

China's Grain for Green policy and farm dynamics: simulating household land-use responses

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Abstract Analyzing the interaction between environmental policies and farmers' responses to them is an important dimension to understand regional agro-ecosystem sustainability. We examine land-use outcomes of perhaps the largest government-planned rural reforestation program in the history of humankind, China's "Grain for Green" (GFG) policy from 1999 to 2006. Specifically, we simulate household responses to the GFG policy in Western China's Shaanxi Province, a region experiencing acute climate and land change-related environmental degradation. We develop a "farmer group decision-making model" to simulate the probability of land-use change. Elevation, slope, and farm household characteristics emerge as key factors influencing farmers' land-use decisions and subsequent land-use patterns. Land reversion and abandonment in the study area have been significantly affected by the GFG program. Policy recommendations suggest potential avenues to enhance the effectiveness of the GFG program and to improve the efficient use of under-used farmland. Results may help inform the Chinese government as it

crafts policy guiding a coupled rural migration and reforestation program of unprecedented scale.

Keywords Grain for Green program · Belief, desire and intention (BDI) model · Land reversion · Land abandonment · Policy scenarios

Introduction

This paper examines rural land-use impacts of the largest government-planned rural reforestation program in the history of humankind. Our study simulates household responses to the Grain for Green (GFG) policy in Western China's Shaanxi Province, a region experiencing acute climate and land change-related environmental degradation. Shaanxi and, more generally Western China, is salient among semi-arid regions around the globe undergoing soil degradation and desertification related to climate change (Hillel and Cynthia 2002). As in other mid-latitude semi-arid regions, soil degradation and desertification in Western China have contributed significantly to climate change feedbacks and biodiversity loss. This causal chain reaches far beyond the locally affected regions (Le and Henry 1996). In this feedback process, regions undergoing forest cover loss may experience changing circulation patterns, increased albedo, and reduced precipitation. Arresting environmental degradation and desertification, therefore, is a high priority among policy options for combating ecosystem impacts of climate change (Xue 1996).

China has several regional climate "hot spots". A northward shift of forest, the disappearance of boreal forests from northeastern China, new tropical forests emerging in the south, and the eastward expanse of deserts are among the more striking outcomes (Ni 2011). Western China's forest–grassland borders are highly sensitive to the

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shifting climate (Wang et al. 2011). Rainfall has decreased significantly (by more than 10 %) across Western China, causing desertification to encroach on farmland (Xin et al. 2011) and to disturb human and natural ecosystems with regional-scale dust storms (Liu et al. 2013).

To reverse desertification and soil erosion and to foster regional socioeconomic development in its vast western region, China implemented the national “Grain for Green” (GFG) policy from 1999 to 2006. As a result, 26.9 million hectares of cropland distributed on steep slopes (defined as a gradient of 25° or greater) were returned to forest or grassland by 2006. Subsequently, the program was extended until 2015 (State Council of China 2007). More than 32 million farmers across 25 provinces have participated in this environmental program (Ke and Zhao 2008), the highest nationwide farmer participation in contemporary history (GFG Office of the State Forestry Administration of China 2003; Kang and Xia 2008).

China’s recent massive reforestation campaigns under GFG policy provide an unprecedented opportunity to observe farm household land-use decisions critical to coupled rural livelihood and ecosystem sustainability. Existing studies of the impact of the GFG program have examined both macro- and micro-level dynamics with varying levels of data validity and reliability. At the macro (regional)-level, a number of studies have examined the program’s impact on spatial and temporal change in land use by employing remote sensing (RS) data (Huang and Zhang 2005; Deng et al. 2010). RS methods, however, are insufficient for analyzing land-use change processes and for understanding the heterogeneity of agents (e.g., farmer households, farmer groups) responsible for land-use change (Cai 2001; Bakker and Van Doorn 2009; Saqalli et al. 2011). To overcome these shortcomings, some researchers (e.g., Zhong and Huang 2006; Chen and Xiao 2008) have constructed farmer land-use decision-making models to explore the influence of GFG policy on farmers’ land-use behavior. Most of these models applied observed data to calibrate parameters based on several informed assumptions. These models did not account for the learning process (Hu 2004; Zhong and Huang 2005; Xi et al. 2009). For example, such simulation models often assume that farmers’ land-use behavior remains unchanged over time. These models, therefore, cannot efficiently capture change in individual or household factors, critical determinants of farmers’ land-use behavior (Gibon et al. 2010; Li 2011). Thus, understanding the micro-mechanisms for agricultural land-use change among different farmer household groups is a methodological challenge potentially facilitated by simulation studies (Valbuena et al. 2010; Souza Soler and Verburg 2010).

There is an emerging consensus among scholars that analyzing interactions between environmental or agricultural

policies and farmers’ responses to them has become an important approach toward a more complete investigation of coupled livelihood and agro-ecosystem sustainability (Parker et al. 2001; Janssen and Ostrom 2006; Prishchepov et al. 2012). Some research in this vein has focused on how farmers’ behavior may impact agricultural land-use change (Scoones 1999; Piya et al. 2013). Yet, how change in environmental or agricultural policies mediates land-use behavior among farmer households continues to be understudied (Thompson et al. 2007; Feola and Binder 2010; Tambo and Abdoulaye 2013).

The belief, desire, and intention (BDI) model, one of the most popular agent decision-making models (Geogheff et al. 1999), has been widely used to construct reasoning systems for complex tasks in dynamic environments (Bordini et al. 2007). But the traditional BDI model does not specify agent communication (or any other aspects at the social level), nor does it account for learning from past behavior (Phung et al. 2005). Revisions of this model, including NoA (Kollingbaum and Norman 2003) and EMIL-A agent architecture (Andrighetto et al. 2007), have addressed this criticism by integrating (social) norms in the agent decision-making process. According to our view, few researchers have adapted the BDI model to incorporate social norms in studying agents’ learning and their interaction to explore agents’ land-use behavior. Therefore, it is worthwhile to design an extension BDI model, which has the ability to communicate among farmers or their groups as well as the ability to incorporate the norm into farmers’ decision-making, to resolve the following question:

- 1) What are the mechanisms by which environmental or agricultural policies impact farmers’ land-use behavior?
- 2) How does change in farmers’ land-use behavior influence agricultural land cover change?

The paper is organized into three major parts. In the first part, the initial version of our model is described. Based on this conceptual framework, “Materials and methods” section reports the results of different scenarios for a case study in Mizhi County of Shaanxi Province of China. Finally, we examine potential advantages and disadvantages of the BDI model, discuss results from focal findings, consider policy implications, and offer conclusions.

Materials and methods

Study area

Shaanxi is the Chinese province which experienced the most reforestation during the first decade of the twenty-first

century. Shaanxi's Mizhi County ranked among the first to carry out the GFG program from 174 counties nationwide. The county occupies 1212 km² of a hilly region of the Loess Plateau within 109° 49'–110° 29' E, 37° 39'–38° 5' N. Prior to the enforcement of the GFG program in 1999, 365 km² of land had experienced severe soil erosion. Erosion intensity (measured as the annual amount of soil erosion per unit area), at 13,000 t/km²/annum (Liu 1992), ranked "very severe" according to national standards (The Ministry of Water Resources of the People's Republic of China 2008). Over the first stage (1999–2006) of the implementation of the GFG program, 115.7 km² of cropland in Mizhi were returned to forest or grassland. The coverage rate of forest and grassland increased from 31.3 % in 1999 to 40.8 % in 2006, while cropland area declined from 65 to 53.2 %.

Situated in northern Mizhi, Gaoqu was selected for the study since it has witnessed the largest growth countywide in woodland and cropland, at 3.3 and 3.2 % per annum, respectively (Xi et al. 2009; Wang and Chen 2009). Land use in Gaoqu can be classified into six types: woodland, cropland, grassland, residential land (for settlements), orchard, and water bodies (Fig. 1a). Cropland and woodland accounted for more than 40 % of the total cropland or woodland area in 2006 (Table 1). More than half (52.8 %) of the land is distributed on moderate-to-steep hill slopes with a gradient of 25° or greater (Fig. 1b; Table 1). The percentages of cropland and woodland relative to the total land area fell dramatically by 32.5 and 40.2 %, respectively, over the 8-year period ending in 2006. In particular, cropland on steep slopes of 25° or greater dropped by 34.1 % over the same time.

There are significant differences in the dominant types of agricultural land use in Gaoqu. Based on these differences, three criteria were used to reclassify 21 administrative villages within the commune into four categories, as

shown in Table 2. Category I villages include five administrative villages where no cropland has been returned to forest or grassland. Primary agricultural production among farmers in Category I villages is scallions and potatoes (Fig. 2). Category II villages include six administrative villages where the returned cropland area accounts for <15 % of the total in the village, and over 85 % of farmers earn their living from off-farm activities such as doing business and exporting labor. Category III villages include five administrative villages where the returned land makes up more than 15 % of the total land area in the village, and 50–60 % of farmers depend on off-farm earnings. Category IV villages include five administrative villages where potatoes are the principal produce.

Extension of BDI model

The interviews were conducted to capture farmers' views on the change mechanisms of land use (Fig. 3). An extension BDI model was built to include farmers' capability and ability. This model was used to simulate three scenarios, which represented the implementation of different GFG scenarios in the region.

Data collection involved farmer households surveyed in seven villages from a total of 21 villages selected randomly in Gaoqu from 2007 to 2009 (refer to Fig. 2). We conducted surveys in the seven villages to collect information on farmer perception of the GFG program, how the program has influenced land-use behavior, and resultant socioeconomic consequences. A valid sample of 309 households spanning 3 years (from 331 total selected farmer households) was obtained with an overall response rate of 93.4 %. Following farm household survey design from China (Xi et al. 2009) and elsewhere (Carr 2005), the questions asked of the household head include demographic and socioeconomic information about the family,

Fig. 1 Land-use types and slope classifications in commune Gaoqu, Mizhi County of Shaanxi Province, China, 2006

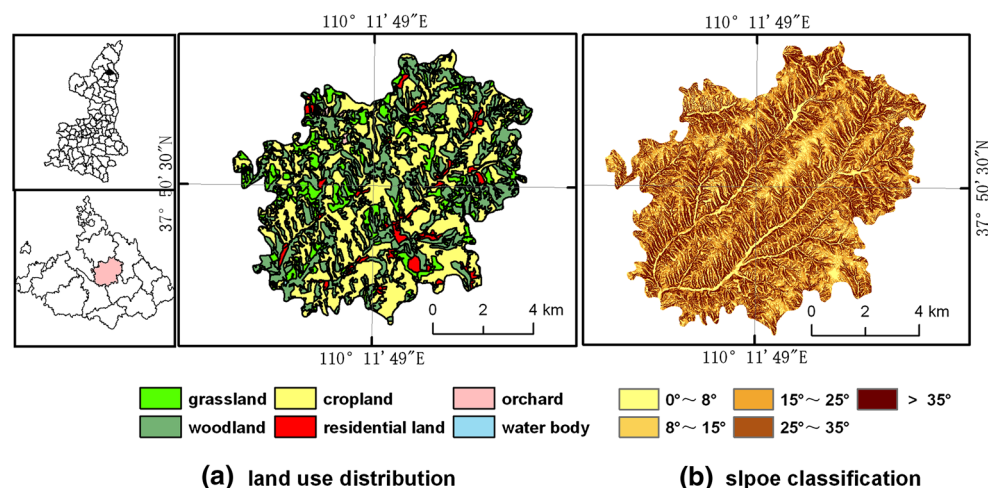


Table 1 Distribution of land use (measured as percentages) in commune Gaoqu, Mizhi county, by slope, 1999 and 2006

Land-use type	<15°		15°–25°		25°–35°		>35°		Total (ha)	
	1999	2006	1999	2006	1999	2006	1999	2006	1999	2006
Cropland	17.9	11.2	18.1	11.4	18.2	11	18.6	10.5	5270.7	3192.8
Woodland	4.1	7.9	4.5	8.6	5.9	10.2	7.6	12.8	1600.1	2859.8
Grassland	0.5	2.6	0.7	2.8	0.7	3.1	1.1	3.4	217.1	861.6
Others	0.5	1.3	0.4	0.9	0.6	1.1	0.6	1.2	152.1	325.8
Total	23	23	23.7	23.7	25.4	25.4	27.9	27.9	7240	7240

Data source: authors' survey in 2007

Table 2 Classification of different villages in commune Gaoqu, Mizhi County

Village category	Has any cropland been returned to forest or grassland?	Is the area of commercial cropland >50 % of the total land area in the village?	Is the area of cropland that has been returned to forest or grassland >15 % of the total land area in the village?
Category I	No	Yes	No
Category II	Yes	No	No
Category III	Yes	No	Yes
Category IV	Yes	Yes	Yes

Data source: authors' survey in 2007

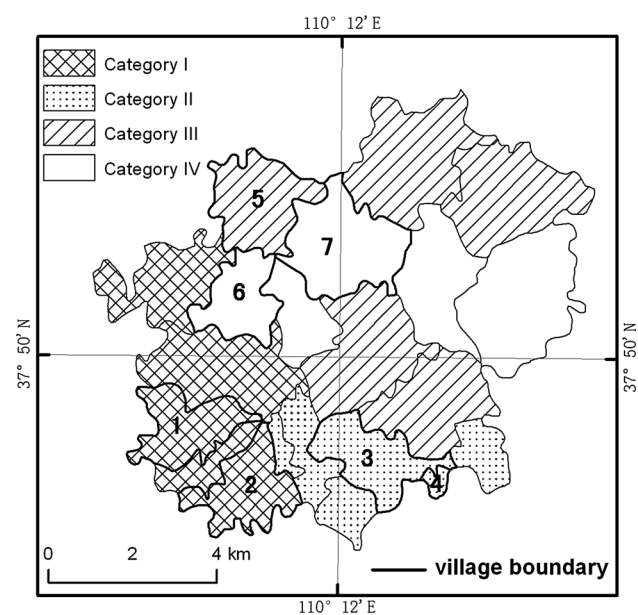


Fig. 2 Village categories and sampled villages in commune Gaoqu, Mizhi County. Note sampled villages: 1. Fenqu; 2. Liuqu; 3. Chenjiagou; 4. Yangshan; 5. Gaoxigou; 6. Mtiwa; 7. Jiangxinzhuang

such as the number of household members, income, consumption, agricultural and non-agricultural activities, and how the implementation of the GFG program has impacted the household's land-use strategies (e.g., growing commercial crops, mixed cropping, self-maintenance cropping, and raising livestock). Particular questions asked whether the household has: reverted to cropland the land that was

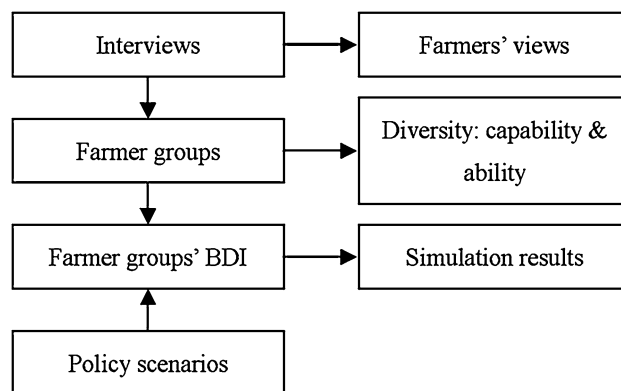


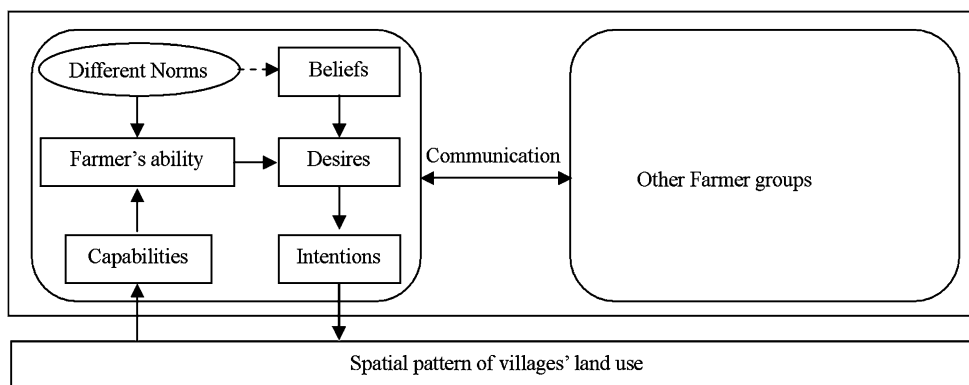
Fig. 3 Overview of the method used in this paper

returned to forest or grassland at an earlier time (hereafter *land reversion*); abandoned the farmland, or used the cropland less (hereafter *land abandonment*). The majority of the respondents (87.9 %) were males, and a small proportion (8.4 %) of the respondents were aged 60 years or above.

Model framework

A conceptual modeling framework was used to simplify and analyze farmer groups' decision-making within study areas. In this framework (Fig. 4), there are two new components: *Capabilities* and *Ability* of farmer groups. *Capabilities* are abstract plans of action which a farmer group

Fig. 4 Conceptual framework of farmer groups' decision-making and their interaction with the space



can use to act upon its environment. In our study, capabilities are *land reversion* plans and *abandonment* plans (find meanings of these two terms in “[Extension of BDI model](#)” section above). This paper has adopted Kollingbourn’s (2003) concept of the norm: what is “allowed, forbidden or permitted to do in a specific social context”.

Farmer’s *Ability* refers to the ability to convert abstract plans to specified plans. It is the basis for the internal representation of desires. It is affected by *Capabilities* and *Norms* (Fig. 4). In this paper, the GFG policy is the only law considered. Social norms come from the interaction among different farmer groups, like the decision of a farmer to re-enroll or not and how that decision conforms to the decisions of the majority around him (Chen et al. 2012).

With the help of *Ability*, the *Capabilities* of farmers are turned into specified plans for implementing the desires of farmer groups. Farmer groups usually are capable of interacting with other farmer groups to learn of their actions. The farmer groups’ social and economic status will impact the intention of farmer households. The execution of the specified intention will result in a new space pattern of their land use. In turn, this new space pattern will have an effect on their beliefs and their capabilities next time.

Description of capability and ability decision-making model

The decision-making model used in the study is expressed in Eq. (1). Three variables are included in the model as B_{ijlt} , D_{ijlt} , and I_{ijlt} , referring to the beliefs, desires, and intentions of farmer group i in village j at time t under norm l , respectively. Namely the action of farmers at time $t + 1$ is affected by the beliefs, desires, and intentions of farmers at time t .

$$A_{ijlt+1} = \{B_{ijlt}, D_{ijlt}, I_{ijlt}\} \tag{1}$$

Three main variables expressed in Eq. (1) will be elaborated as follows.

(1) Farmer groups’ beliefs.

The term beliefs refer to the information a farmer group has about the current environment. Farmer groups’ beliefs are affected by norms at various levels (such as national policies or local managements), and by the natural condition of crop planting. Thus, there are two variables included in farmers’ beliefs, namely $Norm_{ilt}$ and $Physical_{imr}$, where $Norm_{ilt}$ stands for the understanding of farmer group i to the norm l at time t , and $Physical_{imr}$ refers to the impact of environmental factors m on farmer group i at year t . It, in turn, is comprised of two variables: slope and elevation.

Two different norm levels are included in the model. One is the GFG policy. The other is a social norm coming from the interaction between different farmer groups. In order to analyze change in farmer groups’ decisions, we design three scenarios for GFG program. Under scenario I, the GFG program was to be terminated in 2006. Under scenario II, the GFG program will be extended from 2007 to 2015, but will be terminated in 2015. Under scenario III, the GFG program will be extended from 2006 onward, indefinitely. The other social norm is represented by what the majority of farmers do in a specific village.

(2) Farmer groups’ desires

In this paper, the term desire represents which of two specific plans the farmer groups select under a certain policy. *Ability* is the key for turning the abstract plan into a specified plan. Through perceiving the norm, the farmer group will classify the norms. They can distinguish policy, which states what people ought to do (or ought not to do), from other social norms (what farmer households usually do in a given situation). The farmer household will adopt a different plan for different norms. As for policy, farmer groups will strictly abide by its requirements. With the other type of social norm (what the farmers’ majority usually does), the decision direction will be determined by the farmer. The decision direction means a farmer household will adopt one of two plans. The decision direction is affected by the attraction probabilities of different plans for

different farmer groups $P_i^l(t)$ or $A_i^l(t)$ and their *average-age*_{ijlt}. Therefore, there are two variables included in *ability*, designed as the following (Eq. 2):

$$Ability_{ijlt} = \begin{cases} (A_i^l(t), average - age_{ijlt}) & t = 1 \\ (P_i^l(t), average - age_{ijlt}) & t = 2 \end{cases} \quad (2)$$

where *ability*_{ijlt} stands for the possibility of turning into the specified plan *l* of farmer group *i* in village *j* at time *t*, and $A_i^l(t)$ refers to the likelihood of the specified plan *l* collectively selected by all farmer groups during the 1999–2006 period, while $P_i^l(t)$ refers to the likelihood of the specified plan *l* to be selected by all farmers following completion of the first stage of the GFG program in 2006 (the detail method and the mean of the other parameters are in the Supplementary data), and *average_age*_{ijlt} is farmer group’s average age of farmer group *i* in village *j* at time *t*.

(3) Farmer groups’ intentions

The term intentions refer to the farmer groups’ committed plans. The intentions of farmer groups will be influenced by contextual factors of local communities, the local environment (*Context*_{ijlt}), their ability to carry out the specified plan, and the possible quantity of land reversion or abandonment *Transition*_{ijlt}. Therefore, the farmer groups’ intentions can be expressed as Eq. (3):

$$Intention_{ijlt} = Ability_{ijlt} \times Context_{ijlt} \times Transition_{ijlt} \quad (3)$$

where *Context*_{ijlt} represents the effect of contextual factors of village *j* on the specified plan *l* of farmer group *i* at year *t*. Two variables are included: the factors of local environment *Physical*_{imlt} and the local communities *Village-Category*_{ijlt}, designed as the following (Eq. 4):

$$Context_{ijlt} = Physical_{imlt} \times Village - category_{ijlt} \quad (4)$$

There are two environmental factors included in the *Physical*_{imlt}: slope and elevation. *Village-Category*_{ijlt} represents the impacts of village category *j* on the specified plan *l* of farmer group *i* at year *t*. We assume that the value of *Village-Category*_{ijlt} is a mixed result of the $P_i^l(t)$ or $A_i^l(t)$ of all farmer groups. This means that each specific farmer group has a particular weight contributing to the *Village-Category*_{ijlt}. The value of *Village-Category*_{ijlt} is computed by Eq. (5):

$$Village - Category_{ijlt} = \begin{cases} \sum_{i=1}^n (Percent_{ijlt} \times A_i^l(t)) & t = 1 \\ \sum_{i=1}^n (Percent_{ijlt} \times P_i^l(t)) & t = 2 \end{cases} \quad (5)$$

*Transition*_{ijlt} refers to possible quantity of land reversion of farmer group *i* in village category *j* when adopting the specified plan *l*. The quantity of land to be transformed

through reverting and/or abandoning land in each village category is highly associated with farmer group composition. Therefore, *Transition*_{ijlt} is a function of three factors: $P_i^l(t)$ or $A_i^l(t)$, *Percent*_{ijlt}, and *Criterion*_{ijlt}. *Criterion*_{ijlt} is the coefficient of land transition for farmer group *i* in village category *j* at year *t*. The values for *Context*_{ijlt} are split into two parts: one part ranging from the median to the maximum, and the other being less than the median. In the simulation, only the median-to-maximum part is considered in *Criterion*_{ijlt} to estimate the maximal magnitude of land to be transferred and its spatial distribution. The amount of *Transition*_{ijlt} is expressed in Eq. (6):

$$Transition_{ijlt} = \begin{cases} Percent_{ijlt} \times Criterion_{ijlt} \times A_i^l(t) & t = 1 \\ Percent_{ijlt} \times Criterion_{ijlt} \times P_i^l(t) & t = 2 \end{cases} \quad (6)$$

Results

Classification of farmer households

We employ the classification and regression tree (CART) method to classify the farmer households into different groups (Valbuena et al. 2008). Three criteria are used for the classification of farmer households: (1) whether or not they have participated in the GFG program; (2) whether or not land-use patterns have been changed; and (3) whether or not they have introduced diversified strategies in agricultural production or land use.

Based on the CART analysis and household survey data, the farmer households under study are divided into six groups, as shown by F_i in Fig. 5. The demographic, social, and economic characteristics of each group are summarized in Tables 3 and 4. The households that did not carry out the GFG program are divided into three groups: F_1 , F_2 , and F_3 . As a whole, these groups have a relatively high average level of education and remain relatively young. Their main agricultural produce is scallions and potatoes. During the non-intensive working months of the year, some farmers choose to leave home for temporary off-farm work, with most (84 %) working in the local township center or the county seat. Farmer group F_2 received the lowest income among these three groups as expected since they possess the largest area of cropland. The households that carried out the GFG program are classified into three groups: F_4 , F_5 , and F_6 . Their main income derives from off-farm employment and animal husbandry except Group F_5 farmers who mainly work off-farm in local communities. Family members in groups F_4 and F_6 have relatively greater non-farm labor skills and consequently have higher income than other groups.

Fig. 5 Classification of the farmer households in Gaoqu, Mizhi County

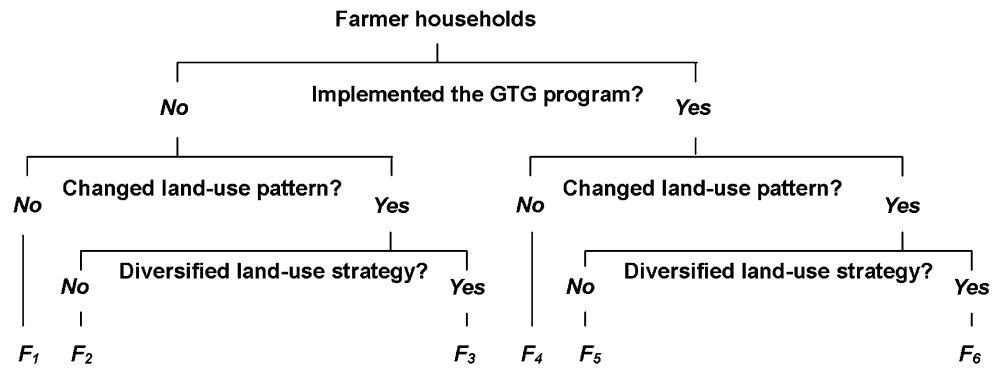


Table 3 Characteristics of farmer groups in commune Gaoqu, Mizhi County

Farmer groups	Sampled households	Persons of the household: mean (SD)	Persons holding non-agricultural household registration status: mean (SD)	Age of the household head: mean (SD)	Years of schooling of the household head: mean (SD)	Cultivated land (ha) of the household: mean (SD)
F ₁	31	3.3 (1.5)	2.4 (1.2)	44 (0.8)	7 (0.7)	0.9 (0.3)
F ₂	39	2.6 (1.1)	1.4 (0.5)	46 (1.4)	5 (0.8)	1.4 (0.6)
F ₃	44	4.2 (1.1)	2.2 (1.1)	38 (1.2)	8 (0.5)	1.1 (0.4)
F ₄	81	2.8 (1.4)	2.5 (1.1)	46 (0.9)	8 (0.8)	0.4 (0.3)
F ₅	55	2.3 (1.3)	2.1 (1.1)	52 (0.7)	4 (0.8)	0.6 (0.4)
F ₆	59	3.2 (1.3)	2.8 (0.9)	47 (0.8)	5 (0.9)	0.5 (0.3)

Data source: authors' survey in 2007–2009

Table 4 Sources and disparity of incomes of different farmer groups in commune Gaoqu, Mizhi County

Farmer groups	Sampled households	Agricultural production (yuan): mean (SD)	Off-farm wages (yuan): mean (SD)	Animal husbandry (yuan): mean (SD)
F ₁	31	10,500 (4149)	11,009 (10,846)	682 (2570)
F ₂	39	18,400 (12,116)	3200 (4604)	0 (0)
F ₃	44	27,900 (6806)	9800 (12,488)	200 (633)
F ₄	81	2014 (2534)	13,245 (11,150)	5332 (7472)
F ₅	55	6564 (6149)	6182 (5618)	4509 (3770)
F ₆	59	2814 (3626)	16,784 (9387)	8162 (11,410)

Data source: authors' survey in 2007, 2008 and 2009

Note USD 1 = RMB 6.2986 yuan as of 25 February 2012

Analysis of farmer groups' beliefs

According to our preview, the information about GFG comes partly from farmer participation, and from various media, such as TV, radio, and newspapers. Most information about farmer groups' interaction comes indirectly through informal communication among themselves. With an appreciation that farmers have a nuanced understanding of the effect of environmental factors (such as slope and elevation) on their land-use behavior, in order to quantify the impact of $Physical_{iml}$, we design the following method to express the probability for land reversion or abandonment:

- Slopes in the study area are divided into five classes: 0°–8° (flat hill foot), 8°–15° (gentle hillside), 15°–25° (moderate hillside), 25°–35° (steep hillside), and >35° (extreme hillside). In order to quantify the impact of slope, the probability for land reversion or abandonment on each of the five slope classes ranging from hill foot to extreme steep hillside is valued at 5, 4, 3, 2, and 1, respectively. The greater the number, the higher the probability of land reversion, but the lower the probability of land abandonment.
- The elevation in the study area ranges from 890 to 1190 m. To quantify its impact on farmers' land-use

behavior, the probability of land reversion at the elevation of 890 m is defined as 1, and at the elevation of 1190 m as 5. For each 75 m increase in elevation, the probability of land reversion increases by 1 unit. The higher the elevation, the lower the likelihood of land reversion, but the higher the likelihood of land abandonment.

Analysis of farmer groups' desire

(1) The calculation of $P_i^l(t)$ and $A_i^l(t)$

The attraction probabilities of different land-use strategies for different farmer groups are calculated according to Eqs. (1), (2), and (3) of the EWA model (in Supplementary data). Table 5 presents the estimated attraction probabilities of land-use strategies for different farmer groups during the 1999–2006 period of GFG program implementation. The maximum probability of the four possible strategies for each farmer group F_i indicates the ultimate land-use strategy utilized. The attraction probabilities of strategy S_1 (i.e., commercial cropping) for the farmer groups which did not carry out the GFG program are notably greater than those for their counterparts who carried out the program. This land-use strategy is also predominant among the four strategies used by farmer groups F_1 , F_2 , and F_3 as these groups have continued a preference for sowing commercial crops. For farmer groups F_4 and F_6 , engaging in off-farm jobs and developing animal husbandry emerge as the key production strategies. These households have large areas of woodland and grassland, which require less labor than cropland. The groups F_1 , F_4 , and F_6 are more likely to reclaim land that has already been returned to forest or grassland. In comparison, the other three groups, F_2 , F_3 , and F_5 , are prone to abandoning underutilized farmland.

Table 6 shows the estimated attraction probabilities for different land-use strategies for each farmer group in an assumed situation without continuation of the GFG program after 2006. The attraction probabilities of strategy S_4 (i.e., off-farm activity) for the farmer groups F_1 , F_3 , F_4 , and

F_6 are estimated to be high, suggesting that leaving the farm and seeking paid employment would become a primary option. Moreover, these groups are likely to reclaim, for agriculture, forest and grassland, returned from previous cropland at an earlier time. In contrast, farmer groups F_2 and F_5 have an increased probability of cropping.

The attraction probabilities of different land-use strategies would have changed significantly in the study area had the GFG program not been continued beyond 2006. Farmer groups F_1 and F_3 would increasingly shift from farming to seeking non-agricultural employment, while the attraction of commercial cropping (S_1) would substantially decline. For farmer groups F_2 and F_5 , the attraction of off-farm employment (S_4) would lessen. A growing number of these households would shift to commercial cropping production mainly because both groups have considerable experience in growing commercial crops. For group F_6 , though off-farm activity (S_4) would remain the first choice as a production strategy, it would not match an increasing proclivity toward developing animal husbandry (S_3). Clearly, the GFG program has influenced, and will continue to greatly impact, farmers' choices about land-use strategies.

(2) The assumption of *average age*

$P_i^l(t)$ and $A_i^l(t)$ are influenced by the age of the household head. When the age reaches 60 years, the possibility of land reversion is reduced significantly. Similarly, the older the household head, the higher the possibility of land abandonment. If the household head is aged 60 years or older, the maximum probability of land reversion for the family is assumed to be 1, and the maximum probability of land abandonment is 5. In contrast, if the household head is younger than 60 years, the age impact on land revision or abandonment is assumed to be none. This assumption reflects the fact that the key working age of population in the rural areas of China is <60 years.

(3) The result of *Ability*

According to the analysis above, the *Ability* of farmer groups can be derived:

Table 5 Attraction of different production strategies for different farmer groups over the 1999–2006 periods

Farmer groups	S1: maintaining traditional agriculture (%)	S2: changing traditional agricultural production (%)	S3: developing animal husbandry (%)	S4: off-farm (%)
F_1	47.5	0.2	2.5	49.8
F_2	63.6	0.6	0.0	35.8
F_3	52.4	0.8	0.1	46.7
F_4	11.3	1.9	24.7	62.1
F_5	36.7	4.6	23.3	35.4
F_6	1.3	8.4	24.2	66.1

Data source: authors' survey in 2007, 2008 and 2009

Table 6 Attraction of different production strategies for different farmer groups if the GFG were not implemented

Farmer groups	S1: maintaining traditional agriculture (%)	S2: changing traditional agricultural production (%)	S3: developing animal husbandry (%)	S4: off-farm (%)
F_1	22.5	0.4	0.9	76.2
F_2	77.8	0.3	0	21.9
F_3	40.1	0.3	0.1	59.5
F_4	13.8	1.7	20.7	63.8
F_5	42.8	2.1	25.8	29.3
F_6	0.9	8.7	31.5	58.9

Data source: authors' survey in 2007, 2008 and 2009

If the average_age of farmer groups is <60 years, then
 $Ability = P_i^l(t)$ (or $A_i^l(t)$)
 or
 $Ability$ of land reversion = 1,
 $Ability$ of land abandonment = 5.

Analysis of farmer groups' intention

(1) The effect of village under different scenarios

After 2006, the impact of the GFG program on land-use types for different groups of farm households under different policy scenarios varies significantly. Under scenario I or II, the values of $P_i^l(t+1)$ for different farmer groups after the assumed completion of the GFG program in 2006 or 2015 are supposed to be the same as they were without the GFG program having been implemented (refer to Table 6). The difference between the two scenarios is that the factor of farmer groups' *average-age*_{ijt} is considered in the model in scenario II, but not considered in scenario I. In policy scenario III, the values of $A_j^j(t)$ are assumed to be the same as they were when the GFG program was carried out in 1999–2006 (refer to Table 5). The impact of *average-age*_{ijt} is also considered in scenario III.

The composition of the farm groups in each of the four village categories is calculated and shown in Table 7. Farmer groups F_2 , F_4 , F_5 , and F_6 make up the largest components within the four village categories. The indicators, which measure the degree of impact on people's land-use behavior (e.g., *reversion*, *abandonment*) for each village category (*Village-Category*_{ijt}) under different policy scenarios, are modeled using Eq. (5). For Category I villages, the major impact of the GFG policy change on farmers was in land reversion as farmer group F_2 comprises the biggest part of the overall village households. These households have the largest area of cropland compared to any other farmer group. Farmers living in Category II villages would be more likely to abandon under-utilized land. This farmer group F_6 is the dominant group of villagers (accounting for 75 %). This group has a strong

preference to pursue off-farm employment. In Category III villages, the probabilities of land reversion appear similar to Category IV villages. Farmer group F_5 represents the main group of total villagers in Category III and IV villages, where farmers mainly invest in the labor-demanding production of potatoes.

(2) The intention of farmer groups under different scenarios

Examining the parameter *Context*_t, the behaviors of *land reversion* and *land abandonment* are highly associated with land elevation and slope. The effects of these two factors are estimated by overlaying the probability map of land reversion and land abandonment using the overlay function of ArcGIS. Accordingly, the magnitude of land to be transformed under the medium-to-maximum scenario is estimated by using Eq. (6). The results are shown in Table 8. For *land reversion*, the maximum average probability and the maximum magnitude of land to be transformed appear in Category I villages, while the minimum probability and least land to be transformed occur in Category II villages. This finding is expected since farmer group F_2 is the dominant group in Category I villages and this group demonstrates a strong and sustained willingness to grow commercial crops. Farmer group F_6 remains the dominant group in Category II villages; these farmers have a strong desire to pursue off-farm jobs. Strikingly, change in the average probability of quantity of land to be transformed in Category III villages is largest under all policy scenarios. Together, these findings suggest that if the GFG program had been terminated after 2006, some villagers would have quickly reclaimed returned land for cropping production, thereby reversing the achievements practiced in the early stage of the GFG program (1999–2006). This indicates that a long-term extension of the GFG program would greatly reduce the magnitude of land reversion. Moreover, the magnitude of land reversion under scenario III is anticipated to be <18 % of the magnitude of land reversed under scenario II (Table 8). While there would be a significant financial burden for China to extend the

Table 7 Effects of village categories on land reversion and land abandonment under different policy scenarios

Effect	Category I village			Category II village			Category III village			Category IV village		
	Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III
	Land reversion	3.2	3.2	2.9	2.3	1.8	1.4	2.6	1.4	1.3	2.9	1.1
Land abandonment	1.8	1.8	2.1	2.7	3.2	3.6	2.4	3.6	3.7	2.1	3.9	4
Composition of farmer groups	$F_1;F_2;F_3 = 20:65:15$			$F_4;F_5;F_6 = 10:15:75$			$F_4;F_5;F_6 = 45:40:15$			$F_4;F_5;F_6 = 15:60:25$		

Data source: authors' survey in 2007, 2008 and 2009

program beyond 2015, these findings suggest that the extension of the GFG program from 2007 to 2015 may represent a rational policy decision.

The maximum probability of *land abandonment* occurs in Category II villages, while the minimum probability emerges in Category I villages. This appears to be largely related to the different land-use strategies adopted by these villages. In policy scenario I, although the average probability of land transition is not the largest in Category III villages, the quantity of land to be transformed will be paramount due to the fragmented topography of the land in these villages. These villages will also be likely to inherit the maximum quantity of under-utilized land under policy scenarios II and III. This result reflects the effects of aging households as well as the land's hilly topography.

Land reversion and farmland abandonment emerge as two consequences under all GFG policy scenarios across all villages. Farmland abandonment will be especially acute in scenarios II and III, regardless of whether or not the GFG program is continued to 2015 and beyond. How policy makers can ensure the effective implementation of the GFG program and enable the efficient use of little used land are challenging issues facing both farmers and policy makers.

Conclusion and discussion

This paper demonstrates an approach to analyze and model household responses to the GFG policy in Western China's Shaanxi Province. The results of the semi-structured interviews demonstrate changes to farmers' land-use behavior under different policy scenarios, including the likelihood of the specified plan collectively selected, such as the possibility of land reversion and abandonment. These results support previous studies that identified changes in farmer households' decision-making under different policies (Zhong and Huang 2006; Valbuena et al. 2010).

The diversity in farmers' capabilities and abilities in the region confirms that the responses of farmers' land-use behaviors are not necessarily the same among farmers. For the study area, part of this diversity includes the factors of the local environment and local communities. As the simulations showed, the diversity of farmers' decision-making needed to be considered when different policies were implemented. The simulations also explore how changes in farmers' decision-making can affect land-use change.

Approach: strengths and limitations

The CA-BDI model presented in this paper offers several advantages. First, it explicitly considers the diversity of farmers' response to changes in policies as a proximate cause of LUC processes in rural regions, and it can include

Table 8 Projected effects of different policy scenarios on land-use behavior, by village categories

Effect	Village category	Policy scenario I		Policy scenario II		Policy scenario III	
		Probability of $Context_t$	Land to be transformed at median-to-maximum possibility (ha)	Probability of $Context_t$	Land to be transformed at median-to-maximum possibility (ha)	Probability of $Context_t$	Land to be transformed at median-to-maximum possibility (ha)
Land reversion	Category I	3.4	117.3	3.4	117.3	3.1	97.6
	Category II	1.4	3.8	1.1	1	1.0	0
	Category III	2.5	51.6	1.4	0	1.3	0
	Category IV	3.2	100.7	1.2	0	1.1	0
Land abandonment	Category I	1.4	3.6	1.4	0	1.6	0
	Category II	3.4	118.7	4.1	32.9	4.6	64.2
	Category III	1.6	167.1	2.5	190.1	2.5	190.1
	Category IV	1.4	14.48	2.6	60.6	2.6	60.6

Data source: authors' survey in 2007, 2008 and 2009

farmer groups' capabilities and abilities to simulate their learning process and interactions. The capacity to include these components contrasts with most LUC spatial models, which disregard farmers' capabilities and abilities, and assumes that decision-making in rural regions is homogeneous among farmers (e.g., Pijanowski et al. 2002; Verburg et al. 2002). Second, this approach explores farmer groups' interactions in a village, which is an appropriate spatial unit to analyze and discuss farmer group decision-making nested within multiple decision-making scales (i.e., field, village, and region). Third, the use of a probabilistic approach to represent farmer groups' decision-making allows us to use both qualitative and quantitative data. It provides flexibility to analyze and explore policy scenarios in different rural regions.

In addition to the possible advantages offered by the approach, there are limitations. First, this approach requires an understanding of farmers' role in a certain village to influence other farmer's decision-making. Detailed knowledge about the effects of farmers' social network on other farmers is necessary (Bodin and Crona 2009; Franz and Nunn 2009). However, to obtain these data for all farmers in a specific rural region and to link them to spatial processes is not often possible. Further, although the model structure offers the possibility of representing the effect of the village on farmer groups' interactions, it is difficult to assign an appropriate weight to village influence on farmers' decisions and to predict how this influence can evolve over time for a whole region. Therefore, it is necessary to incorporate the social networks into farmer household's decision-making. Second, the interactions among the same or different village categories are not considered in this paper. To overcome these limitations, additional empirical methods such as interviews and role-play games could help to achieve a better insight in farmers' or their groups' decision-making (Barreteau et al. 2003; Becu et al. 2008).

Implications for land-use management and policy

A critical concern to both policy makers and researchers is the extent to which implementation of the GFG policy has influenced regional land-use change, food security, and farmers' land-use behavior, particularly at a household scale. The approach described in this paper can be used as a basis for ex-ante tools to analyze and explore the effect of the implementation of environmental policy in LUC in rural regions. Additionally, future research can use this approach in processes of collective decision-making to facilitate the involvement and interaction of different stakeholders.

By identifying the characteristics of the farmer groups, the villages and the mechanisms that can influence farmers' capabilities and abilities, we take an important step toward the recognition of the learning process that may influence farmer groups' decision-making in different policy scenarios. Further, simulation results corroborated that the consequences of land reversion and farmland abandonment coexist, and pointed to possible solutions. This is not an unusual phenomenon; it has occurred in other regions where the GFG program has been implemented (Sheng 2006). The spatial distribution and magnitude of land to be affected by such land-use behaviors vary by village in the study area. The approach described in this paper can be used as a basis to analyze and explore the potential spatial distribution and magnitude of farmland abandonment (or land reversion) in rural regions. To ensure the effectiveness of the GFG policy, it appears imperative to improve the use of abandoned or under-utilized land. Local governments can play a key role in crafting appropriate land-use plans and guiding farmers to develop suitable land release and rotation mechanisms at regional and local (especially county, township) levels, and in liaising with local communities and government departments to manage land use effectively and productively. Policy tools tailored for land-

use circulation among farmers and across administrative boundaries of villages can play an important part in facilitating efficient land use.

Finally, this study did not consider the quantitative change in labor. Results point toward the potential importance of further research investigating the dynamics of such change. From this perspective, it may be useful for improving our understanding of the impacts of GTG policy on land change to explore land-use behavior among households, especially newly formed households, if and when they return to their origin communities. We believe land-use status may become quite different from current estimates under such dynamics. How the demand for migrant labor in urban areas in the coming decades will in turn impact land-use change in rural areas is an important research topic. Enabled by a dynamic perspective, these themes could be further investigated with case study research, where appropriate data are available. Further research into these and related areas will be critical to facilitating suitably informed government policy within China as it undertakes a coupled rural out-migration and reforestation program. Results may also potentially inform governments in other world regions faced with diminishing available arable land and continued high rural population densities.

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