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A study of spatial spillover effects of rural human capital on agroecological wellbeing performance: based on empirical data analysis at the provincial in China

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Introduction: Agroecological wellbeing performance (AWP) plays a crucial role in fostering sustainable agricultural development and improving overall human welfare. The enhancement of rural human capital is a key factor in bolstering AWP, offering substantial support for its improvement.

Methods: This study utilizes data from 30 provincial regions in China over the period from 2011 to 2022 to assess AWP using the super-efficient SBM model. The spatial Durbin model is employed to analyze the spatial spillover effects of rural human capital on AWP and to explore the underlying mechanisms of its influence.

Results and discussion: The findings indicate that improvements in rural human capital have a significant positive impact on AWP, with notable spatial spillover effects. Heterogeneity analysis show that rural human capital significantly enhances AWP in regions with steep topography. In contrast, in Main Grain-Producing Areas (MGPAs), the contribution of rural human capital to AWP is more localized, with limited cross-regional spillover effects. Mechanism analysis further suggests that the development of digital inclusive finance effectively supports high human capital groups in enhancing AWP, while resource mismatches act as a barrier to the full potential of rural human capital in improving AWP. These insights provide valuable guidance for advancing AWP across regions.

KEYWORDS

rural human capital, agroecological wellbeing performance, digital inclusive finance, resource mismatch, spatial spillover effects

1 Introduction

Environmental pollution and climate change pose unprecedented threats to global ecological security and public health. Rapid industrialization, heavy reliance on fossil fuels, and inefficient resource management have accelerated deforestation, soil erosion, and water contamination, significantly endangering food and water security (Shah et al., 2022) and aggravating health risks worldwide (Münzel et al., 2023). As a vital interface between ecosystems and human wellbeing, agriculture is both a victim of and a contributor to these environmental pressures. Unsustainable agricultural practices have intensified biodiversity loss, greenhouse gas emissions, and land degradation, while climate impacts such as extreme weather increasingly jeopardize farming livelihoods and food systems (Lippert et al., 2009; Liu et al., 2023). In this context, enhancing the sustainability of agriculture has become a global imperative. Agroecological wellbeing performance (AWP) has emerges as a critical framework to address this need, defined as the optimization of resource utilization to enhance human welfare while minimizing ecological depletion in agricultural production (Costanza et al., 2016; Feng et al., 2019). AWP advocates a paradigm shift from output-centric models toward agricultural systems that balance productivity, environmental stewardship, and farmer wellbeing.

Transitioning agriculture to a low-carbon system presents unique complexities. Unlike industrial sectors, farming systems hinges on the ecological awareness and practical skills of farmers, who are key actors in decentralized rural economies. Practices such as reducing chemical inputs and adopting straw-returning techniques require not only policy incentives, exemplified by China's "dual carbon goals" aimed at achieving carbon peak by 2030 and carbon neutrality by 2060 (Elahi et al., 2022), but also the capacity of farmers to absorb new knowledge and apply innovative techniques (Benhabib and Spiegel, 2005; Shahbaz et al., 2022). Consequently, rural human capital, which encompasses education, skills, and adaptive capabilities (Luo et al., 2023), emerges as a decisive factor enabling green technology adoption, precision agriculture, and efficient resource use (Hong et al., 2023; Li X. et al., 2024; Zou and Mishra, 2024). Moreover, rural human capital generates spatial spillover effects: improvements in education and skills in one locality often diffuse through labor mobility and social networks, boosting the adoption of sustainable practices and enhancing agroecological welfare performance in neighboring regions (Chen et al., 2023; Hou et al., 2024). Therefore, strengthening rural human capital is essential both to supply the talent support and to catalyze innovations needed for sustainable agricultural transformation.

Although the concept of AWP has gained attention, few studies have directly examined its determinants. Instead, existing research has typically explored factors related to agricultural sustainability or rural wellbeing, thereby addressing AWP only tangentially. These studies have focused on isolated drivers such as technological advancement (Guo et al., 2024), institutional frameworks (Contesse et al., 2018; Abbasi and Zhang, 2024), agricultural infrastructure (Jordan et al., 2021), and resource allocation (Doucet and Requejo, 2022; Li and Gao, 2024). While these factors are undeniably critical, they often overshadow the integrative role of rural human capital, which limits holistic strategies for AWP enhancement. This divergence in focus has left the theoretical underpinnings of AWP underdeveloped, particularly in terms of how cross-cutting factors such as human capital shape agroecological outcomes.

Despite these insights, existing studies remain fragmented, reducing human capital to a unidimensional educational metric while neglecting its cultural and skill-based dimensions. This oversimplification obscures critical mechanisms underlying the relationship between human capital and environmental outcomes. Additionally, spatial analyses investigating the role of human capital in AWP are limited, particularly regarding how regional resource mismatches and digital financial inclusion moderate these relationships. These gaps hinder the development of spatially adaptive policies that could synergize ecological sustainability and farmer welfare across decentralized agricultural systems.

This study makes several significant contributions. First, unlike previous studies that primarily focused on education as a single indicator, this study expands the concept of rural human capital by examining both "cultural human capital" and "skill human capital," offering a dual-dimensional framework to capture its sustainability impacts. Second, this research employs the super-efficient SBM model, which incorporates welfare factors, to assess AWP, providing a more accurate measure of agroecological wellbeing. Finally, it explores spatial spillover mechanisms and the moderating role of factors such as digital financial inclusion and resource mismatch, enriching the spatial dimension of AWP research, which has been underexplored in previous studies. Through these innovations, this study contributes to both the theoretical and empirical understanding of enhancing AWP through the development of rural human capital in developing countries.

2 Theoretical basis and research hypothesis

2.1 Rural human capital and AWP

Human capital theory emphasizes the importance of education and training in human capital accumulation. In the context of agricultural production, enhancing rural human capital plays a significant role in improving social welfare, facilitating the adoption of green production technologies, and raising farmers' environmental awareness, thus enhancing AWP.

Firstly, welfare economics posits that the primary aim of economic activity is to enhance the wellbeing. The accumulation of rural human capital improves farmers' agricultural proficiency and market competitiveness, ultimately leading to higher incomes (De Brauw, 2019). Higher incomes and improved living conditions enable farmers to invest in sustainable agricultural practices, such as straw utilization, further advancing AWP.

Second, the development of rural human capital supports the diffusion and adoption of innovative green technologies, fostering knowledge spillovers and promoting sustainable practices. With enhanced human capital, farmers can more quickly adopt and implement new technologies, such as facility-based agriculture and green practices like straw return. These practices are further disseminated through demonstrations and training courses, driving technological innovation and green development in the agricultural sector (Ciccone and Papaioannou, 2009; Luo et al., 2023). As a result, these efforts accelerate the overall enhancement of regional AWP.

Finally, education and training enhance farmers' production knowledge, skills, and environmental awareness, leading to a greater focus on health and quality of life (Zhu et al., 2023). Rural residents with strong environmental awareness are more attuned to recognize the ecological impacts of agricultural activities and prioritize ecological benefits. This shift in mindset drives the adoption of water-efficient technologies, such as drip and sprinkler irrigation, reducing water wastage and contributing to the enhancement of AWP. This shift in mindset drives the adoption of water-efficient technologies, such as drip and sprinkler irrigation, reducing water wastage and contributing to the enhancement of AWP.

Based on this, we propose that:

> *Hypothesis 1*: Rural human capital enhancement contributes to AWP.

2.2 Rural human capital, digital inclusive finance and AWP

Digital inclusive finance, combining inclusive finance and the digital economy, leverages technologies such as the Internet and big data to provide efficient, low-cost financial support to underserved regions and groups that traditional financial services often overlook (Yue et al., 2022). This innovative financing model is increasingly recognized as a vital support of rural revitalization. With its broad coverage, depth, and digitalization, digital inclusive finance plays a crucial role in enhancing the optimization of rural human capital for AWP.

First, digital inclusive finance uses internet technologies to extend financial services to remote rural areas previously inaccessible to traditional finance systems (Jünger and Mietzner, 2019; Yue et al., 2022). This extension of financial support alleviates the long-standing issues of financial exclusion. In regions where digital inclusive finance is well-developed, farmers with higher education and training tend to be more innovative and motivated to transform their agricultural production (Guo et al., 2024). These farmers are able to leverage digital finance tools to adopt green agricultural technologies (Rastogi et al., 2021), facilitating a green transformation in agricultural production practices and thereby effectively enhancing AWP.

Second, digital inclusive finance has expanded not only in coverage but also in the depth of its services. In regions where digital inclusive finance is well established, the use of big data analytics and tailored services has facilitated the provision of diverse financial products—such as microcredit, digital insurance, and savings products—catering to the varied financial needs of farmers (Mushtaq and Bruneau, 2019). Farmers with higher human capital are better equipped to assess and select the financial products that best meet their specific needs, securing ongoing support for capital and risk management. This enhances resilience in agricultural production, particularly in mitigating risks such as natural disasters (Beck et al., 2018), and contributes to the rural economy's vitality, spurring technological innovation, fostering green agricultural practices, and stabilizing income growth, all of which improve AWP.

Third, digital inclusive finance addresses information asymmetry through the use of technologies like big data, blockchain, and artificial intelligence, promoting rapid knowledge dissemination and information sharing (Hasan et al., 2021). Educated and trained farmers can access the latest agricultural technologies and market information through internet platforms, reducing information acquisition costs (Mushtaq and Bruneau, 2019). This access enables them to quickly recognize the advantages of green production technologies, and increase their willingness and ability to adopt green practices such as Integrated Pest Management (IPM) technologies (Altıntaş and Kassouri, 2020), thus improving eco-efficiency in agricultural production and enhancing AWP.

Therefore, we propose the following hypothesis:

> *Hypothesis 2*: Digital inclusive finance as a positive moderator in the relationship between rural human capital and AWP.

2.3 Rural human capital, resource mismatch and AWP

According to resource allocation efficiency theory, a necessary condition for achieving Pareto optimality is the allocation of resources to the most efficient sectors. Resource mismatch, which includes both capital and labor mismatches, represents a deviation from this optimal allocation (Hsieh and Klenow, 2009). The misalignment between capital and labor can significantly impacts rural human capital upgrading, potentially leading to a loss in AWP. Resource mismatch negatively moderates the relationship between rural human capital and AWP, mainly in lenses of capital mismatch and labor mismatch.

Firstly, from the perspective of capital mismatch, this issue arises when capital is concentrated in inefficient sectors, preventing its efficient allocation to high-productivity areas with technological innovation capacity. According to the new economic growth theory, human capital possesses an "allocative capacity" that optimizes the flow of production factors such as capital. Highly qualified rural laborers have the potential to enhance resource allocation by engaging in large-scale operations through land leasing and the rational deployment of production inputs, such as fertilizers and seedlings, so as to enhance agricultural efficiency. However, financing constraints and "credit exclusion" in capital markets often hinder agricultural development. In regions with significant capital mismatch, laborers with substantial human capital may struggle to identify and select eco-friendly agricultural technologies or models due to a lack of capital, limiting their capacity to invest in the means of agricultural production (Wu et al., 2021). Eco-agriculture typically requires substantial upfront capital investment, and capital mismatch often results in the diversion resources to traditional agriculture or other non-agricultural industries with short-term gains (Li and Gao, 2024). The advancement of ecological agriculture is consequently hindered, slowing the contribution of rural human capital to AWP. Moreover, the mismatch between capital allocation and demand can diminish the productivity of rural labor. In regions with a high resource mismatch, capital does not flow efficiently to productive farmers, leading to wasted resources and inefficiencies (Zhou et al., 2023). While highly qualified labor can optimize resource allocation, substantial improvements in AWP remain challenging due to capital inefficiencies.

Second, from the perspective of labor mismatch, the urbanization-driven siphoning effect attracts skilled labor away from rural areas, leaving a surplus of low-skilled workers (Zhou et al., 2023). This shortage of high-skilled labor directly hinders the contributions of the high-human-capital groups in agriculture. Low-skilled laborers are less inclined to adopt modern production techniques and often rely on traditional practices, resulting in inefficient resource utilization and overexploitation. For example, over-fertilization and pesticide misuse increase production costs and damage agroecological systems (Houghton et al., 2012). While highly skilled laborers have the potential to optimize resource allocation, labor mismatch limits their effectiveness (Gao and He, 2024), ultimately hindering AWP.

Hence, we propose the following research hypothesis:

> *Hypothesis 3*: Resource mismatch negatively moderates the relationship between rural human capital and AWP.

2.4 Spatial spillover effects of rural human capital

The theory of spatial interaction holds that economic activities across regions are spatially correlated through the movement of people, material exchanges and information sharing. Significant resource flows and technology diffusion occur between rural areas, and overlooking spatial factors can lead to estimation biases. The enhancement of rural human capital not only directly improves local AWP, but may also indirectly affect neighboring areas through knowledge sharing and experience transfer. Regions with higher rural human capital serve as benchmarks for agroecological development, with skilled farmers' green production technologies and low-carbon models spreading to neighboring areas through collaboration and experience exchange. This diffusion can lead to broader emission reduction effects, which may subsequently enhance AWP in other regions.

Existing studies have also analyzed the spatial interactions in agriculture-related environmental performance, uncovering significant spatial correlations (Hou et al., 2024). Pan et al. (2015) found notable spatial spillover effects in energy consumption, while Li and Wang (2022) identified that the inverted U-shaped relationship between the digital economy and agricultural carbon emissions, exhibiting spatial spillover characteristics.

In summary, we propose the following hypothesis:

> *Hypothesis 4*: Rural human capital not only positively influences local AWP, but also affects AWP in spatially linked areas.

The theoretical framework of this study is shown in Figure 1.

3 Methodology and data

3.1 Variable selection and measurement

3.1.1 The measurement of AWP

This study utilizes the super-efficient SBM model to measure AWP of 30 provinces, municipalities, and autonomous regions in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2011 to 2022. Traditional SBM models can produce varying performance values due to input and output slack, potentially introducing errors in performance assessment. In contrast, the non-radial super-efficient SBM model improves upon the traditional approach by adopting a non-parametric method that accounts for non-radial deviations in both inputs and outputs. This model directly utilizes data relationships to derive the efficiency of decision-making units, enhancing the accuracy and scientific rigor of efficiency evaluations (Tone and Tsutsui, 2014). The formulae for the super-efficient SBM model are specified as follows:

$$\min \delta = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{ik}}}{\frac{1}{s}\sum_{m=1}^{s}\frac{\overline{y_r}}{y_{rk}}}, s.t. \begin{cases} \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j \leq \overline{x_i}; \ \sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j \leq \overline{y_i} \\ \sum_{j=1, j\neq k}^{n} \lambda_j = 1, \overline{x} \geq x_{ik}, \overline{y} \leq y_{ik} \\ i = 1, 2\ldots, m; r = 1, 2\ldots, s; \\ j = 1, 2\ldots, n\left(j \neq k\right) \\ \overline{y} \geq 0, \lambda \geq 0, s^- \geq 0, s^+ \geq 0 \end{cases} \tag{1}$$

In Equation 1, δ represents the AWP, while x and y denote the input and output variables, respectively. The symbols m, s indicate the number of input and output variables, respectively. Additionally, s^-, s^+ represent the slack variables for the input and output factors. The larger the value of δ, the higher the AWP.

The AWP evaluation index system incorporates rural resource consumption and environmental pollution as input elements, with the Human Development Index (HDI) as the desired output. The primary goal of eco-welfare performance is to maximize local welfare and improve individuals' quality of life while optimizing the use of limited resources. Building on methodologies from previous studies (Feng et al., 2019; Bian et al., 2020; Long et al., 2020), this study identifies resource consumption and environmental pollution as key input indicators. Rural resource consumption is measured through indicators such as electricity, energy, and land resources. Environmental pollution inputs are further categorized into agricultural surface pollution and agricultural carbon emission indicators, reflecting the unique characteristics of rural environmental challenges.

Drawing upon the study of Hou et al. (2024), the measurement index for agricultural surface pollution utilizes a unit survey method to measure pollution levels across regions. This measurement encompasses four survey units: fertilizer pollution, pollution from livestock and poultry, farmland solid waste and pollution from rural households. The specific pollutants assessed are total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD), which are recognized as the most significant pollutants in agricultural surface pollution. The calculation formula is as follows:

$$Pollution_c^t = \sum_{\gamma} Po_{c\gamma t} \times factor_{c\gamma 1} \times factor_{c\gamma 2} \tag{2}$$

In Equation (2), $Pollution_c^t$ represents the emissions of pollutants from agricultural sources in year t within province c, encompassing TN, TP, and COD. The symbol γ denotes the various types of survey modules. $Po_{c\gamma t}$ indicates the number of each survey unit in year t for area c. The $factor_{c\gamma 1}$ represents the attrition coefficient of each survey unit, while $factor_{c\gamma 2}$ signifies the pollution coefficient of each investigation unit.

Carbon emissions are a significant contributor to climate change, with agriculture serving as both a major source of carbon emissions and a critical area for carbon sequestration. As such, total agricultural carbon emissions are incorporated into the rural environmental pollution indicator system. The Total Agricultural Carbon Emissions indicator assesses carbon emissions arising from the utilization of agricultural inputs, typically measured in kilograms of carbon equivalent from different agricultural operations. Emission factors are primarily sourced from the United Nations Intergovernmental Panel on Climate Change (IPCC) and the Oak Ridge National Laboratory (ORNL). These factors are as follows: fertilizer (0.8956 kg/kg), pesticide (4.9341 kg/kg), agricultural film (5.18 kg/kg), diesel fuel (0.5927 kg/kg), ploughing (312.6 kg/km^2), and agricultural irrigation (20.476 kg/Cha).

The output indicator for AWP is wellbeing. Welfare is a crucial element that distinguishes AWP from other environmental performance indicators, such as eco-efficiency and carbon emission performance. While AWP emphasizes environmental quality and economic development, it also prioritizes the health and satisfaction of rural residents. This comprehensive approach reflects the

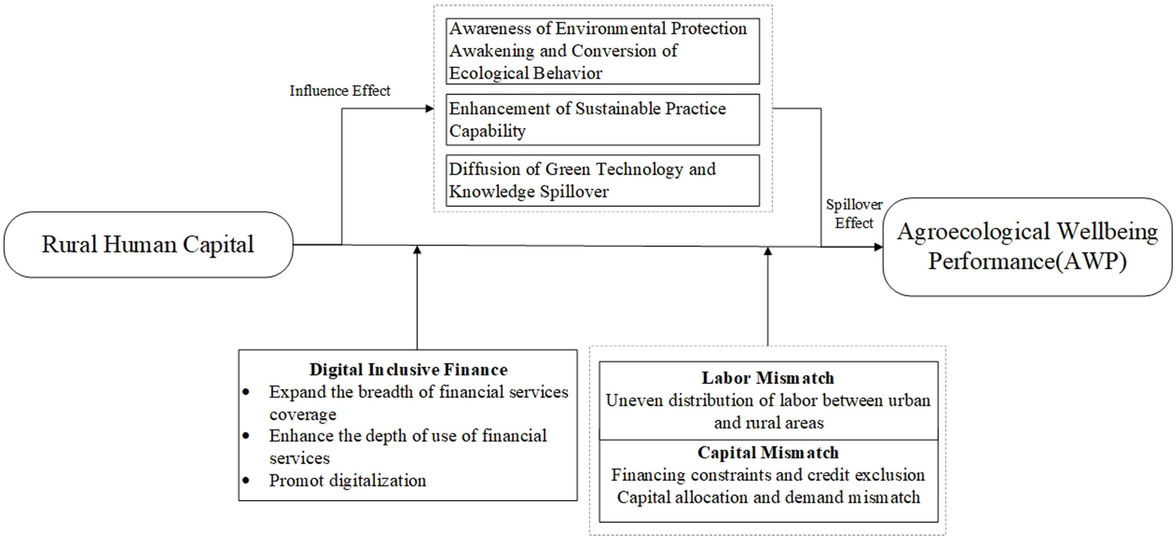

FIGURE 1
Theoretical framework diagram.

synergistic development of economic, environmental and social wellbeing in a more comprehensive way, aligning closely with the global objective of realizing the harmonious coexistence between human beings and nature. This study utilizes the Human Development Index (HDI), a widely recognized metric from the United Nations Development Programme (UNDP). The HDI provides an objective and comprehensive quantitative assessment across three dimensions—economic development, health care, and education—while ensuring accessibility of data. The HDI is calculated as the average of these three dimensions for each province, municipality, and autonomous region. Economic development is assessed using per capita disposable income in rural areas, while healthcare is characterized by the number of beds in rural medical institutions per 10,000 people. Educational development is measured by the average number of years of schooling per capita in rural areas. This assessment follows the methodology outlined in the United Nations Development Programme (UNDP) Human Development Report 2020, which is expressed in the following Equation (3):

$$\text{Schooling years} = \frac{6 \times P_{Primary\ school} + 9 \times P_{Junior\ High\ school} + 12 \times P_{High\ school} + 16 \times P_{College\ or\ above}}{P_{Primary\ school} + P_{Junior\ High\ school} + P_{High\ school} + P_{College\ or\ above}} \quad (3)$$

Table 1 lists the input and output variables for AWP.

3.1.2 The measurement of rural human capital measurement

Existing studies are more likely to measure rural human capital primarily through years of rural education (Shahbaz et al., 2022). However, this study adopts a composite measure of rural human capital that encompasses two dimensions: knowledge-based and skill-based human capital. Given the generally low levels of education development among rural residents, we measure knowledge-based human capital using the ratio of the rural labor force with at least a high school education to the total rural population in each province. Skill-based human capital is characterized by the number of graduates from rural adult cultural and technical training schools.

The entropy value method is employed to provide a comprehensive and objective evaluation of indicators across two dimensions of rural human capital, ensuring the objectivity and accuracy of the assessment results. Higher levels of educational attainment among rural residents are associated with enhanced abilities in literacy, cognitive ability, and technological application. These competencies are critical for driving technological advancements in agriculture, which, in turn, may positively influence AWP. Moreover, targeted skills training for farmers can mitigate capacity constraints stemming from limited formal education, enhancing their competence in areas such as eco-agriculture construction, ultimately contributing to increased AWP.

3.1.3 Mechanism variables

Resource mismatch. Building on the framework established by Wu et al. (2021), resource mismatch is divided into two dimensions: capital mismatch and labor mismatch, The indices for capital mismatch and labor mismatch are as follows. First, the output variable is represented by the gross value of agricultural, forestry, livestock and fisheries production across provinces, adjusted for real output using constant 2011 prices. Second, labor input is measured by the number of people employed in the primary sector within each province. Third, capital inputs are characterized by the stock of agricultural capital within each province, estimated via the perpetual inventory method. Resource mismatch is quantified as a coefficient of relative price distortion, as defined by the following formula:

$$\hat{\gamma}_{Ki} = \left(\frac{K_i}{K}\right) / \left(\frac{s_i \beta_{Ki}}{\beta_K}\right), \hat{\gamma}_{Li} = \left(\frac{L_i}{L}\right) / \left(\frac{s_i \beta_{Li}}{\beta_L}\right) \quad (4)$$

In Equation (4), $\hat{\gamma}_{Ki}$ represents the capital mismatch index and $\frac{K_i}{K}$ denotes the actual proportion of capital utilized by region i relative to the total capital stock. The term $\frac{s_i \beta_{Ki}}{\beta_K}$ indicates the theoretical proportion of capital that should be allocated to region i under efficient capital utilized. Similarly, $\hat{\gamma}_{Li}$ denotes the labor mismatch index, with $\frac{L_i}{L}$ representing the actual ratio of agricultural labor to the total labor force population in region i. The expression $\frac{s_i \beta_{Li}}{\beta_L}$ reflects the theoretical proportion of labor that should be allocated to region i under efficient labor utilization. If the ratio of $\hat{\gamma}_{Ki}$ or $\hat{\gamma}_{Li}$ exceeds 1, it suggests that the cost of using capital or labor is relatively low, indicating an over-allocation of resources in that region. Conversely, if the ratio is less than 1, it implies that the region is under-allocating capital or labor relative to the theoretical level, signaling inefficiency in resource allocation.

Digital inclusive finance. As a key component of the digital transformation, digital inclusive finance transcends traditional geographical boundaries by advanced technologies such as the Internet, big data and artificial intelligence. This innovation has the potential to influence AWP in other regions. To assess the extent of digital inclusive finance across different regions, this study employs the Peking University Digital Inclusive Finance Index. The index is composed of three primary dimensions: the breadth of coverage, the depth of use, and the degree of digitization. Higher index scores on the index indicate a more advanced state of digital inclusive finance development.

3.1.4 Control variables

To mitigate potential bias from omitted variables, this study draws upon existing literature (Shi et al., 2024; Sui et al., 2024) to identify relevant control variables that may influence AWP. Specifically, environmental regulation (ER) is represented by per capita investment in environmental pollution control. Agricultural mechanization (AM) is measured by the ratio of total machinery power to cultivated area. Agricultural infrastructure (AI) is measured by the ratio of effective irrigated area to total sown area. Rural entrepreneurial activity (REA) is assessed using the ratio of the rural private sector employment and self-employment to the total rural population, with a higher ratio indicating greater entrepreneurial activity within the rural economy. Rural aging (RA) is quantified by the proportion of the rural population aged 65 and over.

3.2 Methodology

3.2.1 Spatial econometric model

The influence of rural human capital on AWP extends beyond individual regions, exhibiting spatial dependencies. Given the geographical proximity of rural areas and the interconnectedness of agricultural markets, there is frequent exchange of information, technology and production factors between neighboring regions. Consequently, improvements in one region may affect AWP in spatially adjacent areas. Ignoring the spatial correlations may lead to biased regression results. The Spatial Durbin Model (SDM), a generalized model, is well-suited to account for spatial correlations arising from various factors, including causal relationships, independent variables, or error terms, and provides a more accurate measure of spillover effects on AWP. By adjusting the model's coefficients, the SDM can be transformed into either a Spatial Error Model (SEM) or a Spatial Lag Model (SLM). Therefore, this study constructs a generalized SDM as a benchmark model, which is formulated as follows:

$$\begin{aligned} AWP_{it} = {} & \alpha_0 + \rho W \times AWP_{it} + \alpha_1 HR_{it} + \theta W \times HR_{it} + \\ & \alpha_2 X_{it} + \varphi W \times X_{it} + \delta_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

Where i and t denote the data for province i in year t, respectively, and W denotes the spatial weight matrix. $W \times AEWP_{it}$ represents the spatial lag term of AWP, $W \times HR_{it}$ is the spatial lag term of rural human capital, and $W \times X_{it}$ denotes the spatial lag term of control variables. δ_i, λ_t, and ε_{it} denote province fixed effects, year fixed effects, and random error terms, respectively. The regression coefficients of the independent variables capture both direct and indirect effects. In this study, the direct effect refers to the impact of rural human capital in the region on AWP, while the indirect effect refers to the impact of rural human capital in spatially adjacent regions on AWP, reflecting the spatial spillover effect.

3.2.2 Moderated effects model

Building upon Equation 5, in order to examine the moderating effects of digital inclusive finance, labor mismatch, and capital mismatch, this study adds the interaction terms between rural human capital and the each of the three moderating variables respectively, leading to the construction of the following model:

$$\begin{aligned} AEWP_{it} = {} & \alpha_0 + \rho W \times AEWP_{it} + \alpha_1 HR_{it} + \theta W \times HR_{it} + \\ & \alpha_2 Z_{it} + \sigma W \times Z_{it} + \alpha_3 HR_{it} \times Z_{it} + \tau W \times \\ & HR_{it} \times Z_{it} + \alpha_4 X_{it} + \varphi W \times X_{it} + \delta_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{6}$$

In Equation (6), Z_{it} denotes the moderating variables, including digital inclusive finance, labor mismatch and capital mismatch. $W \times Z_{it}$ denotes the spatial lag term of the moderating variable. $HR_{it} \times Z_{it}$ is the interaction term between the human capital and the moderating variables. $W \times HR_{it} \times Z_{it}$ represents the spatial lag term of the interaction.

3.3 Data sources

Given that the Digital Inclusion Index data begins in 2011, and considering the incomplete disclosure of city- and county-level data on agricultural surface pollution and agricultural carbon emissions, as well as the methodological differences in statistics for Tibet, Hong Kong, Macao, and Taiwan, which hinder comparability with other provinces, this study ensures the completeness and authenticity of the data by using sample data from 30 provinces (including autonomous regions and municipalities) in mainland China, excluding Tibet, Hong Kong, Macao, and Taiwan, for the period from 2011 to 2022. To address large discrepancies in certain indicators, values were log-transformed for consistency.

The raw data used this study were mainly sourced from the China Statistical Yearbook, China Rural Statistical Yearbook, China Education Statistical Yearbook, China Energy Statistical Yearbook, and the provincial statistical yearbooks for each year. Data on the digital inclusive finance are derived from the Peking University Digital Inclusive Finance Index. Price indices have been adjusted using 2011 as the base period, and missing data points were filled using the moving average method. The definitions of the variables and descriptive statistics are shown in Table 2.

4 Empirical results

4.1 Spatial weight matrix setting

To more accurately capture the mechanism through which rural human capital affects AWP and to ensure the robustness of the empirical results, this study adopts the approach proposed by Parent and LeSage (2008), which integrates spatial effects derived from both geographic and economic distance. A spatial weight matrix based on economic geography is utilized to assess whether spatial spillover effects are present in the relationship between rural human capital and AWP. The following economic geography-based spatial weight matrix is constructed:

$$W = \omega W_1 + \left(1-\omega\right) W_2 \tag{7}$$

In Equation (7), W_1 represents the spatial weight matrix for economic distance, defined as the absolute inverse of the difference in GDP per capita between provinces. W_2 denotes the spatial weight matrix for geographic distance, calculated as the reciprocal of the straight-line Euclidean distance between capital cities of each province. The parameters ω and $\left(1-\omega\right)$ denote the weight values assigned to each matrix, with a value of 0.5 applied in this study. Prior to parameter estimation, both weight matrices were normalized.

4.2 Spatial correlation analysis

Before estimating the model, the presence of spatial correlation in AWP was tested using the global Moran's index. The results of the analysis are shown in Table 3. The Moran index for AWP is significantly positive in most years, indicating a positive spatial correlation in AWP. This finding supports the validity of the spatial econometric model employed in this study.

4.3 Benchmark regression

To determine the specific form of the spatial econometric regression model, this study conducts LM, LR, and Hausman tests. The results of the test show that the LM test rejects the null hypothesis at the 1% level of statistical significance, indicating the presence of both spatial error and spatial lag effects. Moreover, the LR test rejects the null hypothesis at the 1% level, suggesting that the spatial Durbin model (SDM) cannot be reduced to either a spatial error model (SEM) or a spatial lag model (SLM). The Hausman test also rejects the null hypothesis, supporting the use of the fixed-effects model over the random effects model. Consequently, this study employs a fixed-effects spatial Durbin model to analyze the spatial spillover effects of rural human capital on AWP.

This study examines the impact of rural human capital on AWP by estimating the SDM and compares the results with those obtained from Ordinary Least Squares (OLS) estimation. The results of the benchmark model are shown in Table 4. The coefficients of HR are higher in the SDM compared to the OLS regression, indicating that the SDM provide a more applicable for analysis. Both the coefficients of HR and the interaction term (W*HR) are significantly positive, indicating that rural human capital significantly enhances AWP and also demonstrates positive spatial spillover effects.

This study further substantiates the relationship between rural human capital and AWP by analyzing direct, indirect and total effects. The partial differentiation method in spatial modeling, as proposed by LeSage and Pace (2009), is employed to decompose the effects of rural human capital and related control variables on AWP. The results are presented in Table 5. Both the direct and indirect effects of rural human capital are significantly positive, indicating substantial positive spatial externalities associated with rural human capital. Specifically, the higher the degree of rural human capital is associated with improved AWP not only within the region but also in spatially related regions.

This can be attributed to two primary factors. On the one hand, well-educated and well-trained farmers are better equipped to advocate for green production technologies, such as facility-based agriculture, precision farming techniques, and waste recycling practices, through participation in cross-regional eco-agricultural cooperation projects and agricultural science and technology exchanges. For example, Shouguang City, known as the "hometown of vegetables" in China, has established vegetable farmers' cooperatives to promote the resource utilization of vegetable straw. This initiative has not only enhanced resource efficiency in surrounding areas but has also contributed to the improvement of AWP.

On the other hand, a highly skilled labor force facilitates the cross-regional extension of the eco-agricultural value chain. A Costa Rican coffee cooperative, certified by the Rainforest Alliance, has assisted Honduran producers in implementing shade-growing practices to develop a Central American "sustainable coffee belt," which promotes sustainable agriculture and contributes to biodiversity and worker

TABLE 1 Input and output variables for the measure of AWP.

Category	Variable	Segmentation variables	Explanation	Units
Input	Rural resource consumption	Electricity	Rural electricity consumption per capita	M^3
		Energy	Agricultural energy consumption per capita	Million tons of standard coal
		Land resources	Sown area per capita	1,000 m^2
	Agricultural surface pollution	COD	Chemical oxygen demand	Million tons of standard coal
		Nitrogen	Nitrogen fertilizer intensity	10^4 tons
		Phosphorus	Intensity of phosphate fertilizer production	10^4 tons
	Carbon emissions	CO_2	Total agricultural carbon emissions	10^4 tons
Output	HDI	Economic	Rural disposable income per capita	10^4 yuan RMB
		Healthcare	Number of beds in medical institutions per 10,000 persons	/
		Education	Years of schooling per capita	Year

TABLE 2 Descriptive statistics of the selected variables.

Variable	Obs	Mean	Minimum	Maximum	Standard deviation
AWP	360	1.011	0.652	1.583	0.126
HR	360	0.191	0.003	0.859	0.193
ER	360	6.088	0.248	31.027	4.492
AI	360	0.441	0.172	1.234	0.179
RA	360	0.133	0.05	0.275	0.045
MI	360	0.652	0.252	1.387	0.235
REA	360	0.276	0.018	2.846	0.441

wellbeing (Snider et al., 2017). Moreover, digital sharing platforms accelerate the flow of knowledge and help overcome geographical barriers. Utilizing digital tools such as WeChat public platforms and TikTok broadcasts, skilled farmers are able to build cross-regional technical exchange networks, disseminating advanced agricultural technologies and ecological concepts to other regions and forming collaborative networks. For instance, tea farmers in Anji, China, demonstrate ecological management techniques for tea gardens through live streaming on Douyin, attracting tens of thousands of farmers from other tea-producing regions to learn and replicate these practices. This initiative has led to a reduction in pesticide usage intensity in the associated areas, thereby improving overall AWP.

TABLE 3 Global Moran's I calculation results from 2012 to 2022.

Year	I	Z
2012	0.123*	1.79
2013	0.104	1.45
2014	−0.028	0.074
2015	0.054	0.968
2016	0.097	1.444
2017	0.113	1.646
2018	0.126**	1.748
2019	0.179***	2.247
2020	0.261***	3.058
2021	0.271***	3.145
2022	0.271***	3.158

*, **, and *** represent the significant level at 10, 5, and 1%, respectively.

4.4 Robustness tests

In analyzing the impact of rural human capital on AWP, a bidirectional causal relationship may exist, which could lead to endogeneity issues that bias the findings. To ensure the robustness of the empirical results, this study conducts three robustness tests: replacing the dependent variable, altering the spatial weight matrix, and changing the parameter estimation method.

4.4.1 Replacement of dependent variable

The previous study has measured AWP using the super-efficient SBM model, which effectively evaluates AWP by integrating both inputs and outputs. To assess the sensitivity of the empirical results to different measures of AWP, this study applies principal component analysis to re-measure AWP prior to parameter estimation. The results corresponding to this approach are presented in column (1) of Table 6. The consistent findings regarding the spatial spillover effects of rural human capital on AWP further validate the reliability and robustness of the empirical results.

4.4.2 Different spatial weight matrices

In addition to employing the economic-geographical nested spatial weight matrix, we also apply the economic distance weight matrix (W1) and inverse distance weight matrix (W2) for robustness testing. As shown in columns (2) and (3) of Table 6, the coefficients for rural human capital and its spatial lag term remain significantly positive, indicating that the positive spatial spillover effects of rural human capital on AWP are both stable and significant. The use of different spatial weight matrices does not change the primary conclusion of this study. Enhancing rural human capital is an effective approach for improving AWP in both local and spatially connected areas.

4.4.3 Changing parameter estimates

To address the potential endogeneity bias of the model, this study employs the generalized spatial panel autoregressive two-stage least squares regression (GS2SLSAR) method. The volume of book collections in township cultural stations is used as an instrumental variable. On the one hand, the volume of these collections serves as an effective indicator of the intensity of regional educational resource allocation and can be considered an endogenous variable for rural human capital. On the other hand, the number of books held in township cultural stations, is less likely to have a direct correlation with AWP, making it a suitable exogenous variable for AWP. Column (4) of Table 6 presents the estimation results from the instrumental variables approach, where the first-stage F-statistic exceeds 10, rejecting the null hypothesis of weak instruments. The estimated coefficients for both w1y_ AWP and rural human capital remain significantly positive, consistent with the benchmark model and maintaining a stable level of significance. These results reinforce the conclusion that the positive spatial spillover effect of rural human capital on AWP is highly robust.

4.5 Heterogeneity analysis

4.5.1 Heterogeneity of planting structure

Food is a strategic resource essential for human survival, and ensuring food security is crucial for national stability. Due to China's diverse and complex geography, regional disparities in food production are inevitable. Previous studies have also highlighted that agricultural carbon emissions are higher in China's Main Grain-Producing Areas (MGPAs) (Zhang et al., 2019; Sui et al., 2024). To further assess the effect of rural human capital upgrading on AWP across different regions, the study area was divided into MGPAs and non-grain-producing areas (including non-grain production cropland and production and sales balance areas). Separate regressions were conducted for each group. The results, presented in Table 7, column (1) and column (2), indicate that enhancement of rural human capital significantly contributes to AWP in the MGPAs. However, no spatial spillover effect is observed. In contrast, the impact of rural human capital on AWP in non-grain-producing areas is not statistically significant, as the spatially lagged term (Rho) fails to attain significance.

TABLE 4 Regression results of panel data.

Variables	OLS	SDM
	(1)	(2)
HR	0.065***	0.095***
	(0.023)	(0.030)
ER	−0.002*	−0.002
	(0.001)	(0.002)
AI	0.012	0.066
	(0.044)	(0.047)
RA	0.821***	1.126***
	(0.170)	(0.190)
AM	0.113***	0.035
	(0.026)	(0.030)
REA	0.094***	0.083***
	(0.013)	(0.019)
W*HR		0.390***
		(0.084)
W*ER		−0.007**
		(0.003)
W*AI		−0.089
		(0.102)
W*RA		−0.900
		(0.561)
W*MI		−0.145**
		(0.065)
W*REA		0.105
		(0.088)
Constant	0.982***	
	(0.009)	
Rho		−0.383***
		(0.107)
N	360	360
R^2	0.328	0.385

*, **, and *** represent the significant level at 10, 5, and 1%, respectively. In addition, there is standard error clustered at province-level in the parentheses.

The phenomenon may be attributed to the concentrated and large-scale nature of grain cultivation in MGPAs, where farmers possess a long history of farming and extensive experience, enabling them to master production skills more proficiently. This promotes continued specialization and organization within MGPAs. High-standard agricultural practices can reduce the fertilizer use intensity and optimize resource allocation (Li Q. et al., 2024), thereby improving AWP. However, subsidy policies in MGPAs often prioritize yield stability over rigorous assessments of ecological indicators. This approach weakens incentives for farmers to share technology, resulting in a local lock-in effect. Consequently, spatial spillovers in AWP are less pronounced. While in non-grain-producing areas, where cash crops or other economic activities are more common, the enhancement of farmers' skills is primarily focused on other sectors such as horticulture and forestry. These skills have a more indirect impact on AWP, and the returns on human capital in these regions may take longer to materialize, resulting in a more limited influence on AWP.

4.5.2 Topographic heterogeneity

The steepness and gentleness of terrain significantly influence agricultural production, resource utilization efficiency, and the sustainability of the agroecological environment. Complex terrain conditions can considerably limit agricultural development and wealth accumulation (Zhou and Xiong, 2018). The impact of rural human capital on AWP may differ depending on the topographical characteristics of the area. To further explore this, the 30 sample provinces (including cities and districts) were categorized into areas with gentle terrain (absolute relief ≤1,000 m) and areas with steep terrain (absolute relief >1,000 m), based on terrain relief. This classification enables the examination of the spatial spillover effects of rural human capital on AWP across different topographical conditions.

As indicated by the data in columns (3) and (4) of Table 7, the enhancement of rural human capital significantly improves AWP in areas with steep terrain, exhibiting notable spatial spillover effects. In contrast, it does not show a significant contribution to AWP in

TABLE 5 Spatial spillover effects variables.

	HR	ER	AI	RA	MI	REA
Direct effect	0.075**	−0.002	0.078	1.210***	0.043	0.080***
	(0.030)	(0.002)	(0.049)	(0.199)	(0.027)	(0.023)
Indirect effect	0.276***	−0.005*	−0.088	−1.029**	−0.125**	0.054
	(0.070)	(0.003)	(0.082)	(0.439)	(0.050)	(0.070)
Total effect	0.351***	−0.007**	−0.010	0.181	−0.082	0.134**
	(0.073)	(0.003)	(0.070)	(0.426)	(0.055)	(0.054)

*, **, and *** represent the significant level at 10, 5, and 1%, respectively. In addition, there is standard error clustered at province-level in the parentheses.

TABLE 6 Results of robustness test.

Variables	Replacement of dependent variable	Different spatial weight Matrices		Changing parameter estimates
	(1)	(2)	(3)	(4)
	W3	W1	W2	W3
w1y_ AWP				0.001***
				(0.000)
HR	0.157***	0.096***	0.067**	0.508***
	(0.051)	(0.030)	(0.032)	(0.106)
W*HR	0.477***	0.389***	0.106	
	(0.147)	(0.084)	(0.241)	
Rho	−0.431***	−0.382***	−0.608**	
	(0.104)	(0.107)	(0.242)	
The first-stage F-statistic				17.17
The second-stage F-statistic				706.97
Control variables	Yes	Yes	Yes	Yes
N	360	330	360	360
R^2	0.368	0.385	0.261	0.171

*, **, and *** represent the significant level at 10, 5, and 1%, respectively. In addition, there is standard error clustered at province-level in the parentheses.

TABLE 7 Results of heterogeneity analysis.

Variables	MGPAs	Non-grain-producing areas	Steep regions	Gentle regions
	(1)	(2)	(3)	(4)
HR	0.109*	0.0524	0.220***	0.0297
	(0.059)	(0.037)	(0.074)	(0.055)
W*HR	−0.315	−0.183*	0.441***	−0.193
	(0.293)	(0.105)	(0.155)	(0.145)
Rho	−0.565***	−0.0313	−0.348**	−0.749***
	(0.104)	(0.147)	(0.165)	(0.141)
Control variables	Yes	Yes	Yes	Yes
N	156	204	132	228
R^2	0.353	0.555	0.026	0.296

*, **, and *** represent the significant level at 10, 5, and 1%, respectively. In addition, there is standard error clustered at province-level in the parentheses.

regions with gentle terrain. This disparity may be attributed to the fragmented nature of cropland in areas with steep topography, where larger slopes result in less favorable conditions for vegetation growth. Soil and nutrients in these regions are more prone to erosion, resulting in heightened ecological vulnerability. Mechanization is also more challenging and less conducive to agricultural development, necessitating a greater reliance on advanced technology and skilled labor to boost agricultural production (Liu et al., 2022).

Highly qualified rural laborers are better equipped to adapt to complex terrain conditions, promoting the adoption of flexible green production techniques, such as terrace farming, conservation tillage, and ecological restoration. The use of precision farming technologies, such as drone spraying and soil sensors, helps reduce soil erosion and the over-application of fertilizers and pesticides, ultimately enhancing AWP. The improvement of rural human capital not only boosts local AWP but also drives surrounding farmers to adopt advanced practices and technologies through information sharing, technology diffusion, and cross-regional labor mobility. This collaborative learning leads to increased AWP across the entire region.

Highly skilled farmers have utilized precision agriculture equipment to achieve water and fertilizer conservation, as well as precise pest control. These practices have been rapidly adopted by neighboring farmers through agronomic extension meetings, training courses, and demonstration plots in regions with similar geographic conditions. This has resulted in the formation of regional eco-agriculture clusters, contributing to the overall improvement of AWP in adjacent regions.

4.6 Mechanism analysis

Based on the previous theoretical analysis, digital financial inclusion and resource mismatch may influence the effect of rural human capital on AWP. Therefore, this study constructs interaction terms between digital financial inclusion, resource mismatch, and rural human capital to further test the moderating effects.

4.6.1 The moderating role of digital inclusive finance

The interaction term between digital inclusive finance and rural human capital (DIFI*HR) is constructed and incorporated into the spatial Durbin model for testing. As shown in columns (1) and (2) of Table 8, the spatial lag term of the interaction between digital inclusive finance and rural human capital (W*DIFI*HR) is significantly positive, indicating that digital inclusive finance plays a positive moderating role in enhancing contribution of rural human capital to AWP in other regions. This result aligns with the conclusions of Lee and Wang (2022). One possible explanation for this phenomenon is the dual role of digital inclusive finance in facilitating both knowledge spillovers and improved financial accessibility.

On the one hand, regions with advanced digital inclusive finance systems tend to exhibit a higher degree of digital infrastructure development. The establishment of cross-regional digital registration systems and integrated information management platforms significantly reduces spatial barriers to the dissemination of knowledge and the transfer of green agricultural technologies. As a result, the technical expertise and sustainable production practices of highly skilled laborers can diffuse more efficiently to adjacent regions, contributing to the broader enhancement of AWP beyond local boundaries.

On the other hand, digital inclusive finance improves the accessibility and efficiency of financial services, especially in geographically dispersed rural areas. By mitigating the challenges of financial exclusion, digital inclusive finance enables educated and trained farmers to obtain green production capital at lower costs through digital payment systems and online credit services. Moreover, digital platforms enable farmers to participate in agricultural cooperative networks, promoting the sharing of green development resources across regions. This interconnectedness allows farmers in neighboring areas to access essential inputs, knowledge, and services for sustainable agricultural practices, thereby further promoting improvements in AWP at a regional scale.

4.6.2 The moderating role of resource mismatches

This study explores the moderating effects of resource mismatches on the relationship between rural human capital and AWP from two distinct dimensions: labor misallocation and capital misallocation.

4.6.2.1 Moderating effect test of capital mismatch

As shown in columns (3) and (4) of Table 8, the spatial lag coefficients of the interaction terms between capital misallocation and rural human capital (W*CM*HR) are significantly negative. This indicates that capital misallocation weakens the positive impact of rural human capital on AWP, acting as a negative moderator. The findings also highlight the presence of spatial spillover effects, suggesting that inefficiencies in capital allocation can hinder the cross-regional transmission of human capital benefits.

The underlying causes of this negative moderating effect may be attributed to several key factors. First, capital misallocation

TABLE 8 Regulatory mechanism test.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
HR	0.107***	0.100***	0.113***	0.176***	0.117***	0.141***
	(0.030)	(0.030)	(0.030)	(0.036)	(0.031)	(0.041)
DIFI	−0.060	−0.059				
	(0.050)	(0.048)				
DIFI*HR		0.063				
		(0.051)				
CM			−0.001	0.039***		
			(0.008)	(0.014)		
CM*HR				−0.155***		
				(0.048)		
LM					−0.002	0.006
					(0.002)	(0.005)
LM*HR						−0.016
						(0.011)
W*HR	0.426***	0.321***	0.368***	0.450***	0.412***	0.729***
	(0.086)	(0.088)	(0.085)	(0.106)	(0.088)	(0.129)
W*DIFI	−0.111	−0.011				
	(0.112)	(0.112)				
W*DIFI*HR		0.617***				
		(0.152)				
W*CM			−0.063**	−0.005		
			(0.025)	(0.035)		
W*CM*HR				−0.220*		
				(0.124)		
W*LM					−0.016**	0.024*
					(0.007)	(0.014)
W*LM*HR						−0.107***
						(0.032)
Rho	−0.407***	−0.450***	−0.385***	−0.425***	−0.399***	−0.461***
	(0.107)	(0.106)	(0.107)	(0.107)	(0.107)	(0.106)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	360	360
R^2	0.172	0.377	0.392	0.403	0.396	0.395

*, **, and *** represent the significant level at 10, 5, and 1%, respectively. In addition, there is standard error clustered at province-level in the parentheses.

constrains both the accumulation and effective utilization of rural human capital, thereby diminishing its potential contribution to AWP. In rural areas, capital mismatches limit agricultural producers' access to necessary financial resources, which are critical for upgrading production technologies and advancing ecological transformation. Insufficient capital availability poses barriers for rural laborers seeking to enhance their education or technical skills, restricting human capital development at its source. These constraints create a cycle of underinvestment and inefficiency in agricultural production, ultimately impeding the improvements in AWP.

Second, capital misallocation can lead to an uneven distribution of resources across regions, thereby reinforcing spatial disparities in AWP. Local agricultural production patterns and market dynamics can affect the adoption and dissemination of ecological production methods in neighboring regions. When capital is concentrated in specific areas, neighboring areas may struggle to access the financial resources needed to invest in human capital development. This imbalance limits the capacity of these regions to improve their labor force and adopt sustainable agricultural practices, ultimately perpetuating regional inequalities in AWP.

Third, capital misallocation also undermines the role of rural human capital in facilitating information spillovers. In areas with significant capital inequality, optimizing resource allocation within the agricultural sector becomes increasingly difficult. As a result, local farmers often lack the means to acquire and effectively apply advanced knowledge and green technologies. The limitation hampers the speed and breadth of information dissemination, thereby reducing the potential for knowledge spillovers to neighboring areas. Consequently, the broader regional improvements in AWP are further constrained.

4.6.2.2 Moderating effect test of labor mismatch

The coefficient of the interaction term between labor mismatch and rural human capital (LM*HR) is initially not significant. However, when spatial correlation is accounted for, the coefficient becomes significantly negative. This suggests that a higher degree of labor mismatch restricts the positive contribution of rural human capital to AWP, primarily through spatial spillover effects.

One possible explanation for this finding lies in the labor market distortions caused by labor mismatch. When labor mismatch is pronounced, highly educated famers are often compelled to migrate to urban areas due to a lack of suitable employment opportunities in their local communities. This results in a "brain drain" effect, leaving rural areas with a labor force that is predominantly lower-skilled and less capable of acquiring or applying advanced green production techniques and eco-agricultural technologies. As a result, local agricultural production tends to remain locked in traditional high-input, high-emission modes, making it difficult to achieve significant improvements in AWP.

Also, the limited capacity of local middle- and low-skilled laborers to adopt and implement advanced green production techniques further constrains the establishment of local demonstration effect-key channels through which sustainable practices gain visibility and credibility. In the absence of such exemplars, opportunities for peer-to-peer learning, knowledge exchange, and cross-regional technology transfer are significantly diminished. This, in turn, restricts the potential for information spillovers, thereby hindering AWP improvements in neighboring regions.

Furthermore, rural areas characterized by a high degree of labor mismatch often lack the economic resources necessary to support a transition toward sustainable agricultural practices, largely due to their overall low incomes. This financial constraint hampers the local adoption of green production methods and may also create competitive pressures on shared ecological resources in neighboring regions. For instance, economically disadvantaged rural communities may be more inclined to adopt resource-intensive and environmentally harmful agricultural strategies as a means of economic survival. Such practices not only undermine their own AWP but also set a negative precedent for adjacent areas, further obstructing the regional diffusion of ecological production models and hindering collective progress toward sustainable agriculture.

5 Conclusions and discussion

5.1 Research findings

Rural human capital plays a crucial role in enabling the low-carbon transition of agriculture and serves as a key driver of sustainable rural development. Drawing on panel data from 30 provinces, municipalities directly under the central government, and autonomous regions in China from 2011 to 2022, this study employs the super-efficient SBM model to evaluate AWP. It empirically examines the spatial spillover effect and the mechanisms through which rural human capital influences AWP. The main findings from the analysis are as follows.

(1) Rural human capital positively contributes to AWP with significant spatial spillover effects. Specifically, a highly skilled labor force enhances AWP within its own region and positively influences the AWP of neighboring regions through knowledge diffusion and technology spillovers. Multiple robustness tests confirm the reliability of these findings.
(2) Heterogeneity analysis reveals that the spatial spillover effect of rural human capital on AWP is more pronounced in regions characterized by steep topography. In contrast, in MGPAs, the contribution of rural human capital to AWP is largely confined to the local region, with limited cross-regional influence. This pattern may be attributed to the complex natural conditions in mountainous regions, which require more adaptive and knowledge-intensive farming practices. Skilled farmers in these regions are more likely to share green technologies across neighboring regions, thereby enhancing spatial spillovers. In contrast, MGPAs rely more on conventional, large-scale production systems, where the role of human capital is more localized and less likely to generate cross-regional effects.
(3) Mechanism tests reveal that digital inclusive finance significantly enhances the impact of rural human capital on AWP by promoting the adoption of green production methods among skilled labor groups. In contrast, capital and labor mismatches weaken the relationship between rural

human capital and AWP, highlighting the adverse effects of inefficient resource allocation. These findings underscore the importance of advancing digital financial inclusion and improving the coordination of capital and labor resources—both within and across regions—to fully harness rural human capital for sustainable agricultural development and broader improvements in AWP.

5.2 Theoretical implications

Rural human capital, encompassing the skills and capabilities of farmers, is crucial for advancing agricultural development and enhancing ecological sustainability. This study introduces the concept of spatial spillover effects, examining how rural human capital influences AWP across regions and the moderating roles of digital financial inclusion and resource mismatches. While previous research has acknowledged the negative impacts of resource mismatches on ecological performance (Wu et al., 2021; Gao et al., 2022), this study introduces the novel idea of spatial spillover effects in the context of resource mismatches. It argues that capital and labor mismatches can undermine AWP, even in regions with strong human capital. By addressing spatial dynamics, the study enriches both theoretical and empirical perspectives on the role of rural human capital in improving AWP, particularly in developing countries.

5.3 Practical implications

To successfully enhance AWP, it is essential to strengthen rural human capital, efficiently allocate resources, and facilitate the advancement of digital financial inclusion, while considering regional diversification. First, efforts should be made to attract talent to enhance rural human capital and foster regional synergies. Modern training models integrating online and offline approaches can boost farmers' environmental awareness and participation in sustainable practices. Additionally, optimized talent recruitment policies, such as tax incentives and startup support, can attract professionals and high-quality farmers back to rural areas, fostering local innovation and regional knowledge spillovers.

Second, innovate rural digital inclusive financial service products and enhance the rural digital inclusive financial service system. Tailored financial products, such as seasonal repayment schemes and integrated microfinance services, should be developed to meet the diverse needs of eco-agriculture. Improving digital infrastructure and encouraging financial institutions to provide green credit and insurance will empower farmers to more easily adopt sustainable technologies and practices.

Third, a more efficient, market-oriented allocation of agricultural production factors should be promoted. This includes building transparent information platforms for pricing and supply–demand matching, strengthening financial support systems, and encouraging integrated development across the agricultural value chain. Models like "industrial park + farmers" can help optimize regional resource allocation and enhance the economic and ecological benefits of resource circulation, promoting circular agriculture.

Finally, green agricultural transformation should be tailored to the geographic characteristics and agricultural functions of different regions. In MGPAs, the focus should be on funding large agricultural cooperatives, technical training, and green agriculture demonstration projects. In regions with steep terrain, priority should be given to developing human capital in terrain-specific green technologies, such as conservation tillage and precision irrigation, to improve resource efficiency and resilience. Promoting technology transfer and the inter-regional diffusion of eco-agriculture through enhanced regional cooperation, information exchange and resource integration will further increase AWP across regions.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.stats.gov.cn/sj/ndsj/.

Author contributions

XL: Conceptualization, Funding acquisition, Project administration, Supervision, Visualization, Writing – review & editing. YJ: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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References

Abbasi, K. R., and Zhang, Q. (2024). Augmenting agricultural sustainability: investigating the role of agricultural land, green innovation, and food production in reducing greenhouse gas emissions. *Sustain. Dev.* 32, 6918–6933. doi: 10.1002/sd.3060

Altıntaş, H., and Kassouri, Y. (2020). The impact of energy technology innovations on cleaner energy supply and carbon footprints in Europe: a linear versus nonlinear approach. *J. Clean. Prod.* 276:124140. doi: 10.1016/j.jclepro.2020.124140

Beck, T., Pamuk, H., Ramrattan, R., and Uras, B. R. (2018). Payment instruments, finance and development. *J. Dev. Econ.* 133, 162–186. doi: 10.1016/j.jdeveco.2018.01.005

Benhabib, J., and Spiegel, M. M. (2005). "Chapter 13 human capital and technology diffusion" in Handbook of economic growth (Amsterdam: Elsevier), 935–966.

Bian, J., Ren, H., and Liu, P. (2020). Evaluation of urban ecological well-being performance in China: a case study of 30 provincial capital cities. *J. Clean. Prod.* 254:120109. doi: 10.1016/j.jclepro.2020.120109

Ciccone, A., and Papaioannou, E. (2009). Human capital, the structure of production, and growth. *Rev. Econ. Stat.* 91, 66–82. doi: 10.1162/rest.91.1.66

Chen, H., Yi, J., Chen, A., Peng, D., and Yang, J. (2023). Green technology innovation and CO2 emission in China: Evidence from a spatial-temporal analysis and a nonlinear spatial durbin model. *Energy Policy* 172, 113338. doi: 10.1016/j.enpol.2022.113338

Contesse, M., van Vliet, B., and Lenhart, J. (2018). Is urban agriculture urban green space? A comparison of policy arrangements for urban green space and urban agriculture in Santiago de Chile. *Land Use Policy* 71, 566–577. doi: 10.1016/j.landusepol.2017.11.006

Costanza, R., Daly, L., Fioramonti, L., Giovannini, E., Kubiszewski, I., Mortensen, L. F., et al. (2016). Modelling and measuring sustainable wellbeing in connection with the UN sustainable development goals. *Ecol. Econ.* 130, 350–355. doi: 10.1016/j.ecolecon.2016.07.009

De Brauw, A. (2019). Migration out of rural areas and implications for rural livelihoods. *Annu. Rev. Resour. Econ.* 11, 461–481. doi: 10.1146/annurev-resource-100518-093906

Doucet, P., and Requejo, I. (2022). Financing constraints and growth of private family firms: evidence from different legal origins. *Financ. Res. Lett.* 44:102034. doi: 10.1016/j.frl.2021.102034

Elahi, E., Khalid, Z., and Zhang, Z. (2022). Understanding farmers' intention and willingness to install renewable energy technology: a solution to reduce the environmental emissions of agriculture. *Appl. Energy* 309:118459. doi: 10.1016/j.apenergy.2021.118459

Feng, Y., Zhong, S., Li, Q., Zhao, X., and Dong, X. (2019). Ecological well-being performance growth in China (1994–2014): from perspectives of industrial structure green adjustment and green total factor productivity. *J. Clean. Prod.* 236:117556. doi: 10.1016/j.jclepro.2019.07.031

Gao, F., and He, Z. (2024). Digital economy, land resource misallocation and urban carbon emissions in Chinese resource-based cities. *Resour. Policy* 91:104914. doi: 10.1016/j.resourpol.2024.104914

Gao, D., Li, G., and Yu, J. (2022). Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* 247:123395. doi: 10.1016/j.energy.2022.123395

Guo, J., Chen, L., and Kang, X. (2024). Digital inclusive finance and agricultural green development in China: a panel analysis (2013–2022). *Financ. Res. Lett.* 69:106173. doi: 10.1016/j.frl.2024.106173

Hasan, M., Le, T., and Hoque, A. (2021). How does financial literacy impact on inclusive finance? *Financ. Innov.* 7:40. doi: 10.1186/s40854-021-00259-9

Hong, M., Tian, M., and Wang, J. (2023). The impact of digital economy on green development of agriculture and its spatial spillover effect. *China Agric. Econ. Rev.* 15, 708–726. doi: 10.1108/CAER-01-2023-0004

Hou, M., Cui, X., Xie, Y., Lu, W., and Xi, Z. (2024). Synergistic emission reduction effect of pollution and carbon in China's agricultural sector: regional differences, dominant factors, and their spatial-temporal heterogeneity. *Environ. Impact Assess. Rev.* 106:107543. doi: 10.1016/j.eiar.2024.107543

Houghton, R. A., House, J. I., Pongratz, J., Van Der Werf, G. R., DeFries, R. S., Hansen, M. C., et al. (2012). Carbon emissions from land use and land-cover change. *Biogeosciences* 9, 5125–5142. doi: 10.5194/bg-9-5125-2012

Hsieh, C.-T., and Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics* 124, 1403–1448. doi: 10.1162/qjec.2009.124.4.1403

Jordan, C., Donoso, G., and Speelman, S. (2021). Measuring the effect of improved irrigation technologies on irrigated agriculture. A study case in Central Chile. *Agric. Water Manag.* 257:107160. doi: 10.1016/j.agwat.2021.107160

Jünger, M., and Mietzner, M. (2019). Banking goes digital: the adoption of FinTech services by German households. *SSRN J.* doi: 10.2139/ssrn.3368133

Lee, C.-C., and Wang, F. (2022). How does digital inclusive finance affect carbon intensity? *Econ. Anal. Policy* 75, 174–190. doi: 10.1016/j.eap.2022.05.010

LeSage, J., and Pace, R. K. (2009). Introduction to spatial econometrics. New York: Chapman and Hall/CRC.

Li, Q., Chen, W., Shi, H., and Zhang, S. (2024). Assessing the environmental impact of agricultural production structure transformation — evidence from the non-grain production of cropland in China. *Environ. Impact Assess. Rev.* 106:107489. doi: 10.1016/j.eiar.2024.107489

Li, B., and Gao, Y. (2024). Impact and transmission mechanism of digital economy on agricultural energy carbon emission reduction. *Int. Rev. Econ. Finance* 95:103457. doi: 10.1016/j.iref.2024.103457

Li, X., Mao, H., and Fang, L. (2024). The impact of rural human capital on household energy consumption structure: evidence from Shaanxi province in China. *Sustain. Futures* 8:100301. doi: 10.1016/j.sftr.2024.100301

Li, Z., and Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: evidence city-level empirical data in China. *J. Clean. Prod.* 351:131570. doi: 10.1016/j.jclepro.2022.131570

Lippert, C., Krimly, T., and Aurbacher, J. (2009). A Ricardian analysis of the impact of climate change on agriculture in Germany. *Clim. Chang.* 97, 593–610. doi: 10.1007/s10584-009-9652-9

Liu, Y., Gu, W., Liu, B., Zhang, C., Wang, C., Yang, Y., et al. (2022). Closing greenhouse gas emission gaps of staple crops in China. *Environ. Sci. Technol.* 56, 9302–9311. doi: 10.1021/acs.est.2c01978

Liu, Z., Zhang, M., Li, Q., and Zhao, X. (2023). The impact of green trade barriers on agricultural green total factor productivity: evidence from China and OECD countries. *Econ. Anal. Policy* 78, 319–331. doi: 10.1016/j.eap.2023.03.011

Long, X., Yu, H., Sun, M., Wang, X.-C., Klemeš, J. J., Xie, W., et al. (2020). Sustainability evaluation based on the three-dimensional ecological footprint and human development index: a case study on the four island regions in China. *J. Environ. Manag.* 265:110509. doi: 10.1016/j.jenvman.2020.110509

Luo, Y., Wang, Q., Long, X., Yan, Z., Salman, M., and Wu, C. (2023). Green innovation and SO_2 emissions: dynamic threshold effect of human capital. *Bus. Strat. Environ.* 32, 499–515. doi: 10.1002/bse.3157

Münzel, T., Hahad, O., Daiber, A., and Landrigan, P. J. (2023). Soil and water pollution and human health: what should cardiologists worry about? *Cardiovasc. Res.* 119, 440–449. doi: 10.1093/cvr/cvac082

Mushtaq, R., and Bruneau, C. (2019). Microfinance, financial inclusion and ICT: implications for poverty and inequality. *Technol. Soc.* 59:101154. doi: 10.1016/j.techsoc.2019.101154

Pan, X., Liu, Q., and Peng, X. (2015). Spatial club convergence of regional energy efficiency in China. *Ecol. Indic.* 51, 25–30. doi: 10.1016/j.ecolind.2014.10.026

Parent, O., and LeSage, J. P. (2008). Using the variance structure of the conditional autoregressive spatial specification to model knowledge spillovers. *J. Appl. Econ.* 23, 235–256. doi: 10.1002/jae.981

Rastogi, S., Panse, C., Sharma, A., and Bhimavarapu, V. M. (2021). Unified payment interface (UPI): a digital innovation and its impact on financial inclusion and economic development. *UJAF* 9, 518–530. doi: 10.13189/ujaf.2021.090326

Shah, N. W., Baillie, B. R., Bishop, K., Ferraz, S., Högbom, L., and Nettles, J. (2022). The effects of forest management on water quality. *For. Ecol. Manag.* 522:120397. doi: 10.1016/j.foreco.2022.120397

Shahbaz, M., Song, M., Ahmad, S., and Vo, X. V. (2022). Does economic growth stimulate energy consumption? The role of human capital and R&D expenditures in China. *Energy Econ.* 105:105662. doi: 10.1016/j.eneco.2021.105662

Shi, R., Yao, L., Zhao, M., and Yan, Z. (2024). Low-carbon production performance of agricultural green technological innovation: from multiple innovation subject perspective. *Environ. Impact Assess. Rev.* 105:107424. doi: 10.1016/j.eiar.2024.107424

Snider, A., Gutiérrez, I., Sibelet, N., and Faure, G. (2017). Small farmer cooperatives and voluntary coffee certifications: rewarding progressive farmers of engendering widespread change in Costa Rica? *Food Policy* 69, 231–242. doi: 10.1016/j.foodpol.2017.04.009

Sui, J., Lv, W., Xie, H., and Xu, X. (2024). Towards low-carbon agricultural production: evidence from China's main grain-producing areas. *Financ. Res. Lett.* 60:104952. doi: 10.1016/j.frl.2023.104952

Tone, K., and Tsutsui, M. (2014). Dynamic DEA with network structure: a slacks-based measure approach. *Omega* 42, 124–131. doi: 10.1016/j.omega.2013.04.002

Wu, H., Hao, Y., Ren, S., Yang, X., and Xie, G. (2021). Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* 153:112247. doi: 10.1016/j.enpol.2021.112247

Yue, P., Korkmaz, A. G., Yin, Z., and Zhou, H. (2022). The rise of digital finance: financial inclusion or debt trap? *Financ. Res. Lett.* 47:102604. doi: 10.1016/j.frl.2021.102604

Zhang, L., Pang, J., Chen, X., and Lu, Z. (2019). Carbon emissions, energy consumption and economic growth: evidence from the agricultural sector of China's main grain-producing areas. *Sci. Total Environ.* 665, 1017–1025. doi: 10.1016/j.scitotenv.2019.02.162

Zhou, D., Hu, Y., Sun, Q., and Xie, D. (2023). Land resource mismatch and energy efficiency: evidence from 243 cities in China. *Energy Policy* 183:113800. doi: 10.1016/j.enpol.2023.113800

Zhou, L., and Xiong, L.-Y. (2018). Natural topographic controls on the spatial distribution of poverty-stricken counties in China. *Appl. Geogr.* 90, 282–292. doi: 10.1016/j.apgeog.2017.10.006

Zhu, H., Ma, W., Vatsa, P., and Zheng, H. (2023). Clean energy use and subjective and objective health outcomes in rural China. *Energy Policy* 183:113797. doi: 10.1016/j.enpol.2023.113797

Zou, B., and Mishra, A. K. (2024). Modernizing smallholder agriculture and achieving food security: an exploration in machinery services and labor reallocation in China. *Appl. Econ. Perspect. Policy* 46, 1662–1691. doi: 10.1002/aepp.13433