



1 **Complex effects of telecouplings on forest dynamics: an agent-based modeling**
2 **approach**

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ABSTRACT

Rural areas are increasingly subject to the effects of telecouplings (socioeconomic-environmental interactions over distances) whereby their human and natural dynamics are linked to socioeconomic and environmental drivers operating far away, such as the growing demand for labor and ecosystem services in cities. Although there have been many studies evaluating the effects of telecouplings, telecouplings in those studies were often investigated separately and how telecouplings may interact and affect dynamics of rural coupled human and natural systems (CHANS) jointly was rarely evaluated. In this study, we developed an agent-based model and simulated the impacts of two globally common telecouplings, nature-based tourism and labor migration, on forest dynamics of a rural CHANS, China's Wolong Nature Reserve (Wolong). Nature-based tourism and labor migration can facilitate forest recovery, and the predicted forest areas in Wolong in 2030 would be reduced by 26.2 km² (6.8%) and 23.9 km² (6.2%), respectively, without their effects. However, tourism development can significantly reduce the probability of local households to have member(s) out-migrate to work in cities and decrease the positive impact of labor migration on forest recovery. Our simulations show that the interaction between tourism and labor migration can reduce the potential forest recovery by 3.5 km² (5.0%) in 2030. Our study highlights that interactions among different telecouplings can generate significant impacts on socioeconomic and environmental outcomes and should be jointly considered in the design, management, and evaluation of telecouplings for achieving sustainable development goals.

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SIGNIFICANCE STATEMENT

41 Rural areas are increasingly connected with other places through telecouplings, such as tourism
42 and labor migration. However, telecouplings' effects were often evaluated separately, and their
43 interaction remains poorly understood. In this study, we evaluated how two globally common
44 telecouplings, tourism and labor migration, jointly affect forest dynamics in a demonstration site
45 using an agent-based modeling approach. Although both tourism and labor migration can benefit
46 forest conservation, we found that their interaction generates an antagonistic effect: households'
47 involvement in tourism activities reduces their probability to have members out-migrate to work
48 in cities and significantly diminishes the beneficial impact of labor migration on forest recovery.
49 Our study highlights the importance of considering interaction among telecouplings in the
50 management of telecouplings for sustainability.

51 **1. Introduction**

52 As globalization continues, rural areas have been increasingly connected to the rest of the
53 world through telecouplings – socioeconomic-environmental interactions over distances (Liu et
54 al. 2013a). As a result, human-nature interactions in rural regions, which were primarily driven
55 by local socioeconomic and biophysical conditions, are now increasingly affected by drivers
56 operating at a distance, such as the growing demand for ecosystem services and labor in cities.
57 This new anthropogenic trend has generated profound impacts on many global sustainability
58 issues such as deforestation (Liu 2014), biodiversity loss (Dou et al. 2018), energy security (Fang
59 et al. 2016), and climate change (Liu et al. 2015b).

60 Among the telecouplings that link rural areas and other places, rural-urban labor migration
61 (rural residents out-migrate to cities for temporary employments) and nature-based tourism
62 (tourism based on the natural attractions of rural areas) are two globally common and
63 increasingly influential ones (Ratha, Yi and Yousefi 2015, Pulido-Fernandez, Ward-Perkins and
64 Krukova 2015). Factors such as urban economic growth, enlarging rural-urban disparity, and
65 development of transportation networks, have been driving a large number of laborers from rural
66 areas to seek job opportunities in cities, especially in developing countries (Ratha et al. 2015). In
67 China alone, the number of rural-urban labor migrants had increased from only 2 million in the
68 early 1980s to more than 150 million in 2010 (Rush 2011). Meanwhile, there has been a rapidly
69 growing demand for visiting the natural and cultural landscapes of rural areas, mostly by
70 residents from cities. For decades, many rural areas around the world have been practicing
71 nature-based tourism. For example, in the late 1990s, about 80% of nature reserves in China had
72 developed nature-based tourism (Li and Han 2001). Several provinces in southwest China (e.g.,
73 Yunnan and Sichuan), where one of the global biodiversity hotspots is located (Myers et al.

74 2000), have designated nature-based tourism as one of the major sources of their economic
75 growth (Liu 2012).

76 Previous studies (e.g., Chen et al. 2012a, Pulido-Fernandez et al. 2015, Dai et al. 2012)
77 suggest that labor migration and nature-based tourism can have substantial impacts on the human
78 and natural systems in rural areas. Many rural residents who traditionally relied on subsistence
79 agricultural livelihoods, are now shifting to off-farm economic opportunities made possible by
80 these two telecouplings (Kramer, Urquhart and Schmitt 2009). This labor shift substantially
81 mitigated the negative impacts of local farmers on ecosystems (Liu et al. 2012, Yang et al. 2013,
82 Fox 2016). For example, previous studies (Chen et al. 2012a, Cao et al. 2009) suggest that the
83 remittances sent back by labor migrants or revenue from tourism development, have promoted
84 the change of rural energy consumption from fuelwood to electricity, and reduced the
85 deforestation by farmers. With an increasing awareness of the importance of tourism and labor
86 migration, there have been many studies evaluating their effects on socioeconomic and
87 environmental outcomes in rural regions (e.g., Chen et al. 2012a, Liu et al. 2012, He et al. 2008,
88 Liu et al. 2016a).

89 However, like studies on other telecouplings, the effects of tourism and labor migration were
90 often evaluated separately and their interaction was often ignored. While both tourism and labor
91 migration have the potential to reduce the negative impacts of local households on the
92 environment (Chen et al. 2012a, Liu et al. 2012), tourism development may limit the growth of
93 labor migration. Previous studies (e.g., Wong, Li and Song 2007) show that rural migrant
94 workers in cities often lack good health insurance coverage, face substantial educational
95 expenses for their children, experience discrimination from urban residents, and suffer high
96 stress and depression due to social displacement. Therefore, local tourism jobs are usually more

97 attractive to rural residents than migrant jobs in cities. Although income opportunities related to
98 nature-based tourism are often seasonal (Cuccia and Rizzo 2011), a household may be less likely
99 to utilize its surplus labor for temporary employments in cities if it can benefit from local tourism
100 development. As a result, the possible positive environmental impacts from labor migration in a
101 rural area with a tourism industry might be smaller than in other rural areas where tourism
102 industry does not exist.

103 In this study, we integrated information from different sources and developed an agent-based
104 model to simulate the evolution of tourism and labor migration and their effects on forest
105 dynamics in China's Wolong Nature Reserve (Wolong hereafter). We used the agent-based
106 model because it has a unique capacity to consider the heterogeneity and complex interactions of
107 the human and natural components (e.g., households and forest landscape) involved in
108 telecoupling processes. Although empirical modeling approaches like regression models can
109 yield useful insights regarding single-step or multi-step human-nature interactions, such
110 knowledge alone can rarely lead to in-depth understanding of long-term dynamics of coupled
111 human and natural systems (CHANS) (An et al. 2014, An et al. 2005). Agent-based modeling
112 can address this limitation by offering an effective way to integrate findings from empirical
113 models with other information to simulate system dynamics over a long period and under
114 alternative scenarios that are hard to be empirically observed (Ligmann-Zielinska and Jankowski
115 2007, Chen et al. 2012b, Dou et al. 2020).

116 After calibrating and validating our agent-based model, we used it as a scenario-envisioning
117 laboratory to evaluate the effects of tourism and labor migration by comparing the forest
118 dynamics under different conditions. Specifically, we simulated and evaluated forest dynamics
119 under the following scenarios: [1] tourism and migration are not present in the model, [2] only

120 tourism is present in the model, [3] only migration is present in the model, [4] tourism and
121 migration are present in the model but their interaction is ignored, and [5] tourism, migration and
122 their interaction are all included in the model.

123 **2. Methods**

124 *a. Study area*

125 Wolong (102°52' to 103°24' E, 30°45' to 31°25' N) was established in 1963 and expanded to
126 its current size of 2,000 km² in 1975 (Liu et al. 1999) (Fig. 1). It provides sanctuary to over 100
127 wild giant pandas and more than 6000 species of plants and other animals such as red panda and
128 golden monkey (China Ministry of Forestry and World Wildlife Fund 1989, Sichuan Forestry
129 Administration 2015). The natural forests in Wolong are mainly composed of evergreen and
130 deciduous broadleaf forests at lower elevations, subalpine coniferous forests at higher elevations,
131 with understory composed of bamboo species such as umbrella and arrow bamboo (Schaller et
132 al. 1985, Reid and Hu 1991, Taylor and Qin 1993). Besides the diverse species of plants and
133 animals, Wolong is also home to about 4900 local residents (Yang 2013). The reserve is managed
134 by the Wolong Administration Bureau, which is hierarchically structured with two townships
135 under its governance – the Wolong Township and the Gengda Township (Lai et al. 2003).

136

137 "Figure 1 about here"

138

139 Before the 2000s, the reserve had few connections with the outside world. Local livelihoods
140 relied primarily on subsistence-based agricultural activities like cropping and livestock
141 husbandry (Zhang et al. 2018). The average annual income per capita in 1990 was only 470 yuan
142 (72 USD, 1 USD = 6.6 yuan as of June 2016) (Lai et al. 2003). As the human population and the
143 number of households grew, local human activities caused serious degradation of panda habitat

144 by the early 2000s (Liu et al. 2001, Bradbury, Peterson and Liu 2014). Of all the human threats,
145 cutting trees for fuelwood by local households was a major one (Bearer et al. 2008). Fuelwood
146 was a major energy source for cooking pig fodder, cooking meals, and sometimes for heating
147 houses during winter (An et al. 2002). Although electricity was available, local households were
148 reluctant to switch from fuelwood to electricity, in aversion to increased household expenses (An
149 et al. 2002). By the mid-1990s, local households consumed around 11,000 m³ of wood annually
150 and contributed to the rapid shrinkage of forest cover from 52% (1070 km²) in 1965 to 35% (706
151 km²) in 2001 (Yang et al. 2013, Viña et al. 2007, Liu et al. 2001).

152 This trend of net forest loss started to change since 2001 (Tuanmu et al. 2016). Between
153 2001 and 2007, the forest cover in Wolong recovered from 35% (706 km²) to 37% (799 km²)
154 (Yang et al. 2013). Several socioeconomic and political factors may have contributed to this
155 forest transition. One of them is the development of tourism. Although tourism has existed in
156 Wolong since the late 1980s, the number of tourist visits then was low, and few local people
157 benefited from it (Liu et al. 2012). In 2002, a tourism development plan was formally approved
158 by the provincial and central government (He et al. 2008). Since then, tourism in Wolong has
159 entered a rapid development stage and became an important alternative source of income for
160 local households. The number of tourist visits increased by 10-fold from about 20,000 in 1996 to
161 about 200,000 in 2006. In 2005, about 30% of local households directly benefited from tourism
162 activities like selling bacon to tourists and working as the tour guides (Liu et al. 2012). Before
163 2008, when the Wenchuan Earthquake interrupted tourism development in Wolong (Liu et al.
164 2016b), tourism seasons in Wolong often started in May and ended in October.

165 Meanwhile, as China's economy has grown rapidly in its cities, the stunning rural-urban
166 disparity attracted a rapid rise of labor migrants from rural areas to urban centers (Liang 2001, Li

167 2011). In Wolong, the percentage of households with labor migrants has doubled from 12% in
168 2004 to 24% in 2009 (Liu et al. 2016a, Liu, McConnell and Luo 2013b). Like many other parts
169 of the world, almost all labor migrants from Wolong find only temporary employments in cities
170 (Chen et al. 2012a). They return to their home villages whenever needed (e.g., in planting or
171 harvesting seasons) and rarely shift to be permanent urban residents (Fan 2008).

172 In addition to tourism development and labor migration, several conservation policies have
173 been implemented in Wolong since the early 2000s, including the Grain-to-Green Program
174 (GTGP) (also called Grain-for-Green Program) started in 2000, Natural Forest Conservation
175 Program (NFCP) started in 2001, and Grain-to-Bamboo Program (GTBP) started in 2002 (Liu et
176 al. 2008). Under the NFCP, local households receive payment to monitor the forest for
177 preventing illegal timber harvesting, while under the GTGP and GTBP, local households receive
178 payments to convert their cropland to forestland or bamboo land. Of them, the NFCP was
179 specifically designed to reduce deforestation (Vina et al. 2016), and is believed to be the major
180 policy that has contributed to the reductions of deforestation in Wolong after the early 2000s
181 (Yang et al. 2013).

182 *b. Model design*

183 Agent-based models are composed of agents and their environment (Dou et al. 2019, An
184 and Liu 2010). In our model, agents are individual persons and households, and landscape in
185 Wolong is their shared environment. Agents and their environment together are treated as a
186 CHANS, which is connected with other systems (cities) through two telecouplings: tourism and
187 labor migration (Fig. 2). Local households affect forest dynamics mainly through collecting
188 fuelwood. The establishment of new households often lead to small-scale forest clearing (An et
189 al. 2006) and constitutes the other pathway affecting forest dynamics (Fig. 2).

190

191

"Figure 2 about here"

192

193 The amount of fuelwood collected by each household is determined by its attributes, such as
194 household size, cropland area, and whether being a tourism household and/or labor migration
195 household. In this study, a household is named a tourism household if it directly benefits from
196 local tourism activities. A household is named labor migration household if it has one or more
197 members who out-migrate to cities for temporary employment. Tourism and labor migration
198 reduce fuelwood collection by local households if the households have member(s) directly
199 benefiting from local tourism industry or out-migrating to work in cities. Although a household
200 can be a tourism household and a labor migration household simultaneously, tourism
201 participation by a household reduces its probability to have labor migrant(s). This interaction is
202 manifested in the evolution of households' attributes (being a tourism and/or a labor migration
203 household) over time.

204 The interactions among local households, telecouplings, and forest dynamics were
205 implemented in three integrated submodels: a demographic submodel, a telecoupling submodel,
206 and a landscape submodel. Households in this study were modeled as autonomous agents that
207 can interact with each other and with the forest. We parameterized the model using data and
208 findings from different sources such as population and agricultural censuses, household
209 interviews, satellite imagery, and published journal articles (e.g., An et al. 2001, Chen et al.
210 2014). The agent-based model was developed using the Java programming language on the
211 Swarm platform (Minar et al. 1996). Below are detailed descriptions of each of the submodels.

212 1) DEMOGRAPHIC SUBMODEL

213 The demographic submodel simulates dynamics of persons and households. In our model,

214 individual persons and households are hierarchically connected with each other (i.e., a household
215 agent consists of a number of person agents). The demographic profile of each household agent
216 was modeled by simulating life histories of individual person agents. Major events of individual
217 persons include birth, marriage, aging, and death. Major household events include: [1] household
218 formation that may occur when young adults get married, [2] change in household size when
219 there are new members coming or old members leaving, and [3] household dissolution when
220 there are no members left. Each household has a specific location in the landscape and its
221 behavior is based on its attributes, including household size, number of laborers, cropland, and
222 whether it is a tourism or a labor migration household. Household behavior is also constrained by
223 environmental conditions like elevation and distance to the main road.

224 Our demographic submodel was largely adopted from the models developed in previous
225 studies (An et al. 2002, Chen et al. 2014, An, Mertig and Liu 2003, An et al. 2005) and was
226 initialized with data from an agricultural census conducted in Wolong in 1996. The data include
227 age, gender, and marital status of each household member, kinship relations among household
228 members, and the amount of the household's cropland. In 1996, there were 4053 residents in
229 Wolong distributed in 892 households. The geocoded locations of households were measured
230 with a GPS receiver in 2002 (An et al. 2002). Details about the modeling of the events of
231 household and person agents can be found in the cited studies (An et al. 2002, Chen et al. 2014,
232 An et al. 2003, An et al. 2005, An et al. 2006).

233 2) TELECOUPLING SUBMODEL

234 The telecoupling submodel was designed to simulate the interactions between households
235 and forest under five different telecoupling scenarios (see the Introduction section).
236 Telecouplings affect the households' status of whether having member(s) work in the local

237 tourism industry or out-migrate to work in cities. This status in turn affects the amount of
238 fuelwood collected by households and forest dynamics. We estimated the probabilities of
239 becoming a tourism household or a labor migration household using household survey data
240 collected in 1999 and 2006.

241 In 1999, our research team conducted the first household survey in Wolong to collect data
242 covering the demographic (e.g., household size, birth year, gender, and education level) and the
243 socioeconomic (e.g., income sources, cropland area, and fuelwood collection) information of
244 individual households in 1998 (An et al. 2001). A total of 220 households (about 20% of all
245 households in Wolong) were randomly selected for survey with strata based on administrative
246 groups (the smallest administrative unit in China). These households sampled in 1999 were
247 revisited in 2006 to collect their information in the previous year (2005). There were 18
248 households missing from the 2006 survey due to various reasons such as deaths, migration to
249 outside areas, or temporarily working outside Wolong during the survey period. In 1998, tourism
250 households and labor migration households accounted for 2.7% and 3.9% of all households,
251 respectively. In 2005, those figures increased to 31% and 22%, respectively.

252
253 "Table 1 about here"

254
255 Using the survey data of the 202 randomly sampled households in 2006, we modeled local
256 households' participation in tourism and labor migration using logistic regression models (Table
257 1). When modeling the participation in labor migration, we included tourism participation status
258 (1, Yes; 0, No) as a predictor as suggested by a previous study in Wolong (Yang et al. 2018). This
259 is because local tourism jobs in Wolong are often more attractive than migrant jobs in cities.
260 Rural migrant workers in cities may lack health insurance coverage, face substantial educational
261 expenses for their children, and suffer from high stress and depression (Cuccia and Rizzo 2011).

262 Therefore, if a household has access to jobs in the local tourism industry, it is less likely to have
263 labor migrants working in cities. Our participation models (Table 1) predict the probabilities of
264 tourism and labor migration households after the development of tourism and labor migration for
265 multiple years. Because only a few households were tourism households or labor migration
266 households in 1998, we approximated the annual probabilities of becoming a tourism or labor
267 migration household by dividing the estimated probabilities by seven years (1998 to 2005). A
268 higher participation probability of a household indicates it has a larger potential to have one or
269 more members to work in local tourism industry or out-migrate to work in cities.

270 In reality, tourism or labor migration households may stop their involvement in those
271 activities for various reasons (e.g., the laborers in the household are getting too old). However,
272 almost all tourism and labor migration households in 1998 remained the same in 2005. We
273 therefore did not have enough observations to develop empirical models to predict the
274 probability of a household exits the status of being a tourism household or labor migration
275 household. In our agent-based model, we used the minimum predicted probability of all the 63
276 tourism households surveyed in 2006 (0.06) as the threshold below which a tourism household
277 exits the status of being a tourism household. As time goes by, a tourism household's attributes
278 may change and have a predicted probability less than this threshold. If this happens, the
279 household's status changes from being a tourism household to a non-tourism household.
280 Similarly, we determined the threshold (0.01) for labor migration households to exit the status of
281 being a labor migration household.

282 Fuelwood collection by each household without considering impacts of tourism, labor
283 migration, and conservation policy, was determined according to a previous study in Wolong (An
284 et al. 2001), which modeled fuelwood collection as a function of household size, presence or

285 absence of senior people in the household, and farmland area. Because all households in the
286 study area enrolled in the NFCP in 2001, we did not have a control group of households to
287 accurately estimate the impact of the NFCP on fuelwood collection. We approximated this
288 impact using the drastic reduction in average household fuelwood collection that occurred after
289 2001 when the NFCP started. Of the 220 households surveyed in 1998, 189, 200, and 215 of
290 them were revisited in 2001, 2002, and 2003 with their fuelwood collection information
291 recorded. Before 2002, the average fuelwood collection by each household was around 12861.5
292 kg (12763 kg in 1998 and 12960 kg in 2001). In 2002, the average fuelwood collection
293 drastically reduced to be around 8618.1 kg (8576.5 kg in 2002 and 8659.7 kg in 2003). We used
294 the difference in the mean fuelwood collections before and after 2001, 4243.4 kg, as the impact
295 of the NFCP on annual household fuelwood collection. In our simulations, this impact on
296 households' fuelwood collection takes effect after 2001.

297
298 "Table 2 about here"

299
300 According to the results of a previous study in Wolong (Chen et al. 2012a), the impact of
301 labor migration on household fuelwood collection was set to be 1827 kg per year. If a household
302 starts to have member(s) out-migrate to work in cities, we deducted its fuelwood collection by
303 this amount. We estimated the impact of tourism participation on household fuelwood collection
304 by comparing the fuelwood collection of tourism and non-tourism households in 2005 using the
305 matching approach (Rubin 1973). For each tourism household, the matching approach finds a
306 counterpart non-tourism household with similar attributes, including the number of adults,
307 household size, distance to the main road, and maximum education level of adult household
308 members. On average, a tourism household collected 1708 kg less fuelwood than a non-tourism

309 household per year (Table 2). Therefore, if a non-tourism household in our model changed to be
310 a tourism household, we deducted its annual fuelwood collection by 1708 kg.

311

312 "Figure 3 about here"

313

314 The decision process of each household's status - become or stop being a tourism or a labor
315 migration household - over time is summarized in Fig. 3. If a household is not a tourism
316 household, we calculated its probability to be a tourism household based on its attributes at this
317 time step using the logistic model in Table 1. If a household is already a tourism household at the
318 current time step, we compared its participation probability with the threshold (0.06) to judge if
319 it is still eligible to be a tourism household. If the tourism household's participation probability is
320 less than the threshold, its status will be changed from being a tourism household to be a non-
321 tourism household. Similarly, if a household is not a labor migration household, we determined if
322 it can become a labor migration household based on its probability to have labor migrants. If a
323 household has already been a labor migration household, we evaluated its eligibility at this time
324 step by comparing its participation probability with the threshold probability (0.01). Only labor
325 migration households with predicted probabilities larger than this threshold can maintain their
326 status of being labor migration households. Households' statuses regarding labor migration and
327 tourism participation were then used to calculate their fuelwood collection.

328 3) LANDSCAPE SUBMODEL

329 The landscape submodel simulates forest dynamics with specific consideration of household
330 fuelwood collection, establishment of new households, and other environmental conditions (e.g.,
331 elevation and slope). Our simulation focuses on a 6 km-buffer region around all households (Fig.
332 1) because almost all deforestation activities in the study area happened within the distance of 6

333 km from the households (Linderman et al. 2005). The total area of the simulated natural
334 landscape is 553 km². The landscape is represented in our model as a digital “world” consisting
335 of 90×90 m cells. Each cell has a set of attributes including elevation, slope, aspect, and forest
336 status (forest or nonforest). The elevation, aspect, and slope were obtained based on a digital
337 elevation model derived from a topographic map (Liu et al. 2001). The forest cover information
338 of the landscape cells was initialized with a published binary forest (forest/nonforest) map
339 derived from Landsat Thematic Mapper images acquired in 1997 (Liu et al. 2001). The
340 classification of the satellite images was performed using unsupervised digital classification
341 based on ISODATA technique (Jensen and Lulla 1987) and was validated using ground-truthing
342 data. The accuracy of the forest cover map is about 80% (An et al. 2005, Liu et al. 2001).

343
344
345

"Table 3 about here"

346 Landscape cells may experience deforestation (from forest to nonforest) or forest recovery
347 (from nonforest to forest). The forest change of each cell is determined by empirical models
348 obtained from a previous study in the reserve (Chen et al. 2014). According to this study, the
349 deforestation or forest recovery probability of each cell was a function of the cell’s elevation,
350 slope, aspect, distance to forest edge, and impacts of fuelwood collection by local households
351 (Table 3). Fuelwood collection has a significant positive effect on forest loss ($p < 0.001$) and a
352 significant negative effect on forest recovery ($p < 0.001$) (Table 3). Household fuelwood
353 collection was translated to fuelwood impact on each cell across the simulated landscape using
354 the equation developed by Chen et al. (2014):

355

$$FI_i = \sum_{dis_{ij} < 6km} fuelwood\ collection_j / dis_{ij}$$

356 where FI_i is fuelwood collection impact on cell i ; dis_{ij} is the distance from household j to cell i ;
357 *fuelwood collection_j* is the annual fuelwood collection by household j . The fuelwood impact on
358 forest dynamics is therefore an inverse-distance weighted aggregation of all households within 6
359 km buffer from the cell, which reflects the fact that forests closer to households are more likely to
360 be degraded or logged.

361 At every time step, we calculated the deforestation probability for each forest cell and
362 recovery probability for each non-forest cell to determine their forest status (forest or nonforest).
363 For a detailed description of the construction and validation of these forest change models,
364 please refer to the cited study (Chen et al. 2014).

365 *c. Model validation*

366 In this study, we validated the agent-based model by comparing the simulated landscape,
367 demography, and telecoupling-related statuses with the corresponding observed patterns at the
368 whole Wolong level. For the demographic submodel, we calibrated it with the 1996 agricultural
369 census data and ran it for 10 years. To consider the influence of stochastic processes in our
370 model, we used the mean results from 20 runs for validation. We compared the simulated mean
371 population size and mean number of households with those obtained from the 2006 household
372 registration data. For the telecoupling submodel, we compared the simulated percentages of
373 tourism households and labor migration households in 2005 with the observed values from our
374 household survey data. If the difference between observed and simulated values is less than the
375 observed mean yearly change (change in the observed values divided by the number of years
376 between the observations), we considered the model simulation as having good validity.

377 We validated the impacts of tourism and labor migration on fuelwood collection, and
378 impacts of fuelwood collection on forest dynamics together by comparing the simulated forest

379 distributions in 2007 with a published empirical forest cover map in 2007 (Viña et al. 2011). This
380 2007 forest cover map was derived from a digital classification of the imagery of Landsat
381 Thematic Mapper. The map was validated using ground truth data and has an accuracy of 82.6%
382 (Viña et al. 2011). The comparison between simulated and actual maps was performed using a
383 receiver operating characteristic (ROC) curve (Hanley and McNeil 1982) with a random sample
384 of 5000 pixels (2500 forest pixels and 2500 nonforest pixels) from the empirical forest cover
385 map as the validation dataset. The predicted probability of being forest of the sample pixels was
386 calculated by averaging simulated binary forest maps of the 20 runs. We used the area under the
387 ROC curve (AUC) as a measure of the overall accuracy of the simulated forest maps. The values
388 of AUC ranges from 0 to 1, where a value of 1 indicates perfect accuracy, while a value of 0.5
389 implies that the accuracy is no better than a random guess (Araújo et al. 2005).

390 *d. Simulation experiments*

391 After validating our model, we simulated the dynamics of households and forest under five
392 different scenarios to evaluate the effects of tourism and labor migration: (1) without tourism and
393 labor migration; (2) only with tourism; (3) only with labor migration; (4) with both tourism and
394 labor migration but ignoring their interaction; and (5) with both tourism and labor migration
395 including their interaction effect. When running scenario #1, we ignored the impacts of tourism
396 and labor migration by setting all households' probabilities being tourism and labor migration
397 households to be zero throughout the simulations. When running scenario #2, we ignored labor
398 migration by setting the probability of labor migration to be zero for all households. Similarly,
399 when running scenario #3, we set tourism participation probability to be zero for all households.
400 When running scenario #4, we ignored the interaction between tourism and labor migration by
401 setting the coefficient of the negative impact of tourism participation on the probability of labor

402 migration to be zero. When running scenario #5, tourism, labor migration, and their interaction
403 all took effect. In these simulations, the numbers of tourism and labor migration households in
404 1996 were assumed to be zero. We ran all simulations for 34 years (from 1996 to 2030). Because
405 the landscape submodel was calibrated using the 1997 forest cover map, it started running one
406 year later than the demographic and telecoupling submodels.

407 **3. Results**

408 *a. Model validation results*

409 Our validation results (Table 4) indicate our model performances accurately. The difference
410 between the mean predicted human population and observed human population in 2006 was 17,
411 which was less than the observed mean yearly population change (45 per year) from 1996 to
412 2006. The predicted number of all households was 1176, which was 21 less than the observed
413 value ($n = 1197$) and less than the mean annual change (31 per year). The predicted percentages
414 of tourism households (28.9%) and labor migration households (22.2%) were close to their
415 observed values (31.2% and 21.7% respectively) in 2005. The differences between observed
416 percentages of tourism and labor migration households in 2005 and simulated means of them
417 (2.3% and 0.5%) were all less than the observed mean yearly changes (3.1% per year and 2% per
418 year) from 1998 to 2005. The example simulated forest map in 2007 were also close to the
419 empirical forest cover map (Fig. 4). The AUC value of the simulated maps ($n = 20$) is 0.743,
420 indicating good simulation accuracy.

421

422

"Table 4 about here"

423

424 *b. Forest and household dynamics under different scenarios*

425 As expected, both tourism and labor migration have contributed to the forest recovery that

426 occurred after 2001 (Fig. 5). In all the five simulation scenarios, the total forest area decreased
427 between 1996 and 2001, and then started to recover at a gradually decreasing rate. Under the
428 scenario without considering the effects of tourism and labor migration (scenario #1), the
429 predicted forest area in 2030 is 361.2 km². Under the scenario only with tourism (scenario #2) or
430 only with labor migration (scenario #3), the forest areas in 2030 are 387.4 km² and 385.1 km²,
431 respectively. The difference in the 2030 forest area between scenario # 1 and scenario #2 is 26.2
432 km², which represents the cumulative effect of tourism development on forest dynamics
433 throughout our simulation period (1996 to 2030). The difference in the 2030 forest area between
434 scenario #1 and scenario # 3 is 23.9 km², which represents the cumulative effect of labor
435 migration on forest dynamics from 1996 to 2030.

436

437 "Figure 5 about here"

438

439 The development of tourism reduced the number of labor migration households by 22%
440 (Fig. 6). Under the scenario that did not consider the negative impact of tourism participation on
441 the probability of labor migration (scenario #4), the number of labor migration households in
442 2030 is predicted at 675 (42.2% of the total), while under the scenario that considered this
443 negative impact (scenario # 5), the number of labor migration household in 2030 is 554 (34.6%
444 of the total) (Fig. 6). The difference in the number of labor migration households in 2030 under
445 scenario #4 and scenario #5 is 121, which represents the cumulative effect of tourism
446 development on growth of labor migration throughout our simulation period from 1996 to 2030.

447

448 "Figure 6 about here"

449

450 This interaction between tourism and labor migration has an evident impact on forest

451 dynamics (Fig. 5). Under the scenario with both tourism and labor migration but without
452 considering their interaction (scenario #4), the forest area in 2030 is 407.1 km², which is 3.5 km²
453 higher than that under the scenario that considered this interaction effect (scenario # 5). In short,
454 development of tourism decreases labor migration in the area, which subsequently negatively
455 affects forest cover.

456 **4. Conclusion and discussion**

457 Our agent-based model provides an efficient way to integrate the information from empirical
458 statistic models and other sources to evaluate the impacts of different telecouplings on
459 environmental outcomes at the landscape level over a long period of time. Our results
460 demonstrated that telecouplings can interact and generated evident impact on the forest dynamics
461 in rural areas. By analyzing labor migration and tourism in tandem, we show that the interaction
462 between these two telecouplings significantly attenuate their positive impact on forest recovery
463 across the landscape. While both tourism and migration increase forested area, their interaction
464 results in a lower forest gain. Using the Wolong case study, we argue that potentially related
465 telecouplings should be evaluated jointly rather than separately to reveal their actual effects on
466 socioeconomic and environmental outcomes.

467 We note that our estimation of tourism's long-term effect on labor migration may be
468 conservative. This is because we only observed the influence of tourism on individuals staying in
469 the area rather than migrating to cities. Therefore, we did not include the potential effect of
470 tourism on labor migration by attracting labor migrants to come back to only work in the local
471 tourism industry. We hypothesize that, with the inclusion of this attraction effect of tourism on
472 labor migration, the reduction of reforestation would be even more pronounced compared to the
473 results in Fig. 5. We did not observe this effect and include it in our current agent-based model

474 perhaps because the tourism development in Wolong was at its early stage and this attraction
475 effect had not been evident yet. As the tourism industry is recovering from the impact of the
476 Wenchuan Earthquake in 2008, future studies in Wolong and other places should also evaluate
477 and consider this negative impact in their analyses.

478 Results from this study have important implications for management of tourism and labor
479 migration. For example, like Wolong, many rural areas implemented tourism development
480 programs with substantial investment and support from governments (Zhao et al. 2021, Yang et
481 al. 2021). To maximize the efficiency of tourism development programs in providing
482 environmental benefits, these programs may target rural areas where the level of labor migration
483 is low to avoid limiting the positive environmental effect of labor migration. On the other hand,
484 labor migration policies in urban settings may play an important role in mitigating the negative
485 effect of tourism on labor migration. This negative impact occurs mainly because labor migrants
486 in cities often have to confront many difficulties (Li 2011). Therefore, management interventions
487 that help overcome these hardships (e.g., offering equal job opportunities for migrant workers)
488 should be considered to increase the benefits labor migrants could obtain from this off-farm
489 livelihood. The increase in benefits farmers could obtain from labor migration may promote
490 tourism households to also have labor migrants and enhance the labor shift from on-farm to off-
491 farm activities.

492 In our model, we only considered the impact of tourism on forest through reducing fuelwood
493 collection because tourism development in Wolong remained at its early stage and did not
494 generate other evident impacts on forest (Liu et al. 2016b, Liu 2012). Although nature-based
495 tourism is widely perceived to be clean and non-consumptive because it relies on existing
496 natural, cultural, and historical resources, unregulated tourism development can cause serious

497 degradation of ecosystems (Dai et al. 2012). The actual impacts of future tourism development in
498 Wolong on forest dynamics will depend on its design and management. Besides avoiding direct
499 disturbances into the forest (e.g., clearing forest for tourism infrastructure development), we
500 suggest that future development of tourism should also increase the share of benefit local
501 households could obtain from it. Economic leakage (i.e., tourism revenue flowing to outside
502 investors or managers rather than locals) is a common issue that plagues the development of
503 tourism in many rural areas around the world (Kiss 2004). Previous studies (He et al. 2008, Liu
504 2012) in Wolong also found that only a small fraction of revenue from tourism development
505 (<5%) went to the local community. This issue may have constrained the impact of tourism
506 participation on fuelwood collection because less income would be available for local
507 households to afford the energy shift from fuelwood to cleaner energy like electricity.

508 Although the telecoupling interaction illustrated in this study is antagonistic, i.e., one
509 telecoupling weakens the other, synergetic interactions also commonly exist among
510 telecouplings. For example, the panda loan is another important telecoupling linking Wolong and
511 other places (Liu et al. 2015a). Every year the China Conservation and Research Center for the
512 Giant Panda, a panda breeding center and tourism site in Wolong, loans captive pandas to zoos
513 inside and outside China. The panda loans have significantly increased the media exposure of
514 Wolong. For example, around 20% of all media reports found in LexisNexi® about Wolong are
515 related to panda loans (Liu et al. 2015a). The spread of information about Wolong may have in
516 turn boosted the tourist visits to Wolong. About 24% of visitors to the Wolong breeding center in
517 2005 expressed that they had previously read media reports on Wolong and 29% of them saw
518 television program about Wolong before the visit (Liu et al. 2015a). This indicates that a
519 synergetic interaction effect may exist between the telecouplings of panda loan and tourism.

520 Currently, neither synergetic nor antagonistic interactions among telecouplings have been well
521 studied (Liu et al. 2013a, Kapsar et al. 2019). They deserve more investigations in the future to
522 improve the understandings of the dynamics of telecouplings and their effects on socioeconomic
523 and ecological outcomes.

524 Our study also illustrates that agent-based models are useful tools to understand interrelated
525 effects of telecouplings. Human-nature interactions are often complex and vary across different
526 settings (Liu et al. 2007, Liu et al. 2013a). Agent-based models provide flexible tools to
527 effectively integrate empirical knowledge, findings, and data from different sources to
528 characterize the heterogeneities and interactions of the human and natural components in a
529 CHANS. This lays a foundation to understand dynamics of human-nature interactions under
530 telecouplings across space and time. With a validated agent-based model, we can further explore
531 the trajectories of the system dynamics under different telecoupling scenarios that cannot be
532 observed empirically.

533 We note that our model mainly focuses on simulating the processes operating within
534 Wolong. We did not specifically consider factors associated with tourism and labor migration in
535 other places because our study aims to understand how labor migration and tourism jointly affect
536 forest dynamics in Wolong (not other places). We framed our study as a telecoupling research to
537 underscore the fact that Wolong is telecoupled with other systems, and our study highlights that
538 telecoupling flows can affect forest covers at the landscape level through influencing agent
539 behaviors. Future research can build upon our study to include other systems and answer other
540 questions. For instance, the nature-based tourism in Wolong may shape urban sustainability
541 through affecting the environmental awareness and behaviors of tourists from cities. A future
542 study may integrate such results with our findings under the framework of telecoupling and

543 assess the possible synergy between sustainability in Wolong and cities.

544 Like all other models, the agent-based model is a simplified representation of the real world.
545 For example, some of the life history events of person agents in our model such as death, child
546 birth, and marriage were simplified as stochastic processes. However, modeling the key dynamic
547 interactions using the agent-based model helps us to improve the understanding the complexities
548 of long-term effects of telecouplings (e.g., nonlinearity, Figs. 5 and 6). We hope that the
549 perspectives and methods proposed in this study can be useful for investigating the effects of
550 telecouplings in Wolong and other CHANS around the world. With improved understanding of
551 telecouplings, policy makers and scientists may be able to develop effective strategies to manage
552 telecouplings for maximizing their positive effects and mitigating their negative effects in an
553 increasingly telecoupled Anthropocene.

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TABLES

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740 Table 1 Logistic estimations of labor migration and tourism participation by households in
 741 Wolong.

Variables	Models	
	Labor migration	Tourism participation
	Coefficient (SE)	Coefficient (SE)
Tourism participation	-1.47 (0.56) **	-
Household size	-0.19 (0.16)	0.26 (0.14) †
The number of adult (age > 18) household members	1.04 (0.20) ***	-0.12 (0.16)
Average age of adult household members	-0.013 (0.029)	-0.012 (0.023)
The maximum school years of adult household members	-0.084 (0.075)	0.26 (0.14) ***
Log transformed distance to main road (m)	0.076 (0.13)	-0.20 (0.10) †
Township (Gengda: 1; Wolong: 0)	-0.33 (0.42)	0.33 (0.34)
Constant	-2.13 (1.68)	-2.85 (1.35) *

742 (1) Significance: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

743

744 Table 2 The impact of tourism participation on household fuelwood collection estimated using
 745 the matching approach.

	Results
Impact estimate using matching (kg) ⁽¹⁾	-1708 *** (488.5)
Γ sensitivity (Wilcoxon) ⁽²⁾	2.4
Γ sensitivity (Hodges-Lehmann) ⁽³⁾	1.2
[Number of treated and control]	[63,139]
Means of the treated and the control (kg)	5063.5, 7341.4

746 (1) The numbers in parentheses of this row are Abadie-Imbens standard errors.

747 (2) The value of Γ at which the null of zero effect would fail to be rejected at $p = 0.05$ level
 748 based on Wilcoxon signed-rank p value.

749 (3) The value of Γ at which the lower bound of 95% confidence interval for the Hodges-
 750 Lehmann point estimate of the effect includes zero.

751 (4) Significance: *** indicate statistical significance at 0.001 level.

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 753

754 Table 3 Summary of the logistic estimations of forest gain and forest loss from the previous
 755 study in Wolong (Chen et al. 2014).

Parameters	Models	Deforestation	Forest recovery
		Coefficient (SE)	Coefficient (SE)
Elevation (100 m)		-0.008 (0.014)	-0.008 (0.011)
Slope (degree)		0.001 (0.006)	-0.009 (0.006)
Aspect (Parker scale (Parker 1982))		-0.054 (0.008) ***	0.064 (0.01) ***
Distance to forest edge (m)		-0.019 (0.001)	-0.014 (0.001) ***
Fuelwood impact (m ³ /m) ⁽²⁾		0.031 (0.008) ***	-0.009 (0.008)
Total fuelwood (m ³)		0.20 (0.003) ***	-0.023 (0.003) ***
Constant		347.46 ***	1.792 ***

756 (1) Significance: *** $p < 0.001$.

757 (2) Fuelwood impact on a cell is defined as the summation of fuelwood impact on the cell by all
 758 households within the 6 km buffer, and each household's impact is defined by its fuelwood
 759 collection divided by its distance to the cell.

760 (3) Because these models were built based on observed forest change for six years (1994 to
 761 2000), the annual forest change (gain or loss) probabilities of landscape cells are the estimated
 762 probabilities using the above models divided by six as suggested by (Chen et al. 2014).

763

764 Table 4 Comparisons of model predictions of population size, numbers of all households,
 765 tourism households, and labor migration households to observed values.

Factors	Observed value	Observed mean yearly change	Model mean	Difference between model mean and observed value	Difference < observed mean yearly change
Population in 2006	4504	45	4487	17	Yes
Household number in 2006	1197	31	1176	21	Yes
Tourism households in 2005 (%)	31.2%	3.1%	28.9%	2.3%	Yes
Labor migration households in 2005 (%)	21.7%	2%	22.2%	-0.5%	Yes

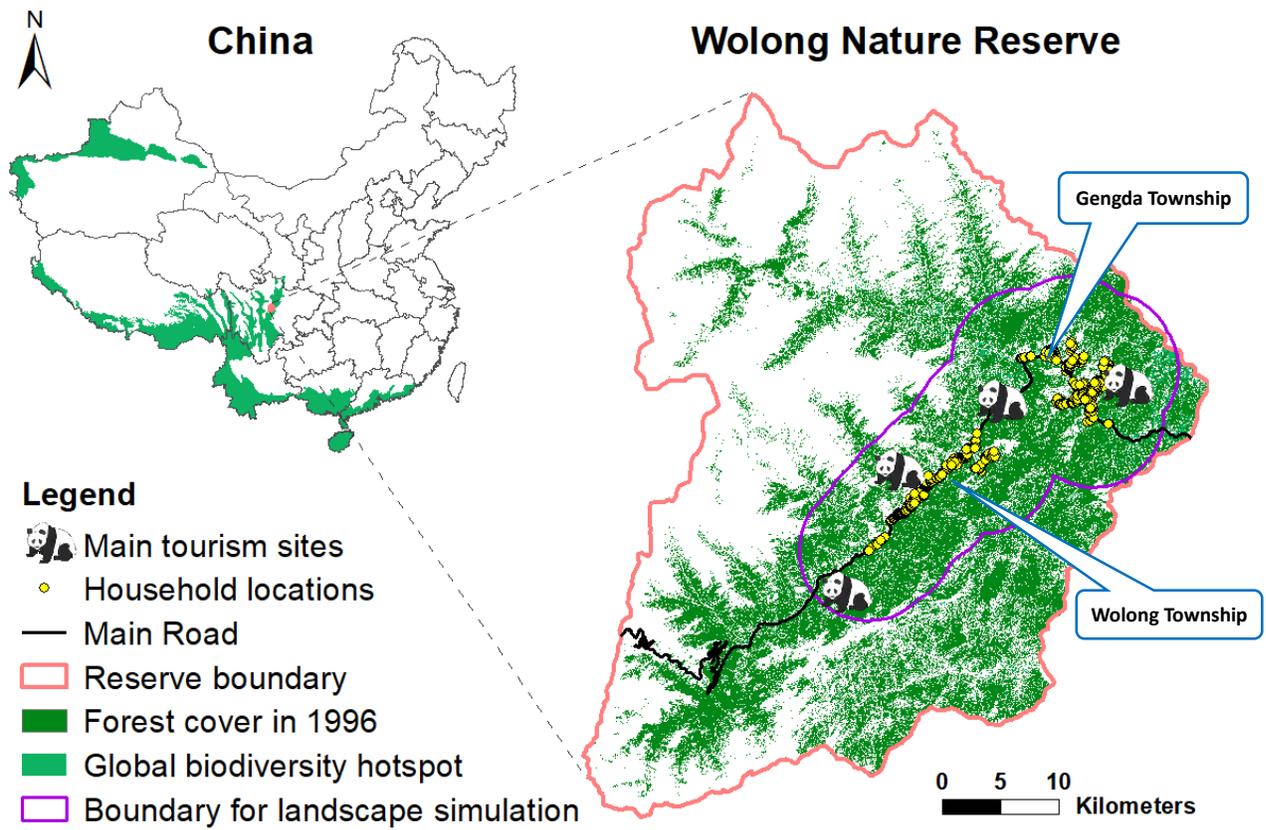
766 (1) The observed mean yearly change is calculated by dividing the observed change by the
 767 number of years between the observations.

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FIGURES

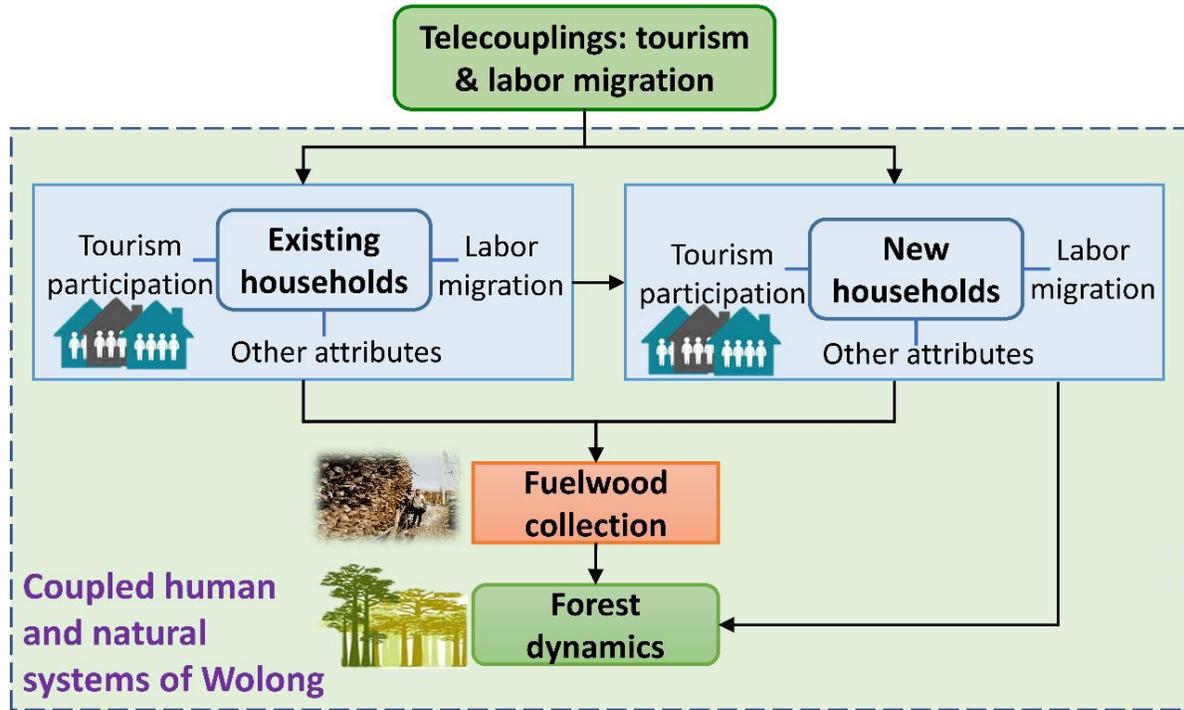
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776

777 Figure 1 Wolong Nature Reserve in Southwest China.

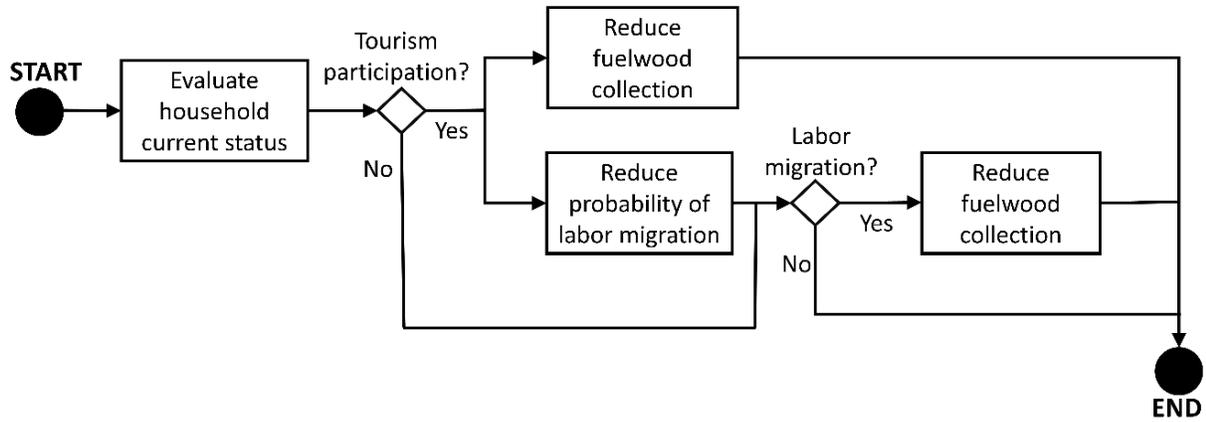
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779

780 Figure 2 Conceptual framework of the model for simulating the effects of tourism and labor
 781 migration on forest dynamics in the coupled human and natural systems of Wolong.

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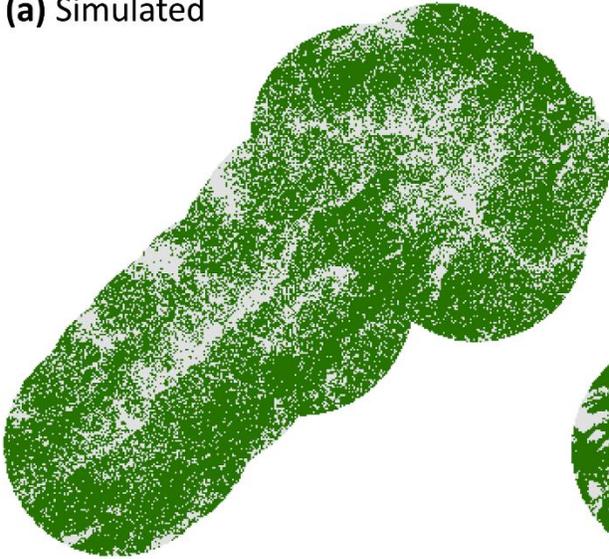


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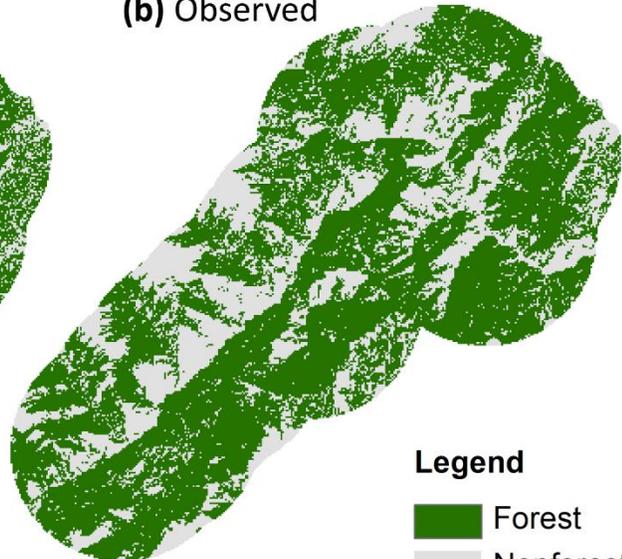
784 Figure 3 Decision process regarding each household's status of being a tourism or a labor
 785 migration household at each simulation step and their effects on fuelwood collection.

786

(a) Simulated



(b) Observed



Legend

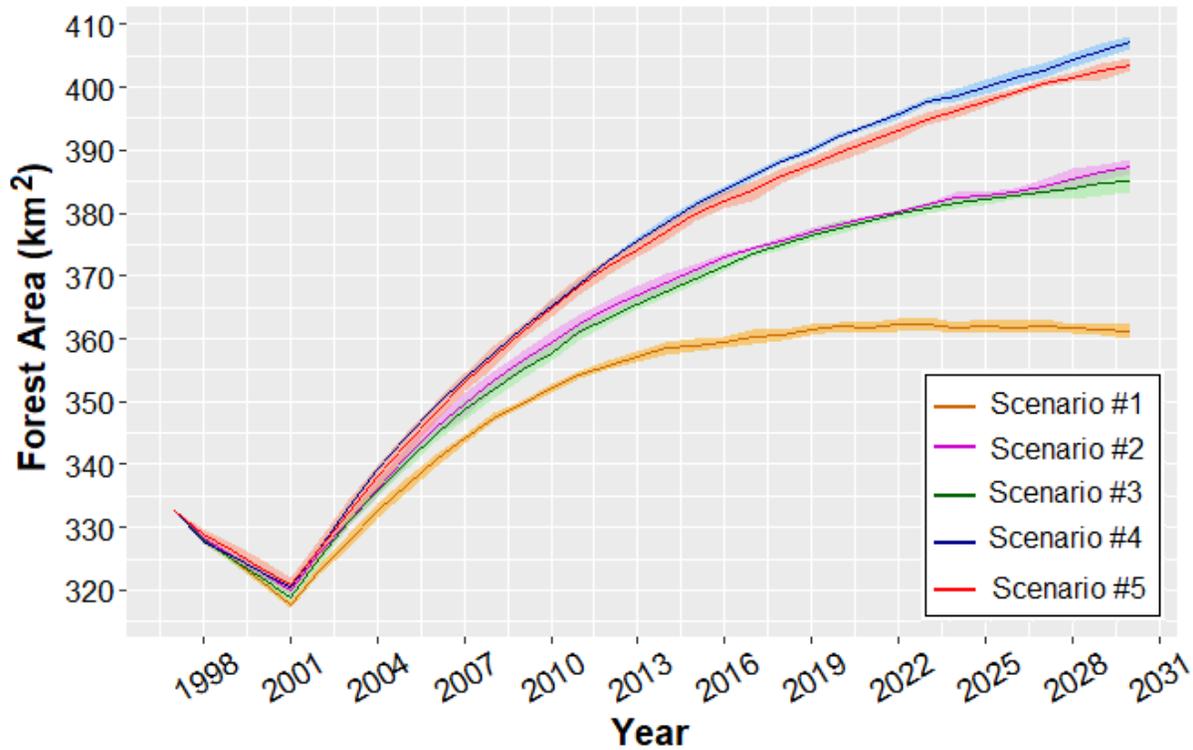


(c) Confusion matrix

Observed \ Simulated	Non-forest	Forest	Accuracy
Non-forest	971	609	0.62
Forest	784	2636	0.77
Accuracy	0.55	0.81	

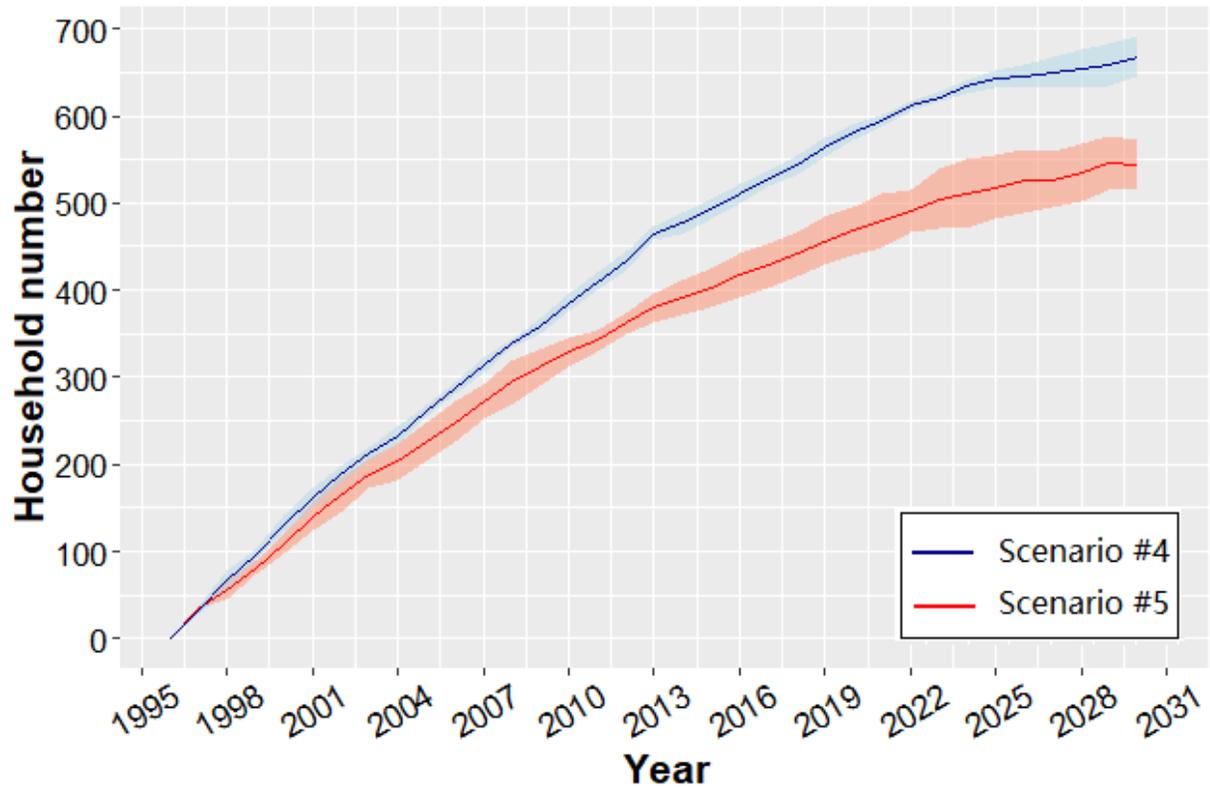
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788 Figure 4 Comparison of simulated and observed forest distribution in 2007. (a) Simulated forest
 789 cover in 2007; (b) Observed forest cover in 2007 derived from classification of Landsat imagery;
 790 (3) Confusion matrix that shows the consistency between the simulated and observed forest
 791 cover based on results of 5000 random pixels. The overall accuracy value is 0.72.



792
 793 Figure 5 Dynamics of the forest areas simulated under five different scenarios: (1) without
 794 tourism and labor migration; (2) with tourism only; (3) with labor migration only; (4) with both
 795 tourism and labor migration but without considering their interaction; and (5) with both tourism
 796 and labor migration and with considering their interactions. Lines and corresponding ribbons
 797 represent the means and standard deviations of the results from 20 runs, respectively.

798



799
 800 Figure 6 Simulated dynamics of the numbers of labor migration households from 1996 to 2030
 801 under scenarios with (Scenario #5) and without (Scenario #4) considering the negative impact of
 802 tourism participation on the probability of labor migration. Lines and corresponding ribbons
 803 represent the means and standard deviations of the results from 20 runs, respectively.