Chapter 9

# HUMAN IMPACTS ON LAND COVER AND PANDA HABITAT IN WOLONG NATURE RESERVE

*Linking Ecological, Socioeconomic, Demographic, and Behavioral Data*


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**Abstract** Understanding patterns, processes, and consequences of land-cover change requires close linkages among various ecological, socioeconomic, demographic, and behavioral data. In this chapter, we present an interdisciplinary study of human impacts on land cover and panda habitat in Wolong Nature Reserve (China). Wolong is one of the largest reserves (200,000 ha) designated for giant panda conservation, but it also includes more than 4,000 local residents whose activities have a substantial impact on panda habitat. We have developed a conceptual framework that outlines the rationale for the linkage of various data. Our household and community surveys were linked with remote sensing and geographic information systems at three stages: data collection, data analysis, and systems modeling and simulation. The integration of various sources of data offers useful insight into the underlying mechanisms behind changes in land cover and panda habitat and allows us to project future ecological and demographic changes under different policy scenarios.

**Keywords:** Wolong Nature Reserve, giant pandas, wildlife habitat, land cover, forest, socioeconomics, demographics, ecology, human behaviors, linkages, households, remote sensing, GIS, modeling, China

# 1. INTRODUCTION

Land-cover changes are a major aspect of global changes (e.g., see Turner et al. 1994). The extent and intensity of such changes vary across space and time, as do their ecological consequences. Whereas some land-cover changes occur naturally, most of them are caused by human activities. In fact, human activities are the main cause of biodiversity loss and habitat fragmentation as well as rapid changes in ecosystems and landscapes around the world (Ehrlich 1988; Wilson 1988; Vitousek et al. 1997). Even in many of the 30,350 protected areas (such as nature reserves) established to protect natural resources and biodiversity (IUCN 1994), humans are also present and carry out various activities detrimental to biodiversity (Dompka 1996; Liu 2001). For example, in the Wolong Nature Reserve of China, established to protect the world-famous, endangered giant pandas *(Ailuropoda melanoleuca),* land cover, especially forest cover, has undergone significant changes due to activities of local residents (Liu et al. 2001a). Because forest cover is a critical component of panda habitat, loss and fragmentation of forest cover lead to degradation in panda habitat. As a result, the panda range has been dramatically reduced from once including many parts of China and several neighboring countries to including only fragmented areas of southwestern China (Giant Panda Expedition 1974; Schaller et al. 1985; China's Ministry of Forestry and WWF 1989).

The objectives of our project were to detect the spatial and temporal patterns of changes in land cover and panda habitat, to understand the mechanisms behind these patterns, and to develop new policy scenarios and evaluate short- and long-term consequences of different scenarios. To achieve these objectives, a variety of spatial and nonspatial (ecological, socioeconomic, demographic, and behavioral) data need to be closely fused, because patterns and processes of changes in land cover and panda habitat cannot be understood and managed using one type of data alone. The primary goals of this chapter are to present a conceptual framework of linkages and to discuss the methods to fuse various types of data for a holistic understanding of human impacts on land cover and panda habitat.

## 2. STUDY AREA

Our study area is Wolong Nature Reserve (Figure 1), a reserve established in 1975 for conserving giant pandas. Wolong is located in Sichuan Province in southwestern China (30°45' – 31°25' North, 102°52' – 103°24' East). It is ideal for our study for four main reasons. First, it is one of the largest protected areas (approximately 200,000 ha) designated for conserving the pandas and contains approximately 10 percent of the wild panda population (Zhang et al. 1997). Second, like many other protected areas, there are local residents in Wolong (more than 4,000 local residents in over 900 households in 1998). Third, Wolong is a "flagship" nature reserve and has received exceptional financial and technical support since its creation, both from the Chinese government and many international organizations. Fourth, many biological studies on giant pandas have been conducted (e.g., Hu et al. 1980; Schaller et al. 1985; Johnson et al. 1988; Reid and Hu 1991), and there is a useful record of economic and demographic statistics. These previous studies and data provided a good foundation for our study.

Wolong is situated between the Sichuan Basin and the Qinghai-Tibet Plateau. It has high mountains and deep valleys with elevations ranging from 1,200 to 6,525 m (Figure 1). Wolong encompasses several climatic zones and has high habitat diversity (Schaller et al. 1985). There are more than 2,200 animal and insect species and approximately 4,000 plant species (Tan et al. 1995). In addition to the giant pandas, twelve other animal species and forty-seven plant species in the reserve are also on China's national protection list. Furthermore, the reserve is part of the international Man and Biosphere Reserve Network (He et al. 1996). It is managed by the Wolong Administration Bureau, which reports to both China's State Forestry Administration and Sichuan Province. Under the Administration Bureau, there are two township governments. Each township consists of three villages, and each village includes three to six groups (a group is the lowest administrative unit in China's rural areas, often comprised of approximately a dozen to several dozen households that are geographically close to one another). Farmers comprise the vast majority of local residents. There are various economic activities in the reserve, including agriculture (maize and vegetables are the major crops), fuelwood collection, timber harvesting, house building, collection of Chinese herbal medicines, and road construction and maintenance.

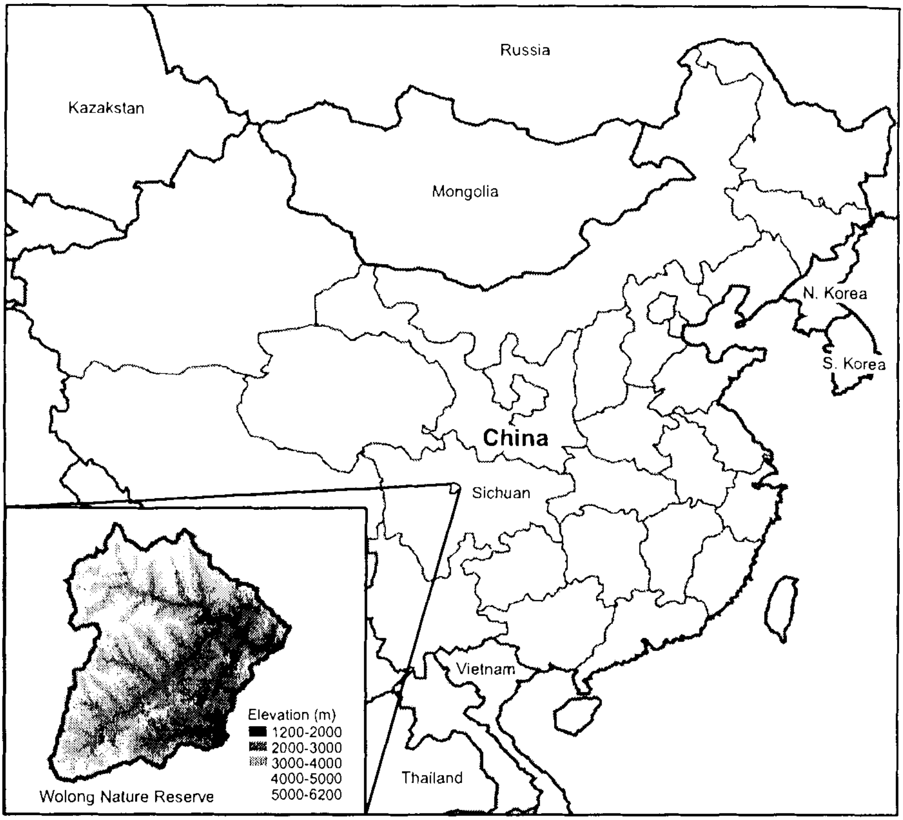


*Figure 1.* Location map of Wolong Nature Reserve

## 3. LINKAGES FROM A CONCEPTUAL PERSPECTIVE

The conceptual framework (Figure 2) provides rationales for linking various factors. It consists of three main interrelated components: panda habitat, forest, and humans. Panda habitat is the area that provides food and cover for pandas' reproduction and daily activities. Suitability of panda habitat depends on abiotic and biotic conditions, as well as the degree of human impact (Liu et al. 1999a). Slope and elevation are two major abiotic factors (Schaller et al. 1985; Liu et al. 1999a; Liu et al. 2001a). Pandas prefer flat areas or gentle slopes in order to move around easily. Major biotic factors include bamboo and forest cover. Bamboo is the staple food for the panda and is an understory species in the forests. Like many other wildlife species, the giant panda depends on forest canopy as cover (mainly deciduous broadleaf forests, conifer forests, and mixed conifer and deciduous broadleaf forests) (Schaller et al. 1985; Liu et al. 1999a).

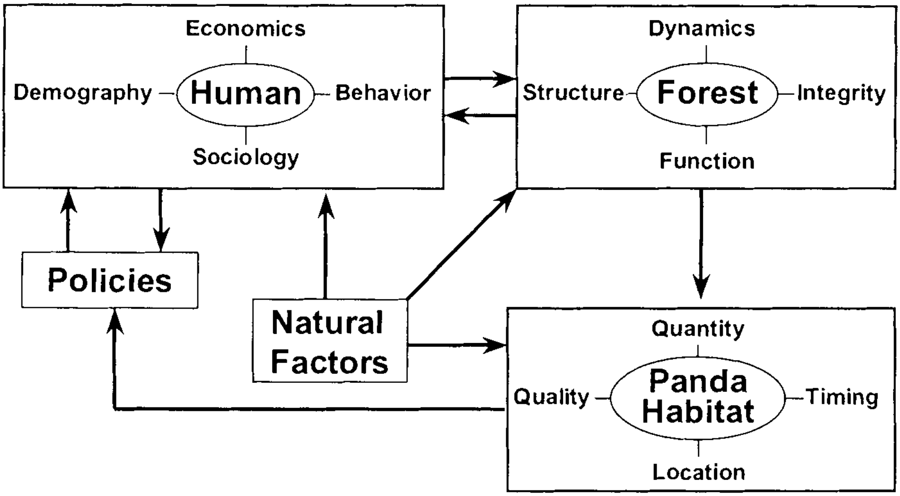


*Figure 2.* A conceptual framework for studying land cover and panda habitat changes

In the past several decades, human activities have been the primary force that changes the forest ecosystem, thereby altering panda habitat (see Figure 2, Liu et al. 1999a). *Human* in this context refers to local residents but not to those government officials and management staff who develop and implement policies (see below). Human factors include demographic (e.g., population size and distribution, household composition), socioeconomic (e.g., income, expenses, production, consumption, needs and wants, perceptions, and attitudes toward panda conservation), and behavioral variables (i.e., activities) such as timber harvesting and fuelwood collection for cooking and heating. Through human activities, local residents influence forests directly and panda habitat indirectly. Because fuelwood is the major source of energy for cooking and heating (a conservative estimate of fuelwood consumed in the reserve was 10,000 $m^3$/year, Liu et al. 1999a), fuelwood consumption has led to a significant loss of forests, including changes in forest structure, species composition, and spatial distribution (ibid.). As bamboo is an understory species, changes in forest cover affect the pandas' food supply (Schaller et al. 1985). Because giant pandas also depend on forests for cover, changes in forests can have an important impact on panda habitat quantity, quality, timing (when the habitat is available), and location (e.g., spatial distribution of panda habitat) (Liu et al. 1999a). Although the reserve is about 200,000 ha in size, approximately half of the area is not suitable for the pandas even without human impacts because some regions are above the tree line and other regions have slopes too steep or elevations too high to be suitable for pandas (ibid.).

All three components (human, forest, and habitat systems) in the framework can be directly or indirectly shaped by government policies and other factors. On the one hand, policies are made by government officials rather than by local residents. Such policies can directly affect various aspects of the local human system and indirectly affect the forest and panda habitat. On the other hand, policy-making process and effectiveness can be influenced by local residents and panda habitat conditions. For example, when panda habitat conditions are seriously deficient and human attitudes toward panda conservation are positive, government policies may be more effective and favorable to panda conservation. Loss and fragmentation of panda habitat may prompt the government to design and implement new policies such as out-migration (Liu et al. 1999a), which affect human population and local economy. Furthermore, the human system may be constrained by feedback from the forest system. For instance, after all trees in a forest are harvested, local residents must adopt a different lifestyle without timber and fuelwood. When forests used for fuelwood collection are getting smaller and farther from households, fuelwood collection becomes more difficult. If the difficulties of life in Wolong increase, more people (especially young people) are willing to move out of the reserve through means such as marriage outside Wolong (ibid.). Other factors such as physical environment (e.g., elevation) and landslides also impact humans, forests, and panda habitat. For example, landslides in 1996 killed seven local residents (Yinchun Tan, Wolong Nature Reserve, personal communication, 1999).

The linkages among the three components as well as policies and other factors in the conceptual framework are represented by arrows in Figure 2. For the sake of simplicity, subcomponents within each main component are not connected by arrows, although they are also interrelated. For example, human behaviors are a function of demographic and socioeconomic characteristics. Furthermore, human-environment interactions take place at different scales. For humans, the organizational scale ranges from individuals, households, villages, and townships to the entire reserve community. Concerning land, spatial scales range from plots or pixels (e.g., 1 x 1 m, 80 x 80 m), patches (e.g., forest stand, agricultural land parcel), to the entire reserve landscape. Individuals or households have a direct impact on the environment at small spatial scales. The cumulative and collective effects of individuals, households, and communities (villages and townships) extend to the entire reserve landscape. To understand the linkages among the main components and subcomponents in each main component and their relationships to policies and other factors, it is essential to couple different types of data at various scales.

# 4. LINKAGES FROM A TECHNICAL PERSPECTIVE

We linked ecological, socioeconomic, demographic, and human behavioral data at three stages: data collection, data analysis, and systems modeling and simulation. For data collection, we combined field studies, interviews, government statistics and documents, information from the literature, and data from remote sensing (satellite imagery and aerial photographs) and global positioning systems (GPS) using GIS and a relational database program (Microsoft ACCESS). In the process of collecting socioeconomic-demographic-behavioral data, we gathered some ecological data (e.g., tree species of fuelwood consumed by households). Similarly, collecting ecological data (e.g., percent of forest canopy cover) also included socioeconomic data (e.g., forest harvesting history such as time and type of harvesting). Socioeconomic-demographic data were often collected simultaneously. For example, in household economic surveys, we also gathered household demographic data. Furthermore, we used ecological data (e.g., land cover from remote sensing imagery) to gather socioeconomic-demographic data (e.g., locations of dwelling units and roads), using the latter (e.g., road intersections as ground control points) to facilitate classification of land-cover types. After the data collection, most of the information was entered into and managed using a relational database program and geographical information systems (including both Arc/Info and ArcView) for analysis.

In the data analysis stage, we used different types of data to explain their interrelationships. For instance, we used ecological data as dependent variables, and socioeconomic-demographic data were treated as independent variables, or vice versa (Liu et al. 1999a; An et al. 2001). We started our analyses with the land because we wanted to find out the patterns of land-cover distribution and temporal changes (Liu et al. 1999a) before attempting to understand the mechanisms underlying the patterns of distribution and changes. We analyzed data using spatial statistics, GIS, and statistical packages such as SAS, SPSS, and LISREL (An et al. n.d.[a]; An et al. n.d.[b]). In the systems modeling and simulation stage, we integrated various types of data and resultant mathematical and statistical models from the data analysis stage into more comprehensive systems simulation models that link demographic-socioeconomic-behavioral-ecological data (Liu et al. 1999a; An et al. 2001). More detailed descriptions about the linkages from a technical perspective are as follows.

## 4.1 Collection and Analysis of Ecological Data

The use of remotely sensed images has become an indispensable tool in environmental assessment (Lillesand and Kiefer 1994). Remote sensing is particularly valuable for large-scale research, especially in topographically complex regions such as Wolong, where assessment of land cover is both urgent and difficult if carried out by field studies alone (Moran et al. 1994). To measure spatial and temporal patterns of land-cover changes, we have acquired a number of remote sensing imagery: Corona data from 1965 (January 20), Landsat Multi-Spectral Scanner (MSS) data from 1974 (January 3), Landsat Thematic Mapper (TM) data from 1987 and 1997 (September 27), SPOT data from 1998 and 1999, and IKONOS data from 2000. The Corona data were stereo-pair photographs acquired as part of the Corona photo-reconnaissance satellite project (USGS EROS Data Center, Sioux Falls, South Dakota). We scanned the area of interest within each photo into a digital image at 1,200 dpi. We then georeferenced these images to topographic maps of the region. Next we mosaicked these small images to a large single image, examined them visually for inconsistencies, and classified them visually into regions of forest cover and nonforest cover (Liu et al. 2001a). We obtained both Landsat MSS and TM data from China's Satellite Ground Station (Beijing, China). SPOT HRV data (7/18/1998: 20-m multispectral 3 band; 3/17/1999: 10-m panchromatic, 20-m multispectral 4 band) were obtained from SPOT Image Co. (Virginia, USA). We acquired four images of IKONOS data (different times between August 31 and November 16, 2000) with 1-m resolution and 4-m resolution (multispectral image) through the National Aeronautics and Space Administration (NASA). Wolong has a high frequency of cloud cover, making the acquisition of data at regular intervals difficult. The difficulty of obtaining cloud-free imagery necessitated the use of data from different seasons. It is not easy to locate readily recognizable landmarks across the study area. In addition, the complex topography in Wolong further complicated the process of georeferencing the remote sensing data. To facilitate the classification of land cover, we developed a Digital Elevation Model (DEM) from topographic maps and employed a number of GPS–measured ground control points (e.g., major road intersections) to georeference the DEM.

In the summer of 1998, the National Survey Bureau of China established two reference points (with accuracy $< 1$ cm) in Wolong for us to place two base stations for differential correction of rover data gathered from ground sample sites. In 1998 and 1999, we surveyed approximately 500 ground-truth sites in Wolong (Linderman et al. n.d.). We selected ground-sample sites where access was feasible, with special focus on gathering a statistically representative sample of the various vegetative compositions and ratios, topographic configurations, and bamboo presence. Because of a lack of prior knowledge of observer position relative to the 30-m satellite data grid, each site was a 60-m homogenous square so that at least one complete 30 x 30-m pixel was contained in the site (Linderman et al. n.d.; Liu et al. 2001a). At least two people on a field team estimated and recorded percentage of overstory, mid-story, and understory cover, as well as species composition along with slope, aspect, and elevation. We georeferenced the remote sensing data using highly accurate data (1–5 m) from GPS receivers (Trimble Pathfinder) with real-time differential corrections. We then used the ground-truth data for training and validating a supervised classification of the remote sensing data. Using ERDAS Imagine software or visual classification, we found that forest cover in Wolong had been dramatically reduced from 1965 to 1997 (Liu et al. 2001a; Linderman et al. n.d.).

We employed over 200 independent ground samples to assess the accuracy of the supervised classification using the accuracy assessment tool in ERDAS Imagine software. The supervised classification had an 88 percent overall prediction rate in distinguishing between forested and nonforested areas. Overall accuracy in classifying individual land-cover classes (e.g., deciduous forest, agriculture, grasslands) was 79 percent. Success in predicting specific classes varied primarily due to spectral similarities between certain classes. For example, due to the variability in regrowth and logging activity, deciduous forest and shrub regrowth areas were often spectrally similar, with the majority of the shrub omission errors being misclassified as deciduous forest. Other factors influencing the accuracy of the classification included extreme topography and mixed pixels.

While remotely sensed data can help identify amounts and spatial distributions of forests at large scales, some detailed structure and composition of forests cannot be easily identified. Thus we conducted field surveys (Liu et al. 1999a; Ouyang et al. 2000). We selected random samples of plots (20 x 25 m each) in areas with different forest conditions (e.g., socioeconomic conditions such as places with and without fuelwood collection and timber harvesting). We chose smaller subplots inside the 20 x 25 m plot for sampling shrubs (5 x 5 m, three in each plot) and herbaceous plants (1 x 1 m, 5 in each plot). In each sampling plot or subplot, we recorded canopy closure, species, and size of vegetation (trees, shrubs, bamboo). In our most recent field studies, we also used GPS receivers to record the plot locations and later incorporated the GPS measurements into a GIS for spatial analysis.

## 4.2. Collection and Analysis of Demographic, Socioeconomic, and Behavioral Data

Demographic, socioeconomic, and behavioral data used in our research were collected either by the Wolong Administration Bureau or by our research team. The Wolong Administration Bureau followed data-collection guidelines set by upper government agencies at the county, province, and national levels, such as the State Statistics Bureau. Although no information about data accuracy is available, the people responsible for data collection received relevant training mandated and provided by upper government agencies. Furthermore, we verified some of the data (e.g., household size) by comparing them with what our team collected and found that the data collected by the Wolong Administration Bureau were good. Using ArcView, Arc/Info, and/or the Microsoft ACCESS relational database, we linked data obtained from the Wolong Administration Bureau with those collected by our research team. For example, for household-level data, names or identification codes of household heads were the linkages among different data sources.

Data collection by our research team began in 1996 (Liu et al. 1999a; Liu et al. 2001a; An et al. 2001), and the most recent survey took place in the summer of 2001. Our data collection followed standard protocols. Our specific methods—though varied depending on the questions and research objectives (e.g., Liu et al. 1999a; An et al. 2001; An et al. n.d.[a]; An et al. n.d.[b])—did not change fundamentally over time so that temporal comparisons would be possible. Although the boundary for a small part of the reserve did change, this portion of the reserve has had no residents and has had no impact on the collection of socioeconomic, demographic, and behavioral data.

In our household surveys, we selected respondents (household heads or other household members, depending on the questions) using simple or stratified random designs. For the pre-interviews (or pilot studies), we used simple random sampling because the goal was to identify all possible major issues and to test the appropriateness of questionnaires (An et al. n.d.[a]). Since simple random sampling could cause omission of some villages in Wolong, we used stratified random sampling (at the village level) to assure that all villages were appropriately represented. Some questions in the formal interviews were modified according to the pilot interviews and preliminary analyses of the data collected. For example, we had expected that money would play an important role in the decision-making process of adolescents leaving parental homes and establishing their own households. However, our pre-interviews indicated that wood and land were the major factors (An et al. n.d.[b]). The pilot studies also allowed us to estimate the amount of time needed for each interview more accurately.

We used face-to-face interviews with local residents because this method is the best and most feasible approach for Wolong (An et al. 2001). Since the majority of the local residents have low educational levels (with an average of 4.2 years/person) (ibid.) and postal service is not readily available to those who live in areas of high elevation, mail surveys would have been extremely problematic. In addition, a telephone survey could not be conducted since the vast majority of local residents have no phones. Face-to-face interviews typically garner higher response (or compliance) rates than other types of surveys (Dillman 1978), and our interviews proved to be highly successful, with nearly 100 percent compliance overall. (Unlike many people in cities of China or developed countries, local residents in Wolong were very cooperative.)

To demonstrate how we conducted cross-sectional interview sessions and then linked them with our remote sensing data, we provide the following example that modeled conditions under which local farmers would be willing to switch from fuelwood (their primary energy source) to electricity for cooking and heating (An et al. n.d.[a]). We hypothesized that this willingness to switch would be explained and predicted by the following four types of variables: (1) demographic features (such as age and gender), (2) economic variables (such as income), (3) electricity price and quality (such as voltage levels), and (4) locational variables (such as whether a specific household is located in Wolong or Gengda Township and distances from household to fuelwood collection sites). The Wolong Administration Bureau has a complete list of all the households in the reserve and household-specific data regarding demographic features and farmland conditions (such as land parcel size). Thus the demographic data needed by our model were directly obtained from the government archives. To cross-check the government data, we also recorded some demographic features in our interview session (see below). The second (economic) and third (electricity price and quality) types of data were elicited from the same interview session. The collection of the fourth (locational) type of data was aided by applying remote sensing techniques. We printed out georeferenced SPOT (1998) maps showing dwelling units and their surrounding features, such as mountain ridges, roads, rivers, and large parcels of land. We then asked the respondents (assisted by our local colleagues) to locate the sites of their fuelwood collection at different times (1970s, 1980s, and 1990s) on the images.

Using the 1996 Wolong Agricultural Census record (containing all the households by villages) as our sampling frame, we conducted our interview session and collected the economic, electricity, and locational data (types 2–4 listed above) that were necessary to construct our quantitative model (An et al. n.d.[a]). A sample of 220 households (about 23 percent of the total number of households) was chosen, reflecting the trade-off between our need for a robust sample and the limitations of time, budget, and manpower. Our stratified sampling process was characterized by proportionally drawing the 220 households from each of the six villages based on its size ($N_i$, the number of households in village i, i = 1, 2, ..., 6). Specifically, for village i, we coded all the households with numbers from 1 to $N_i$, and then took a random sample of $n_i$ (the sample size in village i) households from a total of $N_i$ households in village i.

Before each interview session started, we gave a brief explanation to the interviewee regarding who we were, the purpose of our research, how they had been selected, the estimated time of the interview, the confidentiality of the interview results, and the voluntary nature of the interview. We collected household socioeconomic and demographic data first—for example, household expense items in 1998, educational levels, ages, genders of all household members, and so on. We then collected the stated preference data by asking the head of each household the price, voltage level, and outage frequency for electricity in the summer of 1999. In the session, to elicit their preferences under different electricity conditions, we designed an approach for realizing random combinations of prices, voltage levels, and outage frequency levels. Seven price levels, three voltage levels, and three outage levels were determined to be appropriate for this study, so we prepared seven price cards, three voltage cards, and three outage frequency cards. The cards in each set were shuffled thoroughly and placed face down. We asked the respondent to pick up one card from the seven price cards, one card from the three electricity outage frequency cards, and finally, one card from the three electricity voltage cards. Then a hypothetical condition regarding electricity price and quality was ready for use. We then asked the respondent (in Chinese): "Under this condition, will you switch from fuelwood to electricity completely?" A 100 percent response rate was achieved in these interview sessions, which is understandable in Chinese rural cultures because rural people are more hospitable to visitors than those in cities. Out of these 220 households, 28 were removed from further analysis because the respondents had problems in answering some of the questions—for example, they could not remember the price of electricity.

Discussion about the model construction and results from these interview data (An et al. n.d.[a]) is beyond the scope of this section. But worthy of mention is that we linked all these data (types 1–4 listed above) and remote sensing data (such as IKONOS) in an ArcInfo database in which household IDs (household heads' names could also be used as IDs, but due to concerns about confidentiality, we did not use them) were used as the database key and all the demographic (such as age, from government archives and cross-checked by our interview data), economic (such as income, from our interviews), and electricity-related data (such as price, from our interviews) were attributes of PAT (Point Attribute Table) in ARC or VAT (Value Attribute Table) in GRID module. The georeferenced remote sensing image provided a good basis for identifying the locations of the households and fuelwood collection sites, creating spatially explicit databases (PAT in ARC and VAT in GRID under Arc/Info), measuring the distances between households and fuelwood collection sites, and displaying spatial patterns of the households and the attributes of these households based on the data contained in the spatially explicit database (PAT or VAT).

### 4.2.1 Demographic Data

We obtained data regarding human population and households in Wolong from several sources, including Wolong Administration Bureau (annual population reports; 1984–98 records on birth, death, age, sex, in-migration, and out-migration), national census data in 1982 (Wenchuan County 1983), 1996 Agricultural Census (Wolong Nature Reserve 1996), and national census data in 2000 (Wolong Nature Reserve 2000). The 1996 Agricultural Census produced a variety of data (e.g., household size; name, age, and sex of each household member; land area; number of livestock, such as pigs) at the household level. All these micro-level data are now in digital format and are managed in a relational database. We used names of household heads or identification codes to link these data. Because our team members are the only ones who had access to these data in the database, confidentiality was well protected even when the names of household heads were used as the linkage. These data provide us with useful information to study the past dynamics of population size and structure, such as age composition, sex ratio, and educational composition (Liu et al. 1999a, 1999b).

We have been investigating the demographic dynamics, such as household size, household structure, time of household formation and dissolution (e.g., through divorce and marriage), and time of house construction. (Our unpublished data show that from 1975 to 1998, as a net average, twenty-two new households were added to the reserve every year.) For each individual we recorded information such as age, sex, marital status, time of marriage, separation, or divorce if applicable, years of schooling, and relationship to the household head. In household surveys, we interviewed household heads. Sometimes, we also asked knowledgeable family members and neighbors to confirm some of the information provided by the household heads. (Unlike many neighbors in the cities, most neighbors in Wolong talk to each other on a daily or weekly basis; furthermore, neighbors often help each other, especially with activities requiring intensive labor such as fuelwood collection.)

Spatial distributions of households may be very important for understanding the population-environment interrelationships (Bilsborrow and Okoth-Ogendo 1992; Pebley 1998). We used sketch maps (see an example in Figure 3) to identify the relative locations of dwelling units. The sketch maps were obtained from the 1996 Agricultural Census and the 2000 Population Census. These draft drawings helped the censuses avoid missing any households. We have recorded locations of approximately sixty dwelling units using GPS receivers with real-time differential corrections. Besides x- and y-coordinates, we also recorded slope, elevation, aspect, and vegetation conditions around the houses. After differential corrections, the accuracy of location data was within 1–5 m (unpublished data). As dwelling units are also clearly shown on IKONOS imagery (see an example in Figure 4), the location data from GPS measurements are being used as training and validation data for IKONOS images so that we can identify the accurate coordinates of the remaining dwelling units. In addition, we associated the names of household heads with the locations of their dwelling units on the IKONOS imagery. Thus, the spatial data were linked to the socioeconomic and demographic database using the names of the household heads as the linkage key. To help understand temporal dynamics of spatial locations of dwelling units, we also asked about the years when the houses were built and entered this information on the Microsoft ACCESS database.

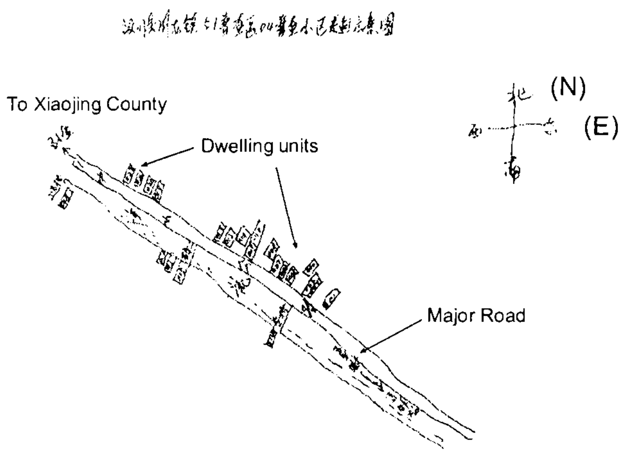


*Figure 3.* Sketch map showing relative locations of some dwelling units

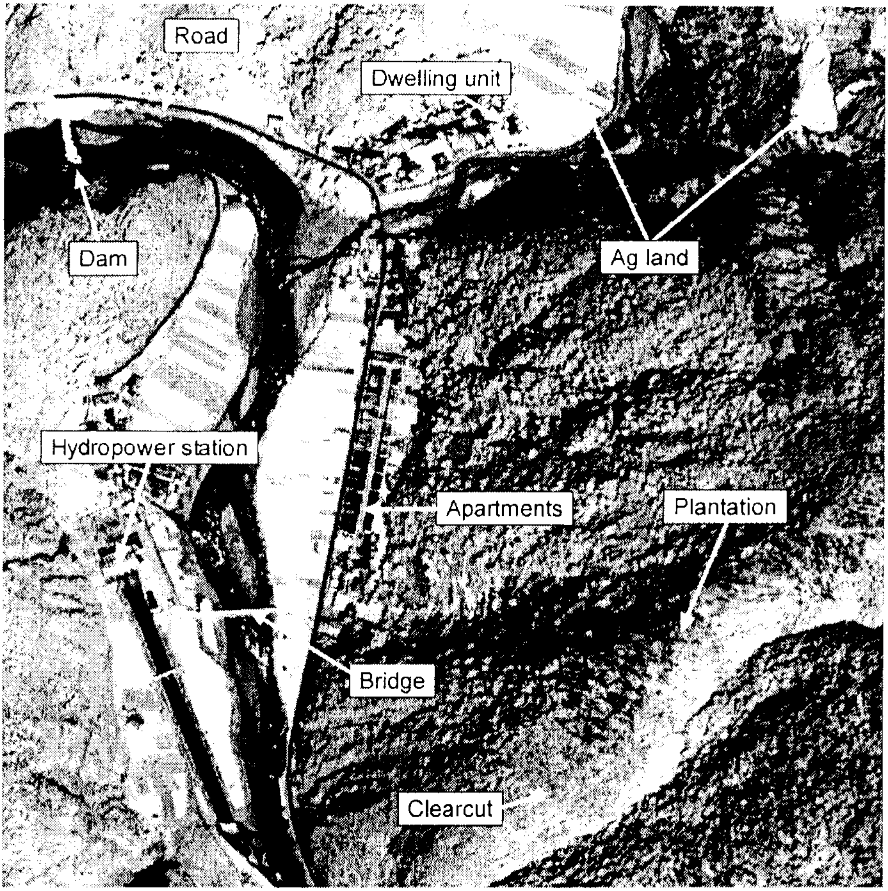


*Figure 4.* A subset of a panchromatic IKONOS image with a 1-m resolution

Unlike the cases in Brazil (Moran et al. this volume), Ecuador (Walsh et al. this volume), and Thailand (Rindfuss et al. this volume), the exact locations of agricultural land parcels in Wolong have not been recorded using GPS receivers, partially because the vast majority of agricultural land is not far from dwelling units, and the locations of dwelling units can be used as a proxy for locations of agricultural land parcels. Despite the rural economic reform in China implemented in the late 1970s and early 1980s, all land still belongs to the government (Xu et al. 1999). Residents in Wolong were "assigned" parcels of land for farming over a period of time (from several years to a couple of decades). In other words, farmers have the right to use the land for agricultural purposes but do not own the land and do not have the right to sell or transfer any land. The implications of this type of farmer-land relationship for land-cover change are not clear and need to be understood for future research efforts.

### 4.2.2 Socioeconomic Data

Micro-level factors (socioeconomic conditions at the household level) in each household include amount of annual income, sources of income, amount of expenses, aspects of expenses (e.g., schooling), labor force, land area, area of the house, crop production, number of livestock (e.g., pigs), use patterns of natural resources (e.g., fuelwood), attitudes toward, out-migration, and amount of electricity for cooking, heating, and electronic appliances (such as TVs and radios). Attitudes and perceptions were analyzed on the basis of individuals, whereas other data (e.g., amount of fuelwood consumption) were examined using households as the unit of analysis. We began micro-level socioeconomic surveys in 1996. The sample size depended on specific research objectives. For example, for household fuelwood consumption, we surveyed 220 households (An et al. n.d.[a]). In addition, household socioeconomic conditions (e.g., number of pigs, area of cropland) are available from the 1996 Agricultural Census and the "1999 Wolong Land Contract and Operation Registration" (Wolong Nature Reserve 1999) for each household. These data, including the number of land parcels, cropland area, and types of land (e.g., newly developed land, abandoned land, area returned for reforestation, and area for house building), helped us parameterize or calibrate our models (Liu et al. 1999a; An et al. 2001).

Macro-level socioeconomic factors (factors beyond the household level, such as roads, trade centers, administration buildings, bridges, dams, and schools) also influence population-environment interactions (Shivakoti et al. 1999) because their relationships with households (e.g., households' distances to major roads or trade centers) are different. For example, children in households that are far away from schools may have less chance for education. We began to measure these macro-level socioeconomic factors in 2000. The measurements include these factors' locations and timing of occurrence. We obtained the information regarding the timing of occurrence from the records of the Wolong Administration Bureau, or by interviewing local residents, officials, and other stakeholders. For example, by interviewing schoolteachers we obtained information about the years when the schools (elementary, middle, and high schools) were built. The locations of these factors were measured using GPS receivers, from remote sensing imagery (IKONOS), or from topographic maps. For example, the stream coverage was digitized from the topographic maps and the road coverage was digitized from the IKONOS imagery and verified with GPS samples. Through GIS and spatial statistics, we will be able to link macro-level data with micro-level data. Examples of results from such linkages include distances of dwelling units from roads, schools, forests, and local markets. Similarly, we can measure the distances between residential areas and areas of suitable habitat for pandas as well as the distances between fuelwood collection sites and panda habitat.

### 4.2.3 Behavioral Data

In 1998, we performed a set of interviews with 329 people (approximately 8 percent of the total population) regarding their activities in the previous year (i.e., 1997) to understand who had a direct impact on the land. Through these interviews we found that the activities of local residents in Wolong were quite diverse, including farming, fuelwood collection, collection of Chinese herbal medicines, road construction and maintenance, small business (e.g., small restaurants), and transportation. With regard to fuelwood collection, approximately 76 percent of the local residents who participated were 25–59 years old, while 21 percent, 2 percent, and 1 percent of the labor for fuelwood collection were 15–24, 60 or older, and 14 or younger, respectively. Furthermore, nearly all the people who collected fuelwood were males. Most women, the elderly, and children do not have a direct impact on forests through fuelwood collection, but their indirect impact must be assessed. For example, households with one or more senior residents consume more fuelwood than those without seniors because the heating season for the elderly is longer (starting early and ending late) (An et al. 2001).

The amount of fuelwood consumption has been measured at the household level (Liu et al. 1999a; An et al. 2001), but we have not yet linked the specific locations of fuelwood collection with individual households due to the enormous difficulty in pinpointing specific locations of harvesting by individual households over time. This difficulty stems from several factors. First, locations of fuelwood collection areas are often several hours (on foot) away from dwelling units owing to the exhaustion of eligible forests near dwelling units, although local residents usually collect fuelwood within administrative boundaries and at locations as close to their dwelling units as possible. Second, the locations of fuelwood collection change over time after the eligible trees in previous locations have been harvested, similar to land-use practices among pastoralists (BurnSilver et al. this volume). Third, fuelwood collection usually takes place in the winter, but our field data collection often occurs in the summer when students in the project are not in class and faculty members are not teaching. Fourth, some residents may not want others to follow them to their sites of fuelwood collection because some of their activities are illegal or against the reserve policy in terms of collection sites, extent of harvesting, species of trees harvested, and sizes of trees harvested. Because of these challenges, we have been testing an alternative approach to identifying locations of fuelwood collection. Thus far, we have interviewed several dozen households and have asked the respondents to indicate approximate locations for fuelwood collection on high-resolution aerial photographs or IKONOS maps. We then made notations on the maps, digitized them, and created location databases and maps using GIS. Currently we are in the process of using field ground-truth data to verify these sites, and we are testing the accuracy of information collected through interviews and high-resolution maps.

## 4.3. Systems Modeling and Simulation

A major purpose of building systems simulation models is to synthesize information from various sources (Costanza et al. 1991; Liu et al. 1999a; An et al. 2001). Thus far, we have built two major types of models: one at the household level (An et al. 2001) and the other at the reserve level (Liu et al. 1999a). The household-level model (Figure 5) integrates household demography (e.g., household size and age and schooling years of each family member), household economy (land-use activities, income/expense sources, etc.), attitudes toward issues of interest (e.g., childbearing), and fuelwood consumption. An et al. (2001) found that the amount of fuelwood consumption is a function of household size and composition, cropland area, and number of pigs raised. The demographic-socioeconomic-ecological model was verified and validated by an independent set of data. Statistical analyses showed no significant differences between the observed and predicted amounts of fuelwood consumption, indicating that the model mimicked the actual amounts of fuelwood consumption accurately.

The reserve-level model considered the collective impact of all households (Liu et al. 1999a). The model was developed using C++ (Liu 1993) with linkages to a GIS. We used computer simulations to project possible demographic and ecological consequences, given different policy scenarios (see Figure 2). For example, under different birthrates and emigration rates, as well as compositions of emigrants (e.g., younger vs. older residents) and levels of fuelwood consumption, we were able to observe future dynamics of human population size and structure as well as panda habitat over a period of fifty years. Our computer simulations (Liu et al. 1999a) indicated that even if only 22 percent of young people (17–25 years old) relocated (e.g., through going to college, finding jobs elsewhere, and marrying people outside the reserve), the human population size in the reserve would be reduced from 4,300 in 1997 to about 700 in the year 2047, and the giant panda habitats will recover and then increase by 7 percent.

Under the status quo, however, the human population size in the reserve will increase to approximately 6,000 and about 40 percent of the giant panda habitats will be further reduced by the year 2047. The results suggest that relocating young people is socially acceptable, economically efficient, and ecologically sound. Our surveys indicate that most young people are willing to relocate, especially if they can receive higher education (Liu et al. 2001b). Furthermore, even though parents and grandparents generally do not want to relocate themselves, they are highly supportive of the relocation of the youth and feel quite proud if these young people can receive higher education (Liu et al. 1999a; Liu et al. 1999b). Furthermore, the costs for relocating young people would be lower, because relocating one young person is equivalent to moving several seniors; young people can have children, while seniors do not have childbearing capacity. Because young people and adults are the direct force behind land-use and land-cover change, reduction in the number of young people will reduce the number of future adults and thus minimize human impacts on forests and panda habitat in Wolong.

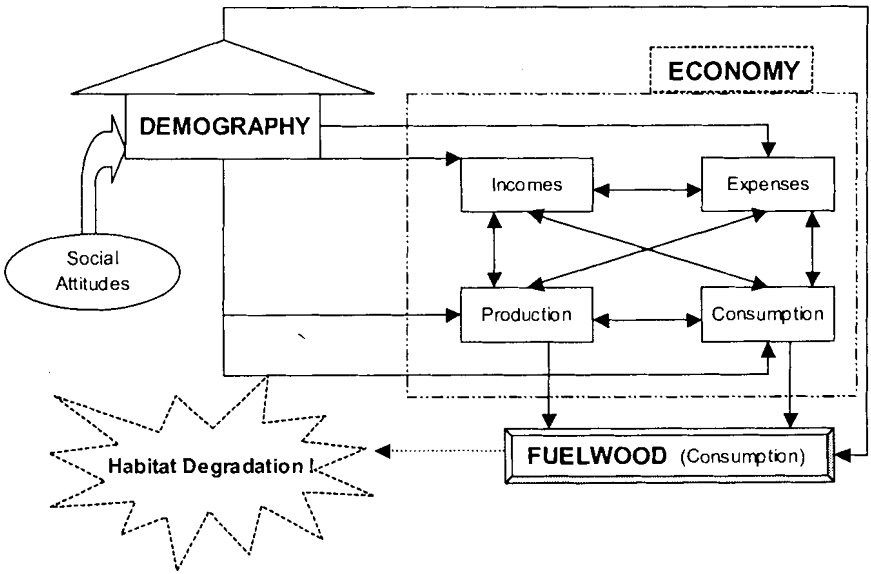


*Figure 5.* Conceptual structure of a household-level model (An et al. 2001)

## 5. CONCLUSIONS AND DISCUSSION

Linking ecological, socioeconomic, demographic, and behavioral factors was essential for us to understand the patterns and mechanisms of changes in land cover and panda habitat in Wolong Nature Reserve. The conceptual framework (Figure 2) provided a useful guidance in our research endeavor. The complementary expertise in different disciplines made the linkages technically possible. To a large extent, effective linkages among various factors resulted from close interactions among collaborators in different subject areas. Clear and explicit communication with each other was the key. It took a while for us to learn the essentials (methods, concepts, and theories) of different disciplines. In this learning process, we have also recognized the differences in meaning of the same terms and in standards among disciplines. For example, *population* almost always means *human population* to social scientists, but it means *animal population* to ecologists. Ecologists perceived that an accuracy of 80 percent remote sensing imagery classification was quite low, although this level of accuracy is more than acceptable to the remote sensing community.

Large and topographically complex study areas like Wolong provide both advantages and challenges for technical linkages among various components. On the one hand, our large area offers a heterogeneous environment and allows us to observe a variety of socioeconomic-demographic-ecological conditions. On the other hand, the heterogeneity requires relatively large sample sizes. The scattered distribution of households across high mountains and deep valleys made our surveys very time consuming and physically exhausting. Vehicles could transport researchers to the foothills of the mountains along the only main road. To reach most households and collect most ground-truth data, however, walking or even crawling in the topographically challenging environment—with its various insects, leeches, ticks, and snakes—is the only feasible way.

For interdisciplinary projects like ours, it is probably not remarkable that there are some surprises. Most importantly, the amount of time required to collect some data was more than what we had originally anticipated. In addition, the costs were somewhat underestimated. At present, we are using IKONOS data (1-m resolution) to refine our analyses of land cover for part of the reserve. Ideally we would like to use IKONOS data for the entire reserve analysis if the high-resolution data are accessible without financial constraints. Of course, greater financial support would also enable us to have larger sample sizes for some data. There were, however, some good surprises as well. For example, the data collected and maintained by the reserve administration were more comprehensive than we had hoped, and we were able to obtain and use these data. The sketch maps from the 1996 Agricultural Census and from the 2000 Population Census helped us to identify relative locations of households. These census data also aided us in choosing appropriate strata for our stratified sampling designs. Some of our results were unexpected as well. One major unforeseen outcome was that high-quality panda habitat in the reserve had been lost and had become fragmented more rapidly after the reserve was established (Liu et al. 2001a).

There are many challenges and opportunities in linking ecological, socioeconomic, demographic, and behavioral factors. Advanced technologies such as remote sensing, GIS, and systems modeling are useful tools to make the linkages technically possible, but amounts of time, financial support, and coordination among researchers of different expertise may increase with the extent of linkages. A critical need is to change the culture of academic institutions so that researchers doing interdisciplinary research can be adequately rewarded. Through our study and other studies presented in this book and elsewhere (e.g., ten examples listed in Liu 2001), we are optimistic that these challenges can be met, thanks to several unprecedented opportunities. First, funds are increasingly available from many funding sources. In the United States, these funding sources include the Biocomplexity Initiative at the National Science Foundation, the Population and Environment Program at the National Institute of Child Health and Human Development, and the Land-Use and Land-Cover Change Program at the National Aeronautics and Space Administration. Second, more researchers are interested in this rapidly growing field. Third, institutional culture is changing. More interdisciplinary research efforts are encouraged and supported. Fourth, policy-making processes and natural resource management require output from interdisciplinary research such as ours. It is our hope that the approaches linking various factors presented in this chapter can be applicable (with some modifications, of course) to other places. We believe that the urgent need for and growing interest in such comprehensive and integrated studies will bring to fruition the theories, methods, and applications for linking household and community surveys with remote sensing and GIS.

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## REFERENCES

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: 31–50.

An, L., F. Lupi, J. Liu, M. Linderman, and J. Huang. n.d.[a] (forthcoming) "Modeling the Choice to Switch from Fuelwood to Electricity: Implications for Giant Panda Habitat Conservation." *Ecological Economics* (in press).

An, L, A. Mertig, and J. Liu. n.d.[b] (forthcoming) "Adolescents' Leaving Parental Home in Wolong Nature Reserve (China): Psychosocial Correlates and Implications for Panda Conservation." In review.

Bilsborrow, R., and H. Okoth-Ogendo. 1992. "Population-Driven Changes in Land Use in Developing Countries." *Ambio* 21: 37–45.

China's Ministry of Forestry and WWF. 1989. *Conservation and Management Plan for Giant Pandas and Their Habitat.* Beijing: Ministry of Forestry.

Costanza, R., H. Daly, and J. Bartholomew. 1991. "Goals, Agenda, and Policy Recommendations for Ecological Economics." In R. Costanza, ed., *Ecological Economics: The Science and Management of Sustainability* (New York: Colombia University Press), 1–20.

Dillman, D. 1978. *Mail and Telephone Surveys: The Total Design Method.* New York: John Wiley & Sons.

Dompka, V. 1996. *Human Population, Biodiversity and Protected Areas: Science and Policy Issues.* Washington, D.C.: American Association for the Advancement of Science.

Ehrlich, P. 1988. "The Loss of Diversity: Causes and Consequences." In E. O. Wilson, ed., *Biodiversity* (Washington, D.C.: National Academy Press), 21–27.

Giant Panda Expedition. 1974. "A Survey of the Giant Panda *(Ailuropoda melanoleuca)* in the Wolong Natural Reserve, Pingwu, Northern Szechuan, China." *Acta Zoologica Sinica* 20: 162–173.

He, N., C. Liang, and X. Yin. 1996. "Sustainable Community Development in Wolong Nature Reserve." *Ecological Economy* 1: 15–23.

Hu, J., Q. Deng, Z. Yu, S. Zhou, and Z. Tian. 1980. "Biological Studies of Giant Panda, Golden Monkey, and Some Other Rare and Prized Animals." *Nanchong Teacher's College Journal* 2: 1–39.

IUCN. 1994. *United Nations List of National Parks and Protected Areas.* Cambridge: World Conservation Monitoring Centre and IUCN Commission on National Parks and Protected Areas.

Johnson, K., G. Schaller, and J. Hu. 1988. "Responses of Giant Pandas to a Bamboo Die-Off." *National Geographic Research* 4: 161–77.

Lillesand, T., and R. Kiefer. 1994. *Remote Sensing and Image Interpretation.* New York: John Wiley.

Linderman, M., J. Liu, J. Qi, Z. Ouyang, L. An, and J. Yang. n.d. (forthcoming) "Mapping the Spatial Distribution of Bamboo in a Giant Panda Reserve: Using Remote Sensing Data to Classify Understory Vegetation Cover." In review.

Liu, J. 1993. "ECOLECON: A Spatially Explicit Model for ECOLogical-ECONomics of Species Conservation in Complex Forest Landscapes." *Ecological Modelling* 70: 63–87.

———. 2001. "Integrating Ecology with Human Demography, Behavior, and Socioeconomics: Needs and Approaches." *Ecological Modelling* 140: 1–8.

Liu, J., M. Linderman, Z. Ouyang, L. An, J. Yang, and H. Zhang. 2001a. "Ecological Degradation in Protected Areas: The Case of Wolong Nature Reserve for Giant Pandas." *Science* 292: 98–101.

Liu, J., M. Linderman, Z. Ouyang, and L. An. 2001b. "The Pandas' Habitat at Wolong Nature Reserve: Response." *Science* 293: 603–604.

Liu, J., Z. Ouyang, W. Taylor, R. Groop, Y. Tan, and H. Zhang. 1999a. "A Framework for Evaluating Effects of Human Factors on Wildlife Habitat: The Case of the Giant Pandas." *Conservation Biology* 13(6): 1,360–1,370.

Liu, J., Z. Ouyang, Y. Tan, J. Yang, and S. Zhou. 1999b. "Changes in Human Population Structure and Implications for Biodiversity Conservation." *Population and Environment* 21: 45–58.

Moran, E., E. Brondizio, P. Mausel, and Y. Wu. 1994. "Integrating Amazonian Vegetation, Land-Use, and Satellite Data." *BioScience* 44: 329–338.

Ouyang, Z., J. Liu, and H. Zhang. 2000. "Community Structure of the Giant Panda Habitat in Wolong Nature Reserve." *Acta Ecologia Sinica* 20: 458–462.

Pebley, A. 1998. "Demography and the Environment." *Demography* 35: 377–389.

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

Schaller, G., J. Hu, W. Pan, and J. Zhu. 1985. *The Giant Pandas of Wolong.* Chicago: University of Chicago Press.

Shivakoti, G., W. Axinn, P. Bhandari, and N. Chhetri. 1999. "The Impact of Community Context on Land Use in an Agricultural Society." *Population and Environment* 20: 191–213.

Tan, Y., Z. Ouyang, and H. Zhang. 1995. "Spatial Characteristics of Biodiversity in Wolong Nature Reserve." *China's Biosphere Reserve* 3: 19–24.

Turner, B. L., II, W. Meyer, and D. Skole. 1994. "Global Land-Use/Land-Cover Change: Towards an Integrated Study." *Ambio* 23: 91–95.

Vitousek, P., H. Mooney, J. Lubchenco, and J. Melillo. 1997. "Human Domination of Earth's Ecosystems." *Science* 277: 494–499.

Wenchuan County. 1983. *Statistics of Population Census of 1982.* Sichuan Province, China.

Wolong Nature Reserve. 1996. *Agricultural Census Data.* Wenchuan County, Sichuan Province, China.

———. 1999. *1999 Wolong Land Contract and Operation Registration.* Wenchuan County, Sichuan Province, China.

———. 2000. *Population Census Data.* Wenchuan County, Sichuan Province, China.

Wilson, E. O. 1988. *Biodiversity.* Washington, D.C.: National Academy of Science Press.

Xu, J., J. Fox, X. Lu , N. Podger, S. Leisz and X. Ai. 1999. "Effects of Swidden Cultivation, State Policies, and Customary Institutions on Land Cover in a Hani Village, Yunnan, China." *Mountain Research and Development* 19: 123–132.

Zhang, H., D. Li, R. Wei, C. Tang, and J. Tu. 1997. "Advances in Conservation and Studies on Reproductivity of Giant Pandas in Wolong." *Sichuan Journal of Zoology* 16: 31–33.