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RESEARCH ARTICLE

The Application of the SOFM Neural Network and Internet of Things in Rural Revitalization

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ABSTRACT To promote rural revitalization under the premise of fully considering the ecological risk factors of land consolidation, this study takes A County in Shaanxi Province as a case study and introduces Self-Organizing Feature Map (SOFM) neural network and Internet of Things (IoT) technology to partition the land. In this study, a comprehensive index system is constructed based on IoT technology, and the relevant factors are quantitatively analyzed from the perspective of land consolidation ecological risk. Then, the land consolidation project area's attribute and geographic space domains are used as the input of the SOFM neural network to reveal the distribution and influence degree of each factor in the area and determine the zoning pattern of land consolidation in A County. The results show that the rural revitalization land zoning pattern of land consolidation in A County, Shaanxi Province, is divided into four land consolidation areas. Firstly, the priority remediation area soon covers 27 administrative villages with a total area of 28090 hm^2, accounting for 32.75%. Secondly, the moderate renovation area is soon classified into 37 administrative villages, with a total area of 15986 hm^2, equivalent to 18.55%. In the medium term, the land-saving renovation area covers 39 administrative villages with a total area of 19686 hm^2, accounting for 22.75% of the total area. Finally, in the long-term restricted remediation area, 37 administrative villages are divided, with a total area of 22081 hm^2, accounting for 25.67% of the total area. These data results provide a quantitative basis for land consolidation planning in this area to achieve the goal of rural land revitalization in different time ranges. This study is significant for implementing land consolidation projects in rural revitalization and provides a valuable reference for developing other similar areas.

INDEX TERMS SOFM neural network, Internet of Things technology, digital finance, rural revitalization, land allocation.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

Rural revitalization holds a crucial position in China's national development strategy. However, the process of rural revitalization is accompanied by a series of complex issues and challenges, including imbalanced regional development and uneven resource allocation [1]. Moreover, the traditional financial system and land consolidation methods have limitations in meeting the demands of rural revitalization. Therefore, the motivation of this study is to explore how digital finance and Internet of Things (IoT) technology can better support rural revitalization to address the following issues. Firstly, rural revitalization faces serious challenges regarding sustainable development and ecological conservation. Traditional land consolidation methods often struggle to consider ecological risk factors rationally, which can easily lead to environmental degradation. Hence, there is a need to find a

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method that can more accurately quantify and control ecological risks. Secondly, rural revitalization requires more refined land allocation and resource management. Digital finance and IoT technology have significant potential to provide real-time data and intelligent decision support, aiding in precise land resource allocation and efficient utilization. Applying digital finance and IoT technology can improve the coverage and convenience of rural financial services and promote rural economic development, thereby enhancing the sense of achievement and happiness among rural residents [2].

The Self-Organizing Feature Map (SOFM) neural network is an artificial neural network model used for unsupervised learning, and its application context spans multiple domains and problems. In the era of big data, high-dimensional datasets have become increasingly common. The SOFM neural network is widely employed to map high-dimensional data into lower-dimensional spaces for visualization and analysis, making them highly useful in data mining, exploration, and visualization.In fields such as image recognition, computer vision, and medical image processing, SOFM can assist in understanding and processing complex image data. In pattern recognition, the SOFM network can identify and classify patterns, encompassing applications in speech recognition, handwritten character recognition, bioinformatics, and more. Additionally, the SOFM network finds utility in financial market data analysis, such as stock price prediction, portfolio optimization, and market trend analysis. It can aid in discovering underlying correlations and patterns within data [3]. In summary, the application scope of the SOFM neural network covers a wide range of fields. Its capabilities in handling complex data, pattern recognition, data dimensionality reduction, and clustering tasks have gained widespread recognition, providing powerful tools for addressing problems across various domains.

IoT is a technology that connects various physical devices, sensors, and objects to the internet for data collection, analysis, and remote control. In rural revitalization, IoT technology plays a crucial role and can help address various issues in rural development, such as resource management, agricultural production, and environmental monitoring. IoT technology can monitor agricultural data such as soil humidity, weather conditions, and crop growth status. This aids in precise agricultural management, involving field irrigation, fertilization, pest monitoring, and more, ultimately improving crop quality and yields.

Therefore, based on the SOFM neural network and IoT technology, this study aims to realize the intelligent application of digital finance in rural revitalization by considering the ecological risk factors of land consolidation. This study seeks to provide new solutions and insights for rural development in rural revitalization.

B. RESEARCH OBJECTIVES

This study explores how sustainable rural revitalization can be achieved through the guidance of digital finance and IoT technology, utilizing the SOFM neural network. Specifically, it focuses on A County in Shaanxi Province, using land consolidation as an entry point. It constructs a comprehensive indicator system from the perspective of ecological risks to quantitatively analyze key factors in the land consolidation project. The research objectives of this study are as follows. 1. Throughquantitative analysis, the extent of ecological risk impact on the land consolidation project in A County, Shaanxi Province, is revealed. 2. Using the SOFM neural network method and combining the attribute and geographical space domains of the land consolidation project area, the land use for rural revitalization in A County, Shaanxi Province, is delineated.

II. LITERATURE REVIEW

Many researchers and scholars have discussed this. Kusadokoro and Chitose used county panel data to evaluate the impact of road infrastructure development in Inner Mongolia in China on regional economic growth and urban-rural income inequality from 1999 to 2018. The results showed that the number of road infrastructure in Inner Mongolia had a strong positive impact on economic growth, but a strong negative impact on urban-rural income inequality at the county level [4]. Qu et al. employed large-scale remote sensing data, a topographic fluctuation range model, and a spatial econometric model to analyze the multifunctional change and its dynamic mechanism of gully agriculture in the Loess Plateau to understand the internal meaning of evolution and differentiation at the basin level. The results indicated that many key policies in the Loess Plateau would directly affect the evolution path of functions, thus providing policy ideas for the high-quality development of agriculture in the Loess Plateau [5]. Luo et al., taking the Shenzhen-Shantou Special Cooperation Zone (SSSCZ) as an example, constructed a runoff model based on SSSCZ and a rainstorm and flood model based on Geographic Information System (GIS). They discussed the spatial distribution characteristics of rainstorms and flood risks lasting for 100 years. It was found that applyingthe neural network method to urban planning and construction can comprehensively consider waterlogging, ecology, population, and so on [6].Jia et al. proposed a more powerful multi-swarm artificial bee colony algorithm (ABCA). The classic ABCA was improved in the algorithm, and multi-group and exclusive operation strategies were adopted to make it suitable for the optimal parameter setting tracking of the SOFM network so that this network could be applied to a dynamic environment. The results denoted that the algorithm was superior to the classical SOFM algorithm in clustering purity and effectiveness. It was a promising classification method for dynamic environment data streams [7]. To improve autonomous vehicles' handling performance and stability, a coordinated control strategy based on stability judgment was proposed by Yao et al. [8]. Firstly, the stability judgment scheme based on the SOFM neural network and K-Means algorithm was adopted to evaluate the real-time stability level of vehicles. The results suggested that the stability judgment scheme and coordinated control strategy of the algorithm could meet the requirements of path-tracking accuracy and enhance its processing and stability [8].

These studies deeply analyze different aspects of rural revitalization and provide an essential theoretical basis for future development and policy formulation. Machine learning algorithms such as SOFM neural network and multi-swarm ABCA, as well as the application of IoT technology, provide a new way for intelligent and accurate decision-making in rural revitalization and construction. These technologies not only optimize the allocation of resources and improve the efficiency of decision-making but also better meet the diverse needs of rural residents and promote the development of rural revitalization in a more sustainable and dynamic direction. It is necessary to tap further the potential of machine learning algorithms and IoT technology, and customize intelligent rural revitalization strategies according to actual needs to inject new impetus into the development of rural revitalization.

III. RESEARCH MODEL

To achieve the goal of rural revitalization and development based on digital finance and IoT technology, the SOFM neural network is adopted as the core method [9].The SOFM neural network, with unsupervised learning characteristics, offers unique advantages for analyzing complex spatial relationships in rural areas. This network can preserve the topological structure of data, meaning it retains the spatial relationships between data points, which is crucial for land consolidation and resource management. For instance, when planning land use in rural areas, SOFM can help identify key information such as land types, land quality, and land-use history and integrate them to formulate more effective land consolidation strategies. Additionally, SOFM can achieve data dimensionality reduction, compressing large datasets into more manageable forms, thus reducing computational and time costs. Furthermore, IoT technology provides rich sources of data for digital finance research. IoT devices can gather information about rural areas through real-time data collection and transmission, such as meteorological data, soil moisture, crop growth conditions, etc. These data can be used for intelligent decision-making, such as precise irrigation and fertilization, and support monitoring and early warning systems, helping farmers better manage agricultural production.

The SOFM neural network is an unsupervised learning algorithm capable of transforming high-dimensional data into a two-dimensional grid structure through self-organizing mapping of input data, thus realizing data clustering and visual analysis [10], [11], [12]. The SOFM neural network operates on the foundational principle of competitive learning, structured around input and competitive layers. The competitive layer is usually a two-dimensional grid, and each node represents the weight of a feature vector [13]. During network training, the input data is compared with the weight vector in the competition layer, and the best-matching neuron is selected as the winning neuron. Subsequently, the topological mapping of the input data is realized by updating the weights of the winning neuron and its surrounding neurons [14], [15], [16].The research method roadmap is illustrated in Figure 1.

Firstly, the SOFM neural network model starts competitive learning by accepting input samples. In this process, samples with similar functional attributes exhibit a similar trend in spatial distribution, while samples with large differences in functional attributes keep a certain interval in space. This principle makes it possible to cluster irregular input samples automatically [17]. When the number of input samples is sufficient, its probability density can be approximately regarded as the weight distribution, which can be expressed in the neurons of the output layer of the neural network. This results in that all samples with large probability density will be gathered in a specific area in the output space [18], [19], [20], [21].

Rural revitalization projects can benefit by combining the SOFM neural network with IoT technology. The richness of data allows decision-makers to gain better insights into the conditions of rural areas, enabling them to formulate policies and plans that are more targeted. The automation and analytical capabilities streamline the decision-making process, reducing the workload associated with manual data processing. Most importantly, real-time capabilities enable decisions to respond more rapidly to changing situations, such as sudden weather variations or disaster events, thereby reducing potential risks.

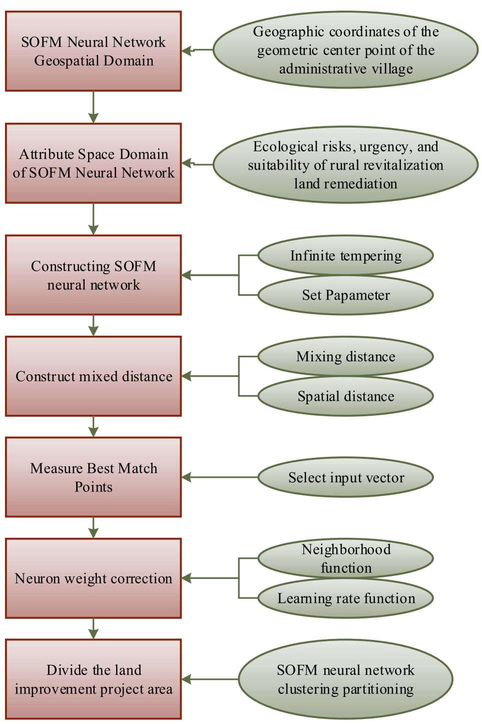

FIGURE 1. Roadmap of research methods.

The topology of the SOFM neural network is presented in Figure 2.

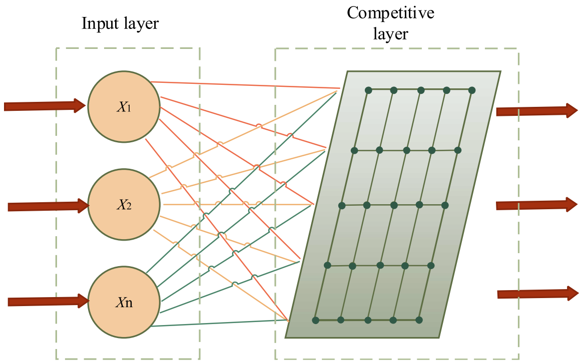

FIGURE 2. Topological structure of SOFM neural network.

A. SOFM NEURAL NETWORK STRUCTURE

Firstly, the SOFM neural network model is established, the parameter values are set, and then the coordinates of the input data set and the index values of various attribute spaces are dimensionless [22], [23], [24]. Subsequently, this study uses the method of mixed distance to describe the similarity between sampling points [25], [26], [27]. A point set has dual attributes of time and space, and its definition is as follows:

$$X_n = \left\{g_N^1, g_N^2, \ldots, g_N^G, a_N^1, a_N^2, \ldots, a_N^D\right\} \tag{1}$$

$$D_{ij} = w_s D_{ij}^s + \omega_a \sqrt{\sum_{d=1}^{D} w_d (a_i^d - a_j^d)^2} \tag{2}$$

$\{g_N^1, g_N^2, \ldots, g_N^G\}$ indicates geographical space, and $G = 1, 2, 3$. $\{a_N^1, a_N^2, \ldots, a_N^D\}$ signifies the attribute space; D denotes the number of attributes; D_{ij}^s refers to the size of the geographical space between two points. w_d stands for the weight of attribute d. $\sum w_d = 1$. a_i^d and a_j^d represent the value of attribute d in point i and the value of attribute d in point j. w_s means the weight of geographical space. w_a indicates the weight of attribute space, $w_s + w_a = 1$.

In the SOFM neural network, the updating rule of neuron weight can be expressed as:

$$\Delta w_{ji} = \alpha(t) \cdot h_{ij} \cdot (x_i - w_{ji}) \tag{3}$$

Δw_{ji} means the weight update, $\alpha(t)$ is the learning rate, h_{ij} indicates the proximity function, x_i refers to the input data;w_{ji} represents the neuron weight [28], [29], [30], [31].

For attribute space index normalization, the following equation can be used:

$$\text{normalized value} = \frac{\text{original value} - \min}{\max - \min} \tag{4}$$

The calculation of mixing distance can be written as:

$$D_{ij} = w_s \cdot D_{ij}^s + w_a \cdot \sqrt{\sum_{d=1}^{D} w_d \cdot (a_i^d - a_j^d)^2} \tag{5}$$

D_{ij} demonstrates mixed distance;D_{ij}^s shows geospatial distance;a_j^d and a_j^d indicate attribute values in attribute space;w_s and w_a are geospatial and attribute space weights, respectively [32], [33], [34], [35]. In self-organizing partition, the spatial distance metric can be represented as:

$$D_{ij}^s = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{6}$$

D_{ij}^s expresses the geographical distance between two points;(x_i, y_i) and (x_j, y_j) represent the coordinates of two points. The proximity function h_{ij} can use the Gaussian function to measure the proximity among neurons:

$$h_{ij} = e^{-\frac{D_{ij}}{2\sigma^2}} \tag{7}$$

D_{ij} represents the distance between neurons;σ refers to the diffusion parameter of the Gaussian function [36], [37]. The adjusted partition boundary can be calculated according to the detection results of outliers, and the examples are as follows:

$$\begin{aligned}\text{Adjusted boundary value} &= \text{Original boundary value} \\ &\quad + \text{Outlier intensity} \times \text{Adjustment coefficient}\end{aligned} \tag{8}$$

B. ZONING STEPS OF RURAL REVITALIZATION LAND BASED ON SOFM NEURAL NETWORK METHOD

The existing land consolidation projects in A County of Shaanxi Province are distributed in various towns and villages in this area, involving many factors, and there are complex relationships among them [38]. By constructing a relative risk model, the results of exposure-hazard analysis are characterized, and the relative risk value of each risk community is calculated. The calculation process reads:

$$RS_i = \sum_{jkm} S_{ij} H_{ik} X_{jk} E_{km} \tag{9}$$

RS_i represents the relative risk value of the ith risk community. j is the source of risk. k means the habitat type. m refers to the ecological receptor type. S_{ij} signifies the density of risk sources. H_{ik} indicates the habitat abundance. X_{jk} is the exposure coefficient. E_{km} expresses the response coefficient [39], [40]. The density of risk sources is the ratio of the area of a risk source in the risk community to the maximum area of this risk source in the risk community. Habitat abundance is the ratio of a habitat area in the risk community to the maximum value of this habitat area in the risk community. The exposure coefficient is the ratio of the area of a risk source in the habitat to the total area of the habitat [41], [42], [43].

The risk area contains various potential sources and the corresponding habitat area, as indicated in Figure 3.

A, B, C, D, E, and F represent six areas in A County of Shaanxi Province, and the habitat area of the risk community in A County of Shaanxi Province is shown in Figure 4.

The density of risk sources in each risk community in A County, Shaanxi Province, is displayed in Figure 5.

The habitat abundance of each risk community in A County, Shaanxi Province is suggested in Figure 6.

This study collected data for the land consolidation project from local government authorities and rural cooperatives in A County, Shaanxi Province. These data encompassed

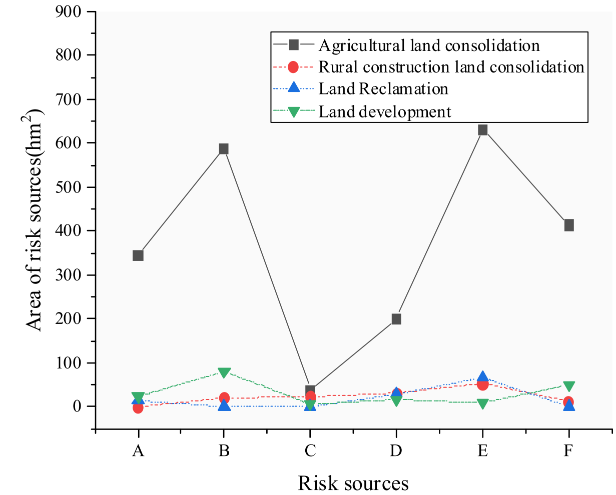

FIGURE 3. The risk area includes all kinds of potential risk sources and the corresponding habitat area.

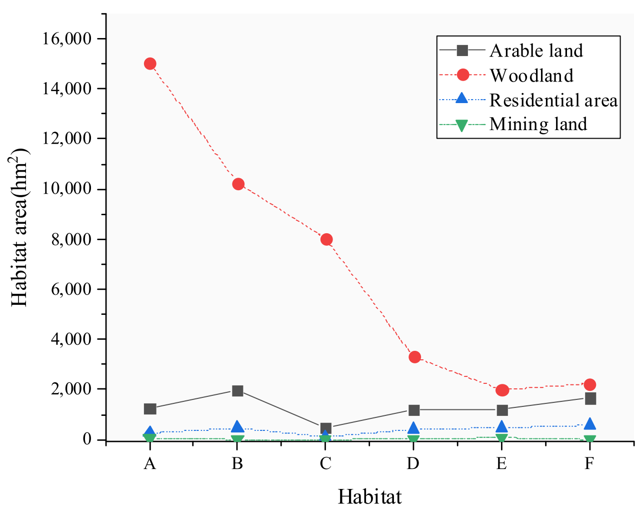

FIGURE 4. Habitat area of risk community in A County of Shaanxi province.

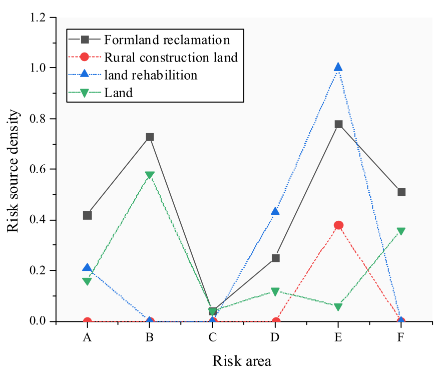

FIGURE 5. Density of risk sources in various risk communities in A County, Shaanxi Province.

historical records of land consolidation, project progress, and resource utilization, among other aspects. IoT sensors were deployed within the land consolidation project areas to monitor soil quality, meteorological conditions, water quality, and farmland conditions. These sensors collected real-time data and transmitted it to a data center through networks. Digital financial data was sourced from rural financial institutions, encompassing information about loan disbursements, the usage of financial products, and the financial behaviors of rural residents. These data helped analyze the effectiveness of digital finance in rural revitalization.Land quality indicators comprised soil pH, organic matter content, nutrient levels, etc., which were used to assess soil fertility and suitability. Meteorological data included temperature, humidity, rainfall, etc., for analyzing the impact of climate on farmland yields. Farmland production information involved variables like crop types, growing seasons, yields, etc., to evaluate the agricultural production outcomes of the land consolidation projects. Digital financial indicators covered metrics like financial product adoption rates, the penetration of rural financial services, loan default rates, etc., to assess the contribution of digital finance to rural revitalization. Quantitative analysis employed spatial data analysis methods, involving GIS analysis of geographic data in the land consolidation project areas to study land use patterns and resource allocation.

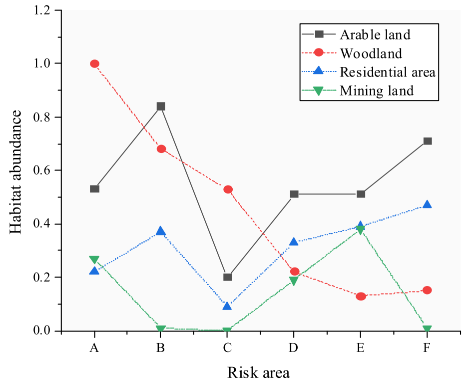

FIGURE 6. Habitat abundance of various risk communities in A County, Shaanxi Province.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

The acquisition of the required basic data mainly covers the following aspects: ① It covers fundamental land use data, comprising surveys of land use status, data concerning land use changes, agricultural land zoning data, and comprehensive land use planning. ② It includes data on natural resources and environmental conditions, including terrain slope, elevation, geological conditions, soil characteristics, hydrological information, etc.③ It spans socio-economic data, including administrative divisions, population statistics, regional gross output value, and road and traffic distribution.

Among the above data, the basic land use data mainly come from the database of land use change (2022 edition) and agricultural land quality classification (2021 edition) in A County of Shaanxi Province. The data on natural resources and environmental conditions are mainly obtained from the image map of A County in Shaanxi Province, the 1: 10000 digital elevation mode (DEM) data of A County in Shaanxi Province, and the statistical yearbook of A County in Shaanxi Province in 2022. Socio-economic data mainly come from the statistical yearbook of A County in Shaanxi Province in 2022, and the accounts of relevant government units. The data on land consolidation status principally comes from the database of land consolidation planning in A County, Shaanxi Province (covering the data from 2016 to 2020), the investigation results of cultivated land reserve resources, and the field survey and research data carried out during the compilation of land consolidation planning.

B. EXPERIMENTAL ENVIRONMENT

To verify the application effect of digital finance and IoT technology in rural revitalization, A County in Shaanxi Province is selected as the research case. In ecology, a risk source is one or more physical, chemical, or biological factors that may negativelyimpact the environment. According to the relevant requirements, the secondary risk sources with little influence and low possibility are excluded.Finally, agricultural land consolidation, rural construction land consolidation, land reclamation, and land development are determined as the four risk sources in this study. After considering the influence degree and object of different risk sources, this study divided cultivated land, woodland, residential area, and mining land into four types of habitats. Ecological receptors refer to biological or abiotic entities adversely affected by the development of land remediation activities. This study selects soil, water environment, biodiversity, and landscape pattern as four ecological receptors to conform to the situation.

C. PARAMETERS SETTING

SOFM neural network parameters: the number of iteration times, input, and output nodes of the SOFM neural network are set. The SOFM neural network can effectively divide A County in Shaanxi Province into land consolidation project areas with similar attributes and adjacent spaces through the input data of the attribute and geographic space domains. Wherein the number of input and output nodes is 10 and 30. The number of iterations is 1000.

Weight of comprehensive index system: According to the research objectives and case characteristics, the weights of different comprehensive indexes are set to analyze the related factors of land consolidation projects quantitatively. The setting of these weights will affect the final rural revitalization land zoning pattern. Among them, the ecological risk weight of land consolidation is 0.4. The time urgency weight is 0.3. The spatial suitability weight is 0.3.

D. PERFORMANCE EVALUATION

The ecological risk analysis results of different ecological receptors are exhibited in Table 1.

The above data results demonstrate differences among different areas regardingsoil ecological risk, water environment ecological risk, biodiversity ecological risk, and landscape pattern ecological risk. Soil ecological risk values reflect soil fertility, pollution levels, and sustainability for land use. Lower soil ecological risk values indicate better suitability for agricultural production and resource utilization, which is crucial for rural economic development in the context of rural revitalization. The extremely low soil ecological risk values in Area C suggest that this area holds potential advantages for agricultural development. Water environment ecological risk values reflect the quality of water resources and the degree of protection in the area. Lower water environment ecological risk values illustrate cleaner and more sustainable water resources, which are essential for rural residents' drinking water safety and agricultural irrigation. Area C's low water environment ecological risk values indicate superior water resources. Biodiversity ecological risk values reflect the health of ecosystems and species diversity within the area. Lower biodiversity ecological risk values signify relatively intact ecosystems, which contribute to maintaining ecological balance and ecosystem services. Landscape pattern ecological risk values reflect the rationality and sustainability of land use patterns within the area. Rational landscape patterns help improve the efficient utilization of land resources and the sustainability of agricultural production. The higher landscape pattern ecological risk values in Areas A and D highlight the necessity of land consolidation projects to optimize land use patterns.

TABLE 1. The ecological risk analysis results of ecological receptors.

	Soil	Water environment	Biological diversity	Landscape pattern
A	0.34	0.20	0.21	0.37
B	1.009	0.67	0.86	0.8628
C	0.009	0.0067	0.0061	0.003
D	0.28	0.170	0.17	0.27
E	0.42	0.338	0.68	0.64
F	0.64	0.45	0.65	0.65

In short, the data results highlight the unique characteristics of different areas regarding ecological risks, which are closely related to the goals of rural revitalization. Analyzing and addressing these ecological risks can help improve the ecological environment in rural areas, enhance the sustainability of rural economies, and facilitate the implementation of rural revitalization strategies.

The specific results of rural revitalization land consolidation zoning in A County, Shaanxi Province are plotted in Figure 7.

The above data presents the rural revitalization land zoning pattern of land consolidation in A County, Shaanxi Province, divided into four land consolidation areas. Firstly, the priority remediation area encompasses 27 administrative villages,spanning a total area of 28090 hm^2. This area constitutes 32.75% of the overall region. Secondly, there are 37 administrative villages in the moderate renovation area

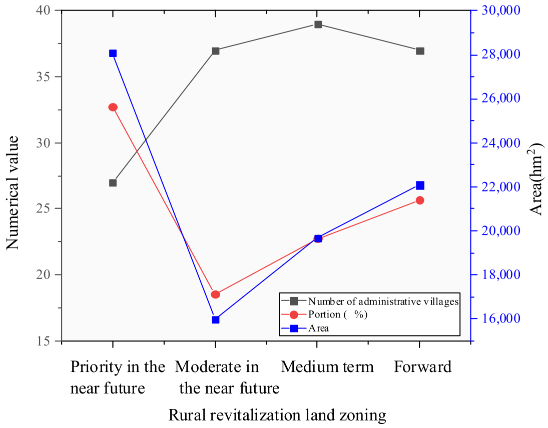

FIGURE 7. Specific results of land consolidation zoning for rural revitalization in A County, Shaanxi Province.

soon, covering 15,986 hm^2, equivalent to 18.55% of the entire area. Thirdly, in the medium term, the land-saving renovation area covers 39 administrative villages with a total area of 19686 hm^2, accounting for 22.75%. Finally, in the long-term restricted remediation area, 37 administrative villages, with a total area spanning 22,081 hm^2, representing 25.67% of the total area. These data findings furnish a quantitative foundation for land consolidation planning within this area, enabling the realization of consolidation objectives across different timeframes.

E. DISCUSSION

The ecological risks of landscape pattern (the ecological risk value is between 0.01 and 1.62) and soil (the ecological risk value is between 0.01 and 1.46) in A County of Shaanxi Province are markedly higher than those of the other three types of ecological receptors. This that improper measures during the land consolidation project's execution may lead to landscape fragmentation and soil degradation in the area.In contrast, the ecological risks of the water environment (ranging from 0.01 to 1.08) and biodiversity (ranging from 0.01 to 1.04) exhibit slightly lower values. This is consistent with that A County in Shaanxi Province is situated in the southeast paddy field agricultural area, with developed irrigation conditions and rich biological species characteristics in the subtropical monsoon climate zone. The results of rural revitalization land consolidation zoning show four different land consolidation areas: the priority consolidation area, moderate consolidation area, medium-term land-saving consolidation area, and restricted consolidation area. In addition, IoT technology is introduced to strengthen the monitoring and management of land remediation. Through IoT technology, land use, soil quality, and water resource utilization can be monitored in real-time, thus providing more accurate data support for remediation planning. Moreover, digital financial technology provides strong financial support and financial services for rural revitalization. Through digital finance, people can realize the accurate investment of funds and promote the development of rural industries and financial inclusion.

The limitation of the study data is that the quality of the data used here may be limited. For instance, the accuracy and coverage of soil, water quality, and meteorological data may affect the precision of ecological risk assessment. Therefore, data collection and processing errors during the process could introduce biases. To enhance the credibility of the results, multiple data sources and various analytical methods can be utilized to validate the findings.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

This study discusses the application of digital finance based on the SOFM neural network and IoT technology in rural revitalization. Taking A County in Shaanxi Province as a case, a comprehensive index system is constructed, and the related factors of land consolidation projects are quantitatively analyzed. Through the results of the SOFM neural network, A county in Shaanxi Province is successfully divided into land consolidation project areas with similar attributes and adjacent space, and the zoning pattern of rural revitalization land is formulated.

The key findings of this study are as follows. (1) Significant differences exist in soil ecological risk, water environment ecological risk, biodiversity ecological risk, and landscape pattern ecological risk among different regions. Area C exhibits lower risk levels across all ecological risk aspects, while Area B shows higher risk values. (2) The study results underscore the importance of land consolidation. Areas A and D have relatively higher landscape pattern ecological risk, indicating the necessity of land consolidation projects to optimize land use patterns and enhance land ecological quality. These key findings have significant implications for rural revitalization and development. Firstly, the differences in ecological risk highlight the need for targeted policies and plans to accommodate the ecological environment needs of different areas. Rural revitalization strategies must consider the ecological variations among areas to ensure sustainable development. Secondly, land consolidation is crucial in improving the land ecological quality and landscape patterns. For areas with higher landscape pattern ecological risk, the planning and implementing land consolidation projects will contribute to more efficient land resource utilization, providing a better land foundation for rural revitalization. In summary, these key findings emphasize the importance of ecological environment and land use in rural revitalization and provide policymakers with insights on effectively promoting sustainable rural development.

This study has made several specific contributions to rural revitalization, advancing existing knowledge. In comparison to other research, the primary contributions are as follows. Firstly, there is an improvement in the ecological risk assessment method. This study has developed a comprehensive ecological risk assessment method by considering multiple ecological factors such as soil, water environment, biodiversity, and landscape patterns. This method is conducive to gaining a more comprehensive understanding of the ecological health status in various areas, providing more specific guidance for rural revitalization planning. Secondly, the importance of land consolidation projects is emphasized. The study results highlight the crucial role of land consolidation in improving land ecological quality and landscape patterns. This offers strong evidence for decision-makers and planners, demonstrating the essential nature of land consolidation projects for the sustainability of rural revitalization.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

In practical application, the quality and availability of data are very important for the model effect. Future research can further explore how to obtain more accurate and comprehensive data and enhance the model's prediction accuracy. Although the SOFM neural network performs well in dividing regions, it can still further improve the model's algorithm and structure to improve the partition results' stability and reliability. Meanwhile, verifying the partition results with the actual situation is necessary to ensure the model's practical application effect. This study focuses on the rural revitalization of land consolidation projects, but rural revitalization involves many factors. Future research can consider more factors, such as industrial layout and infrastructure construction, and realize multi-factor comprehensive planning and decision-making.

In conclusion, with the support of digital finance and IoT technology, this study has successfully utilized the SOFM neural network method to delineate rural revitalization land use in A County, Shaanxi Province. This study provides scientific support for the development of rural revitalization. Future research directions should focus on further investigating the role and impact of digital finance in rural revitalization. This involves examining the contributions of various digital finance tools to rural financial services, agricultural production, and rural economic development to formulate more specific policies and strategies.

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