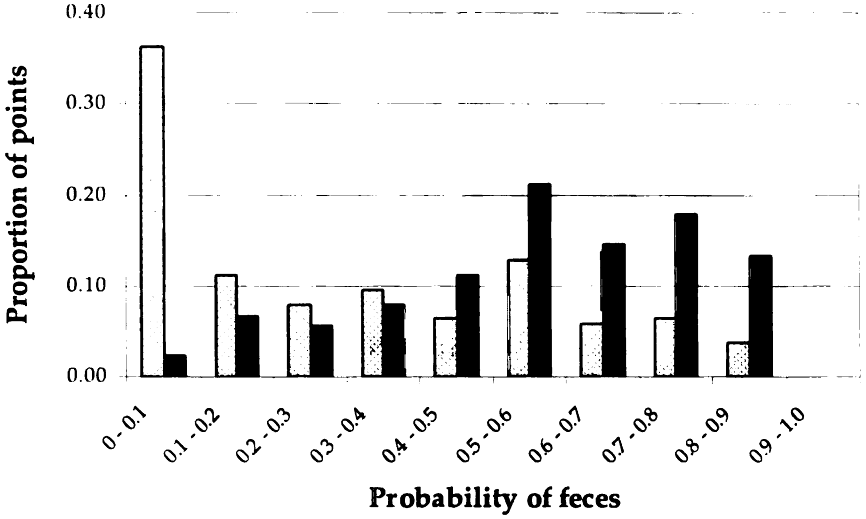
The Simple and Landscape models generally show points with no-feces to have low occurrence probability and points with feces to have high panda probability. However, the distinction between areas with and without feces is less apparent. Histograms of output from Simple and Landscape models appear to have shifted to within 0.1 probability relative to each other, whereas the distinction was greater in the Full and Reduced models. In addition, the Simple and Landscape models do not show the high number of no-feces points in the

Figure 6.4. The proportion of survey plots that did/did not have giant panda feces classified by probability levels of finding feces. Gray bars represent plots without feces. Black bars represent plots with feces.

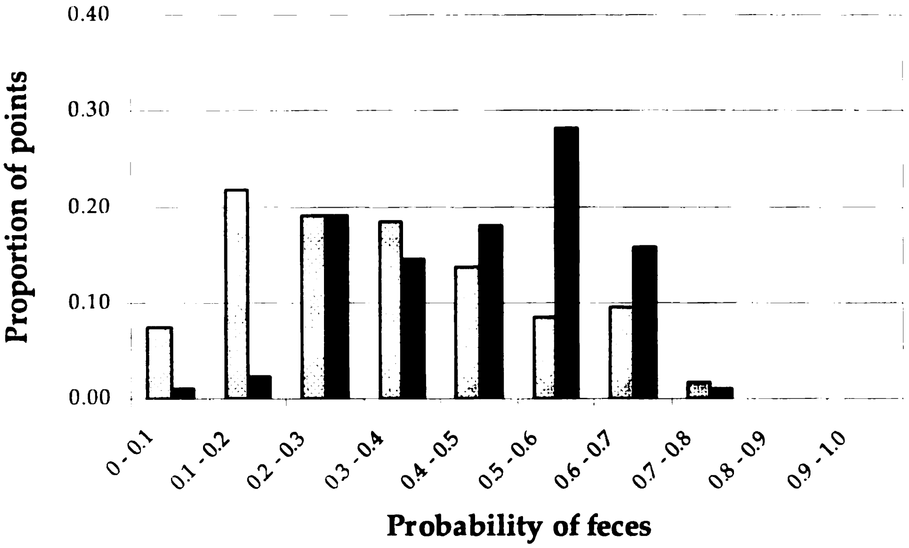
A. Full Model



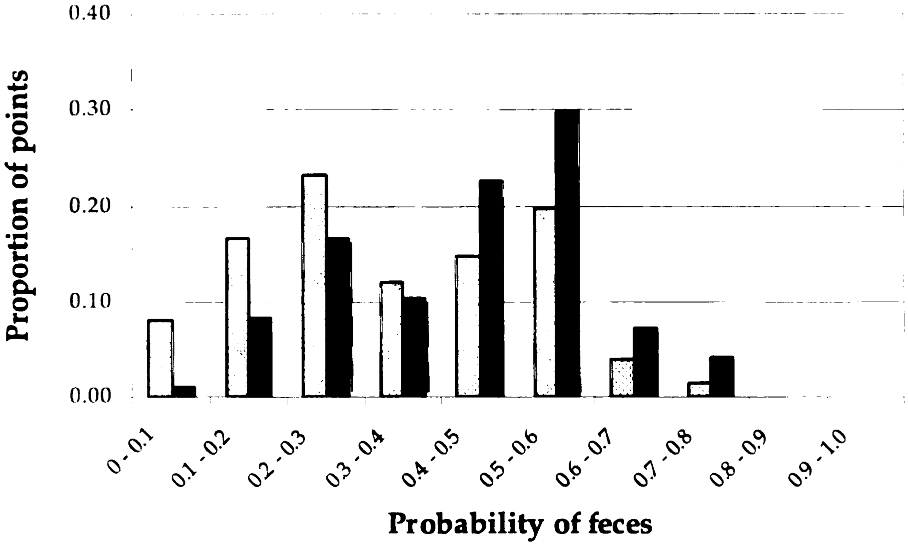
B. Reduced Model



C. Simple Model



D. Landscape Model



very low probability areas (<0.1). Instead, they show an increased proportion of no-feces points in areas of increased panda occurrence probability (Figures 6.4C and 6.4D).

To better understand why the data were converging as models became more simplified, we developed error matrices to describe model performance (Table 6.2). The Full model performs best (25% overall error rate) with a decline in performance to the Landscape model (39% overall error rate) (Table 6.2). The primary source of increasing error is in omission errors (plots predicted to have no feces but feces actually found). Omission errors range from 8% in the Full model to over 30% in the Simple and Landscape models. Commission errors (points predicted to have feces but none found, a scenario which is more likely to occur in nature) range from 43% in the Full model to over 56% in the landscape model (Table 6.2).

Probability Map of Panda Occurrence

The giant panda occurrence probability map from the Landscape model (Figure 6.5) displays trends similar to those in previous panda habitat maps and surveys (DeWulf et al. 1988, Liu et al. 2001). Almost half of the reserve (~48%) has very low probability (< 0.1) and 82% is below 0.4 probability, our threshold for predicting presence (Figure 6.5). Previous studies highlighted the potential problem of fragmentation of remaining habitat, but our map more clearly defines the seriousness of the problem. Several large areas of high occurrence probability occur with numerous smaller patches of medium to high occurrence probability interspersed.

Table 6.2. Error rates associated with the various models. Horizontal error rates denote omission errors while vertical errors denote errors of commission.

Full model		**Model prediction**		
		feces	**no feces**	**Error rate**
Field data	**feces**	**77**	**7**	**0.08**
	no feces	**57**	**115**	**0.33**
	Error rate	**0.43**	**0.06**	**0.25**

Reduced model		**Model prediction**		
		feces	**no feces**	**Error rate**
Field data	**feces**	**70**	**20**	**0.22**
	no feces	**66**	**122**	**0.35**
	Error rate	**0.49**	**0.14**	**0.31**

Simple model		**Model prediction**		
		feces	**no feces**	**Error rate**
Field data	**feces**	**56**	**33**	**0.37**
	no feces	**63**	**126**	**0.33**
	Error rate	**0.53**	**0.21**	**0.35**

Landscape model		**Model prediction**		
		feces	**no feces**	**Error rate**
Field data	**feces**	**64**	**33**	**0.34**
	no feces	**82**	**116**	**0.41**
	Error rate	**0.56**	**0.22**	**0.39**

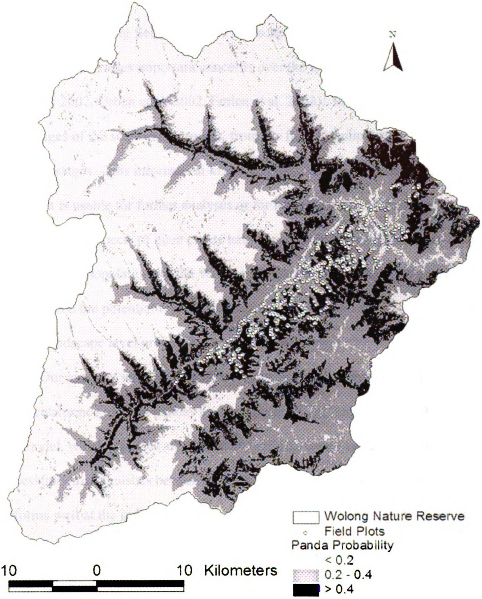


Figure 6.5. The probability map of panda occurrence showing the distribution of field plots (both primary and secondary plots) used to create logistic regression models. Field plots are focused within the central region of Wolong known to have concentrated panda activity.

Discussion

Extrapolating field data to the landscape level is becoming increasingly common in ecology. This raises important concerns over the issue of scale (Levin 1992, Morales and Ellner 2002, Urban et al. 2002, Emlen et al. 2003). Information and power are lost at many stages of the scaling-up process, from the field sampling stage through the various modeling stages. This information loss needs to be thoroughly understood to determine if the output is usable for further analyses or for management practices. In our study, we surveyed many aspects of giant panda habitat and included sampling areas known to have resident panda populations in the Wolong Nature Reserve. From this study, we have demonstrated the potential risks in scaling-up by using field surveys of the giant panda to create a landscape level probability of occurrence map.

Our analyses show that there is a considerable decrease in the ability to predict presence/absence of giant pandas as more variables are removed from the model. The Full model, which includes all significant, non-redundant variables, works best. It successfully distinguishes between feces/no-feces survey plots. While the Full model performs well at the individual plot level, it requires too many data to extend to the landscape level.

The Reduced model, which is less data intensive and possibly extendable to the landscape level in the future, performs nearly as well as the Full model. The removal of five variables between the Full (N=10) and Reduced (N=5) models appears to have had little impact. However, decreasing the total number of variables by one in the Simple model (N=4) had a much larger impact. The ability of the model to distinguish between feces/no-feces points is far less than the Full or Reduced model. Additionally, the proportion of points at the two extremes of panda probability (<0.1= low probability, >0.9=high probability) converges toward the center as variables are removed.

Bamboo, recognized as the most important component of giant panda habitat and found to be the most significant variable in the Full and Reduced logistic models, was removed from the Simple and Landscape models. Total overstory canopy cover, on the other hand, was removed from earlier analyses because it covaried with other significant variables. However, because covarying variables were removed from later analyses and we had spatial data available for this variable, it was included in the Simple and Landscape models. The removal of significant variables for which we do not have landscape level data, and their replacement with covarying, significant variables for which we do have landscape level data, not only decreased the ability of the models to differentiate between areas with/without feces, but also decreased our ability to interpret results.

Sources of increasing error in the models come primarily from the omission error rate, which steadily increased from the Full (8%) to the Simple (37%) and Landscape (34%) models. Commission error rates, although not as significant because they can be explained ecologically, also increased from the Full (43%) to the Simple (53%) and Landscape (56%) models. Results suggest that if a higher number of significant variables can be included in the Landscape model (i.e., spatial datasets are available for more variables) then the predictive ability of the model will be better. However, the decreased distinguishing ability of the Simple and Landscape models suggest that the output from models that typically contain only a few significant variables needs to be carefully examined, and sources of error must be addressed.

The loss of the bamboo and age of forest variables in our Simple and Landscape analyses due to the lack of relevant data not only decreased the models performance, but also made it more difficult to interpret results. A model that does not include bamboo as a variable should raise important questions concerning our results because bamboo is the most important characteristic for the giant panda. Bamboo data for the entire Wolong Nature Reserve were generated by Linderman et al. (2004), who classified Landsat imagery using neural networks and found approximately 80% accuracy in bamboo projections. However, because our study sampled different areas in separate parts of Wolong Nature Reserve, we found decreased accuracy and therefore could not include the data in the Simple or Landscape models.

As mentioned previously, it is not only the number of variables, but also the significance and interpretability of the variables that is important. We demonstrated this by showing that the removal of five variables had little effect as we moved from the Full to the Reduced model. Our ability to differentiate between feces/non-feces plots only decreased by <4%. However, only one less variable was used for the Simple and Landscape models, but our ability to distinguish feces/non-feces plots decreased by approximately 14%. The reason for this is because bamboo and age of forest variables were removed.

Age of forest was the one variable measured in the field that allowed us to determine human impacts on giant panda habitats. By knowing when and where forests had been harvested, we were able to determine at what age a forest began to be used by the panda, and how much panda activity increased with forest age. The probability of finding feces steadily increases as the age of forest increases (Figure 6.6). This suggests that harvesting forests for timber or fuelwood has a negative impact on giant panda habitat and as that forest ages, habitat for the giant panda recovers. Once the forest has 40+ years to regenerate, the probability of finding feces in the area is greater than 0.4, indicating that it is potential habitat (Figure 6.6). Because we are presently unable to map age of forest across the landscape, it was removed from the Simple and Landscape analysis. This made our ability to translate human impacts across the Reserve scale impractical. While removal of forest age and bamboo variables decreased the performance of our models, it does clearly identify those variables as priorities if we are to create better giant panda occurrence models in the future.

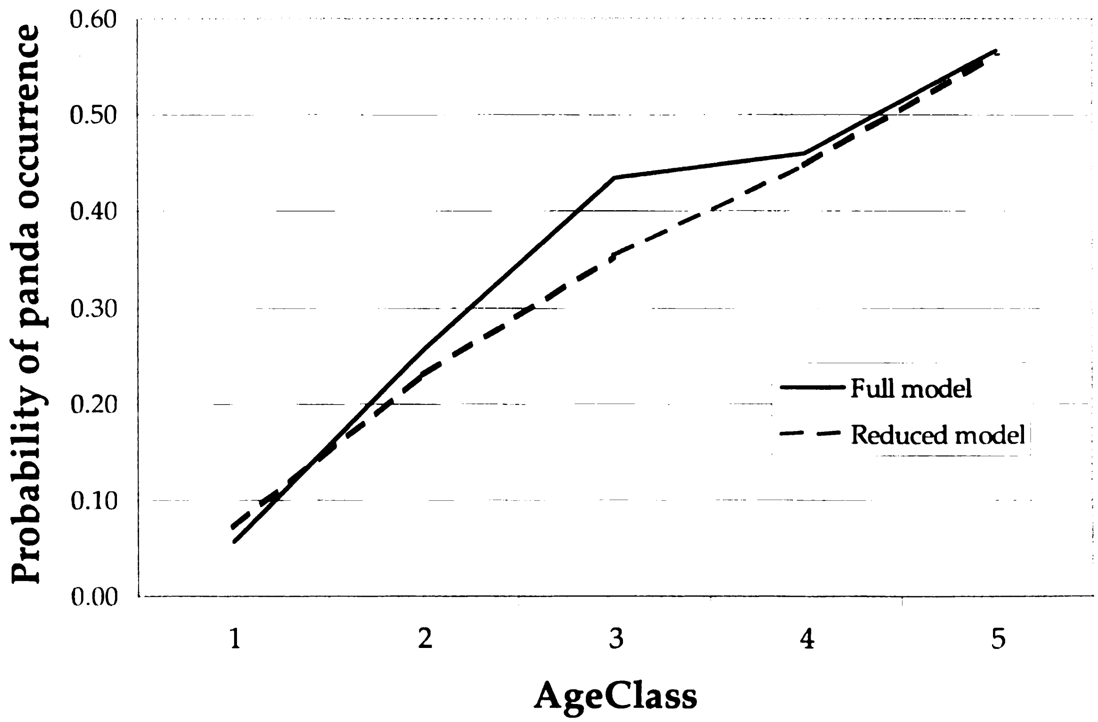


Figure 6.6. Calculated probabilities of giant panda occurrence grouped by age of forest for the Full and Reduced models (Age Class 1= 0-5 years, Age Class 2 = 6-20 years, Age Class 3 = 21-40 years, Age Class 4 = 41-80 years, and Age Class 5 = unharvested forest).

The output of our final Landscape model is a map of the probability of panda occurrence (Figure 6.5). Comparison of this map to previous giant panda habitat maps and diagrams (Schaller et al. 1985, DeWulf et al. 1988, Liu et al. 2001) suggests that our model provides an accurate assessment of panda habitat. In addition, the output of the Landscape model offers a high level of spatial resolution (30x30 m), and allows more detailed spatial analyses to be performed throughout Wolong (Figure 6.5). Results suggest that low probabilities throughout the center of Wolong are due, in part, to their proximity to the road system and human dwellings (Figure 6.5). This impact from humans is also evidenced by the decrease in probability of use in areas with little forest cover (e.g. 0-5 years). This information can be used by future researchers and reserve managers working toward the protection of giant panda habitat.

Our analyses demonstrated that there are many issues concerning scaling up of field survey data to the landscape level. First, information is lost as variables collected in the field are removed in order to achieve a more parsimonious and applicable model. Second, the results from a reduced model need careful examination to determine if it continues to output information useful for its purpose. Third, significant variables may be replaced by other covarying, significant variables as input data into a landscape model due to the limitation of landscape level spatial data. This is more likely to occur in areas with few spatial datasets available. Although this may result in reduced model performance, it also allows researchers to identify data that are necessary for more accurate analyses, thereby guiding future research.

CHAPTER 7

SUMMARY AND CONCLUSIONS

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Forest harvesting has dramatically reduced the total amount of forestland around the world, especially in China. Yet despite the risk this poses to biodiversity and wildlife, impacts from forest harvesting remain largely unexplored. To understand how forest harvesting affects use by wildlife, I examined giant panda (*Ailuropoda melanoleuca*) use in Wolong Nature Reserve, Sichuan Province, southwest China.

I monitored giant panda use by observing the presence/absence of panda feces. Adaptive cluster sampling was used in order to concentrate my research efforts in areas with a greater likelihood of panda activity. A total of 913 plots (443 primary and 470 secondary; total 443 neighborhoods) were sampled in 2001-2003. Due to the binary nature of my response variable, I used logistic and autologistic regression to determine whether harvest age, size, forest and geographical characteristics, and various bamboo characteristics were significant in identifying presence of feces. I coupled this with other analyses, including regression tree analysis, to validate and enhance my interpretation of results. Analyses were performed on all primary plots as well as the Horvitz-Thompson estimator of neighborhood plots to compare results of adaptive cluster analysis.

The analytical methods developed in this dissertation can be applied to other studies that are implementing field investigations of rare and endangered species. I provide a useful characterization of the differences and similarities found in using simple random sampling of field plots versus using an adaptive cluster sample with a neighborhood of 1, 5 or 8 total plots for several statistical methods. Overall, the adaptive cluster sampling was more resource consuming because of the additional samples necessary to survey the entire neighborhood. Limiting the neighborhood to 5 or 8 plots helped to keep down costs. However, the additional costs of adding the adaptive cluster samples must be weighed against the costs of getting the original primary random sampling plot. In Wolong, where accessibility to the primary random sampling plot can be difficult and the initial costs can be high, adding the adaptive cluster samples did not substantially increase the overall costs. In this regard, the adaptive cluster sampling was useful. Although I did not analyze the differences in variance from each of the models, results of logistic regression models were systematically more complex when using neighborhoods as opposed to the logistic regression of primary plots only.

I found significantly less giant panda activity in areas recently harvested. Newly harvested areas (0-10 years) had the lowest percentages of feces presence (9.9%), while unharvested forest had the highest (54.1%). Old harvested areas (31-100 years) (48.1%) had similar amounts of feces presence to unharvested areas. Recent harvests that were small (0-10 years, <10 ha) had some use (15.0%) while large, recent harvests (0-10 years, 10-100 ha) were not used (0.0%). Large, old harvest areas (10-100 ha, 31-100 years) had the highest proportion of feces (56.1%), even greater than those in unharvested areas. Age was an important factor in harvests that exceeded 10.0 ha, suggesting that the larger harvests require more time to recover.

Logistic and autologistic regression along with classification trees on forest characteristics suggests an importance in bamboo cover, overstory and midstory composition, slope and distance to human activity. These results support previous research findings while also providing a useful recharacterization of panda habitat for several time periods after it has been harvested.

I also conducted several analyses to determine how forest harvesting influenced bamboo populations. I studied three bamboo species, including *Bashania fabri*, *Fargesia robusta*, and *Yushania chungii*. A total of 367 plots (30 m^2 each) and 1468 bamboo subplots (1 m^2 each) were sampled and I found that harvesting affected various species in different ways. For all bamboo species, harvesting at the small scale (i.e., fuelwood collection) or large scale (i.e., timber harvesting) did not have an effect on bamboo characteristics. However, the age of forest (i.e., years after harvesting) where each bamboo species occurred was significantly different. *B. fabri* occurred in the oldest stands and frequently in unharvested, old-growth forest while *F. robusta* and *Y. chungii* were also in older forest and areas with no bamboo were in younger forest.

B. fabri occurred in older forest further from the Wolong roadway (2342.4 $\pm$ 40.6 m) and at higher elevations (2478-3214 MSL) than younger *Fargesia* stands, which were found in lower elevation forests and closer to the road (1771-2726 MSL; 1324.7 $\pm$ 52.4 m, respectively). *B. fabri* was rarely found in forests younger than 30 years old, but in these forests it generally had lower percent cover and stem density, as well as thicker stems. In *F. robusta* stands, percent cover and stem density generally increased over time. *F. robusta* responded to harvesting with an initial colonization and subsequent increase in stem density as competition with trees for light and space resources increased. This study is also the first to document how another bamboo species, *Yushania chungii*, which occurs naturally in the forests of Wolong, is affected by harvesting. *Y. chungii* was not as common as *B. fabri* or *F. robusta*, and was typically interspersed among stands of

B. fabri. However, it may be a significant species for pandas because it was found in both very young forests as well as old-growth stands, and due to its high use by pandas, it could play a key role in panda survival when other species of bamboo mass-flower and die off.

In addition to altering the growth characteristics of various bamboo species, forest harvesting also can influence the habitats of the species that rely on that bamboo. In the following chapter, I investigated how pandas are using bamboo patches and how the relationship between pandas and bamboo changed after a harvesting event, how long it may take for changes in habitat to recover from harvesting, and what policy changes would be best for conservation of the panda's bamboo populations. I found feces more frequently in higher elevation *Y. chungii* and *B. fabri* stands, and less frequently in lower elevation *F. robusta*. Giant pandas did not use recently logged (0-30 years) forests that contained *B. fabri* and *F. robusta*. However, forests did not need to be in an old growth stage to be used. Pandas were using areas that had been harvested 31-100 years prior as much as old growth forest, indicating the ability of these forests to regenerate into suitable habitat. More specifically, our data indicate that forests approximately 60 years in age were frequently used. This amount of time may therefore be necessary for forests to regenerate to a stage where bamboo grows at a level where giant pandas can forage.

While forest harvesting may affect giant panda habitats for several decades after the initial logging event, some effort is being made to reforest certain regions of Wolong by means of plantation reforestation. Therefore, I characterized the potential of these reforested areas to provide or mitigate human impacts on giant panda habitat. Comparing use in reforested areas to use in nearby natural forest, I found that pandas rarely used artificially regenerated forest and did so only when the plantation forest had a high percent cover of bamboo and occurred at a far distance from roadways and human disturbance. However, although reforestation areas may not necessarily provide suitable habitat, they do offer a woody biomass source that can be used as an alternative fuelwood. By using reforested areas as their main fuelwood source, local residents of Wolong Nature Reserve may limit their harvesting activities in the nearby natural forests and impacts on giant pandas can then be reduced.

Finally, I used my field data to quantify the amount of information that is lost during the scaling up process. An increasing number of ecological models have used plot data collected in the field to predict species occurrence across landscapes. Despite the popularity of this method, there are problems associated with the process of scaling-up that have been largely ignored in the literature. Issues with the scaling-up method stem from the removal of key variables as researchers move from many variables collected in the field to fewer variables that are used as input into a landscape model. To demonstrate the loss of information and the potential pitfalls of scaling-up field data to the landscape level, I did a case study on the occurrence of pandas in Wolong. I collected field data on the presence/absence of giant panda feces and ran logistic regression models to determine how results responded to the removal of particular variables.

I found that a model including all significant field variables (N=10) successfully distinguished between areas with/without panda feces. However, as the model was reduced to fewer variables (N=4), the ability to distinguish areas with feces present and absent was reduced. More important than the number of variables is the loss of a few key ecologically important variables that may significantly help to predict species occurrence.

The analysis indicates that care should be taken at each stage of scaling-up and that it is vital for researchers to understand the nature of this process when extrapolating their plot data to the landscape level.

Results of this dissertation suggest that forest harvesting activities, such as timber harvesting and fuelwood collection, can have significant impacts on many aspects of the forest, especially bamboo populations, for several decades after harvesting. During this period, panda use may be reduced. However, as the forest regenerates, panda habitat will most likely recover, in some cases after a period of at least 30 years. In addition, the reforestation activities currently being pursued by the central, provincial, and local governments may eventually provide an easily accessible alternative fuelwood source that can further reduce the impacts on natural forests and allow many areas currently unsuitable for giant pandas to reinitiate into a forest stand that can be used by pandas. This suggests that if forestland is maintained via the Natural Forest Conservation Program (China's "logging ban"), habitats of the giant panda that were previously destroyed and made less suitable through forest harvesting may eventually regenerate and increase the potential for the species' long-term survival.

APPENDICES

Appendix 1. Number of sample plots, proportion with feces, and mean values (±SE) of forest and geographic characteristics of plots.

		Total				0-10 years		11-30 years		31-100 years	
		0-10 years	11-30 years	31-100 years	Old-growth	>10 ha	10-100 ha	>10 ha	10-100 ha	>10 ha	10-100 ha
N (Primary Plots Only)		136	83	67	107	94	42	74	9	44	23
Proportion with Feces		0.03	0.07	0.27	0.36	0.04	0	0.08	0	0.18	0.53
Age (years)	Mean	3.47	22.40	46.42	183.64	3.68	3.00	22.43	22.11	44.55	50.00
	SE	*0.31*	*0.69*	*1.40*	*3.80*	*0.36*	*0.60*	*0.74*	*2.08*	*1.70*	*2.31*
Patch Size (ha)	Mean	0.20	0.05	0.19	0.09	2.64	59.79	3.24	21.83	1.49	52.59
	SE	*0.03*	*0.01*	*0.04*	*0.02*	*0.31*	*6.64*	*0.37*	*2.77*	*0.28*	*5.78*
Elevation (MSL)	Mean	2231.24	2270.65	2475.94	2699.20	2127.93	2457.53	2288.04	2127.61	2376.53	2666.12
	SE	*37.05*	*26.93*	*38.48*	*28.09*	*45.28*	*49.17*	*28.47*	*69.73*	*45.10*	*53.22*
Slope (degrees)	Mean	19.68	25.01	17.47	20.38	19.51	20.05	23.25	39.33	16.80	18.76
	SE	*1.16*	*2.33*	*1.23*	*1.21*	*1.48*	*1.83*	*1.22*	*19.10*	*1.52*	*2.11*
Ecological Aspect	Mean	11.48	8.57	9.57	12.26	12.07	10.14	8.95	5.56	10.45	7.87
	SE	*0.41*	*0.65*	*0.71*	*0.52*	*0.46*	*0.79*	*0.67*	*2.31*	*0.82*	*1.32*
Basal Area	Mean	1.44	5.82	8.44	13.41	1.32	1.70	6.12	3.32	8.36	8.60
	SE	*0.31*	*0.75*	*0.93*	*0.85*	*0.34*	*0.66*	*0.80*	*2.03*	*1.19*	*1.52*
Total Overstory Cover (%)	Mean	7.59	27.86	39.27	43.91	7.27	8.29	29.30	16.67	40.01	37.71
	SE	*1.49*	*2.71*	*3.10*	*2.35*	*1.62*	*3.17*	*2.91*	*6.72*	*3.73*	*5.71*
Conifer Overstory Cover (%)	Mean	5.63	17.61	25.54	32.22	5.45	6.03	17.98	15.00	25.21	26.36
	SE	*1.43*	*3.00*	*3.67*	*2.88*	*1.52*	*3.13*	*3.30*	*6.97*	*4.23*	*7.51*
Deciduous Overstory Cover (%)	Mean	1.32	9.68	14.24	12.47	1.58	0.77	10.83	1.67	13.24	16.71
	SE	*0.46*	*1.81*	*2.80*	*1.90*	*0.63*	*0.49*	*2.02*	*1.67*	*3.07*	*6.22*
Average Overstory Height (m)	Mean	5.81	11.59	20.97	23.72	6.46	4.41	12.17	7.44	20.82	21.35
	SE	*0.88*	*0.93*	*1.05*	*0.90*	*1.11*	*1.44*	*1.01*	*2.08*	*1.20*	*2.16*
Total Midstory Cover (%)	Mean	6.58	19.59	22.93	22.61	5.86	8.20	20.26	14.11	23.19	22.41
	SE	*1.28*	*2.24*	*2.39*	*1.50*	*1.13*	*3.31*	*2.44*	*4.69*	*2.94*	*4.18*
Conifer Midstory Cover (%)	Mean	1.52	4.42	3.51	5.38	0.95	2.74	3.45	11.33	3.17	4.35
	SE	*0.74*	*1.20*	*1.07*	*0.85*	*0.33*	*2.27*	*1.18*	*4.56*	*1.27*	*2.06*
Deciduous Midstory Cover (%)	Mean	3.37	13.74	18.22	16.50	4.20	1.56	15.28	2.78	20.62	12.26
	SE	*0.74*	*2.22*	*2.34*	*1.67*	*1.03*	*0.59*	*2.46*	*1.88*	*2.99*	*3.07*
Average Midstory Height (m)	Mean	3.95	6.57	11.37	14.34	4.37	3.00	6.92	3.89	12.00	10.03
	SE	*0.57*	*0.76*	*0.85*	*0.64*	*0.73*	*0.82*	*0.84*	*1.37*	*1.00*	*1.61*
Average Shrub Height (m)	Mean	2.35	3.18	3.91	4.80	2.52	1.99	3.15	3.39	4.01	3.68
	SE	*0.22*	*0.20*	*0.27*	*0.22*	*0.24*	*0.46*	*0.22*	*0.34*	*0.31*	*0.54*
Total Shrub Cover (%)	Mean	19.77	23.78	23.99	22.71	21.77	15.15	21.79	39.89	21.36	29.51
	SE	*2.28*	*2.41*	*2.73*	*1.67*	*2.78*	*3.91*	*2.39*	*9.10*	*2.67*	*6.30*
Bamboo Cover (%)	Mean	23.73	24.87	40.67	69.23	25.98	18.59	25.45	20.11	34.48	53.05
	SE	*2.81*	*3.56*	*4.49*	*3.26*	*3.38*	*4.98*	*3.68*	*13.30*	*5.42*	*7.47*
Total Understory Cover (%)	Mean	59.31	43.33	44.17	20.72	55.33	67.95	43.00	46.00	49.35	33.05
	SE	*3.57*	*3.72*	*4.49*	*2.81*	*4.28*	*6.34*	*4.00*	*10.49*	*5.40*	*7.67*
Average Under Height (cm)	Mean	35.14	33.04	34.93	27.08	37.56	29.93	32.48	37.22	41.66	20.45
	SE	*2.69*	*2.59*	*4.18*	*2.91*	*3.33*	*4.45*	*2.83*	*5.94*	*5.52*	*4.33*

Appendix 2A. Number of sample plots, proportion with feces, and mean values (±SE) of forest and geographic characteristics for arrow bamboo (*Bashania fabri*).

Bashania fabri		Total		0-10 years		11-30 years		31-100 years		Old-growth	
		Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*
N (primary + secondary)		115		19		7		22		67	
Percent with feces	(%)	32.17		0		0		59.09		32.84	
Elevation	(MSL)	2824.74	*14.91*	2731.32	*27.75*	2675.00	*22.87*	2816.95	*24.61*	2858.58	*21.02*
Distance to Roadway	(meters)	2198.37	*77.11*	1319.72	*65.72*	1222.48	*113.92*	1959.82	*107.40*	2553.78	*95.99*
Distance to House	(meters)	2245.02	*81.47*	1272.52	*85.53*	1141.98	*162.26*	1877.77	*91.24*	2683.30	*95.99*
Forest Age	(years)	126.91	*7.92*	5.47	*0.68*	19.33	*4.33*	53.41	*2.22*	190.30	*3.72*
Patch Size	(hectares)	17.87	*2.87*	7.98	*2.30*	7.00	*1.53*	44.03	*8.06*	13.36	*3.57*
Slope	(degrees)	19.56	*1.17*	27.16	*3.64*	34.67	*10.27*	14.45	*1.96*	18.49	*1.40*
Ecological Aspect	(Parker 1982)	12.37	*0.50*	13.11	*1.07*	13.33	*6.17*	9.36	*1.15*	13.42	*0.60*
Basal Area	(m^2/ha)	12.69	*0.90*	2.42	*0.75*	3.67	*3.67*	11.77	*1.99*	16.55	*1.04*
Bamboo Cover	(%)	69.04	*3.14*	41.53	*8.70*	13.33	*8.33*	71.32	*6.23*	80.83	*3.07*
Total Overstory Cover	(%)	43.25	*2.59*	19.71	*5.91*	65.00	*5.07*	48.47	*6.44*	48.21	*2.86*
Conifer Overstory Cover	(%)	37.06	*3.11*	17.29	*9.79*	65.00	*7.20*	32.71	*8.39*	42.63	*3.42*
Deciduous Overstory Cover	(%)	8.21	*1.74*	1.43	*1.43*	0.00	*3.13*	15.18	*6.20*	7.41	*1.76*
Average Overstory Height	(m)	24.03	*1.01*	20.14	*3.58*	19.00	*2.45*	25.06	*2.74*	25.11	*1.05*
Total Midstory Cover	(%)	20.30	*1.76*	15.16	*5.57*	30.00	*25.17*	25.23	*4.80*	20.32	*1.71*
Conifer Midstory Cover	(%)	6.71	*0.98*	1.43	*1.43*	0.00	*0.00*	6.06	*2.14*	7.96	*1.27*
Deciduous Midstory Cover	(%)	10.72	*1.49*	2.14	*2.14*	0.00	*0.00*	16.92	*4.64*	10.77	*1.64*
Average Midstory Height	(m)	12.83	*0.80*	7.65	*2.66*	4.33	*0.05*	14.05	*1.75*	14.61	*0.85*
Total Shrub Cover	(%)	23.85	*1.93*	26.12	*6.42*	18.33	*7.26*	28.43	*6.48*	21.26	*1.96*
Average Shrub Height	(m)	4.35	*0.19*	4.64	*0.75*	4.00	*0.05*	4.65	*0.62*	4.30	*0.20*
Total Understory Cover	(%)	19.19	*2.67*	24.69	*8.25*	37.50	*22.50*	21.15	*6.25*	14.27	*2.89*
Average Understory Height	(cm)	26.22	*3.42*	39.40	*15.94*	11.25	*3.75*	10.75	*3.10*	28.99	*4.21*

Appendix 2B. Number of sample plots, proportion with feces, and mean values (±SE) of forest and geographic characteristics for umbrella bamboo (*Fargesia robusta*).

Fargesia robusta		Total		0-10 years		11-30 years		31-100 years		Old-growth	
		Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*
N (primary + secondary)		121		44		34		17		26	
Percent with feces	(%)	19.01		0		17.65		25		46.15	
Elevation	(MSL)	2326.71	*17.56*	2255.27	*25.62*	2326.26	*31.43*	2422.50	*49.60*	2381.65	*40.16*
Distance to Roadway	(meters)	1025.44	*67.07*	557.24	*61.43*	969.49	*86.39*	1612.67	*185.58*	1509.63	*174.99*
Distance to House	(meters)	1400.06	*89.16*	758.97	*120.41*	1328.04	*121.05*	1755.92	*216.57*	2358.02	*157.66*
Forest Age	(years)	50.75	*5.93*	6.07	*0.47*	22.59	*1.13*	50.31	*3.04*	163.46	*9.01*
Patch Size	(hectares)	7.52	*1.45*	13.36	*3.65*	4.66	*1.11*	5.34	*2.29*	2.66	*0.65*
Slope	(degrees)	24.53	*0.87*	28.73	*1.38*	24.00	*1.65*	19.00	*1.75*	22.04	*1.73*
Ecological Aspect	(Parker 1982)	11.21	*0.42*	13.25	*0.52*	9.29	*0.74*	8.88	*1.30*	11.85	*1.01*
Basal Area	(m^2/ha)	4.01	*0.49*	1.25	*0.52*	4.62	*0.97*	4.81	*1.53*	7.54	*1.02*
Bamboo Cover	(%)	49.42	*2.78*	44.44	*5.01*	52.97	*5.10*	44.56	*5.84*	56.58	*6.05*
Total Overstory Cover	(%)	20.17	*1.97*	7.68	*2.12*	21.09	*3.28*	27.50	*6.22*	36.38	*4.19*
Conifer Overstory Cover	(%)	5.90	*1.40*	4.82	*1.88*	1.46	*0.86*	10.43	*5.82*	10.31	*3.94*
Deciduous Overstory Cover	(%)	13.56	*1.75*	2.86	*1.19*	16.39	*3.25*	19.21	*5.74*	26.08	*4.33*
Average Overstory Height	(m)	14.36	*1.06*	8.58	*1.70*	12.29	*1.64*	20.82	*1.74*	23.50	*1.58*
Total Midstory Cover	(%)	21.86	*1.77*	8.84	*1.95*	26.39	*3.73*	35.75	*3.85*	30.15	*2.99*
Conifer Midstory Cover	(%)	1.46	*0.46*	1.23	*0.54*	1.31	*1.31*	1.86	*1.30*	1.88	*0.81*
Deciduous Midstory Cover	(%)	20.14	*1.84*	7.48	*1.80*	26.14	*4.22*	34.00	*4.35*	27.92	*3.25*
Average Midstory Height	(m)	10.24	*0.64*	6.61	*0.99*	10.00	*1.45*	12.60	*0.74*	15.31	*0.69*
Total Shrub Cover	(%)	26.20	*1.99*	33.50	*4.08*	23.33	*3.10*	23.44	*4.49*	18.46	*2.91*
Average Shrub Height	(m)	4.33	*0.19*	3.68	*0.19*	4.02	*0.31*	4.80	*0.37*	5.49	*0.58*
Total Understory Cover	(%)	26.65	*2.56*	28.91	*4.62*	17.74	*3.00*	37.36	*8.49*	27.81	*5.95*
Average Understory Height	(cm)	33.21	*2.67*	48.53	*5.17*	23.04	*3.35*	26.43	*6.27*	22.33	*3.70*

Appendix 2C. Number of sample plots, proportion with feces, and mean values (±SE) of forest and geographic characteristics for yushania bamboo (*Yushania chungii*).

Yushania chungii		Total		0-10 years		11-30 years		31-100 years		Old-growth	
		Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*
N (primary + secondary)		19		4		5		5		5	
Percent with feces	(%)	52.63		100		0		20		83.33	
Elevation	(MSL)	2428.00	*61.36*	2485.50	*112.84*	2260.00	*87.72*	2236.20	*131.10*	2661.50	*31.05*
Distance to Roadway	(meters)	1185.34	*108.63*	902.27	*257.33*	933.27	*61.92*	1171.17	*207.02*	1553.91	*170.88*
Distance to House	(meters)	1442.35	*197.22*	1183.43	*548.67*	882.63	*28.24*	1135.74	*188.33*	2243.61	*255.27*
Forest Age	(years)	83.00	*21.85*	5.50	*1.66*	22.50	*3.23*	43.00	*3.00*	208.33	*33.17*
Patch Size	(hectares)	3.34	*1.83*	0.65	*0.23*	0.55	*0.17*	9.12	*6.67*	2.17	*0.96*
Slope	(degrees)	18.95	*1.58*	20.00	*2.12*	21.75	*1.31*	20.00	*2.51*	15.50	*3.59*
Ecological Aspect	(Parker 1982)	10.84	*1.30*	12.50	*2.06*	14.00	*2.80*	11.40	*3.08*	7.17	*2.33*
Basal Area	(m^2/ha)	5.58	*1.38*	1.25	*1.25*	1.00	*0.58*	5.00	*1.64*	12.00	*2.59*
Bamboo Cover	(%)	68.53	*6.54*	82.50	*7.50*	49.50	*14.61*	49.40	*14.53*	87.83	*2.50*
Total Overstory Cover	(%)	28.63	*4.81*	5.50	*4.01*	31.25	*8.64*	31.80	*4.05*	39.67	*9.70*
Conifer Overstory Cover	(%)	12.63	*4.71*	5.50	*4.01*	0.00	*0.00*	0.00	*0.00*	36.33	*9.70*
Deciduous Overstory Cover	(%)	16.00	*4.09*	0.00	*0.00*	31.25	*8.64*	31.80	*4.05*	3.33	*0.00*
Average Overstory Height	(m)	19.37	*2.23*	13.25	*7.78*	13.00	*2.74*	19.20	*1.66*	27.83	*1.80*
Total Midstory Cover	(%)	21.84	*3.49*	4.25	*2.84*	21.25	*4.27*	23.40	*4.15*	32.67	*5.69*
Conifer Midstory Cover	(%)	0.84	*0.46*	2.75	*1.60*	0.00	*0.00*	0.00	*0.00*	0.83	*1.00*
Deciduous Midstory Cover	(%)	21.00	*3.58*	1.50	*1.50*	21.25	*4.27*	23.40	*4.15*	31.83	*5.38*
Average Midstory Height	(m)	12.58	*1.57*	7.25	*4.19*	8.25	*2.66*	12.80	*0.58*	18.83	*2.33*
Total Shrub Cover	(%)	27.47	*3.95*	34.00	*10.75*	15.50	*2.47*	21.80	*9.44*	35.83	*5.98*
Average Shrub Height	(m)	5.33	*0.50*	4.78	*0.13*	4.13	*0.52*	3.85	*0.33*	7.75	*0.83*
Total Understory Cover	(%)	16.42	*4.83*	4.50	*4.17*	21.50	*4.11*	36.00	*14.35*	4.67	*1.28*
Average Understory Height	(cm)	26.05	*7.05*	29.38	*18.61*	36.50	*8.84*	40.80	*19.42*	4.58	*1.40*

Appendix 2D. Number of sample plots, proportion with feces, and mean values (+SE) of forest and geographic characteristics for areas with no bamboo.

No bamboo		Total		0-10 years		11-30 years		31-100 years		Old-growth	
		Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*
N (primary + secondary)		140		68		38		22		12	
Percent with feces	(%)	0		0		0		0		0	
Elevation	(MSL)	2188.91	*28.76*	2162.88	*50.98*	2184.03	*42.53*	2203.32	*41.12*	2330.86	*104.38*
Distance to Roadway	(meters)	590.46	*41.00*	607.42	*70.35*	530.24	*50.65*	464.10	*78.68*	744.01	*175.47*
Distance to House	(meters)	858.32	*97.02*	584.83	*82.94*	570.68	*70.21*	2044.68	*461.46*	1219.11	*346.36*
Forest Age	(years)	22.22	*3.48*	1.06	*0.30*	22.18	*0.99*	37.95	*1.26*	178.57	*14.87*
Patch Size	(hectares)	25.62	*5.73*	46.74	*8.72*	6.47	*1.31*	29.18	*22.57*	2.14	*1.00*
Slope	(degrees)	15.93	*1.00*	10.97	*1.17*	21.76	*1.90*	18.32	*2.62*	27.29	*3.68*
Ecological Aspect	(Parker 1982)	8.88	*0.46*	10.22	*0.56*	6.86	*0.99*	9.14	*1.26*	6.43	*1.85*
Basal Area	(m^2/ha)	4.20	*0.54*	1.43	*0.51*	7.53	*1.28*	8.05	*1.37*	3.71	*1.41*
Bamboo Cover	(%)	n/a	*n/a*	n/a	*n/a*	n/a	*n/a*	n/a	*n/a*	n/a	*n/a*
Total Overstory Cover	(%)	19.92	*2.27*	6.09	*2.23*	32.89	*4.55*	39.14	*4.81*	35.57	*12.97*
Conifer Overstory Cover	(%)	17.60	*2.18*	5.68	*2.15*	29.92	*4.54*	34.73	*5.15*	25.29	*12.54*
Deciduous Overstory Cover	(%)	2.32	*0.80*	0.41	*0.24*	2.97	*1.43*	4.41	*3.36*	10.29	*8.73*
Average Overstory Height	(m)	7.44	*0.75*	2.55	*0.77*	10.43	*1.21*	17.18	*1.41*	9.71	*3.77*
Total Midstory Cover	(%)	7.21	*1.23*	3.79	*1.67*	11.45	*2.41*	10.73	*3.34*	8.71	*5.35*
Conifer Midstory Cover	(%)	3.89	*1.00*	2.54	*1.56*	7.50	*1.97*	3.55	*2.17*	1.14	*1.14*
Deciduous Midstory Cover	(%)	3.14	*0.68*	0.85	*0.40*	3.95	*1.38*	7.18	*2.59*	7.57	*5.49*
Average Midstory Height	(m)	3.28	*0.45*	1.47	*0.47*	3.84	*0.74*	7.09	*1.51*	5.71	*2.97*
Total Shrub Cover	(%)	16.23	*1.97*	8.04	*2.33*	23.58	*4.07*	20.77	*4.34*	40.29	*9.46*
Average Shrub Height	(m)	1.87	*0.18*	1.08	*0.30*	2.43	*0.23*	2.73	*0.37*	3.86	*0.30*
Total Understory Cover	(%)	69.16	*2.51*	70.41	*3.87*	65.34	*4.58*	75.86	*4.48*	53.29	*13.78*
Average Understory Height	(cm)	43.32	*2.51*	38.30	*3.71*	41.95	*3.81*	61.14	*6.74*	49.71	*10.82*

LITERATURE CITED

Allan, D. G., J. A. Harrison, R. A. Navarro, B. W. vanWilgen, and M. W. Thompson. 1997. The impact of commercial afforestation on bird populations in Mpumalanga Province, South Africa - Insights from bird-atlas data. Biological Conservation **79**:173-185.

An, L., J. Liu, Z. Ouyang, M. Linderman, S. Zhou, and H. Zhang. 2001. Simulating demographic and socioeconomic processes on household level and implications for giant panda habitats. Ecological Modelling **140**:31-49.

An, L., F. Lupi, J. G. Liu, M. A. Linderman, and J. Y. Huang. 2002. Modeling the choice to switch from fuelwood to electricity Implications for giant panda habitat conservation. Ecological Economics **42**:445-457.

An, L., A. G. Mertig, and J. G. Liu. 2003. Adolescents leaving parental home: Psychosocial correlates and implications for conservation. Population and Environment **24**:415-444.

Anderson, S. H., and B. J. Crompton. 2002. The effects of shelterwood logging on bird community composition in the Black Hills, Wyoming. Forest Science **48**:365-372.

Armstrong, A. J., G. Benn, A. E. Bowland, P. S. Goodman, D. N. Johnson, A. H. Maddock, and C. R. Scott-Shaw. 1998. Plantation forestry in South Africa and its impact on biodiversity. South African Forestry Journal **182**:59-65.

Arnold, M., G. Kohlin, R. Persson, and G. Shepherd. 2003. Fuelwood revisited: What has changed in the last decade? Center for International Forestry Research, Jakarta, Indonesia.

Aust, W. M., and R. Lea. 1991. Soil-Temperature and Organic-Matter in a Disturbed Forested Wetland. Soil Science Society of America Journal **55**:1741-1746.

Caldecott, J. O., M. D. Jenkins, T. H. Johnson, and B. Groombridge. 1996. Priorities for conserving global species richness and endemism. Biodiversity and Conservation **5**:699-727.

Cao, K. 1995. Fagus dominance in Chinese montane forests: natural regeneration of Fagus lucida and Fagus hayatae var. pashanica. Wageningen Agricultural University, Wageningen, The Netherlands.

Carey, A. B., and M. L. Johnson. 1995. Small Mammals in Managed, Naturally Young, and Old-Growth Forests. Ecological Applications **5**:336-352.

Carmosini, N., K. J. Devito, and E. E. Prepas. 2003. Net nitrogen mineralization and nitrification in trembling aspen forest soils on the Boreal Plain. Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere **33**:2262-2268.

Chamberlain, M. J., L. M. Conner, B. D. Leopold, and K. M. Hodges. 2003. Space use and multi-scale habitat selection of adult raccoons in central Mississippi. Journal of Wildlife Management **67**:334-340.

China State Forestry Administration. 2004. Steadily increasing giant panda populations: results from the third giant panda census.:http://www.forestry.gov.cn/DB/news/content.asp?table_type=news&id=14784&pgid=14781.

China-Daily. 2004. Fighting illegal logging. Pages http://www.china.org.cn/english/government/99832.htm *in* China-Daily, Beijing.

China's Ministry of Forestry and World Wildlife Fund. 1989. Conservation and management plan for giant pandas and their habitat. Chinese MOF and WWF., Beijing, PR China.

Choudhury, A. 2001. An overview of the status and conservation of the red panda Ailurus fulgens in India, with reference to its global status. Oryx **35**:250-259.

Cochran, W. G. 2002. Sampling Techniques, Third edition. John Wiley and Sons, New York.

Cole, E. C., W. C. McComb, M. Newton, J. P. Leeming, and C. L. Chambers. 1998. Response of small mammals to clearcutting, burning, and glyphosate application in the Oregon Coast Range. Journal of Wildlife Management **62**:1207-1216.

Convention on Biological Diversity. 2001. The value of forest ecosystems. CBD Technical Series No. 4, Secretariat of the Convention on Biological Diversity, Montreal, Quebec.

Costanza, R., R. d'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. V. O'Neill, J. Paruelo, R. G. Raskin, P. Sutton, and M. van den Belt. 1997. The value of the world's ecosystem services and natural capital. Nature **387**:253-260.

Cramer, P. C., and K. M. Portier. 2001. Modeling Florida panther movements in response to human attributes of the landscape and ecological settings. Ecological Modelling **140**:51-80.

Danks, F. S., and D. R. Klein. 2002. Using GIS to predict potential wildlife habitat: a case study of muskoxen in northern Alaska. International Journal of Remote Sensing **23**:4611-4632.

De Grandpre, L., L. Archambault, and J. Morissette. 2000. Early understory successional changes following clearcutting in the balsam fir-yellow birch forest. Ecoscience 7:92-100.

De Grandpre, L., and Y. Bergeron. 1997. Diversity and stability of understorey communities following disturbance in the southern boreal forest. Journal of Ecology **85**:777-784.

De'ath, G., and K. E. Fabricius. 2000. Classification and regression trees: A powerful yet simple technique for ecological data analysis. Ecology **81**:3178-3192.

deBellefeuille, S., L. Belanger, J. Huot, and A. Cimon. 2001. Clear-cutting and regeneration practices in Quebec boreal balsam fir forest: effects on snowshoe hare. Canadian Journal of Forest Research **31**:41-51.

DeWulf, R. R., R. E. Goossens, J. R. MacKinnon, and S. C. Wu. 1988. Remote sensing for wildlife management: giant panda habitat mapping from LANDSAT MSS images. Geocarto International **1**:41-50.

Dryver, A. L., and S. K. Thompson. 2005. Improved unbiased estimators in adaptive cluster sampling. Journal of the Royal Statistical Society Series B- Statistical Methodology **67**:157-166.

Duffy, D. C., and A. J. Meier. 1992. Do Appalachian Herbaceous Understories Ever Recover from Clearcutting. Conservation Biology **6**:196-201.

Duguay, J. P., and P. B. Wood. 2002. Salamander abundance in regenerating forest stands on the Monongahela National Forest, West Virginia. Forest Science **48**:331-335.

Duguay, J. P., P. B. Wood, and J. V. Nichols. 2001. Songbird abundance and avian nest survival rates in forests fragmented by different silvicultural treatments. Conservation Biology **15**:1405-1415.

Durst, P. B., T. R. Waggener, T. Enters, and T. L. Cheng, editors. 2001. Forests out of bounds: Impacts and effectiveness of logging bans in natural forests in Asia-Pacific. Food and Agricultural Organization of the United Nations, Regional Office for Asia and the Pacific.

Emlen, J. M., D. C. Freeman, M. D. Kirchhoff, C. L. Alados, J. Escos, and J. J. Duda. 2003. Fitting population models from field data. Ecological Modelling **162**:119-143.

Ericsson, S., L. Ostlund, and A. L. Axelsson. 2000. A forest of grazing and logging: Deforestation and reforestation history of a boreal landscape in central Sweden. New Forests **19**:227-240.

FAO. 2000. Global Forest Resources Assessment (FRA 2000). Food and Agriculture Organization of the United Nations, Global Forest Resources Assessment Programme,, Rome.

FAO. 2001. Forests out of bounds: Impacts and effectiveness of logging bans in natural forests in Asia-Pacific. Food and Agriculture Organization of the United Nations, Asia-Pacific Forestry Commission,, Rome.

FAO. 2003. State of the world's forests: Part 1- The situation and developments in the forest sector. Food and Agriculture Organization of the United Nations, Forestry Department,, Rome.

FAO. 2005. State of the World's Forests. Food and Agriculture Organization, United Nations, Rome.

Fertig, W., and W. Reiners. 2002. Predicting presence/absence of plant species for range mapping: A case study from Wyoming. Pages 483-490 *in* M. Morrison, editor. Predicting species occurrences: Issues of accuracy and scale. Island Press, Washington, D.C.

Fidgett, A. L., A. T. C. Feistner, and H. Galbraith. 1996. Dietary intake, food composition and nutrient intake in captive Alaotran gentle lemurs Hapalemur griseus alaotrensis. Dodo-Journal of the Wildlife Preservation Trusts **32**:44-62.

Fleishman, E., R. Mac Nally, J. P. Fay, and D. D. Murphy. 2001. Modeling and predicting species occurrence using broad-scale environmental variables: an example with butterflies of the Great Basin. Conservation Biology **15**:1674-1685.

Forman, R. 1995. Land mosaics : the ecology of landscapes and regions. Cambridge University Press, New York.

Franklin, S. E., D. R. Peddle, J. A. Dechka, and G. B. Stenhouse. 2002. Evidential reasoning with Landsat TM, DEM and GIS data for landcover classification in support of grizzly bear habitat mapping. International Journal of Remote Sensing **23**:4633-4652.

Fredericksen, T. S., B. D. Ross, W. Hoffman, M. L. Morrison, J. Beyea, B. N. Johnson, M. B. Lester, and E. Ross. 1999. Short-term understory plant community responses to timber-harvesting intensity on non-industrial private forestlands in Pennsylvania. Forest Ecology and Management **116**:129-139.

Fredericksen, T. S., B. D. Ross, W. Hoffman, E. Ross, M. L. Morrison, J. Beyea, M. B. Lester, and B. N. Johnson. 2000. The impact of logging on wildlife - A study in northeastern Pennsylvania. Journal of Forestry **98**:4-10.

Frey, B. R., V. J. Lieffers, A. D. Munson, and P. V. Blenis. 2003. The influence of partial harvesting and forest floor disturbance on nutrient availability and understory vegetation in boreal mixedwoods. Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere **33**:1180-1188.

Gardner-Outlaw, T., and R. Engelman. 1999. Forest futures: Population, consumption, and wood resources. Population Action International, Washington, DC.

Ghazoul, J. 2002. Impact of logging on the richness and diversity of forest butterflies in a tropical dry forest in Thailand. Biodiversity and Conservation **11**:521-541.

Gilmour, D. 1999. Rehabilitation of degreaded forest ecosystems in Vietnam, Lao PDR and Cambodia. Regional Overview. IUCN-The World Conservation Union, Gland, Switzerland.

Goodale, C. L., and J. D. Aber. 2001. The long-term effects of land-use history on nitrogen cycling in northern hardwood forests. Ecological Applications **11**:253-267.

Goodale, C. L., J. D. Aber, and W. H. McDowell. 2000. The long-term effects of disturbance on organic and inorganic nitrogen export in the White Mountains, New Hampshire. Ecosystems **3**:433-450.

Gratzer, G., P. B. Rai, and G. Glatzel. 1999. The influence of the bamboo Yushania microphylla on regeneration of Abies densa in central Bhutan. Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere **29**:1518-1527.

Green, R. J., and C. P. Catterall. 1998. The effects of forest clearing and regeneration on the fauna of Wivenhoe Park, south-east Queensland. Wildlife Research **25**:677-690.

Gross, J. E., M. C. Kneeland, D. F. Reed, and R. M. Reich. 2002. GIS-based habitat models for mountain goats. Journal of Mammalogy **83**:218-228.

Grossman, B. C., M. A. Gold, and D. C. Dey. 2003. Restoration of hard mast species for wildlife in Missouri using precocious flowering oak in the Missouri River floodplain, USA. Agroforestry Systems **59**:3-10.

Hamer, K. C., J. K. Hill, S. Benedick, N. Mustaffa, T. N. Sherratt, M. Maryati, and V. K. Chey. 2003. Ecology of butterflies in natural and selectively logged forests of northern Borneo: the importance of habitat heterogeneity. Journal of Applied Ecology **40**:150-162.

Harper, C. A., and D. C. Guynn. 1999. Factors affecting salamander density and distribution within four forest types in the Southern Appalachian Mountains. Forest Ecology and Management **114**:245-252.

Harpole, D. N., and C. A. Haas. 1999. Effects of seven silvicultural treatments on terrestrial salamanders. Forest Ecology and Management **114**:349-356.

Hartley, M. J. 2002. Rationale and methods for conserving biodiversity in plantation forests. Forest Ecology and Management **155**:81-95.

Hawks, M. M., J. S. Stanovick, and M. L. Caldwell. 2000. Demonstration of GIS capabilities for fisheries management decisions: Aanalysis of acquisition potential within the Meramec River Basin. Environmental Management **26**:25-34.

He, D., and C. Barr. 2004. China's pulp and paper sector: an analysis of supply-demand and medium term projections. International Forestry Review **6**:254-266.

Hemami, M. R., A. R. Watkinson, and P. M. Dolman. 2004. Habitat selection by sympatric muntjac (Muntiacus reevesi) and roe deer (Capreolus capreolus) in a lowland commercial pine forest. Forest Ecology and Management **194**:49-60.

Heydon, M., and P. Bulloh. 1996. The impact of selective logging on sympatric civet species in Borneo. Oryx **30**:311-316.

Heydon, M., and P. Bulloh. 1997. Mousedeer densities in a tropical rainforest: The impact of selective logging. Journal of Applied Ecology **34**:484-496.

Heydon, M. J., and J. C. Reynolds. 2000. Demography of rural foxes (Vulpes vulpes) in relation to cull intensity in three contrasting regions of Britain. Journal of Zoology **251**:265-276.

Hill, J. K. 1999. Butterfly spatial distribution and habitat requirements in a tropical forest: impacts of selective logging. Journal of Applied Ecology **36**:564-572.

Hill, J. K., K. C. Hamer, M. M. Dawood, J. Tangah, and V. K. Chey. 2003. Rainfall but not selective logging affect changes in abundance of tropical forest butterfly in Sabah, Borneo. Journal of Tropical Ecology **19**:35-42.

Howard, E. A., S. T. Gower, J. A. Foley, and C. J. Kucharik. 2004. Effects of logging on carbon dynamics of a jack pine forest in Saskatchewan, Canada. Global Change Biology **10**:1267-1284.

Hulbert, I. A. R., G. R. Iason, D. A. Elston, and P. A. Racey. 1996a. Home-range sizes in a stratified upland landscape of two lagomorphs with different feeding strategies. Journal of Applied Ecology **33**:1479-1488.

Hulbert, I. A. R., G. R. Iason, and P. A. Racey. 1996b. Habitat utilization in a stratified upland landscape by two lagomorphs with different feeding strategies. Journal of Applied Ecology **33**:315-324.

Insightful Corp. 2003. S-Plus Academic Site Edition. *in*, Seattle, WA, USA.

Ito, H., and T. Hino. 2004. Effects of deer, mice and dwarf bamboo on the emergence, survival and growth of Abies homolepis (Piceaceae) seedlings. Ecological Research **19**:217-223.

IUCN: The World Conservation Union. 2005. Forest environmental services. IUCN: Forest Conservation Programme, Gland, Switzerland.

Jenkins, M. 2003. Prospects for biodiversity. Science **302**:1175-1177.

Johns, A. G., S. Eltringham, J. Harwood, D. Pimentel, A. Sinclair, and M. Sissenwine, editors. 1997. Timber Production and Biodiversity Conservation in Tropical Rain Forests. Cambridge University Press, Cambridge.

Johnson, K. G., W. Wang, D. G. Reid, and J. C. Hu. 1993. Food-Habits of Asiatic Leopards (Panthera-Pardus Fusea) in Wolong Reserve, Sichuan, China. Journal of Mammalogy **74**:646-650.

Kanowski, J., C. P. Catterall, G. W. Wardell-Johnson, H. Proctor, and T. Reis. 2003. Development of forest structure on cleared rainforest land in eastern Australia under different styles of reforestation. Forest Ecology and Management **183**:265-280.

Kim, C., T. L. Sharik, and M. F. Jurgensen. 1995. Canopy Cover Effects on Soil-Nitrogen Mineralization in Northern Red Oak (Quercus-Rubra) Stands in Northern Lower Michigan. Forest Ecology and Management **76**:21-28.

King, D. I., and R. M. DeGraaf. 2004. Effects of group-selection opening size on the distribution and reproductive success of an early-successional shrubland bird. Forest Ecology and Management **190**:179-185.

Kirkland, G. L. 1990. Patterns of Initial Small Mammal Community Change after Clearcutting of Temperate North-American Forests. Oikos **59**:313-320.

Klute, D. S., M. J. Lovallo, and W. M. Tzilkowski. 2002. Autologistic regression modeling of American woodcock habitat use with spatially dependent data. Pages 335-343 *in* J. M. Scott, P. J. Heglund, M. L. Morrison, J. B. Haufler, M. G. Raphael, W. A. Wall, and F. B. Samson, editors. Predicting species occurrences: Issues of accuracy and scale. Island Press, Washington, D.C.

Knapp, S. M., C. A. Haas, D. N. Harpole, and R. L. Kirkpatrick. 2003. Initial effects of clearcutting and alternative silvicultural practices on terrestrial salamander abundance. Conservation Biology **17**:752-762.

Kristof, N. 1993. The rise of China. Foreign Affairs **72**:59-74.

Kunshan, S., L. Fengming, M. Yongqing, S. Feng, and Z. Zuofeng. 1997. China's forest product consumption and its demand for the market of international tropical forest products by 2010. ITTO PD 25/96 Rev. 2(M), International Tropical Timber Organization and Chinese Academy of Forestry, Beijing.

Laporte, M. F., L. C. Duchesne, and I. K. Morrison. 2003. Effect of clearcutting, selection cutting, shelterwood cutting and microsites on soil surface CO2 efflux in a tolerant hardwood ecosystem of northern Ontario. Forest Ecology and Management **174**:565-575.

Latham, J., B. W. Staines, and M. L. Gorman. 1996. The relative densities of red (Cervus elaphus) and roe (Capreolus capreolus) deer and their relationship in Scottish plantation forests. Journal of Zoology **240**:285-299.

Lechowicz, M. J. 1982. The sampling characteristics of electivity indices. Oecologia **52**:22-30.

Leger, C., and N. Altman. 1993. Assessing Influence in Variable Selection-Problems. Journal of the American Statistical Association **88**:547-556.

Levin, S. A. 1992. The Problem of Pattern and Scale in Ecology. Ecology **73**:1943-1967.

Li, C. B., editor. 1990. The ecological study of Sichuan forests. Sichuan Publishing House of Science and Technology, Sichuan Academy of Forestry, Chengdu, Sichuan, PRC.

Li, W. 2004. Degradation and restoration of forest ecosystems in China. Forest Ecology and Management **201**:33-41.

Li, Y., and D. Wilcove. 2005. Threats to vertebrate species in China and the United States. BioScience **55**:147-153.

Lindenmayer, D. B., and R. C. Lacy. 1995. Metapopulation Viability of Arboreal Marsupials in Fragmented Old-Growth Forests - Comparison among Species. Ecological Applications **5**:183-199.

Linderman, M., L. An, S. Bearer, G. He, Z. Ouyang, and J. Liu. 2005a. Modeling the spatio-temporal dynamics and interactions of households, landscapes, and giant panda habitat. Ecological Modelling **183**:47-65.

Linderman, M., S. Bearer, L. An, Y. Tan, Z. Ouyang, and J. Liu. 2005b. The effects of understory bamboo on broad-scale estimates of giant panda habitat. Biological Conservation **121**:383-390.

Linderman, M., J. Liu, J. Qi, L. An, Z. Ouyang, J. Yang, and Y. Tan. 2004. Using artificial neural networks to map the spatial distribution of understorey bamboo from remote sensing data. International Journal of Remote Sensing **25**:1685-1700.

Litvaitis, J. A. 2001. Importance of early successional habitats to mammals in eastern forests. Wildlife Society Bulletin **29**:466-473.

Litvaitis, J. A., and R. Villafuerte. 1996a. Factors affecting the persistence of New England cottontail metapopulations: The role of habitat management. Wildlife Society Bulletin **24**:686-693.

Litvaitis, J. A., and R. Villafuerte. 1996b. Intraguild predation, mesopredator release, and prey stability. Conservation Biology **10**:676-677.

Liu, J., and J. Diamond. 2005. China's environment in a globalizing world. Nature **435**:1179-1186.

Liu, J., M. Linderman, Z. Ouyang, L. An, and e. al. 2001. Ecological degradation in protected areas: The case of Wolong Nature Reserve for giant pandas. Science **292**:98.

Liu, J., Z. Ouyang, Y. Tan, J. Yang, and H. Zhang. 1999a. Changes in human population structure: Implications for biodiversity conservation. Population and Environment **21**:45-58.

Liu, J., Z. Ouyang, W. W. Taylor, R. Groop, K. C. Tan, and H. M. Zhang. 1999b. A framework for evaluating the effects of human factors on wildlife habitat: the case of giant pandas. Conservation Biology **13**:1360-1370.

Liu, J., and W. W. Taylor, editors. 2002. Integrating landscape ecology into natural resource management. Cambridge University Press, New York, New York.

Liu, S. L., B. J. Fu, Y. H. Lu, and L. D. Chen. 2002. Effects of reforestation and deforestation on soil properties in humid mountainous areas: a case study in Wolong Nature Reserve, Sichuan province, China. Soil Use and Management **18**:376-380.

Lo, N. C. H., D. Griffith, and J. R. Hunter. 1997. Using a restricted adaptive cluster sampling to estimate Pacific hake larval abundance. California Cooperatic Oceanic Fisheries Investigations **38**:103-113.

Maddock, A. H. 1988. Resource partitioning in a viverrid assemblage. Ph.D. Thesis. University of Natal, Pietermaritsburg.

Malcolm, J. R., and J. C. Ray. 2000. Influence of timber extraction routes on central African small-mammal communities, forest structure, and tree diversity. Conservation Biology **14**:1623-1638.

Matlock, R. B., D. Rogers, P. J. Edwards, and S. G. Martin. 2002. Avian communities in forest fragments and reforestation areas associated with banana plantations in Costa Rica. Agriculture Ecosystems & Environment **91**:199-215.

Matsubayashi, H., E. Bosi, and S. Kohshima. 2003. Activity and habitat use of lesser mouse-deer (Tragulus javanicus). Journal of Mammalogy **84**:234-242.

Matthews, E., R. Payne, M. Rohweder, and S. Murray. 2000. Pilot analysis of global ecosystems: Forest ecosystems. World Resources Institute, Washington, D.C.

Mattson, D. J. 1997. Use of lodgepole pine cover types by Yellowstone grizzly bears. Journal of Wildlife Management **61**:480-496.

McLellan, B. N., and D. M. Shackleton. 1989. Grizzly Bears and Resource-Extraction Industries - Habitat Displacement in Response to Seismic Exploration, Timber Harvesting and Road Maintenance. Journal of Applied Ecology **26**:371-380.

Morales, J. M., and S. P. Ellner. 2002. Scaling up animal movements in heterogeneous landscapes: The importance of behavior. Ecology **83**:2240-2247.

Nagaike, T., A. Hayashi, M. Abe, and N. Arai. 2003. Differences in plant species diversity in Larix kaempferi plantations of different ages in central Japan. Forest Ecology and Management **183**:177-193.

Niemuth, N. D. 2003. Identifying landscapes for greater prairie chicken translocation using habitat models and GIS: a case study. Wildlife Society Bulletin **31**:145-155.

NOAA. 2004. Climate monitoring and diagnostic laboratory carbon cycle greenhouse gases.

Noguchi, M., and T. Yoshida. 2004. Tree regeneration in partially cut conifer-hardwood mixed forests in northern Japan: roles of establishment substrate and dwarf bamboo. Forest Ecology and Management **190**:335-344.

Oliver, C., and B. Larson. 1996. Forest stand dynamics. John Wiley and Sons, Inc., New York.

Ott, L. 1993. An introduction to statistical methods and data analysis., 4 edition. PWS-Kent, Boston.

PAI. 1999. One in three people lives in forest-scarce countries. Population Action International, Washington, DC.

Palmer, S. C. F., and A. M. Truscott. 2003. Seasonal habitat use and browsing by deer in Caledonian pinewoods. Forest Ecology and Management **174**:149-166.

Parker, A. 1982. The topographic relative moisture index: an approach to soil-moisture assessment in mountain terrain. Physical Geography **3**:160-168.

Peng, X., and Z. Guo, editors. 2000. The changing population of China. Blackwell, Oxford.

Petranka, J. W. 1994. Response to Impact of Timber Harvesting on Salamanders. Conservation Biology **8**:302-304.

Piirainen, S., L. Finer, H. Mannerkoski, and M. Starr. 2002. Effects of forest clear-cutting on the carbon and nitrogen fluxes through podzolic soil horizons. Plant and Soil **239**:301-311.

Pottinger, A. 2003. Editorial: Special Issue: Illegal Logging. International Forestry Review **5**:ii-iii.

Potvin, F., R. Courtois, and L. Belanger. 1999. Short-term response of wildlife to clear-cutting in Quebec boreal forest: multiscale effects and management implications. Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere **29**:1120-1127.

Pradhan, S., G. K. Saha, and J. A. Khan. 2001. Ecology of the red panda Ailurus fulgens in the Singhalila National Park, Darjeeling, India. Biological Conservation **98**:11-18.

Prior, K. A., and P. J. Weatherhead. 1994. Response of Free-Ranging Eastern Massasauga Rattlesnakes to Human Disturbance. Journal of Herpetology **28**:255-257.

Quinn, G., and M. Keough. 2002. Experimental design and data analysis for biologists. Cambridge University Press, New York.

Rao, K. S., and R. Pant. 2001. Land use dynamics and landscape change pattern in a typical micro watershed in the mid elevation zone of central Himalaya, India. Agriculture Ecosystems & Environment **86**:113-123.

Rawat, G. S. 1997. Conservation status of forests and wildlife in the Eastern Ghats, India. Environmental Conservation **24**:307-315.

Ray, N., A. Lehmann, and P. Joly. 2002. Modeling spatial distribution of amphibian populations: a GIS approach based on habitat matrix permeability. Biodiversity and Conservation **11**:2143-2165.

Reid, D. G., and J. Hu. 1991. Giant Panda Selection between Bashania-Fangiana Bamboo Habitats in Wolong Reserve Sichuan China. Journal of Applied Ecology **28**:228-243.

Reid, D. G., J. Hu, D. Sai, W. Wei, and H. Yan. 1989. Giant Panda Ailuropoda-Melanoleuca Behavior and Carrying Capacity Following a Bamboo Die-Off. Biological Conservation **49**:85-104.

Reid, D. G., M. Jiang, Q. Teng, Z. Qin, and J. Hu. 1991a. Ecology of the Asiatic Black Bear (Ursus-Thibetanus) in Sichuan, China. Mammalia **55**:221-237.

Reid, D. G., A. H. Taylor, J. C. Hu, and Z. S. Qin. 1991b. Environmental Influences on Bamboo Bashania-Fangiana Growth and Implications for Giant Panda Conservation. Journal of Applied Ecology **28**:855-868.

Reid, D. G., A. H. Taylor, J. C. Hu, and Z. S. Qin. 1991c. Environmental-Influences on Bamboo Bashania-Fangiana Growth and Implications for Giant Panda Conservation. Journal of Applied Ecology **28**:855-868.

Roberts, M. R. 2002. Effects of forest plantation management on herbaceous-layer composition and diversity. Canadian Journal of Botany-Revue Canadienne De Botanique **80**:378-389.

Roberts, M. R., and F. S. Gilliam. 1995a. Disturbance effects on herbaceous layer vegetation and soil nutrients in Populus forests of northern lower Michigan. Journal of Vegetation Science **6**:903-912.

Roberts, M. R., and F. S. Gilliam. 1995b. Patterns and Mechanisms of Plant Diversity in Forested Ecosystems - Implications for Forest Management. Ecological Applications **5**:969-977.

Roberts, M. R., and L. X. Zhu. 2002. Early response of the herbaceous layer to harvesting in a mixed coniferous-deciduous forest in New Brunswick, Canada. Forest Ecology and Management **155**:17-31.

Robinson, J. G., K. H. Redford, and E. L. Bennett. 1999. Conservation - Wildlife harvest in logged tropical forests. Science **284**:595-596.

Rodrigues, A. S. L., S. J. Andelman, M. I. Bakarr, L. Boltani, T. M. Brooks, R. Cowling, L. Fishpool, G. da Fonseca, K. Gaston, M. Hoffmann, J. Long, P. Marquet, J. Pilgrim, R. Pressey, J. Schipper, W. Sechrest, S. Stuart, L. Underhill, R. Waller, M. Watts, and X. Yan. 2004. Effectiveness of the global protected area network in representing species diversity. Nature **428**:640-643.

Ruiz-Perez, M., F. Maoyi, Y. Xiaosheng, and B. Belcher. 2001. Bamboo forestry in China. Journal of Forestry **99**:14-20.

Saenz, G. P., and M. R. Guariguata. 2001. Demographic response of tree juveniles to reduced-impact logging in a Costa Rican montane forest. Forest Ecology and Management **140**:75-84.

Sakuragi, M., H. Igota, H. Uno, K. Kaji, M. Kaneko, R. Akamatsu, and K. Maekawa. 2003. Seasonal habitat selection of an expanding sika deer Cervus nippon population in eastern Hokkaido, Japan. Wildlife Biology **9**:141-153.

Sallabanks, R., E. B. Arnett, and J. M. Marzluff. 2000. An evaluation of research on the effects of timber harvest on bird populations. Wildlife Society Bulletin **28**:1144-1155.

SAS Institute. 1985. SAS/STAT guide for personal computers. *in*. SAS Institute.

Sayer, J., U. Chokkalingam, and J. Poulsen. 2004. The restoration of forest biodiversity and ecological values. Forest Ecology and Management **201**:3-11.

Schaller, G. B., J. Hu, W. Pan, and J. Zhu. 1985. The giant pandas of Wolong. University of Chicago Press, Chicago.

Scherer, G., D. Zabowski, B. Java, and R. Everett. 2000. Timber harvesting residue treatment. Part II. Understory vegetation response. Forest Ecology and Management **126**:35-50.

Shi, P., and J. Xu. 2000. Deforestation in China. Center for Chinese Agricultural Sciences, Chinese Academy of Sciences, Beijing, PR China.

Simard, J. R., and J. M. Fryxell. 2003. Effects of selective logging on terrestrial small mammals and arthropods. Canadian Journal of Zoology-Revue Canadienne De Zoologie **81**:1318-1326.

Smil, V. 1984. The bad earth: environmental degradation in China. Zed Press, London.

Smith, A. P., and D. B. Lindenmayer. 1992. Forest Succession and Habitat Management for Leadbeaters Possum in the State of Victoria, Australia. Forest Ecology and Management **49**:311-332.

Smith, D. F., and J. A. Litvaitis. 2000. Foraging strategies of sympatric lagomorphs: implications for differential success in fragmented landscapes. Canadian Journal of Zoology-Revue Canadienne De Zoologie **78**:2134-2141.

Stanturf, J. A., S. H. Schoenholtz, C. J. Schweitzer, and J. P. Shepard. 2001. Achieving restoration success: Myths in bottomland hardwood forests. Restoration Ecology **9**:189-200.

State Environmental Protection Administration of China. 1998. China's biodiversity: A country study. China Environmental Science Press, Beijing.

Stier, S. C., and S. F. Siebert. 2002. The Kyoto Protocol: an opportunity for biodiversity restoration forestry. Conservation Biology **16**:575-576.

Store, R., and J. Jokimaki. 2003. A GIS-based multi-scale approach to habitat suitability modeling. Ecological Modelling **169**:1-15.

Stott, T., and N. Mount. 2004. Plantation forestry impacts on sediment yields and downstream channel dynamics in the UK: a review. Progress in Physical Geography **28**:197-240.

Su, Z., and T. J. Quinn. 2003. Estimator bias and efficiency for adaptive cluster sampling with order statistics and a stopping rule. Environmental and Ecological Statistics **10**:17-41.

Sullivan, T. P., R. A. Lautenschlager, and R. G. Wagner. 1999. Clearcutting and burning of northern spruce-fir forests: implications for small mammal communities. Journal of Applied Ecology **36**:327-344.

Sullivan, T. P., and D. S. Sullivan. 2001. Influence of variable retention harvests on forest ecosystems. II. Diversity and population dynamics of small mammals. Journal of Applied Ecology **38**:1234-1252.

Sullivan, T. P., D. S. Sullivan, and P. M. F. Lindgren. 2000. Small mammals and stand structure in young pine, seed-tree, and old-growth forest, southwest Canada. Ecological Applications **10**:1367-1383.

Sun, X. F., E. Katsigris, and A. White. 2004. Meeting China's demand for forest products: an overview of import trends, ports of entry, and supplying countries, with emphasis on te Asia-Pacific region. International Forestry Review **6**:227-236.

Sun, X. F., L. Q. Wang, and Z. B. Gu. 2005. China and forest trade in the Asia-Pacific region: Implications for forests and livelihoods. A brief overview of China's timber market. Forest Trends.

Sykes, J. M., V. P. W. Lowe, and D. R. Briggs. 1989. Some Effects of Afforestation on the Flora and Fauna of an Upland Sheepwalk During 12 Years after Planting. Journal of Applied Ecology **26**:299-320.

Takahashi, K., and T. Kohyama. 1999. Size-structure dynamics of two conifers in relation to understorey dwarf bamboo: A simulation study. Journal of Vegetation Science **10**:833-842.

Takahashi, K., S. Uemura, J. I. Suzuki, and T. Hara. 2003. Effects of understory dwarf bamboo on soil water and the growth of overstory trees in a dense secondary Betula ermanii forest, northern Japan. Ecological Research **18**:767-774.

Tanaka, N. 1988. Tree invasion into patchy dwarf-bamboo thickets within a climax beech-fir forest in Japan. Pages 253-261 *in* J. H. Willems, editor. Diversity and pattern in plant communities. SPB Academic Publishing, The Hague, The Netherlands.

Taylor, A. H., J. Y. Huang, and S. Q. Zhou. 2004. Canopy tree development and undergrowth bamboo dynamics in old-growth *Abies-Betula* forests in southwestern China: a 12 year study. Forest Ecology and Management **200**:347-360.

Taylor, A. H., and Z. Qin. 1987. Culm Dynamics and Dry Matter Production of Bamboos in the Wolong and Tangjiahe Giant Panda Reserves Sichuan China. Journal of Applied Ecology **24**:419-434.

Taylor, A. H., and Z. Qin. 1988a. Regeneration from Seed of Sinarundinaria-Fangiana a Bamboo in the Wolong Giant Panda Reserve Sichuan China. American Journal of Botany **75**:1065-1073.

Taylor, A. H., and Z. Qin. 1988b. Tree replacement patterns in subalpine Abies-Betula forests, Wolong Natural Reserve, China. Vegetatio **78**:141-149.

Taylor, A. H., and Z. H. Qin. 1989. Structure and composition of selectively cut and uncut Abies-Tsuga forest in Wolong Natural Reserve and implications for panda conservation in China. Biological Conservation **47**:83-108.

Taylor, A. H., and Z. S. Qin. 1988c. Regeneration patterns in old-growth Abies-Betula forests in the Wolong Natural Reserve, Sichuan, China. Journal of Ecology **76**:1204-1218.

Taylor, A. H., and Z. S. Qin. 1993a. Aging Bamboo Culms to Assess Bamboo Population-Dynamics in Panda Habitat. Environmental Conservation **20**:76-79.

Taylor, A. H., and Z. S. Qin. 1993b. Bamboo Regeneration after Flowering in the Wolong Giant Panda Reserve, China. Biological Conservation **63**:231-234.

Taylor, A. H., and Z. S. Qin. 1997. The dynamics of temperate bamboo forests and panda conservation in China. Pages 370 pp. *in* G. P. Chapman, editor. The Bamboos. Academic Press, San Diego.

Taylor, A. H., Z. S. Qin, and J. Liu. 1995. Tree regeneration in an Abies faxoniana forest after bamboo dieback, Wang Lang Natural Reserve, China. Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere **25**:2034-2039.

Taylor, A. H., D. G. Reid, Z. S. Qin, and J. C. Hu. 1991. Bamboo dieback - an opportunity to restore panda habitat. Environmental Conservation **18**:166-168.

Taylor, C. R., V. J. Rowntree, and S. L. Caldwell. 1972. Running up and Down Hills - Some Consequences of Size. Science **178**:1096-&.

Taylor, S., and M. R. Perrin. 1996. Identification of the rodent species involved in tree damage in commercial forestry in the Natal midlands, South Africa. Mammalia **60**:767-773.

Thompson, F. R., and R. M. DeGraaf. 2001. Conservation approaches for woody, early successional communities in the eastern United States. Wildlife Society Bulletin **29**:483-494.

Thompson, S. K. 1991a. Adaptive cluster sampling. Biometrika **78**:389-397.

Thompson, S. K. 1991b. Adaptive cluster sampling - designs with primary and secondary units. Biometrics **47**:1103-1115.

Thompson, S. K., F. L. Ramsey, and G. A. F. Seber. 1992. An Adaptive Procedure for Sampling Animal Populations. Biometrics **48**:1195-1199.

Thompson, S. K., and G. Seber. 1996. Adaptive sampling. John Wiley and Sons, Inc., New York, New York.

Turk, P., and J. J. Borkowski. 2005. A review of adaptive cluster sampling. Environmental and Ecological Statistics **12**:55-94.

Turner, M. G., G. J. Arthaud, R. T. Engstrom, S. J. Hejl, J. G. Liu, S. Loeb, and K. McKelvey. 1995. Usefulness of Spatially Explicit Population-Models in Land Management. Ecological Applications **5**:12-16.

Twedt, D. J., and J. Portwood. 1997. Bottomland hardwood reforestation for Neotropical migratory birds: Are we missing the forest for the trees. Wildlife Society Bulletin **25**:647-652.

Twedt, D. J., and R. R. Wilson. 2002. Development of oak plantations established for wildlife. Forest Ecology and Management **162**:287-298.

Twedt, D. J., R. R. Wilson, J. L. Henne-Kerr, and D. A. Grosshuesch. 2002. Avian response to bottomland hardwood reforestation: The first 10 years. Restoration Ecology **10**:645-655.

Urban, D., S. Goslee, K. Pierce, and T. Lookingbill. 2002. Extending community ecology to landscapes. Ecoscience **9**:200-212.

Venables, W., and B. Ripley. 1999. Modern applied statistics with S-PLUS, 3 edition. Springer-Verlag, New York.

Viljoen, P. 1982. The distribution and population status of the larger mammals in Kaokoland, South West Africa/Namibia. Cimbebasia **7**:7-33.

Waller, J. S., and R. D. Mace. 1997. Grizzly bear habitat selection in the Swan Mountains, Montana. Journal of Wildlife Management **61**:1032-1039.

Wang, S., and L. Chen. 1992. Biodiversity in China: Status and conservation needs. Biodiversity Commission of the Chinese Academy of Sciences., Beijing, China.

Ward, D. H., R. A. Stehn, and D. V. Derksen. 1994. Response of Staging Brant to Disturbance at the Izembek Lagoon, Alaska. Wildlife Society Bulletin **22**:220-228.

WEC. 2004. Energy efficiency: a worldwide review. World Energy Council, London.

Wenger, K., editor. 1984. Forestry Handbook. Wiley Interscience, New York, NY.

White, L. 1992. Vegetation history and logging disturbance: effects on rain forest mammals in Lope Reserve, Gabon. Ph.D. Dissertation. University of Edinburgh, Edinburgh.

Wielgus, R. B., and P. R. Vernier. 2003. Grizzly bear selection of managed and unmanaged forests in the Selkirk Mountains. Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere **33**:822-829.

Wolong Nature Reserve. 2003. Gray literature documentation on extant of reforestation. Wolong Nature Reserve Administration, Wolong, Sichuan, PRC.

World Wildlife Fund. 2004. Giant panda survey 2004: Questions and answers. Beijing.

Wormington, K. R., D. Lamb, H. I. McCallum, and D. J. Moloney. 2002. Habitat requirements for the conservation of arboreal marsupials in dry sclerophyll forests of Southeast Queensland, Australia. Forest Science **48**:217-227.

Xinhua. 2004. Survey: China has over 1,750 giant pandas. *in* China Daily, Beijing.

Xu, J., and A. Wilkes. 2004. Biodiversity impact analysis in northwest Yunnan, southwest China. Biodiversity and Conservation **13**:959-983.

Xu, Z., M. Bennett, R. Tao, and J. Xu. 2004. China's Sloping Land Conservation Programme four years on: current situation and pending issues. International Forestry Review **6**:317-326.

Zar, J. H. 1996. Biostatistical analysis. Prentice Hall, Upper Saddle River, New Jersey.

Zhao, G., and G. F. Shao. 2002. Logging restrictions in China - A turning point for forest sustainability. Journal of Forestry **100**:34-37.

Zhao, M., and G. S. Zhou. 2005. Estimation of biomass and net primary productivity of major planted forests in China based on forest inventory data. Forest Ecology and Management **207**:295-313.

Zheng, S., Y. Yu, H. Zuo, Y. Cao, W. Yuan, and W. Fu. 1995. The present status, distribution, and conservation measure of the black bear in Hanzhong prefecture, Shaanxi province. Acta Theriologica Sinica **15**:93-97.