

Article

Assessing the Impacts of Population Shrinkage on Agricultural Water Resource Utilization and Environmental Carrying Capacity in Northeast China

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Abstract

Investigating the dynamic interplay between population shrinkage and water resource carrying capacity holds critical implications for safeguarding national food security and ecological resilience. This study systematically examines the underlying mechanisms and spatiotemporal evolution of their coupling relationship in Northeast China, thereby advancing the theoretical framework of human–land systems and delivering empirically grounded insights for sustainable regional development. Drawing on balanced panel data from 34 prefecture-level cities in Northeast China over the period 2010–2023, this study develops a population shrinkage index grounded in registered population dynamics. Building upon the DPSIR (driving forces–pressures–state–impacts–responses) conceptual framework, we construct a comprehensive evaluation system for agricultural water resource carrying capacity, explicitly operationalizing each of its five dimensions. Employing a spatial Durbin model (SDM), we rigorously estimate the direct effect of population shrinkage on carrying capacity, while simultaneously testing the mediating pathways through human capital accumulation and fiscal policy interventions. The empirical analysis reveals that (1) over the study period (2010–2023), population shrinkage in Northeast China intensified progressively, expanding spatially from initially localized pockets to widespread, regionally contiguous areas. Concurrently, agricultural water resource carrying capacity displayed pronounced spatial heterogeneity and statistically significant spatial clustering. (2) Overall, the degree of population decline significantly negatively affects agricultural water resource carrying capacity. Further heterogeneity tests showed that this negative effect exhibits significant variation across different population-contracted regions and provinces. Among the control variables, urbanization rate, per capita GDP, and total water resources availability exhibit statistically significant positive associations with agricultural water resource carrying capacity (3) Over the study period, higher human capital endowment and greater fiscal intervention intensity significantly attenuated the adverse effect of population shrinkage on agricultural water resource carrying capacity.

Keywords: population shrinkage; agricultural water resource carrying capacity; DPSIR model; spatial Durbin model



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1. Introduction

Population constitutes a foundational driver of regional development; water resources represent a critical input for agricultural production; and, in conjunction with the ecological

environment, these three factors jointly underpin sustainable regional development. As China's population development enters a new phase, population decline has evolved from a localized phenomenon into a regional issue. The Northeast region—comprising Heilongjiang, Jilin, and Liaoning provinces as well as the eastern prefectures of Inner Mongolia—spans 1.45 million km², geographically located in the northeastern frontier of China, bordering Russia and the Korean Peninsula (Figure 1). It hosts the world's largest contiguous expanse of fertile Chernozem (black soil) and possesses abundant surface and groundwater resources, underpinning its role as China's primary grain production base. Over the past two decades, the region has consistently contributed over 20% of the nation's total grain output, thereby fulfilling a strategically indispensable function in safeguarding national food security. Moreover, the Northeast region constitutes China's most severely affected area in terms of population shrinkage. Data from the Seventh National Population Census (2020) reveal that its total population declined by 11.01 million—approximately 10.1%—between 2010 and 2020, falling to 98.51 million and reducing its share of China's national population by 1.20 percentage points. This sustained demographic contraction reflects a structural, long-term negative growth trajectory rather than a transient fluctuation. Population shrinkage in the Northeast region displays pronounced spatiotemporal heterogeneity: the number and spatial extent of shrinking administrative units—spanning prefecture-level cities and counties—have expanded steadily since 2010, with average annual contraction rates intensifying across successive census periods. Concurrently, population aging is markedly advanced (16.39% aged ≥ 65 years, exceeding the national average of 13.50% in 2020), and structural labor reallocation—from agriculture to industry and services—has accelerated, collectively exacerbating the socioeconomic consequences of demographic decline for regional development. Agricultural water resource environmental carrying capacity—defined as the maximum sustainable yield of an agricultural water system under specified spatiotemporal constraints, while preserving ecosystem integrity and functional resilience—is a foundational indicator for evaluating regional agricultural sustainability. Its stability is instrumental not only to the operational implementation of China's national food security strategy but also to the long-term viability of regional ecological systems. Accordingly, a systematic investigation into the causal mechanisms through which population contraction influences agricultural water resource environmental carrying capacity—and the co-evolutionary pathways enabling their adaptive coordination—in Northeast China not only advances theoretical understanding of human–environment coupling systems, but also yields actionable insights for advancing high-quality agricultural development and optimizing water resource governance. This inquiry thus holds substantial scholarly value and policy relevance.

In recent years, various strategies and policies have been implemented to promote agricultural modernization, advance regional coordinated development, and ensure national food security. The academic community has conducted extensive theoretical research, empirical testing, and policy design in various areas such as water resource carrying capacity assessment, water footprint accounting, optimal allocation of agricultural water resources, and regional factor flows, achieving significant results [1–3]. Nevertheless, the prevailing literature remains largely fragmented: the majority of studies adopt a unidimensional lens—focusing exclusively on either water resource carrying capacity assessment or regional factor flows—while neglecting their structural interlinkages. Consequently, few investigations systematically examine how population decline reshapes agricultural water resource carrying capacity in both directional and quantitative terms. Crucially, the mediating roles of human capital enhancement and targeted fiscal interventions—such as subsidies for water-saving technologies or rural education investment—are seldom incorporated into analytical frameworks. First, under China's prevailing water governance paradigm—formalized as

“determining industrial output and population size by water resource endowment” the assessment and measurement of agricultural water resource carrying capacity have received extensive academic attention. Scholars have developed diverse indicator systems grounded in distinct theoretical foundations—namely, supply–demand equilibrium analysis, ecological carrying capacity theory, and coupled human–natural system frameworks—and applied rigorous quantitative methods—including system dynamics (SD) modeling, data envelopment analysis (DEA), and the DPSIR framework—to estimate agricultural water resource carrying capacity and assess water footprint efficiency [4–6]. However, the prevailing literature predominantly estimates carrying thresholds through static supply–demand matching approaches—thereby neglecting critical external drivers such as inter-basin water transfer infrastructure, sectoral industrial relocation, and cross-regional mobility of labor and capital, all of which substantially shape the adaptive capacity and structural resilience of agricultural water resource networks. Furthermore, indicator systems remain largely confined to intra-regional biophysical and socioeconomic variables, with insufficient integration of spatially explicit, network-based metrics—such as virtual water flows, inter-regional irrigation technology spillovers, or fiscal transfer dependencies—that capture the multidimensional spatial interdependence of agricultural water systems [7,8]. Second, since population evolution is key to reflecting the interaction between socioeconomic factors and resource–environmental issues, measuring population changes and assessing their impacts has become a major research focus. From the urban perspective, scholars have primarily explored population loss by examining industrial decline, aging, and urban shrinkage [9–11]. From the perspective of rural and agricultural sectors, it mainly involves issues such as land marginalization due to the outflow of young and able-bodied labor, village hollowing, and trends in agricultural production efficiency [12,13]. Overall, scholarly attention to the resource and environmental pressures induced by population expansion and rapid urbanization emerged early and has since matured considerably. In contrast, research adopting a “population shrinking” lens—particularly focused on quantifying the adaptive capacity of agricultural water resource systems in depopulating regions—remains scarce. Furthermore, critical structural consequences triggered by demographic shrinkage—including deteriorating maintenance of rural irrigation infrastructure and systemic constraints on agricultural technology adoption and diffusion—have received inadequate theoretical and empirical scrutiny, underscoring an important gap that warrants rigorous investigation and conceptual advancement. Third, some scholars have attempted to incorporate population change characteristics into the study of factors affecting agricultural water resource carrying capacity. Existing studies have primarily focused on examining the impact of factors such as total population, economic development level, and urbanization rate on agricultural water consumption and water pollution, and employ standard panel regression models to empirically test the linear or nonlinear relationships between them [14,15]. Although the aforementioned studies have conducted in-depth analyses of the relationship between population change and resources and the environment from multiple perspectives, existing research fails to accurately capture the spatial interactions and spillover diffusion effects of population decline across different regions. Moreover, few studies have explored the dynamic relationship between the two from a spatial econometric perspective, thus falling short in adequately addressing the practical question, “How exactly does population decline affect agricultural water resource carrying capacity? [16,17]”. More critically, the literature has yet to elucidate the mediating and moderating roles of institutional and human capital-based adaptation pathways—particularly human capital upgrading and targeted fiscal interventions—in shaping how population decline translates into changes in agricultural water resource carrying capacity.

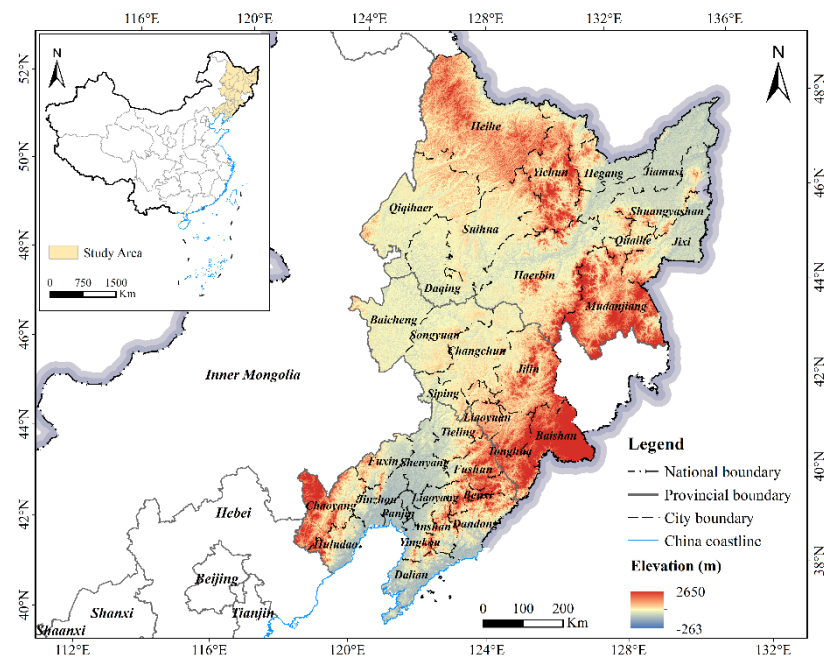


Figure 1. Map of the study area.

Based on the above background and research gaps, this study focuses on the impact of population decline on agricultural water resource environmental carrying capacity in Northeast China, integrating regional characteristics of population contraction, current status of agricultural water use, and ecological features. The research objectives are as follows: first, to scientifically measure the extent of population decline and the overall level of agricultural water resource carrying capacity across the three northeastern provinces during the study period, and to analyze their temporal changes and interaction intensity; second, to empirically examine, through econometric analysis, the overall direction and magnitude of the impact of population decline on agricultural water resource carrying capacity; third, to clarify the internal transmission mechanisms by which population decline affects agricultural water resource carrying capacity, from perspectives such as human capital and fiscal investment.

The marginal contribution of this paper is primarily reflected in the following three aspects: First, the research perspective is highly representative and typical. As a region with China's highest grain production, largest agricultural water consumption, and most severe population decline, Northeast China serves as a prototypical area. By focusing on this region, the study provides a highly representative sample for China. Second, the measurement system is more comprehensive and better aligned with the characteristics of agricultural vulnerability. Based on the DPSIR model, this study constructs an evaluation framework for agricultural water resource carrying capacity across four dimensions—drivers, pressures, state, impacts, and responses—and incorporates meteorological risk factors such as drought and flood disasters. This addresses the shortcomings of previous studies in measuring indicators of agricultural water resource carrying capacity, thereby enhancing the scientific rigor, comprehensiveness, and robustness of the assessment. Third, in constructing the theoretical framework linking population decline to agricultural water resource carrying capacity, we introduce human capital and fiscal intervention as mediating variables to examine their pathways and effects. The structure of this paper is as follows: first, it clarifies the mechanism by which population decline affects agricultural water resource carrying capacity. Second, based on panel data from 34 prefecture-level cities in Northeast China from 2010 to 2023, population contraction models and an agricultural water resource carrying capacity evaluation system were respectively constructed to sci-

tifically measure the degree of population decline and agricultural water resource carrying capacity in the region. Once again, the spatial Durbin model is employed to empirically examine the direction and extent of the impact of population decline in Northeast China on agricultural water resource carrying capacity. Finally, human capital and fiscal intervention are introduced as mediating variables to examine their mediating effects, providing empirical support for formulating regionally tailored water resource management policies and rural revitalization strategies.

2. Mechanisms by Which Population Decline Affects Agricultural Water Resource Carrying Capacity

2.1. *The Direct Effects of Population Decline on Agricultural Water Resources Carrying Capacity*

On one hand, it reduces the capacity for fine-grained water resource utilization, exacerbating the risks of water scarcity and inefficient use. Efficient use of water resources in traditional agriculture relies on precise human control over irrigation timing, volume, and coverage. Irrigation plans must be dynamically adjusted based on crop growth, soil moisture levels, and weather changes, while field irrigation ditches require regular maintenance and inspection for water leakage. This makes it a labor-intensive and highly detailed agricultural management task. After the labor supply shrinks, there is a shortage of agricultural labor in rural areas, leading farmers to commonly adopt extensive irrigation practices such as flood irrigation and excessive watering. They no longer allocate water precisely according to actual field requirements, resulting in significant water loss due to seepage, evaporation, and redundant consumption, which greatly reduces the efficiency of agricultural water use [18,19].

On the other hand, this has led to the idleness and deterioration of irrigation facilities, weakening agricultural water supply infrastructure. The continuous outflow of rural population has led to the shrinkage of agricultural production settlements, causing numerous small- and medium-sized irrigation ditches, machine wells, pumping stations, and water-saving irrigation equipment to gradually suffer from siltation, damage, aging, and functional failure due to significantly reduced usage and lack of maintenance. The widespread abandonment of small, fragmented irrigation facilities has led to the fragmentation of large-scale, contiguous irrigation systems, reducing regional water allocation capacity. Even with sufficient water reserves, efficient delivery to farmland areas is hindered, resulting in a supply–demand mismatch where “water exists but cannot be used effectively [20].” Meanwhile, population decline has led to insufficient human and financial resources for rural water management and maintenance, gradually weakening the grassroots water infrastructure operation and maintenance system. This makes it difficult to carry out facility repairs, dredging, and upgrades, accelerating the deterioration of irrigation systems (Figure 2).

In summary, this paper proposes Hypothesis H1.

H1. *Population decline in the northeastern region will reduce agricultural water resource carrying capacity.*

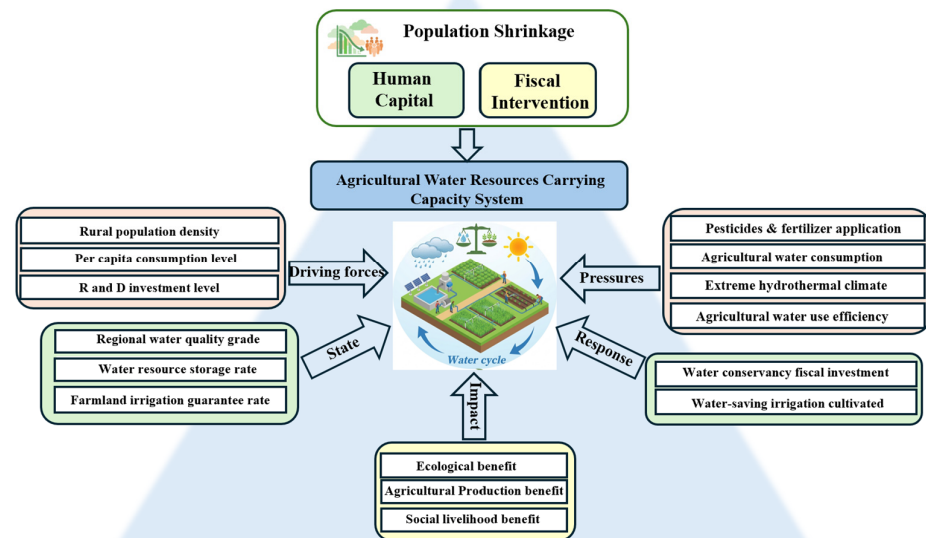


Figure 2. Theoretical mechanism diagram.

2.2. The Indirect Effects of Population Decline on Agricultural Water Resources Carrying Capacity

(1) Human Capital Depletion Pathway

Human capital is a key factor in enhancing water resource management capacity and optimizing resource allocation. The higher the level of human capital, the better it can buffer the negative impact of population decline on agricultural water carrying capacity, creating a compensatory effect: “human capital substitutes for labor quantity—improves water use efficiency—stabilizes carrying capacity.”

On one hand involves enhancing human capital to improve labor quality, offsetting the shortage of labor force, and strengthening the capacity for fine-grained water resource management [21]. Population decline in Northeast China stems predominantly from labor force attrition, not from systemic human capital erosion. High human capital labor force—farmers and new business entities trained in agriculture, knowledgeable about water-saving technologies, and skilled in water management—possesses stronger learning ability, technological adaptability, and management capabilities. On one hand, a workforce with high human capital can quickly master water-saving irrigation technologies and optimize irrigation systems, substituting quality for quantity. This enables the maintenance or even improvement of fine-grained field water management levels despite a declining total labor force, thereby reducing water conveyance losses and ineffective water consumption. On the other hand, focusing on leveraging human capital can improve resource use efficiency and strengthen ecological stewardship, thereby curbing the intensification of extensive land and water use triggered by demographic contraction and attenuating the associated decline in agricultural water resource carrying capacity. Under demographic contraction, labor with low human capital is prone to short-term behavioral responses—including unsustainable groundwater abstraction, non-optimal irrigation scheduling, and excessive agrochemical application—which intensify water scarcity and accelerate aquatic ecosystem degradation. High human capital laborers possess stronger environmental protection awareness and sustainable development concepts, enabling them to balance agricultural production with water resource conservation by reasonably controlling groundwater extraction intensity, adopting site-specific fertilizer application to reduce non-point source pollution, and actively participating in the maintenance of water infrastructure, thus promoting both efficient water use and ecological protection in tandem [22]. Higher levels of human capital are associated with more systematic and evidence-informed resource

utilization and ecological stewardship practices, thereby attenuating the intensification of extensive land and water use induced by demographic contraction and sustaining the resilience of agricultural water resource carrying capacity (Figure 2). This study formally posits Hypothesis H2:

H2. *Higher human capital attenuates the adverse impact of population decline on agricultural water resource carrying capacity.*

(2) Fiscal Intervention Pathway

Fiscal intervention is a crucial policy tool for addressing market failures, overcoming population decline, and enhancing water resource support capacity. The greater the extent of fiscal intervention, the more likely it is to mitigate the negative impact of population contraction on agricultural water resource carrying capacity.

In the first phase, fiscal intervention targets critical deficiencies in irrigation infrastructure and restores institutional capacity for routine maintenance eroded by demographic contraction. Under the backdrop of population decline, rural collectives and households lack the capacity to bear the construction and maintenance costs of large- and medium-scale water conservancy facilities, irrigation district upgrades, and water-saving projects, resulting in aging and deteriorating infrastructure, reduced water conveyance efficiency, and constraints on enhancing agricultural water resource carrying capacity. Fiscal interventions have increased investment in agricultural water conservancy in Northeast China through special water resources funds, subsidies for irrigation district renovations, and subsidies for purchasing water-saving equipment [23]. On the hand, fiscal resources are directed toward the construction of high-standard farmland irrigation systems, rehabilitation of aging canal networks, and modernization of groundwater extraction infrastructure—thereby reducing conveyance losses and strengthening water supply resilience. On the other hand, procurement subsidies for high-efficiency water-saving technologies lower adoption thresholds for smallholder farmers, mitigate labor-constrained extensive irrigation practices, and reinforce the hardware foundation of agricultural water system resilience.

In the second phase, fiscal interventions will optimize water resource allocation and incentive mechanisms, alleviate organizational weakening and insufficient investment caused by population decline, and continuously buffer the pressure of declining carrying capacity. Fiscal interventions not only focus on hardware infrastructure development but also guide agricultural producers to adopt proper water use practices and participate in water resource conservation through policies such as agricultural subsidies, water resource management incentives, and ecological compensation. Provide financial incentives to entities engaged in water-saving irrigation, water recycling, and ecological water conservation to encourage farmers to proactively optimize their water use practices. Support the development of new business entities such as rural cooperatives and agricultural enterprises, promote large-scale operations and integrated water resource management, and address the issue of organizational hollowing caused by population decline. Scaling up targeted fiscal investment in groundwater over-exploitation zones and ecologically fragile watersheds will arrest ecological degradation trends and rehabilitate natural water retention capacity [24] (Figure 2). Greater fiscal intervention strengthens institutional capacity to offset population-driven deficits in financial resources, organizational coherence, and managerial capability—thereby mitigating water supply–demand imbalances and ecological stress while sustaining and incrementally enhancing agricultural water carrying capacity.

H3. *Higher fiscal intervention attenuates the adverse impact of population decline on agricultural water resource carrying capacity.*

3. Methodology and Data Sources

3.1. Research Methodology

3.1.1. Population Decline Measurement

According to the definition of population contraction, registered population data offer advantages such as continuity and consistent statistical methodology. Therefore, this study selects registered population data for prefecture-level cities in Northeast China from 2010 to 2023, based on existing research, to measure the degree of population contraction [25]. The calculation formula is:

$$Shrink = - \left(\ln \frac{pop_{ij}}{pop_{ij_0}} \right) \times 100\% \quad (1)$$

In the formula, pop_{ij} represents the population data of the region in year i and pop_{ij_0} denotes the population data for the base year, which is set at 2009 in this study. $Shrink > 0$ signifies population decline, with magnitude directly reflecting the intensity of shrinkage; conversely, $Shrink < 0$ indicates population growth, with absolute magnitude indicating the intensity of growth.

3.1.2. Evaluation Framework for Agricultural Water Resource Carrying Capacity

The establishment of a scientifically grounded and methodologically robust evaluation indicator system constitutes a critical prerequisite for the accurate assessment of agricultural water resource carrying capacity. Grounded in systems ecology, the DP-SIR (driving forces–pressures–states–impacts–responses) framework offers a theoretically coherent and empirically adaptable methodological foundation for analyzing complex human–water interactions [26–28]. This framework systematically decomposes the complex resource–environment system into five analytically distinct, quantitatively measurable, and policy-actionable components through a fully articulated causal chain: “source—process—outcome—feedback.” The specific operational pathway is outlined below.

The driving forces dimension captures the fundamental socioeconomic, institutional, and biophysical drivers that initiate and sustain long-term changes in agricultural water resource carrying capacity. Population, as a fundamental element of socioeconomic activities, may influence the scale and structure of agricultural water use through its size, distribution, and consumption patterns [29]. This study selects agricultural population density, per capita rural consumption level, and the ratio of R&D expenditure to R&D personnel to accurately capture the comprehensive driving forces behind agricultural water resource carrying capacity. The pressure dimension: agricultural water resource carrying pressure arises from the combined effects of water consumption intensity, water resource load, and extreme climate events. This paper defines pressure as specifically including agricultural water consumption, intensity of agricultural water resource development, intensity of fertilizer application, intensity of pesticide use, and external shocks to agricultural water supply caused by extreme weather events, and together form a multidimensional pressure matrix for the agricultural water resources system. The status dimension, reflecting the quantity and quality of water resource systems, directly determines the sustainability of agricultural production by clearly indicating the water volume status and operational level of agricultural water systems [30]. This article specifically includes total water resources, irrigation reliability, surface water quality meeting or exceeding Class III standards, and reservoir storage rate, thereby comprehensively presenting the overall status of agricultural water resource carrying capacity [31]. The condition of water resource carrying capacity directly affects agricultural production stability, household livelihood security, and ecosystem health [32]. Specifically, this includes the proportion of disaster-affected areas,

the proportion affected by floods, grain yield per unit area, and per capita disposable income in rural areas, which together form the transmission chain of agricultural water resource carrying capacity. The response dimension focuses on government, market, and societal interventions and adjustments to agricultural water resource carrying capacity. This study selects water-saving irrigation area [33], the proportion of agricultural, forestry, and water expenditures, and investment in agricultural water conservancy construction to accurately assess the effectiveness of various measures in enhancing agricultural water resource carrying capacity.

Based on the DPSIR model, this study constructs an evaluation index system for agricultural water resource carrying capacity, comprising five objective layers—driving force, pressure, state, impact, and response—six indicator layers, and 20 specific indicators. Compared with subjective weighting methods such as AHP, the entropy weight method determines weights based on the inherent data dispersion, thereby avoiding human subjectivity and bias, resulting in more objective and reliable evaluation outcomes. It has now been widely applied in research on water resource carrying capacity assessment [34]. The weights of each indicator were calculated using the entropy weight method, as shown specifically in Table 1.

Table 1. Evaluation index system based on the DPSIR model.

Target Layer	Indicator Layer	Specific Indicators	Direction	Weight
Driving forces	Social drivers	Agricultural population density	—	0.0032
		Rural per capita consumption expenditure	+	0.0128
		R&D expenditure/R&D personnel count	+	0.0492
Pressures	Water consumption	Agricultural water consumption	—	0.0047
		Rate of agricultural water resource development and utilization	+	0.0950
	Water resource load	Agricultural fertilizer application intensity	—	0.0049
		Pesticide application intensity	—	0.0003
	Ecological pressure	Extreme precipitation	—	0.0037
State	Water level status	Extreme heat	—	0.0050
		Total water resources	+	0.5602
		Irrigation reliability	+	0.0080
		Proportion of surface water quality meeting or exceeding Class III standards	+	0.0169
		Storage rate: reservoir capacity/number of reservoirs	+	0.0639
Impacts	Ecological Impact	Proportion of drought-affected Area	—	0.0095
		Proportion of flood-affected area	—	0.0059
	Production impact	Grain yield per hectare	+	0.0635
	Social Impact	Rural per capita disposable Income	+	0.0181
Responses	Technical Response	Area equipped for water-saving irrigation	+	0.0158
	Financial Response	Proportion of agricultural, forestry, and water expenditures	+	0.0444
		Investment in agricultural and water conservancy infrastructure	+	0.0150

3.1.3. Spatial Econometric Modeling and Estimation

Assessment of Spatial Autocorrelation

To analyze the geographical distribution of agricultural water resource carrying capacity, this study employs the global *Moran's I* to calculate its spatial autocorrelation, as shown in the following formula:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (2)$$

In Equation (2), *I* is the global Moran's index, W_{ij} is the spatial weight matrix. This study investigates the spatial interactions among cities by constructing a reverse geographic distance matrix, with spatial contiguity defined based on the Euclidean distances between the geographic centroids of each city [35]. Y_i and Y_j are the values of *Y* at the respective spatial units *i* and *j*, $\bar{Y}$ is the mean value of *Y*, *n* is the total number of provinces (cities, autonomous regions), and *i* and *j* represent different provinces (cities, autonomous regions). The range of Moran's *I* index is $[-1, 1]$. If *Moran's I* is greater than 0, it indicates positive spatial autocorrelation, and the larger the value, the more pronounced the spatial correlation. If *Moran's I* is less than 0, it indicates negative spatial autocorrelation, and the smaller the value, the more pronounced the spatial dispersion; if *Moran's I* equals 0, it suggests a random spatial pattern.

Spatial Durbin Model Specification

This study employs a spatial Durbin model based on spatiotemporal dimensions to examine the impact of population decline on agricultural water resource carrying capacity. Specifically, the level of agricultural water resource carrying capacity serves as the dependent variable, population decline as the core independent variable, and urbanization level, economic development level, labor input intensity, and crop structure as control variables. Based on previous studies [36], the spatial Durbin model is constructed as follows:

$$Y_{it} = \alpha_i + \rho \sum_{j=1}^n W_{ij} Y_{jt} + \beta X_{it} + \varphi \sum_{j=1}^n W_{jt} X_{jt} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

In Equation (3), *i* and *j* represent different provinces, *t* represents different years, Y_{it} is the value of the dependent variable in period *t* for unit *i*, namely the agricultural water resource carrying capacity score (AWS) for each city or region; X_{it} is the value of the independent variable in period *t* for unit *i*; W_{ij} is the spatial weight matrix; ρ , β , and φ are the respective regression coefficients; μ_i and δ_t denote spatial and time fixed effects, respectively; and ε_{it} is the random error term.

Mediation Effect Model Specification

To further explore the pathways through which population decline in Northeast China affects sustainable agricultural water use, a mediation model was constructed using stepwise regression [37] based on the baseline regression. The model is specified as follows:

$$\begin{aligned} AWS_{it} &= \alpha_0 + \beta_0 Shrink_{it} + \gamma_0 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \\ M_{it} &= \alpha_1 + \beta_1 Shrink_{it} + \gamma_1 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \\ AWS_{it} &= \alpha_2 + \beta_2 Shrink_{it} + \mu M_{it} + \gamma_2 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \quad (4)$$

3.2. Variable Selection and Data Sources

3.2.1. Variable Selection

In terms of variable selection, this study uses the degree of population decline as the explanatory variable (measured by the population shrinkage rate over a certain period),

and agricultural water resource carrying capacity as the core dependent variable (measured using the entropy method based on a DPSIR model). Regarding mechanism variables, based on the theoretical analysis in the preceding section, this paper identifies two aspects: human capital endowment, proxied by the ratio of higher education enrollment to regional population [38]; the degree of fiscal intervention is measured by government fiscal expenditure [39]. Five control variables were selected from four dimensions—economic, natural, human, and production—including urbanization level, per capita GDP, labor input intensity, and crop structure. The definitions of these variables are shown in Table 2.

Table 2. Indicator definitions for determinants of agricultural water carrying capacity.

Classification	Name	Symbol	Variable Explanation
Dependent variable	Agricultural water carrying capacity	<i>AWS</i>	DPSIR-based entropy measure
Explanatory variable	population shrinkage	<i>Shrink</i>	Rate of change in registered population
Mediating variable	Level of human capital	<i>HCL</i>	Higher education enrollment/year-end population
Control variables	Fiscal intervention	<i>Fis</i>	Government fiscal expenditure
	Urbanization rate	<i>Urb</i>	Level of urbanization
	Level of economic development	<i>GDP</i>	GDP per capita
	Total water resources	<i>TWR</i>	Logarithm of total water resources Agricultural, forestry, animal husbandry, and
	Labor intensity	<i>LII</i>	fishery workers/effective irrigated area
	Cropping structure	<i>PS</i>	Rice sown area/total crop sown area

3.2.2. Study Area and Data Sources

The empirical analysis employs a balanced panel of 34 prefecture-level cities located in Heilongjiang, Jilin, and Liaoning provinces—the three constituent provinces of Northeast China—as the study sample (see Figure 1), spanning the period 2010–2023. The research data are sourced from the China Statistical Yearbook, China Urban Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Yearbook, Heilongjiang Statistical Yearbook, Jilin Statistical Yearbook, Liaoning Statistical Yearbook, EPS database, and CN-RDS database. For missing data from certain years, linear interpolation using adjacent years was applied for smoothing. Descriptive statistics of the main variables are shown in Table 3.

Table 3. Descriptive statistical analysis.

Variable	Observations	Mean	Std.Dev	Min	Max
<i>AWS</i>	476	0.131	0.043	0.052	0.715
<i>Shrink</i>	476	0.045	0.064	−0.121	0.494
<i>Tech</i>	476	216.225	463.015	1	2446
<i>HCL</i>	476	0.016	0.017	0.011	0.097
<i>Fis</i>	476	286.579	239.528	47.3	1162.2
<i>Urb</i>	476	0.574	0.157	0.247	0.917
<i>GDP</i>	476	46,287.809	22,957.888	12,576	148,209
<i>TWR</i>	476	3.426	1.048	0.358	11.026
<i>LII</i>	476	0.074	0.2	0.001	1.455
<i>PS</i>	476	0.205	0.235	0	1.599

4. Results Analysis

4.1. Descriptive Analysis of Population-Declining Regions

As illustrated in Figure 3, between 2010 and 2023, the three northeastern provinces of China experienced a structural demographic transition—from modest population growth to persistent negative change—accompanied by an accelerating rate of decline and pronounced interprovincial divergence. In 2010, the population change rates across all three northeastern provinces were nearly zero, reflecting demographic stability at the regional level. Thereafter, the region transitioned progressively into sustained negative population growth, with Heilongjiang Province exhibiting the most pronounced decline in absolute and relative terms. The population change rate declined steadily from -0.0014 in 2010 to -0.140 in 2023, reflecting both an expanding absolute volume of out-migration and the steepest average annual decline among the three provinces. Jilin Province exhibits a population decline trajectory closely aligned with that of Heilongjiang, as its population change rate decreased from -0.0001 in 2010 to -0.126 in 2023. A marked acceleration in contraction occurred between 2019 and 2020—evidenced by a pronounced spike in net out-migration—resulting in a transient but substantial intensification of demographic outflow pressure. By contrast, Liaoning Province has sustained the mildest population contraction among the three provinces, registering a population change rate of -0.060 in 2023—nearly half that of Heilongjiang (-0.140) and Jilin (-0.126)—thereby demonstrating comparatively greater demographic resilience. Collectively, the Northeast region has entered a phase of sustained population decline, characterized by progressively widening interprovincial disparities in net out-migration. On one hand, the industrial restructuring of the northeastern old industrial base has led to structural unemployment, prompting a large number of young and middle-aged workers to continuously migrate across provinces to the developed coastal regions in the southeast in pursuit of higher wages, thereby creating a sustained outward population flow. On the other hand, the region's natural population growth rate has remained low for a long time, and the outmigration primarily consists of young and working-age individuals in their reproductive years, continuously weakening the region's potential for natural population reproduction. Under the combined effects of push factors from inland areas and pull factors from coastal employment opportunities, population decline in China's three northeastern provinces has continued to intensify.

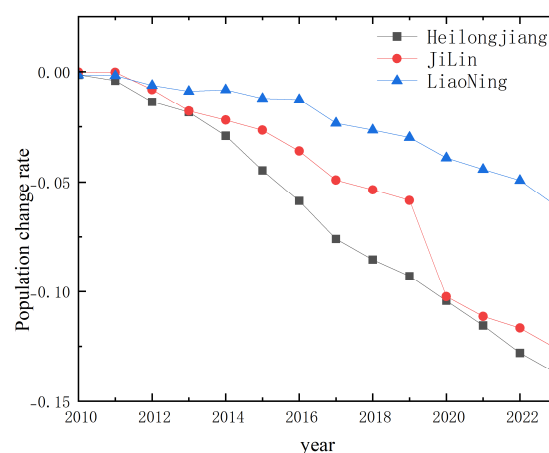


Figure 3. Population decline trend in the three northeastern provinces.

As shown in Table 4, from 2010 to 2023, the population in cities across Northeast China gradually shifted from slight growth to overall decline, with urban differentiation within the region continuing to intensify. In 2010, population contraction rates across most cities were generally close to zero, with cities such as Shenyang, Dalian, and Changchun

recording negative values, still maintaining net population inflow. Even in other cities where population decline has occurred, the magnitude has been extremely slight. In 2017, population decline spread across the entire region, with northern Heilongjiang and western Jilin experiencing the sharpest increase in contraction rates. Liaoning as a whole saw relatively stable changes, while Shenyang and Dalian remained the only cities in the region showing population growth. In 2023, the contraction rate in most cities rose to a high level, with the average population decline across regions reaching its peak for the period. The top five cities in terms of contraction are all located in Heilongjiang Province, with resource-depleted cities such as Qitaihe and Yichun experiencing the most severe shrinkage. Shenyang, Dalian, Changchun, Harbin, and Panjin have experienced the smallest population declines, with Shenyang and Dalian maintaining positive population growth consistently. Overall, small- and medium-sized resource-based cities are experiencing faster population outflows, while provincial capitals and coastal central cities demonstrate stronger resilience in population agglomeration. Population decline in the northeastern region exhibits clear hierarchical differentiation characteristics.

Table 4. Spatial evolution characteristics of annual population shrinkage rate from 2010 to 2023.

	2010	2017	2023
Harbin	−0.0004	0.0376	0.0586
Qiqihar	0.0061	0.0686	0.1159
Mudanjiang	0.0063	0.0601	0.1276
Jiamusi	0.0012	0.0758	0.1240
Daqing	0.0013	0.0085	0.0697
Jixi	0.0078	0.0857	0.1696
Hegang	0.0028	0.0805	0.1571
Shuangyashan	−0.0051	0.0582	0.1137
Yichun	0.0028	0.0936	0.1943
Qitaihe	−0.0010	0.1658	0.2328
Heihe	0.0050	0.0819	0.1470
Suihua	−0.0102	0.0951	0.1378
Changchun	−0.0031	0.0101	−0.1137
Jilin	0.0004	0.0444	0.0960
Siping	−0.0042	0.0568	0.4937
Liaoyuan	0.0002	0.0482	0.0975
Tonghua	0.0030	0.0435	0.0913
Baishan	0.0079	0.0819	0.1592
Songyuan	−0.0059	0.0458	0.0696
Baicheng	0.0026	0.0620	0.1143
Shenyang	−0.0043	−0.0281	−0.0641
Dalian	−0.0028	−0.0171	−0.0403
Anshan	0.0007	0.0232	0.0756
Fushun	0.0077	0.0550	0.1314
Benxi	0.0055	0.0519	0.1194
Dandong	0.0053	0.0311	0.0768
Jinzhou	0.0061	0.0458	0.1085
Yingkou	−0.0021	0.0139	0.0441
Fuxin	−0.0006	0.0321	0.0844
Liaoyang	0.0004	0.0388	0.0870
Panjin	−0.0095	0.0032	0.0117
Tieling	0.0030	0.0412	0.1056
Chaoyang	0.0099	0.0180	0.0604
Huludao	0.0018	0.0190	0.0549

4.2. Regional Characteristics of Agricultural Water Resource Carrying Capacity

Figure 4 illustrates a sustained upward trend in agricultural water resources carrying capacity across the Northeast China region between 2010 and 2023. Overall, in 2010, the agricultural water resource carrying capacity in the northeastern region was generally low, with most cities falling within the lower range. By 2017, agricultural water resources carrying capacity had improved markedly in several jurisdictions, and the spatial extent of medium- to high-capacity zones expanded progressively. By 2023, the spatial coverage of high-capacity zones had expanded further, reflecting measurable progress across the study period in three key domains: agricultural water conservation, modernization of farmland irrigation infrastructure, and integrated agricultural water resource management—collectively enhancing the resilience and functional capacity of the regional agricultural water system. Across cities, the magnitude of improvement in agricultural water resources carrying capacity exhibits pronounced spatial heterogeneity. Provincial capitals and coastal core cities witnessed the most prominent improvement in carrying capacity during the study period: Panjin and Harbin registered the largest growth increments, with their values rising to 0.2091 and 0.1948, respectively. Qiqihar, Jiamusi, Dandong, Fuxin and Liaoyang also achieved considerable growth and maintained robust upward momentum. Although resource-based cities including Mudanjiang, Daqing, Yichun and Qitaihe likewise experienced overall increases, their growth ranges were far lower than those of central cities. This indicates that the evolution of agricultural water resource carrying capacity varies across cities, and the extent of change is closely related to agricultural infrastructure, the level of irrigation facility development, water-saving technology application capabilities, and resource management efficiency.

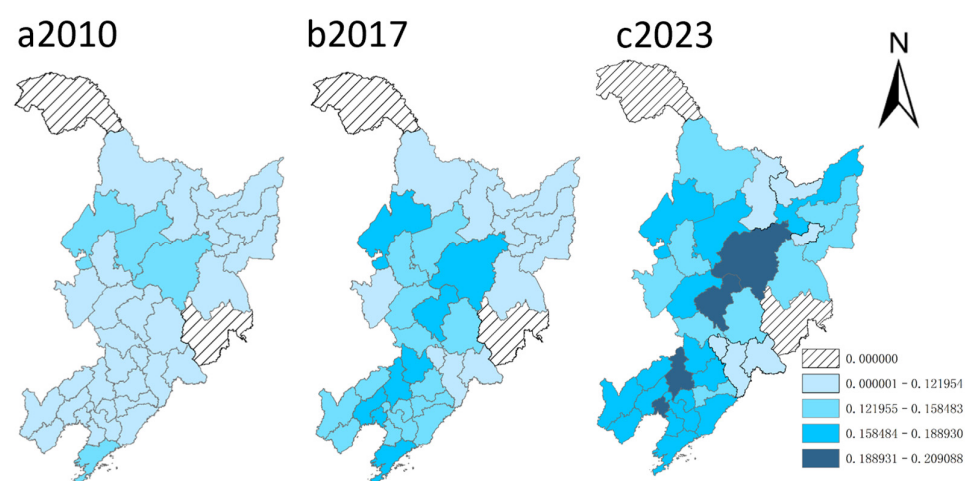


Figure 4. Spatial evolution of agricultural water carrying capacity.

Spatially, agricultural water resources carrying capacity in Northeast China continues to display pronounced regional disparity, characterized by the co-occurrence of high-value agglomeration and low-value concentration—particularly evident in core agricultural counties and ecologically fragile zones, respectively. Overall, although the agricultural water resource carrying capacity has continued to improve, regional disparities have not been fundamentally eliminated. In the future, further efforts are still needed in low-performing areas to strengthen farmland irrigation infrastructure, promote agricultural water-saving technologies, and implement refined management of agricultural water resources, in order to achieve a more balanced enhancement of agricultural water resource carrying capacity in Northeast China.

4.3. Impact of Population Decline on Agricultural Water Resources Carrying Capacity: Empirical Evidence and Mechanism Analysis

4.3.1. Spatial Autocorrelation Analysis of Agricultural Water Resources Carrying Capacity

Before conducting spatial econometric analysis, this study calculated Moran's I for agricultural water resource carrying capacity using an inverse geographic distance matrix to test for spatial autocorrelation. The results show that the Moran's I values for agricultural water resource carrying capacity are all positive and significant at the 1% level, indicating a significant spatial correlation (Table 5). Therefore, a spatial econometric model can be employed for further empirical testing and analysis.

Table 5. Moran's I statistics for agricultural water (2010–2023).

Year	I	$E(I)$	$Sd(I)$	Z	p
2010	0.024	−0.030	0.031	1.754	0.040
2011	0.045	−0.030	0.031	2.400	0.008
2012	0.024	−0.030	0.031	1.737	0.041
2013	0.123	−0.030	0.032	4.863	0.000
2014	0.108	−0.030	0.031	4.403	0.000
2015	0.060	−0.030	0.030	3.012	0.001
2016	0.137	−0.030	0.032	5.275	0.000
2017	0.149	−0.030	0.032	5.692	0.000
2018	0.011	−0.030	0.012	3.376	0.000
2019	0.061	−0.030	0.031	2.907	0.002
2020	0.089	−0.030	0.031	3.793	0.000
2021	0.097	−0.030	0.032	4.051	0.000
2022	0.088	−0.030	0.032	3.762	0.000
2023	0.073	−0.030	0.031	3.297	0.000

4.3.2. Regression Results of Spatial Econometric Models

First, the validity of the spatial Durbin model adopted in this paper is examined through an LM test, LR test, Wald test, and Hausman test, demonstrating that the SDM model outperforms the OLS model and confirming that the SDM model does not degenerate into either the SAR or SEM model. The regression results based on the spatial and temporal double fixed-effects SDM model are reasonable. After including control variables, both the significance and direction of the core explanatory variables remain unchanged, indicating that the inclusion of control variables is appropriate. Therefore, the following analysis will focus in detail on the SDM model with control variables included.

As presented in column (2) of Table 6, the coefficient on the core explanatory variable—degree of population contraction—is negative and statistically significant at the 1% level, indicating that population contraction exerts a robust adverse effect on agricultural water resource carrying capacity. Meanwhile, the spatial lag coefficient of the explanatory variable also significantly negatively affects agricultural water resource carrying capacity at the 1% level. Population decline in the northeastern region exerts a statistically significant negative impact on agricultural water resource carrying capacity. One possible reason is that, on one hand, continuous population decline—especially the outflow of young and working-age labor—leads to a “hollowing-out” phenomenon in rural areas, directly resulting in inadequate maintenance and halted repairs of small- and medium-sized agricultural water infrastructure, thereby reducing the efficiency of water resource allocation and utilization. On the other hand, population decline constrains the diffusion and adoption of agricultural water-saving technologies, thereby attenuating the marginal productivity gains from technological advancement and exerting downward pressure on agricultural water resource carrying capacity.

Table 6. SDM model regression results.

Variable	(1)	(2)
<i>Shrink</i>	−0.0636 **	−0.0515 ***
<i>Urb</i>		0.0214 *
<i>GDP</i>		0.0000 *
<i>TWR</i>		0.0423 ***
<i>LII</i>		0.0065
<i>PS</i>		0.0099
<i>W * Shrink</i>	−0.5179 ***	−0.3698 ***
<i>W * Urb</i>		0.0197
<i>W * GDP</i>		−0.0000 **
<i>W * TWR</i>		−0.0895 ***
<i>W * LII</i>		0.0045
<i>W * PS</i>		0.0447
<i>Moran's I</i>	20.414 ***	21.119 ***
<i>LR(lag)test</i>	372.810 ***	359.472 ***
<i>Robust LM(lag)test</i>	75.712 ***	36.110 ***
<i>LM(error)test</i>	382.392 ***	399.251 ***
<i>Robust LM(error)test</i>	85.294 ***	39.789 ***
<i>Wald test spatial lag</i>	7.70 ***	218.09 ***
<i>LR test spatial lag</i>	48.64 ***	87.64 ***
<i>Wald test spatial error</i>	7.02 ***	113.63 ***
<i>LR test spatial error</i>	283.90 ***	581.26 ***
<i>Hausman test</i>	3.79	73.50 ***
<i>Spatial – rho</i>	−0.4929 **	0.4883 ***
<i>Variance – sigma</i>	0.0006 ***	0.0002 ***
<i>Observations</i>	476	476
<i>Number of id</i>	34	34

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

In the control variables, the regression coefficient for urbanization level is positive and significant at the 10% level, indicating that higher urbanization levels have a certain positive effect on agricultural water resource carrying capacity. One plausible mechanism is that, as urbanization progresses, the outmigration of rural labor from agricultural areas enables moderate-scale land consolidation, thereby promoting the intensification and operational efficiency of irrigation infrastructure. On the other hand, the inflow of capital and technology brought by urbanization provides material support for the upgrading and renovation of agricultural water-saving irrigation facilities. The regression coefficient for economic development level is positive and significant at the 10% level, indicating that improved economic conditions significantly and positively affect agricultural water resource carrying capacity. One plausible explanation is that economically advanced regions possess greater fiscal capacity, facilitating sustained public and private investment in water-saving agricultural technologies and intelligent water resource management systems—thereby accelerating the transition of water use patterns from extensive and low-productivity to intensive and high-efficiency regimes.

4.3.3. Regression Results from the Heterogeneous Spatial Econometric Model

Given the significant differences among the three northeastern provinces in terms of population decline, economic development levels, and agricultural structures, the impact of population contraction on agricultural water resource carrying capacity may exhibit regional heterogeneity. To identify this heterogeneity, this paper conducts in-depth analysis from two dimensions: “administrative divisions” and “degree of population decline.”

(1) Analysis of Provincial Spatial Heterogeneity Based on Administrative Divisions

The regression results in Table 7 show that the impact of population decline on agricultural water resource carrying capacity varies significantly across different provinces, differing both in direction and intensity. This confirms that the population contraction effect has a critical threshold: mild population decline may drive improvements in agricultural water efficiency, but once the threshold is exceeded, it leads to a comprehensive deterioration of the carrying system. Heilongjiang Province has long surpassed the critical point and is now in a severe phase of population decline. The coefficient of population contraction, the core explanatory variable, significantly negatively affects agricultural water resource carrying capacity at the 1% level. One plausible explanation is that Heilongjiang Province—the most severely depopulated and oldest-aging marginal province in Northeast China—has experienced population decline exceeding the agricultural system’s intrinsic resilience threshold. The steep contraction in labor supply, coupled with persistent fiscal strain at the local government level, has precipitated systemic underinvestment in the operation and maintenance of large-scale agricultural water infrastructure, thereby triggering a sharp and sustained decline in water use efficiency. Jilin Province is in a “buffer period” approaching the critical point. The coefficient of population contraction, the core explanatory variable, significantly negatively affects agricultural water resource carrying capacity at the 5% level. The population decline in Jilin Province has begun to exert a restraining effect on water resource carrying capacity, but the absolute value of its coefficient is smaller than that of Heilongjiang Province. One plausible explanation is that Jilin Province’s topographically homogeneous and spatially consolidated landscape facilitates large-scale mechanized agriculture. As a result, the province can partially mitigate the adverse effects of population decline on agricultural water resource carrying capacity through technological adaptation—particularly in response to the sustained outmigration of rural youth and able-bodied workers. Liaoning Province is experiencing a “mildly catalytic” phase of population decline—in marked contrast to Heilongjiang Province, where the coefficient of the primary explanatory variable exhibits a statistically significant negative effect on agricultural water resource carrying capacity at the 5% level, Liaoning’s corresponding coefficient is positive and significant at the same threshold. A plausible explanation is that Liaoning Province hosts major urban centers—including Shenyang and Dalian—that are among the only metropolitan areas in Northeast China experiencing sustained net population inflow, thereby substantially alleviating aggregate demographic contraction at the provincial level. On the other hand, Liaoning Province has a solid industrial foundation; the appropriate outflow of rural labor has accelerated land circulation and driven the transformation toward agricultural modernization, thereby enhancing the carrying capacity of agricultural water resources in the process.

(2) Heterogeneity Analysis Based on the Degree of Contraction

This study further calculates the multi-year average population contraction rate of prefecture-level cities during the research period. After strictly excluding three cities with absolute population growth, the remaining 31 shrinking cities are divided into “severe contraction zones (17 cities)” and “mild contraction zones (14 cities)” based on the median value [40], for heterogeneity analysis. From columns (3) and (4) of Table 7, in the mild contraction area, the coefficient for the core explanatory variable population contraction is 0.1420, which is significant at the 10% statistical level. This indicates that, after eliminating the confounding effect of growing cities, moderate population loss indeed has a positive impact on local agricultural water resource carrying capacity, confirming the objective existence of “early-stage contraction benefits.” The underlying economic logic is that, in the early stages of contraction, those who leave are primarily hidden surplus labor within agriculture; their exit not only directly reduces rigid water consumption associated with rural livelihoods and extensive farming. However, upon exceeding the critical threshold and

entering the severe contraction regime, the effect of population contraction on agricultural water resource carrying capacity reverses in sign and magnitude: the coefficient of the core explanatory variable is “−0.1352” and statistically significant at the 1% level. This indicates that severe population outflow has precipitated irreversible rural hollowing. The acute scarcity of young and working-age labor—the primary agents of on-farm management and infrastructure maintenance—has triggered systemic deterioration of agricultural water infrastructure, eroded the endowment of key production factors, diminished water use efficiency, and thereby constrained the carrying capacity of agricultural water resources.

Table 7. Heterogeneous regression results.

Variable	(1) Helongjiang	(2) Jilin	(3) Liaoning	(4) Mild Constriction	(5) Severe Contraction
<i>Shrink</i>	−0.1893 ***	−0.0234 **	0.2673 ***	0.1420 *	−0.1352 ***
<i>Urb</i>	0.0075	0.0255	0.0539 **	0.0052	0.0288
<i>GDP</i>	0.0000 ***	−0.0000 ***	−0.0000	0.0000	−0.0000
<i>TWR</i>	−0.0005	0.0025	0.0507 ***	−0.0035 **	0.0508 ***
<i>LII</i>	0.0088	0.0283	−0.0785 *	−0.0695 ***	0.0212
<i>PS</i>	0.0058 **	0.0080	−0.0932	−0.1472 ***	0.0072
<i>W * Shrink</i>	−0.6041 ***	0.0234 *	2.4152 ***	−1.0553 **	−0.5432 ***
<i>W * Urb</i>	0.0919	0.0585	0.1154	0.0813	−0.0987
<i>W * GDP</i>	−0.0000	−0.0000 ***	−0.0000 **	0.0000 *	0.0000
<i>W * TWR</i>	−0.0138	0.0056	−0.0303 *	0.0263 ***	−0.0823 ***
<i>W * LII</i>	0.0074	0.0586	−0.4056	−0.3630 ***	0.1109
<i>W * PS</i>	0.0958 ***	−0.0582	1.6482 **	−0.9493 ***	−0.0277
<i>Spatial – rho</i>	−1.4778 ***	−0.9328 ***	0.0154	−1.2235 ***	0.0690
<i>Variance – sigma</i>	0.0000 ***	0.0000 ***	0.0002 ***	0.0000 ***	0.0002 ***
<i>Observations</i>	168	112	196	196	238
<i>Number of id</i>	12	8	14	14	17

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.3.4. The Influence Path of Mechanism Variables

To further identify the underlying causal mechanisms through which population contraction influences agricultural water resource carrying capacity, this study estimates a formal mediation model with human capital (*HCL*) and fiscal intervention (*Fis*) as endogenous mediating variables. Full-sample estimation results are reported in Table 8. In terms of goodness of fit, the mediation model with control variables clearly outperforms the model without control variables; therefore, the following analysis focuses on the results obtained after including the control variables.

Table 8. Mechanism path results analysis.

	(1) <i>HCL</i>	(2) <i>AWS</i>	(3) <i>Fis</i>	(4) <i>AWS</i>
<i>Shrink</i>	0.0230 ***	0.0726 ***	150.2037 **	0.0801 ***
<i>Tech</i>				
<i>HCL</i>		0.9067 ***		
<i>Fis</i>				0.0001 ***
<i>Controls</i>	YES	YES	YES	YES
<i>Constant</i>	0.0115 ***	−0.0614 ***	−97.2029 **	−0.0422 ***
<i>Observations</i>	476	476	476	476
<i>R – squared</i>	0.116	0.460	0.269	0.486
<i>adj – R²</i>	0.0370	0.411	0.203	0.439
<i>F</i>	9.546	52.98	26.67	58.85

Note: *** and ** denote significance at the 1% and 5% levels, respectively.

At the overall sample level, population decline affects agricultural water resource carrying capacity not through a single direct channel, but via multiple pathways. Overall, human capital and fiscal interventions have to some extent mitigated this negative impact. First, along the human capital pathway, the regression results reveal a significant positive buffering effect. The underlying mechanism is labor reallocation under demographic contraction: surplus rural labor—particularly workers lacking modern agricultural skills—is disproportionately displaced, resulting in compositional upgrading among the residual farming population toward more capable, institutionalized operators—including large-scale grain producers and family farms. In this context, human capital enhancement extends beyond a passive rise in mean educational attainment to encompass demonstrable improvements in farm-level managerial capacity, water use efficiency literacy, and collective action competencies. This localized structural upgrading of farm-level operators—driven by specialized, input-efficient irrigation management—functions as a partial quality-based offset to labor-force contraction, thereby attenuating, albeit incompletely, the adverse effect of population decline on agricultural water resource carrying capacity.

Second, in terms of fiscal intervention, local governments' counter-cyclical adjustments have also played a crucial role in providing a safety net. Rapid population decline can easily undermine the foundation of regional agricultural development. Faced with this risk, the northeastern region—serving as a cornerstone of national food security—has triggered a strong institutional response. Local governments have responded by scaling up intergovernmental transfer payments—including enhanced subsidies for high-standard farmland development and expanded capital expenditures on irrigation infrastructure rehabilitation and climate-resilient disaster mitigation—to sustain critical public goods in depopulating rural areas. This externally coordinated fiscal intervention, anchored in a precautionary governance framework, compensates for the erosion of local water governance capacity resulting from labor attrition and private investment withdrawal, thereby functioning as a pivotal short-to-medium-term policy instrument for attenuating the adverse effects of demographic contraction on agricultural water security.

4.3.5. Robustness Analysis

To more comprehensively and accurately reflect the impact of population decline on agricultural water resource carrying capacity, and to avoid biased results caused by the selection of spatial weight matrices and measurement methods for the dependent variable, we select the nested matrix of economic geography distance weights and the inverse square of geographical distance weight matrix to replace the reverse geographical distance weight matrix, and use principal component analysis to re-measure the comprehensive index of agricultural water resource carrying capacity, conducting robustness tests on the full sample (results shown in Table 9). The signs and significance levels of the core explanatory variables and other control variables are largely consistent with the results obtained under the reverse geographic distance weight matrix in the previous analysis, leading to similar conclusions. Therefore, the regression results can be considered robust.

Table 9. Robustness check.

Variable	(1) Economic Geography Nested Matrix		(2) Inverse of the Squared Distance Matrix		(3) Change the Calculation Method	
	Main	Wx	Main	Wx	Main	Wx
<i>Shrink</i>	−0.049 ***	−0.493 ***	0.043 **	−0.124 *	−0.771 ***	5.9419 ***
<i>Spatial – rho</i>		0.329 ***		0.565 ***		0.6131 ***
<i>Variance – sigma</i>		0.002 ***		0.000 ***		0.0234 ***
<i>Controls</i>		YES		YES		YES
<i>Observations</i>		476		476		476

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5. Conclusions and Recommendations

5.1. Conclusions

First, grounded in the dual imperatives of sustained population decline across Northeast China and the strategic priority of national food security, this study quantifies the intensity of population contraction through a refined, multi-dimensional index applied to balanced panel data from 34 prefecture-level administrative units in Northeast China over the period 2010–2023. Second, based on the DPSIR model comprising five dimensions—driving forces, pressures, states, impacts, and responses—we established an evaluation system for agricultural water resource carrying capacity and clarified the logical mechanisms between population decline and agricultural water resource carrying capacity. Finally, we estimate a spatial Durbin model to rigorously identify the direction, magnitude, and spatial spillover effects of population decline on agricultural water resource carrying capacity, while simultaneously quantifying the mediating effects of human capital endowment and fiscal intervention intensity.

Second, heterogeneity analysis reveals that the impact of population decline on agricultural water resource carrying capacity is spatially stratified across Northeast China and exhibits a nonlinear threshold effect contingent upon regional developmental stage. Regionally, the impact of population decline on agricultural water resource carrying capacity varies significantly across Heilongjiang, Jilin, and Liaoning provinces. Among them, Heilongjiang Province exhibits the strongest negative effect of population contraction, indicating that its agricultural water resource system is most sensitive to population loss. Jilin Province also showed a significant negative impact, but the absolute value of its coefficient was notably smaller than that of Heilongjiang Province, indicating a certain degree of resilience in terms of agricultural mechanization substitution, agricultural socialized services, and policy cushioning. In contrast, Liaoning Province displays a qualitatively distinct response: population decline is associated with a statistically significant positive effect on agricultural water resource carrying capacity, indicating adaptive reallocation rather than systemic stress. On the other hand, from the perspective of the evolution in contraction intensity, mild contraction has generated a significant positive “dividend effect” on agricultural water resource carrying capacity by squeezing out hidden surplus labor in agriculture and prompting intensive allocation of production factors. However, once the critical point is crossed and the economy enters a phase of severe contraction, the absolute depletion of core labor will lead to systemic breakdowns in agricultural water infrastructure, thereby generating an extremely pronounced negative inhibitory effect. This indicates that the impact of population decline on agricultural water resource carrying systems is not a single, linear disruption, but rather determined by multiple factors including regional resource endowments, institutional regulatory capacity, and the stage of contraction evolution.

Finally, in terms of transmission pathways, population decline does not affect agricultural water resource carrying capacity through a single linear channel, but primarily

operates via the mechanisms of human capital and fiscal intervention. Human capital and fiscal interventions to some extent mitigate the negative impacts of population decline, indicating that improving the quality of agricultural workers, strengthening the capabilities of agricultural operators, and increasing fiscal support can help alleviate the impact of population decline on the agricultural water resource carrying system. Overall, the impact of population decline on agricultural water resource carrying capacity exhibits pronounced complexity and structural heterogeneity—its magnitude and direction are contingent upon the functional coordination among critical determinants, particularly human capital endowment and policy coherence.

5.2. Suggestions

First, anchor policy design in the non-negotiable imperative of national food security and implement regionally differentiated coordinated governance frameworks for population dynamics and water resource management. Within the strategic framework of the Northeast China Grain Production Base, province-specific interventions must be calibrated to heterogeneity in agricultural production systems, biophysical resource endowments, and institutional governance capacity: As a major grain-producing region experiencing the most pronounced negative impacts of population decline, Heilongjiang Province should prioritize the stable enhancement of agricultural water resource carrying capacity as its core objective. It must strengthen policy coordination in cultivating agricultural labor, maintaining and managing farmland irrigation infrastructure, and optimizing factor allocation efficiency to prevent the weakening of production support systems due to population outflow; Jilin Province should focus on enhancing agricultural production organization capabilities, with priority given to addressing the shortcomings in resource governance caused by population decline; and Liaoning Province, with its relatively strong economic foundation, can explore transformation pathways for efficient water resource utilization amid population decline. By implementing differentiated policies to promote regional coordinated development and avoiding a one-size-fits-all governance approach, it can strengthen the northeastern defense line for national food security.

Second, incorporate population decline management and agricultural water resource conservation into the top-level design of the Northeast Revitalization Strategy and the Rural Revitalization Strategy. In the process of promoting integrated urban–rural development, guide urban areas to radiate and drive upgrades in rural agricultural infrastructure, improve supporting systems for agricultural water resource utilization, and mitigate the negative impacts of population decline on agricultural production. Strengthen the innovation system for modern agricultural water-saving technologies, accelerate the promotion of efficient and low-carbon agricultural technologies such as water-saving irrigation and smart agriculture, and simultaneously improve supporting policy tools including talent attraction and development, financial subsidies, and technical training. Promote a green agricultural production model focused on “water conservation and quality improvement,” achieving a positive interaction between water resource carrying capacity and agricultural development under conditions of population decline. Third, establish a governance system that coordinates talent empowerment with fiscal support. On one hand, it is essential to fully leverage the “reservoir” and cushioning effects of human capital by intensifying the training of high-quality farmers, improving mechanisms for retaining local talent, and strengthening grassroots agricultural technical teams, thereby offsetting the shortfall in quantity with the “quality dividend” of human capital. On the other hand, fiscal intervention should be made more precise by directing agricultural financial support toward areas experiencing significant population decline, prioritizing funding for the renewal of farm-

land irrigation infrastructure, water-saving upgrades, and subsidies for grassroots water management personnel, while establishing a long-term funding guarantee mechanism.

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Institutional Review Board Statement: Measures for Ethical Review of Biomedical Research Involving Humans (National Health Commission of China, 2016), social science studies employing anonymous questionnaires and not collecting sensitive personal data are exempt from mandatory ethical review. This determination was confirmed prior to the commencement of the study. The research employed anonymous survey methods and did not involve clinical trials, the collection of sensitive personal information, or any biomedical procedures. The study adhered to the ethical principles set forth in the Declaration of Helsinki and complied with all applicable local regulations concerning research ethics and academic integrity.

Informed Consent Statement: All participants were fully informed of the study's purpose, the assurance of their anonymity, how their data would be used, and the absence of any foreseeable risks associated with participation. Participation was voluntary and based on verbal informed consent, which is a standard and widely accepted procedure for this type of social science research.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy and ethical restrictions related to the survey participants.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AWS	Agricultural water carrying capacity
Shrink	Population shrinkage
HCL	Level of human capital
Fis	Fiscal intervention
Urb	Urbanization rate
GDP	Level of economic development
TWR	Total water resources
LII	Labor intensity
PS	Cropping structure

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