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<https://doi.org/10.1057/s41599-023-02068-0>

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# The influencing factors underlying the vicious ecological vulnerability-low productivity-poverty cycle in China and overcoming its related policies

Yong Liu <sup>1</sup>✉ & Cuihong Long<sup>2</sup>

There is often a vicious cycle that occurs in China encompassing ecological vulnerability, low productivity, and poverty. Existing research has not applied multiagent modelling and simulation (MAMS), which is a method suitable for analysing such complex systems. Therefore, the MAMS is here used to explore potential strategies for breaking this cycle. The MAMS method is based on complex adaptive systems and computer programs, and it includes both theoretical and simulation models, which can be used to simulate different scenarios and obtain visualized results. To sample representative poverty-stricken areas in China, the authors designed five breakthrough policy scenarios. The simulation results of these scenarios indicate that increasing the amount of arable land decreases the number of poor people. However, increasing the direct interventions of government does not reduce the number of the poor, nor does it change the Gini coefficient. On the other hand, increasing the number and variety of poverty alleviation opportunities available to the poor leads to a decrease in both the number of poor people and the Gini coefficient. These results of our five scenarios indicate that the optimal policy portfolio could be obtained by increasing the amount of arable land and providing more varied opportunities to help the poor participate in market activities while reducing direct government intervention. The combined design of these policies is conducive to breaking the vicious cycle of poverty.

<sup>1</sup>School of Economics, Sichuan University, Chengdu, China. <sup>2</sup>School of Economics, East China Normal University, Shanghai, China.  
✉email: [yonghopeliu@sina.com](mailto:yonghopeliu@sina.com)

## Introduction

Poverty alleviation is a common goal throughout the world. Poor areas face the triple burdens of ecological vulnerability, low productivity, and poverty. Fragile ecological environments lead to economic backwardness and increased levels of poverty. To reduce the number of poor people, governments generally accelerate the pace of economic development in their countries, which leads to further environmental damage and increases the fragility of the ecosystem, hinders sustainable development and mires poor people in poverty. Therefore, a vicious cycle, which traps people and results in a challenge to poverty alleviation, has formed. Therefore, poverty alleviation is a systemic task in which both the environment and economic development must be considered.

China has many relatively poor people. The Chinese government has formulated many policies to reduce the level of poverty, including developing new energy and encouraging tourism and consumption, and these policies have achieved meaningful results. According to United Nations statistics, in China, 61% of the population was extremely poor in 1990, that number dropped to below 30% in 2002, and it fell to 4.2% in 2014. China's contribution to global poverty alleviation exceeds 70% (Yang, 2020). Regional characteristics and practical challenges have affected the effective poverty alleviation models, such as applying poverty alleviation in large-scale industries as well as in e-commerce, tourism, and finance; however, such efforts encounter obstacles in areas of extreme poverty and are difficult to effectively implement (Gao and Guo, 2020). These vicious cycles cannot effectively reduce poverty. In 2017, at the current income threshold of RMB 2952 per year (approximately 416.6 USD), there were 30.46 million poor people in China, and the incidence of poverty was 3.1% (Yang, 2020). The poverty standard set by the Chinese government has been dynamically adjusted. In 2011, it was 2,300 RMB (approximately 323.8 USD), and in 2018, it was 3535 RMB (approximately 497.7 USD) (Huang and Li, 2021). There are multiple standards for poverty lines, and there is no overlap in the distribution of the identified poor population in the results of different methods (Bradshaw and Finch, 2003). The concept of poverty includes absolute poverty and relative poverty, which use different standards. According to the standards of absolute poverty, there are almost no poor people in China. However, based on the standards of relative poverty, regardless of the method used for measurement, the number of poor people in China is still exceedingly large. (Wang et al., 2015; Xia et al., 2007). Therefore, our definition of poor is based on the relative amounts of wealth that individuals possess, with the lower third of the population in the entire system possessing wealth. This definition is suitable for analysing the impoverished population within countries and regions at different stages of development.

Many researchers have studied ecological vulnerability, productivity, and poverty. The relevant research objects include the influencing factors (Sonja et al., 2020; Lehmann et al., 2018; Barrett and Bevis, 2015; Wang, 2004) and their interaction relationships (Cheng et al., 2018; Adjei et al., 2017; Cao et al., 2015; Chen and Gao, 2009) and. What sets this study apart from existing research is the different research method applied, namely, multiagent modelling and simulation. Although this method has been widely successful in other research fields (Salehi et al., 2023; Liu, 2017), it has hardly been applied to this topic. Because of the use of this research method, our analysis of the relevant influencing factors is unique. This method can simultaneously include multiple influencing factors and achieve dynamic simulation.

Therefore, this study offers two contributions: (1) it uses multiagent modelling and simulation methods to explore these problems, and (2) by designing different scenarios for simulation, more feasible policy recommendations are obtained.

## Literature Review

Numerous studies have shown a strong link between ecological vulnerability, productivity, and poverty (Niu and Wang, 2017; Chen and Gao, 2009). There is a geographical coupling between the distribution of poor areas and fragile ecologies, which causes many problems and restricts local economic development (Tong and Long, 2003). Indeed, inappropriate poverty alleviation projects increase the environmental footprint (Malerba, 2020). The existing research can be mainly divided into the following aspects.

Researchers have studied the links between ecological vulnerability, productivity, and poverty. Environmental vulnerability leads to low production efficiency, which hinders economic development and results in poverty. Cheng et al. (2018) linked ecological and environmental degradation to poverty. Poverty, in turn, leads to more ecological vulnerability, principally through improper economic development. For example, unregulated tourism facilities and poverty lead to ecological landscape degradation (Adjei et al., 2017). This vicious cycle also exists in China; in particular, there is a high correlation between ecological vulnerability and economic poverty in some areas (Cao et al., 2015). Western China contains a high concentration of poor people, and research has found a complex two-way causality between its fragile environment and poverty (Chen and Gao, 2009). Many pieces of evidence indicate a close relationship between vulnerability, low productivity, and poverty, which affect each other and have the potential to form vicious cycles. For example, Xinjiang's ecological vulnerability significantly correlates with its poverty level. The more vulnerable that an ecological system is, the poorer the economy, the higher the residential cost of living, and the greater the obstacles to economic development (Wang and Yang, 2015). Meanwhile, in Gansu Province, the overall correlation between ecological vulnerability and poverty is increasing (Niu and Wang, 2017).

The vicious cycle of ecological vulnerability-low productivity-poverty in poor areas results from a combination of natural and human factors, but it is primarily due to human factors. In poor regions, geographical conditions have formed restrictions against participation in market opportunities or the selection of development models, which leads to a lack of development opportunities in those areas (Wang, 2004).

Existing research has revealed that factors such as soil quality (Sonja et al., 2020), climate, mineral resource endowment, water resource profile, land resource conditions (Barrett and Bevis, 2015), and biodiversity (Munthal (2007)) in a region have varying degrees of impact on the poverty level in that region (Liu and Li, 2019). Some studies have proven that increasing ecological services could reduce poverty (Lehmann et al., 2018). However, empirical research from China has revealed some differences in the influence of these factors on poverty. The disposable income of farmers is the critical factor affecting poverty, and natural aspects such as altitude, slope, and vegetation coverage have less influence (Xia et al., 2019). Existing research has also shown that efforts toward synergistic ecological protection and poverty alleviation need to account for the interaction processes and mechanisms of subjects with different interests. Game theory research discusses two core games with stakeholders in ecologically fragile areas that affect poverty, namely, government-to-people and government-to-business (Qi et al., 2013). Furthermore, suboptimal markets, learning abilities, bounded rationality, spillover effects, coordination failures, and economic imbalances affect poverty at different times and places (Barrett, 2008). Other studies have shown that the affordability and appropriateness of infrastructure and natural resource protection technologies (Reardon and Vosti, 1995), as well as modern agricultural technology (Enfors and Gordon, 2008; Altier, 2002; Burney and

Naylor, 2012), affect the links among ecological vulnerability, productivity, and poverty. The characteristics of the poor, such as households with ill members who are vulnerable to poverty, also have an impact (Novignon et al., 2012).

Existing studies have utilized relatively few research methods compared to the number of influencing factors. Liu et al. (2018) used field survey data and a probit model, while others have used uncertain multiobjective programming (Qu et al., (2006)). Other researchers have employed the three-step feasible generalized least squares estimation procedure (Novignon et al. 2012), remote sensing and GIS images (Adjei et al., 2017).

The literature analysis above reveals that studies that analyse potential strategies for eliminating the ecological vulnerability-low productivity-poverty trap are limited. In particular, existing research has not adopted multiagent modelling and simulation, which is suitable for analysing such complex systems. Meanwhile, we have simulated strategies for breaking out of the poverty trap using poor areas in China as case studies to generate systematic proposals for poverty alleviation.

**Method**

**Arguments supporting multiagent modelling and simulation.**

This method is especially suitable for analysing complex systems involving eco-economic poverty. In these complex systems, the adaptive agents (such as poor residents) have a close relationship with other adaptive agents (such as governments and the rich), so the adaptive efforts of agents adjust to other adaptive agents. Therefore, the interactions and adaptations among agents become the main reasons for generating complex, dynamic patterns within the system. These characteristics embody the vicious cycle of ecological vulnerability-low productivity-poverty. Agents influence each other, and together, they determine the evolutionary direction of the complex system. Reducing the poor population involves the actions of multiple agents, including local and central governments, related intermediary enterprises, and residents.

Poverty alleviation policies have different effects on these agents, who interact with each other and determine the effectiveness of these policies. This process also affects the ecological environment, which, in turn, affects economic development and the number of poor people. At the same time, the characteristics of uncertainty, unpredictability, and nonlinearity in this complex adaptive system make the classical scientific method, which has long been dominant, seem simplified (Liu et al., 2017). However, multiagent modelling and simulation methods based on complex adaptive system theory and computer simulation programs can be used to effectively analyse uncertain, unpredictable, and nonlinear systems, and researchers have successfully applied them to many research fields, including economics (Liu, 2020).

**Theoretical Model.** Ecological vulnerability ( $f(ev); ev > 0$ ) leads to low productivity. The natural environment provides ecological services that are the basis for economic development (Chen, Chen, and Peng, 2018). Increased ecological vulnerability degrades ecological functions, damages vegetation, erodes soil, reduces arable land, and even causes desertification.

In 2016 in China, 80% of poverty-stricken counties and 95% of the impoverished population were distributed in ecologically vulnerable areas, with an over 80% correlation between the poverty index and the ecological vulnerability index (Jiang, 2021). For example, in Xide County, Liangshan Yi Autonomous Prefecture, 99% of the 136 poverty-stricken villages are located in mountainous areas above 1900 metres. Over 50% of villages are located in high-altitude mountainous areas above 2500 metres.

Various natural disasters, including landslides, frequently occur in these regions (Cao et al., 2016). Mountainous area accounts for 66% of the entire county, while cultivated land only accounts for 10.6% of the county’s total area, with only 0.1 hectares of cultivated land per capita. However, the poor rely heavily on agriculture, with 49,000 people engaged in agriculture as a primary industry, accounting for 41.5% of the total employed population. In addition, farming in Xide County is difficult, with more than 60% of the land having a slope of over 25 degrees, resulting in poor soil, water, and fertilizer retention capacity (Jiang, 2021). This results in low local productivity and lower output per unit of land (Zhou, 1997). Therefore, we set the following equation:

$$f(ev) = (\text{percent} - \text{arable} - \text{land}) / (\text{Num} - \text{people}) \quad (1)$$

Ecological vulnerability mainly affects productivity ( $f(p); p > 0$ ) through arable land (*percent-arable-land*). Arable land is the mother of wealth, and all wealth in the system is derived from the land. Meanwhile,  $f(p)$  is influenced by growth rates and government policies. Therefore, we set the following equation:

$$f(p) = (\text{percent arable land}) + (\text{grow productivity}) + (\text{productivity} - \text{growth interval}) \quad (2)$$

The reduction in arable land and the fragile ecological environment both lower the level of resources per capita, severely restrict economic development, and maintain wealth per capita ( $f(w), w \geq 0$ ) at a low level, resulting in many people being poor (*poor*). Thus, we set the following equation:

$$f(w) = f(p) - \text{consumption} \quad (3)$$

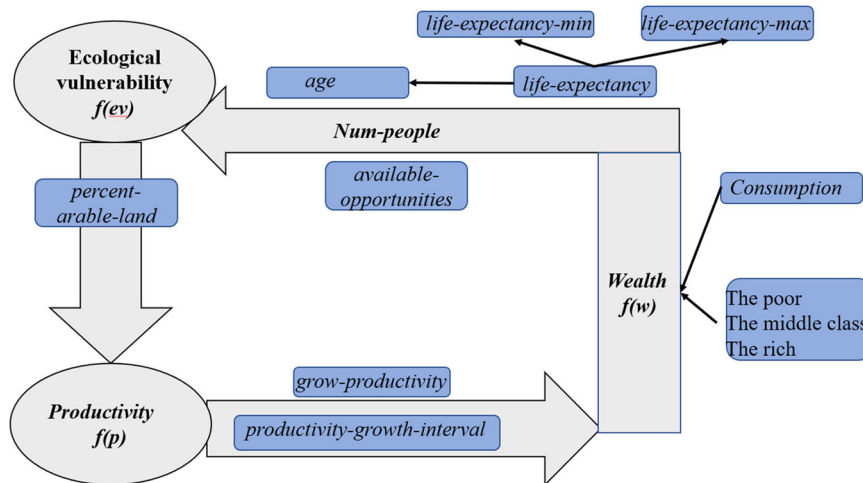
We divided the population ( $f(\text{Num} - \text{people})$ ) into three categories: *poor*, *middle-class*, and *rich*.

$$f(\text{Num} - \text{people}) = \begin{cases} \text{the poor, } 0 \leq f(w) \leq \frac{\text{max} - \text{wealth}}{3} \\ \text{the middle class, } \frac{\text{max} - \text{wealth}}{3} < f(w) \leq \frac{2(\text{max} - \text{wealth})}{3} \\ \text{the rich, } \frac{2(\text{max} - \text{wealth})}{3} < f(w) \leq (\text{max} - \text{wealth}) \end{cases} \quad (4)$$

To characterize the population, we introduced *age* and *life expectancy* into the system. We also designed the influencing factors ( $f(p)$ ), including variables that measure productivity growth (*grow productivity* and *max productivity*) as well as the government’s direct intervention policies that promote productivity growth (*productivity-growth interval*). These direct intervention policies include organizing villagers to relocate and distributing relief funds. In addition, there are also indirect intervention policies, such as encouraging residents in developed areas to purchase products from poverty-stricken areas, encouraging entrepreneurs to start businesses in these areas, and developing green industries. These policies affect  $f(p)$  and resident wealth  $f(w)$ , which are incorporated into the simulation model through the variable *productivity-growth-interval*.

Meanwhile, to survive, residents need to consume resources, which results in the overexploitation of the land and ecological environment. These dynamics, coupled with low technology and a lack of funding for repairing the ecological system, deepen the level of vulnerability in these areas. The opportunities that are available to residents play an important role in this process. These opportunities include factory employment and other means of participation in market-related activities (Wang, 2004) (Fig. 1).

Therefore, ecological vulnerability  $f(ev)$ , low productivity  $f(p)$ , and poverty  $f(w)$  are all closely interrelated. They strengthen each other, form cycles, and constitute a complex poverty trap  $g(ct)$ . As ecosystem vulnerability increases ( $f(ew)' > 0$ ), productivity growth



**Fig. 1 Theoretical model framework.** There are four parts that constitute the theoretical model, including population, wealth, ecological vulnerability, and productivity. Different variables connect the four parts.

becomes severely restricted ( $f(p)' < 0$ ), and local wealth also decreases ( $f(w)' < 0$ ). These results signify that there are not enough funds to repair the ecological system, which leads to further deterioration and plunges the entire system into a vicious cycle. Another scenario is where ecological vulnerability increases but does not exceed the threshold. Thus, productivity and wealth increase in the short term at the expense of the environment, but the system cannot achieve sustainable development and thus remains trapped. The ecological system can only heal if there is a reduction in the vulnerability of the ecological environment. Then, productivity and wealth increase, the system achieves sustainable development, and the trap is broken.

$$g(ct) = \begin{cases} \text{Strong trap, } f(ew)' > 0 \text{ and } f(p)' < 0 \text{ and } f(w)' < 0 \\ \text{trap, } f(ew)' > 0 \text{ and } f(p)' > 0 \text{ and } f(w)' > 0 \\ \text{break the trap, } f(ew)' < 0 \text{ and } f(p)' > 0 \text{ and } f(w)' > 0 \end{cases} \quad (5)$$

**Simulation model and platform.** The simulation model consists of simulation mechanisms and algorithms. Various variables form the basis of the simulation mechanism. The functions mentioned in our theoretical model, such as  $f(ev)$ ,  $f(p)$ , and  $f(w)$ , have corresponding variables, which are included in the simulation model, to describe them. These variables comprise four types: global variables, turtle variables, patch variables, and system variables. Throughout the entire simulation mechanism, there are emergent features presented at the system’s macro level. The interaction between agents in the system forms the basis for this emergent property. In this study, the emergent characteristic of the system is reflected in the dynamic changes in the number of individuals in different wealth levels. The micro mechanism behind these dynamic changes is the interaction between individual agents in the simulated world.

In addition, the simulation mechanism has four other features: (1) The agents in the system are adaptive. These agents can continuously adjust their behaviour based on changing environmental factors with the goal of maximizing their own interests. In this study, this feature manifests as wealth maximization among individual agents. (2) The agents have perceptual abilities. They understand their internal conditions, including age, wealth, and how to obtain wealth, as well as the external variables. (3) The agents are interactive, and they interact when acquiring wealth. These interactions are reflected in the direct or indirect links

between agents and other variables, which ultimately cause emergent properties to arise in the system. (4) The simulation mechanism includes randomness, such as the random distribution of agent positions. Meanwhile, because the focus is on the wealth distribution phenomenon at the system level, some other variables are also random.

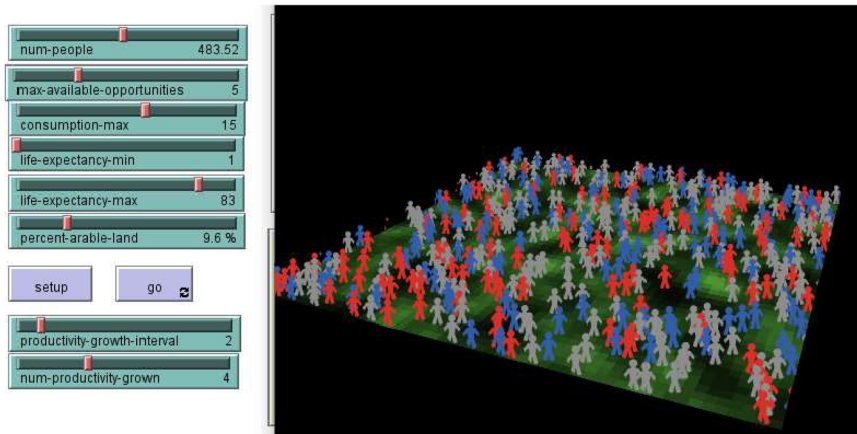
The simulation process design is a description of the mechanism implementation. After naming the variables, we designed program code to build the simulation world and randomly assigned outputs for each plot. Thus, the best land and output speeds were distinguished. The quantity of one of the agents in the simulation world, namely, “people,” was also set, including the variables that belong to these agents, such as life expectancy, consumption, and wealth. According to wealth levels, three types of people were identified and distinguished with different colours. Their rules of behaviour were directly implemented through program commands.

The simulation model also has its own algorithm. Choosing different simulation platforms affects the implementation of the algorithm. We used the NetLogo simulation platform, which belongs to the Lisp language, is based on Java and Scala, and runs on the Java virtual machine, to implement algorithm programming. Therefore, the algorithm of the simulation model is realized through direct instructions, which alleviates the need for complex mathematical formulas. This is a prominent advantage of the NetLogo simulation platform. For example, four instructions, namely, move, eat, age, and die, can be used to directly depict the entire process of agent behaviour, consumption, ageing, and death without the need of assistance from other mathematical formulas.

NetLogo is a programming language and modelling platform used for simulating natural and social phenomena that is especially suitable for simulating complex systems that develop over time. Based on our theoretical model, we constructed a simulation model that the computer could recognize. Such a theoretical model has to be expressed through the use of multiple variables. We placed variables into the following three categories. (1) Global variables, for example, *productivity-growth-interval* and *percent-arable-land*, are common to the entire simulation model. Changes in their values effect the whole model; (2) Patches-own variables are local and only affect a localized area within the simulation model. Changes in their values do not affect the whole simulation. (3) Agent variables for example, *available opportunities*, are specific to each subject in the model (Table 1). The design of these variables, combined with the NetLogo commands used to write the computer program, constitutes the simulation model.

**Table 1 List of simulation model variables.**

Variable	Description	Categories
<i>max-productivity</i>	Maximum productivity per unit of land	global
<i>num-people</i>	Population of the simulation system	global
<i>percent-arable-land</i>	The amount of arable land is closely related to ecological service functions	global
<i>productivity-growth-interval</i>	Degree of direct government intervention in productivity development	global
<i>grow-productivity</i>	Increase in productivity	
<i>the-poor</i>	Number of poor people	global
<i>the-middle-class</i>	Number of middle-income people	global
<i>the-rich</i>	Number of rich people	global
<i>productivity-here</i>	Land-specific productivity	patches-own
<i>max-productivity-here</i>	Maximum land-specific productivity	patches-own
<i>age</i>	Age of each agent	agent-own
<i>wealth</i>	The amount of income	agent-own
<i>max-wealth</i>	Maximum wealth or income	agent-own
<i>life-expectancy</i>	Life expectancy of each agent	agent-own
<i>life-expectancy-max</i>	Maximum life expectancy of each agent	agent-own
<i>life-expectancy-min</i>	Minimum life expectancy of each agent	agent-own
<i>consumption</i>	Consumption required by each agent to survive	agent-own
<i>consumption-max</i>	The maximum amount of consumption	agent-own
<i>available-opportunities</i>	The number of opportunities available to agents to escape poverty	agent-own
<i>max-available-opportunities</i>	Maximum number of opportunities available to various agents to escape poverty	agent-own



**Fig. 2 NetLogo simulation platform.** The variable control modules are located on the left and can achieve variable control in different scenarios. The results of the simulation scenario are located on the right.

For this research, the NetLogo platform, which can model thousands of individuals, was used to run the simulation. NetLogo can be used to simulate the micro behaviour of agents and the emergence of macro modes, as well as the relationship between the two (see Fig. 2).

**Simulation data source.** We used the Sichuan Liangshan Autonomous Prefecture in China as a research object since the state is one of China’s most impoverished regions. It is located in the southwestern region of China, and of the 17 counties and cities under the state’s jurisdiction, 11 are national key poverty alleviation counties.

Poor villages in the district account for 74.6%, and the proportion of poor households exceeds 25% (Yao, 2019). In 2019, there were 45,533 households in Liangshan Prefecture with an annual per capita net income of less than approximately \$570 (Peng, 2019). Sixty percent of the poor lived in high mountains and canyons, where traffic is blocked, and 249,900 people lived in alpine mountains and severely dry areas (Yuan, 2019) at that time. In Liangshan, having too many children, especially the burden of poverty that having children can bring, was a serious

problem. The increased population was beset with increased poverty in Liangshan, so controlling excessive population growth was a factor in helping the poor of Liangshan escape poverty (Liu, 2018). The evidence indicated that Liangshan Prefecture urgently needed to break through the vicious cycle of ecological vulnerability, low productivity, and poverty.

The initial data for the simulation model primarily came from Liangshan Prefecture, and some variables, for example, the variable *available-opportunities*, were manually controlled and set based on the existing research conclusions. Using these variables, we could design simulation scenarios and observe their impacts on the system. The simulation platform can be used to enable these operations. The use of manual variables, which can be regarded as one of the advantages of multiagent modelling and simulation, has been widely designed (Liu, 2020) (See Table 2).

**Simulation scenarios.** To identify successful breakouts from the ecological vulnerability-low productivity-poverty cycle, we designed scenarios to ascertain the optimal policy portfolio. The scenarios consisted of combinations of the three core regulatory variables while holding the remaining system variables constant.

**Table 2 Initial value and source of variables.**

Variable	Initial value	Source
<i>max-productivity</i>	50	Controlled manually
<i>num-people</i>	483.52 (10,000 people)	Sichuan Statistical Yearbook 2018
<i>percent-arable-land</i>	9.6%	Sichuan Statistical Yearbook 2018
<i>productivity-growth-interval</i>	From 1 to 10	Controlled manually
<i>max-productivity-here</i>	Program random assignment	random-float
<i>age</i>	Program random assignment	random-float
<i>life-expectancy</i>	77.1 years	Report on the Health Status and Major Illnesses of Sichuan's Population 2018
<i>life-expectancy-max</i>	100	Report on the Health Status and Major Illnesses of Sichuan's Population 2018
<i>life-expectancy-min</i>	1	Report on the Health Status and Major Illnesses of Sichuan's Population 2018
<i>the-poor</i>	Program calculation	less than a third of the wealth of the richest agent
<i>the-middle-class</i>	Program calculation	between a third and two thirds the wealth of the richest agent
<i>the-rich</i>	Program calculation	over two thirds the wealth of the richest agent
<i>consumption-max</i>	From 1 to 25	Controlled manually
<i>available-opportunities</i>	From 1 to 15	Controlled manually
<i>max-available-opportunities</i>	From 1 to 15	Controlled manually

**Table 3 The description of different scenarios.**

Variable	Initial scenario	Scenario 1	Scenario 2	Scenario 3
<i>percent-arable-land</i>	9.6%	28.8%	9.6%	9.6%
<i>productivity-growth-interval</i>	2	2	6	2
<i>max-available-opportunities</i>	5	5	5	15

The *percent arable land* variable came from the ecosystem and was used to reflect the impact of ecological vulnerability on productivity. Increases in arable land usually indicate an improvement in the environment. If the ecosystem is very fragile, the arable land area shrinks, and it becomes impossible to recultivate the land, as that would increase its ecological vulnerability. The *productivity-growth-interval* variable was used to reflect the degree of government direct intervention. This variable linked the productivity systems and policies. The *max-available-opportunities* variable was used to reflect the opportunities residents had for escaping poverty, particularly poor farmers with other opportunities to increase their incomes outside of farming. These variables connect the ecological system, productivity growth, and governmental policy. Thus, they reflect the core of the system. The initial scenario consisted of actual values and research assumptions taken from Liangshan.

Scenarios 1 to 3 used of a threefold increase in the three core variables while holding the other variables constant (Table 3). These scenarios resulted in different policy effects. This study employed two indicators for evaluating these effects: (1) the number of poor people and (2) the Gini coefficient. The 50-year simulation cycle collected the data for these two indicators, which the written simulation program automatically calculated.

**Results and discussion**

We used the simulation program to run a 50-year simulation cycle, and we used the number of poor people and the Gini coefficient to evaluate the simulation results for all scenarios. Figure 3 displays the simulation results for Scenario 1.

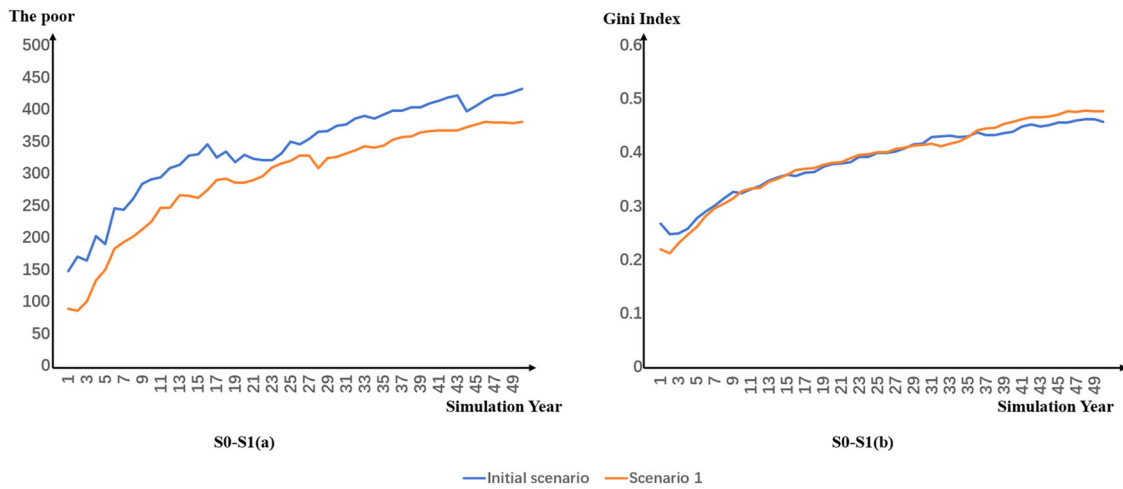
The increase in arable land led to a significant decrease in the number of poor people. Although the number of poor people increased compared to the initial scenario, the increase in arable land increased the number of poor people more slowly. Meanwhile, Levene’s test of the equality of variances was  $F = 0.37$  ( $p = 0.55 > 0.05$ ),  $t = 3.00$  ( $p = 0.00 < 0.05$ ), which indicates a significant difference between the two scenarios. Therefore, increased arable land can support more people, produce more food, and thus help reduce poverty. However, the simulation results revealed no

significant difference in the Gini coefficient between the two scenarios. Levene’s test for equality of variances resulted in  $F = 0.64$  ( $p = 0.43 < 0.05$ ) and  $t = -0.08$  ( $p = 0.93 > 0.05$ ), which indicated no significant difference between the two scenarios. The Gini coefficient in both scenarios displayed an increasing trend, which means that the gap between the rich and the poor expanded throughout the scenarios. Based on the conclusions drawn from running the simulation model, we assessed the reasons behind them. A lack of workers or family members with illnesses who had lost their ability to work are characteristics of some poor households (Novignon et al., 2012). Even if these poor people had more land resources, they could not cultivate such land and thus would not be able to produce enough food. In contrast, healthy households with enough workers would benefit more because they could cultivate additional arable land, which is a dynamic that could widen the gap between the rich and poor.

The simulation results of Scenario 2 revealed that the increased government intervention over the initial scenario did not significantly decrease the number of poor people. Levene’s test for equality of variances resulted in  $F = 0.00$  ( $p = 0.98 > 0.05$ ) and  $t = -0.73$  ( $p = 0.47 > 0.05$ ), which indicates no significant difference between the two scenarios. Further, the Gini coefficients in the two scenarios did not significantly differ. Levene’s test for equality of variances resulted in  $F = 14.94$  ( $p = 0.00 < 0.05$ ) and  $t = -0.878$  ( $p = 0.34 > 0.05$ ) (Fig. 4).

Government intervention policies, such as an exogenous force, must be implemented through the inherent motivation of the poor. The effect of mobilizing the intrinsic motivation of the poor in the quest to reduce poverty became even more important. The effect of a “blood transfusion” intervention policy cannot be sustained. These conclusions are consistent with those of the existing research (Fu, 2016). In particular, poor people often do not completely understand the relevant policies, and coupled with the corruption of some local officials (Hu, 2020), this makes the failure of poverty alleviation policies more likely.

According to the simulation results of Scenario 3, as the number of poverty alleviation opportunities available to the poor increases, the number of poor people and the Gini coefficient



**Fig. 3 Poor population and Gini coefficient after an increase in arable land.** Curves of different colors are used to represent the changes in the poor population and Gini coefficient. The horizontal axis is the simulation year.



**Fig. 4 Poor population and the Gini coefficient following increased direct government intervention.** Curves of different colors are used to represent the changes in the poor population and Gini coefficient. The horizontal axis is the simulation year.

decrease. Scenario 3 had significant differences from the initial scenario. Levene’s test for equality of variances resulted in  $F = 0.034$  ( $p = 0.854 > 0.05$ ) and  $t = 5.33$  ( $p = 0.00 < 0.05$ ) for the poor population in the two scenarios. Comparing the Gini coefficients, Levene’s test for equality of variances resulted in  $F = 6.46$  ( $p = 0.01 < 0.05$ ) and  $t = -4.13$  ( $p = 0.00 < 0.05$ ), which indicated significant differences between the two scenarios (Fig. 5).

There are many reasons for poverty, including illness, loss of work, intellectual disability, or a lack of skills. Therefore, provisioning multiple poverty alleviation options are necessary to meet the poverty alleviation needs of different categories of poor people. Narrowly focused policies, such as providing factory employment opportunities, do not benefit poor people who are incapacitated. Governments can only effectively reduce poverty by providing different poverty alleviation opportunities to deal with the various characteristics of poverty.

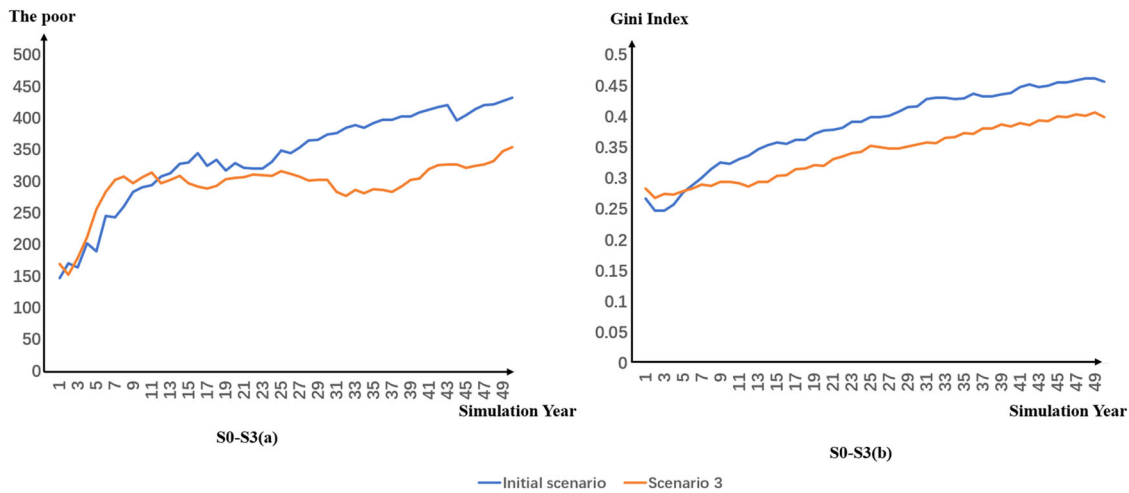
Finally, analysing the different scenarios yields an optimal policy scenario. The ideal values of the three core variables are as follows: *percent arable land* is 28.8%; *productivity-growth interval* is 2; and *max available opportunities* is 15. The simulation results

indicate that the number of poor people and the Gini coefficient decreased, and there were significant differences from the initial scenario. For the poor population, Levene’s test for equality of variances resulted in  $F = 18.27$  ( $p = 0.00 < 0.05$ ) and  $t = 3.76$  ( $p = 0.00 < 0.05$ ). For the Gini coefficient, Levene’s test for equality of variances resulted in  $F = 2.78$  ( $p = 0.01 < 0.05$ ) and  $t = -3.11$  ( $p = 0.00 < 0.05$ ), which indicated that the Gini coefficients between the two scenarios were significantly different (Fig. 6).

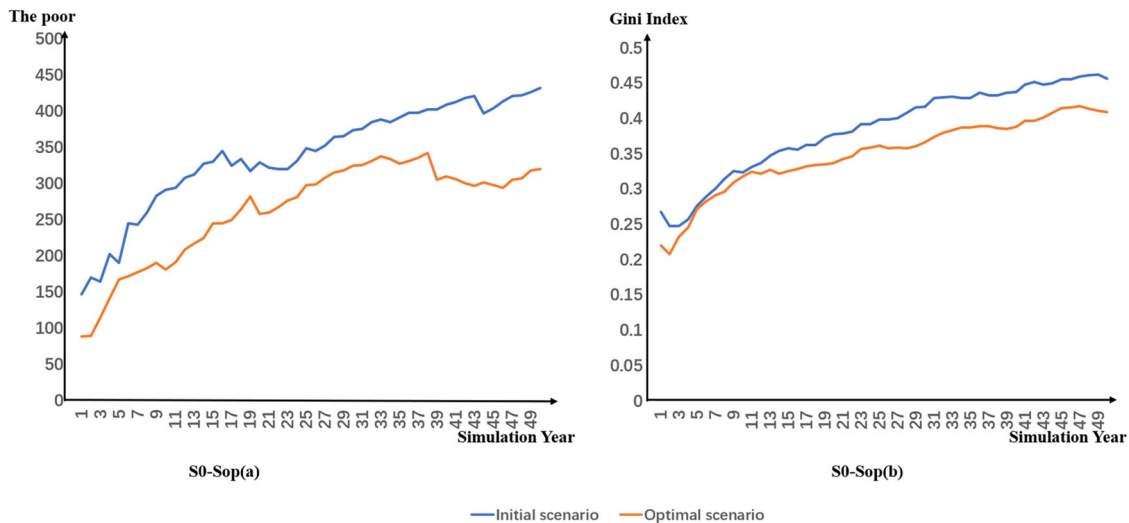
Thus, the optimal policy choice would be to increase the area of arable land and create a variety of opportunities for poverty alleviation while at the same time reducing the direct intervention of external forces such as the government.

**Conclusions and policy recommendations**

Utilizing multiagent modelling and simulation, we devised a method to break through the vicious cycle of ecological vulnerability-low productivity-poverty. Employing representative poverty-stricken areas in China as examples, we designed five policy scenarios and evaluated the effects of those policies by



**Fig. 5 Poor population and the Gini coefficient with increased poverty alleviation opportunities.** Curves of different colors are used to represent the changes in the poor population and Gini coefficient. The horizontal axis is the simulation year.



**Fig. 6 Poor population and the Gini coefficient in the optimal scenario.** Curves of different colors are used to represent the changes in the poor population and Gini coefficient. The horizontal axis is the simulation year.

examining how they influenced the number of poor people and the Gini coefficient. The policy simulation period was set to a 50-year cycle. The simulation results reveal that increased arable land decreased the number of poor people. However, compared with the initial scenario, there was no significant difference in the Gini coefficient. Other simulation results indicate that increasing the level of direct government intervention did not decrease the number of poor people, nor did it change the Gini coefficient. However, as the number of poverty alleviation opportunities available to the poor increased, the number of poor people and the Gini coefficient both decreased. The optimal policy scenario was obtained by combining the results of these different scenarios. The simulation results indicate that the number of poor people and the Gini coefficient significantly decreased from the initial scenario. Therefore, the optimal policy choice would be to increase the amount of arable land and the variety of opportunities for poverty alleviation while reducing the direct intervention of government.

The research findings presented in this study are valuable for policy-makers seeking to help impoverished areas break the cycle of ecological vulnerability, low productivity, and poverty.

One key implication is the need to increase the amount of arable land in these regions, which requires restoring degraded ecosystems to improve their productivity and suitability for farming. Taking measures such as planting trees, digging irrigation canals, desalinizing soil, and insulating against extreme temperatures can help achieve this goal. According to the simulation results, although this policy may not benefit families without sufficient labour resources, it can benefit those with a sufficient labour force.

Next, the government should provide a wider variety of poverty alleviation opportunities. Diverse opportunities enable poor people to choose those that best suit their characteristics and skills, thereby increasing their incomes. For this reason, building factories at the expense of the local environment is not the best option, even though it can increase local employment numbers. The government should provide other opportunities for the poor, such as through the development of quality agricultural products or training poor individuals for online sales. Since some of these areas have high mountains and unique flora and fauna, the government can help such areas develop tourism. The government can provide subsidies or interest-free loans for these areas,



and the money can be used to build family hotels or agricultural product stores.

The result also indicates that it is necessary to eliminate inappropriate external interventions, such as those by local governments. Government intervention cannot replace the inherent motivation of the poor. Mobilizing poor people's inner motivations and providing them with targeted opportunities can enable a satisfactory result in the quest for poverty alleviation. In this way, the poor can become self-reliant. The government can choose some people who have successfully lifted themselves out of poverty for publicity. These people, who received government support, were able to escape poverty and sustain a stable income through their own efforts. Through these incentives, full play can be given to the enthusiasm for eliminating poverty rather than a sole reliance on government relief funds. It is worth noting that these policies do not work unilaterally, nor do they act alone. To break this vicious cycle, these policies must be combined and coordinated so that they can work together.

This study has some limitations. The simulated model did not include every influencing factor. Further, it only analysed the situations in poor regions, and further research should include more samples for a more targeted analysis. Nevertheless, the conclusions have significant value for promoting poverty alleviation while protecting the ecological environment.

### Data accessibility statement

This research involves the analysis of data, and the data are already included in the article.

Received: 28 December 2022; Accepted: 29 August 2023;

Published online: 19 September 2023

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### Author contributions

YL provided substantial contributions to the conception or design of the work. CHL provided oversight and contributed to the writing of the manuscript.

### Competing interests

The authors declare no competing interests.

### Ethics approval

This article does not contain any studies using human participants.

### Informed consent

This article does not contain any studies using human participants.

### Additional information

**Correspondence** and requests for materials should be addressed to Yong Liu.

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