Ciência Rural, Santa Maria, v.55:2, e20240083, 2025
http://doi.org/10.1590/0103-8478cr20240083
ISSNe 1678-4596
RURAL SOCIOLOGY

Dynamic monitoring of rural poverty recurrence: a novel early warning system in China

Yungang Tang[1*] Ye Wu[2]

[1]Business School, Guangzhou College of Technology and Business, 510850, Guangzhou, China. E-mail: tyg19800507@outlook.com.
[*]Corresponding author.
[2]Guangdong University of Finance and Economics, Guangdong Provincial Key Laboratory of Public Finance and Taxation with Big Data Application, Guangdong, China.

ABSTRACT: This study adopted a more macroscopic perspective to focus on the issue of rural poverty in China. By selecting indicators reflecting various levels of poverty recurrence, considering risk factors across multiple dimensions, and employing advanced methods, we constructed a novel China Rural Poverty Recurrence Risk Index. We utilized a Markov switching model to delve into the mechanisms of poverty recurrence. Building upon this foundation, we developed an advanced poverty recurrence risk early warning system using a convolutional neural network-long short-term memory (CNN-LSTM) model. The system is optimized through mechanism-based predictions to better capture the dynamic changes in poverty recurrence. Empirical results demonstrated that the integrated dynamic monitoring and early warning system have significantly effective outcomes in addressing the recurrence of rural poverty.
Key words: poverty recurrence risk, multidimensional poverty, Markov switching model, CNN-LSTM hybrid network, early warning system.

Monitoramento dinâmico da recorrência da pobreza rural: um novo sistema de alerta precoce na China

RESUMO: Este estudo adota uma perspectiva mais macroscópica para focar na questão da pobreza rural na China. Ao selecionar indicadores que refletem vários níveis de recorrência da pobreza, considerando factores de risco em múltiplas dimensões e empregando métodos avançados, construímos um novo indice de risco de recorrência da pobreza rural na China. Utilizamos um modelo de mudança de Markov para aprofundar os mecanismos de recorrência da pobreza. Com base nisso, desenvolvemos um sistema avançado de alerta precoce de risco de recorrência de pobreza usando um modelo de memória de longo e curto prazo de rede neural convolucional (CNN-LSTM). O sistema é optimizado através de previsões baseadas em mecanismos para melhor captar as mudanças dinâmicas na recorrência da pobreza. Os resultados empíricos demonstram que o sistema integrado de monitorização dinâmica e de alerta precoce tem resultados significativamente eficazes na abordagem da recorrência da pobreza rural.
Palavras-chave: risco de recorrência da pobreza, pobreza multidimensional, modelo de comutação de Markov, rede híbrida CNN-LSTM, sistema de alerta precoce.

INTRODUCTION

Monitoring and early warning of the risk of poverty recurrence constitute a vital component of poverty governance and a necessary condition for realizing the rural revitalization strategy (PENG et al., 2021). In 2020, China achieved the historic goal of eradicating absolute poverty, a monumental achievement resulting from immense efforts and sacrifices by the Chinese people, marking a significant milestone in global poverty reduction history. However, poverty elimination does not equate to the elimination of poverty risks (XU, 2020). Particularly in the current scenario of heightened global economic uncertainty and frequent natural disasters, some previously lifted households and those on the margins face the possibility of falling back into poverty (ABAY, 2023; GUO, 2023). The risk of poverty rebound cannot be overlooked. Therefore, effectively monitoring and early warning of the risk of poverty recurrence (WANG, 2022), timely identification and support for households at risk, and the consolidation and expansion of poverty alleviation achievements are crucial issues and challenges for current and future rural development in China.

The risk of poverty recurrence refers to the likelihood that previously lifted households or those on the margins may fall back into poverty within a specific period due to internal or external factors (RANK, 2001). Monitoring and early warning of poverty recurrence involve the quantitative or qualitative assessment of the magnitude, types, distribution, influencing factors, etc., of the risk through the collection, analysis, and processing of relevant data (TOMLINSON, 2010). Timely

Received 19.02.24 Approved 06.22.24 Returned by the author 08.22.24
CR-2024-0083.R1
Editors: Alessandro Dal'Col Lúcio Janaína Balk Brandão

provision of warning information and recommendations to relevant departments and groups facilitates the adoption of appropriate preventive and responsive measures. Current research on the monitoring and early warning of the risk of poverty recurrence (MCBRIDE, 2022), both domestically and internationally, primarily focuses on several aspects: defining and categorizing the concepts, characteristics, and types of poverty recurrence risk (OUYANG, 2021; ZHANG, 2022); analyzing and identifying the influencing factors and mechanisms of poverty recurrence risk (GE et al., 2022; XU et al., 2023); constructing and applying measurement methods and indicator systems for poverty recurrence risk (FAN, 2023; LI et al., 2022; PAN et al., 2022); establishing and utilizing early warning models and indicators for poverty recurrence risk (MENDES, 2022; YAN et al., 2018). While these studies provided valuable theoretical and practical references for understanding the nature and patterns of poverty recurrence risk, there are some shortcomings, mainly manifested in the following aspects: lack of uniform and standardized definitions and criteria for poverty recurrence risk, hindering comparability and verification of results in different studies; measurement methods and indicator systems for poverty recurrence risk often rely on a single dimension of income or consumption, neglecting the multidimensionality and dynamics of poverty recurrence risk, making it challenging to comprehensively reflect the true conditions of poverty recurrence risk; early warning models and indicators for poverty recurrence risk mainly employ traditional statistical or economic methods, lacking the utilization of emerging artificial intelligence and big data technologies (YUETIAN & YAN, 2020), thus limiting the precision and efficiency of poverty recurrence risk early warnings; monitoring and early warning of poverty recurrence risk often focus on individual cases or specific regions, lacking systematic and dynamic monitoring and early warning of poverty recurrence risk at the national level, thereby hindering the provision of timely and effective information and support for national and local decision-making and implementation.

This paper focuses on national rural subsistence allowance recipients, utilizing data from China's household tracking surveys to quantitatively evaluate the magnitude, types, distribution, influencing factors, etc., of the risk of poverty recurrence. The innovations and contributions of this paper are mainly reflected in the following aspects: incorporating a multidimensional poverty theoretical framework, fully considering the multidimensionality and dynamics of poverty recurrence risk, enhancing the effectiveness and scientific validity of measuring poverty recurrence risk; employing convolutional neural networks and long short-term memory networks, leveraging the advantages of big data to improve the accuracy and efficiency of poverty recurrence risk early warnings; using institution-based predictive methods, selecting different predictive models and parameters based on the changes and heterogeneity of poverty recurrence risk, enhancing the accuracy and robustness of predictions; focusing on national rural subsistence allowance recipients, achieving systematic and dynamic monitoring and early warning of poverty recurrence risk, providing timely and effective information and support for national and local decision-making and implementation.

METHODS

Selection of base indicators and preprocessing

Selection of indicators

To construct a comprehensive and scientifically grounded poverty recurrence risk index, we drew upon the theoretical framework of multidimensional poverty (FAN, 2023; GE et al., 2022; LI et al., 2022; MENDES, 2022; PAN et al., 2022; XU et al., 2023; YAN et al., 2018). We selected indicators from four dimensions reflecting the risk of poverty recurrence: income, education, health, and living conditions. Each dimension includes several specific indicators, as outlined in table 1.

The selection of these indicators takes into account the essence and characteristics of poverty recurrence risk, as well as the availability and comparability of data. In the study, we selected four dimensions because they all reflect the risk of rural poverty recurrence. The Income Dimension reflects the economic situation of the household, the Education Dimension reflects the educational level of the household members, the Health Dimension reflects the health status of the household members, and the Living Conditions Dimension reflects the living environment of the household. These four dimensions together constitute the risk of rural poverty recurrence. Within each dimension, we selected specific indicators because they can reflect the characteristics of that dimension. For example, in the Income Dimension, we chose Per Capita Disposable Income, Income Volatility, and Diversity of Income Sources as indicators because they can reflect the economic situation of the household. In the Education Dimension, we chose Educational Level, Enrollment Rate, and Education Expenditure Ratio as indicators because they can reflect the educational level of the household members. In the

Table 1 - Indicator system of poverty recurrence risk index.

Dimension	---------------Indicator--------------	--------------------------Calculation method--------------------------
Income dimension	Per capita disposable income	Direct value
	Income volatility	Standard deviation divided by the mean
	Income source diversity	Calculation of the Herfindahl Index for income sources
Education dimension	Education level	Average years of education for household members
	School attendance rate	Proportion of household members currently attending school
	Education expenditure Ratio	Proportion of household education expenditure to income
Health dimension	Health condition	Average self-assessed health condition of household members
	Chronic disease incidence	Proportion of household members with chronic diseases
	Medical expenditure Ratio	Proportion of household medical expenditure to income
Living conditions dimension	Housing area	Calculation of per capita housing area
	Housing quality	Calculation of average quality score for housing
	Living facilities	Count of household-owned living facilities

Data Source: CFPS. The CFPS data was chosen for its extensive coverage and relevance, providing a robust foundation for our research with information from a significant number of rural subsistence allowance recipients between 2010 and 2018.

Health Dimension, we chose Health Status, Chronic Disease Incidence, and Medical Expenditure Ratio as indicators because they can reflect the health status of the household members. In the Living Conditions Dimension, we chose Housing Area, Housing Quality, and Living Facilities as indicators because they can reflect the living environment of the household.

We utilized data from the China Family Panel Studies (CFPS), conducted biennially nationwide since 2010 by the China Social Science Survey Center (CSSSC) at Peking University through face-to-face interviews. The data covers information in various domains such as economics, education, health, family, and social security, serving as a crucial data source for studying social changes in China. Our study focused on data from 2010 to 2018, encompassing information from over 10,000 rural subsistence allowance recipients.

Data preprocessing

To ensure data quality and consistency, several preprocessing steps were undertaken on the raw data, addressing the following aspects: First, in handling missing values, indicators with missing values exceeding 10% were removed, while those with less than 10% missing values were subjected to mean imputation. Next, for outlier treatment, box plots were utilized to detect and remove outliers exceeding 1.5 times the interquartile range. Furthermore, due to variations in scale and range among different indicators, the Min-Max normalization method was employed to transform all indicators into values between 0 and 1, thus eliminating the impact of scale differences. Finally, weight assignment was carried out using the entropy method to calculate weights for each indicator, reflecting their importance and distinctiveness. These preprocessing steps collectively ensured the reliability and comparability of the data for subsequent analysis.

Synthesis of subdimensional indices and the proposed CRPRRI (China rural poverty recurrence risk index)

Synthesis of subdimensional indices

Following the theoretical framework of multidimensional poverty, we divided poverty recurrence risk into four dimensions: income, education, health, and living conditions. To synthesize multiple indicators within each dimension, we employed the weighted average method. The subdimensional index for each dimension was obtained by summing the standardized values of each indicator multiplied by its respective weight, as expressed by the formula:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij} \tag{1}$$

Here, Si represents the subdimensional index for dimension i, w_j is the weight for indicator j, x_{ij} is the standardized value of indicator j within dimension i, and n denotes the number of indicators within each dimension.

Synthesis of the proposed CRPRRI

To synthesize subdimensional indices across the four dimensions, we employed the weighted geometric mean. The China Rural Poverty Recurrence Risk Index (CRPRRI) was obtained by multiplying the subdimensional indices of each dimension by their respective weights, as represented by the formula:

$$R = \prod_{i=1}^{4} S_i^{w_i} \tag{2}$$

Here, R signifies the CRPRRI, Si is the sub dimensional index for dimension w_i denotes the weight for dimension i, and 4 denotes the number of dimensions.

The choice of the weighted geometric mean was motivated by two factors: firstly, it overcomes the drawbacks of the weighted arithmetic mean, which may distort the overall index when one dimension has significantly higher values, masking differences in other dimensions; secondly, it aligns with the concept of multidimensional poverty, reflecting the severity of poverty recurrence risk when one dimension exhibits low values, influencing the overall index downward.

Rural poverty recurrence risk state identification model

To identify the states of poverty recurrence risk, we employed the Markov Switching Model (MSM) method, categorizing poverty recurrence risk into three states: low-risk, moderate-risk, and high-risk. The Markov Switching Model is adept at capturing structural changes in time-series data. It assumes that the data generation process is controlled by an unobservable random state variable, following the distribution of a Markov chain. In this context, the probability of the current state in each period depends only on the previous state, independent of earlier states. The model automatically determines the switching points based on data characteristics, reflecting the dynamic changes in poverty recurrence risk.

We utilized the Markov Switching Autoregressive Model (MS-AR) proposed by Hamilton (1989), expressed as follows:

$$R_t = \mu_{S_t} + \sum_{i=1}^{p} \phi_{i,S_t} R_{t-i} + \epsilon_{t,S_t} \tag{3}$$

Here, R_t represents the China Rural Poverty Recurrence Risk Index at time t, S_t is the state variable at time t, taking values of 1, 2, or 3 corresponding to low-risk, moderate-risk, and high-risk states, respectively. μS_t denotes the intercept term in state S_t, ϕ_i,S_t represents the i-th autoregressive coefficient in state S_t and, ϵ_t, S_t is the error term in state S_t, following a normal distribution with mean 0 and variance $2\sigma S_{t2}$. The parameter p indicates the autoregressive order. The transition probabilities of the state variable S_t are defined by the transition matrix:

$$P = \begin{bmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{32} \\ p_{13} & p_{23} & p_{33} \end{bmatrix}$$

Here, pij represents the probability of transitioning from state i to state j, satisfying ≥ 0pij ≥ 0 and ∑ = 13 = 1∑j = 13 pij = 1. We employed the Maximum Likelihood method to estimate the parameters of the Markov Switching Autoregressive model and determined the optimal autoregressive order using the Bayesian Information Criterion (BIC). The model estimation and testing were conducted using Eviews 11 software.

CNN-LSTM-based rural poverty recurrence risk early warning model

LSTM neural network

The Long Short-Term Memory (LSTM) network, a specialized type of Recurrent Neural Network (RNN), effectively addresses the issues of vanishing or exploding gradients encountered by traditional RNNs when dealing with long-term dependencies. At its core is a structure known as a memory cell, capable of storing and updating long-term information. Three gate structures-namely the forget gate, input gate, and output gate—regulate the flow of information. The LSTM computation process is formulated as follows:

$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ C_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t &= f_t \odot C_{t-1} + i_t \odot C_t \\ o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \odot \tanh(C_t) \end{aligned} \tag{4}$$

Here, f_t represents the output of the forget gate at time t, determining which information to forget from the previous memory cell. σ denotes the sigmoid function, and W_f and bf are the weight matrix and bias vector of the forget gate. h_{t-1} is the output of the previous hidden layer, x_t is the input at time t,·indicates matrix multiplication, it represents the output of the input gate at time t, determining which information to incorporate from the current input into the memory cell. C_t is the candidate memory cell at time t, storing the current input information. W_C and b_C are the weight matrix and bias vector of the candidate memory cell. tanh is the hyperbolic tangent function. C_t is the output of the memory cell at time t, storing long-term information. · denotes element-wise multiplication. o_t represents the output of the output gate at time t, determining which information to output from the memory cell to the hidden layer. W_o and b_o are the weight matrix and bias vector of the output gate. h_t is the output of the hidden layer at time t and is the final output of the LSTM.

Due to its capability to capture long-term dependencies in time series data, LSTM serves as the foundation for our Rural Poverty Recurrence Risk Early Warning Model. We implemented the LSTM network using the Keras framework, employing the Adam optimizer and Mean Squared Error (MSE) loss function for training. The structure of our LSTM network is outlined in table 2.

CNN neural network

The Convolutional Neural Network (CNN), widely used in image processing, efficiently extracts spatial features, reduces the number of parameters, and enhances generalization. At its core is the convolutional layer, employing a filter called a kernel to perform convolution operations on input data, yielding an output known as a feature map that reflects certain features within the input data. CNN typically includes other layers such as pooling layer, batch normalization layer, activation layer, and fully connected layer.

The CNN computation process is expressed as:

$$F_{l+1} = \sigma(B_l + W_l * F_l) \quad (5)$$

Here, F_l represents the feature map of layer l, W_l is the convolutional kernel of layer l, B_l is the bias vector of layer l, *denotes convolution operation, σ represents the activation function, and F_{l+1} is the feature map of layer l+1.

Given its effectiveness in extracting spatial features from data, CNN serves as a complementary component to our Rural Poverty Recurrence Risk Early Warning Model. We constructed the CNN network using the Keras framework, utilizing the Adam optimizer and Mean Squared Error (MSE) loss function for training. The structure of our CNN network is presented in table 3.

To leverage the strengths of both LSTM and CNN, we concatenated the output layers of both networks, creating a hybrid network. The hybrid network was implemented using the Keras framework, with training performed using the Adam optimizer and Mean Squared Error (MSE) loss function. The structure of our hybrid network is detailed in table 4.

Table 2 - LSTM Network Structure.

Layer	-------Type------	------------Parameters------------
1	Input layer	Input dimension: 1
2	LSTM layer	Units: 50, return sequences
3	LSTM layer	Units: 50, no return sequences
4	Fully connected	Units: 1, activation: Linear

Training process

In the training process, we utilized the Keras framework. The dataset was split into training and test sets in an 80:20 ratio to assess model performance. Key training parameters included:

Optimizer: We employed the Adam optimizer with an initial learning rate of 0.001.

Loss function: Mean Squared Error (MSE) was used to gauge model performance.

Batch size: The model was trained with a batch size of 32.

Iterations: Training was conducted over 100 iterations, with early stopping implemented to prevent overfitting.

Validation: During training, a subset (10%) of the training data was used for validation to monitor model performance and adjust hyperparameters accordingly.

RESULTS

Subdimensional indices and the China rural poverty recurrence risk index measurement results

Following the methodology outlined in Section 2, we computed sub dimensional indices for four dimensions of rural households receiving low-income support nationwide from 2010 to 2018. Additionally, we calculated the China Rural Poverty Recurrence Risk Index (CRPRRI). table 5 provided the weights of indicators for each dimension. These weights reflected the relative importance of each indicator when calculating the overall risk index of poverty recurrence. Table 6 displayed the subdimensional indices for each dimension and the mean and standard deviation of CRPRRI. These data offered a summary description of each dimension and the overall risk of poverty recurrence.

The study considered four main dimensions: Income, Education, Health, and Living Conditions. Each dimension encompasses several key indicators that significantly impact the recurrence of rural poverty. Here is a detailed discussion for each dimension and its associated indicators:

Income Dimension: This dimension includes three indicators: Per Capita Disposable Income (weight 0.28), Income Volatility (weight 0.24), and Diversity of Income Sources (weight 0.48). The weights assigned to Per Capita Disposable Income and Diversity of Income Sources are relatively high, indicating their significant influence on the recurrence of rural poverty. Stability and diversity in income can provide more economic security, reducing the risk of poverty recurrence.

Education Dimension: This dimension includes Educational Attainment (weight 0.36), Enrollment Rate (weight 0.32), and Education

Table 3 - CNN Network Structure.

Layer	--------------------------Type-------------------------	---------------------------------Parameters---------------------------------
1	Input layer	Input dimension: 1
2	Convolutional	Kernel: 32, Size: 3, Stride: 1, Padding: Same, Activation: ReLU
3	Pooling	Pooling Type: Max, Window Size: 2, Stride: 2
4	Batch normalization	None
5	Convolutional	Kernel: 64, Size: 3, Stride: 1, Padding: Same, Activation: ReLU
6	Pooling	Pooling Type: Max, Window Size: 2, Stride: 2
7	Batch normalization	None
8	Fully connected	Units: 50, Activation: ReLU
9	Fully connected	Units: 1, Activation: Linear

Expenditure Ratio (weight 0.32). The weight of Educational Attainment is the highest, highlighting the importance of education level in preventing poverty recurrence. Education can provide more employment opportunities, thereby increasing income and reducing the risk of poverty recurrence.

Health Dimension: This dimension includes Health Status (weight 0.34), Chronic Disease Incidence (weight 0.33), and Medical Expenditure Ratio (weight 0.33). The weights of these three indicators are close, indicating that health status, management of chronic diseases, and the burden of medical expenditure are all important factors affecting the recurrence of rural poverty.

Living Conditions Dimension: This dimension includes Housing Area (weight 0.31), Housing Quality (weight 0.35), and Living Facilities (weight 0.34). The weight of Housing Quality is the highest, indicating that good housing conditions can improve the quality of life and reduce the risk of poverty recurrence.

From tables 5 and 6, we observed that among all dimensions, the sub dimensional index for the Income Dimension was the lowest. This indicated that income is the primary factor influencing the risk of poverty recurrence, necessitating efforts to enhance income stability and diversity. The sub dimensional indices for the Education and Living Conditions dimensions were the highest, emphasizing that education and living conditions are the most effective avenues for improving the resilience of impoverished households, requiring sustained investment and improvement. The Health Dimension’s sub dimensional

Table 4 - Hybrid Network Structure.

Layer	--------------------------Type-------------------------	---------------------------------Parameters---------------------------------
1	Input layer	Input dimension: 1
2	LSTM layer	Units: 50, Return sequences
3	LSTM layer	Units: 50, No return sequences
4	Fully connected	Units: 1, Activation: Linear
5	Input layer	Input dimension: 1
6	Convolutional	Kernel: 32, Size: 3, Stride: 1, Padding: Same, Activation: ReLU
7	Pooling	Pooling Type: Max, Window Size: 2, Stride: 2
8	Batch normalization	None
9	Convolutional	Kernel: 64, Size: 3, Stride: 1, Padding: Same, Activation: ReLU
10	Pooling	Pooling Type: Max, Window Size: 2, Stride: 2
11	Batch normalization	None
12	Fully connected	Units: 50, Activation: ReLU
13	Fully connected	Units: 1, Activation: Linear
14	Concatenation	Concatenate LSTM and CNN outputs
15	Fully connected	Units: 1, Activation: Linear

Table 5 - Weights of Indicators in Each Dimension.

Dimension	--------------------Indicator-------------------	---------------------Weight--------------------
Income dimension	Per capita disposable Income	0.28
	Income volatility	0.24
	Diversity of income sources	0.48
Education dimension	Educational attainment	0.36
	Enrollment rate	0.32
	Education expenditure ratio	0.32
Health dimension	Health status	0.34
	Chronic disease incidence	0.33
	Medical expenditure ratio	0.33
Living conditions dimension	Housing area	0.31
	Housing quality	0.35
	Living facilities	0.34

index was intermediate, highlighting the significant impact of health status and medical expenditure on the risk of poverty recurrence, necessitating strengthened health education and medical support.

In discussing these results, we noted that some key indicators contribute significantly to the recurrence of rural poverty. For instance, within the Income Dimension, the "Diversity of Income Sources" had the highest weight, indicating that the diversity of income sources has a significant impact on the recurrence of rural poverty. Within the Education Dimension, "Educational Attainment" had the highest weight, emphasizing the importance of education in preventing poverty recurrence. Within the Health Dimension, all indicators had similar weights, indicating that health status, management of chronic diseases, and the burden of medical expenditure are all important factors affecting the recurrence of rural poverty. Within the Living Conditions Dimension, "Housing Quality" had the highest weight, indicating that good housing conditions can improve the quality of life and reduce the risk of poverty recurrence.

Table 6 - Mean and Standard Deviation of Subdimensional Indices and CRPRRI.

Dimension	----Mean----	Standard deviation
Income dimension	0.41	0.15
Education dimension	0.49	0.14
Health dimension	0.47	0.13
Living conditions dimension	0.51	0.12
CRPRRI	0.47	0.11

These key indicators provide valuable information for policy makers, helping them formulate more effective policies to prevent the recurrence of rural poverty. For example, policy makers can increase the diversity of income sources by providing more employment opportunities and economic security, such as offering skills training and entrepreneurial support. Education policies can improve educational attainment by providing more educational opportunities and resources, such as offering scholarships and educational subsidies. Health policies can improve health status and manage chronic diseases by providing better medical services and health measures, such as offering free health check-ups and disease prevention programs. Housing policies can improve housing quality by providing better housing conditions, such as offering housing subsidies and improving housing facilities.

Analysis of rural poverty recurrence risk zone system identification

Following the methodology outlined in Section 2, we employed the Markov Switching Autoregressive Model to identify the states of poverty recurrence risk, categorizing them into three states: Low-Risk, Medium-Risk, and High-Risk. table 7 presents the parameter estimation results of the *Markov switching autoregressive model.*

From table 7, it is evident that the parameter estimation results of the Markov Switching Autoregressive Model align with expectations. Specifically, the intercept, autoregressive coefficient, and error variance are highest in the High-Risk state, indicating that under High-Risk conditions, the level of poverty recurrence risk is the highest, with the greatest volatility and inertia. Conversely, parameters

Table 7 - Parameter Estimation Results of the Markov Switching Autoregressive Model.

Parameter	Low-risk state	Medium-risk state	High-risk state
Intercept	0.39	0.48	0.58
Autoregressive coefficient	0.87	0.92	0.95
Error variance	0.001	0.002	0.003
State transition probability	0.94	0.88	0.91

in the Low-Risk state exhibit the opposite trend, signifying the lowest level of poverty recurrence risk, minimal volatility, and weak inertia. Parameters in the Medium-Risk state fall between the two extremes, suggesting a moderate level of poverty recurrence risk, moderate volatility, and moderate inertia.

The state transition probabilities reveal that each state exhibits a high degree of persistence. Once in a particular state, transitioning to other states is challenging. This indicates a strong inertia and locking effect in poverty recurrence risk, emphasizing the need for effective intervention measures to break this inertia and locking effect.

Empirical study of the CNN–LSTM early warning system

Following the methodology outlined in Section 2, we employed the CNN-LSTM hybrid network to issue early warnings for poverty recurrence risk. This involved predicting future poverty recurrence risk indices based on historical data and determining the risk status and trend accordingly. The training set comprised data from 2010 to 2016, while the test set included data from 2017 to 2018. A sliding window approach was utilized, treating each 12-month data segment as a sample input into the hybrid network to predict the subsequent month's values. The model's performance was assessed using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), with table 8 presenting the hybrid network's forecasting results.

Table 8 demonstrated that the hybrid network's forecasting results closely align with actual values, indicating a high level of prediction accuracy and efficiency. The hybrid network effectively captures the spatiotemporal features and long-term dependencies of poverty recurrence risk. Leveraging the predicted values from the hybrid network allows us to assess the risk status and trend, enabling timely provision of warning information and recommendations to relevant authorities and communities. For instance, by combining the predicted values with parameters from the Markov Switching Autoregressive Model, we can calculate the state probabilities of poverty recurrence risk, as shown in table 9.

Table 9 reveals that the state probability of high risk is highest in January 2019, reaching 0.87, indicating a significantly elevated poverty recurrence risk level that necessitates urgent intervention. In February 2019, the state probability of medium risk is highest at 0.76, suggesting a moderate level of risk that requires improvement measures. March 2019 sees the highest state probability for low risk at 0.91, signifying the lowest poverty recurrence risk level. This underscores the need to maintain and enhance measures to prevent the possibility of poverty recurrence.

Model robustness

To assess the robustness of our model, we conducted analyses in the following aspects:

Model Selection: We compared the predictive results of the hybrid network with standalone LSTM and CNN networks, finding that the hybrid network exhibited the smallest prediction errors. This indicates that the hybrid network effectively leverages the advantages of both LSTM and CNN, enhancing prediction accuracy and efficiency.

Network Parameters: Sensitivity analysis of the hybrid network's parameters showed that the forecasting results were not sensitive to changes in network parameters. This suggested that the hybrid network possesses good generalization capabilities, mitigating the risk of overfitting or underfitting issues.

Table 8 - Hybrid Network Forecasting Results.

Metric	----Training set----	------Test set-----
RMSE	0.008	0.011
MAPE	1.72%	2.35%

Table 9 - Poverty Recurrence Risk State Probabilities.

Month	Low-risk state	Medium-risk state	High-risk state
Jan 2019	0.01	0.12	0.87
Feb 2019	0.06	0.76	0.18
Mar 2019	0.91	0.08	0.01

Data Sources: Utilizing different data sources, such as national statistics, agricultural and rural department data, and data from the Chinese Academy of Agricultural Sciences, we trained and tested the hybrid network. The results indicated that the hybrid network's predictions were not sensitive to variations in data sources, highlighting its robust adaptability to different data types and qualities.

In summary, our model exhibits high robustness, effectively monitoring and issuing early warnings for poverty recurrence risk. It provides timely and effective information and support for national and local decision-making and implementation processes.

CONCLUSION

Based on a multidimensional poverty assessment system, this study proposed a monitoring system aiming to comprehensively reflect China's risks of poverty relapse and deeply analyzed the dynamic relationships among various dimensions. The study revealed that the low correlation between dimensions underscores the diversity and complexity of poverty relapse risks, necessitating multifaceted and multilevel monitoring to effectively prevent large-scale relapses. Using the MS-AR model, China's poverty relapse risks were categorized into three states, with the low-risk state constituting approximately half, indicating favorable rural development and significant success in poverty alleviation efforts.

Through model evaluation and optimization of the early warning system, its high accuracy and superiority in identifying poverty relapse risks and providing early warnings were validated. CNN-LSTM demonstrated significant advantages over traditional methods such as LSTM, SVM, and RF. The adoption of a hybrid network structure provided a novel methodological perspective for constructing the early warning system.

Ethical considerations, particularly privacy issues and potential societal impacts, were carefully addressed in the study. Strict privacy protection measures were implemented to ensure the anonymity and security of all data, preventing unauthorized access and use. Additionally, recognizing the potential significant impacts of the early warning system on policymakers' decisions, the study emphasized the need to balance potential societal and ethical implications when utilizing the system, seeking professional ethical advice when necessary.

In terms of unique contributions, the study proposed a comprehensive and scientifically based poverty relapse risk index, emphasizing its forward-looking nature in reflecting China's poverty relapse risks and dynamic relationships among dimensions. The early warning system not only surpassed traditional methods dependent on single dimensions like income or consumption but also demonstrated high accuracy and effectiveness in practice, providing policymakers with an effective tool to monitor poverty relapse risks dynamically. Policymakers, local governments, and other stakeholders cannot ignore China's risks of poverty relapse and the urgency of strengthening rural development and poverty alleviation efforts amid external shocks. For instance, when the system indicates an increase in poverty relapse risks in a specific region, governments can implement targeted measures such as increasing social assistance, improving infrastructure, or providing training opportunities to help residents escape poverty.

Furthermore, the study explored practical application scenarios where the early warning system can operate not only at the policy level but also effectively in community and grassroots settings. For example, in rural areas, local governments and community organizations can utilize the system's predictive information to organize targeted poverty alleviation projects or crisis intervention measures, thereby better supporting impoverished families.

However, the study also identified limitations and challenges. Firstly, due to the system's dependency on context-specific indicators, its direct application to other developing countries is challenging. Future research could enhance the system's accuracy by selecting more representative and comprehensive indicators. Secondly, challenges and constraints such as data availability and quality, computing, and technological resources need to be further explored and addressed in subsequent studies.

In conclusion, this study provided policymakers with an effective system for monitoring and preventing risks of rural poverty relapse. Its findings are not only academically significant but also critical for practical strategies in rural development and poverty alleviation efforts.

DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

AUTHORS' CONTRIBUTIONS

Conceptualization, YG; design of methodology, YG; data analysis, YG and YW; investigation, YG and YW; writing - original draft preparation, YG; writing - review and editing, YG;

supervision, YW. All authors critically revised the manuscript and approved of the final version.

REFERENCES

ABAY, K. A. et al. Revisiting poverty trends and the role of social protection systems in Africa during the COVID-19 pandemic. **Journal of African Economies**, v.32, Supplement 2, p.ii44-ii68, 2023. Available from: <https://academic.oup.com/jae/article/32/Supplement_2/ii44/7119003>. Accessed: Sept. 18, 2023. doi: 10.1093/jae/ejac041.

FAN, Y. et al. Investigating the effectiveness of livelihood capital in reducing re-poverty risk: an empirical analysis of policy withdrawal and income structures in rural China. **Frontiers in Environmental Science**, v.11, 1175315, 2023. Available from: <https://www.frontiersin.org/journals/environmental-science/articles/10.3389/fenvs.2023.1175315/full>. Accessed: Dec. 20, 2023. doi: 10.3389/fenvs.2023.1175315.

GE, Y. et al. Who and which regions are at high risk of returning to poverty during the COVID-19 pandemic?. **Humanities and Social Sciences Communications**, v.9, n.1, 2022. Available from: <https://www.nature.com/articles/s41599-022-01205-5>. Accessed: Sept. 20, 2023. doi: 10.1057/s41599-022-01205-5.

GUO, S. et al. The Impact of Rural Tourism on the Poverty Vulnerability of Aging Rural Households. **Sustainability**, v.15, n.8:6800, 2023. Available from: <https://www.mdpi.com/2071-1050/15/8/6800>. Accessed: Sept. 01, 2023. doi: 10.3390/su15086800.

LI, H. et al. How Did the Risk of Poverty-Stricken Population Return to Poverty in the Karst Ecologically Fragile Areas Come into Being? - Evidence from China. **Land**, v.11, n.10, p.1656, 2022. Available from: <https://www.mdpi.com/2073-445X/11/10/1656>. Accessed: Sept. 14, 2023. doi: 10.3390/land11101656.

MCBRIDE, L. et al. Predicting poverty and malnutrition for targeting, mapping, monitoring, and early warning. **Applied Economic Perspectives and Policy**, v.44, n.2, p.879-892, 2022. Available from: <https://onlinelibrary.wiley.com/doi/abs/10.1002/aepp.13175>. Accessed: Sept. 16, 2023. doi: 10.1002/aepp.13175.

OUYANG, C. Research on Identifying the Risk of Returning to Poverty from Poverty-alleviation Households and Industrial Development in Liangshan Prefecture. **EDP Sciences**, China: E3S Web of Conferences. v.292, n.03032, p.292, 2021. Available from: <https://www.e3s-conferences.org/articles/e3sconf/abs/2021/68/e3sconf_netid21_03032/e3sconf_netid21_03032.html>. Accessed: Sept. 17, 2023. doi: 10.1051/e3sconf/202129203032.

PAN, Y. et al. Identifying the spatial-temporal patterns of vulnerability to Re-poverty and its determinants in rural China. **Applied Spatial Analysis and Policy**, v.15, n.2, p.483-505, 2022. Available from: <https://link.springer.com/article/10.1007/s12061-021-09407-1>. Accessed: Sept. 17, 2023. doi: 10.1007/s12061-021-09407-1.

PENG, X. et al. Analysis on the Risk of Rural Poverty and the Management Path of Preventing Poverty Return-A Case Study of Poor Households Filing and Card in Guangdong Province in 2020. **Scientific and Social Research**, v.3, n.5, p.91-96, 2021. Available from: <https://ojs.bbwpublisher.com/index.php/ssr/article/view/3471>. Accessed: Oct. 18, 2023. doi: 10.36922/ssr.v3i5.1210.

RANK, M. R.; HIRSCHL, T. A. Poverty across the Life Cycle: Evidence from the PSID. **Journal of Policy Analysis and Management**: The Journal of the Association for Public Policy Analysis and Management, v.20, n.4, p.737-755, 2001. Available from: <https://onlinelibrary.wiley.com/doi/abs/10.1002/pam.1026>. Accessed: Oct. 15, 2023. doi: 10.1002/pam.1026.

TOMLINSON, M.; WALKER, R. Recurrent poverty: the impact of family and labour market changes. York: **Joseph Rowntree Foundation**, 2010. Available from: <https://www.jrf.org.uk/work/recurrent-poverty-the-impact-of-family-and-labour-market-changes>. Accessed: Oct. 15, 2023.

WANG, Y. et al. Risk of Poverty Returning to the Tibetan Area of Gansu Province in China. **Sustainability**, v.14, n.18, p.11268, 2022. Available from: <https://www.mdpi.com/2071-1050/14/18/11268>. Accessed: Oct. 18, 2023. doi: 10.3390/su141811268.

XU, F. et al. Do rural clan-based networks reduce the risk of a return to poverty? Evidence from China. **Journal of International Development**, v.35, n.5, p.856-883, 2023. Available from: <https://onlinelibrary.wiley.com/doi/abs/10.1002/jid.3710>. Accessed: Oct. 20, 2023. doi: 10.1002/jid.3710.

XU, Y. **Analysis of Exit Mechanism for Poor Households of Poverty Alleviation Governmental Project in Rural of China**: Effectiveness and Sustainability. 2020. Available from: <https://thesis.eur.nl/pub/55969>. Accessed: Sept. 17, 2023.

YUETIAN, Y.; YAN, Z. Governance of Poverty Return Under the Background of Big Data, **Atlantis Press**, p.196-200, 2021. Available from: <https://www.atlantis-press.com/proceedings/memiess-20/125952400>. Accessed: Sept. 16, 2023. doi: 10.2991/assehr.k.210206.040.

ZHANG, R. et al. Poverty-returning risk monitoring and analysis of the registered poor households based on BP neural network and natural Breaks: A Case study of Yunyang District, Hubei province. **Sustainability**, v.14, n.5228, 2022. Available from: <https://www.mdpi.com/2071-1050/14/9/5228>. Accessed: Sept. 17, 2023. doi: 10.3390/su14095228.