COMPLEX EFFECTS OF TELECOUPLINGS ON A COUPLED HUMAN AND NATURAL SYSTEM

By

Hongbo Yang

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Fisheries and Wildlife – Doctor of Philosophy

2018

ABSTRACT

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Rural areas around the world are increasingly exposed to the effects of telecouplings (socioeconomic and environmental interactions over distances), often with profound implications for sustainability. To support economic growth that is ecologically sound, there is an urgent need for improved understanding of the complex effects of telecouplings on rural areas.

This dissertation presents investigations of the complex effects of telecouplings on an exemplary rural coupled human and natural system (CHANS) – Wolong Nature Reserve (Wolong) in China. Wolong is connected to the outside world through telecouplings, such as payments for ecosystem services (PES) programs [e.g., the Grain-to-Green Program (GTGP) and the Grain-to-Bamboo Program (GTBP)], nature-based tourism, and labor migration. Specific objectives of this dissertation were to: (1) reveal the pathways through which telecouplings affect socioeconomic outcomes; (2) uncover the spillover, feedback, and interaction effects of telecouplings; and (3) assess interrelated changes in livelihoods and human well-being after the sudden changes of telecouplings caused by a natural disaster.

Using the GTGP and the GTBP implemented in Wolong as examples, we showed that telecouplings shaped interrelated livelihood activities and formed complex pathways affecting socioeconomic outcome (Chapter 2). By elucidating the underlying pathways, we identified specific reasons for the unexpected negative impacts of the GTGP and the GTBP on household

income. We also found that the impacts of telecouplings spilled over to nontargeted areas and generated unintended consequences (Chapter 3). In addition to the lost revenue from cropland enrolled in the GTGP, the GTGP intensified crop damage on remaining cropland, leading to a hidden cost that is often ignored in the design of PES programs' compensation scheme. As the impacts of telecouplings on the focal CHANS accumulated, feedback occurred (Chapter 4). Our results showed that the crop damage on remaining cropland caused by the GTGP increased the willingness of local households to enroll it in future GTGP, which triggered a positive feedback that will strengthen the influences of GTGP in Wolong and beyond. Different telecouplings interacted with each other and generated unexpected impacts on environmental outcomes (Chapter 5). Our systems modeling results show that the interaction between the telecouplings of nature-based tourism and labor migration weakened their total effect on forest recovery. Evolution of telecouplings in Wolong was interrupted by a natural disaster, generating profound impacts on post-disaster recovery outcome (Chapter 6). Our analyses show that livelihoods in Wolong experienced substantial changes in response to the changes in telecouplings after the 2008 Wenchuan Earthquake. However, most of these livelihood changes negatively affected, instead of facilitating, human well-being recovery.

This interdisciplinary study provided a solid example showing how the complex effects of telecouplings on a CHANS can be studied by integrating approaches from different disciplines. Findings and methods from this dissertation provide essential information and tools for understanding, predicting, and managing telecouplings to achieve Sustainable Development Goals in an increasingly telecoupled world.

ACKNOWLEDGEMENTS

There are many people without whom I would not have been able to complete this dissertation. All of the work presented is a result of a collaborative team effort of a number of wonderful and dedicated individuals.

I would like to first thank my committee for their guidance, advice, and support throughout my Ph.D. program at Michigan State University. I thank Dr. Frank Lupi and Dr. Thomas Dietz for sparing their precious time and efforts to provide me with constructive, meticulous, and rigorous comments and edits on our collaborative chapters. I thank Dr. Arika Ligmann-Zielinska for leading me to the field of agent-based modeling. I also thank her for her technical guidance and constructive comments and edits on our collaborative chapter. I want to especially thank Dr. Jianguo Liu, my major advisor, for his continuous support, patience, and more importantly, encouragement to aim higher and achieve greater. I have learned so much from him and will carry all the lessons forward in my career and life.

I am grateful for the help from Wenbing Yang, Xuejia Li, Dan Li, Yan Chen, and Xuemei Li to collect the data used in this dissertation research. I am indebted to the interviewees in Wolong Nature Reserve for their time and cooperation in participating our household survey, sharing their insights and life experiences. I appreciate Hemin Zhang at Wolong Nature Reserve and Zhiyun Ouyang at the Chinese Academy of Sciences for their logistical support during the data collection processes.

I thank Wu Yang, Wei Liu, Xiaodong Chen and Li An for their previous research and data collection in Wolong Nature Reserve, which laid a good foundation for this dissertation research. I would also like to thank many other past and current members of the Center for Systems Integration and Sustainability for their support and inputs, especially Andrés Viña, Sue Nichols, William Taylor, Shuxin Li, Jindong Zhang, Yue Dou, Fang Wang, Zhiqiang Zhao, Ying Tang, Min Gon Chung, Thomas Connor, Jacqueline Hulina, Anna Herzberger, Molly Good, So-Jung Youn, Kelly Kapsar, Ciara Hovis, and Yingjie Li.

I would also like to thank my parents and sisters for their unconditional supports and love. In particular, I would like to thank my beloved wife, Yan Zhang, who always stands by me, trusts me, encourages me, and feels proud of me. Any achievement that I made from the completion of this dissertation is equally theirs.

Finally, I gratefully acknowledge the financial support from the National Science Foundation, the Environmental Science and Policy Program, William W. and Evelyn M. Taylor Endowed Fellowship program, Michigan AgBioResearch, and the Key Laboratory of Southwest China Wildlife Resources Conservation at China West Normal University.

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CHAPTER 1

INTRODUCTION

1.1 Background

As globalization continues, different parts of the world have been increasingly connected through telecouplings – socioeconomic and environmental interactions over distances (Liu et al. 2013a). Even rural communities traditionally at the periphery of global markets, are now increasingly subject to effects of telecouplings such as payments for ecosystem services (PES) programs, nature-based tourism, and labor migration (Kramer et al. 2009). This anthropogenic trend has changed rural human-nature interactions in complex ways and posed unprecedented challenges and opportunities for sustainable coexistence between humans and ecosystems around the world (Kramer et al. 2009, Lambin and Meyfroidt 2011, Liu et al. 2013a, Eakin et al. 2014, Liu 2014). Many sustainability issues of our time have been profoundly influenced by telecouplings, such as global land use change (Verburg et al. 2013, Bruckner et al. 2015), urbanization (Alberti 2015, Fang and Ren 2017), trade impacts (Sun et al. 2017), wildlife conservation (Wang and Liu 2016, Hulina et al. 2017), international economic development (Galaz et al. 2015, Yang et al. 2016a), water scarcity (Yang et al. 2016b), energy security (Fang et al. 2016), species invasion (Liu et al. 2014), and forest sustainability (Liu 2014).

Given the great potential of telecouplings for shaping human-nature interactions, understanding their complex effects has become of great practical importance in trying to achieve sustainability objectives such as those targeted by the Millennium Development Goals of the United Nations and its successor, the Sustainable Development Goals, released in 2015 (Assembly 2000, Liu et al. 2013a, Liu 2014, United Nations 2015). Inadequate understanding of the effects of telecouplings poses serious threats to the rapidly growing efforts around the world to achieve sustainability. For example, payments for ecosystem services (PES) programs and nature-based tourism, two globally common telecouplings linking rural areas with other places, have been widely leveraged as tools to promote ecosystem conservation and human well-being in many rural regions. In spite of the potential of these telecouplings to support rural livelihoods while protecting ecosystems, the implementation and management of them in practice have yielded mixed results. For example, an analysis of World Bank Integrated Conservation and Development Projects (ICDPs) implemented between 1993 and 2007 indicates only 16% of them made major progress on both conservation and development objectives (Tallis et al. 2008). The poor understanding of the complexities of telecouplings' impacts has been identified as one of the main reasons for the failures of previous conservation efforts that tried to protect ecosystems while promoting socioeconomic development (Ostrom 2007, Cao et al. 2009).

To address this challenge, there has been a growing number of studies evaluating the socioeconomic and ecological effects of telecouplings. For example, Kramer et al. (2009) show that, as rural areas became increasingly telecoupled with urban areas, access to outside markets can lead to unsustainable harvest of natural resources such as forests and exacerbate global environmental issues (Kramer et al. 2009). He et al. (2008) tracked the benefits brought by another common telecoupling, nature-based tourism, and found revenue from nature-based tourism unevenly distributed among different groups (e.g., the poor and the rich), causing economic leakage and social disparity (He et al. 2008). Despite the negative impacts brought by telecouplings, they have also generated many desirable outcomes in rural areas. For example, Chen et al. (2012) evaluated another globally common telecoupling, labor migration (temporary out-migration to work in cities), and found it has significantly reduced rural households' fuelwood collection, a major threat to habitat of giant panda (Chen et al. 2012a). Viña et al. (2016) evaluated the forest changes in China and found that the implementation of PES programs in rural areas has been a major driver behind the forest transition occurred in China in the past decade (Viña et al. 2016).

Although a growing body of literature has documented the effects of telecouplings in rural settings, many important knowledge gaps remain. First, identifying pathways underlying the effects of telecouplings is key to making results generalizable and for effective policymaking. However, researchers evaluating the effects of telecouplings typically focused on capturing the effects while the underlying pathways were rarely elucidated (Ferraro and Hanauer 2014). Second, the effects of telecouplings may go beyond the target areas they are designed to influence and generate unintended outcomes. However, previous studies evaluating effects of telecouplings often focus on the influences occurred in the target areas, while effects that spill over into nontargeted areas have rarely been considered. Third, telecouplings have usually been treated as static contextual drivers of changes in focal systems, but little is known about how changes in a focal system will in turn affect telecouplings through feedbacks, thus leading to biased estimations of the long-term effects of telecouplings (Mena et al. 2006). Fourth, telecouplings were often studied separately, thus creating potential biases because important interactions among co-occurring telecouplings may have been overlooked (Liu et al. 2013a). Finally, the resilience of coupled human and natural systems (CHANS) is one of the central topics of sustainability science. However, sudden changes in telecouplings due to natural disasters and their impacts on dynamics of CHANS were rarely explored in previous studies.

1.2 Research Objectives

To fill these important knowledge gaps in existing literature, this dissertation research evaluated the complex effects of telecouplings on an exemplary rural CHANS – China's Wolong Nature Reserve (Wolong hereafter). We evaluated the complex effects of telecouplings that occurred under five circumstances where there were complex pathways, spillover, feedback, interaction among telecouplings, and external shock respectively. In addition, this research seeks to advance complexity theory (Waldrop 1993, Liu et al. 2007a) in the context of telecouplings. Complexity theory offers important theoretical foundations for understanding the socioecological changes due to complex human-nature interactions (e.g., feedbacks). However, studies on this topic usually focus on processes operating within a particular area and little attention has been paid to telecouplings between that area and other places (Liu et al. 2013a).

Specifically, this study has five objectives:

(1) Developing a systematic way to reveal the pathways via which telecouplings affect socioeconomic outcomes (Chapter 2);

(2) Assessing the effect of an example telecoupling that spills over from target area to nearby nontargeted land (Chapter 3);

(3) Investigating the influence of the spillover effect evaluated in Chapter 3 on local households' behavioral intention, which may trigger a feedback and affect the telecoupling itself (Chapter 4);

(4) Developing an agent-based model to evaluate the interaction effect of two telecouplings, nature-based tourism and labor migration, on forest dynamics (Chapter 5);

(5) Evaluating interrelated changes in livelihoods and human well-being in response to the changes in telecouplings after a natural disaster (Chapter 6);

Correspondingly, this dissertation includes five core chapters (i.e., Chapter 2 to Chapter 6) that addressed each of the above objectives, respectively. Chapter 2 deals with revealing the pathways through which two PES programs (the focal telecouplings) affected household income (the socioeconomic outcome). A structural equation modeling analysis was performed to examine how PES programs affected interrelated livelihood activities and form complex pathways to affect household income in Wolong. Chapter 3 deals with the spillover effect of an example telecoupling process, a PES program, which delivered payments to farmers to convert their cropland to forest land but unintendedly increased crop damage on remaining cropland. We estimated this impact by comparing damage on remaining cropland parcels close to the former cropland enrolled in the program with their counterparts that are far from the former cropland using the matching method (Stuart 2010). Chapter 4 built upon Chapter 3 and evaluated the impacts of the spillover effect of the PES program on local households' willingness to participate in the program in the future, a change in behavioral intention that may trigger a feedback and influence the program itself. A stated choice method was used here to elicit this potential reaction of the local community to the changes caused by the PES program. Chapter 5 integrated information from different sources and developed an agent-based model to simulate the effects of two telecouplings on forest dynamics over a long period. After validation, this model was used to investigate the effect of the interaction between the two telecouplings on forest dynamics. Chapter 6 deals with interrelated changes in rural livelihoods and human well-being in response to the sudden change in telecouplings caused by a natural disaster. We integrated long-term socioeconomic and biophysical data and empirically show the livelihood adaptations to telecoupling changes after an earthquake and evaluated their influences on human well-being recovery.

1.3 Study Area

To achieve my objectives, I chose Wolong as my study area (Fig. 1.1). Wolong is ideal for this research for several reasons. First, long-term socioeconomic data from household surveys and environment data from field measurements have been accumulated almost yearly since 1998. The rich datasets and indigenous knowledge lay a good foundation for systematic experiment design and causal inference regarding the complex effects of telecouplings. Second, the system components and telecouplings in Wolong are similar to those in many other areas around the world. Therefore, results and lessons drawn from this study may help guide future research and management in many other systems. Third, telecouplings in Wolong have experienced significant changes in recent decades. Before the 2000s, Wolong was a rural area with few connections with outside world (An et al. 2001). Since the early 2000s, a series of development and conservation programs [e.g., Cash-cropping Development Program, Tourism Development Plan, Natural Forest Conservation Program (NFCP), Grain-to-Green Program (GTGP), and Grain-to-Bamboo Program (GTBP)] have been implemented and significantly increased the

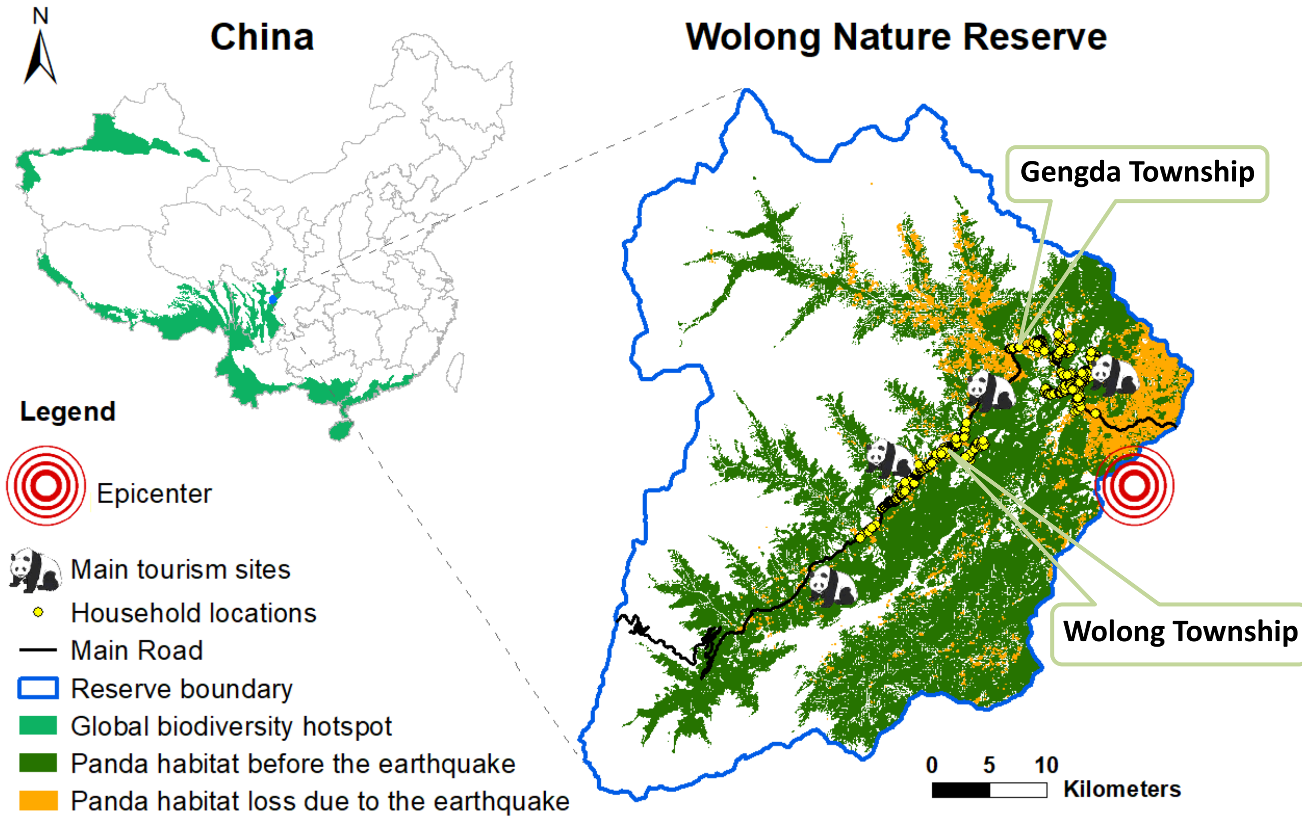

Figure 1.1 Location of study area in China. The information on panda habitat and its change was obtained from the published results in (Ouyang et al. 2008).

linkage between Wolong and the outside world. On May 12, 2008, a devastating earthquake struck Wolong. The earthquake and its associated landslides caused extensive damage to the forest, houses, and infrastructure, including the main road that connects Wolong and the outside world. Transportation of goods became difficult and tourism in the reserve was disrupted. All these conservation programs, development projects, and the natural disaster led to dramatic changes in the telecouplings. Changes in telecouplings in turn significantly shaped human-nature interactions in Wolong (e.g., switch from fuelwood to electricity for energy). The dramatic changes in telecouplings and associated human-nature interactions, again, provide an excellent opportunity to address my research objectives. The following are more detailed descriptions of Wolong.

Wolong (102º52′ to 103º24′ E, 30º45′ to 31º25′ N) was established in 1963 and expanded to its current size of 2,000 km^2 in 1975. It was designed mainly for the protection of the iconic species, giant panda (*Ailuropoda melanoleuca*) (Liu et al. 1999). The elevation in Wolong varies dramatically from 1,150 m to 6,250 m, forming a wide range of micro-environmental conditions that can harbor a large diversity of plant and animal species (Schaller et al. 1985). Wolong is home to about 104 wild giant pandas and more than 6000 species of plants and other animals such as red panda and golden monkey (China Ministry of Forestry and World Wildlife Fund 1989, Lai et al. 2003, Sichuan Forestry Administration 2015). The natural forests here are mainly composed of evergreen and deciduous broadleaf forests at lower elevations and subalpine coniferous forests at higher elevations, with understory composed of bamboo species such as umbrella and arrow bamboo (Schaller et al. 1985, Reid and Hu 1991, Taylor and Qin 1993). Other natural land cover types include grassland/shrubland above the tree line (about 3000 m) and alpine meadows at even higher elevations (> 4000 m).

Besides the diverse species of plants and animals, Wolong is also home to about 4,900 residents, most of whom belong to Tibetan and Qiang ethnic minorities (Yang 2013). The Reserve is managed by the Wolong Administration Bureau, which is hierarchically structured with two townships under its governance – the Wolong Township and the Gengda Township (Fig. 1.1) (Lai et al. 2003). In each township there are three villages, each of which is composed of a number of village groups, the smallest administrative unit in China (Lai et al.

2003).

Before the 2000s, the reserve had few connections with the outside world. Local livelihoods relied primarily on subsistence-based agricultural activities, such as crop production and livestock husbandry, that could generate tiny income for local households. The average annual income per capita in 1990 was only 470 yuan (72 USD, 1 USD = 6.6 yuan as of June 2016) (Lai et al. 2003). As population and number of households grew in Wolong, the impacts of human activities on the environment became increasingly extensive and intensive (Liu et al. 2001). Before the 2000s, fuelwood in Wolong was the major energy source for cooking meals, cooking pig fodder, and heating houses during winter (An et al. 2002). Cutting trees for fuelwood generated serious impacts on giant panda habitat (An et al. 2002). Although electricity was available, local households were reluctant to switch from fuelwood to electricity to avoid increased household expenses (An et al. 2002). In the mid-1990s, local communities annually consumed around 11,000 m^3 of wood and the forest coverage drastically decreased from 52% in 1965 to 35% in 2001 (Liu et al. 2001, Viña et al. 2007, Yang et al. 2013b), which had resulted in severe degradation of panda habitat (Liu et al. 2001). Widespread poverty made illegal logging and poaching common then (Lai et al. 2003). For example, more than 69 endangered wild animals (including giant pandas) were killed by traps between 1975 and 1983 (Lai et al. 2003).

To mitigate the degradation of giant panda habitat, the Wolong Administration Bureau adopted new strategies that integrated poverty alleviation and socioeconomic development in its management efforts since the late 1990s (Lai et al. 2003). As part of these strategies, Wolong invested intensively in improving the transportation conditions and promoting the development of cash-cropping. In 1999, with an investment of about 100 million yuan (15.4 million USD as of June 2016), a provincial highway connecting the reserve with the outside was completed and greatly improved the accessibility of the reserve (Lai et al. 2003). In 1995, with the assistance of Wenchuan Farming Bureau, an off-season cabbage was successfully introduced into the reserve and was widely planted since 1998 (Lai et al. 2003). Special subsidies for buying chemical fertilizers and farming utensils were also provided to farmers (An et al. 2002). Selling cabbage to the outside market contributed significantly to the increase of household income. During the 1990s, the per capita income tripled from 470 yuan in 1990 to 1,414 yuan in 2000 (Lai et al. 2003), of which about 40 percent came from the cabbage-cropping. Increase in households' income in turn may have promoted their investment in livestock, which further diversified their income sources. For example, our data indicate the number of livestock in Wolong has doubled from 666 in 1998 to 1232 in 2007.

Since the early 2000s, Wolong received substantial financial support from the central government (e.g., the State Forestry Administration) and implemented several PES programs to incentivize local households to reduce their negative impacts on the ecosystem. By the end of 2003, about 60% (449 ha) cropland were converted to vegetated land under two PES programs: the GTGP and the GTBP. The GTGP paid local farmers to convert their cropland to forest land and the GTBP paid local farmers to convert their cropland to bamboo land (Liu et al. 2008b). Another important PES program implemented in Wolong is the NFCP. It started in 2001 and paid local households to monitor forests to prevent deforestation activities.

Besides selling agricultural products to outside market and implementing PES programs, Wolong witnessed an evident labor shift from on-farm to off-farm income activities made available via two other telecouplings: nature-based tourism (tourism based on natural attractions in rural areas) and labor migration (rural laborers out-migrate to cities for temporary employments). Nature-based tourism in Wolong started in the middle 1980s. However, back then, the management in Wolong generally followed the “Fine-and-Fence” style, which tried to strictly protect natural resources by separating humans from ecosystems. The reserve was only open to special visitors such as scientists, government officials, or small groups of visitors approved by the government (Lai et al. 2003). It was not until the 1990s that the reserve started to open to the general public. In 2002, a tourism development plan was proposed and approved by the state government (He et al. 2008). Tourism in Wolong entered a rapid development stage and became an important alternative income source for local farmers. The total number of tourists has increased by 10-fold from about 20,000 in1996 to about 200,000 in 2006 with about 31% of households in the reserve directly benefited from the tourism industry in Wolong (Liu et al. 2012).

Meanwhile, as China’s economy grows rapidly in its cities, the stunning rural-urban disparity attracted a rapid rise of labor migrants from rural areas to urban centers (Liang 2001). In Wolong, the percentage of households with labor migrants has doubled from 12% in 2004 to 24% in 2009 (Chen et al. 2012a). A previous study (Chen et al. 2012a) in Wolong indicates that labor migration may have reduced energy needs of households and labor for activities that may disturb the ecosystem (e.g., collection of fuelwood and medicinal plants). As compared with their counterparts, households with labor migrants collected much less fuelwood (Chen et al. 2012a). Due to the impacts of the above socioeconomic and political factors, a forest transition occurred in Wolong. The forest cover in Wolong recovered from 35% in 2001 to 37% in 2007.

Like many other biodiverse areas in the world, Wolong is subjected to frequent seismic activities (Zhang et al. 2014). On May 12, 2008, the catastrophic Wenchuan Earthquake (Ms 8.0, the most devastating in China since the 1950s) struck the southwest China (Zhang et al. 2014). Wolong is within the area of high seismicity and near the epicenter of the earthquake. The earthquake killed 129 people in Wolong, with 6 people missing, and 35 people seriously injured (Wang 2013). The earthquake also caused extensive damage to most buildings and the main road that connects the reserve with the outside world. In response, a series of reconstruction programs were implemented by the government to help restore the ecological and socioeconomic systems in Wolong (e.g., about 2.18 billion yuan has been invested by China's central government alone (Aba Administration 2016)). Plans call for reconstruction of damaged infrastructure, relocation of households from sloping areas with high risk to earthquake-related landslides to flat land, and promotion of the redevelopment of the interrupted tourism industry. Despite the great efforts in post-disaster reconstruction, the condition of the main road that holds the key for the recovery of nature-based tourism and sale of local agricultural products remained poor because of the repeated damage by landslides after the earthquake from 2008 to 2015. In 2012, the third round of road reconstruction project was started. To avoid the impact of landslides, the new road goes through tunnels in areas susceptible to impacts of landslides. The project lasted for four years and was completed in 2016. It may have substantial impacts on the telecouplings (e.g., nature-based tourism) by changing the links between Wolong and the outside world.

Because all the main chapters (i.e., Chapter 2 to 6) have been published in or have been prepared for peer-reviewed journals, more information about the study area such as details on different conservation and development policies are provided in each of the main chapters.

CHAPTER 2

REVEALING PATHWAYS FROM PAYMENTS FOR ECOSYSTEM SERVICES TO SOCIOECONOMIC OUTCOMES

In collaboration with

Wu Yang, Jindong Zhang, Thomas Connor, and Jianguo Liu

Abstract

Payments for ecosystem services (PES) programs have been widely implemented as a promising tool to conserve ecosystems while facilitating socioeconomic development. However, the underlying pathways (or processes) through which PES programs affect socioeconomic outcomes remain elusive and existing literature provides little guidance to quantify them. By integrating linkages among PES programs, livelihood activities, and socioeconomic outcomes, we develop a framework for revealing pathways from PES programs to socioeconomic outcomes. We empirically demonstrate the framework's operationalization and uncover the pathways that lead to unexpected negative effects of two important PES programs on participating households' income. With improved understanding of the pathways (e.g., the programs decreased income through reducing crop production), we provide recommendations to enhance the PES programs' outcomes in our demonstration site and beyond. Our study highlights that elucidating the pathways from PES programs to their outcomes can help identify specific strategies for achieving ecosystem conservation and socioeconomic development simultaneously.

2.1 Introduction

The world is currently threatened by the unprecedented decline of ecosystem services that are essential for human survival (MA 2005). Meanwhile, poverty continues to plague many parts of the world (Atkinson 2017). To eradicate poverty and conserve ecosystems, sustainable development – economic growth that is ecologically sound – has become a practical necessity and the central topic of the Millennium Development Goals of the United Nations and its successor, the Sustainable Development Goals, released in 2015 (Assembly 2000, United Nations 2015). However, activities that are desirable from the point of view of conservation are often unattractive to users of natural resources (e.g., farmers, loggers and fishers). To achieve sustainable development goals, there has been a growing search for possible solutions to the long-existing conflicts between ecosystem conservation and socioeconomic development, especially in rural areas which house a disproportionately large number of the world's poor and provide sanctuary for most of the Earth's biodiversity.

Among the potential solutions, payments for ecosystem services (PES) programs have been widely implemented across the world (Engel et al. 2008, Wunder et al. 2008, Naeem et al. 2015). The central idea of PES is that conservation costs borne by communities in target areas should be compensated by beneficiaries outside conservation regions to avoid impeding socioeconomic development of those local communities. Normally, costs of conservation are not distributed in proportion to their gains. The gains of conservation (e.g., enhanced water supply, wildlife habitat and carbon sequestration) are often shared regionally or even globally, but the costs (e.g., lost livelihood opportunities) are mostly borne by local communities (Engel et al. 2008). For example, forest conservation practices (e.g., logging bans) upstream often bring benefits such as clean water to users downstream (e.g., city dwellers). However, such conservation practices may worsen the livelihood of upstream land users (e.g., farmers) because of the sacrificed opportunities for marketable use of the forest resources. By offering payments to participating households, it is hoped that PES programs can simultaneously facilitate ecosystem conservation and socioeconomic development in target areas (Engel et al. 2008).

To evaluate the effectiveness of PES programs in achieving their sustainability goals, a large number of studies have documented their effects on environmental and socioeconomic outcomes (Liu et al. 2008b, Liu et al. 2010, Liu et al. 2016a). While it is important to capture these effects, such work offers little insight into the processes through which they occur (Ferraro and Hanauer 2014, Law et al. 2017). In conservation areas, PES programs often induce complex human-nature changes (e.g., decrease in traditional livelihood activities) that may constitute pathways through which PES programs affect target outcomes (e.g., household income) indirectly. Revealing these pathways is vital for conservation success in both theory and practice. One of the major goals of conservation research is to produce generalizable understanding of the effects of policy interventions. However, the effects of policies, including PES programs, often vary across different spatial and temporal contexts, which often make them not directly comparable (Liu et al. 2007b). Uncovering pathways underlying these effects will allow more specific explanations to why certain socioeconomic outcomes occur or fail to occur, thereby making different study results more comparable and facilitating the development of theories (Liu et al. 2007b). In conservation practice, better understanding the failures or successes of existing PES programs is also crucial. Armed with such knowledge, conservation practitioners may be able to identify the pathways that have the potential to improve the socioeconomic outcomes of PES programs and design management strategies accordingly. However, the pathways through which PES programs affect socioeconomic outcomes have remained elusive, and existing literature offers little guidance to test and quantify them (Wunder et al. 2008, Naeem et al. 2015).

By integrating the linkages among PES programs, livelihood activities, and socioeconomic outcomes, we propose a conceptual framework for revealing the pathways through which PES programs affect socioeconomic outcomes. We then demonstrate the framework's operationalization using the structural equation modeling approach to analyze the pathways through which two PES programs affected the income of participating households in a demonstration site. Based on our findings, we provide recommendations to improve the socioeconomic outcomes of PES programs for rural communities in the demonstration site and beyond.

2.2 Conceptual Framework

Our conceptual framework (Fig. 2.1) includes three major interrelated components: PES programs, livelihood activities, and socioeconomic outcome. The linkages among them (the black arrows in Fig. 2.1) constitute pathways through which PES programs affect socioeconomic outcome.

Along each specified pathway, one or more livelihood activities work as intermediary variable(s) to transmit the effect of PES programs on socioeconomic outcome. That means PES

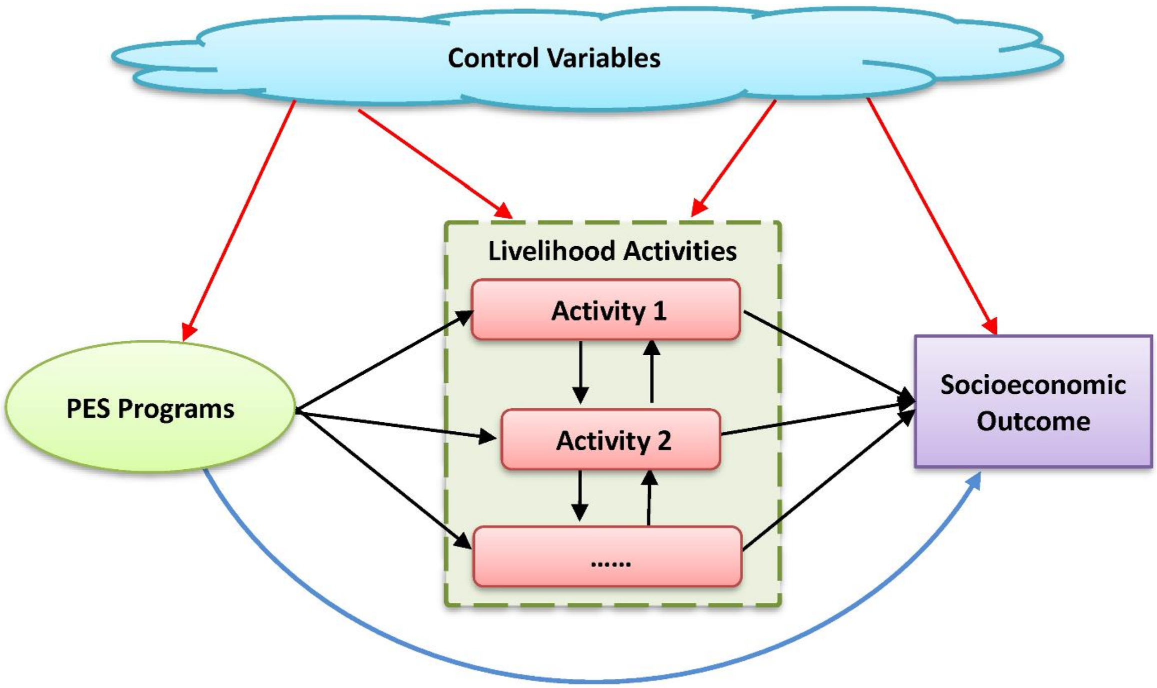

Figure 2.1 Framework for analyzing the effects of PES programs on socioeconomic outcome through influencing different livelihood activities. An arrow represents a linkage through which the variable at the arrow tail affects the variable at the arrow head. Black arrows are the ones that constitute the specified pathways linking PES programs and socioeconomic outcome. The blue arrow represents the unspecified pathway that links PES programs and socioeconomic outcome. Red arrows represent the linkages through which control variables affect other components in the framework. Different livelihood activities might be related and the linkages among them may constitute additional pathways linking PES programs and socioeconomic outcome.

programs affect livelihood activities (e.g., farming) first, which in turn affect the socioeconomic outcome. For example, PES programs often work by paying for land use changes (e.g., cropland conversion to forests or grasslands) that are thought to increase ecosystem services (Engel et al. 2008). Experiences and lessons learned (Wunder et al. 2008, Lin and Yao 2014) over the past decades indicate that land use changes promoted by PES programs may reduce the benefits participating households could obtain from their previous livelihood activities (e.g., agricultural production) and thus negatively affect socioeconomic outcome (e.g., household income). Meanwhile, the resources (e.g., surplus labor and payments) made available by PES programs to participating households may help them to shift to alternative livelihood activities (e.g., working in off-farm sectors). Benefits from these alternative livelihood activities may help to compensate for the losses arising from participating in PES programs and improve the socioeconomic outcome (Liu et al. 2008b).

Since different livelihood activities might be interrelated, the linkages among them may constitute additional pathways to transmit the effects of PES programs on socioeconomic outcome. For example, for various reasons (e.g., higher income, hardships of farming), off-farm jobs are usually attractive to farmers in many rural areas around the world (Chen et al. 2012a). Households that have access to off-farm employment may invest less labor in farming activities and thus reduce their agricultural production. Therefore, if a PES program can prompt participating households to find off-farm employment, it may in turn reduce their agricultural production, and ultimately change the socioeconomic outcome.

In reality, PES programs often affect socioeconomic outcome through many pathways and some may be difficult to specify for practical reasons (e.g., lack data to describe related livelihood activities). Also, the measurements used for characterizing the specified livelihood activities may be unable to capture all dimensions of them (e.g., measuring a household's participation in a livelihood activity by the number of laborers involved may not fully reflect the actual number of labor hours for that activity). Therefore, a direct linkage between PES programs and socioeconomic outcome (the blue arrow in Fig. 2.1) is used in our framework to represent the processes that are not specified, and this linkage we named "unspecified pathway".

To obtain reliable estimates of the linkages among these three components (i.e., PES programs, related livelihood activities, and socioeconomic outcome), control variables should be properly considered in the analysis. In our framework, control variables refer to the factors that may affect (the red arrows in Fig. 2.1) any variables along the pathways. If not controlled, they can bias the estimates of the linkages that constitute the pathways connecting PES programs and socioeconomic outcome (the black arrows in Fig. 2.1). Examples of control variables may include those characterizing the socioeconomic, demographic, and biophysical conditions of analysis units (e.g., households).

2.3 Demonstration of The Framework's Operationalization

2.3.1 Demonstration site and PES programs

We used two PES programs implemented in Wolong Nature Reserve (Wolong hereafter) to demonstrate the operationalization of the framework. Wolong is a flagship protected area in southwest China established mainly for protecting the giant panda (Liu et al. 2016a). Besides featuring rich biodiversity, Wolong is also home to about 4,900 local residents, living in around 1,200 households (Liu et al. 2016a). The local residents mainly rely on crop production and livestock husbandry (Wang 2013). Since the early 2000s, working in the local tourism industry and out-migrating to work in cities have become important income sources for some local households (Chen et al. 2012a, Liu et al. 2012) (see *Supplementary Materials* for details of these livelihood activities in Wolong).

As part of the effort to address the rapid degradation of panda habitat due to human activities (e.g., agricultural expansion, timber harvesting, and fuelwood collection), two PES programs [the Grain-to-Green Program (GTGP, which is a national program and one of the world's largest PES programs) and the Grain-to-Bamboo Program (GTBP, a local program to grow bamboo on cropland for feeding pandas in captivity and for attracting tourists)] have been implemented in Wolong since 2000 and 2002, respectively (Liu et al. 2016a). Under these programs, local households received payments annually from the government based on the amount of cropland they converted to forest land or bamboo land (See text description and Table S2.1 in *Supplementary Materials* for details). As a national conservation program, the GTGP also pays land owners to plant trees on barren land in some regions, but in Wolong, only cropland has been enrolled into the GTGP (Wang 2013).

2.3.2 Specification of framework components

We are interested in the effects of GTGP and GTBP on household income and applied our framework to analyze how these effects occur through influencing different livelihood activities. Since the effects of these programs on household income through direct payment is evident and can be easily observed (e.g., from official records), we used nonpayment income (income from sources other than direct payments from these two PES programs) as the indicator of socioeconomic outcome and focused on how these programs affect nonpayment income through different pathways. Based on our knowledge of Wolong, we selected three livelihood activities that might have worked as intermediary variables to transmit the effects of the GTGP or the GTBP on nonpayment income, including tourism participation (working in local tourism industry), labor migration (temporary out-migration to work in cities), and crop production.

2.3.3 Hypothesized pathways

Based on previous study results (e.g., Chen et al. 2012a, Liu et al. 2012), we hypothesized that linkages among the PES programs, livelihood activities, and nonpayment income constitute different pathways through which the GTGP and the GTBP affected income (Fig. 2.2).

Specifically, we hypothesized that the GTGP and the GTBP provoked changes in each of these three livelihood activities, which then affected the nonpayment income. As previous studies (Chen et al. 2012a, Liu et al. 2012) indicate, we first hypothesized that all the three livelihood activities can increase nonpayment income. We then hypothesized that both the GTGP and the GTBP had a positive effect on households' participation in the local tourism industry and labor migration. This is because previous studies (Liu et al. 2008a, Lin and Yao 2014) show that cropland reduction due to conservation policies could release rural labor from crop production and promote the shift from on-farm to off-farm activities such as working in the local tourism industry or out-migrating for jobs in cities. Furthermore, we hypothesized that both the GTGP and the GTBP had negative impacts on crop production because participating households converted parts of their cropland to forest or bamboo land. These hypothesized linkages can form two-step pathways through which the GTGP and the GTBP affected these three livelihood activities, which in turn affect nonpayment income (Fig. 2.2). For example, the GTGP may affect nonpayment income through the pathway in which the GTGP promotes participation in tourism, which then increases nonpayment income.

In addition, we hypothesized that these three livelihood activities were linked and the linkages among them constituted longer pathways through which the GTGP and the GTBP

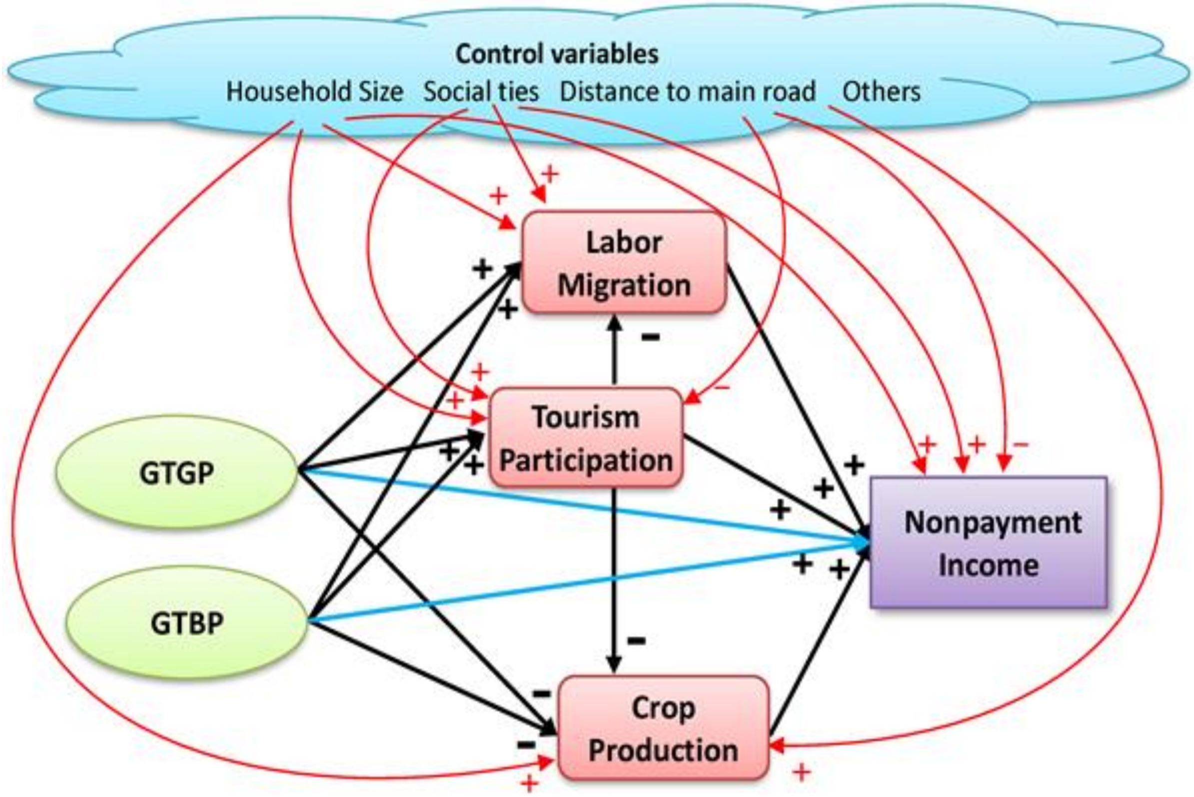

Figure 2.2 Illustration of hypothesized linkages among PES programs, livelihood activities, control variables and non-payment income. We focused on analyzing the effects of the GTGP and GTBP on non-payment income (income from sources other than direct payments from these two PES programs) because the direct contribution of payments from GTGP and GTBP to participating households' income can be directly observed. Arrows in the diagram represent linkages. "+" and "–" refer to hypothetical positive and negative effects of the linkage, respectively. The black arrows represent the ones that constitute the specified pathways that link the GTGP or the GTBP with non-payment income. The two blue arrows represent the unspecified pathways that link the GTGP and the GTBP with non-payment household income, respectively. A complete list of variables considered in Wolong demonstration study is found in Table S2.2.

affected nonpayment income. For example, we hypothesized that tourism negatively affected crop production. This is because tourism activities (e.g., operating a restaurant) are often labor intensive (Shaw and Williams 1994). Households that participate in the local tourism industry may have less labor available for farming activities and thus may maintain less land for crop production. We also hypothesized that tourism had a negative influence on labor migration. Although both tourism and labor migration have the potential to increase rural household income, rural migrant workers in cities may lack health insurance coverage, face substantial educational expenses for their children, experience discrimination from urban residents, and suffer from high stress and depression (Wong et al. 2007). Therefore, local tourism jobs in Wolong are often more attractive than migrant jobs in cities. If a household has access to jobs in the local tourism industry, it is less likely to have labor migrants working in cities. These hypothesized linkages among different livelihood activities, plus the aforementioned linkages between livelihood activities and the other two components (i.e., PES programs and nonpayment income), constitute additional pathways through which PES programs affect household income (Fig. 2.2). For instance, the GTGP may affect nonpayment income through the pathway in which the GTGP promotes participation in tourism, which then decreases crop production and in turn nonpayment income.

To obtain reliable estimates of these hypothesized pathways, we considered a broad set of control variables to characterize the demographic (e.g., household size), socioeconomic (e.g., social ties to government), and biophysical (e.g., distance to the main road) features of local households (Table S2.2).

2.4 Materials and Methods

2.4.1 Household surveys and measurements

In Wolong, households are usually the basic units of decision making in most livelihood activities such as crop production, tourism participation, labor migration as well as enrollment in the GTGP or the GTBP (Liu et al. 2012). Therefore, all measurements used in this case study were derived from data collected at the household level.

For this study, we mainly used data collected from surveys conducted in 1999 and 2006. In 1999 (before the PES programs were implemented), our research team conducted the first household survey in Wolong to collect data covering demographic (e.g., household size, birth year, gender, and education level) and socioeconomic (e.g., income sources, cropland area, and expenditures) information of individual households in 1998. Two hundred and twenty households (about 20% of the total in Wolong) were randomly selected for surveys with strata based on administrative groups (the smallest administrative unit in China). These households sampled in 1999 were revisited for data collection in 2006, when the PES programs had already been implemented for several years. Besides collecting similar demographic and socioeconomic data to those in 1999, we added retrospective questions on households' involvement in tourism activities, labor migration, the GTGP, and the GTBP in previous years. Eighteen households were missing from the survey in 2006 for various reasons such as deaths, migration to outside areas, or temporarily working outside Wolong during the survey period. As a result, in this study, we used data from a total of 202 households surveyed in both years to examine the pathways through which PES programs affected household income. In addition to the household surveys, we measured the location of each household using a Global Positioning System device and calculated the distance of each household to the main road using the software ArcGIS 10.2 (ESRI Inc., California, USA). The survey instruments and data collection procedures we used in this study were reviewed and approved by the Institutional Review Board of Michigan State

University (https://hrpp.msu.edu/).

In this study, we measured the GTGP and the GTBP at household level with the proportions of cropland a household converted to forest land under the GTGP and bamboo land under the GTBP, respectively. We measured crop production in 2005 with the amount of cropland devoted to it. We measured labor migration and participation in the tourism industry in 2005 with two binary variables that indicate whether the household had members temporarily out-migrate to cities for jobs or had members working in the local tourism industry, respectively. Additionally, we generated a set of variables to characterize households' demographic, socioeconomic and physical conditions that are commonly found to be relevant to household income or the livelihood activities mentioned above. Descriptive statistics of all these variables are shown in Table S2.2.

2.4.2 Estimating the effects of different pathways

We tested the hypothesized linkages among PES programs, related livelihood activities, and non-payment household income using structural equation modeling method (Bollen and Noble 2011). Structural equation modeling is statistically unbiased and has been widely used in statistical inference literature (Bollen and Noble 2011).

Since all variables in this study can be reasonably treated as observable, we conducted path analysis using the structural equation modeling technique to test the hypothesized linkages among PES programs, related livelihood activities, and non-payment household income as shown in Fig. 2.2. The general matrix representation of structural equation model with only observed variables is presented in equation (2.1):

$$\mathbf{y} = \mathbf{B}\mathbf{y} + \mathbf{\Gamma}\mathbf{x} + \boldsymbol{\zeta} \qquad (2.1)$$

where $\mathbf{y}$ is the $p \times 1$ vector of endogenous variables, representing variables explained by the model. $\mathbf{x}$ is the $q \times 1$ vector of exogenous variables in the model (i.e., variables not explained by the model). $\boldsymbol{\zeta}$ is the $p \times 1$ vector of error terms. $\mathbf{B}$ is the $p \times p$ coefficient matrix describing the effects of endogenous variables on endogenous variables. $\mathbf{\Gamma}$ is the $p \times q$ coefficient matrix describing the effects of exogenous variables on the endogenous variables. p is the number of endogenous variables. q is the number of exogenous variables. Since some endogenous variables are dichotomous (tourism participation and labor migration), we obtained the path coefficients in the model with the robust weighted least square estimator.

We used a set of validation indices to test how well the data support the hypothesized pathways. All values of these indices indicate our empirical data supported the hypothesized pathways well (Table S2.3). After obtaining path coefficients (Table S2.4), we calculated the effect of each pathway through which the GTGP or the GTBP affected the nonpayment income (Table S2.5). Based on that, we further calculated the net effects transmitted through each observed livelihood activity in this study (crop production, tourism participation, and labor migration), the effect transmitted through unspecified processes (i.e., effect captured by the unspecified pathway), and their total (Table 2.1). We conducted the statistical modeling and analyses using Mplus 7 (Muthén and Muthén 2012).

2.4.3 Estimating net effects of PES programs on household income

Based on estimates of the total effect on nonpayment income and information on the direct payments, we calculated the net economic effect per unit area (mu) of cropland enrolled in the

GTGP and the GTBP with the following equation:

$$Net\ Effect_i = \beta_i \times Percentage_i \times Nonpayment\_Income / Area_i + Payment_i \qquad (2.2)$$

where $i \in \{GTGP, GTBP\}$; β_i is the coefficient of the total effect of program i on the nonpayment income; $Percentage_i$ is the average percentage of cropland enrolled in the program i (56% for the GTGP and 10% for the GTBP); $Nonpayment\_Income$ is the average nonpayment income (14,764 yuan) of local households in 2005; $Area_i$ is the average cropland area enrolled in the program i (5.5 mu for the GTGP and 1 mu for the GTBP); $Payment_i$ is the average payment rate of program i (240 yuan/mu for the GTGP and 1,060 yuan/mu for the GTBP).

2.5 Results

Our results show that the linkages among the two PES programs (the GTGP and the GTBP), livelihood activities and nonpayment income constituted different pathways through which these programs affected household income (Fig. 2.3). For example, the GTBP negatively affected income through a pathway in which the GTBP boosted participation in the local tourism industry ($p < 0.1$), which led to decreased crop production ($p < 0.05$), and then a reduction in nonpayment income ($p < 0.01$).

The net effects on nonpayment income transmitted through tourism participation and labor migration are both positive (Table 2.1), but these effects are not statistically significant ($p > 0.1$) and smaller than the significant ($p < 0.01$) negative effect on nonpayment income transmitted through crop production (Table 2.1). In the case of the GTBP, the magnitude of the positive

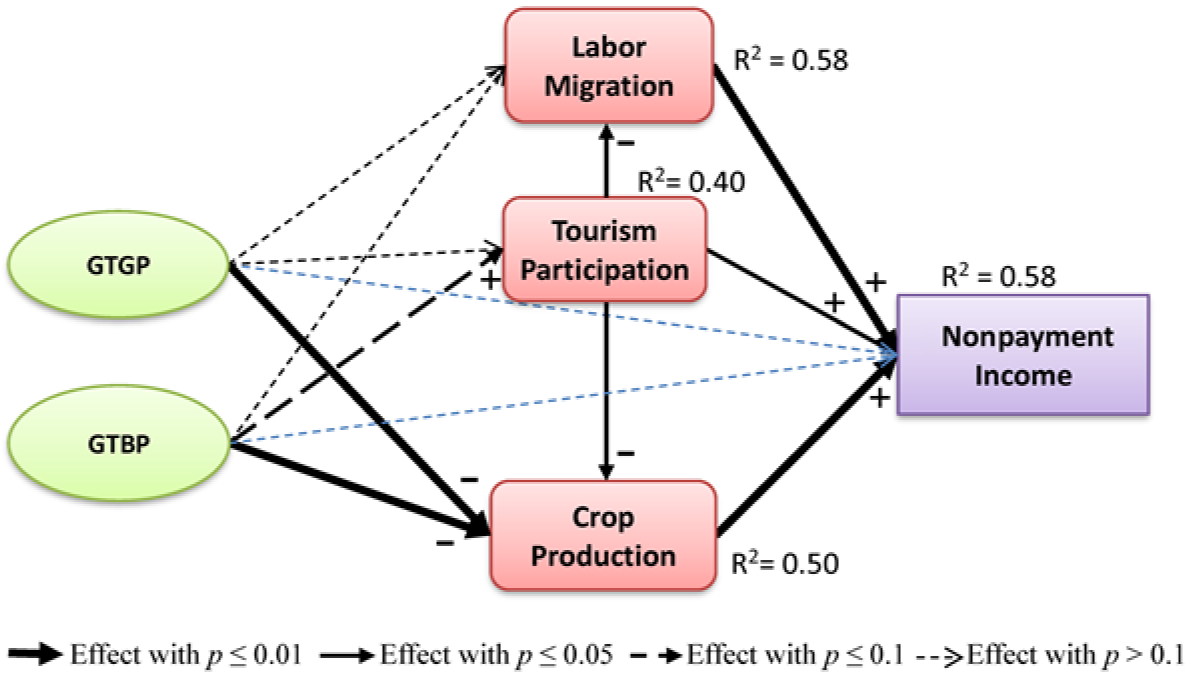

Figure 2.3 Visualization of the structural equation model results. Arrows with different line types represent linkages whose effects are of different statistical significance levels. '+' or '-' indicate the effect of the linkage is positive or negative.

effects on income through promoting tourism participation and labor migration could offset only about 34% of the income loss due to reduced crop production. In the case of the GTGP, these positive effects could offset an even smaller portion (11%) of the loss due to reduced crop production.

For both PES programs, their effects on nonpayment income captured by the unspecified pathways are negative, though not statistically significant ($p > 0.1$) (Table 2.1). As noted in our *Conceptual Framework*, the coefficients of the two unspecified pathways represent effects of the GTGP and GTBP on nonpayment income through all other processes that are not specified in this study, respectively.

Table 2.1 The coefficients of effects transmitted from the GTGP and the GTBP to non-payment income in 2005 through different livelihood activities and other unspecified processes. The number of households included in the analysis is 202.

Livelihood activity/Processes	Descriptions	Coefficients	
		GTGP	GTBP
Crop Production	Cropland devoted for crop production in 2005	-0.664^{***}	-0.563^{***}
Tourism Participation	Whether the household has a member who directly participated in tourism activities in 2005: 1. Yes; 0. No	0.058	0.142
Labor Migration	Whether the household had labor migrants in 2005: 1. Yes; 0. No	0.009	0.048
Other unspecified processes †	Other livelihood activities that are not observed in this study, and/or other dimensions of the observed activities (i.e., crop production, tourism participation and labor migration) that are not captured by their proxies above.	-0.006	-0.477
Total	The sum of all the effects transmitted through all the three livelihood activities and other unspecified processes.	-0.602^{*}	-0.850^{**}

$^{*}\ p \le 0.05$; $^{**}\ p \le 0.01$; $^{***}\ p \le 0.001$.

† The effect transmitted through unspecified processes is represented by the coefficient of the unspecified pathway.

The total effects of the GTGP and the GTBP on nonpayment income have been negative and are statistically different from 0 ($p < 0.05$) (Table 2.1). The results suggest that 1.0% increase in cropland enrollment (as measured by percentage of cropland being enrolled) would decrease nonpayment income by 0.6% under the GTGP and 0.9% under the GTBP. Correspondently, for enrollment of 1 mu of cropland (1 mu = 0.067 ha), the average net loss after considering the direct payments local household received (estimated using Equation (2.2) in *Materials and Methods*) was 634 yuan for the GTGP and 194 yuan for the GTBP (1 yuan = 0.122 USD in 2005). These negative effects on income indicate that the income level of participating households would be better off if they did not participate in these PES programs.

2.6 Discussion

Poverty eradication and ecosystem conservation are among the major goals being targeted by the 2030 Agenda for Sustainable Development of the United Nations (United Nations 2015). To achieve these goals, scientists, policy makers, and conservation practitioners need a better understanding of the underlying pathways through which conservation policies succeed or fail in generating desirable outcomes (Ferraro and Hanauer 2014). Our study here illustrates that integrated analysis of the linkages among PES programs, livelihood activities, and socioeconomic outcomes can help reveal the pathways from PES programs to socioeconomic outcomes.

In contrast to the positive effects of PES programs on income found in many other studies (e.g., Liu et al. 2010, Lin and Yao 2014), we found that the negative effects of the GTGP and the GTBP outweighed their positive effects on income in our study site, even after these programs' payments were counted. These negative net effects on household income occurred perhaps because, as time went by, the fixed payments of the GTGP or GTBP failed to cover the growing gap between their positive and negative effects on income through different pathways. From 2000 to 2003, households in Wolong enrolled a large portion (about 66% on average) of their cropland into these two programs. However, the price of agricultural products in China has increased dramatically since 2004 (Lu et al. 2014). Therefore, the strength of the pathway through which these programs negatively affect income by reducing crop production was increased. Meanwhile, our results indicate that these programs' effects on prompting participating households to find off-farm employment in the local tourism industry or in cities were small, though these livelihood activities can significantly increase household income (Fig. 2.3). Therefore, the gap between the negative effect on income due to forgone crop production and the positive effects on income through promoting off-farm employment increased after the implementation of the GTGP and GTBP. However, the fixed payment levels of these programs did not consider the possible changes in the opportunity costs borne by participating households and thus failed to cover the growing cost of lost crop production in the later years of our study period.

Based on the understood pathways, conservation practitioners may be able to identify the obstacles to improving the socioeconomic performance of PES programs and design effective management strategies accordingly. Our study results in Wolong show that both the GTGP and the GTBP had weak effects on promoting participation in the local tourism industry or labor migration. One major reason might be that the local households have limited access to the benefits brought by tourism development. For example, evidence from previous studies in Wolong (He et al. 2008, Liu et al. 2012) and other areas (Kiss 2004) suggest a large portion of tourism revenue often goes to tourism development companies and the government. Local communities often receive only a small share of the benefits brought by tourism (< 4% in Wolong) (He et al. 2008). In addition, although China has witnessed a dramatic increase of labor migrants (from only 2 million in the early 1980s to more than 150 million in 2010 (Rush 2011)), many barriers that hinder labor migration remain. The major barriers include lack of skills, unequal educational opportunities for children of migrant workers in cities, and administrative restrictions on the shift from rural residence to urban residence (Li 2011). Due to these barriers, participating households may be unable to effectively utilize the payments and surplus labor made available by PES programs to participate in these off-farm livelihood activities. Therefore, management interventions that help overcome these barriers (e.g., providing training to participating households to develop new skills and offering equal opportunities for migrant workers in urban areas) should be considered to increase the benefits participating households could obtain from these off-farm livelihoods, and ultimately improve the socioeconomic outcomes of these PES programs. Otherwise, higher payments should be offered to local households to cover the associated losses from participating these programs, though it may put a heavier financial burden on governments.

Like any other conservation policy, PES programs' socioeconomic effects often vary across space and time. With a better understanding of the underlying pathways, we may be better positioned to explain and anticipate the socioeconomic outcomes of PES programs in different contexts. For example, PES programs similar to the GTGP and the GTBP have been widely implemented around the world, such as the Conservation Reserve Program in the United States (USDA 2016), the Permanent Cover Program in Canada (McMaster and Davis 2001), the Common Agricultural Policy in Europe (European Commission 2013), Pagos de Servicios Ambientales program in Costa Rica (Pagiola 2008), and payments for afforestation programs in Bolivia (Asquith et al. 2008) and Ecuador (Wunder and Albán 2008). Land owners participating in these programs receive payment to convert their cropland to vegetative land. Therefore, pathways as identified in our demonstration case may be applicable to explain the socioeconomic outcomes of these PES programs (e.g., these programs may also negatively affect income through reducing crop production and positively affect income by prompting them to seek alternative livelihoods).

In addition, a better understanding of the pathways may help anticipate the dynamics of PES programs' socioeconomic outcomes across time. For example, the rapid economic growth in China's cities stimulates an ever-growing demand for laborers. In a number of coastal cities in China, many factories have been struggling with labor shortages in recent years (Zhan and Huang 2013). Meanwhile, the Chinese government has implemented a series of policies favorable for labor migrants to work in cities (e.g., reform of the existing urban-biased residence registration system) (Fan 2008). These changes may help rural households find off-farm employments in cities, and thus enhance the socioeconomic outcomes of the GTGP and the GTBP which have released many rural laborers from farming activities. As urbanization continues at an increasing speed in the developing world (Cohen 2006), similar trend in PES programs' effects on socioeconomic outcomes may also occur in other countries.

Although our framework was developed for analyzing the socioeconomic outcomes of PES programs, it can be easily adapted for the analysis of other conservation policies (e.g., protected areas) that also have complex socioeconomic effects by affecting different livelihood activities. Ultimately, to improve the socioeconomic outcomes of conservation policies, it is necessary to develop more elaborate theories (e.g., metacoupling theory that integrates human-nature interactions across space (Liu 2017a)) to guide conservation practices that will enhance positive outcomes while mitigating negative ones. It is our hope that the framework proposed and its operationalization in this study will contribute to the construction of such theories and a collective base of evidence about the effects of pathways underlying conservation programs' socioeconomic outcomes. Armed with such theories and knowledge, scientists, policy makers and conservation practitioners may be able to better use conservation tools for achieving Sustainable Development Goals.

CHAPTER 3

UNCOVERING THE HIDDEN COST OF CONSERVATION

In collaboration with

Frank Lupi, Jindong Zhang, and Jianguo Liu

Abstract

As global efforts to protect ecosystems expand, there is increasing concern about conservation costs borne by rural communities. To date, these costs have often been narrowly estimated in terms of foregone livelihood opportunities directly caused by conservation, while unintended human burdens that accrue with ecological gains from conservation are often ignored. As a first attempt to quantify this previously hidden cost, we estimated the impact of converting cropland to forest under one of the world's largest conservation policies, China's Grain-to-Green Program (GTGP), on crop damage in a demonstration site using the matching approach. We found that GTGP afforestation was responsible for 64% of the crop damage by wildlife, a cost worth 27% of GTGP's total payment to farmers. Our study highlights that the conservation cost to communities through influencing human-wildlife conflicts can be substantial, which should be quantified and considered in global conservation efforts to avoid unintended burdens on rural communities.

3.1 Introduction

Since the start of the 21st century, a remarkable international agreement on the urgency of poverty alleviation has made the conservation costs borne by rural communities an important concern (Andam et al. 2010, Colglazier 2015). In response, there has been a growing search for conservation strategies that integrate mechanisms (e.g., direct payment) to avoid worsening livelihoods of rural communities (Adams et al. 2004, Roe and Elliott 2006). So far, however, it has often been found difficult to achieve wins for both ecosystem conservation and welfare of communities in conservation areas (Muradian et al. 2013, Rasolofoson et al. 2017). Previous studies show a likely approach to address this challenge is to identify, then mitigate, the costs conservation efforts impose on local people (e.g., arrangements that truly compensate) (Ando et al. 1998, Kremen et al. 2000, Ansell et al. 2016). To date, however, conservation costs to communities have often been narrowly estimated based on direct impacts of conservation on livelihoods (e.g., forgone farming revenue due to cropland retirement), while indirect impacts accruing with ecological gains from conservation have often been ignored.

A striking example of such indirect impacts involves the intensification of human-wildlife conflicts. Global conservation efforts over the past decades have generated many ecological gains, as evidenced by the forest transition in China (Viña et al. 2016), the comeback of gray wolves in the USA (USFWS 2013), and the population growth of carnivores in Europe (Chapron et al. 2014). While these efforts have enhanced the provision of ecosystem services, they may also cause a serious disservice: human-wildlife conflict (Linkie et al. 2007, Bonacic et al. 2016). Although it is commonly believed that conservation has driven growing human-wildlife conflicts worldwide (Naidoo et al. 2006, Linkie et al. 2007), losses attributed to conservation programs have rarely been quantified.

As a first attempt to quantify this previously hidden cost, we estimated the effect of afforestation promoted by China's Grain-to-Green Program (GTGP) on crop damage by wild animals using household survey data from Wolong Nature Reserve (Wolong hereafter). GTGP is one of the world's largest payments for ecosystem services (PES) programs, which aims to increase the provision of ecosystem services (e.g., water and soil retention) through converting cropland to vegetative land (Liu et al. 2008b). By the end of 2014, the program had converted about 9.27 million hectares of cropland from more than 30 million households to forest land or pastureland (Liu et al. 2008b, Wu 2015). To offset the associated forgone crop production, GTGP designed a payment scheme to compensate participating households (SFA 2002).

However, afforestation on cropland prompted by GTGP might have intensified crop raiding on remaining cropland unenrolled in GTGP, a cost that was not considered in GTGP's payment scheme. In many rural areas like Wolong, cropland parcels close to forests are often susceptible to damage by wild animals (Linkie et al. 2007) and were more likely to be enrolled into GTGP than cropland farther from forests (Fig. 3.1). But the conversion of cropland to forest may make it new habitat for crop raiders and cause remaining cropland more vulnerable to crop raiding (Fig. 3.1). In addition, crop damage previously borne by cropland enrolled in GTGP may be displaced to nearby remaining cropland and increase crop damage there (Fig. 3.1).

In this study, we aim to estimate the impact of GTGP on crop damage by comparing the observed crop damage on remaining cropland with the counterfactual crop damage that would

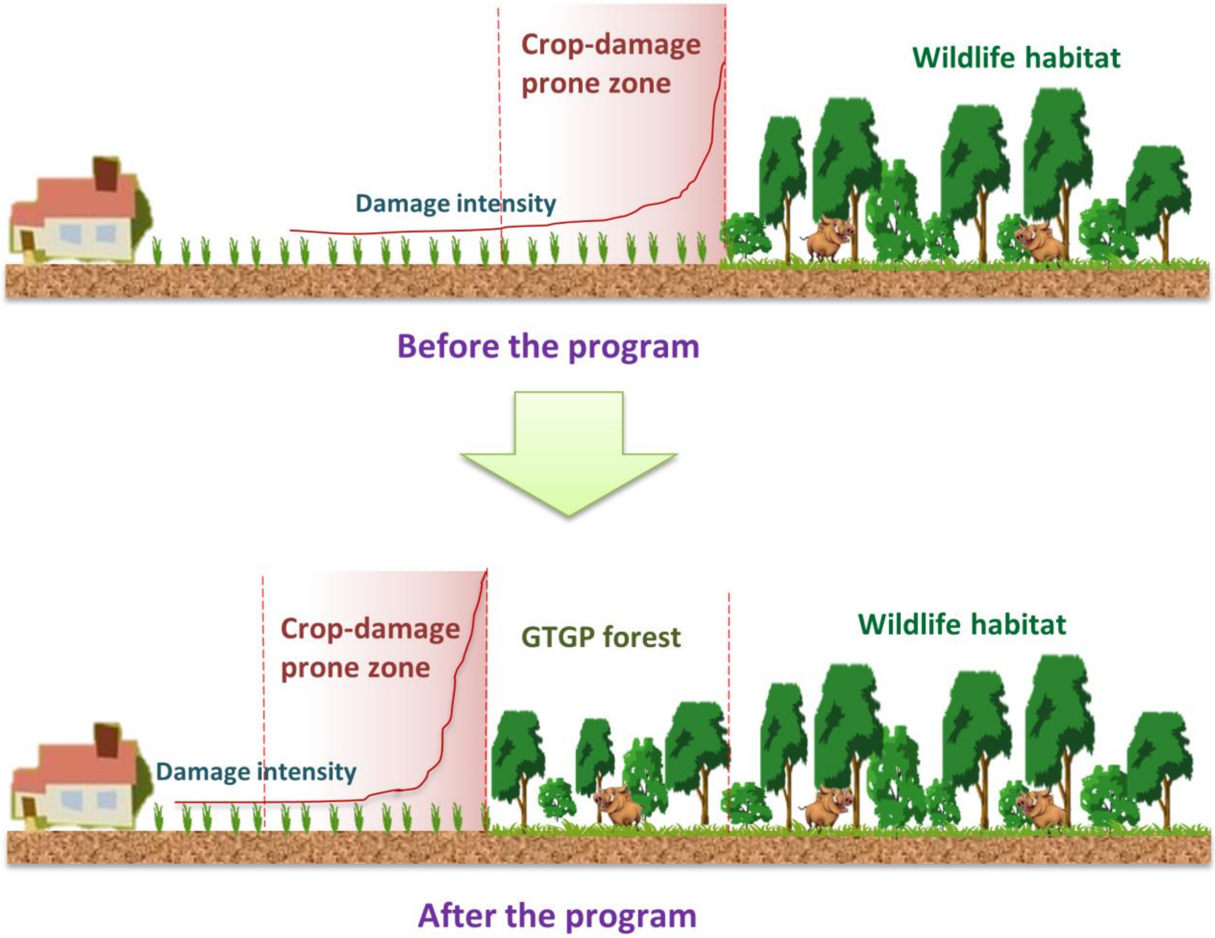

Figure 3.1 Illustration of the change of crop damage by wildlife before and after afforestation on cropland promoted by conservation program. Before afforestation, cropland close to wildlife habitat (e.g., forest) is more severely affected by crop damage by wildlife than distant ones. After afforestation, cropland close to wildlife habitat are afforested and the nearby remaining cropland becomes more severely affected by crop damage by wildlife.

have occurred on the same remaining cropland if the GTGP were not implemented. For practical reasons, we cannot observe this counterfactual crop damage directly. Instead, we estimated the impact by comparing damage on remaining cropland parcels close to and affected by GTGP afforestation with their counterparts that are far from and were not affected by GTGP afforestation using the matching method (Stuart 2010). The difference in crop damage between remaining cropland affected by GTGP and their counterparts unaffected by GTGP represents

GTGP's impact on crop damage.

3.2 Materials and Methods

3.2.1 Study area

Wolong is a flagship protected area in Southwest China and within one of the world's top 25 global biodiversity hotspots (Fig. 3.2) (Liu et al. 2016a). Besides providing sanctuary to hundreds of wildlife species (including the iconic giant panda (*Ailuropoda melanoleuca*)), Wolong houses about 4,900 residents, most of whom are farmers (Liu et al. 2016a). To restore and protect ecosystems, a series of conservation programs have been implemented since the early 2000s, including GTGP (Yang 2013).

In Wolong, GTGP enrollment began in 2000, and additional contracts were signed in 2001 and 2003. Under GTGP, the government paid households about $571 per ha per year for converting their cropland to forest and keeping it vegetated (Yang 2013). In total, about 56% of cropland was converted to forest. Like many other rural areas, crop damage by wild animals, such as wild boar (*Sus scrofa*), sambar deer (*Rusa unicolor*), and hedgehog (*Erinaceinae*), is common in Wolong (Yang 2013). The majority of cropland parcels enrolled in GTGP were close to the forest edge and were susceptible to crop raiding (Chen et al. 2010).

3.2.2 Study design

Our analysis unit is individual remaining cropland parcel after the implementation of GTGP, and our outcome measure is crop damage intensity: the reported proportion of crop lost in a land parcel due to wildlife damage. Based on distance to nearest GTGP land parcel (former cropland enrolled in GTGP and afforested), each analysis unit was placed into one of the three ranges:

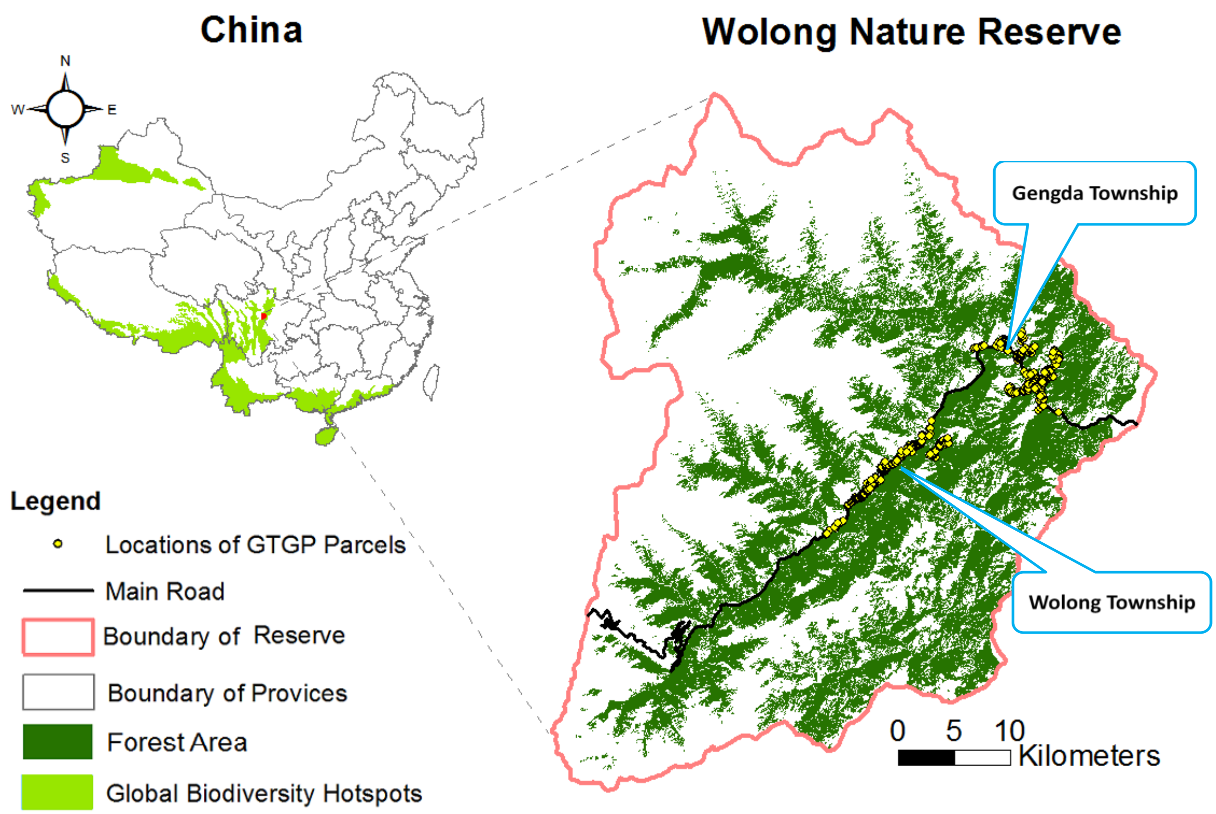

Figure 3.2 Wolong Nature Reserve in Southwest China. The reserve was established in 1963 and expanded to its current size of 20,000 km2 in 1975. It is managed by the Wolong Administration Bureau, which is hierarchically structured with two townships under its governance – Wolong Township and Gengda Township, with a total population of about 4,900.

close (< 10 m); medium (10 m - 40 m); and far (> 40 m). Cropland parcels in the close and medium ranges were considered as treatment groups whose crop damage was highly and moderately affected by GTGP afforestation respectively, with the assumption that close plots were affected more by GTGP afforestation than distant ones. Cropland parcels in the far range were considered as units unaffected by GTGP afforestation because we found that for cropland parcels in this range, being closer or farther to GTGP afforestation does not have any statistically significant effect on crop damage (see *Robustness Checks* of Supplementary Information for details).

We estimated the impacts of GTGP on crop damage intensities of cropland parcels in both the close and medium ranges for all crop types together and for each crop type separately. In these estimations, cropland parcels in the far range that are similar to the parcels in close or medium range in terms of a rich set of attributes (e.g., distance to natural forest) were used to construct the control groups (i.e., counterpart cropland parcels whose crop damage were unaffected by GTGP) using the matching method (see section 2.4). Our hypothesis that GTGP afforestation intensified crop damage on nearby remaining cropland would be supported if impact in the close range is larger than impact in the medium range and both of them are positive.

3.2.3 Data collection

We conducted a household survey in Wolong in 2015. Household heads or their spouses were interviewed because they are familiar with household affairs (e.g., locations of cropland and losses due to wildlife damage). 245 households (about 21% of the total) were randomly sampled and completed the survey. On Google Earth Imagery of Wolong (Google Earth V 7.1.5 2015), we digitized boundaries of all cropland parcels owned by each surveyed household with respondents' help. For each cropland parcel, we asked questions about characteristics of the land plot, including type of crop, the yield, crop loss due to wildlife damage, crop price, and whether preventative measures (e.g., building fences) were taken to avoid damage by crop raiders. In total, we collected information on 423 cropland parcels, of which 169, 97, and 157 fell into the close, medium and far ranges, respectively, and 176 experienced crop raiding in 2014.

Before administering the formal survey, we pretested and revised the questions to enhance data reliability. The pretest involved a sequence of one-on-one cognitive interviews (Willis 2004)

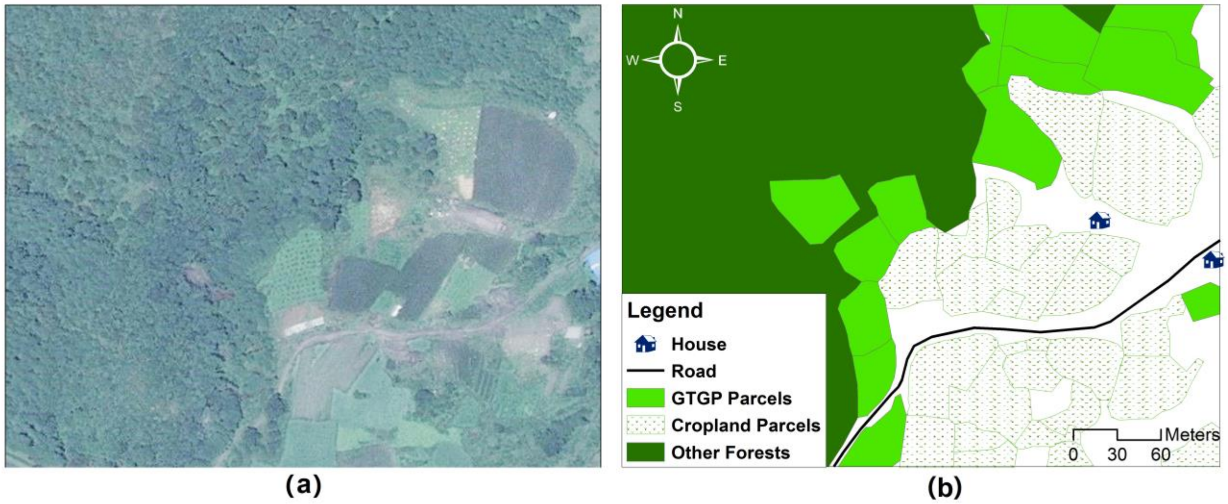

Figure 3.3 The spatial pattern of land cover in an example area of Wolong. (a) Google Earth Image of a sample area in Wolong; and (b) the corresponding classification map based on survey results and visual interpretation.

with 33 individual interviewees participated. The goals of our pretests included assessing respondents' comprehension of our survey questions, the questions' difficulty, and the quality of respondents' answers. As the cognitive interviews progressed, we iteratively updated our questions and improved our survey instrument before administering the formal survey.

Regarding crop loss due to wildlife damage, we designed the questions to be easy for respondents based on feedback from the pretests. Our pretest interviewees told us it was easy to report crop raiding because the size of each cropland plot in Wolong is small (average area is about 2.5 mu or 0.16 ha) and each household does not have much cropland (average area is about 2.9 mu or 0.19 ha) to care for. Therefore, if damage by crop raiders occurred on their cropland, it would be easy for them to know and differentiate that from losses caused by other factors such as insects, diseases, and drought.

In our pretests, we explored alternative ways of eliciting crop damage intensity for each cropland parcel and probed interviewees for ways to avoid biased estimation, which led to several refinements including two major ones. First, before the interview, we determined it was important to explain clearly that the survey information would be used for research purposes only, otherwise some respondents may think the reported loss would be used for damage compensation purposes and thus tend to report a higher loss than the actual amount. Second, it was crucial to ask crop loss in an understandable way for local households. Instead of asking how many kilograms of crop was lost due to crop raiding, our interactions with interviewees led to our approach of asking for the zero-yield area (equivalent area with no yield due to crop raiding) for each cropland parcel. We found respondents could visually estimate the extent to which each part within a land plot was affected. Since the total area of a plot is small, the respondents could easily aggregate damages occurred at different parts of a plot to zero-yield area of that plot by adding up the areas of different parts affected by crop raiding weighted by their levels of damage (damage intensities). We can formally represent this thought process using the following equation:

$$\text{Zero-yield Area} = \sum_{i}^{N} Area_i \times Damage\,Intensity_i \tag{3.1}$$

where N is the number of damage intensity levels occurred within the land plot; $Damage\,Intensity_i$ and $Area_i$ represent the damage intensity level i and the corresponding area within the land plot affected by this level of damage respectively. For example, assume the area of a potato land parcel is 1 mu. Of it, 0.2 mu was affected by crop raiding, with 0.1 mu seriously affected (all potatoes were eaten by crop raiders) and 0.1 mu was moderately affected (half of the potatoes were eaten by crop raiders). The corresponding zero-yield area would be 0.15 mu (= 0.1×1 + 0.1×0.5). Zero-yield area of a cropland parcel divided by the parcel's area is the parcel's crop damage intensity (i.e., proportional crop loss) used in our impact estimation analysis.

Using Google Earth Imagery, we also obtained boundaries of all GTGP parcels in Wolong by interviewing village leaders familiar with the distribution of GTGP land. In addition to the above information, we mapped the distribution of all houses, the main road, and forest areas in Wolong based on visual interpretation of Google Earth Imagery (Fig. 3.3). Average slopes of cropland parcels were calculated using ArcGIS (version 10.4, ESRI Inc., CA) with elevation information from Shuttle Radar Topography Mission. The survey instruments and data collection procedures we used in this study were reviewed and approved by the Institutional Review Board of Michigan State University (https://hrpp.msu.edu/).

3.2.4 Estimating the impact of GTGP on crop damage

We estimated the impact of GTGP on crop damage using the matching method (Stuart 2010). The logic of matching is straightforward. For each cropland parcel in the treatment group (either in the close or medium range), the matching method finds a cropland parcel in the far range as control that is similar in terms of the observable attributes that may correlate to closeness to GTGP land and crop damage (called confounding factors). After controlling these observable cropland attributes using matching, the difference in crop damage intensities between cropland parcels in the treatment group (units in the close or medium range) and the control group (matched units in the far range) will reasonably represent the effect of GTGP afforestation on crop damage. As compared with other approaches, such as generalized linear model, the matching method is more robust to model misspecification, have less strict assumptions, and is more reliable for estimating the effect of GTGP afforestation on crop damage on nearby remaining cropland (see *Matching method for impact estimation* in Supplementary Information for details).

Based on our knowledge of Wolong and literature on crop damage, we controlled for a rich set of variables commonly found to affect crop damage (Table S3.1). We used a one-to-one matching method with replacement to estimate the impacts. A genetic search algorithm (Diamond and Sekhon 2013) and caliper (0.5 standard deviation of each matching covariate) were used to improve the matching quality. After matching, the differences of these covariates between treatment and control groups move dramatically toward zero (Table S3.2 and S3.3), indicating good matching quality (Ho et al. 2007). We then estimated the impacts of GTGP on crop damage intensities using a bias-adjustment estimator (Abadie and Imbens 2006) which can address imperfect matching in our sample (i.e., remaining covariate differences between treatment and control groups). Since different crop types may have different levels of susceptibility to crop damage by wild animals, we estimated the impacts of GTGP on crop damage for all crop types together and for each crop type separately, including corn, potato, and cabbage. We performed the matching analysis in R (R Development Core Team 2013) using the packages named ‘Matching’ (Sekhon 2011).

After estimating the impacts of GTGP on crop damage intensities in the close and medium ranges, we further estimated the average proportion of observed crop damages attributable to

GTGP for all crops together and each crop type separately using:

$$\text{Proportion}_i = \frac{In_{close,i} \times A^s_{close,i} + In_{medium,i} \times A^s_{medium,i}}{I_{close,i} \times A^s_{close,i} + I_{medium,i} \times A^s_{medium,i} + I_{far,i} \times A^s_{far,i}} \tag{3.2}$$

where $i \in \{corn, potato, cabbage, all\ crops\ together\}$; $In_{close,i}$ and $In_{medium,i}$ represent average increases of crop damage intensity caused by GTGP for cropland units of crop type *i* in the close and medium range respectively; $I_{close,i}$, $I_{medium,i}$ and $I_{far,i}$ represent average crop damage intensities for cropland units of crop type *i* in the close, medium and far ranges respectively; $A^s_{close,i}$, $A^s_{medium,i}$ and $A^s_{far,i}$ represent the total areas of sample units of crop type *i* in the close, medium and far ranges respectively.

3.2.5 Estimating the forgone crop revenue due to GTGP-induced crop damage

Based on the impacts of GTGP on crop damage intensities of each crop type in the close and medium ranges, we assessed foregone crop revenue due to crop damage attributable to GTGP in Wolong using:

$$\text{Forgone Revenue}_i = (In_{close,i} \times A_{close,i} + In_{medium,i} \times A_{medium,i}) \times Productivity_i \times Price_i \tag{3.3}$$

where $i \in \{corn, potato, cabbage\}$; Forgone Revenue_i represents the forgone revenue due to the GTGP-induced wildlife damage to crop type *i*; $In_{close,i}$ and $In_{medium,i}$ represent average increases in crop damage intensity caused by GTGP for crop type *i* in the close and medium range respectively; $A_{close,i}$ and $A_{medium,i}$ represent total cropland areas of crop type *i* in close and medium ranges in Wolong estimated based on our sample cropland parcels respectively; $Productivity_i$ represents the average productivity (reported yield divided by area) of crop type *i* on cropland units that were not affected by crop damage in 2014; $Price_i$ represents the average price at which households in our sample sold crop type *i* in 2014.

3.3 Results

Impact estimates (Fig. 3.4) show that afforestation on GTGP land significantly intensified crop damage on remaining cropland, especially in the close range. The overall impact of GTGP on crop damage intensity (the reported proportion of crop lost in a land parcel due to wildlife damage) of cropland parcels in the close range (Fig. 3.4) was 0.189, implying the crop loss increased by18.9% due to GTGP. Impacts of GTGP on crop damage varied across different crop types. On average, GTGP afforestation increased the crop damage intensity on corn and potato parcels in the close range by 0.244 and 0.198 respectively ($p < 0.001$). As compared with corn and potato cropland, GTGP's impact on damage on cabbage cropland in the close range is smaller (0.022, $p < 0.05$).

The impacts of GTGP on crop damage intensity of cropland units in the medium range is smaller than in the close range (Fig. 3.4). On average, afforestation from GTGP increased crop damage intensity in the medium range by 0.044 ($p < 0.001$), which is about 25% of that in the close range (0.189). GTGP increased damage intensity of potato and corn cropland in the medium range by 0.07 and 0.068 respectively ($p < 0.001$), which are about 28.7% and 34.3% of the corresponding impacts in the close range, respectively. This pattern that GTGP caused more wildlife damage on cropland in the close range than in the medium range further supports our hypothesis that GTGP afforestation increased crop damage on nearby remaining cropland.

Based on the impact estimates above, we calculated the proportion of crop damage that

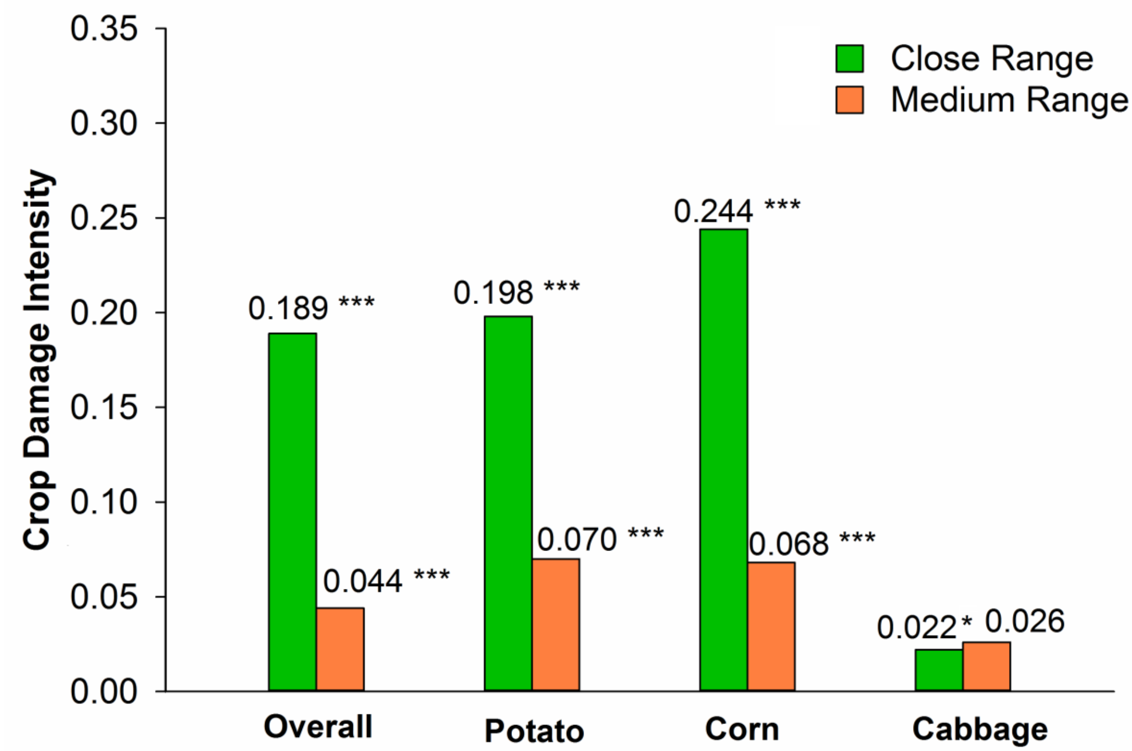

Figure 3.4 Impacts of the GTGP on crop damage intensities of cropland in the close and medium ranges. Tabular presentation of these results can be found in Table S3.4 – S3.7. *, **, and *** indicate significance at $p < 0.05$, 0.01, and 0.001 levels respectively.

occurred on remaining cropland attributable to GTGP (using Equations (3.2) in *Methods*). The results suggest that had there been no GTGP afforestation, the overall crop damage on remaining cropland would be 64% less. For corn, potato, and cabbage, the crop damage would be 63%, 74%, and 40% less respectively if GTGP were not implemented.

With the estimated impacts of GTGP on crop damage for each crop type (Fig. 3.4), we further estimated the forgone revenue (using Equation (3.3) in *Methods*). The total foregone revenue of crop damage attributable to GTGP in Wolong is 364,910 yuan (58,479 USD as of 2014; Fig. 3.5), a cost that amounts to 27% of total annual payments farmers received from GTGP in Wolong. The revenue loss occurs mostly due to GTGP's impact on corn cropland (224,702 yuan), followed by potato land (77,781 yuan), and cabbage land (62,427 yuan).

3.4 Discussion

Our study suggests that China's sweeping conservation effort in returning cropland to forest did so with an until-now hidden consequence: it increased the wildlife damage to remaining cropland and thus caused unintended cost that whittled away at the program's compensation for farmers. To assess the reliability of this conclusion, we performed a set of analyses to evaluate the robustness of our results to variability in study design and assumptions and found that these uncertainties are unlikely to change our conclusion (see *Robustness Checks* of Supplementary Information for details).

Consideration of this previously hidden cost has important implications for conserving ecosystems ethically and sustainably. For instance, payments for ecosystem services (PES) are increasingly implemented to reduce negative impacts of conservation on livelihoods of rural communities (Fischer et al. 2012, Naeem et al. 2015). To date, however, payment levels of PES programs are largely designed based on the foregone productive uses (e.g., farming) of the land being targeted. This would be unfair if a PES program brings other unacknowledged or undisclosed economic loss to communities in target areas. In the case of GTGP, the current payments are solely based on the amount of cropland afforested. The potential impact of GTGP on remaining croplands was not considered. Therefore, rural households that suffered crop damage induced by GTGP might have been undercompensated. Such problems may ultimately compromise the sustainability of conservation. As losses due to human-wildlife conflicts

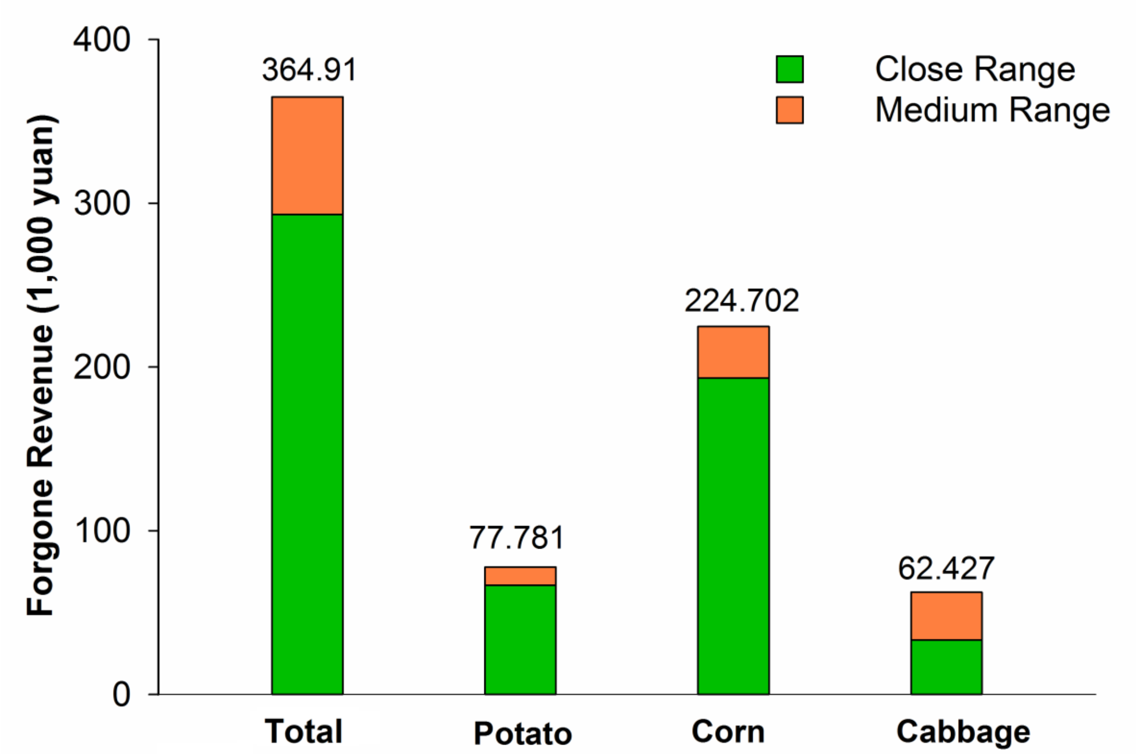

Figure 3.5 Foregone revenue of crop damage in Wolong attributable to GTGP for each crop type and the total of them.

increase, farmers may increasingly resent conservation efforts.

To mitigate these negative impacts, integrated management strategies should be considered. So far, compensating households that experienced wildlife damage (including crop damage and livestock predation by wildlife) has been a common mitigation strategy (Nyhus et al. 2005). However, previous studies indicate that the use of compensation schemes has mixed results due to issues such as inefficient governance (e.g., corruption) and shortage of necessary resources (e.g., financial and human resource to handle all cases) (Nyhus et al. 2005, Storie and Bell 2016). In Wolong, our survey shows that of all the cropland that experienced crop damage by wildlife, only 2% received compensation. Therefore, other complementary measures such as preventative strategies and systematic land-use planning should be jointly considered to mitigate wildlife damage under circumstances like Wolong (Bulte and Rondeau 2005, Gross et al. 2016). For example, given the relatively small size of the remaining cropland area in Wolong (about 0.15% of the whole reserve), establishing fences around the remaining cropland may be a cost-effective way to reduce crop damage without much influence on the connectivity of panda habitats. In addition, switching to crop types less likely to be affected by wildlife damage may also help to address this issue. For example, plum has been introduced to Wolong in recent years and become a promising new type of cash crop. Unlike corn and potato, plum is not susceptible to wildlife damage. Planting plum on cropland close to forest may help reduce the losses due to wildlife damage and the negative impacts of GTGP.

It should be noted that GTGP may generate some indirect benefits to offset the losses from its impacts on crop damage. For example, studies show that labor released from agricultural production due to cropland enrollment in GTGP has prompted the shift from on-farm to off-farm activities such as working in local tourism industry or out-migrating to work in cities (Liu et al. 2008b). In addition, the associated ecological improvements may generate some beneficial services to households. For example, a previous study in Wolong (Chen et al. 2009b) found the planted forests from GTGP offered a new fuelwood source for households, and thereby may reduce households' expenditure for electricity. Future research should be conducted to evaluate the potential trade-offs among different effects of GTGP.

Although our analysis here is restricted to GTGP in China, similar hidden costs are likely to occur in regions where similar conservation efforts have been implemented. For example, in the United States, about 9.52 million hectares of cropland has been enrolled in the Conservation

Reserve Program and become vegetated (USDA 2016). In Europe, the Common Agricultural Policy has afforested about 8 million hectares of cropland (European Commission 2013). In the Russian Federation, about 2.74 million hectares of cropland has been afforested for conservation (Kulik et al. 2015). Although the specific effects of these conservation efforts on human-wildlife conflicts may vary, the general trends may be similar. To truly understand conservation costs to rural communities, more interdisciplinary studies are needed to quantify different sources of costs and understand the underlying processes across different contexts. Armed with such knowledge, conservation practitioners may be able to design more effective conservation programs for win-win outcomes as targeted by the United Nations Sustainable Development Goals (United Nations 2016).

CHAPTER 4

FEEDBACK OF TELECOUPLING: THE CASE OF A PAYMENTS FOR ECOSYSTEM SERVICES PROGRAM

In collaboration with

Frank Lupi, Jindong Zhang, Xiaodong Chen, and Jianguo Liu

Abstract

Around the globe, previously isolated rural areas are increasingly connected with other distant places (e.g., cities) by telecouplings (i.e., environmental and socioeconomic interactions over distances) such as payments for ecosystem services (PES) programs, labor migration, and tourism. Although many studies have estimated impacts of telecouplings in rural areas, little is known about how these impacts might in turn affect telecouplings themselves through feedbacks. Using household survey data collected in China's Wolong Nature Reserve for giant pandas (*Ailuropoda melanoleuca*), we evaluated an unexpected impact of the telecoupling of the Grain-to-Green Program (GTGP) – one of the largest PES programs in the world. This impact may trigger a feedback that can strengthen the GTGP in the future. A previous study in Wolong found that afforestation on marginal cropland promoted by the GTGP has significantly intensified crop damage by wildlife on nearby remaining cropland. Here we evaluated how this change might in turn affect the GTGP by estimating the impact of crop damage induced by the current GTGP on local households' willingness to participate in possible future GTGP. Our results show that, due to the impact of current GTGP on crop damage, local households may enroll 10.4% more cropland that is close to the afforested lands in future GTGP, suggesting positive feedback that will strengthen the influences of the GTGP in Wolong and beyond. Our study highlights that local human-nature interactions driven by telecouplings, such as human-wildlife conflicts, may trigger feedbacks affecting telecouplings themselves. With improved understanding of telecouplings' feedbacks, scientists, policy makers, and conservation practitioners can better anticipate the complex interactions among different places and design effective conservation

strategies for achieving sustainability objectives such as those set by the United Nations' Sustainable Development Goals.

4.1 Introduction

Since the beginning of human history, telecouplings – socioeconomic and/or environmental interactions over long distances (Liu et al. 2013a) – have significantly shaped the Earth (Eakin et al. 2014). With the rapid development and expansion of transportation, information and communication technologies, telecouplings have been occurring at much larger scales and much faster pace than ever before (Liu et al. 2013a). Even previously isolated rural areas have been increasingly connected with distant places like urban centers through telecouplings such as payments for ecosystem services (PES) programs, labor migration, and tourism (Kramer et al. 2009, Liu et al. 2015a).

As different parts of the world are increasingly interconnected, many key issues of our time are profoundly shaped by telecouplings, such as global land use change (Verburg et al. 2013, Bruckner et al. 2015), urbanization (Alberti 2015, Fang and Ren 2017), trade impacts (Sun et al. 2017), wildlife conservation (Wang and Liu 2016, Hulina et al. 2017), international economic development (Galaz et al. 2015, Yang et al. 2016a), water scarcity (Yang et al. 2016b), energy security (Fang et al. 2016), species invasion (Liu et al. 2014), and forest sustainability (Liu 2014). On the one hand, some issues have been exacerbated by telecouplings. A striking example involves species invasion, the second leading cause of biodiversity loss (Kohli et al. 2009). Both incidentally and deliberately, humans have been redistributing an ever-increasing array of species across the world through migration, transport, and commerce, which drastically increased the homogeneity of world biota and the economic damage to many related industries (Mack et al. 2000). On the other hand, some telecouplings offer unique tools to address these issues and drive human-nature interactions toward sustainability. For example, payments for ecosystem services (PES) has been widely used in recent decades as a promising tool to reconcile the conflicting demands of socioeconomic development and ecosystem conservation (Naeem et al. 2015). Through PES programs, beneficiaries of ecosystem services offer incentives (e.g., cash, grain) to users of natural resources who often lie long distances away (e.g., farmers in rural areas) for activities that can enhance the provision of ecosystem services such as cropland retirement (Engel et al. 2008, Liu et al. 2013c). Given the great importance of telecouplings, understanding their complex effects has become a practical need to achieve sustainability objectives such as those targeted by the United Nations' Sustainable Development Goals (United Nations 2015).

Over the past decades, much progress has been made in understanding impacts of telecouplings under systems frameworks such as coupled human and natural systems (Liu et al. 2007b), coupled human-landscape systems (Werner and McNamara 2007) or coupled social-ecological systems (Walker et al. 2004, Ostrom 2009). In them, telecouplings were usually treated as static external drivers with the assumptions that drivers affect local couplings (human-nature interactions at local scale) (Mena et al. 2006). However, as the effects of telecouplings on local couplings accumulate, feedbacks may emerge and strengthen or weaken telecouplings themselves (Liu et al. 2013a). A typical example might be nature-based tourism which has been widely incorporated in Integrated Conservation and Development Projects (ICDPs) as a tool to achieve social and environmental sustainability in many biodiverse rural areas (Liu et al. 2012). However, as tourism life cycle theory (Butler 1980) predicts, local demand for economic growth may interact with outside capital markets looking for high-volume businesses, driving local tourism development beyond the carrying capacity of the local environment (Liu et al. 2012). When the negative environmental effects of tourism accumulate and become manifest, tourist visitation may decline rapidly and cause devastating effects on local livelihoods, thereby defeating the ICDPs' sustainability goals. Therefore, understanding telecouplings' feedbacks is critical for design and management of telecouplings. Ignoring them may lead to biased estimates of the long-term effects of telecouplings and generate unexpected outcomes (Liu et al. 2007a, Hull et al. 2015).

However, empirical and quantitative knowledge of how impacts of telecouplings might trigger feedbacks affecting telecouplings themselves has remained rare in existing literature. To address this important knowledge gap, we used household data collected in China's Wolong Nature Reserve (Wolong) for giant pandas (*Ailuropoda melanoleuca*) to empirically evaluate a change in behavioral intention inspired by the Grain-to-Green Program (GTGP) in China that may create feedback affecting the GTGP itself (State Forestry Administration 2010). The GTGP is a national PES program initiated in the late 1990s and is one of the largest PES programs in the world. By the end of 2014, the program had converted about 9.27 million hectares of cropland from more than 30 million households to forest land or grass land (Liu et al. 2008b, Wu 2015). Evidence shows that the current GTGP has generated substantial socioecological effects in China and constitutes an important telecoupling that links the program's target areas to other places (Liu et al. 2008b, Liu et al. 2015a). Through the GTGP, participating households received payments from distant places (as represented by the Chinese government in Beijing) to convert their cropland to forest land or grass land (Chen et al. 2012b). In return, many other places

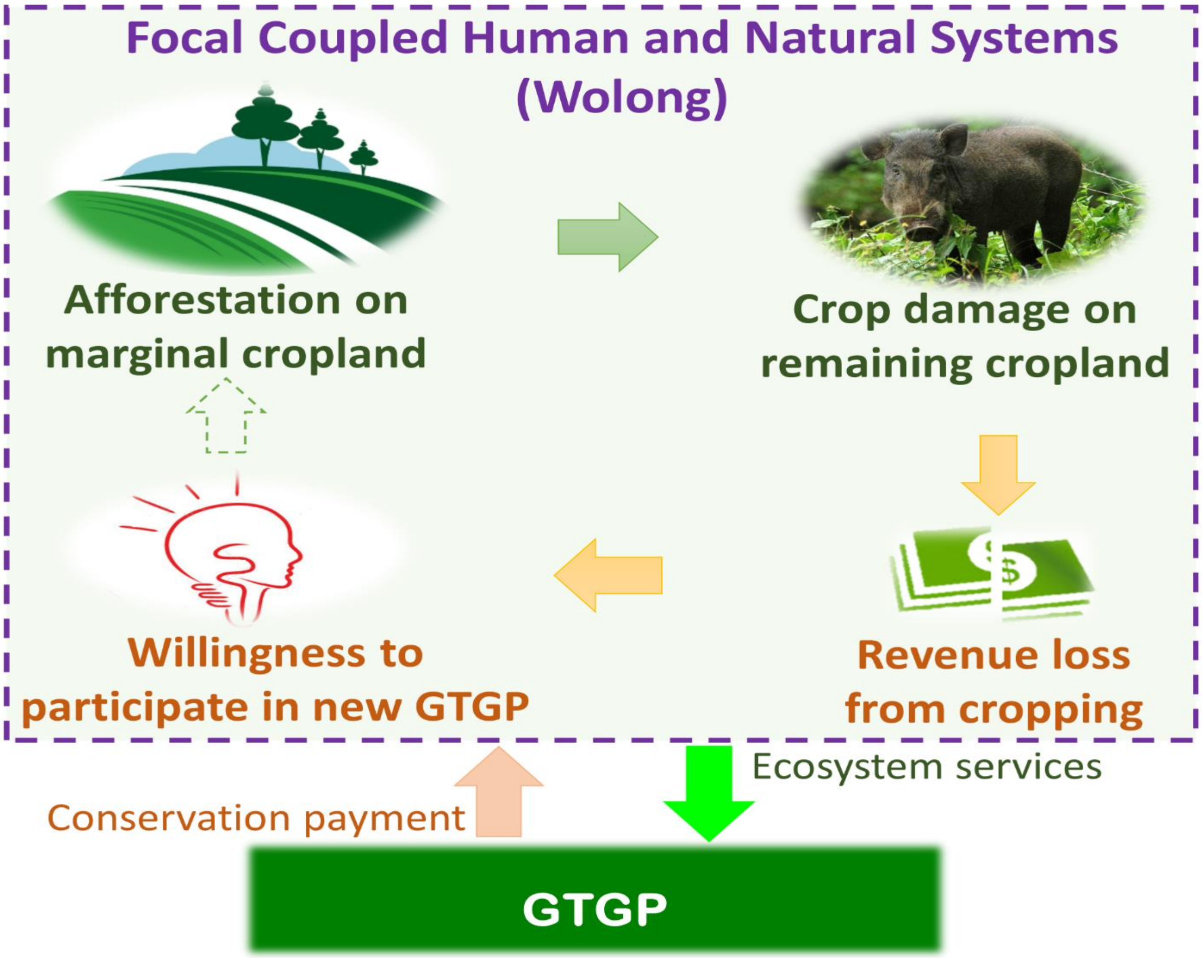

Figure 4.1 Conceptual model of the feedback effect of the Grain to Green Program (GTGP) in Wolong. Through GTGP, other distant places (as represented by the Chinese government in Beijing) paid local farmers for converting their marginal cropland to forestland to secure the provision of ecosystem services. However, afforestation on marginal cropland significantly increased crop damage on nearby remaining cropland in Wolong, and reduced the revenue local households obtained from the affected cropland. This in turn increased local households' willingness to enroll remaining cropland in possible future GTGP and will strengthen the effects of GTGP (e.g., outflows of ecosystem services to other places) in Wolong and beyond if a new round of GTGP is implemented in the future.

benefited from this program as the outflows of ecosystem services from the program's target areas have been enhanced. For example, many of the program's target areas are located upstream of Yangtze River, the third-longest river in the world (Sun et al. 2016). Previous studies show that afforestation promoted by the GTGP has increased the capacity of soil and water retention of the land (Ouyang et al. 2016, Rodríguez et al. 2016) and thus mitigated flooding risk downstream. To enhance gains from the GTGP, the Chinese government has been planning a new round of GTGP to enroll more cropland in the near future (State Forestry Administration 2014).

In this study, we evaluated the feedback of GTGP by estimating the influence of crop damage induced by the current GTGP on local households' willingness to participate in possible future GTGP, an impact that may trigger feedback of the GTGP. A previous study in Wolong found that afforestation on marginal cropland promoted by the GTGP has significantly increased the crop damage by wildlife on nearby remaining cultivated cropland. This is because participating households tend to enroll their land close to forest edges in the GTGP as these croplands are often susceptible to crop damage by wild animals (e.g., wild boar) and typically have a low yield (Chen et al. 2010). However, afforestation on cropland close to forests may create new habitat for crop raiders and displace crop damage previously borne by former cropland now enrolled into the GTGP (GTGP lands) to nearby remaining cropland, resulting in more crop damage there. Since the revenue from remaining cropland may decrease due to this impact, we hypothesize that households may be more willing to enroll them in future GTGP, stimulating a positive feedback that will get more cropland enrolled and strengthen the associated flows between Wolong and other places (e.g., increase inflow of conservation payment and outflows of ecosystem services) (Fig. 4.1).

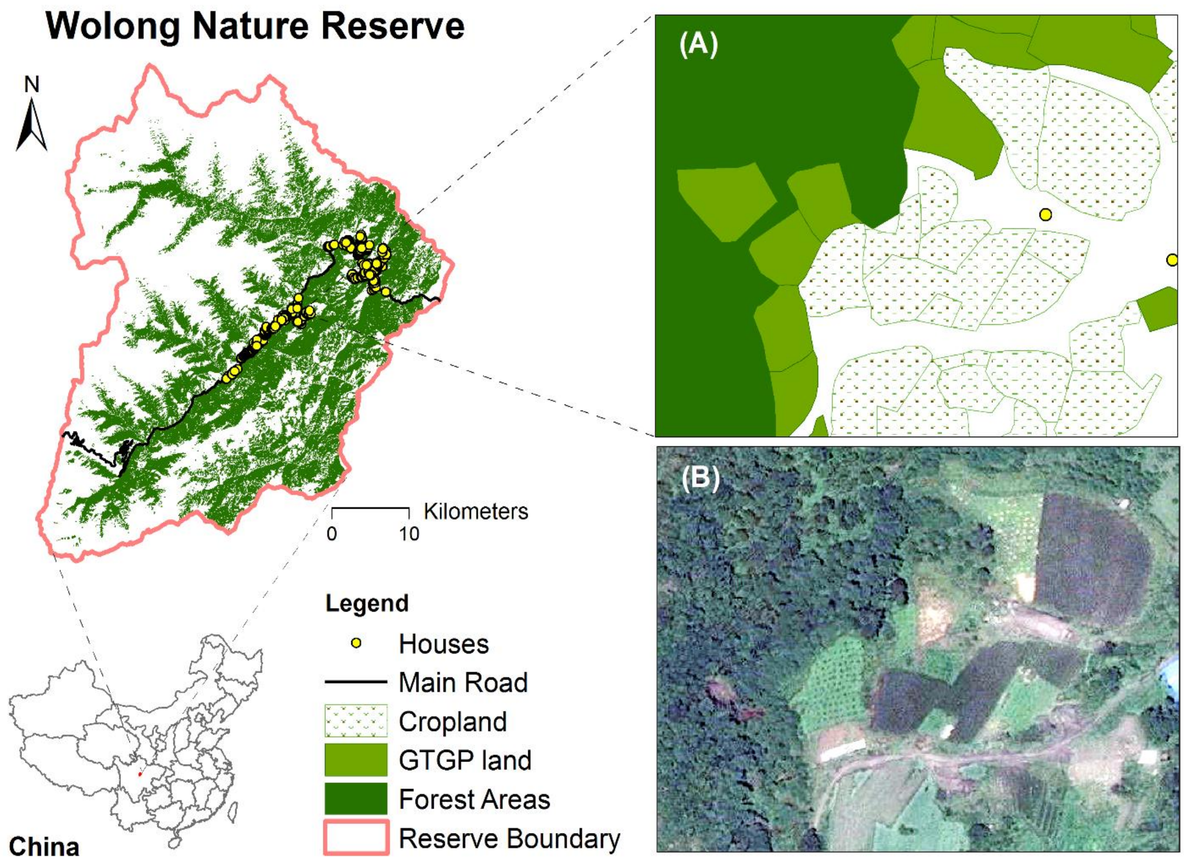

Figure 4.2 Wolong Nature Reserve in Southwest China. Panel (A) shows the digitized information of the distribution of cropland enrolled in the GTGP (GTGP land) and remaining cropland in a sample area of Wolong. Panel (B) shows the corresponding Google Earth imagery of this sample area.

4.2 Materials and Methods

4.2.1 Study area

Wolong is a flagship protected area in Southwest China (Fig. 4.2) and part of the UNESCO World Heritage system (World Heritage Convention 2016). The reserve is characterized by high biological diversity and provides sanctuary to about 10% of the total wild giant panda population (Liu et al. 2016a). Wolong was first established as a national nature reserve in 1963 and expanded to its current size of 20,000 ha in 1975 (Lai et al. 2003). The reserve is managed by the

Wolong Administration Bureau and is home to about 5,300 residents, most of whom are farmers (Liu et al. 2016a). Before 2000, Wolong was a remote area with limited connections to the outside world (An et al. 2001). The vast majority of local residents were primarily involved in subsistence-based agricultural activities such as growing potatoes and corns. Despite the status of being a nature reserve, the establishment and expansion of the reserve did not mitigate the degradation of panda habitat inside its borders (Liu et al. 2001). As the population size and number of households rapidly increased, human activities, such as farmland expansion, fuelwood collection, and timber harvesting, had caused serious degradation of panda habitat before the early 2000s (Liu et al. 2001, Yang et al. 2013b).

In response to this critical issue, a series of conservation programs were implemented, including the GTGP (Yang 2013). In Wolong, GTGP enrollment began in 2000, and additional contracts were signed in 2001 and 2002. Under the GTGP, local households received government payments for converting their cropland to forest land and keeping it forested at an annual rate of about 240 yuan per mu (1 USD = 6.6 yuan as of June 2016; 1 mu = 0.067 ha) for 16 years (Yang et al. 2013b). Totally, 367.3 ha cropland (57% of the total) from 969 households (97% of the total) was converted to forest land from 2000 to 2003. In Wolong, cropland parcels close to forest are often susceptible to crop damage by wild animals, such as wild boar (*Sus scrofa*), sambar dear (*Rusa unicolor*), and hedgehog (*Erinaceinae*). Therefore, they can generate less economic benefit than cropland farther from forest and constitute the majority of the cropland enrolled in the GTGP (Chen et al. 2010).

However, afforestation on these marginal croplands significantly increased crop damage on nearby remaining cropland in Wolong (Fig. 4.1). A previous study in Wolong estimated the impact of the GTGP on crop damage and found that 64% of observed cropland damage on remaining cropland was attributable to the afforestation promoted by the GTGP (Yang et al. 2017a). The majority (88%) of the GTGP-induced crop damage occurred on cropland within close range (distance < 10 m) of GTGP lands. In this range, the GTGP caused about 18.9% increase in yield loss due to wildlife damage (Yang et al. 2017a).

This study benefits from the rich research over the past two decades in the reserve (e.g., Liu et al. 1999, An et al. 2006, Linderman et al. 2006, Tuanmu et al. 2011, Chen et al. 2012b, Tuanmu et al. 2016). The accumulated knowledge from previous studies lays a good foundation for systematic design of this study such as the selection of model variables. As a typical coupled human and natural system, findings and methods developed in the reserve have been applied to many other parts of the world (e.g., Liu et al. 2003, Xu et al. 2006, Yu and Liu 2007, Bawa et al. 2010, Chen et al. 2010, Liu and Raven 2010, Vina et al. 2010, Chen et al. 2011, An et al. 2014, Bradbury et al. 2014). It is our hope that insights from this study (e.g., feedback mechanisms and management implications) will be similarly useful for research and management in many other areas around the world.

4.2.2 Data collection

We conducted a household survey in Wolong from July to August in 2015. Household heads or their spouses were chosen as interviewees because they are the main decision makers in the households and are familiar with household affairs. We iteratively pretested our survey instrument using one-on-one interviews with 33 local households randomly chosen from the

2012 Wolong Household Registration list. After the pretest, we randomly selected 255 other households for the finalized survey. However, 6 households did not have eligible interviewees as the household heads or their spouses were not available during our survey period and 4 households declined to participate, resulting in 245 interviewees (21% of the total) and a 96% response rate.

We collected information on household socioeconomic and demographic conditions (e.g., each household member's age, education, occupation, and income sources). Since cropland characteristics may also affect households' willingness to participate in future GTGP, we also collected information on croplands owned by each surveyed household. On a Google Earth Imagery of Wolong (Fig. 4.2), we digitized the boundary of all cropland parcels owned by each surveyed household with interviewees' help. For each cropland parcel, we recorded related information about its characteristics (e.g., distance to the main road in the reserve and yield loss due to wildlife damage).

To query interviewee's participation willingness (i.e., whether or not to enroll some or all of their remaining cropland in possible future GTGP), the survey included a set of stated choice questions to elicit choices households make under different hypothesized scenarios. The proposed scenarios consisted of 3 attributes: crop damage intensity, payment level of future GTGP, and social norm. Crop damage intensity was defined as the proportional yield loss in a cropland parcel due to wildlife damage. The social norm was defined as the proportion of neighborhood households who will participate in future GTGP. Each of these attributes had three possible levels. The crop damage intensity ranged from 10% to 50% with an interval of 20%.

Table 4.1 Descriptive statistics of variables that were used to construct the stated choice model.

Variables	Description	Mean (SD)
Outcome		
Participation	Whether the household is willing to participate in the future GTGP in the hypothesized scenario: 1, Yes; 0, No.	0.63 (0.48)
Scenario attributes		
Crop damage intensity	The crop damage intensity assumed in the hypothesized scenario.	0.29 (0.16)
Program payment	The payment level of the future GTGP assumed in the hypothesized scenario. (Yuan)	1005.54 (408.78)
Social norm	The percentage of the household's neighbors plan to participate in the future GTGP assumed in the hypothesized scenario.	0.34 (0.27)
Characteristics of interviewee		
Gender	The gender of the interviewee: Male, 1; Female, 0.	0.60 (0.49)
Age	The age of the interviewee. (Year)	50.34 (12.66)
On-farm laborer	Whether the main income activity the interviewee is involved in is farming: Yes, 1; No, 0.	0.62 (0.47)
Household demographic and economic conditions		
Household size	The number of members in the household.	4.48 (1.41)
Education	The average education level of household members. (Year)	6.56 (2.65)
Stable off-farm employment	The number of household members with an off-farm job that will last at least one year.	0.74 (0.89)
Farming income	The log-transformed income obtained from agricultural production. (Yuan)	7.15 (3.82)
Income	The log-transformed gross household income. (Yuan)	10.89 (0.88)
Characteristics of cropland parcels owned by the household		
Cropland area	The total area of the household's remaining cropland. (Mu)	3.03 (3.33)
Cropland renting	Whether the household has cropland currently rented to other households: Yes, 1; No, 0.	0.17 (0.38)
Max distance to road	The maximum distance of the cropland parcels owned by the household to the main road. (m)	404.11 (536.79)

† The observation unit is individual hypothesized scenario.

‡ Sample size = 722.

§ 1 Mu = 0.067 hectares

| 1 USD = 6.6 Yuan as of June 2016

These damage intensity levels used in the scenarios were determined mainly based on the crop damage intensities of cropland parcels close to forest edge (distance < 10 m) reported by interviewees in the pretest. These levels roughly correspond to the 25th, 50th, and 75th percentiles of the reported damage intensities. The payment levels of future GTGP were 500 yuan, 1,000 yuan or 1,500 yuan per mu per year. They roughly correspond to the expected economic returns from 1 mu cropland with high, medium, and low productivity in Wolong reported by households in our pretest. These payments are higher than the current payment of GTGP because cropland productivity and crop price have been increasing in China over past years. The survey explained that all payments would last for a fixed period of 8 years in all scenarios. For the social norm, interviewees were told that either 0%, 33%, or 66% of households in the same group (the smallest administrative unit in rural China) would participate in future GTGP. We used these three levels because they worked well in our pretest as variation in the responses could be observed across these three levels. There were 26 groups in Wolong and each group contained from 14 to 89 households, with a total of 1,156 households.

Given that each of the three scenario attributes has three possible levels, there are 27 ($3\times3\times3$) possible combinations of them and correspondently, 27 different possible stated-choice questions. However, it is generally impractical to ask each household all the 27 questions. Instead, we chose 9 combinations of these attribute levels based on main-effects design as suggested by Louviere et al (2000). This subset of attribute combinations maintains the independent variation among these three attributes required to capture their main effect on households' participation willingness. Before the face-to-face interview with each household, 3 choice questions were randomly drawn without replacement from the 9 questions. Each interviewee was asked if he or she has a cropland parcel exposed to the crop damage by wild animals at the level specified by the scenario whether he or she will enroll it in future GTGP for the given payment and social norm presented in the scenario.

4.2.3 Modeling household willingness to participate in future GTGP

Since households' actual behavior of participating in future GTGP cannot be observed currently, we used households' willingness to participate as an indicator of the actual behavior. As suggested by the theories of reasoned action and planned behavior (Ajzen 1985, Fishbein and Ajzen 2011), willingness or intention is often the strongest predictor of actual behavior. For example, Chen et al (2009) noted that the observed amount of cropland households reenrolled in the Conservation Reserve Program in 2001 in the United States was close to that predicted from households' stated willingness to participate data collected in 1993 (Cooper and Osborn 1998). In other contexts, such as purchase decisions, some literature has found that stated and actual choices are highly correlated (e.g., Loureiro et al. 2003). In this study, we estimated the effect of crop damage by wildlife on farmers' willingness to participate in possible future GTGP using stated choice method (Louviere et al. 2000). This method is a standard procedure in social sciences to elicit particular actions in response to a set of conditions that modify human agency (Louviere et al. 2000) and has been successfully used in Wolong to investigate the likelihood of re-enrollment of cropland in the GTGP (Chen et al. 2009a).

We built a stated choice model to relate the attributes of scenarios (i.e., crop damage intensity, payment level, and social norm) presented in the stated choice questions to households' willingness to participate in future GTGP. Characteristics of the interviewees, their households, and their remaining cropland might also affect interviewees' choices. We thus included a set of variables describing these characteristics in the stated choice model as covariates (Table 4.1). As mentioned, we asked each interviewee 3 stated-choice questions, thereby observing 3 choices for each household. Therefore, the expected number of observations is 735 (245×3). However, there were 13 cases where our interviewees found it is hard to make a choice (i.e., decide to participate or not) in the presented scenarios and responded "not sure". These observations were excluded from our modeling analysis, resulting in 722 observations for our analysis.

In each of the finalized observations, a household either is or is not willing to participate in future GTGP (i.e., willing to enroll cropland in the program) and yields a discrete dependent variable for our model. We assume that farmers are willing to participate in future GTGP if the utility of participating the program is larger than not participating. That is, $U_i^1 > U_i^0$, where U_i^1 and U_i^0 are the utilities of participating and not participating for household i, respectively. The utility function $U(.)$ is unobservable; however, there is a probability of participating $\Pr(Y_i = 1) = \Pr(U_i^1 > U_i^0)$, where $Y_i = 1$ if the plan was to participate and 0 otherwise, and a farmer's participation plan under the hypothesized scenario, Y_i, can be observed. Empirically, the program participation willingness under different scenarios was modeled with a random-effects probit model (Wooldridge 2010):

$$\Pr(participate_{ij} = 1 \mid P_i, H_i, C_i, S_{ij}, \mu_i) = \Phi(P_i\alpha + H_i\beta + C_i\gamma + S_{ij}\delta + \mu_i) \quad (4.1)$$

where $\Pr(participate_{ij} = 1)$ is the probability the *i*th household plans to participate in future

GTGP under the *j*th scenario; $\Phi(\bullet)$ is the cumulative normal distribution; P_i represents the personal traits of the interviewee from the *i*th household; H_i represents household economic and demographic conditions of the *i*th household; C_i represents the characteristics of the cropland parcels owned by the *i*th household; S_{ij} is the attributes of the *j*th scenario that household *i* is exposed to; α, β, γ, and δ are parameter vectors associated with factors describing personal traits of interviewees, household's socioeconomic conditions, features of household's cropland, and scenario attributes, respectively; and μ_i represents the unobserved random effects associated with the *i*th household to account for the panel nature of the data. In the probit model, the marginal effects of explanatory variables are obtained from the formula:

$$\frac{\partial \Pr(participate = 1)}{\partial X} = \varphi(\mathrm{X}\beta)\beta \tag{4.2}$$

where X represents all explanatory variables; $\varphi(\bullet)$ is the standard normal density function; and the derivative is calculated at the mean of the explanatory variables. The marginal effect indicates the change in the participation probability associated with a marginal change in an attribute. For large changes in an attribute, the participation probability (1) can be evaluated to predict the change. With the estimated model, we can also evaluate how much the crop damage that was induced by previous GTGP enrollments will affect future GTGP enrollments.

4.3 Results

Crop damage has significant ($P < 0.001$) positive effects on local households' willingness to participate (i.e., enroll some or all of their remaining cropland) in future GTGP (Table 4.2). It was estimated that an additional 1% increase in crop damage intensity will increase the

Table 4.2 Estimation of model coefficients for scenario attributes and other characteristics and their marginal effect on the households' willingness to participate in future GTGP.

Independent variables	Coefficients	Standard Error	Marginal Effects
Crop damage intensity	1.97 ***	0.333	0.55***
Program payment	0.0015 ***	0.0014	0.00042***
Social norm	1.50 ***	0.204	0.42***
Gender	0.096	0.121	0.027
Age	0.003	0.0046	0.0009
On-farm laborer	0.228	0.139	0.063
Household size	- 0.090 *	0.047	- 0.025 *
Education	- 0.054 *	0.026	- 0.015 *
Stable off-farm employment	0.157 *	0.074	0.044 *
Farming income	0.021	0.017	0.006
Income	0.038	0.074	0.011
Cropland area	- 0.027	0.02	- 0.008
Cropland renting	0.514 ***	0.15	0.143***
Max distance to road	0.0003 **	0.0001	0.00009 **
Constant	- 2.554	0.795	

† Significance: * $p \le 0.05$; ** $p \le 0.01$; *** $p \le 0.001$; two-tailed tests

‡ Sample size = 722.

interviewees' participation probability by 0.55 percentage points on average. Combined with the previous study result that the GTGP has increased the crop damage intensity that occurred on cropland close to the afforested lands (distance < 10 m) by 18.9%, the impact of this crop damage intensity change on households' willingness to participate in future GTGP would be 10.4%. This result indicates that, holding everything else the same, the current GTGP may cause 10.4% more cropland in the nearby range (distance to afforested lands < 10 m) to be enrolled in future GTGP.

The payment level of future GTGP and the social norm also have significant ($P < 0.001$) positive influence on interviewees' willingness to participate in future GTGP (Table 4.2). On average, an additional of 100 yuan in the payment of future GTG will increase the probability of participation by 4.2%. An additional 1% increase in the proportion of neighboring households planning to participate will increase the interviewee's willingness to participate by 0.42%. In other words, people's willingness to participate in future GTGP can be significantly affected by the participation decisions of their neighbors and tend to conform to the majority.

Households' willingness to participate in future GTGP was also influenced by characteristics of households and their cropland (Table 4.2). Both household size and household members' average education had a significant negative effect ($P < 0.05$) on the participation probability. It was estimated that 1 additional member in the household will decrease the participation probability by 2.5% and 1 more year of education decreased households' participation probability by 1.5%. Stable off-farm employment (off-farm employment that will last at least one year) significantly increased participation probability ($P < 0.05$); one more member with stable employment increased the participation probability by 4.4%. Households that currently rent cropland to others had significantly higher ($P < 0.001$) willingness to participate in future GTGP. Compared with other households, their probability of participating in future GTGP is about 14% higher. Households with cropland far from the main road in the reserve are more likely to participate in future GTGP. An additional 1 km from the main road will increase households' participation probability in future GTGP by 9% ($P < 0.05$). Interviewees' personal traits, including gender, age, and occupation (as measured by whether their main income activity involves farming activities), did not show significant influence on household willingness to participate in future GTGP ($P > 0.1$).

4.4 Discussion

Our results suggest that, among the socioeconomic and biophysical factors considered at the household level, crop damage occurring on households' remaining cropland has significant influences on their willingness to enroll the land in future GTGP. Combined with the impact of GTGP on crop damage found in previous research, our study shows that the implementation of current GTGP can prompt more cropland to be enrolled in the future, a positive feedback that strengthens GTGP's effects. Households that had no enrollment plan initially may change their minds as increasing crop damage occurs on their remaining cropland due to the current GTGP. Conservation planners may leverage this feedback and implement the GTGP round by round to increase the enrollment of cropland. As more land is enrolled and become vegetated, outflows of some critical ecosystem services (e.g., clean water and air) will increase and help to address the shortage crisis of ecosystem services in many other parts of China, especially in urban areas where the demand for ecosystem services often goes beyond the local provision capacity (Liu et al. 2016b).

In modeling households' participation willingness, we found that households with stable off-farm income are more likely to enroll their remaining cropland in future GTGP. As tourism in Wolong has been recovering from the devastating impacts of the 2008 Wenchuan Earthquake

(Zhao 2017), tourism development may bring many off-farm employment opportunities for local people and prompt more cropland to be enrolled and converted to forestland. However, to fulfill this potential of tourism, sound development planning and management are indispensable. He et al. (2008) found only a small share (< 5%) of revenue from tourism development in Wolong before the earthquake went to local inhabitants as they often have poor education and lack relevant skills to be involved in tourism activities. Therefore, management interventions that help to overcome these barriers (e.g., providing training to local households to develop related skills) should be considered to increase the benefits households could obtain from tourism development in the future. In addition, tourism is not completely eco-friendly and its development should avoid the occurrence of potential negative feedback (i.e., poorly planned tourism development compromising ecosystem health, which in turn harms tourism development in the long run). For example, the design of tourism facilities (e.g., hiking trails) should avoid the core habitat of giant pandas and the activities of visitors should be regulated to mitigate the negative impacts (e.g., noise pollution) on wildlife health.

Within the 25 provinces in China where the GTGP was implemented, the magnitude of the program's feedback may vary substantially due to the high biological and socioeconomic heterogeneities. For example, unlike Wolong, populations of wild animals that damage crops in some areas may be small. Afforestation on cropland in these regions may generate little influence on crop damage on remaining cropland, thereby little impact on households' willingness to participate in future GTGP. In addition, compensation policies may exist in some areas to cover the loss from wildlife damage or preventive measures (e.g., building fences) may have been taken by local households to reduce wildlife damage. If effectively implemented, these strategies may substantially reduce households' willingness to enroll their land in conservation programs and thus the magnitude of the feedback of GTGP. However, previous studies indicate compensation schemes can be subject to factors like corruption, shortage of funding, and difficulties with handling large numbers of wildlife damage cases (Nyhus et al. 2005, Storie and Bell 2016). In Wolong, 98% of our interviewees said they had never received any compensation for wildlife damage from local government, though they had reported their cases. Preventative measures may also have some limitations. The common preventive measures in Wolong include building fences, tying dogs to stakes at the edge of cropland, and sending a member to frequently patrol cropland during seasons when damage is most likely to occur (e.g., summer when corn and potato mature). However, these measures are either too costly (e.g., building and maintaining iron fences or sending a household member to patrol cropland) or have low efficiency (e.g., building simple wooden fence or tying their dogs to stakes at the edge of cropland). Due to these factors, enrolling cropland in GTGP should be considered as an option for local households in Wolong and perhaps in many other places to address the wildlife damage issue. Otherwise, as losses due to wildlife damage increase, local people may grow to view wildlife and conservation projects negatively.

Although our analysis is restricted to the GTGP in China, similar feedback effects may exist in other parts of the world. For instance, converting marginal cropland to other types of vegetative land-covers (e.g., forest or grassland) has been widely promoted by conservation efforts in other regions around the world, such as the Conservation Reserve Program in the

United States (USDA 2016), the Common Agricultural Policy in the Europe (European Commission 2013), and the Protective Afforestation Program in the Russian Federation (Kulik et al. 2015). Like the feedback effect of the GTGP, these conservation efforts may cause more crop damage on remaining cropland and make the remaining cropland more likely to be enrolled in these or other similar programs in the future.

Besides conservation programs, the dynamics of other types of telecouplings may also be affected by similar feedbacks. For instance, as globalization continues, the stunning rural-urban disparity in many developing countries (e.g., China, Zambia, and Brazil) attracts millions of farmers from rural areas to work in cities every year (Rush 2011, Lucas 2016). In many rural areas, the rapid increase of labor migration has significantly decreased the negative impacts of human activities (e.g., farming and fuelwood collection) on local wildlife habitats (Klooster 2003, Kramer et al. 2009, Xiao 2011, Chen et al. 2012a). This may facilitate the propagation of wildlife populations (e.g., wild boar) that cause crop damage, which in turn may discourage rural households from farming activities and ultimately prompt more rural farmers to out-migrate to work in cities.

Since interactions often exist among different types of telecouplings, a better understanding of the feedback of GTGP may also help to explain or predict the dynamics of other telecouplings. For example, like many other farming areas, Wolong is a sending system selling agricultural products to other places (e.g., cities like Dujiangyan) while a receiving system buying industrial products (e.g., fertilizer and plastic film) from elsewhere (Liu et al. 2015a). As more cropland is enrolled in future GTGP due to the program's feedback, the outflows of agricultural products and inflows of related industrial products may decrease. Tourism development in Wolong may also be affected by the feedback of GTGP. Laborers released from farming activities in Wolong may participate in tourism activities, such as operating a restaurant or leisure farmhouse. This in turn will increase the accommodation capacities of Wolong and facilitate tourism development.

4.5 Conclusion

In response to unprecedented ecological degradation, PES programs have been widely leveraged as a conservation tool to enhance the outflows of ecosystem services from many rural areas to other places and constitute an important telecoupling (Naeem et al. 2015). However, as the effects of PES programs on human-nature interactions in target areas accumulate, feedback may emerge. In this study, we found the intensified human-wildlife conflicts due to the GTGP discouraged farmers from continuing farming activities and increased their willingness to enroll their remaining cropland in possible future GTGP, thereby strengthening the influences of the program within and beyond the target areas in the future. Our findings emphasize that evaluation of PES programs and other telecouplings should properly consider the feedback effects to better anticipate the long-term effects of telecouplings. Future interdisciplinary studies are needed to accumulate empirical evidence across space and time for generalizable results on telecouplings' feedbacks applicable under different contexts. Armed with such knowledge, scientists, policy makers, and conservation practitioners would be better equipped to design effective strategies for managing telecouplings and achieving the United Nations' Sustainable Development Goals in a telecoupled world.

CHAPTER 5

COMPLEX EFFECTS OF TELECOUPLINGS ON FOREST DYNAMICS: AN AGENT-BASED MODELING APPROACH

In collaboration with

Arika Ligmann-Zielinska, Yue Dou, Min Gon Chung, and Jianguo Liu

Abstract

Rural areas are increasingly subject to effects of telecouplings whereby their human and natural dynamics are linked to socioeconomic and environmental drivers operating at a distance, such as the growing demand for labor and ecosystem services in cities. Although there have been many studies evaluating the effects of telecouplings, telecoulplings in them were often investigated separately and it is still not well understood how telecoulplings may interact and jointly affect dynamics of rural coupled human and natural systems (CHANS). 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). We found that both nature-based tourism and labor migration can facilitate forest recovery. Without their effects, the predicted forest areas in Wolong in 2030 would be reduced by 26.2 km^2 (6.8%) and 23.9 km^2 (6.2%), respectively. 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 km^2 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.

5.1 Introduction

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

Among the telecouplings that link rural areas and other places, rural-urban labor migration (rural residents out-migrate to cities for temporary employments) and nature-based tourism (tourism based on the natural attractions of rural areas) are two globally common and increasingly influential ones (Pulido-Fernandez et al. 2015, Ratha et al. 2015). Factors such as urban economic growth, enlarging rural-urban disparity, and development of transportation networks, have been driving a large number of laborers from rural areas to seek job opportunities in cities, especially in developing countries (Ratha et al. 2015). In China alone, the number of rural-urban labor migrants had increased from only 2 million in the early 1980s to more than 150 million in 2010 (Rush 2011). Meanwhile, there has been a rapidly growing demand for visiting the natural and cultural landscapes of rural areas, mostly by residents from cities. For decades, many rural areas around the world have been practicing nature-based tourism. For example, in the late 1990s, about 80% of nature reserves in China had developed nature-based tourism (Li and Han 2001). Several provinces in southwest China (e.g., Yunnan and Sichuan), where one of the global biodiversity hotspots is located (Myers et al. 2000), have designated nature-based tourism as one of the major sources of their economic growth (Liu 2012).

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

However, like any other telecoupling, the effects of tourism and labor migration were often evaluated separately and the interaction among them was often ignored. While both tourism and labor migration have the potential to reduce the negative impacts of local households on the environment (Chen et al. 2012a, Liu et al. 2012), tourism development may limit the growth of labor migration. Previous studies (e.g., Wong et al. 2007) show that rural migrant workers in cities often lack good health insurance coverage, face substantial educational expenses for their children, experience discrimination from urban residents, and suffer high stress and depression due to social displacement. Therefore, local tourism jobs are usually more attractive to rural residents than migrant jobs in cities. Although income opportunities related to nature-based tourism are often seasonal (Cuccia and Rizzo 2011), a household may be less likely to utilize its surplus labor for temporary employments in cities if it can benefit from local tourism development. As a result, the possible positive environmental impacts from labor migration in a rural area with a tourism industry might be smaller than in other rural areas where tourism industry does not exist.

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

After calibrating and validating our agent-based model, we used it as a scenario-envisioning laboratory to evaluate the effects of tourism and labor migration by comparing the forest dynamics under different conditions. Specifically, we simulated and evaluated forest dynamics under the following scenarios: [1] tourism and migration are not present in the model, [2] only tourism is present in the model, [3] only migration is present in the model, [4] tourism and migration are present in the model but their interaction is ignored, and [5] tourism, migration and their interaction are all included in the model.

5.2 Methods

5.2.1 Study area

Wolong (102º52′ to 103º24′ E, 30º45′ to 31º25′ N) was established in 1963 and expanded to its current size of 2,000 km^2 in 1975 (Liu et al. 1999) (Fig. 5.1). It provides sanctuary to about 104 wild giant pandas and more than 6000 species of plants and other animals such as red panda and golden monkey (China Ministry of Forestry and World Wildlife Fund 1989, Sichuan Forestry Administration 2015). The natural forests in Wolong are mainly composed of evergreen and deciduous broadleaf forests at lower elevations, subalpine coniferous forests at higher elevations, with understory composed of bamboo species such as umbrella and arrow bamboo (Schaller et al. 1985, Reid and Hu 1991, Taylor and Qin 1993). Besides the diverse species of plants and animals, Wolong is also home to about 4900 local residents (Yang 2013). The reserve is managed by the Wolong Administration Bureau, which is hierarchically structured with two townships under its governance – the Wolong Township and the Gengda Township (Lai et al. 2003).

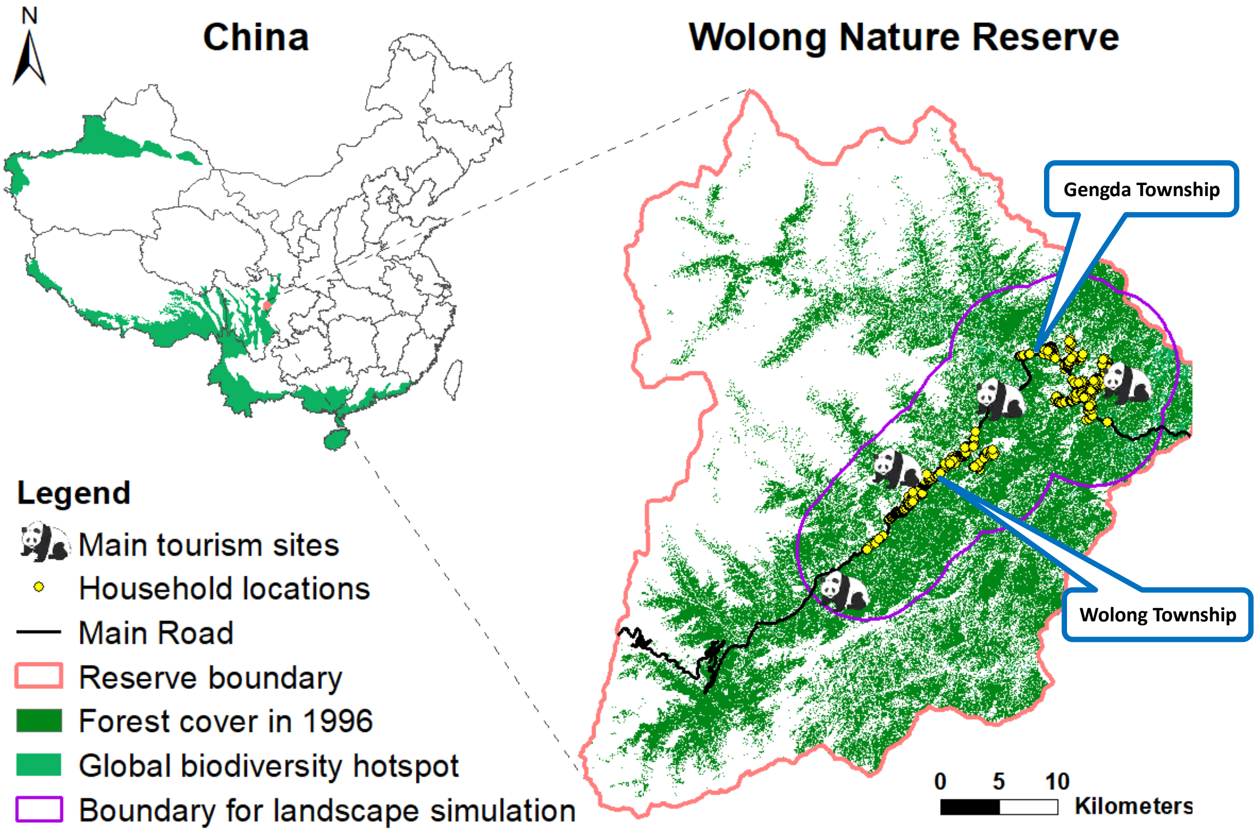

Figure 5.1 Wolong Nature Reserve in Southwest China.

Before the 2000s, the reserve had few connections with the outside world. Local livelihoods relied primarily on subsistence-based agricultural activities like cropping and livestock husbandry. The average annual income per capita in 1990 was only 470 yuan (72 USD, 1 USD = 6.6 yuan as of June 2016) (Lai et al. 2003). As the human population and the number of households grew in Wolong, local human activities caused serious degradation of panda habitat by the early 2000s (Liu et al. 2001). Of all the human threats, cutting trees for fuelwood by local households was a major one. Fuelwood was a major energy source for cooking pig fodder, cooking meals, and sometimes for heating houses during winter (An et al. 2002). Although electricity was available, local households were reluctant to switch from fuelwood to electricity, in aversion to increased household expenses (An et al. 2002). By the mid-1990s, local households consumed around 11,000 m^3 of wood annually and contributed to the rapid shrinkage of forest cover from 52% (1070 km^2) in 1965 to 35% (706 km^2) in 2001 (Liu et al. 2001, Viña et al. 2007, Yang et al. 2013b).

This trend of net forest loss started to change since 2001. Between 2001 and 2007, the forest cover in Wolong recovered from 35% (706 km^2) to 37% (799 km^2) (Yang et al. 2013b). Several socioeconomic and political factors may have contributed to this forest transition. One of them is the development of tourism. Although tourism has existed in Wolong since the late 1980s, the number of tourist visits then was low, and few local people benefited from it (Liu et al. 2012). In 2002, a tourism development plan was formally approved by the provincial and central government (He et al. 2008). Since then, tourism in Wolong has entered a rapid development stage and became an important alternative source of income for local households. The number of tourist visits increased by 10-fold from about 20,000 in 1996 to about 200,000 in 2006. In 2005, about 30% of local households directly benefited from tourism activities like selling bacon to tourists and working as the tour guides (Liu et al. 2012). Before 2008, when the Wenchuan Earthquake interrupted tourism development in Wolong (Liu et al. 2016c), tourism seasons in Wolong often started in May and ended in October.

Meanwhile, as China’s economy has grown rapidly in its cities, the stunning rural-urban disparity attracted a rapid rise of labor migrants from rural areas to urban centers (Liang 2001, Li 2011). In Wolong, the percentage of households with labor migrants has doubled from 12% in 2004 to 24% in 2009 (Liu et al. 2013b, Liu et al. 2016a). Like many other parts of the world, almost all labor migrants from Wolong find only temporary employments in cities (Chen et al. 2012a). They return to their home villages whenever needed (e.g., in planting or harvesting seasons) and rarely shift to be permanent urban residents (Fan 2008).

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

5.2.2 Model design

Agent-based models are composed of agents and their environment. In our model, agents are individual persons and households, and landscape in Wolong is their shared environment. Agents and their environment together are treated as a CHANS, which is connected with other systems (cities) through two telecouplings: tourism and labor migration (Fig. 5.2). Local households affect forest dynamics mainly through collecting fuelwood. The establishment of new households often lead to small-scale forest clearing (An et al. 2006) and constitutes the other pathway affecting forest dynamics (Fig. 5.2).

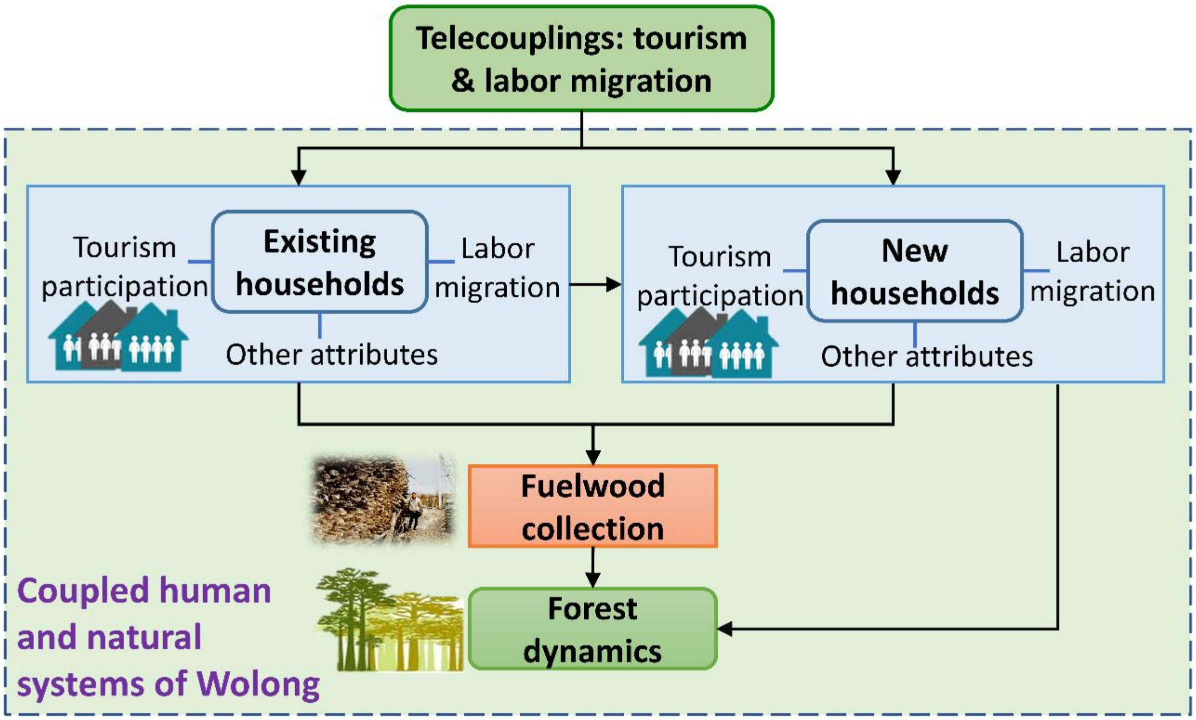

Figure 5.2 Conceptual framework of the model for simulating the effects of tourism and labor migration on forest dynamics in the coupled human and natural systems of Wolong.

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

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

5.2.2.1 Demographic submodel

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

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

5.2.2.2 Telecoupling submodel

The telecoupling submodel was designed to simulate the interactions between households and forest under five different telecoupling scenarios (see the introduction section). Telecouplings affect the households' status of whether having member(s) work in the local tourism industry or out-migrate to work in cities. This status in turn affects the amount of fuelwood collect by households and forest dynamics. We estimated the probabilities of becoming a tourism household or a labor migration household using household survey data collected in 1999 and 2006.

In 1999, our research team conducted the first household survey in Wolong to collect data covering the demographic (e.g., household size, birth year, gender, and education level) and the socioeconomic (e.g., income sources, cropland area, and fuelwood collection) information of individual households in 1998 (An et al. 2001). A total of 220 households (about 20% of all

Table 5.1 Logistic estimations of labor migration and tourism participation by households in 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) *

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

households in Wolong) were randomly selected for survey with strata based on administrative groups (the smallest administrative unit in China). These households sampled in 1999 were revisited in 2006 to collect their information in the previous year (2005). There were 18 households missing from the 2006 survey due to various reasons such as deaths, migration to outside areas, or temporarily working outside Wolong during the survey period. In 1998, tourism households and labor migration households accounted for 2.7% and 3.9% of all households, respectively. In 2005, those figures increased to 31% and 22%, respectively.

Using the survey data of the 202 randomly sampled households in 2006, we modeled local households' participation in tourism and labor migration using logistic regression models (Table 5.1). When modeling the participation in labor migration, we included tourism participation status (1, Yes; 0, No) as a predictor as suggested by a previous study in Wolong (Yang et al. 2018). Our participation models (Table 5.1) predict the probabilities of tourism and labor migration households after the development of tourism and labor migration for multiple years. Because only a few households were tourism households or labor migration households in 1998, we approximated the annual probabilities of becoming a tourism or labor migration household by dividing the estimated probabilities by seven years (1998 to 2005). A higher participation probability of a household indicates it has a larger potential to have one or more members to work in local tourism industry or out-migrate to work in cities.

In reality, tourism or labor migration households may stop their involvement in those activities for various reasons (e.g., the laborers in the household are getting too old). However, almost all tourism and labor migration households in1998 remained the same in 2005. We therefore did not have enough observations to develop empirical models to predict the probability of a household exits the status of being a tourism household or labor migration household. In our agent-based model, we used the minimum predicted probability of all the 63 tourism households surveyed in 2006 (0.06) as the threshold below which a tourism household exits the status of being a tourism household. As time goes by, a tourism household's attributes may change and have a predicted probability less than this threshold. If this happens, the household's status changes from being a tourism household to a non-tourism household.

Table 5.2 The impact of tourism participation on household fuelwood collection estimated using 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

(1) The numbers in parentheses of this row are Abadie-Imbens standard errors.
(2) The value of Γ at which the null of zero effect would fail to be rejected at $p = 0.05$ level based on Wilcoxon signed-rank p value.
(3) The value of Γ at which the lower bound of 95% confidence interval for the Hodges-Lehmann point estimate of the effect includes zero.
(4) Significance: *** indicate statistical significance at 0.001 level.

Similarly, we determined the threshold (0.01) for labor migration households to exit the status of being a labor migration household.

Fuelwood collection by each household without considering impacts of tourism, labor migration, and conservation policy, was determined according to a previous study in Wolong (An et al. 2001), which modeled fuelwood collection as a function of household size, presence or absence of senior people in the household, and farmland area. Because all households in the study area enrolled in the NFCP in 2001, we did not have a control group of households to accurately estimate the impact of the NFCP on fuelwood collection. We approximated this impact using the drastic reduction in average household fuelwood collection that occurred after 2001 when the NFCP started. Of the 220 households surveyed in 1998, 189, 200, and 215 of them were revisited in 2001, 2002, and 2003 with their fuelwood collection information recorded. Before 2002, the average fuelwood collection by each household was around 12861.5 kg (12763 kg in 1998 and 12960 kg in 2001). In 2002, the average fuelwood collection drastically reduced to be around 8618.1 kg (8576.5 kg in 2002 and 8659.7 kg in 2003). We used the difference in the mean fuelwood collections before and after 2001, 4243.4 kg, as the impact of the NFCP on household fuelwood collection. In our simulations, this impact on households' fuelwood collection takes effect after 2001.

According to the results of a previous study in Wolong (Chen et al. 2012a), the impact of labor migration on household fuelwood collection was set to be 1827 kg. If a household starts to have member(s) out-migrate to work in cities, we deducted its fuelwood collection by this amount. We estimated the impact of tourism participation on household fuelwood collection by comparing the fuelwood collection of tourism and non-tourism households in 2005 using the matching approach (Rubin 1973). For each tourism household, the matching approach finds a counterpart non-tourism household with similar attributes, including the number of adults, household size, distance to the main road, and maximum education level of adult household members. On average, tourism households collected 1708 kg less fuelwood than non-tourism households (Table 5.2). Therefore, if a non-tourism household in our model changed to be a tourism household, we deducted its fuelwood collection by 1708 kg.

The decision process of each household's status - become or stop being a tourism or a labor migration household - over time is summarized in Fig. 5.3. If a household is not a tourism household, we calculated its probability to be a tourism household based on its attributes at this time step using the logistic model in Table 5.1. If a household is already a tourism household at

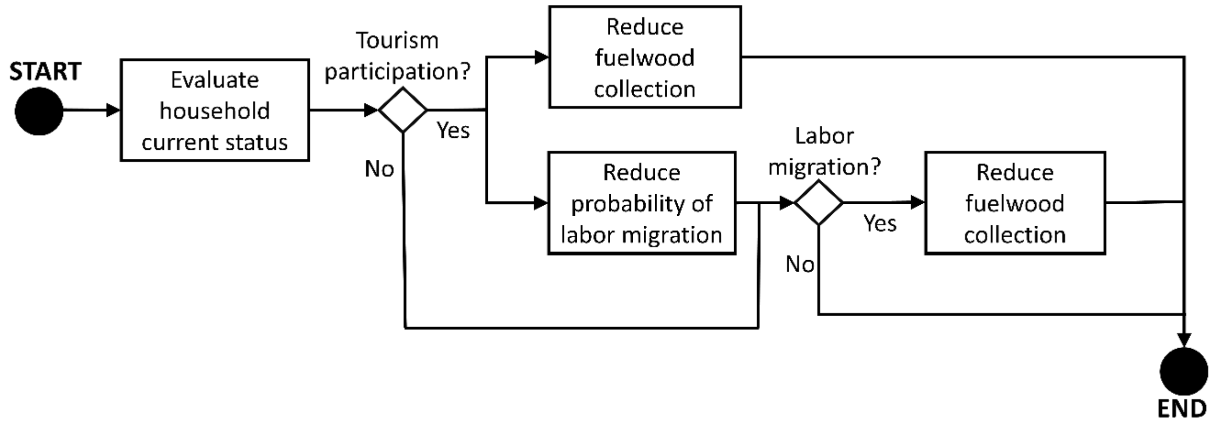

Figure 5.3 Decision process regarding each household's status of being a tourism or a labor migration household at each simulation step and their effects on fuelwood collection.

the current time step, we compared its participation probability with the threshold (0.06) to judge if it is still eligible to be a tourism household. If the tourism household's participation probability is less than the threshold, its status will be changed from being a tourism household to be a non-tourism household. Similarly, if a household is not a labor migration household, we determined if it can become a labor migration household based on its probability to have labor migrants. If a household has already been a labor migration household, we evaluated its eligibility at this time step by comparing its participation probability with the threshold probability (0.01). Only labor migration households with predicted probabilities larger than this threshold can maintain their status of being labor migration households. Households' statuses regarding labor migration and tourism participation were then used to calculate their fuelwood collection.

5.2.2.3 Landscape submodel

The landscape submodel simulates forest dynamics with specific consideration of household fuelwood collection, establishment of new households, and other environmental conditions (e.g., elevation and slope). Our simulation focuses on a 6 km-buffer region around all households (Fig.

Table 5.3 Summary of the logistic estimations of forest gain and forest loss from the previous study in Wolong (Chen et al. 2014).

Models / Parameters	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 ***

(1) Significance: $^{***}p < 0.001$.
(2) Fuelwood impact on a cell is defined as the summation of fuelwood impact on the cell by all households within the 6 km buffer, and each household's impact is defined by its fuelwood collection divided by its distance to the cell.
(3) Because these models were built based on observed forest change for six years (1994 to 2000), the annual forest change (gain or loss) probabilities of landscape cells are the estimated probabilities using the above models divided by six as suggested by (Chen et al. 2014).

5.1) because almost all deforestation activities in the study area happened within the distance of 6 km from the households (Linderman et al. 2005). The total area of the simulated natural landscape is 553 km^2. The landscape is represented in our model as a digital "world" consisting of 90×90 m cells. Each cell has a set of attributes including elevation, slope, aspect, and forest status (forest or nonforest). The elevation, aspect, and slope were obtained based on a digital elevation model derived from a topographic map (Liu et al. 2001). The forest cover information of the landscape cells was initialized with a published binary forest (forest/nonforest) map derived from Landsat Thematic Mapper images acquired in 1997 (Liu et al. 2001). The classification of the satellite images was performed using unsupervised digital classification based on ISODATA technique (Jensen and Lulla 1987) and was validated using ground-truthing. The accuracy of the forest cover map is about 80% (Liu et al. 2001, An et al. 2005).

Landscape cells may experience deforestation (from forest to nonforest) or forest recovery (from nonforest to forest). The forest change of each cell is determined by empirical models obtained from a previous study in the reserve (Chen et al. 2014). According to this study, the deforestation or forest recovery probability of each cell was a function of the cell's elevation, slope, aspect, distance to forest edge, and impacts of fuelwood collection by local households (Table 5.3). Fuelwood collection has a significant positive effect on forest loss ($p < 0.001$) and a significant negative effect on forest recovery ($p < 0.001$) (Table 5.3). At every time step, we calculated the deforestation probability for each forest cell and recovery probability for each non-forest cell to determine their forest status (forest or nonforest). For a detailed description of the construction and validation of these forest change models, please refer to the cited study (Chen et al. 2014).

5.2.3 Model validation

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

We validated the impacts of tourism and labor migration on fuelwood collection, and impacts of fuelwood collection on forest dynamics together by comparing the simulated forest distributions in 2007 with a published empirical forest cover map in 2007 (Viña et al. 2011). This 2007 forest cover map was derived from a digital classification of the imagery of Landsat Thematic Mapper. The map was validated using ground truth data and has an accuracy of 82.6% (Viña et al. 2011). The comparison between simulated and actual maps was performed using a receiver operating characteristic (ROC) curve (Hanley and McNeil 1982) with a random sample of 5000 pixels (2500 forest pixels and 2500 nonforest pixels) from the empirical forest cover map as the validation dataset. We used the area under the ROC curve (AUC) as a measure of the accuracy of the simulated forest maps. The values of AUC ranges from 0 to 1, where a value of 1 indicates perfect accuracy, while a value of 0.5 implies that the accuracy is no better than a random guess (Araújo et al. 2005).

5.2.4 Simulation experiments

After validating our model, we simulated the dynamics of households and forest under five different scenarios to evaluate the effects of tourism and labor migration: (1) without tourism and labor migration; (2) only with tourism; (3) only with labor migration; (4) with both tourism and labor migration but ignoring their interaction; and (5) with both tourism and labor migration including their interaction effect. When running scenario #1, we ignored the impacts of tourism and labor migration by setting all households' probabilities to be tourism and labor migration households to be zero throughout the simulations. When running scenario #2, we ignored labor migration by setting the probability of labor migration to be zero for all households. Similarly, when running #3, we set tourism participation probability to be zero for all households. When running scenario #4, we ignored the interaction between tourism and labor migration by setting the coefficient of the negative impact of tourism participation on the probability of labor migration to be zero. When running scenario #5, tourism, labor migration, and their interaction all took effect. In these simulations, the numbers of tourism and labor migration households in 1996 were assumed to be zero. We ran all simulations for 34 years (from 1996 to 2030). Because the landscape submodel was calibrated using the 1997 forest cover map, it started running one year later than the demographic and telecoupling submodels.

5.3 Results

5.3.1 Model validation results

Our validation results (Table 5.4) indicate our model performances reliably. The difference between the mean predicted human population and observed human population in 2006 was 17, which was less than the observed mean yearly population change (45 per year) from 1996 to

Table 5.4 Comparisons of model predictions of population size, numbers of all households, 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

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

2006. The predicted number of all households was 1176, which was 21 less than the observed value (n = 1197) and less than the mean annual change (31 per year). The predicted percentages of tourism households (28.9%) and labor migration households (22.2%) were close to their observed values (31.2% and 21.7% respectively) in 2005. The differences between observed percentages of tourism and labor migration households in 2005 and simulated means of them (2.3% and 0.5%) were all less than the observed mean yearly changes (3.1% per year and 2% per year) from 1998 to 2005. The simulated forest maps in 2007 were also close to the empirical forest cover map. The AUC values of the simulated maps (n = 20) were between 0.743 and 0.774, indicating good simulation accuracy.

5.3.2 Forest and household dynamics under different scenarios

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

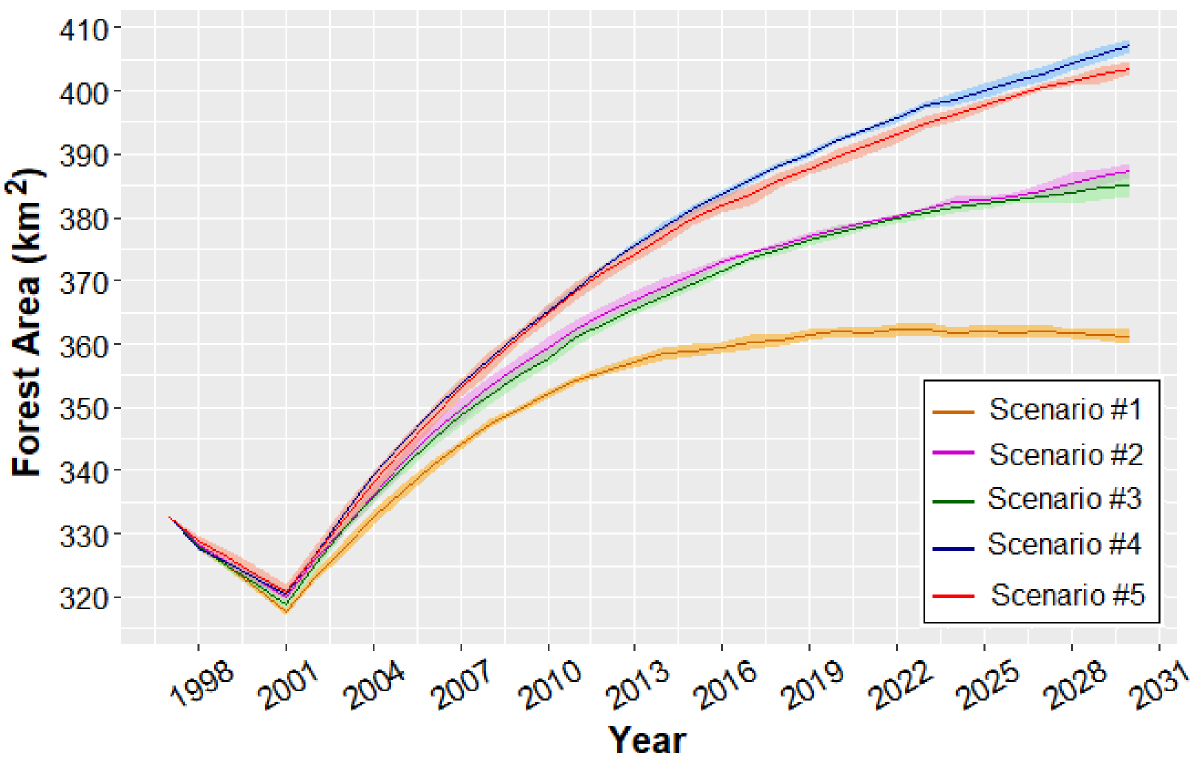

Figure 5.4 Dynamics of the forest areas simulated under five different scenarios: (1) without tourism and labor migration; (2) with tourism only; (3) with labor migration only; (4) with both tourism and labor migration but without considering their interaction; and (5) with both tourism and labor migration and with considering their interactions. Lines and corresponding ribbons represent the means and standard deviations of the results from 20 runs, respectively.

occurred after 2001 (Fig. 5.4). In all the five simulation scenarios, the total forest area decreased between 1996 and 2001, and then started to recover at a gradually decreasing rate. Under the scenario without considering the effects of tourism and labor migration (scenario #1), the predicted forest area in 2030 is 361.2 km^2. Under the scenario only with tourism (scenario #2) or only with labor migration (scenario #3), the forest areas in 2030 are 387.4 km^2 and 385.1 km^2, respectively. The difference in the 2030 forest area between scenario # 1 and scenario #2 is 26.2 km^2, which represents the cumulative effect of tourism development on forest dynamics throughout our simulation period (1996 to 2030). The difference in the 2030 forest area between

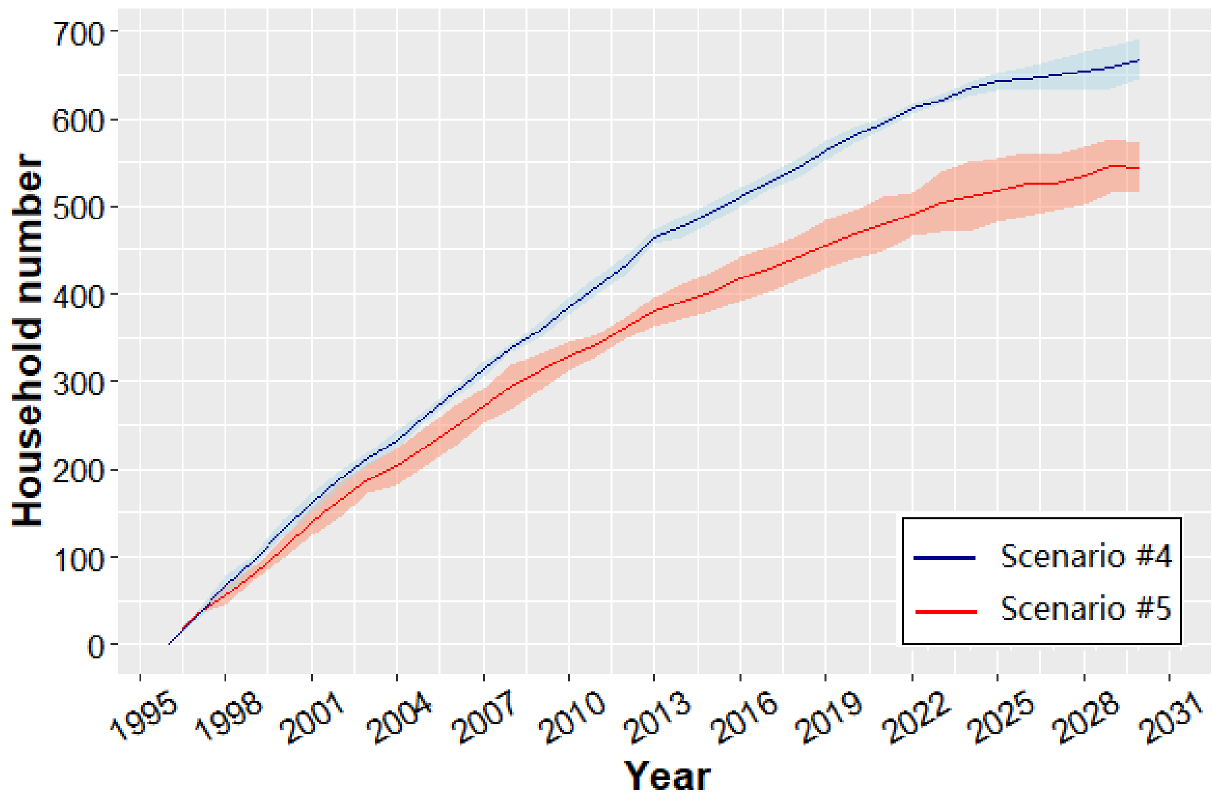

Figure 5.5 Simulated dynamics of the numbers of labor migration households from 1996 to 2030 under scenarios with (Scenario #5) and without (Scenario #4) considering the negative impact of tourism participation on the probability of labor migration. Lines and corresponding ribbons represent the means and standard deviations of the results from 20 runs, respectively.

scenario #1 and scenario # 3 is 23.9 km^2, which represents the cumulative effect of labor migration on forest dynamics from 1996 to 2030.

The development of tourism reduced the number of labor migration households by 22% (Fig. 5.5). Under the scenario that did not consider the negative impact of tourism participation on the probability of labor migration (scenario #4), the number of labor migration households in 2030 is predicted at 554 (34.6% of the total), while under the scenario that considered this negative impact (scenario # 5), the number of labor migration household in 2030 is 675 (42.2% of the total) (Fig. 5.5). The difference in the number of labor migration households in 2030 under scenario #4 and scenario #5 is 121, which represents the cumulative effect of tourism development on growth of labor migration throughout our simulation period from 1996 to 2030.

This interaction between tourism and labor migration has an evident impact on forest dynamics (Fig. 5.4). Under the scenario with both tourism and labor migration but without considering their interaction (scenario #4), the forest area in 2030 is 407.1 km^2, which is 3.5 km^2 higher than that under the scenario that considered this interaction effect (scenario # 5). In short, development of tourism decreases labor migration in the area, which subsequently negatively affects forest cover.

5.4 Conclusion and Discussion

For the first time, we demonstrated that different telecouplings can interact and generated evident impact on the environmental outcomes in rural areas. By analyzing labor migration and tourism in tandem, we show that the interaction between these two telecouplings attenuate their positive impact on forest recovery. While both tourism and migration increase forested area, their interaction results in lower forest gain. In other word, ‘the whole is less than the sum of its parts’. Using the Wolong case study, we argue that potentially related telecouplings should be evaluated jointly rather than separately to reveal their actual effects on socioeconomic and environmental outcomes.

We note that our estimation of tourism’s long-term effect on labor migration may be conservative. This is because we only observed the influence of tourism on individuals staying in the area rather than migrating to cities. Therefore, we did not include the potential effect of tourism on labor migration by attracting labor migrants to come back to only work in the local tourism industry. We hypothesize that, with the inclusion of this attraction effect of tourism on labor migration, the reduction of reforestation would be even more pronounced compared to the results in Fig. 6.4. We did not observe this effect and include it in our current agent-based model perhaps because the tourism development in Wolong was remain at its early stage and this attraction effect had not been evident yet. As the tourism industry is recovering from the impact of the Wenchuan Earthquake in 2008, future studies in Wolong and other places should also evaluate and consider this negative impact in their analyses.

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

In our model, we only considered the impact of tourism on forest through reducing fuelwood collection because tourism development in Wolong remains at its early stage and did not generate other evident impacts on forest (Liu 2012, Liu et al. 2016c). Although nature-based tourism is widely perceived to be clean and non-consumptive because it relies on existing natural, cultural, and historical resources, unregulated tourism development can cause serious degradation of ecosystems (Dai et al. 2012). The actual impacts of future tourism development in Wolong on forest dynamics will depend on its design and management. Besides avoiding direct disturbances into the forest (e.g., clearing forest for tourism infrastructure development), we suggest that future development of tourism should also increase the share of benefit local households could obtain from it. Economic leakage (i.e., tourism revenue flowing to outside investors or managers rather than locals) is a common issue that plagues the development of tourism in many rural areas around the world (Kiss 2004). Previous studies (He et al. 2008, Liu 2012) in Wolong also found that only a small fraction of revenue from tourism development (<5%) went to the local community. This issue may have constrained the impact of tourism participation on fuelwood collection because less income would be available for local households to afford the energy shift from fuelwood to cleaner energy like electricity.

Although the telecoupling interaction illustrated in this study is antagonistic, i.e., one telecoupling weakens the other, synergetic interactions also commonly exist among telecouplings. For example, the panda loan is another important telecoupling linking Wolong and other places (Liu et al. 2015a). Every year the China Conservation and Research Center for the Giant Panda, a panda breeding center and tourism site in Wolong, loans captive pandas to zoos inside and outside China. The panda loans have significantly increased the media exposure of Wolong. For example, around 20% of all media reports found in LexisNexi® about Wolong are related to panda loans (Liu et al. 2015a). The spread of information about Wolong may have in turn boosted the tourist visits to Wolong. About 24% of visitors to the Wolong breeding center in 2005 expressed that they had previously read media reports on Wolong and 29% of them saw television program about Wolong before the visit (Liu et al. 2015a). This indicates that a synergetic interaction effect may exist between the telecouplings of panda loan and tourism. Currently, neither synergetic nor antagonistic interactions among telecouplings have been well studied (Liu et al. 2013a). They deserve more investigations in the future to improve the understandings of the dynamics of telecouplings and their effects on socioeconomic and ecological outcomes.

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

Like all other models, the agent-based model is a simplified representation of the real world.

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

CHAPTER 6

CHANGES IN HUMAN WELL-BEING AND RURAL LIVELIHOODS UNDER NATURAL DISASTERS

In collaboration with

Thomas Dietz, Wu Yang, Jindong Zhang, and Jianguo Liu

Abstract

Rural areas around the world are increasingly exposed to natural disasters. To guide management intervention for sustainable development after natural disasters, scientists and policymakers need a better understanding of the linkages between livelihood changes after natural disasters and recovery outcomes. Despite the growing body of disaster research, systematic evaluation of the relationship between post-disaster changes in rural livelihoods and recovery outcomes is rare, largely due to the lack of relevant data. By taking advantage of the long-term data collection and research conducted in China's Wolong Nature Reserve (Wolong), we empirically evaluated livelihood changes after the catastrophic 2008 Wenchuan Earthquake and how those changes are linked to the recovery of human well-being. Our results show that household livelihoods in Wolong experienced conspicuous changes after the earthquake and that human well-being had been recovering. However, we found most of these livelihood changes negatively affected, instead of facilitating, human well-being recovery. The enriched understanding of the linkages between post-disaster livelihood changes and recovery outcomes have important management implications for achieving Sustainable Development Goals amid natural disasters in Wolong and beyond.

6.1 Introduction

Human vulnerability to natural disasters has been increasing rapidly over the past decades due to factors like human-induced ecological degradation and climate change (Liu et al. 2007b, Field 2012, Simpson et al. 2016). These disasters, such as the series of hurricanes that struck the Caribbean and the North American mainland in fall 2017, can have massive local and regional effects. Besides substantial damage to ecosystems, natural disasters often cause tremendous socioeconomic losses to human communities (van den Berg 2010, Zhang et al. 2011). This challenge is especially acute when considered in the context of global efforts to achieve Sustainable Development Goals (United Nations 2016) in rural areas. Rural areas provide sanctuary to the majority of the world's biodiversity. However, many of the world's biodiversity hotspots are in rural regions with frequent natural disasters (e.g., earthquakes, hurricanes, floods, and droughts) (Myers et al. 2000, Willis et al. 2007). In addition, human populations in those areas have continued to increase in recent decades (Williams 2013, Bacci 2017) and households there are often poor and thus especially vulnerable to natural disasters (Masozera et al. 2007). Without effective management interventions, short-term losses due to natural disasters can easily cause long-term poverty (Hallegatte et al. 2007, Hallegatte and Dumas 2009). This poverty may in turn prompt destructive use of natural resources, and lead to poverty-environment traps in which poverty exacerbates environmental degradation, and environmental degradation worsens poverty (Carter et al. 2007, Cao et al. 2009, van den Berg 2010, Rudel et al. 2013, Barrett et al. 2016, Haider et al. 2017).

In order to shift human-nature interactions toward sustainable development after natural disasters, it is crucial to understand the post-disaster changes in household livelihoods, and how these livelihood shifts affect socioeconomic and ecological outcomes (e.g., human well-being and biodiversity) (Ingram et al. 2006, Resosudarmo et al. 2012, Lawther 2015). Equipped with such knowledge, management agencies may be able to develop specific interventions to shape the post-disaster livelihoods of affected communities in ways that facilitate recovery after disasters while minimizing impacts on ecosystems. Absent such interventions, unregulated livelihood activities (e.g., timber harvesting) after disasters may lead to serious biodiversity loss and compromise the natural capital that is essential for the long-term sustainability of local communities (Ingram et al. 2006).

Although there has been a growing body of research on natural disasters over the past years, examination of livelihoods and human well-being in post-disaster recovery is still in its infancy (Berke and Glavovic 2012, Olshansky et al. 2012, Yi and Yang 2014, Triyanti et al. 2017). The existing literature has examined the restoration of housing conditions, household income, and people's psychological health (e.g., Priebe et al. 2011, Rathfon et al. 2013, Yang 2013), and how these recovery outcomes are influenced by demographic and socioeconomic characteristics, such as race and ethnicity (e.g., Zhang and Peacock 2009, Finch et al. 2010, Wang et al. 2012, Wang et al. 2015), as well as external assistance (e.g., Msilimba 2010, Resosudarmo et al. 2012). However, systematic evaluation of post-disaster livelihood changes and their linkages with recovery of human well-being is rare in existing literature (Burton 2015, Lawther 2015), largely due to the lack of relevant data.

Long-term interdisciplinary research conducted in China's Wolong Nature Reserve (Wolong hereafter), which was seriously affected by the Wenchuan Earthquake, provides an excellent opportunity to address this issue. On May 12, 2008, a catastrophic earthquake (Ms 8.0; the most devastating in China since the 1950s) struck southwestern China, with its epicenter in Wenchuan County, Sichuan Province (Viña et al. 2011, Zhang et al. 2014). The earthquake generated tremendous socioeconomic impacts as it caused 69,227 deaths, 374,643 injuries, and 17,923 missing, in addition to over 84.51 billion yuan (12.6 billion USD as of June 2016) of economic loss associated with property damage (CCTV 2009). The earthquake also caused serious impacts on biodiversity. It was estimated that about 1,221 km^2 of forest, grassland, and wetland was lost (e.g., converted from forest to bare land) due to the earthquake and subsequent landslides (Ouyang et al. 2008). In response, the Chinese government initiated hundreds of post-disaster reconstruction projects to rebuild the facilities, infrastructures, and residential houses with a massive investment of over 1,700 billion yuan (253 billion USD as of June 2016) (China News 2012).

Wolong is among the areas that were most seriously affected by the Wenchuan Earthquake. By taking advantage of the long-term research and data collection efforts in Wolong (e.g., Liu et al. 1999, An et al. 2001, Linderman et al. 2005, Chen et al. 2012b), we are able to empirically evaluate livelihood changes after the earthquake and how those livelihood changes affect human well-being. We first characterized changes in local households' livelihoods in response to the direct and indirect impacts of the 2008 Wenchuan earthquake using multi-year household survey data. We then used a quantitative human well-being index system to characterize changes in human well-being for each surveyed household. Finally, we built empirical models to estimate

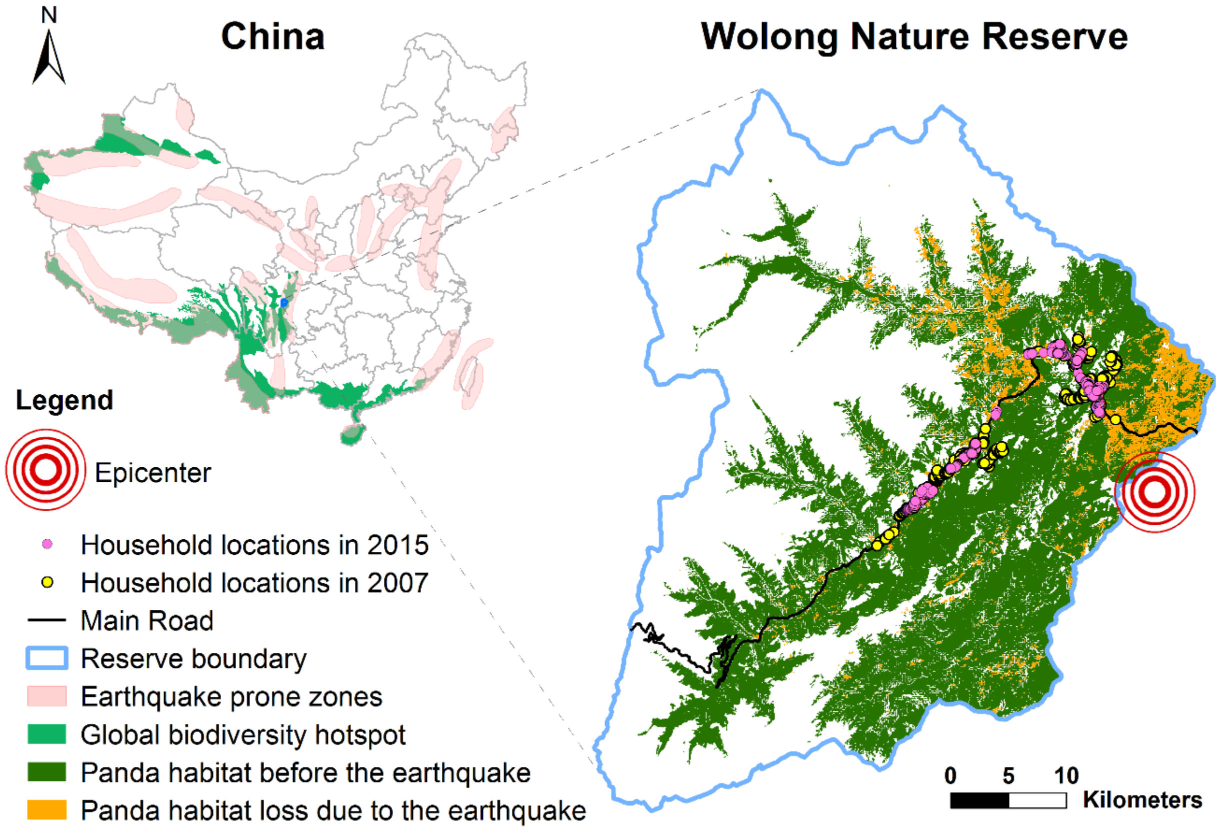

Figure 6.1 Wolong Nature Reserve in Southwestern China. The reserve locates within one of the overlapped regions between earthquake prone zone and global biodiversity hotspots in China. The information on panda habitat and its change was obtained from the published results in (Ouyang et al. 2008).

the effects of different livelihood changes on human well-being recovery. This allows us to discuss the management strategies that would facilitate sustainable development amid natural disasters in Wolong and beyond.

6.2 Materials and Methods

6.2.1 Study area

Our study area is Wolong in southwestern China (102°52′ to 103°24′ E, 30°45′ to 31°25′ N), where the Nature Reserve was designed mainly for the conservation of giant pandas (*Ailuropoda* *melanoleuca*) (Fig. 6.1). The reserve was established in 1963 and expanded to its current size of 2,000 km^2 in 1975 (Liu et al. 2016a). It is within one of the top 25 global biodiversity hotspots and provides sanctuary to more than 6000 species of plants and animals, including the iconic giant panda (Myers et al. 2000, Liu et al. 2003, Yang 2013). Besides the diverse wildlife species, Wolong is also home to about 4,900 local residents, living in around 1,200 households (Liu et al. 2016a).

Wolong is ideal for this research for several reasons. First, Wolong is within a region susceptible to natural disasters and was seriously affected by the Wenchuan Earthquake (Fig. 6.1). The reserve lies on the Longmen Mountain fault and has been subjected to frequent seismic activities (Zhang et al. 2014). Since 1933, there have been ten earthquakes with the magnitude of 7.0 Ms or higher occurred around this region, including the most recent Jiuzhaigou Earthquake occurred in 2017, Lushan Earthquake occurred in 2013, and the Wenchuan Earthquake occurred in 2008 (Xu et al. 2013, Zhang et al. 2014, Lei et al. 2017, Yang et al. 2017b). The epicenter of 2008 Wenchuan Earthquake was only 2 km away from the reserve's boundaries, which makes Wolong among the areas most seriously affected by the earthquake. The Earthquake and its associated landslides killed 129 people in Wolong, with 6 people missing, and 35 people seriously injured (Wang 2013). The earthquake also caused severe damage to local infrastructure and facilities, including residential houses, hospitals, schools, hotels, and the main road that connects Wolong to the outside world. The direct economic loss associated with the earthquake damage in Wolong was estimated up to 1.95 billion yuan (about 291.9 million USD as of June 2016) (Wang 2013). Besides these socioeconomic damages, the earthquake also caused the loss of about 56 km^2 of forest (about 7% of total forest) that is critical for the habitat of giant pandas and many other wildlife species in Wolong (Ouyang et al. 2008, Viña et al. 2011).

Second, household livelihoods in Wolong before the earthquake share many common features with other rural areas around the world. In Wolong, as in many other rural areas, crop production (e.g., growing cabbage, corn and potato) and livestock husbandry (e.g., rearing cattle or yaks) are important livelihood strategies (Liu et al. 2016a). Meanwhile, the rich natural resources in Wolong made it a famous tourism destination. The development of nature-based tourism in the 2000s benefited many local households by bringing off-farm job opportunities (He et al. 2008, Liu et al. 2012, Yang et al. 2015). In recent decades in China, a widening rural-urban disparity of job opportunities has attracted a rapidly growing number of farmers from rural areas to urban centers (Rush 2011). Wolong has not been an exception, with a growing number of households having members out-migrate to cities for temporary jobs (Chen et al. 2012a). Since these livelihood activities in Wolong are commonly found in other rural areas around the world, methods and findings from this study may guide research and management not only in Wolong, but also many other places around the world (Kramer et al. 2009, Pulido-Fernandez et al. 2015).

Finally, our research team has been conducting long-term interdisciplinary research on coupled human and natural systems in Wolong since late 1990s. This lays an essential foundation for examining the linkages between changes in livelihoods and human well-being after the earthquake (Liu et al. 2016a). For example, the detailed household information collected before and after the earthquake constitutes an excellent dataset for characterizing the changes of local livelihoods. In addition, Yang et al. (2013) developed an survey-based approach to quantify human well-being, which offers a feasible way to evaluate human well-being changes of local households (Yang et al. 2013a).

6.2.2 Characterizing livelihood changes

In this study, we focus on four major types of livelihood activities that changed after the earthquake in Wolong, including local off-farm labor, crop production, labor migration (temporary out-migration to work in cities), and livestock husbandry. Since household members often make joint or coordinated decisions regarding livelihood affairs, all data characterizing livelihood changes were collected at the household level.

We used household survey data collected in Wolong in 2007, 2010, and 2015. It contains detailed demographic (e.g., household size, members' age, education, and occupation) and socioeconomic (e.g., cropland area, number of livestock, livestock selling prices, and income sources) information of local households at three important time steps: 2007 (just before the earthquake), 2009 (soon after the earthquake) and 2014 (six years after the earthquake), respectively. We conducted these surveys in the form of face-to-face interviews. During these interviews, we selected household heads or their spouses as interviewees because they usually have the best knowledge about their households' affairs. Before performing the formal surveys, we conducted pretests to assess respondents' comprehension of our survey questions and how difficult they feel it was to answer. Based on interviewees' responses in pretests, we iteratively revised our survey instruments to ensure that interviewees understood and were able to answer our questions correctly. In total, 199, 287, and 245 randomly sampled households completed our formal surveys, with a response rate of 93%, 95%, and 96%, respectively.

Table 6.1 Summary of variables included in the linear regression models that relate changes of human well-being index and sub-indices after the earthquake to different livelihood changes and other socioeconomic factors (sample size = 186).

Variables	Description	Mean (SD)
Outcome variables		
Well-being change	Change in the overall human well-being index value from 2009 to 2014.	0.271 (0.182)
Change in basic material	Change in value of sub-index representing basic materials for good life from 2009 to 2014.	0.32 (0.279)
Change in security	Change in value of sub-index representing security from 2009 to 2014.	0.382 (0.191)
Change in health	Change in value of sub-index representing health from 2009 to 2014.	0.225 (0.186)
Change in social relations	Change in value of sub-index representing social relations from 2009 to 2014.	0.013 (0.081)
Change in freedom	Change in value of sub-index representing freedom of choice and action from 2009 to 2014.	0.195 (0.191)
Livelihood activities and their changes		
Labor work inside 09	The number of laborers earned income through working in local off-farm sectors in 2009.	1.102 (0.775)
Change in labor work inside	Change in the number of laborers working in local off-farm sectors from 2009 to 2014.	-0.054 (1.089)
Labor work outside 09	The number of laborers earned income through working outside the reserve in 2009.	0.409 (0.739)
Change in labor work outside	Change in the number of laborers working outside the reserve from 2009 to 2014.	0.317 (1.081)
Crop production 09	The area of the household's cropland in 2009. (Mu [a])	3.491 (3.228)
Change in crop production	Change in household's cropland area from 2009 to 2014. (Mu)	-0.481 (3.016)

Table 6.1 (cont'd)

Variables	Description	Mean (SD)
Change in laborers	Change in the number of laborers from 2009 to 2014.	-0.183 (1.718)
Laborers' education	The average schoolyears of laborers. (Year)	5.979 (3.037)
Change in laborers' education	Change in laborers' average schoolyears from 2009 to 2014.	1.164 (4.21)
Respondent's gender	The gender of the respondent in our survey (0, female; 1, male)	0.602 (0.491)
Respondent's education	The schoolyears of the respondent. (Year)	5.688 (3.560)

[a] 1 mu = 1/15 hectare; [b] 1 Yuan = 0.14 USD as of June 2016.

The household livelihood information in 2007, 2009, and 2014 comprises an excellent dataset to characterize livelihood changes after the Wenchuan Earthquake. We operationalized local off-farm labor in Wolong as the number of household member(s) working in local off-farm sectors (e.g., construction, operating restaurants). Crop production was operationalized as the average amount of cultivated cropland owned by each local household. Labor migration was operationalized as the number of labor migrants in each household, while the livestock husbandry was operationalized as the average number of livestock raised by each household. To make different types of livestock (sheep, yak, cattle, and horses) comparable, the livestock number we used in this study is the equivalent number of sheep calculated by converting other types of livestock to sheep based on the ratios of their average selling prices derived from our survey.

6.2.3 Measuring human well-being changes

Along with the basic household information collected in 2015, we used a published survey

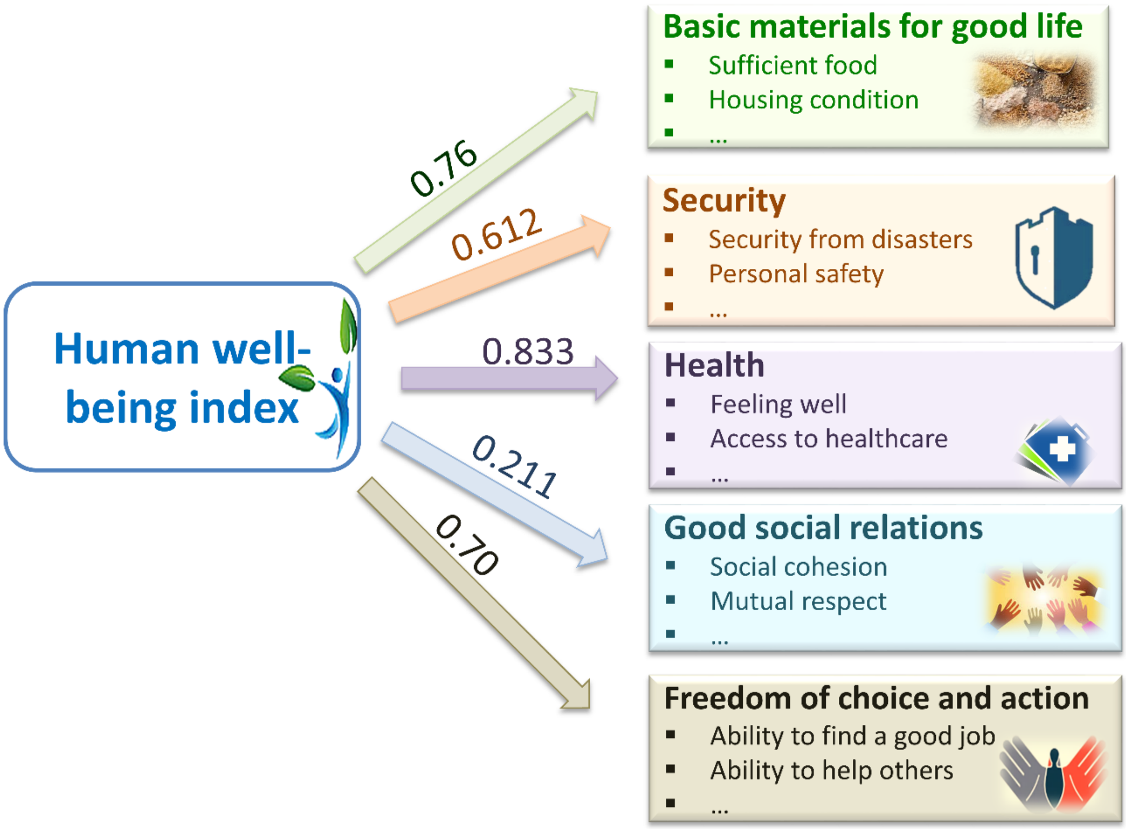

Figure 6.2 The structure of human well-being index system. Besides the overall human well-being (the blue in the left), it has five sub-indecies corresponding to the five demensions of human well-being as proposed in the Millineum Ecosystem Assessment, including basic materials for good life, security, health, good social relation, freedom of choice and action. For each sub-index, we designed a set of indicators measured with five-category Likert-style scale as presented in our survey instrument (Table S6.1). We estimated these indices using confirmatory factor analysis. The single-headed arrows represent direction of causal influence. Number along each arrow is the sandardized coefficient indicating the strength of the empirical relationship between overall human well-being and the corresponding sub-dimension of it.

instrument (Table S6.1) to collect data for quantifying human well-being of each surveyed household in 2007, 2009 and 2014. In collecting retrospective information, we followed standard practices of life history calendars to enhance respondents' recall accuracy (Freedman et al. 1988, Axinn et al. 1999). In total, 244 households randomly sampled in 2015 completed our human well-being survey, with a response rate of 96%.

The survey instrument we used (Table S6.1) was designed based on the framework of human well-being proposed in the Millennium Ecosystem Assessment (MA 2005, Yang et al. 2013a). Human well-being encompasses five interrelated dimensions: basic material for good life, security, health, good social relations, and freedom of choice and action (MA 2005). Fig. 6.2 presents the structural relations between the overall human well-being index and its five sub-indices representing each of the five dimensions. For each sub-index, our survey instrument includes a set of questions to generate indicators to construct it (Table S6.1).

We used confirmatory factor analysis with Mplus, version 7 (Muthén and Muthén 2012) to estimate the overall human well-being index and its five sub-indices. We evaluated the validity of these human well-being indices using a set of criteria (Table S6.2). The validation results indicate that the overall index and sub-indices of human well-being have high reliability (Table S6.2). To allow cross-year comparisons, we normalized the overall index and the sub-indices to the range from 0 to 1 using maximum-minimum normalization method as suggested by Yang et al. (2015). A higher value of the index value suggests higher satisfaction of corresponding human needs. More technical details regarding construction of the indices, validation, and application can be found in previous studies (e.g., Yang et al. 2013a, Yang et al. 2015).

6.2.4 Modeling the linkages between changes in livelihood and human well-being

One of our major goals is to evaluate the relationship between livelihood changes after the earthquake and the recovery of human well-being. Previous work has examined the impact of the earthquake per se (Yang et al. 2016c); our emphasis is what happened during the recovery period, that is, the year following the earthquake (2009) to six years after the earthquake (2014).

We used changes in the overall human well-being index and its five sub-indices between 2009 and 2014 as our measures of recovery outcomes. We hypothesize that the human well-being changes after the earthquake are affected by the mix of livelihood activities of households in 2009 and their changes during the recovery period (2009 to 2014).

To develop indicators characterizing different livelihood changes (Table 6.1), we compiled panel data using socioeconomic information on households in 2009 and 2014. In total, there are186 households surveyed in both years. With these panel data, we constructed linear regression models to relate changes in overall human well-being index and its five sub-indices between 2009 and 2014 to changes in household livelihood activities during the same period as well as their values in 2009.

To control for potential confounding effects, our models included some other socioeconomic and demographic factors that may affect human well-being changes (Table 6.1). Similar to livelihood activities, some of these factors (e.g., number of laborers in a household) may change during the recovery period (i.e., 2009 to 2014). We thus included variable measuring these socioeconomic and demographic conditions in 2009 and their changes between 2009 and 2014 in our models (Table 6.1). Our models also included the changes in human well-being indices between 2007 and 2009 as independent variables because the short-term impact of the earthquake on human well-being may have legacy effect on the long-term recovery. The general form of the models can be given as

$$H_{\Delta} = \beta_0 + \beta_1 H_{2009} + \beta_1 H_{2007-2009} + \beta_3 L_{2009} + \beta_4 L_{\Delta} + \beta_5 X_{2009} + \beta_6 X_{\Delta} + \varepsilon \tag{6.1}$$

where H_{Δ} refers to the vector of changes in overall human well-being index and the sub-indices between 2009 and 2014; H_{2009} refers to the vector of corresponding indices in 2009; $H_{2007-2009}$ represents the vector of changes in corresponding indices between 2007 and 2009; L_{2009} and L_{Δ} represent the vectors of livelihood activity variables in 2009 and their changes between 2009 and 2014 respectively; X_{2009} and X_{Δ} represent the vectors of other socioeconomic and demographic variables in 2009 and their changes between 2009 and 2014 respectively; β_0 is the vector of intercept; $\beta_1 - \beta_6$ are the vectors of coefficients to be estimated; ε is the vector of error term, in which each error term is assumed to be normally distributed with a mean of zero. We conducted the modeling analyses using Stata 13.1 (StataCorp, College Station, Texas, USA).

6.3 Results

6.3.1 Livelihood changes after the earthquake

After the earthquake, all the four major types of livelihood activities in Wolong experienced conspicuous changes in response to the direct and indirect impacts of the earthquake. We observed that the proportion of households having laborer(s) with temporary or permanent off-farm jobs inside Wolong maintained a high level after the earthquake (Fig. 6.3 (a)): 75.6% in 2009 and 65.2% in 2014, as compared to 75.4% in 2007. However, the main source of local off-farm jobs changed after the earthquake. Before the earthquake, about 90% of the off-farm job opportunities were directly (e.g., employment in a hotel) or indirectly (e.g., labor work for construction of tourism facilities) related to tourism development. But the tourism industry collapsed because of earthquake damage to the main road and tourism facilities. Post-disaster reconstruction projects supported by the Chinese government became the main source of off-farm income opportunities for local households. Our survey data show that 74% in 2009 and 63% in 2014 of local off-farm income activities were related to the post-disaster reconstruction projects (e.g., reconstructing roads, schools, hospitals and residential houses). The decline in the local off-farm opportunities between 2009 (75.6%) and 2014 (65.2%) might be explained by the completion of many reconstruction projects in recent years (China News 2012).

In Wolong, crop production plays an important role in local economy. After the earthquake, however, crop production in Wolong decreased due to the impacts of landslides caused by the earthquake and post-disaster reconstruction. The average amount of cropland owned by each household in Wolong decreased from 4.7 mu (1 mu = 0.067 hectare) in 2007, to 3.4 mu in 2009, and to 2.9 mu in 2014 (Fig. 6.3 (b)). Of the cropland loss from 2007 to 2014, about 39% was attributable to the direct damage by the earthquake and the associated landslides, while the rest (about 61%) was due to the appropriation of land for the post-disaster reconstruction. Concomitant with the loss of land, the percentage of average household income from selling crop products to outside markets declined by 32% between 2007 and 2014.

The other two major types of livelihood activities, labor migration and livestock husbandry, increased after the earthquake and may have compensated for the decline in farming and tourist industry employment. The proportion of households with member(s) temporarily out-migrating to work in cities rapidly increased from 2.6% in 2007, to 26.8% in 2009, and to 48.2% in 2014 (Fig. 6.3 (c)). Although the proportion of households that raised livestock after the earthquake maintained at a level similar to what it was before (around 30%), pastoral households

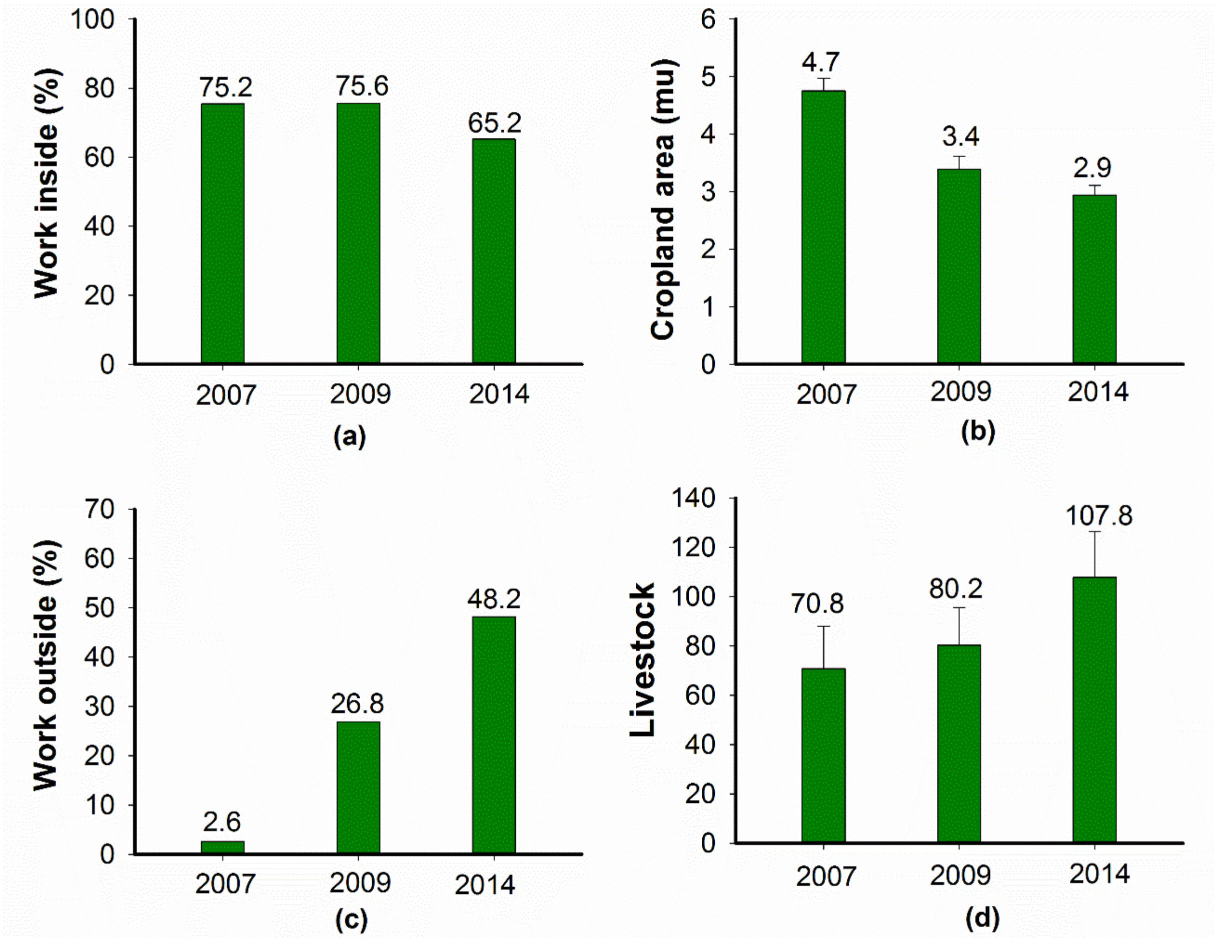

Figure 6.3 Livelihood changes across years in Wolong. (a) The percentage of households with member(s) working in off-farm sectors inside Wolong; (b) The average cropland area each household had in Wolong (No cropland sat fallow); (c) The percentage of households with member(s) working outside Wolong; (d) The average number of livestock (as measured by equivalent number of sheep) raised by pastoral households in Wolong.

(households that raise livestock) had expanded their livestock population after the earthquake. The average equivalent amount of sheep raised by each pastoral household increased from 70.8 in 2007, to 80.2 in 2009, and to 107.8 in 2014 (Fig. 6.3 (d)).

6.3.2 Human well-being changes after the earthquake

Human well-being indices indicate that households' well-being in Wolong has been recovering after the earthquake (Fig. 6.4). The average value of overall human well-being index

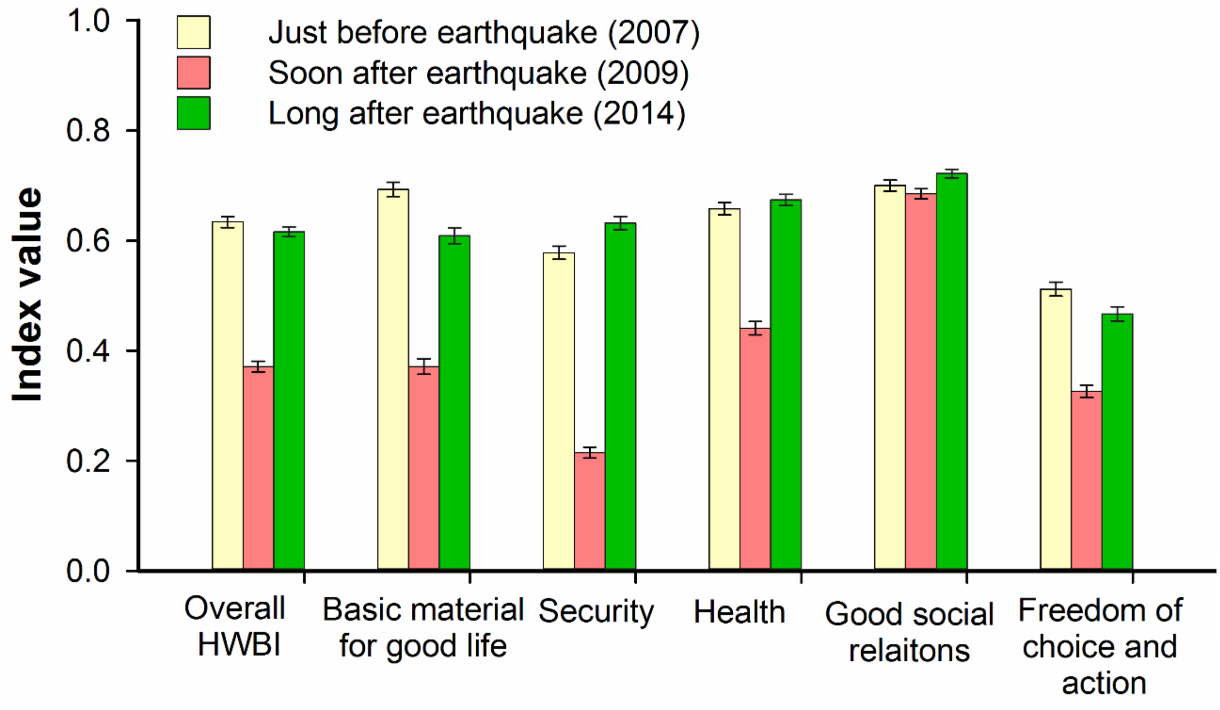

Figure 6.4 Average values of human well-being indices in Wolong before and after the earthquake. A larger index value represents a better state of well-being. All changes in overall human well-being index and its sub-indices between 2007 and 2009, and between 2009 and 2014 are statistically significant ($p < 0.05$).

increased by 68% between 2009 and 2014 (from 0.37 in 2009 to 0.62 in 2014), reaching a level similar to that before the earthquake (0.63 in 2007). The five dimensions of human well-being experienced different levels of recovery. The value of the sub-index representing basic materials for good life increased from 0.37 in 2009 to 0.61 in 2014, a level only slightly lower than that in 2007 (0.69). The value of the sub-index representing security was almost tripled from 0.22 in 2009 to 0.63 in 2014 and became higher than the level before the earthquake (0.59 in 2007). The value of the sub-index representing health increased from 0.44 in 2009 to 0.67 in 2014, a level that was slightly higher than before the earthquake (0.66). The sub-index representing good social relationship did not change much throughout our study period (decreased slightly from

Table 6.2 Results of the linear regression model on human well-being recovery after the earthquake (sample size = 186). R^2 of the ordinary least square regression is 0.517. The model passed all diagnostics of regression assumptions. Variance inflation factors were all tested to be less than 10.

Variables	Coefficients	Robust standard error
Livelihood activities and their changes		
Labor work inside 09	0.0620 **	0.0201
Change in labor work inside	0.0333 *	0.0132
Cropland production 09	0.00641 †	0.0036
Change in crop production	0.0074 †	0.0044
Labor work outside 09	0.0256	0.0230
Change in labor work outside	-0.0150	0.0138
Livestock husbandry 09	-0.00008	0.0001
Change in livestock husbandry	-0.0003 *	0.0002
Socioeconomic and demographic characteristics		
Human well-being 09	-0.6121 ***	0.0874
Change in well-being 07~09	-0.1517 †	0.0913
Total income 09	-0.0124	0.0081
Household size 09	-0.0378 *	0.0147
Change in household size	-0.0255 *	0.0114
Laborers 09	0.0374 †	0.0191
Change in laborers	0.0385 **	0.0134
Laborers' education	0.0025	0.0062
Change in laborers' education	-0.0008	0.0050
Respondent's gender	0.0005	0.0226
Respondent's education	0.0063 †	0.0034
Constant	0.4973 ***	0.1006

$^{\dagger}\ p \leq 0.1$; $^{*}\ p \leq 0.05$; $^{**}\ p \leq 0.01$; $^{***}\ p \leq 0.001$; two-tailed tests.

0.70 in 2007 to 0.69 in 2009, and bounced back to 0.72 in 2014). The sub-index representing freedom of choice and action increased from 0.33 in 2009 to 0.47 in 2014, but was still lower than the level before the earthquake (0.51 in 2007). All value changes in the overall human well-being index and the sub-indices, from 2007 to 2009 and from 2009 to 2014, are statistically significant ($p < 0.05$ based on t-tests).

6.3.3 Linkages between changes in livelihoods and human well-being

Local off-farm labor work has significant positive effects on human well-being recovery. The change in the number of laborers with off-farm jobs inside the reserve during the recovering period (2009 to 2014) are positively related with post-disaster human well-being change ($p < 0.05$) (Table 6.2). The changes in sub-indices of basic materials ($p < 0.01$), health ($p < 0.05$) and freedom of choice ($p < 0.05$) are all positively related to the change in laborers involved in local off-farm income activities (Table 6.3). Therefore, the high participation in local off-farm income activities (> 65%) after the earthquake seems to have promoted the human well-being recovery.

Crop production also has the potential to contribute to human well-being recovery. Cropland change is positively related to overall human well-being recovery ($p < 0.1$) (Table 6.2). Change in the sub-index of security between 2009 and 2014 shows significant positive relation with cropland change ($p < 0.01$) (Table 6.3). Therefore, the conspicuous cropland loss due to the direct impact of the earthquake (e.g., landslides) and post-earthquake reconstruction may have negatively affected the recovery of human well-being.

The coefficient for the relationship between change in labor migration and change in overall human well-being is negative, though not statistically significant ($p > 0.1$) (Table 6.2). Of the

Table 6.3 Results of the linear regression models on changes of sub-indices of human well-being recovery after the earthquake (sample size = 186). The five columns represent results for sub-indices corresponding to basic material for good life, security, health, good social relations, freedom of choice and action, respectively. The models passed all diagnostics of the regression assumptions. Variance inflation factors were all tested to be less than 10.

Variables	Coefficients (Robust standard error)				
	Basic materials	Security	Health	Social relations	Freedom
Livelihood activities and their changes					
Labor work inside 09	0.0800** (0.0291)	0.0146 (0.0224)	0.0548** (0.021)	0.0113 (0.0105)	0.0607** (0.0232)
Change in labor work inside	0.0484* (0.0189)	-0.0022 (0.0157)	0.0322* (0.0132)	0.0082 (0.0071)	0.0313* (0.0152)
Crop production 09	0.0084† (0.0049)	0.0065 (0.0044)	0.0045 (0.0039)	-0.0044† (0.0022)	0.0051 (0.0048)
Change in crop production	0.0057 (0.0055)	0.0122* (0.0049)	0.005 (0.0051)	0.0007 (0.0034)	0.0072 (0.0049)
Labor work outside 09	0.0741* (0.0320)	-0.0116 (0.0270)	-0.0005 (0.0244)	-0.0124 (0.0129)	0.0281 (0.0258)
Change in labor work outside	0.0276 (0.0196)	-0.0084 (0.0175)	-0.0314* (0.0145)	-0.0035 (0.008)	-0.0329* (0.0164)
Livestock husbandry 09	-0.00002 (0.00009)	-0.0003** (0.0001)	0.00005 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
Change in livestock husbandry	-0.0003 (0.0002)	-0.0005† (0.0002)	-0.0002 (0.0002)	0.0001 (0.0001)	-0.0004** (0.0002)

Table 6.3 (cont'd)

Variables	Coefficients (Robust standard error)				
	Basic materials	Security	Health	Social relations	Freedom
Socioeconomic and demographic characteristics					
Index value 09 [a]	-0.8031*** (0.0776)	-0.5046*** (0.0971)	-0.4387*** (0.0812)	-0.0066 (0.0548)	-0.5261*** (0.0751)
Index value change 07~09 [b]	-0.0839 (0.0745)	-0.1916** (0.07)	-0.2584** (0.0917)	-0.273** (0.1003)	-0.0335 (0.1096)
Total income 09	-0.0197 (0.0132)	-0.0158† (0.0086)	-0.0133 (0.0087)	-0.0053 (0.0043)	-0.0009 (0.009)
Household size 09	-0.0365† (0.0199)	-0.0413* (0.0179)	-0.0391* (0.0163)	-0.0217* (0.0106)	-0.0353* (0.0165)
Change in household size	-0.0262 (0.017)	-0.0348* (0.0139)	-0.0297* (0.0115)	-0.0127† (0.0068)	-0.0148 (0.0128)
Laborers 09	0.0201 (0.0273)	0.045* (0.0216)	0.0447* (0.0213)	0.0146 (0.0135)	0.035† (0.0201)
Change in laborers	0.0247 (0.0189)	0.0351* (0.0164)	0.0437** (0.014)	0.0016 (0.0075)	0.0376** (0.0143)
Laborers' education	0.0034 (0.0104)	-0.0089 (0.0071)	0.0057 (0.0061)	0.0034 (0.0028)	0.0041 (0.0073)
Change in laborers' education	-0.0020 (0.0086)	-0.0075 (0.0061)	0.0025 (0.0048)	0.0022 (0.0027)	0.000003 (0.0058)
Respondent's gender	-0.0101 (0.0336)	0.0249 (0.0271)	-0.0024 (0.0228)	0.0109 (0.0129)	-0.0028 (0.0255)
Respondent's education	0.0067 (0.0057)	0.0047 (0.0045)	0.0029 (0.0035)	-0.0023 (0.002)	0.0102* (0.004)
Constant	0.7038*** (0.1501)	0.6002*** (0.1205)	0.4131*** (0.1117)	0.1094 (0.0672)	0.2648* (0.1032)
R^2	0.565	0.350	0.503	0.253	0.401

† $p \le 0.1$; * $p \le 0.05$; ** $p \le 0.01$; *** $p \le 0.001$; two-tailed tests.

[a] The sub-index value of the corresponding dimension of human well-being in 2009.
[b] Change in the sub-index value of the corresponding dimension of human well-being between 2007 and 2009.

five sub-indices of human well-being, only change in sub-index of basic materials shows a positive relationship with labor migration and it is not statistically significant. The other four sub-indices are all negatively related to labor migration changes and two of these are significant: the dimension of health ($p < 0.05$) and freedom of choice and action ($p < 0.05$) (Table 6.3). Therefore, the rapid increase in the number of households with laborers that out-migrated to work in cities after the earthquake may have contributed little, or even impeded, the recovery of human well-being.

Livestock husbandry change is negatively associated with human well-being change ($p < 0.05$) (Table 6.2). The changes in indices representing dimensions of security and freedom of choice are both negatively related with the change of livestock number raised by local households ($p < 0.05$ and 0.01 respectively) (Table 6.3). These results indicate that the livestock expansion occurred in Wolong after the earthquake may have impeded the human well-being recovery.

Some demographic and socioeconomic characteristics of the households also show significant effects on human well-being recovery. Specifically, the number of laborers in a household is positively related to human well-being recovery. Both the number of laborers in 2009 and its change from 2009 to 2014 show significant positive effects ($p < 0.1$ and 0.01 respectively) on human well-being change (Table 6.2). Household size showed significant negative effects on human well-being. Households with a larger size in 2009 or increases in the recovering period (e.g., new birth during 2009 to 2014) tend to have a lower level of recovery ($p < 0.05$) (Table 6.2). The significant negative coefficients of the human well-being index value in

2009 ($p < 0.001$) and its change between 2007 and 2009 ($p < 0.1$) (Table 6.2) indicate households with higher well-being status in 2009 or whose well-being suffered little during the earthquake tend to have a smaller increase in human well-being during the recovering period from 2009 to 2014.

6.4 Discussion

Although human well-being after the earthquake had been recovering, we found many of the livelihood changes that resulted from the earthquake negatively affected well-being. Some of these negative linkages may be due to the limitations of these livelihood activities. For example, previous studies (e.g., Wong et al. 2007, Zhong et al. 2016) show that migrant workers in cities usually find it hard to adapt to urban environment, bear high living expenses, confront an unfair education system for their children, and lack a sense of belonging in cities. Therefore, labor migrants often suffer from high stresses and financial hardships that can harm their mental health and sense of freedom of choice. This is probably the reason for labor migration's negative effects on indices of health and freedom of choice and actions shown in Table 6.3. Another example is livestock husbandry. The extensive livestock husbandry practices in Wolong (e.g., livestock are set to roam in the wild most of the time) may make the productivity of this work and its return on investment relatively low. Meanwhile, the initial investment for livestock (e.g., buying calves) is often high. Therefore, livestock expansion as a response to the earthquake may create heavy financial burdens on households and compromise their financial security and sense of freedom of choices and actions. This may be especially true for those who had experienced greatest loss in the earthquake and had to borrow money to expand their livestock holdings.

In evaluating livelihood changes and their effects on human well-being, we found post-disaster reconstruction generated unintended effects on human well-being through appropriating cropland. Besides reducing income from cropping, cropland loss due to post-disaster reconstruction may increase households' expenditures to buy agricultural products that they could produce on their own land before the earthquake. These negative impacts on the well-being of local households might be exacerbated as the market demand for and price of agricultural products have been increasing (Fukase and Martin 2016).

However, the post-disaster reconstruction in Wolong may have promoted human well-being recovery through pathways in addition to bringing off-farm income opportunities to local households. For example, with the massive investment from the Chinese government, almost all households in Wolong were resettled to areas with flat terrain and close to the main road (Fig. 6.1). These features of the new settlements would make local households less susceptible to possible future disasters and may have contributed to the observed increase in the sub-index of security after the earthquake (from 0.22 in 2009 to 0.63 in 2014). In addition, with support from government, these newly constructed residential houses were designed and constructed with higher quality than had been typical of the previous housing stock (Yang 2013). The improved housing conditions (e.g., larger dwelling area and closer to the main road) seem to help to address households' needs for basic materials for good life after the earthquake and enhance their sense of freedom of choice and action. The housing improvement may also allow local households to develop their own off-farm business (e.g., operating restaurants or tourist farmhouses) and enhance their well-being in the future. Furthermore, the resettlement increased the distance of local households from core panda habitats (Fig. 6.1), which may reduce negative human impacts on ecosystems and enhance the ecosystem services (e.g., tourism) that can be essential for the well-being of local communities in the future.

An enriched understanding of the linkages between livelihood changes and human well-being has important implications for post-disaster management. A major lesson learned from our study is that post-disaster reconstruction should pay special attention to conserving or enhancing household capitals that are essential for livelihoods that can improve human well-being. For example, our results show that cropland is an important capital for the well-being of local households but was compromised due to the post-earthquake reconstructions. In Wolong, crop production has small direct ecological impacts as local cropland parcels are distributed within in a small area (about 0.05% of the whole reserve) and most of them are distant from wildlife habitat. We thus suggest post-disaster reconstruction and other possible future infrastructure development (e.g., construction of tourism facilities) should avoid appropriation of productive cropland to reduce associated stress on well-being of local households. Furthermore, productive cropland previously enrolled into payments for ecosystem services programs (Yang 2013) and distant from wildlife habitat might be allowed to be converted back to cropland after the end of these programs. In other areas where cropping can generate substantial negative impacts on local ecosystems, management agencies may take the opportunity of post-disaster reconstruction to enhance capitals that can promote the shift from on-farm to off-farm activities as in Wolong. For example, the post-disaster reconstruction might relocate affected households to areas close to the main road and tourism sites. The enhanced housing conditions may afford local households to participate in local off-farm activities (e.g., operating a leisure farmhouse) and discourage them from crop production near core wildlife habitat, which ultimately may reduce the negative ecological impacts by local communities while improving their well-being.

A better understanding of the effects of livelihood changes on human well-being can also support adaptive management after earthquakes and other disasters and help to avoid unintended consequences of recovery efforts. For example, an important factor driving the rapid livestock expansion in Wolong is the incentive policy of the local government, which provides interest-free loans to households to raise more livestock (Zhang et al. 2017). Despite the policy's good intention to facilitate the human well-being recovery after the earthquake, our findings show that the resulting livestock expansion actually did the opposite. To make matters worse, several studies in Wolong show that livestock had encroached into core wildlife habitat because the available pasture land is not sufficient to support the rapidly growing number of livestock (Hull et al. 2014, Zhou et al. 2016). The livestock compete with wild animals, such as giant pandas, for food, water, and space, and thus degrade local ecosystems (Zhang et al. 2017). To avoid the continuance of this unexpected "lose-lose" outcome, we suggest that livestock expansion should be discouraged instead of encouraged in Wolong.

As rural livelihoods are increasingly affected by telecouplings (socioeconomic and environmental interactions over distances, such as labor migration from rural to urban areas) (Liu et al. 2013a, Liu et al. 2015a), factors distant from the local system can have important influences on recovery outcomes in disaster-affected areas. For example, as demonstrated in our study, labor migration can negatively affect certain aspects of household well-being as labor migrants in cities often confront many hardships (e.g., poor education resources for their children). However, besides contributing to household income, labor migration can also generate beneficial effects on local ecosystem through reducing human disturbances. In Wolong, for example, Chen et al. (2012a) found that as compared to households without labor migrants working in cities, households with labor migrant(s) collected l,827 kg less fuelwood from local forest. Therefore, policies in cities (e.g., investing more to provide quality education to children of labor migrants) that help to overcome the hardships confronting labor migrants may generate beneficial effects not only on human well-being recovery but also ecosystem conservation in disaster-affected areas distant from cities.

6.5 Conclusions

Using long-term household survey data from Wolong, we found that livelihood after the earthquake experienced conspicuous changes and human well-being has been recovering. However, not all livelihood changes generated desirable effects on the recovery of human well-being, indicating evidence-informed policy interventions are essential for the sustainable development after natural disasters. Of course, in different policy, geographic, and temporal settings, the specific linkages between livelihood changes and human well-being recovery might be different. For example, the reconstruction of the main road connecting Wolong and the outside was completed in October 2016, and is expected to generate substantial impact on the telecouplings linking Wolong and other places (e.g., attract more tourist visitations), change local livelihoods, and thus shape the recovery outcome of human well-being. This specific dynamic might not occur in some other post-disaster recovery areas. More interdisciplinary research is needed in the future to construct a collective base of evidence on how livelihood activities affect human well-being. Such a database should also incorporate information on other outcomes (e.g., ecosystem health) across different spatial and temporal contexts. We believe that the methods presented in this paper can be easily adapted to other contexts to construct such an evidence base and help design effective management strategies to achieve Sustainable Development Goals amid natural disasters around the world.

CHAPTER 7

CONCLUSIONS

Rural areas provide sanctuary to a disproportionately large amount of global biodiversity and house more than half of the world's population (Kramer et al. 2009, UN DESA 2015). As rural areas are increasingly telecoupled with other places, there is an urgent need for improved understanding of human-nature interactions in rural areas not only driven by factors within those regions but also by factors that are operating far away (e.g., in cities) (Liu et al. 2013a).

In this dissertation, I along with my colleagues sought to integrate techniques and perspectives from different disciplines to understand the complex effects of telecouplings on an exemplary coupled human and natural systems (CHANS): Wolong Nature Reserve in southwest China. We evaluated the complex effects of telecouplings that occurred under five circumstances where there are complex pathways, spillover, feedback, interaction among telecouplings, and external shock, respectively. Our investigations into each of the five circumstances filled important knowledge gaps in existing literature, brought to light new questions that warrant future investigation, and informed management of telecouplings to maximize the positive effects and minimize the negative ones.

In Chapter 2, we focused on addressing the research need to quantify pathways underlying the effects of telecouplings. We proposed a conceptual framework for quantifying the pathways through which payments for ecosystem services (PES) programs, our example telecouplings, affected socioeconomic outcome. We demonstrated that telecouplings could affect interrelated livelihood activities and form different pathways generating divergent impacts on the outcomes in the focal CHANS. Elucidating the pathways underpinning the effects of telecouplings, as demonstrated by this research, can help to explain why telecouplings succeed in generating desirable outcomes in some settings but failed in others. The improved understanding of pathways can also facilitate the design of truly effective strategies by targeting the pathways that will generate positive effects while weakening the ones that will generate negative effects.

Effects of telecouplings are not always confined within the regions where they were designed to occur. They may spill over into nontargeted land and generate unintended outcomes. However, the spillover effects of telecouplings were often ignored in previous studies. In Chapter 3, we demonstrated the spillover effects of telecouplings using the Grain-to-Green Program (GTGP) implemented in Wolong as an example. For the first time, we found that the enrollment of cropland into the GTGP increased the crop damage by wild animals on nearby remaining cropland, causing a hidden cost to local communities. The GTGP is a national PES program in China and similar programs have been implemented in many other parts of the world. Our results suggest these sweeping conservation efforts in returning cropland to vegetative land may have done so with an until-now hidden consequence: they increased the wildlife damage to remaining cropland and thus caused unintended cost that whittled away at the programs' compensation for farmers.

As the effects of telecouplings on a CHANS accumulate, feedback may occur and weaken or strengthen telecouplings themselves. We illustrated this previously often ignored effect by investigating how the spillover effect of the GTGP found in Chapter 3 in turn affected households' willingness to enroll their cropland in future GTGP. We found that the crop damage exacerbated by the GTGP on remaining cropland made local households more willing to participate in future GTGP, a change that may trigger positive feedback to strengthen the GTGP itself. Revealing this feedback effect will allow more accurate estimation of the long-term effect of the GTGP. In addition, conservation planners may leverage this feedback and implement the GTGP, or other similar PES programs, round by round to increase the enrollment of cropland and enhance the outflow of ecosystem services from rural regions to other places.

Different telecouplings may interact and affect the magnitude of their joint impacts on the focal rural CHANS. To address the need for understanding such interaction effects of telecouplings, we developed an agent-based model in Chapter 5 and simulated the separate and joint effects of two globally common telecouplings, nature-based tourism and labor migration, on forest dynamics in Wolong. We found an antagonistic effect between tourism and labor migration: the development of tourism can limit the growth of labor migration and its positive effect on the forest recovery. In addition to evaluating the interaction between tourism and labor migration, we discussed the possible solutions to minimize this negative interaction effect and enhance the potential of labor migration and nature-based tourism in conserving ecosystems.

To enhance the resilience of rural CHANS to natural disasters, there is a growing need for understanding the human-nature interactions under natural disasters. In Chapter 6, we addressed this research need by conducting an in-depth evaluation of the livelihood changes in response to the telecoupling changes caused by the 2008 Wenchuan Earthquake and analyzed how these livelihood changes in turn shaped the human well-being recovery. We found that most of these post-earthquake livelihood changes negatively affected, instead of facilitating, human well-being recovery. We also identified the shortfalls in the post-earthquake policies (e.g., encouraging livestock husbandry) that were designed to cope with the negative impacts of telecoupling changes but unintendedly did more bad than good to the post-earthquake recovery of human well-being and ecosystems.

This dissertation research provides a working example showing that how the complex effects of telecouplings can be studied by integrating tools and techniques from different disciplines (e.g., structural equation modeling, stated preference approach, matching, and agent-based modeling). Although our analyses focus on Wolong, the telecouplings evaluated in the dissertation, such as PES programs, nature-based tourism, and labor migration, commonly exist in other rural areas worldwide. The methods developed in this study may be applied to other regions in the world, and will provide useful information for long-term planning, management, and adaptation of rural CHANS to achieve sustainability goals in Wolong and beyond.

While providing new insights about complex effects of telecouplings on rural areas, this dissertation brought to light new unknowns and areas that warrant future work. A priority should be placed on analyzing the complex effects of telecouplings evaluated in this dissertation across other spatial and temporal settings. Such analyses can help to construct a collective base of evidence about the effects of telecouplings that is necessary to develop elaborate and generalizable theories to guide management practices. For example, it would be worthwhile to adapt the conceptual framework we proposed for analyzing PES programs to analyze other telecouplings (e.g., nature-based tourism), evaluate the spillover and feedback effects of the GTGP we detected in Chapter 3 and Chapter 4 in other parts of the world where the similar programs have been implemented, investigate the effects of a great diversity of interactions among other telecouplings building off of Chapter 5, and explore a holistic picture of the effects of telecoupling changes caused by natural disasters on other economic and environmental outcomes expanding on Chapter 6. While assessing effects of telecouplings on rural areas as demonstrated in this dissertation is important, it is also crucial to evaluate how changes in rural areas in turn affect other places for a more comprehensive understanding of telecouplings. For example, we found nature-based tourism, labor migration, and PES programs all showed positive impacts on the forest recovery in Wolong, it would be worthwhile to evaluate how these impacts in turn affected the outflows of ecosystems services from Wolong to other regions.

In conclusion, in the face of the sustainability challenges in an increasingly telecoupled world, improved understanding of the complex effects of telecouplings on rural areas is crucial for effective management. This dissertation made novel contributions to the understanding of telecouplings by explicitly demonstrating that how the complex effects of telecoupling would occur, how they could be quantified, and how knowledge on them could be leveraged to improve the socioeconomic and ecological outcomes in rural areas. The findings and methods from this dissertation hold the promises to provide much needed information and tools for future exploration of the complexities of telecouplings across different settings around the world. It is my hope that this dissertation research together with other telecoupling studies will jointly contribute to the development of elaborated theories (e.g., complexity and metacoupling theory (Waldrop 1993, Liu et al. 2007a, Liu 2017b)) and a collective base of evidence about the complex effects of telecouplings that can guide the management of human-nature interactions for sustainable development in the telecoupled Anthropocene.

APPENDICES

APPENDIX A

SUPPORTING INFORMATION FOR CHAPTER 2

2.1. Description of the demonstration site

Wolong Nature Reserve (102º52′ to 103º24′ E, 30º45′ to 31º25′ N) is a flagship protected area in Southwest China (Fig. S2.1). It was established in 1963 and mainly designed for the protection of the world-famous giant panda (Liu et al. 2016a). The reserve is managed by the Wolong Administration Bureau, which is hierarchically structured with two townships under its governance - Wolong Township and Gengda Township (Fig. S2.1) (Liu et al. 2016a). There are about 4,900 residents in Wolong, most of whom are farmers (Liu et al. 2012). We chose Wolong as our study area for several reasons. First, situated within one of the top 25 global biodiversity hotspots and being part of the UNESCO World Heritage system, Wolong has special ecological importance. It provides a major sanctuary to 10% of the world's wild giant panda population (total=1,864) and more than 6000 species of other animals and plants, some of which are also endangered (e.g., red panda and golden monkey) (Wang 2013). Second, long-term socioeconomic data from household surveys have been collected in Wolong almost yearly since 1998 by our research team, together with a variety of biophysical data (Liu et al. 2013b, Liu et al. 2016a). The rich datasets and indigenous knowledge lay a good foundation for systematic research design and statistical inference regarding the effects of PES programs on socioeconomic outcomes.

Finally, Wolong has been experiencing significant socioeconomic changes since the implementation of PES programs at the early 2000s. Before 2000, Wolong was a remote area with limited connection to the outside (Liu et al. 2016a). The poverty rate in Wolong at that time was as high as 35% (Liu et al. 2012, Liu et al. 2013b). The vast majority of local residents were primarily involved in subsistence-based agricultural activities such as growing potatoes and corn. As population size and the number of households rapidly increased, human activities (e.g., farmland expansion, fuelwood collection, and timber harvesting) caused serious degradation of wildlife habitat (Liu et al. 2001, Liu et al. 2016a). Although the reserve administration had implemented several policies before 2000, such as a logging ban and limiting the sites for fuelwood collection, they were not effective mainly due to the lack of alternative income sources and incentives for eco-friendly behaviors (Liu et al. 2016a). As part of the effort to address this critical issue, two PES programs [i.e., the Grain-to-Green Program (GTGP) and the Grain-to-Bamboo Program (GTBP)] have been implemented in Wolong since the early 2000s (Table S2.1). With financial support from the central government (e.g., the State Forestry Administration), the Wolong Administrative Bureau paid the local households annually based on the amount of cropland they converted to forest land under the GTGP or bamboo land under the GTBP. More than 60% of the cropland in 1998 was converted to vegetated land under these two PES programs from 2000 to 2003, and has been kept vegetated since (Wang 2013). Meanwhile, with the political and financial support from the government and investments from outside tourism companies, tourism facilities (e.g., roads and hotels) in Wolong were greatly improved. The annual number of tourist visits in Wolong increased more than tenfold in a decade, from 20,000 in 1996 to 235,500 in 2006. In 1998, only about 4% of local households directly benefited from local tourism industry (Liu et al. 2012). This number increased to around 31% by the period from 2005 to 2007 (Liu et al. 2012). In addition, as the price of agricultural products increased, selling cash crops (e.g., off-seasonal cabbage) to outside markets gradually became one of the major income sources for local households (Wang 2013). The sale of cash crops constituted as much as 39% of local household income in 2005 (Liu et al. 2013b). Like many other rural areas in China, Wolong experienced an increase in labor migration in the 2000s. The proportion of households with labor migrants nearly doubled from 12% in 2003 to 22% in 2005 (Chen et al. 2012a, Liu et al. 2013b). The average household income significantly increased from 5,000 yuan in 1998 to more than 25,000 yuan in 2007 (Liu et al. 2013b) (1 yuan = 0.122 USD in 2005).

2.2. Model validation analysis

We used a set of model validation indices to evaluate how well the empirical data support the hypothesized pathways in our demonstration study. All these validation indices (Table S2.3) show that the goodness of fit of our structural equation model is high. The ratio of Chi-square to the degree of freedom (df) is 0.62, which is lower than the suggested maximum value of 3 (Hooper et al. 2008). The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are 1.00 and 1.10, respectively, both of which are larger than the suggested minimum value of 0.95 (Hooper et al. 2008). The Root Mean Square Error of Approximation (RMSEA) is smaller than 0.001, lower than the suggested maximum value of 0.05 (Hooper et al. 2008) while Weighted Root Mean Square Residual (WRMR) is 0.30, lower than the suggested maximum value of 0.9 (Yu and Muthen 2002). All these indices indicate a good validation of our model results.

Table S2.1 General information about the payments for ecosystem services (PES) programs and related livelihood activities under investigation in Wolong Nature Reserve.

	Start year / duration	Major Effect
Grain-to-Green program (GTGP)	2000 / 8 years (renewed in 2008 for another 8 years) *	About 56% of local cropland was converted to forest land from 2000 to 2003 for which local households receive payment at a rate of approximately 571 USD per ha per year (Liu et al. 2016a).
Grain-to-Bamboo program (GTBP)	2002 / 8 years (renewed in 2010)	About 10% of local cropland located along each side of the main road was converted to bamboo lands in 2002 for which local households receive payment at a rate of 2,143 to 2,857 USD per ha per year (Wang 2013).
Tourism participation	2002 / Continual unless being terminated †	Approximately 28% of local households received some direct economic benefits from the tourism industry in Wolong and approximately 68% of local households perceived that they received some indirect benefits in 2005 (Liu et al. 2012).
Labor migration	Late 1990s / Continual unless being terminated	Approximately 22% of local households had labor migrants in 2005, and wages from labor migrants constitute, on average, approximately 50 % of the gross income of these households (Chen et al. 2012a).
Crop production	Centuries ago / Continual unless being terminated	Approximately 70% of local cropland were used for cash crop production and income generated from selling agricultural products to outside markets, on average, accounted for approximately 39% of local household income in 2005 (Liu et al. 2013b).

* The enrollment of cropland under the GTGP in Wolong only took place between 2000 and 2003. After 2003, no more cropland was enrolled under the GTGP and local households only received compensation for the cropland they enrolled in the GTGP between 2000 and 2003.

† The Ecotourism Development Plan in Wolong Nature Reserve was officially approved by the State Forestry Administration of China in 2002.

Table S2.2 Summary statistics of variables used in constructing the structural equation model. The number of households included in the analysis is 202.

Variables	Description	Mean (SD)
Socioeconomic outcome		
Nonpayment income	Log-transformed income obtained from sources other than payments from the GTGP and the GTBP in 2005	9.59 (0.84)
PES programs		
GTGP	The proportion of cropland enrolled in the GTGP	0.563 (0.170)
GTBP	The proportion of cropland enrolled in the GTBP	0.100 (0.151)
Livelihood activities		
Tourism participation	Whether the household has member(s) who directly participated in tourism activities in 2005: 1. Yes; 0. No	0.31 (0.46)
Labor migration	Whether the household has labor migrant(s) in 2005: 1. Yes; 0. No	0.22 (0.41)
Crop production	The area of cropland (in mu [*]) owned by the household for cropping in 2005	3.07 (1.99)
Control variables		
Number of laborers	Number of laborers in the household	2.65 (1.30)
Household size	Number of people in the household	4.14 (1.39)
Average age	Average age of adults (age >18) in the household	42.03 (9.28)
Adult education level	Maximum education level (in years) of non-student adults in the household	7.65 (3.27)
Social ties to government	Whether the household has a member or immediate relative working in local governments: 1. Yes; 0. No	0.12 (0.32)
Social ties to local leaders	Whether the household has a member or immediate relative being a village or group leader: 1. Yes; 0. No	0.18 (0.39)
Log (distance to the main road) [†]	Log-transformed distance between the household and the main road	2.77 (1.58)
Log (Income 98)	Log-transformed total income in 1998	8.31 (0.92)
Labor migration (03)	Whether the household had labor migrant(s) in 2003: 1. Yes; 0. No	0.12 (0.47)
Township	Which township the household is located in: 0 = Wolong township; 1 = Gengda township	0.45 (0.50)

[*] 1 mu = 0.0067 ha.

[†] The distance between a household and the main road was calculated using the Path Distance function in ArcGIS 10.2 (ESRI Inc., Redlands, CA, USA).

Table S2.3 Summary of validation results of the structural equation model.

Validation statistics	Rules indicating good validation	Value for the model
Ratio of Chi-Square to df (χ^2/df)	< 3	0.62
CFI (Comparative Fit Index)	> 0.95	1.00
TLI (Tucker-Lewis Index)	> 0.95	1.10
RMSEA (Root Mean Square Error of Approximation)	< 0.07	0.00
WRMR (Weighted Root Mean Square Residual)	< 0.9	0.30

Table S2.4 Results of the structural equation model. The number of households included in the analysis is 202. The numbers within the parentheses are standard errors.

Explanatory variables \ Dependent variables	Tourism participation	Labor migration	Crop production	Nonpayment income
GTGP	0.681(0.6)	0.056(1.041)	-9.518(1.091)***	-0.006(0.351)
GTBP	1.652(0.912)†	0.307(1.036)	-8.066 (1.837)***	-0.477(0.398)
Tourism participation	-	-0.294(0.120)**	-0.667(0.194)***	0.179(0.061)*
Labor migration	-	-	-	0.157(0.043)***
Crop production	-	-	-	0.070(0.015)**
Number of laborers	-0.064(0.135)	0.376(0.150)*	0.638(0.216)***	0.255(0.061)***
Household size	0.099(0.09) †	-	-	-0.049(0.038)
Average age	-	-0.006(0.021)	0.001(0.025)	-
Adult education level	0.129(0.044)**	-0.067(0.057)	0.034(0.080)	0.039(0.020)*
Social ties to government	0.722(0.339)*	-0.610(0.546)	-	0.203(0.170)
Social ties to local leaders	0.424(0.291)	-0.525(0.486)	-	-0.058(0.144)
Log (distance to main road)	-0.109(0.071)†	-0.056(0.101)	0.133(0.111)	-0.008(0.037)
Log (Income 98)	0.258(0.138) †	0.168(0.218)	0.603(0.247)	0.131(0.071)
Labor migration (03)	-0.423(0.287)	1.55(0.340)***	-0.382(0.381)	-
Township	0.161(0.225)	-	-	-

† $p \le 0.1$; * $p \le 0.05$; ** $p \le 0.01$; *** $p \le 0.001$.

Table S2.5 The effects of specified and unspecified pathways by which the GTGP and the GTBP affect nonpayment income. The number of households included in the analysis is 202. An arrow in a pathway represents a linkage through which the variable at the arrow tail affects the variable at the arrow head.

Pathway Type	Pathway	Effect	
		GTGP	GTBP
Specified Pathway	PES Program → Crop production → Nonpayment income	-0.13	-0.098
	PES Program → Tourism Participation → Nonpayment income	0.024	0.051
	PES Program → Labor Migration → Nonpayment income	0.002	0.008
	PES Program → Tourism Participation → Labor Migration → Nonpayment income	-0.006	-0.013
	PES Program → Tourism Participation → Crop production → Nonpayment income	-0.006	-0.013
Unspecified pathway	PES Program → Nonpayment income	-0.001	-0.083

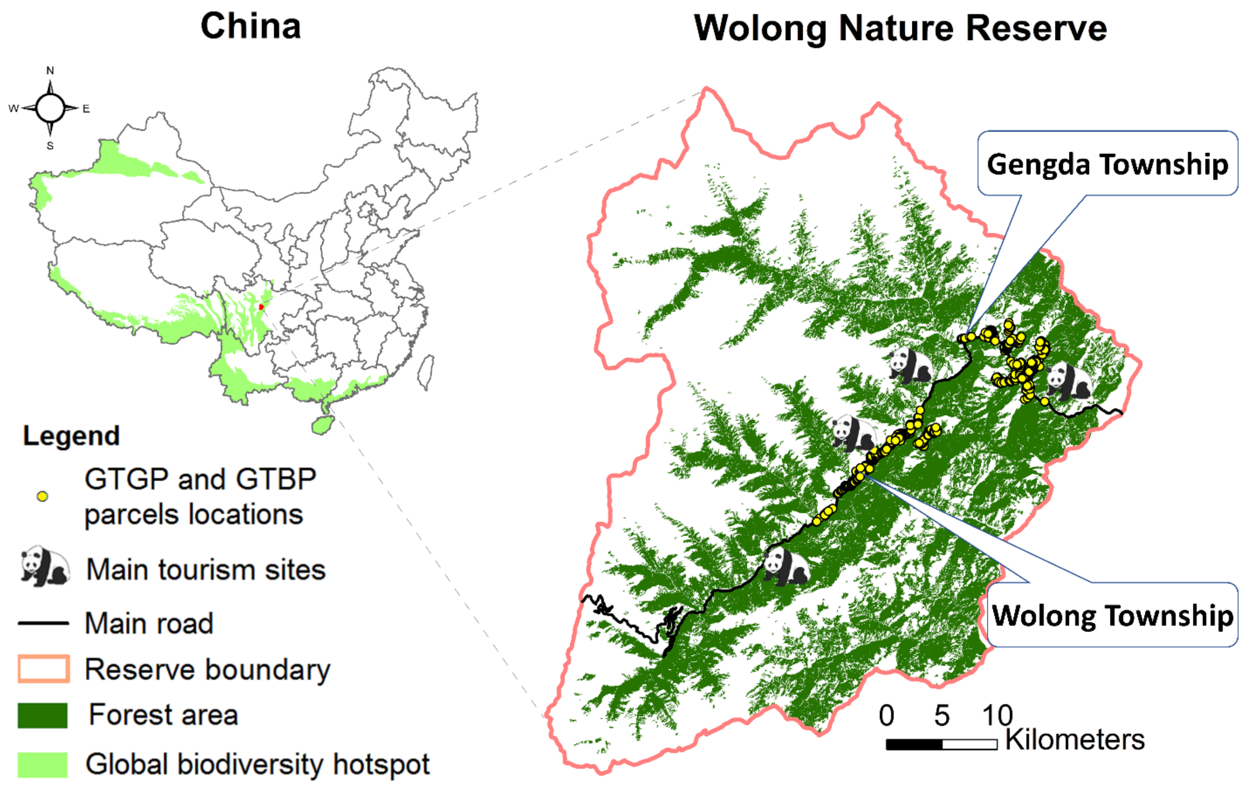

Figure S2.1 Wolong Nature Reserve in Sichuan Province, southwestern China.

APPENDIX B

SUPPORTING INFORMATION FOR CHAPTER 3

3.1 Matching Method for Impact Estimation

The goal of the matching method is to control for observable differences between treated and control cropland parcels that may correlate with both their crop damage intensity and their proximities to GTGP land parcels (confounding factors). Like the conventional regression approach (e.g., generalized linear regression), matching reweights the sample observations to make cropland parcels in control and treatment groups similar in terms of observable confounding factors (called covariate balancing) (Rosenbaum 2002). The fundamental assumption of matching and regression to draw causal inference from observational data is also similar: once we have conditioned on observable confounding factors, the outcome of the treatment and control groups should be the same if they received the same treatment (often called conditional independence assumption).

However, matching and regression methods differ in their ways to weight the data: a regression uses all observations and tries to minimize the squared errors, so observations on the margins get a lot of weight; while matching focuses on observations that have similar attributes, and so observations on the margin might get little or even no weight. In our study, we preferred matching to regression for the following three reasons:

First, our study focuses on estimating the average treatment effect on the treated (ATT): the treatment effect of GTGP afforestation on crop damage of cropland parcels within the close or medium range. Matching offers an effective method for ATT estimation as it focuses on selecting untreated units (cropland parcels in the far range) that are similar to the treated units (cropland parcels in the medium and close ranges) to serve as the controls and abandons untreated units that are not similar. In contrast, linear regression estimates the weighted average of treatment effects (ATE): the average treatment effects of the GTGP afforestation on cropland units in both affected range (close or medium) and unaffected (far) ranges. In regression analysis, all treatment and control units were included in the impact estimation. However, ATE may differ from ATT, as there might be systematic differences between treatment group and control group. In our study, the ATT is policy relevant and we did not intend to estimate what would happen to cropland in the far range had it been placed close to GTGP land (i.e., treatment effect of GTGP on cropland units in the far range).

Second, matching relaxes the functional form restrictions inherent in parametric linear regression, thereby avoiding the risk of misspecification. Assuming a functional form is useful when one wants to predict or interpret the coefficients of confounding factors. However, the actual form of the relationship between outcome and confounding factors is often hard to know and misspecification risks often exist. In this study, the effect of confounding factors on damage is of little interest. Therefore, using the matching approach helps avoid misspecification risks and increases the reliability of impact estimation.

Third, parametric linear regression makes a stronger assumption about the error term than the matching approach does. The regression requires $E(U \mid X, D) = 0$ while matching requires $E(U \mid X, D = 1) = E(U \mid X, D = 0)$, where E is the expectation operator, U is the error term, X are conditioning variables and D is the treatment indicator (1 indicates treated and 0 indicates untreated). This difference may affect the set of reasonable X: a necessary covariate may meet the requirement of matching but not the regression. Therefore, holding everything else equal, matching method is more likely to generate a reliable impact estimation.

In this study, we controlled for a set of variables commonly found to affect crop damage intensity, including distance to natural forests, distance to the main road, slope, crop types and whether preventative measures were used (Table S3.1). Without controlling for these covariates via matching, our estimates may be biased. For example, GTGP lands are mostly located in places distant from human settlements and the main roads and close to forests because cropland there is more susceptible to wildlife damage. Thus, remaining cropland parcels that have similar characteristics are more likely to be located close to GTGP land and experience crop damage by wildlife.

Table S3.2 and Table S3.3 present the covariate balancing results for estimating the impacts of GTGP on crop damage intensities of cropland parcels in the close and medium ranges respectively. The tables include two measures of the differences in the covariate distributions between cropland parcels in the treatment group (close- and medium-range cropland) and the control group (far-range cropland): the difference in means and mean distance between the two empirical quantile functions. Greater values of these values indicate larger differences. After matching, these difference measures between treated cropland units and control cropland units move dramatically toward zero, indicating good matching quality and therefore high estimation reliability (Ho et al. 2007).

3.2 Robustness Checks

We conducted a set of analyses to check the robustness of our results to potential biases and changes in research design. First, we tested whether we had underestimated the distance within which crop damage on remaining cropland was still affected by afforestation on GTGP land. If the GTGP afforestation has a significant influence on crop damage intensity on cropland units farther than 40 m, it would downwardly bias our estimates because the crop damage intensity on control units (cropland parcels unaffected by GTGP) had been overestimated. To test this bias, we divided cropland units in the far range into two halves based on their distance to GTGP land: the closer half (distances to nearest GTGP land are within 40 to 95 m) and the farther half (distances to nearest GTGP land are larger than 95 m). We then compared their average crop damage intensities using the matching method. Since the impact of GTGP afforestation will decline as distance to it increase, the crop damage intensity of cropland in the closer half would be significantly higher than in the farther half if the GTGP afforestation had an impact on crop damage of cropland parcels beyond 40 m. If there is no significant difference between the crop damage intensities of the closer and farther halves, this bias would be negligible.

Results estimated using the matching approach (Table S3.9) indicate that using cropland parcels in the far range (i.e., distance to GTGP parcels > 40 m) to construct control groups for our analyses is reasonable. Crop damage intensities of the two halves of cropland units in the far range shows that the difference is quite small (0.0008) and statistically insignificant ($p > 0.1$). This indicates that afforestation on GTGP land has little impact on crop damage on cropland units beyond 40 m to GTGP land.

Second, to test the robustness of estimated impacts of GTGP on damage intensity, we conducted Rosenbaum's sensitivity tests (Rosenbaum 2002) to estimate how strong a hidden factor would have to be to overturn the conclusion of this study. These tests assume that each cropland parcel has a fixed value of an unobserved covariate (hidden factor) that causes cropland parcels in treatment and control groups to systematically differ in their odds of being affected by afforestation on GTGP land. A sensitivity parameter Γ measures the magnitude of this odds difference. While the actual values of Γ are unknown, one can try different values of Γ to see whether the conclusions of this study change. A Γ value near one indicates a small hidden factor could account for the treatment effect. The larger the Γ value that is required to change the conclusion, the more robust the conclusion is(Rosenbaum 2002).

The Rosenbaum sensitivity test results (i.e., Γ values in the second and third rows of Table S3.4-3.7) indicate that our conclusion that GTGP afforestation intensified crop damage on remaining cropland is robust to potential hidden factors. Take the estimates of overall impacts of GTGP on cropland in close range as an example (Column 2, Table S3.4). The Γ value of 4.3 (Row 2, Table S3.4) shows the result of Rosenbaum sensitivity analysis based on Wilcoxon sign rank test (Rosenbaum 2002). An intuitive interpretation of this statistic is that the crop damage estimate would remain significantly different from zero ($p < 0.05$) even in the presence of a strong hidden bias that could cause the odds of being affected by afforestation on GTGP land to differ by a factor as high as 4.3. The Γ value of 2.6 (Row 3, Table S3.4) shows the result of Rosenbaum sensitivity analysis based on Hodges-Lehmann (HL) point estimate (Rosenbaum 2002). The result indicates the 95% confidence interval of the HL estimate would still exclude zero in the presence of an additive fixed hidden bias that could cause the odds of being affected to differ by a factor of 2.6. These high Γ values suggest that our estimates of GTGP's impact on crop damage by wildlife are robust.

Third, we varied the distance threshold used to differentiate cropland units that are strongly and moderately affected by the afforestation on GTGP land, and checked whether our conclusions still hold. Our results (Table S3.10 and Table S3.11) show that the patterns of the estimated impact of the afforestation on crop damage are consistent when different distance thresholds (i.e., 15 m and 20 m) were used to differentiate cropland units strongly and moderately affected by GTGP. Similar to what we observed using the distance threshold of 10 m, holding all else equal, wildlife damage on cropland units that are closer to GTGP land (i.e., more strongly affected by the afforestation on GTGP parcels) was more seriously affected by GTGP.

Finally, we checked the validity of our calculation of foregone crop revenue (Equation (2) in the *Main Text*) borne by households due to crop damage attributable to GTGP. Our estimation of foregone revenue may be biased if households systematically switched crop types in response to wildlife damage because different crops could have different revenues and production costs. In Wolong, corn, potato and cabbage are the three major crop types. Our results (Table S3.5-3.7) suggest corn and potato were much more likely to experience damage by wildlife than cabbage. Therefore, planting cabbage on cropland close to forests and corn and potato far from forests could help to reduce crop damage. Interestingly, our analysis (Table S3.12) indicates corn and potato plots in Wolong were closer, rather than farther, to forest edge than cabbage plots. This result indicates the spatial arrangement of cropland in Wolong is mainly determined by factors other than crop damage. For example, our survey data indicate that the weight of annual yield of cabbage on the same area of land (about 6000 kg/mu) is much higher than corn (about 500 kg/mu) and potato (about 1000 kg/mu). Meanwhile, croplands close to the forest are often far from main roads and have a steeper slope than croplands far from the forest. If cabbage were planted on cropland close to forest edges, the transportation cost would be much higher than that of corn and potato.

Our measure of foregone crop revenue tends to overstate losses if households defensively lowered their input for crop production (e.g., fertilizer and seeds) on land susceptible to wildlife damage. To test this potential bias, we performed a regression analysis to check whether significant differences in production costs exist among households that experienced different levels of crop damage. If households did change their production costs for cropland susceptible to wildlife damage, the impact of crop damage intensity on production costs would be significant. Our regression result (Table S3.13) shows that the impact of average crop damage intensity on household production costs is insignificant, indicating households did not significantly change their inputs for cropland susceptible to wildlife damage.

It is worth mentioning that the foregone revenue might be a conservative measure of the losses due to increased wildlife damage because some households may have had increased expenditures to prevent damage by wildlife. Our analysis (Table S3.14) indicates cropland close to forest edge, and therefore more susceptible to wildlife damage, was more likely to have preventive measures to avoid crop damage. In Wolong, the preventative measures undertaken by households included building iron fences, building simple wooden fences, tying their dogs to stakes on the edge of cropland, and sending a household member to patrol cropland when crop damage was most likely occurring (e.g., when the corn and potatoes mature). The range and nature of the diverse preventative measures made estimation of their monetized cost difficult, so we note that by omitting these costs we have a conservative measure of the unintended costs to households by afforestation on GTGP land.

We ran all the matching and sensitivity tests in R (R development Core Team 2013) using the packages ‘Matching’ (Sekhon 2011) and ‘Rbounds’(Keele 2011). We performed regression analysis and *t*-tests using Stata 12 (software, STATA Corp., College Station, Texas, USA).

Table S3.1 Descriptive statistics of variables used in estimating the impact of the GTGP on crop damage that occurred on nearby remaining croplands (sample size = 423).

Variables	Description	Mean (SD)
Outcome Variable		
Crop damage intensity	The proportion of crop lost in a parcel due to wildlife damage 2014	0.12 (0.22)
Treatment variable		
Distance to GTGP forests	The straight-line distance from the cropland parcel boundary to the edge of GTGP parcel. (m)	46.48 (64.55)
Covariates		
Distance to natural forest edge	The straight-line distance from the cropland parcel boundary to the edge of forests other than GTGP forest. (m)	66.82 (52.45)
Slope	The average slope of the cropland parcel. (degree)	19.98 (10.09)
Distance to the main road	The straight-line distance from the centroid of the cropland parcel to the main road. (m)	404.67 (599.46)
Distance to nearest house	The straight-line distance from the centroid of the cropland parcel to the nearest house. (m)	57.28 (74.44)
Crop species	Whether the planted crop is corn or potato: 1, Yes; 0, No.	0.68 (0.47)
Preventive measure	Whether preventative measures were taken to avoid crop raiding: 1, Yes; 0, No.	0.14 (0.35)

† The basic unit for these measurements is individual remaining cropland parcels.

Table S3.2 Covariate balance for comparing cropland units in the close range (< 10 m) with units in the far range (> 40 m).

Variable	Status	Mean for units in the close range	Mean for units in the far range	Difference in mean value	Mean eQQ difference†
Distance to natural forest edge	Unmatched	51.75	86.97	-35.22	36.46
	Matched	47.69	49.14	-2.45	3.77
Slope	Unmatched	22.60	16.85	5.75	5.62
	Matched	22.01	21.49	0.52	1.30
Distance to the main road	Unmatched	522.07	251.98	270.09	265.95
	Matched	328.13	291.31	36.82	6.94
Distance to nearest house	Unmatched	73.82	42.77	31.05	29.63
	Matched	46.46	44.73	1.73	4.97
Crop species	Unmatched	0.79	0.57	0.22	0.21
	Matched	0.76	0.76	0.00	0.00
Preventive measure	Unmatched	0.21	0.05	0.16	0.15
	Matched	0.065	0.065	0.00	0.00

†The mean difference in the empirical quartile functions for each covariate.

Table S3.3 Covariate balance for comparing cropland units in the medium range (10 to 40 m) with units in the far range (> 40 m).

Variable	Status	Mean for units in the medium range	Mean for units in the far range	Difference in mean value	Mean eQQ difference†
Distance to natural forest edge	Unmatched	60.46	86.97	-26.51	26.46
	Matched	63.35	63.41	-0.06	4.00
Slope	Unmatched	20.47	16.85	3.62	3.83
	Matched	19.83	19.45	0.38	0.68
Distance to the main road	Unmatched	447.25	251.98	195.27	203.27
	Matched	311.83	289.97	21.86	32.17
Distance to nearest house	Unmatched	51.97	42.77	9.20	10.16
	Matched	20.79	20.72	0.27	2.67
Crop species	Unmatched	0.65	0.57	0.08	0.08
	Matched	0.64	0.64	0.00	0.00
Preventive measure	Unmatched	0.18	0.05	0.13	0.12
	Matched	0.064	0.064	0.00	0.00

† The mean difference in the empirical quartile functions for each covariate.

Table S3.4 Impacts of GTGP afforestation on crop damage intensity of cropland parcels in the close range (< 10 m) and the medium range (10 m to 40 m) estimated using the matching approach.

	Close Range	Medium Range
Impact estimate using matching †	0.189 (0.024) ***	0.044 (0.010) ***
Γ sensitivity (Wilcoxon) ‡	4.3	3.1
Γ sensitivity (Hodges-Lehmann) §	2.6	1.1
[Number of treated and control]	[169, 157]	[97, 157]
Means of the treated and the control	0.255, 0.015	0.073, 0.015

† The numbers in parentheses of this row are Abadie-Imbens standard errors.

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

§ The value of Γ at which the lower bound of 95% confidence interval for the Hodges-Lehmann point estimate of the effect includes zero.

¶ Significance: *** indicates statistical significance at 0.001 level.

Table S3.5 Impacts of GTGP afforestation on crop damage intensity of cropland parcels planted with potato in the close range (< 10 m) and the medium range (10 m to 40 m) estimated using the matching approach.

	Close Range	Medium Range
Impact estimate using matching †	0.198 (0.028) ***	0.07 (0.016) ***
Γ sensitivity (Wilcoxon) ‡	3.6	3.0
Γ sensitivity (Hodges-Lehmann) §	4.6	1.1
[Number of treated and control]	[113,87]	[38, 87]
Means of the treated and the control	0.289, 0.026	0.089, 0.026

† The numbers in parentheses of this row are Abadie-Imbens standard errors.

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

§ The value of Γ at which the lower bound of 95% confidence interval for the Hodges-Lehmann point estimate of the effect includes zero.

¶ Significance: *** indicate statistical significance at 0.001level.

Table S3.6 Impacts of GTGP afforestation on crop damage intensity of cropland parcels planted with corn in the close range (< 10 m) and the medium range (10 m to 40 m) estimated using the matching approach.

	Close Range	Medium Range
Impact estimate using matching †	0.244 (0.029) ***	0.068 (0.016) ***
Γ sensitivity (Wilcoxon) ‡	4.4	2.9
Γ sensitivity (Hodges-Lehmann) §	3.3	1.1
[Number of treated and control]	[130,90]	[58, 90]
Means of the treated and the control	0.302, 0.026	0.077, 0.026

† The numbers in parentheses of this row are Abadie-Imbens standard errors.

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

§ The value of Γ at which the lower bound of 95% confidence interval for the Hodges-Lehmann point estimate of the effect includes zero.

¶ Significance: *** indicates statistical significance at 0.001 level.

Table S3.7 Impacts of GTGP afforestation on crop damage intensity of cropland parcels planted with cabbage in the close range (< 10 m) and the medium range (10 m to 40 m) estimated using the matching approach.

	Close Range	Medium Range
Impact estimate using matching †	0.022 * (0.02)	0.026 (0.05)
Γ sensitivity (Wilcoxon) ‡	1.5	1.6
Γ sensitivity (Hodges-Lehmann) §	1.1	1.1
[Number of treated and control]	[36,67]	[34, 67]
Means of the treated and the control	0.086, 0.0	0.022, 0.00

† The numbers in parentheses of this row are Abadie-Imbens standard errors.

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

§ The value of Γ at which the lower bound of 95% confidence interval for the Hodges-Lehmann point estimate of the effect includes zero.

¶ Significance: * indicate statistical significance at 0.05 level.

Table S3.8 Covariate balance for comparing the first half and second half of cropland units in the far range (> 40 m). Units in the first half are closer to GTGP parcels (40 m to 95 m) while units in the second half are farther from GTGP parcels (> 95 m).

Variable	Status	Mean for units in the first half	Mean for units in the second half	Difference in mean value	Mean eQQ difference†
Distance to natural forest edge	Unmatched	80.33	95.22	-14.89	15.96
	Matched	78.29	79.61	-1.32	7.23
Slope	Unmatched	18.15	15.23	2.92	3.11
	Matched	14.81	14.38	0.43	1.14
Distance to the main road	Unmatched	389.75	80.76	308.99	300.93
	Matched	146.62	131.53	15.09	36.61
Distance to nearest house	Unmatched	47.08	37.41	9.67	11.40
	Matched	29.10	25.85	3.25	0.051
Crop species	Unmatched	0.66	0.47	0.19	0.17
	Matched	0.65	0.65	0.00	0.00
Preventive measure	Unmatched	0.057	0.043	0.014	0.014
	Matched	0.027	0.027	0.00	0.00

† The mean difference in the empirical quartile functions for each covariate.

Table S3.9 Average crop damage intensities on cropland units in the close half (40 m to 95 m) and the farther half (> 95 m) of cropland units in the far range (> 40 m), and their difference estimated using the matching approach.

	Difference
Difference estimate using the matching approach	-0.0008 (0.004) †
[Number of treated and control]	[87, 70]
Means of the treated and the control	0.015, 0.016

† The difference estimate is insignificant ($p > 0.1$).

Table S3.10 Impacts of GTGP afforestation on crop damage intensity of cropland parcels planted with cabbage in the close range (< 15 m) and medium range (15 m to 40 m) estimated using the matching approach.

	Close range	Medium range
Impact estimate using matching †	0.17 (0.02) ***	0.035 (0.003) ***
Γ sensitivity (Wilcoxon) ‡	4.5	2.3
Γ sensitivity (Hodges-Lehmann) §	2.7	1.1
[Number of treated and control]	[203, 157]	[63, 157]
Means of the treated and the control	0.233, 0.015	0.044, 0.015

† The numbers in parentheses of this row are Abadie-Imbens standard errors.

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

§ The value of Γ at which the lower bound of 95% confidence interval for the Hodges-Lehmann point estimate of the effect includes zero.

¶ Significance: *** indicates statistical significance at the 0.001 level.

Table S3.11 Impacts of GTGP afforestation on crop damage intensity of cropland parcels planted with cabbage in the close range (< 20 m) and medium range (20 m to 40 m) estimated using the matching approach.

	Close range	Medium range
Impact estimate using matching †	0.16 (0.02) ***	0.02 (0.005) ***
Γ sensitivity (Wilcoxon) ‡	4.9	1.6
Γ sensitivity (Hodges-Lehmann) §	2.1	1.1
[Number of treated and control]	[228,157]	[38, 157]
Means of the treated and the control	0.215, 0.015	0.027, 0.015

† The numbers in parentheses of this row are Abadie-Imbens standard errors.

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

§ The value of Γ at which the lower bound of 95% confidence interval for the Hodges-Lehmann point estimate of the effect includes zero.

¶ Significance: *** indicates statistical significance at the 0.001 level.

Table S3.12 Unpaired *t*-test of distance to forest edge between cropland plots highly susceptible to crop raiding (corn and potato plots) and the ones not highly susceptible to crop raiding (cabbage plots).

	Susceptible (Mean ± S.D.)	Unsusceptible (Mean ± S.D.)	Unpaired *t*-test (two-tailed)
Distance to forest edge: Corn plots V.S. cabbage plots	26.37±36.23	46.67 ± 41.85	-20.30 ***
Distance to forest edge: Potato plots V.S. cabbage plots	27.46 ±36.82	46.67± 41.85	-19.22 ***

†The unit of analysis is individual cropland plot.

‡ Significance: *** indicates statistical significance at the 0.001 level.

Table S3.13 Regression results on the relation between average crop damage intensity and total production costs, which includes expenses for seeds, fertilizer, pesticide, herbicide and plastic film.

Variables	Description	Coefficient (SE)
Crop damage intensity	Weighted average crop damage intensity of household's cropland parcels based on their areas.	411.22 (421.19)
Flat land area	The total area of household's flat cropland (slope < 5°).	135.40 (32.28) ***
Sloping land area	The total area of households' sloping cropland (slope ⩾ 5°).	184.85 (42.13) ***

†The unit of analysis is individual household.

‡ Significance: *** indicates statistical significance at the 0.001 level.

Table S3.14 Unpaired *t*-test of distance to forest edge between cropland parcels that used preventive measure (e.g., building fence) and the ones did not.

	Prevention (Mean ± S.D.)	No prevention (Mean ± S.D.)	Unpaired *t*-test (two-tailed)
Distance to forest edge	15.06 ± 31.06	33.00 ± 41.32	17.94 **

† Significance: ** indicates statistical significance at the 0.01 level.

APPENDIX C

SUPPORTING INFORMATION FOR CHAPTER 6

Table S6.1 Survey instrument for constructing the human well-being index system based on the Millennium Ecosystem Assessment framework. Reproduced from (Yang et al. 2013).

Dimensions	Indicator and description
Basic material for good life	Q1.1: To what extent it is available to purchase necessities for daily life (Options: 1. Very inconvenient； 2. Inconvenient； 3. Unsure；4. Convenient； 5. Very convenient)
	Q1.2: Your household can afford enough food with nutrition to keep alive and healthy
	Q1.3: Your household can afford to access basic facilities (e.g., television, washer) and services (e.g., transportation)
	Q1.4: You are satisfied with your housing condition (including size and quality)
	Q1.5: Overall, you are satisfied with your household's basic goods and services (e.g., food, clothe, living conditions, transportation) for life
Security	Q2.1: Your household's life safety in daily life is secure
	Q2.2: Your household's property safety in daily life is secure
	Q2.3*: The local crime incidence (e.g., theft, robbery, murder, other violent incidents) is low
	Q2.4*: The police and judicial system is always ready to help
	Q2.5: The police and judicial system can be trusted
	Q2.6*: It is safe to access basic goods and services such as food, water, and medicine etc. for life
	Q2.7: Overall, you are satisfied with your household security (e.g., life and property)

Table S6.1 (cont'd)

Dimensions	Indicator and description
Health	Q3.1*: You are satisfied with your household's physical health (including illness and injury)?
	Q3.2: You are satisfied with your household's mental health (including stress, depression, and problems with emotions)?
	Q3.3: How often your household members do not get enough rest or sleep? (Options: 1. Always; 2. Often; 3. Sometimes; 4. Seldom; 5. Never)
	Q3.4: How often your household members are not healthy or do not have enough energy for everyday life? (Options: 1. Always; 2. Often; 3. Sometimes; 4. Seldom; 5. Never)
	Q3.5: How often do your household members have negative feelings such as blue mood, despair, anxiety, depression? (Options: 1. Always; 2. Often; 3. Sometimes; 4. Seldom; 5. Never)
	Q3.6*: How often do your household members have the opportunity for leisure activities? (Options: 1. Never; 2. Seldom; 3. Sometimes; 4. Often; 5. Always)
	Q3.7: Overall, you are satisfied with your household's health status
Good social relations	Q4.1: This is a close-knit neighborhood
	Q4.2: Most people in this village are basically honest and can be trusted
	Q4.3*: There are many opportunities to meet neighbors and work on solving community problems
	Q4.4*: How active do you think your household members in your community groups or village or township? (Options: 1. Very inactive; 2. inactive; 3. Neither inactive nor active; 4. Active; 5. Very active)
	Q4.5: Do you agree that people here look out mainly for the welfare of their own families and they are not much concerned with village/neighborhood welfare?
	Q4.6*: Suppose someone in your village/neighborhood had something unfortunate happen to them, such as a family member's sudden death, there are always some others would be ready to help
	Q4.7: Overall, you are satisfied with your household's social relationships with others

Table S6.1 (cont'd)

Dimensions	Indicator and description
Freedom of choices and actions	Q5.1*: Do you think that your household members are always treated equally without regard to gender, race, language, religion, political beliefs, socioeconomic status and more? (Options: 1. Never; 2. Seldom; 3. Sometimes; 4. Often; 5. Always)
	Q5.2: Your household has affordable access to quality and nutritious food for an enjoyable life
	Q5.3: Your household has affordable access to quality medical care
	Q5.4: Your household has affordable access to quality education
	Q5.5: Your household has affordable access to spacious and quality house
	Q5.6*: It is difficult to find a satisfied job
	Q5.7: How often do you feel that you want to help others but limited by your socioeconomic or physical conditions that you cannot help them?
	Q5.8: Overall, you are satisfied with your freedom of choice and actions

Notes: Unless response options are specified after indicator contents, the options are designed in the five-category Likert scale (i.e., strongly disagree, mildly disagree, unsure, mildly agree, and strongly agree). *: Indicators not included in the final confirmatory factor analysis due to low variation or internal consistency with other indicators in the same categories.

Table S6.2 Summary of model validation results of the confirmatory factor analysis for constructing human well-being index system.

Validation statistics	Rules indicating good validation	Model validation results
Ratio of Chi-Square to df (χ^2/df)	< 3	1.61
CFI (Comparative Fit Index)	> 0.95	0.977
TLI (Tucker-Lewis Index)	> 0.95	0.972
RMSEA (Root Mean Square Error of Approximation)	< 0.07	0.03
SRMR (Standard Root Mean Square Residual)	< 0.08	0.030

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