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Modeling the spatio-temporal dynamics and interactions of households, landscapes, and giant panda habitat

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Abstract

Human modification of land-cover has been a leading cause of floral and faunal species extirpation and loss of local and global biodiversity. As natural areas are impacted, habitat and populations can become fragmented and isolated. This is particularly evident in the mountainous areas of southwestern China that support the remaining populations of giant pandas (*Ailuropoda melanoleuca*). Giant panda populations have been restricted to remnants of habitat from extensive past land use and land-cover change. Households are a basic socio-economic unit that continues to impact the remaining habitat through activities such as fuelwood consumption and new household creation. Therefore, we developed a spatio-temporal model of human activities and their impacts by directly integrating households into the landscape. The integrated model allows us to examine the landscape factors influencing the spatial distribution of household activities and household impacts on habitat. As an example application, we modeled household activities in a giant panda reserve in China and examined the spatio-temporal dynamics of households, the landscape, and their mutual interactions. Human impacts are projected to result in the loss of up to 16% of all existing habitat within the reserve over the next 30 years. In addition, we found that accessibility largely controls the spatial distribution of household activities and considerable changes in management and household activities will be required to maintain the current level of habitat within the reserve.

Keywords: Landscape; Households; Giant panda; Habitat; Model; Human impacts

1. Introduction

Appropriation of natural areas through urban and agricultural expansion has drastically altered much of the land surface (Vitousek et al., 1997; Rutledge et al., 2001). Modification of habitat through less intense land use such as fuelwood collection has also

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resulted in drastic changes in natural systems (Liu et al., 2001). These changes have enormous implications for ecosystem processes, biodiversity, and species persistence (Ceballos and Ehrlich, 2002). This is particularly relevant for the conservation of the giant panda (*Ailuropoda melanoleuca*). Habitat destruction and poaching have reduced the wild population to approximately 1000 pandas (Schaller et al., 1985). Many studies have been conducted on panda biology and behavior (e.g. Schaller et al., 1985). Most of the studies are empirical or field based. There have been also a number of modeling studies, which have simulated panda population dynamics (Zhou and Pan, 1997), panda relationships to bamboo dynamics (Reid et al., 1989; Wu et al., 1996; Carter et al., 1999), and household preferences and characteristics related to panda habitat (An et al., 2001, 2002). However, few studies have examined the factors influencing the spatio-temporal dynamics of households, their impacts on giant panda habitat, and their mutual interactions (Liu et al., 1999). To better understand household impacts on giant panda habitat, we developed a model in which the interactions between households, the landscape, and giant panda habitat could be studied and based on the analyses provided practical information for conservation and management planning.

Much of human land-cover change is carried out at the household level as households are basic decision and consumption units (Liu et al., 2003). The rapid increase in the number of households increases the demand for more resources (Liu et al., 2003). Coupling household activities with natural processes is therefore essential to accurately model human impacts on natural systems, to increase our understanding of human interactions with landscapes, and to provide viable options for mitigating future impacts. Various approaches to modeling spatially explicit human activities and their impacts on natural systems have been developed, including statistical techniques (Mertens and Lambin, 1997), agent-based models (Berger, 2001; An et al., in press), and cellular approaches (Balzter et al., 1998). Statistical models have provided detailed information of the spatial dynamics of systems, but are often not conducive to generic frameworks (Lambin, 1994). More complex agent-based approaches allow increasingly detailed human interactions with each other and the environment in which they live. However, building descriptive agent-based models is often difficult given the complexity of the models and human–environment systems (Couclelis, 2001). Cellular models, discreet in time and space, allow for simplified modeling relationships and provide a structured environment in which various interactions and levels of detail can be studied (Benenson, 1999).

The overall goal of the model, Household And Landscape Integration Model (HALIM) was to develop a generalized modeling approach in which spatio-temporal household processes could be integrated into realistic landscapes. For this study, we used a generic spatially explicit cellular model to examine the interactions of households and panda habitat through their mutual relationships with the landscape. Using a generic cellular framework facilitated the use of detailed digital data to accurately describe the landscape and household characteristics while providing a means to integrate inherently different natural and household processes. Furthermore, this flexibility provides a practical and accessible framework in which varying aspects and complexity of socio-economic and natural systems and their interactions can be integrated.

As a preliminary study, we used HALIM to evaluate the spatio-temporal effects of landscape-level household activities on giant panda habitat in southwestern China by integrating households, forest cover, and wildlife habitat through their mutual relationships with the landscape. This allowed us to examine the individual spatio-temporal dynamics and the various interactions between the landscape, household activities, and wildlife habitat. Our specific aims of this study were to examine the influence of landscape-level household characteristics on the quantity and spatial distribution of panda habitat and to determine the landscape factors influencing these household activities. Using these results, we examined possible consequences of various policy scenarios, provided suggestions to mitigate damage to the remaining panda habitat, and identified important landscape, household, and habitat interactions for future modeling efforts.

2. Methods

2.1. Study area

Our field study was conducted in the Wolong Nature Reserve in southwestern China (Fig. 1), located

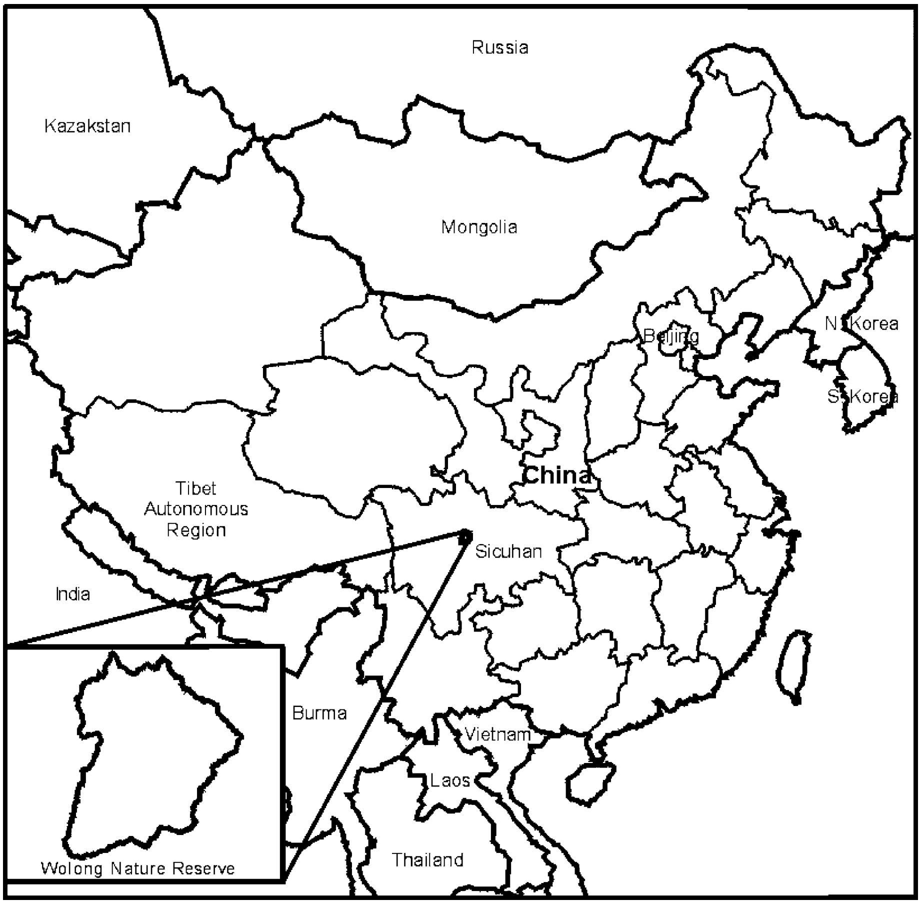

Fig. 1. Wolong Nature Reserve lies in the Qionglai Mountains between the Tibetan plateau and Sichuan basin.

between 102°52′ and 103°24′E and 30°45′ and 31°25′N. Wolong is one of the largest reserves (covering approximately 2,00,000 ha) dedicated to giant panda conservation and is estimated to contain about 10% of the remaining wild panda population (Zhang et al., 1997). Approximately 40% of the reserve is currently forested. Elevations range 1200–6525 m creating several climatic zones and consequently high biological diversity. The distribution of overstory vegetation in the reserve is related to the elevation.

Most forests in the reserve were logged (either clear cut or selectively cut) from 1916 until the reserve was established in 1975, reaching peak intensity between 1961 and 1975 (Schaller et al., 1985). Commercial logging typically resulted in relatively large clearcuts distributed throughout the reserve. Logging has been officially banned in the reserve since 1975; however, to varying degrees illicit logging does continue (M. Linderman, personal observation). Other human activities have also been a major contribution to forest loss and, consequently, to the spatial distribution of habitat (Liu et al., 1999, 2001).

In 2001, approximately 4440 local residents in about 1000 households resided within the reserve. The majority of these residents are farmers with the primary economic activities consisting of farming maize and vegetables, raising livestock such as pigs and yaks, and collecting wild herbs. A household usually relies on fuelwood for heating, cooking, and livestock feed preparation (An et al., 2001). Selective logging for household fuelwood collection typically changes the species composition in the overstory and reduces canopy cover until all overstory vegetation is removed. Since 1974, immigration and new household creation have largely been dictated by local policy with immigration restricted by marriage and new household creation limited or inadvertently encouraged through various policies. Households have traditionally focused on subsistence agriculture, but increasing access to markets has provided some cash crop opportunities.

2.2. Data and model parameterization

Several sources of data were used as model input or used to parameterize and validate the model. Satellite data and topographic maps were resampled to a pixel size corresponding to the landscape grid and used to describe the abiotic features and the distribution of household activities and vegetation throughout the reserve. Socio-economic and demographic data were collected from local government agencies and our household surveys conducted from 1998 to 2001 (An et al., 2001) to determine fuelwood collection, household locations, and household creation rates. Literature on panda behavior and landscape analyses of habitat was used to parameterize the habitat sub-model (Schaller et al., 1985; Ouyang et al., 1996; Liu et al., 2001).

Abiotic information was derived from topographic maps of the reserve. A Digital Elevation Model (DEM) was interpolated from digitized 100-m contours. Slope and aspect data were derived from the DEM. Information on the distribution of forests was obtained from the classification of four dates (1965, 1974, 1987, and 1997) when remote sensing data were obtained. The 1965 data are Corona stereo-pair photographs acquired as part of the Corona photo-reconnaissance satellite project (USGS Eros Data Center, Sioux Falls, South Dakota). The 1974 data are Landsat MSS images, and the 1987 and 1997 data are Landsat TM images. To account for the spectral and spatial differences between the data, each image was visually interpreted into forest and non-forest areas (for classification details see Liu et al., 2001).

Uncertainty in the 1965 stand volume of the various forest types posed the most difficult parameterization problem. While basic coverage information was available from satellite photographs, data on the average volume throughout the reserve were scant. Quantitative information dating back nearly 40 years is either difficult to obtain or non-existent. Schaller et al. (1985) suggest that much of the reserve was commercially logged from 1916 until 1975. Measurements taken in the late 1990s indicated much of the lower altitude forests to be well below old-growth volumes. Average volumes for broadleaf forests below 2600 m were approximately 80 m^3/ha. It is likely that these forests were the first to be harvested in the first half of the century and have regrown to current volume levels.

Based on regrowth data for the broadleaf forests in Wolong, we estimated the average volume for 1965 to be approximately 45 m^3/ha. Stand volume for subalpine conifers was on average approximately 300 m^3/ha. Subalpine stand volume was high enough such that variations in estimates would not significantly influence the model results. Forest regrowth was included in the model to allow for previously logged regions to regenerate and the addition of biomass and regrowth in selectively logged cells. Separate regrowth models were developed for each forest type based on species composition, stand age, and altitudinal zone. Model parameters were derived from over 30 plots distributed throughout the reserve (Liu et al., 1999), and approximation of species regrowth and yield models was derived from the data of the Sichuan Department of Forestry (Yang and Li, 1992).

A household survey was conducted from 1998 to 2001 and included 220 of the households within the reserve (An et al., 2001). Households were queried on fuelwood use, fuelwood collection, agricultural activity, household creation, and other associated socio-economic and demographic information. Additional socio-economic and demographic information was obtained from local government records. Census information was obtained from each township within the reserve. Local governments also maintain information on land allocated to each household. From the surveys and census data, it was found that each household maintains on average 0.7 ha of agricultural land. Including the area of the physical house, garden area, and other buildings, the typical total area is approximately 0.8 ha. Therefore, the scale of the model was chosen to be 90 m × 90 m (0.81 ha). New households have been added to the reserve at a rather steady number each year between 1965 and 1997. On average, approximately 24 new households were created each year.

We measured the location of each household through the use of field measurements or Ikonos 1-m resolution satellite imagery. Ikonos imagery acquired in 2000 by SpaceImaging was georeferenced with ground control points measured using a Global Positioning System with sub-meter accuracy (Trimble Pathfinder Pro XRS receiver and Community Base Station). We then identified households in the images and recorded the location. We used all households created on or before 1965 to create the initial distribution of households to correspond to the initial 1965 forest cover information.

Fuelwood use was calculated based on a survey of over 50 households and physical measurements of annual use (An et al., 2001). The volume of wood varied between 8 and 30 m^3 and averaged 15 m^3. A base annual volume of wood used by each household in the model was then 15 m^3. We derived preference for fuelwood collection and household creation sites by comparing DEM and slope coverages, and house locations and fuelwood sites. Distances between household locations to fuelwood collection sites varied from 50 m to over 5 km. The average distance for 100 households surveyed was approximately 500 m. Households preferred to collect fuelwood in flat areas (<20° slope) and had a decreasing probability relative to elevation.

Behavioral studies have described panda habitat as a function of forest cover, slope, and altitude (Schaller et al., 1985; Ouyang et al., 1996; Liu et al., 2001). Therefore, we determined habitat suitability using a multiplicative combination of the three factors (forest cover, altitude, and slope) available for the 30-year time span (Liu et al., 2001). Because non-forested areas are considered unsuitable habitat for the giant panda, forest/non-forest classifications were multiplicative factors of 1 or 0, respectively. Slope and altitude multiplicative factors were proportional to the observed use by pandas.

2.3. Model description

Our model (HALIM) was developed using SELES (Spatially Explicit Landscape Event Simulator) (Fall and Fall, 2001; Fall et al., 2001). SELES is a high-level programming language that facilitates modeling of the temporal and spatial dynamics of gridded landscapes. SELES also allows the incorporation of georeferenced raster data, the definition of systems that interact on gridded landscapes, and the temporal and spatial dynamics of these systems. SELES provides the flexibility to incorporate these various systems through sub-models and individual modeling aspects of Markov chains, cellular automata, percolation models and others according to the process being modeled.

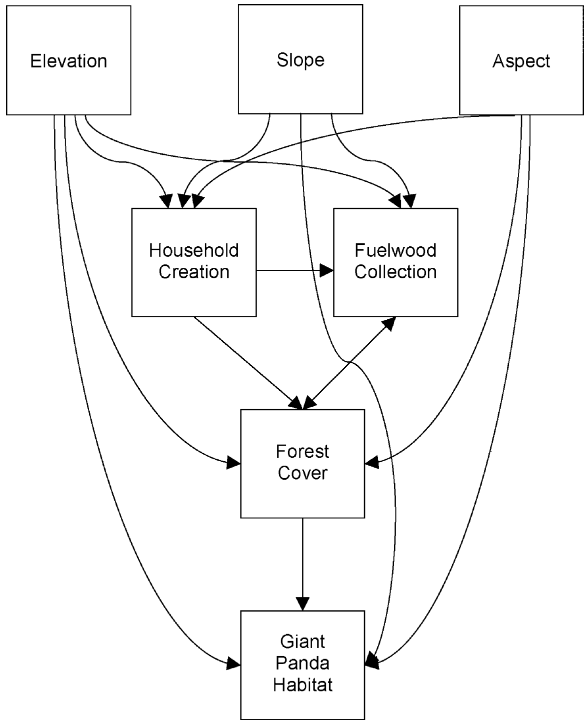

Fig. 2. A conceptual flow schematic diagram of the model.

HALIM includes four sub-models: fuelwood collection, household creation, forest regrowth, and panda habitat. The resulting impacts of the distribution of household activities are integrated directly into giant panda habitat models and allow model predictions to be measured in terms of changes to landscape indices of panda habitat. The sub-models and their interactions are shown in Fig. 2. Household activities and forest dynamics are influenced by the abiotic characteristics of the landscape. Each of the household activities influences the spatial distribution of forest cover. The forest regrowth sub-model allows for forest re-establishment and annual growth of non-climax forests. Finally, the suitability of giant panda habitat is determined from forest cover along with abiotic factors (Liu et al., 2001).

The landscape was divided into a regular lattice composed of 90 m × 90 m grid cells. For this model, the probability of the initiation of most sub-model events (e.g. fuelwood collection, household creation, etc.) occurring at each grid cell was determined by the pixel values (data layer values) of the cell and, depending on the sub-model, surrounding cells. The number of sub-model events is determined by the sub-model parameters with the location of the event stochastically determined by a relative cell probability (e.g. a cell with a probability of 0.5 has twice the probability of the occurrence of a landscape event compared to a cell with a 0.25 probability, but does not have a 50% probability of an event occurrence). Depending on the process of interest the model also allows for landscape events to spread to neighboring cells (e.g. if a cell does not contain sufficient fuelwood for the annual collection of a household's fuelwood needs, necessary fuelwood collection can take place in a neighboring cell).

The sub-models are described below along with examples of the parameters and probability functions:

- *Fuelwood collection* – It was assumed that household residents collect fuelwood based on availability, accessibility, and previous fuelwood collection activity. Typically, fuelwood is collected around the household. As these areas are diminished, foraging extends to the neighboring areas characterized by easy accessibility (Liu et al., 2001). Many residents have been forced to travel several kilometers to collect annual stocks of fuelwood (An et al., 2001). Accessibility is characterized in this model by the distance to collection site, slope, and elevation and is defined as a cost function relative to the distance to roads and main paths and topographic variability (i.e. slope and elevation difference along the path to the cell location). The probability function was a linearly decreasing function of increasing cost:
$$P(\text{fuelwood}|\text{cost}) = \left(1 - \left(\frac{\text{Cost}}{\text{Maximum cost}}\right)\right)$$
Forest cover and average yield per hectare determined availability. Households are also more likely to return to the same cell location, if sufficient forest volume exists, or neighboring cells of previous fuelwood extraction. Therefore, a higher probability of collection was assigned to cells previously harvested and to neighboring cells. The overall probability of fuelwood extraction for each forested cell is then a multiplicative combination of these factors.
- *Household creation* – The number of new households each year was predetermined based on potential policy and socio-economic impacts. For example, past trends have been relatively stable. Policies, however, have been shown to affect household creation. Therefore, a range of household creation rates about the past trend was examined. Each new household was presumed to establish its own agriculture land, clearing the forest area or occupying previously deforested area. The location of each new household was dependant on suitable agriculture land and proximity to transportation routes and other households. The household sub-model was, therefore, determined by three parameters: distance–cost factor to transportation, abiotic factors, and proximity to other households. The precise X and Y coordinates of the actual residence were not included in this model. Rather, households, including the physical residence, agriculture land, garden area, and various other buildings, were presumed to occupy cells of the landscape. Suitable agriculture areas are based on abiotic factors: slope, aspect, and elevation. While agriculture activity occurs on slopes up to 40°, low-slope areas are preferred. Preference for low-elevation areas was also considered. For example, based on survey data probabilities for household placement based solely on elevation were measured as:
$$P(\text{household}|e) = \begin{matrix} \{0.00\,(e > 2500)\} \\ \{0.08\,(2250 < e \leq 2500)\} \\ \{0.82\,(1750 < e \leq 2250)\} \\ \{1.00\,(e \leq 1750)\} \end{matrix}$$
In areas of higher elevation (e), preference was given to slopes facing south to maximize sunlight. Households were also more likely to develop land adjacent to previously established houses and within short distances (typically less than 2 km) of major transportation routes.
- *Forest cover* – Four forest categories (non-forest, evergreen broadleaf, deciduous broadleaf, and subalpine conifer) were identified throughout the reserve based on remote sensing, elevation, and species distribution (Schaller et al., 1985). Initial stand volume was estimated for each elevation zone based on approximate time and intensity of commercial logging activity. Each forested cell was assumed to increase in biomass and each non-forested pixel had a probability to re-establish based on proximity to other forest pixels and time since deforestation. Regrowth models were derived for each of the pre-

dominant species within each elevation zone from published and empirical data (Yang and Li, 1992). Regrowth is calculated based on species and approximations of logistic regrowth curves of total volume. An example of the calculation is given below:

$$V(t, V_{\mathrm{an}}, V_{\max}) = \begin{matrix} \{0.0\,(t < t_{\mathrm{lag}})\} \\ \{V + V_{\mathrm{an}}\,(t > t_{\mathrm{lag}} \text{ and } V < V_{\max})\} \end{matrix}$$

where t is the time since harvest, t_{lag} is a normally distributed lag time since harvest until re-establishment, V_{an} is the annual volume increment, and $V_{\max}$ is the maximum volume according to species type. Upper asymptotic limits on volume were controlled by stand maximum values rather than time due to concurrent fuelwood collection.

- *Habitat suitability* – The final habitat classification was a categorized suitability measure of four classes termed highly suitable, suitable, marginally suitable, and unsuitable (Liu et al., 2001). The impacts from household activities are reflected in the habitat suitability model as impacts from fuelwood activity and agriculture development. Measures of panda habitat quantity and suitability allow analysis of the temporal and spatial dynamics of, the influence of household characteristics on, and future giant panda habitat.

Landscape events (e.g. fuelwood collection, forest regrowth) occurred on an annual time frame. The first landscape event in the model each year is the establishment of new households and associated agricultural development. Each household then collects its annual fuelwood volume. At the end of the year, forest regrowth occurs for each forested cell and the suitability of panda habitat is updated.

2.4. Model validation and sensitivity analyses

Model validation and sensitivity analyses were based on simulations started in 1965 with the initial distribution of forest based on the classification of forest/non-forest categories from the 1965 Corona photographs. The original distribution of households was based on all households established prior to or in 1965. The sensitivity and validation simulations were run for 32 years to correspond to the latest remote sensing data available (1997). We measured sensitivity through varying individual parameters such as the rate of new household creation, fuelwood use, and forest characteristics and the relative influence of each individual parameter on the model output. Validation was done through comparison of model output over this time to measured habitat and household distributions.

We conducted sensitivity analyses for the household and fuelwood collection sub-models. We examined the sensitivity of the household sub-model to each of its components (abiotic, proximity, and cost function) by comparing scenarios excluding components or varying parameter estimations and the measured household distribution in 1997. This was done because we wanted to show the overall influence each function had on the selection of new households and because some functions could not be varied systematically (e.g. abiotic influences were based on conditional probabilities). We measured accuracy and calculated landscape metrics based on the average of 20 simulations. We also conducted systematic analyses of sensitivity of individual parameters for the fuelwood sub-model, such as the propensity to return to previous fuelwood collection sites and distance to fuelwood collection sites. Since parameterization of stand volumes for broadleaf forests below 2600 m contained relatively large uncertainty, several average stand volumes for the broadleaf forests were tested, including 30, 45, 60, 75, and 90 m^3/ha.

The accuracy of the predicted distribution of households was measured through comparison of predicted locations of households in 1997 to measured locations. Precise cell-by-cell prediction, however, was not the intention of this model. Foremost, the model is stochastic. In addition, households do not occupy all potential agricultural areas within the reserve. This leads to areas with similar probabilities available for household establishment. However, as the spatial arrangement of households may have an impact on habitat, particularly crucial secondary habitat, we also examined the percent of predicted households falling in close proximity (1, 2, and 3 cells) of measured households.

Impacts from fuelwood collection were measured by comparison of predicted and measured impacts to forest cover and habitat. Again, we did not expect exact correspondence between the model predictions and the measured distributions. Collections sites are, to a degree, stochastically chosen both by the model (i.e. as with households, not all potential fuelwood sites are chosen) and households (i.e. some degree of household decisions is unpredictable regardless of information available). In addition, the natural variability of the forests was not fully captured in the visual classifications (i.e. the visual interpretation of forest distribution did not include all forest gaps and edge complexity at a 90-m resolution) and illicit logging activities not included in the model make a direct accuracy assessment difficult.

To minimize the effect of natural and other influences on the accuracy assessments, we limited analyses to regions within 5 km of the current household distribution. This distance corresponds to the approximate maximum distance residents travel to collect fuelwood. Within the 5 km buffers, we used three validation methods: visual appraisals of multitemporal data; direct comparison to a supervised classification; and a comparison between landscape indices. We compared predicted fuelwood impacts on forest cover to visual classifications of forest cover from 1974 to 1997 satellite imagery (Liu et al., 2001). We compared measurements of the distribution of households and digital classifications of forest cover as measured in 1997 to final outputs from the model. Digital classification of the 1997 forest cover was possible with extensive ground sample data and provided a more detailed snapshot of the distribution of forest cover. Accuracy is reported as the percentage of predicted cells that correspond to measured cells (e.g. predicted non-forest versus measured non-forest cells). This ignores possible omission errors and was used because of the difficulty in distinguishing natural variability and human impacts (e.g. illicit logging) on forest cover from household activities even within 5 km of the households. Visual comparisons of model predictions and measured forest cover change are shown for comparison between commission and omission errors.

In addition, comparisons were made between the quantity of forest area and disturbed areas and landscape metrics such as patch size, shape, and complexity. Given the difficulty in distinguishing between timber logging, fuelwood collection, and natural variability in forest cover, simple accuracy comparisons of the model predictions relative to the measured landscape (particularly those from the detailed classification) do not provide a complete picture. The impacts measured from simulations were also reported as the landscape indices relative to the impact of interest (e.g. household distribution and forest cover). Indices used include total number of patches, mean patch size, corrected perimeter to area (p/a) ratio (Baker and Cai, 1992) describing patch compactness, and connectivity between patch centroids (Forman and Godron, 1986) that describes clustering of patches.

2.5. Household impacts

To examine the relative influences of different household conditions on the landscape, a variety of scenarios were run from 1965 until 2030. Each scenario was started using 1965 land-cover and household data. From 1965 to 1997, we based the model parameters on measured values. We then varied model parameters for 1997–2030 to examine the impacts of possible changes. These scenarios represent situations where new policies were introduced after 1997. Parameters we examined included fuelwood consumption per household and the household growth rate (or immigration/emigration rate). The length of the simulations was chosen based on the reliability of the model over the previous 32 years and to permit sufficient time to compare various scenarios and predict future impacts. We compared model scenarios based on impacts to giant panda habitat as deforestation from fuelwood and household construction removed habitat.

These scenarios included changes in fuelwood consumption levels of 30, 15, 10, 5, and 0 m^3/year/household and household growth rates of 36, 24, 12, 0, −12, and −24 new households created or removed each year after 1997, as well as combinations of these parameters. We chose these levels to reflect possible future household characteristics resulting from new policies and management efforts such as subsidies, restrictions, and/or increased accessibility to electricity. For example, efforts to limit fuelwood collection and reclaim agriculture land were initiated in 2000. Subsidies have been offered in exchange for maintaining forests. The administration has also attempted to restrict the location and quantity of fuelwood collection. Electricity prices are also currently unaffordable for most local farmers, particularly for heating and cooking purposes. Affordable and consistent alternative energy sources may influence fuelwood use in the future (An et al., 2002). Each of these or the combination of these changes may provide an incentive to reduce fuelwood use. In addition, efforts to encourage emigration out of the reserve are being instituted potentially decreasing the number of households. However, there is an increasing preference by younger adults to establish new households, and in response to subsidy opportunities, new households have actually recently increased at much higher rates than in the past. Therefore, to reflect the possible range of values, we chose fuelwood consumption levels ranging from the current maximum known household consumption (double the current average) to no fuelwood use. We also examined household creation rates varying from a 50% increase in household establishment to a net emigration of households to reflect policy influences on household creation over the next 30 years.

3. Results

3.1. Model validation and sensitivity

To examine the overall influence of the household sub-model parameters (e.g. topography, distance to transportation, and proximity to other households), several variations of the household sub-model were compared. We could not do a typical sensitivity test for this sub-model as some of the parameters were empirical look-up tables. Therefore, to examine the influence of each parameter, model outputs were compared for several combinations of sub-model parameters. For example, the household sub-model including all three hypothesized parameters (abiotic, distance, and proximity) (Fig. 3a) resulted in approximately the same number of patches and similar *p*/*a* ratio as the measured households. This sub-model also led to a 44% larger mean patch size, and slightly higher connectivity compared to the measured distribution (Table 1). Excluding abiotic preferences resulted in 71% more patches of households (Table 1) and caused some households to be placed in regions of atypical topographic relief (e.g. areas of extreme slope) (Fig. 3b). Excluding the distance and topographic variation from main transportation routes yielded a wide distribution of households (Fig. 3c). The number of patches was more than three times the measured distribution. Mean patch size and *p*/*a* ratio were both considerably lower (Table 1). And, the lack of a proximity factor resulted in decreased clumping of households (low connectivity), smaller patch size and an increase in the number of patches (Table 1) relative to the measured distribution of households (Fig. 3d).

Accuracy in terms of predicted household locations agreeing with measured cell locations of household distribution varied from 20 to 27% (Table 2). Incorporating all of the parameters hypothesized to influence household placement resulted in an accuracy of 27, 68, and 82, and 88% for predicted households within 0, 1, 2, and 3 cells from measured households (Table 2). This suggests that the model was predicting households essentially within the same areas as those measured to also contain households. Not including the distance function yielded the lowest accuracy of 63% for predicted households within 3 cells of measured households. The accuracy was 80% when a preference to create new households next to existing households was not included. Excluding the selection based on abiotic factors (i.e. slope and elevation) achieved an accuracy of 81% within 3 cells.

Sensitivity analyses conducted for each of the fuelwood parameters showed influences from variations in the distance and proximity factors (Table 3). Relaxing the tendency for households to collect fuelwood from previously cleared areas led to more fragmentation and is reflected in the landscape metrics. Variation of the proximity factor three times more likely to return to previous sites resulted in 35% fewer patches and 54% larger patch sizes. Reducing the proximity factor three times resulted and 52% more patches and 34% smaller patch size (Table 3). In addition, perimeter and connectivity indices show increasing clustering as the proximity factor is increased. Varying the distance cost factor by 20% resulted in similar results. Easing the influence of the distance factor generated more dispersed impacts occurring in smaller patches. This is seen in the patch characteristics with more and smaller patches and decreased *p*/*a* ratios and diminished connectivity (Table 3). Increased probability of using near areas conversely increased patch size, decreased patch number, and increased connectivity between patches. Patch size varied by 17.9–33.7% and patch number varied by 24.1 and 20.5% for a 20% decrease and increase in the cost factor, respectively (Table 3).

Trends in deforestation relative to initial stand volume were decreasing area of impact and reduced fragmentation since more volume was available in preferred collection areas (Table 3). While the outputs using each of the five initial volumes shown in Fig. 5 do seemingly conform largely to expectations, increased peripheral impacts occur at both increased initial

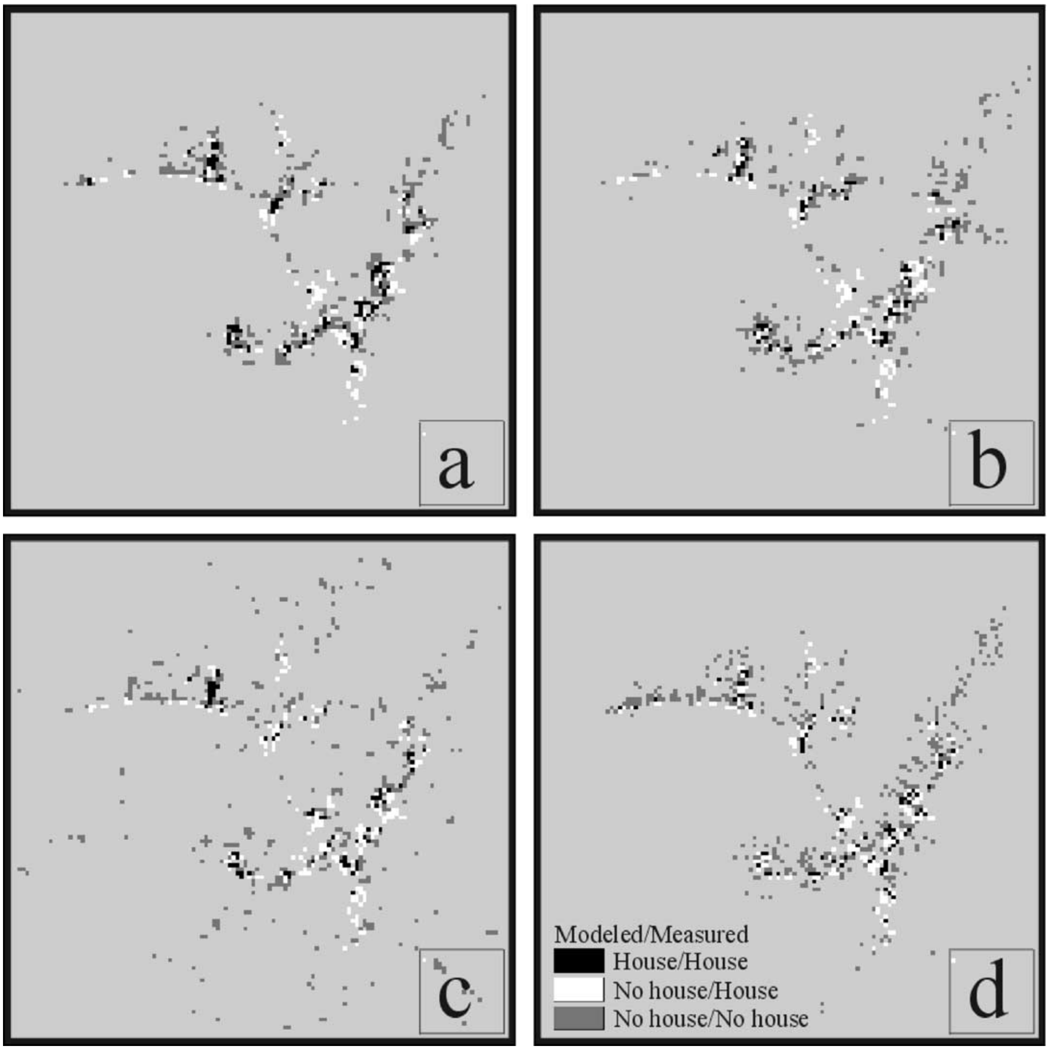

Fig. 3. Comparisons of the influence of the three multiplicative factors contained within the household sub-model. Accuracy of each scenario is shown relative to the measured households with corresponding predicted households and measured households shown in black, incorrectly predicted households are shown in dark gray, actual households where no households were predicted are shown in white: (a) shows the predicted household distribution in 1997 including all factors relative to the actual distribution; (b) is without abiotic preferences; (c) without cost factors; and (d) without proximity influences.

Table 1
Landscape characteristics of the measured households in 1997 (Households 1997) compared to model scenarios

	Number of patches	Mean patch size (ha)	*p*/*a* ratio	Connectivity
Households 1997	94.00	40931	1.49	0.046
All parameters	110.35	59101	1.50	0.053
No proximity factor	261.00	24905	1.41	0.015
No abiotic factor	161.90	40229	1.46	0.034
No cost factor	280.60	23152	1.29	0.009

Values are averages of 20 simulations for each scenario.

Table 2
Accuracy of the predicted household locations for the model scenarios relative to the household locations in 1997

	Cells			
	0[a]	1[b]	2[b]	3[b]
No cost factor	20.6 ± 1.3[c]	47.3 ± 2.4	57.1 ± 2.6	63.0 ± 2.4
No proximity factor	21.2 ± 1.1	54.3 ± 1.7	70.6 ± 1.3	79.8 ± 1.4
No abiotic factor	22.4 ± 1.4	55.8 ± 2.4	71.8 ± 2.0	81.2 ± 2.3
All parameters	27.4 ± 0.7	67.9 ± 1.5	82.5 ± 1.9	88.3 ± 1.9

[a] Accuracy as measured as predicted household locations occurring at measured household locations (titled 0).
[b] Predicted locations within 1, 2, and 3 cells (labeled 1, 2, and 3, respectively) of measured household locations.
[c] Uncertainties represent one standard error of the accuracies of the 20 simulations conducted for each scenario.

volumes and decreased volumes. Landscape metrics and overall model accuracy also follow this trend (Table 3). The lowest number of patches occurred when the initial forest stand volumes was 45 m^3/ha. Decreasing stand volume caused larger overall habitat loss, particularly the core area nearest to households; however, smaller peripheral impacts were more common. As initial stand volume was increased, the overall impact was diminished, however small pockets of impact emerged where more continuous impacts previously existed. These trends are clearly shown in the decreasing patch perimeter and mean patch size.

Fig. 4 shows a multitemporal comparison of the predicted 32-year simulation of household activity and the measured forest cover within 5 km of all households. There appears to be a good correspondence between the model outputs and measured forest distribution. The basic trends in forest cover are comparable between measured and predicted distribution of forest cover, though some differences from natural and other activities are apparent. In addition, the model was successful in capturing the basic trend in the distribution of households based only on the initial 1965 distribution of households.

Accuracy and sensitivity analyses were done to determine the overall validity of the model and the influence of individual parameters. The accuracy of predicted impact sites relative to measured impact also reflects more concentrated impacts as initial volume is increased (Fig. 5). As fuelwood activity is focused on core areas near households, model accuracy increases. At an initial stand volume of 30 m^3/ha, the overall prediction accuracy is approximately 55%. As the volume increased to 90 m^3/ha, model accuracy increased to 64% (Table 3). The increase in accuracy is largely a result of smaller areas being affected only near households and decreased influence of stochasticity in choosing distant fuelwood sites.

Table 3
Sensitivity of individual factors used within the fuelwood sub-model

Factor	Parameter	Number of patches	Mean patch size (ha)	*p*/*a* ratio	Connectivity index
Proximity*	0.33	125.2	75.8	1.668	0.719
	1	**192.2**	**49.2**	**1.606**	**0.336**
	3	291.5	32.7	1.538	0.170
Distance*	0.8	145.8	65.8	1.630	0.546
	1	**192.2**	**49.2**	**1.606**	**0.336**
	1.2	231.6	40.4	1.587	0.277
Initial volume (m^3/ha)	30	211.4	51.9	1.567	0.365
	45	**192.2**	**49.2**	**1.606**	**0.336**
	60	258.7	33.6	1.540	0.212
	75	265.9	30.3	1.502	0.161
	90	246.3	30.5	1.502	0.167

Values in bold represent hypothesized values.
* The proximity and distance coefficients are unitless multiplicative factors.

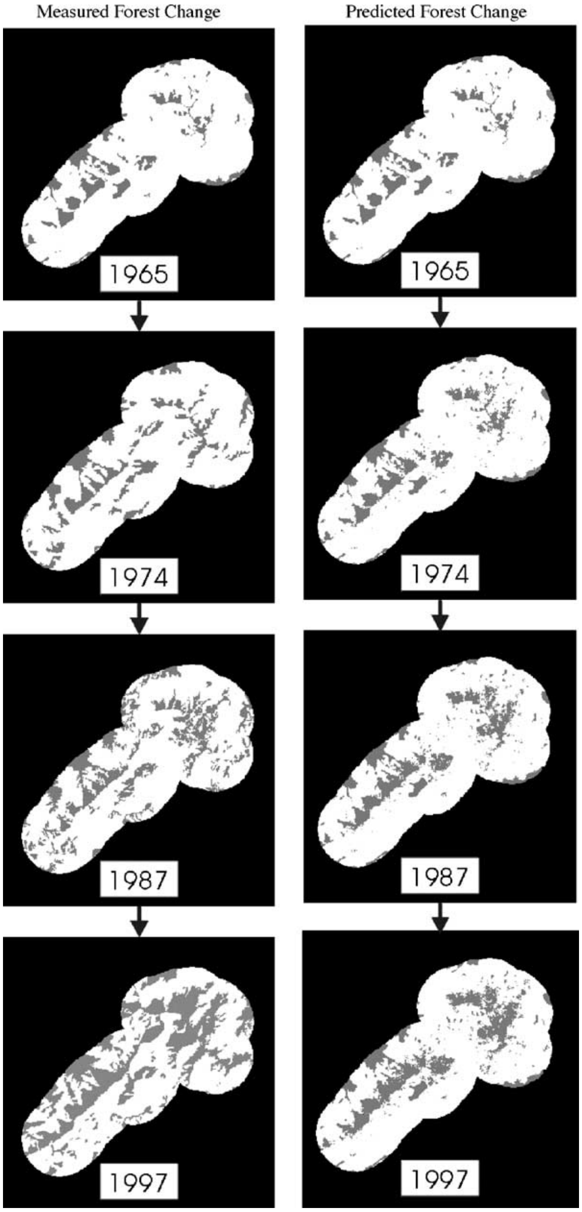

Fig. 4. Comparisons between visual classifications of satellite data from 1965, 1974, 1987, and 1997 and predicted forest cover due to household activities of corresponding years.

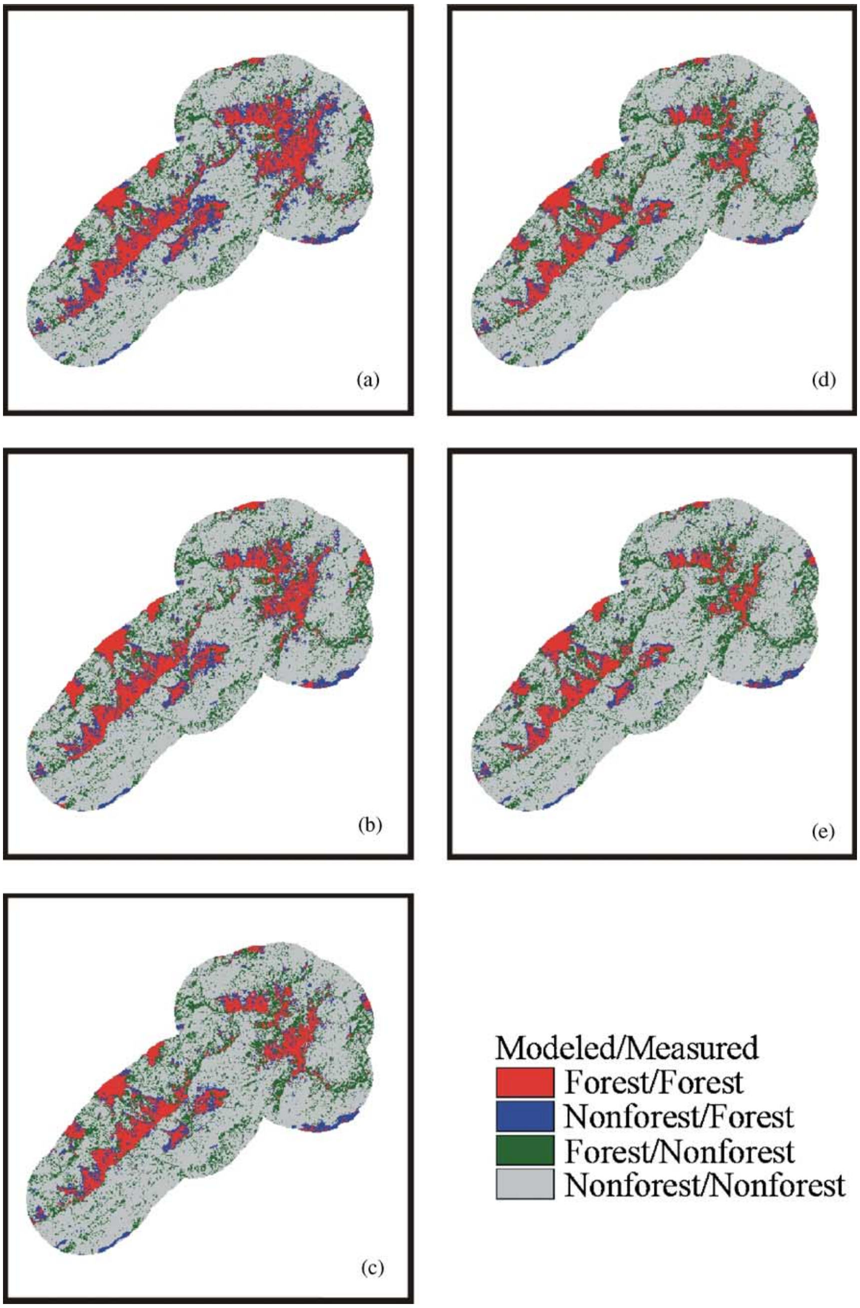

Fig. 5. Differences between predicted forest cover due to fuelwood collection compared to the digital classification at various starting volumes for low-elevation forests. Forest/forest and non-forest/non-forest categories represent agreement between predicted and measured forested and non-forested cells, respectively. The non-forest/forest category represents areas where the model predicted non-forest and the digital classification was forest. Forest/non-forest is the opposite case: (a–e) with starting volumes of 30, 45, 60, 75, and 90 m^3/ha, respectively.

Table 4
The influence of household characteristics on habitat over 65 years (1965–2030) relative to a baseline scenario of 0 new households per year and 0 m^3/year of fuelwood consumed after 1997

Household growth rate (households per year)	Fuelwood consumption (m^3/year)	Change in total habitat (%)	Change in habitat < 2600 m of elevation (%)
0	0	0.00	0.00
24	0	−0.06	−0.18
24	5	−1.34	−3.79
24	10	−2.61	−7.36
24	15	−3.32	−9.33
24	30	−6.06	−15.84
−24	15	−1.84	− 5.17
−12	15	−2.12	− 6.16
0	15	−2.77	−7.74
12	15	−3.21	−8.99
24	15	−3.32	−9.33
36	15	−4.31	−11.74
12	10	−2.26	−6.41

3.2. *Household impacts*

Projected household impacts on panda habitat are shown in Table 4. Current levels of household creation and fuelwood consumption caused nearly an additional 10% habitat loss below 2600 m of elevation compared to conditions in which no additional households and fuelwood collection occurred after 1997. Across the entire reserve, an additional 3% of habitat was lost compared to no new household impacts after 1997. Levels of household fuelwood consumption were systematically varied from 0 to 30 m^3/year to examine the influence of fuelwood consumption on habitat loss. An increase in fuelwood consumption after 1997 to 30 m^3/year would result in a nearly 70% increase in loss of habitat from the current level of 15 m^3/year. Over 6% of the reserve and nearly 16% of the low-elevation forest would be further impacted by doubling the consumption of fuelwood. Reducing fuelwood consumption by two-thirds reduced the loss of habitat below 2600 m of elevation by 59% compared to baseline scenarios. Forest re-establishment will only play a limited role over the next 30 years as re-establishment times are typically 30–50 years. In the next 30 years, habitat loss may largely be dictated by fuelwood consumption and increases in volume of current stocks. Therefore, a near cessation in fuelwood collection over the next 30 years is required to maintain levels of habitat as measured in 1997.

New housing development did not have the same influence on the total habitat co-opted by households as fuelwood consumption levels did. A 50% increase in the number of new household starts resulted in a 26% increase in low-elevation habitat loss relative to baseline scenarios. Cessation of new housing development following 1997 still led to the loss of nearly 3% of the entire reserve and 8% of low-elevation habitat compared to scenarios with no new households and no fuelwood consumption following 1997. And a net removal of 24 households per year (the same number previously being added per year) only resulted in a 45% reduction in habitat loss compared to baseline scenarios. As seen from a 50% increase in household creation with no fuelwood collection, increased population and resulting household creation contributed little to habitat loss because considerable areas around households are already cleared of forest cover. Modest reduction in both future new housing development and fuelwood consumption (12 households per year and 10 m^3/year) led to approximately 30% less habitat loss relative to current levels of new housing and fuelwood consumption.

4. Conclusions and discussion

HALIM was developed to examine the relationship of households to the landscape, to assess the influence of the landscape on household activities, and to provide a practical framework in which the interactions between households and the landscape can be simultaneously studied. The study does point out areas where further analyses are needed. For example, more detailed information on the biophysical characteristics such as total available biomass, growth rates, and efficiency in the conversion of biomass to fuelwood might contribute to the model. Except for the Corona photographs used for this study, very little information on the state of the forest in 1965 was available. However, comparing projections of household creation and fuelwood collection from 1965 to a time when there is more detailed information permitted a better estimate of forest conditions in 1965 and provided insight into factors contributing to habitat loss. Comparisons of predicted forest loss from 1965 to 1997 to measured forest conditions in 1997 for several scenarios of the average starting volume of low-elevation forest further suggests that these forests were already at relatively low volumes. The lower forest volume potentially magnified household impacts on the forests since 1965. It is possible that large-scale logging occurred concurrently with household fuelwood collection from 1965 until 1975 or later. While timber activities continued after 1975, researchers did not note any large-scale commercial logging in the reserve from 1983 to the 1990s. Forest loss after 1975 until 1997 was likely due to a combination of fuelwood collection and fine-scale timber activities, and exacerbated by already low-stand volumes from previous large-scale activity. As these forests are increasingly lost, fuelwood activities are moving to higher elevation forests with increasing losses of core habitat.

In addition, most decisions such as consumption level, propensity to use alternative energy sources, emigration rates, and new household formations are made at the household-level and are not explicitly modeled in this study. Increasingly complex models can be developed within the framework and the influence of household-level socio-economic information is being examined. In addition, other economic and behavioral drivers can be incorporated. However, using landscape-level household factors linked to the landscape already provided considerable insight into human impacts and potential mitigation strategies. The model provided insight into the historical trends and ecological conditions of the reserve, the driving factors of land-cover change, the potential consequences of household alterations of land-cover on panda habitat, the spatial arrangement of these impacts, and the intricate relationships between households and landscapes. The trend toward incorporating household-level data into models may provide more detailed information of these systems, but the necessity of such data to practically model household impacts at the landscape level should be considered.

Using landscape-level data, the model was able to predict household activities relatively accurately and parsimoniously. The placement of new households is explained by only four factors: distance to roads; proximity to other households; slope; and elevation. Using only these four factors; however, the model accurately predicts household creation nearly 90% of the time within 3 cells of the measured distribution of households. Fuelwood collection also is only based on a few landscape variables: distance to roads, previous fuelwood collection locations, slope, and elevation. Again, the model captures the trend in household reductions in forest cover. The simplicity (e.g. four household creation factors) and success of the model suggest a core set of landscape-level characteristics has a considerable influence on the spatial distribution of household activities.

HALIM also provided a means to examine the role of household characteristics on possible future impacts to giant panda habitat. Households were present in the reserve prior to the establishment of the current major transportation routes. New roads and the introduction of mechanized transportation have likely led to growth in agricultural activity along these routes and increased access to forests near roads away from households. In addition, as the reserve is situated in a mountainous area, topography plays a significant role in shaping the spatial distribution of household activities. Farming requires relatively flat land and easy access to transportation. In comparison, fuelwood collection is less dependent on the quality of collection sites than the cost factor of the distance to roads, the slope, elevation change, and overall accessibility of the location of collection sites.

Also, considerable changes in fuelwood consumption and/or household creation rates are required to maintain the current area of forest. While an increase in housing development itself led to only small decreases in forest area, even limited fuelwood consumption resulted in relatively large habitat losses. As most new households are being constructed on previously cleared land, the placement of new households is not likely to directly cause further loss of forest. However, even small amounts of fuelwood required for the large number of households already in the reserve has a greater impact on forest cover. These results are similar to estimates as measured by Liu et al. (1999) who showed that relatively high rates of emigration were necessary to restore habitat and suggested that most efforts should focus on reducing fuelwood collection and providing alternative energy sources for the current households while providing viable means and incentives to encourage emigration.

HALIM provides a basic framework that has practical application for human-dominated or -influenced landscapes. The model incorporates households directly into landscapes alongside naturally occurring dynamics and examines the influences of the landscapes on household activities. In addition, the method used is flexible enough to allow the integration of additional human and landscape components such as the more detailed socio-economic information discussed above and other natural processes such as household impacts on understory bamboo dynamics. This approach provides a useful means to better understand and predict impacts of households on wildlife habitat and interactions with the landscape.

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Appendix A

Sub-model probability functions and description of parameters and factors

Sub-model	Parameter	Factors
Household (h): $P(h\|ab, t, p)$	Local abiotic factors (ab): $P(h\|ab) = P(s)P(e)P(a)$	(See Appendix B)
	Transportation (t): $P(h\|t) = \text{clamp}(1 - \text{cost/max})$	Cost = distance × impedance Distance = horizontal + vertical distance Impedance = f(slope) Max = 2000 m (maximum household distance)
	Proximity to existing households (p): $P(h\|p) = P(d)$	Distance factor (d): $\{1.0\ (d < 90\,m)\}$ $\{0.1\ (d < 200\,m)\}$ $\{0.01\ (d > 2000\,m)\}$
Fuelwood (f): $P(f\|a, d, p)$	Availability (a): $P(f\|a) = P(v)$	Volume (v): $\{1\ (v > 0\,m^3)\}$ $\{0\ (v = 3\,m^3)\}$

Appendix A (*Continued*)

Sub-model	Parameter	Factors
	Cost function from household to collection site: $P(f\|d)$ = clamp(1 − cost/max)	Cost = distance × impedance Distance = horizontal + vertical distance Impedance = f(slope, road) Max = 9000 m (maximum fuelwood collection distance)
	Proximity to previous collection site (d)	Distance factor (d): $\{1.0\ (d \leq 90\,\mathrm{m})\}$ $\{0.1\ (d > 90\,\mathrm{m})\}$
Forest cover: $P(c\|g, r)$	Growth (g): $P(g\|v) = P(v)$	Volume (v): $\{1\ (v <$ maximum, $\mathrm{m}^3)\}$ $\{0\ (v =$ maximum, $\mathrm{m}^3)\}$
	Re-establishment (r): $P(r\|a) = P$(cut age)$P(e)P(p)$	Cut age: normal temporal Pdf(cut age, 10.0, 2.0) Elevation (e): $\{1\ (e \leq$ max species elevation$)\}$; $\{0\ (e >$ max species elevation$)\}$ Proximity (p): $\{1\ (p <$ 1/2 max species re-establishment distance$)\}$; $\{0.5\ (p <$ 1 max species re-establishment distance$)\}$; $\{0.1\ (p >$ 1 max species re-establishment distance$)\}$
Habitat	Suitability	Slope, elevation, aspect, and forest cover

Appendix B

Empirically derived probabilities of household location from abiotic factors

Sub-model	Parameter	Factors
Local abiotic factors, $P(h\|\mathrm{ab}) = \underline{P}(s)P(e)P(a)$	Slope (s): $P(\mathrm{ab}\|s) = P(s)$	$\{0.0\ (s > 50^\circ)\}$ $\{0.09\ (s > 40^\circ)\}$ $\{0.23\ (s > 30^\circ)\}$ $\{0.63\ (s > 20^\circ)\}$ $\{0.86\ (s > 10^\circ)\}$ $\{1.0\ (s \leq 10^\circ)\}$

Appendix B (*Continued*)

Sub-model	Parameter	Factors
	Aspect (a), $P(\text{ab}\|a) = P(a)$	$\{0.14\ (a > 315°)\}$
		$\{0.24\ (a > 270°)\}$
		$\{0.26\ (a > 225°)\}$
		$\{0.35\ (a > 180°)\}$
		$\{1.0\ (a > 135°)\}$
		$\{0.56\ (a > 90°)\}$
		$\{0.30\ (a > 45°)\}$
		$\{0.14\ (a \leq 45°)\}$
	Elevation (e), $P(\text{ab}\|e) = P(e)$	$\{0.00\ (e > 2500)\}$
		$\{0.08\ (2250 < e \leq 2500)\}$
		$\{0.82\ (1750 < e \leq 2250)\}$
		$\{1.00\ (e \leq 1750)\}$

Appendix C. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2004.07.026.

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