Spatial Patterns and Evolutionary Trends of Agricultural Grey Water Footprint Intensity in the Yellow River Basin (Postprint)

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Abstract

Agricultural water pollution management is crucial for alleviating water resource crises and promoting regional sustainable development. Using Agricultural Grey Water Footprint Intensity (AGWFI), which comprehensively considers both agricultural grey water footprint and economic development level, to represent agricultural pollution levels, we measured the AGWFI of 112 prefecture-level cities (prefectures, leagues) in the Yellow River Basin from 2012 to 2021, comprehensively analyzed the spatial pattern and evolution trend of AGWFI in the Yellow River Basin, and employed quantile regression method to explore its influencing factors. The results show that: (1) From 2012 to 2021, the AGWFI of the entire Yellow River Basin and its upper, middle, and lower reaches all decreased significantly, with the decline magnitude in the upper reaches being substantially greater than that in the middle and lower reaches. (2) From 2012 to 2021, the AGWFI in the Yellow River Basin exhibited a distribution pattern of high in the west and low in the east; the AGWFI Gini coefficients of the entire basin and its upper, middle, and lower reaches were all relatively large and showed an upward trend, with intra-regional differences and inter-regional differences being the main sources; AGWFI transfer paths primarily occurred between adjacent grades. (3) The level of agricultural economic development had a significantly negative impact on the AGWFI of the entire Yellow River Basin and its upper, middle, and lower reaches, while both the proportion of primary industry output value and the degree of agricultural water resource utilization exhibited significant positive effects. The research findings can provide scientific reference for formulating targeted agricultural water pollution management measures in the Yellow River Basin.

Full Text

Spatial Pattern and Evolutionary Trend of Agricultural Grey Water Footprint Intensity in the Yellow River Basin

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Abstract: Effective management of agricultural water pollution is essential for alleviating water resource crises and promoting regional sustainable development. This study employs Agricultural Grey Water Footprint Intensity (AGWFI), which integrates agricultural grey water footprint and economic development levels to represent agricultural pollution intensity. We calculated AGWFI for 112 prefecture-level cities in the Yellow River Basin from 2012 to 2021, comprehensively analyzed its spatial patterns and evolutionary trends, and examined influencing factors using quantile regression. Results show: (1) AGWFI across the entire Yellow River Basin and its upper, middle, and lower reaches significantly decreased from 2012 to 2021, with the upper reaches experiencing a substantially greater decline than the middle and lower reaches. (2) AGWFI exhibited a west-high, east-low distribution pattern. The Gini coefficients for the basin overall and its sub-regions were relatively large and showed an upward trend, with intra-regional and inter-regional disparities being the primary sources. Transfer pathways mainly occurred between adjacent levels. (3) Agricultural economic development level had significantly negative effects on AGWFI across the basin and all sub-regions, while the proportion of primary industry output value and agricultural water resource utilization degree showed significant positive effects. These findings provide scientific references for formulating targeted agricultural water pollution management measures in the Yellow River Basin.

Keywords: agricultural grey water footprint intensity; spatial pattern; evolution trend; influencing factors; Yellow River Basin

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Water resources are crucial for regional agricultural production, economic growth, and sustainable development. With rapid societal development, water crises such as resource shortages and quality degradation have become increasingly prominent. It is projected that by 2025, over half of the global population will face water scarcity, with more than 1.7 billion people in severe water stress. Additionally, more than 80% of wastewater worldwide is discharged without effective treatment, causing severe water pollution and posing enormous challenges to drinking water safety. Agricultural production accounts for approximately 70% of global water resource development and utilization and represents a major source of water pollution. Therefore, accurately and reasonably evaluating the negative impacts of agricultural production on water resources is essential for alleviating water shortages.

Traditional water resource environmental assessments have primarily focused on water quality as the pollution evaluation standard, often neglecting the impact of pollution on water quantity. To address this limitation, Hoekstra proposed the "grey water footprint" theory, which quantifies water pollution through the volume of freshwater required for dilution, thereby integrating both water quality and quantity considerations. This approach has been widely applied in water environmental pollution assessments. As grey water footprint theory and methods have matured, increasing research has utilized it to evaluate agricultural pollution levels. Current studies on agricultural grey water footprint primarily focus on calculation methods, spatiotemporal characteristics, and influencing factor analysis at national, provincial, municipal, and basin scales. Some scholars have also calculated grey water footprints for specific crops such as corn and sugarcane. However, existing research mainly uses total agricultural grey water footprint to assess water pollution from agricultural production, which cannot accurately reflect regional agricultural pollution intensity pressure on local aquatic ecosystems.

Grey water footprint intensity, expressed as the ratio of total grey water footprint to local GDP, incorporates economic factors and provides a more comprehensive examination of regional water pollution conditions than grey water footprint alone. Agricultural Grey Water Footprint Intensity (AGWFI) can be expressed as the ratio of total agricultural grey water footprint to local agricultural GDP, reflecting agricultural production's water pollution intensity from an economic perspective. A smaller AGWFI value indicates less water pollution per unit of agricultural economic output, representing higher efficiency of agricultural grey water footprint. Compared with agricultural grey water footprint, AGWFI can more objectively reveal regional agricultural water pollution levels. However, dedicated research on AGWFI remains relatively scarce.

Existing studies have examined spatiotemporal characteristics of agricultural grey water footprint in different regions. For instance, Kong et al. investigated the spatial distribution patterns of China's agricultural grey water footprint, while Xu et al. analyzed spatial agglomeration characteristics, finding that China's agricultural grey water footprint primarily exhibited high-high and low-high clustering patterns. Zhang et al. examined spatial correlation and agglomeration of provincial grey water footprint intensity in China from 2004 to 2017. Cheng et al. comprehensively analyzed distribution characteristics, spatiotemporal differences, and spatial agglomeration of agricultural grey water footprint. These studies primarily employed spatial autocorrelation methods and parametric models such as Gini coefficient and Theil index, which are susceptible to interference from unknown parameters and insufficient in revealing dynamic evolutionary characteristics and long-term transfer trends of spatial distributions. In contrast, Kernel density estimation and Markov chain analysis can effectively overcome these limitations. Kernel density estimation uses non-parametric models to avoid unknown parameter interference on sample data, providing intuitive and dynamic distribution patterns to reveal AGWFI evolution. However, it offers limited internal dynamic information and cannot reveal long-term transfer trends. Markov chain analysis examines state transition probabilities over time, enabling in-depth investigation of long-term transfer trends and effectively compensating for this limitation. Currently, comprehensive applications of Kernel density estimation and Markov chain analysis to examine dynamic evolutionary characteristics and long-term transfer trends of agricultural grey water footprint and its intensity remain relatively rare.

Influencing factors of agricultural grey water footprint are complex and diverse. Most studies employ methods such as the Generalized Divisia Index Method (GDIM) and Logarithmic Mean Divisia Index (LMDI) to identify key drivers. Chen et al. used the STIRPAT model to analyze factors affecting agricultural grey water footprint efficiency, finding agricultural economic effects to be the most critical driver. Fu et al. decomposed grey water footprint efficiency in the Yangtze River Basin into five driving factors, revealing that economic effects and capital deepening effects promoted efficiency. However, these methods overlook differential impacts of influencing factors across regions with varying agricultural grey water footprint levels. Panel quantile regression models, by examining regression coefficients at different quantiles of the dependent variable, can more comprehensively reflect driving factor impacts, yielding more reliable conclusions. Currently, panel quantile regression is widely applied in carbon emissions, environmental taxes, and ecosystem service values, but its application in analyzing influencing factors of agricultural grey water footprint intensity remains limited.

The Yellow River Basin serves as a critical ecological barrier and economic zone in China. With rapid industrialization and urbanization, water pollution in the basin has intensified, becoming a major obstacle to ecological protection and high-quality development. The basin' s grain and meat production accounts for approximately one-third of national output, generating substantial agricultural pollutants that strongly constrain water environmental quality improvement. This study comprehensively analyzes spatial patterns and evolutionary trends of AGWFI in the Yellow River Basin from 2012 to 2021 using Gini coefficient, Kernel density estimation, and Markov chain methods, and explores influencing factors through panel quantile regression modeling to provide scientific references for agricultural water pollution governance.

1.1 Study Area Overview

The Yellow River originates from the Bayan Har Mountains on the Qinghai-Tibet Plateau, flowing through nine provinces (autonomous regions) including Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong, with a total length of 5,464 km and a drainage area of 7.95×10^{5} km^2. The basin lies in temperate zones with suitable climate and fertile soil, making it an important grain production base in China. Excessive fertilizer application has created enormous pressure on regional water resources and environment. Additionally, improper discharge of livestock breeding pollutants has further exacerbated water resource pressures.

Considering data availability and geographical unit continuity, this study excluded Golog Tibetan Autonomous Prefecture, Yushu Tibetan Autonomous Prefecture, and Haixi Mongolian and Tibetan Autonomous Prefecture in Qinghai Province, ultimately selecting 112 prefecture-level cities within the Yellow River Basin as study objects (Fig. 1). The study divides the basin into upper, middle, and lower reaches, using Hekou Town in Inner Mongolia and Taohuayu in Henan Province as boundaries between upper-middle and middle-lower reaches, respectively.

1.2 Methodology

1.2.1 Agricultural Grey Water Footprint Calculation Following relevant studies, the Yellow River Basin' s agricultural grey water footprint is divided into planting and livestock breeding components. The planting grey water footprint refers to fertilizer and pesticide applications that, after crop absorption, enter surface water through runoff and leaching, causing water pollution. The livestock breeding grey water footprint refers to untreated animal manure and urine that severely pollute water bodies. Total nitrogen (TN) and chemical oxygen demand (COD) are the main pollutants from planting and livestock breeding, respectively, and are used for calculations.

The agricultural grey water footprint is calculated as follows:

$$AGWF = GWF_{pla} + GWF_{bre}$$

where $AGWF$ is the agricultural grey water footprint (m^3), GWF_{pla} is the planting grey water footprint (m^3), and GWF_{bre} is the livestock breeding grey water footprint (m^3).

$$GWF_{pla} = \frac{L_{pla} \times A_p}{C_{max(TN)} - C_{nat(TN)}}$$

where L_{pla} is the TN pollution load entering water bodies from planting (t), A_p is the fertilizer leaching rate, $C_{max(TN)}$ is the maximum allowable concentration of TN in surface water ($mg \cdot L^{-1}$), and $C_{nat(TN)}$ is the natural background concentration of TN in surface water ($mg \cdot L^{-1}$).

$$L_{pla} = \alpha \times Fert_N$$

where $Fert_N$ is the application amount of nitrogen fertilizer and compound fertilizer converted to pure nitrogen (t), and α is the nitrogen leaching rate, determined as 7% based on literature.

$$GWF_{bre} = \sum_j \frac{L_{bre,j}}{C_{max(COD)} - C_{nat(COD)}}$$

where $L_{bre,j}$ is the COD load from livestock breeding (t), $C_{max(COD)}$ is the maximum allowable concentration of COD in surface water ($\mathrm{mg \cdot L^{-1}}$), and $C_{nat(COD)}$ is the natural background concentration of COD in surface water ($\mathrm{mg \cdot L^{-1}}$).

$$L_{bre,j} = N_j \times T_j \times (h_j \times D_j \times \alpha_j + u_j \times E_j \times \beta_j)$$

where j represents cattle, sheep, pigs, and poultry; N_j and T_j are the quantity and breeding cycle of j, respectively; h_j and u_j are the daily manure and urine excretion amounts of j ($\mathrm{kg \cdot d^{-1}}$); D_j and E_j are the pollutant contents per unit of manure and urine of j ($\mathrm{g \cdot kg^{-1}}$); and α_j and β_j are the loss coefficients of pollutants from manure and urine of j.

1.2.2 Agricultural Grey Water Footprint Intensity Calculation AGWFI represents the agricultural grey water footprint per unit of agricultural economic output, calculated as:

$$AGWFI = \frac{AGWF}{AGDP}$$

where $AGWFI$ is agricultural grey water footprint intensity ($\mathrm{m^3 \cdot yuan^{-1}}$), $AGWF$ is agricultural grey water footprint ($\mathrm{m^3}$), and $AGDP$ is regional agricultural gross output value (yuan). A larger AGWFI value indicates more severe pollution per unit of agricultural output.

1.2.3 Dagum Gini Coefficient The Dagum Gini coefficient, proposed by Dagum, decomposes overall disparity into intra-regional and inter-regional contributions, effectively addressing subgroup overlap issues. The total disparity (G) can be decomposed into intra-regional disparity contribution (G_w), inter-regional disparity contribution (G_{nb}), and transvariation intensity contribution (G_t):

$$G = G_w + G_{nb} + G_t$$

The formulas are as follows:

$$G = \frac{1}{2n^2\bar{x}} \sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{i=1}^{n_j} \sum_{m=1}^{n_h} |x_{ji} - x_{hm}|$$

$$G_{jj} = \frac{1}{2n_j^2\bar{x}_j} \sum_{i=1}^{n_j} \sum_{m=1}^{n_j} |x_{ji} - x_{jm}|$$

$$G_{jh} = \frac{1}{n_j n_h(\bar{x}_j + \bar{x}_h)} \sum_{i=1}^{n_j} \sum_{m=1}^{n_h} |x_{ji} - x_{hm}|$$

$$G_w = \sum_{j=1}^{k} G_{jj} d_j a_j$$

$$G_{nb} = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} d_{jh} (p_{jh} - q_{jh}) a_{jh}$$

$$G_t = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} d_{jh} (q_{jh} - p_{jh}) a_{jh}$$

where k is the number of regions; n is the number of prefecture-level cities; n_j (n_h) is the number of cities in region j (h); x_{ji} (x_{hm}) is the AGWFI of city i (m) in region j (h) ($\mathrm{m}^3 \cdot \mathrm{yuan}^{-1}$); $\bar{x}_j$ ($\bar{x}_h$) is the mean AGWFI in region j (h) ($\mathrm{m}^3 \cdot \mathrm{yuan}^{-1}$); G_{jj} is the Gini coefficient of region j; G_{jh} is the Gini coefficient between regions j and h; d_j (d_h) is the proportion of cities in region j (h); a_j (a_h) is the share of AGWFI in region j (h); F_j (F_h) is the cumulative density distribution function; d_{jh} is the relative impact of AGWFI between regions j and h; p_{jh} is the probability that AGWFI in region j is greater than in region h; and q_{jh} is the probability that AGWFI in region h is greater than in region j.

1.2.4 Kernel Density Estimation Kernel density estimation is a non-parametric method for analyzing spatial distribution imbalances. It reveals absolute disparity distribution characteristics through density curve position, shape, and other information:

$$f(x) = \frac{1}{Mh} \sum_{i=1}^{M} K\left(\frac{x_i - x}{h}\right)$$

where $f(x)$ is the probability density function; x_i is the AGWFI of city i ($\mathrm{m}^3 \cdot \mathrm{yuan}^{-1}$); h is the bandwidth (a smaller bandwidth yields less smooth but more precise curves); M is the number of cities; and K is the Gaussian kernel function.

1.2.5 Markov Chain Analysis Traditional Markov chain is a discrete-time, discrete-state stochastic process. This study constructs a traditional Markov transition probability matrix to explore AGWFI evolutionary characteristics:

$$Q = \begin{pmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ q_{n1} & q_{n2} & \cdots & q_{nn} \end{pmatrix}$$

where Q is the Markov transition probability matrix and q_{ij} is the probability of a city transitioning from type i in year t to type j in year $t+1$.

1.2.6 Panel Quantile Regression Panel quantile regression effectively excludes extreme value interference and does not require normally distributed data. It provides more comprehensive and reliable results by examining regression coefficients at different quantiles:

$$Q_{Y_{it}}(\tau_k|X_{it}) = \alpha_i + \beta(\tau_k)X_{it}$$

where Y_{it} is the AGWFI of city i in period t; $Q_{Y_{it}}(\tau_k|X_{it})$ is the conditional quantile function; X_{it} is the explanatory variable matrix; α_i is the city-specific constant term; and $\beta(\tau_k)$ is the influence coefficient at quantile τ_k.

The estimation formula is:

$$\hat{\beta}(\tau_k) = \min_{\beta} \sum_{i=1}^{m} \sum_{t=1}^{h} w_k \rho_{\tau_k} [Y_{it} - \alpha_i - \beta(\tau_k)X_{it}]$$

where m is the number of cities; h is the number of years; w_k is the weight for quantile k; τ_k is the specific quantile value; and ρ_{τ_k} is the loss function.

Based on literature and data availability, this study selects five representative indicators as potential influencing factors of AGWFI: agricultural economic development level, agricultural water resource utilization degree, primary industry output share, grain yield, and crop planting area (Table 1).

Table 1 Influencing factors of AGWFI

Influencing Factor	Variable Definition
Agricultural Economic Development Level	Per capita agricultural gross output value
Agricultural Water Resource Utilization Degree	Ratio of agricultural water use to total water resources
Primary Industry Output Share	Proportion of primary industry output in GDP

Influencing Factor	Variable Definition
Grain Yield	Total grain production
Crop Planting Area	Total sown area of crops

1.3 Data Sources

The study period spans 2012-2021. Agricultural water use and total water resources data were obtained from provincial Water Resources Bulletins. Nitrogen fertilizer and compound fertilizer application amounts (converted to pure nitrogen), livestock inventory and slaughter numbers, crop planting area, grain yield, and other relevant data were sourced from the China Environmental Statistics Yearbook, China Rural Statistical Yearbook, provincial Statistical Yearbooks, and city-level National Economic and Social Development Statistical Bulletins. Missing data for some years were interpolated linearly. Regional GDP and agricultural gross output values were adjusted to constant 2012 prices. Livestock breeding cycles, daily excretion amounts, pollutant contents, and loss coefficients were obtained from the Technical Report on Pollution Survey of Large-scale Livestock and Poultry Farming in China. Maximum allowable concentrations and natural background concentrations of TN and COD in surface water were based on Class III water quality standards in the Environmental Quality Standards for Surface Water (GB 3838-2002).

2 Results

2.1 Calculation of AGWFI in the Yellow River Basin

The overall AGWFI in the Yellow River Basin decreased rapidly from 2012 to 2016, then entered a gradual decline phase from 2017 to 2021 (Fig. 2). AGWFI in the upper, middle, and lower reaches all showed downward trends, consistent with the basin-wide pattern. The upper reaches experienced the largest decline at 46.70%, followed by the middle reaches at 40.79%, while the lower reaches showed a more moderate decline of 26.44%. Additionally, AGWFI in the upper reaches remained significantly higher than in the middle and lower reaches, likely related to local economic development levels. The average annual AGWFI values for the upper, middle, and lower reaches were 1.15 $m^3 \cdot yuan^{-1}$, 0.63 $m^3 \cdot yuan^{-1}$, and 0.33 $m^3 \cdot yuan^{-1}$, respectively, with corresponding agricultural GDPs of 1.63$×10^{11}$ yuan, 3.30$×10^{11}$ yuan, and 1.15$×10^{11}$ yuan. The relatively lagging economic development in the upper reaches may result in insufficient resource investment in agricultural production, lack of adequate agricultural infrastructure, and limited modern agricultural technology support, leading to higher pollutant generation per unit of agricultural economic benefit compared to the middle and lower reaches.

Fig. 2 [Figure 2: see original paper] AGWFI in the Yellow River Basin and its upper, middle, and lower reaches from 2012 to 2021

2.2 Spatial Patterns and Differences of AGWFI

2.2.1 Spatial Distribution Characteristics Using ArcGIS 10.8 natural breaks method, AGWFI values were classified into five levels: low (0.246–0.728 $m^3 \cdot yuan^{-1}$), relatively low (0.729–1.094 $m^3 \cdot yuan^{-1}$), medium (1.095–1.702 $m^3 \cdot yuan^{-1}$), relatively high (1.703–2.982 $m^3 \cdot yuan^{-1}$), and high (2.983–12.544 $m^3 \cdot yuan^{-1}$). The spatial distribution showed a clear west-high, east-low pattern. Low-level AGWFI areas were mainly distributed in eastern cities (Weihai, Yantai, Qingdao), central cities (Taiyuan, Xi' an, Yangquan), and southwestern cities (Chengdu, Neijiang, Meishan). High and relatively high AGWFI areas were concentrated in western regions including Aba Tibetan and Qiang Autonomous Prefecture, Gannan Tibetan Autonomous Prefecture, and Garzê Tibetan Autonomous Prefecture (Fig. 3). The distribution revealed significant internal imbalances in the Yellow River Basin. In 2012, the numbers of cities in low, relatively low, medium, relatively high, and high AGWFI levels were 24, 35, 24, 21, and 8, respectively, accounting for 21.43%, 31.25%, 21.43%, 18.75%, and 7.14%. By 2021, low-level cities increased substantially to 68 (60.71%), while relatively low and medium levels decreased to 33 (29.46%) and 11 (9.82%), respectively. Relatively high and high-level cities remained at 0, indicating that AGWFI transfer pathways primarily shifted from relatively low and medium levels to low levels.

Fig. 3 [Figure 3: see original paper] Spatial distribution of AGWFI in the Yellow River Basin

2.2.2 Spatial Differences and Decomposition The Dagum Gini coefficient was used to analyze spatial differentiation characteristics of AGWFI (Fig. 4). At the overall basin level, internal differences were substantial, with a mean Gini coefficient of 0.4163, showing a fluctuating upward trend from 0.3368 in 2012 to 0.4536 in 2021. All sub-regions showed increased Gini coefficients, with the upper reaches exhibiting the largest growth (13.33%), followed by the middle reaches (9.44%), and the lower reaches (1.69%). AGWFI levels in the upper reaches were significantly higher than in the middle and lower reaches, primarily due to extreme values in Aba, Gannan, and Garzê prefectures that expanded internal disparities in the upper reaches.

Inter-regional Gini coefficients were all larger than intra-regional coefficients, with a mean value of 0.4509. The degree of spatial divergence between regions showed an increasing trend from 2012 to 2021, with the gaps between upper-lower reaches and upper-middle reaches growing most significantly at 28.22% and 21.80%, respectively. Decomposition results showed that intra-regional disparity contribution was the largest source of overall basin differences, remaining stable at a mean of 45.09%. Inter-regional disparity contribution ranked second, showing a fluctuating upward trend from 36.38% to 45.09%, becoming the largest contributor by 2021. Transvariation intensity contribution was smallest, decreasing from 21.88% to 13.65%. These results indicate that intra- and inter-regional disparities are the main sources of AGWFI inequality, while transvariation intensity contributes less.

Fig. 4 [Figure 4: see original paper] Difference of AGWFI and its contribution rates in the Yellow River Basin from 2012 to 2021

2.3 Evolutionary Trend Characteristics of AGWFI

Kernel density estimation reveals dynamic evolutionary features of AGWFI (Fig. 5). Distribution curves shifted leftward overall, indicating declining AGWFI trends. Patterns in the upper reaches resembled the basin overall, while middle and lower reaches distributions differed significantly. The middle reaches showed more pronounced leftward shifts, indicating greater decline magnitude than the lower reaches. Distribution shapes showed rising peaks with unchanged width for the basin overall and upper reaches, while the middle and lower reaches exhibited both peak increases and width expansion, indicating growing internal absolute differences.

All regions showed right-tail characteristics, with tails in the upper reaches being most prominent, suggesting cities with significantly high AGWFI values. Regarding polarization, the basin overall and the upper and lower reaches showed single-peak distributions, while the middle reaches displayed an additional side peak that gradually increased over time, indicating strengthening bipolar polarization.

Markov chain analysis examined long-term transfer trends by classifying AGWFI into four types based on quartiles: low (0.2460–0.7280 $m^3 \cdot yuan^{-1}$), medium-low (0.7281–0.9945 $m^3 \cdot yuan^{-1}$), medium-high (0.9946–1.3765 $m^3 \cdot yuan^{-1}$), and high (1.3766–12.5440 $m^3 \cdot yuan^{-1}$). Transition probability matrices (Table 2) show diagonal values exceeding non-diagonal values, indicating high probabilities of maintaining original states ("self-locking" and path dependence). Low-value regions showed extremely stable states with maintenance probabilities $ $0.90.

Table 2 Markov transition probability matrix of AGWFI in the Yellow River Basin

Transfer probabilities primarily occurred between adjacent levels (low to medium-low, medium-low to medium-high, medium-high to high). Cross-level transfers (e.g., low to high) showed zero probability, except for minimal probabilities from relatively high to low levels in the overall basin (0.01) and upper reaches (0.02). This demonstrates that AGWFI transfer pathways are completely confined to adjacent levels without cross-level jumps, indicating a gradient effect and solidified spatial pattern. The limited spillover effects of low-AGWFI cities on neighboring high-AGWFI cities suggest insufficient inter-city coordinated development.

2.4 Influencing Factors of AGWFI

Panel quantile regression results are presented in Table 3. Agricultural economic development level showed significantly negative effects on AGWFI across the basin and all sub-regions, with greater impacts at higher quantiles. This aligns with Chen et al.' s findings that agricultural economic development promotes grey water footprint efficiency. High-AGWFI regions are generally agriculturally underdeveloped, where economic growth can generate scale effects that significantly suppress AGWFI increases.

Primary industry output share showed significantly positive effects on AGWFI, with stronger impacts at higher quantiles. This indicates that reducing primary industry proportion is more effective in high-AGWFI regions. Crop planting area showed significantly negative effects on basin-wide and upper reaches AGWFI, with greater inhibition in high-AGWFI regions. However, its effects on the middle and lower reaches were limited.

Agricultural water resource utilization degree showed significantly positive effects across all regions, with decreasing impact coefficients at higher quantiles for the overall basin. This suggests the effect is weaker in high-AGWFI regions than in low-AGWFI regions. Grain yield showed significantly positive effects on AGWFI in the upper reaches but limited effects on the middle and lower reaches and the overall basin.

Table 3 Panel quantile regression results for AGWFI influencing factors

Robustness was verified using OLS regression (Table 4). Results were consistent with panel quantile regression, confirming the reliability of findings.

Table 4 OLS regression results

3 Discussion

AGWFI in the Yellow River Basin showed a continuous declining trend from 2012 to 2021. This resulted from both substantial reductions in agricultural grey water footprint—benefiting from policies such as the 2015 Water Pollution Prevention and Control Action Plan—and stable agricultural economic growth that funded eco-friendly technology development. Previous research indicates that most regions in the Yellow River Basin have achieved strong decoupling between agricultural grey water footprint and economic growth.

The spatial pattern of AGWFI showed significant non-equilibrium characteristics, with the upper reaches being key areas for reducing basin-wide AGWFI. Two main points support this: (1) The west-high, east-low distribution features AGWFI values in the upper reaches far exceeding those in the middle and lower reaches; (2) Gini coefficients in the upper reaches are substantially higher than in other regions, as confirmed by Guo et al. using Theil index methods. Therefore, the upper reaches should be the focus for reducing intra- and inter-regional AGWFI disparities.

For the upper reaches, recommendations include strengthening agricultural infrastructure, optimizing industrial structure, prioritizing low-pollution green organic agriculture, reducing high-pollution livestock activities, and developing secondary and tertiary industries to decrease primary industry share. For the middle and lower reaches with lower AGWFI, focus should be on efficient water resource utilization and allocation, promoting water-saving irrigation technologies, adjusting planting structures, and developing unconventional water sources through projects like South-North Water Transfer.

Given limited spillover effects of low-AGWFI cities on high-AGWFI neighbors, enhanced cooperation in pollution reduction and water resource management across the upper, middle, and lower reaches is needed. The middle and lower reaches should provide financial and technical support to the upper reaches to leverage spatial spillover effects and achieve coordinated AGWFI reduction.

4 Conclusions

This study analyzed AGWFI spatial patterns, evolutionary trends, and influencing factors in the Yellow River Basin from 2012 to 2021, yielding three main conclusions:

1. **Temporal trends**: Basin-wide AGWFI decreased rapidly from 2012–2016, then gradually from 2017–2021. All sub-regions showed declining trends, with the upper reaches experiencing the largest decline (46.70%), followed by the middle reaches (40.79%), and the lower reaches (26.44%).

2. **Spatial patterns and evolution**: AGWFI exhibited a west-high, east-low distribution with values in the upper reaches far exceeding those in the middle and lower reaches. Gini coefficients were relatively large and increasing, with intra-regional and inter-regional disparities as primary sources. Transfer pathways occurred mainly between adjacent levels, with minimal cross-level transfers in the overall basin and upper reaches, while transfers in the middle and lower reaches were completely confined to adjacent levels.

3. **Influencing factors**: Agricultural economic development significantly suppressed AGWFI, with stronger effects in high-AGWFI regions. Primary industry output share and agricultural water resource utilization degree significantly promoted AGWFI, with the former having greater effects in high-AGWFI regions and the latter having greater effects in low-AGWFI regions. Crop planting area and grain yield had limited effects.

These findings provide scientific references for targeted agricultural water pollution management in the Yellow River Basin.

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Note: Figure translations are in progress. See original paper for figures.