Land use optimization by integrating GLP and CLUE-S model to control land degradation risk in mountainous area of Southwest China

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Abstract. Large-scale artificial plantations in mountainous areas of Southwest China have changed land use status and aggravated land degradation risk (LDR). This study taking Menglian County as an example, optimizes land use in 2025 to reduce the regional LDR, by integrating Grey Linear Programming (GLP) and CLUE-S model. Results showed that: The high-risk and medium-risk levels are main LDR types in Menglian County, accounting for 56.36% of total area. The regions with high LDR consistent with the distribution of concentrated garden land and cultivated land. The regions with low LDR consistent with the forestland. While the distribution of medium-risk regions relates to small plots garden land and cultivated land. In the optimization results, the LDR reduced 461.80, 168.95 and 34.23 in three schemes respectively, comparing to 2015. Thereinto, the strict-demand scheme has good applicability and guidance for study area relatively, in which the LDR is reduced while ensuring sustainable development. After spatial allocation, garden land, cultivated land, forestland and construction land tend to be centralized. It is effective for solving the optimal problem of mountainous land resource by integrating GLP and CLUE-S. The methods and results can provide a scientific reference for controlling LDR in mountainous area in Southwest China.

Keywords: Quantitative Structure, Spatial Allocation, Model Precision, Regions With Large-Scale Artificial Plantations, Menglian

1. Introduction

Land resource is a significant component of geographic environment and an essential carrier for human survival and development [1]. With the rapid progress of social economy, the land demand is more intense [2]. Thus, the rational and efficient use of land resource has become an urgent issue [3]. At the past, socio-economic development often came at the land expense [4]. Moreover, due to the situation of more people and less land, the contradiction is more serious between land supply and demand [5, 6]. Optimizing and adjusting the limited land resource is essential to relieve the economic, social, and ecological pressures [7, 8]. Therefore, land use optimization has attracted the attention of many scholars, aiming at alleviating the land use problems [9]. It can often improve the land-use
efficiency and maintain the dynamic balance of land ecosystem, and finally realize the sustainable use of land resource.

Land degradation is an important part of land resource research, mainly causing by the unreasonable land use [10-12]. It is a continuous decline in land productivity over a long period, due to the poor management of natural capital, such as land, soil, water and forest [13, 14]. Since the 21th century, with the rapid development and urbanization, unreasonable land use has led to aggravation of land degradation. It threatens the sustainable development of mankind and nature [15]. Therefore, the study of land degradation risk (LDR) is concerned, and the LDR control has become an important task of sustainable development [16, 17].

In particular, the ecological environment is fragile and the economic development is backward in the mountainous area of Southwest China. Driven by economic benefits, a large-scale artificial plantations (such as rubber, tea, coffee, eucalyptus, etc.) are introduced to support socioeconomic development. These plantations have replaced local cultivated land and natural forests in recent years, leading to significant land use changes [18]. It inevitably affects regional conditions of biodiversity, soil, ecology, environment and climate [19-21], aggravating the LDR and threatening the sustainable development. Meanwhile, with growth of population and economy, the expansion of construction land has also caused big changes in land use over the past few decades. As a result, conflicts of interests among artificial plantations demand, construction land expansion, cultivated land conservation and ecological environment protection have intensified [22-25]. Therefore, it is necessary to prevent the exacerbation of land degradation and promote the coordinated development of various land-use types in the regions.

Land use optimization is an important way to coordinate regional land use and the interests of beneficiaries [9]. Based on the identification of quantitative relationship between land use and LDR, land use optimization can be a good way for controlling LDR and coordinating land use structure. This is conducive for guiding local managers to formulate policies and restrain the unsustainable land use behavior of enterprises and farmers. However, there is no research on land use optimization from the perspective of controlling LDR in mountainous area with large-scale artificial plantations. Thus, it is important to do this work.

At present, researches on land use quantitative optimization have made some progress. The methods mainly include Linear Programming [26, 27], Multi-objective Programming [28, 29], Grey Linear Programming (GLP) [30, 31], System Dynamics [32], and so on. With the rapid development of GIS and RS technologies, more and more scholars focus on land use spatial allocation. The methods of land use spatial allocation are mostly based on mathematical models, such as Simulated Annealing [33], Genetic Algorithms [34, 35], Particle Swarm [36], Cellular Automata [37, 38], the Conversion of Land Use and its Effects at Small Regional Extent (CLUE-S) model [30, 39], and other technologies [40, 41]. These methods provide references for this study. Land degradation has strong spatial characteristics. In order to effectively control LDR, it is necessary to optimize land use from the aspects of quantitative structure and spatial pattern [42]. In these methods, the gray and flexible characteristics in GLP is suitable for the land use planning on complex environment of mountainous area. It can correspond to the land use spatial allocation more accurately [30]. And the CLUE-S model with the driving mechanism and empirical statistical principles can simulate the temporal and spatial dynamic changes of regional land use [30, 43]. Integrating GLP and CLUE-S model can not only optimize the land use quantitative structure and spatial pattern, but also effectively combine the actual situation in the region to improve the accuracy and application value of model operations.

Thus, in this study, we are committed to achieving two objectives: 1) Optimizing land use in 2025 to decrease the LDR in mountainous areas of Southwest China; 2) Exploring the optimization effect by integrating GLP and CLUE-S model in both quantitative and spatial sides. The Menglian County in Yunnan Province, a typical mountainous area with large-scale plantations of Southwest China, is chosen as the study area. Based on the evaluated LDR value of Menglian County, the land use quantitative structure is optimized to minimize LDR by GLP model. Then, its results are used as constraint conditions (land use demands) in the CLUE-S model to allocate the land use spatial pattern,
intending to achieve the objectives. The results can provide scientific reference for local government to use land resource and control LDR.

2. Data and Methods

2.1. Study area
Menglian County is located in Pu’er City, Yunnan Province, Southwest China, with 133.4 km of border with Myanmar. It consists of six towns with total area about 189338 ha (Figure 1). The county is a mountainous area, ranging the elevation from 497 to 2603 m. It is influenced by subtropical oceanic monsoons. The mean annual temperature is about 19 ℃; the mean annual precipitation is about 1373 mm. With rapid socio-economic growth, the county’s GDP reached ¥ 3.05×10^9 and population had already been more than 1.31×10^5 people in 2018; and GDP per capita increased from ¥ 2470 in 2000 to ¥ 23282 in 2018.

From 2000 to 2015, the area of garden land in Menglian County has increased by 24478.85 ha, of which rubber plantations, tea plantations, coffee plantations and eucalyptus plantations are the main ones. This has taken up a lot of local forests and farmlands to some extent.

![Figure 1. The location of study area.](image)

2.2. Data acquisition and processing
The basic data includes remote sensing data of Landsat TM, Digital Elevation Model (DEM) data, soil data, climate data, Statistical Bulletins of Menglian County (from 2001 to 2013), Land Use General Planning in Menglian County (2010-2020) (hereinafter referred to as General Planning), Land Renovation Planning in Menglian County (2011-2015), Urban System Planning in Pu’er City (2007-2020), etc. Among them, the TM and DEM data were downloaded from Geospatial Data Cloud (http://www.gscloud.cn/); the soil data of whole county were got by interpolation from 69 sampling
points which collected by fieldwork in 2015; the climate data were collected from National Meteorological Information Center (http://data.cma.cn/); the Statistical Bulletins and plannings were collected from Statistical Bureau, Land Resources Bureau and Urban-rural Construction Bureau of Mengliang County respectively. The other data, such as land use data, topographic data and vegetation data, were got by processing from the above basic data.

2.3. Research framework and methods

According to land use characteristics and demands of General Planning of Menglian County, the land is divided into eight types in this study, including cultivated land ($x_1$), garden land ($x_2$), forestland ($x_3$), grassland ($x_4$), other agricultural land ($x_5$), construction land ($x_6$), waters ($x_7$), and unutilized land ($x_8$). Among them, the garden land ($x_2$) mainly includes the rubber plantations, tea plantations, coffee plantations and eucalyptus plantations which planted artificially on a large area since 2000, while the forestland ($x_3$) is mainly the local native evergreen broad-leaved forest and coniferous forest. Through the evaluation of LDR, we explore the LDR situation of each land-use type. Then, the average LDR value of each land-use type is used as the variable constraint coefficient of objective function in GLP to optimize the land use quantitative structure of Menglian County in 2025. The optimal result is set as land use demands in CLUE-S model to allocate the land use spatial pattern (Figure 2).

Figure 2. Research Framework.

2.3.1. Evaluation of LDR. By using the Bibliometric Method based on approaches of document search and statistical analysis [44], the important indexes can be selected from the previous researches. And the weight of each index is calculated based on the comprehensive application rate. The value of LDR is calculated by Weighted Sum Method. The calculating formula is:
where $L$ is the evaluated result of LDR; $Q_i$ is the risk valuation of land degradation of $i$-th index; $P_i$ is weight of $i$-th index; $A_i$ is the comprehensive adoption rate of $i$-th index; $F_{ci}$ and $F_{ei}$ is the adoption frequency of $i$-th index in Chinese and English researches respectively; $T_{ci}$ and $T_{ei}$ is the total number of relative literature in Chinese and English researches respectively; $n$ is total number of indexes.

Domestic and abroad research related to LDR, a total of 546 after 1980, are reviewed comprehensively. There are ten indexes mainly used to study the LDR: vegetation coverage, soil organic matter, slope, economy-income level, soil moisture content, land-use types, background value of soil element, soil texture, agricultural productivity, precipitation. The adoption rate of these indexes is showed in Table 1. So the index system can be built by choosing some of these indexes. First, from the actual situation, Menglian County is a mountainous area, with low level of economic development, and has long been dominated by agriculture. Thus, natural factors have a more influence than socioeconomic factors on development. Second, the objective of this study is land use optimization in 2025. It is inappropriate to set land-use types as a index. Third, the background value of soil elements, agricultural productivity and soil organic matter can all reflect soil fertility. There is a strong correlation between them, so the two indexes with low adoption rate is eliminated. To sum up, after removing unnecessary indexes, six indexes are selected from high-frequency indexes: vegetation coverage, soil organic matter, slope, soil moisture content, soil texture and annual precipitation. Meanwhile, according to the adoption rate and Eq.1, the weights of selected indexes are calculated (Table 1).

### Table 1. Indexes statistics and weights calculation.

| Indexes                  | Vegetation coverage | Soil organic matter | Slope   | Economy-income level | Soil moisture content |
|--------------------------|---------------------|---------------------|---------|----------------------|----------------------|
| $F_{ci}$                 | 128                 | 59                  | 50      | 48                   | 42                   |
| $F_{ei}$                 | 39                  | 9                   | 9       | 3                    | 4                    |
| $A_i$                    | 64.81%              | 21.71%              | 19.65%  | 13.74%               | 13.27%               |
| $P_i$                    | 0.463               | 0.155               | 0.140   | Eliminated           | 0.095                |
| **Indexes**              | **Land-use types**  | **Background value of soil element** | **Soil texture** | **Agricultural productivity** | **Precipitation** |
| $F_{ci}$                 | 40                  | 37                  | 29      | 33                   | 28                   |
| $F_{ei}$                 | 4                   | 4                   | 5       | 3                    | 4                    |
| $A_i$                    | 12.81%              | 12.12%              | 10.44%  | 10.30%               | 10.06%               |
| $P_i$                    | Eliminated          | Eliminated          | 0.075   | Eliminated           | 0.072                |

2.3.2. Building GLP model. The year 2015 and 2025 is set as the base year and planning year respectively in the land use optimization. In this study, GLP model is used to optimize land use quantitative structure by taking the minimization of LDR value as the objective function. The GLP model is as follows [30]:

$$
L = \sum_{i=1}^{n} Q_i \times P_i
$$

$$
P_i = \frac{A_i}{\sum_{i=1}^{n} A_i}
$$

$$
A_i = \left( \frac{F_{ci}}{T_{ci}} + \frac{F_{ei}}{T_{ei}} \right) \times 100\%
$$

(Eq.1)
where \( f(x) \) is the objective function, the value of \( f(x) \) means comprehensive risk degree of regional land degradation. The smaller the value of \( f(x) \) is, the smaller the regional LDR is and the higher the ecological benefits of the land are. Furthermore, \( c_j \) is the LDR coefficient of decision variable \( j \), that is the average LDR value of each land-use type \( j \); \( x_j \) is the decision variable which means the land use \( j \) in this study. The resulting matrix \( \{x_j\} \) is called the optimum solution, which is the optimum land use structure; \( a_{ij} \) is the constraint coefficient, which is the decision variable coefficient; \( b_j \) is the constraint constant, which is the resource limited quantity; \( m \) is the number of constraint equations; and \( v \) is the number of decision variables.

The GLP model includes objective function and constraint conditions:

(1) Objective function.

Based on the GLP model, the eight land-use types are set as the decision variable (Table 2). The average LDR value of each land-use type is used as the variable constraint coefficient of objective function (refers to evaluation results of LDR in part 3.1 below):

\[
f(x) = \sum_{j=1}^{8} c_j x_j \to \min
\]

\[
\sum_{i=1}^{m} a_{ij} x_j \leq (\leq) b_i (i = 1, 2, 3, ..., m) \quad (Eq. 2)
\]

\[x_j \geq 0 (j = 1, 2, 3, ..., n)\]

(2) Constraint conditions.

There are ten constraints according to the real situation and requirements from perspective of food security, geographic features, land use systems and General Planning.

A. Constraint of total area:

\[
x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 = 189339.0 \text{ ha.}
\]

B. Constraint of cultivated land:

Based on statistical data from 2001 to 2015, the population in 2025 is predicted by the Linear Fitting Method and Grey System Model GM(1,1). The forecasting result is 148000 and 153500 respectively. Thus, the Grey Range of total population in 2025 is set as [148000, 159300]. Then, based

| Land-use types            | Year 2015 |            |
|---------------------------|-----------|------------|
|                           | Area (ha) | Percentage (%) |
| Cultivated land \((x_1)\) | 35573.00  | 18.79%     |
| Garden land \((x_2)\)    | 28242.00  | 14.92%     |
| Forestland \((x_3)\)     | 106250.00 | 56.12%     |
| Grassland \((x_4)\)      | 9.00      | 0.0048%    |
| Other agricultural land \((x_5)\) | 11765.00 | 6.21%     |
| Construction land \((x_6)\) | 3129.00  | 1.65%     |
| Waters \((x_7)\)         | 1326.00   | 0.70%      |
| Unutilized land \((x_8)\) | 3044.00   | 1.61%     |
| Total area                | 189338.00 | 100.00%    |

Based on statistical data from 2001 to 2015, the population in 2025 is predicted by the Linear Fitting Method and Grey System Model GM(1,1). The forecasting result is 148000 and 153500 respectively. Thus, the Grey Range of total population in 2025 is set as [148000, 159300]. Then, based
on cultivated land protection and food security, three schemes (standard-demand, strict-demand and policy-oriented) are set up to represent the cultivated land change.

b1. Demand-oriented constraint of cultivated land:

The grain production mainly meets the self-development demand in mountainous area. To reach the target of self-sufficiency, the grain yield need to be more than the food demand of total population in 2025:

\[ b \times x_1 \times f_r \times f_0 \geq S \times P \]  

(Eq. 3)

where \( b \) is the per unit area yield of grain; \( f_r \) is the proportionality coefficient of grain crops to all crops; \( f_0 \) is the multiple-cropping index; \( S \) is the standard of per capita grain consumption; and \( P \) is the total population in the planning year.

Based on the statistic data from 2001 to 2015, the values of \( b, f_r, \) and \( f_0 \) in 2025 are predicted by the Linear Fitting Method. Meanwhile, Jia et al. indicated that the value of \( S \) would be per capita 410-430 kg in 2025 by predicting with dietary structure and nutrition standards [45]. Therefore, the demand-oriented constraints of cultivated land could be divided into two schemes:

Standard-demand scheme (Scheme I). The \( b, f_r, \) and \( f_0 \) all used the predicted values, and \( S \) is set as 420 kg per capita. The predicted value of the total population is [148000, 159300]. The cultivated land demand range is [20853.5, 22445.7] ha which is calculated by using the Eq.3, far less than the current 35573.00 ha of cultivated land area in Menglian County. The constraint condition of cultivated land area is set as:

\[ x_1 \geq 20853.5 \text{ ha}. \]

Strict-demand scheme (Scheme II). The \( b, f_r, \) and \( f_0 \) all used the annual average value from 2001 to 2015, and the \( S \) used the highest standard of per capita food demand (430 kg per capita). The population is set as the biggest result (159300) of the population prediction. In total, the cultivated land demand is 30267.80 ha. The constraint condition of cultivated land area is set as:

\[ x_1 \geq 30267.8 \text{ ha}. \]

b2. Policy-oriented scheme (Scheme III):

Strict protection for cultivated land is a basic state policy of China. So, the cultivated land quantity of Menglian County shall not be lower than the target set by the government in General Planning.

\[ x_1 \geq 37799.0 \text{ ha}. \]

C. Constraint of construction land:

With the development of society, economy and urbanization, the construction land of Menglian County will increase undoubtedly. The area of construction land was 3129.0 ha and the per capita area of construction land was 232.12 sq.m. in 2015. In consideration of Grey Range of total population, if it is necessary that the per capita area of construction land need be nondecreasing, the range of construction land would range in [3435.1, 3697.6] ha in 2025. But according to General Planning, the construction land needed be controlled under 3697.6 ha. In general, to meet the human demands and policy control, the constraint of construction land is set as:

\[ 3435.4 \text{ ha} \leq x_6 \leq 3697.6 \text{ ha}. \]

D. Constraint of unutilized land:

The unutilized land was 3044.0 ha in 2015. It mainly contained wild grassland and bare land. According to the General Planning, the area of unutilized land is 2525.2 ha in 2025. While according to the Land renovation planning in Menglian County, there are 600 ha unutilized land which will be managed and used based on the area of base year. Namely, it could be decreased to 2444.0 ha in 2025. So the constraint of unutilized land is set as:

\[ 2444.0 \text{ ha} \leq x_8 \leq 2525.2 \text{ ha}. \]

E. Constraint of other land-use types:

The constraints of other land-use types mainly reference to the General Planning.

\[ x_7 \geq 25459.4 \text{ ha}. \]

\[ x_8 \geq 106191.3 \text{ ha}. \]
8

$$x_1 = 9.0 \text{ ha.}$$

$$x_5 = 11738.5 \text{ ha.}$$

$$x_7 = 1326.0 \text{ ha.}$$

F. Constraint of model requirements:

$$x_i \geq 0 \ (i = 1, 2, ..., 8).$$

2.3.3. Building CLUE-S model. The CLUE-S model is applicable to a smaller scale. The model realizes the synchronous simulation of different land-use types and their competitive relationships using system theory [46]. The CLUE-S model contains two modules: spatial part and non-spatial part. The non-spatial part is a demands calculation of land use. The spatial part is a spatial allocation process for land use demands according to the total probability of land distribution suitability on raster data, which considers land use distribution current situation, land use demand, land transfer rule, policies and restrictions (Figure 2).

1) Land use demands.

The CLUE-S model requires the data of the "land use demand" which calculated by the other models. In this study, we use GLP to get the data of "land use demand".

2) Land suitability.

The spatial allocation process of the CLUE-S model is based on the land suitability of each land-use type at a specific region. The land suitability is affected by the correlations between driving factors and current land use situation. This study used the Binary Logistic Regression Model (BLRM) to find the correlations [18], and then determined the quantitative relationship between the main factors and the spatial distribution of each land-use type. The equation of BLRM is:

$$\log \left[ \frac{P_i}{1 - P_i} \right] = \beta_0 + \beta_1 V_1 + \beta_2 V_2 + ... + \beta_n V_n$$

(Eq. 4)

where $$P_i$$ is the probability that land-use type $$i$$ appears at the grid (i.e. land suitability), $$V_i$$ is the driving factors, $$\beta_0$$ is the constant term of the logistic regression results, and $$\beta_i$$ ($$i = 1, 2, ..., n$$) is the partial regression coefficient of logistic regression (beta coefficient). The probability that a certain land-use type appears in each grid unit is diagnosed using binary logistic stepwise regression.

A. Selection of driving factors.

Menglian County is a mountainous area with complex topography and its economy is dominated by agriculture. Therefore, natural factors play a key role in spatial distribution of land use. Thus, eight natural driving factors (including slope, elevation, precipitation, soil organic matter, distance to the main roads, distance to the rivers and distance to the waters) and three human driving factors (including distance to the rural settlements, distance to the county town and distance to the towns) are selected.

B. Establishment of binary logistic regression equation.

The Beta Coefficient $$\beta_i$$ and the Constant $$\beta_0$$ between each land-use type and the driving factors are determined using logistic regression statistical analysis (Table 3). We used the Relative Operating Characteristics (ROC) method to test the logistic regression results [47]. As the Table 3 shows, the ROC values are all higher than 0.7 except the unutilized land (0.688). The results indicated that the results of logistic regression are acceptable, and the selected driving factors of spatial distribution are effective.

C. Suitability of each land-use type (probability).

The $$\beta$$ of each land-use type in Table 3 is substituted into the Eq.4 and the regression equations of spatial distribution probability in 2025 could be calculated. The regression equation file and the drive factor file are loaded into the working directory of the CLUE-S model to acquire the spatial distribution probability map (Figure 3).
Table 3. Results of BLRM and ROC Test.

| Driving factors                  | Beta coefficient $\beta$ |
|----------------------------------|--------------------------|
|                                  | Cultivated land and other agricultural land | Garden land | Forestland | Construction land | Unutilized land | Waters |
| Slope                            | -0.01604331              | -0.01095579  | 0.02491604 | -0.02967125       | —               | 0.09425512 |
| Aspect                           | 0.00039955               | —            | -0.00030989| —                 | —               | —         |
| Elevation                        | -0.00072153              | -0.00260765  | 0.00020854 | 0.00059663        | 0.00139263      | -0.00786481 |
| Precipitation                    | 0.00167444               | -0.00263542  | —          | -0.00069543       | -0.00081968     | 0.00549771 |
| Soil organic matter              | 0.04558894               | -0.06353271  | -0.00624491| —                 | 0.04652638      | —         |
| Distance to the main roads       | -0.00004608              | -0.00014973  | 0.00013508 | -0.00021389       | -0.00023563     | -0.00339518 |
| Distance to the rivers           | -0.00040545              | -0.00012450  | 0.00019028 | 0.00060286        | -0.00035849     | —         |
| Distance to the waters           | -0.00004208              | 0.00008880   | -0.00001623| -0.00012435       | 0.00015368      | -0.11349806 |
| Distance to the rural settlements| -0.00074872              | -0.00070474  | 0.0008552  | -0.00761736       | 0.00012028      | —         |
| Distance to the county town      | -0.00004601              | 0.00007024   | -0.00001304| —                 | 0.00001650      | —         |
| Distance to the towns            | -0.00008181              | 0.00008814   | -0.00001547| —                 | 0.00004076      | -0.00024579 |
| Constant $\beta_0$              | -1.55999662              | 5.70181409   | -3.17226516| -0.09951263       | -7.40189510     | 1.71920622 |
| ROC testing results              | 0.752                    | 0.857        | 0.783      | 0.922             | 0.688           | 1.000     |

Note: ‘—’ means that the regression value of the variable is eliminated.

(3) Rule of land use transition.

The possibility of transition between different land-use types is diverse. The CLUE-S model needs the rule of land use transition. It includes the transition matrix and elastic range of land use transition. The transition matrix of land use is set up for the transfer ability among different land-use types. It is coded as 0 if the transition is not permitted between two land-use types (one-way transition). On the contrary, it is coded as 1 if the transition is permitted. According to the General Planning and field survey, there is no water conservancy projects in recent years in Menglian County. Thus, the waters would have no change during the planning period. Therefore, it is coded as 0 between waters and other land-use types (Table 4).

The elasticity of land use transition (ELA) ranges from 0 and 1 which evaluates the stability of the land use transition. The higher the ELA value is, the more stable the land-use type is in the CLUE-S model. Namely, one land-use type has less possibility transfer to other land-use types if its elasticity is high. According to the present land use situation, historical land use transition, regional developing strategy, related literature data [48, 49], the opinion of local land management departments and the provincial experts, the elasticity of land use transition is set in Table 4.
Table 4. Transition matrix and elasticity of land use.

| Land-use types | Cultivated land and other agricultural land | Garden land | Forestland | Construction land | Unutilized land | Waters |
|----------------|---------------------------------------------|-------------|------------|-------------------|-----------------|--------|
| Cultivated land and other agricultural land | 1 | 1 | 1 | 1 | 1 | 0 |
| Garden land | 1 | 1 | 1 | 1 | 1 | 0 |
| Forestland | 1 | 1 | 1 | 1 | 1 | 0 |
| Construction land | 1 | 1 | 1 | 1 | 1 | 0 |
| Unutilized land | 1 | 1 | 1 | 1 | 1 | 0 |
| Waters | 0 | 0 | 0 | 0 | 0 | 0 |
| Elasticity (ELA) | 0.9 | 0.7 | 0.8 | 0.9 | 0.5 | 1 |

Figure 3. The suitability of spatial distribution of each land-use type.

(4) Setting of spatial restrictions.

To protect ecological sources, high quality cultivated land and natural pasture, the government set up some control areas, such as nature reserves, basic farmlands, and natural pastures. These areas are not allowed to use for other purposes.

A. Ecological security-controlled areas. These regions must be specially controlled for land use based on the maintenance of ecological and environmental security. For example, water reservoirs are set as ecological security control areas to protect water sources and environment.
B. Basic farmland protection areas. To guarantee food security and protect cultivated land resources with high quality, basic farmland protection areas are set as restricted regions to provide special protection.

C. Natural pasture controlled areas. The natural pasture areas (e.g. grassland) of Menglian County had only 9.0 ha which accounting only 0.0048% of the total area and had remained unchanged during the planning period. Thus, grasslands are restricted regions, which will ensure the area and the spatial position remains unchanged during the planning period.

3. Results

3.1. Evaluation results of LDR
Based on weighted sum method and overlay analysis of GIS, the spatial evaluation results of LDR are calculated (Figure 4a). There is no land degradation in waters which are not involved in the LDR assessment. The LDR value is divided into five classes in Menglian County by natural breaking method: lowest-risk region, low-risk region, medium-risk region, high-risk region and highest-risk regions (Figure 4b).

![Figure 4. Evaluation Results of LDR: (a) Evaluation Results; (b) Classification of LDR.](image)

The LDR in the county is mainly medium-risk and high-risk level, accounting for 56.36% of total area. The low-risk and highest-risk region had not much difference in area, accounting for 19.50% and 16.82% of total area respectively. The area of lowest-risk region is the smallest. It only accounted for 7.32% of total area. The area of the lower LDR region, such as the lowest-risk and low-risk region, is much less than the area of the higher LDR region, such as the high-risk and highest-risk region. It indicated that the situation of LDR is not optimistic in the county (Table 5).

In terms of space, the lowest-risk and low-risk regions are mainly distributed in the midwest and southern areas of the county. Most of lowest-risk regions are in Fuyan Town and Mengma Town. These areas are dominated by forestland with higher vegetation coverage. The distribution of medium-risk regions is sporadic. They are distributed in most areas in the county irregularly and the area in each town is equal approximately. This is related to the small plots of garden land and cultivated land. The high-risk and highest-risk regions are mainly distributed in western and eastern areas of the county, where mainly located in Mengma Town and Gongxin Town. The western part is dominated by garden land, and the eastern part with high LDR is mainly consistent with the distribution of cultivated land (Figure 4).
Table 5. Area ratio and average LDR value of each land-use type.

| Area Ratio and Average LDR Value | The whole county | Cultivated land | Construction land | Land-use types | Forestland | Grassland | Garden land | Unutilized land |
|--------------------------------|------------------|----------------|------------------|---------------|------------|-----------|------------|----------------|
| Lowest-risk region             | 7.32%            | 3.45%          | 3.04%            | 10.54%        | 0.00%      | 2.39%     | 12.00%     |                |
| Low-risk region                | 19.50%           | 14.07%         | 9.00%            | 25.85%        | 20.82%     | 6.32%     | 28.24%     |                |
| Medium-risk region             | 26.36%           | 26.31%         | 20.01%           | 28.70%        | 79.18%     | 18.78%    | 25.49%     |                |
| High-risk region               | 30.00%           | 35.85%         | 32.58%           | 23.07%        | 0.00%      | 45.30%    | 21.95%     |                |
| Highest-risk region            | 16.82%           | 20.32%         | 35.37%           | 11.84%        | 0.00%      | 27.21%    | 12.32%     |                |
| Average LDR value              | 0.440019         | 0.457553       | 0.470813         | 0.420680      | 0.424621   | 0.477909  | 0.442318 |

In terms of land-use types, according to the evaluation results, the average LDR value of land-use types is calculated. The waters had no land degradation and the other agricultural land did not reach the drawing standard. So, they are not participated in evaluation of LDR. And the average value of land-use types is showed in Table 5. The LDR of forestland is the smallest. Most of forestland are in medium-risk region, accounting for 28.70% of total area of forestland. The forestland’s area is decreasing gradually with the LDR increasing or decreasing. Secondly, the average LDR value of grassland is also low. The grassland only distributed in medium-risk and low-risk region, accounting for 79.12% and 20.82% respectively. The unutilized land and cultivated land are mainly located in medium-risk, high-risk and low-risk regions. And the construction land and garden land are main located in high-risk and highest-risk regions. The average LDR value of garden land is the biggest (Table 5). This is consistent with the spatial distribution of LDR and land use status.

3.2. Land-use quantitative optimization

According to the GLP model, three optimal schemes of land use structure have been designed (Table 6). Comparing with the present situation of land use and General Planning, the LDR value will decrease in the three scenarios. In terms of land use quantitative change, all construction lands can increase 568.60 ha by comparing with land use situation in 2015 and had 283.60 ha more than General Planning. Unutilized land will have 600 ha less than base year and 81.20 ha less than the General Planning. The land utilization rate will be higher. Grassland and waters remain the original area in 2015. Other agricultural lands will be the same as the General Planning, only reduce 26.50 ha from the base year. All the schemes have certain advantages compared with General Planning in the LDR reduction effect and land utilization efficiency.

The LDR showed the greatest reduction in Scheme I, which is up to 461.80. It could meet the food demand in normal condition but is insufficient to prevent food security problems caused by sudden natural disasters. Scheme II could have 168.95 reductions of LDR. In scheme III, the LDR situation could decrease only 34.23. The improvement for decreasing LDR is not dramatic. Compared with schemes I, the cultivated land is enough for food supply in scheme II. Although the area of cultivated land is less than that of scheme III, it also meets a strict demand for cultivated land and ensures local self-sufficiency in food. Meanwhile, forestland has 5363.10 ha more than base year, and the proportion increasing 5.05%, which means the ecological and environmental quality would be maintained. The area of garden land is the same as that of base year, which would be helpful to maintain the economic development in Menglian County.

In addition, scheme II has a better balance of different interests. Therefore, it is selected as the quantitative optimization scheme and putted into the CLUE-S model for spatial optimization.
Table 6. Optimal Schemes and LDR Situation after optimization.

| Land-use types       | Year 2015 | General planning | Scheme I: Standard-demand | Scheme II: Strict-demand | Scheme III: Policy-oriented |
|----------------------|-----------|------------------|---------------------------|-------------------------|-----------------------------|
|                      | Year 2025 |                  |                           |                         |                             |
| Cultivated land ($x_1$) | 35573.00  | 38675.30         | 22325.65                  | 30267.80                | 37799.00                    |
| Garden land ($x_2$)   | 28242.00  | 25459.00         | 28242.00                  | 28242.00                | 25743.60                    |
| Forestland ($x_3$)    | 106250.00 | 106191.00        | 119555.25                 | 111613.10               | 106580.30                   |
| Grassland ($x_4$)     | 9.00      | 9.00             | 9.00                      | 9.00                    | 9.00                        |
| Other agricultural land ($x_5$) | 11765.00 | 11738.50         | 11738.50                  | 11738.50                | 11738.50                    |
| Construction land ($x_6$) | 3129.00  | 3414.00          | 3697.60                   | 3697.60                 | 3697.60                     |
| Waters ($x_7$)        | 1326.00   | 1326.00          | 1326.00                   | 1326.00                 | 1326.00                     |
| Unutilized land ($x_8$) | 3044.00  | 2525.20          | 2444.00                   | 2444.00                 | 2444.00                     |
| LDR value: $f(x)$     | 77294.30  | 77263.63         | 76832.50                  | 77125.35                | 77260.07                    |

Per capita area of construction land (sq.m. / people) 232.12 214.38 232.12 232.12 232.12

3.3. Land use spatial allocation

3.3.1. Test of the model. The applicability and optimization precision of the CLUE-S model is verified by the variation of land utilization risk degradation (LDR) index before and after optimization and kappa coefficient. CLUE-S model operation accuracy test. In general, if kappa coefficient is larger than 0.75, it shows that operating accuracy of the model is higher. By contrasting the land utilization optimal result of Menglian County in 2025 and land use situation in base year, the whole accuracy of CLUE-S model is 90.99% and kappa coefficient is 0.8488. It meets the requirement of spatial optimum allocation.

From the perspective of whether the spatial configuration results meet the land demand, due to the system error and the error from data conversion (e.g., conversion between raster, vector, and ASCII), the final distribution results of land use optimized by the CLUE-S model may not be fully consistent with the optimized demand area. The error rates between the distribution area of the CLUE-S model and the optimized demand area of the GLP model in 2025 is only 0.10% for the total area. Construction land had the largest error rate with 1.12%. The error rate for forests is the smallest with only 0.01%. The results showed that the spatial distribution accuracy of land use had high precision based on the CLUE-S model.

In short, the optimal result of CLUE-S model meets the requirement to decrease land risk deterioration. Model operation accuracy is superior, and it is suitable for land use spatial allocation in Menglian County.

3.3.2. Spatial allocation results. According to the land use demand of scheme II, the land use spatial distribution of Menglian County in 2025 is allocated (Figure 5). The garden land is mainly distributed in the western and central parts of the county. Cultivated land is mainly distributed in the eastern, northern and central parts in where the terrain is low and flat, such as valleys, dam areas and mild hills. In the south of Menglian County, the mountains are undulating with steep slope where are mainly distributed in forestland, which is conducive to control LDR. The construction land is generally distributed around the county and the towns, but in other regions it is scattered around the small residential areas. Unutilized land, grassland and waters have small area and are scattered, with no obvious spatial characteristics.
4. Discussion and Conclusion

4.1. Discussion

4.1.1. Land use optimization for controlling LDR in mountainous area. In this study, land use quantitative optimization and spatial allocation are carried out with the goal of minimized LDR. This paper aims to find a method to control LDR by land use optimization in the mountainous area of Southwest China.

There is now a consensus that land degradation is exacerbated by human interference [11, 13]. The LDR has a strong correlation with land-use types, and land use change can affect the land degradation [44, 50]. In particular, the degree of land degradation will be intensified with the land use change caused by human activities, such as deforestation, agricultural reclamation and tourism development [51, 52]. It provides theoretical basis for this study to seek the optimal land use situation with the LDR control. In fact, some studies have considered that reasonable land management is the way to improve land degradation. They only qualitatively put forward measures and suggestions [12, 52]. However, the qualitative analysis is difficult to guide the regional land management and achieve the purpose of effective LDR control. Based on the objective of LDR minimization, land use optimization can solve this problem.

In this study, three schemes of land use optimization are designed by the GLP model, namely standard-demand, strict-demand and policy-oriented for cultivated land. It can be seen from the results that the LDR is reduced in all three schemes to a certain extent. Of course, there is not the "most-optimal" quantitative structure [35]. When researchers focus on one object, they lose the benefit of the other to some extent. There are also some trade-offs and synergies among various interests [9, 28, 38, 41]. Therefore, further analysis of optimization results is needed to find the suitable land use quantitative structure.

In optimization results of three schemes specifically (Table 6), the difference actually lies in three land-use types of cultivated land, garden land and forestland. Among them, standard-demand (I) and strict-demand (II) schemes can make a better effect on controlling LDR. However, food security in
mountainous area should also be ensured [53]. The area of cultivated land in scheme I is small, which is not a problem in the short term, but the food security and sustainability is affected in the long term development. The policy-oriented scheme (III) ensures the area of cultivated land and reduces the forestland and garden land to a certain extent. But its effect on controlling LDR is not obvious and is even not much better than General Planning. Comparatively, although there is a decrease in cultivated land scheme II, it has been able to meet the food demands of the population for some time. Some studies have pointed out that, in order to achieve regional coordination and other purposes, the food production can be appropriately reduced in mountainous area [53]. There is also a large increase in forestland in scheme II which is in line with the policy requirements of mountain ecological protection [54, 55]. At the same time, garden land is maintained in scheme II which can ensure a stable economic income of farmers. Scheme II can meet the requirements of regional LDR control, food security, ecological protection and economic development. Therefore, its land use structure is reasonable, and can better coordinate the different interests.

Eventually scheme II is selected to conduct spatial allocation in the CLUE-S model. The spatial distribution of each land-use type considers its suitable probability. It will have priority to distribute the land-use type with high probability. Simultaneously, considering land use transition rules, spatial policies and regional restrictions, the allocating results can have more objectivity and wholeness.

In a word, with the increase of human activities, the LDR is increasing in the mountainous area in Southwest China. The land use optimization can reduce regional LDR. At the same time, different optimization results provide a variety of options for decision makers. Through land use optimization, it has a significant effect on LDR reduction and can be applied to other similar areas.

4.1.2. Feasibility of land use optimization by integrating GLP and CLUE-S model. The methods of land use optimization are relatively mature [39-41]. In this study, under the LDR evaluation, a land use optimization method integrating GLP and CLUE-S model is proposed from the perspective of controlling LDR. The grey system principle is an advantage in GLP, which is more flexible than the ordinary linear programming method with the characteristics of simple programming and strong operability [44, 50]. CLUE-S model has been widely used in recent years [42, 43]. It can calculate the suitability of the distribution of different land-use types (Figure 3) in spatial allocation, and the results often have a high accuracy [48, 49]. The integration of GLP and CLUE-S model can make up for the deficiency that GLP model only optimizes the land use quantitative structure and CLUE-S model only optimizes the land use spatial allocation. The optimal results of land use quantity can be obtained by setting a variety of schemes in GLP model, which can be used for land demand in CLUE-S model.

In this study, as mentioned in the results analysis section, the accuracy of the integration model is high. The largest error rate is only 1.12%. The land demand obtained by the GLP model can be allocated well to the space by the CLUE-S model. Meanwhile, it is necessary to discuss the accuracy of land use spatial allocation [34]. Relevant research has shown that optimized results of CLUE-S model are credible [49]. As mentioned above, the accuracy and kappa coefficient have passed the test with a high value. In addition, we also focused on the ROC test of the suitable probability of land use spatial distribution based on logistic regression. The ROC test results can judge whether the suitability degree of land use spatial distribution and its fitting result is accurate [18]. The test results show that the logistic regression between each land-use type and driving factors in this study has achieved good effects. This is the most important basis for optimizing allocation based on the CLUE-S model. In general, if the ROC test results are good and the model parameters (especially land use transfer coefficient of elasticity) are reasonable, the CLUE-S model can achieve the land use spatial allocation efficiently [42].

In general, the integrating method of GLP and CLUE-S can be applied to the mountainous area where the artificial gardens are planted on a large scale, to find out a good land use pattern on two aspects of quantity and space. This can provide a scientific reference for the land development, protection, and strategic decision in mountainous area of Southwest China.
5. Conclusion

(1) Evaluation of LDR.

The risk of land degradation in Menglian County is relatively serious. The LDR in the county is mainly high-risk and medium-risk level, accounting for 56.36% of total area. The regions with high LDR are mainly distributed in the eastern and western part of the county. The regions with low LDR are mainly distributed in the midwest and southern parts of the county. While the distribution of medium-risk regions is sporadic. For land use, the land-use types are ranked by LDR from large to small: garden land, construction land, cultivated land, unutilized land, grassland and forestland.

(2) Land use quantitative optimization by GLP model based on minimize LDR.

Comparing with the land use situation in 2015 and General Planning, the LDR decreased 461.80, 168.95 and 34.23 in three schemes respectively. Each of the three schemes has its advantages and disadvantages. However, the mountainous area needs comprehensive consideration of LDR control, ecological protection, economic development and food security, and the strict-demand scheme for cultivated land (II) is more suitable for the future development of Menglian County.

(3) Land use spatial allocation based on CLUE-S model.

CLUE-S model is used to conduct spatial allocation of optimization result in GLP. The garden land is mainly distributed in the western and central parts of the county. Cultivated land is mainly distributed in the eastern, northern and central parts of the county. Forestland is mainly distributed in the southern parts of the county. Construction land is mainly distributed around the county and the towns. The distribution characteristics of other land-use types are not obvious.

(4) The integration of GLP and CLUE-S model.

The spatial optimized results have passed the test with accuracy of 90.99% and kappa coefficient of 0.8488. Furthermore, the error rates between the distribution area of the CLUE-S model and the land use demand area of the GLP in 2025 is only 0.10%. CLUE-S model can better satisfy the quantitative structure of land use obtained by GLP. The method and result are feasible and can provide a scientific reference for controlling LDR in mountainous area in Southwest China.

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