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How does urbanisation affect agricultural economic resilience? Evidence from China

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Abstract: As an important path to breaking the urban-rural dual system and promoting agricultural modernisation in China, the process of urbanisation might have a strong influence on promoting agricultural economic resilience (AER). Using panel data from provincial-level administrative regions of China's mainland, we constructed a novel indicator system to measure AER, and employ the system generalised method of moments model to examine the impact of urbanisation on AER and the moderating roles of land transfer and heterogeneous human capital. Our study yielded three notable findings. First, the urbanisation process can significantly enhance AER. This finding remained robust after conducting multiple robustness tests and addressing endogeneity using the instrumental variable method. Second, the influencing mechanism analysis results indicated that land transfer and human capital had significant moderating roles, and the level of land transfer and educational improvement can enhance the positive impact of urbanisation on AER, while the migratory human capital weakened this positive effect. Third, the heterogeneity analysis revealed regional differences in the impact of urbanisation on AER, demonstrating that the promotional effect of urbanisation was much greater in the major grain-producing areas. Our study offers a new perspective and evidence for researchers and policymakers investigating how to enhance AER.

Keywords: agricultural policy; agricultural economic system; human capital; land transfer

Since the external environment is changing drastically, China is striving to promote the nation's transformation from a large agricultural country to an agricultural powerhouse. To meet this goal, improving food production and the supply of important agricultural products is the chosen strategic direction for the country. Stated differently, China must strengthen its agricultural economic resilience (AER) to navigate diverse internal and external shocks.

According to Folke (2006), AER refers to the capacity of an agricultural economic system to digest and absorb external disturbances and maintain its original main features. Compared with the concepts of vulnerability and adaptability, resilience emphasises the comprehensive capacity of the economic system and is an important embodiment of agricultural modernisation.

Existing studies have demonstrated that AER is affected by a variety of factors, such as arable land area,

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industrial structure, rural education level, and the intensity of environmental regulations (Rockström et al. 2017; Jung et al. 2021). However, few studies have investigated the effect of urbanisation on AER in China. Furthermore, this effect can be positive or negative. Urbanisation can be a strong impetus for improving AER in China. A reasonable explanation for this positive effect is that urbanisation can break down urban-rural barriers, increase nonagricultural employment opportunities, and encourage labour mobility between urban and rural areas. Therefore, urbanisation can improve agricultural efficiency and promote the transformation of agricultural production toward specialisation and modernisation (Zhu 2011). In contrast, the labour mobility induced by urbanisation may weaken the rural labour force, resulting in insufficient labour capacity, which can lead to a reduction in agricultural income and farm households' productivity. In this sense, urbanisation may have a negative effect on AER. Moreover, as urbanisation in China is imbalanced, its impact on AER may vary across regions (Cao et al. 2014). In this context, it is crucial to clarify the impact of urbanisation on AER, including its mechanism effects and regional heterogeneity.

Literature review

The concept of resilience originated from the physical phenomenon of elasticity. Holling (1973) was the first scholar to introduce the concept to ecology for analysing ecosystems' capacity to recover from external disturbances. In the wake of the profound impact of external factors such as natural disasters, economic crises, and terrorist attacks on the macroeconomy, resilience was introduced into the field of economic analysis (Cellini and Cuccia 2015; Di Pietro et al. 2021). According to Martin (2012), economic resilience (ER) is divided into four dimensions, which encompass an economic system's capacity to withstand shocks, recover from shocks, reintegrate internal resources to adapt to the external environment, and explore and create new paths for economic development. Following this conceptual framework, previous studies have conducted in-depth research on countries' or regions' ERs. In addition to assessing ER, existing research has primarily focused on its influencing factors, such as industrial structure (Davies 2011), social capital (Crespo et al. 2014), and digital finance (Hou et al. 2023). However, gaps remain in the research concerning China's ER.

First, existing literature has predominantly assessed the macro and regional ER of China and its influencing factors. For instance, Zhou et al. (2020) calculated an ER index of the areas that were most severely affected by the 2008 Wenchuan earthquake, and Guo and Gong (2023) measured marine ER in China and analysed its spatial differentiation and driving mechanism. Some studies have measured the ER of various cities and economic zones in China by constructing multidimensional indicator systems (Lu et al. 2022; Zhao et al. 2022). In summary, previous research has commonly demonstrated or argued that ER was on the rise in China over the research period, with notable spatial heterogeneity. In terms of the influencing factors for ER, existing works have analysed the role of carbon emissions (Shi et al. 2022), digital finance (Hou et al. 2023), industrial structure (Tang et al. 2023), and infrastructure construction (Li et al. 2023).

Second, previous research has primarily analysed AER from a single policy perspective, lacking a comprehensive investigation and explanation. Huang et al. (2018) established an index system comprising engineering, ecology, economy, and society, determining that land use policies elevate AER. Taking Lankao County as a case, Cui et al. (2023) investigated the impact of poverty alleviation policies in China on the resilience of rural economies. In addition, evidence from other countries and regions has indicated that digital rural policy (Roberts et al. 2017) and the European Union Common Agricultural Policy's direct payment program (Zickiene et al. 2022) have promotional roles in enhancing AER. To conclude, existing literature has primarily analysed AER from a single policy perspective, and the assessments of AER have significant regional limitations.

Third, concerning the impact of urbanisation on agricultural and rural economies, existing studies have primarily employed two research perspectives. One research approach has been to analyse the correlation between urbanisation and rural development. Zhu et al. (2019) found that the spatial paradigm of rural development in China shifted rapidly after urbanisation. The mass migration triggered by urbanisation has optimised resource allocation efficiency, reduced social costs, and yielded significant economic benefits. Moreover, the steady progress of urbanisation was also found to have a positive impact on the reconfiguration of water resources (Hommes and Boelens 2017) and clean energy consumption (Han et al. 2022). Another research approach has examined the impact of urbanisation on urban-rural income disparity and entitlement inequality. According to Lewis (1954), the urban-rural gap will gradually narrow with increased urbanisation and economic development. Empirical

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studies in China have provided evidence for this argument. For instance, Yao and Jiang (2021) found that urbanisation factors can significantly narrow urban-rural income disparity using a dynamic panel data model. However, several studies have demonstrated that urbanisation is a primary cause of the urban-rural income gap because of biased urbanisation and unjust land expropriation policies amid the urbanisation process (Wu 2004; Feng et al. 2019). In addition, Su et al. (2015) found that urbanisation has a significant positive impact on the urban-rural income gap in China. Therefore, the development pattern of urbanisation may fail to narrow the urban-rural income gap.

ER has emerged as a significant subject of study in macro and regional economics. Nevertheless, the existing research on AER in China remains in its early stages, and theoretical analysis and measurement techniques require further exploration. Moreover, previous literature has predominantly employed micro-level data to examine the impact of urbanisation on agricultural economic indicators. In particular, to the best of our knowledge, minimal research has examined the effect and mechanisms of urbanisation on AER in China.

The contributions of this paper are twofold. First, we constructed an evaluation system for assessing China's AER from three new dimensions of risk resistance, economic recovery, and path innovation. Using this novel evaluation system, we quantitatively assessed the AER of each provincial-level administrative region of China's mainland. Second, we comprehensively examined the effect of urbanisation on AER, encompassing the moderating effects of land transfer and heterogeneous human capital (educational and migratory human capital) and regional heterogeneity.

Research hypotheses

Nexus between urbanisation and AER. Enhancing AER stems from strengthening the three associated capacities of resistance, recovery, and innovation when an agricultural economic system is exposed to unpredictable shocks (Cannon and Müller-Mahn 2010). Specifically, urbanisation can not only enhance agricultural economic systems' risk resistance by increasing farmers' incomes, but can also cultivate the recovery capacity of agricultural economic systems through the flow of information elements. Urbanisation also provides innovative development platforms to enhance the regenerative capacity of agricultural economic systems, which improves AER.

First, urbanisation increases rural residents' income, enriches the sources of income, and promotes large-scale agricultural operations. Liu and Li (2017) found that urbanisation drives rural population migration to cities, which results in the spatial re-optimisation of labour factors. Extensive rural labour mobility significantly contributes to China's economy's growth, notably elevates rural households' income, and improves rural residents' income structure (Liao et al. 2023). As an integral aspect of agricultural economic systems, increased income and diversification of income sources can improve rural households' capacity to withstand external risks. In addition, rural labour migration increases the intensity of agricultural machinery input, which further improves agricultural total factor productivity and ecological efficiency. In this way, urbanisation could enhance AER when confronted with unexpected shocks.

Second, urbanisation can effectively alleviate the information asymmetry between urban and rural areas, promoting factor flow between urban and rural areas (Eloy et al. 2015). This process expedites the speed of information transmission and reduces the degree of information asymmetry between agricultural producers and consumers. This information transmission mechanism enables an agricultural system to rapidly adapt to external shocks and enhances AER. In addition, urbanisation establishes a price transmission pathway between urban and rural areas and promotes factor market integration, which enables agricultural economic systems to respond promptly to external environmental changes and effectively regulates the relationship between agricultural production and consumption. Therefore, urbanisation can increase AER by alleviating information asymmetry between urban and rural areas.

Third, urbanisation can optimise resource allocation efficiency and provide a fertile ground for innovative development, elevating regional innovative capacity and fortifying AER. The urbanisation process in China is transitioning from factor-driven to innovation-driven (Pencea and Baglar 2016; Li et al. 2020). With increased urban populations and improved living standards, the potential pool of individuals capable of participating in innovative endeavours will rise. High-skilled labourers move fluidly between regions, which fosters the development of industrial clusters in areas where high-tech and productive service industries closely align with innovation activities (Andersson et al. 2009). This trend will heighten regional specialisation, minimise the extent of resource misallocation, and elevate resource allocation efficiency. Consequently, rising urbanisation will improve regional

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innovation capacity, capital productivity, and technological efficiency (Mendez et al. 2023).

Therefore, we propose the following hypothesis:

H_1: Urbanisation can enhance agricultural economic resilience in China.

The moderating role of land transfer. Existing studies have revealed that rural labour mobility may result in a shortage of labour in agricultural production and decrease rural households' labour productivity, indicating that labour mobility may have a negative impact on the agricultural system (Liu et al. 2010; De Koning et al. 2021). In contrast, Ali et al. (2014) found that agricultural land transfer can promote land transfer from low-efficiency farmers to high-efficiency farmers, optimising the allocation of land resources. High-production farmers establish new agricultural entities (e.g. family farms and agricultural enterprises) and disseminate advanced agricultural production technologies (Zhu et al. 2022). As a result, agricultural production costs decrease, which improves production efficiency and market competitiveness significantly. Conversely, farmers with low productivity or those who are unable to cultivate land can obtain dividends by transferring land management rights. This will not only increase the household's property income but also liberate family labour for nonagricultural employment (Stampini and Davis 2009). Therefore, land transfer can effectively address issues such as land abandonment and fragmentation of cultivated land that may arise from urbanisation in China (Liao et al. 2023). It ensures the smooth operation of agricultural production and enhances AER in the context of an ongoing decline in agricultural labour quantity and quality in China.

In conclusion, it is evident that land transfer through accelerated agricultural scale management and other approaches may enhance the positive effects of urbanisation on AER. Therefore, we propose hypothesis H_2 as follows:

H_2: The influence of urbanisation on AER is moderated by land transfer. Specifically, land transfer bolsters the positive impact of urbanisation on AER.

The moderating role of heterogeneous human capital. As the main agent of innovation, human capital is primarily derived from formal education and work experience (Mincer 1996). By generating proprietary knowledge and providing feedback within a region, human capital enhances the vitality of regional development. Luo and Hu (2024) found that rural human capital development primarily depends on targeted investment. Considering the actual circumstances in China, we divide it into educated human capital based on educational expenditure and migratory human capital based on transportation and communication expenditure. Educational expenditure can elevate rural labourers' knowledge and skills. The labour force can efficiently use modern mechanical equipment and cultivate skills and experience in the urbanisation process (Ali et al. 2016). The combination of advanced technology and high-quality labour fosters agricultural operators' innovation capabilities, thereby enhancing AER. In contrast, migratory human capital driven by transportation and communication expenditure expands the geographical reach of investment entities. In the process of urbanisation, skilled labour with high human capital engages in a nearly unidirectional flow from rural to urban areas (Long et al. 2011). This phenomenon can diminish the calibre of labour in agricultural production and its innovation potential, eroding the AER.

Therefore, we propose hypothesis H_3 as follows:

H_3: The influence of urbanisation on AER is moderated by rural human capital. Specifically, educational human capital will augment the promotional effect of urbanisation on AER, whereas migratory human capital will diminish the positive impact of urbanisation.

MATERIAL AND METHODS

Econometric models

To examine the effect of urbanisation on AER (hypothesis H_1), the baseline regression model was as follows:

$$AER_{it} = \alpha_0 + \alpha_1 AER_{it-1} + \alpha_2 urban_{it} + \\ + \alpha_3 controls_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

where: AER_{it} –xplained variable and represents the AER level of region i in year t; $urban_{it}$ – core explanatory variable that indicates the level of urbanisation; $controls_{it}$ – control variables; μ_i – area effect; ε_{it} – randomised disturbance term.

Since AER is primarily determined by regions' natural conditions, economic base, and technological level, these factors change in the short term and have temporal continuity, which promotes the stickiness of AER. For this reason, we introduced its lag term on the right-hand side of Equation (1).

To test hypotheses H_2 and H_3, we introduced the variables reflecting the extent of agricultural land transfer ($turn_{it}$), educational human capital (eh_{it}), and migratory human capital (mh_{it}) into the model as intermediate

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variables to examine moderating effects through interaction terms with urbanisation ($urban_{it}$). The moderating effect models were set as follows:

$$AER_{it} = \alpha_0 + \alpha_1 AER_{it-1} + \alpha_2 urban_{it} + \alpha_3 urban_{it} \times turn_{it} + \alpha_4 controls_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

$$AER_{it} = \alpha_0 + \alpha_1 AER_{it-1} + \alpha_2 urban_{it} + \alpha_3 urban_{it} \times eh_{it} + \alpha_4 controls_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

$$AER_{it} = \alpha_0 + \alpha_1 AER_{it-1} + \alpha_2 urban_{it} + \alpha_3 urban_{it} \times mh_{it} + \alpha_4 controls_{it} + \mu_i + \varepsilon_{it} \quad (4)$$

Given the first-order lagged terms of the explanatory variables (AER_{it-1}), our models might have endogeneity issues (Chen et al. 2023). In addition, issues such as bidirectional causality between explanatory variables and the dependent variable and inadequate control variables may exacerbate the models' endogeneity. We employed the generalised method of moments (GMM) for estimation to address these concerns. By taking first differences and using lagged values of the dependent variable and differenced lagged values as instrumental variables (IVs), the GMM method addressed the omitted variable bias, individual heterogeneity, measurement error, and potential endogeneity (Arellano and Bond 1991; Blundell and Bond 2000). Using this approach obtained consistent and efficient coefficient estimates. In addition, following the practice of existing literature (Chen et al. 2023), we conducted two tests on the GMM results. The first was the AR(2) test, which is used to test whether the residuals are second-order serially correlated, and the second was the Sargan test, which is used to identify the rationality of IVs and avoid overidentification issues.

Variables and measurement

Explained variable. The explained variable was agricultural economic resilience (*AER*). Generally, the impact of natural conditions on agricultural output is significant. If we follow the calculation method for ER (Crespo et al. 2014; Di Pietro et al. 2021), and take the change in regional agricultural gross output as a measure for *AER*, the results will have significant limitations; therefore, a sounder method is to measure the *AER* using an indicator system. This method has also been employed in the majority of existing studies. Jiang et al. (2022) argued that AER can be decomposed into production, ecological, and ER, selecting suitable indicators for an associated indicator system. Zhang and Hui (2022) defined AER as the agricultural economic system's resistance and recovery capacity, and constructed an evaluation system from the perspectives of resistance and reconstruction. However, it may be difficult for the economic system to return to its original state following an external shock. Therefore, following the commonly held meaning of resilience, our study emphasises agricultural systems' capacity to adapt and explore new paths in response to the challenges posed by external environment changes.

Subsequently, referencing existing studies, we constructed a novel indicator system that includes three dimensions of AER: resistance, recovery, and innovation capacities. First, resistance refers to an agricultural economic system's capacity to overcome the impact of disasters and emergencies, including three second-level indicators of economic foundation, production conditions, and the ecological environment. Second, as agricultural economic output is the basis for the agricultural system reconstruction, recovery was measured from the perspective of agricultural output to quantify the system's capacity to recover from losses rapidly and flexibly (Turner et al. 2003). Finally, external shocks often generate fundamental changes in the macro environment, and innovation delineates the agricultural system's capacity to pursue self-renewal, technological advancement, and path transformation after experiencing such shocks. Referencing Qiao et al. (2024), we focused on indicators related to the rural ecological environment, agricultural infrastructure, and agricultural output. Considering data availability, we selected agricultural system consumption and investment indicators to measure resilience. The specific indicators are given in Table 1.

Prior to calculating the *AER* value, it was essential to verify the reliability of our indicator system. We used Cronbach's alpha coefficient to test the reliability. The formula was as follows:

$$\alpha = \frac{k\bar{r}}{1+(k-1)\bar{r}} \quad (5)$$

where: k – number of indicators; $\bar{r}$ – mean of indicators' correlation coefficients.

Parameter α ranges between 0 and 1, and we considered the indicator system to denote reliability when $\alpha > 0.7$. Table 2 presents the reliability results using sample data from 2008 as an example, yielding a reliability

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Table 1. Indicator system for evaluating the agricultural economic resilience

Primary indicator	Secondary indicators	Tertiary indicators	Indicator attributes
Resistance	economic foundation	value added of the primary industry/employment in the primary industry	positive
		value added of the agricultural, forestry, animal husbandry, and fishery industry/total sown area	positive
		intermediate consumption value of the agricultural sector/total sown area	positive
	production conditions	effective irrigated area/total sown area	positive
		unit sown area total agricultural machinery power	positive
		area affected by natural disasters/the area of disaster-stricken land.	negative
	ecological environment	amount of chemical fertilizer used per unit sown area	negative
		amount of pesticide used per unit sown area;	negative
		amount of agricultural plastic film used per unit sown area.	negative
		amount of agricultural diesel used per unit sown area	negative
Recovery	economic stability	expenditure on agriculture, forestry, and water from the public finance	positive
		total fixed asset investment of rural households	positive
	economic growth	growth rate of primary industry GDP	positive
		rural residents' expenditure on daily necessities	positive
		rural households' per capita disposable income	positive
Innovation	technological advancement	number of patent applications for agricultural green inventions	positive
		quantity of agricultural technical personnel	positive

Source: Authors' elaboration.

coefficient of 0.77, which indicates that our indicator system demonstrates good reliability. The R^2 of the Friedman test was 89.80, and the *P*-value was significant at the 0.01 level, demonstrating the significant differences between the indicators. Kendall's coefficient was 0.20 (< 1), demonstrating a weak correlation in regions' AER, which allowed us to differentiate diverse regions in the evaluation system. In summary, the evaluation system proposed in Table 1 is reasonable and reliable.

Previous research has generally used the entropy method and factor analysis to weight indicators (Zhang and Hui 2022; Cui et al. 2023). Conducting an analysis using measurement software (SPSS24) revealed that the Kaiser-Meyer-Olkin (KMO) test for historical data was consistently less than 0.6, indicating that our data were unsuitable for factor analysis. Therefore, referencing Kizielewicz et al. (2021) and Paradowski et al. (2021), we used the entropy method to determine the indicator weights.

Table 2. Reliability coefficients

Cronbach's alpha	Cronbach's alpha under standardisation	Friedman R^2	Significance
0.77	0.79	89.80	0.00
Kendall's coefficient W = 0.20			

Source: Authors' calculations

Explanatory variable. The explanatory variable was the level of urbanisation (*urban*). Existing studies have predominantly used the proportion of urban household registration population to the total population as a proxy indicator (Hu et al. 2020; Li et al. 2020). However, many studies have found that this indicator does not truly reflect the degree of urbanisation (Sun and Zhou 2015). First, many rural residents are engaged in nonagricultural labour in county towns. Although rural residents migrate, work, and live in cities, they maintain rural household registration, which leads to an underestimation of the urbanisation level. Furthermore, the quality of publicly available household registration data in some regions is extremely low, with missing or abnormal values and deviations in statistical calibres among regions, which makes it impossible to obtain an accurate proportion of the urban household registration population. Therefore, referencing Wu et al. (2023), we instead used the proportion of the nonagricultural employed population (total employed population minus the population employed in agriculture) to the total population as the proxy variable for measuring urbanisation.

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Moderating variables. Moderating variables included the level of land transfer (*turn*) and increments of rural human capital. Referencing Liao et al. (2023), we used the ratio of the total area of household-contracted farmland circulation to the area of household-contracted farmland management to measure land transfer in different regions and periods. Educational human capital (*eh*) was represented by the proportion of local government expenditure on culture, education, and entertainment to total spending. Migratory human capital (*mh*) was represented by the proportion of spending on transportation and communication to total spending.

Control variables. Based on the relevant research and mathematical model (Huang et al. 2018; Feng et al. 2019), we selected five control variables that may influence AER from natural or social perspectives. *i*) Natural conditions (*rain*), measured by the average annual precipitation in each region; *ii*) Crop cropping structure (*wheat*, *corn*), measured by the respective proportions of planting area of wheat and maise to total cultivated area; *iii*) Electricity infrastructure (*elec*), measured by the ratio of total rural electricity consumption to the rural resident population; *iv*) Density of rural road (*road*), measured by the ratio of the sum of the total mileage of rural roads and village roads to the rural resident population; and *v*) Ecological environment (*envir*), measured by the ratio of erosion control area to urban area (He et al. 2022).

Data sources

Considering data availability and completeness, we examine 30 provincial-level administrative regions in China's mainland (excluding Tibet due to incomplete data) as the research sample, covering 2008–2018. Our sample selection was based on three considerations. First, many core data lacked city-level information, making it impossible to examine them on a smaller geographic scale. Second, after 2018, the statistical authority of China no longer reported the number of agricultural technical personnel. Third, the sample period encompasses the global financial crisis (2008–2009) and the first year of the comprehensive trial of new-type urbanisation (2014) (Zhou et al. 2024). In summary, to ensure data balance and the reliability of results, the sample period of this study is from 2008 to 2018.

The original data were obtained from the China Statistical Yearbook (National Bureau of Statistics of China 2009-2019a), the China Rural Statistical Yearbook (National Bureau of Statistics of China 2009-2019b), the China Transport Statistical Yearbook (Ministry of Transport of the PRC 2010-2019), the Educational Statistics Yearbook of China (Ministry of Education of the PRC 2009-2019), the China Compendium of Statistics 1949-2008 (National Bureau of Statistics of China 2010), the Statistical Annual Report of China's Rural Operation and Management (Ministry of Agriculture of the PRC 2009-2019), the China Statistical Yearbook on Science and Technology (National Bureau of Statistics of China and Ministry of Science and Technology of the PRC 2009-2019), the

Table 3. Descriptive statistics

Variables	Sample size	Average value	SD	Minimum	Maximum
AER	330	0.2754	0.0861	0.1223	0.5665
urban	330	0.6427	0.1489	0.2888	0.9703
rain	330	2.1583	0.5062	0.6973	3.1053
corn	330	0.2944	0.2192	0.0044	0.7937
wheat	330	0.1918	0.1753	0.0000	0.5814
envir	330	11.1956	13.4649	0.2003	68.4950
elec	330	0.1875	0.4712	0.0113	3.6577
road	330	3.9952	0.3933	3.0460	5.2265
turn	330	0.2584	0.1649	0.0192	0.8682
eh	330	0.1183	0.0247	0.0722	0.1788
mh	330	0.0918	0.0249	0.0446	0.1483

AER – agricultural economic resilience; *urban* – urbanisation level; *rain* – average annual precipitation; *corn* – proportion of maize planting area; *wheat* – proportion of wheat planting area; *elec* – rural electricity consumption; *road* – rural road area; *envir* – proportion of erosion control area to urban area; *turn* – land transfer; *eh* – educational human capital; *mh* – migratory human capital

Source: Authors' calculations

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China Statistical Yearbook for Regional Economy (National Bureau of Statistics of China 2009-2014), China's provincial-level statistical yearbooks (2009-2019), and the web of China National Intellectual Property Administration (CNIPA 2024). A small number of missing values were estimared employing a multiple interpolation, and the natural logarithm of data with larger magnitudes was used to address dimensions. We also set relevant economic variables in 2008 as the base period. Table 3 presents the descriptive statistics for each variable.

Table 3 reveals no evident outliers in the sample that could potentially compromise the reliability of our estimation results. The standard deviations of the dependent variable (*AER*) and the core explanatory variable (*urban*) were smaller than their respective means, indicating good data stability. Furthermore, the disparity between the maximum and minimum values of urbanisation level (0.9703 and 0.2888, respectively) reflected significant differences in urbanisation levels between different regions in China.

RESULTS AND DISCUSSION

Baseline regression results. We used the two-step system GMM method to estimate the benchmark regression model. Considering the potential bidirectional causality between urbanisation and AER, we treated urbanization (*urban*) as an endogenous explanatory variable in the regression process, and took its second-order lagged terms as IVs. To address the issue of missing degrees of freedom, we also used the collapse command to control the number of IVs. To clearly demonstrate the process of introducing control variables and their impact on the regression results, we divided them into natural and social dimensions. The natural dimension included annual average precipitation (*rain*), the proportion of maise cultivation area (*corn*), and the proportion of wheat cultivation area (*wheat*). The social dimension included rural road density (*road*), the proportion of soil and water conservation (*envir*), and electricity infrastructure (*elec*). The regression results are presented in Table 4 using a stepwise addition of control variables. The first column is the results, including only the first-order lagged variable of the dependent variable and the core explanatory variable (*L.AER* and *urban*), and the second and third columns show the results after introducing respective natural and social control variables.

Table 4 reveals that the *P*-values for second-order serial correlation were greater than 0.1 and the Sargan statistics were non-significant, indicating no high-order serial correlation or overidentification issues.

Table 4. Benchmark regression

Variables	Model (1)	Model (2)	Model (3)
L.AER	0.8472*** (100.13)	0.8759*** (98.62)	0.8751*** (49.85)
urban	0.2110*** (14.71)	0.1761*** (13.96)	0.1513*** (7.05)
rain	–	0.0008 (−0.43)	−0.0010 (−0.46)
wheat	–	0.0187 (1.16)	0.0147 (0.75)
corn	–	−0.0311*** (−9.01)	−0.0208*** (−2.76)
elec	–	–	0.0080*** (8.09)
road	–	–	−0.0035 (−1.19)
envir	–	–	−0.0001 (−1.49)
cons	−0.0864*** (−10.33)	−0.0630*** (−5.82)	−0.0346 (−1.58)
AR(1)	0.0000	0.0000	0.0000
AR(2)	0.1235	0.1604	0.2049
Sargan	0.9982	0.9980	0.9990

***significance at 1% level; *Z*-test statistics are in parentheses; *L.AER* – one-period lag of agricultural economic resilience; *urban* – urbanisation level; *rain* – average annual precipitation; *wheat* – proportion of wheat planting area; *corn* – proportion of maize planting area; *elec* – rural electricity consumption; *road* – rural road area; *envir* – proportion of erosion control area to urban area; *cons* – constant term; *AR*(1) – test for first-order serial correlation of the residual differences, with *P*-values reported in the table; *AR*(2) – test for second-order serial correlation of the residual differences, with *P*-values reported in the table; *Sargan* – overidentification test for the validity of instrumental variables, with *P*-values reported in the table
Source: Authors' calculations

Therefore, the estimation method was reasonable and the IVs were effective. The coefficient for the first-order lag of *AER* was significant at the 1% level, indicating that *AER* in the previous period had a notable stimulating effect on that of the current period. The results in column (1) demonstrate that urbanisation had a significant positive effect on *AER* in the absence of control variables. In columns (2) and (3), we sequentially introduced control variables at natural and social levels. The results show that the significance level did not change, although the regression coefficient of urbanisation decreased, indicating that the urbanisation process significantly promotes *AER* in China.

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Combined with our theoretical analysis, the potential explanations are threefold. First, the urbanisation process promotes the transfer of surplus rural labour to cities, enhances farmers' willingness to transfer land, promotes large-scale agricultural production, and improves agricultural systems' production efficiency and risk resistance. Second, high-density urban populations require significant consumption for production and living, which will have a radiating effect on rural areas, stimulating the vigorous development of high-profit secondary food and consumer goods such as meat, fruits, eggs, and dairy products. This enhances agricultural production potential and improves the rural industrial structure. Third, urbanisation promotes a reasonable flow of key factors, such as information and human resources, between urban and rural areas, cultivating the innovative capacity of agricultural production. Therefore, H_1 is supported.

Mechanism analysis. Our theoretical analysis indicated that land transfer and human capital may strengthen or weaken the effect of urbanisation on *AER*. To examine these moderating effects, we incorporated the interaction terms of urbanisation and land transfer (*urban* × *turn*), urbanisation and educational human capital (*urban* × *eh*), and urbanisation and migratory human capital (*urban* × *mh*) into the models, and we present the regression results in Table 5.

Table 5. Moderating effects

Variables	Model (1)	Model (2)	Model (3)
L.AER	0.8304*** (31.90)	0.8640*** (46.54)	0.8781*** (40.61)
urban	0.1241*** (6.37)	0.1406*** (7.12)	0.1803*** (8.13)
urban × *turn*	0.0605*** (2.97)	–	–
urban × *eh*	–	0.1037** (2.35)	–
urban × *mh*	–	–	−0.2330*** (−4.65)
rain	−0.0020 (−1.15)	−0.0019 (−1.21)	−0.0012 (−0.47)
wheat	0.0196* (1.87)	0.0224 (0.97)	0.0128 (0.76)
corn	−0.0307*** (−4.38)	−0.0328*** (−3.47)	−0.0117 (−1.63)
elec	0.0045*** (12.20)	0.0081*** (6.17)	0.0061*** (7.21)
road	−0.0080** (−2.51)	−0.0049 (−1.51)	0.0015 (0.53)
envir	−0.0002 (−1.38)	−0.0001 (−1.05)	−0.0001 (−1.41)
cons	0.0044 (0.24)	−0.0229 (−1.08)	−0.0621 (−2.86)
AR(1)	0.0001	0.0001	0.0001
AR(2)	0.1410	0.2258	0.4276
Sargan	0.9990	0.9995	0.9993

*,**,***significance at 10%, 5% and 1% level, respectively; *Z*-test statistics are in parentheses; *L.AER* – one-period lag of agricultural economic resilience; *urban* – urbanisation level; *turn* – land transfer level; *eh* – educational human capital; *mh* – migratory human capital; *rain* – average annual precipitation; *wheat* – proportion of wheat planting area; *corn* – proportion of maize planting area; *elec* – rural electricity consumption; *road* – rural road area; *envir* – proportion of erosion control area to urban area; *cons* – constant term; *AR*(1) – test for first-order serial correlation of the residual differences, with *P*-values reported in the table; *AR*(2) – test for second-order serial correlation of the residual differences, with *P*-values reported in the table; *Sargan* – overidentification test for the validity of instrumental variables, with *P*-values reported in the table

Source: Authors' calculations

The results in the first column of Table 5 show that the coefficient of interaction term was significantly positive at the 1% level and consistent with the sign of urbanisation's regression coefficient. This indicates that land transfer would strengthen the positive impact of urbanisation on AER. The net effect of urbanisation on AER depends on its own promotion and the promotion of *urban* × *turn*. In the second column of Table 5, the coefficient of the core explanatory variable was significantly positive, and the coefficient of interaction term was also significantly positive at the 1% level. This suggests that increased educational human capital reinforces the influence of urbanisation on *AER*. In the third column, the coefficient of interaction term was significantly negative at the 1% level, indicating that migratory human capital weakened the positive effect of urbanisation on *AER*. In summary, the empirical results demonstrate that increased land transfer would strengthen the positive effect of urbanisation on *AER*, enhanced educational human capital would strengthen the promotion of urbanisation on *AER*, and increased migratory human capital would weaken the positive impact on *AER*. Therefore, H_2 and H_3 are confirmed. Furthermore, the AR(2) and Sargan test results in Table 5 demonstrate no higher-order serial correlation in the equation residuals, and the IVs were effective, confirming the validity of the moderating effect model estimation.

Robustness tests. We used the GMM method in the baseline regression, which partially alleviated the impact of endogeneity issues. Next, we employed the IV approach to further address potential endogeneity is-

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sues and re-examine the causal relationship between *AER* and urbanisation. Referencing Hu et al. (2020) and Yang et al. (2024), we used nighttime light (NTL) as the IV to measure urbanisation for the following reasons. First, NTL data comprehensively measure the breadth and intensity of human activity in urban areas, reflecting the scale of population agglomeration and the extent of urban land expansion (Xu et al. 2021). Therefore, a correlation exists between NTL and urbanisation. Second, *AER* is primarily determined by natural resources and agricultural production technology; therefore, it is not directly affected by the NTL intensity. Third, the NTL data used in this study came from the US National Oceanic and Atmospheric Administration's (NOAA) National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS), which were obtained after undergoing cross-sensor calibration referencing the NOAA's US National Centers for Environmental Information Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) and the Suomi National Polar-orbiting Partnership (SNPP-VIIRS). These data overcome discrepancies between data from different satellites and abnormal fluctuations in the light data from the same satellite in different years. In conclusion, although the correlation between NTL intensity and AER cannot be completely ruled out, it remains an acceptable IV in the absence of other alternatives.

Using NTL as the IV for urbanisation level, we employed two-stage least squares (2SLS) to examine the causal relationship between *AER* and urbanisation. The regression results are presented in Table 6. The Kleibergen-Paap Lagrange Multiplier (*KP LM*) statistic confirmed no identification problem in the model, while the comparison of *KP* Wald *F* and Cragg-Donald (*CD*) Wald *F* statistics indicated no weak IV issues. Therefore, the IV was deemed effective. The coefficient of *light* in first stage indicated a significantly positive correlation between urbanisation level and NTL intensity. The second-stage results demonstrated that the effect of urbanisation on *AER* was consistent with the previous analysis after introducing the IV, with only subtle differences in coefficients and significance levels. Therefore, the causal relationship between urbanisation and *AER* remained significant after considering endogeneity issues.

We also used three methods to examine the robustness of the baseline results, i.e. remeasuring the level of urbanisation, reducing the sample size, and lagging control variables by one period. The estimation results demonstrated that the results of benchmark regression and mechanism test were robust. Due to space limitations, the specifics of the robustness tests were omitted. Readers can obtain them from the authors upon request.

Table 6. Instrumental variable results

Variables	(1) IV-2SLS
L.AER	1.0238*** (66.10)
urban	0.0259** (2.00)
rain	−0.0029 (−1.08)
wheat	−0.0047 (−0.77)
corn	−0.0144*** (−2.80)
elec	−0.0143 (−2.80)
road	−0.0072*** (−3.79)
envir	0.0002 (0.29)
cons	0.0329*** (2.56)
First stage: *light*	0.0777*** (10.02)
KP LM	42.114
KP Wald *F*	100.381
CD Wald *F*	109.056

, * significance at the 5% and 1% levels, respectively; significance levels are denoted using *t*-statistics (in parentheses); IV – instrumental variable; 2SLS – two-stage least squares; *L.AER* – a one-period lag of agricultural economic resilience; *urban* – urbanization level; *rain* – average annual precipitation; *wheat* – proportion of wheat planting area; *corn* – proportion of maize planting area; *elec* – rural electricity consumption; *road* – rural road area; *envir* – proportion of erosion control area to urban area; *cons* – constant term; *light* – nighttime light; *KP* – Kleibergen-Paap; *LM* – Lagrange Multiplier; *CD* – Cragg-Donald

Source: Authors' calculations

Heterogeneity analysis. Considerable differences in natural resource endowments, economic foundations, and functional divisions of labour mean that significant regional disparities in urbanisation exist in China. To ensure national food security, China's central government also defines major grain-producing (MGP) areas and provides special policy support. To explore regional differentiation of the impact of ur-

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banisation on AER, we further divided the total sample into MGP and non-MGP areas referencing the Opinions on Reforming and Improving Policies for Comprehensive Agricultural Development released by the Ministry of Finance of the People's Republic of China in 2003. MGP areas include Hebei, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, and Sichuan. The rest of the country is non-MGP areas.

Table 7 reveals that the core variables' regressions for MGP and non-MGP areas were significantly positive; however, the AR(2) value for MGP areas did not pass the test, rendering the estimated results meaningless. The driving role of urbanisation on AER was particularly significant in non-MGP areas, yielding a regression coefficient that exceeded the full sample regression coefficient in Table 4. The potential rationale for this is twofold. First, non-MGP areas included four municipalities and developed provinces such as Guangdong, Zhejiang, and Fujian. Agricultural production in these regions has received strong economic support and policy assistance (Feng et al. 2019). Moreover, non-MGP areas predominantly focus on planting economic crops such as fibers, oilseeds, and sugarcane, making rural households' income relatively higher. Therefore, the large-scale operation brought by urbanisation had a more obvious role in improving the AER. Second, the agricultural foundation in non-MGP areas was relatively weak, which may lead to higher marginal benefits from urbanisation and a greater potential increase in AER. In comparison, although MGP areas possessed stronger agricultural resources, the innovation capacity in these areas was relatively weaker; therefore, urbanisation was not the core factor enhancing AER in MGP areas, which offset a portion of urbanisation's positive effects in the full sample.

Table 7. Heterogeneity analysis

Variables	Grain-producing areas	
	major	nonmajor
L.AER	0.8022*** (3.85)	0.7922*** (10.77)
nonagri	0.3657*** (2.97)	0.5545** (2.38)
cons	–0.1971 (–0.85)	0.0544 (1.35)
Control variables	yes	yes
AR(1)	0.0004	0.0190
AR(2)	0.0166	0.1590
Sargan	1.0000	1.0000

,* significance levels of 5% and 1%, respectively; Z-test statistics are in parentheses; *L.AER* – a one-period lag of agricultural economic resilience ; *nonagri* – ratio of non-agricultural population to total population urbanization; *cons* – constant term; $AR(1)$ – test for first-order serial correlation of the residual differences, with P-values reported in the table; $AR(2)$ – test for second-order serial correlation of the residual differences, with P-values reported in the table; *Sargan* – overidentification test for the validity of instrumental variables, with P-values reported in the table
Source: Authors' calculations

CONCLUSION

Urbanisation is an important path for breaking the limitations of the dual urban-rural system and promoting agricultural modernisation in China's mainland. Although urbanisation has a strong influence on promoting AER, existing literature concerning the nexus between urbanisation and AER is sparse. Using panel data from 30 provincial-level administrative regions from 2008 to 2018, we constructed a novel indicator system that included resistance, resilience, and innovation to measure AER, and used a system GMM model to investigate the impact of urbanisation on AER and the moderating influence of land transfer and heterogeneous human capital. Our study yielded three notable findings. First, increased urbanisation contributes to enhancing the AER. This finding remains robust following multiple robustness tests and after addressing endogeneity with the IV method. Our findings, together with similar studies (Huang et al. 2018; Cui et al. 2023), support the positive impact of China's current macro policies on AER. Second, the influencing mechanism analysis confirms that the moderating roles of land transfer and educational human capital are significant and can enhance the positive impact of urbanisation on AER, while migratory human capital will weaken this positive effect. This conclusion not only explains how urbanisation affects AER theoretically but also serves as a crucial reference for policymakers. Third, the heterogeneity analysis reveals considerable regional differences in the impact of urbanisation on AER, revealing that the promotional effect of urbanisation on AER in MGP areas is much greater than in non-MGP areas.

Admittedly, this study has some limitations. First, some indicators may not be the most accurate choices. For example, concerning the indicators for measuring ecological resistance, the amount of four chemicals used per unit sown area is an anthropogenic factor that

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may not impersonally describe agricultural systems' resistance to changes in natural conditions. Second, the provincial-level data do not precisely characterise regions' urbanisation. Particularly, with the deepening of urbanisation processes, contemporary urbanisation in China is occurring more in smaller townships and rural areas. Third, regional data can describe the overall trends of human capital transfer from a macro perspective but cannot explain the micro-decisions of individual actors. Notably, these problems are mainly attributable to a lack of data availability. Ensuring data comprehensiveness and balance is achieved at the expense of geographic scale. Nonetheless, our study adds new empirical evidence on the urbanization-AER nexus in developing economies, and provides a base for future analysis on this topic at a smaller geographical scale.

REFERENCES

Ali A., Rahut D.B., Behera B. (2016): Factors influencing farmers' adoption of energy-based water pumps and impacts on crop productivity and household income in Pakistan. Renewable and Sustainable Energy Reviews, 54: 48–57.

Ali D.A., Deininger K., Duponchel M. (2014): Credit constraints and agricultural productivity: Evidence from rural Rwanda. Journal of Development Studies, 50: 649–665.

Andersson R., Quigley J.M., Wilhelmsson M. (2009): Urbanization, productivity, and innovation: Evidence from investment in higher education. Journal of Urban Economics, 66: 2–15.

Arellano M., Bond S. (1991): Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies, 58: 277–297.

Blundell R., Bond S. (2000): GMM estimation with persistent panel data: An application to production functions. Econometric Reviews, 19: 321–340.

Cannon T., Müller-Mahn D. (2010): Vulnerability, resilience and development discourses in context of climate change. Natural Hazards, 55: 621–635.

Cao S., Lv Y., Zheng H., Wang X. (2014): Challenges facing China's unbalanced urbanization strategy. Land Use Policy, 39: 412–415.

Cellini R., Cuccia T. (2015): The economic resilience of tourism industry in Italy: What the 'great recession' data show. Tourism Management Perspectives, 16: 346–356.

Chen H., Dai Y., Guo D. (2023): Financial literacy as a determinant of market participation: New evidence from China using IV-GMM. International Review of Economics and Finance, 84: 611–623.

China's Provincial-Level Statistical Yearbooks (2009–2019): Statistical yearbooks by region and year (prepared by the local statistics bureaus of each provincial administrative region). Available at https://data.cnki.net/yearBook?type=type&code=A (accessed May 11, 2024; in Chinese)

CNIPA (2024): Statistics. China National Intellectual Property Administration, Available at https://english.cnipa.gov.cn/col/col2942/index.html (accessed May 11, 2024)

Crespo J., Suire R., Vicente J. (2014): Lock-in or lock-out? How structural properties of knowledge networks affect regional resilience. Journal of Economic Geography, 14: 199–219.

Cui Z., Li E., Li Y., Deng Q., Shahtahmassebi A. (2023): The impact of poverty alleviation policies on rural economic resilience in impoverished areas: A case study of Lankao Country, China. Journal of Rural Studies, 99: 92–106.

Davies S. (2011): Regional resilience in the 2008–2010 downturn: Comparative evidence from European countries. Cambridge Journal of Regions. Economy and Society, 4: 369–382.

Di Pietro F., Lecca P., Salotti S. (2021): Regional economic resilience in the European Union: A numerical general equilibrium analysis. Spatial Economic Analysis, 16: 287–312.

Eloy L., Brondizio E., Do Pateo R. (2015): New perspectives on mobility, urbanisation and resource management in riverine Amazonia. Bulletin of Latin American Research, 34: 3–18.

Feng W., Liu Y., Qu L. (2019): Effect of land-centered urbanization on rural development: A regional analysis in China. Land Use Policy, 87: 104072.

Folke C. (2006): Resilience: The emergence of a perspective for social-ecological systems analyses. Global Environmental Change, 16: 253–267.

Guo Q., Gong X. (2023): Spatial differentiation and driving mechanism of the marine economic resilience in China. Regional Studies in Marine Science, 68: 103244.

Han J., Yang Q., Zhang L. (2022): What are the priorities for improving the cleanliness of energy consumption in rural China? Urbanisation advancement or agriculture development? Energy for Sustainable Development, 70: 106–114.

He Y., Wang H., Liu, Y. (2022): Spatial effects of agricultural carbon emissions from the perspective of industrial agglomeration. Resources Science, 44: 2428–2439.

Holling C. (1973): Resilience and stability of ecological systems. Annual Review of Ecological Systematics, 4: 1–23.

Hommes L., Boelens R. (2017): Urbanizing rural waters: Rural-urban water transfers and the reconfiguration of hydrosocial territories in Lima. Political Geography, 57: 71–80.

Hou S., Zhang Y., Song L. (2023): Digital finance and regional economic resilience: Evidence from 283 cities in China. Heliyon, 9: e21086.

Hu X., Qian Y., Pickett S., Zhou W. (2020): Urban mapping needs up-to-date approaches to provide diverse perspectives of current urbanization: A novel attempt to map urban areas with nighttime light data. Landscape and Urban Planning, 195: 103709.

https://doi.org/10.17221/207/2024-AGRICECON

Huang X., Li H., Zhang X., Zhang X. (2018): Land use policy as an instrument of rural resilience – The case of land withdrawal mechanism for rural homesteads in China. Ecological Indicators, 87: 47–55.

De Koning J., Hobbis Ketterer S., McNeill J., Prinsen G. (2021): Vacating place, vacated space? A research agenda for places where people leave. Journal of Rural Studies, 82: 271–278.

Jiang H., Zhang C., Jiang H. (2022): (Study on effect and mechanism of China's agricultural economic resilience on agricultural high-quality development). Agricultural Economics and Management, 13: 20–32. (in Chinese)

Jung J., Maeda M., Chang A., Bhandari M., Ashapure A., Landivar-Bowles J. (2021): The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. Current Opinion in Biotechnology, 70: 15–22.

Kizielewicz B., Więckowski J., Shekhovtsov A., Watrobski J., Depczynski R., Salabun W. (2021): Study towards the time-based MCDA ranking analysis – A supplier selection case study. Facta Universitatis, Series: Mechanical Engineering, 19: 381–399.

Lewis W. (1954): Economic development with unlimited supplies of labour. The Manchestcr School, 22: 139–191.

Li X., Hui C., Lang W., Zheng S., Qin X. (2020): Transition from factor-driven to innovation-driven urbanization in China:A study of manufacturing industry automation in Dongguan City. China Economic Review, 59: 101382.

Li R., Xu M., Zhou H. (2023): Impact of high-speed rail operation on urban economic resilience: Evidence from local and spillover perspectives in China. Cities, 141: 104498.

Liao X., Qin S., Wang Y., Zhu H., Qi X. (2023): Effects of land transfer on agricultural carbon productivity and its regional differentiation in China. Land, 12: 1358.

Liu Y., Liu Y., Chen Y., Long H. (2010): The process and driving forces of rural hollowing in China under rapid urbanization. Journal of Geographical Sciences, 20: 876–888.

Liu Y., Li Y. (2017): Revitalize the world's countryside. Nature, 548: 275–277.

Long H., Zou J., Pykett J., Li Y. (2011): Analysis of rural transformation development in China since the turn of the new millennium. Applied Geography, 31: 1094–1105.

Lu H., Zhang C., Jiao L., Wei Y., Zhang Y. (2022): Analysis on the spatial-temporal evolution of urban agglomeration resilience: A case study in Chengdu-Chongqing Urban Agglomeration, China, International Journal of Disaster Risk Reduction, 79: 103167.

Luo H., Hu Q. (2024): A re-examination of the influence of human capital on urban-rural income gap in China: College enrollment expansion, digital economy and spatial spillover. Economic Analysis and Policy, 81: 494–519.

Martin R. (2012): Regional economic resilience, hysteresis and recessionary shocks. Journal of Economic Geography, 12: 1–32.

Mendez P., Atienza M., Modrego F. (2023): Urbanization and productivity at a global level: New empirical evidence for the services sector. Regional Science Policy and Practice, 15: 1981–1998.

Mincer J. (1996): Economic development, growth of human capital, and the dynamics of wage structure. Journal of Economic Growth, 1: 29–48.

Ministry of Agriculture of the PRC (2009–2019): Statistical Annual Report of China's Rural Operation and Management (2008–2018). Beijing, China Agriculture Press: 210.

Ministry of Education of the PRC (2009–2019): Educational Statistics Yearbook of China (2009-2019). Available at https://data.cnki.net/yearBook/single?nav=%E7%BB%9F%E8%AE%A1%E5%B9%B4%E9%89%B4&id=N2023030114&pinyinCode=YZKRM (accessed May 11, 2024; in Chinese)

Ministry of Transport of the PRC (2010-2019): China Transport Statistical Yearbooks 2010–2019. Available at https://data.cnki.net/yearBook/single?id=N2022010162&pinyinCode=YJTYT (accessed May 11, 2024; in Chinese)

National Bureau of Statistics of China, Ministry of Science and Technology of the PRC (2009–2019): China Statistical Yearbook on Science and Technology (2009-2019). Available at https://data.cnki.net/yearBook/single?nav=%E7%BB%9F%E8%AE%A1%E5%B9%B4%E9%89%B4&id=N2024010042&pinyinCode=YBVCX (accessed May 11, 2024; in Chinese)

National Bureau of Statistics of China (2010): China Compendium of Statistics 1949–2008. Available at https://data.cnki.net/yearBook/single?id=N2010042091&pinyinCode=YXZLL (accessed May 11, 2024; in Chinese)

National Bureau of Statistics of China (2009–2014): China Statistical Yearbook for Regional Economy (2009–2014). Available at https://data.cnki.net/yearBook/single?id=N2015070200&pinyinCode=YZXDR (accessed May 11, 2024; in Chinese)

National Bureau of Statistics of China (2009–2019a): China Rural Statistical Yearbooks 2009–2019. Available at https://data.cnki.net/yearBook/single?nav=%E7%BB%9F%E8%AE%A1%E5%B9%B4%E9%89%B4&id=N2024010048&pinyinCode=YMCTJ (accessed May 11, 2024; in Chinese)

National Bureau of Statistics of China (2009–2019b): China Statistical Yearbooks 2009–2019. Available at https://www.stats.gov.cn/sj/ndsj/ (accessed May 11, 2024; in Chinese)

Paradowski B., Shekhovtsov A., Bączkiewicz A., Kizielewicz B., Salabun W. (2021): Similarity analysis of methods for objective determination of weights in multi-criteria decision support systems. Symmetry, 13: 1874.

Qiao G., Chen F., Xu C., Li Y., Zhang D. (2024): Study with agricultural system resilience and agroecological efficiency

https://doi.org/10.17221/207/2024-AGRICECON

synergistic evolutionary in China. Food and Energy Security, 13: e514.

Roberts E., Anderson B., Skerratt S., Farrington J. (2017): A review of the rural-digital policy agenda from a community resilience perspective. Journal of Rural Studies, 54: 372–385.

Rockström J., Williams J., Daily G., Noble A., Matthews N., Gordon L., Wetterstrand H., DeClerck F., Shah M., Steduto P., de Fraiture C., Hatibu N., Unver O., Bird J., Sibanda L., Smith J. (2017): Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio, 46: 4–17.

Pencea S., Balgar A.C. (2016): China's transition to the innovation-driven economy: Stepping stones and roadblocks. Global Economic Observer, 4: 31–46.

Shi C., Guo N., Gao X., Wu F. (2022): How carbon emission reduction is going to affect urban resilience. Journal of Cleaner Production, 372: 133737.

Stampini M., Davis B. (2009): Does nonagricultural labor relax farmers' credit constraints? Evidence from longitudinal data for Vietnam. Agricultural Economics, 40: 177–188.

Su C., Liu T., Chang H., Jiang X. (2015): Is urbanization narrowing the urban-rural income gap? A cross-regional study of China. Habitat International, 48: 79–86.

Sun J., Zhou Y. (2015): Urban-rural disparity, labor migration and urbanization. Economic Review, 192: 29–40.

Tang D., Li J., Zhao Z., Boamah V., Lansana D. (2023): The influence of industrial structure transformation on urban resilience based on 110 prefecture-level cities in the Yangtze River. Sustainable Cities and Society, 96: 104621.

Turner B.L., Kasperson R.E., Matson P.A., McCarthy J.J., Corell R.W., Christensen L., Eckley N., Kasperson J.X., Luers A., Martello M.L., Polsky C., Pulsipher A., Schiller A. (2003): A framework for vulnerability analysis in sustainability science. Proceedings of the National Academy of Sciences, 100: 8074–8079.

Wu K., Wang D., Lu H., Liu G. (2023): Temporal and spatial heterogeneity of land use, urbanization, and ecosystem service value in China: A national-scale analysis. Journal of Cleaner Production, 418: 137911.

Wu W. (2004): Sources of migrant housing disadvantage in urban China. Environment and Planning, 36: 1285–1304.

Xu Y., Zhang W., Wang J., Ji S., Wang C., Streets D. (2021): Investigating the spatially heterogeneous impacts of urbanization on city-level industrial SO2 emissions: Evidence from nighttime light data in China. Ecological Indicators, 133: 108430.

Yang S., Yang X., Zhang J., Gao X., Zhou J., Wu X. (2024): Assessing the impacts of rural depopulation and urbanization on vegetation cover: Based on land use and nighttime light data in China, 2000–2020. Ecological Indicators, 159: 111639.

Yao Y., Jiang L. (2021): Urbanization forces driving rural urban income disparity: Evidence from metropolitan areas in China. Journal of Cleaner Production, 312: 127748.

Zhang M., Hui, L. (2022): (Spatial disparities and identification of influencing Factorson agricultural economic resilience in China). World Agriculture, 44: 36–50. (in Chinese)

Zhao R., Fang C., Liu J., Zhang L. (2022): The evaluation and obstacle analysis of urban resilience from the multidimensional perspective in Chinese cities. Sustainable Cities and Society, 86: 104160.

Zhou K., Liu B., Fan J. (2020): Post-earthquake economic resilience and recovery efficiency in the border areas of the Tibetan Plateau: A case study of areas affected by the Wenchuan Ms 8.0 Earthquake in Sichuan, China in 2008. Journal of Geographical Sciences, 30: 1363–1381.

Zhou J., Xu N., Zhang W., Ning X. (2024): Can agricultural low-carbon development benefit from urbanization? Empirical evidence from China's new-type urbanization pilot policy. Journal of Cleaner Production, 435: 140388.

Zhu L. (2011): Food security and agricultural changes in the course of China's urbanization. China and World Economy, 19: 40–59.

Zhu J., Zhu M., Xiao Y. (2019): Urbanization for rural development: Spatial paradigm shifts toward inclusive urban-rural integrated development in China. Journal of Rural Studies, 71: 94–103.

Zhu L., Li M., Shi Y. (2022): Farmland right confirmation, land circulation and farmers' maximum land use efficiency. Western Forum, 32: 111–122.

Zickiene A., Melnikiene R., Morkunas M., Volkov A. (2022): CAP direct payments and economic resilience of agriculture impact assessment. Sustainability, 14: 10546.

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