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A DEEP LEARNING-BASED ALGORITHM FOR UNITIZING ECOLOGICALLY SENSITIVE AREAS IN RURAL LANDSCAPES

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Highlights:

- by selecting six major factors that affect the ecological sensitivity of rural landscape;
- an ecological sensitivity evaluation index system is constructed;
- support vector machine is used to divide the ecological units of the collected rural landscape ecological images;
- the division results and the sensitivity evaluation results of each unit of rural landscape are used as the input data of ArcGIS software to realize the visual presentation of the unit division results of rural landscape ecological sensitive areas.

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Abstract. The ecological sensitivity of rural landscapes exhibits complexity and diversity. Traditional evaluation methods, which merely take into account a single factor or a limited number of factors, struggle to effectively manage uncertain information. This leads to inaccurate classification of ecological units in rural landscape ecological images, thereby undermining the precise assessment of the distribution of ecological sensitivity in rural landscapes. Therefore, a deep learning based algorithm for dividing rural landscape ecological sensitive areas is proposed. By selecting six major factors that affect the ecological sensitivity of rural landscape, such as geological environment, ecological and hydrological conditions, an ecological sensitivity evaluation index system is constructed, which is used as an input vector, and fuzzy neural network is used to output the ecological sensitivity of rural landscape; In addition, support vector machine is used to divide the ecological units of the collected rural landscape ecological images, and the division results and the sensitivity evaluation results of each unit of rural landscape are used as the input data of ArcGIS software to realize the visual presentation of the unit division results of rural landscape ecological sensitive areas. The results showed that with the increase of slope, the ecological sensitivity of rural landscape showed a trend of first increasing and then decreasing, the vegetation coverage rate decreased, and the ecological sensitivity of rural landscape showed a trend of gradually increasing; This algorithm can effectively evaluate the sensitivity of each unit of rural landscape, and visually present the unit division results of ecological sensitive areas of rural landscape. This algorithm can compare and analyze the changes of ecological sensitivity under different time dimensions.

Keywords: deep learning, rural landscape, ecological environment, sensitivity assessment, unit division, evaluation indicator system.

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1. Introduction

The core of dividing ecologically sensitive areas in rural landscapes lies in conducting ecological sensitivity assessments. The so-called ecological sensitivity refers to the degree of sensitivity exhibited by an ecosystem in the face of human activities and natural environmental changes. It reveals the possibility and difficulty of ecological and environmental problems occurring in a certain region. This assessment helps to understand the natural environment quality, land use status, population carrying pressure, and scientific direction of future planning in a region, forming the cornerstone of ecological environment planning and management work in that area. At present, many experts and scholars have studied the division of sensitive areas, such as Roy and Maji (2020) using rough fuzzy clustering algorithm, combined with sRFCM algorithm and local neighborhood information, to deal with the uncertainty caused by class overlap and incomplete definition. The sRFCM algorithm takes into account the spatial distribution of images and leverages local neighbor labels to influence the labels of central pixels, thereby achieving the division of approximate (core region) and probabilistic boundary regions for each cluster based on its probability characteristics. However, the area divided by this method is too rough and mainly suitable for general classification, making it difficult to achieve precise segmentation of rural landscape ecological images; Lee et al. (2020) proposed a CMOS image sensor that performs compressed sensing encoding without affecting operational speed and

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hardware complexity. This sensor utilizes high-order $\sum - \Delta$ ADC to obtain linear measurements, improve conversion rate and frame rate, and solve distortion caused by non constant weight functions through sampling techniques to achieve image region division. However, this method is mainly suitable for optimizing the performance of image sensors and dividing image regions, and its application scope is relatively limited; Atterholt et al. (2021) utilized the characteristics of DAS arrays and the non-uniform scaling properties of Curvelets to represent images in a discontinuous form along segmented continuous differentiable curves, thereby achieving fine segmentation of images. However, this method is mainly applicable to images collected through wavefield, and its applicability is limited for remote sensing images and complex rural landscape ecological images; Belizario et al. (2021) used superpixel pre partitioning to extract color features and construct a graph model, where vertices represent superpixels and edge weights reflect similarity. Image region partitioning was achieved through label propagation. However, this method mainly relies on the color features of the image, ignoring key ecological sensitivity factors such as geological environment and hydrological conditions, which may result in incomplete and inaccurate segmentation results.

Although existing methods for dividing ecologically sensitive areas in rural landscapes have made progress to some extent, they are often limited by the accuracy, efficiency, and scale of data processing, making it difficult to fully meet the complex and changing ecological environment needs of rural areas. In contrast, the deep learning based rural landscape ecological sensitive area unit partitioning algorithm proposed in this article has demonstrated significant advantages in multiple aspects. This algorithm combines the advanced features of fuzzy neural networks and support vector machines (SVM) to achieve precise evaluation of the ecological sensitivity of rural landscapes. Fuzzy neural networks can handle uncertainty and fuzziness, improving the accuracy of ecological sensitivity assessment; Support vector machines, on the other hand, have achieved precise segmentation of rural landscape ecological images through their powerful classification capabilities. Deep learning models can automatically extract useful information by learning feature representations from large amounts of data, and apply them to complex classification and prediction tasks (Muralimohanbabu & Radhika, 2021; Guo et al., 2023, 2024). In the division of ecologically sensitive areas in rural landscapes, deep learning algorithms can fully utilize multi-source information such as remote sensing images and GIS data to achieve refined analysis and recognition of rural landscapes. Secondly, the ability of deep learning algorithms to handle large-scale data can address the complex and ever-changing ecological environment problems in rural areas. By integrating and analyzing multi-source data, deep learning algorithms can reveal the spatial distribution characteristics and evolution laws of rural landscapes, providing more comprehensive and in-depth information support for the division of ecologically sensitive areas in rural landscapes. Meanwhile, deep learning has achieved significant results in environmental factor analysis, satellite image classification, and supervised classification of drone images. For example, using artificial intelligence and machine learning methods for environmental factor analysis can more accurately assess the changing trends and potential risks of the ecological environment; Using machine learning to classify PlanetScope nanosatellite images, high-precision recognition of land cover types has been achieved; The supervised classification of drone images based on deep learning has been successfully applied to forest area classification, improving the accuracy and efficiency of classification. These successful cases provide strong evidence and support for the selection of deep learning in the classification of ecologically sensitive areas in rural landscapes in this article. In addition, this article uses the division results and the sensitivity assessment results of each unit of rural landscape as input data for ArcGIS software, realizing the visualization of the division results of ecological sensitive areas in rural landscape. This not only improves the intuitiveness and readability of the division results, but also helps decision-makers to more accurately understand and respond to ecological environment problems in rural areas. Therefore, this paper addresses the issue of insufficient accuracy in traditional methods for assessing the ecological sensitivity of rural landscapes, and uses deep learning techniques to construct a new evaluation model. Firstly, establish an ecological sensitivity evaluation index system that includes six major influencing factors, and use fuzzy neural networks to calculate the ecological sensitivity values. Then, the support vector machine algorithm is used to divide the region into ecological units. Finally, the spatial visualization of the evaluation results was achieved using the ArcGIS platform. This method improves the accuracy of delineating ecologically sensitive areas by integrating multi-source data and processing fuzzy information, providing quantitative basis and spatial display means for rural ecological protection planning and sustainable development decision-making.

2. Ecologically sensitive area delineation for rural landscapes

2.1. Establishment of rural ecological sensitivity analysis index system

Rural areas are particularly difficult to collect relevant data due to their vast territory, sparse population distribution, and complex and varied terrain and landforms. This often leads to difficulties in fully considering the overall characteristics and interrelationships of the ecosystem when dividing rural landscape ecological zones, resulting in a certain deviation between the designated ecologically sensitive areas and the actual ecosystem conditions. Therefore, building a scientific, practical, and easy to operate evaluation index system, and selecting appropriate evaluation criteria, is crucial for successfully conducting rural landscape ecological sensitivity analysis (Haq et al., 2022). Among them, selecting reasonable and appropriate evaluation indicators is the primary and crucial step in conducting sensitivity analysis of rural landscape ecology.

In the process of constructing the indicator system, we can draw on the advantages of machine learning in multi-source data fusion and feature extraction (Haq, 2022; Haq et al., 2021). On the basis of field investigation of landscape ecological geological environment, this article comprehensively considers the complexity of the region and the coupling characteristics of multiple factors, and constructs an ecological sensitivity evaluation system consisting of 6 categories and 12 secondary indicators. Selecting geological environment, ecological environment, hydrological conditions, human activities, landscape value, and geological hazards as primary indicators, where geological environment indicators reflect regional stability and carrying capacity, ecological environment indicators characterize biological vitality and ecological balance, hydrological condition indicators evaluate water resource distribution and ecological water demand, human activity indicators quantify the degree of human interference, landscape value indicators measure aesthetic and tourism development potential, and geological hazard indicators evaluate regional security risks. This indicator system takes into account both macro characteristics and micro phenomena, providing a systematic framework for comprehensively assessing ecological sensitivity. Macro features refer to significant characteristics or phenomena that can be observed at a larger scale or range. In this article, macro features are defined as the overall or principal characteristics of the landscape ecological-geological environment in the study area. These include geological environmental factors such as geological structure, terrain slope, slope orientation, and elevation, as well as human-activity factors, including the distribution of water systems, roads, residential areas, and tourist facilities. These factors affect the ecological and geological environment of the study area on a large spatial scale. And special microscopic phenomena refer to subtle or special characteristics or phenomena that can only be observed at smaller scales or under specific conditions. In this article, special microscopic phenomena refer to subtle changes in certain specific locations or conditions within the study area, including the growth status of certain specific vegetation, subtle changes in specific geological structures, etc. Although these factors may not be significant on an overall scale, they may have significant impacts on the ecological and geological environment of the study area under specific conditions. Geological environment (Bilgin & Acun, 2021) includes geological structure (fault, etc.), topographic slope, slope direction, elevation; ecological environment includes biodiversity, vegetation coverage, land use type; hydrological conditions include distribution of water system; human activities include distribution of roads, settlements and tourist facilities; landscape value includes distribution of scenic spots;

Table 1. Index system for ecological sensitivity evaluation of rural landscape

Constraint factor	Impact factors	Sensitivity factor level representation and rating				
		Very low	Low	Moderate	Tall	Extremely high
Environment	Scope of geological structure influence	>280 m	230–280 m	180–230 m	130–180 m	<80 m
	Slope	<10°	10–17°	17–24°	24–31°	>31°
	Slope orientation	Flat region	0–23	158.4–201.3	113.2–158.4	23–66.8
		66.8–113.2	338.5–365	248.5–293.5	293.5–338.5	201.3–248.5
	Elevation	<500 m	500–800 m	800–1100 m	1100–1600 m	>1600 m
Ecological environment	Biological diversity	Biodiversity Level 5 Zone	Biodiversity Level 4 Zone	Biodiversity Level 3 Zone	Biodiversity Level 2 Zone	Biodiversity Level 1 Zone
	Vegetation coverage	>80%	75–80%	55–75%	35–55%	<35%
	Land use	Forest land	Grassland	Unutilized land	Industrial and mining residential areas	Cultivated land
Hydrologic condition	Scope of water impact	>280 m	230–280 m	180–230 m	130–180 m	<80 m
Human activities	Road impact range	>280 m	230–280 m	180–230 m	130–180 m	<80 m
	The scope of influence of residential tourism agencies	>280 m	230–280 m	180–230 m	130–180 m	<80 m
Landscape value	Scope of influence of primary scenic spots	>300 m	250–300 m	200–250 m	150–200 m	<150 m
	Scope of influence of secondary scenic spots	>280 m	230–280 m	180–230 m	130–180 m	<80 m
Geological disaster	Geological hazard risk	Hazard level 1	Hazard level 2	Hazard level 3	Hazard level 4	Hazard level 5
Graded rating		1	3	5	7	9
Standard		<2	2–4	4–6	6–8	>8

geologic hazards mainly refer to geologic hazards risk. By referring to the relevant literature and in combination with the actual situation of the landscape in the study area, we obtained the secondary evaluation indexes of the factors affecting the sensitivity of the landscape's ecological and geological environment in the study area, as well as the grading standards for these factors, as shown in Table 1.

The selection and expression of the evaluation factors at each level are described as follows:

(1) Geo-environmental factors

Human beings and other living creatures depend on the geological environment for their survival and development, and at the same time, human beings and other living creatures are constantly changing the geological environment. As an important factor affecting the sensitivity of the ecological and geological environment of the study area, this paper selects four evaluation indexes, namely, geological structure, slope, slope direction and elevation, mainly from the perspective of topography and geology.

Folds, faults, and fault zones in geological structures are active areas of the crust that are prone to earthquakes and other disasters, and can affect the development and changes of the ecological geological environment. To quantify this impact, this article selects the distance from faults and fault zones as an indicator to represent the sensitivity level of the ecological-geological environment. Four grading distances, namely 50 m, 100 m, 150 m, and 200 m, are set. Specifically, the selection of these distances is based on in-depth research on the probability and scope of geological hazards. The closer the distance to faults and fault zones, the higher the probability of geological disasters occurring, and the greater the impact on the ecological geological environment. Therefore, these graded distances can accurately reflect the sensitivity of ecological and geological environments in different regions. By using historical earthquake data, geomechanical models, and other methods, the impact of different fault activities on the surface can be evaluated. Combined with the vulnerability analysis of the ecosystem, a quantitative relationship between fault activity and ecological sensitivity can be established, which helps to more accurately assess the impact of faults on the ecological geological environment.

Slope is one of the most fundamental geomorphological indicators. Generally, the greater the slope is, the more serious the surface erosion will be, and it is also more prone to landslides, mudslides, and other disasters. The possibility of ecological and geological environmental problems can be reflected by the slope size to determine the sensitivity grade, with reference to the grading criteria in the Interim Rules for Ecological Function Zoning Technology.

The impact of slope orientation on geological hazards is mainly reflected in its effects on surface hydrology, soil erosion, and vegetation coverage. Due to the northeast southwest orientation of most mountain peaks, this terrain feature makes it easier for northwest southeast slopes to receive large amounts of water flow during rainfall, increasing the risk of soil erosion and landslides. Meanwhile, slopes in these directions are relatively less exposed to sunlight, which may lead to higher soil moisture and further promote the occurrence of landslides and debris flows. In contrast, slopes in the due east and due south directions, as well as flat areas, have superior lighting conditions, which are conducive to the growth and flourishing of vegetation. The root system of vegetation can stabilize the soil, reduce soil erosion, and thus lower the risk of landslides and mudslides. In addition, slopes in these directions may be more conducive to the rapid discharge of water during rainfall, reducing the possibility of soil over saturation. However, the impact of slope orientation on geological hazards is not absolute. Other key factors such as soil type, rainfall intensity, land use, and geological structure also play important roles in geological disasters. Soft soil types and high-intensity rainfall may exacerbate the occurrence of landslides and debris flows, while reasonable land use planning and engineering measures can help reduce disaster risks. In order to more accurately assess the impact of slope orientation on geological hazards, it is necessary to conduct comprehensive analysis by combining geological surveys, meteorological data, remote sensing monitoring, and geographic information systems. By quantifying indicators such as rainfall characteristics, soil erosion rates, and vegetation coverage in areas with different slope orientations, we can gain a deeper understanding of the relationship between slope orientations and geological hazards, and provide scientific basis for disaster prevention and mitigation.

The elevation also affects the change and development of the ecological geological environment. The higher the altitude, the lower the temperature, the less vegetation, and the simpler the ecosystem (Drake, 2023), which is more likely to cause ecological geological environment problems. According to the specific situation of the elevation, the vegetation on the top of the mountain is scarce at an altitude of more than 1000 m, while the vegetation is relatively lush at an altitude of less than 700 m.

(2) Ecological factors

The factors affecting the ecological environment include biodiversity, vegetation coverage, land use cover, and human activities, among others (He et al., 2025). These factors work together on the ecosystem, affecting the sensitivity and stability of the ecological geological environment. Firstly, biodiversity is an important indicator of the complexity and stability of ecosystems. The higher the level of biodiversity, the more diverse the ecosystem types, the more complex the food chain and web, and the stronger the self-regulation and restoration ability of the ecosystem. Therefore, the possibility of ecological geological environmental problems is relatively small. However, the evaluation of biodiversity is not simply based on classification, but requires comprehensive consideration of multiple aspects such as species richness, inter species relationships, and ecosystem functions. In addition, external factors such as invasive species and climate change may also have significant impacts on biodiversity. Therefore, when evaluating biodiversity sensitivity, it is necessary to fully consider the potential effects of these factors. Secondly, vegetation coverage is an important indicator reflecting the structural diversity of the ecological environment system. In areas with high vegetation coverage, the ecological environment system has a diverse structure, and the risk of soil erosion and water loss is relatively low, which also reduces the likelihood of environmental problems. However, the classification of vegetation coverage is not arbitrarily set, but needs to be determined based on the Interim Technical Regulations for Ecological Function Zoning and the specific ecological environment characteristics of the region. At the same time, changes in vegetation coverage are also influenced by various factors, including climate change, land use patterns, etc. Therefore, when evaluating the sensitivity of vegetation coverage, it is necessary to comprehensively consider the combined effects of these factors. Based on the vegetation coverage classification in the Interim Technical Regulations for Ecological Function Zoning and combined with the specific situation of rural landscape ecological environment, the vegetation coverage classification boundaries in this area are set at 30%, 45%, 60%, and 75%. In terms of land use coverage, different types of land use have varying impacts on the ecological environment. The land use pattern with a single ecological structure is susceptible to human activities and carries a higher risk of ecological and geological environmental problems. Forest systems, due to their strong regulatory capabilities, are able to maintain the stability and diversity of ecosystems, making them less prone to environmental problems. However, the sensitivity of land use patterns is not fixed and unchanging, but is influenced by various factors, including the intensity of human activities, the frequency of changes in land use patterns, and so on. Therefore, when evaluating the sensitivity of land use cover, it is necessary to fully consider the comprehensive effects of these factors. In addition, the impact of human activities on the ecological environment cannot be ignored. Human activities include construction activities, agricultural activities, industrial activities, etc., all of which may have direct or indirect impacts on the ecological environment. However, the impact of human activities is not simply related to distance, but to multiple factors such as activity intensity and duration. Therefore, when evaluating the impact of human activities on ecological sensitivity, it is necessary to comprehensively consider the combined effects of these factors and avoid excessive reliance on fixed distance thresholds. Finally, a more detailed and specific analysis is needed regarding the classification and protection status of landscape values in specific areas such as scenic spots. Different types of scenic spots possess distinct landscape values and protection requirements. Therefore, when conducting sensitivity evaluations, these differences need to be fully taken into account. Meanwhile, maintaining the existing landscape conditions is also an important factor influencing sensitivity evaluation, and full consideration should be given to the effectiveness and sustainability of protection measures.

(3) Hydrologic condition factor

Hydrological conditions are an important element of the sensitivity of the ecological and geological environment of rural landscapes. Surface water systems crisscross in the study area, which is the main water cycle system that affects the ecological environment of rural landscapes. In addition, human activities mostly revolve around these water systems, and water resources are important resources of the ecological environment of rural landscapes. The closer to the water body, the stronger the human impact will be. Therefore, the hydrological conditions in this paper are mainly reflected by the distance from the surface water body. Based on the analysis of the spatial distribution characteristics of the rural landscape ecological environment water system, the area within 100 meters of the water system is generally considered its sensitive zone, while areas beyond 150 meters can be regarded as insensitive or low-sensitivity zones. Therefore, classification boundaries are set at 50 m, 100 m, 150 m, and 200 m to further refine the sensitivity grading.

(4) Human activities

Roads, settlements, tourist facilities and their vicinity are the most active places for human activities. The farther away from these areas, the less affected by human activities. Therefore, the road buffer analysis and the residential tourism facilities buffer analysis have the same effect mechanism on the ecological geological environment sensitivity, and both are related to the distance. The closer to these frequent human activities, the more likely to cause environmental problems. Like the aforementioned water system and geological structure factor analysis, the classification boundary of the road, residential and tourism facilities factors in the human activity impact factors here is also set as 50 m, 100 m, 150 m, and 200 m.

(5) Landscape value

The scenic spots in the study area are divided into Level I and Level II according to the number of tourists per year and the protection value of the scenic spots. Level I scenic spots have a large scope of influence, a large number of tourists, and complete infrastructure construction. The closer to the scenic spots, the more frequent human activities, and the greater the possibility of ecological geological environment problems; The influence scope of Level II scenic spots is relatively small, and the closer the scenic spots are, the greater the possibility of ecological geological environment problems. According to the characteristics of each scenic spot in the rural landscape and ecological environment, the Level I scenic spot classification boundary is 80 m, 160 m, 240 m and 320 m, while the Level II scenic spot classification boundary is 50 m, 100 m, 150 m and 200 m. After the factors at all levels are selected and graded, for the needs of the subsequent analytic hierarchy process, it is necessary to assign new values to each level of the factors after grading in order to unify the dimensions for comprehensive analysis of ecological geological environment sensitivity. Generally, the grade values of each factor can be unified to the dimension unit of 1–10. In this paper, the 5 grade values of the factors at all levels are defined as 1, 3, 5, 7, and 9. Finally, the comprehensive analysis results take 2, 4, 6, 8 as the classification boundary for classification.

(6) Geologic hazard factors

Geological hazards in rural landscape ecological environment mainly include collapse (dangerous rock body) and landslide. This phenomenon is caused by the drastic alteration of the surface geological structure of the earth's crust. Such geological events are typically considered sudden occurrences and exert a significant destructive impact on the ecological and geological environment. Therefore, in this paper, the risk assessment grades of geological hazards are used to represent the high and low levels of the sensitivity factor of geological hazards. Generally, the higher the geohazard risk level, the more likely to produce geohazards, and thus the higher the possibility of ecological and geological environmental problems in these places, i.e., the ecological and geological environmental sensitivity is high (Akgün et al., 2020). Geohazard risk assessment is to investigate, monitor, analyze and evaluate the activity degree of geohazards, mainly assessing the destructive ability of geohazards. In this paper, according to the geohazard characteristics of rural landscape ecological environment, the topographic factors of slope direction and slope gradient, stratigraphic lithology, highway, vegetation cover and geological structure were chosen to approximate the assessment of geohazard risk.

The above evaluation indicators do not exist in isolation, but are interrelated and influence each other. The stability of geological structures directly affects the degree of impact of slope and aspect on disaster risk; The vegetation coverage and land use type jointly determine the stability and sensitivity of the ecological environment; Hydrological conditions and human activities are intertwined, jointly shaping the ecological environment pattern of the study area. In the evaluation process, there was no strict prioritization of evaluation indicators, but rather a comprehensive consideration of the roles and impacts of all factors. Each indicator has been graded and assigned values based on its own importance and sensitivity to the ecological geological environment. In the subsequent comprehensive analysis, the Analytic Hierarchy Process (AHP) method is used to conduct a comprehensive analysis based on the weights of each indicator, in order to obtain more accurate and reliable ecological sensitivity assessment results.

Table 1 provides a detailed breakdown of the grading criteria and corresponding ratings for each evaluation indicator. These grading standards are based on the actual situation of the study area and aim to objectively reflect the contribution of various evaluation indicators to the sensitivity of the ecological geological environment in the study area. In terms of data collection and processing, various methods such as remote sensing images, GIS data, and on-site investigations are used. Remote sensing images and GIS data provide basic information on the topography, vegetation coverage, and water system distribution of the study area; The on-site investigation supplemented detailed data on biodiversity, land use types, geological hazards, and other aspects. After processing and analyzing these data, they are used to construct evaluation models and conduct sensitivity assessments. In the evaluation process, this article did not clearly prioritize the evaluation indicators, as each indicator has a significant impact on the sensitivity of the ecological geological environment in the study area. However, in practical operation, different indicators can be weighted according to research purposes and actual situations to more accurately reflect their contribution to sensitivity.

To sum up, through ecological sensitivity analysis, the ecological strengths and weaknesses of rural areas can be identified, and a comprehensive consideration can be given to multiple aspects of rural landscapes, such as topography, vegetation cover, hydrological conditions, human activities, and other factors, thereby enhancing the accuracy and reliability in delineating ecologically sensitive areas. This indicator system not only provides scientific basis for ecological sensitivity analysis of rural landscapes, but also effectively guides ecological protection and sustainable development planning in rural areas, enhances the accuracy and practicality of ecological sensitive area division, and thus demonstrates high attractiveness and relevance in real-world applications.

2.2. Sensitivity assessment based on fuzzy neural network

In the assessment process of rural ecological sensitivity, various ecological sensitivity indicators are often interrelated, which may lead to repeated accumulation of information and weaken the accuracy of the assessment results. Compared with the spatial data processing advantages of other deep learning models such as convolutional neural networks and the temporal modeling capabilities of recurrent neural networks, fuzzy neural networks are more suitable for handling uncertainty and complex relationships in multi-source unstructured ecological data through membership functions and fuzzy rules. The concise structure and fuzzy reasoning characteristics of fuzzy neural networks (Khuat et al., 2021) can effectively reduce the mutual interference between indicators, accurately quantify the contribution of various factors to ecological sensitivity, and thus improve the reliability and interpretability of evaluation results. In this process, the environmental and ecological indicators mentioned earlier are used as input information, and the output results of the evaluation directly reflect the ecological sensitivity of the rural landscape environment.

In the fuzzy neural network, the algorithm (Abdalmoaty et al., 2020) combining steepest descent and LSE least square estimation is used in this paper, so that the fuzzy neural network has only one output, namely, the sensitivity evaluation result of rural landscape environment ecology, which is expressed as:

$$O = F\left(B_i, S\right). \tag{1}$$

Among them, B_i is the input vector, i.e., the indicators affecting the ecological sensitivity of the countryside as described in 2.1. S is the set of parameters, which are necessary for the realization of the sensitivity assessment of the environmental ecology of the rural landscape. F is the overall function of the sensitivity assessment of the environmental ecology of the rural landscape realized by the network, if the function, if the function H makes the compound function $H \bullet F$ linear to certain elements in S, then these elements can be obtained by least squares identification. The set of parameters S can be partitioned into two sets, i.e., the $S = S_1 \oplus S_2$.

If the $H \bullet F$ is linear to the element in S_2, apply the H operator to Equation (1), including:

$$H(O) = H \bullet F(B_i, S). \tag{2}$$

At this time, $H \bullet F$ is linear to the elements in the S_2, now we give the element value $y = A\theta$ in S_1. Where, θ is the unknown vector whose elements are in the parameters S_2. This can be transformed into a standard linear least squares problem, such that, make the $\|A\theta = y\|^2$ minimize. The optimal solution for θ is the least squares estimator θ^*:

$$\theta^* = \left(A^{\mathrm{T}} A\right)^{-1} A^{\mathrm{T}} y. \tag{3}$$

Among them, A^{T} is the transpose of A. If $A^{\mathrm{T}}A$ is nonchalant, then $\left(A^{\mathrm{T}}A\right)^{-1} A^{\mathrm{T}}$ is the pseudo-reverse of A.

Define the vector of matrix A is a^{T} and the τ th element of y is y_τ^{T}, it can be iterative θ^* in the following equation:

$$\begin{cases} \theta_{t+1} = P_{t+1} + a_{t+1} + \left(y_{t+1}^{\mathrm{T}} - a_{t+1}^{\mathrm{T}}\theta^*\right) \\ \psi_{t+1} = \psi_0 - \dfrac{\psi_0 a_{t+1} + a_{t+1}^{\mathrm{T}} + \psi_0}{1 + a_{t+1}^{\mathrm{T}} + \psi_0 a_{t+1}} \end{cases}. \tag{4}$$

Among them, θ_{t+1} denotes least squares estimator θ^* in the iterative process, t denotes the number of iterations. The initial conditions required to compute Equation (4) is $\psi_0 = \gamma I$, of which γ is a large positive number, the I is the unit matrix with the dimension of $M \times M$, these initial conditions play a great role in identifying θ^*.

The following algorithm combines steepest descent and LSE to calculate the parameters in the sensitivity assessment of rural landscape environment ecology by fuzzy neural network. Each cycle of calculation includes a forward transmission process and a reverse transmission process. In the forward transmission process, each input vector composed of indicators that affect rural ecological sensitivity is given, calculate the sensitivity output of the rural landscape environment ecology of the network node layer by layer until the corresponding rows of the matrix A and y is obtained, repeating this process for all training data to form a complete A and y; Subsequently the parameters in S_2 can then be identified by a pseudo-inverse equation in Equation (3) or by a recursive least squares equation in Equation (2), after identifying the parameters in S_2, the error index (Bento et al., 2023) was calculated for each training data.

In the reverse transmission process, assuming a L layered networks, the l th layer ($l = 0,1,\ldots,L$; $l = 0$ denotes the input layer) has number of $N(l)$ nodes, there are i nodes of l layers $\{i = 1,\ldots,N(l)\}$ and the output function of it can be expressed as $X_{l,i}$:

$$X_{l,i} = \theta_{i+1}\left(X_{l-1,1},\ldots,X_{l-1,N(l-1)},\alpha,\beta,\gamma,\ldots\right). \tag{5}$$

Among them α, β, γ are parameters for this node.

Given the training data set P pair data, the error index of p to $(1 \le p \le P)$ data is defined as the sum of squares of error:

$$E_P = \sum_{l=1}^{L}\left(d_k - X_{l,i,k}\right)^2, \tag{6}$$

where, $E_P = \sum_{k=1}^{N(l)}\left(d_k - X_{L,k}\right)^2$ is the k th component of the expected output vector of the sensitivity of the p th rural landscape ecology, $X_{l,i,k}$ is the k th component of the actual output vector of the sensitivity of the rural landscape environment generated by the p th input vector composed of indicators affecting the sensitivity of the rural ecology imposed to the network (for simplicity of representation, for $E_P = \sum_{k=1}^{N(l)}\left(d_k - X_{L,k}\right)^2$ and $X_{l,k}$ omitting the subscript p). If $E_p = 0$, then the network can accurately reproduce the expected output vector (Kang et al., 2021a) of the rural landscape environment in the p th training data, so in this paper, in order to achieve the purpose of minimizing the overall error of the sensitivity assessment of the rural landscape environment ecology, the definition error $\varepsilon_{L,i}$ is the derivative of the output of layer l and i node of the error index E_P of the fuzzy neural network, and the symbol is expressed as:

$$\varepsilon_{L.i} = \frac{\partial^+ E_p}{\partial X_{L,i}}. \tag{7}$$

Among them ∂^+ indicates that the derivative tends to zero from the right side of the axis, i.e., it tends to zero in the direction of positive numbers. $\varepsilon_{L.i} = \frac{\partial^+ E_p}{\partial X_{L,i}} = \frac{\partial E_p}{\partial X_{L,i}}$ i.e., the internal node error signal in layer l can be represented as a linear combination of the node error signals in layer $l+1$.

For the simple steepest descent method without linear minimization, the overall error index E relative to α has a derivative of:

$$\Delta\alpha = -\eta\frac{\partial^+ E}{\partial\alpha}. \tag{8}$$

Among them η is learning efficiency.

The output of the fuzzy neural network for assessing the ecological sensitivity of the rural landscape environment is:

$$O_{\min} = \frac{\Delta\alpha\omega_i}{\sum_{i=1}^{i}\omega_i}. \quad (9)$$

Among them, ω_i is the weight of the network node i.

As a result, the overall error of the sensitivity assessment results of the rural landscape environment is minimized, which can reflect the actual ecological sensitivity of the rural landscape environment more accurately.

Through the sensitivity assessment of fuzzy neural network, the preliminary results of the ecological sensitivity of rural landscape environment can be obtained, which can provide guidance and direction for the subsequent delineation work.

2.3. Support vector machine-based unit delineation of ecologically sensitive areas in rural landscapes

The definition of ecologically sensitive areas in rural landscapes is a comprehensive consideration process that involves multiple dimensions and indicators. The application of fuzzy neural networks in sensitivity assessment provides a more detailed and accurate data foundation for subsequent support vector machine partitioning. By comprehensively incorporating various ecologically sensitive elements, the geographical scope with different sensitivity levels can be more accurately defined, thereby ensuring the accuracy and pertinence of the division of ecologically sensitive areas.

With the collected rural landscape ecological image as input, the SVM based rural landscape ecological unit division model is constructed to complete the rural landscape ecological unit division. In combination with sections 2.1 and 2.2, the sensitivity influencing factors of each rural landscape ecological unit are taken as the fuzzy neural network input, and the sensitivity of each unit is obtained through evaluation, the results of unit division of rural landscape ecological sensitive areas are visualized with ArcGIS software. The specific unit division process of rural landscape ecological sensitive area is shown in Figure 1.

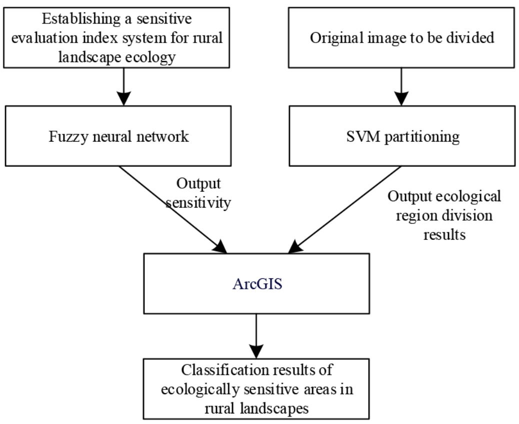

Figure 1. Flow chart of unit division in rural landscape ecological sensitive areas

SVM outperforms decision trees and k-NN when classifying ecologically sensitive areas in rural landscapes, since it demonstrates excellent performance in handling high-dimensional nonlinear data, possesses strong generalization capabilities, and enables accurate classification, making it particularly well-suited for scenarios characterized by limited samples and a multitude of features. SVM flexibly uses kernel functions to handle complex relationships, while decision trees are prone to overfitting, and k-NN has low efficiency in handling high-dimensional data and poor performance on imbalanced data. Therefore, SVM is more suitable for finely dividing ecologically sensitive areas in rural landscapes.

The ecological unit division principle of SVM is to use the separation hyperplane as the linear function of the separated image to solve the nonlinear classification problem (Sing et al., 2022; Neethu et al., 2022). The optimization function (maximization functional) for SVM to obtain the optimal classification surface is defined as follows:

$$Q(x) = O_{\min} g \sum_{\xi=1}^{n} x_\xi. \quad (10)$$

Among them, x is the input rural landscape ecological image sample, representing different features or attributes of the rural landscape, used to train the model to distinguish different ecological units; the n is the total number of rural landscape ecological image samples used for training SVM models; ξ is the classification number of the sample, indicating the ecological unit category to which the sample belongs; and g is the Lagrange coefficient in function optimization (Brown & Balakrishnan, 2021).

In the process of SVM classification of rural landscape ecological units, the selection of basis function is very important. The selection of the basis function corresponds to the selection of the function class that constructs the characteristics of the rural landscape ecological image. According to the Hilbert Schmidt theory, the basis function $H(x, x')$ is a symmetric function that needs to meet the Mercer condition (Khare, 2022). The common basis function class used for support vector machine can calculate the kernel function of inner product, including q order polynomial inner product kernels, radial basis functions:

$$H(x, x') = \left[Q(x)(x \bullet x') + 1\right]^q = \quad (11)$$

$$\operatorname{sgn}\left\{\sum_{i=1}^{n} \exp\left[Q(x)\left|x - x_i\right|^2\right]\right\}. \quad (12)$$

This yields the discriminant function corresponding to Equation (10) as:

$$D(x) = H(x, x')\operatorname{sgn}\left[f(x) w_0^*\right]. \quad (13)$$

Among them, sgn is a symbolic function; the w_0^* is the threshold for categorization.

In the process of SVM partitioning, there are generally two partitioning methods. The simple expansion method is to divide multi class problems into two classes of problems, and then use SVM for training (Satarzadeh et al., 2022; Ahmed et al., 2021). That is, each time the training data of one category is regarded as a category, and other training data not belonging to this category is regarded as another category. That is, for $K(K>2)$ classification issues, the decision function expressed by the K group support vector machine can be used to realize the division of the input rural landscape ecological image space (Kang et al., 2021b). Another method is to establish number of $\frac{K(K-1)}{2}$ SVM, namely training a SVM between each two classes to separate the two classes. The former method has simple calculation and small calculation amount; The latter method can more accurately classify multi class problems, but for the case of more categories, the calculation is relatively complex. Therefore, the first division method is selected in this paper.

In combination with the SVM division results, the powerful map making and spatial analysis functions provided by ArcGIS software are used to visually present the division results of rural landscape ecological sensitive area units. The specific steps are as follows:

(1) Data import and processing: Import the collected rural landscape ecological images, SVM classification results, regional sensitivity assessment results and other relevant geographical data into ArcGIS software. Carry out necessary coordinate system conversion, data format conversion and other processing to ensure the consistency and accuracy of data (Liu & Zhang, 2023).

(2) Map making: In ArcGIS software, select the appropriate map base map as required, such as satellite map, topographic map, etc. The processed data will be superimposed on the base map to form the preliminary division results of rural landscape ecological sensitive area units.

(3) Symbolization and labeling: According to different sensitivity levels, choose appropriate symbols (e.g., colors, shapes, etc.) to differentiate each ecological unit of rural landscape. At the same time, the labeling function is used to provide detailed labels and descriptions for each area.

(4) Map analysis: Use the analysis tools of ArcGIS software to further analyze the rural landscape ecological sensitive area units, such as the calculated area, distance, buffer zone, etc. These analysis results can provide support for subsequent decisions.

(5) Visual output: Export maps to common image formats (such as PNG, JPEG, etc.), or display and share them directly in GIS software.

In this article, fuzzy neural networks and support vector machines outperform traditional models in assessing the ecological sensitivity of rural landscapes. Fuzzy neural networks handle ambiguity and uncertainty, accurately capturing complex relationships; Support vector machine finely divides ecological units and has strong generalization ability. The combination of the two improves evaluation accuracy, addresses complex data challenges, and provides scientific visualization solutions for the division of ecologically sensitive areas.

3. Experimental analysis

3.1. Experimental setup

In order to verify the applicability and effectiveness of the algorithm proposed in this article, the algorithm was used to divide Village A in a certain city into rural landscape ecological sensitive area units. In recent years, Village A has experienced rapid development in tourism due to its unique natural scenery, rich cultural resources, and excellent ecological environment. During this process, the continuous growth of market demand, effective integration of local resources, and strong support from government policies have jointly promoted the prosperity of Village A tourism industry. However, with the rapid development of the tourism industry, how to develop tourism resources reasonably while protecting the environment has become an urgent problem to be solved. Therefore, using the algorithm in this article to divide the ecologically sensitive areas of Village A before and after three years of tourism development is of great significance for balancing economic development and ecological protection, and achieving sustainable development.

Using a self-developed unmanned aerial vehicle based on meteorological standards, remote sensing images of Village A were obtained as the original images to be divided. Considering that there may be certain deviations in the data collected by drones, such as the influence of flight altitude, angle, weather conditions, and sensor accuracy, which may result in distortion, color deviation, or missing information in the acquired images. To avoid these deviations, this article conducts calibration tests on sensors and flight control systems before flight, selects clear and low wind speed weather to perform aerial survey tasks, and obtains redundant data through repeated flights at multiple heights and angles. Finally, image distortion, color deviation, and information loss are eliminated through comparative correction to ensure reliable data quality. In addition to remote sensing images obtained by drones, the experiment also integrated data from other sources, including geographic information system (GIS) data, meteorological data, soil data, etc., providing more comprehensive rural landscape information and helping to more accurately delineate ecologically sensitive areas. In the process of data collection, strictly follow ethical norms, communicate fully with local governments and residents in advance, clearly inform them of the purpose, scope, and method of data collection, obtain their informed consent, and ensure that residents' privacy rights and personal information security are not violated. At the same time, strict confidentiality measures are taken for data involving sensitive geographic information to prevent potential risks to local ecological security and residents' lives caused by data leakage. Meanwhile, considering the limited nature of the data, the experiment employed data augmentation techniques to expand the dataset. By performing operations such as rotation, scaling, and translation on the original remote sensing images, more training samples were

Figure 2. Remote sensing image of Village A

generated, thereby improving the model's generalization ability. After the data preparation is completed, the dataset is divided into a training set and a validation set in a 7:3 ratio, with 70% of the data used to train the model and enable it to learn features and patterns from the data; The remaining 30% of the data will be used as a validation set to evaluate the performance of the model on unseen data, ensuring the scientific and rational training and evaluation of the model. The remote sensing image of Village A is shown in Figure 2.

The specific performance parameters of the UAV are shown in Table 2.

Table 2. Performance parameters of drones

Performance	Numerical value
Flying altitude/m	100–2600
Cruise speed km/h	100
Battery life/h	3.5
Payload/kg	2.6
Navigation accuracy/m	30

The flight record of the UAV in the process of acquiring the remote sensing image of Village A is: the flight speed is 100 km/h; The navigation height is 1000 m; Navigation overlap rate is 92%; Lateral overlap is 65%; 9 roadways are designed; Floor area covered $3500 \times 1800\ m^2$; monolithic coverage of approx $7500 \times 550\ m^2$.

The remote sensing image of Village A is divided into 40 areas numbered 1–40 using the algorithm in this paper, and their sensitivity is evaluated. The specific evaluation results are shown in Table 3.

Table 3. Ecological sensitivity assessment results for each region

Region code	Sensitivity assessment results	Region code	Sensitivity assessment results
1	<2	21	<2
2	<2	22	2–4
3	<2	23	2–4
4	2–4	24	2–4
5	<2	25	4–6
6	<2	26	<2
7	<2	27	4–6
8	4–6	28	4–6
9	2–4	29	4–6
10	2–4	30	6–8
11	2–4	31	6–8
12	>8	32	2–4
13	2–4	33	6–8
14	2–4	34	>8
15	2–4	35	2–4
16	2–4	36	>8
17	2–4	37	>8
18	6–8	38	>8
19	2–4	39	2–4
20	>8	40	>8

According to the sensitivity assessment results of each region in Table 3, combined with ArcGIS software, the sensitivity of each region is visualized, as shown in Figure 3.

As shown in Figure 3, the landscape of Village A is divided into five sensitivity levels, namely, extremely low ecological sensitivity, low ecological sensitivity, medium ecological sensitivity, high ecological sensitivity and high ecological sensitivity. The algorithm proposed in this paper successfully identifies the ecological sensitive areas in the remote-sensing image of Village A's landscape, which verifies its effectiveness and applicability. Moreover, it should be noted that ecological sensitive areas are generally regions characterized by a fragile ecological environment or abundant resources. Dividing these areas will help to strengthen the protection of these areas and prevent irreversible damage to these areas caused by human activities.

In the fuzzy neural network in the method of this paper, the number of neurons in the hidden layer is extremely important, usually the number of neurons in the hidden

Figure 3. Ecological sensitive area division results of Village A

layer is too much or too little will affect the output results of the fuzzy neural network. To verify the significance of the number of hidden – layer neurons on the neural network output in this method, we took different numbers of hidden – layer neurons for the same set of training samples. To this end, by adjusting the learning – rate algorithm, we set the training objective to 10^{-4}. Subsequently, the fuzzy neural network was trained 1000 times for each case. The results of the training errors for different numbers of neurons in the hidden layer are shown in Figure 4.

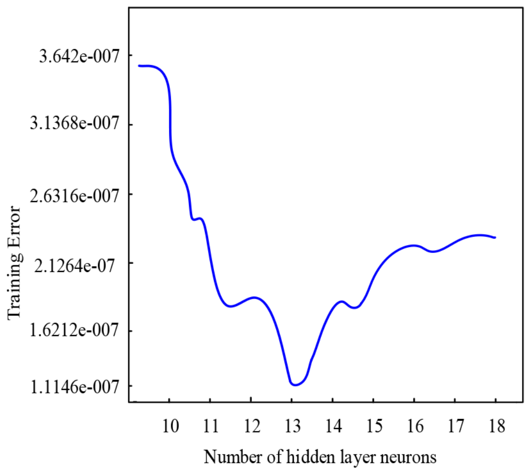

Figure 4. Training error results of different number of neurons in hidden layer

From Figure 4, it can be seen that when the number of hidden layer neurons is set to 13, the training error of the fuzzy neural network reaches its lowest point. This reflects that under this configuration, the network can best fit the training data while maintaining low complexity, which helps prevent overfitting and improve generalization ability. Through further cross validation, the training dataset was divided into multiple parts for training and validation, and it was found that the configuration of 13 neurons also exhibited the best performance on the validation set. In addition, the convergence speed under different numbers of neurons was compared, and it was found that too few neurons can lead to slow convergence and may fall into local optima, while too many neurons can lead to fast convergence but are prone to overfitting. In contrast, the configuration of 13 neurons achieved good generalization performance while maintaining fast convergence. Meanwhile, by observing the difference between training error and validation error to evaluate the risk of overfitting, it was found that the difference between the two was small under the configuration of 13 neurons, indicating a low risk of overfitting in the model. In summary, based on detailed experimental design and result analysis, selecting 13 neurons as the optimal number of hidden layer neurons not only minimizes training errors, but also comprehensively verifies generalization ability, convergence speed, and overfitting risk. Therefore, in the ecological sensitivity assessment of rural landscape environment, using a fuzzy neural network with 13 hidden layer neurons can achieve the best evaluation effect.

3.2. Results and analysis

In order to verify the validity of the factors affecting the ecological sensitivity of rural landscape selected in this paper, the influence of slope and vegetation cover factors on the ecological sensitivity of rural landscape was analyzed.

Setting the evaluation system in the rest of the influencing factors are the same, in the case of different slopes, through this paper's algorithm output rural landscape ecological sensitivity, to analyze it, and to observe the influence of slope on the ecological sensitivity of the rural landscape, specifically as shown in Figure 5.

According to Figure 5, slope has a significant impact on the ecological sensitivity of rural landscape. With the increase of slope, the ecological sensitivity of rural landscape

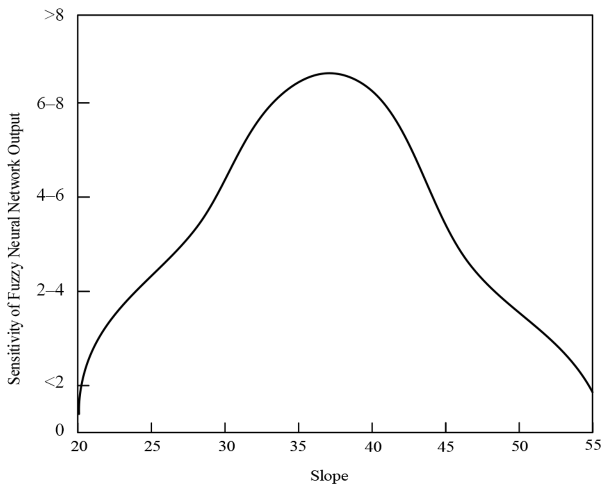

Figure 5. Ecological environment sensitivity under different slopes

showed a trend of first increasing and then decreasing. This may be because the increase of slope will lead to more diversified land use types and increased landscape heterogeneity, thus improving ecological sensitivity. However, when the slope increases to a certain extent, it may lead to the simplification of land use types and the reduction of landscape heterogeneity, thus reducing ecological sensitivity. In the case of gentle slope, the ecological sensitivity of rural landscape is low. This may be because the land use type in the area with gentle slope is relatively single, the landscape heterogeneity is low, and the ecosystem is relatively stable. When the slope is moderate, the ecological sensitivity of rural landscape reaches the highest value. This may be due to the diversity of land use types, high landscape heterogeneity, fragile ecosystem and vulnerability to external interference in areas with moderate slope. When the slope is large, the ecological sensitivity of rural landscape begins to decrease. This may be due to the single land use type, low landscape heterogeneity and stable ecosystem in areas with large slopes.

Setting the evaluation system in the rest of the influencing factors are the same, in the case of different vegetation cover, through this paper's algorithm output rural landscape ecological sensitivity, to analyze it, and to observe the influence of slope on the ecological sensitivity of the rural landscape, specifically as shown in Table 4.

Table 4. Ecological sensitivity under different vegetation coverage

Vegetation coverage	Sensitivity of Fuzzy Neural Network Output
>80%	<2
75–80%	2–4
55–75%	4–6
35–55%	6–8
<35%	>8

According to Table 4, the vegetation coverage rate has a significant impact on the ecological sensitivity of rural landscape. With the decrease of vegetation coverage, the ecological sensitivity of rural landscape shows a gradually increasing trend. This may be because the reduction of vegetation coverage leads to the weakening of land water holding capacity, the increase of water and soil loss, and the reduction of ecosystem stability, thus improving the ecological sensitivity. When the vegetation coverage rate is low, the ecological sensitivity of rural landscape reaches the highest value. This may be because the areas with low vegetation coverage suffer from serious water and soil loss, fragile ecosystems, and are vulnerable to external interference. When formulating rural landscape ecological protection measures, we should fully consider the factor of vegetation coverage, and take different protection measures for areas with different vegetation coverage to achieve the sustainable development of rural landscape ecology.

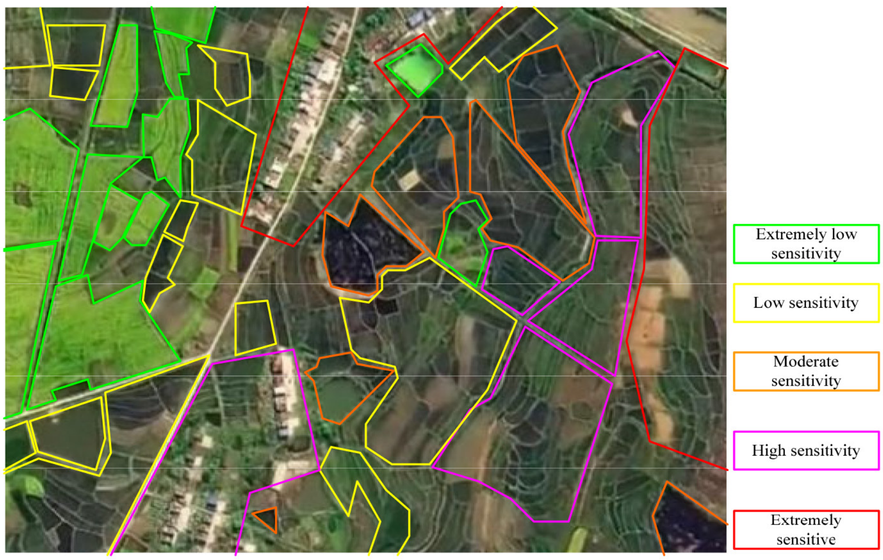

Figure 6. Results of the ecologically sensitive area division in the Village A after three years of tourism development

Village A has developed its tourism industry for three years. Through the rich natural resources, agricultural resources, cultural resources, etc. in the region, it has made in-depth exploration and effective use of these resources to create unique rural tourism products and enhance its attractiveness. However, the development of tourism must be based on the protection of the ecological environment. In the process of development, attention should be paid to the protection of the natural environment and the maintenance of ecological balance to avoid damage to the environment. Therefore, the algorithm in this paper is used to divide the sensitive area of the remote sensing image of Village A obtained three years later. Figure 6 shows the change of ecological sensitivity of Village A after three years of tourism development.

It can be seen from the comparison between Figure 3 and Figure 6 that, after three years of tourism development, the ecological sensitivity of each area in Village A has increased to varying degrees, which is due to the increase of human activities. With the development of tourism, the frequency and intensity of human activities in ecologically sensitive areas have increased. These activities include the construction of tourism facilities, road traffic, and tourist tours. They may disturb and damage the ecosystem, leading to an increase in ecological sensitivity and further exacerbating ecological problems. Over-exploitation of resources, such as over-picking, over-fishing, and over-logging, driven by tourism development, can also cause irreversible damage to the ecosystem, disrupt ecological balance, and heighten ecological sensitivity. The development of tourism may lead to ecological imbalance, such as species invasion, population fluctuation, biodiversity reduction, etc. These factors may cause the ecosystem to become more vulnerable and improve ecological sensitivity; Lack of effective protection measures. In the process of developing tourism, the lack of effective protection measures may cause damage to the ecosystem and lead to the increase of ecological sensitivity.

In order to analyze the accuracy of fuzzy neural network in the division of landscape ecological sensitive area units, the methods in References (Atterholt et al., 2021) and (Belizario et al., 2021) are selected as the comparison methods of this paper. Based on the aforementioned three schemes, the complete landscape ecological sensitive area, core landscape ecological area, and enhanced landscape ecological area in Figure 3 are applied respectively. Then, the effectiveness of unit division of the fuzzy neural network in different landscape ecological sensitive areas is studied through an analysis of the changes in each evaluation metric, namely DSC, Recall, and Precision. The experimental results are shown in Table 5.

The analysis of Table 5 shows that the evaluation method selected by the fuzzy neural network has a certain impact on the division of landscape ecological sensitive area units. The fuzzy neural network employed in this method combines the steepest descent algorithm and the least square estimation (LSE) to identify the complete landscape ecological sensitive area and the core landscape ecological area. Moreover, the evaluation index values of DSC, Recall, and Precision obtained by this network are higher than those of the other two schemes. The fuzzy neural network used in this method has a more accurate division effect on different landscape ecological sensitive area units.

In order to compare the ecological sensitivity unit partitioning methods based on deep learning with other machine learning methods, the performance of deep learning algorithms in rural landscape ecological sensitivity unit partitioning was compared with decision tree algorithms, random forest algorithms, and gradient boosting algorithms. These algorithms will use the same ecological sensitivity evaluation index system as input and output ecological sensitivity prediction results. Evaluate the performance of various algorithms in ecological sensitivity prediction and unit partitioning tasks using metrics such as accuracy, recall, and F1 score. The experimental results are shown in Table 6.

Table 6. Performance comparison of various algorithms in the division of ecological sensitivity units in rural landscapes

Algorithm	Accuracy/%	Recall rate/%	F1 score
Decision tree algorithm	75	70	72
Random forest algorithm	80	78	79
Gradient boosting algorithm	85	82	83
The method of this paper	92	90	91

Table 5. Division of units in landscape ecological sensitive areas

Evaluating indicator	Landscape ecological sensitive areas	Division scheme		
		Atterholt et al. (2021)	Belizario et al. (2021)	The method of this paper
DSC	Landscape ecological sensitive areas	0.7328	0.7918	0.9204
	Core landscape ecological area	0.7815	0.7746	0.9016
	Enhance landscape ecological areas	0.7206	0.7108	0.8976
Recall	Landscape ecological sensitive areas	0.8816	0.8834	0.9518
	Core landscape ecological area	0.7956	0.8027	0.9346
	Enhance landscape ecological areas	0.7608	0.7936	0.9217
Precision	Landscape ecological sensitive areas	0.8915	0.8954	0.9375
	Core landscape ecological area	0.8966	0.9035	0.9369
	Enhance landscape ecological areas	0.7988	0.8345	0.9011

According to the analysis in Table 6, deep learning algorithms have shown significant performance advantages compared to decision tree algorithms, random forest algorithms, and gradient boosting algorithms in the task of dividing sensitive units in rural landscape ecology. Specifically, deep learning algorithms achieved the highest scores in the three key evaluation metrics of accuracy, recall, and F1 score. Its accuracy is as high as 92%, indicating that the algorithm can accurately predict the ecological sensitivity of rural landscapes; The recall rate has also reached 90%, demonstrating the powerful ability of deep learning algorithms in identifying truly sensitive areas; Meanwhile, the F1 score of 91% further confirms the excellent performance of the algorithm in balancing accuracy and recall. These results indicate that deep learning algorithms can more accurately capture and identify complex features in data for ecological sensitivity prediction and unit partitioning tasks, thereby improving the accuracy and robustness of predictions. In contrast, although decision tree algorithms are simple and easy to understand, they cannot fully capture the nonlinear relationships in the data; Although the random forest algorithm improves performance by integrating multiple decision trees, it is still affected by incorrect predictions from certain decision trees; Although the gradient boosting algorithm improves performance by gradually optimizing the model, it is limited by overfitting or underfitting. Deep learning algorithms, on the other hand, better adapt to the complexity and diversity of ecological sensitivity by automatically learning and extracting deep features from data, thus achieving better performance in the task of dividing rural landscape ecological sensitivity units.

To verify the applicability of the method proposed in this article, flood, wildfire, and drought prediction in rural landscapes were selected as experimental subjects. Compared with the methods in References (Atterholt et al., 2021) and (Belizario et al., 2021), the model was applied in rural areas with different soil types, and response speed, root mean square error (RMSE), Nash efficiency coefficient (NSE), and Kappa coefficient were introduced as evaluation indicators. The experimental results are shown in Table 7.

According to Table 7 analysis, the method proposed in this paper has demonstrated significant superiority in predicting floods, wildfires, and droughts in rural landscapes. In two different types of soils, sandy soil and clay, the method proposed in this paper has a faster response speed, lower root mean square error (RMSE), and higher Nash efficiency coefficient (NSE) and Kappa coefficient compared to the methods in References (Atterholt et al., 2021) and (Belizario et al., 2021). Specifically, in flood prediction, the NSE of this method on sandy soil and clay reached 0.85 and 0.90, respectively, which is much higher than the comparative methods. In wildfire prediction, the NSE values of our method on sandy soil and clay are 0.92 and 0.95, respectively, which are also superior to the comparative methods. In drought prediction, the NSE of our method is still superior to the comparative method, and the Kappa coefficient remains at a high level. These results indicate that the method proposed in this paper has high accuracy and reliability in rural landscape prediction, verifying its applicability. In addition, the scalability of this method in large-scale rural landscapes is also worthy of recognition. Due to the consideration of computational efficiency and resource consumption in method design, it can theoretically be applied to real-time monitoring and large-scale rural areas without significant computing resources. However, in practical applications, factors such as

Table 7. Prediction results of floods, wildfires, and droughts in rural areas with different soil types

Experimental subjects	Soil	Method	Response speed/s	RMSE	NSE	Kappa coefficient
Flood forecasting	Sandy soil	The method of this paper	120	0.25	0.85	0.78
		Atterholt et al. (2021)	150	0.30	0.78	0.72
		Belizario et al. (2021)	130	0.28	0.80	0.75
	Clay	The method of this paper	100	0.20	0.90	0.85
		Atterholt et al. (2021)	140	0.28	0.82	0.78
		Belizario et al. (2021)	120	0.25	0.85	0.80
Wildfire prediction	Sandy soil	The method of this paper	80	0.15	0.92	0.88
		Atterholt et al. (2021)	100	0.20	0.85	0.80
		Belizario et al. (2021)	90	0.18	0.88	0.85
	Clay	The method of this paper	70	0.12	0.95	0.92
		Atterholt et al. (2021)	95	0.18	0.88	0.84
		Belizario et al. (2021)	85	0.15	0.90	0.88
Drought prediction	Sandy soil	The method of this paper	150	0.35	0.75	0.70
		Atterholt et al. (2021)	180	0.40	0.70	0.65
		Belizario et al. (2021)	160	0.38	0.72	0.68
	Clay	The method of this paper	130	0.30	0.80	0.75
		Atterholt et al. (2021)	170	0.38	0.74	0.69
		Belizario et al. (2021)	150	0.35	0.78	0.72

data transmission, storage, and processing capabilities in specific scenarios need to be considered to ensure the feasibility and practicality of the method. In summary, the method proposed in this article provides a new and effective solution for predicting natural disasters in rural landscapes.

This experiment tested the computational complexity of the deep learning based rural landscape ecological sensitive area unit partitioning algorithm in rural areas of different scales to evaluate its scalability. The experiment selected three typical rural areas: 5 square kilometers (small area), 20 square kilometers (medium area), and 50 square kilometers (large area), each containing 8, 15, and 25 types of ecological units, with corresponding data collection points of 50, 200, and 500. By collecting data on six major influencing factors including geological environment, ecological environment, and hydrological conditions as inputs for a fuzzy neural network, and using rural landscape ecological images for support vector machine partitioning, the system recorded the computation time and memory usage of the algorithm when running in different regions. The experimental results are shown in Table 8.

According to Table 8, in the relevant experiments of the algorithm for dividing units in rural landscape ecological sensitive areas, as the rural area expands from a small range to a large range, the computational complexity of each part changes significantly. In terms of fuzzy neural networks, the training time requires more iterations to adjust weights due to the large number of data collection points and input data in a large area, which increases significantly from 12 seconds to 80 seconds. The testing time also increases with the expansion of the area, but the growth rate is relatively small and positively correlated with the amount of data; Memory usage is also increasing exponentially, as large-scale data requires more space for storage and processing. The training time of support vector machine is greatly affected by the number of image samples. As the number of samples increases from 100 to 1000, the training time skyrockets from 20s to 150s, resulting in an exponential increase in computational complexity due to the calculation of kernel function values for all samples; The classification time also increases with the increase of samples, as the distance between new samples and support vectors needs to be calculated; The memory usage is related to the number of samples and the size of image data, and increases as the area expands. When visualizing with ArcGIS, the data processing time is extended due to the expansion of regions and the increase in data volume. Data processing requires the integration and transformation of ecological unit division and sensitivity assessment results; The rendering time for a large area is longer due to the abundance of geographic information and ecological units; The memory usage increases with the expansion of the region to meet the demand for storing and processing more geographic data. Overall, with the expansion of rural areas, the computational complexity of the method proposed in this paper has significantly increased, reflected in training, classification, data processing time, and memory usage. However, the performance improvement of modern computing devices still allows for an acceptable total computation time of about 294 seconds (about 5 minutes) in large-scale areas, and operational efficiency can be improved through algorithm optimization, parallel computing technology, and increased computing resources. Therefore, the method proposed in this paper has certain scalability for application in large-scale rural areas, but requires reasonable planning of computing resources and time.

4. Conclusions

The algorithm in this paper can make a good delineation of ecologically sensitive areas in rural landscapes, and the delineation of ecologically sensitive areas is of great help to rural landscapes, which is mainly reflected in the following aspects:

1) Protecting the natural environment and accurately identifying ecologically sensitive areas

Ecological sensitive areas, as key areas with fragile ecological environments or abundant resources, are crucial for their protection. The algorithm in this article, with its high-precision characteristics, can accurately identify and divide

Table 8. Scalability analysis of different regional ranges

Range	Indicator category	Input vector dimension/number of image samples	Training time/s	Test time/s	Classification time/s	Data processing time/s	Rendering time/s	Rendering time/s
Small-scale	Fuzzy neural network	6	12	3	–	–	–	256
	Support vector machine	100	20	–	5	–	–	384
	ArcGIS visualization	–	–	–	–	2	1	256
Medium range	Fuzzy neural network	6	35	8	–	–	–	512
	Support vector machine	400	60	–	12	–	–	768
	ArcGIS visualization	–	–	–	–	5	3	512
Wide range	Fuzzy neural network	6	80	18	–	–	–	1024
	Support vector machine	1000	150	–	30	–	–	1536
	ArcGIS visualization	–	–	–	–	10	6	1024

these regions. The analysis results of slope and vegetation coverage clearly indicate that the algorithm accurately captures the significant impact of these factors on ecological sensitivity. For example, as the slope changes, ecological sensitivity shows a trend of first increasing and then decreasing; When vegetation coverage decreases, ecological sensitivity gradually increases. In practical cases, the changes in ecological sensitivity after the development of tourism in Village A have fully verified the effectiveness of the algorithm in protecting the natural environment. The ecologically sensitive areas identified through algorithms provide clear goals for rural landscape managers, helping to strengthen the protection of these sensitive areas, prevent irreversible damage caused by human activities, and maintain the stability and health of the rural ecological environment.

2) Promote sustainable development, balance economy and ecology

The sustainable development of rural landscapes requires a precise balance between economic development and ecological protection. This algorithm provides a solid scientific basis for rural planners by accurately dividing ecologically sensitive areas. This algorithm has played a key role in the development of tourism in Village A. It ensures that the carrying capacity of the ecological environment is fully considered during the development process, avoiding overexploitation of ecologically sensitive areas. For example, based on the algorithm partitioning results, planners can reasonably plan the construction location and scale of tourism facilities, avoiding large-scale development in ecologically sensitive areas, thereby ensuring the sustainable development of rural areas. This scientific planning is not only beneficial for the long-term stable growth of rural economy, but also for protecting the ecological environment and achieving a positive interaction between economy and ecology.

3) Improve planning and management efficiency, reduce resource waste

The accurate division of ecologically sensitive areas enables rural landscape planners and managers to develop more targeted protection measures and management strategies. The precise partitioning results provided by the algorithm in this article have brought higher efficiency to rural landscape management. In the comparative experiment, the algorithm proposed in this paper outperforms other methods in DSC, Recall, Precision and other indicators of landscape ecological sensitive area unit division, which fully demonstrates its advantages in improving planning and management efficiency. Through algorithm division, managers can clearly understand the ecological sensitivity of different regions, and formulate differentiated management strategies to avoid resource waste caused by blind development and disorderly management. For example, for areas with high ecological sensitivity, strict protection measures can be taken to restrict human activities; For areas with low ecological sensitivity, appropriate development and utilization can be carried out to achieve rational allocation and efficient utilization of resources.

4) Improve the quality of rural landscapes and enhance disaster resistance capabilities

By protecting and managing ecologically sensitive areas, this algorithm helps promote the naturalization and diversification of rural landscapes. This not only enhances the quality and beauty of rural landscapes, but also provides a more livable and tourist friendly environment for local residents and tourists. In flood, wildfire, and drought prediction experiments, the prediction results of our method on different soil types were superior to the comparative methods, indicating its potential in enhancing the disaster resistance of rural landscapes and protecting the ecological environment. For example, in flood prediction, the Nash efficiency coefficient (NSE) of our method on sandy soil and clay reached 0.85 and 0.90, respectively, which is much higher than the comparative methods. This means that the algorithm can more accurately predict the risk of flood occurrence, providing a basis for rural landscape managers to take preventive measures in advance, thereby reducing the damage of natural disasters to rural landscapes and improving the overall quality and disaster resistance of rural landscapes.

5) Promote the development of ecotourism and achieve a win-win situation for both economy and ecology

Ecological sensitive areas have rich natural landscapes and ecological value, and are important resources for the development of ecotourism. This algorithm provides a scientific basis for the development of ecotourism by accurately dividing these areas. Reasonable planning and development not only help increase economic income, but also enhance the visibility and attractiveness of rural areas. In the development process of tourism in Village A, the application of algorithms ensures that ecotourism activities are carried out on the premise of protecting the ecological environment. For example, based on the algorithm division results, suitable routes and areas for ecotourism can be planned, guiding tourists to explore and experience without affecting the ecological environment. This not only meets the needs of tourists for natural landscapes, but also protects the ecological environment, achieving a win-win situation between economy and ecology, and injecting new impetus into the sustainable development of rural areas.

In addition, the algorithm proposed in this article has shown significant effectiveness and wide applicability in the division of ecologically sensitive areas in rural landscapes. It not only has strong adaptability and can be adjusted and optimized according to the actual situation of different regions to cope with changes in the ecological environment, but also has the potential advantages of good scalability and theoretical applicability to real-time monitoring and management of larger rural areas. In practical applications, limitations such as data transmission, storage, and processing capabilities also need to be considered, and it needs to be continuously updated and optimized with changes in the ecological environment and human activities to maintain accuracy and effectiveness, thus providing strong support for the protection, management, and sustainable development of rural landscapes.

Although the deep learning based rural landscape ecological sensitive area unit partitioning algorithm proposed in this article effectively improves the accuracy of evaluation and partitioning by combining fuzzy neural networks and support vector machines, the algorithm still has certain limitations. If the algorithm has high requirements for data quality and quantity, it may be difficult to effectively apply in areas where data is scarce or of poor quality. In addition, the process of model training and tuning is relatively complex, requiring strong professional knowledge and skill support. Future research will further optimize data preprocessing and augmentation techniques to improve the adaptability of algorithms to different quality data. At the same time, exploring more automated and intelligent model training and optimization methods, lowering the threshold for use, and expanding the practical application scope of this algorithm in rural landscape ecological protection and management.

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1. General item of city hall level

Study on the construction of regional rural landscape system in Heilongjiang

Project number: 145209154

2. Provincial level

Research on the Construction and Management Model of Urban Public Art Database from the Perspective of Cultural Time and Space

Project number: 2023A009

3. School level

Research on the Integration of Ideological and Political Education in <Resources Landscape Architecture Planning and Design> Based on Local Cultural

Project number: GJQTZX202210

4. School level

<Cultivation project of demonstration on course ideological and political education in <Resources Landscape Architecture Planning and Design>

Project number: QDJG-2022KCSZ17

5. General subject on Heilongjiang Province art science planning

Research on Digital Activation Path of Neolithic Site in Nenjiang River Basin of Heilongjiang Province during New Media Era

Project number: 2023B37

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