

*Original Research*

# Forest Tree Priority Planting Area Selection Algorithm Based on the CrossViT Model

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*Received: 06 March 2026*

*Accepted: 21 August 2026*

## Abstract

A priority selection algorithm for suitable afforestation land in mountainous areas based on CrossViT is proposed to address multimodal data heterogeneity, difficulties in spatial-attribute fusion, and weak nonlinear modelling capabilities in soil erosion and rock desertification control. We construct a targeted indicator system focusing on soil erosion sensitivity, water and soil conservation, and rock desertification sensitivity. The dual-branch CrossViT fuses numerical indicators and spatial distribution maps; multi-head self-attention and cross-attention capture key ecological correlations. The model accurately identifies suitable afforestation land, and planting priority is ranked by ecosystem service value and benefit–cost ratio. Results show 100% classification accuracy for suitable afforestation land, with the ecosystem quality index reaching 78%-91%, providing support for targeted soil and water conservation afforestation.

**Keywords:** CrossViT model, forest trees, planting areas, forest condition indicators

## Introduction

In southern mountainous regions, soil erosion and rock desertification are the dominant ecological problems, leading to vegetation degradation and difficulties in forest restoration. Scientific selection of priority suitable afforestation land is critical for targeted soil and water conservation and sustainable ecological restoration [1]. Ultimately, this achieves synergistic benefits in terms of restoring ecosystem functions, enhancing services, and mitigating risks.

Toledo-Garibaldi et al. [2] developed a multidimensional, multi-level, nested urban forest community classification system using stratified random

sampling. This optimised the allocation of tree species diversity, protected critical canopy areas and enabled the selection of priority planting zones. However, stratified random sampling relies on predefined stratification variables. Basegmez et al. [3] selected evaluation indicators for greening areas based on ecological adaptability and climate resilience. They employed the Analytic Hierarchy Process (AHP) to dynamically weight multidimensional indicators. They determined selection priorities for greening areas through weighted linear combinations, generated decision maps accordingly and utilised grey relational analysis to assess investment priorities. This approach ultimately achieved the selection of greening planting areas that balance ecological adaptability and climate resilience. However, the AHP method relies on expert scoring to determine indicator weights, which introduces significant subjectivity. If the experts' knowledge is

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0009-0004-8091-4693

biased or limited, critical ecological factors may be overlooked, which could compromise the reliability of the planting area selection outcomes. Moilanen et al. proposed a novel prioritisation algorithm for selecting priority planting areas [4]. This method first collects and pre-processes forest baseline data. It then conducts a regional biodiversity balance analysis through a “target species grouping–demand weight allocation–multi-objective balanced optimization” process, and quantifies ecological connectivity using a dispersed kernel connectivity calculation method. Based on this, it calculates a ‘comprehensive priority score’ for each region by setting weights, integrating multiple indicators and optimising marginal benefits. Ultimately, this generates a spatial priority map, providing a basis for ecologically informed planting planning decisions. However, the dispersed kernel connectivity calculation relies on simplified assumptions about the design of ecological corridors in forests, which could result in the actual impediments to gene flow posed by topography and human barriers being underestimated. This could result in insufficient ecological connectivity within the selected planting areas. Ahmad et al. utilised Landsat satellite imagery [5] to assess temporal changes in forest cover and spatial structure evolution through multidimensional indicators. This allowed them to identify forest hotspots and clusters in order to inform planting planning and prioritise planting areas. Nevertheless, limitations in spatial resolution prevent Landsat imagery from accurately monitoring changes in coverage and spatial structure evolution in small-scale forests.

To address the three key challenges – (i) heterogeneity of multimodal ecological data, (ii) poor integration of spatial and attribute information, and (iii) weak nonlinear modelling capability of traditional methods – this paper introduces a novel priority planting area selection algorithm based on the CrossViT model.

## Materials and Methods

### Algorithm for Selecting Priority Forest Planting Areas

#### *Calculation of Forest Condition Indicators for Planting Areas*

The forest condition indicators for planting areas are as follows:

#### (1) Ecological Niche Breadth and Overlap in Planting Areas

The two forest condition indicators of ecological niche breadth and degree of overlap in planting areas can be used to comprehensively evaluate the rationality of forest structure and the stability of forest ecosystems, thereby prioritising regions capable of establishing stable forest ecosystems for tree planting. Niche breadth represents the sum of resources available to different

forest trees within a planting area, reflecting the strength of their environmental adaptability. The Levins index (BL) and Shannon index (BS) describe niche breadth in planting areas, while the Pianka index (Oik) characterises niche overlap. The calculation formulas are as follows:

Levins niche breadth  $A_1$  is calculated as shown in Equation (1) [6]:

$$A_1 = \frac{1}{\sum_{j=1}^r Y_{ij}^2} \quad (1)$$

Shannon niche breadth  $A_2$  is calculated as shown in Equation (2) [7]:

$$A_2 = -\sum_{j=1}^r (Y_{ij} \times \ln Y_{ij}) \quad (2)$$

Pianka niche overlap  $A_3$  is calculated as shown in Equation (3):

$$A_3 = \frac{\sum_{j=1}^r Y_{ij} \times Y_{kj}}{\sqrt{\sum_{j=1}^r Y_{ij}^2 \times \sum_{j=1}^r Y_{kj}^2}} \quad (3)$$

Where: the utilisation quantities of forest trees  $i$  and  $k$  in the  $j$ -th planting area, relative to their total utilisation across all planting areas, are denoted by  $Y_{ij}$  and  $Y_{kj}$  respectively; the total number of planting areas is represented by  $r$ ; the ranges of  $A_1$  and  $A_2$  are  $[1, r]$  and  $[0, \ln r]$  respectively, with higher values indicating broader ecological niches for forest trees; the range of  $A_3$  is  $[0, 1]$ , with higher values indicating greater overlap. Areas with broad ecological niches and moderate overlap should be prioritised, as they support diverse tree species with balanced competition and complementarity [8].

#### (2) Soil Erosion Sensitivity

The Revised Universal Soil Loss Equation (RUSLE) model is used to assign graded values to evaluation factors within the cultivation area: rainfall erosion factor  $\alpha_j$ , soil erodibility factor  $\theta_j$ , terrain undulation factor  $\mu_j$ , and vegetation cover factor  $C_j$  [9]. Soil erosion susceptibility is assessed as shown in Equation (4):

$$A_4 = \sqrt[4]{\alpha_j \times \theta_j \times \mu_j \times C_j} \quad (4)$$

Where: the soil erosion sensitivity index is denoted as  $A_4$ . Areas with low soil erosion sensitivity indices should be prioritised for forest tree planting, as these regions exhibit lower soil erosion risks, providing more favourable conditions for tree root establishment and growth. This approach lays a solid foundation for the stable development of forest ecosystems.

### (3) Water Conservation Functionality

Water conservation is the combined effect of various hydrological processes within forest ecosystems, which is of great importance to these ecosystems [10]. Vegetation, soil, meteorological and topographical data were selected to evaluate the water conservation capacity of the planting area. Single factors including multi-year net primary productivity  $P$ , soil seepage factor  $\beta$ , multi-year average precipitation factor  $\gamma$ , and slope factor  $\delta$  underwent standardisation. The water conservation service capacity index for the forest ecosystem was then calculated as shown in Equation (5):

$$A_5 = P \times \beta \times \gamma \times (1 - \delta) \quad (5)$$

Where: the forest ecosystem water conservation service capacity index is denoted as  $A_5$ . Areas with high water conservation service capacity indices should be prioritised for forest tree planting.

### (4) Soil and Water Conservation Functionality

This evaluation uses the Revised Universal Soil Loss Equation (RUSLE), as shown in Equation (6):

$$A_6 = \alpha \times \theta \times \mu \times (1 - C) \quad (6)$$

Where: the soil and water conservation functionality importance is denoted as  $A_6$ . Areas with high soil and water conservation functionality should be prioritised for forest tree planting [11].

### (5) Biodiversity Conservation

The calculation method for biodiversity conservation importance is shown in Equation (7):

$$A_7 = P \times \gamma \times G \times (1 - R) \quad (7)$$

Where: the biodiversity conservation functional service capacity index is denoted as  $A_7$ ; the multi-year average temperature and altitude are denoted as  $G$  and  $R$ , respectively. Planting trees in these areas enables them to integrate better into local forest ecosystems, thereby promoting biodiversity conservation and development. At the same time, leveraging rich biodiversity further enhances forest ecosystem stability and service functions.

### (6) Habitat Quality Index

Habitat quality refers to the climatic conditions in the planting area, including temperature, sunlight and precipitation. Favourable habitat quality indicates soil with suitable pH levels, fertility and aeration, which are conducive to forest trees taking root, sprouting and thriving. The habitat quality index is calculated as shown in Equation (8).

$$A_8 = E_j \times \left[ 1 - \frac{F_j^\Phi}{F_j^\Phi + \sigma^\Phi} \right] \quad (8)$$

Where: habitat quality is denoted as  $A_8$ ; Habitat suitability for the  $j$ -th planting area is denoted as  $E_j$ ; The semi-saturation coefficient is denoted as  $\sigma$ ; The conversion coefficient is denoted as  $\Phi$ ; Habitat degradation for the  $j$ -th planting area is denoted as  $F_j^\Phi$ . Areas with high habitat quality indices should be prioritised for forest tree planting, as these habitats are more conducive to tree growth and provide favourable conditions for the construction and stable development of forest ecosystems.

### (7) Sensitivity to Rock Desertification

Rock desertification sensitivity refers to the extent to which ecosystems in areas susceptible to rock desertification respond to natural and human factors. Specifically, it indicates the probability of conditions that are unfavourable for forest tree planting, such as soil degradation and poor vegetation growth, occurring in these planting areas due to the influence of such factors. For the target planting area, key single factors – bedrock exposure rate, slope gradient and vegetation cover – are graded and assigned values to derive the rock desertification susceptibility index. The calculation formula is shown in Equation (9):

$$A_9 = \sqrt[3]{H_j \times \delta_j \times C_j} \quad (9)$$

Where: the rock desertification sensitivity index is denoted as  $A_9$ ; it measures the likelihood of ecological issues unfavourable for forest tree planting occurring in the planting area. The bedrock exposure factor for the  $j$ -th planting area is represented as  $H_j$ , reflecting the degree to which bedrock exposure constrains tree planting in  $D_j$ . The slope factor for the  $j$ -th planting area is denoted as  $\delta_j$ , indicating the impact of terrain slope on forest tree growth and planting. The sensitivities of the individual factors – bedrock exposure rate, slope and vegetation cover – are multiplied to generate a distribution map of rock desertification sensitivity levels. This distribution map indicates the condition of forests within planting areas. Regions with low rock desertification sensitivity indices [12] should be prioritised for forest tree planting, as such areas are more conducive to tree growth and forest ecosystem stability.

When selecting priority planting areas for forest trees, the aforementioned forest condition indicators, including ecological niche breadth and overlap in priority planting areas, soil erosion susceptibility, the importance of water conservation and soil conservation functions, the importance of biodiversity conservation, the habitat quality index and sensitivity to rock desertification, are considered and combined into a multidimensional dataset  $U = [A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9]$ . This dataset is then fed into the CrossViT model to precisely identify planting area categories, ensuring the accuracy of selecting priority planting areas for forest trees.

## Identification of Planting Area Categories Based on the CrossViT Model

### CrossViT Model Architecture

The CrossViT model is applied to identify planting area categories, integrating multi-dimensional forest status indicators such as niche breadth, soil erosion sensitivity, and water conservation function importance [13]. Through deep feature extraction and multi-dimensional information fusion, it accurately outputs forest tree planting area categories, providing reliable classification data for subsequent priority ranking calculations. The network architecture of the CrossViT model is illustrated in Fig. 1.

The CrossViT model employs two data embedding modules. It preprocesses the image data (e.g., rock desertification susceptibility distribution maps) and numerical data from the input planting area forest condition dataset  $U$  to obtain corresponding embedding vectors. The image and numerical data are then fed separately into two Transformer encoding modules. Multidimensional planting area forest condition features are extracted through two branch Transformer encoders. These features are then fed into a cross-attention module to facilitate interaction and fusion of the information. This process fully exploits the correlations and complementary information between the image and numerical data, providing a more comprehensive and representative feature set for the forest conditions in the planting area. This representation is then input into a Softmax classification module to determine the category of the planting area.

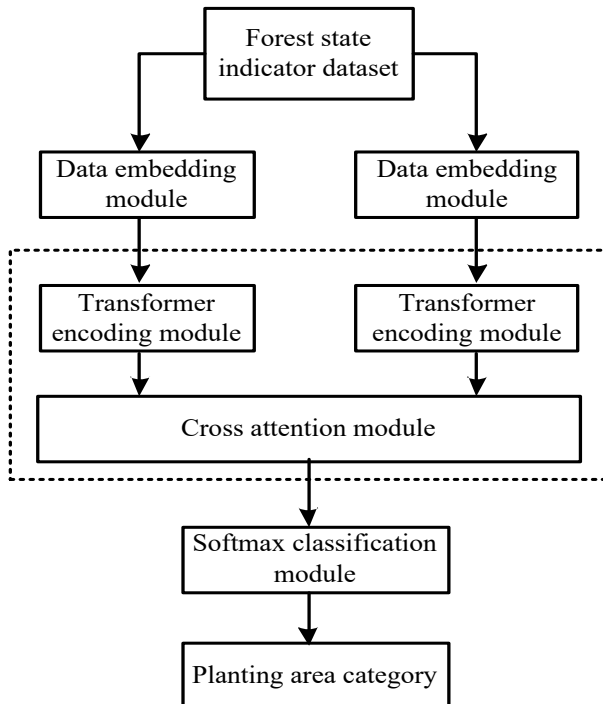


Fig. 1. CrossViT model network structure.

### Transformer Encoding Module

The Transformer encoding module of the CrossViT model uses a multidirectional Transformer encoder. Using the Multi-Head Self-Attention (MHSA) mechanism [14], it improves the characteristics of the input data on forest conditions for planting areas (e.g. niche width and overlap, soil erosion susceptibility and importance of water conservation) across multiple dimensions. This allows the CrossViT model to extract useful information from forest condition indicator data within planting areas more deeply and comprehensively, such as identifying correlations between different indicators and hidden patterns within the data. Fig. 2 illustrates the multi-directional Transformer encoder.

The multi-directional Transformer encoder first processes the input forest condition indicator data for planting areas  $A_x$  (where  $x = 1, 2, 3, \dots, 9$ ) through directional filter groups [15], yielding multidimensional forest condition features  $M$  for planting areas as shown in Equation (10):

$$M = \{B_1, B_2, B_3, \dots, B_i\} = \varphi(A_x) \quad (10)$$

Where: the  $i$ -th dimensional feature is denoted as  $B_i$ ; the directional filter group operation is denoted as  $\varphi()$ .

Further leveraging the self-attention mechanism, the original forest state indicator data  $A_x$  (as query  $Q$ ) actively queries and focuses on the most critical information within the multidimensional forest state features  $M$  (as key  $K$  and value  $V$ ) to enhance  $M$ . Subsequently, the multidirectional Transformer

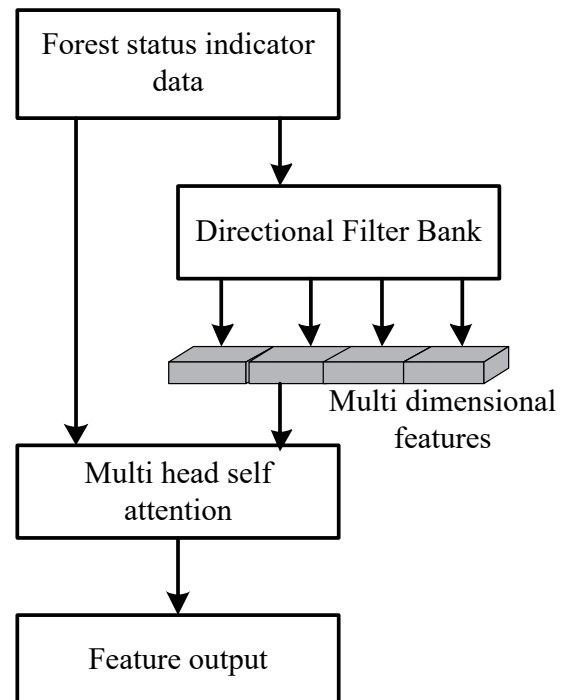


Fig. 2. Multi-directional transformer encoder.

encoder outputs the enhanced forest state features  $M^*$ , represented as shown in Equation (11):

$$M^* = \text{MHSA}(Q, K, V) \quad (11)$$

Where:  $Q = A_x$ ,  $K = V = M$ . The expression for the Multi-Head Self-Attention (MHSA) mechanism is shown in Equation (12):

$$\text{MHSA}(Q, K, V) = \chi(m_1, m_2, \dots, m_n)W^\circ \quad (12)$$

Where: the cascade operation is denoted by  $\chi$ ; the weight matrix is denoted by  $W^\circ$  and is used to aggregate forest state features of planting areas from different attention heads to learn effective feature representations. The self-attention feature  $m_n$  for the  $n$ -th head is shown in Equation (13):

$$m_n = \text{Attention}(QW_n^Q, KW_n^K, VW_n^V) \quad (13)$$

Where: the attention mechanism function is denoted as  $\text{Attention}$ ; the linear projection matrices for  $Q$ ,  $K$ , and  $V$  are represented as  $W^Q$ ,  $W^K$ , and  $W^V$  respectively, and are used to perform linear transformations on  $Q$ ,  $K$ , and  $V$  to compute the self-attention features  $m_n$  for each head. Subsequently, the forest state features of multiple heads are concatenated through a cascade operation, then linearly transformed and fused via the weight matrix  $W^\circ$  to obtain the final forest state feature  $M^*$ .

The forest state features extracted from the two Transformer encoding branches are labelled as  $M_1^*$  and  $M_2^*$  respectively. These are input into the cross-attention module for information fusion processing, yielding a more comprehensive and representative representation of the forest state features within the planting area.

#### Cross-Attention Module

The CrossViT model's cross-attention module employs a cross-attention mechanism to facilitate the exchange and fusion of information between the features from different branches [16]. This provides higher-quality input for the subsequent Softmax classification module, enabling it to accurately identify planting area categories and enhance the accuracy of planting area classification. This, in turn, improves the selection of priority planting areas for forest trees. The cross-attention computation process is as follows:

##### (1) Linear Transformation

Perform linear transformations on the forest state features of planting areas  $M_1^*$ ,  $M_2^*$  to map them into the query  $Q$ , key  $K$ , and value  $V$  spaces, as shown in Equation (14):

$$\begin{cases} Q = M_1^* W^Q \\ K = M_2^* W^K \\ V = M_2^* W^V \end{cases} \quad (14)$$

The linear transformation allows the forest state features extracted by the two Transformer encoding modules to enter a unified feature interaction space, ready for subsequent attention calculations.

##### (2) Attention Score Calculation

Compute the dot product of query  $Q$  and key  $K$ , then divide by the key dimension  $\sqrt{d}$  to obtain the attention score  $L$ , as shown in Equation (15):

$$L = \frac{QK^T}{\sqrt{d}} \quad (15)$$

The attention score reflects the correlation strength between the forest state feature  $M_1^*$  and the key feature  $M_2^*$  [17]. A higher score indicates stronger relevance between the two feature types at corresponding positions. For example, a region's rock desertification image feature may exhibit strong correlation with its soil erosion susceptibility numerical feature.

##### (3) Attention Weight Generation

The attention scores  $L$  are normalised using the Softmax function to obtain attention weights  $W_e$ , as shown in Equation (16):

$$W_e = \text{Softmax}\left(\frac{QK^T}{\sqrt{d}}\right) \quad (16)$$

The normalised weights highlight key correlations between forest state features  $M_1^*$  and  $M_2^*$  in planting areas while suppressing irrelevant or weakly correlated components. This approach prioritises feature associations significantly influencing planting site selection.

##### (4) Cross-Attention Output

Apply the attention weights  $W_e$  to the values  $V$  to compute the cross-attention output  $\hat{M}$  (i.e., the composite forest state feature for the planting area), as shown in Equation (17):

$$\hat{M} = W_e \times V \quad (17)$$

The composite forest status feature  $\hat{M}$  for planting areas, derived from the cross-attention mechanism, integrates critical information extracted by the two Transformer encoding modules [18]. When determining whether an area qualifies as a priority planting zone, this integrated feature simultaneously considers multiple forest state indicators. This enables more precise identification of priority planting zones with suitable ecological conditions capable of supporting diverse

ecological functions, thereby enhancing the scientific rigour and accuracy of selecting priority forest tree planting areas.

#### Softmax Classification Module

The comprehensive forest state features of planting areas obtained from the cross-attention module  $\hat{M}$  are input into the Softmax classification module to obtain the category probabilities for planting areas, as shown in Equation (18):

$$\lambda_j = \text{Softmax}(W^\circ \cdot \hat{M} + b) \quad (18)$$

In the formula: the estimated offset is denoted as  $b$ ; the probability of the  $j$ -th planting area category is denoted as  $\lambda_j$ .

When the value of  $\lambda_j$  exceeds the set probability threshold, the planting area category can be determined. The categories of planting areas include:

- Forested land (areas with tree canopy closure meeting specified standards)
- Open woodland (areas with lower tree canopy closure)
- Shrubland (areas dominated by shrub vegetation)
- Suitable afforestation land (land suitable for afforestation but not yet planted, including suitable barren mountains and wastelands, suitable sandy wastelands, etc.)

#### Calculation of Forest Tree Planting Area Priority Levels

The CrossViT model categorises planting areas, which are used to calculate priority levels for forest tree planting. Areas with higher priority levels generally have greater ecological value. Scientifically appropriate forest tree planting in high-priority areas can rapidly restore and enhance forest ecological functions, promoting the rational layout and development of the forestry industry [19].

During the priority level calculation process, ecosystem service value is a critical reference factor. By comparing ecosystem service values across different planting zones, areas with the greatest potential for ecological improvement can be identified as priority planting zones [20]. The formula for calculating ecosystem service value is shown in Equation (19):

$$S_j = \sum (\phi_j \cdot v_j) \quad (19)$$

Where: the ecosystem service value of the  $j$ -th planting area category is denoted as  $S_j$ ; the area and ecosystem service value coefficient of the  $j$ -th planting area category are denoted as  $\phi_j$  and  $v_j$ , respectively.

After obtaining the ecosystem service values for each planting area category, the priority ranking of

forest tree planting areas is calculated using the benefit-cost ratio targeting method, as shown in Equation (20):

$$Z_i = \frac{S_j}{O_i} \quad (20)$$

Where: the priority level of the  $i$ -th planting area is denoted as  $Z_i$ ; the cost of planting trees of type  $j$  in the  $i$ -th planting area is denoted as  $O_i$ . Here, a higher value of  $Z_i$  indicates that the ecosystem service value per unit cost invested in that area is higher, resulting in better benefits, and thus it should be prioritised for forest tree planting. Based on the priority ranking calculation results, forest tree planting areas are categorised into three tiers: priority planting areas ( $Z_i = 0.8 \sim 1$ ), secondary planting areas ( $Z_i = 0.5 \sim 0.8$ ), and potential planting areas ( $Z_i = 0 \sim 0.5$ ). This approach enables the selection of priority forest tree planting zones.

## Results and Discussion

A test was conducted to select priority suitable afforestation land for soil and water conservation, taking the Yuping Mountain Forest Wellness Base in Hongya County, Meishan City, Sichuan Province (a typical mountainous area with soil erosion risk) as the experimental site. The base is located between  $102^\circ 49'$  and  $103^\circ 32'$  east longitude and  $29^\circ 24'$  and  $30^\circ 00'$  north latitude and encompasses 35,000 mu (approximately 2,333 hectares) of artificial forest. The average annual temperature ranges from  $16.6^\circ\text{C}$  to  $17.9^\circ\text{C}$ , with an annual precipitation of 1,435.5 mm. The base comprises 10 plantable zones (labelled Zone 1 to Zone 10). By collecting data on soil, light, heat and water resources, vegetation coverage and habitat quality across these zones, the proposed method identified priority planting areas and validated its effectiveness. Fig. 3 shows the experimental area, and Table 1 provides an overview.

To verify the classification performance of the proposed CrossViT-based algorithm, 10 plantable zones in the experimental area were used as test samples. The model outputs the category probabilities for 5 land types: tree forest land, sparse forest land, shrub land, suitable afforestation land, and bamboo forest land. Taking field survey land types as the true labels, the classification accuracy and recognition reliability were quantitatively evaluated. The detailed category probabilities and actual labels of each zone are presented in Table 2, and the intuitive classification distribution is displayed in Fig. 4.

As presented in Table 2 and Fig. 4, the CrossViT model achieves 100% overall classification accuracy for all 10 zones. For shrub land (Zones 1, 4, 10), the recognition probabilities reach 0.91, 0.95, and 0.96, all higher than 0.90; sparse forest land (Zones 2, 8) is correctly identified with probabilities of 0.94; tree forest land (Zones 5, 6) and bamboo forest land (Zone 3) are accurately distinguished, and suitable afforestation land (Zones 7, 9) is recognised with probabilities above 0.92.

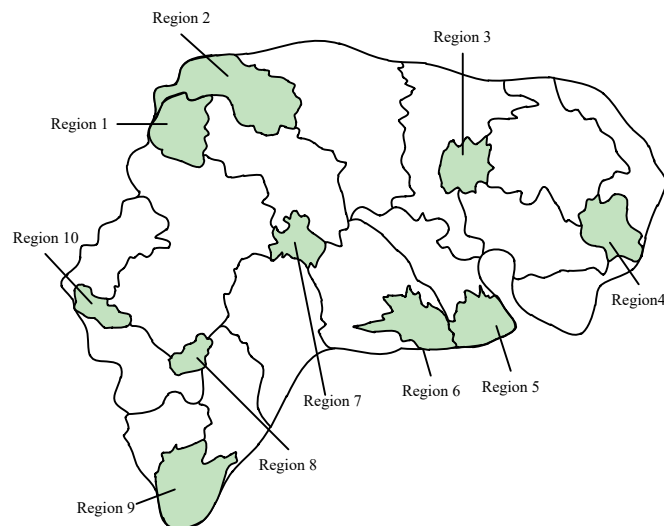


Fig. 3. Experimental area.

The model stably distinguishes tree forest, sparse forest, shrub, suitable afforestation land, and bamboo forest land without misjudgment. High-confidence classification results provide reliable land-type input for the subsequent priority ranking of planting areas.

The priority of forest planting areas was determined based on the classification of cultivable areas, and the 10 zones were divided into priority, secondary, or potential planting areas. The selection results of forest planting priority areas are shown in Fig. 5 and Table 3.

Based on ecosystem service value and benefit-cost ratio, the priority score ( $P_i$ ) of each zone was calculated (Table 3). Based on these results and Fig. 5, the grading rule is defined as:

Priority planting area:  $P_i \geq 0.85$  (red zone)

Secondary planting area:  $0.70 \leq P_i < 0.85$  (orange zone)

Potential planting area:  $P_i < 0.70$  (green zone) Zone 7 ( $P_i = 0.95$ ) and Zone 9 ( $P_i = 0.89$ ) are classified as priority planting areas. These 2 zones belong to suitable afforestation land with low forest coverage (30.92% and

Table 1. Overview of experimental area.

| Plantable area | Sensitivity Index of Soil Erosion | Habitat Quality Index | Forest coverage rate/% | Regional Overview                                                                                                                            |
|----------------|-----------------------------------|-----------------------|------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|
| Region1        | 0.2                               | 0.8                   | 63.52                  | Mainly planting shrubs such as Salix, Southern Bamboo, and Alpine Cypress                                                                    |
| Region2        | 0.5                               | 0.6                   | 31.84                  | Planting tree species such as beech, pine, and weeping willow, with sparse distribution of trees                                             |
| Region3        | 0.3                               | 0.9                   | 81.37                  | Planting bamboo species, with fertile, moist soil and good drainage                                                                          |
| Region4        | 0.3                               | 0.8                   | 65.24                  | Mainly planting shrubs such as rosewood, southern bamboo, and lemon twig                                                                     |
| Region5        | 0.4                               | 0.8                   | 58.33                  | Planting woody plants such as pine trees, elm trees, and poplar trees with a height exceeding 3 m                                            |
| Region6        | 0.2                               | 0.7                   | 60.29                  | Planting woody plants such as beech, fir, poplar, etc. with a height exceeding 3 m                                                           |
| Region7        | 0.7                               | 0.4                   | 30.92                  | Planting tree species such as <i>Pinus tabulaeformis</i> , larch, and <i>Robinia pseudoacacia</i> is suitable for afforestation and greening |
| Region8        | 0.5                               | 0.6                   | 29.37                  | Planting maple, ash, pine and other tree species, with sparse tree distribution                                                              |
| Region9        | 0.6                               | 0.3                   | 32.94                  | Planting tree species such as <i>Pinus tabulaeformis</i> , willow, elm, etc., suitable for afforestation and greening                        |
| Region10       | 0.2                               | 0.9                   | 68.57                  | Planting mainly shrubs such as rosewood, tamarisk, and seabuckthorn                                                                          |

Table 2. Classification and recognition results of plantable areas.

| Plantable area | Class Probabilities |                    |             |                             |                    | Actual category             |
|----------------|---------------------|--------------------|-------------|-----------------------------|--------------------|-----------------------------|
|                | Tree forest land    | Sparse forest land | Shrub       | Suitable afforestation land | Bamboo forest land |                             |
| Region1        | 0.02                | 0.02               | <b>0.91</b> | 0.05                        | 0                  | Shrub                       |
| Region2        | 0.01                | <b>0.94</b>        | 0.03        | 0.02                        | 0                  | Sparse forest land          |
| Region3        | 0.02                | 0.01               | 0.04        | 0                           | <b>0.93</b>        | Bamboo forest land          |
| Region4        | 0.03                | 0                  | <b>0.95</b> | 0                           | 0.02               | Shrub                       |
| Region5        | <b>0.93</b>         | 0.02               | 0.01        | 0.02                        | 0.02               | Tree forest land            |
| Region6        | <b>0.92</b>         | 0.04               | 0.03        | 0                           | 0.01               | Tree forest land            |
| Region7        | 0                   | 0.03               | 0.02        | <b>0.95</b>                 | 0                  | Suitable afforestation land |
| Region8        | 0.02                | <b>0.94</b>        | 0           | 0.03                        | 0.01               | Sparse forest land          |
| Region9        | 0                   | 0.03               | 0.02        | <b>0.92</b>                 | 0.03               | Suitable afforestation land |
| Region10       | 0.02                | 0                  | <b>0.96</b> | 0.02                        | 0                  | Shrub                       |

32.94%), high soil erosion sensitivity, and low habitat quality. Afforestation here can significantly improve water and soil conservation, control soil erosion, and improve soil stability. Mixed afforestation with suitable tree species can quickly increase forest coverage and enhance ecosystem functions. Zone 2 and Zone 8 are secondary planting areas, and the remaining zones are potential planting areas.

Following the selection of priority forest tree planting areas using this method, the ecosystem quality index was adopted as the core metric to analyse the method's performance advantages. Method efficacy validation was conducted through comparative experiments. The method was applied to select priority planting areas for forest trees, alongside the urban biocommunity classification method from Toledo-Garibaldi et al. [2] and the hierarchical analysis method from Basegmez et al [3]. Planting was then carried out based on the priority results generated by each method. The performance

of the three methods was compared by quantitatively analysing the differences in ecosystem quality after implementation. The formula for the ecosystem quality index is shown in Equation (21), and the comparison results are presented in Fig. 6.

$$RQI = \frac{\beta_i}{\eta} \times 100\% \quad (21)$$

Where: the number of planting areas is denoted as  $i$ ; Relative forest ecosystem quality index is denoted as  $RQI$ ; Forest ecosystem biomass in the  $i$ -th planting area is denoted as  $\beta_j$ ; Top-level forest community biomass within the area is denoted as  $\eta$ .

The ecosystem quality index (EQI) is used to quantify the restoration effect of priority planting areas selected by different methods, and the comparison

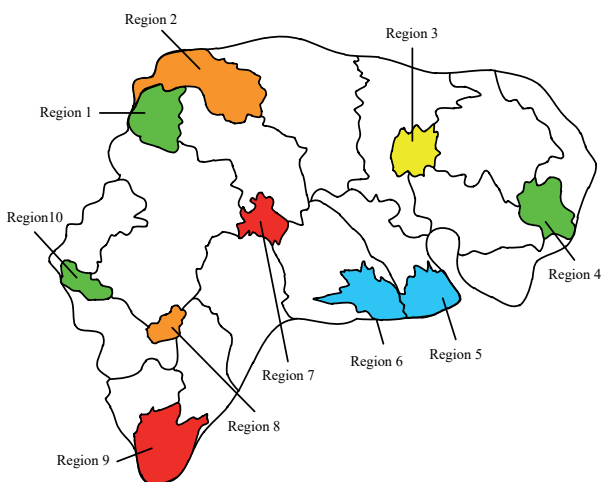


Fig. 4. Classification and recognition results of cultivable areas.

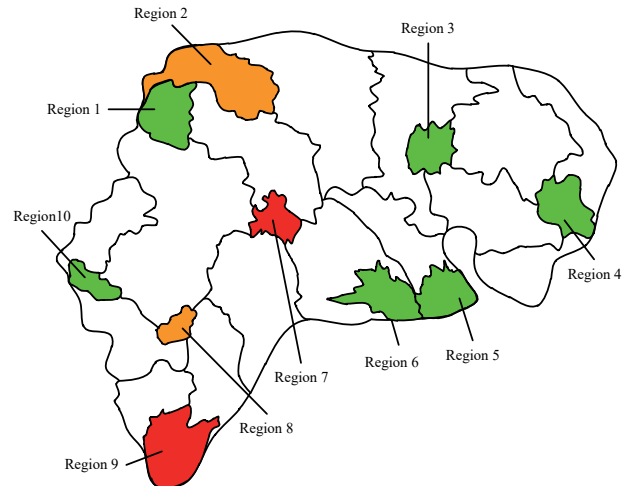


Fig. 5. Selection results of priority planting areas for forest trees.

Table 3. Selection results of priority planting areas for forest trees.

| Plantable area | $Z_i$ | Priority level           |
|----------------|-------|--------------------------|
| Region1        | 0.39  | Potential planting areas |
| Region2        | 0.76  | Secondary planting area  |
| Region3        | 0.22  | Potential planting areas |
| Region4        | 0.36  | Potential planting areas |
| Region5        | 0.41  | Potential planting areas |
| Region6        | 0.45  | Potential planting areas |
| Region7        | 0.95  | Priority planting area   |
| Region8        | 0.71  | Secondary planting area  |
| Region9        | 0.89  | Priority planting area   |
| Region10       | 0.32  | Potential planting areas |

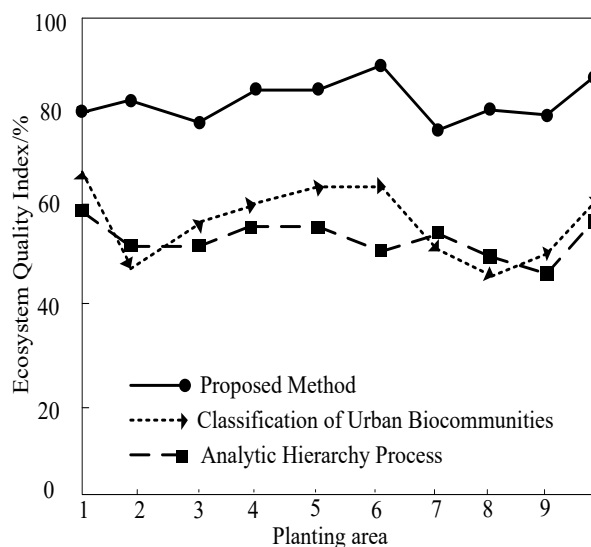


Fig. 6. Comparison results of ecosystem quality index.

is shown in Fig. 6. The EQI of priority areas selected by the CrossViT-based method is 78%-91%, with an average of 84.5%, which is close to the climax forest community level. The urban biocommunity classification method obtains an EQI of 42%-63%, and the AHP method obtains an EQI of 55%-70%, both significantly lower than the EQI obtained using the proposed method. The proposed method fuses numerical indicators and spatial image features through CrossViT, fully mining nonlinear relationships among ecological factors. The selected priority areas have greater restoration potential and higher biomass growth efficiency. In contrast, the two traditional methods ignore multi-modal data fusion and nonlinear correlations, leading to insufficient ecological improvement of selected zones.

## Conclusions

This study proposes a novel priority planting area selection algorithm for forest trees based on the CrossViT model, which effectively solves the problems of multimodal ecological data heterogeneity, difficulty in spatial-attribute information fusion, and insufficient nonlinear modelling ability of traditional methods.

(1) A seven-dimensional forest condition indicator system is constructed, covering ecological niche, soil erosion, water and soil conservation, biodiversity, habitat quality and rock desertification, providing a standardised quantitative basis for planting area evaluation.

(2) The dual-branch CrossViT architecture is innovatively adopted to realise the deep fusion of numerical ecological indicators and spatial image features via multi-head self-attention and cross-attention mechanisms, achieving 100% classification accuracy for five planting area types.

(3) Based on ecosystem service value and the benefit-cost ratio, planting areas are divided into priority, secondary and potential levels. The selected priority areas reach an ecosystem quality index of 78%-91%, significantly outperforming traditional methods. The proposed method features high precision, strong objectivity and good scalability, providing a reliable technical solution for scientific site selection and efficient decision-making in forest ecological restoration projects.

## Acknowledgments

This study received no funding.

## AI Usage Disclosure Statement

The author confirms that no AI tools or systems were used in the research design, data analysis, manuscript writing, language editing, or graphic preparation of this study. All works are original and completed solely by the author.

## Conflict of Interest

The authors declare no conflict of interest.

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