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Research Article

Evaluation Model of Land Use Spatial Equilibrium Based on Regional Collaborative Remote Sensing Observation

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In order to improve the evaluation effect of the balance of land use space, this paper uses computer intelligence technology to assist land space observation and provide basic data for land space planning. Moreover, this paper analyzes the existing land space assessment algorithms, identifies the shortcomings of the traditional algorithms, and improves the traditional methods by combining random forest classification and image texture features. In addition, this paper builds a regional collaborative remote sensing observation model based on the improved algorithm. Furthermore, after the system structure is constructed, the system performance is tested by the simulation method, and the system performance is verified by the experimental analysis method. Finally, the validity of the improved algorithm in this paper is also verified by simulation experiments, and the validity of the model in this paper is verified. The research shows that the method proposed in this paper has certain reliability.

1. Introduction

The land use type can be simply understood as grouping the same land with the same use pattern into one type of unit and classifying it according to the purpose of land use and spatial differences, so as to reflect the nature and use of the land. Moreover, land use types have two attributes, one is a natural attribute and the other is a social attribute, and the function and form of land are just the specific reflections of the combination of land use types. The land use type has the following delineation principles: First, land use should reflect its own uniqueness. It is precisely because of this that the differences in regional land use can be expressed macroscopically. Second, the natural and social attributes of land should be displayed, especially for land in different regions. The third is to reflect the relationship between land use structures in different regions. Although the performance of land differences is complicated, there are still certain regularities. The fourth is to link up with the development of the local economy as much as possible and divide the land types reasonably and effectively according to the actual local conditions, according to industrial production and planning.

The quantitative structure analysis of land use, in a basic sense, is to analyze the area of each land use type in a certain area, analyze its internal relationship, and make relevant statistics on the area or proportion of the land use type [1]. Now, with the maturity of other land-related theories, especially landscape ecology, more and more scholars have paid attention to it, and related principles such as landscape pattern analysis in the theory of landscape ecology have been introduced into the study of the quantitative structure of land use [2]. The analysis of the quantitative structure of land use can not only objectively and scientifically reflect the proportion of the local or global land use types and areas but also reflect the differences and stability of the spatial pattern of land under the influence of natural and social conditions. By analyzing its quantitative structure, it can reflect the characteristics of land resource utilization, which plays a vital role in the progress and development of local society. Maintaining a good quantitative structure of land use types can lay a solid foundation for rapid economic development and sustainable utilization of environmental resources [3].

The development of land use zoning is closely related to the development of natural geographical zoning and economic location. The geographical division is defined as the continuous decomposition of the whole into parts, and these parts are spatially connected to each other, but the composition types can be distributed [4]. Combining climate and vegetation and dividing the world into 16 different regions according to the difference in vegetation landscape, the concept of flora was studied and established, and phytogeography was created [5]. The main geographical units are divided into a four-level classification system of "community-region-region-large-region," thus pioneering the study of modern natural zoning [6]. The natural soil zone is divided, and the zonal law of natural phenomena is demonstrated. The research at this stage did not systematically elaborate on the connotation of ecological zoning [7]. The idea of regional ecological division is proposed, and it is believed that the division of regions should combine different natural units according to their spatial relationship [8].

With the deepening of research, the relationship between land use zoning and eco-geographical zoning has become more and more close in terms of the research method content and index system. Similarly, the development of land use zoning is closely related to economic location. With the development of the economy, the theoretical research ideas of related areas are also becoming more and more mature [9]. Using the isolation method, from the perspective of agricultural production layout, the zoning theory is proposed, that is, the optimal location layout theory [10]. Emphasized the concept of land use and led a land economic survey in Michigan, pioneering the modern comprehensive zoning of land [11].

With the development of the economy, the importance of social and economic factors in the process of land use zoning has gradually become prominent and has attracted extensive attention of experts and scholars [12]. The close connection between land use and the ecological environment has gradually gained people's attention and attention. In the study of land use zoning, the ecological environmental factors in the region, such as natural, social, and economic conditions, are comprehensively considered an important basis for land use zoning [13]. In the study of land use zoning, from natural factors to socioeconomic factors to ecological and environmental factors, from single to comprehensive, the understanding of land use zoning is constantly deepening and improving [14]. At present, the research on land use zoning can be summarized as follows: regional zoning to guide regional development, use of zoning for different development purposes, and functional zoning [15]. As the concept of environmental protection has become increasingly popular among the people, the research on land use zoning has paid more and more attention to the role of the ecological environment, which has also become an important direction of current research.

The transformation of natural land surfaces into urban land is one of the most irreversible processes by which human activities have affected the earth's biosphere. In order to meet the needs of urban development, human beings continue to increase their intervention on land, and the changes in land use patterns are significantly intensified, which in turn affects the allocation of resources and changes in habitats. Rapid urbanization causes changes in land use patterns and functions, triggering various ecological and environmental responses, including threatening biodiversity, changing the climate system, and accelerating environmental pollution [16].

Land use zoning refers to the process of dividing a certain area into several regions based on the regional differentiation law of land use, according to the current land use status, development and utilization conditions, and directions of the research area, and according to the principles of similarity and difference. It also puts forward measures and suggestions on land use development methods according to the divided regions, combined with the needs of use control, natural conditions, and economic and social development methods, and implements differentiated management [17]. Therefore, land use zoning has the characteristics of comprehensiveness, operability, practicability, and hierarchy. Land use zoning is for the efficient use of land resources, to determine a reasonable land use structure, to improve land utilization, and to promote regional social and economic sustainability. This development is of great significance [18].

Location theory is a theory that explains the spatial distribution of human activities and their interrelationships in space. It is a theory that studies the selection of human economic behavior in the spatial location and the optimal combination of economic activities in that spatial region. The initial research focus of location theory is the economic field, but with the passage of time, the research content has been deepened, and the theoretical connotations have been gradually enriched, including agricultural location theory, industrial location theory, central location theory, and modern location theory [19]. The application scope is gradually expanding, and it also has an important impact on research in other fields. Land use requires corresponding development and utilization methods for different types of land. In this process, location theory plays an important role in guiding land use zoning. Under different location conditions, the advantages of land resources are different, and the resulting economic and ecological benefits are also different. In the process of land use zoning, it is important to clarify the location advantages of different regions, to take different measures according to different location conditions, to formulate land use methods, and to play an important role in promoting the efficient and sustainable use of land resources. Therefore, location theory provides an important theoretical basis for the comprehensive study of land use zoning [20].

This paper combines the regional coordination remote sensing observation technology to study the land use spatial equilibrium evaluation model, explores the scientific nature of land use, and provides a theoretical reference for subsequent land planning.

2. Regional Collaborative Remote Sensing Observation

2.1. Basic Theory of D-InSAR. Differential Interferometry Synthetic Aperture Radar (D-InSAR) is an extension of traditional InSAR technology. The principle is to use

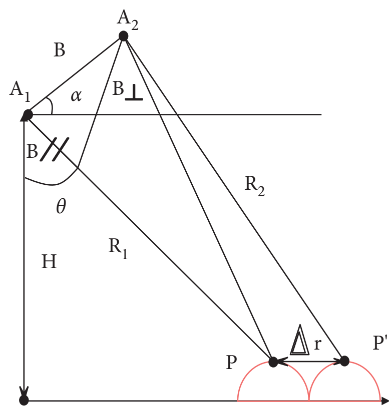

Figure 1: Basic principle of D-InSAR technology based on the two-track method.

synthetic aperture radar (SAR) to image the same scene area before and after deformation multiple times at the same orbital position at different times. There are usually five parts in the obtained initial interference phase:

$$\varphi = \varphi_{\text{topo}} + \varphi_{\text{flap}} + \varphi_{\text{disp}} + \varphi_{\text{atmo}} + \varphi_{\text{noi}}. \tag{1}$$

In the formula, φ_{topo} is the phase of the terrain factor, which needs to be removed by the existing DEM or redundant SAR images. In general, if the external DEM data are easy to obtain, it is more convenient to choose two-track differential interferometry. When the DEM data in the study area are missing or the accuracy is not high, the three-track method or the four-track method can be used. At present, the two-track differential method and the three-track differential method are the more commonly used interferometry methods.

As shown in Figure 1, A_1, A_2 are the corresponding sensors before and after the observation deformation, H is the observation elevation, and P and P' are the positions of the target object before and after the deformation. When A_1 acquires the undistorted SAR image, the signal returned by point P can be expressed as

$$A_1(R_1) = |A_1(R_1)| \exp\left(\frac{-4\pi}{\lambda}\cdot R_1\right). \tag{2}$$

When A_2 acquires the second SAR image after deformation, the signal returned by point P' is

$$A_2(R_2) = |A_2(R_2)| \exp\left(\frac{-4\pi}{\lambda}\cdot (R_2 + \Delta r)\right). \tag{3}$$

Among them, the interferogram phase φ contains not only the topographic information of the study area but also the surface deformation information.

$$\begin{aligned} \varphi &= \frac{-4\pi}{\lambda}\cdot (R_1 - R_2) + \frac{4\pi}{\lambda\cdot\Delta r} \\ &\approx \frac{-4\pi}{\lambda} B\sin(\theta-\alpha) + \frac{-4\pi}{\lambda}\Delta r \\ &= \frac{-4\pi}{\lambda}\cdot B. \end{aligned} \tag{4}$$

The surface deformation information can be obtained by using the following formula:

$$\begin{aligned} \Phi_{\text{disp}} &= \varphi - \varphi_{\text{topo}} - \varphi_{\text{flap}} - \varphi_{\text{nol}} \\ &= \frac{-4\pi}{\lambda\cdot\Delta r}. \end{aligned} \tag{5}$$

According to the above-given formula, the sensitivity of the differential phase to the surface deformation can be obtained by using the following formula:

$$\frac{\Phi_{\text{disp}}}{\Delta r} = \frac{-4\pi}{\lambda}. \tag{6}$$

It can be seen from the above-given formula that the surface deformation variable changes with the phase change. When $\Phi_{\text{disp}} = 2\pi$, $\Delta r = \lambda/2$ is the surface deformation ambiguity.

In order to measure the quality of the interferogram, the interferometric coherence value is usually used as an important standard to measure, and it can also provide important information about the ground target scatterers, so the ground objects can be classified according to the coherence characteristics. The complex coherence coefficient can usually be expressed as

$$r = \frac{E[S_1 S_2 *]}{\sqrt{E\left[|S_1|^2\right]E\left[|S_2|^2\right]}}, \quad 0 \le r \le 1. \tag{7}$$

In the formula, $E[\,*\,]$ is the mathematical expectation, and S_1, S_2 is a complex variable that satisfies the zero-mean circular Gaussian distribution. The phase arithmetic evaluation value of the pixels in the region is usually used to estimate its mathematical expectation:

$$r' = \frac{\sum_{m=i}^{M}\sum_{n=i}^{N} S_1(m,n) S_2(m,n)}{\sqrt{\sum_{m=i}^{M}\sum_{n=i}^{N}|S_1(m,n)|^2 \sum_{m=i}^{M}\sum_{N=i}^{N}|S_2(m,n)|^2}}. \tag{8}$$

In the formula, M, N is the window size when calculating the coherence coefficient. Spatial decoherence refers to the difference in the geometric relationship and frequency components between the radar images caused by the spatial baseline between the two SAR antennas, which reduces the correlation of the radar signals and can be expressed as

$$R_{\text{spatial}} = 1 - \frac{2\cos\theta |B\perp| R_{\text{GRR}}}{\lambda r}. \tag{9}$$

In the formula, θ is the angle of incidence; $B\perp$ is the vertical baseline; R_{GRR} is the slant range resolution; λ is the radar wavelength; and r is the slant range distance.

Doppler centroid decoherence is caused by the difference in Doppler centroid frequency Δf_{DC}:

$$r_{DC} = 1 - \frac{\Delta f_{DC}}{B_A}. \tag{10}$$

In the formula, B_A is the azimuthal bandwidth of the system.

In the monitoring of surface subsidence, the difference in random reflection phase should be minimized to obtain higher-resolution SAR images. The expression for bulk scattering decoherence is

$$r_{\text{volume}} = \int f(z)\exp(-jk_z Z)\mathrm{d}z,$$
$$f(z) = \frac{\delta(z)}{\int \delta(z)\mathrm{d}z}. \tag{11}$$

In the formula, k_z is the number of bands in the Z direction; $f(z)$ is the effective scattering probability density function.

Thermal noise decoherence is caused by thermal noise in radar systems. If the ground reflection signals obtained by two radar antennas at the same time are S_1, S_2 and both contain the same scattering information c of the ground target, the thermal noise of the two antennas can be expressed as

$$S_1 = c + \varepsilon_1,$$
$$S_2 = c + \varepsilon_2,$$
$$r_{\text{thermal}} = \frac{E\left[cc\prime + 2c\varepsilon_1 + 2c\varepsilon_2 + \varepsilon_1\varepsilon_2\right]}{\sqrt{E\left[cc\prime + 2c\varepsilon_1 + \varepsilon_{111}\right]E\left[cc\prime + 2c\varepsilon_2 + \varepsilon_2\varepsilon_2\right]}}. \tag{12}$$

If $c, \varepsilon_1, \varepsilon_2$ is independent of each other, then

$$r_{\text{thermal}} = \frac{E[cc']}{\sqrt{E[cc' + \varepsilon_{11}^{\varepsilon}]E[cc' + \varepsilon_{22}^{\varepsilon}]}}. \tag{13}$$

When the radar repeats the orbit measurement, the thermal noise is approximately equal, $E[\varepsilon] = E[\varepsilon_1] = E[\varepsilon_2]$; at this time, the thermal noise decoherence is

$$r_{\text{thermal}} = \frac{c^2}{c^2 + \varepsilon^2}. \tag{14}$$

Among them, thermal noise decoherence is usually expressed by the signal-to-noise ratio between SAR images, that is, $\text{SNR} = (|c|^2/|\varepsilon|^2)$. Therefore, thermal noise decoherence can be expressed as

$$r_{\text{thermal}} = \frac{1}{1 + 1/\text{SNR}} = \frac{1}{\sqrt{\left(1 + 1/\text{SNR}^2\right)\left(1 + 1/\text{SNR}^2\right)}}. \tag{15}$$

2.2. Land Use Classification Based on Random Forest Classification. In the process of differential interferometry, when performing image registration, resampling, or digital elevation model simulation of interferograms, errors are often introduced, resulting in decoherence of interferograms, that is, decoherence of interferometric data processing. The experimental results show that when the accuracy of image registration is due to 0.2 pixels in azimuth and range directions, the effect of coherence will be less than 10%. Therefore, when performing image registration, try to select high-precision registration and interpolation algorithms. The decoherence in the range and azimuth directions can be expressed as [21]

$$r_{\text{coreg},r} = \begin{Bmatrix} \sin(vr) = \dfrac{e(\pi vr)}{\pi vr}, & 0 \le vr \le 1, \\ 0, & vr > 1, \end{Bmatrix}$$
$$r_{\text{coreg},az} = \begin{Bmatrix} \sin(\text{vaz}) = \dfrac{e(\pi \text{vaz})}{\pi \text{vaz}}, & 0 \le \text{vaz} \le 1, \\ 0, & \text{vaz} > 1. \end{Bmatrix} \tag{16}$$

Among them, vr and vaz are the relative registration errors in the range and azimuth directions, respectively. Then, the image registration decoherence is

$$R_{\text{coreg}} = r_{\text{coreg},r} * r_{\text{coreg},az}. \tag{17}$$

When performing differential interference processing, any small link may introduce errors, thereby affecting the interference pattern. Therefore, when monitoring the surface deformation, the error in the data processing should be minimized and the obstacle of phase unwrapping should be broken. For example, in order to remove the interferometric phase error caused by the atmospheric delay, n independent interferograms can be averaged, and the mean value can be removed as an estimate of the atmospheric delay, or it can be calibrated with data other than SAR images.

The external DEM data covering the study area are mosaicked from three shuttle radar topography mission (SRTM) data. The land remote sensing image recognition process is shown in Figure 2.

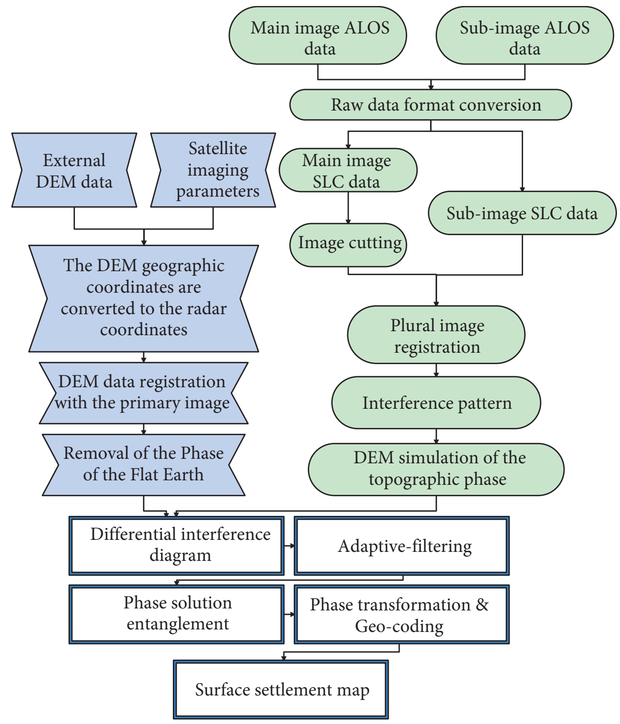

Figure 2: Land remote sensing image recognition process.

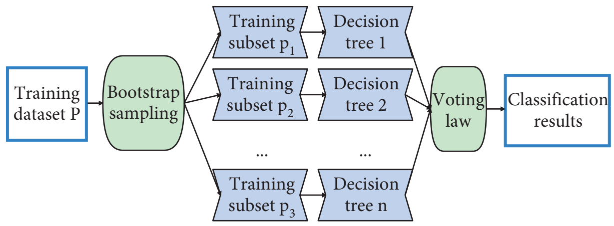

FIGURE 3: Training classification of the random forest algorithm.

The acquired remote sensing images often require postprocessing such as classification interpretation or quantitative inversion, from which more intuitive and useful information can be obtained for further analysis and application [22]. Land use classification of land images is the basis for studying the evolution of landscape patterns, and its classification accuracy determines the accuracy of subsequent research. In addition, the common phenomena in remote sensing images, such as "same-spectrum and different-spectrum," "same-spectrum foreign objects," and mixed pixels, reduce the classification accuracy. Therefore, the classification method using the traditional single classifier can no longer meet the classification accuracy requirements of some industrial applications. Among them, some improved classification methods such as support vector machine (SVM), decision trees, and neural networks have achieved good classification results. Multiclassifier integration is to combine multiple classifiers with independent decision-making ability to form a strong classifier, and the final classification result is often higher than the classification accuracy of a single weak classifier. Therefore, this paper selects the random forest classification method to classify the land use in the study area based on the IDL8.4 platform [23].

The random forests algorithm is composed of many decision trees such as classification and regression tree (CART) . Through the bootstrap resampling technology, training samples and test samples are continuously generated, and multiple classification trees are generated from the training samples to form a random forest. Finally, the voting method is used to vote on many classification trees to obtain the final classification result, which is essentially an improvement of the decision tree algorithm. The training and classification process of the random forest algorithm is shown in Figure 3.

The randomness of random forest is mainly manifested in two aspects, namely, randomness of training sample set selection where the bootstrap dataset is obtained by random and replaceable sampling using the Bagging method and randomness of split dataset set selection in which parts of the attributes that are randomly selected from the attribute set are split in the best split way. Among them, each tree grows as follows [24]:

(1) The algorithm randomly selects N training datasets from the original dataset as training samples for the growth of each decision tree

(2) M is the number of input variables, and m is a subdataset randomly selected from the M dataset. If $m << M$, the algorithm uses this subdataset to calculate the optimal splitting method of each node;

(3) Each decision tree will grow to the maximum extent and will not be pruned

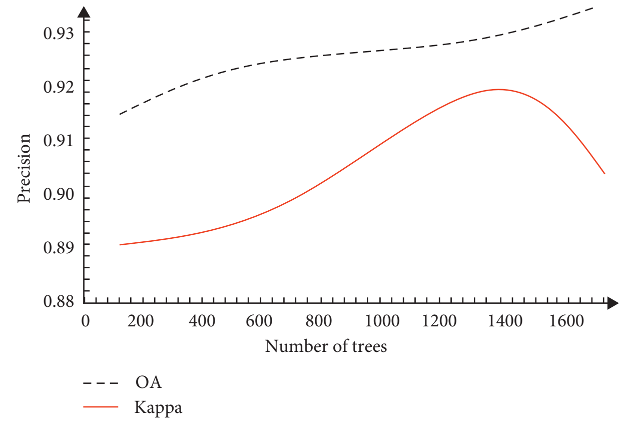

FIGURE 4: The relationship between the number of random forest decision trees and precision.

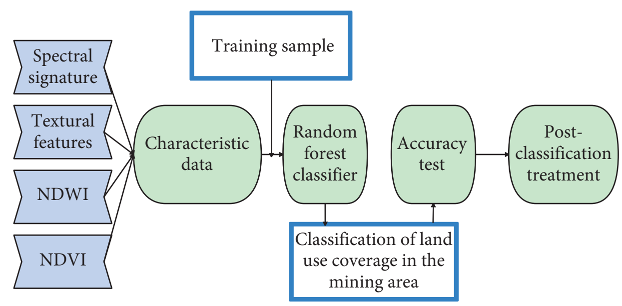

FIGURE 5: Classification flowchart.

The quantitative analysis function in the random forest algorithm is a marginal function. $\{h_1(x), h_2(x), \ldots, h_K(x)\}$ is the classifier dataset. The training dataset is randomly selected from the randomly distributed vectors X, Y, and the marginal function is defined as

$$mg(X,Y) = av_k I(h_k(X) = Y) - \max_{j \neq Y} av_k I(h_k(X) = j). \tag{18}$$

Among them $I(\bullet)$ is the indicator function, and the marginal value can be reflected in the total number of votes X, the degree to which the average number of votes Y of the correct classification exceeds the average number of votes for the wrong classification. The larger the marginal value, the greater the confidence in the classification. Therefore, the corresponding generalization error is defined ast

$$PE^* = P_{X,Y}(mg(X,Y) < 0). \tag{19}$$

The subscripts X, Y indicate that the generalization error is calculated from the X, Y distribution. In a random forest, $h_k(X) = h(X, \Theta_k)$, and a large number of decision tree structures obey the law of large numbers.

Theorem 1. *As the number of decision trees increases, for all tree parameter sequences Θ_1、 Θ_2 . . . . ., the generalization*

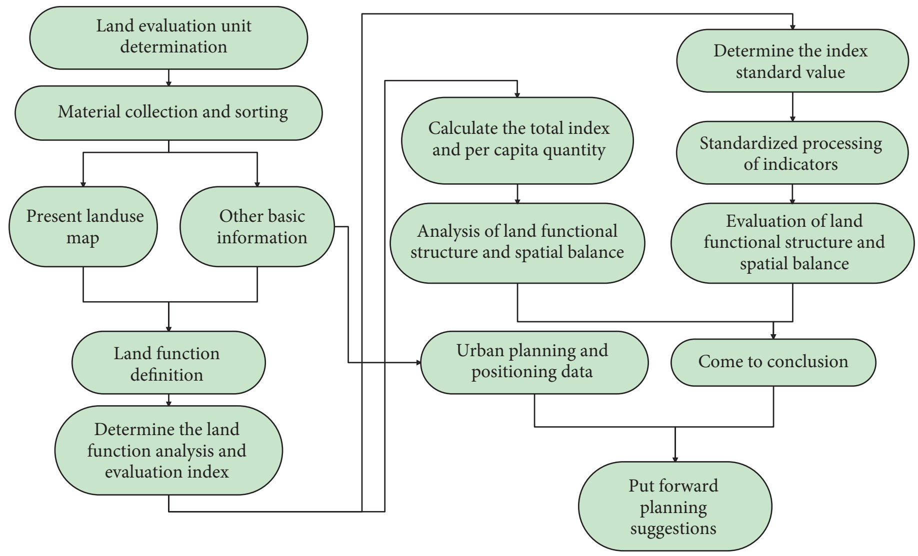

Figure 6: Technology roadmap.

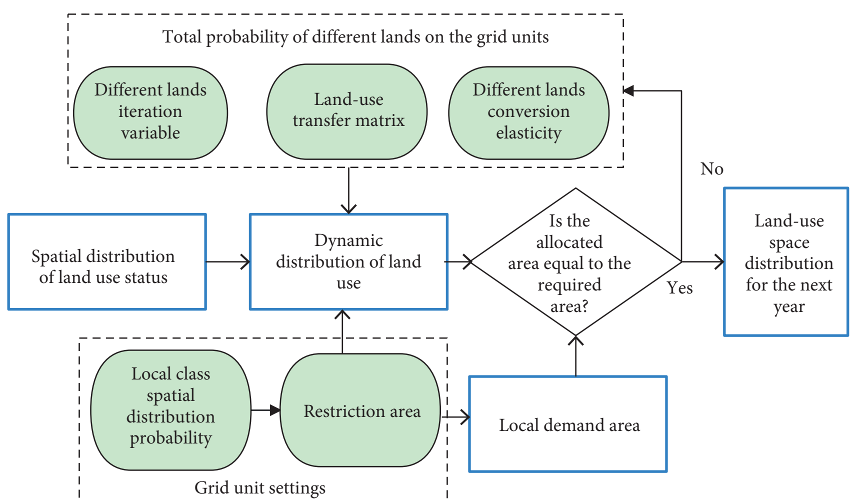

Figure 7: Iterative process of dynamic allocation of land use space.

error is reduced to $P_{X,Y}(P_{\Theta}(h(X,\Theta) = Y) - max_{j\neq Y} P_{\Theta}(h(X,\Theta) = j) < 0)$ *[25].*

3. Evaluation of Land Use Spatial Equilibrium

There are only two parameters in random forest classification, the number of decision trees in the forest and the number of features F selected by the decision tree. The selection of F is controlled by OOB, and the selection of decision trees needs to be obtained through experiments. Therefore, in order to choose the appropriate number of decision trees, the relationship between the number of decision trees and the precision is analyzed in Figure 4. Since each image selects the same number of features, only the relationship between decision trees and accuracy is considered here. According to the analysis of the experimental results, ntree = 1000 was finally selected as the construction parameter.

In order to prevent each decision tree from selecting the same samples and the correlation between the constructed decision trees being too high, feature selection is not carried out in this paper. Instead, 4 spectral features, 32 texture features (variance, mean, entropy, energy, contrast, and dissimilarity) of each band, and NDVI (normalized difference vegetation index) and NDWI (normalized difference water index) are combined as the input feature set. Moreover, this paper reduces the probability of selecting the same sample by increasing the number of feature attributes and selecting 60–80 point training samples for each category. The classification flowchart and interface diagram are shown in Figure 5.

The classification accuracy evaluation of remote sensing images is an important link in land use cover classification, and the classification accuracy of images directly determines the credibility of the classification results. In this paper, total classification accuracy and Kappa coefficient are selected as the evaluation criteria for land classification accuracy. The

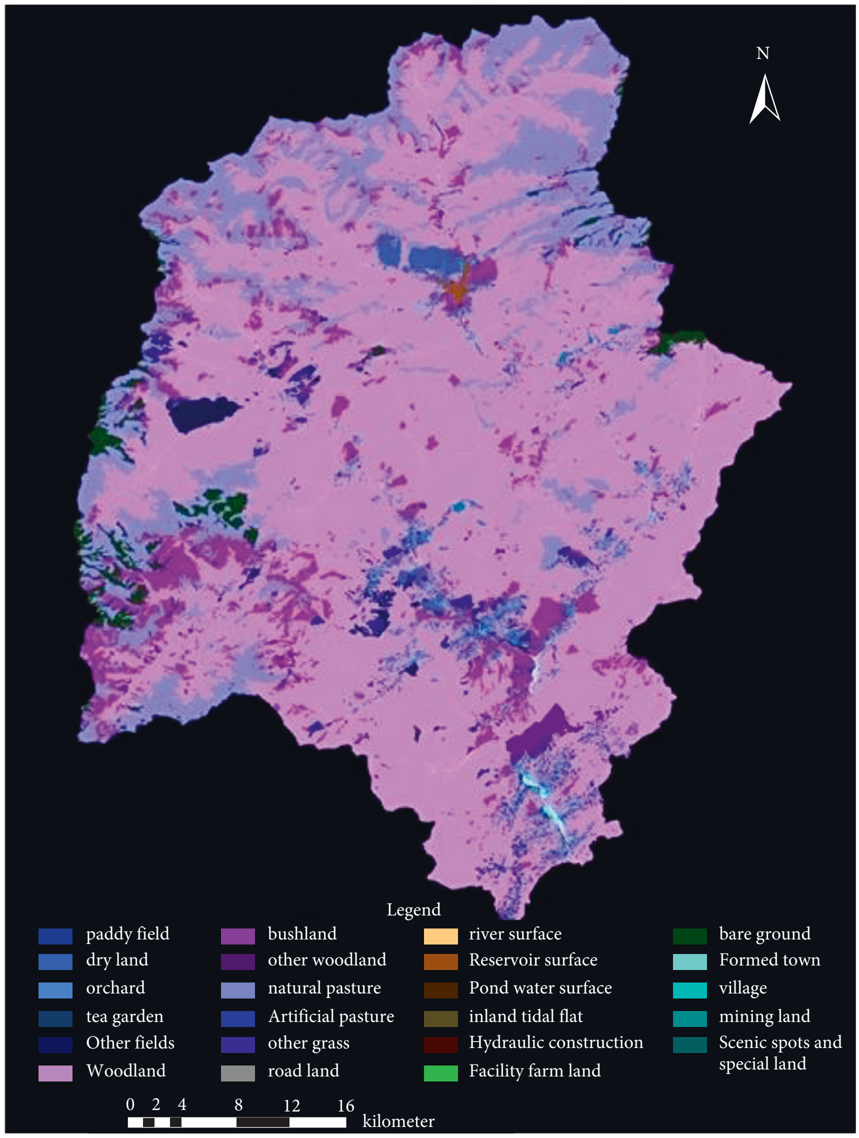

Figure 8: Schematic diagram of dynamic identification of land use status.

total classification accuracy refers to the sum of correctly classified pixels in remote sensing images divided by the total number of pixels. The expression of the Kappa coefficient is

$$\text{Kappa} = \frac{N\sum_{i}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+}\cdot x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+}\cdot x_{+i}\right)}. \tag{20}$$

In the formula, r is the number of types of objects in the error matrix; N is the total number of verification pixels; x_{ii} is the element on the main diagonal in the error matrix; x_{i+} is the total number of observations in row i; andx_{+i} is the total number of observations in column i. When kappa > 0.8, it means that the matching degree between the classification result and the ground reference information is very high, that is, the classification accuracy is very high. When Kappa < 0.4, the classification accuracy is poor, and the classification results are not suitable for analysis.

This paper selects a certain area for research. The research mainly adopts a combination of qualitative and quantitative approaches to evaluate the land function of the study area. In terms of quantitative analysis, the analysis and evaluation are carried out on the total amount of functional index factors and the per capita amount of each region. Figure 6 shows the technical roadmap of this paper.

The dynamic allocation process is a process of spatial dynamic allocation of land use demand according to the size of the total probability TPROP on the basis of a comprehensive analysis of the status quo of land use distribution, the spatial distribution of the probability of occurrence of each land use type, the restricted area of land use change, and the conversion rules between different land types. The dynamic allocation process is shown in Figure 7.

Figure 8 is a schematic diagram of the dynamic identification of the land use status of a certain area by the model proposed in this paper.

On this basis, the regional collaborative remote sensing observation technology in this paper is evaluated, and the role of this model in the evaluation of land use spatial

Table 1: Evaluation of regional collaborative remote sensing observation technology.

Number	Remote sensing observation
1	87.78
2	84.12
3	88.70
4	87.24
5	85.44
6	85.63
7	87.11
8	88.79
9	87.78
10	89.08
11	89.61
12	86.94
13	88.11
14	89.97
15	89.99
16	88.15
17	86.29
18	89.19
19	87.53
20	84.25
21	89.95
22	85.62
23	86.54
24	85.22
25	87.49
26	89.99
27	89.13
28	84.63
29	86.97
30	86.53
31	88.76
32	84.50
33	89.84
34	88.27
35	86.33
36	88.17
37	89.78
38	88.92
39	89.89
40	89.99
41	86.00
42	88.05
43	87.26
44	87.90
45	88.28

Table 2: Evaluation of land use spatial equilibrium.

Number	Equilibrium
1	81.58
2	82.85
3	85.56
4	84.57
5	82.86
6	82.41
7	79.97
8	82.94
9	85.70
10	82.06
11	82.51
12	78.39
13	82.10
14	82.58
15	85.03
16	84.03
17	78.17
18	85.96
19	83.96
20	81.93
21	82.18
22	80.12
23	79.43
24	79.04
25	79.17
26	80.18
27	80.82
28	79.72
29	80.09
30	78.61
31	78.76
32	83.56
33	82.00
34	78.17
35	79.40
36	78.30
37	80.58
38	79.52
39	80.73
40	79.27
41	85.08
42	85.71
43	84.03
44	85.40
45	83.71

equilibrium is analyzed. The results are shown in Tables 1 and 2.

It can be seen from Table 1 that the evaluation results of the regional collaborative remote sensing observation technology are all above 85 points, which belong to the excellent range. Therefore, the method in this paper has better performance in the regional collaborative remote sensing observation technology than the traditional method. It can be seen from Table 2 that the evaluation results of the land spatial balance degree are all above 78 points; there is room for improvement, and there is also a certain improvement compared with the traditional algorithm. This verifies the reliability of the method in this paper.

The above simulation experiments verify that the evaluation model of land use spatial equilibrium based on regional collaborative remote sensing observations proposed in this paper has a good role in land space use evaluation.

4. Conclusion

In this paper, combined with regional coordinated remote sensing observation technology, the research on the evaluation model of land use spatial equilibrium degree is carried out to explore the scientific nature of land use. This paper mainly draws the following conclusions:

(1) This paper proposes a dynamic land remote sensing technology to evaluate the spatial balance of land use. This model improves the timeliness of the traditional model and is helpful for the dynamic implementation of land planning.

(2) The model proposed in this paper can effectively improve the evaluation effect of land use spatial balance and has a certain role in promoting rational land classification planning

(3) The model in this paper is an improved model based on the traditional algorithm, which integrates random forest and the traditional algorithm, and has a certain role in promoting the scientific application of the land use spatial balance evaluation method.

In remote sensing image classification, although the accuracy and efficiency of random forest classification implemented by programming are greatly improved compared with traditional classification methods, there are still some defects in random forests. Therefore, how to make up for random forest classification is of major concern The shortcomings of the method, combined with the classification of active and passive remote sensing image features, will be the focus of future research.

Data Availability

The datasets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

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